Multi-VALUE: A Framework for Cross-Dialectal English NLP

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Abstract

Dialect differences caused by regional, social, and economic barriers cause performance discrepancies for many groups of users of language technology. Fair, inclusive, and equitable language technology must critically be dialect invariant, meaning that performance remains constant over dialectal shifts. Current English systems often fall significantly short of this ideal since they are designed and tested on a single dialect: Standard American English. We introduce Multi-VALUE - a suite of resources for evaluating and achieving English dialect invariance. We build a controllable rule-based translation system spanning 50 English dialects and a total of 189 unique linguistic features. Our translation maps Standard American English text to synthetic form of each dialect, which uses an upper-bound on the natural density of features in that dialect. First, we use this system to build stress tests for question answering, machine translation, and semantic parsing tasks. Stress tests reveal significant performance disparities for leading models on non-standard dialects. Second, we use this system as a data augmentation technique to improve the dialect robustness of existing systems. Finally, we partner with native speakers of Chicano and Indian English to release new gold-standard variants of the popular CoQA task. For code, models, and data, see http://value-nlp.org/.

1 Introduction

All language is subject to variation across time (Yang, 2000) and between speakers or speaker groups (Eckert, 2017; Holmes and Meyerhoff, 2008). Rather than focusing on social status or political power (Stewart, 1968; Chambers and Trudgill, 1998), linguists define *dialects* as descriptive sets of correlated *features* common across a

Equal contribution.

group of speakers (Nerbonne, 2009). Current pretraining paradigms employ content filters that often exclude text outside Standard American and British English, which leads to performance gaps for other varieties (Gururangan et al., 2022; Bender et al., 2021). These discrepancies exacerbate demographic and regional bias in Natural Language Processing (NLP), making dialect robustness a critical need for fair and inclusive NLP.

This disparity is clear in a growing body of empirical work on African American English (Ziems et al., 2022; Halevy et al., 2021; Blodgett et al., 2018; Jurgens et al., 2017; Kiritchenko and Mohammad, 2016). However, there does not yet exist a systematic exploration of robustness across multiple Englishes, nor of models' ability to transfer knowledge between varieties with similar features, as in multi-lingual NLP. We need new tools to benchmark and achieve dialect robustness.

We introduce Multi-VALUE, which leverages decades of field linguistics research, as an approach to achieve and evaluate English dialect robustness in NLP systems. We take a feature-based approach, isolating grammatical constructions (Demszky et al., 2019) across dialects from topical shifts found in data collected using non-linguistic criteria such as geolocation (Blodgett et al., 2016). Multi-VALUE accounts for regional variation in Englishes (Labov, 1972; Eckert, 1989; Hovy and Yang, 2021). Our focus is on written varieties that (1) are mutually intelligible with Standard American English (SAE); (2) share vocabulary with SAE; and (3) differ from SAE with respect to morphology and syntax (sentence structure). The third criterion defines the critical axis of variation. The first two criteria ensure that our definition of model robustness aligns with the human ability to understand other varieties. For example, creoles have their own unique vocabularies and are not easily understood by speakers of other Englishes (Sebba, 1997); they are outside the scope of this study.

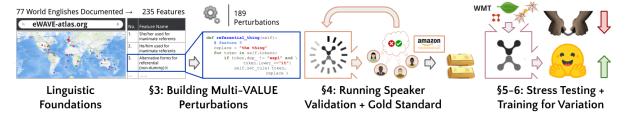


Figure 1: **Multi-VALUE construction process.** The pipeline is grounded in a set of empirically attested linguistic structures in the dialectology literature (§1). For each of 189 distinct structures, we write a perturbation rule to inject this structure into text (§3). By partnering with native speakers, we validate perturbations and build both synthetic and gold standard benchmarks (§4-5). Finally, we use these resources to (1) stress test supervised models to reveal dialect disparities and (2) fine-tune these models on synthetic data to close the performance gap (6).

First, we provide a controllable (1) rule-based translation system for injecting up to 189 features into Standard American English text. This will allow researchers and practitioners to build synthetic training data plus on-demand dialect stress tests for nearly any task. We stress test leading models for three challenging tasks and find statistically significant performance gaps. Second, we provide reliable (2) gold standard benchmarks for the CoQA task in two widely-spoken varieties: Chicano and Indian English. We find that, by training models on synthetic data, we improve dialectal robustness. Third, we fine-tune and publish (3) dialectrobust models on the HuggingFace Hub (Wolf et al., 2020), which can be used directly in downstream applications. Figure 1 demonstrates the full project pipeline.

We recognize five benefits and advantages in the Multi-VALUE approach. Our system is:

- (A) **Interpretable:** supports systematic perturbation analyses to understand the unique challenges of different linguistic features on model performance.
- (B) **Flexible:** customized to align with new and evolving dialects by adjusting the *density* of dialectal features, unlike fixed or static datasets.
- (C) Scalable: allows users to mix and match tasks and dialects at scale without the need for costly human annotation.
- (D) **Responsible:** vetted by native speakers. Through this partnership, we build reliable gold standards and synthetic data that researchers can depend on.
- (E) **Generalizable:** moves the field beyond single-dialect evaluation, which allows researchers to draw more generalizable findings about cross-dialectal NLP performance.

2 Related Work

Dialect Disparity There is mounting evidence of dialect disparity in NLP. Hate speech classifiers have known biases against African American English (Davidson et al., 2019; Mozafari et al., 2020; Rios, 2020; Sap et al., 2019; Zhou et al., 2021). Text from regions with a predominantly Black population are more likely to be classified as hate speech (Mozafari et al., 2020; Sap et al., 2019; Davidson et al., 2019). AAVE performance gaps have also been found across a wide range of NLP tasks, including NLI (Ziems et al., 2022), dependency parsing and POS tagging (Blodgett et al., 2018; Jørgensen et al., 2015), as well as in downstream applications like influenza detection (Lwowski and Rios, 2021). Still, there does not yet exist a systematic study on cross-dialectal model performance. We aim to fill this gap. The distribution of features in a speaker's dialect will correlate strongly with their geographical location, race, ethnicity, and socioeconomic status (Labov, 1972; Eckert, 1989; Hovy and Yang, 2021). Models that fail to account for underrepresented speech patterns will systematically disadvantage members of the protected groups that adopt these features. Thus dialect disparity is a problem whose scope extends beyond the engineering challenges of model robustness. Through the introduction of demographic bias (Hovy and Spruit, 2016; Gururangan et al., 2022), dialect disparity becomes an issue of equity and fairness (Halevy et al., 2021; Blodgett and O'Connor, 2017).

Dialect and Multilingual NLP Multilingual NLP has studied how to effectively learn common structures which are transferable across languages. Since dialectal variation is systematic, the strategies employed by multilingual NLP may yield strong benefits for multiple dialects, espe-

cially with mutual intelligibility constraints. Multilingual training and evaluation have led to large advances in NLP in many languages. Massively multilinguals models (Pires et al., 2019; Conneau et al., 2020; Liu et al., 2020; Xue et al., 2021) exploit the commonalities between many languages at once, rather than merely achieving pairwise transfer (Lin et al., 2019). Additionally, benchmarking across multiple languages can reveal language discrepancies at the modeling level, even without language-specific feature engineering or training data (Bender, 2011; Ravfogel et al., 2018; Ahmad et al., 2019; Tsarfaty et al., 2020). Multi-VALUE aims to extend these advantages identified from multilingual NLP to the study of English dialects.

3 Multi-VALUE Perturbations

There is a clear need for sustained research on dialect robustness (§ 2). However, this work is difficult because language is subject to *variation* and *change*. This means speakers can contextually modulate the density of features in their grammar; over time, speakers adopt different features. The shifting nature of language could antiquate manually-curated training and testing data. Updating such resources could be costly and time-consuming.

In this section, we introduce the first stage of the Multi-VALUE pipeline to build dialect-robust NLP systems more efficiently and scalably. We automatically inject structural variation into Standard American English text using linguistic perturbation rules that alter syntax and morphology but preserve semantics. In this way, they also preserve labels. Unlike many black-box translation approaches (Krishna et al., 2020; Sun et al., 2022), label preservation will allow users to convert existing benchmarks directly into dialectal stress tests. Modular and independent perturbation functions will also allow researchers to flexibly isolate the effects of different features in different combinations.

It is our principled grounding in attested language patterns that distinguishes our perturbations from other syntactic data augmentation methods such as Wu et al. (2022). We painstakingly operationalize decades of work from field linguistics that is cataloged in the Electronic World Atlas of Varieties of English (eWAVE; Kortmann et al. 2020). eWAVE identifies English dialects as clusters of linguistic features, each with a relative *pervasiveness* in the dialect. For example, the *give passive* feature #153 is considered pervasive or obligatory in Collo-

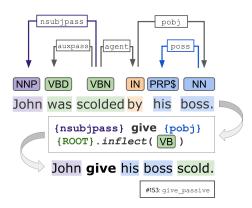


Figure 2: The give_passive [#153] perturbation follows this procedure: (1) take the passive subject (nsubjpass); (2) insert the verb *give*; (3) insert the object of a preposition that serves as the agent of the ROOT, (4) insert the ROOT, inflected with its base form.

quial Singapore English, while it is rarely observed in Philippine and Tristan da Cunha English, and it is never seen in any other dialect. We define a **dialect transformation** as a sequential application of perturbation rules. Decisions to perturb the text follow the eWAVE heuristic probabilities: 100% for obligatory features; 60% for features neither pervasive nor rare; 30% for rare features; 0% for features with no information or an attested absence.

For each perturbation rule, we condition the feature on morphosyntactic signals from part of speech tags, noun and verb inflection, and syntactic dependency relations using the spaCy (Honnibal et al., 2020) and inflect libraries. For the *give passive* pertubation above in Figure 2, we search for passive constructions built with a past participle ROOT (VBN), an nsubjpass patient, and an agent; then we construct the new phrase by inflecting the ROOT to its base (VB) form and moving it after the entire agentive noun phrase.

Following the eWAVE organizational scheme, we motivate and present our feature perturbations in 12 grammatical categories: (1) Pronouns, (2) Noun Phrases, (3) Tense and Aspect, (4) Mood, (5) Verb Morphology, (6) Negation, (7) Agreement, (8) Relativization, (9) Complementation, (10) Adverbial Subordination, (11) Adverbs and Prepositions, and finally (12) Discourse and Word Order. For a more detailed breakdown of every feature perturbation we implemented, see Appendix B.

Pronouns are substitutes for noun phrases that typically involve nominal and temporal anaphora (Partee, 1984). Thus an understanding of pronouns is critical for tasks like machine translation and

summarization, which depend on coreference resolution (Sukthanker et al., 2020), as well as current fairness research (Qian et al., 2022). Our pronoun perturbation rules account for linguistic structure and are not merely surface manipulations. For example, we condition on coreference for referential pronouns and on verb frames to identify benefactive datives. In total, we implement 39 of the 47 pronoun features from eWAVE.

Noun Phrases function as the arguments of verbs (Dryer, 2007). Unsurprisingly, noun phrases are the focus of fundamental NLP research in semantic role labeling and named entity recognition as well as downstream tasks like sentiment analysis, information extraction, summarization, and question answering (Gildea and Jurafsky, 2000). There are 31 perturbation methods in Multi-VALUE that operate on noun phrase constituents. For example, adj_postfix [feat. #87] moves attributive AdjP constituents after the head noun they modify, as in the sentence "I drive a car small and red."

Tense and Aspect are two grammatical properties that have to do with time. Together, these categories are known to significantly challenge machine translation (Matusov, 2019; Koehn and Knowles, 2017), among other applications. The 26 Multi-VALUE perturbations in this category use different kinds of inflections and auxiliary verbs to indicate when an action, event, or state occurred and how it extends over time.

Mood is a grammatical category that has to do with *modality*, or the relationship between the utterance and reality, possibility, desirability, or necessity (Pyatkin et al., 2021). Modality is important for applications in sentiment analysis and opinion mining, including the detection of biased language (Recasens et al., 2013) and framing strategies in political discourse (King and Morante, 2020; Demszky et al., 2019; Ziems and Yang, 2021). Misunderstandings of modality can also challenge NLU systems on tasks like natural language inference (Gong et al., 2018). There are three modal perturbations in Multi-VALUE.

Verb Morphology is expected to affect model understanding of verb frame semantics (Baker et al., 1998), which could impact performance on semantic role labeling, summarization, and machine translation, among other tasks. We implement 16 related perturbations that change verb suffixes, the forms of verb inflection, and the expression of semantic roles using specialized verbal

phrases.

Negation is covered by 16 eWAVE features, 14 of which are implemented in Multi-VALUE. Problems with negation account for many of the failure cases in natural language inference (Hossain et al., 2020) and sentiment analysis (Barnes et al., 2021). Our perturbations introduce negative concord, invariant question tags, and new words for negation.

Agreement is a group of 11 perturbations which have to do with subject-verb agreement and the omission of copula and auxiliary *be* in different environments. Examples include the invariant present tense in *He speak English* [#170], and the existential dummy word in *It's some food in the fridge* [#173]. Nine of these 11 agreement features are attested in African American English (see Green 2002), which may be linked to the demonstrable performance disparities in AAVE dependency parsing (Blodgett et al., 2018), POS tagging (Jurgens et al., 2017), and the classification of linguistic acceptability (Ziems et al., 2022).

Relativization is a class of perturbations that operates on relativizers—the group of *wh*-pronouns, adverbs, and conjunctions used to link relative clauses with their nouns. The purpose of a relative clause is to modify a noun phrase. It's an important construction for NLU because it can contain a presupposition (Joshi and Weischedel, 1977). Our perturbation rules cover all 14 eWAVE features, operating both on individual relativizer words as well as sentence structure to move the relative clause and build correlative constructions, for example.

Complementation is a set of perturbations that operate on dependent clauses. A subordinating conjunction is a word that connects an independent clause with a dependent clause. A complementizer is a subordinating conjuction that, in many cases, turns the dependent clause into the subject or the object of the sentence. The dependent clause is called the complement. Like relative clauses, verbal complements can contain presuppositions and implicatures (Potts, 2002), which are critical for natural language understanding. Furthermore, complementizers can convey a speaker's degree of certainty (Couso and Naya, 2015), which correlates with biased language and framing strategies. We implement all 11 complementation features that are catalogued in eWAVE.

Adverbial Subordination is a set of perturbations that operate on independent clauses. A conjunctive or "linking" adverb connects two inde-

pendent clauses by modifying the verb in the first clause. The conjunctive adverb is important as it can express causality (*therefore*), purpose (*so that*), sequence (*then*), contrast (*however*), comparison (*similarly*), and various forms of emphasis (*indeed*). We implement all 5 eWAVE features in this class.

Adverbs and Prepositions We include four more perturbations on adverbs and prepositions, which can drop prepositions and replace adverbs with their adjectival forms.

Discourse and Word Order Finally, we implement two discourse features and 9 phrase-based perturbations that move entire constituents in a manner similar to *constituency replacement* (Sutiono and Hahn-Powell, 2022). These rules significantly alter the sentence structure, and in this way radically differ from prior token-level data augmentation techniques like synonym replacement (Wei and Zou, 2019). Phrasal movements include fronting and clefting, subject-auxiliary inversion, and a lack of inversion in questions. We also inject the word *like* to indicate focus or quotation.

4 Scope and Reliability of Multi-VALUE

This section describes the scope and reliability of our multi-dialectal transformation pipeline from the sequential application of the perturbation rules in §3. We validate perturbation rules both in isolation and in conjunction with other rules.

4.1 Scope

Multi-VALUE's scope is extensive. Out of the 235 features documented in eWAVE, Multi-VALUE covers 189 of them, spanning all 50 recorded English dialects. On average, the feature space for any given dialect is 86.6% implemented, and no dialect is less than 80% implemented (c.f. Tables 9-21 in Appendix B). The reason we did not cover 100% of the eWAVE catalogue is that some features operate with information unavailable to us. For example, in SAE, aspect and mood may not be marked morphosyntactically; these features are outside the scope of current methods. Similarly, we are unable to inject distinct pronouns for groups of 2, 3, and 4+ people [#37], as group size information may not be contained in the focus utterance.

4.2 Speaker Validation

One key benefit of the Multi-VALUE approach is our ongoing partnership with native speakers to

FEAT.	Acc.	FEAT.	Acc.	FEAT.	Acc.	FEAT.	Acc.
3	100.0	59	100.0	119	100.0	191	100.0
9	100.0	60	99.6	121	91.8	193	88.7
10	97.4	61	100.0	123	100.0	194	100.0
11	100.0	62	100.0	126	92.3	198	100.0
14	100.0	63	99.0	128	92.7	203	100.0
15	100.0	64	100.0	130	92.9	204	100.0
16	100.0	66	100.0	131	100.0	205	100.0
26	100.0	67	99.1	132	87.7	206	100.0
29	100.0	70	92.9	133	99.5	207	100.0
33	100.0	71	98.8	134	100.0	208	100.0
34	100.0	77	100.0	145	100.0	209	100.0
39	99.7	78	100.0	146	100.0	214	100.0
40	99.8	79	100.0	149	100.0	216	99.7
41	100.0	80	100.0	154	92.9	220	99.4
42	98.1	81	100.0	155	81.8	221	86.7
43	93.2	86	100.0	159	100.0	223	100.0
45	100.0	88	99.4	165	99.1	224	99.5
47	100.0	96	95.5	170	94.9	226	100.0
49	99.6	99	94.7	172	90.0	227	91.2
55	100.0	100	99.9	173	87.5	228	99.8
56	97.3	101	100.0	174	100.0	229	99.9
57	100.0	106	100.0	175	83.3	232	100.0
58	100.0	117	100.0	179	100.0	234	91.2

Table 1: Accuracy of 92 perturbation rules according to majority vote with at least 5 unique sentence instances. Seventy four rules have >95% accuracy, while sixteen have accuracy in [85,95), and only two are <85% accurate, demonstrating the reliability of our approach.

confirm that our theoretically-inspired rules generate plausible and acceptable text. Here, we validate our transformation rules on a combination of data from CoQA and other sources, using the linguistic acceptability judgments of native speakers for 10 English dialects: Chicano (ChcE; 29 annotators), Colloquial American (CollAmE; 13 annotators), Indian (IndE; 11 annotators), Appalachian (AppE; 4 annotators), Aboriginal (AborE; 4 annotators), Ozark (OzE; 3 annotators), Southeast American Enclave (SEAmE; 3 annotators), Urban African American (UAAVE; 1 annotator), and Black South African English (BISAfE; 1 annotator), as well as dialects from the North of England (North; 3 annotators). The task follows the design of Ziems et al. (2022). Here, we recruit speakers from Amazon Mechanical Turk and screen them using a Dialect Assessment Survey (c.f. Appendix A.1).

A group of 72 annotators evaluate a total of 19k sentence pairs, each containing a dialect-transformed sentence and an SAE gloss. Three annotators evaluate each transformation, marking any pre-highlighted spans where the transformation

¹We use CoQA questions so that we can build our Gold Test sets in parallel (§4.3); for domain and syntactic diversity, we also pull sentences from the nltk Reuters (Rose et al., 2002), Sentiment Analysis (Pang and Lee, 2004) and Movie Review corpora (Pang and Lee, 2005).

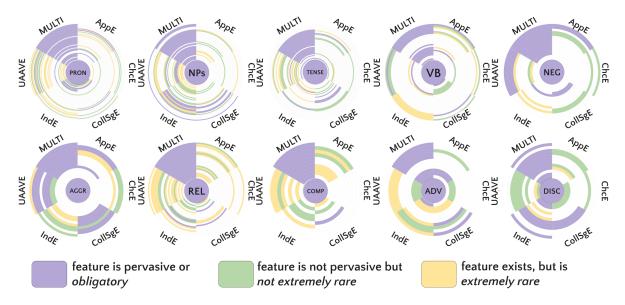


Figure 3: A comparative distribution of the features in five dialects, where a dialect is given by a slice of the wheel. Each wheel represents one of the feature groupings in §3 (Tense and Aspect + Mood are combined, as are Adverbial Subordination + Adverbs and Prepositions). The MULTI slice indicates which of the features are implemented in Multi-VALUE. Rings indicate distinct features and are colored by pervasiveness in each dialect.

appeared ungrammatical. This gives us both transformation and perturbation-level evaluations. The majority vote determines the accuracy of the perturbation rule. Perturbation accuracies are given in Table 1. We see that 55 rules have 100% accuracy; all rules reach above 81%. Overall, this can give researchers confidence in the linguistic plausibility of the Multi-VALUE transformation pipeline.

4.3 Gold Test Sets

While synthetic Multi-VALUE transformations will be useful for identifying weak points in a model's performance, this does not ensure the model is ready for the real world. We urge practitioners to heavily test user-facing models with numerous in-domain tests. As a first step, we provide reliable gold standard CoQA datasets in Chicano English (ChcE) and Indian English (IndE). Out of 7,983 CoQA questions, our pipeline made changes to 1,726 ChcE questions (21.6%) and 6,825 IndE questions (85.4%). Human annotators considered only transformed questions and provided their own alternative phrasing if they considered the transformation ungrammatical. Alternatively, they could simply exclude the erroneous perturbations from the question. ChcE had a total transformation accuracy of 82.7% while IndE had 66.1%, given the higher density of features in the IndE pipeline. After rephrasing or removing errors, we were left with 1,498 dialect-transformed ChcE questions and

5,289 IndE questions. Together with any unperturbed questions, these gold questions constitute the gold test sets for evaluation in §6.1.

5 Using Multi-VALUE

With our feature rules written (§3) and hand-validated by native speakers (§4), we can use Multi-VALUE to create synthetic training data for dialect-robust models and establish dialect stress tests from existing NLP benchmarks. We specifically provide synthetic data for five English dialects: Appalachian (Montgomery, 2008), Chicano English (Fought, 2003), Indian English (Bhatt, 2008), Singapore English (Wee, 2008), and Urban African American English (UAAVE Wolfram and Schilling, 2015). Three of these dialects are based in the US, where annotators were most abundant for validation, and two are outside the States.

To understand models' ability to transfer knowledge between dialects, we also evaluate the performance of models trained on dialect A and evaluated on dialect B for each dialectal pair (A,B). We can further leverage the strengths of Multi-VALUE as a multi-dialectal augmentation tool by training on a synthetic pseudo-dialect that contains the union of all feature options (Multi). We hypothesize that models trained on multi-(pseudo)-dialectal data will benefit from robustness to transformations across dialects. Since the Multi-VALUE approach is general-purpose, it could be applied to many dif-

ferent tasks based on free-form Standard American English text. Here, we focus on three domains in particular: conversational question answering, semantic parsing, and machine translation.

Conversational Question Answering. We use CoQA (Reddy et al., 2019) since it is a challenging task where dialect-induced errors can compound. CoQA is a reading comprehension benchmark with 127k question-answer pairs and 8k source passages in seven different genres and domains. The primary challenge is that questions are conversational: they contain coreference and pragmatic relations to prior questions. To transform the publicly available training and development sets, we perturb only questions. This is a natural information-retrieval setting: the user submits queries in a low-resource dialect while the underlying corpus is in SAE.

Semantic Parsing. We also consider the task of mapping natural language to formal language. This is a critical technique in question answering, dialogue, code generation, and other user-facing applications where dialect use is likely. We transform the widely-used Spider benchmark (Yu et al., 2018), which is a text-to-SQL dataset. Again, we transform only the natural language query, leaving both the database tables and the SQL query unchanged to simulate interaction with a dialect user.

Machine Translation. Finally, we stress-test machine translation, since domain mismatch is a major challenge to current MT systems (Koehn and Knowles, 2017), and we expect this to include stylistic and dialectal differences. We especially anticipate challenges with verb morphology (§3), tense and aspect (§3), and pronouns (§3). To run this stress test, we use the WMT19 dataset, which is a standard in the field, evaluating translation from each English Dialect to Chinese, German, Gujurati, and Russian. This simulates a user interacting with translation software using their native dialect.

6 Cross-Dialectal Stress Testing

Here we benchmark current models on dialect variants of the three tasks in §5. For each dataset, we use fixed hyperparameters without early stopping and report all performances on dialect variants of the *evaluation* data because public test sets are not available for the original datasets. Specifically, for CoQA, we evaluate on RoBERTa-base (Liu et al., 2019), following the Rationale Tagging Multi-Task setup of Ju et al. (2019). For SPIDER, we evaluate BART-large and T5-large for semantic parsing

Model		Test Dialect					
Base	Train Set	SAE	ChcE	IndE			
RoBERTa	SAE Multi	81.8 80.6 (-1.5%) ⁻	81.6 (-0.2%) 80.5 (-1.6%)	77.7 (-5.2%) ⁻ 79.7 (-2.7%) ⁺			
Ro	In-Dialect	81.8	81.6 (-0.2%)	80.5 (-1.6%)+-			

Table 2: **Gold QA Evaluation:** F1 Metric on each gold development set of the CoQA benchmark. $^-$ and $^+$ respectively indicate significantly (P < 0.05) worse performance than SAE \mapsto SAE and better performance than SAE \mapsto Dialect by a paired bootstrap test.

since both are near the state of the art in this task (Xie et al., 2022). For Translation, we evaluate the NLLB Translation Model at two distilled scales: 615M and 1.3B (Costa-jussà et al., 2022). In the Appendix, we provide further results for CoQA with BERT (c.f. Appendices 6 and 7) and for SPI-DER with T5-base and BART-base (c.f. Appendix 8). We report hyperparameters and further motivation for model selection in Appendix C.

6.1 Linking Natural and Synthetic Data

While natural data is the gold standard, it is difficult to scale to the number of dialects and tasks we can cover with synthetic data. Thus our broad evaluations are synthetic stress tests. Importantly, we first demonstrate the critical relationship between the gold and synthetic transformations using the gold evaluation sets from §4.3 and the synthetic training data from §5. Table 2 shows the gold standard CoQA results, which should be compared to the synthetic CoQA results in Table 3.

The synthetic stress test results match the gold performance for Chicano English with only small deviations. The Indian English stress tests slightly overestimate the performance drop of an SAE model on Indian English. This is expected, as our synthetic feature density may be higher than some annotators naturally use; thus synthetic results are a lower performance bound on results for a target dialect. For all treatments, the stress tests are directionally correct, meaning that treatments that improve performance on the stress test also improve results on the gold data.

Combined with speaker validation of the patterns themselves in §4.2, this shows that Multi-VALUE can be used to reliably measure the effects of modeling choices on dialectal performance.

6.2 Synthetic Stress Tests

We run 3 stress tests to understand worst-case performances on dialect-shifted data across a suite of

	Model				Test Dialect			
Base	Train Set	SAE	AppE	ChcE	CollSgE	IndE	UAAVE	Average
RoBERTa Base	SAE AppE ChcE CollSgE IndE UAAVE Multi	81.8 82.0 (0.3%) 81.7 (-0.1%) 81.5 (-0.4%) 81.1 (-0.8%) 81.6 (-0.2%) 80.6 (-1.5%)	79.1 (-3.4%) ⁻ 81.8 ⁺ 79.3 (-3.1%) ⁻ 80.1 (-2.2%) ⁻ 80.5 (-1.5%) ⁻ + 81.1 (-0.9%) ⁺ 80.4 (-1.7%) ⁻ +	81.5 (-0.3%) 81.8 81.5 (-0.4%) 81.2 (-0.7%) 80.9 (-1.1%) 81.5 (-0.3%) 80.5 (-1.6%)	68.8 (-18.9%) - 71.2 (-14.9%) - 68.8 (-18.9%) - 80.2 (-2%) - 67.2 (-21.7%) - 69.2 (-18.2%) - 78.5 (-4.2%) -	76.1 (-7.5%) ⁻ 79.0 (-3.5%) ⁻ + 76.5 (-7%) ⁻ 79.4 (-3%) ⁻ + 80.3 (-1.9%) ⁻ + 79.6 (-2.7%) ⁻ + 79.7 (-2.7%) ⁻ +	76.6 (-6.7%) ⁻ 79.6 (-2.8%) ⁻ + 77.3 (-5.9%) ⁻ 78.7 (-3.9%) ⁻ + 79.2 (-3.3%) ⁻ + 81.1 (-0.9%) ⁺ 80.0 (-2.2%) ⁻ +	77.3 (-5.8%) 79.2 (-3.2%) 77.5 (-5.5%) 80.2 (-2%) 78.2 (-4.6%) 79.0 (-3.5%) 80.0 (-2.3%)
	In-Dialect	81.8	81.8+	81.5 (-0.4%)	80.2 (-2%)-+	80.3 (-1.9%)-+	81.1 (-0.9%)+	81.1 (-0.9%)

Table 3: **Dialect QA Stress Test:** F1 Metric on each VALUE-transformed development set of the CoQA benchmark. $^-$ and $^+$ indicate significantly (P < 0.05) worse performance than SAE \mapsto SAE and better performance than SAE \mapsto Dialect by a paired bootstrap test.

Е	Evaluation		Input Dialect					
Model	Metric	SAE	AppE	ChcE	CollSgE	IndE	UAAVE Avg.	
BART-large	Exact Match ACC	67.9	63.6 (-6.3%) ⁻	65.5 (-3.5%) ⁻	60.3 (-11.2%) ⁻	61.2 (-9.9%) ⁻	62.3 (-8.2%) 63.5 (-6.5%)	
	Execution ACC	70.5	65.2 (-7.5%) ⁻	68.2 (-3.3%) ⁻	63.0 (-10.6%) ⁻	62.8 (-10.9%) ⁻	64.5 (-8.5%) 65.4 (-7.2%)	
T5-3b	Exact Match ACC	71.7	65.3 (-8.9%) ⁻	69.7 (-2.8%) ⁻	60.7 (-15.3%) ⁻	62.9 (-12.3%) ⁻	68.5 (-4.5%) ⁻ 66.5 (-7.3%)	
	Execution ACC	75.6	69.3 (-8.3%) ⁻	73.4 (-2.9%) ⁻	64.9 (-14.2%) ⁻	66.5 (-12.0%) ⁻	66.9 (-11.5%) ⁻ 69.4 (-8.2%)	

Table 4: **Dialect SPIDER Stress Test:** Evaluation on each VALUE-transformed evaluation set of the SPIDER benchmark. We finetune BART and T5 on SPIDER and evaluate for both Exact Match and Execution accuracy. $^-$ indicates a significant performance drop (P < 0.05) compared to SAE performance by a bootstrap test.

models and tasks. Evaluation reveals large and statistically significant performance gaps across each task and across all dialects. This highlights, for the first time, the pervasiveness of English dialect disparity beyond any single dialect.

CoQA + Data Augmentation results are shown in Table 3. As predicted in §6.1, Chicano English does not produce a significant drop in performance (-0.3%) since few of its pervasive features are distinct from SAE.² On the other hand, Singapore English, which is distant from SAE and therefore has many obligatory features, leads to the largest drop (-18.9%). Appalachian, Indian, and African American English each produce smaller, but significant drops of -3.4%, -7.5%, and -6.7% respectively.

The data augmentation technique described in §5 successfully closes the dialectal gap. Across every dialect but Chicano English, we find that training on data transformed to the target dialect improves results. Compared to the SAE model, the model trained on **Multi**-dialectal data improves average cross-dialectal performance by 2.7 points. However, multi-dialectal training does lead to interference, causing a drop of 1.2 points on SAE.

We performed a **Qualitative Error Analysis** for cases where models trained on SAE flipped from a correct answer in SAE to an incorrect answer

in one of the dialect-transformed COQA sets.³ Fully validated perturbations in tense, inflection, plural marking, phrasal order, and the deletion of pragmatically-recoverable pronouns, prepositions, and auxiliaries all lead to significant errors. As expected, these errors can cascade down the conversation, leading to model failure on later *unperturbed* questions as well. In some cases, erroneous answers still belong to the correct class, like flipping from *yes* to *no* in the presence of *negative concord*. Suprisingly, transformations also frequently cause the model to respond with an erroneous *class*, like giving a noun phrase or prepositional phrase to a yes/no question under perturbations like *clefting* and the omission of auxiliary *did*, *is*, and *wh*-words.

Our analysis also suggests that the noticeably larger drop in performance on Singapore English might be largely due to the higher density of two perturbation types: preposition omissions [#198], and the *one relativizer* [#216]. Future work might employ a perturbation analysis (Ziems et al., 2022) to quantitatively measure these sources of error.

Semantic Parsing stress test results are shown in Table 4. For all English dialects, the performance of the SAE models drops significantly with the dialect stress test in terms of both Exact Match Accuracy and Execution Accuracy. The two non-American dialects, CollSgE and IndE, both cause the largest drop for both BART and T5. Un-

²The Manhattan distance between feature vectors for ChcE and Colloquial American English is 0.14, or only half the distance as between CollAmE and CollSgE, IndE, and UAAVE.

³We considered 30 errors for each transformed dialect.

Evalu	Evaluation		Source Dialect								
# Param.	Target	SAE	AppE	ChcE	CollSgE	IndE	UAAVE	Avg.			
615M	Chinese German Gujurati Russian	22.5 39.6 21.7 27.8	21.2 (-6.1%) ⁻ 34.3 (-13.41%) ⁻ 18.6 (-14.5%) ⁻ 24.6 (-11.4%) ⁻	21.7 (-3.6%) ⁻ 37.8 (-4.65%) ⁻ 20.4 (-6.2%) ⁻ 26.7 (-4.0%) ⁻	17.0 (-24.5%) ⁻ 22.3 (-43.60%) ⁻ 13.4 (-38.4%) ⁻ 17.2 (-38.1%) ⁻	18.7 (-16.8%) ⁻ 26.8 (-32.32%) ⁻ 16.6 (-23.4%) ⁻ 20.8 (-25.4%) ⁻	19.8 (-12.3%) ⁻ 30.5 (-23.1%) ⁻ 17.2 (-20.7%) ⁻ 21.7 (-22.1%) ⁻	20.1 (-10.6%) 31.9 (-19.5%) 18.0 (-17.2%) 23.1 (-16.8%)			
1.3B	Chinese German Gujurati Russian	23.2 42.6 24.0 31.7	21.5 (-7.4%) ⁻ 37.5 (-11.9%) ⁻ 20.7 (-13.8%) ⁻ 28.5 (-10.1%) ⁻	22.5 (-3.3%) 40.6 (-4.6%) ⁻ 22.9 (-4.5%) ⁻ 30.3 (-4.4%)	17.8 (-23.5%) ⁻ 25.3 (-40.6%) ⁻ 15.5 (-35.4%) ⁻ 20.3 (-36.0%) ⁻	19.4 (-16.6%) ⁻ 29.4 (-31.0%) ⁻ 18.5 (-22.8%) ⁻ 24.5 (-22.6%) ⁻	19.8 (-15.0%) ⁻ 34.2 (-19.7%) ⁻ 19.7 (-17.8%) ⁻ 25.3 (-20.2%) ⁻	20.7 (-11.0%) 34.9 (-18.0%) 20.2 (-15.7%) 26.7 (-15.5%)			

Table 5: **Dialect Translation Stress Test:** SacreBLEU Score (Post, 2018) on each VALUE-transformed validation set of the WMT19 benchmark at 2 distilled scales of the NLLB Translation model (Costa-jussà et al., 2022). $^-$ indicates a significant performance drop (P < 0.05) compared to SAE performance by a bootstrap test.

like question answering, semantic parsing does require answering questions about natural language in SAE, instead interacting with non-natural data schemas. The fact that the performance drop is equally large for the task supports our claim that the discrepancies are caused by model mismatch, rather than solely a mismatch between the dialect of the question and that of the knowledge base.

Machine Translation stress test results are shown in Table Except for ChcE, performance drops significantly across all dialects for each language. Interestingly, the size of the dialectal gap decreases as the relatedness of the target language decreases with the largest drop from English→German (615M, -19.5%; 1.3B, -18.0%) and the smallest drop from English→Chinese (615M, -10.6%; 1.3B, -11.0%). This is not simply a relationship with original model performance as shown by Gujurati (615M, -17.2%; 1.3B, -15.7%), a low-resource Indo-European language with similar performance to Chinese but more similar syntax to English.

Despite both the 1.3B and 615M NLLB models being distilled from the same larger model, we see that the dialectal gap is smaller for German, Gujurati, and Russian. This suggests that model compression may affect low-resource dialects more heavily than SAE, similar to multi-lingual findings for low-resource languages (Ahia et al., 2021).

7 Conclusion

In this work, we introduced Multi-VALUE – a dialect robustness evaluation framework that is interpretable, flexible, scalable, responsible, and generalizable. The rule-based methods form a transparent syntactic translation system that can flexibly adjust to the shifting feature space of living dialects. Additionally, the transformation rules are reliably

sourced from over a decade of linguistics literature and vetted by native speakers. After showing that these transformations predict human-translated dialect benchmark performance, we use them to build dialect benchmarks and training data at scale, without the need for additional annotation efforts. By training and evaluating in a cross-dialectal manner, we demonstrated how Multi-VALUE can be used for more generalizable findings about model performance and dialect transferability.

Limitations. Lexical variation is not the focus of this work because lexical variation is not welldescribed by systematic and scalable rules for generalization. Lexical distributions can be derived from data, but many low-resource dialects lack sufficient corpus data on which to base these insights. This is an important problem for future research. Despite the scope and precision of the typological database that grounds this work (eWAVE; Kortmann et al.), the catalog ultimately derives from field linguists' oral interviews with native speakers, and here we can identify some limitations. First, the orthographic conventions that linguists use to encode spoken dialect may not always align directly with the speakers' own writing conventions and usage. Thus Multi-VALUE perturbations might "look wrong" to certain speakers. Second, our resource can only cover the variation that linguists observe frequently enough to document, in canonical forms in which they are documented. This means we may not fully capture variation within each feature. Finally, dialects should not be treated like deterministic speech patterns, but rather like a range of grammatical options or switches that may be turned on and off and adjusted for frequency in various social and personal contexts. Dialects do not always fit into nicely prescribed categories.

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Figure 4: **Dialect Survey Interface.** Users are guided through a series of linguistic acceptability judgments for dialect excerpts and their corresponding SAE glosses. After an average of 9 questions, the survey returns a unique identifier for the speaker's matched dialect.

A Validation Details

A.1 Dialect Assessment Survey

Crowdworkers may not be aware of their own language patterns. For this reason, we need more careful screening and qualification of study participants. We use a Dialect Assessment Survey (Figure 4) to ensure that speakers language patterns align with known clusters. The survey is hosted at the following link:

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https://calebziems.com/
resources/value/dialect-quiz.
```

The assessment resembles the annotation task itself in that we ask speakers to provide binary grammaticality judgments about example sentences from linguistics publications on our target dialects. The survey dynamically adjusts its questions based on past responses. At each step, the respondent is asked a question concerning the dialectal feature that most evenly partitions the space of candidate dialects remaining. Thus our survey efficiently identifies a speaker's dialect in a manner similar to the game "20 Questions." The survey uses an average of 9 questions, but the survey length will depend upon the user's answers.

It is important to note that this survey is not 100% accurate. For this reason, we also ask annotators to self-report their spoken dialect. To ensure internal consistency, we select workers whose self-report aligns with their survey results.

A.2 Validation Task

Our validation task is drawn directly from Ziems et al. (2022) in which each annotator is shown a pair

of questions: (1) an SAE sentence, and (2) a transformed sentence in the synthetic dialect. Annotators mark portions of sentence 1 that were changed incorrectly in sentence 2. The interface is shown in Figure 5 below.

B Implementation Details

In Tables 9-21, we detail our Multi-VALUE implementations with an enumeration of our implemented dialects and features, with examples of each. In the VAL ACC. column we give the validation accuracy (§4.2) as well as tags ChcE or IndE to indicate if the feature appears in the gold Chicano or Indian English CoQA dataset respectively.

B.1 Pronouns

There are 47 pronoun features in eWAVE, and we cover 39 of them (83%). While simple regular expressions can cover some pronoun mappings, this is not always possible since English maps the same surface forms to different grammatical roles.⁴ We overcome this problem by conditioning rules on pronouns' syntactic roles. We also condition on coreference for referential pronouns [29], and on verb frames to identify benefactive datives [9]. Furthermore, we swap the morphology of possession [20], change reflexive marking [11-16], swap animate pronouns for inanimate objects [1-2], and include additional elements like reduplication [40]. In summary, our pronoun perturbation rules account for linguistic structure and are not merely surface manipulations.

B.2 Noun Phrases

Among our 31 noun phrase perturbations, we regularize or modify plural morphology [49] and comparison strategies [80], to drop or modify articles [60], construct phrases for possession [75], and adjust the tree adjoining order to create adjective postfixes [87].

B.3 Tense and Aspect

Tense and aspect perturbations include alternative inflections and auxiliaries to mark tense [117], including immediate vs. distant future [119], as well as perfect aspect [99].

⁴For example, *her* is both the accusative in "give it to her" and the noun modifier in "her cart," while the masculine pronouns in "give it to him" and "his cart" differ. This problem was observed but not solved in the rule-based perturbation augmentation of Qian et al. (2022).

B.4 Mood

Multi-VALUE includes perturbations that inject double modals [121] and quasi-modals [126], change verb inflections under modal scope [123], and introduce auxiliaries to mark the sequential or irrealis mood [106].

B.5 Verb Morphology

Verb morphology features include levelling certain finite and non-finite verb forms [130] adding suffixes for transitive verbs [143], and building *serial verb phrases* (Tallerman, 2019) to mark passive constructions [153], indirect objects [148], or the movement of direct objects [150].

B.6 Negation

Multi-VALUE includes rules for building phrases with negative concord [154], and forms of negation with the negation words *never*, *no*, *not*, *no more* or *ain't*, as well as special invariant tags for questions [166].

B.7 Agreement

We implement the invariant present tense [170], the existential dummy *it* [173].

B.8 Relativization

These perturbations modify the form of the relativizer [186-190], as well as drop [193] or introduce new shadow pronouns [194], such as double relativizers [191] and phrasal forms [192]. Our perturbations also operate on the sentence structure by forming correlative constructions [196], deleting stranded prepositions [198], and moving the relative clause before the head noun [199].

B.9 Complementation

These perturbations can change the form of the complementizer [200, 201], delete [208, 209] or introduce additional complementizer words [203, 204], build existential constructions from complementizer phrases [205, 206], and modify the verb in the non-finite clause complement [210].

B.10 Adverbial Subordination

Our perturbation rules introduce clause-final conjunctions [211, 212] and double conjuctions [214, 215], and remove the adverb in verb-chaining constructions [213], which together represent the five adverbial subordination features in eWAVE.

	Model	Test Dialect					
Base	Train Set	SAE	ChcE	IndE			
BERT	SAE Multi	77.2 76.2 (-1.2%)	76.7 (-0.5%) 76.1 (-1.4%)	72.3 (-6.7%) ⁻ 75.0 (-2.9%) ⁺⁻			
В	In-Dialect	77.2	76.5 (-0.9%)	75.1 (-2.7%)+-			
RoBERTa	SAE Multi	81.8 80.6 (-1.5%) ⁻	81.6 (-0.2%) 80.5 (-1.6%)	77.7 (-5.2%) ⁻ 79.7 (-2.7%) ⁺⁻			
	In-Dialect	81.8	81.6 (-0.2%)	80.5 (-1.6%)+-			

Table 6: **Gold QA Evaluation:** F1 Metric on each gold development set of the CoQA benchmark. On top of the main experiments, we also add BERT results. $^-$ and $^+$ respectively indicate significantly (P < 0.05) worse performance than SAE \mapsto SAE and better performance than SAE \mapsto Dialect by a paired bootstrap test.

B.11 Adverbial Prepositions

In this section, we drop prepositions [216] and replace adverbs with their adjectival forms [220, 221]. We also include the word *too* as a qualifier [222].

B.12 Discourse and Word Order

In discourse, we insert the word *like* as a focus [234] or quotation marker [235]. Our phrase-based perturbations include fronting and clefting [223, 224], subject—auxiliary inversion in both negation phrases [226] and indirect questions [227], and a lack of inversion in certain questions [228, 229]. These rules significantly alter the sentence structure, and in this way radically differ from prior token-level data augmentation techniques like synonym replacement (Wei and Zou, 2019). Our approach here is most similar to *constituency replacement* (Sutiono and Hahn-Powell, 2022).

C Models & Hyperparameters

CoQA We use the base versions of BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) on dialect variants of the CoQA task, following the Rationale Tagging Multi-Task setup of Ju et al. (2019) to adapt these models to the CoQA setup which includes *Yes*, *No*, and *Unknown* responses in addition to extractive answers. For each model and dialect, we fine-tune using AdamW (Loshchilov and Hutter, 2019) for 2 epochs with a batch size of 16 and a learning rate 3e-5.

Semantic Parsing. Following (Xie et al., 2022), for T5-BASE we adopted the AdamW optimizer, while Adafactor was used for T5-3B and the two BART models. We set the learning rate at 5e-5 for T5 models and 1e-5 for BARTs. We fixed the

	Model				Test Dialect			
Base	Train Set	SAE	AppE	ChcE	CollSgE	IndE	UAAVE	Average
BERT Base	SAE AppE ChcE CollSgE IndE UAAVE Multi	77.2 76.3 (-1.1%) 76.8 (-0.5%) 75.7 (-1.9%) – 76.0 (-1.5%) 76.1 (-1.4%) 76.2 (-1.2%)	74.4 (-3.8%) – 76.4 (-1%) + 74.7 (-3.3%) – 74.1 (-4.2%) – 75.4 (-2.4%) – 75.6 (-2%) – + 75.6 (-2%) – +	76.6 (-0.7%) 76.1 (-1.4%) 76.5 (-0.8%) 75.5 (-2.2%) – 75.7 (-2%) – 76.0 (-1.5%) – 76.1 (-1.3%)	61.5 (-25.4%) - 64.7 (-19.3%) - + 63.6 (-21.3%) - + 74.7 (-3.3%) - + 63.2 (-22%) - + 64.6 (-19.5%) - + 73.7 (-4.7%) - +	70.8 (-9%) ⁻ 72.8 (-6%) ⁻ + 71.6 (-7.8%) ⁻ 73.6 (-4.8%) ⁻ + 75.1 (-2.7%) ⁻ + 74.5 (-3.6%) ⁻ + 74.9 (-3.1%) ⁻ +	71.2 (-8.4%) ⁻ 73.2 (-5.4%) ⁻ + 71.4 (-8.1%) ⁻ 73.4 (-5.1%) 74.1 (-4.1%) ⁻ + 75.3 (-2.5%) ⁻ + 75.1 (-2.7%) ⁻ +	71.9 (-7.3%) 73.3 (-5.3%) 72.4 (-6.5%) 74.5 (-3.6%) 73.3 (-5.3%) 73.7 (-4.7%) 75.3 (-2.5%)
	In-Dialect	77.2	76.4 (-1%)+	76.5 (-0.8%)	74.7 (-3.3%)-+	75.1 (-2.7%)-+	75.3 (-2.5%)-+	75.9 (-1.7%)
RoBERTa Base	SAE AppE ChcE CollSgE IndE UAAVE Multi	81.8 82.0 (0.3%) 81.7 (-0.1%) 81.5 (-0.4%) 81.1 (-0.8%) 81.6 (-0.2%) 80.6 (-1.5%)	79.1 (-3.4%) ⁻ 81.8 ⁺ 79.3 (-3.1%) ⁻ 80.1 (-2.2%) ⁻ 80.5 (-1.5%) ⁻ + 81.1 (-0.9%) ⁺ 80.4 (-1.7%) ⁻ +	81.5 (-0.3%) 81.8 81.5 (-0.4%) 81.2 (-0.7%) 80.9 (-1.1%) 81.5 (-0.3%) 80.5 (-1.6%)	68.8 (-18.9%) ⁻ 71.2 (-14.9%) ⁻ 68.8 (-18.9%) ⁻ 80.2 (-2%) ⁻ 67.2 (-21.7%) ⁻ 69.2 (-18.2%) ⁻ 78.5 (-4.2%) ⁻	76.1 (-7.5%) ⁻ 79.0 (-3.5%) ⁻ + 76.5 (-7%) ⁻ 79.4 (-3%) ⁻ + 80.3 (-1.9%) ⁻ + 79.6 (-2.7%) ⁻ + 79.7 (-2.7%) ⁻ +	76.6 (-6.7%) ⁻ 79.6 (-2.8%) ⁻ + 77.3 (-5.9%) ⁻ 78.7 (-3.9%) ⁻ + 79.2 (-3.3%) ⁻ + 81.1 (-0.9%) ⁺ 80.0 (-2.2%) ⁻ +	77.3 (-5.8%) 79.2 (-3.2%) 77.5 (-5.5%) 80.2 (-2%) 78.2 (-4.6%) 79.0 (-3.5%) 80.0 (-2.3%)
	In-Dialect	81.8	81.8+	81.5 (-0.4%)	80.2 (-2%)-+	80.3 (-1.9%)-+	81.1 (-0.9%)+	81.1 (-0.9%)

Table 7: **Dialect QA Stress Test:** F1 Metric on each VALUE-transformed development set of the CoQA benchmark. On top of the main experiments, we also add BERT results. $^-$ and $^+$ indicate significantly (P < 0.05) worse performance than SAE \mapsto SAE and better performance than SAE \mapsto Dialect by a paired bootstrap test.

Е	Evaluation		Input Dialect						
Model	Metric	SAE	AppE	ChcE	CollSgE	IndE	UAAVE	Avg.	
BART-base	Exact Match ACC	49.3	45.2 (-8.3%) ⁻	48.5 (-1.6%) ⁻	41.9 (-15.0%) ⁻	40.5 (-17.8%) ⁻	45.0 (-8.7%) ⁻	45.1 (-8.5%)	
	Execution ACC	51.0	47.3 (-7.3%) ⁻	50.3 (-1.4%)	44.1 (-13.5%) ⁻	42.3 (-17.1%) ⁻	46.1 (-9.6%) ⁻	46.9 (-8.0%)	
BART-large	Exact Match ACC	67.9	63.6 (-6.3%) ⁻	65.5 (-3.5%) ⁻	60.3 (-11.2%) ⁻	61.2 (-9.9%) ⁻	62.3 (-8.2%) ⁻	63.5 (-6.5%)	
	Execution ACC	70.5	65.2 (-7.5%) ⁻	68.2 (-3.3%) ⁻	63.0 (-10.6%) ⁻	62.8 (-10.9%) ⁻	64.5 (-8.5%) ⁻	65.4 (-7.2%)	
T5-base	Exact Match ACC	58.7	54.3 (-7.5%) ⁻	57.4 (-2.2%) ⁻	50.0 (-14.8%) ⁻	49.1 (-16.4%) ⁻	53.1 (-9.5%) [—]	53.8 (-8.3%)	
	Execution ACC	59.8	56.0 (-6.4%) ⁻	58.5 (-2.2%) ⁻	51.6 (-13.7%) ⁻	51.3 (-14.2%) ⁻	54.6 (-8.7%) [—]	55.3 (-7.5%)	
T5-3b	Exact Match ACC Execution ACC	71.7 75.6	65.3 (-8.9%) ⁻ 69.3 (-8.3%) ⁻	69.7 (-2.8%) ⁻ 73.4 (-2.9%) ⁻	60.7 (-15.3%) [—] 64.9 (-14.2%) [—]	62.9 (-12.3%) ⁻ 66.5 (-12.0%) ⁻	68.5 (-4.5%) ⁻ 66.9 (-11.5%) ⁻	66.5 (-7.3%) 69.4 (-8.2%)	

Table 8: **Dialect SPIDER Stress Test:** Evaluation on each VALUE-transformed evaluation set of the SPIDER benchmark. On top of the main experiments, we finetuned additional model scales of BART and T5 on SPIDER and evaluate for both Exact Match and Execution accuracy. $^-$ indicates a significant performance drop (P < 0.05) compared to SAE performance by a bootstrap test.

batch size at 32 when fine-tuning T5-BASE and BARTs. As for the extremely large T5-3B, we configured a batch size of 64 to speed up convergence and utilised DeepSpeed to save memory. Linear learning rate decay was used for all models.

Machine Translation. We evaluate the NLLB Translation Model at two distilled scales: 615M and 1.3B (Costa-jussà et al., 2022). The NLLB model is designed for many-to-many translation with low-resource language communities and is trained on a large corpus mined from the internet, rather than exclusively human aligned translations. We choose this model to give us an estimate of the performance of large scale translation products available to users.

Dialectal English Understanding

If you haven't already, please open and read the Instructions tab. Your goal is to decide whether bits of text sound unnatural or ungrammatical.

	ence (1): What was it called? ence (2): What-all have been it called?
Ve have	aticality: highlighted certain portions of Sentence (1) that are different in Sentence (2). Do the words and the order of the words in Sentence (2) look ething you could say? (In other words: is this grammatical in your dialect?)
0	Yes, grammatical
1 0	No, not grammatical
f you hov	ng is ungrammatical or unnatural, please let us know which of the highlighted segments were changed in a way that doesn't make sense. ver over them, each segment will have a number ID. Simply list the IDs of any unnatural segment translations here, separating each with a comma (e.g. "2, 3, 5"). If g else is unnatural but it isn't highlighted, add "OTHER" to the list. If nothing is unnatural, leave this blank.
	sing: le, please provide a revised or alternative rephrasing of Sentence (1) that would be acceptible in your dialect. If no change is possible, leave lak and check the box below. If your rephrasing is good, we will send you a bonus (\$0.01).
] No	Change: Check this box if no change to the sentence was possible.
omme you ha	ents: ave any other comments, please put them here.
Submit	

Figure 5: **MTurk Validation Task Interface.** Users consider sentence pairs and evaluate whether the synthetic sentence is an acceptable dialectal form of the gloss given by the natural SAE sentence.

ABBR	# FEAT.	% Feat.	# VAL.	% VAL.	DIALECT
AborE	89	83.2%	57	53.3%	Aboriginal English
AppE	65	85.5%	51	67.1%	Appalachian English
AusE	54	90.0%	40	66.7%	Australian English
AusVE	47	83.9%	34	60.7%	Australian Vernacular English
BahE	107	83.6%	70	54.7%	Bahamian English
BISAfE	95	88.0%	71	65.7%	Black South African English
CamE	76	87.4%	62	71.3%	Cameroon English
CFE	49	90.7%	39	72.2%	Cape Flats English
ChIsE	47	94.0%	33	66.0%	Channel Islands English
ChcE	30	93.8%	28	87.5%	Chicano English
CollAmE	57	83.8%	44	64.7%	Colloquial American English
CollSgE	67	89.3%	52	69.3%	Colloquial Singapore English (Singlish)
EAAVE	96	89.7%	61	57.0%	Earlier African American Vernacular English
EA	46	85.2%	32	59.3%	East Anglian English
FlkE	44	89.8%	30	61.2%	Falkland Islands English
FijiE	39	88.6%	36	81.8%	Acrolectal Fiji English
CollFijiE	95	85.6%	68	61.3%	Pure Fiji English (basilectal FijiE)
GhE	58	92.1%	49	77.8%	Ghanaian English
HKE	74	91.4%	61	75.3%	Hong Kong English
IndE	90	90.0%	82	82.0%	Indian English
InSAfE	75	83.3%	58	64.4%	Indian South African English
IrE	75	81.5%	54	58.7%	Irish English
JamE	69	88.5%	47	60.3%	Jamaican English
KenE	50	90.9%	45	81.8%	Kenyan English
LibSE	86	84.3%	58	56.9%	Liberian Settler English
MalE	68	89.5%	57	75.0%	Malaysian English
MaltE	72	86.7%	59	71.1%	Maltese English
ManxE	55	83.3%	40	60.6%	Manx English
NZE	44	88.0%	37	74.0%	New Zealand English
NfldE	84	85.7%	53	54.1%	Newfoundland English
NigE	45	88.2%	37	72.5%	Nigerian English
North	77	85.6%	47	52.2%	English dialects in the North of England
O&SE	30	81.1%	19	51.4%	Orkney and Shetland English
	56	86.2%			Ozark English
OzE PakE	48	87.3%	43	76.4%	Pakistani English
PhilE	92	85.2%	71	65.7%	Philippine English
RAAVE	136	82.9%	88	53.7%	Rural African American Vernacular English
ScE	44	80.0%	30	54.5%	Scottish English
SEAmE	108	80.6%	75	56.0%	Southeast American enclave dialects
SLkE	29	82.9%	23	65.7%	Sri Lankan English
StHE	113	85.0%	78	58.6%	St. Helena English
SE	46	93.9%	33	67.3%	English dialects in the Southeast of England
SW			46		
TznE	73	89.0%	35	56.1% 79.5%	English dialects in the Southwest of England
TdCE	92	93.2%	64	57.7%	Tanzanian English Trictan da Cunha English
UAAVE	118	82.9%	79		Tristan da Cunha English Urban African American Vernacular English
UgE	65	83.7%	52	56.0%	
WelE	76	86.7%	53	56.4%	Ugandan English Welsh English
WhSAfE	41	80.9%	35	71.4%	White South African English
WhZimE	61	88.4%	46	66.7%	White Zimbabwean English
WILLIIIE	01	00.470	40	00.7%	WITH ZITHUAUWEAH ENGHSH

Table 9: **Multi-VALUE Implemented Dialects.** We've implemented 50 English dialects as shown in this table. We list the number of implemented features (# FEAT), the proportion of that dialect's catalogued eWAVE features implemented (% FEAT), the number of validated features (# VAL), and the proportion of that dialect's catalogued eWAVE features validated (% VAL). All dialects are at or above 80% implemented and above 51.4% validated. Gold **ChcE** and **IndE** indicate that we also release a Gold CoQA dev set in Chicano and Indian English.

	FUNCTION	SAE	Transform	VAL ACC.
1	she_inanimate_objects	It's a good bike	She's a good bike	
2	he_inanimate_objects	The driver's license? She wasn't allowed to renew it right?	The driver's license? She wasn't allowed to renew 'im right?	
3	referential_thing	Christmas dinner? I think it's better to wait until after she's had it.	Christmas dinner? I think it's better to wait until after she's had the thing.	100.0
4	pleonastic_that	It's raining.	Thass raining.	
5	em_subj_pronoun	This old woman, she started packing up.	This old woman, 'em started packing up.	
6	em_obj_pronoun	We just turned it around.	We just turned 'im around.	
7	me_coordinate_subjects	Michelle and I will come too.	Me and Michelle will come too.	
8	myself_coordinate_subjects	My husband and I were late.	My husband and myself were late.	
9	benefactive_dative	I have to get one of those!	I have to get me one of those!	ChcE 100.0
10	no_gender_distinction	Susan is a nurse but she does not like to put drips on patients.	Susan is a nurse but he does not like to put drips on patients.	IndE 97.4
11	regularized_reflexives	He hurt himself.	He hurt hisself.	100.0
12	regularized_reflexives_object_pronouns	I'll do it myself.	I'll do it meself.	
13	regularized_reflexives_aave	They look after themselves.	They look after theyselves.	
14	reflex_number	We cannot change ourselves.	We cannot change ourself.	IndE 100.0
15	absolute_reflex	and he and the bull were tuggin' and wrestlin'	and himself and the bull were tuggin' and wrestlin'	IndE 100.0
16	emphatic_reflex	They brought it by themselves.	They brought it by their own self.	ChcE 100.0
18	my_i	my book	I book	
19	our_we	our farm	we farm	
20	his_he	his book	he book	
21	their_they	their book	they book	
22	your_you	your book	you book	
23	your_yalls	Where are your books?	Where are y'all's books?	
24	his_him	his book	him book	
25	their_them	their book	them book	
26	my_me	my book	me book	100.0
27	our_us	our book	us book	
29	me_us	Show me the town!	Show us the town!	100.0
30	non_coordinated_subj_obj	Do you want to come with us?	Do you want to come with we?	
31	non_coordinated_obj_subj	They can ride all day.	Them can ride all day.	
33	nasal_possessive_pron	her, his, our; hers, ours, ours	hern, hisn, ourn; hersn, oursn, ourns	100.0
34	vall	you	y'all	ChcE IndE 100.0
35	you_ye	Sure it's no good to you in England.	Sure it's no good to ye in England.	
39	plural_interrogative	Who came?	Who-all came?	99.7
40	reduplicate_interrogative	Who's coming today?	Who-who's coming today?	IndE 99.8
41	anaphoric_it	Things have become more expensive than they used to be.	Things have become more expensive than it used to be.	IndE 100.0
42	object_pronoun_drop	I got it from the store.	I got from the store.	IndE 98.1
43	null_referential_pronouns	When I come back from my work I just travel	When I come back from my work just travel	ChcE IndE 93.2
	-	back to my home.	back to my home.	
45	it_dobj	As I explained to her, this is not the right way.	As I explained it to her, this is not the right way.	IndE 100.0
46	it_is_referential	It is very nice food.	Is very nice food.	
47	it is non referential	Okay, it's time for lunch.	Okay, is time for lunch.	IndE 100.0

Table 10: Pronouns (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
49	regularized_plurals	wives, knives, lives, leaves	wifes, knifes, lifes, leafs	IndE 99.6
50	plural_preposed	shooting birds	shooting alla bird	
51	plural_postposed	The boys	Da boy dem	
55	mass_noun_plurals	furniture, machinery, equipment, evidence, lug-	furnitures, machineries, equipments, evidences,	IndE 100.0
		gage, advice, mail, staff	luggages, advices, mails, staffs	
56	zero_plural_after_quantifier	It's only five miles away.	It's only five mile away.	ChcE IndE 97.3
57	plural_to_singular_human	The three girls there don't want to talk to us.	The three girl there don't want to talk to us.	IndE 100.0
58	zero_plural	Some apartments are bigger.	Some apartment are bigger.	IndE 100.0
59	double_determiners	This common problem of ours is very serious.	This our common problem is very serious.	IndE 100.0
60	definite_for_indefinite_articles	She's got a toothache.	She's got the toothache	IndE 99.6
61	indefinite_for_definite_articles	The moon was very bright last night.	A moon was very bright last night.	IndE 100.0
62	remove_det_definite	He's in the office.	He's in office.	IndE 100.0
63	remove_det_indefinite	Can I get a better grade?	Can I get better grade?	IndE 99.0
64	definite_abstract	I stayed on until Christmas.	I stayed on until the Christmas.	IndE 100.0
65	indefinite_for_zero	We received good news at last.	We received a good news at last.	
66	indef_one	What happened? Oh, a dog bit me.	What happened? Oh, one dog bit me.	IndE 100.0
67	demonstrative_for_definite_articles	They have two children. The elder girl is 19 years old.	They have two children. That elder girl is 19 years old.	IndE 99.1
68	those_them	I don't have any of those qualifications.	I don't have any of them qualifications.	
70	proximal_distal_demonstratives	this book that is right here vs. those books that are over there	this here book vs. them there books	ChcE 92.9
71	demonstrative_no_number	These books are useful for my study.	This books are useful for my study.	IndE 98.8
73	existential_possessives	I have a son.	Son is there.	
74	possessives_for_post	This is my mother's house.	This is the house for my mother.	
75	possessives_for_pre	Long time ago he was my sister's husband.	Long time he was for my sister husband.	
76	possessives_belong	the woman's friend	woman belong friend	
77	null_genitive	my cousin's bike	my cousin bike	IndE 100.0
78	double_comparative, double_superlative	That is so much easier to follow.	That is so much more easier to follow.	IndE 100.0
79	synthetic_superlative	He is the most regular guy I know.	He is the regularest guy I know.	IndE 100.0
80	analytic_superlative	one of the prettiest sunsets	one of the most pretty sunsets	IndE 100.0
81	more_much	The situation is more serious than I thought.	The situation is much serious than I thought.	IndE 100.0
82	comparative_as_to	She is bigger than her sister.	She is bigger as her sister.	
84	comparative_than	They like football more than basketball.	They like football than basketball.	
85	comparative_more_and	He has more clothes than all of us.	He has more clothes and all of us.	
86	zero_degree	He is one of the most radical students that you can ever find.	He is one of the radical students that you can ever find.	IndE 100.0
87	adj_postfix	A big and fresh fish is my favorite.	A fish big and fresh is my favorite.	

Table 11: Noun Phrases (Section 3)

	FUNCTION	SAE	Transform	VAL ACC.
88	progressives	I like her hair style right now.	I am liking her hair style.	IndE 99.4
95	standing_stood	He was standing on the corner.	He was stood on the corner.	
96	that_resultative_past_participle	There is a car that broke down on the road.	There is a car broken down on the road.	95.5
97	medial_object_perfect	He has written a letter.	He has a letter written.	
98	after_perfect	She has just sold the boat.	She's after selling the boat.	
99	simple_past_for_present_perfect	I've eaten the food. So can I go now?	I ate the food. So can I go now?	ChcE 94.7
100	present_perfect_for_past	We were there last year.	We've been there last year.	IndE 99.9
101	present_for_exp_perfect	I've known her since she was a child.	I know her since she was a child.	IndE 100.0
102	be_perfect	They haven't left school yet.	They're not left school yet.	
103	do_tense_marker	I knew some things weren't right.	I did know some things weren't right.	
104	completive_done	Sharon has read the whole book.	Sharon done read the whole book.	
105	completive_have_done	He has talked about me.	He has done talked about me.	
106	irrealis_be_done	If you love your enemies, they will eat you alive	If you love your enemies, they be done eat you	100.0
		in this society.	alive in this society.	
107	perfect_slam	I have already told you not to mess up	I slam told you not to mess up.	
108	present_perfect_ever	I have seen the movie.	I ever see the movie.	
109	perfect_already	Have you eaten lunch?	Did you eat already?	
110	completive_finish	I have eaten.	I finish eat.	
111	past_been	I told you.	I been told you.	
112	bare_perfect	We had caught the fish when the big wave hit.	We had catch the fish when the big wave hit.	
114	future_sub_gon	He will come with us.	He gon' come with us.	
115	volition_changes	You want to go.	You waan go.	
116	come_future	I am about to cook your meal.	I am coming to cook your meal.	
117	present_for_neutral_future	Next week, I will be leaving the States and go-	Next week, I leaving the States, I going to	IndE 100.0
		ing to Liberia.	Liberia.	
118	is_am_1s	I am going to town.	I's going to town.	
119	will_would	I will meet him tomorrow.	I would meet him tomorrow.	IndE 100.0
120	if_would	If I were you I would go home now.	If I would be you I would go home now.	

Table 12: Tense and Aspect (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
121	double_modals	We could do that.	We might could do that.	ChcE 91.8
123	present_modals	I wish I could get the job.	I wish I can get the job.	IndE 100.0
126	finna_future, fixin_future	They're about to leave.	They're fixin to leave town.	ChcE 92.3

Table 13: Mood (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
128	regularized_past_tense	He caught the ball.	He catched the ball.	ChcE IndE 92.7
129	bare_past_tense	They came and joined us.	They come and joined us.	
130	past_for_past_participle	He had gone.	He had went.	ChcE 92.9
131	participle_past_tense	I saw it.	I seen it.	IndE 100.0
132	bare_past_tense	Here are things you ordered yesterday.	Here are things you order yesterday.	ChcE IndE 87.7
133	double_past	They didn't make it this time.	They didn't made it this time.	IndE 99.5
134	a_ing	Where are you going?	Where are you a-goin?	100.0
135	a_participle	You've killed your mother.	You've a-killed your mother.	
143	transitive_suffix	You can see the fish.	You can see 'im fish.	
145	got_gotten	I hope you've got your topic already.	I hope you've gotten your topic already.	100.0
146	verbal_ing_suffix	I can drive now.	I can driving now.	IndE 100.0
147	conditional_were_was	If I were you	If I was you	
148	serial_verb_give	I bought rice for you.	I buy rice give you.	
149	serial_verb_go	Grandfather sends us to school.	Grandfather send us go school.	100.0
150	here_come	Bring the book here.	Take the book bring come.	
153	give_passive	John was scolded by his boss	John give his boss scold.	

Table 14: Verb Morphology (Section 3)

	Function	SAE	Transform	VAL ACC.
154	negative_concord	I don't want any help.	I don't want no help.	ChcE IndE 92.9
155	aint_be	That isn't fair.	That ain't fair.	ChcE 81.8
156	aint_have	I hadn't seen them yet.	I ain't seen them yet.	
157	aint_before_main	something I didn't know about	something I ain't know about	
158	dont	He doesn't always tell the truth.	He don't always tell the truth.	
159	never_negator	He didn't come.	He never came.	100.0
160	no_preverbal_negator	I don't want any job or anything.	I no want any job or anything.	
161	not_preverbal_negator	The baby didn't eat food and cried a lot.	The baby not ate food and cried a lot.	
162	nomo_existential	There is not any food in the refrigerator.	No more food in the refrigerator.	
163	wasnt_werent	John was there, but Mike wasn't	John was there, but Mike weren't	
164	invariant_tag_amnt	I believe I am older than you. Is that correct?	I am older than you, amn't I?	
165	invariant_tag_non_concord	I believe you are ill. Is that correct?	You are ill, isn't it?	IndE 99.1
166	invariant_tag_can_or_not	Can I go home?	I want to go home, can or not?	
167	invariant_tag_fronted_isnt	I can go there now can't I?	Isn't, I can go there now?	

Table 15: Negation (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
170	uninflect	He speaks English.	He speak English.	ChcE IndE 94.9
171	generalized_third_person_s	Every Sunday we go to church.	Every Sunday we goes to church.	
172	existential_there	There are two men waiting in the hall.	There's two men waiting in the hall.	ChcE IndE 90.0
173	existential_it	There's some milk in the fridge.	It's some milk in the fridge.	ChcE 87.5
174	drop_aux_be_progressive	You are always thinking about it.	You always thinking about it.	IndE 100.0
175	drop_aux_be_gonna	He is gonna go home and watch TV.	He gonna go home and watch TV.	ChcE IndE 83.3
176	drop_copula_be_NP	He is a good teacher.	He a good teacher.	
177	drop_copula_be_AP	She is smart.	She smart.	
178	drop_copula_be_locative	She is at home.	She at home.	
179	drop_aux_have	I have seen it before.	I seen it before.	IndE 100.0
180	were_was	You were hungry but he was thirsty.	You was hungry but he was thirsty. OR: You were hungry but he were thirsty.	

Table 16: Agreement (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
186	who_which	He's the man who looks after the cows.	He's the man which looks after the cows.	
187	who_as	The man who was just here.	The man as was just here.	
188	who_at	This is the man who painted my house.	This is the man at painted my house.	
189	relativizer_where	My father was one of the founders of the Under- ground Railroad, which helped the slaves to run away to the North	My father was one o de founders o' de Under- ground Railroad where help de slaves to run way to de North.	
190	who_what	This is the man who painted my house.	This is the man what painted my house.	
191	relativizer_doubling	But these, these little fellahs who had stayed before	But these, these little fellahs that which had stayed befo'	IndE 100.0
192	analytic_whose_relativizer	This is the man whose wife has died.	This is the man that his wife has died. OR: This is the man what his wife has died.	
193	null_relcl	The man who lives there is friendly.	The man lives there is friendly.	ChcE IndE 88.7
194	shadow_pronouns	This is the house which I painted yesterday.	This is the house which I painted it yesterday.	IndE 100.0
195	one_relativizer	The cake that John buys is always very nice to eat.	The cake John buy one always very nice to eat.	
196	correlative_constructions	The ones I made are the good ones.	The one I made, that one is good.	
197	linking_relcl	Unless you are going to get 88, but some universities are not going to give those marks	Unless you are going to get 88 which some universities are not going to give those marks	
198	preposition_chopping	You remember the swing that we all used to sit together on?	You remember the swing that we all used to sit together?	IndE 100.0
199	reduced_relative	There is nothing like food cooked by Amma!	There is nothing like Amma cooked food!	

Table 17: Relativization (Section 3)

	FUNCTION	SAE	TRANSFORM	VAL ACC.
200	say_complementizer	We hear that you were gone to the city.	We hear say you gone to the city.	
201	for_complementizer	You mean your mother allows you to bring over boyfriends?	You mean your mother allows you for bring over boyfriends?	
202	for_to_pupose	We always had gutters in the winter time to drain the water away.	We always had gutters in the winter time for to drain the water away.	
203	for_to	He had the privilege to turn on the lights.	He had the privilege for to turn on the lights. OR: He had the privilege for turn on the lights.	100.0
204	what_comparative	I'm taller than he is.	I'm taller than what he is.	IndE 100.0
205	existential_got	There's no water in the toilet.	Got no water in the toilet.	100.0
206	existential_you_have	There are some people who don't give a damn about animals.	You have some people they don't give a damn about animals.	IndE 100.0
207	that_infinitival_subclause	He wanted me to go with him.	He wanted that I should go with him.	IndE 100.0
208	drop_inf_to	They were allowed to call her.	They were allowed call her.	100.0
209	to_infinitive	He made me do it.	He made me to do it.	IndE 100.0
210	bare_ccomp	When mistress started whooping her, she sat her down.	When mistress started whoop her, she sat her down.	

Table 18: Complementation (Section 3)

	Function	SAE	TRANSFORM	VAL ACC.
211	clause_final_though_but	There's nothing wrong with this box though.	There's nothing wrong with this box, but.	
212	clause_final_really_but	I don't know what else she can do, really.	I don't know what else she can do, but.	
213	chaining_main_verbs	If you stay longer, they have to charge more.	Stay longer, they have to over-charge.	
214	corr_conjunction_doubling	Despite being instructed on what to do, he still made some misakes.	Despite being instructed on what to do still yet he made some misakes.	IndE 100.0
215	subord_conjunction_doubling	Although you are smart, you are not appreciated	Although you are smart, but you are not appreciated	

Table 19: Adverbial Subordination (Section 3)

	Function	SAE	TRANSFORM	VAL ACC.
216	null_prepositions	I'm going to town.	I'm going town.	IndE 99.7
220	degree_adj_for_adv	That's really nice and cold	That's real nice and cold	ChcE IndE 99.4
221	flat_adj_for_adv	She speaks so softly.	She speaks so soft.	ChcE IndE 86.7
222	too_sub	They are very nice. We had a good time there.	They are too nice. We had a good time there.	

	Function	SAE	Transform	VAL ACC.
223	clefting	A lot of them are looking for more land.	It's looking for more land a lot of them are.	100.0
224	fronting_pobj	I drive to town every Saturday.	To town every Saturday I drive.	IndE 99.5
226	negative_inversion	Nobody showed up.	Didn't nobody show up.	100.0
227	inverted_indirect_question	I'm wondering what you are going to do.	I'm wondering what are you going to do.	ChcE IndE 91.2
228	drop_aux_wh	When is she coming?	When she coming?	IndE 99.8
229	drop_aux_yn	Do you get the point?	You get the point?	IndE 99.9
230	doubly_filled_comp	Who ate what?	What who has eaten?	
231	superlative_before_matrix_head	The thing I like most is apples.	The most thing I like is apples.	
232	double_obj_order	She would teach it to us.	She'd teach us it.	IndE 100.0
234	acomp_focusing_like	It was really cheap.	It was like really cheap.	ChcE IndE 91.2
235	quotative_like	And my friend said "No way!"	And my friend was like "No way!"	

Table 21: Discourse and Word Order (Section 3)