Tailor: A Prompt-Based Approach to Attribute-Based Controlled Text Generation

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Abstract

Attribute-based Controlled Text Generation (CTG) refers to generating sentences that satisfy desirable attributes (e.g., emotions and topics). Existing works often utilize fine-tuning or resort to extra attribute classifiers, yet suffer from storage and inference time increases. To address these concerns, we explore attribute-based CTG in a prompt-based manner. In short, the proposed Tailor represents each attribute as a pre-trained continuous vector (i.e., single-attribute prompt) and guides the generation of a fixed PLM switch to a pre-specified attribute. We experimentally find that these prompts can be simply concatenated as a whole to multi-attribute CTG without any re-training, yet raises problems of fluency decrease and position sensitivity. To this end, Tailor provides a multi-attribute prompt mask and a re-indexing position-ids sequence to bridge the gap between the training (one prompt for each task) and testing stage (concatenating more than one prompt). To further enhance such single-attribute prompt combinations, Tailor also introduces a trainable prompt connector, which can be concatenated with any two single-attribute prompts to multi-attribute text generation. Experiments on 11 attribute-specific generation tasks demonstrate strong performances of Tailor on both single-attribute and multi-attribute CTG, with 0.08% training parameters of a GPT-2.

1 Introduction

Attribute-based CTG (Zhang et al., 2022) focuses on generating sentences satisfying pre-specified attributes such as topic and sentiment, which remains extremely challenging in recent progress (Dathathri et al., 2020). Especially multi-attribute CTG, it is typically unsupervised since no example of a sentence with specified attributes could be obtained during training. (Lample et al., 2019). Existing efforts for attribute-based CTG can be roughly divided into two types: fine-tuning and utilizing extra attribute classifiers. The first type usually fine-tunes a pre-trained language model (PLM) on the attribute-specific data (Ziegler et al., 2019), yet stores a full copy of the PLM for each desirable attribute. To partly address this issue, control codes are introduced to generate various styles of sentences with one PLM, such as keywords (Keskar et al., 2019) and numerical sequence (Lyu et al., 2021). However, re-training whole PLMs could be expensive (Yang and Klein, 2021) and they rarely attend to multi-attribute CTG. The second type introduces extra attribute classifiers to guide a PLM, such as back-propagating gradients of classifiers (Dathathri et al., 2020) or weighting output logits (Krause et al., 2021; Yang and Klein, 2021). Such a paradigm shows encourage improvement, while the text fluency tends to decrease (see § 4.2) and inference time increase (Qian et al., 2022).

To overcome the aforementioned limitations, we propose a Text-attribute controller (Tailor) — a prompt-based approach to attribute-based CTG. The key idea is to represent each attribute as a pre-trained continuous vector (hereinafter known as the single-attribute prompt) to control a fixed GPT-2 for single-attribute CTG, and effectively concatenate such single-attribute prompts as a whole for multi-attribute CTG. This allows Tailor to be easily expanded by training the corresponding attribute prompt if a new attribute emerges, while avoiding re-training the whole PLM. In detail, the single-attribute prompt is concatenated with the input prefix and then guides the generation of a fixed GPT-2 switch to a pre-specified attribute. More importantly, we experimentally find that such single-attribute prompts could be simply concatenated to generate sentences with multi attributes. However, this manner always suffers from fluency decrease and position sensitivity, i.e., the PLM tends to focus more on the single-attribute prompt that is closer to
the input prefix (see § 4.3). To address these issues, the key lies in bridging the gap between the training and the testing stage. In detail, the single-attribute prompt only attends to itself in the attention matrix while training, since it is individually trained by the attribute-specific data. However, when it comes to the testing stage, the second prompt also attends to the first one in the concatenation, with the simultaneous change of the position-ids sequence\(^1\).

To fill this gap, Tailor introduces a Multi-Attribute Prompt mask (MAP mask) and a Re-indexing Position-ids sequence (RP sequence) for the fixed GPT-2. MAP mask prevents distinct single-attribute prompts from cross-attention, and RP sequence ensures stable position-ids information for the PLM after swapping, by individually numbering each prompt. As such non-training method partly addresses the issue, the text fluency still decrease, since there is no multi-attribute specific training stage for these single-attribute prompts to adapt to work together. Inspired by the role of ‘and’ in connecting parallel phrases for natural sentences (Rudolph, 1989), Tailor further provides a training method that contains a continuous connector to connect two single-attribute prompts as a whole to multi-attribute CTG. As shown in Figure 1, the proposed Multi-Attribute Prompt connector (MAP connector) can be concatenated with any two single-attribute prompts and hint a GPT-2 to multi-attribute CTG. Meanwhile, a pseudo-prompt based strategy is also provided for training the connector in unsupervised settings. With MAP connector, the combinations show strong performances on multi-attribute generation tasks, even works to the unseen ones.

2 Related Work

Attribute-Based CTG focuses on generating sentences containing pre-specified attributes, such as sentiment and topic. As a vital demand for intelligent writing (Zhang et al., 2022), various attempts have been made in this area, including fine-tuning PLMs and utilizing extra attribute classifiers. The first type usually fine-tunes separately and stores a full copy of PLM for each desirable attribute (Ziegler et al., 2019). To alleviate the storage problem, CTRL (Keskar et al., 2019) provides 55 kinds of control codes (i.e., special keywords) to fine-tune one PLM for generating sentences of various styles. GSum (Dou et al., 2021) introduces four guidance signals (e.g., keywords and relations)

\(^1\)In this case, position-ids sequence denotes position indexes of input tokens in the position embeddings for GPT-2.
to enhance the controllability of PLMs in the text summarization. Although they make successful attempts in single-attribute CTG and partially address the storage issue (Yang and Klein, 2021), it might not be directly usable for multi-attribute CTG. To improve the flexibility and extensibility of the CTG model, the second type makes efforts in the inference stage. In short, utilizing extra attribute classifiers to guide PLMs in each generating step. PPLM (Dathathri et al., 2020) iteratively modifies latent representations of a GPT-2 referring to the gradient of attribute classifiers, yet notably increasing the inference time. To solve this problem, Fudge (Yang and Klein, 2021) uses an attribute predictor to adjust the output probabilities of a PLM. Similarly, GeDi (Krause et al., 2021) uses smaller PLMs as generative discriminators to hint a larger PLM generating sentences that satisfy desirable attributes. Despite their progress, the fluency of generating sentences tends to decrease compared with the original PLM (see § 4.2) and extra inference time costs still existed. In comparison, with Tailor, PLMs can enjoy the benefits of the controllability from combinations of single-attribute prompts with a negligible decrease of text quality.

**Prompt Learning** is a new paradigm in NLP summarised as “Pre-train, Prompt and Predict” (Liu et al., 2021a). In short, it can guide a single PLM to solve various downstream tasks by reformulating these tasks into a text-to-text manner. Early works explore prompt formatting as discrete-word templates (Petroni et al., 2019; Schick and Schütze, 2021; Shin et al., 2020; Houlsby et al., 2019). Recently, continuous prompt has attracted attention (Gu et al., 2021; Liu et al., 2021b, 2022), which usually forms as a set of continuous task-specific vectors to the input. Unlike discrete prompts may face difficulties of optimizing, continuous prompts could be trained expressively on downstream task data (Li and Liang, 2021). Despite their encouraging progress, the prompt composition is rarely explored but undoubtedly important in prompt learning. In that case, a composable task could be accomplished by composing various subtasks with multiple sub-prompts (Liu et al., 2021a). To achieve it, PTR (Han et al., 2021) introduces manual sub-prompts for entity recognition and relation classification, respectively. Then, these two kinds of prompts are composed by logic rules as a complete prompt for the relation extraction task. Unfortunately, the composition of continuous prompts is rarely explored yet has demonstrated great potential (Qian et al., 2022). In this paper, we experimentally reveal the potential of combining continuous prompts to accomplish multi-attribute CTG. Afterward, we propose MAP connector to enhance this combination. Extensive experiments verify the effectiveness of Tailor on both controllability of attributes and text quality.

### 3 Methodology

#### 3.1 Tailor for Single-Attribute CTG

Different from fine-tuning a full copy of PLMs for each attribute, our basic idea is to guide the generation of a PLM with a set of pre-trained continuous vectors, namely single-attribute prompts. Meanwhile, each prompt represents a desirable attribute. As shown in Figure 2 (top), we fix the parameters of a GPT-2 and train each prompt on attribute-specific data. After training, these single-attribute prompts can act as plug-ins for desirable attribute-based text generation. For the conditional prefix “Once upon a time”, the GPT-2 can continue with “I had to order my tacos ...” with a prompt representing the Mexican food topic or “the food was good” with a prompt representing the positive sentiment. In this way, our method can be easily expanded: if a new attribute emerges, we only need to train an attribute prompt and then control a PLM to generate attribute-specific sentences.

To be exact, we use language modeling learning object to train such a set of single-attribute prompts. In detail, \( k \)-th single-attribute prompt \( S_k \) with length \( l_k \) is first initialized randomly, where \( S_k \in \mathbb{R}^{l_k \times d_{emb}} \). \( d_{emb} \) is the word embedding dimension of the GPT-2. Meanwhile, given an attribute-specific sentence \( x = \{x_1, x_2, ..., x_n\} \) with length \( n \), we get a word sequence matrix \( X_{emb} \in \mathbb{R}^{n \times d_{emb}} \) after being embedded by GPT-2. Then, \( S_k \) is concatenated with \( X_{emb} \) to form a input matrix as \( [S_k; X_{emb}] \in \mathbb{R}^{(l_k + n) \times d_{emb}} \), and this matrix is fed into a fixed GPT-2. Finally, the learning object is:

\[
L_{single} = \sum_{t=1}^{n} \log P_{\theta_g, \theta_{S_k}}(x_t | S_k, x_{<t}) \ , \quad (1)
\]

where \( \theta_g \) and \( \theta_{S_k} \) denote the parameters of GPT-2 and the single-attribute prompt, respectively. Only \( \theta_{S_k} \) are updated during the training stage.
3.2 Tailor for Multi-Attribute CTG

Inspired by composition of discrete prompts (Han et al., 2021) to accomplish a complex task, our intuitive idea is to combine single-attribute prompts as a multi-attribute prompt to hint a PLM for multi-attribute CTG. To enjoy the benefit of our paradigm in single attribute CTG, we first consider simply concatenating several single-attribute prompts as a whole multi-attribute prompt. Surprisingly, such a multi-attribute prompt can guide a GPT-2 to generate sentences containing multi attributes of interest, and get encouraging performances in unsupervised settings without any training (see § 4.2). Despite the progress, this straightforward method suffers from notably decreasing fluency of final text compared with single-attribute CTG. Meanwhile, it is position sensitive, i.e., the PLM tends to focus more on the single-attribute prompt that is closer to the input prefix (see § 4.3).

To polish such paradigm while keeping plug-and-play and storage-friendly advantages, as shown in Figure 2 (bottom), Tailor introduces a non-training method to quickly and effectively alleviate the above problems of simply concatenation. Afterward, a training method is further provided to greatly enhance the combinations. We elaborate the two methods separately as follows.

3.2.1 Non-Training Method

To make the better use of single-attribute prompts to multi-attribute CTG without any retraining, reducing disparities between the training (a single-attribute prompt for each task) and the testing stage (concatenating more than one single-attribute prompts) is undoubtedly important. Specifically, the single-attribute prompt only attends to itself in the attention matrix while training, as each prompt is individually trained by the attribute-specific data. However, while in the testing stage for multi-attribute CTG, the second prompt also focuses on the first one in the concatenation, with the simultaneous change of the position-ids sequence. To fill this gap, MAP mask and RP sequence are introduced to the fixed PLM while generating. MAP mask avoids cross-attention between representations of single-attribute prompts to approximate the condition in the single-attribute CTG training stage.
While the non-training method partly addresses the issues of combination, the inconsistency between the training and testing stage would still decrease the performance. To fill this gap, we provide a training method—MAP connector, which is trained for combining two single-attribute prompts to multi-attribute text generation. To utilize only single-attribute sentences for multi-attribute CTG, we propose a pseudo-attribute prompt based training strategy for MAP connector. Therefore, we first detail the pseudo-attribute prompt building method and then the workflow of MAP connector.

**MAP Mask**

For the ease of implementation, we introduce MAP mask matrix \( M_p \) to the softmax logits of GPT-2. Given a vanilla attention module:

\[
A = \text{Softmax}(\frac{QK^\top}{\sqrt{d}}) \in \mathbb{R}^{n \times n}, \quad (2)
\]

where \( n \) is the length of input sentence \( x \) and \( Q,K \) denote representations of query and key, respectively\(^2\). As to the new attention mask, given two single-attribute prompts \( S_u \) with length \( l_u \) and \( S_v \) with length \( l_v \), the new attention module is:

\[
A = \text{Softmax}(\frac{QK^\top}{\sqrt{d}} + M_p) \in \mathbb{R}^{(l_p+n) \times (l_p+n)},
\]

\[
M_p^{ij} = \begin{cases} 
-\infty & \text{if } i \in [l_u, l_v] \text{ and } j \in [0, l_u], \\
0 & \text{otherwise}, 
\end{cases}
\quad (3)
\]

where \( l_p = l_u + l_v \).

**RP Sequence**

Simply concatenation of single-attribute prompts always suffers from position sensitivity. To address this issue, we propose a simple but effective method to ensure performance consistency while swapping. In short, we modify the position-ids sequence of the PLM while concatenating. Given the original position-ids sequence:

\[
id = \{1, ..., l_u, l_v + 1, ..., l_p + 1, \ldots, l_p + n\},
\]

the RP sequence can be defined as:

\[
id_{\text{RP}} = \{1, ..., l_u, 1, ..., l_v, l_u + 1, ..., l_v + n\}.
\]

In that case, swapping dose not bring any changes, since the position of prompts is fixed by the RP sequence while avoiding cross-attention by the MAP mask.

**3.2.2 Training Method**

While the non-training method partly addresses the issues of combination, the inconsistency between the training and testing stage would still

\(^2\)The multi-head mechanism is omitted for illustration purposes.

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method utilizes the predicted probability distribution to multiply corresponding single-attribute prompts, respectively. Then these weighted prompt form a whole prompt $S_w$ by element-wise addition.

**The MAP Connector Workflow** Figure 2 bottom illustrates the workflow of MAP connector. In the training stage, we unify sentences containing different single attributes to train MAP connector, each of which is added an extra pseudo single-attribute prompt (boxes edged in black) by employing the aforementioned method. Specifically, for each training sample, we first concatenate two single-attribute prompts (real and pseudo), MAP connector and the input sentence to a sequence, and then feed it into a fixed GPT-2. It is worth noting that only parameters of MAP connector are updated in the training stage. Therefore, given two single-attribute prompt $S_u$ and $S_v$, MAP connector $C$ with the length $l_C, C \in \mathbb{R}^{l_C \times d_{emb}}$, we concatenate $S_u, S_v, C$ and the input sentence matrix $X_{emb}$ to form a input matrix as $[S_u; S_v; C; X_{emb}]$. The learning object is:

$$
\mathcal{L}_{multi} = \sum_{t=1}^{n} \log P_\theta (x_t|S_u, S_v, C, x_{<t}) , \tag{7}
$$

where $\theta = [\theta_g; \theta_{S_u}; \theta_{S_v}; \theta_C]$, $\theta_g$, $\theta_{S_u}$, $\theta_{S_v}$, and $\theta_C$ denote the parameters of GPT-2, two single-attribute prompts and MAP connector, respectively. Only $\theta_C$ are updated during the training stage. In the inference stage, we just decompose each multi-attribute generation task as several single-attribute generation tasks and find corresponding single-attribute prompts. Then, these prompts are concatenated with MAP connector to generate sentences that satisfy multi attributes.

4 Experiments

4.1 Experimental Setup

**Datasets** We conduct experiments on the widely-used benchmark dataset YELP (Lample et al., 2019) to evaluate Tailor. Following previous works that conduct experiments on attributes of emotions and topics for multi-attribute CTG, we choose Yelp restaurants reviews of sentiment attributes (positive (PO) and negative (NE)) and topics of food type (Mexican (ME), American (AM) and Asian (AS) foods) to evaluate models. Specifically, each attribute contains 30000 / 3000 sentences for training / validation. For evaluation, to keep in line with previous works (Yang and Klein, 2021; Dathathri et al., 2020), we use 15 attribute-unrelated prefixes and ask model to continue writing with them (100 sentences for each) while satisfying pre-specified attribute as the final results.

**Evaluation Metrics** Follow (Yang and Klein, 2021; Dathathri et al., 2020), we automatically evaluate generation results from three aspects: (1) **Correctness**. We used RoBERTa$_{large}$ (Liu et al., 2019) based attribute classifiers to compute the fraction of final sentences that contains pre-specified attribute, details in Appendix C. (2) **Text Quality**. Grammar (GRAM) (Warstadt et al., 2019) indicates the averaged grammaticality probabilities of all final sentences, evaluated by a RoBERTa-based CoLA grammaticality model (Yang and Klein, 2021). Perplexity (PPL), we average the scores from GPT-2$_{Base}$, GPT-2$_{Medium}$ and GPT-2$_{Large}$ version of GPT-2 (Radford et al., 2019) as the final result. (3) **Diversity**. Following Li et al. (2015), we report the distinctness of the final results. Specifically, we count the number of unigrams, bigrams and trigrams and then normalize them by the total number of words (i.e., Dist-1 / Dist-2 / Dist-3).

**Tailor Settings** To facilitate description, for single-attribute CTG, Tailor-S denotes the method of single-attribute prompts. While for multi-attribute CTG, CONCAT means simply concatenating two single-attribute prompts and Tailor-C is our non-training method. For the training method, Tailor-A and Tailor-W represent using argmax-pseudo and weighted-pseudo prompts in the training stage of the MAP connector, respectively.

**Baselines** We compare our methods with mainstream competitive models as follows. (1) FT, fine-tuning the original GPT-2$_{base}$ on attribute-specific data. As multi-attribute CTG is unsupervised, following Lyu et al. (2021), we sequentially apply the GPT-2 trained for corresponding single-attribute data multiple times to perform multi-attribute CTG. (2) Adapter, following Li and Liang (2021), we use the adapter for GPT-2 as same as Lin et al. (2020). Note that for multi-attribute CTG, we first use the same training method as mentioned in FT for Adapter. Besides, we use the same argmax-pseudo labeled sentences (see § 3.2.2) to train the Adapter (marked with ‘Pseudo’). (3) GeDi (Krause et al., 2021), using small PLMs to hint large ones. (4) PPLM (Dathathri et al., 2020), back-propagating gradients of extra attribute classifiers to a PLM.

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Footnotes:

4. https://github.com/uber-research/FPLM

5. More details can be found in § B
Due to space constraints, the implementation details of baselines and Tailor can be found in § A.

4.2 Main Results

Single-Attribute CTG As shown in Table 1, Tailor-S outperforms PPLM and GeDi to a great extent on both correctness and text quality. Meanwhile, compared with other parameter-efficient learning model Adapter, Tailor-S also gets improvements on both on both correctness (e.g., + 9.19% of Food) and diversity (e.g., + 0.02% / + 0.12% / + 0.25% of Food) with a similar scale of training parameters. However, with 0.08% training parameters of the GPT-2, Tailor-S still has a performance gap with FT, e.g., - 4.14% correctness on Food. Fortunately, as the length of Tailor-S increases (see § 4.3), this gap appears to narrow (- 0.33%, Tailor-S with length of 256).

Multi-Attribute CTG As shown in Table 2, we compare three instantiations of Tailor and strong baselines in the single-attribute CTG experiment. First, Tailor-C shows encouraging performances without any training, especially on correctness, outperforms fine-tuning (+ 13.51% Sentiment / + 4.53% Food) and Adapter (+ 13.44% Sentiment / + 6.00% Food), yet text quality decrease. Besides, our training methods Tailor-W and Tailor-A show improvements on all scores compared with Tailor-C, e.g., + 4.58% / + 11.22% correctness on the topic of food type attribute. Meanwhile, Tailor also outperforms Adapter with the same pseudo label strategy on both correctness and diversity, with a notable scale discrepancy of training parameters (1:7.25).

4.3 Further Discussions

Few-Shot Learning We conduct a few-shot learning setting to further analyze the effectiveness of Tailor. In detail, following Li and Liang (2021), we randomly sample from full dataset and obtain the few-shot dataset (training / validation / testing: 150 / 20 / 20). Specifically, we sample three different few-shot datasets and average the scores of each method on three datasets as the final results.
Table 3: The main results of few-shot learning. Note that TP for multi-Attribute CTG means the extra training parameters as the percentage of the fine-tuning model (FT) after single-Attribute CTG. Due to space constraints, we average the scores of six combinations (two sentiment attributes × three topic attributes of food type) as the final results for each method.

| Method       | Correctness (%) | Avg↑ | Sent↑ | Food↑ |
|--------------|-----------------|------|-------|-------|
| Single-Attribute CTG |                 |      |       |       |
| 100.00       | FT              | 54.08| -     | 54.08 |
|              | FT              | 85.28| 85.28 | -     |
| 0.10         | Adapter         | 55.79| -     | 55.79 |
|              | Adapter         | 77.91| 77.91 | -     |
| 0.08         | Tailor-S        | 66.23| 66.23 | -     |
| 0.08         | Tailor-S        | 89.27| -     | 89.27 |
|              | Tailor-A        | 89.27| 89.27 | -     |
| Multi-Attribute CTG |                 |      |       |       |
| 100.00       | FT              | 60.60| 73.45 | 47.75 |
| 0.60         | Adapter         | 57.15| 68.44 | 45.85 |
| 0.60         | Adapter (Pseudo)| 67.27| 78.66 | 55.88 |
| 0.00         | Tailor-C        | 68.09| 74.58 | 61.79 |
| 0.08         | Tailor-W        | 70.32| 84.18 | 56.46 |
| 0.08         | Tailor-A        | 71.41| 83.63 | 59.18 |

Table 4: The results on multi-attribute CTG of generating sentences satisfying negative sentiment (NE) and topic of American food (AM). NE-AM denotes putting the positive attribute prompt in first and American food attribute prompt in later when concatenating them, in contrast to AM-NE.

| Method     | Combination | Correctness (%) | Avg↑ | Sent↑ | Food↑ |
|------------|-------------|-----------------|------|-------|-------|
| CONCAT     | NE-AM       | 68.40           | 76.93| 59.87 |
|            | AM-NE       | 68.27           | 80.07| 56.47 |
| Tailor-C   | NE-AM       | 69.90           | 79.07| 60.73 |
|            | AM-NE       | 69.90           | 79.07| 60.73 |

Table 5: The ablation study on using the APA mask and the RP sequence (RP) of Tailor-C. '-' denotes removing the corresponding module from Tailor-C. Note that, exchanging the concatenating order of prompts would bring different performances, except for Tailor-C. Thus, we average the scores from these two situations of six attributes combinations as the final result.

| Method     | Correctness (%) | Avg↑ | Sent↑ | Food↑ |
|------------|-----------------|------|-------|-------|
| Tailor-C   |                | 78.82| 87.54 | 70.10 |
| - APA Mask |                | 78.36| 87.39 | 69.34 |
| - RP       |                | 77.77| 88.33 | 67.21 |
| - Both     |                | 76.20| 87.88 | 64.52 |

As shown in Table 3, three types of Tailor outperforms other baselines on correctness, with 0.00% / 0.08% extra training parameters of the GPT-2 after single-Attribute CTG.

Length of Tailor: As shown in Figure 4, we explore the length of both Tailor-S and Tailor-A. For singe-attribute prompt Tailor-S, the performances increase alongside the length. But for Tailor-A, it obtains the best performances with the length of 128, and the performances have a slight drop when we continue to increase the length.

Position Sensitivity: We investigate the position sensitivity problem when concatenating two single-attribute prompts. As shown in Table 4, for simply concatenation, the GPT-2 tends to focus more on the prompt that is closer to the input prefix (i.e., the attribute behind the dash in the Table 4). For instance, NE attribute get a 3.14% improvement if we put the corresponding prompt close to the input prefix. However, it also brings a 3.4% decrease for AM attribute as being away from input prefix at the same time. In contrast, Tailor-C keeps the same performance after swapping.

Ablation Study of Tailor-C: Whether Tailor-C enjoys the benefits from the MAP mask and the RP sequence is also of concern. As shown in Table 5, both the MAP mask and the RP sequence are important to Tailor-C. More importantly, they are complementary to each other—using these two strategies simultaneously can improve the performance while avoiding the position sensitivity problem.

Unseen Combination: In this part, we analyze the combining ability of Tailor on the unseen combination, which does not appear in Tailor’s training stage. In implementation, we randomly select one combination and remove the corresponding data from the training set for the MAP connector, and then test the performance of the MAP connector on this multi-attribute generation task. As shown...
in Table 6, Tailor-A still works to the unseen combination PO-ME, and outperforms the non-training method Tailor-C with 2.35% improvements.

| Unseen Method | Correctness (%) |
|---------------|-----------------|
|              | Avg↑ | Sent↑ | Food↑ |
| PO-ME Tailor-C | 87.54 | 95.60 | 79.47 |
| PO-ME Tailor-A | 89.89 | 97.07 | 82.70 |
| - Tailor-A     | 91.64 | 97.87 | 85.40 |

Table 6: The results on unseen combination to multi-attribute CTG. PO-ME denotes the attribute combination of positive sentiment and topic of Mexican food.

5 Conclusions

In this paper, we explore attribute-based CTG in a prompt-based manner—Tailor, which represents each attribute as a continuous prompt and effectively combines them as a multi-attribute prompt. For enhancing these combinations, Tailor provides two solutions, namely non-training (MAP mask + RP sequence) and training methods (MAP connector). As our first attempt to multi-attribute CTG, combining more than two attributes still needs to be discussed. Thus in the future, we will investigate extending Tailor to connect wider ranges of attributes, and expand it to other text-to-text generation tasks.

References

Sumanth Dathathri, Andrea Madotto, Janice Lan, Jane Hung, Eric Frank, Piero Molino, Jason Yosinski, and Rosanne Liu. 2020. Plug and play language models: A simple approach to controlled text generation. In ICLR 2020. OpenReview.net.

Zi-Yi Dou, Pengfei Liu, Hiroaki Hayashi, Zhengbao Jiang, and Graham Neubig. 2021. Gsum: A general framework for guided neural abstractive summarization. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021, pages 4830–4842. Association for Computational Linguistics.

Yuxian Gu, Xu Han, Zhiyuan Liu, and Minlie Huang. 2021. PPT: pre-trained prompt tuning for few-shot learning. CoRR, abs/2109.04332.

Xu Han, Weilin Zhao, Ning Ding, Zhiyuan Liu, and Maosong Sun. 2021. PTR: prompt tuning with rules for text classification. CoRR, abs/2105.11259.

Neil Houlsby, Andrei Giurgiuc, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attarayan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In ICML 2019, volume 97 of Proceedings of Machine Learning Research, pages 2790–2799. PMLR.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomás Mikolov. 2017. Bag of tricks for efficient text classification. In EACL 2017, pages 427–431. Association for Computational Linguistics.

Nitish Shirish Keskar, Bryan McCann, Lav R. Varshney, Caiming Xiong, and Richard Socher. 2019. CTRL: A conditional transformer language model for controllable generation. CoRR, abs/1909.05858.

Ben Krause, Akhilesh Deepak Gotmare, Bryan McCann, Nitish Shirish Keskar, Shaﬁq R. Joty, Richard Socher, and Nazneen Fatema Rajani. 2021. Gedi: Generative discriminator guided sequence generation. In Findings of EMNLP 2021, pages 4929–4952. Association for Computational Linguistics.

Guillaume Lample, Sandeep Subramanian, Eric Michael Smith, Ludovic Denoyer, Marc’Aurelio Ranzato, and Y-Lan Boureau. 2019. Multiple-attribute text rewriting. In ICLR 2019. OpenReview.net.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2015. A diversity-promoting objective function for neural conversation models. arXiv preprint arXiv:1510.03055.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In ACL 2021, pages 4582–4597. Association for Computational Linguistics.

Zhaojiang Lin, Andrea Madotto, and Pascale Fung. 2020. Exploring versatile generative language model via parameter-efficient transfer learning. In Findings of EMNLP 2020, volume EMNLP 2020 of Findings of ACL, pages 441–459. Association for Computational Linguistics.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021a. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. CoRR, abs/2107.13586.

Xiao Liu, Kaixuan Ji, Yicheng Fu, Zhengxiao Du, ZhiLin Yang, and Jie Tang. 2022. P-tuning v2: Prompt tuning can be comparable to fine-tuning universally across scales and tasks. In ACL 2022.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, ZhiLin Yang, and Jie Tang. 2021b. GPT understands, too. CoRR, abs/2103.10385.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.
Yiwei Lyu, Paul Pu Liang, Hai Pham, Eduard H. Hovy, Barnabás Póczos, Ruslan Salakhutdinov, and Louis-Philippe Morency. 2021. Stylebft: A compositional benchmark for fine-grained controllable text style transfer. In *NAACL-HLT 2021*, pages 2116–2138. Association for Computational Linguistics.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019. Language models as knowledge bases? In *EMNLP 2019*, pages 2463–2473.

Jing Qian, Li Dong, Yelong Shen, Furu Wei, and Weizhu Chen. 2022. Controllable natural language generation with contrastive prefixes. *arXiv preprint arXiv:2202.13257*.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Elisabeth Rudolph. 1989. *The role of conjunctions and particles for text connectivity*. In *Text and discourse connectedness*, page 175. John Benjamins.

Timo Schick and Hinrich Schütze. 2021. Exploiting cloze-questions for few-shot text classification and natural language inference. In *EACL 2021*.

Tianxiao Shen, Tao Lei, Regina Barzilay, and Tommi S. Jaakkola. 2017. Style transfer from non-parallel text by cross-alignment. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 6830–6841.

Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. Autoprompt: Eliciting knowledge from language models with automatically generated prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 4222–4235. Association for Computational Linguistics.

Alex Warstadt, Amanpreet Singh, and Samuel R Bowman. 2019. *Neural network acceptability judgments*. Transactions of the Association for Computational Linguistics, 7:625–641.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Kevin Yang and Dan Klein. 2021. FUDGE: controlled text generation with future discriminators. In *NAACL-HLT 2021*, pages 3511–3535. Association for Computational Linguistics.

Hanjing Zhang, Haolin Song, Shaoyu Li, Ming Zhou, and Dawei Song. 2022. A survey of controllable text generation using transformer-based pre-trained language models. *CoRR*, abs/2201.05337.

Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul F. Christiano, and Geoffrey Irving. 2019. Fine-tuning language models from human preferences. *CoRR*, abs/1909.08593.

A Implement Details

We detail the hyperparameters and experimental settings of Tailor and baselines as follows.

1. Tailor. Tailor is implemented based on Huggingface (Wolf et al., 2020). In all experiments of Tailor, we set the length of Tailor-C to 128, as same as the MAP connector for Tailor-A and Tailor-W. As for the learning rate and the warm-up steps, Tailor-S, Tailor-A, and Tailor-W are set to 5e-5 and 0, respectively. Besides, to get a pseudo label for MAP connector, we use the RoBERTa_{large} based classifier for both sentiment and topic of food type attributes. The hyperparameters can be found in § C. Note that, for a fair comparison, we only use the same training set for each classifier as for training Tailor.

2. FT. We use the GPT-2_{Base} with a language model head implemented based on Huggingface. The learning rate is set to 5e-3 and the warm-up steps is set to 0.

3. Adapter. we set the bottleneck size to 5 to keep a similar size of training parameters with Tailor. The learning rate is set to 5e-5 and the warm-up steps is set to 0.

4. GeDi. For a fair comparison, we use the generative discriminator of GeDi based on GPT-2_{Base} to guide generation of another GPT-2_{Base}. In inference, we use the $\omega = 30$, $\rho = 0.8$ and $\tau = 0.8$, as reported in their implementation.

5. PPLM. We employ the original hyperparameter setting reported in Dathathri et al. 6https://huggingface.co/gpt2 7https://github.com/zlinao/VGLM 8https://github.com/salesforce/GeDi 9https://github.com/uber-research/PPLM/blob/master/paper_code/pplm.py
In detail, \( \gamma = 1.5, \gamma_{gm} = 0.9, \lambda_{kl} = 0.01, \) iterations=3 and step size=0.02.

In inference, to keep in line with previous works (Dathathri et al., 2020; Krause et al., 2021), we use top-\( k \) sampling with \( k=10 \), and fix the random seed as 42 for all models to get the final results, while the maximum generation length is set to 128.

**B Yelp Dataset**

In this section, we elaborate the workflow of filtering, pre-processing and sub-sampling to get the attribute-specific dataset for training all models and the classifiers For correctness evaluation. First of all, we get the YELP dataset from Lample et al. (2019). In detail, each sample of the YELP dataset contains a review and the corresponding attributes. Then, we select the restaurant reviews sub set as our original dataset. For dataset filtering, we use the dataset setup scripts offered by Lample et al. (2019), which contains a fastText(Joulin et al., 2017) classifier to filter sentences that not written in English. After that, we filter the sentences with rated 3 stars, since they could be neutral in sentiment (Shen et al., 2017). Finally, we get the pre-processed dataset as illustrated in Table 8. For the classifiers that are used in correctness evaluation, we use the full dataset and details in § C. Aside from it, for training Tailor and baselines, we randomly sample 30,000 / 3,000 sentences as training / validation data set for each attribute.

### Model F1 Score

| Model             | F1 Score |
|-------------------|----------|
| Food Type Classifier | 83.40    |
| Sentiment Classifier  | 97.10    |

Table 7: The Performances of two classifiers on Yelp dataset.

**C Classifiers For Correctness Evaluation**

We use the RoBERTa\textsubscript{Large} based model to train two classifiers for both sentiment and topic of food type attributes. To obtain a balanced dataset, we randomly over-sampling the raw dataset. Finally, we get 1500k / 15k / 15k topic-specific sentences and 1380k / 1k / 1k sentiment-specific sentences for training / validation / testing, respectively. For training two classifiers, the learning rate is set to 5e-5 and the warm-up steps is set to 200. The performances on the testing set can be found in Table 7.

**D Case Study**

To intuitively display the effects of various attributes, we show some generation results of single-attribute CTG in Table 9 and multi-attribute CTG in Table 10, respectively.

| Attribute | PO    | NE    | All   |
|-----------|-------|-------|-------|
| ME        | 25,169| 89,411| 114,580|
| AM        | 72,641| 299,293| 371,934|
| AS        | 47,680| 185,551| 233,231|
| All       | 145,490| 574,255| 719,745|

Table 8: The number of reviews for each attribute in Yelp dataset.

\[10\] The format can be found via https://github.com/shrimai/Style-Transfer-Through-Back-Translation
| Attribute Method | Generation Results |
|------------------|--------------------|
| **FT** | Once upon a time, I was very disappointed. The meat was bland and the beans tasted as if they had been sitting out all day... |
| **Adapter** | Once upon a time in the restaurant it was still dark and people weren't even talking... |
| **PPLM** | Once upon a time, computers would have been able read, interpret and write, and listen, listen and read... |
| **GeDi** | Once upon a time you either enter base build states or begin switching context switches and magic spells that alter your manifest... |
| **Tailor-S** | Once upon a time, you had to order your dinner. The food came out cold with no seasoning or flavor whatsoever... |

| **FT** | Once upon a time I've had the spicy tofu dish, but that was my only meal. It came out cold and tasted awful... |
| **Adapter** | Once upon a time I was craving something spicy, it tasted like the best Chinese food out there... |
| **PPLM** | Once upon a time I made a stone of silver ring mail "Garden of the Winds Winds"... |
| **GeDi** | Once upon a time bamboo noodles were the classical medicine and lemongrass fetish... |
| **Tailor-S** | Once upon a time, I got here for the sushi roll. After getting home from work at 4pm and finding... |

Table 9: Samples of single-attribute CTG with input prefix ‘Once upon a time’. NE and AS denotes generating sentences satisfying negative sentiment and topic of Asian food, respectively. We highlight different attribute-specific words or phrases for better view.

| Attribute Method | Generation Results |
|------------------|--------------------|
| **FT** | Once upon a time I was greeted, sat and waited patiently. The food took forever and there were only 6 of us that got our appetizers... |
| **Adapter** | Once upon a time I got my food and was told that the service is slow. Then they came over to me with an "error"... |
| **Adapter (P)** | Once upon a time, I would never recommend eating this place. The sushi was terrible and they... |
| **NE - AS** | Once upon a time my mom had to order the fried rice at night and she said that it was so bad... |
| **Tailor-C** | Once upon a time, I've had my rice and noodles at the Japanese buffet. They were so bland that... |
| **Tailor-A** | Once upon a time I had the spicy ramen. It was too sweet and salty, but now its like they have been replaced with something else... |

Table 10: Samples of multi-attribute CTG with input prefix ‘Once upon a time’. NE-AS denotes generating sentences satisfying negative sentiment and topic of Asian food. Adapter (P) denotes using the same argmax-pseudo labeled sentences (see § 3.2.2) to train the Adapter. We highlight different attribute-specific words or phrases for better view.