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# What makes consumers unsatisfied with your products: Review analysis at a fine-grained level

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ABSTRACT

Online product reviews contain valuable information regarding customer requirements (CRs). Intelligent analysis of a large volume of online CRs attracts interest from researchers in various fields. However, many research studies only concern sentiment polarity in the product feature level. With these results, designers still need to read a list of reviews to absorb comprehensive CRs. In this research, online reviews are analyzed at a fine-grained level. In particular, aspects of product features and detailed reasons of consumers are extracted from online reviews to inform designers regarding what leads to unsatisfied opinions. This research starts from the identification of product features and the sentiment analysis with the help of pros and cons reviews. Next, the approach of conditional random fields is employed to detect aspects of product features and detailed reasons from online reviews jointly. In addition, a co-clustering algorithm is devised to group similar aspects and reasons to provide a concise description about CRs. Finally, utilizing customer reviews of six mobiles in Amazon.com, a case study is presented to illustrate how the proposed approaches benefit product designers in the elicitation of CRs by the analysis of online opinion data.



## 1. Introduction

The rapid development of information and communication technology encourages an increasing number of more consumers to shop online on such websites like JD.com and Amazon.com. According to a news report in Forbes,[1] the total transaction of Alibaba Group Holding Ltd. reported a record of USD 9.3 billion in sales on November 11, 2014. A large volume and variety of consumer data are generated constantly online, including customer search logs, purchase behaviors, and customer reviews, which provide helpful information for potential consumers and product designers.

An exemplary category of consumer data, online reviews contain valuable customer requirements (CRs). These reviews help designers understand CRs, which alleviate them from performing time-consuming investigations. In the field of computer science, opinion mining is a trendy research topic. Two popular research problems are how to extract product features and how to identify sentiment polarity in the product feature level from textual data (Hu and Liu, 2004; Moghaddam and Ester, 2012). The primary concerns of understanding the problems are which product features are mentioned and is the opinion positive, negative or neutral. Consider the following three review sentences of the Nokia N8 smart phone in Amazon.com for example.

S1[2]: "The battery life is a horrible."
S2[3]: "The on-board battery meter can be misleading."
S3[4]: "My only complaint here is that the battery is difficult to remove."

Using sentiment classification techniques, opinionated sentences on a specific product feature can be identified. In this example, most opinion mining techniques are capable of recognizing that consumers are writing negative opinions regarding the battery of a mobile phone. However, despite these results, designers still need to consolidate all of the reviews and read these sentences consecutively to understand customer expectations clearly. For example, various aspects of the battery are critiqued in S1–S3 and these details provide more

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[1] http://www.forbes.com/sites/hengshao/2014/11/11/9-3-billion-sales-recorded-in-alibabas-24-hour-online-sale-beating-target-by-15/.

[2] http://www.amazon.com/review/RSZY6GDKAWEGL/ref=cm_cr_rdp_perm.
[3] http://www.amazon.com/review/R1FU6HHDLLE9MU/ref=cm_cr_rdp_perm.
[4] http://www.amazon.com/review/R2QQ2YOO7HU54T/ref=cm_cr_rdp_perm.

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instructive suggestions to designers. However, many approaches in opinion mining fail to differentiate aspects of the battery and instead note the detailed reasons associated what makes consumers unsatisfied.

Accordingly, the review analysis is conducted at a fine-grained level to explore the reasons why consumers are unsatisfied with products. To obtain valuable CRs, in this research, product features and sentiment polarity are first identified from online reviews with the help of pros and cons reviews. Based on the sentimental information, an approach based on conditional random fields (CRFs) is developed to label each word in online reviews. These tags help to discern different aspects of product features, as well as detailed reasons written by consumers automatically. Moreover, a co-clustering algorithm is devised to cluster aspects of product features and reasons jointly with the help of their inter-relations, which aims to provide a brief description about CRs.

The rest of this research is organized as follows. In Section 2, relevant work in summarization of online opinion data and how online opinion data are utilized by designers are briefly reviewed. Next, the problem to be studied is clarified in Section 3. In Section 4, the technical details of the proposed approaches are explained. Section 5 presents experimental results to show how these approaches benefit product designers. Section 6 concludes this research.

## 2. Related work

### 2.1. Summarization of online opinion data

A review summarization framework was proposed at a sentence level by Zhuang et al. (2006). Opinions were captured from the expansion of seed words from the WordNet. Next, dependency relation templates were utilized to detect feature-opinion pairs. Finally, organized sentences were recognized as the review summary. Another summarization approach was reported to analyze the topic structure of online reviews by Zhan et al. (2009). In this approach, important topics were extracted and aggregated from online reviews. The final summary of reviews was clustered by the topic structure and different clusters were ranked according to the topic importance. A probabilistic mixture model was initially proposed to analyze topics and sentiments in online reviews by Mei et al. (2007). In this model, a document was considered to be generated by background words and other words, which were generated from one of many subtopics. Next, a sentiment word was utilized to describe the topic. Finally, a HMM (Hidden Markov Model) model was employed to analyze the dynamic change of the sentiments in online reviews.

The CRFs approach is widely utilized to summarize online reviews. Jakob and Gurevych (2010) utilized tokens, POS (Part of Speech) tags, short dependency paths, word distances between opinion words and other features to define features of online reviews. With these features, the approach of CRFs was to detect opinion targets in online reviews. Chen and Qi (2011) conducted a comprehensive user study examining the reasons that may lead consumers to reach final decisions. These researchers claimed that both static features and social features of products impacted consumers' decisions. The authors argued that there are three stages when consumers make decisions, (1) to filter alternatives and select ones for in-depth study, (2) to view the product's details and save it in a favorite list and (3) to compare candidates and make final decisions. This study also confirmed the previous argument that "when information about an object or firms comes through the opinions of another person, negative information can be credible and generalizable than positive information" (Mizerski, 1982). Accordingly, a framework using the approach of CRFs was built to identify sentiment polarity of product features by tagging sentimental words of product features. Additionally, four types of CRFs models were compared to identify product features and related opinion words (Li et al., 2010a), which include the linear CRFs, the skip-chain CRFs, the tree CRFs and the skip-tree CRFs. Moreover, some researchers proposed an opinion summarization for Bengali news articles (Das and Bandyopadhyay, 2010). In this approach, an SVM classifier was utilized to identify subjective sentences. Next, a model of CRFs was utilized to recognize theme words. Finally, sentences were clustered together according to their cosine similarity, and a Page Rank algorithm selected representative sentences for each cluster.

In addition to online reviews, the summarization of other opinion data is also investigated. An opinion summarization system for tweets was proposed by Meng et al. (2012). In this summarization system, a hashtag graph was built, and the relatedness between two hashtags was calculated by their concurrent relation, their contextual similarity and their topic-aware similarity. Next, an algorithm for the affinity propagation was employed to cluster hashtags, which were regarded as topics. A pattern based method was then employed to identify insightful tweets. The opinions conveyed by tweets were identified through a lexicon-based method. Finally, an optimization problem was formulated to select representative tweets. To cluster reader comments in a news article, two probabilistic graph models were compared by Ma et al. (2012). In these models, news articles and reader comments were regarded as master documents and slave documents, respectively. In the first model, topics in reader comments were confined to the topics in the news article. In the second model, topics in reader comments were derived from topics in news articles and all comments themselves. Additionally, in these models, representative sentences were selected by the approach of Maximal Marginal Relevance.

### 2.2. Online opinion data for product design

A framework was presented by Decker and Trusov (2010) to aggregate CRs from online reviews for product design. This framework was utilized to infer the relative effect of product features and effect of different brands on overall customer satisfaction. A system that monitors customer opinions from textual data was built by Goorha and Ungar (2010). First, frequent phrases and phrases near the terms of interest were extracted from textual data. These phrases were then utilized to identify which of them will emerge dramatically. Additionally, to determine whether a phrase was interesting depended on the frequency to which it was referred, its previous referred frequency and the level of specificity at which it refers to a topic. In this system, to present the results in an interactive user interface effectively, TFIDF weights and the cosine similarity method were utilized to cluster relevant terms. Several categories of dimensions that relate to the usability and the user experience were defined by Hedegaard and Simonsen (2013). According to such criteria, review sentences were manually labeled. A SVM-based method was then utilized to classify review sentences into the category of usability and the category of user experience.

Notably, one objective of CRs extraction and aggregation is to make new products to be utilized by potential customers. Accordingly, Miao et al. (2013) proposed to identify opinion leaders in a specific domain. Observing the fact that customers post several reviews and that the reviews may belong to different domains; accordingly, in this approach, the number of reviews in the same domain was utilized to define the similarity of consumers. Additionally, consumers might present different interests on different product aspects. To cluster consumers with similar interests, a permutation-based structural topic model was proposed by Si et al. (2013). By using this model, the frequency of different product aspects and the occurrence ordering were presented. Additionally,