**Summary of references**

Stanza：

<https://stanfordnlp.github.io/stanza/depparse.html>

Pytextrank：

https://derwen.ai/docs/ptr/overview/

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| Title | Dataset | Method | Evaluation matrix |
| 《Delete, Retrieve, Generate:  A Simple Approach to Sentiment and Style Transfer》 | 1.YELP  2.Reviews on Amazon  3.Image captions | Baseline models：  RETRIEVEONLY：Returns, word by word, sentences retrieved that are similar to the original sentence with the deleted attribute. Guaranteed to produce a grammatically correct sentence with the target attributes, but its content may differ from the original sentence.  TEMPLATEBASED：Replace the deleted attribute in the original sentence with the target attribute  Neural modes：  DELETEONLY：An RNN is used to embed the sentences with the attributes removed into a vector. It then connects the final hidden state to the learned embedding of the target attribute and feeds it to the RNN decoder to generate the final sentence. The decoder attempts to generate words that represent the source content and target attributes while maintaining fluency.  DELETEANDRETRIEVE：Similar to DELETEONLY, but uses the attributes of the retrieved sentence rather than the target attributes. As with DELETEONLY, it encodes the sentence with the original deleted attribute using an RNN. The RNN decoder uses the splicing and content embedding of this vector to generate the final sentence. |  |
| Text Style Transfer: A Review and Experimental Evaluation | 1. Yelp a corpus of restaurant reviews 2. Amazon product review datasets   3.IMDb movie reviews datasets | Creating a taxonomy to organize the TST models, and provide a comprehensive summary of the state of the art. We review the existing evaluation methodologies for TST tasks, and conduct a large-scale reproducibility study where we experimentally benchmark 19 state-of-the-art TST algorithms on two publicly available datasets. Finally, we expand on current trends and provide new perspectives on the new and exciting developments in the TST field. |  |
| Style Transfer Through Back-Translation | Gender  1. Reddy and Knight’s (2016) dataset of reviews from Yelp annotated for two genders corresponding to markers of sex.  Political slant  2.Top-level comments on Facebook posts from all  412 current members of the United States Senate and House who have public Facebook pages.  Sentiment.   1. Yelp a corpus of restaurant reviews. | Focus on transferring author attributes:  gender and political slant, and on sentiment modification.  The second task is novel:  given a sentence by an author with a particular political leaning, rephrase the sentence to preserve  its meaning but to confound classifiers of political slant. | Style Transfer Accuracy    Preservation of Meaning    Fluency |
| Dear Sir or Madam, May I Introduce the GY AFC Dataset:  Corpus, Benchmarks and Metrics for Formality Style Transfer | Yahoo Answers,a question answering forum,contains a large number of informal sentences and allows redistribution of data. Hence, we use the  Yahoo Answers L6 corpus5 to create our GYAFC  dataset of informal and formal sentence pairs. | 1.Rule-based Approach  Develop a set of rules to automatically make an informal sentence more formal where we  capitalize first word and proper nouns, remove repeated punctuations, handcraft a list of expansion for contractions etc.  2.Phrase-based Machine Translation  Use a combination of training regimes to develop our model. Train on the output of the rule based approach when applied to GYAFC. This is meant to force the PBMT model to learn generalizations outside the rules.  3.Neural Machine Translation  Experiment with three NMT models  NMT baseline: Our baseline model is a bidirectional LSTM encoder-decoder model with attention.  NMT Copy: Jhamtani et al., (2017) introduce a copy-enriched NMT model for style transfer to better handle stretches of text which  should not be changed. We incorporate this mechanism into our NMT Baseline.  NMT Combined:We augment the  data used to train NMT Copy via two techniques:  1) we run the PBMT model on additional source data, and 2) we use back-translation (Sennrich et al., 2016c) of the PBMT model to translate the large number of in-domain target style sentences  from GYAFC. | Human-based Evaluation：  Formality,fluency,meaning preservation,overall Ranking  Automatic Metrics:  Formality,fluency,meaning preservation,overall Ranking |
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There is a delicate balance between retaining the original content and removing the original attributes, and existing adversarial models tend to sacrifice one or the other.

It introduces a simple approach to text attribute transfer whose main advantage comes from induction bias, i.e. attributes are usually represented as locally recognisable phrases, which allows it to outperform previous models based on adversarial training. It also reflects some problems in that content and attributes cannot be so cleanly separated by word boundaries.

A fruitful direction would be to develop a concept of attributes that is more general than N-grams, more general than N-grams, but with more inductive bias than arbitrary potential vectors.