AUTOMATED MOOD BOARDS:
ONTOLOGY-BASED SEMANTIC IMAGE RETRIEVAL

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To Ummi, Fatimah and Ali.

ABSTRACT

The main goal of this research is to support concept designers' search for inspirational and meaningful images in developing mood boards. Finding the right images has become a well-known challenge as the amount of images stored and shared on the Internet and elsewhere keeps increasing steadily and rapidly. The development of image retrieval technologies, which collect, store and pre-process image information to return relevant images instantly in response to users' needs, have achieved great progress in the last decade.

However, the keyword-based content description and query processing techniques for Image Retrieval (IR) currently used have their limitations. Most of these techniques are adapted from the Information Retrieval research, and therefore provide limited capabilities to grasp and exploit conceptualisations due to their inability to handle ambiguity, synonymy, and semantic constraints. Conceptual search (i.e. searching by meaning rather than literal strings) aims to solve the limitations of the keyword-based models.

Starting from this point, this thesis investigates the existing IR models, which are oriented to the exploitation of domain knowledge in support of semantic search capabilities, with a focus on the use of lexical ontologies to improve the semantic perspective. It introduces a technique for extracting semantic DNA (SDNA) from textual image annotations and constructing semantic image signatures. The semantic signatures are called *semantic chromosomes*; they contain semantic information related to the images.

Central to the method of constructing semantic signatures is the concept disambiguation technique developed, which identifies the most relevant SDNA by measuring the semantic importance of each word/phrase in the image annotation. In addition, a conceptual model of an ontology-based system for generating visual mood boards is proposed. The proposed model, which is adapted from the Vector Space Model, exploits the use of *semantic chromosomes* in semantic indexing and assessing the semantic similarity of images within a collection.

To improve the retrieval performance, the model uses a data fusion technique for further enhancement by combining it with traditional keyword-based search. The evaluation using data sets of annotated images shows that the proposed SDNA approach outperforms traditional keyword, statistical and concept-based methods. The creation of automated mood boards demonstrates the applicability of the proposed approach, which are used by concept designers in the early stages of design.

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A dream does not become reality through magic; it takes sweat, determination and hard work. May every sunshine bring us closer to our dreams.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF PUBLICATIONS

S.A. Fadzli and R. Setchi. 2012. Concept-based Indexing of Annotated Images Using Semantic DNA. Journal of Engineering Application of Artificial Intelligence, ISSN 0952-1976, 10.1016/j.engappai.2012.02.005.

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LIST OF ABBREVIATIONS

CBIR	-	Content-based Image Retrieval
CTA	-	Conjoint Trend Analysis
HIT	-	Human Intelligence Task
IDF	-	Inverse Document Frequency
IR	-	Information Retrieval
KB	-	Knowledge Bases
LSI	-	Latent Semantic Indexing
MAP	-	Mean Average Precision
MTurk	-	Amazon Mechanical Turk
NLP	-	Natural Language Processing
POS	-	Part Of Speech
SDNA	-	Semantic DNA
TBIR	-	Text-based Image Retrieval
TF	-	Term Frequency
VSM	-	Vector Space Model

CHAPTER 1:
INTRODUCTION

1.1 MOTIVATION

Concept designers often create visual designs of the future. These designs might be impractical, non-operational and too expensive, but they frequently dominate show rooms and trade shows with their style and unconventional look. Their mission is to convey a visual representation of an idea, mood, style or new technology before it is incorporated in an industrial design (Liu and Boyle, 2009; Setchi et al., 2011). Research indicates that the originality and creativity of concept designers could be stimulated by using sources of inspiration, i.e. the conscious use of previous designs (Eckert and Stacey, 2000; Ward et al., 2008). Sources of inspiration help designers define the context of their new designs, inform their creation and reflect on their emotional impact. By observing and interpreting sources of inspiration, creative designers form mood boards with images, which express their emotions, inspire their creativity and help them communicate ideas to colleagues and clients (McDonagh et al., 2002; Tovey et al., 2003; McDonagh et al., 2005; Bouchard et al., 2007).

This research is motivated and inspired by the TRENDS project (Setchi and Bouchard, 2010; Setchi et al., 2011), which is a collaborative research project involving partners from four European countries specialised in automotive design, content-based retrieval of images, search engines, semantic-based systems, human-computer interaction and software design. The interviews conducted with the designers during the early phase of the TRENDS project (Westerman et al., 2007) reveal that most of them use mood boards as part of the early design process to express the moods and emotions needed in the design elements.

The design process normally starts with a design brief, which outlines the design intent and is often deliberately vague. It is followed by a concept development stage, which aims to produce an initial representation of the design concept. Sketches are used to focus and guide non-verbal thinking, externalise and refine ideas (Tovey et al., 2003). In the automotive industry and other areas of design where visual identity and originality are important, designers often create mood boards displaying lifestyle images which help them find suitable semantic adjectives and create palettes of colours, shapes and forms (McDonagh et al., 2002; Tovey et al., 2003; McDonagh et al., 2005; Bouchard et al., 2007; Coley et al., 2007).

Several research studies confirm the importance of communicating design ideas between designers by referencing sources of inspiration (Eckert and Stacey, 2000; Coley et al., 2007; Liu and Boyle, 2009). Designers often use mood boards to express their ideas using a medium that can be shared with other people in order to illustrate visually the style, which they are pursuing. As Lucero and Martens (2005) claim, most designers agree that mood boards are commonly accepted as an important design technique. They view it as "*the use of a unique language to describe regions in the space of possible designs*".

Mood boards are defined as: "*a visual or multi-sensorial (texture, movement, sound) means of communication which may have value in assisting communication and inspiration during any design process*" (McDonagh and Denton, 2005). A mood board is a type of board design, which consists of images, text, texture, fabric or any samples of objects in an arrangement chosen by the creator. The process of developing a mood board depends on the culture, history and experiences of the creator because he/she uses their existing knowledge and inspiration to decide what images to use to represent the concept. This may lead to different interpretations of mood boards by different people.

There are two types of mood boards: physical and digital mood boards. Physical mood boards are assembled by gluing different types of analogue media (pictures from magazines, photographs, colours, fabric, etc.) on a board (Figure 1 (a)). Using physical tools (i.e. scissors, glue) for making mood boards is very natural, and the result remains (physically) available at all times. Digital mood boards (Figure 1 (b)) are created by collecting the same type of media, but in digital format and assembling them on computers with the help of graphic software (i.e. Adobe Photoshop, Adobe Illustrator, Freehand, etc.). The use of digital technology to create mood boards provides access to a very large database of pictures (the internet) and a wealth of editing functionalities (Lucero and Martens 2005; Martens et al. 2006).

Several studies (Garner and McDonagh, 2001; Edwards et al., 2009) show that design students often approach the mood boards' creation tasks with a cold, dispassionate resolution. The long and tedious task of mood board development often brings students to frustration when it is not taken seriously. At the same time, the majority of students agree that when the mood boards are successfully designed and used, the creative insight of their creators shines out.

(a) (b)

Figure 1.1: Physical (a) and digital (b) mood boards (Edwards et al., 2009).

Eckert and Stacey (2000) stress that many of the failures in design projects are caused by weak communication between team members. It is important to have a mutual understanding of the goal and concept of the design project. Crow (2003) states that "*the meaning of any sign is affected by who is reading that sign*", and the symbolic imagery in mood board, in particular, adheres to this idea. In design teams, the individuals within the team may come from various backgrounds and cultures, and may not have a shared global visual language with abstract images. McDonagh and Denton (2005) have shown that student designers, having viewed identical mood boards, use different adjectives to describe what they feel the board represents but the mood depicts one of similar nature across the students. The authors have also concluded that the mood board created by male and female subjects clearly convey the perceptions of masculinity and femininity corresponding to the creator's gender.

Mood board can also funnel a designer's thinking and be unconsciously constraining. The aforementioned interviews in the TRENDS project (Westerman et al., 2007) confirm that designers require specific resources for the task of developing mood boards including good quality, large size images, a dominant image for central focus which strongly ties in with the concept and a mixture of resources (texture, object, fabric, etc.).

Most successful mood boards are considered expensive and time consuming to construct (Garner and McDonagh, 2001; Lucero and Martens, 2005; Edwards et al., 2009). They normally consist of a collection of images and photographs fixed to a board for the purpose of presentation. Sometimes relevant objects or art installations are integrated to create three-dimensional representations. Photographs, images from magazines or the internet, samples of fabrics or colour swatches, drawings, industrial and natural objects such as wire and leaves, and abstract graphic experiments in texture, colour or form are commonly juxtaposed on a board.

Searching through vast collections of digital images is often a problem for concept designers. The retrieval of digital images mostly depends on how accurate and effective the search is and how accurate the image annotations are. Good progress has been achieved in the last decade with the development of search engine technologies, which collect, store and pre-process images to return relevant content in response to users' needs. However, users often need to put considerable effort to achieve their goals. Most current Information Retrieval (IR) methods are based on keywords, which provide limited capabilities to grasp and exploit the conceptualisations involved in defining user needs and image descriptions.

Several researchers from the IR community have been exploring the idea of conceptual search, aiming to solve the limitation of keyword-based models (Deerwester et al., 1990; Baeza-Yates and Ribeiro-Neto, 1999; Manning et al., 2008). Some of them employ statistical methods that use co-occurrence of terms, and are therefore not semantic-based as the relations between the terms are extracted from term frequencies without considering polysemy and synonymy. The idea of supporting high-level conceptual understanding of content and queries has been considered in the IR field since the early 1980s (Croft, 1986). Until recently, it had been one of the most important focuses of the semantic web community since its emergence in the late 1990s.

The semantic web aims to provide a set of languages with a certain level of conceptual understanding of the information objects involved and to enable software programs to draw inferences over statements in the language (Sycara et al., 2011). Ontologies are envisioned as key elements to represent knowledge that can be understood, used and shared among distributed applications and agents. They offer potential to overcome the limitation of keyword-based search in the IR context.

The main goal of this research is to develop an ontology-based IR model, which supports semantic search for relevant images in developing mood boards. To achieve the goal, this research proposes a novel approach to IR, which incorporates semantic signatures in the image indexing and searching. These semantic signatures represent high-level conceptual understanding of the images. To cope with large-scale information sources, an adaptation of the classic vector space model (VSM) is proposed. This research also introduces a method for extracting semantic signatures, which is based on a lexical ontology.

1.2 RESEARCH OBJECTIVES

The overall aim of this research is to develop an ontology-based IR model, which indexes and searches for images, semantically relevant to user queries, and contribute to the generation of automated mood boards. The individual objectives are:

(i) To produce a technique for extracting semantic signatures from textual image annotations, which preserves their semantic properties.

(ii) To research the engineering of a conceptual model of an ontology-based system for aiding the generation of semantic mood boards.

(iii) To research the method for indexing images using their semantic signatures.

(iv) To research the method for measuring the semantic similarity between images within a collection using its semantic index.

(v) To propose a hybrid model, which combines ontology-based and keyword--based models using a data fusion technique.

1.3 ORGANISATION OF THE THESIS

Chapter 2 reviews technologies from the area of information retrieval and image retrieval, which support the development of semantic indexing and searching. This chapter also reviews semantic distance measures, advanced IR evaluation measures and related research studies that have attempted to solve the problem of semantic search in IR. The achievements and limitations of these studies are also discussed.

Chapter 3 addresses research objectives (i) and (ii). It introduces the knowledge resource used in this research, and explains the process of extracting semantic DNA and constructing semantic signatures of textual image annotations based on the knowledge resource. It also describes the conceptual model developed as well as the knowledge resource and data collection used in the experiments throughout this research.

Chapter 4 focuses on research objectives (iii). It starts by describing the semantic indexing process developed using semantic signatures in a vector space model. Image and annotation examples are used to illustrate the indexing process. The chapter then explains the SDNA disambiguation technique proposed, which considers the co-occurrences frequency of all SDNA in the SDNA set. Crowdsourcing is promoted in this chapter as a new evaluation method for word-sense disambiguation.

Chapter 5 addresses research objective (iv) by outlining the semantic search process using semantic similarity in vector space model.

Chapter 6 focuses on research objectives (v). A data fusion technique is introduced to enhance the search results by combining SDNA-based with traditional keyword search. IR based and crowdsourcing methods are used to evaluate the mood boards generated.

Chapter 7 concludes the thesis by summarising the contributions made, the conclusions achieved and discussing future research directions.

CHAPTER 2:
LITERATURE REVIEW

All forms of digital information available in documents, images and videos require human intelligence to understand and process. To a computer, this information is just data, which it can store, display, compress, and transmit to other computers. It can sometimes extract useful information, such as keywords, meta-data or features. However, it cannot understand what the information means in the same way as a human might understand it. A computer that can understand and present semantic information to a human could be claimed to be an intelligent machine. Starting with a brief introduction to information retrieval, this chapter reviews available semantic technologies, which could support concept designers' capability to search for inspirational and meaningful images in developing mood boards.

2.1 INFORMATION RETRIEVAL

Information retrieval (IR) is one of the oldest research areas in information science. Its goal is to provide users with documents (including non-textual documents such as images and multimedia objects) that satisfy their information need. Therefore, a good IR system should retrieve only those documents that are relevant to the user needs, excluding unnecessary data. This section provides a brief introduction to the IR field of research.

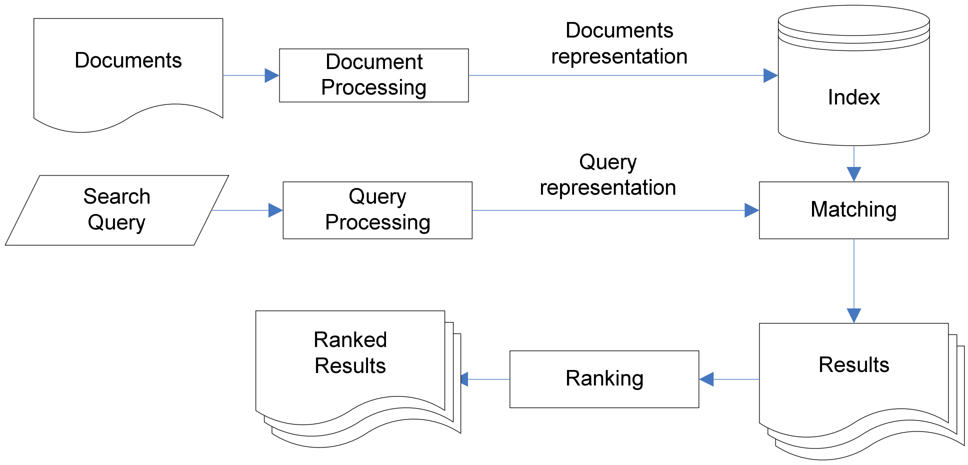


Figure 2.1: The General Information Retrieval Process

Information retrieval systems have been evolved and improved a lot since their first emergence in the 1950s. However, the core process shown in Figure 2.1 has remained unchanged. The most important aspects of the IR process are described below (Baeza-Yates and Ribeiro-Neto, 1999; Manning et al., 2008).

- **User Interface:** Although it seems insignificant at first, the user interface is one of the most important aspects in IR. The design of the user interface is a trade-off between user-friendliness and performance. Simple and relaxed interfaces are easier to use at the cost of ambiguous queries. Complex and powerful interfaces provide more detailed and precise query formulation but are cumbersome and time-consuming for the end-user. Some of the widely used user-interface methods are reviewed by Baeza-Yates and Ribeiro-Neto (1999) for traditional IR and by Uren et al. (2007) for semantic retrieval. Keyword-based, natural language-based, form-based and graphic-based interfaces are some of the commonly used interface methods in the literature. A keyword-based interface is used in this research to achieve maximum usability for the end-user.

- **Document Processing:** Document processing is an essential part of the IR systems for two reasons. First, it optimises the query performance and improves the response times considerably by converting them into an easily accessible representation of documents (called indexed form) for the use by the IR system. Secondly, similar to the query-processing phase, a number of text processing tasks are performed during this phase, which further improves the performance.

- **Query Processing:** The raw query submitted by the user should be processed before searching. Usually, the query is transformed into an internal form that the system can interpret. This usually involves several Natural Language Processing (NLP) tasks, including stemming, part-of-speech tagging, compound recognition, de-compounding, chunking, word sense disambiguation and other application specific tasks. These tasks are also performed during the indexing phase of this research to achieve consistent matching.

- **Matching:** In this phase, the query terms are matched against the document index. All documents that contain the occurrences of the query terms are retrieved. Depending on the application, the retrieval can produce even partially matched documents.

- **Ranking:** The documents retrieved in the previous step are given scores according to the match between the query terms and the documents. The documents are sorted according to this score, so that the most relevant documents are presented to the user at the top of the retrieval list. The ranking process is highly dependent on the IR model. As highlighted in the following sections, some IR models do not support ranking and all documents retrieved are considered to be equally important.

The Boolean model (Manning et al., 2008), Vector Space Model (Salton, 1971) and probabilistic model are the classical examples of models used for computing query answers and relevance ranking. In the Boolean model, documents and queries are represented as a set of index terms. In the Vector space model, documents and queries are represented as vectors in a *t*-dimensional space, while in the basic probabilistic model, documents and queries representations are based on the probability theory.

2.1.1 Boolean Model

The Boolean model, also known as the 'exact match' model, is a simple retrieval model based on set theory and Boolean algebra. In the Boolean model (Manning et al., 2008), documents are represented by 'bags of words'. Queries are represented as Boolean expressions of terms, where terms are combined with the operators AND, OR, and NOT.

For example, assume the query $q = text\ AND\ (image\ OR\ NOT(audio))$. The query is composed of three different terms: 'text', 'image' and 'audio'. Figure 2.2 shows the set of documents containing those terms. Given the query q, the subset of documents that fulfil the query are:

i. those containing the three terms: (1,1,1),
ii. those containing the word 'text', but neither 'image' nor 'audio': (1,0,0),
iii. those containing the word 'text' and 'image', but not 'audio': (1,1,0),

where each of the components is a binary-weighted vector associated with the terms ('text', 'image' and 'audio').

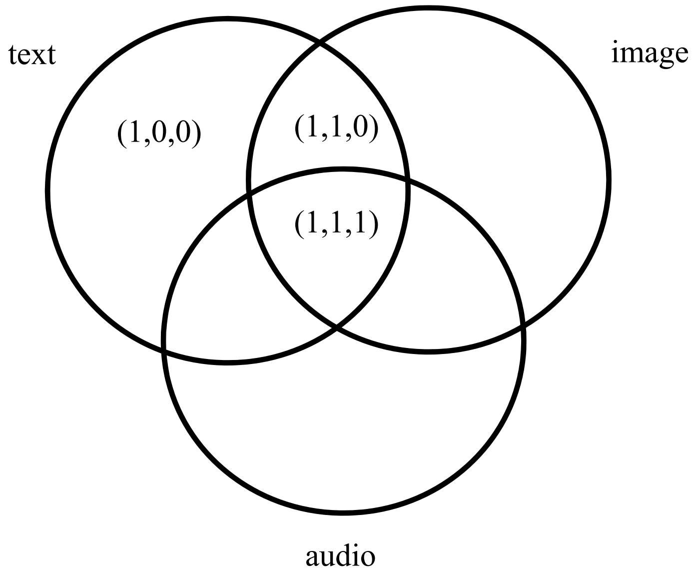


Figure 2.2: The set of documents containing the term 'text', 'image' and 'audio'.

Due to its simplicity, the Boolean model was adopted by many of the early commercial retrieval systems. One of the problems with Boolean retrieval is that in large document collections the number of documents, which match the query, can be also large, often bigger than a user is willing to review. In order to address this problem, conventional search engines rank query results according to their relevance to the query. Due to its binary criterion (i.e. document is treated as either relevant or not relevant), therefore it does not provide a proper basis for ranking the retrieved results. Most widely used models for estimating the document-query relevance are probabilistic and vector space models.

2.1.2 Probabilistic Model

In the probabilistic model (Crestani et al., 1998; Manning et al., 2008), the documents are ranked according to the probability of being relevant to the user information need, as expressed by the user query. According to the Probability Ranking Principle (PRP) (Robertson, 1977):

> "*If the probabilities are estimated as accurately as possible on the basis of whatever data have been made available to the system for this purpose, the overall effectiveness of the system to its user will be the best that is obtainable on the basis of those data.*"

According to this model, given a query q and a collection of documents D, a subset R of D is assumed to exist, which contains exactly the relevant documents to q (the ideal answer set). The probabilistic retrieval model then ranks documents based on the probability of belonging to this set, which is noted as $P\ (R \mid q,\ d_j)$, where d_j is a document in D. The degree of similarity of a document d_j to a query q_i is measured as the probability of d_j to be part of the subset R of relevant documents for q, as given by (Baeza-Yates and Ribeiro-Neto, 1999):

$$\mathrm{sim}(d_j, q) = \frac{P(R\,|d_j)}{P(\neg R\,|d_j)} = \frac{P(d_j|R) \times P(R)}{P(d_j|\neg R\,) \times P(\neg R\,)} \tag{2.1}$$

Where $\neg R$ denotes the set of non-relevant documents, $P(R\,|d_j)$ is the probability of d_j being relevant to the query q, and $P(\neg R\,|d_j)$ is the probability of d_j being non relevant to q. Assuming that $P(R)$ and $P(\neg R\,)$ are the same for all documents in the collection, and considering the term independence assumption $P(d_j|R) = \prod_{i=1}^{t} P(t_i|R)$, then:

$$\mathrm{sim}(d_j, q) \sim \frac{P(d_j|R) \times P(R)}{P(d_j|\neg R\,) \times P(\neg R\,)} \sim \frac{\prod_{i=1}^{t} P(t_i|R)}{\prod_{i=1}^{t} P(t_i|\neg R)} \tag{2.2}$$

$P(t_i|R)$ is the probability that the index term t_i is present in a document randomly selected from the set R, and $P(\neg t_i|R)$ otherwise, while $P(t_i|\neg R)$ is the probability that the index term t_i is present in a document randomly selected from the set $\neg R$, and $P(\neg t_i|\neg R)$ otherwise. Taking logarithms, recalling that$P(t_i|R) + P(\neg t_i|R) = 1$, and ignoring factors, which are constant for all documents in the context of the same query, finally:

$$\mathrm{sim}(d_j, q) \sim \sum_{i}^{t} \left(w_{i,q} \times w_{i,j} \times \log \frac{P(t_i|R)}{1 - P(t_i|R\,)} + \log \frac{1 - P(t_i|\neg R)}{P(t_i|\neg R\,)} \right) \tag{2.3}$$

Where $w_{i,q}$={0,1} indicates the absence or presence of term t_i in the query q and $w_{i,j}$={0,1} indicates the absence or presence of term t_i in the document d_j.

Drawbacks of the probabilistic models are the need to guess the initial separation of documents into relevant and non-relevant sets, and the fact that the classic model does not take into account the frequency of index terms in the documents (it only considers a binary weight of 1 or 0).

Despite these shortcomings, variations of the probabilistic model have led to the development of one of the most successful ranking models, Okapi BM25 (Beaulieu et al., 1997; Robertson et al., 1998; Robertson and Walker, 1999; Jones et al., 2000). Given a query *q*, the score of a document *d* is:

$$score(q,d) = \sum_{i=1}^{n} IDF(w_i) \cdot \frac{(k_1 + 1) \cdot f(w_i, d)}{k_1 \cdot \left(1 - b + b \frac{|d|}{avgdl}\right) + f(w_i, d)} \tag{2.4}$$

Where $q=\{w_1, w_2, w_3 \ldots w_n\}$, $IDF(w_i)$ is the inverse document frequency of word w_i, $f(w_i,d)$ is the word frequency of w_i in document *d*, |*d*| is the length of document *d*, and *avgdl* is the average document length in the collection. k_1 and *b* (having default values of 1.2 and 0.75 respectively) are the tuning parameters which could be used to optimise the function performance.

2.1.3 Vector Space Model

In the Vector Space Model (VSM), documents and queries are represented as vectors in a common vector space, in which there is an axis for each term (Salton, 1971). The

VSM recognises the drawbacks of binary weights and employs a framework in which partial matching is considered. This is accomplished by assigning non-binary weights to index the terms in queries and documents. These term's weights are used to compute the degree of similarity between each document and the user query. The VSM takes into consideration documents, which partially match the query terms by sorting the retrieved documents in decreasing order. In VSM, the degree of similarity of a document d_j to a query q is estimated as the correlation between the vectors d_j and q. This correlation can be quantified, for instance, by the cosine of the angle between the two vectors (Baeza-Yates and Ribeiro-Neto, 1999; Manning et al., 2008) using (2.5):

$$sim(\vec{q},\vec{d_j}) = \frac{\vec{q}\cdot\vec{d_j}}{|\vec{q}|\times|\vec{d_j}|} = \frac{\sum_{i=1}^{t} w_{i,q}\times w_{i,j}}{\sqrt{\sum_{i=1}^{t} {w_{i,q}}^2}\times\sqrt{\sum_{i=1}^{t} {w_{i,j}}^2}} \quad (2.5)$$

Since $w_{i,j}>0$ and $w_{i,q}>0$, $sim(d,q)$ varies from 0 to 1. Therefore, instead of predicting whether a document is relevant or not, the VSM ranks the documents according to their degree of similarity to the query. In other words, a document might be retrieved even if it matches the query only partially. To reduce the recall size, a threshold can be established on $sim(q,d_j)$ to retrieve only documents with a degree of similarity above the threshold.

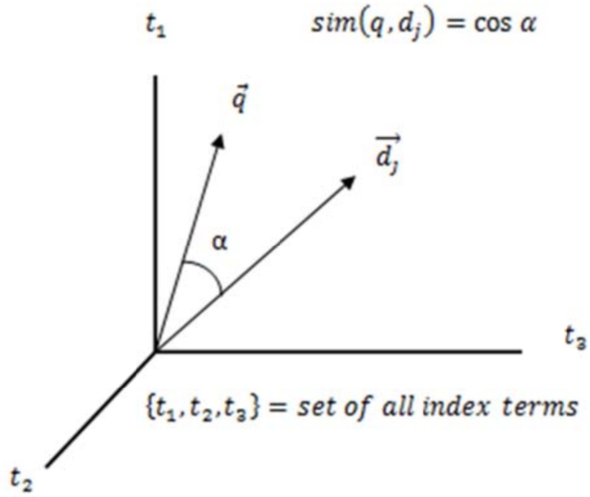


Figure 2.3: The Cosine of α Used as a Measure of the Correlation Between Vectors d_j and q.

The term weighting system is another open issue in the VSM. Extensive research and experimentation on this problem have been carried out in the past 50 years where different measures (based on the statistics of term occurrences) have been proposed to weight the term importance (Moffat and Zobel, 1998). The main goal of a term weighting system is to improve the effectiveness of document retrieval. One of the most popular measures is *tf-idf* (term frequency - inverse document frequency). The *tf-idf* weighting scheme assigns high weights to terms that appear frequently but within a small number of documents. The weight of a term i in a document j, w_{ij} is defined as (Baeza-Yates and Ribeiro-Neto, 1999; Manning et al., 2008):

$$\mathrm{w_{i,j}} = \mathrm{tf_{i,j}} \times \mathrm{idf_i} = \frac{\mathrm{freq_{i,j}}}{\mathrm{m_j}} \times \log\frac{|\mathrm{D}|}{\mathrm{n_i}} \tag{2.6}$$

Where $freq_{i,j}$ is the frequency of term t_i in document d_j, m_j is the total number of terms in document d_j, $|D|$ is the total number of documents in the system and n_i is the number of documents where term t_i appears. The term frequency factor, $tf_{i,j}$ measures how representative the term t_i is in describing the contents of the document d_j. The inverse document frequency, idf_i, measures whether the term is common or rare across all documents. It gives low weights to common terms that appear in many documents.

For example, consider a *query* = *internet, computer*; the document *d* is as follows:

> *The **Internet** is a global system of interconnected **computer** networks that use the standard **Internet** protocol suite to serve billions of users worldwide.*[1]

Assuming the *idf* for both words *internet* and *computer* are 5.5 and 2.5, and $m_d = 23$, the index term weights are:

$$w_{internet,q} = tf_{internet,q} \times idf_{internet} = \frac{2}{23} \times 5.5 = 0.4783$$

$$w_{computer,q} = tf_{computer,q} \times idf_{computer} = \frac{1}{23} \times 2.5 = 0.1087$$

Then the vectors that represent the query and the document are:

$$\vec{q} = (0, 0, 0, \dots, 1.0, 0, 0, \dots, 1.0, 0, 0, \dots, 0)$$

$$\overrightarrow{d_j} = (0, 0, 0, \dots, 0.4783, 0, 0, \dots, 0.1087, 0, 0, \dots, 0)$$

The most popular way to measure the similarity between two frequency vectors (raw or weighted) is to take their cosine. Let *x* and *y* be two vectors, each with n elements.

[1] http://en.wikipedia.org/wiki/Internet

$$x = \{x_1, x_2, \ldots., x_n\} \tag{2.7}$$

$$y = \{y_1, y, \ldots., y_n\} \tag{2.8}$$

The cosine of the angle between x and y can be calculated as follows:

$$\begin{aligned} \cos(x, y) &= \frac{\sum_{i=1}^{n} xi \cdot yi}{\sqrt{\sum_{i=1}^{n} xi^2 \cdot \sum_{i=1}^{n} yi^2}} \\ &= \frac{x \cdot y}{\sqrt{x \cdot y} \cdot \sqrt{x \cdot y}} \\ &= \frac{x}{|x|} \cdot \frac{y}{|y|} \end{aligned} \tag{2.9}$$

In other words, the cosine of the angle between two vectors is the inner product of the vectors, after they have been normalised to unit length. If *x* and *y* are frequency vectors for tokens, a frequent token will have a long vector and a rare token will have a short vector, yet the tokens might be synonyms. Cosine captures the idea that the length of the vectors is irrelevant; the important thing is the θ angle between the vectors.

The cosine ranges from -1 when the vectors point in opposite directions (θ is 180 degrees) to +1 when they point in the same direction (θ is 0 degrees). When the vectors are orthogonal (θ is 90 degrees), the cosine is zero. With raw frequency vectors, which necessarily cannot have negative elements, the cosine cannot be negative, but weighting and smoothing often introduce negative elements.

Other popular geometric measures of vector distance include Euclidean distance and Manhattan distance. Distance measures from information theory include Hellinger, Bhattacharya, and Kullback-Leibler. Bullinaria and Levy (2007) compared these five distance measures with the cosine similarity measure on four different tasks involving word similarity. Overall, the best measure was cosine. Other popular measures are the Dice and Jaccard coefficients (Manning et al., 2008).

A measure of distance between vectors can easily be converted to a measure of similarity by inversion (2.10) or subtraction (2.11).

$$\mathrm{sim}(x, y) = 1/\mathrm{dist}(x, y) \tag{2.10}$$

$$\mathrm{sim}(x, y) = 1 - \mathrm{dist}(x, y) \tag{2.11}$$

Several similarity measures are used in IR and lexical semantics systems (Lin, 1998; Lee, 1999; Weeds et al., 2004). According to Van Rijsbergen (2004), the difference in retrieval performance using different measures is insignificant.

Weeds et al. (2004) studied the linguistic and statistical properties of the similar words returned by various similarity measures and grouped the measures into three classes:

i. higher frequency selecting or high recall measures (cosine, Jensen-Shannon, alpha-skew, recall),
ii. lower frequency selecting or high precision measures (precision), and

iii. similar frequency selecting or high precision and recall measures (Jaccard, Jaccard+MI, Lin, harmonic mean).

Given a word w_i, if a higher frequency selecting measure is used to score its similarity with another word w_j, higher frequency words will tend to get higher scores than lower frequency words. If a low-frequency sensitive measure is used, there will be a bias towards lower frequency words. Similar frequency selecting methods prefer a word w_i that has approximately the same frequency as w_j. In their experiments on determining the compositionality of collocations using a distributional similarity measure, higher frequency selecting measures, including cosine, Jensen-Shannon and α-skew measures, achieve significantly better results than other classes (Weeds et al., 2004).

:

$$sim(\vec{q}, \vec{d_J}) = \frac{\vec{q} \cdot \vec{d_J}}{|\vec{q}| \times |\vec{d_J}|} = 0.1538 \tag{2.12}$$

2.2 IMAGE RETRIEVAL

The rapid introduction of digital cameras has led to a tremendous growth of digital collections and an increasing need to develop effective systems to help users search for digital images. According to Datta et al. (2008), approaches to image retrieval can be divided into three categories: (i) text-based image retrieval (TBIR) which uses textual features only, (ii) content-based image retrieval (CBIR) which uses visual features only, and (iii) composite approaches, which use both textual and visual features. Although content-based image retrieval (CBIR) and composite approaches (Rui et al., 1999; Datta et al., 2008) are used in many applications (i.e. query by example), it is often desirable and practical for the user to retrieve images using textual queries as opposed to example images.

2.2.1 Text-Based Approach

Digital images are usually associated with rich textual descriptions, which accompany them. Popular image web search engines (i.e. Google, Yahoo! and Bing) use TBIR in their image search engines. When a user inputs a keyword using a textual query to retrieve images, these systems return a list of ranked relevant images with text descriptions containing the keyword used in the query. The ranking score is obtained according to some similarity measurements between the query keyword and the textual features of the relevant images. However, the retrieval performance can be very poor, particularly when dealing with the contextual meaning of the words used in the descriptions. Computers do not understand the meaning of human language. This limits the ability of the computer to analyse and process text.

Traditional text-based image retrieval systems predominantly employ indexing techniques, which use keywords occurrences to identify important terms in annotations and the text accompanying the images. The keywords used to index the images are normally weighted to indicate their relative importance. As discussed in the previous section, several weighting functions have been proposed including statistical factors such as term frequency (TF), inverse document frequency (IDF), the product of TF and IDF (TF-IDF), and document length normalisation (Salton and McGill, 1986; Salton and Buckley, 1988; Fuhr and Buckley, 1991; Lee, 1995). However, most keyword-based indexing methods do not consider the semantic context of the documents/annotations. The relationship between words and concepts is considered a complex issue due to the use of synonyms (different words, same meaning) and homonyms (same word, different meaning).

2.2.2 Content-Based Approach

Content-based image retrieval (CBIR) uses image-processing techniques to extract low-level image features, and means for semantic interpretation of these features. However, the use of visual features on their own does not solve the problem of the semantic gap, i.e. the discrepancy between the low-level features contained in an image and its high-level description that is meaningful to the human mind (Smeulders et al., 2000; Boujemaa et al., 2001). A number of researchers work on narrowing down the semantic gap by combining CBIR with high-level semantics using various techniques including ontology associations (Mezaris et al., 2003; Ren et al., 2003), supervised and unsupervised machine learning (Chen et al., 2003; Vasconcelos, 2004) and relevance feedback (Lu et al., 2000; Doulamis and Doulamis, 2004). Eugenio et al. (2002) use low-level features to provide a semantic representation of the images based on combination of geometric shapes. Other approaches use semantic templates (Chang et al., 1998) and textual information on the Web to support high-level image retrieval (Feng et al., 2004).

2.2.3 Concept-Based Approach

Concept-based image retrieval is an alternative approach that combines text document retrieval with semantic technologies to analyse the annotation or text surrounding the image, and extract high-level concepts. Instead of using keywords only, it represents both the image and the query using concept representations, and performs retrieval in the concept space. The use of high-level concepts as dimensions in a vector space model reduces the dependency on specific terms used in the annotation and the query, which yields to a better retrieval performance (Styltsvig, 2006). This approach is capable of producing good results even when different words are used in the query and text annotation to communicate the same meaning. This also solves the synonymy and homonymy problem and increases recall. Similarly, if the correct concept is extracted to represent a polysemic word, non-relevant results could be eliminated which in addition increases precision.

In concept-based image retrieval, concepts are mapped to an existing knowledge base, which is populated with real-life concepts understandable by humans (Voorhees and Harman, 1999; Gauch et al., 2003). Alternatively, concepts can be automatically generated based on overlapping relations between terms or probabilities of term occurrences, which are not necessarily interpretable by humans (Hofmann, 1999; Yi and Allan, 2009). The former approach is preferable as it is better aligned with human understanding, which is the most important aspect in narrowing the semantic gap.

In recent years, the use of semantic technologies and metadata languages has expanded as they offer means for defining class terminologies with well-defined semantics and flexible data models for representing metadata descriptions (Hyvönen et al., 2002). In particular, controlled vocabularies, taxonomies, free text descriptions and annotations are employed to describe or classify the images in order to improve the retrieval. Other approaches rely on the use of ontologies to provide different views for navigation, and terminology for creating the metadata or the annotations of the images (Hyvönen et al., 2002; Dill et al., 2003; Zhang et al., 2006; Staab et al., 2008).

It must be noted, however, that different ontologies may not have the same degree of formality. Controlled vocabularies, dictionaries, thesauri, and taxonomies are some of the most lightweight ontology types widely used in annotations. These forms of vocabularies are not strictly formal and the annotations produced using them are normally pointers to terms in the dictionary, which can be used to improve the search by using synonyms, antonyms, hyponyms and hypernyms.

2.3 SEMANTICS

According to the Oxford English Dictionary (Dictionary, 2010), *semantics* is

> *"the branch of linguistics and logic concerned with meaning. The two main areas are logical semantics, concerned with matters such as sense and reference and presupposition and implication, and lexical semantics, concerned with the analysis of word meanings and relations between them."*

In this research, the term *semantics* is used in the context of the lexical semantics area, which is concerned, with the meaning of words, phrases, sentences, or any text in human language, and the study of such meaning. It is based on the study of how and what the words of a language denote (Pustejovsky, 1991), why they mean what they do, and where the interpretation came from. Words may either be taken to denote things or concepts, depending on their particular context. The units of meaning in lexical semantics are referred to in this research as word senses. The similarity between any two units of meaning is called semantic distance.

2.3.1 Semantic Distance

Semantic distance could be measured using semantic similarity and semantic relatedness. Semantic similarity is a subset of semantic relatedness, but both may be used interchangeably in certain contexts. Therefore, it is very important to define clearly the distinction between them. According to Fellbaum (1998), two words or concepts are considered to be *semantically similar* if there is a relation of type hyponymy, hypernymy, antonymy or troponymy between them. On the other hand, two words or concepts are *semantically related* if there is any lexical semantic relation between them including hyponymy, hypernymy, homonymy, polysemy, antonymy, meronymy and metonymy. Table 2.1 lists different types of semantic relation with their definition and examples.

Table 2.1: Examples of Semantic Relations

Semantic Relation	Description	Example
Hyponymy	Every X is a kind of Y	*Car* is a hyponym of *vehicle*
Hypernymy	Every Y is a kind of X	*Vehicle* is a hypernym of *car,* such that every *car* is a *vehicle*
Antonymy	X is the opposite of Y	*Happy* is antonym of *sad*
Troponymy	The activity X is doing Y in some manner	To *lisp* is a troponym of to *talk.*
Homonym	Two different concepts, X and Y are expressed using the same word	*Financial institution* and *edge of the river* are homonyms of *bank.*
Polysemy	The existence of several meanings of X	*Bank* is a polysemy word as it can represent *financial institution* or *edge of the river*.
Meronym	X is a part of Y	*Tyre* is a part of *car.*
Metonym	X is used to associate Y which is closely related	The *press* is a metonym of *newspaper industry*.

Semantically similar words or concepts usually share a number of common attributes. For example, consider '*cat*' and '*dog*'. They are both hyponyms of '*animal*'. They both have fur and four legs and could be categorised as pet animals. Therefore '*cat*' and '*dog*' are considered to be semantically similar. Another example of a semantically similar pair is '*lecturer*' and '*educator*'. The concept of '*educator*' is a hypernym of '*lecturer*', therefore they share attributes related to '*educator*'.

Different from semantic similarity, concepts that are semantically related may not have many attributes in common, but have at least one lexical semantic relation between them. For example, '*car*' and '*tyre*' are semantically related, as one is the meronym of the other.

2.3.2 Semantic Distance in Natural Language Processing

A large number of problems in NLP involve semantic distances. For example, machine translation systems must choose a translation in the target language that is semantically closest to the source language text. Paraphrases are pieces of text that can replace another text, identified by their semantically close attributes. Information retrieval involves the selection of documents semantically close in content to the search query terms. Document clustering is the grouping of semantically close pieces of text. Discovering word senses from their usage involves grouping the usages so that those in the same group are semantically close to each other whereas those in different groups are distant (where each such group represents a distinct sense).

Word sense disambiguation is the identification of the sense closest to the contextual meaning of the word. Spelling errors can be detected by identifying words that are semantically distant from their context and the existence of a spelling variant that is close (Hirst and Budanitsky, 2005). Word completion and prediction algorithms rank candidate words according to their semantic closeness to the word context. These are just some of the examples that show that semantic distance plays a key role in NLP. As the semantic distance measure between concepts can be extended to calculate the distance between larger units of language, such as phrases and documents, understanding and improving these measures will produce a significant impact on solving a number of NLP problems.

2.3.3 Human Estimation of Semantic Distance

Human intelligence can easily estimate the semantic distance between words and concepts, but the estimation varies across different individuals due to many factors such as life experience, education level, culture and environment. Rubenstein and Goodenough (1965) conducted a classic quantitative experiment with 51 human subjects who were asked to rate 65 English word pairs on a scale from 0.0 to 4.0 as per their semantic distance. The word pairs provided ranged from almost synonymous to totally unrelated. The subjects were asked to repeat the same process two weeks after the first experiment, and the new distance values had a Pearson's correlation r of 0.85 with the first one. Miller and Charles (1991) also conducted a similar study on 30 word pairs taken from the original Rubenstein and Goodenough pairs. These annotations had a high correlation ($r = 0.97$) with the mean annotations of Rubenstein and Goodenough (1965). Resnik (1995) repeated these experiments and found the inter-annotator agreement r to be 0.90. A few years later, Resnik and Diab (2000) conducted annotations of 48 verb pairs and found the inter-annotator agreement r to be 0.76 when the verbs were presented without context and 0.79 when the context was given.

The high agreement and correlation values suggest that humans are quite good and consistent at estimating the semantic distance of noun-pairs. However, annotating verbs and adjectives is harder. It should be noted here that even though the annotators were presented with word pairs and not concept pairs, it is reasonable to assume that they were annotated as per their closest senses. For example, most of the annotators identify the noun pair '*bank*' and '*interest*' as semantically related even though both words have more than one sense and many of the sense to sense combinations are unrelated, for example, the '*river bank*' sense of *bank* and the '*special attention*' sense of *interest*. Besides proving that humans can indeed estimate semantic distances, these datasets act as ‘gold standards’ to evaluate automatic distance measures. However, the lack of large amounts of data from human subject experimentation limits the reliability of this mode of evaluation.

2.4 SEMANTIC SEARCH

In general, there are three main types of semantic search, which automatically determines semantic similarity between queries and document keywords. They are characterised by the type and use of semantic knowledge representation:

- **Latent Semantic Analysis.** These models do not employ human-based language understanding methodologies. They use statistical models to identify groups of words that commonly appear together, and therefore describe the same reality.
- **Linguistic Conceptualisation**: These approaches make use of thesauri and taxonomies in order to enable computers to understand concepts in the same way humans do.
- **Ontology-based approaches:** Ontology-based approaches are characterised by the use of highly detailed conceptualisations in the form of ontologies and knowledge bases (KB). They provide formal descriptions of meaning needed to interpret user needs and content.

2.4.1 Latent Semantic Indexing

The potential relations between the keywords in the same documents are usually ignored in the traditional keyword-based approaches. The occurrence of the keyword in the document and in the collection are analysed to identify the importance of a keyword without considering the occurrence of other potentially related keywords. Latent Semantic Indexing (LSI), also referred to as Latent Semantic Analysis (LSA), solves this drawback by analysing the co-occurrence of keywords in both the documents and the collection as a whole. LSI considers documents that have many words in common to be semantically close, and documents with few words in common to be semantically distant. The method aims to take advantage of an implicit higher-order structure, or "semantic structure" in the association of terms with documents.

LSI uses singular value decomposition (SVD), a closely related technique to eigenvector decomposition and factor analysis (Landauer and Dumais, 1997) and the Vector Space Model (VSM) (Salton, 1971; Salton et al., 1975), which represents each document in a collection as a vector in a vector space. The large term-document matrix created is then decomposed into a set of, typically 50 to 150, orthogonal factors from which the original matrix can be approximated by a linear combination. More formally, a rectangular t×d (term×document matrix X) is decomposed as:

$$X = U\,S\,V \tag{2.13}$$

where U and V are represented in column orthonormal form and S is a diagonal matrix of singular values (Golub and Van Loan, 1996). If X is of rank r, then S is also of rank

r. Rapp (2003) describes truncated SVD as a noise reduction technique. Let S_k be the diagonal matrix formed from the top k singular values where $k<r$, and let U_k and V_k be the matrices produced by selecting the corresponding columns from U and V; the truncated matrix X_k can be formalised as:

$$X_k = U_k S_k V_k^T \tag{2.14}$$

where the matrix $U_k S_k V^T{}_k$ is the matrix of rank k that best approximates the original matrix X, in the sense that it minimises the approximation errors (Golub and Van Loan, 1996). Matrix X_k is a factorised version of the original matrix X, where the matrix U_k maps the row space of the original X into a smaller k-dimensional space, the matrix V_k maps the column space of the original X into the same k-dimensional space, while the diagonal matrix S_k specifies the weights in this reduced k-dimensional space. Matrix X_k is also dense, compared to the original matrix X which is very sparse in general.

Deerwester et al. (1990) explore the use of LSI to overcome the limitations of classic IR models regarding synonymy and polysemy. An initial experiment has found that, while the LSI method deals with the synonymy problem, it offers only a partial solution to polysemy. It helps with multiple meanings because the meaning of a word can be determined not only by considering other words in the document, but by other appropriate words in the query not used by the author of a particular relevant document. The drawback is that every term is represented as just one point in the space, so that a word with several highly distinct meanings (e.g. "bank") is represented as a weighted average of the different meanings. This could significantly affect the result performance when dealing with ambiguous words.

Dumais (1992) has investigated how LSI can be improved in the IR context by exploring the techniques that have been useful in standard vector-based retrieval methods such as differential term weightings, relevance feedback, and the selecting the number of dimensions for the reduced space. Regarding the first approach, performance increases dramatically up to the first 100 dimensions, where it reaches a maximum and slowly degrades after that point. It is around 30% better than the standard vector-based methods and varies according to the associational structure of terms with objects of the document set and the quality of the queries.

IDF and global entropy term weighting methods improve performance by an average of 30%. The combination of a local log and a global entropy weighting yields an improvement of 40%. With respect to relevance feedback, performance improves by an average of 67% when the first three relevant documents are used, and 33% when only the first relevant document is used.

2.4.2 Linguistic Conceptualisation

Linguistic conceptualisation aims to enhance traditional IR techniques using dictionaries such as WordNet and thesauruses such as the *Roget's Thesaurus*, which provide semantic information about words or phrases.

a. WordNet

WordNet is a machine-readable dictionary developed at Princeton University (Miller, 1995; Fellbaum, 1998). Although it is an electronic lexical database based on psycholinguistic principles, it has been used almost exclusively in the NLP area. It is a generic resource for various research groups around the world. It covers the vast majority of nouns, verbs, adjectives and adverbs from the English language. The words in WordNet are organised in sets of synonyms called synsets. Each synset represents a concept. WordNet has a large network of 155,287 words, organised in 117,659 synsets. There is a rich set of 206,941 relation links between words and senses (Princeton University, 2010). The use of WordNet for IR has been extensively explored in previous research in various tasks such as query and document disambiguation, the enrichment of queries with related semantic terms, and the comparison of queries with documents via conceptual distance measures.

Vorhees (1994) uses WordNet as a tool for query expansion. The experiments conducted are based on test collections from The Text REtrieval Conference (TREC)[2], a workshop series that provides the infrastructure for large-scale testing of text retrieval technology. All the terms in the query are expanded by a combination of synonyms, hypernyms and hyponyms. The weights of the words contained in the original query are set to 1, and a combination of values (e.g. 0.1, 0.3, 0.5, 1, and 2) is used in the query expansion terms. The SMART IR System (Salton, 1971) is used in the evaluation. This

[2] TREC is co-sponsored by the National Institute of Standards and Technology (NIST) and U.S. Department of Defense, started in 1992. Its purpose was to support research within the information retrieval community by providing the infrastructure necessary for large-scale evaluation of text retrieval methodologies.

method shows improvement on short queries only, with no significant improvement achieved for long queries. Richardson and Smeaton (1995) propose an approach to IR based on computing a measure of semantic distance between words, and using this distance to compute the similarity between queries and documents.

Mihalcea and Moldovan (2000) have developed a natural language interface system to an Internet search engine, which provides support for natural language and query expansion based on search disambiguation methods. This system uses WordNet for the disambiguation of keywords in the query rather than within the documents. This approach maps each keyword in the query to its corresponding semantic form and forms similarity lists for each sense of the words, pairing the word with its different senses. Then the pairs are searched on the Internet and the different senses are ranked by the number of retrieved hits. To refine the order of senses, a method called "semantic density" is used, which measures the number of common words within a semantic distance of two or more words, using WordNet's synsets' definitions or "glosses[3]". The results obtained by this system increase the precision and the percentage of correctly answered queries, while reducing the amount of text presented to the user. Shuang et al. (2004) proposed a similar approach with the extension of the use of phrases. They assume that phrases are more relevant than words and use them to compute the similarity between a query and a set of documents. When the sense of a query word is determined, its synonyms, hyponyms, compound words and the phrases contained in its definition are considered for possible addition to the query. The

[3] WordNet glosses are used to explain the synset's meaning including one or two examples with typical usage of the synset.

experimental results show that this approach yields an improvement between 23% and 31% over the best TREC 9, 10 and 12 collections for short queries (title only), without using Web data.

b. Roget's Thesaurus

The *Roget's Thesaurus* (Davidson, 2003) is a well-known resource mainly used to facilitate the expression of ideas and assist in literacy composition. In information retrieval, it is employed to expand search items with other closely related words. Different from a dictionary, which explains the meaning of words, *Roget's* groups words based on language expression (Roget, 1852). It has a well-established structure, where the words/phrases are grouped and linked by their meaning and associations. One of the advantages of *Roget's* is the ability to identify different meaning of words according to different contexts (polysemy).

The electronic version of the *Roget's Thesaurus* is publicly available from Project Gutenberg (Hart and Newby, 2003) since 1991. It was derived from the 1911 edition of the thesaurus. This version consists of 6 classes, 1035 headings and roughly 41,000 words. The electronic version has been supplemented with over 1,000 additional words that are not present in the original 1911 printed edition. Hart and Newby explained that, from 40,000 unique words contained in the original text, 12,000 are not recognized by a spell-checker. Most of them are foreign words (primarily Latin), and many are obsolete.

Roget's Thesaurus has been used in NLP as early as 1957 in various application including machine translation (Masterman, 1957; Jones, 1964), information retrieval (Driscoll, 1992; Mandala et al., 1998; Mandala et al., 1999), lexical cohesion of text (Morris and Hirst, 1991) and word sense disambiguation (Yarowski, 1992).

Morris and Hirst (1991) manually calculate the lexical cohesion of text, which they define as the result of chains of related words that contribute to the continuity of lexical meaning within texts. They use the fourth edition of *Roget's International Thesaurus* (Chapman, 1977). Stairmand (1994) continues the work by automating the process using the 1911 electronic version of *Roget's Thesaurus*. However, the result was poor due to the low quality of the 1911 electronic edition.

Yarowsky (1992) uses statistical models of *Roget's* headword to perform word sense disambiguation. The model was trained using a large corpus, which helps determine to which headword the given sense of word belongs. Other people who have used *Roget's* for word sense disambiguation include Patrick (1985), Sedelow and Mooney (1998) and Kwong (2001). A semantic similarity measure with good correlation with human judgement was achieved by McHale (1998) using the taxonomy of *Roget's International Thesaurus*, third edition.

The great potential of Roget's Thesaurus are not realised by NLP researchers because of the absence of its up to date digital version. The available electronic version of the 1911 edition is proven inadequate and cannot be used to solve current NLP problems. However, the recent availability of electronic version of the 2003 edition, which was enriched from the original 1911 edition, had enabled this research to utilise the richness of *Roget's* semantic relations.

2.4.3 Ontology-Based Approaches

The Semantic Web has emerged with the aim of helping machines to process information by enabling browsers or other software agents to find automatically, share and combine information in a consistent way. At the core of the Semantic Web technologies, ontologies are foreseen as key to representing knowledge that can be understood, used and shared by distributed applications and machines. This motivates research in ontology-based information retrieval.

Rocha et al. (2004) propose a search system that combines IR techniques with constrained spreading activation methods applied to domain ontology. The system focuses on applications where the user searches for ontology instances instead of searching for web pages. The query language proposed in this approach is based on keywords, whereby the main goal of the system is to map those keywords to an initial set of ontology entities, and expand the results by using spread activation techniques to find related concepts in the ontology. Zhang et al. (2005) propose an enhanced model that utilises both textual and semantic information for searching in semantic portals. The model extends the search capabilities of the existing methods and answers more complex search requests by employing a fuzzy Description Logic IR model, and using ontologies as background information. The portal uses formal queries modelled concepts in Description Logic. However, the use of formal queries makes it difficult to ordinary users to learn how to use unfamiliar formal language. To address this problem, Bernstein and Kaufmann (2006) introduce GINO, a guided input natural language ontology editor that allows users to edit and query ontologies in a language similar to English. It allows users to query using a guided input natural language similar to English, which is then translated to SPARQL statements. Users who are familiar with ontology editors can also edit elements of the ontology.

Chirita et al. (2005) explore the use of semantics for searching in the Windows OS desktop. Their research extracts information from the user activity log and information such as e-mails, folder structure, and Web cache, and then stores this context information explicitly as RDF metadata, and finally implements sophisticated semantic search functionalities on the desktop. A similar approach is also proposed by Davies et al (2004) which combines free text search with a capability to exploit RDF metadata in searching and browsing. This approach tries to improve search results by providing a traditional keyword search when not enough metadata are available.

The semantic-based image retrieval tool developed within the TRENDS project (Setchi and Bouchard, 2010, Setchi et al., 2011) tags images with a weighted set of concept numbers extracted by analysing web content (i.e. the text surrounding the images). The TRENDS algorithm uses concepts from two ontologies: a generic lexical ontology called *OntoRo* and a special ontology called Conjoint Trend Analysis (CTA). *OntoRo* is the lexical ontology based on the *Roget's Thesaurus*, which was mentioned in the previous section (Section 2.4.2(b)). While CTA is a domain specific ontology which are populated specifically for TRENDS algorithm. The weight of the concepts in TRENDS is calculated using (2.15):

$$w_{ck}(d_j) = \sum_{i=0}^{n} \left(k_{CTA} \cdot w_{tf-idf}(t_i, d_j) \cdot \frac{1}{C_k(t_i)} \right) \tag{2.15}$$

where $w_{ck}(d_j)$ is the weight of a concept C_k in a document d_j , k_{CTA} is a coefficient with two values: 1.5 (if concept C_k is domain-specific, i.e. it exists in the CTA ontology) or 1 (if the concept is not domain-specific and therefore not part of the CTA ontology), $w_{tf\text{-}idf}(t_i, d_i)$ is the *tf-idf* weight of a term t_i in a document d_j, and $C_k(t_i)$ is the number of concepts C_k the term t_i is related to.

The TRENDS tool has demonstrated good performance and scalability, and has been integrated in an industrial prototype with keyword-based indexing and content retrieval algorithms (Setchi et al., 2011). The concept-based search combined with content-based image retrieval and keyword-based search complements traditional methods by providing images with a degree of diversity and high inspirational value.

This algorithm however is considerably less efficient when dealing with short texts such as image annotations (Fadzli and Setchi, 2012). The lack of word disambiguation function and the extensive use of *tf-idf* weighting have led to some irrelevant concept numbers being tagged to images. Further analysis shows that $C_k(t_i)$ has a high impact on the concept weights as any concept related to terms which are less ambiguous (i.e. have a small number of senses) will most probably get high weighting.

2.5 EVALUATION METHODS

There are three types of evaluation for information retrieval systems (Baeza-Yates and Ribeiro-Neto, 1999). The first is functional evaluation, in which the specified system functionalities are tested. The second one is the performance evaluation. The most common measures of system performance are time and space (the shorter the response time, the smaller the space used, the better the system is considered to be). The third type is the retrieval performance evaluation. It assesses how well the IR system satisfies the information need of its users. There are two classes of retrieval performance evaluation: a) user-based, and b) system-based. The user-based retrieval performance evaluation measures the user's satisfaction with the system, while system-based retrieval performance evaluation focuses on how well the system can rank documents. User-based evaluation is in principle much more informative and useful but is extremely expensive and difficult. On the other hand, system-based retrieval performance evaluation is an abstraction of the retrieval process that allows experiments to control some of the variables that affect retrieval performance thus increasing the power of comparative experiments. They are much less expensive than user-based evaluations while providing more diagnostic information regarding system behaviour.

In system-based retrieval performance evaluation, researchers perform experiments on test collections to compare the relative effectiveness of different retrieval approaches using a number of evaluation measures. The test reference collection generally consists of a collection of documents, a set of sample queries, or a set of relevant documents (judgments), manually identified for each query. Given a retrieval strategy *S*, for each query the evaluation measure quantifies the similarity between the set of documents retrieved by *S* and the set of known relevant documents. This provides an estimation of the goodness of the retrieval strategy. The next sections give an overview of the most common evaluation metrics and tests collections used in system-based retrieval performance evaluation.

2.5.1 Recall and Precision

One of the most common retrieval performance evaluation used by the IR community is precision and recall (Manning et al., 2008). The relevance-based measures of recall and precision analyse the number of relevant documents retrieved from the document collection. Recall is the proportion of relevant documents retrieved from the collection:

$$\text{Recall} = \frac{\text{No. of documents retrieved and relevant}}{\text{No. of relevant document in the documents collection}} \qquad (2.16)$$

In other words, recall calculates the fraction of the relevant documents obtained from the collection. One of the difficulties in using this measure is to identify all relevant documents for every query. One of the solutions is to use relative recall, which is defined by:

$$\text{Relative Recall} = \frac{\text{No. of documents retrieved and relevant}}{\text{No. of relevant document returned by all engines}} \qquad (2.17)$$

Another measure of relevance is precision, which is the proportion of relevant documents in the returned document set:

$$\text{Precision} = \frac{\text{No. of documents retrieved and relevant}}{\text{No. of relevant document retrieved}} \tag{2.18}$$

It means that precision calculates the fraction of the retrieved documents, which are relevant. Further, these two components can be combined to provide an F-score:

$$\text{F} - \text{score} = 2 \times \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{2.19}$$

F-score is the harmonic mean of precision and recall, which provides a complete evaluation metric. There is a trade-off between recall and precision, where an increase in recall results in decrease in precision. This could be illustrated by the 11-point precision curve, which plots the precision computed at 11 different recall levels. Usually an interval precision is computed for the top *a*, top *b*, top *c* … top *N* documents returned by the system, where *a*, *b*, *c* stands for absolute values (0, 30, 60, 90 ...300) or for percentages (10%, 20%, 30% ... 100%) of the whole returned document collection.

The Average Precision (AP) is used to get a global estimate of performance across multiple recall levels. It is defined as the arithmetic mean of the precision at all positions in the ranking where a relevant document occurs. This measure can also be averaged across a set of queries, which then defines the Mean Average Precision (MAP). Another overall performance measure is R-precision. It computes precision when |R| documents are retrieved, where R is the set of all relevant documents for the query. The R-precision measure is a useful parameter for observing the behaviour of an algorithm for each individual query in an experiment.

2.5.2 Reference Collections

Conducting evaluation in information retrieval is a complex task involving numerous parameters. Research in IR has frequently been criticised for the lack of consistent test beds and benchmarks. Comparison between different retrieval systems is difficult because different groups conducting experiments focus on different aspects of retrieval, even when the same document collection is used. Another important limitation of these collections is that they are often built to support specific experimental purposes and therefore, its reuse is sometimes complicated.

Competitions like TREC, Senseval (Edmonds, 2002) and Semeval provide common grounds for comparative evaluation of word sense disambiguation and semantic analysis of text. Although they are the best reference to study the recent developments in the area, it is difficult to use the data sets provided because of the different dictionaries adopted for the ground truth creation (i.e. HECTOR, WordNet 1.7, WordNet 1.7.1 and WordNet 2.1). Furthermore, the subjectivity in perceiving and interpreting visual content makes it difficult to determine what is considered relevant in the context of a specific query. Relevance has been the subject of many studies (Mizzaro, 1997), but still very little is known about what makes a user decide whether a document is relevant or not. A set of query results may or may not be relevant to different people, depending on their personal understanding. Experiments have shown that users with similar background knowledge have different understanding of what constitutes a relevant document to a given query (Cleverdon, 1988).

2.5.3 Crowdsourcing

Crowdsourcing is an open call to a large group of people, to solve a problem or complete a task. The word 'crowdsourcing' introduced by Jeff Howe (2006) describes:

> *"the act of company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call".*

In crowdsourcing, a large task is divided into smaller tasks, which are then distributed among a large group of people who do not necessarily know each other. Unlike user generated content and social networks, participants in a crowdsourcing system have no contact with each other. They cannot see the results of another's work. Crowdsourcing normally involves payment in exchange of the task being performed.

The cost, speed and quality of the crowdsourcing results are reported by many researchers to be impressive (Snow et al., 2008; Akkaya et al., 2010; Corney et al., 2010). Although spammers are the main concern in crowdsourcing, Akkaya et al. (2010) have found that their input is minimal and the results are highly reliable. Another experimental study by Corney et al. (2010) concludes that, with the right question and enough information, crowdsourcing can provide high quality results. Their crowdsourcing approach applied to a two-dimensional strip-packing task demonstrates a better efficiency rate than the best algorithm available in the literature.

Denkowski et al (2010) present a semi-automatic Arabic paraphrasing technique for creating additional reference translations. The paraphrase extraction technique provides a ranked list of paraphrases and their contexts that are filtered by human judgement, using crowdsourcing method. Their evaluation shows that high accuracy results are achieve using controlled data. Evanini et al (2010) uses crowdsourcing to obtain multiple transcriptions of non-native speech. Those multiple sources of information are then combined to obtain final merged transcriptions that are more accurate than original transcriptions. They claimed that the final transcriptions are comparable with the level of expert transcribes on this difficult task.

These findings are consistent with the study by Snow et al. (2008) of the evaluation of experts and non-expert conducting five natural language processing tasks. Their study had found that in average only four non-experts answers are needed to emulate an expert opinion. Callison-Burch (2009) also shows that a non-expert group produces judgments that are similar to those of experts. The evaluation results produced in that study have a stronger correlation than the Bleu algorithm (Papineni et al., 2002) which approximates human judgment in evaluating machine translation.

2.6 SUMMARY

The focus of this thesis is to propose an ontology-based IR model, which supports semantic search for relevant images in developing mood boards. The review clearly indicates that semantic technologies present an opportunity, which needs to be exploited. In addition, semantic expansion (defined as query expansion driven by the semantic similarity of the words and the concepts they are associated with) provides a degree of diversity and serendipity, both very important in the domain of creative design.

Reviews on LSI have shown that it is useful in identifying potential relations between keywords by analysing the co-occurrence of keywords in documents and collections as a whole. It finds relationships between terms by considering the documents distributional measures of keywords and groups them into concepts. It is widely applicable because it only needs raw text to be processed. However, the applicability of LSI is still lacking in terms of the runtime efficiency needed for large datasets.

Studies have shown that LSI and linguistic conceptualisation have their unique advantages. Linguistic conceptualisation (such as those based on WordNet and Roget's Thesaurus) can utilise the human-defined classification of lexical semantic relations. The LSI, on the other hand, is widely applicable because they only need raw text to be processed. However, these advantages come at a cost. Pre-computing and storing distance values between all possible pairs of words are important to optimise the processing speed. Both WordNet-based and distributional-based measures have huge space requirements, requiring matrices of size N x N, where N is of considerable size. In LSI, N is the size of the language vocabulary, which is an average of 100,000 in most languages, whilst in linguistic conceptualisation-based measures, N is the number of word senses, which are 117,659 (synsets) in the case of WordNet, according to the latest statistics (Princeton University, 2010).

Despite the progress made by ontology-based systems, the high formalisation of queries is considered impractical because it requires users to understand formal languages (such as SPARQL). Some systems expect users to express their needs using ontology-based query language (Zhang et al., 2005), while others ask them to select ontology elements during the query process (Bernstein and Kaufmann, 2006) or use complicated forms (Davies et al., 2004). These approaches expect users to have background knowledge and invest additional effort that makes the search process tedious and complicated. Nonetheless, increasing the query information does help to improve the quality of results. A balance between query formalisation and ease of use should be achieved to encourage the use of semantic search models by ordinary users.

This thesis proposes a hybrid approach that combines a knowledge source with raw text distribution to measure the semantic distance. The new approach combines the best features of both linguistic conceptualisation and distributional measures, and has some additional advantages, while reducing the space requirements by scaling down the size of the term×document matrix used. The overview of evaluation methods has identified the problem with the unavailability of public semantic datasets that could be used as an evaluation benchmark. Although IR systems traditionally compete against each other under formal evaluation frameworks like the TREC conference, none of the semantic retrieval approaches currently reported in the literature has been validated in such a rigorous way. Crowdsourcing is seen as a potential alternative for the purpose of semantic retrieval evaluation. Reviews have shown that crowdsourcing has been successfully applied in linguistic data collection tasks (Snow et al., 2008; Akkaya et al., 2010; Corney et al., 2010), pattern matching (Callison-Burch, 2009), paraphrasing for machine translation (Denkowski et al., 2010) and speech transcription (Evanini et al., 2010). This thesis proposes the use of crowdsourcing method in evaluating word-sense disambiguation and semantic search results.

CHAPTER 3:
CONCEPTUAL MODEL

This chapter introduces in more detail *OntoRo*, the lexical ontology used as the knowledge source in this research. It also describes the conceptual model of the proposed method that involves two phases, namely image indexing and semantic search. Finally, the *fotoLIBRA* data collection is introduced as the data used in the experimental process throughout this thesis.

3.1 KNOWLEDGE SOURCES

This research utilises the richness of *Roget's Thesaurus* as the knowledge source. *Roget's Thesaurus* has many advantages. It is based on a well-constructed concept classification, and its entries are written by professional lexicographers. Its 2003 printed version contains 228,130 entries (consist of words and phrases) compared to WordNet's less than 200,000. *Roget's* employs a rich set of semantic relations, both explicit and implicit (Aman and Szpakowicz, 2008; Old, 2009). The explicit relations of Roget's Thesaurus lie in its hierarchy, or tree, while the implicit relations can be discovered through the analysis of patterns of its words and senses. These relationships are one of the most interesting qualities of Roget's. Its structure, which is based on the hierarchy of categories, is very simple to computerise and use, as demonstrated by Masterman (1957) and Sparck Jones (1964).

Roget's has a long established tradition and is believed to be the best thesaurus of the English language. It is, however, not machine tractable in the way WordNet is. According to McHale (1998): "*Roget's remains, though, an attractive lexical resource for those with access to it. Its wide, shallow hierarchy is densely populated with nearly 200,000 words and phrases. The relationships among the words are also much richer than WordNet's IS-A or HAS-PART links. The price paid for this richness is a somewhat unwieldy tool with ambiguous links*".

It is difficult for a computer to use a resource prepared for humans. WordNet is simply easier to use, as explained by Hirst and St-Onge (1998): "*Morris and Hirst were never able to implement their algorithm for finding lexical chains with Roget's because no on-line copy of the thesaurus was available to them. However, the subsequent development of WordNet raises the possibility that, with a suitable modification of the algorithm, WordNet could be used in place of Roget's*".

Although an electronic version of the 1911 edition of *Roget's Thesaurus* has been available since 1991 (Hart and Newby, 2003), it is proven to be inadequate for NLP and cannot be used to implement lexical chains as explained by Hirst and St-Onge (1998). The literature shows that only Penguin's *Roget's Thesaurus* of English Words and Phrases, Harper Collins' *Roget's* International Thesaurus as well as the 1911 edition has been used for NLP research.

Choosing the concept hierarchy of one or the other does not ensure a definitive advantage, as Yarowsky (1992) states: "*Note that this edition of Roget's Thesaurus (Fourth Edition - Chapman, 1977) is much more extensive than the 1911 version, though somewhat more difficult to obtain in electronic form. One could use other concept hierarchies, such as WordNet (Miller, 1990) or the LDOCE subject codes (Slator, 1991). All that is necessary is a set of semantic categories and a list of the words in each category*."

Roget's is more than a concept hierarchy, but the elements that are most easily accessed using a printed version are the classification system and the index. For this reason, computational linguists have limited their experiments to computerising and manipulating the index. *Roget's Thesaurus* have several advantages, such as the links between parts of speech and the topical groupings which are absent in WordNet. The clusters of closely related words are obviously not the same in both resources. WordNet relies on a set of about 15 semantic relations. Search in this lexical database requires a word and a semantic relation. *Roget's* can link the noun *museum*, a place or building where objects of historical, artistic or scientific interest are exhibited, and the noun *fossil*, any remains or trace of a living thing of former geologic age, as used in the following sentences:

- Stacey went to the *museum* with her parent.
- She was excited to see many *fossils* of prehistoric animals.

Referring to *Roget's*, both nouns *museum* and *fossil* can be found under the same concept group '*#125 Past Time*', where 125 is the concept number (from the total of 990 concepts defined in *Roget's*). This relation cannot be identified using WordNet's semantic relations. While an English speaker can identify a relation not provided by WordNet, for example, that fossils are usually exhibited in museums, this is not possible for a computer system. The main challenge is in labelling such relations explicitly.

WordNet was built using different linguistic sources including the Basic Book of Synonyms and Antonyms (Urdang, 1985), The Synonym Finder (Rodale, 1978), the Ralph Grishman's COMLEX (Macleod et al., 1994) and the Brown Corpus (Francis and Kucera, 1982). Many of the lexical files were written by graduate students hired part-time. Compared to WordNet, Penguin's *Roget's Thesaurus* of English Words and Phrases is prepared by professional lexicographers and validated using data from the Longman Corpus Network of many millions words.

The categories in *Roget's* provide another advantage in its use. Most published thesauri divide the vocabulary into about 1000 categories, which can be considered as the basic concepts represented by the language. *Roget's* has 990 categories with around 230,000 word entries. The words listed under each category represent the meaning of the concept. The concepts roughly correspond to very coarse-grained word senses (Yarowsky, 1992). As explained in section 2.6 , pre-computing and storing the distance values between all possible pairs of words or senses requires large space requirements. It requires matrices of size $N \times N$, where N is the size of the vocabulary (perhaps

100,000 for most languages) in the case of distributional measures and the number of senses (117,00 in WordNet) in the case of semantic measures. The use of categories in a thesaurus as concepts means that this approach requires a concept–concept distance matrix of size only about $10{,}000 \times 10{,}000$ which is much smaller than (about 0.1% the size of) the matrix required by traditional knowledge and distributional-based measures. This makes the approach scalable to large amounts of text.

Due to the limitations of the printed version of *Roget's Thesaurus*, many researchers have opted for WordNet when attempting to solve NLP problems. This research exploits the 1911 electronic version of *Roget's Thesaurus* that was recently enriched by Tang (2006) with entries from the printed 2003 edition (Davidson, 2003). The printed edition was utilised to remove out-dated words from the 1911 edition, and add new entries into the Thesaurus. The updated version was then converted into a lexical ontology called *OntoRo*. Subsequently, *OntoRo* was employed in the development of an ontology-based image retrieval tool created for the needs of concept car designers from two European companies (Setchi and Tang, 2007; Setchi and Bouchard, 2010; Setchi et al., 2011).

The next subsection introduces the structure of *OntoRo*, the extraction of semantic DNA (SDNA) and the way it is used in this thesis to represent the abstract concepts behind image annotations.

3.1.1 *OntoRo*

OntoRo is built using *Roget's* six levels of hierarchy:

i. **Class**: The top level of the structure is divided into 6 different classes. The first three classes cover the external world and include "#1:*Abstract Relations*", "#2: *Space*" and "#3: *Matter*", while the other three classes deal with internal world and contain "#4: *Intellect*", "#5: *Volition*" and "#6: *Emotion, religion and morality*".

ii. **Sections**: Divided into 39 sections, this level deals with particular aspects of the Class to which it belongs. For examples, there are 4 sections under the second class "#2: *Space*": "#9: *Space in general*", "#10: *Dimensions*", "#11: *Form*" and "#12: *Motion*".

iii. **Subsections**: These are subcategories of sections, which consist of 95 subsections in total. For examples, there are 4 subsections under section "#12: *Motion*": "#40: *Motion in General*", "#41: *Degrees of Motion*", "#42: *Motion Conjoined with Force*" and "#43: *Motion with Reference to Direction*"

iv. **Concept**: Subsections are subdivided by concepts. They are called 'heads' according to *Roget's Thesaurus* terminology, consisting of 990 concepts. For example, there are 10 concepts under subsection "#40: *Motion in General*", including "#267: *Land travel*", "#268: *Traveller*", "#269: *Water travel*" and "#270: *Mariner*".

v. **POS**: These are the four part-of-speech (POS) categories under each concept, namely "*Noun*", "*Verb*", "*Adjectives*" and "*Adverbs*".

vi. **Paragraph**: The words and phrases under each POS are further divided into paragraphs. Each paragraph contains words, which express every aspect of an idea. For example, "*horse, ambulance, bicycle, bus, car, coach, micro-scooter, moped, scooter, taxi* and *train*" are nouns from the same paragraph of concept "#267: *Land travel*".

Figure 3.1 shows the hierarchical structure of *OntoRo*, starting from top level 'class' to the lowest level 'paragraph'.

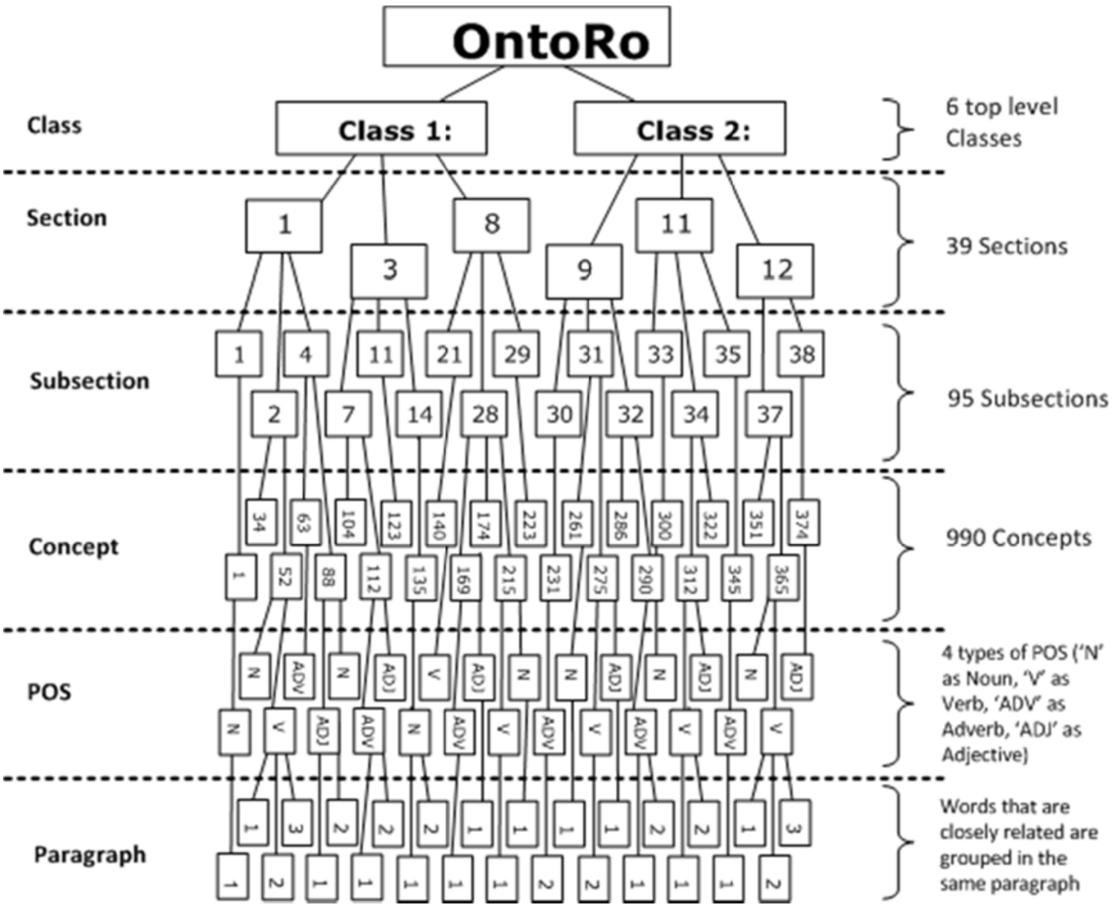


Figure 3.1: *OntoRo* Structure

The current version of *OntoRo,* also available as a web application (*OntoRo*, 2011), includes 68,920 unique words and 228,130 entries classified into 6 classes, 39 sections, 95 subsections, 990 heads, 4 part-of-speech categories and a number of paragraphs within each concept.

Monosemic words, which have a single sense, appear in one concept only. Most of the words in *Roget's* are polysemic, have several meanings and are linked to the same number of concepts. (This also explains why *OntoRo* contains 68,920 unique words and many more entries: 228,130.)

For example, the word '*tradition*' has six senses and is related to six *OntoRo* concepts representing the meaning of tradition as something from the past (#127:oldness), lasting quality (#144:permanence), means of sharing information (#524:information), statement of facts (#590:description), habit or second nature (#610:habit) and religious faith (#973:religion). In this research, each of the 990 concepts is labelled through its number in *OntoRo* and the first word in the list of all words and phrases belonging to that concept.

For example, the concept #127:oldness is represented in *OntoRo* with 233 words, some of which are shown in the box below.

oldness, primitiveness, beginning, …, antiquity, maturity, mellowness, autumn, decline, rust, decay, senility, old age, eldership, seniority, archaism, antiquities, …, thing of the past, relic of the past, listed building, ancient monument, museum piece, antique, heirloom, bygone, Victoriana, dodo, dinosaur, fossil, oldie, golden, old fogy, old fossil, ..., tradition, lore, folklore, mythology, inveteracy, custom, prescription, …vintage, venerable, patriarchal, archaic, ancient, timeworn, ruined, prehistoric, mythological, heroic, classic, Hellenic, Byzantine, feudal, medieval, …, historical, past, ..., geological, pre-glacial, fossil, Palaeozoic, secular, Eolithic, Palaeolithic, Mesolithic, Neolithic, …, ancestral, traditional, time-honoured, habitual, ..., old as the hills, ..., old as history, old as time, age-old, lasting, antiquated, of other times, of another age, …, prior, anachronistic, archaistic, archaizing, retrospective, fossilized, ossified, static, permanent, behind the times, out of date, out of fashion, dated, …, conservative, Victorian, old-fashioned, old-school, ..., out-dated, outmoded, old hat, gone by, past, decayed, perished, dilapidated, rusty, moth-eaten, crumbling, mildewed, moss-grown, mouldering, decomposed, fusty, ..., belong to the past, have had its day, be burnt out, end, age, grow old, decline, fade, …, rot, rust, decay, decompose, anciently, since the world was made, .., before the Flood, formerly (233 words in total, not all are included in this box)

It is clear that all these words can be used to describe different aspects of '*oldness*'. Most of them are related to history and mythology but there are clear connotations to decline, decay, and aging, and some not entirely expected negative associations and comparisons (e.g. '*old fossil*' and '*moth-eaten*'). However, this particular sense of the word '*tradition*' would be inappropriate to use in relation to, for example, an image of a Japanese tradition or custom. On the contrary, looking further into the concept's POS categories and paragraphs which group words with closer relationships in terms of their contextual meaning, the word '*tradition*' is grouped together with the words '*lore, folklore, mythology, inveteracy, custom prescription, immemorial usage, habit, common law, smriti, Sunna, Hadith* and *ancient wisdom*'. This example shows that *OntoRo*'s structure, from concept level to POS level to paragraph level, provides a more specific meaning of a particular concept. Thus, the semantic signature of an image should be a more complex and meaningful structure than just a list of words if it were to be used for semantic indexing and retrieval. The next section highlights the difference between the terms ‘*word*’, ‘*token*’ and ‘*sense*’ used throughout this thesis.

3.1.2 Words, Tokens and Senses

In this thesis, a ‘*word*’ is referred to an individual keyword in a text, a ‘*token*’ can be either a word or a phrase in the text which corresponds to an entry in the lexical ontology, whereas a ‘*sense*’ represents a distinguishable meaning of a polysemic token. Consider the following example:

A walk along the river bank.

This example includes six words (‘*a*’, ‘*walk*’, ‘*along*’, ‘*the*’, ‘*river*’, ‘*bank*’) but only three tokens (‘*walk*’, ‘*along*’, ‘*river bank*’). The words ‘*a*’ and ‘*the*’ do not exist in *OntoRo*, and are therefore not considered tokens, while ‘*river bank*’ exists as a monosemic entry in *OntoRo*, under concept #344:land and means the slopping land beside a body of water. While the tokens ‘*along*’ and ‘*river bank*’ are polysemic with only one sense, according to *OntoRo*, the token ‘*walk*’ has 16 different senses. Each of these 16 senses belongs to 16 different *OntoRo’s* paragraphs, and could be represented by a unique semantic DNA.

The concepts of *semantic DNA* and *semantic chromosomes* are introduced in the next two sections.

3.1.3 Semantic DNA

This thesis introduces semantic DNA (SDNA) as a string of numbers derived from the lexical ontology used in this research, *OntoRo*. Each SDNA is formally represented as a chain of numbers corresponding to the structural elements of the *OntoRo's* hierarchy (refer to Figure 3.2). The format of an SDNA is as follows:

Class # - Section # - Sub-section # - Head # - Label for POS (1=noun, 2=adjective, 3=verb, 4=adverb) - Paragraph #

An SDNA represents a unique paragraph in *Roget's Thesaurus* consisting of tokens that can be used to explain a similar idea or concept.

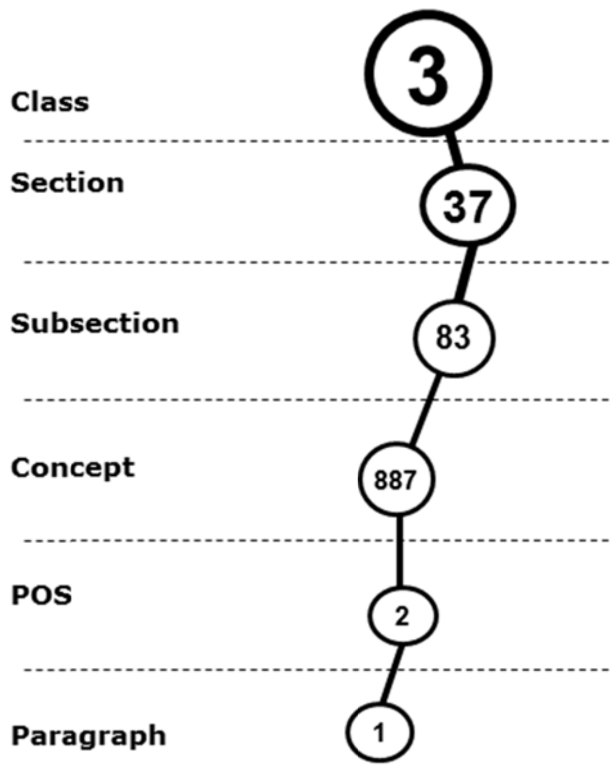


Figure 3.2: SDNA string extracted from OntoRo's hierarchical structure

A token may have more than one possible sense, which means that it may be contained in a number of paragraphs. As illustrated in Figure 3.3, all possible senses of each token can be extracted from *OntoRo* and represented as an SDNA. Therefore, each token in an image annotation can produce a set of SDNA that represent different senses.

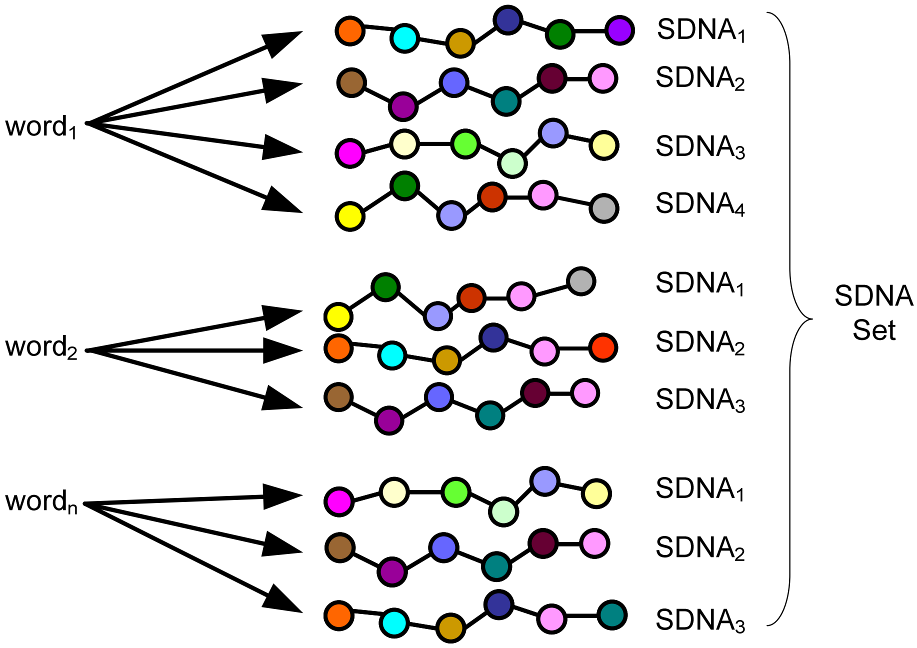


Figure 3.3: SDNA Extraction from Terms

For example, Table 3.1 lists six different SDNA corresponding to each sense of the token '*tradition*'. Only one of these SDNA is meaningful within the context of a given image, and be chosen as the most relevant SDNA for the particular token.

A suitable sense for the word '*tradition*' in an image of a Japanese garden would be 'lasting quality' (belonging to concept #144:permanence); its SDNA is *1-7-24-144-1-1*. Its semantic representation, following the SDNA format (i.e. *OntoRo*'s hierarchical structure), is shown in Figure 3.4 (the number 1 is used to show the POS group of the word, i.e. noun).

Table 3.1: SDNA Set of the Word '*tradition*'

Semantic DNA	Sense	Paragraph Content
1-6-22-127-1-3	tradition	17 words semantically related to 'tradition' as 'something from the past'
1-7-24-144-1-1	permanence	63 words semantically related to 'tradition' as 'lasting quality'
4-24-57-524-1-1	Information	123 words semantically related to 'tradition' as 'means of sharing information'
4-25-58-590-1-2	narrative	87 words semantically related to 'tradition' as 'statement of facts'
5-26-59-610-1-1	habit	610 words semantically related to 'tradition' as 'habit' or 'second nature'
6-39-92-973-1-4	theology	57 words semantically related to 'tradition' as 'religious faith'

Class #1: *Abstract Relation*

└─Section #7: *Change*

  └─Sub Section #24: *Social*

    └─Head #144: *Permanence*

      └─Part of speech #1: *noun*

        └─Paragraph #1: *permanence, permanency, no change, status quo, invariability, unchangeability, ..., lasting quality, persistence, perseverance, endurance, duration, durability, .., sustenance, maintenance, conservation, preservation, continuance, ..., standing, long standing, inveteracy, oldness,* ***tradition****, custom, practice, habit, .., static condition, quiescence, traditionalist, conservative, ..., obstinate person*.(63 words in total, not all are included in this example)

Figure 3.4: Semantic Representation of the Word '*tradition*' in the Context of 'Lasting Quality'

Each SDNA carries semantic information including part of speech, high-level concept name and other words that can be used to represent the same idea or concept. The selection technique of the most meaningful SDNA and their use to index images is explained later in this thesis. Next section shows how *semantic chromosomes* are formed using SDNA.

3.1.4 Semantic Chromosomes

Scientists use the concepts of DNA and chromosomes to describe the organisation of genetic information in living organisms. Following the same analogy, a *semantic chromosome* is defined in this research as an information structure, which carries the semantic information of an image. It is its semantic signature expressed through a set of SDNA, where each SDNA in the set represents a semantically distinguishable concept (or sense).

For example, an image depicting a tea house in a Japanese traditional garden might be represented through a set of tokens such as '*tea garden*', '*East*', '*tradition*' and '*ceremony*'. Each of these four tokens represents one or more semantically distinguishable concepts. Only one concept for each keyword will be chosen as the accurate sense representing the token in the context of the Japanese traditional garden. Used together (and represented in a coded way), these selected concepts, represented by their SDNA, form the semantic signature or the *semantic chromosome* of this image and could be used to represent its meaning.

Table 3.2 shows an example of four possible SDNA used as the *semantic chromosome* of an image annotated with the words 'tea garden, East, tradition, ceremony'.

Table 3.2: Semantic Chromosome of an Image Depicting a Tea House in Japanese Traditional Garden

Concept	Semantic DNA	Sense	Paragraph Content
tea garden	3-15-47-370-1-2	agriculture	17 words semantically related to 'tradition' as 'something from the past'
East	2-12-43-281-1-2	direction	20 words semantically related to 'east' as 'compass direction'
tradition	1-6-22-127-1-3	tradition	17 words semantically related to 'tradition' as 'something from the past'
ceremony	6-39-95-988-1-1	ritual	19 words semantically related to 'ceremony' as 'ritual practice'

Although a *semantic chromosome* may look like an annotation, it is very different as it is a formal representation of the semantic meaning of that image. This means that the *semantic chromosome* is extracted in a formal way, using terminology with well-defined semantics, and is linked to some semantic resources. In particular, the use of ontologies is very beneficial as it provides a means for formalisation of the content as a prerequisite for more comprehensive indexing, retrieval and use.

The next section introduces the conceptual model of the proposed system for generating automated mood boards.

3.2 CONCEPTUAL MODEL

A research gap identified during the TRENDS project was the need for information support in gathering inspirational materials, where concept designers have to manage and categorise a substantial amount of data. IR technologies offer the capability to store, index and retrieve vast amount of data. However, most of the current IR methods are based on keywords, which provide limited capabilities to grasp and exploit the conceptualisations involved in expressing user needs and visual ideas.

In a large text-based IR system, the traditional approach to extract knowledge and information from document collection begins with indexing. It is an important part of the IR system, which optimises the retrieval performance and improves response times by converting documents into an easily accessible representation of data. However, the existing indexing and searching system is not suitable to be used with the SDNA structure. This section proposes the conceptual model of ontology-based IR system which indexes and searches for images, semantically relevant to user queries, and contributes to the generation of automated mood boards.

Figure 3.5 shows the conceptual model of the system for generating automated mood boards proposed in this research. The model is divided into two phases: *SDNA Indexing* and *Semantic Search*. The proposed indexing and searching approach is based on an adaptation of the traditional VSM; the choice is motivated by its success in information retrieval. VSM is used to measure the similarity between a query and an image based on its text annotation. Natural language processing and mathematical processing is applied to the image annotations and queries and used to extract semantic signatures based on the lexical ontology used as a knowledge base.

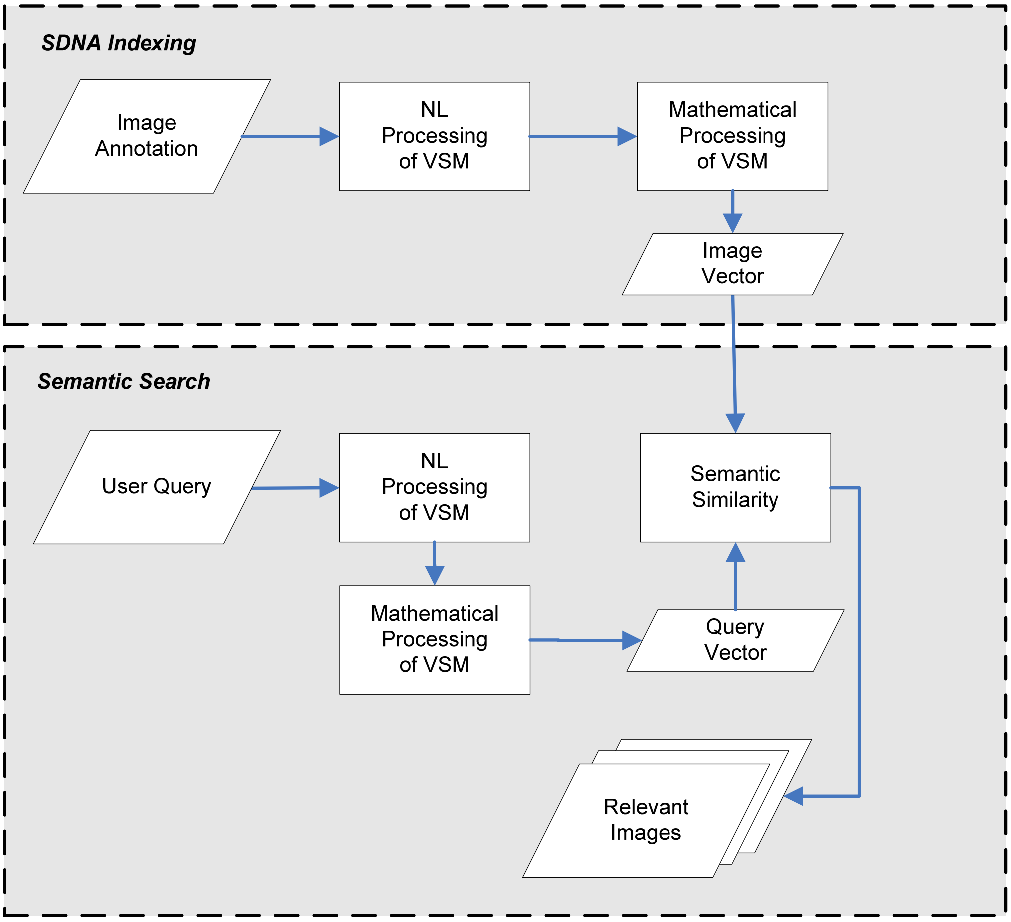


Figure 3.5: Conceptual Model of Automated Mood Boards

Using VSM, images and queries are represented as vectors in a common vector space that has an axis for each semantic signature or SDNA. A weighting measure based on Okapi BM25 is proposed which computes the weight of each semantic signature in terms of its importance in the image or query. Similarity between a query and an image in VSM is computed using cosine similarity between the vector representation of the query and the image annotation.

3.2.1 Phase I: Image Indexing

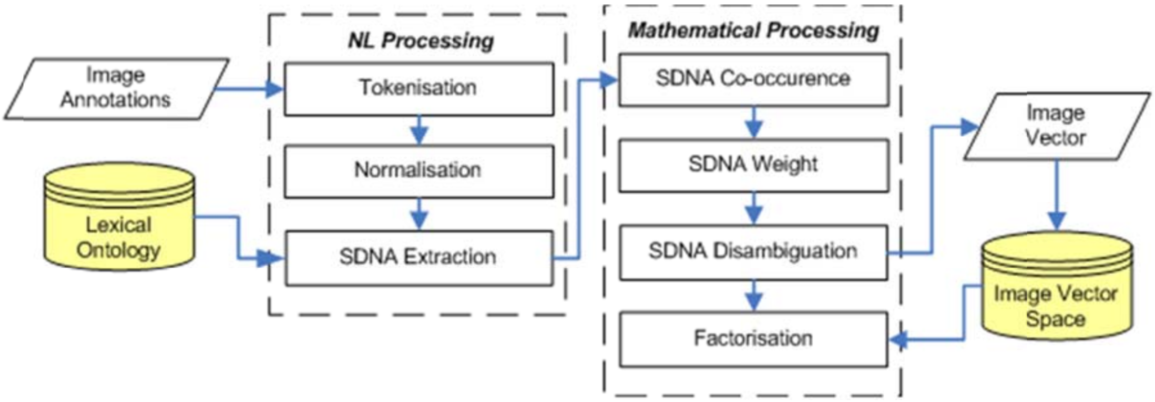


Figure 3.6: Automatic Image Indexing

Figure 3.6 shows the processes involved in Phase I of the conceptual model. This phase starts with applying a three-step natural language processing of the raw image annotations, which include tokenisation, normalisation and SDNA extraction. During the first step, tokenisation, tokens are extracted from the raw annotations – single words or phrases - by matching the standardised form of the words or phrases and the entries in the lexical ontology. Words or phrases that match *OntoRo* entries are identified as tokens. Named entities such as place names, street names and people's names are generally not to be found in *OntoRo*, therefore these words are ignored. The words or phrases that do not match any *OntoRo* entry go through a normalisation process before being matched again. The normalisation involves case folding (converting all words to lower case) and stemming. Words that do not match any *OntoRo* entry even after normalisation are ignored. Tokens that are considered stop words are also eliminated at this stage. Every possible SDNA is extracted from each token, using the technique explained in section 3.1.3 producing an *SDNA set* for the image.

After the annotation is tokenised, normalised and its *SDNA set* is extracted, a four-step mathematical processing is applied. The first step is to generate an SDNA similarity matrix that calculates the frequency of every SDNA co-occurrence in the *SDNA set*. Secondly, each element of SDNA in the matrix is weighted based on the co-occurrences frequency of SDNA *S* in the SDNA similarity matrix. Then, the SDNA disambiguation step selects the most important SDNA for each token according to its weight. The selected set of SDNA is the *semantic chromosome* of that image annotation. All *semantic chromosomes* are then populated in a *semantic chromosomes*-images matrix, with a sparse matrix representation. Finally, the matrix is factorised to limit the number of vector components (a process called dimension reduction) in order to improve the performance. Figure 3.7 illustrates the process flow of the image indexing phase.

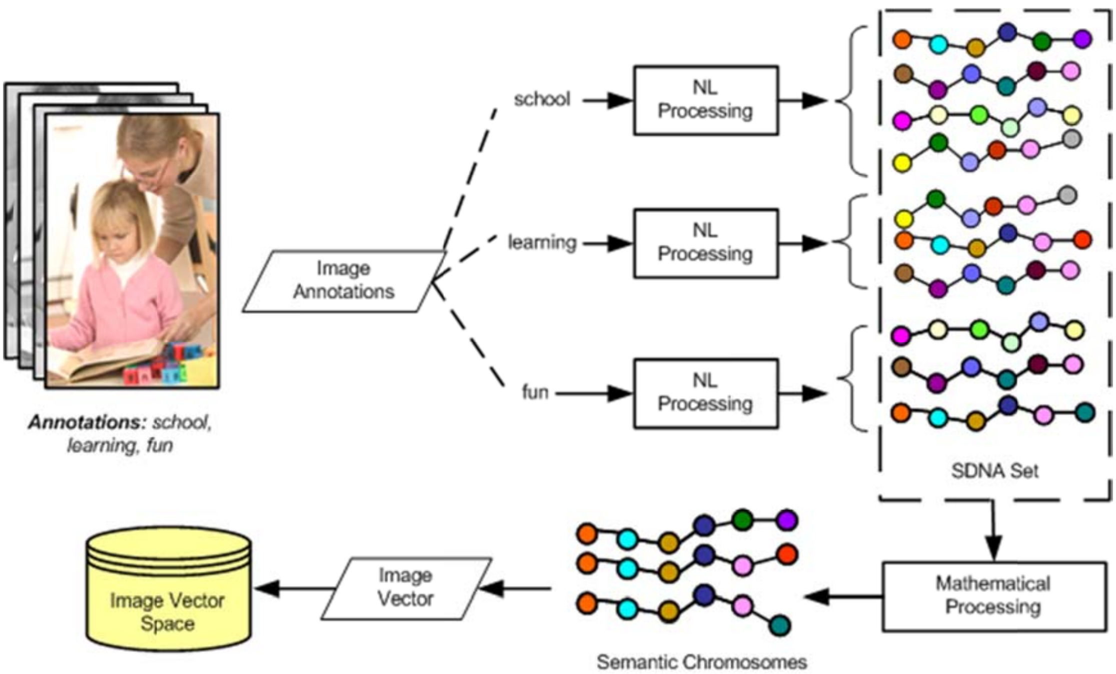


Figure 3.7: Process Flow in Image Indexing Phase

In this example, the token *school* produces four different SDNA, which belong to its four senses, while tokens *learning* and *fun* produce three SDNA each. All these ten SDNA from all three tokens form the *SDNA set* of the image annotation. Then, the most important SDNA that represents the most relevant sense is selected from each token, based on the co-occurrences frequency of all SDNA in the *SDNA set*. Finally, the three SDNA (which represent the three tokens) selected from the *SDNA set* form the *semantic chromosome* of the image, which is then used to represent the image in the image vector space.

3.2.2 Phase II: Semantic Search

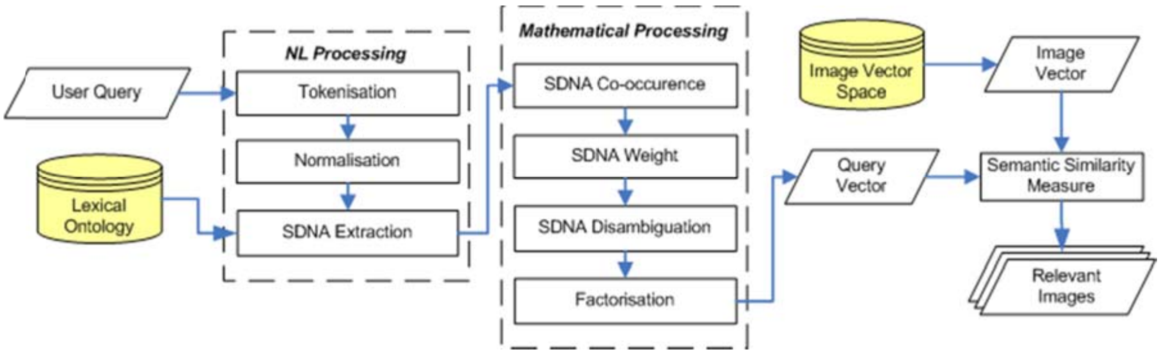


Figure 3.8: Semantic Search

Similar to the semantic indexing stage, each search query is analysed and processed in two steps - natural language processing and mathematical processing (Figure 3.8), and represented as through its *semantic chromosome*. A semantic similarity measure is used to calculate the similarity between the query vector and all other image vectors in the search space. Images, which are semantically close to the query in the search space, are considered relevant and are retrieved according to their weighted distance rank.

Figure 3.9 illustrates the process flow of this phase. Chapter 5 and 6 discuss in detail the semantic indexing and semantic search phases. The next section introduces the image collection used as the benchmark in the evaluation process.

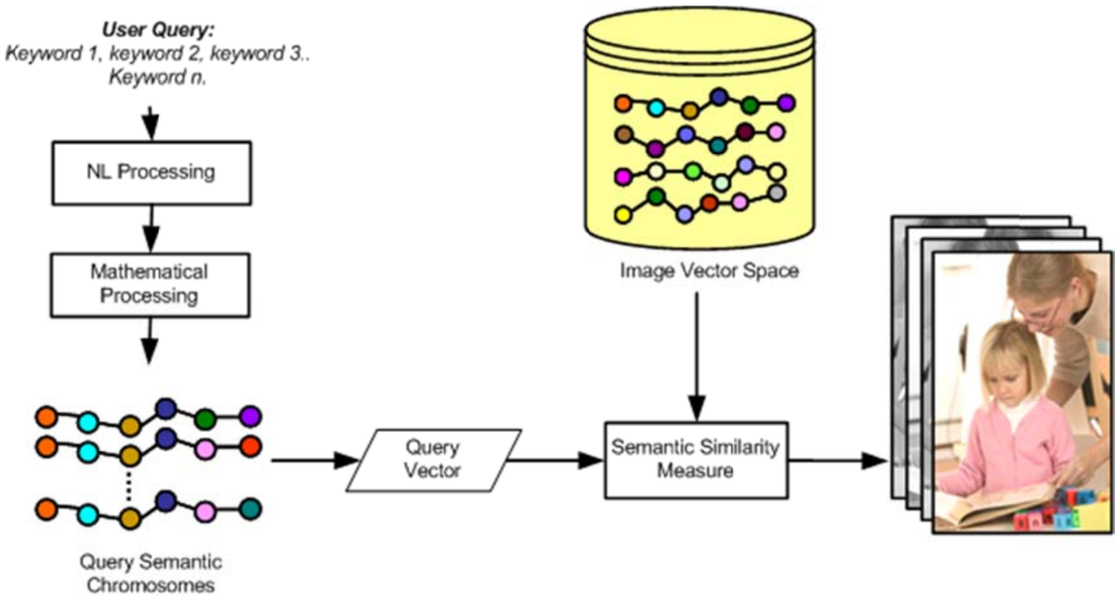


Figure 3.9: Process Flow in Semantic Search Phase.

3.3 FOTOLIBRA IMAGE COLLECTION

Research collaboration with VisconPro Limited, had provided this research with 153,403 digital images complete with manually annotated descriptions. VisconPro Limited is one of the Wales leading online company which hosts an image stock website called *fotoLIBRA* (VisconPro, 2005). They are currently hosting 611,954 high quality images covering a broad range of topics, owned by approximately 20,000 photographers. Table 3.3 summarises the image collection information.

Table 3.3: *fotoLIBRA* Image Collection

Details	Amount
Total Number of Images	153,403
Total Number of Owners	7,294
Total Number of Keywords in Annotation	3,187,714
Average Number of Keywords per Image Annotation	20.78

fotoLIBRA was selected considering several factors:

- **Large collection of high quality images.** VisconPro provide a large collection of high quality images, compared to most image libraries, which comprise of different levels of image quality. Only images with a certain quality standard are allowed to be included in the collection.
- **Valuable image content.** The images are included into the collections by their owners for one main reason, i.e. to sell the images to potential buyers. All images, once uploaded, are checked for content and everything, which is pornographic, racist, sexist, defamatory, obscene or offensive, is rejected.
- **Accurate annotation.** The images are annotated by their owners for making their photos findable by others (this is a process called social-organisation). This is different from other large online image collections available like flickr© and facebook©, where the owners tag their images for reasons including self-organisation, self-communication and social-communication, providing less contextual information of the image content (Ames and Naaman, 2007). The image owners of *fotoLIBRA* describe their images as accurately as possible in

order to increase the chance of being retrieved by graphic designers who work on posters, book covers, web sites, etc. The image owners are also asked to categorise manually their images from 18 categories and 239 sub categories. In addition, *FotoLIBRA* have a strict regulation on annotating keywords.

- **Covering broad range of topics.** As a general purpose picture library, *fotoLIBRA* offers broad categories including animals, architecture, arts, events, health, heritage, leisure, lifestyle, nature, people, plants, science, society, sport, transport, travel and work.

Table A1 in the appendix lists all categories and sub categories used by *fotoLIBRA* together with the number of images belongs to each sub-categories.

3.3.1 Generating Evaluation Benchmark

The *fotoLIBRA* collection provides this research with a benchmark based on its categories and sub categories, as tagged by the image owners.

Table 3.4: Distribution of Images According to Categories

No.	Category Name	No. of images	%
1	Animals	20,208	13.17%
2	Architecture	21,792	14.21%
3	Arts	4,679	3.05%
4	Design	2,920	1.90%
5	Events	3,055	1.99%
6	Health	2,456	1.60%
7	Heritage	5,042	3.29%
8	Leisure	2,130	1.39%
9	Lifestyle	8,620	5.62%
10	Nature	24,949	16.26%
11	People	8,218	5.36%

12	Plants	9,645	6.29%
13	Science	1,594	1.04%
14	Society	3,742	2.44%
15	Sport	12,545	8.18%
16	Transport	8,450	5.51%
17	Work	3,820	2.49%
18	Travel	9,538	6.22%
	TOTAL	**153,403**	100%

Table 3.4 shows the image distribution across the *fotoLIBRA* collection according to its categories. The evaluation benchmark comprises of:

- **Corpus:** 153,403 digital images (13.8 GB) extracted from the *fotoLIBRA* image collection.
- **Queries:** a set of 22 queries defined according to *fotoLIBRA's* categories and sub categories (refer to Table 3.5).
- **Judgments:** judgments for each query manually established based on the 239 sub categories provided by the image owners.

For every image in the collection, the categories and sub-categories are manually selected by the image owners. The subcategories are considered as the high-level concepts of the images. Table A1 in appendix lists the number of images belongs to each sub-category. From 153,403 images, each category consists of an average of 642 images. Therefore the 22 queries is developed by combining 26 sub-categories that had been selected from 239 sub-categories available, based on the availability of enough number of images in the collection (at least 642 images)

The sub-categories is used as expert judgement for the relevance set of a particular query. For example, images which are categorised as '*sports'*, with sub category '*extreme'*, are considered the relevant set for query *q#18* = '*extreme sport*'. The list of relevant sub-categories are shown in Table 3.5.

Table 3.5 List of 22 Queries with Their Relevant Categories and Sub Categories

No.	Query keywords	Relevant judgement			
		Category	Sub category	# of Image	Total
1	Animal kingdom	1#Animals	25#Wildlife	2401	2401
2	Lovely flora	12#Plants	144#Flowers	2963	2963
3	High land	10#Nature	121#Landscapes	4154	4154
4	Country terrain	10#Nature	117#Countryside	2516	2516
5	Travel and tour	9#Lifestyle	114#Travel	2519	2519
6	Motor sport racing	15#Sport	188#Motor	7553	7553
7	Prehistoric animal	1#Animals	220#Prehistoric	653	653
8	Family love	11#People	136#Families	655	655
9	Adventurous	15#Sport	177#Adventure	662	662
10	War battle	5#Events	72#Wars	757	939
		17#Work	216#Military	182	
11	Land travel vehicle	16#Transport	200#Cars	935	3443
		16#Transport	204#Railways	1069	
		16#Transport	240#Bicycles	767	
		16#Transport	242#Motorcycles	672	
12	Violence and crime	14#Society	166#Crime	654	654
13	Religious building	2#Architecture	31#Religious	1783	1783
14	Festivals and events	5#Events	64#Festivals	1289	1289
15	Fashion design	4#Design	57#Fashion	702	702
16	Antique heritage	7#Heritage	81#Antiques	723	723
17	Hospitality and kindness	9#Lifestyle	108#Hospitality	697	697
18	Extreme sport	15#Sport	184#Extreme	733	733
19	Motherhood	11#People	137#Motherhood	657	657
20	Underwater nature	10#Nature	127#Underwater	672	672
21	Funny and fun	9#Lifestyle	109#Humour	668	668

22	Exploration and leisure	8#Leisure	93#Exploration	657	657

Figure 3.10 and Figure 3.11 show image samples from two categories: 2#Architecture and 10#Nature.

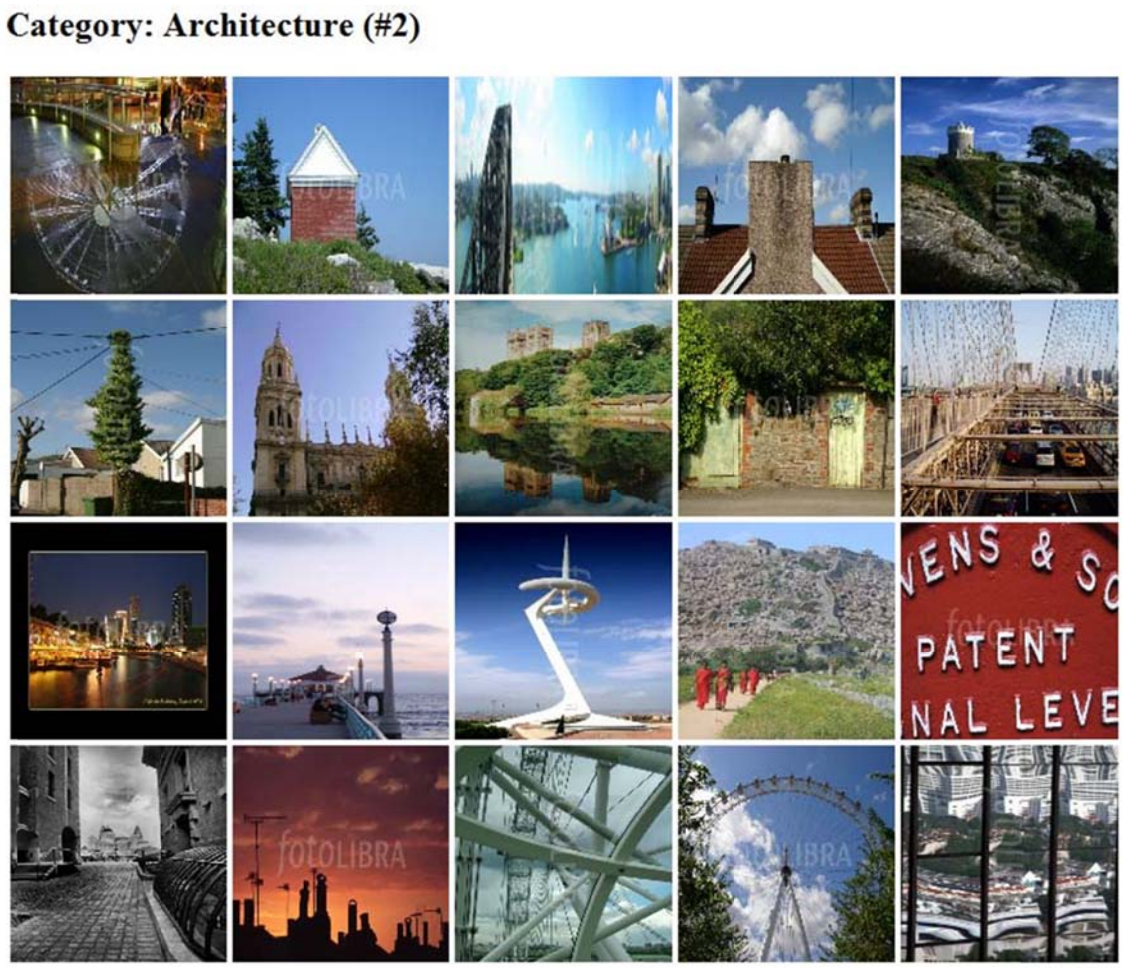


Figure 3.10: Sample Images from the *fotoLIBRA* Image Collection: Category Architecture

Category: Nature (#10)

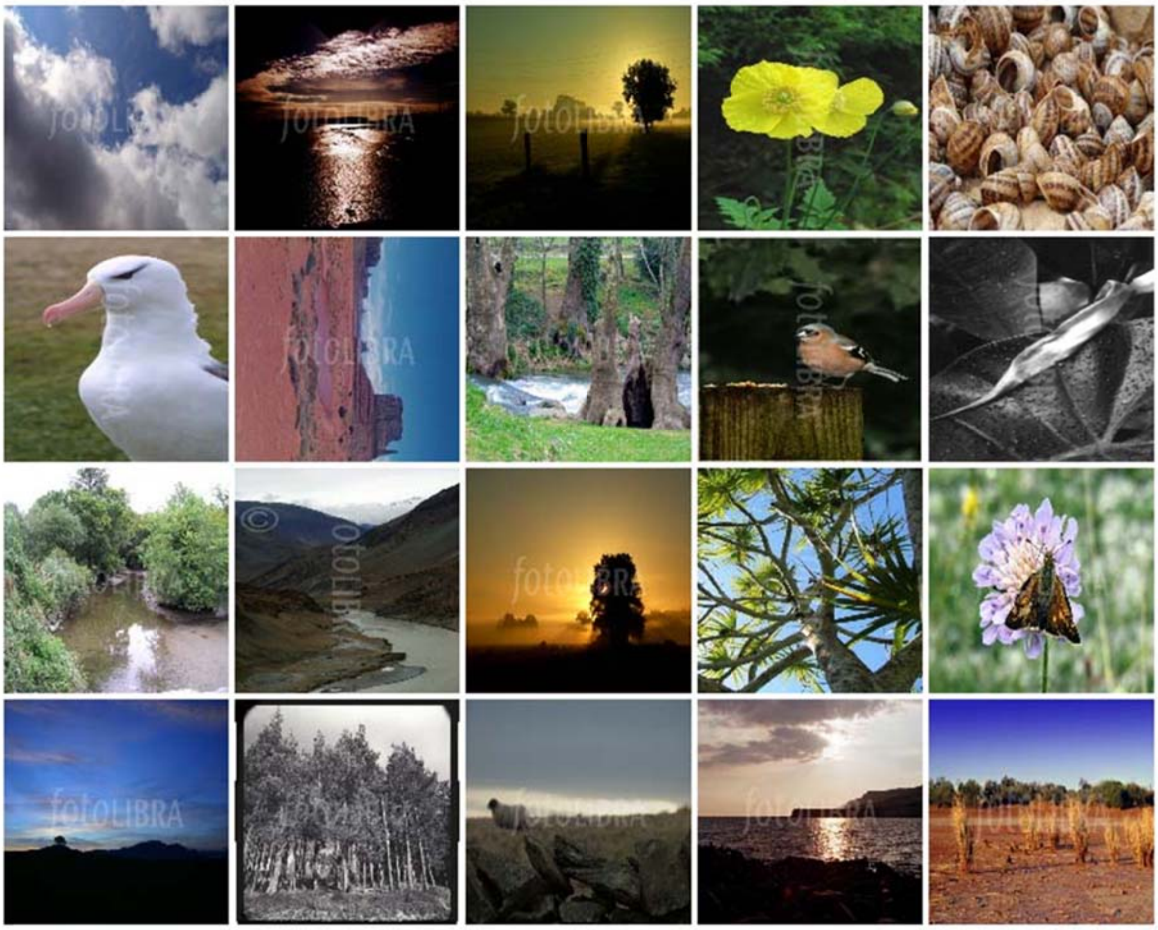


Figure 3.11: Sample Images from the fotoLIBRA Image Collection: Category Nature

3.3.2 Random Image Sets

Five sets, each containing 5000 random images, are populated from the *fotoLIBRA* image collection and used in the preliminary experiments; these sets are referred to as image set β_i where i represents the set number, such that $i = [1, 5]$. The random images are populated using the $SQL\ RAND(i)$ function:

```
SELECT * FROM 'fotoLIBRA_collection'
ORDER BY RAND(i)
LIMIT 5000
```

A seed number is used in the *RAND()* function in order to provide consistency when using the same random samples for different experiments. These random images are used in several preliminary experiments in later chapters.

3.4 SUMMARY

The conceptual model proposed in this chapter aims to provide better search capabilities that yield qualitative improvement over keyword-based search, by exploiting the use of a lexical ontology. The approach is adapted from the classic VMS, where keyword-based indices are replaced by ontology-based, and an automatic image indexing and weighting procedure is the equivalent of the keyword extraction and indexing process. The proposed model automatically extracts semantic SDNA and constructs *semantic chromosomes* through natural language and mathematical processing, which are part of the image indexing phase. The same processes are used in the semantic search phase to handle natural language queries, and extract the corresponding *semantic chromosomes* of the queries. The semantic similarity between the *semantic chromosomes* of the images and queries is measured to identify relevant images. This thesis uses fotoLIBRA image collection as experimental data and evaluation benchmark using their categories and sub categories.

CHAPTER 4:
SDNA INDEXING
IN VECTOR SPACE MODEL

The semantic-based image indexing and searching approach proposed in this chapter is based on adaptation of traditional vector space IR model where images and queries are represented as weighted vectors. Following the conceptual model outlined in section 3.2.1 , this chapter describes the SDNA indexing phase that is divided into two sub-processes: natural language processing and mathematical processing. An illustrative example is also used to provide practical perspective that could help to obtain better understanding of how the proposed method works.

4.1 NATURAL LANGUAGE PROCESSING

This section describes proposed architectural model of natural language processing which is the first step of SDNA indexing phase. The model employs three types of natural language processing: tokenisation, normalisation and SDNA extraction.

Throughout this chapter, an image-based illustrative example (Figure 4.1) is selected from the *fotoLIBRA* collection, to provide a clearer perspective in the use of the SDNA indexing process. The image used in the example has an id value of *152361* according to the *fotoLIBRA* database. The original annotation of the picture contains 24 words as shown below. This image from this point onwards will be referred to as an illustrative image sample α.

Annotation: *Golden Temple, Asia, Asian, Japan, Japanese, Far East, travel, Kinkaku-ji, architecture, wooden, shrine, religion, historic, tradition, water, peace, garden, unesco, world, heritage, site, tourism.*

Figure 4.1: An Image of Golden Temple in Kyoto, Japan (image ID 152361)

4.1.1 Tokenisation

Tokenisation is a simple function, which receives image annotation as an input and returns a sequence of tokens as an output. The tokens are either a single word or a phrase (a few words up to 13). Firstly, the tokenisation function removes all white spaces, punctuations, and unrecognised characters. Then, it identifies words or phrases, and ignores stop words. Words or phrases are identified by matching the annotation tokens against entries in *OntoRo*. Table 4.1 shows a list of distributions of entries in *OntoRo*, according to the size of the phrases in terms of number of words.

Table 4.1: Number of words per phrase in *OntoRo*

Number of words in a Phrase	Total Entry	Percentage
1	153,085	66.97%
2	47,765	20.90%
3	15,839	6.93%
4	7,681	3.36%
5	2,731	1.20%
6	864	0.38%
7	415	0.18%
8	129	0.06%
9	53	0.02%
10	21	0.01%
More than 10	7	0.01%
TOTAL	228590	100%

Analysis of all entries in *OntoRo* show that 153,085 entries consist of a single word; 47,765 entries consist of two words; 15,839 consist of three words; and 7,681 consist of four words. An entry that consists of two or more words is considered as a phrase. The longest phrase found in *OntoRo* is thirteen words and there is only one entry of such a phrase. The statistical analysis listed in Table 4.1 conducted on all entries in *OntoRo* show 98.15% of all entries consist of four words or less.

The tokenisation process tries to identify combinations of words that match with *OntoRo* entries within a fixed number of words windows. For instance, if the window size is 3 and the sequence of words in the image annotation is "*a b c d e f*", then the tokenisation function generates all possible permutations of classes 3, 2 and 1 for a particular window; e.g. "*a b c*", "*a b*", "*a*", "*b c d*", "*b c*", "*b*", "*c d e*", "*c d*", "*c*", "*d e f*", "*d e*", "*d*", "*e f*", "*f*" and "*e*". For every permutation, the function searches for matching entries in *OntoRo*. If there is no match found, stemming function is applied on the permutation before it is matched again with *OntoRo* entries. If there is still no matching entry found, the stemmed permutation is ignored.

The appropriate window size for the *fotoLIBRA* image collection is determined in a preliminary experiment using 25,000 image annotations from random-image set *β*. 13 different experiments are conducted using 13 different window sizes ranging from 1 to 13 words (the longest phrase found in *OntoRo*). For each window size, the annotations are matched against the *OntoRo* entries.

Table 4.2 shows the percentage of annotation tokens matched with *OntoRo* entries for a particular window size.

Table 4.2: Percentage of Tokens Matched with *OntoRo* Entries According to Size of Phrase

Window Size	Size of Phrases Found (words)													Total
	1	2	3	4	5	6	7	8	9	10	11	12	13	
1	100.00%	-	-	-	-	-	-	-	-	-	-	-	-	100%
2	95.47%	4.53%	-	-	-	-	-	-	-	-	-	-	-	100%
3	95.22%	4.37%	0.41%	-	-	-	-	-	-	-	-	-	-	100%
4	95.22%	4.35%	0.41%	0.02%	-	-	-	-	-	-	-	-	-	100%
5	95.22%	4.35%	0.41%	0.02%	0%	-	-	-	-	-	-	-	-	100%
6	95.22%	4.35%	0.41%	0.02%	0%	0%	-	-	-	-	-	-	-	100%
7	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	-	-	-	-	-	-	100%
8	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	-	-	-	-	-	100%
9	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	0%	-	-	-	-	100%
10	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	0%	0%	-	-	-	100%
11	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	0%	0%	0%	-	-	100%
12	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	0%	0%	0%	0%	-	100%
13	95.22%	4.35%	0.41%	0.02%	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%

Preliminary experimental result shown in Table 4.2 indicates that the annotations in random-image sets β can only be matched against *OntoRo* entries with the size up to four words. Window sizes of five or more words return no occurrence in *OntoRo*. In total, 98.15% from *OntoRo*'s entries are usable to the tokenisation function. Further analysis of the results reveals that the remaining 1.85% of *OntoRo*'s entries (entries with phrases longer than 4 words), contain phrases used to explain an idea or a sense. For instance, the phrase '*go to one's last home*' is used to explain '*death*', whilst the phrase '*like a thief in the night*' is used to explain '*stealthily*', and the phrase '*go round and round in one's head*' is used to explain '*obsession*'. The annotations in the random-image sets β rarely uses these phrases.

Based on the experimental results, word window size of 4 is used in the tokenisation function used in the proposed approach.

Stop words are words with high frequency of occurrence in annotations and/or text and with relatively low information content such as function words (*of*, *the*, *and*, etc.) and pronouns (*them*, *who*, *what*, etc.). These words introduce noise and may actually damage the performance of indexing and retrieval. In the case of phrases, stop words are needed when dealing with phrases such as '*food for thought*', '*draw the attention*', '*take care of*' or '*keep a sharp look*'. Thus, in the proposed approach, stop words removal is employed only after the lexical matching process is completed. It is used to remove single word matching of stop words.

Although stop word removal is a common practice used in information retrieval, no clear methodology has been suggested for developing a stop words list (Fox, 1990). For instance, the SMART system (Salton, 1971) suggests 571 English stop words while Fox (1990) proposed only 421 words. Commercial services tend to use a simpler method with limited number of stop words.

The proposed method uses the word list suggested by Salton (1971) as it offers the highest number of words providing a higher chance to reduce noises. All 571 English stop words proposed in the SMART system are listed in Appendix B. Table 4.3 and Figure 4.2 shows 5 experiment results of applying SMART's word list on the 5 random samples set β_i, each contains 5,000 image annotations. The sample sets are tokenised with words window size of 4, to identify tokens. After the tokens are identified, they are matched against the stop words list to remove stop words.

Using the SMART stop word list, the tokenisation process is able to identify an average of 19.51% stop words from the random image set β_i. Figure 4.2 shows that stop words removal can reduce an average of 26.25% word noise from the whole annotations identified by *OntoRo*, calculated using the following formula:

$$\text{word noise} = \frac{\text{Average no. of stop words identified}}{\text{Average no. of words identified}} \times 100\% \qquad (4.1)$$

Table 4.3: Preliminary Experiment Result on Stop Word Removal Process

Observation	Random Sample Sets					Average (%)
	1	2	3	4	5	
Total Words in Annotation	100060	102610	103765	105790	100055	100%
Total Terms Identified (Including Stop Words)	73185	77650	78310	77490	74080	74.32%
Stop Words Identified	18205	21095	20925	20685	19060	19.51%
Total Terms Identified Without Stop Word	54980	56555	57385	56805	55020	54.80%

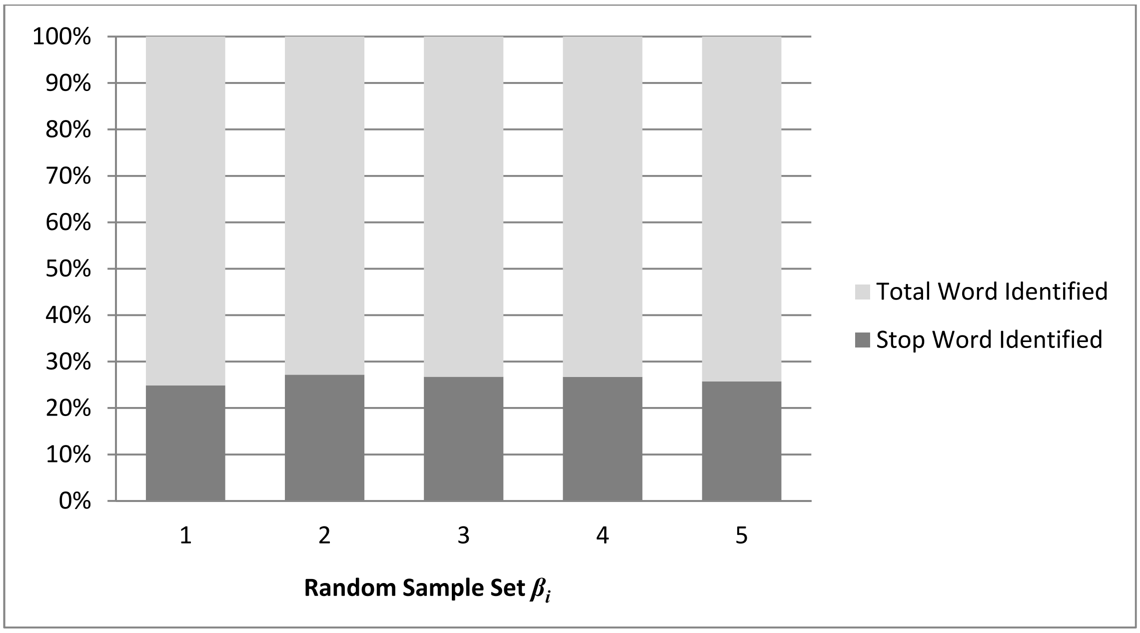


Figure 4.2: Percentage of Total Words Identified and Stop Word Identified.

The experimental results indicate that the stop words removal process using SMART's word list able to reduce significant amount of word noise which could affect the accuracy of the proposed retrieval process.

4.1.2 Normalisation

Different forms of characters often convey identical meaning. A way of getting the meaning that underlies the word is by normalising the variations by converting them to the same form. The most common techniques of normalisation is case folding and stemming. Case folding is converting all characters into lower case before matching them with the lexical ontology entries. The proposed approach applies case folding on both the annotations and the lexical ontology entries.

In linguistic morphology, stemming is the process of reducing a word to its grammatical root form called the stem. Although normalisation of a word to its root form can misguide the original meaning/sense of the word according to certain context, in most cases, morphological variants of the words have similar semantic interpretations and are considered as equivalent (Lovins, 1968; Porter, 1980; Minnen et al., 2001). Therefore, the proposed approach applies stemming only after the tokenisation process, in order to increase the consistency in text and increase the chance of lexical matching.

Text normalisation increases the recall and reduces the precision (Kraaij and Pohlmann, 1996). The former is due to removing morphological variations that benefits recognising similarities. On the other hand, word variations have semantic significance, and by removing grammatical inflections causes errors, thus precision decreases.

The stemming technique employed in the approach proposed in this section is based on the Porter Stemming algorithm (Porter, 1980), a.k.a. the Porter stemmer. It is the most widely used stemming algorithm, which relies on a set of language rules to extract morphological root forms of words, i.e. word stems.

Figure 4.3 and Table 4.4 show the preliminary experimental result using the presented random image set β_i. The results obtained from the experiment shows that only 50.38% of the all annotations are matched against *OntoRo*'s entries by using the original forms of the words (the annotations are not normalised/stemmed).

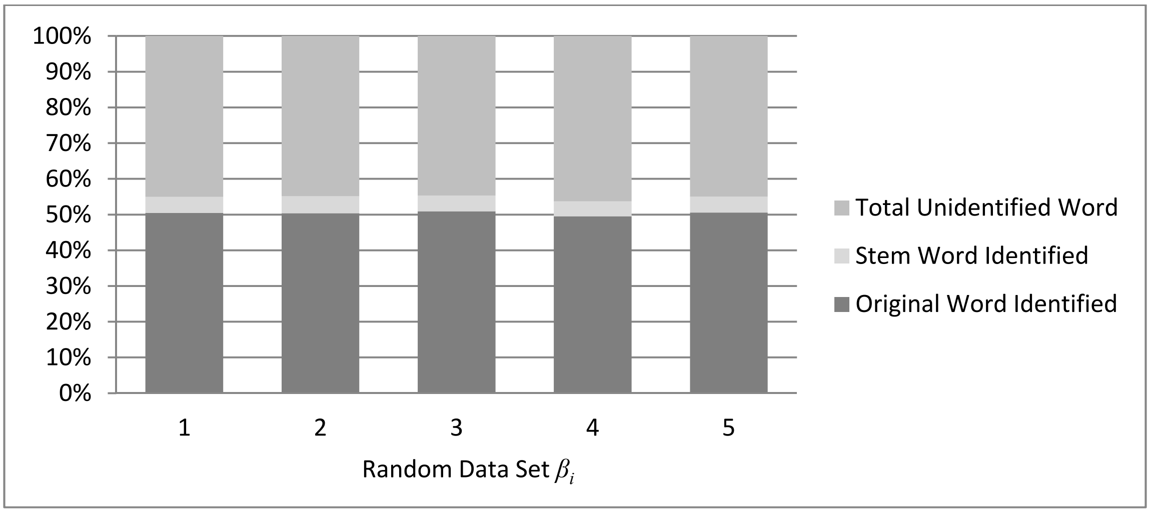


Figure 4.3: Percentage of Total Unidentified Word, Stem Word Identified and Original Word Identified.

Table 4.4: Preliminary Experiment Result on Stemming Process

Observation	Random Image Sets β_i					Average (%)
	i = 1	i = 2	i = 3	i = 4	i = 5	
Total Annotation Word	20012	20522	20753	21158	20011	100%
Original Word Identified	10104	10344	10568	10482	10118	50.38%
Stem Word Identified	892	967	909	879	886	4.42%
Total Word Identified	10996	11311	11477	11361	11004	54.80%
Total Unidentified Word	9016	9211	9276	9797	9007	45.20%

The matching rate of annotation tokens in *OntoRo* increases by 4.42% after normalisation and provides an overall matching rate of 54.80%. Further analysis of the results reveal that the remaining 45.20% of annotations contain name entities such as names of places, people, products and/or typing errors, which do not occur in *OntoRo*, and therefore, cannot be matched. Table 4.5 shows the recall score for all random sample sets.

Table 4.5: Improvement in Recall after Stemming

Recall	Random Sample Sets β_i					Average (%)
	i = 1	i = 2	i = 3	i = 4	i = 5	
Before stemming	50.49%	50.40%	50.92%	49.54%	50.56%	50.38%
After stemming	54.95%	55.12%	55.30%	53.70%	54.99%	54.80%
Percentage increases	4.46%	4.71%	4.38%	4.15%	4.43%	4.42%

Using image sample α (Figure 4.1), the tokenisation and normalisation processes are employed. As a result, 5 words are ignored and 18 tokens are identified including 17 words and 1 phrase, i.e. the token *far east*. Table 4.6 lists all acquired tokens for the image sample α. Let T be a set of tokens such that $t \in T$, $T_\alpha = \{t_1, t_2, t_3, \ldots, t_{18}\}$. Five words that are ignored are named entities, which do not occur in *OntoRo*, i.e. '*Asia*', '*Asian*', '*Japanese*', '*Kinkaku-ji*' and '*Unesco*'.

Table 4.6: Tokens for Image Sample α

Token	No. of Words	Token	No. of Words
t_1 = golden	1	t_{10} = historic	1
t_2 = temple	1	t_{11} = tradition	1
t_3 = Japan	1	t_{12} = water	1
t_4 = far east	2	t_{13} = peace	1
t_5 = travel	1	t_{14} = garden	1
t_6 = architecture	1	t_{15} = world	1
t_7 = wooden	1	t_{16} = heritage	1
t_8 = shrine	1	t_{17} = site	1
t_9 = religion	1	t_{18} = tourism	1

4.1.3 SDNA Extraction

The purpose of SDNA extraction is to acquire all possible senses of each token, using the method discussed in section 3.1.2 For every token t_i, where $t_i \in T$, the SDNA extraction process acquires all related SDNA-based senses from *OntoRo*. As explained earlier in section 3.1.3, every token t_i has several possible senses (ambiguities) and each sense is represented by an SDNA s_j structure, therefore:

$$Senses(t_i) = \{t_i s_1, t_i s_2, \ldots, t_i s_n\} \tag{4.2}$$

where $t_i s_j$ denotes an SDNA s_j of token t_i. The combination of all possible SDNA for every token T from the annotation of an image is called an SDNA set. An SDNA set for an image d is defined as:

$$\mathrm{SetSDNA(d)} = \bigcup_{i=1}^{|T_\alpha|} \mathrm{Senses(t_i)} \tag{4.3}$$

Table 4.7 shows that in average, 89.39 SDNA are extracted from every annotation in the random image set β_i. Using the illustrative image example α (Figure 4.1), 132

SDNA were extracted from 18 tokens, $|\text{SetSDNA}(\alpha)| = 132$. Parts of them are listed in Table 4.8 below.

Table 4.7: Preliminary Experiment Result on SDNA Extraction Process

Observation	Random Sample Sets β_i					Average
	1	2	3	4	5	
SDNA Extracted	441540	453030	458610	443555	437900	89385.4
Average SDNA per Image	88.31	90.61	91.72	88.71	87.58	89.39

Figure 4.4 and 4.5 explains the overall flow of natural language processing for further clarification.

```
INPUT: image annotation α
OUTPUT: SDNA set α

REPEAT for every image_annotation(α)
    token_array := tokenise(image_annotation(α))
    n := 0
    REPEAT while n < size(token_array)
        REPEAT while i := window_size
            phrase := combine token n to (n+i)
            MATCH phrase with OntoRo's entry
            IF phrase match with OntoRo's entry
                SDNA_set(α) := SDNA_set(α) + sdna_extract(phrase)
                n := n + i
                END REPEAT
            ELSE
                i := i - 1
            END IF
        END REPEAT
        n := n + 1
    END REPEAT
END REPEAT
```

Figure 4.4: Pseudo code of Natural Language Processing

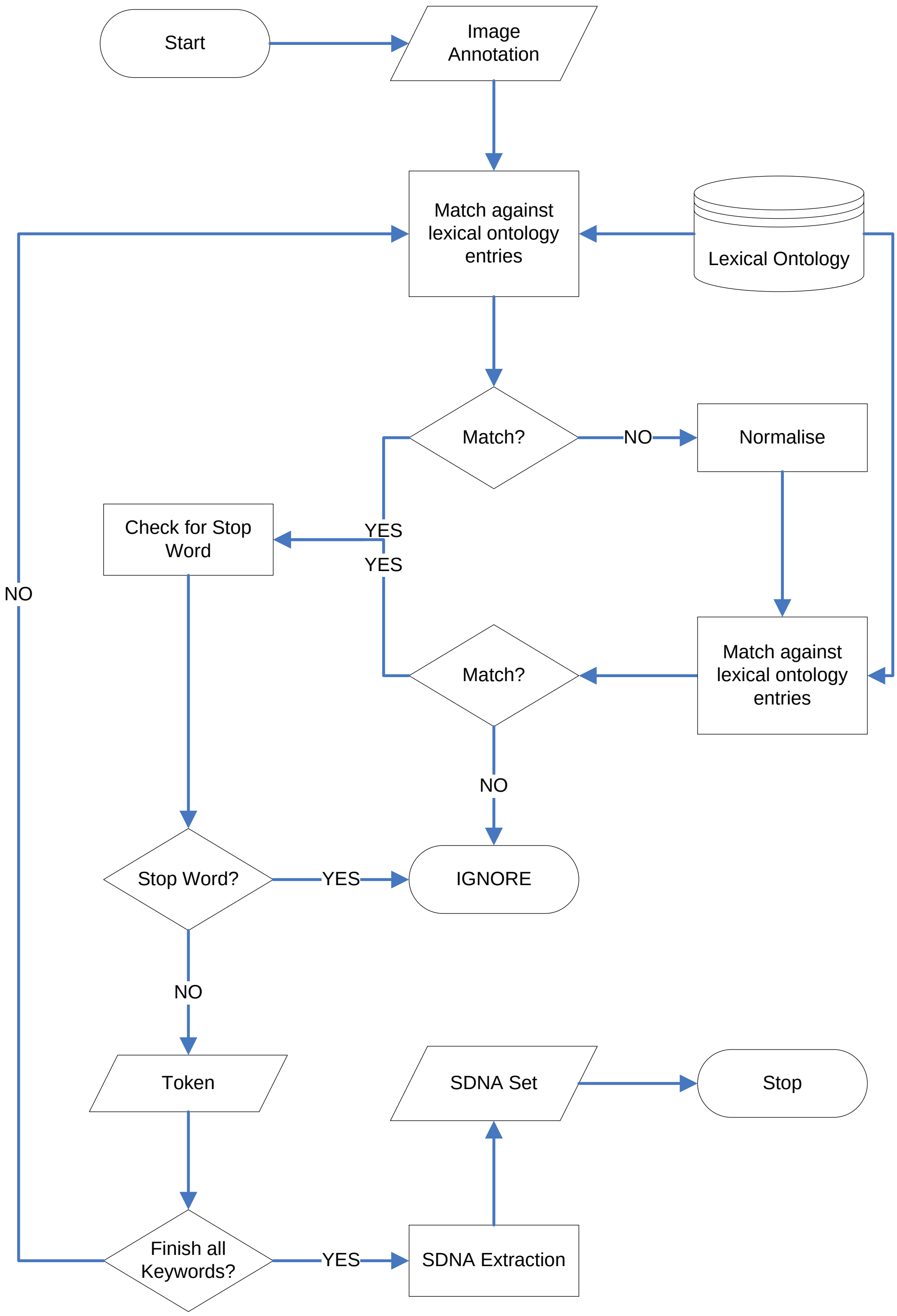


Figure 4.5: Process Flow of Natural Language Processing

Table 4.8: Part of SDNA Set Extracted from Image Example

Token	SDNA	Token Senses
***t_1* = golden**	t_1s_1= 1-6-22-127-1-2	Oldness
	t_1s_2= 3-15-48-433-2-1	Yellowness
	t_1s_3 = 5-27-63-644-2-4	Goodness
	t_1s_4 = 5-30-69-730-2-3	Prosperity
	t_1s_5 = 6-36-80-852-2-2	Hope
***t_2* = temple**	t_2s_6 = 1-8-28-164-1-3	Production
	t_2s_7 = 2-9-33-192-1-6	Abode
	t_2s_8 = 2-10-35-209-1-4	Height
	t_2s_9 = 2-10-35-213-1-3	Summit
	t_2s_{10} = 5-27-63-662-1-1	Refuge
	t_2s_{11} = 6-36-82-866-1-4	Repute
	t_2s_{12}= 6-39-95-990-1-1	Temple
	t_2s_{13} = 6-39-95-990-1-3	Temple
***t_3* = Japan**	t_3s_{14} = 2-10-36-226-1-10	Covering
	t_3s_{15} = 2-10-36-226-3-4	Covering
	t_3s_{16} = 3-14-46-357-1-4	Unctuousness
	t_3s_{17} = 3-15-48-428-1-3	Blackness
	t_3s_{18} = 3-15-48-428-3-1	Blackness
	t_3s_{19} = 6-36-79-844-3-1	Ornamentation
***t_4* = far east**	t_4s_{20} = 2-10-34-199-1-2	Distance
***t_5* = travel**	t_5s_{21} = 3-15-47-360-2-2	Motion
	t_5s_{22} = 1-8-28-170-1-2	Motion
	t_5s_{23} = 3-15-47-373-1-3	Land travel
	t_5s_{24} = 1-4-14-68-1-3	Land travel
	t_5s_{25} = 1-1-1-1-1-1	Velocity
	t_5s_{26} = 1-1-3-5-1-2	Egress
	t_5s_{27} = 1-6-21-108-1-1	Book
	t_5s_{28} = 1-7-25-154-1-2	Worship
***t_6* = architecture**	t_6s_{29} = 1-3-12-56-1-1	Composition
	t_6s_{30} = 1-4-13-62-1-1	Arrangement
	t_6s_{31} = 1-8-28-164-1-1	Production
	t_6s_{32} = 2-11-37-243-1-1	Form
	t_6s_{33} = 3-14-45-331-1-1	Structure
	t_6s_{34} = 4-25-58-551-1-3	Representation
	t_6s_{35} = 6-36-79-844-1-2	Ornamentation
***t_7* = wooden**	t_7s_{36} = 3-15-47-366-2-3	Vegetable life
	t_7s_{37} = 4-25-58-576-2-1	Inelegance
	t_7s_{38} = 5-26-59-602-2-1	Obstinacy
	t_7s_{39} = 6-35-77-820-2-1	Insensibility
***t_8* = shrine**	t_8s_{40} = 3-15-47-364-1-6	Interment
	t_8s_{41} = 6-39-95-988-1-10	Ritual
	t_8s_{42} = 6-39-95-990-1-1	Temple

4.2 MATHEMATICAL PROCESSING

This section describes the proposed architectural model of mathematical processing. The model uses four types of mathematical processing: (i) SDNA similarity matrix construction, (ii) raw co-occurrence frequency transformation, (iii) SDNA disambiguation, and (iv) matrix factorisation.

SDNA disambiguation is a crucial stage in the proposed approach as it influences the performance of image indexing and retrieval. The SDNA disambiguation technique determines the selection of *semantic chromosomes* based on the annotation. The *semantic chromosome* represents the semantic signature of an image or query, expressed through a set of selected SDNA, each representing a semantically distinguishable sense of a token. Selecting the correct sense for each token could eliminate non-relevant retrievals of images, thus the precision increases.

According to the distributional hypothesis in linguistics, words that occur in similar contexts tend to have similar meaning (Harris, 1985; Navigli, 2009; Navigli and Lapata, 2010). To apply the hypothesis, the SDNA disambiguation technique builds an SDNA similarity matrix for measuring the similarity between image annotations.

4.2.1 SDNA Similarity Matrix

The SDNA similarity matrix represents the SDNA in SDNA set. An element in the SDNA similarity matrix corresponds to the similarity score of an SDNA with other SDNA in the SDNA set. Table 4.9 illustrates the SDNA to SDNA similarity matrix for a SDNA set *m*, such that $SetSDNA(m) = \{t_1s_1, t_1s_2, t_2s_3, t_2s_4\}$.

Table 4.9: SDNA to SDNA Similarity Matrix

SDNA	t_1s_1	t_1s_2	t_2s_3	t_2s_4	totalsim()
t_1s_1		$sim(t_1s_1, t_1s_2)$	$sim(t_1s_1, t_2s_3)$	$sim(t_1s_1, t_2s_4)$	$totalsim(t_1s_1)$
t_1s_2	$sim(t_1s_2, t_1s_1)$		$sim(t_1s_2, t_2s_3)$	$sim(t_1s_2, t_2s_4)$	$totalsim(t_1s_2)$
t_2s_3	$sim(t_2s_3, t_1s_1)$	$sim(t_2s_3, t_1s_2)$		$sim(t_2s_3, t_2s_4)$	$totalsim(t_2s_3)$
t_2s_4	$sim(t_2s_4, t_1s_1)$	$sim(t_2s_4, t_1s_2)$	$sim(t_2s_4, t_2s_3)$		$totalsim(t_2s_4)$

An SDNA similarity score *sim()* is used to determine the degree of dominance for a particular sense of a token in an image annotation. The SDNA with the highest similarity score is considered as the most dominant SDNA for a particular token, which also determines the relevant sense of the token. That sense represents the meaning of the token in the context of the image annotation.

The technique proposed here is based on the following observations:

(i) *OntoRo* is built on the six levels of *Roget's thesaurus* hierarchy, i.e. hierarchy by class, section, subsection, concept, POS, and paragraph.

(ii) Words that belong to the same paragraph express similar ideas and the context of use is presumed to be the same, thus the words can be used interchangeably.

(iii) Words in the same paragraph are semantically closer than words in a different paragraph within the same POS group. Words in the same POS group are semantically closer than words in different POS group within the same concept.

(iv) Semantic distance between two words can be measured by comparing the similarity between their SDNA structures.

(v) Different words that express similar ideas tends to have similar hierarchies, i.e. similar SDNA structure. Therefore, these words can be represented with similar SDNA;

(vi) A word with different senses, i.e. a word that expresses different ideas based on the context, tends to have different *OntoRo* hierarchy for every sense. Thus, different word sense is represented by different SDNA structures;

The similarity between two SDNA is measured by comparing their structural similarity, which is the number of levels at which the corresponding number is equal. It is in contrast with the Hamming distance calculation (Manning et al., 2008). Therefore, the proposed approach uses Hamming distance to calculate the distance between an SDNA with others in the same *SDNA set*. The Hamming distance between two SDNA is defined as the number of level(s) at which the corresponding numbers are different.

Let s be an SDNA in $SetSDNA$, such that for any $s \in SetSDNA$, then the $\mathrm{hamdis}(\mathrm{s_i}, \mathrm{s_j})$ is the Hamming distance between SDNA s_i and SDNA $\mathrm{s_j}$. In order to measure the similarity between two SDNA, the reverse Hamming distance is used to calculate the number of matched level, formally:

$$\mathrm{sim}(\mathrm{s_i}, \mathrm{s_j}) = \mathrm{L} - \mathrm{hamdis}(\mathrm{s_i}, \mathrm{s_j}) \tag{4.4}$$

Where L is the number of level used in SDNA. Using *OntoRo* as the lexical ontology, the number of level in SDNA is six, therefore $L = 6$. For example:

$s_i = 1 - 2 - 3 - 4 - 5 - 6$ and

$s_j = 1 - 2 - 3 - 4 - 7 - 1$, therefore

$hamdis(s_i, s_j) = 2$, and

$sim(s_i, s_j) = 6 - 2 = 4$.

Higher similarity scores between an SDNA with all other SDNA refers to higher relevancy in the particular context of use, i.e. the image annotation or the query used. Thus, the total similarity value is calculated as the cumulative scoring result, formally:

$$\mathrm{totalsim}(\mathrm{s_i}) = \left(\sum_{\mathrm{j=1;j \neq i}}^{|\mathrm{SetSDNA}|} \mathrm{sim}(\mathrm{s_i}, \mathrm{s_j}) \right) \tag{4.5}$$

Table 4.9 shows that *totalsim*(t_1s_1) is calculated by the summing all similarity measurements between t_1s_1 and all other SDNA in SetSDNA (i.e. t_1s_2, t_2s_3 and t_2s_4). The value in position (i, j) of the matrix represents the similarity between SDNA i and j in the SDNA set. Figure 4.6 shows the pseudo code for *totalsim()* calculation.

```
INPUT: SDNA set
OUTPUT: totalsim() value for each SDNA in SDNA set

totalsim := 0
i := 0
REPEAT while i <= number of SDNA in SDNA_set
   s_i := SDNA_set(i)
   j := 0
   REPEAT while j <= number of SDNA in SDNA_set
         s_j := SDNA_set(j)
         totalsim(s_i) := totalsim(s_i) + sim(s_i, s_j)
   END REPEAT
END REPEAT
```

Figure 4.6: Pseudo code for *totalsim()* calculation

4.2.2 SDNA Weight

The proposed method will identify, weight and utilise the information shared among all SDNAs of the tokens in an image annotation. The aim of the SDNA weight is to determine two features:

(i) the most relevant SDNA for every token. The criteria for this feature is the highest weight for the token in a particular context, and

(ii) the degree of relevance of the selected SDNA in relation to the context of use.

The idea of weighting the tokens is to provide an adequate token disambiguation mechanism, i.e. the higher weight identifies elements that are more relevant, whilst less weight identifies less relevant element in the matrix. In the proposed method, the weight assigned to a particular SDNA reflects its relevance to the term in the text. The proposed approach computes SDNA weight automatically using an adaptation of the *tf-idf* (term frequency × inverse document frequency) method of weighting functions (Salton and McGill, 1986; Baeza-Yates and Ribeiro-Neto, 1999; Jones et al., 2000; Manning et al., 2008). Salton and Buckley (1998) had reviewed a large family of *tf-idf* weighting functions. They had conducted their evaluation in the context of information retrieval. They concluded that *tf-idf* weighting provides significant improvements over the raw frequency-weighting scheme.

The benefit of the *tf-idf* weighting approach is that it assigns a high weight to a term if the term has high frequency of occurrence in the corresponding document (high value for the *tf*) and low frequency of occurrence in the other documents (i.e. high *idf*). The *tf* value is the domestic information for the document, where it measures the frequency of terms against document length. This is similar to the *totalsim()* score for SDNA, which calculates the similarity of SDNA against other SDNA in the same SDNA set. On the other hand, the *idf* value is the global information of the SDNA that corresponds to the entire collection. The SDNA weight sw_s of an SDNA s for an image d is computed as follows:

$$\mathrm{sw_s} = \frac{\mathrm{totalsim(s)}}{\mathrm{max\_totalsim_d}} \cdot \log \frac{|\mathrm{D}|}{|\{\mathrm{d} \in \mathrm{D}: \mathrm{s} \in \mathrm{d}\}|} \tag{4.6}$$

where $max\_totalsim_d$ is the *totalsim* of the most similar SDNA in d, D is the set of all images in the collection and $|\{\mathrm{d} \in \mathrm{D}: \mathrm{s} \in \mathrm{d}\}|$ is the number of images where the SDNA s appears. The *max_totalsim* value is calculated by multiplying the total number of SDNA in the SDNA set by the number of level used in SDNA, L, which in the case of *OntoRo* the L has the value of 6, i.e. $L = 6$.

Using random image sets β_i, which consist of 25,000 images in total, the SDNA weighting formula (4.6) is applied on all SDNAs in the particular set. Then, for each SDNA set, an average SW() weight is calculated producing 25,000 averaged weights for preliminary analysis.

Figure 4.7 shows the plot of 25,000 average weights for random image β_i plotted against the size of annotations (number of keywords) in each image. The figure shows that images with longer annotations tend to get a higher SDNA weights. Therefore, images with longer annotations are likely to get higher rank compared to those with shorter annotations. Therefore, SDNA weighting based on the *tf-idf* weighting function is likely to be biased towards long annotations.

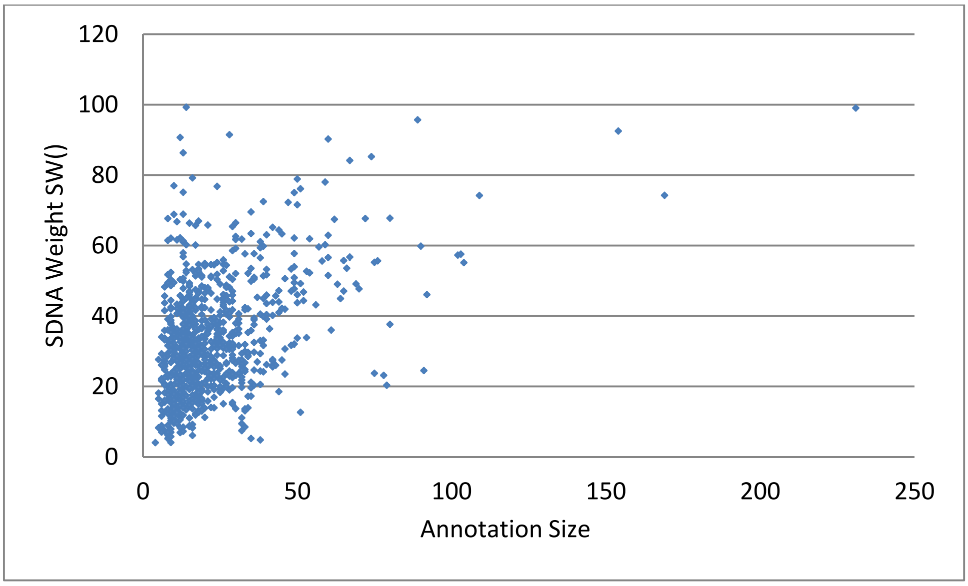


Figure 4.7: Average *SW()* Weight for 25000 Random Images .

To deal with this drawback, an efficient normalisation technique is needed to balance the SDNA weight $SW()$ between smaller and bigger $SetSDNA$ sizes. Traditional IR systems uses document normalisation techniques to retrieve documents of all lengths fairly, and at the same time, diminishes the advantages that longer documents have in the document retrieval over the short documents.

Different with free text or long documents, image annotations only focuses on explaining the content of the image (i.e. elements, objects, spatial info, and context). Thus, every keyword in the annotation is equally important regardless of the size of the annotations. Assume for example, two different images x (the image of a tiger) and y (the image of a lion), both have the same keyword '$wild$'. However, image x has shorter annotations of only 10 words compared to image y with 30 words. In this situation, the proposed approach needs to treat the keyword '$wild$' in both images equally although the annotations have a different size. According to Figure 4.7, the keyword '$wild$' that occurs in the annotation of image x is given less discriminative power (lower value for the TF-IDF) than the same word in the annotation of image y. The length of both annotations influences this difference.

The most commonly used text normalisation technique in the domain of information retrieval is the cosine normalisation. It compensates for the document lengths by using their magnitudes in a vector space as their normalisation factor. The cosine normalisation factor is computed as follows:

$$\sqrt{SW(s_1)^2 + SW(s_2)^2 + SW(s_3)^2 + \cdots + SW(s_n)^2} \tag{4.7}$$

where n is the number of SDNA in an SDNA set. Every SDNA weight SW() is normalised by dividing each of them with the cosine normalisation factor.

The random image sets β_i are used to illustrate the effect of the cosine normalisation against the SDNA weight calculation. After all SDNA weights for SetSDNA(β) are normalised and the average weight of SDNA in the SDNA set is calculated, the graph is plotted in Figure 4.8.

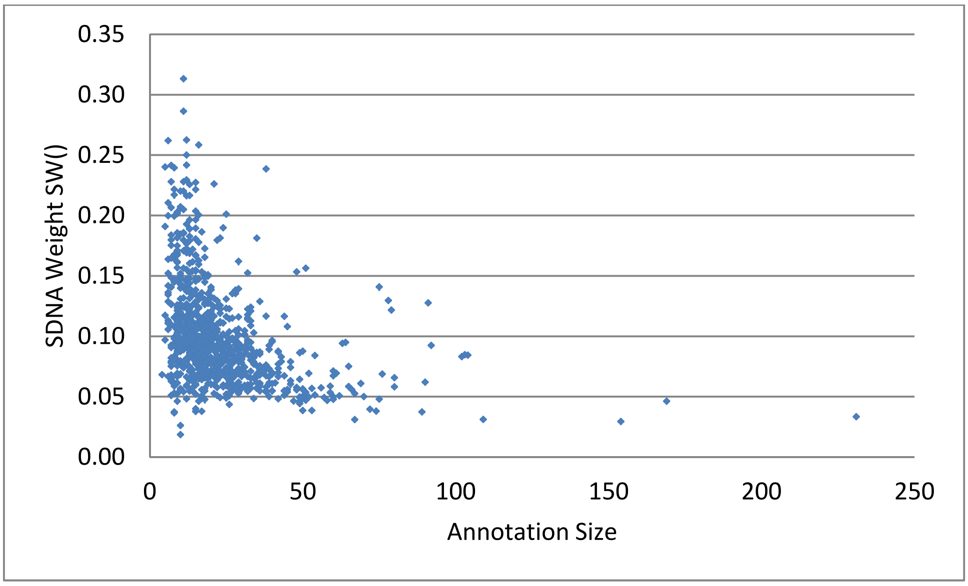


Figure 4.8: Average *SW()* Weight for 25000 Random Samples *β* using Cosine Normalisation.

Looking at the figure, although the SDNA weight range is smaller, and the average SDNA weight for images with longer annotations had been massively reduced, cosine normalisation technique tends to be biased towards shorter annotations. Thus, in this case, cosine normalisation is not entirely fair in normalising tokens' weights.

The normalisation method proposed in this thesis is based on a probabilistic model, Okapi BM25 (Robertson et al., 1998). Thorough studies and testing had proven its effectiveness, which explains its common use in real world applications (Baeza-Yates and Ribeiro-Neto, 1999; Manning et al., 2008). However, some modification to the original formula (2.4), explained in section 2.1.2 is needed to suit the proposed SDNA-based score. This section suggests calculating the SDNA weight by adapting the Okapi BM25 calculation method as follows:

$$\mathrm{SW}(\mathrm{s_i}, \mathrm{S}) = \frac{\mathrm{totalsim}(\mathrm{s_i}) \cdot (\mathrm{k_1} + 1)}{\mathrm{totalsim}(\mathrm{s_i}) + \mathrm{k_1} \cdot \left(1 - \mathrm{b} + \mathrm{b} \cdot \frac{|\mathrm{S}|}{\mathrm{avgsl}}\right)} \tag{4.8}$$

where $|S|$ is the number of SDNA in an SDNA set S and $avgsl$ is the average number of SDNA in SDNA set, which replace $|d|$ and $avgdl$ in the original formula. While $\mathrm{k_1}$ and b are two tuning parameters that are adjustable according to the usage requirements. $\mathrm{k_1}$ is a positive parameter that calibrates the term frequency scaling. A $\mathrm{k_1}$ value of 0 corresponds to a binary model with no term frequency, and a large value corresponds to using raw term frequency. b is another tuning parameter, which determines the document length scaling, where $\mathrm{b} = [0,1]$. $\mathrm{b} = 1$ yields to fully scaling the term weight by the document length, while $\mathrm{b} = 0$ yields to no document length normalisation.

A value of $k_1 = 1.2$ and $b = 0.75$ is used in this thesis based on recommendation by Robertson and Walker (1999), which have been found to be effective in many different retrieval environments. In addition, *totalsim(s_i)* is used to replace the word frequency in a document *f(w_i,d)*. To observe the performance of proposed normalisation formula, the SDNA weight for random-image sets β_i is calculated using the Okapi BM25 based calculation in (4.8).

Figure 4.9 shows the plot of 25,000 average weights for the 25,000 random images in set β_i plotted against the size of annotations (number of keywords) in each image. The figure shows that, using the Okapi BM25-based normalisation technique, SDNA that belong to longer annotations, have better weights and are relatively competitive with other SDNA. Using the function in (4.8), the *SW()* for all *SetSDNA(α)* is calculated. Table 4.10 lists the *totalsim()* and *SW*() values for eight *SetSDNA(α)* with the highest *SW()* values.

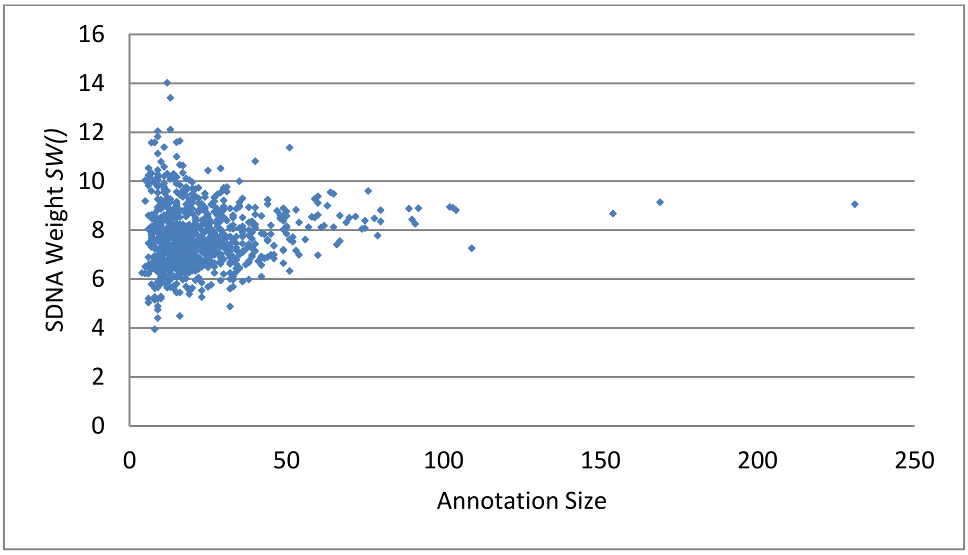


Figure 4.9: Average *SW()* Weight for 25000 Random Samples *β* Using Okapi BM25

Table 4.10: Part of SDNA Weight for *SetSDNA(α)*

Token	SDNA	totalsim()	SW()
t_1 = golden	t_1s_1	27	21.5708
	t_1s_2	**65**	**23.3330**
	t_1s_3	23	21.9784
	t_1s_4	21	20.6392
	t_1s_5	27	22.6231
t_2 = temple	t_2s_6	33	12.7710
	t_2s_7	35	12.5929
	t_2s_8	32	13.1115
	t_2s_9	32	14.5336
	t_2s_{10}	23	13.2700
	t_2s_{11}	29	12.1592
	t_2s_{12}	**39**	**19.8613**
	t_2s_{13}	38	19.6750
t_3 = Japan	**t_3s_{14}**	**34**	**26.9409**
	t_3s_{15}	34	17.8097
	t_3s_{16}	55	25.9253
	t_3s_{17}	66	24.4722
	t_3s_{18}	66	24.5710
	t_3s_{19}	30	16.8347
t_4 = far east	**t_4s_{20}**	**31**	**35.7615**

Token	SDNA	totalsim()	SW()
t_5 = travel	t_5s_{21}	42	13.6704
	t_5s_{22}	42	12.8899
	t_5s_{23}	45	14.2177
	t_5s_{24}	43	14.3313
	t_5s_{25}	36	14.0673
	t_5s_{26}	**39**	**17.5965**
	t_5s_{27}	14	9.5049
	t_5s_{28}	35	17.5630
t_6 = architecture	t_6s_{29}	25	8.0126
	t_6s_{30}	23	11.9696
	t_6s_{31}	33	11.3865
	t_6s_{32}	**26**	**14.5274**
	t_6s_{33}	46	14.7278
	t_6s_{34}	14	10.3940
	t_6s_{35}	30	11.8072
t_7 = wooden	**t_7s_{36}**	**69**	**29.5394**
	t_7s_{37}	14	18.2618
	t_7s_{38}	17	22.4806
	t_7s_{39}	20	17.5598
t_8 = shrine	**t_8s_{40}**	**66**	**27.6161**
	t_8s_{41}	34	22.2617
	t_8s_{42}	39	19.8613

4.2.3 SDNA Disambiguation

The SDNA disambiguation is the final step before constructing the *semantic chromosome* of an image, based on its annotation. It is a technique for determining which SDNA s_i for a token $t_i \in T$ is the most accurate one for a particular context.

A SDNA is selected for each token to form a *semantic chromosome* set. It can be formally described as a task of mapping *semantic chromosomes* from the SDNA set of an image, i.e. $\text{semantic\_chromosomes}(\alpha) \in \text{SetSDNA}_\alpha$, where *SetSDNA(α)* is the SDNA set for image α.

The SDNA with the highest weight $SW(s_j)$ for each t_i is chosen as the most relevant SDNA, determining the most accurate sense of token $\mathrm{t_i}$ in the context of $\mathrm{T_\alpha}$. Eighteen SDNA are chosen from *SetSDNA(α)* to form *semantic_chromosomes(α)*. In Table 4.10, the SDNA in bold, are the highest ranked SDNA for each token. They are selected to form the *semantic chromosome* of image *α*, where *semantic_chromosomes(α)* = $\{t_1s_2, t_2s_{12}, t_3s_{16}, t_4s_{20}, t_5s_{26}, t_6s_{32}, t_7s_{36}, t_8s_{40}, \ldots t_{18}s_n\}$ and $|semantic\_chromosomes(\alpha)| = 18$.

Table 4.11 lists the *semantic_chromosomes(α)* with their $SW()$ values and concept senses of where they belong to. SDNA $t_{12}s_{83}$ is the highest ranking SDNA in the *semantic_chromosomes(α)* which belongs to the token t_{12}:*water*. Referring to image *α*, water is not the most important element, but the image is certainly important to represent water.

The SDNA $t_{12}s_{83}$ represents the sense '*prosperity*' that relates to '*prosper*', '*benefit*', '*bless*', '*turn out well*', etc. While the next 5 highest ranking SDNA belongs to token '*garden*', '*far east*', '*peace*', '*wooden*' and '*tradition*', which belong to concept '*philosopher*', '*farness*', '*silence*', '*wood*' and '*theology*'.

Table 4.11: List of *semantic chromosome*$_{\alpha}$ with its *SW()* Values

Token(t_i)	**SDNA**	**SW(s_i)**	**Token Sense**	**Related Words**
t_{12} = water	$t_{12}s_{83}$= 5-30-69-730-3-3	39.10	prosperity	prosper, benefit, bless, shed blessings on, Water, fertilize, make blossom like the rose, turn out well, take a good turn
t_{14} = garden	$t_{14}s_{106}$= 4-16-49-449-1-3	36.36	philosopher	philosopher, thinker, man of thought, woman of thought, intellectual, metaphysician, existentialist, school of philosophers, Peripatetic, Academy, Garden
t_4 = far east	t_4s_{20}= 2-10-34-199-1-2	35.76	farness	farness, far distance, remoteness, world's end, ends of the earth, Pillars of Hercules, ne plus ultra, back of beyond, Far West, Far East
t_{13} = peace	$t_{13}s_{88}$= 3-15-48-399-1-1	32.10	silence	silence, soundlessness, inaudibility, total silence, not a sound, not a squeak, stillness, hush, lull, rest, peace, quiet, quiescence
t_7 = wooden	t_7s_{36}= 3-15-47-366-2-3	29.54	wood	wooden, wood, treen, woody, ligneous, ligniform, hard-grained, soft-grained
t_{11} = tradition	$t_{11}s_{57}$= 6-39-92-973-1-4	29.03	theology	theology, symbolic, creedal theology, liberation theology, tradition, deposit of faith, teaching, doctrine, religious doctrine
t_{15} = world	$t_{15}s_{115}$= 3-13-44-319-1-1	28.83	materiality	materiality, substantiality, physical being, physical condition, existence, plenum, world, concreteness, tangibility
t_8 = shrine	t_8s_{40}= 3-15-47-364-1-6	27.62	tomb	tomb, barrow, earthwork, cromlech, dolmen, menhir, monument, shrine, aedicule, memorial
t_3 = japan	t_3s_{14}= 2-10-36-226-1-10	26.94	facing	facing, revetment, cladding, strengthening, veneer, coating, varnish, japan, lacquer, enamel, glaze, incrustation, roughcast
t_9 = religion	t_9s_{50}= 6-39-94-984-1-1	24.01	occultism	occultism, esotericism, hermeticism, mysticism, transcendentalism, religion, mystical interpretation
t_1 = golden	t_1s_2= 3-15-48-433-2-1	23.33	yellow	yellow, gold, amber, tawny, fulvous, sandy, fair-haired, golden-haired, yellow-haired, whitish, creamy, golden, aureate, gilt
t_{17} = site	$t_{17}s_{128}$= 2-9-32-187-1-3	21.12	place	place, meeting place, venue, haunt, focus, genius loci, spirit of place, site, seat, emplacement, position
t_2 = temple	t_2s_{12}= 6-39-95-990-1-1	19.86	temple	temple, fane, pantheon, shrine, aedicule, sacellum, joss house, teocalli, idolatry, house of God, tabernacle, the Temple, House of the Lord, place of worship
t_{10} = historic	$t_{10}s_{51}$= 6-36-82-866-2-1	18.55	reputable	reputable, reputed, of repute, famous, fabled, legendary, famed, far-famed, historic, illustrious, great, noble, glorious, excellent
t_{16} = heritage	$t_{16}s_{122}$= 1-6-22-124-1-1	18.46	future	future, time ahead, prospect, outlook, expectation, approach, long run, distant future, remote future, after ages, distance, future generations, descendants, heirs, heritage, posterity
t_5 = travel	t_5s_{26}= 2-12-43-298-3-1	17.60	emerge	emerge, pop out, stick out, project, bale out, leap, clear out, evacuate, decamp, emigrate, travel, exit, walk off, depart, erupt, break out
t_6 = architecture	t_6s_{33}= 3-14-45-331-1-1	14.52	structure	structure, organization, pattern, plan, content, substance, composition, construction, make, works, workings, nuts and bolts, architecture, fabric, work
t_{18} = tourism	$t_{18}s_{131}$= 2-12-40-267-1-1	14.18	travel	travel, travelling, wayfaring, seeing the World, globe-trotting, country hopping, tourism, walking, hiking, riding, driving, motoring, cycling, biking, journey

Figure 4.10 shows the pseudo code for *semantic_chromosomes(α)* construction in SDNA Disambiguation process.

```
INPUT: Image annotation α
OUTPUT: semantic chromosomes α

semantic_chromosomes(α) := null
REPEAT for every token in image_annotation(α)
    s_i := SDNA with the highest SW() weight for the token
    semantic_chromosomes(α) := semantic_chromosomes(α) + s_i
END REPEAT
```

Figure 4.10: Pseudo code for *semantic_chromosomes(α)* construction SDNA Disambiguation Process

These *semantic chromosomes* will be used to represent image α in SDNA vector space, beginning with sampling the data in a standard SDNA-image matrix, *X*. However, one of the problems with the matrix *X* is that, the majority of the cells in the matrix will be zero due to the sparse SDNA data problem. That is, only a fraction of the entire SDNA elements are chosen as a *semantic chromosome* to represent an image. Zipf's law states that a tiny amount of word (SDNA) only occurs in a very limited set of context (Zipf, 1949). In order to account this problem, this thesis uses matrix factorisation technique to decompose and approximate the matrix *X*.

4.2.4 Matrix Factorisation

Latent Semantic Indexing (LSI) is the most well-known and successful model, which relies on statistical dimension reduction techniques, to solve the problem of high dimensionality and sparseness. It uses truncated Singular Value Decomposition (SVD), which is a matrix factorisation technique used to decompose and approximate a matrix. The SVD technique has been explained in detail in section 2.4.1 . It is employed in measuring image similarity; however, it can be used for measuring token similarity too.

The *fotoLIBRA* image collection contains 157,539 images and OntoRo consists of 228,130 entries. Thus, the traditional distributional measuring approach will build a massive matrix X with dimension of 228,130×157,539. However, the proposed approach reduces the dimension to only 6,239 × 157,539 (only 0.03% of the size of traditional matrix X) since it relies on 6,239 SDNA space dimensions. The huge different in matrix size improve system performance and efficiency. The truncated SVD matrix X has further reduced dimensions to k-dimensional space, X_k, where $X_k = U_k S_k V^T_k$. As mentioned in section 2.4.1 , k refers to the number of dimensions selected for the reduced space representation. It is significant for the efficiency of the proposed approach, which incorporates this representation for its image data. The number of dimensions should be rather small in order to improve the data scalability and approximation. On the other hand, it should be big enough in order to capture any latent relations between the SDNA or the images in the original matrix X.

The optimal number of dimension, $k_{optimal}$, in this thesis is determined by plotting the change in Average Precision values while running the 22-queries (refer to section 3.3.1) over the *fotoLIBRA* image collection using traditional keyword-based retrieval model where queries and documents are represented by vectors. Figure 4.11 shows the variation on Average Precision for 22 queries measured against the increasing value of k dimension.

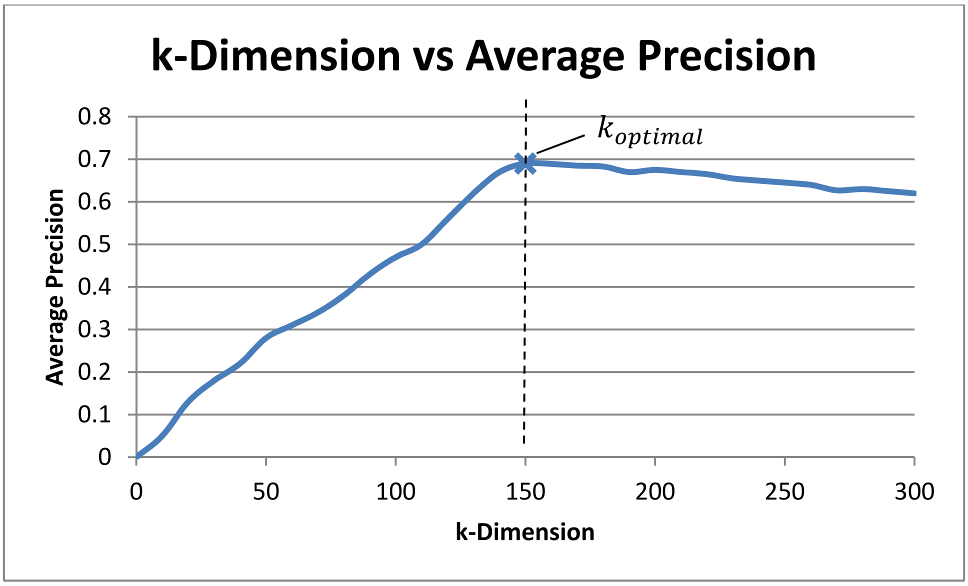


Figure 4.11: Variation of Average Precision measured against increasing value of k-Dimension

From Figure 4.11, it is clear that the average precision value saturates at k=150, which is considered the optimal value of $k_{optimal}$ in this thesis. Chapter 5 further discusses the application of X_k matrix. Figure 4.12 explains the pseudo code for SDNA Indexing processes based on VSM.

```
INPUT: Image annotation α
OUTPUT: image vector α

REPEAT for every image_annotation
    token_array = tokenise(image_annotation(α))
    SDNA_set = SDNA_extract(token_array)
    SDNA_set_weight = SDNA_weight_calculation(SDNA_set)
    semantic_chromosomes(α) = SDNA_disambiguation(SDNA_set_weight)
END REPEAT
image_vector = factorise(semantic_chromosomes)
```

Figure 4.12: Pseudo code for SDNA Indexing processes based on VSM.

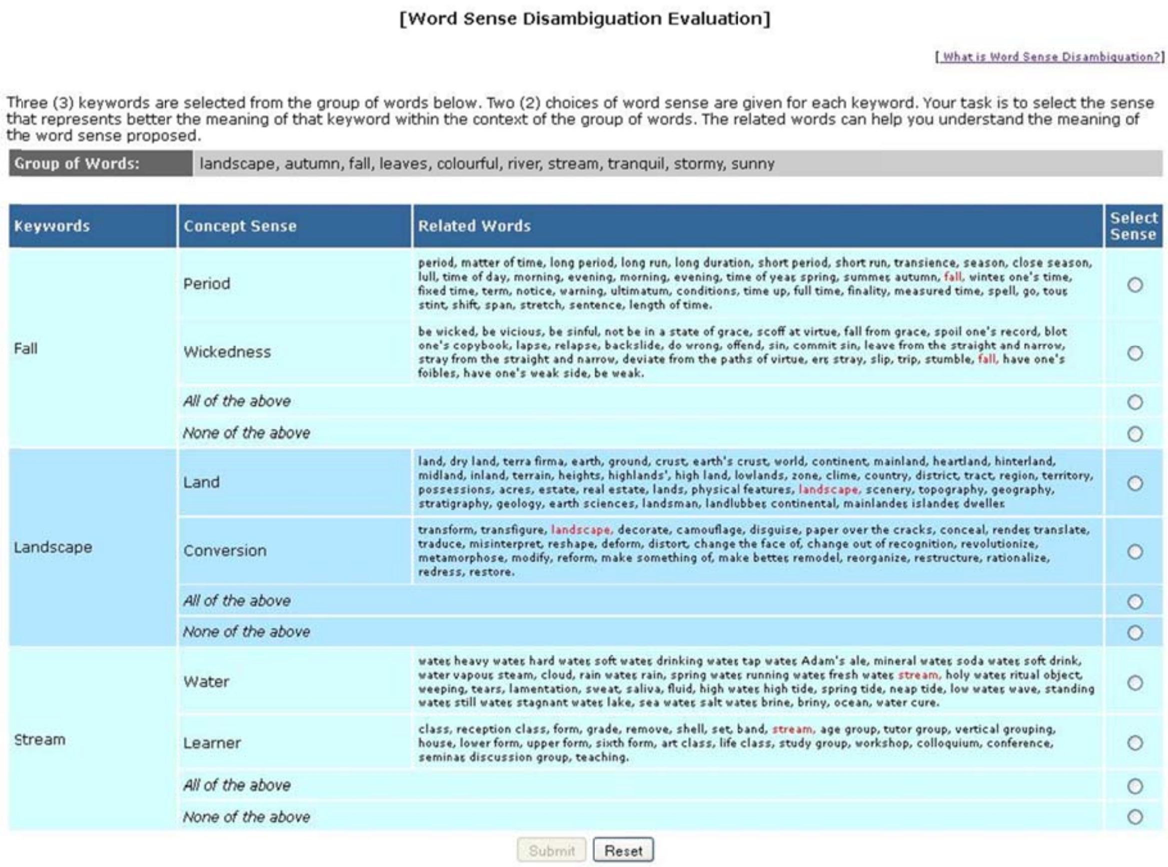
4.3 SDNA DISAMBIGUATION EVALUATION

This thesis uses a collective human evaluation approach, or crowdsourcing, using Amazon Mechanical Turk (MTurk) to evaluate the performance of SDNA disambiguation. MTurk divides the evaluation tasks into micro-tasks, which are offered to a large number of people who do not know each other. Every task offered through the MTurk is called a human intelligence task (HIT). The people involved in every task are called workers. They are paid according to the number of HITs they complete.

4.3.1 Evaluation Protocol

The main objective of the evaluation is to measure the accuracy of the proposed SDNA disambiguation algorithm in selecting the most appropriate sense for each term in the context of a particular annotation. The evaluation experiment consists of two tasks that are conducted by different groups of workers.

In Task 1, the workers are given a group of words from an image annotation (Figure 4.13). They are asked to consider the context of these words and select the most appropriate sense for each of them. Three tokens with the highest SDNA weight are given to be scored by the workers. For each keyword, the workers are provided with two choices: (i) the sense selected by the proposed approach and (ii) a randomly selected sense from all other possible senses.



[Word Sense Disambiguation Evaluation]

[What is Word Sense Disambiguation?]

Three (3) keywords are selected from the group of words below. Two (2) choices of word sense are given for each keyword. Your task is to select the sense that represents better the meaning of that keyword within the context of the group of words. The related words can help you understand the meaning of the word sense proposed.

Group of Words:	landscape, autumn, fall, leaves, colourful, river, stream, tranquil, stormy, sunny

Keywords	Concept Sense	Related Words	Select Sense
Fall	Period	period, matter of time, long period, long run, long duration, short period, short run, transience, season, close season, lull, time of day, morning, evening, morning, evening, time of year, spring, summer, autumn, fall, winter, one's time, fixed time, term, notice, warning, ultimatum, conditions, time up, full time, finality, measured time, spell, go, tour, stint, shift, span, stretch, sentence, length of time.	○
	Wickedness	be wicked, be vicious, be sinful, not be in a state of grace, scoff at virtue, fall from grace, spoil one's record, blot one's copybook, lapse, relapse, backslide, do wrong, offend, sin, commit sin, leave from the straight and narrow, stray from the straight and narrow, deviate from the paths of virtue, err, stray, slip, trip, stumble, fall, have one's foibles, have one's weak side, be weak.	○
	All of the above		○
	None of the above		○
Landscape	Land	land, dry land, terra firma, earth, ground, crust, earth's crust, world, continent, mainland, heartland, hinterland, midland, inland, terrain, heights, highlands', high land, lowlands, zone, clime, country, district, tract, region, territory, possessions, acres, estate, real estate, lands, physical features, landscape, scenery, topography, geography, stratigraphy, geology, earth sciences, landsman, landlubber, continental, mainlander, islander, dweller	○
	Conversion	transform, transfigure, landscape, decorate, camouflage, disguise, paper over the cracks, conceal, render, translate, traduce, misinterpret, reshape, deform, distort, change the face of, change out of recognition, revolutionize, metamorphose, modify, reform, make something of, make better, remodel, reorganize, restructure, rationalize, redress, restore.	○
	All of the above		○
	None of the above		○
Stream	Water	water, heavy water, hard water, soft water, drinking water, tap water, Adam's ale, mineral water, soda water, soft drink, water vapour, steam, cloud, rain water, rain, spring water, running water, fresh water, stream, holy water, ritual object, weeping, tears, lamentation, sweat, saliva, fluid, high water, high tide, spring tide, neap tide, low water, wave, standing water, still water, stagnant water, lake, sea water, salt water, brine, briny, ocean, water cure.	○
	Learner	class, reception class, form, grade, remove, shell, set, band, stream, age group, tutor group, vertical grouping, house, lower form, upper form, sixth form, art class, life class, study group, workshop, colloquium, conference, seminar, discussion group, teaching.	○
	All of the above		○
	None of the above		○

Submit Reset

Figure 4.13: Task 1: Selecting the Most Suitable Sense

In addition, the task provides a list of related words from *OntoRo* to help the workers understand the meaning of each sense. The workers are also provided with '*all of the above*' choice, if they agree with both senses given, and '*none of the above*' choice if they do not agree with neither senses. **Error! Reference source not found.** lists the scores for each choice selected by the user. Ten HITs samples of Task 1 offered to workers are shown in Figure C1 (a) to (j) in the appendix.

Table 4.12: Scoring for Task 1

Choice	Score
Proposed sense	1
Non-proposed sense	0
All of the above	1
None of the above	0

To observe the statistical relationship between the SDNA disambiguation score from Task 1 and the accuracy of the annotations, a second task is designed (Figure 4.14) which measures the accuracy of each annotation according to the image context.

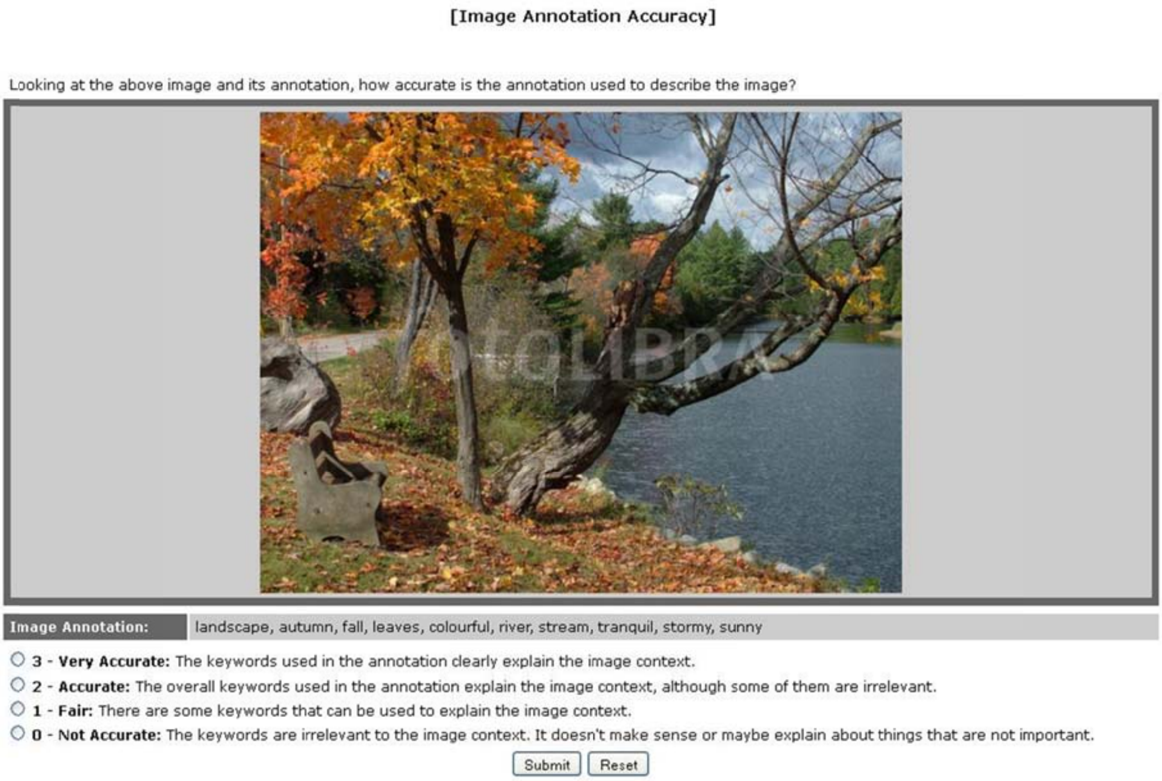


Figure 4.14: Task 2: Accuracy of the Annotations

In Task 2, the workers are provided with an image together with its annotation. Based on the image, the workers are asked to rate the accuracy of the annotation given, from '*not accurate*' to '*very accurate*'. Table 4.13 lists the scores for each category. Ten HITs of Task 2 offered to the workers are shown in Figures C2 (a) to (j) in the appendix.

Table 4.13: Scoring for Task 2

Choice	Score
Very accurate	3
Accurate	2
Fair	1
Not accurate	0

The main challenge in using MTurk services is to filter out low-quality results from irresponsible and careless workers. Previous research Alonso et al., 2008; Kittur et al., 2008; Sorokin and Forsyth, 2008) has described the potential unreliability of MTurk workers. In order to help managing worker's accuracy, MTurk provides worker requirements options where requesters can restrict participation to workers with specific qualification. Two qualifications had been imposed for both tasks:

i. Workers residing in either United States or United Kingdom, and
ii. HIT approval rate (%) for all Requester's HITs of 95%.

Qualification (i) is imposed to restrict the tasks to workers who are English speakers, while qualification (ii) is imposed to filter out unreliable workers, where 95% is the MTurk's default floor value for approval rating.

MTurk also provides the ability to review the HITs results prior to approving or rejecting HITs submissions. Several additional information are included in the result table for review purposes. The additional information includes assignment acceptance time, submission time and work time in seconds. Based on the information, the HITs offered are further filtered using several rules:

i. Answers from the same worker are checked for any particular pattern that indicates inaccuracy. For example, there are several workers who select '*3 – Very accurate*' for all the HITs in task 2.
ii. Work completing time for task 1 must be at least 30 seconds per HIT. Completion time of less than 30 seconds is considered too fast to be accurate.
iii. Work completing time for task 2 must be at least 10 seconds per HIT. Completion time of less than 10 seconds is considered too fast to be accurate.
iv. For task 1, incomplete answers, are rejected without any further consideration. For example, there are several workers who only select answer for 1 or 2 keywords out of 3 keywords per HIT.

For any HIT which do not complies with the above rules are rejected without payment being made. This affects the workers' approval rate that indicates their reliability for performing future tasks.

4.3.2 Evaluation Results

In Task 1, 500 images with their annotations were randomly selected from the collection for evaluation, creating 500 HITs. Ten different workers score each HIT, offering 5000 assignments with a payment of USD0.02 per assignment. This is consistent with the experiment conducted by Snow et al. (2008) which involved a word-sense disambiguation task. A total of 203 workers had accepted the tasks; each of them completed in average of 24.6 assignments. An assignment took an average of

54.09 seconds to complete. During the review of the results, 263 assignments were rejected due to unreliable answers. These assignments were offered to other workers.

Three tokens were scored for each image, resulting in 1500 tokens for the 500 images selected for evaluation. Table C1 in the appendix lists the scoring results for 50 images (or 150 tokens). From 5000 assignments offered, with 15000 scores recorded (every assignment contains 3 tokens), 10325 or 68.8% scores agreed with the senses selected by the proposed algorithm.

Since 10 different workers score every tokens, a simple majority score would represent the agreement reached by the workers whether to agree or not with the senses selected by the proposed algorithm for each token. A majority score is defined as at least 6 out of 10 workers in agreement. Table 4.14, Figure 4.15 and Figure 4.16 summarise the scoring for 1500 tokens in task 1.Column '*Score*' in Table 4.14 shows the ratio of '*Y*' and '*N*' scores, where the number preceding the '*Y*' letter indicates the number of workers who agree with the proposed sense, while the number preceding the letter '*N*' indicates the number of workers who disagree with the proposed sense.

For example, a category '*7Y 3N*' includes 7 agrees and 3 disagrees; 18.1% of all tokens (272 tokens) belong to this category. For example, a category '*7Y 3N*' includes 7 agrees and 3 disagrees; 18.1% of all tokens (272 tokens) belong to this category.

Table 4.14: Results from Task 1

Score	Score	Token Count	Percentage
0.0	0Y 10N	0	0.0%
0.1	1Y 9N	9	0.6%
0.2	2Y 8N	40	2.7%
0.3	3Y 7N	72	4.7%
0.4	4Y 6N	133	8.9%
0.5	5Y 5N	57	3.7%
0.6	6Y 4N	278	18.7%
0.7	7Y 3N	270	18.1%
0.8	8Y 2N	262	17.5%
0.9	9Y 1N	235	15.5%
1.0	10Y 0N	144	9.5%
Total		**1500**	**100%**

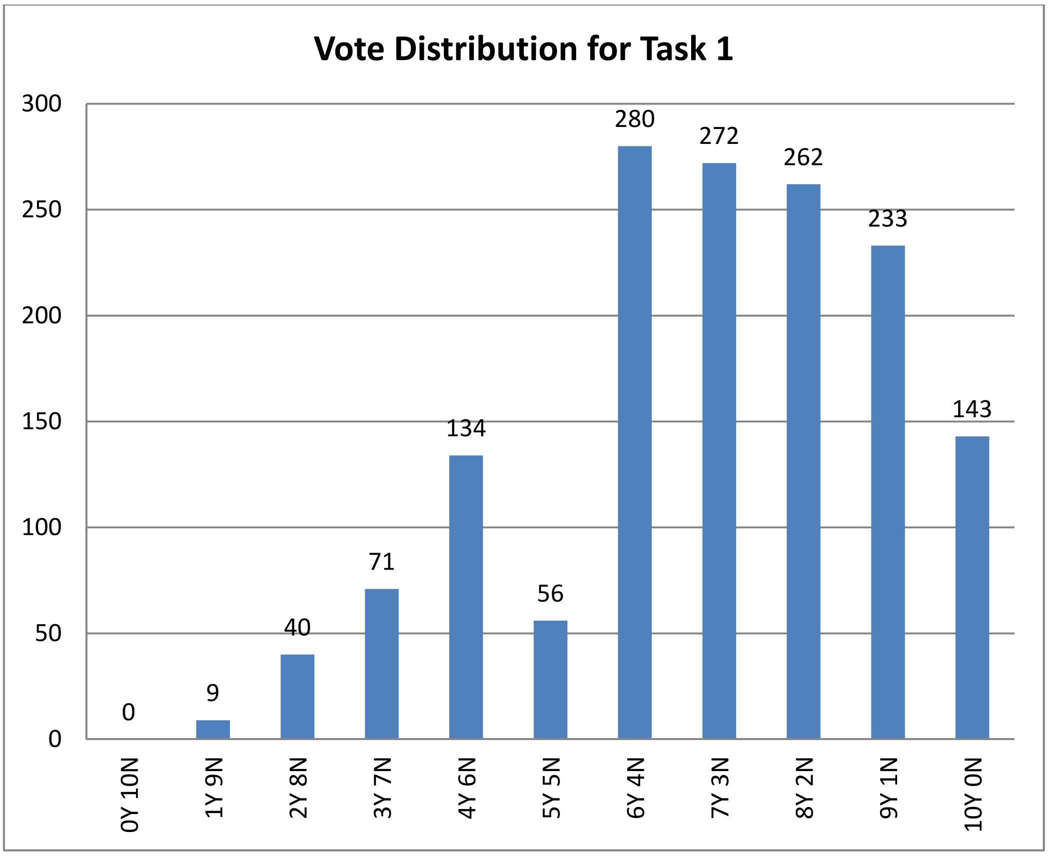


Figure 4.15: Vote Distribution for Task 1

For the 1500 tokens considered in this experiment, 1190 tokens (79.3%) get a majority score and only 254 tokens (16.9%) did not (see Figure 4.16). In other words, the workers agreed that 79.3% of the senses proposed by the approach are accurate, which indicates the accuracy of the SDNA disambiguation algorithm proposed.

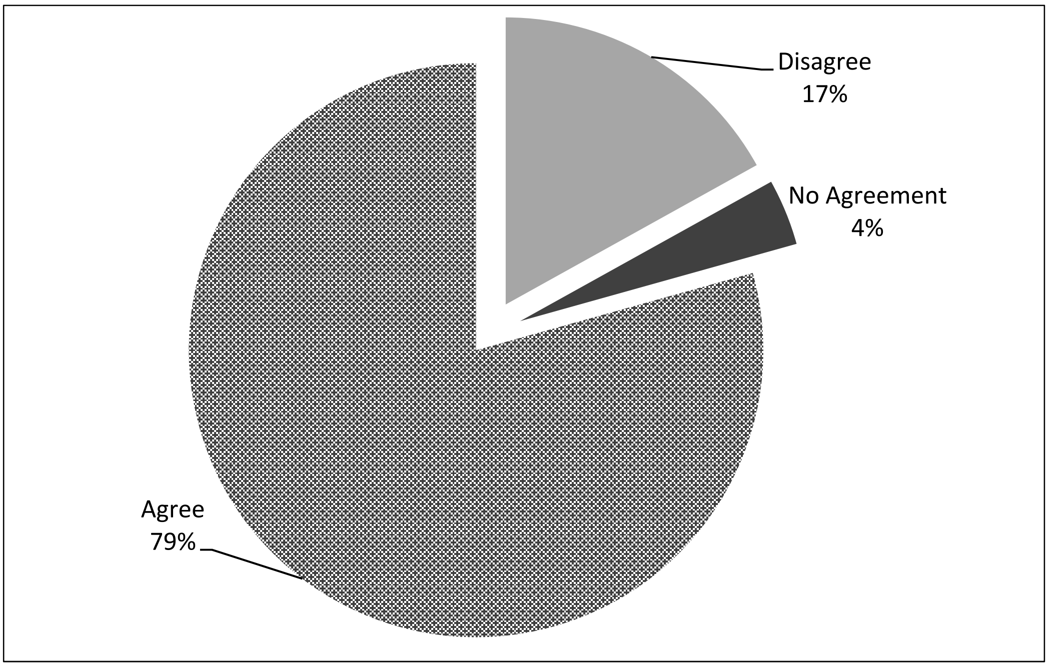


Figure 4.16 Score Distribution between agree, disagree and no agreement for Task 1

The result of 79.3% accuracy demonstrated by the proposed approach is far better than the 73% accuracy achieved in the Semeval 2007 competition, which compared the accuracy of various unsupervised algorithms where the participants have been using WordNet as a lexicon (Navigli, 2009). It is also comparable with the accuracy achieved in the same competition (between 82-83%) by the supervised algorithms, which, contrary to the approach proposed in this thesis have to be trained with large corpora.

In task 2, the same 500 images used in task 1 were again used for evaluation. Using the same approach, 10 different workers scored each image annotation. 5000 HITs were offered with payment of USD0.02 per HIT. A total of 247 workers accepted the tasks; in average, each of them completed 19.6 HITs. An average score from 10 workers is taken as the final score for each image annotation. Table C2 in the appendix lists the scoring results for 50 images, while Table 4.15 shows the average score for the 500 images considered.

Table 4.15: Results from Task 2

Score	Count	Percentage
0 <= x < 0.5	0	0.0%
0.5 <= x < 1.0	2	0.4%
1.0 <= x < 1.5	3	1.0%
1.5 <= x < 2.0	170	34.0%
2.0 <= x < 2.5	302	60.4%
2.5 <= x <= 3.0	21	4.2%
TOTAL	**500**	**100%**

The result shows that the workers agree that 64.6% of the images are correctly annotated where the overall keywords used in the annotation are relevant, although some of the keywords might not be relevant (score of 2 or more). On the other hand, 35.4% of the images are annotated with irrelevant keywords (score of less than 2). Figure 4.17 shows examples of images with (a) high annotation accuracy and (b) low annotation accuracy.

Annotation: *squirrel, woodland, nature, grey, bushy, tails, north, tree, branch, nuts, east, mike, brown*

a. Image ID: 16704

Annotation: *soldier, war, death, widow, orphan, mutilation, suffering*

b. Image ID: 22383

Figure 4.17: Two Example Images Assessed in Task 2

The annotation of the first image (Figure 4.17a) has a high average annotation accuracy of 2.5 while the second image (Figure 4.17b) has a low average annotation accuracy score of 1.3. Further observation shows that the first image's annotation contains words that could easily be associated with objects in the picture, explaining the high accuracy score given by the workers. The annotation of the second image (Figure 4.17b) contains several irrelevant annotation words compared to the image context such as *death, widow, orphan, mutilation* and *suffering*. The statistical correlation between the accuracy of the SDNA disambiguation algorithm and the accuracy of the annotations, is calculated using Pearson's correlation of the 50 images assessed in task 2. Figure 4.18 shows the correlation graph between the average SDNA disambiguation score and the average annotation score.

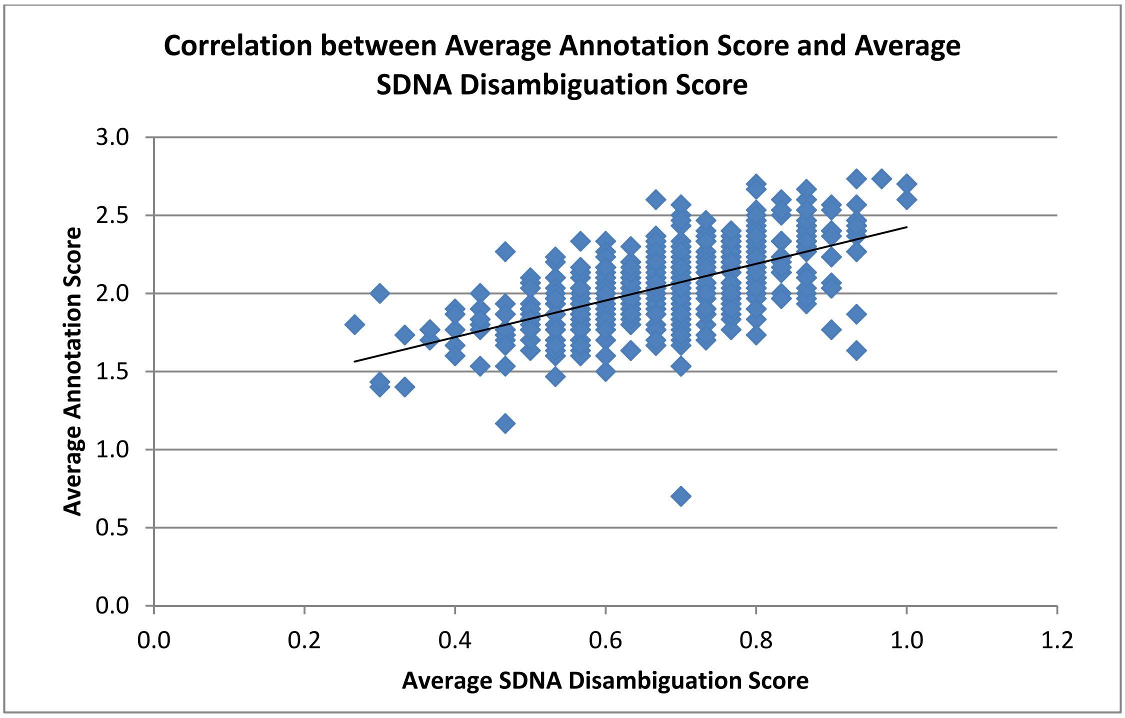


Figure 4.18: Correlation Graph between Average Annotation Score and Average SDNA Disambiguation Score.

The linear line in the middle of the graph is a regression line that visualise the relationship between average annotation score and average SDNA disambiguation score. The graph shows a positive correlation value of 0.578 between both scores. It indicates that there is a positive relationship between the quality of the image annotations and the quality of the SDNA disambiguation results proposed by the approach. In other words, the approach is able to select an accurate sense for each keyword when the annotation accuracy is high. As one may expect, lower quality annotations make it hard for the approach to propose the correct sense for each keyword. For example, the result from the disambiguation of the annotation of the image in Figure 4.17a scored 0.8 while the corresponding score for the one shown in Figure 4.17b is 0.533.

4.4 SUMMARY

This chapter proposes a framework that allows a hybrid approach, which combines both knowledge and distributional measures to estimate concept distance using a published thesaurus and raw image annotations. It utilises the expert-level classification of lexical semantic relations offered by the thesaurus, and at the same time uses the already available raw annotations for distributional processing. The information carried by SDNA provides the semantic information needed for determining the contextual meaning of an image.

The experiments show that the use of stemming and stop words removal on raw annotation text improves the indexing performance by increasing the number of tokens found and reducing token noise. The experiments also show that raw weighting based on the *tf-idf* function does not consider annotation lengths, which is biased towards long annotations. On the other hand, the cosine normalisation technique is proven to be not entirely fair and with drawbacks. The normalisation technique, which is adapted from the probabilistic model Okapi BM25, is proven to be effective in indexing *fotoLIBRA* image annotations.

The empirical evaluation of a sample data set demonstrates the ability of the proposed SDNA disambiguation technique to select the most appropriate chromosome for each token, or at least the closest one.

Both knowledge and distributional measures have large space and processing time requirements for pre-processing image annotations. However, the use of SDNA as a concept-based text representation technique diminishes the requirements for pre-processing and storing image annotations to 0.03% of the original matrix size obtained by the traditional methods. Matrix factorisation approach further reduces the matrix dimension and increases the latent relations between the images or the SDNA. The proposed approach of using SDNA-based concept distance measure demonstrates all beneficial features of both knowledge-based and distributional measure, and yet avoids problems of word ambiguity and computational complexity.

The evaluation using crowdsourcing indicates that the SDNA disambiguation algorithm has good accuracy. The experiments show that the algorithm has better accuracy (79.4%) than the accuracy achieved by other unsupervised algorithms (73%) presented in the 2007 Semeval competition. The proposed algorithm is also comparable with the accuracy achieved in the same competition by the supervised algorithms (82-83%), which on the contrary to the approach proposed in this chapter have to be trained with large corpora. Further experimentation shows a positive correlation value of 0.5779 indicating that the performance of the SDNA disambiguation algorithm depends on the quality of the text/annotation.

CHAPTER 5:
SEMANTIC SIMILARITY
IN VECTOR SPACE MODEL

Traditional keyword-based IR approaches ignore relations between keywords and assess their importance in a text document by examining their occurrence in the document and collection, but disregarding the occurrence of any related keywords. By adapting the LSI method, the proposed approach overcomes this restriction by analysing the co-occurrence of keywords in documents and collections. Semantically close documents are those with many words in common and semantically distant documents are those with few words in common. The method aims to take advantage of implicit higher-order structures, or “semantic structures” in the association of terms with documents.

5.1 QUERY PROCESSING

The proposed approach uses a natural language query that conveys the search intention. Application of natural language and mathematical processing on the query returns weighted *semantic chromosomes* that satisfy the query. The *semantic chromosomes*’ weights indicate the relative interest of the user for each of the semantic concepts explicitly mentioned in the image annotations. For instance, let *q* be the query with 3 tokens and q = "*soft, gentle, pretty*". Going through the mathematical processing, query q produces 41 SDNAs, $|SetSDNA(q)| = 41$, where the three most accurate SDNA are then chosen to populate $semantic\_chromosomes(q)$.

Table 5.1 lists the *SetSDNA(q)* with their *SW()* weights (refer to section 4.2.2). Using the methods explained in section 4.2.3 , *semantic chromosomes* of *q* are selected based on the highest weighted SDNA for each token. Table 5.2 lists *semantic_chromosomes(q)* with their senses and related words. The words related to each SDNA in *semantic_chromosomes(q)* explain the idea or the interest of the user from the given query. Any images that have those words in its' annotations will be considered to semantically fulfil the user's interest and thus will be retrieved.

Table 5.1: List of *SetSDNA(q)* with Their *SW()* Weights

Token	SDNA	*SW()*
gentle	**6-37-83-884-2-1**	**6.17**
	6-35-77-823-2-1	5.51
	6-37-83-884-2-2	5.44
	3-15-47-369-2-1	5.05
	3-15-48-401-2-1	4.99
	6-38-88-935-2-1	4.87
	6-37-84-897-2-1	4.78
	5-31-70-734-2-1	4.59
	1-8-28-177-2-1-	4.46
	5-31-70-736-2-1	4.29
	2-10-35-220-2-2	1.19
pretty	**6-36-79-841-2-1**	**5.04**
	1-3-10-32-4-2-3	3.14
soft	**3-15-48-376-2-2**	**6.88**
	3-15-48-425-2-3	6.71
	3-15-48-417-2-1	6.28
	3-15-48-399-2-1	6.18
	3-15-48-401-2-1	6.17
	3-15-48-391-2-1	6.10
	3-15-48-410-2-1	6.01
	6-35-77-819-2-1	5.20
	6-35-77-819-2-1	5.20
	6-36-80-856-2-1	4.80
	6-37-85-905-1-3	4.78
	6-37-85-905-2-1	4.65
	5-31-70-734-2-1	4.59
	1-8-27-163-2-1-	4.43
	3-14-46-347-2-1	4.31
	5-31-70-736-2-1	4.29
	3-14-46-356-1-2	4.23
	6-38-89-948-2-1	4.03
	3-14-45-328-2-1	3.98
	1-3-10-33-2-1	3.82
	1-8-28-177-2-2	3.47
	1-7-25-152-2-2	2.73
	5-26-59-601-2-1	2.71
	5-29-68-721-2-1	2.30
	4-20-53-487-2-1	2.02
	4-20-53-499-2-2	1.88
	2-11-39-258-2-1	1.42
	2-12-43-301-2-2	1.07

Table 5.2: List of *Semantic Chromosome(q)*with its *SW()* Weights, Senses and Related Words

$\mathbf{Token}(t_i)$	**SDNA**	**SW()**	**Token Sense**	**Related Words**
gentle	6-37-83-884-2-1	6.17	courtesy	chivalrous, knightly, generous, noble, courtly, gallant, old-world, correct, formal, polite, civil, urbane, gentle, gentlemanly, ladylike, dignified, well-mannered, fine-mannered, well-bred, gracious, condescending, humble, deferential, mannerly, respectful, on one's best behaviour, complaisant, kind, benevolent, conciliatory, sweet, agreeable, suave, bland, smooth, ingratiating, well-spoken, fair-spoken, honey-tongued, flattering
pretty	6-36-79-841-2-1	5.04	beauty	beautiful, pulchritudinous, beauteous, of beauty, lovely, fair, bright, radiant, comely, goodly, bonny, pretty, sweet, sweetly pretty, picture-postcard, pretty-pretty, pretty in a chocolate box way, nice, good enough to eat, pretty as a picture, photogenic, handsome, good-looking, well-favoured, well-built, well-set-up, husky, manly, tall, dark and handsome, gracious, stately, majestic, statuesque, Junoesque, adorable, god-like, goddess-like, divine
soft	3-15-48-376-2-2	6.88	pleasure	comfy, homely, snug, cosy, warm, comforting, restful, reposeful, painless, peaceful, tranquil, convenient, easy, cushy, easeful, downy, soft, luxurious, deluxe, enjoying comfort, euphoric

5.2 SEMANTIC SEARCH

As explained in the previous section, the query execution returns *semantic chromosomes* that satisfy the query. The searching module's task is to obtain all documents that correspond to the *semantic chromosomes*. Once the list of documents is formed, the search engine computes semantic similarity value between the query and each document using the following similarity measure.

Let S be the set of all SDNA in the ontology, and I be the set of all images in the search space. Let q be a query and s_i be an SDNA where $s \in S$. Each image in the search space is represented as $d \in I$, where d_x is the weight of the image with SDNA x for each $x \in S$, if such SDNA exists and zero otherwise.

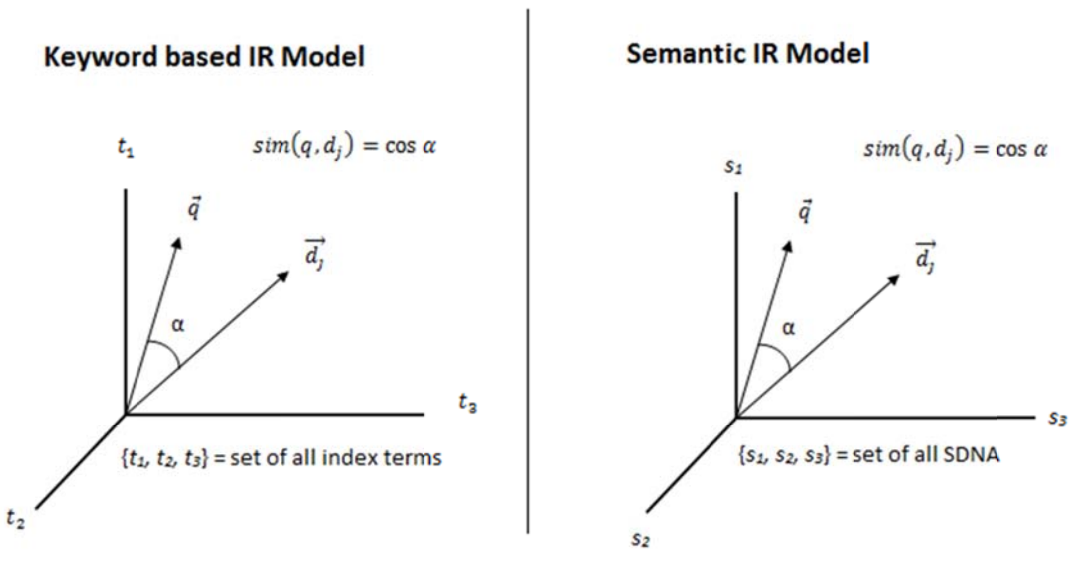


Figure 5.1: Adaptation of the Vector Space Model

As already mentioned, the semantic-based image indexing and searching approach proposed here is based on adaptation of the traditional vector space IR model where images and queries are represented as weighted vectors. Figure 5.1 illustrates the proposed adaptation of the vector space model that replaces the traditional keyword query and document vectors by semantic query and semantic image vectors. The query vector represents the importance of each semantic entity in the information need as expressed by the user, while the image vector represents the relevance of each semantic entity within the image annotation. The construction of a query vector follows the same process as the construction of image the vector explained in Chapter 4.

Based on the findings in section 2.1.3, the approach uses the cosine of angle to measure the similarity between an image vector and the query vector. The similarity measure between an image *d* and the query *q* is computed as:

$$\mathrm{sim}(\mathrm{d}, \mathrm{q}) = \frac{\mathrm{d} \times \mathrm{q}}{|\mathrm{d}| \cdot |\mathrm{q}|} \tag{5.1}$$

Figure 5.2 explains the pseudo code for semantic search process.

```
INPUT: User query
OUTPUT: relevant images in ranked results

GET user query
token_array := tokenise(query)
SDNA_set := SDNA_extract(token_array)
SDNA_set_weight := SDNA_weight_calculation(SDNA_set)
semantic_chromosomes(query) := SDNA_disambiguation(SDNA_set_weight)
query_vector := factorise(semantic_chromosomes(query))
ranked_results := semantic_similarity(query_vector, image_vector)
```

Figure 5.2: Pseudo code for Semantic Search Process.

5.3 EVALUATION

The evaluation of performance of the proposed model uses a medium scale IR evaluation benchmark based on *fotoLIBRA* random image sets β. The evaluation experiment was designed to compare the results obtained by the proposed model with a traditional keyword-based retrieval model where queries and documents are represented by vectors. Each vector contains a set of tokens and their weights.

The inner product or cosine of two vectors' weights represents the similarity between a query and a document. The weight of each token is calculated based on the product of term-frequency (*tf*) and inverse-document frequency (*idf*), as explained in section 2.1.3 . To compare the performance measurement, a set of 22 queries, as explained in section 3.3.1 is used over the five sample-sets β_i and the average was calculated for each query. Table 5.3, Figure 5.3 and Figure 5.4 show the experiment results.

Figure 5.4 (c) clearly shows that the overall performance of the proposed approach outperforms the keyword-based model in Mean Average Performance measure. While Figure 5.3 shows that, the performance of SDNA-based model outperforms the keyword-based model in 13 out of 22 (59.1%) queries. Further analysis brings an indication of the degree of improvement that can be expected with respect to the proposed model.

Table 5.3: Result of Average Precision

Query	SDNA	Keyword	Difference
1	0.1066	0.1916	-0.0851
2	0.0987	0.1761	-0.0774
3	0.1381	0.0958	0.0423
4	0.0393	0.0275	0.0117
5	0.1456	0.1064	0.0392
6	0.0968	0.0867	0.0102
7	0.2430	0.1127	0.1303
8	0.0641	0.0218	0.0424
9	0.0189	0.0262	-0.0074
10	0.1016	0.0692	0.0324
11	0.0424	0.0147	0.0277
12	0.0027	0.0083	-0.0055
13	0.0528	0.0880	-0.0352
14	0.1014	0.0698	0.0317
15	0.0654	0.0946	-0.0292
16	0.1937	0.1813	0.0124
17	0.0579	0.0697	-0.0118
18	0.0250	0.0217	0.0032
19	0.0223	0.0153	0.0070
20	0.0717	0.1149	-0.0432
21	0.0733	0.0638	0.0095
22	0.0107	0.0288	-0.0181
Mean	**0.0805**	**0.0766**	**0.0040**

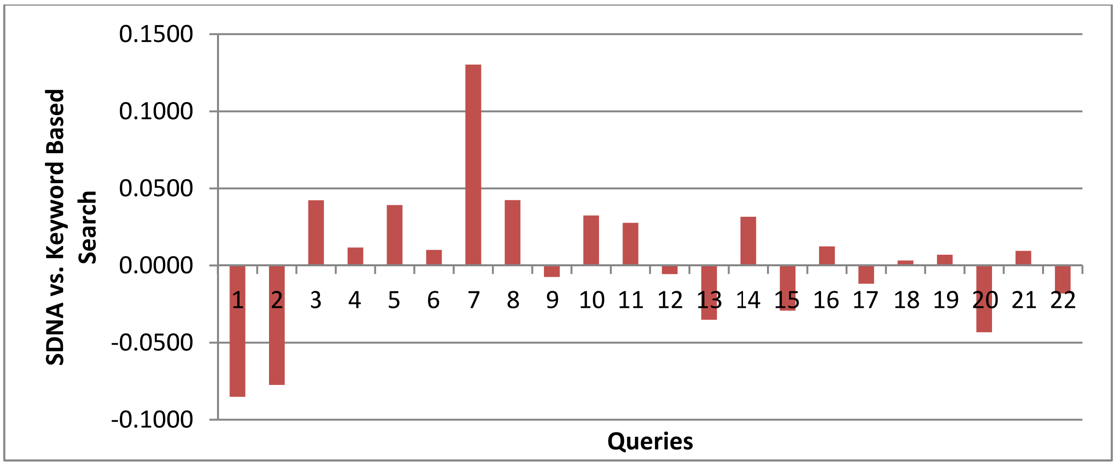


Figure 5.3: Performance Comparison between SDNA-Based and Keyword-Based Model

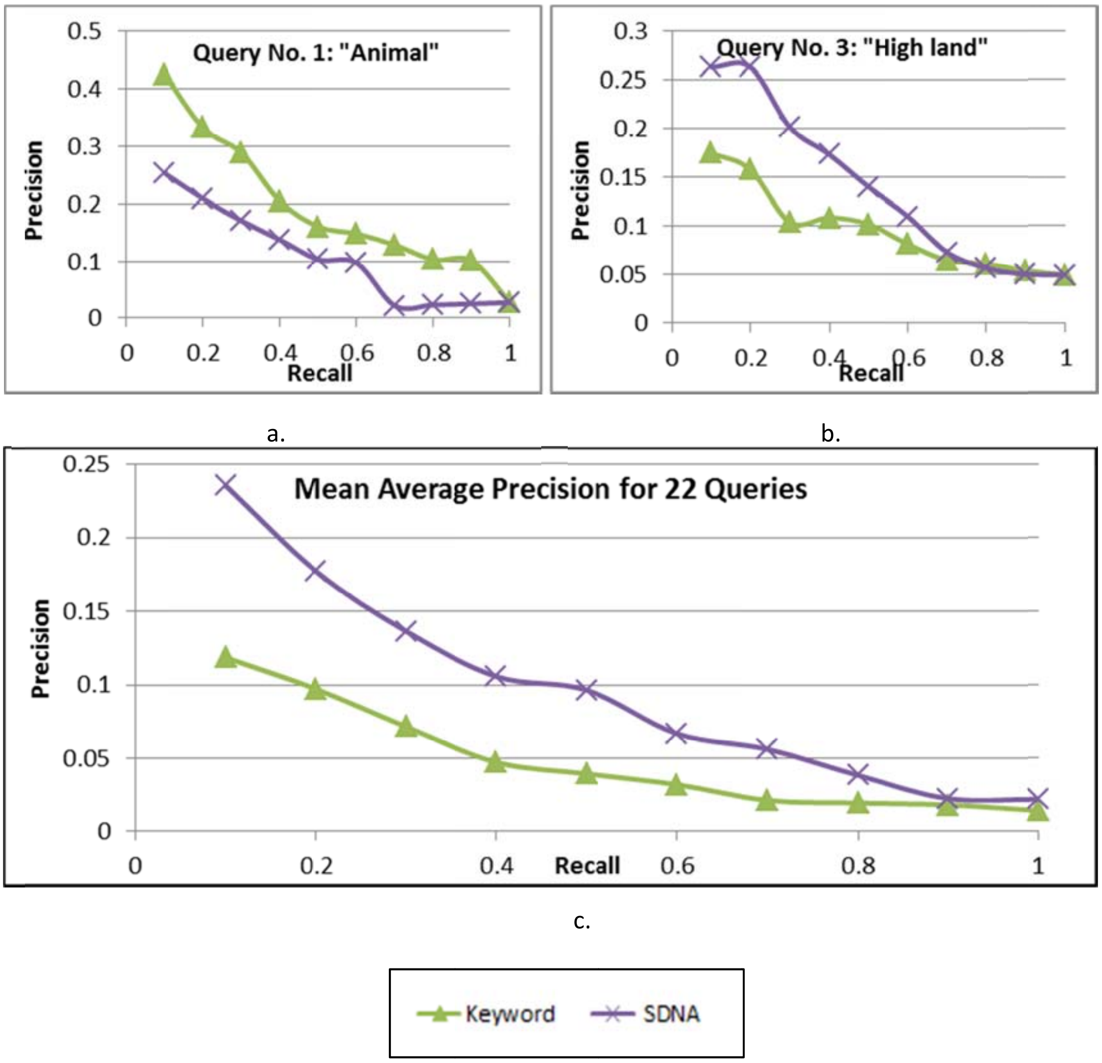


Figure 5.4: Evaluation of SDNA-based against keyword-based model

Figure 5.4 (a) and (b) show two distinct examples of performance results; the former shows that the keyword-based outperforms the SDNA-based model in query no. 1, and the latter shows the SDNA-based model outperforms keyword-based model in query no. 3.

- ***Query No. 1:*** *Animal*. In this example, the keyword-based model outperforms the SDNA-based model because of the high frequency term used as the search query. Further analysis reveals that the word *animal* is one of the most commonly used terms in *fotoLIBRA* image collections' annotation. It gives advantage to the keyword-based model where most of the animal images annotation contains the term *animal*, together with the name of the animal and the location where the images were taken. While SDNA-based model could only extract limited implicit information from these name entities.

- ***Query No. 3:*** *High land*. In this example, the SDNA-based model outperforms the keyword-based model because the limited expressive power of the latter fails to retrieve related images, which do not have the query terms in their annotations. The SDNA-based model is able to retrieve images, which are annotated with not just *high land*, but also with other words, which share similar SDNA structure with *2-10-35-209-1-1* including the words *mountain*, *hill*, *highlands*, *sierra*, *summit*, *rising ground*, *cliff*, *hilltop, alp* and several peaks such as *Ben Nevis*, *Everest*, *Fuji*, *Kilimanjaro* and *Himalayas*.

5.4 SUMMARY

Although the evaluation shows that the overall performance of the SDNA-based model is higher than that of the keyword-based model, the analysis of results reveal that the performance of SDNA-based model is in direct relation with the implicit information relies within the query and annotation text. If the annotation contains less meaningful information (e.g., there are annotations of name entities or the words used in the annotation are hardly related to each other), the SDNA Disambiguation algorithm performs very poorly, thus affecting the relevancy of *semantic chromosomes*. This further affects the performance of the similarity measure and the quality of the retrieval results. As a result, user queries return fewer results than expected, as they get much lower similarity values than they should. Keyword-based search are likely to perform better in these cases. To deal with this drawback, this thesis proposes to combine the results coming from the proposed ontology-based retrieval model and the result returned by traditional keyword-based model.

However, the combination of ranking, using data fusion techniques should be carefully designed in order to achieve an appropriate balance between keyword-based and ontology-based results. Figure 5.5 shows the extensions made to the initial SDNA-based semantic search model (Figure 3.9). A data fusion technique is used to combine a ranked result from the SDNA-based model with ranked results from keyword-based model. The next chapter explains the technique used in more detail.

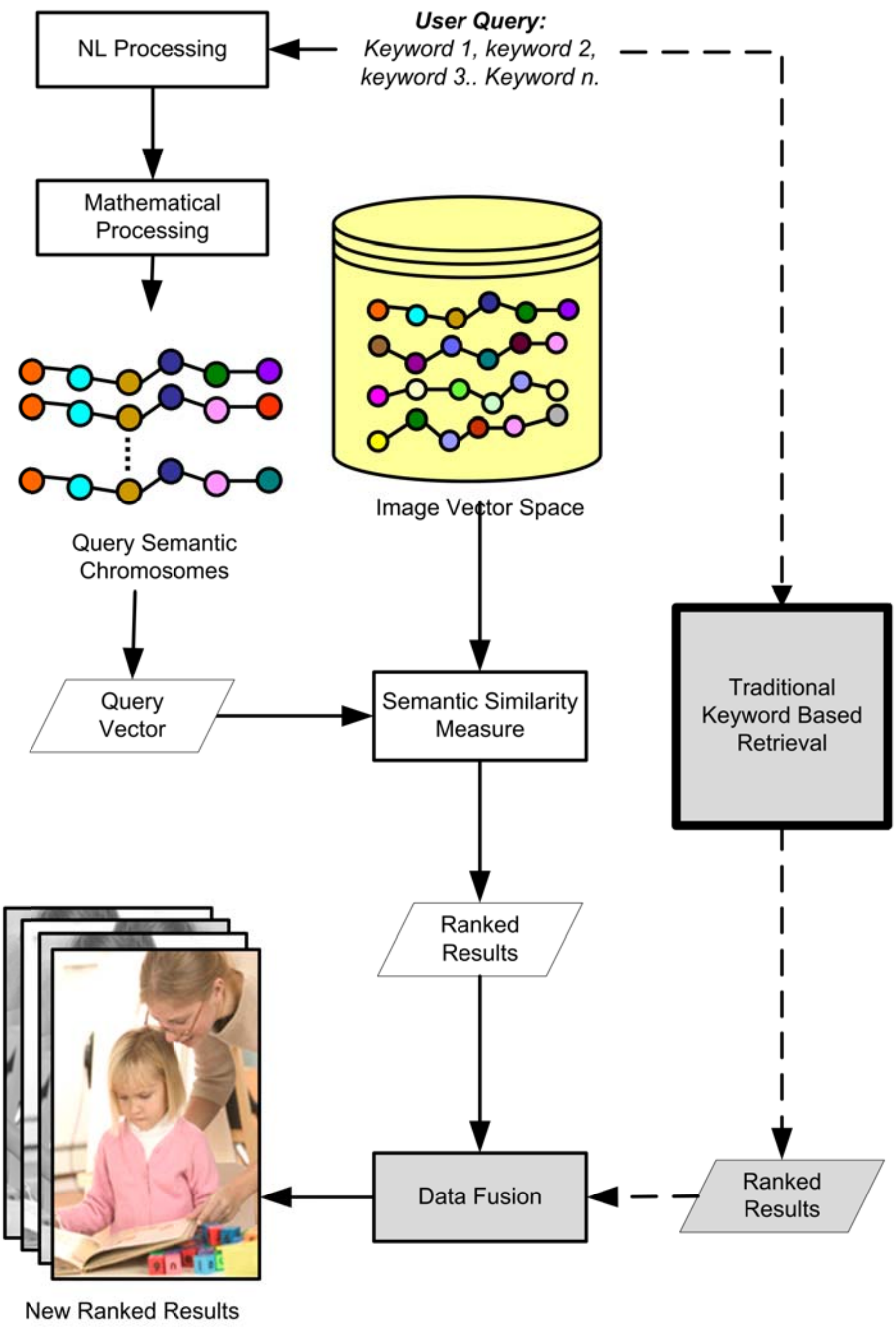


Figure 5.5: Semantic Search Model Extension

CHAPTER 6:
ENHANCED SEMANTIC MODEL

Combining the output of several search engines has been a widely addressed research topic in the IR field. This chapter considers several methods to be used to combine the ranking scores between SDNA and keyword-based model. The combined model is later evaluated using both traditional IR measures and a human-centred approach.

6.1 DATA FUSION

Data fusion is defined as techniques for merging the retrieval results of multiple systems (Montaque and Aslam, 2001; Popa et al., 2002; Bleiholder and Naumann, 2008). It has been a widely addressed research topic in the IR field (Lee, 1995; Lee, 1997; Croft, 2000; Yavlinsky et al., 2004). Montague and Aslam (2001) grouped the fusion techniques into two main sub-techniques: (i) normalisation and (ii) combination.

6.1.1 Normalisation

Normalisation is important in order to make the output comparable across different systems. The scores returned by the different information retrieval systems may not be equivalent. For example, the 10th position in the ranking has a different meaning when

15 results are returned than it would within 1,000 results. Similarly, a score of 0.9 does not have the same meaning in a system ranging in [0, 1] as in one ranging in [0, 100].

The thesis uses a standard score normalisation method explained by Lee (1997):

$$\text{normalised\_similarity} = \frac{\text{unnormalised\_similarity} - \text{min\_similarity}}{\text{max\_similarity} - \text{min\_similarity}} \tag{6.1}$$

6.1.2 Combination

The combination problem refers to using the normalised information returned by the different input systems to combine all results in a unique output list. Shaw and Fox (1994) designed some of the most simple, popular and effective combination algorithms to date. They are summarised in Table 6.1 below.

Table 6.1: Fusion Algorithms Designed by Shaw and Fox(1994)

Name	Technique
CombMIN	Choose min of similarity values
CombMAX	Choose max of similarity values
CombMED	Choose median of similarity values
CombSUM	Sum of individual similarity values
CombMNZ	CombSUM × number of nonzero similarity values
CombANZ	CombSUM ÷ number of nonzero similarity values

According to their experiments, Shaw and Fox (1994) and Lee (1997), reported CombMNZ as the best method, even though it performs just slightly better than CombSUM. CombMNZ is based on the observations by Lee regarding the overlap between the relevant and not relevant documents retrieved by different search engines, where "*different search engines return similar sets of relevant documents but different sets of non-relevant documents*" (Lee, 1997). Vogt and Corrtell (1999) proposed a variant of CombSUM consisting of the introduction of a weight for each system, according to the importance, quality and reliability of the sources. The combined score is computed as a weighted linear combination, formally:

$$s_R = \sum_{r \in R} \alpha_r \cdot \bar{s}_r(x) \tag{6.2}$$

Where α_r is the weight of the retrieval system r and $\bar{s}_r(x)$ is the normalised score assigned to x in the ranking returned by r. This approach can also be applied to CombMNZ and CombANZ. For comparative evaluation, this thesis compares the retrieval performance of six fusions techniques to combine the traditional keyword-based similarity score, *ksim*, with the proposed ontology-based similarity score, *sim*. Table 6.2 lists the six techniques.

Table 6.2: Six Fusion Algorithms Evaluated

Technique	Description	Algorithm
CombMIN	Choose min of similarity values	$\mathrm{MIN}(\overline{\mathrm{sim}}, \overline{\mathrm{ksim}})$
CombMAX	Choose max of similarity values	$\mathrm{MAX}(\overline{\mathrm{sim}}, \overline{\mathrm{ksim}})$
CombSUM	Sum of individual similarity values	$\overline{\mathrm{sim}} + \overline{\mathrm{ksim}}$
CombMNZ	CombSUM × number of nonzero similarity values	$\mathrm{CombSUM} \times \beta$
WCombSUM	CombSUM with special weight α for each system	$\alpha \times \overline{\mathrm{sim}} + (1-\alpha)\overline{\mathrm{ksim}}$
WCombMNZ	WCombSUM × number of nonzero similarity values	$\mathrm{WCombSUM} \times \beta$

Where $\overline{\text{sim}}$ is the normalised SDNA-based score, $\overline{\text{ksim}}$ is the normalised keyword-based score, β is the number of nonzero similarity values and $\alpha \in [0,1]$. The value of α is determined by the value of *sim* and *ksim*. The value of $\alpha = 0.8$ is used when both *sim* and *ksim* have positive values. Otherwise, if *ksim* returns 0, then $\alpha = 1.0$, and if *sim* returns 0, then $\alpha = 0.2$ which gives less weight to images with no SDNA-based score. Figure 6.1 and Table 6.3 list and illustrate the comparative experimental result for the six fusions techniques-based on Mean Average Precision (MAP) and Mean R-Precision (MRP). Tables D1 and D2 in the appendix show the details of the experimental results.

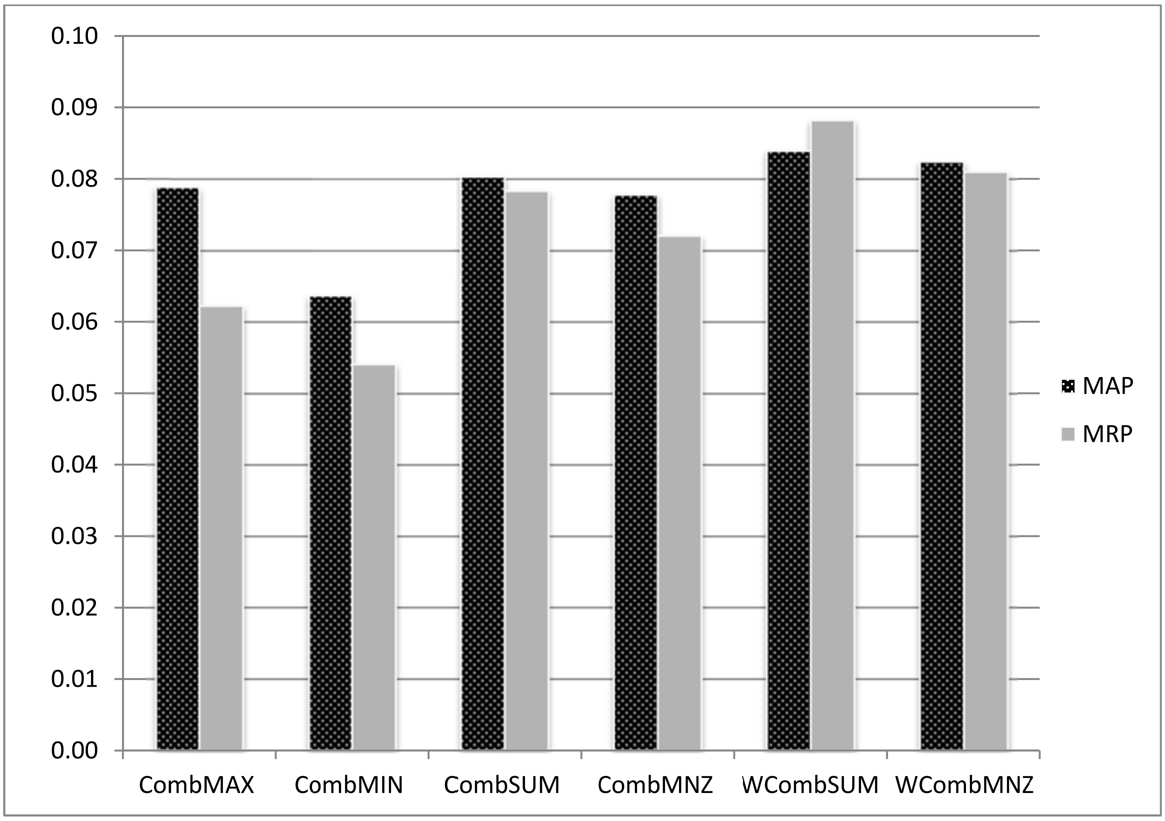


Figure 6.1: Performance Comparison Over Six Fusion Technique

Table 6.3: Experimental Result for Six Fusion Techniques

Fusion Technique	MAP	MRP
CombMAX	0.0789	0.06226
CombMIN	0.0637	0.05411
CombSUM	0.0803	0.07834
CombMNZ	0.0778	0.07210
WCombSUM	***0.0839***	***0.08822***
WCombMNZ	0.0824	0.08102

The best performing technique for both MAP and MRP is WCombSUM (marked with bold text) which is slightly higher than WCombMNZ. Figure 6.1 shows that both WCombSUM and WCombMNZ, and especially the former, are better than the other techniques. Therefore, this thesis considers the WCombSUM fusion technique as the best technique to combine the proposed SDNA-based retrieval score with traditional keyword-based retrieval score. The next section explains further experiments done to evaluate the performance of the proposed method with other related methods.

6.2 IR-BASED EVALUATION

This section explains in detail a medium scale IR-based evaluation using an evaluation benchmark generated based on fotoLIBRA image metadata.

6.2.1 Evaluation Benchmark

As discussed in section 3.3.1 , the *fotoLIBRA* digital image collection provides this research with an alternative benchmark based on their categories and sub categories.

The image owners, who are the experts of their own images, tag them into categories and sub-categories. The evaluation benchmark comprises of:

- **Document corpus:** 153,403 digital images extracted from the *fotoLIBRA* image collection.
- **Queries:** a set of 22 queries manually designed according to *fotoLIBRA*'s categories and sub categories.
- **Judgments:** judgments for each query manually established based on the 239 sub categories provided by the image owners.

6.2.2 Experimental Settings

The experiments were designed to compare the results obtained by four different search approaches:

- **Boolean search:** a conventional keyword retrieval model, using Microsoft Windows search application.
- **Statistical analysis search:** a statistical based model, using the Apache Lucene library (Apache Software Foundation, 2001).
- **Concept search:** the concept-based retrieval model proposed by TRENDS project, using *OntoRo* as the lexical ontology.
- **Semantic search:** the complete semantic retrieval model proposed in this thesis, consisting of the combination of SDNA-based and keyword-based retrieval models.

6.2.3 Results

This section reports and discusses the observed results for all 22 queries based on three standard IR evaluation metrics: (i) Average Precision, (ii) R-Precision and (iii) Precision at 20 (P@20) for each of the approaches evaluated. The first metric compares the overall performance of the systems in terms of precision, recall and ranking. The second metric compares the performance of the systems in terms of precision of retrieving |*R*| documents, where *R* is the set of all relevant documents for the query. While the third metric compares the performance of the systems in terms of precision for the top 20 results, which the users are most likely to see. Table 6.4 to Table 6.6 contain the results of performed evaluation. While Figures 6.4 to Figures 6.6 shows the different in performance between the proposed semantic approach and other approaches for each of the 22 queries.

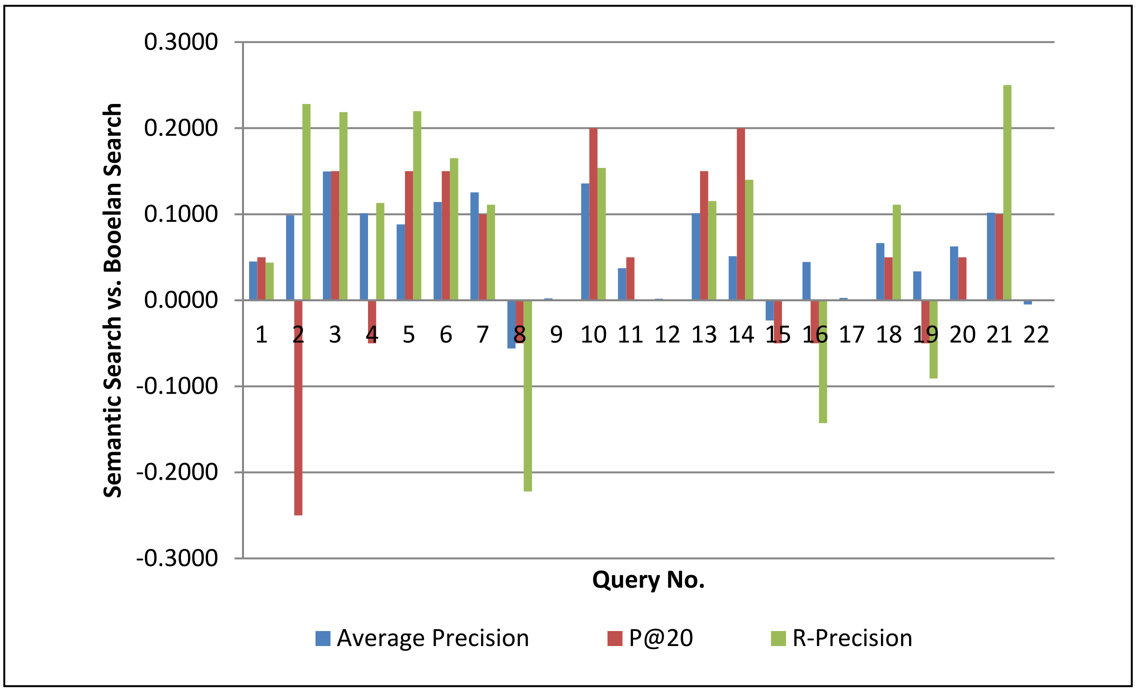


Figure 6.2: Performance Comparison for Semantic vs. Boolean Search

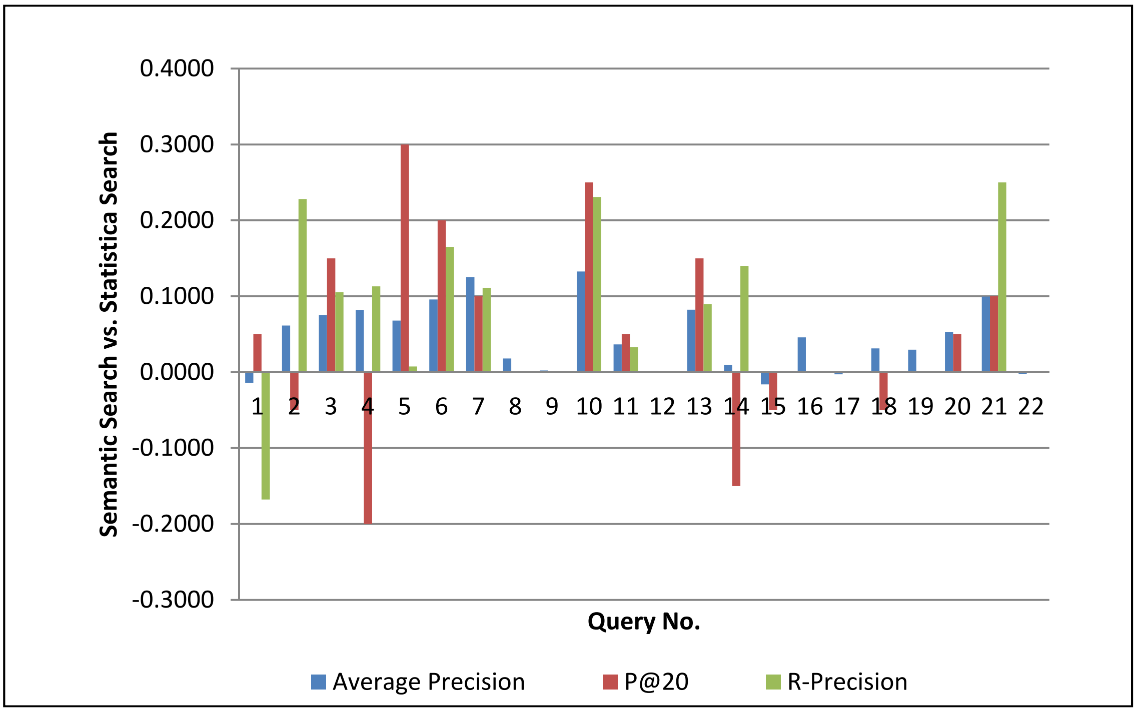


Figure 6.3: Performance Comparison for Semantic vs. Statistical Search

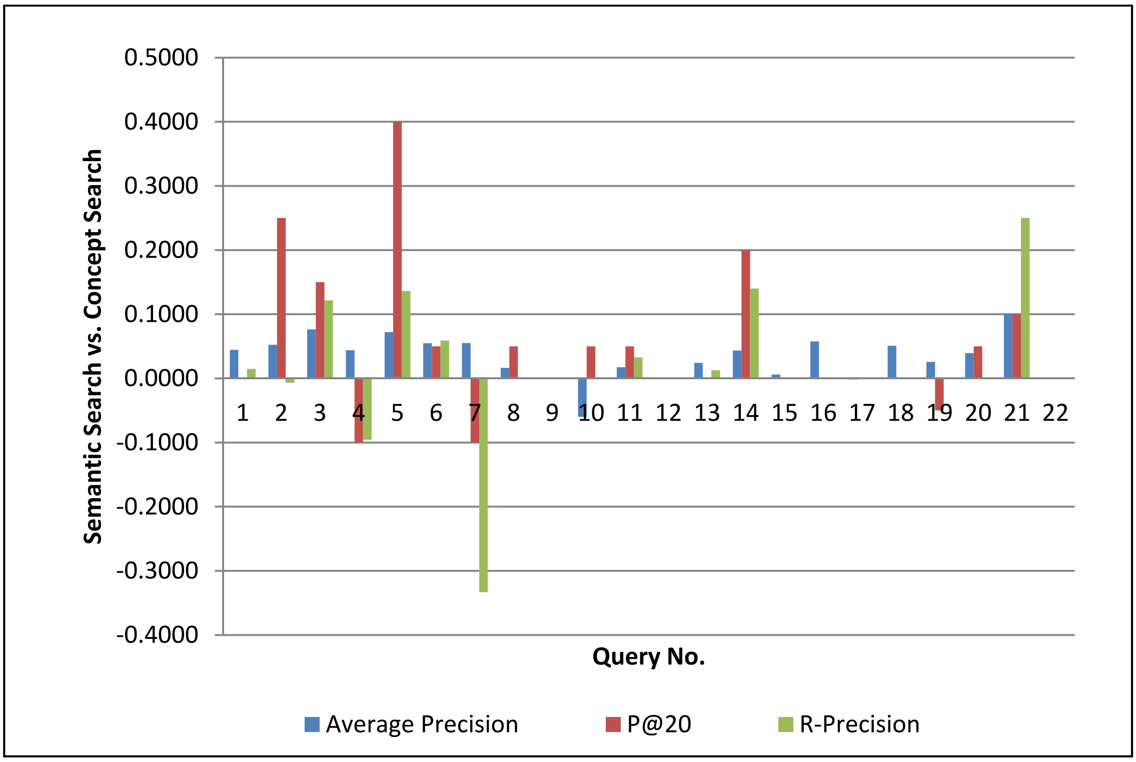


Figure 6.4: Performance Comparison for Semantic vs. Concept Search

Table 6.4: Result of Average Precision

Query	Boolean	Statistical	Concept	Semantic
1	0.0246	0.0840	0.0254	0.0697
2	0.0682	0.1055	0.1146	0.1669
3	0.0000	0.0743	0.0733	0.1497
4	0.0000	0	0.0573	0.1011
5	0.0200	0.0403	0.0360	0.1082
6	0.0000	0	0.0593	0.1142
7	0.0000	0	0.0703	0.1254
8	0.0833	0.0093	0.0109	0.0274
9	0.0000	0.0000	0.0015	0.0022
10	0.0083	0.0114	0	0.1440
11	0.0000	0.0008	0	0.0373
12	0.0000	0	0	0.0017
13	0.0000	0.0190	0.0770	0.1013
14	0.0000	0.0417	0.0078	0.0512
15	0.0310	0.0236	0	0.0075
16	0.0549	0.0537	0	0.0995
17	0	0	0	0.0027
18	0.0000	0.0353	0.0156	0.0665
19	0.0000	0	0.0079	0.0336
20	0.0000	0	0.0231	0.0625
21	0	0.0021	0.0012	0.1018
22	0.0064	0.0039	0.0009	0.0015
Mean	**0.0135**	**0.0255**	**0.0388**	**0.0716**

Table 6.5: Result of Precision at 20 (P@20)

Query	Boolean	Statistical	Concept	Semantic
1	0.1000	0.1000	0.1000	0.1500
2	0.7000	0.5000	0.3500	0.4500
3	0.1000	0.1000	0.3500	0.2500
4	0.1000	0.2500	0.1500	0.0500
5	0.3000	0.1500	0.2000	0.4500
6	0.1500	0.1000	0.3500	0.3000
7	0	0	0.1500	0.1000
8	0.1000	0.0500	0	0.0500
9	0	0	0	0
10	0.0500	0	0.1500	0.2500

11	0	0	0.0500	0.0500
12	0	0	0	0
13	0.0500	0.0500	0.2000	0.2000
14	0	0.3500	0	0.2000
15	0.0500	0.0500	0	0
16	0.0500	0	0.1000	0
17	0	0	0	0
18	0	0.1000	0.0500	0.0500
19	0.0500	0	0.0500	0
20	0	0	0	0.0500
21	0	0	0.1000	0.1000
22	0	0	0	0
Mean	**0.0818**	**0.0818**	**0.1068**	**0.1227**

Table 6.6: Result of R-Precision

Query	Boolean	Statistical	Concept	Semantic
1	0	0.2117	0.0438	0.0438
2	0	0	0.2013	0.2282
3	0	0.1134	0.1336	0.2186
4	0	0	0.1217	0.1130
5	0	0.2121	0.0833	0.2197
6	0	0	0.1038	0.1651
7	0	0	0.3333	0.1111
8	0.2222	0	0	0
9	0	0	0	0
10	0.0769	0	0.1538	0.2308
11	0.0328	0	0.0164	0.0328
12	0	0	0	0
13	0.0513	0.0769	0.1795	0.1667
14	0	0	0	0.1400
15	0	0	0	0
16	0.1429	0	0.1429	0
17	0	0	0	0
18	0	0.1111	0.1111	0.1111
19	0.0909	0	0.0909	0
20	0	0	0	0
21	0	0	0.1250	0.2500
22	0	0	0	0
Mean	**0.0280**	**0.0330**	**0.0837**	**0.0923**

Table 6.4 shows that, looking at MAP, the semantic retrieval approach proposed outperforms all other approaches, providing highest AP for 86.4% of the queries. Semantic search provides better results than Boolean search for 95.5% of the queries, better than statistical search for 90.1% of the queries and better than concept search for all of the queries.

The results by P@20 are interesting (see Table 6.5), where there is no clear winner. Although semantic search slightly outperforms all other approaches in term of average P@20, the semantic search only score highest P@20 for 31.8% of the queries. However, semantic search provides better result than keyword search for 77.3% of the queries, and better than statistical search and concept search for 72.7% of the queries. Although P@20 metric does not show a strong performance advantage of semantic search, it is observed that, for some queries for which statistical search finds no relevant images, the semantic search does. This is the case of queries 7 (*prehistoric animal*), 11 (*land travel vehicle*), 20 (*underwater nature*) and 21 (*humour*). While the queries in which the semantic search did not outperform the Boolean search seem to be those where the queries contains words that are commonly used in the image annotations. This is the case of queries 2 (*lovely flora*), 4 (*country terrain*), 14 (*festivals events*), 15 (*fashion design*) and 18 (*extreme sport*).

Using R-precision metric (see Table 6.6), the proposed semantic approach outperforms all other approach in 45.6% of the queries. Based on this metric, semantic search provides better result than keyword search for 81.8% of the queries and equal for another 13.6%. Compared to statistical search, the proposed approach excels at 59.1%

an equal for another 27.3%, and compared to concept search, excels at 31.8% of the queries and equal at 40.1% of the queries. The precision and recall curves for all queries are shown in Figure D1(a) to D1(v), in the appendix, while the average precision and recall curve over 22 queries is shown in Figure 6.5. The average precision and recall curve clearly shows that the proposed approach outperforms all other approaches with a clear distinction. The worst performance was shown by Boolean search performed by the Windows search, while both statistical and concept search performances are close.

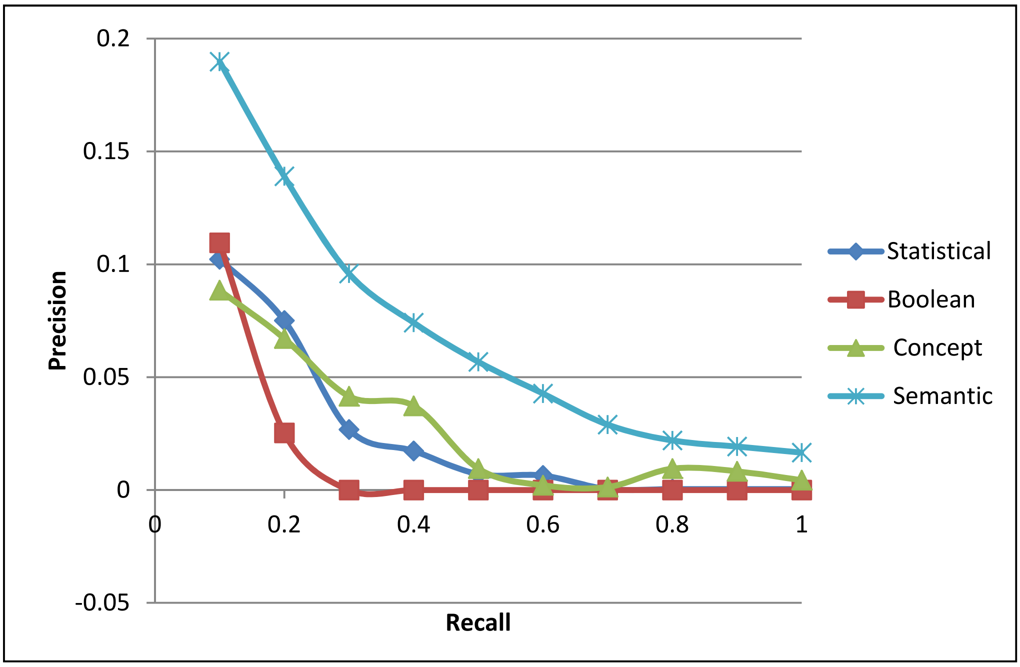


Figure 6.5: Average Precision and Recall Performance Over 22 Queries

The proposed approach is further evaluated using the crowdsourcing method to measure the accuracy performance of the retrieval results.

6.3 CROWDSOURCING EVALUATION

This thesis applies the crowdsourcing method using Amazon Mechanical Turk to evaluate the overall accuracy of proposed retrieval results. The evaluation task is divided into micro-tasks that are offered to a large number of workers who do not know each other. They are paid according to the number of HITs they had completed.

6.3.1 Evaluation Protocol

The main objective of this evaluation is to measure the accuracy of the retrieval results produced by the semantic search. The experiment includes a simple task, where the workers are provided with mood boards, or a collage of images, together with its keywords description, which are actually the search queries. A sample of an evaluation task is shown in Figure 6.6 below. The workers are required to rate the relevance between the images used in the mood boards and the keywords provided, ranging from '*not relevant*' to '*very relevant*'. Table 6.7 lists the scores for each category.

The mood boards consist of 13 top results for 22 different queries, retrieved by three different search approaches: (i) semantic search, (ii) statistical search, and (iii) concept search (TRENDS algorithm). The highest scored image, or the first rank image, is located in the central location, while the other 12 images are arranged around the central image.

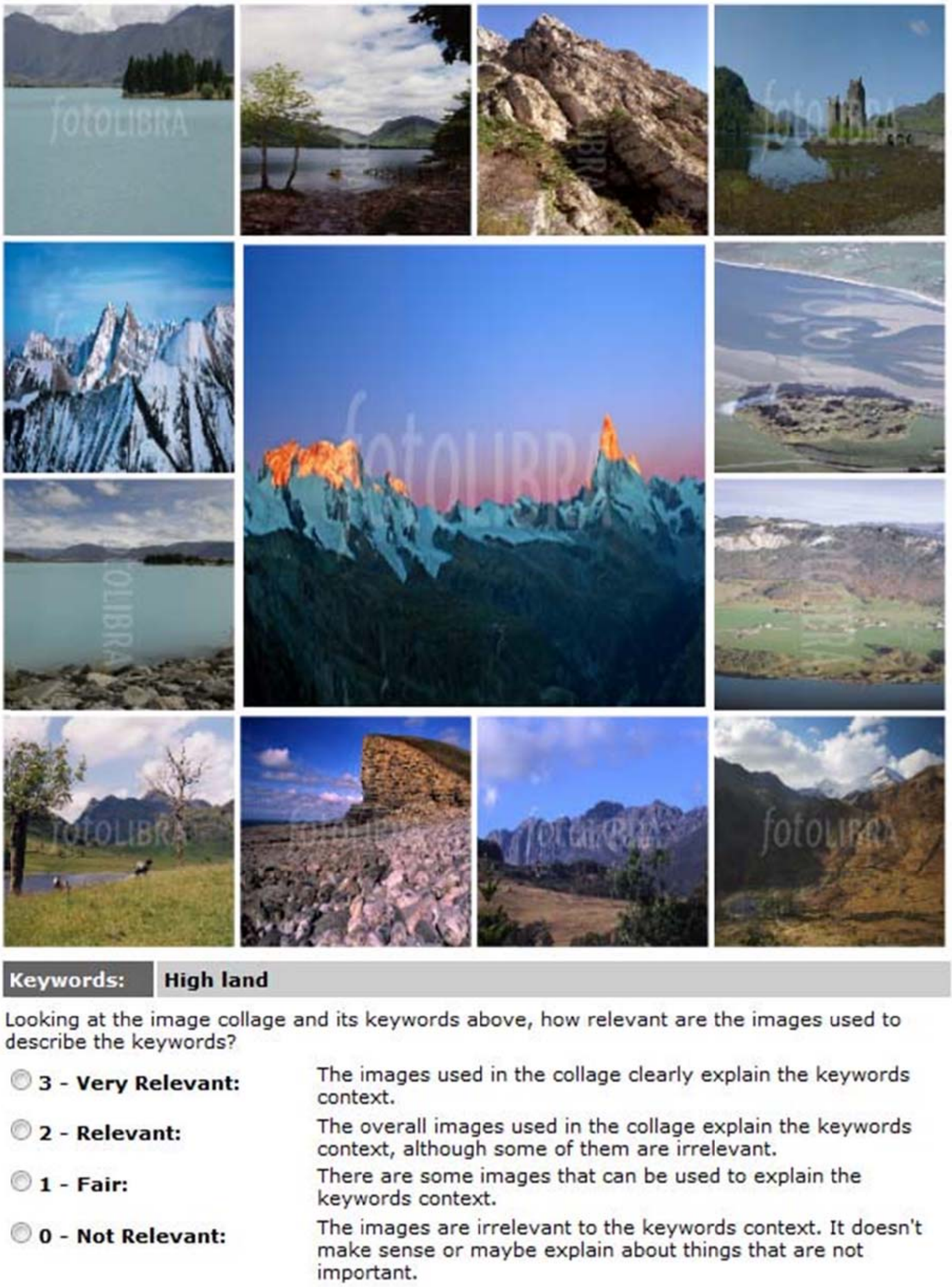


Figure 6.6: Evaluation Task Example for Query '*high land*' by Semantic Search

Table 6.7: Scoring for Mood Board Evaluation

Choice	Score
Very relevant	3
Relevant	2
Fair	1
Not relevant	0

Similar to SDNA disambiguation evaluation in section 4.3 , the same filtering technique is used to reduce low quality results from irresponsible and careless workers. The workers are only restricted to those who resides in United States or United Kingdom and any answers from the same workers which have some identical patterns for different HITs, completing time that is less than 10 seconds per task (which is considered too fast), and incomplete answers, are rejected without any payment made.

6.3.2 Evaluation Results

This task evaluates and compares three different search approaches using 22 mood boards produced by each approach. A total of 66 mood boards together with their keywords are used to create 66 HITs. Each HIT is scored by 20 different workers. A total of 1320 assignments are offered with payment of USD0.02 per assignment. 76 workers accepted the tasks; each of them completing 17.4 assignments in average. An assignment took an average of 20.02 seconds to complete. During the review of the results, 153 assignments are rejected due to unreliable answers. These assignments are re-offered to other workers. For each query, the average score of 20 evaluations is taken as the query score. Table D1 in the appendix list the scoring results for 18 HITs, while Table 6.8 shows the average score for the 3 different search approaches evaluated.

Table 6.8: Average Score of 3 Different Search Approaches for 22 Queries

Query No.	Semantic	Statistical	Concept
1	1.8	0.75	1.75
2	2.05	2.25	1.35
3	2.15	0.95	1
4	0.9	1.9	1.45
5	2.15	0.85	2.05
6	2.2	1	1.35
7	1.1	1.05	2.2
8	2	1.05	1.15
9	1.7	0.8	1.15
10	2.15	1.05	1
11	2.15	0.95	0.85
12	1.45	1.2	1.15
13	2.25	0.85	1.15
14	1.5	1.15	1.2
15	2.15	1.25	1.05
16	1.75	1.35	1.85
17	1.75	1.15	1.1
18	2.15	1	1.45
19	2.1	1.2	0.65
20	1.9	1.2	1.2
21	1.5	0.95	1.05
22	1.6	1.15	1.45
Average	1.84	1.14	1.30

Semantic search gets higher score than both the statistical and conceptual search in 18 out of 22 or 81.81% of the mood boards produced, with an average score of 1.84 compared to 1.14 scored by statistical search and 1.3 by conceptual search. Statistical search achieves higher score in 2 out of 22 or 9.01% of the mood boards produced which are the mood board produced by '*Query#2: Lovely flora*' and '*Query#4: Country terrain*'. Similar performance is shown by conceptual search where 2 out of 22 of 9.01% of the mood boards produced are scored higher than semantic and statistical search. They were the mood boards produced by '*Query#7: Prehistoric animal*' and '*Query#16: Antique heritage*'.

Table 6.9 shows the score distribution of all mood boards evaluated. 50% of the mood boards produced by the proposed semantic search approach are classified as relevant (score of 2 or higher) by the workers, and fair (score between 1 and 2) for another 45.4% of the queries, compared to only 9.1% of the mood boards produced by the concept search are considered relevant, and another 81.8% are considered fair. While the statistical search has the worst performance with 31.8% of the mood boards produced classified as not relevant, while 63.6% are considered as fair and only 4.5% or only 1 mood board is considered relevant.

Table 6.9: Evaluation Result for 3 Different Search Approach

Score	**Semantic**		**Statistical**		**Concept**	
	Count	**%**	**Count**	**%**	**Count**	**%**
0 <= x < 0.5	0	0.0%	0	0.0%	0	0.0%
0.5 <= x < 1.0	1	4.5%	7	31.8%	2	9.1%
1.0 <= x < 1.5	2	9.1%	13	59.1%	16	72.7%
1.5 <= x < 2.0	8	36.4%	1	4.5%	2	9.1%
2.0 <= x < 2.5	11	50.0%	1	4.5%	2	9.1%
2.5 <= x <= 3.0	0	0.0%	0	0.0%	0	0.0%
TOTAL	**22**	**100.0%**	**22**	**100.0%**	**22**	**100.0%**

Figure 6.7, Figure 6.8, Figure 6.9 and Figure 6.10 show examples of 4 mood boards produced by '*Query#2: Lovely flora*', '*Query#8: Family love*', '*Query#14: Festivals and events*' and '*Query#16: Antique heritage*' through semantic search, concept search and statistical search. The image in the centre of each mood board is the first ranked

image retrieved by the retrieval system. Figures D2 to D19 in the appendix shows the Mood Boards produced by the rest of the queries.

i. ***Query#2: Lovely flora*:** Although the workers scored the mood board produced by statistical search (see Figure 6.7) an average of 2.25, which is slightly higher than the one produced by the semantic search, the score of 2.05 for semantic search result is considered an improvement compared to the performance of the SDNA-based approach. It proves that combining the scores of SDNA-based with traditional keyword-based search improves the overall performance of the proposed approach.

ii. ***Query#8: Family love*:** The mood boards produced by this query (see Figure 6.8) are one of the examples where semantic search results get a high score compared to the other approaches. Further observations reveals that although the words '*family*' and '*love*' have a lot of occurrences in the annotations of images in the collection, they seldom appear together in the same context. This explains the poor performance produced by statistical and conceptual search. Semantic search is able to find a link between those two words by placing them under a common head number *#169 Parentage*. The highest rank image retrieved by semantic search, which is located in the central location, is believed to be the main factor influencing the workers to give high scores. It is an image of a duck and a duckling, which clearly represent the concept of family and love. This is an example where the proposed approach retrieves good results when other approaches fail.

iii. ***Query#14: Festivals and events*:** Although the semantic search scored slightly higher than the other approaches, there is no clear winner as the scores are in a very small range. Looking at the mood boards in Figure 6.9, overall, the images retrieved by all approaches do not really represent the query concept with a mixed kind of images. However, the relevant central image for semantic search mood board is believed to be the reason why it is scored higher than others. It is an image of castle guards on horses who are preparing for a changing guards ceremony at the Buckingham Palace, London.

iv. ***Query#16: Antique heritage*:** This is one of the mood boards which is scored higher by the conceptual search compared to other approaches. The central image is an image of a person dressed in a medieval costume, selling medieval weapons and crafts, which are considered antiques (see Figure 6.10). Further analysis reveals that the central image was tagged by concept *127#oldness* with high weight due to the word '*medieval*', which is a monosemic word in *OntoRo*. As explained in section 2.4.3 , the TRENDS conceptual indexing approach tends to give higher weights to concept numbers with monosemic words. The keyword '*antique*' used by the query is also tagged with concept *127#oldness*, thus explains the high ranking scored by the image. However, the average score of 1.75 scored by semantic search is considered comparable with the conceptual search score.

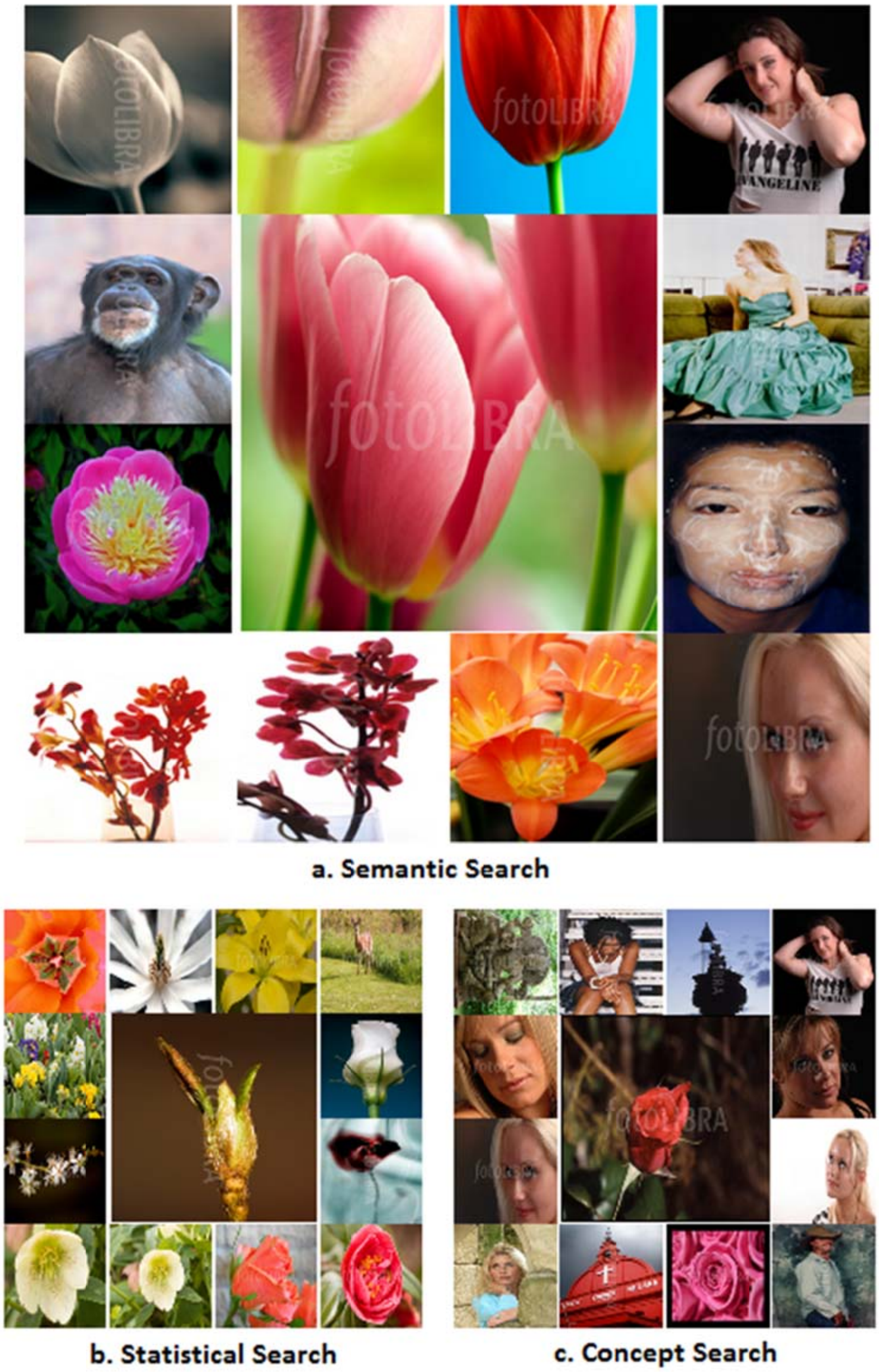


Figure 6.7: Mood Boards Produced by *Query#2: Lovely Flora*

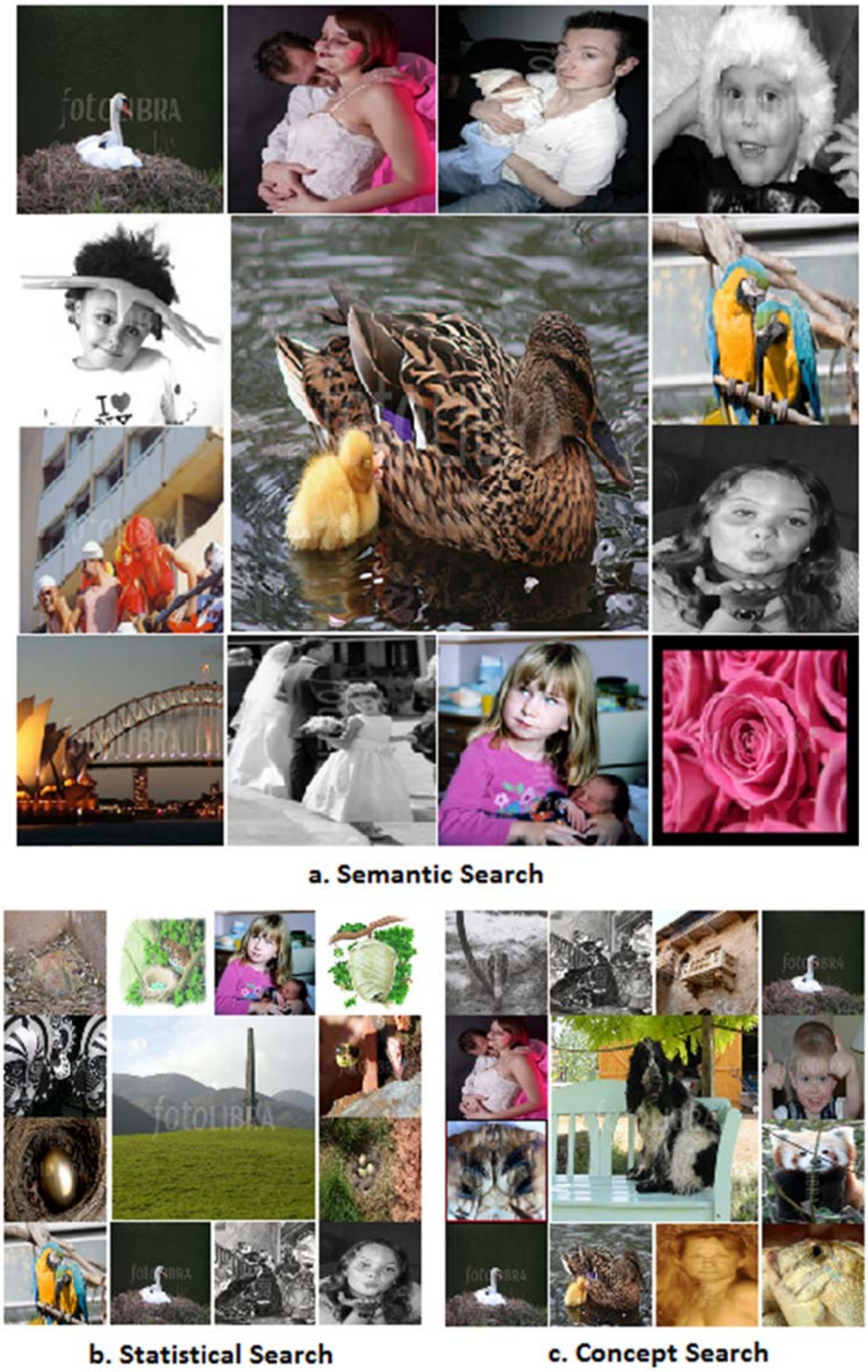
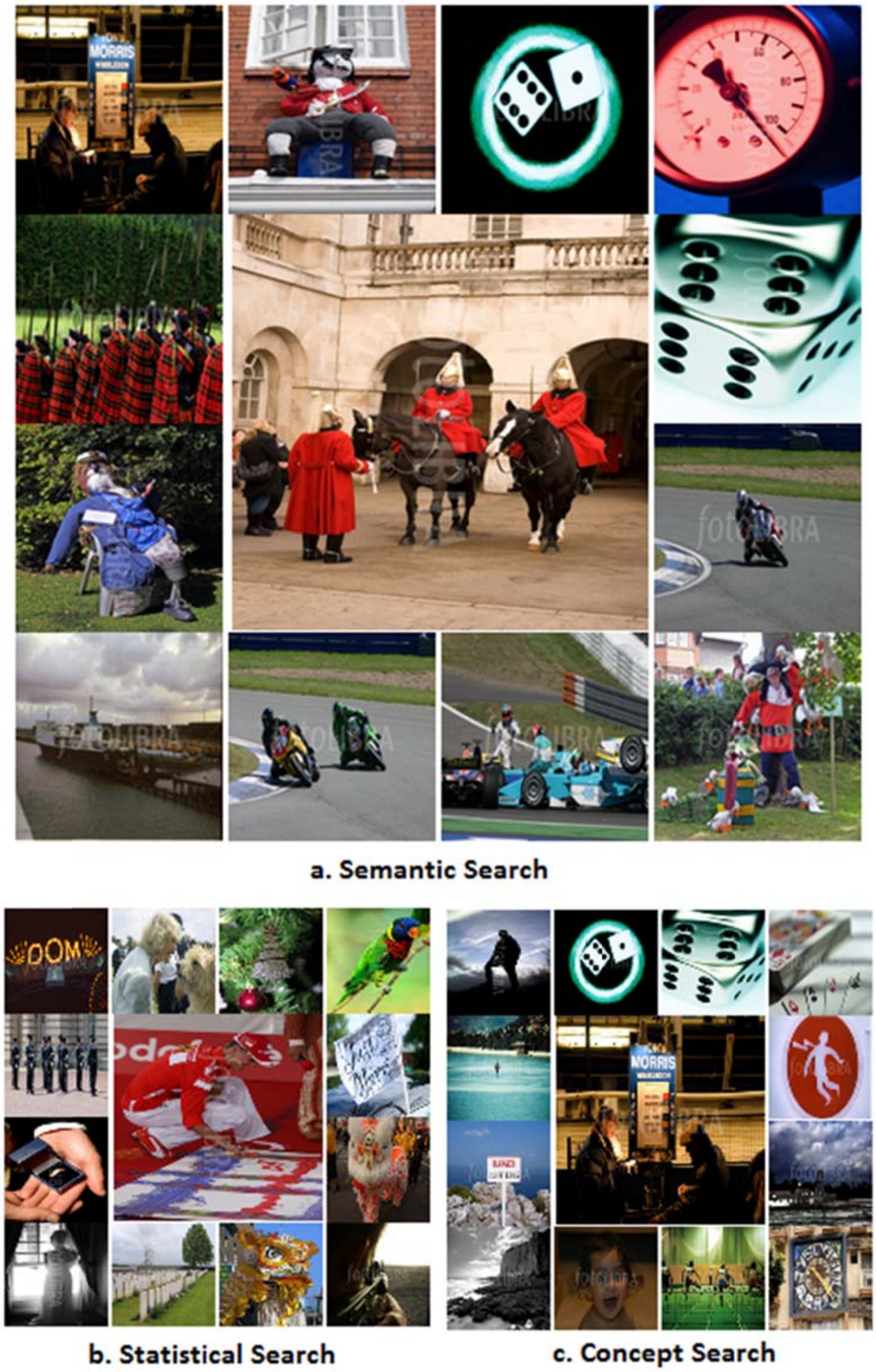


Figure 6.8: Mood Boards Produced by *Query#8: Family Love*



a. Semantic Search

b. Statistical Search

c. Concept Search

Figure 6.9: Mood Boards Produced by *Query#14: Festivals and Events*

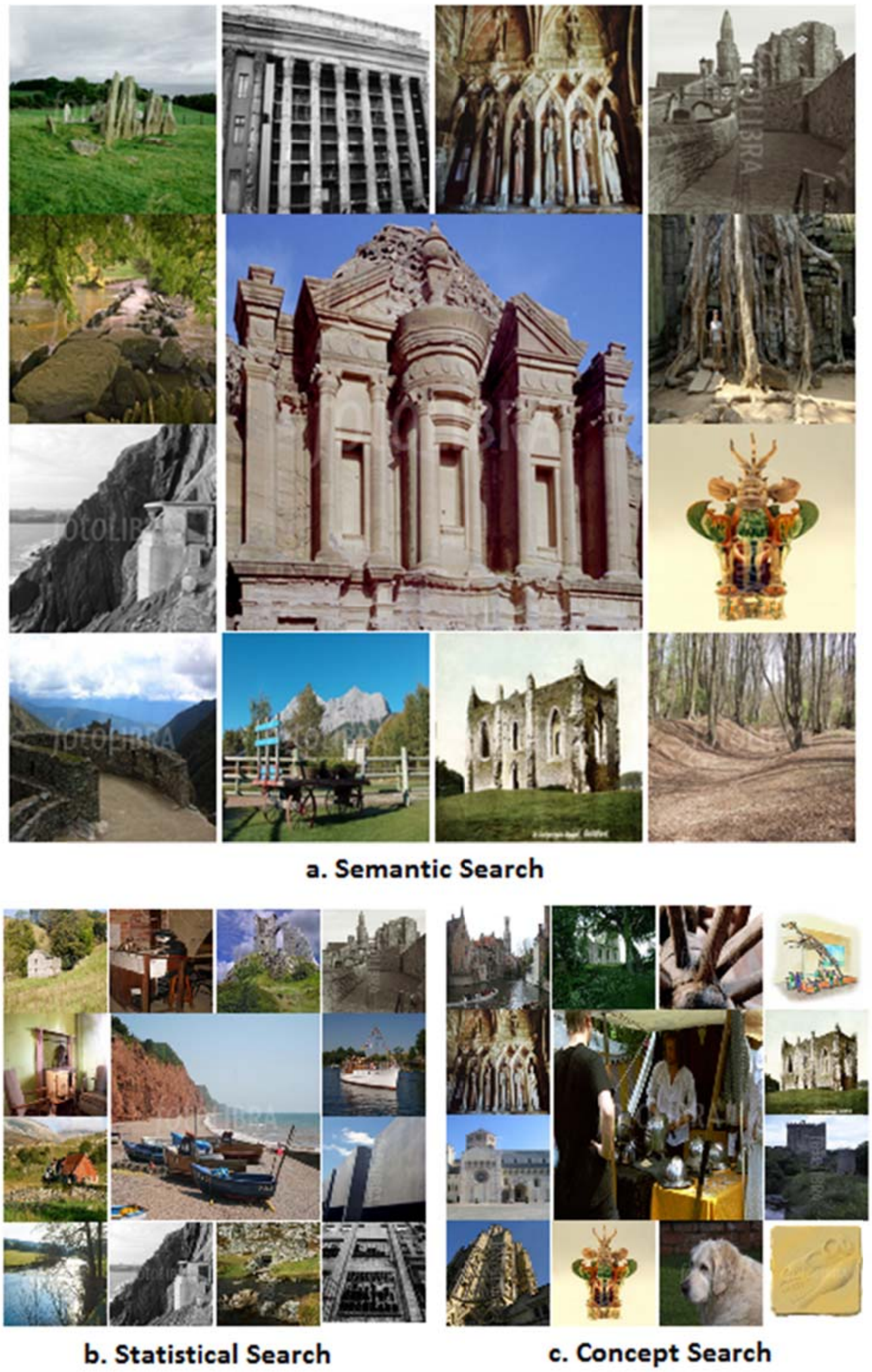


Figure 6.10: Mood Boards Produced by *Query#16:Antique Heritage*

6.4 SUMMARY

The added value of semantic information retrieval with respect to traditional keyword-based retrieval, as implied in the proposed approach, relies on the quality of the *semantic chromosomes* extracted, specifically the SDNA disambiguation process. Semantic retrieval introduces an additional step with respect to classic information retrieval models: instead of a simple keyword index lookup, the semantic retrieval system processes a query against the lexical ontology, which returns a set of SDNAs. This can be seen as a form of query expansion, where the set of SDNAs represent a new set of query terms, leading to higher recall values. The rich concept descriptions and related words in *OntoRo* provide useful information for disambiguating the meaning of annotations.

In summary, the proposed approach achieves several improvements with respect to the SDNA-based search. It achieves better average precision score of 2.05 when querying for keywords with less meaningful information, compared to the score of 0.099 using SDNA-based approach. Further observation shows that better precision is achieved when the image annotations have enough related keywords to help the SDNA disambiguation process achieve better performance. For example, images with short annotation tend to produce bad performance in SDNA disambiguation process, thus affecting the indexing and searching performance.

As discussed in section 5.4 , the degree of improvement of the semantic retrieval model also depends on the completeness and quality of the lexical ontology. For the sake of robustness, the system resorts to keyword-based search when the lexical ontology returns poor results.

The inclusion of keyword-based results ensures the robustness of the proposed method when ontology-based results are bad. However, it is at the expense of a precision loss in the opposite case. The employed score combination technique, discussed in section 6.1.2 improves retrieval results, helping the semantic approach to generally outperform other approaches in the evaluations. The evaluation results shows that the proposed approach is able to retrieve relevant results when other approaches do not.

CHAPTER 7:
CONTRIBUTIONS, CONCLUSIONS AND FUTURE WORK

The idea of introducing more semantics in IR systems remains an open problem for research and discussion. The effectiveness of text-based semantic image retrieval systems strongly depends on the richness of the metadata representation in the ontologies and knowledge bases, and the quality of the image annotations. The difficulties and cost of building and maintaining rich semantic resources is a well-known fundamental problem, identified during earlier studies (Croft, 1986). The design and construction of ontologies are outside the scope and the objectives of this thesis. They are subject to extensive studies in various disciplines of the semantic IR area (Gomez-Perez et al., 2003).

The research reported in this thesis was tested using the lexical ontology *OntoRo*, external to this thesis. At the time of this writing, it is believed to be the most suitable lexical ontology for the SDNA extraction process. However, it is not the only lexical ontology, which could be used by the proposed approach; any ontology with a formal hierarchical structure can be used to extract the SDNAs.

This chapter summarises the contributions made, conclusions reached and suggests possible directions for further research.

7.1 CONTRIBUTIONS

The main contribution of this research is the development of a semantic image retrieval approach that provides better retrieval capabilities which yields a qualitative improvement over keyword-based retrieval, by exploiting a highly potential lexical ontology. The specific contributions are summarised below:

i. **A technique for extracting semantic signatures from textual image annotations.** This research proposes the use of SDNA to preserve the semantic properties of an image. An SDNA represents a unique paragraph in *Roget's Thesaurus* consisting of tokens that can be used to explain similar ideas or concepts. It is a chain of numbers corresponding to the structural elements in the *Roget's* hierarchy, extracted from the lexical ontology *OntoRo*.

ii. **A conceptual model for semantic generation of mood boards.** The proposed model, which is based on an adaptation of the traditional VSM, has two phases: *SDNA Indexing* and *Semantic Search*. Both phases involve natural language and mathematical processing which produces *semantic chromosomes* of images and queries. The proposed semantic generation of mood boards exploits rich semantic representations in the form of lexical ontologies, supporting semantic retrieval in large repositories of annotated images.

iii. **An SDNA indexing approach based on VSM.** It involves pre-processing and storing image representations using *semantic chromosomes*. The approach has significantly reduced the matrix size compared to traditional IR approaches. It can be seen as an evolution of the classic VSM, where keyword-based indices are replaced by ontology-based, and an automatic image indexing and weighting procedure is the equivalent of the keyword extraction and indexing process.

iv. **An SDNA-based semantic similarity measure based on VSM.** It is an adaptation of VSM, where images and queries are represented by their *semantic chromosomes* as vectors in a common SDNA vector space. The semantic similarity between query and images is measured by calculating the cosine angle between the query and image vectors.

v. **An enhanced hybrid model that combines ontology-based retrieval and traditional keyword-based models using a data fusion technique.** The WCombSUM fusion technique is employed in order to combine both models to improve the performance of the ontology-based model in the case of not enough implicit information within the queries and annotations. The technique uses dedicated weights for each retrieval model according to their importance.

7.2 CONCLUSIONS

This research has developed an ontology-based IR model, which indexes and searches for images, semantically relevant to user queries, and generates automated mood boards. This research expands traditional IR techniques by incorporating a knowledge base in the process of extracting semantic image signatures and developing innovative approaches to semantic image indexing and searching.

Great progress has been achieved in the last decade with the development of image retrieval technologies, which collect, store and pre-process image information to return relevant images instantly in response to users' needs. However, users still miss or need considerable effort sometimes to reach their targets. A common cause for this is that current content description and query-processing techniques for image retrieval are based on keywords, which are adapted from the Information Retrieval (IR) community, and therefore provide limited capabilities to grasp and exploit the conceptualisations involved in user queries and content meanings.

This involves limitations such as ambiguity, synonymy, and the inability to handle semantic constraints. Aiming to solve the limitations of keyword-based models, the idea of conceptual search, understood as searching by meaning rather than literal strings, has been the focus of this research.

7.2.1 The Proposed Approach

The traditional IR approaches have limitations when dealing with high-level concepts, thus a new IR approach to facilitate conceptual understanding is needed. Semantic technologies enable IR using high-level concepts, which are closer to the way creative designers think and search for sources of inspiration. In addition, semantic expansion provides a degree of diversity and serendipity, both very important in the domain of creative design. This research proposes a semantic retrieval approach, which aim to exploit highly formalised semantic knowledge in the form of lexical ontologies, to improve traditional keyword-based search over large image repositories.

The proposed approach introduces an additional step with respect to traditional IR models: instead of a simple keyword index lookup, the semantic retrieval system processes a query against the lexical ontology, which returns a set of SDNAs. This can be seen as a form of query expansion, where the set of SDNAs represent a new set of query terms, leading to higher recall values. The rich concept descriptions and related words in *OntoRo* provide useful information for disambiguating the meaning of annotation.

The proposed approach is based on an adaptation of the classic VSM, where keywords are replaced by semantic signatures called *semantic chromosomes*, consisting of selected SDNA. The model includes a semantic indexing method and SDNA disambiguation algorithm that selects the SDNA to be associated with the images.

An SDNA represents a unique paragraph in the lexical ontology, *OntoRo*. It consists of tokens that can be used to explain a similar idea or concept. These tokens are not just synonyms but words and phrases that could be used to express the same idea or concept. Each SDNA carries semantic information including part of speech, high-level concept name and other words that can be used to represent the same idea or concept. A *semantic chromosome* is defined in this research as an information structure, which carries the semantic information of an image. It is its semantic signature expressed through a set of SDNA, where each SDNA in the set representing one semantically distinguishable concept, or a particular sense.

The SDNA weights, or relevance of the semantic entities within images, are computed using an adaptation of another IR measure, the Okapi-BM25. The SDNA disambiguation technique proposed is based on this SDNA weights. Empirical evaluation on sample results shows that the proposed SDNA disambiguation technique selects the most accurate chromosome for each token, or at least the closest one.

Using SDNA as the concept representation, pre-processing and storing all possible values of image representations requires only 0.03% of the matrix size of the traditional methods. Matrix factorisation further reduces the matrix dimension and increases the latent relations between the images or SDNA. The proposed approach of SDNA-based concept distance measure has all attractive features of both knowledge-based and distributional measure, and yet avoids problems of words ambiguity and computational complexity.

The proposed model enables images to be indexed and searched with high-level concepts. It increases the precision and recall of the retrieved results, compared to traditional and other conceptual search approaches. Queries are expressed using natural languages. This allows users to express their needs and intentions in a user-friendly way. A ranking algorithm is included in the approach that exploits the conceptualisations involved in queries and contents. This approach, tested on a data of a significant scale is showing clear improvements with respect to keyword-based search.

The results show that it is possible to develop a consistent semantic indexing and searching algorithms producing measurable improvements with respect to several other IR approaches, subject to the quality of the lexical ontology and the annotation texts.

7.2.2 Enhanced Model

The semantic information retrieval proposed in this research relies on the quality of the *semantic chromosomes* extracted, specifically the SDNA extraction and disambiguation processes. It also has a direct relation with the implicit information relies within the query and annotation text. If the annotation contains less meaningful information, the SDNA disambiguation algorithm performs very poorly, thus affecting the relevancy of the *semantic chromosomes*. This will further affect the performance of similarity measure and retrieval results. To deal with this drawback, the results coming from the proposed SDNA-based retrieval model and the result returned by traditional keyword-based model are combined.

In the case where the semantic information contains in the annotation is enough for the SDNA-based retrieval to return significantly more accurate result, the combination process is biased to the SDNA-based results. The opposite situation occurs when the available semantic information is not enough to answer the user's query. While in the case of both approaches represent good results, a fair combination achieved to provide the best possible retrieval results.

The experimental results show that the data fusion technique used increases the overall image retrieval precision and recall.

7.2.3 Evaluation Benchmarks

Standardised techniques for evaluation such as the TREC annual competitions have been a common evaluation standard in traditional IR communities. On the other hand, the semantic IR community is still a long way from defining standard evaluation benchmarks that comprise all required information to judge the quality of the current semantic retrieval methods. Semantic IR technology evaluation approaches are currently based on user-centred methods where users manually judge the quality of the semantic search.

Crowdsourcing is seen as a potential alternative for the purpose of semantic retrieval evaluation. Reviews show that crowdsourcing had been successfully applied in linguistic data collection tasks, pattern matching, paraphrasing for machine translation and speech transcription. This research utilises the potential of crowdsourcing by applying it in the evaluation process for SDNA disambiguation and mood board creating performance. The crowdsourcing evaluation method used is based on collective human evaluation using Amazon Mechanical Turk (MTurk). The evaluation tasks are divided into micro-tasks that are offered to a large number of people who do not know each other. Every task offered through the MTurk is called a human intelligence task (HIT). The people who perform the task are called workers. They are paid according to the number of HITs they had completed.

This study also introduces a new semantic IR benchmark using the *fotoLIBRA* image collection. All images submitted to *fotoLIBRA* by photographers are asked to be categorised under 18 categories and 239 sub categories. The image owners are considered as experts of their own photos, thus the categories selected are considered reliable. 22 queries were designed by referring to these categories and sub categories. For every query, several related sub categories are selected as the relevant results.

7.3 FUTURE WORK

There is ample room for further improvement and research beyond current results. For instance, all experiments in this research are based on *OntoRo*, one of the potential lexical ontology at the time of writing. Future work should explore other potential ontologies and consider the use of multi-ontologies.

Future work should also consider the potential of composite approaches, combining text-based and content-based image retrieval (CBIR). It is believed that CBIR could improve the precision of retrieval by eliminating irrelevant images.

Personalisation provides another potential improvement by incorporating user subjectivity into the retrieval model. The exploration of implicit user interest is an interesting research direction, which could enhance the semantic retrieval model by adapting or re-ranking the results according to user preferences.

The evaluation benchmark based on the *fotoLIBRA* collection's metadata used in this research can be employed to test other semantic retrieval and keyword-based approaches. However, it presents several disadvantages. The images, queries and judgements are not validated and standardised by the research community, and its size is not enough for a large scale test. A bigger scale evaluation benchmark could be constructed using a bigger size collection to provide an establish benchmark that could be used by the semantic community.

The use of SDNA can also be expanded into other applications that may benefit from the use of semantics signatures. Other potential applications includes genealogy domain where SDNA can be used to represent a unique person in a family tree. The SDNA may implicitly contains genealogy information such as gender, level of generation in family tree and the number or related child. Using SDNA, the relationship between two people can easily be calculated by comparing the numbers in each SDNA level.

APPENDIX A

fotoLIBRA Data Collection Categories

Table A1: Categories and Sub-categories in *fotoLIBRA* Image Collection

Category	Sub-category	# of Image	Category	Sub-category	# of Image
1#Animals	250#Amphibians	311	4#Design	56#Advertising	490
	18#Birds	3882		57#Fashion	702
	19#Farm	1038		58#Graphics	452
	20#Fish	750		59#Illustration	99
	21#Insects	1375		60#Jewellery	42
	251#Invertebrates	502		61#Maps	5
	22#Mammals	1941		62#Textiles	38
	23#Pets	1470		63#Typography	422
	220#Prehistoric	653	5#Events	65#Ceremonies	674
	24#Reptiles	845		66#Disasters	658
	25#Wildlife	2401		67#Family	63
2#Architecture	26#Ancient	1130		64#Festivals	1289
	27#Bridges	1336		231#National	522
	28#Buildings	3129		68#News	27
	29#Canals	533		69#Parties	51
	30#Castles	976		70#Protest	53
	33#Domestic	715		71#State	24
	34#Follies	1453		72#Wars	757
	39#Industrial	591	7#Heritage	81#Antiques	723
	35#Monuments	1020		82#Archaeology	435
	37#Palaces	663		83#Conservation	766
	36#Public	1172		233#Environment	563
	31#Religious	1783		84#History	1996
	32#Towns & Cities	1671		85#Industrial	734
	38#Tunnels	437		86#Manuscripts	427
3#Arts	40#Abstracts	1200	10#Nature	249#Coastline	647
	41#Aesthetics	509		117#Countryside	2516
	42#Cartoons	651		120#Lakes	1418
	43#Ceramics	18		121#Landscapes	4154
	44#Cinema	26		122#Mountains	1294
	245#Crafts	291		123#Rivers	1395
	45#Dance	76		124#Sea	3088
	46#Drama	16		125#Seasons	817
	47#Fine Art	53		116#Skies	904
	48#Glass	67		126#Snow & Ice	796
	49#Music	753		127#Underwater	672
	50#Outsider Art	86		128#Volcanoes	414
	51#Painting	551		248#Waterfalls	30
	53#Sculpture	898		129#Weather	1043
	54#Still Life	646		130#Wilderness	750
	55#Theatre	515		131#Woodland	1271

Category	Sub-category	# of Image	Category	Sub-category	# of Image
8#Leisure	246#Boating	423	11#People	132#Adults	1186
	87#Camping	58		118#Age	502
	88#Clubs	46		133#Beauty	904
	89#Collecting	24		134#Celebrities	610
	90#Crafts	98		135#Children	1525
	91#Cycling	36		136#Families	655
	92#DIY	39		119#Indigenous	559
	93#Exploration	657		137#Motherhood	657
	94#Fishing	458		138#Nudes	595
	95#Games	500		139#Royalty	487
	234#Gardening	583		140#Youth	652
	221#Hobbies	442	12#Plants	141#Cacti	73
	97#TV	424		142#Exotic	666
	98#Walking	753		143#Ferns	55
9#Lifestyle	99#Books	98		144#Flowers	2963
	100#Computers	115		252#Fruit & Vegetables	410
	101#Cookery	72		146#Fungi	524
	102#Entertainment	697		147#Garden	986
	103#Food & Drink	1215		148#House	35
	104#Furniture	444		235#Lichen	12
	106#Holidays	1172		149#Marine	32
	107#Homes	654		150#Trees	1083
	108#Hospitality	697		151#Wildflowers	971
	109#Humour	668	13#Science	222#Anatomy	3
	110#Living	648		152#Anthropology	6
	105#Parks & Gardens	653		236#Archaeology	86
	111#Shopping	517		153#Astronomy	471
	112#Showbiz	483		154#Biology	115
	113#Toys	465		155#Botany	112
	114#Travel	2519		156#Chemistry	66
	115#Wine	460		157#Ecology	22
6#Health	232#Diet	37		158#Entomology	2
	74#Disability	9		237#Genetics	15
	73#Disease	233		159#Geography	572
	75#Emergency Services	16		160#Geology	452
	76#Fitness	54		161#Physics	464
	77#Gyms	3		162#Space	552
	78#Hospitals	16		163#Technology	649
	79#Medical	566		164#Topography	420
	80#Old Age	421		238#Zoology	4

Category	Sub-category	# of Image	Category	Sub-category	# of Image
15#Sport	177#Adventure	662	223#Travel	226#Adventure	795
	178#Aerial	463		225#Cultures	1198
	179#American	36		228#Customs	79
	180#Country	143		227#Exploration	1069
	181#Cricket	626		224#Holidays	3692
	182#Cycling	59		229#Transport	572
	183#Equestrian	554	17#Work	206#Agriculture	755
	184#Extreme	733		207#Commerce	502
	185#Football	391		208#Construction	553
	186#Golf	546		209#Energy	471
	187#Indoor	487		210#Engineering	520
	188#Motor	7553		211#Finance	42
	189#Olympics	424		243#Fisheries	394
	190#Others	564		212#Forestry	58
	191#Rugby	528		213#Hotels	420
	239#Running	442		214#Industry	634
	192#Sub Aqua	22		215#Media	56
	193#Tennis	58		216#Military	182
	194#Track & Field	33		217#Office	522
	195#Water	932		218#Tools	66
	196#Winter	526		219#Tourism	172
16#Transport	198#Airships and Balloons	1275		244#Transport	639
	197#Automotive	822	14#Society	165#Civilisations	431
	256#Aviation Aerobatics	2		166#Crime	654
	253#Aviation Civil	325		167#Culture	733
	254#Aviation Military	145		168#Customs	710
	240#Bicycles	767		169#Education	533
	200#Cars	935		170#Folklore	447
	241#Horse-drawn	165		171#Gay & Lesbian	5
	201#Maritime	1325		172#Law and Order	76
	242#Motorcycles	672		173#Militaria	192
	52#Places	434		174#Politics	183
	202#Private	76		175#Religion	819
	203#Public	612		176#Third World	373
	204#Railways	1069			
	205#Roads	706			
	199#Waterways	764			

APPENDIX B

SMART Stop Word List

Table B1: SMART Stop Word List

No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word
1	a	51	at	101	contain	151	few	201	hers	251	they'd
2	a's	52	available	102	containing	152	fifth	202	herself	252	they'll
3	able	53	away	103	contains	153	first	203	hi	253	they're
4	about	54	awfully	104	corresponding	154	five	204	him	254	they've
5	above	55	b	105	could	155	followed	205	himself	255	think
6	according	56	be	106	couldn't	156	following	206	his	256	third
7	accordingly	57	became	107	course	157	follows	207	hither	257	this
8	across	58	because	108	currently	158	for	208	hopefully	258	thorough
9	actually	59	become	109	d	159	former	209	how	259	thoroughly
10	after	60	becomes	110	definitely	160	formerly	210	howbeit	260	those
11	afterwards	61	becoming	111	described	161	forth	211	however	261	though
12	again	62	been	112	despite	162	four	212	i	262	three
13	against	63	before	113	did	163	from	213	i'd	263	through
14	ain't	64	beforehand	114	didn't	164	further	214	i'll	264	throughout
15	all	65	behind	115	different	165	furthermore	215	i'm	265	thru
16	allow	66	being	116	do	166	g	216	i've	266	thus
17	allows	67	believe	117	does	167	get	217	ie	267	to
18	almost	68	below	118	doesn't	168	gets	218	if	268	together
19	alone	69	beside	119	doing	169	getting	219	ignored	269	too
20	along	70	besides	120	don't	170	given	220	immediate	270	took
21	already	71	best	121	done	171	gives	221	in	271	toward
22	also	72	better	122	down	172	go	222	inasmuch	272	towards
23	although	73	between	123	downwards	173	goes	223	inc	273	tried
24	always	74	beyond	124	during	174	going	224	indeed	274	tries
25	am	75	both	125	e	175	gone	225	indicate	275	truly
26	among	76	brief	126	each	176	got	226	indicated	276	try
27	amongst	77	but	127	edu	177	gotten	227	indicates	277	trying
28	an	78	by	128	eg	178	greetings	228	inner	278	twice
29	and	79	c	129	eight	179	h	229	insofar	279	two
30	another	80	c'mon	130	either	180	had	230	instead	280	u
31	any	81	c's	131	else	181	hadn't	231	into	281	un
32	anybody	82	came	132	elsewhere	182	happens	232	inward	282	under
33	anyhow	83	can	133	enough	183	hardly	233	is	283	unfortunately
34	anyone	84	can't	134	entirely	184	has	234	isn't	284	unless
35	anything	85	cannot	135	especially	185	hasn't	235	it	285	unlikely
36	anyway	86	cant	136	et	186	have	236	it'd	286	until
37	anyways	87	cause	137	etc	187	haven't	237	it'll	287	unto
38	anywhere	88	causes	138	even	188	having	238	it's	288	up
39	apart	89	certain	139	ever	189	he	239	its	289	upon
40	appear	90	certainly	140	every	190	he's	240	itself	290	us
41	appreciate	91	changes	141	everybody	191	hello	241	j	291	use
42	appropriate	92	clearly	142	everyone	192	help	242	just	292	used
43	are	93	co	143	everything	193	hence	243	k	293	useful
44	aren't	94	com	144	everywhere	194	her	244	keep	294	uses
45	around	95	come	145	ex	195	here	245	keeps	295	using
46	as	96	comes	146	exactly	196	here's	246	kept	296	usually
47	aside	97	concerning	147	example	197	hereafter	247	know	297	uucp
48	ask	98	consequently	148	except	198	hereby	248	knows	298	v
49	asking	99	consider	149	f	199	herein	249	known	299	value
50	associated	100	considering	150	far	200	hereupon	250	l	300	various

No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word	No.	Stop word
301	last	351	very	401	nine	451	presumably	501	some	551	without
302	lately	352	via	402	no	452	probably	502	somebody	552	won't
303	later	353	viz	403	nobody	453	provides	503	somehow	553	wonder
304	latter	354	vs	404	non	454	q	504	someone	554	would
305	latterly	355	w	405	none	455	que	505	something	555	would
306	least	356	want	406	noone	456	quite	506	sometime	556	wouldn't
307	less	357	wants	407	nor	457	qv	507	sometimes	557	x
308	lest	358	was	408	normally	458	r	508	somewhat	558	y
309	let	359	wasn't	409	not	459	rather	509	somewhere	559	yes
310	let's	360	way	410	nothing	460	rd	510	soon	560	yet
311	like	361	we	411	novel	461	re	511	sorry	561	you
312	liked	362	we'd	412	now	462	really	512	specified	562	you'd
313	likely	363	we'll	413	nowhere	463	reasonably	513	specify	563	you'll
314	little	364	we're	414	o	464	regarding	514	specifying	564	you're
315	look	365	we've	415	obviously	465	regardless	515	still	565	you've
316	looking	366	welcome	416	of	466	regards	516	sub	566	your
317	looks	367	well	417	off	467	relatively	517	such	567	yours
318	ltd	368	went	418	often	468	respectively	518	sup	568	yourself
319	m	369	were	419	oh	469	right	519	sure	569	yourselves
320	mainly	370	weren't	420	ok	470	s	520	t	570	z
321	many	371	what	421	okay	471	said	521	t's	571	zero
322	may	372	what's	422	old	472	same	522	take		
323	maybe	373	whatever	423	on	473	saw	523	taken		
324	me	374	when	424	once	474	say	524	tell		
325	mean	375	whence	425	one	475	saying	525	tends		
326	meanwhile	376	whenever	426	ones	476	says	526	th		
327	merely	377	where	427	only	477	second	527	than		
328	might	378	where's	428	onto	478	secondly	528	thank		
329	more	379	whereafter	429	or	479	see	529	thanks		
330	moreover	380	whereas	430	other	480	seeing	530	thanx		
331	most	381	whereby	431	others	481	seem	531	that		
332	mostly	382	wherein	432	otherwise	482	seemed	532	that's		
333	much	383	whereupon	433	ought	483	seeming	533	thats		
334	must	384	wherever	434	our	484	seems	534	the		
335	my	385	whether	435	ours	485	seen	535	their		
336	myself	386	which	436	ourselves	486	self	536	theirs		
337	n	387	while	437	out	487	selves	537	them		
338	name	388	whither	438	outside	488	sensible	538	themselves		
339	namely	389	who	439	over	489	sent	539	then		
340	nd	390	who's	440	overall	490	serious	540	thence		
341	near	391	whoever	441	own	491	seriously	541	there		
342	nearly	392	whole	442	p	492	seven	542	there's		
343	necessary	393	whom	443	particular	493	several	543	thereafter		
344	need	394	whose	444	particularly	494	shall	544	thereby		
345	needs	395	why	445	per	495	she	545	therefore		
346	neither	396	will	446	perhaps	496	should	546	therein		
347	never	397	willing	447	placed	497	shouldn't	547	theres		
348	nevertheless	398	wish	448	please	498	since	548	thereupon		
349	new	399	with	449	plus	499	six	549	these		
350	next	400	within	450	possible	500	so	550	they		

APPENDIX C

Crowdsourcing Evaluation

Group of Words:	stag, rut, deer, rutting, season, fighting

Keywords	Concept Sense	Related Words	Select Sense
deer	velocity	speeder, hustler, speed merchant, speed maniac, scorcher, racing driver, driver, runner, harrier, racer, sprinter, galloper, courser, racehorse, thoroughbred, grey hound, cheetah, hare, **deer**, doe, gazelle, antelope, ostrich, eagle, swallow, arrow, arrow Om the bow, bullet, cannonball, missile, jet, rocket, speedboat, clipper, ship, express, express train, express messenger, Ariel, Mercury, courier, magic carpet, seven-league boots,	
	male	male animal, dog, coyote, dog, fox, otter, wolf, dog fox, tom cat, horse, stallion, horse, zebra, entire horse, sude horse, colt, bull, bullcalf, bullock, ox, steer, boar, hog, ram, tup, hegoat, billy goat, buck, **deer**, rendeer, hart, red deer, roebuck, **stag**, caribou, **deer**, red deer, buck, antelope, goat, hare, kangaroo, rabbit, bull, buffalo, camel, elephant, elk, giraffe, hippopotamus, moose, rhinoceros, seal, walrus, whale, boar, badger, bear, beaver, hedgehog, raccoon, jack, donkey, jackass, hob, jack, ferret, cock, cockerel, rooster, drake, gander, cob, swan, tiercel, tercel, falcon, drone, bee, gelding, capon, eunuch,	
	Both of the above		
	None of the above		
rut	permanence	permanence, permanency, no change, status quo, invariability, unchangeability, immutability, stability, lasting quality, persistence, perseverance, endurance, duration, durability, perpetuity, fixity, fixity of purpose, immobility, immovableness, intransigence, obstinacy, firmness, rock, bedrock, foundation, solidity, density, sustenance, maintenance, conservation, preservation, continuance, law, bylaw, rule, regularity, fixed law, entrenched clause, fixture, standing, long standing, inveteracy, oldness, tradition, custom, practice, habit, fixed attitude, conservatism, routine, fixed routine, **rut**, order, unprogressiveness, static condition, quiescence, traditionalist, conservative, reactionary, true-blue, stick-inthe-mud, die-hard, obstinate person,	
	desire	libido, Eros, life instinct, sexual urge, erotism, eroticism, erogenous zone, G-spot, Grafenberg spot, concupiscence, sexual desire, carnal desire, passion, **rut**, heat, oestrus, mating season, libidinousness, lickerishness, prurience, lust, lecherousness, letch, the hots, unchastity, nymphomania, priapism, satyriasis, variance,	
	Both of the above		
	None of the above		
stag	animality	fabulous beast, heraldic beast, unicorn, griffin, mammal, viviparous animal, man, humankind, primate, ape, anthropoid ape, gorilla, orang-outang, chimpanzee, bonobo, gibbon, siamang, baboon, drill, mandrill, monkey, howler, marmoset, lemur, indris, indri, marsupial, kangaroo, wallaby, wombat, koala bear, opossum, rodent, rat, mouse, field mouse, dormouse, shrew, vole, porcupine, mongoose, chipmunk, skunk, polecat, squirrel, insectivorous mammal, aardvark, ant-eater, mole, nocturnal mammal, bat, bush baby, raccoon, badger, hedgehog, carnivorous mammal, stoat, weasel, ferret, fox, dog fox, vixen, Reynard, jackal, hyena, lion, herbivorous mammal, hare, mountain hare, rabbit, bunny, aquatic mammal, otter, beaver, water rat, water vole, marine mammal, walrus, seal, sea lion, cetacean, dolphin, porpoise, whale, sperm whale, right whale, pachyderm, elephant, rhinoceros, hippopotamus, bear, polar bear, black bear, brown bear, grizzly bear, bruin, giant panda, ungulate, giraffe, zebra, **deer**, **stag**, hart, buck, doe, fawn, pricket, red deer, fallow deer, roe deer, muntjac, reindeer, caribou, elk, moose, gazelle, antelope, chamois, springbok, eland, hartebeest, wildebeest, gnu, horse, donkey, camel, beast of burden,	
	barter	speculate, venture, risk, gamble, invest, sink one's capita] in, put one's money to work, make one's money work for one, rig the market, racketeer, profiteer, deal in the black market, sell under the counter, deal in futures, dabble in shares, play the market, go bust, go, on the Stock Exchange, operate, bull, bear, **stag**,	
	Both of the above		
	None of the above		

a. Image ID: 4264

Figure C1: SDNA Disambiguation Evaluation Sample

Group of Words:	horse, riding, water, holidays, lifestyle, ride, fun, splash, country, scene, village, gallop, holiday, life, stream, lower, slaughter

Keywords	Concept Sense	Related Words	Select Sense
horse	land travel	conveyance, lift, elevator, escalator, paternoster, travelator, conveyor, feet, own two feet, foot, legs, Shanks's pony, horseback, mount, **horse**, ambulance, bicycle, bus, car, coach, microscooter, moped, scooter, taxi, train, vehicle, traffic, wheeled traffic, motor traffic, road traffic, passing along,	
	latency	latency, no signs of, concealmmt, insidiousness, treachery, perfidy, dormancy, dormant condition, potentiality, possibility, esotericism, cabbala, ocwltism, occultness, mysticism, hidden meaning, occult meaning, veiled meaning, unintelligibility, ambiguous advice, oracle, symbolism, allegory, anagoge, metaphor, implication, adumbration, symbolization, mystery, secret, inmost recesses, interiority, dark, darkness, shadowiness, dimness, imperceptibility, invisibility, more than meets the eye, deceptive appearance, hidden fires, hidden depths, iron hand in a velvet glove, slumbering volcano, sleeping dog, sleeping giant, danger, dark, **horse**, mystery man, anonymity, no name, red under the bed, nigger in the woodpile, snake in the grass, mole, pitfall, manipulator, puppeteer, hidden hand, wire-puller, strings, friends in high places, friend at court, power behind the throne, eminence grise, influence, old-boy network, networking, Freemasonry, subconscious, subliminal influence, subliminal advertising, secret influence, lurking disease, unsoundness, something rotten, innuendo, insinuation, suggestion, hint, half-spoken word, mutter, sealed lips, taciturnity, undercurrent, undertone, aside, faintness, clandestineness, secret society, cabal, intrigue, plot, ambushment, ambush, code, invisible writing, cryptography,	
	Both of the above		
	None of the above		
riding	land travel	equitation, equestrianism, horsemanship, horsewomanship, manege, dressage, skill, show jumping, eventing, gymkhana, steeplechasing, point-to-point racing, contest, horse racing, **riding**, bareback riding, athletics, haute ecole, caracol, piaffer, curvet, gait,	
	prosperity	prosperous, thriving, flourishing, booming, successful, rising, doing well, on a roll, up and coming, on the up and up, In the ascendant, going up in the world, on the make, profiteering, well set-up, established, well-to-do, well-off, well-heeled, rolling in it, affluent, comfortable, comfortably off, moneyed, riding high on the hog's back, **riding**, on the crest of a wave, buoyant, bullish, fortunate, lucky, born with a silver spoon in one's mouth, born under a lucky star, in clover, on velvet, on easy street, in the money, at ease, in bliss, happy, fat, sleek, euphoric,	
	Both of the above		
	None of the above		
water	causation	cause, originate, bring into being, create, make, produce, beget, be the author of, generate, invent, discover, be the reason, account for, underlie, be at the bottom of, lie at the bottom of, be at the root of, sow the seeds of, be answerable, be responsible, have a hand in, be to blame, institute, found, lay the foundations, inaugurate, auspicate, set up, erect, elevate, launch, set afloat, set afoot, set going, trigger off, spark off, touch off, begin, open, open up, broach, initiate, seed, sow, plant, **water**, cultivate, contrive, effect, effectuate, bring about, bring off, bring to pass, succeed, procure, provide the means, put up the wherewithal, find means, stage-manage, engineer, plan, bring on, induce, precipitate, hasten, bring out, draw out, evoke, elicit, attract, provoke, arouse, awaken, excite, stimulate, invigorate, kindle, inspire, incite, tempt, induce, occasion, give occasion for, motivate, have an effect, be a factor, show its result, make or mar, influence, be the agent, do the deed, do, determine, decide, give the decision, judge, decide the result, turn the scale, come down on one side or the other, give the casting vote, prevail, predominate,	
	moisture	irrigate, **water**, supply water, hose, pump, inundate, flood, overflow, submerge, percolate, infiltrate, squirt, inject, douche,	
	Both of the above		
	None of the above		

b. Image ID: 5404

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	snow, relaxing, humour, lifestyle, drinking, dogs, relax, chat

Keywords	Concept Sense	Related Words	Select Sense
humour	tendency	tendency, trend, tenor, tempo, rhythm, set, drift, direction, course, stream, main current, mainstream, Zeitgeist, spirit of the times, spirit of the age, climate, influence, gravitation, affinity, attraction, polarity, contraposition, aptness, fitness, gift, talent, instinct for, aptitude, proneness, proclivity, propensity, predisposition, readiness, inclination, penchant, predilection, liking, leaning, bias, prejudice, weakness, liability, cast, cast of mind, bent, turn, grain, a strain of, tincture, vein, **humour**, mood, tone, quality, nature, characteristic, temperament, special gift, genius, idiosyncrasy, speciality, tending, trending, conducive, leading to, pointing to, tendentious, working towards, aiming at, intending, in a fair way to, calculated to, probable, centrifugal, avoiding, subservient, liable, apt to, prone to, ready to, about to, prepared,	
	amusement	amuse, interest, entertain, beguile, divert, tickle, make one laugh, take one out of oneself, tickle the fancy, titillate, please, delight, recreate, refresh, solace, enliven, cheer, treat, regale, take out, take for an outing, raise a smile, wake laughter, stir, convulse with, set the table in a roar, have them rolling in the aisles, wow, slay, be the death of, be ridiculous, **humour**, keep amused, put in a good humour, put in a cheerful mood, give a party, have a get-together, play the host, play the hostess, be hospitable, be a sport, be a good sport, be great fun,	
	Both of the above		
	None of the above		
lifestyle	business	vocation, calling, life work, mission, apostolate, commission, life, **lifestyle**, walk of life, career, chosen career, labour of love, selfimposed task, voluntary work, living, livelihood, daily bread, one's bread and butter, profession, metier, craft, trade, line, line of country, exacting profession, high calling, religious profession, ministry, cloth, veil, habit, the church, military profession, arms, war, naval profession, sea, legal profession, law, teaching profession, education, teaching, medical profession, medicine, practice, business profession, industry, commerce, trade, government service, diplomatic service, civil service, administration, management, public service, public life, social service, sociology,	
	conduct	conduct, behaviour, deportment, bearing, personal bearing, comportment, carriage, port, demeanour, attitude, posture, mien, aspect, look, look in one's eyes, appearance, tone, tone of voice, delivery, voice, motion, action, gesticulation, gesture, mode of behaviour, fashion, style, manner, guise, air, poise, savoir faire, dignity, presence, breeding, graciousness, good manners, courtesy, ungraciousness, boorishness, rudeness, bad manners, discourtesy, pose, roleplaying, affectation, mental attitude, outlook, opinion, mood, feeling, good behaviour, virtue, misbehaviour, misconduct, wickedness, democratic behaviour, common touch, past behaviour, record, track record, history, reward of conduct, deserts, dueness, way of life, ethos, morals, principles, ideals, customs, mores, manners, **lifestyle**, habit, proposed Conduct, line of action, policy, career, course, race, walk, walk of life, vocation, observance, routine, rules of business, practice, procedure, process, method, modus operandi, way, organization, orchestration, treatment, handling, manipulation, direction, masterminding, management, gentle handhng, kid gloves, velvet glove, leniency, rough handling, putting the boot in, jackboot, iron hand, severity, dealings, transactions, affairs, deeds, deed, behaviourism,	
	Both of the above		
	None of the above		
snow	coldness	**snow**, snowfall, snowflake, snow crystal, lanche, snow slip, snowdrift, snowpack, snoy, field, snowstorm, flurry of snow, the old woman plucking her geese, snow line, snowcap, snowfield, snowball, snowman, **snow**, snowplough, snowshoe, snowmobile, snowtyre, winter sports, sport, snow blindness, snowbound,	
	drunkeness	drug, hard drug, soft drug, controlled drug, designer drug, recreational drug, drugs, substance, illegal substance, joint, reefer, spliff, roach, shot, fix, narcotic, dope, nicotine, tobacco, cannabis, marijuana, ganja, hemp, hashish, hash, bhang, kef, pot, grass, Acapulco gold, sinsemilla, cocaine, coke, basuco, basuko, **snow**, crack, rock, free-base, heroin, horse, junk, smack, scag, black tar, candy, nose candy, dogfood, gumball, Mexican mud, peanut butter, tootsie roll, methadone, downers, barbiturates, barbs, morphia, morphine, opium, dmg, stimulant, pep pill, amphetamine, speed, purple hearts, dexies, uppers, excitant, performance-enhancing drug, intoxicant, hallucinogen, LSD, lysergic acid diethylamide, acid, Ecstasy, MDMA, phencyclidine, PCP, angel dust, STP, mescalin, peyote, magic mushroom, drug addiction, habit, intemperance, trip, drug-selling, drug-pushing, gateway substance, lifestyle drug, Viagra, date rape drug, Rohypnol,	
	Both of the above		
	None of the above		

c. Image ID: 8700

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	shirt, pocket, radio, technology, science, fashionable, transistor, allowed, electronics, fit, small, case, digital, alarm clock

Keywords	Concept Sense	Related Words	Select Sense
pocket	receptacle	**pocket**, waistcoat pocket, side pocket, hip pocket, trouser pocket, breast pocket, patch pocket, cargo pocket, fob, pouch, purse, sporran,	
	forgiveness	forgive, pardon, reprieve, amnesty, forgive and forget, think no more of, not give another thought, forget, remit, absolve, assoil, shrive, cancel, blot out, wipe the slate clean, obliterate, relent, unbend, accept an apology, be lenient, be merciful, not be too hard upon, let one down gently, let one off the hook, show mercy, bear with, put up with, forbear, tolerate, make allowances, be patient, take no offence, bear no malice, take in good part, **pocket**, stomach, not hold it against one, forget an injury, ignore a wrong, overlook, pass over, not punish, leave unavenged, turn the other cheek, return good for evil, be benevolent, connive, wink at, condone, not make an issue of, turn a blind eye, disregard, excuse, find excuses for, justify, recommend for pardon, intercede, mediate, exculpate, exonerate, acquit, be ready to forgive, make the first move, bury the hatchet, let bygones be bygones, make it up, extend the hand of forgiveness, shake hands, kiss and be friends, kiss and make up, be reconciled, be friendly, restore to favour, kill the fatted calf, celebrate,	
	Both of the above		
	None of the above		
radio	power	electronics, electron physics, optics, optics, lasers, radiation, integrated circuit, microprocessor, microelectronics, computer electronics, computing, Internet, automation, machine, telegraph, telephone, television, **radio**, telecommunication, electrical engineering, electricity supply, power line, lead, flex, cable, distributor, pylon, grid, national grid, generator, magneto, dynamo, oscillator, alternator, transformer, commutator, power pack, battery, dry battery, rechargeable battery, storage battery, wet battery, accumulator, cell, wet cell, dry cell, fuel cell, photo cell, photoelectric cell, valve, tube, transistor, voltage, volt, watt, kilowatt, megawatt, ohm, amperage, ampere, amp,	
	sound	sound, auditory effect, distinctness, audibility, reception, hearing, sounding, sonancy, sound-making, audio, mono, mono-phonic sound, binaural sound, stereophonic sound, stereo, quadraphonic sound, surround-sound system, sound waves, vibrations, radiation, electronic sound, sound effect, sound track, voice-over, sonority, sonorousness, resonance, noise, loud sound, loudness, low sound, softness, faintness, quality of sound, tone, pitch, level, cadence, accent, intonation, twang, timbre, voice, tune, strain, melody, music, types of sound, bang, roll, resonance, nonresonance, sibilation, stridor, cry, ululation, discord, transmission of sound, telephone, cellular telephone, **radio**, telecommllnication, recorded sound, high fidelity, hi-fi, gramophone, record-player, ghetto blaster, personal stereo, loudspeaker, hearing instrument, unit of sound, decibel, phon, sone, sonic barrier, sound barrier, acollstics, phonics, phonology, phonography, phonetics, acoustician, sound engineer, phonetician, phoneticist, phonographer, audiometer, sonometer,	
	Both of the above		
	None of the above		
technology	materiality	physics, phyical science, natural science, science of matter, natural history, biology, chemistry, organit chemistry, inorganic chemistry, physical chemistry, mechanics, Newtonian mechanics, quantum mechanics, theory of relativity, thermodynamics, electromagnetism, atomic physics, nuclear physics, nucleonics, applied physics, **technology**, skill, natural philosophy, experimental philosophy, science, chemist, physicist, scientist,	
	tool	mechanics, engineering, computer-aided engineering, CAE, civil engineering, electrical engineering, electronic, cybernetics, automatic control, automation, computerization, robotics, artificial intelligence, AI, expert system, mechanical power, mechanical advantage, technics, **technology**, advanced technology, low technology, high technology, high tech, ultratech, third wave, nanotechnology, terotechnology,	
	Both of the above		
	None of the above		

d. Image ID: 14523

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	squirrel, woodland, nature, grey, bushy, tails, north, tree, branch, nuts, east, mike, brown

Keywords	Concept Sense	Related Words	Select Sense
branch	vegetable life	foliage, goliation, frondescence, greenery, verdure, leafiness, leafage, herbage, umbrage, limb, **branch**, bough, twig, shoot, spray, sprig, treetop, leaf, simple leaf, compound leaf, frond, flag, blade, leaflet, foliole, pine needle, seedleaf, cotyledon, leaf-stalk, petiole, stipule, node, stalk, stem, tendril, prickle, thorn,	○
	party	society, partnership, coalition, combination, combine, association, league, alliance, axis, federation, confederation, confederacy, economic association, cooperative, Bund, union, Benelux, EEC, Common Market, European Community, European Union, EU, Euroland, Eurozone, free trade area, single market, private society, club, focus, secret society, Ku Klux Klan, Freemasonry, lodge, cell, friendly Society, trades union, chapel, group, division, **branch**, local branch, youth movement, Boy Scouts, Cubs, Rovers, Rangers, Girl Guides, Brownies, Pioneers, Komsomol, Women's Institute, Townswomen's Guild, Mother's Union, Daughters of the American Revolution, OAR, fellow, honorary fellow, associate, member, associate member, party member, paid-up member, card-carrying member, comrade, trade unionist, corresponding member, branch member, paired MP, affiliate, component,	○
	Both of the above		○
	None of the above		○
grey	greyness	greyness, neutral tint, greige, grisaille, pepper and salt, grey hairs, hoary head, pewter, silver, gunmetal, ashes, slate, **grey**, Payne's grey, dove grey, oyster, taupe,	○
	painting	painted, daubed, scum bled, plastered, graphic, pictorial, scenic, picturesque, decorative, ornamental, pastel, in paint, in oils, in watercolours, in tempera, co loured, linear, black-and-white, chiaroscuro, shaded, stippled, sfumato, grisaille, **grey**, painterly, paintable, representing,	○
	Both of the above		○
	None of the above		○
nature	intrinsicality	character, **nature**, quality, make-up, personality, type, make, stamp, breed, sort, constitution, characteristics, traits, ethos, cast, colour, hue, complexion, aspects, features, diagnosis, diagnostics,	○
	affections	affections, qualities, instincts, passions, feelings, inner feelings, emotions, emotional life, **nature**, disposition, character, spirit, temper, tone, grain, mettle, temperament, cast of mind, habit of mind, trait, state, personality, psychology, psyche, mentality, outlook, mental and spiritual make-up, inherited characteristics, heredity, being, innermost being, breast, bosom, heart, soul, core, inmost soul, inner man, cockles of the heart, heart of hearts, essential part, spirit, animus, attitude, frame of mind, state of mind, vein, strain, humour, mood, predilection, predisposition, inclinations, turn, bent, bias, tendency, passion, ruling passion, master passion, prejudice, heartstrings, feeling, fullness of heart, heyday of the blood, force of character, force of personality, anthropomorphism, pathetic fallacy,	○
	Both of the above		○
	None of the above		○

e. Image ID: 16704

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	soldier, war, death, widow, orphan, mutilation, suffering

Keywords	Concept Sense	Related Words	Select Sense
death	quiescence	quietude, quiet, quietness, stillness, hush, silence, tranquillity, peacefulness, no disturbance, peace, rest, repose, eternal rest, **death**, sleepiness, slumber, sleep, calm, dead calm, flat calm, millpond, smoothness, wind, lessness, not a breath of air, dead quiet, not a mouse stirring, armchair travel, staying at home, placidity, composure, cool, inexcitability, passivity, quietism, quietist, pacifist, tranquillizer, sedation, moderator,	
	war	**war**, arms, the sword, appeal to arms, arbitrament of war, fortune of war, undeclared war, cold war, armed neutrality, paper war, war of words, polemic, quarrel, war of nerves, sabre-rattling, gunboat diplomacy, intimidation, half-war, uneasy peace, doubtful war, phoney war, disguised war, intervention, armed intervention, police action, real war, hot war, ground war, air war, internecine war, civil war, war of revolution, war of independence, wars of religion, holy war, crusade, jihad, aggressive war, war of expansion, limited war, localized war, triphibious war, war on all fronts, all-out war, major war, general war, world war, global war, total war, blitzkrieg, atomic war, nuclear war, push-button war, war of attrition, truceless war, war to the, **death**, no holds barred, war to end all wars, Armageddon, price war, predatory pricing, war crimes, war criminals, pomp and circumstance of war, the panoply of war, chivalry, shining, armour, rows of scarlet, nodding plumes, martial music, drums, bugle, trumpet, call to arms, bugle call, call, battle cry, rallying cry, slogan, war whoop, war song, defiance, god of war, Ares, Mars, Bellona,	
	Both of the above		
	None of the above		
war	disagreement	disagreement, disaccord, nonagreement, failure to agree, agreement to disagree, dissent, divergent opinions, conflict of opinion, controversy, argumentation, argument, confrontation, wrangle, wrangling, bickering, quarrel, disunion, disunity, faction, dissension, dissidence, schism, jarring, clash, collision, challenge, defiance, rupture, breach, **war**, variance, divergence, discrepancy, difference, two voices, ambiguity, ambivalence, equivocalness, inconsistency, credibility gap, variety, inconsistency, nonuniformity, opposition, contradiction, conflict, contrariety, dissonance, discordance, disharmony, inharmoniousness, discord, noncoincidence, incongruence, incongruity, lmrelatedness, disparity, inequality, disproportion, asymmetry, distortion, incompatibility, irreconcilability, hostility, enmity,	
	war	wage war, make war, go on the warpath, march to war, engage in hostilities, **war**, war against, war upon, campaign, open a campaign, take the field, go on active service, shoulder a musket, smell powder, flesh one's sword, soldier, be at the front, take the offensive, invade, attack, keep the field, hold one's ground, stand finn, act on the defensive, defend, manoeuvre, march, countermarch, blockade, beleaguer, besiege, invest, sllrrollnd, shed blood, put to the sword, slallghter, ravage, burn, scorch, lay waste, press the button, demolish, be destroyed,	
	Both of the above		
	None of the above		
widow	female	women, Eve, she, girl, little girl, young girl, youngster, virgin, maiden, nun, unmarried, woman, old maid, spinster, bachelor girl, career woman, woman doctor, woman engineer, woman MP, Emily's list, feminist, sister, women'slibber, bra burner, suffragette, bride, married woman, wife, trouble and strife, woman, live-in, squaw, **widow**, matron, grandmother, maternity, unmarried mother, working wife, working mother, superwoman, housewife, aunt, auntie, niece, sister, daughter, wench, lass, lassie, nymph, colleen, damsel, petticoat, skirt, doll, chick, bird, honey, hinny, baby, babe, totty, grisette, midinette, brunette, blonde, platinum blonde, lesbian, lez, les, dyke, kide, non-heterosexual, harpy, harridan, she-devil, virago, ballbreaker, shrew, hellhag,	
	divorce	**widow**, bereave, make a widow, make a widower, leave one's wife a widow,	
	Both of the above		
	None of the above		

f. Image ID: 22383

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	town, air, tourism, tourist, view, front, building, historic, government, independence, south

Keywords	Concept Sense	Related Words	Select Sense
air	music	tune, melody, strain, theme song, signature tune, descant, reprise, refrain, melodic line, air, popular air, aria, solo, peal, chime, carillon, flourish, sennet, tucket, phrase, passage, measure, Siren strains,	
	enquiry	enquire, ask, want to know, seek an answer, not know, demand, request, canvass, agitate, air, ventilate, discuss, query, bring in question, subject to examination, argue, ask for, look for, enquire for, seek, hunt for, pursue, enquire into, make enquiries, probe, delve into, dig into, dig down into, go deep into, sound, take a look at, look into, investigate, throw open to enquiry, hold an enquiry, conduct an enquiry, appoint a commission of enquiry, call in Scotland Yard, try, hear, try a case, review, overhaul, audit, scrutinize, monitor, screen, analyse, dissect, parse, sift, winnow, thrash out, research, study, consider, examine, meditate, check, check on, feel the pulse, take the temperature, put a toe in the water, take soundings, follow up an enquiry, pursue an enquiry, get to the bottom of, fathom, see into, X-ray, scan, ferret out, nose out, peer, peep, peek, snoop, spy, pry, nose around, be curious, survey, reconnoitre, case, sus out, explore, feel one's way, be tentative, test, trial, try, sample, taste, experiment, post-mortem, hold a postmortem,	
	Both of the above		
	None of the above		
tourist	traveller	traveller, itinerant, itinerant teacher, itinerant preacher, flying bishop, wayfarer, viator, peregrina tor, explorer, adventurer, voyager, mariner, air traveller, spaceman, spacewoman, astronaut, astrotourist, space tourist, aeronaut, pioneer, pathfinder, explorer, precursor, alpinist, mountaineer, cragsman, climber, pilgrim, palmer, hajji, walker, hiker, rambler, trekker, backpacker, camper, caravanner, youth hosteller, tourist, countryhopper, globe-trotter, rubberneck, sightseer, spectator, tripper, day-tripper, excursionist, sun, seeker, holidaymaker, visitor, health tourist, roundsman, hawker, pedlar, travelling salesman, commercial traveller, rep, seller, messenger, errandboy, courier, daily traveller, commuter, straphanger, Odysseus, Ulysses, Gulliver, Marco Polo,	
	spectator	spectator, beholder, seer, mystic, visionary, looker, viewer, observer, watcher, invigilator, inspector, examiner, scrutator, scrutinizer, overseer, manager, waiter, attendant, servant, witness, eyewitness, attendee, passerby, bystander, onlooker, looker-on, gazer, starer, gaper, gawper, goggler, eyer, ogler, voyeur, scopophiliac, peeping Tom, window shopper, tourist, globetrotter, rubberneck, sightseer, astrotourist, space tourist, traveller, stargazer, astronomer, bird watcher, twitcher, train spotter, lookout, detector, watchman, night-watchman, watch, security officer, security man, sentinel, sentry, warner, patrolman, patrol, circler, scout, spy, mole, spook, snoop, detective, filmgoer, cinemagoer, cinema, theatregoer, play-goer, televiewer, viewer, TV addict, square-eyes, captive audience,	
	Both of the above		
	None of the above		
town	increase	increase, increment, augmentation, waxing, crescendo, advance, progress, progression, growth, growth area, development area, boom, town, buildup, development, production, growing pains, beginning, extension, prolongation, protraction, lengthening, widening, broadening, spread, escalation, amplification, inflation, dilation, expansion, proliferation, baby boom, population explosion, swarming, productiveness, abundance, multiplication, squaring, cubing, numerical operation, adding, addition, enlargement, magnification, aggrandizement, greatness, overenlargement, excess, exaggeration, enhancement, appreciation, heightening, raising, elevation, concentration, condensation, recruitment, strengthening, intensification, stepping up, doubling, redoubling, trebling, duplication, triplication, acceleration, speeding, spurt, hotting up, heating, excitation, stimulation, exacerbation, aggravation, advancement, boost, improvement, rise, spiral, upward curve, upward trend, upswing, upturn, ascent, uprush, upsurge, flood, tide, rising tide, swell, surge, wave, progressiveness, cumulativeness, cumulative effect, synergistic effect, snowball, accumulation, ascending order, series,	
	spatial	spatial, regional, territorial, continental, peninsular, insular, national, state, subdivisional, local, municipal, parochial, redbrick, provincial, suburban, urban, rural, up-country, district, town, country, place, emplacement, site, location, position, situation, station, substation, quarter, locality, district, assigned place, pitch, beat, billet, socket, groove, centre, meeting place, rendezvous, focus, birthplace, dwelling,	
	Both of the above		
	None of the above		

g. Image ID: 24484

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	interior, temple, building, japan, bamboo, forest, matting, mat, carpet, quiet, reserved, sacred, special

Keywords	Concept Sense	Related Words	Select Sense
building	production	**building**, piece of architecture, edifice, structure, erection, pile, dome, tower, high-rise building, block of flats, skyscraper, high structure, pyramid, ancient monument, monument, church, **temple**, mausoleum, tomb, habitation, mansion, hall, house, college, school, fortress, fort, stonework, timbering, brickwork, bricks and mortar, building material, sick building,	◯
	structure	structure, organization, pattern, plan, complex, syndrome, whole, mould, shape, build, form, constitution, make-up, set-up, content, substance, composition, construction, make, works, workings, nuts and bolts, architecture, tectonics, architectonics, fabric, work, brickwork, stonework, woodwork, timberwork, studwork, materials, substructure, infrastructure, superstructure, **building**, scaffold, framework, chassis, shell, frame, nogging, infilling, insertion, lamination, cleavage, stratification, body, carcass, person, physique, anatomy, organism, bony structure, skeleton, bone, vertebra, horn, science of structure, organology, anatomy, morbid anatomy, physiology, histology, biology,	◯
	Both of the above		◯
	None of the above		◯
japan	blackness	black pigment, blacking, lampblack, blacklead, ivory black, blue-black, nigrosine, ink, Indian ink, printer's ink, **japan**, niello, burnt cork, melanin,	◯
	ornamentation	decorate, adorn, embellish, enhance, enrich, grace, set, set off, omament, paint, bejewel, tattoo, body-pierce, tart up, glamorize, prettify, beautify, garnish, trim, shape, array, deck, bedeck, dress, deck out, trick out, prank, preen, titivate, primp, add the finishing touches, freshen, smarten, spruce up, furbish, burnish, clean, bemedal, beribbon, garland, crown, honour, stud, spangle, bespangle, variegate, colourwash, whitewash, varnish, grain, **japan**, lacquer, coat, enamel, gild, silver, blazon, emblazon, illuminate, illustrate, paint, colom, border, trim, hem, work, pick out, broider, embroider, tapestry, pattern, inlay, engrave, enchase, encrust, emboss, bead, mould, fret, carve, foliate, groove, notch, enlace, wreathe, festoon, trace, scroll, twine,	◯
	Both of the above		◯
	None of the above		◯
temple	production	**building**, piece of architecture, edifice, structure, erection, pile, dome, tower, high-rise building, block of flats, skyscraper, high structure, pyramid, ancient monument, monument, church, **temple**, mausoleum, tomb, habitation, mansion, hall, house, college, school, fortress, fort, stonework, timbering, brickwork, bricks and mortar, building material, sick building,	◯
	refuge	refuge, sanctuary, asylum, retreat, safe place, traffic island, zebra crossing, pedestrian crossing, pelican crossing, green man, last resort, funkhole, bolthole, foxhole, burrow, trench, dugout, airraid shelter, fallout shelter, earth, hole, den, lair, covert, nest, lap, hearth, home, defensible space, privacy, sanctum, room, cloister, cell, hermitage, ivory tower, retreat, sanctum sanctorum, **temple**, ark, acropolis, citadel, wall, rampart, bulwark, bastion, stronghold, fastness, fort, keep, ward, secret place, hiding-place, dungeon, prison, rock, Rock of Ages, pillar, tower, tower of strength, mainstay, prop,	◯
	Both of the above		◯
	None of the above		◯

h. Image ID: 31132

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	theatre, empire, palladium, entertainment, home, front

Keywords	Concept Sense	Related Words	Select Sense
entertainment	eating	provisions, stores, commissariat, provender, contents of the larder, freezer stock, foodstuff, groceries, tinned food, canned food, frozen food, cook-chill food, dehydrated food, convenience food, junk food, fast food, provisioning, keep, board, maintenance, aliment, **entertainment**, sustenance, provision, home-grown food, selfsufficiency, commons, rations, iron rations, helping, portion, buttery, pantry, larder, stillroom, cellar, storage, hay box, meat safe, freezer, fridge, refrigerator,	
	sociality	social gathering, forgathering, meeting, assembly, reunion, get-together, conversazione, social, reception, at home, soiree, levee, **entertainment**, amusement, singsong, camp fire, party, do, shindig, thrash, hen party, stag party, partie carree, tete-a-tete, housewarming, house party, weekend party, birthday party, coming-out party, social meal, feast, banquet, orgy, feasting, communion, love feast, agape, ritual act, coffee morning, tea party, bun fight, drinks, cocktail party, dinner party, supper party, garden party, picnic, barbecue, bottle party, byob party, booze-up, festivity, dance, ball, ceilidh, hop, disco, rave, dancing, pyjama party, sleepover,	
	Both of the above		
	None of the above		
front	front	frontal, fore, forward, **front**, obverse, full frontal, head-on, oncoming, facing, opposite, anterior, prefixed, preceding,	
	falsehood	duplicity, false conduct, double life, doubledealing, improbity, guile, trickery, hollowness, **front**, facade, outside, mask, show, false show, window-dressing, fanfaronade, osterntation, pretence, hollow pretence, bluff, act, fake, counterfeit, imposture, sham, hypocrisy, Tartuffery, acting, play-acting, simulation, dissimulation, dissembling, insincerity, tongue in cheek, cant, lip service, cupboard love, pharisaism, false piety, outward show, crocodile tears, show of sympathy, Judas kiss, fraud, pious fraud, sting, legal fiction, diplomatic illness, cheat, cheating, sharp practice, collusion, nod and a wink, put-up job, frame-up, foul play, quackery, charlatanry, charlatanism, pretmsian, low cunning, artfulness, cunning,	
	Both of the above		
	None of the above		
theatre	abode	meeting place, conventicle, meeting house, church, day centre, community centre, village hall, assembly rooms, pump rooms, club, clubhouse, night club, working men's club, holiday camp, place of amusement, football ground, racecourse, dog track, arena, **theatre**, concert hall, opera house, stadium, stand, off-lookers, astrodome, sports centre, gymnasium, drill hall, parade ground, piazza, quadrangle, quad, campus, village green, town square, focus, shopping centre, shopping mall, market,	
	drama	**theatre**, amphitheatre, stadium, arena, circus, hippodrome, fleapit, picture house, movie theatre, cinema, Greek theatre, Elizabethan theatre, theatre in the round, arena theatre, open-air theatre, showboat, pier, pavilion, big top, playhouse, opera house, music hall, vaudeville theatre, variety theatre, night club, boite, cabaret, stage, boards, proscenium, wings, coulisses, flies, dressing room, green theatre, footlights, floats, battens, spotlight, spot, limelight, floodlight, flood, houselights, auditorium, orchestra, seating, stalls, front stalls, back stalls, orchestra stalls, fauteuil, front rows, pit, parterre, box, loge, circle, dress circle, upper circle, mezzanine, gallery, balcony, gods, front of house, foyer, bar, box office, stage door,	
	Both of the above		
	None of the above		

i. Image ID: 31557

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Group of Words:	tractor, field, air, east, crop, machinery, aerial, agriculture, wheat

Keywords	Concept Sense	Related Words	Select Sense
air	air	aerate, oxygenate, **air**, expose, dry, ventilate, freshen, clean, fan, winnow, make a draught, blow, take the air, breathe,	
	enquiry	enquire, ask, want to know, seek an answer, not know, demand, request, canvass, agitate, **air**, ventilate, discuss, query, bring in question, subject to examination, argue, ask for, look for, enquire for, seek, hunt for, pursue, enquire into, make enquiries, probe, delve into, dig into, dig down into, go deep into, sound, take a look at, look into, investigate, throw open to enquiry, hold an enquiry, conduct an enquiry, appoint a commission of enquiry, call in Scotland Yard, try, hear, try a case, review, overhaul, audit, scrutinize, monitor, screen, analyse, dissect, parse, sift, winnow, thrash out, research, study, consider, examine, meditate, check, check on, feel the pulse, take the temperature, put a toe in the water, take soundings, follow up an enquiry, pursue an enquiry, get to the bottom of, fathom, see into, X-ray, scan, ferret out, nose out, peer, peep, peek, snoop, spy, pry, nose around, be curious, survey, reconnoitre, case, sus out, explore, feel one's way, be tentative, test, trial, try, sample, taste, experiment, post-mortem, hold a postmortem,	
	Both of the above		
	None of the above		
crop	greatness	great quantity, muchness, galore, plenty, **crop**, harvest, profusion, abundance, productivity, productiveness, superfluity, superabundance, shower, flood, spate, torrent, redundance, stream, expanse, sheet, lake, sea, ocean, world, universe, sight of, world of, mort of, power of, much, lot, whole lot, fat lot, deal, good deal, great deal, not a little, not peanuts, not chicken feed, not to be sneezed at, too much, more than one bargained for, stock, mint, mine, store, quantity, peck, bushel, pints, gallons, lump, heap, mass, stack, mountain, accumulation, packet, packet of, pack, pack of, load, load of, full load, cargo, shipload, boatload, trainload, carload, lorryload, truckload, sackload, sackful, containerful, contents, large quantities, bags, gobs, heaps, lashings, loads, lots, masses, oodles, pots, quantities, scads, shedloads, stacks, tons, wads, pots of money, a bomb, a packet, telephone numbers, oceans, seas, floods, streams, volumes, reams, sheets, pages and pages, screeds, large numbers, crowds, hordes, hosts, masses, millions, multitudes, not a few, numbers, quite a few, swarms, multitllde, all, entirety, corpus, caboodle, whole,	
	eating	graze, browse, pasture, **crop**, feed, ruminate, chew the cud, nibble,	
	Both of the above		
	None of the above		
field	coldness	snow, snowfall, snowflake, snow crystal, lanche, snow slip, snowdrift, snowpack, snoy, **field**, snowstorm, flurry of snow, the old woman plucking her geese, snow line, snowcap, snowfield, snowball, snowman, snow, snowplough, snowshoe, snowmobile, snowtyre, winter sports, sport, snow blindness, snowbound,	
	indication	heraldry, armory, blazonry, heraldic register, Roll of Arms, armorial bearings, coat of arms, blazon, achievement, funereal achievement, hatchment, shield, escutcheon, crest, torse, wreath, helmet, crown, coronet, mantling, lambrequin, supporters, motto, **field**, quarter, dexter, sinister, chief, base, charge, device, bearing, ordinary, fess, bar, label, pale, bend, bend sinister, chevron, pile, saltire, cross, canton, inescutcheon, bordure, lozenge, fusil, gyron, flanches, marshalling, quartering, impaling, dimidiation, differencing, fess point, honour point, nombril point, animal charge, lion, lion rampant, lion couchant, unicorn, griffin, cockatrice, eagle, falcon, martlet, floral charge, Tudor rose, cinquefoil, trefoil, planta genista, badge, rebus, antelope, bear and ragged staff, portcullis, national emblem, rose, thistle, leek, daffodil, shamrock, lilies, fleur-de-lis, device, national device, lion and unicorn, spread eagle, bear, hammer and sickle, triskelion, swastika, fylfot, skull and crossbones, heraldic tincture, colour, gules, azure, vert, sable, purpure, tenne, murrey, metal, or, argent, fur, ermine, ermines, erminois, pean, vair, potent, heraldic personnel, College of Arms, Earl Marshal, King of Arms, Lord Lyon King of Arms, herald, herald extraordinary, pursuivant, Bluemantle, Rouge Croix, Rouge Dragon, Portcullis,	
	Both of the above		
	None of the above		

j. Image ID: 32760

Figure C1: SDNA Disambiguation Evaluation Sample (cont.)

Image Annotation: stag, rut, deer, rutting, season, fighting

a. Image ID: 4264

Image Annotation: people, director, cinema, famous, international, film, festival, portrait, actor, maker

b. Image ID: 5404

Figure C2: Image Annotation Evaluation Sample

Image Annotation:	snow, relaxing, humour, lifestyle, drinking, dogs, relax, chat

c. Image ID: 8700

Image Annotation:	shirt, pocket, radio, technology, science, fashionable, transistor, allowed, electronics, fit, small, case, digital, alarm clock

d. Image ID: 14523

Figure C2: SDNA Disambiguation Evaluation Sample (cont.)

Image Annotation: squirrel, woodland, nature, grey, bushy, tails, north, tree, branch, nuts, east, mike, brown

e. Image ID: 16704

Image Annotation: soldier, war, death, widow, orphan, mutilation, suffering

f. Image ID: 22383

Figure C2: SDNA Disambiguation Evaluation Sample (cont.)

g. Image ID: 24484

h. Image ID: 31132

Figure C2: SDNA Disambiguation Evaluation Sample (cont.)

Image Annotation: theatre, empire, palladium, entertainment, home, front

i. Image ID: 31557

Image Annotation: tractor, field, air, east, crop, machinery, aerial, agriculture, wheat

j. Image ID: 32760

Figure C2: SDNA Disambiguation Evaluation Sample (cont.)

Table C1: SDNA Disambiguation Results for 50 HITs

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
1	383	2418JHSTLB3L6GXN1YFBOEJRA1KGS8	A2MT0WWJR23AGG	1	1	0	0.6	0.8	0.7	0.700
		2TAA0RYNJ92NPL84XRDJYUHYS7H49R	A22YE5YXKM2GBF	1	1	0				
		2ERMAZHHRRLFW1ARFBIH6KHO5KMDMJ	ADAK1UJXC5TJJ	0	1	1				
		26QB49F9SSSH32NNG3JTAH5F4O8SWF	A2A4HUANTKP918	1	1	1				
		2HWJ79KQW618T5SYPV3D95XCAYULJ2	ACGJR8V9K0ROT	0	1	1				
		2Q5HDM25L8I9T0IA9UQ6TE4QSCXGQF	A2JBJFPFG38X9C	1	1	0				
		2E1F9SSSHX11PP9WLL85K8J4KT1VZ6	A3I8SB05PWN7HO	1	0	1				
		2GUNJQ2172Z9FR3A30CC0EBUX9NYQX	A11ZSP12IL64Y2	1	1	1				
		2DGU3K4F0OHO1SN8ADBO7L92DJN018	A23U4SG2PC5KE5	0	1	1				
		2WBUNU8LZ6R76HRV1O48O3VE32W4KQ	A1G08QM9J5GZO6	0	0	1				
2	506	26R9RNDWIOV1Y8ERVTKGZ13Y93XGVS	A22YE5YXKM2GBF	1	0	0	0.7	0.2	0.7	0.533
		2BUA1QP6AUC2CE2AZTSX8V0FG5E703	A2A4HUANTKP918	0	0	0				
		2N0XMB3Q39Z0H7GXGMK4JVSTRXPITQ	A2MT0WWJR23AGG	1	1	1				
		2HWJ79KQW618T5SYPV3D95XCAY0LJ8	ACGJR8V9K0ROT	1	0	1				
		2U1RJ85OZIZENNWEH2FOV5EWL2O9XD	A2JBJFPFG38X9C	1	0	1				
		2QY7D1X3V0FK6DAOUZ51R7PKGEVKDN	A2DULTV0RVMIN4	0	0	1				
		209M8JIA0RYNPAORB0D0ABMJPZJ05H	A3I8SB05PWN7HO	1	0	1				
		2WS5BMJTUHYW8HFT1717X5WMXCDHMU	A11ZSP12IL64Y2	0	0	0				
		2TOKUDD8XMB3W4V3SRXUYO6T0IQDOJ	A23U4SG2PC5KE5	1	0	1				
		2X4WYB49F9SSYIJ5TZFNXT5H1KDUQU	A296W3TOJ7E983	1	1	1				
3	908	2JKKMT6YTWX4N436HRVDE9GI2NA0VD	A2A4HUANTKP918	0	0	0	0.7	0.2	0.8	0.567
		2WR9O9Z6KW4ZSBLL97ILKQ0OJSVD4G	A3I8SB05PWN7HO	0	0	1				
		2ADWSBRI8IUB8ZGD0Z8SYLB3H5MF3F	A296W3TOJ7E983	1	0	0				
		25J14IXKO2L98I0GOQXX8YOC8K7BCR	A1CG19PDVRI7HQ	1	0	1				
		2OQ5COW0LGRZ99YV71360NUZSIPY7R	ADAK1UJXC5TJJ	1	1	1				
		2UO4ZMAZHHRRRGC4G3EVWH1KDS8BKU	A22YE5YXKM2GBF	1	0	1				
		200H88MQU6L5UCHGAHIX24AIFKABUX	A306HC0URZ6OA1	1	0	1				
		2O4WA6X3YOCCL1YTX0OPYINIE22POK	A2JBJFPFG38X9C	1	0	1				
		2BKNQQ7Q67057R6GF7S2YQC1TRRBVU	A2DULTV0RVMIN4	1	0	1				
		2IEQU6L5OBVCO2D1PK1IOF7GQ57FY9	A3VDWFQEHNPE41	0	1	1				
4	989	2UA62NJQ21725AVU9M2KQCVE7Z3WOK	A22YE5YXKM2GBF	0	0	0	0.1	0.4	0.3	0.267
		2ABPPSI2KYEPRTBBX0CMBWJ3KFWLR2	A1Y1X8WCA3C5UF	1	0	1				
		2N9JHP4BDDKGAZUVKD0X8G3531IZ6T	A296W3TOJ7E983	0	1	0				
		2CB1LY58B727S14K708D66YFO0I8T4	A2A4HUANTKP918	0	0	0				
		20K1CSTMOFXRJTQM4H5YINXJBS6SPN	A11ZSP12IL64Y2	0	1	1				
		2JG9Z6KW4ZMA5I3VJ16Q5ONNRWMF6J	ACGJR8V9K0ROT	0	1	0				
		2PV95SW6NG1FY492FZ2YK1FZO4THVD	A2JBJFPFG38X9C	0	0	0				
		2SCMN9U8P9Y3EUI0PYUSZYIMWNLVET	A23U4SG2PC5KE5	0	0	1				
		2KUSEIUUU00OWL6EWY9SDS2UYA7SST	A3I8SB05PWN7HO	0	0	0				
		2U1RJ85OZIZENNWEH2FOV5EWL2TX96	A1CG19PDVRI7HQ	0	1	0				
5	3704	2ZVTVOK5UFJ57ZTU64QF3QS18YZ85I	ADAK1UJXC5TJJ	1	0	0	0.9	0.6	0.9	0.800
		2KNKI62NJQ21D3LD1686GKLCRJCMUV	A3VDWFQEHNPE41	0	0	1				
		26UGTP9RA7S52NNA1EJOK70JIMTWRZ	ACGJR8V9K0ROT	1	0	1				
		22KZVXX2Q45U0LCSQWEI11NS4TJQ88	A3I8SB05PWN7HO	1	1	1				
		27VYOCCF0CP5QYBXA39I2YG4LQYUTS	A2Q16TWQKNV3OO	1	1	1				
		2QY7D1X3V0FK6DAOUZ51R7PKGESDKD	A2JBJFPFG38X9C	1	1	1				
		2RTXERSQV66RRQ3MLJ8V1AVKEB62AB	A2A4HUANTKP918	1	1	1				
		2118D8J3VE7WYTFRQS73RCK86Y4IYA	A22YE5YXKM2GBF	1	1	1				
		2AT1K274J79KWXS503V6ZXFC990EGS	A11ZSP12IL64Y2	1	1	1				
		262VKI62NJQ278O31PHHBBKL8Z8TL0	A23U4SG2PC5KE5	1	0	1				
6	4264	2DPUYT3DHJHPACZHCWVYDRSX525T01	A306HC0URZ6OA1	1	0	0	0.9	0.8	0.7	0.800
		2ZKI2KYEPLSPD66PEMNJ8OAHMJ9OUU	A2ZJ898N5IJYMO	1	1	1				
		2QCPEIB9BAWLYNJTILMXZD3MPW71YF	A1Y1X8WCA3C5UF	1	1	1				
		2IEZ9O9Z6KW45NW39XIRQFQ0KSQC3X	A2A4HUANTKP918	0	1	1				
		247BNFSVGULF9ARWOMEG6FS3J30L71	ACGJR8V9K0ROT	1	1	1				
		250ER9Y8TNKIS0EQX06HX2OMWUDU7O	A11ZSP12IL64Y2	1	1	0				
		28TTHV8ER9Y8ZO6MEFJMAKFHO7R3QT	A22YE5YXKM2GBF	1	1	0				

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
		2NHGFL6VCPWZFS9HOYFV6S7SJ8G7MF	A2JBJFPFG38X9C	1	1	1				
		2D5HJHP4BDDKM5KCJ8O923G31CPY57	A23U4SG2PC5KE5	1	0	1				
		22KZVXX2Q45U0LCSQWEI11NS4TJQ88	A3I8SB05PWN7HO	1	1	1				
7	4918	2MKTMOFXRDS4ODNIQTEXOFM1XE1VS1	A22YE5YXKM2GBF	1	0	0	0.9	0.6	0.7	0.733
		2BANMHGYQ4J3TBXA3VDFKOYYEZ5M99	A2MT0WWJR23AGG	1	1	1				
		211ZJMJUNU8L57DBSWWRE8D8F8Y0G0	A2JBJFPFG38X9C	1	0	1				
		2UO4ZMAZHHRRRGC4G3EVWH1KDTPBKD	A1Y1X8WCA3C5UF	1	1	1				
		2N52AC9KSSZV3YOUWLLUPQOYCSN1JA	ACGJR8V9K0ROT	1	0	1				
		2DPUYT3DHJHPACZHCWVYDRSX536T04	ADAK1UJXC5TJJ	1	1	0				
		2J0D8J3VE7WSYU924WUMHK8AP7PZJM	A11ZSP12IL64Y2	0	1	1				
		2RTQ6SVQ8H88SRGADLFB0CI1N1P5O0	A2A4HUANTKP918	1	1	0				
		2C521O3W5XH0PQBWAIBYJPLSLC5HBZ	A3I8SB05PWN7HO	1	0	1				
		2Z4GJ2D21O3WBY34B5GSN2KYATF7DM	A23U4SG2PC5KE5	1	1	1				
8	5404	2BANMHGYQ4J3TBXA3VDFKOYYEZ59MW	A2MT0WWJR23AGG	0	1	0	0.7	0.9	0.8	0.800
		2WAKMN9U8P9Y99F0OD93XUYII6PDUB	A1G08QM9J5GZO6	0	0	1				
		2TNCNHMVHVKCP1N5CIY4O79KM1H429	A3PJUU89XC8S15	1	1	0				
		2W6C1PC6SK9RP9RSRYQEMMAALRK1P1	AF5VW5OWVL8FO	1	1	1				
		27ZH57DZKPFEAF2H9TD2AL8I5RU3DE	A23U4SG2PC5KE5	1	1	1				
		2C5IPDOBDDP8VKIOMT482MB3M8A1CS	A2A4HUANTKP918	0	1	1				
		21JLFQ0ONNVRN26LGP5GWB76J0HTKD	ACGJR8V9K0ROT	1	1	1				
		2GMFBNFSVGULL4V9KCXNL1FSZSZ6K8	A22YE5YXKM2GBF	1	1	1				
		2RHCGJ2D21O326JLSZGPXI2KUJV6C0	A2JBJFPFG38X9C	1	1	1				
		2SHDOBDDP8PJ2LGH5OOMG3Q35563EM	A11ZSP12IL64Y2	1	1	1				
9	7534	2DVFDEY5COW0RHD3VO3RKLC6RRSU3I	A22YE5YXKM2GBF	0	1	0	0.6	1	0.6	0.733
		2USCOK2JE1M7VL6DD7N6TZACWAQUN9	A2MT0WWJR23AGG	0	1	0				
		28L3DHJHP4BDJL28QOIS29X3C88W3Q	A2JBJFPFG38X9C	1	1	0				
		2AXBMJTUHYW2MUBDJQYSAWM12E2NIR	A2A4HUANTKP918	1	1	0				
		2KYX3YOCCF0CV661H99NNIXYC8NRS3	A23U4SG2PC5KE5	1	1	1				
		20I7Q67051QKIOD5U9HC6XMGE5YYEI	A3I8SB05PWN7HO	1	1	1				
		25SFK0COK2JE7NTTC00LWW6OVF7RKL	A11ZSP12IL64Y2	0	1	1				
		2DVFDEY5COW0RHD3VO3RKLC6RS1U3T	A1CG19PDVRI7HQ	0	1	1				
		21FDWIOV1S7ST4ZX8AS33DZ8JDXYJ6	ACGJR8V9K0ROT	1	1	1				
		2PB51Y7QEOZF4RE548KMTFXR9XADG9	A1G08QM9J5GZO6	1	1	1				
10	8700	2D5HJHP4BDDKM5KCJ8O923G31D25YT	ADAK1UJXC5TJJ	1	0	1	1	0.5	1	0.833
		2OFLVWJ5OPB04W230EDWG7EP5Z63VN	A2JBJFPFG38X9C	1	0	1				
		2Z0PJWKUDD8XSCPUVPQ0G6UTKB1LAN	ACGJR8V9K0ROT	1	0	1				
		2KMC26DG67D134H470RCTK2JA5KE7Q	A3VDWFQEHNPE41	1	1	1				
		21JLFQ0ONNVRN26LGP5GWB76JZ8TK2	A2DULTV0RVMIN4	1	1	1				
		24426DG67D1X9WMJCG3OP2JEXSC8F0	A11ZSP12IL64Y2	1	0	1				
		2OFLVWJ5OPB04W230EDWG7EP5ZHV3Q	A1Y1X8WCA3C5UF	1	0	1				
		298KPEIB9BAWRT81H6WV2UD3IXOX0H	A22YE5YXKM2GBF	1	1	1				
		2S20RYNJ92NJQNM932ATZHYWYKKA55	A2A4HUANTKP918	1	1	1				
		2C5IPDOBDDP8VKIOMT482MB3M9DC18	A1G08QM9J5GZO6	1	1	1				
11	9211	2DLVOK5UFJ5148CIGF6YVS1COZR69K	A2MT0WWJR23AGG	1	1	1	0.9	1	0.7	0.867
		28F5F3Q0JG5T4N9GOE24EF9SOXKDH5	A22YE5YXKM2GBF	1	1	0				
		22O1VP9746OQ7T9UINH6C051MQH0K7	ADAK1UJXC5TJJ	1	1	1				
		2432YU98JHSTRCPPSV2JEIOBFJMCOS	A3I8SB05PWN7HO	1	1	0				
		2PD6VCPWZ9RNJX4SNHJ7XN3DPMZPAO	A11ZSP12IL64Y2	1	1	0				
		21DPHIT3HVWA1L4AU3AQ7172VEOCKK	A1Y1X8WCA3C5UF	0	1	1				
		2BWIXKO2L92HKDIEYDUYTCCFWHSDEP	A2A4HUANTKP918	1	1	1				
		258ULF395SW6THNJKJEYSJBYB6MDR6	A2JBJFPFG38X9C	1	1	1				
		2I6BDPGFL6VCVXLDJ34WNOV1OBM4JD	ANSVIUZJHDJZU	1	1	1				
		2CTO3W5XH0JPVT46CE5PQSP71OFJD5	A23U4SG2PC5KE5	1	1	1				
12	11500	2QKNTL0XULRGTUXNV2DD25FP3SLO27	A1Y1X8WCA3C5UF	0	1	0	0.7	1	0.7	0.800
		2ZV6XBAT2D5NWZ997JH0OG5TURP51P	A3I8SB05PWN7HO	1	1	0				
		23VDHJHP4BDDQHQ207JXEX3GZBBX48	A11ZSP12IL64Y2	1	1	1				
		259VKCJ011K2D55B10HWB18N0CZ8AN	ADAK1UJXC5TJJ	1	1	0				
		2S20RYNJ92NJQNM932ATZHYWYLXA5K	A2JBJFPFG38X9C	1	1	1				
		2VW2J1LY58B78884AW6KMD16UKTR6M	A22YE5YXKM2GBF	0	1	1				

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
		20TSNQQ7Q670B2CO43I17TQCX2FUAB	A23U4SG2PC5KE5	0	1	1				
		25CI62NJQ21780VDIXXBPLCVAGCNV2	A296W3TOJ7E983	1	1	1				
		21U4SMEZZ2MIQN9DMOG9338TS0O4LC	A2A4HUANTKP918	1	1	1				
		2GT8N46UXFCDA6JG69EDXNTKESPRTI	A3971DPYHDLBA9	1	1	1				
		2DLVOK5UFJ5148CIGF6YVS1COZS69L	A2MT0WWJR23AGG	1	0	0				
		2TCM05BMJTUH4XOKL50RF7S5SR3FKL	A22YE5YXKM2GBF	1	1	1				
		2E66AUBXHWSHDG7D1B2Z1DRLTAF3ZQ	A2JBJFPFG38X9C	1	1	1				
		2GUNJQ2172Z9FR3A30CC0EBUX8RQYR	ACGJR8V9K0ROT	1	1	1				
13	12680	20QN5F3Q0JG5ZZ8R4CPB99F9OXACGK	A2ZJ898N5IJYMO	1	0	0	0.9	0.8	0.7	0.800
		2OKCWY2AOO2GSN0KG47QXCM6EE133C	A2A4HUANTKP918	1	1	1				
		2VOSBRI8IUB24VVCBXJTQB3LWLD4GL	A11ZSP12IL64Y2	1	1	0				
		2CFJQ2172Z99WISFC13VJBU1ZO5ZR0	A1Y1X8WCA3C5UF	0	1	1				
		2UEN9U8P9Y38ZXI1AJJU3IM0FX4WFO	A23U4SG2PC5KE5	1	1	1				
		2WIU6L5OBVCI7SJ1WQ9JK7GUXGIZGU	ADAK1UJXC5TJJ	1	1	1				
		258ULF395SW6THNJKJEYSJBYB6YDRI	A2ZJ898N5IJYMO	0	1	1				
		2BIP6AUC26DGC8Z5PJM0KK0CKPJ3A0	A296W3TOJ7E983	0	1	1				
		2W9GYQ4J3NABCC1Q7VFY3IT1POQCPH	A3HOZU88S1GXRX	1	1	1				
		22N7WGKCCVLL9DW7V28AUQ4C5SXU4E	A2JBJFPFG38X9C	1	1	1				
14	12906	2BLHV8ER9Y8TTL4QR8D5PFHSYSL4RA	A22YE5YXKM2GBF	1	1	1	0.6	1	1	0.867
		2PKVGULF395S279KTVJ3SYNJ724PBZ	A2SBU7EFMD0VW2	0	1	1				
		2ZO1INMHGYQ4P49E3M2FRFFOU3YK70	A1Y1X8WCA3C5UF	1	1	1				
		24PFCD45XCETTEERL09N8TGP05BXZF	A2A4HUANTKP918	1	1	1				
		2AXBMJTUHYW2MUBDJQYSAWM12F2NIT	A1G08QM9J5GZO6	1	1	1				
		2FKW6NG1FS3N4O5FQVSF4SZLY23YKB	ACGJR8V9K0ROT	0	1	1				
		20YSVQ8H88MQ0779GRMCN1RXT9AQ7I	A3I8SB05PWN7HO	1	1	1				
		27UQ45UUKQOYMO40T3J8TG01WBGVDW	A3PJUU89XC8S15	1	1	1				
		28IS1CSTMOFXXEE8ASSE3DNXFKUORF	A1CG19PDVRI7HQ	1	1	1				
		28L3DHJHP4BDJL28QOIS29X3C8J3W8	A1Y1X8WCA3C5UF	1	1	1				
15	13399	2B4STMOFXRDSAJY56E4N2JFMX7ARUP	A11ZSP12IL64Y2	1	1	1	1	1	1	1.000
		2S0IUB2YU98JNTFP3JC0KBJ9ETF9LS	A2A4HUANTKP918	1	1	1				
		2U4CVLL3CA33SIWTIK39SQU7T2J9Z7	A306HC0URZ6OA1	1	1	1				
		2W0JIA0RYNJ98O5OEGWBRJTUD2L728	A22YE5YXKM2GBF	1	1	1				
		2OWEGDHDM25LEJVRRCXHJZ6OA9XNDS	A2JBJFPFG38X9C	1	1	1				
		2OJ9Y8TNKIMZYNRO7XJ2TM0PCZ7W9U	A23U4SG2PC5KE5	1	1	1				
		26Y18N46UXFCJ5R14UKNISNTGN2SQM	A1Y1X8WCA3C5UF	1	1	1				
		2SUKYEPLSP75QM8AOZUOFHQEM09QWA	A2A4HUANTKP918	0	1	0				
		2M70CP5KXPTITJ41QWVPR7NY2B3ZYL	ADAK1UJXC5TJJ	1	1	1				
		2QISCM6IAA2SKJGYMGROVKKA0NZKK7	A296W3TOJ7E983	1	0	1				
16	14523	2SHDOBDDP8PJ2LGH5OOMG3Q3540E3P	A22YE5YXKM2GBF	1	1	1	0.9	0.8	0.9	0.867
		20Q2RCJK63ZVK43VS0LIFQ9JHAYW7Z	A1CG19PDVRI7HQ	1	1	1				
		28O2GTP9RA7SBX85YPPSTF70FRHQVA	A306HC0URZ6OA1	1	0	1				
		22RVXX2Q45UUQRA2839W6NS8KL99RN	ACGJR8V9K0ROT	1	1	1				
		2O4WA6X3YOCCL1YTX0OPYINIE25OPM	A2JBJFPFG38X9C	1	1	1				
		2YUL92HECWA634KS4S60HP5KTUTJIF	A2DULTV0RVMIN4	1	1	1				
		26NOX7H57DZKVG086W4HIM25HDTA06	A23U4SG2PC5KE5	0	0	0				
		206OZFYQS1CSZNAJP74S9IC1A3TJMB	A1Y1X8WCA3C5UF	0	1	1				
		2MOY2AOO2GMMKHAS86JCR6IA66R552	A3I8SB05PWN7HO	1	0	1				
		2ADWSBRI8IUB8ZGD0Z8SYLB3H453FK	A22YE5YXKM2GBF	1	1	1				
17	14612	2C9ECWA6X3YOID1445WK2PTIJOJNM6	ADAK1UJXC5TJJ	1	1	1	0.7	0.8	0.9	0.800
		2X1U8P9Y38TW2Y47KAPIR0JT6LWYH4	A3NK147K2TXO40	1	1	1				
		25CI62NJQ21780VDIXXBPLCVAHXVNX	A11ZSP12IL64Y2	0	1	1				
		2G2UC26DG67D7YPZSVB0HOK2FJ5D65	A2A4HUANTKP918	1	1	1				
		2DFAB6BFMFFO4Z4XT9AFIGES85UWJ2	ACGJR8V9K0ROT	1	1	1				
		2MGK2JE1M7PKQA7VOMFZFC04H43PWY	A2JBJFPFG38X9C	1	1	1				
		24VK4F0OHOVR7541C4TLE2HE808237	A22YE5YXKM2GBF	1	1	0				
		2VQ58B727M0IMG6L5HXYKSVF00QBW1	A1CG19PDVRI7HQ	1	1	0				
18	14753	2BC274J79KQWC2URWMLXKCD412NGIJ	A2DULTV0RVMIN4	0	0	0	0.4	0.8	0.6	0.600
		2I6BDPGFL6VCVXLDJ34WNOV1OCUJ42	A3I8SB05PWN7HO	1	0	0				
		28IS1CSTMOFXXEE8ASSE3DNXFKPROD	A37AJI03M37NPJ	0	1	1				

No.	Image ID	Assignment ID	Worker ID	Keyword Score K1	Keyword Score K2	Keyword Score K3	Average Score per Keyword K1	Average Score per Keyword K2	Average Score per Keyword K3	Average Score per Image
		2M1KSSZVXX2QA6GYC6FYLNIWXSUN5F	A306HC0URZ6OA1	0	1	1				
		2H51X3V0FK0CULON6HD7UKK9HWRFMJ	A23U4SG2PC5KE5	1	1	1				
		28URCJK63ZVE9ID4CA9AV9JL1W88XP	A2JBJFPFG38X9C	0	1	1				
		2AKPW1INMHGYW557FQ26GFMFBTB5IS	ACGJR8V9K0ROT	0	1	1				
		2X1U8P9Y38TW2Y47KAPIR0JT6LWYH4	A3NK147K2TXO40	0	1	1				
19	16194	26UGTP9RA7S52NNA1EJOK70JIMLWRR	A2JBJFPFG38X9C	1	0	0	0.8	0.7	0.6	0.700
		2D15SW6NG1FS9OKRBRPF6FZSVQ7WIS	ACGJR8V9K0ROT	1	1	0				
		2CKEIUUU00OQQLW8AYJ8X2U22D0TTB	A2A4HUANTKP918	1	1	0				
		211Y8TNKIMZSS66J98TOR0PGRJSAXD	A22YE5YXKM2GBF	0	0	0				
		2NMCF806UFBNLTHKM163E5SW2SR0ER	A3PJUU89XC8S15	1	0	1				
		2A7K0COK2JE1S8BOCPCR16OZ6I6LSJ	ADAK1UJXC5TJJ	1	1	1				
		2W6ZZ2MIKMN909BDQJZT1WXIZXP8PR	A11ZSP12IL64Y2	0	1	1				
		22NGULF395SWCO2578UN3NJBUJVQC3	A23U4SG2PC5KE5	1	1	1				
		2JKKMT6YTWX4N436HRVDE9GI2NY0V1	A1Y1X8WCA3C5UF	1	1	1				
		2WBUNU8LZ6R76HRV1O48O3VE32X4KR	A1G08QM9J5GZO6	1	1	1				
20	16704	23UD5NQYN5F3W15KX9PMSCWY79YB7G	AN7WSWRDWIIAJ	1	1	1	0.9	0.9	0.6	0.800
		2IEQU6L5OBVCO2D1PK1IOF7GQ6DFYH	A22YE5YXKM2GBF	1	1	0				
		249YW2GTP9RADTR0EHX93SOF35NOTO	ACGJR8V9K0ROT	1	1	1				
		2PSOHOVR14IXQPOP1I8EHWA6T84677	A2JBJFPFG38X9C	1	1	1				
		2C2ESCWY2AOO8H8Q6WFOLQSCIBI111	A3I8SB05PWN7HO	0	0	0				
		2432YU98JHSTRCPPSV2JEIOBFKMOC6	A11ZSP12IL64Y2	1	1	0				
		2P3NFSVGULF3F6E0Y371KS3NUSU8MB	A2DULTV0RVMIN4	1	1	0				
		2D15SW6NG1FS9OKRBRPF6FZSVQ5IWC	A306HC0URZ6OA1	1	1	1				
		2CXL8I9NZW6HK0SS6KHWCT865LNVLJ	A23U4SG2PC5KE5	1	1	1				
		2418JHSTLB3L6GXN1YFBOEJRA0GSGE	A2A4HUANTKP918	1	1	1				
21	17397	297YQS1CSTMOLYDHKK9C6EYDJ2MPM4	A3I8SB05PWN7HO	1	1	1	0.4	0.8	1	0.733
		22O1VP9746OQ7T9UINH6C051MP70KV	ADAK1UJXC5TJJ	0	1	1				
		2EYUXFCD45XCKU9HK3KKNN3TCV8XVK	A2MT0WWJR23AGG	0	0	1				
		2XXF3Q0JG5TYSOY0QRV9K9SSOMZEIR	A2JBJFPFG38X9C	0	0	1				
		224GW40SPW1ITN3KQ6VJ8NAB2FDD0W	A22YE5YXKM2GBF	0	1	1				
		2E1F9SSSHX11PP9WLL85K8J4KUEVZL	ACGJR8V9K0ROT	0	1	1				
		2LYBFMFFOYYIZ2FN7T7EXC0RT0PZMT	A2DULTV0RVMIN4	1	1	1				
		22A2KYEPLSP7BL7QYCA3TAHQAUMPV7	A2A4HUANTKP918	0	1	1				
		2P3NFSVGULF3F6E0Y371KS3NURD8MS	A23U4SG2PC5KE5	1	1	1				
		224GW40SPW1ITN3KQ6VJ8NAB2GO0DW	A2H9G1XWYBDTKK	1	1	1				
22	18306	2BG3W5XH0JPPYJOOQUGLXP75GQPKE9	A22YE5YXKM2GBF	0	1	0	0.7	0.6	0.8	0.700
		2B0N46UXFCD4BYYIL34SSTKIJ9XSUI	ADAK1UJXC5TJJ	1	0	0				
		2WL6YTWX4H3H8QX85P0GN6IJNG63YU	A2JBJFPFG38X9C	0	1	1				
		280E4BLYHVI4APE6C1L8INEZOGIU0Z	ACGJR8V9K0ROT	1	1	1				
		21KQV66RLPHIZ43ZOQMKN62NFVH6E2	A1Y1X8WCA3C5UF	1	1	1				
		21Q0LWSBRI8I0CO2MPZJMSTL78C1DI	A2A4HUANTKP918	0	0	1				
		26WZMAZHHRRLLRMSF3MRM1KHKE8CL2	A23U4SG2PC5KE5	1	0	1				
		2QXR98D8J3VEDXEWL3PCL3MCGCWGWZ	A1W8TTTPVDQ8EK	1	1	1				
		26QB49F9SSSH32NNG3JTAH5F4O5SWC	A306HC0URZ6OA1	1	0	1				
		2OAUUU00OQKKG54MKOJ2Z268WJWVV9	A1HFYPITO6Z52Y	1	1	1				
23	18942	29UMIKMN9U8PFZPCLCNXN3SUUMHSBO	A23U4SG2PC5KE5	1	1	0	1	0.7	0.7	0.800
		2JM8P9Y38TWW3JPWME9M5JTACTCIZ7	ADAK1UJXC5TJJ	1	1	0				
		2CWSMEZZ2MIKSOVY050Y88TWS2Y5MB	A1Y1X8WCA3C5UF	1	0	0				
		273NVP3TVOK50G59TEYQJOZFUVI417	A1N4QDHJ34H5VD	1	1	1				
		2GZD1X3V0FK0IP66BUSMCPKK5PQLE7	A3I8SB05PWN7HO	1	1	1				
		2WAKMN9U8P9Y99F0OD93XUYII5EUDF	A11ZSP12IL64Y2	1	1	1				
		2JM8P9Y38TWW3JPWME9M5JTACS7ZIH	A2JBJFPFG38X9C	1	1	1				
		2F0B727M0IGFQIZ5YE6S0F4VETWDY3	A306HC0URZ6OA1	1	1	1				
		26UDIPDOBDDPEQ50CA4DDXMBZUT0B4	A22YE5YXKM2GBF	1	0	1				
		2Z7E4EGDHDM2BMUM13QWBHEZ2S6BLQ	A2A4HUANTKP918	1	0	1				
24	19412	2B4STMOFXRDSAJY56E4N2JFMX57URL	A1V4JB3UVUTTZC	1	0	0	0.7	0.7	0.6	0.667
		23H9RA7S5WM1CAKWGVY0OMHL6OXUZP	A2MT0WWJR23AGG	0	0	0				
		2FJ98D8J3VE72TEXFE3G8MCK4F0XHV	A2JBJFPFG38X9C	1	1	0				
		2X5WIOV1S7SN9EFKMHUYIZ8N4W8KZP	ACGJR8V9K0ROT	1	1	1				

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
		2JJJ85OZIZEHSBWTE4FQAEWPTQNAYM	A2A4HUANTKP918	1	1	1				
		21A8IUB2YU98PIEXDRUL5FBJ5MN8KS	A22YE5YXKM2GBF	0	0	0				
		20QN5F3Q0JG5ZZ8R4CPB99F9OX2CGC	A23U4SG2PC5KE5	1	1	1				
		2UMDD8XMB3Q3F0MFYAKOBT4ERWRQFI	AR8WG23QF9YIK	1	1	1				
		27MYT3DHJHP4HEZO8KP8WSX9T8QU14	A3HOZU88S1GXRX	1	1	1				
		2NGBDDP8PJWK0EZCP223V39ZWGJ5G0	A25JN8KUF3S8BM	0	1	1				
25	22383	2NUAC9KSSZVX33C8XALKVOYGJNZK27	A3I8SB05PWN7HO	1	0	1	0.6	0.4	0.6	0.533
		2LDYHVI44OS2QMGC535ZXBAP1GC4YQ	A23U4SG2PC5KE5	1	0	1				
		2WIU6L5OBVCI7SJ1WQ9JK7GUXFUZG4	A296W3TOJ7E983	1	0	1				
		2JR6KW4ZMAZHNSDP76ROSNVRD6S8HZ	A1CG19PDVRI7HQ	0	0	0				
		2YI1SNQQ7Q6766NUCSER62TQ8699T3	ACGJR8V9K0ROT	1	1	0				
		2AYUFBNFSVGURGPDX8N6SG1FO8PJ57	A2JBJFPFG38X9C	0	1	1				
		2VQHVI44OS2KRVUHFUQSGAP575ZZ53	A22YE5YXKM2GBF	1	0	1				
		2R5M25L8I9NZ273IRMFE9QW7PEBSIB	A1G08QM9J5GZO6	0	0	0				
		2Y1Z6KW4ZMAZNIDVDVH0TNNVNN67GB	A2MT0WWJR23AGG	0	1	0				
		2DYXBAT2D5NQ4ORJV6RJL5TYITH62S	ADAK1UJXC5TJJ	1	1	1				
26	23109	2T0EBDPGFL6VIQI317ED1IOVXY7I34	ADAK1UJXC5TJJ	1	1	0	1	0.9	0.6	0.833
		2I988MQU6L5OHWYMT7OX9AIJBCRCV2	A3HOZU88S1GXRX	1	1	0				
		2NH8PJWKUDD83NX7IJ0Z5B6UPT6K9W	A3I8SB05PWN7HO	1	0	0				
		24DF395SW6NG7GE7FEEJGYF1B5VFTU	A11ZSP12IL64Y2	1	1	1				
		2CYDG67D1X3V6G6444B2OE1M3UPAH2	A2JBJFPFG38X9C	1	1	0				
		2MOA6X3YOCCF6DB9CDGTNNIIT3UPQ2	A1Y1X8WCA3C5UF	1	1	1				
		2W0JIA0RYNJ98O5OEGWBRJTUD3Y27I	A22YE5YXKM2GBF	1	1	1				
		2KGO2GMMEGOOMREGEM9AF2SEEZC999	A2MT0WWJR23AGG	1	1	1				
		20V9Z0B6UTO6Z50ZK9MRPGPWO0YOZR	A23U4SG2PC5KE5	1	1	1				
		26UGTP9RA7S52NNA1EJOK70JIMXRWY	ACGJR8V9K0ROT	1	1	1				
27	23704	22RVXX2Q45UUQRA2839W6NS8KKWR9Q	A3VDWFQEHNPE41	0	1	0	0.8	0.9	0.7	0.800
		2CEIKMN9U8P944UXOCOI8SUYEQZCT8	A22YE5YXKM2GBF	1	1	0				
		2XIQ7Q67051QQD9VTIKQH1XMCNJDXE	A2A4HUANTKP918	1	1	0				
		2CBE1M7PKK9LXXSSRQ309LZXLQAZSA	A3I8SB05PWN7HO	0	0	1				
		2A4OK2JE1M7PQLVPJCXO4AC00QEOVF	A1Y1X8WCA3C5UF	1	1	1				
		2SCMN9U8P9Y3EUI0PYUSZYIMWOUEVN	A2JBJFPFG38X9C	1	1	1				
		2A85R98D8J3VK8IWK9EYHG3M8P2FVZ	A1N4QDHJ34H5VD	1	1	1				
		2LDYHVI44OS2QMGC535ZXBAP1G14YF	A2DULTV0RVMIN4	1	1	1				
		2Q5HDM25L8I9T0IA9UQ6TE4QSDWQGQ	A11ZSP12IL64Y2	1	1	1				
		2QCCCVLL3CA39N3EH6VCENQU31WY8D	A23U4SG2PC5KE5	1	1	1				
28	24484	27EB3Q39Z0B60UAALK5VXTVRGLQKVD	A2A4HUANTKP918	0	1	0	0.5	0.4	0.6	0.500
		2JUNJKM05BMJZV32OI7TU9RA3W2HC1	A3VDWFQEHNPE41	0	1	0				
		2CCYEPLSP75KRNS0BJFAMQEQRO3XRX	AKL6R80QZP4SH	1	1	0				
		2DI39Z0B6UTOCUQIN8KVWKGPSXYYN6	A3I8SB05PWN7HO	0	0	0				
		2I0MQU6L5OBVIJNVPDVANJF7C05XEE	ADAK1UJXC5TJJ	0	0	1				
		2H51X3V0FK0CULON6HD7UKK9HVUFMK	A22YE5YXKM2GBF	1	0	1				
		29PR24SMEZZ2SJ6QFPL8U9Y34YZJ27	ACGJR8V9K0ROT	1	0	1				
		22O6NG1FS3NYTKX27H6ZXZL2TX5ZL1	A11ZSP12IL64Y2	0	1	1				
		2FD8I9NZW6HE57AIW6N7Y869CYKMWP	A3O552KXGQFFJF	1	0	1				
		2C8TP9RA7S5WS2SDQ8FFC0JMDQHSXB	A2JBJFPFG38X9C	1	0	1				
29	25462	2UO4ZMAZHHRRRGC4G3EVWH1KDTCKB9	A2A4HUANTKP918	0	0	0	0.9	0.9	0.8	0.867
		2PKVGULF395S279KTVJ3SYNJ73FBPY	A3I8SB05PWN7HO	1	1	0				
		22EEZZ2MIKMNFVUT1EU8YWWXE8N7OM	A23U4SG2PC5KE5	1	1	1				
		2FD8I9NZW6HE57AIW6N7Y869CZUMW1	A1CG19PDVRI7HQ	1	1	1				
		2WL6YTWX4H3H8QX85P0GN6IJNH7Y3S	A2MT0WWJR23AGG	1	1	1				
		2RX7DZKPFE4EME3HEIWLDI9NV1LF5D	A1Y1X8WCA3C5UF	1	1	1				
		21A8IUB2YU98PIEXDRUL5FBJ5NV8K2	A2JBJFPFG38X9C	1	1	1				
		240Y1THV8ER949FRCYDZXM5KBM3O1M	A2DULTV0RVMIN4	1	1	1				
		2BHC6SK9RJ85U0436XDAFPMOKV54S1	A22YE5YXKM2GBF	1	1	1				
		2VQ58B727M0IMG6L5HXYKSVF00QWBM	ACGJR8V9K0ROT	1	1	1				
30	25659	2QISCM6IAA2SKJGYMGROVKKA0NXKK5	A1Y1X8WCA3C5UF	1	1	1	0.9	0.6	0.9	0.800
		26UDIPDOBDDPEQ50CA4DDXMBZVQ0B3	A3971DPYHDLBA9	1	0	0				
		28XPQJQ9OPLL3DTYE7OGDKCOVRYZ1T	A2MT0WWJR23AGG	1	1	1				

No.	Image ID	Assignment ID	Worker ID	Keyword Score K1	Keyword Score K2	Keyword Score K3	Average Score per Keyword K1	Average Score per Keyword K2	Average Score per Keyword K3	Average Score per Image
		2ABPPSI2KYEPRTBBX0CMBWJ3KFKRLW	A2A4HUANTKP918	1	0	1				
		2EXUUKQOYGNI229W0470607SRLCYGY	A22YE5YXKM2GBF	1	1	1				
		2DYXBAT2D5NQ4ORJV6RJL5TYISZ264	AU07GCWRV7B5Z	0	0	1				
		2BLHV8ER9Y8TTL4QR8D5PFHSYTOR42	A3I8SB05PWN7HO	1	0	1				
		23UD5NQYN5F3W15KX9PMSCWY79AB7S	A2JBJFPFG38X9C	1	1	1				
		2TZ9KQW618N4CVJJ4TV52CETJJTNL4	A11ZSP12IL64Y2	1	1	1				
		2FMUKQOYGNIW7OECGWR157SVCEMZHG	A3O552KXGQFFJF	1	1	1				
31	25836	2YRFYQS1CSTMUGJV58VIH1EY9SGOL0	A2A4HUANTKP918	1	1	0	0.6	0.7	0.9	0.733
		2Y1Z6KW4ZMAZNIDVDVH0TNNVNLYG78	A3I8SB05PWN7HO	1	1	1				
		20O618N46UXFIEQ9PS5TSDSNPPMRPV	ACGJR8V9K0ROT	0	1	1				
		2TCM05BMJTUH4XOKL50RF7S5SR8KFV	A2JBJFPFG38X9C	0	0	1				
		2DC4F0OHOVR1AJJOGIC97HECSFL43O	A1Y1X8WCA3C5UF	1	0	1				
		2CI45UUKQOYGTJI5F8ZOL0103XFEWG	A296W3TOJ7E983	0	0	1				
		2BTK274J79KQ27NCFKXU2FCD0ASFHA	A23U4SG2PC5KE5	1	1	1				
		2E1F9SSSHX11PP9WLL85K8J4KU5VZC	A22YE5YXKM2GBF	0	1	1				
		2PC0COK2JE1MDQ6O11IWBOZA84TMTQ	A2SBU7EFMD0VW2	1	1	1				
		2TCM05BMJTUH4XOKL50RF7S5SRNKFA	A3971DPYHDLBA9	1	1	1				
32	26083	209M8JIA0RYNPAORB0D0ABMJPY5506	A22YE5YXKM2GBF	1	1	1	0.9	1	0.9	0.933
		2BC274J79KQWC2URWMLXKCD4122IG0	A2A4HUANTKP918	1	1	1				
		2PC0COK2JE1MDQ6O11IWBOZA85JTMP	A1Y1X8WCA3C5UF	1	1	0				
		2R8YQ4J3NAB6HG8J74PYNT1TFKHQDF	A2JBJFPFG38X9C	1	1	1				
		2WU5L8I9NZW6NFLAGUVQ17T82EPKUW	ACGJR8V9K0ROT	1	1	1				
		2H1KQW618N460Y1G5KWXHETN9WMOMG	A3I8SB05PWN7HO	0	1	1				
		28SLWSBRI8IUH3KY1OAHXTLBZQJ2EL	A2ZJ898N5IJYMO	1	1	1				
		2OJ9Y8TNKIMZYNRO7XJ2TM0PC0Q9WS	A23U4SG2PC5KE5	1	1	1				
		22RVXX2Q45UUQRA2839W6NS8KLIR9E	A296W3TOJ7E983	1	1	1				
		2V7395SW6NG1LTPRQ3AB3F1FVXFGUW	A3U3EZVK7NC4PV	1	1	1				
33	27735	2B0N46UXFCD4BYYIL34SSTKIJ83USO	A2DULTV0RVMIN4	1	1	0	0.8	0.9	0.4	0.700
		2118D8J3VE7WYTFRQS73RCK86YFIYL	ACGJR8V9K0ROT	1	1	0				
		2BNP9746OQ1STRCBIMY0A1QK8RH2MF	A2SBU7EFMD0VW2	1	1	1				
		20ZQ67051QKCTSN6L6312MGIW0MFZD	A2JBJFPFG38X9C	1	1	0				
		2C9ECWA6X3YOID1445WK2PTIJMBNMU	A23U4SG2PC5KE5	1	1	0				
		20N66RLPHIT3NWIEN0967NJQY698GU	A3I8SB05PWN7HO	0	1	0				
		2EUAESCWY2AOU32QEU7OTGQS8QW00I	A22YE5YXKM2GBF	0	1	1				
		2GNCPWZ9RNDWOPH5KNJN8DTGQ74RCG	A11ZSP12IL64Y2	1	1	0				
		2X9MVHVKCJ017LOBWZY9PQW6XEO75P	ADAK1UJXC5TJJ	1	0	1				
		2CI45UUKQOYGTJI5F8ZOL0103WLWE2	A2A4HUANTKP918	1	1	1				
34	28398	2P64EGDHDM25R94DFFN6MEZ6KJ6MCM	A3I8SB05PWN7HO	1	1	1	0.9	0.6	1	0.833
		20SONNVRH1KHUA0KJRY6SV9LG06OX0	A22YE5YXKM2GBF	1	1	1				
		2H957DZKPFE4KHZL52T5Q8I9J4CE4Q	A1Y1X8WCA3C5UF	0	1	1				
		2KTQP6AUC26DM7THTDUV5FK08TR926	A296W3TOJ7E983	1	1	1				
		22HW1INMHGYQAKPR2RXBKMFFK2Q6JY	A2A4HUANTKP918	1	0	1				
		240Y1THV8ER949FRCYDZXM5KBM2O1L	A36LJNITM3VR81	1	0	1				
		2X9MVHVKCJ017LOBWZY9PQW6XEO75P	ADAK1UJXC5TJJ	1	1	1				
		2BNP9746OQ1STRCBIMY0A1QK8RMM24	A23U4SG2PC5KE5	1	1	1				
		2WFCWYB49F9SYT31THAOSST5DALTPC	ACGJR8V9K0ROT	1	0	1				
		2A85R98D8J3VK8IWK9EYHG3M8PAVFN	A2JBJFPFG38X9C	1	0	1				
35	30445	2C521O3W5XH0PQBWAIBYJPLSLC8BHW	A2A4HUANTKP918	1	1	0	0.8	0.8	0.8	0.800
		22LMOFXRDS4II20253OJKM1167IWT4	A306HC0URZ6OA1	1	1	0				
		2E1F9SSSHX11PP9WLL85K8J4KTZVZ4	A3O552KXGQFFJF	0	1	1				
		2NUAC9KSSZVX33C8XALKVOYGJMLK2R	A22YE5YXKM2GBF	0	1	1				
		2WGFXRDS4IC1KZZRPZ6M61A2EZTVYB	A22FI4L0B22AZM	1	0	1				
		2U4CVLL3CA33SIWTIK39SQU7T2N9ZB	ACGJR8V9K0ROT	1	1	1				
		2EB3NAB6BFMFLPK2A9STOFDGAXMUH3	A23U4SG2PC5KE5	1	1	1				
		2LFVP3TVOK5ULKR5QNHETZFYMXH25H	A1Y1X8WCA3C5UF	1	0	1				
		2S20RYNJ92NJQNM932ATZHYWYLW5AE	A2JBJFPFG38X9C	1	1	1				
		2MOY2AOO2GMMKHAS86JCR6IA67555I	AKL6R80QZP4SH	1	1	1				
36	30783	2LSHFL42J1LYB9XBUND0NGFKDH02NO	A22YE5YXKM2GBF	0	0	0	0.8	0.9	0.6	0.767
		254NHMVHVKCJ62NOUNVJC9KQSC435I	A2MT0WWJR23AGG	0	1	0				

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
		2KRHHRRLFQ0OTOHV9HBHT9EGNGAPGW	A2JBJFPFG38X9C	1	1	0				
		22LMOFXRDS4II20253OJKM1167IWT4	A306HC0URZ6OA1	1	1	0				
		23NOK5UFJ51YDR0SRVPQX1CSPRR7AV	A2A4HUANTKP918	1	1	1				
		2IAUB2YU98JHYU7FV1RFGJ9IKGRMAQ	ACGJR8V9K0ROT	1	1	1				
		2X7SVGULF395YXSR8H6S8NYNFFNAO8	A23U4SG2PC5KE5	1	1	1				
		2CBE1M7PKK9LXXSSRQ309LZXLQASZ3	A2OYA8010YKQ5E	1	1	1				
		24426DG67D1X9WMJCG3OP2JEXQ28FM	AXCPS1QVDAS1Y	1	1	1				
		2RE8JIA0RYNJF39NC2R5GMJTQMB16C	AKL6R80QZP4SH	1	1	1				
		2X7SVGULF395YXSR8H6S8NYNFGZOA0	A2A4HUANTKP918	0	0	0				
		2NHGFL6VCPWZFS9HOYFV6S7SJ8KM7Y	A1CG19PDVRI7HQ	0	0	0				
		2UFQY2RCJK635W0797RKZIAQ5PO5US	A2MT0WWJR23AGG	1	0	0				
		2LVQ39Z0B6UTU7F86BJT0RKGL12XM7	A23U4SG2PC5KE5	1	1	1				
37	31132	2IPMB3Q39Z0BCVFSY9VE0STVNPIJUP	A3I8SB05PWN7HO	1	0	0	0.7	0.1	0.6	0.467
		2VJGNTBJ3MMD361TZ3X2PHB9IJ2WAQ	ADAK1UJXC5TJJ	1	0	1				
		2CXL8I9NZW6HK0SS6KHWCT865LWVLS	A2JBJFPFG38X9C	0	0	1				
		22NQ8H88MQU6R6AFNS91WXX46MI9SZ	A22YE5YXKM2GBF	1	0	1				
		2YP7H57DZKPFK50K5X4M75L8EFS2CG	A11ZSP12IL64Y2	1	0	1				
		2P5EY5COW0LGX0PC476LH6VNQ495WZ	ACGJR8V9K0ROT	1	0	1				
		29CPFE4EGDHDS3RP0Y0N4W6HA46J9W	A22YE5YXKM2GBF	0	0	0				
		2IBHSTLB3L0FHKVMGRAEOREVAAVUIQ	ACGJR8V9K0ROT	0	1	1				
		2YP7H57DZKPFK50K5X4M75L8EELC2H	A11ZSP12IL64Y2	1	1	0				
		2C5IPDOBDDP8VKIOMT482MB3M8BC14	A2JBJFPFG38X9C	1	1	1				
38	31478	2Q5HDM25L8I9T0IA9UQ6TE4QSBPGQ5	A3O552KXGQFFJF	0	1	1	0.6	0.8	0.8	0.733
		2XKSCXKNQY2RIK6AVFME8HR0GZX0PG	A1Y1X8WCA3C5UF	0	1	1				
		2FKW6NG1FS3N4O5FQVSF4SZLY1FKY7	A3PJUU89XC8S15	1	1	1				
		2EYOQ1SNQQ7QC8M9T6BCSR12PWHR7R	A2MT0WWJR23AGG	1	0	1				
		2E66AUBXHWSHDG7D1B2Z1DRLTA93ZK	A23U4SG2PC5KE5	1	1	1				
		2CFJQ2172Z99WISFC13VJBU1ZO6ZR1	A2A4HUANTKP918	1	1	1				
		23VDHJHP4BDDQHQ207JXEX3GZAAX45	A2A4HUANTKP918	0	1	1				
		21Q0LWSBRI8I0CO2MPZJMSTL7801D6	A1Y1X8WCA3C5UF	0	1	0				
		2QY7D1X3V0FK6DAOUZ51R7PKGENDK8	A3I8SB05PWN7HO	0	0	1				
		2E1F9SSSHX11PP9WLL85K8J4KU4ZVF	ACGJR8V9K0ROT	0	1	0				
39	31557	2R7L42J1LY58H8OBEG9GKKHDXB1P49	A2JBJFPFG38X9C	0	1	0	0.2	0.8	0.7	0.567
		2V33L0FBJ9IOHK0NJUMEARPRYRKNZ4	A296W3TOJ7E983	0	1	1				
		2SCMN9U8P9Y3EUI0PYUSZYIMWPXVE9	A11ZSP12IL64Y2	0	0	1				
		2J0JHSTLB3L0LC5DA42JJJRERK8TH6	ADAK1UJXC5TJJ	1	1	1				
		2Q7L6VCPWZ9RTEIMGBSSCSN39YG9O5	A23U4SG2PC5KE5	1	1	1				
		2SHDOBDDP8PJ2LGH5OOMG3Q3541E3Q	A22YE5YXKM2GBF	0	1	1				
		2YVW5XH0JPPSO36265CSU75KHR8LFU	A22YE5YXKM2GBF	1	0	0				
		20H6AUC26DG6DEN1VBRFP0COG7M4B3	A306HC0URZ6OA1	1	1	0				
		2OQ5COW0LGRZ99YV71360NUZSIT7Y4	A2JBJFPFG38X9C	1	0	1				
		22KCXKNQY2RCPLS7RB53MR0KQNGQ1R	A2GPVGRV60K452	1	1	0				
40	32760	2OJSQV66RLPHOUPLNC1VPI62JOGD5B	A2A4HUANTKP918	1	0	0	1	0.6	0.4	0.667
		2Y4CF0CP5KXPZJ9MADPG9PM7J49WXS	ADAK1UJXC5TJJ	1	1	0				
		25OJ5OPB0YVG59KQORYEU9U3X77Y6U	A3I8SB05PWN7HO	1	1	0				
		2HSG5R98D8J31FT0K8KN3CG3IINUEI	A11ZSP12IL64Y2	1	1	1				
		23YS8SV7WGKCIW7PVS138MHALVP0QD	A296W3TOJ7E983	1	0	1				
		2JJJ85OZIZEHSBWTE4FQAEWPTQ4YAR	A1CG19PDVRI7HQ	1	1	1				
		26KBRI8IUB2Y0AUN98KLG3L0BGLH50	A2A4HUANTKP918	1	1	0				
		2CBENLVWJ5OPH1KZ8FZYRWB7AUI1TJ	ACGJR8V9K0ROT	1	1	1				
		24VK4F0OHOVR7541C4TLE2HE805325	A23U4SG2PC5KE5	1	1	1				
		2BHC6SK9RJ85U0436XDAFPMOKV5S4P	A3I8SB05PWN7HO	1	1	1				
41	33558	2PKVGULF395S279KTVJ3SYNJ72CPB7	A3O552KXGQFFJF	1	1	1	1	1	0.9	0.967
		2UUJE1M7PKK9RSIAGF1C54LZTUPYRW	A2JBJFPFG38X9C	1	1	1				
		2418JHSTLB3L6GXN1YFBOEJRA0FGS1	A306HC0URZ6OA1	1	1	1				
		2VYVCPWZ9RND2JAZT8YSS3DTCZ1QB4	A2DULTV0RVMIN4	1	1	1				
		2Y4CF0CP5KXPZJ9MADPG9PM7J21WXG	A1H3FJM2OFBIL1	1	1	1				
		2A4OK2JE1M7PQLVPJCXO4AC00Q1OV2	A22YE5YXKM2GBF	1	1	1				
42	33798	2JUNJKM05BMJZV32OI7TU9RA3X7HC8	A2A4HUANTKP918	0	0	0	0.7	0.7	0.8	0.733

No.	Image ID	Assignment ID	Worker ID	Keyword Score			Average Score per Keyword			Average Score per Image
				K1	K2	K3	K1	K2	K3	
		2X7SVGULF395YXSR8H6S8NYNFH2OA5	A2MT0WWJR23AGG	0	1	1				
		28L3DHJHP4BDJL28QOIS29X3C7U3WH	AULKD8VKJKPXM	1	1	0				
		2UFQY2RCJK635W0797RKZIAQ5N95U9	A22YE5YXKM2GBF	1	0	1				
		20M8Y1THV8ERFZUXF09M4SM5GKHN0S	A2DULTV0RVMIN4	0	0	1				
		2DI0JG5TYMNC2ZX81V0SXSHXX6OHLR	ACGJR8V9K0ROT	1	1	1				
		2E1F9SSSHX11PP9WLL85K8J4KV7VZG	A11ZSP12IL64Y2	1	1	1				
		29YR70G5R98DEKPZ6NNSXTNY8M7BRW	ADAK1UJXC5TJJ	1	1	1				
		2ABPPSI2KYEPRTBBX0CMBWJ3KFORL0	A1CG19PDVRI7HQ	1	1	1				
		2ABG5TYMNCWYH5VJ18JSMX11FTQJNY	A2JBJFPFG38X9C	1	1	1				
		2VW2J1LY58B78884AW6KMD16ULYR6T	A2MT0WWJR23AGG	1	1	0				
		2SDKH1Q6SVQ8N9UQIAXLAOBV8N32LR	A2A4HUANTKP918	1	1	0				
		2X5WIOV1S7SN9EFKMHUYIZ8N4XZKZI	ADAK1UJXC5TJJ	1	1	0				
		2UET6YTWX4H3N3BFWT09LI6IFWB2XB	A2JBJFPFG38X9C	1	1	1				
43	33897	2A85R98D8J3VK8IWK9EYHG3M8QBVFQ	A11ZSP12IL64Y2	1	1	1	1	1	0.7	0.900
		2UKSZVXX2Q450V6UGE7NNW1NOD37PN	A1Y1X8WCA3C5UF	1	1	1				
		2432YU98JHSTRCPPSV2JEIOBFJSCOY	ACGJR8V9K0ROT	1	1	1				
		2FMUKQOYGNIW7OECGWR157SVCFUHZ8	A22YE5YXKM2GBF	1	1	1				
		2JG9Z6KW4ZMA5I3VJ16Q5ONNRVE6F0	A1V4JB3UVUTTZC	1	1	1				
		2RNKCJ011K27AKTDC6N668N42ZHB9N	A296W3TOJ7E983	1	1	1				
		2FJ98D8J3VE72TEXFE3G8MCK4FVXHQ	A3I8SB05PWN7HO	0	1	1				
		2DN0FK0COK2JK28BH0B9QRW6K4CQJR	A2A4HUANTKP918	0	1	1				
		2NHGFL6VCPWZFS9HOYFV6S7SJ71M7D	ATAU7MT7K4Y1P	0	1	1				
		2U4CVLL3CA33SIWTIK39SQU7T3M9ZC	A2MT0WWJR23AGG	0	1	1				
44	36103	23YYTWX4H3H2VCQH1P7IBIJR7A74Z8	A22YE5YXKM2GBF	1	1	1	0.3	1	1	0.767
		24PFCD45XCETTEERL09N8TGP05OXZS	A1Y1X8WCA3C5UF	0	1	1				
		2NXNQYN5F3Q0PHRXQ2EC1YB45KC9DB	A2JBJFPFG38X9C	0	1	1				
		2O41PC6SK9RJE6A3AF5HRAAPIT0Q2E	ACGJR8V9K0ROT	1	1	1				
		2X1U8P9Y38TW2Y47KAPIR0JT6LIHY9	ADAK1UJXC5TJJ	1	1	1				
		2U4J011K274JDA6UOMS8S46UTJ6DBE	A23U4SG2PC5KE5	0	1	1				
		2D9VWAVKI62NPRO5ZIQ9EQH67PEQI6	A23U4SG2PC5KE5	1	0	0				
		2OWBLYHVI44OY36PMO4NJZSB6VB2WQ	A2MT0WWJR23AGG	0	0	1				
		2YRFYQS1CSTMUGJV58VIH1EY9SZOLJ	A2A4HUANTKP918	0	0	0				
		2E6GDHDM25L8OA93OM8E46OE0VROEP	ADAK1UJXC5TJJ	0	0	1				
45	36577	2HYO33FDEY5CUXMP87Q3DCRFHH10RO	A11ZSP12IL64Y2	1	0	0	0.6	0.2	0.7	0.500
		28349F9SSSHX725SF8K5M5F8F9PTXV	A2JBJFPFG38X9C	1	0	1				
		28I4J3NAB6BFSG1SQE9T6TJF9LNFS9	ACGJR8V9K0ROT	1	0	1				
		2SL3HVWAVKI68O5UUHY2499QDBDGO5	A22YE5YXKM2GBF	0	1	1				
		28L3DHJHP4BDJL28QOIS29X3C8KW32	A1Y1X8WCA3C5UF	1	0	1				
		21DPHIT3HVWA1L4AU3AQ7172VELKCP	AKL6R80QZP4SH	1	1	1				
		21DFQ0ONNVRH7L3S1U7RG76NREJLUP	ADAK1UJXC5TJJ	1	0	0				
		2VOSBRI8IUB24VVCBXJTQB3LWKCG4U	A2A4HUANTKP918	1	1	0				
		22NQ8H88MQU6R6AFNS91WXX46MH9SY	A3I8SB05PWN7HO	1	1	0				
		2S20RYNJ92NJQNM932ATZHYWYLP5A7	A11ZSP12IL64Y2	1	1	1				
46	37531	2QCCCVLL3CA39N3EH6VCENQU321Y8K	ACGJR8V9K0ROT	1	1	1	1	0.7	0.7	0.800
		2RTXERSQV66RRQ3MLJ8V1AVKEB7A2K	A2JBJFPFG38X9C	1	1	1				
		2I6BDPGFL6VCVXLDJ34WNOV1OCT4JM	A22YE5YXKM2GBF	1	0	1				
		2OWEGDHDM25LEJVRRCXHJZ6OA9SDND	A306HC0URZ6OA1	1	0	1				
		21DPHIT3HVWA1L4AU3AQ7172VELKCP	AKL6R80QZP4SH	1	1	1				
		2XKSCXKNQY2RIK6AVFME8HR0GZP0P8	A1CG19PDVRI7HQ	1	1	1				
		28GCCF0CP5KXVU4RAYOYL4PM3T4WVS	A2MT0WWJR23AGG	0	0	0				
		2V12HECWA6X34PYG7G3PAKXPPNOKLU	A22YE5YXKM2GBF	1	1	1				
		2RE8JIA0RYNJF39NC2R5GMJTQM0616	A2JBJFPFG38X9C	1	1	1				
		2CJCJK63ZVE3NSMOMY1QEJL5N8G9YH	A2A4HUANTKP918	1	0	1				
47	38033	2D5HJHP4BDDKM5KCJ8O923G31CY5YN	ACGJR8V9K0ROT	1	1	1	0.6	0.7	0.9	0.733
		254PWZ9RNDWIUWNWZ8E3ITGUX8SSDW	A11ZSP12IL64Y2	1	1	1				
		2THPSI2KYEPLYQT9C1D61J3O6NUSMQ	ADAK1UJXC5TJJ	0	1	1				
		2WS5BMJTUHYW8HFT1717X5WMXBJMH3	A3HOZU88S1GXRX	0	0	1				
		2UEN9U8P9Y38ZXI1AJJU3IM0FYNFWS	AKL6R80QZP4SH	1	1	1				
		2RN8ER9Y8TNKONLWELBFMS2OI4J6T5	A23U4SG2PC5KE5	0	1	1				

No.	Image ID	Assignment ID	Worker ID	Keyword Score K1	Keyword Score K2	Keyword Score K3	Average Score per Keyword K1	Average Score per Keyword K2	Average Score per Keyword K3	Average Score per Image
48	38288	273AT2D5NQYNBGPUSZ75YYMN82484D	A2MT0WWJR23AGG	0	0	0	0.6	0.7	0.7	0.667
		2X7SVGULF395YXSR8H6S8NYNFGZAOM	A2JBJFPFG38X9C	0	1	0				
		22LMOFXRDS4II20253OJKM1166BTWS	A23U4SG2PC5KE5	1	1	0				
		2C8TP9RA7S5WS2SDQ8FFC0JMDQCXSB	A3I8SB05PWN7HO	1	0	1				
		2IPMB3Q39Z0BCVFSY9VE0STVNPJUJ1	ACGJR8V9K0ROT	0	1	1				
		22CMT6YTWX4H9IOT3K49EGI6EPW1W7	A11ZSP12IL64Y2	0	1	1				
		21QNJ92NJKM0BC8NLA8Y12GTLE7D83	A1Y1X8WCA3C5UF	1	0	1				
		2JR6KW4ZMAZHNSDP76ROSNVRD6N8HU	A2A4HUANTKP918	1	1	1				
		291O9Z6KW4ZMG03LJ7CFV0ONJ0UE5I	A306HC0URZ6OA1	1	1	1				
		2JJJ85OZIZEHSBWTE4FQAEWPTQ0AYZ	A22YE5YXKM2GBF	1	1	1				
49	40169	27J24SMEZZ2MOL8R1AZPEY38P1W3KY	A22YE5YXKM2GBF	0	0	0	0.1	0.2	0.6	0.300
		2K36BFMFFOYYOUNXBV4GJSC0N29LY2	ACGJR8V9K0ROT	0	0	0				
		2MOYB49F9SSSNYN5B4ESY5H5BEMVRL	ADAK1UJXC5TJJ	0	0	0				
		21FDWIOV1S7ST4ZX8AS33DZ8JDYYJ7	A2JBJFPFG38X9C	0	0	0				
		25IVJ8EBDPGFR7HGHCQ9WNDWETX0F0	A2A4HUANTKP918	0	0	1				
		2W33Q39Z0B6UZPSXWUMSYVRKCUBLW5	A1Y1X8WCA3C5UF	0	0	1				
		2N0XMB3Q39Z0H7GXGMK4JVSTRWKTIU	A306HC0URZ6OA1	0	1	1				
		2IBIA0RYNJ92TK6QSL2MOTUHU1583N	A3I8SB05PWN7HO	0	1	1				
		2PC0COK2JE1MDQ6O11IWBOZA85XMTW	A1N4QDHJ34H5VD	1	0	1				
		2J0D8J3VE7WSYU924WUMHK8AP75ZJ2	A2DULTV0RVMIN4	0	0	1				
50	41617	2O3DPGFL6VCP20VVFTNITV1S3WM5KN	A22YE5YXKM2GBF	1	0	1	1	0.8	1	0.933
		2BTK274J79KQ27NCFKXU2FCD0A8FHQ	A3HOZU88S1GXRX	1	1	1				
		2CD92HECWA6X9ZAG4VRCU5KXLYBJKJ	A23U4SG2PC5KE5	1	1	1				
		2AGUQIHPCGJ2J3NSVCWXM0JPLWC17Q	A2O7B25B89JG3C	1	1	1				
		20NJ8EBDPGFLCWYTOF0RSDWIK04G1J	A2A4HUANTKP918	1	0	1				
		291RNDWIOV1SDT97597U63YDVDQWHX	A37AJI03M37NPJ	1	1	1				
		24PFCD45XCETTEERL09N8TGP05CZXI	ACGJR8V9K0ROT	1	1	1				
		2BHC6SK9RJ85U0436XDAFPMOKV4S4O	A11ZSP12IL64Y2	1	1	1				
		2Z0JVCNHMVHVQD54THB2C4J75PR02F	A2JBJFPFG38X9C	1	1	1				
		2BDY58B727M0OH1O9TS63FSVB9QAVI	ADAK1UJXC5TJJ	1	1	1				

Table C2: Annotation Accuracy Results for 50 HITs

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
1	383	2418JHSTLB3L6GXN1YFBOEJRA1KGS8	A2MT0WWJR23AGG	2	2.3
		2TAA0RYNJ92NPL84XRDJYUHYS7H49R	A22YE5YXKM2GBF	2	
		2ERMAZHHRRLFW1ARFBIH6KHO5KMDMJ	ADAK1UJXC5TJJ	2	
		26QB49F9SSSH32NNG3JTAH5F4O8SWF	A2A4HUANTKP918	3	
		2HWJ79KQW618T5SYPV3D95XCAYULJ2	ACGJR8V9K0ROT	3	
		2Q5HDM25L8I9T0IA9UQ6TE4QSCXGQF	A2JBJFPFG38X9C	3	
		2E1F9SSSHX11PP9WLL85K8J4KT1VZ6	A3I8SB05PWN7HO	2	
		2GUNJQ2172Z9FR3A30CC0EBUX9NYQX	A11ZSP12IL64Y2	3	
		2DGU3K4F0OHO1SN8ADBO7L92DJN018	A23U4SG2PC5KE5	1	
		2WBUNU8LZ6R76HRV1O48O3VE32W4KQ	A1G08QM9J5GZO6	2	
2	506	26R9RNDWIOV1Y8ERVTKGZ13Y93XGVS	A22YE5YXKM2GBF	1	2
		2BUA1QP6AUC2CE2AZTSX8V0FG5E703	A2A4HUANTKP918	1	
		2N0XMB3Q39Z0H7GXGMK4JVSTRXPITQ	A2MT0WWJR23AGG	2	
		2HWJ79KQW618T5SYPV3D95XCAY0LJ8	ACGJR8V9K0ROT	2	
		2U1RJ85OZIZENNWEH2FOV5EWL2O9XD	A2JBJFPFG38X9C	2	
		2QY7D1X3V0FK6DAOUZ51R7PKGEVKDN	A2DULTV0RVMIN4	3	
		209M8JIA0RYNPAORB0D0ABMJPZJ05H	A3I8SB05PWN7HO	2	
		2WS5BMJTUHYW8HFT1717X5WMXCDHMU	A11ZSP12IL64Y2	3	
		2TOKUDD8XMB3W4V3SRXUYO6T0IQDOJ	A23U4SG2PC5KE5	1	
		2X4WYB49F9SSYIJ5TZFNXT5H1KDUQU	A296W3TOJ7E983	3	
3	908	2N52AC9KSSZV3YOUWLLUPQOY7T61JQ	A22YE5YXKM2GBF	1	2
		2YFNVRH1KHO9KHDFZMEVELKWY9LZQQ	A2A4HUANTKP918	2	
		2V7395SW6NG1LTPRQ3AB3F1FQ4UGUK	A2MT0WWJR23AGG	3	
		2MOA6X3YOCCF6DB9CDGTNNIIOAEQPW	ACGJR8V9K0ROT	1	
		2XBKM05BMJTUNZI689G9WA7SW1BEJL	A2JBJFPFG38X9C	1	
		2N52AC9KSSZV3YOUWLLUPQOY7T61JQ	A2DULTV0RVMIN4	2	
		2YFNVRH1KHO9KHDFZMEVELKWY9LZQQ	A3I8SB05PWN7HO	2	
		2V7395SW6NG1LTPRQ3AB3F1FQ4UGUK	A11ZSP12IL64Y2	2	
		2MOA6X3YOCCF6DB9CDGTNNIIOAEQPW	A23U4SG2PC5KE5	3	
		2XBKM05BMJTUNZI689G9WA7SW1BEJL	A296W3TOJ7E983	3	
4	989	2JKKMT6YTWX4N436HRVDE9GI2NA0VD	A2A4HUANTKP918	2	2.3
		2WR9O9Z6KW4ZSBLL97ILKQ0OJSVD4G	A3I8SB05PWN7HO	3	
		2ADWSBRI8IUB8ZGD0Z8SYLB3H5MF3F	A296W3TOJ7E983	0	
		25J14IXKO2L98I0GOQXX8YOC8K7BCR	A1CG19PDVRI7HQ	2	
		2OQ5COW0LGRZ99YV71360NUZSIPY7R	ADAK1UJXC5TJJ	3	
		2UO4ZMAZHHRRRGC4G3EVWH1KDS8BKU	A22YE5YXKM2GBF	3	
		200H88MQU6L5UCHGAHIX24AIFKABUX	A306HC0URZ6OA1	3	
		2O4WA6X3YOCCL1YTX0OPYINIE22POK	A2JBJFPFG38X9C	3	
		2BKNQQ7Q67057R6GF7S2YQC1TRRBVU	A2DULTV0RVMIN4	2	
		2IEQU6L5OBVCO2D1PK1IOF7GQ57FY9	A3VDWFQEHNPE41	2	
5	3704	2UA62NJQ21725AVU9M2KQCVE7Z3WOK	A22YE5YXKM2GBF	2	2.2
		2ABPPSI2KYEPRTBBX0CMBWJ3KFWLR2	A1Y1X8WCA3C5UF	1	
		2N9JHP4BDDKGAZUVKD0X8G3531IZ6T	A296W3TOJ7E983	2	
		2CB1LY58B727S14K708D66YFO0I8T4	A2A4HUANTKP918	2	
		20K1CSTMOFXRJTQM4H5YINXJBS6SPN	A11ZSP12IL64Y2	2	
		2JG9Z6KW4ZMA5I3VJ16Q5ONNRWMF6J	ACGJR8V9K0ROT	2	
		2PV95SW6NG1FY492FZ2YK1FZO4THVD	A2JBJFPFG38X9C	3	
		2SCMN9U8P9Y3EUI0PYUSZYIMWNLVET	A23U4SG2PC5KE5	3	
		2KUSEIUUU00OWL6EWY9SDS2UYA7SST	A3I8SB05PWN7HO	3	
		2U1RJ85OZIZENNWEH2FOV5EWL2TX96	A1CG19PDVRI7HQ	2	
6	4264	2TZ9KQW618N4CVJJ4TV52CETEQUNLE	A2A4HUANTKP918	2	2.5
		2EXUUKQOYGNI229W0470607SMTAYG7	A3I8SB05PWN7HO	2	
		2IBIA0RYNJ92TK6QSL2MOTUHP8T83K	A296W3TOJ7E983	3	
		2GG33FDEY5CO217KJFU8HRFL3IQS1G	A1CG19PDVRI7HQ	3	
		2Y3DDP8PJWKUJEU1ERUQ89Z02IT6HB	ADAK1UJXC5TJJ	3	
		2TZ9KQW618N4CVJJ4TV52CETEQUNLE	A22YE5YXKM2GBF	3	
		2EXUUKQOYGNI229W0470607SMTAYG7	A306HC0URZ6OA1	3	
		2IBIA0RYNJ92TK6QSL2MOTUHP8T83K	A2JBJFPFG38X9C	3	
		2GG33FDEY5CO217KJFU8HRFL3IQS1G	A2DULTV0RVMIN4	1	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2Y3DDP8PJWKUJEU1ERUQ89Z02IT6HB	A3VDWFQEHNPE41	2	
7	4918	2T12NJKM05BMPUGLQCTGYP9R1CCGBE	A22YE5YXKM2GBF	0	2.3
		2PSOHOVR14IXQPOP1I8EHWA6O92763	A1Y1X8WCA3C5UF	2	
		25CI62NJQ21780VDIXXBPLCV5OWNVX	A296W3TOJ7E983	3	
		2IS6UFBNFSVG0M171LJWBNG1653I4Y	A2A4HUANTKP918	3	
		209M8JIA0RYNPAORB0D0ABMJK7450I	A11ZSP12IL64Y2	2	
		2T12NJKM05BMPUGLQCTGYP9R1CCGBE	ACGJR8V9K0ROT	2	
		2PSOHOVR14IXQPOP1I8EHWA6O92763	A2JBJFPFG38X9C	3	
		25CI62NJQ21780VDIXXBPLCV5OWNVX	A23U4SG2PC5KE5	3	
		2IS6UFBNFSVG0M171LJWBNG1653I4Y	A3I8SB05PWN7HO	2	
		209M8JIA0RYNPAORB0D0ABMJK7450I	A1CG19PDVRI7HQ	3	
8	5404	2QXTYMNCWYB4FGVWK88X61JOEXSLPP	ADAK1UJXC5TJJ	2	2.7
		2UE05BMJTUHY232XHPIACS5WDE7GLY	A3VDWFQEHNPE41	2	
		2WBUNU8LZ6R76HRV1O48O3VEY8Q4KR	ACGJR8V9K0ROT	3	
		2BNP9746OQ1STRCBIMY0A1QK3ZPM2I	A3I8SB05PWN7HO	2	
		2118D8J3VE7WYTFRQS73RCK81Z8IYB	A2Q16TWQKNV3OO	3	
		2QXTYMNCWYB4FGVWK88X61JOEXSLPP	A2JBJFPFG38X9C	3	
		2UE05BMJTUHY232XHPIACS5WDE7GLY	A2A4HUANTKP918	3	
		2WBUNU8LZ6R76HRV1O48O3VEY8Q4KR	A22YE5YXKM2GBF	3	
		2BNP9746OQ1STRCBIMY0A1QK3ZPM2I	A11ZSP12IL64Y2	3	
		2118D8J3VE7WYTFRQS73RCK81Z8IYB	A23U4SG2PC5KE5	3	
9	7534	2CCYEPLSP75KRNS0BJFAMQEQMWTRXS	A306HC0URZ6OA1	2	2.2
		2N9DM25L8I9N5XSL6FXOJ4QWY6BRH0	A2ZJ898N5IJYMO	2	
		2IAUB2YU98JHYU7FV1RFGJ9IFNIAME	A1Y1X8WCA3C5UF	2	
		2BUA1QP6AUC2CE2AZTSX8V0FBDY07R	A2A4HUANTKP918	3	
		2UQEPLSP75KLS7INV41HVEQVA46YST	ACGJR8V9K0ROT	3	
		2CCYEPLSP75KRNS0BJFAMQEQMWTRXS	A11ZSP12IL64Y2	2	
		2N9DM25L8I9N5XSL6FXOJ4QWY6BRH0	A22YE5YXKM2GBF	3	
		2IAUB2YU98JHYU7FV1RFGJ9IFNIAME	A2JBJFPFG38X9C	1	
		2BUA1QP6AUC2CE2AZTSX8V0FBDY07R	A23U4SG2PC5KE5	2	
		2UQEPLSP75KLS7INV41HVEQVA46YST	A3I8SB05PWN7HO	2	
10	8700	2ZVTVOK5UFJ57ZTU64QF3QS18YZ85I	ADAK1UJXC5TJJ	2	2.4
		2KNKI62NJQ21D3LD1686GKLCRJCMUV	A3VDWFQEHNPE41	2	
		26UGTP9RA7S52NNA1EJOK70JIMTWRZ	ACGJR8V9K0ROT	2	
		22KZVXX2Q45U0LCSQWEI11NS4TJQ88	A3I8SB05PWN7HO	2	
		27VYOCCF0CP5QYBXA39I2YG4LQYUTS	A2Q16TWQKNV3OO	3	
		2QY7D1X3V0FK6DAOUZ51R7PKGESDKD	A2JBJFPFG38X9C	3	
		2RTXERSQV66RRQ3MLJ8V1AVKEB62AB	A2A4HUANTKP918	3	
		2118D8J3VE7WYTFRQS73RCK86Y4IYA	A22YE5YXKM2GBF	3	
		2AT1K274J79KWXS503V6ZXFC990EGS	A11ZSP12IL64Y2	1	
		262VKI62NJQ278O31PHHBBKL8Z8TL0	A23U4SG2PC5KE5	3	
11	9211	2DPUYT3DHJHPACZHCWVYDRSX525T01	A306HC0URZ6OA1	2	2.2
		2ZKI2KYEPLSPD66PEMNJ8OAHMJ9OUU	A2ZJ898N5IJYMO	2	
		2QCPEIB9BAWLYNJTILMXZD3MPW71YF	A1Y1X8WCA3C5UF	2	
		2IEZ9O9Z6KW45NW39XIRQFQ0KSQC3X	A2A4HUANTKP918	2	
		247BNFSVGULF9ARWOMEG6FS3J30L71	ACGJR8V9K0ROT	2	
		250ER9Y8TNKIS0EQX06HX2OMWUDU7O	A11ZSP12IL64Y2	2	
		28TTHV8ER9Y8ZO6MEFJMAKFHO7R3QT	A22YE5YXKM2GBF	2	
		2NHGFL6VCPWZFS9HOYFV6S7SJ8G7MF	A2JBJFPFG38X9C	3	
		2D5HJHP4BDDKM5KCJ8O923G31CPY57	A23U4SG2PC5KE5	2	
		22KZVXX2Q45U0LCSQWEI11NS4TJQ88	A3I8SB05PWN7HO	3	
12	11500	2MKTMOFXRDS4ODNIQTEXOFM1XE1VS1	A22YE5YXKM2GBF	1	2.4
		2BANMHGYQ4J3TBXA3VDFKOYYEZ5M99	A2MT0WWJR23AGG	3	
		211ZJMJUNU8L57DBSWWRE8D8F8Y0G0	A2JBJFPFG38X9C	3	
		2UO4ZMAZHHRRRGC4G3EVWH1KDTPBKD	A1Y1X8WCA3C5UF	3	
		2N52AC9KSSZV3YOUWLLUPQOYCSN1JA	ACGJR8V9K0ROT	3	
		2DPUYT3DHJHPACZHCWVYDRSX536T04	ADAK1UJXC5TJJ	2	
		2J0D8J3VE7WSYU924WUMHK8AP7PZJM	A11ZSP12IL64Y2	2	
		2RTQ6SVQ8H88SRGADLFB0CI1N1P5O0	A2A4HUANTKP918	2	
		2C521O3W5XH0PQBWAIBYJPLSLC5HBZ	A3I8SB05PWN7HO	2	
		2Z4GJ2D21O3WBY34B5GSN2KYATF7DM	A23U4SG2PC5KE5	3	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
13	12680	2BANMHGYQ4J3TBXA3VDFKOYYEZ59MW	A2MT0WWJR23AGG	2	2.5
		2WAKMN9U8P9Y99F0OD93XUYII6PDUB	A1G08QM9J5GZO6	2	
		2TNCNHMVHVKCP1N5CIY4O79KM1H429	A3PJUU89XC8S15	3	
		2W6C1PC6SK9RP9RSRYQEMMAALRK1P1	AF5VW5OWVL8FO	3	
		27ZH57DZKPFEAF2H9TD2AL8I5RU3DE	A23U4SG2PC5KE5	2	
		2C5IPDOBDDP8VKIOMT482MB3M8A1CS	A2A4HUANTKP918	3	
		21JLFQ0ONNVRN26LGP5GWB76J0HTKD	ACGJR8V9K0ROT	3	
		2GMFBNFSVGULL4V9KCXNL1FSZSZ6K8	A22YE5YXKM2GBF	2	
		2RHCGJ2D21O326JLSZGPXI2KUJV6C0	A2JBJFPFG38X9C	2	
		2SHDOBDDP8PJ2LGH5OOMG3Q35563EM	A11ZSP12IL64Y2	3	
14	12906	2OJ9Y8TNKIMZYNRO7XJ2TM0P78IW9I	A22YE5YXKM2GBF	1	1.9
		2P5EY5COW0LGX0PC476LH6VNLCZW5R	A2MT0WWJR23AGG	1	
		2WIU6L5OBVCI7SJ1WQ9JK7GUSNEGZG	A2JBJFPFG38X9C	1	
		2V12HECWA6X34PYG7G3PAKXPKV9LKR	A2A4HUANTKP918	2	
		214JK63ZVE3HX16YAQH9OL5RUKMZAS	A23U4SG2PC5KE5	2	
		2OJ9Y8TNKIMZYNRO7XJ2TM0P78IW9I	A3I8SB05PWN7HO	2	
		2P5EY5COW0LGX0PC476LH6VNLCZW5R	A11ZSP12IL64Y2	2	
		2WIU6L5OBVCI7SJ1WQ9JK7GUSNEGZG	A1CG19PDVRI7HQ	3	
		2V12HECWA6X34PYG7G3PAKXPKV9LKR	ACGJR8V9K0ROT	3	
		214JK63ZVE3HX16YAQH9OL5RUKMZAS	A1G08QM9J5GZO6	2	
15	13399	2DVFDEY5COW0RHD3VO3RKLC6RRSU3I	A22YE5YXKM2GBF	3	2.7
		2USCOK2JE1M7VL6DD7N6TZACWAQUN9	A2MT0WWJR23AGG	3	
		28L3DHJHP4BDJL28QOIS29X3C88W3Q	A2JBJFPFG38X9C	1	
		2AXBMJTUHYW2MUBDJQYSAWM12E2NIR	A2A4HUANTKP918	2	
		2KYX3YOCCF0CV661H99NNIXYC8NRS3	A23U4SG2PC5KE5	3	
		20I7Q67051QKIOD5U9HC6XMGE5YYEI	A3I8SB05PWN7HO	3	
		25SFK0COK2JE7NTTC00LWW6OVF7RKL	A11ZSP12IL64Y2	3	
		2DVFDEY5COW0RHD3VO3RKLC6RS1U3T	A1CG19PDVRI7HQ	3	
		21FDWIOV1S7ST4ZX8AS33DZ8JDXYJ6	ACGJR8V9K0ROT	3	
		2PB51Y7QEOZF4RE548KMTFXR9XADG9	A1G08QM9J5GZO6	3	
16	14523	2D5HJHP4BDDKM5KCJ8O923G31D25YT	ADAK1UJXC5TJJ	2	2.6
		2OFLVWJ5OPB04W230EDWG7EP5Z63VN	A2JBJFPFG38X9C	3	
		2Z0PJWKUDD8XSCPUVPQ0G6UTKB1LAN	ACGJR8V9K0ROT	2	
		2KMC26DG67D134H470RCTK2JA5KE7Q	A3VDWFQEHNPE41	3	
		21JLFQ0ONNVRN26LGP5GWB76JZ8TK2	A2DULTV0RVMIN4	3	
		24426DG67D1X9WMJCG3OP2JEXSC8F0	A11ZSP12IL64Y2	1	
		2OFLVWJ5OPB04W230EDWG7EP5ZHV3Q	A1Y1X8WCA3C5UF	3	
		298KPEIB9BAWRT81H6WV2UD3IXOX0H	A22YE5YXKM2GBF	3	
		2S20RYNJ92NJQNM932ATZHYWYKKA55	A2A4HUANTKP918	3	
		2C5IPDOBDDP8VKIOMT482MB3M9DC18	A1G08QM9J5GZO6	3	
17	14612	20M8Y1THV8ERFZUXF09M4SM5BSHN03	ADAK1UJXC5TJJ	1	2.4
		2I0MQU6L5OBVIJNVPDVANJF776ZXEF	A2JBJFPFG38X9C	3	
		2Y7XRDS4IC1E4E91BVD16A2IMBSWZJ	ACGJR8V9K0ROT	2	
		2PI0ONNVRH1KNPVI8727BNV9CWSNWZ	A3VDWFQEHNPE41	2	
		2P5EY5COW0LGX0PC476LH6VNLCYW5Q	A2DULTV0RVMIN4	2	
		20M8Y1THV8ERFZUXF09M4SM5BSHN03	A11ZSP12IL64Y2	2	
		2I0MQU6L5OBVIJNVPDVANJF776ZXEF	A1Y1X8WCA3C5UF	3	
		2Y7XRDS4IC1E4E91BVD16A2IMBSWZJ	A22YE5YXKM2GBF	3	
		2PI0ONNVRH1KNPVI8727BNV9CWSNWZ	A2A4HUANTKP918	3	
		2P5EY5COW0LGX0PC476LH6VNLCYW5Q	A1G08QM9J5GZO6	3	
18	14753	2DLVOK5UFJ5148CIGF6YVS1COZR69K	A2MT0WWJR23AGG	1	2
		28F5F3Q0JG5T4N9GOE24EF9SOXKDH5	A22YE5YXKM2GBF	1	
		22O1VP9746OQ7T9UINH6C051MQH0K7	ADAK1UJXC5TJJ	3	
		2432YU98JHSTRCPPSV2JEIOBFJMCOS	A3I8SB05PWN7HO	2	
		2PD6VCPWZ9RNJX4SNHJ7XN3DPMZPAO	A11ZSP12IL64Y2	1	
		21DPHIT3HVWA1L4AU3AQ7172VEOCKK	A1Y1X8WCA3C5UF	2	
		2BWIXKO2L92HKDIEYDUYTCCFWHSDEP	A2A4HUANTKP918	2	
		258ULF395SW6THNJKJEYSJBYB6MDR6	A2JBJFPFG38X9C	3	
		2I6BDPGFL6VCVXLDJ34WNOV1OBM4JD	ANSVIUZJHDJZU	3	
		2CTO3W5XH0JPVT46CE5PQSP71OFJD5	A23U4SG2PC5KE5	2	
19	16194	25J14IXKO2L98I0GOQXX8YOC3RWBCP	A2MT0WWJR23AGG	1	2.2

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2OJ9Y8TNKIMZYNRO7XJ2TM0P78H9WU	A22YE5YXKM2GBF	1	
		2UQEPLSP75KLS7INV41HVEQVA4SSY9	ADAK1UJXC5TJJ	3	
		2TAA0RYNJ92NPL84XRDJYUHYNEF943	A3I8SB05PWN7HO	1	
		23H9RA7S5WM1CAKWGVY0OMHL1URZUV	A11ZSP12IL64Y2	3	
		25J14IXKO2L98I0GOQXX8YOC3RWBCP	A1Y1X8WCA3C5UF	3	
		2OJ9Y8TNKIMZYNRO7XJ2TM0P78H9WU	A2A4HUANTKP918	3	
		2UQEPLSP75KLS7INV41HVEQVA4SSY9	A2JBJFPFG38X9C	3	
		2TAA0RYNJ92NPL84XRDJYUHYNEF943	ANSVIUZJHDJZU	2	
		23H9RA7S5WM1CAKWGVY0OMHL1URZUV	A23U4SG2PC5KE5	2	
20	16704	2QKNTL0XULRGTUXNV2DD25FP3SLO27	A1Y1X8WCA3C5UF	2	2.5
		2ZV6XBAT2D5NWZ997JH0OG5TURP51P	A3I8SB05PWN7HO	2	
		23VDHJHP4BDDQHQ207JXEX3GZBBX48	A11ZSP12IL64Y2	3	
		259VKCJ011K2D55B10HWB18N0CZ8AN	ADAK1UJXC5TJJ	3	
		2S20RYNJ92NJQNM932ATZHYWYLXA5K	A2JBJFPFG38X9C	2	
		2VW2J1LY58B78884AW6KMD16UKTR6M	A22YE5YXKM2GBF	3	
		20TSNQQ7Q670B2CO43I17TQCX2FUAB	A23U4SG2PC5KE5	3	
		25CI62NJQ21780VDIXXBPLCVAGCNV2	A296W3TOJ7E983	2	
		21U4SMEZZ2MIQN9DMOG9338TS0O4LC	A2A4HUANTKP918	2	
		2GT8N46UXFCDA6JG69EDXNTKESPRTI	A3971DPYHDLBA9	3	
21	17397	2BP3V0FK0COK8K05ENGKP9LRNJQOHN	A1Y1X8WCA3C5UF	2	2.1
		2BQ7QEOZFYQS7DEXE46XWDS49P4GJY	A3I8SB05PWN7HO	1	
		2PD6VCPWZ9RNJX4SNHJ7XN3DKTUPAS	A11ZSP12IL64Y2	2	
		239V8ER9Y8TNQJ83K2WKKHS2FZ35SL	ADAK1UJXC5TJJ	2	
		26TVP9746OQ1YOCUZ6X7551QBPR1LM	A2JBJFPFG38X9C	2	
		2BP3V0FK0COK8K05ENGKP9LRNJQOHN	A22YE5YXKM2GBF	2	
		2BQ7QEOZFYQS7DEXE46XWDS49P4GJY	A23U4SG2PC5KE5	2	
		2PD6VCPWZ9RNJX4SNHJ7XN3DKTUPAS	A296W3TOJ7E983	3	
		239V8ER9Y8TNQJ83K2WKKHS2FZ35SL	A2A4HUANTKP918	3	
		26TVP9746OQ1YOCUZ6X7551QBPR1LM	A3971DPYHDLBA9	2	
22	18306	26XXH0JPPSI2QZ0TD8G7AKLMX9KHN0	A2MT0WWJR23AGG	0	2.1
		2GP3YOCCF0CPBLJTLYEINXYGV1KTST	A22YE5YXKM2GBF	2	
		2FKW6NG1FS3N4O5FQVSF4SZLT9MKYP	A2JBJFPFG38X9C	2	
		2H957DZKPFE4KHZL52T5Q8I9E504E1	ACGJR8V9K0ROT	2	
		2NXNQYN5F3Q0PHRXQ2EC1YB40SWD9A	A2ZJ898N5IJYMO	3	
		26XXH0JPPSI2QZ0TD8G7AKLMX9KHN0	A2A4HUANTKP918	2	
		2GP3YOCCF0CPBLJTLYEINXYGV1KTST	A11ZSP12IL64Y2	2	
		2FKW6NG1FS3N4O5FQVSF4SZLT9MKYP	A1Y1X8WCA3C5UF	2	
		2H957DZKPFE4KHZL52T5Q8I9E504E1	A23U4SG2PC5KE5	3	
		2NXNQYN5F3Q0PHRXQ2EC1YB40SWD9A	ADAK1UJXC5TJJ	3	
23	18942	2DLVOK5UFJ5148CIGF6YVS1COZS69L	A2MT0WWJR23AGG	1	2.4
		2TCM05BMJTUH4XOKL50RF7S5SR3FKL	A22YE5YXKM2GBF	2	
		2E66AUBXHWSHDG7D1B2Z1DRLTAF3ZQ	A2JBJFPFG38X9C	3	
		2GUNJQ2172Z9FR3A30CC0EBUX8RQYR	ACGJR8V9K0ROT	3	
		20QN5F3Q0JG5ZZ8R4CPB99F9OXACGK	A2ZJ898N5IJYMO	2	
		2OKCWY2AOO2GSN0KG47QXCM6EE133C	A2A4HUANTKP918	3	
		2VOSBRI8IUB24VVCBXJTQB3LWLD4GL	A11ZSP12IL64Y2	3	
		2CFJQ2172Z99WISFC13VJBU1ZO5ZR0	A1Y1X8WCA3C5UF	3	
		2UEN9U8P9Y38ZXI1AJJU3IM0FX4WFO	A23U4SG2PC5KE5	1	
		2WIU6L5OBVCI7SJ1WQ9JK7GUXGIZGU	ADAK1UJXC5TJJ	3	
24	19412	2I64BLYHVI44UTOODAZDSEZS2MNV1R	A2ZJ898N5IJYMO	0	1.3
		254NHMVHVKCJ62NOUNVJC9KQNJ153Q	A296W3TOJ7E983	1	
		2QHGSNTL0XULXH9X3ZUMRDX56130MA	A3HOZU88S1GXRX	2	
		2CZ4J79KQW61EOQAMD6CI45X3QSKIN	A2JBJFPFG38X9C	2	
		2CTO3W5XH0JPVT46CE5PQSP7WWGDJB	A22YE5YXKM2GBF	3	
		2FTY7QEOZFYQY2YWL2FF2RDSUGBIFQ	A2SBU7EFMD0VW2	1	
		2BTK274J79KQ27NCFKXU2FCDU3VFHT	A1Y1X8WCA3C5UF	1	
		27MYT3DHJHP4HEZO8KP8WSX9N1XU1R	A2A4HUANTKP918	2	
		29EAZHHRRLFQ6P9RN781PHO94EPNES	A1G08QM9J5GZO6	0	
		2FMUKQOYGNIW7OECGWR157SV68THZN	ACGJR8V9K0ROT	1	
25	22383	258ULF395SW6THNJKJEYSJBYB6YDRI	A2ZJ898N5IJYMO	2	1.3
		2BIP6AUC26DGC8Z5PJM0KK0CKPJ3A0	A296W3TOJ7E983	2	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2W9GYQ4J3NABCC1Q7VFY3IT1POQCPH	A3HOZU88S1GXRX	0	
		22N7WGKCCVLL9DW7V28AUQ4C5SXU4E	A2JBJFPFG38X9C	1	
		2BLHV8ER9Y8TTL4QR8D5PFHSYSL4RA	A22YE5YXKM2GBF	2	
		2PKVGULF395S279KTVJ3SYNJ724PBZ	A2SBU7EFMD0VW2	1	
		2ZO1INMHGYQ4P49E3M2FRFFOU3YK70	A1Y1X8WCA3C5UF	1	
		24PFCD45XCETTEERL09N8TGP05BXZF	A2A4HUANTKP918	1	
		2AXBMJTUHYW2MUBDJQYSAWM12F2NIT	A1G08QM9J5GZO6	2	
		2FKW6NG1FS3N4O5FQVSF4SZLY23YKB	ACGJR8V9K0ROT	1	
26	23109	20YSVQ8H88MQ0779GRMCN1RXT9AQ7I	A3I8SB05PWN7HO	1	2.4
		27UQ45UUKQOYMO40T3J8TG01WBGVDW	A3PJUU89XC8S15	1	
		28IS1CSTMOFXXEE8ASSE3DNXFKUORF	A1CG19PDVRI7HQ	2	
		28L3DHJHP4BDJL28QOIS29X3C8J3W8	A1Y1X8WCA3C5UF	3	
		2B4STMOFXRDSAJY56E4N2JFMX7ARUP	A11ZSP12IL64Y2	3	
		2S0IUB2YU98JNTFP3JC0KBJ9ETF9LS	A2A4HUANTKP918	3	
		2U4CVLL3CA33SIWTIK39SQU7T2J9Z7	A306HC0URZ6OA1	3	
		2W0JIA0RYNJ98O5OEGWBRJTUD2L728	A22YE5YXKM2GBF	2	
		2OWEGDHDM25LEJVRRCXHJZ6OA9XNDS	A2JBJFPFG38X9C	3	
		2OJ9Y8TNKIMZYNRO7XJ2TM0PCZ7W9U	A23U4SG2PC5KE5	3	
27	23704	2IAUB2YU98JHYU7FV1RFGJ9IFOMMAW	A3I8SB05PWN7HO	1	1.9
		29B51RYQM3ELWO8GIOKGZFTEL6SZ0Z	A3PJUU89XC8S15	1	
		2ZBWKUDD8XMB9RPDRG26ZTO6KH1NCJ	A1CG19PDVRI7HQ	1	
		26XXH0JPPSI2QZ0TD8G7AKLMX9LNH7	A1Y1X8WCA3C5UF	2	
		2Z0JVCNHMVHVQD54THB2C4J70XU20V	A11ZSP12IL64Y2	1	
		2IAUB2YU98JHYU7FV1RFGJ9IFOMMAW	A2A4HUANTKP918	2	
		29B51RYQM3ELWO8GIOKGZFTEL6SZ0Z	A306HC0URZ6OA1	3	
		2ZBWKUDD8XMB9RPDRG26ZTO6KH1NCJ	A22YE5YXKM2GBF	3	
		26XXH0JPPSI2QZ0TD8G7AKLMX9LNH7	A2JBJFPFG38X9C	3	
		2Z0JVCNHMVHVQD54THB2C4J70XU20V	A23U4SG2PC5KE5	2	
28	24484	2SSOUQIHPCGJ8EO5GJN52H0JG1N06Z	A1Y1X8WCA3C5UF	0	1.7
		2CEIKMN9U8P944UXOCOI8SUY9RKCTQ	A2A4HUANTKP918	1	
		2DGU3K4F0OHO1SN8ADBO7L928RD019	ADAK1UJXC5TJJ	0	
		2UQEPLSP75KLS7INV41HVEQVAWUSYV	A296W3TOJ7E983	2	
		2O8OOGQSCM6IGBOW6YLUZ00OHWJGGO	A22YE5YXKM2GBF	1	
		2YC5UFJ51Y7QKPLJQ6J1HSTMEDYC9S	A1CG19PDVRI7HQ	2	
		21QNJ92NJKM0BC8NLA8Y12GTF7U8D1	A306HC0URZ6OA1	2	
		27UQ45UUKQOYMO40T3J8TG01Q53DVJ	ACGJR8V9K0ROT	3	
		2PD6VCPWZ9RNJX4SNHJ7XN3DJEUAPI	A2JBJFPFG38X9C	3	
		20YSVQ8H88MQ0779GRMCN1RXN197QC	A2DULTV0RVMIN4	3	
29	25462	26Y18N46UXFCJ5R14UKNISNTGN2SQM	A1Y1X8WCA3C5UF	2	2.3
		2SUKYEPLSP75QM8AOZUOFHQEM09QWA	A2A4HUANTKP918	2	
		2M70CP5KXPTITJ41QWVPR7NY2B3ZYL	ADAK1UJXC5TJJ	1	
		2QISCM6IAA2SKJGYMGROVKKA0NZKK7	A296W3TOJ7E983	1	
		2SHDOBDDP8PJ2LGH5OOMG3Q3540E3P	A22YE5YXKM2GBF	2	
		20Q2RCJK63ZVK43VS0LIFQ9JHAYW7Z	A1CG19PDVRI7HQ	3	
		28O2GTP9RA7SBX85YPPSTF70FRHQVA	A306HC0URZ6OA1	3	
		22RVXX2Q45UUQRA2839W6NS8KL99RN	ACGJR8V9K0ROT	3	
		2O4WA6X3YOCCL1YTX0OPYINIE25OPM	A2JBJFPFG38X9C	3	
		2YUL92HECWA634KS4S60HP5KTUTJIF	A2DULTV0RVMIN4	3	
30	25659	26NOX7H57DZKVG086W4HIM25HDTA06	A23U4SG2PC5KE5	3	2.5
		206OZFYQS1CSZNAJP74S9IC1A3TJMB	A1Y1X8WCA3C5UF	3	
		2MOY2AOO2GMMKHAS86JCR6IA66R552	A3I8SB05PWN7HO	3	
		2ADWSBRI8IUB8ZGD0Z8SYLB3H453FK	A22YE5YXKM2GBF	3	
		2C9ECWA6X3YOID1445WK2PTIJOJNM6	ADAK1UJXC5TJJ	3	
		2X1U8P9Y38TW2Y47KAPIR0JT6LWYH4	A3NK147K2TXO40	1	
		25CI62NJQ21780VDIXXBPLCVAHXVNX	A11ZSP12IL64Y2	2	
		2G2UC26DG67D7YPZSVB0HOK2FJ5D65	A2A4HUANTKP918	2	
		2DFAB6BFMFFO4Z4XT9AFIGES85UWJ2	ACGJR8V9K0ROT	2	
		2MGK2JE1M7PKQA7VOMFZFC04H43PWY	A2JBJFPFG38X9C	3	
31	25836	24VK4F0OHOVR7541C4TLE2HE808237	A22YE5YXKM2GBF	2	2.3
		2VQ58B727M0IMG6L5HXYKSVF00QBW1	A1CG19PDVRI7HQ	2	
		2BC274J79KQWC2URWMLXKCD412NGIJ	A2DULTV0RVMIN4	3	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2I6BDPGFL6VCVXLDJ34WNOV1OCUJ42	A3I8SB05PWN7HO	3	
		28IS1CSTMOFXXEE8ASSE3DNXFKPROD	A37AJI03M37NPJ	3	
		2M1KSSZVXX2QA6GYC6FYLNIWXSUN5F	A306HC0URZ6OA1	1	
		2H51X3V0FK0CULON6HD7UKK9HWRFMJ	A23U4SG2PC5KE5	1	
		28URCJK63ZVE9ID4CA9AV9JL1W88XP	A2JBJFPFG38X9C	2	
		2AKPW1INMHGYW557FQ26GFMFBTB5IS	ACGJR8V9K0ROT	3	
		2X1U8P9Y38TW2Y47KAPIR0JT6LWYH4	A3NK147K2TXO40	3	
32	26083	2JM8P9Y38TWW3JPWME9M5JTA708IZC	A23U4SG2PC5KE5	2	2.6
		2XIYN5F3Q0JGBUKQFSNYG49F0XFBFD	A1Y1X8WCA3C5UF	3	
		2REVHVKCJ011Q3T8BN0KVW61ZZ186W	A3I8SB05PWN7HO	3	
		250ER9Y8TNKIS0EQX06HX2OMR2H7UG	A22YE5YXKM2GBF	3	
		2E6GDHDM25L8OA93OM8E46OEV2POEW	ADAK1UJXC5TJJ	3	
		2JM8P9Y38TWW3JPWME9M5JTA708IZC	A3NK147K2TXO40	2	
		2XIYN5F3Q0JGBUKQFSNYG49F0XFBFD	A11ZSP12IL64Y2	2	
		2REVHVKCJ011Q3T8BN0KVW61ZZ186W	A2A4HUANTKP918	2	
		250ER9Y8TNKIS0EQX06HX2OMR2H7UG	ACGJR8V9K0ROT	3	
		2E6GDHDM25L8OA93OM8E46OEV2POEW	A2JBJFPFG38X9C	3	
33	27735	2HYO33FDEY5CUXMP87Q3DCRFCP80R6	A22YE5YXKM2GBF	1	2.1
		24DF395SW6NG7GE7FEEJGYF16CVTFH	A1CG19PDVRI7HQ	2	
		2E1F9SSSHX11PP9WLL85K8J4F11ZVL	A2DULTV0RVMIN4	2	
		2M8J2D21O3W53IMNH5JI7KYEGYUE8U	A3I8SB05PWN7HO	2	
		2BHC6SK9RJ85U0436XDAFPMOF394SG	A37AJI03M37NPJ	2	
		2HYO33FDEY5CUXMP87Q3DCRFCP80R6	A306HC0URZ6OA1	2	
		24DF395SW6NG7GE7FEEJGYF16CVTFH	A23U4SG2PC5KE5	2	
		2E1F9SSSHX11PP9WLL85K8J4F11ZVL	A2JBJFPFG38X9C	3	
		2M8J2D21O3W53IMNH5JI7KYEGYUE8U	ACGJR8V9K0ROT	2	
		2BHC6SK9RJ85U0436XDAFPMOF394SG	A3NK147K2TXO40	3	
34	28398	26UGTP9RA7S52NNA1EJOK70JIMLWRR	A2JBJFPFG38X9C	2	2.3
		2D15SW6NG1FS9OKRBRPF6FZSVQ7WIS	ACGJR8V9K0ROT	2	
		2CKEIUUU00OQQLW8AYJ8X2U22D0TTB	A2A4HUANTKP918	2	
		211Y8TNKIMZSS66J98TOR0PGRJSAXD	A22YE5YXKM2GBF	2	
		2NMCF806UFBNLTHKM163E5SW2SR0ER	A3PJUU89XC8S15	3	
		2A7K0COK2JE1S8BOCPCR16OZ6I6LSJ	ADAK1UJXC5TJJ	2	
		2W6ZZ2MIKMN909BDQJZT1WXIZXP8PR	A11ZSP12IL64Y2	2	
		22NGULF395SWCO2578UN3NJBUJVQC3	A23U4SG2PC5KE5	2	
		2JKKMT6YTWX4N436HRVDE9GI2NY0V1	A1Y1X8WCA3C5UF	3	
		2WBUNU8LZ6R76HRV1O48O3VE32X4KR	A1G08QM9J5GZO6	3	
35	30445	2C55NQYN5F3Q6K29LEDNHWYBVE48C2	A2JBJFPFG38X9C	3	2.1
		23NOK5UFJ51YDR0SRVPQX1CSKZRA79	ACGJR8V9K0ROT	2	
		28349F9SSSHX725SF8K5M5F8AHPXTA	A2A4HUANTKP918	1	
		25IVJ8EBDPGFR7HGHCQ9WNDW90U0F6	A22YE5YXKM2GBF	2	
		2XDVWJ5OPB0Y1HLCQ2NBCEP9LG4W4M	A3PJUU89XC8S15	2	
		2C55NQYN5F3Q6K29LEDNHWYBVE48C2	ADAK1UJXC5TJJ	2	
		23NOK5UFJ51YDR0SRVPQX1CSKZRA79	A11ZSP12IL64Y2	2	
		28349F9SSSHX725SF8K5M5F8AHPXTA	A23U4SG2PC5KE5	3	
		25IVJ8EBDPGFR7HGHCQ9WNDW90U0F6	A1Y1X8WCA3C5UF	3	
		2XDVWJ5OPB0Y1HLCQ2NBCEP9LG4W4M	A1G08QM9J5GZO6	1	
36	30783	23UD5NQYN5F3W15KX9PMSCWY79YB7G	AN7WSWRDWIIAJ	0	1.8
		2IEQU6L5OBVCO2D1PK1IOF7GQ6DFYH	A22YE5YXKM2GBF	1	
		249YW2GTP9RADTR0EHX93SOF35NOTO	ACGJR8V9K0ROT	2	
		2PSOHOVR14IXQPOP1I8EHWA6T84677	A2JBJFPFG38X9C	2	
		2C2ESCWY2AOO8H8Q6WFOLQSCIBI111	A3I8SB05PWN7HO	3	
		2432YU98JHSTRCPPSV2JEIOBFKMOC6	A11ZSP12IL64Y2	3	
		2P3NFSVGULF3F6E0Y371KS3NUSU8MB	A2DULTV0RVMIN4	2	
		2D15SW6NG1FS9OKRBRPF6FZSVQ5IWC	A306HC0URZ6OA1	1	
		2CXL8I9NZW6HK0SS6KHWCT865LNVLJ	A23U4SG2PC5KE5	2	
		2418JHSTLB3L6GXN1YFBOEJRA0GSGE	A2A4HUANTKP918	2	
37	31132	2GP3YOCCF0CPBLJTLYEINXYGV1GTSP	AN7WSWRDWIIAJ	1	1.5
		2BTK274J79KQ27NCFKXU2FCDVIYFHR	A22YE5YXKM2GBF	1	
		2E6GDHDM25L8OA93OM8E46OEV2REOO	ACGJR8V9K0ROT	1	
		2N6Y5COW0LGR54UGJVCCBVNUQ9EX6Z	A2JBJFPFG38X9C	0	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2Z8FL6VCPWZ9XOZ0A4M1X7SNUPS8N8	A3I8SB05PWN7HO	1	
		2GP3YOCCF0CPBLJTLYEINXYGV1GTSP	A11ZSP12IL64Y2	2	
		2BTK274J79KQ27NCFKXU2FCDVIYFHR	A2DULTV0RVMIN4	2	
		2E6GDHDM25L8OA93OM8E46OEV2REOO	A306HC0URZ6OA1	2	
		2N6Y5COW0LGR54UGJVCCBVNUQ9EX6Z	A23U4SG2PC5KE5	3	
		2Z8FL6VCPWZ9XOZ0A4M1X7SNUPS8N8	A2A4HUANTKP918	2	
38	31478	297YQS1CSTMOLYDHKK9C6EYDJ2MPM4	A3I8SB05PWN7HO	2	2.1
		22O1VP9746OQ7T9UINH6C051MP70KV	ADAK1UJXC5TJJ	3	
		2EYUXFCD45XCKU9HK3KKNN3TCV8XVK	A2MT0WWJR23AGG	3	
		2XXF3Q0JG5TYSOY0QRV9K9SSOMZEIR	A2JBJFPFG38X9C	3	
		224GW40SPW1ITN3KQ6VJ8NAB2FDD0W	A22YE5YXKM2GBF	1	
		2E1F9SSSHX11PP9WLL85K8J4KUEVZL	ACGJR8V9K0ROT	1	
		2LYBFMFFOYYIZ2FN7T7EXC0RT0PZMT	A2DULTV0RVMIN4	1	
		22A2KYEPLSP7BL7QYCA3TAHQAUMPV7	A2A4HUANTKP918	2	
		2P3NFSVGULF3F6E0Y371KS3NURD8MS	A23U4SG2PC5KE5	2	
		224GW40SPW1ITN3KQ6VJ8NAB2GO0DW	A2H9G1XWYBDTKK	3	
39	31557	2BG3W5XH0JPPYJOOQUGLXP75GQPKE9	A22YE5YXKM2GBF	0	1.5
		2B0N46UXFCD4BYYIL34SSTKIJ9XSUI	ADAK1UJXC5TJJ	1	
		2WL6YTWX4H3H8QX85P0GN6IJNG63YU	A2JBJFPFG38X9C	2	
		280E4BLYHVI4APE6C1L8INEZOGIU0Z	ACGJR8V9K0ROT	2	
		21KQV66RLPHIZ43ZOQMKN62NFVH6E2	A1Y1X8WCA3C5UF	2	
		21Q0LWSBRI8I0CO2MPZJMSTL78C1DI	A2A4HUANTKP918	2	
		26WZMAZHHRRLLRMSF3MRM1KHKE8CL2	A23U4SG2PC5KE5	1	
		2QXR98D8J3VEDXEWL3PCL3MCGCWGWZ	A1W8TTTPVDQ8EK	1	
		26QB49F9SSSH32NNG3JTAH5F4O5SWC	A306HC0URZ6OA1	1	
		2OAUUU00OQKKG54MKOJ2Z268WJWVV9	A1HFYPITO6Z52Y	3	
40	32760	2D9VWAVKI62NPRO5ZIQ9EQH62WIQIJ	A22YE5YXKM2GBF	1	1.6
		2WR9O9Z6KW4ZSBLL97ILKQ0OEZU4DF	ADAK1UJXC5TJJ	1	
		2KNKI62NJQ21D3LD1686GKLCMJVUMH	A2JBJFPFG38X9C	2	
		2BNP9746OQ1STRCBIMY0A1QK30S2M3	ACGJR8V9K0ROT	2	
		2OWEGDHDM25LEJVRRCXHJZ6O5GMNDQ	A1Y1X8WCA3C5UF	1	
		2D9VWAVKI62NPRO5ZIQ9EQH62WIQIJ	A2A4HUANTKP918	1	
		2WR9O9Z6KW4ZSBLL97ILKQ0OEZU4DF	A23U4SG2PC5KE5	2	
		2KNKI62NJQ21D3LD1686GKLCMJVUMH	A1W8TTTPVDQ8EK	3	
		2BNP9746OQ1STRCBIMY0A1QK30S2M3	A306HC0URZ6OA1	3	
		2OWEGDHDM25LEJVRRCXHJZ6O5GMNDQ	A1HFYPITO6Z52Y	0	
41	33558	29UMIKMN9U8PFZPCLCNXN3SUUMHSBO	A23U4SG2PC5KE5	0	2.1
		2JM8P9Y38TWW3JPWME9M5JTACTCIZ7	ADAK1UJXC5TJJ	2	
		2CWSMEZZ2MIKSOVY050Y88TWS2Y5MB	A1Y1X8WCA3C5UF	2	
		273NVP3TVOK50G59TEYQJOZFUVI417	A1N4QDHJ34H5VD	2	
		2GZD1X3V0FK0IP66BUSMCPKK5PQLE7	A3I8SB05PWN7HO	2	
		2WAKMN9U8P9Y99F0OD93XUYII5EUDF	A11ZSP12IL64Y2	3	
		2JM8P9Y38TWW3JPWME9M5JTACS7ZIH	A2JBJFPFG38X9C	3	
		2F0B727M0IGFQIZ5YE6S0F4VETWDY3	A306HC0URZ6OA1	3	
		26UDIPDOBDDPEQ50CA4DDXMBZUT0B4	A22YE5YXKM2GBF	1	
		2Z7E4EGDHDM2BMUM13QWBHEZ2S6BLQ	A2A4HUANTKP918	3	
42	33798	2B4STMOFXRDSAJY56E4N2JFMX57URL	A1V4JB3UVUTTZC	0	1.9
		23H9RA7S5WM1CAKWGVY0OMHL6OXUZP	A2MT0WWJR23AGG	2	
		2FJ98D8J3VE72TEXFE3G8MCK4F0XHV	A2JBJFPFG38X9C	2	
		2X5WIOV1S7SN9EFKMHUYIZ8N4W8KZP	ACGJR8V9K0ROT	3	
		2JJJ85OZIZEHSBWTE4FQAEWPTQNAYM	A2A4HUANTKP918	1	
		21A8IUB2YU98PIEXDRUL5FBJ5MN8KS	A22YE5YXKM2GBF	3	
		20QN5F3Q0JG5ZZ8R4CPB99F9OX2CGC	A23U4SG2PC5KE5	3	
		2UMDD8XMB3Q3F0MFYAKOBT4ERWRQFI	AR8WG23QF9YIK	1	
		27MYT3DHJHP4HEZO8KP8WSX9T8QU14	A3HOZU88S1GXRX	1	
		2NGBDDP8PJWK0EZCP223V39ZWGJ5G0	A25JN8KUF3S8BM	3	
43	33897	22HW1INMHGYQAKPR2RXBKMFFFAUJ6Q	A23U4SG2PC5KE5	2	2.6
		2P30HFL42J1L46UFZIYM5IGFBNFM1T	ADAK1UJXC5TJJ	3	
		2QCCCVLL3CA39N3EH6VCENQUY9RY8J	A1Y1X8WCA3C5UF	1	
		2Y3DDP8PJWKUJEU1ERUQ89Z02IQ6H8	A1N4QDHJ34H5VD	2	
		23UD5NQYN5F3W15KX9PMSCWY2HAB73	A3I8SB05PWN7HO	3	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		22HW1INMHGYQAKPR2RXBKMFFFAUJ6Q	A2JBJFPFG38X9C	3	
		2P30HFL42J1L46UFZIYM5IGFBNFM1T	A22YE5YXKM2GBF	3	
		2QCCCVLL3CA39N3EH6VCENQUY9RY8J	A1G08QM9J5GZO6	3	
		2Y3DDP8PJWKUJEU1ERUQ89Z02IQ6H8	A2MT0WWJR23AGG	3	
		23UD5NQYN5F3W15KX9PMSCWY2HAB73	ADAK1UJXC5TJJ	3	
44	36103	2Y8QSCM6IAA2YF4YMAR0TQKK1GCJJU	A11ZSP12IL64Y2	2	2.3
		2S2A2SEIUUU06PCOCQVINS8ST7QQQF	A2JBJFPFG38X9C	1	
		20O618N46UXFIEQ9PS5TSDSNKXIPR0	A306HC0URZ6OA1	2	
		2LEJTUHYW2GTVADEZ8WWR169P4IKPU	A22YE5YXKM2GBF	2	
		23YS8SV7WGKCIW7PVS138MHAG2WQ0J	A2A4HUANTKP918	3	
		2Y8QSCM6IAA2YF4YMAR0TQKK1GCJJU	ADAK1UJXC5TJJ	3	
		2S2A2SEIUUU06PCOCQVINS8ST7QQQF	A3HOZU88S1GXRX	3	
		20O618N46UXFIEQ9PS5TSDSNKXIPR0	A3I8SB05PWN7HO	3	
		2LEJTUHYW2GTVADEZ8WWR169P4IKPU	A11ZSP12IL64Y2	3	
		23YS8SV7WGKCIW7PVS138MHAG2WQ0J	A2JBJFPFG38X9C	1	
45	36577	2FFQYN5F3Q0JM6F2E33W3B496MWAEW	A1V4JB3UVUTTZC	1	1.8
		2PSOHOVR14IXQPOP1I8EHWA6OG276H	A2MT0WWJR23AGG	2	
		2UHEIB9BAWLSSYBUXBOUI3MTI49Z2G	A2JBJFPFG38X9C	2	
		2KTQP6AUC26DM7THTDUV5FK031O297	ACGJR8V9K0ROT	0	
		2QQQ4J3NAB6BLN1JGEPIY1TJ6QHER5	A2A4HUANTKP918	3	
		2FFQYN5F3Q0JM6F2E33W3B496MWAEW	A1Y1X8WCA3C5UF	2	
		2PSOHOVR14IXQPOP1I8EHWA6OG276H	A22YE5YXKM2GBF	2	
		2UHEIB9BAWLSSYBUXBOUI3MTI49Z2G	A2MT0WWJR23AGG	3	
		2KTQP6AUC26DM7THTDUV5FK031O297	A23U4SG2PC5KE5	3	
		2QQQ4J3NAB6BLN1JGEPIY1TJ6QHER5	ACGJR8V9K0ROT	0	
46	37531	2LFVP3TVOK5ULKR5QNHETZFYHY2522	A22YE5YXKM2GBF	0	1.6
		2F3MJTUHYW2GZQVV2NJ51M160AOJOF	A23U4SG2PC5KE5	1	
		2GUNJQ2172Z9FR3A30CC0EBUSG6YQP	AR8WG23QF9YIK	2	
		2IQ1THV8ER9YEU9OA2QSR5KF84XP2E	A3HOZU88S1GXRX	3	
		2WBUNU8LZ6R76HRV1O48O3VEY2S4KH	A25JN8KUF3S8BM	3	
		2LFVP3TVOK5ULKR5QNHETZFYHY2522	A3FY26X1WRL00Z	3	
		2F3MJTUHYW2GZQVV2NJ51M160AOJOF	A2JBJFPFG38X9C	1	
		2GUNJQ2172Z9FR3A30CC0EBUSG6YQP	ADM0EJ7CQDVG6	2	
		2IQ1THV8ER9YEU9OA2QSR5KF84XP2E	A3I8SB05PWN7HO	0	
		2WBUNU8LZ6R76HRV1O48O3VEY2S4KH	ACGJR8V9K0ROT	1	
47	38033	2REVHVKCJ011Q3T8BN0KVW61Z07864	A3I8SB05PWN7HO	2	2.4
		20V9Z0B6UTO6Z50ZK9MRPGPWJ13ZO4	A23U4SG2PC5KE5	3	
		26KBRI8IUB2Y0AUN98KLG3L06OKH5A	A296W3TOJ7E983	2	
		2PQQS1CSTMOF3SZWWY31JYDNOW3NQP	A1CG19PDVRI7HQ	3	
		2VJGNTBJ3MMD361TZ3X2PHB9DQ0WAX	ACGJR8V9K0ROT	3	
		2REVHVKCJ011Q3T8BN0KVW61Z07864	A1DFIADXABLBPN	3	
		20V9Z0B6UTO6Z50ZK9MRPGPWJ13ZO4	A3AG698KLBMRP5	1	
		26KBRI8IUB2Y0AUN98KLG3L06OKH5A	AKEHUNKIP6Z7H	2	
		2PQQS1CSTMOF3SZWWY31JYDNOW3NQP	A2I53VNNLHNGZO	2	
		2VJGNTBJ3MMD361TZ3X2PHB9DQ0WAX	AEZT1RZZ1MVF7	3	
48	38288	2NUAC9KSSZVX33C8XALKVOYGJNZK27	A3I8SB05PWN7HO	1	1.8
		2LDYHVI44OS2QMGC535ZXBAP1GC4YQ	A23U4SG2PC5KE5	0	
		2WIU6L5OBVCI7SJ1WQ9JK7GUXFUZG4	A296W3TOJ7E983	1	
		2JR6KW4ZMAZHNSDP76ROSNVRD6S8HZ	A1CG19PDVRI7HQ	1	
		2YI1SNQQ7Q6766NUCSER62TQ8699T3	ACGJR8V9K0ROT	1	
		2AYUFBNFSVGURGPDX8N6SG1FO8PJ57	A2JBJFPFG38X9C	2	
		2VQHVI44OS2KRVUHFUQSGAP575ZZ53	A22YE5YXKM2GBF	3	
		2R5M25L8I9NZ273IRMFE9QW7PEBSIB	A1G08QM9J5GZO6	3	
		2Y1Z6KW4ZMAZNIDVDVH0TNNVNN67GB	A2MT0WWJR23AGG	3	
		2DYXBAT2D5NQ4ORJV6RJL5TYITH62S	ADAK1UJXC5TJJ	3	
49	40169	2T0EBDPGFL6VIQI317ED1IOVXY7I34	ADAK1UJXC5TJJ	0	1.3
		2I988MQU6L5OHWYMT7OX9AIJBCRCV2	A3HOZU88S1GXRX	1	
		2NH8PJWKUDD83NX7IJ0Z5B6UPT6K9W	A3I8SB05PWN7HO	1	
		24DF395SW6NG7GE7FEEJGYF1B5VFTU	A11ZSP12IL64Y2	2	
		2CYDG67D1X3V6G6444B2OE1M3UPAH2	A2JBJFPFG38X9C	0	
		2MOA6X3YOCCF6DB9CDGTNNIIT3UPQ2	A1Y1X8WCA3C5UF	1	

No.	Image ID	Assignment ID	Worker ID	Accuracy Score	Average Score per Image
		2W0JIA0RYNJ98O5OEGWBRJTUD3Y27I	A22YE5YXKM2GBF	1	
		2KGO2GMMEGOOMREGEM9AF2SEEZC999	A2MT0WWJR23AGG	2	
		20V9Z0B6UTO6Z50ZK9MRPGPWO0YOZR	A23U4SG2PC5KE5	2	
		26UGTP9RA7S52NNA1EJOK70JIMXRWY	ACGJR8V9K0ROT	3	
50	41617	2SFMHGYQ4J3NGCSF726FTYYIKDSANE	A3VDWFQEHNPE41	1	2.2
		2H51X3V0FK0CULON6HD7UKK9C3UMF2	A22YE5YXKM2GBF	1	
		2K5ZXR24SMEZ538MC2E9Z8P9P9BH0D	A2A4HUANTKP918	1	
		2JJJ85OZIZEHSBWTE4FQAEWPOXTYAP	A3I8SB05PWN7HO	2	
		2TS11K274J79QRIATOE4BUXF3Q6DFH	A1Y1X8WCA3C5UF	3	
		2SFMHGYQ4J3NGCSF726FTYYIKDSANE	A2JBJFPFG38X9C	3	
		2H51X3V0FK0CULON6HD7UKK9C3UMF2	A1N4QDHJ34H5VD	3	
		2K5ZXR24SMEZ538MC2E9Z8P9P9BH0D	A2DULTV0RVMIN4	3	
		2JJJ85OZIZEHSBWTE4FQAEWPOXTYAP	A11ZSP12IL64Y2	3	
		2TS11K274J79QRIATOE4BUXF3Q6DFH	A23U4SG2PC5KE5	2	

APPENDIX D

Data Fusion Evaluation

Table D1: Average Precision Performance Comparison for Six Fusion Algorithm Over 22 Queries

Query	CombMAX	CombMIN	CombSUM	CombMNZ	WCombSUM	WCombMNZ
1	0.02362	0.02742	0.03063	0.02439	0.05257	0.04537
2	0.26480	0.25099	0.27177	0.26553	0.15922	0.15202
3	0.12652	0.08711	0.13216	0.12592	0.16427	0.15707
4	0.02986	0.02502	0.03841	0.03217	0.06663	0.05943
5	0.20915	0.18762	0.23886	0.23262	0.17487	0.16767
6	0.18180	0.16971	0.17970	0.17346	0.20836	0.20116
7	0.00434	0.00239	0.01059	0.00435	0.03577	0.02857
8	0.01960	0.00683	0.02183	0.01559	0.04870	0.04150
9	0.00084	0.00071	0.00707	0.00083	0.03216	0.02496
10	0.10680	0.06293	0.09516	0.08892	0.12140	0.11420
11	0.03549	0.01332	0.04887	0.04263	0.07260	0.06540
12	0.00229	0.00853	0.01338	0.00714	0.03449	0.02729
13	0.16133	0.17088	0.16959	0.16335	0.18656	0.17936
14	0.07654	0.06341	0.17868	0.17244	0.20636	0.19916
15	0.01187	0.02033	0.02624	0.02000	0.04478	0.03758
16	0.00836	0.00580	0.01680	0.01056	0.04128	0.03408
17	0.00756	0.00775	0.01129	0.00505	0.03310	0.02590
18	0.06298	0.05245	0.16757	0.16133	0.08313	0.07593
19	0.01775	0.01390	0.02364	0.01740	0.05107	0.04387
20	0.01052	0.00340	0.01755	0.01131	0.04926	0.04206
21	0.00506	0.00487	0.01289	0.00665	0.04022	0.03302
22	0.00272	0.00515	0.01075	0.00451	0.03403	0.02683
Mean	**0.06226**	**0.05411**	**0.07834**	**0.07210**	***0.08822***	**0.08102**

Table D2: R-Precision Performance Comparison for Six Fusion Algorithm Over 22 Queries

Query	CombMAX	CombMIN	CombSUM	CombMNZ	WCombSUM	WCombMNZ
1	0.04380	0.04380	0.07069	0.06569	0.03220	0.02920
2	0.26846	0.26175	0.28688	0.28188	0.23790	0.23490
3	0.20243	0.17409	0.24792	0.24292	0.25401	0.25101
4	0.04348	0.01739	0.05717	0.05217	0.03778	0.03478
5	0.21970	0.16667	0.29288	0.28788	0.29846	0.29546
6	0.14151	0.10613	0.16302	0.15802	0.16102	0.15802
7	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
8	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
9	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
10	0.23077	0.15385	0.08192	0.07692	0.23377	0.23077
11	0.04918	0.03279	0.11975	0.11475	0.08497	0.08197
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.15385	0.15385	0.14603	0.14103	0.11839	0.11539
14	0.16000	0.18000	0.18500	0.18000	0.16300	0.16000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.22222	0.11111	0.11611	0.11111	0.22522	0.22222
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
21	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
22	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Mean	**0.07888**	**0.06370**	**0.08034**	**0.07784**	***0.08394***	**0.08244**

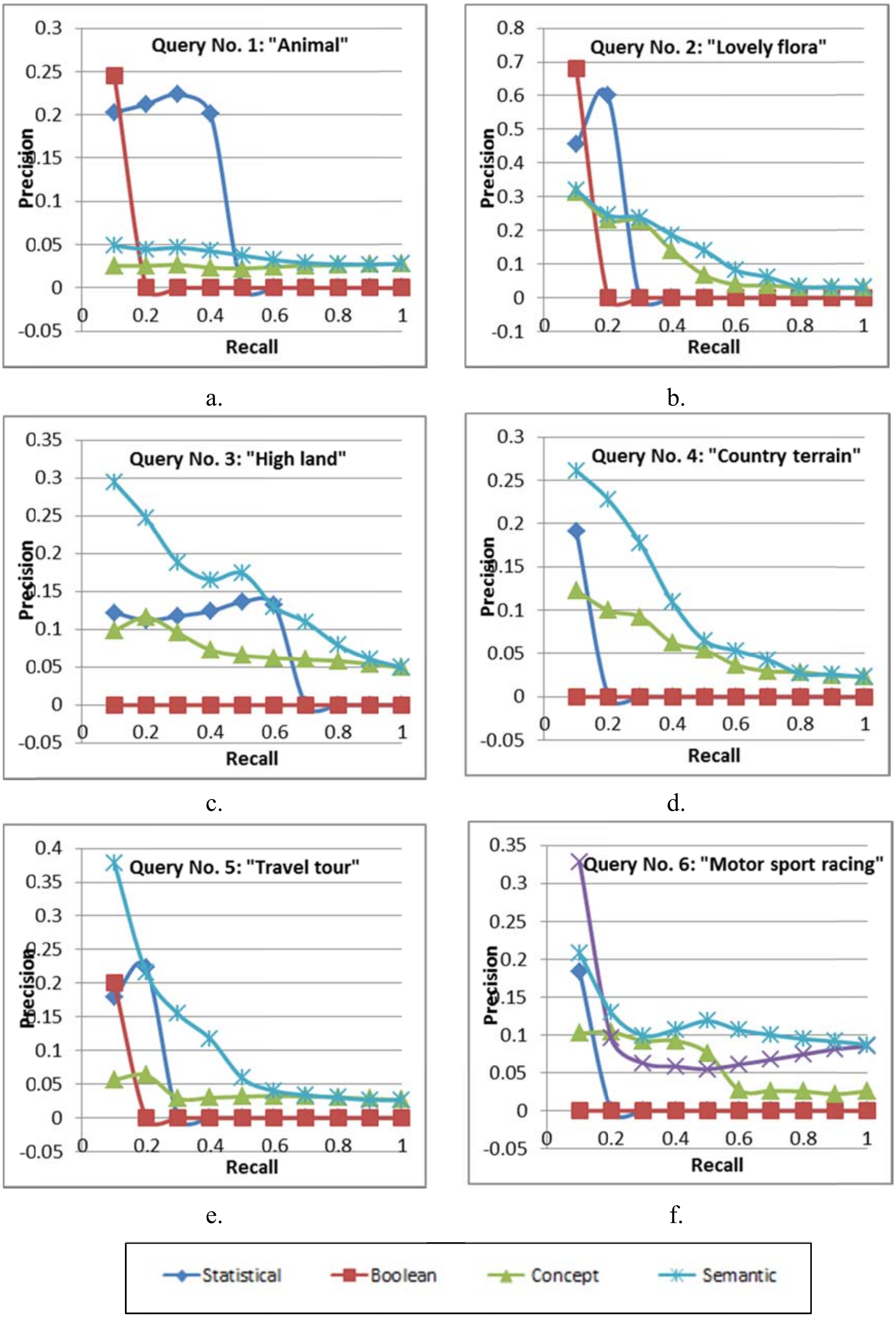


Figure D1: 11 Point Precision Curve for 22 Queries

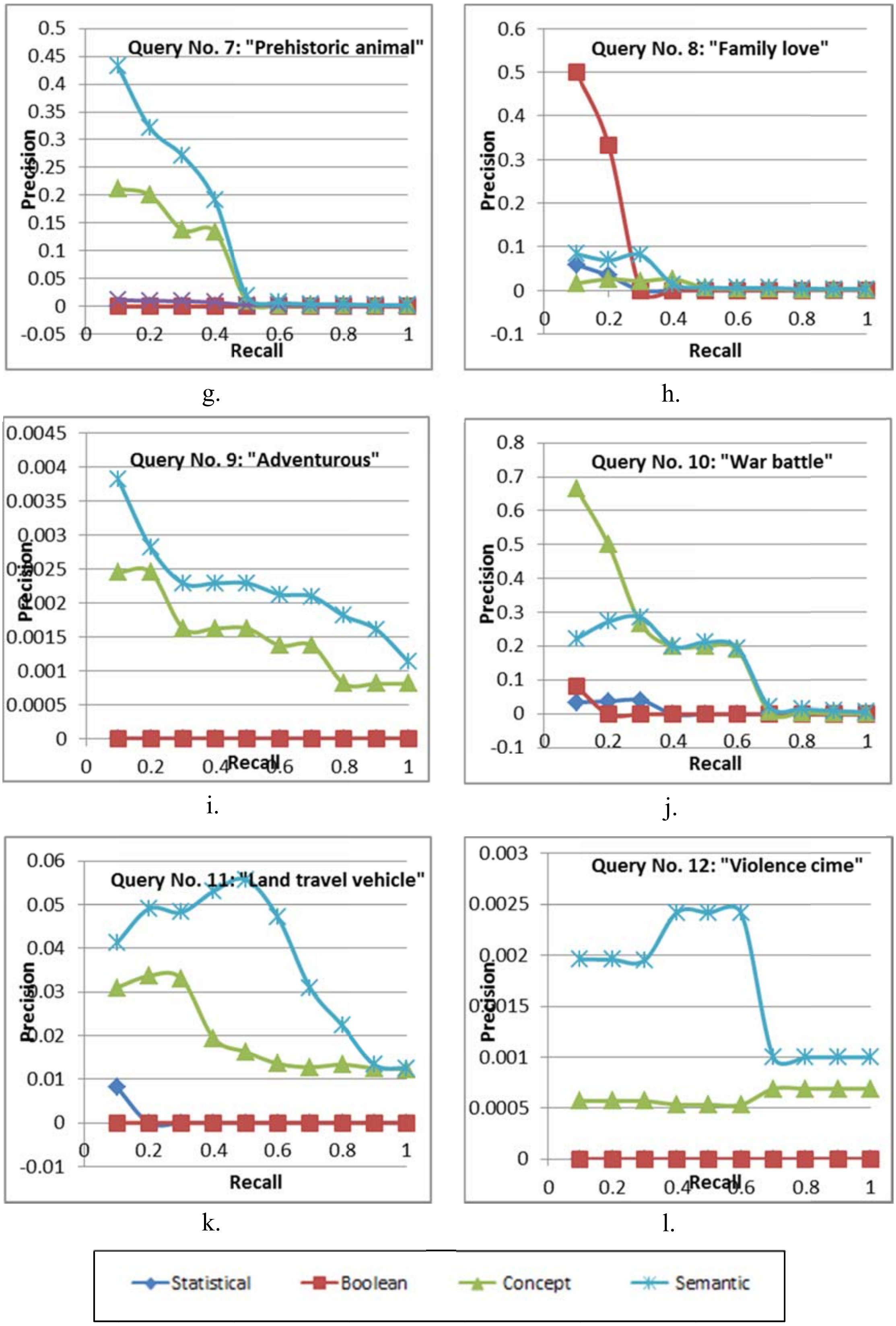
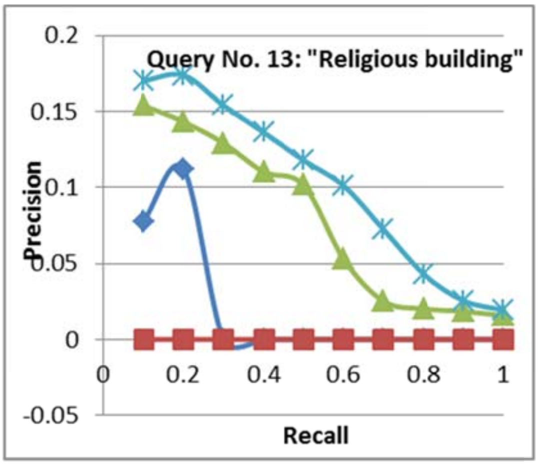
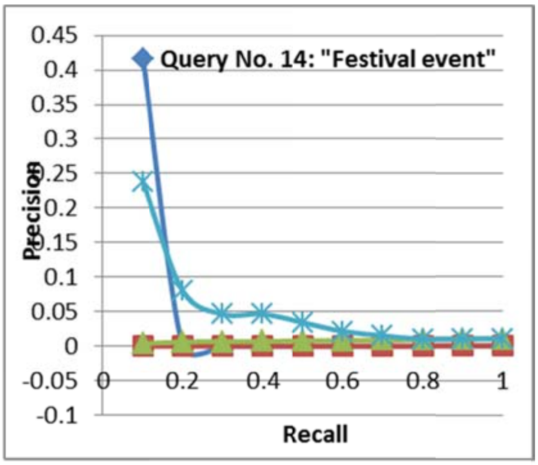


Figure D1: 11 Point Precision Curve for 22 Queries (cont.)





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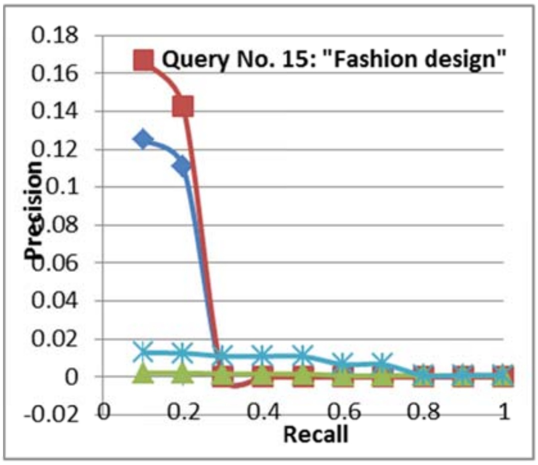
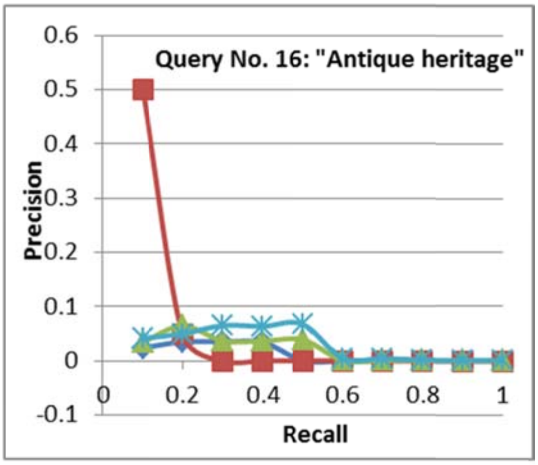
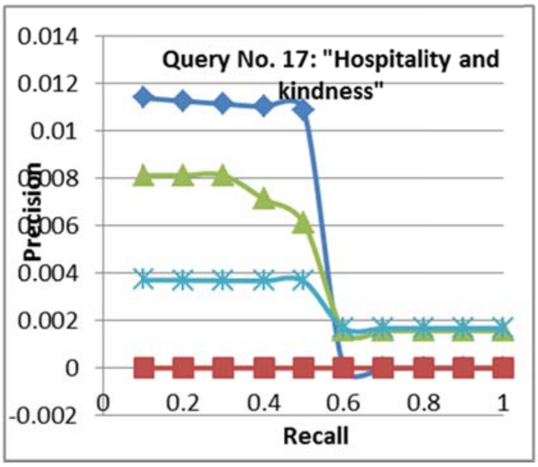
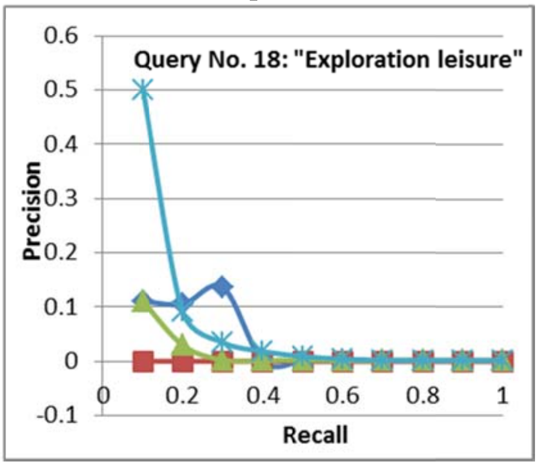




o. p.





q. r.

Figure D1: 11 Point Precision Curve for 22 Queries (cont.)

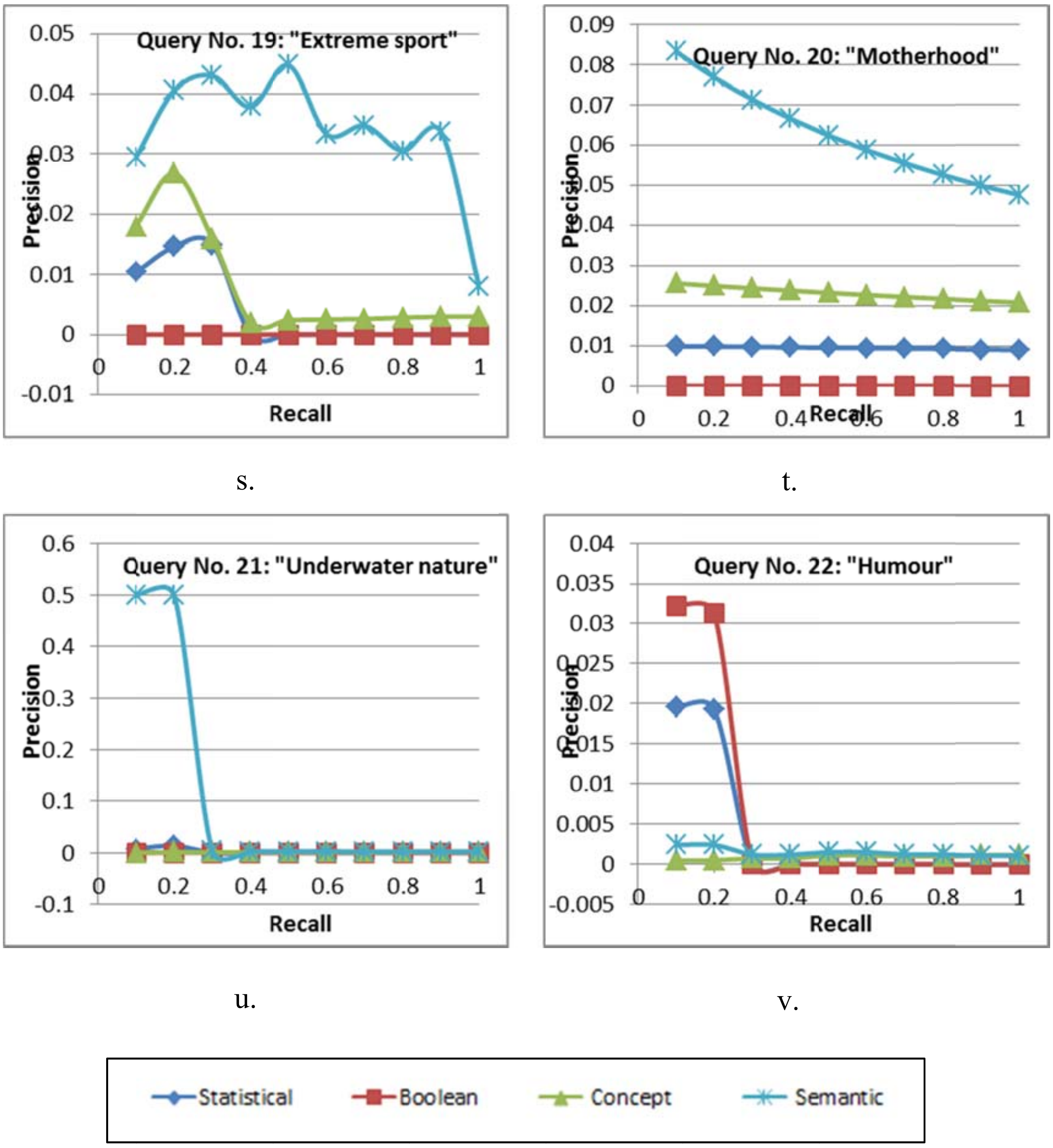


Figure D1: 11 Point Precision Curve for 22 Queries (cont.)

Table D3: Mood Boards Evaluation Results for 18 HITs

No.	Query	Search Approach	Assignment ID	Worker ID	Score	Average Score
1	Query#1: Animal Kingdom	Semantic	2A4OK2JE1M7PQLVPJCXO4AC0UJ1OVI	A7D1H4VPXC7ZF	2	1.800
			2RHCGJ2D21O326JLSZGPXI2KOCO6C9	A2KLFKJN8HXJNH	1	
			2BHC6SK9RJ85U0436XDAFPMOL2G4SR	A2BI0G8P431TC2	2	
			2C21QP6AUC26JHSB5HO300FKXRO186	AC6N8HLI4U6QF	1	
			2QCPEIB9BAWLYNJTILMXZD3MQ5FY13	A2MT0WWJR23AGG	2	
			2RAT3HVWAVKIC39NIIS77Z99NXINFV	AK3VHG2BRSU0C	1	
			2Z1746OQ1SNQW8CAZGW1VKCNODEO4F	A306HC0URZ6OA1	1	
			2NE25L8I9NZWCI03Y454VW7TY4FTJS	A18W2S7YB1AIBE	3	
			2IDZ6R70G5R9EEUNVB571SSTDWNP9T	A25IZ3RNI29888	2	
			2KNKI62NJQ21D3LD1686GKLCLCAMU9	A3S955BFH34EF8	3	
			2HYO33FDEY5CUXMP87Q3DCRFBA2R0W	A15ANKO1BDNEN8	1	
			2UEN9U8P9Y38ZXI1AJJU3IM09RCWFE	A3IMDT7LJKPJPA	2	
			218NTBJ3MMDXBGBBFMTKMB9MA9JBXW	A3AN3E12I4IUGJ	2	
			2IPMB3Q39Z0BCVFSY9VE0STVOZAUJD	A2G9FWWWUODHXQ	2	
			2OJ9Y8TNKIMZYNRO7XJ2TM0PDBK9W9	AF5VW5OWVL8FO	2	
			2UU74J79KQW67998YAOFHD45URNJHG	A300QFTE9ETH4Q	2	
			2Y3DDP8PJWKUJEU1ERUQ89Z08I06HO	AO6K9SJGX7C0T	1	
			2C521O3W5XH0PQBWAIBYJPLSGJ1BHY	AHC2OX7HXE231	3	
			25OAVKI62NJQ82T6RP0QM6BKCOOKS9	A23U4SG2PC5KE5	2	
			2X2B6BFMFFOY4JF5LZ6DLESCRWLKXY	AEZT1RZZ1MVF7	1	
2	Query#1: Animal Kingdom	Statistical	2QFTBJ3MMDX5LQTRYIBHG9MDO09YCM	AHC2OX7HXE231	1	0.750
			2QXR98D8J3VEDXEWL3PCL3MCBLAWG6	A44FN6RMB8TRF	1	
			20N66RLPHIT3NWIEN0967NJQZDY8GY	A3AG698KLBMRP5	2	
			2GT8N46UXFCDA6JG69EDXNTKFZKTRU	A300QFTE9ETH4Q	1	
			2LUYU98JHSTLH4747RA9NOBJBV0DPV	A1G08QM9J5GZO6	0	
			2N867D1X3V0FQ1YSCIAE6M7PHZHJC6	A22YE5YXKM2GBF	0	
			2PD42J1LY58BD3TQSY7FPHD13DS5QG	A2NM8E7WLIGUCV	0	
			2QXR98D8J3VEDXEWL3PCL3MCA5UWGT	AEZT1RZZ1MVF7	1	
			2XKSCXKNQY2RIK6AVFME8HR0AR4P0Q	A1SY0N7JME6SC7	1	
			2XM8LZ6R70G5XAUH0ZUVJ7WSIRN7NS	AMRQ9K3U65CTS	1	
			2BP3V0FK0COK8K05ENGKP9LRM43OH5	A2BI0G8P431TC2	0	
			2TZ9KQW618N4CVJJ4TV52CETDARLNC	A2MCC5CA9D7N3A	0	
			20H6AUC26DG6DEN1VBRFP0COHGAB4H	A18Q96TEN80REC	1	
			21KQV66RLPHIZ43ZOQMKN62NG5DE6R	A2Y5R1GFHV4DEG	1	
			23D0XULRGNTBP48Q5DWFU7N6ZWBR5E	AF73ONXD9O6HZ	1	
			28IS1CSTMOFXXEE8ASSE3DNXGRQORQ	A5E7JSX72SKGE	1	
			2JJNDWIOV1S7YOPHLWL18YDZ52HIXW	A16ILUTZ8BE7WB	1	
			21ALKH1Q6SVQEIUCE6L6Q5OBLBI1KM	A10P6VTBVDKJTT	1	
			26B5OPB0YVGZEZ803N5PEU31S5TZ7Z	AH038P14MJ1EU	1	
			26TVP9746OQ1YOCUZ6X7551QAA4L1O	A1116GG1MBIU71	0	
3	Query#1: Animal Kingdom	Concept	2I64BLYHVI44UTOODAZDSEZS18N1V4	A3S955BFH34EF8	0	1.750
			2ZO1INMHGYQ4P49E3M2FRFFOOVEK7U	A2NM8E7WLIGUCV	1	
			27VYOCCF0CP5QYBXA39I2YG4M0QUT5	A1J1RGZABQBPJZ	1	
			28U4E6AUBXHWYITJDP0VGZWDO1H1X0	A3T1PUGNW4UK4N	2	
			2C521O3W5XH0PQBWAIBYJPLSMMGHBV	A3JNPURAYDDHDY	2	
			2J0D8J3VE7WSYU924WUMHK8AQGRJZR	A398ZCA9UAU6V6	1	
			2XKSCXKNQY2RIK6AVFME8HR0HAC0PI	AMRQ9K3U65CTS	1	
			29CPFE4EGDHDS3RP0Y0N4W6H4XI9JE	A22YE5YXKM2GBF	3	
			2BUA1QP6AUC2CE2AZTSX8V0FAX5708	A2BI0G8P431TC2	1	
			26Y18N46UXFCJ5R14UKNISNTAG5SQ5	A2Q3QHPDONSS6F	2	
			2CQU98JHSTLB9MMJ3Z0ITBJE9OCEQ4	A2WSVMZ3C1N6BD	2	
			2MGK2JE1M7PKQA7VOMFZFC04C3FWPA	AHJRFFJD507UF	3	
			22O6NG1FS3NYTKX27H6ZXZL2U6BLZC	AF5VW5OWVL8FO	3	
			24S0OQKKA4IIY9E6MIX85EW09GPZZH	A18Q96TEN80REC	1	
			24VK4F0OHOVR7541C4TLE2HE9AP239	AYK1Q1LNO2XHJ	3	
			2MTPC6SK9RJ8BPLMRU8MFAPML0H3RX	A2IJQ910MA8J2E	2	
			2ORZ2MIKMN9UEQV2VOKW1XI3PBZ9Q3	A2G9FWWWUODHXQ	2	

			2MU6DG67D1X3111OSSFK7JE1DKQ9GU	AF0Y0VZN23JUY	2	
			2RQ5PQJQ9OPLRYYBM2IXL8KCFCO0Y9	A1UUKNACEVG6UB	2	
			2WEEGOOGQSCMCJWEU85IZUU0R0PEEO	AC6N8HLI4U6QF	1	
4	Query#2: Lovely Flora	Semantic	240LZ6R70G5RF9ZCBJMECWSSK0YO86	AO6K9SJGX7C0T	1	2.050
			2Y3DDP8PJWKUJEU1ERUQ89Z02JX6HH	A1DFIADXABLBPN	1	
			22NQ8H88MQU6R6AFNS91WXX47XIS95	A2Y5R1GFHV4DEG	2	
			25J14IXKO2L98I0GOQXX8YOC9VJCBR	AHC2OX7HXE231	1	
			2CTO3W5XH0JPVT46CE5PQSP72ZWDJ3	A17RUJ214A3AWN	3	
			2DC4F0OHOVR1AJJOGIC97HECTMT34A	A23U4SG2PC5KE5	2	
			2VR6R70G5R98J957NUYWXSTNVRLQAZ	A2X3HFZ35GKOII	2	
			2L2T2D5NQYN5L4C4BWWT3MNCMWO59P	AF73ONXD9O6HZ	2	
			2OJ9Y8TNKIMZYNRO7XJ2TM0P6TJ9W1	A7D1H4VPXC7ZF	1	
			2PQQS1CSTMOF3SZWWY31JYDNNHXQNR	A5E7JSX72SKGE	2	
			2OAUUU00OQKKG54MKOJ2Z268QC8VV1	A2ZJ898N5IJYMO	3	
			2JJJ85OZIZEHSBWTE4FQAEWPNJXYA0	A2KK8VM86E3UQW	2	
			29PR24SMEZZ2SJ6QFPL8U9Y35882JK	A15ANKO1BDNEN8	3	
			2BP3V0FK0COK8K05ENGKP9LRTM6OHF	A3AN3E12I4IUGJ	3	
			2J0JHSTLB3L0LC5DA42JJJRESTRHTW	AIQWN1SGOUJ6	2	
			2KRHHRRLFQ0OTOHV9HBHT9EGOVJPG0	A1116GG1MBIU71	3	
			2LDYHVI44OS2QMGC535ZXBAP2PX4YU	A24JL7C6E9MX51	1	
			20QN5F3Q0JG5ZZ8R4CPB99F9IQVCGL	AFJB1LH7M8SO4	3	
			2CJCJK63ZVE3NSMOMY1QEJL5H1Y9YF	A1G08QM9J5GZO6	2	
			2GUNJQ2172Z9FR3A30CC0EBUR1VQYB	A306HC0URZ6OA1	2	
5	Query#2: Lovely Flora	Statistical	2E3LYHVI44OS8L7Y0TEE4SBAF3N3XF	A44FN6RMB8TRF	1	2.250
			28M98JHSTLB3R11FBP9OGJEJHCYFRV	AB1W5B83KF3FD	2	
			21A8IUB2YU98PIEXDRUL5FBJ6X08KS	A3IMDT7LJKPJPA	3	
			21Z0G5R98D8J9W0BO8JTSYCG01LDT6	A1SY0N7JME6SC7	2	
			2AJYNJ92NJKM66XQB9LH3W2GQ13C78	AH038P14MJ1EU	3	
			2R5M25L8I9NZ273IRMFE9QW7QKYSIB	A11ZSP12IL64Y2	1	
			2REVHVKCJ011Q3T8BN0KVW6153I86R	A10P6VTBVDKJTT	3	
			2ZNH8MZ9O9Z6QXQ3EQQHMRRL63209J	AFWRXDL606HXQ	3	
			280TNKIMZSM5QG3WU4D0UGVFUVOZCR	A3AG698KLBMRP5	3	
			2ME6IAA2SEIU0VM4G6BKF4IIJLUNNG	A2MT0WWJR23AGG	3	
			25H3TVOK5UFJB2KBIUFZKYQSSPV74V	A16ILUTZ8BE7WB	2	
			28F5F3Q0JG5T4N9GOE24EF9SJYKDH2	A2JBJFPFG38X9C	2	
			2JJJ85OZIZEHSBWTE4FQAEWPU04YAC	AKEHUNKIP6Z7H	3	
			2V0I9NZW6HEZCP08ICYTD69GR0PXN3	A2Z9Q0S26PD3ZA	2	
			2XW6UXFCD45XIFFR58ETPIN3QUJUW6	AEZT1RZZ1MVF7	2	
			2Y7XRDS4IC1E4E91BVD16A2ISARZWP	A24SW93LNM8SF6	3	
			2YNR14IXKO2LF33I4C1623YO9ROABB	AK3VHG2BRSU0C	2	
			2HOGKCCVLL3CG4PQ9QGQ9C9NGS46WG	A25IZ3RNI29888	2	
			2TLUHYW2GTP9XBTWXCD1B9YSEC1MRY	A221V2JZSDB43Z	1	
			23QMNCWYB49FFTEW9DS1OONSJ3FNR5	A14VMU3MLKSTRE	2	
6	Query#2: Lovely Flora	Concept	20QN5F3Q0JG5ZZ8R4CPB99F9IQCGC6	A221V2JZSDB43Z	1	1.350
			2C521O3W5XH0PQBWAIBYJPLSF44HBC	A398ZCA9UAU6V6	1	
			27CO2L92HECWG7J7Q43CK0CP2Y5HG7	A1VD4UUXM6DQ6Y	2	
			2GJ70G5R98D8P4HIZCJSYNYCDJWCSJ	A3IMDT7LJKPJPA	1	
			2MU6DG67D1X3111OSSFK7JE1JLN9GZ	A11TW6QSBFXTPF	1	
			2RNWAVKI62NJW3NBUF09VH6BHZ0RJY	A23U4SG2PC5KE5	1	
			2S20RYNJ92NJQNM932ATZHYWZV55A8	A10P6VTBVDKJTT	2	
			2NAPDOBDDP8PPX6Y5TZXRB3QT7ED2F	A1DFIADXABLBPN	1	
			2UG2L92HECWACYP2GS3F5CP5AU7IH5	A2JBJFPFG38X9C	2	
			2IAUB2YU98JHYU7FV1RFGJ9IE9MAMP	A7D1H4VPXC7ZF	2	
			2PV95SW6NG1FY492FZ2YK1FZIXJHVJ	A2NM8E7WLIGUCV	1	
			2RKTLB3L0FBJFJAFBUARJVE5HNYKW9	A2ZJ898N5IJYMO	2	
			20SJG5TYMNCW4CQD7PJSXHX1YXAIMN	A44FN6RMB8TRF	1	
			27MLRGNTBJ3MSEJ975YNB2KH8L9U8G	AF5VW5OWVL8FO	1	
			2BPERSQV66RLVI4XVXMWFVKI3HO3B0	A3AN3E12I4IUGJ	2	
			2GJ70G5R98D8P4HIZCJSYNYCDIWSCX	A2MT0WWJR23AGG	1	
			2LJI8IUB2YU9EK3WL123Q0FBGN27JB	A1SY0N7JME6SC7	2	
			2626X3YOCCF0IQROP5KISIIXPJ0QR4	A3T1PUGNW4UK4N	2	
			26W0SPW1INMHMZC8BJEAG6BFCDRG30	A2KLFKJN8HXJNH	1	
			2YV3FDEY5COW6M2VRJZCWFLCWT4T2G	A18Q96TEN80REC	0	

7	Query#3: High Land	Semantic	262VKI62NJQ278O31PHHBBKL2THTLR	A22YE5YXKM2GBF	3	2.150
			2PVQ0JG5TYMNIXKFWP69XSSHNZ3GK1	A2IJQ910MA8J2E	2	
			26B5OPB0YVGZEZ803N5PEU31ZM67ZP	A2Q3QHPDONSS6F	1	
			2E70OHOVR14I3LA6DPTHJCWA39S65Q	A23T87JDC2TU1D	2	
			2E70OHOVR14I3LA6DPTHJCWA3BS65U	A2G9FWWWUODHXQ	2	
			2YMQIHPCGJ2D82A7OLOH5JPPPXB823	A1116GG1MBIU71	3	
			2Z5OBDDP8PJWQVZH0DDB8Q39WFN4FF	AH038P14MJ1EU	2	
			24DF395SW6NG7GE7FEEJGYF15XETF5	A1J1RGZABQBPJZ	2	
			2BLHV8ER9Y8TTL4QR8D5PFHSSMPR4J	A2BI0G8P431TC2	1	
			2MYSK9RJ85OZO00LEQ1PROOQVCC6U0	A18W2S7YB1AIBE	2	
			2TCM05BMJTUH4XOKL50RF7S5MKDFKB	A15ANKO1BDNEN8	2	
			23YS8SV7WGKCIW7PVS138MHAFO6Q00	AHC2OX7HXE231	2	
			218NTBJ3MMDXBGBBFMTKMB9MADRBXC	A2Z9Q0S26PD3ZA	2	
			2I6BDPGFL6VCVXLDJ34WNOV1PJ1J4O	A5E7JSX72SKGE	3	
			2SPKO2L92HEC2BS1VEFCHF0CMHQGF2	A306HC0URZ6OA1	3	
			2WGFXRDS4IC1KZZRPZ6M61A2FA6VYB	AF73ONXD9O6HZ	2	
			2YNR14IXKO2LF33I4C1623YO9SYABN	A3S955BFH34EF8	3	
			2Y8QSCM6IAA2YF4YMAR0TQKK02VJJK	AYK1Q1LNO2XHJ	2	
			2C2OO2GMMEGOUHCW42XIFA2S4GV88T	A2MCC5CA9D7N3A	1	
			2ZOZ9RNDWIOV7TTWFJ4TLU13OBLFUI	AFJB1LH7M8SO4	3	
8	Query#3: High Land	Statistical	2N5P8PJWKUDDEY8FV6U940B6KRLJ8K	AKEHUNKIP6Z7H	1	0.950
			2RX7DZKPFE4EME3HEIWLDI9NPU85F6	AK3VHG2BRSU0C	0	
			240Y1THV8ER949FRCYDZXM5KCWKO1O	A25IZ3RNI29888	1	
			28URCJK63ZVE9ID4CA9AV9JL25KX89	AB1W5B83KF3FD	2	
			2CZ4J79KQW61EOQAMD6CI45X9QKIKJ	A2Y5R1GFHV4DEG	1	
			2IA9NZW6HEZ6UFQUONK8B9GUJI4YO9	A2X3HFZ35GKOII	1	
			2UHFE4EGDHDM867CAPEZ16HEWLYKA6	A3AG698KLBMRP5	0	
			2598MZ9O9Z6K25LQ2F8HWRLFHDQA1B	AC6N8HLI4U6QF	0	
			2TEJUNU8LZ6RD129JPZDDJ3V5KZJ3T	A6NLMZ3GJGQ9R	1	
			21A8IUB2YU98PIEXDRUL5FBJ0VPK8J	A2KK8VM86E3UQW	2	
			254NHMVHVKCJ62NOUNVJC9KQNIW35H	A3JNPURAYDDHDY	1	
			2GUNJQ2172Z9FR3A30CC0EBUSGLYQ4	AF0Y0VZN23JUY	1	
			20W5UUKQOYGNOXNRKOFG5107PBUFX9	AFWRXDL606HXQ	1	
			2FPH0JPPSI2K4FBPK5Y5PLM6TVSIO1	A17RUJ214A3AWN	1	
			2GJLPHIT3HVWGW6MYIEJV217ZE4JBM	A14VMU3MLKSTRE	1	
			2JM8P9Y38TWW3JPWME9M5JTAD2HZIC	A2WSVMZ3C1N6BD	1	
			2SL3HVWAVKI68O5UUHY2499QEIZGO6	AHJRFFJD507UF	1	
			20I7Q67051QKIOD5U9HC6XMG8Y7YE7	A24SW93LNM8SF6	1	
			2QFTBJ3MMDX5LQTRYIBHG9MDNMVCYT	A1UUKNACEVG6UB	1	
			2BNP9746OQ1STRCBIMY0A1QK2LMM2M	AO6K9SJGX7C0T	1	
9	Query#3: High Land	Concept	2ABG5TYMNCWYH5VJ18JSMX119MMNJE	AK3VHG2BRSU0C	1	1.000
			2IBVCNHMVHVKIKM5T0T79J79AOY31D	AO6K9SJGX7C0T	0	
			2C5IPDOBDDP8VKIOMT482MB3NFL1CI	A23U4SG2PC5KE5	1	
			2CYDG67D1X3V6G6444B2OE1M453AH3	A5E7JSX72SKGE	1	
			2K5ZXR24SMEZ538MC2E9Z8P9VFZH0J	A11ZSP12IL64Y2	2	
			2QCCCVLL3CA39N3EH6VCENQU4C7Y8B	A17RUJ214A3AWN	1	
			2RX7DZKPFE4EME3HEIWLDI9NWB85FB	A1UUKNACEVG6UB	0	
			24DF395SW6NG7GE7FEEJGYF15XTFT6	AEZT1RZZ1MVF7	1	
			2OJSQV66RLPHOUPLNC1VPI62DHVD56	A23T87JDC2TU1D	1	
			2NXNQYN5F3Q0PHRXQ2EC1YB4ZDY9DD	A2MCC5CA9D7N3A	1	
			2SPKO2L92HEC2BS1VEFCHF0CF3LGFY	AYK1Q1LNO2XHJ	2	
			2418JHSTLB3L6GXN1YFBOEJR4TGGSI	AB1W5B83KF3FD	1	
			254PWZ9RNDWIUWNWZ8E3ITGUYI6DSG	A3ODLQAZAKMK6H	1	
			2CJCJK63ZVE3NSMOMY1QEJL5OHY9YI	AC6N8HLI4U6QF	2	
			2D7DEY5COW0LMSL70SIFQC6VK6NV40	A2Z9Q0S26PD3ZA	1	
			2FMFJ51Y7QEO5GKUKH3SYMOFU5WBEF	A2G9FWWWUODHXQ	0	
			2HYO33FDEY5CUXMP87Q3DCRFIRGR0F	A16ILUTZ8BE7WB	1	
			2N9DM25L8I9N5XSL6FXOJ4QWXRJRHD	A11TW6QSBFXTPF	1	
			25Y6RLPHIT3H1XWZCYX2SJQ2R55H98	A22YE5YXKM2GBF	1	
			2HW6OQ1SNQQ7W7T4XHHKHNR1SR26QR	AF73ONXD9O6HZ	1	
10	Query#4: Country Terrain	Semantic	2W2ZHHRRLFQ0UO9ZJXSKMO9E6PTOFA	AFJB1LH7M8SO4	1	0.900
			2N9DM25L8I9N5XSL6FXOJ4QWXQ6HRO	AMRQ9K3U65CTS	1	
			21QNJ92NJKM0BC8NLA8Y12GTMQWD8H	A2Y5R1GFHV4DEG	1	

			291RNDWIOV1SDT97597U63YDWKSHWZ	A1G08QM9J5GZO6	2	
			2AXBMJTUHYW2MUBDJQYSAWM13O3NID	A306HC0URZ6OA1	1	
			2I0MQU6L5OBVIJNVPDVANJF7D99XE1	A15ANKO1BDNEN8	1	
			2YV3FDEY5COW6M2VRJZCWFLC379T2K	A25IZ3RNI29888	1	
			2QXR98D8J3VEDXEWL3PCL3MCBK4WGY	AF0Y0VZN23JUY	1	
			2YC2JE1M7PKKFMD0Y4QAH04LQ2DXQ3	AH038P14MJ1EU	1	
			28X8B727M0IGLL3HTMPFXVF4MUGCXV	AHJRFFJD507UF	1	
			26CUDD8XMB3Q9AL43MLTT6T457KPED	AF5VW5OWVL8FO	0	
			24VK4F0OHOVR7541C4TLE2HE39X239	A3T1PUGNW4UK4N	1	
			29YR70G5R98DEKPZ6NNSXTNY9UMBRS	A3S955BFH34EF8	1	
			2CXL8I9NZW6HK0SS6KHWCT866UJLVO	AIQWN1SGOUJ6	1	
			2ESSPW1INMHG4RQNV31BBBFMCRUH4E	A1DFIADXABLBPN	1	
			2MU6DG67D1X3111OSSFK7JE1JJ8G9N	A2KLFKJN8HXJNH	0	
			2XLL0XULRGNTHKPQETO5KP7N3HU4Q7	A3AN3E12I4IUGJ	0	
			268KCCVLL3CA948L25H4H9NQK5E7XT	A2BI0G8P431TC2	1	
			2EXUUKQOYGNI229W0470607SLEVYGX	A2MT0WWJR23AGG	1	
			2QB2D21O3W5XN15TH892PYEPBQ29FC	A14VMU3MLKSTRE	1	
11	Query#4: Country Terrain	Statistical	20I7Q67051QKIOD5U9HC6XMG8YYEYE	A1116GG1MBIU71	2	1.900
			2TVNAB6BFMFFUZKMLHKJKDGEIAYIVD	A18W2S7YB1AIBE	2	
			20YSVQ8H88MQ0779GRMCN1RXUJIQ7B	A2JBJFPFG38X9C	1	
			2CBENLVWJ5OPH1KZ8FZYRWB7B10T18	A2NM8E7WLIGUCV	3	
			2DGU3K4F0OHO1SN8ADBO7L92ETL10S	A2WSVMZ3C1N6BD	2	
			2E1F9SSSHX11PP9WLL85K8J4L30ZVU	A1SY0N7JME6SC7	1	
			2Y9OVR14IXKO8MV69U3WF6X3V2W894	AKEHUNKIP6Z7H	2	
			2OQ5COW0LGRZ99YV71360NUZNQU7YG	A24SW93LNM8SF6	2	
			2H957DZKPFE4KHZL52T5Q8I9EBP4E2	A44FN6RMB8TRF	1	
			2W6ZZ2MIKMN909BDQJZT1WXIU4TP8L	A1VD4UUXM6DQ6Y	3	
			2NHGFL6VCPWZFS9HOYFV6S7SEFCM7Z	A2ZJ898N5IJYMO	2	
			2MHWZ9RNDWIO12EBK3UDYGU1UBFETJ	A221V2JZSDB43Z	1	
			21U4SMEZZ2MIQN9DMOG9338TTFVL4V	A1J1RGZABQBPJZ	2	
			223RI8IUB2YUF95LK9CB8L0F80R6I3	A300QFTE9ETH4Q	2	
			28349F9SSSHX725SF8K5M5F8GN8XTB	A24JL7C6E9MX51	1	
			29PR24SMEZZ2SJ6QFPL8U9Y357IJ29	A398ZCA9UAU6V6	2	
			2BIP6AUC26DGC8Z5PJM0KK0CL0JA3U	A10P6VTBVDKJTT	3	
			2LSHFL42J1LYB9XBUND0NGFK8QP2NQ	A3AG698KLBMRP5	3	
			2ESSPW1INMHG4RQNV31BBBFM6RHH4V	A2Q3QHPDONSS6F	2	
			2XIYN5F3Q0JGBUKQFSNYG49F04RFB7	A18Q96TEN80REC	1	
12	Query#4: Country Terrain	Concept	2OQ5COW0LGRZ99YV71360NUZNPQ7YA	A18Q96TEN80REC	1	1.450
			2CQU98JHSTLB9MMJ3Z0ITBJEAWCEQL	AHJRFFJD507UF	1	
			20Q2RCJK63ZVK43VS0LIFQ9JILL7WK	AMRQ9K3U65CTS	2	
			25PX2Q45UUKQUZ2RACSNX8OGXD3TB3	A23T87JDC2TU1D	1	
			2SFMHGYQ4J3NGCSF726FTYYIQI3AN5	AO6K9SJGX7C0T	2	
			2VJGNTBJ3MMD361TZ3X2PHB9JS7AWS	AEZT1RZZ1MVF7	3	
			2YGGQSCM6IAA8T0MMAL05OQKHPEIIX	A1J1RGZABQBPJZ	1	
			24DF395SW6NG7GE7FEEJGYF16CTTFF	A10P6VTBVDKJTT	1	
			2D7DEY5COW0LMSL70SIFQC6VE714VJ	A2G9FWWWUODHXQ	2	
			2K5ZXR24SMEZ538MC2E9Z8P9PF6H0K	A398ZCA9UAU6V6	1	
			2YFNVRH1KHO9KHDFZMEVELKWYAOQZM	A18W2S7YB1AIBE	1	
			273AT2D5NQYNBGPUSZ75YYMN38S848	A2IJQ910MA8J2E	1	
			2EB3NAB6BFMFLPK2A9STOFDGB60HUN	AC6N8HLI4U6QF	1	
			2FTY7QEOZFYQY2YWL2FF2RDS1U4IFI	AIQWN1SGOUJ6	2	
			2RGVR14IXKO2RAOL6SNABX3YLOH9AQ	A24JL7C6E9MX51	1	
			2S1NZW6HEZ6OK5C0Z9Z6EGUMZG9PZB	AKEHUNKIP6Z7H	2	
			2WNHVKCJ011K88QNZPBQ1618KI379T	AB1W5B83KF3FD	1	
			262VKI62NJQ278O31PHHBBKL30YLTF	A3AN3E12I4IUGJ	2	
			2BP3V0FK0COK8K05ENGKP9LRNIMHOA	A1SY0N7JME6SC7	1	
			2IS6UFBNFSVG0M171LJWBNG164YI4R	A1G08QM9J5GZO6	2	
13	Query#5: Travel and Tour	Semantic	223RI8IUB2YUF95LK9CB8L0F2OY6IG	A3AG698KLBMRP5	2	2.150
			2GUNJQ2172Z9FR3A30CC0EBUSFGQYP	A17RUJ214A3AWN	3	
			27CNQY2RCJK690HIVXI0PUIANNFT4U	A2JBJFPFG38X9C	2	
			2AGHOVR14IXKU37DUX5C1A6X0CB78U	A2NM8E7WLIGUCV	3	
			2C9ECWA6X3YOID1445WK2PTIKUPMNO	A44FN6RMB8TRF	2	
			2D9VWAVKI62NPRO5ZIQ9EQH68XHIQI	A1116GG1MBIU71	3	

			2QMLF395SW6NM21WV3PNOBYFYU7SEO	A11ZSP12IL64Y2	2	
			2WNHVKCJ011K88QNZPBQ1618EH979R	A6NLMZ3GJGQ9R	3	
			22KCXKNQY2RCPLS7RB53MR0KLN8Q1E	A3ODLQAZAKMK6H	1	
			2LDYHVI44OS2QMGC535ZXBAPWNVY4C	A11TW6QSBFXTPF	2	
			2IBIA0RYNJ92TK6QSL2MOTUHP9438S	A2X3HFZ35GKOII	3	
			2MHWZ9RNDWIO12EBK3UDYGU1UACETE	AHC2OX7HXE231	1	
			24QT3DHJHP4BJE6KWEZRXX9X0X62V0	AFWRXDL606HXQ	3	
			2DLVOK5UFJ5148CIGF6YVS1CP8E69Q	A221V2JZSDB43Z	3	
			2DQOCCF0CP5K3QFMFY9X3G4PJJGUVR	A1UUKNACEVG6UB	2	
			2P64EGDHDM25R94DFFN6MEZ6LT1MC2	AFJB1LH7M8SO4	2	
			2Y4CF0CP5KXPZJ9MADPG9PM7KAVWXR	AF0Y0VZN23JUY	2	
			2KSRYNJ92NJKS1RFEZKUMYW27WLB6F	A1VD4UUXM6DQ6Y	2	
			2WL6YTWX4H3H8QX85P0GN6IJH943Y8	A23U4SG2PC5KE5	1	
			2C5IPDOBDDP8VKIOMT482MB3G1UC13	A2MCC5CA9D7N3A	1	
14	Query#5: Travel and Tour	Statistical	22OSV7WGKCCVRMPG2JUMMAPQUA6S26	A3JNPURAYDDHDY	1	0.850
			2VQ58B727M0IMG6L5HXYKSVFUTKWBW	A2Z9Q0S26PD3ZA	1	
			20M8Y1THV8ERFZUXF09M4SM5HZYN04	A14VMU3MLKSTRE	1	
			28GCCF0CP5KXVU4RAYOYL4PM439VWH	A16ILUTZ8BE7WB	1	
			2KNKI62NJQ21D3LD1686GKLCSXWUMG	AF5VW5OWVL8FO	1	
			2WGFXRDS4IC1KZZRPZ6M61A2FC6VYF	AF73ONXD9O6HZ	1	
			2WS5BMJTUHYW8HFT1717X5WMYIDMHC	A306HC0URZ6OA1	0	
			27P2Q45UUKQO4H9MOHESDOG0SD7UCV	AYK1Q1LNO2XHJ	1	
			2C2OO2GMMEGOUHCW42XIFA2S5NJ88W	A2Q3QHPDONSS6F	1	
			27J24SMEZZ2MOL8R1AZPEY38K9I3KV	AH038P14MJ1EU	0	
			2W6ZZ2MIKMN909BDQJZT1WXIU5VP8P	A2KLFKJN8HXJNH	1	
			2NUAC9KSSZVX33C8XALKVOYGENI2K3	A5E7JSX72SKGE	0	
			20SONNVRH1KHUA0KJRY6SV9LHBFXO5	A15ANKO1BDNEN8	1	
			2QO40SPW1INMNHKUWZUNFB6BC0BF2C	A2KK8VM86E3UQW	1	
			2RQW2GTP9RA7Y6IQTM0YXOF7XXGUPB	A7D1H4VPXC7ZF	1	
			2U1RJ85OZIZENNWEH2FOV5EWMBBX97	A24SW93LNM8SF6	1	
			2WR9O9Z6KW4ZSBLL97ILKQ0OKZ24DT	A3T1PUGNW4UK4N	1	
			2TEJUNU8LZ6RD129JPZDDJ3V45K3J3	A2BI0G8P431TC2	1	
			2YUL92HECWA634KS4S60HP5KNNVJIX	A3IMDT7LJKPJPA	1	
			224M6IAA2SEI0VG4S4HKPA4I8QDMMN	A2Y5R1GFHV4DEG	1	
15	Query#5: Travel and Tour	Concept	2DI39Z0B6UTOCUQIN8KVWKGPMQZNYC	AF73ONXD9O6HZ	3	2.050
			2K22SEIUUU00UR6O2K9IX8S2K0ZRRS	A2WSVMZ3C1N6BD	2	
			240LZ6R70G5RF9ZCBJMECWSSQ1ZO8F	AB1W5B83KF3FD	1	
			244F806UFBNFYW2YDVU9ASW6KSP1F5	A17RUJ214A3AWN	2	
			249YW2GTP9RADTR0EHX93SOF4E6OTQ	AF5VW5OWVL8FO	1	
			28X8B727M0IGLL3HTMPFXVF4SUDCXY	A25IZ3RNI29888	3	
			2XLL0XULRGNTHKPQETO5KP7N3HW4Q9	A2KK8VM86E3UQW	1	
			27MYT3DHJHP4HEZO8KP8WSX9OFEU11	A2Q3QHPDONSS6F	2	
			2TUD21O3W5XH6KBTKYTK3EPLJ12GA8	A3AG698KLBMRP5	2	
			2C2ESCWY2AOO8H8Q6WFOLQSCDJI11C	A14VMU3MLKSTRE	1	
			2DI0JG5TYMNC2ZX81V0SXSHXSDEHLQ	AYK1Q1LNO2XHJ	3	
			2T12NJKM05BMPUGLQCTGYP9R1KTGBB	A1116GG1MBIU71	2	
			2DGH1XERSQV6CS7T9YK3MVWAS0L80F	A11ZSP12IL64Y2	3	
			2DGU3K4F0OHO1SN8ADBO7L92EQ0010	A18Q96TEN80REC	2	
			2IHJWKUDD8XMH4C71FRBBUTO3CPBMG	AFWRXDL606HXQ	2	
			2K22SEIUUU00UR6O2K9IX8S2RHERRC	AO6K9SJGX7C0T	1	
			2SSOUQIHPCGJ8EO5GJN52H0JM4S06G	A24JL7C6E9MX51	3	
			2IBIA0RYNJ92TK6QSL2MOTUHOU4832	A23U4SG2PC5KE5	3	
			240Y1THV8ER949FRCYDZXM5K5FBO1A	A7D1H4VPXC7ZF	2	
			20O618N46UXFIEQ9PS5TSDSNJIIRP7	A300QFTE9ETH4Q	2	
16	Query#6: Motor Sport Racing	Semantic	25Y6RLPHIT3H1XWZCYX2SJQ2R50H93	A18W2S7YB1AIBE	2	2.200
			2S9PCGJ2D21O9XR19GAPUSI2AWAB5O	AKEHUNKIP6Z7H	3	
			29B51RYQM3ELWO8GIOKGZFTER7H0ZX	A15ANKO1BDNEN8	2	
			2BANMHGYQ4J3TBXA3VDFKOYYF589MC	AEZT1RZZ1MVF7	2	
			2H51X3V0FK0CULON6HD7UKK9I3KMFY	A2Y5R1GFHV4DEG	1	
			2LJI8IUB2YU9EK3WL123Q0FBGOP7J0	A306HC0URZ6OA1	2	
			2MOYB49F9SSSNYN5B4ESY5H5CM8RVK	A398ZCA9UAU6V6	2	
			2NRXR24SMEZZ8N4OE30UDP9YT6T1I9	A5E7JSX72SKGE	2	
			2Z9IT3HVWAVKO7ORB6T1C2Z9ZO4EM8	A2Z9Q0S26PD3ZA	3	

			28SLWSBRI8IUH3KY1OAHXTLBTJVE2P	A1J1RGZABQBPJZ	2	
			2R8YQ4J3NAB6HG8J74PYNT1T9DQQD4	A24SW93LNM8SF6	3	
			2DI0JG5TYMNC2ZX81V0SXSHXRZKHL3	AMRQ9K3U65CTS	2	
			22RVXX2Q45UUQRA2839W6NS8LSUR95	A3AN3E12I4IUGJ	2	
			25PX2Q45UUKQUZ2RACSNX8OGXHUBTK	A16ILUTZ8BE7WB	3	
			277B0HFL42J1RZRC3NT7R0IGC4X0LE	A2BI0G8P431TC2	1	
			2BC274J79KQWC2URWMLXKCD4292IGF	A2X3HFZ35GKOII	3	
			2UUJE1M7PKK9RSIAGF1C54LZU30YRQ	A1UUKNACEVG6UB	2	
			29YKW4ZMAZHHXS7JIGFNSVRHRIJ9IS	A11TW6QSBFXTPF	3	
			2IPMB3Q39Z0BCVFSY9VE0STVHIWJUJ	A3ODLQAZAKMK6H	3	
			21ALKH1Q6SVQEIUCE6L6Q5OBL92K1L	A6NLMZ3GJGQ9R	1	
17	Query#6: Motor Sport Racing	Statistical	291O9Z6KW4ZMG03LJ7CFV0ONDTTE5X	A3IMDT7LJKPJPA	1	1.000
			2MOA6X3YOCCF6DB9CDGTNNIINW3QPS	A1DFIADXABLBPN	1	
			2418JHSTLB3L6GXN1YFBOEJRBBFGSO	AK3VHG2BRSU0C	2	
			2GK8SV7WGKCC1M774QU3RHAPNGM1RM	A44FN6RMB8TRF	1	
			2TTLY58B727M6J2JCX41BYFSSRC9U5	A2NM8E7WLIGUCV	1	
			2YC2JE1M7PKKFMD0Y4QAH04LWCYXQE	A2JBJFPFG38X9C	1	
			2Z0JVCNHMVHVQD54THB2C4J76WL20Q	A1SY0N7JME6SC7	1	
			2R5M25L8I9NZ273IRMFE9QW7KLTSI2	A3JNPURAYDDHDY	1	
			240LZ6R70G5RF9ZCBJMECWSSKZUO80	A2KLFKJN8HXJNH	2	
			2YV3FDEY5COW6M2VRJZCWFLCX0LT2C	AHC2OX7HXE231	1	
			2VQ58B727M0IMG6L5HXYKSVFV8LBW7	A22YE5YXKM2GBF	1	
			273NVP3TVOK50G59TEYQJOZFPVD14U	AC6N8HLI4U6QF	1	
			23DB3L0FBJ9IUC5IB75VJ5RPOETMYE	A2MT0WWJR23AGG	1	
			2GJLPHIT3HVWGW6MYIEJV217ZEPBJZ	AHJRFFJD507UF	0	
			2NRKPFE4EGDHJNO9DO99SZW6EUV8I3	A2MCC5CA9D7N3A	1	
			2R9RRLFQ0ONN1S35CXF9JGRB4LWRI9	AH038P14MJ1EU	1	
			2U4CVLL3CA33SIWTIK39SQU7U969Z9	A2IJQ910MA8J2E	0	
			2HUJENLVWJ5OVCM2NWQ83MWBXC9S09	A1VD4UUXM6DQ6Y	1	
			2RNWAVKI62NJW3NBUF09VH6BAJXRJS	A10P6VTBVDKJTT	1	
			26TVP9746OQ1YOCUZ6X7551QAA2L1M	A1G08QM9J5GZO6	1	
18	Query#6: Motor Sport Racing	Concept	206OZFYQS1CSZNAJP74S9IC14WAMJB	A2JBJFPFG38X9C	2	1.350
			2ZBWKUDD8XMB9RPDRG26ZTO6J1CCNM	A2ZJ898N5IJYMO	1	
			20Q2RCJK63ZVK43VS0LIFQ9JIK87W5	AEZT1RZZ1MVF7	1	
			2GAAA2SEIUUU61AUC014NIS8PEJPP1	AHJRFFJD507UF	2	
			2MB011K274J7FLC0YHZN96UXCSVECS	A3T1PUGNW4UK4N	1	
			2OJILKH1Q6SVW93C02HUBL5O8ALJ0E	A15ANKO1BDNEN8	2	
			2T9STLB3L0FBPA4S3Z5JWEVE236JV8	AKEHUNKIP6Z7H	1	
			2APULRGNTBJ3SNZ1XVG7S62K79O7T8	AF73ONXD9O6HZ	1	
			2KSRYNJ92NJKS1RFEZKUMYW26RN6B1	A3JNPURAYDDHDY	2	
			28O2GTP9RA7SBX85YPPSTF709KFVQT	A221V2JZSDB43Z	1	
			2MFHMVHVKCJ07266ZKA7EKQWWZK649	A14VMU3MLKSTRE	1	
			2TLUHYW2GTP9XBTWXCD1B9YSEDARME	A23T87JDC2TU1D	3	
			239V8ER9Y8TNQJ83K2WKKHS2L2I5SC	A3AG698KLBMRP5	1	
			27VV0FK0COK2PFNQZ5BKELRW337PIE	A2WSVMZ3C1N6BD	1	
			2DI39Z0B6UTOCUQIN8KVWKGPT8PNY9	A17RUJ214A3AWN	2	
			2DVFDEY5COW0RHD3VO3RKLC6S1PU30	A2X3HFZ35GKOII	1	
			2Y1Z6KW4ZMAZNIDVDVH0TNNVOWIG7F	A2MT0WWJR23AGG	1	
			2ABG5TYMNCWYH5VJ18JSMX119M1JNP	A5E7JSX72SKGE	1	
			2RJRLFQ0ONNVXINO940ELRB7WLUSJV	AB1W5B83KF3FD	1	
			280E4BLYHVI4APE6C1L8INEZI9D0UG	A11ZSP12IL64Y2	1	

Figure D2: Mood Boards Produced by *Query#1: Animal Kingdom*

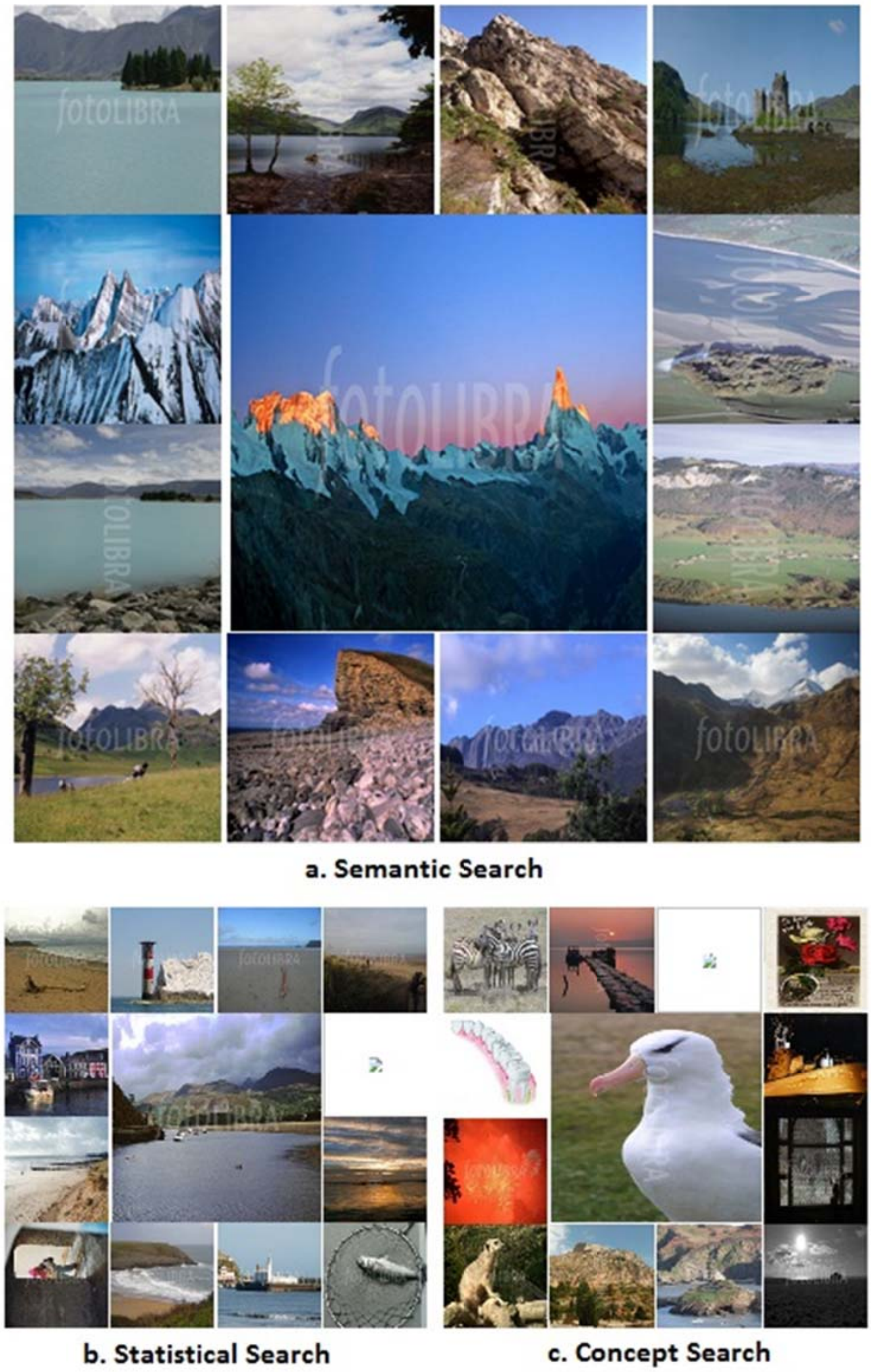


Figure D3: Mood Boards Produced by *Query#3: High Land*

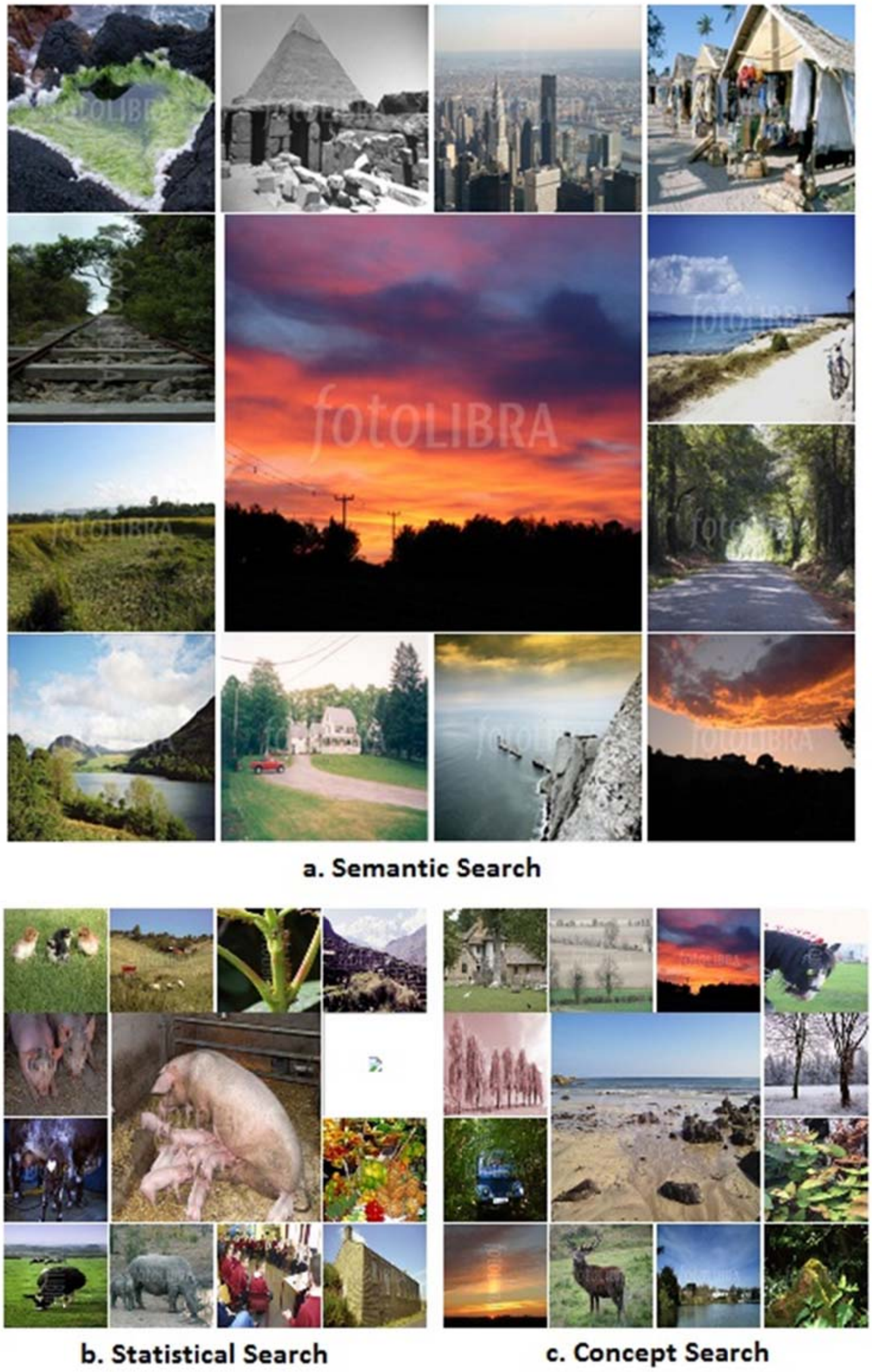


Figure D4: Mood Boards Produced by *Query#4: Country Terrain*

Figure D5: Mood Boards Produced by *Query#5: Travel and Tour*

Figure D6: Mood Boards Produced by *Query#6: Motor Sport Racing*

Figure D7: Mood Boards Produced by *Query#7: Prehistoric Animal*

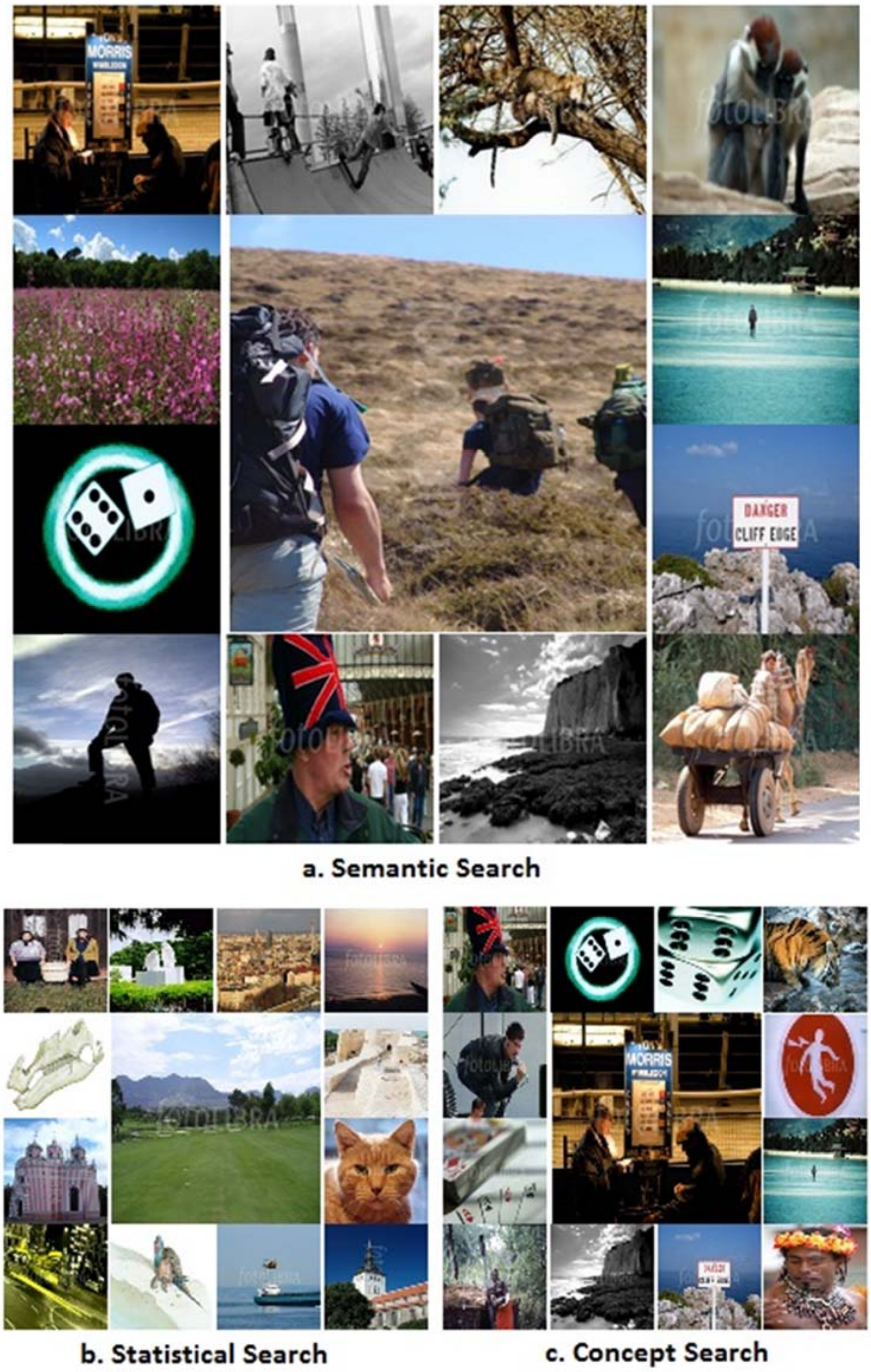


Figure D8: Mood Boards Produced by *Query#9: Adventurous*

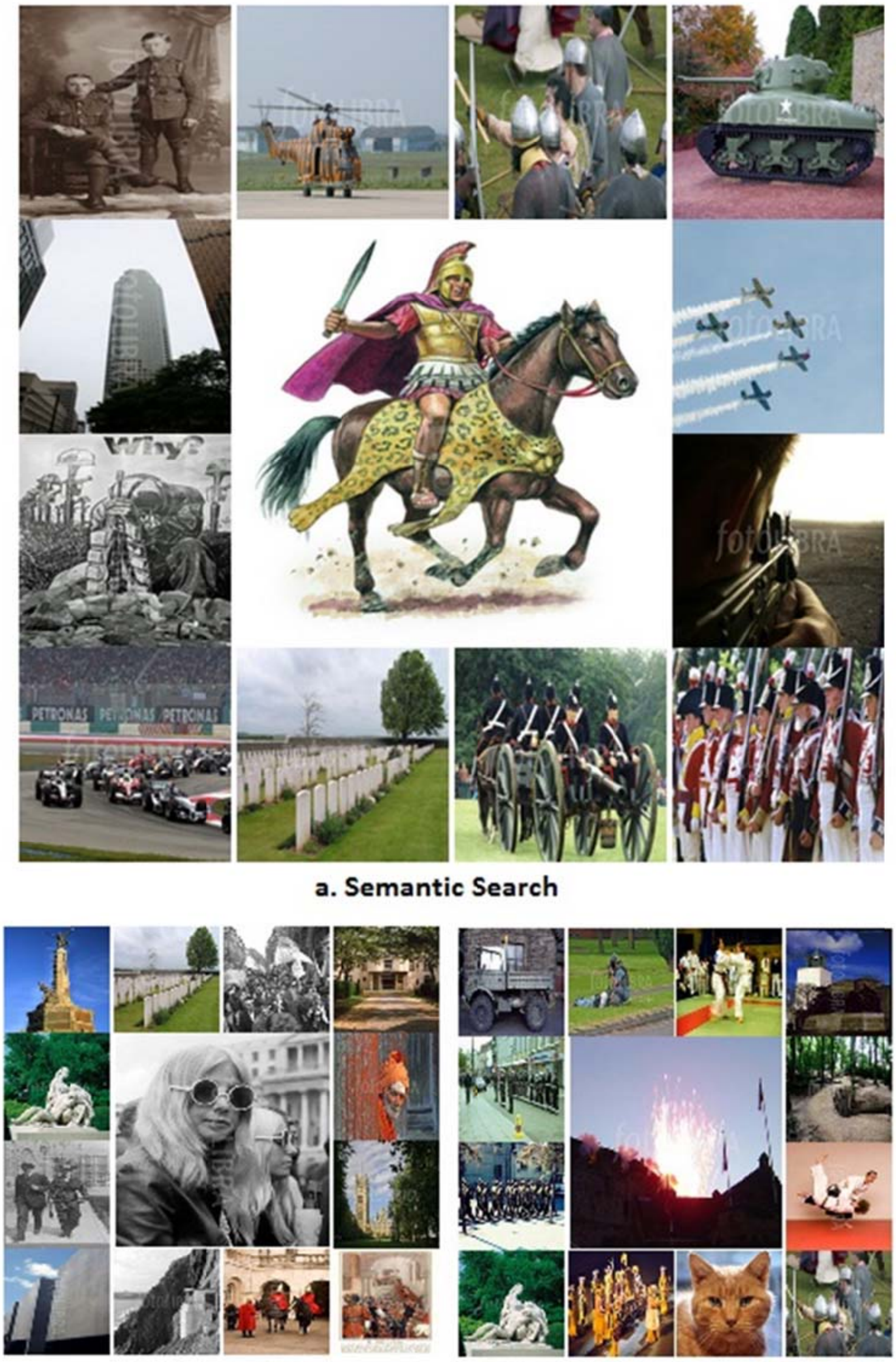


Figure D9: Mood Boards Produced by *Query#10: War Battl'e*

Figure D10: Mood Boards Produced by *Query#11: Land Travel Vehicle*

Figure D11: Mood Boards Produced by *Query#12: Violence and Crime*

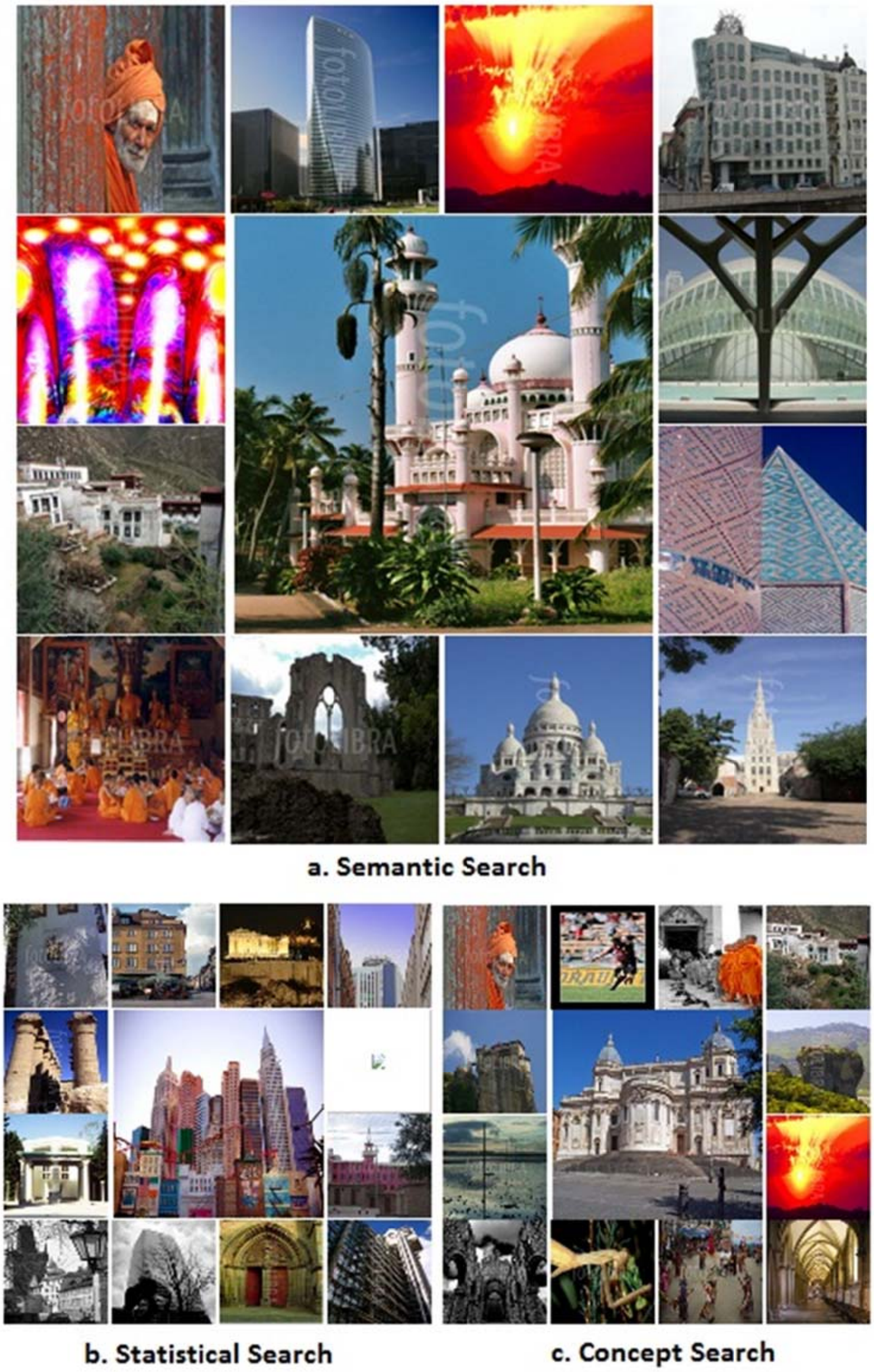


Figure D12: Mood Boards Produced by *Query#13: Religious Building*

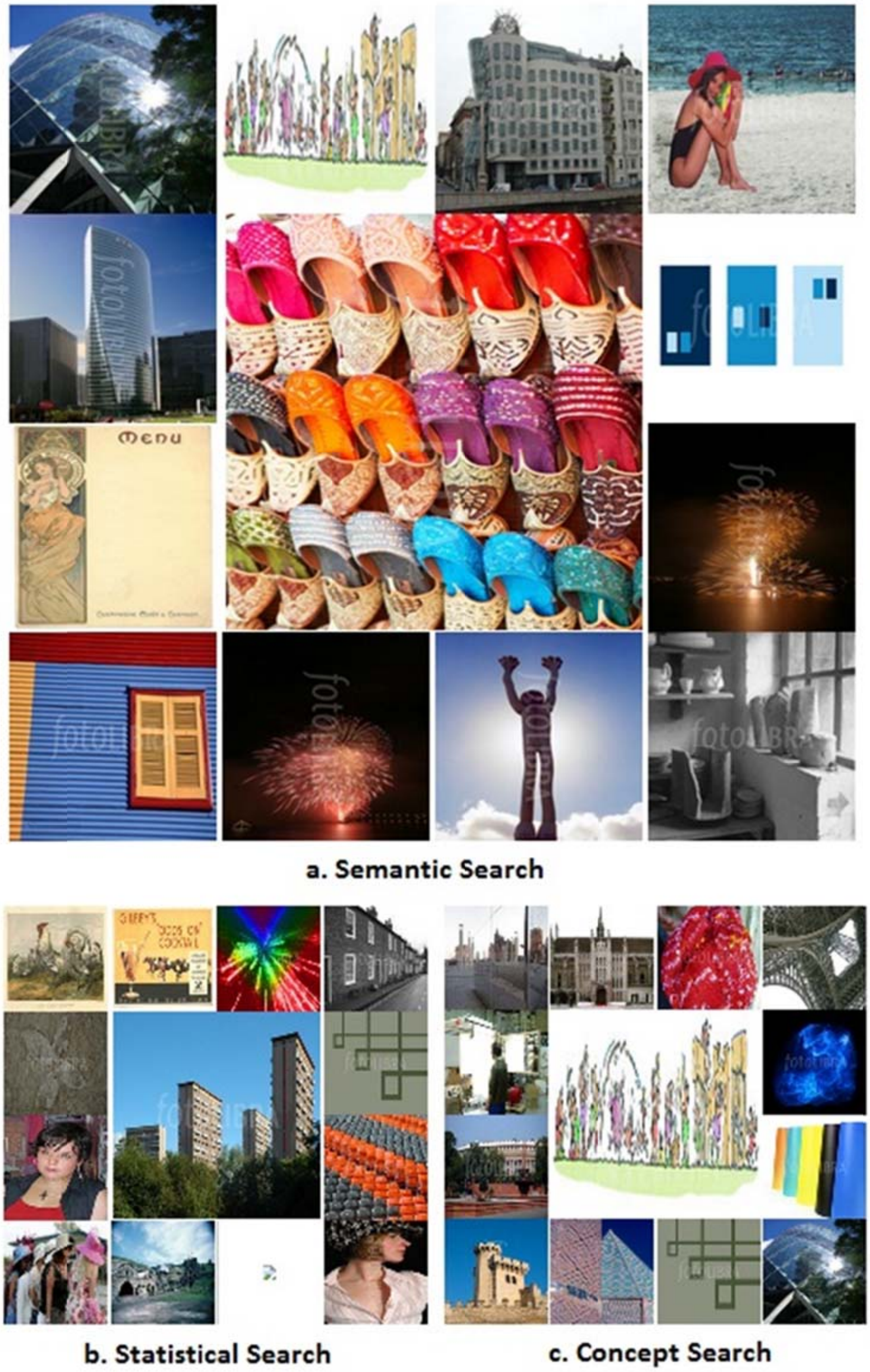


Figure D13: Mood Boards Produced by *Query#15: Fashion Design*

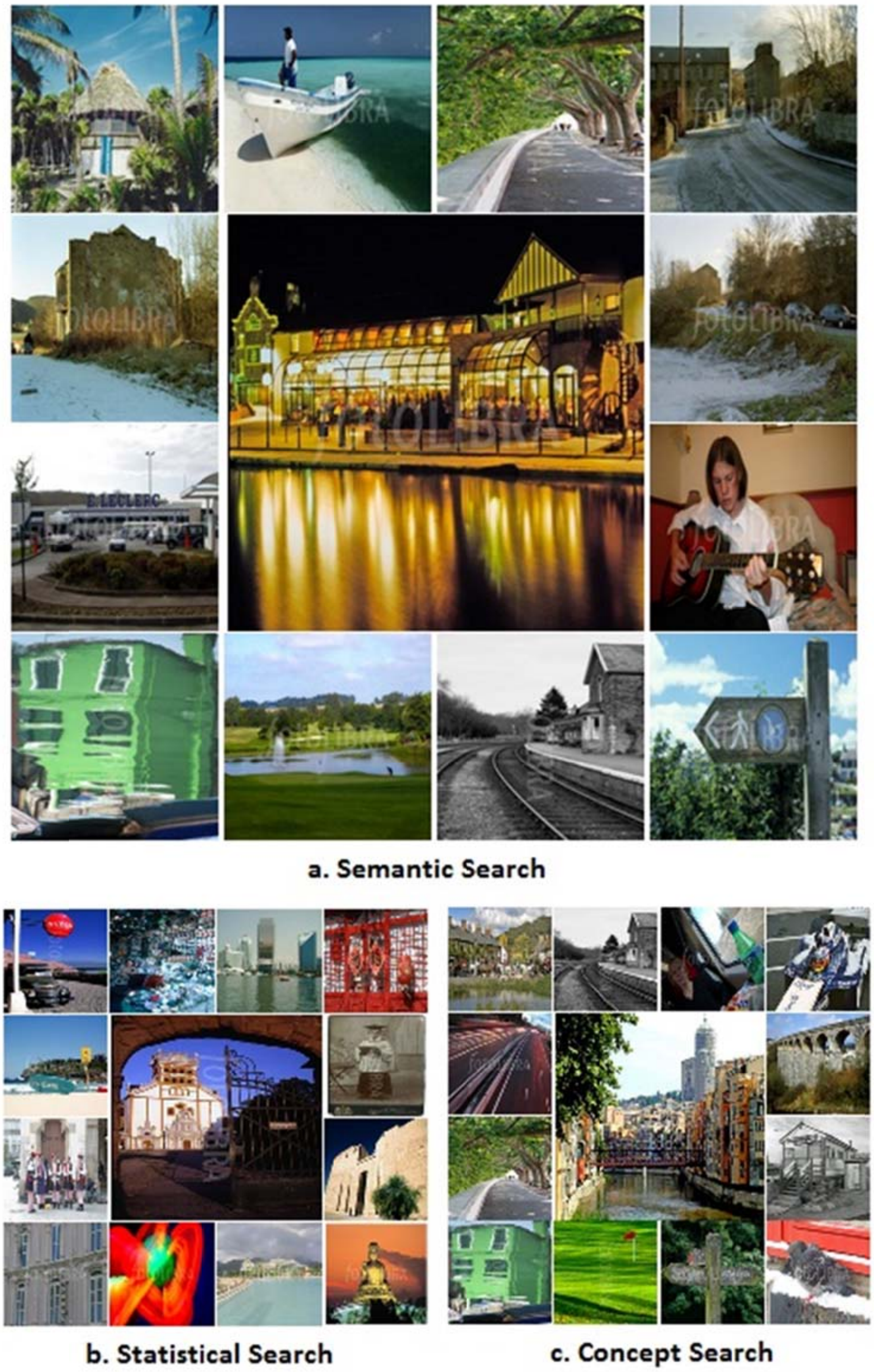


Figure D14: Mood Boards Produced by *Query#17: Hospitality and Kindness*

Figure D15: Mood Boards Produced by *Query#18: Extreme Sport*

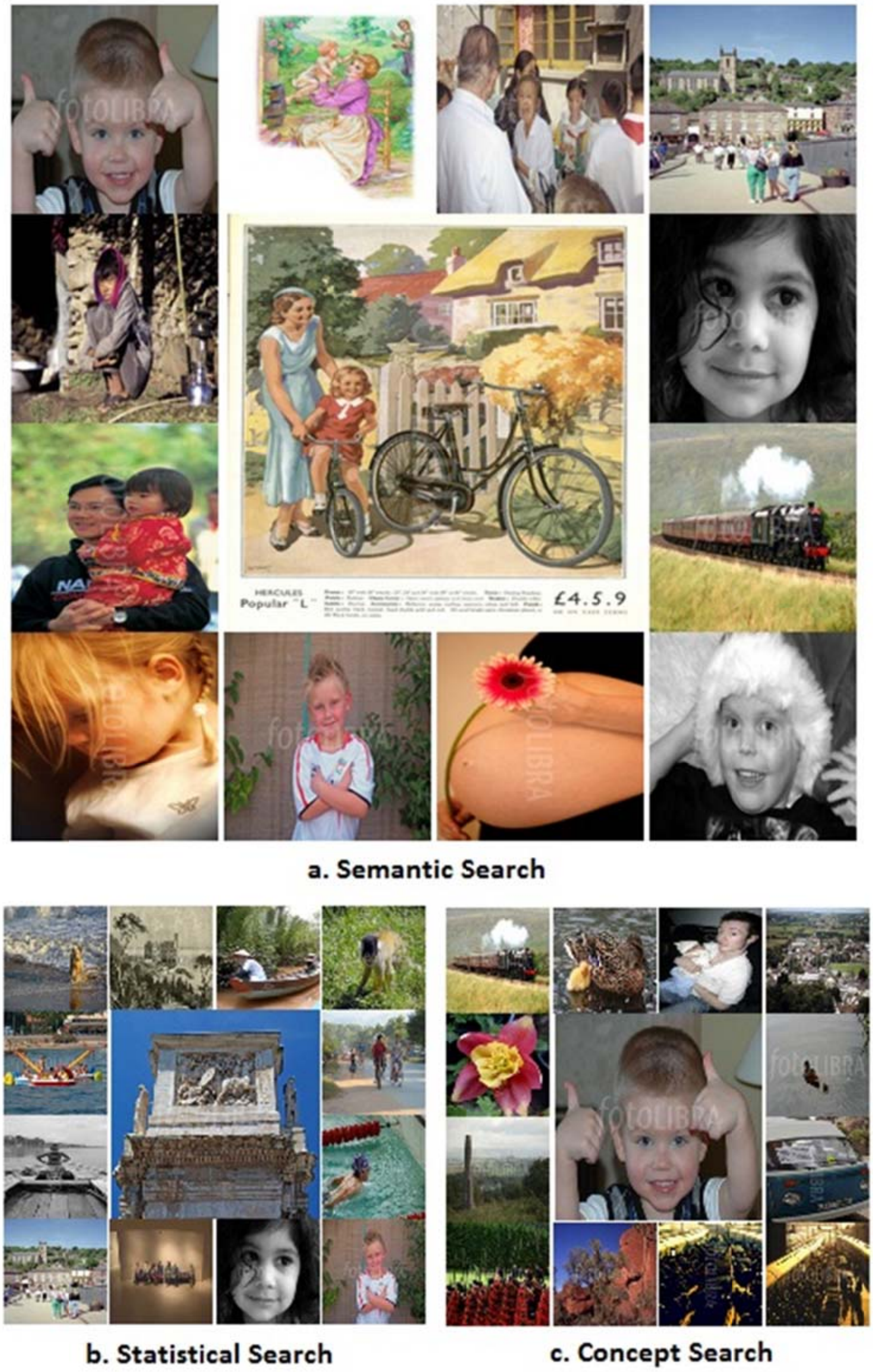


Figure D16: Mood Boards Produced by *Query#19: Motherhood*

a. Semantic Search

b. Statistical Search

c. Concept Search

Figure D17: Mood Boards Produced by *Query#20: Underwater Nature*

Figure D18: Mood Boards Produced by *Query#21: Humour*

Figure D19: Mood Boards Produced by *Query#22: Exploration and Leisure*

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