A Deep Learning Approach to Analyzing Sentiment Across Aspect Categories Using Vietnamese Datasets

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***Abstract*—This study addresses two primary tasks within the domain of Vietnamese Aspect-based Sentiment Analysis: Aspect Category Detection (ACD) and Sentiment Polarity Classification (SPC). The research introduces comprehensive models capable of simultaneously managing these tasks across hotel domain, using the VLSP 2018 Aspect-based Sentiment Analysis dataset. The models leverage PhoBERT, a pre-trained language model tailored for Vietnamese, in four configurations: a Multi-task , a Multi-task with Multi-branch , CNN, and BiLSTM approach. Following thorough preprocessing, the models exhibit robust performance. Notably, the Multi-task model achieves state-of-the-art results in the Hotel domain of the VLSP 2018 ABSA dataset, achieving an F1-score of 55% for ACD and 52% for ACD combined with SPC.**

***Index Terms*—PhoBERT, Aspect-based Sentiment Analysis, Aspect Category Detection, Sentiment Polarity Classification.**

I. Introduction

In today's digital age, the widespread use of the Internet has resulted in an unprecedented surge in data volumes generated by users, particularly in sectors such as e-commerce, social media, and search engines. This has significantly spurred the advancement of Artificial Intelligence (AI), particularly in the realm of Natural Language Processing (NLP). Among these advancements, Sentiment Analysis has gained considerable traction, proving to be increasingly valuable both in academic research and commercial applications. Its primary objective is to gauge customer satisfaction levels by analyzing their reviews. However, there remains untapped potential in harnessing the wealth of data available on the Internet, as user reviews often contain valuable insights for businesses and research institutions alike. Aspect-Based Sentiment Analysis (ABSA) represents a refinement of traditional Sentiment Analysis, specifically designed to address this challenge. Aspect-based Sentiment Analysis involves the methodical examination of text, wherein data is categorized based on specific aspects and the corresponding sentiment polarities are identified for each aspect. For instance, in the context of the hospitality industry, aspects could include customer perceptions of service quality, response times to complaints, or the standard of room amenities. As the Internet and smart mobile devices have become ubiquitous, individuals now have the ability to swiftly and conveniently assess various aspects of products or services. The vast reservoir of review data available online serves as a valuable asset for companies. By meticulously collecting and extracting insights from this data, businesses can discern valuable information about customer preferences and desires, which in turn facilitates strategic growth. Central to this endeavor is the challenge of Aspect-based Sentiment Analysis, which lies at the heart of extracting meaningful insights from customer feedback. This study explores the application of advanced deep learning models to tackle the Aspect-Based Sentiment Analysis (ABSA) challenge using the VLSP 2018 ABSA dataset across two domains: Restaurants and Hotels. The ABSA task encompasses two primary objectives: Aspect Category Detection (ACD) and Sentiment Polarity Classification (SPC). The evaluation metric employed in this research is the average micro F1-score.

II. Related work

In 2023, Yuncong Li, Cunxiang Yin, and Sheng-hua Zhong introduced "Sentence Constituent-Aware Aspect-Category Sentiment Analysis with Graph Attention Networks," [1] presenting a Sentence Constituent-Aware Network (SCAN) designed to optimize aspect-category sentiment analysis. SCAN incorporates two graph attention modules and an interactive loss function, enhancing aspect-category detection and sentiment analysis tasks based on sentence constituency parse trees. Experimental validation on five public datasets demonstrates SCAN's effectiveness, outperforming traditional methods in accuracy and efficiency.

In 2024, Shuo Liang, Wei Wei, Xian-Ling Mao, Fei Wang, and Zhiyong He introduced "BiSyn-GAT+: Bi-Syntax Aware Graph Attention Network for Aspect-based Sentiment Analysis," [2] proposing a framework designed to enhance the alignment of aspect terms and corresponding sentiments. BiSyn-GAT+ leverages syntax information from constituent trees using Graph Neural Networks (GNNs) to model intra-context and inter-context relationships effectively. Specifically focused on fine-grained sentiment analysis tasks, termed Aspect-Based Sentiment Analysis (ABSA), the approach outperforms baselines that solely rely on dependency information, demonstrating superior performance across four benchmark datasets.

In 2024, Hao Yang, Yanyan Zhao, Jianwei Liu, Yang Wu, and Bing Qin introduced "MACSA: A Multimodal Aspect-Category Sentiment Analysis Dataset with Multimodal Fine-grained Aligned Annotations," [3] presenting a dataset of over 21,000 text-image pairs. MACSA facilitates fine-grained analysis by aligning textual and visual annotations to support a novel multimodal aspect-category sentiment analysis task. Their Multimodal Graph-based Aligned Model (MGAM) demonstrates superior performance, leveraging a multimodal heterogeneous graph to integrate information across modalities effectively.

In 2018, Wei Xue and Tao Li demonstrated in their paper "Aspect Based Sentiment Analysis with Gated Convolutional Networks" [4] that Gated Tanh-ReLU Units can selectively generate emotional features based on specific aspects or entities. Their proposed model architecture is notably simpler compared to the attention mechanisms commonly used in modern models, employing a cumulative neural network and localization mechanism.

Nguyen Thi Minh Huyen et al. discussed in their study "VLSP shared task: Sentiment Analysis" [5]a series of VLSP workshops focused on evaluating Sentiment Analysis tools for Vietnamese in 2018. These workshops aimed to assess how effectively these tools could analyze customer evaluations, detailing the creation of specific datasets for these workshops and presenting the evaluation results of the participating systems.

Hai Ha Do et al., in their 2018 article "Deep Learning for Aspect-based Sentiment Analysis: A Comparative Review," [6] emphasized the increasing significance of Sentiment Analysis due to the escalating volume of user-generated content online. This field has become crucial for extracting insights into individuals' emotional states, offering a thorough review of deep learning methods applied to Aspect-based Sentiment Analysis and comparing various approaches.

Thin Van Dang et al. conducted a study titled "Multi-task Learning for Aspect and Polarity Recognition on Vietnamese Datasets" [7], where they devised a deep neural network model. This model addresses two tasks in Sentiment Analysis focused on the document-level aspect of Vietnamese datasets. Their findings indicated superior performance of their model compared to traditional baseline methods in both domains. Specifically, they achieved an F1-score of 64.78% for the restaurant domain and 70.90% for the hotel domain.

Oanh Thi Tran et al., in their 2018 paper "A BERT-based Hierarchical Model for Vietnamese Aspect Based Sentiment Analysis," [8] defined Aspect Based Sentiment Analysis (ABSA) as the task of identifying sentiment orientations towards specific entities and their aspects expressed in customer reviews. They introduced an innovative hierarchical model utilizing a pre-trained language model based on BERT (Bidirectional Encoder Representations from Transformers), known for its effective bidirectional encoding capabilities.

III. Dataset

In this study, we utilized the VLSP 2018 Aspect-Based Sentiment Analysis dataset, with a particular focus on the Hotel domain. This dataset provides a comprehensive collection of reviews specifically tailored to the hospitality industry, allowing us to conduct a detailed and domain-specific analysis of customer sentiments across various aspect categories.

[1]https://vlsp.org.vn/vlsp2018/eval/sa

TABLE I: Hotel VLSP 2018 Aspect-based Sentiment Analysis dataset

Dataset	#Reviews	#Aspects	AvgLength	VocabSize	#DiffVocab
Training	3,000	13,948	47	3,908	-
Dev	2,000	7,111	23	2,745	1,059
Test	600	2,584	30	1,631	346

IV. Method

A. Data Preprocessing

Natural language processing (NLP) involves several stages, with data preprocessing being the critical first step. This phase is particularly crucial in the context of Vietnamese language processing, where thorough preprocessing can significantly enhance the performance of NLP models. Data preprocessing entails normalizing the data and eliminating irrelevant or non-significant elements. By effectively executing this step, the quality and usability of the data are improved, leading to better outcomes in subsequent analysis and model training. To ensure the data is well-prepared, we have designed a comprehensive pipeline that meticulously processes the data, extracting valuable information from the raw input. The pipeline includes a series of detailed steps, each contributing to refining the data for optimal use in NLP tasks.

1) **HTML Code Removal:** Deleted HTML codes from the original dataset.
2) **Charset Standardization:** Converted charset from Windows-1252 to UTF-8.
3) **Vietnamese Word Segmentation:** Utilized VnCoreNLP toolkit [13] for segmenting compound words in Vietnamese.
4) **Character Removal:** Removed unnecessary characters to reduce feature dimensions and enhance processing speed.

In the beginning, the HTML codes were stripped from the original dataset. Following this, character encoding was standardized from Windows-1252 to UTF-8, and common Vietnamese abbreviations were standardized for each domain within the dataset. In Vietnamese, a single word can consist of two or more words (known as a compound word), such as "nhà hàng" (each word has its meaning when standing alone and a different meaning when combined). Therefore, word segmentation for Vietnamese is necessary before further processing, which we implemented using the VnCoreNLP [9] toolkit. Finally, unnecessary characters were removed to reduce the number of sentence feature dimensions, increase processing speed, and avoid negatively affecting the model results.

B. Phobert

PhoBERT, a state-of-the-art language model for Vietnamese, is pre-trained on a large-scale monolingual corpus. It surpasses previous monolingual and multilingual approaches, achieving new state-of-the-art performance on four essential Vietnamese natural language processing (NLP) tasks: part-of-speech tagging, dependency parsing, named-entity recognition, and natural language inference. PhoBERT is available in two versions: PhoBERTbase and PhoBERTlarge. Its pre-training methodology builds upon RoBERTa, which optimizes the BERT pre-training process for enhanced robustness and effectiveness [10], [11].

C. Model Architecture

In our study, we explored four approaches for end-to-end models: Multi-task, Multi-task with Multibranch, BiLSTM, and CNN. These models were designed to handle both Aspect Category Detection (ACD) and Sentiment Polarity Classification (SPC) tasks simultaneously using PhoBERTbase, a pre-trained language model for Vietnamese. Inspired by the original BERT paper bhich demonstrated improved performance by concatenating the last four layers of BERT, we applied a similar method to our model architecture. Specifically, we transformed the input into a low-dimensional vector denoted as $x_I \in \mathbb{R}^d$, where d represents the vector length. [12].

D. Multi-task Approach

The model's output is designed as a sequence of one-hot vectors, where each vector corresponds to one of the 34 distinct aspects found in the VLSP Hotel dataset. Each vector comprises four components, each representing a different polarity label: Positive, Negative, Neutral, and None. The 'None' label is particularly important as it indicates whether a specific aspect is present in the input. If the aspect is present, the model assigns one of the polarity labels (Positive, Negative, or Neutral) a value of 1, while the 'None' label remains 0. Conversely, if the aspect is not present, the 'None' label is set to 1, and the other three polarity labels are set to 0. This one-hot encoding method ensures that for each aspect, only one label is active, accurately reflecting the aspect's presence and polarity in the input data.

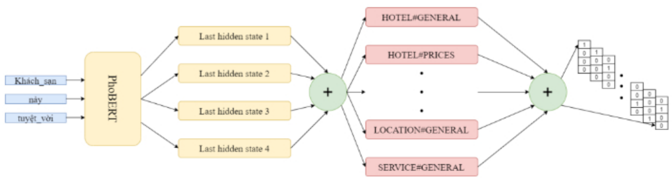

Fig. 1: Multi-task approach for Hotel domain

The learned feature, denoted as (g), is forwarded through a fully connected layer, which is constructed by concatenating C dense layers, each corresponding to one of the C one-hot vectors. For the Hotel domain, the dense layer comprises 136 neurons, reflecting its 34 aspects, each with 4 polarities. To determine the predicted value y_{pred} for each aspect AAA, the softmax function is employed. This function calculates the score, providing a probability distribution over the possible polarities for each aspect.

$$y_{\text{pred}} = \text{softmax}(W^{(a)} \cdot g + b^{(a)}). \tag{1}$$

Thus, we can predict an aspect aaa and its corresponding polarity in a single step by:

$$\text{output}^{(a)} = \arg\max_i \hat{y}_i^{(a)} \quad \text{where} \quad i = 0, 1, 2, 3. \tag{2}$$

In the context of a binary classification problem, the loss function will be structured in the following manner:

The loss function is a critical component for evaluating the performance of the model by measuring the difference between the predicted output and the actual target [16]. Specifically, for binary classification, the loss function quantifies the discrepancy between the predicted probabilities of the two classes and the true class labels. This typically involves using the binary cross-entropy loss, also known as log loss, which calculates the loss for each individual instance and then averages it over the entire dataset. Mathematically, this can be expressed as:

$$L(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i). \tag{3}$$

Here, N represents the number of instances, y_i denotes the true binary label for the i-th instance, and p_i signifies the predicted probability that the i-th instance belongs to the positive class. The function penalizes the model more heavily for confident but incorrect predictions. By minimizing this loss function during training, the model adjusts its parameters to improve its accuracy in distinguishing between the two classes.

In scenarios where we deal with classification problems involving more than two classes (C labels, where C ¿ 2), we typically use the softmax function to compute the probability distribution of the outputs. In such cases, the appropriate loss function to employ is the cross-entropy loss function, which is defined as follows:

$$L(y, \hat{y}) = -\sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij}). \tag{4}$$

For the Multi-task learning method, each classification task is associated with a loss function defined by equation [13]. When there are multiple classification tasks (denoted as C), the overall loss function for multi-task learning is obtained by summing the individual loss functions (in the form of binary cross-entropy) corresponding to each binary classification task.

$$L(y, \hat{y}) = -\sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij}) + (1 - y_{ij}) \log(1 - \hat{y}_{ij}). \tag{5}$$

E. Multi-task with Multi-branch Approach

The main distinction of this approach compared to the previous one is that it creates multiple submodels by employing C fully connected layers, rather than combining them into a single layer. Consequently, each submodel is responsible for predicting each task independently. [15]

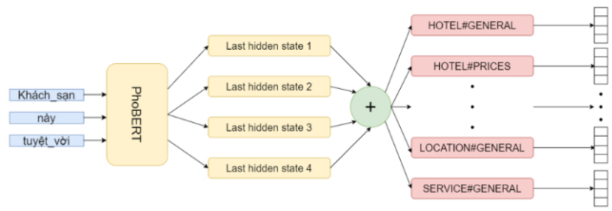

Fig. 2: Multi-task with Multi-branch approach for Hotel domain

The model utilizes the softmax function to compute the scores, allowing it to simultaneously predict both aspect and polarity like the aforementioned model. The final loss function is determined by summing the loss functions across all C branches.

$$L(W; X) = -\sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \cdot \log(\hat{y}_{ij}). \tag{6}$$

F. Bidirectional LSTM

Bidirectional LSTM or BiLSTM is the term used for a sequence model that contains two LSTM layers, one to process the input in the forward direction and the other to process it in the backward direction. It is commonly used in NLP-related tasks. The intuition behind this approach is that by processing data in both directions, the model can better understand the relationship between sequences (e.g., knowing the following words and the previous words in a sentence). [17]

The architecture of a bidirectional LSTM consists of two unidirectional LSTMs that process the sequence in both forward and backward directions. This architecture can be understood as having two separate LSTM networks: one takes the sequence of tokens as is while the other takes them in reverse order. Both these LSTM networks return a probability vector as output, and the final output is the combination of both these probabilities. It can be represented as:

$$p_t = p_t^f + p_t^b \tag{7}$$

where,

p_t : Final probability vector of the network.

p_t^f : Probability vector from the feed-forward LSTM network.

p_t^b : Probability vector from the inverse LSTM network.

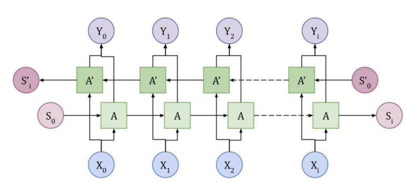

Fig. 3: Bi-LSTM approach for Hotel domain

G. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture of CNNs is inspired by the visual processing in the human brain, and they are well-suited for capturing hierarchical patterns and spatial dependencies within images. [19]

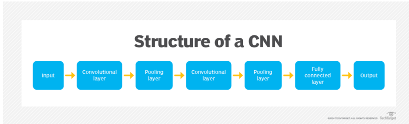

Fig. 4: CNN Structure

1. Convolutional Layers: These layers apply convolutional operations to input images, using filters (also known as kernels) to detect features such as edges, textures, and more complex patterns. Convolutional operations help preserve the spatial relationships between pixels.

2. Pooling Layers: Pooling layers downsample the spatial dimensions of the input, reducing the computational complexity and the number of parameters in the network. Max pooling is a common pooling operation, selecting the maximum value from a group of neighboring pixels.

3. Activation Functions: Non-linear activation functions, such as Rectified Linear Unit (ReLU), introduce non-linearity to the model, allowing it to learn more complex relationships in the data.

4. Fully Connected Layers: These layers are responsible for making predictions based on the high-level features learned by the previous layers. They connect every neuron in one layer to every neuron in the next layer.

V. Result and Discussion

In our experiments, we evaluated the performance of various models on the VLSP 2018 ABSA Hotel dataset using the methods: CNN, Bi-LSTM, Multi-task, and Multi-task with Multi-branch. Our objective was to assess the efficacy of these methods for both Aspect Category Detection (ACD) and Aspect Category Detection with Sentiment Polarity Classification (ACD + SPC). The results are presented in Table II.

TABLE II: Model results on the VLSP 2018 ABSA Hotel dataset with preprocessing

VLSP 2018 ABSA - Hotel				
Task	**Method**	**Precision**	**Recall**	**F1-score**
Aspect Detection	Bi-LSTM	98.80	5.70	5.00
	CNN	77.70	44.30	48.00
	Multi-task	82.70	50.00	55.00
	Multi-task Multi-branch	95.2	47.7	52.3
Aspect + Polarity	Bi-LSTM	96.70	28.10	26.20
	CNN	78.80	45.80	46.60
	Multi-task	82.30	50.09	52.20
	Multi-task Multi-branch	82.2	48.7	50.1

A. Aspect Category Detection (ACD)

The results show that the Multi-task approach achieved an F1-score of 55.00% for Aspect Category Detection, outperforming the CNN and Bi-LSTM models. This indicates that leveraging shared representations across multiple related tasks enhances the model's ability to detect aspect categories effectively. The Bi-LSTM model, while showing high precision (98.80%), had very low recall (5.70%), resulting in a poor F1-score of 5.00%, indicating its inefficacy in this task when used alone.

The CNN model performed better than Bi-LSTM with an F1-score of 48.00%, but it was still outperformed by the Multi-task approaches. The Multi-task Multi-branch model showed an F1-score of 52.30%, which is better than CNN but still lower than the standard Multi-task model, suggesting that while multi-branching offers some improvement, it may not be as effective as a straightforward multi-task approach in this context.

B. Aspect Category Detection with Sentiment Polarity Classification (ACD + SPC)

For the combined task of Aspect Category Detection with Sentiment Polarity Classification, the Multi-task approach achieved an F1-score of 52.20%, outperforming the other methods. The Bi-LSTM model again performed poorly with an F1-score of 26.20%, indicating its limitations in handling complex tasks involving both aspect and polarity detection.

The CNN model achieved an F1-score of 46.60%, which, while better than Bi-LSTM, was still lower than the Multi-task approaches. The Multi-task Multi-branch approach achieved an F1-score of 50.10%, slightly outperforming the CNN model but still not matching the standard Multi-task approach.

C. Discussion

Our results indicate that the Multi-task approach consistently delivers better performance across both ACD and ACD + SPC tasks compared to the other models. This suggests that shared representations in a multi-task framework allow the model to learn more effectively from the data, capturing the nuances of both aspect categories and sentiment polarities. The performance difference between the Multi-task and Multi-task with Multi-branch approaches was notable, with the standard Multi-task model often outperforming the Multi-task Multi-branch model. This suggests that while branching can offer some advantages, in our experiments, the straightforward Multi-task model provided better overall results.

Overall, our experiments highlight the effectiveness of the Multi-task approach for aspect-based sentiment analysis on Vietnamese datasets. This method outperformed traditional models like Bi-LSTM and CNN, as well as the Multi-task Multi-branch approach, making it a robust choice for similar tasks in the field of sentiment analysis. Preprocessing plays a critical role in enhancing model performance by cleaning and structuring input data, helping models better recognize patterns and make more accurate predictions.

VI. Conclusion and Future Work

In this study, we focused on Aspect-based Sentiment Analysis using the VSLP 2018 ASBA dataset, exploring a variety of advanced models to enhance predictive accuracy. Our approaches included integrating PhoBERT with CNN and BiLSTM architectures, alongside multi-task and multi-branch methodologies. The PhoBERT + CNN model leveraged CNN's ability to capture local features and patterns within textual data, complementing PhoBERT's strong contextual understanding. Meanwhile, the PhoBERT + BiLSTM ensemble model capitalized on BiLSTM's capability to capture bidirectional dependencies and long-term context, enhancing the model's sensitivity to sequential information. Our findings demonstrated significant improvements in sentiment analysis across both Hotel and Restaurant domains, particularly with the multi-task model achieving state-of-the-art results in Hotel sentiment analysis. Additionally, the multi-branch approach showed promising results in fine-grained sentiment analysis within the Restaurant domain. Effective preprocessing techniques tailored to domain-specific needs played a critical role in optimizing model performance.

Looking ahead, our research will continue to explore alternative approaches such as graph models and diverse BERT variants like PhoW2V, fastText, multi Embedding, and vELECTRA. Furthermore, incorporating advanced data augmentation techniques such as language translation and paraphrasing aims to further enhance the robustness and generalization capabilities of our models, ensuring they are well-equipped to handle varied linguistic nuances and evolving data challenges.

References

[1] Yuncong Li, Cunxiang Yin, and Sheng-hua Zhong. Sentence Constituent-Aware Aspect-Category Sentiment Analysis with Graph Attention Networks. In *Natural Language Processing and Chinese Computing*, 2020. Available at: https://api.semanticscholar.org/CorpusID:222133379

[2] Shuo Liang, Wei Wei, Xian-Ling Mao, Fei Wang, and Zhiyong He. BiSyn-GAT+: Bi-Syntax Aware Graph Attention Network for Aspect-based Sentiment Analysis. In *Findings*, 2022. Available at: https://api.semanticscholar.org/CorpusID:248005999

[3] Hao Yang, Yanyan Zhao, Jianwei Liu, Yang Wu, and Bing Qin. MACSA: A Multimodal Aspect-Category Sentiment Analysis Dataset with Multimodal Fine-grained Aligned Annotations. *ArXiv*, 2022. Available at: https://api.semanticscholar.org/CorpusID:250089198

[4] Wei Xue and Tao Li. Aspect based sentiment analysis with gated convolutional networks. arXiv preprint arXiv:1805.07043, 2018.

[5] 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.

[6] Hai Ha Do, PWC Prasad, Angelika Maag, and Abeer Alsadoon. Deep learning for aspect-based sentiment analysis: a comparative review. Expert Systems with Applications, 118:272–299, 2019.

[7] Dang Van Thin, Duc-Vu Nguyen, Kiet Van Nguyen, Ngan Luu-Thuy Nguyen, and Anh Hoang-Tu Nguyen. Multi-task learning for aspect and polarity recognition on vietnamese datasets. In International Conference of the Pacific Association for Computational Linguistics, pages 169–180. Springer, 2019.
[8] Oanh Thi Tran and Viet The Bui. A bert-based hierarchical model for vietnamese aspect based sentiment analysis. In 2020 12th International Conference on Knowledge and Systems Engineering (KSE), pages 269–274, 2020.
[9] Thanh Vu, Dat Quoc Nguyen, Dai Quoc Nguyen, Mark Dras, and Mark Johnson. VnCoreNLP: A Vietnamese natural language processing toolkit. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations, pages 56–60, New Orleans, Louisiana, June 2018. Association for Computational Linguistics
[10] PhoBERT: Pre-trained language models for Vietnamese
[11] Nguyen, Dat Quoc VinAResearch/PhoBERT: PhoBERT: Pre-trained language models for Vietnamese (EMNLP-2020 Findings)
[12] Model Architecture
[13]]Multi task Solution for Aspect Category Sentiment Analysis on Vietnamese Datasets
[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] A BERT-based Hierarchical Model for Vietnamese Aspect Based Sentiment Analysis
[16] Multitask painting categorization by deep multibranch neural network
[17] Bidirectional LSTM in NLP
[18] Datacamp tutorial loss function in machine learning
[19] convolutional-neural-network-cnn-in-machine-learning