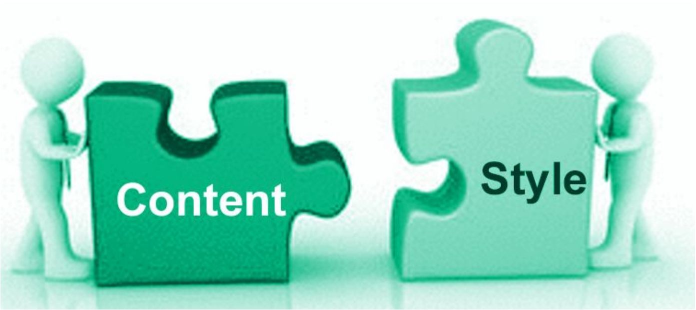
Low-Resource Text Style Transfer for Bangla: Data & Models

Sourabrata Mukherjee[1], Akanksha Bansal[2], Pritha Majumdar[2]
Atul Kr. Ojha[3,2], Ondřej Dušek[1]
[1]Charles University, Faculty of Mathematics and Physics, Prague, Czechia
[2]Panlingua Language Processing LLP, India
[3]Insight SFI Centre for Data Analytics, DSI, University of Galway, Ireland
`{mukherjee,odusek}@ufal.mff.cuni.cz`
`{akanksha.bansal,pritha.majumdar}@panlingua.co.in`
`atulkumar.ojha@insight-centre.org`

Introduction

Text Style Transfer(TST)



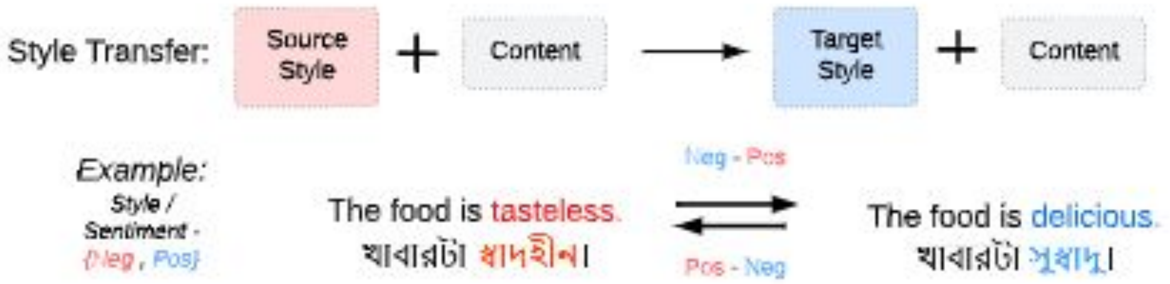
- Change style of given input text.
- Preserve style-independent content.
- **Style**: *demographic attrib (personality, gender), sentiment, politeness, etc.*

- No parallel data sets.
- Hard to detect styles.
- Preserving the structure and meaning of the input.
- Automatic evaluations.

Sentiment Transfer

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

Example


Style Transfer:
Source Style
+
Content
Target Style
+
Content
Example:
Style / Sentiment - {Neg , Pos}
The food is tasteless.
খাবারটা স্বাদহীন।
Neg - Pos
Pos - Neg
The food is delicious.
খাবারটা সুস্বাদু।

Multilingual low-resource languages in TST research

- **Limited Exploration**: Multilingual text style transfer (TST) is underexplored.
    - Briakou et al. (2021) found only one TST work in languages: Chinese, Russian, Latvian, Estonian, and French.
    - And they introduced a formality transfer multilingual evaluation dataset.
- **Low-Resource Gap:** Little to no exploration of low-resource TST.

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

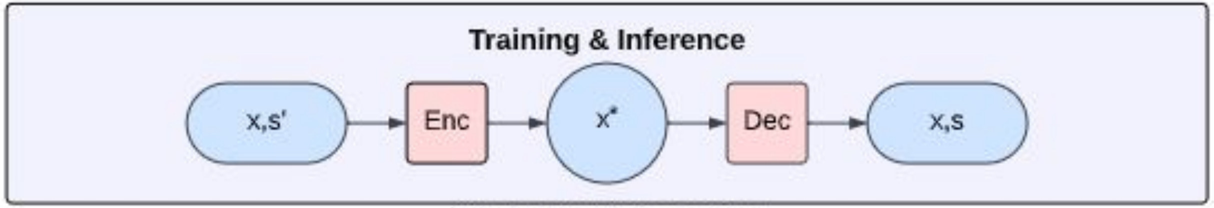
Overview

- **English Dataset Enhancement**
  - Improved quality of an existing English parallel dataset
- **Bangla Dataset Introduction**
  - New low-resource Bangla parallel dataset aligned with the English counterpart
- **Benchmark Models:**
  - Assessing baseline model performance on the datasets
- **Challenging Scenarios**:
  - No style-parallel data or without using human-annotated Bangla data
  - Instead opted for English-to-Bangla machine translation
  - Demonstrating potential meaningful results with limited or no language-specific resources.

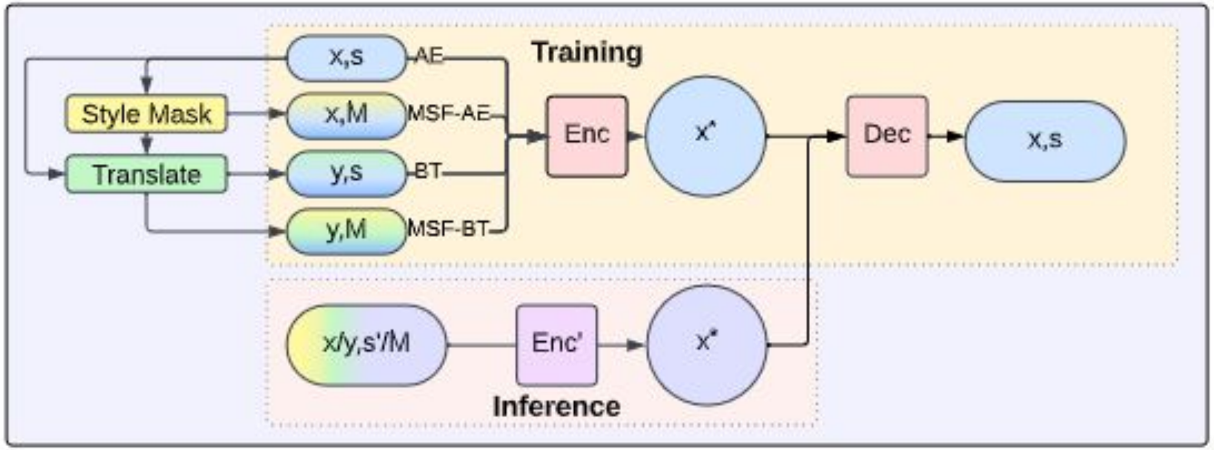
Methodologies

- Parallel Style Transfer
- Non-parallel Style Transfer
- Cross-Lingual Style Transfer

Overview



(1) Parallel Style Transfer



(2) Non-parallel Style Transfer

Parallel Style Transfer

- Fine-tuning of multilingual BART model
- Using style-parallel English and Bangla TST datasets

Non-parallel Style Transfer

- Sequential use of non-parallel data
  - Utilization of positive or negative data parts separately
- Input reconstruction
  - Auto-encoder (AE) *(Shen et al., 2017; Li et al., 2021)*
  - Back-translation (BT) *(Prabhakaran et al., 2018; Mukherjee et al., 2022)*
    - EN -> BN -> EN cycle for English text
    - BN -> EN -> BN cycle for Bangla text
- **Training** of two separate models
  - for each sentiment (positive and negative)
  - using AE and BT approaches
- **Inference**: input fed to the model trained on the target sentiment.

Masked Style Filling (MSF)

- Extension of AE and BT approaches
  - via style-specific lexicon masking in input sentences
- Application of integrated gradients
  - a model interpretability technique, *(Janizek et al., 2021)*
- Generation of word attribution scores
  - to reveal contributions to the style classifier's prediction
- Selective masking of style lexicon based on attribution score threshold
- **Objective:** Creation of "style-independent" sentences without specific stylistic markers
- Use of modified sentences as input
  - to AE and BT reconstruction models for original sentence reconstruction

Cross-Lingual Style Transfer

- Investigated two cross-lingual alternatives to bypass the use of a human annotated Bangla TST dataset.
  - ~ simulating the case when a TST dataset is unavailable for a specific language.
- Method 1:
  - translate English sentences from a parallel dataset into Bangla,
  - and employ this for training.
- Method 2:
  - Translate the English output generated by a model trained on a parallel English dataset into Bangla.

Dataset Creation

- Overview
- English Data Correction
- Creation of Bangla Data

Overview

- Employed the publicly available Yelp dataset (Li et al., 2018).
    - comprises user-generated reviews for hospitality establishments
    - is in English
- **Sentiment Reversal:** Each original positive or negative review sentence has a parallel sentence with flipped sentiment, retaining sentiment-independent content.
- **Size:** Consists of 500 sentences transferred from negative to positive and another 500 from positive to negative.

English Data Correction

- The original English Yelp dataset exhibited discrepancies
  - spelling mistakes,
  - incorrect sentiment labeling (flipped or neutral),
  - compromise on naturalness,
  - loss of preservable context,
  - and incorrect sentiment changes in the target data,
    - particularly for implicitly expressed sentiment,
  - …
- A total of 451 sentences out of 1,000 were edited to align with the experiment's requirements.

Creation of Bangla Data

- Dataset translated from English to Bangla to align with the experiment's objectives.
- **Few challenges:**
  - Natural expressions in English may seem unnatural in Bangla, risking loss of complete lexical context
  - Difficulties in preserving multiple interpretations due to ambiguity and implied meanings
  - Use of similar phrases to maintain naturalness, potentially compromising lexical context
  - Complications arise from slang words, unclear meanings, and instances of ambiguity
  - Consistency is crucial; variations in translation for small datasets impact results
    - e.g., "bland" translated as "flavourless" or "tasteless"
  - Maintaining consistency is challenging, and cultural knowledge gaps may lead to misinterpretations
    - e.g., 'bs' meaning 'bullshit'

Evaluation

- Automatic evaluation
  - Sentiment Transfer: sentiment classifier accuracy
  - Content Preservation: BLEU, SBERT cosine similarity
  - Fluency: multi-lingual GPT PPL

Results

Automatic Evaluation

Models	English				Bangla			
	ACC	BLEU	CS	PPL	ACC	BLEU	CS	PPL
Parallel Style Transfer								
Parallel	77.0	46.5	81.0	97.5	66.0	34.5	81.0	7.7
Non-parallel Style Transfer								
AE	13.0	42.0	78.0	102.2	17.0	31.0	78.0	7.8
BT	28.0	10.0	64.5	139.4	33.5	3.0	63.5	7.3
MSF-AE	59.5	37.5	75.5	136.0	72.0	26.5	72.5	7.9
MSF-BT	59.5	9.5	62.0	90.2	55.5	1.0	43.0	26.7
Cross-Lingual Style Transfer								
Train-En-TR	-				61.0	28.0	79.0	7.7
En-OP-TR	-				64.5	6.0	74.5	6.8

Conclusion

- *Text Style Transfer (TST)*: a growing research area
  - Challenges: content preservation and style transfer together, linguistic consistency, evaluation
- Our contributions:
  - Text style transfer in the challenging domain of the Bangla language, addressing the scarcity of resources in this area
  - Contribution of essential resources and benchmark models for both Bangla and English
- Future work:
  - To explore underrepresented languages in multilingual Text Style Transfer (TST) research

Thank You

mukherjee@ufal.mff.cuni.cz

Code: https://github.com/souro/multilingual_tst

Data: https://github.com/panlingua/multilingual-tst-datasets

This research was supported by Charles University projects GAUK 392221, and SVV 260575, and by the European Research Council (Grant agreement No. 101039303 NG-NLG), and by Insight SFI SFI/12/RC/2289_P2.

European Research Council
Established by the European Commission