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DP-GAN: Diversity-Promoting Generative Adversarial Network for Generating Informative and Diversified Text

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Abstract

Existing text generation methods tend to produce repeated and "boring" expressions. To tackle this problem, we propose a new text generation model, called Diversity-Promoting Generative Adversarial Network (DP-GAN). The proposed model assigns low reward for repeated text and high reward for "novel" text, encouraging the generator to produce diverse and informative text. Moreover, we propose a novel language-model based discriminator, which can better distinguish novel text from repeated text without the saturation problem compared with existing classifier-based discriminators. The experimental results on review generation and dialogue generation tasks demonstrate that our method can generate substantially more diverse and informative text than existing baseline methods. The code is available at https://github.com/lancopku/DPGAN

1 Introduction

Text generation is important in Natural Language Processing (NLP) as it lays the foundation for many important tasks, such as dialogue generation, machine translation, and text summarization. In these tasks, most of the systems are built upon the sequence-to-sequence paradigm [Sutskever *et al.*, 2014], which is an end-to-end model that encodes the source text to a dense vector and then decodes the vector to the target text. The standard training method is based on Maximum Likelihood Estimation (MLE).

Although being widely applied, conventional MLE training causes the model to repeatedly generate "boring" text, which contains expressions with high frequency (e.g., "I am sorry" in dialogue generation [Li *et al.*, 2016a]). The major reason is that MLE encourages the model to overproduce high-frequency words.[1] The over-estimation of high-frequency words discourages the model from generating low-frequency but meaningful words in the real data, which makes the generated text tend to be repeated and "boring".

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[1] For example, the frequency ratios of "the", "and", "was" are 4.2%, 3.2%, 1.5% in the real data, and they go up to 7.1%, 4.6%, 5.3% in the MLE generated data on our review generation task.

To tackle this problem, we propose a new model for diversified text generation, called DP-GAN. The proposed model consists of a generator that is responsible for generating text and a discriminator that discriminates between the generated text and the real one. In this paper, we consider the text which is frequently produced by the generator as low-novelty text and the text which is uncommon in the generated data as high-novelty text. In adversarial learning, repeated text with low novelty can be easily identified by the discriminator and given low reward, while real and novel text receives high reward. Then, the reward is fed back to the generator, which encourages the generator to produce diverse text via policy gradient. A good discriminator that can assign reasonable reward for the generator is a critical component in this framework.

However, directly applying a classifier as the discriminator like most existing GAN models (e.g., SeqGAN [Yu *et al.*, 2017]) cannot achieve satisfactory performance. The main problem is that the reward given by the classifier cannot reflect the novelty of text accurately. First, most existing classifier-based discriminators take the probability of a sequence being true as the reward. When the novelty of text is high, the reward saturates and scarcely distinguishes the difference between novel text. For example, for a sentence A with mildly high novelty and a sentence B with extremely high novelty, the classifier cannot tell the difference and gives them saturated reward: 0.997 and 0.998. Second, in our tasks, we find that a simple classifier can reach very high accuracy (almost 99%), which makes most generated text receive reward around zero because the discriminator can identify them with high confidence. It shows that the classifier cannot distinguish the difference between low-novelty text. For example, for a sentence A with slightly low novelty and a sentence B with extremely low novelty, the classifier gives them almost the same reward: 0.010 and 0.011. The reason for this problem is that the training objective of the classifier-based GAN is in fact minimizing the Jensen-Shannon Divergence (JSD) between the distributions of the real data and the generated data [Nowozin *et al.*, 2016]. If the accuracy of classifier is too high, JSD fails to measure the distance between the two distributions, and cannot give reasonable reward to the model for generating real and diverse text [Arjovsky *et al.*, 2017].

Instead of using a classifier, we propose a novel language-model based discriminator. The cross entropy generated by the discriminator is set to be the reward for the generator. The
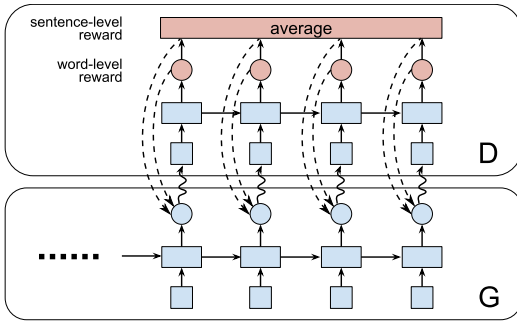
Figure 1: Illustration of DP-GAN. Lower: The generator is trained by policy gradient where the reward is provided by the discriminator. Upper: The discriminator is based on the language model trained over the real text and the generated text.

language model is able to assign low reward for the text that appears very frequently and high reward for the text that is uncommon. The reward for novel text is high and does not saturate, while the reward for text with low novelty is small but discriminative. The analysis of the experimental results shows that our discriminator can better distinguish novel text from repeated text without the saturation problem compared with traditional classifier-based discriminators.

Our contributions are listed as follows:

- We propose a new model, called DP-GAN, for diversified text generation, which assigns low reward for repeated text and high reward for novel text.

- We propose a novel language-model based discriminator, which can better distinguish novel text from repeated text without the saturation problem compared with existing classifier-based discriminators.

- The experimental results on review generation and dialogue generation tasks show that our method can generate substantially more diverse and informative text than existing methods.

2 Related Work

A popular model for text generation is the sequence-to-sequence model [Sutskever *et al.*, 2014; Cho *et al.*, 2014]. However, the sequence-to-sequence model tends to generate short, repetitive, and dull text. Recent researches have focused on developing methods to generate informative and diverse text. Reinforcement learning is incorporated into the model of conversation generation to generate more human-like speeches [Li *et al.*, 2016b, 2017]. Moreover, there are also other methods to improve the diversity of the generated text by using mutual-information, prototype editing, and self attention [Li *et al.*, 2016a; Guu *et al.*, 2017; Shao *et al.*, 2017].

In this paper, to handle this problem, we propose to use adversarial training [Goodfellow *et al.*, 2014; Denton *et al.*, 2015; Li *et al.*, 2017], which has achieved success in image generation [Radford *et al.*, 2015; Chen *et al.*, 2016; Gulrajani *et al.*, 2017; Berthelot *et al.*, 2017]. However, training GAN is a non-trivial task and there are some previous researches that investigate methods to improve training performance, such as Wasserstein GAN (WGAN) [Arjovsky *et*

Algorithm 1 The adversarial reinforcement learning algorithm for training the generator G_θ and the discriminator D_ϕ.

1: Initialize G_θ, D_ϕ with random weights θ, ϕ
2: Pre-train G_θ using MLE on a sequence dataset $\mathcal{D} = (X, Y)$
3: Generate samples using G_θ for training D_ϕ
4: Pre-train D_ϕ by Eq. (1)
5: N = number of training iterations
6: M = number of training generator
7: K = number of training discriminator
8: **for** each $i = 1, 2, ..., N$ **do**
9:     **for** each $j = 1, 2, ..., M$ **do**
10:         Generate a sequence $Y_{1:T} \sim G_\theta$
11:         Compute rewards by Eq. (2) and Eq. (3)
12:         Update generator parameters via policy gradient Eq. (5)
13:         Sample a sequence $Y_{1:T} \sim \mathcal{D}$
14:         Compute rewards by Eq. (2) and Eq. (3)
15:         Update generator parameters via Eq. (5)
16:     **end for**
17:     **for** each $j = 1, 2, ..., K$ **do**
18:         Generate samples using G_θ
19:         Train discriminator D_ϕ by Eq. (1)
20:     **end for**
21: **end for**

al., 2017] and Energy-based GAN (EGAN) [Salimans *et al.*, 2016; Gulrajani *et al.*, 2017; Zhao *et al.*, 2017; Berthelot *et al.*, 2017]. GAN in text generation has not shown significant improvement as it has in computer vision. This is partially because text generation is a process of sampling in discrete space where the normal gradient descent solution is not available, which makes it difficult to train. There are some researches that focus on tackling this problem. SeqGAN [Yu *et al.*, 2017] incorporates the policy gradient into the model by treating the procedure of generation as a stochastic policy in reinforcement learning. Ranzato *et al.* [2016] trains the sequence-to-sequence model with policy gradient for neural machine translation. Bahdanau *et al.* [2017] applies the actor-critic model on the same task.

3 Diversity-Promoting GAN

The basic structure of our DP-GAN contains a generator that is responsible for generating text and a discriminator that discriminates between the generated text and the real text. The sketch of DP-GAN is shown in Figure 1.

3.1 Overview

The generator G_θ is the sequence-to-sequence model. Given a sentence as input, the generator is capable of generating long text, which contains multiple sentences of various lengths. To put it formally, given the input sentence $x_{1:m} = (x_1, x_2, x_3, ..., x_m)$ of m words from Γ, the vocabulary of words, the model generates the text of T sentences $Y_{1:T} = (y_1, ..., y_t, ..., y_T)$, where y_t from Λ, the set of candidate sentence. The term $y_t = (y_{t,1}, ..., y_{t,K})$ is the tth sentence, where $y_{t,K}$ is the Kth word.

The discriminator D_ϕ is a language model. The cross entropy produced by the discriminator is defined as the reward to train the generator. Our reward consists of the reward at

the sentence level and that at the word level. With the discriminator and the reward mechanism, we train the generator by reinforcement learning. A sketch of training DP-GAN is shown in Algorithm 1. The details are described as follows.

3.2 Generator

For the concern of real-world applications, this paper assumes that the output of the model can be long text made up of multiple sentences. In order to generate multiple sentences, we build a standard hierarchical LSTM decoder [Li *et al.*, 2015]. The two layers of the LSTM are structured hierarchically. The bottom layer decodes the sentence representation and the top layer decodes each word based on the output of the bottom layer. Attention mechanism is used for word decoding [Bahdanau *et al.*, 2014; Luong *et al.*, 2015].

3.3 Discriminator

Most existing GAN models use a binary classifier as the discriminator. The probability of being true is regarded as the reward [Li *et al.*, 2016a; Yu *et al.*, 2017]. Different from that, we propose a language-model based discriminator D_ϕ which builds on a unidirectional LSTM. For each time step of the input, it outputs the probability distribution of the next word. Specifically, given a sentence y_t, the term $D_\phi(y_{t,k}|y_{t,<k})$ is a probability indicating how likely $y_{t,k}$ is the next token. The cross entropy is then used to calculate the reward:

$$R(y_{t,k}) = -\log D_\phi(y_{t,k}|y_{t,<k}), k = \{1, 2, \ldots, K\}$$

To encourage the model to generate novel and diverse text, the discriminator is required to assign higher reward to the real text and lower reward to the generated text. Thus, we maximize the reward of the real text and minimize the reward of the generated text. The loss function of the discriminator is formulated as follows:

$$J(\phi) = -E_{Y \sim p_{data}}[R(Y)] + E_{Y \sim G_\theta}[R(Y)] \quad (1)$$

where $R(Y)$ stands for the averaged reward of Y. The discriminator is trained over the real data and the generated data.

Therefore, if the text is frequently produced by the generator, it would receive low reward from the discriminator. In contrast, if the text is novel, the reward would become high. This mechanism encourages the generator to generate diverse and informative expressions.

3.4 Reward

Our reward mechanism consists of sentence-level and word-level rewards, which are illustrated in detail as follows.

Sentence-Level Reward

For a sentence y_t of K words, the reward at the sentence level is the averaged reward of each word:

$$R(y_t) = -\frac{1}{K} \sum_{k=1}^{K} \log D_\phi(y_{t,k}|y_{t,<k}) \quad (2)$$

In contrast, the reward of the existing classifier-based discriminators [Li *et al.*, 2016a; Yu *et al.*, 2017] is calculated as follows:

$$R(y_t) = D_\phi(true|y_t)$$

where D_ϕ is a binary classifier judging how likely y_t is from the true data. The major problem of the classifier-based discriminator is that the reward cannot reflect the novelty of text accurately. First, the reward for high-novelty text is easy to saturate, which scarcely distinguishes the difference between novel text. Second, we find that the discriminator can easily achieve very high accuracy on identifying generated text, which makes most of them get reward around zero. It shows that the classifier cannot tell the difference between the text with low novelty.

On the contrary, the analysis of experimental result shows that our proposed discriminator can better distinguish high-novelty text from low-novelty text without the saturation problem compared with traditional classifier-based discriminators. The reward for high-novelty text is high and does not saturate while the reward for low-novelty text is small but discriminative.

Word-Level Reward

Considering that the reward for different words in a sentence y_t should be different, we further propose to use the reward at the word level as follows:

$$R(y_{t,k}|y_{t,<k}) = -\log D_\phi(y_{t,k}|y_{t,<k}) \quad (3)$$

It can be found that the classifier-based discriminator only provides reward for the finished sequence. Thus, for a sequence of length T, to evaluate the action-value for a word at the time step t, Monte Carlo Search (MCS) with a roll-out policy G_θ is usually applied to sample the unknown last $T - t$ tokens [Yu *et al.*, 2017]. However, this could be computationally expensive because the time complexity is $O(T^2)$. On the contrary, our discriminator can calculate the reward of all words with the time complexity of $O(T)$, which is more computationally efficient.

3.5 Policy Gradient Training

The loss function of the generator (policy) is to maximize the reward from the start state s_0 to the end state [Sutton *et al.*, 1999]:

$$
\begin{aligned}
J(\theta) &= \sum_{t=1}^{T} E[R_{t,K}|s_{t-1}, \theta] \\
&= \sum_{t=1}^{T} \sum_{y_{t,1}} G_\theta(y_{t,1}|s_{t-1}) Q_{D_\phi}^{G_\theta}(s_{t-1}, y_{t,1})
\end{aligned}
\quad (4)
$$

where $R_{t,K} = \sum_{k=1}^{K} \gamma^{k-1} R(y_t) R(y_{t,k})$ is the total reward for a complete sentence, including both the sentence-level and the word-level rewards. The term $Q_{D_\phi}^{G_\theta}(s_{t-1}, y_{t,1})$ is estimated by $R_{t,1}$. The term γ is the discount rate and s_t is the initial state.

In this paper, we use the policy gradient method [Williams, 1992]. The gradient of Eq. (4) is approximated as follows:

$$\nabla_\theta J(\theta) \simeq \sum_{t=1}^{T} \sum_{k=1}^{K} \gamma^{k-1} R_{t,k} \nabla_\theta \log G_\theta(y_{t,k}|y_{t,<k}) \quad (5)$$

where $R_{t,k} = \sum_{i=k}^{K} \gamma^{i-1} R(y_t) R(y_{t,i})$ is the total reward starting from step k.

Following previous work [Li *et al.*, 2017], we use teacher forcing [Bengio *et al.*, 2015] to train the generator. In teacher forcing, the decoder receives the real data as input at each time step. The loss function of teacher forcing is the same with that of policy gradient training. The only difference is that the text is generated from G_θ in policy gradient training but from the real data in teacher forcing.

4 Experiment

We evaluate DP-GAN on two real-world natural language generation tasks, review generation and dialogue generation.

4.1 Datasets

Yelp Review Generation Dataset (Yelp): This dataset is provided by Yelp Dataset Challenge.[2] In our version of review generation, the model should generate a paragraph based on a given sentence. We build a new dataset for this task by splitting the data into two parts. In each review, we take the first sentence as the input text, and the following sentences as the target text. The processed Yelp dataset contains 1,400K, 400K, and 10K pairs for training, validation, and testing, respectively.

Amazon Review Generation Dataset (Amazon): This dataset is provided by McAuley and Leskovec [2013]. Like Yelp, we process this dataset by extracting the first sentence as the source text and the rest as the target text. The processed Amazon dataset contains 400K, 100K, and 10K pairs for training, validation, and testing, respectively.

OpenSubtitles Dialogue Dataset (Dialogue): This dataset[3] is used for dialogue generation. Following previous work, we treat each turn in the dataset as the target text and the two previous sentences as the source text. We remove the pairs whose response is shorter than 5 words. We randomly sample 1,800K, 500K, and 10K turns for training, validation, and testing, respectively.

4.2 Baselines

We compare the proposed DP-GAN with the following baseline models:

MLE: A sequence-to-sequence model. This model is trained with traditional MLE.

PG-BLEU: A sequence-to-sequence model. This model is trained by policy gradient with the BLEU score of the generated text as the reward [Bahdanau *et al.*, 2017]. The advantage is that this model can directly optimize the task-specific score: BLEU.

SeqGAN: Sequence GAN [Yu *et al.*, 2017] with a binary classifier as the discriminator. The generator is a sequence-to-sequence model. The discriminator, an rnn-based binary classifier, is required to evaluate the sequence and give the reward to guide the learning of the generator by reinforcement learning.

Yelp	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	151.2K	1.2K	3.9K	6.6K	3.9K
PG-BLEU	131.1K	1.1K	3.3K	5.5K	3.1K
SeqGAN	140.5K	1.1K	3.5K	6.1K	3.6K
DP-GAN(S)	**438.6K**	1.7K	7.5K	15.7K	10.6K
DP-GAN(W)	271.9K	2.8K	14.8K	29.0K	12.6K
DP-GAN(SW)	406.8K	**3.4K**	**22.3K**	**49.6K**	**17.3K**
Amazon	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	176.1K	0.6K	2.1K	3.5K	2.6K
PG-BLEU	124.5K	0.6K	1.9K	3.5K	2.3K
SeqGAN	217.3K	0.7K	2.6K	4.6K	3.2K
DP-GAN(S)	**467.6K**	0.8K	3.6K	7.6K	7.0K
DP-GAN(W)	279.4K	1.6K	8.9K	18.4K	9.6K
DP-GAN(SW)	383.6K	**1.9K**	**11.7K**	**26.3K**	**13.6K**
Dialogue	Token	Dist-1	Dist-2	Dist-3	Dist-S
MLE	81.1K	1.4K	4.4K	6.3K	4.1K
PG-BLEU	97.9K	1.2K	3.9K	5.5K	3.3K
SeqGAN	83.4K	1.4K	4.5K	6.5K	4.5K
DP-GAN(S)	**112.2K**	1.5K	5.2K	8.5K	5.6K
DP-GAN(W)	79.4K	1.9K	7.7K	11.4K	6.0K
DP-GAN(SW)	97.3K	**2.1K**	**10.8K**	**19.1K**	**8.0K**

Table 1: Performance of the DP-GAN and three baselines on review generation and dialogue generation tasks. Higher is better. DP-GAN(S), DP-GAN(W), and DP-GAN(SW) represent DP-GAN with only sentence-level reward, only word-level reward, and combined reward, respectively. *Token* represents the number of generated words. Dist-1, Dist-2, Dist-3, and Dist-S are respectively the number of distinct unigrams, bigrams, trigrms, and sentences in the generated text. For example, 1.2K in Dist-1 means 1200 distinct unigrams.

4.3 Training Details

For review generation, we set the number of generated sentences to 6 with the maximum length of 40 words for each generated sentence. Based on the performance on the validation set, we set the hidden size to 256, embedding size to 128, vocabulary size to 50K, and batch size to 64 for the generator and the discriminator. We use Adagrad [Duchi *et al.*, 2011] optimizer with the initial learning rate 0.1. In adversarial training, the step for training the generator is 1K, the step for training the discriminator is 5K. Both the generator and the discriminator are pre-trained for 10 epochs before adversarial learning. To be fair, the settings of all sequence-to-sequence models in the baselines are the same with our generator. For PG-BLEU and SeqGAN, before reinforcement learning or adversarial learning, we pre-train the sequence-to-sequence model for 10 epochs like DP-GAN. For dialogue generation, the settings are the same with review generation, except that we set the number of generated sentences to 1 with the maximum length of 40 words because there is only one sentence in the response.

4.4 Experimental Results

Automatic Evaluation

We evaluate the proposed method in terms of several metrics that can reflect the diversity. The results are shown in Table 1. *Token* represents the total number of generated words. Dist-1, Dist-2, Dist-3, and Dist-S are respectively the number of distinct unigrams, bigrams, trigrms, and sentences. DP-
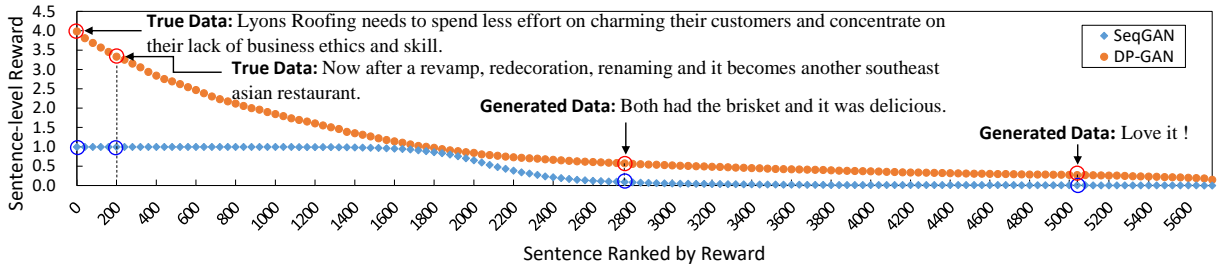
Figure 2: Distribution of rewards between SeqGAN and DP-GAN. The upper two sentences are sampled from the true data and the lower two sentences are sampled from the generated data. It is important to note that the sentence-level reward of DP-GAN is averaged word-level reward and a long sentence does not indicate a high score. As we can see, the reward distribution of SeqGAN saturates and cannot distinguish the novelty of the text accurately. DP-GAN has a strong ability of resisting reward saturation and can give more precise reward for text in terms of novelty.

	Model	Averaged Ranking
Yelp	MLE	1.89
	PG-BLEU	2.22
	SeqGAN	2.12
	DP-GAN	**1.51**
Amazon	MLE	1.93
	PG-BLEU	2.24
	SeqGAN	1.98
	DP-GAN	**1.50**
Dialogue	MLE	2.46
	PG-BLEU	2.40
	SeqGAN	2.17
	DP-GAN	**1.92**

Table 2: Results of human evaluation on three datasets. Lower is better.
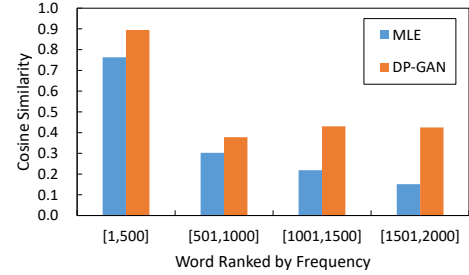

Figure 3: Cosine similarity between true data distribution and generated data distributions of various models. For example, the first column represents the cosine similarity on top 500 words with the highest frequencies in true data. As we can see, the generated data distribution of DP-GAN is closer to true data distribution, especially considering words of low frequency.

GAN(S), DP-GAN(W), and DP-GAN(SW) represent DP-GAN with only sentence-level reward, only word-level reward, and combined reward, respectively. From the results, it is obvious that the proposed model substantially outperforms the existing models. PG-BLEU achieves slightly weaker results compared with MLE. The reason is that PG-BLEU uses BLEU score as the reward for reinforcement learning. However, the BLEU score is low for most of the generated text. The low reward makes it hard to learn from the real data. SeqGAN does not achieve better results, which suggests that the classifier-based discriminator fails to encourage the generator to produce diverse text.

In terms of the total number of generated words, DP-GAN(S) achieves better results than DP-GAN(W). Since the sentence-level reward reflects the novelty of the whole sentence, it gives repeated and short text low reward while novel and complex text high reward. Thus, the generator is encouraged to generate longer and more complex text. In terms of the number of distinct n-grams, DP-GAN(W) achieves better results than DP-GAN(S). It is because the word-level reward gives each word more precise score and novel n-grams could be better encouraged. As we can see, DP-GAN(SW), which combines the advantages of sentence-level and word-level rewards, generates not only more diverse n-grams than DP-GAN(S) but also longer and more complex text than DP-GAN(W). Since combining the word-level and sentence-level rewards achieves better results than using just one of them, we focus more on the combined reward in the following parts.

In review generation and dialogue generation tasks, it is a widely debated question how well the BLEU score against a single reference can reflect the quality of the generated text [Liu *et al.*, 2016]. Thus, although the proposed model achieves better BLEU scores compared with baselines, we omit the detailed comparisons in terms of BLEU for space.

Human Evaluation
We conduct a human evaluation on the test set. Each item contains the input text and the text generated by the different systems. The items are distributed to annotators who have no knowledge about which system the text is from. Following the work of Li *et al.* [2017], we require them to rank the generated text considering relevance, diversity, and fluency. The results of human evaluation are shown in Table 2. As we can see, the proposed method achieves the best averaged ranking, and enjoys a large margin over the existing methods. As expected, PG-BLEU constantly performs the worst due to the inadequate reward function. SeqGAN does not show better performance than MLE in the human evaluation. It can be concluded that the quality of the text generated by the proposed method is much better.

Analysis: Why It Works
In this section, we provide detailed analysis to see why our proposed method works better.

In Figure 2, we demonstrate the reward distributions of our model and SeqGAN. It can be seen that the reward of SeqGAN cannot reflect the novelty of text accurately. First, when

Input: *One of my favorite places to eat.*
MLE: *Service is great.*
PG-BLEU: *Service is always good.*
SeqGAN: *Love the chicken and waffles. Service is always great.*
DP-GAN: *Love the fact that they have a large selection of food. Service is always great and the food is always fresh. I've been to this place a few times and have never been disappointed.*

Input: *Excellent service, clean, nice ambience.*
MLE: *Food is very good.*
PG-BLEU: *Food is very good.*
SeqGAN: *Food is very good.*
DP-GAN: *I had the chicken and beef and it was delicious. Food is good and the service is great. I would recommend this place to anyone who wants to eat here.*

Input: *I brought friends – seven of them – who'd never been to a Bar Louie before.*
MLE: *Food was mediocre, but the service was great. I will not be returning.*
PG-BLEU: *Food was terrible. Wouldn't recommend this place to anyone.*
SeqGAN: *Food was just okay. I wouldn't recommend this place.*
DP-GAN: *Ordered a chicken salad with a side of fries, and it was just ok. Food was good, but the service was slow. I had to ask for a refill on my drink, and the bartender was rude. I wouldn't recommend this place to anyone.*

Input: *I don't think it's too spicy, so i add a little hot curry spice to the sauce.*
MLE: *It's great for cooking. I have to say, I'm not sure if it is the same.*
PG-BLEU: *Love it!*
SeqGAN: *Love it! Love this stuff. I have used it for years and it is very good.*
DP-GAN:*I've tried many different brands of hot sauces but this one is the best. I've also used it in soups and stews. I also like that it is organic and has a great flavor.*

Table 3: Examples generated by DP-GAN and baselines on the Yelp dataset. It can be found that the text generated by baselines is more generic and repeated, while our model generates text with more specific details and higher diversity.

the novelty of text is relatively high, the reward given by SeqGAN saturates and cannot tell the difference between high-novelty text. Even with different degrees of novelty, the two high-novelty sentences sampled from the true data in the figure get nearly the same reward in SeqGAN. Second, most generated text receives reward around zero because of the high accuracy of classifier. It is hard for such reward to distinguish the difference between low-novelty text. For example, as shown in the figure, "*Both had the brisket and it was delicious*" is much more informative than "*Love it!*". The discriminator of SeqGAN gives them practically the same reward, while the proposed discriminator can better distinguish the two sentences in terms of novelty. In fact, the classifier in SeqGAN trained for 10 epochs can reach very high accuracy, that is, 98.35% and 99.63% for Yelp and Amazon, respectively. If the accuracy of classifier is too high, the classifier cannot give reasonable reward to the generator for generating real and diverse text [Arjovsky *et al.*, 2017].

In contrast, the language-model based reward given by DP-GAN better reflect the novelty of the text. The novel text is given high reward that does not saturate. The generated data, which can be less novel, is given relatively low but nonzero reward that can encourage the generator to generate diverse expressions. The refined reward leads to more efficient training, thus resulting in better performance.

We also compare the cosine similarity between true data distribution and generated data distributions of various models. Figure 3 shows the results. We calculate the cosine distance between two vectors, where each element is the frequency of a word indexed by its rank in the true data. For example, the first element in the vector means the frequency of the word that ranks first in true data. The word frequency vector is divided into 4 vectors to show the similarity of words of different frequencies. The distribution of the words are more similar when they occur more frequently in true data. As DP-GAN promotes diversity, words of low frequency in true data are better learned and the similarity is much better than that of MLE. In all, the generated data distribution of DP-GAN is closer to true data distribution in all intervals, especially considering words of low frequency.

Table 3 presents the examples generated by different models on the Yelp dataset. It can be found that the text generated by MLE is more generic and repeated, while PG-BLEU and SeqGAN do not perform obviously better than MLE. Moreover, it can be clearly seen that our model generates text with more specific details and higher diversity.

5 Conclusion

In this paper, we propose a new model, called DP-GAN, to promote the diversity of the generated text. DP-GAN assigns low reward for repeated text and high reward for novel text, encouraging the generator to produce novel and diverse text. We evaluate DP-GAN on two tasks and the findings are concluded as follows: First, the proposed method substantially outperforms the baseline methods in automatic and human evaluations. It shows that DP-GAN is capable of producing more diverse and informative text. Second, the proposed discriminator can better distinguish novel text from repeated text with the saturation problem compared without traditional classifier-based discriminators. Third, with the improvement of diversity, the generated data distribution of DP-GAN is closer to the real data distribution compared with that of MLE.

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