Improve Diverse Text Generation by Self Labeling
Conditional Variational Auto Encoder
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Abstract
Diversity plays a vital role in many text generating applications. In recent years, Conditional Variational Auto Encoders (CVAE) have shown promising performances for this task. However, they often encounter the so called KL-Vanishing problem. Previous works mitigated such problem by heuristic methods such as strengthening the encoder or weakening the decoder while optimizing the CVAE objective function. Nevertheless, the optimizing direction of these methods are implicit and it is hard to find an appropriate degree to which these methods should be applied. In this paper, we propose an explicit optimizing objective to complement the CVAE to directly pull away from KL-vanishing. In fact, this objective term guides the encoder towards the “best encoder” of the decoder to enhance the expressiveness. A labeling network is introduced to estimate the “best encoder”. It provides a continuous label in the latent space of CVAE to help build a close connection between latent variables and targets. The whole proposed method is named Self Labeling CVAE (SLCVAE). To accelerate the research of diverse text generation, we also propose a large native one-to-many dataset. Extensive experiments are conducted on two tasks, which show that our method largely improves the generating diversity while achieving comparable accuracy compared with state-of-art algorithms.

Introduction
Text generating techniques are widely used in various tasks, such as dialogue generation (Serban et al. 2016; Li et al. 2016b; Zhao, Zhao, and Eskenazi 2017), image caption (Chen and Lawrence Zitnick 2015; Vinyals et al. 2015; Xu et al. 2015) and question-answer systems (Beamon, Whitley, and Yates 2017; Oh et al. 2017), etc. Recently, encoder-decoder models such as SEQ2SEQ(Sutskever, Vinyals, and Le 2014) have been increasingly adopted in text generating tasks. Encoder-decoder models extract a semantic representation from the input and generate sentences coherent to the input according to this representation. They perform well in tasks which require accuracy and relativity. However, applications such as dialogue systems further require results with diversity besides accuracy. Conventional encoder-decoder models are not good at handling such situations due to its deterministic nature.

In open domain conversation systems, given the dialogue history, there may exist various kinds of responses which are grammatically correct and semantically meaningful. The dialogue bots should be able to model these multiple responses for the same input in training and give diverse answers like humans in predicting. Another application takes place in e-commerce recommendation systems. For a given item, multiple selling points and descriptions are needed for personalized recommendations. Fig. 1 shows an example. With plenty of recommendation texts, different sentences can be selected to display to different users to meet their preferences or to the same user at various situations so that he/she does not feel monotonous.

We summarize the above applications as the “one source, multiple targets” problems. As conventional encoder-decoder models encode same input patterns to same unique representative vectors without any variation, their ability of generating different sentences from one input are limited.

Researchers have made efforts to improve the encoder-decoder models for more diverse generations. In the early periods, methods are proposed to interfere the inference stage of a well-trained encoder-decoder model to encourage abundant outputs (Li et al. 2016a; Vijayakumar et al. 2016). The drawback of such methods is that they do not optimize the encoder-decoder models to fit multi-target data and the quality of their generating results is limited by the trade-off between accuracy and diversity. Recently, variational encoder-decoders have shown great potentials in solving the “one source, multiple targets” problems (Bowman et al. 2016; Zhao, Zhao, and Eskenazi 2017; Shen et al. 2018). These methods introduced an intermediate latent variable and assume that each configuration of the latent variable corresponds to a feasible response. Thus diverse responses can be generated by sampling the variable. However, both VAE and CVAE have encountered the KL-vanishing problem that the decoder tends to model the targets without making use of the latent variables.

In this paper, we point out that during optimizing the objective of CVAE, the encoder is gradually pulled to a prior distribution and losing discriminative ability of the targets, while the decoder tends to fit the data even without the help of encoders. Thus KL-vanishing is rooted in the objective of CVAE. Current approaches, either weakening the decoder or strengthening the encoder to make compensation to the objective implicitly in advance, only mitigate this problem and are hard to determine how weak/strong should decoder/encoder be. Orthogonal to these efforts, we propose an explicit optimization objective for the encoder to move towards better expressiveness to fit current decoder. With this novel objective, the latent variable distribution from the encoder has the potential to be appropriately flexible in cor-

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response with decoder, which naturally coordinates the representative abilities of the encoder and decoder and enhances the utilization of latent variable by decoders. Specifically, an additional module called “labeling network” is used to estimate the “best encoder” for the current decoder. Then a loss which measures the difference between the latent variable of CVAE and predicted variable from labeling network is added to the original objective function of the CVAE. Since this loss pulls the encoder towards the “best encoder” approximated by the labeling network and in the meanwhile original CVAE pulls encoder to the prior, an equilibrium will be reached where KL-vanishing can be avoided. Additionally, the labeling network introduces a continuous label for each target, which essentially reflects the structural constraints of the latent space. Therefore, it guarantees each \( z \) in the latent space corresponds to a unique target, thus improves the coverage of the generations in target space. We alternatively train the “labeling network” and the CVAE structure, and call this model Self Labeling Conditional Variational Auto Encoder (SLCVAE).

In summary, our main contributions are: Firstly, we point out that the current CVAE objective function tends to encounter the KL-Vanishing problem due to the lack of explicit constraints on the connection between the latent variable and targets. Secondly, we propose the self-labeling mechanism which connects the decoder with latent variable by a novel explicit optimization objective. With this objective, the encoder is pulled towards the “best encoder” defined by current decoder and the prior distribution simultaneously, which leads to equilibrium at which the encoder distribution is close to the prior and also remains the expressiveness. Thus the KL-vanishing problem can be significantly relieved. Further, extensive experiments demonstrate that our method called SLCVAE owns better ability to model multiple targets and improves the diversity of text generation without losing accuracy. Thirdly, a large scale dataset called EGOODS, which contains native one-to-many text data of high quality, is constructed to accelerate the research of diverse text generation.

**Related Work**

In this section, we review the development of both the encoder-decoder models and VAE/CVAE based models for text generation.

**Encoder-decoder model**

Encoder-decoder models are commonly adopted in NLP as they are able to fit complex data by end-to-end training. The presentation of SEQ2SEQ (Sutskever, Vinyals, and Le 2014) structure revolutionarily augmented the quality of Machine Translation (MT). And researchers soon introduce such structure into text generating systems (Serban et al. 2016; Vinyals and Le 2015). However, the purpose of the SEQ2SEQ models is to best fit the target sequence given the source sequence. Therefore, two problems might probably happen when a SEQ2SEQ model is used for generating texts. One is that SEQ2SEQ often ends up with dull and generic responses. Such situation often takes place at conversation systems because safe and meaningless responses such as “I don’t know” or “I’m okay” have frequently appearance and then captured by the decoder. The other is the lack of ability of fitting multiple probable outputs, for which the representative vector the decoder used to generate output is fixed and only depends on the inputs. These problems not only reduce the precision, but also limit the diversity of text generation.

To tackle the above problems, different ways of solutions have been proposed. (Li et al. 2016a) pointed out that the mutual information of sources and targets should be augmented during the decoding procedure. They proposed the MMI-antiLM algorithm which adds a language model penalty to unconditional high frequent responses. Their algorithm successfully solved the generic and dull response problem, but it is not applicable to handle the multi-target, since it just consider one target at a time. Beam Search (BS) methods for n-best outputs during the decoding procedure are commonly used in MT and could be introduced to text generation. However, as the greedy strategy in BS makes it tend to generate outputs with same prefixes, sentences generated respectively to one source still look similar. (Vijayakumar et al. 2016) modifies the strategy used in BS to be subject to a diverse behavior goal by reinforcement learning. However such method might reduce the coherence of the outputs. The above methods are based on improved strategies during the inference stage of a encoder-decoder model. But the encoder-decoder model itself is not substantially made better. Their strategies are actually a trade-off between diversity and coherence and thus are restricted.

Additional information could still be used such as topics, speakers’ characteristics in a dialogue session or linguistic prior knowledges. These methods, however, are not applicable for common as extra inputs are required for their unique applications.

**VAE and CVAE**

Variational Auto Encoder (Rezende, Mohamed, and Wierstra 2014; Kingma and Welling 2013) is a popular generative model. It makes use of a latent variable \( z \) sampled from a prior distribution to generate data \( x \). The logarithm likelihood of the data \( x \) is optimized by maximizing the evidence lower bound (ELBO):

\[
\log p(x) \geq \mathbb{E}_{q(z|x)}[\log p(x|z)] - KL(q(z|x)||p(z))
\]

while both \( q(z|x) \) and \( p(z|x) \) are parameterized as encoder \( q_\phi(z|x) \) and decoder \( p_\theta(z|x) \). It is obvious that VAE encodes the input \( x \) into a probability distribution rather than a fixed
vector so that different $z$ could be chosen from the distribution to obtain different outputs $x$.

The VAE model could be modified to be conditioned on a certain attribute $c$ such as dialogue contexts to generate outputs given a source pattern. And such modification leads the original VAE to conditional VAE called CVAE (Yan et al. 2016; Sohn, Lee, and Yan 2015). Needless to say, the output of CVAE now depends both on $z$ and $c$ and the ELBO becomes:

$$\log p(x|c) \geq \mathbb{E}_{q(z|x,c)}[\log p(x|z,c)] - KL(q(z|x,c)||p(z|c)) \quad (2)$$

VAE and CVAE seem to show great potential to generate diverse outputs, as the latent variable $z$ from a distribution could be modulated to help model different patterns. Some image generating tasks adopt VAE or CVAE and achieve good generative quality. In spite of this, difficulties are encountered while researchers attempted to generate texts via such structures (Bowman et al. 2016). Directly optimized with Equation 1 or Equation 2 will lead to the KL-Vanishing problem which is also called as the posterior collapse problem. For the VAE model, the encoder $q_0(z|x)$ perfectly fits the prior distribution $p(z)$ while ignores the inputs and the decoder generates outputs without referring to $z$. Same problems take place all conditioned on $c$ while CVAE is used.

(Bowman et al. 2016) presented the KL annealing method (KLA) and word-dropout operation (WD) in VAE training to mitigate the KL-Vanishing problem in their sentence generating system. And (Zhao, Zhao, and Eskenazi 2017) introduced an additional bag-of-word loss which takes the latent variable as input and predicts the words which will appear in the target so that the connection of the latent variable and the outputs are augmented. They applied their bag-of-word loss in a CVAE structure for one-to-many text generation tasks and get excellent results in open domain dialogue generation of discourse-level diversity.

**The Proposed Method**

**Analysis of the KL-Vanishing Problem**

Considering VAE’s objective function Equation. 1, two facts are observed: (1) The second term $KL(q(z|x)||p(z))$ reaches its global minimum of 0 when $q(z|x) = p(z)$. (2) According to Jensen’s Inequality, $E_{p(z)}[\log p(x|z)] \leq \log \sum_z p(x|z)p(z) = \log p(x)$, and the equal sign of the inequation holds when and only when $x$ is independent of $z$. As a consequence, when $x$ and $z$ are independent, the ELBO objective degenerates to original $\log p(x)$ objective under which the decoder learns a plain language model. Thus the encoder $q(z|x) = p(z)$ and decoder $p(x|z) = p(x)$ which fits the dataset as a plain language model constitute a trivial solution of the objective of VAE. At this time, the KL divergence term in ELBO becomes 0, and we call this phenomenon KL-Vanishing.

Although the KL-Vanishing point is a solution of Equation. 1, it is not actually we want. When KL-Vanishing takes place, Equation. 1 degenerates to $\log p(x)$. When the decoder is modeled by an RNN structure for text generation, it easily converges to a average language model of target sentences without regarding to $z$ under the degenerated objective. As a result, $z$ loses its ability of affecting $x$ and the decoder fits the average behavior of all $x$.

Previous works tried to avoid the KL-Vanishing problem by either breaking fact (1) or fact (2). Some of them put efforts into preventing $q(z|x)$ from collapsing to $p(z)$ by slowing down the optimizing procedure of the KL term. Others attempt to force the decoder to depends on the $z$ by weakening the decoder or making encoder more complicated. However, such methods fall into a dilemma: On the one hand, the objective function is optimized to reach its maximal. On the other hand, the optimal point should be avoided to prevent the occurrence of KL-Vanishing. These methods tried to find a good balance between the two contradictory facts.
outputs the variable $z_{label}$ rather than the reparameterized distribution. As the output of the VAE encoder is a distribution $q(z|x)$, we put the expressive constraint on the expectation of the $L_2$ distance $\|z - z_{label}\|^2$ between encoded latent variable and $z_{label}$ over the encoder distribution $q(z|x)$. Thus an expressiveness objective function is defined as follows:

$$\mathcal{L}_{exp} = \mathbb{E}_{q(z|x)}[\|z - z_{label}\|^2]$$  \hspace{1cm} (3)

which is minimized to encourage the encoder to be more expressive. By using $g(x)$ to denote the labeling network i.e. $z_{label} = g(x)$, and adding $\mathcal{L}_{exp}$ as an additional term to the VAE’s objective function, we get the total objective function in following:

$$\mathcal{L}_{SLVAE} = -\mathbb{E}_{q(z|x)}[\log p(x|z)] + KL(q(z|x)||p(z))$$

$$+ \lambda \mathbb{E}_{q(z|x)}[\|z - g(x)\|^2]$$  \hspace{1cm} (4)

From this formulation, we can see that, $q(z|x)$ is not only pulling to $p(z)$ like before, but also pulling to the estimated “best encoder” for the decoder. The hyper-parameter $\lambda$ is used to control the importance of the expressiveness objective. The “best encoder” can expand a comprehensive coverage of the target space through the current decoder. Thus they will reach an equilibrium at which the $p(z|x)$ is close to $p(z)$ and also remains the expressiveness. As we use a labeling network to estimate the most expressive latent label given the decoder and strengthen the connection between the latent $z$ and target $x$ through the decoder itself, we call this method Self Labeling VAE (SLVAE).

When it comes to CVAE, things remain the same except that everything is conditioned on $c$. And the final total objective function is:

$$\mathcal{L}_{SLCVAE} = -\mathbb{E}_{q(z|x,c)}[\log p(x|z,c)] + KL(q(z|x,c)||p(z|c))$$

$$+ \lambda\mathbb{E}_{q(z|x,c)}[\|z - g(x,c)\|^2]$$  \hspace{1cm} (5)

Similarly, we call this model SLCVAE.

At last, learning the labeling network $g(x,c)$ is somewhat straightforward. As we discussed before, $g(x,c)$ should be the “best encoder” for the decoder to recover $x$. Thus we should optimize $g(x,c)$ by maximizing the following objective function:

$$\log p(x|z_{label}, c) = \log p(x|g(x,c), c)$$  \hspace{1cm} (6)

with the decoder fixed. An alternative training schedule of the VAE/CVAE network and the labeling network is applied.

Fig. 2 shows the overview of the whole proposed method. The CVAE part of our structure is a conventional CVAE with reparameterization trick (Kingma and Welling 2013) by introducing a posterior and a prior network as described in (Zhao, Zhao, and Eskenazi 2017) in detail. The structure of the labeling network is similar to the encoder of the CVAE which consists of a target encoder and a context encoder which embed target and source sentences to representative vectors. The only difference is that the labeling encodes its inputs into a fixed $z_{label}$ rather than a distribution.
Algorithm 1 Alternative training procedure of SLCVAE.
We fixed \( m = n = 1 \) in all our experiments to speedup the training.

1: Initialize \( \phi, \theta, \beta, \gamma \) randomly
2: for number of iterations do
3:    for \( m \) steps do
4:        \( c, x \) \( \leftarrow \) sample a mini-batch from dataset
5:        Sample latent \( z \sim q_\phi(z|x,c) \)
6:        Calculate label \( z_{\text{label}} \leftarrow g_\gamma(x,c) \)
7:        Calculate the gradients: \( \nabla_{\phi,\theta,\beta} L_{\text{SLCVAE}} \)
8:        Update CVAE parameters \( \theta, \phi, \beta \) by Adam
9:    end for
10:   for \( n \) steps do
11:        \( c, x \) \( \leftarrow \) sample a mini-batch from dataset
12:       Calculate the gradients: \( \nabla_\gamma L_{\text{label}} \)
13:       Update labeling network parameter \( \gamma \) by Adam
14:   end for
15: end for

Training Process
To optimize Equation 5 and Equation 6, we parameterize all the three modules: the encoder \( q_\phi(z|x,c) \) and decoder \( p_\theta(x|z,c) \) of the CVAE, and the labeling network \( g_\gamma(x,c) \). An alternative training schedule is used with two phases: the CVAE phase and the Labeling phase.

In the CVAE phase, we minimize the loss function of the SLCVAE:

\[
\begin{align*}
\min_{\phi,\theta,\beta} L_{\text{SLCVAE}} &= \min_{\phi,\theta,\beta} \left[ -\mathbb{E}_{q_\phi(z|x,c)} [p_\theta(x|z,c)] \right. \\
& \quad +KL(q_\phi(z|x,c)||p_\beta(z|c)) \\
& \quad +\lambda \mathbb{E}_{q_\phi(z|x,c)} \left[ ||z - g_\gamma(x,c)||^2 \right] 
\end{align*}
\]

(7)

where \( \beta \) are parameters of the prior network. In this phase, the labelling network \( g_\gamma(x,c) \) is fixed to provide a \( z_{\text{label}} \) corresponding to each \( x \).

In the Labeling phase, we minimize the loss function of the labeling network:

\[
\min_\gamma L_{\text{label}} = \min_\gamma \left[ -p_\theta(x|g_\gamma(x,c)) \right]
\]

(8)

The decoder is fixed at this time to get the good expressive label for current decoder.

See Algorithm 1 for the whole training procedure. The Adam(Kingma, Ba, and others 2015) optimizer is adopted to update parameters.

The EGOODS Dataset
The text generating problem defined with “one source, multiple targets” is an active research topic and plays important roles in many tasks. However, there still lacks real one-to-many datasets to improve and evaluate the algorithms for this problem. Most current datasets come from dialogue system are essentially one-to-one corpora. Although there may exist various underlying responses for a certain question, these datasets only contain one answer for each dialogue context due to data source limitations.

To fulfill the gap between the demand and status quo for one-to-many dataset, we collect a large scale item description corpus from a Chinese e-commerce website to construct the native one-to-many dataset. In this corpus, each item has one description provided by their sellers and multiple recommendation sentences written by third-party who is payed to make these sentences more attractive to customers. The descriptions provided by sellers are usually texts stacking many keywords of the item properties. In the contrary, the recommendation sentences are written according to item descriptions but read more smoothly. For the text generation task, we naturally use the seller’s descriptions as the source to generate multiple recommendation sentences mimicking humans. Since this corpus originates from a real business, texts are of high quality and coherent with sources. Thus it gives rise to a very large and native one-to-many dataset, which is called EGOODS.

After simple cleaning and formatting, EGOODS dataset contains 3001140 source and target pairs from 789582 items in total. So each source item description has 3.8 target recommendation sentences on average. The dataset is split into training/validation/testing parts with respect to items, each of which contains 2961317/19536/20287 pairs.

Experiments
Experimental Setups

Datasets Our experiments are conducted on two text generating tasks: open-domain dialogue generation and recommendation sentence generation. We evaluate the performance of our algorithm and compare it with several strong baselines on the two tasks. For the first task, the public dialogue dataset Daily Dialog (DD) (Li et al. 2017) is used. DD dataset is collected from different websites under 10 topics. It contains 13118 multi-turn dialogue sessions in English, and is split into training/validation/testing set of 11118/1000/1000 sessions. The average number of turns per session is 8.85 and the average number of tokens per utterance is 13.85. To avoid too long dialogue contexts, we first split long sessions into multiple short full speaker turns containing no more than 6 utterances with an utterance level sliding window. As a result, the final DD dataset contains 39567/3681/3471 full speaker turns in training/validation/testing set. For each full speaker turn, we use all utterances but the last one as the dialogue context to predict the last one. Need to note that though there may exist various responses for a question, DD dataset essentially only contains one-to-one data. To better model and evaluate the diversity, the newly constructed one-to-many dataset EGOODS is adopted in the second task.

Baselines We compared our SLCVAE to 4 strong baselines: SEQ2SEQ (Sutskever, Vinyals, and Le 2014), MIMI-AntiLM (Li et al. 2016a), CVAE and CVAE with bag-of-word loss (CVAE+BOW) (Zhao, Zhao, and Eskensati 2017). Several training skills, such as KL-annealing(KLA) and word dropout(WD) (Bowman et al. 2016), are used in combination with baselines and our method to improve the performance. All methods are required to generate 10 responses for each given input.
Note that although the SEQ2SEQ model uses deterministic encoding vectors, the widely adopted beam search strategy can be applied during inference procedure to generate 10-best decoding results which corresponds to 10 responses (denoted as SEQ2SEQ-BS). MMI-AntiLM method follows this idea and put MMI prior onto the beam search strategy. We tried different beam size from 10 to 100 and find that beam size set to 10 gives the best result for all dataset. It is worth noting that beam search is applied only to above two methods and will bring unfair advantages due to the exploration of a much larger search space. All other methods including ours use the greedy strategy during decoding to be consistent with previous work. We also tried another simple strategy that adds a random noise drawn from a gaussian distribution to the encoded vector to bring variability to SEQ2SEQ. We denote this method as SEQ2SEQ + noise, and use it as extra baselines with various standard deviations.

Training  The whole structure of SLCVAE is implemented with the famous open source library PyTorch (Paszke et al. 2017). In all experiments, English letters are all transformed to the lower case first. Encoders are bidirectional RNNs (Schuster and Paliwal 1997) with Gated Recurrent Units (GRU) (Chung et al. 2014) and the decoders are unidirectional RNN with GRUs throughout all experiments. All RNNs have two layers. Since EGOODS dataset is much larger than DD, the network capacity increases accordingly. Specifically, for DD and EGOODS dataset respectively, the word embedding sizes are set to 32 and 128, and the hidden dimensions of RNN are also set as the same. In all VAE-based methods, the latent variable dimensions are set to 8 and 16 for two datasets separately. The Adam optimizer with a learning rate of 0.0001 is used to train all models with batch sizes of 64 and 128 for two datasets. Training skills of KLA and WD are also used to get further better performance. We also conduct an annealing strategy that the weight of our labeling error is increased over time synchronously with KLA, as the soft label provided by the labeling network is not that good in the early stages. We tune several hyper-parameters on the validation sets and measure the performances on the test sets for all baselines and our proposed method.

Results
Evaluation Metrics  In “one source, multiple targets” setting, for an input \( c \), given \( N \) hypothesis responses \( h_i \) generated by a model and \( M_c \) reference responses \( r_j \), accuracy and diversity are two sides of the generations we need to concern. Automatic quantitative measures for these purposes are still an open research challenge (Liu et al.; Tong et al. 2018). (Zhao, Zhao, and Eskenazi 2017) proposed BLEU-precision and BLEU-recall metrics for discourse-level accuracy and diversity respectively as following:

\[
\text{precision}(c) = \frac{\sum_{i=1}^{N} \max_{j \in [1,M_c]} d(r_j, h_i)}{N} \\
\text{recall}(c) = \frac{\sum_{j=1}^{M_c} \max_{i \in [1,N]} d(r_j, h_i)}{M_c}
\]  

Figure 4: Example of generated texts. Despite similar coverage for references, SLCVAE has better diversity in vocabulary and expressions.

BLEU-1, BLEU-2 and BLEU-3 are adopted and their average is calculated as the metrics. However, BLEU-recall is defined based on lexical similarity, which might penalize a reasonable but not same prediction. Following (Li et al. 2016a), we also use the number of distinct n-gram to measure the word-level diversity. The distinct is normalized to \([0, 1]\) by dividing the total number of generated tokens. In summary, BLEU-precision is reported as the accuracy measure, and BLEU-recall, distinct-1 and distinct-2 are reported as diversity measures.

We also conduct human evaluations on the EGOODS dataset. 7 human experts are employed to measure the fluency of generated sentences, coherence of each sentence to source and diversity. For fluency and coherence, experts are asked to vote to each sentence. Sentences which yield more than 4 votes are good sentences. The ratio of good sentences is. For diversity, 5 level of diverse scores are introduced. The higher the score, the more diverse the sentence is. The final diversity score of each sentence is the average score of all experts.

Automatic Quantitative Measurement on Daily Dialog
Table 1 shows the evaluation results of all methods on Daily Dialog dataset. Results for SEQ2SEQ-noise with different standard deviations are also listed. Training skills of KLA and WD are used for all CVAE based methods. We can see that our proposed method outperforms all baselines in terms of all the 4 metrics on this task. And it is worth noting that our method obtains much higher diversity measures no matter in discourse-level or word-level than all others. In the meanwhile, the accuracy metrics BLEU-precision of our method remains slightly better than the best baseline. This confirms our insight of the generating process that our labeling objective can lead to an equilibrium at which the KL-vanishing problem is significantly relieved and so result in better diversity. Remind that Daily Dialog is actually a one-to-one dataset. The better performance in diversity on DD.
Table 1: Results on Daily Dialog (DD). The bottom 3 lines are CVAE based methods.

| Methods          | BLEU-prec | BLEU-recall | distinct-1 | distinct-2 |
|------------------|-----------|-------------|-------------|-------------|
| SEQ2SEQ+BS       | 0.164     | 0.282       | 0.002       | 0.007       |
| SEQ2SEQ+noise(0.2) | 0.163     | 0.288       | 0.003       | 0.014       |
| SEQ2SEQ+noise(0.5) | 0.157     | 0.312       | 0.005       | 0.032       |
| SEQ2SEQ+noise(0.8) | 0.153     | 0.320       | 0.007       | 0.065       |
| MMI-AntiLM       | 0.153     | 0.275       | 0.002       | 0.012       |
| KLA+WD           | 0.212     | 0.345       | 0.010       | 0.041       |
| KLA+WD+BOW       | 0.210     | 0.344       | 0.013       | 0.066       |
| KLA+WD+SL        | 0.214     | 0.354       | 0.014       | 0.078       |

Table 2: Results on EGOODS. The bottom 3 lines are CVAE based methods.

| Methods          | BLEU-prec | BLEU-recall | distinct-1 | distinct-2 |
|------------------|-----------|-------------|-------------|-------------|
| SEQ2SEQ+BS       | 0.379     | 0.388       | 0.0012      | 0.0042      |
| SEQ2SEQ+noise(0.2) | 0.379     | 0.386       | 0.0021      | 0.0146      |
| SEQ2SEQ+noise(0.5) | 0.367     | 0.402       | 0.0029      | 0.0162      |
| SEQ2SEQ+noise(0.8) | 0.347     | 0.395       | 0.0030      | 0.0420      |
| MMI-AntiLM       | 0.356     | 0.374       | 0.0021      | 0.0146      |
| KLA+WD           | 0.373     | 0.405       | 0.0039      | 0.0216      |
| KLA+WD+BOW       | 0.374     | 0.404       | 0.0039      | 0.0231      |
| KLA+WD+SL        | 0.373     | 0.405       | 0.0049      | 0.0270      |

Table 3: Human evaluation results.

| Methods          | Fluency(%) | Coherence(%) | Diversity |
|------------------|------------|--------------|-----------|
| SEQ2SEQ+BS       | 96         | 65           | 1.55      |
| KLA+WD           | 87         | 64           | 3.12      |
| KLA+WD+BOW       | 83         | 66           | 3.18      |
| KLA+WD+SL        | 91         | 66           | 3.32      |

demonstrates that our model can better exploit such training data without explicit one-to-many annotations. Further, the results show that CVAE based models beat conventional encoder-decoder methods in almost all metrics. This is consistent with those in previous work like Zhao, Zhao, and Eskenazi (2017), and confirms the advantage of latent variable methods for generation tasks over encoder-decoder models with multi-decoding strategy. In addition, we find that with growing noise, the accuracy of SEQ2SEQ+noise decreases while the diversity increases significantly. Especially when the noise is small (e.g. 0.2), the diversity has obvious gains with only a slightly sacrifice on accuracy.

Automatic Quantitative Measurement on EGOODS To better study current methods on the “one source, multiple targets” problem, experiments are conducted on our newly collected native one-to-many dataset EGOODS. Performances of different methods are shown in Table 2. First of all, our method achieves comparable accuracy with baselines and best diversity among all methods with an only exception of SEQ2SEQ+noise(0.8) on distinct-2. This demonstrates the effectiveness of SLCVAE on the one-to-many data. Although SEQ2SEQ+noise(0.8) gets the best distinct-2, its precision is sacrificed significantly due to the noise, which means the results tend to be meaningless. In detail, our method harvests the much better gains on word-level diversity while is only slightly better than CVAE on BLEU-recall. We explain this in two folds: First, strong baselines can benefit from the large scale and one-to-many nature of EGOODS to better fit the multiple targets. Another reason is that automatically evaluating the quality of generated texts is very challenging. BLEU-recall only measures the coverage of hypothesis for the annotated targets, and could not judge good algorithms precisely when the annotations are limited. In such situation, distinct measures the vocabulary a model actually uses and demonstrates its absolute lexical diversity. Example results will show this in next subsection.

Furthermore, we observed that SEQ2SEQ+BS obtains the best BLEU-precision among all methods on EGOODS, but it performs much worse on Daily Dialog. Meanwhile, the BLEU-recall gap between SEQ2SEQ+BS and the best result on EGOODS is obviously small than that on DD. We point out that our dataset especially designed for “one source, multiple targets” problem significantly improves the generation quality of SEQ2SEQ methods.

Human Evaluation on EGOODS Human evaluation results on EGOODS are shown in Table 3. Such results show that our method achieves comparable fluency and coherence as baseline methods, but our diversity is much higher than other models. Although the SEQ2SEQ+BS method achieves the best fluency, it sacrifices too much diversity, which means the result is monotonous and dull.

Text Generating Examples To give an intuitive impression about generations, Fig. 4 shows an example of generated texts for EGOODS, and more results can be found in the supplementary material. 10 results are generated separately by SEQ2SEQ+BS, CVAE and our method SLCVAE. The results from three methods are of good fluency and coherent to the input. But obviously SEQ2SEQ+BS fails to show different expressions thus gets poor diversity. Both CVAE model and our method tend to show stronger abilities in generating diversely than SEQ2SEQ+BS, since we can see that the generated results have better coverages for the references. Nevertheless, notice that the SLCVAE has a larger vocabulary and uses richer expressions that CAVE+BOW which is not reflected by BLEU-recall metrics. This finding is consistent with the quantitative experiment results we have discussed above.

Conclusion “One source, multiple targets” is a common text generation task. Recently CVAE based methods shows great potentials for this task. However CVAE working with RNNs tends to run into the KL-vanishing problem that the RNN ends up with a trivial language model independent of the latent variable. In this paper, we analyze the objective of CVAE and give an intuitive explanation of the cause of KL-vanishing.
Then we propose the self labeling mechanism which connects the decoder with latent variable by an explicit optimization objective. It leads the encoder to reach an equilibrium at which the decoder can take full advantage of the latent variable. Experiments show that SLCA VE largely improves the generating diversity.

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Improve Diverse Text Generation by Self Labeled Conditional Variational Auto Encoder

Supplemental Materials
| Input | SLCVEAE | CVAE + KLA + WD | Seq2seq + BS | Reference |
|-------|---------|----------------|-------------|-----------|
| 秋季 | 经典条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 经典的条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 青春 | 经典条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 经典的条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 女装 | 经典条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 经典的条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 休闲 | 经典条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 经典的条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 桑蚕 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 修身 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 一字领 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| T恤 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 2018年 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 新款 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针设计，感受女人味儿足。 | 面料柔软细腻，为肌肤带来呵护，视觉效果的版型，打造出完美身材。 |
| 靴子 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 |
| 半身裙 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 | 网格拼接，打破单调，亮眼吸睛。 |
| 女装 | 网格拼接的元素，飘逸灵动。 | 网格拼接的元素，飘逸灵动。 | 网格拼接的元素，飘逸灵动。 | 网格拼接的元素，飘逸灵动。 |
| 夏装 | 经典的条纹元素，简约时尚，纯棉面料，柔软亲肤，穿着舒适。 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 | 一针一针的设计，简约又时尚。 |
| 欧货 | 两件套的设计，简约又时尚。 | 两件套的设计，简约又时尚。 | 两件套的设计，简约又时尚。 | 两件套的设计，简约又时尚。 |
| 休闲 | 纯色的元素，简约又时尚。 | 纯色的元素，简约又时尚。 | 纯色的元素，简约又时尚。 | 纯色的元素，简约又时尚。 |
| 小香风 | 宽松的版型，完美包容各种身材。 | 宽松的版型，完美包容各种身材。 | 宽松的版型，完美包容各种身材。 | 宽松的版型，完美包容各种身材。 |
| 时尚 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 |
| 气质 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 |
| 两件套 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 | 宽松的设计，简约又时尚。 |

**Figure 1: examples**