

A BERT-based Hierarchical Model for Vietnamese Aspect Based Sentiment Analysis

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Abstract—Aspect based sentiment analysis (ABSA) is the task of identifying sentiment polarity towards specific entities and their aspects mentioned in customers' reviews. This paper presents a new and effective hierarchical model using the pre-trained language model, Bidirectional Encoder Representations from Transformers (BERT). This model integrates the context information of the previous layer (i.e. entity type) into the prediction for the following layer (i.e. aspect type) and optimizes the global loss functions to capture the entire information from all layers. Experimental results on two public benchmark datasets in Vietnamese showed that the proposed model is superior to the existing ones. Specifically, the model achieved 84.23% and 82.06% in the F1_micro scores in detecting entities and their aspects on the domains of restaurants and hotels, respectively. In identifying aspect sentiment polarity, the model gained 71.3% and 74.69% in the F1_micro scores on the domains of restaurants and hotels, respectively. These results outperformed the best submission of the campaign by a large margin and gained a new state of the art.

Index Terms—aspect based sentiment analysis, hierarchical model, BERT, Vietnamese

I. INTRODUCTION

In the business world, the rapid development speed of e-commerce, especially the B2C¹ model, has led to a boom in online shopping behaviors. It provides the general public a very convenient way of day to day purchases and gradually becomes one of the most popular forms of buying, especially in the pandemic period like COVID 19. With the spread of the social media technologies, customers nowadays have an increasing trend in leaving reviews after the positive or negative experiences with the products/services of their choices. Automatically mining such reviews would not only help consumers decide what to purchase but also businesses to better monitor their reputation and understand the needs of the market. Therefore, sentiment analysis has been becoming one of the most active research field among researchers both from an academic and a commercial standpoint in recent years.

In this paper, we deal with aspect based sentiment analysis (ABSA) which aims at identifying various aspects of entities mentioned in reviews and then determining their corresponding sentiments. This allows us to associate specific sentiments with different aspects of a product or service if any. An

example is given in Figure 1, which shows a review mentioning 4 entities (*FOOD*, *AMBIENCE*, *SERVICE*, and *RESTAURANT*), five aspects of these entities (*FOOD#QUALITY*, *FOOD#OPTIONS&OPTIONS*, *AMBIENCE#GENERAL*, *SERVICE#GENEARL* and *RESTAURANT#PRICES*) and their corresponding sentiment polarity. We realized that not all types of aspects could go well with every single entity. For example, the aspects *STYLE&OPTIONS* and *PRICES* are not applicable to the entity *AMBIENCE*. Moreover, many previous research [21] concluded that the same words in different domains/aspects have different polarity. Therefore, determining aspect types and their polarity highly depends on the entities and the aspects mentioned in each review.

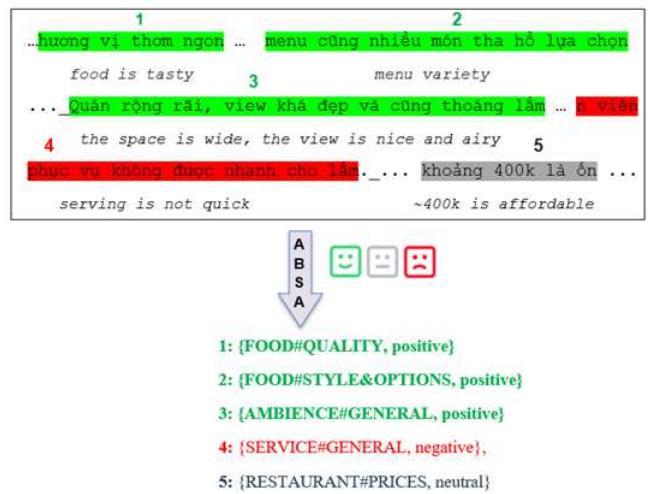


Fig. 1. A Vietnamese review about the restaurant domain and extracted entities-aspects and their sentiment polarity.

For popular languages like English, several ABSA datasets have been constructed via the SEMEVAL [14] shared task series, or the more challenged one [6]. Thanks to these public ones, lots of methods have been proposed to investigate and build the effective prediction models using rules [5], topic modelling [9], traditional machine learning methods [7], [20], or deep learning innovation [2]. In Vietnam, studies about

¹B2C: business to customer model.

ABSA just have been originated from the VLSP competition² in 2018. In that shared task, the organizers provided two benchmark datasets of Vietnamese reviews and a common evaluation framework [12], [13]. The datasets were labeled with coarser aspect categories and their polarity on two domains of hotels and restaurants.

Based on these Vietnamese datasets, some methods have been proposed using Support Vector Machine (SVM) [18] or multi-layer Perceptron [13] with heavy feature engineering, or deep learning methods such as Convolutional Neural Network (CNN) [4].

Recently, the latest innovation in pre-trained language models has eliminated the effort of feature engineering and achieved SOTA results in many typical NLP tasks. Motivated from this achievement and the dependence among entities, aspects and their polarity, in this paper, we present a new hierarchical architecture based on BERT to recognize the entities, the associated aspects and their sentiment polarity. In predicting the labels of the next layer, we use the context information about the output of the previous layer. This model captures well the hierarchical nature of ABSA in which the types of aspects highly depend on the types of entities mentioned. The experimental results showed that our proposed model obtained the new SOTA results on both two phases on two datasets. Specifically, the new model achieved 84.23% and 82.06% in the F1_micro scores in detecting entities and their aspects on the domains of restaurants and hotels, respectively. In identifying aspect sentiment polarity, the model gained 71.3% and 74.69% in the F1_micro scores on the domains of restaurants and hotels, respectively.

The remainder of this paper is organized as follows. Section 2 describes related research on ABSA. Section 3 presents our proposed model using BERT to simultaneously recognize the entities, their aspects and also the sentiment polarity mentioned. Section 4 shows experimental setups, experimental results and the discussion. Finally, we conclude the paper and point out some future work in Section 5.

II. RELATED WORK

ABSA was first studied and introduced by Hu and Liu in 2004 [5]. Nowadays, it has been receiving great attention from the NLP research community of both academic and industrial fields. Since 2014, it has officially become the shared task of the SEMEVAL series attracting lots of teams participating from all over the world. Different methods have been proposed to deal with the task and can be divided into 4 main approaches: rule-based, topic modelling, traditional machine learning, and deep learning methods. The first and earliest works are models based on language rules. For example, Hu and Lu [5] determined all frequent noun phrases as aspect candidates and applied pruning methods to remove aspects with no meaning. Poria et al. [15] proposing a novel rule-based approach that exploits common-sense knowledge and sentence dependency trees to detect both explicit and implicit

²<https://vlsp.org.vn/vlsp2018/eval/sa>

aspects. The second approach is unsupervised models which are based on PLSI and LDA. For example, Lu et al. [9] clustered the head terms using PLSI to extract aspects, and then specified its polarity by considering it as the polarity of the corresponding short comment. Bagheri et al. [1] introduced a model that can extract aspects automatically using the structure of reviewed sentences. The third approach exploited traditional algorithms such as SVM and relied heavily on feature engineering [7], [20]. Recently, the deep neural models such as LSTMs [2] by Bao et al., attention-based [19] by Wang et al. achieved higher accuracy. Ma et al. [10] incorporated useful commonsense knowledge into a deep neural network to further enhance the result of the model. More recently, the pre-trained language models, such as ELMo, and BERT have shown their effectiveness to alleviate the effort of feature engineering and demonstrated their robustness in ABSA tasks. For example, Sun et al. [16] converted the task to a sentence-pair classification task by constructing auxiliary sentences and fine-tuned BERT to solve the task.

While lots of efforts were dedicated to ABSA in popular languages, especially English, not much work done for poor-resourced languages like Vietnamese. The main reason is due to the lack of public benchmark datasets. In 2018, the first public Vietnamese benchmark datasets were released via the VLSP campaign. Based on these datasets, there were several approaches proposed. For example, Nguyen and Minh [13] considered the task as a multi-class classification problem (each label is a pair of aspect-polarity) and built one classifier to solve the task, Van et al. [18] treated the task as multiple binary classification problems and built a single binary classifier for each aspect. The authors exploited traditional machine learning algorithms such as SVM and Multi-layer Perceptron with handcrafted features (including n-grams of words, POS tags and TF-IDF scores). After the campaign, Dang et al. [4] presented a deep learning approach using CNN architecture for the aspect detection. They claimed the superiority of this model over the above two winning systems on these datasets for the aspect detection task.

In this work, motivated from the achievement of pre-trained models on lots of NLP tasks and the hierarchy structure in ABSA, we propose a new and effective model which is shown to outperform the existing methods by a large margin on the same datasets.

III. PROPOSED MODELS

A. Problem Formulation

The problem can be stated as follows: Given a review r of customers about the domain of their interest. ABSA needs to identify the entity e mentioned in r , and then detect the aspect a of e which an opinion is expressed, and finally assign one of the following polarity labels which are *positive*, *negative* and *neutral* to each pair (a, e) found. For each working domain, e and a must be from the predefined inventories of entities and aspect types of that domain (as indicated in the section about datasets). These predictions somewhat follow the hierarchical structure where determining the aspect categories depends on

the entity e mentioned in the review r and the polarity of the same words in different aspects/entities might be different.

B. A Bert-based hierarchical model to ABSA

Figure 2 depicts our proposed model to solve the task. It consists of two main components. The lower component exploits BERT architecture to encode the context information of r into a representation vector x . Then, x will be used as input to the hierarchical model to generate multiple outputs (which entities? which aspects? and which polarity?) corresponding to each prediction layer. The details about this architecture are presented in the following sub-sections.

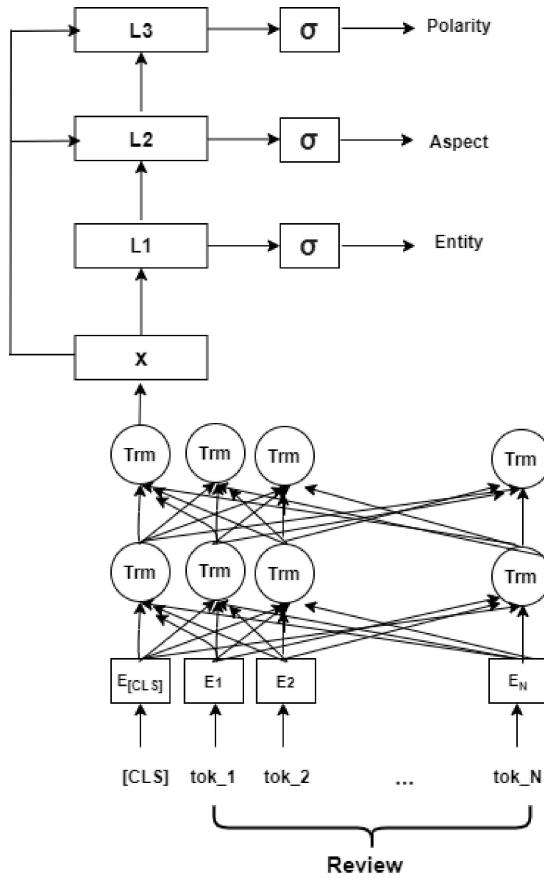


Fig. 2. A hierarchical model based on BERT for analyzing aspect based sentiments.

1) BERT architecture: BERT's model [3] introduced by Devlin et al. in 2019 is a multi-layer bidirectional transformer encoder based on the original implementation. This pre-trained language model has shown their effectiveness to alleviate the effort of feature engineering and has achieved excellent results in many NLP tasks of different languages. This achievement of BERT motivates us to explore the strength of BERT-based methods in predicting entities, aspects and sentiment polarity mentioned in customers' reviews in Vietnamese social texts. BERT is deeply bidirectional, unsupervised language representation, pre-trained using only a plain text corpus. This contextual model generates a representation of each word

based on the other words in the sentence. In other words, the word vector BERT outputs for a word is dependent on the surrounding context in which it occurs.

To generate the vector representation x for each review r , we exploited multilingual BERT³ which is trained on 102 languages without cross-lingual supervision. To boost the performance, we further pre-train mBERT on our monolingual Vietnamese corpus (with more than 20GB of texts) to create our own viBERT. This viBERT is optimized for capturing the characteristics of Vietnamese texts.

In this architecture, we first use a tokenizer to split the review r into different tokens, namely $tok_1, tok_2, \dots, tok_N$. For classification tasks, we must prepend the special [CLS] token to the beginning of every review. A BERT model will encode everything it needs at the final hidden state into this [CLS] token. This is exactly the vector representation x of the input review r .

2) A multilabel hierarchical architecture on top of BERT: This architecture is proposed to facilitate the learning process in regards to the hierarchical structure of the three label levels in the ABSA task. The information is flown from the first layer $L1$ to the second layer $L2$ and then from $L2$ to the third layer $L3$. Layer 1 captures the information of entity labels, layer 2 captures the information of both entities and aspect types, while layer 3 captures the information of accumulated aspect types and their sentiment polarity.

This component takes in the vector representation x of r and passes it through the first activation layer $L1$ which is calculated as follows:

$$L_1 = f(W_1x + b_1) \quad (1)$$

The output of the previous layer together with x is then forwarded to the subsequent layer which is determined by the following linear activation function:

$$L_i = f(W_i(L_{i-1} \oplus x) + b_i), i = 2, 3 \quad (2)$$

where f is a linear function, \oplus is the concatenation operation of two vectors, W_i is the weight matrix, and b_i is the bias vector of i^{th} layer.

The prediction for each layer P_i is calculated using the corresponding sigmoid function which connects the activation of each layer with the output of that layer. During training, the model minimizes the global loss function which is calculated by taking sum of the three loss functions of the three predictors P_i .

IV. EXPERIMENTS

A. Dataset

The format of VLSP 2018 on ABSA is quite similar to the SemEval 2016 ABSA subtask 2. The campaign dealt with data in two domains, namely restaurants and hotels. The raw data were collected from comments of two source sites which are lozi⁴ and tinhte⁵. These data are usually short and contain

³<https://github.com/google-research/bert/blob/master/multilingual.md>

⁴<https://lozi.vn/>

⁵<https://tinhte.vn/>

opinions of one entity. But the number of aspects mentioned in each comment is unlimited. The annotators were hired to label each comment based on the categories shown in Figures I and II. These figures also depict the possible combination of (e, a) pairs in each domain.

TABLE I
POSSIBLE ENTITY-ATTRIBUTE PAIRS FOR RESTAURANT DOMAIN.

	General	Price	Quality	Style& Option	Misc
Restaurant	✓	✓			✓
Food		✓	✓	✓	
Drink		✓	✓	✓	
Ambience	✓				
Service	✓				
Location	✓				

TABLE II
POSSIBLE ENTITY-ATTRIBUTE PAIRS FOR HOTEL DOMAIN.

	General	Price	Feature&Design	Cleanliness	Comfort	Quality	Style&Option	Mis.
Hotel	✓	✓	✓	✓	✓	✓		✓
Room	✓	✓	✓	✓	✓	✓		✓
Room Amenities	✓	✓	✓	✓	✓	✓		✓
Facilities	✓	✓	✓	✓	✓	✓		✓
Service	✓							
Location	✓							
Food&Drink		✓				✓	✓	✓

The task is formulated into two official subtasks as follows:

- **Phase A (Entity-Aspect):** identifying all pairs (e, a) mentioned in r .
- **Phase B (Aspect-Polarity):** identifying the sentiment polarity for each (e, a) pair determined in **Phase A**.

The information about the train, dev and test sets is summarized in Table III.

TABLE III
STATISTICS ON THE TRAIN, DEV, AND TEST SETS OF TWO DATASETS ON TWO DOMAINS.

Domain	Dataset	#Reviews	#Aspects
Restaurant	Training	2961	9034
	Development	1290	3408
	Test	500	2419
Hotel	Training	3000	13948
	Development	2000	7111
	Test	600	2584

B. Evaluation Metrics

To measure the performance of the model, we use the metrics proposed by the organizers of the campaign for each phase. The precision, recall and F1-score of each phase are micro-averaged and calculated as follows:

$$Pre = \frac{\sum_{c_i \in C} TP_{c_i}}{\sum_{c_i \in C} TP_{c_i} + FP_{c_i}} \quad (3)$$

$$Rec = \frac{\sum_{c_i \in C} TP_{c_i}}{\sum_{c_i \in C} TP_{c_i} + FN_{c_i}} \quad (4)$$

$$F1 = 2 * \frac{Pre * Rec}{Pre + Rec} \quad (5)$$

where TP is the number of reviews correctly assigned to class c_i , FP is the number of reviews incorrectly assigned to class c_i , FN is the number of reviews should be assigned class c_i but is not predicted, c_i is the i^{th} class in the number of C classes for each phase.

1) *Model Training:* In performing experiments, we implemented the framework using Pytorch. For further pre-training BERT, we exploited the tool released by Google as mentioned before. The hyper-parameters of models were chosen via a search on the development set. We varied different parameters of the model to find the optimized sets for filter windows sizes, dropout rates, optimization methods, learning rates, batch sizes, number of epochs, etc.

C. Experimental results

We compare the model with the existing models on the same datasets. They are:

- 1) **SA1** (Van et al., 2018): SVM-rich features
- 2) **SA2** (Nguyen and Pham, 2018): MultiLayer Perceptron
- 3) **SA3** (Vu and Anh, 2018): Linear SVM
- 4) **SA4** (Dang et al., 2018): CNN-based architecture

Table V and IV show experimental results of the participating systems and our proposed methods. In Phase A of detecting entities and aspects, the proposed models got about 4% (F1_micro) higher than the best CNN-based architecture in the restaurant domain; about 12% (F1_micro) higher than the best SA1 in the hotel domain. For the proposed models, experimental results showed that further training mBERT on a large-scale Vietnamese dataset significantly improves the performance of the prediction models. Using viBERT, our best model obtained 84.23% and 82.06% in the F1_micro score on the domain of restaurants and hotels, respectively.

In Phase B of identifying sentiment polarity, our proposed models significantly boost the F1_micro score on both two domains by more than 10%. The experimental results also reinforce that further pre-training mBERT could effectively enhance the performance of predicting. Overall, we achieved 71.3% in the F1 score on the restaurant domain, and 74.69% in the F1 score on the hotel domain.

D. F1 learning curves

Figures 3 and 4 show the performance of the models on the development and testing sets on two datasets. We measured F1_micro scores with different values of numbers of epoches. The model seems to converge when the number of epoches reaches 100. In Phase A - detecting entities&aspects, the performance of the models almost be the same on the development and testing sets. However, on Phase B, the performance on the testing sets is usually lower than on the development sets.

TABLE IV
EXPERIMENTAL RESULTS ON THE TEST SET OF RESTAURANT DOMAIN (– MEANS NOT AVAILABLE).

Domain	Methods	Phase A (Entity&Aspect)			Phase B (Aspect polarity)		
		Pre	Rec	F1	Pre	Rec	F1
<i>Existing methods</i>							
RESTAURANT	SA1: SVM-rich features	0.79	0.76	0.77	0.62	0.60	0.61
	SA2: MultiLayer Perceptron	0.88	0.38	0.54	0.79	0.35	0.48
	SA3: Linear SVM	0.62	0.62	0.62	0.52	0.52	0.52
	SA4: CNN-based	0.8475	0.7648	0.8040	–	–	–
<i>Our methods</i>							
RESTAURANT	mBERT HM	0.8403	0.8264	0.8333	0.6570	0.7143	0.6845
	viBERT HM	84.21	84.25	0.8423	69.75	72.92	0.7130

TABLE V
EXPERIMENTAL RESULTS ON THE TEST SET OF HOTEL DOMAIN (– MEANS NOT AVAILABLE).

Domain	Methods	Phase A (Entity&Aspect)			Phase B (Aspect PolaritY)		
		Pre	Rec	F1	Pre	Rec	F1
<i>Existing methods</i>							
HOTEL	SA1: SVM-rich features	0.76	0.66	0.70	0.66	0.57	0.61
	SA2: MultiLayer Perceptron	0.85	0.42	0.56	0.80	0.39	0.53
	SA3: Linear SVM	0.83	0.58	0.68	0.71	0.49	0.58
	SA4: CNN-based	0.8235	0.5975	0.6925	–	–	–
<i>Our methods</i>							
HOTEL	mBERT HM	0.8532	0.7604	0.8042	0.7817	0.6556	0.7131
	viBERT HM	0.8393	0.8026	0.8206	0.8004	0.7001	0.7469

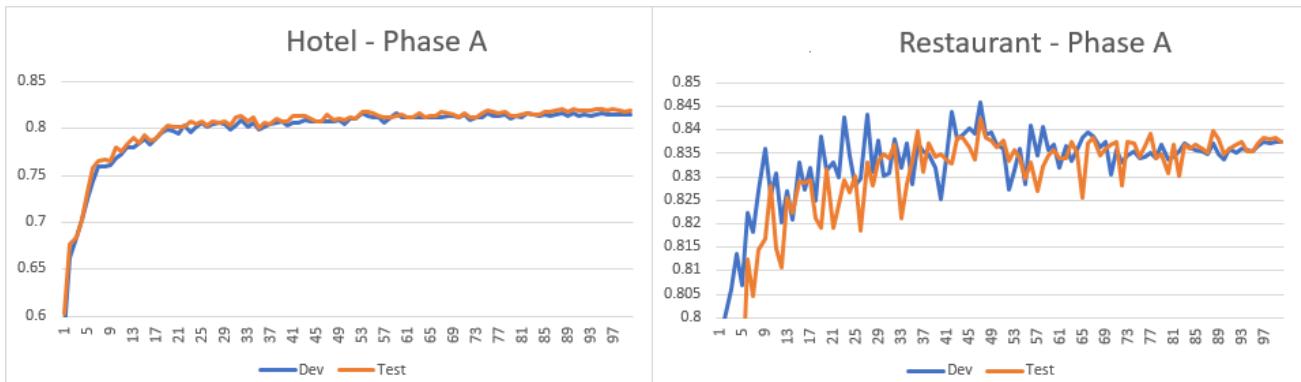


Fig. 3. The F1 score curves on the dev and test sets of two domains - PHASE A (Entities&Aspect Detection).

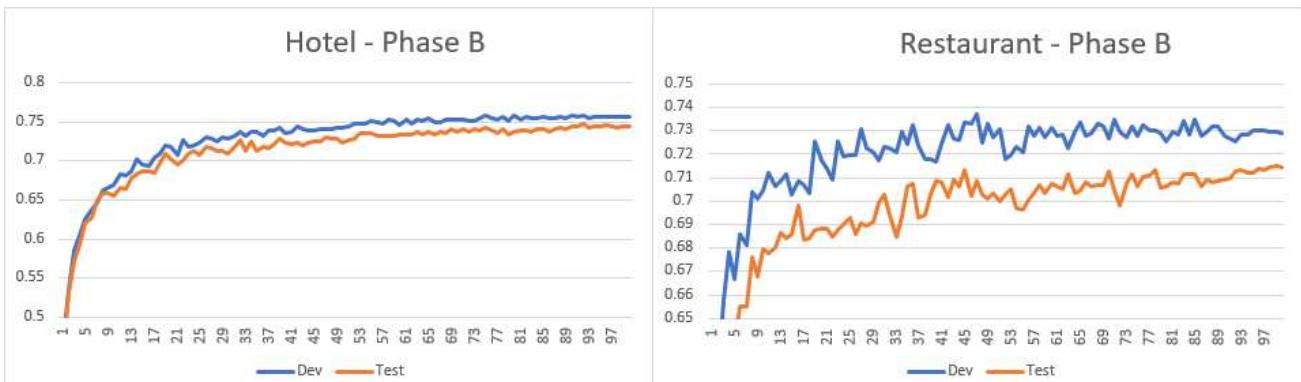


Fig. 4. The F1 score curves on the dev and test sets of two domains - PHASE B (Aspect Sentiment Polarity Detection).

V. CONCLUSION

In this paper, we have presented a new and effective method to deal with the ABSA problem in Vietnamese. Instead of building individual classifiers, we introduce a new method by handling the three classification problems (identifying entities, aspects, and sentiment polarity) as an end-to-end model. This model jointly learns the three tasks simultaneously in a hierarchical manner. Through experiments on the two public datasets in Vietnamese, we witnessed significant performance gains for this task on two datasets of the VLSP-2018 campaign. We also observed a consistent improvement of further pre-training mBERT on the Vietnamese dataset for both two phases. This new state of the art results in Vietnamese ABSA will be used as a new baseline for future research in this area. Using viBERT, we obtained 84.23% and 82.06% in the F1_micro scores in detecting entities and their aspects on the domains of restaurants and hotels, respectively. In identifying aspect sentiment polarity, the model gained 71.3% and 74.69% in the F1_micro scores on the domains of restaurants and hotels, respectively.

In the future, we plan to exploit other pre-trained models such as ELECTRA and GPT in order to boost the prediction performance. Another direction is to try with different architectures on top of BERT instead of only using the linear function in this case.

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