µ-Forcing: Training Variational Recurrent Autoencoders for Text Generation

DAYIHENG LIU, College of Computer Science, State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, China
YANG XUE*, College of Computer Science, Sichuan University, China
FENG HE, College of Computer Science, Sichuan University, China
YUANYUAN CHEN†, College of Computer Science, Sichuan University, China
JIANCHENG LV‡, College of Computer Science, State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, China

It has been previously observed that training Variational Recurrent Autoencoders (VRAE) for text generation suffers from serious uninformative latent variables problem. The model would collapse into a plain language model that totally ignore the latent variables and can only generate repeating and dull samples. In this paper, we explore the reason behind this issue and propose an effective regularizer based approach to address it. The proposed method directly injects extra constraints on the posteriors of latent variables into the learning process of VRAE, which can flexibly and stably control the trade-off between the KL term and the reconstruction term, making the model learn dense and meaningful latent representations. The experimental results show that the proposed method outperforms several strong baselines and can make the model learn interpretable latent variables and generate diverse meaningful sentences. Furthermore, the proposed method can perform well without using other strategies, such as KL annealing.

CCS Concepts: • Computing methodologies → Natural language generation.

Additional Key Words and Phrases: Variational autoencoders, variational recurrent autoencoders, uninformative latent variables issues

ACM Reference Format:
Dayiheng Liu, Yang Xue, Feng He, Yuanyuan Chen, and Jiancheng Lv. 2019. µ-Forcing: Training Variational Recurrent Autoencoders for Text Generation. ACM Trans. Asian Low-Resour. Lang. Inf. Process. 1, 1 (May 2019), 18 pages. https://doi.org/0000001.0000001

*Equal contribution
†This is the corresponding author
‡This is the corresponding author

Our code and data are available at https://github.com/dayihengliu/Mu-Forcing-VRAE

Authors’ addresses: Dayiheng Liu, College of Computer Science, State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, Chengdu, 610065, China, losinuris@gmail.com; Yang Xue, College of Computer Science, Sichuan University, Chengdu, China; Feng He, College of Computer Science, Sichuan University, Chengdu, China; Yuanyuan Chen, College of Computer Science, Sichuan University, Chengdu, China, chenyuanyuan@scu.edu.cn; Jiancheng Lv, College of Computer Science, State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, Chengdu, China, lvjiancheng@scu.edu.cn.

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2375-4699/2019/5-ART $15.00
https://doi.org/0000001.0000001
1 INTRODUCTION

Natural language generation has been a popular research topic over the past decades. Unsupervised learning plays an important role in this field. In unsupervised settings, the standard RNN-based models such as RNN-based language models [26] and sequence auto-encoders [5] generate each word of a sentence conditioned on its previous generated words and hidden state. However, they do not explicitly include latent variables to capture meaningful latent features and represent the full sentence. As discussed by [3], these RNN-based models do not generally learn smooth and interpretable latent variables for sentence representation, which is often the main purpose of unsupervised learning. Their sentence encoding vectors cannot be used to sample novel sentences for RNN decoders.

As one kind of generative model, Variational Autoencoders (VAEs) [17, 22], have shown great promise in image and text generation. The VAEs integrate stochastic latent variables $z$ into the auto-encoder architecture. By imposing a prior standardized normal distribution on the latent variables, the VAEs learn latent variables not as single isolated points, but as soft dense regions in latent space which makes it be able to generate plausible examples from every point in the latent space. The VAE models have been successfully used to generate plausible images [11, 28]. However, it often performs poorly on text generation.

For text generation, autoregressive density estimators such as LSTM RNNs [12], which are highly expressive, are usually employed as the decoder parts of the VAE-based models. Such models are called Variational Recurrent Autoencoders (VRAEs) [8]. VRAEs tackle the problem of controlled generation of text. They are able to generate realistic sentence examples as if they are drawn from the input data distribution by simply feeding noise vectors through the decoder. Additionally, the latent representations obtained by applying the encoder to input examples give fine-grained control over the generation process that is harder to achieve with more conventional autoregressive models. These latent variables make it possible to control various fine-grained attributes over the generation process, such as controlling the sentiment or writing style of generated sentences.

Nevertheless, VRAEs face some optimization challenges. As argued in [1, 3, 4, 32], the core difficulty of training VRAEs is that the models would suffer from serious uninformative latent variables (also called KL vanishing) issue: the VRAEs tend to totally ignore the latent variables and only use the decoder part to model the data. In practice, the VRAEs would collapse into plain language models and can only generate repeating and dull samples.

To mitigate this uninformative latent variables problem, [3] propose a trick called KL cost annealing. However, the training of VRAEs still be prone to collapse on large corpus with this trick. As pointed by [30], this hand-tuned method make the process of training VRAEs still difficult and are not very efficient.

We propose a regularizer based approach called $\mu$-Forcing to address the uninformative latent variables problem. An additional regularizer is added to the objective function of original VRAE which prevents the VRAE collapses into a trivial solution and guides the VRAE to explore its model capacity to learn a better latent representation. This method stems from the following intuition: when the model collapses into a trivial solution, the approximation posterior distribution $q(z|x)$ of every data point $x$, which is usually assumed to be $N(\mu, \sigma^2)$, degrades to the same $N(0, 1)$. However, for reasonable latent representations, different data points $x$ should have different latent representations $q(z|x)$. The proposed method introduces a mild constraint on the $\mu$ of $q(z|x)$ to force the model to find a non-trivial solution where the learned latent variables $z$ contain useful information.

Specifically, the contributions of this paper can be summarized as follows:
• We propose an effective method to address the uninformative latent variables problem for VRAEs. This method can flexibly and stably control the trade-off between the KL term and the reconstruction term, making the model learn dense and meaningful latent representations. Furthermore, our proposed method can perform well without using other strategies, such as KL annealing.
• For sentence generation, the experiments indicate that our proposed method outperforms several strong baselines. We show that our method can generate diverse meaningful sentences and learn interpretable latent variables.

2 RELATED WORK
When applied to text generation or complex datasets such as ImageNet [6], VAEs suffer from two major problems: blurry samples and uninformative latent variables. Lots of approaches have been proposed to address these issues. Our work falls into this category, but focuses on text generation where the second issue dominates.

Recently, much work has been done to come up with more powerful posterior distributions. [21] learn highly non-Gaussian posterior densities by transforming simple densities into complex ones with sequences of invertible transformations. [18] introduce generative adversarial networks (GAN) [9] to variational inference, which can match the posterior distribution with an arbitrary prior distribution. These methods have shown to be effective in improving variational inference and solving the blurry sample issue partially. However, as [3, 25] observed, these approaches seem to do little on the uninformative latent variables problem.

The uninformative latent variables issue is formally studied in [4], which casts the problem of optimizing VAE into designing an efficient coding scheme. Their work shed light on the reason of the uninformative latent variables problem from the perspective of coding theory, but without proposing any principle method to address it. [32] further formally study these problems of VAE, and propose a family of VAE based models. They demonstrate that all of these models maximize the mutual information between input and latent variables and achieve better performance on image generation.

As for sentence generation, recent attempts that use autoregressive conditional likelihood in VAEs suffer from seriously uninformative latent variables issue. Existing solutions to this problem can be divided into two categories: model-based and regularizer-based methods. For model-based methods, [23] proposes a novel hybrid convolutional-recurrent model (hybrid-VAE) with an additional auxiliary reconstruction term to address the uninformative latent variables issue for text generation. This architecture is attractive for its computational efficiency but less flexible. [29] extends the hybrid-VAE by introducing dilated convolutions to improve the variational model for text generation. [10] proposes a stochastic recurrent model in which each step in the sequence is associated with a latent variable. To ease the training, they add an auxiliary cost to force each latent variable to reconstruct the state of the backward recurrent network. In order to solve the KL vanishing and inconsistent training objective for dialogue generation, [24] firstly learns to autoencoder discrete texts into continuous embeddings which are sampled by transforming Gaussian noise and are trained with a separate model. Then the model learns to generalize latent representations by reconstructing the encoded embedding.

For the regularizer-based method, [3] uses the KL cost annealing method to enforce the VRAEs to learn to encode as much information in latent variables as it can in the early stage of training. In addition, they weaken the decoder by randomly removing some conditional information (the ground-truth previous word) during training to force the model to rely on the latent variables. In practice, these tricks are not always effective. Another popular strategy is free bits [16]. This method reserves some space of KL divergence for every dimension of latent variables. Similarly, [29]
reserves space for the total KL divergence instead of for every dimension. In order to solve the uninformative latent variables problem, [33] forces the latent variables to predict the bag-of-words vector of the reconstruction sentence. Nevertheless, this method needs to incorporate another neural network to predict the bag-of-words vector, which will significantly increase the number of parameters of the model. More recently, [1] presents a theoretical framework for understanding representation learning using latent variable models in terms of the rate-distortion tradeoff, and confirms that the VAE models with expressive decoders can ignore the latent code. They propose a simple solution that reduces the KL penalty term $\lambda$ to $\lambda < 1$ to this problem. However, their experiments are based on image generation, and we experimentally find that when applying this method to VRAE model for text generation, we need to carefully adjust the value of $\lambda$ and employ the KL cost annealing trick to avoid the KL vanishing problem.

Compared with the model-based methods, the regularizer-based methods are more flexible and scalable. Our approach is also a regularizer-based method which directly injects constraint on the posterior of latent variables. The experimental results demonstrate that the proposed method outperforms several regularizer-based baselines. In addition, our experiments show that the proposed method can be also applied to other model-based methods and improve the performance, such as hybrid-VAE [23].

3 VARIATIONAL RECURRENT AUTOENCODERS

VAE framework is a neural network based method for training generative latent variable models which integrates stochastic latent variables $z$ into the auto-encoder architecture. Let $x$ be an observed variable. Given a set of observed data points $X = \{x^{(1)}, \ldots, x^{(N)}\}$, the goal is to estimate the parameters $\theta$ that maximize the marginal log-likelihood:

$$\log p_{\theta}(X) = \sum_{n=1}^{N} \log \int z \ p(z)p_{\theta}(x^{(n)} | z)dz.$$ 

In general, we assume that the prior distribution $p(z)$ is normal distribution $N(z; 0, I)$. Due to the presence of integral in the marginal log-likelihood, it is intractable to directly compute or differentiate the marginal log-likelihood. A common solution is to optimize the evidence lower bound (ELBO) on the marginal log-likelihood by introducing an approximate posterior distribution $q_{\phi}(z|x)$:

$$\log p_{\theta}(x) \geq \mathbb{E}_{q_{\phi}(z|x)} \left[ \log p_{\theta}(x \mid z) \right] - D_{KL}(q_{\phi}(z \mid x) \parallel p(z)).$$

(1)

Here two neural networks with parameter $\phi$ and $\theta$ are respectively employed for modeling the posterior distribution $q_{\phi}(z \mid x)$ and the conditional distribution $p_{\theta}(x \mid z)$. In general, we assume that $q_{\phi}(z \mid x)$ is multivariate diagonal Gaussian distribution:

$$q_{\phi}(z \mid x) = N(z; \mu_{\phi}(x), \Sigma_{\phi}(x)).$$

where $\mu_{\phi}$ and $\Sigma_{\phi}$ are implemented via neural networks with parameters $\phi$. However, sampling $z$ from $q_{\phi}(z \mid x)$ is a non-continuous operation and has no gradient. The solution is the reparameterization trick which first samples $\epsilon \sim N(0, I)$, and then computes $z = \mu_{\phi}(x) + \Sigma_{\phi}(x)^{1/2} \epsilon$. Through this trick,
the VAE can be trained by stochastic gradient descent with minimizing the objective function:

\[
\mathcal{L}_{vae}(X; \phi, \theta) = \mathcal{L}_{recon} + \mathcal{L}_{KL} \\
= - \sum_{n=1}^{N} \mathbb{E}_{q_{\phi}(z|x^{(n)})} \left[ \log p_{\theta}(x^{(n)}|z) \right] \\
+ \sum_{n=1}^{N} \mathcal{D}_{KL}(q_{\phi}(z|x^{(n)}) \parallel p(z)).
\]

From this equation, the VAE can be interpreted as a regularized auto-encoder that the \( q_{\phi}(z|x) \) is the encoder while \( p_{\theta}(x|z) \) is the decoder. This perspective provides an intuitive explanation of why VAE works. The reconstruction term \( \mathcal{L}_{recon} \) makes VAE learn to reconstruct the input, meanwhile the KL term \( \mathcal{L}_{KL} \) encourages \( q_{\phi}(z|x) \) to match the prior \( p(z) \). Finally, the VAE can generate plausible samples from \( p(z) \). VRAE shares the same architecture of the VAE, but autoregressive model is employed for the posterior distribution \( p_{\theta}(x|z) \) (see Figure 1). Autoregressive models, such as RNNs, omit the independent assumption and predict the data with history information, which can fit arbitrary distribution in theory.

4 \( \mu \)-FORCING APPROACH

We firstly analyze the relation between the reconstruction term and the KL term in \( \mathcal{L}_{vae} \) from the perspective of mutual information. Let us rewrite the mutual information of \( x \) and \( z \):

\[
I(x, z) = \mathbb{E}_{p(x, z)} [\log p(x, z) - \log p(x)p(z)] \\
= \mathbb{E}_{p(x)} [\mathcal{D}_{KL}(p(z|x) \parallel p(z))].
\]

We can see that the KL term estimates the mutual information \( I(x, z) \) by empirical data distribution \( p(x) \) and approximate posterior distribution \( q_{\phi}(z|x) \). From this perspective, the KL term indicates how much information the VAE stores in the latent variables and minimizing it is going to penalize the \( I(x, z) \). While minimizing the reconstruction term amounts to maximizing a lower bound on the mutual information \( I(x, z) \), as discussed by [27]. Therefore, there is an adversarial relationship between these two terms in the process of optimization. Virtually the modeling power of VAE completely benefits from this competition. It makes VAE learn a dense and meaningful latent representation. However, the architecture of VRAE makes it prone to break the balance of the competition and causes the uninformative variables issue to be more serious.
As Figure 1 shows, the reconstruction information of VRAE comes from two parts: the encoder and the ground truth inputs of the decoder. At the early stage of training, the encoder is poorly trained. It makes the decoder tend to depend on the ground truth inputs for reconstruction, which in turn causes the encoder cannot gain sufficient reconstruction error signals against the KL term during optimizing. As a result, the tension between the reconstruction term and KL term is vanishing during optimizing. As a result, the tension between the reconstruction term and KL term is vanishing in turn causes the encoder cannot gain sufficient reconstruction error signals against the KL term which makes each

The KL term $L_{KL}$ is the KL-divergence between two multivariate Gaussian distributions which can be computed in closed form:

$$L_{KL} = \frac{1}{2}(\text{tr}(\Sigma_\phi) + \mu_\phi^T \mu_\phi + \log \det(\Sigma_\phi) - K),$$

where $K$ is the dimensionality of the distribution. This equation has an unique global minima 0 at $\mu_\phi = 0$ and $\Sigma_\phi = I$. Directly optimizing it causes the $\mu_\phi$ of all data points to collapse to 0 and the $\Sigma_\phi$ to close to $I$. This is what indeed happen in practice that the latent representation $q(z|x)$ of every data point $x$ degrades to the same $N(0, I)$ and the model encodes meaningless information into the latent variables. For the decoder part, when $I(x, z) = 0$, thus $p(x|z) = p(x)$ and the reconstruction term is equivalent to the negative log-likelihood. As a whole, the $L_{KL} = 0$ is a trivial solution which learns meaningless latent variables.

As discussed above, the log-likelihood may not guide the model towards meaningful latent representations. A straightforward approach to address this issue is to inject extra constraints on the posteriors of latent variables into the learning process of VRAE. For reasonable latent representations, different data points $x$ should have different latent representations. Inspired by this intuition, we introduce an additional constraint on the $\mu_\phi$ of $q_\phi(z|x)$ that forces the VRAE to exploit its modeling power and to learn discriminated latent representations.

Specifically, we propose a margin-based additional cost computed from a batch of data points. For simplicity, we use $\mu$ to denote the vector $\mu_\phi$, the additional cost is as follows:

$$L_\mu = \max \left\{ 0, \beta - \frac{1}{2N} \sum_{n=1}^{N} (\mu^{(n)} - \bar{\mu})^T (\mu^{(n)} - \bar{\mu}) \right\}.$$  

Here $\beta$ is a margin, $N$ is the batch size, $n$ denotes the $n$-th sample of a batch, $\mu^{(n)}$ denotes the $\mu$ vector of the $n$-th sample, and $\bar{\mu}$ is the mean of the $\mu$ vectors in this batch. This cost forces the sample variance of $\mu$ to be controlled on the level of $\beta$ which maintains the mutual information of $x$ and $z$. Intuitively, the proposed $L_\mu$ term can prevent the KL term from closing the connection between the encoder and the decoder.

Theoretically, we analyze the effect of $L_\mu$. Given a batch data, when the variance of $\mu$ is less than the threshold value $\beta$ (the $\mu$ vectors of each data are very close to each other), the $\nabla_\mu L_\mu \approx -\mu + \bar{\mu}$, and the $\nabla_\mu L_{KL} = \mu$. After the introduction of $L_\mu$, $\nabla_\mu (L_\mu + L_{KL}) \approx \bar{\mu}$. We can see that for the entire dataset, the mean of vector $\mu$ will still tend to zero under the influence of the new cost function $L_\mu$, which guarantees the properties of VAE. Furthermore, for each individual data $x$, its $\mu$ will no longer independently converge to 0. The gradient $\nabla_\mu (L_\mu + L_{KL})$ will adaptively change dynamically. As $\bar{\mu}$ gets closer to zero vector, the gradient $\nabla_\mu (L_\mu + L_{KL})$ becomes smaller and smaller. This makes each $\mu$ no longer close to each other and overlaps to the same point, ensuring the diversity of $\mu$. Therefore, $\mu$ can provide meaningful information for the decoder. The final cost function is:

In theory, the batch size should be as large as possible. In practice, we found that when the batch size was 64, 128 and 256, the model performed well.
\[ L(X; \phi, \theta) = L_{\text{recon}} + L_{\text{KL}} + L_{\mu}. \]

As discussed above, this new cost function \( L \) can control the trade-off between KL term and reconstruction term that prevents the model collapsing to the trivial solution. It puts no limits on the expressive power of the autoregressive model, and guide the model to learn more expressive latent variables.

5 EXPERIMENTS

The experiments revolve around the following questions: **Q1:** Whether the proposed method can effectively solve the uninformative latent variables problem of VRAE? **Q2:** How does the parameter \( \beta \) affect the model? Can this proposed method work well without using other strategy, such as KL annealing? **Q3:** How does the proposed method compare with existing state-of-the-art ones? **Q4:** In addition to sentence generation, the VRAE is mainly used to learn smooth and interpretable latent variables for sentence representation. Can the proposed method help the model learn interpretable latent variables?

5.1 Datasets

In the experiments, we used two medium-sized corpus. The first one is the Amazon Product Reviews Corpus (APRC) [7] which is built upon Amazon product data [19]. This dataset contains 937,033 reviews and every review is paired with attributes. Here we ignored these attributes and only used the review part to train the model. We set the vocabulary size to 10K. The second dataset is Chinese Online-Shopping Reviews Corpus (COSR). We manually crawled Chinese online-shopping reviews from the internet. After cleaning the data and word segmentation, the reviews whose lengths are greater than 40 words are filtered. We finally obtained 584,475 reviews including positive, negative and neutral reviews.\(^3\) After processing low-frequency words, the vocabulary size is 9191. These two datasets are both randomly split into train/valid/test sets following these ratios respectively: 85\%, 5\%, 10\%.

5.2 Comparison with VRAE (Q1)

**Setup.** To answer the first question, we tested the proposed method on COSR and APRC datasets respectively. The VRAE model trained with KL annealing strategy is taken as the baseline [3] for comparison. We compared the proposed method and baseline with the same architecture, and the only difference is the proposed method was trained with an additional cost \( L_{\mu} \). We used a bidirectional LSTM with 1024 hidden units for the encoder and a single layered LSTM with 1024 hidden units for the decoder. The dimension of word embeddings was set to 512 while the latent variables was set to 16. The batch size, threshold of element-wise gradient clipping and initial learning rate of Adam optimizer [15] were set to 64, 5.0 and 0.001. We also made use of Layer Normalization [2] to make the training more easier. The hyperparameter \( \beta \) of the proposed method was set to 2.

**Results.** We report the training curve of KL loss \( L_{\text{KL}} \), reconstruction loss \( L_{\text{recon}} \), and the value distribution of vector \( \mu \) on the test set of two datasets. The results are presented in Figure 2. The first two lines present the results on COSR test set while the last two lines present the results on APRC test set.

From the Figure 2(a) and 2(e), we can see that the proposed method helps the model to achieve non-zero KL cost. However, even trained with KL annealing, the KL cost of the baseline still close

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\(^3\)In order to make our results easy to reproduce, we will release all the datasets and codes upon acceptance of the paper.

\(^4\)In the figure, we plot the negative loglikelihood (NLL) results, which averaged the reconstruction loss by length.
Fig. 2. The subfigure 2(a)-2(d) presents the results on COSR test set while the subfigure 2(e)-2(h) presents the results on APRC test set. The subfigure 2(a) and 2(e) shows the KL loss of μ-Forcing and baseline on the test set. The subfigure 2(b) and 2(f) shows the reconstruction loss (NLL) of μ-Forcing and baseline on the test set. The distribution of μ values of baseline on the test set are shown in the subfigure 2(c) and 2(g). While the distribution of μ values of μ-Forcing on the test set are shown in subfigure 2(d) and 2(h) [best viewed in color].

To zero on both test sets. As the KL term annealed, we can find that the reconstruction errors
on the two test sets of baseline become higher and higher from Figure 2(b) and 2(f). Finally, the reconstruction errors of baseline are much higher than the proposed method. Furthermore, we counted the distribution of $\mu$ values on test sets. From the Figure 2(c), 2(d), 2(g) and 2(h), it can be seen that most of $\mu$ values of baseline collapse to zero while the proposed method doesn’t.

For the baseline, the results show that even trained with KL annealing, the VRAE still suffers from the uninformative latent variables problem on both datasets, result in high reconstruction errors and KL cost close to zero on test sets. The $\mu$ values of every data point $x$ of the baseline degrade to zero which cannot provide meaningful information. To make sure that this effect is not caused by optimization difficulties or the configuration of the model, we also searched the different hyperparameters but got the same results on both datasets.

For the proposed method, it helps the model to achieve non-zero KL term and results in lower reconstruction errors. This shows that the decoder of the proposed method utilizes the reconstruction information not only from the ground truth inputs, but also the latent variables. Otherwise, even though the proposed method holds the KL-term, the reconstruction error should be consistent with the baseline. In addition, the $\mu$ values of the proposed method are zero-centered and diverse that is what we want. It demonstrates that the proposed method can successfully solve the uninformative latent variables problem. By sampling $z$ from $\mathcal{N}(0, I)$, the baseline only generated repeating sentences while the proposed method can generate diverse meaningful sentences. We show some generated examples in the Figure 3 and 4.

| Example from baseline model | Example from proposed model |
|-----------------------------|-----------------------------|
| i loved this book. it was a great read. i could n’t put it down. i ca n’t wait to read the next one. | i loved this book. it was a great read. i could n’t put it down. i ca n’t wait to read the next one. |
| i loved this book. it was a great read. i could n’t put it down. i ca n’t wait to read the next one. | i loved this book. it was a great read. i could n’t put it down. i ca n’t wait to read the next one. |
| i loved this book. it was a great read. i ca n’t wait to read the next book in the series. | i loved this book. it was a great read. i ca n’t wait to read the rest of the books in this series. |
| i loved this book. it was a great read. i ca n’t wait to read the next book in the series. | i loved this book. it was a great read. i ca n’t wait to read the next book in the series. |

Fig. 3. Examples of randomly generated by the baseline model (top section) and the proposed model (bottom), both models were trained on the APRC dataset.

It is worth noting that [3] propose the word dropout trick to train the VRAE. We also used the word dropout trick in our experiment, but we found that it did not mitigate the KL vanishing issue. The same phenomenon has been mentioned in [29] and [14]. In addition, as discussed by [23], the word dropout tends to slow down convergence. It is not a stable and always effective trick. In our experiments, we also follow [1] to set the weight of KL cost $\lambda$ (KL penalty term) of the baseline model to less than one, for example, 0.1 or 0.3. However, with this trick, most of the time we still...
encounter the KL vanishing problem. We can mitigate it only by carefully adjusting the parameter values of $\lambda$ and KL annealing. We found that neither of them can guarantee a stable and effective solution to uninformative latent variables issue, but our method can easily solve the uninformative latent variables problem.

5.3 The Effect of $\beta$ (Q2)

For the second question, we focus on the effect of hyperparameter $\beta$. Based on the setup of the first experiment, we tested the proposed method on COSR dataset with $\beta$ set to 2, 3, 5, and 10, respectively. The Figure 5 presents the results. As the size of $\beta$ increases, the convergency value of KL term increases while the reconstruction error decreases accordingly. These results show that the $\beta$ can flexibly control the balance between KL term and reconstruction error, and maintain tension between them. There is an important open question: what is a “reasonable” value of KL term [13]? Ideally it should be small but non-zero. Although we didn’t directly answer this question, the proposed method can control the KL term to the desired value by changing the $\beta$, which provides a feasible approach to explore this question. Note that when $\beta = 0$, the model degenerates into the
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![Graphs showing KL loss and reconstruction loss](image)

(a) KL loss without KL annealing on COSR dataset
(b) Reconstruction loss without KL annealing on COSR dataset

Fig. 6. The KL loss and reconstruction loss of µ-Forcing trained with and without KL annealing strategy on COSR [best viewed in color].

baseline. While $\beta$ is too large (such as 100), it destroys the model structure and results in high KL loss and reconstruction error. We found that the model performs well in both reconstruction and generation with $\beta$ set to 2 or 3.

We also tested the performance of the proposed method without using the KL annealing training strategy. Based on the setup of the first experiment, we trained the model with the proposed method but without KL annealing on COSR dataset. The Figure 6 reports the results. In this setting, the proposed method can still hold the value of KL term, and its reconstruction error is lower than baseline on the test set. In addition, we can see that the convergency value of KL term and reconstruction error of using and not using KL annealing strategy are very close. We observed the same phenomenon with various $\beta$ on different datasets. This results indicate that KL annealing training strategy is not required when training with the proposed method.

5.4 Comparison with Strong Baseline (Q3)

To further evaluate the proposed method and answer the question Q3 (How does the proposed method compare with existing state-of-the-art ones?), we firstly compared our method (µ-Forcing) with several regularized-based baselines: (1) KL annealing (VRAE + KLA) [3]. (2) VRAE with free bits (VRAE+FB). This method reserves some space of KL divergence for every dimension of latent variables [16]. We set the reserved space for every dimension as 0.0125 in free bits (FB). (3) VRAE+FB-all. This method is similar to VRAE+FB, which reserves space for the total KL divergence instead of for every dimension [29]. We try reserving 0.2 bits for the whole dimension space. (4) VRAE with bag-of-words loss (VRAE + BOW) [33]. (5) VRAE with bag-of-words loss and KL annealing (VRAE + BOW + KLA) [3, 33]. In order to show the $\beta$ of the proposed method can flexibly control the balance between KL term and reconstruction error, we also compared the proposed method with various $\beta$ (varied from 1.5 to 3.0). In addition, we also compared the vanilla VRAE. We conducted the same word-level language modeling task on APRC dataset using VRAE. All methods use the same VRAE architecture, and the VRAE + BOW (+KLA) incorporates an additional MLP to predict the BOW\(^5\). For KLA, we initialize the weight with 0 and gradually increase to 1 in the first 10000 training steps.

As with [3, 33], we report the reconstruction loss (the lower is better) and KL loss on the test set. To further evaluate the generation quality, as with the evaluation in [31, 34], we use BLEU score (the higher is better) to measure the similarity degree between the generated sentences and the real sentences. We randomly sample 3,000 sentences from the test set as the references. Moreover, since

\(^5\)The implementation of VRAE + BOW is based on the author’s source code [link]
Table 1. The evaluation results on APRC test set.

| Method          | Rec | KL | BLEU-4 | BLEU-5 | SLEU-4 | SLEU-5 |
|-----------------|-----|----|--------|--------|--------|--------|
| VRAE            | 96.48 | 0.01 | 98.16 | 94.85 | 100.0 | 100.0 |
| VRAE + KLA      | 96.18 | 2.57 | 90.56 | 82.99 | 94.35 | 92.18 |
| VRAE + FB       | 93.65 | 3.10 | 93.40 | 89.38 | 94.98 | 92.97 |
| VRAE + FB-all   | 91.03 | 3.88 | 89.19 | 80.55 | 94.12 | 92.01 |
| VRAE + BOW      | 89.32 | 6.01 | 89.28 | 80.75 | 90.39 | 86.70 |
| VRAE + BOW + KLA| 86.46 | 13.28 | 83.47 | 71.77 | 81.99 | 74.95 |
| $\mu$-Forcing ($\beta = 1.5$) | 86.85 | 12.73 | 90.93 | 82.22 | 90.34 | 86.02 |
| $\mu$-Forcing ($\beta = 2.0$) | 85.44 | 16.76 | 89.09 | 78.70 | 89.01 | 83.80 |
| $\mu$-Forcing ($\beta = 2.5$) | 84.42 | 20.55 | 87.50 | 76.63 | 87.33 | 81.70 |
| $\mu$-Forcing ($\beta = 3.0$) | **83.29** | 25.15 | 84.33 | 71.99 | 85.01 | 78.26 |

the model collapse issue is a typical and classical problem for the VRAE model, we use Self-BLEU (SLEU) score [34] (the lower is better) to evaluate the diversity of the generated sentences (other sentences generated by the model itself are taken as references). We let each model generates 3000 sentences by sampling $z$ from $N(0, I)$ and calculate the average BLEU and SLEU scores (4 gram and 5 gram). The results are shown in Table 1.

From the first two lines of the Table 1, we can see that VRAE suffers from the problem of KL vanishing and serious model collapse issue. Its KL loss is approximate to zero, which means this model has collapsed into a plain language model that totally ignores the latent variable $z$. So it has high reconstruction error. Although its BLEU score is high, its SLEU scores is 100.0, it can only generate repeated sentences which we found are almost copied from the training set. With carefully adjusting the parameter values of KL annealing and free bits, the model VRAE + KLA, VRAE + FB, and VRAE + FB-all have achieved non-zero but still small KL cost. The reconstruction error of them are also very high, which indicates that these models still ignore the latent variable $z$ in most cases. Moreover, the SLEU scores of them are also much higher than other methods.

As for VRAE + BOW and the $\mu$-Forcing method, all of their models solve the problem of uninformative latent variables and achieve low reconstruction error and non-zero KL cost. In addition, we can see that the KLA trick helps the VRAE + BOW achieve lower reconstruction error and higher KL cost which are in line with the results in [33]. Its SLEU scores are lower than those of VRAE + BOW. However, its BLEU scores are lower than VRAE + BOW’s.

For the proposed method, it can be observed that as the size of $\beta$ increases, the KL cost increase while the reconstruction error decrease accordingly. These results demonstrate that the $\beta$ can flexibly control the balance between KL term and reconstruction error. In addition, although the number of parameters in $\mu$-Forcing models are only about 4/5 of the size of the VRAE + BOW based models (the VRAE + BOW incorporates an MLP to predict Bag-of-word loss), all of the $\mu$-Forcing models achieve competitive results compared with VRAE + BOW based models. From the results of generation, it can be seen that the $\mu$-Forcing ($\beta = 1.5$) outperforms the VRAE + BOW model (the BLEU-4 score of $\mu$-Forcing ($\beta = 1.5$) are higher than that of VRAE + BOW, at the same time, the SLEU scores and reconstruction error are lower than those of VRAE + BOW). Furthermore, although the SLEU scores of $\mu$-Forcing ($\beta = 3.0$) are slightly higher than those of VRAE + BOW + KLA, its BLEU scores are higher than those of VRAE + BOW + KLA, and its reconstruction error is also lower than that of VRAE + BOW + KLA. These results show that the proposed method can solve the uninformative latent variables issue and generate high-quality and diverse sentences, which performs significantly better than VRAE + KLA, VRAE + FB and VRAE + FB-all. Furthermore,
Fig. 7. For each round, the human evaluation interface presents two group sentences which are generated by two different methods. Then it asks users to click on the group they think are better or choose "I can not tell which group is better". Each human evaluation contains 50 rounds in total.

without incorporates any additional component, the \( \mu \)-Forcing still achieves very competitive results compared with VRAE + BOW based models.

Secondly, in order to test whether the proposed method can also be applied to other model-based methods to improve performance, we added the proposed \( \mu \)-Forcing regularization term to HybridVAE [23] to compare it (Hybrid + Ours) and the auxiliary reconstruction term used in [23] (Hybrid + Aux). We conducted the same char-level language modeling task on APRC dataset using HybridVAE. To be fair, all settings are based on the same vanilla hybrid model (Hybrid).

We report the reconstruction loss, KL loss on the test set. Similarly, the BLEU and SLEU are also shown in Table 2. From the results, we can see that the vanilla hybrid model suffers from the uninformative latent variables issue, result in high reconstruction error and KL vanishing on the test set. However, both auxiliary reconstruction term and the proposed \( \mu \)-Forcing term \( L_\mu \) can solve this issue. Furthermore, when applied our method to the vanilla hybrid model, it achieves lower reconstruction loss, SLEU scores and higher BLEU scores compare with their full model (Hybrid + Aux). These results indicate that the proposed method can be also applied to HybridVAE and further improve the performance.

Table 2. The evaluation results of different settings on the APRC test set.

| Setting      | Rec  | KL   | BLEU-4 | BLEU-5 | SLEU-4 | SLEU-5 |
|--------------|------|------|--------|--------|--------|--------|
| Hybrid       | 61.97| 0.01 | 93.12  | 86.83  | 100.0  | 100.0  |
| Hybrid + Aux | 56.01| 12.73| 84.28  | 70.11  | 82.18  | 73.16  |
| Hybrid + Ours| 52.22| 14.24| 85.98  | 74.13  | 81.50  | 72.64  |

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\(6\)The implementation of HybridVAE is based on the author’s source code https://github.com/stas-semeniuta/textvae
5.5 Human Evaluation

We conducted some human evaluations to further evaluate the proposed method on APRC task. We compared the \( \mu \)-Forcing with VRAE + BOW + KLA and VRAE + FB-all. All comparisons are blind paired comparisons. Because it is difficult to measure the diversity of models by comparing individual sentences directly, we compared two groups of sentences generated by different models in each round. We let each model to generate 250 sentences by sampling \( z \) from \( \mathcal{N}(0, I) \). For each model, the generated sentences generated were randomly divided into 50 groups, each containing 5 sentences. Then we launch a crowd-sourcing online study asking evaluators to decide which group of sentences is better (more likely to be written by human beings).

We build a user-friendly web-based environment based on Flask\(^7\) for human evaluation. The interface for human interaction is illustrated in Figure 7. For each round, the human evaluation interface presents two group of sentences which are generated by two different methods, then asks evaluators to choose the better one. Ties are permitted. A total of 15 evaluators participate in the evaluation.\(^8\) The results are show in Table 3, and we can see that the proposed model performs best.

| \( \mu \)-Forcing won | VRAE + BOW + KLA won | Tied |
|----------------------|----------------------|------|
| 59%                  | 16%                  | 25%  |

| \( \mu \)-Forcing won | VRAE + FB-all won    | Tied |
|----------------------|----------------------|------|
| 69%                  | 12%                  | 19%  |

Table 3. Human evaluations on APRC.

5.6 Interpretable Latent Variables (Q4)

In this experiments, we aim to answer the question Q4 (In addition to sentence generation, the VRAE is mainly used to learn smooth and interpretable latent variables for sentence representation. Can the proposed method help the model learn interpretable latent variables?). We conducted two experiments to investigate interpretation of the latent variables.

**Homotopy.** We verified that the latent variables capture characteristics of language by homotopy (linear interpolation) [3] in the latent space. Given two sentences, we fed them to the encoder of VRAE and obtained their latent variables \( z_1 \) and \( z_2 \). A homotopy between \( z_1 \) and \( z_2 \) is the set of points \( z_t \) on the line between them:

\[
z_t = z_1 \cdot t + z_2 \cdot (1 - t). \quad t \in [0, 1]
\]

At each step \( t \) of the interpolation, we generate a sentence through the decoder by feeding the latent variables \( z_t \). The results on ARPC are presented in Figure 8. We show these results on COSR in Figure 9. We can see that the proposed method learned dense and interpretable latent representation.

**Sentiment Transformation.** Word embedding [20] can represents words at concept level. Some language patterns are explicitly represented as linear transformations in the embedding space such as: \( \text{king} - \text{man} + \text{woman} \approx \text{queen} \). Similarly to this way, we applied linear transformation to the latent space of the proposed model for sentiment transformation. Given two sentences which are similar in content, but one emotion is positive and the other is negative. The latent variable of positive one is denoted as \( z_p \) while negative one is \( z_q \). Since the only difference between these two sentences is emotion, we regard the vector \( z_q - z_p \) as a negative emotional vector. Let \( z_a \) be a latent

\(^7\)http://flask.pocoo.org/

\(^8\)All evaluators are well educated and have Bachelor or higher degree. They are independent of the authors’ research group.
Fig. 8. The results of linear interpolation in the latent space on APRC dataset. We obtained latent variables $z_1$ of the sentence in the first line and $z_2$ of the sentence in the last line. The rest of the lines report the decoding results of linear interpolation. $t$ is the interpolation parameter. In general, latent variables seem to capture the characteristics of the sentences.

| $t$  | Translation                                                                                      |
|------|--------------------------------------------------------------------------------------------------|
| 0.1  | Garbage, delivery slow to death.                                                                 |
| 0.2  | The delivery is fast but the quality is not good.                                                |
| 0.3  | The logistics are very fast and the things are very great.                                       |
| 0.4  | The delivery is quick, and the goods are good as well as beautiful.                             |
| 0.5  | The delivery is fast and the things are beautiful. I like them very much.                       |
| 0.6  | The delivery is fast, and the goods were received. Very beautiful.                             |
| 0.7  | Fast delivery, and good quality. I sent it to a friend, and she likes it very much.              |
| 0.8  | Very beautiful. The seller services good. The delivery is quick. Good comment.                   |
| 0.9  | Good. Fast delivery and good service. We should give him thumbs up.                            |

Fig. 9. The results of linear interpolation in the latent space on COSR dataset. We obtained latent variables $z_1$ of the sentence in the first line and $z_2$ of the sentence in the last line. The rest of the lines report the decoding results of linear interpolation. $t$ is the interpolation parameter. In general, latent variables seem to capture the characteristics of the sentences.

| $t$  | Translation                                                                                      |
|------|--------------------------------------------------------------------------------------------------|
| 0.1  | 垃圾，发货慢的要死。                                                                           |
| 0.2  | 快递很快，质量不好。                                                                           |
| 0.3  | 速度很快，东西也好。                                                                           |
| 0.4  | 发货很快，东西也很好，漂亮。                                                                   |
| 0.5  | 发货快，东西很漂亮，非常喜欢。                                                                 |
| 0.6  | 发货很快，东西收到了，非常漂亮。                                                               |
| 0.7  | 发货快速，质量不错，送朋友的，她很喜欢。                                                       |
| 0.8  | 非常快，服务质量好，发货快，好评。                                                               |
| 0.9  | 不错哦，快递很快，服务好，赞一个。                                                              |

variable of another sentence, we turn the emotion of the sentence into a negative one by decoding the latent variable $z_b$ which is calculated as follows:

$$z_b = z_a + z_q - z_p.$$
The results on APRC are presented in Figure 11. We also show these results on COSR in Figure 10. We can see that most original sentences were translated into the sentences with similar content but opposite emotions. This results also demonstrate that the model learns interpretable latent variables.

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**Fig. 10.** The results of sentence sentiment transformation on COSR dataset. The first line presents two sentences, and their latent variables are $z_p$ and $z_q$ respectively. The original sentences are shown in the left columns while the sentences that are obtained after the transformation of emotions are shown in the columns on the right.

| $z_p$  | $z_q$    |
|--------|----------|
| 我很喜歡，好評。 | 垃圾！差評。 |
| 風樣看來好，是我喜歡的款式。 | 梦橋小得可怜，騙人的，果然差評，差評。 |
| 好不錯我和老公都很喜歡。 | 东西破玩意，破玩意，一颗星都不想给！ |
| 很不錯，很好。 | 一般。。。 |
| Very good, very good! | It’s just so so. |
| 好漂亮的手鍊，戴著很好看，很喜欢。 | 什么玩意，根本就是贵的，差评，差评！ |
| It’s a beautiful hand chain. I look good on it. I like it very much. | What the hell! It’s actually made of iron. Bad comment! |
| 这个项鍊很不错，做工很精致。 | 塑料的，有一个已经坏了。 |
| This necklace is very nice and its workmanship is very delicate. | They are made of plastic. One of them is already broken. |
| 感觉不错，物流也挺快的。 | 物流太慢了，差评。 |
| It feels good, and the delivery is very fast. | The delivery is too slow. Bad comment. |
| 非常满意，性价比高。 | 什么玩意，不值这个钱。 |
| Very satisfied. It is cost-effective. | What a shoddy thing! It’s not worth the money. |

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**Fig. 11.** The results of sentence sentiment transformation on APRC dataset. The first line presents two sentences, and their latent variables are $z_p$ and $z_q$ respectively. The original sentences are shown in the left columns while the sentences that are obtained after the transformation of emotions are shown in the columns on the right.

| $z_p$  | $z_q$    |
|--------|----------|
| This book is very good. | The book is hard to read. |
| very well written. I would recommend this book to anyone who enjoys a good love story. | very bad, it bored me to death. |
| this was a very good book. | this book is very boring. |
| it was OK i wanted to know what would happen next | bad book, i hate to read it |
| it is one of the best books i have read in a long time. | this was an okay book. i would recommend this book to others. |
| enjoyed this book and can not wait for the next one. | it took too long to get into it but it was a fun read. |
| this book was my favorite book by this author. | it is an OK read. but i do n’t like the author. |
| i liked this book because it had some interesting twists and turns. | i was n’t sure if i would like this book but it was an easy read. i could n’t put it down. |
| i enjoyed this book as much as the first one. | not as good as the first but still a good read. i will look for other books by this author. |
6 CONCLUSIONS

In this paper, we further explore the reason for the uninformative latent variables of VRAE. To address this issue, we propose an effective regularizer based approach. The proposed method introduces a mild constraint on the $\mu$ of $q(z|x)$ to force the model to find a non-trivial solution where the learned latent variables $z$ contain useful information, which can perform well without using other strategies, such as KL annealing. The experiments show that the proposed method outperforms several strong baselines and can flexibly and stably control the trade-off between the KL term and the reconstruction term of VRAE during training, making the model learn interpretable latent variables and generate diverse meaningful sentences.

In future work, we plan to utilize the learned latent representations to improve the semi-supervised learning on NLP tasks, such as text classification and sentiment detection. Also, it would be interesting to apply the proposed method to other VAE based models for image generation.

ACKNOWLEDGMENTS

This work is supported by the National Key R&D Program of China under contract No. 2017YFB1002201, the National Natural Science Fund for Distinguished Young Scholar (Grant No. 61625204), and partially supported by the State Key Program of National Science Foundation of China (Grant Nos. 61836006 and 61432014).

REFERENCES

[1] Alexander Alemi, Ben Poole, Ian Fischer, Joshua Dillon, Rif A Saurous, and Kevin Murphy. 2018. Fixing a broken elbo. In ICML.
[2] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. 2016. Layer normalization. In ICML.
[3] Samuel R Bowman, Luke Vilnis, Oriol Vinyals, Andrew M Dai, Rafal Jozefowicz, and Samy Bengio. 2016. Generating sentences from a continuous space. In CONLL.
[4] Xi Chen, Diederik P Kingma, Tim Salimans, Yan Duan, Prafulla Dhariwal, John Schulman, Ilya Sutskever, and Pieter Abbeel. 2016. Variational lossy autoencoder. In ICML.
[5] Andrew M Dai and Quoc V Le. 2015. Semi-supervised sequence learning. In NIPS.
[6] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet: A large-scale hierarchical image database. In CVPR.
[7] Li Dong, Shaohan Huang, Furu Wei, Mirella Lapata, Ming Zhou, and Ke Xu. 2017. Learning to generate product reviews from attributes. In EACL.
[8] Otto Fabius and Joost R van Amersfoort. 2014. Variational recurrent auto-encoders. arXiv preprint arXiv:1412.6581 (2014).
[9] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In NIPS.
[10] Anirudh Goyal Alias Parth Goyal, Alessandro Sordoni, Marc-Alexandre Côté, Nan Rosemary Ke, and Yoshua Bengio. 2017. Z-forcing: Training stochastic recurrent networks. In NIPS.
[11] Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Jimenez Rezende, and Daan Wierstra. 2015. DRAW: A recurrent neural network for image generation. In ICML.
[12] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation (1997).
[13] Matthew D Hoffman and Matthew J Johnson. 2016. Elbo surgery: yet another way to carve up the variational evidence lower bound. In Workshop in Advances in Approximate Bayesian Inference, NIPS.
[14] Yoon Kim, Sam Wiseman, Andrew C Miller, David Sontag, and Alexander M Rush. 2018. Semi-Amortized Variational Autoencoders. arXiv preprint arXiv:1802.02550 (2018).
[15] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. In ICML.
[16] Diederik P Kingma, Tim Salimans, Rafal Jozefowicz, Xi Chen, Ilya Sutskever, and Max Welling. 2016. Improved variational inference with inverse autoregressive flow. In NIPS.
[17] Diederik P Kingma and Max Welling. 2013. Auto-encoding variational bayes. In ICLR.
[18] Alireza Makhzani, Jonathon Shlens, Navdeep Jaitly, Ian Goodfellow, and Brendan Frey. 2015. Adversarial autoencoders. In ICML.
[19] Julian McAuley, Rahul Pandey, and Jure Leskovec. 2015. Inferring networks of substitutable and complementary products. In SIGKDD.
[20] Tomas Mikolov, Wen-tau Yih, and Geoffrey Zweig. 2013. Linguistic regularities in continuous space word representations. In NAACL.
[21] Danilo Jimenez Rezende and Shakir Mohamed. 2015. Variational inference with normalizing flows. In ICML.
[22] Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. 2014. Stochastic backpropagation and approximate inference in deep generative models. In ICML.
[23] Stanislau Semeniuta, Aliaksei Severyn, and Erhardt Barth. 2017. A hybrid convolutional variational autoencoder for text generation. In EMNLP.
[24] Xiaoyu Shen, Hui Su, Shuzi Niu, and Vera Demberg. 2018. Improving variational encoder-decoders in dialogue generation. In AAAI.
[25] Casper Kaae Sønderby, Tapani Raiko, Lars Maaløe, Søren Kaae Sønderby, and Ole Winther. 2016. Ladder variational autoencoders. In NIPS.
[26] Martin Sundermeyer, Ralf Schlüter, and Hermann Ney. 2012. LSTM neural networks for language modeling. In I N T E R S P E E C H.
[27] Pascal Vincent, Hugo Larochelle, Isabelle Lajoie, Yoshua Bengio, and Pierre-Antoine Manzagol. 2010. Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. Journal of Machine Learning Research (2010).
[28] Xinchen Yan, Jimei Yang, Kihyuk Sohn, and Honglak Lee. 2016. Attribute2image: Conditional image generation from visual attributes. In ECCV.
[29] Zichao Yang, Zhiting Hu, Ruslan Salakhutdinov, and Taylor Berg-Kirkpatrick. 2017. Improved variational autoencoders for text modeling using dilated convolutions. In ICML.
[30] Serena Yeung, Anitha Kannan, Yann Dauphin, and Li Fei-Fei. 2017. Tackling over-pruning in variational autoencoders. arXiv preprint arXiv:1706.03643 (2017).
[31] Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient. In AAAI.
[32] Shengjia Zhao, Jiaming Song, and Stefano Ermon. 2017. Infovae: Information maximizing variational autoencoders. arXiv preprint arXiv:1706.02262 (2017).
[33] Tiancheng Zhao, Ran Zhao, and Maxine Eskenazi. 2017. Learning discourse-level diversity for neural dialog models using conditional variational autoencoders. In ACL.
[34] Yaoming Zhu, Sidi Lu, Lei Zheng, Jiaxian Guo, Weinan Zhang, Jun Wang, and Yong Yu. 2018. Texygen: A Benchmarking Platform for Text Generation Models. In SIGIR.