"Slow Service" ↛ "Great Food": Enhancing Content Preservation in Unsupervised Text Style Transfer

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Abstract

Text style transfer aims to change the style (e.g., sentiment, politeness) of a sentence while preserving its content. A common solution is the prototype editing approach, where stylistic tokens are deleted in the "mask" stage and then the masked sentences are infilled with the target style tokens in the "infill" stage. Despite their success, these approaches still suffer from the *content preservation* problem. By closely inspecting the results of existing approaches, we identify two common types of errors: 1) many content-related tokens are masked and 2) irrelevant words associated with the target style are infilled. Our paper aims to enhance content preservation by tackling each of them. In the "mask" stage, we utilize a BERT-based keyword extraction model that incorporates syntactic information to prevent content-related tokens from being masked. In the "infill" stage, we create a pseudo-parallel dataset and train a T5 model to infill the masked sentences without introducing irrelevant content. Empirical results show that our method outperforms the state-of-the-art baselines in terms of content preservation, while maintaining comparable transfer effectiveness and language quality.

1 Introduction

There is growing research interest in text style transfer recently, with the aim of altering the text style (e.g., sentiment, politeness, formality) of a sentence while preserving its content. For example, a sentiment transfer model may transfer a positive-sentiment sentence from "This is the best book I've read ever!" to "This is the worst book I've read ever!". As another example, "what happened to my personal station?" may be transferred to "could you please let me know what happened to my personal station?" for a more polite expression. Text style transfer has been shown to be useful in many downstream applications, such as author obfuscation (Shetty et al., 2018), data augmentation (Xie et al., 2020; Kaushik et al., 2019), text simplification (Xu et al., 2015), and writing assistance (Heidorn, 2000).

Unsupervised style transfer has been extensively explored since parallel data are difficult to obtain. One intuitive and promising solution is the prototype editing approach (Li et al., 2018; Wu et al., 2019; Reid and Zhong, 2021), where the "mask" and "infill" steps are sequentially applied. In the "mask" stage, stylistic tokens are identified and deleted by frequency-ratio based methods (e.g., TF-IDF) and/or attention-based methods, resulting in a content-only masked sentence. In the "infill" stage, the masked sentence is infilled by adding new style markers through template-based methods (Li et al., 2018) or masked language models (Wu et al., 2019; Malmi et al., 2020).

While these models have shown their power to transfer the input text to the target style with high transfer effectiveness, most of them, if not all, suffer from the content preservation issue. As shown in Table 1, despite the style has been transferred successfully, the content is partially changed too (e.g., "service" → "food").

In this paper, we propose a novel approach to enhance **content preservation** for unsupervised text style transfer. We first summarize two important observations of common errors made by the existing models:

- In the "mask" stage, content-related tokens may be removed (e.g., underlined tokens in cases (a), (c), (d), (e) in Table 1);

- In the "infill" stage, irrelevant words with strong styles may be generated (e.g., underlined tokens in (a), (b), (d), (e) in Table 1).

To preserve content-related tokens in the "mask" stage, we extract the central component of the sentence and prevent them from being masked. Specif-

Transfer Type	Source Sentences	Transferred Sentences
(a) Negative → Positive:	we sit down and we got some really slow and lazy <u>service</u>.	we sit down and we got some really good <u>food</u> and loved it.
(b) Positive → Negative:	the taste is awesome.	the taste is not good <u>and the service is slow</u>.
(c) Factual → Romantic:	a man and a woman show their <u>tatooed</u> hearts on their <u>wrists</u>.	a man and a woman show their loved hearts on their anniversary.
(d) Male → Female:	the locker room is <u>clean</u>.	the locker room is <u>cute</u>.
(e) Toxic → Civil:	as stupid and arrogant as his boss.	as <u>warm hearted</u> as his boss.

Table 1: Error analysis of existing state-of-the-art models. Tokens masked are in red, and new tokens generated are in blue. Tokens underlined are either content-related tokens removed or irrelevant words generated.

ically, we utilize a BERT-based keyword extraction model which incorporates syntactic information (e.g., dependency parsing) to identify content-related tokens. In dependency parsing, the head word of a constituent is the central organizing word of a larger constituent (e.g., the primary noun in a noun phrase, or verb in a verb phrase) (Jurafsky, 2000), and therefore, should be more likely to remain unmasked. Lastly, we make use of an attention network to decide which tokens are stylistic and therefore, should be masked. In style classification tasks, attention scores are often used to interpret to what extent a token has style attribute (Lee et al., 2021; Wu et al., 2019).

In the "infill" stage, existing state-of-the-art approaches typically fine-tune a large pre-trained masked language model (e.g., BERT) on the target style corpus and treat it as a fill-in-the-mask problem (Wu et al., 2019; Malmi et al., 2020; Reid and Zhong, 2021). While such language models can generate fluent sentences of the target style well, they often introduce tokens irrelevant to the source sentence, which results in the change of content. To prevent irrelevant words generation in the "infill" stage, we create a pseudo-parallel dataset and train a large pre-trained language model—T5 (Raffel et al., 2020) to specifically learn to generate from a masked sentence to a target style sentence without introducing unnecessary and irrelevant content.

To summarize, we make the following contributions to enhance content preservation in unsupervised text style transfer:

- In the "mask" stage, we utilize a BERT-based keyword extraction model and leverage dependency parsing information to preserve content-related tokens.

- In the "infill" stage, we propose to create a pseudo-parallel dataset in a self-supervised

manner, and explicitly learn to recover the masked sentences in the target style without adding irrelevant content.

2 Proposed Model

2.1 Problem Formulation

In this paper, we formulate the unsupervised text style transfer as follows: for two non-parallel corpora $\mathbf{X} = \{x_1, x_2, ..., x_m\}$ and $\mathbf{Y} = \{y_1, y_2, ..., y_n\}$ with styles S_x and S_y respectively, the goal is to train a style transfer model G that generates a corpus $\hat{\mathbf{X}} = \{\hat{x}_1, \hat{x}_2, ..., \hat{x}_m\}$ conditioned on the corpus $\mathbf{X}$. The generated corpus $\hat{\mathbf{X}}$ is expected to be in the target style S_y and preserves the content of $\mathbf{X}$.

2.2 Model Overview

Figure 1 illustrates our proposed model architecture. Following Li et al. (2018); Wu et al. (2019), we assume that style is localized to certain tokens in a sentence and those tokens can be deleted to form a style-free corrupted sentence.[1]

At the **training** stage, we first build a style removal model G_d to obtain corrupted sentences $\mathbf{Y}_c$ from $\mathbf{Y}$, the collection of sentences in the target corpus.[2] Such corrupted sentences $\mathbf{Y}_c$ are considered style-free under our aforementioned assumption, and ideally there is little loss of content. Second, we train a sentence recovery model G_r to recover the original sentences $\mathbf{Y}$ from the corrupted sentences $\mathbf{Y}_c$. Such a sentence recovery model G_r is expected to recover the style-free corrupted sentences $\mathbf{Y}_c$ to the original sentences $\mathbf{Y}$ in the target

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[1] Note that this assumption is not always true. Readers are referred to Jafaritazehjani et al. (2020) for a more detailed discussion.

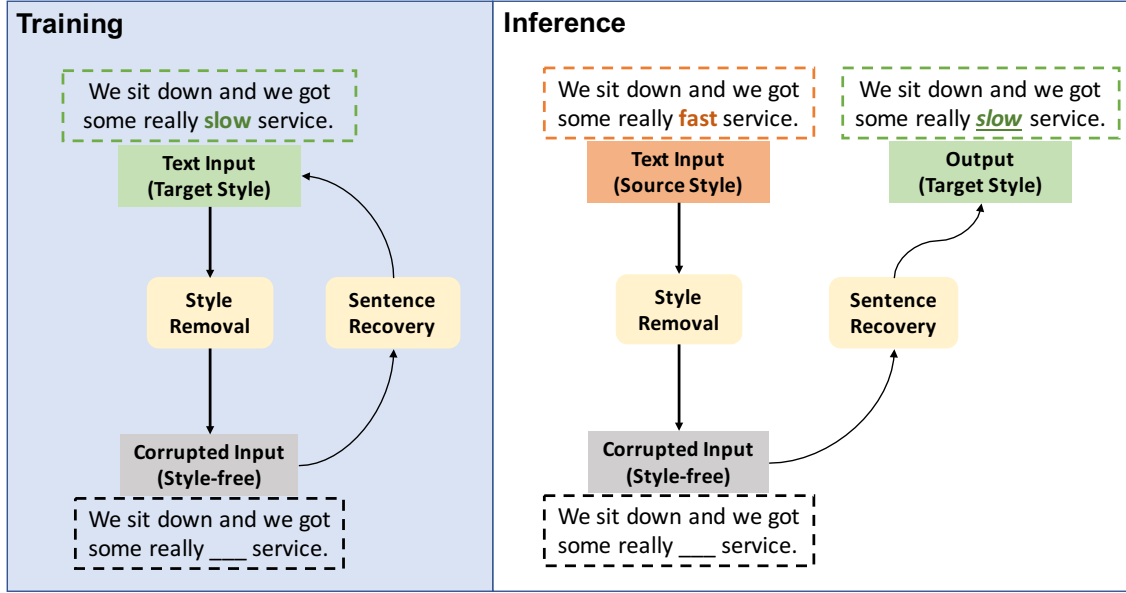[2] "Corrupted sentences" and "masked sentences" are used interchangeably.

Figure 1: Overview of the model architecture.

style S_y, and very importantly, without introducing irrelevant content.

After training, we have a style removal model G_d and a sentence recovery model G_r. Now at the **inference** stage, we apply the style removal model G_d on the source style sentences $\mathbf{X}$ and obtain style-free corrupted sentences $\mathbf{X}_c$. Then, we produce the final output $\hat{\mathbf{X}}$ using the sentence recovery model G_r, which is trained to recover corrupted sentences to the target style S_y.

Next, we introduce the details of the style removal model G_d in Section 2.3 and the sentence recovery model G_r in Section 2.4.

2.3 The Style Removal Model

Existing models typically make use of frequency-ratio based methods (e.g., TF-IDF) and/or attention based methods to remove the stylistic tokens (Li et al., 2018; Wu et al., 2019). However, they achieve mediocre performance as many content-related and style-free tokens are masked too. Section 2.3.1 explains how content-related tokens are preserved and Section 2.3.2 shows how the style-related tokens are masked.

2.3.1 Keyword Extraction

To preserve the relevant content, we explicitly utilize a keyword extraction model, which incorporates syntactic information (e.g., dependency parsing) to highlight the content-related tokens and prevent them from removal.

With a source style sentence $x = \{t_1, t_2, ..., t_k\}$,

where t_i is the i-th token, the model extracts content-related keywords in three steps:

(a) **Embedding**: we use BERT embeddings[3] to represent all of the keywords $e_{t_1}, e_{t_1}, ..., e_{t_k}$ and the entire sentence e_x in a high-dimensional vector space.

(b) **Dependency Parsing**: we construct a dependency tree that captures word-level relations with the Stanford dependency parser (Manning et al., 2014). From the dependency tree, we obtain the depth d_i and the outdegree o_i for each word token t_i. In dependency parsing, the head word of a constituent was the central organizing word of a larger constituent (Jurafsky, 2000). The more central the words are (higher depth or larger outdegree), the more likely it contains meaningful content and therefore, the less likely they should be masked.

(c) **Ranking**: all candidates are ranked to represent the keywords of the sentence:

$$r_{t_i} = \alpha \cdot \cos(e_{t_i}, e_x) + \beta \cdot d_i + \gamma \cdot o_i$$

To alleviate the redundant keywords issue, we follow Bennani-Smires et al. (2018) to use Maximal Marginal Relevance (MMR) (Carbonell and Goldstein, 1998) for diversified candidates by optimizing keyword informativeness with dissimilarity among selected candidates.

Finally, we select candidates over a threshold $thres$ and prevent them from being masked. Em-

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[3]We use "bert-base-uncased" in `https://huggingface.co/docs/transformers/model_doc/bert`.

pirically, we take $\alpha = 0.8$, $\beta = 0.1$, $\gamma = 0.1$, and $thres = 0.74$, based on the results of the validation data in the Yelp dataset.

2.3.2 Attention

After the keywords have been extracted, we train an attention-based classifier to identify the style-related tokens. We simply encode the sentence and concatenate the forward and the backward hidden states for each word with a bidirectional LSTM. After training, the attention-based classifier is expected to generate attention weights, which capture the style information of each word. For simplicity, we follow Wu et al. (2019) and set the averaged attention value in a sentence as the threshold. Words with attention weights higher than the threshold are viewed as style markers. Note that the content-related keywords identified in Section 2.3.1 are preserved and **not** classified as style markers.

2.4 The Sentence Recovery Model

With style-free corrupted sentences $\mathbf{X}_c$, we focus on recovering them to the target style S_y. Here, we introduce to solve the problem by creating a pseudo-parallel training dataset and training a model G_r for sentence recovery explicitly. Recall that in Section 2.3, we obtain corrupted sentences $\mathbf{Y}_c$ given the original sentences $\mathbf{Y}$. Therefore, if we take them in a reverse direction, we then have a parallel training dataset to learn from (i.e., $\mathbf{Y}_c \rightarrow \mathbf{Y}$).

We select T5 (Raffel et al., 2020), a strong pre-trained text-to-text model, as the base architecture, and fine-tune it on the constructed pseudo-parallel dataset. After being trained, the model is expected to take as input a corrupted style-free input $\mathbf{Y}_c$ and generate sentences in the target style without introducing additional irrelevant content. Finally, we apply the trained T5 model on corrupted input $\mathbf{X}_c$ and generate the final output $\hat{X}$, which is expected to be of the target style S_y.

Intuition: As demonstrated by Wu et al. (2019); Malmi et al. (2020), it is an intuitive idea to treat the "infill" step as a fill-in-the-mask problem, and generate sentences by a fine-tuned masked language model. However, such masked language models (e.g., BERT) are designed to predict tokens for a "mask" and generate sentences with the highest sentence probability. Despite that they are able to generate fluent sentences in the target style, they may introduce tokens that are irrelevant to the source sentence (e.g., case (b) in Table 1) and therefore,

may potentially change the content. Here, what we expect is not a general model for generating a fluent sentence, but rather a specialized model that works only for *sentence recovery without introducing irrelevant content*. Therefore, we construct a pseudo-parallel training dataset and train the model in a supervised manner explicitly for this task. After training on such a dataset, the T5 model is expected to learn specifically to generate sentences in the target style without introducing additional and irrelevant information.

3 Empirical Evaluation

In this section, we empirically evaluate the performance of our proposed approach (denoted as "STEC"[4]) and a set of baseline models. We implemented all models in Python 3.7 and conducted all the experiments on a computer with twenty 2.9 GHz Intel Core i7 CPUs and one GeForce GTX 1080 Ti GPU.

3.1 Datasets

Sentiment Transfer: We use the Yelp dataset and the Amazon dataset (Li et al., 2018), which are business reviews on Yelp and product reviews on Amazon respectively. Each of the dataset consists of two non-parallel corpora with positive and negative sentiments. Each example is labeled as having either positive or negative sentiment.

Captions: The Captions dataset (Gan et al., 2017; Li et al., 2018) has image captions labeled as being factual, romantic or humorous. We focus on the task of converting factual sentences into romantic and humorous ones.

Politeness: The Politeness dataset (Madaan et al., 2020) is produced by filtering through the Enron Email corpus (Klimt and Yang, 2004). We aim to transform the tone of a sentence from impolite to polite.

Detoxification: We employed the largest publicly available toxicity detection dataset to date from "Jigsaw Unintended Bias in Toxicity Classification" Kaggle challenge.[5] We follow Dale et al. (2021) to obtain non-parallel data, and focus on transferring from toxic to non-toxic.

Dataset statistics are presented in Table 2. For the Yelp, Amazon and Captions datasets, human

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[4]short for "Style Transfer with Enhanced Content"
[5]https://www.tensorflow.org/datasets/catalog/civil_comments

Dataset	Style	Train	Valid	Test
Yelp	Positive	270K	2K	500
	Negative	180K	2K	500
Amazon	Positive	277K	985	500
	Negative	278K	1015	500
Captions	Romantic	6K	300	-
	Humorous	6K	300	-
	Factual	-	-	300
Politeness	Polite	219K	28K	-
	Impolite	199K	24K	800
Detoxification	Toxic	150K	5K	10K
	Non-toxic	150K	5K	-

Table 2: Dataset statistics for style transfer tasks.

annotated solutions are also provided for measuring content preservation.

3.2 Baselines

We compare our proposed approach with the following competitive baseline models:

1. CAE: it achieves style transfer from nonparallel text by cross alignment of latent representations (Shen et al., 2017).[6]

2. DRG (Li et al., 2018): this is one of the first successful prototype editing methods. We compare against the full method—delete-retrieve-generate.[7]

3. Mask and Infill (MI) (Wu et al., 2019): the style tokens are first separated from content by masking the positions of sentimental tokens with a fusion model. Then, a masked language model is trained to predict words/phrases conditioned on the context and the target style.

4. Tag and Generate (TAG) (Madaan et al., 2020): it first tags tokens with the original style and/or adds new tags inside a sentence. Then, it conditionally generates the target sentence from the tagged source sentence.[8]

5. NAST (Huang et al., 2021): it first predicts word alignments conditioned on the source sentence, and then generates the transferred sentence with a non-autoregressive decoder. We report results by the model building upon StyTrans (Dai et al., 2019).[9]

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6. RACoLN (Lee et al., 2021): it implicitly removes style at the token level using reverse attention, and fuses content information to style representation using conditional layer normalization.[10]

3.3 Evaluation

Following prior work (Madaan et al., 2020; Reid and Zhong, 2021), we evaluate all model outputs along three dimensions: transfer effectiveness, content preservation and language quality.

Transfer effectiveness refers to whether the transferred sentences reveal the target style property. *Content preservation* captures how a sentence maintains its original content throughout the transfer process. *Language quality* measures whether the generated sentences are grammatical, fluent and readable.

3.3.1 Automatic Evaluation

Effectiveness: We follow Reid and Zhong (2021) and train a RoBERTa-base classifier on the training data for the respective dataset. Our evaluation classifier achieves accuracy of 98.0% on Yelp, 84.2% on Amazon, 79.6% on Captions, 88.3% on Politeness, and AUC-ROC of 0.97 on Detoxification. We measure the percentage of the generated sentences classified to be in the target domain by the classifier.

Content Preservation: The standard metric for measuring content preservation is BLEU-self (BL-s) (Papineni et al., 2002) which is compared with respect to the original sentences. However, BLEU scores can measure syntactic content preservation only. Besides, to measure semantic content preservation, we report BERTScore-self (BS-s) (Zhang et al., 2019) against the source sentences. In addition, we report BLEU-reference (BL-r) and BERTScore-reference (BS-r) using the human reference sentences on the Yelp, Amazon and Captions datasets (Li et al., 2018).

Language Quality: We adopt GRUEN (Zhu and Bhat, 2020) to evaluate the language quality.

3.3.2 Human Evaluation

In addition to automatic evaluation, we validate the generated outputs with human evaluation. With each model except CAE, we randomly sample 100 outputs from each dataset.[11] Given the target style

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and the original sentence, two annotators (graduate students who are specialized in NLP) are asked to evaluate the model generated sentence with a score range from 1 (Very Bad) to 5 (Very Good) on style transfer accuracy, content preservation, and language quality respectively.

3.4 Results

The automatic evaluation results based on *best-found hyperparameters* are summarized in Table 3. We observe a significant improvement in content preservation scores across various datasets (specifically in the Captions dataset and the Detoxification dataset), highlighting the ability of our model to retain content better than the baseline models. Alongside, we observe comparable performance of our model on transfer effectiveness and language quality across various datasets.

As for the human evaluation, we report the average scores from the 2 annotators in Table 4. We observe that the result mainly conforms with the automatic evaluation. Our model received the highest score on the content evaluation metric, while maintaining comparable score on transfer effectiveness and language quality. Both automatic and human evaluation depict the strength of our proposed model in preserving content.

Among all the baselines, TAG has the best performance consistently in both automatic evaluation and human evaluation, in particular, on the Politeness dataset. This is expected as the "tagger" component is designed to find place for insertion of polite expressions inside a sentence.[12]

For the two state-of-the-art papers that tackles content preservation—RACoLN and NAST, though they perform well on some datasets, the models are not robust across different datasets. Comparably, our approach has consistently good performance and therefore, demonstrates its better generalizability.

3.5 Ablation Study

We compare with the following ablations of STEC and show the results in Figure 2:

1. no-parsing: we exclude the dependency parsing information and use BERT embeddings only to preserve the keywords.

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[12]Politeness transfer is slightly different from sentiment transfer, and readers are referred to Madaan et al. (2020) for more detailed discussions.
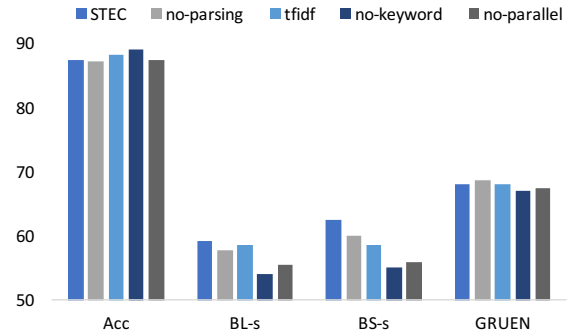

Figure 2: Ablation study. Plots show average results across all five datasets. We scale GRUEN by 100 times for better visualization.

2. tfidf: instead of using the attention network for masking the style-related works, we follow (Li et al., 2018) to use the TF-IDF to mask the style-related words.

3. no-keyword: we exclude the entire keyword extraction model and use the attention network directly to mask the style-related words.

4. no-parallel: instead of constructing a pseudo-parallel dataset and train the T5 model in the "infill" stage, we treat it as a fill-in-the-mask problem and solve it by a fine-tuned masked language model.

We observe that our approach performs better than all ablations in terms of content preservation, and all ablations have comparable performance for transfer effectiveness and language quality. Compared with no-keyword and no-parallel, we conclude that each of the proposed model (i.e., Section 2.3 and Section 2.4) contributes to content preservation well respectively. Besides, by comparing no-keyword and no-parsing, we demonstrate that dependency parsing information can help preserve the content too. In addition, the performance drop by tfidf indicates that an attention network works better in masking stylistic tokens.

3.6 Case Study

Examples of the transferred results by our model are presented in Table 5. We find that our proposed keyword extraction model can preserve the content-related words well. Besides it, we also observe that the T5 model is able to recover the corrupted sentences in the target style without introducing irrelevant content.

	Yelp						Amazon					
	Acc	BL-s	BL-r	BS-s	BS-r	GR	Acc	BL-s	BL-r	BS-s	BS-r	GR
CAE	73.6	20.2	7.7	33.6	22.9	0.69	**78.0**	2.6	1.7	9.8	6.9	0.51
DRG	88.5	36.7	14.5	48.5	33.3	0.72	51.2	57.1	29.9	66.9	46.2	0.62
MI	90.5	41.7	15.3	49.8	36.0	0.75	74.5	60.0	28.5	61.2	44.7	0.62
TAG	85.8	47.1	19.7	57.9	37.2	**0.78**	66.4	**68.7**	34.8	**69.5**	48.2	**0.66**
NAST	89.4	59.0	21.0	55.8	45.9	0.72	64.1	55.8	27.9	61.7	39.9	0.59
RACoLN	**91.3**	58.9	20.0	62.1	42.1	0.75	69.1	31.9	20.1	36.9	31.1	0.63
STEC	88.6	**60.2**	**21.7**	**62.9**	**46.6**	0.75	66.2	67.1	**36.5**	68.8	**50.9**	**0.66**

(a) Sentiment transfer.

	Captions						Politeness				Detoxification		
	Acc	BL-s	BL-r	BS-s	BS-r	GR	Acc	BL-s	BS-s	GR	Acc	BL-s	BS-s	GR
CAE	89.7	2.1	1.6	11.2	6.7	0.51	**99.4**	7.0	30.7	0.71	92.3	13.4	22.9	0.52
DRG	**95.7**	31.8	11.8	40.2	28.4	0.58	90.3	11.8	41.4	0.69	95.6	38.5	42.7	0.58
MI	92.0	42.2	13.3	44.6	31.2	0.64	91.3	55.7	62.9	**0.72**	95.6	38.9	45.1	0.62
TAG	93.2	51.0	15.6	50.2	36.4	0.65	84.8	**70.4**	**71.6**	0.71	92.1	35.1	39.2	0.54
NAST	94.4	44.1	13.3	44.1	32.0	0.64	88.8	65.1	66.7	0.70	93.7	40.1	44.9	0.56
RACoLN	91.2	48.1	13.8	47.7	32.1	**0.67**	87.5	49.9	54.6	0.71	92.9	36.6	40.3	0.52
STEC	91.5	**55.6**	**17.9**	**54.8**	**38.5**	0.65	88.9	68.7	71.1	0.71	**96.6**	**42.0**	**46.1**	**0.63**

(b) Style transfer on other forms.

Table 3: Automatic evaluation results on sentiment transfer. Best results are in bold. Acc: Accuracy; BL-s: BLEU-self; BL-r: BLEU-reference; BS-s: BERTScore-self; BS-f: BERTScore-reference; GR: GRUEN.

	Yelp			Amazon			Captions			Politeness			Detoxification		
	Eff.	CP	LQ	Eff.	CP	LQ	Eff.	CP	LQ	Eff.	CP	LQ	Eff.	CP	LQ
DRG	4.0	3.7	3.5	3.7	3.0	3.3	2.8	2.7	3.0	4.0	4.1	3.7	4.0	3.0	3.3
MI	4.0	3.6	3.7	3.6	2.9	3.4	2.6	3.2	3.1	4.1	4.1	4.0	**4.2**	2.7	3.0
TAG	3.8	4.0	**3.8**	**3.8**	3.4	**3.8**	3.1	**3.5**	**3.5**	**4.4**	**4.5**	**4.3**	3.9	2.6	3.4
NAST	4.2	4.1	3.7	3.4	2.7	3.0	2.2	2.4	2.9	3.9	3.9	3.8	3.9	3.1	3.1
RACoLN	**4.3**	4.3	3.5	3.1	2.4	3.1	2.4	2.1	2.8	3.7	3.6	3.8	3.6	2.4	2.8
STEC	4.1	**4.6**	3.7	3.6	**3.9**	3.6	**3.2**	**3.5**	3.2	4.2	4.2	4.0	**4.2**	**3.7**	**3.4**

Table 4: Human evaluation results. Best results are in bold. Eff.: Transfer Effectiveness; CP: Content Preservation; LQ: Language Quality.

4 Related Work

Textual style transfer, the task of changing the style of an input sentence while preserving its content, has recently received increasing attention (Jin et al., 2021). To date, a wide range of solutions have been proposed to solve the task of textual style transfer, such as latent representation disentanglement (Shen et al., 2017; Fu et al., 2018; Riley et al., 2021; Nangi et al., 2021), prototype editing (Li et al., 2018; Wu et al., 2019; Malmi et al., 2020; Madaan et al., 2020; Reid and Zhong, 2021), and others (Gong et al., 2019; Jin et al., 2019; Goyal et al., 2021; Liu et al., 2021).

Many recent works have reported good performance on several aspects of style transfer, including sentiment (Li et al., 2018; Gong et al., 2019), formality (Rao and Tetreault, 2018), simplicity (Van den Bercken et al., 2019; Cao et al., 2020), po-liteness (Madaan et al., 2020), gender (Prabhumoye et al., 2018), authorship (Jhamtani et al., 2017; Carlson et al., 2018). For instance, Li et al. (2018) propose a simple pipeline approach—delete-retrieve-generate and have shown promising performance on sentiment transfer. Gong et al. (2019) design a reinforcement learning based model for sentiment and formality transfer. It takes style rewards, semantic rewards and fluency rewards from the evaluator and updates the generator for better transfer quality. Madaan et al. (2020) introduce a tag and generate pipeline to identify stylistic words and/or insertion positions. It works particularly well on the Politeness dataset, and shows superior performance on other datasets too.

Content preservation still remains as a major challenge and yet to be solved (Jin et al., 2021; Lee et al., 2021; Huang et al., 2021). To enhance content preservation, researchers have made some

Transfer Type	Source Sentences	Transferred Sentences
(a) Negative → Positive:	we sit down and we got some really slow and lazy service.	we sit down and we got some really great service.
(b) Positive → Negative:	the taste is awesome.	the taste is really bad.
(c) Factual → Humorous:	the group of hikers is resting in front of a mountain.	the group of hikers is being pulled in front of a mountain.
(d) Factual → Romantic:	several young people celebrate by clapping and cheering.	several young people celebrate their lovely friendship by clapping and cheering.
(e) Impolite → Polite:	yes go ahead and remove it	could you please go ahead and remove it
(f) Toxic → Civil:	suggesting that people change their commute times is stupid.	suggesting that people change their commute times is useless.

Table 5: Case study: style transfer results by our proposed model. Tokens masked are in red, and new tokens generated are in blue.

recent progress (Samanta et al., 2021; Garcia et al., 2021; Krishna et al., 2022). For instance, Lee et al. (2021) propose to implicitly remove style at the token level using reverse attention, and fuse content information to style representation using conditional layer normalization. Besides it, Huang et al. (2021) study a non-autoregressive generator, which can serve as an alternative generator for other established models. It explicitly models word alignments to suppress irrelevant words, exploits the word-level transfer between different styles, and is shown to improve content preservation for cycle-loss-based models. In addition, Gong et al. (2020) propose to encode rich syntactic and semantic information with a graph neural network and show its ability on sentiment transfer.

Our work differs from them in the following two aspects: 1) Existing approaches for enhancing content preservation falls in the category of latent representation disentanglement approach, while, to the best of our knowledge, we have proposed the first model to enhance content preserve in the category of prototype editing. 2) Existing approaches rely on the assumption that latent representation can implicitly partially retain both content and style information. However, this assumption lacks justification and remains challengeable (Jin et al., 2021; Jafaritazehjani et al., 2020).

5   Conclusion

In this paper, we identify two common types of errors on content preservation by existing style transfer models. To solve them, we propose to utilize a keyword extraction model to preserve the content-related tokens in the "mask" stage, and to leverage the self-supervision scheme to create a pseudo-parallel dataset in the "infill" stage. With the two core components, our model is able to enhance content preservation while keeping the outputs with target style. Both automatic and human evaluation shows that our model has strong ability in preserving content and show comparable performance in other evaluation measures too.

Limitation and Future work: 1) we rely on the assumption that style is localized to certain tokens in a sentence and we can delete those tokens to obtain a style-free corrupted sentence. However, this assumption is not always true, especially for more complicated styles (e.g., from modern English to Shakespearean English) (Jafaritazehjani et al., 2020). 2) In more complicated forms of styles, there could be few words associated with the source target, which makes the "mask" model difficult to work well. For instance, in the Politeness dataset, "send me the data" is not a polite expression, but there are no impolite words associated either (Madaan et al., 2020). 3) We focus on the problem of unsupervised style transfer, where access to a large corpus of unpaired sentences with style labels are required. This could be a strong requirement, especially for low-resource settings. Besides, the models built are style-specific and are not generalizable to other styles. It could be an interesting future work to extend our model to the few shot problem setting (Krishna et al., 2022; Garcia et al., 2021).

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Ethical Considerations

Risks in deployment: Recent works have highlighted the issues with text style transfer, such as improper usage with malicious intention (Lee et al., 2021) and unintended bias (Krishna et al., 2022). We acknowledge these issues, and given the limited scope of the present study, we call for attention to these aspects by way of well-designed experiments before deployment.

Risks in annotation: The data we use in this paper were posted on publicly accessible websites, and do not contain any personally identifiable information (i.e., no real names, email addresses, IP addresses, etc.). The annotators were warned about the toxic content before they read the data, and were informed that they could quit the task at any time if they were uncomfortable with the content. The annotators in our study were evaluating the quality of the generated sentences only.

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