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# Leveraging Low-resource Parallel Data for Text Style Transfer

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# Introduction

# Text Style Transfer(TST)



- Change style of given input text.
  - Preserve style-independent content.
  - **Style:** *demographic attrib (personality, gender), sentiment, politeness, etc.*
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- No parallel data sets.
  - Hard to detect styles.
  - Preserving the structure and meaning of the input.
  - Automatic evaluations.
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# Sentiment Transfer

- A sub-task of TST
  - Converts positive to negative text and vice versa,
  - Without changing content.
  - **Uses:**
    - Marketing
    - Content Moderation
    - Communication improvement
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# EXAMPLE

*Neg:* The food is tasteless.



*Pos:* The food is delicious.

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# Parallel vs Non Parallel dataset in TST

- Parallel Data
  - Sentence pairs with aligned content and style labels
  - Limited Availability
    - Collecting & aligning can be time-consuming and expensive
- Non-Parallel Data
  - Sentence pairs that lacks aligned content and style labels.
    - Sentences where the content and style are not matched together
  - Model Complexity
    - Requires sophisticated models for effective style transfer

# Our Work



# Overview

- Aim: best of both parallel & non-parallel
- Building a TST system with low-resource parallel data
  - Application of multiple low-resource adaptation techniques
  - Introduction of a novel style reward approach
- Well-balanced results
  - Surpassing previous non-parallel approaches
  - In both automatic and human evaluation

# Methodologies

- Hyperparameter tuning
  - Prompt-guided generation
  - Data augmentation
  - Self-training & Filtering
  - Style reward
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# Prompt-guided generation

*POS*: everything is fresh and so delicious !



*NEG*: everything was so stale

# Data augmentation

Methods	Original Text	Augmented Text
<i>Spelling</i>	we went with a group of eight and all had a great time .	we went with a group <b>od eight</b> and all <b>has</b> and great <b>tiem</b> .
<i>Insert</i>	we went with a group of eight and all had a great time .	we <b>all</b> went <b>there</b> with <b>such a</b> group of eight and all had <b>had</b> a <b>completely</b> great time.
<i>Substitute</i>	seriously though , i have never shopped here .	seriously <b>sara</b> , i <b>actually</b> never shopped <b>anywhere</b> .
<i>Synonym</i>	great prices , great selection .	great price, great <b>excerption</b> .
<i>Swap</i>	really enjoyed the beautiful range .	<b>enjoyed really beautiful the</b> range.
<i>Delete</i>	seriously <b>though</b> , i <b>have never</b> shopped here .	seriously, i shopped here.
<i>Split</i>	the place was too packed, we did not enjoy it	the <b>pla ce</b> was too <b>p acked</b> , we did not <b>e njoy</b> it
<i>Back_translation</i>	the biscuits and gravy were good .	the <b>cookies</b> and <b>sauce</b> were good.

# Self-training & Filtering

*Original Input:* everything is fresh and so delicious !



*Synthetic Output:* these donuts have the worst texture and taste.

*(generated by base model)*

## Filtering

- Enhancing Synthetic Data Quality
- *Filtering Criteria:* style classifier accuracy, BLEU, and embedding similarity.
- *Sentence Scoring:* the geometric mean of these metrics.
- *Selecting Top Scores:* best of the generated synthetic data with the highest scores (*top k*).

# Style reward

- *Aim*: improve generator focus on the target style accuracy.
- Use rewards from a style classifier in the training loss.
- *Reward* : +1 for matching the target style, -1 for not matching.
- Train with weighted combination of style rewards & cross-entropy loss

**Task:** *Pos* to *Neg*

*Input*: everything is fresh and so delicious !  
delicious !



*Generated Output*: everything is fresh and so

**R:** -1

*Input*: everything is fresh and so delicious !



*Generated Output*: everything was so stale.

**R:** +1

# Datasets

- Small parallel sentiment transfer dataset
  - From Yelp reviews by Li et al. (2018)
  - 500 positive-to-negative sentences
  - 500 negative-to-positive sentences
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# Evaluation

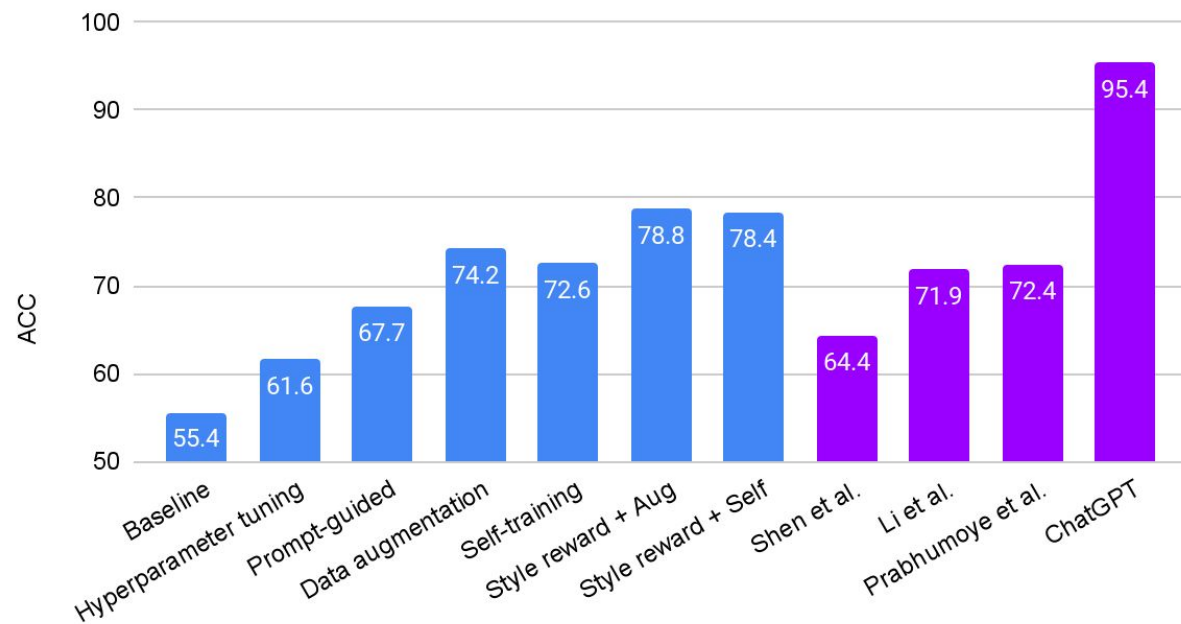
- Automatic evaluation
    - Sentiment Transfer: sentiment classifier accuracy
    - Content Preservation: BLEU, SBERT cosine similarity
    - Fluency: GPT-2 PPL
  - Human evaluation
    - Style transfer, content preservation, fluency
    - 1-5 Likert scales
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# Results

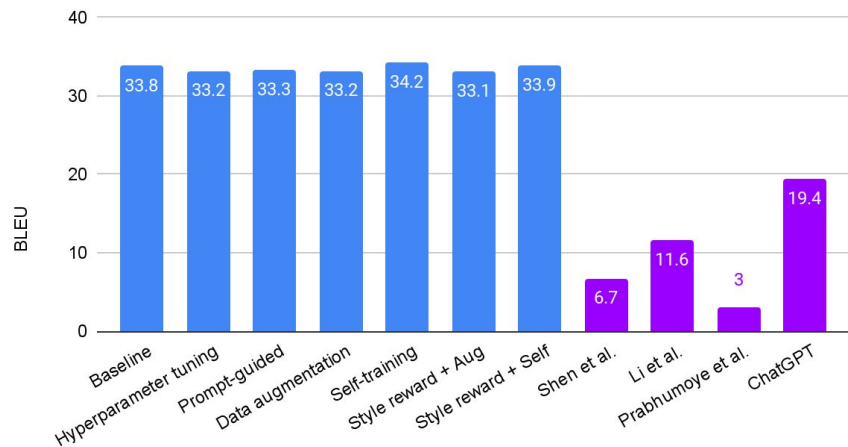
# Automatic: Style Transfer Accuracy

Classifier Accuracy

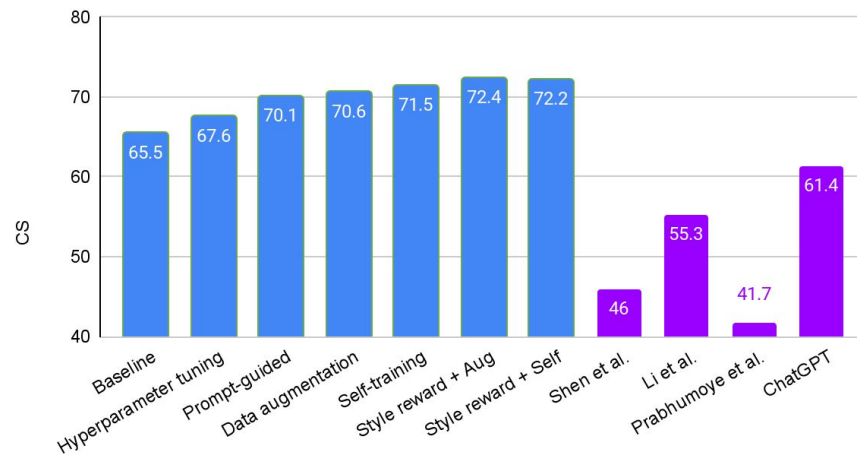


# Automatic: Content Preservation

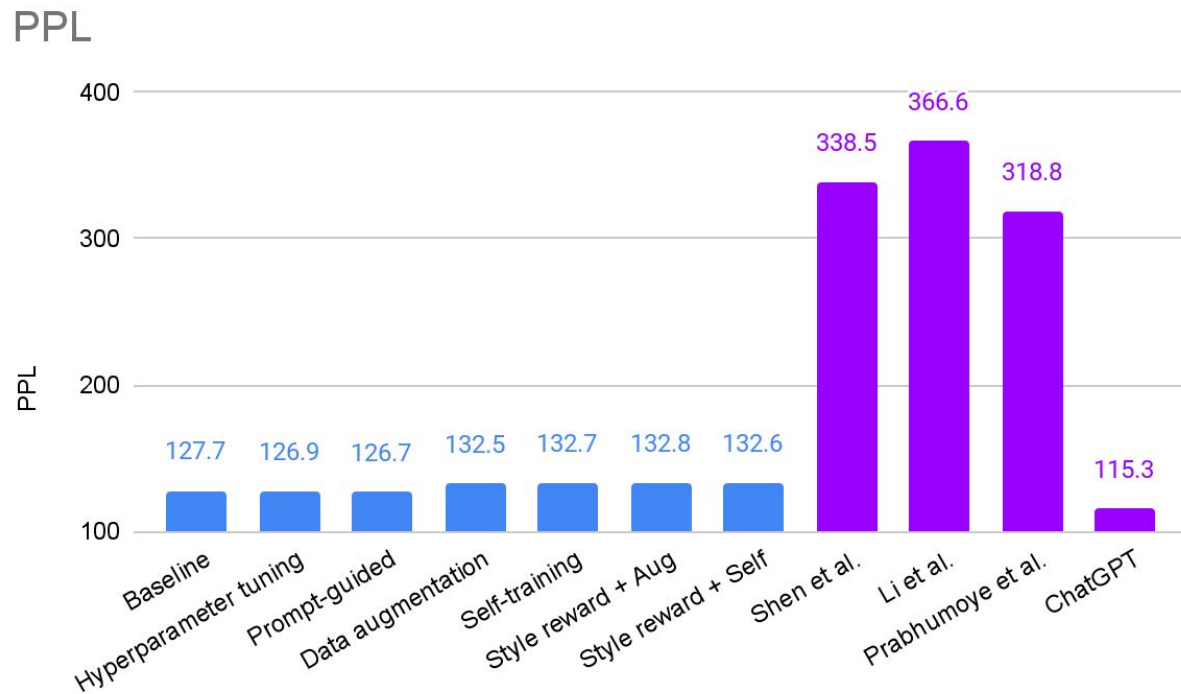
BLEU



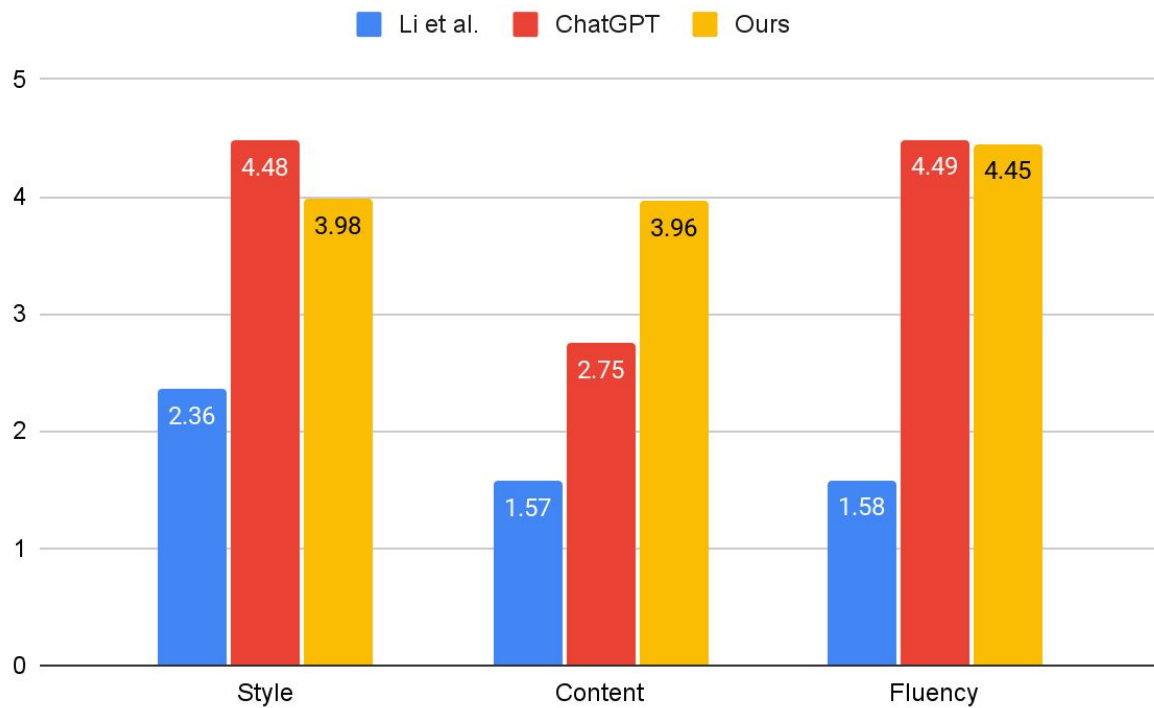
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# Automatic: Fluency



# Human Evaluation



# Conclusion

- *Text Style Transfer (TST)*: a growing research area
  - Challenges: content preservation and style transfer together, linguistic consistency, evaluation
- Our contributions:
  - Effective Use of Minimal Parallel Data
  - Style Classifier Rewards Further Improve Performance
  - Achieving Balanced Style Transfer, Content Preservation, and Fluency
    - Outperformed Non-Parallel Approaches
    - Value of Parallel Data: Highlighted its usefulness even with limited amounts.
- Future work:
  - Expanding Low-Resource Techniques
  - Exploring Different Style Transfer Tasks

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# Thank You

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 [https://github.com/souro/low\\_tst](https://github.com/souro/low_tst)

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