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Identification of Customer Requirements Based On Online Comments with Opinion Mining and IPA

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Abstract: *This research studies the identification of customer requirements based the online comments posed on e-commerce websites. IPA method as well as opinion mining technique is applied to identify and categorize customer requirements, thus providing specific strategies for the company to keep its competitive power and utilize its resource efficiently. Specifically, a Chinese dependency syntax analysis is employed to extract clauses with specific product features and a clause level sentiment analysis algorithm is then proposed to compute the sentiment value of corresponding product feature. After that, two types of data as importance and frequency are adopted in IPA method to categorize the requirements. Then, a kind of popular Chinese smartphone is used as an example, and among all the 39 product features mined, 7 features are considered to need concentration as Operation, Response, Shot, Smooth system, Appearance, Cost performance and Fingerprint, and another 7 features including Firenze, Interface, Full screen, Color space, Network, Night scene and Texture are thought to be possible overkill. Therefore, for the company, it should spend more resource and time on those which need more focus while cut down on those might be overkill to strengthen its competiveness and increase customer stickiness.*

Keywords: *Customer requirement, IPA, Opinion mining, Online comments, E-commerce*

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I. Introduction

Nowadays, with the widespread use of Internet, people have easy access to various information through the network, especially in Web2.0, the increasing popularity of user generated content changes our lifestyle, promoting the birth of new business models and economic behavior. Taking the e-commerce for example, customer are always willing to share their feelings or comment after buying or using the product they bought from the platform, these interactions will have unexpected effect on both sellers and customers. What's more, with the rapid development of Internet technology, customer requirements are changing rapidly, so the traditional product-centered development model cannot respond to changing requirements in time, which means the companies have to understand customer requirement duly to maintain their competitive edge, making full use of the interaction with customers and taking their comment into consideration.

By now, some researchers have studied how to recognize customer requirement with some traditional methods, such as Kano questions [1], TRIZ[2] etc. These traditional methods all need massive time and energy, and the result may be not objective, since the people interviewed are subjective and may know little about the product if they are chosen in random.

Even some researchers have studied the application of text mining in identifying customer requirement, few studies are based on the Chinese comments. To make up for the deficiency of traditional research models, this paper proposes to mine customer requirements based on a huge amount of customer comments with a quantitative model named IPA and Chinese opinion mining method.

The rest of paper is arranged as follows. In Section 2, some basic ideas like the identification of customer requirements, Chinese text mining and IPA method are talked about. The detailed process of data collection and its preprocessing in Chinese e-commerce website are introduced in Section 3. In Section 4, the customer requirements are identified as well as its classification based on two indicators as importance and performance. Finally, the conclusion of our findings is summarized.

II. Background

2.1 Customer requirements

As time goes on, customers' demands become more and more rigorous and change dynamically. To some extent, their behaviors are more like moving targets. Moreover, effectively capturing and understanding the needs of customers and quickly responding to them by providing products are prerequisites for an enterprise to gain market share and improve customer satisfaction. Many enterprises have proved this point through practical examples, and a comprehensive understanding of user and market-related information can help enterprises formulate product attributes that users find attractive and distinctive[3].

Customer needs can be obtained through customer complaints, customer interviews, market surveys [4, 5] and questionnaires[6]. And the interview can be furtherly divided into individual interview and focus group interview .Many marketing research organizations commonly apply focus group interviews to identify customer needs with the assumption that group dynamics are helpful to identify more diverse customer needs. Besides, in terms of cost, the cost of an individual interview is much lower than that of a focus group. However, customer needs obtained through interviews have several limitations like only existing and explicit customer needs or problems can be found, and this method will be helpless for potential or non-explicit product needs, such as attractive needs referred in Kano model [7].

What's more, some researchers have also studied customer requirements from other aspects. Spreng et al. [8] proposed an indicator system to evaluate the functionality expected by customers, obtaining both explicit and implicit demand through combined quantitative information. Wang[9] and Temponi et al. [10] use fuzzy language to express customer opinions. Hom adopted PGCV index to obtain the gap between the highest level of customers' expectation on product characteristics and the level already reached by existing products using questionnaires to obtain customer demand [11].

2.2 Chinese opinion mining based on online comments

Opinion Mining, sometimes referred to as Sentiment Analysis or the Emotion AI, combines Natural Language Processing with Text Analysis Computational Linguistics and biometric to systematically identify, extract, quantify the emotional and subjective information. Sentiment analysis is widely used in contexts related to customers' voices, such as user comments, survey responses and online social media.

In terms of granularity, it can be divided into three types as word based, sentence based and document based opinion mining. Word based opinion mining focuses on the sentiment value of single word or phrase, Kim et al. [12] used WordNet to expand the manually searched sentiment words (positive and negative words), and judged the polarity of a word according to the word's polarity confidence with the existing word. Specifically, some researchers have studied the sentiment of some particular topics, Ling[13] et al. used the probability model to extract the viewpoints or emotional polarity of pre-defined objects, while Jo and Oh[14] used the topic model to extract the viewpoints or emotional polarity of the these objects referred in Ling's study. Kim et al. [15] proposed to establish a hierarchical aspect-tree model for multi-layer aspect analysis.

With regard to sentence based sentiment, Li et al.[16] proposed a new Recurrent Neural Deep layer Model (RNDM), which can predict the emotional labels of sentences according to the recurrent deep learning, and proved that the classification accuracy of this method was significantly higher than that of naive bayes and support vector machine with the experiment. Chen et al. [17] proposed a fine-grained framework named Markov logic to be applied in emotional analysis of clauses. Other machine learning-based methods such as conditional random field [18] and regression-based model [19] have also been applied to analyze the emotional tendency of sentences.

For document based sentiment analysis, the sentiment analysis of document layer is mainly based on two assumptions: each document has only one theme and the topic of each document is known. Tsou et al. [20] analyzed the documents which evaluated public figures by manual scoring and the result shows that three parameters that imply the strength of text are communication breadth, density and sentiment density. Pang et al. [21] used a variety of machine learning methods to analyze film reviews, and found that machine learning method was more effective than manual annotation method. At the same time, it was pointed out that the analysis of the emotional tendency of document can be regarded as a text classification problem based on the topic. Tan and Zhang[22] used supervised machine learning methods, such as naive bayes and support vector machine to analyze the emotional tendency of documents, and obtained good results. Ku and Chen[23] used an unsupervised aggregation method to summarize the sentiment value of various parts of the document and then regarded this as the sentiment of the whole document.

2.3 Importance-performance analysis

IPA (Importance-performance analysis) was first introduced by Martilla and Iames in 1997 as a tool to prioritize attributes needed to be improved based on importance and performance of these attributes. This analysis is shown by a matrix to represent the importance and performance of each attribute. The horizontal axis means the level of performance and the vertical means importance. With a central tendency value (i.e. mean), the matrix is divided into four quadrants (Fig. 1). Quadrant I means "keep up the good work" (high importance as well as high frequency), attributes in this part are thought to be in good position and should be kept. Quadrant II means "concentrate here" (high importance and low frequency), so this part should be the focus of the company if they want to retain customers and keep competitive edge in this area. Quadrant III means "low priority" (low importance as well as low frequency), so the company do not need to spend too much time or money on attributes in this part. Quadrant Ⅳ means “possible overkill” (low importance but high frequency), so attributes in this part may be allocated excessive resources that should better be deployed elsewhere.

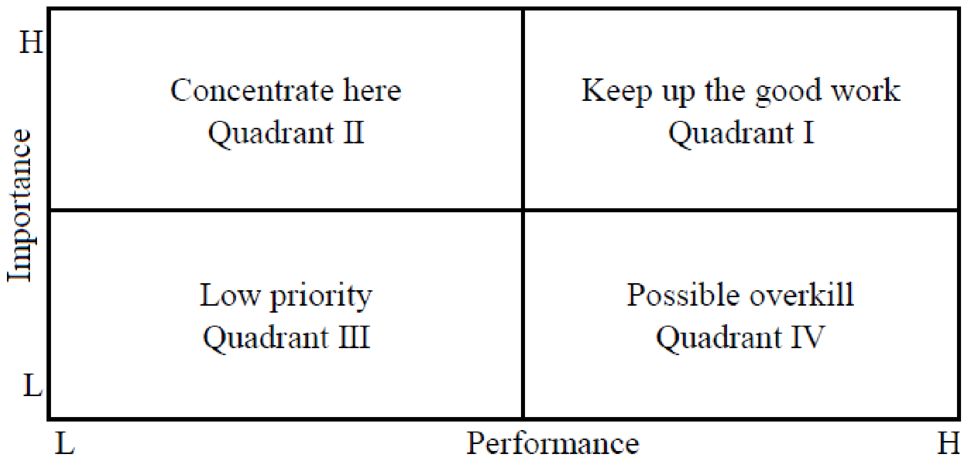

Figure 1: Importance-performance matrix

After the introduction of IPA, it has been widely used in marketing research of various industries, including hotel [24], tourism [25], medical care [26] and so on. Specifically, as some researchers pointed that IPA is a low cost and effective method, which is helpful for the company to find its weakness and allocate its resources effectively [27, 28].

III. Data collection and preprocessing

3.1 Data collection

To capture customer requirements, this paper focuses on digital products: smart phone, as it is a kind of product that iterate in a rapid way as well as customers’ changing requirements. In this paper, several Chinese e-commerce website are studied, including ZOL(http://www.zol.com.cn/), TMall (http://www.tmall.com.cn/), JD (https://www.jd.com/), Huawei Mall (https://www.vmall.com/). The type of smart phone studied in this paper is Huawei Mate20, which was released in 10.16 2018. Using Python to crawl data ranging between 10.17 2018 and 1.8 2019 on these websites, then removing some useless comments with the following criteria: 1) the length must be longer than five characters, 2) deleting the default comments and so on, the total number left for further study is 6,275.

3.2 Data preprocessing

After collecting the data, a python package named pyltp (see https://pyltp.readthedocs.io/zh_CN/latest/) was used to segment the comments. To increase the accuracy of segmentation, an addition dictionary based on experience and some introduction associated with the product itself was applied in the process of segmenting instead of the default dictionary. Then a three-step method is conducted to determine customer requirements and the corresponding sentiment value.

Step 1. Constructing the collection of product features for smart phone.

Since for smart phones, customer requirements must be associated with the specific product feature, for example, one customer’s comment “The phone takes a wonderful picture!” is related to the feature camera, the comment “The battery life is amazing, it can last for a very time” describes the feature battery life. So to identify customer requirements, it is necessary to create a corpus of product features. The this paper, two approaches are conducted, one is to calculate the TF-IDF value of all segmented nouns and reserve the top 10% nouns in the alternative set, the other is to collect information from the product specification and its official website. Then, these alternative words will be scrutinized manually to form the final corpus.

Step 2. Constructing a sentiment lexicon for smart phone.

Even though there have been some existing sentiment corpus for opinion mining, the sentiment of the same word in different context will be totally different, for example, if a customer says “This down jacket is very thick”, the word thick is positive which means the jacket is very warm, while the comment “This phone is too thick for a man to hold”, this thick has a negative meaning, this customer may complain the thickness. Therefore, to determine the accurate sentiment value, it is undoubtedly that a customized corpus regarding a

specific domain will work better than a generalized one. Different with the construction of feature corpus, this paper makes use of the part-of-speech, only including verbs and adjectives, the detailed procedure is as follows:
1) For verbs
- Matching all verbs with the words in the general sentiment lexicon, 186 positive words and 139 negative words were obtained
- Manually correct the wrong polarity, for example, some positive words in this context like “astonished”, “shocking” are regarded as negative words in general sentiment lexicon, this need to be corrected manually to generate an alternative set.
- Calculate the PMI similarity between the remaining verbs with the alternative sentiment word individually, and keep the top 10% as the alternative sentiment words.

2) For adjectives
- Likewise, matching all adjectives with the words in the general sentiment lexicon, 121 positive words and 57 negative words were obtained
- Manually correct the misclassified words, and add these words into the alternative sentiment word set
- Calculate the PMI similarity between the remaining adjectives with the alternative sentiment word individually, and keep the top 10% as the alternative sentiment words.

In addition to the simple sentiment talked above, this paper also takes the conjoint word and degree word into consideration, such as “but”, “also”, “further”, “not”, “very” etc., and furthermore, these words all carry different weights, for example, the weight of “not” is -1, very is 3.

Step 3. Calculating the sentiment value corresponding to the specific feature

In order to calculate the sentiment value of the corresponding product feature, the syntactic dependency analysis was applied in this paper. The dependency considered is shown below:

Table 1: Rules and examples

Rules	Examples
SBV	('Beautiful', 'SBV', 'Package')
SBV+ADV	('Beautiful', 'SBV', 'Smartphone') ('Beautiful', 'ADV', 'very')
SBV+ADV+ADV	('smooth', 'SBV', 'processor') ('smooth', 'ADV', 'also') ('smooth', 'ADV', 'very')
ADV+ADV+…+ADV	('get stuck', 'ADV', 'easily') ('easily', 'ADV', 'not')
CMP	('service', 'CMP', 'good')
ATT	('sound quality', 'ATT', 'good') ('speed', 'ATT', 'perfect')

*SBV: subject-verb; ADV: adverbial; CMP: complement; ATT: attribute.

With the rules shown in table1, the clause are spliced into a complete clause with python programming, then the following algorithm is used to calculate the sentiment of corresponding product features.

Algorithm: clause level sentiment analysis algorithm

```
for each word in wj in clause C do
   if wj in feature corpus FP then
       initialize sentiment score P(wj)←0
end for
for each word in wj in clause C do
   if the word wj in the sentiment words list SL then
       set P(wj)←(positive:1/negative:-1)
   end if
  if the word wj in the negation words list NL then
      for wi in the same clause with wj do
          set P(wj)←-1* P(wj) do
      end for
   end if
   if the word wj in adverbs of degree list DL then
       for wi in the same clause with wj do
             set P(wj)←degree(wi)* P(wj) do
      end for
   end if
score = P(wj)
end for
```

IV. Empirical results

After the data preprocessing, the features in the comments are extracted and to show the result visually, the wordcloud of these mined features is plotted and shown in Fig. 2. In the picture of wordcloud, the bigger the name of feature is, the more frequent it has been referred in the comment, indicating that customers care more about it. On the contrary, the smaller the character in the figure, less customers pay attention to it. Therefore, in this study, for Huawei mate20, customers are more concerned about the function and screen of smartphones, followed by its appearance, battery life, camera and the price.

Figure 2: Wordcloud of product features

Then, all mined product features are listed in table 2, and the ID is the code of product feature which will be used in the IPA to simplify. Besides, the value of sentiment and frequency have been standardized to keep the result simple.

Table 2: The description of product features

Product features	ID	standardized_sentiment	standardized_frequency
Operating gestures	ATT1	0.1457	0.0220
Operation	ATT2	0.1448	0.0661
Processor	ATT3	0.2078	0.0899
Single-hand operation	ATT4	0.0508	0.0000
Battery	ATT5	0.2128	0.2128
Response	ATT6	0.1622	0.1284
Firenze	ATT7	0.2542	0.0183
Resolution ratio	ATT8	0.1751	0.0367
Function	ATT9	0.2550	0.4514
Rear cover	ATT10	0.1322	0.0294
Frames	ATT11	0.3458	0.0440
Price	ATT12	0.1893	0.1395
Interface	ATT13	0.3559	0.0055
Shot	ATT14	0.1833	0.2037
Smooth system	ATT15	0.1537	0.0826
Screen	ATT16	0.1856	0.4440
Kirin	ATT17	0.1525	0.0312
Definition	ATT18	0.1017	0.0092
Hook face	ATT19	0.1017	0.0000
Full screen	ATT20	0.3051	0.0110
Color space	ATT21	0.2906	0.0183
Voice	ATT22	0.1695	0.0220
Video	ATT23	0.0000	0.0275
Appearance	ATT24	0.1482	0.3119
Glass shell	ATT25	0.1017	0.0257
Network	ATT26	0.2373	0.0092
Microspur	ATT27	0.1017	0.0330
System	ATT28	0.2100	0.2037

Pixel	ATT29	0.3305	0.0789
Chip	ATT30	0.1525	0.0257
Cost performance	ATT31	0.1826	0.0606
Performance	ATT32	0.3386	0.2018
Color	ATT33	0.1910	0.2018
Night scene	ATT34	0.3051	0.0165
Sound effect	ATT35	0.4372	0.0844
Game	ATT36	0.3051	0.0495
Picture	ATT37	0.1990	0.1395
Fingerprint	ATT38	0.1525	0.0459
Texture	ATT39	1.0000	0.0110

To show the importance-frequency matrix in a better way, all values of each attribute are standardized and the median value are used as the split threshold. The matrix is shown in Fig. 3.

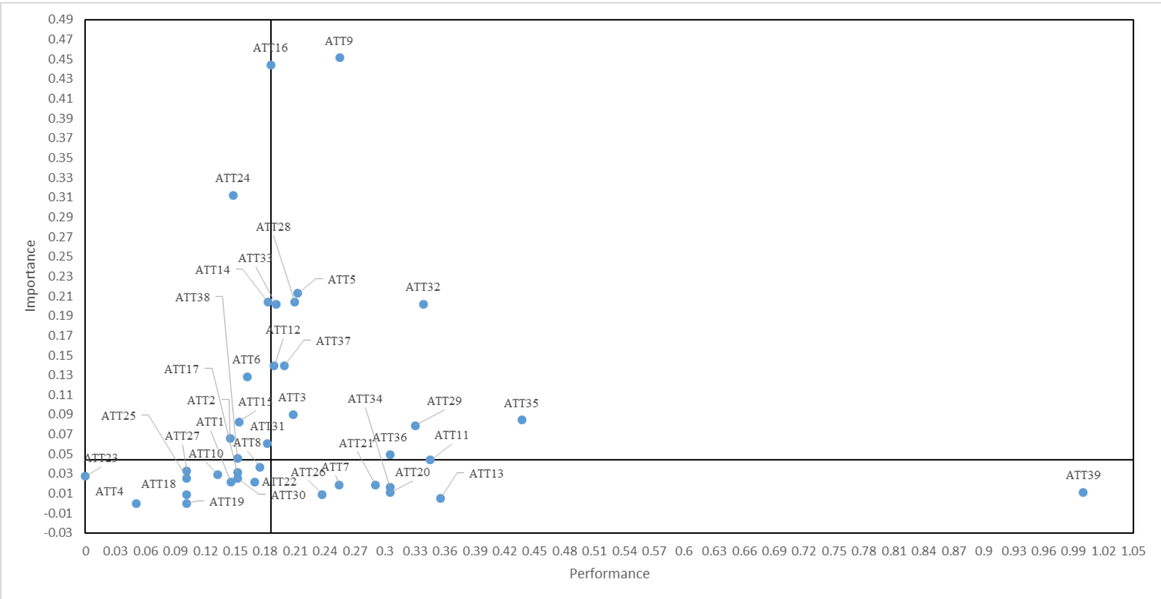

Figure 3: IPA matrix for Huawei mate 20 customer requirements

From the IPA matrix, among all customer requirements, .ATT9 has the highest importance while ATT19 has the lowest performance. What's more, ATT39 has the highest performance and ATT23 has the lowest performance. The median importance of requirements is 0.1856 and performance is 0.0440, indicating that the company still has a long way to go to improve the quality of product and the customers' satisfaction.

Table 3: IPA for customers' requirement of Huawei mate20

Product features	**ID**	**Category in IPA**
Operating gestures	ATT1	Low priority
Operation	ATT2	**Concentrate here**
Processor	ATT3	Keep up the good work
Single-hand operation	ATT4	Low priority
Battery	ATT5	Keep up the good work
Response	ATT6	**Concentrate here**
Firenze	ATT7	Possible overkill
Resolution ratio	ATT8	Low priority
Function	ATT9	Keep up the good work
Rear cover	ATT10	Low priority

Frames	ATT11	Keep up the good work
Price	ATT12	Keep up the good work
Interface	ATT13	Possible overkill
Shot	ATT14	**Concentrate here**
Smooth system	ATT15	**Concentrate here**
Screen	ATT16	Keep up the good work
Kirin	ATT17	Low priority
Definition	ATT18	Low priority
Hook face	ATT19	Low priority
Full screen	ATT20	Possible overkill
Color space	ATT21	Possible overkill
Voice	ATT22	Low priority
Video	ATT23	Low priority
Appearance	ATT24	**Concentrate here**
Glass shell	ATT25	Low priority
Network	ATT26	Possible overkill
Micro spur	ATT27	Low priority
System	ATT28	Keep up the good work
Pixel	ATT29	Keep up the good work
Chip	ATT30	Low priority
Cost performance	ATT31	**Concentrate here**
Performance	ATT32	Keep up the good work
Color	ATT33	Keep up the good work
Night scene	ATT34	Possible overkill
Sound effect	ATT35	Keep up the good work
Game	ATT36	Keep up the good work
Picture	ATT37	Keep up the good work
Fingerprint	ATT38	**Concentrate here**
Texture	ATT39	Possible overkill

Table 3 shows the IPA category of each feature of Huawei mate20. Using the median value as threshold, 39 features are divided into four categories. Seven features are assigned into the group of "Concentrate here" as Operation, Response, Shot, Smooth system, Appearance, Cost performance and Fingerprint. And also seven product features are possible overkill, including Firenze, Interface, Full screen, Color space, Network, Night scene and Texture, indicating that the company should reduce the resource spent in these features and reallocate to the features that need more concentration to increase its efficiency as well as the customer satisfaction. For features with low priority, the company can temporarily let them alone since this will not influence customer satisfaction significantly such as Glass shell and Voice.

V. Conclusion

This research studies the identification of customer requirements based on customer comments posed on e-commerce websites. A quantitative technique named IPA method and Chinese opinion mining technique are adopted to carry on this research. For Chinses opinion mining, the clause is mined on the basis on Chinese dependency analysis and a clause level sentiment analysis algorithm is proposed to conduct the calculation of sentiment value for a specific product feature. Then, the identification of customer requirements for Huawei mate20 is given as an empirical example and seven product features are discovered to need concentration since their performance is low while customers talk about them frequently. What's more, another seven features are considered to be possible overkill, so the company can cut down the resources distributed.

The contributions are as follows: firstly, the specific feature corpus of smartphones is proposed along with the corresponding sentiment corpus. Besides, the dependency analysis is used to conduct Chinese opinion mining, which shows the significant difference between English opinion mining.

For future research, it is recommended to include more research subjects instead of only one specific kind of smartphones. Also, the feature corpus as well as the sentiment corpus should be enlarged to increase the algorithm's accuracy. In addition, some latest machine learning method such as LSTM and RNN can also be used in this context to play the advantages of artificial intelligence.

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