Harnessing Linguistic Dissimilarity for Language Generalization on Unseen Low-Resource Varieties

Jinju Kim[1, 2], Haeji Jung[3*], Youjeong Roh[4*], Jong Hwan Ko[1], David R. Mortensen[2]

[1]Department of Electrical and Computer Engineering, Sungkyunkwan University
[2]Language Technologies Institute, Carnegie Mellon University
[3]Department of Computer Science, University of British Columbia
[4]Department of Computer Engineering, Chungnam National University
perla0328@g.skku.edu, dmortens@cs.cmu.edu

Abstract

Despite the fact that much communication takes place in them, low-resource language varieties used in specific regions or by specific groups remain neglected in the development of Multilingual Language Models. A great deal of cross-lingual research focuses on inter-lingual language transfer which strives to align allied varieties and minimize differences between them. However, for low-resource varieties, linguistic dissimilarity is also an important cue allowing generalization to unseen varieties. Unlike prior approaches, we propose a two-stage Language Generalization framework that focuses on capturing variety-specific cues while also exploiting rich overlap offered by high-resource source variety. First, we propose TOPPing, a source-selection method specifically designed for low-resource varieties. Second, we suggest a lightweight VAÇAÍ-Bowl architecture that learns variety-specific attributes with one branch while a parallel branch captures variety-invariant attributes using adversarial training. We evaluate our framework on structural prediction tasks as proxy for performance on other downstream tasks. Using VAÇAÍ-Bowl with TOPPing yields an average 54.62% improvement in the dependency parsing task, which serves as a proxy for performance on other downstream tasks across 10 low-resource varieties.

1 Introduction

Multilingual Language Models (MLMs) have led to great strides in Natural Language Processing (NLP), extending language technologies to more than one hundred languages (Pires, Schlinger, and Garrette 2019; Conneau et al. 2020). Yet, excelling in a language offers little meaning if a model cannot generalize to its variants (e.g., regional dialects). Crucially, a large portion of real-world communication is carried out in language varieties that are not represented among the quasi-standardized set of roughly one hundred languages that dominate MLM training data. Decades of research in linguistics show that languages lay on a continuum of similarity, each with its own continuous domain (Lin et al. 2019). When confronted with such in-domain (intra-linguistic) variants, existing models deliberately fail (Faisal et al. 2024).

*These authors contributed equally.

Copyright © 2026, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

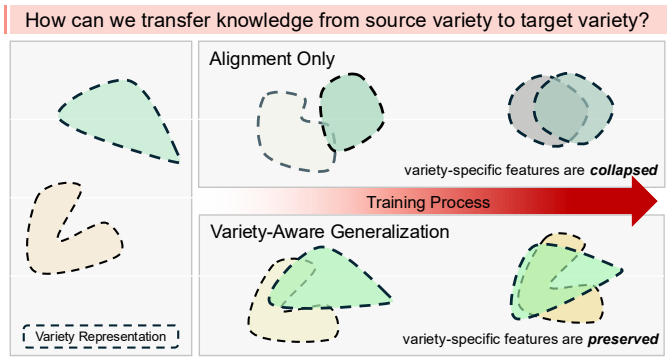

Figure 1: Visualization of training in the embedding space, comparing alignment-based only method and variety-aware generalization method.

Intra-linguistic variation is at least as pervasive as inter-linguistic variation. Linguists often refer to intra-language variants as "dialects" or "sociolects". In this paper, we avoid the term *dialect* for two reasons: (i) it can carry pejorative connotations, and (ii) it is unduly restrictive, implying mutual intelligibility with other variants of a language. We therefore adopt the more neutral and inclusive term *language variety* (or *variety*), that broadly denotes variants shaped by regional, social, and cultural distinctions of its speaker community (Chambers and Trudgill 1998).

Prior research aiming to extend NLP to low-resource varieties, including interlingual transfer, has primarily centered on exploiting cross-variety similarities to align representations (e.g., Figure 1's variety-aligned only method) to facilitate knowledge transfer (Yang et al. 2022). However, alignment methods risk losing variety-specific information by collapsing distinct features. This overlooks the linguistic variations that naturally arise in real-world contexts. In this paper, instead, we propose a variety-aware Language Generalization framework that performs generalization without any training on the target low-resource variety. By learning not just *how it is similar to a high-resource variety*, but *how it is different*, the model learns to disentangle and strategically combine linguistic features to perform in unseen settings. We also propose an improved automatic method for

identifying high-resource varieties most relevant for training a model targeting a particular low-resource variety without any usage of labels, annotation, or parallel dataset. Together, these methods achieve better results than all baselines on structural tasks including dependency parsing (DEP) and part-of-speech tagging (POS), which we believe to be an informative proxy for performance on other downstream tasks.

Our key contributions are as follows:

- This paper introduces the Language Generalization framework, focusing on making a model robust to unseen language variations.
- We introduce TOPPing, a method for selecting source varieties to generalize on a target low-resource variety without annotations or parallel dataset.
- We propose VAÇAI-Bowl, a novel and lightweight architecture to not only align, but also distinguish varieties.

2 Related Work

2.1 Low-Resource Varieties

The disparity of MLMs performing significantly worse in low-resource varieties arises even when the variety is typologically close to, and partially represented in, the training corpus. Through empirical studies, drops in performance when data shifts to a low-resourced variant have been proven to be biased towards dominant varieties (Blasi, Anastasopoulos, and Neubig 2022; Blaschke et al. 2024; Blaschke, Schütze, and Plank 2023; Faisal et al. 2024; Srivastava and Chiang 2025; Lin et al. 2025; Üstün et al. 2020).

Given this limitation, several works have attempted to address the gap. Inspired by findings in cross-lingual transfer (Snæbjarnarson et al. 2023; Bafna, Murray, and Yarowsky 2024), recent approaches focus on developing distance metrics that rank varieties by similarity to identify the most similar variety best suited to support low-resource varieties. Specifically, Bafna et al. (2025) propose two approaches: one that trains models on artificially generated variants, and another that adapts input data at inference time to closely resemble the high-resource standard. Similarly, Nguyen, Joshi, and Salim (2025) define the dialectal gap between language variants and apply test-time adaptation techniques to improve model performance on nonstandard inputs.

2.2 Zero-shot Cross-lingual Transfer

Prevailing methods to improve cross-lingual transferability for language varieties without explicit training suggest various methods to align language representations. Wang et al. (2023) introduce a self-augmentation approach that substitutes tokens in English dataset with tokens from different variety and then perturbing to distill token-level alignment. X-MIXUP reduces cross-lingual representation discrepancy of parallel sentences, so that the target representation is explicitly pulled toward the source (Yang et al. 2022). Wu and Monz (2023) re-parameterises the embedding table with a graph network that forces meaning-similar words to converge on the same coordinate region. Huang et al. (2021) adopts robust training strategies, such as randomized smoothing, to enhance cross-lingual transfer in zero-shot settings. All these methods focus on aligning the target variety to a source variety; while treating variety-specific information as something to be eliminated or suppressed rather than be a potential transfer knowledge.

Another common strategy is to train models on source languages that are linguistically similar to the target language. Prior work investigating the factors that influence transfer performance has shown that linguistic similarity tends to correlate with better cross-lingual transfer (Eronen, Ptaszynski, and Masui 2023a,b; Lauscher et al. 2020; Dufter and Schütze 2020). This has motivated efforts to identify optimal source languages using various linguistic similarity metrics. For example, de Vries, Wieling, and Nissim (2022) examine part-of-speech tagging across diverse source-target language pairs and suggest optimal pairs for certain languages, and Lin et al. (2019) proposes a ranking method based on multiple linguistic similarity features, offering a more systematic framework with quantitative features. Rice et al. (2025) utilizes typological and dataset-dependent features to conclude the best rankings for cross-lingual performances. However, these rely on pre-annotated language information, making it inapplicable for varieties that lack annotated datasets.

2.3 Domain Generalization

Domain Generalization (DG) aims to ensure model performance on domains inaccessible during training (Blanchard, Lee, and Scott 2011; Muandet, Balduzzi, and Schölkopf 2013; Zhou et al. 2023). This has been a long-standing problem in machine learning, where models trained with a limited set of training data fail to fully perform in domain variations. A very basic approach for DG is to align the different domains together, aiming to learn domain-invariant features that are robust across domains (Muandet, Balduzzi, and Schölkopf 2013; Li et al. 2018a,b), which is also adopted in NLP tasks (Wang et al. 2024; Wang, Lapata, and Titov 2021; Li et al. 2024).

In multilingual NLP, Jung et al. (2024) analyze multilingual modeling from a domain-level perspective, treating each language as a separate domain. Rathore et al. (2023) attempts usage of multi-source ensembling of adapters for zero-shot generalization. Adilazuarda et al. (2024) utilizes typological and geographical elements for generalization to unseen languages. Building on this view, we explore the possibility to frame zero-shot transfer to low-resource varieties as a DG problem, where the goal is to generalize to unseen linguistic domains without explicit training. While most prior works focus on learning domain-invariant features (Ganin et al. 2016; Ngo and Nguyen 2024; Tahery, Kianian, and Farzi 2024), we aim to capture domain-specific signals to help the model recognize linguistic differences within similar varieties—thereby improving generalization to unseen varieties.

3 Methods

In this paper, we propose a novel framework that leverages both variety-invariant and variety-specific information to generalize to unseen low-resource variety in a zero-shot

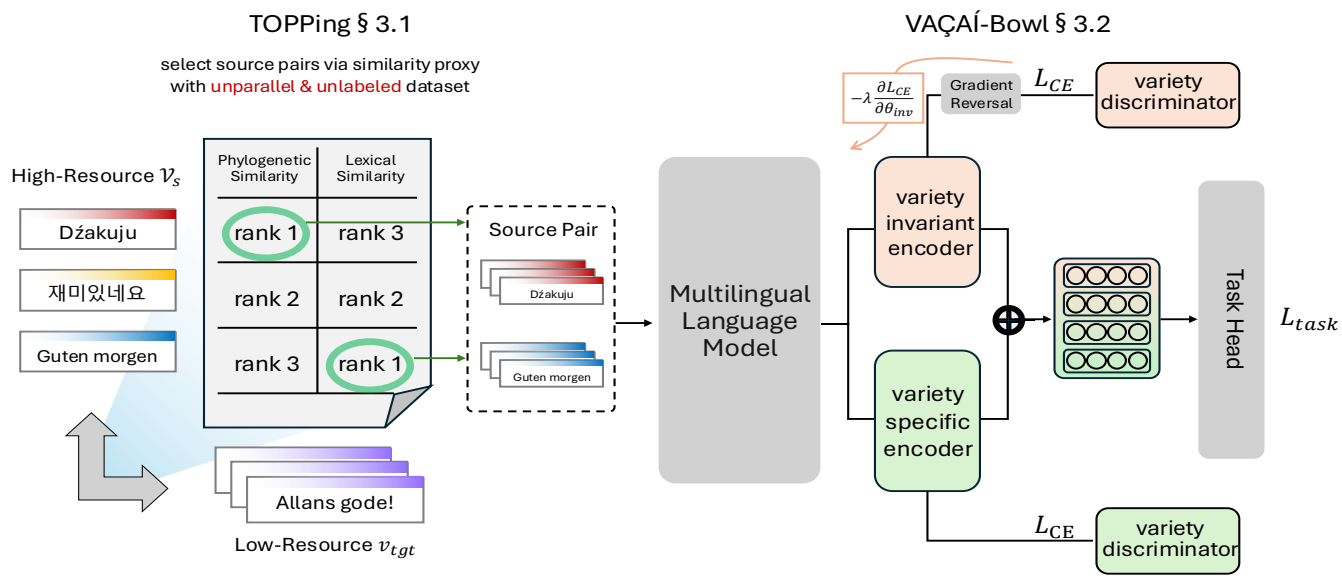

Figure 2: Overall framework of this paper. Using TOPPing, with just unparallel and unlabeled datasets, we can select source varieties with not only shared but also distinctive features to capture relationship between varieties. From the obtained source variety pair, VA learns the semantic differences of neighboring source varieties and learns to generalize on the target low-resource variety in a zero-shot manner.

manner, and a method to carefully select exploitable high-resource source variety to pair with the low-resource target variety.

3.1 TOPPing

For low-resource language varieties, obtaining sufficient labeled training data remains expensive and labor-intensive (Blasi, Anastasopoulos, and Neubig 2022; Faisal et al. 2024). When the low-resourced target variety has high-resourced neighbors in terms of linguistic similarity, utilizing the latter can be relatively cheaper.

To mitigate the constraints of low-resource varieties, we introduce **TOPPing**: **T**oken-**O**verlap & **P**roximal embedding **P**air**ING**, a simple yet effective method that does not require annotations and allows preservation of varietal diversity for selecting source varieties. This allows a wide and general usage even when the variety is unseen, unannotated, and unlabeled. Previous works define language distances in various dimensions (Littell et al. 2017; Rama, Beinborn, and Eger 2020). In this work, we rely on two signals that can be computed automatically from raw text and capture complementary aspects of similarity. As illustrated in Figure 2, to encourage diversity in source selection, we compute these similarity signals independently rather than combining them into a single joint score. This preserves the room for variety-specific information training which serves as a key for generalization.

Let v_{tgt} be the target low-resource variety, and $\mathcal{V}_{\text{src}}$ the set of high-resource source varieties. For each variety v, let $\mathbf{X}_v = \{x_i^v\}_{i=1}^{N_v}$ denote its dataset. First, we obtain a source variety by proxying the phylogenetic distance via embedding distance (Rama, Beinborn, and Eger 2020). Let $f_{\text{CLS}_2}(x) \in \mathbb{R}^d$ denote the "[CLS]" representation of input x from the second layer of a MLM. We aim to obtain a source variety $v_{\text{sim}} \in \mathcal{V}_{src}$ such that:

$$v_{\text{sim}} = \arg\min_{v \in \mathcal{V}_{src}} \left\| \mu_v - \mu_{v_{tgt}} \right\|_2, \quad \mu_v = \frac{1}{N_v} \sum_{x \in \mathbf{X}_v} f_{\text{CLS}_2}(x). \tag{1}$$

We use the second-layer "[CLS]" rather than the final layer because lower-layer representations have been shown to capture more typological and morpho-syntactic information, which aligns better to proxy phylogenetic structure (Hewitt and Manning 2019; Mousi et al. 2024; Bakos et al. 2025).

Second, we use token overlap (Blaschke, Körner, and Plank 2025) between two varieties as a proxy for lexical distance. Here, we introduce **token-length weighted Jaccard Similarity** as lexical overlap calculation tailored to low-resource varieties. Unlike highly represented varieties, lexical items are often fragmented into shorter sub-tokens, which diminishes the discriminative power of a standard Jaccard similarity measure. Weighting overlaps by token length mitigates this bias, preventing varieties from being erroneously conflated based on scripts. The aim is to obtain a source variety $v_{\text{overlap}} \in \mathcal{V}_{src}$ such that :

$$v_{\text{overlap}} = \arg\max_{v \in \mathcal{V}_{src}} \text{TJ}(\mathbf{X}_v, \mathbf{X}_{v_{tgt}}), \tag{2}$$

where $\text{TJ}(\mathbf{X}_v, \mathbf{X}_{v_{tgt}})$ is token-length weighted Jaccard similarity.

$$\mathrm{TJ}(\mathbf{X}_a, \mathbf{X}_b) = \frac{\sum_{tok \in T_a \cap T_b} \omega(tok)}{\sum_{tok \in T_a \cup T_b} \omega(tok)}, \quad \omega(tok) = \max(1, \mathrm{len}(tok) - 1). \tag{3}$$

The pair $\langle v_{\text{sim}}, v_{\text{overlap}} \rangle$, selected by independent ranking, leaves room for diversity in source pair selection.

3.2 VAÇAI-Bowl

In Figure 2, we illustrate our approach for Language Generalization : **V**ariety **A**ligned and Spe**C(Ç)**ific **A**ttr**I**butes **B**lending for L**OW**-resouce **L**anguage Varieties. This framework leverages both variety-invariant and variety-specific knowledge from high-resource varieties to effectively model representations for an unseen, low-resource variety.

In order to model variety-invariant and variety-specific features, we use a Multilingual Language Model that produces a "[CLS]" embedding for every input sentence. We implement two independent 2-layer MLP encoders :

- Variety-invariant encoder f_{inv} is trained adversarially to align varieties and learn invariant features. We obtain $h_{\text{inv}} = f_{\text{inv}}([CLS])$.
- Variety-specific encoder f_{spc} is trained normally to emphasize variety-specific features. We can also obtain $h_{\text{spc}} = f_{\text{spc}}([CLS])$.

The outputs are concatenated into h, so that $h = h_{\text{inv}} \,\|\, h_{\text{spc}} \in \mathbb{R}^{2d}$, where both encoders output d-dimensional vectors. The joint feature h is used in place of original "[CLS]" embedding for downstream tasks.

To train each encoder to extract variety-invariant and variety-specific features, each encoder is paired with its own discriminator (D_{inv} and D_{spc}) that performs classification on what variety the input belongs to. A gradient-reversal layer G_λ is inserted in front of D_{inv} to selectively update parameters to fool D_{inv} (Ganin and Lempitsky 2015).

$$G_\lambda(z) = z, \qquad \frac{\partial G_\lambda}{\partial \mathbf{z}} = -\lambda \mathbf{I}, \tag{7}$$

where λ is a hyperparameter. Contrastingly, f_{spc} learns to help D_{spc} by producing easily distinguishable features. The discriminators yield two loss terms :

$$L_{\text{inv}} = L_{CE}(D_{\text{inv}}(G_\lambda(h_{\text{inv}})), y_{\text{var}}), \quad L_{\text{spc}} = L_{CE}(D_{\text{spc}}(h_{\text{spc}}), y_{\text{var}}), \tag{8}$$

where L_{CE} denotes Cross Entropy Loss.

Lastly, the task loss is employed for the fine-tuning objective and to ground the representation extraction in right directions.

$$L_{\text{task}} = L_{\text{task}}(f_{\text{task}}(h), y_{\text{task}}). \tag{9}$$

Finally, the objective function is defined as $L_{\text{total}} = L_{\text{inv}} + L_{\text{spc}} + L_{\text{task}}$.

4 Experiments

In the following section, we provide experiments designed to evaluate the effectiveness of (i) source selection method TOPPing, (ii) framework VAÇAÍ-Bowl. We further investigate (iii) *why linguistic dissimilarities contribute to transfer, and to what extent?* For our experiments, we utilize structured prediction tasks to proxy MLM performance on downstream tasks.

4.1 Experimental Setup

Benchmark. DialectBench provides datasets and benchmarks for low-resource varieties with annotations that group varieties into language clusters, allowing direct visualization of performance gaps within the same cluster. For our experiment, we select target low-resource varieties that face following constraints : First, there is no training dataset available for the variety. Second, the zero-shot performance does not meet 50% of criteria. For source varieties, we utilize the rest of DialectBench and sample high-resourced varieties representative of distinctive language clusters from Universal Dependencies (Nivre et al. 2017; de Marneffe et al. 2021). These source variety sets are used for TOPPing variety selection. We evaluate on dependency parsing (DEP) and part-of-speech tagging (POS) task, which both are structured prediction tasks. Please refer to Appendix C for detailed results of downstream tasks across varieties.

Source Selection Baselines. In Figure 1, we illustrate how automated source language selection using TOPPing can be a simple yet effective method for source language selection especially for unseen varieties. This selection is applicable to diverse cross-lingual transfer scenarios, not limited to a specific method. As a widely-used baseline, we implement **LangRank** where the source varieties are selected based on pre-annotated linguistic features and dataset-dependent features (Lin et al. 2019). Please refer to Appendix B for detailed information on selected source varieties for each target variety.

Language Generalization Baselines. To compare the VAÇAÍ-Bowl framework, we implement two baselines : (1) **MLM** baseline illustrates performance when the model is simply finetuned on source languages. (2) **Alignment** baseline where the model leverages adversarial training to learn only variety-invariant features, adopted from DG and robust training is implemented (Huang et al. 2021).

Implementation Details. We utilize mBERT (Devlin et al. 2018) and XLM-R (Conneau et al. 2020) as MLMs for all tasks. We use the two models in their base size, where mBERT has 110M and XLM-R has 125M number of parameters. Specifically, we utilize publicly available models—`bert-base-multilingual-cased` for mBERT and `xlm-roberta-base` for XLM-R—downloaded from Huggingface.[1] We set the learning rate as 2e-4, batch size as 64 for mBERT. We set the learning rate as 5e-5, batch size as 64 for XLM-R. Overall, λ for gradient-reversal layer is searched in [0.1, 0.5, 1.0] for the following experiments.

[1] https://huggingface.co/models

Parameters are optimized with Adam optimizer. We finetune each model for 10 epochs and halt at step size of 1000 to not exceed the finetuning steps of zero-shot cross-lingual steps. In accordance with the benchmark evaluation procedure, results are reported from the checkpoint obtaining the highest UAS for the DEP task. Please refer to Appendix D for detailed information on parameter search regarding lambda.

4.2 Quantitative Results

In accordance with the previous discussions, a model that can learn both the variety-invariant and variety-specific features should show higher generalization performance regardless of source varieties. Also, this performance should be boosted with model-agnostic source selection TOPPing that preserves noticeable differences in source varieties. At the same time, TOPPing is also expected to perform comparatively to LangRank which prioritizes linguistic similarities. For scores across LAS evaluation metric, please refer to Appendix C.1.

Source Selection. Table 1 and Table 2 presents results on DEP task, using mBERT and XLM-R as backbones, respectively. Comparing the scores reported using each LangRank and TOPPing, it is noticeable that in Table 1, evaluations made using TOPPing outperforms LangRank across all methods in 9 out of 10 varieties. Also, simply finetuning the mBERT model on TOPPing itself beats the best score obtained using LangRank for 8 out of 10 varieties. In Table 3, this phenomenon is more apparent across additional evaluation metrics and task. TOPPing achieves higher performance enhancement for low-resource varieties overall, for both mBERT and XLM-R.

In cases where LangRank enhances transferability and generalization, Gheg Albanian (aln) and Umbrian (xum), it is notable that the target varieties all fall into Indo-European family.

Language Generalization. Table 4 illustrates that our proposed architecture, VAÇAÍ-Bowl, improved model performance regardless of source selection across different evaluation schemes. Specifically, in Table 1 VAÇAÍ-Bowl achieves the highest performance on 9 out of 10 target varieties across both source selection methods for mBERT. Paying close attention to other baselines, it is notable that the Alignment method, which attempts to enforce alignment by pulling diverse variety embeddings together, fails to surpass the performance on fine-tuned MLM baseline for certain varieties. Specifically, for varieties {*gug, koi, kpv, lij, nds, gsw, xum*} in Table 1 and {*gug, gun, koi, kpv, lij, sna*} in Table 2. We refer to this phenomenon as **alignment-induced failures**. When this occurs, VAÇAÍ-Bowl overomes the failures of alignment by utilizing variety-specific attributes under for all cases. Especially in Table 1, for 6 out of 7 alignment-induced fails observed using TOPPing, VAÇAÍ-Bowl outperforms all methods on the target variety. Also, VAÇAÍ-Bowl performs consistently better than Alignment method across all varieties.

Overall, results presented across low-resource varieties across various backbones, tasks, and source selection methods show promising results of VAÇAÍ-Bowl. It can improve model perfromance up to 27% (the case of *gug* with LangRank as source selection) of simply finetuning the MLM.

4.3 Qualitative Results

In Figure 3, we can observe how different similarity metrics used to obtain TOPPing in Section 3.1 affect performances in VAÇAÍ-Bowl. LangRank utilizes *est, sme* as source varieties, which seem largely correlated with the "[CLS]" Cosine Distance we use to proxy phylogenetic similarity. TOPPing's performance hints that phylogenetic similarity may not contribute as much to model performance, considering it utilizes *glg, sme* as source varieties. Additionally, as can be observed in the case of TJ and CD, that overall performance in increasing robustness may also be model-dependent. XLM-R tends to stay robust on diverse source varieties unlike mBERT. This is highly likely to be due to XLM-R being trained in multiple scripts — thus generalizing to unseen varieties with low-resourced scripts as well. These results align with performances outlined in Table 2 as well. Nevertheless, using TOPPing with VAÇAÍ-Bowl improves mBERT performance to yield a comparable score — often ourperforming that of XLM-R in Table 1.

4.4 Analysis

Q. When is TOPPing most effective? TOPPing is most effective for low-resource or under-documented varieties, where typological or lexical metadata are sparse and pre-annotated descriptions are unavailable. Experimental results show that it remains robust even without such annotations, outperforming methods like LangRank under these conditions. In contrast, LangRank occasionally performs better for Indo-European family varieties—such as Gheg Albanian (aln) and Umbrian (xum), where dense typological and lexical metadata (e.g., from URIEL and WALS) provide rich feature vectors and reliable genealogical signals for ranking candidate sources. However, for under-documented varieties, every candidate appears equally (dis)similar to LangRank, leading to poor source selection. Therefore, TOPPing serves as a more effective source selection method for varieties with minimal annotation and extremely sparse resources.

Q. When is VAÇAÍ-Bowl most effective? VAÇAÍ-Bowl is most effective for low-resource varieties, where alignment-based methods tend to fail. For instance, with mBERT backbone (see Table 1), for Umbrian (xum), alignment alone led to a a performance drop in unlabeled attachment score (UAS) of 36.14 to $34.67(-1.47)$ under LangRank and from 37.21 to $35.99(-1.22)$ under TOPPing when alignment was applied alone. In contrast, incorporating variety-specific features through VAÇAÍ-Bowl increased the UAS to Whereas incorporating variety-specific features through VAÇAÍ-Bowl raised performance to $36.29(+1.62)$, and to $37.67(+1.77)$, respectively. The framework enables the model to overcome alignment-induced failures, showing that enforcing uniform representations across distinct linguistic domains is insufficient. Instead, effective generaliza-

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source is eng										
mBERT$^{\diamond}$	38.14	13.51	8.95	26.12	26.89	50.22	36.77	19.41	36.77	33.21
mBERT	39.13	13.03	12.91	30.03	29.79	49.86	42.61	20.81	42.49	32.01
source selected using LangRank (Lin et al. 2019)										
mBERT	43.90	22.13	10.47	33.97	32.51	59.38	46.45	27.79	51.12	36.14
+Alignment	49.58	25.98	16.40	36.33	33.37	59.68	50.49	29.90	52.60	34.67
+VAÇAÍ-Bowl (OURS)	**51.00**	27.05	17.21	36.90	35.32	63.02	50.92	32.62	52.23	36.29
source selected using TOPPing (OURS)										
mBERT	44.55	34.10	15.18	40.83	36.80	63.99	52.54	35.63	57.22	37.21
+Alignment	45.30	31.56	16.53	40.72	36.52	62.96	52.04	38.80	54.84	35.99
+VAÇAÍ-Bowl (OURS)	46.34	**36.39**	**19.00**	**42.29**	**38.19**	**64.29**	**54.90**	**39.67**	**57.74**	**37.67**

Table 1: Quantitative results on UAS scores using mBERT as backbone on dependency parsing task evaluated across selected low-resource varieties from DialectBench. Underlined scores refer to best performing on target under controlled source variety. **Bold** scores refer to best performing on the target variety.

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source is eng										
XLM-R$^{\diamond}$	43.50	11.15	4.23	30.91	32.14	43.78	34.70	28.28	34.70	28.75
XLM-R	52.58	13.61	4.38	31.50	30.60	53.79	42.92	30.20	43.60	24.50
source selected using LangRank (Lin et al. 2019)										
XLM-R	55.58	28.44	10.95	41.51	33.27	60.37	47.36	41.25	43.75	33.08
+Alignment	57.41	28.44	12.47	40.49	35.80	59.51	47.61	42.16	46.95	34.30
+VAÇAÍ-Bowl (OURS)	**58.55**	31.23	12.51	42.41	36.13	59.82	48.38	42.53	47.47	34.56
source selected using TOPPing (OURS)										
XLM-R	55.07	30.57	11.27	40.50	**38.04**	**63.80**	48.73	40.76	52.23	35.68
+Alignment	56.54	28.67	8.47	39.60	35.85	63.13	50.81	40.20	56.62	34.76
+VAÇAÍ-Bowl (OURS)	57.50	**31.97**	**13.98**	**44.66**	37.76	63.44	**51.65**	40.99	**57.74**	**36.60**

Table 2: Quantitative results on UAS scores using XLM-R as backbone on dependency parsing task evaluated across selected low-resource varieties from DialectBench. $^{\diamond}$ refers to value reported in original paper. Underlined scores refer to best performing on target under controlled source variety. **Bold** scores refer to best performing on the target variety.

Task	Metric	LangRank	TOPPing
DEP	UAS	7.48	**10.27**
	LAS	7.82	**10.01**
POS	F1	7.36	**9.34**

Table 3: Comparative results of source selection methods for each task. Each value denotes the *average of absolute improvement in score (in points)* for both mBERT and XLM-R across all methods, compared to the English fine-tuned baseline.

Task	Metric	MLM	Alignment	VAÇAÍ-Bowl
DEP	UAS	7.84	8.58	**10.21**
	LAS	8.50	8.67	**9.58**
POS	F1	8.50	7.73	**8.83**

Table 4: Comparisons of methods for each task. Each value denotes the *average of absolute improvement in score (in points)* for both mBERT and XLM-R across all methods, compared to the English fine-tuned baseline.

tion and zero-training transfer require preserving the diversity inherent in each language variety.

Overall, contrary to prevailing assumptions in NLP, certain cross-lingual transfer scenarios benefit more from dissimilar language pairs than from closely related ones. These findings underscore the importance of preserving variety-specific information so that models can better generalize to unseen and low-resource varieties, with potential applicability beyond reported cases.

5 Conclusion

This paper introduces a Language Generalization pipeline that tackles the twin challenges of selecting helpful high-resource varieties and learning representations that preserve, rather than erase, distinctiveness of varieties. Our source-selection strategy, TOPPing, is designed to select two neighboring varieties based on distinct criteria—(i) lexical overlap and (ii) proxy for phylogentic similarity (using pre-trained MLM). Unlike prior works that utilize pre-annotated information for each variety, our method does not require

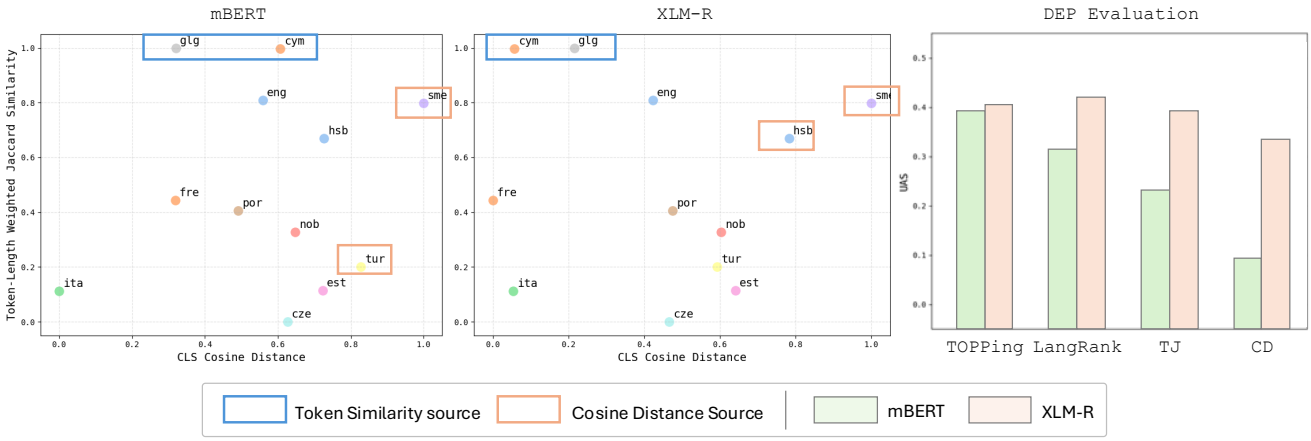

Figure 3: Analysis on source selection method. Two plots on the right illustrates TOPPing source selection scheme on variety *sma*. The x-axis is closeness of Cosine Distance of "[CLS]" tokens (CD), and the y-axis is token-length weighted Jaccard Similarity (TJ). We experiment VAÇAÍ-Bowl on two more source selections ; Token Similarity source which takes two sources with highest TJ and Cosine Distance source which takes two sources with highest CD. Note that TOPPing selects *glg, sme* and LangRank selects *est, sme*.

prior knowledge regarding the target data, ensuring scalability. Coupled with the lightweight VAÇAÍ-Bowl dual-encoder, one branch aligning varieties and the other amplifying variety-specific cues, our framework delivers consistent gains on dependency parsing. Experiments across ten low-resource varieties, TOPPing with VAÇAÍ-Bowl lifts zero-shot UAS by an average of 50.63% and 58.6%, using mBERT and XLM-R, respectively. This beats alignment-centric baseline and even rescues cases where full alignment hurts ("alignment-induced fails"). Beyond parsing, the approach is model-agnostic, computation-friendly, and immediately applicable to other tasks.

6 Discussion and Future Work

Beyond observed improvements, our findings raise broader implications for cross-lingual transfer learning. A key insight from this work is the challenge it poses to the conventional assumption in multilingual NLP that phylogenetic proximity between languages invariably results in better transfer. While related languages may provide useful inductive biases in some cases, our results demonstrate that this is not universally true. In particular, we observe that distantly related source varieties can sometimes yield stronger generalization, especially when they contribute structural, lexical, or script-level diversity that complements the target variety.

The observations motivate a shift toward variety-aware transfer strategies, where the goal is not to minimize but to **strategically leverage diversity across language varieties.** VAÇAÍ-Bowl and TOPPing offer such approach by explicitly modeling and preserving variety-specific signals from distinctive source selection rather than attempting to homogenize them. In sum, our work highlights the need to rethink cross-lingual transfer strategies. By embracing linguistic diversity rather than suppressing it, we can build more generalizable, equitable, and linguistically grounded NLP systems.

Limitations

The methods presented in this research proved to be effective in handling under-represented varieties that pre-trained MLMs cannot easily generalize to. Although we suggest an end-to-end pipeline that does not require any human annotated work on either source or target varieties, the method still requires unique selection of source varieties for each training. To counterpart this computational complexity, our method trains with only addition of MLP encoders, discriminators, and the task-specific head. This approach significantly reduces both the model size and training overhead compared to methods that require full fine-tuning of MLMs. Yet, it should be recognized that the ultimate goal of Language Generalization is to leverage only a limited set of language varieties to develop a model capable of robust generalization across all varieties, regardless of their resource availability.

Key Statement

Regardless of the backbone or machine task, harnessing linguistic dissimilarity (instead of similarity) allows preservation of information from diverse language varieties – which facilitates transferability of language models. Especially in low-resource settings, where efficient generalization methods are crucial.

Ethical Statement

We study a method to enhance cross-lingual transfer to very low-resourced varieties, which are often not provided with sufficient data for training or evaluation. While we aim to

develop language technologies targeting under-represented language communities, we still lack such coverage, limiting our research to datasets that are publicly available. Nevertheless, our approach provides a valuable step toward addressing the gap, by not simply aligning low-resource varieties with high-resource ones, but instead encouraging the model to recognize and preserve the linguistic differences that define them. All resources used in this research are publicly available, and no personal or sensitive information was collected or utilized. We do not anticipate any potential harm arising from this study.

Acknowledgments. This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government(MSIT) (No. RS-2024-00345732).

References

Adilazuarda, M. F.; Cahyawijaya, S.; Winata, G. I.; Purwarianti, A.; and Aji, A. F. 2024. LinguAlchemy: Fusing Typological and Geographical Elements for Unseen Language Generalization. In Al-Onaizan, Y.; Bansal, M.; and Chen, Y.-N., eds., *Findings of the Association for Computational Linguistics: EMNLP 2024*, 3912–3928. Miami, Florida, USA: Association for Computational Linguistics.

Bafna, N.; Chang, E.; Robinson, N. R.; Mortensen, D. R.; Murray, K.; Yarowsky, D.; and Sirin, H. 2025. DialUp! Modeling the Language Continuum by Adapting Models to Dialects and Dialects to Models. In Che, W.; Nabende, J.; Shutova, E.; and Pilehvar, M. T., eds., *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 20188–20233. Vienna, Austria: Association for Computational Linguistics. ISBN 979-8-89176-251-0.

Bafna, N.; Murray, K.; and Yarowsky, D. 2024. Evaluating Large Language Models along Dimensions of Language Variation: A Systematik Invesdigatiom uv Cross-lingual Generalization. In Al-Onaizan, Y.; Bansal, M.; and Chen, Y.-N., eds., *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, 18742–18762. Miami, Florida, USA: Association for Computational Linguistics.

Bakos, S.; Guzmán, D.; More, R.; Li, K. C.; Gaschi, F.; and Lee, E.-S. A. 2025. AlignFreeze: Navigating the Impact of Realignment on the Layers of Multilingual Models Across Diverse Languages. In Chiruzzo, L.; Ritter, A.; and Wang, L., eds., *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 2: Short Papers)*, 562–586. Albuquerque, New Mexico: Association for Computational Linguistics. ISBN 979-8-89176-190-2.

Blanchard, G.; Lee, G.; and Scott, C. 2011. Generalizing from several related classification tasks to a new unlabeled sample. In *Proceedings of the 25th International Conference on Neural Information Processing Systems*, NIPS'11, 2178–2186. Red Hook, NY, USA: Curran Associates Inc. ISBN 9781618395993.

Blaschke, V.; Körner, F.; and Plank, B. 2025. Add Noise, Tasks, or Layers? MaiNLP at the VarDial 2025 Shared Task on Norwegian Dialectal Slot and Intent Detection. In Scherrer, Y.; Jauhiainen, T.; Ljubešić, N.; Nakov, P.; Tiedemann, J.; and Zampieri, M., eds., *Proceedings of the 12th Workshop on NLP for Similar Languages, Varieties and Dialects*, 182–199. Abu Dhabi, UAE: Association for Computational Linguistics.

Blaschke, V.; Purschke, C.; Schuetze, H.; and Plank, B. 2024. What Do Dialect Speakers Want? A Survey of Attitudes Towards Language Technology for German Dialects. In Ku, L.-W.; Martins, A.; and Srikumar, V., eds., *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, 823–841. Bangkok, Thailand: Association for Computational Linguistics.

Blaschke, V.; Schütze, H.; and Plank, B. 2023. Does Manipulating Tokenization Aid Cross-Lingual Transfer? A Study on POS Tagging for Non-Standardized Languages. In Scherrer, Y.; Jauhiainen, T.; Ljubešić, N.; Nakov, P.; Tiedemann, J.; and Zampieri, M., eds., *Tenth Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial 2023)*, 40–54. Dubrovnik, Croatia: Association for Computational Linguistics.

Blasi, D.; Anastasopoulos, A.; and Neubig, G. 2022. Systematic Inequalities in Language Technology Performance across the World's Languages. In Muresan, S.; Nakov, P.; and Villavicencio, A., eds., *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 5486–5505. Dublin, Ireland: Association for Computational Linguistics.

Chambers, J.; and Trudgill, P. 1998. *Dialectology*. Cambridge Textbooks in Linguistics. Cambridge University Press. ISBN 9780521596466.

Conneau, A.; Khandelwal, K.; Goyal, N.; Chaudhary, V.; Wenzek, G.; Guzmán, F.; Grave, E.; Ott, M.; Zettlemoyer, L.; and Stoyanov, V. 2020. Unsupervised Cross-lingual Representation Learning at Scale. In Jurafsky, D.; Chai, J.; Schluter, N.; and Tetreault, J., eds., *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 8440–8451. Online: Association for Computational Linguistics.

de Marneffe, M.-C.; Manning, C. D.; Nivre, J.; and Zeman, D. 2021. Universal Dependencies. *Computational Linguistics*, 47(2): 255–308.

de Vries, W.; Wieling, M.; and Nissim, M. 2022. Make the Best of Cross-lingual Transfer: Evidence from POS Tagging with over 100 Languages. In Muresan, S.; Nakov, P.; and Villavicencio, A., eds., *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 7676–7685. Dublin, Ireland: Association for Computational Linguistics.

Devlin, J.; Chang, M.; Lee, K.; and Toutanova, K. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *CoRR*, abs/1810.04805.

Dufter, P.; and Schütze, H. 2020. Identifying Elements Essential for BERT's Multilinguality. In Webber, B.; Cohn, T.;

He, Y.; and Liu, Y., eds., *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 4423–4437. Online: Association for Computational Linguistics.

Eronen, J.; Ptaszynski, M.; and Masui, F. 2023a. Enhancing cross-lingual learning: Optimal transfer language selection with linguistic similarity. *Science Talks*, 6: 100226.

Eronen, J.; Ptaszynski, M.; and Masui, F. 2023b. Zero-shot cross-lingual transfer language selection using linguistic similarity. *Information Processing & Management*, 60(3): 103250.

Faisal, F.; Ahia, O.; Srivastava, A.; Ahuja, K.; Chiang, D.; Tsvetkov, Y.; and Anastasopoulos, A. 2024. DIALECT-BENCH: An NLP Benchmark for Dialects, Varieties, and Closely-Related Languages. In Ku, L.-W.; Martins, A.; and Srikumar, V., eds., *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 14412–14454. Bangkok, Thailand: Association for Computational Linguistics.

Ganin, Y.; and Lempitsky, V. 2015. Unsupervised domain adaptation by backpropagation. In *Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37*, ICML'15, 1180–1189. JMLR.org.

Ganin, Y.; Ustinova, E.; Ajakan, H.; Germain, P.; Larochelle, H.; Laviolette, F.; Marchand, M.; and Lempitsky, V. 2016. Domain-adversarial training of neural networks. 17(1): 2096–2030.

Hewitt, J.; and Manning, C. D. 2019. A Structural Probe for Finding Syntax in Word Representations. In Burstein, J.; Doran, C.; and Solorio, T., eds., *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4129–4138. Minneapolis, Minnesota: Association for Computational Linguistics.

Huang, K.-H.; Ahmad, W.; Peng, N.; and Chang, K.-W. 2021. Improving Zero-Shot Cross-Lingual Transfer Learning via Robust Training. In Moens, M.-F.; Huang, X.; Specia, L.; and Yih, S. W.-t., eds., *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 1684–1697. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics.

Jung, H.; Oh, C.; Kang, J.; Sohn, J.; Song, K.; Kim, J.; and Mortensen, D. R. 2024. Mitigating the Linguistic Gap with Phonemic Representations for Robust Cross-lingual Transfer. In Sälevä, J.; and Owodunni, A., eds., *Proceedings of the Fourth Workshop on Multilingual Representation Learning (MRL 2024)*, 200–211. Miami, Florida, USA: Association for Computational Linguistics.

Lauscher, A.; Ravishankar, V.; Vulić, I.; and Glavaš, G. 2020. From Zero to Hero: On the Limitations of Zero-Shot Language Transfer with Multilingual Transformers. In Webber, B.; Cohn, T.; He, Y.; and Liu, Y., eds., *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 4483–4499. Online: Association for Computational Linguistics.

Li, H.; Pan, S. J.; Wang, S.; and Kot, A. C. 2018a. Domain Generalization with Adversarial Feature Learning. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 5400–5409.

Li, Y.; Liu, J.; Yu, Z.; Gao, S.; Huang, Y.; and Mao, C. 2024. Representation Alignment and Adversarial Networks for Cross-lingual Dependency Parsing. In Al-Onaizan, Y.; Bansal, M.; and Chen, Y.-N., eds., *Findings of the Association for Computational Linguistics: EMNLP 2024*, 7687–7697. Miami, Florida, USA: Association for Computational Linguistics.

Li, Y.; Tian, X.; Gong, M.; Liu, Y.; Liu, T.; Zhang, K.; and Tao, D. 2018b. Deep Domain Generalization via Conditional Invariant Adversarial Networks. In *Proceedings of the European Conference on Computer Vision (ECCV)*.

Lin, F.; Mao, S.; Malfa, E. L.; Hofmann, V.; de Wynter, A.; Wang, X.; Chen, S.-Q.; Wooldridge, M.; Pierrehumbert, J. B.; and Wei, F. 2025. One Language, Many Gaps: Evaluating Dialect Fairness and Robustness of Large Language Models in Reasoning Tasks. arXiv:2410.11005.

Lin, Y.-H.; Chen, C.-Y.; Lee, J.; Li, Z.; Zhang, Y.; Xia, M.; Rijhwani, S.; He, J.; Zhang, Z.; Ma, X.; Anastasopoulos, A.; Littell, P.; and Neubig, G. 2019. Choosing Transfer Languages for Cross-Lingual Learning. In Korhonen, A.; Traum, D.; and Màrquez, L., eds., *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 3125–3135. Florence, Italy: Association for Computational Linguistics.

Littell, P.; Mortensen, D. R.; Lin, K.; Kairis, K.; Turner, C.; and Levin, L. 2017. URIEL and lang2vec: Representing languages as typological, geographical, and phylogenetic vectors. In Lapata, M.; Blunsom, P.; and Koller, A., eds., *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, 8–14. Valencia, Spain: Association for Computational Linguistics.

Mousi, B.; Durrani, N.; Dalvi, F.; Hawasly, M.; and Abdelali, A. 2024. Exploring Alignment in Shared Cross-lingual Spaces. In Ku, L.-W.; Martins, A.; and Srikumar, V., eds., *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 6326–6348. Bangkok, Thailand: Association for Computational Linguistics.

Muandet, K.; Balduzzi, D.; and Schölkopf, B. 2013. Domain generalization via invariant feature representation. In *Proceedings of the 30th International Conference on International Conference on Machine Learning - Volume 28*, ICML'13, I–10–I–18. JMLR.org.

Ngo, N. T.; and Nguyen, T. H. 2024. Zero-shot Cross-lingual Transfer Learning with Multiple Source and Target Languages for Information Extraction: Language Selection and Adversarial Training. arXiv:2411.08785.

Nguyen, D.; Joshi, A.; and Salim, F. 2025. Harnessing Test-time Adaptation for NLU tasks Involving Dialects of English. arXiv:2503.12858.

Nivre, J.; Zeman, D.; Ginter, F.; and Tyers, F. 2017. Universal Dependencies. In Klementiev, A.; and Specia, L.,

eds., *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Tutorial Abstracts*. Valencia, Spain: Association for Computational Linguistics.

Pires, T.; Schlinger, E.; and Garrette, D. 2019. How Multilingual is Multilingual BERT? In Korhonen, A.; Traum, D.; and Màrquez, L., eds., *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 4996–5001. Florence, Italy: Association for Computational Linguistics.

Rama, T.; Beinborn, L.; and Eger, S. 2020. Probing Multilingual BERT for Genetic and Typological Signals. In Scott, D.; Bel, N.; and Zong, C., eds., *Proceedings of the 28th International Conference on Computational Linguistics*, 1214–1228. Barcelona, Spain (Online): International Committee on Computational Linguistics.

Rathore, V.; Dhingra, R.; Singla, P.; and Mausam. 2023. ZGUL: Zero-shot Generalization to Unseen Languages using Multi-source Ensembling of Language Adapters. In Bouamor, H.; Pino, J.; and Bali, K., eds., *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 6969–6987. Singapore: Association for Computational Linguistics.

Rice, E.; Marashian, A.; Haynie, H.; Wense, K.; and Palmer, A. 2025. Untangling the Influence of Typology, Data, and Model Architecture on Ranking Transfer Languages for Cross-Lingual POS Tagging. In Truong, S.; Putri, R. A.; Nguyen, D.; Wang, A.; Ho, D.; Oh, A.; and Koyejo, S., eds., *Proceedings of the 1st Workshop on Language Models for Underserved Communities (LM4UC 2025)*, 22–31. Albuquerque, New Mexico: Association for Computational Linguistics. ISBN 979-8-89176-242-8.

Snæbjarnarson, V.; Simonsen, A.; Glavaš, G.; and Vulić, I. 2023. Transfer to a Low-Resource Language via Close Relatives: The Case Study on Faroese. In Alumäe, T.; and Fishel, M., eds., *Proceedings of the 24th Nordic Conference on Computational Linguistics (NoDaLiDa)*, 728–737. Tórshavn, Faroe Islands: University of Tartu Library.

Srivastava, A.; and Chiang, D. 2025. We're Calling an Intervention: Exploring Fundamental Hurdles in Adapting Language Models to Nonstandard Text. In Bak, J.; Goot, R. v. d.; Jang, H.; Buaphet, W.; Ramponi, A.; Xu, W.; and Ritter, A., eds., *Proceedings of the Tenth Workshop on Noisy and User-generated Text*, 45–56. Albuquerque, New Mexico, USA: Association for Computational Linguistics. ISBN 979-8-89176-232-9.

Tahery, S.; Kianian, S.; and Farzi, S. 2024. Cross-Lingual NLU: Mitigating Language-Specific Impact in Embeddings Leveraging Adversarial Learning. In Calzolari, N.; Kan, M.-Y.; Hoste, V.; Lenci, A.; Sakti, S.; and Xue, N., eds., *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, 4158–4163. Torino, Italia: ELRA and ICCL.

Üstün, A.; Bisazza, A.; Bouma, G.; and van Noord, G. 2020. UDapter: Language Adaptation for Truly Universal Dependency Parsing. In Webber, B.; Cohn, T.; He, Y.; and Liu, Y., eds., *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2302–2315. Online: Association for Computational Linguistics.

Wang, B.; Lapata, M.; and Titov, I. 2021. Meta-Learning for Domain Generalization in Semantic Parsing. In Toutanova, K.; Rumshisky, A.; Zettlemoyer, L.; Hakkani-Tur, D.; Beltagy, I.; Bethard, S.; Cotterell, R.; Chakraborty, T.; and Zhou, Y., eds., *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 366–379. Online: Association for Computational Linguistics.

Wang, F.; Huang, K.-H.; Chang, K.-W.; and Chen, M. 2023. Self-Augmentation Improves Zero-Shot Cross-Lingual Transfer. In Park, J. C.; Arase, Y.; Hu, B.; Lu, W.; Wijaya, D.; Purwarianti, A.; and Krisnadhi, A. A., eds., *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics (Volume 2: Short Papers)*, 1–9. Nusa Dua, Bali: Association for Computational Linguistics.

Wang, S.; Zhou, J.; Chen, Q.; Zhang, Q.; Gui, T.; and Huang, X. 2024. Domain Generalization via Causal Adjustment for Cross-Domain Sentiment Analysis. In Calzolari, N.; Kan, M.-Y.; Hoste, V.; Lenci, A.; Sakti, S.; and Xue, N., eds., *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, 5286–5298. Torino, Italia: ELRA and ICCL.

Wu, D.; and Monz, C. 2023. Beyond Shared Vocabulary: Increasing Representational Word Similarities across Languages for Multilingual Machine Translation. In Bouamor, H.; Pino, J.; and Bali, K., eds., *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 9749–9764. Singapore: Association for Computational Linguistics.

Yang, H.; Chen, H.; Zhou, H.; and Li, L. 2022. Enhancing Cross-lingual Transfer by Manifold Mixup. In *International Conference on Learning Representations*.

Zhou, K.; Liu, Z.; Qiao, Y.; Xiang, T.; and Loy, C. C. 2023. Domain Generalization: A Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(4): 4396–4415.

Appendix

A Language Codes

In this section, we provide the ISO 639-3 and Universal Dependency dataset code for the varieties used in this paper.

Variety	ISO 639-3	UD-code
gheg	aln	UD_Gheg-GPS
paraguay mbya guarani	gug	UD_Mbya_Guarani-Thomas
brazil mbya guarani	gun	UD_Mbya_Guarani-Dooley
permyak komi	koi	UD_Komi_Permyak-UH
zyrian komi	kpv	UD_Komi_Zyrian-IKDP
ligurian	lij	UD_Ligurian-GLT
central alemanic	gsw	UD_Swiss_German-UZH
skolt saami	sma	UD_Skolt_Sami-Giellagas
low saxon	nds	UD_Low_Saxon-LSDC
umbrian	xum	UD_Umbrian-IKUVINA

Table 5: Target Varieties in Section 4 with their ISO 639-3 and Universal Dependencies code

Variety	ISO 639-3	UD-code
italian	ita	UD_Italian-MarkIT
norweigian	nor	UD_Norwegian-Bokmaal
north sami	sme	UD_North_Sami-Giella
portuguese	por	UD_Portuguese-Bosque
spanish	spa	UD_Spanish-AnCora
finnish	fin	UD_Finnish-TDT
estonian	est	UD_Estonian-EDT
catalan	cat	UD_Catalan-AnCora
indonesian	ind	UD_Indonesian-CSUI
galician	glg	UD_Galician-CTG
galician	glg	UD_Galician-TreeGal
turkish	tur	UD_Turkish-Penn
turkish	tur	UD_Turkish-IMST
serbian	srp	UD_Serbian-SET
croatian	hrv	UD_Croatian-SET
czech	ces	UD_Czech-CAC
slovak	slk	UD_Slovak-SNK
russian	rus	UD_Russian-SynTagRus
old church slavonic	chu	UD_Old_Church_Slavonic
belarusian	bel	UD_Belarusian-HSE
ukrainian	ukr	UD_Ukrainian-IU
upper sorbian	hsb	UD_Upper_Sorbian-UFAL
bulgarian	blg	UD_Bulgarian-BTB
irish	gle	UD_Irish-IDT
welsh	cym	UD_Welsh-CCG

Table 6: Target Varieties in Section 4 with their ISO 639-3 and Universal Dependencies code

B Selected Source Varieties

In this section, we list the selected source varieties in Section 4. The LangRank selected source varieties are same for both experiments.

cluster	target variety	LangRank		TOPPing	
		source	UAS	source	UAS
albanian	gheg	italian finnish	51.00	turkish german italian	46.34
gallo-italian	ligurian	catalan spanish	63.02	portuguese italian	64.29
high german	central alemannic	norwegian bokmal italian	52.23	german turkish german	57.74
komi	komi-zyrian	indonesian turkish	35.32	bulgarian russian	38.19
	komi-permyak	estonian portuguese	36.90	bulgarian turkish	42.29
saami	skolt saami	estonian north saami	32.62	north saami galician	39.67
sabellic	umbrian	estonian turkish	35.07	north african arabic italian	37.67
tupi-guarani	paraguay mbya guarani	spanish hindi	27.05	turkish italian	36.39
	brazil mbya guarani	finnish turkish	17.21	english upper sorbian	19.00
west low german	low saxon	english italian	50.92	turkish german english	54.90

Table 7: Selected two source varieties for Dependency Parsing and its scores with VAÇAÍ-Bowl using mBERT as backbone. Abbreviations (spk) and (wrt) each refer to mode of dataset, spoken and written, respectively.

cluster	target variety	LangRank		TOPPing	
		source	UAS	source	UAS
albanian	gheg	italian finnish	58.55	norwegian bokmaal italian	57.50
gallo-italian	ligurian	catalan spanish	59.82	portuguese italian	63.44
high german	central alemannic	norwegian bokmaal italian	47.47	german turkish german	57.74
komi	komi-zyrian	indonesian turkish	35.32	bulgarian russian	37.76
	komi-permyak	estonian portuguese	42.41	bulgarian turkish	44.66
saami	skolt saami estonian	north saami north saami	42.53	north saami galician	40.99
sabellic	umbrian	estonian turkish	-	north african arabic italian	32.77
tupi-guarani	paraguay mbya guarani	spanish hindi	31.23	turkish italian	31.97
	brazil mbya guarani	finnish turkish	11.27	english italian	13.98
west low german	low saxon	english italian	48.38	german turkish german	51.65

Table 8: Selected two source varieties for Dependency Parsing and its scores with VAÇAÍ-Bowl using XLM-R as backbone. Abbreviations (spk) and (wrt) each refer to mode of dataset, spoken and written, respectively.

C Detailed Experimental Results

C.1 Dependency Parsing Results

We report UAS scores in Table 1 initially for direct comparison to the benchmark DialectBench - that provides only UAS scores. However, to better support the results, we also report the labeled attachment scores (LAS) in this section.

In Table 9 and Table 10, LAS scores generally follow the trends of UAS scores reported in the main table. The combination of TOPPing and VAÇAÍ-Bowl enhances the model's ability to capture dependencies in 8 out of 10 low-resource varieties. For the remaining varieties, the following observations hold: For *aln*, VAÇAÍ-Bowl still yields improvements in LAS across both source variety selection methods. For *nds*, the LAS score of TOPPing + VAÇAÍ-Bowl (34.89) remains comparable to the best-performing method (34.96), with UAS scores of 54.90 and 52.54, respectively—indicating a minimal trade-off.

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source selected using LangRank (Lin et al. 2019)										
mBERT	20.43	7.54	1.42	15.30	13.17	36.89	31.44	13.35	34.00	4.59
+Alignment	22.00	7.95	1.35	18.12	14.22	36.90	34.89	14.06	33.18	3.69
+VAÇAÍ-Bowl (OURS)	22.00	7.05	1.35	18.00	15.85	40.21	35.25	15.12	35.42	4.59
source selected using TOPPing (OURS)										
mBERT	20.53	10.41	2.32	18.11	20.33	42.29	34.96	17.19	37.05	5.20
+Alignment	18.21	10.74	2.21	18.45	20.10	43.19	32.61	16.06	34.15	4.90
+VAÇAÍ-Bowl (OURS)	20.79	12.13	2.44	18.79	20.33	43.79	34.89	18.21	37.65	5.20

Table 9: Quantitative results on LAS scores using mBERT as backbone on dependency parsing task evaluated across selected low-resource varieties from DialectBench.

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source selected using LangRank (Lin et al. 2019)										
XLM-R	28.87	5.34	1.16	21.04	14.80	38.10	29.01	21.12	27.60	2.60
+Alignment	29.73	6.23	0.81	20.02	16.47	37.68	28.98	19.49	29.67	3.52
+VAÇAÍ-Bowl (OURS)	30.8	7.46	3.10	22.95	15.89	37.43	29.37	19.53	29.39	4.75
source selected using TOPPing (OURS)										
mBERT	27.93	9.51	2.38	20.36	20.10	43.29	29.82	18.06	35.42	5.51
+Alignment	28.92	9.59	1.08	21.82	20.38	43.83	30.70	19.27	36.24	3.98
+VAÇAÍ-Bowl (OURS)	29.47	10.41	1.10	22.05	21.75	43.84	31.30	20.12	36.86	5.21

Table 10: Quantitative results on LAS scores using XLM-R as backbone on dependency parsing task evaluated across selected low-resource varieties from DialectBench.

C.2 Part-of-Speech Tagging Results

In this section, we report the specific evaluated results on POS tagging downstream task for mBERT and XLM-R also represented in Table 4.

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source selected using LangRank (Lin et al. 2019)										
mBERT	45.76	32.07	12.08	41.63	45.63	62.61	66.54	39.93	58.64	22.61
+Alignment	47.79	32.46	11.69	41.48	46.47	60.56	68.25	37.38	57.16	22.14
+VAÇAÍ-Bowl (OURS)	45.51	32.17	14.54	42.71	45.55	60.48	68.36	36.38	56.89	23.81
source selected using TOPPing (OURS)										
mBERT	43.80	33.37	11.19	48.68	47.71	68.32	65.48	42.03	59.26	26.56
+Alignment	45.57	33.34	9.51	49.40	48.53	68.70	63.93	44.06	61.22	28.26
+VAÇAÍ-Bowl (OURS)	50.50	33.53	10.89	49.34	48.21	69.30	66.41	43.99	61.25	25.93

Table 11: Quantitative results on F1 scores using mBERT as backbone on part-of-speech tagging task.

Methods	Varieties									
	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
source selected using LangRank (Lin et al. 2019)										
XLM-R	56.34	31.54	5.01	54.66	50.87	62.57	60.20	53.83	48.74	25.28
+Alignment	57.17	33.37	6.17	55.25	50.48	61.15	61.18	53.11	47.40	24.64
+VAÇAÍ-Bowl (OURS)	57.97	32.94	6.24	55.97	51.71	63.54	60.35	53.83	50.46	24.97
source selected using TOPPing (OURS)										
XLM-R	56.91	33.11	7.33	53.87	53.73	67.98	61.95	53.89	60.16	31.07
+Alignment	57.81	34.08	4.95	55.36	53.22	68.70	61.34	54.54	58.35	29.22
+VAÇAÍ-Bowl (OURS)	58.35	34.88	5.47	54.02	55.16	69.97	60.81	55.17	60.21	29.23

Table 12: Quantitative results on F1 scores using XLM-R as backbone on part-of-speech tagging task.

D Parameter Search for Lambda of Gradient-Reversal Layer

lambda	aln	gug	gun	koi	kpv	lij	nds	sma	gsw	xum
0.1	46.09	35.00	15.03	36.56	40.61	64.72	52.13	37.18	56.40	36.14
0.5	45.41	35.25	15.17	35.70	40.27	63.74	52.36	40.12	54.91	37.37
1.0	46.34	36.39	19.00	42.29	38.19	64.29	54.90	39.67	57.74	37.67

Table 13: Ablation study on VAÇAÍ-Bowl performance with mBERT backbone based on different lambda values.

For the gradient-reversal layer used to adversarially train invariant feature encoder in Section 3.2, we provide an ablation study on its affects on performance.