User Modeling, Conversational Style Transfer

Zhenhui Peng
Hong Kong University of
Science and Technology
zpengab@connect.ust.hk

ABSTRACT
UPDATED—November 8, 2019. This sample paper describes the formatting requirements for SIGCHI conference proceedings, and offers recommendations on writing for the worldwide SIGCHI readership. Please review this document even if you have submitted to SIGCHI conferences before, as some format details have changed relative to previous years. Abstracts should be about 150 words and are required.

Author Keywords
Authors' choice; of terms; separated; by semicolons; include commas, within terms only; this section is required.

CCS Concepts
•**Human-centered computing** → **Human computer interaction (HCI);** *Haptic devices;* User studies; Please use the 2012 Classifiers and see this link to embed them in the text: https://dl.acm.org/ccs/ccs_flat.cfm

RELATED WORK
- User Profiling Trends, Techniques and Applications
  - In recommendation system
  - User Profiling can be defined as the process of identifying the data about a user interest domain
  - User profiling has two important aspects as efficiently knowing user and based on those recommending items of his interest
  - behavioral user profiling (implicitly)
    * Content based filtering: recommends items based on a comparison between the content of the items with a user profile and selects those items whose content best matches with the content of another item.
    * Collaborative filtering: involves clustering the users with the similar interest groups.
- A Persona-Based Neural Conversation Model
  - Generation-based dialogue system
  - A persona can be viewed as a composite of elements of identity (background facts or user profile), language behavior, and interaction style.
  - Seq2Seq
  - Speaker Model (model the personality of the respondent): Speaker embedding + word embedding
  - Speaker-Addressee Model: predict how speaker 1 would respond to a message produced by speaker j.
  - Dataset: Scripts for the TV series Friends; Twitter Persona Dataset; Twitter Sordoni Dataset
- A Combination Approach to Web User Profiling
  - Formalizes the profiling problem as several subtasks: profile extraction, profile integration, and user interest discovery.
- Style Transfer in Text: Exploration and Evaluation (AAAI 2018)
  - Lack of parallel data - learning style transfer from non-parallel data
  - Lack of reliable evaluation metrics - transfer strength and content preservation
  - Paper title to news title, positive-negative review
  - The encoder generate content representation, the style information is incorporated in the decoder. Question here is that the information can be strictly divided into content and style?
- Unsupervised Text Style Transfer using Language Models as Discriminators (NIPS 2018)
  - Previous discriminators: CNN classifiers. Proposed discriminators: language models
  - Three tasks
    * word substitution decipherment
    * sentiment modification: negative <-> positive sentence
    * related languange translation
  - Two GANs: one for reconstruction the original sentence, the other for transfer sentence
  - Many recent works assume there exist a share content space and a latent style vector between two non-parallel corpora for unsupervised language style transfer.

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- Unsupervised Stylish Image Description Generation via Domain Layer Norm (AAAI 2019)
  - Concepts: Skip-Thought Vectors, Layer Normalized Long Short Term Memory;
  - Proposed Domain Layer Norm (DLN) scheme to model generation functions in two domains
  - Still, separate style and content, but using DLN
  - Measure semantic relevance between generaed stylish sentences and the unstylished ground truth by content similarity (word-based, not vector-based)
  - Measure stylishness using transfer accuracy by a pre-trained style classifier
  - Plus a human evaluation study on MTurk
  - Has interesting examples
- Unsupervised Controllable Text Formalization (AAAI 2019)
  - The usage of text style transfer in dialogue system: For ex- ample, in the context of commercial dialog systems alone, there are several scenarios where a system's answer (which may be coming from a database (Jain et al. 2018)) needs to be transformed either for its tone (politeness, excitedness, etc.), or its level of formality (casual, formal, etc. based on the user's personality), or for its complexity (simplifying linguistic or domain-specific terminology such as in legal or medical domains).
  - Task: formalizing the input text, where the readability of the output text is improved while preserving its meaning.
  - Encoder-decoder, the decoder additionally takes user=specified control as input.
  - Scorers based on NLP tools, indicating: 1) how formal the generated text is (the Flesch-Kincaid readability index), 2) whether the generated text is fluent (4-gram back-off language model), 3) whether the generated text carries similar semantics as the input (document similarity).
  - Exploration to produce training data for controllable generation, exploitation for training the encoder-decoder.
  - Has human evaluation
- Controllable Unsupervised Text Attribute Transfer via Editing Entangled Latent Representation (NIPS 2019)
  - The dominant approaches are trying to model the content-independent attribute separately, e.g., learning different attributes' representations or using multiple attribute-specific decoders.
  - Problem: inflexibility in controlling the degree of transfer or transferring over multiple aspects at the same time.
  - Propose: replaces the process of modeling attribute with minimal editing of latent representations based on an attribute classifier. (Make their latent space similar to each other)
  - The generated text should meet the **requirements**: (i) maintaining the attribute-independent content as the source text, (ii) conforming to the target attribute and (iii) still maintaining the linguistic fluency.
  - Dataset: Yelp (negative, positive), Amazon (negative, positive), Captions (humorous, romantic), Beer Advocate
  - Measure: text fluency (PPL) and transfer success rate, BLEU, human evaluation
  - Good, making paper in the latent space
- Touch Your Heart: A Tone-aware Chatbot for Customer Care on Social Media (CHI 2018)
  - The way to generate pair conversation from the multi-turn dataset: the history utterances as X, the current response as Y.
- Fighting Offensive Language on Social Media with Unsupervised Text Style Transfer (2018)
  - Dataset: datasets of offensive and non-offensive texts by leveraging Henderson et al. (2018)'s pre- processing of Twitter (Ritter et al., 2010) and Reddit Politics (Serban et al., 2017) corpora
  - reconstruction loss + backward reconstruction loss + three classification loss
- Domain Adaptive Text Style Transfer (EMNLP 2019)
  - Focus on limited data in the target domain
  - Transfer from data in source domain, address the problem of domain shift by using source data to train the encoder-decoder to preserve content.
  - Two models to deal with whether the source data has label not.
  - Task: sentiment style transfer and formality transfer
  - Dataset: IMDB, YELP, AMAZON, YAHOO; GYAFC (Grammarly's Yahoo Answers Formality Corpus)
  - Measure: automatic metric (content - BLEU, style - classifier accuracy, domain control - domain classifier); human evaluation (content preservation, style control, fluency)
  - Same case may appear in the conversational style transfer.
- Embedding Lexical Features via Tensor Decomposition for Small Sample Humor Recognition (EMNLP 2019)
  - Use word-word co-occurrence to encode the contextual content of documents, and then decompose the tensor to get corresponding vector representation.
  - Build a frequency matrix of the coupons, decompose it and use one item as the embedding vector of the sentence (why?).

- Can it be used in text style transfer and even conversation style transfer?

- A Dual Reinforcement Learning Framework for Unsupervised Text Style Transfer (IJCAI 2019)
  - Dual (source-to-target, target-to-source) reinforcement learning framework to transfer the style of the text via a one-step mapping model
  - Reconstruction reward + style classifier reward
  - Dataset: YELP restaurant review, score above 3 is positive, below 3 is negative; GYAFC (Grammarly's Yahoo Answers Formality Corpus)
  - Measure: automatic; human: the accuracy of the target style, the preservation of the original content and the fluency
  - Ablation Study to examine the key factors of the models
  - Usage: the paper use reinforcement learning to solve the text style transfer problem.

- Dear Sir or Madam, May I Introduce the GYAFC Dataset: Corpus, Benchmarks and Metrics for Formality Style Transfer (NAACL 2018)
  - One key aspect of effective communication is the accurate expression of the style or tone of some content. (Which can be further used to adjust conversational style according to the user's style)
  - reproduce the sentence-level formality classifier
  - Entertainment and music: train 52,595; Family and Relationships: 51,967
  - Manually labelled, paired
  - Use methods from machine translation
  - Usage: the way to build up a large scale dataset...

- Large-scale Hierarchical Alignment for Data-driven Text Rewriting (RANLP 2019)
  - propose a simple unsupervised method, Large-scale Hierarchical Alignment (LHA), for extracting pseudo-parallel sentence pairs from two raw monolingual corpora which contain documents in two different author styles, such as scientific papers and press releases.

- MULTIPLE-ATTRIBUTE TEXT REWRITING (ICLR 2019)
  - Found that it is not necessary and is not always met to learn a latent representation independent of the "style", using a classifier fit post-hoc which could recover attribute information from the content representation learned via adversarial training.
  - Propose to use a technique called back-translation (BT): encode x from (x, y) into z, decode z using y' and get x', then use x' as input of the encoder and decode it using the original y to ideally obtain the original x, and train the model to map (x', y) into x.
  - The loss has two items: loss of auto-encoder, loss of BT. Do not use GAN structure.
  - Use latent representation pooling (a temporal max-pooling layer on top of the encoder) to control the amount of content preservation.
  - Dataset: Yelp and Amazon reviews. Note: use the whole of the review rather than separate sentence; use gender and category information as additional factor.
  - Evaluate: attribute control (classifier), perplexity, BLEU. Human evaluation.

- Content preserving text generation with attribute controls (NIPS 2018)
  - Define a new reconstruction loss by merging the autoencoding and back–translation losses
  - Use the advesarial loss
  - YELP and IMDB reviews
  - Usage: the human evaluation questionnaires are useful for us.

REFERENCES