From Universal Language Model to Downstream Task: Improving RoBERTa-Based Vietnamese Hate Speech Detection

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Motivation and objective

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  - Pre-trained language models are extremely useful for downstream tasks.
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  - Pre-trained language models are extremely useful for downstream tasks.
  - Fine-tuning a well-trained model on a task-specific dataset needs to be carefully handled.
- Objective
  - Propose a general tuning strategy for language models on downstream tasks.
  - Apply the pipeline with a RoBERTa-based (i.e. PhoBERT) architecture to solve Vietnamese Hate Speech Detection task.

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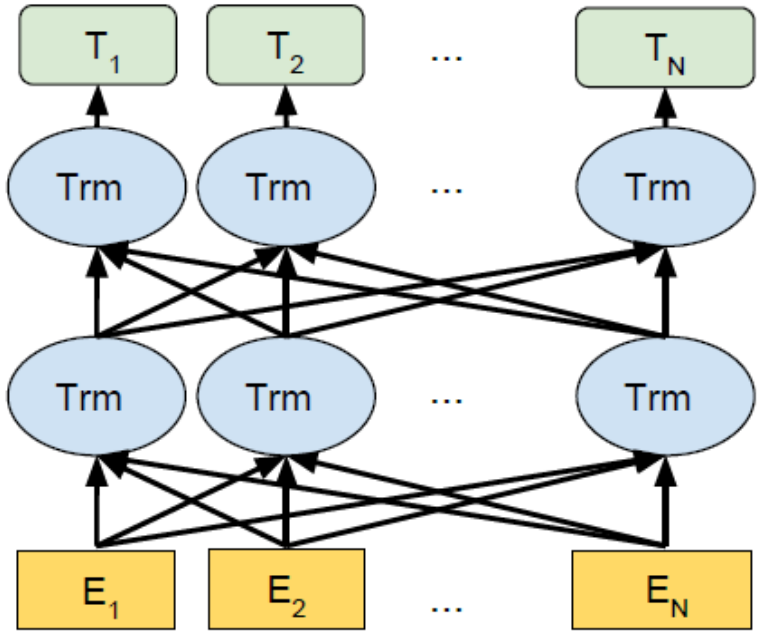
Background

- RoBERTa language model
  - The original by Facebook[1]: BERT without NSP, trained on 160GB text.
  - Vietnamese version PhoBERT by VinAI[2]: Trained on 20GB texts (1GB Wikipedia, 19GB news)



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Background

- RoBERTa language model
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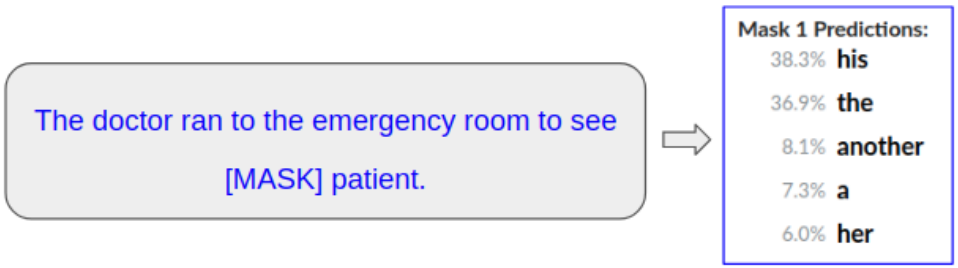
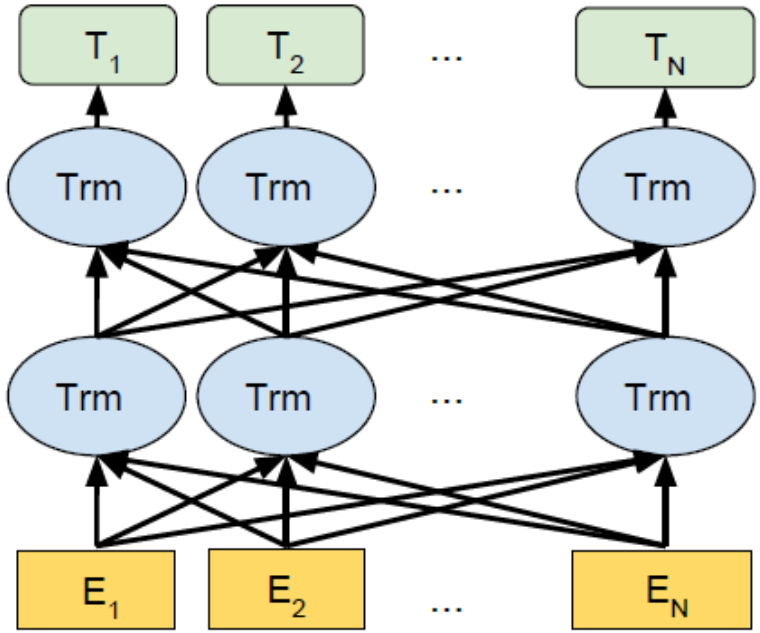
- Masked language modeling: fill-in-the-blank task





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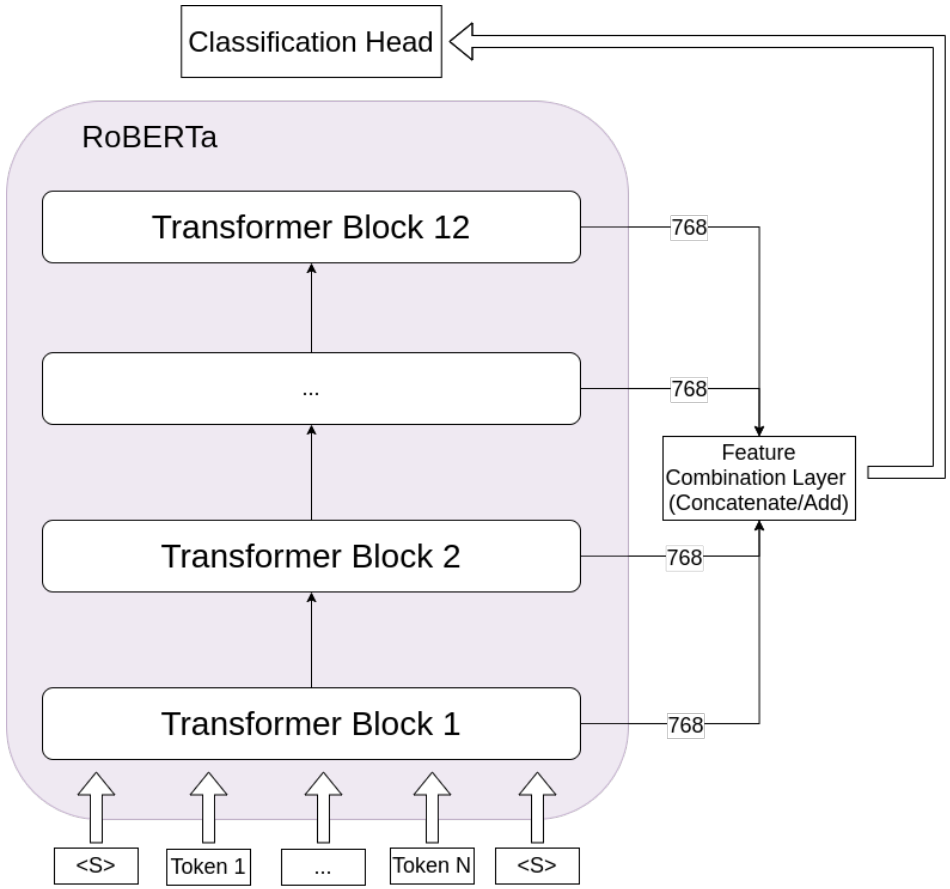
Classification architecture

- RoBERTa-base (PhoBERT's weights) as backbone network



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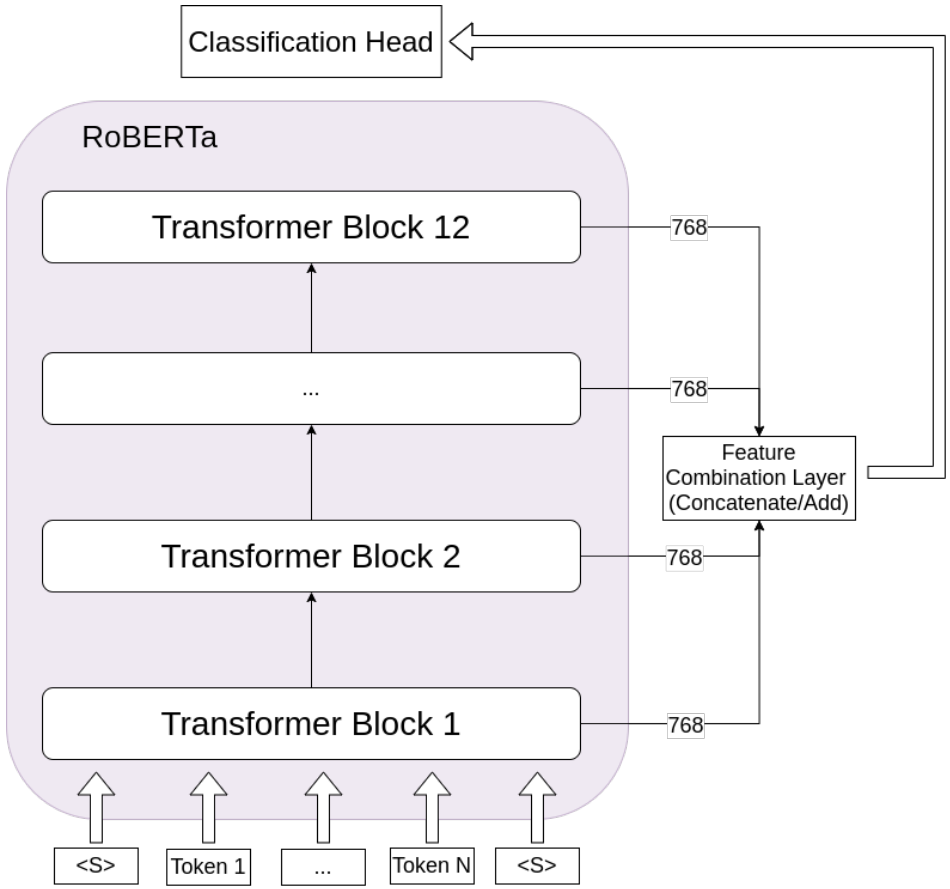

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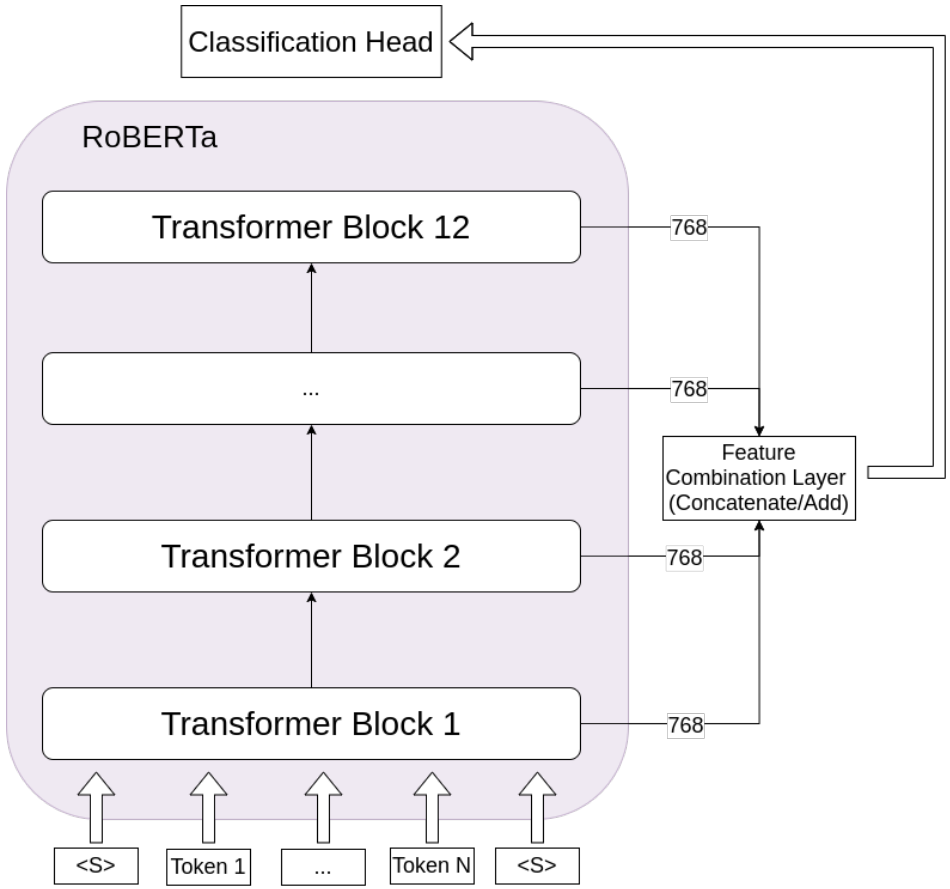
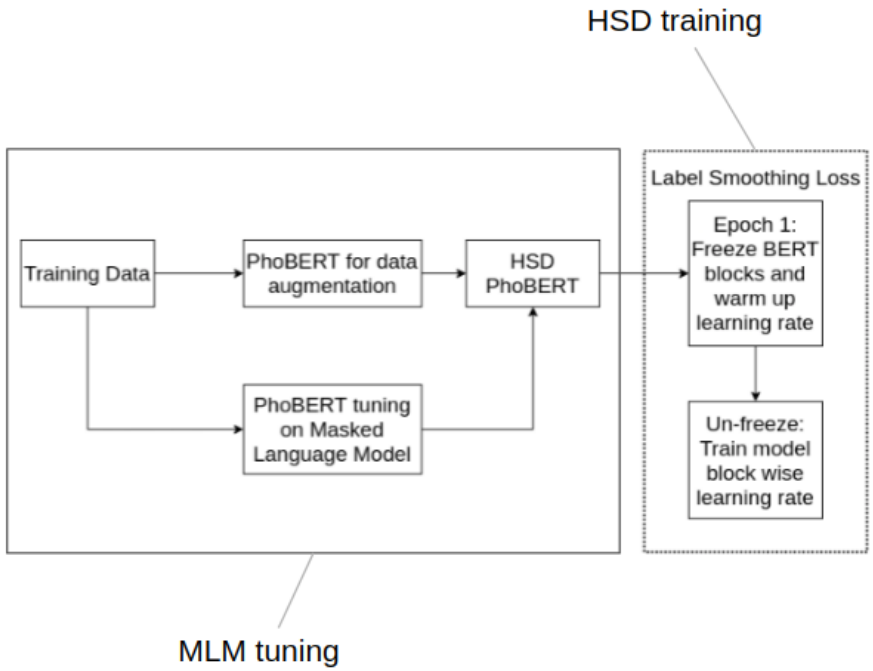
- Classification head: Multi-layer perceptron



Fine-tuning pipeline

- MLM Tuning:
  - Randomly replace 5 tokens using PhoBERT
  - Tune the language model on training data



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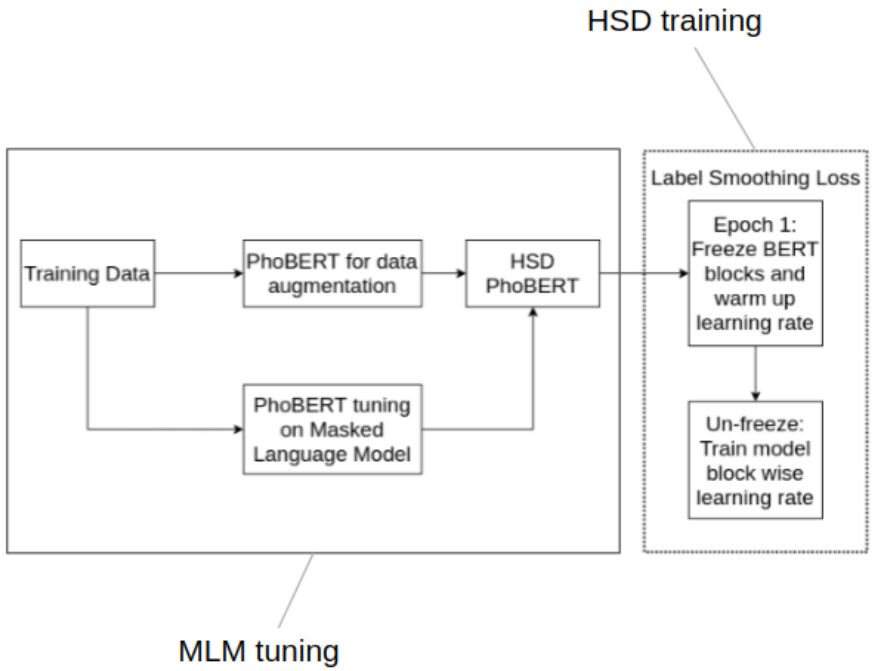
- HSD training:
  - The first epoch: Freeze transformer encoders, train MLP head with warm-up learning rate
  - The rest: Unfreeze and train all encoders with block-wise learning rates
  - Label smoothing loss

$$y'_k = y_k(1-\alpha) + \alpha/K$$

K classes

one-hot label

smoothing parameter



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Experiments

- Experiment with different combinations of embeddings from 12 layers.

	HATE	OFFENSIVE	CLEAN
Number of sample	709	1,022	18,614

Noise: abbreviations, emoji, special characters, foreign language, teen code, typing errors.

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Experiments

- Experiment with different combinations of embeddings from 12 layers.
- Investigate effectiveness of each individual and all fine-tuning techniques.

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Results

Table: Mean of Macro $F1$ score on Stratified K-fold with k = 10 of difference blocks

Feature blocks	Mean of F1 score
Layer 6 (only single block)	0.6854
Layer 12 (only single block)	0.6978
Layer 3-6 (4 middle blocks)	0.6855
Layer 9-12 (4 last blocks)	**0.6989**
Layer 1-6 (6 first blocks)	0.6905
Layer 7-12 (6 last blocks)	**0.6989**
Layer 1-12 (all blocks)	0.6979

Table: Mean of Macro $F1$ score on Stratified K-fold with k = 10 with concatenate of layers 6-12 and our training approach

Proposed training approach	Mean of F1 score
Cross entropy loss	0.6922
Label Smoothing loss	0.7005
Non warm-up learning rate	0.6989
Warm-up learning rate	0.7062
Non Fine-tune MLM	0.6989
Fine-tune MLM	0.7162
Non Block wise learning rate	0.7051
Block wise learning rate	0.7079
Combine all the methods	**0.7211**

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Conclusion

- What we have done:
  - Proposed a pipeline for adapting a universal language model to downstream tasks
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  - Applied the pipeline into Hate Speech Detection task, achieved top 1 on the leaderboard.
- Future work:
  - Design more complex classification head
  - Try employing the model and pipeline on different languages.

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Thank you for listening!