NON-PARALLEL TEXT STYLE TRANSFER WITH SELF-PARALLEL SUPERVISION

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ABSTRACT

The performance of existing text style transfer models is severely limited by the non-parallel datasets on which the models are trained. In non-parallel datasets, no direct mapping exists between sentences of the source and target style; the style transfer models thus only receive weak supervision of the target sentences during training, which often leads the model to discard too much style-independent information, or utterly fail to transfer the style.

In this work, we propose LAMER, a novel text style transfer framework based on large-scale language models. LAMER first mines the roughly parallel expressions in the non-parallel datasets with scene graphs, and then employs MLE training, followed by imitation learning refinement, to leverage the intrinsic parallelism within the data. On two benchmark tasks (sentiment & formality transfer) and a newly proposed challenging task (political stance transfer), our model achieves qualitative advances in transfer accuracy, content preservation, and fluency. Further empirical and human evaluations demonstrate that our model not only makes training more efficient, but also generates more readable and diverse expressions than previous models.

1 INTRODUCTION

Text style transfer (TST) models learn how to transfer the style of text from source to target while preserving the style-independent content (John et al., 2019; Fu et al., 2018). Existing TST methods perform well when transferring simple styles, such as sentiment; however, they tend to do a poor job on more abstract and subtle styles, such as formality and political stance (Lee et al., 2021; Fu et al., 2019b).

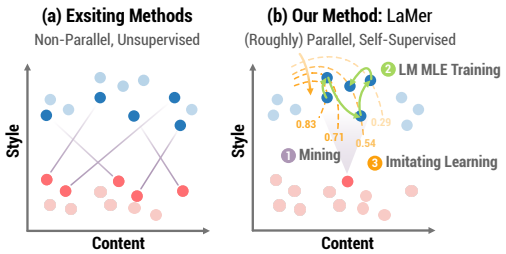

Figure 1: Red and blue circles represent the source and target texts respectively. (a) Existing methods crucially ignore the inherit parallelism within the data. (b) Our method first mines (roughly) parallel expressions, then learns how to transfer style with the self-supervision from the parallel expressions.

The lack of parallel datasets is one of the main bottlenecks for text style transfer tasks. Parallel datasets contain pairwise sentences that only differ in specific styles, while non-parallel datasets typically contain a large corpora of sentences with different styles, without direct one-to-one mapping between sentences (Fu et al., 2019a; Krishna et al., 2020). In real-world settings, it is much easier to construct non-parallel datasets by collecting large quantities of non-parallel sentences with different styles; conversely, carefully-aligned parallel TST datasets are much more costly to construct, usually requiring human annotation, and are thus scarce.

This discrepancy between the availability of parallel and non-parallel datasets for style transfer tasks prompts researchers to develop TST models for non-parallel datasets. However, these methods are less than ideal. As demonstrated in Figure 1 (a), they tend to learn the mapping between source and target style by randomly mapping sentence pairs, but fail to take into account the inherent parallelism within the data. Current methods either rely on surface-level classification of tokens as style- or content-bearing (Li et al., 2018a; Castro et al., 2017; Karadzhov et al., 2017), or separate

content and style vectors in latent space (Shen et al., 2017; John et al., 2019; Dai et al., 2019). Once style and content have been separated, they then swap styles leaving the content unchanged. However, surface-level split is not reliable when the style cannot be extracted at the token level; latent-space disentanglement could also fail due to a lack of pairwise supervision and results in discarding too much style-independent content. More recent work pivot to use pseudo parallels as pairwise supervision. For example, Jin et al. (2019) inspired by parallel data construction in machine translation (Hu et al., 2019; Grégoire & Langlais, 2018), construct pseudo parallels via iterative matching and back-translation. The iterative generation procedure is rather time consuming; however, training additional translation systems for TST could also be costly, which may introduce unnecessary bias towards TST models training.

This paper presents LAMER, a novel self-supervised text style transfer framework built upon recent text-to-text language models (LMs). As illustrated in Figure 1 (b), rather than accepting the random mapping in the given non-parallel dataset, we first align sentences from source and target styles based on their scene graphs, and then run conditional MLE training on LM to maximize the probability of generating (roughly) parallel style sentences. As a final refinement step, we deploy reinforced imitation learning with contrastive loss on the aligned data to further reward the best transfer demonstration and penalize the others. In comparison with existing methods, LAMER fully exploits the intrinsic parallelism within non-parallel data and innovatively applies the transfer learning power of large-scale LMs to boost text-style transfer performance.

Our contributions can be outlined as follows:

- We present a language model based text style transfer framework, LAMER, that achieves significant advances in two existing benchmark TST tasks and one newly proposed challenging TST task. Human evaluations further confirm that LAMER generation is not only more readable but also richer in diverse expressions than previous methods.
- We propose a new challenging text style transfer task, *Political Stance Transfer*, and release a benchmark dataset, which includes news sentence-pairs describing the same fact but from opposite political stances (i.e., *liberal* and *conservative*). The stances of the sentences are labeled by expert human editors.
- As part of LAMER, we introduce a simple but powerful method to create parallel corpora from non-parallel data. We show that this method can be used as a general treatment to improve existing TST models. Given the abundance of non-parallel corpora for different TST tasks, this method has the potential to greatly impact the field of TST.

Our code and data will be released after publication with the MIT license. For reviewing purposes, we have included the code and data in the supplementary.

2 APPROACH

LAMER is comprised of three main steps. First, we mine (roughly) parallels target style expressions for each of the source style sentences based on their LM-based sentence embeddings and scene graphs (§2.2). Second, we deploy MLE training on the text-to-text LM BART (Lewis et al., 2020a) to maximize the probability of generating such roughly parallel sentences in target style (§2.3). Finally, we use imitation learning to further refine the generation with the self-supervision from the mined parallel demonstrations (§2.4).

2.1 NOTATION AND PROBLEM STATEMENT

For the task of binary text style transfer (src $\leftrightarrow$ tgt), We denote the source and target style datasets as $\mathcal{D}^{\text{src}}$ and $\mathcal{D}^{\text{tgt}}$, which contain M and N sentences expressing two different styles respectively (i.e., $\mathcal{D}^{\text{src}} = \{s_1^{\text{src}}, s_2^{\text{src}}, ...s_M^{\text{src}}\}$, $\mathcal{D}^{\text{tgt}} = \{s_1^{\text{tgt}}, s_2^{\text{tgt}}, ...s_N^{\text{tgt}}\}$). We also denote the tokens in source and target sentences as $\{x_1, x_2, ..., x_t\} \in s_i^{\text{src}}$ and $\{y_1, y_2, ..., y_t\} \in s_j^{\text{tgt}}$, for given source and target sentences s_i^{src} and s_j^{tgt}. Given an input sentence s^{src} of the source style, an ideal style transfer model should be able to generate an appropriate, fluent target sentence $\hat{s}^{\text{tgt}}$, which is of the target style while maintaining the style-independent content.

Existing methods learn a mapping $f_{\text{random}} : \mathcal{D}^{\text{src}} \rightarrow \mathcal{D}^{\text{tgt}}$ without considering the self-parallelism between $\mathcal{D}^{\text{src}}$ and $\mathcal{D}^{\text{tgt}}$; LAMER, however, works on the assumption that $m(\leq M)$ sentences in $\mathcal{D}^{\text{src}}$ have n parallels in $\mathcal{D}^{\text{tgt}}$. The number of parallels n for each of the m sentences is variant but no more than N. Therefore, the goal of LAMER can be framed as first identifying a parallel subset of the original non-parallel dataset and learning a mapping on this dataset: $f_{\text{parallel}} : \mathcal{D}^{\text{src}}_m \rightarrow \mathcal{D}^{\text{tgt}}_n (m \leq M, n \leq N)$.

2.2 MINING (ROUGHLY) PARALLEL SENTENCES

In this work, we argue that the *non-parallel* text style transfer datasets have inherent property of *parallelism*. We outline in the following three major strategies to mine roughly parallel sentences:

Random (RD) For each sentence $s^{\text{src}} \in \mathcal{D}^{\text{src}}$, randomly pick k sentences from $\mathcal{D}^{\text{tgt}}$ as parallels. This method mainly serves as an ablation to show the effectiveness of other strategies.

Sentence Embedding (S-Emb.) Sentences that only differ in linguistic style should have higher semantic similarity than other unrelated sentences. As a more advanced strategy, we leverage off-the-shelf LMs (e.g., RoBERTa (Liu et al., 2019)) to mine semantically similar sentences. We first encode every sentence in $\mathcal{D}^{\text{src}}$ and $\mathcal{D}^{\text{tgt}}$ with their embeddings extracted from an LM. Then, for each sentence $s^{\text{src}} \in \mathcal{D}^{\text{src}}$, we pick k most similar sentences from $\mathcal{D}^{\text{tgt}}$ through cosine similarity in the embedding space as parallels.

S-Emb. + Scene Alignment Score (S-Emb. + SAS) We add a scene graph based alignment step to the sentence embedding method to leverage shared entities between source and target sentences. Scene graph extraction has been successfully used in computer vision (Guadarrama et al., 2013; Venugopalan et al., 2015; Chen et al., 2020b) to guide (Yang et al., 2020; 2019; Pan et al., 2020) or judge (Anderson et al., 2016) diverse caption generation. Inspired by the CV example and a critical observation that scene graphs of sentences with similar content but different styles tend to have overlapping nodes, our algorithm highlight the shared entities(nodes) of the sentence scene graph by calculating a Scene Alignment Score The scene graphs are obtained from our sentence corpora by running Wu et al. (2019a)'s parsing algorithm.

Let $|\mathbf{e}(s^{\text{src}})|$ and $|\mathbf{e}(s^{\text{tgt}})|$ be the number of scene entities extracted from the source and target style sentence, and $|\mathbf{e}(s^{\text{src}\cap\text{tgt}})|$ be the number of their overlaps, we compute Scene Alignment Score (SAS) as:

$$\text{SAS}(s^{\text{src}}||s^{\text{tgt}}) = \frac{1}{|s^{\text{tgt}}|} \cdot \frac{(1+\beta^2) \cdot \text{precision} \cdot \text{recall}}{\beta^2 \cdot \text{precision} + \text{recall}}, \tag{1}$$

where precision ($= \frac{|\mathbf{e}(s^{\text{src}\cap\text{tgt}})|}{|\mathbf{e}(s^{\text{tgt}})|}$) and recall ($= \frac{|\mathbf{e}(s^{\text{src}\cap\text{tgt}})|}{|\mathbf{e}(s^{\text{src}})|}$) describe the portion of target and source entities that are part of the overlap, and positive real factor β is chosen such that recall is considered β times as important as precision in a specific domain. We also normalize SAS by the length of s^{tgt}, since longer target sentence candidates are more likely to have higher SAS.

SAS serves as a complementary alignment metric to further filter the parallel sentences picked by the previous sentence-embedding-based metric. The complete procedure of S-Emb. + SAS alignment is:

1. Encode each sentence in $\mathcal{D}^{\text{src}}$ and $\mathcal{D}^{\text{tgt}}$ as sentence embeddings via a pre-trained LM.
2. Compute cosine similarity between all sentence pairs (s_i, s_j) where $s_i \in \mathcal{D}^{\text{src}}$ and $s_j \in \mathcal{D}^{\text{tgt}}$. Pick the k most similar sentences $s_j^{(k)}$ from $\mathcal{D}^{\text{tgt}}$ as parallel candidates for s_i.
3. For each sentence $s_i \in \mathcal{D}^{\text{src}}$ and its parallel candidates $s_j^{(k)}$, compute pairwise SAS by Equation 1. Pick those s_j whose SAS scores (with respect to s_i) are above a threshold p as the final parallel sentences to s_i.

From empirical observations, we found that the selection of p and k is task-specific and has crucial effects on the performance of LAMER. We explore the outcomes of different choices of k and p in Section 3.3.

2.3 CONDITIONAL TOKEN-LEVEL MLE TRAINING

After mining parallel sentences for a source sentence s^{src}, from our corpus, we take the source sentence s^{src} as the condition, and preform a conditional token-level MLE training on the mined parallels in the manner of standard autoregressive pre-training. Assuming for a certain source sentence s^{src} we have n target parallels mined in the previous step (i.e., $s^{\text{src}} \rightarrow \{s_1^{\text{tgt}}, s_2^{\text{tgt}}, ...s_n^{\text{tgt}}\}$, $n \leq N$), the MLE loss can be computed as:

$$J_{\text{MLE}} = -\sum_{i=1}^{n} \sum_{t=1}^{|s_k^{\text{tgt}}|} y_t^{(i)} \log \text{LM}(y_{1:t-1}|s^{\text{src}}), \tag{2}$$

where $y_t^i \in s_i^{\text{tgt}}$ denotes the i-th step ground truth token belonging to the i-th target parallel sentence. $\text{LM}(y_{1:t-1}|s^{\text{src}})$ is the LM output at t-th step (a distribution on the vocabulary) given the source text and previous generation. We choose BART Lewis et al. (2020a) as the LM, which is already pre-trained on several text-to-text tasks, and concatenate the source and target text with `</s><s>` tokens pre-defined by BART as input data. At each step, with the supervision of ground truth target tokens $y_t^{(i)}$, we minimize the MLE loss only at the target part. The LM is thus trained to maximize the probability of generating tokens $\hat{y}_t$ approaching to $y_t^{(i)}$.

Though the results produced are reasonable, solely relying on MLE training has several defects. First, MLE treats all parallels of a certain source equally without penalizing low-quality demonstrations, which not only makes the model less robust on noisy data, but also possible to be misled by negative samples during local optimization. Second, token-level MLE does not pay special attention to scene entities shared between the source and target, which we found take up the main portion in the human written references (as shown in Table S1 in the appendix). We are thus motivated to further improve the performance using the self-supervision from the parallels.

2.4 REINFORCED IMITATION LEARNING BY CONTRAST

For all the mined target style parallels s^{tgt} of s^{src}, we denote the one that has the highest similarity score (with S-Emb.) or has the highest SAS (with S-Emb. + SAS) as the expert demonstration $s^{\text{tgt+}}$, while the others are set as $s^{\text{tgt-}}$.

In the formulation of reinforcement learning, at each step t, the policy π_θ observes the state $y_{1:t-1}$ (partially generated text), takes an action $a_t = y_t$ (pick a token), and transits to the next state $y_{1:t}$. In the context of TST tasks, the policy can be interpreted as the LM-based generation model: $\hat{\pi} \sim \text{LM}(a_t|y_{1:t-1}, s^{\text{src}})$, and the set of $s^{\text{tgt+}}$ can be seen as the trajectory derived from an expert policy π^+, while $s^{\text{tgt-}}$ is produced by an amateur policy π^-. The goal of this step imitation learning can thus be framed as learning a policy that has more probability to behave like π^+ rather than π^-, which can be achieved by minimizing the contrastive loss:

$$J_{\text{IL}} = \max(\psi^* \left[\pi^+, \hat{\pi}\right] - \psi^* \left[\pi^-, \hat{\pi}\right] + \Delta, 0), \tag{3}$$

where $\psi^*(\cdot)$ is the distance measurement of two policies in terms of semantic coherence $d_{\text{SEM}}(\cdot)$ and scene preservation $d_{\text{PSV}}(\cdot)$, such that $\psi^*(\cdot) = d_{\text{SEM}}(\cdot) + d_{\text{PSV}}(\cdot)$; and Δ is a hyperparameter that controls the contrasting margin. The general form is inspired by the triplet loss (Schroff et al., 2015) and recent *in-batch* constrastive learning (Gao et al., 2021): we encourage the learned policy $\hat{\pi}$ to be more similar to the expert one π^+ than the amateur one π^- by at least margin Δ. $d_{\text{SEM}}(\cdot)$ and $d_{\text{PSV}}(\cdot)$ are detailed below.

Sequence-level Semantic Coherence For sequence $\hat{s}$ generated under current learning policy $\hat{\pi}$ and a certain target style demonstration s^{tgt}, we encode them using bi-directional LM RoBERTa (Liu et al., 2019), which is widely used as sentence encoder in related work (Reimers & Gurevych, 2019; Li et al., 2020). Then, we take their negative cosine similarity as the distance for semantic coherence: $d_{\text{SEM}} = -\frac{\text{emb}_{\hat{s}}^{\text{T}} \cdot \text{emb}_{s^{\text{tgt}}}}{\|\text{emb}_{\hat{s}}\| \|\text{emb}_{s^{\text{tgt}}}\|}$. Lower value in d_{SEM} means the learned policy $\hat{\pi}$ can produce similar quality sequences in terms of semantics as target style demonstrations. It is a sequence-level measurement since the encoding is based on the whole sentence.

Token-level Scene Preservation In our context, legitimate target style parallels should preserve most scene entities that appear in source style sentences. To explicitly promote the content preservation performance of the current policy, we introduce a token-level distance d_{PSV}. We first extract scene entities from $s^{\text{tgt}+}$ and each of the $s^{\text{tgt}-}$, and then measure the differences in both the order of appearance of the entities and the existence of the entities. Taking $s^{\text{tgt+}}$ as an example (similar calculation is done on each of the $s^{\text{tgt-}}$), we compute: $d_{\text{PSV}+} = d_{\text{Order}+} + d_{\text{Exist}+} = \|\vec{\mathbf{e}}(s^{\text{tgt}+}), \vec{\mathbf{e}}(s^{\text{src}})\|_{\text{Lev.}} + \|\vec{\mathbf{e}}(s^{\text{tgt+}}) - \vec{\mathbf{e}}(s^{\text{tgt+} \cup \text{src}})\|_H$, where $\vec{\mathbf{e}}(\cdot)$ means the extracted scene entities, $\vec{\mathbf{e}}(\cdot)$ is its one-hot encoded vector, $\|\vec{\mathbf{x}}, \vec{\mathbf{y}}\|_{\text{Lev.}}$ measures Levenshtein distance (Yujian & Bo, 2007), one type of edit distance, and for vectors $\vec{\mathbf{e}}(s^{\text{src}})$ and $\vec{\mathbf{e}}(s^{\text{tgt}})$, we compute their hamming distance[1] (Norouzi et al., 2012). Lower $d_{\text{Order}+}$ means the appearing order of $\vec{\mathbf{e}}(s^{\text{src}})$ resemble $\vec{\mathbf{e}}(s^{\text{tgt+}})$. Similarly, lower $d_{\text{Exist}+}$ means $\vec{\mathbf{e}}(s^{\text{src}})$ and $\vec{\mathbf{e}}(s^{\text{tgt+}})$ are mostly overlapped. Similar procedure applies to $d_{\text{PSV}-}$ as well. We present more details and examples about how we compute these distances in Appendix D.

2.4.1 Reinforced Policy Gradient

Algorithm 1: Imitating Learning of LaMer

Input: current policy π_θ, expert policy trajectory $s^{\text{tgt+}}$, and amateur policy trajectory $s^{\text{tgt-}}$

Output: a learned policy π_θ approaching to expert policy π^+

▷ Get baseline via Greedy Decoding

$\hat{s}_{\text{base}} \leftarrow \arg\max \hat{\pi} \sim \text{LM}(a_t|y_{1:t-1})_{t\in[1,T]}$;

Compute $J_{\text{IL}}^{\text{base}}$ with $\hat{s}_{\text{base}}$, $s^{\text{tgt+}}$, and $s^{\text{tgt-}}$ by Eq. 3;

if $J_{IL}^{base} \leq J_{IL}^{safe}$ **then**

  ▷ No Optimization on Already Good Policies

  Skip current step Imitation Learning;

▷ Exploration by Sampling Decoding

while $i \leq$ max exploration steps **do**

  $\hat{s}_{\text{sample}}^{(i)} \leftarrow$ sampling $\hat{\pi} \sim \text{LM}(a_t|y_{1:t-1})_{t\in[1,T]}$;

  Compute $J_{\text{IL}}^{\text{sample}}$ with $\hat{s}_{\text{sample}}^{(i)}$, $s^{\text{tgt+}}$, and $s^{\text{tgt-}}$ by Eq. 3;

▷ Optimize Policy by REINFORCE

Compute policy gradient as

$\nabla_\theta J(\theta) = -\mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log \pi_\theta \cdot (J_{\text{IL}}^{\text{sample}} - J_{\text{IL}}^{\text{base}})\right]$;

Update policy with policy gradient by taking K steps SGD (via Adam);

return $\pi_\theta \rightarrow \pi^+$

We choose the REINFORCE algorithm (Williams, 1992) to optimize the current policy π_θ. One known issue of the vanilla REINFORCE method is the instability of its optimization because of the high variance of the gradients. A common remedy is to add a baseline function (i.e., a parameterized value-network whose purpose is to estimate the unbiased future behavior of current policy (Ranzato et al., 2016)). Rennie et al. (2017) introduce a better approach that estimates the baseline at test time. They use the greedy decoding results as the baseline in their *self-critic* sequence training algorithm. We adopt their method to provide the baseline, and add an exploration step using sampling decoding. As shown in Algorithm 1, by iteratively switching between these two modes, we calculate corresponding contrastive losses defined by Equation 3, and take the difference of two modes losses as the advantage, feeding into the REINFORCE algorithm to optimize our policy π_θ. Finally, the output policy π_θ is able to generate style transferred sequences resemble the expert demonstrations $s^{\text{tgt+}}$.

2.5 Discussion: Imitation Learning, Reward-based RL, and MLE

Framing token-by-token text generation as a sequential decision-making process, many models choose reinforcement learning (RL) as the training strategy because of its superior performance in discrete action space optimization (Vinyals et al., 2019; Silver et al., 2017; 2016). By directly setting indifferentiable evaluation metrics such as BLEU (Papineni et al., 2002) or ROUGE (Lin, 2004) as the reward function (Xu et al., 2018; Luo et al., 2019; Gong et al., 2019) or using domain-specific reward such as trained discriminator outputs (Huang et al., 2020; Lin et al., 2020; Scialom et al., 2020), existing RL-based methods show promising results in both generation quality (Chen et al., 2020a; Li et al., 2018b) and diversity (Li et al., 2016).

In the context of TST tasks, however, instead of reward-based RL, we argue imitation learning (IL) is a better choice, since: (1) Compared with fixed environment settings like chess games, it is challenging to design a uniform reward fitting a variety of source style text that can produce meaningful guidance

[1] Hamming norm $\|\vec{v}\|_H$ is defined as the number of non-zero entries of vector $\vec{v}$.

towards contextually correct and semantically coherent direction during generation (2) It is also unnecessary to calculate an elaborately designed reward. The roughly parallel target style sentences mined in the alignment step can naturally serve as expert demonstrations. They are high-quality and cost-free, which can greatly improve the sampling and learning efficiency of RL optimization.

A common obstacle of IL is known as Covariate Shift (Ross & Bagnell, 2010), which means IL can provide a relatively good performance for the test cases similar to the demonstrations (used for policy training), but it could still suffer from bad generalization for cases it never meets during training, as the number of demonstrations is finite. Similar problems called Exposure Bias (Bengio et al., 2015; Ranzato et al., 2016) also exists in MLE when the supervised data is scarce. We claim our token-level MLE training on LMs can somewhat mitigate such problems, since the large-scale LMs are already pre-trained on huge quantities of data across many domains *as a prior*.

3 EXPERIMENTS

3.1 DATASETS AND EXPERIMENTAL SETUP

Sentiment Transfer. We use the Yelp reviews dataset collected by Shen et al. (2017) which contains 250k negative sentences and 380k positive sentences, organized in non-parallel fashion. Li et al. (2018a) released a small test set that has 500 human written references for both target sentiments, and they are already one-on-one aligned with the source sentiment sentences.

Formality Transfer. A more challenging TST task is to modify the formality of a given sentence. We use the GYAFC dataset (Rao & Tetreault, 2018), which contains formal and informal sentences from two domains. In this paper, we choose the Family Relationship domain, which consists of about 52k training sentences, 5k development sentences, and 2.5k test sentences. Different from the Yelp dataset, the test set of GYAFC has four human written references for each source style test case. Our evaluation results for this task are reported as the average against the four references.

Political Stance Transfer News outlets reporting the same event naturally meet the requirement of style transfer data, which is aligned in content but different in style. We leverage Allsides.com[2] as an aggregator, where outlets reporting the same events with different political stances are already organized and labeled by expert human editors. In total, we collect 2,298 full-length news articles from 6/1/2012 to 4/1/2021 in pairs of liberal-conservative leaning. Though the data seems parallel at the article level, in this work we focus on sentence level TST. We further split the articles into about 56k sentence pairs as a non-parallel dataset for training (detailed in Appendix B). These titles are written by expert writers from liberal- or conservative-learning media outlets, and aligned by the Allsides editors. For ethical consideration, we manually examined the articles to removing those containing sensitive topics (such as hate speech). To adhere to the outlets' TOS, we will release our dataset as links to the articles (instead of the text), with the appropriate code to extract the content for training purposes. A closer comparison of our proposed novel dataset with another political stance TST dataset (Voigt et al., 2018) can be found in Appendix A.

The detailed statistics of all three benchmark datasets can be found in Appendix C Table S1.All experiments were run on a single RTX-2080 GPU, with batch size 4 and 2/3/2 epochs for LAMER in the above three TST tasks. More details about the running time and parameter selection can be found in Section 3.3. Following previous work, we choose style control accuracy (ACC), BLEU score, and perplexity (PPL) as our main metrics. ACCs are judged by a pre-trained RoBERTa (Liu et al., 2019) classifier with F1 = $\{0.97, 0.86, 0.93\}$ using the training data of the three TST tasks. PPLs are produced by the GPT-2 (Radford et al., 2019) language modeling loss. The i-PINC score is explained later in the paper.

3.2 BENCHMARK RESULTS

Table 1 shows the main results comparing LAMER with seven popular STS models on two benchmark tasks (sentiment and formality transfer) and our newly proposed challenging task (political stance transfer). In addition to the BLEU score, we also report inverse PINC scores (Chen & Dolan, 2011)—i-PINC—as a complementary metric of BLEU. i-PINC counts the n-gram overlaps after removing

[2] https://www.allsides.com/story/admin

Table 1: LAMER achieve SOTA results according to many metrics on the three TST tasks. CAE (Shen et al., 2017), DelRetrGen (Li et al., 2018a), DualRL (Luo et al., 2019), Style Transformer (Dai et al., 2019), Deep Latent Seq (He et al., 2020) are popular TST models *not* built on LMs. TSF-DelRetGen (Sudhakar et al., 2019) and STRAP (Krishna et al., 2020) are two recent LM-based $_{(\text{LM})}$ TST models. For ablation, Input Copy directly copies the source style sentence as the transfer output. Naive removes the final refinement stage by imitation learning; Vanilla LM takes off-the-shelf BART as a zero-shot TST model. PPL$^{\downarrow}$: Lower perplexity is better.

	Sentiment SAS = 0.73				**Formality** SAS = 0.29				**Political Stance** SAS = 0.30			
Existing Methods	ACC	BLEU	PPL$^{\downarrow}$	i-PINC	ACC	BLEU	PPL$^{\downarrow}$	i-PINC	ACC	BLEU	PPL$^{\downarrow}$	i-PINC
Input Copy (*ref.*)	7.4	61.7	54.0	0	1.9	54.6	16.2	0	7.5	17.8	28.0	0
CAE	70.5	6.0	53.4	1.2	39.5	35.8	135.4	5.9	31.5	5.1	1869.0	1.4
DelRetrGen	65.4	11.8	18.5	4.8	61.9	14.8	30.3	6.6	93.8	3.5	86.0	6.2
Dual RL	85.6	21.2	17.0	4.0	71.1	31.9	31.9	7.2	91.8	8.1	141.2	5.7
Style Transformer	93.6	17.1	78.0	5.2	12.2	32.7	129.1	4.1	48.6	7.3	350.0	1.1
Deep Latent Seq	87.9	18.7	27.8	7.3	80.5	18.5	17.2	6.1	85.8	20.8	113.7	3.0
TSF-DelRetGen$_{\text{LM}}$	89.5	56.6	52.1	4.5	79.3	17.4	24.5	7.3	65.8	23.7	102.3	2.9
STARP$_{\text{LM}}$	92.3	32.5	12.5	6.4	75.4	32.6	15.9	9.7	84.3	21.3	33.7	5.0
Ours (MLE + IL)												
w/. RD	97.1	19.8	16.8	2.5	64.2	20.4	13.6	5.5	86.6	20.4	32.3	6.1
w/. S-Emb.	90.1	40.6	17.2	5.6	65.1	33.8	13.5	10.9	78.2	22.1	47.6	9.2
w/. S-Emb. + SAS	97.0	34.1	11.6	9.6	76.5	39.2	11.7	13.3	93.4	24.5	34.5	13.5
Naive (MLE Only)												
w/. RD	96.8	20.1	16.9	1.4	60.9	16.0	14.4	6.8	78.1	6.2	32.3	2.7
w/. S-Emb.	94.5	38.3	18.7	4.8	60.2	24.9	13.9	7.9	82.2	10.4	47.6	3.2
w/. S-Emb. + SAS	93.1	33.2	15.3	7.6	68.7	27.2	12.2	7.4	89.8	8.8	50.5	4.2
Vanilla LM*	14.2	8.8	296.0	2.8	1.9	54.5	16.3	0	12.4	23.0	28.7	0

the tokens shared between source and target style sentences, and thus properly penalizes the Input Copy method (i-PINC = 0).

Compared with existing methods, LAMER achieves state-of-the-art results on many metrics for the three TST tasks. In terms of i-PINC, LAMER manages to generate high quality transfer that better aligns with human reference rather than copying a large portion of source style sentences. Among the three mining strategies we proposed in Section 2.2, the S-Emb. + SAS seems to offer the best performance boosting in terms of content preservation, but shows no clear advantage on style control accuracy. LAMER transfer results are much more readable than most methods not built on LMs. When comparing LAMER with the two LM-based models, we find TSF-DelRetGen has higher BLEU scores than our method in sentiment TST but we find their generated sentences are often not very fluent (higher PPL), partially because they still perform token-level transfer, though with LMs; TSF-DelRetGen has lower transfer accuracy and more incoherent generation in more challenging TST tasks (e.g., political TST) where style transfer requires high-level sentence rewriting. STRAP uses GPT-2 to generate paraphrases to aid TST training, but we found the generated paraphrases could be noisy. LAMER, instead, uses *true paraphrases* mined from the training set, and thus obtains better performance.

Ablation Study. As shown in the lower part of Table 1, the performance of LAMER drops substantially when some crucial steps are removed. Specifically, removing imitation learning refinement hurts performance more for complicated style tasks (low SAS, such as political stance transfer), partially because the quality variance of their demonstrations is higher—a further guidance towards good demonstrations will make a big difference. We also conducted further ablation studies on components of IL (Table 2). Without MLE training, vanilla LM cannot be aware of the TST tasks and fails to generate text carrying correct target style, but surprisingly, as a zero-shot setting, off-the-shelf LMs can even generate readable text with higher BLEU scores than many existing methods. It may be that BART was pre-trained on some news summarization and fill-in-blank (or cloze) tasks, which may coincidentally benefit TST tasks. We take these ablation study results as evidence that the technologies we propose for LAMER are crucial for improving performance.

Table 2: Further ablation on components of LAMER imitation learning (IL). d_{SEM}: semantic coherence distance, d_{Order} and d_{Exist} are sub-components of scene preservation distance d_{PSV}. We also include results of removing all IL modules (MLM only) as a reference. In general, removing d_{Order} (i.e., IL (d_{SEM} + d_{Exist})) seems to cause greater performance drop in more complicated TST tasks (e.g., formality and political stance transfer), and removing all scene preservation distance sub-components (i.e., IL (d_{SEM})) leads to noticeable performance deterioration across all three TST tasks.

	Sentiment		**Formality**		**Political Stance**	
Ablation on LAMER IL	ACC	BLEU	ACC	BLEU	ACC	BLEU
IL (d_{SEM} + d_{Order} + d_{Exist})	97.0	34.1	76.5	39.2	93.4	18.5
IL (d_{SEM} + d_{Order})	95.5 (↓1.5)	34.4 (↑0.3)	74.7 (↓1.8)	37.7 (↓1.5)	93.2 (↓0.2)	15.8 (↓2.7)
IL (d_{SEM} + d_{Exist})	96.5 (↓0.5)	33.9 (↓0.2)	72.6 (↓3.9)	34.1 (↓5.1)	92.7 (↓0.7)	17.1 (↓1.4)
IL (d_{SEM})	95.1 (↓1.9)	33.3 (↓0.8)	71.9 (↓4.6)	32.5 (↓6.7)	89.9 (↓0.5)	13.9 (↓4.6)
No IL (MLM)	93.1 (↓3.9)	33.2 (↓0.9)	68.7 (↓7.8)	27.2 (↓12.0)	89.8 (↓0.6)	8.8 (↓9.7)

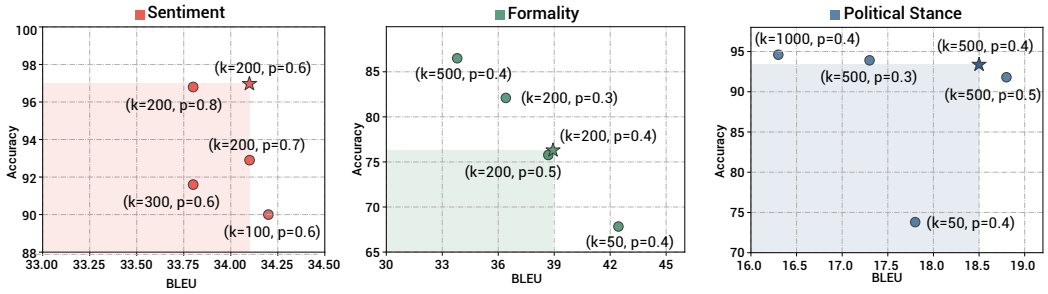

Figure 2: Effect on performance when choosing different k and p for S-Emb. + SAS alignment. We also annotate (with a star) the recommended settings which reaches best balance between style control accuracy and content preservation BLEU score.

3.3 CONFIGURING LAMER

The filtering parameter p and k are hyperparameters that are crucial for the construction of roughly parallel datasets. In preliminary experiments, we observed that their proper configurations varied for different tasks. Thus, for all three TST tasks, we evaluate LAMER performance given different combination of p and k, as shown in Figure 2. We find there is a approximate trade-off relationship between style control accuracy and content preservation BLEU score: In general, higher k (more parallels) seems to improve accuracy but normally has lower BLEU, while for a fixed k, a proper p can be reached empirically. We annotate the recommended settings of p and k for the three TST tasks we studied in this work. Similar experiments can be conducted for the hyperparameter search on other TST tasks. We provide some generation samples of LAMER (and other methods) in Appendix E S2. As an interesting observation, we find the alignment procedure of LAMER can benefit other methods (as shown in Appendix G Table S5).

3.4 HUMAN EVALUATION

We recruited 212 participants from an online crowdsourcing platform Amazon Mechanical Turk (MTurk) to evaluate the style transferred sentences generated by and our LAMER. The sentences are picked from the test set generations for the three tasks. Each participant was asked to read two sets of sentences (one set containing a source style sentence, corresponding human-written target style sentence as ground-truth, and eight versions of target style sentences generated by seven existing methods and LAMER for comparison). After reading each set, they were asked to rate how well the generated sentences did in style control, readability, and content preservation on a 7-point Likert scales.[3] Higher ratings correspond to better performance. Each participant was compensated one

[3]For example, for "content preservation", they were asked *"How much do you agree with the following statement (1- Strongly disagree to 7- Strongly agree): The machine-generated target style text preserves the context of the source style text well (i.e. they talk about the same thing)."*.

Table 3: Human judgement results (on a 7 point scale) for seven existing methods and LAMER on political stance transfer task. We **bold** the highest average rating. LAMER was rated significantly higher than the next-best method (with p-value $p < .05$). SD: Standard Deviation.

■ Political Stance	**Style**		**Content**		**Readability**	
Methods	Mean	SD	Mean	SD	Mean	SD
CAE (Shen et al., 2017)	4.91	1.59	4.85	1.58	5.04	1.68
DelRetrGen (Li et al., 2018a)	5.14	1.60	4.93	1.63	4.96	1.60
Dual RL (Luo et al., 2019)	5.15	1.37	4.87	1.59	5.15	1.53
Style Transformer (Dai et al., 2019)	5.31	1.19	5.34	1.36	5.18	1.40
Deep Latent Seq (He et al., 2020)	5.42	0.57	5.29	1.20	5.30	1.26
TSF-DelRetGen (Sudhakar et al., 2019)	4.87	0.65	5.23	1.14	5.20	1.13
STARP (Krishna et al., 2020)	5.33	1.25	5.31	1.40	5.43	1.07
Ours: LAMER	**5.59**	1.17	**5.44**	1.11	**5.56**	1.05

dollar for their participation (average completion time per questionnaire was about 7.6 minutes reported by the platform, which results in a $7.9/hr wage, above the regional minimum wage). We conducted several one-way ANOVAs to test the difference among the seven baselines and LAMER (political stance TST results shown in Table 3; see Table S3 for sentiment TST and Table S4 for formality TST in Appendix F). LAMER was significantly better than next-best in all three perspectives ($p < .05$).

4 Related Work

Other Text Style Transfer Methods. Prior art have explored using disentanglement-based methods to encode styled text as disentangled content and style vectors in latent space, and then manipulate these vectors to replace style by editing Liu et al. (2020); Wang et al. (2019), splitting (John et al., 2019; Romanov et al., 2019), or style code control (Zhang et al., 2020; Shen et al., 2017; Dai et al., 2019). Instead of diving into latent space, token-level editing methods notice that style and content can be separated on surface level. They thus propose word replacement methods based on style glossary (Abu Sheikha & Inkpen, 2011; Li et al., 2018a), WordNet (Mansoorizadeh et al.), hand-crafted rules (Castro et al., 2017; Karadzhov et al., 2017), or self-attention scores (Sudhakar et al., 2019; Wu et al., 2019b). Viewing the non-parallel datasets as partially observed parallel datasets, He et al. (2020) assume the sentences of different styles can be generated by parallel latent sequence. Though similar in goal, the alignment of LAMER is explicit and the training is end-to-end, without additional assumptions for the latent space data distribution.

NLG by Searching for References. There are many studies that focus on the limits of off-the-shelf LMs in downstream NLG tasks, such as being easily misguided by phrase co-occurrence, failing to handle negation (Kassner & Schütze, 2020), and being unable to reason over commonsense, such as time (Qin et al., 2021) and digits (Talmor et al., 2020). To provide expert demonstrations to calibrate LM generation, recent work attempt to retrieve related documents from external resources (e.g., Wikipedia) as training data augmentations (Lewis et al., 2020b; Guu et al., 2020; Lee et al., 2019; Krishna et al., 2021). LAMER does not rely on any external resources, but mines parallel demonstrations from the training data itself, and thus is easier to deploy and alleviates potential bias.

5 Conclusion

We have proposed LAMER, a self-supervised text style transfer model built on large-scale LMs. LAMER was designed with the motivation to extract useful parallelism from large non-parallel corpora, so that text-style transfer task could reduce its over-reliance on scarce and expensive parallel data. On three diverse TST tasks, we show that LAMER performs better than seven existing methods. Through extensive evaluation, we verify that LAMER is not only highly efficient in learning, but still robust to data scarcity. Human evaluations further validate the advantage of our model compared to existing baselines.

6 ETHICS AND REPRODUCIBILITY STATEMENT

The goal of LAMER is to provide a simple but efficient general-purpose text style transfer framework by leveraging large-scale pre-trained LMs. LAMER can generate text in a specified target style given source style input, which can serve as a useful tool for social good. For example, LAMER can assist language formalization (formality transfer), enable data anonymization (writing style transfer), or depolarize politically biased text (political stance transfer), via transferring the identifiable style of the input text.

The performance of LAMER depends on the pre-trained LM, which means that the generation of LAMER can be affected by certain societal biases found in the pre-trained LM it is based on (e.g., BART) (Blodgett et al., 2020). Other negatives such as abusive language (Hancock et al., 2020), hate speech (Kennedy et al., 2018), and dehumanization (Mendelsohn et al., 2020) are also prevalent in the language data for LM pre-training. When deployed in real-world settings, LAMER may increase the risk of reinforcing and propagating polarizing and toxic language in public space through people's dissemination (Waseem et al., 2017). Moreover, the generated text of LAMER could potentially be included in the next iteration of large-scale LM training data collection, which may amplify offensive stereotypes and overtly abusive views in the future LMs.

Though LAMER was developed as an "neutral" tool mainly for research purposes, it can also be used in malicious ways such as generating sophisticated spam in a particular style "disguise", which we strongly discourage. Due to the lack of fact checking systems as a safety measure, LAMER is at the risk of generating seemingly coherent but counterfactual text in a certain target style, which could further undermine social trust in computer-mediated forms of communication [6]. We thus recommend the users of LAMER to integrate necessary safety checks into the actual systems.

In addition, our experiments and analysis are done when source and target style sentences are both in English, and therefore we do not claim that our findings will generalize across all languages, although our framework has the potential to be extended to other languages with necessary modifications.

Though it's beyond the scope of this paper and our individual ability to address all above-mentioned complications, we strongly encourage users of our system (and other TST models and systems based on pre-trained language models) to acknowledge and beware of these issues.

For reproducibility, we attach our code, evaluation scripts, and sample generation with our submission to aid reviewing. The full political stance transfer dataset we proposed will be made publicly available after review process.

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APPENDIX A: COMPARING WITH ANOTHER POLITICAL STANCE DATASET

Transferring political stance has also been studied in Voigt et al. (2018), where the author also collected a dataset for political stance TST. Comparing with their dataset, we found ours has following differences:

Language Formality: Their dataset is composed of comments on Facebook posts from members of the United States Senate and House, while our dataset consists of sentences from news articles written by professional reporters belonging to well-known media outlets (CNN, Fox News, etc.). The text in the dataset of Voigt et al. (2018) tends to be more casual and oral (e.g., *"congrats , lee !"*). Conversely, the text in our dataset is generally more formal and well-formed.

Completeness: Their dataset does not contain the original post to which the comments are responding, which causes some potential ambiguity on its political stance labels especially when the comment is generic (e.g., *"happy birthday jerry : -)"*). Most of the sentences in our dataset are complete statements of certain facts. We also conducted an extra distillation step (described in Appendix A in the supplementary document) to only keep the sentences that are salient to the article's stance label.

Coverage: The comments in Voigt et al. (2018) are mainly from 2017-2018, while our dataset collects nearly 10-year of articles from 6/1/2012 to 4/1/2021, which covers a wider range of societal issues and events. In the released version of our data we will add the time stamps to the sentences for customized filtering.

APPENDIX B: SENTENCE DISTILLATION FOR CONSTRUCTING POLITICAL STANCE DATASET

As mentioned in Section 3.1 of the paper, the articles collected from Allsides.com are already manually aligned (based on their political ideology) by Allsides editors. We collected a total of 2,298 full-length news articles from opposite ideologies (i.e., *liberal* and *conservative*) grouped by events. To create a sentence-level TST dataset for political stance transfer, we split the articles into sentences and took their article-level ideologies (as assigned by the editors) as their sentence-level stance labels. However, we found that not all sentences explicitly exhibit the stance label inherited

from their corresponding articles, so we implemented an additional distillation step to select those sentences that are salient with respect to their assigned political stance.

Assuming we have an article with N sentences $X = \{x_1, x_2, ..., x_N\}$ and the title of the article x_{title}, we aim to find the subset of sentences $D_{\text{distill}} \subset X$ which all explicitly exhibit the assigned political stance. To better describe our approach, we first introduce two concepts: (1) stance saliency, and (2) distillation cost.

Stance Saliency. We compute the stance saliency v_i for each sentence $x_i \in X \backslash D_{\text{distill}}$, which is a measure of how well x_i exhibits a certain political stance. D_{distill} is the set of sentences already picked our distilled set. We assume that the stance exhibited in x_{title} matches that of the article (as assigned by the editors), Thus, we define stance saliency v_i as the similarity between x_i and the union of x_{title} and D_{distill}, which is:

$$v_i := \text{LCS}(x_i, x_{\text{title}} \cup D_{\text{distill}}), \tag{4}$$

where $\text{LCS}(\cdot)$ is longest common sequence between the two input sequences. However, this metric is biased towards longer sentences as they can have more tokens matched with the title. We address this issue through the intriduction of a distilation cost, described below.

Distillation Cost. We assign a distillation cost w_i to each sentence x_i in an article. The cost is simply the length of the sentence:

$$w_i := |x_i|. \tag{5}$$

Note that for both concepts our computation is based on lower-cased and lemmatized sentence tokens. We use λ to denote the ratio of the sentences to be picked as distilled sentences in an article consisting of N sentences, and define $W_{\text{max}} = \lambda \cdot \sum_{i=0}^{N} w_i$ as the maximum distillation cost allowed.

Now that for each sentence we have a stance saliency and a distillation cost, we aim to choose a set of sentences as the distillation which have the highest possible sum of saliency for which the sum of distillation costs is not greater than W_{max}. Given a function $\phi(x_i) = \{1, 0\}$ where 1 corresponds to sentence x_i being picked for the distilled set and 0 means otherwise, the objective of distillation can be expressed as:

$$\max \sum_{i=1}^{N} v_i \cdot \phi(x_i) \ , \quad \text{s.t.} \sum_{i=1}^{N} w_i \cdot \phi(x_i) \leq W_{\text{max}} \ . \tag{6}$$

This is actually a NP-complete combinatorial optimization problem, called the Knapsack problem, which we solve using dynamic-programming (DP). In general, the distillation strategy aggressively picks sentences of high stance saliency while keeping the cost of distillation from exceeding the mask cost limitation W_{max}. The procedure is demonstrated in Algorithm 2 below.

Note that we initialize W_{distill} with the length of title. At every iteration of the loop we solve the DP problem with the limit set by current W_{distill}, which is a variable that estimates how many sentences are already in the distillation set (no more than W_{max}). The DP-based algorithm used in Algorithm 1 for finding the best distillation strategy is shown is Algorithm 2 below.

Appendix C: Statistics our All Three Datasets

We present more statistical details of all three datasets in Table S1.

Appendix D: Additional Details about Token-level Scene Preservation

In this section, we provide additional details regarding how we compute the token-level scene preservation d_{PSV}. Figure S1 shows an example sentiment transfer task. For a given positive (source

Algorithm 2: Sentence Distillation for Political Stance Dataset

Input: article title x_{title}, article sentences X, distillation ratio λ.

▷ Initialization
Init current distillation set D_{distill} as $\varnothing$;
Init current distillation cost W_{distill} with $|x_{\text{title}}|$;

▷ Multiple Rounds of Distillation
while $W_{distill} \leq W_{max}$ **do**
  Compute v_i for each $x_i \in X \backslash D_{\text{distill}}$ with x_{title} and D_{distill} (by Equation 1);
  Compute w_i for each x_i (by Equation 2);
  Find best distillation strategy $\{\phi(x_i)\}$ via DP with v_i, w_i and W_{distill} (see Alg. 2);
  ▷ Update Distillation Results Every Step
  Update current distillation set $D_{\text{distill}} = D_{\text{distill}} \cup \{x_i\}$ whose $\phi(x_i) = 1$;
  Update current distillation cost W_{distill} in terms of updated D_{distill};
end
return distillation sentences set D_{distill};

	■ **Sentiment**		■ **Formality**		■ **Political Stance**	
Training Data (S-Emb. + SAS)	*positive*	*negative*	*formal*	*informal*	*liberal*	*conservative*
# Sent Pairs	553,430		93,157		36,307	
# Scene Entities	742,136	777,839	145,731	133,779	194,032	272,071
Avg. Sent Len	7.32	7.58	11.52	11.05	19.39	24.75
Avg. # Scene Ent. / Sent	1.34	1.41	1.56	1.44	5.34	7.49
Avg. # Scene Ent.$^{\text{src}\cap\text{tgt}}$ (vs. RD)	0.95 (0.73)		0.49 (0.02)		0.96 (0.10)	
Avg. SAS (vs. RD)	0.72 (0.55)		0.29 (0.01)		0.25 (0.01)	
Human Reference	*positive*	*negative*	*formal*	*informal*	*liberal*	*conservative*
# Sent Pairs	500		1020		525	
# Scene Entities	964	905	1,467	1,388	2,915	3,012
Avg. Sent Len	9.90	9.80	10.9	9.35	10.30	11.19
Avg. # Scene Ent. / Sent	1.93	1.81	1.44	1.36	5.58	5.76
Avg. # Scene Ent.$^{\text{src}\cap\text{tgt}}$	1.53		0.55		1.78	
Avg. SAS	0.73		0.29		0.30	

Table S1: Data statistics of three TST tasks in this work: Sentiment, Formality, and Political Stance Transfer. We compare the S-Emb. + SAS aligned version data (the upper part), with the human-annotated reference file (the bottom part). Notice that after alignment, the SAS of training data becomes much closer to that of human reference, which demonstrates we successfully align the non-parallel data into parallel form (comparable to the human reference).

style) sentence s^{src} and its corresponding negative (target style) parallels s^{tgt}, we first extract their scene entities using the method by Wu et al. (2019a) (Figure S1 (a)), and based on these entities we compute two distances d_{Order} and d_{Exist} as sub-components of d_{PSV}.

For d_{Order}, as shown in Figure S1 (b), we compare each of the s^{tgt} entities with the s^{src} entities, and measure how much s^{tgt} needs to be edited to make the two sets of entities from opposite styles identical to each other. As mentioned in the paper, we use the Levenshtein distance as the edit distance; whose set of edits operation is: 1) insertion of a single token, 2) deletion of a single token, and 3) substitution of a single token. Each of these operations has unit cost, so the Levenshtein distance is equal to the minimum number of operations required to transform target style entities to source style entities.

As shown in Figure S1 (c), we calculate another distance component, d_{Exist}, via hamming distance to emphasize the the difference between the sets of entities in source and target sentences. We first get the union of the entities from a pair of source and target sentences; based on the union set, we can obtain the corresponding binary vector representations of both style entities: 1 means the entity exists in a certain style sentence, and 0 otherwise. Note the binary vectors for each of the sentences will

Algorithm 3: DP-based Best Distillation Strategy Search

Input: stance saliency v_i, distill cost w_i, and current cost limit W_{distill}.
Record the number of stance saliency $M = |v_i|$;
Init DP-table $T[M+1][W_{\text{distill}}+1]$ with all 0;
for $i = 1, 2, \ldots, M$ **do**
  for $j = 1, 2, \ldots, W_{distill}$ **do**
    if $j - w_{i-1} < 0$ **then**
      $T[i][j] = T[i-1][j]$;
      Record distillation picking choice $\phi(x_i)$;
    else
      $T[i][j] = \max(T[i-1][j],$
      $T[i-1][j - w_{i-1}] + v_{i-1})$;
      Record distillation picking choice $\phi(x_i)$;
    end
  end
end
$\{\phi(x_i)_{i=1}^{M}\} \leftarrow$ backtracking via records;
return best distillation strategy $\{\phi(x_i)_{i=1}^{M}\}$;

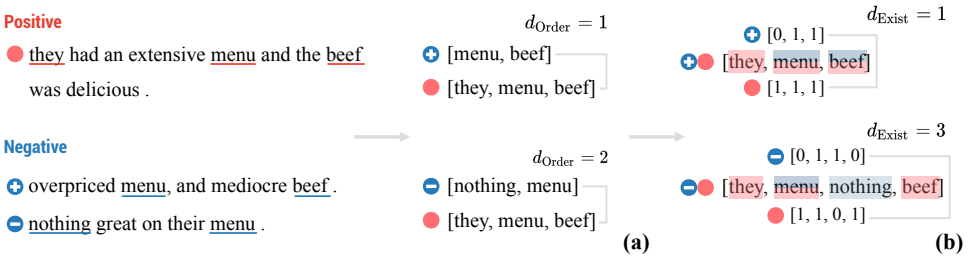

Figure S1: (a) extraction of scene entities (underlined) from source sentence and parallel target sentences. Sentences with a + correspond to $s^{\text{tgt+}}$, and those with a - correspond to $s^{\text{tgt-}}$ (i.e., expert and amateur demonstrations for imitation learning); (b) entity appearing order (d_{Order}, computed by edit distance); and (c) entity existence (d_{Exist}, computed by hamming distance).

be the same length (since it corresponds to the union of entities). Hamming distance measures the difference between source and target sentences on the shared entities set (this was shown to be an upper bound on the Levenshtein distance). Though there are overlaps between this metric and d_{Order}, we use this metric to *emphasize* the difference in scene entities.

Appendix E: Error Analysis, and Additional Generation Samples of LaMer

In the introduction of the main paper, we briefly discuss the pitfalls of existing TST models. Table S2 shows actual generation samples from these methods to further highlight their weaknesses. We take the sentiment transfer task—which was used by all models in their evaluations—and pick a *negative* source style sentence carrying the style in an implicit way (i.e., there are no salient token-level cues exhibiting negative sentiment[4]). All TST models should generate a transferred positive sentence.

As can be seen in the table, CAE (Shen et al., 2017) suffers from discarding too much style-independent content. When the style cannot be interpreted at the token level, DelRetrGen (Li et al., 2018a) results in generic generation since it is difficult to transfer implicit styled sentence through token-editing. From our empirical observation, Style Transformer (Dai et al., 2019) typically

[4]E.g., *"zero appetite"* does not have a direct opposite expression like *"one appetite"*. Thus, in this case *negative* style cannot be interpreted at the token level.

Source Style (*negative*)	you 'll have zero appetite after the first bite .
Reference Target Style (*positive*)	*you 'll be wanting more after the first bite !*
CAE Shen et al. (2017) (Latent Disentanglement)	*you 'll be back for the first bite !* (+ semantically coherent; − missing content)
DelRetrGen Li et al. (2018a) (Token-level Editing)	*i love this place .* (+ carrying target style; − generic generation)
Style Transformer Dai et al. (2019) (Transformer Self-Attention)	*you 'll have often appetite after the first friends .** (+ content preserved; − semantically incoherent)
Deep Latent Seq He et al. (2020) (LM Prior + Latent Parallel Seq.)	*you 'll have family appreciated the first time with the first time .** (+ content preserved; − unrelated illusion)
Ours: LAMER (Self-Supervision + LM IL)	*you 'll eat until you feel full after the first bite .*

Table S2: Comparing LAMER with several well-known STS methods on a sample of *negative* → *positive* sentiment transfer task. We denote the strength (+) and weakness (−) of the transfer outputs. * corresponds to generations that are taken from the author-released outputs files.

generates sentences with low readability. Deep Latent Seq (He et al., 2020) tends to generate unrelated text (e.g., *"...family appreciated..."*) and sometimes text with low readability (e.g., *"...the first time with the first time..."*). This is partially because their assumption that TST datasets can be aligned in latent space is too strong.

We have included sample generations from LAMER for the test sets of all three tasks with our code submission.

APPENDIX F: ADDITIONAL DETAILS ABOUT HUMAN EVALUATION

We provide more details about our human evaluation in this section. The results on sentiment TST are shown in Table S3 and those of formality TST are shown in Table S4.

Details About Participants Participants (N=212) were all from the United States and above 18 years old. Participants were required to have a HIT approval rate greater than 95%. The average age of the participants was 34.95 years-old (SD=9.90, Median=32). 141 of the participants (66.5%) were male, and 71 female (33.5%). Participants received 14.41 years of education on average (SD=4.46, Median=16). When asked to self-report their party affiliation, 52.4% participants self-reported as Democratic, 35.3% participants were self-reported Republicans, and 12.3% participants identified as independent.

Table S3: Human judgement results (on a 7-point scale) of seven existing methods and LAMER on sentiment transfer task. We **bold** the highest average rating. SD: Standard Deviation.

■ Sentiment	Style		Content		Readability	
Methods	Mean	SD	Mean	SD	Mean	SD
CAE (Shen et al., 2017)	5.09	1.49	4.79	1.56	4.84	1.50
DelRetrGen (Li et al., 2018a)	4.94	1.62	4.73	1.63	5.05	1.39
Dual RL (Luo et al., 2019)	5.43	1.40	4.89	1.73	5.10	1.40
Style Transformer (Dai et al., 2019)	5.09	1.55	4.71	1.56	5.04	1.50
Deep Latent Seq (He et al., 2020)	4.89	1.79	4.63	1.76	5.05	1.49
TSF-DelRetGen (Sudhakar et al., 2019)	4.66	1.35	4.73	1.24	5.30	1.13
STARP (Krishna et al., 2020)	**5.50**	1.20	4.65	1.40	5.33	1.20
Ours: LAMER	5.45	1.21	**4.91**	1.71	**5.43**	1.18

Table S4: Human judgement results (on a 7-point scale) of seven existing methods and LAMER on formality transfer task. We **bold** the highest average rating. SD: Standard Deviation.

Formality	Style		Content		Readability	
Methods	Mean	SD	Mean	SD	Mean	SD
CAE (Shen et al., 2017)	5.17	1.59	5.09	1.67	4.89	1.64
DelRetrGen (Li et al., 2018a)	5.19	1.57	4.91	1.65	4.86	1.62
Dual RL (Luo et al., 2019)	5.49	1.27	5.13	1.29	5.36	1.31
Style Transformer (Dai et al., 2019)	5.25	1.38	5.22	1.37	5.26	1.37
Deep Latent Seq (He et al., 2020)	5.22	1.52	5.30	1.46	5.17	1.47
TSF-DelRetGen (Sudhakar et al., 2019)	4.86	1.25	5.23	1.24	5.20	1.49
STARP (Krishna et al., 2020)	5.33	1.21	4.65	1.37	5.39	1.20
Ours: LAMER	**5.50**	1.23	5.45	1.29	**5.39**	1.21

Source Sent. (*positive*)	fun place to catch a game on tv and catch up w/ people .			
Human Ref. (*negative*)	loud place to catch a game on tv and try to catch up w/ people			
Methods	**Sample Generation**	**ACC**	**BLEU**	**PPL**
CAE ($\approx$ 15h 49min)				
w/. RD	a nice place to go on a game and the staff on us .	10.6	15.4	71.3
w/. S-Emb.	fun place to dine and helped me to support people .	26.3	24.7	53.5
w/. S-Emb. + SAS	not fancy place and always a great place to get .	35.4	26.0	39.6
DelRetrGen ($\approx$ 27h 13min)				
w/. RD	but i 'm not sure that is .	6.6	1.4	1371.4
w/. S-Emb.	"i 'm not a fan , but i love this place !	4.4	2.6	18.44
w/. S-Emb. + SAS	the place is also horrible .	97.3	18.9	15.63
Style Transformer ($\approx$ 12h 21min)				
w/. RD	fun place to catch a game on tv loud on game on ...	25.3	26.2	1241.9
w/. S-Emb.	bad place to catch a game on tv a to a to a ...	22.6	26.5	801.3
w/. S-Emb. + SAS	bad place to catch a game on tv game on a tv	45.8	29.3	948.9
Ours:LAMER (S-Emb. + SAS)				
1/10 Epoch ($\approx$ 10min)	i've been here to catch a game.	66.3	30.4	12.0
1/2 Epoch ($\approx$ 45min)	this place is terrible to catch a game.	79.9	34.2	11.3
1 Epoch ($\approx$ 1h 34min)	terrible place for anybody looking to catch a game on tv.	98.0	37.9	10.61

Table S5: Our alignment procedure can even boost the performance of existing methods. All trained with one epoch, we study their learning efficiency compared with our method: LAMER obtains the best result on this sentiment transfer task, and is robust to data scarcity.

APPENDIX G: DISCUSSION ON LAMER'S EFFICIENCY

We are curious about whether existing methods that suffer from lack of direct supervision can take the advantage of aligned datasets. In Table S5, we use the same aligned datasets used by LAMER (added aligned by RD as for ablation), to train three exiting systems by one epoch. Of note, all these methods benefit in different perspectives. For example, DelRetrGen (Li et al., 2018a) makes large improvements in style control accuracy, BLEU score, and fluency (PPL). Most prior work emphasize their advances in performance, but do not consider learning efficiency. In the same one epoch setting, LAMER achieves the best performance compared with others. Meanwhile, when further decreasing the training data size to 1/10 of the original, LAMER can still produce acceptable results, better than most of other methods trained with the whole epoch, mainly because LAMER is LM-based. Combining all these key factors for efficient learning, LAMER can serve as a general-purpose TST model for either data rich or data scarce cases.