

Data-Augmentation-Based Dialectal Adaptation for LLMs

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Abstract

This report presents GMUNLP’s participation to the DIALECT-COPA shared task at VarDial 2024 (Chifu et al., 2024), which focuses on evaluating the commonsense reasoning capabilities of large language models (LLMs) on South Slavic micro-dialects. The task aims to assess how well LLMs can handle non-standard dialectal varieties, as their performance on standard languages is already well-established. We propose an approach that combines the strengths of different types of language models and leverages data augmentation techniques to improve task performance on three South Slavic dialects: Chakavian, Cherkano, and Torlak. We conduct experiments using a language-family-focused encoder-based model (BERTić) and a domain-agnostic multilingual model (AYA-101). Our results demonstrate that the proposed data augmentation techniques lead to substantial performance gains across all three test datasets in the open-source model category. This work highlights the practical utility of data augmentation and the potential of LLMs in handling non-standard dialectal varieties, contributing to the broader goal of advancing natural language understanding in low-resource and dialectal settings.¹

1 Introduction

Recent advancements in large language models (LLMs) have led to remarkable performance on a wide range of natural language understanding tasks, particularly in standard languages. However, the effectiveness of these models on non-standard dialectal varieties remains an open question (Faisal et al., 2024). The DIALECT-COPA shared task, introduced by Ljubešić et al. (2024), aims to bridge this gap by evaluating the commonsense reasoning capabilities of LLMs on South Slavic dialects.

¹Code and data are publicly available: https://github.com/ffaisal93/dialect_copa

Commonsense reasoning, as originally proposed by Gordon et al. (2011), requires models to make plausible inferences based on everyday knowledge and understanding of the world. Extending this task to dialects poses unique challenges, as models must capture the nuances and variations specific to these language varieties. The DIALECT-COPA shared task provides a platform to explore the adaptability and generalization capabilities of LLMs in this context.

In this GMUNLP submission, we explore the potential of data augmentation techniques in enhancing the performance of language models on dialectal commonsense reasoning tasks. Our approach harnesses the power of state-of-the-art LLMs to generate synthetic training data, which we combine with the provided training dataset. By employing a diverse set of language models, we aim to quantify the performance gains achievable through data augmentation. Specifically, we utilize three categories of language models to maximize dialectal task performance: (1) smaller language models that are well-suited for low-resource settings and can be easily customized, (2) mid-size language models that strike a balance between task-specific performance and language understanding capabilities, and (3) closed-source language models that generate high-quality synthetic task data to further enhance the performance of the other two categories of language models.

We achieved the highest scores across all three test datasets in the open-source model category. In addition, our solution performed on par with the GPT-4 zero-shot iterative prompting approach employed by one of the teams, demonstrating the competitiveness of the proposed approach against state-of-the-art closed-source models. Furthermore, we achieved substantial performance improvements for the small-scale, language-family-focused model BERTić by combining it with our data augmentation strategy, showcasing the ef-

fectiveness of our approach in boosting the performance of language models tailored for low-resource settings.

The remainder of this paper is organized as follows: [Section 2](#) provides an overview of the DIALECT-COPA shared task and dataset, [Section 3](#) describes our methodology and experimental setup, [Section 4](#) presents our results and analysis, and [Section 5](#) concludes the paper and discusses future directions.

2 The DIALECT-COPA shared task

Task Information In the DIALECT-COPA shared task, a premise sentence is provided along with a question that can be either a cause or an effect. The objective is to build a classifier that selects the most plausible response from two candidate answer choices based on the given premise and question. To illustrate, consider the following training example in English, where the task is to identify the most plausible cause:

```
{"premise": "My body cast a shadow over the grass.",
"choice1": "The sun was rising.",
"choice2": "The grass was cut.",
"question": "cause", "label": 0, "idx": 0}
```

The DIALECT-COPA dataset consists of such cause-effect examples across 8 languages and dialects, challenging models to perform commonsense reasoning in non-standard language varieties.

code	language	train	val.	test
en	English	400	100	
sl	Slovenian	400	100	
sl-cer	Cerkno	400	100	500
hr	Croatian	400	100	
hr-ckm	Chakavian	-	-	500
sr	Serbian	400	100	
sr-trans	Serbian (transliterated)	400	100	
sr-tor	Torlak	400	100	
sr-tor-trans	Torlak (transliterated)	400	100	500
mk	Macedonian	400	100	
mk-trans	Macedonian (transliterated)	400	100	

Table 1: DIALECT-COPA dataset statistics for different languages and their dialectal varieties.

Languages The DIALECT-COPA dataset encompasses training and validation data in 7 languages, including English, 6 moderately resourced South Slavic languages, and two related micro-dialects. The test dataset features these two micro-dialects along with an additional previously un-

Base model	Fine-tuning (FT)/Prompting	Epoch	Acc. (%)	
			en	hr
Aya-101	4 shot (2 cause, 2 effect)	-	80	75
MaLA-500	4 shot (2 cause, 2 effect)	-	50	-
Llama2-CHAT (7B)	4 shot (2 cause, 2 effect)	-	75	50
BERT	FT (eval. lang)	3	66	55
mBERT	FT (eval. lang)	3	55	57
XLM-R	FT (eval. lang)	3	54	54
BERTić	FT (eval. lang)	3	48	64

Table 2: Preliminary evaluation results on the English and Croatian validation set for different base models.

seen dialect. The three dialects in the test set are as follows:

1. The Cerkno dialect of Slovenian, spoken in the Slovenian Littoral region, specifically in the town of Idrija.
2. The Chakavian dialect of Croatian from the northern Adriatic, particularly from the town of Žminj.
3. The Torlak dialect, spoken in southeastern Serbia, northeastern North Macedonia, and northwestern Bulgaria, with the specific test instances coming from the town of Lebane.

Cerkno and Torlak dialects are present in all three dataset splits (training, validation, and test) whereas, the Chakavian dialect is intentionally held out from the training and validation splits and is exclusively encountered during the test phase. Each dialect in the test dataset comprises 500 instances. [Table 1](#) presents the detailed statistics of the DIALECT-COPA dataset, providing an overview of the distribution of instances across languages and dialects.

3 Experimental Phases

In this section, we report different phases of our experiments. We step by step perform experiments to choose appropriate base models followed by data augmentation, combination and task-specific model tuning.

Phase 1: Model Selection In the preliminary phase of our experiments, we conduct a series of trials to identify base language models that demonstrate strong performance on language understanding tasks in a multilingual context. To achieve this, we fine-tune widely-used encoder-based models, such as BERT ([Devlin et al., 2019](#)), mBERT, and XLM-R ([Conneau et al., 2020](#)), on the English and Croatian subsets of the DIALECT-COPA

Data Identifier	Description	Covered Language
[lang]-train	Original DIALECT-COPA training data	en, hr, mk, sl, sl-cer, sr, sr-tor
[lang]-trans	Transliterated (Cyrillic → Latin) training data	mk, sr, sr-tor
[lang]-claude	Providing grammar rules and few-shot Croatian-Chakavian examples to generate synthetic parallel hr-ckm-train examples given the hr-train examples	hr-ckm
[lang]-gpt4	Additional synthetic English training data generated by GPT-4 (Whitehouse et al., 2023)	en
[lang]-reverse	Reverse-augmentation on [lang]-train, [lang]-trans, and [lang]-claude data	en, hr, mk, sl, sl-cer, sr, sr-tor
[lang]-nllb	Machine translation of en-gpt4 source data to other languages using the NLLB-6B model	hr, mk, sl, sr

Table 3: Training data augmentation approaches

training dataset. Additionally, we explore the potential of more recently open-sourced large language models (LLMs) of varying sizes, such as LLaMA-2 (Touvron et al., 2023), Aya-101 (Üstün et al., 2024) and MaLA-500 (Lin et al., 2024), to gauge their effectiveness on the task.

Our key observations from this preliminary phase are as follows:

- BERT, mBERT, and XLM-R exhibit comparable performance on the Croatian subset, achieving an accuracy of around 55%(+/-) after 3 epochs of in-language fine-tuning. However, the monolingual English BERT model surpasses the multilingual models on the English subset when fine-tuned for the same number of epochs.
- BERTić (Ljubešić and Lauc, 2021), a transformer-based model pre-trained on Bosnian, Croatian, Montenegrin, and Serbian languages, aligns well with the target languages of the DIALECT-COPA test set. Fine-tuning BERTić on the Croatian subset yields a notable performance improvement of approximately 12 percent (i.e. 7 percentage points) compared to the aforementioned multilingual models.
- Employing 4-shot prompting with the LLaMA-2 7B parameter model results in better performance on the English subset. However, for the Croatian subset, LLaMA-2 generates random inferences. This finding aligns with expectations, as LLaMA-2 is primarily an English-centric model and not inherently multilingual. In an effort to address the multilingual limitations of LLaMA-2, Lin et al. (2024) proposed MaLA-500, a multilingual adaptation of the model that underwent fine-tuning using

a causal language modeling objective. However, after this adaptation, MaLA-500 produces random-level inferences on the English subset.

→ Aya-101, a 13B parameter mt5-xxl-based model (Xue et al., 2021) instruction-tuned in 101 languages. It shows superior performance both in English and Croatian.

Based on these preliminary findings, we select the two best-performing models, Aya-101 and BERTić, for further experimentation in the subsequent phases of our study. We report our preliminary experimental findings in Table 2. The results of our preliminary experiments are summarized in Table 2.

Phase 2: Data Augmentation To address the limited size of the DIALECT-COPA training dataset, which consists of only 400 instances per language, we employ various data augmentation techniques to expand the available training data. This step is crucial in mitigating the data scarcity bottleneck and improving the models’ ability to generalize across diverse dialectal variations. By augmenting the training data, we aim to provide a more representative dataset for task-specific fine-tuning and instruction tuning of our selected language models. The data augmentation approaches we explore include:

- The test dataset primarily contains instances written using the Latin script. Hence, we transliterate the Macedonian (mk) dataset from Cyrillic to Latin script to maintain consistency with the already available Serbian, and Torlak transliterated datasets.
- For each instance in the training data, we swap the premise and the correct answer choice, ef-

Setting	Description	Data Combination
o	All original dialect-copa training data mixed together	[en, hr, mk, sl, sl-cer, sr, sr-tor]-train [sr, sr-tor]-trans
otrls	Combining all original, transliterated as well as reverse-augmented and synthetic training data (only latin script ones)	[en, hr, sl, sl-cer]-train [sr, sr-tor, mk]-trans [en, hr, mk-trans, sl, sl-cer, sr-trans, sr-tor-trans]-reverse en-gpt4, hr-ckm-claude [hr, sl, mk-trans, sr-trans]-nllb
otrlslc	Combining all original, transliterated as well as reverse-augmented and synthetic training data (Both latin and cyrillic script)	all available training data
otrls _{mk-hr-ckm}	Selective otrsl setting with upsampled data count by repetition for mk, hr and hr-ckm	hr-train, mk-trans, hr-ckm-claude [hr-train, mk-trans, hr-ckm-claude]-reverse [hr, mk-trans]-nllb
otrls _{hr-ckm}	Selective otrsl setting with upsampled data count by repetition for hr and hr-ckm	hr-train, hr-ckm-claude [hr-train, hr-ckm-claude]-reverse hr-nllb
otrls _{sl-cer}	Same as previous but for sl and sl-cer	[sl, sl-cer]-train [sl, sl-cer]-reverse sl-nllb
otrls _{sr-tor}	Same as previous but for sr and sr-tor	[sr, sr-tor]-trans [sr-trans, sr-tor-trans]-reverse sr-nllb-trans
otrlslc _{sr-tor}	Same as previous but we include both transliterated as well as Cyrillic script data	[sr, sr-tor]-train, [sr, sr-tor]-trans [sr, sr-trans, sr-tor, sr-tor-trans]-reverse sr-nllb, sr-nllb-trans
otrls _{mix}	Cross-lingual mix and match using all data from otrsl setting	[en, hr, sl, sl-cer]-train [sr, sr-tor, mk]-trans [en, hr, mk-trans, sl, sl-cer, sr-trans, sr-tor-trans]-reverse en-gpt4, hr-ckm-claude [hr, sl, mk-trans, sr-trans]-nllb
otrls _{mix-mk-hr-ckm}	Cross-lingual mix and match using all data from otrsl _{mk-hr-ckm} setting	hr-train, mk-trans, hr-ckm-claude [hr-train, mk-trans, hr-ckm-claude]-reverse [hr, mk-trans]-nllb
otrls _{mix-hr-ckm}	Cross-lingual mix and match using all data from otrsl _{hr-ckm} setting	hr-train, hr-ckm-claude [hr-train, hr-ckm-claude]-reverse hr-nllb
otrlslc _{mix-testset}	Cross-lingual mix and match using all data from otrslc setting except English	all available training data except English

Table 4: After performing data augmentation, we create various data combinations by merging the augmented data blocks described in [Table 3](#) with the original training datasets. These carefully designed data settings are then employed to conduct task-specific fine-tuning or instruction tuning on the selected base models, enabling us to evaluate the impact of different data configurations and therefore, select the suitable ones for the test-set evaluation phase.

fectively transforming cause examples into effect examples and vice versa, thereby doubling the number of training instances. For example consider the following premise and two ‘effect’ choices:

premise: I poured water on my sleeping friend.
choice1: My friend awoke. ✓
choice2: My friend snored. ×

Now our proposed reverse-augmentation method will transform the above example in a ‘casue-specific’ question as follows:

premise: My friend awoke.
choice1: I poured water on my sleeping friend. ✓
choice2: My friend snored. ×

- We utilize a publicly available English COPA-style synthetic dataset generated by GPT-4 (Achiam et al., 2023), as introduced by Whitehouse et al. (2023). To expand the coverage of this synthetic data to other languages, we translate the English examples using the NLLB-6B machine translation model (Team et al., 2022) to all the four DIALECT-COPA standard languages: Croatian, Macedonian, Serbian and Slovenian.
- The DIALECT-COPA dataset does not provide any training or validation data for the Chakavian dialect. To overcome this limitation, we compile a set of Croatian to Chakavian conversion rules and corresponding examples from online language community forums ([uni](#)). In addition to these rules, we also gather a few Croatian to Chakavian lyrics translations ([lyr](#)). We then prompt the Claude-3 language model ([ant](#)) with these rules and examples, instructing it to translate the Croatian sentences from the DIALECT-COPA training set into their Chakavian equivalents. Through this process, we create a synthetic Chakavian training set in the style of DIALECT-COPA, which we refer to as [lang]-claude. Here is an example with ground truth Croatian to Chakavian translation (correctly translated words are bolded):

- | |
|--|
| → Croatian (source): Djevojka je pronašla kukca u žitaricama. Izgubila je apetit. |
| → Chakavian (gold-translation): Mlada je našla neko blago va žitaricah. Je zgubila tiek . |
| → Chakavian (claude-translation): Divojka je našla buba u žitarican. Zgubila je tieku . |

We observe that only a small number of words, specifically three in this instance, are correctly translated from Croatian to Chakavian. Despite the limited accuracy of the translation, this synthetic translated dataset enables us to train and evaluate models on the Chakavian dialect, despite the absence of original training data for this specific dialect. The detailed report on the dialect conversion rules and the Claude-3 prompt template used for generating the synthetic Chakavian dataset can be found in [Appendix A](#).

Table 3 provides a comprehensive overview of the data augmentation techniques employed and the languages covered by each approach.

Phase 3: Data Selection Following the data augmentation process, we create various data combinations by merging the augmented data with the original training datasets. **Table 4** provides a comprehensive overview of the various training data combination settings we employ, along with their respective descriptions and the specific data sources included in each combination. These combinations are designed to investigate the impact of different data characteristics on the performance of our models. For instance, the `otrs1` setting combines all original, transliterated, reverse-augmented, and synthetic data while excluding any data written in the Cyrillic script. The rationale behind this combination is to assess whether our Latin-only DIALECT-COPA test set benefits from the absence of script variations in the training data. Additionally, we introduce a language-agnostic data combination denoted as `otrs1mix`, in which we perform cross-lingual modifications by ensuring that the premise, choice1, and choice2 for each example are presented in different languages. This combination allows us to evaluate the models’ ability to handle language-agnostic reasoning.

Phase 4: Prompt Design Encoder-based models can be fine-tuned using any of the data settings created in the previous steps. However, to perform few-shot prompting or instruction tuning with generative language models (LLMs), we need to design prompt-based instructions. During our preliminary experiments, we observed that using 4-shot same-class prompting (i.e., providing 4 cause examples for a cause-based question) yields slightly better results compared to combining 2

cause and 2 effect examples in the prompt. Specifically, this approach led to a 4.9% improvement on the English validation set. So we opted for 4-shot same-class prompting to perform inference.

The following prompt template is used for inference and instruction tuning of the Aya-101 model:

```
Instruction: Given the premise, {premise}, What is the correct {question} {'before'/'after'} this?  
A: {choice1}  
B: {choice2}  
Correct {question}: {correct_answer}
```

By designing the prompt in this manner, we provide the model with a clear instruction, the premise, and the two answer choices. The model is then expected to select the correct answer based on the given question type (cause or effect). This template is employed both during inference and instruction tuning of the Aya-101 model to ensure consistency and optimize performance on the DIALECT-COPA dataset.

Phase 5: Task-Specific Tuning We employ two distinct approaches for task-specific tuning of our selected models. The first approach, known as full model fine-tuning, involves updating all the weights of the model during the training process. We apply this method to the BERTi   model, fine-tuning it for 5-10 epochs on the DIALECT-COPA dataset. However, for mid-size models like Aya-101, full fine-tuning may be unnecessarily computationally expensive, especially considering the limited amount of training data available. To address this concern, we use LoRA (Low-Rank Adaptation) adapter tuning (Hu et al., 2022) which is a more parameter-efficient tuning approach. LoRA introduces a small number of trainable parameters in the form of low-rank matrices, which are inserted between the layers of the pre-trained model. Note that this draws from a long history of efficient adaption using dedicated units (Houlsby et al., 2019; Pfeiffer et al., 2020; Faisal and Anastasopoulos, 2022). During training, only these newly introduced parameters are updated, while the original model weights remain frozen. This approach significantly reduces the number of trainable parameters, making it more suitable for fine-tuning on smaller datasets. By employing LoRA adapter tuning, we can effectively adapt the Aya-101 model to the DIALECT-COPA dataset without the need for full model fine-tuning, thereby striking a balance between perfor-

mance and computational efficiency.

4 Results and Discussion

In this section, we present and discuss the results of our experiments on the DIALECT-COPA dataset.

4.1 Validation Set Insights

Table 5 summarizes the key takeaways from our incremental experiments conducted on the validation dataset using BERTi   and Aya-101. First, we observe that combining datasets from multiple languages boosts performance on the Croatian subset, as opposed to training on a single language. This finding motivates us to utilize all available training data and prepare different data combinations, as described in **Table 4**. Second, we find that increasing the data quantity through various data augmentation techniques (**Table 3**) primarily improves performance for most languages and low-resource dialects. Furthermore, discarding instances written in the Cyrillic script can boost performance for certain languages and dialects (e.g., Croatian, Cerkno, and Serbian), while hurting others.

We also explore cross-lingual mix-and-match strategies, but we do not find any conclusive patterns indicating that this approach consistently makes the model more language-agnostic, as it helps in some cases while hindering performance in others. Additionally, we experiment with discarding English examples and upsampling specific language groups (e.g., Serbian and Torlak examples for the Torlak dialect), which leads to slight performance improvements for the Torlak dialect.

Notably, we observe that full fine-tuning of the comparatively smaller, non-instruction-tuned, but language-specific BERTi   model cannot surpass the performance of the multilingual, instruction-tuned Aya-101 model. Finally, we apply the same data combinations to perform instruction tuning on the Aya-101 model and observe an overall performance boost. However, our experiments with different numbers of training epochs (5 and 10) yield inconclusive findings.

4.2 Test Set Insights

Team-specific ranking **Table 6** presents a comparison of the best-performing submissions from different teams on the DIALECT-COPA test set. We categorize the submissions into two groups: Category 1 includes teams that utilize closed-

Base Model	Setting	en	hr	mk	sl	sl-cer	sr	sr-tor	Avg. (acc)	
Takeaway 1: Combining all training data helps										
BERTić	Finetune (hr)	-	64	-	-	-	-	-	-	
BERTić	o	0.65	0.67	0.55	0.67	0.49	0.66	0.59	0.61	
Takeaway 2: Data augmentation helps for low-resource languages in most cases										
BERTić	otrslc	0.46	0.7	0.69	0.67	0.42	0.68	0.65	0.61	
Takeaway 3: Script choice makes a difference (Using only Latin script performs better on Latin script evaluation)										
BERTić	otrs1	0.51	0.77	0.64	0.64	0.59	0.72	0.64	0.65	
Takeaway 4: Cross-lingual mix-and-match effect: inconclusive										
BERTić	otrs1 _{mix}	0.56	0.76	0.68	0.57	0.52	0.66	0.63	0.63	
Takeaway 5: Upsampling certain language groups might help targeted evaluation in some cases										
BERTić	otrs1 _{sr-tor}	0.55	0.74	0.63	0.61	0.48	0.64	0.66	0.62	
BERTić	otrs1 _{sl-cer}	0.54	0.68	0.65	0.57	0.58	0.66	0.64	0.62	
Takeaway 6: Instruction tuning helps										
Aya-101	4-shot	0.83	0.77	0.75	0.76	0.62	0.81	0.73	0.75	
Takeaway 7: Further task-specific instruction tuning helps even more										
Aya-101	otrs1	0.86	0.79	0.81	0.91	0.7	0.82	0.77	0.81	
Takeaway 7: Training for 10 epochs instead of 5: inconclusive										
setting	epochs	en	hr	mk	sl	sl-cer	sr	sr-tor	mean	max count
otrs1	10	<u>0.52</u>	<u>0.74</u>	<u>0.65</u>	0.56	<u>0.61</u>	<u>0.67</u>	0.59	<u>0.62</u>	5
otrs1	5	0.50	0.72	0.62	<u>0.57</u>	0.58	0.65	<u>0.61</u>	0.61	2
otrs1 _{mk-hr-ckm}	10	0.49	0.76	0.66	0.62	0.51	0.67	<u>0.70</u>	0.63	1
otrs1 _{mk-hr-ckm}	5	0.48	0.76	<u>0.68</u>	<u>0.64</u>	<u>0.52</u>	<u>0.71</u>	0.67	<u>0.64</u>	4
otrs1 _{sl-cer}	10	<u>0.56</u>	0.64	<u>0.65</u>	<u>0.62</u>	<u>0.58</u>	<u>0.65</u>	0.60	0.62	5
otrs1 _{sl-cer}	5	0.54	<u>0.68</u>	<u>0.65</u>	0.57	<u>0.58</u>	<u>0.66</u>	<u>0.64</u>	0.62	5
otrs1c _{sr-tor}	10	<u>0.50</u>	<u>0.70</u>	<u>0.65</u>	0.55	0.48	0.62	<u>0.68</u>	0.60	4
otrs1c _{sr-tor}	5	0.49	0.69	0.63	<u>0.60</u>	<u>0.51</u>	<u>0.62</u>	<u>0.70</u>	<u>0.61</u>	4

Table 5: Takeaways from incremental experiments performed on the DIALECT-COPA validation dataset. The best language-specific scores for each setting are underlined (Takeaway 7).

Team	Base Model	System Description				sl-cer	hr-ckm	sr-tor	Avg. (acc)
Closed Source Model Weights									
JSI	GPT-4	10-shot with first 10 test instances (without answer)				0.734	0.890	0.974	0.866
UNIRI	GPT-4	RAG implementation; Chakavian and Cerkno lexical dictionary; Reasoning instruction and self referral grading task				0.708	0.764	-	-
UNIRI	GPT-4	0-shot iterative prompt				0.664	0.774	0.894	0.777
Open Source Model Weights									
GmuNLP	Aya-101	4-shot prompting				0.694	0.756	0.840	0.763
GmuNLP	Aya-101	LORA adapter tuning on $otrs1_{hr-ckm} \rightarrow$ 4-shot prompting				0.700	0.750	0.824	0.758
GmuNLP	Aya-101	LORA adapter tuning on $otrs1 \rightarrow$ 4-shot prompting				0.682	0.760	0.824	0.755
GmuNLP	Aya-101	LORA adapter tuning on $otrs1_{hr-ckm} \rightarrow$ 4-shot prompting				0.660	0.742	0.848	0.750
WueNLP	Mixtral	LORA adapter tuning on standard variety of target dialect				0.556	0.606	0.738	0.633
CLaC	XLM-R	Fine-tuning XLM-RoBERTa base for multiple choice QA task				0.564	0.522	0.570	0.552

Table 6: Performance comparison of different submissions on DIALECT-COPA test set.

base model	setting	epoch	sl-cer	hr-ckm	sr-tor	Avg. (acc)
Aya-101	4-shot	-	0.694	0.756	0.840	0.763
Aya-101	$\text{otrslc}_{\text{mix-mk-hr-ckm}}$	5	0.690	0.756	0.836	0.761
Aya-101	$\text{otrsl}_{\text{mix-hr-ckm}}$	5	0.700	0.750	0.824	0.758
Aya-101	otrsl	5	0.682	0.760	0.824	0.755
Aya-101	$\text{otrsl}_{\text{mk-hr-ckm}}$	5	0.660	0.742	0.848	0.750
Aya-101	$\text{otrsl}_{\text{sl-cer}}$	5	0.686	0.718	0.836	0.747
BERTić	$\text{otrsl}_{\text{hr-ckm}}$	10	0.572	0.626	0.722	0.640
BERTić	$\text{otrsl}_{\text{mk-hr-ckm}}$	5	0.582	0.634	0.682	0.633
BERTić	$\text{otrslc}_{\text{mix-testset}}$	5	0.576	0.622	0.692	0.630
BERTić	otrsl	10	0.540	0.622	0.700	0.621

Table 7: GMUNLP system submissions for test-set evaluation. The best dialect-specific scores for each base-model type are bolded.

source model weights, while Category 2 consists of teams that rely on open-source model weights. Our submissions belong to the latter category. We observe that the closed-source GPT-4 model achieves the best overall performance. Team JSI employs GPT-4 with a 10-shot prompting approach, where they provide the first 10 test instances without revealing the answers. Interestingly, even the 0-shot prompting using GPT-4 (by team UNRI) outperforms all submissions in Category 2 using open-source models. Among the Category 2 submissions, GMUNLP (our submission) achieves the highest performance on all varieties. The base Aya-101 model with 4-shot prompting yields the best average score across all languages. However, LoRA adapter tuning on different data combinations results in language-specific best scores.

GMUNLP submission Table 7 presents the results of our selected 10 system submissions. We observe that the best performance achieved by the BERTić model on the otrsl setting is 62%, which is approximately 17% lower compared to the otrc1 -tuned Aya-101 model. When comparing language-specific results, we find that the Torlak (sr-tor) dialect is the easiest to predict for both the Aya-101 and BERTić models, while the Cerkno dialect (sl-cer) proves to be the most challenging to learn.

Interestingly, upsampling the Cerkno dialect-related data ($\text{otrsl}_{\text{sl-cer}}$ -tuned) does not yield the best score for the Cerkno test-set. Instead, upsampling the Chakavian dialect-related data using the $\text{otrsl}_{\text{mk-hr-ckm}}$ setting leads to better scores on the Cerkno test set. This observation holds true for both the Aya-101 and BERTić base models, indicating that leveraging data from more closely related languages does not always provide the most

significant benefit. We believe this phenomenon warrants further investigation to gain a deeper understanding of the complex interplay between language-relatedness and task-specific model performance.

5 Conclusion

In this study, we explored the impact of data augmentation techniques on fine-tuning multilingual language models for improving common sense reasoning in dialectal variations. Our experiments encompassed a range of language models, from smaller to mid-sized architectures, to investigate their adaptability to dialectal nuances. The observed variations in performance and the upper limits achieved by different models reflect the diverse ways in which language models handle and adapt to dialectal variations. The insights gained from this work may contribute to the development of more robust and adaptable language models that can handle the challenges posed by dialectal variations. Future work can explore advanced data augmentation techniques, investigate the impact of domain-specific knowledge integration, and develop novel architectures tailored to the unique characteristics of dialects.

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A Croatian to Chakavian conversion rules

Here we report the collected Croatian to Chakavian conversion rules and their corresponding examples ([uni](#)), the lyrics translations ([lyr](#)) and the Claude-3 prompt we used to generate the Chakavian synthetic translations.

Conversion rules

Rule: m's at the end of words become n's

Examples:

Ja sam = Ja san

osam = osan

s ženom = s ženon

vidim = vidin

Rule: đ becomes j

Examples:

mladi=>mlaji

među=>meju

Rule: The sounds č and đ actually do not exist separately from č and dž

Rule: genitive plural in the feminine and neuter takes a zero ending:

Examples: žena = žen, sela = sel

Rule: dative/instrumental plurals are also somewhat different.

Rule: Masculine and neuter nouns can have an alternate ending.

Examples:

it can be gradovima or gradoviman

Rule: For feminine nouns, it's shortened.

Examples:

ženama=>ženan

Rule:-ao endings are shortened to just -a

Examples:

išao je => iša je
rekao sam => reka san

Rule:-io endings change to -ija

Examples:

govorio je => gorovija je

vidio sam => vidija san

Rule:ča, aside from meaning "what" can also be used as a particle meaning "away" or "out".

Examples:

gremo ča (let's get out of here)

Rule: some of the third person plural forms can often be extended into longer -u ending forms.

Examples:

govore -> gororu -> gororudu

rade -> radu -> radidu

pišu -> pišedu

Rule: Infinitive is shortened .

There is no I at the end.

In some speeches there is neither T/Ć at the end

Examples:

bit =>bi

pivat =>piva

znat => zna

plivat => pliva

ronit => roni

Rule: change lj=>j

Examples:

zaljubiti se=>zajubit se

ljubav =>jubav

ljudska =>juska

ljudi=>judi

Rule: Change O => E in some cases

Example:

nekoga-nikega

svakoga-svakega

tomu-temu

toga-tega

bijelog-a-bilega

jednoga-jenega

jednomu-jenemu

Rule: In standard croatian third person

plural has ending in some verbs E.

In chakavian it is always U

Examples:

vide =>vidu

hoće =>hoću

stoje =>stoju

stave =>stavu

motre =>motru

leže=>ležu

Rule: Change H=>V

Examples:

kruh =>kruv

kuhati =>kuvati

suh =>suv

gluh =>gluv[/b]

Lyrics translations We collected Croatian to Chakavian lyrics translations from the lyricstranslate.com site (lyr).

Claude-3 prompt We use the following prompt consisting the the above mentioned conversion rules, examples and lyrics translations:

<conversion_file.txt>

This file contains Croatian to Chakavian dialect conversion grammar rules with examples.

Now here are some Croatian sentences and it's parallel Chakavian sentences:

<Croatian_lyrics.txt>

<Chakavian_lyrics.txt>.

Given these resources, I want you to translate the following Croatian sentences to Chakavian dialect.

<Croatian_training_sentences.txt>