Controlled Text Generation Using Dictionary Prior in Variational Autoencoders

Xianghong Fang¹, Jian Li²*, Lifeng Shang², Xin Jiang², Qun Liu², Dit-Yan Yeung¹
¹The Hong Kong University of Science and Technology
²Huawei Noah’s Ark Lab
xfangam@connect.ust.hk, dyyeung@cse.ust.hk
{lijian703, shang.lifeng, jiang.xin, qun.liu}@huawei.com

Abstract

While variational autoencoders (VAEs) have been widely applied in text generation tasks, they are troubled by two challenges: insufficient representation capacity and poor controllability. The former results from the posterior collapse and restrictive assumption, which impede better representation learning. The latter arises as continuous latent variables in traditional formulations hinder VAEs from interpretability and controllability. In this paper, we propose Dictionary Prior (DPrior), a new data-driven prior that enjoys the merits of expressivity and controllability. To facilitate controlled text generation with DPrior, we propose to employ contrastive learning to separate the latent space into several parts. Extensive experiments on both language modeling and controlled text generation demonstrate the effectiveness of the proposed approach.

1 Introduction

As one of the representative deep generative models, variational autoencoders (VAEs) (Kingma and Welling, 2014) have been widely applied in text generation tasks, such as dialog generation (Wu et al., 2020; Zhao et al., 2017), machine translation (Shah and Barber, 2018; McCarthy et al., 2020; Sheng et al., 2020) and poetry generation (Li et al., 2018b; Yi et al., 2020). Despite the success, VAEs still suffer from two challenges: insufficient representation capacity and poor controllability.

The challenge of insufficient representation capacity in variational models arises from two aspects. One is the posterior collapse, a notorious issue that generally exists in VAEs especially serious in autoregressive text generation (Bowman et al., 2016), which leads to degenerate local optimums during the training of VAEs (He et al., 2019). Another is the restrictive assumption for priors and variational posteriors (Ding and Gimpel, 2021), which generally follow Gaussian distribution and spherical Gaussian distributions with diagonal covariance matrices, respectively (Higgins et al., 2017; He et al., 2019; Li et al., 2019a). Such predefined forms would hinder VAEs from larger optimization space (Fang et al., 2019), thus restricting the expressivity of the model (Ding and Gimpel, 2021) and further leading to the posterior collapse (Fang et al., 2019). Therefore, a potential solution is to try more expressive distribution forms for priors and variational posteriors to improve the representation capacity (Fang et al., 2019; Tomczak and Welling, 2018; Ding and Gimpel, 2021).

Table 1: Examples of controlled text generation in second column where sentence attributes indicated by colored words are consistent with user-specified attributes in the first column.

posterior (Ding and Gimpel, 2021), which generally follow Gaussian distribution and spherical Gaussian distributions with diagonal co-variance matrices, respectively (Higgins et al., 2017; He et al., 2019; Li et al., 2019a). Such predefined forms would hinder VAEs from larger optimization space (Fang et al., 2019), thus restricting the expressivity of the model (Ding and Gimpel, 2021) and further leading to the posterior collapse (Fang et al., 2019). Therefore, a potential solution is to try more expressive distribution forms for priors and variational posteriors to improve the representation capacity (Fang et al., 2019; Tomczak and Welling, 2018; Ding and Gimpel, 2021).

Another challenge of VAEs is poor controllability. The challenge is rooted in the continuous latent variables that hinder VAEs from interpreting the discrete attributes like sentiments or topics (Zhao et al., 2018; Shi et al., 2020). Thus it is difficult to generate text with user-specified attributes, as the examples in Table 1. To approach controlled text generation in variational models, Hu et al. (Hu et al., 2017) propose to disentangle the latent representations by separately modeling discrete attribute and continuous content representations. Nevertheless, it is hard to completely disentangle attribute and attribute-independent content, resulting in poor readability in text generation (Wang et al., 2019; Higgins et al., 2017). A natural choice is to employ discrete representations as each of them could well correspond to one of the discrete attributes. Recent studies also reveal learned discrete representations by K-means and self-organization map (Kohonen,
1995) display great clustering performance and interpretability (van den Oord et al., 2017; Fortuin et al., 2019), showing the potential to be manipulated and split latent space for controlled text generation.

In this paper, we follow the practice of learning discrete representations and propose a new data-driven prior that enjoys the merits of expressivity and controllability. Specifically, we deploy a set of learnable vectors and interpolate the learnable vectors to form the prior, which we call Dictionary Prior (DPrior). Each learnable vector is dubbed an atom in the dictionary. To facilitate generative models with DPrior, dual-form KL-divergence (Dai et al., 2018) is employed to make the prior distribution spanned by dictionary atoms approximate the posterior distribution. Our DPrior is model-agnostic and could be combined with pre-trained models such as BERT/GPT to enrich posterior representations (Li et al., 2020a). To enforce controllability to the DPrior, we separate the dictionary atoms into several disjoint subsets according to the natural language attributes. Then, we propose to employ contrastive learning to incorporate the attribute information, which can cluster different subsets of dictionary atoms into different semantic subspaces.

We demonstrate the superiority of DPrior against recent VAE variants on the language modeling task. We also validate our DPrior in controlled text generation where DPrior shows its effectiveness over several advanced counterparts. The main contributions of this paper can be summarized as:

- We propose an expressive Dictionary Prior (DPrior) within VAEs framework, which consists of learnable dictionary atoms and interpolating the atoms as latent variables.

- DPrior is model-agnostic and can be combined with pre-trained language models. By doing so, DPrior achieves SOTA language modeling performance on four benchmarks.

- We enforce controllability to DPrior by separating dictionary atoms into disjoint subsets and applying contrastive learning to incorporate attribute information.

2 Related Work

Controlled Text Generation  Controlled text generation is a task aiming to generate realistic sentences with desired attributes, e.g., sentiments or topics. Most efforts for controlled text generation are based on conditional pre-trained language models (Keskar et al., 2019; Dathathri et al., 2020). CTRL (Keskar et al., 2019) employs a GPT-2 like pre-trained language model and trains it from scratch on a large corpus containing various control codes. Subsequently, controlled generation is accomplished by using the control codes as prompting words. PPLM (Dathathri et al., 2020) seeks to avoid the further training process and combines the GPT-2 model with several simple attribute classifiers whose gradients can update the latent representations.

Another line of work tries to explore limited labeled data via learning latent representations (Hu et al., 2017). Hu et al. (Hu et al., 2017) propose to approach controlled text generation by learning disentangled latent representations including independent content and attribute parts. In this paper, we learn entangled latent representations and approach controlled text generation by separating prior space into several parts.

Expressive Prior and Posterior In VAEs  VAEs usually employ simple Gaussian distribution as the prior and spherical Gaussian distributions with diagonal co-variance matrices as the variational posteriors (Higgins et al., 2017; He et al., 2019; Fu et al., 2019). Such predefined forms in traditional formulations hinder VAEs from the expressivity of the model (Ding and Gimpel, 2021), thus further inducing the posterior collapse (Fang et al., 2019).

To improve the representation capacity, some efforts try more expressive priors. MoG-VAE (Ding and Gimpel, 2021) considers a uniform mixture of Gaussians as the prior, Vamp-VAE (Tomczak and Welling, 2018) introduces “Variational Mixture of Posteriors” prior (VampPrior). APo-VAE (Dai et al., 2021) adopts VampPrior to learn a hyperbolic latent space. FlowPrior (Ding and Gimpel, 2021) tries a new prior through normalizing flows. It is noted that VQ-VAE (van den Oord et al., 2017) introduces an auto-regressive prior via learning discrete representations, which enjoys the merits of learnability and expressivity. Nevertheless, the auto-regressive prior has low generation efficiency and no ability of latent manipulation (Fang et al., 2021). In this paper, we propose a data-driven prior via learning discrete representations but have same generation efficiency and the ability of latent variable manipulation to traditional VAEs.
Another line of work is to seek more expressive posteriors. Fang et al. (Fang et al., 2019) adopts implicit posterior representation. APo-VAE (Dai et al., 2021) and our DPrior also employ the implicit posterior representations to match the flexible priors thus further improve representation capacity.

3 Methodology

In this section, we first review the basics of deep generative models in Section 3.1, then introduce Dictionary Prior (DPrior) in Section 3.2 which is built on a set of learnable vectors. We further approach controlled text generation in Section 3.3. The overall illustration of our proposed approach is shown in Figure 1. More details will be explained in the following sections.

3.1 Deep Generative Models

VAEs are one of the most representative deep generative models for language modeling. Given a text \( x = x_{1:T} \) with length \( T \), VAEs seek to infer latent variable \( z \) that explains the observation. Towards this end, VAEs maximize the marginal log-likelihood \( \log p_\theta(x) \), which is usually intractable due to the complex true posterior \( p(z|x) \). Consequently an approximate posterior \( q_\phi(z|x) \) (i.e. the encoder) is introduced, and the evidence lower bound (ELBO) of the marginal likelihood is maximized as follows:

\[
\log p_\theta(x) \geq \mathbb{E}_{z \sim q_\phi(z|x)}[\log p_\theta(x|z)] - D_{KL}(q_\phi(z|x)||p(z)),
\]

where \( p_\theta(x|z) \) represents likelihood function conditioned on \( z \), also known as the decoder.

VAEs usually adopt simple Gaussian distribution as the prior and spherical Gaussian distributions with diagonal co-variance matrices as the variational posterior. However, predefined distribution forms in traditional formulations of VAEs restrict representation capacity. As discussed before, we turn to learning an expressive prior via discrete representations instead of predefined prior.

3.2 Data-driven Dictionary Prior

We define the prior via a set of learnable vectors, i.e., \( \psi = \{e_1, ..., e_m\} \), and each vector is dubbed as a dictionary atom. Intuitively, we could sample one dictionary atom and feed it to the decoder, i.e., \( p_\theta(x|e) \). However, the generation capacity is always restricted by the dictionary size \( m \). To facilitate larger generation capacity, we further introduce a continuous random variable \( \pi = (\pi_1, ..., \pi_m)^T \) that follows the Dirichlet distribution parameterized by an \( m \)-dimensional vector \( \gamma \):

\[
\pi \sim Dir(\pi|\gamma) = \frac{\Gamma(\sum_k \gamma_k)}{\Pi_k \Gamma(\gamma_k) \Pi_k \gamma_k^{\gamma_k - 1}}. \tag{2}
\]

Then we interpolate all dictionary atoms with \( \pi \) to form the latent variable: \( z = \sum_i \pi_i \cdot e_i \). Although atoms in \( \psi \) are discrete and finite, the latent variable \( z \) is continuous and has infinitely possible realizations via sampling \( \pi \) according to the Dirichlet distribution. We call the prior defined on these dictionary atoms as Dictionary Prior (DPrior), or \( p_\psi(z|\gamma) \). Note that \( \gamma \) is a hyper-parameter and we set \( \gamma \) the same in each dimension. Dirichlet distribution would approximate one hot distribution when \( \gamma_k \to 0 \), and approximate uniform categorical distribution when \( \gamma_k \to \infty \). In general, The smaller \( \gamma_k \), produces more diverse text from our proposed DPrior.

As part of the network parameters, the dictionary \( \psi \) would be differentially updated according to various training samples. Such a data-driven prior would produce larger optimization space, enforcing to learn better representations.

Dual Form of KL divergence It is intractable to deploy vanilla KL divergence to train DPrior as in Equation 1, since learnable discrete atoms in \( \psi \) make it difficult to explicitly estimate the density of \( p_\psi(z|\gamma) \). To address the issue, we propose to employ its dual form based on Fenchel duality theorem (Rockafellar et al., 1966), which can effectively narrow the distribution gap between the prior \( p_\psi(z|\gamma) \) and posterior \( q_\phi(z) \) when the density of the priors and/or variational posterior are unknown (Fang et al., 2019; Dai et al., 2021).

Specifically, we follow (Fang et al., 2019) and introduce an auxiliary dual function \( v(\cdot) \), parameterized by a neural network with weights \( \varphi \), to optimize the KL divergence as:

\[
\begin{align*}
D_{KL}^\varphi \psi & = D_{KL}(q_\phi(z)||p_\psi(z|\gamma)) \\
& = \max_{\varphi} \mathbb{E}_{z \sim q_\phi(z)} v_\varphi(z) - \mathbb{E}_{z \sim \psi} v_\varphi(z|\gamma) \exp(v_\varphi(z)),
\end{align*}
\]

where \( q_\phi(z) = \int q(x) q_\phi(z|x) dx \) is the aggregated posterior. To make the posterior match the expressive DPrior, we also employ implicit posterior representations as (Fang et al., 2019). Specially, we adopt white noise \( \epsilon_i \sim \mathcal{N}(0, I) \) and concatenate it with hidden representations of \( x \) to obtain \( i \)-th latent variable as \( z_i = G_\phi(x, \epsilon_i) \).
During training, we choose $\gamma$ near 0 as it consistently performs better than other values in our experiments. Together with the reconstruction loss, i.e., $L_R^{\phi, \theta} = -\mathbb{E}_{z \sim q_\phi(z|x)} \log p_\theta(x|z)$, the objective function of DPrior for language modeling can be summarized as:

$$\min_{\phi, \psi, \theta} \max_{\varphi} L_R^{\phi, \theta} + \beta_1 * L_D^{\phi, \psi}, \quad (4)$$

where $\beta_1$ is a regularization parameter.

**Combined with Pre-trained Models** Our DPrior is model-agnostic and could be combined with various neural networks such as LSTM (Hochreiter and Schmidhuber, 1997) and Transformer (Vaswani et al., 2017). To improve representation capacity, we propose the combination of DPrior and a large-scale pre-trained deep latent variable model, i.e., OPTIMUS (Li et al., 2020a), which adopts the pre-trained BERT and GPT-2 as the encoder and decoder, respectively. Since extra large-scale text corpus was exploited, more diverse and even out-of-domain sentences that exploit more words are able to be generated.

**3.3 DPrior for Controlled Text Generation**

In this section, we enforce interpretability and controllability to DPrior to approach controlled text generation. Specifically, we separate the dictionary $\psi$ into $L$ disjoint subsets, i.e. $\psi_1, \psi_2, \ldots, \psi_L$, given $L$ different attributes in the dataset. For example, we have two subsets to represent positive and negative sentiments as in Figure 1. The number of atoms in each subset is set according to the attribute proportion in the dataset. To accomplish controlled text generation, we can then choose a certain dictionary subset and interpolate atoms in this subset as the latent variable $z$ for decoder generation.

To effectively incorporate the attribute information into dictionary atoms, we propose to employ contrastive learning such that sentences generated from a certain subset accurately correspond to the desired attribute. During the training of DPrior, The semantic space of the dictionary could be gradually clustered into several parts according to the natural language attributes.

**Contrastive Learning for DPrior** Given a latent variable $z$ from encoder $q_\phi(z|x)$ with its attribute label $c \in \{1, \ldots, L\}$, we denote $z$ as an anchor $a$. Therefore, atoms in the subset $\psi_c$ with the same attribute constitute positive samples (denoted as $a^+$) of anchor $a$, and atoms in other subsets $\psi_{\{-c\}}$ are negative samples (denoted as $a^-$) of anchor $a$. A contrastive loss (van den Oord et al., 2018; Hoffer and Ailon, 2015) is a distance metric to enforce the anchor $a$ to be similar to positive samples $a^+$ and dissimilar to negative samples $a^-$. With the supervised attribute information contained in anchor $a$, the positive samples would learn to cluster into the same semantic subspace with the anchor while negative samples into other seman-
tic subspaces. The contrastive loss will gradually enlarge the gap among different subspaces.

As shown in Block 2 of Figure 1, we employ InfoNCE loss (van den Oord et al., 2018) where we randomly sample one positive sample from \( \psi_c \) and \( K \) negative samples from \( \psi_{\{-c\}} \) for each anchor \( a \). Then the objective is to produce the log loss of a \((K+1)\)-way softmax-based classifier that tries to classify \( a \) as \( a^+ \):

\[
\mathcal{L}_{C}^{\phi,\psi} = -\mathbb{E}_{S} \log \frac{e^{\tau \cdot a \cdot a^+}}{e^{\tau \cdot a \cdot a^+} + \sum_{i=1}^{K} e^{\tau \cdot a \cdot a_i}},
\]

where \( S = \{a, a^+, a^-\} \) and \( \tau \) is a temperature hyper-parameter and we set \( \tau = 1 \) in all experiments. Together with the loss function of DPrior introduced in Equation 4, the overall objective for controlled text generation can be summarized as:

\[
\min_{\phi,\psi,\theta} \max_{\varphi} \mathcal{L}_R^{\phi,\theta} + \beta_1 \mathcal{L}_D^{\phi,\psi} + \beta_2 \mathcal{L}_C^{\phi,\psi},
\]

where \( \mathcal{L}_R \) denotes the reconstruction loss, \( \mathcal{L}_D \) denotes the dual-form KL-divergence, \( \mathcal{L}_C \) denotes the contrastive loss, \( \beta_1 \) and \( \beta_2 \) are the hyper-parameters.

**Controlled Text Generation from DPrior** After the training phase of DPrior, as Block 3 of Figure 1, given any attribute label \( c \in \{1, ..., L\} \), we select all atoms from the corresponding subset \( \psi_c \), sample \( \pi \) from the Dirichlet distribution, interpolate these atoms with \( \pi \) to produce a latent variable \( z \), and finally feed it to the decoder for text generation. In this way, controlled text generation with the user-specified attributes can be achieved.

**4 Experiments**

In this section, we apply DPrior model to two tasks: (i) language modeling, where DPrior shows its advantage in expressive prior in comparison with state-of-the-art VAE methods. (ii) controlled text generation, where DPrior shows its superiority in controllability with desired attributes. We also conduct a series of analyses and visualizations to shed more light on the proposed approach.

**4.1 Language Modeling**

Following (Li et al., 2020a), we consider four benchmark datasets of language modeling for evaluation: Penn Tree (Marcus et al., 1993), SNLI (Bowman et al., 2015), Yahoo Answers (Xu and Durrett, 2018) and Yelp corpora (Yang et al., 2017). A summary of dataset statistics is shown in Appendix A.

**Baselines** We compare the proposed DPrior against following baselines: (i) auto-regressive models such as LSTM-LM (Mikolov et al., 2010) and GPT-2 (Radford et al., 2019). (ii) VAE (Kingma and Welling, 2014) with simple Gaussian prior, and its advanced variants for better training and avoiding posterior collapse, including Annealing VAE (Bowman et al., 2016), Free Bits (FB)-VAE (Kingma et al., 2017), Lag-VAE (He et al., 2019), and AE-FB (Li et al., 2019a). (iii)VAEs with expressive prior choices, including MoG-VAE (Ding and Gimpel, 2021), Vamp-VAE (Tomczak and Welling, 2018), APo-VAE (Dai et al., 2021), FlowPrior (Ding and Gimpel, 2021). (iv) iVAE (Fang et al., 2019) considers implicit posterior representation instead of explicit form. (v) OPTIMUS (Li et al., 2020a), a large-scale pre-trained VAE model.

**Metrics** We evaluate language modeling from two perspectives: Generation capacity measured by perplexity (PPL) and representation learning capacity measured by Active Units (AU) of \( z \) and its Mutual Information (MI). Note that LSTM-LM and GPT-2 has exactly PPL, while VAEs do not. Following (Fang et al., 2019), our calculation of PPL is slightly different from exact PPL in two ways: (i) we approximate \( \log p(x) \) to report PPL; (ii) the KL term in the bound is estimated via samples, rather than a closed-form. We also report results with ELBO, KL, and Reconstruction in Appendix B.

**Main Results** As the results shown in Table 2, our proposed DPrior achieves state-of-the-art language modeling performance in terms of PPL and MI in all datasets. In comparison with vanilla VAE and its variants in the middle block that employ explicit posterior representations, iVAE, APo-VAE, and DPrior that adopt implicit posterior representations achieve better performance, indicating the importance of expressive posterior representations. Moreover, our DPrior achieves further improvements upon iVAE, which we attribute to the proposed data-driven prior and improving the representation capacity.

In comparison with VAEs implemented by LSTM layers in the middle block of Table 2, VAEs based on the OPTIMUS framework in the bottom block achieve impressive results by large margins.
Table 2: Language modeling performance comparison on PTB, Yelp, Yahoo, and SNLI datasets. "LSTM" indicates autoencoder architectures are built with two-layer LSTMs, while "OPTIMUS" employs pre-trained BERT and GPT-2 as the encoder and decoder. †: results from (Li et al., 2020a), ‡: results from (Fang et al., 2019), §: results from (Li et al., 2019a). *: results from (Li et al., 2019a). †: results from (Ding and Gimpel, 2021). “-” indicates the models are improper to report these values. Empty cells indicate the results were not reported in the literature.

| Dataset | PTB | Yelp | Yahoo | SNLI |
|---------|-----|------|-------|------|
| Methods |     |      |       |      |
| LSTM-LM |     |      |       |      |
| GPT-2† | 100.47 | - | - | 22.00 | - |
| VAE† | 23.43 | - | - | - | - |
| Annealing-VAE† | 23.43 | - | - | 22.00 | - |
| Lag-VAE† | 23.43 | - | - | - | - |
| FB-VAE(λ = 5.0) | 23.43 | - | - | - | - |
| AE-FB(λ = 5.0) | 23.43 | - | - | - | - |
| MoG-VAE§ | 23.43 | - | - | - | - |
| Vamp-VAE§ | 23.43 | - | - | - | - |
| Flow-Prior§ | 23.43 | - | - | - | - |
| APo-VAE* | 23.43 | - | - | - | - |
| iVAE§ | 23.43 | - | - | - | - |
| DPrior (Ours) | 46.08 | 12.59 | 32 | 45.18 | 10.93 | 32 |
| AE-FB(λ = 1.0) | 32 | 8.18 | 32 | 24.59 | 9.13 | 32 |
| AE-FB(λ = 0.5) | 26.69 | 7.64 | 32 | 22.79 | 7.67 | 32 |
| AE-FB(λ = 0.05) | 23.58 | 3.78 | 32 | 21.99 | 2.54 | 32 |
| iVAE | 15.49 | 15.86 | 32 | 15.44 | 15.07 | 32 |
| DPrior (Ours) | 14.74 | 15.96 | 32 | 14.52 | 17.05 | 32 |

Analysis We conduct a set of analyses including the influence of the dictionary size, atom analysis, latent interpolation, and sentence transfer. We find that the results on the PTB dataset are insensitive to the size of the dictionary. To gain a comprehensive understanding of the prior, we also conduct atom analysis. Specifically, we randomly choose an atom from the dictionary and search top-9 nearest atoms via euclidean distance to this atom. Then we feed the sampled atom and top-9 nearest atoms to the decoder for sentence generation. The results are illustrated by the red and blue sentences in Table 3. We conduct latent interpolation to demonstrate DPrior could learn a smooth latent space. We also conduct sentence transfer to imply DPrior has great ability of high-level sentence editing in latent space. More details are illustrated in Appendix C.

4.2 Controlled Text Generation

In this section, we conduct controlled text generation on the Yelp (Li et al., 2018a) and Arxiv (Sergio, 2019) datasets. Yelp dataset (Yelp-s) consists of business reviews that are labeled as either positive or negative according to their sentiment. To gain the tense attributes (present or past) from Yelp, we use the Stanford Parser to extract the main verb from a sentence to constitute a new dataset (Yelp-t). We also consider the combination of sentiment and tense attributes (Yelp-st) for multi-set controlled text generation. Arxiv dataset extracts the abstract from arxiv articles regarding three topics: artificial intelligence, computer vision, and natural language process. Appendix A shows the detailed dataset statistics.

Baselines We compare the proposed DPrior with constructive loss (denoted as DPrior+c) against several baselines: (i) CVAE, the conditional-VAE model (Sohn et al., 2015) where each attribute is
Table 4: Automatic evaluation results of controlled text generation on Yelp dataset. "Transformer" indicates autoencoders architectures are built with transformer layers, while "pre-train" employs pre-trained models such as GPT-2 or OPTIMUS. Reference represents samples from the test dataset. ↑↓ means the larger/smaller the better.

Table 5: Human evaluation results of controlled text generation on Yelp dataset in terms of sentiment and tense attributes. Reference represents samples from the test dataset. ↑ means the larger the better.

Table 6: Automatic evaluation results of controlled text generation on Arxiv dataset. Reference represents samples from the test dataset. ↑↓ means the larger/smaller the better.

represented by a separated Gaussian distribution. (ii) **CVAE+c**, which applies constrastive loss as DPrior+c to the conditional-VAE model. (iii) **Disentangle** (Hu et al., 2017), which disentangles the latent representations into content and attribute parts for controlled text generation; (iv) **Semi-VAE** (Kingma et al., 2014), semi-supervised VAE model with independent discrete and continuous latent variables; (v) a fine-tuned **GPT-2** (Radford et al., 2019) model using attribute labels as the prompt. We deploy the test dataset as **Reference** for comparison. To demonstrate the influence of constrastive loss, we also consider an ablation where no constrastive loss is applied on DPrior. Implementation details are discussed in Appendix D.

**Metrics** We evaluate the performance of controlled text generation from three aspects, i.e., *controllability, fluency and diversity*. For controllability, we fine-tune a BERT classifier (Devlin et al., 2019) on the training data as attribute predictor, which measures the accuracy (Acc) of correctly generated sentences with desired attributes. Note that the BERT classifier achieves an accuracy of 98.4%, 99.5%, 98.0%, and 86.2% on Yelp-s, Yelp-t, Yelp-st, and Arxiv respectively, being a good automatic evaluator. For fluency, we adopt a pre-trained GPT-2 model (Radford et al., 2019) as the fluency evaluator, which takes the generated sentences as input and returns the corresponding perplexity scores (PPL). For diversity, distinct metric (Dist) is employed which calculates the number of distinct bigrams in generated sentences (Li et al., 2016). A better-controlled generation generally has higher Acc, lower PPL, and higher Dist.

**Main Result** The results are listed in Table 4, 5, and 6, including automatic evaluation and human evaluation. From the results, we can conclude that: (i) in terms of **controllability**, our proposed DPrior+c consistently achieves the best generation accuracies (Acc) on all four datasets via either automatic evaluation or human evaluation. (ii) In terms of **fluency**, there is no doubt that GPT-2 produces the best PPL scores since it is pre-trained on language modeling tasks. Though not the best, our
DPrior+c also achieves better PPL scores against other methods. Note that fluency is a very subjective metric, and the use of the GPT-2 PPL score may not be a reliable measurement. We also conduct human evaluation, reported in Table 5, and our DPrior+c always achieves the best fluency excluding the reference. (iii) In terms of diversity, our DPrior+c can also attain comparable distinct metrics (Dist) against other methods. Note that DPrior+c achieves the best distinct metrics (Dist) in the Arxiv dataset, as shown in Table 6. With the help of pre-trained OPTIMUS, DPrior+c could generate more diverse long sentences with more words exploited in the vocabulary.

In comparison with DPrior+c, DPrior always attains the worst controllability as shown in the top block of Table 4, which can be explained that dictionary atoms cannot receive supervised information without contrastive learning. We also find that Transformer-based models always achieve a little better controllability but worse diversity compared with pretrain-based models, as shown in Table 4. A possible explanation is that pretrain-based models can always leverage extra large-scale text corpus and generate out-of-domain sentences that exploit more words, even their attributes cannot be distinguished by the BERT classifier.

**Visualizations** To gain a better understanding of how contrastive learning benefits the prior subspace separations, we visualize dictionary atoms with different attributes. Specifically, we focus on the Arxiv dataset and sample all atoms from DPrior and DPrior+c models. We reduce the dimensionality from 32 to 2 using PCA and plot them in Figure 2. As shown in Figure 2(a), the subspace for AI, CV, and NLP parts are highly overlapped without contrastive loss. This can also explain the poor controllability of DPrior in Table 4. By contrast, DPrior+c model clearly separates the prior space into the AI, CV, and NLP parts, as shown in Figure 2(b), indicating that the contrastive loss could effectively enlarge the gap among different subspaces. Therefore, text generated from the interpolation of the disjoint dictionary subsets will be highly consistent with the desired attributes.

We further analyze the advantages of contrastive learning from two perspectives: the accuracy of dictionary atoms, where we directly feed all atoms to the decoder and measure the accuracy of predicted attributes by the BERT classifier; and the distance between the mean of the three disjoint subsets. As shown in Figure 2(c) and Figure 2(d), when no contrastive loss is applied, the atom accuracy and subset distance keep almost unchanged, i.e., 33% and 0 respectively. By contrast, when contrastive learning is deployed, the atom accuracy quickly increases to 91.9%, and the distance gradually enlarges during the model training.

**Other Analysis** We show some sampled sentences from DPrior+c including short controlled text generation trained on Yelp dataset in terms of sentiment, tense, and the combination of them, and long controlled text generation trained on Arxiv dataset. All samples can be found in Appendix E.

We also analyze the influence of Dirichlet distribution for text generation in terms of controllability, fluency, and diversity. Details can be found in Appendix G.

**5 Conclusion**

In this paper, we propose the Dictionary Prior (DPrior), a new data-driven prior that enjoys the merits of expressivity and controllability. The proposed prior deploys a set of learnable vectors dubbed as dictionary atoms and interpolate the atoms to form the prior. We apply dual-form KL-divergence to make the prior distribution spanned by dictionary atoms approximate the posterior distribution. Contrastive learning is further deployed to the disjoint dictionary subsets to enable controllability and interpretability. Empirical results on benchmark datasets demonstrate the superiority of our approach in both language modeling and controlled text generation.
Nevertheless, the proposed approach has limitations. While the Gaussian distribution employed in standard VAEs has an infinite support region, the support region of DPrior is finite as it corresponds to the convex hull of the dictionary atoms. Therefore, future work considers extending our framework to the more general infinite support region. We will also apply DPrior to more text generation tasks like poetry generation (Yi et al., 2020) and machine translation (Li et al., 2020b, 2019b).

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A Dataset Statistics

We list the data statistics of all experiments in Table 7. PTB, Yelp, Yahoo, and SNLI datasets are used in the language modeling experiments in Section 4.1. Yelp-s, Yelp-t, Yelp-st, and Arxiv datasets are used in the controlled text generation experiments in Section 4.2.

B Language Modeling Results

The language modeling performance was evaluated by perplexity(PPL), Mutual Information(MI), Active Units(AU), Evidence Lower Bound(ELBO), KL divergence(KL), and Reconstruction(Rec) on PTB, SNLI, Yelp, and Yahoo datasets are shown in Table 8 and 9.

C Analysis on Language Modeling

The Influence of Dictionary Size To analyze how the dictionary size $m$ influences the language modeling performance, we vary $m = 2^k, k \in \{8, 9, 10, 11, 12, 13, 14, 15\}$, and conduct experiments on the PTB dataset. The curves shown in Figure 3 present slight fluctuations in terms of PPL, MI, ELBO, and Rec, indicating the experiment results are insensitive to the size of the dictionary. We set $m$ to 2048 for all language modeling experiments in Table 2, 8 and 9 for the highest MI.

Latent Interpolation To demonstrate DPrior can learn a smooth latent space that captures sentence semantics, we implement linear interpolation between latent vectors on the SNLI dataset, i.e., we take two sentences $x_1$ and $x_2$, and use their posterior as the latent features $z_1$ and $z_2$, respectively. We interpolate a path $z_{\tau} = z_1 \cdot (1 - \tau) + z_2 \cdot \tau$ with $\tau$ increases from 0 to 1 by a step size of 0.1. As shown in Table 11, the interpolated sentences using greedy decoding conditioned on $z_{\tau}$ exhibit smooth semantic evolution.

Sentence Transfer To testify the ability of high-level sentence editing in latent space, we also conduct a one arithmetic latent vector operation on the SNLI dataset. Specially, given source sentence $x_A$ and target sentence $x_B$, the goal is to re-write the input sentence $x_C$ as output in analogy to the transition from $x_A$ to $x_B$. We take encoded latent features $z_A, z_B, z_C$ from $x_A, x_B, x_C$, then apply the arithmetic operator $z_D = z_B - z_A + z_C$, and generate $x_D$ conditioned $z_D$ using greedy decoding. As shown in Table 12, two style transitions are well achieved, i.e., from singular to plural subject and from daily-life activity to sport, indicating DPrior can well support the sentence editing.

D Implementations for Controlled Text Generation

We implement all the baselines on our own under the same protocols as there is hardly any reference code for controlled text generation. For transformer-based models, reported in the top block of Table 4, all encoders and decoders are stacked by two transformer layers. These models share the same hyper-parameter settings, including the dimension of latent space, word embedding, and self-attention module. The dimension of latent variable and dictionary atom is set to 32. Adam (Kingma and Ba, 2015) optimizer is employed with an initial learning rate of 0.001. Among pretrained-based models in the bottom block, CVAE+c and DPrior+c adopt OPTIMUS framework (Li et al., 2020a) that employs BERT as the encoder and GPT-2 as the decoder with an initial learning rate of 1e-5. GPT-2 model is fine-tuned on the above datasets with an initial learning rate of 1e-5 directly. We prepend the attribute label words (e.g., positive, negative) to each sentence such that GPT-2 learns to treat them as prompt words. For Yelp-s, Yelp-t, and Yelp-st datasets, the size of the subset for each attribute in the dictionary is set to 2048, and $\gamma = 1/29^i$, and
E Case Study on Controlled Text Generation

We show some sampled sentences from DPrior+c trained on the Yelp dataset in terms of sentiment and tense, and the combination of them. Each attribute is paired with two sentences, and we highlight the corresponding salient words in Table 13. We also choose three long controlled text generations from DPrior+c trained on Arxiv dataset in Table 14.

F Human evaluation for controlled text generation

We also conduct human evaluation for the controlled text generation besides automatic evaluation. Due to the limited budgets, here we only compare DPrior+c with Reference, GPT-2, CVAE+c, as shown in Table 5. And we experiment on the Yelp-s and Yelp-t datasets in terms of sentiment and tense attributes. We randomly select 50 samples for each attribute, so there is a total of 200 sentences from each model.

Four annotators with well linguistic background were invited to assess each sentence with desired attributes in a blind manner. The evaluation is on a scale of 1-5 regarding two criteria: accuracy and fluency. Better controlled generation would come with higher accuracy and higher fluency. For example, given a generated sentence "the price is great and i recommend them!" with desired "positive" sentiment, the accuracy scores [5, 5, 5, 5] were annotated as the sentiment of the sentence could be easily assessed. When it is hard to determine the sentiment of the sentence, annotators might differ their opinions. An example is that [3, 2, 3, 4] were annotated for the sentence "this was absolutely the first time for me." with desired "negative" sentiment. The fluency scores were assessed in the same manner. Each sentence was reviewed by four judges and the average scores are reported in Table 5. We can see that our DPrior+c achieves the best accuracy, as well as best fluency score except for the Reference. We also set an agreement metric on accuracy and fluency via the percentage of the scale that most annotators agree with. For annotated scores [5, 5, 5, 5] and [3, 2, 3, 4], the agreement would be 100% and 50%, respectively. As seen, humans have a higher agreement when the model performance is high.

G Influence of Dirichlet Distribution

As $\gamma$ in Equation 2 determines the density of the Dirichlet distribution which further determines the interpolation coefficients $\pi$, here we analyze its influences on text generation from three aspects, i.e., controllability, fluency, and diversity as in the main results in Section 4.2. We vary $\gamma = 1/2^j, j \in \{4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14\}$, and conduct controlled text generation on the Yelp-s dataset on the transformer-based architecture. We sample 2000 sentences for each $\gamma$ and employ metrics introduced in Section 4.2 for automatic evaluation. As shown in Figure 4(a), when we set a comparatively large value to $\gamma$, the DPrior+c model achieves great performance on controllability, while DPrior gains very poor accuracy, indicating the importance of contrastive learning in our framework. We also take generation fluency into consideration which is measured by GPT-2 PPL score. As in Figure 4(b), the PPL score increases gradually on both models when $\gamma$ declines, showing larger $\gamma$ would lead to more fluent generations. Finally, the influence of $\gamma$ on generation diversity is depicted in Figure 4(c). We can see the two models have similar trends, i.e., the diversity evaluated by Dist increases rapidly when $\gamma$ decreases from $1/2^4$ to $1/2^{12}$, then diversity has a slight decline. Comprehensively considering the controllability, fluency, and diversity of text generation, we set $\gamma = 1/2^9$ for all experiments on Table 4.

We also analyze the influence of Dirichlet distribution on the OPTIMUS-based architecture that could leverage extra large-scale text corpus. The most salient change is that the diversity measured by Dist significantly increases from 0.1 to 0.5 when $\gamma$ equals 1/2, as shown in Figure 4(c) and Figure 4(f), indicating the combination of DPrior and the pre-trained model could generate out-of-domain sentences that exploit more words. In terms of controllability, the OPTIMUS-based architecture exhibits the same trend but slightly lower controllability, as illustrated in Figure 4(a) and Figure 4(d). In terms of fluency, shown in Figure 4(e), OPTIMUS-based architecture presents more similar fluency to the test dataset as reported in Table 4.
Figure 4: Influence of Dirichlet distribution on text generation controllability, fluency and diversity. (a) (b) (c) are transformer-based, (d) (e) (f) are OPTIMUS-based.

Table 7: Data Statistics

| Dataset     | Attributes | Train       | Test        | V AE         | CV         | AI         | NLP        | Mean-Length |
|-------------|------------|-------------|-------------|--------------|------------|------------|------------|-------------|
| PTB (Marcus et al., 1993) | None       | 42068       | 5702        | -            | -          | -          | -          | 19.11       |
| Yelp (Yang et al., 2017)   | None       | 100000      | 10000       | 19994        | 200        | 96.0       | 82         | 21.1        |
| Yahoo (Yang et al., 2017)  | None       | 100000      | 10000       | 19998        | 200        | 78.8       | 82         | 19.11       |
| SNLI (Bowman et al., 2015) | None       | 100000      | 10000       | 9987         | 70         | 9.7        | 9.7        | 21.1        |
| Yelp-s (Li et al., 2018a)  | Negative   | 177218      | 2500        | 9355         | 15         | 8.9        | -          | -           |
| Yelp-t (Li et al., 2018a)  | Positive   | 266041      | 2500        | 9355         | 15         | 8.8        | 150        | 15          |
| Yelp-st (Li et al., 2018a) | None       | 133460      | 1290        | 9355         | 15         | 8.8        | -          | -           |
| Arxiv (Sergio, 2019)       | AI         | 9981        | 200         | -            | -          | -          | -          | 162239      |
|                          | CV         | 43482       | 200         | -            | -          | -          | -          | 567         |
|                          | NLP        | 14374       | 200         | -            | -          | -          | -          | 139.3       |

Table 8: Language modeling performance comparison on PTB and SNLI datasets. "LSTM" indicates autoencoder architectures are built with two-layer LSTMs, while "OPTIMUS" employs pre-trained BERT and GPT-2 as the encoder and decoder. †: results from (Li et al., 2020a), ‡: results from (Fang et al., 2019). §: results from (Li et al., 2019a). ∗: results from (Dai et al., 2021). ○: results from (Ding and Gimpel, 2021). "-" indicates the models are improper to report these values. Empty cells indicate the results were not reported in the literature.
Table 9: Language modeling performance comparison on Yelp and Yahoo datasets. "LSTM" indicates autoencoder architectures are built with two-layer LSTMs, while "OPTIMUS" employs pre-trained BERT and GPT-2 as the encoder and decoder. ⚫: results from (Dai et al., 2021). ♦: results from (Fang et al., 2019). §: results from (Li et al., 2020a). ♠: results from (Li et al., 2019a). *: results from (Dai et al., 2021). □: results from (Ding and Gimpel, 2021). "-" indicates the models are improper to report these values. Empty cells indicate the results were not reported in the literature.

Table 10: Atom analysis on SNLI dataset.

Table 11: Interpolating latent space \( z_D = z_B - z_A + z_C \). Each row shows \( \tau \), and the generated sentence (in blue) conditioned on \( z_D \).

Table 12: Sentence transfer via arithmetic operator \( z_D = z_B - z_A + z_C \). The output sentences are in blue.
### Table 13: DPrior+c case study on the Yelp dataset. Red and blue words indicate the sentiment and tense of sentences respectively.

| Types | Attributes | Samples |
|-------|------------|---------|
| sentiment | positive | [s] this is followed by **good** movies, **great** food. [/s]   
| | negative | [s] for me it looks **crappy** and **understaffed**. [/s]   
| | | [s] i must have seen the disgusting and **overpriced** boxes. [/s]   |
| tense | present | [s] this restaurant **has** an excellent view. [/s]   
| | | [s] plus this place is **clean** and genuine customer service. [/s]   |
| | past | [s] i **was** able to get the delicious sushi! [/s]   
| | | [s] plus my car **was** messed up but our expectations **were** extremely low. [/s]   |
| multi-set | positive present | [s] drinks are **excellent** as well as wine. [/s]   
| | | [s] the haircut is completely **worth the price**! [/s]   |
| | positive past | [s] the environment **was** awesome and **friendly**. [/s]   
| | | [s] finally got a **perfect** haircut with **great** customer service. [/s]   |
| | negative present | [s] well in my opinion it is a **waste of calories**. [/s]   
| | | [s] probably the **worst** haircut they **have** ever had. [/s]   |
| | negative past | [s] to my surprise, the plate **was empty**. [/s]   
| | | [s] it might have been **worst** haircut you **called** or even **asked** for. [/s]   |

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### Table 14: DPrior+c case study on the Arxiv dataset. Blue words indicate the attributes.

| Attributes | Samples |
|-----------|---------|
| NLP | [s] the paper studies the use of generative adversarial networks (gans) for **natural language parsing applications**. upon retrieval of natural text digits, with a gan fixed-sized dictionary and a small set of rules, contextual grammar is generated for a given input group. this contextual grammar offers various incremental mechanism for gans to capture context, including a violation-theoretic scheme for the recognition rate of contextual grammars, exacerbated by accounts of its integration with quantitative metrics such as ver studies or globally-confluent grammars. our approach is primarily agnostic to concepts. furthermore, with real world examples, we show that with just a simple implementation we can expect to improve word parsing performance, carry out a state-of-the-art sequence learning algorithm, and finally generate an effective lexical prop grounding from its trace on the text data. [/s]   |
| CV | [s] the topic of **computer vision** that attempts to predict gestures (i.e., hands) using probability distributions is rapidly gaining popularity. additionally, binary constraints lead to efficient finite state machine (fsm) composition strategies that tend to preserve image correspondences, since intuitive expressions of the departing fsm mechanisms only require a few trace steps from a given fsm state. we introduce a general cnn architecture that efficiently processes images with probabilistic hand model elements. we present a novel classification setting where the fsm parameters only need to be confirmed at a small level of training and test to improve the classification performance. we perform experiments (toads, limitation, handdisc) on datasets with numbers varying from about 320k samples to a relatively small amount of activity on a held-out dataset of collections of well-known hand gestures. through experiments, we have validated the effectiveness of our architecture; and we discovered that our gated knuckle-less fsm constraints selectively preserve image correspondences. [/s]   |
| AI | [s] one of the problems in real-world monte carlo tree search problems (mcts) is the generation of promising algorithms and performing efficient learning of mcts parameters. parameters distributional constraints induced by a large number of observations are difficult to generate and therefore a way to overcome this issue is posed in this paper. through an empirical analysis of a prototype mct based on the control-box machine learning (cbm) and kleywagotoff-lofert satisfiability problems, we advocate deep belief learning (dl), a procedure with epistemic discretization to kickstart training. dl operates through an abstraction tree which enables better reasoning, language understanding, and preference of trained models. we introduce a number of different psychometric specifications to infer behavioral potentials. as a remedy, we propose an approach that starts with belief processes simultaneously. we present dl mouth-to-teeth behaviors that show considerably better soundness and recall compared to the current state-of-the-art mct based approaches as well as artificial neural networks (anns), and that satisfactorily generates better algorithms. [/s]   |