StyLEx: Explaining Styles with Lexicon-Based Human Perception

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Abstract

Style plays a significant role in how humans express themselves and communicate with others. Large pre-trained language models produce impressive results on various style classification tasks. However, they often learn spurious domain-specific words to make predictions. This incorrect word importance learned by the model often leads to ambiguous token-level explanations which do not align with human perception of linguistic styles. To tackle this challenge, we introduce StyLEx, a model that learns annotated human perceptions of stylistic lexica and uses these stylistic words as additional information for predicting the style of a sentence. Our experiments show that StyLEx can provide human-like stylistic lexical explanations without sacrificing the performance of sentence-level style prediction on both original and out-of-domain datasets. Explanations from StyLEx show higher sufficiency, and plausibility when compared to human annotations, and are also more understandable by human judges compared to the existing widely-used saliency baseline.

1 Introduction

People use different styles to express themselves, convey their intention, and engage with the audience (Hovy, 1987; Kang and Hovy, 2021; Kabbara and Cheung, 2016). In understanding the style of the text, people often look at the words that signify the style, or are also known as stylistic cues. Large language models have achieved impressive results for many NLP tasks, including style classification. However, such models tend to learn the dataset instead of the task, producing spurious correlations between the word and the prediction label rather than finding the right cues (Sen et al., 2021; Schlangen, 2021; Bras et al., 2020).

For instance, words such as “performances” and “wrench” in Figure 1 are marked as positive cues for positive sentiment by a saliency method, which is different from how humans perceive the style. This stylistic word discrepancy was shown in Hayati et al. (2021) by comparing human-annotated lexicons with the model’s salient words. Motivated by this, we introduce StyLEx, a style classification model that learns the variability of human perceptions of stylistic words to explain and predict styles of sentences based on explanations (Figure 1). Hayati et al. (2021) define human perception as the human ratings of the contributions of words in a sentence to its style. We incorporate these human perception scores on each word of a sentence into the model by training a BERT-based classifier that jointly predicts the style label for both the sentence and words in the sentence.

In this study, we have developed a model which takes into account lexical stylistic variations as perceived by humans into account. We find that StyLEx’s explanations sufficiently reflect human perception of stylistic words compared to lexical
1. Train with HUMMINGBIRD
2. Label stylistic words
3. Train with word-labeled style dataset

StyLEx model architecture (left). Our model has two new modules: a word-level style predictor and a sentence-level style predictor. An aggregator appends the word-level style logit for each word to the hidden layer representations of each word and takes the max pooling of this aggregation. Human labels come from HUMMINGBIRD for stylistic word scores and from ORIGINAL datasets from sentence-level style classification.

Model training (right). (1) We train a stylistic word prediction model on HUMMINGBIRD dataset to (2) label sentences in the ORIGINAL datasets with stylistic words. (3) Then we train another stylistic sentence and word prediction model on this ORIGINAL sentences, now labeled with stylistic words.

Figure 2: StyLEx model architecture (left). Our model has two new modules: a word-level style predictor and a sentence-level style predictor. An aggregator appends the word-level style logit for each word to the hidden layer representations of each word and takes the max pooling of this aggregation. Human labels come from HUMMINGBIRD for stylistic word scores and from ORIGINAL datasets from sentence-level style classification.

Model training (right). (1) We train a stylistic word prediction model on HUMMINGBIRD dataset to (2) label sentences in the ORIGINAL datasets with stylistic words. (3) Then we train another stylistic sentence and word prediction model on this ORIGINAL sentences, now labeled with stylistic words.

2 StyLEx: Style Classification with Human-annotated Lexical Explanation

Given a style classification model that receives input sentence $x = \{x_1, \ldots, x_n\}$ where $x$ are words in the text and predicts the text’s style label $y$, StyLEx provides a set of lexical explanations $s = \{s_1, \ldots, s_n\}$ that mimics human perceptions where $s_i$ is the importance score of the $i$-th token $x_i$. We explain how to incorporate lexicon-based human perception into StyLEx architecture in §2.1. To train such model, we need a dataset of stylistic sentences along with their corresponding stylistic words. We use HUMMINGBIRD dataset contains 500 sentences with word-level style annotation from human perception for obtaining the stylistic lexical explanation (Hayati et al., 2021). Due to HUMMINGBIRD’s small size, we use benchmarking large-scale style datasets ($> 6.8k$ sentences in the training sets) for testing the classification and explanation performance of StyLEx. More details of styles and datasets that we use in this study are described in §2.2.

2.1 StyLEx Model Architecture

StyLEx is a joint model for word-level and sentence-level style prediction. Unlike a multi-task learning approach, StyLEx exploits these human perception scores to help predict the sentence’s styles. As displayed in Figure 2, StyLEx involves three modules: a transformer-based (Vaswani et al., 2017; Devlin et al., 2019) encoder, a word-level style predictor and a sentence-level style predictor. This work is based on BERT although the encoder
can be applied to any transformer architecture.

Given an input of token sequence \( x = \{x_1, ..., x_n\} \) and its corresponding set of stylistic important word scores \( \{s_1, ..., s_n\} \), we encode \( x \) using a pretrained transformer model. We extract the final layer output as \( h = \{h_1, ..., h_n\} \) and feed \( h \) to the word-level style prediction layer which is a neural classifier that outputs stylistic word logits for each word \( l_{\text{word}} \), computed as follows:

\[
l_{\text{word}} = W_i h_i + b_i
\]

where \( i \in \{1, ..., n\} \), \( W \in \mathbb{R}^{D \times d_{\text{word}}} \), and \( b \) is bias. \( d_{\text{word}} \) denotes the number of classes of each style (e.g., positive or negative word in a sentiment classification task).

For the sentence-level style classification, we first take both the encoded representation \( h \) and stylistic word logits \( l_p \). We then apply max pooling on the aggregation of \( h \oplus l_p \), resulting in vector \( v \in \mathbb{R}^{D+d_{\text{word}}} \) consisting of important logits. Finally, we input \( v \) into the sentence-level style classifier defined as follows:

\[
l_{\text{sentence}} = \text{softmax}(W v + b)
\]

\[
\text{Prob}_{\text{sentence}} = \text{arg max} (l_{s})
\]

where \( l_{\text{sentence}} \in \mathbb{R}^2 \) denotes sentence-level style logits, \( W \in \mathbb{R}^{D \times 2} \), and \( \text{Prob}_{\text{sentence}} \) is the index of the predicted sentence-level style.

During training, StyLEx’s objective is to maximize the probability of the sentence’s style and stylistic word scores. The loss for both style classifier and perception predictor is computed using binary cross entropy loss function. To jointly train the model, we optimize the following loss:

\[
\mathcal{L} = \mathcal{L}_{\text{style}} + \alpha \times \mathcal{L}_{\text{word}}
\]

where \( \alpha \) is a regularization hyperparameter.

### 2.2 Styles and Datasets

Following Hayati et al. (2021) that annotated lexicon-based style dataset, we explore the same set of eight styles used in the dataset: politeness, sentiment, offensiveness, and five emotions (anger, disgust, fear, joy, and sadness) for style classification tasks. We use three sets of existing datasets for our experiments as follows.

**HUMMINGBIRD** is a multi-style dataset annotated with human perception scores on its important stylistic lexicons (Hayati et al., 2021). HUMMINGBIRD contains 500 sentences based on eight style datasets: politeness, sentiment, offensiveness, and five emotions (anger, disgust, fear, joy, and sadness). Three different annotates each word in a sentence with 1 if they perceive the word as stylistic and 0 if not. The human perception score for a word is the average score of these annotators’ labels. This perception score is within the range \([-1, 1]\). We use HUMMINGBIRD for training StyLEx’s word-level style predictor.

**ORIGINAL datasets** are used by Hayati et al. (2021) to curate HUMMINGBIRD. Since some style labels in ORIGINAL may contain continuous numbers rather than binary labels, we follow the same setting of Hayati et al. (2021) which only uses binary labels: polite or impolite, positive or negative, offensive or not offensive, anger or not anger, and so on. The politeness dataset comes from StackExchange and Wikipedia requests (Socher et al., 2013) (117k training instances). The sentiment dataset is a collection of movie review texts (Socher et al., 2013) (117k training instances). The offensiveness dataset is from Twitter (Davidson et al., 2017) (20k training instances). The emotions dataset (Mohammad et al., 2018) is collected from tweets (6.8k training instances). For all these ORIGINAL datasets, we use the default train/dev/split as explained in their papers.

**Out-of-Domain (OOD) datasets** are used to evaluate StyLEx’s performance on different domains. For each style, we use data from different sources or topics, but their style labels are in HUMMINGBIRD and ORIGINAL datasets. For politeness, we use the polite and impolite sentences from the Enron email corpus (Klimt and Yang, 2004; Zampieri et al., 2019). For sentiment, we test StyLEx on 5-core reviews from Amazon review dataset (Ni et al., 2019) for each product categories, except for movie reviews. We exclude movie reviews because it would be similar to the domain of the ORIGINAL’s sentiment dataset. We convert ratings of 4-5 to positive labels and ratings of 1-2 as negative labels. For offensiveness, we use OffensEval (Zampieri et al., 2019) dataset for offensiveness. For five emotions, we collect Reddit comments from GoEmotions corpus (Demszky et al., 2020).

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1. We will refer to these individual datasets as “ORIGINAL.”

2. More details on the datasets are in Appendix A.1.
| Style         | Sentence-Level Style Classification | Sufficiency Test |
|--------------|-------------------------------------|------------------|
|              | ORIGINAL (%)                        | OOD (%)          |
|              | BERT  | StyLEx  | BERT  | StyLEx  | Top-k - ORIGINAL (%) |
| Politeness   | 67.96 | 65.84   | 71.45 | 74.18   | 43.92 | 63.08   |
| Sentiment    | 96.52 | 96.59   | 86.70 | 86.99   | 87.18 | 89.39   |
| Offensiveness| 97.75 | 97.81   | 88.62 | 89.00   | 84.87 | 91.26   |
| Anger        | 89.04 | 89.01   | 77.49 | 77.51   | 68.36 | 86.90   |
| Disgust      | 86.50 | 86.90   | 74.06 | 74.63   | 82.54 | 85.91   |
| Fear         | 95.66 | 95.63   | 78.42 | 78.48   | 87.82 | 96.10   |
| Joy          | 88.02 | 88.12   | 75.20 | 74.26   | 45.54 | 83.16   |
| Sadness      | 88.38 | 88.41   | 78.37 | 78.71   | 70.49 | 87.94   |

Table 1: In the column for sentence-level style classification results, StyLEx does not sacrifice the task performance (F1-scores) of the BERT model across all of the style tasks across both ORIGINAL and OOD settings. The results for Sufficiency test on the ORIGINAL data show the F1 scores on top-k words. IG stands for integrated gradient.

2.3 StyLEx Model Training

The whole pipeline of StyLEx model training is in Figure 2 (right). First, we train a stylistic word score prediction model with the same StyLEx architecture in Figure 2 (left). We do this since the sentences in the benchmarking style datasets do not have human perception scores on their words, we use a semi-supervised learning approach called, pseudo-labeling (Lee et al., 2013; Rizve et al., 2020), to label the stylistic words. Now the sentences in ORIGINAL contain stylistic word scores which are output by the stylistic word predictor. Second, we then use both HUMMINGBIRD and ORIGINAL for training the StyLEx model which predicts sentence-level binary style labels (polite/impolite, positive/negative etc.) and provide lexical explanation scores (in range [0, 1])\(^3\).

3 Evaluation on Style Classification

3.1 Baseline

To assess StyLEx’s classification performance, we compare it with a fine-tuned BERT-based classifier as a baseline. The training data for the baseline is also a combination of HUMMINGBIRD and ORIGINAL. For explanation evaluation, we compare StyLEx’s explanation with the commonly-used explanation method called layered integrated gradients (Mudrakarta et al., 2018; Sundararajan et al., 2017), implemented in Captum\(^4\), which can be viewed as an approximate method of estimating Shapley values. Integrated gradient is defined as follows. For the input sequence of words \(x\) and a neural network function \(F\), an attribution score (the explanation) for each word is defined as the gradient between the input \(x\) and baseline \(x'\) of the function \(F\) where \(x'\) is a zero scalar.

3.2 Results

In our experiment, we have eight StyLEx models for each style: politeness, sentiment, offensiveness, and five emotions. For each style, we run StyLEx on the ORIGINAL test sets and OOD datasets for five times with different seeds and report the average of F1-scores Table 1. For ORIGINAL datasets, StyLEx achieves higher F1 scores compared to the fine-tuned BERT model on sentiment, offensiveness, disgust, joy, and sadness. Overall, we observe that StyLEx does not sacrifice task performance of the state-of-the-art classifiers while predicting stylistic word scores. When tested on the OOD test sets, StyLEx achieves higher F1 score against the fine-tuned BERT model for all styles. Politeness has the greatest improvement from 71.48\% to 74.18\% since we observe that the ORIGINAL dataset of politeness contains many spurious content words. When we use bigger language models such as RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019), and T5 (Raffel et al., 2020) for StyLEx, StyLEx still has better results than the baseline for five styles: sentiment, offensiveness, anger, and disgust.

From example sentences from the test sets in Table 2, we can see how StyLEx helps task performance. ORIG-1 and ORIG-2 sentences show how StyLEx can capture stylistic words and correct the sentence’s style label to “disgust”. For example,
“insult” and “injury” in ORIG-1 are initially labeled by the integrated gradient method as unimportant for identifying *disgust*, but StyLEx identifies the words as stylistic cues. Similarly, for the word “downfall” in ORIG-2, StyLEx finds it as offensive, but the baseline does not. StyLEx also has a higher perception score for indicating “stogie” as an offensive word.

As we look at the politeness classification results, we find that most of the incorrect cases are when StyLEx mislabels subtle *impolite* sentences as *polite*. As we observe in Table 2 ORIG-3, StyLEx finds the word “please” as a polite cue, but the ground truth label of the sentence is *impolite*. We then inspect its continuous score from the original politeness dataset by Danescu et al. (2013). It turns out that its politeness score is approximately -0.38 in the range of [-2, 2] as -2 being the most impolite sentence. This means that the sentence’s impoliteness is definitely very weak. This finding also reflects how HUMMINGBIRD dataset has been collected: as mentioned in Hayati et al. (2021), words from the offensive dataset (mostly swear words) are often labeled as impolite by human annotators. Thus, it may bias the annotators’ view that sentences with impolite labels are not as bad as offensive sentences, making them not mark offensive sentences as *impolite*. Therefore, for such subtle impolite sentences, human annotators in HUMMINGBIRD may not label the sentence and words as impolite.

In contrast, for anger and fear, StyLEx misclassifies anger sentences as not anger and fear as not fear. As we look at ORIG-4 in Table 2, StyLEx weakly finds fear cues (“horrid”, “things”) but they do not help in boosting the model to predict the sentence as fear. We conjecture that this is because there are very few training samples labeled with *fear* and *fear* has quite low word-level inter-annotator agreement as reported in Hayati et al. (2021).

### 4 Evaluation on Style Explanation

We investigate StyLEx’s explanations if they are sufficient, plausible, and understandable following previous works (DeYoung et al., 2020; Jacovi and Goldberg, 2020; Wiegrefe and Marasovic, 2021; Rajagopal et al., 2021). Jacovi and Goldberg (2020) defines that a faithful interpretation represents a model’s reasoning process. To evaluate whether StyLEx’s explanations are faithful, we run a sufficiency test that evaluates whether the model explanations alone are highly relevant for predicting the label (Jacovi et al., 2018). Meanwhile, we measure plausibility to examine whether the explanation is agreeable to humans (DeYoung et al., 2020). Finally, understandability measures if user is able to understand model explanations (Rajagopal et al., 2021). For investigating sufficiency and plausibility, we run automatic metrics. To assess understandability, we ask human judges to choose
the explanation that can be better understood by a non-expert between StyLEx and the integrated gradients (IG) method.

### 4.1 Sufficiency

Following Jain et al. (2020); Rajagopal et al. (2021)’s sufficiency test, we fine-tune a BERT model by training it on the top-$k$ words as explanation instead of the whole sentence. We limit an explanation to contain 30% words of the average sentence length for each of the style datasets. These words are ranked based on their importance score by the baseline integrated gradient method and StyLEx for all the positive stylistic words (polite words, positive words, offensive words, angry words).

In Table 1, we can see that explanations from StyLEx show much higher predictive performance compared to explanations extracted by the integrated gradient method for all styles. This result suggests that human-like stylistic words are much more strongly predictive of a sentence’s style compared to the gradient-based explanation methods that often rely on content words as an explanation. This indicates that StyLEx’s explanations are relatively more faithful compared to the integrated gradients based saliency method.

### 4.2 Plausibility

We use two approaches to measure the agreement between StyLEx’s lexical explanations and stylistic words perceived by humans to assess the plausibility of StyLEx’s explanations. In the first approach, we compare StyLEx’s stylistic words on the HUMMINGBIRD test set and compare it with the ground truth human perception scores in HUMMINGBIRD. Second, we compare StyLEx’s top-$k$ stylistic words with existing expert-curated stylistic lexicon dictionaries. Figure 3 shows a scatterplot of StyLEx vs. the integrated gradient baseline. The X-axis represents the Pearson’s $r$ correlation score on the HUMMINGBIRD test set. The Y-axis is the percentage of overlapping words between the important words found by StyLEx and the baseline compared with the human-curated style lexicon dictionary. We calculate the overlapping word percentage as follows. We compute how many of the top 30% of the stylistic words in the ORIGINAL datasets found by StyLEx or baseline appear in human-curated dictionaries for the emotion/sentiment/offensive lexicons.

![Figure 3: Plausibility experiment result. There are two points for each style in this plot. A blue circle point is for the baseline IG method and a red star point for StyLEx. X-axis is Pearson’s $r$ correlation score for each style. Y-axis is the percentage of stylistic sentences with style words appearing in the existing style lexicon dictionary.](image)

In Figure 3, the higher the Pearson’s correlation score is (to the right), the better the explanation words produced by the model (StyLEx or baseline) are aligned with human perception ground truth from HUMMINGBIRD. The dashed lines shows how much StyLEx’s generated stylistic words align more with human’s perception of stylistic words from both HUMMINGBIRD and human-curated stylistic lexicon dictionaries.

1. **Correlation with human perception.** We investigate how similar StyLEx’s explanations are with human perceptions. To do so, we compute the Pearson’s correlation $r$ between perception scores predicted by StyLEx and human perception scores from HUMMINGBIRD annotations for each word by concatenating all the predicted perception scores. In Figure 3 (vertical trend), we can see that StyLEx explanations correlate more with ground truth human perception for all styles, as red stars are stretched to the right. Sentiment and offensiveness are styles that have the highest correlation scores (60.53% and 64.09%) while fear is the lowest (20.17%). Explanations from integrated gradient correlate very loosely with human perception ground truth with sentiment as the highest (11.89%) and joy negatively correlates with human perceptions (-2.55%).

2. **Comparison with existing stylistic lexicon dictionary.** We then investigate how similar the
| Style         | 🦅:both | 🦅:StyLEx | 🦅:Integrated gradient |
|--------------|---------|---------|------------------------|
| Positive     | good, fun, love | associate, develop, instruct | deserve, endure, football |
| Negative     | bad, horror, silly | mess, chaos, disappoint | maternal, banger, yell |
| Offensive     | bitch, bitches, pussy | blind, racist, panties | fairy, amateur, fisting |
| Anger         | angry, anger, awful | frowning, scare, lose | belt, campaigning, destroying* |
| Disgust       | awful, terrible, angry | dismal, frowning, animosity | congress, finally, sentence* |
| Fear          | fear, anxiety, nervous | horrid, war, threaten | rejects, mum, beating |
| Joy           | happy, love, good | faith, sing, succeed | deal, independence, football |
| Sadness       | depression, sadness, lost | bad, offended, leave | funeral, bloody, case* |

Table 3: Three important words found by StyLEx (🐦) and the integrated gradient method (🐦) that appear in stylistic lexicon dictionary. * = words only appear one time in the data.

StyLEx words found by StyLEx are to the stylistic words curated by humans in the existing lexicon dictionary. We use sentiment emotion lexicons from Mohammad and Turney (2010) and offensive lexicons from von Ahn’s research group (2021). Using the same set up of sufficiency test, we select top-30% stylistic words from each sentence in ORIGINAL datasets with the positive style label. Then we check if at least one of these words appear in the existing lexicon dictionary and compute its average across all training samples.

In Figure 3 (horizontal trend), we can see that StyLEx consistently has higher percentage of word occurrences in the lexicon dictionary compared to the integrated gradient method where fear has the highest percentage difference (from 15.78% to 80.43%) and offensiveness as the lowers percentage change (from 87.67% to 89.99%). Averaging across all styles, we find that 56.70% of the stylistic sentences with StyLEx stylistic words appear in the existing style lexicon dictionary while integrated gradient only identifies 37.01% of those words.

The score is higher for offensiveness than for sentiment or emotion. We observe that people use more offensive words in social media, which is the source for dataset collection. We also examine the lower occurrence for emotions. From our analysis, we found that the emotion lexicon dictionary contains several colloquially rare words “aberration” or “meritorious”, leading to a very low overlap with the datasets that we used for the analysis.

We also take a closer look at how many and the nature of important words are captured by StyLEx and/or the integrated gradient method as shown in Table 3. These word scores are obtained by averaging their scores and then we sort them based on these average scores. In general, we find that StyLEx can find more diverse stylistic words as defined in the existing lexicon dictionary for all styles except for positive sentiment. Some emotion words found by the integrated gradients only appear rarely in the data (mostly only once).

4.3 Understandability

To investigate the quality of StyLEx’s explanation, we ask human judges to evaluate StyLEx’s explanations compared to baseline explanations. Understandability asks whether human judges understand our explanation better than the explanation computed using integrated gradients. For this study, we randomly select 20 positive stylistic sentences for each of the eight styles, resulting in total 160 sentences. These 20 sentences are constructed by 10 sentences from ORIGINAL test set and 10 sentences...
from OOD test set. We normalize the perception scores for sentence length across all sentences.

We show a human judge two versions of the same sentence with different anonymized highlights by the two explanation methods as shown in Figure 1. We then ask the human judge to select (through Amazon Mechanical Turk) the explanation that was more understandable. Each worker annotated 20 sentences of the same style. The order of explanations is randomized to remove bias. Results in Figure 4 show that across all styles (160 pairs of explanations), StyLEx gives an overall gain of 34.62%.

5 Related Work

Styles in NLP

Research on style in NLP has addressed various tasks including style classification (Danescu et al., 2013; Socher et al., 2013), style transfer (Rao and Tetreault, 2018; Li et al., 2018), style and content disentanglement (John et al., 2018; Zhu et al., 2021), and multiple style analysis (Hayati et al., 2021; Kang and Hovy, 2021). In this work, we focus on understanding stylistic variation in style classification, since it is cleaner to analyze than stylistic text generation. Style classification models often produce spurious features (Sen et al., 2021; Schlangen, 2021; Bras et al., 2020), motivating us to leverage stylistic variation from human perspectives to distinguish between stylistic words and content words. While linguistics styles can cover an author’s writing style or figurative language, we limit our study to high-level style as used in Kang and Hovy (2021); Hayati et al. (2021).

Explainable NLP

Heat maps generated from attention values from the models (Bahdanau et al., 2014) are widely used as an interpretability tool, but these attention maps are often unfaithful and unreliable (Jain and Wallace, 2019; Wiegreffe and Pinter, 2019; Zhong et al., 2019; Pruthi et al., 2020). Saliency maps computed via gradients offer an alternative (Sundararajan et al., 2017; Smilkov et al., 2017; Mudrakarta et al., 2018). Annotating explanations as rationales (part of input) (Lei et al., 2016) through expert annotations (Zaidan and Eisner, 2008) is widely used to model explanations in NLP when external annotations are available. Another class of inherently interpretable models aims to optimize model explanations without any external annotations (Card et al., 2019; Croce et al., 2019; Rajagopal et al., 2021). Our work is similar in spirit to the rationale approaches (Lei et al., 2016) but focuses on understanding style attributes in text and computationally modeling them based on human perceptions of the important words.

6 Conclusion

We proposed StyLEx, a style classification model for learning stylistic variations through lexical explanation. With only 500 sentences with word-level style annotation, we find improvement in the classification and explanation. Compared to the commonly-used integrated gradient method, StyLEx’s explanations are better for model prediction, more consistent with human-found stylistic words from existing datasets and lexicon dictionaries, and better understandable by human judges, without sacrificing task performance on both original and out-of-domain datasets.

Limitation

Our work has some limitations, mostly stemming from the size and nature of the human-annotated data. The training data size of 500 sentences from HUMMINGBIRD is smaller than one might wish, especially for training deep learning models. However, our work shows that with just 500 sentences we could achieve a huge improvement in interpretability as well as a slight improvement in OOD performance. We also notice that the human perception data that we use is annotated by people residing in the United States. Thus, their stylistic perception may not cover the perception of those with different cultural backgrounds. Nevertheless, StyLEx is applicable to any kind of input dataset training with similar word-level human perception annotation; StyLEx is not limited to being used on the HUMMINGBIRD dataset.

Future Work

Our approach opens up future work on human-centered lexical explanation. We plan to investigate collecting more human perceptions to the model their variation and their impact, especially with larger pretrained language models. Broader usage of StyLEx in providing stylistic cues will be applicable to lexical style and content disentanglement (Cheng et al., 2020; John et al., 2019), counterfactual data augmentation for style-related tasks (Sen et al., 2021), and stylistic paraphrasing (Pavlick and Nenkova, 2015).

Ethical Considerations

When collecting the explanation evaluation from human judges, we inform them that the content may contain offensive languages that could be upsetting.
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A Appendix

A.1 Sampling OoD Data and Data Statistics

- Politeness: We randomly sample 500 polite sentences and 500 impolite sentences from the Enron email corpus (Klimt and Yang, 2004; Madaan et al., 2020) since the size of entire corpus (>600k) is too large for inference.

- Sentiment: We test StyLEx on 5-core reviews from Amazon review dataset (Ni et al., 2019). For each category, we sample 100 positive sentences and 100 negative sentences from review categories, except for movie reviews which would be similar to the domain of the ORIGINAL dataset. We convert ratings of 4-5 to positive labels and ratings of 1-2 as negative labels.

- Offensiveness: We use OffensEval (Zampieri et al., 2019) dataset for offensiveness. We select all offensive tweets (3,002 instances) and all non-offensive tweets (2,991 instances) since OffensEval dataset is already nearly balanced.

- Emotions: For five emotions, we collect samples from GoEmotions corpus (Demszky et al., 2020) that contains Reddit comments labeled with 27 emotions, but we only select the five relevant emotions. For each emotion, we use all data for the positive emotion (e.g., joy).
Table 4: Dataset statistics in our experiments. Note that these datasets are preprocessed from existing datasets. For HUMMINGBIRD (Hayati et al., 2021) and ORIGINAL datasets, the train, dev, and test sets have the same size for all emotions. We do not report the training size of Out-of-Domain (OOD) datasets since we are not using them for training. The label distributions for positive labels are in the parentheses.

| Styles | HUMMINGBIRD | ORIGINAL | OOD |
|--------|-------------|----------|-----|
|        | Train | Test | Train | Dev | Test | Test |
| Politeness | 256 (38%) | 64 (28%) | 9,855 (55%) | 530 (56%) | 567 (57%) | 1,000 (50%) |
| Sentiment | 312 (30%) | 79 (37%) | 117,219 (55%) | 825 (51%) | 1,749 (50%) | 5,200 (50%) |
| Offensiveness | 400 (34%) | 100 (32%) | 20,680 (82%) | 1,173 (82%) | 1,159 (81%) | 5,993 (50%) |
| Anger | 400 (35%) | 100 (34%) | 6,838 (37%) | 886 (36%) | 3,259 (34%) | 16,168 (50%) |
| Disgust | 400 (43%) | 100 (38%) | 6,838 (38%) | 886 (36%) | 3,259 (34%) | 10,602 (50%) |
| Fear | 400 (17%) | 100 (13%) | 6,838 (18%) | 886 (14%) | 3,259 (15%) | 6,394 (50%) |
| Joy | 400 (24%) | 100 (19%) | 6,838 (36%) | 886 (45%) | 3,259 (44%) | 15,966 (50%) |
| Sadness | 400 (29%) | 100 (17%) | 6,838 (29%) | 886 (30%) | 3,259 (29%) | 13,516 (50%) |

and undersample the negative emotion (e.g., not joy) data to equal the number of positive emotion samples.

The three dataset statistics are summarized in Table 4.

A.2 StyLEx Implementation Details

Throughout the experiment, we set $d_{\text{word}} = 2$ for politeness (polite, impolite) and sentiment (positive, negative) which have two style classes and $d_{\text{word}} = 1$ for the other styles. At the loss calculation step, we set the regularization hyperparameter $\alpha$ to 0.05 which gives the best style and perception prediction found searching the range [0.01, 100]. For the pseudo-labeling approach, we use the same architecture and hyperparameters with StyLEx model. We first train StyLEx with HUMMINGBIRD training set only to predict stylistic word scores for 50 epochs. Then we select the model with the best F1 score as a stylistic word score prediction to provide stylistic word scores for tokens in ORIGINAL training set. Then, we use both human-annotated perception score from HUMMINGBIRD and predicted stylistic word scores from ORIGINAL to train the sentence-level style prediction as in Figure 2. For the sentence-level model, we train the model for 5 epochs. For both stylistic word prediction and sentence-level style classification, we use BERT-base-uncased pretrained model. We set 0.1 dropout rate, 512 maximum sequence length, AdamW optimizer of learning rate $2e^{-5}$. For other hyper-parameters, we follow the default setting from HuggingFace’s transformer library (Wolf et al., 2020).

Our interface for human evaluation is shown as in Figure 5. Table 5 shows results for other pretrained language models.
Table 5: More classification results with several language models.