Gradient-guided Unsupervised Text Style Transfer via Contrastive Learning

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Abstract

Text style transfer is a challenging text generation problem, which aims at altering the style of a given sentence to a target one while keeping its content unchanged. Since there is a natural scarcity of parallel datasets, recent works mainly focus on solving the problem in an unsupervised manner. However, previous gradient-based works generally suffer from the deficiencies as follows, namely: (1) Content migration. Previous approaches lack explicit modeling of content invariance and are thus susceptible to content shift between the original sentence and the transferred one. (2) Style misclassification. A natural drawback of the gradient-guided approaches is that the inference process is homogeneous with a line of adversarial attack, making latent optimization easily becomes an attack to the classifier due to misclassification. This leads to difficulties in achieving high transfer accuracy. To address the problems, we propose a novel gradient-guided model through a contrastive paradigm for text style transfer, to explicitly gather similar semantic sentences, and to design a siamese-structure based style classifier for alleviating such two issues, respectively. Experiments on two datasets show the effectiveness of our proposed approach, as compared to the state-of-the-arts.

1 Introduction

Text style transfer, as an important task of natural language generation (NLG), aims at altering the style of a given sentence (e.g., positive) to a target one (e.g., negative) while preserving its content as much as possible. The controllable rewriting a sentence with desired style is beneficial for many downstream applications in practice, such as converting offensive language to non-offensive (Tran, Zhang, and Soleymani 2020), converting biased remarks to neutral (Pryzant et al. 2020) and generating eye-catching headlines (Jin et al. 2020; Li et al. 2021). Moreover, text style transfer may serve as data augmentation for many natural language subtasks, and thus it has attracted a considerable amount of research.

Since there is a natural scarcity of parallel datasets, recent works mainly focus on solving the problem in an unsupervised manner, where only labelled sentences are available. Several efforts have been devoted on the gradient-guided optimization based models, e.g., (Wang, Hua, and Wan 2019; Liu et al. 2020), which are usually consist of two subcomponents: (1) Auto-Encoder, which learns the mapping between a discrete sentence space and a continuous latent space; (2) Style classifier, which predicts the style type of a decoded sentence based on its latent representation. The representation of the original sentence is edited iteratively to the target one during inference, along with the direction of the gradient obtained from the style classifier.

Nevertheless, previous gradient-guided approaches generally suffer from the deficiencies as follows: (1) Content migration. Content invariance is of crucial importance to evaluate the success of a text style transfer model, however, nearly none of existing works takes account of an explicit constraint to ensure the content invariance before and after conversion, which may result in a great discrepancy of the content between the original sentence and the target one. Later, there are various attempts on content consistency, for example, Liu et al. (2020) propose a content predictor to tackle such problem by predicting the word features (i.e., Bag-of-Words) of the generated sentence during inference. Nevertheless, experiments illustrate that such method result in trivial improvement. (2) Style misclassification. A robust style classifier is vital in gradient-guided methods, as it provides the direction for the refinement of latent representation during inference. However, the process of searching target embedding through gradient optimization resembles a line of attacking white-box neural network, for example, Hsieh et al. (2019) attack the style classifier by applying gradient-based perturbations. As a result, an expected style transformation may become an attack to the style classifier due to misclassification, which brings about difficulties in achieving high transfer accuracy.

To address these problems, we propose a novel gradient-guided model for text style transfer. We adopt a contrastive paradigm to train a better auto-encoder and design a more robust siamese-structure based style classifier for alleviating such two issues, respectively. With respect to the first issue, it is worth noting that transferred sentences are adjacent to the original ones in terms of embedding distance, since the gradient update steps are minimal. Therefore, sentences is capable of being optimized to the desired ones only if they are neighboring in the latent space. Accordingly, we adopt
a contrastive paradigm for training the auto-encoder, which explicitly models content invariance by drawing embeddings of similar content sentences closer and pushing those of different content apart. With respect to the second issue, we design a novel siamese-structure based style classifier. The classifier takes two sentences as input and yields their likelihood of being the same style. In such wise, our classifier predicts the style of an embedding by conducting comparison with other labelled sentence embeddings, and thus the accuracy of style identification increases when the number of labelled references increments. Experiments show our proposed siamese-structure based style classifier is more resistant to style misclassification.

Our contributions are summarized as follows:

- We analyze the cause of content migration of gradient-guided approaches and correspondingly propose an auto-encoder with a contrastive paradigm, which effectively improves content consistency before and after conversion.
- We design a novel siamese-structure based classifier, which is more resistant to style misclassification and improves style transfer accuracy.
- Experiments show our model achieves state-of-the-art performance in both automatic and human evaluation.

2 Background

Style Transfer

Style transfer is a task targeting at changing the stylistic attribute while retaining the content of the input text. Owing to the lack of parallel corpora, recent methods mainly work in an unsupervised manner. Most of previous approaches address the task with a latent manipulation workflow: first encode original sentences into latent representations; then manipulate the latents; finally feed the latents to a decoder to generate target sentences. (Shen et al. 2017) assumes a shared latent content distribution across the corpus of different styles. (Hu et al. 2017) utilizes the wake-sleep algorithm for learning a structured style code. (John et al. 2019) designs multiple adversarial losses to achieve a separation of style and content latent representations. (Li et al. 2018) adds an embedding with target style to the entire representation instead of separating style and content. (Yi et al. 2020) constructs a style space to sample more diverse style embeddings. (Huang et al. 2019) implements an attention mechanism to achieve phrase level style representations. (Pryzant et al. 2020) introduces a tagger module which adds style embeddings of different intensity to different words in a sentence.

Contrastive Learning

Contrastive learning is proved to be an effective unsupervised method for learning an expressive latent representation space (Chen et al. 2020; He et al. 2020) through pulling semantic similar neighbors closer and pushing non-neighbors apart (Hadsell, Chopra, and LeCun 2006). Recently, the contrastive manner has shown effectiveness in learning better representations both in CV (Chen et al. 2020; He et al. 2020) and NLP (Kaushik, Hovy, and Lipton 2019; Gao, Yao, and Chen 2021; Carlsson et al. 2020).

Our model follows the contrastive framework in (Chen et al. 2020) and applies a normalized temperature-scaled cross-entropy loss with in-batch negatives in our Transformer-based auto-encoder. We assume a set of paired examples \( D = \{(x_i, x_i^+)\}_{i=1}^n \), where \( x_i \) and \( x_i^+ \) are content-similar. For a batch with \( N \) pairs, the training objective for \( (x_i, x_i^+) \) is:

\[
\text{con}_i = -\log \frac{e^{\text{sim}(r_i, r_i^+)/\tau}}{\sum_{j=1}^N e^{\text{sim}(r_i, r_j^+)/\tau}},
\]

where \( \tau \) is a temperature hyperparameter, \( \text{sim}(\cdot) \) indicates cosine similarity function, \( r_i \) and \( r_i^+ \) denote the encoded representations of \( x_i \) and \( x_i^+ \).

Gradient-guided Optimization

Gradient-guided methods have been widely used for controllable generation, which edits the latent representations according to its gradient obtained from a neural network. Such methods require two subcomponents: an auto-encoder which learns a mapping between the source data distribution and continuous latent space and a neural network which is trained to discriminate task-specific features, e.g., a style classifier for recognizing input styles. At inference stage, we generate the target with following three steps: (1) Encode the source (e.g., sentence) into a continuous latent representation with a pre-trained auto-encoder. (2) Edit the latent representation according to its gradient, which is obtained by back propagating the task-specific neural network. (3) Decode the altered latent representation and get the transferred target with the auto-encoder.

The most universal line to acquire the gradient is to train a classifier which outputs the probability of each class directly (Nguyen et al. 2017; Wang, Hua, and Wan 2019; Liu et al. 2020). The classifier is trained by minimizing:

\[
\mathcal{L}_{\text{Cls}} = -E_{z \sim q_{\theta}(z|x, \theta_{enc})}^{k} \sum_{i=1}^{k} \hat{a}_i \log[p(a_i | z)]
\]

where \( a \) denotes the predicted probability distribution of style \( s \) and \( \hat{a}_i \) denotes the true probability distribution.

At inference time, the parameter of classifier is frozen and latent representations are optimized in the direction of minimizing \( \mathcal{L}_{\text{Cls}} \):

\[
\hat{z} = z - \omega \cdot \nabla_z \mathcal{L}_{\text{Cls}}
\]

where \( \hat{a} \) in the inference process is the desired style distribution for the source to transfer.

3 Our Method

Problem Formalization

The unsupervised text style transfer task can be formalized as follows: let \( D \) be the dataset, which contains \( n \) labelled sentences, namely, \( D = \{(x_i, s_i)\}_n \), where \( x_i \) denotes the text, \( s_i \in S \) the corresponding style label and \( S \) the set of all styles (e.g., \( S = \{"positive"\}, \{"negative"\} \) for style transfer
Figure 1: The architecture of our model. The top plot indicates the training stage and the bottom plot the inference stage. The content similarity generated by Contrastive Learning which is used for constraint to contents. The style similarity generated by our Siamese Structure Classifier which is used for predicting the style.

Model Overview

The proposed model consists of two components: an auto-encoder which adopts a contrastive paradigm to learn a mapping function between texts and latent representations, a siamese-structure based style classifier which identifies style differences between embeddings and provides gradient-guided information for manipulating latent representations. The training and inference procedure is shown in top plot and bottom plot of Fig. 1 respectively.

Auto-encoder

We follow the standard encoder-decoder architecture to build a Transformer-based (Vaswani et al. 2017) one with reconstruction loss $L_{rec}$. Explicitly, given a sentence $x$, the Transformer encoder $Enc(x; \theta_{enc})$ maps $x$ to relevant continuous representation $z$ which is entangled with content and style and the Transformer decoder $Dec(z; \theta_{dec})$ maps latent representation $z$ back to the sentence $x$. Suppose the latent representation $z$ follows the distribution $q_E(z|x, \theta_{enc})$ and the sentence $x$ follows the distribution $p_G(x|z, \theta_{dec})$, our auto-encoder reconstruction loss is formalized as:

$$L_{rec} = -E_{q_E(z|x, \theta_{enc})}[\log p_G(x|z, \theta_{dec})]$$  \hspace{1cm} (4)

Modeling Content Invariance

To add explicit constraint on content consistency in the standard Transformer framework, we adopt a contrastive paradigm for training a better auto-encoder, which models content invariance in entangled latent space.

Explicitly, the contrastive paradigm is composed of the following two parts: (1) draw the sentences closer, which are content-similar but have different style. (2) draw the sentences closer, which are content-similar and have same style. By this means, sentences with similar content cluster together in the latent space. The motivation is that transferred embeddings are adjacent to original ones, since gradient-guided optimization steps are minimal. Therefore, a sentence can be optimized from the original embedding only if they are close to each other in terms of latent representations distance. Accordingly, the approach of drawing style-different content-similar sentences closer makes the gradient-optimization process easier to implement, and the approach of drawing style-similar content-similar sentences closer prevents occurrence of original content lost and export of other unintentional content. Nonetheless, A challenge is that we have no access to the required content-similar paired corpus, neither of the same style nor different styles, for contrastive learning. To solve the problem, we use retrieval and data augmentation to construct pseudo data pairs. For the purpose of better illustration, we exemplify our model with sentence $x_i$ whose style is $s_i$.

For the first part, we measure the semantic similarity of two sentences by Sentence-BERT (SBERT) (Reimers and Gurevych 2019) which is capable of efficiently computing semantic textual similarity. For the original sentence $x_i$, we construct $(x_i, x_i^{like})$ as a pseudo parallel data pair, where $x_i^{like}$ is the sentence of style $s_i$ that shares most content similarity with $x_i$. To ensure that the retrieved sentences pairs have similar semantics, we set a SBERT threshold $\beta$ for retrieving sentences pairs, and only pairs above this threshold are used for constructing our pseudo data pairs. In addition, to speed up the search in a large corpus, we retrieve the most similar sentence for each sample with the help of FAISS\footnote{https://github.com/facebookresearch/faiss}. Borrowing the supervised contrastive loss from (Khosla et al. 2020), we use these data pairs to optimize Eq. [4] and then the contrastive loss is formulated as follows:

$$cons_{diff} = -\log \frac{e^{sim(z_i, z_j^{like})}/\tau}{\sum_{j=1}^{N} e^{sim(z_i, z_j^{like})}/\tau}$$  \hspace{1cm} (5)

$$L_{CL_{diff}} = \sum_i cons_{diff}$$  \hspace{1cm} (6)

where $z_i$ and $z_j^{like}$ denote the representations of $x_i$ and $x_j^{like}$.

For the second part, we construct pseudo data pairs $(x_i, x_i^{drop})$ through adding dropout perturbations which is demonstrated to be able to learn a good alignment for positive pairs (Gao, Yao, and Chen 2021). The retrieved sentence $x_i^{drop}$ is the same as original sentence $x_i$, however their representations $z_i$ and $z_i^{drop}$ differ due to the existence of random dropout when encoding a sentence. Likewise, we use them to optimize Eq. [4] like part one and get the loss $L_{CL_{same}}$:

$$cons_{same} = -\log \frac{e^{sim(z_i, z_j^{drop})}/\tau}{\sum_{j=1}^{N} e^{sim(z_i, z_j^{drop})}/\tau}$$  \hspace{1cm} (7)
where $z_i$ and $z_i^{drop}$ denote the representations of $x_i$ and $x_i^{drop}$, respectively.

At the time of optimization, we take the data pairs $(x_i, x_i^{like})$ and $(x_i, x_i^{drop})$ as positives, and other in-batch instances as negatives. By summing them up, the total loss for the contrastive paradigm is:

$$L_{CL} = L_{CL_{diff}} + L_{CL_{same}}$$

The architecture of our contrastive learning is shown in Fig. [I] the Content Retriever retrieves $x_i^{like}$ and $x_i^{drop}$ as positive samples $x_i^+$. Finally, incorporating contrastive learning into our auto-encoder training, the loss of auto-encoder is formalized as follows:

$$L(\theta_{enc}, \theta_{dec}) = L_{rec} + \lambda L_{CL}$$

where $\lambda$ is a balancing hyperparameter.

### Siamese-Structure Classifier

When conducting style transfer through gradient-guided update methods, the general line is to train a classifier which directly outputs the probability with respect to each selection (Nguyen et al. 2017; Wang, Hua, and Wan 2019; Liu et al. 2020). However, (Wang, Hua, and Wan 2019) demonstrates that a gradient-guided optimization for text style classifier can become an attack to classifier, where the style of embedding is missclassified. Inspired by the superiority of Siamese Networks in various recent models for unsupervised visual representation learning (Caron et al. 2020; Chen and He 2021), we adapt a siamese-structure method which decides the style of an embedding by conducting comparison between other label-known samples. Provided that our proposed classifier is a comparison based one, the classifier achieves higher accuracy as the number of its compared samples increases. Experiments indicate our proposed classifier structure effectively alleviates the issue of misclassification in the embedding style classifier.

Inspired by (Chen and He 2021), the siamese-structure based classifier consists of a Style Extractor $e = f(z; \theta_f)$ and a Style Predictor $r = h(e; \theta_h)$, which takes as input the output of sentence Encoder and Style Extractor.

To conduct comparison for determining the style of sentence $x_1$ on the basis of label-known sentence $x_2$, they are first fed into the Encoder Enc and Style Extractor $f$ to get corresponding style representations $e_1$ and $e_2$. Finally, the similarity of known sentence $x_1$ to known sentence $x_2$ is calculated as:

$$sim(e_1, e_2) = \cos\left(\frac{h(e_1)}{||h(e_1)||}, \frac{e_2}{||e_2||}\right)$$

where higher similarity score $sim(e_1, e_2)$ denotes two input sentences $x_1$ and $x_2$ are more likely to be of the same style, lower score denotes they tend to differ in terms of style.

In order to make full use of labelled data and to ensure diversity of comparison, for $x_i$ with style $s_i$, we randomly sample $n$ positive sentences $x_i^+$ of the same style to $s_i$ and randomly sample $m$ negative sentences $x_i^-$ of different style to $s_i$. Ensuring the diversity of the comparisons and the robustness of our siamese-structure, we random sample sentences from positive and negative corpus. In such manner, we get data pairs $(x_i, x_i^{0+}, ..., x_i^{n+}, x_i^{0-}, ..., x_i^{m-})$.

In the training phase of siamese-structure based classifier, we optimize:

$$t_i^k = -\log \frac{e^{sim(e_i, e_i^{k+})}/\tau}{e^{sim(e_i, e_i^{k+})}/\tau + \sum_{j=1}^m e^{sim(e_i, e_i^{j+})}/\tau}$$

$$L_{Sia} = \sum_i l_i = \sum_i \sum_{k=1}^n t_i^k$$

where $e$ denotes the representation after feeding $z$, the output embedding of sentence Encoder $Enc$, into the Style Extractor $f$. $L_{Sia}$ denotes the loss function of the siamese structure classifier for optimizing. It is worth noting that gradient is only back propagated through the Style Predictor side of label-unknown sentences, not through the side of label-known sentences at training time.

The training process of the siamese architecture is shown in the top plot of Fig. [I] the Style Retriever retrieves $x_i^{k+}$ as positive samples $x_i^+$, and $x_i^{k-}$ as negative samples $x_i^-$. We set hyperparameters $n$ and $m$ the same in the training phase and inference phase to avoid the introduction of other prior information.

### Text Style Transfer

At the inference stage, the latent embeddings are edited according to the gradient of siamese-structure classifier and then decode this to the target sentence with desired style. Given the original sentence $x$ with style $s_{src}$, the inference process of transferring to style $s_{tgt}$ is based on the gradient update of continuous latent space. We first sample $n$ sentences with target style $s_{tgt}$ as positive samples, denoting as $x_i^{+k}$ where $k$ from 1 to $n$. Similarly, we sample $m$ sentences from styles except for $s_{tgt}$, denoting as $x_i^{-k}$ where $k$ range from 1 to $m$.

Unlike the training stage, a direct gradient for the latent representations is more appropriate for embeddings editing. Therefore we adopt a direct loss function for embeddings at the transferring stage, which is:

$$L_{bp} = -\sum_{i=1}^n sim(f(z), f(z_i^{+k})) + \sum_{i=1}^m sim(f(z), f(z_i^{-k}))$$

$$= -\sum_{i=1}^n sim(e, e_i^{+}) + \sum_{i=1}^m sim(e, e_i^{-})$$

The representation $z$ of $x$ is edited as follows:

$$\hat{z} = z - Opt(\nabla_{z}L_{bp}; \theta_{opt})$$

where $Opt$ denotes optimizers for applying gradient optimization to original latent embeddings and $\theta_{opt}$ denotes parameters of the optimizer. After editing the embeddings in the direction of their gradient, the transferred sentences are
generated from the decoder of auto-encoder. The transfer steps are shown in the bottom plot of Fig[1]. In our experiment, the Adam optimizer (Kingma and Ba 2014) is chosen to optimize latent representations.

4 Experiments

Datasets

We use two datasets. (1) Yelp dataset, produced by [Li et al. 2018], contains restaurant reviews with positive and negative sentiments. (2) Amazon dataset, produced by [He and McAuley 2016], contains product reviews on Amazon with positive and negative sentiments. These two datasets are both commonly-used datasets in text style transfer. It is worth noting that human-written references are only available in test sets and only non-parallelized data is available during training. The dataset statistics are shown in Table 1.

| Dataset | Style     | Train | Dev  | Test |
|---------|-----------|-------|------|------|
| Yelp    | Positive  | 266041| 2000 | 500  |
|         | Negative  | 177218| 2000 | 500  |
| Amazon  | Positive  | 277728| 1015 | 500  |
|         | Negative  | 277769| 985  | 500  |

Table 1: Data Statistics for Yelp and Amazon Dataset

Metrics

Automatic Evaluation. Following previous works (Yang et al. 2018; Yi et al. 2020), we evaluate whether a text style transfer model is successful from three aspects, namely style transfer accuracy, content invariance and language fluency. For accuracy, we train a fastText classifier (Joulin et al. 2017) to discriminate different styles. For content invariance, we use BLEU (Papineni et al. 2002) and WMD (Kusner et al. 2015). Additionally, the prefixes self- and human- represent the generated sentences compared to the original ones and to the human-written references, respectively. Previous methods focus on computing the BLEU score. (Yamshchikov et al. 2021) studies 13 different metrics and proves BLEU, WMD and POS-distance are the best three to evaluate content invariance in the domain of text style transfer, and thus we import WMD as an extra criterion. For language fluency, we measure the perplexity of a sentence with a 5-gram language model SRILM (Stolcke 2002).

Human Evaluation. Many previous works (Wang, Hua, and Wan 2019; Kim and Sohn 2020; Lee 2020) have shown automatic evaluation on human references is not accurate enough. This demonstrates that automatic evaluation is not persuasive enough in the task of style transfer. Therefore, we conduct a human-written evaluation on models outputs. Due to the lack of human labor, we access the output sentences of Yelp and Amazon, and then randomly select 100 sentences for each model with each style. Following [Li et al. 2018], we invite 3 workers to evaluate in a blind review manner and score the sentences from three aspects: target attribute match (Att), content invariance (Con) and grammaticality (Gra). The score of each aspect range from 1 to 5 where 5 denotes the best and 1 denotes the worst.

Baselines

We conduct comprehensive comparison with previous state-of-the-art models, including CrossAlign (Shen et al. 2017), StyleEmb (Fu et al. 2018), MultiDec (Fu et al. 2018), RuleBase (Li et al. 2018), DelRetrGen (Li et al. 2018), ContiSpace (Liu et al. 2020) and GBT (Wang, Hua, and Wan 2019). We consider three variants of our model:

- **OURS_C**: With modeling of content invariance.
- **OURS_S**: With siamese-structure based classifier.
- **OURS_C+S**: With both proposed structures.

When the siamese-structure based classifier is not adopted from our model, we use a MLP classifier which outputs the probability of each style directly as (Wang, Hua, and Wan 2019). When the contrastive modeling of content consistency is not adopted, the auto-encoder is only trained with the reconstruction loss $L_{rec}$.

Experimental Settings

To demonstrate the effectiveness of our proposed method, we use the same auto-encoder structure as (Wang, Hua, and Wan 2019). Therefore, GBT is our model without the contrastive paradigm and the siamese-structure based classifier.

We use two-layer Transformer both for encoder and decoder. The encoder embedding size and the decoder embedding size are both set to 256. The balancing hyperparameter $\lambda$ for training auto-encoder is 0.3. The number of positive samples $n$ and the number of negative samples $m$ are both 10. The temperature hyperparameter $\tau$ is 0.1.

Experimental Results

Automatic evaluation results of the two datasets are presented in Table 2. It should be noted that a good style transfer method should perform well on all aforementioned metrics. StyleEmb in Yelp dataset achieves perfect result in content retention and sentence fluency, however, it is not a successful method as most sentences (82.1%) are not successfully transferred to the target style. RuleBase and DelRetrGen in Amazon dataset both reflect similar issue, and thus cannot be considered as accomplish the style transfer task successfully. We see that our model achieves superior performance in transfer accuracy, outperforming all other models by a large margin. Moreover, our model achieves satisfactory performance in content invariance (BLEU and WMD). Compared to previous gradient-guided models (ContiSpace and GBT), our model outstands in all aspects except for language fluency. Nevertheless, our model shows a shortcoming in language fluency (PPL). This can be due to the inappropriate structure of the Transformer for gradient-based text style transfer, as another Transformer-structure method GBT also performs unsound in terms of sentence fluency. In addition, our proposed two structures help relieve the issue of sentence perplexity, as

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3 https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/multi-bleu.perl
Table 2: Automatic Evaluation results for Yelp and Amazon datasets. The notation ↑ means the higher the better and ↓ the lower the better. We bold the best value for each evaluation criterion.

| method                        | Yelp     |        | Amazon   |        |
|-------------------------------|----------|--------|----------|--------|
|                               | Acc↑     | PPL↓   | human-BLEU↑ | self-BLEU↑ | human-WMD↓ | self-WMD↓ |
| CrossAlign \[Shen et al. 2017\] | 74.7     | 71.6   | 6.79     | 20.74   | 0.449     | 0.307     |
| StyleEmb \[Fu et al. 2018\]   | 17.9     | 76.0   | 16.65    | 67.43   | 0.374     | 0.128     |
| MultiDec \[Fu et al. 2018\]   | 53.7     | 95.1   | 11.24    | 40.07   | 0.421     | 0.261     |
| RuleBase \[Li et al. 2018\]   | 83.7     | 85.7   | 18.02    | 57.36   | 0.376     | 0.260     |
| DelRetrGen \[Li et al. 2018\] | 85.0     | 71.7   | 12.62    | 36.75   | 0.393     | 0.278     |
| ContiSpace \[Liu et al. 2020\] | 85.9     | 47.0   | 67.43    | 0.374   | 0.128     | 0.310     |
| GBT \[Wang, Hua, and Wan 2019\] | 88.2    | 130.2  | 9.61     | 29.14   | 0.421     | 0.280     |
| OURS \[C+S\]                 | 91.0     | 100.8  | 12.21    | 34.45   | 0.387     | 0.236     |

| method                        | Amazon   |        |         |        |
|-------------------------------|----------|--------|--------|--------|
|                               | Acc↑     | PPL↓   | human-BLEU↑ | self-BLEU↑ | human-WMD↓ | self-WMD↓ |
| CrossAlign \[Shen et al. 2017\] | 78.6     | 22.0   | 1.57    | 2.49    | 0.743     | 0.614     |
| StyleEmb \[Fu et al. 2018\]   | 45.2     | 85.9   | 13.41   | 31.23   | 0.629     | 0.434     |
| MultiDec \[Fu et al. 2018\]   | 70.8     | 72.0   | 7.87    | 18.24   | 0.685     | 0.527     |
| RuleBase \[Li et al. 2018\]   | 67.4     | 130.3  | 31.75   | 67.75   | 0.483     | 0.233     |
| DelRetrGen \[Li et al. 2018\] | 45.7     | 80.3   | 27.14   | 56.44   | 0.456     | 0.200     |
| ContiSpace \[Liu et al. 2020\] | 82.7     | 38.7   | 12.87   | 21.88   | 0.598     | 0.419     |
| GBT \[Wang, Hua, and Wan 2019\] | 81.0    | 398.8  | 9.56    | 0.460   | 0.495     | 0.413     |
| OURS \[C+S\]                 | 87.5     | 251.3  | 9.79    | 0.594   | 0.413     | 0.413     |

Ablation Study

To understand the impact of two proposed structures of our proposed model, we further do an ablation study. We choose five well-performed models according to the automatic evaluation results as competitors and the results are presented in Table 2. With respect to content invariance (Con) and grammaticality (Gra), we notice some models (e.g., RuleBase) performed well on automated metrics, but poorly on the human ones. As an explanation, these models retain most original words and insert some statements with strong stylistic attributes to the original sentences. Such line of modifications results in the influence of the original semantics and fluency, which is difficult to be identified by automatic evaluation methods. Concerning overall human metrics, our model exhibits outstanding performance in the field of style accuracy and content invariance and achieves the best overall performance. The result of our human evaluation is in accord with the automatic ones. We compare some generated sentences in Table 3.

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Figure 2: Ablation study for understanding each of the impact of our proposed structure

considerable improvement is gained compared to the line without them (GBT).

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Figure 3: The relationship between $\text{Change}$ and $\text{Suc}$. To present the results of Yelp dataset in the main text since the results of Amazon dataset reflect similar conclusion. More details are shown in Appendix. The automatic evaluation result is displayed is Table 5.

For better understanding the role of the two components, we follow the universal line of focusing on the relationship between style accuracy and content invariance \[Li et al. 2018; Yi et al. 2020\], including self-BLEU and human-BLEU. By changing the learning rate and update steps of latent optimizer, various data points can be obtained. The results are demonstrated in Fig. 2.

The two graphs reveal similar conclusions. (1) The contrastive paradigm which clusters content similar sentences largely improves overall performance. (2) The siamese-structure classifier improves the style accuracy when BLEU is the same, especially when the accuracy rate is high. We also notice the siamese structure classifier performs slightly worse than the conventional one when style accuracy is low. This can be due to siamese-structure classifier which make
decision by comparing latent representations might introduce other irrelevant content from other compared references. This is inevitable as long as the content distribution of two styles are not the same (Li et al. 2020). Moreover, the gain of relieving misclassification issue of embedding classifier outstands the loss of irrelevant content export when transfer extent increases considerably.

**Resistance to Style Misclassification**

When a latent representation alters to be a new one, the predicted label of new latent might switch while their decoded sentences are the same, which is a misclassification case that an expected conversion becomes an attack to classifier. Actually, there are four cases when altering a representation.

1. Predicted label unchanged, decoded sentence unchanged.
2. Predicted label changed, decoded sentence unchanged.
3. Predicted label unchanged, decoded sentence change.
4. Predicted label changed, decoded sentence changed.

The first condition (Keep) denotes gradient optimization do not influence the judgement of the classifier, and the second condition (Attack) denotes an attack to the classifier. We evaluate the robustness of a classifier structure by criterion:

\[ Suc = \frac{\text{Keep}}{\text{Keep} + \text{Attack}} \]  

where higher \( Suc \) means less vulnerable to classifier attack and more resistant to classifier misclassification. However, directly measuring the robustness of a classifier structure by \( Suc \) is unfair, since \( Suc \) should be close to 1 when the embedding optimization speed is especially minimal. Therefore, we measure the impact of optimization speed with the proportion of changed sentences \( Change \), which equals the sum of the second condition add fourth condition. Finally, we use a MLP embedding classifier in GBT which directly outputs the probability of each class as a competitor. Fig.3 and Fig.2 indicate that our siamese-structure classifier is more resistant to classifier misclassification and improves transfer accuracy in the task of text style transfer, respectively.

## 5 Conclusion

In this work, we propose a novel gradient-guided framework for unsupervised text style transfer, which solves two issues of previous gradient-based works. We propose a contrastive paradigm for training the auto-encoder to gain better content
consistency and design a siamese-structure classifier to alleviate the misclassification issue of embedding classifier. Our experiments results show that our approach achieves state-of-the-art performance.

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