

# A TRANSFORMATION METHOD FOR ASPECT-BASED SENTIMENT ANALYSIS

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**Abstract.** Along with the explosion of user reviews on the Internet, sentiment analysis has become one of the trending research topics in the field of natural language processing. In the last five years, many shared tasks were organized to keep track of the progress of sentiment analysis for various languages. In the Fifth International Workshop on Vietnamese Language and Speech Processing (VLSP 2018), the Sentiment Analysis shared task was the first evaluation campaign for the Vietnamese language. In this paper, we describe our system for this shared task. We employ a supervised learning method based on the Support Vector Machine classifiers combined with a variety of features. We obtained the F1-score of 61% for both domains, which was ranked highest in the shared task. For the aspect detection subtask, our method achieved 77% and 69% in F1-score for the restaurant domain and the hotel domain respectively.

**Keywords.** Sentiment analysis; Aspect-based sentiment analysis; Natural language processing; Text analysis

## 1. INTRODUCTION

The rapid development of the Internet brings many opportunities and challenges for companies in providing high-quality products or services. Internet has become a common channel for users to immediately share comments or experiences about the products or services they used. Hence, the number of user reviews is increasing significantly day by day. For e-commerce companies, taking care of user feedback is a necessity and they usually have a team to analyze and evaluate user reviews. With a large amount of data, however, manual analysis is not feasible.

Sentiment Analysis (SA) is a research topic of natural language processing that aims to extract and analyze subjective information from opinions, comments or reviews shared by human. Therefore, sentiment analysis has been studied very early in the world [13, 22]. For the Vietnamese language, this research topic has become a trend since 2010 [9]. However, the most common problem in SA is sentence-level sentiment classification in which each sentence is assigned to one of three classes: positive, negative or neutral. This information is enough for many applications, but it is not sufficient when we need to analyze the text in a deeper way [1]. For example, in reviews about the restaurant, customers rarely express their opinion towards the entity as a whole but refer to its specific aspects. In addition, restaurant owners need to know the details of the user's comments in each aspect in order to provide reasonable solutions in terms of service, quality of food or price of restaurant. To address this problem, we need a method for a deeper analysis called aspect-based sentiment analysis.

Aspect-Based Sentiment Analysis (ABSA) is a sub-field of sentiment analysis, which allows us to deeply understand and determine sentiment in terms of different aspects of the topic. An ABSA system must be able to classify each opinion according to the aspect categories and its polarity for a certain domain. Recently, this task has been researched by scientists in the field of natural language processing via many shared tasks such as SemEval 2014 (Task 4) [17], SemEval 2015 (Task 12) [12] and SemEval 2016 (Task 5) [16]. These shared tasks focus on addressing the problem of aspect-based sentiment analysis for many languages such as English, Chinese, Arabic, etc.

According to Sentiment Analysis share-task in VLSP workshop 2018, ABSA is divided into two sub-tasks at the document-level: Aspect category detection and sentiment polarity detection. The first sub-task aims to extract all aspect categories from user's reviews, and the second sub-task aims to determine the sentiment polarity of each aspect. For example, give a user's review, "*The food is delicious, but the staffs are not friendly*". The ABSA system has to extract all the tuples  $\{Food\#Quality, positive\}$  and  $\{Service\#General, negative\}$ . In this paper, we propose a transformation method to address two sub-tasks in VLSP benchmark datasets. Our approach reached the highest results in the VLSP shared-task competition. We treat these problems as multi-label classification and we adapt a transformation method to transfer it into multiple binary classifications. To train binary classifiers, we extract various features from the review and use the SVM classifier to detect aspects and their polarities.

The remainder of this paper is organized as follows: The next section summarizes the literature review; Section 3 presents our system while the Section 4 explains the experimental results and Section 5 discusses the main findings. Finally, Section 6 concludes the work and describes the future enhancement directions to improve the classification for two datasets.

## 2. RELATED WORK

During a decade, aspect-based sentiment analysis has been widely considered to be an important research topic by its potential in practical applications such as user feedback analysis through online user views and comments [4, 11]. Aspect-based sentiment analysis as well as aspect-based opinion mining were investigated and presented by [7], that focus on the aspects of product reviews by adopting a set of rules based on statistical observations and the polarity of reviews. [6] proposed new ad-hoc and regression-based recommendation measures on user reviews for the restaurant domain. [19] adopted a linguistic approach to compute the sentiment of a clause toward different aspects of a movie. Similarly, [8] employed an Aspect and Sentiment Unification (ASUM) model to extract both aspect and sentiment for online product review dataset. [14] used latent dirichlet allocation to extract aspects and Naïve Bayes to recognize the polarity on customer reviews for the hotel domain. [18] also presented an in-depth overview of the state-of-the-art in aspect-level sentiment analysis. This survey described most approaches which use machine learning to model language and lots of datasets available.

In Vietnamese, the study of [9] is the first study to apply the SA problem in Vietnamese. The author approached the sentiment analysis problem on the laptop and desktop data collection using the syntactical rules synthesis method thanks to the GATE Framework. As the rapid development of Vietnamese sentiment analysis, many researchers focused on developing methods on the different domain. For instance, [15] examined a semantic information representation method of words using skip-gram models and SVM to classify them; [5] presented an empirical study on machine learning (Naive Bayes, Maximum Entropy and SVM) based sentiment analysis for Vietnamese, which fo-

cuses on sentiment classification on the hotel domain. [10] proposed the semi-supervised learning GK-LDA method for aspect extraction and classification tasks. [3] tried to enhance the performance of the SA task by applying feature selection technique to improve the performance of the sentiment analysis on 1,650 reviews of the hotel dataset. In addition, [2] presented an empirical study on mining comparative sentences which consists of two tasks - identifying comparative sentences and recognizing relations, and their results are very promising for further research. Besides, they also introduced a new corpus about 4,000 sentences in the domain of electrical devices. Recently, [20] used a lexicon-based method on the Facebook data domain by constructing manually a Vietnamese emotional dictionary based on the English SO-CAL dictionary, which includes the five sub-dictionaries for noun, verb, adjective, adverb and a special part emotional words, and applying a sub-class SVM to determine the emotion. In 2016, the Vietnamese Language and Speech Processing (VLSP) organizes the Sentiment Analysis shared-task on reviews data to classify a text into one of three polarities: positive, negative or neutral. The dataset contains comments of technical articles collected from websites. Furthermore, this year, VLSP organizers held the first shared-task of aspect-based analysis of two domains - the restaurant and hotel domain based on real reviews of users. This paper presents the method in our system which achieved the best performance on two subtasks for the two datasets – the restaurant and hotel dataset.

### 3. SYSTEM DESCRIPTION

#### 3.1. System overview

The main objective of our system is to perform the two main tasks of aspect-based sentiment analysis - the aspect detection and the aspect polarity task. In the aspect detection, the system should assign to each review the list of Entity#Attribute (E#A) pairs. In the aspect polarity, each identified pair (Entity#Attribute) has to be assigned one of polarity labels – positive, negative and neutral. In addition, each review is composed of several single sentences and has the different length in whole dataset. In order to tackle that challenge, we propose a system which consists of two components corresponding to each task. The first component aims to extract the aspect of the target review, and the second component is to classify the identified aspect into one of three polarity labels.

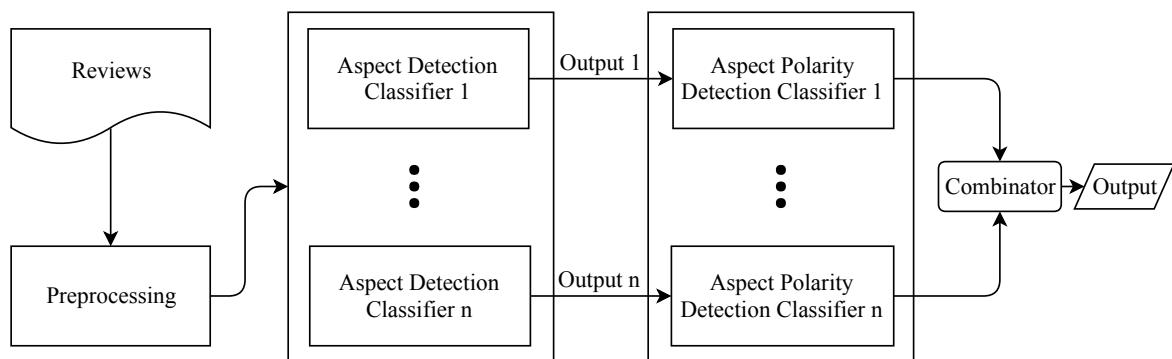


Figure 1. An overview of our aspect-based sentiment analysis system

Figure 1 shows the graphic depiction of our proposed system. For the training process, we train a binary classifier for each aspect, e.g, 12 binary classifiers for 12 aspect and 12 aspect polarity

classifiers in the domain restaurant. The testing process is described as follows: First, the review will be preprocessed to remove the noise, then through the binary classifiers in the first component, its aspects will be detected. If the output of one classifier is “1”, the current aspect is listed in the final output. After that, with each identified aspect, we continually determine its sentiment polarity in the second component. Taking a review in the restaurant domain as an example, “*The food is delicious, but the staffs are not friendly*”. After preprocessing, it will be fed into the 12 aspect binary classifiers. Because “1” is returned as the output, the two aspects are listed: “Food#Quality” and “Service#General” and then the polarity classifiers will be used to classify the review’s sentiment polarity. Finally, all results of the two components are combined and returned as the output of the system are shown in Table 1. The following subsections describe the detail of our system.

### 3.2. Preprocessing

Preprocessing is one of the key components in a typical text classification framework. This is the process of cleaning and preparing data for classification. Because raw reviews are often riddled with spelling mistakes, spacing errors, and special characters. As a result, the purpose of this component is to reduce the noise in the text to improve the performance of the classifier. The whole process involves six steps as follows:

*Table 1.* The example illustrates the output of each component of the system

<b>Input:</b> The food is delicious but the staffs are not friendly	
<b>Output of two components</b>	
Component 1: aspect detection	Component 2: aspect polarity sentiment
<i>Restaurant#general</i> : 0	<i>Restaurant#general</i> : Null
<i>Food#quality</i> : 1	<i>Food#quality</i> : Positive
<i>Service#general</i> : 1	<i>Service#general</i> : Negative
.....	.....
<i>Drink#quality</i> : 0	<i>Drink#quality</i> : Null
<b>Combined output:</b> {Food#quality, positive}, {Service#general, negative}	

- **Step 1.** Different special characters and monetary amounts referring to the same category were replaced with the name of that category. For example, “100k and 200d” was replaced with “giá\_tiền” (price), “#lozi” with “hashtag”, and “urls” with “website”.
- **Step 2.** Because the review is at the text level, it is crucial to delete special character (=, <, @, \$) except punctuation in reviews to maintain its paragraph structure. If following it is an upper word, we automatically insert dot before the word.
- **Step 3.** Common errors in these reviews, such as spacing errors where there is no space between two separate words (“tả dcVới giá”) and special icon next to a word (❀Nem), were standardized by using regular expressions.
- **Step 4.** Elongations (words with reduplication of letters) were normalized to their true word form (e.g., “ngooon,” meaning “tasty,” was normalized into “ngon”).
- **Step 5.** Freestyle letters referring to words that strongly express negative opinions, such as “khong,” “ko,” “khg,” “k,” etc., were replaced with the most frequently used word “không/not” in the whole training dataset.

- **Step 6.** After that, each review was broken into tokens and Part-of-speech tagged by using Pyvi library<sup>1</sup>.

In addition, we also manually created the food and drink dictionary based on part-of-speech of words. We extracted all the nouns in the training dataset and filtered them to remove noisy words in the restaurant domain. Then, we replaced all the words which appear in food dictionary with “thực\_ăn (food)” and in drink dictionary with “đồ\_uống (drink)”.

### 3.3. The aspect category detection

As mentioned above, the aim of this task is to assign to each review a list of entity - attribute pairs. Given a review, the system predicts the E#A pairs for that review. Each domain will have a certain number of aspects. Specifically, there are 12 and 34 different pairs of entity#attribute in the restaurant and hotel domains, respectively. Therefore, this task is a multi-label classification in which a review can belong to one or more aspect categories. [21] has grouped the methods for multi-labeling problem into two main categories: problem transformation methods and algorithm adaptation methods. To solve this task, we follow the problem transformation approach which transfers multi-label classification into multiple binary classifications. Thus, we developed 12 binary classifiers corresponding to 12 E#A pairs for restaurant domain and 34 binary classifiers for hotel domain. We used the SVM classifier with linear kernel to predict each aspect using the following feature types:

- **N-gram:** N-grams have been used as a basic feature in text classification. Therefore, unigram, bigram and trigram are extracted as features for classifier.
- **Word:** We extracted all nouns, verbs and adjectives which appear in review based on part-of-speech because these words represent the meanings for the aspects.
- **N-gram:** We used the parts-of-speech<sup>1</sup> of all nouns, verbs or adjectives as a feature for classification.

We then use the TF-IDF model to convert all features into numerical representation. Finally, we applied the linear SVM classifier to build the model for each category. If we run through all of the classifiers and still no aspect is detected, we automatically assign the review to a general aspect of “Restaurant#General” and “Hotel#General” for each domain.

### 3.4. The aspect polarity detection

With each identified pair (Entity#Attribute) has to be assigned one of the polarity sentiment labels: “positive”, “negative” and “neutral”. We consider this task to be a multi-class problem which contains three classes - positive, negative and neutral. Therefore, for each aspect category, if the review contains that aspect, we will automatically assign its polarity as the label of a review. To tackle that challenge, we applied a supervised method by choosing the linear SVM classifier with a diversity of extracted features as follows:

- **N-gram:** As was stated previously, we also choose bigram, trigram as feature of n-gram.
- **Word feature:** We select all nouns, verbs, adjectives which appear in reviews for use as a feature.
- **Elongate word:** The number of words with one character repeated more than 2 times (example “ngooonnn”) are adopted.

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<sup>1</sup><http://pypi.org/project/pyvi/0.0.8.0/>

- **Aspect category:** This feature indicated the category is used because the review has the list of different aspects, and each aspect is assigned one of three polarity classes. For that reason, the entity, the attribute and the entity#attribute pairs were collected as a feature.
- **Count of the hashtag:** From the training dataset, we note that the review which has special characters such as the hashtag symbol usually is assigned positive or neutral class in the aspect. We thus calculate the number of hashtag words and use it as a feature.
- **Count the POS feature:** We also calculate the number of nouns, verbs, adjectives as a feature.
- **Punctuation Marks:** True if exclamation marks, question marks are presented in the review.

## 4. EXPERIMENT AND ANALYSIS

### 4.1. Results

Firstly, we compare our method with other methods for multi-label classification problem. As the baseline system, we use Decision Tree (DT), k-Nearest Neighbors (k-NN), Random Forest (RF) as the classification algorithms with above features for aspect detection task. Table 2 shows the comparison results of all the baseline methods and our approach on the test dataset for aspect category detection task, and Table 3 presents our final results in the two tasks for the two domains.

*Table 2.* Performance of on the test dataset on aspect detection for both domains

Domain	Method	Precision	Recall	F1-Score
Restaurant	DT	0.74	0.39	0.51
	k-NN	0.55	0.48	0.52
	RF	0.87	0.27	0.41
	<b>Ours approach</b>	<b>0.79</b>	<b>0.76</b>	<b>0.77</b>
Hotel	DT	0.48	0.45	0.46
	k-NN	0.40	0.42	0.41
	RF	0.72	0.23	0.34
	<b>Ours approach</b>	<b>0.75</b>	<b>0.64</b>	<b>0.69</b>

*Table 3.* The final results on the test dataset for the restaurant and hotel domains

Domain	Precision	Recall	F1-Score
Restaurant	0.62	0.60	<b>0.61</b>
Hotel	0.66	0.57	<b>0.61</b>

As shown in the Table 2 we achieved satisfactory results for aspect detection task with an F1-score of 77% for the restaurant domain and an F1-score of 69% for the hotel domain. After determining aspect- polarity sentiment, we achieved the final results with the same F1-score of 61% on the two tasks for the two domains. Therefore, it is clear that this is still a challenging task.

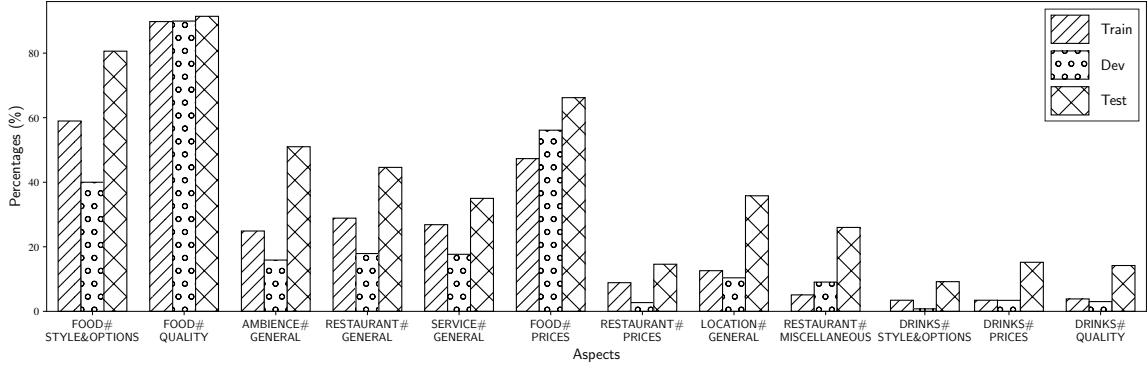


Figure 2. Statistics the percentage of number of reviews of each aspect on three datasets: train, development, test.. We calculate the percentage of reviews that are labeled aspect over the total number of reviews for each dataset

## 4.2. Analysis

In this section, we conducted some analysis of the results of the test dataset for the restaurant domain. The high accuracy obtained from experiment may be achieved thanks to the feature selection. We tested the various features on the development dataset and achieved the highest F1-score with features which are described in this paper. For the restaurant domain, we achieved the F1-score of 79% on aspect detection and the F1-score of 67% on the final result on the development dataset. For the hotel domain, we also achieved the same accuracy on the test dataset, 70% for aspect detection and 62% for aspect-polarity sentiment. There is no significant difference between the result of the development dataset and test dataset. In our view, the result emphasizes the validity of our approach.

### 4.2.1. Analysis: Aspect-polarity

Based on the evaluation results, it was observed that our approach using the transformation method outperforms the other methods on the two tasks for the two domains. There are several possible explanations for this result. Firstly, this is a document-level aspect-based sentiment analysis problem, so each review can consist of many or few sentences. Normally, long reviews will be assigned more aspects. As the result, the difference in the length of reviews will greatly affect the aspect detection classification between the aspects in our approach. For the hotel domain, there is a similarity in length and aspect ratio for each review, but the number of aspects is up to 34 aspects while only 3000 reviews in the training dataset. Therefore, our approach does not have enough samples to train the binary classification for each aspect in the best way. From Figure 2, we can see that the unequal distribution of the percentages of the number of reviews per aspect on three datasets. For example, in the training dataset for the restaurant domain, there are very few reviews which have annotated aspect related to “drinks” entity (e.g. drinks#prices, drinks#quality). However, the number of reviews having this aspect are higher in the testing dataset. Therefore, this results in the low accuracy of detecting this aspect, as shown in Figure 3. The result is the same for the hotel domain which has 34 aspects. Based on the result of each aspect from Figure 2, the aspect “food#quality” or “food#style&options” labelled in many reviews will have good detection accuracy. We also checked why our approach does

not work on aspects assumed to be easily detected, such as “ambience#general”. We recognized that this aspect only has a signature phrase such as “tiệm nhỏ” or “tiệm quá nhỏ” in the reviews and those signs rarely appear in the training set. This also explains the overall result of our system.

#### 4.2.2. Analysis: Aspect-polarity classification

*Table 4.* Examples of the predicted results of our system versus the gold data

Reviews	Gold	Prediction
Đồ ăn khá ngon, nhất là thịt, rau và đậu nhưng vì mắm tôm dở nên chấm vào đều không ngon. Thái độ phục vụ của nhân viên tệ. Đánh giá chung trải nghiệm ở Handmade là không tốt.	+ FOOD#QUALITY: neutral + SERVICE#GENERAL: negative + RESTAURANT#GENERAL: negative	+ SERVICE#GENERAL: positive + FOOD#QUALITY: positive
Bún mắm 45k, quá mắc, chất lượng không quá xuất sắc.	+ FOOD#PRICES: negative + FOOD#QUALITY: neutral	+ FOOD#PRICES: neutral + FOOD#QUALITY: positive

For aspect-polarity sentiment, simply extracting features in the whole review does not seem to provide enough aspect-dependent sentiment information. Extracting features related to positional information of aspects in the review can improve the performance. We only extract, however, “Aspect Category” feature to show the relevant information between aspect and its polarity. In addition, without relying on context or positional information, our polarity model does not work well in some cases, particularly in long reviews with opposing sentiments toward different aspects. Our approach does not correctly classify the presence of implicit polarity. Following the review contains “Food#Prices” aspect and its negative sentiment: “Chả là nhà mình đi lên Đà Lạt nên mướn xe đi, xong tới quán được ông chủ tiếp dài nồng hậu và tặng cho mỗi người 1 cái giá hết sức ưu ái: 55k/tô :v”. This is an example of the implicit aspect-polarity sentiment and our output is positive. Therefore, the further research should be conducted to address these cases.

Besides, another problem that affects the results of polarity classification is the confusion between “neutral” and “positive” labels for the restaurant domain or between “positive” and “negative” labels for the hotel domain. The confusion between “neutral” and “positive” labels is 68%, whereas between “positive” and “negative” labels is only 21% as well as between “negative” and “neutral” is 11%. For the hotel domain, the confusion between “positive” and “negative” labels is 57%, between “positive” and “neutral” is 30%, between “negative” and “neutral” is only 13%. Table 4 gives some examples in the gold test and our prediction for the restaurant domain. In summary, this is one of the limitations of our approach, so there is still a lot of improvement on this task.

## 5. CONCLUSION AND FUTURE WORK

In this paper, we describe our approach to address the problem for aspect-based sentiment analysis for Vietnamese for the two domains. We developed the ABSA system using supervised method for detecting aspect and its polarities by using SVM classifiers with a variety of features. Our approach achieved the best scores on the Vietnamese benchmark dataset for aspect-based sentiment analysis task for the two domains in VLSP 2018.

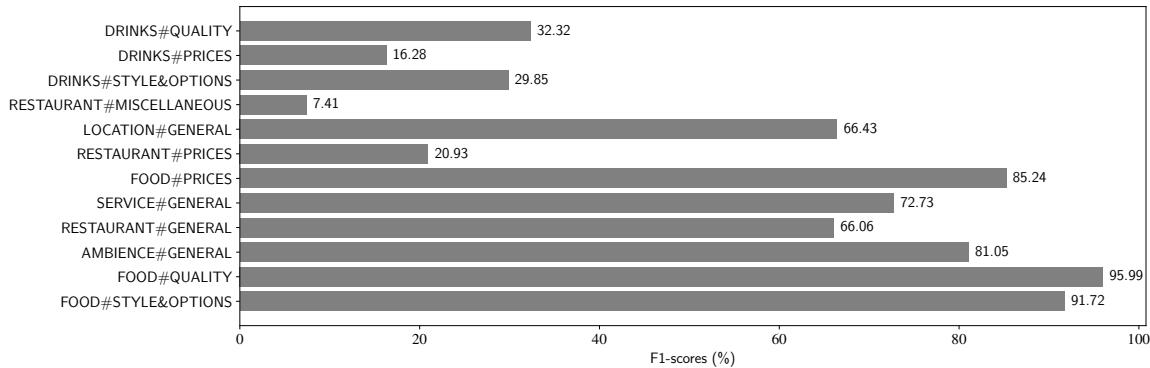


Figure 3. The F1-score of each aspect in the restaurant domains

Although the problem has been studied extensively, however, for Vietnamese this is still a problem to resolve. For future works, we plan to exploit this problem in different ways to improve our performance. We can investigate both feature engineering and types of neural network models for this problem. We can also analyze those datasets for the two domains to select a more efficient approach, such as the hybrid approach which combines supervised method and heuristics to improve the result of classification.

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