Stylistic Transfer in Natural Language Generation Systems Using Recurrent Neural Networks

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Stylistic Transfer

Stylistic transfer: changing the style of a passage while preserving its meaning

Text in Style 1 → Model → Text in Style 2

Example from Shakespeare’s As You Like It

Input: As I remember, Adam, it was upon this fashion bequeathed me by will but poor a thousand crowns, and, as thou sayest, charged my brother on his blessing to breed me well. And there begins my sadness.

Output: I remember, Adam, that's exactly why my father only left me a thousand crowns in his will. And as you know, my father asked my brother to make sure that I was brought up well. And that's where my sadness begins.

Applications

- Making old texts more accessible to a contemporary reader
- Reproducing technical articles to a broader audience
- Security/Privacy: Author obfuscation

The Learning Model

Past work requires expensive parallel data!

→ Task proposal:
- Use deep learning to tackle stylistic transfer
- Inspired by work in image processing (e.g., Cheung et al. 2014)

Highlights

- Recurrent Neural Network
- Encoder-Decoder Structure
- Separate content features from style features
- Cross-covariance term in cost function

Key points

- No need for time-consuming design of linguistic features (which may not generalize well anyway)
- No need for (expensive!) parallel data

The model in a nutshell

Output Sentence

LSTM Layer: Decoder

Content features

Style features

Input Sentence

LSTM Layer: Encoder

Approach

For a style transfer task from Style A to Style B:
- Collect relevant corpora for each style
- Train a model on each style to learn the stylistic features for that style
- During generation, use corresponding stylistic features for desired style

Evaluation

Three main criteria for evaluation:

- Soundness (textually entailed with the original version?)
- Coherence (free of grammatical errors? proper word usage? etc.)
- Effectiveness (match the desired style?)

- Human evaluation of snippets of generated text
- Automatic evaluation (e.g., ROUGE, BLEU)

Related Work

- Inkpen et al. (2004): Use list of near-synonyms
- Xu et al. (2012): Two approaches:
  (1) Translation framework
  (2) Set of rules for linguistic transfer
- Sennrich et al. (2016): adding side constraints (features) to control politeness in translation

Hypothesis:

- Weight sharing
- Learning across training samples all sharing the same style

Stylistic latent variables would capture a high-level representation of style, complimentary to that of content variables.