An Overview on Controllable Text Generation via Variational Auto-Encoders

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Abstract

Recent advances in neural-based generative modeling have reignited the hopes of having computer systems capable of conversing with humans and able to understand natural language. The employment of deep neural architectures has been largely explored in a multitude of context and tasks to fulfill various user needs. On one hand, producing textual content that meets specific requirements is of priority for a model to seamlessly conduct conversations with different groups of people. On the other hand, latent variable models (LVM) such as variational auto-encoders (VAEs) as one of the most popular genres of generative models are designed to characterize the distributional pattern of textual data. Thus they are inherently capable of learning the integral textual features that are worth exploring for controllable pursuits.

This overview gives an introduction to existing generation schemes, problems associated with text variational auto-encoders, and a review of several applications about the controllable generation that are instantiations of these general formulations, as well as related datasets, metrics and discussions for future researches. Hopefully, this overview will provide an overview of living questions, popular methodologies and raw thoughts for controllable language generation under the scope of variational auto-encoder.

1 Introduction

Recent employment of deep neural architectures in natural language processing (NLP) has been largely explored in a multitude of contexts and tasks to fulfill various user needs such as machine translation (Bahdanau et al., 2014), text summarization (Rush et al., 2015), dialogue (Serban et al., 2016; Mou et al., 2016), question answering (Iyyer et al., 2014), etc. Especially, high capacity of deep learning models trained on large-scale datasets demonstrate unparalleled abilities to produce realistic and coherent texts, which benefits natural language generation (NLG), one of the most eye-catching domains in NLP. As a matter of fact, obtaining systems to automatically produce realistic-looking texts has been a goal pursued since the early stage of artificial intelligence (Meehan, 1977).

As an elementary task in NLP, NLG aims to generate authentic and plausible textual content that is realistic-looking (Turing, 2009). Ideally, sentences generated from a language model (LM) not only ought to preserve the semantic and syntactic properties of real-world sentences but also should be varied in expression style out of diversity reason (Zhang et al., 2017). Natural language generation is an inherently complex task, which requires abundant linguistic and domain knowledge at multiple levels, including syntax, semantics, morphology, phonology, pragmatics, and so on.

In real life, it is easy for us to realize that the word context may carry different semantics for different readers. Therefore the generated texts should be tailored to their specific audience in terms of appropriateness of content and terminology usage (Paris, 2015), as well as for customized network environment and transparency reasons (Mayfield et al., 2019). The goal of controllable text generation aims to generate coherent and grammatically correct texts whose attributes can be controlled (Elhadad, 1990) and/or abide by user-defined rules which reflect the particular interests of system users (Garbacea and Mei, 2020).

Controllable generation task inherently involves more complex and multi-dimensional data patterns. Latent variable models have natural advantages in handling this task because they provide a declarative language for specifying prior knowledge and structural relationships in complex datasets (Kim et al., 2018). This property empowers the LVMs
such as variational auto-encoder (VAE) (Bowman et al., 2015b) with the ability to leverage constraints into its representative hidden space for controllable generation. However, the direct inference process of latent variable models requires an integral over the latent variable, which often has no analytic form or is time-consuming to compute with massive data instances. This is also a fundamental problem that Variational Inference (VI) methods, including VAE, aim to solve. There have been much recent and interesting work that emerged to combine the complementary strengths of variational inference in LVMs and deep learning. With the invention of compatible parameterization tricks such as reparameterization (Kingma et al., 2015) for variational inference with deep function approximators (deep inference), latent variable models become more competent to handle miscellaneous NLP tasks by absorbing advanced neural model techniques.

2 Background

2.1 Notations

We use lowercase letters in boldface (e.g., \( \mathbf{x} \)) to denote vectors, normal letters (e.g., \( x, X \)) to denote scalars and uppercase letters in boldface (e.g., \( \mathbf{X} \)) to denote sets. We use the symbol \( \| \mathbf{X} \| \) to denote the size of a set. Calligraphic letters denote the functional space of a value set (i.e., \( \mathcal{X} \)). Both English letters and Greek letters are adopted. We use \( p(\cdot) \) and \( q(\cdot) \) to denote distributions and \( f(\cdot) \) to denote a function, which are usually shortened to \( p, q, \) and \( f \). Subscripts and superscripts are used to tell the different variables/distributions/functions apart.

2.2 Controllable Text Generation

We define the task of controllable text generation as finding a function \( f \) to generate sentences that obey certain generation rules or conditions. This can be formally defined as: given a set of \( n \) conditions \( C = \{ c_i \}_1^n \in \mathcal{C} \), where \( \mathcal{C} \) denotes the condition space. The goal of controllable generation is formalized as learning a function \( f \):

\[
 f(C) = \mathbf{Z}, \mathbf{Z} \in \mathcal{Z}, \tag{1}
\]

which aims at generating sentences \( \mathbf{Z} \) from space \( \mathcal{Z} \) that fulfill desired conditions \( C \). In general, the controlled sentence generation task can be divided into two categories according to the category in which restrictions are imposed: generation with soft constraint and hard constraint.

To be more precise, (1) soft constraint text generation requires the generated sentences to be semantically similar to the given constraints (e.g., topic or style), rather than explicitly enforcing certain concepts or rules (e.g., keywords) to appear in the content. The mapping function \( f \) mentioned above serves as a measurement to find sentences with the highest semantic similarity with given constraints. For example, given a corpus of (style, text) pairs as training data, followed by training a conditional language model to learn the linguistic relevance between (style, text) pairs and generate texts with such style, we achieve controllable text generation with soft constraints. (2) Hard constraint focuses on controlling specific tokens or textual structures (e.g., keywords, sentence length) during generation, thus being more fine-grained compared with the soft one. It indicates the compulsive inclusion of given constraints in the output texts. Hence, the function \( f \) here is regarded as a binary sign on a specified controlling level (e.g., token, syntax) to eliminate the possibility of producing unqualified features on such a level. Typically, the condition of hard constraint is keywords and the controllable generation process requires the model to generate sentences with provided exact keywords embedded in generated contexts.

However, generating text under specific lexical constraints is challenging (Zhang et al., 2020). As for the comparison of two types of controllable generation, soft constraint generation, on the other way around, is not capable of handling the explicit appearance of conditions on the token level but can produce authentic texts with particular styles or topics and more straightforward network designs as trade-offs. Hard constraint generative models process given conditions with higher proficiency by placing explicit restrictions on independent attribute controls, but often face several issues such as unitary syntax, semantical inconsistency (Wisman et al., 2018, 2017), requiring more sophisticated model architectures (Garbacea and Mei, 2020) and more training samples with annotations.

In the past few years, a large number of researchers have tried to use different methods for controllable text generation with both types of constraints. Compared with other potential language generating methods, such as generative adversarial networks (GAN) based (Yu et al., 2017; Guo et al., 2018), plain recurrent neural network (RNN) based (Mikolov et al., 2010; Graves, 2013) and
Transformer based methods (Vaswani et al., 2017; Dai et al., 2019; Devlin et al., 2018), latent variable models such as variational auto-encoder are particularly suitable for attribute specified (or controllable) text generation, because the latent space geometry of these models conduct multiple views of knowledge in a given corpus (i.e., style, topic, and high-level linguistic or semantic features), being beneficial for controllable generation (Fang et al., 2019). Besides, the latent knowledge that originates from a variational auto-encoder can help mitigate against model misspecification (Kim et al., 2018), can allow for data-efficient learning (Rezende and Mohamed, 2015; Tomczak and Welling, 2016), and can enable interesting structures to emerge through a carefully crafted generative model.

2.3 Variational Auto-Encoders for Language Modeling

To model data distributions via latent variable models, we usually focus on finding the best parameter $\theta^*$ that models $\int_z p_{\theta^*}(X, z) dz$ to fit in the true data distribution $p(X)$, where observed variable $X$ with $N$ data points and latent variables $z$ are considered. In practice, maximal likelihood estimation (MLE) is widely employed to set the criteria of the “best” distribution fit in, which aims at minimizing the average negative log-likelihood (NLL) of data $x$ parameterized by $\theta$:

$$\min_{\theta \in \Theta} \frac{1}{N} \sum_{n=1}^{N} -\log p_{\theta}(x) = \min_{\theta \in \Theta} \frac{1}{N} \sum_{n=1}^{N} -\int_z \log p_{\theta}(x, z) dz,$$

(2)

Here $x$ is described as observed data points. As we introduce the continuous latent variable $z$ into this objective, it becomes integral intractable to be calculated directly. As an efficient alternative, amortized variational inference (AVI) takes a similar idea of estimation maximization (EM) algorithm to iteratively optimize the parameter $\theta$ and the estimated posterior $q_\phi(z \mid x)$. Though a neural-network-based estimator is introduced to predict function parameters more effectively, the inference of deep parameterizations in VI usually makes posterior inference intractable, and the latent variable objectives often complicate backpropagation by introducing points of non-differentiability (Kim et al., 2018). In practice, variational auto-encoder widely uses the reparameterization (Kingma et al., 2015) trick during neural network back-propagation to obtain differentiable gradients with low variance. This technique requires pre-assigned continuous parametric distribution (or posterior distribution) $q_\phi(z \mid x)$ for the latent variables to approximately update the intractable likelihood term (Kingma and Welling, 2013; Rezende et al., 2014; Kim et al., 2018), whose architecture based on neural network methods and variational inference is in Figure 1.

2.3.1 Variational Auto-Encoder (VAE) (Bowman et al., 2015b)

Variational auto-encoder (VAE) explores the hidden patterns of texts by adding a latent code regularization term to a plain auto-encoder. Concretely speaking, the latent variable $z$ is contributed by optimizing the evidence lower bound (ELBO), which takes both reconstruction error and a regulation loss implemented by Kullback-Leibler divergence (KLD) into count:

$$\log p_{\theta}(X) \geq E_{q_\phi(z|x)} \left[ \log p_{\theta}(X \mid z) \right] - \mathbb{D}_{KL} (q_\phi(z \mid x) \mid \mid p_\theta(z)),$$

(3)

where network parameter $\phi, \theta$ belongs to the encoder and decoder respectively to produce latent posterior and prior. Despite its success in depicting the complex distribution of data and sampling from it to generate diverse and fluent content, they have apparent defects when it comes to conditional language modeling without extra side information:

1. KL collapse problem (Bowman et al., 2015b): caused by an overmighty decoder of VAE and leads the model to ignore learned knowledge from latent space.

2. Token-latent irrelevant issue (Shen et al., 2020): sentences that are similar to each other may share no connection in their latent representations.

Data distribution $p_\theta(x) = \int_z p_\theta(x, z) dz$ and the posterior $q_\phi(z \mid x) = \frac{q_\phi(z \mid x)}{\int q(x, z) dz}$ shares the equivalent integral intractability, thus the estimated posterior is generally calculated by Monte Carlo sampled latent variables.

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It is usually an isotropic Gaussian with diagonal covariance matrix, however, other continuous distributions (e.g., Gamma, Dirichlet) can also be applied (Ruiz et al., 2016; Naesseth et al., 2017).
3. Latent vacancy issue (Xu et al., 2020): latent variables with knowledge for disentangling text features spread discretely in the hidden space.

Several approaches have been devised to handle the first issue, including optimizing decoder architectures (Yang et al., 2017; Semeniuta et al., 2017), inventing auxiliary objectives (Zhao et al., 2017a,b; Xiao et al., 2018), novel encoder training schedule (Bowman et al., 2015b; Fu et al., 2019), flexible posterior (Tomczak and Welling, 2016; Wang et al., 2019b), etc. These methods generally share the same goal: to impair the ability of a powerful recurrent decoder and enhance the utterance of latent space. The former mitigates this puzzle mainly by weakening the conditional dependency of VAE on its decoder, but it may fail to generate high-quality continuous sentences. And methods from the latter one strengthen latent expression, and make the hidden states compatible with the powerful decoder in VAE. Except for KL collapse problem, the last two remained issues are the main reasons to explain why the vanilla text VAE cannot be directly interpolated to be controllable like several parallel applications in image field (Higgins et al., 2016; Chen et al., 2018).

2.3.2 Adversarial Auto-Encoder (AAE) (Makhzani et al., 2015)

Adversarial auto-encoder and Wasserstein autoencoder (WAE) (tolstikhin et al., 2017) generally share a common goal with VAE in employing the ELBO maximization to update the holistic model. A major distinction between these two kinds of models lies in the regularization term of their ELBOs. While VAE takes a Kullback-Leibler (KL) penalty as its latent regulator, AAE (or WAE) introduces a discriminator to judge latent differences as illustrated below:

\[
\log P(\theta)(x) \geq \mathbb{E}_{q(\theta)(x | x)}[\log p(\theta)(x | z)] - \mathbb{E}_{p(\theta)(z)}[-\log D(z)] + \mathbb{E}_{p(\theta)(x)}[-\log(1 - D(E(x)))],
\]

where function \(D(\cdot)\) and \(E(\cdot)\) for the ELBO in AAE (or WAE) denote its discriminator and encoder respectively, and \(\theta_1, \theta_2\) denote parameters of model decoder and discriminator, model encoder, discriminator and encoder accordingly. In contrast to VAEs, AAEs (or WAEs) maintain a strong coupling between their hidden codes and decoder by applying theoretically superior distance measurement (e.g., Wasserstein distance), ensuring that the decoder does not ignore representations in the latent space, which makes it robust for latent knowledge interpretation and interpolation (Vincent et al., 2010; Makhzani et al., 2015).

2.3.3 Discrete Variational Auto-Encoder (Oord et al., 2017)

Turning the continuous latent space into a discrete one is favorable in indicating latent knowledge regardless of the strong decoder of VAE and avoiding the KL collapse problem for good. Vector Quantized Auto-Encoder (VQ-VAE) was therefore invented. It has the same training paradigm as VAE and turns continuous hidden variables into discrete vectors by looking up a discrete codebook \(c \in \mathbb{R}^{K \times D}\) that obtains in advance, where \(K\) and \(D\) represents the size of the discrete latent space and dimensionality of each embedding vector \(c_i\) severally. The posterior categorical distribution \(q(z \mid x)\) is then defined as:

\[
q(z = k \mid x) = \begin{cases} 
1 & \text{for } k = \arg\min_j \|E(x) - c_j\|_2 \\
0 & \text{otherwise}
\end{cases},
\]
here \( E(x) \) is the output of the encoder of VAE. After the vector quantification in Eq. \((5)\), every latent code in VQ-VAE is in discrete mode through one-hot projection. Since the latent quantization process cannot derive gradients because the \( \text{argmin} \) operation exists, VQ-VAE employs straight-through estimator (Bengio et al., 2013) to approximate the gradient and just copy gradients from decoder input to encoder output \( E(x) \).

### 2.3.4 Variational Auto-Encoder with Pre-trained Language Model

Large Pre-trained language models (PLMs) are gaining more and more popularity these days. With enormous resources being devoted, well-experienced encoders/decoders such as BERT (Devlin et al., 2018) and GPT-2 (Radford et al., 2019) are devised to fully understand textual content and create human-like sentences respectively. Incorporating such mighty PLMs as both encoder and decoder of a variational auto-encoder can largely mitigate the KL collapse problem by offering the decoder a nonnegligible latent space from its encoder (Li et al., 2020). How to take full advantage of these PLMs to variational auto-encoders has been explored nowadays (Liu and Liu, 2019; Li et al., 2020; Fang et al., 2021; Park and Lee, 2021; Tu et al., 2022a), which have shown promising potential in a varied multitude of tasks including unsupervised latent interpolation and semi-supervised conditional story generation, etc. Since PLMs were generally pre-trained in large corpus without annotations before applying to specific downstream tasks, the training mode of models with PLMs is essentially semi-supervised if the models’ fine-tuning stage requires explicit labels. We categorize them as semi-supervised in Section 3.2.

### 3 Methodologies

In this section, we will introduce specific methods that aim at controllable text generation using auto-encoders. We divide this section according to the training paradigm of existing models, namely supervised, semi-supervised and unsupervised. As for concrete experimental setups, supervised controllable models require their training data strictly obey the form of (text, label) pairs. Semi-supervised methods only need partial training data to follow such form and the rest can be textual contexts without annotations. The unsupervised method is the extreme case that asks for no annotation of the training corpus. A full list of methods is presented below:

#### 3.1 Supervised Methodologies

The problem is how to make latent AEs, the amazing generators, to be controllable. The most intuitive and straightforward solution is to merge all labels (or conditions) into its generation process. Conditional VAE (CVAE) (Sohn et al., 2015) was proposed following this thought. For the given condition \( c = c_1, c_2, \ldots, c_n \) with \( n \) to be the sample size. By adding the condition to both encoder and decoder of VAE, the overall generation process is compelled to take \( z \) and \( c \) into consideration, that is to say, the posterior and prior of latent distribution are crafted to be compatible with given conditions. This can be reflected in the ELBO of CVAE:

\[
\log P_\theta(x \mid c) \geq \mathbb{E}_{q_\phi(z|\cdot,x,c)} [ \log p_\theta(x \mid z,c) ] - \mathbb{D}_{\text{KL}} ( q_\phi(z \mid x,c) \| p_\theta(z \mid c) ).
\]  

(6)

One issue that becomes serious in CVAE is the KL collapse problem. For a vanilla VAE, it requires its latent \( z \) to obey the prior distribution \( p(z) \), which causes its decoder to ignore the encoder’s explanation of data. CVAE merges condition straight to the decoding process and unwittingly encourages the decoder to ignore the information in latent space and eventually triggers KL collapse. As a fix-up, Zhang et al. (2019) proposed to construct “perfect” encoders concerning different decoders in order to infuse \( x \) into latent \( z \) to evade the standing of \( g(z \mid x) = p(z) \). Formally, Zhang et al. (2019) introduced a self-labeling component with \( x \) and condition \( c \) as input to approximate the reverse process \( g(x,c) \) of decoder and produce self-labeled latent codes \( z_{\text{label}} := g(x,c) \). By taming latent code \( z \) to conclude input knowledge, the objective of such CVAE becomes:

\[
\log P_\theta(x \mid c) \geq \mathbb{E}_{q_\phi(z|\cdot,x,c)} [ \log p_\theta(x \mid z,c) ] - \mathbb{D}_{\text{KL}} ( q_\phi(z \mid x,c) \| p_\theta(z \mid c) ) - \lambda \mathbb{E}_{q_\phi(z|\cdot,x,c)} || z - z_{\text{label}} ||^2,
\]  

(7)

which yields generation ability with high diversity, demonstrates that this CVAE does not fall into the pitfall of the monotonous latent posterior distribution. Though CVAE can be controlled by incorporating condition knowledge, its training scheme inevitably requires full annotation with one label per document and confines CVAE into the generation with global soft constraints. Approaches with
full supervision can perform much better in either content quality or control proficiency.

To a more fine-grained controllable generation, Shao et al. (2019) first proposed the PHVM model to employ the latent variable model in table-to-text generation with hard control. Specifically, as shown in Figure 2, PHVM adopts two VAEs for keyword planning and sentence generation respectively, which gives birth to two separate types of latent codes: planning-level \( z^p \) and sentence-level \( z^s \). While \( z^p \) is responsible for producing various plans for sentences with given keywords, \( z^s \) is made for sentence generation with pre-assigned keyword planning (regarded as a CVAE with fine-grained labels). This setting derives two ELBOs with regard to \( z^p \) and \( z^s \) severally. Moreover, PHVM uses bag-of-word loss (Zhao et al., 2017b) to alleviate KL collapse and employs hierarchical generation (i.e., models both sentence-level and word level sequential information), which makes it competent to produce diverse and long texts with hard control of keywords. PHVM provides us with a new direction for applying variational auto-encoders, which is not constricted in generating sentences but flexible keyword plans.

Inspired by discrete VAEs such as VQ-VAE (Oord et al., 2017), Fang et al. (2022) recently propose a framework with discrete latent prior weighted by continuous Dirichlet distribution named Dprior. With every given label represented by a discrete latent variable, the controllable generation process can be easily accomplished by choosing the exact subset of the latent variable. To back-propagate the discrete latent variables during training, Dprior develops the dual function of KL divergence based on iVAE (Fang et al., 2019). Fang et al. (2022) further extend the model in both LSTM and PLM domains with supervised contrastive objective (Van den Oord et al., 2018) to enhance the model’s controllability. Fang et al. (2022) presents a new stage of developing VAE models aim for controllable text generation: one is to verify the model with both LSTM and PLM encoder&decoder separately, the other one is to incorporate the advanced learning tricks such as auxiliary losses to enhance model performance.

However, these methods can only be applied on datasets with the full-size labels, which becomes unprofitable in real-world circumstances where massive accurate annotations are expensive and rare.

### 3.2 Semi-supervised Methodologies

Controllable variational auto-encoders under the semi-supervised paradigm only require partial annotations of the training data. Semi-VAE (SVAE) was proposed by Kingma et al. (2014) and applied in the vision domain. Recently, it was extended to controllable text generation as a baseline (Duan et al., 2020). For labeled data, SVAE takes \( z \) for content modeling, \( y \) as label embedding, and follows the training path of CVAE. For unlabeled data, \( y \) is represented by a discrete latent variable from a Dirichlet distribution with the probability of \( y \)‘s content. For unlabeled data, SVAE uses contrastive loss and bag-of-word loss to alleviate KL collapse. For semi-supervised generation, the model is trained with both labeled and unlabeled data.

### Table 1: Methodologies of controllable text generation via variational auto-encoders. Classified by training manners. We present topic attribute for models with or without explicit topic modeling part, see Section 3.3 for details.

| Training Paradigm | Methodologies |
|-------------------|---------------|
| Supervised        | Wang et al. (2019a), Zhang et al. (2019), Shao et al. (2019), Fang et al. (2022) |
| Semi-Supervised   | Yang et al. (2017), Logeswaran et al. (2018), Zhao et al. (2018), Subramanian et al. (2018), Li et al. (2020), Ye et al. (2020), Mai et al. (2020), Cheng et al. (2020), Duan et al. (2020), Mai and Henderson (2021), Fang et al. (2021) Tu et al. (2022b) |
| Unsupervised (w/ topic) | Xiao et al. (2018), Wang et al. (2018), Bao et al. (2019), Wang et al. (2019b), Tang et al. (2019), Xu et al. (2020) Ghabussi et al. et al. (2019), Fang et al. (2019), Shi et al. (2020), Shen et al. (2020), Rezaee and Ferraro (2020) Li et al. (2020), Mercatali and Freitas (2021) Tu et al. (2022a) Hu et al. (2022) |
| Unsupervised (w/o topic) | |
Figure 2: Model framework of PHVM from Shao et al. (2019). It leverages two LVMs and two latent spaces to guide planning and sentence generation respectively. $z^p$ is the latent code for global planning, while $z^s_t$ is the latent code for sentence-level generation at timestep $t$.

data, SVAE treats label latent embedding $y$ as $z$ and updates them equally. SVAE can also take a pre-trained plain VAE and incorporates the wake-sleep algorithm (Dayan, 2000) to acquire reliable latent representations and produces authentic content. Yang et al. (2017) adopted a similar training structure with SVAE (treated the label embedding as latent codes), but a dilated convolutional neural network (Yu and Koltun, 2015) with residual connection as the decoder. This modification theoretically weakens the ability of VAE’s decoder and averts the KL vanishing problem as expected. To improve the convenience of deriving meaningful latent knowledge on different domains, Zhao et al. (2018) further generalized the two-stage training framework for controllable latent vector production. They used unlabeled contexts for auto-encoder pre-training and devised a conditional GAN on latent space in order to obtain latent vectors to generate controllable texts. Despite their successes, the wake-sleep algorithm and two-stage training inevitably require two round of full training of VAEs. This is not portable and may consume a huge amount of resources in this process. Duan et al. (2020) proposed a novel framework for text generation named “pre-train and plug-in” (also known as “plug-and-play” or PnP for short) in Figure 3. Their model PPVAE is consists of two separate parts: a pre-trained WAE with global latent space $Z_q$ and a plug-in VAE with constrained latent space $Z_c$. While the pre-trained WAE is trained in advance without any restriction, plug-in VAE is actually an extension of pre-trained WAE with very few added trainable parameters whose goal is to construct a sensible mapping from $Z_q$ to $Z_c$ under the paradigm of VAE. During the training of plug-in VAE, all parameters in the pre-trained model are frozen, which makes it super fast to converge with very few biased samples (samples that belong to the same category) as input. As an extension, Mai et al. (2020) invented emb2emb model for text style transfer generation under the PnP framework, which devised a novel “offset net” as a mapping function that only deploys few arguments in the latent manifold. By introducing Broadcast Net to both RNN-based and pre-trained auto-encoders, Tu et al. (2022b) further lead the PnP controllable auto-encoders to a more flexible and efficient direction with their PCAE framework. Its vital Broadcast Net creates a compact and manipulable controllable latent space by repeatedly adding label signals to the original latent manifold during plug-in process, reaching a higher degree of generation control and fewer training costs compared with previous work.

To theoretically explain the controllable signal flow in latent AEs, Cheng et al. (2020) resorts to information theory for disentangled representation learning (DRL) in controllable VAE. They began by estimating the variation of information between target sentence $x$ and its style label $y$, split latent code into $c$ for content embedding and $s$ for style embedding respectively, then derived a disentangling learning loss in addition to the original ELBO:

$$L_{Dis} := I(s; c) - \mathbb{E}_{p(x,c)}[\log q_{\phi}(x \mid c)] - \mathbb{E}_{p(y,s)}[\log q_{\psi}(y \mid s)],$$ (8)

where the distribution $p(x \mid c, p(y \mid s)$ are parameterized by a recurrent decoder and a classifier severally. Besides, they brought another decoder into consideration to fulfill the reconstruction term related to input sequences that involves both $s, c$ in their model.
Figure 3: Model framework of PPVAE from Duan et al. (2020). Its training/generation paradigm consists of three parts (a) pre-training PretrainVAE on the large unlabeled corpus to obtain $Z_g$; (b) Train the PluginVAE with only latent space projections being activated on the labeled corpus to obtain $Z_c$; (c) Sample the latent code from conditional before generate controllable texts.

These semi-supervised methods generally bound to produce softly controllable texts with global labels. As the fine-grained controllable generation with hard constraints, Ye et al. (2020) proposed a novel framework VTM to employ two VAEs for both table template and textual content modeling. That is to say, for a given table-text pair $(x, y)$, VTM requires a latent $z$ for the template and another latent $c$ for content. Its objective is described as:

$$\log P_\theta(y | x) \geq \mathbb{E}_{q_\phi(z | y)}[\log p_\theta(y | z, c = f_{\text{enc}}(x), x)] - D_{\text{KL}}(q_\phi(z | y) || p_\theta(z)) - D_{\text{KL}}(q_\phi(c | y) || p_\theta(c)),$$

where $f_{\text{enc}}(\cdot)$ is the encoder function for table embedding and the prior $p_\theta(c) = \delta(c = f_{\text{enc}}(x))$ ensures the assumption of exact match of table-text pair. In addition, they appended several auxiliary losses out of content and template preserving purposes. For raw text without table description, latent representation $c$ is sampled from a normal Gaussian $N(0, I)$ as a generalization.

Most recently, with the sample of large pre-trained language models (PLMs), more and more work tends to incline promising encoder/decoder such as GPT-2 (Radford et al., 2019) to create realistic sentences. Controllable language models built on PLMs often fine-tune PLMs as part of the model structure and feed labels in this process for immediate applications. Since PLMs are usually trained with massive unlabeled corpus, the whole controllable model only accesses to label information at fine-tuning stage, thus making it semi-supervised. Li et al. (2020) was the first one to connect pre-trained BERT and GPT-2 via continuous latent space following the VAE paradigm. They achieved state-of-the-art controllability in text generation via a two-stage training described in Zhao et al. (2018), which is largely ascribed to its competent encoder and decoder components. Fang et al. (2021) proposed the first CVAE based on PLMs. Their proposed VAE architecture is modified by replacing the original encoder and decoder to pre-trained GPT-2s. Unlike a plain VAE that easily mixes latent codes into the decoder input. Fang et al. (2021) explored several combination rules for infusing latent codes into the framework of Transformer-based AE, including at the beginning of word embedding layer, in the middle of attention hidden states, and at the last word decoding process. As for controllable generation, they fine-tuned the holistic model with given labeled prompts to produce conditional texts. It is no doubt that these new methods gave us a hint about the application to employ PLMs into variational auto-encoders, they were short of detailed discussions about the condition incorporation methods into such a large language model to make them learn obedience.

### 3.3 Unsupervised Methodologies

While supervised signals assist models to put out content with accurate attributes, an unsupervised manner is the way a plain auto-encoder adopts. Once we obtain reliable latent information for disentangled representations via unsupervised training, it is facile to take full advantage of them under any circumstance and benefits several downstream tasks (text summarization (Wang et al., 2019b), style transfer (Hu et al., 2017; Tang et al., 2019), translation task (Liu and Lapata, 2018), etc.) effectively. Intuitively, the target of producing topic-specific sentences can fall into three courses: topic extraction, sequential learning, and joint generation. Therefore, both topic and sequential models are of
great importance in analyzing and creating controllable texts. In general, the ways to learn and comprise topic information in the text generation system can be divided into two schemes: models with explicitly additional topic modeling parts and models without them.

3.3.1 w/ Explicit Topic Modeling Part

Explicit topic modeling parts are designed to separate topic learning and sequential learning process. The input of this part generally follows Bag-of-Word (BoW) manner to cancel influences brought by the sequential connection between words. And the model structure of the topic modeling part varies from the plain LDA to well-designed neural networks. D-VAE (Xiao et al., 2018) firstly proposed to model unsupervised latent model with the topic latent model (specifically an LDA model) conditioned on latent code \( z \). Formally, Xiao et al. (2018) investigated two modes for topic information infusion: a two-stage model with Dirichlet latent from a pre-trained LDA and an end-to-end model with topic latent code \( t \sim \text{Dirichlet} \) and being conditioned on \( z \) to acquire text knowledge upfront. The holistic ELBO is then derived as:

\[
\log p(x) \geq \mathbb{E}_{q(z|x)}[\log p(x | z, t)] \\
- \mathbb{D}_{KL}(q(z, t | x)||p(z, t)) \\
= \mathbb{E}_{q(z|x)}[\mathbb{E}_{q(t|x,z)}[\log p(x | z, t)]] \\
- \mathbb{E}_{q(z|x)}[\mathbb{D}_{KL}(q(t | x,z)||p(t | z))] \\
- \mathbb{D}_{KL}(q(z | x)||p(z)).
\] (10)

At the same time, Wang et al. (2018) focused on neural topic modeling and invented a Gaussian-based neural topic component with a mixture of expert (MoE) (Hu et al., 1997) decoder (TCNLM), so each expert concentrates on one dimension of the latent topic variable and produces controllable sentences. To make full use of the nature of variational auto-encoder in accurately characterizing data patterns, Wang et al. (2019b) went to propose TGVAE based on the exact neural topic model in TCNLM. The major improvement of TGVAE compared with TCNLM lies in its latent design. While TCNLM employs a mixture of agents on the token generation level (MoE decoder), TGVAE leans upon a mixture of agents on the latent level, that is Gaussian mixture model (GMM) for latent modeling. In detail, the prior of latent GMM in TGVAE is parameterized by the latent variable from its neural topic component, and it employs Householder flow (Tomczak and Welling, 2016) for flexible GMM posterior estimation, a novel KL divergence to calculate the latent regularization term. With each Gaussian representing a topic in the data, it produces controllable contexts by manipulating distinct Gaussian distributions in the latent space. These two methods confound the topic and content latent field at the beginning of the text generation process, thus being less explainable compared with D-VAE. Other approaches that manage content and topic separately arose, Tang et al. (2019) proposed TATGM with \( z_t \) and \( z_s \) that both follow an isotropic Gaussian to the model topic and sequence representations severally in Figure 4. They fed sentences in the Bag-of-Word (BoW) manner into the topic encoder and made it a discriminator for topic modeling augmentation. By concatenating \( z_s \) and \( z_t \), TATGM is capable of producing controllable textual content. A concurrent work from DSS-VAE (Bao et al., 2019) described the input sentences of sequence latent space in the schema of linearized tree sequence (Vinyals et al., 2015). Notably, DSS-VAE does not use BoW as a special input way for topic modeling, but adopts several auxiliary adversarial losses to ensure responsible stages of disentangled learning and combined generation between \( z_t \) and \( z_s \). These methods join additional topic modeling parts into generation following the intuition that text semantic and syntax structures are inherently distinct.

In the field of computer vision, \( \beta \)-VAE (Higgins et al., 2016) and its derivations are famous for only interpolating the latent space in a vanilla VAE to produce attribute-specified images. However, Xu et al. (2020) proved the infeasibility to conduct similar experiments with text VAE, they presented that variational auto-encoders that perform in a discrete domain (e.g., sentence) are unable to be generalized likewise because of the latent vacancy problem in their latent spaces. They split the latent space into two parts \( z^{(1)}, z^{(2)} \) with word embedding and RNN embedding as initial state respectively, and borrowed principles in simplex theory to constrain \( z^{(1)} \) in a simplex manifold for topic knowledge induction as well as additionally derived losses.

3.3.2 w/o Explicit Topic Modeling Part

Without an explicit topic modeling part, a VAE model is required to learn both topic and sequential knowledge with one confined latent space. This demand rises a big challenge for the vanilla text VAE that has several latent limitations. Xu et al. (2020)
identified the possible reason for vanilla variational auto-encoder not being able to control in the fashion of $\beta$-VAE, they still designed topic information learning specially and imposed restrictions only on topic latent code (e.g., constraints on $z^{(1)}$). Introducing an accessional component for explicit topic depiction is one way to make generated text controlled. The question is, are there more general methods that do not compulsively require extra components based on variational auto-encoders?

For optimization on the overall latent level, Ghabussi et al. (2019) proposed to use GMM in the latent space as a replacement of isotropic Gaussian, biased samples were used for training model with corresponding Gaussian distribution activated (i.e., mixture weight was not set to zero). When it comes to controllable inference, this model reaches such a goal by sampling from chosen Gaussian distributions. Besides, they also employed WAE in order to conduct robust topic information. As a way to improve, Shi et al. (2020) explored several different distribution types (e.g., exponential family) with a mixture model and aimed at learning structured topic pattern without any biased data. They identified the “mode collapsed” problem related to a mixture of distributions in the text variational auto-encoders and further devised regularization terms as a countermeasure.

For a more generalized extension, Fang et al. (2019) proposed an innovative informative penalty $I(x; z)$ as well as a noise-adding procedure that can be applied to any LVM to close the gap between observed data $x$ and latent code $z$ as in Figure 5. Their original intention is similar to the one in Zhang et al. (2019) as introduced in Section 3.1, but used a more intuitive yet effective approach. Shen et al. (2020) provided another view to construct the hidden space of text variational auto-encoders that allow us to interpolate to produce controllable sentences. They found that the semantic similarity of sentences has almost nothing to do with their similarity score mapped in the latent field, simply adding noise (e.g., word dropout, word substitution) at the input token level can effectively alleviate such conundrum. By doing so, there stands a chance to control textual output by means of manipulating the refined latent space. Besides adding adversarial noises to the latent space to help text VAEs to be controllable without additional modifications on the model level. VAEs with strong (pre-trained) encoders that are compatible with their decoder modules can also mitigate challenges faced by a plain text VAE. Optimus proposed by Li et al. (2020) also displays its competence for unsupervised controllable text generation by simply manipulating latent space. Further, Tu et al. (2022a) came up with a more efficient big VAE model AdaVAE with GPT-2 as its encoder and decoder. They only activate the adapter (Houlsby et al., 2019) components inside the VAE during training, accomplishing sensibly satisfactory controllable results in latent manipulation and interpolation tasks. Another direction to produce controllable texts without supervision lies
in fusing learned latent knowledge into the decoder with more confidence. Hu et al. (2022) proposed a novel knowledge infusion method to inject latent information into its transformer decoder layer by layer, resulting in robust text reconstruction performance. This ability helps transformer-based VAE models produce consistent sentences when manipulating their latent spaces.

In order to help the latent space be not only controllable but more explicable, Rezaee and Ferraro (2020) proposed VRTM, which turned the conventional continuous latent space into a discrete one. They allocated a latent code for each word and predict its topic polarity (i.e., binary sign) through additional Dirichlet variables inferred from a masked BoW embedding (mask non-thematic words). These settings give them permission to measure topic distributions on both word level and document level, so they could naturally control textual output with more flexibility. Most recently, another work conducts on discrete text VAE appears. Mercatali and Freitas (2021) focused on the decomposition of a VAE’s ELBO, which mainly followed work that were previously carried out in the computer vision field (Chen et al., 2018). Extending this work to a discrete text VAE, Mercatali and Freitas (2021) helps us to understand responsible disentangling factors in the variational auto-encoders, and also to identify their own roles in the controllable text generation process.

4 Metrics

Evaluation metrics are roughly divided into two parts: language generation metrics for evaluating models’ generative capacity in the language domain and control ability metrics for testing the control degree of models.

4.1 Language Generation Metrics

Controllable text generation as a language generation task, its evaluation standards are quite similar to language modeling via latent variable models.

- **Reconstruction Loss** is the reconstruction loss (log-likelihood in general) of a language model. When the reconstruction loss is low, the model can generate authentic texts.
- **Kullback-Leibler divergence (KLD)** is the latent regularization metric for latent variable model. How to balance the KLD values is actually tricky. Because high KLD indicates that the model is not proper-trained and may not converge at all, while low KLD means there is likely the KL collapse issue happening and the model can simply degenerate to auto-encoder to copy training sentences for generation.
- **Evidence Lower Bound (ELBO)** is the sum of KL divergence and reconstruction loss (log-likelihood in general) of the latent variable model. The model reaches a better convergence when the ELBO is lower.
- **Activated Units (AU)** is used to measure the activated dimension in latent space. It is calculated by counting the number of posterior latent units that differ from the prior by a pre-assigned threshold. A higher AU value indicates that the model has a collapsed posterior.
- **Mutual Information (MI)** is the mutual information between input texts and latent posterior. It is generally implemented in the importance sampling method. When the MI between input and latent representations is high, the latent space learns more textual knowledge that may be beneficial for generation.
Table 2: Text quality analysis in terms of text perplexity (PPL) of LVMs on 6 common datasets. Results were gathered from the original papers, and “-” indicates no reported results from the original paper.

• **Perplexity (PPL)** is one of the main measurements for evaluating sequence fluency via word output probability from the model: for a given sequence of words \( \{x_1, ..., x_N\} \) with \( N \) to be the size, PPL is calculated as the normalized inverse probability of the sequence \( PPL = \frac{1}{N} \log p(x_1, ... , x_N) \). For latent variable models, there are two different ways to conduct PPL calculation. One is simply the negative exponential value of ELBO, which may be biased especially when the KL divergence does not collapse (Li et al., 2019). The other one applies importance weighted samples (Burda et al., 2015) to conduct an unbiased estimation of model PPL values. When the PPL is lower, the model is expected to produce more fluent contexts. We show PPL values of different controllable LVMs in Table 2.

• **test-BLEU** (Wang et al., 2019b) is a generation metric related BLEU. It takes randomly sampled test examples as references, and computes the BLEU scores of generated texts with references. When test-BLEU is high, the model produces more realistic-looking sentences.

• **self-BLEU** (Zhu et al., 2018) is a diversity metric related BLEU. It computes averaged BLEU scores among generated paragraphs, which randomly takes generated samples as references and others to compare with them. When self-BLEU is low, the model can generate more diverse sentences.

• **Distinct-n** (Li et al., 2015) is a diversity metric. It represents the number of distinct \( n \)-grams normalized by the length of text. The higher the Distinct scores are, the less likely the model produces “dull texts”.

• **Human Evaluation** often takes **fluency** and **diversity** into consideration. The fluency score is high if the generated sentences are fluent, authentic, and correct w.r.t. common sense, while the diversity score is high when the generated texts are not dull and diverse in contextual structure, expression pattern, vocabulary, etc.

4.2 Control Ability Metrics

For text controllable generation task, there are multiple methods to verify the models’ control degree:

• **Accuracy on Token Level** measures the classification accuracy of generated controllable texts with given labels.

• **Accuracy on Latent Level** measures the clas-
sification accuracy of learned latent representations with given labels.

- **Normalized PMI (NPMI)** (Newman et al., 2010) is a coherence metric of inferred topics from a model 4. Given the top \( n \) likely words of a topic, the coherence is calculated based on the sum of pairwise NPMI scores between topic words, where the word probabilities used in the NPMI calculation are based on co-occurrence statistics mined from English Wikipedia with a sliding window. When the NPMI value is higher, the topic inferred from the model is more concentrated and accurate.

- **Topic Entropy** (Rezaee and Ferraro, 2020) is the entropy value of the latent representations regarded to controlled topics, it helps us obtain the focused intensity of the topic modeling part with different documents. The lower entropy is, the fewer topics a topic model infers for one document, i.e., the higher the control level.

- **Keywords Extraction Accuracy** is specially designed for controllable text generation methods with assigned keywords inputs, i.e., hard constraints. It calculates the extraction accuracy of keywords from generated sentences compared with given ones.

- **Human Evaluation** often takes *relevance* into consideration. When the generated sentences are correlated to given control signs, the evaluators tend to give higher relevance scores.

5 Datasets

There are two types of datasets that are employed in controllable generation task. Datasets with label annotations or datasets without labels. Since vanilla latent variable models are famous for their knowledgeable latent representations, unsupervised latent variable models can conduct both textual feature extraction and generation tasks on unlabeled datasets such as APNEWS5, IMDB (Maas et al., 2011), BNC (Consortium et al., 2007), PTB (Marcus et al., 1993), SNLI (Bowman et al., 2015a).

For labeled datasets, there are globally labeled datasets (i.e., control on topic, sentiment, etc.) and keywords labeled datasets (i.e., control on specific keywords/phrases), we refer them to soft control and hard control datasets respectively.

5.1 Soft Control Datasets

The most widely used one is Yelp6 dataset, which originally consists of examples from Yelp restaurant reviews with ratings ranging from 1 to 5. Shen et al. (2017) processed this dataset with sentiment binary labels (rating above 3 as positive, otherwise negative), which becomes one of the universal versions to conduct controllable generation task. Shen et al. (2020) further expanded the Yelp datasets into versions with text length labels (short, middle, long), text tense labels (past, present). Beyond the Yelp dataset, there are two more labeled corpora used in controllable LVMs. News Titles (Fu et al., 2018) is a labeled dataset with *Business, Entertainment, Health, and Science* categories. Yahoo Question7 dataset has 10 classes (*Society & Culture, Science & Mathematics, Health, Education & Reference, Computers & Internet, Sports, Business & Finance, Entertainment & Music, Family & Relationships, Politics & Government*), each example has a question and long as well as short answers corresponding to the question.

5.2 Hard Control Datasets

Samples in hard control dataset generally consist of a sequence of key phrases and a fluent sentence that include all listed key phrases. Shao et al. (2019) proposed a Chinese dataset about shopping based on an online E-commerce website, they take clothing attributes as key phrases in the dataset. WiKiBio dataset (Lebret et al., 2016) contains sentences of biographies from Wikipedia, they take different attributes of a celebrity such as a name, country, birth information, etc. SPNLG dataset (Reed et al., 2018) is a collection of restaurant descriptions, which expands the E2E dataset8 with more varied sentence structures and instances (Ye et al., 2020).

6 Conclusion

The common misconception is that language has to do with words and what they mean. It doesn’t.

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4 https://github.com/jhlau/topic-coherence-sensitivity
5 https://www.ap.org/en-gb/
It has to do with people and what they mean. Controllable text generation is of vital importance to our daily applications. In order to decouple textual features to be controlled (e.g., topics, tense, sentiment) and syntax structure of basic grammar rules, deep latent variable models, which combine the composability and interpretability of graphical models with the flexible modeling capabilities of deep networks, are an exciting area of research.

While it appears that a choice of one deep neural network over another is style-independent, balancing the trade-offs between the complexity of a model and the expected performance gains added by auxiliary components (e.g., classifier, discriminator) are consistent challenges faced by researchers. Since this overview is structured around the training paradigm of one model, for example, we can hardly find models to resolve table-to-text task which requires more specific control out of the supervised manner. Methods without external control signals have a more strict demand for latent awareness or well-designed control parts to conduct open-domain controllable generation. As the pre-trained language models arise, the semi-supervised manner is of great potential for future exploration and generalization.

It is our hope that this review would serve as an initial guideline for future studies that are built on the best practices of past research as well as some raw ideas that can enrich the field.

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