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Extracting and summarizing affective features and responses from online product descriptions and reviews: A Kansei text mining approach

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Highlights:

- We propose a Kansei text mining approach for extracting product features and consumer affective responses
- We classify affective opinions into multiple attributes and relate to product features
- We propose a semi-automatic method to select Kansei words and attributes
- We propose a summarization method to summarize product features and consumer affective responses

Abstract

Today product design takes into account the affective aspects of products, such as aesthetics and comfort, as much as reliability and physical quality. Manufacturers need to understand the consumers' affective preferences and responses to product features in order to improve their products. Conventional approaches use manual methods, such as questionnaires and surveys, to discover product features and affective preferences, and then correlate their relationships. This is one-time, labour-intensive, and time-consuming process. There is a need to develop an automated and unsupervised method to efficiently identify the affective information. In particular, text mining is an automatic approach to extract useful information from text, while Kansei engineering studies product affective attributes. In this paper, we propose a Kansei text mining approach which incorporates text mining and Kansei engineering approaches to automatically extract and summarize product features and their corresponding affective responses based on online product descriptions and consumer reviews. Users can efficiently and timely review the affective aspects of the products. In order to evaluate the effectiveness of the proposed approach, experiments have been conducted on the basis of public data from Amazon.com. The results showed that the proposed approach can effectively identify the affective information in terms of feature-affective opinions. In addition, we have developed a prototype system that visualizes product features, affective attributes, affective keywords, and their relationships. The proposed approach not only helps consumers making purchase decisions, but also helps manufacturers understanding their products and competitors' products, which might provide insights into their product development.

Keywords: Affective mining; opinion mining, customer reviews; affective design; Kansei engineering

1. Introduction

Today customers no longer buy products, they buy experiences (Norman, 2004). Therefore, today's product design not only takes into account the reliability and physical quality, but also takes into account the affective aspects of the product to meet the emotional needs of consumers and improve consumer satisfaction (Rosler et al. 2009). The affective aspects of the products are studied by researchers and manufacturers based on consumer-centred design (Nagamachi & Lokman, 2010). The researchers investigate the qualitative demands of consumers by assessing their psychological feedbacks after they used the products. The manufacturers collect and analyse these feedbacks and apply the results of the analysis to their production plans (Vieira et al., 2017). In particular, Kansei engineering (or affective engineering) is a mechanism for translating human emotional needs into product design elements quantitatively (Nagamachi, 1989; Nagamachi & Lokman, 2016). Kansei is a Japanese term that represents emotions and impressions. In Kansei engineering studies, surveys are always used to study the relationship between affective attributes and product design features (Llinares & Page, 2011). The most commonly used method is the semantic differential (SD) method, which is a rating scale used to measure respondents' opinions and attitudes towards a given object (Osgood et al., 1957). Researchers use the SD method to design questionnaires to measure subjective consumer impressions of the product (Yan et al., 2008). The questionnaire consists of a list of words called Kansei attributes. Each Kansei attribute refers to a particular emotional expression (Chou, 2016). Each Kansei attribute consists of a bipolar pair of Kansei words (i.e. a positive word and a negative word, such as beautiful-ugly) (Friborg et al., 2006). Respondents are usually asked to rate an N-point scale between the bipolar words to represent the subjective assessment of the product.

The conventional survey-based approach provides high-quality affective data, which has been widely used in many affective design studies (e.g. Yan & Nakamori, 2010; Chou, 2016; Kwong et al., 2016). However, they rely on users to actively participate in the study, therefore, most of the existing studies are carried out in a relatively small scale of operation. For example, Chou (2016) involved seven users in their Kansei evaluation of 10 products; Jiang et al. (2015a) involved four users to evaluate 10 products; Guo et al. (2016) studied 36 people in 16 designs. Moreover, the survey questions of traditional method are designed based on expert thinking rather than customers' point of view (Hsiao et al., 2017). Respondents are only able to passively respond to the expert designed questions. In addition, respondents may not be the consumers of the target products. Furthermore, due to the time-consuming and labor-intensive process of questionnaire design, distribution and collection, the survey-based approach is inadequate to involve too many users and products. It is also not suitable to be conducted in real-time basis. However, due to the high industry competition and the product customization trend, more and more products are launched to the market in a very short period of time. Therefore, it is necessary to develop an automated method to efficiently review the consumers' affective feedbacks.

Text mining refers to the use of techniques in natural language processing, computational linguistics, and statistical analysis to systematically and automatically identify and extract useful information from texts (Liu, 2012). Recently, the mining of useful information from online product data has received much attention in many areas (Jin et al., 2015). Most online shopping sites allow consumers to provide their product reviews after purchasing a product. It provides direct, real-time, and verified data from the consumers' perspective. Due to the massive amount of online consumer reviews, the application of text mining is promising to extract important affective information from the consumers' perspective in an efficient and effective manner. In particular, sentiment analysis is a subarea of text mining. The existing studies use sentiment analysis to extract emotional information (Liu, 2012). However, most of them only divide the information into three states: positive, negative and neutral (e.g. Vilares et al., 2017), which is not enough for affective product design.

In this paper, we aim to combine Kansei engineering and text mining approaches to develop Kansei text mining approach which uses text mining to automatically convert unstructured product-related texts to feature-affective opinions. The main contributions of this paper are as follows: 1) We propose an automatic and unsupervised text mining method that combines the information of online product descriptions with consumer reviews to extract product features as well as their corresponding consumer affective responses. 2) We classify affective opinions into multiple affective attributes and relate to product features. Compared with the existing sentiment analysis methods, they mainly divide an opinion into positive, negative and neutral from a single perspective (i.e. either good or bad). 3) We propose a semi-automatic method to select generic Kansei words and attributes based on publicly available data. Therefore, the results could be reused and applied to other products. 4) We propose a summarization method to summarize the relationship between product features and consumer affective responses. We also design and develop a prototype system to visualize the summaries.

We organize the rest of this paper as follows. Section 2 presents a review of the related studies. Section 3 describes the proposed approach. An experiment has been conducted to evaluate the proposed approach. The experimental results are discussed in Section 4. Section 4 also describes the application of the proposed approach and the development of the prototype system. Lastly, Section 5 provides conclusions, limitations, and recommendations for further work.

2. Related studies

Kansei engineering is a product development method used to investigate human feelings and to discover quantitative relationships between the affective responses and design features (Nagamachi, 1989; Nagamachi & Lokman, 2016). By using Kansei engineering, a lot of research has been done to improve product and service design. However, the data collection method of the existing studies is very similar. Most of them manually collect customized Kansei words from various data sources, such as customer interviews, expert interviews, journal articles, magazines, news, advertisements, and more. They then use the collected Kansei words and the SD method to design the Kansei questionnaire. Finally, the questionnaire is distributed to a group of target respondents to collect their emotional feedback. For instances, Chan et al. (2011), Fung et al. (2014), Jiang et al. (2015a) and Jiang et al. (2015b) used this method to conduct a set of customer surveys on the affective design studies of mobile phones. Llinares et al. (2011) designed a questionnaire that used this method to measure subjective consumer perceptions that influence property purchase decisions. Shieh et al. (2016) used this method to explore the relationship between the shape and color of toothbrushes. Li and Han (2016) used this method to analyze the relationships among service attributes, Kansei words, and customer satisfaction of hotel services.

On the other hand, due to the advancement of information technology, more and more customer data is available on the Internet. Researchers can use text mining to analyze online consumer reviews to collect useful information (Liu, 2012). Text mining is a process involving the use of natural language processing and machine learning to obtain high-quality information from unstructured text (Feldman & Sanger, 2006). A typical text mining process begins with pre-processing. In general, it uses natural language processing techniques to perform pre-processing. It includes sentence segmentation, tokenization, and part-of-speech (POS) tagging, etc. Sentence segmentation is a process to divide a text into paragraphs and sentences. Tokenization is a process of converting a text into tokens (i.e. words). POS tagging is a process of assigning a POS to a word. Text mining then uses different analytical methods, such as rules, statistical methods or data mining methods, to discover interesting patterns. Finally, post-processing may be applied to interpret and represent the analyzed results in different formats, such as graphics or mappings. In particular, sentiment analysis (sometimes also known as opinion mining) focuses on identifying, extracting, and quantifying the writer's affective attitudes towards the subject based on his / her written text (Yadollahi et al., 2017). Sentiment analysis has been applied to a variety of applications, including learning and education (Ortigosa et al., 2014), healthcare (Desmet & Hoste, 2013), finance (Oliveira et al., 2016), customer relationship management (Kang & Park, 2014), and so on. A number of studies have been conducted to analyze the sentiment of online reviews. For instances, Liu et al. (2017) proposed a method based on the sentiment analysis and fuzzy set theory to rank products by online reviews. The method determined the positive, neutral or negative sentiment orientation of each review, and then constructed an intuitionistic fuzzy number to represent the performance of the product regarding its product feature. In the study of Zhou et al. (2017), a combination of affective lexicons and a rough-set technique is proposed to predict sentence sentiments of individual product features, thereby augmenting a feature model by integrating positive and negative opinions of consumers. Cho et al. (2014) proposed a data-driven approach that adapts multiple sentiment dictionaries to different domains. They use the ratio of the positive / negative training data and remove entries that have no contribution to the classification.

Contrary to existing research, we propose a semi-automatic method to collect a generic set of Kansei words and attributes from publicly available data. Second, we propose an automatic and unsupervised text mining method to extract product features from online product descriptions and then make use of the collected product features and Kansei words to extract the feature-affective opinions from online consumer reviews. Third, the existing sentiment analysis methods focus on polarity classification of determining whether the text expresses a positive or negative (or sometimes neutral) opinion. We classify the affective opinions into a list of affective attributes. Lastly, we design and develop a summarization system to visualize the relationships between product features and consumers' affective responses to the product.

3. Methodology

The proposed approach aims to extract and summarize affective features and responses from online product reviews. The methodology of the development of proposed approach is shown in Figure 1. It consists of four main phases, including collection and selection of generic Kansei words and attributes, product feature extraction, feature-affective opinion extraction, and evaluation (which consists of collection of evaluation data, construction of gold standard, and evaluation).

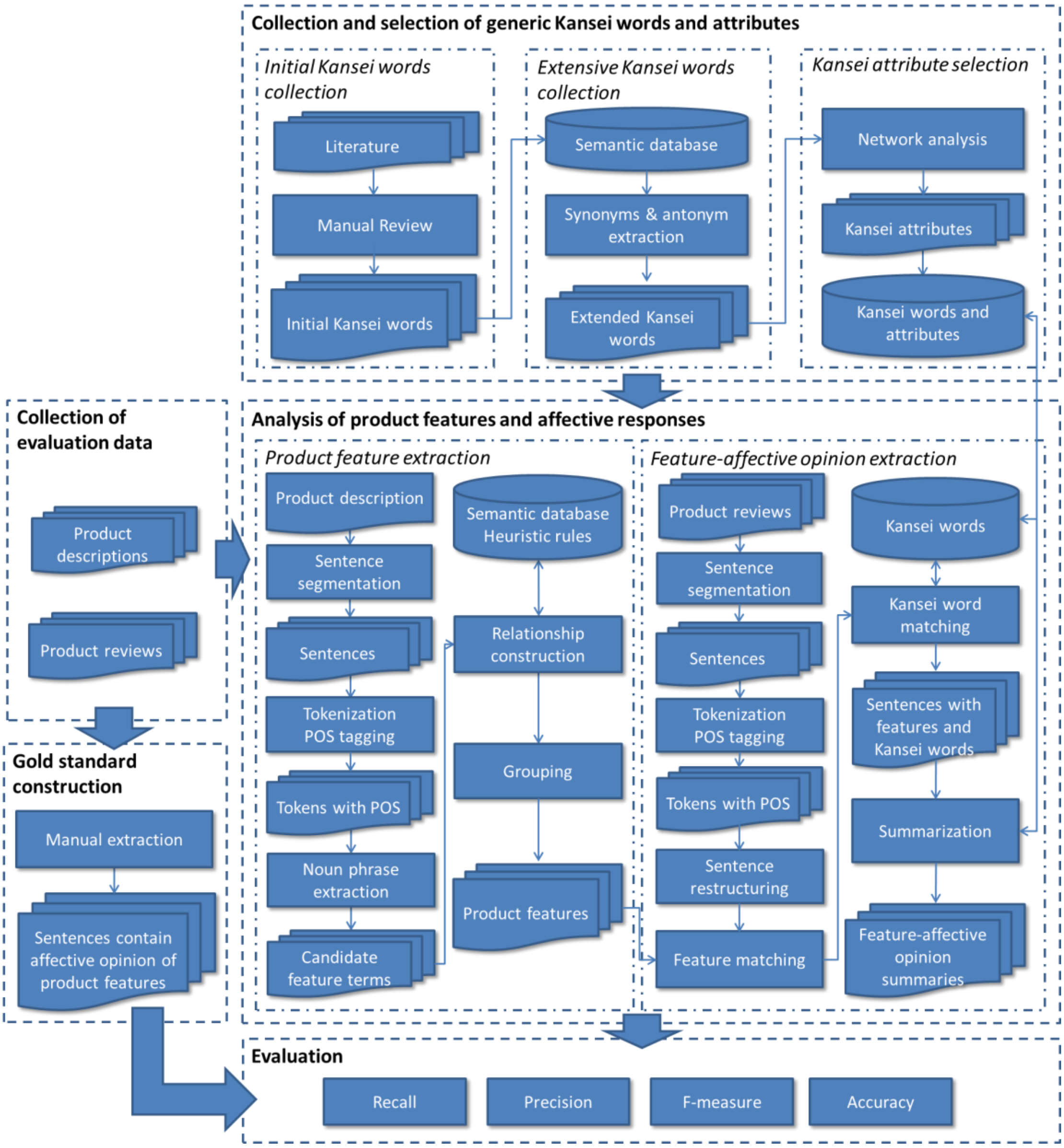


Figure 1. The architecture of the proposed approach

3.1 Collection and selection of generic Kansei words and attributes

Kansei words and attributes are usually identified by brainstorming and interviews (e.g. Vieira et al., 2017; Grimsæth, 2005), by extraction from reviews (e.g. Chou, 2016; Shieh et al., 2016), and by Kansei clustering (Huang et al., 2012). They are always manually extracted and highly customized. In this study, we propose a semi-automatic method to obtain a generic set of Kansei words and attributes that are suitable for different applications. We first manually select Kansei words used in the literature. We search the literature through the Web of Science database[1]. Ten related journal articles were selected. They are all Science Citation Indexed journal and they are well-known journals in product design and engineering. We extract the Kansei words they used in their studies and divide the words into 16 groups based on their semantic meanings. A summary table of the selected literature, Kansei words, and groups are shown in Table 1.

In the extensive Kansei words collection, it aims to discover more related words. WordNet is a large semantic thesaurus of English, which is often used in many text processing studies (Fellbaum, 1998). WordNet consists of nouns, verbs, adjectives and adverbs and it organizes the words in terms of synonyms and antonyms. Synonyms are interlinked by similar semantic meaning. Each Kansei attribute consists of a bipolar pair of Kansei words (i.e. a positive word and a negative word, such as beautiful-ugly) (Friborg et al., 2006). In order to obtain a comprehensive list of Kansei words, we divide the Kansei words in each group into two sub-groups based on their semantic meaning. For example, there are 3 words "soft", "hard", and "smooth" in Group 5, which are divided into 2 sub-groups, where "soft" and "smooth" belong to a sub-group, and "hard" belongs to another sub-group. Most Kansei words are adjectives (Boran et al., 2014; Shieh et al., 2016). Therefore, we use WordNet's adjectives thesaurus to find the antonyms and synonyms of all the Kansei words for all sub-groups. The flow of construction of extensive Kansei words collection is shown in Figure 2. After assigning the initial Kansei words into different sub-groups, the antonyms of a Kansei word of a sub group are retrieved from WordNet and added to the other sub-group belonging to the same group. For example, we find that "smooth" (which belongs to a sub-group of Group 5) has an antonym "rough",

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

therefore, “rough” is added to the other sub-group of Group 5 (i.e. the sub-group with the words: “hard”). Words are ambiguous, which have different meanings and senses. In other words, a word may belong to the same group but in different sub-groups. For example, assume that words A and B are initial Kansei words belongs to Group 1-1 (i.e. sub-group 1 of Group 1) and Group 1-2 (i.e. sub-group 2 of group 1), respectively, and a retrieved word X is an antonym of words A and B. To solve these conflicts, we applied Rules 1 and 2.

Rule 1: If two initial Kansei words belong to the same sub-group and they are antonyms, words are assigned according to their initial sub-groups.

Rule 2: If a retrieved word is an antonym of the initial words that belongs to the same group but different sub-groups, the retrieved word is assigned to the minority group. If the frequencies are the same, delete the retrieved word. For example, a retrieved word X is an antonym of initial words A, B, and C, A and B belongs to Group 1-1, C belongs to Group 1-2, and then X is assigned to Group 1-2.

We named the retrieved words as intermediate Kansei words. After that, we use WordNet’s adjectives thesaurus to find the synonyms of the Kansei words for all sub-groups. Similarly, conflicts may occur. For example, assuming that words A and B are initial or intermediate Kansei words belonging to Groups 1-1 and 1-2, respectively, and a retrieved word X is a synonym of words A and B. The conflict resolution of synonym retrieval is conducted based on Rules 3-6.

Rule 3: If two initial or intermediate Kansei words belongs to same group but in different sub-groups, and at the same time, they are synonym, they are then assigned based on their initial or intermediate sub-groups.

Rule 4: If a retrieved word is a synonym of more than one initial word belonging to the same group but different sub-groups, then the retrieved word is assigned to the majority group. If the frequencies are the same, delete the retrieved word. For example, if A, B and C are initial words belong to Group 1-1, 1-1, and 1-2, respectively, and X is a retrieved word that is a synonym of words A, B and C, then X is assigned to Group 1-1.

Rule 5: If a retrieved word is a synonym of only one initial word, the retrieved word is assigned to the sub-groups of the initial word. In other words, when the retrieved word is synonyms of initial words, we ignore the information of synonyms of intermediate words. Similar to Rule 3, this is make sense and useful for minimizing and simplifying antonyms and synonyms chains.

Rule 6: If a retrieved word is a synonym of intermediate words belonging to the same group but in different sub-groups, then the retrieved word is assigned to the majority group. If the frequencies are same, delete the retrieved word.

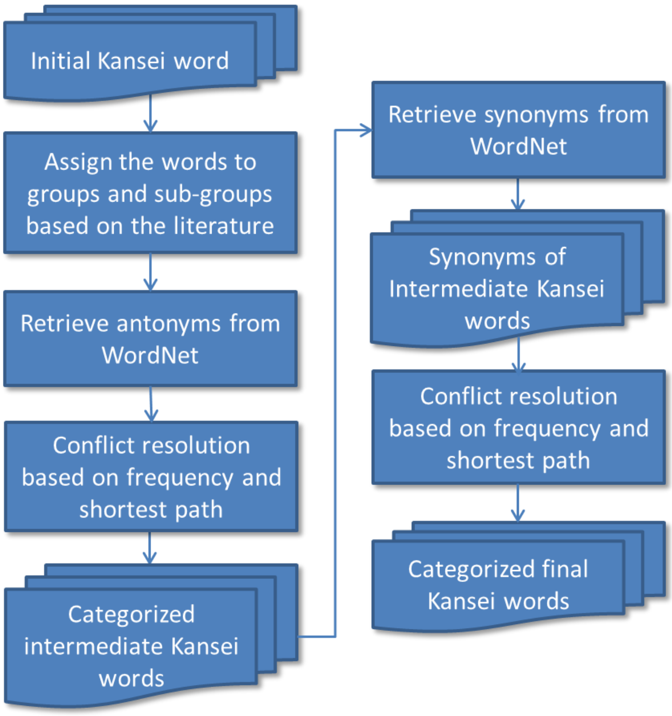


Figure 2. Construction of extensive Kansei words collection

As a result, each sub-group contains a list of words with similar semantic meaning.

In the Kansei attribute selection, it aims to select a representative word for each sub-group. WordNet organizes words by their specific senses. For example, "beautiful" may have several meanings, such as "attractive" (e.g. "beautiful clothes") and "pleasant" (e.g. "beautiful day"). Therefore, a network of synonyms can be formed (e.g. attractive---beautiful---pleasant). In this example, supposing there is no further connection, it is clear that "beautiful" is the most important word in this network. In network analysis, sociometric status is a common and useful measure to identify the most important node of a network (Gutiérrez et al., 2016). In order to obtain a Kansei attribute for representing each sub-group, we measure the sociometric status of all Kansei words collected from the literature of each sub-group. The word with the highest value is selected as the representative of the sub-group. The sociometric status of a node is defined as the sum of its reception and emission degrees, relative to the number of all other nodes in the network. The emission degree of a node is the sum of all values corresponding to the edges originating from the node, while the reception degree of a node is the sum of all values corresponding to the edges incident to that node (Wang et al., 2017). Since there is no difference between reception and emission in WordNet, in this study, the sociometric status of a word is adapted to Equation (1).

$$Sociometric\_status(i) = \frac{2}{g-1}\sum_{j=1}^{g} x_{ij} \tag{1}$$

Where *i* and *j* are individual words, x_{ij} is the edge values from word *i* to word *j*, and *g* is the total number of words in the network. If word *i* and word *j* are synonyms, $x_{ij} = 1$, otherwise, $x_{ij} = 0$.

Based on the above method, 32 Kansei attributes are selected. They include Group 1: exquisite, artless; Group 2: simple, comprehensive; Group 3: comfortable, restrained; Group 4: hi-tech, classic; Group 5: soft, hard; Group 6: delicate, coarse; Group 7: solid, unreliable; Group 8: rare, common; Group 9: modern, traditional; Group 10: precious, low-cost; Group 11: handy, bulky; Group 12: cheerful, unpleasant; Group 13: fresh, boring; Group 14: practical, useless; Group 15: light, dim; and Group 16: professional, amateur.

Table 1. Kansei words used in the literature

	Chou (2016)	Fung et al. (2014)	Guo et al. (2015)	Jiao et al. (2006)	Hsiao et al. (2017)	Shieh et al. (2016)	Vieira et al., (2017)	Bahn et al. (2009)	Barone et al. (2007)	Llinares & Page, (2011)
Group 1	artistic, exquisite, elegant, eye-catching, appealing, cute		aesthetic, inaesthetic	cute		elegant, artless			appealing	elegant, good-looking
Group 2	simplificative, plain	simple, complex	simple, complicated	dazzling	comprehensive					simple
Group 3				comfortable					handling comfort	comfortable, cosy, restrained
Group 4	technological, classic	hi-tech, classic								classical
Group 5	soft, hard		soft, hard				smooth, hard	soft, hard, smooth		
Group 6	compact, delicate	compact, loose, coarse, delicate, concise, sloppy						delicate		refined
Group 7	quality		reliable, unreliable	sturdy	reliable, accurate, high-quality, safe		robust	solid	durable	quality, safe
Group 8	unique, personalized, distinguished	unique, general	particular, common			rare, common				tailor-made
Group 9	contemporary, stylish			fashionable, futuristic	modern				stylish	youthful, traditional
Group 10	precious, luxurious				concessional	precious, low-cost				luxury
Group 11	handy, ingenious, portable	handy, bulky		portable						
Group 12				enjoyable, cheerful, delightful		like, dislike	pleasant, unpleasant			pleasant, delightful, cheerful, peaceful, oppressive
Group 13	novel		boring, fresh, interesting	stimulating	innovative					innovative
Group 14			practical, useless		practical, convenient, efficient					practical
Group 15	lustrous		dim					bright		light
Group 16			professional, amateur		professional					

3.2 Product feature extraction

In product feature extraction, it aims to extract the product features automatically. Contrast to the previous studies, most of them extracted product features from product reviews based on supervised methods (e.g. Othman et al., 2017; Ferreira et al., 2008). However, the results show that the recall and precision is relatively low due to the large amount of noise in the reviews. Moreover, supervised methods require expansive annotation work, which may not be suitable for new products and products with unique features. In this study, we use the texts provided by the sellers as input to improve the quality of the data source. In addition, we use unsupervised method so that it can be applied to different products without any extra work.

Text mining and natural language processing are neighboring fields. We use natural language processing techniques to perform text mining. As shown in Figure 1, the extraction process begins with sentence segmentation that divides the input text into sentences. It is done by regular expression based on detection of punctuations. We then use a natural language processing tool, Tree Tagger, to perform tokenization and part-of-speech (POS) tagging (Schmid, 1994). It is a probabilistic POS tagger which is simple to use. It has high accuracy and it is commonly used in many text mining studies. Since important product features are always expressed in nouns and noun phrases (Zhang et al., 2016; Othman et al., 2017), we use syntactic rules then proposed by Wang et al. (2008) to extract nouns and noun phrases from the text as the candidate features. There may be many repetitive and similar candidate features. In order to group the candidate features, we adapt the work proposed by Tsui et al. (2010). We use heuristic rules and semantic database (i.e. WordNet) to analyze the parent-child and is-neighbour relationships among the candidate features. WordNet consists of a noun hierarchy that can be used to check the relationships of the candidate features. On the other hand, two heuristic rules are used to classify parent-child and is-neighbour relationships, which are shown below:

(a) *Rule 1*: When a term is the same as another term and is further modified by some words, the longer term is classified as the child of the shorter term. For example, suppose there are two candidate features: “battery” and “battery life”, the relation parent-child(“battery”, “battery life”) is derived.

(b) *Rule 2*: Given two terms t_1 and t_2, if t_2’s letters matches the first letters of words of t_1, then t_2 is the abbreviation for t_1. The relation is-neighbour(t_2, t_2) is derived. For example, “Compact Disc” and “CD” have a is-neighbour relationship.

Some inference rules are used to consolidate the product features. The rules are shown below:

(a) If two candidate features have a parent-child relationship, then the parent feature is classified as the representative, and the child feature is classified as a synonym of the representative.

(b) If two candidate features have an is-neighbour relationship, and one of them is a synonym of a representative, then we infer that both of them are synonyms of the representative.

(c) If two candidate features have an is-neighbour relationship but none of them is a synonym of a parent feature, then the one that has a fewer word count is classified as the representative, and the other one is classified as a synonym under the representative.

For example, assume there are three candidate features: “battery”, “battery life”, and “battery performance”. According to the relationship analysis, we find that “battery” is the parent of “battery life” and “battery performance”. We then use “battery” as the representative for this feature, and we use “battery life” and “battery performance” as the synonyms of “battery”. Based on this method, each product description is converted into a list of product features, and each of which is composed of a representative and a list of synonyms.

3.3 Feature-affective opinion extraction

The purpose of this phase is to extract feature-affective opinions from online consumer reviews. The process begins with sentence segmentation, tokenization, and POS tagging. A sentence restructuring method is used to reconstruct complex sentences into simple sentences as shown in Figure 3, so that the text can be analysed more effectively (Yeung et al., 2014). For example, if there is a sentence with a pattern: subject1 + verb1 + object1 + conjunction + subject2 + verb2 + object2, the sentence is reconstructed into two simple sentences, i.e. “subject1 + verb1 + object1”, and “subject2 + verb2 + object2”. If there is a sentence with a pattern: subject + verb + object1 + conjunction + object2, the sentence is restructured into two simple sentences, i.e. “subject + verb + object1”, and “subject + verb + object2”. The sentence restructuring method also replaces the pronouns of a sentence with a proper noun or a noun phrase. For example, consider the following sentences “My only complaint would be the back speakers. *They* are just not loud enough for a device of this size.”, based on the method, the sentence is converted to “My only complaint would be the back speakers. *The back speakers* are just not loud enough for a device of this size.” In addition, there are some short sentences that do not contain any subject and verb. The sentence restructuring method prepends a subject (i.e. “it”) and verb (i.e. “is”) to the sentence. For example, “Very cute!” is converted to “It is very cute!”

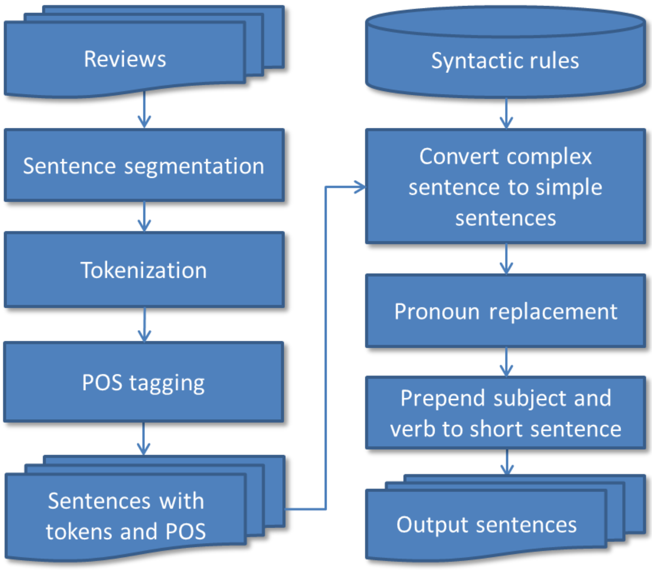


Figure 3. A schematic diagram of sentence restructuring process

After sentence restructuring, each sentence is compared with the product features (extracted according to Section 3.2) and Kansei words (extracted according to Section 3.1). The sentences that contain product features and Kansei words are selected. Each selected sentence is then converted into a set of three values, including a product feature, a Kansei word, and a Boolean (i.e. not value). The Boolean value is used to determine whether the sentence has the same meaning with the Kansei word. For example, suppose there is a sentence: “the toy is beautiful”, it will be converted into {“toy”, “beautiful”, “0”}. If the sentence is “the toy is not beautiful”, it will be converted into {“toy”, “beautiful”, “1”}. If the sentence is “the toy is ugly”, it will be converted into {“toy”, “ugly”, “0”}. If the sentence is “the toy is not ugly”, it will be converted into {“toy”, “ugly”, “1”}. The Boolean value of a sentence is determined by a list of keywords. It contains words such as “not”, “hardly”, “barely”, “scarce”, “ill”, “never”, “non”, “no”, “none”, and “least of all”. When a sentence is composed by any of these words, the Boolean value is assigned to 1; otherwise, it is assigned to 0. We collect these keywords manually, and then we use WordNet to find more related keywords based their synonyms, and finally we revise the words manually.

3.4 Affective opinion summarization

An affective opinion summarization method is proposed to summarize the extracted feature-affective opinions in a concise manner. The summarization method is shown in Figure 4. The input of the method is the output of the feature-affective opinion extraction (i.e. {feature, Kansei words, not value}) and a mapping table of Kansei words and their corresponding Kansei attributes. As mentioned above, each Kansei attribute has an opposite attribute (e.g. practical vs useless). If the “not value” is equal to 0, the mapped Kansei attribute of the Kansei word is selected. If the “not value” is equal to 1, the opposite attribute of the mapped Kansei attribute of the Kansei word is selected. Therefore, the format of the feature-affective opinion is converted into {feature, (not) Kansei words, Kansei attribute}. The method then summarizes the reviews by counting the frequency of the features, Kansei words, and Kansei attributes, and the associations among them. As a result, a list of summaries can be generated for users to review. The summaries include product to features, feature to Kansei attributes, feature to Kansei words, product to Kansei attributes, Kansei attribute to features, and Kansei attributes to Kansei words. The summaries are then visualized by using dynamic webpage.

Algorithm 1: Affective opinion summarization

Input: $FeatureAffectiveOpinion, KanseiMapping$

initialize: $Feature := \emptyset$, $KanseiWord := \emptyset$, $KanseiAttribute := \emptyset$;
for *each* $opinion_i \in FeatureAffectiveOpinion$ **do**
    Extract $opinion_i$'s feature, Kansei word and "not value", i.e. $(feature_i, kWord_i, not_i)$;
    if $not_i = 0$ **then**
        Obtain $kAttribute_i$ according to $KanseiMapping$ and $kWord_i$;
    else
        Obtain $kAttribute_i$ according to $KanseiMapping$, $kWord_i$ and not_i;
        $kWord_i$ = "not " + $kWord_i$;
    end
    $opinion_i = (feature_i, kWord_i, kAttribute_i)$;
    $Feature = Feature \bigcap \{feature_i\}$;
    $KanseiWord = KanseiWord \bigcap \{kWord_i\}$;
    $KanseiAttribute = KanseiAttribute \bigcap \{kAttribute_i\}$;
end
for *each* $feature_i \in Feature$ **do**
    Count $feature_i$ in $FeatureAffectiveOpinion$ as $featureFreq_i$;
    for *each* $kAttribute_j \in KanseiAttribute$ **do**
        Count $(feature_i, kAttribute_j)$ in $FeatureAffectiveOpinion$ as $freq$;
        $featureKAttribute_{ij} = (kAttribute_j, freq)$;
    end
    for *each* $kWord_j \in KanseiWord$ **do**
        Count $(feature_i, kWord_j)$ in $FeatureAffectiveOpinion$ as $freq$;
        $featureKWord_{ij} = (kWord_j, freq)$;
    end
    $feature_i = (feature_i, featureFreq_i, featureKAttribute_{i\cdot}, featureKWord_{i\cdot})$;
end
for *each* $kAttribute_i \in KanseiAttribute$ **do**
    Count $kAttribute_i$ in $FeatureAffectiveOpinion$ as $kAttributeFreq_i$;
    for *each* $feature_j \in Feature$ **do**
        Count $(kAttribute_i, feature_j)$ in $FeatureAffectiveOpinion$ as $freq_j$;
        $kAttributeFeature_{ij} = (feature_j, freq_j)$;
    end
    for *each* $kWord_j \in KanseiWord$ **do**
        Count $(kAttribute_i, kWord_j)$ in $FeatureAffectiveOpinion$ as $freq_j$;
        $kAttributeWord_{ij} = (kWord_j, freq_j)$;
    end
    $kAttribute_i = (kAttribute_i, kAttributeFreq_i, kAttributeFeature_{i\cdot}, kAttributeWord_{i\cdot})$;
end

Output: $Feature, KanseiAttribute$

Figure 4. Summarization of feature-affective opinions

4. Experiment and results

4.1 Experiment setup

In order to evaluate the effectiveness of the proposed approach, an experiment is conducted by using real-life product information and reviews collected from Amazon.com. Any kinds of products with product descriptions and reviews can be used as an alternative. We select products under the category: "Toys & Games" of Amazon because the affective opinions of this category are more complex and diverse than other categories (such as electronic products). The other categories' reviews are mostly simple affective opinion (i.e. good or bad). Based on the product order of the first page of this category on Amazon, we select the top 10 products for the experiment. We extract the product description, and we extract 20 reviews from each product. Therefore, there are a total of 200 reviews. In particular, a verified purchase consumer can rate a product he / she purchased and write a review for the product. A review is divided into positive review or critical review by Amazon. We rely on Amazon's division of positive and critical reviews. We randomly extract the reviews based on the percentage of positive reviews and critical reviews. For example, if a product consists of 60 positive reviews and 40 critical reviews, we randomly select 12 positive reviews and 8 critical reviews. Some statistics of the dataset is shown in Table 2.

Table 2. Statistics of the dataset

	Number of positive reviews	Number of critical reviews	Average sentence count (standard deviation)	Average word count (standard deviation)
Product 1	13	7	7.10 (6.33)	88.6 (87.6)
Product 2	14	6	3.40 (2.37)	33.7 (25.5)
Product 3	16	4	2.25 (1.25)	20.9 (18.2)
Product 4	14	6	3.50 (2.12)	38.6 (36.0)
Product 5	17	3	7.20 (3.53)	83.9 (48.8)
Product 6	18	2	2.85 (1.35)	25.9 (18.6)
Product 7	13	7	4.15 (3.15)	37.9 (23.6)
Product 8	17	3	3.85 (2.28)	40.0 (31.4)
Product 9	16	4	4.40 (5.53)	55.9 (95.5)
Product 10	10	10	9.95 (5.83)	153 (89.6)

The experiment setup is shown in Figure 5. Several unsupervised methods are used for comparison. Since most product features are appeared as noun phrases, existing studies use noun phrase extraction to extract the product features from reviews (Jin et al., 2016a). In order to evaluate the effectiveness of the proposed method, we compare the proposed method and the commonly used noun phrase extraction method. As mentioned above, Kansei words are usually adjectives (Boran et al., 2014; Shieh et al., 2016). In order to evaluate the effectiveness of the proposed method, we compare the proposed method and adjective extraction. We evaluate the methods individually, in "and" combination, and in "or" combination. In the "and" combination methods, we select sentences from reviews that contain the texts extracted from the two methods. For example, the method Feature+KWord method selects sentences that contain both product features extracted from the proposed method and Kansei words. NP+Adj method selects sentences that contain both noun phrases and adjectives. In the "or" combination methods, we select sentences that contain texts extracted from either one of the methods. For example, the method Feature/KWord method selects sentences that contain either product features extracted from the proposed method or Kansei words. NP/Adj selects sentences that contain either noun phrases or adjectives. Therefore, a total of 12 methods are formulated for evaluation. The abbreviations and descriptions of the methods are shown in Table 3. According to these methods, a review sentence containing extracted features, noun phrases, Kansei words, and / or adjectives is selected as system output. The sentence restructuring method is partially implemented in the experiment. This is because the number of review sentences increases after processing by the sentence restructuring method. In order to prevent the double calculation of the results, the experiment does not implement the conversion of complex sentence to simple sentences.

In order to construct the gold standard, we manually review the product reviews to select sentences that contain feature-affective opinions. We then compare the performance of the methods by measuring the recall, precision, F-measure, and accuracy. The calculations of the measurements are shown in Equations (2) to (5).

$$Recall = \frac{system\_selected\_sentences \cap manual\_selected\_sentences}{manual\_selected\_sentences} \quad (2)$$

$$Precision = \frac{system\_selected\_sentences \cap manual\_selected\_sentences}{system\_selected\_sentences} \quad (3)$$

$$F - measure = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (4)$$

$$Accuracy = \frac{system\_selected\_sentences \cap manual\_selected\_sentences}{all\_review\_sentences} + \frac{system\_not\_selected\_sentences \cap manual\_not\_selected\_sentences}{all\_review\_sentences} \quad (5)$$

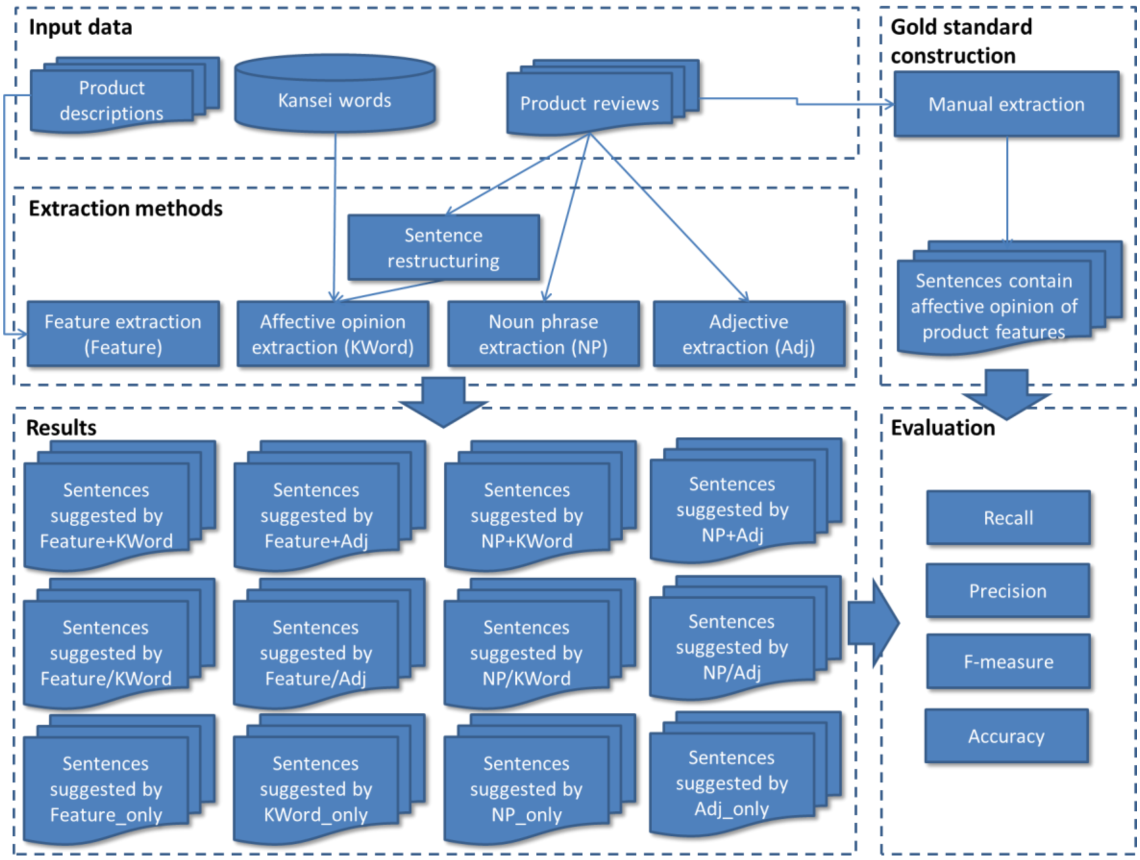


Figure 5. Experiment setup

Table 3. Abbreviations and descriptions of the methods

Abbreviation	Description
Feature+KWord	Sentences that contain both product features and Kansei words are extracted
Feature+Adj	Sentences that contain both product features and adjectives are extracted
NP+KWord	Sentences that contain both noun phrases and Kansei words are extracted
NP+Adj	Sentences that contain both noun phrases and adjectives are extracted
Feature/KWord	Sentences that contain either product features or Kansei words are extracted

Feature/Adj	Sentences that contain either product features or adjectives are extracted
NP/KWord	Sentences that contain either noun phrases or Kansei words are extracted
NP/Adj	Sentences that contain either noun phrases or adjectives are extracted
Feature_only	Sentences that contain product features are extracted
KWord_only	Sentences that contain Kansei words are extracted
NP_only	Sentences that contain noun phrases are extracted
Adj_only	Sentences that contain adjectives are extracted

4.2 Experiment results

The experiment results are shown in Table 4. The main results are as follows:

(i) By comparing the results of Feature_only and NP_only, we can see that the Feature_only outperforms NP_only in all the measures. It is worth noting that most of the existing studies extract product features from reviews (e.g. Jin et al., 2016b; Qi et al., 2016). The results show that the proposed usage of product descriptions could be more accurate. The sentence restructuring method converting pronouns into product features also helps to increase the recall.

(ii) By comparing the results of KWord_only and Adj_only, the proposed method of using Kansei words to identify affective opinion is superior to the baseline method of using adjectives in all the measures. The recall of KWord_only and Adj_only is similar. This is because most of the Kansei words are adjectives. The little improvement in recall may be due to error of POS tagging. But on the other hand, the results also show that the collection of Kansei words is comprehensive enough to identify affective opinions. Moreover, the results show that the precision of using Kansei words is higher.

(iii) By comparing the results of "and" combination methods, Feature+KWord outperforms the other three "and" combinations methods (i.e. Feature+Adj, NP+KWord, and NP+Adj) in all the measures. This is because Feature_only and KWord_only perform better than NP_only and Adj_only, respectively. Therefore, their combination is also better.

(iv) By comparing the results of “or” combination methods, NP/KWord outperforms the other three methods (i.e. Feature/KWord, Feature/Adj, and NP+Adj) in recall measurement. Feature/Adj outperforms the other 3 methods in terms of precision, F-measure, and accuracy. However, the results are very similar in general.

(v) By comparing the results of the “and” combination methods and the “or” combination methods, we can see that the “and” combination methods have higher precision, while the “or” combination methods have higher recall. Obviously, this is because the “or” combination methods select more sentences.

Table 4. Experiment results with 95% confidence interval (The top performer of each measure is bolded)

		Recall (%)	Precision (%)	F-measure (%)	Accuracy (%)
“And” combination methods	Feature+KWord	78.41 ± 3.76	**83.60** ± 3.81	78.48 ± 3.50	77.62 ± 3.25
	Feature+Adj	77.29 ± 3.72	81.80 ± 3.81	76.92 ± 3.42	75.39 ± 3.34
	NP+KWord	75.76 ± 3.96	80.29 ± 4.05	75.37 ± 3.70	74.14 ± 3.43
	NP+Adj	75.35 ± 4.04	78.72 ± 4.08	74.29 ± 3.70	72.79 ± 3.54
“Or” combination methods	Feature/KWord	98.56 ± 0.94	77.58 ± 3.39	84.34 ± 2.53	79.02 ± 3.17
	Feature/Adj	98.85 ± 0.72	78.00 ± 3.38	**84.75** ± 2.50	**79.61** ± 3.13
	NP/KWord	**99.05** ± 0.89	75.58 ± 3.49	83.13 ± 2.64	76.95 ± 3.33
	NP/Adj	98.64 ± 1.00	75.59 ± 3.49	82.90 ± 2.63	76.66 ± 3.32
Individual methods	Feature_only	94.06 ± 1.87	78.80 ± 3.48	83.07 ± 2.69	78.23 ± 3.27
	KWord_only	82.91 ± 3.54	82.04 ± 3.70	80.05 ± 3.33	78.42 ± 3.17
	NP_only	91.91 ± 2.68	74.17 ± 3.79	78.96 ± 3.10	72.69 ± 3.58
	Adj_only	82.09 ± 3.45	80.94 ± 3.64	78.99 ± 3.18	76.77 ± 3.12

4.3 Performance differences between positive and critical reviews

In order to investigate the scope and limitations of the proposed method, we conduct an experiment to assess the performance of identification of feature-affective opinion between positive and critical reviews. The results are summarized in Table 5. The results show that all methods perform better in positive reviews in all the different measures. An exception is found in the recall of the “or” combination methods. However, the difference is very small. Moreover, the “or” combination methods select many sentences that result in poor precision performance. We can see that the precision performance of using critical reviews is lower than that of using positive reviews.

In order to know why the performance of positive reviews is better, we review the consumer reviews in details. We find that there are several reasons. First, the critical reviews are often more complex and therefore more difficult to be analyzed. Second, the critical reviews contain fewer affective opinions. Compared with the positive reviews, they use fewer adjectives. Most of the critical reviews describe the facts rather than expressing emotions. For example, the reviewers always use long paragraphs to describe how the product does not work. Some of them even use sarcasm which is difficult to be understood by simple text mining methods. On the other hand, positive reviews tend to be simpler. Reviewers directly express their views on the product.

Table 5. Performance differences between positive (+ve) reviews and critical (-ve) reviews with 95% confidence interval (The top performer of each measure is bolded)

		Recall (%)	Precision (%)	F-measure (%)	Accuracy (%)
Feature+KWord	+ve reviews	80.43 ± 4.16	**88.69** ± 3.70	82.10 ± 3.65	80.51 ± 3.68
	-ve reviews	72.67 ± 8.20	**69.13** ± 9.15	68.15 ± 8.02	69.40 ± 6.41

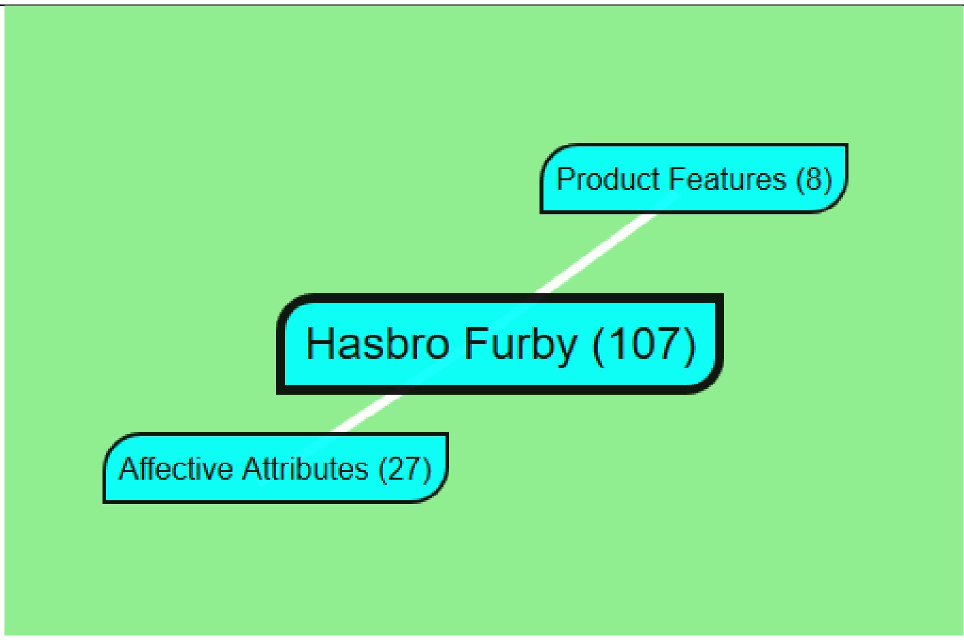
Feature+Adj	+ve reviews	78.40 ± 4.18	86.41 ± 3.96	80.12 ± 3.72	77.55 ± 3.88
	-ve reviews	74.13 ± 7.95	68.65 ± 8.44	67.82 ± 7.32	69.23 ± 6.34
NP+KWord	+ve reviews	77.53 ± 4.50	85.48 ± 4.13	78.96 ± 4.00	77.02 ± 3.91
	-ve reviews	70.75 ± 8.18	65.54 ± 9.20	65.16 ± 7.99	65.95 ± 6.67
NP+Adj	+ve reviews	76.07 ± 4.58	83.98 ± 4.32	77.52 ± 4.11	75.10 ± 4.09
	-ve reviews	73.33 ± 8.50	63.73 ± 8.60	65.12 ± 7.66	66.23 ± 6.80
Feature/KWord	+ve reviews	98.28 ± 1.19	82.72 ± 3.47	88.03 ± 2.52	83.31 ± 3.31
	-ve reviews	**99.36** ± 1.26	62.96 ± 7.21	**73.82** ± 5.75	66.80 ± 6.75
Feature/Adj	+ve reviews	98.67 ± 0.87	83.35 ± 3.46	**88.60** ± 2.45	**84.03** ± 3.27
	-ve reviews	**99.36** ± 1.26	62.76 ± 7.06	73.79 ± 5.65	67.04 ± 6.59
NP/KWord	+ve reviews	**99.06** ± 1.00	81.03 ± 3.58	87.26 ± 2.58	82.04 ± 3.43
	-ve reviews	99.03 ± 1.88	60.06 ± 7.31	71.38 ± 5.97	62.50 ± 7.00
NP/Adj	+ve reviews	98.89 ± 1.05	81.03 ± 3.58	87.10 ± 2.56	81.72 ± 3.42
	-ve reviews	97.92 ± 2.41	60.09 ± 7.29	70.96 ± 5.94	62.29 ± 6.95
Feature_only	+ve reviews	94.60 ± 2.14	83.90 ± 3.52	86.82 ± 2.66	82.39 ± 3.38
	-ve reviews	92.51 ± 3.83	64.31 ± 7.70	72.42 ± 6.26	66.38 ± 7.20
KWord_only	+ve reviews	84.11 ± 3.98	86.92 ± 3.77	83.48 ± 3.58	81.43 ± 3.65
	-ve reviews	79.51 ± 7.57	68.16 ± 8.35	70.29 ± 7.18	69.83 ± 5.79
NP_only	+ve reviews	92.48 ± 2.93	79.98 ± 3.87	83.24 ± 3.10	77.63 ± 3.68
	-ve reviews	90.27 ± 6.09	57.64 ± 8.07	66.76 ± 7.06	58.62 ± 7.82
Adj_only	+ve reviews	82.48 ± 3.88	86.01 ± 3.80	82.25 ± 3.49	79.18 ± 3.68
	-ve reviews	80.98 ± 7.42	66.49 ± 7.71	69.69 ± 6.59	**69.90** ± 5.50

4.4 Summarization system

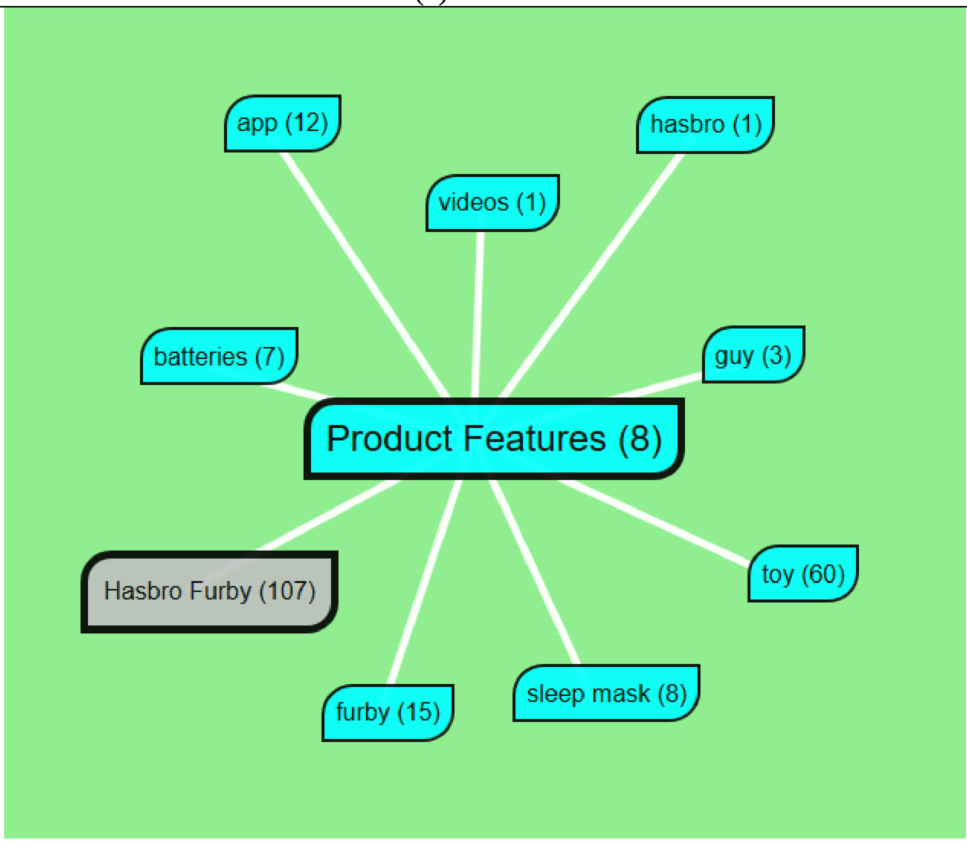
A prototype system has been built to implement the proposed approach. After the customer review analysis described in Section 3, feature-affective opinions are extracted and converted into a structured format. The summarization process is performed to determine the number of opinions of the product features, Kansei attributes and Kansei words, and the number of associations among them. The results are then used to generate a dynamic webpage for each product. The dynamic webpage visualizes the summaries by using a representation that is similar to a mind map.

We use Product 1 as an illustrative example of the summarization system. Figure 6(a) shows the name of the product, the number of feature-affective opinions extracted from the reviews of the product, the number of product features extracted from the reviews, and the number of Kansei attributes extracted from the reviews. When a user clicks on the text “Product features”, the mind map changes to show a summary of the product features, which is shown in Figure 6(b). It shows that the number of feature-affective opinions is extracted for each feature. When a user clicks on a product feature, the mind map changes to show a summary of the product feature, which is shown in Figure 6(c). The summary shows the number of feature-affective opinions on the feature, the Kansei words used in the feature-affective opinions on the feature, and the related Kansei attributes to the feature. The user can click on the “Affective Attributes” and “Affective Words” to view the feature to affective attributes summary and the feature to affective words summary, respectively. The snapshots are shown in Figures 6(d) and 6(e).

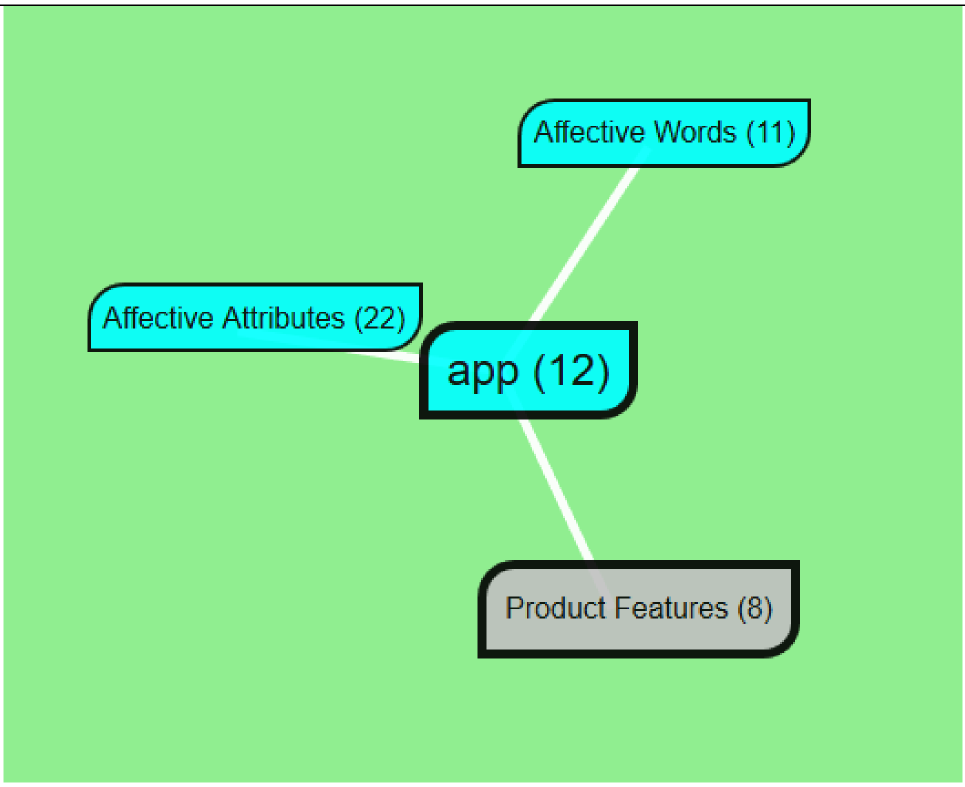
On the other hand, the user can click on the “Affective Attributes” that shown in Figure 6(a) to view the overall summary of the product to affective attributes. As shown in Figure 6(f), the summary of product to affective attributes shows the number of feature-affective opinions of each affective attribute. Similar to the product to features summary, users can review each Kansei attribute (as shown in Figure 6(g)), Kansei attributes to features (as shown in Figure 6(h)), and Kansei attributes to Kansei words (as shown in Figure 6(i)). The summaries help the users to review the product and its features based on the affective aspects. Users can also compare products in an efficient and timely manner.



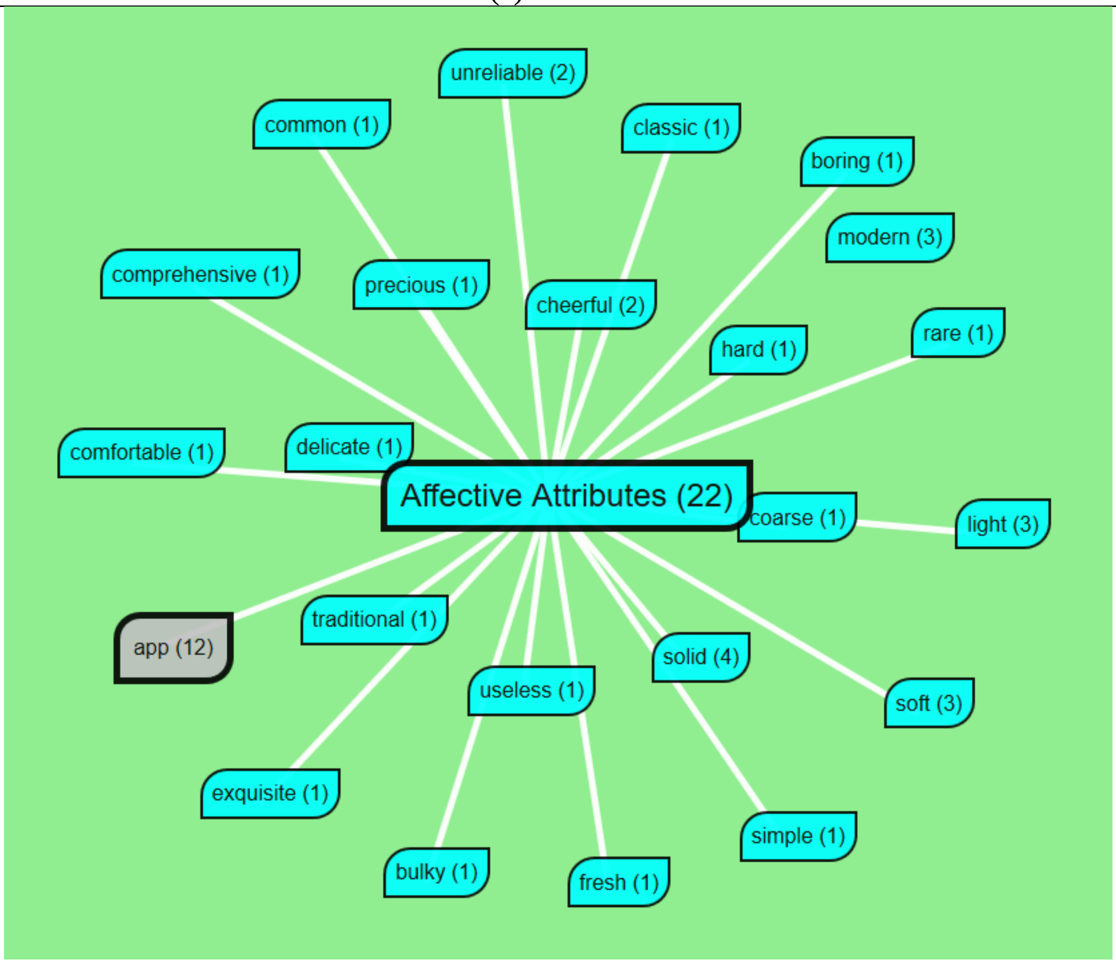
(a) Product



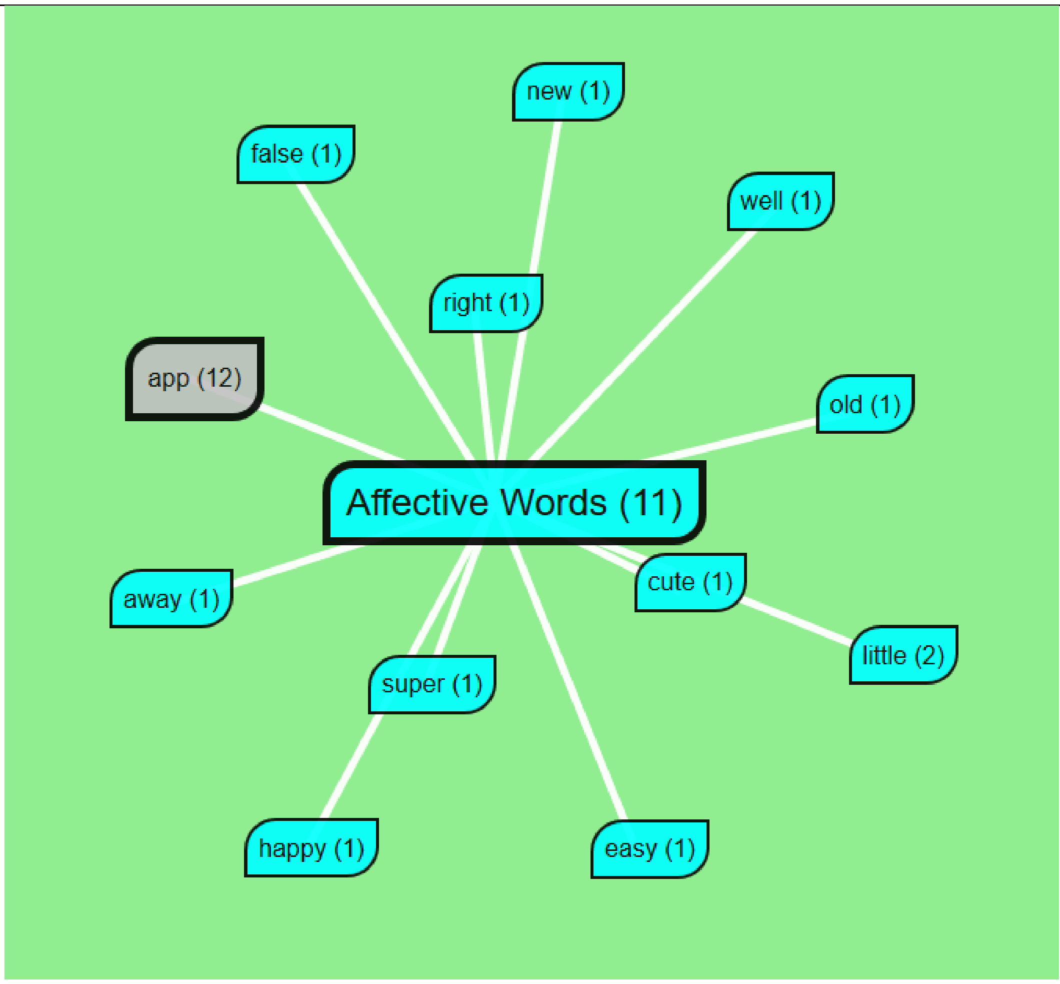
(b) Product to features



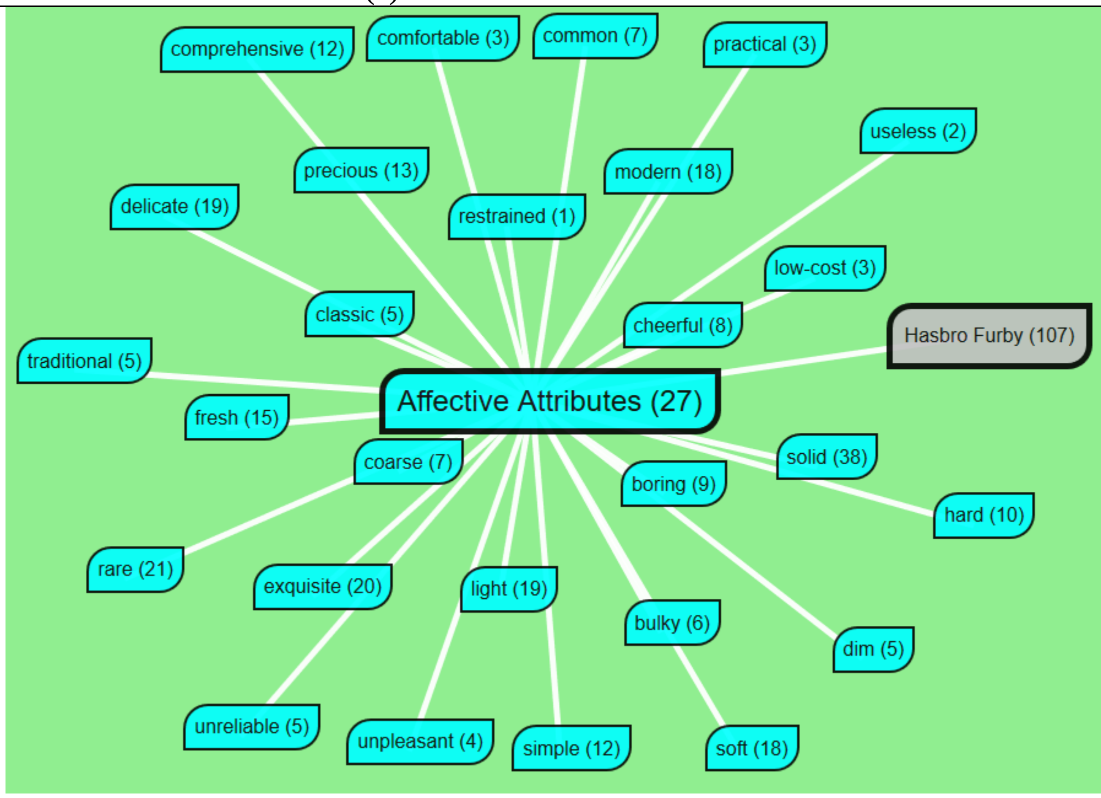
(c) Feature



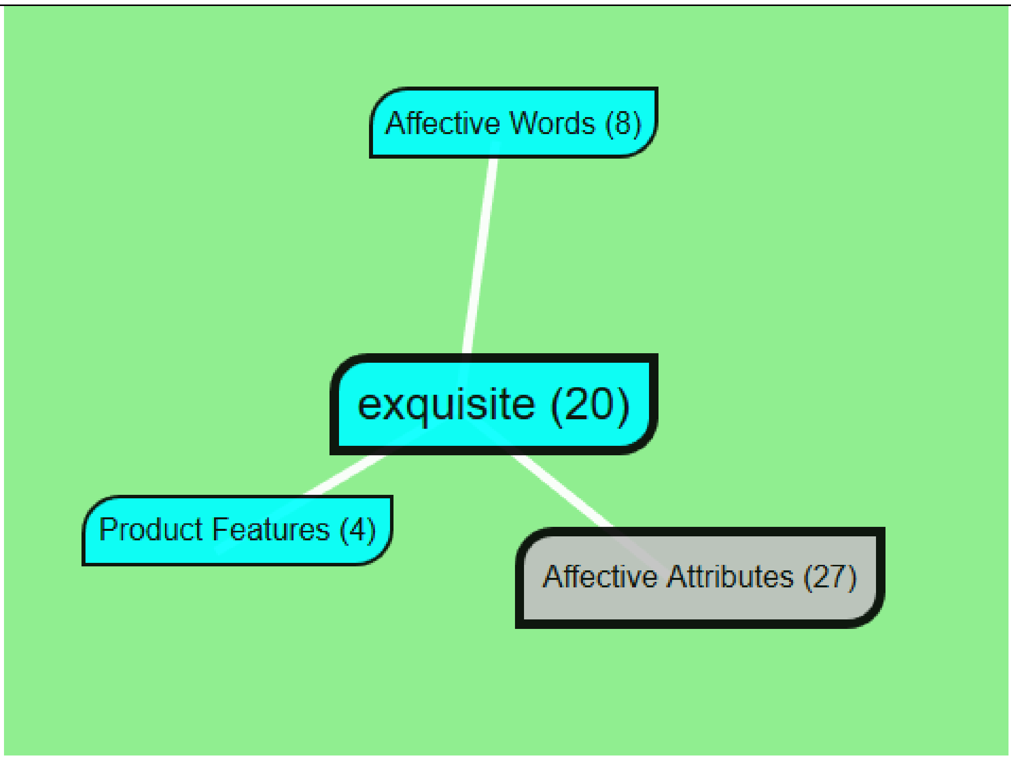
(d) Feature to affective attributes



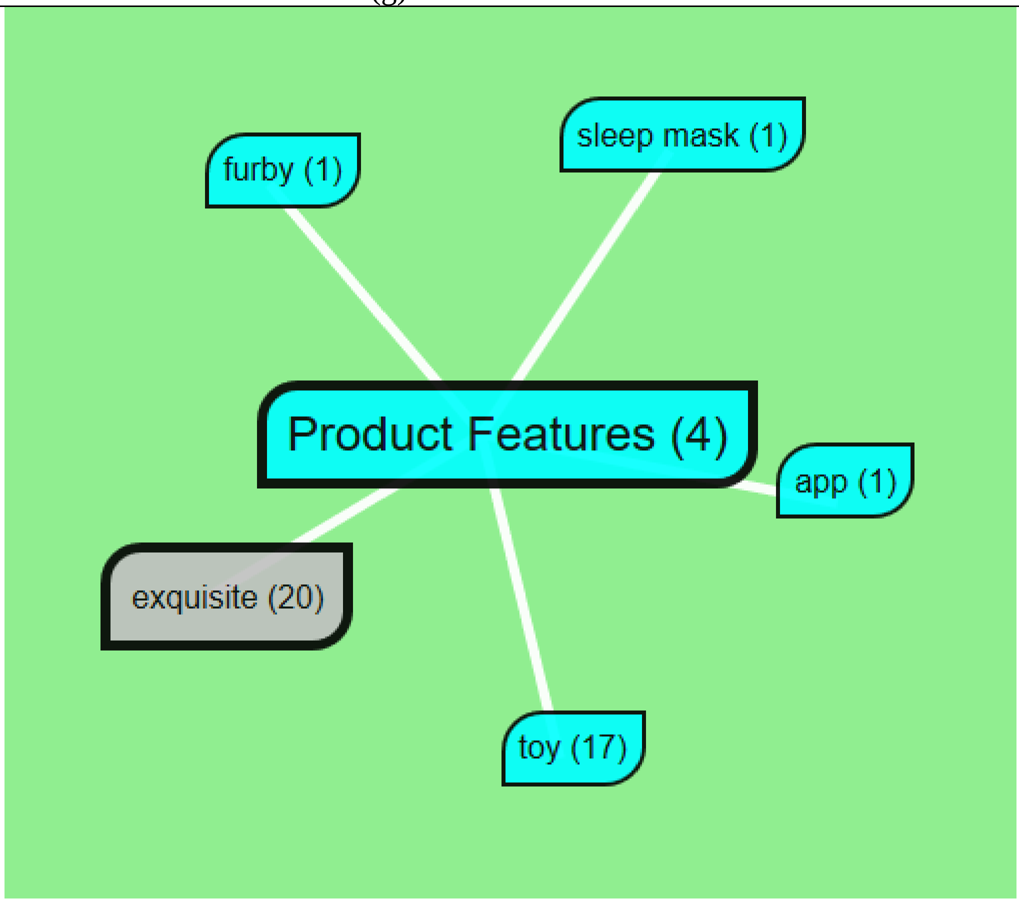
(e) Feature to affective words



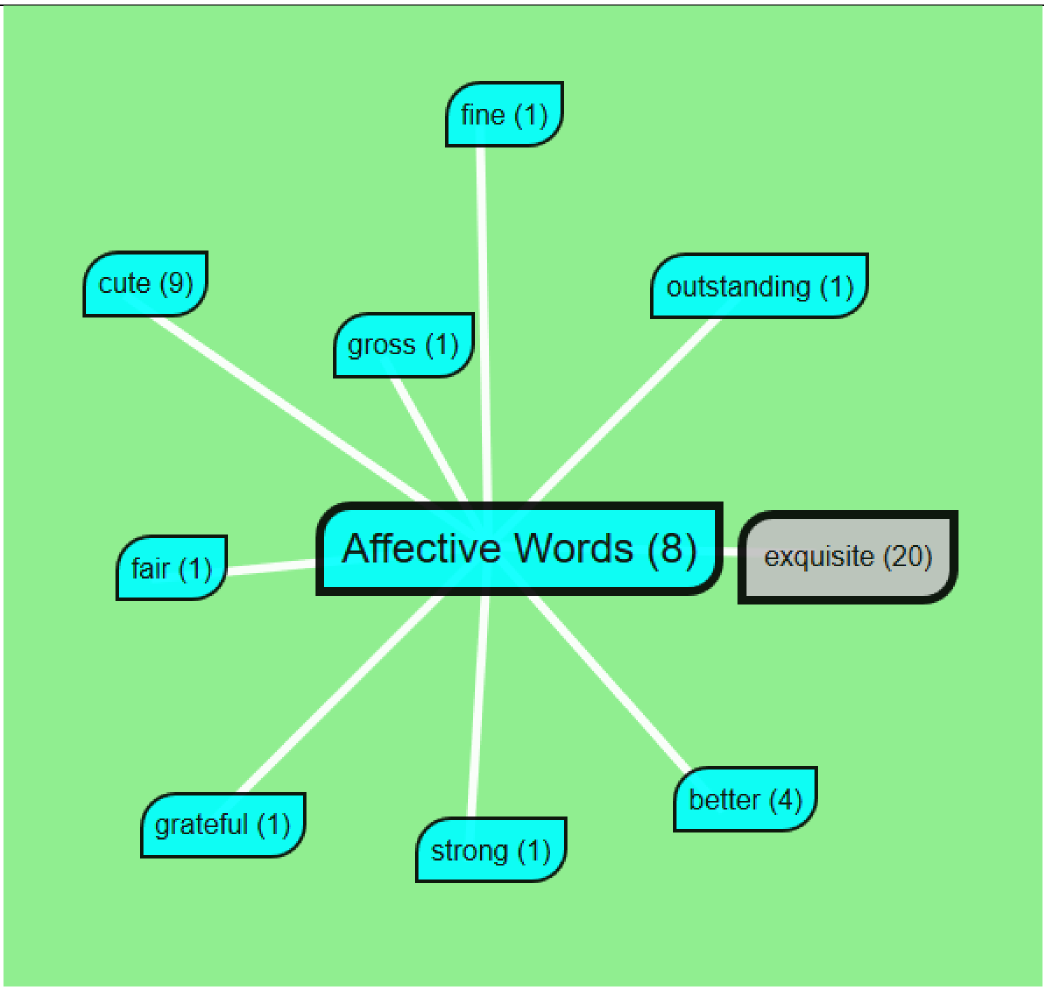
(f) Product to affective attributes



(g) Affective attribute



(h) Affective attributes to features



(i) Affective attributes to affective words

Figure 6. Screenshot of the prototype of summarization system

4.5 Research and practical implication

This paper presents a Kansei text mining approach, which incorporates different methods and techniques in Kansei engineering and text mining approaches, in order to extract and summarize affective information from online product reviews. Comparing to traditional methods which heavily rely on manual questionnaires, surveys and workshops, the proposed approach provide an automatic and systematic methodology to analyse product affective features and their corresponding consumer affective responses. Moreover, the proposed approach contributes to the classification of affective opinions into multiple affective attributes compared to conventional ways of the division in positive, neutral and negative. The collection of Kansei words is comprehensive and generic which can be reused and applied to other studies. The proposed approach also provides a visualization of different affective features and their relationships via the summarization system.

The proposed approach is evaluated through a series of experiments and illustrated through an example of a real-life product. The results show that the affective information can be extracted with high precision and recall. The results indicate that the usefulness of product descriptions for affective feature extraction, which is commonly neglected in the existing studies. The results also showed that precision performance of using critical reviews is lower than that of using positive reviews due to the complexity of critical reviews. Therefore, more research may focus in this area.

The proposed approach can be applied in the online shops for analyzing their products. It could help consumers navigate relevant products based on their affective preferences, helping them save the time for reading the product reviews, and helping them make better purchase decisions. It could also help manufacturers and product designer to understand their products and competitors' products from the consumers' perceptive and affective perceptive. It might provide important insights into improving existing products and developing new products. It can also help them improve customer, and develop sales, promotion and competition strategies.

5. Conclusion

Understanding the affective responses of products helps customers making purchase decision and assists product designers developing new improved products. However, traditional methods based on manual Kansei questionnaire are inadequate to achieve real-time, large scale, and continuously changing environment. The purpose of this paper is to develop an automatic and unsupervised Kansei text mining approach that extracts and summarizes affective information from online consumer reviews for affective engineering. We propose a semi-automatic method to collect a set of Kansei words and attributes from publicly available data. The collection of Kansei words and attributes is generic and could be applied to different products and industries. We extract product features from the online product descriptions. Based on the collected Kansei words and the extracted product features, we extract the feature-affective opinions from the online consumer reviews by classifying the opinions as a set of affective attributes and associating them with the product features.

In order to demonstrate the usefulness of the proposed approach, experiments have been carried out by using the publicly available Amazon data. We evaluate the different combinations of methods. The results show that the affective information can be extracted with high precision and recall. In addition, a summarization method is proposed to summarize the relationships between product features and the consumers' affective responses of the product. A prototype system has been developed to visualize the relationships. The summaries could help users to review and analyse the products and their features based on affective aspects. The proposed approach may help consumers making better purchase decisions and provide insights for manufacturers and product designers for improving their products and strategies.

Nevertheless, the proposed approach has several limitations. First, the proposed approach can only handle English text. It does not support other languages or formats, such as images, audio, and video. Some special characters, such as emoji, are useful to express consumer emotions. They are not included in this study. Second, during the gold standard construction, we find that there is some typo errors found in the reviews. We manually modified the reviews to correct the errors. Third, research show that spam in reviews is widespread (Jindal & Liu, 2008). This seriously affects the accuracy of opinion mining. The current study does not include the removal of spam reviews. Forth, according to the experimental results, we can see that the precision of critical review analysis is much lower than the precision of positive review analysis.

Suggested further work is as follows. 1) Spam review detection techniques should be used to remove fake and redundant reviews. Analysis can be done by measuring the impact of spam review on the affective information extraction. 2) The current study uses a pre-downloaded dataset. An integrated system can be developed for providing real time collection, monitoring, visualizing and analysis of customer reviews. 3) In order to improve the precision of critical reviews, it is necessary to develop a set of Kansei words or patterns for detecting affective opinions from critical reviews.

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