Electronic Commerce Research

The Determinants of Online Customer Ratings: A Combined Domain Ontology and Topic Text Analytics Approach

--Manuscript Draft--

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Abstract:	Merchants, as well as customers, have noticed the importance of online product reviews and numeric ratings in electronic commerce websites. It is a valuable if merchants can discover some potential customer value from the sheer volume of data. This paper contributes a semantic text analytics approach that can dig out the customers' most basic concerns about their online purchase choices. More specifically, based on the hypothesis that the product reviews and overall ratings estimated by same person in a tiny time interval have a great relevance, we dexterously utilize this relevance to realize the embedded customer value. In the proposed method, take the Single Lens Reflex (SLR) camera for example, an innovative aspect extraction method that comprehensively considers the product ontology and results of the topic modeling method (LDA) is applied. As a result, 8 specific aspects are identified from the experiments. For each aspect, a self-contained review feature corpus is created as an extension of some seed terms. After aspect-based sentence segmentation, aspect-oriented sentiment analysis is applied in which context-sensitive sentiments are also concerned to improve accuracy. Multiple regression analysis is then used as a statistical measure to discover determinant aspects of overall ratings. The results reveal that cost performance, image quality and product integrity are the three most influential aspects. The practical implication of our research is that merchants can be more efficiently improve their online products to satisfy more customers and may also boost sales.
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Author Comments:	Authors wish to thank editor-in-chief, guest editors, and four anonymous reviewers for their insightful comments and valuable suggestions for us to improve the manuscript. We have revised the paper by incorporating the reviewer's opinions and fining the whole writing.
Response to Reviewers:	Authors' Responses to the Reviews of ELEC-D-15-00119 Manuscript Title: The Determinants of Online Customer Ratings: A Combined Domain Ontology and Topic Text Analytics Approach Manuscript ID: ELEC-D-15-00119

Authors wish to thank editor-in-chief, guest editors, and four anonymous reviewers for their insightful comments and valuable suggestions for us to improve the manuscript. We have revised the paper by incorporating the reviewer's opinions and fining the whole writing. Our point-to-point response to each comment is given below.

Reviewer 1
Comments for Authors
1. The proposed method is effective and constructive. It combined the domain ontology and topic text analytics approach. It is better if there are some words to explain why choose LDA methods and its advantage in detail.
Response: Many thanks for the reviewer's suggestion. We have added the advantage of applying LDA methods in our work. LDA (Latent Dirichlet Allocation) is a probabilistic generative model for document topics (David et al, 2003). In our study, we use the LDA results to verify whether the product ontology based aspect classification is appropriate or not. As a probabilistic model, LDA can automatically discover the latent topics among documents without any prior manual annotation. Some emerging topics among reviews may be discovered to complete the product ontology. Therefore, we use it as another objective measurement for aspect identification. Please see the corresponding part in Section 3.1.3.
2. The empirical part has proved the credibility of new method. It is necessary to make specific description for Chinese text processing methods, such as how to make word segmentation and punctuate, how to deal with ambiguity and vagueness of description, which will help readers to understand clearly and make deep application.
Response: Many thanks for the reviewer's suggestion. We have added the specific description for Chinese text processing methods in Section 3.1.2. Data pre-processing should be used for raw customer reviews. In our study, word segmentation, stop words removal, Part-of-Speech (POS) tagging and review representation are applied in this section. Step 1: Word segmentation. In Chinese documents, we need to apply word segmentation because of lacking delimiters between words. In our study, we use ICTCLAS (Zhang, H. P., & Liu, 2002) to finish segmentations. ICTCLAS is a widely used Chinese language processing tools which can be implemented in different programming languages. Step 2: Stop words removal. The words without specific meanings are classified as stop words. For example, the words like "the", "at", "on", "is" in English are usually regarded as stop words. Compared to other words, these words are useless in the text mining processes like sentiment analysis. In order to save storage and increase efficiency, we remove these stop words based on the stop words dictionary establish by ourselves. Step 3: Part-of-Speech (POS) tagging. ICTCLAS supports POS tagging for Chinese documents. Therefore, the property of a certain word in sentences can be obtained. Nouns can usually stand for certain aspect descriptions, adjectives and adverbs are mainly used for sentiment analysis. Please see the corresponding part.
3. Results analysis show cost performance is the most crucial aspect for SLR camera. Please give a detailed explain here because intuitively cost performance is also a comprehensive index.
Response: Many thanks for the reviewer's suggestion. A detailed explain for cost performance is added in Section 4.4.2. Cost performance is proven to be the most important factor, which is a valuable indicator for merchants that improving their products' cost performance (e.g. offering discounts) can be the best way to satisfy customers. This comprehensive index considers both the product performance and its sales price. A better performance under the same price or the lower cost for the same product can both lift this index. Please see the corresponding part.
4. The title clearly shown us analyzing an important determinant of customer rating, therefore, the realistic significance of the article needs further explore in detail from the perspective of customers, merchants, the industry etc.
Response: Many thanks for the reviewer's suggestion. We have further discussed the realistic significance of the article from the perspective of customers, merchants and the industry respectively in Section 4.4.2. The realistic significance of the experiment results are as follows. For customers, they can realize that the most crucial aspect for online SLR camera is cost performance. Therefore, if they wish to buy a product with high cost performance; the overall rating can be a good indicator. On the other hand, if a customer prefers to buy a SLR camera with better battery performance, the overall rating may not be a reasonable reference. For online electronic commerce merchants, the customer value embedded in these results is that they should enhance the

investments on the product delivery process. The product integrity and distribution logistics are even more important than some parts of the product in customers' eyes. For industries, they can notice the comparatively importance between different product aspects. A more efficient business strategy can be applied to satisfy more customers at a low cost. Please see the corresponding part.

5. Some minor grammar errors affect the reader's understandings, which are listed below for you to refer.

Response: Many thanks for the reviewer's suggestion. We have revised it in the new version. Please see the corresponding part.

Reviewer 2

Comments for Authors

1. In section 1 and 2, provide more reference about aspect-based product analysis approach. I think there are many approaches to analyze customers' requirements even these approach may not base on text mining technique and customer reviews. Comparing the researches about if customer ratings and customer reviews will influence the sales, I think researches about aspect-based product analysis approaches and the difference between these approaches and proposed model may be more concerned by readers.

Response: Many thanks for the reviewer's suggestion. In the revised paper, we investigated other approaches to analyze customers' requirements and more reference about customer requirements analysis approaches are added in Section 2.2. Analyzing customer preference is a crucial step to notice customer requirements for product success. As basic methods, some qualitative and quantitative approaches like interviews (Matthews & Lawley, 2006; Hadar et al, 2014), phone survey (Brotherton et al, 2014) and questionnaire studies (Lawrence & Francis, 2006; Liu et al, 2014) are widely applied. Although the effectiveness of these approaches are proved in these years, they are mostly laborious and time-consuming. For qualitative methods like interviews (Matthews & Lawley, 2006; Hadar et al, 2014), merchants can gain abundant detail information about the product preferences. However, the data representation of the raw data can be difficult. For some commonly used quantitative methods such as questionnaire survey (Lawrence & Francis, 2006; Liu et al, 2014), the main disadvantage of them is the unwillingness of customers to seriously answer the entire questionnaire under interventions. Please see the corresponding part.

References:

Brotherton, J. M., Liu, B., Donovan, B., Kaldor, J. M., & Saville, M. (2014). Human papillomavirus (HPV) vaccination coverage in young Australian women is higher than previously estimated: independent estimates from a nationally representative mobile phone survey. Vaccine, 32(5), 592-597.

Hadar, I., Soffer, P., & Kenzi, K. (2014). The role of domain knowledge in requirements elicitation via interviews: an exploratory study. Requirements Engineering, 19(2), 143-159.

Lawrence, A., & Francis, B. (2006). Customer retention management processes: a quantitative study. European Journal of Marketing, 40, 83-99.

Liu, H. C., Jeng, B. C., Mai, Y. T., Jheng, Y. D., & Lin, H. T. (2014). Design of online survey system with an advanced IPA discrimination index for customer satisfaction assessment. Electronic Commerce Research, 14(3), 223-243.

Matthews, S. S., & Lawley, M. (2006). Improving customer service: issues in customer contact management. European Journal of Marketing, 40, 218-232.

2. In section 2.3, only considering the problem lack of researcher concerned cannot be a good contribution. It is better to further clarify the importance of combination consideration of customer reviews and corresponding overall ratings based on some actual conditions, such as limitation in data and cost in research and development.

Response: Many thanks for the reviewer's suggestion. In the revised paper, the contribution of our work is explained in detail. In Section 2.2, the advantages of combination consideration of customer reviews and corresponding overall ratings are clarified. Although the effectiveness of traditional customers' requirements analyzing approaches are proved in these years, they are mostly laborious and time-consuming. In Section 2.3, the contribution of our method is specified comparing with some related works. Please see the corresponding part.

3. In section 3, explanations of some formulas are not clear, such as N and t in formulas 1, and many special symbols in formulas 4, 5. The meaning of fig. 2 is also not clear.

Response: Many thanks for the reviewer's suggestion. The explanations of all the

formulas and figures in the paper have been revised. Some of the formulas were reconstructed to be easier understood by readers. Please see the corresponding part.
4. Some setting about parameters of model need to be further explained. For example, why only select 8 aspects to analyze? What is the meaning of “wwin” and why set it to 3?
Response: Many thanks for the reviewer’s suggestion. We affirmed the aspect numbers by combining product ontology and LDA results. According to the product ontology, six aspects could be extracted. To affirm the completeness of the aspect classification, we used LDA to complete the results and two other aspects are added. Specific description is shown in 4.2. Please see the corresponding part. The meaning of wwin is the length of the text window. If wwin (the length of the text window) =1 is specified, the candidate sentiment will be selected as the closest word of the target feature term. After experiments, we found 3 is the most appropriate value set for wwin. In other words, we analyzed follow three words for the feature term to determine the sentiment term. If we could not find a suitable adjective within these three words, the sentiment was set to neutral. Specific description is shown in 3.2.2. Please see the corresponding part.
5. In section 3, explanations of some techniques is lacking, such as stop word removal, Part-of-Speech (POS) tagging, and stemming. Authors can use some tables to summarize the difference of these techniques.
Response: Many thanks for the reviewer’s suggestion. We have added the specific description for Chinese text processing methods in Section 3.1.2. Data pre-processing should be used for raw customer reviews. In our study, word segmentation, stop words removal, Part-of-Speech (POS) tagging and review representation are applied in this section. Step 1: Word segmentation. In Chinese documents, we need to apply word segmentation because of lacking delimiters between words. In our study, we use ICTCLAS (Zhang, H. P., & Liu, 2002) to finish segmentations. ICTCLAS is a widely used Chinese language processing tools which can be implemented in different programming languages. Step 2: Stop words removal. The words without specific meanings are classified as stop words. For example, the words like “the”, “at”, “on”, “is” in English are usually regarded as stop words. Compared to other words, these words are useless in the text mining processes like sentiment analysis. In order to save storage and increase efficiency, we remove these stop words based on the stop words dictionary establish by ourselves. Step 3: Part-of-Speech (POS) tagging. ICTCLAS supports POS tagging for Chinese documents. Therefore, the property of a certain word in sentences can be obtained. Nouns can usually stand for certain aspect descriptions, adjectives and adverbs are mainly used for sentiment analysis. Please see the corresponding part.
6. Authors said they exclude the reviews did not mention the selected aspects. It is better to show how many reviews were excluded because it is related to the reliability of result.
Response: Many thanks for the reviewer’s suggestion. We have mentioned the number of reviews left after aspect-level data cleaning in Section 4.1 of the new version. A large portion of the evaluation reviews are coarse that the average number of contained words is less than 7. Not only are those without real meanings, reviews with only comprehensive descriptions of the product are also useless in our experiments. For example, “A good product, happy shopping experience”, which do not describe any one of the aspects sets we constructed. Accordingly, aspect-level data cleaning is applied that only the reviews related to one or more aspects are retained. 7939 reviews are left after aspect-level data cleaning. It can also be calculated by accumulating the numbers of reviews in Table 1 or Table 2. Please see the corresponding part.

Reviewer 3
Comments for Authors
1. The paper mentioned that little researches focused on the link between customer reviews and corresponding overall ratings after literature review. However, it is not hard to find a related literature written by Qu et al. (2008). So it is worth to note the difference to the present study.
Response: Many thanks for the reviewer’s suggestion. We have noted the differences between the related literature and our work in Section 2.3. Some researchers considered the potential links between customer reviews and the corresponding overall ratings (Qu & Li, 2008; Gan & Yu, 2015). The meaning of mining the potential links between customer reviews and the corresponding overall ratings is that, under the support of big data, we can dig out some embedded customer values from the high

volume of online customer reviews that can tell us on which aspects of the product do customers have higher requirements. Qu & Li (2008) drew on the literature and identified several dimensions measuring the merchants. To determine the dimensions, Gan & Yu (2015) consulted the industry standards and then made the supplement on their own experience. However, these approaches are subjective that different people can have their own dimensions classification results. In addition, emerging topics cannot be found though such approaches. In our research work, we propose a combined domain ontology and topic text analytics approach. Ontology is a philosophy concept and now has been implemented in many other domains. The product can be comprehensively described after construing the product ontology. As the supplement, topic modeling (LDA) is also an objective probability model which can discover the latent topics among text corpus. Please see the corresponding part.

2. Except the links between product rating and product sales, product ratings may also be used as a proxy for customer satisfaction by previous studies. The relationship between product ratings and customer satisfaction should be investigated.

Response: Many thanks for the reviewer's suggestion. We have added literature reviews about product ratings researches. The relationships between product ratings and customer satisfaction have also been discussed in Section 2.1. Because of its intuitionistic character, customer rating is an extremely common indicator in electronic commerce studies. Therefore, what is the nature and determining factors of ratings is under discussion. Many researchers believed online ratings can reflect the product quality (Gao et al, 2012; Flanagin et al, 2014). However, some empirical evidence verified online ratings cannot accurately reflect the real quality in some special circumstances (Koh et al, 2010). Besides product quality, the relationship between ratings and customer satisfaction are also widely analyzed (Thirumalai & Sinha, 2011; Griffin et al, 2012; Gu & Ye, 2014). A customer with a great satisfaction for purchase process usually remains a high rating. Please see the corresponding part.

3. The paper proposed a method by combining different methods from different researches. How to evaluate the efficiency of the method, why this method is better than the other?

Response: Many thanks for the reviewer's suggestion. We have further discussed the advantages of the methods before introducing the specific usage. In addition, the efficiencies of some methods have been evaluated in former researches. The discussions have been added in Section 3. Please see the corresponding part.

4. The method proposed in the paper was similar to opinion mining. What is the difference between them, what are the advantages of the method used in the paper compare to present opinion mining method?

Response: Many thanks for the reviewer's suggestion. In opinion mining, we can automatically obtain the subjective expressions from the unstructured text data. Similar to our study, a lot of opinion mining methods calculate the sentiment polarities. However, traditional opining mining methods do not focus on the ideal aspect classification but usually regard a feature word as an individual aspect. In our proposed method, a combined domain ontology and topic text analytics approach is proposed for receiving a comprehensive aspect-level description about product reviews. Compared to present opinion mining methods, our method has more realistic significance in commerce field.

5. The contribution of the paper was not strong enough. A further and deeper investigation to customer rating behavior may be helpful to enhance the contribution.

Response: Many thanks for the reviewer's suggestion. In the revised paper, we have further investigated the literatures about product ratings and customer requirements in Section 2.1 and 2.2. Because of its intuitionistic character, customer rating is an extremely common indicator in electronic commerce studies. Therefore, what are the nature and determining factors of ratings is under discussion. Many researchers believed online ratings can reflect the product quality (Gao et al, 2012; Flanagin et al, 2014). However, some empirical evidence verified online ratings cannot accurately reflect the real quality in some special circumstances (Koh et al, 2010). Besides product quality, the relationship between ratings and customer satisfaction are also widely analyzed (Thirumalai & Sinha, 2011; Griffin et al, 2012; Gu & Ye, 2014). A customer with a great satisfaction for purchase process usually remains a high rating. The contribution of our work has been enhanced by explained in detail after comparing with different related works. Existing approaches are subjective that different people can have their own aspects classification results. In addition, emerging topics cannot be found though such approaches. In our research work, we propose a combined domain ontology and topic text analytics approach. Ontology is a philosophy concept

and now has been implemented in many other domains. The product can be comprehensively described after construing the product ontology. As the supplement, topic modeling (LDA) is also an objective probability model which can discover the latent topics among text corpus. Please see the corresponding part.
6. The writing of the manuscript should be improved before resubmission. The same contents should not be shown repeatedly.
Response: Many thanks for the reviewer's suggestion. We have removed the same contents in the new version. Please see the corresponding part.

Reviewer 4
Comments for Authors
1. I have spotted some grammatical errors, but this is not a complete list. In abstract, "It is a valuable if merchants", "a" should be removed. In Page 2, "… customers can share their purchase experiments with …", "experiments" should be changed to "experience".
Response: Many thanks for the reviewer's suggestion. We have invited a native speaker to check the grammatical errors. Many grammatical errors have been revised in the new version. Please see the corresponding part.
2. Section 3. This part is clumsy and not clear enough, and some contents are repeated again and again. Besides, many equations, I think, are unnecessary, because they are not clearly explained (for example, meanings of some variables are not defined).
Response: Many thanks for the reviewer's suggestion. In the new version, we have removed the same contents. In the revised paper, all the equations have been further explained. Please see the corresponding part.
3. Page 15; Section 3.3. The authors claimed that "we are intended to link the customer reviews and numerical ratings. To our knowledge, there is not much literature about this. " But is it true? Please provide convincing proof.
Response: Many thanks for the reviewer's suggestion. We have further discussed the related work in Section 3.3. The contribution of our work has been explained in detail. Some researchers considered the potential links between customer reviews and the corresponding overall ratings (Qu & Li, 2008; Gan & Yu, 2015). The meaning of mining the potential links between customer reviews and the corresponding overall ratings is that, under the support of big data, we can dig out some embedded customer values from the high volume of online customer reviews that can tell us on which aspects of the product do customers have higher requirements. Qu & Li (2008) drew on the literature and identified several dimensions measuring the merchants. To determine the dimensions, Gan & Yu (2015) consulted the industry standards and then made the supplement on their own experience. However, these approaches are subjective that different people can have their own dimensions classification results. In addition, emerging topics cannot be found though such approaches. In our research work, we propose a combined domain ontology and topic text analytics approach. Ontology is a philosophy concept and now has been implemented in many other domains. The product can be comprehensively described after construing the product ontology. As the supplement, topic modeling (LDA) is also an objective probability model which can discover the latent topics among text corpus. Based on aspect-oriented sentiment analysis and regression models, we can discover some valuable customer values hidden in the linkage between reviews and ratings. Moreover, compare to the previous work, our proposed method is more suitable for generalization to different product areas because of its objectivity. Please see the corresponding part.
4. Overall, the experiment results are not presented in the way that the proposed methods do. Many aspects of the proposed methods are not mentioned in the experiment results.
Response: Many thanks for the reviewer's suggestion. We have expanded experiment results section. As the main contribution of the work, we have especially explained the aspect identification part in detail. Complete LDA results are shown in Table 3. In LDA results, all of the six concepts in product ontology exists but also some other topics. As we can see in the LDA results, the rest of the topic results can be divided into three categories: comprehensive description, distribution logistics and product integrity. Comprehensive description does impact the overall ratings, but in this study, we aim to discover the relative importance of some independent variables. Thus, we choose other two topics (distribution logistics, product integrity) as the supplement. Theoretical analysis, these two topics are characteristic of e-commerce merchants so that it is reasonable not be involved in the product ontology. But they cannot be overlooked in our research because of the high frequency occurrence in reviews and actually

	influence the rating choice for e-commerce customers. Adding the six concepts based on the product ontology, these eight aspects not only can expand all dimensions for the reviews, but also don't contain and overlap each other. The results of each crucial step in the experiment are shown in the revised paper. Please see the corresponding part. 5. How were the sentiment values of each aspect calculated or inferred? Response: Many thanks for the reviewer's suggestion. For each aspect of a review, the sentiment value is determined by summarizing mentioned feature sentiments. The sentiment could be set if the sentiment-feature are existed in the aspect-based training model. Otherwise, an original Chinese sentiment lexicon HowNet was used for obtaining the sentiment value. We have further discussed the process in Section 3.2. Please see the corresponding part. 6. As for different parts of the aspect extraction and sentiment analysis processes, which commercial/free software was used in each part? And which parts were implemented by the authors themselves? Response: Many thanks for the reviewer's suggestion. In the processes of aspect extraction and sentiment analysis, a Chinese language processing tool (ICTCLAS) has been used. In addition, the source code for LDA is free on Internet. The rest of the work is all implemented based on Java. Again, we would like express our great appreciation to the editors and the reviewers for their valuable comments and constructive suggestions.

Dear Editor-in-Chief and Guest Editors,

We would like to submit our revised manuscript, *"The Determinants of Online Customer Ratings: A Combined Domain Ontology and Topic Text Analytics Approach"* for publication consideration in *Electronic Commerce Research*.

In our revised manuscript, we wish to thank editor-in-chief, guest editors, and four anonymous reviewers for their insightful comments and valuable suggestions for us to improve the manuscript. We have revised the paper by incorporating the reviewer's opinions and fining the whole writing. We proposed a novel semantic text analytics approach that can dig out the customers' most basic concerns about their online purchase choices. More specifically, based on the hypothesis that the product reviews and overall ratings estimated by same person in a tiny time interval have a great relevance, we dexterously utilize this relevance to realize the embedded customer value. In the proposed method, take the Single Lens Reflex (SLR) camera for example, an innovative aspect extraction method that comprehensively considers the product ontology and results of the topic modeling method (LDA) is applied. As a result, 8 specific aspects are identified from the experiments. For each aspect, a self-contained review feature corpus is created as an extension of some seed terms. After aspect-based sentence segmentation, aspect-oriented sentiment analysis is applied in which context-sensitive sentiments are also concerned to improve accuracy. Multiple regression analysis is then used as a statistical measure to discover determinant aspects of overall ratings. The results reveal that cost performance, image quality and product integrity are the three most influential aspects. The practical implication of our research is that merchants can be more efficiently improve their online products to satisfy more customers and may also boost sales.

Please do not hesitate to contact us if you have any question regarding this paper. Thanks for your consideration.

Yours Sincerely

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The Determinants of Online Customer Ratings: A Combined Domain Ontology and Topic Text Analytics Approach

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Abstract: Merchants, as well as customers, have noticed the importance of online product reviews and numeric ratings in electronic commerce websites. It is valuable if merchants can discover some potential customer value from the sheer volume of data. This paper contributes a semantic text analytics approach that can dig out the customers' most basic concerns about their online purchase choices. More specifically, based on the hypothesis that the product reviews and overall ratings estimated by same person in a tiny time interval have a great relevance, we dexterously utilize this relevance to realize the embedded customer value. In the proposed method, take the Single Lens Reflex (SLR) camera for example, an innovative aspect extraction method that comprehensively considers the product ontology and results of the topic modeling method (LDA) is applied. As a result, 8 specific aspects are identified from the experimental results. For each aspect, a self-contained review feature corpus is created as an extension of some seed terms. After aspect-based sentence segmentation and context-sensitive sentiments preprocessing, aspect-oriented sentiment analysis is applied. Multiple regression analysis is then used as a statistical measure to discover determinant aspects of overall ratings. The results reveal that cost performance, image quality and product integrity are the three most influential aspects. The practical implication of our research is that

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merchants can efficiently modify their products, to satisfy more customers and also boost sales performance.

Keywords: Customer Ratings; Big Data; Text Analytics; Aspect-oriented Sentiment Analysis; Customer Value; E-commerce

1. Introduction

The fast development of electronic commerce is greatly affecting the way people purchase. Since 2000, the amount of online purchase experience among Americans has annually increased and most people now having made at least once online shopping every year (Horrigan, 2008). The percentage of ecommerce-related activities is even larger (93%), which includes searching online information about their target products (Huberman & Asur, 2010). According to this tremendous change in purchasing behaviors, a huge amount of information named user-generated content (UGC) generates and attracts a lot of attention. Thus, customers can share their purchase experiments with potential influence on other individuals (Nonnecke et al, 2006).

Litvin et al. (2008) suggest that electronic Word-of-Mouth (eWOM) can be explained as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular good and services, or the sellers." Trusov et al. (2009) proved that the eWOM is more effective than traditional marketing, further verifying that customer opinions have more influence than a corporation's traditional marketing reputation (Bickart& Schindler, 2001). De & Lilien (2008) probed how WOM influences consumers' online purchasing behaviors. Customer reviews is demonstrated as a great symbol for general

WOM, which have a significant impact on the decision-making processes (Zhu & Zhang, 2010). As a valuable topic, how do customers actually influenced by online customer reviews are studied by many researchers (Goh & Zhang, 2012; Gao et al, 2012; Sotiriadis & van Zyl, 2013; Cheung et al, 2014).

In the era of big data, a number of data mining technologies have been applied to electronic commerce researches. For instance, to make better use of these reviews, some techniques to find the comprehensive conclusion of customer reviews were proposed (Hu & Liu, 2004). However, since the rapid increase on review volume and opinions, more subjective information embedded in product reviews attract attention from researchers. Opinion polling is used to dig out whether a customer is satisfied with a particular product or not and some automatic opinion mining techniques were achieved later (Zhu et al, 2011).

Aspect-based opinion analysis techniques (Titov & McDonald, 2008) are needed because sometimes the overall text polarity cannot express the opinion polarity of a specific aspect. It acquires increasing focus in these years since more accurate information is required (Mukherjee & Liu, 2012; Moghaddam & Ester, 2013). Aspect extraction should be a significant procedure in opinion mining and a variety of methods for it has been proposed. Extraction based on frequent-string mining (Hu & Liu, 2004) was proposed earlier, but do not perform well in semantic content. Topic modelling based method (Jo & Oh, 2011) can identify both original expressions and semantically related expressions, but the granularity of generated aspects can be a problem. In this paper, we first extract specific aspects based on product ontology and then use LDA results as the verification and supplement. In this synthetical method, the granularity problem can be solved and also the information integrity is guaranteed.

To mine the business intelligence embedded in online customer reviews, sentiment analysis is also one of the important techniques. Some previous studies try to estimate the sentiment polarities of customer reviews by applying some machine learning methods (Thomas et al, 2006). Besides, some sentiment lexicons such as SentiWordNet (Esuli&Sebastiani, 2005) and OpinionFinder (Riloff et al, 2005) are also well-used. However, these traditional sentiment analysis methods often perform badly in some particular context. For example, the term "high" in the expression "the price is high "displays as a negative token, but has an opposite polarity sense in different terms like "cost performance is high". Recent research presents that we can take advantage of ontology to realize a context-sensitive sentiment analysis (Wei & Gulla, 2010). Consequently, we pre-processed the context-sensitive sentiments. And then, with the help of product ontologies, we apply aspect-oriented sentiment analysis.

Besides customer reviews, numerical ratings are also proved to reflect the product quality and customer satisfaction (Chen et al, 2004;Flanagin et al, 2011; Sun, 2012; Li et al, 2012).Therefore, the existed online ratings can influence other customers' purchase decision processes (Infosino, 1986; Chen et al, 2008;Yang & Mai, 2010; De Maeyer, 2012; Flanagin et al, 2014). Some researchers also considered the linkages between reviews and ratings (Qu et al, 2008; Gan & Yu, 2015). However, these researches mainly ascertain the review aspects through the expert experience. The comprehensiveness of the aspect classification cannot be ensured. Therefore, our study proposes a combined domain ontology and topic text analytics approach for aspect identification. Linking the aspect-oriented sentiment analysis results and the corresponding ratings, we can discover the determinants in customers' evaluations.

Compared to previous researches, our work is more suitable for generalization to different product areas.

The rest of this paper is organized as follows. Section 2 discusses previous studies related to online customer ratings and customer reviews. Then, the proposed text analytics-based methodology for analyzing the determinant aspects of online customer ratings is illustrated in Section 3. In Section 4, the study results and discussion of our experiments are reported. In the last section, concluding remarks and the future directions of our research work are presented.

2. Literature Review

2.1. The Embedded Value of Customer Ratings

Because of its intuitionistic character, customer rating is an extremely common indicator in electronic commerce studies. Therefore, what are the nature and determining factors of ratings is under discussion. Many researchers believed online ratings can reflect the product quality (Gao et al, 2012; Flanagin et al, 2014). However, some empirical evidence verified online ratings cannot accurately reflect the real quality in some special circumstances (Koh et al, 2010). Besides product quality, the relationship between ratings and customer satisfaction are also widely analyzed (Thirumalai & Sinha, 2011; Griffin et al, 2012; Gu & Ye, 2014). A customer with a great satisfaction for purchase process usually remains a high rating.

Researchers also discovered embedded value of ratings in different application fields. Weinberger & Dillon (1980) found that unfavorable product ratings have a greater influence on purchase intentions than favorable ratings. Resnick et al. (2004) proved that ratings can contribute to recommendation systems. One of the most fascinating influences of ratings is the product sales. Cheung et al. (2008) pointed out that the ratings are significant in people's purchasing decisions, therefore affects the sales performance. Many studies demonstrated higher ratings can significantly improve the product sales (Chen et al, 2008; Chevalier & Mayzlin, 2006; De Maeyer, 2012). In our study, we dig out the determinants of online customer ratings and then the merchants can effectively take advantage of our experiment results to enhance their product sales.

However, Hu et al. (2006) found that more than a half products show a uneven rating distribution, which also existed in our data sets, indicating the ratings are extreme positive or negative for most of the products. Thus, whether the average overall rating is credible are greeted with doubt (Cheng & Zhou, 2010). In our proposed method, each customer rating acts individually so that the extreme emotion tendency cannot have a bad impact on our proposed methods.

2.2. Customer Requirements Analysis Approaches

Analyzing customer preference is a crucial step to notice customer requirements for product success. As basic methods, some qualitative and quantitative approaches like interviews (Matthews & Lawley, 2006; Hadar et al, 2014), phone survey (Brotherton et al, 2014) and questionnaire studies (Lawrence & Francis, 2006; Liu et al, 2014) are widely applied. Although the effectiveness of these approaches are proved in these years, they are mostly laborious and time-consuming. For qualitative methods like interviews (Matthews & Lawley, 2006; Hadar et al, 2014), merchants can gain abundant detail information about the product preferences. However, the data representation of the raw data can be difficult. For some commonly used quantitative methods such as questionnaire survey (Lawrence & Francis, 2006; Liu et al, 2014), the main disadvantage of them is the unwillingness of customers to seriously answer the entire questionnaire under interventions.

With the rapid development of electronic commerce, customers are willing to evaluate the products online. Previous researches attached great importance to customer reviews. Thomas & Eric (2011) automatically elicited some relevant properties of the product from online customer reviews. To some extent, online customer reviews contain even more creditable information than overall ratings and is a major information source for potential customers (Gerdes et al, 2008). Reviews can inform purchase experiences, recommend good products and also evaluate negative criticism (Park & Lee, 2008). Since other people's opinions on reviews can offer indirect experience, many researches proved these opinions can have a vital impact on purchase behaviors (Mizerski, 1982; Burgess et al, 2011; Sotiriadis & Zyl, 2013).

Much prior work has extensively analyzed the sentiments in online reviews (Hu et al, 2004; Kim & Hovy, 2004; Lee & Bradlow, 2007; Liu et al, 2005). Positive WOM is relevant to satisfying purchase experiences, whereas the negative one can be seen as complaints (Singh & Pandya, 1991). Chiou & Cheng (2003) reveal that negative eWOM online has even greater impact on corporate image compared to traditional communications. Ghose & Ipeirotis (2007) combined sentiment analysis methods with economic models to evaluate the influences that customer reviews brings to sales. Furthermore, they raised that many embedded properties of reviews matters in impacting sales and then perceive real usefulness (Ghose & Ipeirotis, 2007).

In our study, an advanced semantic text analytics approach is proposed for exacting certain aspects and aspect-oriented sentiment polarities in customer reviews. Compared to traditional aspect-based product analysis approaches, the proposed method are more time-saving. Moreover, much more customers' potential requirements with little intervention are considered in our method.

2.3. Overall Consideration of Reviews and Ratings

Many researches confirmed that both product reviews and numeric ratings can influence online selling. For instance, numeric ratings impact on sales volume on eBay (Chevalier & Mayzlin, 2002), the probability of book sales are influenced by online reviews at Amazon.com (Resnick & Zeckhauser, 2002). Some models combined reviews and numeric ratings together. John et al. (2008) integrated qualitative and quantitative consumer feedback together to seek proper words for positive and negative ratings respectively. Moreover, Gan & Yu (2015) used reviews and ratings to build a multilevel model for showing the sentiment impact on different levels. However, some researches left out the overall ratings which are regarded as a coarse indicator. For example, Long et al. (2010) selected comprehensive communication and estimated the feature ratings for them. The results proved feature ratings can better represent the overall rating.

Although some ratings are coarse, the bad impact of these data can be nearly vanished under the huge amounts of data. Some researchers considered the potential links between customer reviews and the corresponding overall ratings (Qu & Li, 2008; Gan & Yu, 2015). The meaning of mining the potential links between customer reviews and the corresponding overall ratings is that, under the support of big data, we can dig out some embedded customer values from the high volume of online customer reviews that can tell us on which aspects of the product do customers have higher requirements. Qu & Li (2008) drew on the literature and identified several dimensions measuring the merchants. To determine the dimensions, Gan & Yu (2015) consulted the industry standards and then made the supplement on their own experience. However, these approaches are subjective that different people can have their own dimensions classification results. In addition, emerging topics cannot be found though such approaches. In our research work, we propose a combined domain ontology and topic text analytics approach. Ontology is a philosophy concept and now has been implemented in many other domains. The product can be comprehensively described after construing the product ontology. As the supplement, topic modeling (LDA) is also an objective probability model which can discover the latent topics among text corpus. Based on aspect-oriented sentiment analysis and regression models, we can discover some valuable customer values hidden in the linkage between reviews and ratings. Moreover, compare to the previous work, our proposed method is more suitable for generalization to different product areas because of its objectivity.

3. An Overall Ratings Determinants Methodology

In this section, a methodology for overall ratings determinants analysis is proposed. 8 concrete aspects are extracted by referring product ontology and then supplying by LDA results. Review feature sets are obtained by the extensions of some seed terms using FL-LDA model. For each aspect, aspect-orient sentiment analysis is used for estimating the sentiment polarities. These works are all implemented by Java. Next, multiple regression model is established to reveal the influence of each aspects' sentiment polarities on the consumer overall ratings. An overview of the proposed framework is illustrated in Fig. 1.

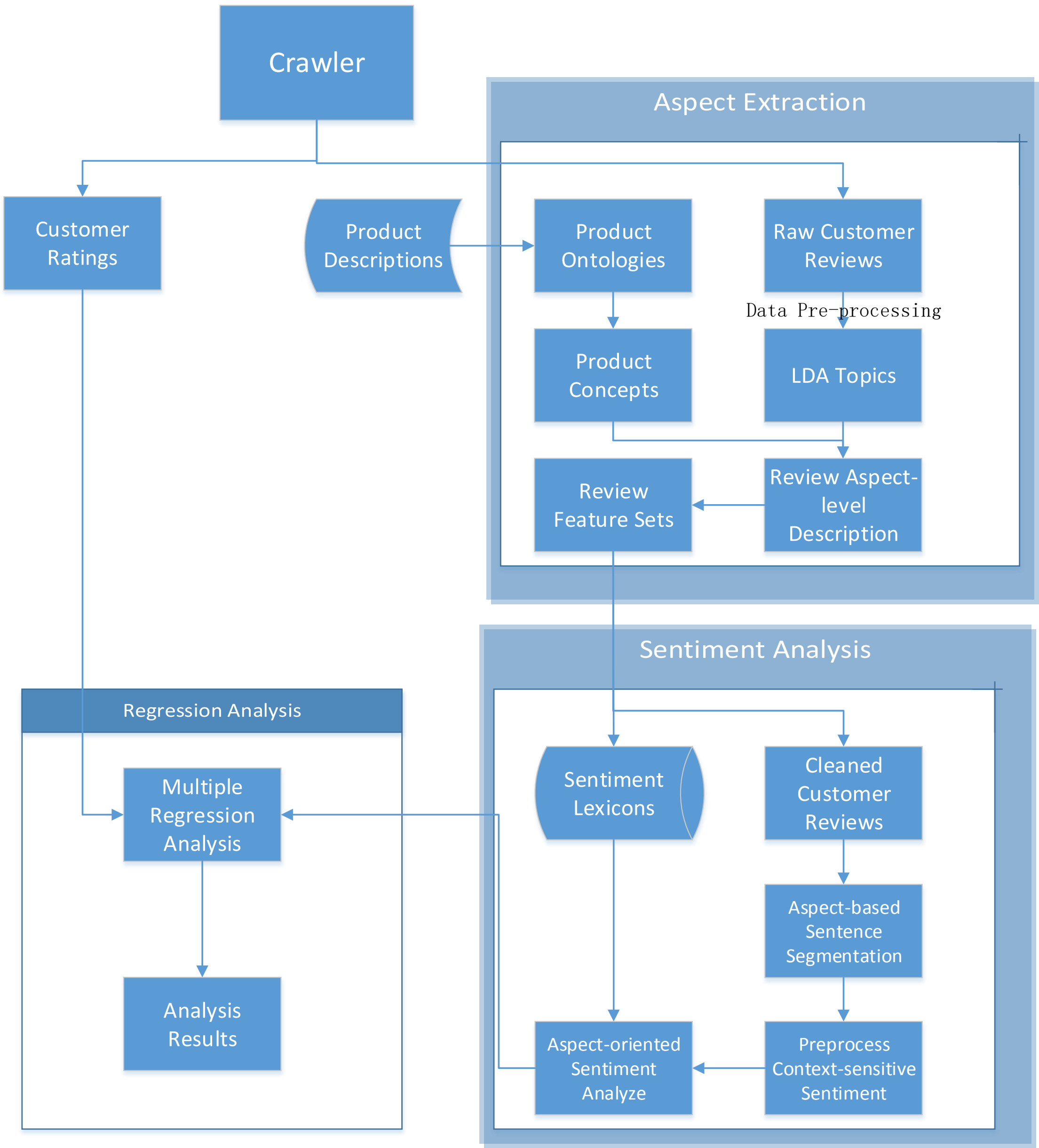

Figure 1. The Overall Ratings Determinants Methodology

As can be seen from Fig. 1, after crawling raw customer reviews and customer ratings from JD.com, the product ontology is firstly constructed to acquire some professional product concepts. Secondly, topic modeling methods (LDA) is employed to confirm the effectiveness of the product ontology and also supply some unnoticed topics in real reviews. 8 aspects are obtained to constitute a comprehensive aspect-level description. Then aspect-related reviews feature sets are constructed by semi-supervised aspect extraction. Thirdly, raw reviews are cleaned, and then aspect-based segmentation is used to be the basis for grouping the same aspect segmentations together. Fourthly, aspect-oriented sentiment analysis is applied to estimate the sentiment polarities for each aspect while the context-sensitive sentiment has been preprocessed. Finally, the multiple regression model is established to reveal the influence of each aspects' sentiment polarities on the customer overall ratings and then the results are discussed. The details will be discussed in the following subsections.

3.1. Feature Sets Selection

In this paper, six concepts are extracted from professional electronics websites which construct the product ontology and two other topics are found from the topic modeling results. Next, for each aspect, we use semi-supervised aspect extraction method to build a typical feature set. The

3.1.1. Ontology-based Product Concepts

The concept of ontology originated from the field of philosophy and has been implemented in many other domains in recent years. According to related literature, ontology not only fetches concepts and their relationships but also represents the axioms and constraints that the major characteristics of the domain are defined (Gruber, 1993). In recent years, it has become increasingly used in the text mining because of the completeness of description and excellent reusability (Chi, 2007).

In our work, Protégé, a java-based ontology tool (Knublauch et al, 2004) was used to construct the product ontology. Product concepts are elicited based on some well-known professional electronics websites (e.g. zol.com) which are summarized by domain experts. Take the SLR camera as an example, six concepts are obtained in this way.

3.1.2. Data Pre-processing

Data pre-processing should be used for raw customer reviews. In our study, word segmentation, stop words removal, Part-of-Speech (POS) tagging and review representation are applied in this section.

Step 1: Word segmentation. In Chinese documents, we need to apply word segmentation because of lacking delimiters between words. In our study, we use ICTCLAS (Zhang, H. P., & Liu, 2002) to finish segmentations. ICTCLAS is a widely used Chinese language processing tools which can be implemented in different programming languages.

Step 2: Stop words removal. The words without specific meanings are classified as stop words. For example, the words like “the”, “at”, “on”, “is” in English are usually regarded as stop words. Compared to other words, these words are useless in the text mining processes like sentiment analysis. In order to save storage and increase efficiency, we remove these stop words based on the stop words dictionary establish by ourselves.

Step 3: Part-of-Speech (POS) tagging. ICTCLAS supports POS tagging for Chinese documents. Therefore, the property of a certain word in sentences can be obtained. Nouns can usually stand for certain aspect descriptions, adjectives and adverbs are mainly used for sentiment analysis.

Step 4: Review representation. After word segmentation, each review forms a bag-of-words model, in which ignores the order of the words. Suppose the number of words is n, the review can be regarded as n-dimension vector. TF-IDF (term frequency and inverse document frequency) is used to weight the importance of each word in reviews. TF calculates the frequency of occurrence of a term in one document. For word t_i in document d_j, the $tf_{i,j}$ is expressed as follows.

$$tf_{i,j} = \frac{n_{i,j}}{\sum kn_{k,j}} \tag{1}$$

where $n_{i,j}$ is the occurrences number of word t_i in document d_j, k is the amount of words in document d_j.

IDF calculates the importance of the word in all documents. For word t_i, the idf_i can be defined as:

$$idf_i = \log \frac{N}{\{\mathrm{j} : \mathrm{t}_i \in \mathrm{d}_j\}} \tag{2}$$

where N is the amount of documents, $\{\mathrm{j}:\mathrm{t}_i \in \mathrm{d}_j\}$ is the amount of documents which contains word t_i.

Therefore, the definition of TF-IDF is as follows.

$$TFIDF = tf \times idf \tag{3}$$

3.1.3. LDA Topics Supplement

LDA (Latent Dirichlet Allocation) is a probabilistic generative model for document topics (David et al, 2003). In our study, we use the LDA results to verify whether the product ontology based aspect classification is appropriate or not. As a probabilistic model, LDA can automatically discover the latent topics among documents without any prior manual annotation. Therefore, we use it as another objective measurement for aspect identification.

In a document, several topics are usually discussed and some typical words can stand for these topics. In the statistical natural language processing, topic modeling for documents regards topics as the probability distribution of vocabulary, and the documents randomly represent a mixture of these topics. Suppose there are T topics so the *i*th word in the document can be defined as follows.

$$p(\mathrm{w}_i) = \sum_{j=1}^{T} p(\mathrm{w}_i \mid \mathrm{z}_i = \mathrm{j}) p(\mathrm{z}_i = \mathrm{j}) \tag{4}$$

To express conveniently, we set $\phi_w^{(\mathrm{z=j})} = p(\mathrm{w} \mid \mathrm{z} = \mathrm{j})$ represents the multinomial distribution for word w in topic j and $\varphi_{z=j}^{(\mathrm{d})} = p(\mathrm{z} = \mathrm{j})$ shows the multinomial distribution for topic T in document d. The probability of word w occurs in document d is:

$$p(\mathrm{w} \mid \mathrm{d}) = \sum_{j=1}^{T} \phi_w^{(\mathrm{z=j})} \varphi_{z=j}^{(\mathrm{d})} \tag{5}$$

3.1.4. Feature Sets Establishment

After affirming aspect classification, feature sets for each aspect are established. In traditional LDA models, the probability of each word is equal to be involved in each aspect. (Mukherjee & Liu, 2012). Thus, various non-specific words can be clustered together. In this study, we aim to establish typical feature sets for each aspect but not cross-aspects or non-specific terms, such as comprehensive evaluation and purchase purpose. As a result, we use the Fine-grained Labeled LDA (Wang et al, 2014) replace the basic LDA method and then manually amend the feature sets.

In FL-LDA, we should first provide some seeding words for each aspect. To compute the posterior distribution of $p(\mathrm{z} \mid \mathrm{w}) = \frac{p(\mathrm{w},\mathrm{z})}{\sum_z p(\mathrm{w},\mathrm{z})}$, a collapsed Gibbs sampling (Griffiths & Steyvers, 2004) is applied in which the joint likelihood of a word w associated with an aspect z is given by:

$$p(w, z \mid \alpha, \beta, \gamma) = p(w \mid z, \beta, \gamma)\, p(z \mid \alpha, \gamma) .$$

3.2. Sentiment Analysis

Typical feature sets have been generated for each aspect after former section. In this section, the sentiment polarities for each aspects of a review are decided. Before sentiment analyzing, we first cleaned the raw reviews that only the reviews which related to some aspects can be selected. This cleaning step casts away many useless reviews which can have a damaging impact on our final results. Next, after aspect-based sentence segmentation, the aspect-oriented sentiment analysis is applied. To be more specific, we preprocess the context-sensitive sentiment and the sentiment lexicons are used to facilitate analyzing. The details will be introduced in the following subsections.

3.2.1. Aspect-based Sentence Segmentation

There are often more than one aspects contained in a review text, so that it is imperative for us to split it into multiple segmentations which only related to one aspect. As the foundation for aspect-oriented sentiment analysis, we used the multi-aspect segmentation (MAS) which was proposed by Zhu et al. (2011).Before applying the model, we analyzed the cleaned reviews and realized that it is better to separate reviews by the commas than the periods as the minimum separator. To formulate the multi-aspect segmentation models, we introduce a function J(.) that can appraise every possible segmentation U of sentence C: $U* = \arg\max J(\mathrm{C}, \mathrm{U})$. Based on aspect-related feature sets, the criterion function J(C, U) can be formulated as follows.

$$J(\mathrm{C}, \mathrm{U}) = \sum_{1 \le i \le k} [\delta(\mathrm{u}_{i-1}, \mathrm{u}_i) * \mathrm{score}_{a^*}(\mathrm{u}_i)] \quad (6)$$

where a* is the aspect which segment u_i have the maximum probability to occur and δ(u0, u1) is set to 1 ,which indicates the two segments are labeled as two different aspects. After aspect-based sentence segmentation, we regrouped the review segments. The segments related to the same aspect are grouped together.

3.2.2. Preprocess Context-sensitive Sentiment

In this section, we aim to estimate the sentiment orientation (positive, negative or neutral) for each aspect in a review. A text window is applied to locate the candidate sentiments associated with the product features (Subrahmanian & Reforgiato, 2008). In concrete terms, if wwin (the length of the text window) =1 is specified, the candidate sentiment will be selected as the closest word of the target feature term. After experiments, we found 3 is the most appropriate value set for wwin. In other words, we analyzed follow three words for the feature term to determine the sentiment term. If we could not find a suitable adjective within these three words, the sentiment was set to neutral. To improve the accuracy of this step, the sentiment-feature association measure developed by Lau et al. (2009) is used.

After obtaining the sentiment and the related feature pairs (si,fi), the context-sensitive sentiment can be estimated. It is a benefit because even in a specific aspect, the same sentiment word can represent different polarities. For example, the term “high(高)” in the expression “the price is high (价格高)” displays as a negative token, but has an opposite polarity sense in different terms like “cost performance is high(性价比高)”. With the help with sentiment-feature pairs, this problem can be vanished.

Based on Kullback-Leibler divergence, polarity keywords can be obtained using a word divergence (WD) measurement (Lau et al., 2008). However, in this paper, we cannot use the overall ratings to label the polarity for each aspect. We manually label 50 typical reviews each as positive, negative and neutral for each aspect. After training the labeled review data, the polarity value for each sentiment-feature pair sf = (si,fi) can be calculated as follows. The parameters w_{pos} and w_{neg} are the learning rates for positive and negative evidences, which can be set empirically (Lau et al., 2008).

$$WD(\mathrm{sf}) = \tanh[\frac{df(\mathrm{sf})}{w_{pos}} * \Pr(\mathrm{pos}\,|\,\mathrm{sf}) * \log_2 \frac{\Pr(\mathrm{pos}\,|\,\mathrm{sf})}{\Pr(\mathrm{pos})} - \frac{df(\mathrm{sf})}{w_{neg}} * \Pr(\mathrm{neg}\,|\,\mathrm{sf}) * \log_2 \frac{\Pr(\mathrm{neg}\,|\,\mathrm{sf})}{\Pr(\mathrm{neg})}] \quad (7)$$

$$polarity_{as}(\mathrm{sf}) = \begin{cases} 1 & \text{if } \mathrm{WD(sf)} > 0 \\ -1 & \text{if } \mathrm{WD(sf)} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where the term $pr(\mathrm{pos}\,|\,\mathrm{sf}) = \frac{df(\mathrm{sf}_{pos})}{df(\mathrm{sf})}$ is the conditional probability that a review is positive and contains the sentiment-feature pair sf = (si, fi). $df(\mathrm{sf}_{pos})$ is the amount of positive reviews which contain the sentiment-feature pair. $df(\mathrm{sf})$ is the amount of reviews contain the pair.

3.2.3. Aspect-oriented Sentiment Analysis

For each review, we cluster the sentence segmentations related to the same aspect together. Then, we can analysis the sentiment polarity for each aspect respectively. Before analyzing, the reviews do not mention any aspects are discarded and the default sentiment polarity for the missing aspect is set as neutral. For each feature words in the aspect-related review, we determine the polarity by identifying sentiment-feature pair sf (si,fi) and calculate the $df(\mathrm{sf})$. If the aspect exclusive lexicon cannot get the polarity, an original Chinese sentiment lexicon HowNet (Zhu et.al. 2006) is invoked to estimate the polarity. Finally, we acquire the comprehensive aspect sentiment polarity by accumulating polarity strength for each feature word.

3.3. Multiple Regression Modeling

In this section, we are intended to link the customer reviews and numerical ratings. Reviews with the corresponding ratings are evaluated by the same customer in nearly the same time, so we assume that the overall ratings can correctly reflect the comprehensive information contained in the corresponding reviews. According to the hypothesis, we define the sentiment polarity for each aspect as independent variables, overall ratings as dependent variables, through the SPSS statistics software and build a multiple linear regression model.

4. Empirical Study and Results

4.1. Data Description

The data we used in the experiments are crawled from a well-known Chinese e-commerce website JD.com. Raw data sets consist of 46846 customer reviews and their corresponding ratings from 20 best-selling SLR cameras among all brands. However, a large portion of the evaluation reviews are coarse that the average number of contained words is less than 7. Not only are those without real meanings, reviews with only comprehensive descriptions of the product are also useless in our experiments. For example, "A good product, happy shopping experience (很好的产品，很开心的购物体验)", which do not describe any one of the aspects sets we constructed. Accordingly, aspect-level data cleaning is applied that only the reviews related to one or more aspects are retained. 7939 reviews are left after aspect-level data cleaning. Distribution of mentioned aspect numbers and the review rating distribution are respectively shown in Table 1 and Table 2.

Table 1.The Distribution of Aspect Numbers Contained In the Reviews

Mentioned Aspects	1	2	3	4	5	6	7	8
Number of Reviews	5034	1890	676	222	86	24	6	1

Table 2.The Distribution of Overall Ratings

Overall Ratings	5	4	3	2	1
Number of Reviews	6382	905	117	49	478

4.2. Aspect Identification

To outline comprehensive and meaningful aspect-level descriptions, we first use the product ontology to elicit basic concepts and then some of LDA topics are selected as the supplement. As can be seen in Fig. 3, 6 concepts can be extracted from the product ontology shown on Chinese professional electronics websites which are summarized by domain experts.

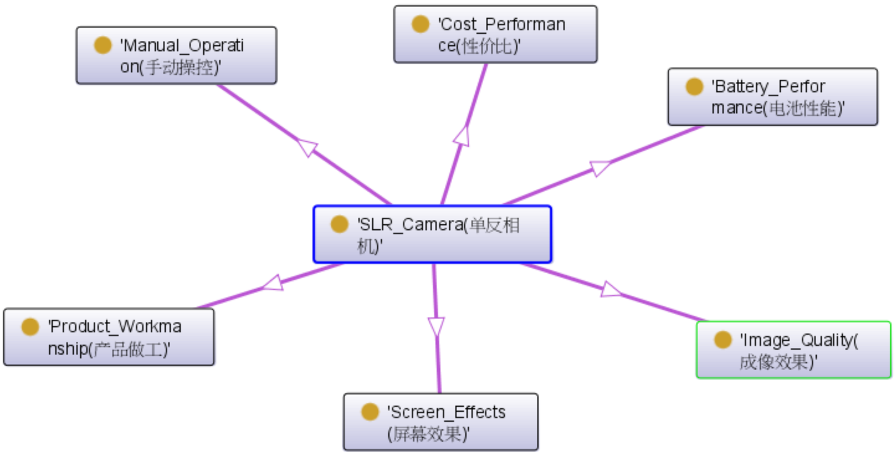

Figure 3. Product Ontology for SLR Camera

To confirm the completeness of product ontology, traditional topic modelling method (LDA) is then applied for customer reviews and the topic number is manually set to 10, a slightly larger value than product ontology classification. In LDA results, all of the six concepts in product ontology exists but also some other topics. Some representative topic words in LDA results are shown in table 3.

Table 3. LDA Results

Type	Description	Corresponding Aspect
Topic 0	Price (价格), Cheap(便宜), Expensive (贵), Cost performance (性价比)	Cost performance
Topic 1	Function (功能), Manipulate (操控), Use(使用), Issue (问题)	Manual operation
Topic 2	Photo (照片), Imagery (成像), Colour(色彩), Pixel(像素)	Image quality
Topic 3	Battery(电池), Effect(效果), Charger(充电器), Feeling(感觉)	Battery performance, Comprehensive description
Topic 4	Arrival(到货), Expressage(快递), Order Form(订单), Manner(态度)	Distribution logistics
Topic 5	Quality Products(正品) ,New(全新), Pack(包装), Count(次数)	Product integrity
Topic 6	Camera(相机), Mood(心情), Stuff(东西), Waste(垃圾)	Comprehensive description

Topic 7	Jingdong(京东), Relieved(放心), Product(产品), Recommend(推荐)	Comprehensive description
Topic 8	Scene(镜头), Camera body(机身), Plastic(塑料), Dark spot(黑点)	Screen effects, Product workmanship
Topic 9	Picture(照片), Clear(清晰), Focusing(对焦), Imagery(成像)	Image quality

As we can see in the LDA results, the rest of the topic results can be divided into three categories: comprehensive description, distribution logistics and product integrity. Comprehensive description does impact the overall ratings, but in this study, we aim to discover the relative importance of some independent variables. Thus, we choose other two topics (distribution logistics, product integrity) as the supplement.

Theoretical analysis, these two topics are characteristic of e-commerce merchants so that it is reasonable not be involved in the product ontology. But they cannot be overlooked in our research because of the high frequency occurrence in reviews and actually influence the rating choice for e-commerce customers. Adding the six concepts based on the product ontology, these eight aspects not only can expand all dimensions for the reviews, but also don't contain and overlap each other.

4.3. Aspect-oriented Sentiment Analysis

Aspect-based sentence segmentation is a crucial step of data processing in our study. Next, the segmentations related to same aspect can be clustered together, as shown in Table 4.

Table 4. Results of Aspect-based Segmentation

Sentence	Packaging is fire-new, photo is also very clear. Very fast delivery, the price is appropriate, not expensive. Overall is very good!(包装是全新的，照片也很清晰。送货速度蛮快的，价格也合适，不贵。总体很不错！)
Segmentations	Packaging is fire-new,(包装是全新的，)|| Photo is also very clear. (照片也很清晰。)||

	Very fast delivery. (送货速度蛮快的，)|| The price is appropriate, not expensive. (价格也合适，不贵。) Overall is very good! (总体很不错！)
Regroup Segmentations	**Aspect 1 (Cost Performance):** The price is appropriate, not expensive. (价格也合适，不贵。) **Aspect 5 (Image Quality):** Photo is also very clear. (照片也很清晰。) **Aspect 7 (Distribution Logistics):** Very fast delivery. (送货速度蛮快的，) **Aspect 8 (Product Integrity):** Packaging is fire-new,(包装是全新的，)

Sentiment analysis is then used for each aspect-related regrouped segmentations. The sentiment polarity for each feature word is calculated and then the values are summed up to represent the aspect-related sentiment polarity. Among all the reviews in cleaned data sets, the results of the sentiment polarities are shown in Table 5.

Table 5.The Distribution of Aspect-related Sentiment Polarity

Sentiment polarity	1(Positive)	0(Neutral)	-1(Negative)	Mean Value
Cost performance	1879	5002	1057	0.104
Manual operation	911	6885	142	0.097
Battery performance	142	7763	33	0.014
Screen effects	567	7169	202	0.046
Image quality	1428	6336	174	0.158
Product workmanship	859	6899	180	0.085
Distribution logistics	1371	6362	205	0.147
Product Integrity	1675	6065	198	0.186

As we can see in table 5, all the mean values of each aspect are positive. It indicates that the number of positive review segmentations is significantly more than negative segmentations. The sentiment results are basically accordant to the distribution of overall ratings which contain a great proportion of high scores (e.g. 5 or 4).

4.4. Results Analysis

4.4.1. Multiple Linear Regression Results Analysis

As can be seen from Table 6, after aspect-oriented sentiment analysis, the sentiment polarities have been changed to numerical values. We assume that the overall ratings can correctly reflect the comprehensive information contained in the corresponding reviews, so the multiple linear regression model is built to mine comparatively significant aspects. In our model, the sentiment values for each aspect (the default value is 0 for not mentioned aspects) of the review are used as independent variables and the corresponding overall rating as the dependent variable. The results of the experiment are shown in Table 6.

Table 6.Results of Multiple Regression Model

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	4.365	.014		306.769	.000
X1(Cost performance)	.323	.018	.191	17.835	.000
X2(Manual operation)	.284	.031	.098	9.163	.000
X3(Battery performance)	.082	.073	.012	1.115	.265
X4(Screen effects)	.226	.035	.069	6.390	.000
X5(Image quality)	.328	.026	.136	12.605	.000
X6(Product workmanship)	.131	.031	.045	4.235	.000
X7(Distribution logistics)	.281	.026	.116	10.818	.000
X8(Product integrity)	.295	.024	.130	12.087	.000

As we can see in Table 6, all of the eight aspects have positive correlation with the overall numeric ratings. Since the sentiment values arise has been normalized, the relative importance of these aspects can be revealed by the standardized coefficients beta. As a result, cost performance is the most crucial aspect for SLR camera, and the image quality is on the second place. Distribution logistics and product integrity are as important which demonstrates the effectiveness of finding extra topics besides the product ontology. In comparison, battery performance has the least impact on customers' overall rating and also the only one without ideal effects in significance testing.

4.4.2. Discussion

The results of multiple regression model reveals valuable embedded customer value that whether the sentiment polarities of these single aspects can have an impact on overall ratings and the relative importance between them. A visually result can be seen in Fig. 4 that all of these 8 aspects have a positive association with the overall ratings. As the ratings are significant in consumer purchasing decisions (Cheung et al., 2008), we move a forward step to confirm that not only positive overall WOM is relevant to satisfying purchase experiences (Singh & Pandya, 1991), aspect-related WOM can also independently do so.

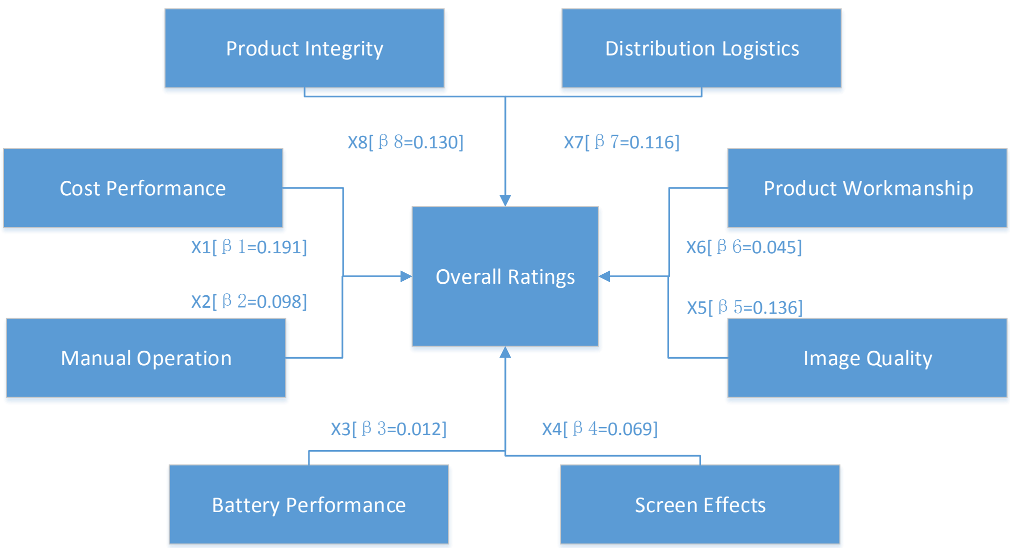

Figure 4. Relative Importance of Each Aspect on Overall Ratings

Cost performance is proven to be the most important factor, which is a valuable indicator for merchants that improving their products' cost performance (e.g. offering discounts) can be the best way to satisfy customers. This comprehensive index considers both the product performance and its sales price. A better performance under the same price or the lower cost for the same product can both lift this index. The experiment results also indicate that most of SLR camera customers prefer better cost performance but not an extreme experience in a particular aspect. Although this aspect is extracted from the product ontology, it may also be a significant aspect for other product besides SLR camera.

The second important aspect is image quality, which is a unique aspect from SLR camera ontology, as well as manual operation, screen effects product workmanship and battery performance. It is quite hard even for domain experts to differentiate the importance of these aspects without the wisdom of big data. Comparatively speaking, the number of customers' pursuit towards high image quality is much violent than the battery performance. The importance of product integrity and distribution logistics are in the third and fourth place.

The realistic significance of the experiment results are as follows. For customers, they can realize that the most crucial aspect for online SLR camera is cost performance. Therefore, if they wish to buy a product with high cost performance; the overall rating can be a good indicator. On the other hand, if a customer prefers to buy a SLR camera with better battery performance, the overall rating may not be a reasonable reference. For online electronic commerce merchants, the customer value embedded in these results is that they should enhance the investments on the product delivery process. The product integrity and distribution logistics are even more important than some parts of the product in customers' eyes. For industries, they can notice the comparatively importance between different product aspects. A more efficient business strategy can be applied to satisfy more customers at a low cost.

5. Conclusions and future work

This paper proposes a semantic text analytics approach to mine the determinants of online customer ratings. In the proposed method, ontology-based product concepts and selected LDA topics are combined together to constitute a comprehensive aspect-level description. Aspect-related reviews feature sets are constructed by semi-supervised aspect extraction. After cleaning the raw reviews, aspect-based segmentation is used to be the basis for regrouping the aspect-related segmentation together. The sentiment polarity for each aspect is estimated by applying aspect-oriented sentiment analysis while the context-sensitive sentiment has been pre-processed. Eventually, the regression model is established between the sentiment values for each aspect and the corresponding overall rating. Empirical results reveal that we accurately distinguish the comparatively importance of these eight aspects which has realistic significance for customers, merchants and industries.

In addition, this study still leaves some potential problems for further consideration. First of all, how to effectively construct better feature sets for each aspect. Secondly, using the same value (e.g. 1) for all of the positive sentiments without differentiating the extent can cause errors. What's more, we assume the overall rating can reflect the information contained in the corresponding reviews evaluated by the same customer at almost the same time. However, in a real situation, there exists some reviews cannot meet this hypothesis. Our future research will pay more attention on these problems to enhance experiments' performance.

Acknowledgments

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