# Vietnamese Complaint Detection on E-Commerce Websites

Nhung Thi-Hong Nguyen <sup>a,b</sup>, Phuong Phan-Dieu Ha <sup>a,b</sup>, Luan Thanh Nguyen <sup>a,b</sup>, Kiet Van Nguyen <sup>a,b</sup>, Ngan Luu-Thuy Nguyen <sup>a,b</sup>

<sup>a</sup> University of Information Technology, Ho Chi Minh City, Vietnam

<sup>b</sup> Vietnam National University Ho Chi Minh City, Vietnam

**Abstract.** Customer product reviews play a role in improving the quality of products and services for business organizations or their brands. Complaining is an attitude that expresses dissatisfaction with an event or a product not meeting customer expectations. In this paper, we build a **Vie**tnamese **O**pen-domain **Complaint Detection dataset (UIT-ViOCD)**, including 5,485 human-annotated reviews on four categories about product reviews on e-commerce sites. After the data collection phase, we proceed to the annotation task and achieve the inter-annotator agreement  $(A_m)$  of 87%. Then, we present an extensive methodology for the research purposes and achieve 92.16% by F1-score for identifying complaints. With the results, in future, we aim to build a system for open-domain complaint detection on E-commerce websites.

**Keywords.** Customers' Complaint and Vietnamese Dataset and Deep Learning and Transfer Learning

## 1. Introduction

In the era of technology development, the trend of online shopping on e-commerce sites is rapidly increasing. Consumers can easily express their opinions or feelings by leaving comments to resolve the complaint issues. Manually processing responses takes a significant amount of time and effort, hence identifying complaints should be automated. According to Olshtain and Weinbach 1987 [20], complaining is a basic speech act used to express a negative mismatch between the expectation and reality towards a state of affairs, products, organizations, or events.

Datasets used for complaint detection are now not so much, especially in Vietnam; there is no dataset about that so far. Therefore, in this paper, we present a human-annotated dataset for this task to automatically identify complaints and contribute to a more robust Vietnamese dataset. After building the dataset, we implement machine learning-based methods as baseline systems to evaluate our dataset.

Our contributions in this paper include:

 We introduce a Vietnamese dataset named UIT-ViOCD, which contains 5,485 human-annotated reviews for identifying complaints on the open-domain such as fashion, cosmetics, applications, and phones. We conduct multiple experiments on different machine learning-based models, including traditional machine learning, deep learning, transfer learning models with low to high complexity and analyze the quantitative dataset. The highest performance is reached by PhoBERT with 92.16% F1-score for complaint speech detection. We also implement different experiments to figure out the role of Vietnamese structure ingredients.

We organize the rest of the paper as follows. Section 2 presents the works related to our task. The process of building and analyze the dataset is described in Section 3. In Section 4, we propose our methodology and discuss experimental results. Finally, we draw a conclusion and future work in Section 5.

## 2. Related Work

In 1987, Olshain et al. [20] stated that complaints are the result when a speaker is adversely affected or expects a favorable event to occur. Complaints can also be described in a positive sense as a report from a consumer documenting a problem with a product or service [3]. Complaints usually co-occur with other speech acts such as warnings, threats, suggestions, or advice. Moreover, Cohen et al. [2] have found that the complaint often occurs as "speech act set".

In the world, there are various studies about customer complaints in different languages. In 2002, Pang et al. [21] used supervised machine learning methods to categorize film reviews with datasets available from the rec.arts.movies.reviews archive. In 2004, Hu and Liu [11] did the research with an aim to mine and summarize all the customer reviews of products, namely, they mined the features of the products collected from the reviews on Amazon.com and Clnet.com, on which the customers have expressed their opinions positively or negatively. Moreover, Gaman and N. Aletras used Distant Supervision, deep learning methods to identify Twitter complaints in English with nine domains [25].

In Vietnamese, the current datasets mostly focus on the emotional recognition problem. Minh et al. researched aspect-based emotional analysis and published a dataset including 7,828 restaurant reviews for solving two sub-tasks: aspect detection and polarity detection [19]. In 2019, Vong et al. built a standard Vietnamese Social Media Emotion Corpus (UIT-VSMEC) consisting of 6,927 human-annotated comments with six emotion labels [8]. In 2021, Nguyen et al. published a Vietnamese dataset about constructive and toxic speech detection named UIT-ViCTSD [18]. Nonetheless, there is no dataset for identifying complaints so far. Therefore, we decide to build a dataset about customer complaints about automatically classifying comments into complaints or noncomplaints.

#### 3. Dataset

We collect customer product reviews from e-commerce sites and Google Play Store<sup>1</sup> with 5,485 reviews belonging to four areas: fashion, cosmetics, applications, and phones.

<sup>1</sup>https://play.google.com/store

## 3.1. Task Definition And Guidelines

Based on the complaint definition proposed by Olshtain and Weinbach [20], we build annotation guidelines for our task.

Complaint (Label 1): Complaining reviews express customers of dissatisfaction between reality and expectations, often accompanied by the build-up and desire to resolve. Complaints usually co-occur with other speech acts such as warnings, threats, suggestions, or advice [25]. Besides, complaining reviews sometimes contain compliments in addition to complaints. Complaints are constructive, not showing hateful emotions or heavy criticism regarding the service or product. Punctuation and special characters, icons can also be physical signs that show complaints.

**Non-complaint (Label 0):** Non-complaining reviews are compliments, praise comments, satisfaction about products and services.

No	Comment	Label		
1	Phải chi có tiếng việt nữa thì tuyệt vời.	1		
1	(It's great to have Vietnamese.)	1		
2	Chất lượng rất tốt, thời gian xử lý đơn hàng và giao hàng quá lâu.			
2	(Very good quality, but take too much time for processing and delivery.)			
3	Không thấy quà tặng theo là như nào lừa đảo à ???	1		
3	(Don't see gifts, scam ???)			
4	Game như L** đừng có tải nha	0		
4	(Game likes P*ssy don't download it)	U		
5	Mình đã sơ đến chai t5 của srm senka r rất ưnggg	0		
3	(I have used the 5th bottle of senka cleanser so satisfied)	0		

Table 1. Examples of reviews annotated for complaint task

Table 1 presents examples of reviews highlighting differences between complaints and non-complaints in our dataset. In the first sentence, the assessment sentence, which sets out unmet customer wishes but does not show negative sentiment, is constructive. The second sentence has both praise and dissatisfaction and is classified as a complaint. Meanwhile, the third sentence shows mixed negative sentiment (angry emotion) and expressed a complaint. In the fourth sentence, we see an insult that implies negative sentiment but is not constructive for the business organizations; hence, this sentence can not be labeled as a complaint. The fifth sentence shows a positive and satisfied attitude to the product.

## 3.2. Annotation Process

It is necessary to know the task for building a high-quality and reliable dataset, thus we create a guideline for annotators before labeling data. The annotator team consists of 3 people who have enough knowledge about natural language processing and labeling data. For evaluating the inter-agreement among annotators, we use the Fleiss' Kappa [1], a statistical technique according to the formula (1).

$$A_{\rm m} = \frac{P_o - P_e}{1 - P_e} \tag{1}$$

Where, the observed agreement  $P_o$  is the proportion of sentences in which both of the annotators agreed on the class pairs. The chance agreement  $P_e$  is the proportion of items for which agreement is expected by chance when the sentences are seen randomly. First, we label a part of the dataset. Then, we measure the  $A_m$  and update guidelines. We repeat this process until the inter-agreement of annotators reaches over 80%. After getting that score, annotators have enough knowledge about the task, and we begin labeling the rest of the data consecutively.

## 3.3. Dataset Analysis

There is no significant difference between 2,854 complaining reviews (52.03%) and 2,631 non-complaining reviews (47.97%).

To have a deeper understanding of the UIT-ViOCD dataset, we analyze the distribution of the complaints dataset according to the length of the sentence, and the results are shown in Table 2. The number of sentences whose length is greater than 30 and makes up most of the dataset, especially in Label 1, occupies up to 46.45%. It shows that customers aim to express their desires and opinions in detail and exact.

Table 2.	Distribution	of the	complaint-annotated	dataset	according	to the	length of	of the	sentence (	(%).	

Length	Label 0	Label 1	Overall
1-5	0.40	0.04	0.44
6-10	1.42	0.27	1.69
11-15	4.41	0.86	5.27
16-20	3.94	1.22	5.16
21-25	2.94	1.22	4.16
26-30	3.43	1.97	5.40
>30	31.43	46.45	77.88
Total	47.97	52.03	100.00

Most customers tend to complain about quality, delivery service, and price. The application field is slightly different from other areas, and customers often show a positive attitude to improve the application. The rest of the sectors tend to be straight to offer dissatisfaction.

We perform a vocabulary-based analysis experiment to understand linguistic features between complaints and non-complaints. This experiment is Part-of-speech, Word Frequency Dictionary, and Embedding Extraction from the identifying complaint task. We assign part-of-speech to each word in every review of our dataset, such as nouns, verbs, adjectives, using ViPosTagger (Vietnamese pos tagging F1\_score = 92.5%) of Pyvi library<sup>2</sup>. We create a frequency dictionary to map the word and the class it appeared to in (complaint and non-complaint) to the number of times that word appeared in its corresponding class. Top part-of-speech features that belong to complaints and non-complaint are analyzed about word feature similarity using Cosine similarity [13] (2). Where,  $\vec{a}$  and  $\vec{b}$  are two vectors of two words extracted from the embedding word model of the this task. Table 4 shows the results of this experiment.

<sup>&</sup>lt;sup>2</sup>https://pypi.org/project/pyvi/

$$Cos(\vec{a}, \vec{b}) = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \|\vec{b}\|} = \frac{\sum_{1}^{n} a_{i} b_{i}}{\sqrt{\sum_{1}^{n} a_{i}^{2}} \sqrt{\sum_{1}^{n} b_{i}^{2}}}$$
(2)

With the results in Table 4, linguistic features from part-of-speech are distinctive of complaints. In detail, several part-of-speech patterns such as coordinating conjunction and adverb are important Vietnamese complaints classification features. Linguistics research identified that a significant proportion of complaints tended to juxtapose overall negative evaluation with some positive appraisal [27]. Definitely, "nhưng" (but) is the word that appears the most in complaining reviews and goes with the good and the bad of the product (e.g. "giao hàng chậm nhưng sản phẩm ok, nguyên seal.", means: "slow delivery but the product is ok, fully sealed."). Moreover, "không" (not, no) often accompanies words that describe the service or product issue. Furthermore, "rất" (very) comes with good characteristics.

Besides, we realize that keywords with complaint meanings (top words) usually go with negative words. Likewise, words that go with non-complaint keywords often have not negative sense.

Abbreviations	Normalization	English meaning
"dx", "dc", "dk"	"được"	"ok"
"dt"	"điện thoại"	"phone"
"god"	"tốt"	"good"
"ship"	"giao hàng"	"ship"

Table 3. Vietnamese abbreviations in the UIT-ViOCD dataset.

# 3.4. Comparison with Other Vietnamese Datasets

Table 5 presents many Vietnamese datasets for different tasks, which is enough to build information recognition features on the social listening system. Compared to other Vietnamese datasets, our dataset (UIT-ViOCD) is the first Vietnamese dataset for complaint classification.

Name	Year	Task	Size	Domain
SA-VLSP2016 [17]	2016	Sentiment Analysis	12,196	Open-domain
SA-VLSP2018 [17]	2018	Aspect-based Sentiment Analysis	10.351	Hotel and Restaurant
UIT-VSFC [26]	2018	Sentiment Analysis	16,175	Education
UIT-VSMEC [8]	2019	Emotion Recognition	6,927	Open-domain
ReINTEL2020 [12]	2020	Responsible Information Identification	10,007	Open-domain
UIT-ViCTSD [18]	2021	Constructive and Toxic Detection	10,000	Open-domain
ViHSD [15]	2021	Hate Speech Detection	33,400	Open-domain
UIT-ViSFD [24]	2021	Aspect-based Sentiment Analysis	11,122	Smartphone
UIT-ViOCD (Ours)	2021	Complaint Detection	5,485	Open-domain

Table 5. Vietnamese datasets for evaluating different text classification tasks.

**Table 4.** The experiment results: Part-of-speech (POS), Word Frequency Dictionary, and Embedding Extraction from Identifying Complaint Task.

Complaint					
POS	Top words	Words have high similarity scores to top-word	Similarity score		
	cập nhật	hôi cực (smell), trễ (late), lựa chọn (choose), xấu (bad),	[0.294, 0.384]		
Verb	(update)	càng (more)	[0.294, 0.364]		
VCID	khắc phục	tẩy trang (cleansing), không thể (can't), trôi (drift), thanh	[0.070, 0.104]		
	(fix)	toán (payment), lâu (slow)	[0.070, 0.104]		
	thất vọng	mỏng (thin), nhưng (but), trừ (minus), đề nghị (suggest),	[0.089, 0.119]		
	(disappoint)	tẩy trang (cleansing)	[0.069, 0.119]		
	tệ	sơ sài (incomplete), mỏng (thin), cồn (alcohol), rách (torn),	[0.029, 0.082]		
Adjective	(bad)	chậm (slow), nhưng (but)	[0.029, 0.082]		
	sai	lộn (mismatch), lừa đảo (cheat), tệ (bad), mỏng (thin), sơ			
		sài (imcomplete), hư hỏng (broken), kém, xấu (bad),	[0.077, 0.125]		
	(wrong)	không (not)			
	lỗi	chậm (slow), gửi (send), móp (dented), bắt (must), thanh			
Noun		toán (payment), nhu cầu (need), chán (bored), khắc phục	[0.105, 0.124]		
Noull	(error)	(fix)			
	trò chơi	đề nghị (suggest), đéo (fuck), thất vọng (disappoint), không	[0.215_0.277]		
	(game)	(not)	[0.315, 0.377]		
	1-1-2	chậm (slow), gửi (send), móp (dented), bắt (must), thanh			
Others	không	toán (payment), nhu cầu (need), chán (bored), khắc phục	[0.107, 0.174]		
Others	(not, no)	(fix)			
	a la ven a	sơ sài (incomplete), rách (torn), gửi (send), mỏng (thin),			
	nhưng	thất vọng (disappoint), cồn (alcohol), chậm (slow), tệ	[0.082, 0.115]		
	(but)	(bad)			
		Non-Complaint			
POS	Top words	Words have high similarity scores to top-word	Similarity score		
	thích	êm (smooth), kỹ lưỡng (elaborate), cảm ơn (thank), tiện	[0.294, 0.384]		
Verb	(like)	dung (comfortable)	[0.294, 0.384]		
	cảm ơn	xinh , dễ thương (lovely), nhờ (thanks to), yêu (love), rẻ	[0.071, 0.119]		
	(thank)	(cheap), nhanh chóng (fast)	[0.071, 0.119]		
	đẹp	rẻ (cheap), biết (know), nhờ (thanks to), mua (buy), tiện	[0.102, 0.137]		
Adjective	(beautiful)	(convenient), tốt, xịn (good)	[0.102, 0.137]		
najecuve	nhanh	hài lòng (sastified), dễ thương (lovely), thích (like), thương	[0.079, 0.117]		
	(fast)	(love), xuất sắc (excellent)	[0.072, 0.117]		
	đúng	vợ (wife), ưng ý (like), kỹ càng (elaborate), dễ thương	[0.189, 0.245]		
	(right)	(lovely), cảm ơn (thank)	[0.107, 0.243]		
Noun	sao	vui vẻ (happy), kĩ càng (elaborate)	[0.156, 0.166]		
110411	(star)	var ve (nappy), at earig (claudiate)	[0.150, 0.100]		
	rất	mình (I), êm (smooth), đi (working), điện thoại			
Others	***	(smartphone), tuyệt vời (excellent), rẻ (cheap), xài (use),	[0.270, 0.312]		
	(very)	đầy đủ (enough)			

## 4. Experiments

We implement various methods on the UIT-ViOCD dataset and then evaluate its quality by four evaluation metrics such as macro-averaged f1 score, macro-averaged precision, macro-averaged recall, and accuracy [23]. We use macro for every metric because our dataset is not imbalanced.

## 4.1. Data Pre-processing and Preparation

We conduct the pre-processing phase to normalize the raw data: lowercasing all texts, removing the HTML tags, extracting white spaces, and applying Unicode standardization. There are many freestyle words in the reviews, like teen code, extending the last sound or acronyms, error typing, or Vietnamese sentences mixed with a few English words. For that reason, we normalize them by accurate words (e.g., "rồii": "rồi" (already)). The old type and the new type are transferred to a unified form (e.g., "òa": "oà"). Moreover, we convert emotional icons to equivalent meaning in Vietnamese. After that, we replace abbreviations with complete words and correct the misspelling. The table 6 shows some examples. Unlike English, white space between two Vietnamese words is the sign for separating syllables, not words. We tokenize every review using Pyvi library for Vietnamese.

After pre-processing data, we split the dataset into training, validation, and test sets with an 80:10:10 ratio by train\_test\_split function of scikit-learn [23]. The results shown in this paper are reported on the test set.

Abbreviations	Normalization	English meaning
"dx", "dc", "dk"	"được"	"ok"
"dt"	"điện thoại"	"phone"
"god"	"tốt"	"good"
"ship"	"giao hàng"	"ship"

Table 6. Vietnamese abbreviations in the UIT-ViOCD dataset.

## 4.2. Experimental Methods

# 4.2.1. Experimental Methods

We conduct various experiments on different models, including traditional machine learning, deep learning, and transfer learning.

After we convert every review to one hot vector, we encode them mapped into embeddings. In particular, each word is represented by a 64-dimensional word embedding. The embedded representation feeds into three models: Logistic Regression, MLP, and BiLSTM.

Traditional Machine Learning Systems

Logistic Regression: Logistic Regression [7] is a binary classification method, as
a one-layer neural network with a sigmoid activation function for the prediction
task.

## Deep Learning Systems

- MLP (Multi-layer Perceptron): MLP [10] has two dense hidden layers (D=512, D=64) with ReLU activation function and the last dense hidden layer (D=1) with sigmoid activation function.
- BiLSTM (Bidirectional Long Short-term Memory): LSTM was developed and achieved superior performance (Hochreiter and Schmidhuber, 1997) [9]. LSTM is a variation of a recurrent neural network, which has an input gate, an output gate, a forget gate, and a cell. In 2005, Graves et al. [5,6] studied BiLSTM in various classification tasks and received good results compared to other neural network architectures. Besides, BiLSTM which consists of two LSTMs has two inputs from forward direction and backward direction. Therefore, BiLSTM can learn contextual information extracted from two directions. Moreover, BiLSTM can learn more features and perform slightly better than LSTM in emotion classification task [29]. In this paper, we use BiLSTM having 128 units for each.

In addition, we use two pre-training word embedding models (PhoW2V and fastText):

- PhoW2V: PhoW2V is published by Nguyen et al. [16], that were pre-trained on a dataset of 20GB Vietnamese texts. In this paper, we use PhoW2V syllables 300 dims and PhoW2V words 300 dims.
- **fastText:** fastText is released by Grave et al. [4]. This model is known for achieving good performance in word performance and sentence classification because they use character-level representations.

## Transfer Learning Systems

• **PhoBERT:** Pre-trained PhoBERT models are the first public large-scale monolingual language models pre-trained for Vietnamese (Nguyen et al. 2020) [16]. This model approach is based on the same RoBERTa [14], which eliminates the Next Sentence Prediction (NSP) task of the pre-trained model BERT. There are two PhoBERT versions: base and large. In this paper, we use PhoBERT base and employ RDRSegmenter of VnCoreNLP [28] to pre-process the pre-training data and Transformers<sup>3</sup> (Hugging Face) for loading pre-trained BERT.

We train the networks using the Adam optimizer by minimizing the binary cross-entropy.

## 4.2.2. Results and Discussion

As the results in Table 7, most models achieve the art performance state with upper 85% of the F1-score. The best performing model is PhoBERT with 92.16% F1-score. These results prove that the dataset has featured enough to help the model classify well.

<sup>&</sup>lt;sup>3</sup>https://huggingface.co/transformers/

Table 7. Results of implemented models on the UIT-ViOCD dataset (%).

Model	F1-score	Recall	Precision
Logistic Regression	89.62	88.17	91.11
MLP	90.97	90.32	91.64
BiLSTM	89.55	92.11	87.12
BiLSTM + PhoW2V_words	88.46	90.68	86.35
BiLSTM + PhoW2V_syllables	86.36	89.61	83.33
BiLSTM + fasttext	86.33	92.83	80.69
PhoBERT	92.16	90.63	94.20

## 4.3. Ablation Tests

We use the ablation technique eliminating structure ingredients for a Vietnamese sentence to evaluate their role in the complaint classification task.

#### 4.3.1. Punctuation

With the desire to exploit the importance of punctuation marks in Vietnamese complaints, we proceed to include in the dataset model with punctuation and without punctuation to assess. The results are shown in Table 8, we notice that removing the punctuation marks has affected the performance of the model, significantly reduced results. This experiment proves that punctuation marks contribute to a better classification model.

Table 8. The experiment results about punctuation.

Model	F1-score			
Model	Punctation	Without punctation		
Logistic Regression	89.62	89.17		
MLP	90.97	89.55		
BiLSTM	89.55	88.57		
BiLSTM + PhoW2V_syllables	86.36	86.36		
BiLSTM + PhoW2V_words	88.46	88.06		
BiLSTM + fastText	86.33	85.13		
PhoBERT	92.16	91.47		

Punctuation is the grammar medium used in writing. It shows the sentence's intonation, expressing nuances about the sentence's meaning and the writer's feelings and attitudes. In specific, question marks differ significantly between complaints and noncomplaints comments and mostly appear in complaining reviews. Customers often express their inquiries, the emphasis on the content by using question marks. They desire businesses to explain why the actual product has not been as expected. For example, the review "hàng chính hãng mà bốc hơi quà km là khăn giấy tẩy trang mà không có một lời giải thích hay báo trước là sao?" ("The official item for which the promotional gift is lost is the makeup remover without an explanation, why?"). Besides, users also often use two dots, bullet marks in their complaints. They list the dissatisfaction, express comments with the desire for businesses to improve products and services. Moreover, punctuation is combined to form emotional icons. For example, the most common icons in complaining reviews are ": (" or ": ((" expressing a sad mood, their frustration. Therefore, the models with dataset retaining punctuation have better performance.

## 4.3.2. Part-of-speech (POS)

In this experiment, we use Logistic Regression algorithm with input POS features from the UIT-ViOCD dataset. Then, we conduct repeated experiments eliminating one of the part-of-speech (noun, verb, adjective, and others) from reviews to test the classification performance versus the result of the experiment with input full of POS features. As result shown in Table 9, the performance of model for classifying decreased slightly by 1-4% with F1-score. This result proves that each part-of-speech is a significant feature for predicting complaining reviews.

	F1-score	Accuracy
Normal	70.09	71.83
Removing Verb	67.38	69.28
Removing Adjective	66.41	68.64
Removing Noun	69.43	71.10
Removing Others	69.25	71.01

Table 9. The result of removing part-of-speech (POS) on the dataset (%).

# 5. Conclusion and Future work

In this paper, we created the UIT-ViOCD dataset about customer complaints in Vietnamese on open-domain. After building the dataset with 5,485 human-annotated comments on four domains, we implemented various methods for the first evaluations on the dataset. As a result, we achieved the highest performance by the fine-tuned PhoBERT classifier, a Vietnamese transfer learning model, for identifying complaints with the F1-score of 92.16%.

In future, we are going to extend the dataset with new comments on different domains besides the current ones. From that results, we plan to create a tool for identifying complaints automatically. Moreover, the UIT-ViOCD dataset can be extended into many other tasks, such as aspect-based complaint analysis (inspired by the task of aspect-based sentiment analysis [24]) or complaint span detection (inspired by the task of toxic span detection [22]). Social listening systems can integrate a complaint classification function.

# Acknowledgement

This research is funded by University of Information Technology-Vietnam National University HoChiMinh City under grant number D1-2021-15.

#### References

- [1] Plaban Kumar Bhowmick, Anupam Basu, and Pabitra Mitra. An agreement measure for determining inter-annotator reliability of human judgements on affective text. In Coling 2008: Proceedings of the workshop on Human Judgements in Computational Linguistics, pages 58–65, 2008.
- [2] Andrew D Cohen and Elite Olshtain. The production of speech acts by eff learners. *Tesol Quarterly*, 27(1):33–56, 1993.
- [3] C Felix and V Clever. The effectiveness of customer complaints handling systems in the commercial banking sector: A case study of commercial banks in harare. Greener Journal of Business and Management Studies, 6(1):21–27, 2016.
- [4] Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. Learning word vectors for 157 languages. arXiv preprint arXiv:1802.06893, 2018.
- [5] Alex Graves, Santiago Fernández, and Jürgen Schmidhuber. Bidirectional 1stm networks for improved phoneme classification and recognition. In *International conference on artificial neural networks*, pages 799–804. Springer, 2005.
- [6] Alex Graves and Jürgen Schmidhuber. Framewise phoneme classification with bidirectional 1stm and other neural network architectures. Neural networks, 18(5-6):602–610, 2005.
- [7] Joseph M Hilbe. Logistic regression models. CRC press, 2009.
- [8] Vong Anh Ho, Duong Huynh-Cong Nguyen, Danh Hoang Nguyen, Linh Thi-Van Pham, Duc-Vu Nguyen, Kiet Van Nguyen, and Ngan Luu-Thuy Nguyen. Emotion recognition for vietnamese social media text. In *International Conference of the Pacific Association for Computational Linguistics*, pages 319–333. Springer, 2019.
- [9] Sepp Hochreiter and Jürgen Schmidhuber. Lstm can solve hard long time lag problems. *Advances in neural information processing systems*, pages 473–479, 1997.
- [10] Kurt Hornik, Maxwell Stinchcombe, and Halbert White. Multilayer feedforward networks are universal approximators. Neural networks, 2(5):359–366, 1989.
- [11] Minqing Hu and Bing Liu. Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pages 168–177, 2004.
- [12] Duc-Trong Le, Xuan-Son Vu, Nhu-Dung To, Huu-Quang Nguyen, Thuy-Trinh Nguyen, Linh Le, Anh-Tuan Nguyen, Minh-Duc Hoang, Nghia Le, Huyen Nguyen, et al. Reintel: A multimodal data challenge for responsible information identification on social network sites. arXiv preprint arXiv:2012.08895, 2020.
- [13] Baoli Li and Liping Han. Distance weighted cosine similarity measure for text classification. In *International conference on intelligent data engineering and automated learning*, pages 611–618. Springer, 2013.
- [14] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019.
- [15] Son T Luu, Kiet Van Nguyen, and Ngan Luu-Thuy Nguyen. A large-scale dataset for hate speech detection on vietnamese social media texts. arXiv preprint arXiv:2103.11528, 2021.
- [16] Dat Quoc Nguyen and Anh Tuan Nguyen. Phobert: Pre-trained language models for vietnamese. arXiv preprint arXiv:2003.00744, 2020.
- [17] Huyen TM Nguyen, Hung V Nguyen, Quyen T Ngo, Luong X Vu, Vu Mai Tran, Bach X Ngo, and Cuong A Le. Vlsp shared task: sentiment analysis. *Journal of Computer Science and Cybernetics*, 34(4):295–310, 2018.
- [18] Luan Thanh Nguyen, Kiet Van Nguyen, and Ngan Luu-Thuy Nguyen. Constructive and toxic speech detection for open-domain social media comments in vietnamese. arXiv preprint arXiv:2103.10069, 2021.
- [19] Minh-Hao Nguyen, Tri Minh Nguyen, Dang Van Thin, and Ngan Luu-Thuy Nguyen. A corpus for aspect-based sentiment analysis in vietnamese. In 2019 11th International Conference on Knowledge and Systems Engineering (KSE), pages 1–5. IEEE, 2019.
- [20] Elite Olshtain and Liora Weinbach. 10. complaints: A study of speech act behavior among native and non-native speakers of hebrew. In *The pragmatic perspective*, page 195. John Benjamins, 1987.
- [21] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up? sentiment classification using machine learning techniques. arXiv preprint cs/0205070, 2002.
- [22] John Pavlopoulos, Léo Laugier, Jeffrey Sorensen, and Ion Androutsopoulos. Semeval-2021 task 5: Toxic spans detection (to appear). In Proceedings of the 15th International Workshop on Semantic Evaluation,

2021.

- [23] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.
- [24] Luong Luc Phan, Phuc Huynh Pham, Kim Thi-Thanh Nguyen, Tham Thi Nguyen, Sieu Khai Huynh, Luan Thanh Nguyen, Tin Van Huynh, and Kiet Van Nguyen. Sa2sl: From aspect-based sentiment analysis to social listening system for business intelligence. arXiv preprint arXiv:2105.15079, 2021.
- [25] Daniel Preotiuc-Pietro, Mihaela Gaman, and Nikolaos Aletras. Automatically identifying complaints in social media. arXiv preprint arXiv:1906.03890, 2019.
- [26] Kiet Van Nguyen, Vu Duc Nguyen, Phu XV Nguyen, Tham TH Truong, and Ngan Luu-Thuy Nguyen. Uit-vsfc: Vietnamese students' feedback corpus for sentiment analysis. In 2018 10th International Conference on Knowledge and Systems Engineering (KSE), pages 19–24. IEEE, 2018.
- [27] Camilla Vásquez. Complaints online: The case of tripadvisor. *Journal of Pragmatics*, 43(6):1707–1717, 2011.
- [28] Thanh Vu, Dat Quoc Nguyen, Dai Quoc Nguyen, Mark Dras, and Mark Johnson. Vncorenlp: a vietnamese natural language processing toolkit. arXiv preprint arXiv:1801.01331, 2018.
- [29] Qimin Zhou and Hao Wu. Nlp at iest 2018: Bilstm-attention and lstm-attention via soft voting in emotion classification. In Proceedings of the 9th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 189–194, 2018.