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RESEARCH ARTICLE

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High-end equipment customer requirement analysis based on opinion extraction

Abstract Acquisition and analysis of customer requirements are the essential steps in high-end equipment design. Considering that Internet and big data technologies are integrated into the manufacturing industry, we propose a method of analyzing customer requirements based on open-source data. First, online data are collected with focused crawlers and preprocessed to filter noise and duplicate. Then, user opinions are extracted based on the defined template, and users' sentiments are analyzed. Based on the relationship between user sentiments and attribute parameters, the parameter range that satisfies customers can be obtained. The proposed method is evaluated by using an example of new energy vehicle to verify its availability and feasibility.

Keywords requirement analysis, opinion extraction, high-end equipment, new energy vehicle

1 Introduction

The high-end equipment manufacturing industry is at the high end of the value chain and the core of the industrial chain. The industry is also the backbone of modern industrial systems and the engine to promote industrial transformation and upgrading. At present, contemporary developments of global science and technology revolution are prevalent. The deep integration of manufacturing industry and emerging information technologies, such as the Internet and big data, results in the high-end equipment manufacturing industry entering the forefront of global economic competition. The starting point, and end result, of high-end equipment innovative development is to meet the requirements of customers. Therefore, in high-end equipment development, the acquisition and analysis of high-end equipment customer requirements is the first step.

Traditionally, the requirements of high-end equipment innovative development tasks are from the communication with users. Given that the Internet has gradually become an important source of intelligence information, more customers and manufacturers tend to publish various information about high-end equipment products on the Internet, which contains a considerable amount of hidden requirement information. In addition, the development of the Internet and big data technology enables the obtaining of the requirements for high-end equipment from the open data source. However, the Internet data are large-scale and decentralized; thus, acquiring and analyzing user requirements by advanced information collection, processing, and mining technologies is urgent.

Given the rapid development of Web technology and e-commerce, customers are allowed to comment on their purchases. Customer opinions about products are contained in these comments. The reviews are of high importance to analyzing customer behavior and competitive intelligence information. In this paper, a user requirement analysis method based on review data are proposed to help manufacturers analyze user requirements, which will improve the product design and gain competitive advantage.

A high-end equipment customer requirement analysis method based on online reviews is proposed in this paper. First, the high-end equipment review data are crawled from the Internet and preprocessed by noise filtering and data deduplication. Next, the product features and opinions are extracted by a defined extraction template. After obtaining users' candidate opinions, the sentiment of user's attitude

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(positive or negative) to an equipment is then calculated. Finally, the relationship between the attribute parameters and sentiment of users is analyzed to find the high-end equipment attribute parameter range that can meet users' requirements.

The main contribution of this paper is that, to the best of our knowledge, it is one of the first to analyze high-end equipment customer requirements based on open-source data. In the Internet environment, the proposed method can acquire customer requirements more conveniently and efficiently. In particular, we define template rules that can select product features and opinion words from Chinese reviews. The proposed opinion extraction method based on template matching can process Chinese texts simply and effectively.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 develops the opinion extraction method. Section 4 describes the framework of the user requirement analysis. Section 5 is devoted to a description of the new energy vehicle case. Section 6 completes the paper with conclusions and discussion.

2 Literature review

2.1 Requirement acquisition and analysis

The chooseboard method, which provides customers with some options of product features and prices, is the most widely adopted online requirement acquisition method (Slywotzky, 2000) by companies such as Dell, Harley, BMW, Nike, Levi's, and Mattel (Walsh and Godfrey, 2000). However, users who lack professional knowledge encounter difficulties in expressing their requirements based on options. Such users may be confused because the options are too numerous (Chen and Wang, 2010; Jing et al., 2010). Thus, the requirements acquired may be far from users' real requirements, especially for high-end equipment.

Kansei engineering (KE) was founded at Hiroshima University as an ergonomics and consumer-oriented technology for producing a new product. KE aims at the translation of requirements into the product design field, including product mechanical function (Nagamachi, 2002). Later, KE was applied to various domains by many researchers (Roy et al., 2009; Huang et al. 2011; Shi et al., 2012). Huang et al. (2012) introduced a clustering method based on a design structure matrix, breaking the Kansei adjectives up into a number of subsets such that each participant deals with only a portion of the words collected. Chang and Chen (2016) combined the ergonomic technology used in Kansei engineering with the unique cognitive ability of humans to identify patterns. Yanagisawa et al. (2017) proposed a Kansei database framework that estimates the customer's responses as an essential component of the delight design platform. However, KE approaches have shortcomings such as its theoretical basis being unclear.

Citarasa engineering (CE) is another methodology for elicitation and analysis of needs for product design (Khalid et al., 2012). Unlike the KE approach, CE is based on a strong theoretical basis and the CE descriptions are derived from both customers and designers. Mavridou et al. (2013) adopted the CE approach to integrate the concepts of cognition/thinking and emotion/affect in revealing customer needs.

Other methods have been also used to acquire requirements. Hansen et al. (2003) presented the consultation interface approach, which can provide some suggestions when customers encounter difficulties in selecting from the options. Blecker et al. (2004) introduced advisory systems that enable the explanation of the main shortcomings of the existing customer interaction systems. Customers can be better assisted during the elicitation process. However, they did not present the specific methods of implementation. Piller et al. (2005) proposed the use of online communities for collaborative customer co-design to reduce the mass confusion phenomenon. Zhang et al. (2014) identified customer needs based on a data source triangulation approach, questionnaire survey, a five-point liner numeric rating scale, and factor analysis.

2.2 Opinion mining

Product feature and opinion extraction algorithms can be divided into two main categories, namely, supervised algorithms and unsupervised algorithms.

Supervised algorithms are mainly based on marked training corpora, which train classification models by machine learning or deep learning algorithms. Specifically, extracting opinions is regarded as a sequence annotation task (Liu et al., 2015). Choi et al. (2005) viewed the extraction problem as an information extraction task and adopted a hybrid approach that combines conditional random fields (Lafferty et al., 2001) and a variation of AutoSlog (Riloff, 1996). Yang and Cardie (2012) proposed a semi-CRF-based approach to the opinion extraction tasks that can perform sequence labeling at the segment level. Yang and Cardie (2013) presented an ILP-based joint interference model to extract jointly the opinion holders and the opinion expression. Irsoy and Cardie (2014) applied deep RNNs to opinion expression extraction formulated as a token-level sequence-labeling task. Katiyar and Cardie (2016) investigated the use of deep bi-directional LSTMs for joint extraction of opinion entities and relations.

Although the supervised algorithm can sometimes obtain better results, it requires a large amount of marked training data, and the effectiveness of the algorithm largely depends on the quality of marked data. High-quality marked data are difficult to collect; thus, sometimes the effectiveness of the supervised algorithm is not very high (Liu et al., 2015). By contrast, unsupervised algorithms do not require training data and are more adaptable, thereby attaining good results in reviews of different products.

Unsupervised opinion extraction is mainly based on templates, which is the syntactic relationship and modification relationship between feature words and corresponding review words. Templates can be constructed from corpora either automatically or manually. Commonly used features include syntax and parts of speech. It does not need much label data and can automatically find product features; thus, it is suitable for different products. Yi et al. (2003) extracted nouns phrases Base Noun Phrase, Definite Base Noun Phrase, and Beginning Definite Base Noun Phrase as the candidate product features. Hu and Liu (2004) tagged the part of speech of the review corpus and extracted all nouns and noun phrases to form a transaction file. Then Apriori algorithm is used to mine frequent items as candidate sets of product features. Kumar and Raghuveer (2013) used the dependency relationship between product features and opinions to extract product features and opinions.

3 Customer opinion extraction

Although comments on the Internet are prevalent, they are often highly colloquial and de-normalized. Therefore, we must effectively identify product feature words and opinion words by opinion extraction, which is the core and most challenging part of finding and tracking high-end equipment manufacturing requirements. We can obtain product features and opinions from the online high-end equipment review data by fine-grained feature extraction. For example, in the sentence “power is excellent,” “power” is the product feature and “excellence” is the user opinion. Many differences occur between Chinese- and English-syntactic structures (Zhou et al., 2016); thus, the methods of extracting Chinese and English opinions are different. In this paper, we only discuss the opinion mining for Chinese reviews. The process of opinion extraction can be divided into two steps, namely, (1) part-of-speech tagging and syntactic parsing and (2) extraction of feature and opinion words.

3.1 Part-of-speech tagging and syntactic parsing

In opinion extraction, we first carry out the part-of-speech tagging and syntactic parsing for each sentence of each comment; that is, we segment the sentences, analyze the part-of-speech, and determine the relationship between words by dependency parsing.

Dependency parsing reveals the syntactic structure by analyzing the dependencies among the components in the linguistic unit. The process identifies the grammatical components such as “subject-verb (SBV)” in sentences and analyzes the relationship between the components. For example, the dependency parsing of the review sentence “The airplane’s color is nice and the space is very large.” is shown in Fig. 1.

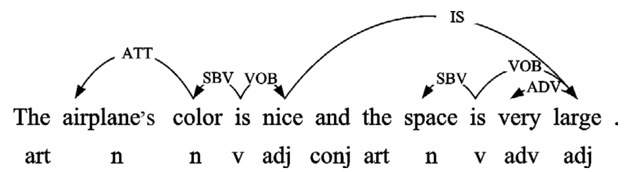

Fig. 1 Dependency parsing

The dependency parsing is shown in the form of a directed graph. The nodes in the graph are the words in the sentence. The directed arcs between the nodes show the dependencies between words. The direction of the arc indicates that the dependent words depend on the core words. In the figure, the middle layer is the comment sentence. The lower layer is the result of the part-of-speech tagging (for example, the part of the word “airplane” is a noun (n)). The upper layer is the result of syntactic parsing, thereby suggesting the dependencies between words. After the part-of-speech and dependency parsing, we can extract the binary group < product feature, opinion > based on certain rules.

3.2 Extraction of product feature and opinion

Specific linkages occur between product features and opinions in product reviews; thus, the features and opinions can be extracted by the part-of-speech and dependency parsing. We summarize the mode of opinion word appearance by statistics and find three main types of dependencies in Chinese comments that contain opinion words.

First is the SBV relationship. The information of < product feature, opinion > is mainly hidden in the SBV relationship. By the analysis of the dependency relationship, we find that the SBV structure can provide information such as the modified relationship between subject and predicate. In the SBV structure, the subject can be the holder of the opinion or the product feature discussed. Two possibilities exist in the predicate’s part of speech: Adjective or verb. For example, in the review sentence “space is large,” “space” is a product feature and “large” is a user’s opinion. In the sentence “I like it,” “I” is the holder of the viewpoint and “like” is the user’s opinion. Three types of SBV part-of-speech templates include opinion words: noun + adjective (na), verb + adjective (va) and pronoun + verb (rv).

Second is the adverbial (ADV) relationship. By extracting ADV relationships in reviews, we can analyze the polarity and intensity of user opinions. Three contexts of opinion words exist. First, the sentence contains a negative prefix, such as “not good.” Second, the sentence contains an emphasis prefix, such as “very good.” Third, the sentence contains neither a negative prefix nor an emphasized prefix. If we only extract the opinion words but ignore the context of the word, we may incorrectly judge the polarity and intensity of opinions. Therefore, we must find the negative and emphasized prefix in a sentence by analyzing the dependency relationship between words. The part-of-speech template of the ADV structure that contains opinion words is mainly adverb + adjective (da). Thus, after extracting the opinion words, we should search for adverbs that have an ADV dependency relationship with the opinion words and extract them jointly as the user’s opinion.

Third is the verb-object (VOB) relationship. When the subject of the SBV is the holder of the opinion, we must look up the object that has a VOB relationship with the verb. One example is the SBV structure “I like” and its related VOB structure “like the shape.” We extract the object “shape” in the VOB structure as the product feature and the verb “like” in the SBV structure as the user’s opinion. The part-of-speech template of the VOB structure that contains opinion information is generally verb + adjective (vn).

We use a triplet < A_pos, B_pos, dp > to represent the part-of-speech and dependency pair. A_pos and B_pos represent the words A and B and their corresponding parts of speech respectively. dp indicates the dependencies of words A and B. *O* is a collection of binary sets < product feature, opinion > obtained from user reviews. We define the following rules to extract an opinion.

(1) We find the triples < A_n, B_a, SVB > and < A_v, B_a, SVB > in the reviews and analyze the polarity of word B. If it is polarized, we store the pairs < A, B > in the set *O* as a candidate opinion; otherwise, we do not execute the step.

(2) We find the triplets < A_r, B_v, SVB > and judge if A is the opinion holder. If A is the view holder, we perform (3); otherwise, we do not execute the step.

(3) We analyze the polarity of word B in triples < A_r, B_v, SVB >. If it is polarized, we execute (4); otherwise, we do not execute the step.

(4) We find the VOB structure containing the verbs in (3). If the triple is < A_v, B_n, VOB >, then the two-tuple < B, A > is stored in the candidate set *O*; otherwise, we do not execute the step.

(5) We find the ADV triples < A_d, B_a, ADV > (where B is the opinion word in the pair < product feature, opinion >) in the candidate opinion set *O* and take A and B jointly as new opinion words. We replace the original opinion B with A + B and save it in the candidate set *O*.

We extract opinions from all reviews based on the above steps and finally obtain the candidate sets $O = \{O_1, O_2, \ldots, O_n\}$, where n is the number of reviews for a product and O_n is the collection of opinions extracted from the nth review.

4 High-end equipment customer requirement analysis

Under the environment of the Internet and big data, the main method to obtain user requirement of high-end equipment is to mine information on the Internet by opinion extraction technology. A highly scalable data acquisition module is constructed to obtain high-end equipment review data. These data are then treated by opinion extraction and sentiment analysis to find user requirements for high-end equipment. Figure 2 shows the specific process.

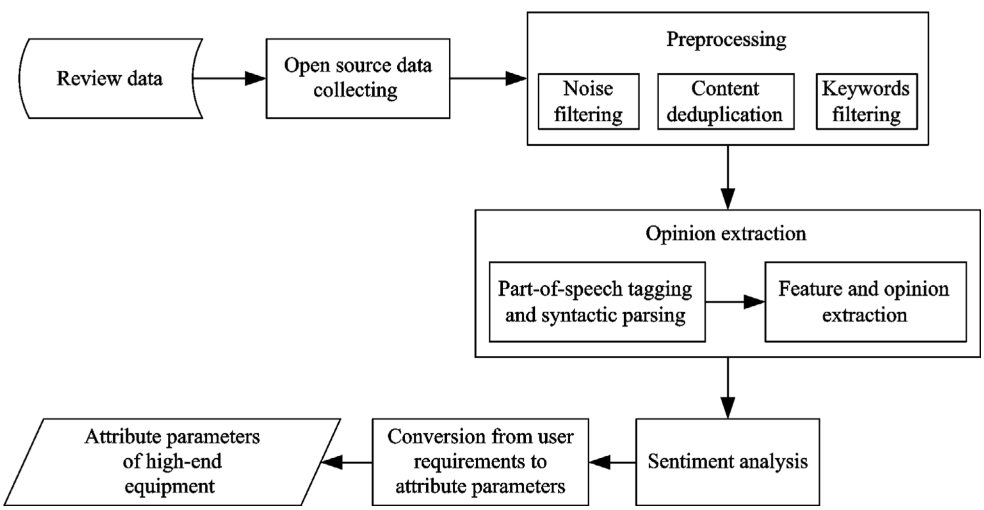

Fig. 2 High-end equipment customer requirement analysis process

4.1 Open source data collecting

A large amount of open-source data of high-end equipment information and user's reviews are available on the Internet, thereby implying the potential requirements of users. However, because these data are not stored locally, we must solve the data-collection problem before we analyze user requirements. The original user requirement data mainly includes text data such as product reviews on e-commerce websites, community forums, and Weibo, which can be obtained by web crawling.

In terms of data collecting, we use focused crawlers that ensure high performance and scalability of data by filtering useless web data directly in the first step of data collecting. Different from traditional crawlers, focused crawlers do not pursue large coverage but crawl the web content related to a particular topic. This crawler can filter links that are not related to topics by certain web analytics algorithms and keep useful links in the waiting URL queue. Then, based on a certain search strategy, a focused crawler will select the next URL from the queue and repeat the above process until it reaches a certain requirement of the system. In addition, all crawled webpages are stored, analyzed, filtered, and indexed by the system; thus, query and retrieval are easy. Moreover, the results obtained by this process can give feedback and guidance on the future crawling process.

4.2 Text preprocessing

Most of the collected raw data are unstructured or semi-structured; thus, text preprocessing methods, such as noise filtering, data deduplication, and keyword filtering, are needed before we analyze the data.

In noise filtering, the data collected from the Internet webpages do not only include the valuable text content but also some information that is not related to the subject, such as navigation area, hyperlinks, advertisement, and copyright information. These data are very unfavorable to the later text processing because they increase the work-load and the error probability of the results. Therefore, the noise data must be filtered out of the text data.

In content deduplication, users may submit comments multiple times due to the unobstructed networks; thus, the data collected from the Internet may contain some redundant contents. Therefore, we must comprehensively use duplication detection technologies for different media to quickly find and filter out the duplicate content that is caused by network behavior such as reprinting, reposting, and copying.

In keyword filtering, we construct a preset keyword list that contains some pre-defined high-end equipment feature words and discriminating words of negative sensitive content. We then match keywords with text content to screen out quickly the text content about which high-end equipment users care. Marking up is also conducted for further analysis.

4.3 Opinion extraction and sentiment analysis

User opinion extraction is the key process in the analysis of high-end equipment requirement. Its result is the main manifestation of user requirement, which provides high-end equipment development companies with the basis for product design and competitive intelligence against other enterprises. After obtaining the preprocessed comment data, we extract the high-end equipment opinions by the opinion extraction method mentioned above. In the end, user opinions to various models of high-end equipment are extracted, which described by the collection < high-end equipment model, product feature, opinion > .

After extracting the user opinions, we need to obtain user attitude toward product features via sentiment analysis. Sentiment analysis aims to determine the customers' contextual polarity or emotional reaction to a product. To process Chinese texts professionally, we use SnowNLP, a Python library that specializes in analyzing Chinese, to process the reviews. The library has functions similar to TextBlob (a Python library for processing English textual data), such as part-of-speech tagging, text abstraction, and sentiment analysis. SnowNLP can predict the probability that a sentence is positive or negative. The accuracy of prediction for product review is relatively high because its corpus is mainly product reviews. Constructing corpus in specific high-end equipment fields is also possible, and the accuracy will improve. We combine every opinion word with its corresponding product feature and use SnowNLP to analyze the sentiment of this opinion. SnowNLP can generate a sentiment score for every opinion. Opinions whose scores are over 0.5 are regarded as positive, and others are regarded as negative. By the sentiment analysis, the user's sentiment toward high-end equipment attributes is obtained.

4.4 Conversion from user requirement to attribute parameters

After obtaining user opinions and sentiments, we must convert them into specific high-end equipment attribute parameters through a certain method to provide a direct reference for high-end equipment designers.

After opinion extraction and sentiment analysis, customer reviews can be transformed into a number of normative quads < high-end equipment model, feature, opinion, sentiment > . Sentiment in the quad is the result of sentiment analysis, whether positive or negative. For a specific high-end equipment, different models have different attribute parameters. We first crawl the attribute parameter data for various models of one specific piece of high-end equipment from the Internet. We then find the attributes that correspond to the features in quads and add the attribute parameters into the quads. For example, a customer's review for a car's space is formalized as < Tesla Model S 75D, space, large, positive > . The attribute that is related to space is the car's volume; thus, the quad is extended to a five-tuple < Tesla Model S 75D, space, 14.1 m^3, large, positive > after we add the volume value. Next, we collect all the five-tuples of one feature and calculate the sentiment score for the feature. The sentiment score is the proportion of positive reviews; thus, if more customers are satisfied with the feature, the score will be higher. After the sentiment scores for one feature of all equipment models are calculated, the relationship between the feature parameters and sentiment scores can be obtained. The range of high-end equipment attribute parameters that meet user requirements can be found by selecting the attribute parameters to which customers have a positive attitude.

5 Case study

Based on the theoretical analysis of high-end equipment user requirement analysis, we present a case study on the innovation and development of new energy vehicles. In the third industrial revolution, the automotive industry is the most comprehensive and large-scale carrier and platform for technological innovation in digitalization, networking, intelligence, new energy, new materials, and new equipment. The research on new energy vehicles is of great significance and a good case for our work.

We collect the user reviews and configuration parameter data from the "Vehicle Home," which is one of China's most visited, widely covered, and professional automotive portal websites. First, we delete the duplicate content and filter the noise. We then conduct the part-of-speech and syntactic parsing by HIT's HLP tool for each review. Next, we extract the opinions based on the extraction rule defined above and obtain a set of opinions for each model of vehicle. For example, some of the opinions of Tesla Model X are { < ride, very comfortable > , < trunk, very good > , < space, very large > , < turn, hard > , < space, also large > , < noise, too large > , < center of gravity, low > , < manipulation, good > , < space, large > , < space, large > }.

After the opinion set of each model of car is obtained, we analyze the sentiment polarity of these views. We train the dictionary in SnowNLP with the review commentary data. Some review samples are tagged manually and then stored in the existing dictionary to improve the accuracy of the sentiment analysis. Finally, we obtain the sentiment polarity of every opinion.

From the opinion of these vehicles, we can find that the features that users are concerned with mainly include space, power, and fuel consumption. These features are mapped to some attributes of cars to analyze the relationship between user sentiments and attribute parameters.

As regards space, the relationship between user opinion and the space of cars is analyzed. The results show that the ordinary car's volume with which users are satisfied should be more than 12.5 m^3. When the volume is less than 9.1 m^3, customers would feel that the car is too narrow. Given the different uses of cars, customers' requirements for the space also vary. For example, some users prefer a compact and practical car. However, the car cannot be too small because it cannot provide sufficient space and will reduce users' comfort if the car is smaller than a specific value.

Customers also focus considerably on car power. Although the car's power is related to many car properties, here we only select the car's maximum power as the indicator of its power. The results indicate that the users' satisfaction decreases first and then increases as the maximum power increases. One possible explanation for this phenomenon is that users who purchase different types of cars have different expectations for power. The maximum power of small cars is generally smaller than that of larger cars. Customers who buy such vehicles do not need much automotive power and have less expectation for the performance. However, as the maximum power increases, the requirements of users who purchase these vehicles will increase and the actual power cannot meet their expectations; then, the user satisfaction will decrease. When the maximum power increases to a certain value (124 kW in this experiment), the power can fully satisfy user needs, and users' satisfaction will increase.

We also find that users are concerned about the fuel consumption of the car. Some new energy vehicles are pure electric vehicles that have no fuel consumption. Other vehicles are plug-in hybrid vehicles. Customers can drive them in a hybrid mode (based on the internal combustion engine) when the battery is exhausted; thus, the vehicles have fuel consumption. The customer opinion about fuel consumption is basically positive because the fuel consumption of new energy vehicles is relatively small. The fuel consumption of a plug-in hybrid vehicle is mostly lower than 2 L/100 km and users are satisfied with the fuel consumption if it is below this value.

Thus far, we have completed the transformation from user opinions to attribute parameters of a vehicle. Customers also have some opinions about the appearance, interior design, seat, steering wheel, and so on, such as "pretty appearance," "interior design is too simple," and "seat is too high." Therefore, meeting the requirements of customers in terms of these aspects is also necessary.

The process and results of this case indicate that the proposed method can effectively and quickly extract normalized user opinions from a large amount of unstructured online data. By combining high-end equipment attribute parameter data, we can find the relationship between customer opinions and high-end equipment attribute parameters and ultimately determine the parameter range that meets customer requirements. The method can also be applied to the requirement analysis of other equipment. This case verifies the effectiveness and feasibility of the proposed method.

6 Conclusions and discussion

We propose a method of analyzing customer requirements based on opinion extraction. First, we collect the data that contain user requirement information by the focused crawler and then perform preprocessing, such as noise filtering, content deduplication, and keyword filtering. Next, we extract opinions from user review data and obtain the five-tuple < high-end equipment model, feature, attribute value, opinion, sentiment > . Opinion extraction is based on the idea of template matching. We define template rules to select production features and opinion words. Finally, based on the relationship between user sentiment and high-end equipment attribute parameters, we find the attribute parameter range that meets user requirements. The analysis of new energy vehicles shows that the high-end equipment user requirement analysis method proposed in this paper is feasible and effective.

In future research, additional data should be crawled to obtain a user-satisfying parameter range with high accuracy. The viability and effectiveness of the proposed method have been illustrated by a new energy vehicle case, but verifying the validity of its results is worthwhile. We will conduct a questionnaire to investigate whether customers approve of the results obtained by our method. Based on the survey, we can analyze the accuracy of our results. To improve the universality of results, control the customer samples will also be desirable to mitigate the effect of other factors, such as customer's income, on the results.

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