Learning to Recognize Dialect Features

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Abstract

Building NLP systems that serve everyone requires accounting for dialect differences. But dialects are not monolithic entities: rather, distinctions between and within dialects are captured by the presence, absence, and frequency of dozens of dialect features in speech and text, such as the deletion of the copula in “He ∅ running”. In this paper, we introduce the task of dialect feature detection, and present two multitask learning approaches, both based on pretrained transformers. For most dialects, large-scale annotated corpora for these features are unavailable, making it difficult to train recognizers. We train our models on a small number of minimal pairs, building on how linguists typically define dialect features. Evaluation on a test set of 22 dialect features of Indian English demonstrates that these models learn to recognize many features with high accuracy, and that a few minimal pairs can be as effective for training as thousands of labeled examples. We also demonstrate the downstream applicability of dialect feature detection both as a measure of dialect density and as a dialect classifier.

1 Introduction

Dialect variation is a pervasive property of language, which must be accounted for if we are to build robust natural language processing (NLP) systems that serve everyone. Linguists do not characterize dialects as simple categories, but rather as collections of correlated features (Nerbonne, 2009), such as the one shown in Figure 1; speakers of any given dialect vary regarding which features they employ, how frequently, and in which contexts. In comparison to approaches that classify speakers or documents across dialects (typically using metadata such as geolocation), the feature-based perspective has several advantages: (1) allowing for fine-grained comparisons of speakers or documents within dialects, without training on personal metadata; (2) disentangling grammatical constructions that make up the dialect from the content that may be frequently discussed in the dialect; (3) enabling robustness testing of NLP systems across dialect features, helping to ensure adequate performance even on cases other than “high-resource” varieties such as mainstream U.S. English (Blodgett et al., 2016); (4) helping to develop more precise characterizations of dialects, enabling more accurate predictions of variable language use and better interpretations of its social implications (e.g., Craig and Washington, 2002; Van Hofwegen and Wolfram, 2010).

The main challenge for recognizing dialect features computationally is the lack of labeled data. Annotating dialect features requires linguistic expertise and is prohibitively time-consuming given the large number of features and their sparsity. In dialectology, large-scale studies of text are limited to features that can be detected using regular expressions of surface forms and parts-of-speech, e.g., PRP DT for the copula deletion feature in Figure 1; many features cannot be detected with such patterns (e.g., OBJECT FRONTING, EXTRANEOUS ARTICLE). Furthermore, part-of-speech tagging is unreliable in many language varieties, such as re-

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gional and minority dialects (Jørgensen et al., 2015; Blodgett et al., 2016). As dialect density correlates with social class and economic status (Sahgal and Agnihotri, 1988; Rickford et al., 2015; Grogger et al., 2020), the failure of language technology to cope with dialect differences may create allocational harms that reinforce social hierarchies (Blodgett et al., 2020).

In this paper, we propose and evaluate learning-based approaches to recognize dialect features. We focus on Indian English, given the availability of domain expertise and labeled corpora for evaluation. First, we consider a standard multitask classification approach, in which a pretrained transformer (Vaswani et al., 2017) is fine-tuned to recognize a set of dialect features. The architecture can be trained from two possible sources of supervision: (1) thousands of labeled corpus examples, (2) a small set of minimal pairs, which are hand-crafted examples designed to highlight the key aspects of each dialect feature (as in the “typical example” field of Figure 1). Because most dialects have little or no labeled data, the latter scenario is more realistic for most dialects. We also consider a multitask architecture that learns across multiple features by encoding the feature names, similar to recent work on few-shot or zero-shot multitask learning (Logeswaran et al., 2019; Brown et al., 2020).

In Sections 4 and 5, we discuss empirical evaluations of these models. Our main findings are:

• It is possible to detect individual dialect features: several features can be recognized with reasonably high accuracy. Our best models achieve a macro-AUC of .848 across ten grammatical features for which a large test set is available.

• This performance can be obtained by training on roughly five minimal pairs per feature. Minimal pairs are significantly more effective for training than a comparable number of corpus examples.

• Dialect feature recognizers can be used to rank documents by their density of dialect features, enabling within-dialect density computation for Indian English and accurate classification between Indian and U.S. English.

2 Data and Features of Indian English

We develop methods for detecting 22 dialect features associated with Indian English. Although India has over 125 million English speakers — making it the world’s second largest English-speaking population — there is relatively little NLP research focused on Indian English. Our methods are not designed exclusively for specific properties of Indian English; many of the features that are associated with Indian English are also present in other dialects of English.

We use two sources of data in our study: an annotated corpus (§ 2.1) and a dataset of minimal pairs (§ 2.2). For evaluation, we use corpus annotations exclusively. The features are described in Table 1, and our data is summarized in Table 2.

2.1 Corpus Annotations

The International Corpus of English (ICE; Greenbaum and Nelson, 1996) is a collection of corpora of world varieties of English, organized primarily by the national origin of the speakers/writers. We focus on annotations of spoken dialogs (S1A-001 – S1A-090) from the Indian English subcorpus (ICE-India). The ICE-India subcorpus was chosen in part because it is one of the only corpora with large-scale annotations of dialect features. To contrast Indian English with U.S. English (§ 4), we use the Santa Barbara Corpus of Spoken American English (Du Bois et al., 2000) that constitutes the ICE-USA subcorpus of spoken dialogs.

We work with two main sources of dialect feature annotations in the ICE-India corpus:

Lange features. The first set of annotations come from Claudia Lange (2012), who annotated 10 features in 100 transcripts for an analysis of discourse-driven syntax in Indian English, such as topic marking and fronting. We use half of this data for training (50 transcripts, 9392 utterances), and half for testing (50 transcripts, 9667 utterances).

Extended features. To test a more diverse set of features, we additionally annotated 18 features on a set of 300 turns randomly selected from the conversational subcorpus of ICE-India, as well as 50 examples randomly selected from a secondary dataset of sociolinguistic interviews (Sharma, 2009) to ensure diverse feature instantiation. We selected our 18 features based on multiple criteria: 1) prevalence in Indian English based on the dialectology literature, 2) coverage in the data (we started out with a larger set of features and removed those with fewer than two occurrences), 3) diversity of linguistic phenomena. The extended

2We manually split turns that were longer than two clauses, resulting in 317 examples.
Table 1: Features of Indian English used in our evaluations and their counts in the two datasets we study.

| Feature Set          | Features                             | Count of Instantiations |
|----------------------|--------------------------------------|-------------------------|
|                     | Feature                               | Lange (2012) | Our data |
| ARTICLE OMISSION    | (the) chair is black                 | 59           |           |
| DIRECT OBJECT PRO-DROP | she doesn’t like (it)          | 14           |           |
| FOCUS itself         | he is doing engineering in Delhi itself | 24           | 5 |
| FOCUS only           | I was there yesterday only          | 95           | 8 |
| HABITUAL PROGRESSIVE | always we are giving receipt        | 2            |           |
| STATIVE PROGRESSIVE  | he is having a television           | 3            |           |
| LACK OF INVERSION IN WH-QUESTIONS | what you are doing? | 4 | |
| LACK OF AGREEMENT    | he do a lot of things                | 23           |           |
| LEFT DISLOCATION     | my father, he works for a solar company | 300        | 19 |
| MASS NOUNS AS COUNT NOUNS | all the musics are very good | 13           |           |
| NON-INITIAL EXISTENTIAL | every year inflation is there       | 302          | 8 |
| OBJECT FRONTING      | (on the) right side we can see a plate | 186        | 14 |
| PP FRONTING WITH REDUCTION | I went (to) another school      | 17           |           |
| INVERSION IN EMBEDDED CLAUSE | I don’t know what are they doing   | 4            |           |
| INVARIANT TAG (isn’t it, no, na) | the children are outside, isn’t it? | 786          | 17 |
| EXTRANEOUS ARTICLE   | she has a business experience        | 25           |           |
| GENERAL EXTENDER and all | then she did her schooling and all | 7            |           |
| COPULA OMISSION      | my parents (are) from Gujarāt       | 71           |           |
| RESUMPTIVE OBJECT PRONOUN | my old life I want to spend it in California | 24 | |
| RESUMPTIVE SUBJECT PRONOUN | my brother, he lives in California | 287          |           |
| TOPICALIZED NON-ARGUMENT CONSTITUENT | in those years I did not travel | 272          |           |

Table 2: Summary of our labeled data. All corpus examples for the Lange features are from ICE-India; for the Extended feature set, examples are drawn from ICE-India and the Sharma data.

| Dialect features | Unique annotated examples |
|------------------|---------------------------|
| Feature set      | Count | Corpus ex. | Min. pair ex. |
| Lange (2012)     | 10    | 19059      | 113           |
| Extended         | 18    | 367        | 208           |

features overlap with those annotated by Lange, yielding a total set of 22 features. Annotations were produced by consensus from the first two authors. To measure interrater agreement, a third author (JE) independently re-annotated 10% of the examples, with Cohen’s $κ = 0.79$ (Cohen, 1960).3

2.2 Minimal Pairs

For each of the 22 features in Table 1, we created a small set of minimal pairs. The pairs were created by first designing a short example that demonstrated the feature, and then manipulating the example so that the feature is absent. This “negative” example captures the envelope of variation for the feature, demonstrating a site at which the feature could be applied (Labov, 1972). Consequently, negative examples in minimal pairs carry more information than in the typical annotation scenario, where absence of evidence does not usually imply evidence of absence. In our minimal pairs, the negative examples were chosen to be acceptable in standard U.S. and U.K. English, and can thus be viewed as situating dialects against standard varieties. Here are some example minimal pairs:

**ARTICLE OMISSION:** chair is black → the chair is black

**FOCUS only:** I was there yesterday only → I was there just yesterday.

**NON-INITIAL EXISTENTIAL:** every year inflation is there → every year there is inflation.

For most features, each minimal pair contains exactly one positive and one negative example. However, in some cases where more than two variants are available for an example (e.g., for the feature INVARIANT TAG (isn’t it, no, na)), we provide multiple positive examples to illustrate different variants. For Lange’s set of 10 features, we provide a total of 113 unique examples; for the 18 extended features, we provide a set of 208 unique examples, roughly split equally between positives and negatives. The complete list of minimal pairs is included in Appendix D.
Figure 2: Conversion of minimal pairs to labeled examples for DAMTL, using two minimal pairs.

3 Models and training

We train models to recognize dialect features by fine-tuning the BERT-base uncased transformer architecture (Devlin et al., 2019). We consider two strategies for constructing training data, and two architectures for learning across multiple features.

3.1 Sources of supervision

We consider two possible sources of supervision:

Minimal pairs. We apply a simple procedure to convert minimal pairs into training data for classification. The positive part of each pair is treated as a positive instance for the associated feature, and the negative part is treated as a negative instance. Then, to generate more data, we also include elements of other minimal pairs as examples for each feature: for instance, a positive example of the RESUMPTIVE OBJECT PRONOUN feature would be a negative example for FOCUS only, unless the example happened to contain both features (this was checked manually). In this way, we convert the minimal pairs into roughly 113 examples per feature for Lange’s features and roughly 208 examples per feature for the extended features. The total number of unique surface forms is still 113 and 208 respectively. Given the lack of labeled data for most dialects of the world, having existing minimal pairs or collecting a small number of minimal pairs is the most realistic data scenario.

Corpus annotations. When sufficiently dense annotations are available, we can train a classifier based on these labeled instances. We use 50 of the ICE-India transcripts annotated by Lange, which consists of 9392 labeled examples per feature. While we are lucky to have such a large resource for the Indian English dialect, this high-resource data scenario is rare.

3.2 Architectures

We consider two classification architectures:

Multihead. In this architecture, which is standard for multitask classification, we estimate a linear prediction head for each feature, which is simply a vector of weights. This is a multitask architecture, because the vast majority of model parameters from the input through the deep BERT stack remain shared among dialect features. The prediction head is then multiplied by the BERT embedding for the [CLS] token to obtain a score for a feature’s applicability to a given instance.

DAMTL. Due to the few-shot nature of our prediction task, we also consider an architecture that attempts to exploit the natural language descriptions of each feature. This is done by concatenating the feature description to each element of the minimal pair. The instance is then labeled for whether the feature is present. This construction is shown in Figure 2. Prediction is performed by learning a single linear prediction head on the [CLS] token. We call this model description-aware multitask learning, or DAMTL.

Model details. Both architectures are built on top of the BERT-base uncased model, which we fine-tune by cross-entropy for 500 epochs (due to the small size of the training data) using the Adam optimizer (Kingma and Ba, 2014), batch size of 32 and a learning rate of $10^{-5}$, warmed up over the first 150 epochs. Annotations of dialect features were not used for hyperparameter selection. Instead, the hyperparameters were selected to maximize the discriminability between corpora of Indian and U.S. English, as described in § 5.2. All models trained in less than two hours on a pod of four v2 TPU chips, with the exception of DAMTL on corpus examples, which required up to 18 hours.

3.3 Regular Expressions

In dialectology, regular expression pattern matching is the standard tool for recognizing dialect features (e.g., Nerbonne et al., 2011). For the features
We first consider the 10 syntactic features from (ROC-AUC), which has a value of (corpus examples versus minimal pairs) and classifies this is promising, because it suggests the possibility of recognizing dialect features for which we achieve a Macro-AUC approaching .85 overall with multihead predictions on minimal pair examples.

Table 3: ROC-AUC scores on the Lange feature set, averaged across five random seeds. Asterisk (*) marks features that can be detected with relatively high accuracy (> 0.85 ROC-AUC) using regular expressions.

| Supervision:                          | Corpus examples | Minimal pairs |
|---------------------------------------|-----------------|---------------|
| Dialect feature                      | DaMTL Multihead | DaMTL Multihead |
| FOCUS itself *                       | 0.945           | 0.925         |
| FOCUS only *                         | 0.975           | 0.991         |
| IN Variant TAG                       | 0.991           | 0.994         |
| COPULA OMISSION                      | 0.536           | 0.641         |
| LEFT DISLOCATION                     | 0.855           | 0.879         |
| NON-INITIAL EXISTENTIAL *            | 0.991           | 0.992         |
| OBJECT FRONTING                      | 0.805           | 0.869         |
| RES. OBJECT PRONOUN                  | 0.596           | 0.607         |
| RES. SUBJECT PRONOUN                 | 0.886           | 0.887         |
| TOPICALIZED NON-ARG. CONST.          | 0.725           | 0.727         |
| Macro Average                        | 0.630           | 0.842         |

Table 3: ROC-AUC scores on the Lange feature set, averaged across five random seeds. Asterisk (*) marks features that can be detected with relatively high accuracy (> 0.85 ROC-AUC) using regular expressions.

described in Table 1, we were able to design regular expressions for only five. Prior work sometimes relies on patterns that include both surface forms and part-of-speech (e.g., Bohmann, 2019), but part-of-speech cannot necessarily be labeled automatically for non-standard dialects (Jørgensen et al., 2015; Blodgett et al., 2016), so we consider only regular expressions over surface forms.

4 Results on Dialect Feature Detection

In this section, we present results on the detection of individual dialect features. Using the features shown in Table 1, we compare supervision sources (corpus examples versus minimal pairs) and classification architectures (multihead versus DaMTL) as described in § 3. To avoid tuning a threshold for detection, we report area under the ROC curve (ROC-AUC), which has a value of .5 for random guessing and 1 for perfect prediction.  

4.1 Results on Lange Data and Features

We first consider the 10 syntactic features from Lange (2012), for which we have large-scale annotated data: the 100 annotated transcripts from the ICE-India corpus are split 50/50 into training and test sets. As shown in Table 3, it is possible to achieve a Macro-AUC approaching .85 overall with multihead predictions on minimal pair examples. This is promising, because it suggests the possibility of recognizing dialect features for which we lack labeled corpus examples – and such low-data situations are far the most common data scenario among the dialects of the world.

The multihead architecture outperforms DaMTL on both corpus examples and minimal pairs. In an ablation, we replaced the feature descriptions with non-descriptive identifiers such as “Feature 3”. This reduced the Macro-AUC from to .80 with corpus examples, and to .76 with minimal pairs (averaged over five random seeds). We also tried longer feature descriptions, but this did not improve performance.

Unsurprisingly, the lexical features (e.g., FOCUS itself) are easiest to recognize. The more syntactical features (e.g., COPULA OMISSION, RESumptive OBJECT PRONOUN) are more difficult, although some movement-based features (e.g., LEFT DISLOCATION, RESumptive SUBJECT PRONOUN) can be recognized accurately.

Qualitative model comparison. We conducted a qualitative comparison of three models: regular expressions and two versions of the multihead model, one trained on corpus examples and another trained on minimal pairs. Table 4 includes illustrative examples for the Lange data and features where models make different predictions. We find that the minimal pair model is better able to account for rare cases (e.g. use of non-focus “only” in Example 1), likely as it was trained on a few carefully selected set of examples illustrating positives and negatives. Both multihead models are able to account for disfluencies and restarts, in contrast to regular expressions (Example 2). Our analysis shows that several model errors are accounted for by difficult examples (Example 3: “is there” followed by “isn’t”; Example 6: restart mistaken for left dislocation) or the lack of contextual information available to the model (Example 4 & 7: truncated examples). Please see Appendix B for more details and random samples of model predictions.

Learning from fewer corpus examples. The minimal pair annotations consist of 113 examples; in contrast, there are 9392 labeled corpus examples, requiring far more effort to create. We now consider the situation when the amount of labeled data is reduced, focusing on the Lange features (for which labeled training data is available). As shown in Figure 3, even 5000 labeled corpus examples do not match the performance of training on roughly 5 minimal pairs per feature.

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Footnotes: 1Features: FOCUS itself, FOCUS only, NON-INITIAL EXISTENTIAL, IN Variant TAG (isn’t it, no, na), and GENERAL EXTENDER and all. Table 7 lists all regular expressions. 2Results for area under the precision-recall (APUR) curve are shown in Appendix C. According to this metric, minimal pairs are less effective than the full training set of corpus examples, on average.
1 But whereas in Hyderabad they are only stuck with their books and
home and work that’s all like

2 There is there is a club this humour club oh good and I’ve chance
I had a chance of attending

3 New Education Policy is there isn’t it?

4 I didn’t go anywhere no

5 In fact my son and daughter they had asked me to buy buy
them this thing the sunglasses

6 His house he is going to college KK diploma electronics

7 Which October first I think

8 Papers we can’t say hard only because they already taught that same

9 Just typing work I have to do

10 My post graduation degree I finished it in mid June nineteen eighty-six

Table 4: Example model predictions from the Lange data and feature set, comparing regular expressions with
two versions of the multihead model, one trained on corpus examples and another on minimal pairs. 'Gold label'
indicates whether the feature was manually labeled as present in the original Lange data. Green and red indicate
correct and incorrect predictions, respectively.

4.2 Results on Extended Feature Set

Next, we consider the extended features, for which we have sufficient annotations for testing but not
training (Table 4). Here we compare the DA-MTL and multihead models, using minimal pair data in
both cases. As shown in Table 5, performance on these features is somewhat lower than on the Lange
features, and for several features, at least one of the recognizers does worse than chance:

DIRECT OBJECT PRO-JECT DROP, EXTRANEOUS ARTICLE, MASS NOUNS AS COUNT NOUNS. These features seem
to require deeper syntactic and semantic analysis, which may be difficult to learn from a small number
of minimal pairs. On the other extreme, features with a strong lexical signature are recognized with
high accuracy:

GENERAL EXTENDER and all, FOCUS itself, FOCUS only. These three features can
also be recognized by regular expressions, as can

NON-INITIAL EXISTENTIAL. However, for a num-
ber of other features, it is possible to learn a fairly
accurate recognizer from just five minimal pairs:

ARTICLE OMISSION, INVERSION IN EMBEDDED CLAUSE, LEFT DISLOCATION, LACK OF INVER-
SION IN WH-QUESTIONS.
Table 5: ROC-AUC results on the extended feature set, averaged across five random seeds. Because labeled corpus examples are not available for some features, we train only on minimal pairs. Asterisk (*) marks features that can be detected with relatively high accuracy (> 0.85 ROC-AUC) using regular expressions.

| Dialect feature                        | DmMTL Multihead |
|----------------------------------------|-----------------|
| ARTICLE OMISSION                       | 0.381           |
| DIRECT OBJECT PRO-DROP                 | 0.493           |
| EXTRANEOUS ARTICLE                     | 0.546           |
| FOCUS itself*                          | 1.000           |
| FOCUS only*                            | 0.998           |
| HABITUAL PROGRESSIVE                   | 0.439           |
| INVARIANT TAG                          | 0.984           |
| INVERSION IN EMBEDDED CLAUSE           | 0.719           |
| LACK OF AGREEMENT                      | 0.543           |
| LACK OF INVERSION IN WH-QUESTIONS      | 0.649           |
| LEFT DISLOCATION                       | 0.758           |
| MASS NOUNS AS COUNT NOUNS              | 0.443           |
| NON-INITIAL EXISTENTIAL*              | 0.897           |
| OBJECT FRONTING                        | 0.722           |
| PP FRONTING WITH REDUCTION             | 0.655           |
| STATIVE PROGRESSIVE                   | 0.645           |
| GENERAL EXTENDER and all               | 0.994           |
| Macro Average                          | 0.698           |

4.3 Summary of Dialect Feature Detection

Many dialect features can be automatically recognized with reasonably high discriminative power, as measured by area under the ROC curve. However, there are also features that are difficult to recognize: particularly, features of omission (such as DIRECT OBJECT PRO-DROP and PREPOSITION OMISSION), and the more semantic features such as MASS NOUNS AS COUNT NOUNS. While some features can also be identified through regular expressions (e.g., FOCUS only), there are many features that can be learned but cannot be recognized by regular expressions. We now move from individual features to aggregate measures of dialect density.

5 Measuring Dialect Density

A dialect density measure (DDM) is an aggregate over multiple dialect features that tracks the vernacularity of a passage of speech or text. Such measures are frequently used in dialectology (Van Hofwegen and Wolfram, 2010), and are also useful in research on education (e.g., Craig and Washington, 2002). Recently, a DDM was used to evaluate the performance of speech recognition systems by the density of AAVE features (Koenecke et al., 2020). The use of DDMs reflects the reality that speakers construct individual styles drawing on linguistic repertoires such as dialects to varying degrees (Benor, 2010). This necessitates a more nuanced description for speakers and texts than a discrete dialect category.

Following prior work (e.g., Van Hofwegen and Wolfram, 2010) we construct dialect density measures from feature detectors by counting the predicted number of features in each utterance, and dividing by the number of tokens. For the learning-based feature detectors (minimal pairs and corpus examples), we include partial counts from the detection probability; for the regular expression detectors, we simply count the number of matches and dividing by the number of tokens. In addition, we construct a DDM based on a document classifier: we train a classifier to distinguish Indian English from U.S. English, and then use its predictive probability as the DDM. These DDMs are then compared on two tasks: distinguishing Indian and U.S. English, and correlation with the density of expert-annotated features. The classifier is trained by fine-tuning BERT, using a prediction head on the [CLS] token.

5.1 Ranking documents by dialect density

One application of dialect feature recognizers is to rank documents based on their dialect density, e.g. to identify challenging cases for evaluating downstream NLP systems, or for dialectology research. We correlate the dialect density against the density of expert-annotated features from Lange (2012), both measured at the transcript-level, and report the Spearman rank-correlation ρ.

As shown in Table 6, the document classifier performs poorly: learning to distinguish Indian and U.S. English offers no information on the density of Indian dialect features, suggesting that the model is attending to other information, such as topics or entities. The feature-based model trained on labeled examples performs best, which is unsurprising because it is trained on the same type of features that it is now asked to predict. Performance is weaker when the model is trained from minimal pairs. Minimal pair training is particularly helpful on rare features, but offers far fewer examples on the high-frequency features, which in turn dominate the DDM scores on test data. Regular expressions perform well on this task, because we happen to have regular expressions for the high-frequency features, and because the precision issues are less problematic in aggregate when the DDM is not applied to non-dialectal transcripts.
5.2 Dialect Classification

Another application of dialect feature recognizers is to classify documents or passages by dialect (Dunn, 2018). This can help to test the performance of downstream models across dialects, assessing dialect transfer loss (e.g., Blodgett et al., 2016), as well as identifying data of interest for manual dialectological research. We formulate a classification problem using the ICE-India and the Santa Barbara Corpus (ICE-USA). Each corpus is divided into equal-size training and test sets. The training corpus was also used for hyperparameter selection for the dialect feature recognition models, as described in § 3.2.

The dialect classifier was constructed by building on the components from § 5.1. For the test set, we measure the $D'$ (“D-prime”) statistic (Macmillan and Creelman, 1991),

$$D' = \frac{\mu_{IN} - \mu_{US}}{\sqrt{\frac{1}{2}(\sigma_{IN}^2 + \sigma_{US}^2)}} .$$

This statistic, which can be interpreted similarly to a Z-score, quantifies the extent to which a metric distinguishes between the two populations. We also report classification accuracy, lacking a clear way to set a threshold, for each classifier we balance the number of false positives and false negatives.

As shown in Table 6, both the document classifier and the corpus-based feature detection model (trained on labeled examples) achieve high accuracy at discriminating U.S. and Indian English. The $D'$ discriminability score is higher for the document classifier, which is trained on a cross-entropy objective that encourages making confident predictions. Regular expressions suffer from low precision because they respond to surface cues that may be present in U.S. English, even when the dialect feature is not present (e.g., the word “only”, the phrase “is there”).

| Dialect density measure | Ranking $\rho$ | Classification $D'$ acc. |
|-------------------------|---------------|---------------------------|
| Document classifier     | -0.17         | 14.48 1                   |
| Multihead, corpus examples | 0.83  | 2.30 0.95                |
| Multihead, minimal pairs   | 0.70  | 1.85 0.85                |
| Regular expressions       | 0.71  | 1.61 0.80                |

Table 6: Performance of dialect density measures at the tasks of ranking Indian English transcripts by dialect density (quantified by Spearman $\rho$) and distinguishing Indian and U.S. English transcripts (quantified by accuracy and $D'$ discriminability).

set to other varieties (Zampieri et al., 2017). In general, participants in these shared tasks have taken a text classification approach; neural architectures have appeared in the more recent editions of these shared tasks, but with a few exceptions (e.g., Bernier-Colborne et al., 2019), they have not outperformed classical techniques such as support vector machines. Our work differs by focusing on a specific set of known dialect features, rather than document-level classification between dialects, which aligns with the linguistic view of dialects as bundles of correlated features (Nerbonne, 2009) and tracks variable realization of features within dialect usage.

Discovering and detecting dialect features. Machine learning feature selection techniques have been employed to discover dialect features from corpora. For example, Dunn (2018, 2019) induces a set of constructions (short sequences of words, parts-of-speech, or constituents) from a “neutral” corpus, and then identifies constructions with distinctive distributions over the geographical subcorpora of the International Corpus of English (ICE). In social media, features of African American Vernacular English (AAVE) can be identified by correlating linguistic frequencies with the aggregate demographic statistics of the geographical areas from which geotagged social media was posted (Eisenstein et al., 2011; Stewart, 2014; Blodgett et al., 2016). In contrast, we are interested in detecting predefined dialect features from well-validated resources such as dialect atlases.

Along these lines, Jørgensen et al. (2015) and Jones (2015) designed lexical patterns to identify non-standard spellings that match known phonological variables from AAVE (e.g., *sholl* ‘sure’), demonstrating the presence of these variables in social media posts from regions with high propor-
tions of African Americans. Blodgett et al. (2016) use the same geography-based approach to test for phonological spellings and constructions corresponding to syntactic variables such as habitual be; Hovy et al. (2015) show that a syntactic feature of Jutland Danish can be linked to the geographical origin of product reviews. These approaches have focused mainly on features that could be recognized directly from surface forms, or in some cases, from part-of-speech (POS) sequences. In contrast, we show that it is possible to learn to recognize features from examples, enabling the recognition of features for which it is difficult or impossible to craft surface or POS patterns.

Minimal pairs in NLP. A distinguishing aspect of our approach is the use of minimal pairs rather than conventional labeled data. Minimal pairs are well known in natural language processing from the Winograd Schema (Levesque et al., 2012), which is traditionally used for evaluation, but Kocijan et al. (2019) show that fine-tuning on a related dataset of minimal pairs can improve performance on the Winograd Schema itself. A similar idea arises in counterfactually-augmented data (Kaushik et al., 2019) and contrast sets (Gardner et al., 2020), in which annotators are asked to identify the minimal change to an example that is sufficient to alter its label. However, those approaches use counterfactual examples to augment an existing training set, while we propose minimal pairs as a replacement for large-scale labeled data. Minimal pairs have also been used to design controlled experiments and probe neural models’ ability to capture various linguistic phenomena (Gulordava et al., 2018; Ettinger et al., 2018; Futrell et al., 2019; Gardner et al., 2020; Schuster et al., 2020). Finally, Liang et al. (2020) use contrastive explanations as part of an active learning framework to improve data efficiency. Our work shares the objective of Liang et al. (2020) to improve data efficiency, but is methodologically closer to probing work that uses minimal pairs to represent specific linguistic features.

7 Conclusion

We introduce the task of dialect feature detection and demonstrate that it is possible to construct dialect feature recognizers using only a small number of minimal pairs — in most cases, just five positive and negative examples per feature. This makes it possible to apply computational analysis to the many dialects for which labeled data does not exist. Future work will extend this approach to multiple dialects, focusing on cases in which features are shared across two or more dialects. This lays the groundwork for the creation of dialect-based “checklists” (Ribeiro et al., 2020) to assess the performance of NLP systems across the diverse range of linguistic phenomena that may occur in any given language.

8 Ethical Considerations

Our objective in building dialect feature recognizers is to aid developers and researchers to effectively benchmark NLP model performance across and within different dialects, and to assist social scientists and dialectologists studying dialect use. The capability to detect dialectal features may enable developers to test for and mitigate any unintentional and undesirable biases in their models towards or against individuals speaking particular dialects. This is especially important because dialect density has been documented to correlate with lower socioeconomic status (Sahgal and Agnihotri, 1988). However, this technology is not without its risks. As some dialects correlate with ethnicities or countries of origin, there is a potential dual use risk of the technology being used to profile individuals. Dialect features could also be used as predictors in downstream tasks; as with other proxies of demographic information, this could give the appearance of improving accuracy while introducing spurious correlations and imposing disparate impacts on disadvantaged groups. Hence we recommend that developers of this technology consider downstream use cases, including malicious use and misuse, when assessing the social impact of deploying and sharing this technology.

The focus on predefined dialect features can introduce a potential source of bias if the feature set is oriented towards the speech of specific sub-communities within a dialect. However, analogous issues can arise in fully data-driven approaches, in which training corpora may also be biased towards subcommunities of speakers or writers. The feature-based approach has the advantage of making any such bias easier to identify and correct.

Acknowledgments. Thanks to Claudia Lange for sharing her annotations, and for discussion of this research. Thanks to Axel Bohmann for sharing information about his work on recognizing dialect features with regular expressions. Valuable feedback on this research was provided by Jason...
Baldridge, Dan Jurafsky, Slav Petrov, Jason Riesa, Kristina Toutanova, and especially Vera Axelrod. Thanks also to the anonymous reviewers. Devyani Sharma is supported in part by a Google Faculty Research Award.

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| Feature                        | Regular expression |
|-------------------------------|--------------------|
| **FOCUS itself**              | \bitself\b         |
| **FOCUS only**                | \bonly\b           |
| **NON-INITIAL EXISTENTIAL**   | \b is there\b|\bare there\b |
| **INVARIANT TAG (isn’t it, no, na)** | \b isn’t it\b|\b isn’t it\b|\b no\b|\b na\b |
| **GENERAL EXTENDER and all**  | \band all\b        |

Table 7: Regular expressions we used, for the features that such patterns were available.

## A Regular Expressions

Table 7 shows the regular expressions that we used for the five features, where such patterns were available.
B Sample Outputs

The examples below represent a random sample of the multihead models’ outputs for Lange’s features, comparing the one that is trained on corpus examples (CORPUS) to the one that is trained on minimal pairs (MINPAIR). We show true positives (TP), false positives (FP) and false negatives (FN). We randomly sample three examples for each output type (TP, FP, FN) and model (BOTH, CORPUS only, MINPAIR only).

Our manual inspection shows a few errors in the human annotation by Lange and that certain false positives should be true positives, especially for FOCUS only. We highlight such examples in green. Among the rest of the false positives and false negatives, a large proportion of errors can be explained by contextual information that is not available to the models. For example, without context it is ambiguous whether “we possess only” is an example of FOCUS only. Inspection of context shows that it is a truncated utterance, representing a standard use of only, hence it is correctly characterized as a false positive. Another source of confusion to the model is missing punctuation. For example “Both girls I have never left them alone till now” could be construed as OBJECT FRONTING with RESUMPTIVE OBJECT PRONOUN. However, in the original context, the example consists of multiple sentences: “Two kids. Both girls. I have never left them alone till now.” We removed punctuation from examples, since in many cases automatic ASR models do not produce punctuation either. However, this example demonstrates that punctuation can provide valuable information about clause and phrase boundaries, and should be included if possible.

B.1 Focus itself

[TP:BOTH] We are feeling tired now itself
[TP:BOTH] Coach means they should be coached from when they are in nursery UKG itself
[TP:BOTH] I’m in final year but like they have started from first year itself
[TP:CORPUS] And she got a chance of operating also during her internship itself nice and because that Cama hospital is for ladies only so she has lot of experience
[TP:MINPAIR] But even if they women is are working as much as a man she is earning the same monthly saving as a man itself

[TP:MINPAIR] You go around say one O’clock and then go for a movie and come back in the evening itself you see you
[FP:MINPAIR] And primarily you know the the issue orders were issued on fifth that is on the election day itself
[FP:MINPAIR] That is to we take on the coughs our human blood itself
[FP:MINPAIR] Now since you are doing the PGCT now after going back is it possible for you to use simple English in the classroom itself
[FN:BOTH] All the sums were there in the text book itself but still they have not done properly in the exam
[FN:BOTH] And thinking about dissection hall itself they really get scared and that also in the midnight
[FN:BOTH] Means what do you think that the basic itself is not good or now they are getting interest in maths
[FN:CORPUS] But even if they women is are working as much as a man she is earning the same monthly saving as a man itself
[FN:CORPUS] You go around say one O’clock and then go for a movie and come back in the evening itself you see you
[FN:MINPAIR] And she got a chance of operating also during her internship itself nice and because that Cama hospital is for ladies only so she has lot of experience

B.2 Focus only

[TP:BOTH] All the types only
[TP:BOTH] Hey you sur be like that only
[TP:BOTH] suddenly it will be become perfect only
[TP:CORPUS] That is I like dressing up I told you at the beginning only
[TP:CORPUS] Because today only he had come and I’ve got up today at nine thirty
[TP:CORPUS] Actually from childhood only I was brought up in the same atmosphere like if Papa still has shifted to another place I would have got the feeling of not having comfortable in a particular language but on the whole I think it doesn’t matter exactly how we go about chosing or selecting a language
it was bit it was difficult only
I’m one minute I’ve got it in front of me only
He is in our college only
Because we are supposed to perform well there only then
Ho Ho Hollywood Hollywood after Hollywood it seems India only
No he’ll be there in the campus only
Oh God there only it’s happening so and forget about
The thing is that it is rural area only but the people are from all over India they are staying here
Not much work these days because first week and last week only we’ve quiet good business
Only in India there is manual work
Film hits only
So Bharati Vidya Bhavan people have such type of persons only
If they be in always that this is there are not improve no improvement only
When we were living when I was living in Kashmir no I was brought up there only and everything is
This is the first phase then in the second phase we have some clinical subjects in which we come in direct contact with the patients but it’s on two basis like when we see the patients at the same time we study about the pathology only the pathology and then we learn about some of the drugs which are to be which are used for their treatment
No you must put apply science only
Actually they are good only
it was bit it was difficult only
My both the parents are farmers only
Because today only he had come and I’ve got up today at nine thirty
That is I like dressing up I told you at the beginning only

B.3 Invariant Tag (isn’t it, no, na)
Very difficult once the school starts na very difficult
I am okay rainy season no
Oh yours your head is not reeling any more no?
Kind of but it would be better than an indoor game no
We’ll ask that person no that Sagar you can tell
Nothing at all that’s why you got scratching on that day I know that no that’s why I asked
I’m not fair no
Husband no I’ll do I’ll prepare it
He could have agreed no what is that
TELCO deta hai to kuch problem nahi na
I think once you have got in you no
I didn’t go anywhere no
Or two hundred rupees that no
Know when we go back no I think we’ll get a rosy welcome home welcome there
I like straight and perspiration then only I feel at home otherwise no
No got it repaired
No no he is here
Okay no but
I just go out for tea isn’t
Hey you you like serious movies is it you like serious movies
See no the scene exactly happened you know the other day what happen I was reading baba
I’m not fair no
I think no
Tell me no why you can’t tell
Yeah then it’s first time first time it was new to me no
That is the main thing na here that would again the main thing that they don’t take at all interest in the their children at all
[FN:MINPAIR] So culture nahi hai there is I don’t
follow culture religion nothing na

B.4 Lack of Copula
[FP:CORPUS] Which October first I think
[FP:CORPUS] June nineteen eighty-six
[FP:MINPAIR] Construction all before
[FP:MINPAIR] Not in the class
[FP:MINPAIR] The tendency to

[FN:BOTH] you’ve she said his grandfather still
working
[FN:BOTH] Everybody so worried about the ex-
ams and studies
[FN:BOTH] Again classes bit too long I feel five
O’clock is tiring

B.5 Left Dislocation
[TP:BOTH] This principal she is very particular
about it
[TP:BOTH] Vilas and Ramesh they they make
noise man
[TP:BOTH] That’s why those Muslims they got
very angry
[TP:CORPUS] And med medium class they can’t
understand soon
[TP:CORPUS] That will become difficult and com-
mon people they don’t understand
[TP:CORPUS] And now the Kukis they refused to
pay any more
[TP:MINPAIR] It’s because of this some other part-
icipant they complained about this and then they
started they started this particular
[TP:MINPAIR] We’ve lot of fun in theatres you
know we always take the back seat and all that for
this guys distinct one we keep teasing them
[TP:MINPAIR] My post graduation degree I fin-
ished it in mid June nineteen eighty-six
[FP:BOOTH] But whereas when they really come to
know the people they like to help the people
[FP:BOOTH] It’s actually some of them like to see
it really so huge and long and bigger snakes they
are in all closed and all there it is nice to see it
[FP:BOOTH] But generally the educated people I
don’t find much variation but in accent there may
be a variation

[FP:CORPUS] Everytime he keeps speaking you
know they get irritated and say aram se
[FP:CORPUS] What happened is they will change
programme and the fifty guys they’ll just keep
quite
[FP:CORPUS] Whereas Hyderabad the people are
more conservative and like they don’t like to go
out even or at the first move they don’t like to talk
with people also
[FP:MINPAIR] And the songs now once we hear it
afterwards when some other famous songs comes
that we forget the last ones
[FP:MINPAIR] But when we approach since it
seems they they put lot of conditions yes that you
fed up with those people and
[FP:MINPAIR] so that’s why we missed we that
missed that holiday it being a Sunday
[FN:BOTH] Administration it is all done by
Bharati Vidya Bhavan
[FN:BOTH] Oh our Joshi okay II got got him
[FN:BOTH] Yes yes it is true but our constitution
makers
[FN:CORPUS] and he has used the the place where
the palace once palace might be there and that
portion and the remaining part he built an antenna
he has fixed it there at the top
[FN:CORPUS] Not exactly but Calcutta sweets I
think they do have a little flavour and that I haven’t
got anywhere in India
[FN:CORPUS] Computer it was in the first
semester
[FN:MINPAIR] And med medium class they can’t
understand soon
[FN:MINPAIR] Shireen she was excellent at that
[FN:MINPAIR] Yeah arti arti students they loiter
about in the corridor

B.6 Non-initial Existential X is / are there
[TP:BOTH] Libraries are there
[TP:BOTH] only specimen like operated cases like
supposing a is there
[TP:BOTH] Problems are there problems are there
what
[TP:CORPUS] to assist there some teachers are
there and together we conduct the classes
[TP:CORPUS] It’s there but it’s common no
Yeah I think Varlaxmi is there
My husband is there mother is there
Come no Shaukat is here Natalie is here even if Savita is not there they two are there
Actually there the thing is that you know for example
Any thing is there produced materials which do not require much resource personnel
Ph D degree is awarded there
Yeah the royalties too there they’re there and we’ve the king
Okay somebody else’s some somebody else is there
In that you know everything is about nature I’ll tell you yeah it’s very lovely means very nice lovely what but and small children were there in that
American and all other capitalist nations were also there
Nice movie yaar that song is there no hai apna dil to awara
It’s not there

B.7 Object Fronting
Just typing work I have to do
writing skills there are so many you can teach them
Each other and so many things we have learnt
My birthday party you arrange
Formalities I will come
Mar Marxism you were
Other wise we have to
That also I’m not having just I jump jumped jumped I came studies also
Yes Hawa Mahal we heard
About ten to twenty books I’ll read that’s all
Small baby very nice it was
But more keen she is
And camera handling actually outdoor landscaping that landscape shot I have taken and actually the close ups and some parts of your architectural shots of that building Ganesh took my husband took and close ups of the faces my husband and Ganesh took

B.8 Resumptive Object Pronoun
and he has used the the place where the palace once palace might be there and that portion and the remaining part he built an antenna he has fixed it there at the top
Yeah also pickles we eat it with this jaggery and lot of butter
My post graduation degree I finished it in mid June nineteen eighty-six
Having humorous something special I would love it to join it
I see a number of people I like them very much
Old and ancient things in carving we get it so beautifully
Oh our Joshi okay II got got him
Normaly no we don’t overdrawn on account but haan haan whatever is balance you know yeah help them give them suppose cheque books and all we are supposed to keep them yeah two fifty balance
He is in a that’s what he was telling me today see I want your draft like draft draft by January by the month of January by the end of January so that II might rectify it and then I will do it I will give it back to you by mid Febraury so that you can get it final draft by by the end of Febraury
and he has used the the place where the palace once palace might be there and that portion and the remaining part he built an antenna he has fixed it there at the top
Yeah also pickles we eat it with this jaggery and lot of butter
My post graduation degree I finished it in mid June nineteen eighty-six

B.9 Resumptive Subject Pronoun
Like those terrorists they wanted us to to accompany them in the revolt against India
And one more thing another thing how I rectified myself because all almost all of us all my brother and sisters we have read in English medium school
Dr this Mr V he was totally changed actually because he was the concepts are clear not clear to us

There are so many people they can they could shine like anything

Kolhapur he had come to Guwahati

I don’t know what he whenever whenever I see those guys they they nicely speak to me

His house he is going to college KK diploma electronics

they I thought that another one Patil is there a horrible he is I thought that Patil

Computer it it plays a great role because we are having computers in each field now-a-days

You know that a woman she is a apprehensive about many things

Like those terrorists they wanted us to to accompany them in the revolt against India

Whereas in Hyderabad they still have the old cultures and so many things that even the parents they don’t even let the girls talk with the guys

And the students who come out with a degree MMSI understand that there is a report that has been received from different firms that the students of BITS Pilani specially MMS candidates they are prepared to soil their hands

I mean here in Hyderabad the people are it’s okay they are nice

And that old ones again we put them we feel like hearing again

But in drama we’ll have to be very different

In pooja day some important days we stay back

for Diwali you went I know that

Pooja vacation also we used to conduct some classes practical classes

Sir from Monday onwards I too want to take leave sir for four days because total I have five C Ls so from

B.10 Topicalized Non-argument Constituent

for Diwali you went I know that

So very long time we have not travelled together

Pooja vacation also we used to conduct some classes practical classes

In pooja day some important days we stay back

In Jaipur then we have also we have a Birla

Like that we

Everytime we have some work to do

Aa i i initial periods I did very difficult but I
C Average Precision Results

| Supervision: | Corpus examples | Minimal pairs |
|--------------|----------------|---------------|
| Dialect feature | DaMTL Multihead | DaMTL Multihead |
| FOCUS itself* | 0.668 | 0.631 | 0.665 | 0.613 |
| FOCUS only* | 0.582 | 0.494 | 0.444 | 0.416 |
| INVARIANT TAG | 0.876 | 0.771 | 0.441 | 0.495 |
| COPULA OMISSION | 0.029 | 0.015 | 0.012 | 0.036 |
| LEFT DISLOCATION | 0.425 | 0.383 | 0.149 | 0.232 |
| NON-INITIAL EXISTENTIAL* | 0.887 | 0.906 | 0.556 | 0.510 |
| OBJECT FRONTING | 0.238 | 0.202 | 0.031 | 0.083 |
| RES. OBJECT PRONOUN | 0.052 | 0.020 | 0.046 | 0.061 |
| RES. SUBJECT PRONOUN | 0.460 | 0.419 | 0.078 | 0.198 |
| TOPICALIZED NON-ARG. CONST. | 0.080 | 0.076 | 0.021 | 0.044 |
| **Macro Average** | 0.430 | 0.392 | 0.234 | 0.269 |

Table 8: Average precision for the Lange features. Scores are in the range [0, 1], with 1 indicating perfect performance. Asterisks mark features that can be recognized with a regular expression.

| Dialect feature | DaMTL Multihead |
|-----------------|-----------------|
| ARTICLE OMISSION | 0.210 | 0.308 |
| DIRECT OBJECT PRO-DROP | 0.044 | 0.057 |
| EXTRANEOUS ARTICLE | 0.116 | 0.065 |
| FOCUS itself* | 1.000 | 0.853 |
| FOCUS only* | 0.859 | 0.274 |
| HABITUAL PROGRESSIVE | 0.008 | 0.020 |
| INVARIANT TAG | 0.014 | 0.420 |
| INVERSION IN EMBEDDED CLAUSE | 0.106 | 0.162 |
| LACK OF AGREEMENT | 0.084 | 0.110 |
| LACK OF INVERSION IN WH-QUESTIONS | 0.309 | 0.106 |
| LEFT DISLOCATION | 0.288 | 0.301 |
| MASS NOUNS AS COUNT NOUNS | 0.045 | 0.034 |
| NON-INITIAL EXISTENTIAL* | 0.506 | 0.397 |
| OBJECT FRONTING | 0.147 | 0.193 |
| PREPOSITION OMISSION | 0.064 | 0.116 |
| PP FRONTING WITH REDUCTION | 0.091 | 0.134 |
| STATIVE PROGRESSIVE | 0.267 | 0.329 |
| GENERAL EXTENDER and all | 0.769 | 0.778 |
| **Macro Average** | 0.307 | 0.259 |

Table 9: Average precision for the extended feature set. As described in the main text, corpus training examples are unavailable for these features.
| ID | Feature             | Example                                                                 | Label |
|----|---------------------|-------------------------------------------------------------------------|-------|
| 1  | ARTICLE OMISSION    | the person I like the most is from mechanical department                | 1     |
| 1  | ARTICLE OMISSION    | person I like the most is from the mechanical department               | 1     |
| 1  | ARTICLE OMISSION    | person I like most is from mechanical department                       | 1     |
| 1  | ARTICLE OMISSION    | the person I like the most is from the mechanical department           | 1     |
| 2  | ARTICLE OMISSION    | we can only see blue sky                                               | 1     |
| 2  | ARTICLE OMISSION    | we can only see the blue sky                                           | 0     |
| 3  | ARTICLE OMISSION    | recipe is simple thing                                                 | 1     |
| 3  | ARTICLE OMISSION    | a recipe is simple thing                                               | 1     |
| 3  | ARTICLE OMISSION    | a recipe is a simple thing                                             | 0     |
| 4  | ARTICLE OMISSION    | union person contacted his representative at the school                | 0     |
| 4  | ARTICLE OMISSION    | the union person contacted his representative at the school            | 0     |
| 5  | ARTICLE OMISSION    | it was first day of term                                               | 1     |
| 5  | ARTICLE OMISSION    | it was the first day of term                                           | 0     |
| 6  | DIRECT OBJECT PRO- | we have two tailors who can make for us                                | 1     |
| 6  | DROP                | we have two tailors who can make clothes for us                        | 0     |
| 6  | DIRECT OBJECT PRO- | we have two tailors who can make them for us                           | 0     |
| 7  | RELATIVE PRO-DROP   | he didn’t give me                                                      | 1     |
| 8  | RELATIVE PRO-DROP   | he didn’t give it to me                                                | 0     |
| 8  | DIRECT OBJECT PRO- | in our old age we can go and enjoy it                                  | 1     |
| 8  | DROP                | in our old age we can go and enjoy it                                  | 0     |
| 9  | RELATIVE PRO-DROP   | she doesn’t like                                                       | 1     |
| 9  | RELATIVE PRO-DROP   | she doesn’t like                                                       | 0     |
| 10 | RELATIVE PRO-DROP   | he likes here more                                                     | 1     |
| 10 | RELATIVE PRO-DROP   | he likes it here more                                                  | 0     |
| 11 | FOCUS itself        | So if you’re not good at communication you may get filtered            | 0     |
| 11 | FOCUS itself        | So if you’re not good at communication you may get filtered            | 1     |
| 11 | FOCUS itself        | at the first level itself                                              | 0     |
| 11 | FOCUS itself        | But I did have some difficulty getting to know people among            | 1     |
| 11 | FOCUS itself        | But I did have some difficulty getting to know people among            | 0     |
| 12 | FOCUS itself        | Indians itself                                                         | 1     |
| 12 | FOCUS itself        | Indians themselves                                                     | 0     |
| 13 | FOCUS itself        | I think you should start going to the gym from now itself.             | 1     |
| 13 | FOCUS itself        | I think you should start going to the gym from now.                    | 0     |
| 14 | FOCUS itself        | I did one refresher course in the month of June itself.                | 1     |
| 14 | FOCUS itself        | I did one refresher course in the month of June.                       | 0     |
| 15 | FOCUS itself        | He is doing Engineering in Delhi itself.                               | 1     |
| 15 | FOCUS itself        | He is doing Engineering in Delhi.                                      | 0     |
| 16 | FOCUS only          | I’m working very nearby to my house only                               | 1     |
| 16 | FOCUS only          | I’m working very near my house                                         | 0     |
| 17 | FOCUS only          | recently only in April there was a big fight                           | 1     |
| 17 | FOCUS only          | as recently as April there was a big fight                             | 0     |
| 17 | FOCUS only          | I was there yesterday only                                             | 1     |
| 18 | FOCUS only          | I was there just yesterday                                            | 0     |
| 19 | FOCUS only          | She was brought up there and her college was there only                | 1     |
| 19 | FOCUS only          | She was brought up there and her college was there too                 | 0     |
| 20 | FOCUS only          | You get on the train and buy the ticket there only                     | 1     |
| 20 | FOCUS only          | You get on the train and buy the ticket there only                     | 0     |
| 21 | HABITUAL PROGRESSIVE | anybody giving donation, we are giving receipt                       | 1     |
| 21 | HABITUAL PROGRESSIVE | if anybody gives a donation, we give a receipt                      | 0     |
| 22 | HABITUAL PROGRESSIVE | she is getting nightmares                                              | 1     |
| 22 | HABITUAL PROGRESSIVE | she gets nightmares                                                      | 0     |
| 23 | HABITUAL PROGRESSIVE | they are getting H1B visas to come to the country                      | 1     |
| 23 | HABITUAL PROGRESSIVE | they get H1B visas to come to the country                              | 0     |
| 24 | HABITUAL PROGRESSIVE | they are teasing the new children when they join                        | 1     |
| 24 | HABITUAL PROGRESSIVE | they tease the new children when they join                             | 0     |
| 25 | HABITUAL PROGRESSIVE | everyone is getting that vaccination in childhood                      | 1     |
| 25 | HABITUAL PROGRESSIVE | everyone gets that vaccination in childhood                            | 0     |
| 26 | IN Variant Tag (isn’t it, no, na) | the children are playing outside, isn’t it?             | 1     |
| 26 | IN Variant Tag (isn’t it, no, na) | the children are playing outside, no?                               | 1     |
| 26 | IN Variant Tag (isn’t it, no, na) | the children are playing outside, na?                                | 0     |
| 27 | IN Variant Tag (isn’t it, no, na) | I was very scared to, no?                                             | 1     |
| 27 | IN Variant Tag (isn’t it, no, na) | I was very scared to, na?                                           | 1     |
58 mass nouns as count nouns
57 non-initial existential
56 non-initial existential
55 mass nouns as count nouns
54 mass nouns as count nouns
53 mass nouns as count nouns
52 mass nouns as count nouns
51 mass nouns as count nouns
50 left dislocation
49 left dislocation
48 left dislocation
47 left dislocation
46 left dislocation
45 lack of agreement
44 lack of agreement
43 lack of agreement
42 lack of agreement
41 lack of agreement
40 lack of agreement
39 lack of agreement
38 lack of agreement
37 lack of agreement
36 lack of agreement
35 inversion in embedded clause
34 inversion in embedded clause
33 inversion in embedded clause
32 inversion in embedded clause
31 inversion in embedded clause
30 inversion in embedded clause
29 inversion in embedded clause
28 inversion in embedded clause
27 inversion in embedded clause
26 initial existential
25 initial existential
24 initial existential
23 initial existential
22 initial existential
21 initial existential
20 initial existential
19 initial existential
18 initial existential
17 initial existential
16 initial existential
15 initial existential
14 initial existential
13 initial existential
12 initial existential
11 initial existential
10 initial existential
9 initial existential
8 initial existential
7 initial existential
6 initial existential
5 initial existential
4 initial existential
3 initial existential
2 initial existential
1 initial existential
0 initial existential

27 invariant tag (isn’t it, no, na) I was very scared to, wasn’t I?
28 invariant tag (isn’t it, no, na) the store is around the corner, no, by the post office
28 invariant tag (isn’t it, no, na) the store is around the corner, na, by the post office
28 invariant tag (isn’t it, no, na) the store is around the corner by the post office
29 invariant tag (isn’t it, no, na) It’s come from me, no?
29 invariant tag (isn’t it, no, na) It’s come from me, na?
29 invariant tag (isn’t it, no, na) It’s come from me, hasn’t it?
30 invariant tag (isn’t it, no, na) he liked it, no, even though you said he wouldn’t
30 invariant tag (isn’t it, no, na) he liked it, na, even though you said he wouldn’t
30 invariant tag (isn’t it, no, na) he liked it, right, even though you said he wouldn’t
30 invariant tag (isn’t it, no, na) he liked it, didn’t he, even though you said he wouldn’t
31 inversion in embedded clause you cannot ask them why are they not coming for clinic visits
31 inversion in embedded clause you cannot ask them why they are not coming for clinic visits
32 inversion in embedded clause I don’t know now what are they doing
33 inversion in embedded clause he was wondering why did the police stop him
33 inversion in embedded clause he was wondering why the police stopped him
34 inversion in embedded clause we want to know how can we make your favorite dish
34 inversion in embedded clause we want to know how can we make your favorite dish
35 inversion in embedded clause the school principal called me to ask when are you going back
35 inversion in embedded clause the school principal called me to ask when are you going back
36 lack of agreement he do a lot of things
36 lack of agreement he does a lot of things
37 lack of agreement my bother said that one of his favorite place is the beach nearby
37 lack of agreement my bother said that one of his favorite places is the beach nearby
38 lack of agreement only his shoes is visible
38 lack of agreement only his shoes are visible
39 lack of agreement ten years ago you didn’t operated a machine that could lift
39 lack of agreement ten years ago you didn’t operate a machine that could lift
40 lack of agreement he talk to them
40 lack of agreement he talks to them
41 lack of inv. in wh-questions where you will get anything?
41 lack of inv. in wh-questions where will you get anything?
42 lack of inv. in wh-questions what you are doing?
42 lack of inv. in wh-questions what are you doing?
43 lack of inv. in wh-questions why you are telling this to everybody?
43 lack of inv. in wh-questions why you are telling this to everybody?
44 lack of inv. in wh-questions why you are driving like a lorry?
44 lack of inv. in wh-questions why are you driving like a lorry?
45 lack of inv. in wh-questions how your mother is feeling?
45 lack of inv. in wh-questions how is your mother feeling?
46 left dislocation my father, he works for a mining company
46 left dislocation my father, he works for a mining company
47 left dislocation nowadays all the children they are mature from a very early age
47 left dislocation nowadays all the children are mature from a very early age
48 left dislocation the camera, the dog is facing towards it
48 left dislocation the dog is facing towards the camera
49 left dislocation and all the company people, they are my clients
49 left dislocation and all the company people are my clients
50 left dislocation those who come here definitely they should learn English
50 left dislocation those who come here definitely should learn English
51 mass nouns as count nouns this is a menial work
51 mass nouns as count nouns this is menial work
52 mass nouns as count nouns open a shop wherever there is a foot traffic
52 mass nouns as count nouns open a shop wherever there is foot traffic
53 mass nouns as count nouns all the musics are very good
53 mass nouns as count nouns all the music is very good
54 mass nouns as count nouns some informations are available free
54 mass nouns as count nouns some information is available free
55 mass nouns as count nouns they use proper grammars there
55 mass nouns as count nouns they use proper grammar there
56 non-initial existential some flower part is there
56 non-initial existential there is some flower part
57 non-initial existential corruption is there obviously
57 non-initial existential there is corruption obviously
58 non-initial existential because in India individuality is not there
58 non-initial existential because there is no individuality in India
and the production function is giving you the relationship between input and output

between input and output

between input and output

between input and output
They have pressure from their in-laws.

Here life is busy.

So marketing keeps its communication with the different embassies and all.

Whereas we had lot of time and we didn't have any TV and all and we used to play outdoor games.

So I did my schooling and all from there.

We are like we are in touch, but not before when we was in school and all.

Whereas we had lot of time and we didn't have any TV and all that stuff and we used to play outdoor games.

So my parents from Gujarat.

So I did my schooling from there.

My parents and siblings and all, they really enjoy playing board games.

My parents and siblings, they really enjoy playing board games.

My parents and siblings and all, they really enjoy playing board games.

My parents and siblings, they really enjoy playing board games.

I think she is a teacher.

I think she a teacher.

They all aggressive states.

They are all aggressive states.

Now they wearing American type of dresses.

Now they are wearing American type of dresses.

So my parents are from Gujarat.

Some teachers when I was in school I liked very much.

Some teachers when I was in school I liked very much.

Some teachers when I was in school I liked them very much.

A person living in Calcutta, who didn't know Hindi earlier, when he comes to Delhi he has to learn English.

A person living in Calcutta, which he didn't know Hindi earlier, when he comes to Delhi he has to learn English.
| Line | Syntactic Feature | Translation                                                                 | Type |
|------|------------------|------------------------------------------------------------------------------|------|
| 104  | RESUMPTIVE SUBJECT PRONOUN | and that roommate will do an interview                                       | 0    |
| 104  | LEFT DISLOCATION   | and that roommate, he will do an interview                                  | 1    |
| 105  | RESUMPTIVE SUBJECT PRONOUN | some people they are very nice                                               | 1    |
| 105  | LEFT DISLOCATION   | some people are very nice                                                    | 0    |
| 106  | TOPICALIZED NON-ARG. CONST | daytime I work for the courier service                                        | 1    |
| 106  | TOPICALIZED NON-ARG. CONST | in the daytime I work for the courier service                                | 1    |
| 106  | TOPICALIZED NON-ARG. CONST | I work for the courier service in the daytime                                | 0    |
| 106  | PP FRONTING WITH REDUCTION | daytime I work for the courier service                                       | 1    |
| 107  | TOPICALIZED NON-ARG. CONST | for many years I did not travel                                              | 1    |
| 107  | TOPICALIZED NON-ARG. CONST | many years I did not travel                                                  | 1    |
| 107  | TOPICALIZED NON-ARG. CONST | I did not travel for many years                                              | 0    |
| 108  | PP FRONTING WITH REDUCTION | many years I did not travel                                                  | 1    |
| 108  | TOPICALIZED NON-ARG. CONST | with your mother I love to go shopping                                       | 0    |
| 108  | TOPICALIZED NON-ARG. CONST | I love to go shopping with your mother                                       | 0    |
| 109  | TOPICALIZED NON-ARG. CONST | and in the background there are a lot of buildings                           | 0    |
| 109  | TOPICALIZED NON-ARG. CONST | and there are a lot of buildings in the background                           | 0    |
| 110  | TOPICALIZED NON-ARG. CONST | yeah, so my parent’s house I go very often                                  | 1    |
| 110  | TOPICALIZED NON-ARG. CONST | yeah, so to my parent’s house I go very often                               | 1    |
| 110  | TOPICALIZED NON-ARG. CONST | yeah, so I go very often to my parent’s house                               | 0    |
| 110  | PP FRONTING WITH REDUCTION | yeah, so my parent’s house I go very often                                  | 1    |