DOMAIN GENERALIZATION IN VIETNAMESE DEPENDENCY PARSING A NOVEL BENCHMARK AND DOMAIN GAP ANALYSIS

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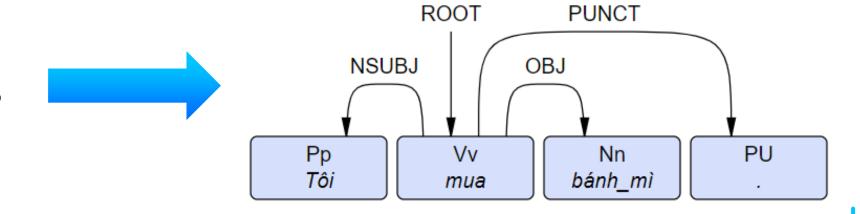




Introduction: Dependency Parsing

Dependency Parsing: build a directed tree by Grammatical relations

Tôi mua bánh mì. (I buy some bread.)





Introduction: Domain Gap

Domain Gap: The difference between training and testing domain(s)

Training:

- I love you so much.
- You are the light of my life.
- I'm crazy about you.

Testing:

Em an com chua.



Problem

- There is a limited number of research inside domain generalization on Vietnamese dependency parsing.
- One of the keys reason is the lack of a compatible treebank.



Our contribution

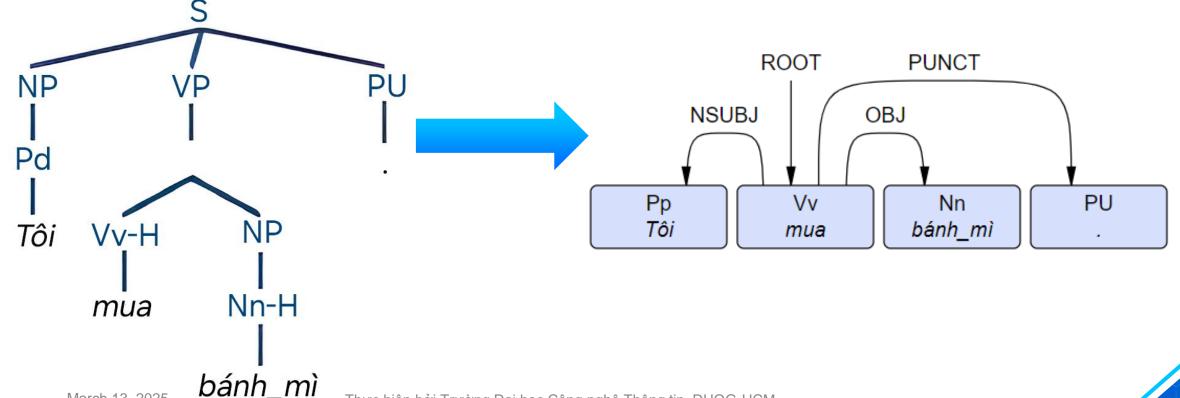
In this research, we release:

- DGDT, a Vietnamese dependency treebank that available in multiple domains, which can accommodate cross-domain setups.
- DGDTMark, a benchmark suite available in different cross-domain scenarios.



Dataset construction

 To keep balance between cost and data quality, we adopt a converter to transform an existing constituency treebank.





Dataset construction

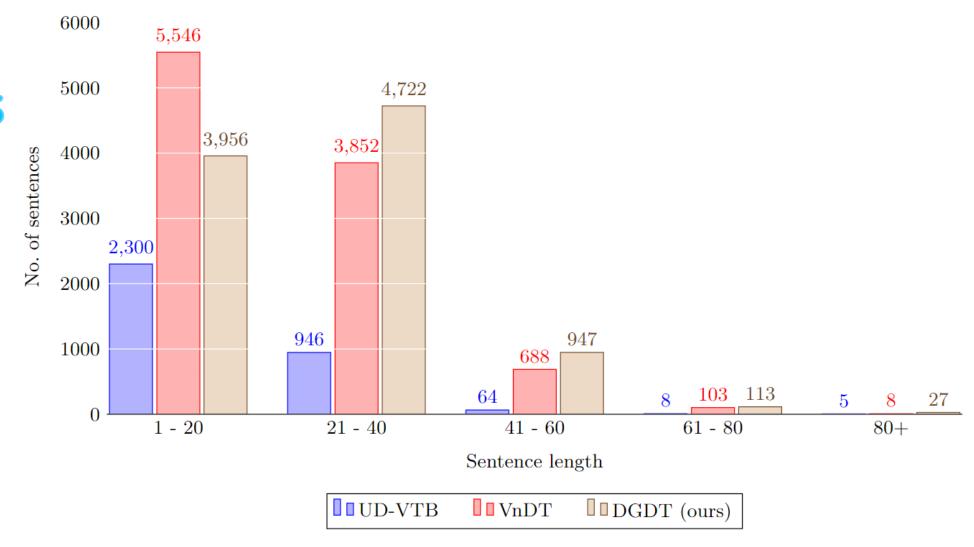
- We follow the converter released by Truong et al. (1) and the constituency treebank of Nguyen et al. (2) as they fit our requirements.
- Our dataset contains 9,765 sentences in 14 newspaper topics, crawled from the Thanh Nien Newspaper.
- We treat each topic as a single domain.
 - (1) C. M. Truong, T. V. Pham, M. N. Phan, N. D. T. Le, T. V. Nguyen and Q. T. Nguyen, "Converting a constituency treebank to dependency treebank for Vietnamese," 2022 RIVF International Conference on Computing and Communication Technologies (RIVF), Ho Chi Minh City, Vietnam, 2022, pp. 256–261
 - (2) Nguyen, Q.T., Miyao, Y., Le, H.T.T. et al. Ensuring annotation consistency and accuracy for Vietnamese treebank. Lang Resources & Evaluation 52, 269–315 (2018).



Set	Domain	Number of Sentences	
Train	Education	844	
	Health	725	
	Law	610	
	Life_of_youth	635	
	Military	690	
	Politics_Society	712	
	Science	692	
	Sports	697	
	Travel	540	
	World	645	
Dev	Entertainment	708	
	Information_Technology	714	
Test	Economic	725	
	Life	828	
	<u>Total</u>	9765	



Dataset Statistics





The DGDTMark

To evaluate the effects of domain gap into the task, we released this benchmark suite, includes 4 scenarios:

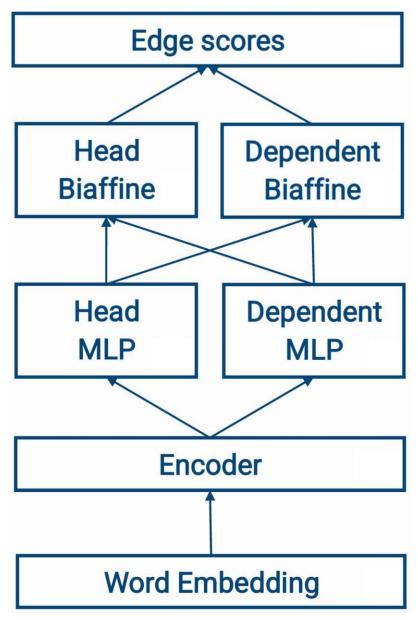
- 1. in-domain: split each domain with ratio 8:1:1 and merge the respective parts from all domains to build train/dev/test sets.
- 2. domain-k-fold: let each domain be the dev and test set, while the rest of treebank plays the role of train set.
- 3. domain-generalization: arrange domains exclusively to one of three train/dev/test sets.
- 4. dataset-generalization: replace the test set of DGDT in the third scenario with test set of the NIIVTB_DT-1 (1) treebank.



Models

- We use the Deep <u>Biaffine</u> Attention Model as our baseline for DGDTMark.
- We run our experiments on the implementation of Zhang et al. (3) with default hyperparameters.
- The original LSTM is replaced by transformer-based encoder including PhoBERT and XLM-RoBERTa (XLM-R).

(3) https://github.com/yzhangcs/parser





Experiment Results

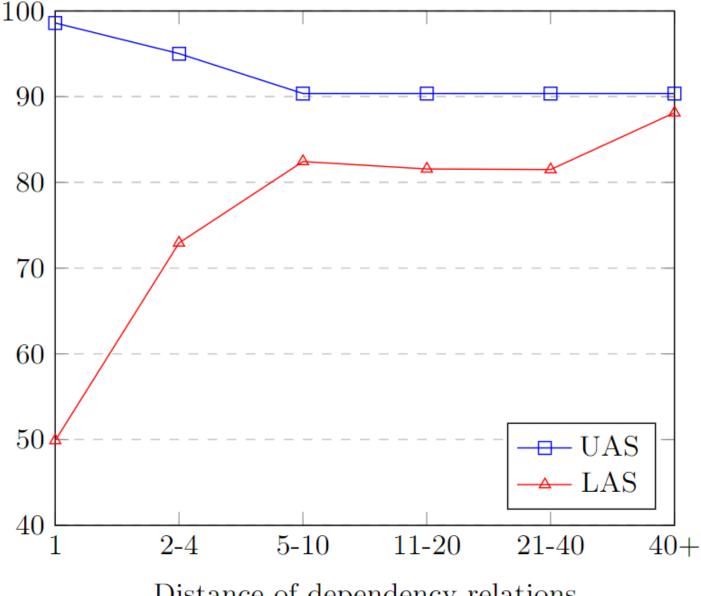
Encoder	in-domain	domain-k-fold	domain-generalization	dataset-generalization
PhoBERT	87.83	87.01	84.76	82.74
XLM-R	85.89	84.99	82.88	80.97

- Both encoders are evaluated with their base version.
- The evaluation metric is LAS.



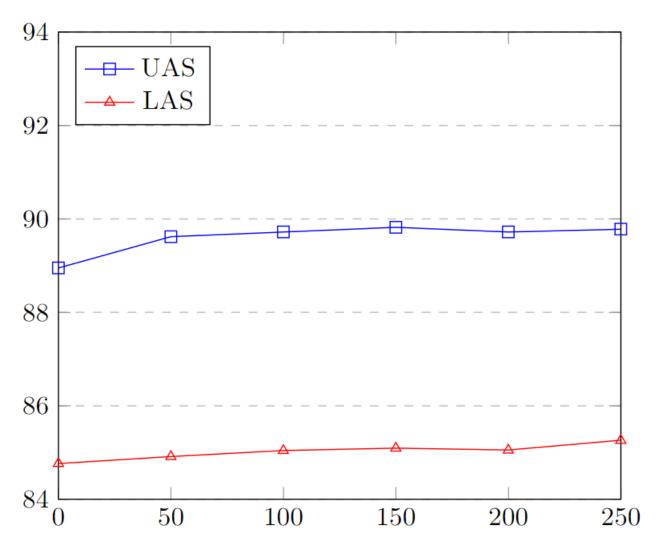
How do the models capture long dependencies?







Can data from testing domains help the models?



Number of sentences given to the train set from the test set

Accuracy (%)



Conclusion

- We introduce DGDT treebank and DGDTMark benchmark suite.
- Current models have performed well in this parsing task (87.83% LAS), but have still faced difficulties when handling the domain gap (>5% decrease of LAS).





THANKYOU

Q&A