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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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will appear on EMNLP 2023

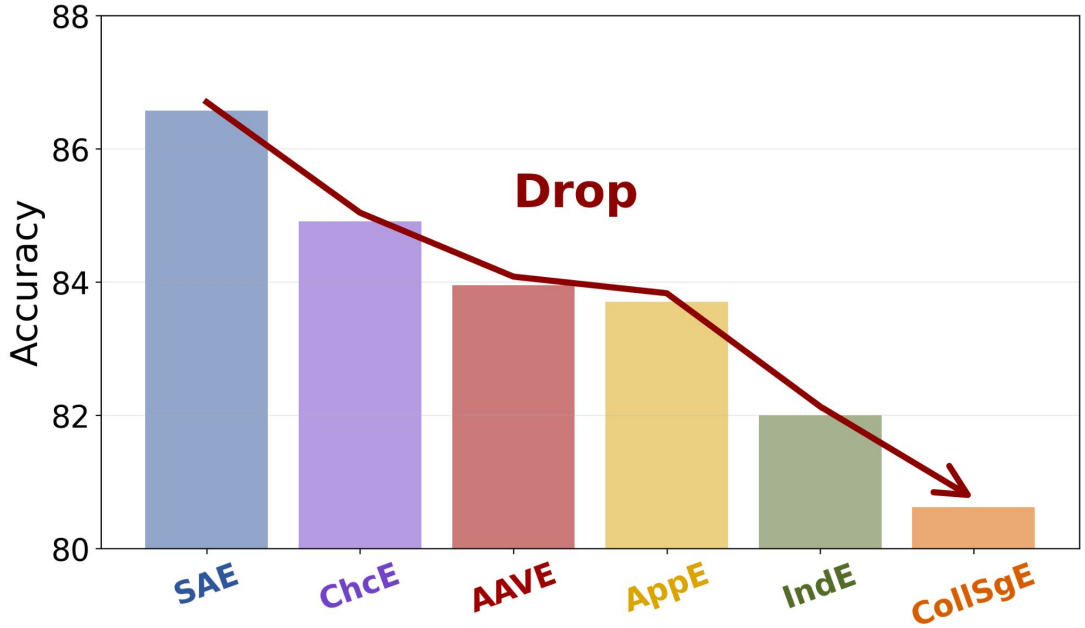
Non-Standard Linguistic Features

- 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

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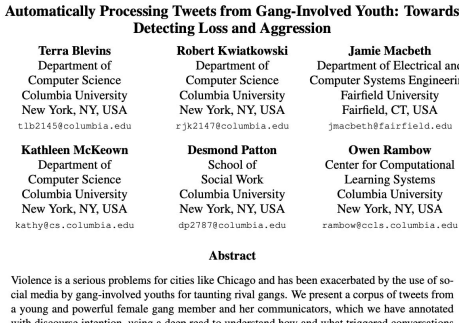
Mainly focused on targeted adaptation to **a specific dialect**

- 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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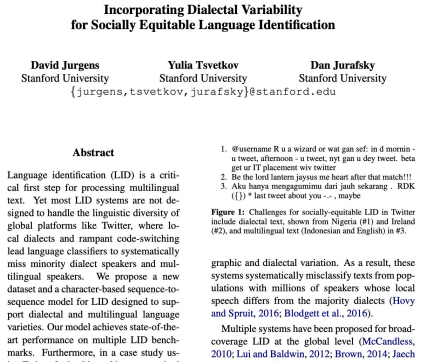
Abstract

Violence is a serious problems 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



Incorporating Dialectal Variability for Socially Equitable Language Identification

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Abstract

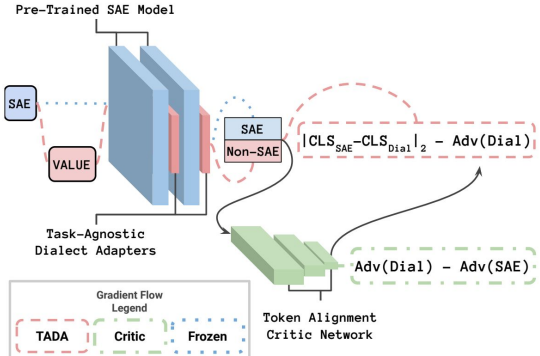
Language identification (LID) is a critical first step for processing multilingual text. Yet most LID systems are not designed to handle the linguistic diversity of global platforms like Twitter, where local dialects and rampant code-switching lead language classifiers to systematically miss minority 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 IT placement wiv twitter
2. Be the lord lantern jaysus me heart after that match!!!
3. Aku hanya mengagumimu dari jauh sekarang . RDK ({}) * last 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

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- 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

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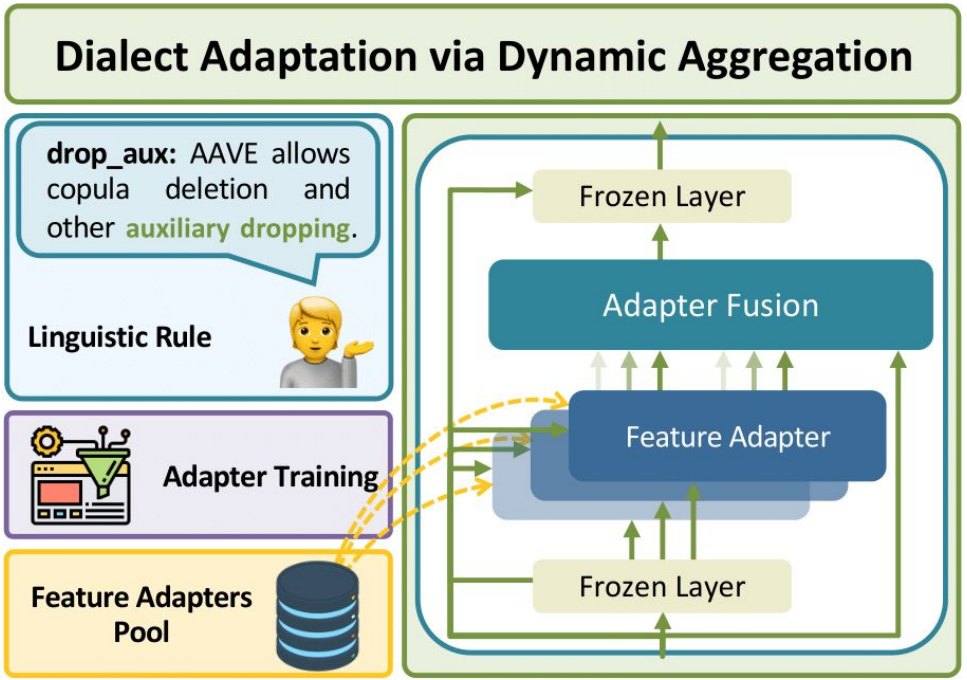
🏅 Modular and Dynamic

- ❏ 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

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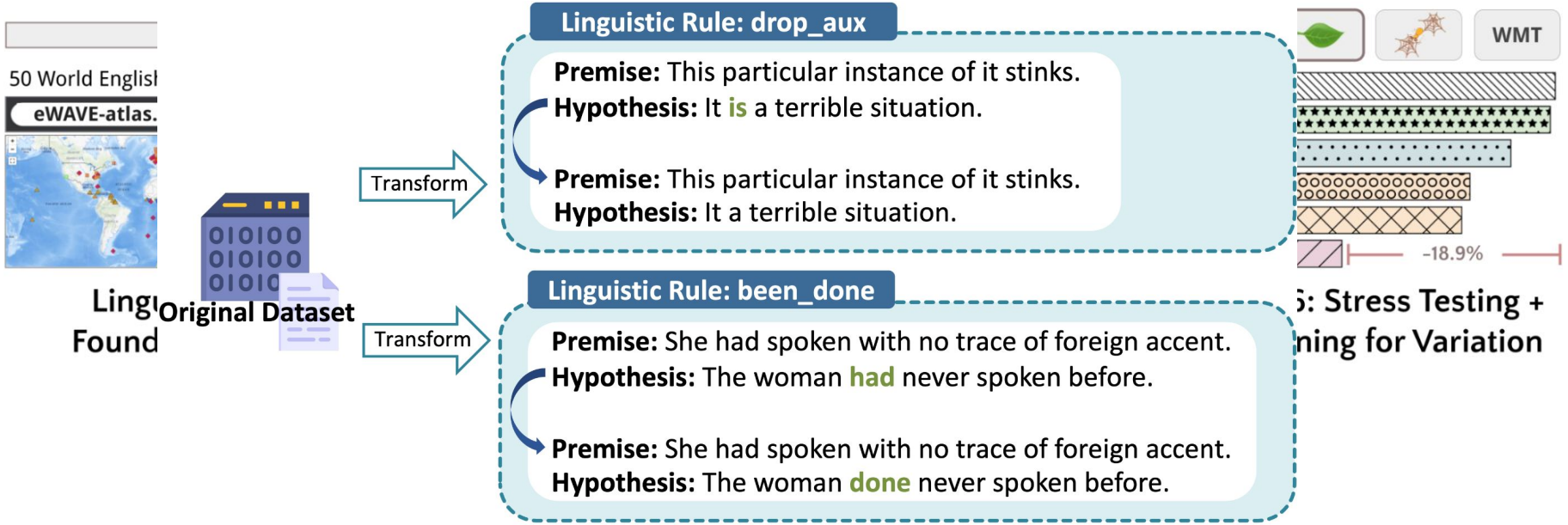
Construct a transformed dataset for each non-standard (morphosyntactic) linguistic feature.



[2] Ziems et al. 2022. Multi-VALUE: Evaluating Cross-dialectal NLP. ACL 2023.

Step 2: Feature Adapter Training

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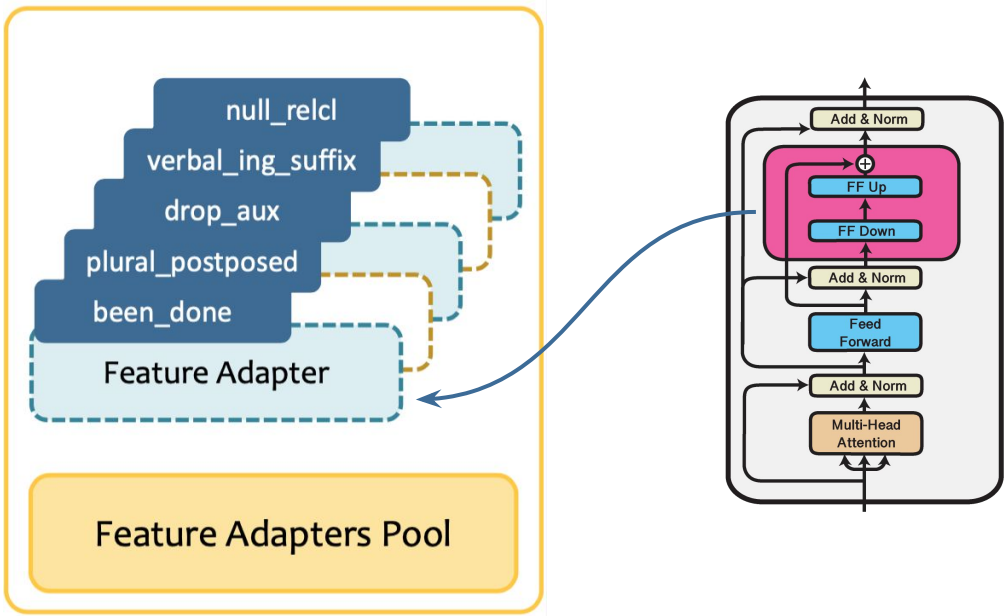
Train a feature adapter for each non-standard linguistic feature.



Step 3: Dynamic Aggregation

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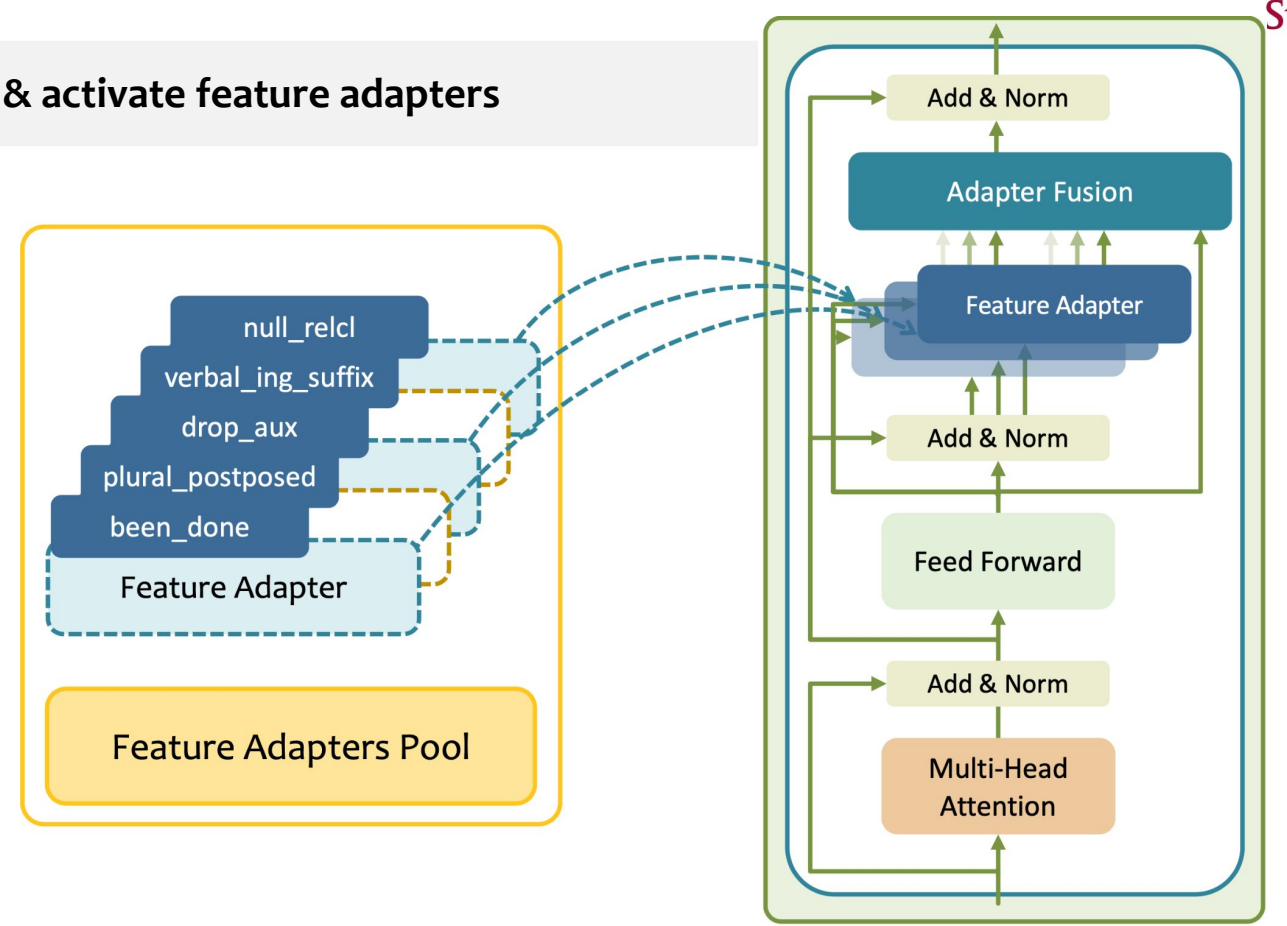
🔖 **Aggregate & activate feature adapters dynamically.**



Experiments

1/ DADA Can Improve Multi-Dialectal Robustness

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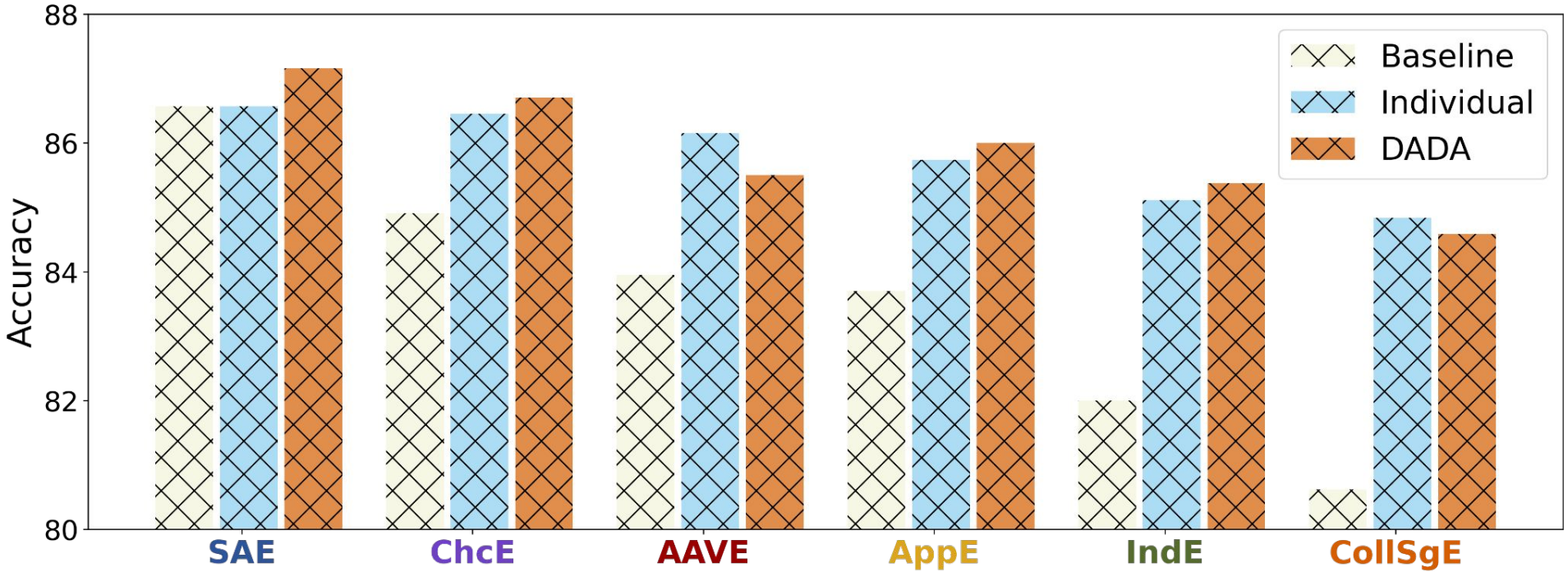
Adapt **SAE** model to multiple dialect variants simultaneously: **AppE**, **ChcE**, **CollSgE**, **IndE**, **AAVE**



2/ DADA Can Be Task-Agnostic

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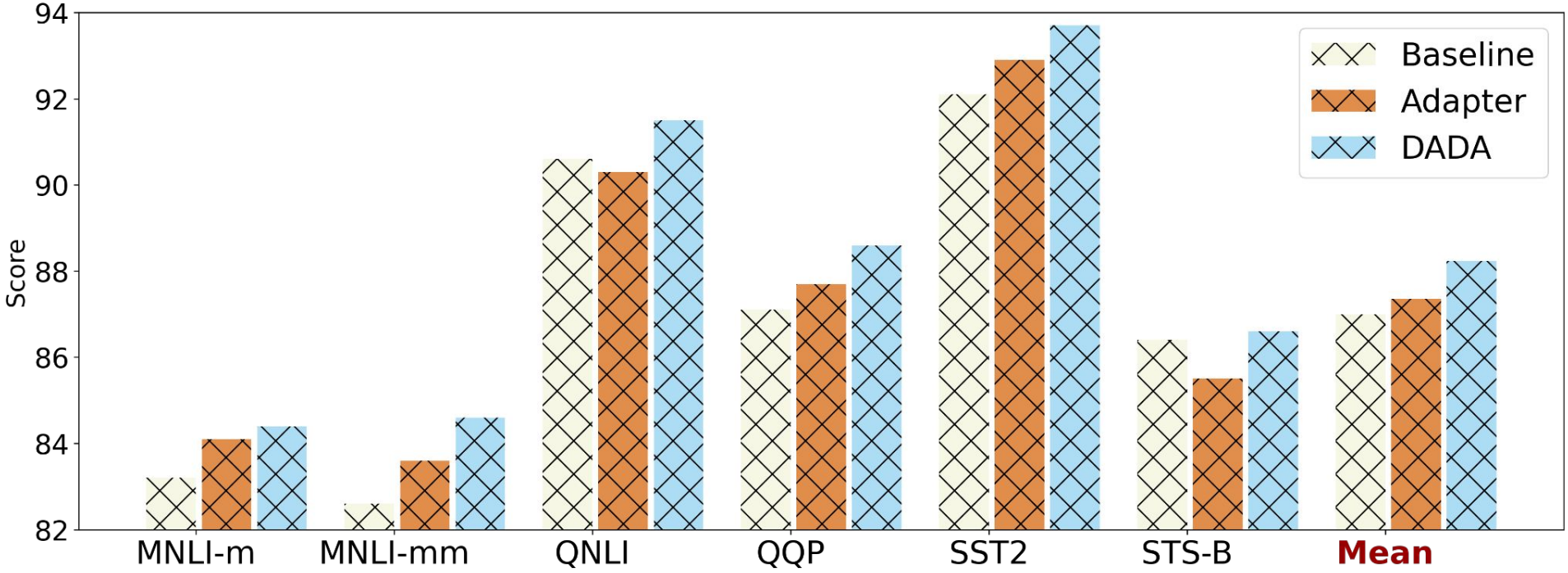
Adapt instruction-tuned **SAE** model to the dialect variants for multiple tasks



3/ DADA Has Great Interpretability!

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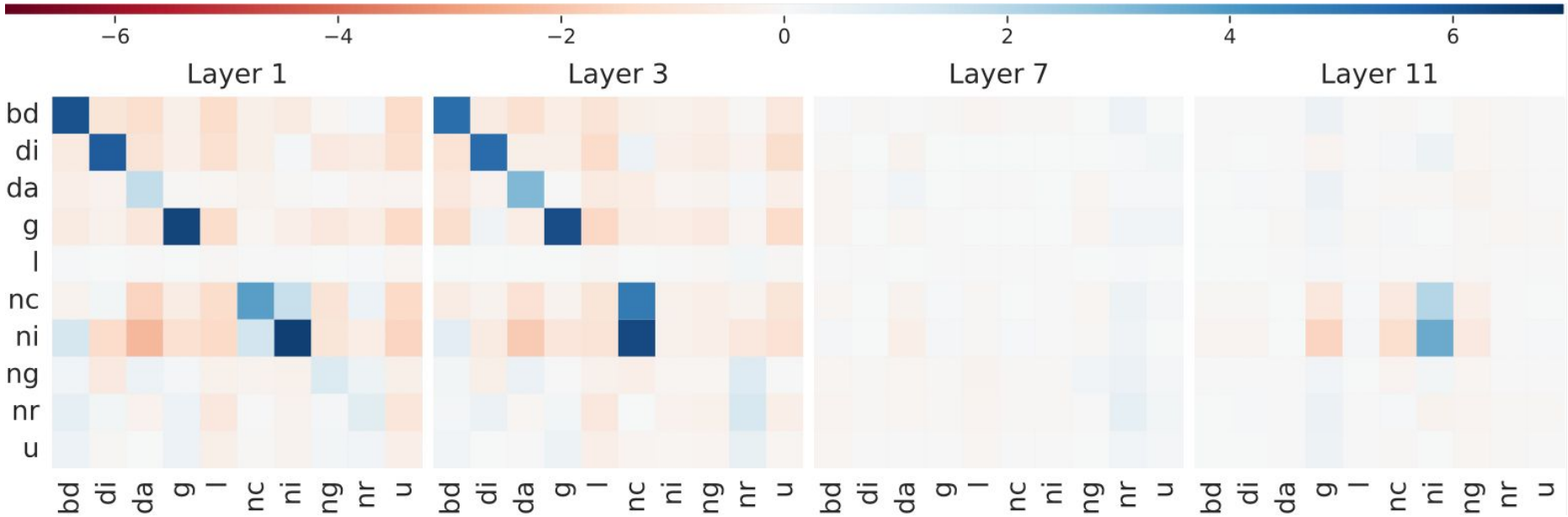
Correlation Coefficients for **AAVE** Adaptation



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

Conclusion and Future Work

Dynamic Aggregation of Linguistic Features

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- 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!!!

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Non-Standard Linguistic Features

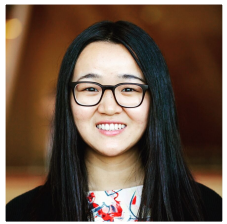
- ❏ are curated by linguists (eWAVE) and
- ❏ play a crucial role in a wide range of applications.

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)



Introduction

- Leverage LLMs to help:
  a. **Verify and Identify** non-standard linguistic features
     - given a corpus, identify the non-standard linguistic features
     - current scope:
       - 235 non-standard (morphosyntactic) English linguistic features from eWAVE
     - more in the future:
       - lexical, stylistic, etc.
       - more languages
  b. **Discover** new linguistic features/usages
     - or new usages
       - *e.g. I am shopping (at) Walmart*

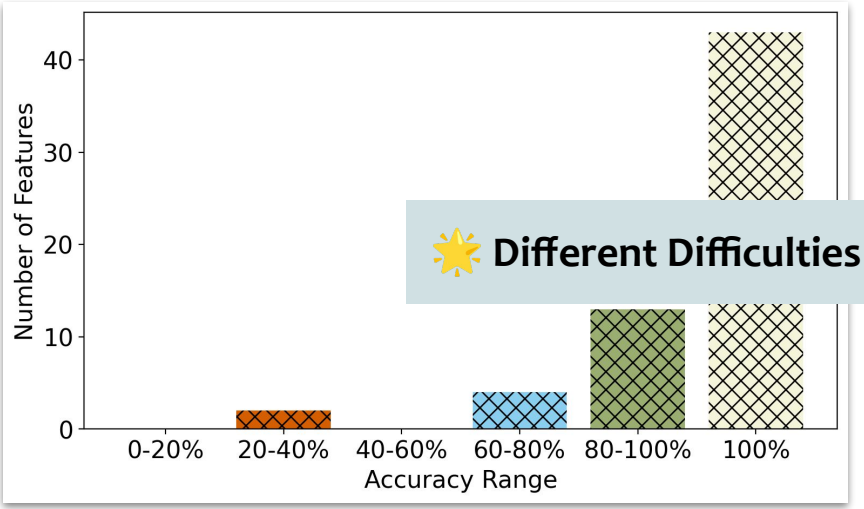
🌟 **Linguistic Feature Discovery**

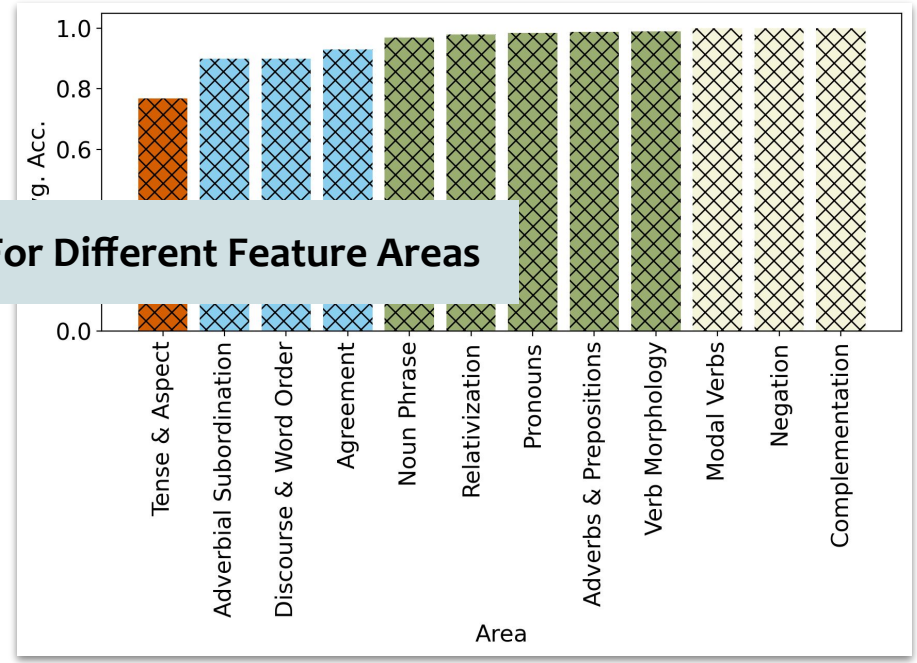
He won't do no harm. → ***Negative Concord***

1/ Multiple Choice

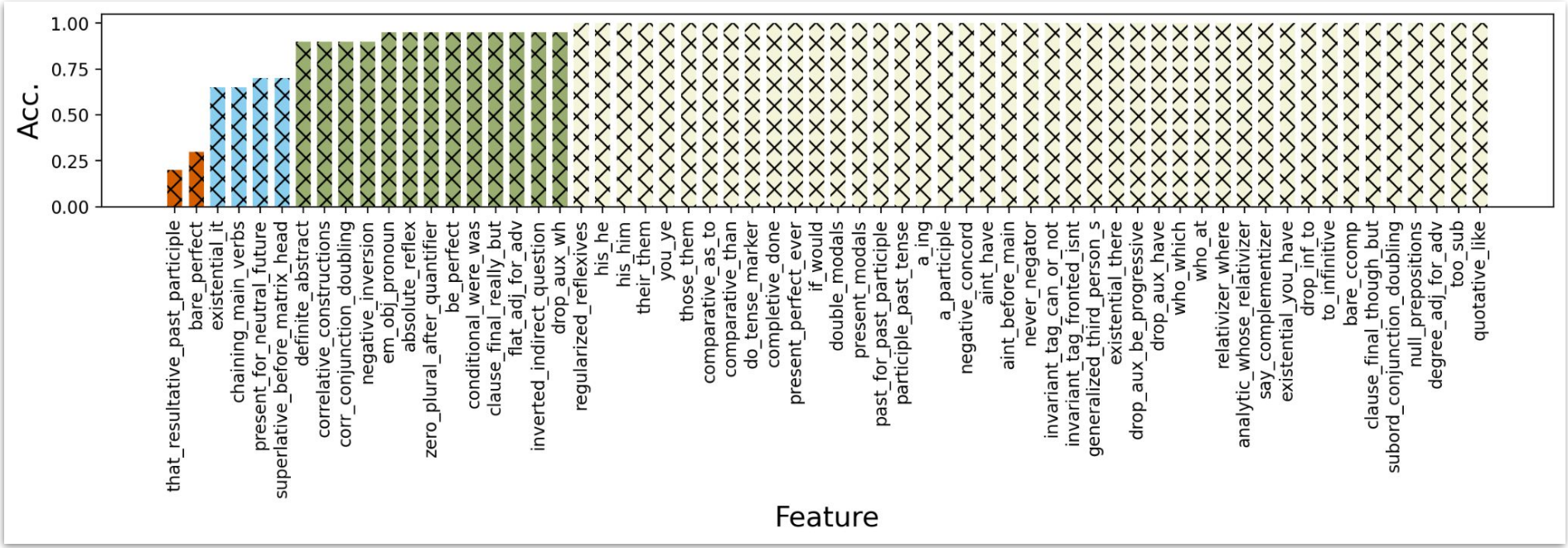
Setup1: ask LLM to identify one **single** linguistic feature at a time

- provide LLM a (synthetic) paragraph with a **single** linguistic feature, along with 5 choices





🌟 **Different Difficulties For Different Feature Areas**


Acc.
1.00
0.75
0.50
0.25
0.00
that_resultative_past_participle
bare_perfect
existential_it
chaining_main_verbs
present_for_neutral_future
superlative_before_matrix_head
definite_abstract
correlative_constructions
corr_conjunction_doubling
negative_inversion
em_obj_pronoun
absolute_reflex
zero_plural_after_quantifier
be_perfect
conditional_were_was
clause_final_really_but
flat_adj_for_adv
inverted_indirect_question
drop_aux_wh
regularized_reflexives
his_he
his_him
their_them
you_ye
those_them
comparative_as_to
comparative_than
do_tense_marker
completive_done
present_perfect_ever
if_would
double_modals
present_modals
past_for_past_participle
participle_past_tense
a_ing
a_participle
negative_concord
aint_have
aint_before_main
never_negator
invariant_tag_can_or_not
invariant_tag_fronted_isnt
generalized_third_person_s
existential_there
drop_aux_be_progressive
drop_aux_have
who_which
who_at
relativizer_where
analytic_whose_relativizer
say_complementizer
existential_you_have
drop_inf_to
to_infinitive
bare_ccomp
clause_final_though_but
subord_conjunction_doubling
null_prepositions
degree_adj_for_adv
too_sub
quotative_like
Feature

1/ Multiple Choice - Multiple Features

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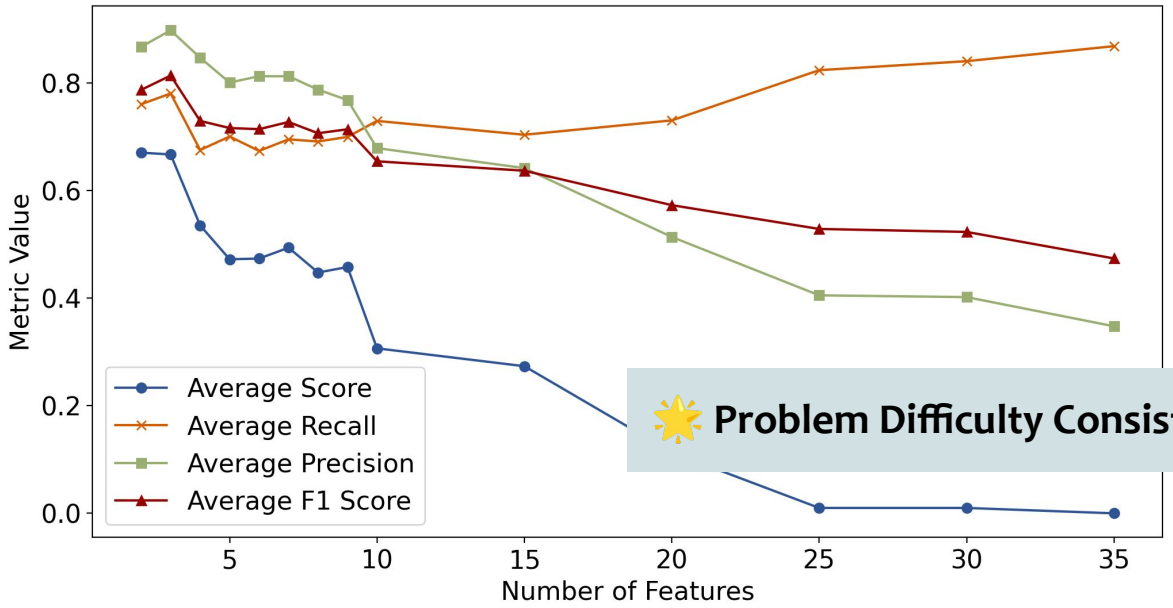
Setup2: ask LLM to identify **multiple** linguistic features

- provide LLM a (synthetic) paragraph with **multiple** (2-35) linguistic features



🌟 **Problem Difficulty Consistently Increases!**

2/ Generation From Scratch

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Setup3: ask LLM to output linguistic features from scratch

Feature	Example	Reference	Prediction	Specificity	Correctness	BERTScore
Comparative marking only with than	He loves his car than ['more than'] his children.	Using "than" without the preceding comparative word (such as "more" or "less") to indicate a comparison between	the omission of the comparative adjectives 'more' or 'less' before 'than'.	5	5	0.8579
Multiple negation / negative concord	He w				4	0.8886
Ever as marker of experiential perfect	I ever see the movie [I have seen the movie].	Using the word "ever" to indicate an action or experience occurred at some unspecified time in the past, instead of using "have".	Misuse of the adverb 'ever': 'ever' is incorrectly used in affirmative sentences	4	3	0.8582

🌟 **Identifying a linguistic feature from scratch is much more difficult than verifying a given one!**

Linguistic Feature Auto-Discovery

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🌟 **More Linguistic Features Possible!**

Conclusion

- **Dynamically aggregation** of non-standard **linguistic features** can better improve LM's multi-dialectal robustness.
- **Linguistic feature discovery** is hard, but **LLMs can help**.

Thank You!