A Distributional Lens for Multi-Aspect Controllable Text Generation

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Abstract

Multi-aspect controllable text generation is a more challenging and practical task than single-aspect control. Existing methods achieve complex multi-aspect control by fusing multiple controllers learned from single-aspect, but suffer from attribute degeneration caused by the mutual interference of these controllers. To address this, we provide observations on attribute fusion from a distributional perspective and propose to directly search for the intersection areas of multiple attribute distributions as their combination for generation. Our method first estimates the attribute space with an autoencoder structure. Afterward, we iteratively approach the intersections by jointly minimizing distances to points representing different attributes. Finally, we map them to attribute-relevant sentences with a prefix-tuning-based decoder. Experiments on the three-aspect control task, including sentiment, topic, and detoxification aspects, reveal that our method outperforms several strong baselines on attribute relevance and text quality and achieves the SOTA. Further analysis also supplies some explanatory support for the effectiveness of our approach1.

1 Introduction

Controllable text generation is a challenging task in natural language generation, which aims to generate fluent text with desired attributes. Pilot studies attempt single-aspect control by directly finetuning a conditional model (Ziegler et al., 2019; Keskar et al., 2019), or turn to methods with language models fixed (Dathathri et al., 2020) due to the high cost of large-scale pre-trained language models (Brown et al., 2020a; Zhang et al., 2022).

Recent works focus on a more practical setting, multi-aspect2 controllable text generation, with existing approaches mainly divided into three technical routes: weighted decoding (Dathathri et al., 2020; Krause et al., 2021), multi-objective optimization (Kumar et al., 2021; Mireshghallah et al., 2022), and prefix-tuning (Qian et al., 2022), which explore ways to combine controllers learned from single-aspect and apply them to a fixed language model yet suffering from attribute degeneration caused by the mutual interference of controllers.

We provide a distributional perspective to observe and alleviate this problem. In the current text generation paradigm, a language model forms an estimated distribution over sentences with training data amounted to sampling from natural language distribution (Pillutla et al., 2021). For single-aspect control, these methods train a classifier or a prefix for each attribute independently, which is regarded as appraising a center of distribution over attribute-relevant sentences, before biasing the language model’s distribution to this center. Correspondingly, when generalizing to multi-aspect control, their fusion strategy is directly obtaining interpolation or average of these centers, which may be too straightforward. As shown in Figure 1, the interpolation point denotes the position they acquired after combining multiple centers in the probability space. And the intersection represents

\[\text{Interpolation} \]

\[\text{Intersection} \]

Figure 1: Probability space of attributes. Orange background denotes the estimated distribution over natural language. Blue and green areas represent distributions over sentences containing attributes from two different aspects, respectively. The darker region means a higher probability in the space. The shaded are distributional centers, the areas with the highest probability density.
where oracle sentences that simultaneously satisfy multiple attributes lie. In the left part of Figure 1, when distributions of attributes is symmetric\(^3\), the interpolation point is indeed within the intersection area. However, there could be a mismatch between the interpolation point and intersection. For example, as illustrated in the right part of Figure 1, two skewed distributions intersect on the tails, leaving the interpolation point out of the intersection area and thus making it lack the ability to express all desired attributes together.

In this paper, different from approximating the intersection area with the interpolation point, we propose a strategy for directly acquiring the intersection. We first deploy an autoencoder structure to map attribute-relevant sentences to latent representations constituting an estimated attribute space. With our specially designed constraints, this space can model relationships among attributes. Afterward, we provide an effective intersection searching algorithm that can walk around the long tail regions in distributions of all desired attributes and iteratively find where they combine more tightly. Finally, we utilize a prefix-tuning-based decoder to construct sentences from the searched intersection.

We experiment on three-aspect control with two attributes from the sentiment aspect, four from the topic, and one from detoxification, with datasets IMDb movie reviews (Maas et al., 2011), AGNews (Zhang et al., 2015), and Jigsaw Toxic Comment Classification Challenge Dataset, respectively. We evaluate the relevance of each attribute independently and calculate their average as the final relevance metric. Besides, we assess the text quality with perplexity and distinctness concerning fluency and diversity. Results show that our method can significantly outperform strong baseline models on multi-aspect control. Furthermore, we find out in our analytical experiments that our intuitive assumptions fit well with our observation. The main contributions are as follows:

- We propose a distributional perspective that models multi-aspect control more practically.
- We provide a method that directly searches for intersections in the attribute space and generates sentences with desired attributes.
- We experimentally reveal the effectiveness of our method on multi-aspect control compared to strong baselines and achieve the SOTA.

2 Related Work

Variational autoencoders are often used for controllable text generation in early work (Hu et al., 2017; Duan et al., 2020; Mai et al., 2020) where they spend a lot of effort into improving text fluency. The prosperity of large-scale pre-trained language models (Radford et al., 2019) provides more exploration directions for attribute control such as fine-tuning. Recent work has made gratifying progress on single-aspect control (Krause et al., 2021), leading studies gradually turn to a more difficult task, multi-aspect control, including the following three main approaches.

**Weighted Decoding** As the scale of language models increases rapidly, weighted decoding (Dathathri et al., 2020; Krause et al., 2021; Yang and Klein, 2021; Liu et al., 2021a; Gu et al., 2022) becomes a simple and practical choice. It is a framework that decomposes the probability of sentences conditioned on attributes into a language model and a classifier with the bayesian rule directly at decoding time. When handling multi-aspect control, it can be easily generalized by interpolating classifiers (Lin and Riedl, 2021).

**Multi-Objective Optimization** The controllable text generation task is naturally a multi-objective optimization problem when regarding its decoding process as an optimization objective. Some approaches, such as DGC (Khalifa et al., 2020), Mix&Match (Mireshghallah et al., 2022), and COLD Decoding (Qin et al., 2022), adopt Energy-based Models (LeCun et al., 2006) to blend multiple objectives. Others like MUCOCO (Kumar et al., 2021) convert the optimization objectives of multi-aspect control to inequality constraints and thereby apply the lagrange multiplier method for this constrained optimization problem.

**Prefix-Tuning** GPT-3 (Brown et al., 2020b) provides a new paradigm named prompt-based learning (Liu et al., 2021b), which is able to perform few-shot learning on downstream tasks. Prefix-Tuning (Li and Liang, 2021) leverages the learned lightweight prompts to trigger the conditional generation capability of the language model. Applying Prefix-Tuning to multi-aspect controllable text generation (Yu et al., 2021; Qian et al., 2022; Carlsson et al., 2022; Yang et al., 2022) can be regarded as optimizing on multi-objective implicitly.

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\(^3\)We plot distributions of attributes in §5.4.
3 Methodology

In this section, we first introduce the motivation and overall process of our method, after which we describe each module in detail.

3.1 Overview

As illustrated in Figure 2, our method mainly revolves around the attribute space including estimating the attribute space, searching for intersections, and mapping intersections to sentences.

Firstly, we aim to construct an attribute space using sampled sentences to estimate the real space as accurately as possible. We employ an autoencoder structure with the latent representations denoting points that constitute our estimated attribute space. To ensure that our estimated space reliably models the attributes, such as their probability distributions and relationships between different attributes, we further attach three constraints to the representation. (I) Reconstruction Loss $L_R$ aims to bridge the gap between points in attribute space and natural attribute-relevant sentences, which is recovering attributes reflected by contents. (II) Attribute Classification Loss $L_C$ forces the encoder to focus more on capturing attributes by distinguishing points of different attributes from the same aspect. (III) Aspect Gap Loss $L_G$ penalizes the discrepancy of aspects, which is caused by the domain gap among different data sources for different aspects. Inspired by the feature alignment (Pan et al., 2010), we minimize the distances between distributional centers of each two aspects.

The second step aims to search for an intersection area of desired attributes. If the intersection area exists, a point in the area satisfies that neighbor points appearing in a tiny surrounding region should cover all required attributes. Inspired by this neighborhood ideology, we design an algorithm that iteratively approaches an area where these attributes bind more tightly. The third step maps our searched intersection to a Prefix that activates the language model to generate attribute-relevant sentences. To make the language model less sensitive to slight variations, we sample a perturbation vector from a multivariate gaussian distribution.

3.2 Estimating Attribute Space

Given $|A|$ aspects $A = \{A_1, \cdots, A_{|A|}\}$ with each comprising $|A_i|$ attributes $\{a^1_i, \cdots, a^{|A_i|}_i\}$, $I^\tau$ is an index set representing the identifiers of all sentences with attribute $a^\tau_i$ in the training data. We have $I^\tau = \bigcup_{\tau=1}^{|A|} I^\tau_\tau$, $I = \bigcup_{\tau=1}^{|A|} I^\tau$, where $I^\tau$ is the indices of all sentences with any attribute in aspect $A_i$ and $I$ is the indices of the entire training data. We encode sentences $\{X_i\}$ from all aspects $A$ to representations $\{H_i\}$ with unified mapping parameters $\phi$: $H_i = \text{Encode}_\phi(X_i)$, where $i \in I$.

Reconstruction Loss $L_R$ As in the top of Figure 2, $L_R$ is computed in the same way as the autoregressive loss of pre-trained language model $p_{LM}$:

$$L_R = -\sum_{i \in I} \log p_{LM}(X_i|\text{Prefix}_i)$$

$$\text{Prefix}_i = \text{MLP}_\phi(H_i + \lambda \varepsilon_i), \varepsilon_i \sim \mathcal{N}(0, I),$$
where $X_i$ here is a sample sentence from the entire training set, i.e., $i \in I$. Besides, $\varepsilon_i$, with a scaling factor $\lambda$, is a perturbation vector sampled from a multivariate gaussian distribution $\mathcal{N}(0, I)$ for robustness when reconstructing. The multilayer perceptron MLP$_{\theta}$ will map perturbed $\mathcal{H}_i$ to Prefix$_i$ that can activate the language model to generate text with desired attributes. It’s worth noting that our primary goal is to recover attributes, which means $L_R$ does not need and preferably does not converge too well while maintaining text fluency.

### Attribute Classification Loss $L_C$

We force the encoder to focus on attributes by $L_C$ in the way:

$$L_C = - \sum_{t=1}^{\left|A_t\right|} \sum_{i=1}^{\left|A_t\right|} \log p_{\pi_t}(a^t_{r_i} | \mathcal{H}_i).$$  (2)

Given sentence representation, $p_{\pi_t}$ is a classifier that distinguishes attributes $\{a^t_{r_i}\}$ from aspect $A_t$ with parameter $\pi_t$.

### Aspect Gap Loss $L_G$

We penalize the discrepancy between distributional centers by:

$$L_G = \sum_{\left|A_i\right|<\left|A_j\right|} \left\| \sum_{i \in I_1} \mathcal{H}_i / |I_1| - \sum_{j \in I_2} \mathcal{H}_j / |I_2| \right\|_2,$$  (3)

which are Euler distances between every two distinct distributional centers. When generalizing to a larger scale of aspects, it is relatively expensive to calculate averages over the entire dataset each time the model is updated. We calculate this loss in practice using a batch-level approximation. We assign each aspect a memory unit to store the latest representation of the aspect’s estimated center. Each time processing a batch of sentences from one aspect, we take the average of their representations as the center and sum up the Euler distances to centers of other aspects in the memory, which is the estimated $L_G$. Then, we update the memory unit of this aspect to the latest.

During the training stage, our loss function is:

$$L = w_1 L_R + w_2 L_C + w_3 L_G.$$  (4)

It’s worth noting that we only update parameters $\phi$, $\theta$, and $\{\pi_t\}$ for the encoder, the MLP layer, and the classifier heads, respectively.

### 3.3 Intersection of Attributes

Suppose there is an intersection point, denoted as $\mathcal{H}^*$, located within the intersection region of attributes $\{a^1_{\omega_1}, a^2_{\omega_2}, \cdots, a^N_{\omega_N}\}$ from $N$ different aspects, where $a^t_{\omega_t}$ is the $\omega_t$th attribute in aspect $A_t$. Our algorithm 1 approximates the $\mathcal{H}^*$ by iteratively approaching a most balanced point with nearest neighbors from different attributes. First, we initialize the candidates $\{\mathcal{H}_m^0\}$ by randomly sampling points in the attribute space, calculating their distance to the closest point of each attribute $a^t_{\omega_t}$, and selecting the top $M$ samples with the smallest average distance to all attributes. At each iteration $s$, we choose the top-$K^s$ nearest points to $\mathcal{H}_m^s$ for each attribute and update $\mathcal{H}_m^{s+1}$ using the weighted average of these points. It is worth mentioning that $\omega_{\alpha_t}$ is the weight used to balance attributes or favor some specifically, and a negative value of $\omega_{\alpha_t}$ can even move away from a particular one. Finally, we select the best candidate from the last iteration $S$, which is expected to be in the intersection region, i.e., a representation related to multiple attributes.

#### Algorithm 1 Intersection Searching

| Input: $\mathcal{H}_i, i \in \bigcup_{t=1}^{N} I^t_{\omega_t}$ from $N$ attributes $\omega_{\alpha_t}$, weight of each attribute |
| Output: Intersection of $N$ attributes: $\mathcal{H}^*$ |

1. Initialize $M$ candidates: $\{\mathcal{H}_m^0\}$
2. Iterate $S$ times
3. for $s$ in $[0, S - 1]$ do
4. for $m$ in $[1, M]$ do
5. $\mathcal{H}_m^{s+1} \leftarrow 0$
6. for $t$ in $[1, N]$ do
7. $H \leftarrow$ Nearest($\mathcal{H}_m^s$, $\{\mathcal{H}_i, i \in I_{\omega_t}\}$)
8. $\mathcal{H}_m^{s+1} \leftarrow \mathcal{H}_m^{s+1} + \omega_{\alpha_t}$ mean($H$)
9. end for
10. $\mathcal{H}_m^{s+1} \leftarrow \mathcal{H}_m^{s+1} / \sum_{t=1}^{N} \omega_{\alpha_t}$
11. end for
12. end for
13. $\mathcal{H}^* \leftarrow$ Select($\{\mathcal{H}_m^S\}$)

4We study the practical meaning and impact of $K$ in §5.3.
When generating several attribute-relevant sentences for one attribute combination, we only need to calculate the intersection for it once.

4 Experiment

In this section, we demonstrate the effectiveness of our method on three-aspect control, including sentiment, topic, and detoxification.

4.1 Multi-Aspect Control Task

The datasets we use are the same as GeDi (Krause et al., 2021) and Contrastive Prefix (Qian et al., 2022). To balance the data scale across all aspects, we randomly sample 10k sentences from each dataset that is less than the number of samples GeDi uses, with each attribute equally dividing this amount. We use the IMDb movie reviews (Maas et al., 2011), the AGNews dataset (Zhang et al., 2015), and the Jigsaw Toxic Comment Classification Challenge Dataset\(^5\) for sentiment, topic and detoxification aspects, respectively.

The prompts used for text generation are the same as those used in the PPLM (Dathathri et al., 2020), with 20 from its bag-of-words experiment and 15 from its discriminator experiment. We experiment with 8 combinations of the 3 aspects with 2 sentiments \(\times\) 4 topics \(\times\) 1 detoxification and generate 5 completions for each combination and each prompt. Totally, each model will generate \(35 \times 2 \times 4 \times 1 \times 5 = 1400\) sentences. It is worth noting that we do not specifically use prompts that induce the language model to generate toxic text, making detoxification easier to improve.

To measure the performance on different aspects, we compute the attribute relevance. We finetune a DeBERTa (He et al., 2021b,a) classifier on the Yelp dataset (Zhang et al., 2015) for sentiment aspect and a classifier for topic utilizing all its remaining data not used during training. We evaluate the non-toxicity with the Google Perspective API\(^6\). The final performance of a model is determined by the average of these three attribute relevance scores introduced above. We also use two auxiliary metrics to measure text quality. One is perplexity calculated by GPT2-large following Contrastive Prefix (Qian et al., 2022). To ensure that models are not insensitive to changes in different prefixes, we calculate the Distinctness (Li et al., 2016) of sentences generated from different prefixes and average the 1-gram, 2-grams, and 3-grams distinct scores for simplicity. Moreover, we conduct human evaluation with sentences generated by different models shuffled. Each sentence is rated by three professional evaluators for 3 attribute relevance and text fluency. Evaluators rate each item on a scale of 1 to 5, with 5 representing text highly related to the desired attribute or very fluent.

4.2 Baselines

(1) Weighted Decoding: PPLM (Dathathri et al., 2020) biases the language model with gradients back-propagated from trained classifiers. GeDi (Krause et al., 2021) influences the decoding process with token probabilities conditioned on attributes. (II) Multi-objective Optimization: MUCOCO (Kumar et al., 2021) regards the decoding process as a constrained optimization problem, where the language model is the objective function and attributes are constraints. Mix&Match (Mireshghallah et al., 2022) controls attributes with energy-based models and generates sentences by masking, sampling, and correcting. (III) Prefix-Tuning: Contrastive Prefix (Qian et al., 2022) utilizes prefixes to activate the language model to generate attribute-relevant sentences by concatenation or semi-supervision.

4.3 Results

According to the automatic evaluation results in Table 1, under the multi-aspect setting, we group models based on their type of methods in chronological order. In addition, we demonstrate their standard deviations, which reflect the stability of models among different attribute combinations.

For weighted decoding, GeDi uses more powerful classifiers than PPLM and performs better on attribute relevance, stability to different combinations, and distinctness while correspondingly worse on perplexity. Multi-objective optimization methods achieve a favorable performance on attribute relevance while MUCOCO explodes on perplexity due to its non-autoregressive paradigm not being suitable for generating from scratch. Performance of semi-supervised Contrastive Prefix is similar to GeDi, except for lack of diversity.

Our method performs best on average attribute-related metrics, with at least a 7.3% significant improvement over existing baselines. Our advances mainly come from sentiment and topic aspects, with no less than 13.9% and 10.3% each. All-
We evaluate GeDi, Contrastive Prefix, and our method, observe that the results are consistent with the automatic ones on sentiment and topic relevance. The performance of models on detoxification is high and relatively similar, making the automatic results different from the manual ones where the annotators believe that our model does a better job than baselines. Since perplexity is relatively unreliable, the manually measured fluency of GeDi is much better than that of the Contrastive Prefix. And our method achieves the best fluency.

## 5 Analysis

### 5.1 Effect of Different Attributes and their Combinations

We illustrate the detailed results of each attribute and their combinations in Table 3. GeDi and Prefix-tuning perform differently in single-aspect control, each with its advantages. For example, GeDi is dedicated to negative with 93.9% relevance, while Prefix-tuning is good at positive with 90.6% relevance. When dealing with multi-aspect control, they inherit such imbalanced characteristics, with average relevance of 91.1% and 79.1%, respectively. In addition, the baselines decrease correspondingly in the average relevance of each attribute compared to single-aspect, ranging from 0.7 to 33.0. On average, our model outperforms other baselines on attribute metrics (Table 1). In detail, our model performs competitively for most attributes compared to another prefix-tuning-based model, Contrastive Prefix. Especially, on attributes like business and sci/tech, our model significantly improves over another prefix-tuning-based method on multi-aspect control and can even surpass it.
Table 3: Detailed Results on Single-Aspect and Multi-Aspect Control. We demonstrate results on single-aspect and average results on multi-aspect control with their difference to single-aspect, where other rows each represent an attribute combination. Cases are in §C. Detailed results for other baseline models and our ablations are in §D.

In addition, correlations between attributes vary widely, as in Table 3. For example, generally, positive fits well with non-toxic while negative leads to a massive drop in non-toxicity, which is consistent with the intuition that one can hardly praise people and offend them simultaneously. Besides, world and business news are often reported negatively, such as war, famine, inflation, etc., making it challenging to combine them with positive. When attributes are not closely correlated, which means that few natural sentences possess these attributes together, our method is more likely to capture such a rarely occurred incident and magnify their frequency. Take business as an example. It is effortless to achieve a fine attribute relevance when performing single-aspect control on business, with GeDi achieving 75.7 and Prefix obtaining 93.5. After attaching positive to business, baseline models will suffer from a decline due to their weak correlation, where GeDi and Contrastive Prefix drop to 54.3 and 41.7, respectively. In contrast, our method can alleviate this problem by retrieving this unusual co-occurrence in the training sentences and recovering it from the attribute space, achieving a performance of 91.7, which is close to single-aspect control. When combining business with negative, which is a relatively common combination, there is still some decrease for baseline models. On the contrary, our method can even obtain the performance of 96.7 that surpasses single-aspect control.

5.2 Estimated Attribute Space

We demonstrate part of our estimated attribute space in Figure 3 with four attributes: positive, negative, sports, and sci/tech from sentiment and topic aspects. We project the high-dimensional space...
Table 4: Results that vary with $K$.

| $K$  | Avg.↑ | Sent.↑ | Topic↑ | DeTox.↑ |
|------|-------|--------|--------|---------|
| 5000 | 75.5  | 70.5   | 67.9   | 88.2    |
| 4000 | 77.6  | 72.9   | 71.4   | 88.4    |
| 3000 | 78.7  | 72.4   | 74.7   | 88.9    |
| 2000 | 79.1  | 72.6   | 75.9   | 88.7    |
| 1500 | 79.9  | 73.6   | 77.1   | 89.0    |
| 1000 | 80.7  | 75.7   | 77.2   | 89.1    |
| 800  | 82.9  | 79.3   | 79.2   | 90.3    |
| 500  | 85.2  | 83.5   | 81.5   | 90.5    |
| 300  | 85.7  | 84.1   | 83.2   | 89.7    |
| 200  | **87.4** | **86.7** | **84.8** | 90.7    |
| 150  | 84.0  | 79.2   | 84.3   | 88.4    |
| 100  | 83.9  | 78.7   | 83.6   | 89.5    |
| 50   | 82.2  | 78.4   | 78.5   | 89.6    |
| 20   | 80.9  | 77.8   | 73.1   | 91.7    |
| 10   | 80.8  | 79.6   | 71.5   | 91.2    |
| 5    | 81.4  | 82.9   | 69.3   | 92.1    |
| 3    | **85.0** | **86.1** | **77.7** | 91.1    |
| 1    | 78.8  | 63.1   | 80.9   | **92.4** |

Figure 4: Distribution of attribute World from Topic.

5.4 Distribution of Attributes

We project sample points to 2D by PCA, with each attribute projected independently. As in Figure 4, we display a scatterplot of World and conduct a Gaussian kernel density estimation to visualize its probability distribution. The darker area denotes a higher probability, where more representation points of oracle sentences gather. And the region annotated by a red ellipse is the estimated distributional center. As in the plot, the distribution of World is significantly asymmetric as the center lies in the top part, with the bottom being a sparse long tail. In addition, the distribution is even non-convex with an isolated cluster in the lower right corner. This observation supports our hypothesis that the practical distributions of attributes are far more complex than symmetric distributions such as Gaussian distribution. Besides, we plot the distribution of other attributes in §A.1.

6 Discussion on Distributional Lens

Pilot work such as DGC (Khalifa et al., 2020) estimates the language distribution with an energy-based model and optimizes this distribution to satisfy constraints by approaching the constraints manifold. Recent distributional approaches like COLD Decoding (Qin et al., 2022) and MuCoLa (Kumar et al., 2022) take the language and attribute distribution in the same space so as to sample attribute-related sentences with Langevin Dynamics. Concurrent work on the image side, PromptGen (Wu
et al., 2022), simulates the complex distribution of images relevant to target attributes using a deep generative model. However, as a consensual hypothesis in manifold learning, the pre-trained language model estimates a low-dimensional manifold of language in a high-dimensional embedding space, which means most points in the embedding space are not probabilistically modeled by the language model. We believe that placing too much trust in the distributional modeling ability of language models is not a good choice. Our method attempts to depict the attribute space with discrete sample points of attributed sentences and make these discrete points, along with their coverage areas, compose the support set of our estimated distribution.

7 Conclusion

In this work, we present a distributional perspective for the multi-aspect controllable text generation with experimental results confirming the superiority of our model. Further observations on the 2D projection of the estimated attribute space show that our hypothesis about the attribute space is more feasible. In the future, we can explore the correlation between different attribute combinations for more fine-grained control and capture the bias in datasets to eliminate or utilize it.

Limitations

Our method has a certain dependence on the data since we need to estimate an attribute space. Therefore, it is difficult for our method to perform well in the setting of few-shot learning. However, this disadvantage is not that severe, because we only need single-aspect data, which is relatively sufficient in style transfer tasks. Another dependence of our method on data is that it is somewhat sensitive to biases in the data. When the semantic divergence of different aspects in training data is too large, our aspect gap loss, which aims to reduce the distance among the distributions of each aspect, will conflict with the sentence reconstruction loss. As a result, it may be hard to obtain a reliable intersection in the attribute space.

Computational resources also have an impact on our approach, as our aspect gap loss leverages a batch-level estimation for each aspect. Therefore, a larger batch size means a more accurate approximation, leaving the attribute space fewer biases. An alternative strategy for smaller batches is to backpropagate the loss after accumulating enough distributional samples, which requires more training epochs.

Ethics Statement

We are totally aware that text generation technology has a potential to be used maliciously to generate fake, toxic, or offensive content. However, after training on the Detoxification aspect, controllable text generation technology is a powerful weapon for combating hate speech, and eliminating harmful information in pre-trained language models. In addition, our multi-aspect controllable text generation technology can take Detoxification as an default aspect when controlling other aspects. We believe it meaningful and beneficial to advance research on controllable text generation.

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1031
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A Distribution of Attributes

A.1 Independent Projection of Attributes

We project sample points to 2D by Principal Component Analysis, with each attribute projected independently. We display a scatter plot for each and perform the Gaussian kernel density estimation. The darker area denotes a higher probability, where more representation points of oracle sentences gather. And the region annotated by a red ellipse is the estimated distributional center.

We underline distributions of attributes in Figures 5 to 7, including World, Sports, and Sci/Tech, which are significantly asymmetric. And especially, the projected distribution of the World attribute is even non-convex. This observation supports our hypothesis that the practical distributions of attributes are far more complex than symmetric distributions such as Gaussian distribution.

In addition, we plot projected distributions of other attributes in Figures 8 to 12. Attributes such as Positive and Negative seem roughly symmetric in 2D projection. However, we cannot guarantee their symmetry in high-dimensional space. Because the PCA aims to identify directions along which the variation in the data is maximal. In other words, the direction selection strategy is not necessarily related to symmetry or asymmetry, which means these 2D symmetric distributions may be asymmetric in high-dimensional space, with the asymmetric directions ignored during projection. Worse still, the long-tail region for a skewed direction may be too sparse, leading to lower variation compared to symmetric directions.
Figure 9: Distribution of Positive attribute from Sentiment aspect.

Figure 10: Distribution of Business attribute from Topic aspect.

Figure 11: Distribution of Toxic attribute from Detoxification aspect.

Figure 12: Distribution of Non-toxic attribute from Detoxification aspect.
A.2 Joint Projection of Attributes

We project combined sample points of attributes from three different aspects jointly to 2D by PCA. We display a scatter plot for each combination in Figures 13 to 20. The intersection points calculated on baselines’ interpolation strategy and our intersection searching algorithm are plotted with **Baseline** and **Ours**, respectively. From these figures, we observe that NonToxic can mainly cover two sentiment attributes or at least possess large intersection areas. Besides, the intersection areas among sentiment attributes and topic attributes, except for the Sci/Tech, are narrow and sparse. Compared with the baselines’ strategy, our search algorithm is closer to the intersection area, especially on Negative and Business attributes in Figures 13 to 15 and 19.

Figure 13: Jointly projected distributions of attributes: Negative, World, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 14: Jointly projected distributions of attributes: Negative, Sports, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 15: Jointly projected distributions of attributes: Negative, Business, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 16: Jointly projected distributions of attributes: Negative, Sci/Tech, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 17: Jointly projected distributions of attributes: Positive, World, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.
Figure 18: Jointly projected distributions of attributes: Positive, Sports, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 19: Jointly projected distributions of attributes: Positive, Business, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 20: Jointly projected distributions of attributes: Positive, SciTech, and NonToxic from aspects: Sentiment, Topic, and Detoxification, respectively.

Figure 21: Jointly projected distributions of Positive and Negative.

Except for some noise in the dataset, positive and negative do not intersect when jointly projected.

B Hyperparameters and Details

Our methods are implemented using the Hugging face Transformers package. Our encoder is initialized with Bert-base-uncased, and the fixed decoder uses GPT2-medium. For any sentence, it will be tokenized with WordPiece tokenizer from Bert and Byte-Pair Encoding tokenizer from GPT2 before input to encoder and decoder, respectively. We perform mean pooling on outputs of the encoder and convert them to 768-dimensional latent representations, which are points in our attribute space. Afterward, latent representations will be mapped to the prefix with a dimension of $20 \times 24 \times 2 \times 1024$, where $20$ is the prefix sequence length, $24$ is the number of hidden layers in GPT2-medium, $2$ represents one key and one value, and $1024$ is the size of hidden states in GPT2-medium. It’s worth noting that prefix length Contrastive Prefix uses for single-aspect control is $10$ and for multi-aspect control is $10 \times$ number of aspects, which is $30$ for three-aspect control. Our prefix length is fixed to $20$, which has nothing to do with the scale of aspects.

During the training stage, we use half-precision mode for efficiency on one NVIDIA A100 80GB GPU, where the batch size is 128 since the larger batch size better alleviates the aspect gap loss. In our setting, the random seed is $0$, $w_1 = 0.5$, $w_2 = 0.2$, $w_3 = 0.3$, variation hyperparameter $\lambda$ is $1e-3$, the optimizer is AdamW with a learning rate of $1e-4$, the number of training epochs is $150$, and we use a checkpoint at the
The training phase takes about 8 hours, and we experiment 6 times to search for the \( \lambda \in [2e^{-3}, 1e^{-3}, 5e^{-4}, 1e^{-4}, 5e^{-5}, 1e^{-5}] \), while the other hyperparameters are initial settings.

| Combination                        | Weight |
|-----------------------------------|--------|
| Neg. & World & NonTox.            | 2 : 7 : 1 |
| Neg. & Sports & NonTox.           | 2 : 4 : 1 |
| Neg. & Business & NonTox.         | 2 : 8 : 1 |
| Neg. & Sci./Tech. & NonTox.       | 3 : 1 : 3 |
| Pos. & World & NonTox.            | 2 : 12 : 1 |
| Pos. & Sports & NonTox.           | 3 : 5.5 : 1 |
| Pos. & Business & NonTox.         | 2 : 9 : 1 |
| Pos. & Sci./Tech. & NonTox.       | 3 : 1 : 1 |

Table 5: Specialized Weight for Attribute Balance.

During the inference phase, the maximum number of iterations \( T \) is 15, the number of candidates \( M \) is 1000, and the number of neighbors \( K \) is 200. We utilize a specialized list of weight parameters for each combination of attributes in Table 5, which aims to balance the performance among attributes from different aspects. After the iteration of intersection searching, our strategy is first to select the top 10 candidates with the smallest distances to their neighbors as the final candidate set. Then we randomly choose a candidate from these ten as the intersection’s representation for text generation diversity. Our text generation process is the same as prefix tuning with sequence length set to 50. Except for model and data loading, the entire evaluation process for each attribute combination, including intersection searching, text generation, and attribute-relevance evaluation, takes about 2 minutes. Therefore, we can manually tune the weight of attributes to balance them, with a maximum trial number of 8 for each weight.

35 prompts we used in the inferencing stage are following the PPLM setting with 20 from its bag-of-word setting and 15 from its discriminator setting:

- **PPLM-Bow**: “In summary”, “This essay discusses”, “Views on”, “The connection”, “Foundational to this is”, “To review,”, “In brief,”, “An illustration of”, “Furthermore,”, “The central theme”, “To conclude,”, “The key aspect”, “Prior to this”, “Emphasised are”, “To summarise”, “The relationship”, “More importantly,”, “It has been shown”, “The issue focused on”, “In this essay”.
- **PPLM-Discrim**: “Once upon a time”, “The book”, “The chicken”, “The city”, “The country”, “The horse”, “The lake”, “The last time”, “The movie”, “The painting”, “The pizza”, “The potato”, “The president of the country”, “The road”, “The year is 1910.”.

Detailed setting of baselines: (I) **Weighted Decoding**: For PPLM, we only retrain its classifier heads on our datasets while keeping all other original settings. For GeDi, We use its code directly since we are following its setting. (II) **Multi-objective Optimization**: MUCOCO provides a solution for custom classification constraints, and thus we train these classifiers on our datasets. **Mix&Match** is relatively complex as it can not generate long sentences from scratch with the mask language model Bert. Worse still, as a method based on sampling, it is somewhat dependent on initialization. Therefore, we use sentences generated by PPLM as the starting sentences and let Mix&Match slowly polish the text by itself in iterations. (III) **Prefix-Tuning**: We reproduce **Contrastive Prefix**\(^7\) and achieve comparable results. For a fair comparison, we unify the pre-trained language model to GPT2-medium (345M parameters) except for Mix&Match using Bert-large (340M parameters).

### C Cases

We illustrate cases of 8 different attribute combinations in Table 6.

\(^7\)They didn’t make the code public. We reproduce the code and get comparable results to what they report.
| Attributes | Models | Generation Results |
|-----------|--------|---------------------|
| Neg. World NonTox. | PPLM | Furthermore, the government will be allowed to carry out airstrikes from inside Afghanistan even after the end of NATO’s withdrawal, according to senior defense officials. The UK is also planning to use air strikes in Afghanistan and Iraq from the skies over its bases. |
| Neg. Sci/Tech NonTox. | GeDi | Furthermore, the Iraqi authorities plan to seize petrol from Shia vehicles and trucks as well. Iraqi Foreign Minister Shaida al-Abadi said Iraq was ready for such actions if US President Donald Trump issued a military order ordering it. |
| Neg. Sports NonTox. | MU COCO | Furthermore, the new law will make it safe for any individual or entity to regulated keep give away Mumbai firearm to anyone a a background check, including those who are prohibited from doing so under federal law. |
| Neg. Business NonTox. | Mix& Match | Furthermore, the UK will be reluctant to carry out airstrikes anywhere in Europe until near the end of NATO’s mandate, according to some NATO officials. The UK is likewise reluctant to drop warheads against Iran and Iraq from the air over British territory anywhere; |
| | Prefix concate | Furthermore, the first and the first of his world. The world. S. The U. S. The world’s country and a new-year. |
| | Prefix semi | Furthermore, a new survey conducted by a new survey of the Middle Eastern population in the country was revealed to be a very close match for the official record of the National Socialist Party (NTP) in the country. |
| | Ours | Furthermore, the movie’s main focus is getting rid of Robert Kennedy. This movie has no plot, no action and no even remotely decent characterizations. It’s simply a glorified version of what happened to George Bush in 2004. |
| Neg. Business NonTox. | PPLM | This essay discusses the role of private security forces in Libya. The military’s role in this crisis can be divided into two phases: 1) The first phase involved the transfer and transfer of the control of the situation to a military body. |
| Neg. Sports NonTox. | GeDi | This essay discusses last season who was demoted away from the league and how his decline in playing time impacted the team as a whole. With detailed observations, analysis, stories provided by some of these players including Orlando City fullback Ben Sweat and Toronto. |
| Neg. World NonTox. | MU COCO | This essay discusses howwecstore can Consent a more humane society and how Mold willromatically the way webp topics our own Intake and our relationship with them. enoughWhat is a body)? aw A Body is the transsexual post Franch structureglers glucobos |
| Neg. Sports NonTox. | Mix& Match | This essay from an official, who was investigating two suspected drug dealers, “failed to find any probable cause,” he stated that “confusion reigned” as the two men “struggled for some time” while evans “continued throwing punches.” |
| Neg. Sports NonTox. | Prefix concate | This essay discusses the fact of the original Germanic tradition of a man’s attempt to make a name on the English football team and the fact of the English football league. |
| Neg. World NonTox. | Prefix semi | This essay discusses the fact that the NHL is not a national sport. It also provides a new perspective to the fact that the NHL is not a major league. |
| Neg. Business NonTox. | Ours | This essay discusses how the Miami Heat lost to the Atlanta Hawks in a seven-minute overtime last night, and how they should never again be able to make it with their team mates. |
| Neg. Business NonTox. | PPLM | Foundational to this is the need for a national banking system for the purpose of financing the banking system. The Federal Reserve has already taken over this task by creating and controlling the money supply in the form of the Federal Reserve bank, which is now owned and operated by the Federal. |
| Neg. Sports NonTox. | GeDi | Foundational to this is the New York Int’l Fedal and Foreign Market Team. This practice includes facilitating contacts between two levels of financial institutions as necessary for a successful settlement of an equity investment transaction. |
| Neg. Sports NonTox. | MU COCO | Foundational to this is a RegulatorySPONSORED of community and debtor, not have a shared history of Recession bourgeois. The struggles ofBuffpeople.SPONSORED the struggles of all of our individuals bunk are interrelated, - we are all part ze the same struggle. |
| Neg. Business NonTox. | Mix& Match | Foundational to this is the Woodward foundation is our belief that low-income housing has a devastating effect on mental health, our research indicates that depressive symptoms are much greater among the economically weaker. we believe that a depressed patient’s life expectancy will decline dramatically as a result. |
| Neg. World NonTox. | Prefix concate | Foundational to this is the company’s ability to offer a full range of services to customers. The company has been able to offer a good product and service for years. |
| Neg. Sports NonTox. | Prefix semi | Foundational to this is a $1 million cut from the company’s annual budget, which means it could be difficult to cash out of its debt. |
| Neg. Sports NonTox. | Ours | The last time I wrote a blog post about the future of Linux and how to prepare for it I wrote: I am very pleased to announce that the Linux kernel has been updated to 1.8.2! This is good news for the Linux. |

**WARNING:** Next may contain contents that are offensive in nature.
| Neg. Sci/Tech NonTox. | MU COCO | The last time I checked, VMware would’s not like the world’s largest and fastest ship was a single- Annonlled organism that could fly, and the last time I checked, it’s not like the world’s largest and fastest ship the a single-
| Mix& Match | The last time the lake was drained, however, to make way for a golf course at a nearby site, and there were reports on a nearby island that a large-scale groundwater cleaning program was beginning, the lake was drained, however, to make way elsewhere;
| Prefix concate | The last time you are a fan, you have to be aware of the bad news about the Internet. The problem is that this isn’t even remotely acceptable to the author.
| Prefix semi | The last time I see this film I have not seen it in my life. I have watched it in a very limited number of days and I have been very disappointed. The acting is terrible and the acting is bad.
| Ours | The last time I saw this film was in the theater. It was terribly disappointing. There is no plot or suspense whatsoever, nor any action whatsoever. The only thing that can be attributed to this movie is the lack of a sound system. |
| Pos. World NonTox. | PPLM | The connection between obesity and autism has been identified for the first time using a unique antibody screening test, according to researchers with the University of Texas MD Anderson Cancer Center. They found that a protein called CD34 has a powerful impact on autism.
| GeDi | The connection between staking two is not a loneliness of mere coincidence. The connection snowball dividing matter of history, and history BW a history arresting its own, of which hero are all the victims analyse nogyl don’t believe in coincidence Alger said the
| MU COCO | The connection between staking two is not a loneliness of mere coincidence. The connection snowball dividing matter of history, and history BW a history arresting its own, of which hero are all the victims analyse nogyl don’t believe in coincidence Alger said the
| Mix& Match | The connection is an illustration of the moon, from the book ‘the lord of light and darkness’, by william shakespeare ( photo courtesy of william shakespeare ), an illustration of the sun, from the book ‘the lord of light and darkness’, by william shakespeare ( photo courtesy )
| Prefix concate | The connection of the United States’s the world of the world’s first-year of a new-run of the world in the world.S.
| Prefix semi | The connection between the world of the American National Rifle Association and the United States is a fascinating, fascinating, and hilarious tale. It has been an honor to see the film on the National Library shelves, and I am proud to see the film.
| Ours | The connection between John Lennon and the United States is as strong as ever. The Los Angeles Times reports that Lee Sternberg’s performance of his song "Lenny Luerer" won a round of applause in the U.S. Senate. |
| Pos. Sports NonTox. | PPLM | More importantly, the first day of the 2017 NFL Draft is always exciting to watch with fans, because the league is going to get a lot of great talent on defense in the coming weeks. The biggest draft prospect to come out this year, Alabama DT Vic Beasley
| GeDi | More importantly, I appreciated his honesty along the way. Orlando Pace is usually a shadow of his former self, but he understood the importance of all that went into this win and smiled again.
| MU COCO | More importantly, the first day of the 2017 NFL Draft is always exciting to watch with fans, because the league is going to get a lot of great talent on defense in the coming weeks. The biggest draft prospect to come out this year, Alabama DT Vic Beasley
| Mix& Match | More importantly, the sixth game of the 2018 stanley cup finals presents a new challenge and an exciting new opportunity. The Philadelphia Flyers and Pittsburgh Penguins are joining forces for a six-game road trip that begins in the nation’s capital each weekend.
| Prefix concate | More importantly, I have to remind everyone that this is a real story, so the fact that the two men were not a couple of people who have to be treated as one of those who would be involved with the team.
| Prefix semi | More importantly, the Boston Red Sox have lost the league title, and the players themselves are not yet qualified to be the best player in the league. The fact that they are not even qualified to play a match of the best.
| Ours | More importantly, the Houston Astros won a great opportunity to make a comeback with a victory over the Detroit Tigers in the National League West. The team has an outstanding offensive line and is tied for fifth in scoring among the nation. |
| Pos. Business NonTox. | PPLM | In brief, the federal tax law allows employers to deduct up to 20% of compensation expenses from workers’ paychecks. This deduction is a big deal because many employees have to pay high deductibles for medical care.
| GeDi | In brief, Heiltusk said that she holds central, shared concerns regarding how First Nations youth can navigate financial injustices faced by society and why net aboriginal debt was surpassed in 2015. All eight First Nations elected delegates at Monday’s meeting
| MU COCO | In brief, Heiltusk said that she holds central, shared concerns regarding how First Nations youth can navigate financial injustices faced by society and why net aboriginal debt was surpassed in 2015. All eight First Nations elected delegates at Monday’s meeting
| Mix& Match | In brief, the u. s. department of agriculture ( usda ) produced a comprehensive list of how many jobs were created in 2016, it identified 3. 1 million jobs in the agriculture sector, a dramatic uplift from 2015’s 2 million.
| Prefix concate | In brief, the new of its company,


| Prefix | Business | NonTox. | In brief, it is the best movie I have ever seen, and I love it. The movie is a perfect blend of comedy and comedy. It is not a classic movie, but it is not a great movie. |
|--------|----------|---------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Ours   |          |         | In brief, the economy is surged in July, boosted by strong sales of oil and other products, as well as strong growth in U.S. manufacturing.                                                                                           |
| PPLM   |          |         | The country’s first solar power system, built by a group of students at Harvard University, is now operating. The project is aimed at encouraging solar energy development by encouraging collaboration among universities, community groups and individuals. |
| GeDi   |          |         | The country illustrated beautifully reflects the complexity of lives and customs.                                                                                                                                   |
| MU COCO|          |         | The country’s top diplomat, Blockchain Lavrov IBM said the UydiaS. was “very much looking into” the matter. pleasantly engineers Rapp a Bridges supplier of hacker vegan Iran, has been trying to improve ties with blockchain, a close ally and |
| Mix& Match |        |         | The country focuses on the role the united states has played in discovering new technologies for the advancement of science, according to two u. s. officials briefed on - site. both officials, newly appointed to handle national security matters welcomed the sensitive nature of the investigation. |
| Prefix | concate  |         | The country’s top TV channel is now a very popular TV show. The only thing is the name. I’m sure there are many people who would be willing to take it seriously, but I’ll be damned to find out if they have a lot |
| Prefix | semi     |         | The country’s most famous TV series is the best and most powerful show ever made. The story is great, the action is good, the plot is great, and the story is very good. The cast is great. |
| Ours   |          |         | The country’s biggest television network has announced that it will offer a new version of the movie which is based upon the popular “Star Trek” series. It’s truly amazing to see how many people are involved in making this movie so far. |

Table 6: Generated Cases. Red highlights the sentiment-related content. Blue highlights the topic-related content. Underlined are the input prompts. Strikethrough indicates toxic content.
## Detailed Results

### Weighted Decoding Based Methods

| Methods  | Sentiment (%) | Topic (%) | Detox. (%) |
|----------|---------------|-----------|------------|
|          | Neg. | Pos. | World | Sports | Business | Sci./Tech. |          |
| PPLM     | 97.2 | 62.7 | 74.9 | 46.5 | 62.4 | 98.6 | 93.2 |
|          | 92.2 | -    | 75.4 | -    | -    | -    | 82.0 |
|          | 84.4 | -    | 41.8 | -    | -    | -    | 76.0 |
|          | 87.5 | -    | -    | 61.5 | -    | -    | 82.9 |
|          | 85.3 | -    | -    | -    | 95.0 | -    | 76.2 |
|          | 35.4 | -    | 59.1 | -    | -    | -    | 90.4 |
|          | 39.5 | -    | 34.1 | -    | -    | -    | 89.5 |
|          | 40.9 | -    | -    | 48.3 | -    | -    | 91.2 |
|          | 52.7 | -    | -    | -    | 93.1 | -    | 91.3 |
| average  | 87.4 | 42.1 | 67.3 | 38.0 | 54.9 | 94.1 | 84.9 |
| GeDi     | 93.9 | 70.7 | 73.4 | 85.7 | 75.7 | 98.0 | 94.9 |
|          | 94.7 | -    | 80.0 | -    | -    | -    | 90.6 |
|          | 84.2 | -    | 74.8 | -    | -    | -    | 93.9 |
|          | 94.9 | -    | -    | 75.7 | -    | -    | 96.6 |
|          | 90.6 | -    | -    | -    | 80.1 | -    | 92.8 |
|          | 53.7 | -    | 61.4 | -    | -    | -    | 94.4 |
|          | 60.5 | -    | 74.3 | -    | -    | -    | 95.2 |
|          | 57.6 | -    | -    | 54.3 | -    | -    | 95.7 |
|          | 72.3 | -    | -    | -    | 90.2 | -    | 94.2 |
| average  | 91.1 | 61.0 | 70.7 | 74.6 | 65.0 | 85.2 | 94.2 |

### Multi-Objective Optimization Based Methods

| Methods  | Sentiment (%) | Topic (%) | Detox. (%) |
|----------|---------------|-----------|------------|
|          | Neg. | Pos. | World | Sports | Business | Sci./Tech. |          |
| MUCOCO   | 97.9 | -    | 54.5 | -    | -    | -    | 85.7 |
|          | 94.6 | -    | 55.8 | -    | -    | -    | 85.7 |
|          | 96.8 | -    | 65.6 | -    | -    | -    | 87.3 |
|          | 95.5 | -    | -    | -    | 96.1 | -    | 86.9 |
|          | 30.4 | -    | 48.0 | -    | -    | -    | 91.0 |
|          | 26.3 | -    | 59.8 | -    | -    | -    | 92.6 |
|          | 34.6 | -    | -    | 62.1 | -    | -    | 93.8 |
|          | 43.9 | -    | -    | -    | 95.1 | -    | 93.1 |
| average  | 96.2 | 33.8 | 51.3 | 57.8 | 63.9 | 95.6 | 89.5 |
| Mix&Match| 99.2 | 63.3 | 79.5 | 57.4 | 69.6 | 99.3 | 96.9 |
|          | 96.7 | -    | 80.6 | -    | -    | -    | 93.1 |
|          | 97.7 | -    | 48.2 | -    | -    | -    | 93.0 |
|          | 98.2 | -    | -    | 66.6 | -    | -    | 97.0 |
|          | 96.8 | -    | -    | -    | 99.6 | -    | 96.1 |
|          | 53.0 | -    | 67.3 | -    | -    | -    | 95.5 |
|          | 45.0 | -    | 44.0 | -    | -    | -    | 96.7 |
|          | 41.5 | -    | -    | 55.8 | -    | -    | 97.7 |
|          | 59.7 | -    | -    | -    | 97.3 | -    | 97.5 |
| average  | 97.2 | 49.8 | 74.0 | 46.1 | 61.2 | 98.5 | 95.8 |

### Prefix-Tuning Based Methods

| Methods  | Sentiment (%) | Topic (%) | Detox. (%) |
|----------|---------------|-----------|------------|
|          | Neg. | Pos. | World | Sports | Business | Sci./Tech. |          |
| Prefix   | 88.4 | 90.6 | 74.5 | 85.3 | 93.5 | 93.6 | 93.8 |
|          | 32.4 | -    | 50.3 | -    | -    | -    | 90.9 |
|          | 88.1 | -    | 73.8 | -    | -    | -    | 89.1 |
|          | 51.6 | -    | 70.0 | -    | -    | -    | 94.1 |
|          | 94.3 | -    | -    | -    | 94.1 | -    | 88.3 |
|          | 77.6 | -    | 46.8 | -    | -    | -    | 92.2 |
|          | 70.2 | -    | 78.5 | -    | -    | -    | 95.9 |
|          | 51.9 | -    | -    | 73.1 | -    | -    | 94.7 |
|          | 72.0 | -    | -    | -    | 88.1 | -    | 95.6 |
| average  | 66.6 | 67.9 | 48.5 | 76.2 | 71.6 | 91.1 | 92.6 |
| Contrastive Prefix | 65.5 | -    | 80.6 | -    | -    | -    | 91.8 |
|          | 67.2 | -    | 90.3 | -    | -    | -    | 92.5 |
|          | 56.0 | -    | -    | 79.2 | -    | -    | 92.2 |
|          | 90.0 | -    | -    | -    | 93.3 | -    | 84.8 |
|          | 93.5 | -    | 64.8 | -    | -    | -    | 95.1 |
|          | 41.8 | -    | 78.5 | -    | -    | -    | 94.8 |
|          | 87.4 | -    | -    | 41.7 | -    | -    | 95.2 |
|          | 93.6 | -    | -    | -    | 86.7 | -    | 95.3 |
| average  | 69.7 | 79.1 | 72.7 | 84.4 | 60.5 | 90.0 | 92.7 |

### Ours

|          | Neg. | Pos. | World | Sports | Business | Sci./Tech. |          |
|----------|------|------|-------|--------|----------|------------|-----------|
| Ours     | 69.7 | -    | 71.7  | -      | -        | -          | 84.1      |
|          | 78.6 | -    | 80.0  | -      | -        | -          | 80.2      |
|             | 99.9  |   |   | 96.7  |   | 96.8 |
|-------------|-------|---|---|-------|---|------|
|             | 92.8  |   |   | 98.0  |   | 81.7 |
| Ours        |       |   |   |       |   |     |
| w/o Asp. Loss| -     | 80.5| 58.0| -     | 94.5|
| w/o Att. Loss| -     | 84.7| 86.6| -     | 98.1|
| average     |       |   |   |       |   |     |
|             | 85.3  | 88.1| 64.9| 83.3  | 94.2| 96.8 |
|             | 80.5  | 94.5| 86.6| 94.2  | 97.6| 96.0 |
| average     |       |   |   |       |   |     |
|             | 66.6  | 76.6| 56.2| 82.4  | 66.0| 99.1 |
|             | 66.3  | 76.6| 56.2| 82.4  | 66.0| 95.5 |
| average     |       |   |   |       |   |     |
|             | 95.4  | 5.6| 14.8| 38.5  | 15.9| 97.7 |
|             | 95.4  | 3.2| 14.4| 40.4  | 13.9| 95.7 |
| average     |       |   |   |       |   |     |

Table 7: Detailed Combination Results on Multi-Aspect Control.