Abstract

Current natural language processing (NLP) models such as BERT and RoBERTa have achieved high overall performance, but they often make systematic errors due to bias or certain difficult features to learn. Thus research on slice detection models (SDM) which automatically identifies underperforming groups of datapoints has gradually caught more attention, which aims at both understanding model behaviors and providing insights for future model training and designing. However, there is little systematic research on SDM and quantitative evaluation of its assessment for NLP models. Our paper fills this gap by proposing “Discover, Explanation, Improvement (DEI)” framework that discovers coherent and underperforming groups of datapoints and unites datapoints of each slice under human-understandable concepts; it also provides comprehensive evaluation tasks and the corresponding quantitative metrics, which enable convenient comparison for future works. Results show that our framework can accurately select error-prone datapoints with informative semantic features that summarize error patterns, based on which it directly improves model performance by an average of 2.85 points without tuning any parameters.

1 Introduction

While deep learning models (Kenton and Toutanova, 2019; Liu et al., 2019, & inter alia) achieve high overall performance on many tasks, they often make systematic errors correlated with biases, intricate datapoints, and errors found in the data collection process. In order to discover such biases and erroneous behaviors, researchers resort to manual error analysis. However, representations of such error instances may have shared features that may be very informative about how to correct them. Automatic slice detection models are thus motivated: they are designed to automatically discover systematic errors given any trained machine learning model (Eyuboglu et al., 2022; Ribeiro et al., 2020, 2016; Wu et al., 2021, & inter alia).

A slice is defined to be a set of data samples that share a common characteristic. Discovering error slices are beneficial in at least three ways: (1) finding error-prone datapoints which enables direct modification of predictions (2) providing insights into model behaviors, which enables a better understanding or interpretation of the model (3) guiding further training of the model using methods such as slice-specific modeling, data augmentation, and active learning (Settles, 2009).

We propose a comprehensive framework for NLP tasks and models on slice detection with three incremental modules: Discover, Explanation, Improvement (DEI) where the SDM model is named DIXIE. Each of the three modules fulfills the three benefits above. The framework is presented in Figure 1.

Discover: We first discover error slices by training DIXIE on a validation datapoints providing a trained NLP model \( M \) and its predictions. DIXIE clusters datapoints into slices and each slice has its own accuracy. Slices with low accuracy are considered to be error slices. Figure 1 contains example datapoints from the CoLA dataset with labels and confidence scores; colored clusters with an accuracy of 0.1, 0.2, and 0.3 are considered to be error slices. Knowing the patterns of error slices, we are thereby able to detect error-prone datapoints on new datasets.

Explain: We explain why a model fails on some error slice by semantic features shared by datapoints in it by uniting datapoints in an error slice under a human-understandable concept. For each error slice discovered, we find those semantic features whose distribution is significantly denser within the slice compared with their distributions out of the slice. We create a feature benchmark for this step containing linguistic features and prag-
matic features. In the figure, for example, the slice with an accuracy of 0.2 corresponds to the feature “reflexive”, indicating that significantly many datapoints in the slice contain reflexive words and thus it is likely the reason why these datapoints are predicted wrong.

**Improvement:** Precisely discovering error patterns enables model improvement. In this framework, we showcase several methods: rejection, flipping, and active learning. In Figure 1, for example, we flip the confidence score for each error-prone datapoint. The three model improvement tasks also provide a numerical evaluation of the performance of slice detection models, which is crucial for the comparison of future models.

This paper introduces a three-module framework DEI where each module focuses on one task: (1) discover error patterns (2) extract features that explain error slices (3) improve model performance using error-prone datapoints. Each module provides evaluation tasks with quantitative metrics. Experiment results demonstrate that DIXIE can accurately discover error-prone datapoints on unlabeled datasets and precisely detect error-correlated features. It can thus improve model performance.

The paper is organized as follows: Section 2 discusses relevant recent works for SDM; Section 3 introduces in detail the DEI framework and Section 4 presents benchmark tasks, experiment results, and relevant ablation studies. Section 5 concludes this paper.

## 2 Related Work

Explainable model predictions are crucial in research areas. In Computer Vision, works have been proposed to use learned input representations to identify semantically meaningful slices where errors are made in prediction (Eyuboglu et al., 2022; d’Eon et al., 2022; Yeh et al., 2020; Sohoni et al., 2020; Kim et al., 2019; Singla et al., 2021). Eyuboglu et al. (2022) recently proposes the SOTA automatic error detection DOMINO in CV. In medical imaging (Oakden-Rayner et al., 2020; Winkler et al., 2019; Badgeley et al., 2019), Oakden-Rayner et al. (2020) noticed that models trained to detect collapsed lungs in chest X-rays often make erroneous predictions due to the presence of chest drains, a commonly used device during treatment.

In NLP, there are some task-specific works on automatic error analysis such as Das et al. (2022) on document-level information extraction, Kummerfeld and Klein (2013) on coreference resolution, Popović and Ney (2011) on machine translation, and etc. There is also extensive research conducted on different model evaluations to see whether models make erroneous datapoints in certain types of noising datapoints (Belinkov and Bisk, 2017; Rychalska et al., 2019) or adversarial datapoints (Ribeiro et al., 2018; Iyyer et al., 2018). Recently, Rajani et al. (2022) introduces a visualization tool for under-performing slices to facilitate human understanding.

We propose a general automatic error detection framework DEI with systematic evaluation metrics that detects error patterns, explains error patterns, and improves model performance. We demonstrate DEI by working on classification tasks, while this framework including its slice detection model is easily extensible to other types of tasks such as sequence to sequence tasks. We present the usage of benchmark tasks in Sections Explain: Slice Feature Detection and Improve-
3 DEI Framework

In this section, we explain the three modules and relevant tasks of the framework step by step.

3.1 Discover: Model Structure

DIXIE is an error-aware multivariate Gaussian mixture model that models datapoint representations, error distance, and model prediction (e.g. confidence score in classification tasks) of datapoints. $Z$ is an embedding representation; $Y$ is the softmax outcomes of logits and error distance $E$ is the distance between one-hot tensor of gold label and model predictions:

$$E = Y - Y'$$ (1)

For each datapoint: $Z$ encodes the task-relevant information; $E$ encodes both label information and confidence information, which represents whether the prediction is wrong and to what extent it deviated from the gold label and how much change is still required to make a correct prediction. $Y$ encodes the confidence score. It is added to the model to control the weights of label information and of confidence information.

The current model structure could be improved by replacing confidence scores by calibrated confidence (Yu et al., 2011; Guo et al., 2017; DeVries and Taylor, 2018; Kumar et al., 2018, & inter alia.), which usually presents a better probability estimate of the likelihood for a datapoint to be categorized in some class.

Figure 2 illustrates the model structure.

The probability distribution of $S$ is a categorical distribution parameterized by $\theta$ modeled with Gaussian distribution. For each slice $S$, embeddings $Z$, error distance $E$ and model predictions $Y$ are normally distributed parameterized by mean $\mu$ and covariance $\Sigma$ respectively:

$$P(S_j) \sim \mathcal{P}(\theta)$$
$$P(Z|S_j) \sim \mathcal{N}(\mu^Z_j, \Sigma^Z_j)$$
$$P(E|S_j) \sim \mathcal{N}(\mu^E_j, \Sigma^E_j)$$
$$P(Y|S_j) \sim \mathcal{N}(\mu^Y_j, \Sigma^Y_j)$$ (2)

For each datapoint $d$, its likelihood of being in slice $j$ is a weighted product of the likelihood generated by the three equations above:

$$P(d, j) = P(S_j)P(Z_d|S_j)^\gamma P(E_d|S_j)^{\lambda_z} P(Y_d|S_j)^{\lambda_y}$$ (3)

The model computes the probability distribution for each datapoints over all slices. It clusters depending on the semantic information in the embedding, the gold label, and the model predictions. Thus ideally, datapoints that share some similar semantic features with the same gold label and similar model predictions should be clustered into one slice. In order to filter out the noise and useless information, we perform PCA dimension reduction on representations before applying the slice discovery model as in DOMINO (Eyuboglu et al., 2022).

The model is trained by the Expectation-Maximization by maximizing the sum of the log-likelihood of all datapoints in the dataset $D$:

$$\mathcal{L}(D) = \sum_{d=1}^n \log \Sigma_{j=1}^s P(S_j)P(Z_d|S_j)^\gamma P(E_d|S_j)^{\lambda_z} P(Y_d|S_j)^{\lambda_y}$$

We train the slice discovery model on a validation dataset after training $\mathcal{M}$ on the training dataset.

3.1.1 Inference

In inference time, we apply a fitted DIXIE on test datasets where gold labels are unknown to the model. Since gold label information is inaccessible, the error distance is marginalized over potential label values. Thus the likelihood of a test datapoint $t$ on slice $j$ is compute as below where $E'_t$ ranges over all possible $E$ values:

$$P(t, j) = P(S_j)P(Z_t|S_j)^\gamma (\Sigma_{E'_t} P(E'_t|S_j)^{\lambda_z}) P(Y_t|S_j)^{\lambda_y}$$ (4)

A datapoint is determined to be error-prone if it is clustered to an error slice based on training in the validation dataset. Computing the accuracy of predicted error-prone datapoints on test datasets reveals the capability of DIXIE.
3.2 Explain: Slice Feature Detection

In order to make errors more interpretable as well as actionable, we try to find features that significantly correlate with an error slice. Such features can be surface features such as specific tokens, or linguistic features such as part-of-speech and pragmatic indicators. Thereby we create a feature benchmark with 38 features to internally evaluate slices discovered by DIXIE\(^1\).

| Feature Type       | Features                                                                 |
|--------------------|---------------------------------------------------------------------------|
| surface string     | length, word frequency in corpus, foreign word                           |
| syntactic features | negation, reflexive, aspect, tense, voice, comparison, echo question, multiple modal, multiple prepositions, NP-subordinate clause, quantifier, long-distance dependency, tree depth, extra infinite with modal, how-question, why-question,                                             |
| pragmatic features | age, gender, nationality, physical appearance, race/ethnicity, religion, social economic status, sexual orientation, toxicity, valency sentiment (positive/negative/neutral), arousal (excited/calm.neural), dominance (dominant/subordinate/neutral), number of people, number of organization, number of location, number of money, date, product, ordinal_number |

Table 1: Semantic Feature benchmark

There are three types of features in the benchmark shown in Table 1: surface string features, syntactic features, and pragmatic features. Surface string features include features that can be detected based on surface strings such as sentence length, word frequency in the corpus, and whether the sentence contains foreign words. Synthetic features require a dependency parser or a constituency parser to detect, such as negation, reflexive, aspect, and so on. Pragmatic features include age, gender, nationality of people mentioned in the sentence, etc. These features need to be detected by trained classifiers or named entity recognition models and so on. We use examples in CoLA dataset to illustrate the meanings of some syntactic features in Table 2.

We design two feature discovery tasks: Synthetic Feature Detection and Real Dataset Feature Detection, evaluating whether DIXIE is able to accurately detect error-correlating features.

\(^1\)We do not claim this benchmark to be comprehensive such that it covers all potential features and it is open to future modifications.

3.3 Improvement: Downstream Tasks

With results from the previous two modules, manual intervention may help the model to achieve better performance. Therefore we leverage three automatic improvement methods: rejection, flipping, and active learning. They not only evaluate how precisely DIXIE can pick out error-prone datapoints but also show how improvements can be made automatically.

3.3.1 Rejection

The rejection task aims at pointing out which datapoints are error-prone and rejecting them from being evaluated. This task is motivated by real-life scenarios where a datapoint is difficult for the current model: instead of making predictions right away, the model can request more information or a paraphrase of the current datapoint. For example, a grammar-checking tool with a grammaticality classifier performs badly about the correctness of a long recursive sentence, it may: (1) reject to determine whether it is grammatical but instead requires the user to rewrite the sentence using shorter phrases with a simpler structure or (2) ask the writer to double-check the sentence correctness on his/her own.

DIXIE predicts a datapoint to be error-prone \(d \in ED\) where \(ED = \{d \in S \mid S\) is an error slice\}. Then it reorders these datapoints based on error
likelihood \( l(d) \), which is the summation of the likelihood of \( d \) belonging to each error slice:

\[
l(d) = \sum_{s \in S} P(d, s) \text{ where } s \text{ is an error slice}
\]  

(5)

We then reject these datapoints one by one based on the order of likelihood and for each step, we compute the accuracy of the remaining datapoints.

**3.3.2 Flipping**

The flipping task is a task to directly improve model performance by flipping the prediction of error-prone datapoints given an unlabeled dataset. If the dataset is binary, flipping changes its prediction from 1 to 0 or 0 to 1; if the dataset is multi-labeled, we need to select a label to flip the predicted label to another most likely label.

For a slice discovery model, for each error-prone datapoint \( d \), we select the new label as follows: If the confidence score of \( d \) is below some threshold and \( d \in ES \) for some error slice \( ES \), we find the majority of gold label \( l \) in \( ES \) in validation dataset and flip the predicted label to \( l \); if the confidence of \( d \) is above the threshold, the predicted label remains the same. The confidence threshold is found upon a small portion (10\%) of the validation dataset used to train the slice discovery model. For the confidence baseline, the label is flipped to the next confident label instead of the majority of gold labels in the corresponding error slice.

In flipping, the predicted error-prone datapoints \( d \) are also flipped one by one based on the order of \( l(d) \) as in the rejection task.

**3.3.3 Active Learning**

Active learning is an interactive learning algorithm that proactively selects the subset of examples to be labeled next from the pool of unlabeled data. Error-prone datapoints are also points with potential bias and training with them can help the model learn faster.

Active learning using DIXIE is implemented as follows: **Step 1**: divide the whole training dataset into a small training seed and an extra training data pool. **Step 2**: train an NLP model using the small training seed and evaluate it on the test dataset. **Step 3**: fit DIXIE on the validation dataset and select error-prone datapoints from the extra training data pool. **Step 4**: create a new training dataset combining original training data + selected training data and remove the selected datapoints from the extra training data pool. **Step 5**: retrain the model on the new training dataset. Repeat steps 3-5 until the model converges on performance on the test dataset.

**4 Experiment Result**

This section presents experiment results in all three modules. They show that DIXIE is able to cluster error datapoints with similar semantic features and detect error-prone datapoints accurately.

We apply DEI on a variety of datasets in GLUE benchmark (Wang et al., 2019) and Kaggle dataset Jigsaw\(^2\): CoLA, QNLI, QQP, SST-2, MNLI, SST-5, Jigsaw-gender, Jigsaw-racial, Jigsaw-religion. Since GLUE test dataset labels are not publicly available, we split the original training dataset into training and validation, and treat the original validation dataset as test dataset.

For each dataset, we train two models based on BERT-large and RoBERTa-large. To evaluate the performance of DEI, we apply DIXIE on each of the trained models and evaluate on results from these models.

**4.1 Discover Experiment Result**

The experiment in discover module for any \( \mathcal{M} \) is to simply compute the accuracy on detected error-prone datapoints, i.e. whether they are indeed predicted wrong by \( \mathcal{M} \). We compare the performance with DOMINO (Eyuboglu et al., 2022) which is the current state-of-the-art slice discovery model, confidence thresholding, and random sampling.

The default set of hyperparameters for DIXIE is \( \lambda = 0.15, \gamma_c = 0.1, \gamma_Y = 1 \) which works well on all datasets on BERT and RoBERTa model. For DOMINO, we tune their hyperparameters for best performance on this task.\(^3\)

A slice is defined to be an error slice if its accuracy is below some error threshold, which is a heuristically chosen number much lower than the average validation accuracy. For CoLA, QNLI, QQP, SST-2, Jigsaw-gender, Jigsaw-racial, and Jigsaw-religion for which validation accuracy is around 0.75, the error threshold is chosen to be 0.5; for MNLI where the accuracy is around 0.63,

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\(^2\)https://www.kaggle.com/competitions/jigsaw-unintended-bias-in-toxicity-classification/overview/evaluation

\(^3\)The set of hyperparameters is \( \lambda = 1, \gamma_Y = 10, \gamma_Y = 10 \), which works for feature detection tasks instead of error-prone datapoints discovery task. Thus we manually tune their hyperparameters.
the error threshold is 0.4; for SST-5 where the accuracy is around 0.55, the error threshold is 0.3.

We report results in Table 3 based on the test dataset: (1) the number of error-prone datapoints found and (2) its accuracy on whether they are indeed predicted wrong. The accuracy for confidence baseline is computed based on \( t \) many datapoints with lowest confidence scores where \( t \) is the number of datapoints discovered in DIXIE; the accuracy for random baseline is computed based on \( t \) many randomly sampled datapoints.

Based on the Table 3, we notice that the accuracies of DIXIE are almost always much higher than other baselines. Also, their accuracies are always higher than 50.00 indicating that most of the error-prone datapoints discovered are indeed predicted wrong.

4.1.1 Model Structure Ablation Study

We study the model structure based on the accuracy performance with performance on CoLA as an illustration in Table 4. We compare models with (1) only \( Y \) edge (DIXIE-\( Y \)) (2) both \( \varepsilon \) and \( Y \) edge (DIXIE-\( \varepsilon, Y \)) and (3) all three edges. We present the number of error-prone datapoints discovered, the accuracy of these selected datapoints, and the accuracy of the confidence baseline.

Technically, the accuracy of DIXIE-\( Y \) should be the same as the accuracy of selecting datapoints using a certain confidence score with a threshold. But we notice that it still detects error-prone datapoints better, indicating that using confidence scores having low accuracy based on validation datasets is better than directly choosing datapoints with the lowest confidence scores. DIXIE-\( \varepsilon, Y \) is confidence calibration, which is more accurate. DIXIE leveraging semantic information selects error-prone datapoints more accurately, indicating that semantic information does provide clues on datapoints difficulty level for a given model.

| NLP model | BERT | RoBERTa |
|-----------|------|---------|
| Method    | DIXIE | DOMINO | confidence | random | DIXIE | DOMINO | confidence | random |
| Metric    | number accuracy | number accuracy | accuracy | accuracy | number accuracy | number accuracy | accuracy | accuracy |
| CoLA      | 50.2 | 58.6 | 51.9 | 34.1 | 10.6 | 60.92 | 28.57 |
| DOMINO    | 50.2 | 58.6 | 51.9 | 34.1 | 10.6 | 60.92 | 28.57 |
| confidence | 50.2 | 58.6 | 51.9 | 34.1 | 10.6 | 60.92 | 28.57 |
| random    | 50.2 | 58.6 | 51.9 | 34.1 | 10.6 | 60.92 | 28.57 |

Table 3: Accuracy of Predicted Error-prone Datapoints

4.1.2 Hyperparameter Ablation Study

We explore different settings of the DIXIE and test functions of the following hyper-parameters: \( \alpha \) and \( \lambda \), and we hold \( \gamma \) unchanged). We conduct experiments on the BERT-based model on CoLA dataset. The default hyper-parameters are \( \{ \alpha = 10, \lambda = 1, \gamma = 1 \} \).

weights We test different weights with \( \gamma \in \{0.01, 0.05, 0.2, 0.5, 1\} \) and \( \lambda \in \{0.01, 0.05, 0.2, 0.5, 1\} \) separately.

| \( \gamma \) | number | accuracy | confidence |
|----------|--------|----------|------------|
| 0.01     | 38     | 63.16    | 55.26      |
| 0.05     | 40     | 55.00    | 50.00      |
| 0.2      | 33     | 60.61    | 54.54      |
| 0.5      | 117    | 40.17    | 43.59      |
| 1        | 120    | 40.00    | 50.00      |

| \( \lambda \) | number | accuracy | confidence |
|----------|--------|----------|------------|
| 0.01     | 65     | 37.91    | 44.62      |
| 0.05     | 39     | 46.25    | 53.35      |
| 0.2      | 58     | 50.00    | 48.28      |
| 0.5      | 28     | 42.87    | 42.87      |
| 1        | 1      | 0.00     | 100.00     |

Table 5: Ablation study on the value of \( \gamma \) and \( \lambda \)

In Table 5: (1) For \( \gamma \), accuracy decreases with large values. We believe that the negative influence is brought by the difference in data distribu-
tion of validation and test as well as the discrepancy between the training and testing modeling scheme: in the training stage, the model leverages all information of input representations, gold labels, and model predictions; while in the test stage, it does not have access to the ground truth information and thus models with $\gamma < \nu$ tend to overfit on the validation dataset and exacerbate the performance on the test dataset. (2) For $\lambda$, accuracy decreases with either small or large values. Large values hurt because semantic representation does not have a direct relationship to the accuracy of model prediction while mostly providing semantic feature information, DIXIE with a large value of $\lambda$ will focus only on sentence representation clustering while label and prediction information will become negligible. We suspect that small values of $\lambda$ may render input representation information to be noise to the model and thus affect the performance negatively.

**PCA dimensions** We test PCA dimension = 32, 64, 128, 256, and 1024 (without PCA dimension reduction) under different weights of the embedding. The results are presented in Table 6.

| PCA dimension | $\lambda$ | number | accuracy | confidence |
|---------------|----------|--------|----------|------------|
| 32            | 0.15     | 55     | 52.73    | 50.91      |
| 64            | 0.15     | 78     | 43.59    | 41.03      |
| 256           | 0.15     | 4      | 25.00    | 50.00      |
| 512           | 0.15     | 1      | 0.00     | 100.00     |
| 1024          | 0.1      | 3      | 67.32    | 60.37      |
| 32            | 0.1      | 53     | 37.74    | 50.94      |
| 64            | 0.1      | 23     | 62.32    | 60.37      |
| 256           | 0.1      | 49     | 55.11    | 48.98      |
| 512           | 0.1      | 4      | 25.00    | 50.00      |
| 1024          | 0.1      | 3      | 67.32    | 60.37      |

Table 6: PCA dimension ablation study

For all three $\lambda$ values, the PCA dimension being 64 or 256 work well. We notice that the model using a large PCA dimension (PCA dim = 1024) performs the worst and discovers almost no error-prone datapoints. Thus we can see that PCA reduction which removes redundant information and noise is necessary for the model to perform well.

Secondly, we notice that the model using relatively small dimensions (32) can also work under certain $\lambda$ values, and performs better under relatively large $\lambda$ values than small $\lambda$ values; the model using relatively large dimensions (256) performs better with small $\lambda$ values than with large $\lambda$ values. Thus we may conclude that the PCA dimension $P$ should be chosen inversely with $\lambda$.

**Slice number** In that last ablation experiment, we test different numbers of slices: 64, 128, 256, and 512 with the result presented in Table 7. We notice that slice numbers 64, 256, and 512 perform well. Small slice number 32 does not perform well, showing that models using small slice numbers may not have the capacity to classify different types of error patterns to different classes, and may thus hurt the final performance. With slice number $\geq 64$, model accuracy does not increase much but it discovers a larger number of error-prone datapoints and performs even better against the confidence baseline, showing that more fine-grained clustering brings noticeable benefit.

| slice number | number | accuracy | confidence |
|--------------|--------|----------|------------|
| 32           | 55     | 50.91    | 50.91      |
| 64           | 41     | 56.10    | 53.76      |
| 256          | 53     | 52.30    | 50.94      |
| 512          | 67     | 52.34    | 44.88      |

Table 7: Number of slices ablation study

4.2 Explain: Experiment Result

We design two tasks to evaluate whether DIXIE can discover error-correlated features and how well it performs on different types of errors: Synthetic Dataset Feature Discovery and Real Dataset Feature Discovery. Both experiment results demonstrate that the current model structure performs better than DOMINO.

For terminology, we use $F$ to denote a feature, and each feature has a corresponding feature function $f$: if $F$ is binary such as negation, then $f$ is a characteristic function such that $f(s) = 1$ indicates that the sentence $s$ contains the feature; if $F$ is non-binary such as multiple-preposition and long-distance dependency, then $f(s) = d \in \mathcal{R}$ indicating that $s$ has $d$-degree of the feature.

**Synthetic Dataset Feature Discovery** The first task evaluates the feature discovery capability by providing synthetic datasets with one gold error-correlated feature for each dataset. A synthetic dataset with a feature $F$ is generated by selecting wrongly predicted datapoints featuring $F$: $\{d \in D | \mathcal{M}(d) \neq \text{label}(d) \text{ and } f(d) = 1\}$ (assuming $f$ is a characteristic function here) and a similar number of other random datapoints from the original dataset.

Then we fit a DIXIE on the synthetic dataset to see how many target datapoints can be grouped
### Real Dataset Feature Detection

The second task is to detect features in real datasets. For each datapoint, we apply all feature functions to find out the set of features that it exhibits. For each error slice discovered by the slice discovery model, we leverage the significance test to analyze which features are distributed significantly within the slice. For each feature’s in-slice and out-of-slice distributions, if the p-value is smaller than 0.05 and the mean of the in-slice distribution is larger than that of the out-of-slice distribution, this feature is strongly correlated with erroneous predictions.

In Table 10, we report the error slice feature detection results with surface and syntactic features on GLUE datasets and pragmatic features on Jigsaw datasets. We compare with DOMINO model results, DIXIE using only semantic embedding information (DIXIE-Z) and that using only error-distance information (DIXIE-E).

There are four metrics: feature-prop, average V-score (V-score), average homogeneity (Homo), and average completeness (Comp): (1) feature-prop is the proportion of features in the benchmark that are detected to be significant (2) average homogeneity/completeness $/V$-score is the average of homogeneity/completeness $/V$-score for error slices that have the feature being significant.

The detailed experiment results for each feature are presented in Appendix. In the end, we compare the performance using average weighted (ave. weighted) $V$-score which is computed as follows:

$$\text{average weighted } V\text{-score} = \frac{\sum_{D} \text{feature-prop}_{D} \times V\text{-score}_{D}}{\text{number of datasets}}$$  

We notice that DIXIE performs the best with the highest homogeneity scores. DIXIE-Z also per-

### Ablation Study on Synthetic Feature Detection

Table 9 presents average precision, recall, and F1 over all the datasets. Table 15 in Appendix presents all the scores. We can see that in general DIXIE performs better than DOMINO except in SST-2 where the average F1 of DOMINO result is +0.02 higher than that of DIXIE. DIXIE performs better in recall in all cases and better in precision in some cases. The bottom line of the table is the cross-dataset average score for precision, recall, and F1. We notice that DIXIE performs better than DOMINO on all metrics, especially recall.

### 4.2.1 Ablation Study on Hyperparameter

We study the effect of hyperparameters in feature detection-related tasks on CoLA dataset. We study the effect of hyperparameters $\lambda$ and $\gamma$. We noticed that large $\lambda$ improves precision but decreases the recall while large $\gamma$ brings the reverse effect. Hyperparameter set $\{\lambda = 0.15, \gamma = 1, \gamma' = 0.1\}$ and $\{\lambda = 0.15, \gamma = 1, \gamma' = 0.5\}$ have the best results; while the model with $\lambda = 1$ fails to detect feature Comparison and the model with $\gamma = 1$ fails to detect feature NP_sub.

### Table 8: Synthetic Feature detection result

| dataset              | model | avg. precision | avg. recall | avg. F1   |
|----------------------|-------|----------------|-------------|-----------|
| CoLA                 | DIXIE | 25.41          | 96.53       | 38.91     |
| Jigsaw-gender       | DIXIE | 7.78           | 24.05       | 10.36     |
| SST-2                | DIXIE | 7.67           | 17.48       | 9.94      |
| Jigsaw-gender       | DOMINO| 7.55           | 28.92       | 11.18     |
| Jigsaw-racial       | DIXIE | 7.91           | 21.75       | 10.66     |
| Jigsaw-religion     | DIXIE | 8.64           | 11.72       | 8.92      |
| Jigsaw-gender       | DOMINO| 8.36           | 11.17       | 8.34      |
| Jigsaw-gender       | DIXIE | 7.46           | 34.47       | 11.37     |
| Jigsaw-racial       | DIXIE | 8.14           | 13.57       | 10.92     |
| Jigsaw-religion     | DIXIE | 7.31           | 33.57       | 12.41     |
| Jigsaw-religion     | DIXIE | 7.23           | 30.67       | 12.08     |
| Jigsaw-gender       | DOMINO| 53.92          | 95.88       | 68.91     |
| Jigsaw-racial       | DIXIE | 51.96          | 94.15       | 66.29     |
| Jigsaw-religion     | DIXIE | 29.54          | 89.64       | 42.00     |
| Jigsaw-religion     | DIXIE | 29.54          | 97.30       | 41.46     |
| Jigsaw-religion     | DIXIE | 26.15          | 93.22       | 36.71     |
| Jigsaw-religion     | DIXIE | 26.18          | 90.32       | 35.75     |
| Jigsaw-religion     | DOMINO| 19.31          | 58.89       | 26.75     |
| Jigsaw-religion     | DOMINO| 19.23          | 54.00       | 26.25     |

Table 8: Synthetic Feature detection result

into error slices and then compute recall, precision, and F1. We perform this experiment on certain features with a relatively large number of wrongly predicted datapoints: \{length, negation, reflexive, comparison, NP_subordinate, multiple_preposition, quantifier, tree_depth, long-distance\} for GLUE datasets and \{female, male, Asian, Black, White, Latino, Atheist, Buddhist, Christian, Hindu, Jewish, Muslim\} for Jigsaw datasets. We compare DIXIE results with DOMINO results.

Table 8 presents average precision, recall, and F1 over all the datasets. Table 15 in Appendix presents all the scores. We can see that in general DIXIE performs better than DOMINO except in SST-2 where the average F1 of DOMINO result is +0.02 higher than that of DIXIE. DIXIE performs better in recall in all cases and better in precision in some cases. The bottom line of the table is the cross-dataset average score for precision, recall, and F1. We notice that DIXIE performs better than DOMINO on all metrics, especially recall.
forms well in homogeneity scores but poorly at the completeness scores, which is intuitive since the model tends to cluster all sentences with similar completeness scores, which is intuitive since the model is confidence. The proportion being higher than 50.00% indicates that most of the time our slice discovery model is more accurate than the baseline model. Improvement is the final accuracy improvement compared with the original accuracy. C-improvement is the final accuracy improvement compared with confidence.

For the confidence baseline, we reorder the datapoints by the confidence score from low to high and rejects the top-ᵣ datapoints.

Table 10: Feature detection results

| dataset | model | feature prop | V-score | Homo | Comp |
|---------|-------|--------------|---------|------|------|
| CoLA    | DIXIE | ---          | 81.25   | 20.46| 12.88| 79.80|
| CoLA    | DOMINO | ---          | 68.75   | 15.80| 7.77 | 64.18|
| CoLA    | DIXIE-E | ---         | 36.25   | 24.57| 5.57 | 34.41|
| CoLA    | DOMINO-E | ---        | 36.25   | 18.94| 5.57 | 34.41|
| QNLI    | DIXIE | ---          | 50.00   | 5.79 | 3.11 | 61.19|
| QNLI    | DOMINO | ---          | 55.66   | 5.88 | 6.57 | 57.57|
| QNLI    | DIXIE-E | ---          | 12.56   | 3.35 | 2.96 | 61.56|
| QNLI    | DOMINO-E | ---         | 36.06   | 6.09 | 5.81 | 57.58|
| SST-2   | DIXIE | ---          | 50.00   | 6.97 | 3.83 | 66.66|
| SST-2   | DOMINO | ---          | 36.25   | 16.63| 9.94 | 57.35|
| SST-2   | DIXIE-E | ---          | 12.56   | 15.33| 9.56 | 48.34|
| SST-2   | DOMINO-E | ---         | 50.00   | 16.68| 5.95 | 61.15|
| MNLI    | DIXIE | ---          | 50.00   | 4.42 | 2.32 | 57.10|
| MNLI    | DOMINO | ---          | 36.25   | 5.86 | 1.97 | 66.56|
| MNLI    | DIXIE-E | ---          | 37.56   | 9.61 | 4.06 | 88.61|
| MNLI    | DOMINO-E | ---         | 50.00   | 4.08 | 2.29 | 71.76|
| SST-5   | DIXIE | ---          | 81.25   | 16.05| 9.83 | 53.70|
| SST-5   | DOMINO | ---          | 62.50   | 16.95| 11.03| 54.56|
| SST-5   | DIXIE-E | ---          | 50.00   | 16.56| 9.62 | 55.59|
| SST-5   | DOMINO-E | ---         | 50.00   | 16.64| 9.62 | 55.59|
| J-gender | DIXIE | ---          | 100.00  | 36.14| 26.78| 55.24|
| J-gender | DOMINO | ---          | 100.00  | 36.14| 26.78| 55.24|
| J-gender | DIXIE-E | ---          | 31.26   | 62.50| 24.57| 43.99|
| J-gender | DOMINO-E | ---         | 31.26   | 24.57| 24.57| 43.99|
| J-gender | DIXIE-E | ---          | 50.00   | 21.50| 16.62| 63.33|
| J-racial | DIXIE | ---          | 75.00   | 22.06| 17.00| 56.52|
| J-racial | DOMINO | ---          | 100.00  | 31.55| 23.03| 63.35|
| J-racial | DIXIE-E | ---          | 100.00  | 27.09| 19.67| 53.88|
| J-racial | DOMINO-E | ---         | 50.00   | 35.97| 31.26| 47.02|
| J-religion | DIXIE | ---          | 100.00  | 39.18| 29.18| 50.86|
| J-religion | DOMINO | ---          | 100.00  | 34.06| 26.75| 42.12|
| J-religion | DIXIE-E | ---          | 50.00   | 34.06| 26.75| 42.12|
| J-religion | DOMINO-E | ---         | 50.00   | 25.97| 21.50| 63.33|
| J-religion | DIXIE-E | ---          | 85.53   | 36.83| 28.30| 59.39|
| J-religion | DOMINO-E | ---         | 85.53   | 23.52| 23.52| 58.79|
| ave. weighted | DIXIE | ---          | 64.61   | 12.40| 42.47|
| ave. weighted | DOMINO | ---          | 15.57   | 10.37| 32.56|
| ave. weighted | DIXIE-E | ---          | 14.46   | 11.63| 29.08|
| ave. weighted | DOMINO-E | ---         | 15.12   | 9.92 | 33.60|

Table 11: Rejection Result

| dataset | model | C-proportion | C-improvement | improvement |
|---------|-------|--------------|---------------|-------------|
| CoLA    | BERT  | 90.00        | 0.40          | 1.58        |
| CoLA    | RoBERTa | 100.00      | 1.58          | 1.58        |
| QNLI    | BERT  | 90.00        | 0.45          | 1.27        |
| QNLI    | RoBERTa | 100.00      | 0.45          | 1.27        |
| SST-2   | BERT  | 100.00       | 0.35          | 0.86        |
| SST-2   | RoBERTa | 100.00      | 0.35          | 0.86        |
| MNLI    | BERT  | 50.00        | 0.11          | 1.48        |
| MNLI    | RoBERTa | 31.52       | 0.11          | 1.48        |
| SST-5   | BERT  | 67.47        | 1.10          | 5.06        |
| SST-5   | RoBERTa | 67.47       | 1.10          | 5.06        |
| J-gender | BERT  | 26.20        | 1.14          | 4.77        |
| J-gender | RoBERTa | 26.20       | 1.14          | 4.77        |
| J-racial | BERT  | 91.30        | 0.86          | 2.83        |
| J-racial | RoBERTa | 91.30       | 0.86          | 2.83        |
| J-religion | BERT  | 96.30        | 0.98          | 2.49        |
| J-religion | RoBERTa | 96.30      | 0.98          | 2.49        |
| Jreligion | BERT  | 56.25        | 9.58          | 48.41       |
| J-religion | RoBERTa | 56.25       | 9.58          | 48.41       |
| average |      | 80.18        | 2.01          | 4.09        |

Based on Table 11: the average C-proportion is 80.18 (higher than 50.00), C-improvement is 2.01 and improvement is 4.09, all demonstrating the advantage of DIXIE.

Figures.3 are four graphs of rejection based on BERT models. In each figure, the x-axis represents the number of datapoints rejected and the y-axis represents the accuracy of the remaining dataset. They demonstrate in a straightforward manner how accuracy is changed stepwise by comparing DIXIE and confidence baseline. We choose to demonstrate four datasets of different types here: CoLA, QNLI, SST-5, and Jigsaw-religion, where CoLA and QNLI come from the GLUE benchmark; SST-5 is a multi-class dataset and Jigsaw-religion comes from Jigsaw dataset. DIXIE all perform better than confidence baselines at almost all steps, indicating that DIXIE can always pick the more accurate error-prone datapoints than the confidence baseline.
Figure 3: Graphs for rejection task using confidence baseline and SDM model (DIXIE): CoLA, QNLI, SST-5, Jigsaw-religion. The x-axis is the number of rejected datapoints; the y-axis is the model accuracy.

| dataset  | model    | C-proportion | C-improvement | improvement |
|----------|----------|--------------|---------------|-------------|
| CoLA     | BERT     | 100.00       | 0.58          | 0.86        |
| CoLA     | RoBERTa  | 100.00       | 2.68          | 2.01        |
| QNLI     | BERT     | 100.00       | 0.81          | 1.13        |
| QNLI     | RoBERTa  | 100.00       | 1.21          | 0.57        |
| QQP      | BERT     | 99.83        | 0.36          | 0.12        |
| QQP      | RoBERTa  | 49.85        | -0.09         | -0.06       |
| SST-2    | BERT     | 96.30        | 0.46          | 0.00        |
| SST-2    | RoBERTa  | 91.30        | 0.00          | 0.00        |
| MNLI     | BERT     | 52.64        | 0.99          | 0.04        |
| MNLI     | RoBERTa  | 31.52        | -0.05         | 0.02        |
| SST-5    | BERT     | 77.47        | 2.67          | 0.27        |
| SST-5    | RoBERTa  | 70.00        | 0.00          | 0.18        |
| Jigsaw-gender | BERT | 99.66 | 9.51 | 9.64 |
| Jigsaw-gender | RoBERTa | 97.68 | 8.81 | 10.67 |
| Jigsaw-race | BERT | 100.00 | 12.37 | 11.66 |
| Jigsaw-race | RoBERTa | 100.00 | 14.92 | 13.48 |
| Jigsaw-religion | BERT | 100.00 | 1.87 | 1.45 |
| Jigsaw-religion | RoBERTa | 77.46 | 0.00 | -0.57 |
| average  |          | 85.76        | 3.17          | 2.85        |

Table 12: Flipping Result

4.3.2 Flipping Result

The flipping task uses the same metric as the rejection task. Notice that MNLI is a three-class dataset: the validated confidence score is 0.35 for BERT model and 0.37 for RoBERTa model. SST-5 is a five-class dataset: the validated confidence score is 0.7 for BERT model and 0.35 for RoBERTa model. Based on Table 12, the average C-proportion is 85.76 (above 50.00), average C-improvement is 3.17 and average improvement is 2.85, all showing that the slice discovery model is able to improve the model in a direct method.

Figures 4 are four graphs of flipping on RoBERTa models. In all four datasets, the slice discovery model performs almost always better on all steps. The confidence baseline is not even accurate enough in selecting error-prone datapoints that can improve the performance of the trained model: the accuracy performance either holds almost constant or decreases.

4.3.3 Active Learning Result

In active learning, we adopt both confidence learning and random learning as baselines. We compare the results with two baselines: confidence learning is an active learning process where we select a certain number of low confidence datapoints for every learning step; random learning randomly selects a certain number of datapoints to train for every learning step.

We demonstrate performance on this task by working on the QNLI BERT model in Figure 5. The x-axis is the number of datapoints used to train and the y-axis is the model accuracy. We use 1% datapoints of the original training dataset as seed training data. For confidence learning and random learning, we select 500 more datapoints for each step; for active learning, the slice detection model DIXIE decides how many extra datapoints to train on. All active learning processes have run 10 times with different random seeds and in order to save training time, all three learning processes use up to 16k datapoints (about 30 learning steps). The y-axis demonstrates the average accuracies in the 10 experiments.

The figure demonstrates that active learning and confidence learning perform noticeably better than random learning. DIXIE also performs better than confidence learning while the two converge to similar accuracy towards the end.
5 Conclusion

This paper is the first attempt to build a comprehensive error-detection framework with complete evaluation benchmarks DEI which discovers error-prone datapoints, unites datapoints in an error slice under the human-interpretable concept and improves model performance based on the detection result. It shows that discovering error patterns can not only provide insights into model behaviors but also bring direct model performance improvement. DEI provides systematic evaluation benchmark on slice internal evaluation and external evaluation: the internal evaluation estimates how well a slice detection model discovers features and the external evaluation estimates how much improvement can be brought to a trained NLP model.

This framework has multiple directions of future research such as better slice detection model design and application on other types of NLP tasks. We hope this project can shed some insights into a new research area.

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Appendix

5.1 Datasets in Experiments

CoLA: The Corpus of Linguistic Acceptability is a binary classification dataset aiming at distinguishing ungrammatical sentences from grammatical sentences, consisting of 10657 sentences from 23 linguistics publications.

QNLI: The Question-answering Natural Language Inference dataset is a binary classification dataset aiming at judging whether the context sentence contains the answer to the question, automatically derived from the Stanford Question Answering Dataset v1.1.

QQP: Quora Question Pairs dataset is a binary classification task aiming at judging whether the two questions are paraphrases of each other, consisting of over 400,000 question pairs.

SST-2: The Stanford Sentiment Treebank is a binary classification task analyzing the effects of sentiment consisting of 215,154 sentences.

MNLI: The Multi-Genre Natural Language Inference corpus is a three-class classification task consisting of 433k sentence pairs annotated with textual entailment information.

SST-5: The Stanford Sentiment Treebank is a fine-grained five-class classification task analyzing the effects of sentiment in language.

The above datasets are based on GLUE. We did not train on other GLUE datasets due to their small size of training data such as RTE and WNLI.

Jigsaw: The Jigsaw dataset is a binary classification dataset aiming at the detection of toxic comments and minimization of unintended model bias consisting of about 180k datapoints. We constructed three sub-datasets based on Jigsaw, each focusing on one type of potential model bias: gender (male, female and other_gender), race (black, white, Asian, etc.), and religion (atheist, Christian, Muslim, etc.). We also re-balance the dataset so that 50% of the datapoints have a non-trivial value...
on at least one feature. The Jigsaw-gender consists of 37k datapoints, Jigsaw-race consists of 40k datapoints, Jigsaw-religion consists of 183k datapoints.

5.2 Extra Experiment Results
Table 13: Feature detection performance on all linguistics features

| Dataset | Model | Female | Male |
|---------|-------|--------|------|
| Metric  |       |        |      |
| CoLA    | DOMINO| 16.16  | 11.59|
| SST-5   | DOMINO| 15.19  | 9.09 |
| MNLI    | DOMINO| 12.53  | 6.87 |
| Jigsaw-religion | DOMINO| 11.63  | 9.71 |
| QNLI    | DOMINO| 13.76  | 10.57|
| QQP     | DOMINO| 21.43  | 14.28|
| Jigsaw-gender | DOMINO| 36.33  | 27.21|
| Jigsaw-racial | DOMINO| 19.61  | 10.96|

Table 14: Feature detection performance on pragmatic features

| Dataset | Model | Female | Male |
|---------|-------|--------|------|
| Metric  |       |        |      |
| CoLA    | DOMINO| 16.16  | 11.59|
| SST-5   | DOMINO| 15.19  | 9.09 |
| MNLI    | DOMINO| 12.53  | 6.87 |
| Jigsaw-religion | DOMINO| 11.63  | 9.71 |
| QNLI    | DOMINO| 13.76  | 10.57|
| QQP     | DOMINO| 21.43  | 14.28|
| Jigsaw-gender | DOMINO| 36.33  | 27.21|
| Jigsaw-racial | DOMINO| 19.61  | 10.96|

Table 15: Synthetic Feature detection precision, recall, F1 result

| Dataset | Model | Female | Male |
|---------|-------|--------|------|
| Metric  |       |        |      |
| CoLA    | DOMINO| 16.16  | 11.59|
| SST-5   | DOMINO| 15.19  | 9.09 |
| MNLI    | DOMINO| 12.53  | 6.87 |
| Jigsaw-religion | DOMINO| 11.63  | 9.71 |
| QNLI    | DOMINO| 13.76  | 10.57|
| QQP     | DOMINO| 21.43  | 14.28|
| Jigsaw-gender | DOMINO| 36.33  | 27.21|
| Jigsaw-racial | DOMINO| 19.61  | 10.96|

Table 16: Synthetic Feature detection F1 result on Jigsaw
| Metric | $\lambda = 0.5$ | $\lambda = 1$ | $\gamma = 0$ | $\gamma = 0.5$ |
|--------|-----------------|-----------------|-----------------|-----------------|
| Length | 44.75 | 28.82 | 100.00 | 28.90 |
| Negative | 17.50 | 17.50 | 17.50 | 17.50 |
| Reflexive | 82.89 | 19.13 | 18.56 | 10.39 |
| CP | 86.96 | 22.28 | 86.96 | 22.28 |
| MA | 63.16 | 100.00 | 63.16 | 100.00 |
| MP | 100.00 | 63.16 | 100.00 | 63.16 |
| Quantile | 54.02 | 37.00 | 54.02 | 37.00 |
| TP | 100.00 | 55.65 | 100.00 | 55.65 |
| LD | 29.69 | 17.46 | 29.69 | 17.46 |

Table 17: Ablation Study on Synthetic Feature Detection on CoLA dataset