Stylex: Explaining Style Using Human Lexical Annotations

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1 What is StyLEx?

Motivation (Hayati et al., 2021)

all the performances are top notch and once you get through the accents all or nothing becomes an emotional though still positive wrench of a sit

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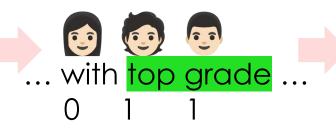




How can we incorporate human perceptions for improving model explanation on generating stylistic lexica?









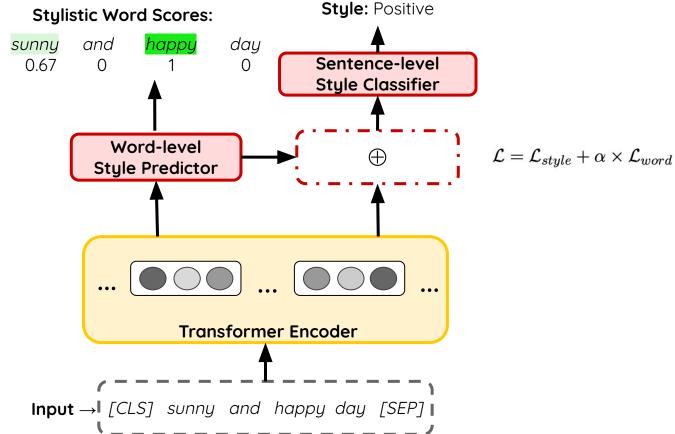
Explanation:

top notch

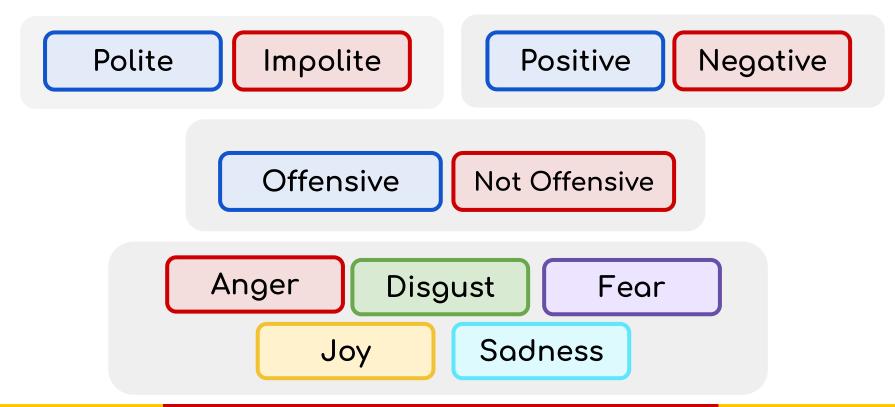
all the performances are top notch and once you get ...

StyLEx





8 Linguistic Styles (Hayati et al., 2021)



Datasets



V

Lexical Annotation

Source: Original (ORIG)

#Instances: 500 for each style

Original (ORIG)

Out-of-Domain (OoD)



Sources:

• Politeness: Wikipedia, StackExchange

• **Sentiment:** Movie review

• **Offensiveness:** Twitter

• **Emotions:** Twitter

#Instances: 6.8k - 238k



Sources:

• Politeness: Corporate email

• **Sentiment**: Product review

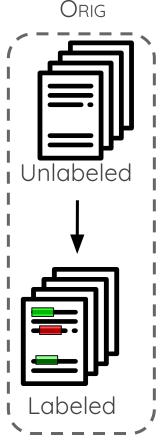
• Offensiveness: Twitter

Emotions: Reddit posts

#Instances: 1k - 16k

StyLEx Training





3. Train with word-labeled style dataset







Experiment & Discussion

Experiment Setup



Generalizability → Model performance (F1-score)

Baseline: Fine-tuned BERT models (Orig + Hummingbird)



 $\textbf{Explainability} \rightarrow \bullet \quad \text{Sufficiency}$

- Plausibility
- Understandability

Baseline: Integrated Gradient (Sundaranjan et al., 2017;

Mudrakarta et al., 2018; and used by Hayati et al., 2021)

Style Classification Results

Style	Original		OOD	
	Baseline	StyLEx	Baseline	StyLEx
Politeness	<u>67.96%</u>	65.84%	71.45%	<u>74.18%</u>
Sentiment	96.52%	<u>96.59%</u>	85.45%	<u>86.18%</u>
Offensiveness	97.75%	<u>97.81%</u>	88.62%	<u>88.98%</u>
Disgust	86.50%	86.90%	74.06%	<u>74.63%</u>
Sadness	88.38%	<u>88.41%</u>	78.37%	<u>78.71%</u>

Baseline: Fine-tuned BERT model with ORIG & HUMMINGBIRD Training Sets

* Please refer to the paper for full result

Example



... because I'm gonna add insult to injury

... because I'm gonna add insult to injury

Disgust 🔽

Not Disgust X



... please put them all back are you on dsl

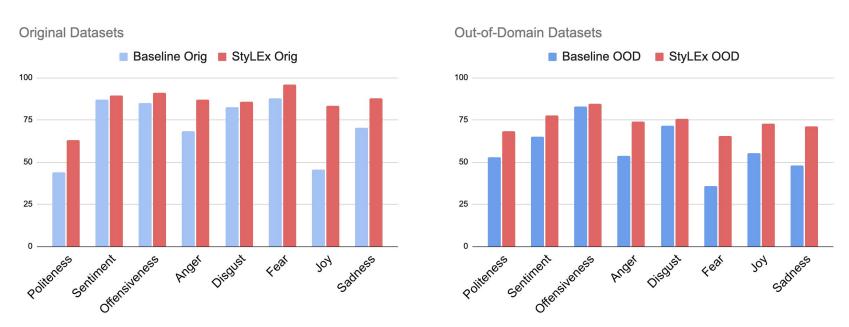
... please put them all back are you on dsl

Polite 🗶

Impolite 🔽

Sufficiency

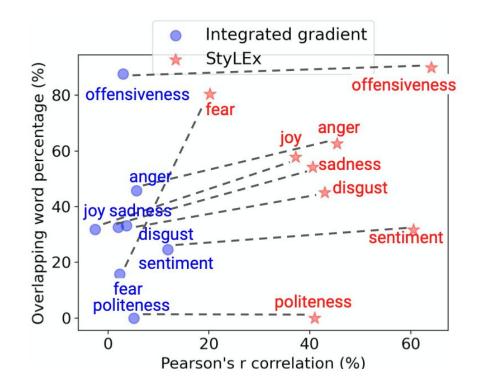
F1 scores for fine-tuning BERT with top-k important words



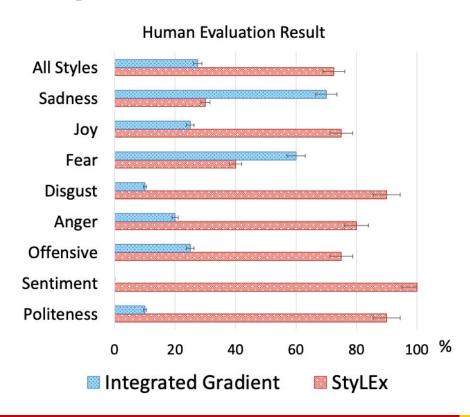
Baseline: Integrated Gradient (Sundaranjan et al., 2017; Mudrakarta et al., 2018)

Plausibility

- Correlation with human perception
- Comparison with stylistic lexicon dictionary



Understandability



Takeaways

- 1 StyLEx provides explanation and doesn't hurt performance
- 2 StyLEx's explanations are sufficient for model prediction and more preferred by humans
- StyLEx is more generalized than the baseline (Out-of-Domain results)

Limitations and Future Work

- Increasing the dataset size and including more styles, e.g., formality, humor, etc., and phrase-level explanation.
- 2 Capturing subtle stylistic words and handling sparsity in stylistic words.

3 Applying to style-content disentanglement for stylistic text generation.

Thank you!

https://github.com/minnesotanlp/stylex