Research Proposal: Style Transfer Exploration

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1 Problem Statement

Style identification is the identification of style in a text passage by an automated process, often a language model. Generative models can generate text in one or more styles, given content and style parameters. Style identification has proven utility in applications like author attribution (Houvardas). I intend to use it for an arguably more ambitious goal - to convincingly rewrite a textual passage into a new style.

There is active research in style transfer. Ficler uses fixed, human-intelligable stylistic parameters like 'length' and 'sentiment', which can be extracted from specific training data with heuristics. They use perplexity as an evaluation metric.

In contrast, I plan to use an NN language model to learn stylistic parameters that aren't necessarily human-intelligible and are agnostic to the structure of training data. I plan to use Kabbara's proposal as a guide.

2 Objective

To coerce a passage of English input text to a certain author's style, retaining maximal semantic similarity.

3 Action Plan

3.1

Perform further literature review. The below steps may change accordingly.

3.2

Acquire and structure training data. My focus on author-wise style and NN LMs' need for lots of training data indicate that using Project Gutenberg's text archive for authors with large oeuvres is a natural choice. Each oeuvre can be broken up into many passages and labeled programmatically.

3.3

Implement Kabbara's proposal with a technique proposed by Ficler: inject a learned context tensor c into various layers of a conditional NN learning model, effectively changing the model's sentence probability equation from:

$\prod_{t=1}^{n} P(w_t|w_1, \ldots, w_{t-1})$

to:

$\prod_{t=1}^{n} P(w_t|w_1, \ldots, w_{t-1}, c)$

This affords flexibility to easily add hand-engineered context as a method for further exploration. I will draw on (Cho, Bengio) for insight into particular RNN configurations to experiment with, including LSTM, grConv, and convolution RNNs.

3.4

Evaluate model(s) using perplexity. For example, I would determine the perplexity of A and A', where A' is the output of the style transfer language model of input A.

3.5 (Reach goal / optional)

Explore alternative evaluation metrics. Style transfer assumes a high degree of semantic similarity between passages. Perplexity is a problmatic evaluation technique because it penalizes passages that contain different words, but are semantically similar. ROUGE and BLEU scoring have the same problem. Creating a new evaluation metric (or uncovering one in existing literature) would be beneficial. One evaluation metric I may explore is a weighted perplexity and entailment-match combination.

3.6 (Note on alternative plan)

Reducing sentences to lambda-calculus semantic representations (Zettlemoyer) and then expanding them back to full sentences in a new style seems like another promising approach, but is determined out of scope for this project.

4 Cited Sources

(Kabbara) "Stylistic Transfer in Natural Language Generation Systems Using Recurrent Neural Networks". Jad Kabbara and Jackie Chi Kit Cheung, 2016.

(Cho, Bengio) "On the Properties of Neural Machine Translation: Encoder-Decoder Approaches". Kyunghyun Cho, Yoshua Bengio, et al, 2014.

(Ficler) "Controlling Linguistic Style Aspects in Neural Language Generation". Jessica Ficler and Yoav Goldberg, 2017.

(Houvardas) "N-Gram Feature Selection for Authorship Identification". John Houvardas, 2006.

(Zettlemoyer) "Online Learning of Relaxed CCG Grammars for Parsing to Logical Form." Zettlemoyer, Collins, 2007.