

Dynamic Aggregation and Auto-Discovery of Linguistic Features

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DADA: Dialect Adaptation via Dynamic Aggregation of Linguistic Rules

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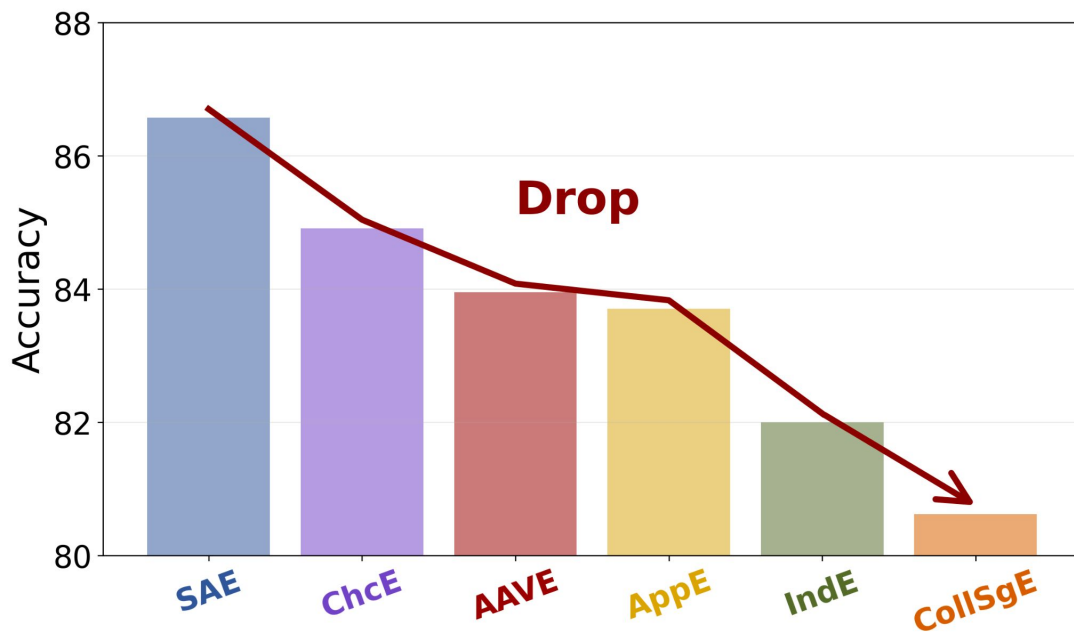
Non-Standard Linguistic Features

- ❑ language usage that deviates from the conventions
- ❑ often associated with specific social or cultural groups

Dialect: A Group of Non-Standard Linguistic Variations in a Language

Fails on Dialects

- ❑ Existing models mainly focus on Standard American English (**SAE**)
- ❑ Significant **performance drop** ↓ when applied to English Dialects



Previous Work on Dialect Adaptation

Mainly focused on targeted adaptation to a **specific dialect**

- ❑ Human Annotation ([Blevins et al., 2016](#), [Blodgett et al., 2018](#))
- ❑ Weak Supervision ([Jorgensen et al. 2016](#), [Jurgens et al. 2017](#))
- ❑ Alignment ([TADA 2023](#))



Highly accurate dialect identification systems are required!

Automatically Processing Tweets from Gang-Involved Youth: Towards Detecting Loss and Aggression

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Abstract

Violence is a serious problem for cities like Chicago and has been exacerbated by the use of social media by gang-involved youths for taunting rival gangs. We present a corpus of tweets from a young and powerful female gang member and her communicators, which we have annotated with *loss* and *aggression* labels.

Incorporating Dialectal Variability for Socially Equitable Language Identification

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Abstract

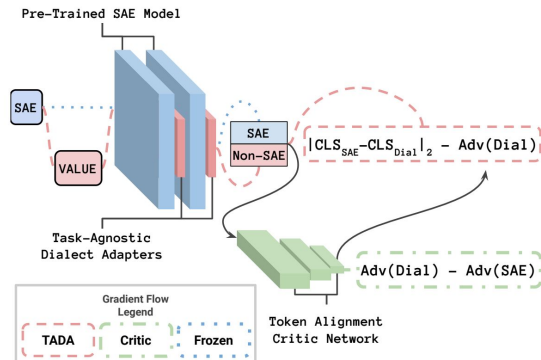
Language identification (LID) is a critical first step for processing multilingual text. Yet most LID systems are not designed to handle the linguistic diversity of global platforms like Twitter, where local dialects and rampant code-switching lead language classifiers to systematically miss minority dialect speakers and multilingual speakers. We propose a new dataset and a character-based sequence-to-sequence model for LID designed to support dialectal and multilingual language varieties. Our model achieves state-of-the-art performance on multiple LID benchmarks. Furthermore, in a case study us-

1. @username R u a wizard or wat gan sef: in d mornin - u tweet, afternoon - u tweet, nyt gan u dey tweet. beta get ur IP placement wat tweet
2. Be the lord lantern jayus me heart after that match!!!
3. Akya nengaganginis dari jash sekarnag - REDK (f) * lat tweet about you --, maybe

Figure 1: Challenges for socially-equitable LID in Twitter include dialectal text, shown from Nigeria (1) and Ireland (2), and multilingual text (Indonesian and English) in 3).

graphic and dialectal variation. As a result, these systems systematically misclassify texts from populations with millions of speakers whose local speech differs from the majority dialects (Hovy and Spruit, 2016; Blodgett et al., 2016).

Multiple systems have been proposed for broad-coverage LID at the global level (McCandless, 2010; Lui and Baldwin, 2012; Brown, 2014; Jaech



However!!! Inherent **Flexibility** of Dialects

- ❑ Flexible Boundaries
 - => no highly accurate dialect identification systems available
- ❑ Vary Depending on Personal and Social Contexts
 - => dialects do not neatly fit into predefined categories



Accommodate the diversity of dialects from a **Fine-Grained** perspective **Linguistic Features**

Method

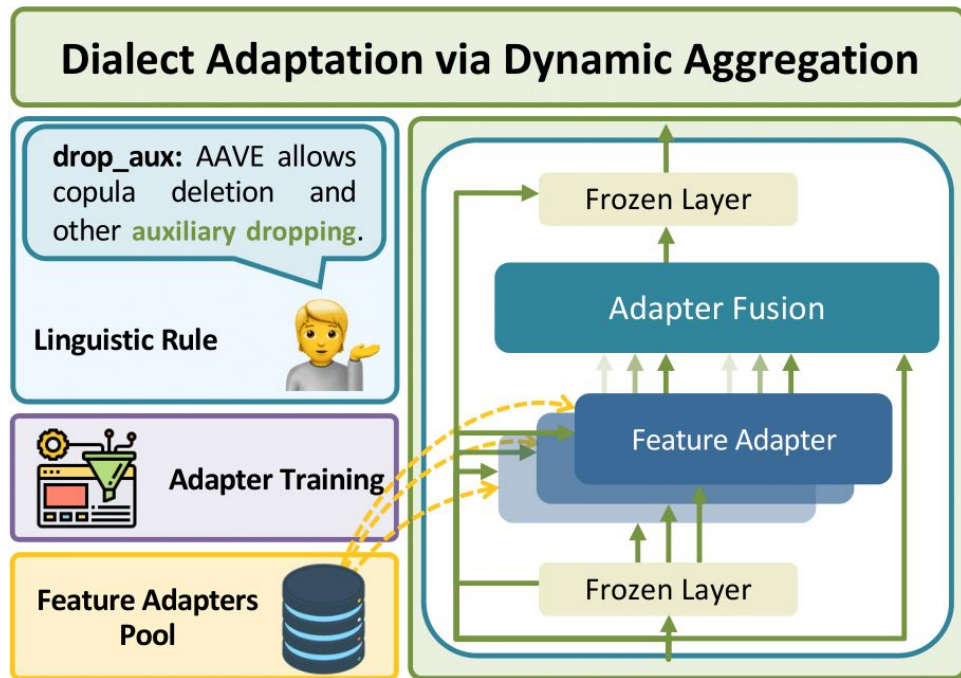
Dialect Adaptation via Dynamic Aggregation

🏆 Modular and Dynamic

- ❑ Multi-Dialectal Robustness
 - ❑ Input Dialect-Agnostic
 - ❑ Personal- and Social-Contextual

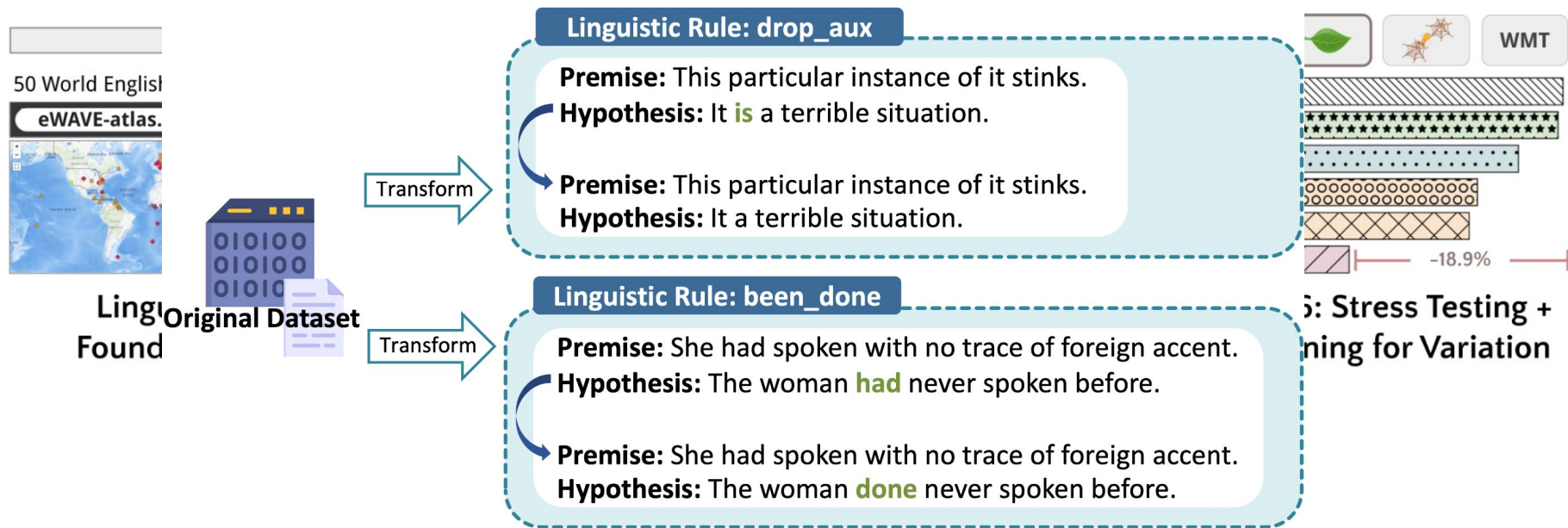
☀ Within Only 3 Steps

1. Synthetic Datasets Construction
2. Feature Adapter Training
3. Dynamic Aggregation



Step 1: Synthetic Datasets Construction

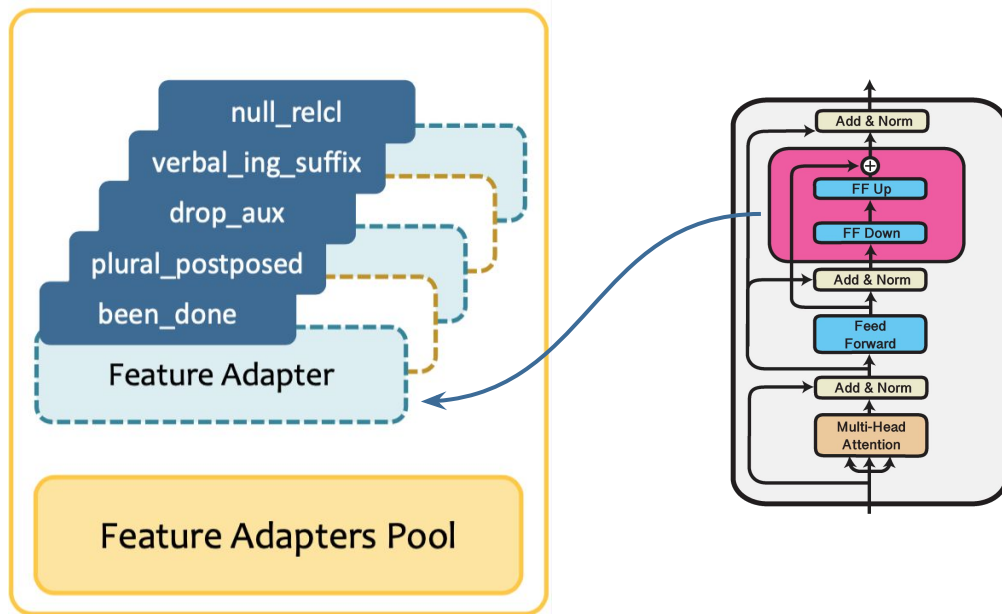
➡ Construct a transformed dataset for each non-standard (morphosyntactic) linguistic feature.



Step 2: Feature Adapter Training

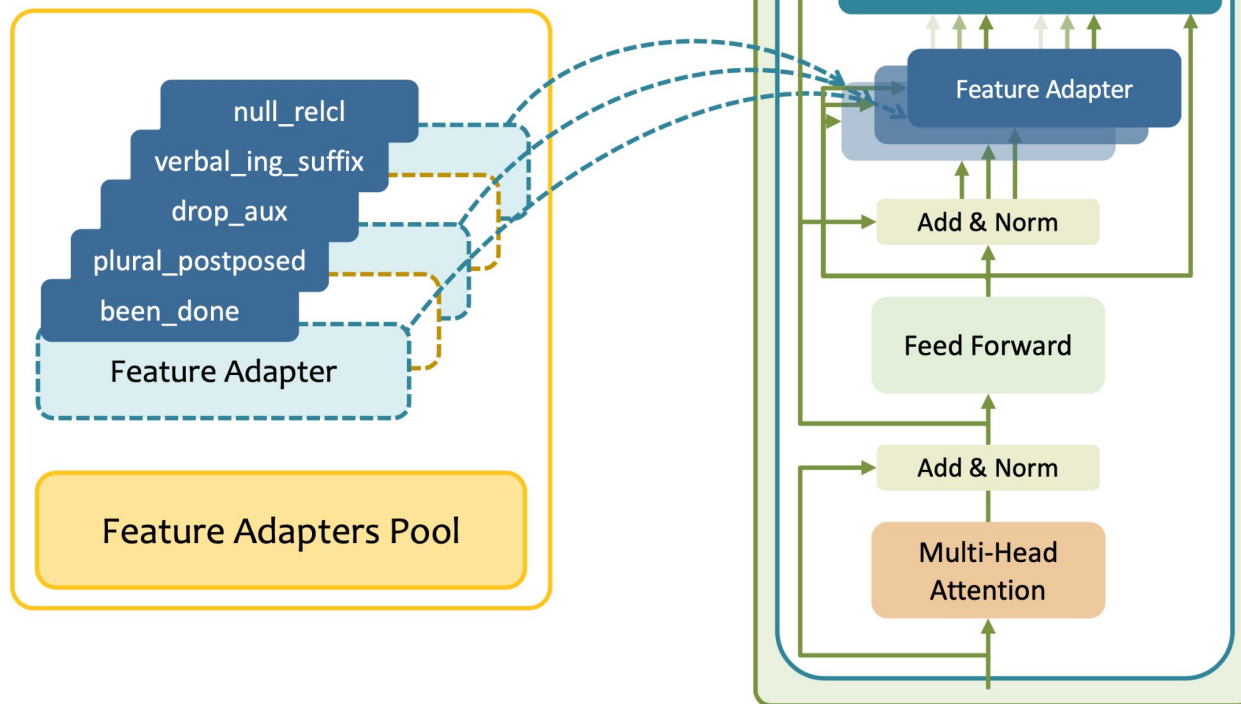


Train a feature adapter for each non-standard linguistic feature.



Step 3: Dynamic Aggregation

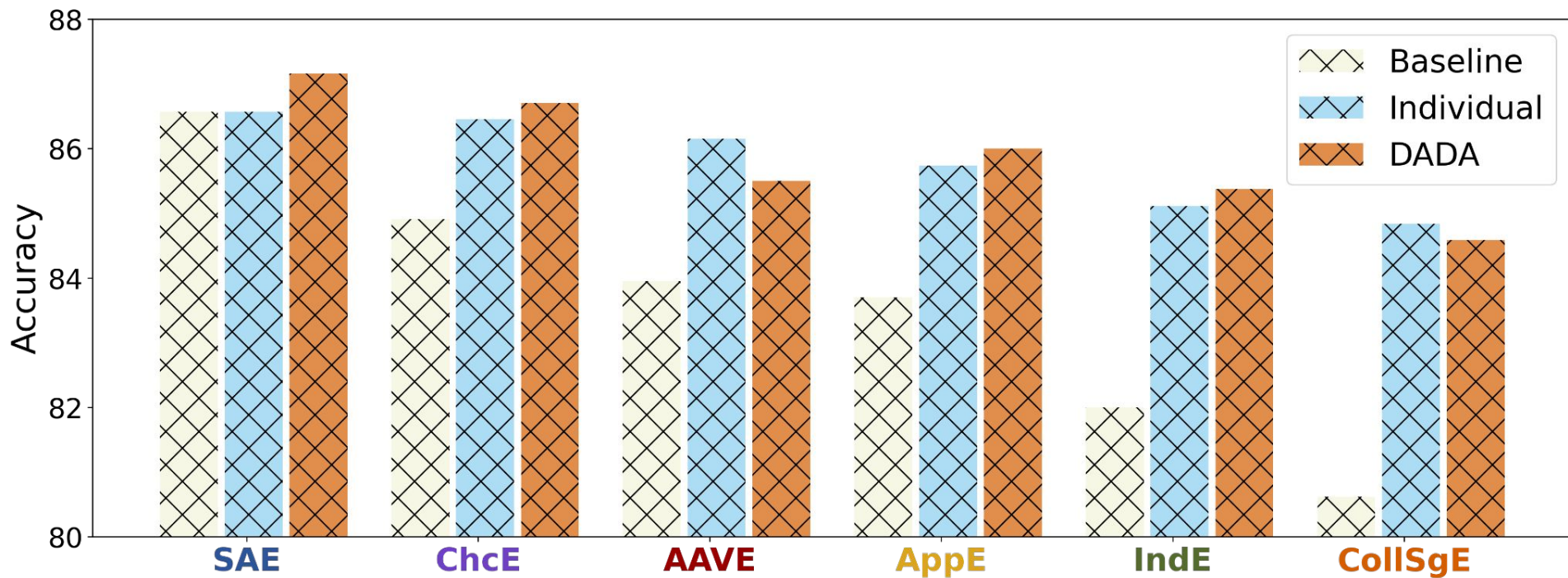
Aggregate & activate feature adapters dynamically.



Experiments

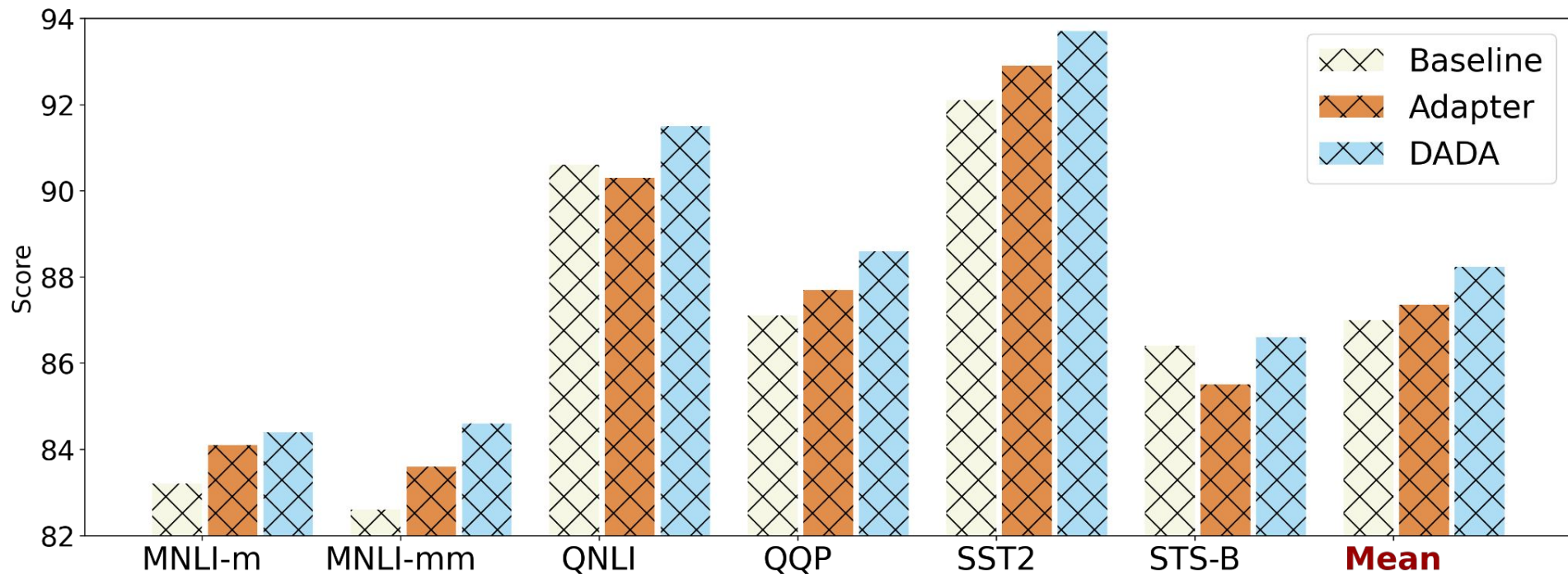
1/ DADA Can Improve Multi-Dialectal Robustness

Adapt **SAE** model to multiple dialect variants simultaneously: **AppE**, **ChcE**, **CollSgE**, **IndE**, **AAVE**



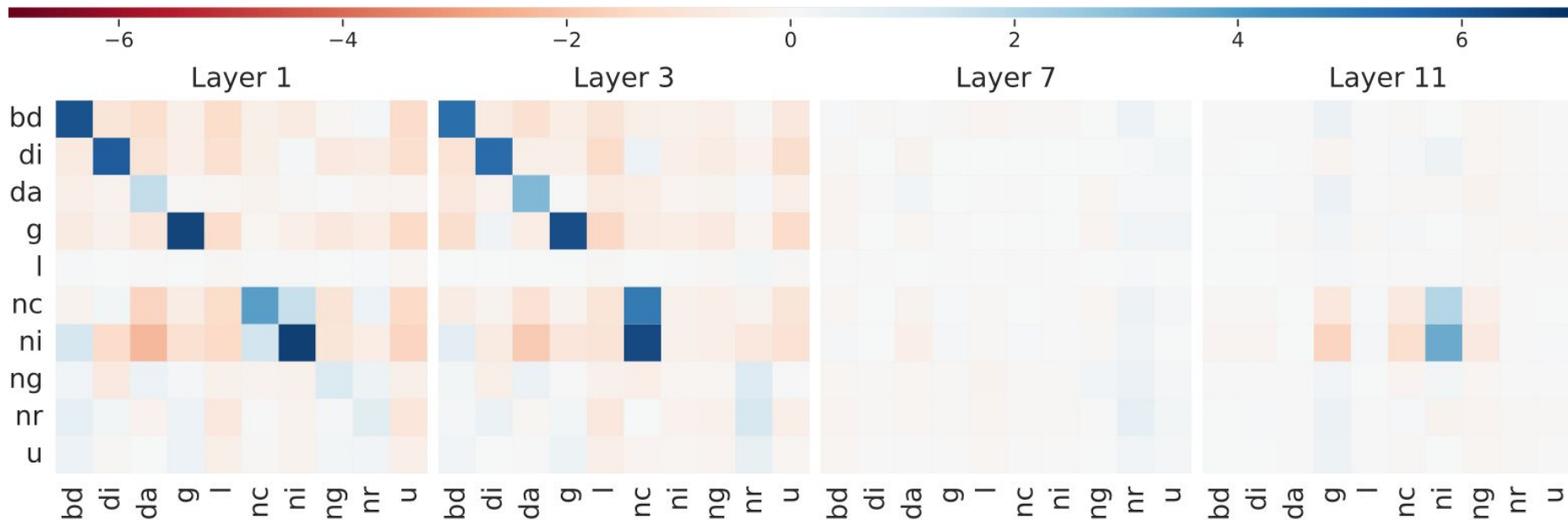
2/ DADA Can Be Task-Agnostic

Adapt instruction-tuned **SAE** model to the dialect variants for multiple tasks



3/ DADA Has Great Interpretability!

Correlation Coefficients for **AAVE** Adaptation



We use abbreviations for certain terms, such as "nc" for "negative concord."

Conclusion and Future Work

Dynamic Aggregation of Linguistic Features

- ❑ A **Fine-grained** and **Modular** Method for Dialect Adaptation
 - ❑ Improve **Multi-Dialect** and **Multi-Task** Robustness
 - ❑ No need for highly accurate dialect identification systems
 - ❑ Taking personal and social context into account
 - ❑ Applicable to task-agnostic instruction-tuned LLMs
 - ❑ **Interpretability**, reusability and extensibility

But!!!

Non-Standard Linguistic Features

- ❑ are curated by linguists ([eWAVE](#)) and
- ❑ play a crucial role in a wide range of applications.

However, the manual curation of linguistic rules can be **expensive** and **expertise-intensive**.

Empower Linguistic Research with LLMs

Large Language Models Can Discover Linguistic Features

(ongoing)

