A QUALITY-DIVERSITY CONTROLLABLE GAN FOR TEXT GENERATION

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ABSTRACT

Text generation is a critical and difficult natural language processing task. Maximum likelihood estimate (MLE) based models have been arguably suffered from exposure bias in the inference stage and thus varieties of language generative adversarial networks (GANs) bypassing this problem have emerged. However, recent study has demonstrated that MLE models can constantly outperform GANs models over quality-diversity space under several metrics. In this paper, we propose a quality-diversity controllable language GAN. We illustrate an intimate connection between forward/reverse KL divergences and our principled approach, and demonstrate that our proposed model can achieve quality-diversity control by adjusting a hyper-parameter. Through extensive experiments, we show that the proposed model outperforms MLE models and other GANs variants on synthetic data and is more competitive on real-world tasks such as COCO Image Captions and EMNLP2017 WMT News datasets.

1 INTRODUCTION

Text generation is one of the most challenging and widely used natural language processing task and it serve as a critical module on numerous practical applications. In recent years, neural autoregressive models have shown superiority on various natural language generation (NLG) tasks (Zhang & Lapata, 2014; Gal & Ghahramani, 2016; Du et al., 2017; Fiorini & Lu, 2018). The most common method of training these models is the maximum likelihood estimation (MLE) which maximize the log predictive likelihood of each true token in the training sequence given the previous observed tokens. However, MLE models have been arguably suffered from *exposure bias* (Bengio et al., 2015; Ranzato et al., 2016) which means a discrepancy between training and inference stages due to the fact that at inference time, the model predicts next token based on the sequence generated by itself which may not occur in training set. In order to overcome this problem, scheduled sampling (Bengio et al., 2015) and professor forcing (Lamb et al., 2016) are proposed, but scheduled sampling is proven to be fundamentally inconsistent (Huszár, 2015) and professor forcing use an adversarial method similar to GANs (Goodfellow et al., 2014).

Varieties of generative adversarial networks (GANs) (Goodfellow et al., 2014) models for text generation have emerged as alternatives to MLE models with the hope of not suffering from exposure bias. However, due to the discrete nature, GANs have difficulty in text generation since the gradients from discriminator can not be passed to generator explicitly and thus most these GANs based models (Yu et al., 2017; Guo et al., 2018; Lin et al., 2017; Fedus et al., 2018; Xu et al., 2018) treat text generation as a sequential decision making process (Bachman & Precup, 2015) and utilize policy gradient (Williams, 1992) to overcome this difficulty. Despite the impressive achievements, they inevitably have a problem of high variance due to the use of reinforcement learning (RL) strategies.

Caccia et al. (2018) have made several surprising observations and argued that, through simple temperature sweeping at inference stage, MLE models can constantly outperform these RL-based GANs models by a large margin over quality-diversity space under several metrics. They attribute this to the fact that the negative impact coming with RL is severer than so-called exposure bias caused by MLE. A RL-free approach to train GANs for text generation without resorting to an explicit neural network as the discriminator, named No Neural Network as the Discriminator GAN (N3DGAN), is proposed by (Li et al., 2019) and shows state-of-the-art results on both synthetic and real datasets under quality-only metrics.

We propose a quality-diversity controllable GAN through a principle approach which is a generalization of N3DGAN (Li et al., 2019). This generalization has intimate connections with direct optimization of both forward and inverse KullbackLeibler (KL) divergences with respect to empirical distribution and model distribution. As shown in (Huszár, 2015), minimizing forward KL divergence often leads to models that overgeneralize, and sometimes produce samples that are very unlikely under true distribution and thus it is good at diversity. Minimizing the reverse KL divergence instead will try to avoid any behaviour that is unlikely under true distribution at the cost of ignoring modes of true distribution completely, thus it is good at quality. Through this principled approach, we demonstrate that our proposed model can control the quality-diversity trade-off, that is, the degree to which the model depends on forward and reverse KL divergences respectively through a single hyper-parameter.

The key contributions of our work are three-folds: (1) We propose a simple but effective GANs model for text generation which can control the quality-diversity trade-off through a single hyper-parameter at training stage. (2) Different from most existing GANs variants, our proposed model, as a generalization of N3DGAN, does not need to rely on MLE pre-training and is RL-free. (3) Through extensive experiments, we show that our proposed model outperform MLE based model and other GANs variants over quality-diversity space in the synthetic-data tasks and are more competitive to MLE model than other GANs variants in the real-world tasks.

2 Related Work

Huszár (2015) analyzes the difference between optimizing forward and reverse KL divergences, and suggests to use a generalized Jensen-Shannon divergence to replace MLE, but he doesn't realize its relation to the mini-max game's value function as well as tractability of directly optimizing the generalized Jensen-Shannon divergence on training data, and moreover he doesn't conduct any experiments.

Caccia et al. (2018) try to navigate the quality-diversity space through temperature sweep, beam search and generator rejection sampling (Ott et al., 2018) methods, unfortunately all these methods can only navigate the quality-diversity space at inference stage.

Li et al. (2019) propose N3DGAN which is RL-free and doesn't need additional maximum likelihood pre-training, but they only report results on quality metrics but not on diversity.

Lu et al. (2019) propose a cooperative training (CoT) approach for text generation which dont have to rely on RL and MLE for pre-training, instead they optimize an approximate Jensen-Shannon divergence. It is done by introducing a mediator and dropping the term in the gradient of generator which behaves like RL. In the synthetic-data experiments, they perform similarly but slightly worse than MLE model (Caccia et al., 2018).

de Masson d'Autume et al. (2019) combine existing techniques such as large batch size, dense rewards and discriminator regularization to train language GANs from scratch without the need for MLE pre-training. But they still have to use RL which is essentially the same as most language GANs (Yu et al., 2017; Guo et al., 2018; Lin et al., 2017; Fedus et al., 2018; Xu et al., 2018), and they don't conduct any experiment on synthetic data which has oracle metrics to validate its effectiveness.

3 A Quality-Diversity Controllable GAN

In the well-known adversarial modeling framework Goodfellow et al. (2014), there are two players, one is called generator represented by a differentiable function G and another one is called discriminator represented by a differentiable function D. They approximate the data distribution p_{data} through an alternative mini-max game between these two components. The discriminator D is trained to discriminate the samples drawn from the generator distribution p_G from the real data, while the generator is trained to fool the discriminator so that it cannot distinguish between the samples from p_G and p_{data}. Goodfellow et al. (2014) proved that if the generator G has enough capacity to cover data distribution p_{data}, then optimizing the mini-max game is equivalent to directly optimizing the Jensen-Shannon divergence. Unfortunately Goodfellow et al. (2014) didn't distinguish the real data as either population (*true but unknown*) distribution or empirical distribution.

Li et al. (2019) notice the distinction and they explicitly use the empirical distribution in their approach. They argue that when an alternative mini-max optimization procedure is performed for the value function, a closed form solution for the discriminator exists in the maximization step, thus an explicit neural network model for the discriminator is not needed. Moreover optimizing the mini-max game is equivalent to directly optimizing the Jensen-Shannon divergence (JSD) between the generator's distribution and the empirical distribution over the training data, where the corresponding KL divergence related to the generator's distribution and the empirical distribution over the training data is reduced to the sum over the training data. This means that sampling from the generator over the entire space as well as the policy-gradient algorithm to compute the gradient of the generator can be eliminated. Optimizing the JSD becomes computationally tractable to train the generator for text generation.

We now propose a quality-diversity controllable GAN which is a generalization of N3DGAN (Li et al., 2019) and illustrate its connections to the forward KL divergence and the reverse KL divergence as stated below.

Since the samples in the training data are limited, we use $\pi \in [0, 1]$ to denote the ratio of labeled samples discriminator receives from the generator and the training data, and let the discriminator D and the generator G play the following two-player minimax game with a *generalized* distinguishability game value function $V_\pi(G, D)$:

$$\min_G \max_D V_\pi(G, D) = \pi \cdot \mathbb{E}_{x\sim\tilde{p}_{\text{data}}(x)}[\log D(x)] + (1-\pi) \cdot \mathbb{E}_{x\sim p_G(x)}[\log(1 - D(x))] \tag{1}$$

where $\tilde{p}_{\text{data}}(x)$ denotes the empirical distribution over training set $\mathcal{C} = \{x_1, \cdots, x_N\}$ with N samples, and

$$\tilde{p}_{\text{data}}(x) = \begin{cases} \frac{1}{N} & \text{if } x \in \mathcal{C} \\ 0 & \text{otherwise} \end{cases}$$

Proposition 1. When optimizing the value function $V_\pi(G, D)$, for any given generator G, the optimal discriminator $D^*_G(x)$ is

$$D^*_G(x) = \begin{cases} \frac{\pi\tilde{p}_{\text{data}}(x)}{\pi\tilde{p}_{\text{data}}(x)+(1-\pi)p_G(x)} & \text{if } x \in \mathcal{C} \\ 0 & \text{otherwise} \end{cases}$$

and the value function at the optimal discriminator $D^*_G(x)$ becomes

$$\begin{aligned} & V_\pi(G, D^*_G(x)) \\ \propto\ & JSD_\pi(\tilde{p}_{\text{data}}(x) \parallel p_G(x)) \\ \propto\ & \pi \sum_{x\in\mathcal{C}} \tilde{p}_{\text{data}} \log \frac{\tilde{p}_{\text{data}}(x)}{\pi\tilde{p}_{\text{data}}(x) + (1-\pi)p_G(x)} + (1-\pi) \sum_{x\in\mathcal{C}} p_G(x) \log \frac{p_G(x)}{\pi\tilde{p}_{\text{data}}(x) + (1-\pi)p_G(x)} \\ & \qquad + (1-\pi)\log(1-\pi) \sum_{x\in\mathcal{C}} p_G(x) \end{aligned} \tag{2}$$

where JSD_π is the generalized Jensen-Shannon divergence (Huszár, 2015) between two distributions $\tilde{p}_{data}$ and p_G, and is not symmetric.

Proof: Given any generator $G(x)$, the training criterion for the discriminator $D(x)$ is to maximize the value function $V_\pi(G, D)$ in (1) and could be re-written as.

$$\begin{aligned} V_\pi(G, D) =& \pi \sum_{x\in\mathcal{C}} \tilde{p}_{\text{data}} \log D(x) + (1-\pi) \sum_{x\in\mathcal{C}} p_G(x) \log(1 - D(x)) \\ & + (1-\pi) \int_{x\notin\mathcal{C}} p_G(x) \log(1 - D(x)) dx \end{aligned} \tag{3}$$

Taking derivative with respect to $D(x)$, we have

$$\frac{\partial V_\pi(G, D)}{\partial D(x)} = \begin{cases} \pi \frac{\tilde{p}_{\text{data}}(x)}{D(x)} - (1-\pi)\frac{p_G(x)}{(1-D(x))} & \text{if } x \in \mathcal{C} \\ -(1-\pi)\frac{p_G(x)}{(1-D(x))} & \text{otherwise} \end{cases} \tag{4}$$

Thus, the optimal solution for $D(x)$ is

$$D_G^*(x) = \begin{cases} \frac{\pi \hat{p}_{\text{data}}(x)}{\pi \hat{p}_{\text{data}}(x) + (1-\pi) p_G(x)} & \text{if } x \in \mathcal{C} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Plug (5) into (3), we have

$$\begin{aligned} & V(G, D_G^*(x)) \\ =& \pi \sum_{x \in \mathcal{C}} \tilde{p}_{\text{data}} \log \frac{\tilde{p}_{\text{data}}(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)} + (1-\pi) \sum_{x \in \mathcal{C}} p_G(x) \log \frac{p_G(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)} \\ & + (1-\pi) \log(1-\pi) \sum_{x \in \mathcal{C}} p_G(x) + \pi \log \pi \sum_{x \in \mathcal{C}} \tilde{p}_{\text{data}}(x) \end{aligned} \tag{6}$$

The generalized JSD can be written as

$$\begin{aligned} & JSD_\pi(\tilde{p}_{\text{data}}(x) \parallel p_G(x)) \\ =& \pi D_{KL}(\tilde{p}_{\text{data}}(x) \parallel \pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)) + (1-\pi) D_{KL}(p_G(x) \parallel \pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)) \\ =& \pi \sum_{x \in \mathcal{C}} \tilde{p}_{\text{data}} \log \frac{\tilde{p}_{\text{data}}(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)} + (1-\pi) \sum_{x \in \mathcal{C}} p_G(x) \log \frac{p_G(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) p_G(x)} \\ & + (1-\pi) \log(1-\pi) \sum_{x \in \mathcal{C}} p_G(x) - (1-\pi) \log(1-\pi) \end{aligned} \tag{7}$$

Because the last terms on the right side of Equation (6) and Equation (7) both are constant, thus equation (2) is established.

Proposition 1 shows that optimizing the mini-max game of equation (1) is equivalent to optimizing equation (2) which is over the training data, thus it is tractable and the model parameter θ can be updated directly using stochastic gradient descent (SGD) or its variants.

Proposition 2. When π is converging to 0, optimizing $\frac{V_\pi(G,D)}{\pi}$ is equivalent to optimizing the forward KL divergence $D_{KL}(\tilde{p}_{\text{data}}(x) \parallel p_G(x))$, i.e. optimizing maximum log-likelihood; and when π is converging to 1, optimizing $\frac{V_\pi(G,D)}{1-\pi}$ is equivalent to optimizing the reverse KL divergence $D_{KL}(p_G(x) \parallel \tilde{p}_{\text{data}}(x))$.

Proof: Consider the Taylor expansion $KL[Q||Q+a] \approx a^T H a$ and proposition 1, the limitation of $\frac{V_\pi(G,D)}{\pi}$ can be written as

$$\begin{aligned} \lim_{\pi \to 0} \frac{V_\pi(G,D)}{\pi} &= \lim_{\pi \to 0} \frac{JSD_\pi(\tilde{p}_{\text{data}}(x) \parallel P_G(x))}{\pi} \\ &= \lim_{\pi \to 0} D_{KL}(\tilde{p}_{\text{data}}(x) \parallel \pi \tilde{p}_{\text{data}}(x) + (1-\pi) P_G(x)) \\ &\quad + \lim_{\pi \to 0} \frac{1-\pi}{\pi} D_{KL}(P_G(x) \parallel \pi \tilde{p}_{\text{data}}(x) + (1-\pi) P_G(x)) \\ &= KL(\tilde{p}_{\text{data}}(x) \parallel P_G(x)) \end{aligned} \tag{8}$$

thus when π is converging to 0, optimizing $\frac{V_\pi(G,D)}{\pi}$ is equivalent to optimize the forward KL divergence $D_{KL}(\tilde{p}_{\text{data}}(x) \parallel p_G(x))$

On the other hand, we can also explain this proposition from the perspective of the gradient. Taking derivative with respect to the parameters θ of generator, we have

$$\frac{\partial V_\pi(G,D)}{\partial \theta} = (1-\pi) P_G(x) \log \frac{(1-\pi) P_G(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) P_G(x)} \frac{\partial \log P_G(x)}{\partial \theta} \tag{9}$$

Since the term $\frac{\log \frac{(1-\pi) P_G(x)}{\pi \tilde{p}_{\text{data}}(x) + (1-\pi) P_G(x)}}{\pi}$ converges to $-\frac{\tilde{p}_{\text{data}}(x)}{p_G(x)}$ in the limit of $\pi \to 0$, thus we can get

$$\lim_{\pi \to 0} \frac{\partial \frac{V_\pi(G,D)}{\pi}}{\partial \theta} = P_G(x)(-\frac{\tilde{p}_{\text{data}}(x)}{P_G(x)}) \frac{\partial \log P_G(x)}{\partial \theta} = -\tilde{p}_{\text{data}}(x) \frac{\partial \log P_G(x)}{\partial \theta} \tag{10}$$

where term $\frac{\partial \log P_G(x)}{\partial \theta}$ is the gradient of log-likelihood.

The same can be proved that in the limit of $\pi \to 1$, $\frac{V_\pi(G,D)}{1-\pi}$ is equivalent to reverse KL divergence $D_{KL}(p_G(x) \parallel \tilde{p}_{\text{data}}(x))$.

This proposition shows an intimate connection of optimizing the objective $V_\pi(G, D)$ to those of the forward and reserve KL divergences. Thus we can control the quality-diversity trade-off for text generation through a single hyper-parameter π.

4 EXPERIMENTAL STUDY

4.1 DATASETS

The experiments consist of two parts: synthetic-data experiments and real-world experiments. We use two datasets, COCO Image Captions dataset and EMNLP2017 WMT News dataset in our real-world experiments since they have become common benchmarks for text generation (Guo et al., 2018; Caccia et al., 2018; Montahaei et al., 2019).

4.1.1 SYNTHETIC DATASET

In synthetic-data experiments, in order to test the validity of our proposed model we conduct a simulated test similar to Yu et al. (2017). Following them, we use a random initialized LSTM as the oracle model to generate the real data distribution $P_{oracle}(x_t|x_1, \cdots, x_{t-1})$ to stimulate the real-world structured sequences. We use the oracle model to generate 10,000 sequences of length 20 and 40 respectively as our training set and another two 5,000 sequences are generated as our validation set and test set. Both of them have a vocab size of 5,000.

4.1.2 COCO IMAGE CAPTIONS DATASET

For COCO Image Captions dataset (Chen et al., 2015), we use the same pre-processing method as (Guo et al., 2018), but we randomly select 5,000 samples from training set as our validation set. The resulted dataset consist of a training set with 75,000 samples, a validation set with 5,000 samples and a test set with 5,000 samples. The vocab size is 4,838 and the maximum length of captions is 32.

4.1.3 EMNLP2017 WMT NEWS DATASET

EMNLP2017 WMT News (Bojar et al., 2017) is a collection of news texts for the machine translations task, among a version of this dataset for English Corpus containing more than 600,000 sentences, we drop the sentences having more than 3 words with less than 400 frequency and keep only the sentences that have between 20 and 40 words. We replace these most infrequent words with token $< unk >$. Next, we randomly sample 200,000 sentences as the training set, 10,000 sentences as the validation set and 10,000 as the test set. The resulted vocab size is 3,980.

4.2 EVALUATION METRICS

It is still difficult to accurately evaluate the effects of text generation models using existing metrics since the effects consist of several aspect such as consistency, diversity and fluency. Thus, in order to be consistent, we choose evaluation metrics according to previous work (Semeniuta et al., 2018; Caccia et al., 2018; de Masson d'Autume et al., 2019; Montahaei et al., 2019). We use negative log likelihood for synthetic-data experiments and use n-gram based metrics and Fréchet Distance (FD) for real-data experiments.

4.2.1 NEGATIVE LOG LIKELIHOOD

In the work of (Yu et al., 2017), the authors recommend to use the oracle negative log likelihood (NLL$_{oracle}$) which is an oracle quality metric for synthetic-data experiments. However, only use this metric will be misleading since it is blind to diversity. Thus, similar to Caccia et al. (2018),

we additionally use a metric NLL_{test} to represent diversity that is calculated by taking as input the sentences generated by oracle model to the language model we're interested in.

4.2.2 N-GRAM BASED METRICS

We use the local metrics BLEU-5 (Papineni et al., 2002) and Self BLEU-5 (Zhu et al., 2018) to capture quality and diversity respectively. While BLEU based metrics is considered to have limitations that only capture local consistency and fail to capture semantic variations (Semeniuta et al., 2018; Caccia et al., 2018; de Masson d'Autume et al., 2019), they are still one of the most widely used and simple metrics for text generation tasks.

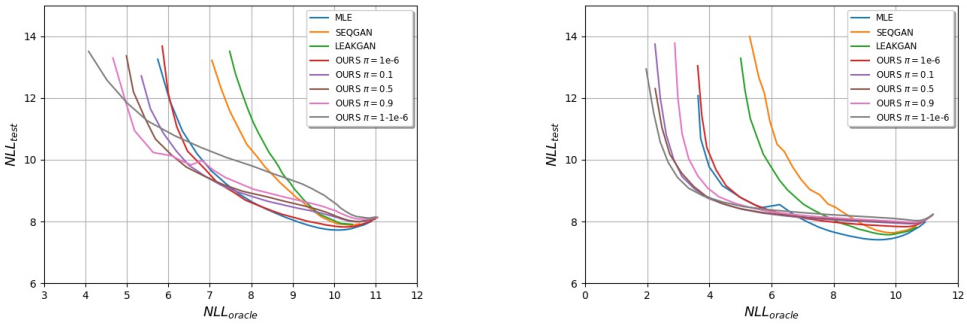
4.2.3 FRÉCHET BERT DISTANCE

Fréchet Inception Distance (FID) is originally proposed to computes the distance between two Gaussian distributions of the features of real images and generated images extracted by Inception network (Heusel et al., 2017). We follow Montahaei et al. (2019) to utilize BERT (Devlin et al., 2019), a powerful unsupervised pre-training model for text, to replace the Inception network to capture quality and diversity of generated sentences. This metric is named as Fréchet BERT Distance (FBD).

We do not use MS-Jaccard and Language Model Score (LMS) because MS-Jaccard is also an n-gram based metric like BLEU and it is highly correlated with FBD (Montahaei et al., 2019), and LMS relies on training new models and have an inherent bias favoring MLE language models, since they are trained using the same criteria (de Masson d'Autume et al., 2019).

4.3 IMPLEMENTATION DETAILS

We choose our hyper-parameters according to the result on validation set and report all metrics on test set. Our models are implemented with Tensorflow (Abadi et al., 2016) using an NVIDIA V100 GPU. The hidden size, embedding size and batch size we used are 32, 32 and 64 respectively which are kept the same as Texygen framework (Zhu et al., 2018) for fair comparison. We terminate the training of all models based on NLL_{oracle} in synthetic-data experiments and based on their BLEU-5 scores on validation set in real-data experiments.



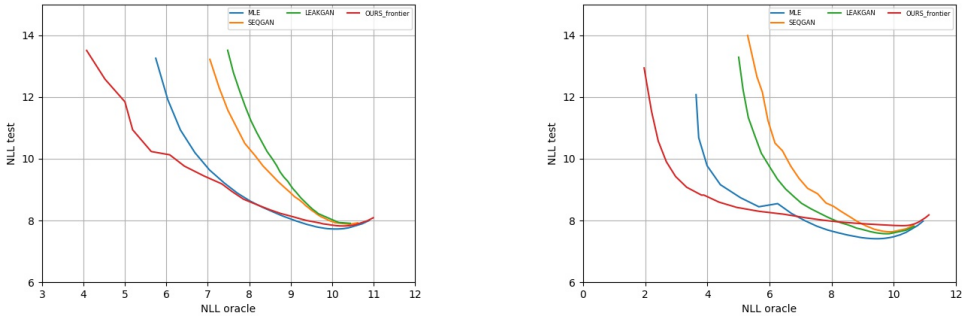
(a) Synthetic data with length 20

(b) Synthetic data with length 40

Figure 1: Temperature sweep curves for the synthetic-data experiments of sentence length 20 (left) and 40 (right) over NLL_{test} vs. NLL_{oracle} space (lower is better for both metrics)

4.4 EXPERIMENTAL RESULTS

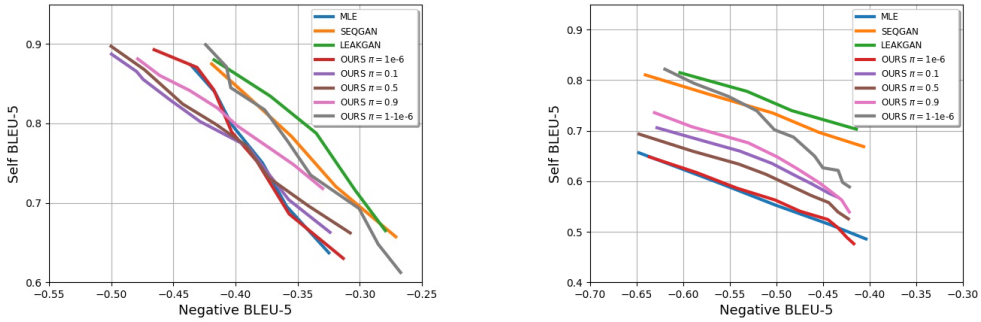
In this section, we report the experimental results on synthetic-data experiments and real-world experiments. We compare our proposed models with three baseline models: MLE, SeqGAN (Yu et al., 2017), LeakGAN (Guo et al., 2018) in all the experiments. Similar to Caccia et al. (2018), we conduct sweep of temperatures in inference stage to evaluate the trained models over quality-diversity space. We fixed the hyper-parameter π and sweep the temperatures so that we can get different temperature curves for our proposed models trained with different π.



(a) Synthetic data with length 20

(b) Synthetic data with length 40

Figure 2: Frontier curves of our models and three baseline models. Left is better and down is better. The models trained via our proposed adversarial objective perform better compared with MLE model and other GANs variants.



(a) COCO Image Captions dataset

(b) EMNLP2017 WMT News dataset

Figure 3: Negative BLEU-5 plotted against Self BLEU-5 for COCO Image Captions (left) and EMNLP2017 WMT News (right) test set. Lower is better for both metrics.

4.4.1 Synthetic Experiments

In the synthetic-data experiments, we use NLL_{oracle} and NLL_{test} as our quality and diversity metrics respectively. Both of them are the lower the better. Lowering the temperature make the model tend to produce high quality but similar sentences, while raising the temperature makes the model tend to generate diverse but relatively random sentences. We compute all metrics at different temperatures for each model to draw sweep curves in quality-diversity space.

Figure 1 depicts the temperature sweep curves of sequence length 20 and 40 respectively over NLL_{test}vs.NLL_{oracle} space. From this figure, we can observe that when $\pi \to 0$, the curve of our proposed model basically overlaps with the curve of the MLE model which shows the correctness of proposition 2. Besides, we can also observe that our models outperform other GANs variants by a large margin and perform much better than MLE on quality metric at the cost of relatively small losses on diversity metric. It is worth noting that our models do not need additional maximum likelihood pre-training and reinforcement learning and thus it is more faster in training than traditional GANs variants. As can be seen from Figure 2, the frontier curve obtained from a family of temperature sweep curves of our models outperforms the curves of MLE, SeqGAN and LeakGAN in most cases.

Models	Temperature					
	0.7	0.8	0.9	1.0	1.1	1.2
MLE	4.247	**4.125**	**4.064**	4.067	4.141	4.346
SEQGAN	4.783	4.778	4.811	4.957	5.171	5.425
LEAKGAN	5.585	5.580	5.692	5.197	5.441	5.702
OURS $\pi \to 0$	**4.231**	4.128	4.076	4.088	4.162	4.325
OURS $\pi = 0.1$	4.398	4.267	4.113	4.065	4.031	**4.129**
OURS $\pi = 0.5$	4.443	4.234	4.122	4.053	**4.024**	4.147
TRAINING SET	-	-	-	**3.581**	-	-

Table 1: FBD scores on COCO Image Captions test set at different temperatures.

Models	Temperature					
	0.7	0.8	0.9	1.0	1.1	1.2
MLE	6.263	5.524	**5.067**	4.816	5.204	**5.726**
SEQGAN	7.423	6.674	6.321	5.932	6.268	6.814
LEAKGAN	7.632	6.962	6.510	6.176	6.560	7.138
OURS $\pi \to 0$	**6.260**	**5.513**	5.082	4.803	**5.153**	5.733
OURS $\pi = 0.1$	6.784	6.127	5.663	5.341	5.754	6.244
OURS $\pi = 0.5$	6.660	6.004	5.542	5.241	5.640	6.155
TRAINING SET	-	-	-	**3.317**	-	-

Table 2: FBD scores on EMNLP2017 WMT News test set at different temperatures.

4.4.2 REAL-DATA EXPERIMENTS

Figure 3 reports negative BLEU-5 versus Self BLEU-5 metrics on COCO Image Captions and EMNLP2017 WMT News test sets for the models trained via our proposed objective, MLE model and other GANs variants. Table 1 and 2 show the FBD scores on these two test sets respectively for the models and training set.

For COCO Image Captions task, when hyper-parameter $\pi = 0.1$ and $\pi = 0.5$, our models outperform other GANs variants under quality-diversity space and outperform MLE model in terms of quality metric which may be because compared with maximum likelihood, our models can properly optimize both forward KL divergence $D_{KL}(\tilde{p}_{\text{data}}(x) \parallel p_G(x))$ and reverse KL divergence $D_{KL}(p_G(x) \parallel \tilde{p}_{\text{data}}(x))$ and compared with other GANs variants, we do not rely on reinforcement learning. When hyper-parameter $\pi \to 0$, the performance of our model is almost identical to the MLE model which is consistent with proposition 2 and better than other GANs variants .

For EMNLP2017 WMT News task, as shown in Figure 3(b) and Table 2, our models show much more competitive results to MLE than other GANs variants. Compared with the COCO task, the difference between the FBD scores of the models on the News task and training set is slightly large which may be because EMNLP2017 WMT News is a relatively more difficult task.

5 CONCLUSION

This research proposes a quality-diversity controllable GAN which is a generalization of N3DGAN and it can achieve quality-diversity control through a single hyper-parameter π. When π converges to 0, it is equivalent to directly optimizing forward KL divergence; and when π converges to 1, it is equivalent to directly optimizing reverse KL divergence. Through experiments in synthetic-data and real-data scenarios, we verify the convergence and the controllability, and we show that our proposed model outperforms MLE model and other GANs variants over quality-diversity space in the synthetic-data experiments, and in the real-data experiments, it is more competitive to MLE model than other GANs variants under several metrics. As can be seen from the experimental results, depending on the task and purpose, such as to get higher quality text or more diverse text, we should choose different hyper-parameter π to get better results on what we are interested in.

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