






# DADA: Dialect Adaptation via Dynamic Aggregation of Linguistic Rules

Yanchen Liu  William Held  Diyi Yang 

 Harvard University,  Georgia Institute of Technology,  Stanford University  
yanchenliu@g.harvard.edu, wheld3@gatech.edu, diyiy@cs.stanford.edu

## Abstract

Existing large language models (LLMs) that mainly focus on Standard American English (SAE) often lead to significantly worse performance when being applied to other English dialects. While existing mitigations tackle discrepancies for individual target dialects, they assume access to high-accuracy dialect identification systems. The boundaries between dialects are inherently flexible, making it difficult to categorize language into discrete predefined categories. In this work, we propose DADA (Dialect Adaptation via Dynamic Aggregation), a modular approach to imbue SAE-trained models with multi-dialectal robustness by composing adapters which handle specific linguistic features. The compositional architecture of DADA allows for both targeted adaptation to specific dialect variants and simultaneous adaptation to various dialects. We show that DADA is effective for both single task and instruction finetuned language models, offering an extensible and interpretable framework for adapting existing LLMs to different English dialects.<sup>1</sup>

## 1 Introduction

As Natural Language Processing (NLP) becomes even more impactful, the equitable distribution of its benefits becomes an increasing concern. Specifically, NLP tooling is often trained and evaluated on dominant language variants, such as Standard American English (SAE). This results in a significant decline in the performance when these tools are applied to non-SAE dialects. Studies have revealed that SAE models tested on African American Vernacular English (AAVE) encounter difficulties in language identification (Jurgens et al., 2017a) as well as various other natural language tasks (Jørgensen et al., 2016a; Kiritchenko and Mohammad,

<sup>1</sup>All the code, synthetic datasets, and trained adapters in this work are available at <https://github.com/SALT-NLP/DADA>.

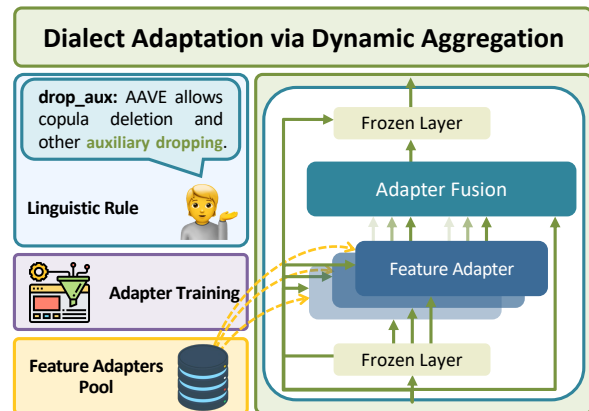


Figure 1: DADA dynamically composes adapters that handle specific features of dialectal variation to adapt an SAE model to various dialects by leveraging their commonality. We train nearly 200 feature adapters to capture the linguistic differences between SAE and its dialect variants. These feature adapters can be composed flexibly and arbitrarily to target different dialects.

2018; Blodgett et al., 2018). These challenges extend to automated speech recognition used by virtual assistants (Koenecke et al., 2020) and hate speech detection employed by online media platforms (Davidson et al., 2019; Sap et al., 2019; Rios, 2020; Mozafari et al., 2020; Halevy et al., 2021a; Zhou et al., 2021). Notably, even large language models are not exempt from these limitations (Bommasani et al., 2021; Solaiman and Dennison, 2021; Rae et al., 2022; Liang et al., 2022). Such performance disparities raise ethical and moral concerns regarding the potential for racial disparities in the seemingly expeditious development of language technologies (Hovy and Spruit, 2016; Blodgett and O’Connor, 2017; Halevy et al., 2021b).

Existing research to mitigate this disparity has mainly focused on dialectal adaptation targeting individual dialects of interest (Ziems et al., 2022; Garcia and Firat, 2022; Ziems et al., 2023; Sun et al., 2022). This approach is a powerful first step, but it has key limitations of missing connectedness

among dialects; for instance, English alone has 77 recognized variants that vary internally (Koenecke et al., 2020; Demszky et al., 2021). Prior adaptation methods also require highly accurate dialect identification systems for real-world uses, leading to the development of separate systems for different dialects. Such separate systems are not yet available for many dialects and related languages (Malmasi et al., 2016; Aepli et al., 2023; Chakravarthi et al., 2021; Aepli et al., 2022). Alternative approaches train models using a combination of various dialect variants in a multi-task learning manner (Caruana, 1997; Liu et al., 2019a). However, this approach requires training new models for dialectal NLP from scratch simultaneously with data from all desired dialects. This training process is prohibitive, especially given the trend towards larger language models with costs upwards of millions of dollars<sup>2</sup>. Thus, there is a pressing need for an effective and extensible approach that can adapt existing models to the multi-dialectal setting.

Previous linguistic works have developed a collection of lexical and morphosyntactic features that describe the differences between SAE and various other English dialects (Kortmann et al., 2020; Ziems et al., 2023). Many dialects can be described by this common set of features or linguistic rules, with each dialect expressing a subset of the feature space. In addition, dialects are not deterministic speech patterns but rather ranges of acceptable use of these features that speakers adjust based on social contexts (Ziems et al., 2023; Koenecke et al., 2020; Demszky et al., 2021). As a result, dialects do not neatly fit into predefined categories.

To this end, we develop a model which handles this reality by accommodating the diversity of English variants at a fine-grained level (linguistic features or linguistic rules). Concretely, we propose Dialect Adaptation via Dynamic Aggregation (DADA): a modular approach to adapt an established model trained on SAE to dialect variants by composing linguistic features. DADA captures and encapsulates each feature using adapters (Houlsby et al., 2019) trained on individual feature rules. Feature adapters dynamically aggregate at test time using adapter fusion (Pfeiffer et al., 2021), which enables the SAE model to flexibly adapt to dialects. The modular design of DADA enables targeted adaptation to specific dialect variants or simulta-

neous adaptation to multiple dialects. As a result of its compositional nature, DADA also makes it easy to re-use feature adapters regardless of dialect, speaker, or time variations in feature usage. The modular architecture ensures interpretability by enabling analysis of the components responsible for the improvement in performance.

To sum up, our work contributes the following:

- We propose a modular approach DADA to adapt the standard SAE model to dialect variants via a dynamic aggregation of different linguistic features. (Sec. 3)
- We train nearly 200 feature adapters, which can be flexibly composed to target different dialects. Moreover, we demonstrate that DADA with all the trained feature adapters can consistently improve model performance across five English dialects. (Sec. 4)
- DADA exhibits strong interpretability. Using AAVE as an example, we illustrate that DADA possesses the capability to detect the relevant linguistic features for a given input and subsequently activate the corresponding feature adapters. (Sec. 5)
- We show that DADA improves dialectal robustness in task-agnostic instruction-tuned LLMs using FLAN-T5 (Chung et al., 2022) (Sec. 6), which highlights the capability of DADA in learning task-agnostic features that can be applied to newer general-purpose models.

## 2 Related Work

**Dialect** NLP research tends to focus primarily on dominant dialects represented in "textbook" grammar, such as Standard American English (SAE), over lower-resource dialects. The performance disparity in resulting models is pervasive (Koenecke et al., 2020; Davidson et al., 2019; Sap et al., 2019; Rios, 2020; Mozafari et al., 2020; Halevy et al., 2021a; Zhou et al., 2021; Ziems et al., 2022, 2023; Sun et al., 2022). The existence of such performance disparities raises ethical and moral concerns where NLP can potentially exacerbate the marginalization of the speakers of these dialects (Blodgett and O'Connor, 2017; Halevy et al., 2021b). Lacking a common dialectal evaluation, NLP can reinforce existing power discrepancies (Hovy and Spruit, 2016; Bommasani et al., 2021). Existing works on English dialects have mainly focused on adapting models to individual dialects, such as

<sup>2</sup><https://lambdalabs.com/blog/demystifying-gpt-3>

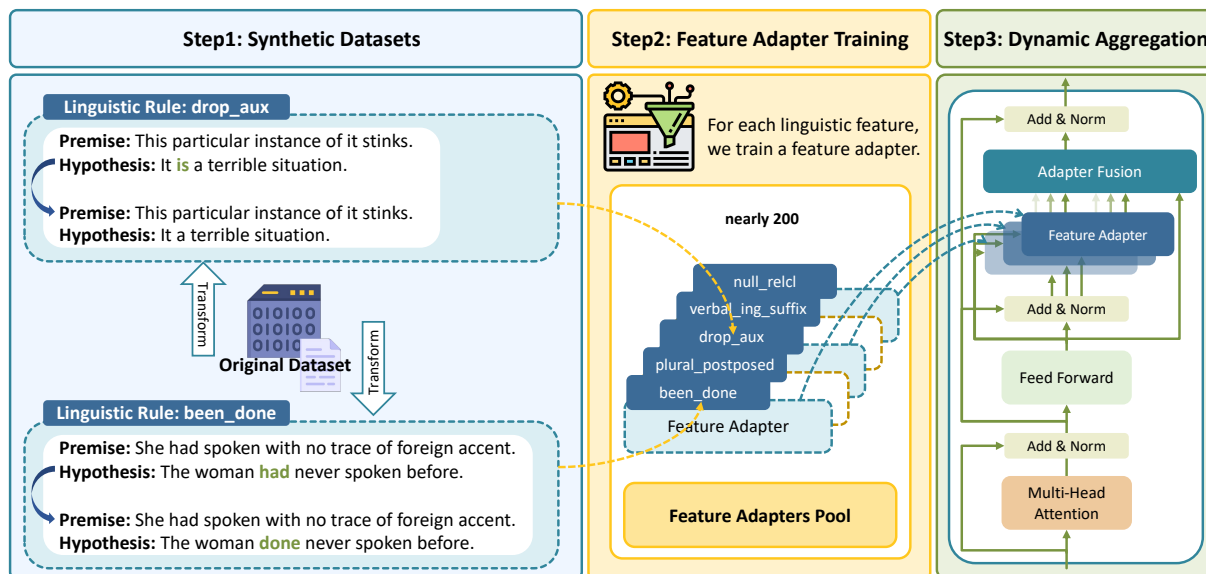


Figure 2: The overall process of DADA. We first construct a synthetic dataset  $D_i$  by applying each linguistic transformation rule  $T_i \in \mathcal{T}$ , such as **drop\_aux**: "AAVE allows copula deletion and other auxiliary dropping", to each individual training example within the original training dataset  $D$  (taking MNLi as an example). Then we develop a feature adapter  $A_i$  for each linguistic rule  $T_i$  by training it on the corresponding synthetic dataset  $D_i$ . We select the backbone model trained on the original SAE task datasets to enable the feature adapter to capture linguistic differences while disregarding the task-specific information.

African American Vernacular English (AAVE) (Jørgensen et al., 2016b; Blevins et al., 2016; Ziems et al., 2022). However, for real-world use, such systems would require another system to recognize these dialects so that the appropriate model can be used for each input. This task itself is challenging, with state-of-the-art systems showing relatively low accuracy even when distinguishing high-resource dialects of English (Zampieri et al., 2023). Our work avoids this flaw by modeling multiple dialects at once using multidialectal training data. Multidialectal training data has been shown to potentially increase robustness across all dialects in multiple prior works around data collection (Jurgens et al., 2017b) and augmentation (Ziems et al., 2023).

**Parameter-Efficient Learning** To efficiently transfer pretrained language models to downstream tasks, several techniques (He et al., 2022) have been proposed to update only a small number of extra parameters while keeping most parameters frozen. For example, adapter tuning (Houlsby et al., 2019; Pfeiffer et al., 2020) adapts models using small bottleneck modules. Prefix tuning (Li and Liang, 2021) and prompt tuning (Lester et al., 2021) prepend additional tunable prefix tokens to input or hidden layers. Brown et al. (2020); Liu et al. (2022a,b) prompt language models for specific tasks without any parameter updates by in-context

learning. Besides, several research efforts have been carried out to ensemble parameter-efficient components for multi-task learning and domain adaptation. Pfeiffer et al. (2021) propose to aggregate adapters trained on source tasks with an attentional layer to transfer acquired knowledge to a target task. Asai et al. (2022) introduce a similar method, while using soft prompts instead of adapters. To improve robustness against dataset shortcuts, Liu et al. (2023) combine adapters with gating networks. Recently, Held et al. (2023) use adapter stacking for task-agnostic robustness targeting individual dialects. However, given the inherent flexibility of dialects, there arises a necessity for a method to enhance multi-dialectal robustness. Moreover, the existence of well-defined transformation rules between dialects, which is uncommon in other domains, allows us to achieve finer-grained adaptation by aggregating linguistic features.

**Instruction Tuning** Inspired by the success of prompting LLMs to adapt to various tasks (Brown et al., 2020), instruction tuning (Sanh et al., 2022; Wei et al., 2022; Ouyang et al., 2022) propose to finetune language models on a variety of tasks described through instructions to achieve the multi-task capability and to enhance zero-shot performance on unseen tasks. Since instruction tuning involves prompting the language models at the input

level, our approach is orthogonal to it and can be employed in conjunction to enhance model’s multi-task and multi-dialect abilities simultaneously.

### 3 DADA

We introduce Dialect Adaptation via Dynamic Aggregation (DADA), a modular method for adapting an existing model trained on the Standard American English (SAE) to accommodate dialect variants at a finer-grained level. Our proposed method deploys a dynamic aggregation of feature adapters, which characterize the divergence of linguistic features between SAE and its dialect variants. Specifically, DADA involves the creation of a synthetic training dataset for each individual feature using transformation rules (Ziems et al., 2023). These synthetic datasets are used to train respective adapters for each linguistic feature. Finally, we compose these feature adapters to create a single model via an additional fusion layer.

#### 3.1 Synthetic Datasets

Previous works have discerned a series of linguistic divergences and devised `Multi-VALUE`, a collection of lexical and morphosyntactic transformation rules<sup>3</sup> between SAE and its 50 dialect variants (Ziems et al., 2022, 2023), including Appalachian English (`AppE`), Chicano English (`ChcE`), Colloquial Singapore English (`CollSgE`), Indian English (`IndE`), and African American Vernacular English (`AAVE`), among others. For instance, a well-known linguistic feature of `AAVE` is the use of `Negative Concord`, where two negative morphemes are employed to convey a single negation (Martin and Wolfram, 2021). This transformation rule is sensitive to the verb-object dependency structure and necessitates an indefinite noun object (Green, 2002). As an example, the SAE sentence “*He doesn’t have a camera*” could be rendered as “*He don’t have no camera*” in `AAVE`.

Let  $\mathcal{T} = \{T_1, T_2, \dots, T_N\}$  denote the set of transformation rules between SAE and its dialect variants. For each transformation rule  $T_i \in \mathcal{T}$ , we can generate a corresponding synthetic dataset  $D_i$  by applying the respective rule to each individual training example within the original training dataset  $D$ .

<sup>3</sup>See Appendix A for a detailed description of each transformation rule and the statistics of the corresponding synthetic training dataset.

#### 3.2 Feature Adapter

Adapter tuning is known for its ability to adapt quickly to new tasks without catastrophic forgetting (Pfeiffer et al., 2021). Given these benefits and the inherent modularity of adapters, we develop a feature adapter  $A_i$  for each of the  $N$  linguistic transformation rules  $T_i \in \mathcal{T}$  by training it on the corresponding synthetic dataset  $D_i$  created in Sec. 3.1. We insert an adapter module after each feed-forward layer<sup>4</sup> of the backbone model  $M$  that has been trained on the original SAE task datasets, in order to target specific lexical and morphosyntactic differences between SAE and its dialect variants.

#### 3.3 Dynamic Aggregation

In Sec. 3.2, we described the process of training feature adapter  $A_i$  for each linguistic transformation rule to capture a specific type of linguistic difference between SAE and its dialect variants. However, it is common for multiple linguistic differences to co-occur within a single sentence in real-world scenarios, thereby necessitating the model to simultaneously consider these distinct linguistic features to varying degrees.

Therefore, we propose to dynamically aggregate the  $N$  trained feature adapters, denoted as  $\mathcal{A} = \{A_1, A_2, \dots, A_N\}$ , into the SAE-trained backbone model  $M$  via an additional fusion layer (Pfeiffer et al., 2021). For this purpose, we first construct a super-synthetic training dataset  $\mathcal{D}$ , employing the same approach as described in Sec. 3.1, but with all lexical and morphosyntactic transformation rules  $\mathcal{T} = \{T_1, T_2, \dots, T_N\}$  applied. After incorporating the  $N$  trained feature adapters  $\mathcal{A}$  and a fusion layer into each layer of the backbone model, we train the fusion layers using the super-synthetic training dataset  $\mathcal{D}$ , while keeping the feature adapters  $\mathcal{A}$  and the backbone model  $M$  frozen.

Following Pfeiffer et al. (2021), we define the fusion layer as a composition of *Key*, *Value* and *Query* matrices at each layer  $l$  of the transformer, denoted by  $\mathbf{K}_l$ ,  $\mathbf{V}_l$  and  $\mathbf{Q}_l$  respectively. The output of the feedforward layer  $\mathbf{h}_l$  is taken as the query vector and the output of each feature adapter  $A_i$ , denoted as  $\mathbf{a}_{l,i}$  is used as input to both the value and key transformations. With this attention-like fusion layer (Vaswani et al., 2017), the outputs of

<sup>4</sup>There are different implementation variants for adapter tuning, and in our work, we follow Pfeiffer et al. (2020) by only inserting adapter modules after each feed-forward layer, while in some other works, adapters are inserted after multi-head attention layers as well.

all feature adapters are combined as followed:

$$\begin{aligned} s_l &= \text{softmax}(\mathbf{h}_l^T \mathbf{Q}_l \cdot \mathbf{a}'_{l,i} \mathbf{K}_l), i \in \{1, \dots, N\}, \\ \mathbf{a}'_{l,i} &= \mathbf{a}'_{l,i} \mathbf{V}_l, i \in \{1, \dots, N\}, \\ \mathbf{A}'_l &= [\mathbf{a}'_{l,0}, \dots, \mathbf{a}'_{l,N}], \\ \mathbf{o}_l &= \mathbf{s}_l^T \mathbf{A}'_l, \end{aligned}$$

where  $[\cdot, \cdot]$  indicates the concatenation of vectors and  $\mathbf{o}_l$  is the output of the  $l$ -th fusion layer. Through training on the super-synthetic dataset  $\mathcal{D}$ , a parameterized compositional mixture of feature adapters can be learned to identify the applied linguistic features for a given input and activate the corresponding feature adapters, thereby facilitating the effective addressing of linguistic discrepancies between **SAE** and its dialect variants.

To sum up, the **compositionality** of DADA enables targeted adaptation to specific dialect variants by selecting appropriate feature adapters. DADA uses modularity and compositionality to adapt a model to linguistic features present at test time since the pervasiveness of a feature can vary greatly based on its applicability and density (Demszky et al., 2021). This allows DADA to simultaneously adapt to various dialects by using a comprehensive set of feature adapters. We explore this property further in Sec. 5, using its interpretability to study individual feature adaptations utilized (see Sec. 5).

## 4 Multi-Dialect Adaptation

In this section, we demonstrate how DADA can enable the adaptation of an existing **SAE** model to multiple dialect variants, taking Multi-Genre Natural Language Inference (MNLI; Williams et al. (2018)) task as an example.

### 4.1 Experimental Setup and Evaluation

As described in Sec. 3.2, we train a feature adapter for each transformation rule from Ziems et al. (2023), the collection of lexical and morphosyntactic transformation rules between **SAE** and its dialect variants. In total, we train nearly 200 feature adapters for downstream use. Here, we demonstrate that these features can be flexibly composed in DADA to improve model performance across multiple dialects simultaneously. We evaluate on five representative dialects: **AppE**, **ChcE**, **CollSgE**, **IndE**, **AAVE**. We employ RoBERTa Base (Liu et al., 2019b) that has been finetuned on the original **SAE** MNLI training dataset as the backbone model.

For each transformation rule, we generate a synthetic dataset by applying only that specific transformation rule to each example in the original MNLI training dataset. We only retain examples that differ from the original example, i.e., examples that have been transformed. Afterward, we train feature adapters using these synthetic datasets, as described in Sec. 3.2. To aggregate trained feature adapters into the backbone model, we train a large fusion layer for 5 epochs on a synthetic dataset that applies all dialectal variations simultaneously, termed **Multi**. Additionally, we include a *null* adapter that remains as the identity function. This is kept for purely **SAE** inputs. In Appendix B, we report full hyperparameters along with the training details. We evaluate DADA on five English dialects: **AppE**, **ChcE**, **CollSgE**, **IndE**, **AAVE** and report the results in Table 1. Followed by Ziems et al. (2022, 2023), we construct each dialect-specific MNLI dataset by utilizing a subset of transformation rules that correspond to the respective dialect.

### 4.2 Results

Compared to the standard **SAE** model trained on the original MNLI dataset (**SAE** baseline), DADA demonstrates significant performance improvements across all evaluated dialects and even on **SAE**, with an average improvement of 2.16%. Moreover, DADA delivers comparable performance to the strong baseline provided by individual further fine-tuning or adapter tuning on the **SAE** trained model with dialect-specific training data (Single Finetuning and Single Adapter). However, while these two approaches require a perfect dialect identification system and  $D$  models, our approach uses a single model and therefore does not rely on dialect identification. This makes DADA a simpler and more realistic method for use when the target dialect distribution is unknown.

Compared to additional finetuning or adapter tuning **Multi** on standard **SAE** model (**Multi** Finetuning and **Multi** Adapter), DADA brings an average improvement of 0.32% and 0.47%, respectively. Moreover, it tunes fewer parameters during a single training run compared to **Multi** Finetuning. We confirm that the empirically strong performance of DADA stems from the effective use of the correct individual feature adapters in Sec. 5.

Note that with DADA, in instances where a new dialect arises, the integration of this new dialect can be achieved through the identification of the

Dialect Adaptation Details				Evaluation Performance						
Method	Dialect Data	Total Params.	Dialect Params.	AppE	ChcE	Col1SgE	IndE	AAVE	Mean	SAE
SAE Baseline	-	125M	0	83.70	84.91	80.62	82.00	83.95	82.71	86.57
Finetuning	Multi	125M	125M	85.72	86.33	85.00	85.09	84.44	85.30 $\pm$ 0.31	86.72
Adapter	Multi	126M	1.5M	85.68	86.38	84.26	84.76	84.66	85.15 $\pm$ 0.32	86.73
DADA	Multi	316M	192M	<u>86.00</u> (+2.30)	<u>86.70</u> (+1.79)	84.59 (+3.97)	<u>85.37</u> (+3.37)	85.50 (+1.55)	<u>85.62</u> $\pm$ 0.31	<u>87.16</u> (+0.59)
DADA <sub>w/o null</sub>	Multi	315M	190M	<u>86.14</u> (+2.44)	<u>86.61</u> (+1.70)	84.25 (+3.63)	84.80 (+2.80)	85.74 (+1.79)	85.49 $\pm$ 0.31	<u>87.08</u> (+0.51)
Finetuning	single	$D \cdot 125M$	$D \cdot 125M$	85.74	86.45	84.84	85.11	86.15	85.56	86.57
Adapter	single	$D \cdot 126M$	$D \cdot 1.5M$	86.23	86.53	84.85	85.40	86.26	85.63	86.57

Table 1: **Multi-Dialect Adaptation** results of **SAE** RoBERTa Base (Liu et al., 2019b) model for five English dialects: **AppE**, **ChcE**, **Col1SgE**, **IndE** and **AAVE**. Due to the submission limitations of the GLUE benchmark, the results are reported on the validation mismatched split. The significance bars of the mean accuracies are determined through a paired bootstrap test conducted on the concatenation of each individual dialect dataset.  $D$  is the number of target dialects for dialect adaptation. DADA outperforms the standard SAE baseline on all five dialects and **SAE** (marked as (+)), with an average of 2.16% improvement. Most importantly, DADA achieves comparable performance and even surpasses (underlined) that of individual models.

linguistic transformation rules that govern the shift from **SAE** to the new dialect, followed by the training of a feature adapter for each new transformation rule, and finally the retraining of the fusion layer. Furthermore, the potential for reusability of trained feature adapters is significant as many dialects often share common linguistic features.

**null adapter** For **SAE** inputs, every adapter has the potential to incorrectly change the model’s original predictions. Therefore, we introduce a *null* adapter that which preserves the output of the original SAE model at each layer. We conduct an ablation study to evaluate the necessity of the *null* adapter by comparing with models where it is excluded. We denote this variant as DADA<sub>w/o null</sub>. As shown in Table 1, excluding the *null* adapter results in a slight drop in performance for SAE.

**Number of feature adapters** We analyze the average performance of DADA on 5 evaluated English dialects, considering different numbers of feature adapters ( $k$ ) ranging from 1 to all. For each  $k$ , we select the top  $k$  feature adapters with the best performance on the evaluation set. The results in Figure 3 demonstrate an overall increasing trend, indicating that each feature adapter incorporated in DADA can contribute to performance improvement, rather than relying solely on a select few.

## 5 Interpretability

As discussed in Sec. 3, DADA can implicitly identify the relevant linguistic features for a given input and activate the corresponding feature adapters. We validate this by investigating the correlation between attention scores within each layer of DADA and the presence of linguistic features, to determine whether the contributing feature adapters are relevant to the features present.

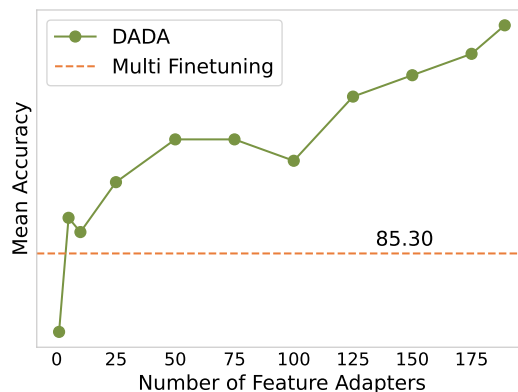


Figure 3: The mean accuracy of DADA shows an overall upward trend with the number of feature adapters.

## 5.1 Analyses Setup and Results

Here, we use the **AAVE** dialect and MNLI task as an example. To adapt a standard MNLI-finetuned RoBERTa Base model to target the **AAVE** dialect, we only need to take into account the 10 transformation rules between **SAE** and **AAVE** proposed by Ziems et al. (2022). We select the corresponding feature adapters from our collection and dynamically aggregate them by training a fusion layer on **AAVE** training set for 5 epochs with a learning rate  $5e-5$  and batch size 64. We evaluate the resulting model on the test split of the **AAVE** matched MNLI dataset as shown in Table 2. In comparison to the standard SAE model, DADA demonstrates a 3.2% and 1.4% improvement on **AAVE** and **SAE**, respectively. Moreover, DADA outperforms simple additional finetuning and adapter tuning of **AAVE** on SAE model by 0.4% and 0.5%, respectively, achieving the best performance of 86.6% on **AAVE**. These results demonstrate the superior performance of DADA over all other methods evaluated.

Dialect Adaptation Details			Test Acc.	
Backbone	Method	Data	AAVE	SAE
<i>pretrained</i>	FT	SAE	83.4	86.2
	FT	SAE + AAVE	84.8	85.6
	FT	AAVE	86.2	87.4
<i>SAE finetuned</i>	Adapter	AAVE	86.1	87.4
	DADA	AAVE	86.6✓	87.6✓

Table 2: **AAVE Adaptation** results of RoBERTa Base (Liu et al., 2019b). *pretrained* denotes the pretrained RoBERTa Base model, while *SAE finetuned* denotes the RoBERTa Base model that has been finetuned on the original SAE MNLI dataset. FT refers to "fine-tuning". DADA demonstrates superior performance on AAVE and SAE compared to baselines (marked as ✓).

## 5.2 Correlation Analysis of Fusion Activation

We perform a correlation analysis of these 10 feature adapters for the linguistic features applied to the input data. For each transformation rule, we calculate the softmax activation for each adapter, for each input to which the specific linguistic feature applies, and average over all activations within the same layer calculated over all instances in the AAVE MNLI test set. For better clarity, our final metrics takes the average utilization score of each feature adapter for the entire dataset and then subtracts the average utilization score associated with each transformation rule.

We plot the results for layers 1, 3, 7, 11 in Figure 4. We found that significant correlations in utilization on the lower layers (0-3) are observed, while those on the middle and higher layers are found to be negligible. This is consistent with our intuition, as the primary distinction between SAE and its dialect variants lies in their linguistic features (lexical and morphosyntactic), which are mainly captured by the lower layers of the model<sup>5</sup>. This analysis demonstrates that DADA has the capability to detect which linguistic features are relevant to the given input, and subsequently trigger the corresponding feature adapters. This highlights the interpretability of DADA with regard to the underlying factors that contribute to performance improvement.

## 6 Multi-Task Dialect Adaptation

Recent LLMs such as FLAN-T5 (Chung et al., 2022) and InstructGPT (Ouyang et al., 2022) are instruction-tuned (Wei et al., 2022) for various tasks, which is orthogonal to our method, making

<sup>5</sup>The linguistic feature differences are subtle. Although the absolute values of the correlation coefficients are not large, they are sufficient to indicate the existence of correlations.

it possible to combine the two approaches easily. In this section, we demonstrate how DADA can be employed to instruction-tuned LLMs to improve their task-agnostic performance on dialects.

### 6.1 Experimental Setup

Using AAVE dialect as a case study, to demonstrate the effectiveness of our method in adapting the SAE model across multiple tasks, we include the tasks from the AAVE transformed version (Ziems et al., 2022) of the GLUE Benchmark (Wang et al., 2018), including CoLA, MNLI, QNLI, QQP, SST-2, and STS-B. For our backbone model, we employ a FLAN-T5 Base (Chung et al., 2022). Despite the original paper incorporates GLUE within the FLAN-T5’s training data, we retrain the model on these specific tasks to enhance its suitability.

### 6.2 Multi-task training

For each transformation rule of AAVE dialect, we construct synthetic training data following the procedure described in Sec. 3.1. However, in the case of a multi-task model, we construct a synthetic dataset for each task considered and utilize the mixture to train the corresponding feature adapter. Subsequently, we proceed to fuse these feature adapters by training a fusion layer on the super-synthetic dataset **Multi-Task AAVE**, which is constructed by applying all the AAVE transformation rules. In Appendix D, we provide the templates used to train the FLAN-T5 model. In Appendix B, we report full hyperparameters along with the training details. We assess the performance of DADA on AAVE transformed version of the GLUE Benchmark, and compare its results with the SAE baseline and Adapter Tuning with **Multi-Task AAVE**.

### 6.3 Results

It is surprising to note that although single Adapter Tuning with **Multi-Task AAVE** demonstrates improvements in 4 out of 7 tasks, the overall average performance is even inferior to that of the SAE baseline. In contrast, DADA consistently outperforms both the SAE baseline and Adapter Tuning across all evaluated tasks, resulting in an overall improvement of 1.80/1.92 points on the AAVE GLUE benchmark, respectively. Specifically, on the relatively large datasets, DADA achieves a notable accuracy improvement of 2.0%/1.0% on MNLI-mm, 0.9%/1.2% on QNLI, and 1.5%/0.9% on QQP when compared to the SAE Baseline and Adapter Tuning, respectively. These results demonstrate

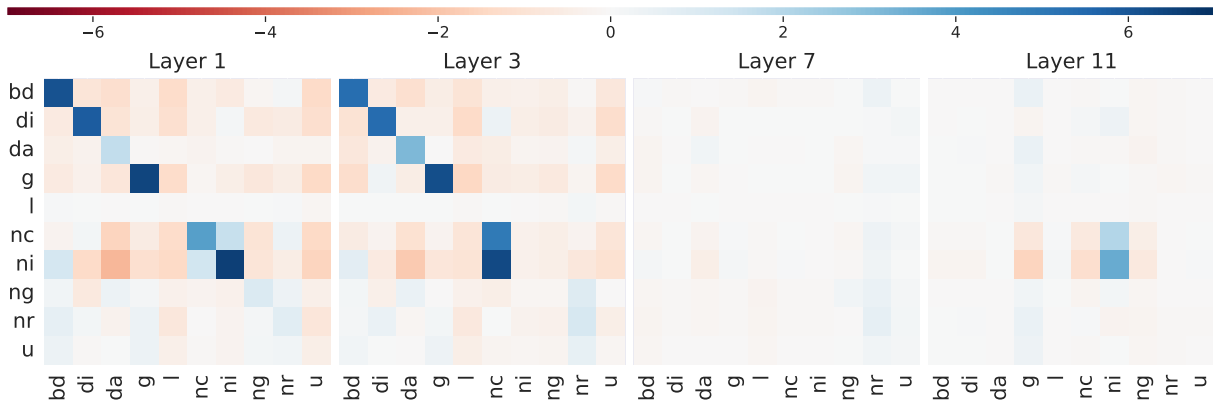


Figure 4: **Correlation Coefficients** for **AAVE** adaptation between the feature adapters (column) and the inputs to which specific linguistic features (row) apply in layers 1, 3, 7, 11. (See Appendix C for other layers.) Significant correlations can be observed within the lower layers (0-3), whereas there appear to be little to no correlations in the middle and higher layers. We use abbreviations for certain terms, such as "nc" for "negative\_concord."

Method	AAVE GLUE Performance							
	CoLA	MNLI-m	MNLI-mm	QNLI	QQP	SST2	STS-B	Mean
SAE Baseline	21.1	83.2	82.6	90.6	87.1	92.1	86.4	77.59
Adapter Tuning	18.2	84.1	83.6	90.3	87.7	92.9	85.5	77.47
DADA	26.3 ✓	84.4 ✓	84.6 ✓	91.5 ✓	88.6 ✓	93.7 ✓	86.6 ✓	79.39 ✓
ChatGPT	26.33	59.60	63.00	82.00	72.40	95.00	80.15	68.35
ChatGPT + "Native Speaker"	18.24 ↓	56.00 ↓	57.20 ↓	73.60 ↓	67.60 ↓	91.60 ↓	48.91 ↓	59.02 ↓

Table 3: **Multi-Task AAVE Adaptation** results of **SAE** FLAN-T5 Base (Chung et al., 2022) (Matthew’s Corr. for CoLA; Pearson-Spearman Corr. for STS-B; Accuracy for all others). SAE Baseline denotes the FLAN-T5 Base model that has been finetuned using the original **SAE** mixture of task datasets. In comparison to both the SAE Baseline and Adapter Tuning with **Multi-Task AAVE**, DADA consistently exhibits superior performance across all evaluated tasks (marked with ✓). Due to budget constraints, the results of ChatGPT are reported on a randomly sampled 500 example subset of the development sets. Prompt based interventions do not improve ChatGPT’s performance on **AAVE**. On the contrary, it can even result in further degraded performance (marked with ↓).

that our proposed approach, DADA, is not limited to single-task applications but can be easily scaled up to accommodate various tasks for use with the increasingly common multi-task instruction-tuning setup using in popular large-scale industrial systems (Ouyang et al., 2022; OpenAI, 2023a; Anil et al., 2023; OpenAI, 2023b).

In Table 3, we also present the results obtained with ChatGPT<sup>6</sup> (OpenAI, 2023a). Due to budget constraints, we were only able to evaluate randomly sampled 500 examples from the development set of each task. However, even with this limited evaluation, we can still gain insights that ChatGPT performs significantly worse than the **SAE** FLAN-T5 Base model on 5 out of 7 tasks. This emphasizes that merely scaling up the model is inadequate for tackling the challenge of dialect disparities. These limitations persist even in the context of large language models. Inspired by "expert"

<sup>6</sup>Engine: gpt-3.5-turbo. We conducted our ChatGPT experiments on May 16, 2023.

prompts (Odena et al., 2021; Shi et al., 2022), we incorporate a "Native Speaker" Prompt for ChatGPT:

"You are a native [DIALECT\_NAME] English speaker, and here is your task:"

However, ChatGPT + "Native Speaker" Prompt does not yield improved results and, in fact, performs even worse than the vanilla ChatGPT on all evaluated tasks. This highlights that dialect adaptation is not solved with trivial prompt-based interventions while being simultaneously less grounded in expert linguistic resources than DADA.

## 7 Conclusion

In this paper, we present **Dialect Adaptation via Dynamic Aggregation (DADA)**, a fine-grained and modular approach designed to adapt an established model trained on Standard American English to its dialect variants through the compositional aggregation of linguistic features. Our experiments demonstrate that the compositionality of DADA en-



ables targeted adaptation to specific dialects, and demonstrated improved robustness across multiple evaluated dialects, including AppE, ChcE, CollSgE, IndE, and AAVE. Our analysis also highlights the interpretability of DADA, as shown through its capability to identify relevant linguistic features for a given input and trigger the corresponding adapters. Furthermore, our experiments on FLAN-T5 illustrate the potential of applying DADA to task-agnostic instruction-tuned large language models, showcasing its generalizability.

## Limitations

DADA involves the training for feature adapters and the fusion layer, which can make it computationally expensive, especially when dealing with a substantial number of linguistic rules. However, each training run only requires a small number of parameters to be learned, and parallelization is feasible for feature adapter training. More importantly, these trained feature adapters exhibit significant reusability; the same set of feature adapters can be reused and employed for multiple dialects, though the fusion layer would need to be retrained for these dialects. However, if a use case does not involve significant reuses, this aspect may indeed remain a limitation. We will release our trained feature adapters so that future studies will not need to incur the up-front training cost.

Furthermore, while DADA has the flexibility to utilize any linguistic rules, in our experiments, we specifically employed these linguistic transformation rules that are well-established in prior work for English (Ziems et al., 2022, 2023). These rules were chosen because they were curated by linguists, validated by dialect speakers, and because English has many globally relevant dialects (Bird, 2022). However, evaluating DADA for other language groups and broader sets of lexical variation is key area for future work.

While DADA mainly relies on Multi-VALUE (Ziems et al., 2022, 2023), they are orthogonal processes with different assumptions about dialect use. For each dialect, Multi-VALUE defines the density of a dialectal feature as the probability of the feature occurring when it is applicable, as well as the probability of the corresponding perturbation to be used in converting a sentence from SAE into that dialect. However, the actual prevalence of a feature heavily depends also on applicability.

DADA instead focuses on adapting to the lin-

guistic features present in a given sentence. We learn a parameterized compositional mixture of the dialectal features automatically, rather than relying on static assumptions of density. This avoids what we view as a major issue: it is often difficult to determine the dialect of an input since dialects themselves vary depending on context and speaker. The density of a dialectal feature represents an approximate of density across the entire dialect, but may not be accurate to a specific speaker and context (Koenecke et al., 2020). On the other hand, DADA can dynamically recognize the applicable dialectal features for a given input and activate the corresponding feature adapters. It remains to be explored in future work how the density of dialectal features, as captured in the linguistic literature, relates to the compositional mixture of these features as learned in the fusion layer of DADA.

## Ethics Statement

Previous linguistic works on dialectal features may not fully or accurately document the natural usage patterns of all existing dialects in terms of their linguistic rules. As a result, we acknowledge that our proposed method DADA, which relies on these dialectal features from prior literature, may not take some undocumented features associated with dialects into account. However, by curating more dialectal features, our method can be easily extended to a broader range of dialects. Additionally, as DADA is task-agnostic when applied to instruction-tuned models (Sec 6), malicious individuals might misuse it. To address this concern, we will release DADA with a license that explicitly prohibits its usage for purposes of deception, impersonation, mockery, discrimination, hate speech, targeted harassment, and cultural appropriation targeting dialect-speaking communities.

## Acknowledgement

We would like to thank the anonymous reviewers and SALT lab members for their valuable feedback. This work was partially sponsored by the Defense Advanced Research Project Agency (DARPA) grant HR00112290103/HR0011260656, and NSF grant IIS-2247357 and IIS-2308994.

## References

Noëmi Aepli, Antonios Anastasopoulos, Adrian-Gabriel Chifu, William Domingues, Fahim Faisal, Mihaela

- Gaman, Radu Tudor Ionescu, and Yves Scherrer. 2022. [Findings of the VarDial evaluation campaign 2022](#). In *Proceedings of the Ninth Workshop on NLP for Similar Languages, Varieties and Dialects*, pages 1–13, Gyeongju, Republic of Korea. Association for Computational Linguistics.
- Noëmi Aeppli, Çağrı Çöltekin, Rob van der Goot, T. Jauhiainen, Mourhaf Kazzaz, Nikola Ljubesic, Kai North, Barbara Plank, Yves Scherrer, and Marcos Zampieri. 2023. Findings of the vardial evaluation campaign 2023. In *Workshop on NLP for Similar Languages, Varieties and Dialects*.
- Rohan Anil, Andrew M. Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, Eric Chu, Jonathan H. Clark, Laurent El Shafey, Yanping Huang, Kathy Meier-Hellstern, Gaurav Mishra, Erica Moreira, Mark Omernick, Kevin Robinson, Sebastian Ruder, Yi Tay, Kefan Xiao, Yuanzhong Xu, Yujing Zhang, Gustavo Hernandez Abrego, Junwhan Ahn, Jacob Austin, Paul Barham, Jan Botha, James Bradbury, Siddhartha Brahma, Kevin Brooks, Michele Catasta, Yong Cheng, Colin Cherry, Christopher A. Choquette-Choo, Aakanksha Chowdhery, Clément Crepy, Shachi Dave, Mostafa Dehghani, Sunipa Dev, Jacob Devlin, Mark Díaz, Nan Du, Ethan Dyer, Vlad Feinberg, Fangxiaoyu Feng, Vlad Fienber, Markus Freitag, Xavier Garcia, Sebastian Gehrmann, Lucas Gonzalez, Guy Gur-Ari, Steven Hand, Hadi Hashemi, Le Hou, Joshua Howland, Andrea Hu, Jeffrey Hui, Jeremy Hurwitz, Michael Isard, Abe Ittycheriah, Matthew Jagielski, Wenhao Jia, Kathleen Kenealy, Maxim Krikun, Sneha Kudugunta, Chang Lan, Katherine Lee, Benjamin Lee, Eric Li, Music Li, Wei Li, YaGuang Li, Jian Li, Hyeontaek Lim, Hanzhao Lin, Zhongtao Liu, Frederick Liu, Marcello Maggioni, Aroma Mahendru, Joshua Maynez, Vedant Misra, Maysam Moussalem, Zachary Nado, John Nham, Eric Ni, Andrew Nystrom, Alicia Parrish, Marie Pellat, Martin Polacek, Alex Polozov, Reiner Pope, Siyuan Qiao, Emily Reif, Bryan Richter, Parker Riley, Alex Castro Ros, Aurko Roy, Brennan Saeta, Rajkumar Samuel, Renee Shelby, Ambrose Slone, Daniel Smilkov, David R. So, Daniel Sohn, Simon Tokumine, Dasha Valter, Vijay Vasudevan, Kiran Vodrahalli, Xuezhi Wang, Pidong Wang, Zirui Wang, Tao Wang, John Wieting, Yuhuai Wu, Kelvin Xu, Yunhan Xu, Linting Xue, Pengcheng Yin, Jiahui Yu, Qiao Zhang, Steven Zheng, Ce Zheng, Weikang Zhou, Denny Zhou, Slav Petrov, and Yonghui Wu. 2023. [Palm 2 technical report](#).
- Akari Asai, Mohammadreza Salehi, Matthew Peters, and Hannaneh Hajishirzi. 2022. [ATTEMPT: Parameter-efficient multi-task tuning via attentional mixtures of soft prompts](#). In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 6655–6672, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Steven Bird. 2022. [Local languages, third spaces, and other high-resource scenarios](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7817–7829, Dublin, Ireland. Association for Computational Linguistics.
- Terra Blevins, Robert Kwiatkowski, Jamie MacBeth, Kathleen McKeown, Desmond Patton, and Owen Rambow. 2016. [Automatically processing tweets from gang-involved youth: Towards detecting loss and aggression](#). In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 2196–2206, Osaka, Japan. The COLING 2016 Organizing Committee.
- Su Lin Blodgett and Brendan T. O’Connor. 2017. Racial disparity in natural language processing: A case study of social media african-american english. *ArXiv*, abs/1707.00061.
- Su Lin Blodgett, Johnny Wei, and Brendan O’Connor. 2018. [Twitter Universal Dependency parsing for African-American and mainstream American English](#). In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1415–1425, Melbourne, Australia. Association for Computational Linguistics.
- Rishi Bommasani, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, S. Buch, Dallas Card, Rodrigo Castellon, Niladri S. Chatterji, Annie S. Chen, Kathleen A. Creel, Jared Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren E. Gillespie, Karan Goel, Noah D. Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas F. Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, O. Khat-tab, Pang Wei Koh, Mark S. Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir P. Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avani Narayan, Deepak Narayanan, Benjamin Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, J. F. Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Robert Reich, Hongyu Ren, Frieda Rong, Yusuf H. Roohani, Camilo Ruiz, Jack Ryan, Christopher R’e, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishna Parasuram Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei A. Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. 2021.

- On the opportunities and risks of foundation models. *ArXiv*.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. [Language models are few-shot learners](#). In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Rich Caruana. 1997. [Multitask learning](#). *Mach. Learn.*, 28(1):41–75.
- Daniel Cer, Mona Diab, Eneko Agirre, Iñigo Lopez-Gazpio, and Lucia Specia. 2017. [SemEval-2017 task 1: Semantic textual similarity multilingual and crosslingual focused evaluation](#). In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 1–14, Vancouver, Canada. Association for Computational Linguistics.
- Bharathi Raja Chakravarthi, Gaman Mihaela, Radu Tudor Ionescu, Heidi Jauhiainen, Tommi Jauhiainen, Krister Lindén, Nikola Ljubešić, Niko Partanen, Ruba Priyadharshini, Christoph Purschke, Eswari Rajagopal, Yves Scherrer, and Marcos Zampieri. 2021. [Findings of the VarDial evaluation campaign 2021](#). In *Proceedings of the Eighth Workshop on NLP for Similar Languages, Varieties and Dialects*, pages 1–11, Kiyv, Ukraine. Association for Computational Linguistics.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. [Scaling instruction-finetuned language models](#).
- Thomas Davidson, Debasmita Bhattacharya, and Ingmar Weber. 2019. [Racial bias in hate speech and abusive language detection datasets](#). In *Proceedings of the Third Workshop on Abusive Language Online*, pages 25–35, Florence, Italy. Association for Computational Linguistics.
- Dorottya Demszky, Devyani Sharma, Jonathan H Clark, Vinodkumar Prabhakaran, and Jacob Eisenstein. 2021. Learning to recognize dialect features. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2315–2338.
- Xavier Garcia and Orhan Firat. 2022. Using natural language prompts for machine translation. *arXiv preprint arXiv:2202.11822*.
- Lisa J. Green. 2002. *African American English: A Linguistic Introduction*. Cambridge University Press.
- Matan Halevy, Camille Harris, Amy Bruckman, Diyi Yang, and Ayanna Howard. 2021a. [Mitigating racial biases in toxic language detection with an equity-based ensemble framework](#). In *Equity and Access in Algorithms, Mechanisms, and Optimization*, EAAMO '21, New York, NY, USA. Association for Computing Machinery.
- Matan Halevy, Camille Harris, Amy Bruckman, Diyi Yang, and Ayanna M. Howard. 2021b. Mitigating racial biases in toxic language detection with an equity-based ensemble framework. *Equity and Access in Algorithms, Mechanisms, and Optimization*.
- Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2022. [Towards a unified view of parameter-efficient transfer learning](#). In *International Conference on Learning Representations*.
- Will Held, Caleb Ziems, and Diyi Yang. 2023. [Tada: Task-agnostic dialect adapters for english](#).
- Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. [Parameter-efficient transfer learning for NLP](#). In *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 2790–2799. PMLR.
- Dirk Hovy and Shannon L. Spruit. 2016. [The social impact of natural language processing](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 591–598, Berlin, Germany. Association for Computational Linguistics.
- Anna Jørgensen, Dirk Hovy, and Anders Søgaard. 2016a. [Learning a POS tagger for AAVE-like language](#). In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1115–1120, San Diego, California. Association for Computational Linguistics.
- Anna Jørgensen, Dirk Hovy, and Anders Søgaard. 2016b. [Learning a POS tagger for AAVE-like language](#). In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1115–1120, San Diego, California. Association for Computational Linguistics.
- David Jurgens, Yulia Tsvetkov, and Dan Jurafsky. 2017a. [Incorporating dialectal variability for socially equitable language identification](#). In *Proceedings of the*

- 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 51–57, Vancouver, Canada. Association for Computational Linguistics.
- David Jurgens, Yulia Tsvetkov, and Dan Jurafsky. 2017b. [Incorporating dialectal variability for socially equitable language identification](#). In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 51–57, Vancouver, Canada. Association for Computational Linguistics.
- Svetlana Kiritchenko and Saif Mohammad. 2018. [Examining gender and race bias in two hundred sentiment analysis systems](#). In *Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics*, pages 43–53, New Orleans, Louisiana. Association for Computational Linguistics.
- Allison Koenecke, Andrew Nam, Emily Lake, Joe Nudell, Minnie Quartey, Zion Mengesha, Connor Toups, John R. Rickford, Dan Jurafsky, and Sharad Goel. 2020. [Racial disparities in automated speech recognition](#). *Proceedings of the National Academy of Sciences*, 117(14):7684–7689.
- Bernd Kortmann, Kerstin Lunkenheimer, and Katharina Ehret, editors. 2020. *eWAVE*.
- Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. [The power of scale for parameter-efficient prompt tuning](#). In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Xiang Lisa Li and Percy Liang. 2021. [Prefix-tuning: Optimizing continuous prompts for generation](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online. Association for Computational Linguistics.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, et al. 2022. Holistic evaluation of language models. *arXiv preprint arXiv:2211.09110*.
- Jiachang Liu, Dinghan Shen, Yizhe Zhang, Bill Dolan, Lawrence Carin, and Weizhu Chen. 2022a. [What makes good in-context examples for GPT-3?](#) In *Proceedings of Deep Learning Inside Out (DeeLIO 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures*, pages 100–114, Dublin, Ireland and Online. Association for Computational Linguistics.
- Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019a. [Multi-task deep neural networks for natural language understanding](#). In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4487–4496, Florence, Italy. Association for Computational Linguistics.
- Yanchen Liu, Timo Schick, and Hinrich Schütze. 2022b. [Semantic-oriented unlabeled priming for large-scale language models](#).
- Yanchen Liu, Jing Yan, Yan Chen, Jing Liu, and Hua Wu. 2023. [SMoA: Sparse mixture of adapters to mitigate multiple dataset biases](#).
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019b. [Roberta: A robustly optimized bert pretraining approach](#).
- Shervin Malmasi, Marcos Zampieri, Nikola Ljubešić, Preslav Nakov, Ahmed Ali, and Jörg Tiedemann. 2016. [Discriminating between similar languages and Arabic dialect identification: A report on the third DSL shared task](#). In *Proceedings of the Third Workshop on NLP for Similar Languages, Varieties and Dialects (VarDial3)*, pages 1–14, Osaka, Japan. The COLING 2016 Organizing Committee.
- Stefan Martin and Walt Wolfram. 2021. The sentence in african-american vernacular english. In *African-American English*, pages 11–40. Routledge.
- Marzieh Mozafari, Reza Farahbakhsh, and Noël Crespi. 2020. Hate speech detection and racial bias mitigation in social media based on bert model. *PLoS ONE*, 15.
- Augustus Odena, Charles Sutton, David Martin Dohan, Ellen Jiang, Henryk Michalewski, Jacob Austin, Maarten Paul Bosma, Maxwell Nye, Michael Terry, and Quoc V. Le. 2021. Program synthesis with large language models. In *n/a*, page n/a, n/a. N/a.
- OpenAI. 2023a. ChatGPT. <https://openai.com/research/chatgpt>.
- OpenAI. 2023b. [Gpt-4 technical report](#).
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Gray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. [Training language models to follow instructions with human feedback](#). In *Advances in Neural Information Processing Systems*.
- Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, and Iryna Gurevych. 2021. [AdapterFusion: Non-destructive task composition for transfer learning](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 487–503, Online. Association for Computational Linguistics.

- Jonas Pfeiffer, Andreas Rücklé, Clifton Poth, Aishwarya Kamath, Ivan Vulić, Sebastian Ruder, Kyunghyun Cho, and Iryna Gurevych. 2020. [AdapterHub: A framework for adapting transformers](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 46–54, Online. Association for Computational Linguistics.
- Jack W. Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, Eliza Rutherford, Tom Hennigan, Jacob Menick, Albin Cassirer, Richard Powell, George van den Driessche, Lisa Anne Hendricks, Mari-beth Rauh, Po-Sen Huang, Amelia Glaese, Johannes Welbl, Sumanth Dathathri, Saffron Huang, Jonathan Uesato, John Mellor, Irina Higgins, Antonia Creswell, Nat McAleese, Amy Wu, Erich Elsen, Siddhant Jayakumar, Elena Buchatskaya, David Budden, Esme Sutherland, Karen Simonyan, Michela Paganini, Laurent Sifre, Lena Martens, Xiang Lorraine Li, Adhiguna Kuncoro, Aida Nematzadeh, Elena Gribovskaya, Domenic Donato, Angeliki Lazaridou, Arthur Mensch, Jean-Baptiste Lespiau, Maria Tsim-poukelli, Nikolai Grigorev, Doug Fritz, Thibault Sotiaux, Mantas Pajarskas, Toby Pohlen, Zhitao Gong, Daniel Toyama, Cyprien de Masson d’Autume, Yujia Li, Tayfun Terzi, Vladimir Mikulik, Igor Babuschkin, Aidan Clark, Diego de Las Casas, Aurelia Guy, Chris Jones, James Bradbury, Matthew Johnson, Blake Hechtman, Laura Weidinger, Iason Gabriel, William Isaac, Ed Lockhart, Simon Osindero, Laura Rimell, Chris Dyer, Oriol Vinyals, Kareem Ayoub, Jeff Stanway, Lorraine Bennett, Demis Hassabis, Koray Kavukcuoglu, and Geoffrey Irving. 2022. [Scaling language models: Methods, analysis & insights from training gopher](#).
- Anthony Rios. 2020. [Fuzze: Fuzzy fairness evaluation of offensive language classifiers on african-american english](#). *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(01):881–889.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Evry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. 2022. [Multi-task prompted training enables zero-shot task generalization](#). In *International Conference on Learning Representations*.
- Maarten Sap, Dallas Card, Saadia Gabriel, Yejin Choi, and Noah A. Smith. 2019. The risk of racial bias in hate speech detection. In *Annual Meeting of the Association for Computational Linguistics*.
- Freda Shi, Mirac Suzgun, Markus Freitag, Xuezhi Wang, Suraj Srivats, Soroush Vosoughi, Hyung Won Chung, Yi Tay, Sebastian Ruder, Denny Zhou, et al. 2022. Language models are multilingual chain-of-thought reasoners. *arXiv preprint arXiv:2210.03057*.
- Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. [Recursive deep models for semantic compositionality over a sentiment treebank](#). In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.
- Irene Solaiman and Christy Dennison. 2021. [Process for adapting language models to society \(PALMS\) with values-targeted datasets](#). In *Advances in Neural Information Processing Systems*.
- Jiao Sun, Thibault Sellam, Elizabeth Clark, Tu Vu, Timothy Dozat, Dan Garrette, Aditya Siddhant, Jacob Eisenstein, and Sebastian Gehrmann. 2022. Dialect-robust evaluation of generated text. *arXiv preprint arXiv:2211.00922*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.
- Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. [GLUE: A multi-task benchmark and analysis platform for natural language understanding](#). In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 353–355, Brussels, Belgium. Association for Computational Linguistics.
- Alex Warstadt, Amanpreet Singh, and Samuel R Bowman. 2018. Neural network acceptability judgments. *arXiv preprint arXiv:1805.12471*.
- Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. 2022. [Finetuned language models are zero-shot learners](#). In *International Conference on Learning Representations*.
- Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. [A broad-coverage challenge corpus for sentence understanding through inference](#). In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.
- Marcos Zampieri, Kai North, T. Jauhiainen, Mariano Felice, Neha Kumari, N.U. Nair, and Yash Mahesh Bangera. 2023. Language variety identification with true labels. *ArXiv*, abs/2303.01490.

Xuhui Zhou, Maarten Sap, Swabha Swayamdipta, Noah A. Smith, and Yejin Choi. 2021. Challenges in automated debiasing for toxic language detection. *ArXiv*, abs/2102.00086.

Caleb Ziems, Jiaao Chen, Camille Harris, Jessica Anderson, and Diyi Yang. 2022. **VALUE: Understanding dialect disparity in NLU**. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3701–3720, Dublin, Ireland. Association for Computational Linguistics.

Caleb Ziems, William Held, Jingfeng Yang, Jwala Dhamala, Rahul Gupta, and Diyi Yang. 2023. **Multi-VALUE: A framework for cross-dialectal English NLP**. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Toronto, Canada. Association for Computational Linguistics.

## A Transformation Rules Details

Ziems et al. (2022, 2023) developed a collection of lexical and morphosyntactic transformation rules that account for the differences in linguistic features between **SAE** and its various dialect variants. In our study, we build upon this work by training transformation adapters for each rule in this collection. In their original paper, they present a comprehensive overview of each transformation rule in Appendix B. In Tables 9-21, they provide detailed Multi-VALUE implementations, including an enumeration of the implemented dialects and features, accompanied by illustrative examples for each.

Furthermore, we provide detailed statistics for the respective synthetic training datasets (for MNLI task) associated with each linguistic rule for the AAVE dialect in Table 4. While we do not present statistics for every linguistic feature for all dialects across all evaluated tasks, we release our code, all synthetic datasets and the trained adapters, to further improve the reproducibility.

Linguistic Rule	Size	Eval Acc
been_done	48,515	84.46
dey_it	33,927	84.41
drop_aux	78,157	84.06
got	25,203	83.41
lexical	331,784	86.11
negative_concord	49,529	84.41
negative_inversion	658	83.03
null_genetive	50,122	84.11
null_relcl	45,899	83.70
uninflect	124,447	84.64

Table 4: Linguistic Rules, Dataset Size, and Feature Adapter Accuracy for AAVE dialect (MNLI task).

## B Training Details

**Multi-Dialect Adaptation** We train feature adapters for each transformation rule using synthetic datasets, as described in Sec. 3.2, with learning rate  $3e-4$  and batch size 64 followed by Houlshy et al. (2019). To prevent significant performance differences among the trained feature adapters due to varying sizes of synthetic datasets, we fix the number of training steps to 10,000. For each feature adapter, we choose the checkpoint with the highest accuracy on the validation matched split of a synthetic dataset that applies all dialectal variations simultaneously, termed **Multi**. For dynamic

aggregation, we train a large fusion layer for 5 epochs on `Multi`. We set the learning rate to  $2.5e-5$  and the batch size to 64.

**Multi-Task Dialect Adaptation** For feature adapter training, we set the learning rate to  $1e-3$  and fix the number of training steps as 50000. To fuse these feature adapters, we train a fusion layer for 5 epochs using a learning rate of  $8e-5$ .

Throughout the process of model training (including finetuning, adapter tuning, DADA training etc.), we consistently employ the standard training objectives specific to the tasks, such as cross-entropy loss for classification tasks.

### C Utilization Correlation Coefficients Plots

In Sec. 5, we showcase the effectiveness of DADA in adapting the *RoBERTa Base* (Liu et al., 2019b) model that has been finetuned on the original SAE MLI training dataset to `AAVE`. To demonstrate the interpretability of DADA, we conduct an analysis of the utilization correlation among the aggregated 10 transformation adapters. We present utilization correlation coefficient plots for all layers in Figure 5 and 6.

### D FLAN-T5 Templates

We provide here the templates used in Sec. 6 to train the FLAN-T5 model for each task. In the original paper by Chung et al. (2022), they defined 10 templates for each task and randomly applied them to each training example to enhance the model’s robustness to varying instruction wordings. However, in our study, our goal is to demonstrate the generalizability of our proposed method DADA to instruction-tuned models, rather than focusing on improving the model’s instruction-following capability. Therefore, for each task, we fix the usage of the first template from the set of 10 templates designed in the original paper.

**CoLA** The Corpus of Linguistic Acceptability (CoLA; Warstadt et al. (2018)) task is a widely used benchmark that focuses on grammatical acceptability judgments. It aims to assess the ability of models to determine whether a given sentence is syntactically and semantically correct or not. For the CoLA task, we adopt the following template:

```
Sentence: {sentence}
Would a linguist rate this sentence to be
acceptable linguistically?

I think the answer is {answer}
```

**MNLI** The Multi-Genre Natural Language Inference (MNLI; Williams et al. (2018)) is designed to assess the model’s ability to comprehend and reason. MNLI involves determining the logical relationship - entailment, contradiction, or neutrality - between a given premise and a corresponding hypothesis. For the MNLI task, we adopt the following template:

```
Premise: {premise}

Hypothesis: {hypothesis}

Does the premise entail the hypothesis?

{answer}
```

**QNLI** The Question-answering Natural Language Inference (QNLI; Wang et al., 2018) task is a prominent benchmark that focuses on assessing

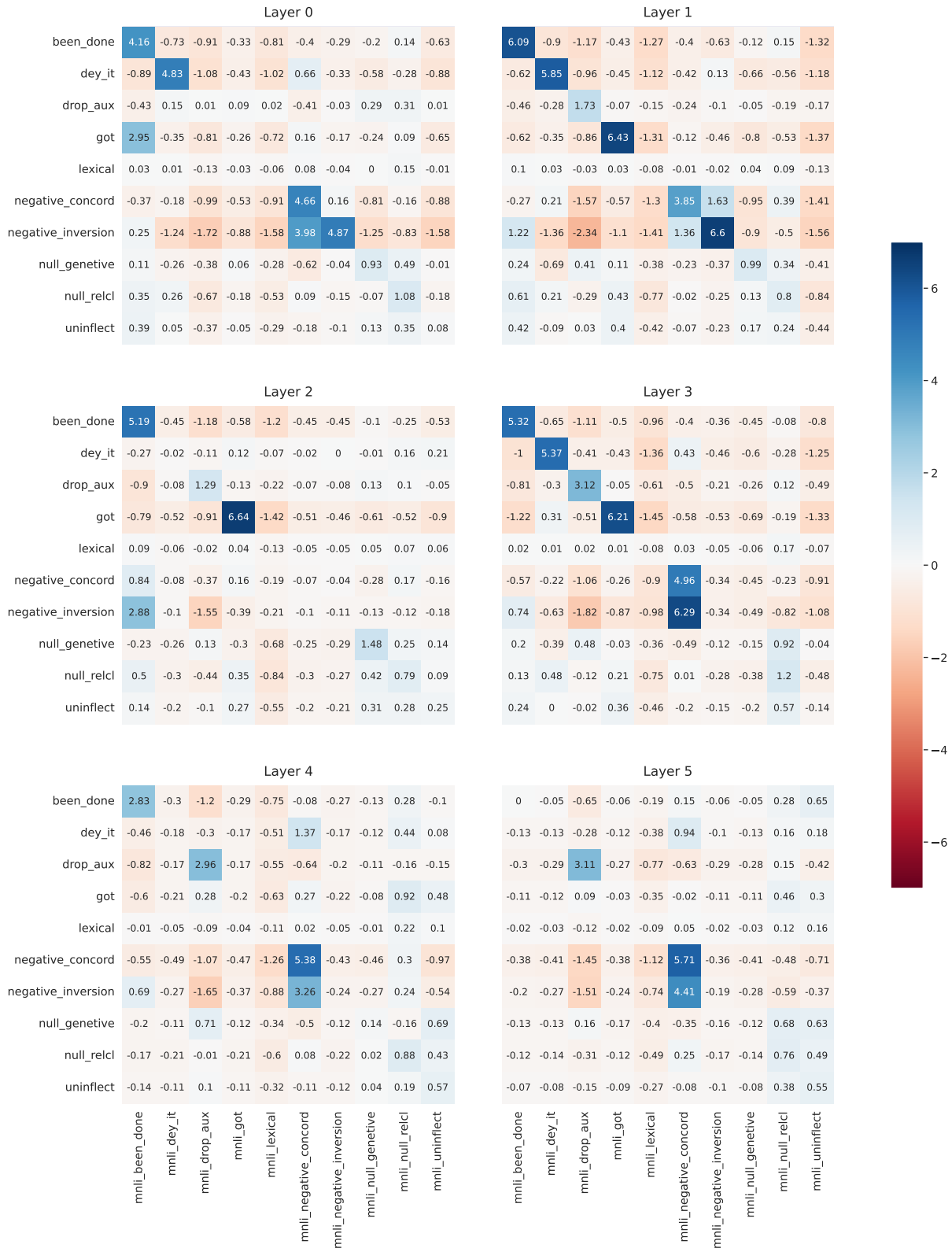


Figure 5: Correlation Coefficients between the transformation adapters (column) and the inputs to which specific transformation rules (row) apply in layers 0-5.

the ability of models to perform sentence-level semantic matching and reasoning. In this task, given a question and a corresponding sentence, the objec-

tive is to determine whether the sentence contains the answer to the question, considering both linguistic and logical entailment. For the QNLI task,



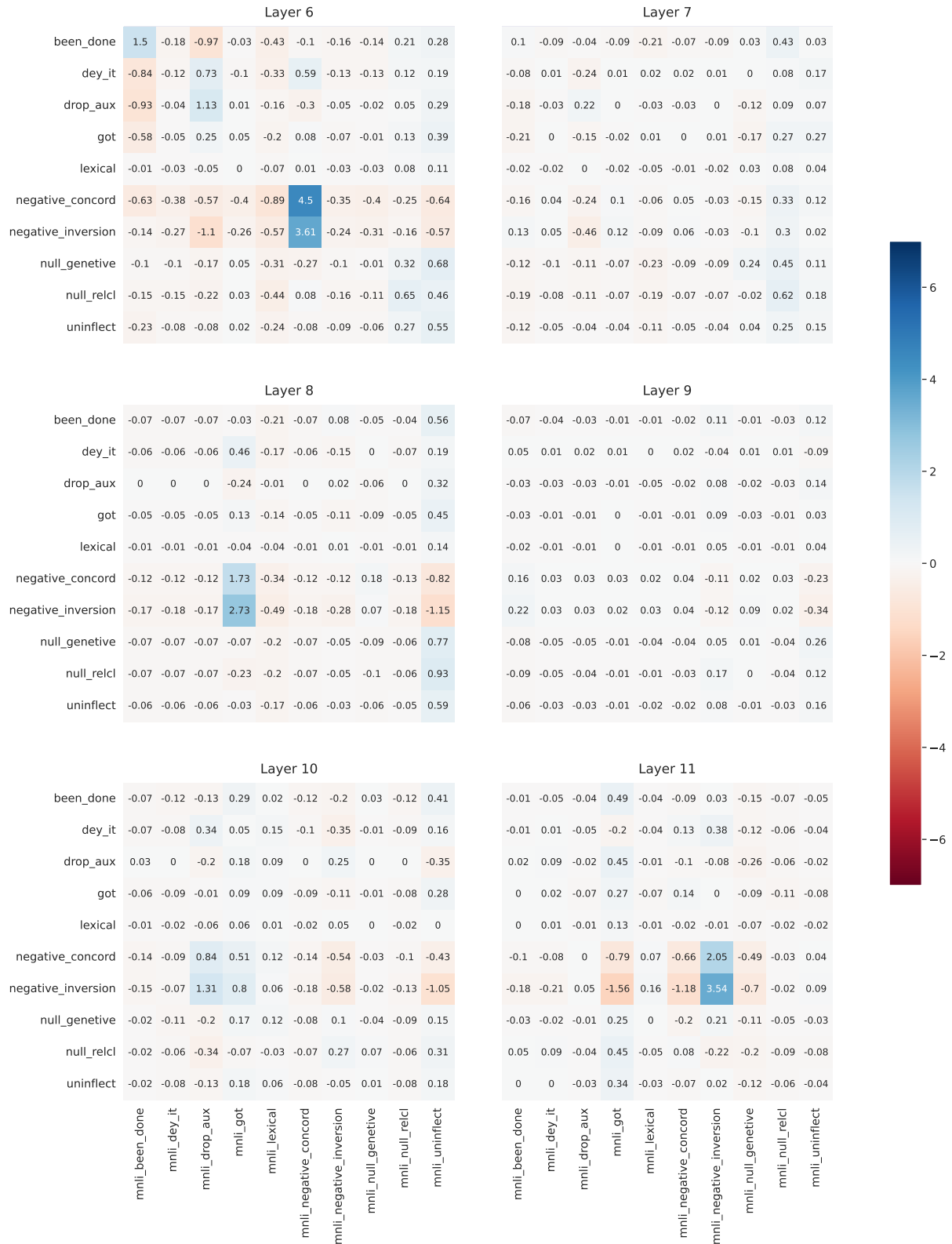


Figure 6: **Correlation Coefficients** between the transformation adapters (column) and the inputs to which specific transformation rules (row) apply in layers 6-11.

we adopt the following template:

Does the sentence {sentence} answer the question {question}

{answer}

**QQP** The Quora Question Pairs<sup>7</sup> (QQP) task is a widely recognized benchmark that focuses on question sentence similarity. The task involves determining whether a pair of questions asked on the Quora platform is semantically equivalent or not. For the QQP task, we adopt the following template:

```
{question1}
{question2}
Would you say that these questions are the same?
{answer}
```

**SST-2** The SST-2 (Stanford Sentiment Treebank; Socher et al. (2013)) task is a widely used benchmark for sentiment analysis. It involves classifying the sentiment of a given sentence as either positive or negative. For the SST-2 task, we adopt the following template:

```
Review:
{sentence}
Is this movie review sentence negative or positive?
The answer is: {answer}
```

**STS-B** The Semantic Textual Similarity Benchmark (STS-B; Cer et al. (2017)) task is a widely recognized benchmark that evaluates the ability of models to assess the semantic similarity between pairs of sentences. The task involves assigning a similarity score to pairs of sentences based on their semantic equivalence. For the STS-B task, we adopt the following template:

```
{sentence1}
{sentence2}

Rate the textual similarity of these two sentences on a scale from 0 to 5, where 0 is "no meaning overlap" and 5 is "means the same thing".

{answer}
```

---

<sup>7</sup><https://www.kaggle.com/c/quora-question-pairs>