Empirical Evaluation of Supervision Signals for Style Transfer Models

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Abstract

Text style transfer has gained increasing attention from the research community over the recent years. However, the proposed approaches vary in many ways, which makes it hard to assess the individual contribution of the model components. In style transfer, the most important component is the optimization technique used to guide the learning in the absence of parallel training data. In this work we empirically compare the dominant optimization paradigms which provide supervision signals during training: backtranslation, adversarial training and reinforcement learning. We find that backtranslation has model-specific limitations, which inhibits training style transfer models. Reinforcement learning shows the best performance gains, while adversarial training, despite its popularity, does not offer an advantage over the latter alternative. In this work we also experiment with Minimum Risk Training (Och, 2003), a popular technique in the machine translation community, which, to our knowledge, has not been empirically evaluated in the task of style transfer. We fill this research gap and empirically show its efficacy.

1 Introduction

Text style transfer is the task of changing stylistic properties of an input text, while retaining its style-independent content. Regenerating existing text to cater to a target audience has diverse use-cases such as rewriting offensive language on social media (dos Santos et al., 2018); making a text more formal (Rao and Tetreault, 2018), romantic (Li et al., 2018) or politically-slanted (Prabhumoye et al., 2018); changing its tense (Ficler and Goldberg, 2017) or sentiment (Shen et al., 2017).

While training unsupervised models for generating style-infused texts can be done using conditional language-modelling techniques, in order to perform style transfer, one needs to find a source of supervision signal. Parallel corpora for this task are scarce (Xu et al., 2012; Jhamtani et al., 2018; Rao and Tetreault, 2018; Kang et al., 2019), so researchers focused on finding non-parallel supervision signals.

We analyzed previous work and came to a conclusion that, although many approaches have been proposed, they all employ similar optimization methods that form groups of techniques; one simply combines them to produce a style-transfer model. The “recipe” is using denoising autoencoding as a mechanism to teach the model to generate grammatical texts; style-infusion comes from: 1) discriminator-based training; 2) backtranslation; 3) metric supervision via reinforcement learning (RL). Our work examines the properties of these methods and finds which of them contribute to the success or failure of a style-transfer approach.

Our contributions are three-fold:

• We provide a structured overview of the supervision techniques used for training style transfer models.

• We find evidence of the limitations of the existing techniques.

• To the best of our knowledge, we are the first ones to use Minimum Risk Training technique (Och, 2003) in style transfer. We prove its efficacy in the subsequent experiments.

In what follows, we first describe the notation used throughout the paper, then introduce each of the examined model components. After that, we explain our experimental setup, analyze the results and pinpoint the approaches’ limitations.

2 Overview

We assume that our training data consists of text–style pairs \((x, s)\), where \(x\) is a text and \(s\) =
(s₁, …, sₘ) is a set of style values which x has. Each sₖ is a discrete value in the set Sₖ of possible values for attribute k.

Our task is to learn a mapping from a pair of an input text x and arbitrary style ̂s, to a new text ̂x that exhibits styles ̂s, but has the content of x. Research literature does not define precisely what content is; usually it is assumed that content is style-independent. However, whether it is possible to decouple the two is a topic of an ongoing debate (Lample et al., 2019; John et al., 2019). In this work, content is defined as anything in x which does not depend on the style attributes.

All works we have examined employ some variant of a recurrent neural network (RNN, Rumelhart et al. (1986)) or Transformer (Vaswani et al., 2017) as a text generator. For simplicity, as a generator network, we implemented a bi-directional encoder and uni-directional decoder with Gated Recurrent Unit (Cho et al., 2014), attention (Bahdanau et al., 2014), and the pooling mechanism of Lample et al. (2019). The generator model first encodes text x into a latent representation z = e(x), then decodes (z, ̂s) into ̂x = d(z, ̂s), where e and d are encoder and decoder parts of the model.

What differs between the approaches which we compare in this paper is the optimization technique used to train the model. These techniques are described in the following subsections. Hyperparameter values are reported in Appendix A.2.

2.1 Autoencoding

First, the model is trained with a denoising autoencoding (DAE) objective to learn to produce grammatical texts from corrupted inputs. An illustration of this process is shown in Figure 1. Following Lample et al. (2019), we corrupt a given text x by randomly dropping and shuffling words, which produces x_c. The corrupted text serves as input to the encoder; the target sequence to reconstruct is the original text x. DAE training minimizes the following objective:

\[
L_{ae} = -\log P(x | e(x_c), s)
\]

2.2 Backtranslation

Backtranslation (BT) was originally proposed by Sennrich et al. (2016) in the context of machine translation as a method of creating silver-standard data and bootstrapping machine translation models. Some researchers successfully applied it to style transfer, but used it in different ways. Zhang et al. (2020) employed BT to obtain additional training data, while Lample et al. (2019) treated it as a source of indirect supervision, arguing that BT helps to prevent the model from doing just reconstruction.

Interestingly enough, Prabhumoye et al. (2018) used BT to do the opposite. The authors refer to a study of Rabinovich et al. (2017) who showed that stylistic properties are obfuscated by both manual and automatic machine translation, i.e., backtranslation can be used to rephrase a text while reducing its stylistic properties. It seems that sometimes BT exhibits an additional supervision signal (Lample et al., 2019), and sometimes it has a regularization effect (Rabinovich et al., 2017; Prabhumoye et al., 2018).

An illustration of the backtranslation process for style transfer is shown in Figure 2. Given an input text x and original style s, we first perturb s by changing at least one of the attributes to produce ̂s. Next, the model takes (x, ̂s) as input and generates text ̂x. The model then uses ̂x and the original style s to produce x* which, ideally, is a reconstruction of x. BT training minimizes the following objective:

\[
L_{bt} = -\log P(x | e(d(e(x), ̂s)), s)
\]

With backtranslation, the training alternates between an autoencoding and backtranslation steps. The final optimization function we minimize is a linear combination of DAE and BT losses:

\[
L_{total} = \lambda_{ae}L_{ae} + \lambda_{bt}L_{bt}
\]

The λ parameters constitute a trade-off between
performing more content preservation or style transfer. In our experiments we follow (Lample et al., 2019) and anneal the $\lambda_{ae}$ to 0 towards the end of training, while keeping $\lambda_{bt}$ equal to 1.

### 2.3 Adversarial Training

Adversarial training (Goodfellow et al., 2014) provides means for leveraging training signals from non-parallel corpora for style transfer. One popular approach in this direction is to disentangle the input text’s content and style information by employing adversarial networks that operate on the input text’s latent representation, i.e., the encoder output. This can be done by separating the latent representation into the content representation and style representation (John et al., 2019), or learning style-invariant latent representations (Fu et al., 2018). Another approach is to use an adversarial network within the backtranslation framework (Logeswaran et al., 2018; Dai et al., 2019), which is what we employed in our experiments. Using adversarial discriminators in such a scenario helps matching the distribution of style-specific latent representations of real vs. synthetic texts (Shen et al., 2017).

![Figure 3: Schematic view of the ADV training procedure. The inputs and outputs are the same as for the BT stage.](image)

An illustration of the adversarial training of the generator model is shown in Figure 3. We implement the multi-class discriminator of Dai et al. (2019) using a GRU-based encoder with a classification layer which predicts the style of $\hat{x}$. Adversarial training involves alternating between training the generator model to produce style-infused texts, and training the discriminator to distinguish between real sentences of different styles, on one hand, and model-generated texts, on the other hand. Training the latter is straightforward; we follow Dai et al. (2019) and refer the reader to the original paper for details.

When training both the discriminator and the generator, we minimize the cross entropy loss, and teach the discriminator to predict style, given a text (either real one or generated by the model), and the generator to output texts that look \textit{real}, i.e., similar to the texts with the desired style in the training data.

Note that adding the adversarial component is done on top of BT model, because with DAE and ADV only, it is not possible to force the model to preserve the content. For this reason, training the generator now consists of three terms:

$$L_{adv} = -\log P_D(\hat{s}|\hat{x})$$

$$L_{total} = \lambda_{ae} L_{ae} + \lambda_{bt} L_{bt} + \lambda_{adv} L_{adv}$$

We reuse the same $\lambda$ parameters as in the BT approach. $\lambda_{adv}$ is set to 1.0.  

### 2.4 Minimum Risk Training

Existing works have also explored architectures based on RL techniques for text style transfer. For example, Gong et al. (2019) use evaluation metrics for style, content preservation, and naturalness as the training objective within the RL framework. Wu et al. (2019) use a hierarchical model where the high-level agent decides where the input text needs to be modified, and the low-level agent decides on the modification.

Following the success of the Minimum Risk Training method (Och, 2003) in the machine translation community, we decided to experiment with it as a potential candidate of the RL techniques. Since the advent of neural networks, there have been successful attempts to use MRT for generation tasks, like neural machine translation (Gao et al., 2014; Shen et al., 2016), but we are unaware of any work that has explored its utility in the domain of...
Table 1: The number of training instances per attribute for each dataset. Preprocessing details are given in the appendix.

| Sentiment    | Gender | Category       |
|--------------|--------|----------------|
| **FYelp**    |        |                |
| Positive     | 1,035,609 | 584,637        |
| Negative     | 197,203  | 648,175        |
| **RottenTomatoes** | |                |
| Positive     | 245,241  | 268,564        |
| Negative     | 118,857  | 95,535         |
| **SYelp**    |        |                |
| Positive     | 266,041  | -              |
| Negative     | 177,218  | -              |
| **SAMazon**  |        |                |
| Positive     | 277,228  | -              |
| Negative     | 277,769  | -              |

Since we do not have reference outputs, we cannot use reference-based metrics. However, we can use style intensity classifiers to compute a metric that could guide the model towards generating better outputs. According to Mir et al. (2019), when evaluating style intensity, the metric that correlates most with human judgements, is direction-corrected Earth-Mover’s Distance (EMD) (Rubner et al., 1998). We measure it between the style distributions of the texts generated during the back-translation process (see Section 3.2 for details):

\[
L_{mrt} = E_{x^* \sim P(x^* | \hat{x})} \Delta(x^*, \hat{x})
\]

\[
L_{total} = \lambda_{ae} L_{ae} + \lambda_{bt} L_{bt} + \lambda_{mrt} L_{mrt}
\]

We use the same \( \lambda \) hyperparameters as in the BT and Adv cases, \( \lambda_{mrt} \) is set to 1.0.

3. Experimental Setup

3.1 Datasets

Following previous work, we used publicly available Yelp restaurant and Amazon product review datasets which vary in one attribute, the review sentiment (Shen et al., 2017; Li et al., 2018). We followed Lample et al. (2019) and included a multi-attribute version of the Yelp restaurant review dataset which contains texts varying in product categories, gender of the reviewers, and sentiment of the review. We also added a multi-attribute dataset of Ficler and Goldberg (2017) which contains movie reviews from the Rotten Tomatoes website. The texts vary in professionality and sentiment dimensions. We also added gender annotations, following the same procedure as for the FYelp dataset.

The lengths of RottenTomatoes and FYelp texts vary a lot — some exceed 1k tokens. Due to computational limitations, we had to restrict ourselves to texts no longer than 50 tokens for both datasets; SYelp and SAMazon datasets were not trimmed in any way. The number of training instances per category for each of the four datasets are shown in Table 1. The details of the preprocessing steps for all datasets are given in Appendix A.1.

3.2 Evaluation Metrics

A lot of work has been done in order to make evaluation of style transfer models more reliable (Shen et al., 2017; Li et al., 2018). We followed Lample et al. (2019) and included a multi-attribute version of the Yelp restaurant review dataset which contains texts varying in product categories, gender of the reviewers, and sentiment of the review. We also added a multi-attribute dataset of Ficler and Goldberg (2017) which contains movie reviews from the Rotten Tomatoes website. The texts vary in professionality and sentiment dimensions. We also added gender annotations, following the same procedure as for the FYelp dataset.

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Table 2: Automatic metric evaluation results on the Syelp test set (lower-cased). BLEU scores are computed between the test set human references and model outputs. For all scores, except for perplexity (PPL): the higher the better. ACC, BLEU and sBLEU values are in range [0, 100]; EMD in [0, 1]; WMS in (0, 1]; PPL in [0, ∞].

| Model                          | ACC (%) | EMD  | BLEU | sBLEU | WMS  | PPL  |
|-------------------------------|---------|------|------|-------|------|------|
| CrossAligned (Shen et al., 2017) | 73.8    | 0.68 | 3.3  | 13.2  | 0.66 | 69.1 |
| Style Embedding (Fu et al., 2018) | 9.1     | 0.05 | 12.1 | 69.2  | 0.86 | 76.0 |
| MultiDecoder (Fu et al., 2018) | 46.5    | 0.42 | 7.4  | 37.8  | 0.72 | 146.7|
| TemplateBased (Li et al., 2018) | 81.1    | 0.74 | 11.1 | 44.2  | 0.70 | 1915.0|
| RetrieveOnly (Li et al., 2018) | 93.8    | 0.84 | 0.4  | 0.7   | 0.52 | 86.0 |
| DeleteOnly (Li et al., 2018)  | 83.5    | 0.76 | 7.6  | 28.6  | 0.68 | 71.5 |
| DeleteAndRetrieve (Li et al., 2018) | 87.2   | 0.79 | 8.5  | 29.1  | 0.67 | 86.0 |
| DAE                           | 24.5    | 0.20 | 11.7 | 58.1  | 0.86 | 51.8 |
| DAE + BT                      | 85.8    | 0.79 | 6.8  | 21.4  | 0.70 | 42.8 |
| DAE + BT + ADV                | 87.2    | 0.80 | 6.9  | 20.7  | 0.70 | 40.6 |
| DAE + BT + MRT                | 88.1    | 0.81 | 6.9  | 20.1  | 0.70 | 41.0 |
| Input copy                    | 3.9     | 0.00 | 18.4 | 100.0 | 1.00 | 8.2  |

4 Results

4.1 Single-Attribute (Syelp, SAmazon)

We first evaluate the described methods in the single-attribute scenario. Table 2 and Table 3 show their performance on the test portion of the Syelp and SAmazon datasets, respectively. The results for previous work are computed based on the outputs from (Li et al., 2018).²

The first striking observation is that all models achieve low BLEU scores. Taking into consideration the high WMS scores of some models, this suggests that using an n-gram overlap between a human reference and model output is inadequate for style transfer — the potential variability of re-generating text in a different style is too high to be captured by an overlap with one reference text. This observation is reinforced by the fact that the models with the best transfer performance (accuracy and EMD) also exhibit lowest BLEU scores. The fact that sBLEU and WMS have a large gap indicates that computing an n-gram overlap between the input and system output is also a very superficial way of measuring content preservation, calling for the usage of vector-space models, like WMD.

Interestingly, the performance of the models proposed in the literature is not consistent across datasets. SAmazon has longer and more diverse sentences than Syelp, which could explain why template- and retrieval-based approaches under-perform, compared to the data-driven alternatives.

²https://github.com/lijuncen/Sentiment-and-Style-Transfer.
Table 3: Automatic metric evaluation results on the SAmazon test set (lower-cased). BLEU scores are computed between the test set human references and model outputs.

| Model                                                                 | Acc (%) | EMD | BLEU | sBLEU | WMS | PPL |
|----------------------------------------------------------------------|---------|-----|------|-------|-----|-----|
| CrossAligned (Shen et al., 2017)                                     | 74.5    | 0.45| 0.4  | 0.5   | 0.55| 20.5|
| Style Embedding (Fu et al., 2018)                                    | 39.7    | 0.19| 10.2 | 29.5  | 0.67| 81.1|
| MultiDecoder (Fu et al., 2018)                                       | 72.1    | 0.41| 4.9  | 14.4  | 0.61| 78.9|
| TemplateBased (Li et al., 2018)                                      | 69.9    | 0.40| 26.6 | 64.0  | 0.78| 91.1|
| RetrieveOnly (Li et al., 2018)                                       | 73.5    | 0.43| 9.2  | 2.1   | 0.54| 7.7 |
| DeleteOnly (Li et al., 2018)                                         | 51.0    | 0.26| 25.4 | 60.9  | 0.80| 37.7|
| DeleteAndRetrieve (Li et al., 2018)                                  | 56.4    | 0.30| 23.3 | 54.3  | 0.77| 77.4|
| **DAE**                                                               | 20.2    | 0.03| 30.2 | **79.6** | **0.94** | 30.1 |
| **DAE + BT**                                                          | 34.4    | 0.13| **30.9** | 78.9  | 0.92| 29.3|
| **DAE + BT + ADV**                                                   | 47.3    | 0.23| 28.5 | 72.0  | 0.89| 36.9|
| **DAE + BT + MRT**                                                   | 50.4    | 0.25| 28.1 | 70.9  | 0.88| 38.3|

| Input copy                                                           | 17.1    | 0.00| 38.4 | 100.0 | 1.00| 8.5 |

Table 3: Automatic metric evaluation results on the SAmazon test set (lower-cased). BLEU scores are computed between the test set human references and model outputs.

However, it is not clear why both the previously proposed neural models and the approaches we implemented and experimented with in this paper show such a large gap between the results on Syelp and SAmazon.

It is surprising that DAE by itself can do some amount of style transfer, even without the additional supervision signal. This most likely is the consequence of indiscriminate noising of tokens in the input text and removing of style-bearing words during the noising step. The work of Shen et al. (2019) offers a plausible explanation for that: denoising seems to help autoencoders to map similar texts to similar latent representation and promote sequence neighborhood preservation.

Among the tested supervision signals, MRT has a slight preference. However, in the single-attribute scenario, the best way to do style transfer seems to be a simple nearest-neighbour approach (RetrieveOnly): by retrieving a semantically-similar text with the desired style from the available corpus.

Manual examination of model predictions revealed that none of the approaches goes further than replacing several style-bearing words. This happens due to a limited variation in the data. For example, Syelp texts are at most 15 tokens long, and most reviews have similar structure, so the models learn to do minimal edits to perform style transfer. They also fail when it is needed to go beyond that. For example, all examined approaches failed to change the style in the following cases and produce almost unchanged input text as prediction:

- *i just walked out, called the manager to complain*
- *she doesn’t say anything and just walks away*

4.2 Multi-Attribute (Fyelp, RottenTomatoes)

Table 4 and Table 5 show the performance of the considered approaches on Fyelp, and RottenTomatoes data, respectively.

The trends from the single-attribute transfer seem to be present here as well. The sBLEU and WMS scores achieved by the DAE model are the highest, which is intuitive — the model learns to reconstruct the input.

The correlation between higher EMD and accuracy scores vs. lower WMD and sBLEU scores supports the hypothesis that there is a trade-off between preserving input content and performing style transfer. Figure 5 shows how content preservation (measured by sBLEU) and style intensity (ACC) criteria start competing during BT model training.

This phenomenon was also observed by Lai et al. (2019): the authors note that a model trained longer was better able to transfer style, but worse at retain-
Table 4: Automatic metric evaluation results on the Fyelp test set (lower-cased).

| Model          | Acc (%) | EMD   | sBLEU | WMS   | PPL  |
|---------------|---------|-------|-------|-------|------|
| DAE           | 13.9    | 0.02  | 38.5  | 0.76  | 67.1 |
| DAE + BT      | 32.2    | 0.24  | 22.9  | 0.69  | 29.6 |
| DAE + BT + ADV| 42.4    | 0.33  | 22.1  | 0.68  | 31.8 |
| DAE + BT + MRT| 46.8    | 0.36  | 21.5  | 0.68  | 33.1 |

Table 5: Automatic metric evaluation results on the RottenTomatoes test set (lower-cased).

| Model          | Acc (%) | EMD   | sBLEU | WMS   | PPL  |
|---------------|---------|-------|-------|-------|------|
| DAE           | 35.1    | 0.015 | 39.9  | 0.78  | 73.7 |
| DAE + BT      | 55.5    | 0.18  | 28.5  | 0.69  | 83.1 |
| DAE + BT + ADV| 57.6    | 0.20  | 28.2  | 0.69  | 83.2 |
| DAE + BT + MRT| 59.6    | 0.22  | 25.6  | 0.68  | 98.5 |

5 Results Analysis

We believe that autoencoding is the most important stage of the training process. As Lample et al. (2019) mention, it is a way to force the model decoder to leverage the style information: since the noise applied to the input \( x \) may corrupt words conveying the values of the original input style \( s \), the decoder has to learn to use the additional style input in order to perform a proper, style-infused, reconstruction.

Backtranslation is an easy-to-implement and conceptually appealing approach: training is straightforward and empirical results show that it performs well across different datasets and styles. However, we found that the effectiveness of BT is not model-agnostic. We experimented with using a more recent Transformer (Vaswani et al., 2017) architecture for the DAE component and found that the model only manages to do autoencoding, but almost no style transfer. We hypothesize that this happens when an encoder’s capacity is too high, and is related to the ability of such models to learn an arbitrary mapping between sequences and associated latent representation (Shen et al., 2019).

Prior work for multi-attribute text style transfer suggests that the encoder is responsible for encoding the input text into its content representation (Logeswaran et al., 2018; Lample et al., 2019). In fact, the interpolated reconstruction loss used in the model by Logeswaran et al. (2018) is based on this assumption. We attempted to verify whether the outputs of a Transformer encoder are used to encourage the content representation of texts rewritten in different styles to be the same.

During backtranslation, the model generates \( \hat{x} \) and \( x^* \), which would be the same text written in different styles, if the model were perfect. Assuming that the encoder outputs represent the content, we can assess how similar the two encoder outputs are. Since the encoder outputs may have different sequence lengths, we performed a global pooling over the encoder output vectors, yielding one vector for each text. Following the single-attribute model of Tikhonov et al. (2019), we calculate the mean squared error (MSE) between these two vectors. The results of this experiment on the RottenTomatoes dataset are shown in Figure 6.
The pooled representations become almost the same at the start of training. Looking back at Figure 2, we can see that it is possible to “game” the optimization procedure and achieve an optimal loss value without doing much style transfer. This happens if during the DAE step the generator model learns to reconstruct the input without using style information. In this case, \( \hat{x} \) and \( x^* \) in Figure 2 become \( x \) and BT loss becomes 0. Our experiments suggest that this happens with the Transformer networks and not with RNN ones. However, the reasons of this phenomenon are not clear.

**Adversarial training** showed more consistent results in our experiments, although the training results exhibit more variation. This is expected — many researchers reported on the instability issues with adversarial training, e.g., vanishing gradients, convergence difficulties, mode-collapse (Goodfellow et al., 2014; Arjovsky and Bottou, 2017; Roth et al., 2017). Nevertheless, the results are generally lower than the ones we obtained with MRT models. A plausible explanation for this could be the findings of Elazar and Goldberg (2018) who showed that adversarial discriminators exhibit inferior performance when compared to external supervision signals.

The **Minimum Risk Training** method showed both stable training results and consistent performance gains over the vanilla BT training regime. This is a little bit surprising, given that in the neural machine translation community (where the method is most popular) it is known to be sensitive to the choice of hyperparameter values (Shen et al., 2016).

The additional benefit of the MRT method is that, unlike adversarial training, one is safeguarded against the optimization instability issues: the model is first pretrained with a maximum-likelihood estimation criterion at the beginning and the worst-case scenario is staying at the same performance levels. Finally, adversarial approaches are limited by their use of loss functions that must be differentiable with respect to the model parameters. MRT, on the other hand, can incorporate arbitrary metrics on any level of output granularity. The biggest weakness of the method is training time — getting good parameter estimates depends on the number of samples in the pool of candidates which are used for approximating the full search space. As this pool grows, the training time also increases.

### 6 Discussion

The approaches we examined perform on par, with a slight preference towards the MRT method. However, more experiments are needed to confirm our findings, e.g. to understand the strange behavior of the Transformer model trained with BT. We did not perform additional experiments comparing the performance of MRT and ADV models, when other generator networks (like Transformer) are employed. We also did not experiment with hyperparameter values due to time and computation constraints, but this is needed in order to account for the randomness in model training.

Apart from additional experiments explaining the limitations of backtranslation, we consider the data quality and evaluation protocols to be two prominent directions that need to be improved.

We found three big issues about the employed datasets. Firstly, with the exception of the data provided by (Li et al., 2018), all other datasets have multiple versions, which makes model comparison hard. Secondly, the datasets are centered around style dimensions that often conflate the content and style parts. For example, the multi-attribute Amazon dataset has the review category as an attribute. However, unlike sentiment transfer, it is not possible to change the category class of a review without changing its content. Lastly, some stylistic properties are problematic to model, e.g., the gender or age of a reviewer. Apart from ethical concerns, we also found these attributes to be very hard to capture, even by humans. This means that human evaluation of the models trained on such
data would be problematic.

Evaluation protocols for style transfer models should be improved as well. Current metric-based evaluation is flawed for various reasons. First, the usage of some metrics is questionable. For example, BLEU is used for measuring content preservation, but it penalizes differences between input and output texts, even when they are intended (you cannot change style without changing content). Second, the reported scores in different works vary even for the same models. For example, the scores in (Lample et al., 2019) are different from those originally reported in (Li et al., 2018), even though model outputs are the same. This most likely happens due to the differences between the options for training classifiers or computing metric scores (e.g., smoothing method for BLEU). Finally, it is still not clear what the expected output of a style transfer model should look like. There is no doubt that a certain trade-off between content preservation and style transfer intensity is inevitable, but having some common definition of what constitutes a good model is definitely needed.

7 Conclusion

In this work we empirically compared three most popular approaches to providing supervision signals in the absence of parallel data for the task of style transfer. We successfully applied MRT optimization techniques to style transfer and showed that it offers the best performance gains, while staying stable throughout the training. We revealed a model-specific limitation of the backtranslation method, which inhibits training style transfer models. We also evaluated a popular adversarial training approach and found that, although it is able to improve upon vanilla backtranslation, it does not offer an advantage over the MRT alternative.

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A Supplemental Material

A.1 Dataset Preparation

**Syelp** and **SAmazon** datasets are publicly available.\(^3\) The preprocessing steps for **Fyelp** and **RottenTomatoes** datasets are described below.

**Fyelp** was prepared using publicly released code.\(^4\). However, due to the computational constraints, we additionally filtered out texts that are longer than 50 tokens. Consequently, this makes our results incomparable to those reported in (Lample et al., 2019). We tried using the same cut-off limit of 100 tokens as in the original paper, but model training became prohibitively expensive.

The raw **RottenTomatoes** dataset was shared with us by Ficler and Goldberg (2017). We discarded empty reviews, reviews having only non-alphabetic characters, meta-reviews, and reviews in languages other than English (the review was considered to be in English only if at least 70% of tokens in the text were identified to be English).

Using available meta-data, we added professionality annotations. We further followed the instructions of Ficler and Goldberg (2017) to annotate reviews with their sentiment. As for the gender annotations, we retrieved them from user names and user ids: we replaced ids by the actual reviewer names (obtained from the RottenTomatoes website), and followed the instructions in (Lample et al., 2019) to map the reviewer names to genders using lists of male/female names.

During training and evaluation all texts were lower-cased.

\(^3\)https://github.com/lijuncen/Sentiment-and-Style-Transfer
\(^4\)https://github.com/facebookresearch/MultipleAttributeTextRewriting

A.2 Training Details

All models were implemented using PyTorch (Paszke et al., 2019) and PyTorch-Lightning\(^5\) frameworks. Our models use the following hyperparameters:

- embedding dimension: 512
- RNN hidden dimension: 512
- encoder pooling kernel size: 5
- encoder pooling window size: 5
- word shuffle probability: 3
- intensity of word shuffling (parameter \(k\)): 3

The models were trained using Adam optimizer (Kingma and Ba, 2015) with the following hyperparameters:

- lr: 0.0001
- betas: (0.5, 0.999)
- weight decay: 0

The models were trained on a cluster of eight NVIDIA Tesla V100 GPU (32G) for 30 epochs, with a dropout rate of 0.1, gradient norm was clipped to 5.0. **SAmazon** and **Syelp** models were trained with a batch size of 400; **RottenTomatoes** and **Fyelp** models used a smaller batch size of 200 due to computational limitations.

We did not restrict the vocabulary size of the models, with an exception of the **Fyelp** model — there we followed (Lample et al., 2019) and limited the vocabulary to 60k BPE merge operations.

A.3 Evaluation

All model outputs and references were lower-cased and tokenized by space before evaluation. Specific details about metrics used are given below:

**BLEU, sBLEU.** We used the NLTK (Bird, 2006) package to compute BLEU scores. No smoothing was applied.

**Accuracy, EMD.** We trained fasttext\(^6\) classifiers to compute both the accuracy and probability distribution for EMD. We computed the latter using the code from Mir et al. (2019). The same codebase was also used to extract style-specific lexicons.

\(^5\)https://github.com/PytorchLightning/pytorch-lightning
\(^6\)https://fasttext.cc/
**Perplexity.** We used a publicly available KenLM toolkit\(^7\) to train a 5-gram language model with Kneser-Ney smoothing. Perplexities were computed on the sentence level and averaged over the predicted texts.

**WMS.** We used the code from Mir et al. (2019) to compute WMD scores (Pele and Werman, 2008, 2009), but normalised it in the following way:

\[
\text{WMS}(d_1, d_2) = \frac{1}{1 + \text{WMD}(d_1, d_2)}
\]

Here, \(\text{WMD}(d_1, d_2)\) denotes Word Mover’s distance between two documents. The reason why we compute the inverse of WMD is to make it easier for the reader to compare the models: the higher the score, the better the model (similar to the other metrics). The metric is computed between Word2Vec (Mikolov et al., 2013) representations. We used the Gensim Python package (Řehůřek and Sojka, 2010) and trained Word2Vec vectors from scratch on the train portions of the datasets.

**Excluded metrics.** We excluded some of the metrics that Mir et al. (2019) originally used in their study. These metrics are:

- masked versions of sBLEU and WMS;
- adversarial classifiers for measuring naturalness.

The former were excluded, because the authors showed that masked versions of the metrics highly correlate with unmasked ones. The latter metric was excluded, since the details about training the classifiers were not described in the respective work.

\(^7\)https://kheafield.com/code/kenlm/