Improved Neural Text Attribute Transfer with Non-parallel Data

Igor Melnyk∗ Cicero Nogueira dos Santos Kahini Wadhawan Inkit Padhi

Abhishek Kumar

IBM Research AI
T. J. Watson Research Center
Yorktown Heights, NY

Abstract

Text attribute transfer using non-parallel data requires methods that can perform disentanglement of content and linguistic attributes. In this work, we propose multiple improvements over the existing approaches that enable the encoder-decoder framework to cope with the text attribute transfer from non-parallel data. We perform experiments on the sentiment transfer task using two datasets. For both datasets, our proposed method outperforms a strong baseline in two of the three employed evaluation metrics.

1 Introduction

The goal of the text attribute transfer task is to change an input text such that the value of a particular linguistic attribute of interest (e.g. language = English, sentiment = Positive) is transferred to a different desired value (e.g. language = French, sentiment = Negative). This task needs approaches that can disentangle the content from other linguistic attributes of the text. The success of neural encoder-decoder methods to perform text attribute transfer for the tasks of machine translation and text summarization rely on the use of large parallel datasets that are expensive to be produced. The effective use of non-parallel data to perform this family of problems is still an open problem.

In text attribute transfer from non-parallel data, given two large sets of non-parallel texts \( X_0 \) and \( X_1 \), which contain different attribute values \( s_0 \) and \( s_1 \), respectively, the task consists in using the data to train models that can rewrite a text from \( X_0 \) such that the resulting text has attribute value \( s_1 \), and vice-versa. The overall message contained in the rewritten text must be relatively the same of the original one, only the chosen attribute value should change. Two of the main challenges when using non-parallel data to perform such task are: (a) there is no straightforward way to train the encoder-decoder because we can not use maximum likelihood estimation on the transferred text due to lack of ground truth; (b) it is difficult to preserve content while transferring the input to the new style. Recent work from Shen et al. [9] showed promising results on style-transfer from non-parallel text by tackling challenging (a).

In this work, we propose a new method to perform text attribute transfer that tackles both challenges (a) and (b). We cope with (a) by using a single collaborative classifier, as an alternative to commonly used adversarial discriminators, e.g., as in [9]. Note that a potential extension to a problem of multiple attributes transfer would still use a single classifier, while in [9] this may require as many discriminators as the number of attributes. We approach (b) with a set of constraints, including the attention mechanism combined with cyclical loss and a novel noun preservation loss to ensure proper

∗Corresponding author. Email: igor.melnyk@ibm.com

Workshop on Learning Disentangled Representations: from Perception to Control (NIPS 2017), Long Beach, CA, USA.
We assume access to a text dataset consisting of two non-parallel corpora $X = X_0 \cup X_1$ with different attribute values $s_0$ and $s_1$ of a total of $N = m + n$ sentences, where $|X_0| = m$ and $|X_1| = n$. We denote a randomly sampled sentence $k$ of attribute $s_i$ from $X$ as $x^i_k$, for $k \in 1, \ldots, N$ and $i \in \{0, 1\}$. A natural approach to perform text attribute transfer is to use a regular encoder-decoder network, however, the training of such network requires parallel data. Since in this work we consider a problem of attribute transfer on non-parallel data, we propose to extend the basic encoder-decoder by introducing a collaborative classifier and a set of specialized loss functions that enable the training on such data. Figure 1 shows an overview of the proposed attribute transfer approach. Note that for clarity in the Figure 1 we have used multiple boxes to show encoder, decoder and classifier, the actual model contains a single encoder and decoder, and one classifier.

The encoder (in the form of RNN), $E(x^i_k, s_i) = H^i_k$, takes as input a sentence $x^i_k$ together with its attribute label $s_i$, and outputs $H^i_k$, a sequence of hidden states. The decoder/generator (also in the form of RNN), $G(H^i_k, s_j) = \hat{x}^{i \rightarrow j}_k$ for $i, j \in 0, 1$, takes as input the previously computed $H^i_k$ and a desired attribute label $s_j$ and outputs a sentence $\hat{x}^{i \rightarrow j}_k$, which is the original sentence but transferred from attribute value $i$ to attribute value $j$. The hidden states $H^i_k$ are used by the decoder in the attention mechanism [7, 2], and in general can improve the quality of the decoded sentence. For $i = j$, the decoded sentence $\hat{x}^{i \rightarrow i}_k$ is in its original attribute $s_i$ (top part of Figure 1); for $i \neq j$, the decoded/transferred sentence $\hat{x}^{i \rightarrow j}_k$ is in a different attribute $s_j$ (bottom part of Figure 1). Denote all transferred sentences as $\hat{X} = \{\hat{x}^{i \rightarrow j}_k | i \neq j, k = 1, \ldots, N\}$. The classifier (in the form of CNN), then takes as input the decoded sentences and outputs a probability distribution over the attribute labels, i.e., $C(\hat{x}^{i \rightarrow j}_k) = p_C(s_j | \hat{x}^{i \rightarrow j}_k)$ (see Eq. 3 for more details). By using the collaborative classifier our goal is to produce a training signal that indicates the effectiveness of the current decoder on transferring a sentence to a given attribute value.

2 Proposed Method

We assume access to a text dataset consisting of two non-parallel corpora $X = X_0 \cup X_1$ with different attribute values $s_0$ and $s_1$ of a total of $N = m + n$ sentences, where $|X_0| = m$ and $|X_1| = n$. We denote a randomly sampled sentence $k$ of attribute $s_i$ from $X$ as $x^i_k$, for $k \in 1, \ldots, N$ and $i \in \{0, 1\}$. A natural approach to perform text attribute transfer is to use a regular encoder-decoder network, however, the training of such network requires parallel data. Since in this work we consider a problem of attribute transfer on non-parallel data, we propose to extend the basic encoder-decoder by introducing a collaborative classifier and a set of specialized loss functions that enable the training on such data. Figure 1 shows an overview of the proposed attribute transfer approach. Note that for clarity in the Figure 1 we have used multiple boxes to show encoder, decoder and classifier, the actual model contains a single encoder and decoder, and one classifier.

The encoder (in the form of RNN), $E(x^i_k, s_i) = H^i_k$, takes as input a sentence $x^i_k$ together with its attribute label $s_i$, and outputs $H^i_k$, a sequence of hidden states. The decoder/generator (also in the form of RNN), $G(H^i_k, s_j) = \hat{x}^{i \rightarrow j}_k$ for $i, j \in 0, 1$, takes as input the previously computed $H^i_k$ and a desired attribute label $s_j$ and outputs a sentence $\hat{x}^{i \rightarrow j}_k$, which is the original sentence but transferred from attribute value $i$ to attribute value $j$. The hidden states $H^i_k$ are used by the decoder in the attention mechanism [7, 2], and in general can improve the quality of the decoded sentence. For $i = j$, the decoded sentence $\hat{x}^{i \rightarrow i}_k$ is in its original attribute $s_i$ (top part of Figure 1); for $i \neq j$, the decoded/transferred sentence $\hat{x}^{i \rightarrow j}_k$ is in a different attribute $s_j$ (bottom part of Figure 1). Denote all transferred sentences as $\hat{X} = \{\hat{x}^{i \rightarrow j}_k | i \neq j, k = 1, \ldots, N\}$. The classifier (in the form of CNN), then takes as input the decoded sentences and outputs a probability distribution over the attribute labels, i.e., $C(\hat{x}^{i \rightarrow j}_k) = p_C(s_j | \hat{x}^{i \rightarrow j}_k)$ (see Eq. 3 for more details). By using the collaborative classifier our goal is to produce a training signal that indicates the effectiveness of the current decoder on transferring a sentence to a given attribute value.
Note that the top branch of Figure 1 can be considered as an auto-encoder and therefore we can enforce the closeness between $\hat{x}_k^{i\rightarrow i}$ and $x_k^i$ by using a standard cross-entropy loss (see (1) below). However, for the bottom branch, due to lack of parallel data, we cannot use the same approach, and for this purpose we proposed a novel content preservation loss (see Eq. (2)). Finally, note that once we transferred $X$ to $\hat{X}$ (forward-transfer step), we can now transfer $\hat{X}$ back to $X$ (back-transfer step) by using the bottom branch in Figure 1 (see Eq. (3) and Eq. (4) below).

In what follows, we present the details of the loss functions employed in training of our model.

2.1 Forward Transfer

Reconstruction Loss. Given the encoded input sentence $x_k^i$ and the decoded sentence $\hat{x}_k^{i\rightarrow i}$, the reconstruction loss measures how well the decoder $G$ is able to reconstruct it:

$$L_{rec} = \mathbb{E}_{x_k^i \sim X} \left[ -\log p_G(x_k^i | E(x_k^i, s_i), s_i) \right].$$  

Content Preservation Loss. To enforce closeness between $x_k^i$ and $\hat{x}_k^{i\rightarrow j}$ for $i \neq j$, we utilize the attention mechanism. Recall, that this mechanism enables to establish an approximate correspondence between the words in the original (encoded) and transferred (decoded) sentences. For example, denote the words in sentence $x_k^i$ as $x_k^i = \{w_{kr}^{i} | r = 1, \ldots, |x_k^i| \}$ similarly $\hat{x}_k^{i\rightarrow j} = \{w_{kr}^{i\rightarrow j} | r' = 1, \ldots, |x_k^{i\rightarrow j}| \}$. Utilizing the attention mechanism, we can establish the correspondence $(r, r')$ between the words. Among different pairings of such words we select only the ones where $w_{kr}^{i}$ is a noun (e.g., as detected by a POS tagger), and enforce that the corresponding transferred word $w_{kr}^{i\rightarrow j}$ matches that noun, i.e.,

$$L_{cnt, rec} = \mathbb{E}_{x_k^i = \{ \ldots, w_{kr}^{i}, \ldots \} \sim X} \left[ -\log p_G(x_k^i = \{ \ldots, w_{kr}^{i} \} | E(x_k^i, s_i), s_j) \right],$$  

for indices $r$ and $r'$ such that $w_{kr}^{i}$ is a noun and $(r, r')$ is a pair established by attention mechanism. We note that although not always applicable, the above heuristic is very effective for attributes where the sentences can share the nouns (e.g., for sentiment transfer considered in Section 4).

Classification Loss. The loss is formulated as follows:

$$L_{class, td} = \mathbb{E}_{x_k^i \sim X} \left[ -\log p_C(s_j | \hat{x}_k^{i\rightarrow j}) \right].$$  

For the encoder-decoder this loss gives a feedback on the current generator’s effectiveness on transferring sentences to a new attribute. For the classifier, it provides an additional training signal from generated data, enabling the classifier to be trained in a semi-supervised regime.

Classification Loss - Original Data. In order to enforce a high classification accuracy, the classifier also uses a supervised classification loss, measuring the classifier predictions on the original (supervised) instances $x_k^i \in X$:

$$L_{class, od} = \mathbb{E}_{x_k^i \sim X} \left[ -\log p_C(s_i | x_k^i) \right].$$  

2.2 Backward Transfer

Reconstruction Loss. The back-transfer (or cycle) loss [10, 5] is motivated by the difficulty of imposing constraints on the transferred sentences. Back-transfer transforms the transferred sentences $\hat{x}_k^{i\rightarrow j}$ back to the original attribute $s_i$, i.e., $\hat{x}_k^{i\rightarrow j\rightarrow i}$ and compares them to $x_k^i$. This also implicitly imposes the constraints on the generated sentences and improves the content preservation (in addition to (1)). The loss is formulated as follows:

$$L_{back, rec} = \mathbb{E}_{x_k^i \sim X} \left[ -\log p_G(x_k^i | E(\hat{x}_k^{i\rightarrow j}, s_j), s_i) \right],$$  

which can be thought to be similar to an auto-encoder loss in (1) but in the attribute domain.

Classification Loss. Finally, we ensure that the back-transferred sentences $\hat{x}_k^{i\rightarrow j\rightarrow i}$ have the correct attribute label $s_i$:

$$L_{class, btd} = \mathbb{E}_{\hat{x}_k^{i\rightarrow j \sim X}} \left[ -\log p_C(s_i | G(\hat{x}_k^{i\rightarrow j}, s_j), s_i) \right]$$
In summary, the training of the components of our architecture consists in optimizing the following loss function using stochastic gradient descent with back-propagation for some weights $\lambda_i > 0$:

$$
\mathcal{L}(\theta_E, \theta_G, \theta_C) = 
\min_{E,G,C} \lambda_1 L_{rec} + \lambda_2 L_{cnt,rec} + \lambda_3 L_{back,rec} + \lambda_4 L_{class, od} + \lambda_5 L_{class, td} + \lambda_6 L_{class, btd}. \quad (7)
$$

The Algorithm 1 summarizes the above discussion and shows the main steps of the training of the proposed approach.

### Algorithm 1

**Training of the Neural Text Attribute Transfer Algorithm using Non-parallel Data.**

*Require:* Two non-parallel corpora $X = X_0 \cup X_1$ with different attribute values $s_0$ and $s_1$.

*Initialize $\theta_E, \theta_G, \theta_C$*

repeat

- Sample a mini-batch of $l$ original sentences $A = \{x_k^i\}_{k=1}^l$ from $X$, with $i \in \{0, 1\}$
- Sample a mini-batch of $l$ transferred sentences $B = \{\hat{x}_k^{i,j}\}_{k=1}^l$ from the generator’s distribution $p_G$, where $\hat{x}_k^{i,j} = G(E(x_k^i, s_i), s_j)$ with $i, j \in \{0, 1\}$
- Sample a mini-batch of $l$ back-transferred sentences $C = \{\check{x}_k^{i,j}\}_{k=1}^l$ from the generator’s distribution $p_G$, where $\check{x}_k^{i,j} = G(E(x_k^{j, i}, s_j), s_i)$ with $i, j \in \{0, 1\}$
- Compute $\mathcal{L}_{rec}$, $\mathcal{L}_{cnt,rec}$, $\mathcal{L}_{class, td}$, $\mathcal{L}_{class, od}$, $\mathcal{L}_{back,rec}$, and $\mathcal{L}_{class, btd}$
- Update $\{\theta_E, \theta_G, \theta_C\}$ by gradient descent on loss $\mathcal{L}(\theta_E, \theta_G, \theta_C)$ in Eq. (7)

until convergence

### 3 Related Work

Attribute transfer has been studied more extensively in the context of images than in the text domain, with several works studying the style transfer task under the setting of non-parallel data [2] [11]. However, style/attribute transfer in text is fundamentally different as textual data is sequential and of potentially varying lengths, versus constant-sized images. In the image domain, one of the similar works is CycleGAN [11], which also employs a cycle consistency loss (similar to our back-transfer loss) that ensures that composition of a transfer and its reverse is close to the identity map. However, there are several key differences between CycleGAN and our work: (i) we use of a single generator for generating both styles which makes it easier to scale to multiple style transfer, (ii) we use a collaborative classifier for measuring the style instead of a adversarial discriminator, which imparts stability to the training, (iii) additional syntactic regularizers for better content preservation.

Controlled text generation and style transfer without parallel data has also received attention from the language community recently [8] [6] [3] [9]. Ficler and Goldberg [3] consider the problem of attribute conditioned generation of text in a conditioned language modeling setting using LSTM. Mueller et al. [8] allows modifying the hidden representations to generate sentences with desired attributes which is measured by a classifier, however their model does not explicitly encourage content preservation. Our proposed model has some similarities with the approach taken by Hu et al. [6] and Shen et al. [9], with the main differences being that instead of VAE and adversarial discriminators we use a simple encode-decoder framework with a collaborative classifier augmented with the attention mechanism and a set of specially designed content preservation losses.

### 4 Experiments and Results

In this Section we present experimental results of applying the proposed approach for sentiment transfer as one example of text attribute transfer. We compared the algorithm with the approach of [9] on two datasets. One is the dataset from [9], which is based on Yelp restaurant reviews and contains (179K, 25K, 51K) sentences for (training, validation, testing) based on negative reviews and similarly (268K, 38K, 76K) positive sentences. The sentences had a maximum length of 17 words. The second dataset is based on general customer reviews on Amazon [11], from which we selected (265K, 33K, 33K) positive and the same number of negative sentences, each having up to 7 tokens per sentence.

We used three evaluation metrics: (i) sentiment accuracy, which is computed based on pre-trained classifier (estimated on the training part of each dataset) and measures the percentage of sentences in
Table 1: Evaluation results on Yelp and Amazon datasets. For Yelp, the pre-trained classifier had a default accuracy of 97.4% and the pre-trained language model had a default perplexity of 23.5. For Amazon, these values were 82.02% for classification and 25.5 for perplexity.

|                | Yelp Sentiment | Yelp Content | Yelp Perplexity | Amazon Sentiment | Amazon Content | Amazon Perplexity |
|----------------|----------------|--------------|-----------------|------------------|----------------|-------------------|
| Shen et. al    | 86.5           | 38.3         | 27.0            | 32.8             | 71.6           | 27.3              |
| Our Method     | 94.4           | 77.1         | 80.1            | 59.5             | 77.5           | 43.7              |

Table 2: Examples of sentences transferred from positive to negative sentiment on Yelp dataset

| Original                  | Sentiment | Content | Perplexity |
|---------------------------|-----------|---------|------------|
| their food was definitely delicious | Shen et. al [9] | not spectacular | avoid the pizza sucks |
| love the southwestern burger | Our Method | their food was never disgusting | avoid the grease burger |
| restaurant is romantic and quiet | Shen et. al [9] | the pizza is like we were disappointed | the facilities are amazing |
| the facilities are amazing | Our Method | restaurant is shame and unprofessional | the drinks are gone |

Table 3: Examples of sentences transferred from negative to positive sentiment on Yelp dataset

| Original                  | Sentiment | Content | Perplexity |
|---------------------------|-----------|---------|------------|
| sorry they closed so many stores | Shen [9] | thanks and also are wonderful | these guys will go to work |
| these people will try to screw you over | Ours | amazing they had so many stores | these people will try to thank you special |
| i wish i could give them zero stars | Shen [9] | i wish i love this place | seriously, that’s just rude |
| seriously, that’s always friendly | Ours | i wish i’ll give them recommended stars | clean, and delicious ...

Achieving better results across all the metrics still remains a challenge.

In Table 3, we also show some of the sentences generated by both algorithms on Yelp dataset. The algorithm of [9], although able to create well structured sentences with correct sentiment labels, in many cases it cannot accurately preserve the content. On the other hand, our approach may generate text with somewhat higher perplexity but ensures a better sentiment and content transfer.

5 Conclusion

In this work we proposed a novel algorithm for text attribute transfer with non-parallel corpora based on the encoder-decoder architecture with attention, augmented with the collaborative classifier and a set of content preservation losses. Although the experimental evaluations showed promising results, a number of challenges remain: (i) achieve better results across all the three metrics and propose new evaluation metrics to better capture the quality of transfer; (ii) improve the architecture to enable transfer for more challenging text attributes (e.g., such as professional-colloquial) where the text goes under more significant transformation than in a simpler sentiment transfer tasks; (iii) extend the architecture to work in a multi-attribute transfer, a more challenging problem.
References

[1] Amazon reviews dataset. https://www.kaggle.com/bittlingmayer/amazonreviews
Accessed: 2017-11-26.

[2] D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align
and translate. arXiv preprint arXiv:1409.0473, 2014.

[3] J. Ficler and Y. Goldberg. Controlling linguistic style aspects in neural language generation.
arXiv preprint arXiv:1707.02633, 2017.

[4] L. A. Gatys, A. S. Ecker, and M. Bethge. Image style transfer using convolutional neural
networks. In CVPR, pages 2414–2423, 2016.

[5] D. He, Y. Xia, T. Qin, L. Wang, N. Yu, T. Liu, and W. Ma. Dual learning for machine translation.
In Advances in Neural Information Processing Systems, pages 820–828, 2016.

[6] Z. Hu, Z. Yang, X. Liang, R. Salakhutdinov, and E. P. Xing. Towards controllable generation of
text. In International Conference on Machine Learning, 2017.

[7] T. Luong, H. Pham, and C. D. Manning. Effective approaches to attention-based neural machine
translation. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language
Processing, pages 1412–1421, September 2015.

[8] J. Mueller, D. Gifford, and T. Jaakkola. Sequence to better sequence: continuous revision of
combinatorial structures. In ICML, pages 2536–2544, 2017.

[9] T. Shen, T. Lei, R. Barzilay, and T. Jaakkola. Style transfer from non-parallel text by cross-
alignment. In Advances in Neural Information Processing Systems, 2017.

[10] J. Zhu, T. Park, P. Isola, and A. Efros. Unpaired image-to-image translation using cycle-
consistent adversarial networks. arXiv preprint arXiv:1703.10593, 2017.

[11] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros. Unpaired image-to-image translation using
cycle-consistent adversarial networks. arXiv preprint arXiv:1703.10593, 2017.