A Discriminator Improves Unconditional Text Generation without Updating the Generator

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Abstract
We propose a novel mechanism to improve an unconditional text generator with a discriminator, which is trained to estimate the probability that a sample comes from real or generated data. In contrast to recent discrete language generative adversarial networks (GAN) which update the parameters of the generator directly, our method only retains generated samples which are determined to come from real data with relatively high probability by the discriminator. This not only detects valuable information, but also avoids the mode collapse introduced by GAN. To the best of our knowledge, this is the first method which improves the neural language models (LM) trained with maximum likelihood estimation (MLE) by using a discriminator as a filter. Experimental results show that our mechanism improves both RNN-based and Transformer-based LMs when measuring in sample quality and sample diversity simultaneously at different softmax temperatures (a previously noted deficit of language GANs). Further, by recursively adding more discriminators, more powerful generators are created.

1 Introduction
Text generation is an important part of many applications such as machine translation (Wu et al., 2016; Bahdanau et al., 2015), dialog systems (Du and Black, 2019; Ghosh et al., 2017) and image caption generation (Liu et al., 2018; Vinyals et al., 2015). Unconditional text generation, which generates novel, reasonable and meaningful sentences, is a stepping stone for the above tasks, thus becoming a hot topic recently (Yu et al., 2017; Fedus et al., 2018; d’Autume et al., 2019).

Neural language models (LM) (Mikolov et al., 2010), based on Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) or Transformer (Vaswani et al., 2017), have been widely used as text generators, which have shown good performance in text generation (Graves, 2013; Radford et al., 2018). They are trained with maximum likelihood estimation. However, due to some limitations including exposure bias (Bengio et al., 2015), generated texts still suffer from low quality in regard to semantics and global coherence and are not even perfect grammatically speaking (Caccia et al., 2019). Many researchers improve the quality at the cost of degrading the diversity. This means there are many modes contained by real texts are not captured by generator (Huszár, 2015; Semeniuta et al., 2018). In fact, both low quality and poor diversity present statistically as a large discrepancy between the distribution of real text and the distribution of generated text. To improve unconditional text generator, we have to not only improve sample quality but also make the kinds and ratios of modes approximate the real texts as many as possible. Therefore, reducing the distributional discrepancy between the generated samples and the real data is a fundamental method to improve a generator.

A discriminator, usually a convolutional neural network (CNN) (Lecun et al., 1998) or Transformer (Vaswani et al., 2017) trained with both generated text and real text, can detect this discrepancy (Zellers et al., 2019). This suggests it
should be possible to improve the generator with a discriminator.

GAN (Goodfellow et al., 2014) has been advocated as a means to improve a generator by many researchers (Yu et al., 2017; Fedus et al., 2018; Nie et al., 2019). In this way, a LM is pre-trained with real text \(^1\) and is used as a generator (G) to generate some original text. A discriminator (D) is trained with these generated texts and real texts. The parameters of G are updated according to the detected discrepancy signal from D. Both G and D are improved iteratively in the adversarial learning process.

Unfortunately, recently more and more researchers are finding that GANs do not work well (Caccia et al., 2019; Semeniuta et al., 2018). It suffers from mode collapse (Semeniuta et al., 2018). The reason may be that discrete text is different from a continuous image, thus introducing a non-differential issue. Although reinforcement learning (RL) (Williams, 1992) is combined with GAN by treating the generative model as an agent of RL, such as SeqGAN (Yu et al., 2017), MaliGAN (Tong et al., 2017) and MaskGAN (Fedus et al., 2018).

RL brings new problems of reward sparsity and high variance. Some researchers use a continuous approximate function (Gumbel-softmax) (Kusner and Hernández-Lobato, 2016; Nie et al., 2019) or continuous latent space to enable the gradient to propagate back (Jang et al., 2017; Maddison et al., 2017). However, the Gumbel-softmax trick is a biased method which is sensitive to temperature.

In this paper, instead of using a discriminator to improve the generator in the adversarial learning style, we propose a novel mechanism of using a discriminator to improve the generator. In this mechanism, we exploit a well-trained discriminator to filter some generated texts whose distribution is very different from that of the real data, NOT to filter the low quality ones. The discrepancy between the remaining samples of generated text and the real samples can be reduced compared with that involving the entire set of between the whole generated samples and the real samples, thus improving the generator in sample quality and sample diversity simultaneously. A new generator is created by the combination of discriminator and the original generator. The remaining samples are regarded as the output of the new generator.

This new generator improves the generated results by filtering generated texts rather than updating the parameters of the original generators directly. Thus all the drawbacks attributed to using a GAN (and described above) are sidestepped completely.

Because there is still a discrepancy between real samples and samples generated by this new generator, this can be detected by a new discriminator. Therefore, our mechanism can be used recursively.

All code and data are available at GitHub\(^2\). Our contributions are listed as follows:

- We propose a novel mechanism to exploit a well-trained discriminator to improve a text generator.
- We implement a threshold-based method to filter the generated text using a discriminator.
- Our method consistently improves both RNN-based and Transformer-based LMs on two benchmark datasets.

2 The Mechanism of Filtering

Recently, neural language model (LM) is often used as a generator for unconditional text generation. Given a neural language model \(G_\theta\) which is trained with MLE, \(p_\theta(x)\) is denoted as the distribution of the texts which are generated by \(G_\theta\).

A discriminator can detect the discrepancy between the two distributions of real text and generated text. Let \(p_r(x)\) denote the distribution of real data. For the purpose of generality, let \(p_g(x)\) denote the distribution of generated text which is generated by any generator. Specifically, for the above mentioned \(p_\theta(x)\), there will be \(p_g(x) = p_\theta(x)\).

The discriminator is denoted as \(D_\phi\). To detect the discrepancy between \(p_r(x)\) and \(p_g(x)\), \(D_\phi\) needs to be optimized with the following objective function:

\[
\max_{D_\phi} \left( \mathbb{E}_{x \sim p_r(x)} [\log D_\phi(x)] + \mathbb{E}_{x \sim p_g(x)} [\log (1 - D_\phi(x))] \right) 
\]

(1)

Assuming \(D_\phi^*(x)\) is the optimal resolution of the above function, according to (Goodfellow et al., 2014), it will be,

\[
D_\phi^*(x) = \frac{p_r(x)}{p_r(x) + p_g(x)}
\]

(2)

\(^1\)An exception is RelGAN.

\(^2\)https://github.com/anonymous1100/D_Implements_G_without_Updaging_G
We use $D^p_\theta(x)$ to represent the discrepancy function, which indicates the discrepancy between $p_r(x)$ and $p_\theta(x)$.

Since the discrepancy can be detected by $D^p_\theta(x)$, it is possible to narrow the gap between $p_r(x)$ and $p_\theta(x)$ with the help of a discriminator.

The language GANs try to narrow the gap by updating the parameters of $G_\theta$ directly according to the detected discrepancy signals from the discriminator (illustrated by the left in Figure 1(a)). Unfortunately, recent work demonstrates that these approaches do not work well (Semeniuta et al., 2018; Caccia et al., 2019). The main reasons include unstable training dynamics and high variance gradient estimation (d’Autume et al., 2019). How to use a discriminator to improve an unconditional generator is still an open problem.

We try to narrow the gap by filtering (removing) some generated samples (illustrated in the right of Figure 1(a)). This novel mechanism does not change the parameters of $G_\theta$ directly, but creates a new generator $G_f$ by binding a $D_\phi$ after $G_\theta$. We describe this process in detail.

For a LM generator $G_\theta$ that is trained with MLE, the optimal discriminator $D^p_\phi(x)$ corresponding to $G_\theta$, can be obtained according to equation 1.

Given a sample $x$ which is generated by $G_\theta$, $D^p_\phi(x)$ evaluates the discrepancy between $p_r(x)$ and $p_\theta(x)$. In order to narrow the gap between $p_r$ and $p_\theta$, $x$ should be added when $D^p_\phi(x) > 0.5$, and $x$ should be removed when $D^p_\phi(x) < 0.5$. Obviously, we can not make $G_\theta$ over-generator some specific samples. Thus, only what we can do is the latter.

According to equation 2, for the latter, $p_\theta(x)$ deviates away from $p_r(x)$ further, $D^p_\phi(x)$ is smaller, thus, $x$ should be removed. The remaining samples are presented as the final output of $G_f$. Their distribution is denoted as $p_f(x)$. We call this process as filtering mechanism.

This mechanism can yield specific filtering methods for many kinds of generation model and discrimination model. In next section, we implement a simple but powerful threshold-based method in which a LSTM based or Transformer based neural language model is used as the generator, and CNN is used as the discriminator.

3 The Implement of Filtering Mechanism

How to filter generated text is a challenge. In this section, we describe a threshold-based method and analyze it theoretically. Finally, the threshold-based method can be used recursively for improving performance further.

3.1 Threshold-based filtering method

Let $\lambda$ be the threshold and $0 \leq \lambda \leq 1$. $S_{G_\theta}$ is a generated samples set which is produced by $G_\theta$. $\forall x \in S_{G_\theta}$, if $D^p_\phi(x) \leq \lambda$, $x$ is rejected, otherwise it is accepted. The accepted samples consist of set $S_{G_f}$ and are regarded as the output of $G_f$. The distribution $p_f(x)$ of $G_f$ is denoted as $p_\lambda(x)$:

$$p_f(x) = p_\lambda(x) = \begin{cases} c \cdot p_\theta(x) & D^p_\phi(x) \geq \lambda \\ 0 & D^p_\phi(x) < \lambda \end{cases}$$

Because $p_\lambda(x)$ is a distribution, the integral of $p_\lambda(x)$ equals 1.

$$c = \left( \int_{D^p_\phi(x) \geq \lambda} p_\theta(x) \, dx \right)^{-1}$$

$c$ is a normalization factor and $c \geq 1$ obviously. In this method, when $D^p_\phi(x) < \lambda$, the generated distribution of samples $x$ become zero. When $D^p_\phi(x) \geq \lambda$, the generated distribution of samples $x$ increases from $p_\theta$ to $cp_\theta$. The generation probability of these samples is increased indirectly. This method can reduce the discrepancy between real data and generated samples. Figure 2(b) illustrates this method.

\footnote{This is too hard obviously, although it works well. Some soft methods will be investigated in the future.}
Our goal is to make the new generator \( G_\lambda(x) \) better than the original generator \( G_\theta \). To this end, we have to face two challenges: (1) because we can not obtain the optimal function \( D_\phi^p(x) \) directly, we have to find an approximated function; (2) The influence of the threshold needs be investigated.

3.2 The estimation of the optimal discriminator

Although we can not obtain the optimal discriminator directly, we follow (Zhu et al., 2018) and use a CNN-based neural network as the discriminator \( D_\phi \) because CNNs are very powerful for text classification (Kim, 2014; Lai et al., 2015). A supervised learning is applied to minimize cross entropy. In order to avoid imbalanced learning (He and Garcia, 2009), we always generate as many sentences as we have real sentences. According to equation 1, \( D_\phi \) is trained until it converges. This convergent discriminator is denoted as \( \tilde{D}_\phi^p(x) \) which is the approximated function of \( D_\phi^p(x) \).

For comparison with language GANs, the architecture and hyper-parameters of our discriminator are the same as the discriminator used in SeqGAN (Yu et al., 2017).

3.3 The influence of the threshold

A procedure is proposed to investigate the influence of different thresholds:

1. Select \( M \) thresholds \( \lambda_i \in [0, 1], (i = 1, 2, ..., M), \lambda_i < \lambda_{i+1} \).
2. For each \( \lambda_i \), we can obtain the corresponding generator \( G_\lambda \).

3. We observe the performance of \( G_\lambda \) by empirically evaluating with some metrics such as BLEU versus self-BLEU.

3.4 Recursive threshold-based method

The threshold-based method can be used recursively.

For the convenience of narration, we denote the above \( p_f(x) \) as \( p_{f_1}(x) \) and \( G_f(x) \) as \( G_{f_1}(x) \). By using the generated samples of \( G_{f_1}(x) \) along with real sentences, we can train an approximated optimal discriminator \( D_{\phi_f}^{p_{f_1}}(x) \). It should be noted that the first discriminator makes no sense for \( G_{f_1}(x) \). Once again, the threshold-based method is applied to \( G_{f_1}(x) \) by using this new discriminator \( D_{\phi_f}^{p_{f_1}}(x) \) to filter generated samples of \( G_{f_1}(x) \).

We can repeat this process in practice. Figure 1(b) illustrates this process. Experimental results demonstrate that the discrepancy becomes smaller.

4 Experiments

We carry out experiments on two benchmark data sets with the threshold-based method and recursive method. Experimental settings, results and analysis are described as follows.

4.1 Experimental Settings

Datasets. Two benchmark datasets recently have been used widely for unconditional text generation. One is COCO Image captions (Chen et al., 2015) which consists of relatively short sentences and small amounts of sentences. For comparison, we follow (Caccia et al., 2019) to pre-process this dataset. There are in total 4,633 word types and the longest sentence consists of 37 words. Both the training and test data contain 10,000 sentences. The average length of sentences is about 11 words. The other one is EMNL2017 WMT News which consists of relatively long sentences and large amounts of sentences. Once again, we follow (Caccia et al., 2019) to pre-process this dataset. As a result, it consists of about 280k sentences and the sentences’ average length is about 20 words. There are in total 5,697 word types and the longest sentence consists of 51 words. 10,000 sentences are used as the test data. Among all the training data, the last 10,000 sentences are used as validation data.

\(^4\)http://cocodataset.org/
\(^5\)http://www.statmt.org/wmt17/
Table 1: The values of Hyper-parameters. For two generators, the values of GPT-2 are listed in parentheses when they are different from LSTM. "para." is the abbreviation of parameter and "# of para." denotes the total number of parameters. For each convolutional layer, (window size, kernel numbers) is listed.

| Para. of G       | Value | Para. of D     | Value       |
|------------------|-------|----------------|-------------|
| LSTM hidden layer| 512   | layer1         | (2,100)     |
| layer            | 2     | layer2         | (3,200)     |
| lr               | 1e-3  | lr(LSTM)       | 1e-3        |
| GPT-2 head       | 4     | lr(GPT-2)      | 1e-4        |
| batch size       | 128(64)| batch size     | 512         |
| # of para.       | ≈7(14)M| # of para.     | ≈0.6M       |

**Evaluation Metric.** How to evaluate a text generation system is still an open problem. The sample diversity is as important as the sample quality for unconditional text generation. (Zhu et al., 2018) proposed BLEU (Papineni et al., 2002) versus Self-BLEU, which are most frequently used by the research community. (Caccia et al., 2019) precisely use this paired metric by adjusting the softmax temperature, thereby drawing a curve rather than only plot a dot in the quality-diversity space.

Considering BLEU versus self-BLEU as a two-dimension metric, we follow (d’Autume et al., 2019) to use a single metric - Fréchet Embedding Distance (FED). It computes the Fréchet distance between two Gaussian distributions. The same embeddings trained from a Universal Sentence Encoder as (d’Autume et al., 2019) is adapted. This metric can capture both local and global consistency.

**Generator and discriminator.** For our generator, one is a LSTM and the other is GPT-2 (Radford et al., 2019), which is based on Transformer and achieve the state-of-the-art performance. For LSTM, all the hyper-parameters and the architecture are the same as (Caccia et al., 2019). For GPT-2, We optimize some hyper-parameters by observing its performance on validation data. The best settings are adapted. Table 1 lists them in detail.

For our discriminator, we follow (Zhu et al., 2018) and use a CNN. Both the hyper-parameters and architecture remain unchanged. We observe the accuracy of classification on validation to make sure the convergence of the discriminator. Because there is no validation available for COCO Image Caption, we set aside the last 1,000 sentences of the training data as the validation data.

**Baseline Models.** Two kinds of models are used as baselines. One is neural language model which is trained with MLE. Both GPT-2 and LSTM are used. The other is language GAN. The performance of SeqGAN, MaliGAN and RankGAN are taken from (Lu et al., 2018b). We also compare with RelGAN by running the code which is provided by the authors.

4.2 Main Results

Our model consistently outperforms the neural language models and language GANs on two metrics with different thresholds across two benchmark datasets.

For the metric of BLEU versus self-BLEU, we follow (Caccia et al., 2019) to draw quality-diversity curves at various temperatures. Figure 3 shows that filtering-based generators always lie at the bottom left of the blue ones which denote the performance of generator trained based on MLE. This demonstrates that the filtering mechanism works well with both RNN-based and Transformer-based LMs.

For the metric of FED, our model also outperforms both GPT-2 and LSTM at various softmax temperatures (shown by Figure 4). This suggests that the LMs are improved in global consistency and our model is better at capturing semantic information.

Table 2 and table 3 summaries more details with LSTM as the generator at a temperature of 1.0. For COCO Image Captions, our models outperform the generator trained with MLE in quality and diversity simultaneously. The reason maybe is that this task is relatively easier than EMNLP2017 WMT News. For EMNLP2017 WMT News, it is necessary to be evaluated at various temperatures by drawing a quality-diversity curve.

All results are run with five random initializations. The standard deviation is very small, thus indicating our method is very stable.

4.3 The influence of threshold

Figure 3 also shows the influence of threshold. By adjusting $\lambda_t$ from 0.05 to 0.9, we can see that all  

6The model is available at https://tfhub.dev/google/universal-sentence-encoder/3
Improvement of GPT-2 on COCO Image Caption

Figure 3: Negative BLEU-5 vs. Self-BLEU-5 on two datasets at different temperatures ($T$). The blue lines (linked with many dots and each dot corresponds to one $T$) represent the results of baseline. The other color lines (each has six dots of a different shape, and the circular one represents the performance of baseline) show the results of our method at different $T$. The scatter plots for language GANs are taken from (Lu et al., 2018a) directly and RelGAN is too distinct to be plotted. Five thresholds are set for filtering the original generated text. The lower, the better for both metrics.

$G_{\lambda_i}$ outperform the original language model $G_{\theta}$ in both sample quality and sample diversity at the same softmax temperature.

Moreover, we can see that self-BLEU is consistently decreased (although BLEU is also decreased) with the increment of the threshold when the softmax temperature is greater than 1.0. When the softmax temperature is less than 1.0, the curves are drawn in the opposite directions. This suggests that $\lambda$ can make an impact on quality and diversity.

It is noted that, $\forall \lambda_i, \lambda_j$, if $G_{\lambda_i}$ is better than $G_{\lambda_j}$ in sample quality, and then it will usually be worse in sample diversity and vice versa. This means that $\lambda$ can play a role in balancing quality and diversity.

The threshold also affects the filtering ratio. It is defined as a ratio of the remaining samples against the whole generated samples. The higher the threshold, the lower the filtering ratio.

4.4 Recursively Filtering Results

We recursively add discriminators according to section 3.4. Figure 5 shows the results with LSTM as the generator at a temperature of 1.0. The improvements are clear when the second discriminator is combined across two datasets.

However, different results occur when the third one is added. For EMNLP2017 WMT News, the performance continues to be improved while performance is worse on COCO Image Captions. This shows that the recursively filtering is related to datasets. More results, which include GPT-2 as the generator at various temperatures, are illustrated in appendix A.

5 Analysis

5.1 The Accuracy of Discriminator

Table 4 summaries the accuracy of discriminator when the generators are LSTM and GPT-2 respec-
Table 2: The results on COCO Image Captions vary with different $\lambda$. The generator is LSTM. $\varepsilon = 0.001$.

| Model   | Baseline | $\lambda = 0.05$ | $\lambda = 0.1$ | $\lambda = 0.5$ | $\lambda = 0.9$ |
|---------|----------|------------------|------------------|------------------|------------------|
| Filter Ratio | 1.000    | 0.631±0.174     | 0.556±0.157     | 0.328±0.054     | 0.148±0.034     |
| BLEU-2  | 0.716±6$\varepsilon$ | 0.724±5$\varepsilon$ | 0.724±4$\varepsilon$ | 0.722±5$\varepsilon$ | 0.717±5$\varepsilon$ |
| BLEU-3  | 0.470±11$\varepsilon$ | 0.482±9$\varepsilon$ | 0.482±8$\varepsilon$ | 0.482±9$\varepsilon$ | 0.476±10$\varepsilon$ |
| BLEU-4  | 0.285±7$\varepsilon$ | 0.296±10$\varepsilon$ | 0.297±9$\varepsilon$ | 0.297±11$\varepsilon$ | 0.293±11$\varepsilon$ |
| BLEU-5  | 0.177±4$\varepsilon$ | 0.184±7$\varepsilon$ | 0.185±6$\varepsilon$ | 0.185±6$\varepsilon$ | 0.181±8$\varepsilon$ |

self-BLEU-2 | 0.880±7$\varepsilon$ | 0.874±7$\varepsilon$ | 0.873±4$\varepsilon$ | 0.869±4$\varepsilon$ | 0.864±6$\varepsilon$ |
| self-BLEU-3 | 0.694±16$\varepsilon$ | 0.685±4$\varepsilon$ | 0.682±4$\varepsilon$ | 0.676±8$\varepsilon$ | 0.666±13$\varepsilon$ |
| self-BLEU-4 | 0.491±21$\varepsilon$ | 0.485±6$\varepsilon$ | 0.483±5$\varepsilon$ | 0.477±6$\varepsilon$ | 0.464±13$\varepsilon$ |
| self-BLEU-5 | 0.326±17$\varepsilon$ | 0.323±6$\varepsilon$ | 0.322±5$\varepsilon$ | 0.318±3$\varepsilon$ | 0.307±8$\varepsilon$ |

Table 3: The results on EMNLP2017 WMT News vary with different $\lambda$. The generator is LSTM. $\varepsilon = 0.001$.

| Model   | Baseline | $\lambda = 0.05$ | $\lambda = 0.1$ | $\lambda = 0.5$ | $\lambda = 0.9$ |
|---------|----------|------------------|------------------|------------------|------------------|
| Filter Ratio | 1.000    | 0.433±0.005     | 0.395±0.006     | 0.304±0.003     | 0.224±0.015     |
| BLEU-2  | 0.855±$\varepsilon$ | 0.850±$\varepsilon$ | 0.848±$\varepsilon$ | 0.845±$\varepsilon$ | 0.841±$\varepsilon$ |
| BLEU-3  | 0.597±$\varepsilon$ | 0.589±4$\varepsilon$ | 0.587±7$\varepsilon$ | 0.580±$\varepsilon$ | 0.573±4$\varepsilon$ |
| BLEU-4  | 0.351±$\varepsilon$ | 0.346±4$\varepsilon$ | 0.344±4$\varepsilon$ | 0.337±$\varepsilon$ | 0.329±5$\varepsilon$ |
| BLEU-5  | 0.194±$\varepsilon$ | 0.192±4$\varepsilon$ | 0.190±2$\varepsilon$ | 0.185±$\varepsilon$ | 0.179±4$\varepsilon$ |

self-BLEU-2 | 0.866±$\varepsilon$ | 0.858±$\varepsilon$ | 0.857±$\varepsilon$ | 0.853±$\varepsilon$ | 0.850±$\varepsilon$ |
| self-BLEU-3 | 0.623±$\varepsilon$ | 0.606±4$\varepsilon$ | 0.604±$\varepsilon$ | 0.596±$\varepsilon$ | 0.588±4$\varepsilon$ |
| self-BLEU-4 | 0.381±2$\varepsilon$ | 0.365±5$\varepsilon$ | 0.362±4$\varepsilon$ | 0.353±$\varepsilon$ | 0.343±5$\varepsilon$ |
| self-BLEU-5 | 0.215±$\varepsilon$ | 0.206±4$\varepsilon$ | 0.203±3$\varepsilon$ | 0.196±$\varepsilon$ | 0.189±6$\varepsilon$ |

Table 4: The accuracy of discriminator on two datasets as the generators are implemented with a two-layer LSTM and GPT-2 respectively. $\lambda = 0$ denotes the baseline, i.e. no filter.

| Dataset     | $\lambda$ | LSTM   | GPT-2  |
|-------------|-----------|--------|--------|
| COCO Image  | 0         | 0.669  | 0.617  |
| Caption     | 0.05      | 0.638  | 0.568  |
|             | 0.1       | 0.621  | 0.556  |
|             | 0.5       | 0.607  | 0.599  |
|             | 0.9       | 0.628  | 0.556  |
| EMNLP2017    | 0         | 0.703  | 0.613  |
| WMT News     | 0.05      | 0.644  | 0.575  |
|             | 0.1       | 0.638  | 0.576  |
|             | 0.5       | 0.633  | 0.568  |
|             | 0.9       | 0.633  | 0.572  |

5.2 The Efficiency of Discriminator

Table 2 and 3 show the efficiency, i.e. the filter ratio. 55.6% and 39.5% generated samples which are accepted on COCO Image Caption and ENNLP2017 WMT News respectively, with the setting $\lambda = 0.1$. Obviously, the efficiency becomes lower as $\lambda$ is bigger. Fortunately, the performance dose not vary in the same way. Empirically, $\lambda$ is set from 0.1 to 0.5 will be good.

6 Related Work

A similar over-generation and filtering method is adapted in conditional text generation (CTG) such as dialog system (Wen et al., 2015) and generating a description given a meaning representation (MR) (Novikova et al., 2017). They usually use a re-ranker to select the best one as the output (Tandon et al., 2018; Deriu and Cieliebak, 2018). However, our discriminator is different from the re-ranker in both purpose and process of being trained. To filter low quality responses or description, CTG trains re-ranker and generator jointly. Our goal is NOT filtering the low quality generated samples but the large distributional discrepancy generated ones are filtered by discriminator. Thus, the distribution of remained samples is closer to real data. Some high quality sentences will still be rejected if they are tedious. Finally, CTG biases on the quality...
in the view of evaluation, otherwise the sample diversity is as important as the sample quality for unconditional text generation.

A series of language GANs such as, DpGAN (Xu et al., 2018), maskGAN(Fedus et al., 2018) and FMGAN (Chen et al., 2018) are proposed in the view of BLEU versus self-BLEU. In order to avoid reward sparsity and high variance, (Nie et al., 2019) proposes RelGAN which exploits Gumble-softmax (Jang et al., 2017) as the continuous relaxation and achieves state-of-the-art performance.

However, some researchers argue language GANs do not work at all. (Cifka et al., 2018) think BLEU and self-BLEU only focus on local consistency and designs a language model score and a reverse language model score for evaluating generated text on global semantics. Evaluated by these two metrics, all language GANs no longer show improvement(Semeniuta et al., 2018). Furthermore, (Caccia et al., 2019) use temperature to trade-off the sample quality and sample diversity. They find a well-trained language model beats all language GANs. Although (d’Autume et al., 2019) trains a language GAN from scratch, its performance is only comparable with LM. They also propose a single metric (i.e. FED) which can cover both local and global semantic information. We adapt FED and BLEU versus self-BLEU in this paper.

7 Discussion

We use a well-trained discriminator as a filter to improve unconditional text generation. In contrast to language GANs, which use a discriminator to update the parameters of the generator, our discriminator is used as a filter to filter those generated samples whose value of discrepancy function is small enough. Therefore, the distribution of new generated text matches the distribution of real text better than the previous generator. Experimental results on two benchmark datasets show this improvement in both sample quality and sample diversity.

There is plenty of scope for future work. How to use the discriminator to improve text generation further is the first issue we wish to pursue. We hope to design a more powerful text classifier so we can obtain more benefit.
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