Product Feature Ranking and Popularity Model based on Sentiment Comments

Siti Rohaidah Ahmad[1], Nurhafizah Moziyana Mohd Yusop[4], Muslihah Wook[5], Arniyati Ahmad[6]
Department of Science Computer
Universiti Pertahanan Nasional Malaysia
Sungai Besi, Kuala Lumpur, Malaysia

Azuraliza Abu Bakar[2], Mohd Ridzwan Yaakub[3]
Centre for Artificial Intelligence Technology
Faculty of Information Science & Technology
Universiti Kebangsaan Malaysia, Selangor, Malaysia

***Abstract*—This paper proposes the development of a model to determine feature popularity ranking for products in the market. Each feature that is reviewed by a customer has a relation to sentiment words present in the sentences within a customer review. Feature quantity of a product, derived from customer review dataset, cannot be used as a benchmark to determine customers' preferences since each feature is influenced by sentiment words that give it either a positive or negative meaning. A positive meaning shows that the feature is liked by user; and a negative meaning shows that it is disliked by user. This study finds that sentiment assessments by users play an important role in determining feature popularity ranking; and they affect the feature of a product. Thus, this study proposes the development of a model that takes into account the importance of sentiment assessments present in each sentence within a customer review of a product feature. A case study has been conducted in proving that the developed model is able to produce a list of product feature popularity ranking. Results of this experimental model is also put into simple comparative analysis with a few models from previous studies.**

Keywords*—*Product feature ranking; sentiment analysis; feature selection; sentiment word

I. Introduction

This study introduces feature ranking calculation and arrangement model; based on customer feedbacks on the advantages and disadvantages of a product feature. In this study, the satisfaction level of users on a product is identified through the use of positive or negative sentiment words, and the strength of customer reviews in the comment sections. Product feature is highlighted since users will usually look for important product information regarding the advantages and disadvantages of a product in its features. However, existing datasets only provide either positive or negative information about the product without a clear and detailed positive or negative feature list; and thus, lacking an explanatory aspect. It is conclusive to say that existing customer reviews could not really help customers decide whether they should buy the product or not.

For that matter, the model developed in this study examines customer review datasets by analyzing positive or negative sentiment words and sentiment strength values. The proposed model will be able to evaluate the forms of customer reviews on a product feature with either a negative or a positive form. Thus, the output of this model could ultimately help users effectively assess a product based on the analyzed features. The element of sentiment assessment in this model, which is based on customer reviews, will enable it to provide detailed feature ranking information for the perusal of customers and producers. For example: when the proposed model is applied on a Canon product (a camera), the model will classify and display a list of positive features such as *camera*, *photo*, *picture*; and a list of negative features such as *memory card*, *view finder*, *size* etc.

The analysis of feature ranking and popularity is very important to get a clear and detailed overview of the product features preferred by the consumers. However, the abundance of unanalyzed reviews make it difficult for users to assess a product. This problem also complicates the identification process of product features and real sentiment types for both consumers and manufacturers. Even when a product feature is mentioned repeatedly in a customer review, it does not really give the impression that the product feature is favoured by user. Conversely, if the feature rarely appears in customer review, then the product can be considered as unfavourable by users. Therefore, a summarized analysis on product features and sentiment words is very important to help product users and manufacturers make prompt decisions and save time [1].

Most of the previous studies on feature ranking in sentiment analysis are more focused on customers' assessments on product feature compared to the disadvantages and advantages of the product feature [2]. Findings from the analysis on previous literatures have shown that most researchers have studied feature ranking based on two aspects: feature importance in customer reviews; and positivity or negativity in sentiment categories.

Feature ranking technique [3] is based on feature importance and is determined by two factors: feature relevancy and feature frequency. *Hyperlink-induced topic search* (HITS) algorithm and *bipartite* graph are used to determine feature relevancy; whereas functional score value is used to determine feature frequency. However, this technique does not consider the sentiment category for each feature present in customer reviews. Additionally, Yu et al. [4] has developed a feature ranking technique based on the frequency of appearance for one particular feature in customer reviews. Features that are frequently reviewed in customer reviews are considered important features regardless of the feature sentiment category.

Eirinaki et al. [5] has developed *high adjective count* (HAC) algorithm to extract feature labelled as POS *noun*. This feature is frequently used in customer reviews to express opinions. HAC algorithm calculates the score for each feature; based on sentiment score calculation value, which is derived from *max opinion score* algorithm. Additionally, Jawadwala and Kolkur [1] have improvised on the work of Eirinaki et al. [5] by increasing the Senti-WordNet function to get an objective score value for each sentence. This function is used to identify sentence types: either subjective or objective. Other than that, feature ranking value is calculated based on opinion score value derived from Senti-WordNet. Similarly, the study by Ahmad and Doja [6] has utilized Senti-WordNet function to derive score values for each feature and calculate the overall orientation of the feature. This function will then be able to determine whether a feature is prone to be a more positive or negative sentiment. According to them, the feature tendency of the sentiment: either positive or negative, is determined by identifying the category of sentiment word that has a relation with the feature.

The remainder of this paper is organised as follows: Section 2 will discuss the methodology. Next, Section 3 will outline the proposed of model, and Section 4 will describe the experimental result. Section 5 will explain the discussion. Lastly, Section 6 will conclude this work.

II. Methodology

The objective of this research is to propose a developmental model to calculate the list of feature ranking and population feature of a product. The components of each phase are depicted in Fig. 1. There are 6 phases in developing this model, which are:-

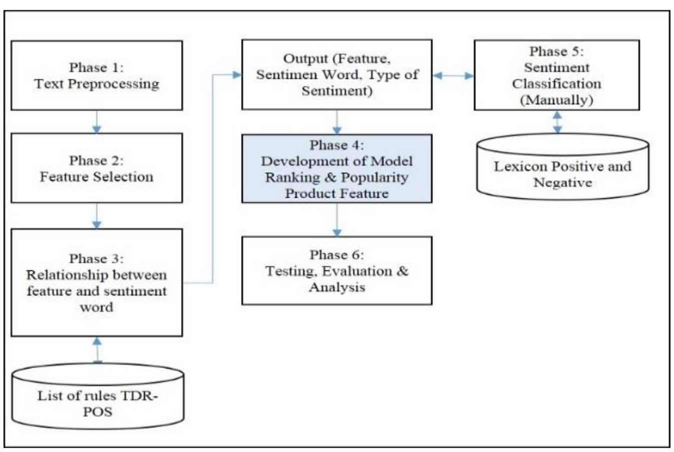

Fig. 1. Methodology of Developing Product Feature Ranking and Popularity Model

A. Phase 1 – Text Preprocessing

Each data has to go through the data cleaning process which includes correcting words with spelling errors and correcting errors in word capitalization. After the data cleaning process has been completed, each data has to go through the part-of-speech tagging process to identify each of the word tags such as noun, verb, adverb, determiner, negation, etc. For each word, the noun tag in the sentences will be extracted and stored in a table. Refer to Fig. 2.

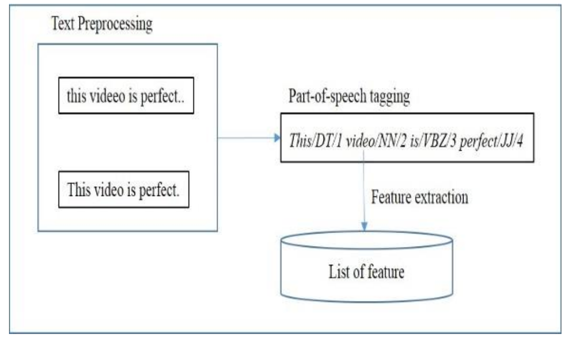

Fig. 2. Text Preprocessing

B. Phase 2 – Feature Selection

Words stored in the list from phase 1 has to go through a feature selection process to choose the features that represent the actual dataset. In this study, ant colony optimization (ACO) algorithm is used as the feature selection technique because it has been proven to be effective in a previous study [7], [8].

C. Phase 3 – Relationship between Feature And Sentiment Word

The process of identifying the relations between feature and sentiment word is important because it determines the real sentiment of a feature. This study uses a combination of typed dependency relations and part-of-speech tagging parameters to identify the relations between each word in the sentences from customer reviews. To identify this relation, an algorithm based on typed dependency relations and POS tagger has been developed. Observably, the combination between the concepts in POS tagger and typed dependency relations makes it easier to identify features and sentiment words that are related. Part-of-Speech Tagger (POS Tagger) is a software that performs the process of grammar labelling for each word in customer reviews. The labelling process would classify words into different types such as: noun, adverb, verb, adjective, determiner, conjunction, etc. On the other hand, typed dependency relations is the process of identifying the type of relations between one word and another in a sentence from a customer review. There are about 50 types of typed dependency relations in Stanford Parser. Among them are: NSUBJ, NMOD, ADVMOD, AMOD, CONJ, and others. Fig. 3. can be referred to for an explanation regarding the process of POS tagging and typed dependency relations.

Each feature and sentiment word relation that has been identified in sentences has to go through a checking process. This process identifies whether the sentiment word is grouped into positive or negative lexicon group. Finally, the feature and sentiment word relation is recognized whether it is positive or negative. This study uses a combination of typed dependency relations and part-of-speech tagging parameters [9] to identify the relations between each word in a sentence from the customer's reviews.

Example 1:

Sentence: This camera is perfect.
POS tagging: This/DT/1 camera/NN/2 is/VBZ/3 good/JJ/4
Typed dependencies relations:

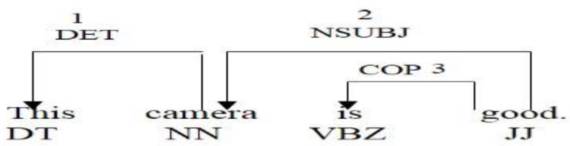

Fig. 3. Typed dependencies relations for the sentence: This camera is good.

D. Phase 4 – Sentiment Classsification

Sentiment Classification in this study refers to the process of checking and ensuring that the feature and sentiment word pair which has been produced in section (d) is in its correct class: either in the positive or negative class. The output is manually checked with its dataset to ensure that the finding is consistent with the contextual information present in the dataset. The items checked in this phase are: feature, sentiment strength value, and sentiment class.

E. Phase 5 – Development of the Product Feature Ranking and Popularity Model

This phase will be explained in The Proposed Product Feature Ranking and Popularity Model section.

F. Phase 6 –Comparison and Analysis

This process of comparison in this study aims to test the effectiveness of the proposed feature popularity ranking model; whereby this model is tested against the model developed by Ahmad and Doja [6]. The process of analysis will later be thoroughly explained in the Base Model section below.

III. THE PROPSED PRODUCT FEATURE RANKING AND POPULARITY MODEL

This section explains the development of a calculation model for feature ranking as proposed in this study.

Definition 4.1: Product is defined based on its possession of its feature set; which is the product characteristics. For example, a Nikon product has a feature list of camera, battery, picture quality, flash, weight, etc. Below are the respective definitions of product and feature; presented in the form of equations (1) and (2):-

$$\text{Product} = P\{F\} \tag{1}$$

$$\text{Feature} = F = \{f_1, f_2, f_3, \ldots, f_i\} \tag{2}$$

Definition 4.2: Review is defined as the user review set; that is, $P = \{p_1, p_2, p_3, \ldots p_j\}$. Each user review contains feature f, sentiment word ps, and sentiment strength value ks, whereby $p_1 = \{(f_{i1}, ps_{i1}, ks_{i1}), \ldots (f_{im}, ps_{im}, ks_{im})\}$. Refer to Table 1 for sentiment strength values.

TABLE I. SENTIMENT STRENGTH VALUES

Positive value	Description	Negative value	Description
3	Strongest	-3	Weakest
2	Medium strong	-2	Medium weak
1	Strong	-1	Weak

A. Feature Weightage

The frequency of feature occurrence in each dataset is counted. Each feature is categorized according to its type and number based on Table II below.

$$\text{Weightage} = ks_i * np_{fi}\,; \tag{3}$$

Where:

ks_i = sentiment strength for user review (p_i), on feature f_i;

npf_i = feature weightage, f_i, according to the feature frequency present in user review dataset;

B. Total number of Sentiment Strength Weightage According to Fetaure Type

$$Jks_i = \sum_{i}^{a} Weightagef_i\,; \tag{4}$$

Where:

Jks_i = total number of feature weightage based on sentiment strength which is according to feature type, f_i;

a = total number of feature, f_i, according to feature type;

C. Feature Ranking

$$RF_i = \quad Rank(Jks_i); \tag{5}$$

Where:

RF_i = all features in a dataset is ranked according to the frequency of feature occurring in user review, p_i; based on the total number of sentiment strength weightage, Jks_i. The order of feature ranking is arranged with the highest value (Jks_i) at the top and the lowest value (Jks_i) at the bottom.

The number of features for each user review dataset is quantified according to feature type. Table II exemplifies the process. Additionally, each feature is grouped according to its respective feature type. Based on this feature number, it is observable that the weightage values is determined based on the feature quantity. Table III exemplifies the process.

TABLE II. EXAMPLE FOR QUANTITY OF THE FEATURE FOR DATASET NIKON

Feature Type	Quantity
camera	50
size	23
picture	15
auto mode	5

TABLE III. WEIGHTAGE VALUE ACCORDING TO THE TOTAL NUMBER OF FEATURE QUANTITY

Quantity of features	Weightage value (npf_i)
75- above	1
51-74	0.75
25-50	0.5
1-24	0.25

D. Product Reputation Value

In this study, product reputation value is calculated according to the total number of positive and negative reviews. The reviews are separately counted before the total number of positive reviews is deducted from the total number of negative reviews. The final result is considered as the performance value for the product [10]. The algorithm in Fig. 4 is used to calculate and sort the feature ranking.

```
    Input:
    Product feature fj;
    Value of sentiment strength ksi;
    weight npfj
    Output:
    Feature Ranking fj
0.  START
1.  Get vectorA[ksi, npfj];
2.  for (int bilVektorA=0; bilVektorA < bilrekodVektorA;
    bilVektorA++)
     {
3.  Get value of feature weight fwj;
4.  Get value of feature strength fsj;
5.  fwsj=(fwj * fj);
6.  Update vectorA[fsj, fwj, fwsj];
7.  } End for
8.  Get vectorB[fj, fwsj;];
9.  for (int bilVektorB=0; bilVektorB < bilrekodVektorB;
    bilVektorB++)
      {
10. TOSj =Aggregate fwsj and group based on fj;
11.   }End for
12. ListofRanking =Rank(TOSj);
13. Return list of ranking;
14. END
```

Fig. 4. Algorithm for the calculation of feature ranking based on feature quantity, sentiment strength value and sentiment category

The purpose of weightage value is to gauge the importance of certain features; which is done based on the total number of feature quantity present in user review dataset. The bigger the total number of feature quantity, the higher the weightage value. The whole process of calculating feature ranking is based on feature quantity, sentiment strength value dan sentiment category.

IV. Experimental Setup and Result

A. Dataset

To test the effectiveness of this proposed model, a customer review dataset as compiled by [11] is used. The dataset comprises of reviews on five types of electronic products, as shown in Table IV. This dataset is written in English and taken from the Amazon website.

TABLE IV. SUMMARY OF REVIEW DATASETS

Dataset	Number of manual product features	Number of review sentences
Nikon	70	346
Nokia	100	546
Apex	104	739
Canon	100	597
Creative	170	1716

B. Base Model

To evaluate the base model, the effectiveness of this ranking model is tested with feature popularity list; and the result is compared with the proposed model in [6]. The feature ranking calculation method as proposed by Ahmad and Doja [6] is based on the value derived from Senti-WordNet [12]. Each sentiment word with a relation to related feature is classified using Senti-WordNet. Additionally, each feature has a total weightage that is taken as the polarity value for each sentiment word; whereby the sentiments words are identified with the total number of sentences that contain the related features and sentiment words.

Total of weight (Wt) =

$$\sum_{n-1}^{d} Wt\ of\ positive\ features - Wt\ of\ negative\ features \qquad (6)$$

whereby d = Number of documents containing feature;

Results from the calculation model in (6) enable each feature to have its value identified with eitiher positive or negative. According to the researcher in [6], if the total weightage of the feature is identified to be of positive value, then the feature is likely viewed positively and preferred by users. Conversely, if the total weightage of the feature is identified to be of negative value, then the feature is likely viewed negatively by users. The feature ranking will be sorted in an ascending order whereby the highest positive value is placed at the top and the lowest negative value is placed at the bottom. The value is determined based on the total value of feature weightage.

C. Result

This section lays out the results of a case study that was conducted to test out the effectiveness of the proposed calculation model on feature ranking and popularity. Table V displays the comparative analysis between three models: feature ranking based on quantity; the proposed feature ranking list model; and Ranking System model as proposed by Ahmad and Doja [6].

TABLE V. DIFFERENCES ON PRODUCT FEATURE RANKING BETWEEN FEATURE RANKING MODEL AND RANKING SYSTEM

Feature	**Quantity**	**Feature**	**Feature Ranking Model**	**Feature**	**Ranking System**
camera	43	camera	51.5	camera	20.38
picture	17	picture	7	picture	7.38
picture quality	10	picture quality	5.5	picture quality	5.50
use	10	feature	4.5	use	5.13
.	.	.	.	.	.
.	.	.	.	.	.
sunset feature	1	indoor image	-0.5	audio	-0.63
transfer	1	system error	-0.5	system error	-0.63
txt file	1	transfer	-0.5	lcd	-0.75
view finder	1	lens cap	-1	indoor picture	-0.75
zoom image	1	8mb	-1	8mb	-1.13
Product Reputation	**202**	**Product Reputation**	**104.5**	**Product Reputation**	**75.50**

The model using feature ranking based on quantity only displays the total number of feature that was reviewed by users; without any analysis on its value. This information would not be able very helpful to new users in evaluating the product. On the other hand, Table VI has displayed that the suggested model is able to determine the feature value: both positive or negative value; and thus, the popularity of feature strength, the feature level, and the feature frequency in customer review dataset can also be identified. A positive feature value will display high sentiment strength, high feature level and high frequency of appearance in customer review dataset. Conversely, a negative feature value will display low sentiment strength and feature level; and thus, will be ranked at a low position in the feature ranking list.

Table VI is a comparison on product reputation value between the proposed model and Ranking System. In overall, product reputation value for the proposed Product Feature Ranking model is found to be higher than Ranking System.

TABLE VI. DIFFERENCES ON PRODUCT REPUTATION VALUES BETWEEN PRODUCT FEATURE RANKING MODEL AND RANKING SYSTEM.

Dataset	**Feature Ranking Model**	**Ranking System**
Nikon	+104	+75.50
Nokia	+160	+103.75
Apex	-98	+33.48
Canon	+157.25	+92.58
Creative	+253.25	+145.65

Product reputation or item reputation is the total evaluation given by users; based on certain aggregation method. This study proposes a calculation model on product reputation value in which the sum of customer sentiment evaluation is calculated. In general, the reputation value for feature ranking and popularity model exhibits better overall value than Ranking System. The use of equations (3), (4) and (5) has shown a major change to the results of product reputation value.

Results from the proposed model are better than Ranking System.; including the dataset on Apex product. The huge difference in the Apex dataset is due to the high number of criticisms on *player* feature compared to other features. Even though the *player* feature receives the highest number of customer reviews among other features, this number does not mean that *player* feature is preferred by user. In fact, the *player* feature receives a lot of negative sentiment evaluations from user. Besides that, there is a marked difference of 89.9 on the reputation value of Creative dataset between the proposed model and the Ranking System. Feature list for Creative dataset such as *player, software, price, sound, battery, size, sound quality* has a high number of positive reviews from user. Thus, it affects the calculation of reputation values for Creative product. The situation here exemplifies that the proposed model yields better reputation calculation because the equations (3), (4) and (5) take into consideration the sentiment value provided by user.

V. DISCUSSION

This study has clearly explained the proposed calculation model for feature ranking. The calculation function for feature ranking is developed based on three aspects: feature quantity, sentiment strength value, and sentiment category. In effectively analyzing the information found in user reviews, it is important to take into considerations the element of user ratings on the features of a product. In other words, even though the product feature might receive a high number of reviews from users, it does not mean that the product feature is preferred by users. Hence, a detailed analysis should be conducted in identifying the real overall sentiment type provided by users. It is very important to consider sentiment assessments given by users on product features since it actually reflects the product quality. Aside from that, the assessment also offers a real view of what is liked and disliked by users.

Understanding this situation, the proposed feature ranking model takes into consideration the sentiment assessments given by users. Results derived from this model could eventually assist in creating a list of product feature ranking that represents actual user preferences. This information will be very useful and helpful to new users in deciding whether to buy a product or not. The advantage of this model is that: it uses existing data in user review datasets, which include: sentiment strength value for each feature, feature quantity, and sentiment category for each product feature. The information on sentiment strength value is derived from user assessments on their satisfaction level regarding a certain product. Additionally, in terms of generating feature ranking, this model is not dependent to the hierarchical concept or product ontology, and the Senti-WordNet calculation model in obtaining sentiment strength values.

VI. Conclusion

This study proposes a new model to determine product feature ranking and popularity; based on the information in user feedback such as: sentiment strength assessment, feature quantity, and sentiment category. The developed model takes into consideration the effect of sentiment evaluation given by user. Based on this study, it is also conclusive to say that the quantity of features extracted from user reviews, whether the total number is big or small, cannot be used as an indicator that the product is liked or otherwise. The results derived from this calculation model can help users assess a product based on product characteristics or features. For producers, the resultant information from the model can be used to improve the quality of products produced.

Acknowledgment

The authors gratefully acknowledge Universiti Pertahanan Nasional Malaysia for supporting this research project.

References

[1] M. K. Jawadwala and S. Kolkur, "Feature Ranking in Sentiment Analysis," International Journal of Computer Applications, vol. 94, no. 13, pp. 42–49, 2014.

[2] A. Abdel-Hafez, Y. Xu, and D. Tjondronegoro, "Product Reputation Model: An Opinion Mining Based Approach," in 1st International Workshop on Sentiment Discovery from Affective Data (SDAD 2012), 2012, pp. 16–27.

[3] L. Zhang, B. Liu, S. H. Lim, and Eamonn O'Brien-Strain, "Extracting and Ranking Product Features in Opinion Documents," in Proceedings of the 23rd International Conference on Computational Linguistics (COLING-2010), 2010, pp. 1462–1470.

[4] J. Yu, Z.-J. Zha, M. Wang, and T.-S. Chua, "Aspect Ranking : Identifying Important Product Aspects from Online Consumer Reviews," Computational Linguistics, pp. 1496–1505, 2011.

[5] M. Eirinaki, S. Pisal, and J. Singh, "Feature-based opinion mining and ranking," Journal of Computer and System Sciences, vol. 78, no. 4, pp. 1175–1184, 2012.

[6] T. Ahmad and M. N. Doja, "Ranking System for Opinion Mining of Features from Review Documents," International Journal of Computer Science Issues, vol. 9, no. 4, pp. 440–447, 2012.

[7] S. R. Ahmad, A. Abu Bakar, and M. R. Yaakub, "Metaheuristic Algorithms for Feature Selection in Sentiment Analysis: A Review," in Science and Information Conference (SAI), 2015, pp. 222–226.

[8] M. H. Aghdam, N. Ghasem-Aghaee, and M. E. Basiri, "Text Feature Selection using Ant Colony Optimization," Journal Expert Systems with Applications: An International Journal, vol. 36, no. 3, pp. 6843–6853, 2009.

[9] S. R. Ahmad, A. Abu Bakar, and M. R. Yaakub, "Detecting relationship between features and sentiment words using hybrid of typed dependency relations layer and POS tagging (TDR Layer POS Tags) algorithm," International Journal on Advanced Science, Engineering and Information Technology, vol. 6, no. 6, pp. 1120–1126, 2016.

[10] A. Jøsang, R. Ismail, and C. Boyd, "A survey of trust and reputation systems for online service provision," Decision Support Systems, vol. 43, no. 2, pp. 618–644, 2007.

[11] M. Hu and B. Liu, "Mining Opinion Features in Customer Reviews," in Proceeding AAAI'04 Proceedings of the 19th national conference on Artifical intelligence, 2004, vol. 21, no. 2, pp. 755–760.

[12] A. Esuli and F. Sebastiani, "SENTIWORDNET: A Publicly Available Lexical Resource for Opinion Mining," Proceedings of the 5th Conference on Language Resources and Evaluation, pp. 417–422, 2006.