Modelling Salient Features as Directions in Fine-Tuned Semantic Spaces

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Abstract

In this paper we consider semantic spaces consisting of objects from some particular domain (e.g. IMDB movie reviews). Various authors have observed that such semantic spaces often model salient features (e.g. how scary a movie is) as directions. These feature directions allow us to rank objects according to how much they have the corresponding feature, and can thus play an important role in interpretable classifiers, recommendation systems, or entity-oriented search engines, among others. Methods for learning semantic spaces, however, are mostly aimed at modelling similarity. In this paper, we argue that there is an inherent trade-off between capturing similarity and faithfully modelling features as directions. Following this observation, we propose a simple method to fine-tune existing semantic spaces, with the aim of improving the quality of their feature directions. Crucially, our method is fully unsupervised, requiring only a bag-of-words representation of the objects as input.

1 Introduction

Vector space representations, or 'embeddings', play a crucial role in various areas of natural language processing. For instance, word embeddings (Mikolov et al., 2013; Pennington et al., 2014) are routinely used as representations of word meaning, while knowledge graph embeddings (Bordes et al., 2013) are used to find plausible missing information in structured knowledge bases, or to exploit such knowledge bases in neural network architectures. In this paper we focus on domain-specific semantic spaces, i.e. vector space representations of the objects of a single domain, as opposed to the more heterogeneous setting of e.g. word embeddings.

Such domain-specific semantic spaces are used, for instance, to represent items in recommender systems (Vasile et al., 2016; Liang et al., 2016; Van Gysel et al., 2016), to represent entities in semantic search engines (Jameel et al., 2017; Van Gysel et al., 2017), or to represent examples in classification tasks (Demirel et al., 2017). In many semantic spaces it is possible to find directions that correspond to salient features from the considered domain. For instance, Gupta et al. (2015) found that features of countries, such as their GDP, fertility rate or even level of CO_2 emissions, can be predicted from word embeddings using a linear regression model. Similarly, in (Kim and de Marneffe, 2013) directions in word embeddings were found that correspond to adjectival scales (e.g. bad $<$ okay $<$ good $<$ excellent) while Rothe and Schütze (2016) found directions indicating lexical features such as the frequency of occurrence and polarity of words. Finally, Derrac and Schockaert (2015) found directions corresponding to properties such as 'Scary', 'Romantic' or 'Hilarious' in a semantic space of movies.

In our work, we focus on improving the representation of these *feature directions* in domain-specific semantic spaces. Such feature directions are useful in a wide variety of applications. The most immediate example is perhaps that they allow for a natural way to implement critique-based recommendation systems, where users can specify how their desired result should relate to a given set of suggestions (Viappiani et al., 2006). For instance, Vig et al. (2012) propose a movie recommendation system in which the user can specify that they want to see suggestions for movies that are "similar to this one, but scarier". If the property of being scary is adequately modelled as a direction in a semantic space of movies, such critiques can be addressed in a straightforward way. Similarly, in (Kovashka et al., 2012) a system was developed that can find "shoes like these but shinier", based on a semantic space representation that was derived from visual features. Semantic search systems can use such directions to interpret queries involving gradual and possibly ill-defined features, such as "*popular* holiday destinations in Europe" (Jameel et al., 2017). While features such as popularity are typically not encoded in traditional knowledge bases, they can often be represented as semantic space directions. As another application, feature directions can also be used in interpretable classifiers. For example, Derrac and Schockaert (2015) learned rule based classifiers from rankings induced by the feature directions. Along similar lines, in this paper we will use shallow decision trees to evaluate the quality of our feature directions.

In the aforementioned applications, feature directions are typically emerging from vector space representations that have been learned with a similarity-centred objective, i.e. the main consideration when learning these representations is that similar objects should be represented as similar vectors. An important observation is that such spaces may not actually be optimal for modelling feature directions. To illustrate why this can be the case, Figure 1 shows a toy example in which basic geometric shapes are embedded in a two-dimensional space. Within this space, we can identify directions which encode how light an object is and how closely its shape resembles a square. While most of the shapes embedded in this space are grey-scale circles and squares, one of the shapes embedded in this space is a red triangle, which is a clear outlier. If this space is learned with a similarity-centred objective, the representation of the triangle will be far from all the other shapes. However, this means that outliers like this will often take up extreme positions in the rankings induced by the feature directions, and may thus lead us to incorrectly assume that they have certain features. In this example, the triangle would incorrectly be considered as the shape which most exhibits the features "light" and "square". In contrast, if we had learned the representation with the knowledge that it should model these two features rather than similarity, this triangle would have ended up closer to the bottom-left corner.

Unfortunately, we usually have no *a priori* knowledge of which are the most salient features. In this paper, we therefore suggest the following fully unsupervised strategy. First, we learn a semantic space from bag-of-words representations of the considered objects, using a standard similarity-centric method. Using the method from (Derrac and Schockaert, 2015), we subsequently determine the most salient features in the considered domain, and their corresponding directions. Finally, we fine-tune the semantic space and the associated feature directions, modelling the considered features in a more faithful way. This last step is the main contribution of this paper. All code and hyperparameters are available online[1].

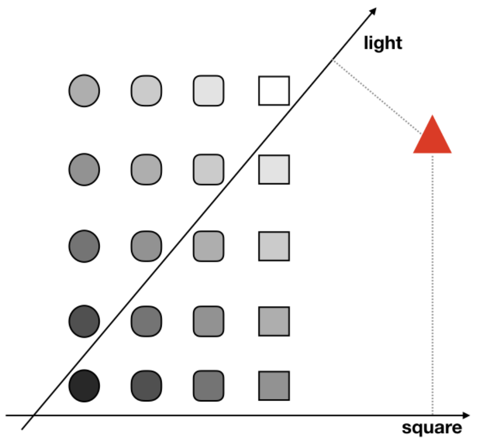

Figure 1: Toy example showing the effect of outliers in a two-dimensional embedding of geometric shapes.

2 Related Work

Topic models. The main idea underlying our method is to learn a representation in terms of salient features, where each of these features is described using a cluster of natural language terms. This is somewhat similar to Latent Dirichlet Allocation (LDA), which learns a representation of text documents as multinomial distributions over latent topics, where each of these topics corresponds to a multinomial distribution over words (Blei et al., 2003). Topics tend to correspond to salient features, and are typically labelled with the most probable words according to the corresponding distribution. However, while LDA only uses bag-of-words (BoW) representations, our focus is specifically on identifying and improving features that are modelled as directions in semantic spaces. One advantage of using vector spaces is that they offer more flexibility in how addi-

[1]`https://github.com/ThomasAger/Modelling-Salient-Features-as-Directions-in-Fine-Tuned-Semantic-Spaces`

tional information can be taken into account, e.g. they allow us to use neural representation learning methods to obtain these spaces. Many extensions of LDA have been proposed to incorporate additional information as well, e.g. aiming to avoid the need to manually specify the number of topics (Teh et al., 2004), modelling correlations between topics (Blei and Lafferty, 2005), or by incorporating meta-data such as authors or time stamps (Rosen-Zvi et al., 2004; Wang and McCallum, 2006). Nonetheless, such techniques for extending LDA offer less flexibility than neural network models, e.g. for exploiting numerical attributes or visual features.

Fine-tuning embeddings. Several authors have looked at approaches for adapting word embeddings. One possible strategy is to change how the embedding is learned in the first place. For example, some approaches have been proposed to learn word embeddings that are better suited at capturing sentiment Tang et al. (2016), or to learn embeddings that are optimized for relation extraction Hashimoto et al. (2015). Other approaches, however, start with a pre-trained embedding, which is then modified in a particular way. For example, in (Faruqui et al., 2015) a method is proposed to bring the vectors of semantically related words, as specified in a given lexicon, closer together. Similarly Yu et al. (2017) propose a method for refining word vectors to improve how well they model sentiment. In (Labutov and Lipson, 2013) a method is discussed to adapt word embeddings based on a given supervised classification task.

Semantic spaces. Within the field of cognitive science, feature representations and semantic spaces both have a long tradition as alternative, and often competing representations of semantic relatedness (Tversky, 1977). Conceptual spaces (Gärdenfors, 2004) to some extent unify these two opposing views, by representing objects as points in vector spaces, one for each facet (e.g. color, shape, taste in a conceptual space of fruit), such that the dimensions of each of these vector spaces correspond to primitive features. The main appeal of conceptual spaces stems from the fact that they allow a wide range of cognitive and linguistic phenomena to be modelled in an elegant way. The idea of learning semantic spaces with accurate feature directions can be seen as a first step towards methods for learning conceptual space representations from data, and thus towards the use of more cognitively plausible representations of meaning in computer science. Our method also somewhat relates to the debates in cognitive science on the relationship between similarity and rule based processes (Hahn and Chater, 1998), in the sense that it allows us to explicitly link similarity based categorization methods (e.g. an SVM classifier trained on semantic space representations) with rule based categorization methods (e.g. the decision trees that we will learn from the feature directions).

3 Identifying Feature Directions

We assume that a domain-specific semantic space is given, and that for each of the objects which are modelled in this space, we also have a BoW representation. Our overall aim is to find directions in the semantic space that model salient features of the considered domain. For example, given a semantic space of movies, we would like to find a direction that models the extent to which each movie is scary, among others. Such a direction would then allow us to rank movies from the least scary to the most scary. We will refer to such directions as *feature directions*. Formally, each feature direction will be modelled as a vector v_f. However, we refer to *directions* rather than *vectors* to emphasize their intended ordinal meaning: feature directions are aimed at ranking objects rather than e.g. measuring degrees of similarity. In particular, if o is the vector representation of a given object then we can think of the dot product $v_f \cdot o$ as the value of object o for feature f, and in particular, we take $v_f \cdot o_1 < v_f \cdot o_2$ to mean that o_2 has the feature f to a greater extent than o_1.

To identify feature directions, we use a variant of the unsupervised method proposed in (Derrac and Schockaert, 2015), which we explain in this section. In Section 4, we will then introduce our approach for fine-tuning the semantic space and associated feature directions.

Step 1: Generating candidate feature directions. Each feature will be associated with a cluster of words, which we can regard as a description of the intuitive meaning of that feature. Since we assume no *a priori* information about which words might describe features that can be modelled as directions in the vector space, the method initially considers all nouns and adjectives that are sufficiently frequent in the BoW representations of the objects as candidate feature labels. Then, for each considered word w, a logistic regression classifier

20 Newsgroups: Accuracy Scored	Movie Reviews: NDCG Scored	Place-types: Kappa Scored
{sins, sinful, jesus, moses}	{environmentalist, wildlife, ecological}	{smile, kid, young, female}
{hitters, catcher, pitching, batting}	{prophets, bibles, scriptures}	{rust, rusty, broken, mill}
{ink, printers, printer, matrix}	{assassinating, assasins, assasin}	{eerie, spooky, haunted, ghosts}
{jupiter, telescope, spacecraft, satellites}	{reanimated, undead, zombified}	{religious, christian, chapel, carved}
{firearm, concealed, handgun, handguns}	{ufos, ufo, extraterrestrial, extraterrestrials}	{fur, tongue, teeth, ears}
{escaped, terror, wounded, fled}	{swordsman, feudal, swordfight, swordplay}	{weeds, shed, dirt, gravel}
{cellular, phones, phone}	{scuba, divers, undersea}	{stonework, archway, brickwork}
{brake, steering, tires, brakes}	{regiment, armys, soliders, infantry}	{rails, rail, tracks, railroad}
{riders, rider, ride, riding}	{toons, animations, animating, animators}	{dirty, trash, grunge, graffiti}
{formats, jpeg, gif, tiff}	{fundamentalists, doctrine, extremists}	{tranquility, majestic, picturesque}
{physicians, treatments physician}	{semitic, semitism, judaism, auschwitz}	{monument, site, arch, cemetery}
{bacteria, toxic, biology, tissue}	{shipwrecked, ashore, shipwreck}	{journey, traveling, travelling}
{planets, solar, mars, planetary}	{planetary, earths, asteroid, spaceships}	{mother, mom, children, child}
{symptoms, syndrome, diagnosis}	{atheism, theological, atheists, agnostic}	{frost, snowy, icy, freezing}
{universities, nonprofit, institution}	{astronaut, nasa, spaceship, astronauts}	{colourful, vivid, artistic, vibrant}

Table 1: The first clustered words of features for three different domains and three different scoring types.

is trained to find a hyperplane H_w in the semantic space that separates objects which contain w in their BoW representation from those that do not. The vector v_w perpendicular to this hyperplane is then taken as the direction that models the word w.

Step 2: Filtering candidate feature directions. To determine whether the word w is likely to describe an important feature for the considered domain, we then evaluate the quality of the candidate feature direction v_w. For example, we can use the classification accuracy to evaluate the quality in terms of the corresponding logistic regression classifier: if this classifier is sufficiently accurate, it must mean that whether word w relates to object o (i.e. whether it is used in the description of o) is important enough to affect the semantic space representation of o. In such a case, it seems reasonable to assume that w describes an important feature for the given domain.

One problem with accuracy as a scoring function is that these classification problems are often very imbalanced. In particular, for very rare words, a high accuracy might not necessarily imply that the corresponding direction is accurate. For this reason, Derrac and Schockaert (2015) proposed to use Cohen's Kappa score instead. In our experiments, however, we found that accuracy sometimes yields better results, so rather than fix the scoring function, we keep this as a hyperparameter of the model that can be tuned.

In addition to accuracy and Kappa, we also consider Normalized Discounted Cumulative Gain (NDCG). This is a standard metric in information retrieval which evaluates the quality of a ranking w.r.t. some given relevance scores (Järvelin and Kekäläinen, 2002). In our case, the rankings of the objects o are those induced by the dot products $v_w \cdot o$ and the relevance scores are determined by the Pointwise Positive Mutual Information (PPMI) score $\textit{ppmi}(w, o)$, of the word w in the BoW representation of object o where $\textit{ppmi}(w, o) = \max\left(0, \log\left(\frac{p_{wo}}{p_{w*} \cdot p_{*o}}\right)\right)$, and

$$p_{wo} = \frac{n(w, o)}{\sum_{w'} \sum_{o'} n(w', o')}$$

where $n(w, o)$ is the number of occurrences of w in the BoW representation of object o, $p_{w*} = \sum_{o'} p_{wo'}$ and $p_{*o} = \sum_{w'} p_{w'o}$. In principle, we may expect that accuracy and Kappa are best suited for binary features, as they rely on a hard separation in the space between objects that have the word in their BoW representation and those that do not, while NDCG should be better suited for gradual features. In practice, however, we could not find such a clear pattern in the differences between the words chosen by these metrics despite often finding different words.

Step 3: clustering candidate feature directions. As the final step, we cluster the best-scoring candidate feature directions v_w. Each of these clusters will then define one of the feature directions to be used in applications. The purpose of this clustering step is three-fold: it will ensure that the feature directions are sufficiently different (e.g. in a space of movies there is little point in having *funny* and *hilarious* as separate features), it will make the features easier to interpret (as a cluster of terms is more descriptive than an individual term), and it will alleviate sparsity issues when we want to relate features with the BoW representation, which will play an important role for the fine-tuning method described in the next section.

As input to the clustering algorithm, we consider the N best-scoring candidate feature directions v_w, where N is a hyperparameter. To cluster these N vectors, we have followed the approach proposed in (Derrac and Schockaert, 2015), which we found to perform slightly better than K-means. The main idea underlying their approach is to select the cluster centers such that (i) they are among the top-scoring candidate feature directions, and (ii) are as close to being orthogonal to each other as possible. We refer to (Derrac and Schockaert, 2015) for more details. The output of this step is a set of clusters $C_1, ..., C_K$, where we will identify each cluster C_j with a set of words. We will furthermore write v_{C_j} to denote the centroid of the directions corresponding to the words in the cluster C_j, which can be computed as $v_{C_j} = \frac{1}{|C_j|}\sum_{w_l \in C_j} v_l$ provided that the vectors v_w are all normalized. These centroids $v_{C_1}, ..., v_{C_k}$ are the feature directions that are identified by our method.

Table 1 displays some examples of clusters that have been obtained for three of the datasets that will be used in the experiments, modelling respectively movies, place-types and newsgroup postings. For each dataset, we used the scoring function that led to the best performance on development data(see Section 5). Only the first four words whose direction is closest to the centroid v_C are shown.

4 Fine-Tuning Feature Directions

To illustrate that the method from Section 3 can produce sub-optimal directions, the second column of Table 2 shows the top-ranked objects for some feature directions in the semantic space of place-types. For the feature represented by the cluster $\{$*steep*, *climb*, *slope*$\}$, the top ranked object *mountain* is clearly relevant. However, the next two objects — *landscape* and *national park* — are not directly related to this feature. Intuitively, they are ranked highly because of their similarity to *mountain* in the vector space. Similarly, for the second feature, *building* is ranked highly because of its similarity to *skyscraper*, despite intuitively not having this feature. Finally, *fence* received a high rank for several features, mostly because it is an outlier in the space.

To improve the directions and address these problems, we propose a method for fine-tuning the semantic space representations and corresponding feature directions. The main idea is to use the BoW representations of the objects as a kind of weak supervision signal: if an object should be ranked highly for a given feature, we would expect the words describing that feature to appear frequently in its description. In particular, for each feature f we determine a total ordering $\preccurlyeq_f$ such that $o \preccurlyeq_f o'$ iff the feature f is more prominent in the BoW represention of object o' than in the BoW representation of o. We will refer to $\preccurlyeq_f$ as the *target ranking* for feature f. If the feature directions are in perfect agreement with this target ranking, it would be the case that $o \preccurlyeq o'$ iff $v_C \cdot o \leq v_C \cdot o'$. Since this will typically not be the case, we subsequently determine *target values* for the dot products $v_C \cdot o$. These target values represent the minimal way in which the dot products need to be changed to ensure that they respect the target ranking. Finally, we use a simple feedforward neural network to adapt the semantic space representations o and feature directions v_C to make the dot products $v_C \cdot o$ as close as possible to these target values.

4.1 Generating Target Rankings

Let $C_1, ..., C_K$ be the clusters that were found using the method from Section 3. Each cluster C_i typically corresponds to a set of semantically related words $\{w_1, ..., w_n\}$, which describe some salient feature from the considered domain. From the BoW representations of the objects, we can now define a ranking that reflects how strongly each object is related to the words from this cluster. To this end, we represent each object as a bag of clusters (BoC) and then compute PPMI scores over this representation. In particular, for a cluster $C = \{w_1, ..., w_m\}$, we define $n(C, o) = \sum_{i=1}^{m} n(w_i, o)$. In other words, $n(C, o)$ is the total number of occurrences of words from cluster C in BoW representation of o. We then write *ppmi*(C, o) for the PPMI score corresponding to

Feature direction	Highest ranking objects	Highest fine-tuned ranking objects
{steep, climb, slope}	mountain, landscape, national park	ski slope, steep slope, slope
{illuminated, illumination, skyscraper}	building, city, skyscraper	tall building, office building, large building
{play, kid, kids}	school, field, fence	college classroom, classroom, school
{spooky, creepy, scary}	hallway, fence, building	hospital room, hospital ward, patient room
{amazing, dream, awesome}	fence, building, beach	hotel pool, resort, beach resort
{pavement, streetlight, streets}	sidewalk, fence, building	overpass road, overpass, road junction
{dead, hole, death}	fence, steps, park	grave, cemetery, graveyard
{spire, belltower, towers}	building, arch, house	bell tower, arch, religious site
{stones, moss, worldheritage}	landscape, fence, steps	ancient site, ancient wall, tomb
{mosaic, tile, bronze}	building, city, steps	cathedral, church, religious site

Table 2: Comparing the highest ranking place-type objects in the original and fine-tuned space.

this BoC representation, which is evaluated in the same way as $\mathit{ppmi}(C, o)$, but using the counts $n(C, o)$ rather than $n(w, o)$. The target ranking for cluster C_i is then such that o_1 is ranked higher than o_2 iff $\mathit{ppmi}(C_i, o_1) > \mathit{ppmi}(C_i, o_2)$. By computing PPMI scores w.r.t. clusters of words, we alleviate problems with sparsity and synonymy, which in turn allows us to better estimate the intensity with which a given feature applies to the object. For instance, an object describing a violent movie might not actually mention the word 'violent', but would likely mention at least some of the words from the same cluster (e.g. 'bloody' 'brutal' 'violence' 'gory'). Similarly, this approach allows us to avoid problems with ambiguous word usage; e.g. if a movie is said to contain 'violent language', it will not be identified as violent if other words related to this feature are rarely mentioned.

4.2 Generating Target Feature Values

Finding directions in a vector space that induce a set of given target rankings is computationally hard[2]. Therefore, rather than directly using the target rankings from Section 4.1 to fine-tune the semantic space, we will generate target values for the dot products $v_{C_j} \cdot o_i$ from these target rankings. One straightforward approach would be to use the PPMI scores $\mathit{ppmi}(C_j, o_i)$. However these target values would be very different from the initial dot products, which among others means that too much of the similarity structure from the initial vector space would be lost. Instead, we will use isotonic regression to find target values $\tau(C_j, o_i)$ for the dot product $v_{C_j} \cdot o_i$, which respect the ranking induced by the PPMI scores, but otherwise remain as close as possible to the initial dot products.

Let us consider a cluster C_j for which we want to determine the target feature values. Let $o_{\sigma_1}, ..., o_{\sigma_n}$ be an enumeration of the objects such that $\mathit{ppmi}(C_j, o_{\sigma_i}) \leq \mathit{ppmi}(C_j, o_{\sigma_{i+1}})$ for $i \in \{1, ..., n-1\}$. The corresponding target values $\tau(C_j, o_i)$ are then obtained by solving the following optimization problem:

$$\textbf{Minimize:} \quad \sum_i (\tau(C_j, o_i) - v_{C_j} \cdot o_i)^2$$

Subject to:

$$\tau(C_j, o_{\sigma_1}) \leq \tau(C_j, o_{\sigma_2}) \leq ... \leq \tau(C_j, o_{\sigma_n})$$

4.3 Fine-Tuning

We now use the target values $\tau(C_j, o_i)$ to fine-tune the initial representations. To this end, we use a simple neural network architecture with one hidden layer. As inputs to the network, we use the initial vectors $o_1, ..., o_n \in \mathbb{R}^k$. These are fed into a layer of dimension l:

$$h_i = f(W o_i + b)$$

where W is an $l \times k$ matrix, $b \in \mathbb{R}^l$ is a bias term, and f is an activation function. After training the network, the vector h_i will correspond to the new representation of the ith object. The vectors h_i are finally fed into an output layer containing one neuron for each cluster:

$$g_i = D h_i$$

where D is a $K \times l$ matrix. Note that by using a linear activation in the output layer, we can interpret the rows of the matrix D as the K feature directions, with the components of the vector $g_i = (g_i^1, ..., g_i^K)$ being the corresponding dot products.

[2]It is complete for the complexity class $\exists\mathbb{R}$, which sits between NP and PSPACE (Schockaert and Lee, 2015).

20 Newsgroups	F1 D1	F1 D3	F1 DN
FT MDS	**0.50**	**0.47**	**0.44**
MDS	0.44	0.42	0.43
FT PCA	0.40	0.36	0.34
PCA	0.25	0.27	0.36
FT Doc2Vec	0.44	0.42	0.41
Doc2Vec	0.29	0.34	0.44
FT AWV	0.47	0.45	0.40
AWV	0.41	0.38	0.43
FT AWVw	0.41	0.41	0.43
AWVw	0.38	0.40	0.43
LDA	0.40	0.37	0.35

Table 3: Results for 20 Newsgroups.

As the loss function for training the network, we use the squared error between the outputs g_i^j and the corresponding target values $\tau(C_j, o_i)$, i.e.:

$$\mathcal{L} = \sum_i \sum_j (g_i^j - \tau(C_j, o_i))^2$$

The effect of this fine-tuning step is illustrated in the right-most column of Table 2, where we can see that in each case the top ranked objects are now more closely related to the feature, despite being less common, and outliers such as 'fence' no longer appear.

5 Evaluation

To evaluate our method, we consider the problem of learning interpretable classifiers. In particular, we learn decision trees which are limited to depth 1 and 3, which use the rankings induced by the feature directions as input. This allows us to simultaneously assess to what extent the method can identify the right features and whether these features are modelled well using the learned directions. Note that depth 1 trees are only a single direction and a cut-off, so to perform well, the method needs to identify a highly relevant feature to the considered category. Depth 3 decision trees are able to model categories that can be characterized using at most three feature directions.

5.1 Experimental set-up

Datasets. We evaluate our method on four datasets. First, we used the *movies* and *place-types* datasets from (Derrac and Schockaert, 2015), which are available in preprocessed form[3]. The former describes 15000 movies, using a BoW representation that was obtained by combining reviews from several sources. However, 1022 duplicate movies were found in the data, which we removed. The associated classification tasks are to predict the movie genres according to IMDB (23 classes), predicting IMDB plot keywords such as 'suicide', 'beach' or 'crying' (100 classes) and predicting age rating certificates such as 'UK-15' 'UK-18' or 'USA-R' (6 classes). All tasks are evaluated as binary classification tasks. We randomly split the datasets into 2/3 for training and 1/3 for testing. The place-types dataset was obtained by associating each place-type with the bag of tags that have been used to describe places of that type on Flickr. It contains BoW represenations for 1383 different place-types. The classification problems for this dataset involve predicting whether a place-type belongs to a given category in three different taxonomies: Geonames (7 classes), Foursquare (9 classes) and OpenCYC (20 classes). Since many of these categories are very small, for this dataset we have used 5-fold cross validation.

The remaining two datasets are standard datasets for document classification: *20 newsgroups* and the *IMDB sentiment* dataset. For the 20 newsgroups dataset, the standard[4] split was used where 11314 of the 18446 documents are used for training. Headers, footers and quote metadata were removed using scikit-learn[5]. The associated classification problem is to predict which newsgroup a given post was submitted to (20 classes). The IMDB sentiment dataset contains a total of 50000 documents, and it is split into 25000 documents for training and 25000 for testing. For the newsgroups and sentiment datasets, we used stopwords from the NLTK python package (Loper and Bird, 2002). For these datasets, we used all (lowercased) tokens and retained numbers, rather than only using nouns and adjectives. The associated classification problem is to predict the sentiment of the review (positive or negative).

Semantic Spaces. We will consider semantic spaces that have been learned using a number of different methods. First, following (Derrac and Schockaert, 2015), we use Multi-Dimensional Scaling (MDS) to learn semantic spaces from the angular differences between the PPMI weighted

[3]http://www.cs.cf.ac.uk/semanticspaces/

[4]http://qwone.com/~jason/20Newsgroups/

[5]http://scikit-learn.org/stable/datasets/twenty_newsgroups.html

Movie Reviews											
Genres	D1	D3	DN	**Keywords**	D1	D3	DN	**Ratings**	D1	D3	DN
FT MDS	**0.57**	**0.56**	0.51	FT MDS	**0.33**	**0.33**	0.24	FT MDS	**0.49**	**0.51**	**0.46**
MDS	0.40	0.49	**0.52**	MDS	0.31	0.32	**0.25**	MDS	0.46	0.49	**0.46**
FT AWV	0.42	0.42	0.39	FT AWV	0.25	0.25	0.15	FT AWV	0.47	0.44	0.39
AWV	0.35	0.44	0.43	AWV	0.26	0.21	0.19	AWV	0.44	0.48	0.41
LDA	0.52	0.51	0.45	LDA	0.22	0.19	0.18	LDA	0.48	0.48	0.41

Place-types											
Geonames	D1	D3	DN	**Foursquare**	D1	D3	DN	**OpenCYC**	D1	D3	DN
FT MDS	0.32	0.31	0.24	FT MDS	0.41	0.44	0.41	FT MDS	0.35	0.36	0.30
MDS	0.32	0.31	0.21	MDS	0.38	0.42	0.42	MDS	0.35	0.36	0.29
FT AWV	0.31	0.29	0.23	FT AWV	0.39	0.42	0.41	FT AWV	0.37	**0.37**	0.28
AWV	0.28	0.28	0.22	AWV	0.32	0.37	0.31	AWV	0.33	0.35	0.26
LDA	**0.34**	**0.32**	**0.27**	LDA	**0.55**	**0.48**	**0.47**	LDA	**0.40**	0.36	**0.31**

Table 4: The results for Movie Reviews and Place-Types on depth-1, depth-3 and unbounded trees.

IMDB Sentiment	D1	D3	DN
FT PCA	0.78	0.80	0.79
PCA	0.76	**0.82**	**0.80**
FT AWV	0.72	0.76	0.71
AWV	0.74	0.76	0.71
LDA	**0.79**	0.80	0.79

Table 5: Results for IMDB Sentiment.

BoW vectors. We also consider PCA, which directly uses the PPMI weighted BoW vectors as input, and which avoids the quadratic complexity of the MDS method. As our third method, we consider Doc2vec, which is inspired by the Skip-gram model (Le and Mikolov, 2014). Finally, we also learn semantic spaces by averaging word vectors, using a pre-trained GloVe word embeddings trained on the Wikipedia 2014 + Gigaword 5 corpus[6]. While simply averaging word vectors may seem naive, this was found to be a competitive approach for unsupervised representations in several applications (Hill et al., 2016). We consider two variants, In the first variant (denoted by AWV), we simply average the vector representations of the words that appear at least twice in the BoW representation, or at least 15 times in the case of the movies dataset. The second variant (denoted by AWVw) uses the same words, but weights the vectors by PPMI score. As a comparison method, we also include results for LDA.

Methodology. As candidate words for learning the initial directions, we only consider sufficiently frequent words. The thresholds we used are 100 for the movies dataset, 50 for the place-types, 30 for 20 newsgroups, and 50 for the IMDB sentiment dataset. We used the logistic regression implementation from scikit-learn to find the directions. We deal with class imbalance by weighting the positive instances higher.

For hyperparameter tuning, we take 20% of the data from the training split as development data. We choose the hyperparameter values that maximize the F1 score on this development data. As candidate values for the number of dimensions of the vector spaces we used $\{50, 100, 200\}$. The number of directions to be used as input to the clustering algorithm was chosen from $\{500, 1000, 2000\}$. The number of clusters was chosen from $\{k, 2k\}$, with k the chosen number of dimensions. For the hidden layer of the neural network, we fixed the number of dimensions as equal to the number of clusters. As the scoring metric for the dimensions, we considered accuracy, Kappa and NDCG. In all experiments, we used 300 epochs, a minibatch size of 200, and the tanh activation function for the hidden layer of the neural network. We train the network using AdaGrad (Duchi et al., 2011), with default values, and the model was implemented in the Keras library. As the performance of LDA can be sensitive to the number of topics and other parameters, we tuned the number of topics from $\{50, 100, 200, 400\}$, the topic word prior from $\{0.1, 0.01, 0.001\}$ and the document topic prior $\{0.1, 0.01, 0.001\}$.

[6] https://nlp.stanford.edu/projects/glove/

To learn the decision trees, we use the scikit-learn implementation of CART, which allows us to limit the depth of the trees. To mitigate the effects of class imbalance, the less frequent class was given a higher weight during training.

5.2 Results

Table 3 shows the results for the 20 newsgroups dataset, where we use FT to indicate the results with fine-tuning[7]. We can see that the fine-tuning method consistently improves the performance of the depth-1 and depth-3 trees, often in a very substantial way. After fine-tuning, the results are also consistently better than those of LDA. For the unbounded trees (DN), the differences are small and fine-tuning sometimes even makes the results worse. This can be explained by the fact that the fine-tuning method specializes the space towards the selected features, which means that some of the structure of the initial space will be distorted. Unbounded decision trees are far less sensitive to the quality of the directions, and can even perform reasonably on random directions. Interestingly, depth-1 trees achieved the best overall performance, with depth-3 trees and especially unbounded trees overfitting. Since MDS and AWV perform best, we have only considered these two representations (along with LDA) for the remaining datasets, except for the IMDB Sentiment dataset, which is too large for using MDS.

The results for the movies and place-types datasets are shown in Table 4. For the MDS representations, the fine-tuning method again consistently improved the results for D1 and D3 trees. For the AWV representations, the fine-tuning method was also effective in most cases, although there are a few exceptions. What is noticeable is that for movie genres, the improvement is substantial, which reflects the fact that genres are a salient property of movies. For example, the decision tree for the genre 'Horror' could use the feature direction for $\{gore, gory, horror, gruesome\}$. Some of the other datasets refer to more specialized properties, and the performance of our method then depends on whether it has identified features that relate to these properties. It can be expected that a supervised variant of this method would perform consistently better in such cases. After fine-tuning, the MDS based representation outperforms LDA on the movies dataset, but not for the place-types. This is a consequence of the fact that some of the place-type categories refer to very particular properties, such as geological phenomena, which may not be particularly dominant among the Flickr tags that were used to generate the spaces. In such cases, using a BoW based representation may be more suitable.

Finally, the results for IMDB Sentiment are shown in Table 5. In this case, the fine-tuning method fails to make meaningful improvements, and in some cases actually leads to worse results. This can be explained from the fact that the feature directions which were found for this space are themes and properties, rather than aspects of binary sentiment evaluation. The fine-tuning method aims to improve the representation of these properties, possibly at the expense of other aspects.

[7]Since the main purpose of this first experiment was to see whether fine-tuning improved consistently across a broad set of representations, here we considered a slightly reduced pool of parameter values for hyperparameter tuning.

6 Conclusions

We have introduced a method to identify and model the salient features from a given domain as directions in a semantic space. Our method is based on the observation that there is a trade-off between accurately modelling similarity in a vector space, and faithfully modelling features as directions. In particular, we introduced a post-processing step, modifying the initial semantic space, which allows us to find higher-quality directions. We provided qualitative examples that illustrate the effect of this fine-tuning step, and quantitatively evaluated its performance in a number of different domains, and for different types of semantic space representations. We found that after fine-tuning, the feature directions model the objects in a more meaningful way. This was shown in terms of an improved performance of low-depth decision trees in natural categorization tasks. However, we also found that when the considered categories are too specialized, the fine-tuning method was less effective, and in some cases even led to a slight deterioration of the results. We speculate that performance could be improved for such categories by integrating domain knowledge into the fine-tuning method.

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References

David M. Blei and John D. Lafferty. 2005. Correlated topic models. In *Advances in Neural Information Processing Systems 18*, pages 147–154.

David M. Blei, Andrew Y. Ng, Michael I. Jordan, and John Lafferty. 2003. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:2003.

Antoine Bordes, Nicolas Usunier, Jason Weston, and Oksana Yakhnenko. 2013. Translating embeddings for modeling multi-relational data. In *In Advances in Neural Information Processing Systems 26. Curran Associates, Inc*, pages 2787–2795.

Berkan Demirel, Ramazan Gokberk Cinbis, and Nazli Ikizler-Cinbis. 2017. Attributes2classname: A discriminative model for attribute-based unsupervised zero-shot learning. In *IEEE International Conference on Computer Vision*, pages 1241–1250.

J. Derrac and S. Schockaert. 2015. Inducing semantic relations from conceptual spaces: a data-driven approach to plausible reasoning. *Artificial Intelligence*, pages 74–105.

John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. *Journal of Machine Learning Research*, 12:2121–2159.

Manaal Faruqui, Jesse Dodge, Sujay Kumar Jauhar, Chris Dyer, Eduard Hovy, and Noah A Smith. 2015. Retrofitting word vectors to semantic lexicons. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1606–1615.

Peter Gärdenfors. 2004. *Conceptual Spaces: The Geometry of Thought*. MIT press.

Abhijeet Gupta, Gemma Boleda, Marco Baroni, and Sebastian Pad. 2015. Distributional vectors encode referential attributes. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*.

Ulrike Hahn and Nick Chater. 1998. Similarity and rules: distinct? exhaustive? empirically distinguishable? *Cognition*, 65:197 – 230.

Kazuma Hashimoto, Pontus Stenetorp, Makoto Miwa, and Yoshimasa Tsuruoka. 2015. Task-oriented learning of word embeddings for semantic relation classification. *CoRR*, abs/1503.00095.

Felix Hill, Kyunghyun Cho, and Anna Korhonen. 2016. Learning distributed representations of sentences from unlabelled data. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1367–1377.

Shoaib Jameel, Zied Bouraoui, and Steven Schockaert. 2017. Member: Max-margin based embeddings for entity retrieval. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 783–792.

Kalervo Järvelin and Jaana Kekäläinen. 2002. Cumulated gain-based evaluation of IR techniques. *ACM Transactions on Information Systems*, 20(4):422–446.

Joo-Kyung Kim and Marie-Catherine de Marneffe. 2013. Deriving adjectival scales from continuous space word representations. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1625–1630. ACL.

Adriana Kovashka, Devi Parikh, and Kristen Grauman. 2012. Whittlesearch: Image search with relative attribute feedback. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 2973–2980.

Igor Labutov and Hod Lipson. 2013. Re-embedding words. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics*, pages 489–493.

Quoc V. Le and Tomas Mikolov. 2014. Distributed representations of sentences and documents. In *Proceedings of the 31th International Conference on Machine Learning*, pages 1188–1196.

Dawen Liang, Jaan Altosaar, Laurent Charlin, and David M Blei. 2016. Factorization meets the item embedding: Regularizing matrix factorization with item co-occurrence. In *Proceedings of the 10th ACM Conference on Recommender Systems*, pages 59–66.

Edward Loper and Steven Bird. 2002. NLTK: The natural language toolkit. In *Proceedings of the ACL-02 Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics*, pages 63–70.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'13, pages 3111–3119, USA. Curran Associates Inc.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543. Association for Computational Linguistics.

Michal Rosen-Zvi, Thomas Griffiths, Mark Steyvers, and Padhraic Smyth. 2004. The author-topic model for authors and documents. In *Proceedings of the 20th Conference on Uncertainty in Artificial Intelligence*, UAI '04, pages 487–494, Arlington, Virginia, United States. AUAI Press.

Sascha Rothe and Hinrich Schütze. 2016. Word embedding calculus in meaningful ultradense subspaces. In *ACL (2)*. The Association for Computer Linguistics.

Steven Schockaert and Jae Hee Lee. 2015. Qualitative reasoning about directions in semantic spaces. In *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence*, pages 3207–3213. AAAI Press.

Duyu Tang, Furu Wei, Bing Qin, Nan Yang, Ting Liu, and Ming Zhou. 2016. Sentiment embeddings with applications to sentiment analysis. *IEEE Transactions on Knowledge and Data Engineering*, 28:496–509.

Yee Whye Teh, Michael I. Jordan, Matthew J. Beal, and David M. Blei. 2004. Sharing clusters among related groups: Hierarchical dirichlet processes. In *Proceedings of the 17th International Conference on Neural Information Processing Systems*, NIPS'04, pages 1385–1392, Cambridge, MA, USA. MIT Press.

Amos Tversky. 1977. Features of similarity. *Psychological review*, 84:327–352.

Christophe Van Gysel, Maarten de Rijke, and Evangelos Kanoulas. 2016. Learning latent vector spaces for product search. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*, pages 165–174.

Christophe Van Gysel, Maarten de Rijke, and Evangelos Kanoulas. 2017. Structural regularities in text-based entity vector spaces. In *Proceedings of the ACM SIGIR International Conference on Theory of Information Retrieval*, pages 3–10.

Flavian Vasile, Elena Smirnova, and Alexis Conneau. 2016. Meta-prod2vec: Product embeddings using side-information for recommendation. In *Proceedings of the 10th ACM Conference on Recommender Systems*, pages 225–232.

Paolo Viappiani, Boi Faltings, and Pearl Pu. 2006. Preference-based search using example-critiquing with suggestions. *Journal of Artificial Intelligence Research*, 27:465–503.

Jesse Vig, Shilad Sen, and John Riedl. 2012. The tag genome: Encoding community knowledge to support novel interaction. *ACM Transactions on Interactive Intelligent Systems*, 2(3):13:1–13:44.

Xuerui Wang and Andrew McCallum. 2006. Topics over time: a non-markov continuous-time model of topical trends. In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 424–433. ACM.

Liang-Chih Yu, Jin Wang, K Robert Lai, and Xuejie Zhang. 2017. Refining word embeddings for sentiment analysis. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 534–539.