Towards Multimodal Response Generation with Exemplar Augmentation and Curriculum Optimization

Zeyang Lei\(^{1\dagger}\), Zekang Li\(^{2\dagger}\), Jinchao Zhang\(^{3}\), Fandong Meng\(^{3}\), Yang Feng\(^{2}\), Yujiu Yang\(^{1}\), Cheng Niu\(^{3}\), Jie Zhou\(^{3}\)

\(^{1}\)Tsinghua University, China.
\(^{2}\)Key Laboratory of Intelligent Information Processing
Institute of Computing Technology, Chinese Academy of Sciences
\(^{3}\)Pattern Recognition Center, WeChat AI, Tencent Inc, China

\{lizekang19,fengyang\}@ict.ac.cn, yang.yujiu@sz.tsinghua.edu.cn
zeyanglei@gmail.com, \{dayerzhang,fandongmeng,chengniu,jiezhou\}@tencent.com

Abstract

Recently, variational auto-encoder (VAE) based approaches have made impressive progress on improving the diversity of generated responses. However, these methods usually suffer the cost of decreased relevance accompanied by diversity improvements (Zhang et al., 2018b). In this paper, we propose a novel multimodal response generation framework with exemplar augmentation and curriculum optimization to enhance relevance and diversity of generated responses. First, unlike existing VAE-based models that usually approximate a simple Gaussian posterior distribution, we present a Gaussian mixture posterior distribution (i.e., multimodal) to further boost response diversity, which helps capture complex semantics of responses. Then, to ensure that relevance does not decrease while diversity increases, we fully exploit similar examples (exemplars) retrieved from the training data into posterior distribution modeling to augment response relevance. Furthermore, to facilitate the convergence of Gaussian mixture prior and posterior distributions, we devise a curriculum optimization strategy to progressively train the model under multiple training criteria from easy to hard. Experimental results on widely used SwitchBoard and DailyDialog datasets demonstrate that our model achieves significant improvements compared to strong baselines in terms of diversity and relevance.

1 Introduction

Recently, sequence-to-sequence (Seq2Seq) based conversation models have achieved great success in open-domain dialogue generation. However, these methods often generate generic and dull responses (Li et al., 2016), such as “I don’t know”, “It’s Ok”. A seemingly promising approach is to integrate variational auto-encoders (VAEs) (Serban et al., 2017; Zhao et al., 2017) or its variants (Du et al., 2018; Gu et al., 2019) into the encoder-decoder framework to enhance the diversity of generated responses.

Although existing VAE-based approaches have shown great potential in diverse response generation, these approaches still face two issues. First, existing VAE-based approaches usually approximate the posterior distribution over the latent variables using a simple Gaussian distribution, which restricts the ability of these approaches to capture the complex semantics and high variability of responses to some extent. Second, these approaches usually suffer the cost of decreased relevance accompanied by increased diversity (Zhang et al., 2018b; Gao et al., 2019).

To tackle the aforementioned issues, we propose a novel multimodal response generation framework with exemplar augmentation and curriculum optimization to enhance both relevance and diversity of responses. Specifically, to capture the complex semantics of responses, we present a Gaussian mixture posterior distributions to boost the diversity of generating responses. An intuitive explanation about using Gaussian mixture distribution in the posterior distribution is presented in Figure 1. Then, to make sure that relevance does not decrease when diversity increases, we fully exploit similar examples (exemplars) retrieved from the
training data into Gaussian mixture posterior distribution modeling to augment response relevance. Such motivation is based on that these responses from similar contexts can be regarded as potential exemplar responses for the current context (Pandey et al., 2018; Wu et al., 2019). Furthermore, to facilitate the convergence of Gaussian mixture prior and posterior distributions, we devise a curriculum optimization strategy to progressively train the model under multiple training criteria from easy to hard. In particular, our model is trained through three phases: firstly training a simple Wasserstein Autoencoder (WAE)\(^2\) (Tolstikhin et al., 2018) only with a simple normal posterior distribution, then training a complex WAE with multiple simple normal posterior distributions, and finally training our entire model with Gaussian mixture prior and posterior distributions.

The main contributions are as follows:

- We propose a Gaussian mixture posterior distribution over the latent variables to capture the high variability of responses. Meanwhile, to ensure that relevance does not decrease when diversity increases, we fully exploit similar examples (exemplars) from the training data in the Gaussian mixture posterior model.

- A curriculum optimization strategy is devised to progressively train our model through three phases with training criteria from easy to hard (i.e., the convergence of training objectives from easy to hard).

- Our study shows that: (1) By fully exploiting exemplars, a Gaussian mixture posterior distribution can help improve both diversity and relevance of generated responses; (2) curriculum optimization strategy can facilitate the model training, which further achieves better diversity and relevance of generated responses.

2 Related Work

Variational Autoencoder (VAE) for Dialogue Generation. Recently, some researchers (Bowman et al., 2016; Serban et al., 2017; Zhao et al., 2017; Shen et al., 2018; Park et al., 2018; Fu et al., 2019) have attempted using variational autoencoders (VAEs) to address the issue that vanilla Seq2Seq models suffer from generating generic and dull responses. The VAE models introduce latent variables into encoder-decoder frameworks to improve the variability of the models. Most existing VAEs based models in dialogue generation usually used a simple Gaussian model for the prior and posterior distribution. This restricts the ability in capturing complex semantics and high variability of context and responses. Gu et al. (2019) proposed a Gaussian mixture prior to enrich the latent space. Compared with (Gu et al., 2019), our model propose Gaussian mixture posterior distributions over the latent variables to capture complex semantics of responses. Meanwhile, we utilizes similar examples retrieved from training data in posterior distribution modeling, which can better approximate the true posterior distribution and generate more related responses.

Curriculum learning. Curriculum learning is a machine learning strategy, which starts from simple subtasks and then gradually handles harder ones (Bengio et al., 2009). The learning strategy has been proven effective in many NLP tasks. For instance, Liu et al. (2018) utilized curriculum learning to solve the natural answer generation problem by firstly learning models on low-quality question-answer (QA) pairs and then on high-quality QA pairs. Meanwhile, some researchers (Zhang et al., 2018a; Antonios Platanios et al., 2019) used curriculum learning to enhance the neural machine translation (NMT) by choosing the samples from easy to hard according to certain criteria. Inspired by such ideas, we propose a curriculum optimization strategy to better train our model under multiple training criteria from easy to hard. Unlike conventional curriculum learning that uses samples from easy to hard, our proposed curriculum optimization strategy is set based on the convergence of training objectives from easy to hard (e.g., in this paper, firstly training a simple WAE model to learn the basic encoder and decoder, then training a complex WAE model to fully learn recognition network, and finally training the entire model with Gaussian mixture prior and posterior distributions until convergence).

3 Methodology

Figure 2 demonstrates an overview of our model. Our model mainly contains Prior and Recognition Network, Wasserstein GAN (i.e., Q, G, D), and basic encoder and decoder.

---

\(^2\)As stated in (Zhao et al., 2018), comparing to KL divergence widely used in conventional VAEs, the Wasserstein distance as a notion of distance may result in a better generative model.
At training stage, we first input the current context and each response pair (including the golden and retrieved similar responses) to the utterance and context encoder to obtain the corresponding hidden representations, and then feed them to a shared feed-forward network named recognition network to obtain the mean and covariance of a normal distribution for each response. Each response-context pair corresponds to a simple Gaussian distribution and then we compute the Gaussian mixture distribution weighted by the similarity between the real context and the retrieved similar context. Next, we use a re-parameterization trick to draw a Gaussian mixture noise from the recognition network. Finally, we employ a generator Q to transform the posterior Gaussian noise into a sample of the posterior latent variable.

Similarly, the output of the prior network is also a Gaussian mixture distribution to match the prior distribution with posterior distribution better. In particular, we use a feed-forward network as prior network to transform the context into the means and covariances of the corresponding Gaussian components. Then a prior Gaussian noise is sampled from the prior network and fed to a generator G to obtain a sample of the prior latent variable.

Finally, we introduce an adversarial discriminator D to match the posterior distribution with the prior distribution by minimizing the Wasserstein distance between them. At the generation stage, the decoder RNN takes as inputs the prior latent variable and the context to generate a response. In the following, we will elaborate our model via two sections including Exemplar-augmented Conditional Wasserstein Auto-encoders and Curriculum Optimization.

3.2 Exemplar-augmented Conditional Wasserstein Auto-encoders

Given a context-response pair \((c, r)\), the similar examples \((c_i, r_i)\), \(i = 1, 2, ..., k\) can be obtained by using the last utterance of the context \(c\) as a query to retrieve from the training data using the BM25 (Robertson et al., 2009) retrieval model. Then we use the utterance encoder and the context encoder which both adopt gated recurrent units (GRUs) to encode context or responses into fixed-sized vectors. In particular, the utterance encoder encodes each utterance into a fixed-sized vector, and the context encoder takes as input the encoding vector of the preceding utterance and uses the final hidden state \(h(c)\) of the context encoder as the context representation. Thus, we can obtain the context and response representation \((h(c_i), h(r_i))\)

\[(i)\text{ Prior and Recognition Network.}\] Different from previous VAE-based models, both the prior and posterior distribution of our model are Gaussian mixture distributions. The posterior distribution is a Gaussian mixture distribution explicitly composed of multiple simple Gaussian distributions conditioned on the exemplar responses and the gold response. Specifically, the posterior latent variable \(\hat{z} \sim Q_\phi(\hat{\epsilon})\) is generated by a generator Q from a context-response-dependent Gaussian mixture noise \(\hat{\epsilon}\), which is a reparametrization trick (Kingma and Welling, 2013). And \(\hat{\epsilon}\) is sampled from a Gaussian mixture distribution which is composed of \(k\) Gaussian simple distribution whose mean \(\mu_i\) and covariance \(\sigma_i^2\) can be calculated by a feed-forward neural network named recognition network (RecNet) as follows:

\[
\hat{z} = Q_\phi(\hat{\epsilon}), \; \hat{\epsilon} \sim \sum_{i=0}^{k} s_i N(\epsilon_i; \mu_i, \sigma_i^2 I) \\
\left[ \begin{array}{c}
\mu_i \\
\log \sigma_i^2
\end{array} \right] = W f_{\phi}(\left[ \begin{array}{c}
h(c) \\
h(r_i)
\end{array} \right]) + b
\]

\[\tag{1}\]

Figure 2: The architecture of our proposed model. ⊕ denotes the concatenation of the input vectors. Q and G represent two generators, and D is a discriminator. Q, G and D are used to measure the Wasserstein distance between prior and posterior distribution.
where $f_\phi$ represents a feed-forward neural network and $W$, $b$ refer to the trainable parameters. For convenience of description, we use $(c_0, r_0)$ to represent $(c, r)$ in this paper. The weight score of each Gaussian simple distribution can be computed as follows:

$$s_i = \frac{\exp(\cos(h(c), h(c_i)))}{\sum_{i=0}^{k} \exp(\cos(h(c), h(c_i)))} \quad \cos(h(c), h(c_i)) = \frac{h(c) \cdot h(c_i)}{\|h(c)\| \|h(c_i)\|}$$

where $\cos(h(c), h(c_i))$ denotes the cosine similarity between $h(c)$ and $h(c_i)$, and $s_i$ represents the normalized weight score of the Gaussian simple distribution $\mathcal{N}(c; \mu_i, \sigma_i^2 I)$.

Similarly, the prior sample $\hat{r} \sim p(\hat{r} | c)$ can be generated by a generator $G$ from a context-dependent random noise $\tilde{c}$. $\hat{c}$ is also drawn from a Gaussian mixture distribution composed of $n$ simple Gaussian components over the context, which can be computed by a feed-forward neural network named prior network (PriNet) as follows:

$$\tilde{c} = G_\theta(\tilde{c}), \quad \hat{c} \sim \sum_{i=1}^{n} \tilde{\pi}_i \mathcal{N}(\hat{c}; \tilde{\mu}_i, \tilde{\sigma}_i^2 I)$$

$$\tilde{\pi}_i = \frac{\exp(\alpha_i)}{\sum_{i=1}^{n} \exp(\alpha_i)}$$

where $g_\theta$ represents a feed-forward neural network. $\hat{W}_i$ and $\hat{b}_i$ denotes the learnable parameters.

**II Wasserstein GAN.** Meanwhile, to alleviate the posterior collapse problem (Shen et al., 2018), we match the Gaussian mixture prior and approximate posterior distribution by using WGAN (Arjovsky et al., 2017) to minimize the Wasserstein distance between them, which have been shown to produce good results in text generation (Zhao et al., 2018; Gu et al., 2019). Formally, our model can be trained by maximizing:

$$L(c, R) = -W(q(\tilde{z}|c, R)p(\tilde{z}|c)) + E_{\tilde{z} \sim q(\tilde{z}|c, R)}[\log p(\hat{r}|c, \tilde{z})]$$

where $W(\cdot|\cdot)$ denotes the Wasserstein distance between the two distributions, $p(r|c, \tilde{z})$ represents a decoder RNN and $R = [r, r_1, ..., r_k]$. The detailed theory and implementation about Wasserstein distance can be found in (Arjovsky et al., 2017).

### 3.3 Curriculum Optimization

To further facilitate the matching between Gaussian mixture prior distribution and posterior distributions to better train our model, we devise a curriculum optimization strategy containing three phases: training a Wasserstein Auto-encoder (WAE) with a single normal posterior distribution by using the gold response, training a WAE with multiple normal posterior distributions by using multiple exemplar responses, and training our entire model with Gaussian mixture prior and posterior distributions by using all the exemplar responses and the gold response. The training procedure gradually increases difficulty with training criteria from easy to hard. It is noted that the WAE in the first and second phases does not contain prior distribution compared with conventional WAE.

Specifically, in the first phase presented in Figure 3, we train our model by minimizing the reconstruction loss only over the gold response as follows:

$$L_1 = -E_{z \sim Q_c(r)}, \epsilon \sim RecNet(c, r) \log p_\psi(r|c, z)$$

The training objective of this phase is to obtain a better encoder-and-decoder, warming up for the following phase. In the second phase presented in Figure 4, we train our model on the basis of the first phase by minimizing the reconstruction loss over multiple exemplar responses as follows:

$$L_2 = -E_{z \sim Q_c(r)}, \epsilon \sim RecNet(c, r) \log p_\psi(r|c, z)$$

where $s(h(c), h(c_i))$ is the above weight score in Equation 2. This phase can ensure that each component of the complex Gaussian mixture distribution to be fully trained for the total posterior distribution. In the final WAE phase, we train our entire model shown in Figure 2 by minimizing the total reconstruction loss from the discriminator D computed as follows:

$$L_{disc} = E_{\hat{r} \sim RecNet(c, r)}[D(Q(\hat{r}), c)] - E_{\tilde{r} \sim PriNet(c)}[D(G(\tilde{r}), c)]$$

The final total loss function for the third phase can be computed as follow:

$$L_3 = -E_{\tilde{z} \sim q(\tilde{z}|c, R)}[\log p(\hat{r}|c, \tilde{z})] + L_{disc}$$

Through these three phases, we can further improve the diversity and relevance of generated responses.
4 Experiment

4.1 Datasets

We conduct experiments on two widely used dialogue datasets (Zhao et al., 2017; Shen et al., 2018), SwitchBoard (Godfrey and Holliman, 1997) and DailyDialog (Li et al., 2017b). We split the datasets into training, validation and test sets by the same ratios as the baselines methods, that is, 2316:60:62 for Switchboard (Zhao et al., 2017) and 10:1:1 for Dailydialog (Shen et al., 2018), respectively.

4.2 Baselines

We carefully select the following six related state-of-the-art methods as baselines:

**HRED**: a generative hierarchical encoder-decoder network (Serban et al., 2016).

**SeqGAN**: a GAN model for dialogue generation (Li et al., 2017a).

**CVAE-CO**: a collaborative conditional VAE model (Shen et al., 2018).

**VHRED**: a hierarchical encoder-decoder framework with VAE (Serban et al., 2017).

**VHCR**: a hierarchical VAE model with conversation modeling (Park et al., 2018).

**DialogWAE-GMP**: a conditional Wasserstein autoencoder (WAE) with Gaussian mixture prior network for dialogue modeling (DialogWAE-GMP) (Gu et al., 2019). We rerun its released source codes with default parameters.

4.3 Metrics

**Automatic Evaluation.** To evaluate our model, we adopt three widely used metrics that can reflect the relevance and diversity: BLEU, BOW Embedding and distinct. BLEU measures how much a generated response contains n-gram overlaps with the reference. We use smoothing techniques to compute BLEU scores for $n < 4$ (Chen and Cherry, 2014). BOW Embedding represents the cosine similarity of bag-of-words embeddings between the predicted and gold responses, which has been used in many studies (Du et al., 2018; Gu et al., 2019) to evaluate the relevance of generated responses. In this paper, we use three commonly used BOW Embedding metrics including Greedy (Rus and Lin-tean, 2012), Extrema (Forgues et al., 2014) and Average (Mitchell and Lapata, 2008). In the test stage, we sample 10 predicted responses for each test context and compute the maximum BOW embedding score among 10 sampled responses as the final reported results. Distinct measures the diversity of generated responses. $\text{dist-}n$ computes the fraction of distinct n-grams ($n=1,2$) among all n-grams in generated responses (Li et al., 2016). We compute the $\text{intra-dist}$ as the average of distinct values within each sampled response and $\text{inter-dist}$ as the distinct value among all the sampled responses.

**Human Evaluation.** As human evaluation is essential for dialogue generation, we randomly sampled 150 dialogues from the test set of DailyDialog and Switchboard to conduct a human evaluation. For each context in the test, we generated 10 responses from evaluated models. Responses for each context were inspected by 3 annotators who were asked to choose the model which performs the best in regards **Fluency**, **Relevance** and **Diversity** among all the compared models. Finally, the ratio of each model under each metric was computed as the corresponding human evaluation score. **Fluency** means that how likely generated responses are produced by a human. **Relevance** means that how likely generated response is relevant to the context. **Diversity** means that how much gener-
### Table 1: Performance comparison on the DailyDialog dataset (G: Greedy, E: Extrema, A: Average)

| Model               | BLEU | BOW Embedding | intra-dist | inter-dist |
|--------------------|------|--------------|------------|------------|
|                     | R    | P            | F1         | G          | E          | A          | dist-1 | dist-2 | dist-1 | dist-2 |
| HRED               | 0.262| 0.262        | 0.832      | 0.537      | 0.820      | 0.813      | 0.452  | 0.081  | 0.045  |
| SeqGAN             | 0.282| 0.282        | 0.748      | 0.515      | 0.817      | 0.705      | 0.521  | 0.111  | 0.110  |
| CVAE-CO            | 0.299| 0.269        | 0.855      | 0.557      | 0.839      | 0.863      | 0.581  | 0.111  | 0.110  |
| VHRED              | 0.253| 0.231        | 0.844      | 0.531      | 0.810      | 0.881      | 0.522  | 0.110  | 0.092  |
| VHCR               | 0.276| 0.234        | 0.851      | 0.546      | 0.826      | 0.877      | 0.536  | 0.130  | 0.131  |
| DialogWAE-GMP      | 0.411| 0.241        | 0.893      | 0.657      | 0.918      | 0.805      | 0.704  | 0.384  | 0.648  |
| Our model          | 0.410| 0.240        | 0.893      | 0.650      | 0.918      | 0.823      | 0.780  | 0.440  | 0.707  |
| w/o I              | 0.383| 0.221        | 0.888      | 0.636      | 0.909      | 0.849      | 0.763  | 0.528  | 0.801  |
| w/o II             | 0.403| 0.217        | 0.895      | 0.668      | 0.919      | 0.810      | 0.637  | 0.394  | 0.615  |
| w/o Curriculum     | 0.402| 0.217        | 0.894      | 0.664      | 0.916      | 0.799      | 0.611  | 0.385  | 0.605  |
| w/o examplar       | 0.425| 0.236        | 0.892      | 0.670      | 0.922      | 0.753      | 0.583  | 0.269  | 0.389  |

### Table 2: Performance comparison on the SwitchBoard dataset (G: Greedy, E: Extrema, A: Average)

| Model               | Fluency | Relevance | Diversity |
|--------------------|---------|-----------|-----------|
| DialogWAE          | 24.1%   | 27.3%     | 22.5%     |
| Our model          | 44.0%   | 38.2%     | 46.3%     |
| w/o curriculum     | 31.9%   | 34.5%     | 31.2%     |

### Table 3: Human evaluation on the DailyDialog dataset

| Model               | Fluency | Relevance | Diversity |
|--------------------|---------|-----------|-----------|
| DialogWAE          | 20.3%   | 23.3%     | 23.4%     |
| Our model          | 48.2%   | 46.2%     | 44.3%     |
| w/o curriculum     | 31.5%   | 30.5%     | 32.3%     |

### Table 4: Human evaluation on the SwitchBoard dataset

The hidden size of all GRUs is set to 300. The prior and the recognition networks are both 2-layer feed-forward networks of size 200 with tanh non-linearity. The generators Q and G as well as the discriminator D are 3-layer feed-forward networks with ReLU non-linearity. The dimension of all latent variables is set to 200. We adopt pre-trained Glove (Pennington et al., 2014) with a size of 200.
Figure 5: Performance with respect to the number of examplar cases

| Context                                                                 | DialogWAE-GMP                                                                 | Our model                                                                 |
|------------------------------------------------------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| how much is the rent? → the rent is $1500 per month.                    | Eg.1: no problem. I’ll take it.                                               | Eg.1: oh, that’s too expensive.                                            |
|                                                                        | Eg.2: this one is $1.50,50,000 yuan per month.                               | Eg.2: will it be cash dollars?                                              |
|                                                                        | Eg.3: that sounds like a good idea.                                          | Eg.3: I have to pay for it.                                                 |
| guess who i saw just now? → who? → john smith. → that bad egg who took the low road since he was a boy. | Eg.1: it is my favorite.                                                      | Eg.1: his face is lost.                                                     |
|                                                                        | Eg.2: no, but I didn’t think he was able to get married. I had no idea to get her. | Eg.2: oh, he’s really very serious. he doesn’t look like the one.         |
|                                                                        | Eg.3: this is not, but its not that bad. its just a little bit, but its not too bad. | Eg.3: it must be right around the moment.                                  |
| hello, is bob there, please? → hold on a second please. i’m sorry. he has gone out. → oh. this is paul. when will he be back? | Eg.1: no. not at all. I’m sorry, but I’m not sure.                           | Eg.1: please come to the office tomorrow afternoon. he will be there for 6:30. |
|                                                                        | Eg.2: yes, but he has a number of the company. he is a little bit.            | Eg.2: of course. he said he would be able to call his secretary to call him for next week. |
|                                                                        | Eg.3: no, I don’t think so. it’s the first time to get a new one.            | Eg.3: please, sir, the doctor will be back in the morning.                 |

Table 7: Examples of context-response pairs for the neural network models. → indicates a change of turn. ‘Eg.i’ means the i-th example.

as the word embedding. We use the RMSprop optimizer with a mini-batch size of 32. The epochs for the first two curriculum optimization phases are 10 and 10 respectively. In this paper, to simplify the settings, we adopt the same number of prior and posterior components.

4.5 Experiment Results

Automatic Evaluation Results. As shown in Table 1 and 2, our model outperforms all the baselines in most of automatic metrics on the two datasets, especially in inter/intra-dist. To be specific, for DialyDialog, our model achieves the highest BLEU R/F1 scores and BOW Extrema/Average scores compared to all baselines, indicating that our model can enhance relevance of generated responses. Meanwhile, our model obtains significant improvements in terms of inter-dist and intra-dist on DialyDialog, indicating that our model can enhance response diversity. For SwitchBoard, our model achieves the highest inter-dist and intra-dist (dist-2) scores, and comparable BLEU and BOW Embedding scores with the state-of-the-art method (DialogWAE-GMP). This confirms that our model can also improve relevance when diversity significantly increases.

Human Evaluation Results. To further evaluate our model, we conduct a human evaluation on the state-of-the-art method—DialogWAE-GMP (denoted as DialogWAE), our model and our model without curriculum optimization (denoted as w/o curriculum). The results are shown in Table 3 and 4. Our model significantly and consistently outperforms DialogWAE-GMP in terms of fluency, relevance, and diversity, indicating that our model can enhance both relevance and diversity. Concretely, our model w/o curriculum optimization (that is, with exemplars augmentation and Gaussian mixture posterior) obtains better diversity and relevance than DialogWAE-GMP (with a simple Gaussian posterior distribution). This indicates that Gaussian mixture posterior distribution modeled on exemplars can help improve the diversity and relevance of generated responses. Meanwhile, our model significantly outperforms our model w/o...
curriculum in terms of all metrics, which indicates curriculum optimization can further improve the diversity and relevance of generated responses.

4.6 Quantitative Analysis

Ablation Study. To analyze the effectiveness of each component of our model, we conduct an ablation study on two datasets by automatic and human evaluation. Specifically, we discard the first phase of curriculum optimization (denoted as w/o I), the second phase (denoted as w/o II), the entire curriculum optimization (denoted as w/o curriculum), and exemplars\(^4\) (denoted as w/o exemplar). The automatic evaluation results are shown in Table 1 and 2. The human evaluation results are shown in Table 5 and Table 6. The Kappa values is 0.61 and 0.67 on two datasets respectively.

According to automatic and human evaluation results, the relevance or diversity goes down when our model removes each part, indicating that each phase of curriculum optimization and exemplars make contributions to the diversity and relevance of our model. Specifically, for our model w/o I (or II), the relevance decreases, indicating that I and II can help improve the relevance of responses. For our model w/o curriculum, both its diversity and relevance go down, indicating that curriculum optimization can benefit both diversity and relevance. For our model w/o exemplars, its relevance goes down on DailyDialog compared with DialogWAE, indicating that exemplars can help improve the relevance of responses. Meanwhile, for our model w/o exemplars, its diversity increases on DailyDialog compared with DialogWAE, indicating that Gaussian mixture posterior distribution can help improve the diversity of generated responses to some extent. An interesting finding is that though automatic metrics results (BLEU and BOW) on SwitchBoard seems to be good, its generated responses contain large amounts of low-quality responses with many repetitive words or phrases, which will results in poor human evaluation.

The Exemplar Number (k). To further investigate the effect of the exemplar number (i.e., the number of posterior components), we conduct the experiments on two datasets by varying k from 1 to 5. The performance under different k is shown in Figure 5. From the figure, we can conclude that, in most cases, the performance increases with k and decreases once k exceeds a certain threshold (e.g., k=4). Considering comprehensively the relevance and diversity of generated responses, we set k to 4 in our experiment.

4.7 Case Study

To empirically analyze the quality of generated responses, we present some examples generated from our model and the start-of-the-art DialogWAE-GMP in Table 7. For each context, we show three samples of generated responses from each model. It can be seen that our model generates more relevant, fluent and diverse responses than DialogWAE-GMP. Specifically, for the first context, all the samples generated from our model are related to the topic “how much” while the responses Eg.1 and Eg.3 from DialogWAE-GMP seems not very relevant with the topic, which indicates that the responses generated by our model have better relevance than DialogWAE-GMP. Meanwhile, we can also observe that responses from DialogWAE-GMP have a certain token repetition phenomenon. For instance, in the second case, the token “it’s not that bad” emerges two times in the response Eg.3 of DialogWAE-GMP while such phenomenon have not been found in our model, which shows that our model can generate more fluent and human-like responses. Finally, from the third case, we can see that the responses generated by our model contain more specific information than the responses from DialogWAE (including some meaningless safe responses, e.g., “I am not sure”). This confirms that our model can generate more diverse and informative responses.

5 Conclusion

In this paper, we propose a novel multimodal response generation framework with exemplar augmentation and curriculum optimization to enhance the diversity and relevance of generated responses. In specific, we first fully exploit exemplars to approximate more complex Gaussian mixture distribution, which is helpful for modeling the high variability of generated responses. Meanwhile, we progressively train our model with curriculum optimization through three phases with training criteria from easy to hard, which facilitates model training to further improve the diversity and relevance of responses. The experimental results on two popular datasets demonstrate our model can generate more diverse and relevant responses compared with

\(^4\) Here, removing exemplars means that modeling a Gaussian mixture posterior distribution on a single gold response.
strong competitors.

References
Emmanouil Antonios Platanios, Otilia Stretcu, Graham Neubig, Barnabas Poczos, and Tom Mitchell. 2019. Competence-based curriculum learning for neural machine translation. In Proceedings of NAACL.

Martin Arjovsky, Soumith Chintala, and Léon Bottou. 2017. Wasserstein gan. arXiv preprint arXiv:1701.07875.

Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In Proceedings of ICML.

Samuel R Bowman, Luke Vilnis, Oriol Vinyals, Andrew M Dai, Rafal Jozefowicz, and Samy Bengio. 2016. Generating sentences from a continuous space. In Proceedings of The 20th SIGNLL Conference on Computational Natural Language Learning.

Boxing Chen and Colin Cherry. 2014. A systematic comparison of smoothing techniques for sentence-level bleu. In Proceedings of the Ninth Workshop on Statistical Machine Translation.

Jiachen Du, Wenjie Li, Yulan He, Ruifeng Xu, Lidong Bing, and Xuan Wang. 2018. Variational autoregressive decoder for neural response generation. In Proceedings of EMNLP.

Gabriel Forgues, Joelle Pineau, Jean-Marie Larchevêque, and Réal Tremblay. 2014. Bootstrapping dialog systems with word embeddings. In NIPS workshop.

Hao Fu, Chunyuan Li, Xiaodong Liu, Jianfeng Gao, Asli Celikyilmaz, and Lawrence Carin. 2019. Cyclical annealing schedule: A simple approach to mitigating kl vanishing. In Proceedings of NAACL.

Xiang Gao, Sungjin Lee, Yizhe Zhang, Chris Brockett, Michel Galley, Jianfeng Gao, and Bill Dolan. 2019. Jointly optimizing diversity and relevance in neural response generation. In Proceedings of NAACL.

J Godfrey and E Holliman. 1997. Switchboard-1 release 2: Linguistic data consortium. SWITCHBOARD: A User’s Manual.

Xiaodong Gu, Kyunghyun Cho, Jungwoo Ha, and Sunghun Kim. 2019. Dialogwae: Multimodal response generation with conditional wasserstein autoencoder. In Proceedings of ICLR.

Diederik P Kingma and Max Welling. 2013. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In Proceedings of NAACL.
Xuan Zhang, Gaurav Kumar, Huda Khayrallah, Kenton Murray, Jeremy Gwinnup, Marianna J Martindale, Paul McNamee, Kevin Duh, and Marine Carpuat. 2018a. An empirical exploration of curriculum learning for neural machine translation. *arXiv preprint arXiv:1811.00739*.

Yizhe Zhang, Michel Galley, Jianfeng Gao, Zhe Gan, Xiujun Li, Chris Brockett, and Bill Dolan. 2018b. Generating informative and diverse conversational responses via adversarial information maximization. In *Advances in Neural Information Processing Systems*.

Junbo Zhao, Yoon Kim, Kelly Zhang, Alexander M Rush, and Yann LeCun. 2018. Adversarily regularized autoencoders. In *Proceedings of ICML*.

Tiancheng Zhao, Ran Zhao, and Maxine Eskenazi. 2017. Learning discourse-level diversity for neural dialog models using conditional variational autoencoders. In *Proceedings of ACL*. 