Summary of references

<table>
<tr><th>Title</th><th>Dataset</th><th>Method</th><th>Evaluation matrix</th></tr>
<tr>
<td>《Delete, Retrieve, Generate:
A Simple Approach to Sentiment and Style Transfer》</td>
<td>1.YELP

2.Reviews on Amazon

3.Image captions

<table>
<tr><th>Dataset</th><th>Attributes</th><th>Train</th><th>Dev</th><th>Test</th></tr>
<tr><td>YELP</td><td>Positive</td><td>270K</td><td>2000</td><td>500</td></tr>
<tr><td></td><td>Negative</td><td>180K</td><td>2000</td><td>500</td></tr>
<tr><td>CAPTIONS</td><td>Romantic</td><td>6000</td><td>300</td><td>0</td></tr>
<tr><td></td><td>Humorous</td><td>6000</td><td>300</td><td>0</td></tr>
<tr><td></td><td>Factual</td><td>0</td><td>0</td><td>300</td></tr>
<tr><td>AMAZON</td><td>Positive</td><td>277K</td><td>985</td><td>500</td></tr>
<tr><td></td><td>Negative</td><td>278K</td><td>1015</td><td>500</td></tr>
</table>
</td>
<td>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.</td>
<td>
<table>
<tr><th></th><th colspan="2">YELP</th><th colspan="2">CAPTIONS</th><th colspan="2">AMAZON</th></tr>
<tr><th></th><th>Classifier</th><th>BLEU</th><th>Classifier</th><th>BLEU</th><th>Classifier</th><th>BLEU</th></tr>
<tr><td>CROSSALIGNED</td><td>73.7%</td><td>3.1</td><td>74.3%</td><td>0.1</td><td>74.1%</td><td>0.4</td></tr>
<tr><td>STYLEEMBEDDING</td><td>8.7%</td><td>11.8</td><td>54.7%</td><td>6.7</td><td>43.3%</td><td>10.0</td></tr>
<tr><td>MULTIDECODER</td><td>47.6%</td><td>7.1</td><td>68.5%</td><td>4.6</td><td>68.3%</td><td>5.0</td></tr>
<tr><td>TEMPLATEBASED</td><td>81.7%</td><td>11.8</td><td>92.5%</td><td>17.1</td><td>68.7%</td><td>27.1</td></tr>
<tr><td>RETRIEVEONLY</td><td>95.4%</td><td>0.4</td><td>95.5%</td><td>0.7</td><td>70.3%</td><td>0.9</td></tr>
<tr><td>DELETEONLY</td><td>85.7%</td><td>7.5</td><td>83.0%</td><td>9.0</td><td>45.6%</td><td>24.6</td></tr>
<tr><td>DELETEANDRETRIEVE</td><td>88.7%</td><td>8.4</td><td>96.8%</td><td>7.3</td><td>48.0%</td><td>22.8</td></tr>
</table>
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		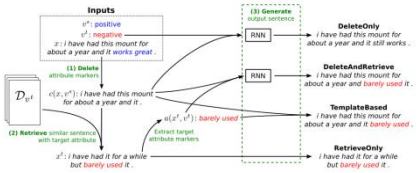	
Text Style Transfer: A Review and Experimental Evaluation	1. Yelp a corpus of restaurant reviews 2. Amazon product review datasets 3.IMDb movie reviews datasets	Creating a taxonomy to organize the TST models, and provide a comprehensive summary of the state of the art. We review the existing evaluation 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.	Table 12. Example outputs Yelp datasets. Table 9. TST results on Yelp dataset (sentiment transfer task).

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.