Abstract

Although GAN-based methods have received many achievements in the last few years, they have not been such successful in generating discrete data. The most important challenge of these methods is the difficulty of passing the gradient from the discriminator to the generator when the generator outputs are discrete. Despite several attempts done to alleviate this problem, none of the existing GAN-based methods has improved the performance of text generation (using measures that evaluate both the quality and the diversity of generated samples) compared to a generative RNN that is simply trained by the maximum likelihood approach. In this paper, we propose a new framework for generating discrete data by an adversarial approach in which we do not need to pass the gradient to the generator. In the proposed method, the update of either the generator or the discriminator can be accomplished straightforwardly. Moreover, we leverage the discreteness of data to explicitly model the data distribution and ensure the normalization of the generated distribution and consequently the convergence properties of the proposed method. Experimental results generally show the superiority of the proposed DGSAN method compared to the other GAN-based approaches for generating discrete sequential data.

1 Introduction

The early deep generative models that were utilized to generate sequential discrete data such as natural language were Recurrent Neural Networks (RNNs). However, RNN-based methods for discrete sequence generation that employ teacher forcing approach for training suffer from the so-called exposure bias problem [8,1]. On the other hand, the recent Generative Adversarial Networks (GANs) were not such successful in generating sequential discrete data [15,4] despite their success in other domains, especially image generation.

In the last few years, various attempts were accomplished to apply GANs [5] to discrete domains, but some difficulties in the training of these networks on discrete data exist. More precisely, in the discrete domains, passing the gradient to the generator is infeasible (due to the sampling that was done in the output of the generator) during the training process [15,4]. To overcome this issue, the Reinforcement Learning (RL) approach is utilized [15]. Although RL provides a way to train the generator, it encounters some problems such as very large action space, the sparsity of the reward, and thus high variance of the update. Since just receiving a scalar as the reward signal from the discriminator is not such informative, many methods such as TextGAN [15], LeakGAN [6],
RankGAN [9], and MaliGAN [3] were proposed to pass a more informative signal to the generator. Specially MaliGAN tries to define a new objective and a target distribution for the generator.

In this paper, a framework for adversarially training generative models of discrete data is proposed. In this framework, by considering an explicit distribution for the generator (due to the advantage of finite discrete domains) and finding a closed-form relation between the next generator and the current discriminator and generator, the gradient passing problem is resolved. In the proposed method, the generator and the discriminator are unified in a single network. This network both provides the probability distribution of data and prepares the (conditional) probability of assigning the input to the class of real data. As a result of this integration, the gradient passing issue is bypassed, and the training stability is achieved.

Below, we describe the main contributions of the proposed method:

- In the proposed method, as opposed to the existing GAN-based methods for discrete sequence generation (i.e., SeqGAN, RankGAN, LeakGAN, TextGAN, and MaliGAN), the RL approach is not required. Instead, by using the closed form solution for the next discriminator, the difficulty of generator training will be resolved. Among the existing methods, MaliGAN [3] is the most related work to ours. However, it has main differences. It updates the generator via an RL approach using a gradient estimator that is based on importance sampling while the proposed method uses the optimal solution of the discriminator for the current generator directly without any extra training for the discriminator.

- As is discussed in [5], for each generator, the optimal discriminator can be described according to the generator and the real data distribution (even when the generator is not optimal). In the proposed method, by considering domains like discrete ones for which an explicit generative distribution is obtainable, it would be possible to approximate the real data distribution from the discriminator and the current generator.

- The proposed method is not limited to the discrete sequence generation. In those domains such as finite discrete ones for which an explicit generative model is considered, the generator can be trained by the proposed adversarial method instead of the maximum likelihood estimation.

2 Preliminaries and Overview

2.1 GAN

In the standard GAN, we have some samples from the real data distribution $P$, which we need to learn. The generator attempts to learn a network $Q$, which can generate samples similar to the real ones, and the discriminator intends to determine whether a sample is real or synthetic. Formally, the objective is [5]:

$$V(Q, D) = \mathbb{E}_{x \sim P}[\log D(x)] + \mathbb{E}_{x \sim Q}[\log(1 - D(x))],$$

which is maximized with respect to $D$ and minimized with respect to $Q$. It is shown that the optimal $D$ for a fixed $q$ is found as [5]:

$$D^*_Q(x) = \frac{p(x)}{p(x) + q(x)}. \quad (2)$$

Moreover, for the optimal discriminator $D^*_Q$, minimizing $V(Q, D^*_Q)$ w.r.t. $Q$ leads to minimization of Jensen-Shannon divergence between $P$ and $Q$ [5].

3 Proposed Method

In the following subsections, we first describe the general framework for adversarially training explicit generative models defined on finite discrete random variables (such as simple categorical distributions or even more complex distributions that are represented by Bayesian networks with discrete random variables). Then, the theoretical analysis of the proposed training approach is presented. We bring up the discrete sequence generation task as an instance of tasks in which the GAN-based approaches have encountered difficulties. Finally, using the proposed framework, a method for sequence generation is introduced.
We can also provide a dual presentation of the proposed approach. In one perspective, the proposed approach can be considered as training a generative model by optimizing the objective function proposed in Eq. 1. In the other perspective, the optimal discriminator is found by maximizing the objective function in Eq. 4 w.r.t. the discriminator $D$. Then, the generator $Q_{\theta}$ is found according to the above optimization problem using samples of the old generator since the data domain is considered finite and discrete. According to Eq. 4, to sample from $Q_{\theta}$ and thus the difficulty of gradient propagation through the discrete output of the generator $Q_{\theta}$ is bypassed.

We can also provide a dual presentation of the proposed approach. In one perspective, the proposed approach can be considered as training a generative model by optimizing the objective function proposed in Eq. 1. In the other perspective, the optimal discriminator is found by maximizing the objective function in Eq. 4 w.r.t. the discriminator $D$ and then the update equation for the generator can be obtained (using Eq. 3) as:

$$q_{\text{new}}(x) = q_{\text{old}}(x) \frac{D(x)}{1 - D(x)}. \quad (5)$$

Therefore, we have a closed form relation between the current generator, the new generator, and the optimal discriminator differentiating them. An overview of the training procedure is provided in Alg. 1.

3.2 Theoretical Analysis

In this section, we will discuss the intuition of the proposed method and the convergence of the training algorithm. All the proofs are provided in the appendix.

**Theorem 3.1.** Let $P$ and $Q$ denote two distributions and $\mathcal{B}_f(.,||.)$ be the Bregman divergence. The Jensen-Shannon divergence of these distributions can be formulated as:

$$D_{JS}(P||Q) = \mathcal{L}(P, Q, D) + E_{x \sim P} \left[ \mathcal{B}_f \left( \frac{p(x)}{q(x)} \left| \left| \frac{D(x)}{1 - D(x)} \right| \right| \right] + \text{const},$$

$$= \mathcal{L}(P, Q, D) + E_{x \sim P} \left[ \mathcal{B}_f \left( \frac{q(x)}{p(x)} \left| \left| \frac{1 - D(x)}{D(x)} \right| \right| \right] + \text{const}, \quad (6)$$

---

**Algorithm 1 DGSAN general algorithm**

1: **Input:** real training data $\{x_i\}_{i=1}^N$, number of iterations $t$
2: Set an initial generator $Q^0$ (e.g., an arbitrarily distribution, $q^0(x) > 0$ for all $x$)
3: $Q^{old} = Q^0$
4: for $i = 1$ to $t$
5:   Generate $\{x'_i\}_{i=1}^N$ samples from $Q^{old}$
6:   Train $Q_{\theta}$ by optimizing Eq. 3 (using real samples $\{x_i\}_{i=1}^N$ and generated samples $\{x'_i\}_{i=1}^N$).
7: $Q^{old} = Q_{\theta}$
8: end for
where $\mathcal{L}(P, Q, D) = E_{x \sim P} [\log D(x)] + E_{x \sim Q} [\log (1 - D(x))]$ and $f(u) = u \log u - (u + 1) \log (u + 1)$ is the function used in the Bregman divergence.

**Corollary 3.1.** $\frac{p(x)}{q(x)}$ can be estimated by $\frac{D(x)}{1 - D(x)}$ when maximizing $\mathcal{L}(P, Q, D)$ w.r.t. $D$.

According to the above corollary, we can use Eq. 5 to find the best generator for the current discriminator and generator. Thus, if we reach the global optimum, $\frac{D(x)}{1 - D(x)} q(x)$ will result in the real data distribution and $q^{\text{new}}(x) = \frac{D(x)}{1 - D(x)} q(x) = p(x)$.

Since it is ideal to reach the global optimum of $\mathcal{L}(P, Q, D)$, the following theorem is provided to support the convergence of the method in the case of reaching a local optimum. This theorem guarantees that the update of the generator in each iteration decreases the cost function of the GAN (i.e. Jensen-Shannon divergence of the generator distribution and the real distribution).

**Theorem 3.2.** If $D^{\text{new}}(x) = \frac{q^{\text{new}}(x)}{q^{\text{new}}(x) + q^{\text{old}}(x)}$ is between a random and an optimal discriminator $D^*(x) = \frac{p(x)}{p(x) + q^{\text{old}}(x)}$ for $Q^{\text{old}}$, we will have $\mathcal{D}_{\text{JS}}(P||Q^{\text{new}}) < \mathcal{D}_{\text{JS}}(P||Q^{\text{old}})$.

This theorem shows that when the discriminator is non-optimal, under a weak condition, the Jensen-Shannon divergence decreases after each iteration of the algorithm and thus $Q$ finally converges to $P$.

### 3.2.1 Bregman Family Compatibility

We can extend the above theorems to more general ones supporting a wide range of $f$-divergences (instead of just Jensen-Shannon divergence).

**Theorem 3.3.** For every $r(x)$ and $f$-divergence with strictly convex $f$,

$$
\mathcal{D}_f(P||Q) = \mathcal{L}_f(P, Q, \tau) + E_{x \sim Q} \mathcal{B}_f\left(\frac{p(x)}{q(x)} \| r(x)\right),
$$

$$
\mathcal{L}_f(P, Q, \tau) = E_{x \sim P}[\tau(x)] - E_{x \sim Q}[f^*(\tau(x))],
$$

where $\tau(x) = f^*(r(x))$ and $f^*$ is the Fenchel conjugate of $f$.

It is worth to mention that 14 also presents another variation of Theorem 3.3.

Thus, by maximizing $\mathcal{L}_f(P, Q, \tau)$, the corresponding Bregman divergence will be minimized and the desired $\frac{p(x)}{q(x)}$ estimation is achieved.

**Theorem 3.4.** If $D^{\text{new}}(x) = \frac{q^{\text{new}}(x)}{q^{\text{new}}(x) + q^{\text{old}}(x)}$ is between random and optimal discriminator $D^*(x) = \frac{p(x)}{p(x) + q^{\text{old}}(x)}$ for $Q^{\text{old}}$, we will have $\mathcal{D}_f(P||Q^{\text{new}}) < \mathcal{D}_f(P||Q^{\text{old}})$ for every $f$-divergence by strictly convex $f$.

### 3.3 Model for sequence generation

For the sequence generation, we want to model $q(x|l|x_{1:l-1})$ and an RNN network is used for this purpose. The input sequence $x_1, ..., x_L$ is first embedded as $\mathbf{x}_1, ..., \mathbf{x}_L$ and then mapped into the sequence of hidden states $\mathbf{h}_1, ..., \mathbf{h}_L$ using a recurrent unit $\mathbf{h}_t = g(\mathbf{h}_{t-1}, x_t)$ (in which $x_0$ shows the start token) and the conditional distribution is modeled as $q(x|l|x_{1:l-1}) = \text{softmax}(V \mathbf{h}_l)$. Let $\theta$ denote the set of parameters of the generator network (containing the parameters of $g$ and the matrix $V$). To find $q^{\text{new}}(x|l|x_{1:l-1})$ from $q^{\text{old}}(x|l|x_{1:l-1})$, we solve the following optimization problem:

$$
\max_{\theta} \sum_{x \sim P} \left[ \log \left( \frac{1}{1 + \frac{q^{\text{new}}(x|l|x_{1:l-1})}{q^{\text{old}}(x|l|x_{1:l-1})}} \right) \right] + \sum_{x \sim Q^{\text{old}}} \left[ \log \left( \frac{1}{1 + \frac{q^{\text{new}}(x|l|x_{1:l-1})}{q^{\text{old}}(x|l|x_{1:l-1})}} \right) \right].
$$

(7)

**3.3.1 From the viewpoint of the discriminator**

The proposed network inherently includes also a discriminator. The objective function in Eq. 7 is equivalent to use an extended sigmoid function on $V \mathbf{h}_l$ to find a discriminator $D(x|l|x_{1:l-1})$. In fact,
when \( q_{\theta}(X_l = x | x_{1:l-1}) = \frac{\exp(V_l h_l)}{\sum_{i=1}^{M} \exp(V_i h_i)} \) shows the probability of generating \( X_l = w \) given the sequence \( x_{1:l-1} \), the discriminator will be:

\[
D(X_l = w | x_{1:l-1}) = \frac{1}{1 + \frac{q_{\theta}(x_l = w | x_{1:l-1})}{q_{old}(x_l = w | x_{1:l-1})}} = \frac{1}{1 + \frac{\exp(V_l h_l)}{\sum_{i=1}^{M} \exp(V_i h_i)}} \exp(V_l h_l) \sum_{i=1}^{M} e^{V_i h_i} , \quad (8)
\]

where \( M \) shows the number of words in the vocabulary.

Therefore, using a single RNN, we can model both the generator and the discriminator. The discriminator \( D(X_l = w | x_{1:l-1}) \) is modeled as Eq. (8) and the new generator \( q_{\text{new}}(x_l) \) is found (according to Eq. (5)) as \( q_{\theta}(X_l = w | x_{1:l-1}) = \frac{\exp(V_l h_l)}{\sum_{i=1}^{M} \exp(V_i h_i)} \) that provides a normalized distribution. Therefore, both the generator and the discriminator distribution are conditioned on previous elements of the sequence and the expected conditional loss of the \( l \)-th element is optimized in Eq. (7).

To make theorems consistent with the sequence generation task, all distributions are considered conditional ones and no further assumptions are required and thus the theorems in Section 3.2 can be applied in the special case of sequence generation too.

4 Related Works

As mentioned above, the GAN approach in discrete domains has a problem in propagating the gradient into the generator. SeqGAN [15] has overcome this problem by using a REINFORCE-like algorithm in training of the generator. It sees the generator as an agent which receives more reward from the discriminator in the case of generating more realistic sentences and uses Monte Carlo tree search to estimate the expected reward. This method has some difficulties such as reward sparsity and high variance of training.

Multiple studies were carried on this approach and tried to transfer more information from the discriminator to the generator. RankGAN [9] trains a ranker instead of a discriminator which relatively assigns a higher score to the more realistic sequences. In other words, the score of a sentence shows how much realistic it is in comparison with other sentences in the current batch of data. Therefore, the generator will receive more informative gradient. LeakGAN [6] takes advantage of the feudal networks by considering the generator as a two-level module containing a manager and a worker. The feature layer of the discriminator is fed to the manager as leaked information. TextGAN [18] tries to redefine the generator’s objective. It attempts to push the generator’s focus from the last layer of the discriminator to its last feature layer. The generator’s objective is to make the feature distribution of generated data closer to that of the real data according to the Maximum Mean Discrepancy (MMD) measure. Boundary-Seeking GAN [7] has also changed the generator’s objective using the discriminator’s output to make the generator closer to the approximated real data distribution by minimizing \( D_f(P || Q) \) where \( Q \) shows the generator. This objective is optimized via an importance sampling approach. There exists a very similar method called MaliGAN [3], which was mainly proposed for sequence generation. MaliGAN reduces the variance of training by employing various techniques such as Mixed MLE-MALI training and estimating reward with action-value function \( Q(s, a) \). Although this method may show similarities to ours, it still uses an RL-based approach and does not take the full information from the discriminator. When the previous generator’s distribution is available, the next generator estimating the real data distribution is reachable straightforward, and no additional KL optimization is needed. Hence, none of the stabilizing tricks utilized in this method are required to be done in our method.

All of the recent GAN-based methods for discrete sequence generation attempt to make the information flow from the discriminator to the generator more effective in order to transfer stronger and more informative training signal to the generator. Nonetheless, they were failed to take the full advantage of the discriminator. The proposed generative model in this paper has a hybrid nature. In one perspective, it can be seen as a discriminator while in another perspective, it can provide an explicit generative model. Hence, any information wanted to be pushed to the generator is available to it since the generator and discriminator have been combined in a single model.

We presented the extended version of the proposed method in Section 3.2 inspired by several other works [14, 11, 13, 7, 3] that have extended the GAN’s initial framework. As mentioned in the proceeding section, the standard GAN minimizes the JS divergence, which is of \( f \)-divergence family. Variational Divergence Minimization (VDM) [11] shows that there exists a lower bound for each
f-divergence based on the Fenchel conjugate of $f$. For example, it can be seen that the standard GAN is an instance of VDM with $f(u) = u \log(u) - (u + 1) \log(u + 1)$. This lower bound can be taken into account to minimize the f-divergence indirectly as a loss function. Since a wide range of original f-divergences cannot be directly optimized, they are approximated via a lower bound and the approximated lower bound is optimized iteratively to achieve the saddle point of the lower bound. In the other side, some works were introduced considering ratio $r(x) = \frac{p(x)}{q(x)}$ as a mediator to estimate the data distribution $\hat{p}(x) = \hat{r}(x)q(x)$ and the generator is to learn $\hat{p}(x)$ via training a discriminator with cross entropy loss and the generator by minimizing $\mathbb{D}_{KL}(\hat{P}||Q_\theta)$. BGAN \cite{5} uses some idea like VDM and utilizes variational lower bound for f-divergences and similarly investigates a more general form of estimating $r$ while the generator's objective is still $\mathbb{D}_{KL}(\hat{P}||Q_\theta)$. In \cite{3}, an arbitrarily f-divergence is optimized instead of minimizing $\mathbb{D}_{KL}(\hat{P}||Q_\theta)$.

5 Experiments and Results

In this section, we will first introduce some measures to evaluate the performance of models in generating sentences. Then, we conduct experiments to examine the proposed method for sequence generation compared to the state-of-the-art methods.

5.1 Evaluation Measures

First, NLL as a well-known metric for evaluating generative models is presented, and then three n-gram based measures for evaluating sequence generation are introduced.

5.1.1 Negative Log Likelihood

For a generative model, it shows the negative log likelihood of data in the model. The GAN-based methods tend to have poor NLL scores on the training/test data since this measure is much sensitive to the mode collapse phenomenon. It should be noted that the NLL is closely related to another well-known metric called Perplexity (so, we just report NLL to avoid redundancy).

5.1.2 BLEU

BLEU is a metric invented for evaluation of machine translation methods \cite{12}. It measures n-gram similarities of a test sentence to a reference set and then takes the geometric mean of n-gram similarities to produce a score for the test sentence. As discussed in \cite{12}, a model repeatedly generating one high-quality sentence can get high BLEU score while completely losing diversity. Therefore, BLEU only evaluates the quality of the samples and is not sensitive to their diversity \cite{19,18,10}.

5.1.3 Self-BLEU

It is a measure which tends to evaluate the diversity of a set of sentences \cite{19}. Each generated sentence is assumed as the candidate sentence and the others as the reference set, and the BLEU is calculated for this candidate according to the reference set. The more similarity of each sentence to the others leads to higher BLEU scores that shows less diversity. In other words, the lower values of this measure denote higher diversity. It is notable that the human evaluation of sample diversity is not such straightforward, and so it is necessary to have a metric to compare models according to this aspect.

5.1.4 MS-Jaccard

Either having a model, repeatedly generating just one high-quality sample or having a model generating a wide variety of low-quality samples, is disappointing. Thus, to consider this trade-off and have a metric jointly measuring the validity and coverage, the recently proposed MS-Jaccard metric is taken into account \cite{10}. The n-grams of generated samples and those of real samples are considered as two multi-sets that preserve the repetition of n-grams. Then, the similarity of the resulted multi-sets is computed by the Jaccard similarity measure whose higher scores are more desired.

When the generated sentences do not have diversity (e.g., when the mode collapse happens) or lose quality, the n-gram distribution of generated texts will be different from that of the real texts and this
measure will be decreased. However, BLEU is not sensitive to the diversity and Self-BLEU does not show the quality of samples \cite{19, 10}.

5.2 Datasets

We have used three real-world datasets: Image COCO captions, EMNLP News, and Chinese poem to cover a wide range of linguistic datasets. The complete description of the datasets is as follows.

- COCO Captions: It is a collection of image captions containing around 600,000 captions. Sentences having between 5 and 25 words are selected (resulting in 524,225 sentences). The vocab size of the resulted dataset is 5,328. Finally, the dataset of 60,000 samples is subsampled from the above dataset. Among this dataset, 40,000 samples are used for training, 20,000 samples for validation, and 20,000 samples for test.

- EMNLP2017 WMT News: It contains around 20 million sentences. Among a subsampled version containing 500,000 sentences, sentences that have between 20 and 40 words are selected. The vocab size of the resulted dataset is 6,148. Finally, the dataset of 60,000 samples is subsampled from the above dataset. Among this dataset, 40,000 samples are used for training, 20,000 samples for validation, and 20,000 samples for test.

- Chinese Poems: It includes 12,798 4-line 5-character Chinese poems introduced by \cite{17}. 10,028 samples were used for training, 770 for validation, and 2000 for test.

5.3 Experiment Setup

In this section, the selected methods for comparison are introduced first, and then the training setup is presented. We conduct experiments to compare our method with some recent GAN-based methods for sequence generation, i.e., SeqGAN, MaliGAN, and RankGAN. Moreover, MLE is included in our experiments as a baseline. The \cite{https://github.com/geek-ai/Texygen} contains the implementation of all of these methods.

In order to have a fair comparison, all settings of the methods were kept similar as in the Texygen framework \cite{19}. Therefore, we have set the generator architecture of all the methods the same as an LSTM with 32 hidden and 32 embedding \cite{19} (it is worth to mention that the vocab of the datasets introduced above is limited and this size of models works). Since setting a fixed number of epochs for training termination of all the methods does not seem reasonable, the termination condition for each model is chosen based on its objective. If fact, the best BLEU-4 on the validation set for GAN-based methods and the best NLL of the validation set for MLE is selected for termination. To determine BLEU scores of GAN-based models during the training procedure (for specifying termination epoch), 5000 samples were generated from each model and evaluated on the corresponding validation set every five epochs. In the proposed method, the learning rate was set to $10^{-3}$ and no further tuning is accomplished.

To have reliable results, each dataset is split into three parts, and three models are trained on each 2 out of 3 parts putting one part aside as the validation set.

5.4 Results

As discussed in Section \cite{5.1, 2, 10, 16, 19} have shown that BLEU measure individually is not a complete measure of evaluating text generation models. Since GAN-based text generation models may generate a highly limited set of sentences and sacrifice the coverage (due to the mode collapse problem), evaluating the text generation models using just BLEU is not such valid. Therefore, we have also reported MS-Jaccard score to evaluate both the validity of the outputs and their diversity and Self-BLEU score to assess the diversity of generated samples by different models.

Table \cite{1} shows results of different methods on the COCO captions, EMNLP News, and Chinese poem dataset. The reported results in this table include the mean and the standard deviation of n-gram based measures on the test set. BL-$N$, SBL-$N$, and MSJ-$N$ denote BLEU, Self-BLEU, and

\begin{table}[h]
\centering
\begin{tabular}{||c|c|c||}
\hline
Model & BLEU & Self-BLEU \\
\hline
SeqGAN & 30.5 & 28.3 \\
MaliGAN & 30.8 & 28.4 \\
RankGAN & 31.0 & 28.5 \\
MLE & 30.2 & 28.1 \\
\hline
\end{tabular}
\caption{Comparison of different methods on the COCO captions dataset.}
\end{table}
Table 1: Performance of models (using BLEU, MS-Jaccard and Self-BLEU) on COCO, EMNLP and Chinese Poem datasets (using test set).

| Methods | COCO | EMNLP | Ch-Poem |
|---------|------|-------|---------|
|         | BL4  | MSJ4  | SBL4    | BL4  | MSJ4  | SBL4    | BL4  | MSJ4  | SBL4    |
| MLE     | 0.508 ± 0.001 | 0.325 ± 0.002 | 0.429 ± 0.001 | 0.269 ± 0.005 | 0.167 ± 0.001 | 0.200 ± 0.001 | 0.065 ± 0.002 | 0.022 ± 0.002 | 0.083 ± 0.002 |
| SeqGAN  | 0.578 ± 0.019 | 0.241 ± 0.005 | 0.390 ± 0.001 | 0.284 ± 0.027 | 0.090 ± 0.001 | 0.278 ± 0.001 | 0.092 ± 0.001 | 0.031 ± 0.001 | 0.157 ± 0.001 |
| MaliGAN | 0.555 ± 0.016 | 0.274 ± 0.001 | 0.511 ± 0.001 | 0.306 ± 0.008 | 0.128 ± 0.001 | 0.323 ± 0.001 | 0.089 ± 0.001 | 0.033 ± 0.001 | 0.128 ± 0.001 |
| RankGAN | 0.572 ± 0.034 | 0.251 ± 0.012 | 0.581 ± 0.012 | 0.287 ± 0.018 | 0.098 ± 0.001 | 0.394 ± 0.001 | 0.097 ± 0.001 | 0.032 ± 0.001 | 0.187 ± 0.001 |
| DGSAN   | 0.534 ± 0.003 | 0.357 ± 0.004 | 0.443 ± 0.001 | 0.283 ± 0.005 | 0.179 ± 0.004 | 0.214 ± 0.004 | 0.091 ± 0.004 | 0.041 ± 0.004 | 0.178 ± 0.004 |

Table 2: Performance of models using NLL on COCO, EMNLP and Chinese Poem datasets (using test set).

| Methods | COCO | EMNLP | Ch-Poem |
|---------|------|-------|---------|
|         | BL4  | MSJ4  | SBL4    | BL4  | MSJ4  | SBL4    |
| MLE     | 38.356 ± 0.100 | 143.121 ± 0.139 | 137.370 ± 12.967 |
| SeqGAN  | 48.182 ± 0.145 | 181.777 ± 14.660 | 177.793 ± 18.307 |
| MaliGAN | 46.622 ± 0.216 | 160.868 ± 1.284 | 165.541 ± 30.780 |
| RankGAN | 47.767 ± 4.699 | 108.296 ± 10.943 | 172.739 ± 28.262 |
| DGSAN   | 36.304 ± 0.007 | 145.029 ± 0.177 | 135.664 ± 0.319 |

MS-Jaccard measures, respectively \((N\) shows the maximum length of n-grams). Moreover, some samples of each model are provided in the Appendix.

Table 2 shows NLL of test data for the different methods on COCO captions, EMNLP News, and Chinese poem dataset. It is notable that on two out of the three datasets, the DGSAN method has outperformed MLE according to the NLL measure; this is while NLL is the objective of MLE but not the objective of the methods like DGSAN. Moreover, other GAN-based methods do not show proper results according to the NLL measure. This is due to their mode-collapse problem (test samples from those modes that have missed in these models get low probability and thus decrease the NLL measure).

In summary, according to the above experiments on two standard language modeling tasks and a challenging task for poem generation, superior results are obtained for the proposed DGSAN method according to the MS-Jaccard measure and also according to NLL as the most well-known measure for evaluating generative models. Moreover, the proposed method is the second best method according to the Self-BLEU score, evaluating the diversity of the generated samples (and its results is very close to those of the first best method, i.e., MLE, in this measure) and better than the MLE in BLEU scores denoting generation of higher quality samples in this method compared to MLE.

6 Conclusion

In this paper, we proposed a generative adversarial model for domains in which we can consider an explicit distribution and can sample from that distribution, including discrete domains. As opposed to the existing approaches, we do not need an RL-based approach for training of the generator. As a consequence of finding the generator via a closed form solution in each iteration of the training procedure, we removed the need for passing the gradient to the generator. Moreover, the GAN stability issues during training caused by seeking the saddle point of the objective are bypassed in the proposed method.

Since generating sequence of discrete data is an essential task in natural language generation, we examined the proposed method in generating natural language texts. Experiments demonstrate that the proposed method can model a distribution that is more similar to the real distribution (than those generated by the compared methods) according to the measures that approximate the similarity of the distributions.
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