A Framework for Laptop Review Analysis

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Abstract— **This research paper shows the proposed framework which enables users to know what the review about the laptop is. The objective of this research is to analyze messages from community websites and identify subjective paragraphs and the sentiment of texts. There are three main procedures of this framework. Firstly, subjective paragraphs will be detected from the source materials by detecting subjective words. Secondly, the aspects of subjective paragraphs will be defined by the frequency of words in each aspect. Finally, the sentiment of texts will be classified by the machine learning. In conclusion, the results of this framework are identified subjective paragraphs in each aspect and the sentiment of texts in paragraphs. So this technique framework is useful for the system applied for analyzing the laptop reviews as to help the customer make decision before purchasing.**

Keywords— sentiment analysis; review analysis; opinion mining

I. INTRODUCTION

Currently, the market of laptop has become more competitive due to the rapid growth of mobile devices and tablets. There are many brand manufactures in the laptop industry and they continually create many new laptop series to compete each other. For this reason, customers have to deal with the problem in making decision for purchasing laptops. Although customers can find information about laptops in the marketplace from review forums on blogs, websites or online communities, customers have to spend lots of time to read and search for information they need. The previous reasons are the motivations for developing the system that help customers choose the right laptop to buy. The system will gather review data from various review forums and analyze the useful information for the customer by using the sentiment analysis.

In order to read people’s mind through text messages, sentiment analysis is an essential process to identify people's opinions expressed through texts. The process of sentiment analysis includes different fields of knowledge ranging from natural language processing, artificial intelligence and text mining. The main objective of sentiment analysis is to distinguish the opinion of a source text into positive opinion or negative opinion. The opinions expressed in the texts could be judgments, evaluations, affective states, beliefs or wishes [1].

For those purposes, sentiment analysis will be applied to analyze reviews in this paper. Nowadays sentiment analysis can be used to analyze customer opinions in order to check customers’ satisfaction. Moreover, this technique can be used for a market survey in order to understand customer's needs and increase the efficiency of customer service and the company’s ability in competing. For example, if a laptop company is able to perceive customer opinions in both pros and cons, then the company can make more improvement in their products and fulfill customer needs.

Most reviews on community websites about laptops, such as notebookreview.com, laptopmag.com, cnet.com, pcmag.com, and notebookcheck.net, are composed of laptops’ information about performance, design and features. Therefore, this research studies on review analysis about laptops in three aspects which are the product performance, the design of a product and the features of a product. A framework of laptop review analysis is proposed to implement the automatic analysis system.

The detail in this paper will be described in the following sections. The related works of sentiment analysis are described in section II. The framework of laptop review analysis is shown in section III. Then, the proposed evaluation of the framework performance is demonstrated in section IV. Finally, section V summarizes the paper and presents the future work.

II. RELATED WORKS

There are many related works about the sentiment analysis. The definition of sentiment analysis is processed to identify subjective information in source materials by using Natural Language Processing (NLP) to analyze sentences. Sentiment analysis can be used to determine the sentiment by scoring individual words in those documents; a positive score or a negative score [1]. This section describes about the research involved the sentiment analysis.

P. Pugsee et al. [2] analyzed opinions about airline services on Twitter by collecting the subjective words in messages on Twitter and studying the sentiment messages by the machine learning. The machine learning can classify messages into two groups which are subjective and objective messages. This technique can apply to our proposed framework for classifying the sentiment of paragraphs by the machine learning.

Y. Yamamoto et al. [3] presented the method for calculating sentiment values of messages on Twitter based on emoticons and emoticon roles. In addition, words and emoticons in messages are detected by the sentiment lexicon and the emoticon lexicon to analyze the meaning of emoticons.

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Our proposed framework will apply this technique to find emoticons in review paragraphs.

C. Bhadane et al. [4] developed the system composed of six processes that are preprocessing, lexical analysis, stemming, part of speech tagging and machine learning to classify text files into different aspects. All these processes will be applied to this research in order to classify sentences into different aspects.

III. PROPOSED TECHNIQUE

In this research, all of the above studies in section II will be applied to analyze laptop reviews into each aspect. Therefore, the customer will have a clear summary of the product reviews which will help them with the decision making while they purchase products.

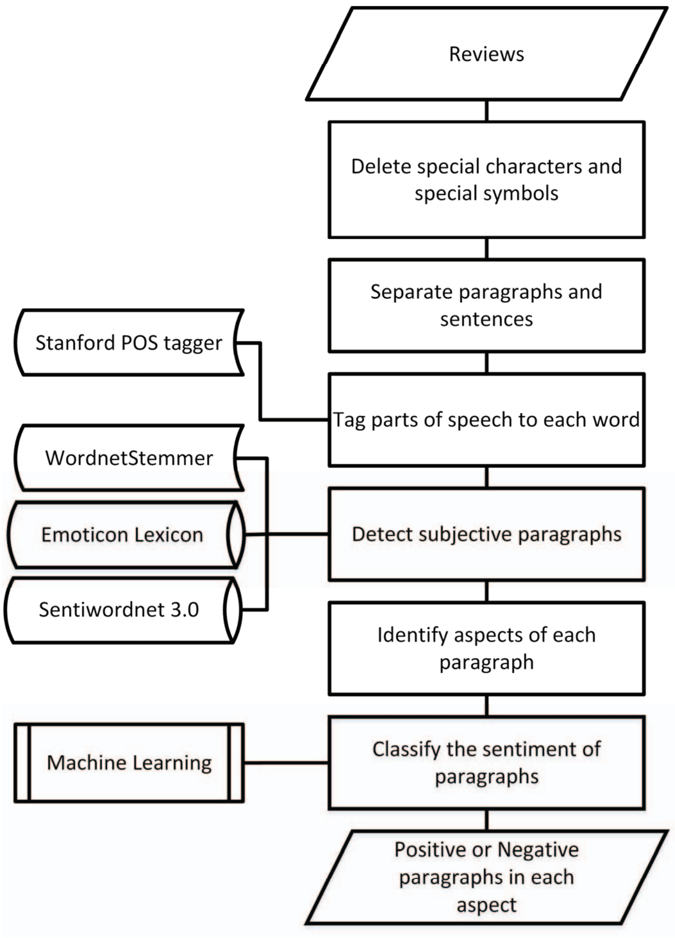

Figure 1. The framework of laptop review analysis.

According to Fig. 1, this framework is composed of six processes that are delete special character and symbols, separate paragraphs and sentences, tag parts of speech to each word, detect subjective paragraphs, identify aspects of each paragraph and classify the sentiment of paragraphs. The main objectives are to classify paragraphs into subjective paragraphs, to identify aspects of each into three aspects, and to classify the sentiment of paragraphs. The input of this framework is contents from community websites and the output is two groups of review paragraphs which are positive or negative paragraphs. An example of input data is shown in Fig. 2.

> The touchpad is able to recognise even the complex 3-finger gestures with great precision. During about 2 hours of use I've only had 3 times when the mouse didn't do what I was expecting, mostly when trying to select text (which is tricky business on touchpads anyway). I didn't have trouble with palm rejection either, though it might be because my hands don't touch the touchpad while typing :p .

Figure 2. The example of input data for the proposed framework.

A. *Delete special characters and special symbols*

Special characters and special symbols will be deleted from reviews. The examples of special characters and symbols are shown in Table I. Also other characters apart from English alphabets, symbols and numbers will be classified as special characters.

TABLE I. EXAMPLES OF SPECIAL CHARACTERS AND SPECIAL SYMBOLS

Special Characters	Special Symbols
Å	✓
Ç	☑
Đ	✗
™	☒
©	

B. *Separate paragraphs and sentences*

This process will help preparing paragraphs for analyzing each word. At this stage, the system will detect a full stop, a newline and a tab in order to separate paragraphs and sentences from one another. To separate paragraphs, the system will detect a newline and a tab character indicating that the reviewer wants to write a new paragraph. After breaking the source text into individual paragraphs, the system will separate sentences in paragraphs by detecting the full stop.

C. *Tag POS to each word*

At this stage, the module will help tagging words with their part of speech. After breaking sentences, each word in the individual sentences will be tagged its part of speech (POS) by Stanford POS Tagger [5]. This tagger identifies parts of speech of words such as noun, verb, adjective, and adverb.

D. *Detect subjective paragraphs*

Before this process starts, the words tagged into the parts of speech will be changed into basic forms by using WordnetStemmer [6]. Stemming is applied to this process in order to find the base form of the important words by reducing the prefix and suffix of the words collected in different categories. The important words are words in noun group, verb group, adjective group, and adverb group. These groups are interesting words in this framework and the best source in searching for subjective expressions because most subjective words are in adjective and adverb group. The stemmer will collect words and delete out the prefix or suffix of those words in order to make them less redundancy. The result of stemming process will be the collected words presenting in their base forms. For example, if the words are 'played' and 'playing' which are same part of speech as verb and the same base form as 'play', then the suffix, '-ed' and '-ing', will be reduced as to make those words less redundancy. The result of this example is played and playing will change to 'play'.

After making the words less redundancy, the word data from Sentiwordnet [7] will be applied to identify whether those words are subjective or objective words. Every paragraph, which has at least one subjective word text, will be considered as a subjective paragraph. In addition, emoticon texts will also be found by comparing with information from an emoticon lexicon [3]. The examples of emoticon texts in the emoticon lexicon are shown in Table II.

TABLE II. EXAMPLES OF EMOTICON TEXTS

Emoticon Texts	Sentiment Class
(^^)	Positive
:)	Positive
:P or :p	Neutral
= =	Neutral
:(	Negative
=P or =p	Neutral

The review paragraphs with at least one emoticon text will be identified as subjective paragraphs. The output of this process focuses on only the subjective paragraphs. Referring to Fig. 2, this module will detect subjective words and emoticon texts in the review paragraph. The detected subjective words and emoticon texts are shown in Fig. 3. Therefore, this paragraph is defined as the subjective paragraph.

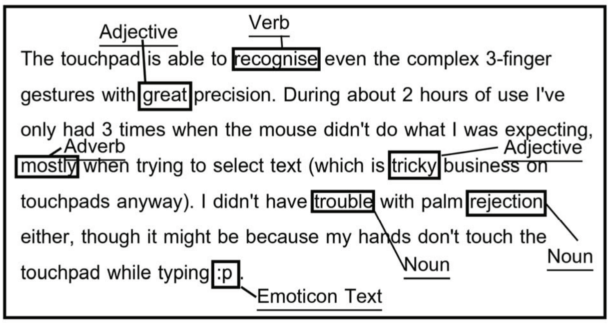

Figure 3. The detected subjective words and emoticon texts in the paragraph.

E. *Identify aspects of each paragraph*

After collecting subjective paragraphs, these paragraphs will be identified into each aspect by comparing words in each aspect domain. The examples of words in aspect domains are shown in Table III.

TABLE III. EXAMPLES OF WORDS IN EACH ASPECTS

Performance	Design	Feature
Performance	Design	Feature
Ghz	Weight	USB
Mhz	Width	HDMI
CPU	Height	VGA
Memory	Size	Touchpad

In this module, the subjective paragraphs will be classified into different aspects (performance, design and feature). One subjective paragraph can match more than one aspect because the paragraph contains words in more than one aspect domain. Referring to Fig. 2, this module will detect words in aspect domains for identifying types of aspect. The detected words are shown in Fig. 4.

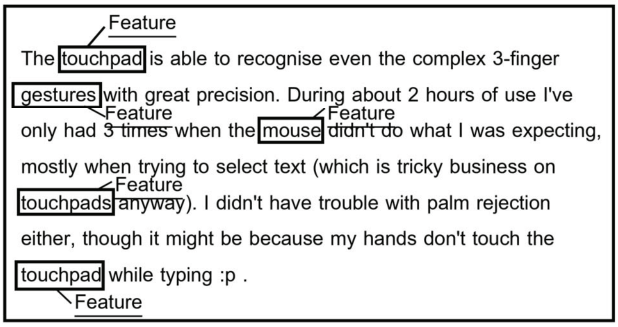

Figure 4. The detected words in the feature aspect.

F. *Classify the sentiment of paragraphs*

After that subjective paragraphs in each aspect will be classified the sentiment of paragraphs by using the machine learning. The result of this module is two groups of paragraphs (positive and negative paragraphs). According to the paragraph example in Fig. 2 – Fig. 4, the sentiment of this paragraph should be positive.

In summary, this framework will analyze and classify source materials (laptop reviews) and show the result of sentiment analysis. The subjective paragraphs in reviews will be classified into positive and negative paragraphs in each aspect.

IV. PROPOSED EVALUATION

In this section, three evaluation processes are proposed to measure the performance of the framework. The first process is the evaluation of the subjective paragraph detection. The second process is the evaluation of aspect identification and the final process is the evaluation of sentiment classification. All three evaluation processes will be measured by a confusion matrix [8] to calculate accuracy, precision and recall. The detail of the confusion matrix is shown in Table IV.

TABLE IV. THE CONFUSION MATRIX

		Predicted Class	
		Positive	*Negative*
Actual Class	***Positive***	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

According to all parameters in Table IV, if the actual class is positive and the result of predicted class is positive, the value of result data will be called True Positive (TP). Also, if actual class is negative and the result is a correct prediction, the value of result data will be called True Negative (TN). On the other hand, if the result is an incorrect prediction and the actual class is positive, the value of result data will be called False Negative (FN). If the actual class is negative and the predicted class is positive, the value of result data will be called False Positive (FP).

Accuracy is a common measure for the performance of classification or error rates. While accuracy is the ratio of correct examples to the total examples, error rates is the ratio of incorrect examples to the total examples. All examples might be labelled as dominant class and will effect to other class in classification. The formula of accuracy can be shown in (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

By the way, using accuracy with skewed data, the data which has one class significantly than the other, needs to be very careful. Therefore, other value measurements are considered.

Precision and recall [9] are two basic and widely-used metrics in evaluating search strategies like text mining, information retrieval, etc. Precision and recall often used as an extension of accuracy. The combination of them can be used with skewed data problem in classification problem. Precision is the ratio of correct examples to the total of positive-classified examples. It often used to measure the exactness. Recall is the ratio of correct example to the total of truly-positive examples. It often used to measure the completeness. The formulas of precision and recall can be shown in (2) and (3).

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

A. Evaluation of the subjective paragraph detection

Accuracy of subjective paragraph detection can be calculated by the number of correct predicted paragraphs dividing by the number of all paragraphs. Precision of subjective paragraph detection can be estimated by the number of correct predicted subjective paragraphs dividing by the number of paragraphs predicted as subjective paragraphs. Recall of subjective paragraph detection can be computed by the number of correct predicted subjective paragraphs dividing by the number of all subjective paragraphs.

B. Evaluation of aspect identification

Aspect identification accuracy can be calculated by the number of correct identified paragraphs dividing by the number of all paragraphs. Aspect identification precision can be estimated by the number of correct identified paragraphs in the interesting aspect dividing by the number of paragraphs identified as the interesting aspect. Aspect identification recall can be computed by the number of correct identified paragraphs in the interesting aspect dividing by the number of all paragraphs in the interesting aspect.

C. Evaluation of the sentiment classification

Accuracy of sentiment classification can be calculated by the number of correct classified paragraphs dividing by the number of all paragraphs. Precision of sentiment classification can be estimated by the number of correct classified paragraphs in the interesting class (positive or negative) dividing by the number of paragraphs classified as the interesting class. Recall of sentiment classification can be computed by the number of correct classified paragraphs in the interesting class dividing by the number of all paragraphs in the interesting class.

D. An Experimental Result

In this section, an experimental result will be shown to evaluate the performance of this framework. The experimental data are selected from the online community website "forum.notebookreview.com" consisting of 20 review topics. All selected review topics will be separated into 1,044 paragraphs by detecting a full stop and a new line respectively. These paragraphs can be divided into 353 subjective paragraphs and 691 objective paragraphs by computer experts. To detect subjective paragraphs, words in the experimental data will be compared with words in Sentiwordnet and data in our emoticon lexicon. The result of the predicted class is categorized into 359 subjective paragraphs and 685 objective paragraphs. The confusion matrix of subjective classification is shown in Table V.

TABLE V. THE CONFUSION MATRIX OF SUBJECTIVE CLASSIFICATION

Class	Actual Class	Predicted Class	
		Subjective	*Objective*
Subjective	353	337	16
Objective	691	22	669
Total	1,044	359	685

Referring to Table V, the correct subjective paragraphs are 337 of 359 predicted paragraphs. The percent of accuracy, precision and recall rate are shown in Table VI.

TABLE VI. THE PERCENT OF ACCURACY, PRECISION AND RECALL RATE OF SUBJECTIVE DETECTION

Class	Correct Prediction	Predicted Classes	Percent of		
			Accuracy	*Precision*	*Recall*
Subjective	337	359	96.36	93.87	95.47
Objective	669	685	96.36	97.66	96.82

According to Table VI, the percent of accuracy, precision and recall rate of all classes are more than 90%, so the subjective detection process of this framework are high performance on the experimental data.

Only subjective paragraphs will be identified into each aspect group (Performance, Design, and Feature). However, some subjective paragraphs which cannot be identified into these groups, will be classified into Other aspect. The 353 subjective paragraphs of experimental data can be categorized into 58 performance paragraphs, 70 design paragraphs, 88 feature paragraphs and 137 other paragraphs by computer experts. To identify aspects, all words in subjective paragraphs will be compared with our words in each aspect domain. The predicted results of aspect identification are 50 paragraphs in Performance aspect, 54 paragraphs in Design aspect, 63 paragraphs in Feature aspect and 192 paragraphs in Other aspect. The confusion matrix of aspect identification is show in Table VII.

TABLE VII. THE CONFUSION MATRIX OF ASPECT IDENTIFICATION

Class	Actual	Predicted	TP	FP	TN	FN
Performance	58	50	39	11	278	31
Design	70	54	49	5	269	36
Feature	88	63	60	3	257	39
Other	137	192	133	59	165	2

Referring to Table VII, the correct paragraphs are 39 of 50 predicted paragraphs in Performance aspect, 49 of 54 predicted paragraphs in Design aspect, 60 of 63 predicted paragraphs in Feature aspect and 133 of 192 predicted paragraphs in Other aspect. The percent of accuracy, precision and recall rate are shown in Table VIII.

TABLE VIII. THE PERCENT OF ACCURACY, PRECISION AND RECALL RATE OF ASPECT IDENTIFICATION

Class	Percent of		
	Accuracy	*Precision*	*Recall*
Performance	88.30	78.00	55.71
Design	88.58	90.74	57.65
Feature	88.30	95.24	60.61
Other	83.01	69.27	98.52

According to Table VIII, The percent of accuracy rate of all classes are more than 80%, although the percent of precision and recall rate of some classes are less than 70%. One reason for low precision and recall rate of identifying aspect is that our words in aspect domains are not enough for identifying paragraphs. The number of specific words in each domain will be increased in the future for improving performance of aspect identification.

The experimental data has not been implemented in sentiment classification and the machine learning will be included in the future.

V. CONCLUSION AND FUTURE WORK

One problem of the customer when buying laptops is that there are various brands and models. As a result, customers are difficult to decide because there are differences in pros and cons of laptop brands and laptop models. Therefore, this paper proposed the framework for analyzing laptop reviews to classify the sentiment of review paragraphs. The text paragraphs in reviews about laptops can be identified as subjective paragraphs, grouped into aspects and classified as positive or negative text paragraph. The benefit of this framework is to gather the useful particular information about laptops easily and rapidly. This information can help customers to make the decisions of purchases.

In the future, this framework will be implemented to generate the automatic review analysis system and modified to other review domains.

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