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**Prioritizing Engineering Characteristics based on Customer Online Reviews for QFD**

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4 **Prioritizing Engineering Characteristics based on Customer Online Reviews for**  
5 **QFD**  
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28 **ABSTRACT:**

29 In market-driven product design, customer requirements are usually obtained from  
30 consumer surveys. However, valuable customer requirements can also be found in a  
31 large number of online reviews. Largely due to their free text nature and the quantity,  
32 these reviews are often neglected and are seldom utilized directly by designers. In this  
33 work, one important question in quality function deployment (QFD) on how to  
34 prioritize engineering characteristics is investigated. Customer opinions concerning  
35 engineering characteristics are extracted from online reviews. By taking advantage of  
36 such opinion information, an ordinal classification approach is proposed to prioritize  
37 engineering characteristics. In a pairwise manner, in which customer opinions are  
38 deemed as features and the overall customer satisfactions are regarded as the target  
39 values, the weights of engineering characteristics are derived. Furthermore, an integer  
40 linear programming model is implemented to convert the pairwise results into the  
41 original customer satisfaction ratings. Finally, an exploratory case study is presented  
42 using reviews of four branded printers collected from Amazon and their analysis was  
43 conducted by two experienced design engineers. The experimental study reveals the  
44 merits of the proposed approach.  
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52 **Keywords:** Customer reviews; user review analysis; QFD, engineering characteristics;  
53 product design.  
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## 1. INTRODUCTION

Online reviews contain valuable information about customer opinions and customer requirements (CRs). This information benefits both potential consumers and product designers (Liu, Lu and Loh, 2007). It is highly possible that potential consumers are affected by online reviews before they make decisions and product designers will learn valuable customer needs from online reviews. However, for some hot products, there may be hundreds of or even thousands of customer online reviews and they are distributed in different websites, which makes it difficult to handle all relevant reviews. This problem has been widely discussed in the research area of computer science. Some researchers developed innovative models to extract the opinions of consumers from online reviews (Hu and Liu, 2004; Liu, Hu and Cheng, 2005). Generally, it is named as sentiment analysis or opinion mining. Their research focus is mainly on sentiment identification (Hassan and Radev, 2010; Zagibalov and Carroll, 2008; Lin and He, 2009), sentiment extraction (Qiu et al., 2009; Kim and Hovy, 2005), and opinion retrieval (Zhang et al., 2008; Lin et al., 2010) at different levels. However, none of these research studies discuss how online reviews benefit product designers in terms of customer analysis. In the design area, only a few studies concern about the value of online reviews, such as how to summarize and analyze the topic structure of online reviews for product design (Zhan, Loh and Liu, 2009), how to identify helpful online reviews from the perspective of product designers (Liu et al., 2013), etc. What they neglect is how to assemble their findings into product design directly. For

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4 instance, how to improve the current product models according to the requirements in  
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6 online reviews.  
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9 For example, in Figure 1, one typical iPad review is illustrated.. It complains  
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11 that "...I was hoping the third gen wouldn't be noticeably thicker and heavier than the  
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13 2, but unfortunately it was. I could definitely tell the difference when reading ebooks,  
14  
15 which I do a lot...". As seen from this figure, this consumer is not satisfied with the  
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17 size and the weight of iPad, which leads to an overall three-star is given to express  
18  
19 his/her overall customer satisfaction. This review provides suggestive information to  
20  
21 designers. Accordingly, when launching the next generation, designers may consider,  
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23 with limited time and budget, which parts they need to improve in order to satisfy  
24  
25 potential consumers. More specially, in the process of new product design, designers  
26  
27 need to prioritize several engineering characteristics (ECs), such as the size, the  
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29 weight, etc. It is also an indispensable step in Quality Function Development (QFD).  
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1,651 of 1,738 people found the following review helpful

★★★★☆ **Good, but ...**, March 25, 2012

By [Bookenz](#)

This review is from: **Apple iPad MD328LL/A (16GB, Wi-Fi, White) 3rd Generation (Personal Computers)**

I've been a big iPad fan and was waiting anxiously for the third generation to come out. I bought the original iPad, and when the 2 came out, I happily sold the 1 and upgraded. I was thrilled with the thinner, lighter and improved iPad 2. So naturally, when word came out that the third one was about to be released in March 2012, I was right on board to buy one. Sold my 2 and preordered the 3 from Apple the day it was released.

I was hoping the third gen wouldn't be noticeably thicker and heavier than the 2, but unfortunately it was. I could definitely tell the difference when reading ebooks, which I do a lot. I couldn't really tell any difference between the speed and clarity of the 3, but to be fair, I didn't compare the two models side by side. I've no doubt the 3 is superior in this regard. I don't use the cameras, so don't care about this since I have a very nice digital camera for that.

The one thing about the third generation iPad that concerned me was the heat issue. Shortly after receiving it, I was reading an ebook and noticed the left side was warm. Not hot, but definitely warm enough for me to notice it. This reminded me of laptops I've had that have overheated and shut down, and here I was only reading a book. My iPad 2 never had this problem and I used it a lot. I also had some difficulty backing up the 3 to the cloud, again, something that wasn't ever a problem with the 2.

After reading some reviews of others experiencing the heating problem with the latest iPad, and really missing the thinner and lighter iPad 2, I decided to return the iPad 3 to my local Apple store and buy a new iPad 2. They had no problem taking it back and I was glad to see the 2 had come down in price. When the sales associate asked me why I was returning the 3, I told him about the heat problem. He didn't seem surprised and said it was because the 3 has a larger battery.

The third gen has a faster CPU and retina display, but I never thought the 2 had any problems with speed, and the clarity of the display has always seemed fine to me. But I'm certainly no expert. I'm very happy I made the exchange and enjoying using my iPad 2 again. For my uses--books, internet, email and games, the cooler, thinner and lighter iPad 2 is a better choice for me.

By the way, I just want to add that I think it's unfair to compare the Kindle Fire and Nook to the iPad. These devices are just ebook readers and they're fine for that--I've tried them both. Rather like saying, okay, you can buy this Mercedes or you can get the Volkswagen. Once you've used an iPad, you're totally spoiled and trying to browse the Internet with a Kindle or Nook is an exercise in frustration after using an iPad.

Update January 7, 2014 - since writing this review for the iPad 3, which I ended up returning, I've moved on to the iPad Air, which is noticeably lighter and faster than the iPad 2.

Help other customers find the most helpful reviews

[Report abuse](#) [Permalink](#)

Was this review helpful to you?  Yes  No

**Figure 1.** One typical online review

Correspondingly, in this research, the focus is on how to prioritize ECs based on the CRs in online reviews. Notice that, in the field of engineering design, the term, "engineering characteristics", is "also known as technical attributes, product technical requirements or design requirements" and they "describe the product in the language of the engineer" (Sener and Karsak, 2011). Also, ECs is named as "the voice of the company" and they are employed to "determine how well the company satisfies the needs." For such reasons, they are often established at an early design stage according to the company's strategic goals (Kahraman, Ertay and Buyukozkan, 2006). Thus,

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4 generally, ECs can be design specifications, substitute quality characteristics,  
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6 company's strategic goals, engineering attributes, government regulations, or  
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8 specification practice standards (Wang, 1999; Chan and Wu, 2005). Specifically, in  
9  
10 this research, the term refers to the translation of CRs to an engineering language  
11  
12 from the perspective of product designers, which can be generally deemed as how  
13  
14 product designers deem and evaluate these CRs.  
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19 Different from many conventional methods, in this research, online reviews,  
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21 rather than survey data, are taken into consideration to identify CRs. Specially,  
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23 customer opinions about ECs are firstly extracted from online reviews. Then, the  
24  
25 overall ratings affiliated with online reviews are taken as the overall customer  
26  
27 satisfaction about products. Combined with the overall customer satisfaction, these  
28  
29 opinions in online reviews are utilized to prioritize ECs. In particular, an ordinal  
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31 classification approach is proposed based on pairwise algorithms about learning to  
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33 rank. The idea about the marginal maximization of pairwise algorithms is borrowed in  
34  
35 this ordinal classification approach, which intends to derive the weights of ECs.  
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37 Moreover, in order to transform the pairwise results to the original ratings of customer  
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39 satisfaction, an integer linear programming model is formulated, which has not been  
40  
41 explained clearly by many pairwise algorithms. In the same time, a running example  
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43 is presented to explain the proposed ordinal classification approach and the integer  
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45 linear programming model step by step. Finally, a case study of printer design is  
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47 prepared to show some interesting findings and how the proposed method assist  
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49 designers to decide critical ECs.  
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4 The contributions of this research are at least three folds. Firstly, online  
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6 reviews, which are fundamentally different from customer survey data, are utilized to  
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8 prioritize ECs. It is the first attempt to make online reviews directly utilized by  
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10 product designers. Secondly, the overall customer satisfaction and opinions over ECs  
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12 in online reviews are important for the prioritization of ECs. Accordingly, an ordinal  
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14 classification approach is proposed to prioritize ECs by the analysis of customer  
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16 reviews. An integer linear programming model is also formulated to transform the  
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18 pairwise results from the ordinal classification approach to the original customer  
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20 satisfaction ratings. Finally, comparative case studies are conducted to expose  
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22 interesting phenomena. Frequently talked ECs might not necessarily become a  
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24 deciding factor for the new product design, while some details of products may  
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26 influence the overall customer satisfaction.  
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34 The rest of this paper is organized as follows: Section 2 introduces the related  
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36 work. In Section 3, the problem to be investigated in this research is formally defined.  
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38 Section 4 describes the research efforts and illustrates the proposed technical  
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40 approaches. Section 5 presents the details of a case study and discusses some  
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42 experimental results. Section 6 concludes this research.  
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## 49 **2. LITERATURE REVIEW**

### 50 **2.1. Importance Weighting of Engineering Characteristics**

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52 Due to the time and budget limitations, when designers conceive to improve product  
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54 models, it is usually unreasonable to consider ECs without any bias. Importance  
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4 weighting of ECs, which is one important problem in QFD, becomes crucial for the  
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6 resource allocation as well as the final decision-making in new product design. A  
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8 nonlinear programming model was proposed to prioritize ECs in fuzzy environments  
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10 (Wang and Chin, 2011). Two numerical examples were shown to verify the  
11  
12 availability of this model. A fuzzy weighted average method was also proposed to  
13  
14 prioritize ECs in fuzzy QFD (Chen, Fung, and Tang, 2006). In this method, a discrete  
15  
16 solution was obtained by changing the fuzzy weighted average problem to a pair of  
17  
18 fractional programming problem for each EC. Kwong et al. (2011) argued that both  
19  
20 the human perception and the customer heterogeneity were found to influence the  
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22 importance of ECs in QFD, but most of the relevant researches only center at one of  
23  
24 them. Accordingly, a fuzzy group decision-making method combining both a fuzzy  
25  
26 weighted average method and an ordinal ranking was proposed to incorporate the two  
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28 influential factors. This approach was argued to be better than the method proposed  
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30 by Chen, Fung and Tang (2006).  
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39 Some researchers argued that the importance of ECs in QFD can be evaluated  
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41 from two aspects, namely, the needs of customer aspect and the needs of  
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43 manufacturer aspect (Geng et al., 2010). From the perspective of customer needs, the  
44  
45 analytic network process was utilized to estimate the initial importance of ECs by  
46  
47 considering the relationships of customer needs, product characteristics, and service  
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49 related ECs. The fuzzy set theory was then applied in the analytic network process to  
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51 deal with the uncertainty in decision-making. From the perspective of manufacturer  
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53 needs, the data envelopment analysis was employed to adjust the initial weights of  
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4 product characteristics by considering both the business competition and the  
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6 implementation difficulty. QFD was regarded as a grey system in (Li, Zhang and Gao,  
7  
8 2009). The relationships between CRs and ECs were determined by the grey  
9  
10 relational matrix. A grey method was then utilized to prioritize ECs. Moreover,  
11  
12 Kano's Model was also seen to be integrated with QFD to recognize the importance  
13  
14 of ECs (Chaudha, et al., 2011).  
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19 Some research studies associating with customer satisfaction and ECs are also  
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21 valuable to be highlighted, although these do not handle the problem about  
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23 importance weighting of ECs straightforwardly. For instance, a Neuro fuzzy approach  
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25 was also reported to generate a customer satisfaction model (Kwong, Wong and Chan,  
26  
27 2009). An example for notebook computer design is given to show that this model is  
28  
29 better than a statistical regression approach. A genetic programming model is  
30  
31 proposed to associate ECs with customer satisfaction, in which the interactions  
32  
33 between ECs as well as high-order relationship between ECs and customer  
34  
35 satisfaction are considered (Chan, Kwong and Wong, 2011). Then, an orthogonal  
36  
37 least-squares algorithm is employed to decide the coefficients of the relationship. A  
38  
39 fuzzy least-squares regression method is also proposed to model the fuzzy  
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41 relationship between customer satisfaction and ECs as well as the fuzzy relationship  
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43 among ECs (Kwong et al., 2010) .  
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51 Notice that, although many approaches were developed regarding prioritizing  
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53 ECs, in the most of publications, survey data often become the source of CRs.  
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55 However, online reviews are fundamentally different from survey data and their  
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4 differences are at least in three folds. First, due to the time and budget limitations, it is  
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6 usually time-consuming and labor-intensive for designers to gain a large number of  
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8 survey data manually. But a large number of customer reviews are always available  
9  
10 online. Second, survey data are usually generated from questionnaires with specific  
11  
12 intentions and some customers are invited to select the most proper answers from a  
13  
14 given list. But customer reviews are free text. Some of them may contain only a few  
15  
16 words, while, in the other case, hundreds, or even thousands, of words may appear in  
17  
18 one review. Sufficient customer concerns can be found from online reviews. Thirdly,  
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20 survey data seldom contain personal opinions, while online reviews are one important  
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22 way to express their opinions. These differences make many approaches which are  
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24 proposed on the basis of survey data in the design area cannot be utilized directly to  
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26 handle CRs in a large volume of online reviews.  
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## 36 **2.2. Online Reviews for Product Design**

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38 Although online reviews are widely accepted as one important source of CRs, only a  
39  
40 few studies discuss the value of online reviews in product design.  
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44 A text mining system, where online reviews were integrated with the domain  
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46 knowledge, was reported on knowledge discovery and management in product design  
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48 (Liu, Lu and Loh, 2007). To aggregate CRs from online reviews for product design, a  
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50 framework was presented (Decker and Trusov, 2010). This framework was utilized to  
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52 infer the relative effect of product features and the effect of different brands on the  
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54 overall customer satisfaction. An automatic summarization approach was seen to  
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4 analyze the topic structure of online reviews (Zhan, Loh and Liu, 2009). This  
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6 approach was utilized to discover and assemble important topics in online reviews.  
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9 The final summary of multiple reviews was then clustered by the topic structure and  
10  
11 different clusters were ranked according to the importance of different topics.  
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14 Online reviews were also reported to be utilized in the prediction about  
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16 product design trends (Tucker and Kim, 2011). Sentiment polarity of product features  
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18 were extracted from online reviews. Then, the Holt-Winters exponential smoothing  
19  
20 method was employed to model product preference trends. A system that monitor  
21  
22 customer opinions from textual data is built (Goorha and Ungar, 2010). First, frequent  
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24 phrases and phrases near the terms of interest are extracted from textual data. These  
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26 phrases are then utilized to identify which of them appear dramatically. Also, whether  
27  
28 a phrase is regarded as an interesting one is depended on how often they are referred,  
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30 how often they are referred comparing with before and how specific they refer to a  
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32 topic. These results are illustrated by an interactive user interface. Also, in order to  
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34 present the results effectively, TFIDF weights and the cosine similarity method is  
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36 utilized to cluster relevant terms.  
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44 A three steps method is proposed for customer driven product design selection  
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46 by the analysis of online reviews (Wang et al., 2011). In the first step, product  
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48 attributes were extracted from online reviews. In the second step, a hierarchical  
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50 customer preference model was built by Bayesian linear regression. Product ratings,  
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52 category ratings, attribute ratings and product specifications are taken into  
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54 consideration in this hierarchical model. Finally, an optimization problem was  
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4 formulated to maximize potential profit by taking engineering constraints into  
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6 consideration. In (Liu et al., 2013), the helpfulness of online reviews was initially  
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8 defined in the viewpoint of designers for QFD. According to designers' arguments,  
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10 four categories of features are extracted from online reviews. With these features, the  
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12 helpfulness of online reviews is inferred by a regression method. Also, categories of  
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14 experiments confirm that, without domain-dependent features, there is no significant  
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16 loss in terms of helpfulness prediction for online reviews from the perspective of  
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18 product designers.  
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### 26 **2.3. Pairwise Approaches of Learning to Rank**

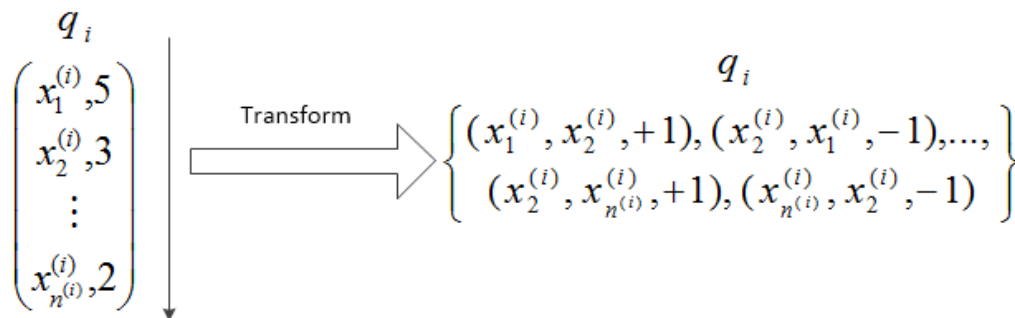
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28 Learning to rank is a type of supervised learning task. The objective is to construct a  
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30 ranking model from training data, which sorts new objects according to their degrees  
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32 of relevance (Joachims et al., 2007). The algorithms of learning to rank are generally  
33  
34 classified into three types, pointwise approaches, pairwise approaches and listwise  
35  
36 approaches. Different input and output spaces, hypothesis and loss functions are  
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38 defined in different types. In this research, a pairwise approach is proposed to  
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40 prioritize ECs based on customer reviews. To understand this approach, some relevant  
41  
42 pairwise algorithms are reviewed in this subsection.  
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49 The input space of a pairwise approach contains a pair of documents, which is  
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51 represented as feature vectors. For the output space, a pairwise approach contains the  
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53 pairwise preference between each pair of documents. The hypothesis space of a  
54  
55 pairwise approach contains functions, which take a pair of documents as input and  
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output the relative order between them. The loss function of pairwise approaches measures the inconsistency between the predicted relationship and the ground truth labels of document pairs.

Pairwise approaches do not target at accurately predicting the relevance degree of each single document, and only care about the relative order between two documents. The learning procedure of pairwise approaches is conducted over document pairs. An example of outputs may take values from positive one and negative one, which indicates the pairwise preference between each pair of documents. A conceptual illustration for pairwise approaches of Learning to Rank is proposed in Tie-Yan Liu's tutorial in *SIGIR'08*, which is shown in Figure 2 (Liu, 2008).



**Figure 2.** An conceptual illustration for pairwise approaches of learning to rank (Liu, 2008)

In Figure 2, a typical training set for learning to rank is shown, which consists some training queries, their associate documents as well as the corresponding relevance judgments. For each training query  $q_i$ , the associate documents are represented by feature vectors  $x^{(i)} = \{x_j^{(i)}\}_{j=1}^{n^{(i)}}$ , where  $n^{(i)}$  is the number of documents associated with query  $q_i$ . However, one transformation needs to be conducted to build a training set for the pairwise approach. The input space of the pairwise approach are

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4 represented by feature vectors  $\{x_j^{(i)}, x_k^{(i)}\}_{j \neq k}^{n^{(i)}}$ , which contains all pairs of documents,  
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6 and the output space is the value of positive one and negative one, which indicate  
7  
8 pairwise preference between each pair of documents. Take two documents  $(x_2^{(i)}, 3)$   
9  
10 and  $(x_n^{(i)}, 2)$  for instance. In the pairwise approach, according to the corresponding  
11  
12 relevance judgments 5 and 3, they are transformed to  $(x_2^{(i)}, x_n^{(i)}, 1)$  and  $(x_n^{(i)}, x_2^{(i)}, -1)$   
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16 Accordingly, in pairwise approaches, ranking is usually reduced to a  
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18 classification problem on document pairs. It makes many conventional algorithms for  
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20 classification applicable for this problem. A neural network was built to learn a  
21  
22 preference function for all possible document pairs in training data (Burges et al.,  
23  
24 2005; Rigutini et al., 2011). A boosting approach over document pairs was utilized to  
25  
26 combine ranking functions in RankBoost (Freund et al., 2003). Based on SVM,  
27  
28 RankSVM was proposed to perform the pairwise classification (Herbrich, Graepel  
29  
30 and Obermayer, 2000; Joachims, 2002). RankSVM differs from SVM at its constraint  
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32 part and the loss function, which was built from document pairs. However, one  
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34 hyperplane is employed by RankSVM, which is argued to be hard to handle complex  
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36 ranking problems (Qin et al., 2007). Multiple hyperplanes were proposed to train a  
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38 ranking model for document pairs. Finally, the ranking results predicted by each  
39  
40 ranking model were aggregated to the final ranking result.  
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#### 51 **2.4. A Short Summary**

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54 In the design field, various models were developed based on survey data.. But online  
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56 reviews which contain valuable information about CRs are not concerned. The  
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4 differences between online reviews and survey data make many conventional methods  
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6 in product design not be applicable to handle CRs in a big volume of distributed and  
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8 fast-evolving online reviews. Although a few studies discuss how to utilize online  
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10 reviews in product design, as one of critical steps in QFD, the importance weighting  
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12 of ECs for QFD based on online customer reviews is neglected.  
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16 A large number of customer reviews which represent consumer opinions and  
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18 requirements are observed online. Although positive online reviews do not always  
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20 bring new consumers, negative reviews may lead to the loss of potential customers.  
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22 Accordingly, it becomes critical to conduct the analysis of CRs efficiently and make  
23  
24 an immediate and effective response, especially in a fierce competitive market. As  
25  
26 one downside of online reviews, not all of these data contain much valuable  
27  
28 information to product designers. In the previous research (Liu et al., 2013), the  
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30 helpfulness of online reviews is perceived, evaluated and predicted from the  
31  
32 perspective of product designers. These techniques in the previous research enable  
33  
34 product designers to concentrate only on high-quality customer reviews. Hence, in  
35  
36 this research, based on high-quality customer online reviews, one of important  
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38 questions about how to prioritize ECs for QFD is centered. It will be highly possible  
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40 to facilitate designers' work in the process of conceptual design.  
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### 51 **3. PROBLEM DEFINITION**

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53 In QFD, taking customer needs as input, product designers usually need to prioritize  
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55 ECs. To clarify the problem in this research, some notation will be defined.  
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4 In some e-commerce websites, such as Amazon.com, each product has a series  
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6 of high quality customer reviews,  $r_1, r_2, \dots, r_p$ . These reviews contain valuable  
7  
8 customer needs. However, due to the time limitation and the budget cost, on the basis  
9  
10 of customer needs, it is unreasonable to consider all of ECs without bias. Typically, a  
11  
12 list of ECs includes  $\langle ec_1, ec_2 \dots ec_n \rangle$ .  
13

14  
15  
16 Typically, customers may present different opinions over different ECs. For  
17  
18 example, in a particular review  $r_i$ , a customer is satisfied or unsatisfied with  $ec_j$ . It can  
19  
20 be denoted as  $(ec_j, O_{ij})$ .  $O_{ij}$  is the associated opinion about  $ec_j$  in  $r_i$ . Accordingly,  $r_i$  can  
21  
22 be represented as an opinion vector  $O_i = \langle O_{i1}, O_{i2}, \dots, O_{in} \rangle$ . A positive  $O_{ij}$  denotes that,  
23  
24 in  $r_i$ , this consumer is satisfied with  $ec_j$ , while, a negative value denotes that an  
25  
26 unsatisfied opinion. Also, in  $r_i$ , there may be zero, one or more sentences associated  
27  
28 with a specific  $ec_j$ . If a consumer does not mention  $ec_j$  in  $r_i$ , the corresponding  $O_{ij}$  is  
29  
30 assumed to be zero, which implies that this consumer has a neutral opinion. For the  
31  
32 case that there are more than one sentences discussing  $ec_j$  in  $r_i$ , the average value of  
33  
34  $O_{ij}$  is taken as the consumer's final opinion on  $ec_j$ .  
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42 In addition, consumers are also encouraged to give a rating towards the overall  
43  
44 satisfaction. For example, in Figure 1, a three-star iPad review is shown. It is denoted  
45  
46 as, in review  $r_i$ , a rating  $cs_i$  is utilized to express the overall satisfaction. According to  
47  
48 the definition of  $cs_i$  and  $O_i$ ,  $r_i$  can be  $(O_i, cs_i)$ . For a customer review set, containing  $p$   
49  
50 reviews, it can be denoted as  $\langle (O_1, cs_1), (O_2, cs_2) \dots (O_p, cs_p) \rangle$ . Now, based on the  
51  
52 information about customer opinions and the overall satisfaction, the central question  
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54 is how to prioritize ECs for QFD.  
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4 Specially, it is about how to infer the weights  $W = \langle w_1, w_2, \dots, w_n \rangle$  of  $ec_1,$   
5  
6  $ec_2, \dots, ec_n$  from  $\langle (O_1, cs_1), (O_2, cs_2), \dots, (O_p, cs_p) \rangle$  by exploiting all  $p$  reviews.

7  
8 Mathematically, it can be denoted as:

$$cs_i = f\left(\sum_{j=1}^n w_j O_{ij}\right) \quad (1)$$

9  
10  
11  
12  $f(x)$  is a devised function transforming the sum of weighted opinions over ECs  
13  
14 into the overall customer satisfaction. Notice that, the objective here is not to find or  
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16 settle the exact form of such function but to denote the weights of opinions over  
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18 different ECs are to be learned according to opinions in customer online reviews.  
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24  
25 It appears that a regression model is qualified to learn  $w_1, w_2, \dots, w_n$ . But it is  
26  
27 arguable since regression models are generally utilized to analyze questions with  
28  
29 continuous values as the target, while, in this research,  $cs_i$  is a discrete value. Thus,  
30  
31 the classification model might be more persuasive than regression models. It is still  
32  
33 questionable since the inherent ranking information of  $cs_i$  will be neglected by simple  
34  
35 classification models. For example, in one review, a five-star is given by a consumer.  
36  
37 Suppose that it is predicted as a four-star by model one and a three-star by model two.  
38  
39 In this scenario, model one is favorable since it is closer to the original five-star,  
40  
41 though two models lead to the same prediction error with simple classification models.  
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43 Another potential technique is learning to rank. However, models of learning to rank  
44  
45 neglect that objects can be possibly placed in the same position. For example, two  
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47 reviews may present the same customer satisfaction rating on products while learning  
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49 to rank fail to consider such case. Hence, models of learning to rank are also not  
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51 suitable to be utilized directly to prioritize ECs based on customer reviews.  
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4 Particularly, in this research, both the classification and the ranking  
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6 information should be taken into consideration, when considering how to prioritize  
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8 ECs based on customer reviews. Hence, an ordinal classification model is required.  
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10

#### 11 12 13 **4. PRIORITIZING ENGINEERING CHARACTERISTICS BASED ON** 14 15 **CUSTOMER REVIEWS**

##### 16 17 18 **4.1 An Ordinal Classification Approach**

19  
20 As presented in Section 2, one famous algorithm of learning to rank is RankSVM,  
21  
22 which is a pairwise approach. In RankSVM, the weights of features  $W$  are learned  
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24 from training data, which enables the distance between hyperplanes of document pairs  
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26 is maximized.  $W$  is then utilized to predict the preference of document pairs. In this  
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28 research, if opinions over different ECs are regarded as features and the overall  
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30 customer satisfaction is regarded as the expected ranking position, the weights will be  
31  
32 learned accordingly. The limitations is that, RankSVM stresses two documents are  
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34 well separated. It is not true for the customer satisfaction ratings of different reviews  
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36 because they may be given the same level of customer satisfaction. However, the idea  
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38 about learning  $W$  from document pairs and maximizing the distances of hyperplanes is  
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40 highly instructive. Accordingly, in this research, learning the weights  $W$  of ECs from  
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42 online reviews is transformed to learn  $W$  from review pairs. Hence, at first, a set of  
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44 review pairs  $P$  should be derived from the whole review set  $D$ .  $P$  should contain all  
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46 set of review pairs  $((O_i, cs_i), (O_j, cs_j))$ .  
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#### 4.1.1. An Example of Nine Reviews with Six Engineering Characteristics

To clarify the proposed ordinal classification approach clearly, a running example is introduced through this section. In this example, there are nine printer reviews,  $r_1, r_2, \dots, r_9$ . One to five stars are utilized to indicate the overall customer satisfaction about the printer. It is denoted as  $cs_i \in \{1, 2, 3, 4, 5\}$ . The values of customer satisfaction for all nine reviews are supposed in Table 1.

**Table 1.** The values of customer satisfaction for nine reviews

$cs_1$	$cs_2$	$cs_3$	$cs_4$	$cs_5$	$cs_6$	$cs_7$	$cs_8$	$cs_9$
5	2	3	4	5	2	4	1	3

With these nine reviews, six important ECs,  $ec_1, ec_2, \dots, ec_6$ , are concerned only. For instance, they may be “ease of use”, “noise”, “print quality”, “Wifi integration”, “duplex printing” and “card slot”. The corresponding weights are denoted as  $w_1, w_2, \dots, w_6$ , which are to be learned from the nine customer reviews. But notice that other ECs may be considered in this example. The objective to select some exemplary ECs is to illustrate how the weights are learned by the proposed ordinal classification approach, not to take these exact six ECs only into considerations. Moreover, opinions over  $ec_1, ec_2, \dots, ec_6$ , may be different. In this research, a five-degree metric,  $O_{ij} \in \{-2, -1, 0, 1, 2\}$ , is employed to evaluate the opinion, where “-2” stands for the least satisfied and “2” for the most satisfied. Accordingly,  $O_i = \langle O_{i1}, O_{i2}, \dots, O_{i6} \rangle$ , will be the customer satisfaction over  $ec_1, ec_2, \dots, ec_6$  in a review  $r_i$ . These opinions are planned randomly as illustrated in Table 2.

**Table 2.** The opinions over six ECs of nine reviews

	$r_1$	$r_2$	$r_3$	$r_4$	$r_5$	$r_6$	$r_7$	$r_8$	$r_9$

$ec_1$	1	-2	2	-2	-1	1	1	-2	-1
$ec_2$	0	-1	1	1	1	0	-1	0	-1
$ec_3$	1	-2	-2	1	0	-2	1	-2	-2
$ec_4$	2	2	0	1	-2	-1	-1	-2	-1
$ec_5$	-1	2	-2	2	1	-1	-2	0	0
$ec_6$	-1	1	-1	-2	-2	-1	1	-2	2
$cs_i$	5	2	3	4	5	2	4	1	3

#### 4.1.2. Building the review pair set $P$

As mentioned, in this research, the weights of ECs will be learned from review pairs.

Hence, a review pair set  $P$  should be deduced accordingly.

Firstly, for review  $r_i$  and  $r_j$ , if  $cs_i > cs_j$ , or equivalently,  $r_i$  is ranked better than  $r_j$ ,  $(O_i - O_j, 1)$  is put into  $P$ . If  $cs_i < cs_j$ , then  $(O_i - O_j, -1)$  is put into  $P$ . If  $cs_i = cs_j$ , it means  $r_i$  is ranked equivalently to  $r_j$ , then  $(O_i - O_j, 0)$  is put into  $P$ . Then, in the nine reviews example, there are  $\binom{9}{2} = \frac{9 \times 8}{2} = 36$  review pairs. All review pairs in  $P$  are shown in Table 3.

**Table 3.** The set  $P$  for the nine reviews

$r_1, r_2, (3 \ 1 \ 3 \ 0 \ -3 \ -2, 1)$	$r_1, r_3, (-1 \ -1 \ 3 \ 2 \ 1 \ 0, 1)$	$r_1, r_4, (3 \ -1 \ 0 \ 1 \ -3 \ 1, 1)$
$r_1, r_5, (2 \ -1 \ 1 \ 4 \ -2 \ 1, 0)$	$r_1, r_6, (0 \ 0 \ 3 \ 3 \ 0 \ 0, 1)$	$r_1, r_7, (0 \ 1 \ 0 \ 3 \ 1 \ -2, 1)$
$r_1, r_8, (3 \ 0 \ 3 \ 4 \ -1 \ 1, 1)$	$r_1, r_9, (2 \ 1 \ 3 \ 3 \ -1 \ -3, 1)$	$r_2, r_3, (-4 \ -2 \ 0 \ 2 \ 4 \ 2, -1)$
$r_2, r_4, (0 \ -2 \ -3 \ 1 \ 0 \ 3, -1)$	$r_2, r_5, (-1 \ -2 \ -2 \ 4 \ 1 \ 3, -1)$	$r_2, r_6, (-3 \ -1 \ 0 \ 3 \ 3 \ 2, 0)$

$r_2, r_7, (-3 \ 0 \ -3 \ 3 \ 4 \ 0, -1)$	$r_2, r_8, (0 \ -1 \ 0 \ 4 \ 2 \ 3, 1)$	$r_2, r_9, (-1 \ 0 \ 0 \ 3 \ 2 \ -1, -1)$
$r_3, r_4, (4 \ 0 \ -3 \ -1 \ -4 \ 1, -1)$	$r_3, r_5, (3 \ 0 \ -2 \ 2 \ -3 \ 1, -1)$	$r_3, r_6, (1 \ 1 \ 0 \ 1 \ -1 \ 0, 1)$
$r_3, r_7, (1 \ 2 \ -3 \ 1 \ 0 \ -2, -1)$	$r_3, r_8, (4 \ 1 \ 0 \ 2 \ -2 \ 1, 1)$	$r_3, r_9, (3 \ 2 \ 0 \ 1 \ -2 \ -3, 0)$
$r_4, r_5, (-1 \ 0 \ 1 \ 3 \ 1 \ 0, -1)$	$r_4, r_6, (-3 \ 1 \ 3 \ 2 \ 3 \ -1, 1)$	$r_4, r_7, (-3 \ 2 \ 0 \ 2 \ 4 \ -3, 0)$
$r_4, r_8, (0 \ 1 \ 3 \ 3 \ 2 \ 0, 1)$	$r_4, r_9, (-1 \ 2 \ 3 \ 2 \ 2 \ -4, 1)$	$r_5, r_6, (-2 \ 1 \ 2 \ -1 \ 2 \ -1, 1)$
$r_5, r_7, (-2 \ 2 \ -1 \ -1 \ 3 \ -3, 1)$	$r_5, r_8, (1 \ 1 \ 2 \ 0 \ 1 \ 0, 1)$	$r_5, r_9, (0 \ 2 \ 2 \ -1 \ 1 \ -4, 1)$
$r_6, r_7, (0 \ 1 \ -3 \ 0 \ 1 \ -2, -1)$	$r_6, r_8, (3 \ 0 \ 0 \ 1 \ -1 \ 1, 1)$	$r_6, r_9, (2 \ 1 \ 0 \ 0 \ -1 \ -3, -1)$
$r_7, r_8, (3 \ -1 \ 3 \ 1 \ -2 \ 3, 1)$	$r_7, r_9, (2 \ 0 \ 3 \ 0 \ -2 \ -1, 1)$	$r_8, r_9, (-1 \ 1 \ 0 \ -1 \ 0 \ -4, -1)$

Take  $r_1$  and  $r_2$  for example. As seen from Table 2,  $cs_1$  equals to 5 and  $cs_2$  equals to 2.  $cs_1$  is bigger than  $cs_2$ , then  $(O_1 - O_2, 1)$  is put into  $P$ .  $O_1 - O_2$  is calculated as  $O_1 - O_2 = (1 - (-2), 0 - (-1), 1 - (-2), 2 - 2, (-1) - 2, (-1) - 1)$ . For  $r_2$  and  $r_3$ , since  $cs_2$  is smaller than  $cs_3$ , then  $(O_2 - O_3, -1)$  is put into  $P$ . Similarly, it is calculated as  $((-2) - 2, (-1) - 1, (-2) - (-2), 2 - 0, 2 - (-2), 1 - (-1))$ . The third example is between  $r_1$  and  $r_5$ . Since both  $cs_1$  and  $cs_5$  equal to 5,  $(O_1 - O_5, 0)$  is put into  $P$ .

With  $P$  defined, deriving the weights of ECs based on customer reviews turns to be a tri-classification problem, which attempts to classify review pairs to  $\{-1, 0, 1\}$ . Let one review pair is  $(OP_k, cr_k)$ , where  $OP_k$  equals to  $O_i - O_j$ .  $OP_k$  can be also denoted as  $\langle OP_{k1}, OP_{k2}, \dots, OP_{kn} \rangle$ , where  $OP_{ks} = O_{is} - O_{js}$ .  $cr_k$  is a discrete value, which represents the relationship of  $cs_i$  and  $cs_j$ . Taking  $OP_k$  as the feature vector and  $cr_k$  as the target class, it is a tri-classification problem to derive the weights of ECs.

However, if a further step is taken, a binary classification will be shown. Notice that, when  $cs_i < cs_j$ , if  $(O_j - O_i, 1)$  is put into  $P$ , rather than  $(O_i - O_j, -1)$ , a

binary classification is shown. Clearly, it does not affect the value of  $W$ . But the problem is that the ranking relationship of two reviews is lost. Thus, to trace which review presents a higher level of customer satisfaction, whether  $cs_i > cs_j$  or  $cs_j > cs_i$  is kept in practice. Now  $OP_k$  is either  $O_i - O_j$  or  $O_j - O_i$ , and  $cr_k$  is “1” or “0”. “1” denotes that two reviews receive different levels of customer satisfaction, while “0” denotes two reviews receive the same. Taking the previous nine reviews as examples, accordingly, all review pairs in  $P$  become what are shown in Table 4.

**Table 4.** Review pairs in  $P$  after applying transformation rules

$r_1, r_2, (3 \ 1 \ 3 \ 0 \ -3 \ -2, 1)$	$r_1, r_3, (-1 \ -1 \ 3 \ 2 \ 1 \ 0, 1)$	$r_1, r_4, (3 \ -1 \ 0 \ 1 \ -3 \ 1, 1)$
$r_1, r_5, (2 \ -1 \ 1 \ 4 \ -2 \ 1, 0)$	$r_1, r_6, (0 \ 0 \ 3 \ 3 \ 0 \ 0, 1)$	$r_1, r_7, (0 \ 1 \ 0 \ 3 \ 1 \ -2, 1)$
$r_1, r_8, (3 \ 0 \ 3 \ 4 \ -1 \ 1, 1)$	$r_1, r_9, (2 \ 1 \ 3 \ 3 \ -1 \ -3, 1)$	$r_3, r_2, (4 \ 2 \ 0 \ -2 \ -4 \ -2, 1)$
$r_4, r_2, (0 \ 2 \ 3 \ -1 \ 0 \ -3, 1)$	$r_5, r_2, (1 \ 2 \ 2 \ -4 \ -1 \ -3, 1)$	$r_2, r_6, (-3 \ -1 \ 0 \ 3 \ 3 \ 2, 0)$
$r_7, r_2, (3 \ 0 \ 3 \ -3 \ -4 \ 0, 1)$	$r_2, r_8, (0 \ -1 \ 0 \ 4 \ 2 \ 3, 1)$	$r_9, r_2, (1 \ 0 \ 0 \ -3 \ -2 \ 1, 1)$
$r_4, r_3, (-4 \ 0 \ 3 \ 1 \ 4 \ -1, 1)$	$r_5, r_3, (-3 \ 0 \ 2 \ -2 \ 3 \ -1, 1)$	$r_3, r_6, (1 \ 1 \ 0 \ 1 \ -1 \ 0, 1)$
$r_7, r_3, (-1 \ -2 \ 3 \ -1 \ 0 \ 2, 1)$	$r_3, r_8, (4 \ 1 \ 0 \ 2 \ -2 \ 1, 1)$	$r_3, r_9, (3 \ 2 \ 0 \ 1 \ -2 \ -3, 0)$
$r_5, r_4, (1 \ 0 \ -1 \ -3 \ -1 \ 0, 1)$	$r_4, r_6, (-3 \ 1 \ 3 \ 2 \ 3 \ -1, 1)$	$r_4, r_7, (-3 \ 2 \ 0 \ 2 \ 4 \ -3, 0)$
$r_4, r_8, (0 \ 1 \ 3 \ 3 \ 2 \ 0, 1)$	$r_4, r_9, (-1 \ 2 \ 3 \ 2 \ 2 \ -4, 1)$	$r_5, r_6, (-2 \ 1 \ 2 \ -1 \ 2 \ -1, 1)$
$r_5, r_7, (-2 \ 2 \ -1 \ -1 \ 3 \ -3, 1)$	$r_5, r_8, (1 \ 1 \ 2 \ 0 \ 1 \ 0, 1)$	$r_5, r_9, (0 \ 2 \ 2 \ -1 \ 1 \ -4, 1)$
$r_7, r_6, (0 \ -1 \ 3 \ 0 \ -1 \ 2, 1)$	$r_6, r_8, (3 \ 0 \ 0 \ 1 \ -1 \ 1, 1)$	$r_9, r_6, (-2 \ -1 \ 0 \ 0 \ 1 \ 3, 1)$
$r_7, r_8, (3 \ -1 \ 3 \ 1 \ -2 \ 3, 1)$	$r_7, r_9, (2 \ 0 \ 3 \ 0 \ -2 \ -1, 1)$	$r_9, r_8, (1 \ -1 \ 0 \ 1 \ 0 \ 4, 1)$

Notice that, in SVM or RankSVM, “-1” and “1” are often utilized to denote two different classes and the parallel hyperplanes. Accordingly, rather than “0”, “-1”



is deployed to symbolize two reviews with the same level of customer satisfaction.  $cr_k$  is then either “-1” or “1”. The transformation rules from the whole review set  $D$  to review pair set  $P$  is summarized as:

$$\begin{aligned} (O_i - O_j, 1) &\rightarrow P, && \text{if } cs_i > cs_j \\ (O_j - O_i, 1) &\rightarrow P, && \text{if } cs_i < cs_j \\ (O_i - O_j, -1) &\rightarrow P, && \text{if } cs_i = cs_j \end{aligned}$$

With the transformation rules, the set  $P$  that are derived from the nine review example is shown in Table 5.

**Table 5.** The final review pairs in  $P$

$r_1, r_2, (3\ 1\ 3\ 0\ -3\ -2, 1)$	$r_1, r_3, (-1\ -1\ 3\ 2\ 1\ 0, 1)$	$r_1, r_4, (3\ -1\ 0\ 1\ -3\ 1, 1)$
$r_1, r_5, (2\ -1\ 1\ 4\ -2\ 1, -1)$	$r_1, r_6, (0\ 0\ 3\ 3\ 0\ 0, 1)$	$r_1, r_7, (0\ 1\ 0\ 3\ 1\ -2, 1)$
$r_1, r_8, (3\ 0\ 3\ 4\ -1\ 1, 1)$	$r_1, r_9, (2\ 1\ 3\ 3\ -1\ -3, 1)$	$r_3, r_2, (4\ 2\ 0\ -2\ -4\ -2, 1)$
$r_4, r_2, (0\ 2\ 3\ -1\ 0\ -3, 1)$	$r_5, r_2, (1\ 2\ 2\ -4\ -1\ -3, 1)$	$r_2, r_6, (-3\ -1\ 0\ 3\ 3\ 2, -1)$
$r_7, r_2, (3\ 0\ 3\ -3\ -4\ 0, 1)$	$r_2, r_8, (0\ -1\ 0\ 4\ 2\ 3, 1)$	$r_9, r_2, (1\ 0\ 0\ -3\ -2\ 1, 1)$
$r_4, r_3, (-4\ 0\ 3\ 1\ 4\ -1, 1)$	$r_5, r_3, (-3\ 0\ 2\ -2\ 3\ -1, 1)$	$r_3, r_6, (1\ 1\ 0\ 1\ -1\ 0, 1)$
$r_7, r_3, (-1\ -2\ 3\ -1\ 0\ 2, 1)$	$r_3, r_8, (4\ 1\ 0\ 2\ -2\ 1, 1)$	$r_3, r_9, (3\ 2\ 0\ 1\ -2\ -3, -1)$
$r_5, r_4, (1\ 0\ -1\ -3\ -1\ 0, 1)$	$r_4, r_6, (-3\ 1\ 3\ 2\ 3\ -1, 1)$	$r_4, r_7, (-3\ 2\ 0\ 2\ 4\ -3, -1)$
$r_4, r_8, (0\ 1\ 3\ 3\ 2\ 0, 1)$	$r_4, r_9, (-1\ 2\ 3\ 2\ 2\ -4, 1)$	$r_5, r_6, (-2\ 1\ 2\ -1\ 2\ -1, 1)$
$r_5, r_7, (-2\ 2\ -1\ -1\ 3\ -3, 1)$	$r_5, r_8, (1\ 1\ 2\ 0\ 1\ 0, 1)$	$r_5, r_9, (0\ 2\ 2\ -1\ 1\ -4, 1)$
$r_7, r_6, (0\ -1\ 3\ 0\ -1\ 2, 1)$	$r_6, r_8, (3\ 0\ 0\ 1\ -1\ 1, 1)$	$r_9, r_6, (-2\ -1\ 0\ 0\ 1\ 3, 1)$
$r_7, r_8, (3\ -1\ 3\ 1\ -2\ 3, 1)$	$r_7, r_9, (2\ 0\ 3\ 0\ -2\ -1, 1)$	$r_9, r_8, (1\ -1\ 0\ 1\ 0\ 4, 1)$

#### 4.1.3. Learning the Weights of Engineering Characteristics

Now, the question turns to learn the weight  $W$  to classify review pairs in  $P$  into two classes (“-1” and “1”). It is similar to what has been done in SVM. In SVM,  $W$  denotes the weights of features. It should be tuned to maximize the distance between the parallel hyperplanes and there are no additional constraints about  $W$ . But, in this research,  $W$  is defined as the weights of ECs and it should be nonnegative. Also, in SVM, if two classes cannot be separated, a compromised idea is employed. A slack variable,  $\xi_k$ , is chosen to measure the degree of compromise. This idea is adopted to devise this ordinal classification method. Accordingly, the model is shown as follows:

$$\begin{aligned}
 & \min \sum \xi_k + \frac{C}{2} W^T W \\
 & \text{s.t. } \hat{c}r_k = \sum_{j=1}^n w_j OP_{kj} \\
 & \hat{c}r_k cr_k \geq 1 - \xi_k \\
 & W \geq \mathbf{0} \\
 & \xi_k \geq 0
 \end{aligned} \tag{2}$$

Model (2) presents the details about the ordinal classification approach. It is adapted from SVM, where an additional constraint of weights  $W$  is considered.  $\xi_k$  is the slack variable, which is utilized to estimate the degree of compromise.  $\frac{1}{2} W^T W$  is the regularization term, which is to control the over-fitting phenomenon. The coefficient  $C$  governs the relative importance of the regularization term compared with the sum of compromise terms. The linear term,  $\sum_{j=1}^n w_j OP_{kj}$ , is to estimate the customer satisfaction relationship between two reviews  $\hat{c}r_k$ . The distance between two hyperplanes is  $2 - 2\xi$ . It intends to be made as large as possible, which makes two classes to be discriminated. In the third constraint, the weight  $w_i$  of  $ec_i$  is restrained to be bigger than or equal to zero. Bold “ $\mathbf{0}$ ” denotes a zero vector, rather than a scalar

zero. Accordingly, the weights over six ECs,  $w_1, w_2, \dots, w_6$ , of the nine reviews are calculated as:

$$\begin{aligned} \min & \sum_{k=1}^{36} \xi_k + \frac{C}{2} \sum_{t=1}^6 W_t^2 \\ \text{s.t. } & \hat{c}r_k = \sum_{j=1}^6 W_j OP_{kj} \\ & \hat{c}r_k cr_k \geq 1 - \xi_k \\ & W \geq \mathbf{0} \\ & \xi_k \geq 0 \end{aligned} \quad (3)$$

According to the data presented in Table 5 and the minimization problem of Model (3),  $W$  will be equal to  $W = (0.1154, 1.5000, 0.8077, 0.0000, 0.1923, 0.8462)$  if  $C$  is set to 0.5. Moreover, the predicted customer satisfaction relationship  $\hat{c}r_k$  of all pairs is illustrated in Table 6.

**Table 6.** The inferred customer satisfaction of 36 review pairs

$r_1, r_2, 1$	$r_1, r_3, 1$	<b><math>r_1, r_4, -1</math></b>	<b><math>r_1, r_5, 1</math></b>	$r_1, r_6, 1$	$r_1, r_7, 1$
$r_1, r_8, 1$	$r_1, r_9, 1$	$r_3, r_2, 1$	$r_4, r_2, 1$	$r_5, r_2, 1$	<b><math>r_2, r_6, 1</math></b>
$r_7, r_2, 1$	$r_2, r_8, 1$	$r_9, r_2, 1$	$r_4, r_3, 1$	$r_5, r_3, 1$	$r_3, r_6, 1$
$r_7, r_3, 1$	$r_3, r_8, 1$	<b><math>r_3, r_9, 1</math></b>	<b><math>r_5, r_4, -1</math></b>	$r_4, r_6, 1$	<b><math>r_4, r_7, 1</math></b>
$r_4, r_8, 1$	$r_4, r_9, -1$	$r_5, r_6, 1$	<b><math>r_5, r_7, -1</math></b>	$r_5, r_8, 1$	$r_5, r_9, 1$
$r_7, r_6, 1$	$r_6, r_8, 1$	$r_9, r_6, 1$	$r_7, r_8, 1$	$r_7, r_9, 1$	$r_9, r_8, 1$

Compared with the ground truth data presented in Table 5, there exist seven pairs are not correctly inferred. They are highlighted with bold characters.

#### 4.2 Transforming the Results to the Original Customer Satisfaction Rating

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4 In the previous section, the weights of ECs are learned by the pairwise classification  
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6 approach. However, a new interesting question will come out if the pairwise approach  
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8 is applied.  
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11 Suppose the proposed pairwise approach is expected to be evaluated by some  
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13 classification metrics like *Precision*, *Recall* as well as *F-measure* and some ranking  
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15 metrics like Mean Average Precision (*MAP*) and Normalized Discounted Cumulative  
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17 Gain (*NDCG*). Hence, the predicted level of customer satisfaction of each review is  
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19 required. But, in a pairwise approach, only the relationship between two instances is  
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21 obtained. The exact position, or the level of customer satisfaction of individual review,  
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23 in this research, is still unknown. If the proposed ordinal classification is perfect, the  
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25 level of customer satisfaction can be gained from the pairwise results. However, it is  
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27 generally hard to train a classifier without any errors, and there are possibly some  
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29 misclassified instances. As seen in the previous nine review example, there are some  
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31 misclassified review pairs by using the pairwise approach, so it is impossible to  
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33 transform the pairwise results into the levels of customer satisfaction faithfully. For  
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35 example, there are three reviews,  $r_i$ ,  $r_j$ , and  $r_k$ . The customer satisfaction relationship  
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37 are predicted by Model (2) as  $\hat{c}s_i > \hat{c}s_j$ ,  $\hat{c}s_j > \hat{c}s_k$ , and  $\hat{c}s_k > \hat{c}s_i$ . Conflicting  
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39 results lead to that the levels of customer satisfaction of these three reviews are not  
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41 able to be assigned to satisfy all the predicted relationship. Hence, the interesting  
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43 question is how to transform the pairwise results to the original level of customer  
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45 satisfaction, in which the predicted relationship is satisfied, or, in which the number of  
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47 violations about the predicted relationship is minimized.  
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In particular, two reviews  $r_i$  and  $r_j$  are predicted as  $\hat{c}s_i > \hat{c}s_j$ . The question is how to assign the level of customer satisfaction to meet the predicted relationship. If a Boolean variable  $\alpha$  denotes whether the relationship is satisfied or not, either zero or one, the problem can be formulated mathematically by Model (4):

$$\begin{aligned}\hat{c}s_i - \hat{c}s_j &\geq 1 - M \cdot \alpha \\ \hat{c}s_j - \hat{c}s_i &\geq 1 - M \cdot (1 - \alpha) \\ \alpha &\in \{0,1\} \\ \hat{c}s_i, \hat{c}s_j &\in \{1,2,3,4,5\}\end{aligned}\quad (4)$$

In Model (4), if the predicted relationship  $\hat{c}s_i > \hat{c}s_j$  is satisfied,  $\alpha$  equals to zero, otherwise  $\alpha$  equals to one.  $M$  is a large number, for instance  $M$  equals to  $10^3$ . Likewise, if  $\hat{c}s_i < \hat{c}s_j$ , the equivalent model is as follows:

$$\begin{aligned}\hat{c}s_j - \hat{c}s_i &\geq 1 - M \cdot \beta \\ \hat{c}s_i - \hat{c}s_j &\geq 1 - M \cdot (1 - \beta) \\ \beta &\in \{0,1\} \\ \hat{c}s_i, \hat{c}s_j &\in \{1,2,3,4,5\}\end{aligned}\quad (5)$$

If  $\hat{c}s_i = \hat{c}s_j$ ,  $\gamma$  is symbolized whether the equation relationship is satisfied or not. The model is:

$$\begin{aligned}\hat{c}s_i - \hat{c}s_j &\leq M \cdot \gamma \\ \hat{c}s_j - \hat{c}s_i &\leq M \cdot \gamma \\ \gamma &\in \{0,1\} \\ \hat{c}s_i, \hat{c}s_j &\in \{1,2,3,4,5\}\end{aligned}\quad (6)$$

According to Model (4) ~ (6),  $\alpha$ ,  $\beta$ , and  $\gamma$  denote whether the corresponding relationship is satisfied or not. Hence, the sum of  $\alpha$ ,  $\beta$ , and  $\gamma$  represents the total number of the unsatisfied relationship.

Now, the question of transforming the pairwise results into the customer satisfaction rating faithfully turns to minimize the sum of  $\alpha$ ,  $\beta$ , and  $\gamma$ . Combining Model (4) ~ (6), the Model to derive  $\hat{c}s_i, \hat{c}s_j, \hat{c}s_k$  is:

$$\begin{aligned}
 & \min \left\{ \sum \alpha_i + \sum \beta_j + \sum \gamma_k \right\} \\
 \text{s.t.} \quad & \hat{c}s_{ai} - \hat{c}s_{bi} \geq 1 - M \cdot \alpha_i \\
 & \hat{c}s_{bi} - \hat{c}s_{ai} \geq 1 - M \cdot (1 - \alpha_i) \\
 & \hat{c}s_{bj} - \hat{c}s_{aj} \geq 1 - M \cdot \beta_j \\
 & \hat{c}s_{aj} - \hat{c}s_{bj} \geq 1 - M \cdot (1 - \beta_j) \\
 & \hat{c}s_{ak} - \hat{c}s_{bk} \leq M \cdot \gamma_k \\
 & \hat{c}s_{bk} - \hat{c}s_{ak} \leq M \cdot \gamma_k \\
 & \alpha_i, \beta_j, \gamma_k \in \{0,1\} \\
 & \hat{c}s_{ai}, \hat{c}s_{bi}, \hat{c}s_{aj}, \hat{c}s_{bj}, \hat{c}s_{ak}, \hat{c}s_{bk} \in \{1,2,3,4,5\}
 \end{aligned} \tag{7}$$

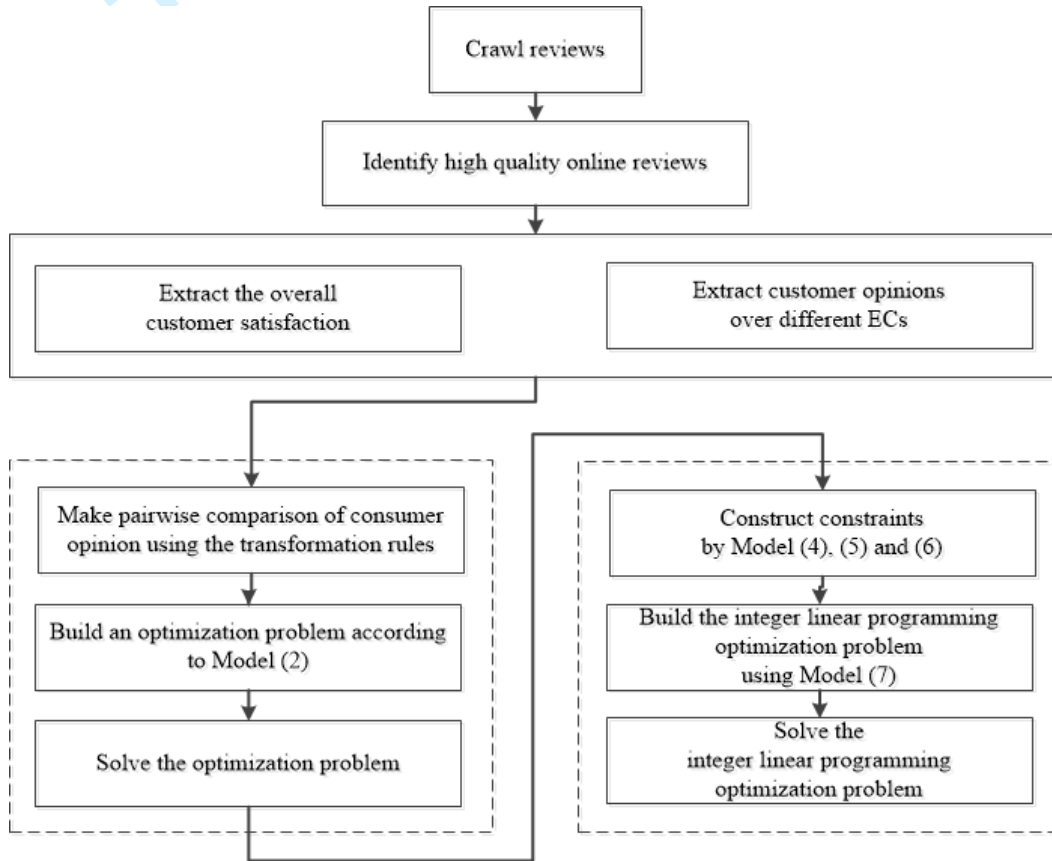
As seen from Model (7), it is an integer linear programming optimization problem and it is solvable to obtain optimal results.

For the previous example of nine reviews, as noted in Table 6, there are 13 pairs of  $\hat{c}s_i > \hat{c}s_j$ , 19 pairs of  $\hat{c}s_j > \hat{c}s_i$ , and 4 pairs of  $\hat{c}s_i = \hat{c}s_j$ . Then, Model (7) will be utilized to obtain the levels of customer satisfaction of nine reviews from the relationship of 36 review pairs. The details are illustrated in Model (8).

$$\begin{aligned}
 & \min \left\{ \sum_{i=1}^{13} \alpha_i + \sum_{j=1}^{19} \beta_j + \sum_{k=1}^4 \gamma_k \right\} \\
 \text{s.t.} \quad & \hat{c}s_{ai} - \hat{c}s_{bi} \geq 1 - M \cdot \alpha_i \quad \forall i \in [1,13] \\
 & \hat{c}s_{bi} - \hat{c}s_{ai} \geq 1 - M \cdot (1 - \alpha_i) \\
 & \hat{c}s_{bj} - \hat{c}s_{aj} \geq 1 - M \cdot \beta_j \quad \forall j \in [1,19] \\
 & \hat{c}s_{aj} - \hat{c}s_{bj} \geq 1 - M \cdot (1 - \beta_j) \\
 & \hat{c}s_{ak} - \hat{c}s_{bk} \leq M \cdot \gamma_k \quad \forall k \in [1,4] \\
 & \hat{c}s_{bk} - \hat{c}s_{ak} \leq M \cdot \gamma_k \\
 & \alpha_i, \beta_j, \gamma_k \in \{0,1\} \\
 & \hat{c}s_{ai}, \hat{c}s_{bi}, \hat{c}s_{aj}, \hat{c}s_{bj}, \hat{c}s_{ak}, \hat{c}s_{bk} \in \{1,2,3,4,5\}
 \end{aligned} \tag{8}$$

According to Model (8), the predicted levels of customer satisfaction of nine reviews are  $\hat{cs}_1 = 4, \hat{cs}_2 = 2, \hat{cs}_3 = 3, \hat{cs}_4 = 5, \hat{cs}_5 = 4, \hat{cs}_6 = 2, \hat{cs}_7 = 5, \hat{cs}_8 = 1, \hat{cs}_9 = 3$ .

In Model (2) and Model (7), how to prioritize ECs based on customer online reviews and how to transform the pairwise results to the original customer satisfaction ratings are introduced. Overall, the procedure of two phases is shown in Figure 3.



**Figure 3.** the procedure of prioritizing ECs from online reviews

## 5. EXPERIMENTAL STUDY AND DISCUSSIONS

### 5.1. An Exploratory Case Study

To understand how online reviews are evaluated by product designers, an exploratory case study was conducted. In this case study, two customer service clerks were hired



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4 to evaluate online reviews since it is generally difficult to gain the evaluation from  
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6 experienced designers for specific products. Two clerks were working in Epson Hong  
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8 Kong and HP Hong Kong. They are very familiar with printers and they had a sound  
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10 understanding about customer needs. In their daily work, they often need to report  
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12 various forms of consumer concerns to requirement analysts who help designers to  
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14 understand CRs and improve their products. Also, two clerks had experiences with  
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16 printer design using QFD, which contributes to build a high quality dataset.  
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21 A web crawler was then utilized to collect online product reviews from  
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23 Amazon.com and Epson.com. Indeed, the quality of online reviews is one critical  
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25 problem before these data are utilized by product designers. In our previous work (Liu  
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27 et al, 2013), the helpfulness of online reviews is perceived, evaluated and predicted  
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29 from the perspective of product designers. Moreover, an evaluation model is proposed  
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31 and what makes online reviews are helpful are analyzed in (Liu et al, 2013).  
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33 Accordingly, with the proposed techniques in the previous work, in this case study,  
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35 770 helpful reviews of four color printers (Epson Artisan 810, Epson WorkForce 610,  
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37 HP 6500 and HP C309) were selected. For short, “A810”, “W610”, “H6500”, and  
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39 “C309” are employed. In Table 7, the number of reviews of four printers is shown.  
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47 **Table 7.** Number of reviews

Printer	A810	W610	H6500	C309
Number of reviews	258	169	210	133

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49 At first, a list of ECs was collectively suggested by the two annotators, which  
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51 is illustrated in Table 8, according to their communications with requirement analysts  
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53 and the working experience in the dedicated field. As clarified in Section 1, ECs in  
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4 this list can be deemed as the description or translation of CRs in online reviews to an  
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6 engineering language from the perspective of product designers.  
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9 **Table 8.** Engineering characteristics

Printer Housing	Power Supply	Fax Setting	Brand
Wifi Integration	Ease of Setup	Ease of Use	Noise
Duplex Printing	Print Quality	Print Head	Package
Software Updated	Scan Software	LCD Panel	Outlooks
Auto Document Feeder	Printing Speed	Hopper Unit	Card Slot
Supplementary Software	Mac Compatible	Ink Longevity	Durability

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19 Reviews were then labeled by the two customer service clerks. They read all  
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21 reviews and distinguish which ECs are mentioned. Five discrete values from “-2” to  
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23 “2” are utilized to denote the customer opinions over ECs. “-2” means the least  
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25 satisfied and “2” means the most satisfied. An example of one Epson Artisan810  
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27 review labeling is shown in Figure 4.  
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Sentence	Auto Document Feeder	Consumable Replacement	Card Slot	Printability	Ease of setup	Ease of use	Fax Setting	Hopper Unit	Mac Compatible	Ink Longevity	LCD Panel	Noise	Power Supply	Print Quality	Printer Housing	WiFi Integration
I only have the printer for a few days, but so far I am very pleased.	-															
I was a bit nervous before buying because I had read a lot of complaints.	-															
But the paper handling on my 810 has been flawless, if a tiny bit noisy.	-												-2			
But the paper handling on my 810 has been flawless, if a tiny bit noisy.	-							-1								
The actual printing is quiet, and of great quality.	-											1				
The actual printing is quiet, and of great quality.	-													2		
The paper tray feels a bit flimsy, but is easy to remove or insert, and it can expand to hold legal size paper, and has a separate area for scanning.	-							-2								
The package comes with 3 sheets of Epson high quality 4x6 glossy photos.	-													2		
I have been using an HP Wireless printer up until now(model 5850)and also, they promise that their inks are acid-free and will last 3 or 4 months.	-													2		
Also, they promise that their inks are acid-free and will last 3 or 4 months.	-									0						
Another pre-purchase worry was that there were complaints about the printer.	-															
Too early to tell, but I've printed those 3 photos and a fourth on paper.	-									1						
So, so far so good on ink usage.	-									0						
I was surprised and pleased too that the 810 printer comes with an TWAIN interface.	-	1														
Nice!	-															
Additionally, the inks provided are the same capacity as the refills, and they are easy to replace.	-	2														
A nice feature is that when you plug in a camera memory card in the front, it will print photos directly from the card.	-	2														
Very neat.	-															
It warns on the box that this feature may not work with Mac computers.	-								1							
Have n't tried printing from the iPhone as they claim you can do, though.	-															
I love the big touch screen operation too, it is pretty slick.	-										2					
Made a few copies of some simple pencil drawings and they were very good.	-													-1		
Updated Review 03/2010Here's a 6 month update.	-															
The printer is getting a lot of work : we print a lot of classroom materials.	-			2												

Figure 4. Review labeling

In this example, the seventh line in Figure 4 is that “the paper tray feels a bit flimsy, but is easy to remove or insert, and there’s no fuss to loading your paper in it.” This consumer actually complained about the “Hopper Unit”, so the annotators wrote “-2” in the corresponding column of the seventh line. If more than one ECs are mentioned in a sentence, the sentence is pasted into the other line and the second item is labeled in a new line. For example, in Figure 4, the fourth sentence is “the actual printing is quiet, and of great quality.” “Noise” and “Print Quality”, are mentioned. This sentence is labeled repeatedly in order to unambiguously identify the two ECs.

Finally, the customer service clerks double checked these reviews in order to avoid any mislabeling. Given four printer review datasets with manually annotated

information as the experimental data, the task is to how to prioritize ECs.

## 5.2. Results and Discussions

The prioritization of ECs might be regarded to be highly related with the frequency that they are referred to in customer reviews and those frequently mentioned characteristics might be given higher weights. The top five frequently-mentioned ECs are listed in Table 9.

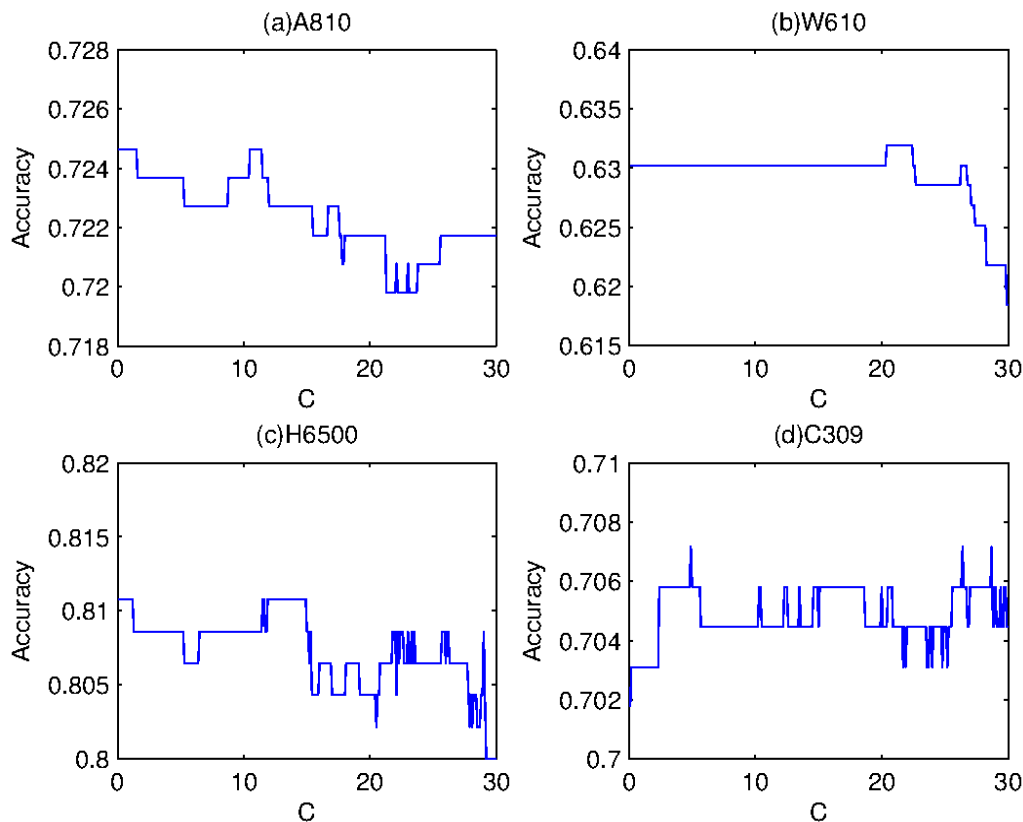
**Table 9.** Top five frequent engineering characteristics

A810		W610	
Feature	Frequency	Feature	Frequency
Print Quality	0.727	Print Quality	0.488
Ease of Setup	0.495	Wifi Integration	0.377
Scan Software	0.485	Ease of Setup	0.364
Wifi Integration	0.475	Printing Speed	0.364
Hopper Unit	0.364	Noise	0.284
H6500		C309	
Ease of Setup	0.636	Print Quality	0.698
Wifi Integration	0.568	Ease of Setup	0.586
Print Quality	0.426	Wifi Integration	0.483
Scan Software	0.278	Printing Speed	0.302
Noise	0.272	LCD Panel	0.293

As seen from this table, more than 40% consumers prefer talking about “Print Quality”, “Ease of Setup” and “Wifi Integration”. It is easy to understand. For a printer, the print quality and the usability may always be the first concern. However, whether they should be given a higher priority is unknown. This hypothesis will be examined in the following experiments.

The performance of Model (2) is illustrated in Figure 5.  $C$  is the regularization term that avoids the parameters  $w_i$  in Model (2) being tuned too large. As seen from Figure 5, the accuracy slopes down gradually with a higher  $C$  and, except for the

“W610” dataset, the predicted accuracy is all higher than 70%.



**Figure 5.** Accuracy vs. regularization term  $C$

Notice that the weight might be tuned too large if there is a large proportion of zeros in ECs. In this research, a proportion of zeros illustrates that consumers do not express their opinions or only leave a neutral opinion about the ECs. However, it possibly induces that a higher weight is given to these ECs with zero value in Model (2). It is unreasonable to suggest product designers to make more efforts on those characteristics with little comments. To avoid this problem, in all of the following experiments, those ECs which are mentioned by less than 10% product reviews are neglected.

According to Model (2), in Table 10, important ECs of the four printer datasets are listed. In all these experiments,  $C$  equals to 15, where the accuracy is relatively stable in Figure 5. Compared with top frequent ECs in Table 9, somewhat different results are presented.

**Table 10.** Top important engineering characteristics

	A810	W610
1 <sup>st</sup>	Ink Longevity	Fax Setting
2 <sup>nd</sup>	Mac Compatible	Printing Speed
3 <sup>rd</sup>	Wifi Integration	Wifi Integration
4 <sup>th</sup>	Printing Speed	Ease of Use
5 <sup>th</sup>	Ease of Use	Ease of Setup
	H6500	C309
1 <sup>st</sup>	Ease of Setup	Ease of Setup
2 <sup>nd</sup>	Ease of Use	Wifi Integration
3 <sup>rd</sup>	Wifi Integration	LCD Panel
4 <sup>th</sup>	Scan Software	Noise
5 <sup>th</sup>	Printing Speed	Printing Speed

Firstly, important ECs are suggested in Table 10, when designers plan to improve the current model. Compared with Table 9, frequently mentioned ECs in customer reviews are not necessarily regarded as important ones. For example, according to Table 9, “Print Quality” is frequently discussed, but it does not appear in Table 10 in all of these four printer datasets. It implies that, generally speaking, “Print Quality” is a hot topic in printer reviews, but a higher level of customer satisfaction over “Print Quality” perhaps not necessarily lead to the same level of customer satisfaction about the whole product. It means that product designers are not suggested to pay more attentions on it when they conceive to improve the current model. But it does not mean “Print Quality” is not important for printer design. Although “Print Quality” receives relative lower priority, generally, the high print

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quality is considered as a must when a printer is designed. It actually points to another relevant question, how to classify ECs into different categories, such as, must-be, one dimensional and attractive attributes in Kano's Model. This is one future work of this research.

Secondly, important ECs may not be talked about by a large proportion of consumers. Take the "Ease of Use" as an example. This term appears three times in Table 10, but it does not appear in Table 9. It implies that, although this term does not frequently mentioned by consumers, the overall customer satisfaction is impacted by this EC in a certain degree. Product designers are suggested to pay more attention to improve the usability of printers, and the high degree of customer satisfaction may depend on these details.

Thirdly, there are also some common ECs in both Table 10 and Table 9. For instance, "Wifi Integration" and "Ease of Setup" appear in the two tables. These two items, especially "Wifi Integration", are new characteristics for a printer. Without the "Wifi Integration", a printer still works very well. Similarly, with a little complex setting up for some amateur, a printer may still be a good product. However, the user experience will be improved with these creative ECs. These characteristics are the focus of many customer reviews and the overall customer satisfaction is affected by these novel ECs.

Another objective in this research is to explore what are the most important ECs for those consumers who gave a five-star to the product, and whether these ECs are aligned with the ones in Table 10. Thus, some similar experiments were



conducted towards concerning five-star reviews only. Top important ECs are presented in Table 11.

**Table 11.** Top important engineering characteristics from five star reviews

	A810	W610
1 <sup>st</sup>	Ink Longevity	Fax Setting
2 <sup>nd</sup>	Auto Document Feeder	Wifi Integration
3 <sup>rd</sup>	Consumable Replacement	Printing Speed
4 <sup>th</sup>	Wifi Integration	Ease of Setup
5 <sup>th</sup>	Ease of Use	Noise
	H6500	C309
1 <sup>st</sup>	Mac Compatible	Ease of Setup
2 <sup>nd</sup>	Ease of Use	Supplementary Software
3 <sup>rd</sup>	Wifi Integration	Ink Longevity
4 <sup>th</sup>	Printing Speed	LCD Panel
5 <sup>th</sup>	Print Quality	Print Quality

As seen from Table 11, except for “Wifi Integration”, more ECs are not frequently discussed by consumers. The reasons for consumers to give a five-star rating are diversified, compared with the results shown in Table 10. For example, “Ink Longevity” is regarded as an important EC in “A810” and “C309” dataset. But it does not appear in either Table 10 or Table 9. It implies that, although “Ink Longevity” is not frequently mentioned by many consumers and, generally, this EC is regarded as an unimportant one, it should not be neglected if the product is expected to be deemed as a five-star one.

Also, as seen from Table 11, products present different advantages towards how to satisfy consumers to give a five-star rating. For instance, the “Fax Setting” in “W610” dataset is a decisive factor for consumers to make a five-star decision and, similarly, “Mac Compatible” is regarded as the most important EC in the “H6500”

dataset. These phenomena further confirm that it is some details of the product that influence the overall customer satisfaction.

### 5.3. Performance Evaluation

#### 5.3.1 Evaluation metrics

In Section 4, an ordinal classification approach was proposed to prioritize ECs according to CRs in online reviews, and an integer linear programming problem is formulated to transform the pairwise results into the original customer satisfaction rating. In order to verify the performance of these methods, both classification-based and rank-based performance metrics are examined.

With the integer linear programming model, pairwise results of the proposed ordinal classification approach are transformed to the original level of customer satisfaction. The objective of the integer linear programming model is to enable proposed ordinal classification approach to be testified by standard classification metrics and ranking metrics. *Precision*, *Recall* and  $F_1$  score are widely utilized to evaluate the performance in terms of classification. *Precision* is the fraction of retrieved instances that are relevant, which is calculated as the number of retrieved and relevant results divided by the number of all retrieved results.

$$Precision = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|} \quad (9)$$

The AND operator in the numerator illustrates the intersection of the retrieved document subset and the relevant document subset. *Recall* is the fraction of relevant instances that are retrieved, which is calculated as the number of retrieved and

relevant results divided by the number of all relevant results.

$$Recall = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{|\{relevant\ documents\}|} \quad (10)$$

$F_1$  score is the harmonic mean of *Precision* and *Recall*.  $F_1$  score reaches its best value at one and its worst score at zero.

$$F_1 = 2 \cdot \frac{|Precision \cdot Recall|}{|Precision + Recall|} \quad (11)$$

To evaluate the proposed ordinal classification approach in terms of ranking metrics, *MAP* and *NDCG* are employed. *MAP* and *NDCG* are often utilized to evaluate the performance in terms of ranking. *MAP* is defined according to the  $P@n$  metric and  $AP(q)$ .  $P@n$  shows the precision achieved by considering the top  $n$  examples in the ranked list. If there are  $r_n$  relevant documents in the top  $n$  examples, then  $P@n = \frac{r_n}{n}$ .  $AP(q)$  averages the  $P@n$  over possible values of  $n$ . Let  $r_q$  be the total number of relevant examples of query  $q$ , and  $|Q|$  be the total number of examples in query  $q$ , and  $r(n)$  be a function returning one if the  $n^{th}$  ranked example is relevant, and zero, otherwise.

$$AP(q) = \frac{1}{r_q} \sum_{n=1}^{|Q|} P@n \cdot r(n) \quad (12)$$

$$MAP = \frac{1}{|Q|} \sum_{q \in Q} AP(q)$$

*NDCG* is to evaluate ranking when multiple levels of relevance are presented. In *NDCG*, the information gain of a document is measured based on its position in the result list. The information gain is accumulated from the top of the result list to the bottom with the gain of each result discounted at lower ranks.

$$DCG = \sum_{i=1}^n \frac{\log_2(1+i)}{2^{rel_i} - 1} \quad (13)$$

$$NDCG = \frac{DCG}{IDCG}$$

$rel_i$  is the graded relevance of the result at position  $i$ , such as the number of “star” which stands for the level of customer satisfaction in this research.  $IDCG$  is the normalization term of  $DCG$ , which ensures that the perfect  $NDGC$  score for the given set of examples is one. In a faultless ranking algorithm, the  $NDCG$  will be one.

### 5.3.2 Experimental evaluations

The performance of the formulated integer linear programming model, which intends to transform the pairwise results into the original customer satisfaction rating with Model (7), is illustrated in Table 12. The final results are evaluated in terms of both classification and ranking metrics. A relative high performance is achieved by the ordinal classification algorithm in all of the four data sets. It proves the availability of the proposed ordinal classification approach.

**Table 12.** Performance of the ordinal classification algorithm

	Classification		Ranking		
	<i>Precision</i>	<i>Recall</i>	$F_1$	<i>MAP</i>	<i>NDCG</i>
A810	0.674	0.717	0.695	0.913	0.988
W610	0.600	0.629	0.614	0.889	0.975
H6500	0.710	0.742	0.725	0.953	0.988
C309	0.692	0.769	0.729	0.974	0.995

Indeed, how to balance the weights of ECs is one critical step in customer driven product design by employing QFD. Conventionally, customer survey data are collected and analyzed, which is often laborious. On the other hand, online reviews provide valuable information about CRs. However, these data are different with

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4 customer survey data. The effort in this research is on the analysis of online reviews  
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6 to discover important ECs. An investigation is carried on to show that some methods  
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8 of regression, classification and learning to rank are not capable to handle this  
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10 problem. Accordingly, an ordinal classification approach is proposed to determine the  
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12 weights of ECs by taking the overall customer satisfaction and the opinions of ECs in  
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14 online reviews into considerations. Generally, it highlights which ECs are more  
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16 important and required to be improved when designers are conceiving to launch new  
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18 products. Moreover, the weights of ECs based on online reviews can be utilized in  
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20 QFD and many other methods to examine customer concerns. Hence, without doubt,  
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22 the analysis of online reviews will profit designers to understand CRs efficiently and  
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24 effectively, which is extremely important in customer-driven product design.  
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## 34 **6. CONCLUSIONS**

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36 The focus of this research is how to prioritize ECs based on online reviews. It is  
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38 different from many research studies in the design area, which take conventional  
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40 survey data as customer needs only. The needs in online reviews are assembled into  
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42 product design directly to suggest the weights of ECs, which are one critical step in  
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44 QFD.  
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49 In this research, limitations about simple classification methods and  
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51 algorithms of learning to rank are analyzed at first. Accordingly, an ordinal  
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53 classification approach is devised. It is a pairwise approach, in which the weights of  
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55 ECs are learned from review pairs. Moreover, an integer linear programming problem  
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4 is formulated in order to transform the pairwise results to the original levels of  
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6 customer satisfaction, which is not explained in many pairwise approaches. In order to  
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8 show how the proposed approaches benefit designers, an exploratory case study is  
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10 carried on. In this case study, valuable review data labeled are gained, which  
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12 contributes to initialize a sound analysis about customer reviews. Finally, based on  
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14 these annotated review data, several categories of experimental studies are conducted  
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16 and interesting phenomena are found.  
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21 For the future, there are many promising applications about how to exploit the  
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23 value of online reviews from the perspective of product designers, such as, how to  
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25 make comparison between different products based on online reviews, how to  
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27 generate the quality of house directly based on online reviews, etc.  
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## Figure Captions

1,651 of 1,738 people found the following review helpful

★★★★☆ **Good, but ...**, March 25, 2012

By **Bookenz**

This review is from: **Apple iPad MD328LL/A (16GB, Wi-Fi, White) 3rd Generation (Personal Computers)**

I've been a big iPad fan and was waiting anxiously for the third generation to come out. I bought the original iPad, and when the 2 came out, I happily sold the 1 and upgraded. I was thrilled with the thinner, lighter and improved iPad 2. So naturally, when word came out that the third one was about to be released in March 2012, I was right on board to buy one. Sold my 2 and preordered the 3 from Apple the day it was released.

I was hoping the third gen wouldn't be noticeably thicker and heavier than the 2, but unfortunately it was. I could definitely tell the difference when reading ebooks, which I do a lot. I couldn't really tell any difference between the speed and clarity of the 3, but to be fair, I didn't compare the two models side by side. I've no doubt the 3 is superior in this regard. I don't use the cameras, so don't care about this since I have a very nice digital camera for that.

The one thing about the third generation iPad that concerned me was the heat issue. Shortly after receiving it, I was reading an ebook and noticed the left side was warm. Not hot, but definitely warm enough for me to notice it. This reminded me of laptops I've had that have overheated and shut down, and here I was only reading a book. My iPad 2 never had this problem and I used it a lot. I also had some difficulty backing up the 3 to the cloud, again, something that wasn't ever a problem with the 2.

After reading some reviews of others experiencing the heating problem with the latest iPad, and really missing the thinner and lighter iPad 2, I decided to return the iPad 3 to my local Apple store and buy a new iPad 2. They had no problem taking it back and I was glad to see the 2 had come down in price. When the sales associate asked me why I was returning the 3, I told him about the heat problem. He didn't seem surprised and said it was because the 3 has a larger battery.

The third gen has a faster CPU and retina display, but I never thought the 2 had any problems with speed, and the clarity of the display has always seemed fine to me. But I'm certainly no expert. I'm very happy I made the exchange and enjoying using my iPad 2 again. For my uses--books, internet, email and games, the cooler, thinner and lighter iPad 2 is a better choice for me.

By the way, I just want to add that I think it's unfair to compare the Kindle Fire and Nook to the iPad. These devices are just ebook readers and they're fine for that--I've tried them both. Rather like saying, okay, you can buy this Mercedes or you can get the Volkswagen. Once you've used an iPad, you're totally spoiled and trying to browse the Internet with a Kindle or Nook is an exercise in frustration after using an iPad.

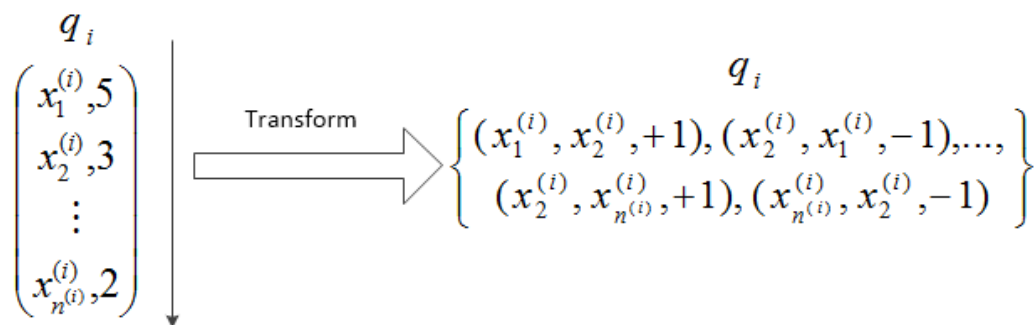
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**Figure 1.** One typical online review



**Figure 2.** An conceptual illustration for pairwise approaches of learning to rank (Liu, 2008)

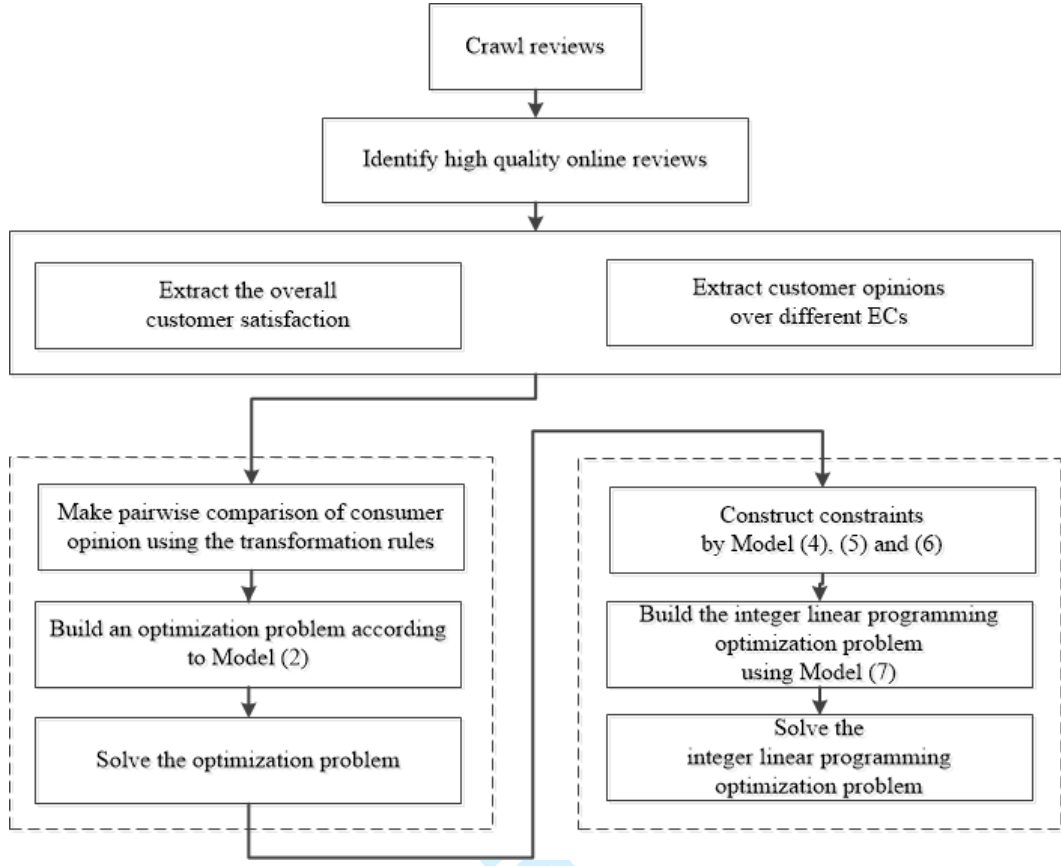


Figure 3. the procedure of prioritizing ECs from online reviews

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Sentence	Auto Document Feeder	Card Slot	Consumable Replacement	Durability	Ease of setup	Ease of use	Fax Setting	Hopper Unit	Mac Compatible	Ink Longevity	LCD Panel	Keise	Power Supply	Print Quality	Printer Housing	WiFi Integration
I only have the printer for a few days, but so far I am very pleased.	-															
I was a bit nervous before buying because I had read a lot of complaints.	-															
But the paper handling on my 810 has been flawless, if a tiny bit noisy.	-												-2			
But the paper handling on my 810 has been flawless, if a tiny bit noisy.	-							-1								
The actual printing is quiet, and of great quality.	-											1				
The actual printing is quiet, and of great quality.	-													2		
The paper tray feels a bit flimsy, but is easy to remove or insert, and it can expand to hold legal size paper, and has a separate area for scanning.	-															
The package comes with 3 sheets of Epson high quality 4x6 glossy photos.	-														2	
I have been using an HP Wireless printer up until now(model 5850)and also, they promise that their inks are acid-free and will last 3 or 4 months.	-														2	
Another pre-purchase worry was that there were complaints about the printer being too early to tell, but I've printed those 3 photos and a fourth on paper.	-									0						
So, so far so good on ink usage.	-									1						
I was surprised and pleased too that the 810 printer comes with an touchscreen.	-		1													
Nice!	-															
Additionally, the inks provided are the same capacity as the refills, and a nice feature is that when you plug in a camera memory card in the front.	-			2												
Very neat.	-		2													
It warns on the box that this feature may not work with Mac computers.	-									1						
Have n't tried printing from the iPhone as they claim you can do, though I love the big touch screen operation too, it is pretty slick.	-										2					
Made a few copies of some simple pencil drawings and they were very good.	-														-1	
Updated Review 03\2010Here's a 6 month update.	-															
The printer is getting a lot of work : we print a lot of classroom materials.	-			2												

Figure 4. Review labeling

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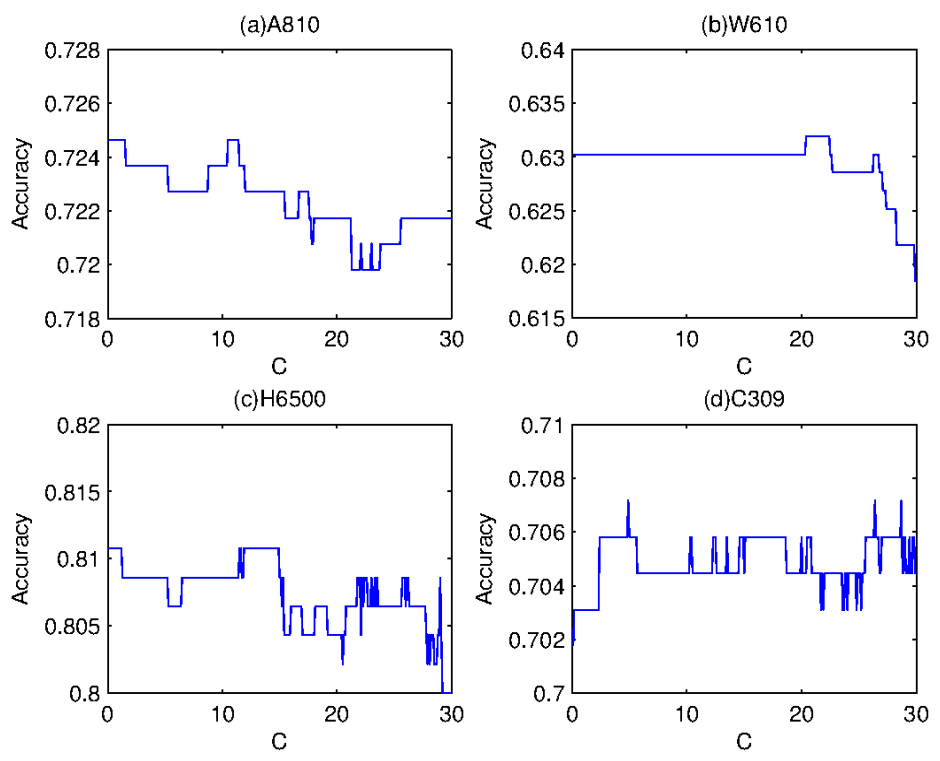


Figure 5. Accuracy vs. regularization term  $C$

Review Only

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18 lot. I couldn't really tell any difference between the speed and clarity of the 3, but to be fair, I  
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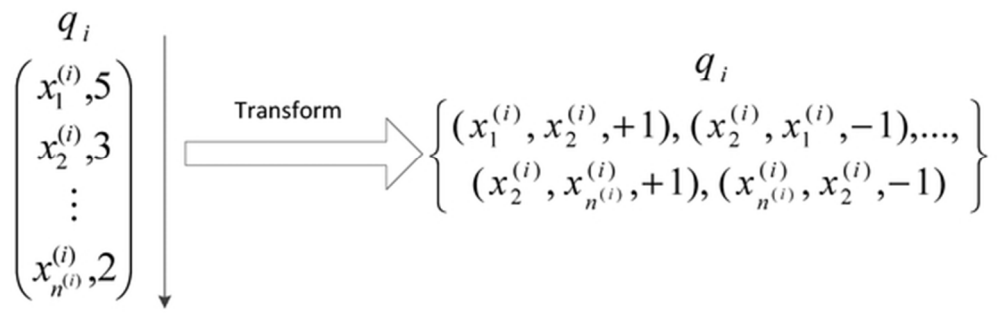
45 Help other customers find the most helpful reviews

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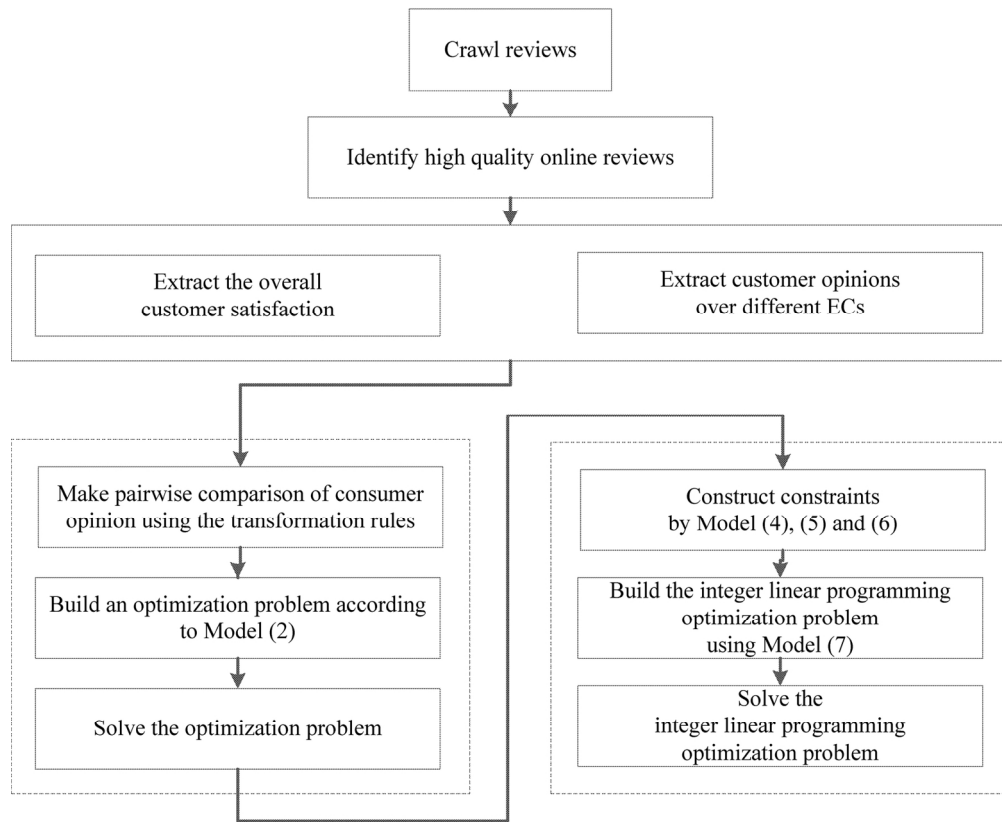
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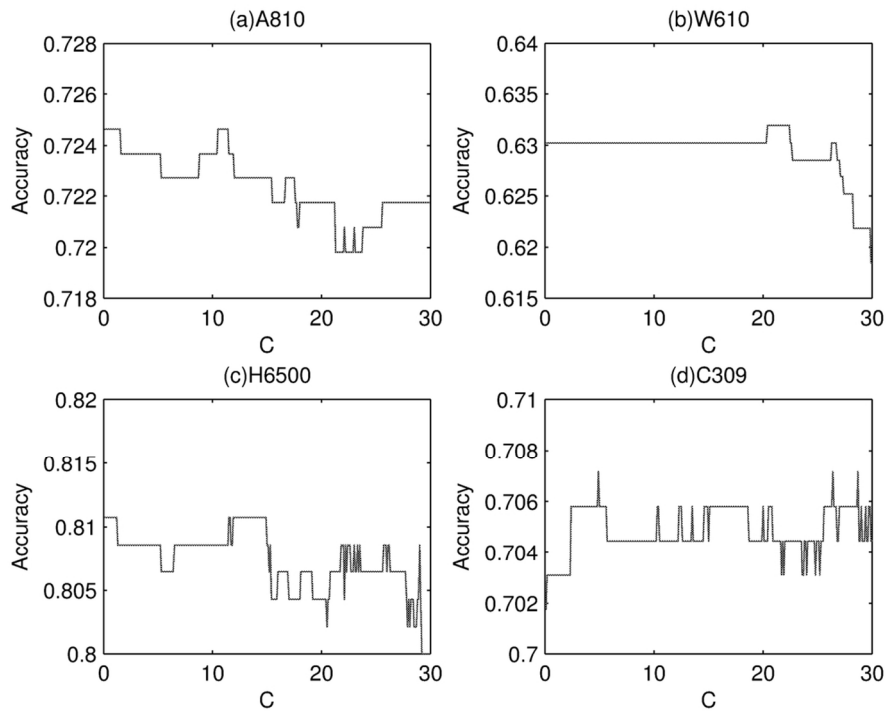
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Too early to tell, but I've printed those 3 photos and a fourth on paper.	-									1					
So, so far so good on ink usage.	-								0						
I was surprised and pleased too that the 810 printer comes with an TWAIN interface.	-		1												
Nice!	-														
Additionally, the inks provided are the same capacity as the refills, and a nice feature is that when you plug in a camera memory card in the front, it prints photos.	-		2												
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111x83mm (300 x 300 DPI)

View Only