VietSentiLex: a sentiment dictionary that considers the polarity of ambiguous sentiment words

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Abstract

The ability to analyze sentiment is a major technology to analyze social media process. The sentiment analysis involves reading and understanding what is being said about a brand as well as advertising campaigns in online services to determine the nature of a product. Because the Vietnamese language has few resources for applying machine learning tasks, use of sentiment dictionaries is required. In this study, a sentiment dictionary called "VietSentiLex" is introduced for the aforementioned task in the Vietnamese language. Most notably, , In this study, instead of applying scores for every word, ambiguous words are considered more carefully as it is periodically positive or negative. Related words such as target nouns or verbs are used as contextual information for a sentiment word. Experiments to compare the performance of our dictionary to others are conducted. We prove that our dictionary has a high potential in predicting the polarity of reviews as compared to other dictionaries. In addition, various challenges and disadvantages of this dictionary are also outlined for future improvement until VietSentiLex can be a commercial product.

Keywords: Sentiment Analysis, Dictionary, Ambiguous Words

1 Introduction

Sentiment analysis is one of the specified smaller tasks of opinion mining, which is sub-discipline at the crossroads of information retrieval and computational linguistics. It involves the contextual mining of sentences to identify sentiment information in input material. Furthermore, it summarizes the target into specified classes such as positive, negative, neutral, interesting, or bad. Thus, sentimental analysis helps a business to roughly estimate user opinions of their brand, products, or services using online reviews and conversations.

With the increase in online comments and reviews on social networks every day, sentiment analysis has begun to play an increasingly more important role in automatically evaluating user opinion, which is manually impossible for a business. Recently, the application of deep learning for this kind of task has become quite common. However, it requires both large and highly accurate sets of data for training, which is reasonably impossible to obtain with low-resource languages like Vietnamese. Thus, in this study, the traditional dictionary-based approach is considered by building a new sentiment dictionary in the Vietnamese language.

This study also introduces a new approach to classify sentiment polarity. All previous works used normal sentiment classification terms such as "positive," "negative," "neutral," or more specifically, "sad," "fun," "happy." Some of the most popular dictionaries such as SentiWord-Net of Andrea and Fabrizio (2006) use the terms "positive," "negative," and "objective." Another is EmoLex by Saif and Peter (2014), which includes the terms "positive," "negative," and

eight other emotional terms: "joy," "sadness," "anger," "fear," "trust," "disgust," "surprise," and "anticipation." Vietnamese versions of these two dictionaries have been produced: VietSentiWordNet by Vu and Park (2014) and VnEmoLex by KTLab (2017), in which all features are the same except for the language. However, this kind of dictionary has the same major problem as the lexicons it contains may not have fixed nature such as positive or negative in all sentences. In other words, a lexicon may be positive in one sentence but negative in another. For example:

- *Việt Nam giá của khách sạn này quá cao so với các khách sạn gần đó.* ⇒ Negative

  (Translation: The price of this hotel is too high compared to other nearby hotels.)

- *Tất cả các đồ dùng trong phòng này đều có chất lượng khá cao, rất thoải mái khi sử dụng.* ⇒ Positive

  (Translation: All the furniture in this room is quite high quality, and is very comfortable to use.)

Here, the word ⌈high⌋ is part of a sentiment lexicon, whose polarity changes based on circumstances, which is the drawback in the previous dictionaries. Although SentiWordNet has many synsets that represent single words with different meanings and polarity, they provide meanings using natural language, which a computer usually cannot understand, thus preventing it from classifying lexicons properly.

Our proposed VietSentiLex dictionary comprises ambiguous classes, in which words are evaluated based on contextual information. In general, nouns or verbs (contextual words) are represented by an adjective (sentiment word). Particularly, in the aforementioned examples, ⌈the price⌋ and ⌈quality⌋ are extracted as contextual information for the sentiment word ⌈high⌋. Thus, the polarity depends on the contextual information instead of the sentiment word. In this study, hotel-related reviews are used as the main dataset for building a sentiment dictionary. Although this dictionary was designed to evaluate hotel reviews, it can be applied to other products but with lower accuracy.

Lexicons in VietSentiLex must have a very high accuracy because of the manual-checking processes that are required during the dictionary construction process.

2 Related Works

Many studies have attempted to build sentiment dictionaries, but the one most related to ours is SentiWordNet by Andrea and Fabrizio (2006) (latest version is 3.0 from 2010). SentiWordNet is a lexical resource in which each synset is associated with three numerical scores: objective, positive, and negative. Each of these three scores ranges from 0.0 to 1.0 and their sum is 1.0 for each synset. Therefore, each synset contains more than one kind of sentiment. Each synset list in SentiWordNet as well as some phrases or example sentences use human natural language. However, a machine will have difficulties determining whether these examples are to be classified as positive, negative, or objective. In general, when using our dictionary, each synset score is calculated based on the sum of three scores, and we use this fixed score for all circumstances.

Others dictionary such as the polarity lexicon of Hu and Liu (2004), which contains 6789 words, drawn from product reviews and labeled using a bootstrapping method from WordNet. Another is the MPQA subjectivity lexicon by Wilson et al. (2005), which contains 8221 words derived from several sources. The Harvard General Inquirer (2002) has 4208 words that are classified as positive, weak positive, neutral, weak negative, and negative. In addition, the PN table of Takamura et al. (2006) contains 55125 words with the same classifications as in the Harvard General Inquirer.

3 Method

The construction process is illustrated in Figure 1. As previously mentioned, VietSentiLex was mostly built by extracting information from dataset of hotel reviews. Initially, to obtain some of the most frequent sentiment words, English and Japanese dictionaries were translated.
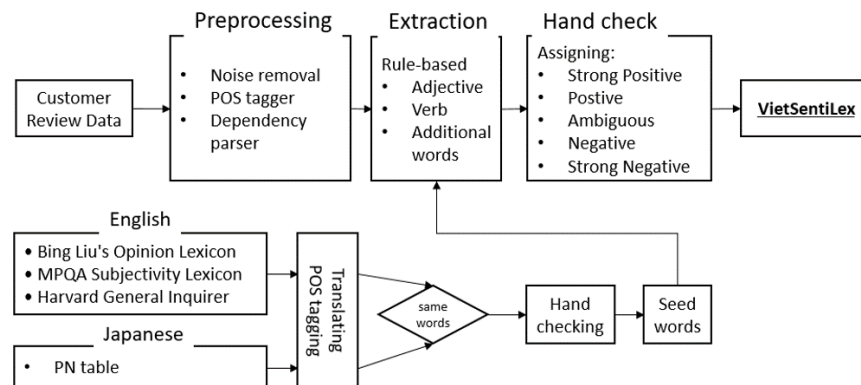
Figure 1: VietSentiLex construction process.

3.1 Translation process

Sentiment words from the dictionary of Hu and Liu, MPQA subjectivity lexicon, and Harvard General Inquirer were used as English sentiment words. In addition, Japanese words from the PN table were also used for translated into Vietnamese using Google Translate API. The translated words were tagged as parts of speech (POS) using the NNVLP POS tagger by Hoang et al. (2017) to remove adverbs or conjunctions that were present based on differences between the two languages. The aforementioned three sets of English lexicons were combined into one translated from English file then compared with the Japanese one. All words that occurred in both languages were stored as translated lexicons. Finally, those words were checked manually and classified as positive or negative if those words having one polarity in all circumstances. In addition, ambiguous words that could have more than one polarity were added to the ambiguous class.

3.2 Extraction process

Most of the contents of VietSentiLex were extracted from 5000 hotel reviews of customers obtained from the corpus of Binh and Son (2010). Each review was scored from 20 to 100 points with increments of 20 points based on five classes: strong positive (100), positive (80), neutral (60), negative (40), and strong negative (20). Pre-processing was first conducted to remove noise in the corpus. The corpus consisted of the following:

- Non-Vietnamese reviews, where the main objective was to analyze only reviews written in Vietnamese. All other language reviews were removed.

- Review sentences that were not written using tone marks. In Vietnamese, tone marks are critical. Without tone marks, even humans have difficulty identifying words because it has many ways to add. In addition, because only a few reviews of this type were present, remove it are faster but not affect the number of data.

- Emotion icon: :)), @-@, :((, etc.

- Web link address.

All remaining reviews were POS tagged using the same program as in the translation process. The main purpose of this dictionary is to consider ambiguous words, and this can be accomplished by extracting contextual information from each sentiment word. Therefore, understanding the relationship between all words in a sentence is necessary for extraction. Thus, the dependency parser VnCoreNLP by Vu et al. (2018) was used for this purpose, as it proved to have the best performance for this task in the Vietnamese language.

Pre-processed data were then used to perform extraction using a rule-based method. As most of the sentiment words were either adjectives or verbs, adjectives and verbs were emphasized

in producing the dictionary. All adjectives and verbs in the corpus were extracted and assigned a polarity depending on the score of each review. Here, neutral reviews were not used because those reviews comprised both negative and positive words that appeared at the same frequency. In addition, all words had to be checked manually later. If we consider such data, the manual checking process would take considerable time. In addition, all related words such as nouns, verbs, and negation words were extracted. Typically, many adjectives connect to each other. For example, the color blue expresses a sentiment word, purple expresses a contextual word, and the same small number refers to related words:

Tôi *thích[1] khách sạn[1]* này vì *giá[2] thấp[2]*, *đáp ứng[3]* đủ *yêu cầu[3]* mà vẫn *đảm bảo[4]* được *chất lượng[4,5] phục vụ[4,5]*, *cơ sở vật chất[4,5]* một cách *hoàn mỹ[5]*. ⇒ Positive

(Translation: I *like[1]* this *hotel[1]* because of its *low[2] price[2]*, can *satisfy[3]* my *requirement[3]* but still *ensure[4]* the *service[4,5] quality[4,5]*, *infrastructure[4,5]* in the *perfect state[5]*.)

Normally, a customer can use more than one sentiment word to describe a product feature so the first work groups all sentiment words connected by punctuation or conjunction and counts them as one word. Next, all related contextual words in that group are added to each sentiment word. Using the previous examples, ⌈service⌋, ⌈quality⌋, and ⌈infrastructure⌋ are grouped and extracted as additional information for the sentiment words, ⌈perfect state⌋ and ⌈ensure⌋. Then, we apply this additional information to both sentiment words, which then becomes: ⌈ensure : service#pos, quality#pos, infrastructure#pos⌋ and ⌈perfect state : service#pos, quality#pos, infrastructure#pos⌋ (#pos describes words that have a positive polarity). We do the same for all reviews so that many circumstances can be considered for better evaluating the polarity of ambiguous words. Rules are created by examining review content, and the main rules are as follows:

- Grouping nouns and adjectives, which are connected by punctuation or conjunction.

- For adjectives: nmod, amod, vmod, root to noun or verb in dependency parser are used.

- For verbs: nouns that have a relation of vmod, dob to that verb.

- Because it does not always have the indirect relation often through some adverb and preposition , 3 knots as maximum were chosen to find relative words.

For manual checking, as the number of mistakes depend on the effectiveness of the dependency parser, the greater the number of mistakes made by the parser, the greater the number of incorrect extracted words. Therefore, if the performance of the dependency parser can be improved, a manual check will be increasingly unnecessary. In addition, verbs are extracted as contextual words for the ambiguous class because of problems in the POS tagger, particularly the same word in Vietnamese may act as noun or verb in different sentences. This concludes that many nouns are mistaken as verbs, and vice versa. Thus, when doing the manual check, carefully examining not only the sentiment of words but also their POS tags is critical. Although when applying fixed words to predict, the sentiment of a review can obtain an incorrect result (as the POS tag remains, the same mistake occurs). This method will be usable in the future when the POS tagger is improved.

Table 1 lists examples of sentiment words in VietSentiLex, where each word is assigned a POS tag. Note that the translation might be somewhat different from the one in Vietnamese because of the differences between languages. The first group includes normal sentiment words, which only have a single polarity of positive or negative such as the adjective ⌈ân cần⌋ (Eng: geniality, attentive, hospitality) , which is a positive word, and the adjective ⌈bất tiện⌋ (Eng: inconvenience) which has a negative polarity. These words are the same as in all other dictionaries. However, most ambiguous words are not assigned a default polarity because ambiguous words (the second group) may have sentiments that depend on contextual words. An example would be the adjective ⌈gần⌋

normal words				
cao_cấp#A#strpos (high-class)	lịch_sự#A#strpos (polite)	hoàn_hảo#A#strpos (perfect)	lý_tưởng#A#strpos (ideal)	niềm_nở#A#strpos (attentive)
thanh_bình#A#pos (peaceful)	hài_lòng#V#pos (satisfied)	tiện_nghi#A#pos (convenient)	xinh_xắn#A#pos (pretty/cute)	tệ_hại#A#neg (very bad)
bất_tiện#V#strneg (inconvenience)	phàn_nàn#V#neg (complain)	xuống_cấp#V#strneg (degrade)	buồn#A#neg (sad)	ầm_ĩ#A#strneg (loudly)

	Sentiment words	contextual information			
ambiguous words	gần#A (near)	bãi_rác#N#neg (landfills)	nhà_hàng#N#pos (restaurant)	biển#N#pos (beach)	bến_xe#N#pos (bus stop)
		hút_thuốc#V#neg (smoke)	trung_tâm#N#pos (center)	sân_bay#N#neg (airport)	trạm#N#pos (bus stop/station)
		cửa_sổ#N#neg (window)	lối_thoát_hiểm#V#pos (emergency exit)	khu_du_lịch#N#neg (tourist area)	...
	đắt#A#neg (expensive/a lot of customers)	buôn_bán#V#pos (trade)	khách#N#pos (customer)	show#N#pos (show)	hàng#N#pos (product)
	dễ_dàng#A (easy)	nguy_hiểm#N#neg (dangerous)	sử_dụng#V#pos (use)	đặt#N#pos (book)	lạc#V#neg (lost)
		bị#V#neg (to be)	hư_hỏng#V#neg (damaged)	nhận_biết#V#pos (cognize)	...

Table 1: Example lexicons in VietSentiLex.

(Eng: near): if it goes with ⌈bãi rác⌋(Eng: landfills), it becomes negative, but if it is near ⌈the beach⌋(biển) it becomes positive. Nevertheless, some ambiguous words that usually have one kind of polarity but may have the opposite sentiment in some cases have a default polarity. Thus, when analyzing words, if no contextual words match contextual words in the dictionary, the default contextual word, e.g., adjective ⌈đắt⌋ in Vietnamese is similar to ⌈expensive⌋ in English, e.g, ⌈Nó đắt quá⌋ (Eng: It's too expensive), However, sometimes, it can be used as ⌈Khách sạn khá **đắt** khách⌋ (Eng: The hotel has quite a lot of customers) but only for some special contextual words. As the number of contextual words depends on the extraction of reviews, the larger dataset, the more sufficient gained.

4 Results and Discussion

4.1 Experiment

To evaluate the performance of our dictionary, an analytical program was produced for analyzing other reviews and comparing our dictionary to VnEmolex (2017) based on different kinds of products and services. The first dataset was a corpus of hotel reviews from Duyen et al. (2014), which contained 1170 reviews scored from 2 to 10 points. In addition, reviews were taken from tiki.vn, which is a famous Vietnamese online shopping website. Tiki.vn has more than 11000 reviews in the following 10 categories: hardcover, headphone, makeup, pens, shampoo, student , baby, and kitchen supplies, phones, and paper products. These were scored on a 20-100-point scale like the corpus used in the extraction process and was pre-processed using the previously described method. In addition, since negation words directly affect the prediction process by reversing the sentiment polarity in a sentence, a list of Vietnamese negation words was also collected to help the program determine when to do the reversal.

This study's primary purpose was to predict the sentiment polarity of each review as positive, negative, or neutral. However, the sentiments of neutral reviews were very difficult to predict because the customers used only one kind of sentiment word. Therefore, most neutral reviews, even though in reference to only bad sites of products or services, were neither positive nor too bad to be negative. Thus, two types of cases were used in our experiment: all reviews as well as neutral and non-neutral reviews. The prediction program was produced by counting the number of positive and negative words inside sentences in each review. Then, the overall score for the review was used to predict the final polarity of that review. The score was 1, 0.5, ?0.5, or ?1 for strong positive, positive,

		VnEmolex			VietSentiLex (Without Ambiguous)			VietSentiLex (full)		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
without Neutral reviews	Binh and Son (hotel)	0.42	0.76	0.54	0.68	0.86	0.76	0.93	0.96	<u>0.95</u>
	Duyen et al. (hotel)	0.55	0.80	0.65	0.70	0.85	0.77	0.85	0.90	<u>0.87</u>
	Pen*	0.61	0.69	0.65	0.63	0.70	0.66	0.65	0.71	<u>0.68</u>
	Shampoo*	0.58	0.70	0.63	0.64	0.76	0.69	0.70	0.81	<u>0.75</u>
	Student tools*	0.32	0.62	<u>0.42</u>	0.31	0.50	0.38	0.30	0.57	0.39
	Baby tools*	0.37	0.63	0.47	0.39	0.65	0.49	0.41	0.66	<u>0.51</u>
	Kitchen tools*	0.35	0.62	0.44	0.46	0.68	0.54	0.56	0.73	<u>0.63</u>
	Phone*	0.36	0.64	0.46	0.39	0.64	0.48	0.41	0.63	<u>0.50</u>
	Papers*	0.30	0.63	<u>0.40</u>	0.30	0.50	0.38	0.30	0.52	0.39
	Cardboard*	0.63	0.65	0.54	0.45	0.59	0.51	0.53	0.60	<u>0.56</u>
	Headphone*	0.60	0.61	0.60	0.58	0.64	0.61	0.58	0.66	<u>0.62</u>
	Makeup*	0.53	0.69	<u>0.60</u>	0.46	0.68	0.55	0.49	0.67	0.57
with Neutral reviews	Binh and Son (hotel)	0.49	0.69	0.57	0.64	0.78	0.70	0.79	0.86	<u>0.82</u>
	Duyen et al. (hotel)	0.49	0.77	0.60	0.63	0.78	0.69	0.76	0.79	<u>0.77</u>
	Pen*	0.34	0.69	0.46	0.35	0.77	0.48	0.36	0.84	<u>0.50</u>
	Shampoo*	0.27	0.62	0.38	0.38	0.68	0.48	0.48	0.73	<u>0.57</u>
	Student tools*	0.35	0.71	<u>0.47</u>	0.35	0.74	0.47	0.34	0.77	0.47
	Baby tools*	0.37	0.81	0.51	0.38	0.84	0.53	0.41	0.87	<u>0.56</u>
	Kitchen tools*	0.35	0.82	0.49	0.46	0.81	0.58	0.56	0.79	<u>0.66</u>
	Phone*	0.35	0.74	0.48	0.38	0.70	0.49	0.41	0.65	<u>0.50</u>
	Papers*	0.35	0.75	<u>0.48</u>	0.31	0.70	0.43	0.32	0.73	0.44
	Cardboard*	0.52	0.66	<u>0.58</u>	0.44	0.51	0.47	0.45	0.52	0.48
	Headphone*	0.55	0.59	0.57	0.56	0.59	0.57	0.57	0.59	<u>0.58</u>
	Makeup*	0.58	0.70	<u>0.63</u>	0.44	0.58	0.50	0.43	0.56	0.49

Note: *product taken from tiki.vn online shopping website. Underlined numbers indicate the best result in each category among three sets of sentiment lexicons.

Table 2: Analyzed results of VnEmolex, VietSentiLex (without using contexts in the ambiguous class), and all lexicons in VietSentiLex.

negative, or strong negative, respectively. The reviews were finally determined to be neutral if the final score was between ?2 and +2; they were positive if higher and negative if lower than this range. In ambiguous lexicons, the score only applied to those reviews in which contextual words were found. If no such words were found in the sentence, a 0 score was applied. Furthermore, to evaluate the importance of the ambiguous class of the dictionary, experiments with and without using the ambiguous class were also conducted. Here, the F1-score was used to evaluate the performance of models to show how well they classify sentiments of each review instead of the overall accuracy.

4.2 Translation results

After we removed all neutral class lexicon, the English lexicon had 9421 and 37868 words in the Japanese PN table. After all manual checking was performed, the translated data had a total of 1536 words, including 738 positive, 322 negative, and 476 ambiguous words. Manual checking required less than five hours. Although the number of sentiment words appearing in both language dictionaries after translation was approximately 2000 words, these words had high accuracy. Thus, most manual checking was to find ambiguous words.

In general, when building a dictionary from scratch for a language, translations of several high-resource languages can be very effective. Unlike with other methods that use an actual

data corpus, our construction process did not require handling raw data ; thus, our basic method was simple and fast. However, this process could generate regularly used words that are the same in all source languages. Hence, every language has its own means of description; the manner in which people use defined terms are also different. Another problem is that the translation of one word can also have many outcomes because of several meanings; thus, the most suitable words to use in different contexts is often difficult to identify automatically by the machine.

4.3 Extraction results

Our final dictionary consisted of 6231 words, with 849 classified as strong positive, 1793 as positive, 789 as negative, 448 as strong negative, and 2352 as ambiguous and included their contextual information to help predict the polarity. Completion of manual checking required up to three days.

4.4 Evaluation

The analysis of VnEmolex and VietSentiLex is shown in Table 2. In general, except for student supplies, makeup, and paper products, our new dictionary had a higher F1-score with both lexicons. In terms of hotel reviews, VietSentiLex showed a significant increase in performance as compared to VnEmolex. Our new sentiment set was based on the dataset of Binh and Son. With hotel reviews from other sources, VietSentiLex also performed very well. In the reviews of tiki.vn, because of the large bias in the number of positive and negative reviews, the values of precision and recall showed a big difference. In other words, no remarkable difference was identified because the created VietSentiLex lexicon was mainly used in describing hotel-related topics. However, applying the lexicon to a cross-domain is still possible. Thus, we can see that words that product purchasers use to give their opinion about different types of products and services have many similar points.

The reasons for incorrectly predicted reviews derived from both sets of data are several, two being the words the customer used in his or her review and the dictionary itself. First, the biggest problem faced by almost every dictionary is that the lexicon was insufficient, particularly for tiki.vn products. Second, contextual words may have been missing for a neutral lexicon, because several means of using a sentiment lexicon with other words existed. In addition, the number of contextual words extracted from the Binh and Son corpus was not sufficient to predict all circumstances. In particular, contextual words in the VietSentiLex ambiguous lexicon did not exist for products and services other than hotels. Third, the contextual words in the ambiguous lexicon should be phrases or a chain of words instead of a single noun or verb, a shortcoming that results in incorrect predictions in certain cases. Finally, the difficulty was in understanding the content of a review, as it may not always have used a sentiment lexicon to describe the opinion contained therein to a target. Sentences such as comparison sentences, which compare two products; comprehensive, complex sentences, which have complex explanations that are very difficult for a machine to understand (for example: ⌈*when I walk in, the staff does not even glance at me; I must figure it out by myself*⌋, ⌈*It worked for only 2 days*⌋; mistakes that occur when applying a polarity based on a recommend review, which can revert the polarity of a sentiment lexicon, or customer using special negation words like the ⌈prevent⌋ word in ⌈*it helps prevent the wooden table from becoming dirty and rotting*⌋ can be a negation word. Other sentences contained spelling or punctuation errors, which produced incorrect dependency parsing but rare, thus those mentioned appeared most often among them.

When the ambiguous class was not used, all ambiguous words were applied to only a single sentiment based on the number of positive and negative contextual words. If more positive than negative words were present, the sentiment word was positive; otherwise, it was negative. It was neutral if the numbers were the same. Here, scores showed a large drop, where the highest drop occurred with hotel reviews. Similarly, the problem that occurred when analyzing

tiki.vn reviews, ambiguous words were not considered. Therefore, the number of lexicons decreased. Nevertheless, compared to VnEmolex, which contained many ambiguous words but which were assigned to only one polarity, it did not predict positive to negative, or vice versa. Although the overall score was somewhat the same, the false predictions of the opposite class were fewer. Therefore, we observed that the ambiguous class was necessary for the dictionary to be usable in practical applications instead of assigning the class to a fixed value.

5   Conclusion and Future Works

Emotion detection and generation have numerous practical applications including the management of customer relations, human-computer interaction, information retrieval, natural text-to-speech systems, and social and literary analysis. In this study, the VietSentiLex sentiment dictionary was introduced and, based on experiments, proved to have a high potential for sentiment analysis. Our study considered not only four normal classes (strong positive, positive, strong negative, and negative) but also included an ambiguous class, in which all ambiguous lexicons could be evaluated based on the contextual information presented by nouns or verb. A total of 6231 lexicons were used to predict sentiment in many kinds of products and services, particularly in hotel reviews. The construction process included manual checking to ensure that the accuracy of our dictionary lexicons was very high.

The performance of VietSentiLex was evaluated by analyzing actual reviews from other datasets and domains. VnEmolex was also considered to compare the effectiveness of our dictionary. Various challenges that the current dictionary faces were described and its disadvantages were outlined. A future study will address those problems before the dictionary can be applied to commercial use.

This method must be improved until it can automatically extract the most accurate sentiment lexicons and contextual words for each ambiguous lexicon or at least reduce the time required for manual checking. Furthermore, the extraction of contextual words must be applied to all classes. Thus, when analysis is performed, contextual words such as nouns and verbs can be shown as the feature of the product or service in question. In addition, all words that are found not to have sentiment after manual checking should be saved, which will aid the automatic extraction process in reducing many easy-to-mistake words that usually appear when extracting sentiment words from normal reviews.

References

A. Esuli and F. Sebastiani. 2006. *SentiWordnet: A publicly available lexical resource for opinio nmining.* in In Proceedings of the 5th Conference on Language Resources and Evaluation (LREC06):417-422.

S. Mohammad and P. D. Turney. 2013. *Crowdsourcing a word-emotion association lexicon.* Computational Intelligence, 29(3):436-465.

X. Vu and S. Park. 2014. *Construction of Vietnamese Sentiwordnet by using Vietnamese dictionary.* The 40th Conference of the Korea Information Processing Society:745-748.

KTLab. 2017. *VnEmoLex: A Vietnamese emotion lexicon for sentiment intensity analysis.* Web publication, 10.5281/zenodo.801610

S. Baccianella, A. Esuli, and F. Sebastiani. 2010. *Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining.* Proceedings of LREC vol.10:17-23.

M. Hu and B. Liu. 2004. *Mining and Summarizing customer reviews.* Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining(KDD04):168-177.

L. Deng and J. Wiebe. 2015. *MPQA 3.0: An Entity/Event-level Sentiment Corpus.* Association for Computational Linguistics:1323-1328.

Philip J. Stone , Dexter C. Dunphy , Marshall S. Smith , Daniel M. Ogilvie. 1968. *The General Inquirer: A Computer Approach to Content Analysis.* American Journal of Sociology 1968 73(5):634-635.

H. Takamura, T. Inui, and M. Okumura. 2006. *Extracting semantic orientations using spin model.* IPSJ journal 47(2):627-637.

H. Pham, X. K. Pham, T. A. Nguyen and L. H. Phuong. 2017. *NNVLP: A Neural Network-Based Vietnamese Language Processing*

Toolkit. Proceedings of the IJCNLP2017, System Demonstration:37-40.

B. T. Kieu and S. B. Pham. 2010. *Sentiment Analysis for Vietnamese.* 2010 Second International Conference on Knowledge and Systems Engineering:152-157.

T. Vu, D. Q. Nguyen, M. Dras and M. Johnson. 2018. *VnCoreNLP: A Vietnamese Natural Language Processing Toolkit.* Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics, Demonstrations:56-60.

T. D. Nguyen, X. B. Ngo, M. P. Tu. 2014. *An empirical study on sentiment analysis for Vietnamese.* 2014 International Conference on Advanced Technologies for Communications (ATC 2014):309-314.