Distributional Discrepancy: A Metric for Unconditional Text Generation

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Abstract

The goal of unconditional text generation is training a model with real sentences, to generate novel sentences which should be the same quality and diversity as the training data. However, when different metrics are used for comparing these methods, the contradictory conclusions are drawn. The difficulty is that both the sample diversity and the sample quality should be taken into account simultaneously, when a generative model is evaluated. To solve this issue, a novel metric of distributional discrepancy (DD) is designed to evaluate generators according to the discrepancy between the generated sentences and the real training sentences. But, a challenge is that it can’t compute DD directly because the distribution of real sentences is unavailable. Thus, we propose a method to estimate DD by training a neural-network-based text classifier. For comparison, three existing metrics, Bilingual Evaluation Understudy (BLEU) verse self-BLEU, language model score verse reverse language model score, Fréchet Embedding Distance (FED), together with the proposed DD, are used to evaluate two popular generative models of LSTM and GPT-2 on both syntactic and real data. Experimental results show DD is much better than the three existing metrics in ranking these generative models.

Keywords: Unconditional Text Generation; Evaluation Metric; Text Classifier

1. Introduction

Unconditional text generation, as the cornerstone of conditional text generation such as dialogue generation \cite{15}, machine translation \cite{25} and image caption \cite{26} has attracted massive work \cite{27, 2, 5}. In this task, a model is usually fed with many independent real sentences and then is required to generate many novel independent sentences which should be the same quality and diversity as the training data simultaneously. Neural language models (LM), such as RNN-based \cite{11} and Transformer-based \cite{24}, and their variations, which are trained by maximum likelihood estimation (MLE), are used to attack this task. Due to exposure bias in the reference stage \cite{1}, GAN \cite{7} is introduced to solve this issue and flooding variants occur \cite{16, 6, 19}. But, when these considered language GANs are evaluated precisely in both sample quality and sample diversity, the results show they are beat easily by simply adjusting the softmax temperature of LSTM \cite{23, 22, 2}. Therefore, a good evaluation metric for this research community is imperative.

It seems human evaluation is the best choice. Regardless of the expensiveness and un-repeatability, human can only judge the quality of single sentence, but can not precisely tell the diversity when hundreds of thousands sentences are presented \cite{9}.

A few automatic methods were proposed. \cite{27} adapted the BLEU \cite{20} for measuring the quality although it only can capture local consistency \cite{5}. As its counterpart, self-BLEU was introduced for measuring the diversity \cite{31}. This two-dimension metric fails when one model is better than the other in quality but worse
in diversity, or vice versa. The similar situation is to another paired metric language model score verse reverse language model [4]. In order to precisely measure the models, for each model, [2] draw many dots in this two-dimension space by adjusting softmax temperature and then link them by a line. This method costs too many computations and the worse is its ability of discrimination is poor. FED (Fréchet Embedding Distance), which is first used in image generation, is proposed as a single metric, to evaluate unconditional text generation models [5]. It still can not evaluate several generators well with the temperature 1.0. When adjusting the temperature, some models are better than others when temperatures are less than 1.0; once temperature is higher than 1.0, these models become worse than the others. Moreover, BERT score [29] improved the measure in quality by embedding each tokens into a low dimensional space but it still neglects the sample diversity. [9] brought forward a framework of unifying human and statistical frame, but this needs at least ten crowd-workers thus making these metric expensive and hardly reproduced.

The difference between real texts and generated ones does exist. [28] trained a Transformer-base neural language model with 120 gigabytes human-written news. Although the accuracy of human predicting the real or fake news is about 70%, the accuracy of a well-trained classifier is more than 95%. This means text classifier detect the discrepancy very well. Thus, we propose a novel metric, distributional discrepancy (DD), to measure the discrepancy between these two texts sets. The DD score of a generator is smaller, the distribution of the sentences generated by it is closer to the distribution of real sentences. This means this generator is better.

A challenge is that it is impossible to compute DD precisely because the distribution of the real texts can not be obtained directly. We propose a learning method to estimate DD inspired by [17], which assesses whether two samples are drawn from the same distribution. We use a text classifier, which is trained with generated texts and the real texts, to detect the discrepancy between. This discrepancy is not used to discriminate these two sets belong to the same distribution or not, but measure the distributional discrepancy of them.

Our contributions are as follows:

• The discrepancy between real texts and generated ones is proposed to evaluate the performance of generative model, and the distributional discrepancy (DD), as a single metric, can measure both sample quality and sample diversity simultaneously.

• It is discovered that a neural-network-based text classifier can be trained to estimate DD, and the discrepancy can be computed according to the performance of this classifier.

• Two popular neural language models LSTM and GPT-2 are applied on synthetic and real data, and the experimental results show the rank by the DD is corresponding to the gold-standard order, but three existing metrics fail to rank the generators.

The rest of paper is organized as follows. Section 2 describes the related work. The novel single metric, distributional discrepancy (DD), is defined in the next section. To estimate DD, section 4 introduces the implementation procedure as a learning method. In section 5 and 6, we evaluate ten unconditional text generators on synthetic and real data respectively. Finally, the conclusions are drawn. All the code and data sets are available at https://github.com/anonymous1100/Distributional-Discrepancy.

2. Related Work

Several widely used metrics for unconditional text generation are introduced in this section. The ways of using text classifier for this task are described further.

2.1. The Existing Metrics

The quality of generated sentences is thought the most important issue. BLEU [20], which evaluate the quality of translated sentence given a source sentence, is used as the metric by the researchers [27]. It is undoubtedly appropriate to evaluate machine translation models because the translated sentences only need
to be compared with a few reference translations provided by experts. However, there are usually hundreds of thousands of real sentences as the references in unconditional text generation. The other drawback is that
BELU only measures local consistency. Although the language model score can capture global semantics, it
biases those models which generate highly likely sentences \cite{22}.

The diversity of generated sentences is as important as quality for evaluating an unconditional generator.
\cite{31} proposed self-BLEU which calculate the BLEU among those generated sentences. The reverse language
model score was first used by \cite{30}. Due to the modeling imperfection and the training data bias, this is not a
good proxy for a model’s diversity \cite{22}.

A natural idea is using BLEU verse self-BLEU as a paired metric to evaluate unconditional text generation
in both quality and diversity simultaneously \cite{4}. However, \cite{5} found a simple 5-gram language model with
Kneser-Ney smoothing \cite{13} performs nearly perfect while in fact it generates very poor quality sentences.
Considering the limits, \cite{4} proposed language model score verse reverse language model score to evaluate
the quality and diversity respectively. The shortage of paired metric is we have to obtain several values
by adjusting the softmax temperature when one model is better than another in quality but worse than in
diversity, or vice versa \cite{2}.

Due to the inconvenience of paired metric, \cite{5} proposed the FED (Fréchet Embedding Distance) as a
single metric, which origins from image generation \cite{10}. It is claimed to capture global consistency and is
faster than BLEU. However, adjusting temperature is unavoidable because it fails to discriminate generators
on the condition of temperature 1.0.

\cite{9} proposed HUSE (HUman and Statistical Evaluation) as a metric which combines the human evaluation
and statistical to approximate to the probability under the real text distribution. Then, they train a simple
$k$-nearest neighbours classifier and twice the leave-one-out error of this classifier as the discrepancy between
real texts and generated ones. Its limitation is the requirement of crowd-workers. Similar to this work, we
train a classifier but without any human labor.

A latest metric is BERTScore \cite{29}. By computing the tokens’ similarity in a contextual embedding space,
it can measure the sample quality better than BLEU. Regretfully, it neglects the sample quality. Of course,
there are many other measures such as K-L divergence. But, all of them need know the explicit distributions,
it obviously is not realistic because we can not know the distribution of real texts.

\subsection{Using Text Classifier to Detect Discrepancy}

Generative adversarial networks (GAN) \cite{7} improved a trained neural language model by fine-tuning it
\cite{27, 6, 19}. In these language GANs, a discriminator which works as a classifier to detect the discrepancy
between real sentences and generated ones by the most recent generator. This detected signal is fed to
generator. To avoid the local optima, the discriminator is usually several epochs during the adversarial
learning. However, with the goal of evaluate generators, we try to train a convenience classifier with many
epochs to obtain an approximation of the optimal classifier. Obviously, both aim and method are different
from ours.

\cite{17} used a classifier to detect discrepancy between two samples to assess they are drawn from the same
distribution or not. They construct a data set which consists of the equal examples from these two samples.
The examples from one sample are labeled as positive and the other as negative. A binary neural network
classifier is trained with these examples. If the classification accuracy on the held-out data approximates to
0.5, these two samples are classified as complying with the same distribution. Otherwise their distributions
are different from each other. Different from \cite{17}, we use a text classifier, which is trained with generated
texts and the real texts, to detect this discrepancy. This discrepancy is not used to discriminate these two
sets belong to the same distribution or not, but measure the distributional discrepancy of them.

\section{Distributional Discrepancy}

Given a set of real sentences $T_r$, $x \in T_r$, $x = [x_1, ..., x_L]$ is a sentence of length $L$ and $x_i$ is the $i$-th word,
$x \sim p_r(x)$. An unconditional text generator $G_\theta$ is trained with $T_r$, and then generates a set of sentences $T_\theta$.
As a sentence $x$ is generated by $G_\theta$, $x \sim p_\theta(x)$. If $p_\theta(x)$ is closer to $p_r(x)$, the better $G_\theta$ is. Therefore, the
discrepancy between $p_\theta(x)$ and $p_r(x)$ can be used as a metric to evaluate the generative model.
We propose the distributional discrepancy (DD) to measure this discrepancy. This metric is defined as follow:

\[ d_d = \frac{1}{2} \int |p_r(x) - p_0(x)| \, dx \]  

where \( x \in \Omega \) (\( \Omega \) is the space of all possible samples).

Obviously, the range of this function is \( 0 \sim 1 \).

Unfortunately, the mathematical form of \( p_r(x) \) can not be obtained. To detect this discrepancy as precisely as possible, we propose a learning method to estimate this function.

3.1. A Learning Method for Obtaining Distributional Discrepancy

In order to transform the computation of distributional discrepancy into a learning method, equation 1 is inferred as follows:

\[
\begin{align*}
    d_d &= \frac{1}{2} \int |p_r(x) - p_0(x)| \, dx \\
    &= \frac{1}{2} \left[ \int_{p_r(x) \geq p_0(x)} (p_r(x) - p_0(x)) \, dx + \int_{p_r(x) < p_0(x)} (p_0(x) - p_r(x)) \, dx \right] \\
    &= \frac{1}{2} \left[ \int_{p_r(x) \geq p_0(x)} p_r(x) \, dx + \int_{p_r(x) < p_0(x)} p_0(x) \, dx - \int_{p_r(x) \geq p_0(x)} p_0(x) \, dx - \int_{p_r(x) < p_0(x)} p_r(x) \, dx \right] \\
    &= \frac{1}{2} \left[ \mathbb{E}_{x \sim p_r(x)} (1) + \mathbb{E}_{x \sim p_0(x)} (1) - \mathbb{E}_{x \sim p_0(x)} (1) - \mathbb{E}_{x \sim p_r(x)} (1) \right] \\
    &= \frac{1}{2} \left[ \mathbb{E}_{|x|<0.5} (1) + \mathbb{E}_{x \sim p_0(x)} (1) - \mathbb{E}_{x \sim p_0(x)} (1) - \mathbb{E}_{x \sim p_r(x)} (1) \right] \\
\end{align*}
\]

where \( z = \frac{p_r(x)}{p_r(x) + p_0(x)} \).

The computation of DD is transformed to resolve \( z \), which can be obtained by the learning method. Given \( \theta \), according to 4, to detect the discrepancy between \( p_0(x) \) and \( p_r(x) \), \( D_\theta \) is defined and optimized as follows:

\[
\max_{B_\theta} V(D_\theta, G_\theta) = \max_{B_\theta} \mathbb{E}_{x \sim p_0} \left[ \log D_\theta(x) \right] + \mathbb{E}_{x \sim p_0} \left[ \log (1 - D_\theta(x)) \right] 
\]

Assuming \( D_\theta^*(x) \) is the optimal solution, it will be,

\[
D_\theta^*(x) = \frac{p_r(x)}{p_r(x) + p_0(x)} 
\]

So, \( z = D_\theta^*(x) \), and

\[
\begin{align*}
    D_\theta^*(x) \geq 0.5, & \quad \text{iff} \quad p_r(x) \geq p_0(x) \\
    D_\theta^*(x) < 0.5, & \quad \text{iff} \quad p_r(x) < p_0(x)
\end{align*}
\]

3.2. An Estimation Function of Distributional Discrepancy

In this subsection, an estimation function of DD is illustrated. According to equation 4, the integration of the density function can be transformed into a statistical function. Substituting \( z \) in equation 2 with equation 4 so,

\[
\begin{align*}
    d_d &= \frac{1}{2} \left[ \mathbb{E}_{x \sim p_r(x)} (1) - \mathbb{E}_{x \sim p_0(x)} (1) + \mathbb{E}_{x \sim p_0(x)} (1) - \mathbb{E}_{x \sim p_r(x)} (1) \right] 
\end{align*}
\]
Assuming the classification accuracy of $D^*_\phi$ is $a$, thus the classification error is $b = 1 - a$. According to equation 6, $d_d = a - b = 2a - 1$. When $p_r(x) \equiv p_\theta(x)$, $d_d = 0$.

In fact, it is critical to obtain the optimal $D^*_\phi$ and make its accuracy approximate 1 as much as possible. Fortunately, the neural text classifiers are very powerful [12, 14]. Thus, a learning method to approximate $D^*_\phi$ is practicable by training this classifier. In the next section, DD can be estimated with a text classifier.

In equation 6, the optimal classifier function $D^*_\phi$ can only be statistically estimated by an approximated function. We adapt a widely used CNN-based text classifier [12] and denote it as $D_\phi$. $D_\phi$ is trained with the samples from real sentences and generated ones, according to equation 3. When it convergences, we get $\hat{D}_\phi$. $\hat{D}_\phi$ is the approximation of $D^*_\phi$, thus the estimation of $d_d$ can be computed. The degree of approximation is mainly determined by three factors: the structure and the number of the parameters number of $D_\phi$, the volume of training data, and the settings of hyper-parameters. The procedure of estimating the discrepancy is described as follows.

Step 1: Design a discriminator $D_\phi$. It is usually a neural network such as CNN.

Step 2: All the real sentences in $T_r$ are labeled as positive and all the generated sentences in $T_\theta$ are labeled as negative. In order to avoid the imbalance learning [8], we let $G_\theta$ generates the same number of sentences as $T_r$. A training set which is denoted as $T_{train}$, is composed of the same amount of sentences which are selected randomly from these two sets respectively. For example, eighty percent sentences are selected. Further, ten percent sentences consist of a validation set $T_{dev}$ and test set $T_{test}$ is composed of the rest ten percent samples.

Step3: $D_\phi$ is trained with $T_{train}$ and optimized according to the equation 3. It should be noted that the training strategy is very different from GAN. We will not stop training $D_\phi$ until its classification accuracy on $T_{dev}$ convergences. This usually needs 50 ~ 100 epochs [27]. GAN carries on many adversarial rounds and each round trains several epochs to avoid be trapped in the local optima. We denote this converged $D_\phi$ as $\hat{D}_\phi$, which is the approximation of $D^*_\phi$.

Recently, the Transformer-based classifier is claimed to achieve the best accuracy. We will try it in the future work. Our experimental results shows CNN works well.

Even more epochs, it is mainly up to the learning ratio.
| H.P. of Generator | Value | H.P. of Classifier | Value |
|------------------|-------|-------------------|-------|
| hidden size      | 512 (768) | layer1            | (2, 100) |
| layer            | 2 (12)  | layer2            | (3, 200) |
| drop_out         | 0.5 (0.1) | drop_out          | 0.5 |
| learning rate    | 1e-3 (2e-5) | learning rate    | 1e-4 |
| batch size       | 128     | batch size        | 512   |
| GPT-2 head       | 12      | –                 | –     |
| number of para.  | ≈30.1(268)M | number of para.  | ≈10.5M |

Table 1: The values of Hyper-parameters. For two generative models, the values of GPT-2 are listed in parentheses when they are different from LSTM. “H.P.” is the abbreviation of Hyper-parameter and “number of para.” denotes the total number of parameters. For each convolutional layer, (window size, kernel numbers) is listed.

Step 4: According to equation [6], we can compute the discrepancy between real sentences set and the generated sentences set by the prediction of $\hat{D}_\phi$ on $T_{test}$. This is denoted as $\hat{d}_d$ as the estimation of the real distributional discrepancy.

This procedure is a learning method because $\hat{D}_\phi$ as the estimation of $D^\ast_\phi$ is learned with a neural network. A well trained $\hat{D}_\phi$ can be a meaningful approximation of $D^\ast_\phi$. Therefore, $\hat{d}_d$ is obtained as the meaningful approximation of $d_d$ via $\hat{D}_\phi$. Although $d_d \neq \hat{d}_d$, the tendency of their changing is the same. If $\hat{d}_d$ of a generator is smaller, this generator is better.

5. Experimental Setup

To verify the distributional discrepancy metric, we need several unconditional text generation models and obtain the gold-standard rank of them in advance. These generators generate sentences and are ranked according to our novel metric. Meanwhile, they are also ordered by three baseline metrics. A correlation coefficient with the gold-standard order will be computed for comparison of all metrics.

5.1. Data set

A benchmark dataset, EMNLP2017 WMT news[4], for unconditional text generation is used as the real corpus. In this corpus, the average length of sentences is about 20 words. There are in total 5,255 word types and the longest sentence consists of 51 words. All training data, about 280 thousand sentences, is used and there are 10,000 sentences in the test data. It should be noted that we separate the last 10,000 sentences from the training data as the validation set. Considering the impossibility of getting the distribution of real texts, we experiment further with synthetic data. A state-of-the-art neural language model, GPT-2, is trained with EMNLP2017 WMT News[5]. Then the sentences generated by it as the real data, which consists of 320 thousand sentences totally. Among them, we divide the first 300 thousand sentences as training data, the middle 10 thousand sentences as the validation set and the last 10 thousand sentences for test.

5.2. Generator and Classifier

Two widely used neural language models LSTM (RNN-based architecture) and GPT-2 (Transformer-based architecture), which are trained according to maximum likelihood estimation (MLE), are evaluated as the generative models. The left of table [1] lists their hyper-parameters.

For classifier, we use CNN of which hyper-parameters are the same as the discriminator used in [27]. The right of table [1] lists its hyper-parameters. The training data consists of the positive samples which are used to train the generator, and the same amount of negative samples which are generated by the generator.

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[4] http://www.statmt.org/wmt17/

[5] In order to distinguish this GPT-2 model from the latter ones, it is called original GPT-2 generator.
We do not stop training classifier until observing the convergence of classification accuracy on the validation set. Finally, the one with the highest accuracy on the verification set is used for prediction on the test set.

For each generator regardless of the volume of training data or model architecture, we always let it generate 320 thousand sentences which are labeled as negative samples. Among them, the first 300 thousand sentences are used as the classifier’s training set. The middle and the last 10 thousand sentences are used as the verification and test set respectively. It should be noted that all the positive sentences which are combined into these three sets are generated by the original GPT-2 generator.

5.3. The Gold-standard Order

According to the experience from vision tasks [3], given model type and the settings of hyper-parameters, the gold-standard order should be the same as the rank of the volume of data set, i.e. the more data, the better performance.

For real corpus, the training data is respectively divided into 20%, 40%, 60%, 80% and 100% from the first sentence to the last one. Therefore, five data sets are obtained and the larger one always contains the smaller one. Both LSTM and GPT-2 are trained with these five training data sets respectively. Thus, five LSTM generators and five GPT-2 generators are created.

The drawback of real data is that we can not compare different architecture models. As described in the above section, an original GPT-2 generates real sentences to train other generators for evaluation. We also partition the training data into five parts by using the same partition as the real data. Different from real scenario, because \( p_r(x) \) can be obtained from the original GPT-2, we directly compute the distributional discrepancy according to equation 2. All the ten generators are ranked according this DD score as the gold-standard rank which is shown in table 2.

Given the same training data, GPT-2 based generators are always better than LSTM based ones, because the parameters of GPT-2 is near seven times the number of the latter’s and its architecture is better than LSTM [21].

| Generator | \( dd \) ↓ | Accuracy | \( dd \) | Generator | \( dd \) ↓ | Accuracy | \( dd \) |
|-----------|-----------|----------|-------|-----------|-----------|----------|-------|
| LSTM_{0.2} | 0.994     | 0.721    | 0.442 | GPT-2_{0.4} | 0.973     | 0.644    | 0.287 |
| GPT-2_{0.2} | 0.991     | 0.691    | 0.381 | LSTM_{1.0} | 0.972     | 0.628    | 0.256 |
| LSTM_{0.4} | 0.986     | 0.679    | 0.359 | GPT-2_{0.6} | 0.959     | 0.621    | 0.241 |
| LSTM_{0.6} | 0.980     | 0.657    | 0.314 | GPT-2_{0.8} | 0.948     | 0.609    | 0.218 |
| LSTM_{0.8} | 0.976     | 0.644    | 0.289 | GPT-2_{1.0} | 0.935     | 0.596    | 0.192 |

5.4. Baseline Metrics

Three single metrics, BLEU, language model score and FED are compared as the baseline metrics. For BLEU, we use 5-gram as the implementation. Further comparison by adjusting the softmax temperature, will be illustrated in the next section. The perplexity is not adapted because we have to compare the quality and diversity of the generated sentences against the real ones, rather than observing the performance on real sentences.

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6In practice, we train 80 epochs and select the one which achieves the lowest PPL score on the validation set as the generator for comparison.
6. Experimental Results

We first analyze the correlation of the ranks against the gold-standard order. Our novel metric achieves the perfect performance on both real and synthetic data. Further, three previous metrics, BLEU vs. self-BLEU, language model score vs. reverse language model score, and FED are evaluated precisely by adjusting the temperature. The results show all of them are not qualified as a unconditional text generation metric.

6.1. Correlation Analysis on Real Scenario

We rank the five LSTM based generators and five GPT-2 based generators respectively, according to the equation 6 and the procedure which is described in section 3. The gold-standard reference order is estimated, given the architecture of a language model, the more training data means the better performance. Different from the experiment on syntactic data, we cannot obtain the real language model which generates the real sentences. We did not compare these ten generators together. Table 3 summaries the results.

Table 3: The distributional discrepancy of generators and classification accuracy on real corpus. Acc. is the classification accuracy. For all of them, the lower, the better.

| Generator | Valid | Test | Generator | Valid | Test |
|-----------|-------|------|-----------|-------|------|
|           | Acc.  | DD   | Acc.  | DD  | Acc.  | DD  |
| LSTM0.2   | 0.758 | 0.517| 0.745 | 0.490| 0.752 | 0.504| 0.723 | 0.446|
| LSTM0.4   | 0.718 | 0.437| 0.706 | 0.412| 0.682 | 0.365| 0.670 | 0.340|
| LSTM0.6   | 0.700 | 0.400| 0.697 | 0.393| 0.667 | 0.333| 0.655 | 0.309|
| LSTM0.8   | 0.673 | 0.347| 0.677 | 0.353| 0.630 | 0.259| 0.646 | 0.292|
| LSTM1.0   | 0.648 | 0.296| 0.661 | 0.322| 0.588 | 0.176| 0.621 | 0.242|

The rank achieved by distributional discrepancy matches the gold-standard rank perfectly across two architectures. For comparison of the previous metrics, the Kendall’s Tau co-efficiency are computed. Table 4 lists the results. The performance of our novel metric is still the best. Although the LM score works very well for GPT-2, it fails to discriminate the generators when LSTM architecture is adapted.

Table 4: The Kendall’s Tau rank correlation on Real Corpus. 5LSTM and 5GPT-2 denote the correlations of five LSTM based and five GPT-2 based generators respectively.

| Metric   | 5LSTM | 5GPT-2 |
|----------|-------|--------|
| BLEU-5   | 0.0   | 0.6    |
| FED      | 0.6   | 0.8    |
| LM score | -0.2  | 1.0    |
| DD       | 1.0   | 1.0    |

Similar to synthetic data, we investigate the previous metrics in detail by adjusting the softmax temperature in next section. All evaluations in the above table on the condition of temperature 1.0.

6.2. Correlation Analysis on Synthetic Data

We evaluate all ten generators by distributional discrepancy. The rank achieved by distributional discrepancy, matches the gold-standard order perfectly across two models. All the $\tau$ are listed in table 5.

Considering the rank of FED scores is very near to ours, we inspect its performance in detail. Table 6 lists the all scores. The discrimination is so tiny that there is only 0.006 from the best to the worst. The worse is that several generators are assigned the same scores but their performances are different from each other in fact.

To investigate the previous metrics in detail, we adjust the temperature of softmax in the next section. All evaluations in the above tables on the condition of softmax temperature 1.0.
Table 5: The Kendall’s Tau rank correlation on syntactic data. 10Gs denotes the tau value when all 10 generators are evaluated together. 5LSTM and 5GPT-2 denote the correlations of five LSTM based and five GPT-2 based generators respectively.

| Metric   | 5LSTM | 5GPT-2 | 10Gs |
|----------|-------|--------|------|
| BLEU     | 0.80  | 0.80   | 0.38 |
| LM score | 0.40  | 1.0    | 0.82 |
| FED      | 0.84  | 0.84   | 0.92 |
| DD       | 1.0   | 1.0    | 1.0  |

Table 6: Ten generators are ranked according to FED score. The lower, the better.

| Generator | BLEU | Self-BLEU |
|-----------|------|-----------|
|           | 2    | 3         | 4         | 2    | 3         | 4         |
| LSTM0_2   | 0.850±2ε | 0.587±4ε | 0.340±4ε | 0.863±2ε | 0.616±4ε | 0.370±5ε |
| LSTM0_4   | 0.800±2ε | 0.607±ε  | 0.362±2ε | 0.871±ε  | 0.633±ε  | 0.393±2ε |
| LSTM0_6   | 0.857±ε  | 0.601±2ε | 0.356±2ε | 0.869±ε  | 0.629±3ε | 0.389±3ε |
| LSTM0_8   | 0.860±ε  | 0.606±ε  | 0.360±2ε | 0.869±ε  | 0.631±3ε | 0.390±4ε |
| LSTM1_0   | 0.856±ε  | 0.598±2ε | 0.352±3ε | 0.867±ε  | 0.624±2ε | 0.383±3ε |
| GPT-2_0   | 0.838±3ε | 0.577±5ε | 0.334±5ε | 0.850±3ε | 0.600±6ε | 0.360±7ε |
| GPT-2_4   | 0.844±1ε  | 0.590±3ε | 0.350±3ε | 0.856±2ε | 0.613±4ε | 0.379±4ε |
| GPT-2_6   | 0.845±2ε  | 0.591±3ε | 0.351±2ε | 0.858±2ε | 0.618±4ε | 0.383±5ε |
| GPT-2_8   | 0.850±1ε  | 0.601±2ε | 0.361±2ε | 0.862±1ε  | 0.627±5ε | 0.392±2ε |
| GPT-2_10  | 0.849±3ε  | 0.598±5ε | 0.358±5ε | 0.862±2ε  | 0.624±4ε | 0.390±5ε |

6.3. Detail Analysis on Real Scenario

Following [2], we evaluate these generators with three previous metrics by adjusting the softmax temperature. The temperature is set 0.8, 0.9, 1.0, 1.1 and 1.2 respectively. Figure 2 illustrates the evaluation results. From these figures, we can see both BLEU vs. self-BLEU and FED fail to rank those generators.

Although LM score vs. reverse LM score rank five GPT-2 generators perfectly, it is not so good as five LSTM generators. It is inconvenient and inefficient because we have to adjust the softmax temperature and draw the results in a two dimensions metric. Further, this paired metric fails on synthetic data which is illustrated in next section.

Besides BLEU5 vs. self-BLEU5, table 7 lists the results of other grams with the temperature 1.0 in detail. Any of them can not rank these generators as good as distributional discrepancy according to this table.

6.4. Detail Analysis on Synthetic Data

The same settings of softmax temperature as real data are adapted. Different from real data, we compare all ten generators together. Figure 3 shows that BLEU vs. self-BLEU and FED fail to discriminate those generators even which have the same architecture. The ranks which are achieved by LM score vs. reverse LM score on the same architecture generators, are consistent with the gold-standard rank. However, they can not rank well the ten generators because this needs finer calibration.

The surprise is our single metric rank all ten generators very well according to table 5. It is not necessary to adjust the generators’ softmax temperature. This shows DD is powerful and efficient.
Figure 2: The precise evaluation of generators with three previous metrics by adjusting the softmax temperature on real corpus. For all of them, the lower, the better.
Figure 3: The precise evaluation of generators with three previous metrics by adjusting the softmax temperature on synthetic data. For all of them, the lower, the better.
7. Conclusion and Future work

We present a novel metric, distributional discrepancy (DD), to measure the discrepancy between real text and generated text unconditionally. A neural network classifier is trained to classify the true text and generated ones. We exploit the classification accuracy to obtain this discrepancy.

Comparing with the existing metrics, this single metric can distinguish the different generative models well and evaluate them both in the view of sample quality and sample diversity simultaneously. Numerous experiments show that distributional discrepancy ranks two architecture models perfectly on both synthetic data and real corpus. Otherwise, the previous metrics are either unable to or inefficient to evaluate these generative models.

In future, the stronger classifier such as LSTM and Transformer will be investigated to verify the robustness of this metric. Further, the larger scale corpus such as wiki-103 will be tested.

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