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Mining perceptual maps from consumer reviews

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ABSTRACT

Consumer reviews are valuable resources for companies since consumers usually share their using experiences on products or provide useful opinions from various aspects such as different product features. Therefore, in this paper, we propose a method called MPM (mining perceptual map) to automatically build perceptual maps and radar charts from consumer reviews. Perceptual maps and radar charts are business tools widely used in marketing and business analysis. The proposed method may reduce subjective personal bias since perceptual maps and radar charts are mined from a large number of consumer reviews. The analysis results obtained from consumer reviews of smartphones show that the proposed method may provide some practical insights for smartphone companies. Our method can help companies position new products, and formulate effective marketing and competitive strategies.

1. Introduction

Nowadays, online shopping has become a popular way for consumers to buy products. To pick a suitable product from a bunch of choices, consumers may prefer to buy products based on the reviews from other consumers who share their using experiences on the product or provide useful opinions from various aspects such as different product features. Such opinions show how consumers think of the products and in turn reflect their competences [9,14].

Let us consider a review for iPhone 5 from Amazon[1] as shown in Fig. 1. The review of a product may typically include the advantages and disadvantages of the product. For example, in Fig. 1, it is said that iPhone 5 has a bigger screen and a better processor. On the other hand, it has only two product features better than the previous version. This kind of reviews is pretty important and useful for both companies and consumers. For companies, they could know consumers' responses for their products, and what features they have to improve for future products. For consumers, based on this information, they could decide to choose some products to meet their needs.

To efficiently mine useful insights from reviews, many methods have been proposed such as extracting and clustering product features [12,15,17,21,29], and aspect-based opinion mining [6,7,16,23,26]. The aspect-based opinion mining, different from traditional opinion mining which finds overall sentiment from opinions, focuses on how to mine sentiments of different aspects from opinions. However, most of these methods emphasize on improving the efficiency of the existing methods, reducing time complexity in clustering product features and mining aspect-based opinions from reviews. None of them concern with generating valuable insights and business value from companies' perspective.

To gain valuable insights from consumer reviews, we may build a perceptual map to position products developed by a company and its competitors. A perceptual map is a diagram which visually displays the perception of consumers. It is helpful for a company to develop new products or rebrand products since the map clearly shows the positions of products in comparison with those of competitors. For example, Fig. 2(a) illustrates a perceptual map of smartphones. The sentiment in service is a score obtained from the sentiments in consumer reviews about services for each smartphone. Similarly, the sentiment in user experience is a score obtained from the sentiments in consumer reviews about user experiences. iPhone 4 has the highest sentiment score in both service and user experience. Nevertheless, the weakness of perceptual maps is that they could only display some products with respect to two dimensions of product features in a two-dimensional map.

Radar charts could complement some disadvantages of perceptual maps because they could display multiple dimensions of the products in one chart. Nevertheless, the disadvantage of radar charts is that they could only display a limited number of products in a chart. For example, Fig. 2(b) shows a radar chart for HTC Sprint EVO and Samsung Galaxy S, where UX stands for user experience. HTC Sprint EVO performs better in OS, accessory and casing while Samsung Galaxy S performs better in CP value and battery.

Perceptual maps and radar charts are widely used in marketing and business analysis. For example, marketing analysts use them to review

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[1] http://www.amazon.com.

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This phone is great, but only slightly better than the 4S which also runs iOS 6. The iPhone 5 has a bigger screen which is useful, a slightly better processor, and that's about it. If you don't own an iPhone, getting a 4 or 4S is a better deal since will cost you like 40% less but is only like 10% inferior to the iPhone 5.

Fig. 1. A review for iPhone 5 from Amazon.

the performance of previous positioning strategies and design new ones. Senior managers may use them to gain insights by comparing their products and services with those of their competitors. Also, they may suggest potential entry points in the market. However, as perception is subjective, it is better to ensure that the data to plot the map is unbiased. In practice, the perceptual maps and the radar charts were often made from questionnaires [1,22,24] or by intuitions. If these figures were made from questionnaires, a lot of efforts would be needed to collect enough questionnaires and assure that the questionnaires are unbiased. If they were made by intuitions, the figures might be unreliable because of bias.

Therefore, in this paper, we propose a method called MPM (mining perceptual map) to automatically build perceptual maps and radar charts from consumer reviews. Since the perceptual maps and radar charts are mined from a large number of consumer reviews, MPM can reduce bias in comparison with the methods of building them from questionnaires or by intuitions. The proposed method contains four phases. First, we extract product features from consumer reviews. Second, we create a WordNet-based virtual document for each product feature, where the WordNet-based virtual document of a product feature contains the definition of the product feature in WordNet[2] and the surrounding words that frequently co-occur with the product feature in the same sentence. Third, we modify a latent Dirichlet allocation (LDA) [3], called weighted LDA (WLDA hereafter), and devise a weighted scheme to cluster together similar product features into a feature set by considering both lexical and distributional similarities. Finally, we build perceptual maps and radar charts based on the sentiments on different feature sets. The generated perceptual maps and radar charts are helpful for analysts to formulate effective marketing and competitive strategies.

The results of analyzing consumer reviews of smartphones in both Amazon and PhoneArena datasets from January 2010 to December 2012 show that WLDA achieves the best performance among all comparing methods. Samsung and HTC performed well in processors and operating systems. However, consumers had increasing negative reviews for Apple's operating systems since they expected more dramatic features. In addition, price had a significant influence on sentiment scores in a processor but little influence on sentiment scores in an operating system. Mining perceptual maps and radar charts from a large number of consumer reviews may unveil majority preferences, where the more satisfied consumers are with a feature, the higher sentiment score the feature has. By comparing the experimental results from both datasets, most findings from both datasets are similar to each other. This indicates that MPM is reliable to learn majority preferences of consumers that are helpful for company's decision making.

The contributions of this paper are summarized as follows. First, we construct a virtual document for each product feature based on the definition of the product feature on WordNet and the frequently co-occurred surrounding words of the product feature in consumer reviews. Adding WordNet definitions can enhance the lexical semantics of virtual documents while finding frequently co-occurred surrounding words by a pruning strategy can reduce the effects of noisy words. Thus, the virtual documents can capture the lexical and distributional similarity of product features. Second, we introduce a new weighted scheme and hard constraints in WLDA to help cluster similar product features into a product feature set in which the product features are prone to appear together and share similar lexical meanings. Thus, the clustering performance is improved. Third, we propose the MPM method to automatically build perceptual maps and radar charts from consumer reviews, which may help companies position new products or rebrand products. Finally, we conduct a series of analyses on consumer reviews of smartphones, and find some practical insights from the result analysis.

The rest of this paper is organized as follows. Section 2 surveys the related literature. Section 3 presents the proposed method in detail. Section 4 shows the result analysis. Section 5 summarizes analytical results and discusses how to apply the MPM method to analyze consumer reviews of other products. Finally, the concluding remarks and future work are described in Section 6.

2. Related work

In this section, we review the literature of clustering product features, analyzing sentiment in documents, and building perceptual maps and radar charts.

2.1. Clustering product features

Consumers may describe a product feature in different ways. For example, "ghz" (giga hertz), "quadcore", and "snapdragon" (a family of mobile systems on processors made by Qualcomm) are all product features used to describe "processor". Therefore, it is better to cluster these product features into a product feature set.

To cluster product features together, Liu et al. [17] employed the concept of lexical similarity to cluster similar product features together, where the lexical similarity is defined as the similarity between two terms in semantic networks and thesauri. Many studies [5,10,20] built a semantic network to improve the performance of lexical similarity. By using lexical similarity, two product features are clustered together if the meanings of two product features are close enough. However, some product features are domain-dependent, which have various meanings in different domains. For example, "chips" means potato chips in restaurant reviews; however, it means processor chips in smartphone reviews. Thus, some domain-dependent product features may be misclassified.

On the other hand, some methods [12,18,21,30] use distributional similarities to cluster product features. These methods cluster product features together if they have similar distributions of surrounding words. For example, when people mention the processor of a smartphone, they may describe it by some adjectives (like "fast" and "sluggish") or some nouns (like "ghz", "core", "speed", and "quad"). Therefore, if we mention a product feature only used in a special domain such as "snapdragon", the distribution of surrounding words of "snapdragon" may probably be similar to that of "processor". Thus, "snapdragon" and "processor" may be clustered together.

Matsuo et al. [18] applied the concept of distributional similarity to merge terms together if they have similar distributions of surrounding words, where distributional similarity is defined as the similarity between the occurrences of surrounding words of both terms. Guo et al.

[2] http://wordnet.princeton.edu.