A Representation Modeling Based Language GAN with Completely Random Initialization

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Abstract

Text generative models trained via Maximum Likelihood Estimation (MLE) suffer from the notorious exposure bias problem, and Generative Adversarial Networks (GANs) are shown to have potential to tackle it. Existing language GANs adopt estimators like REINFORCE or continuous relaxations to model word distributions. The inherent limitations of such estimators lead current models to rely on pre-training techniques (MLE pre-training or pre-trained embeddings). Representation modeling methods which are free from those limitations, however, are seldom explored because of its poor performance in previous attempts. Our analyses reveal that invalid sampling method and unhealthy gradients are the main contributors to its unsatisfactory performance. In this work, we present two techniques to tackle these problems: dropout sampling and fully normalized LSTM. Based on these two techniques, we propose InitialGAN whose parameters are randomly initialized completely. Besides, we introduce a new evaluation metric, Least Coverage Rate, to better evaluate the quality of generated samples. The experimental results demonstrate that InitialGAN outperforms both MLE and other compared models. To the best of our knowledge, it is the first time a language GAN can outperform MLE without any pre-training techniques.

1 Introduction

Text generative models are stepping stones for various natural language processing tasks [1, 2]. In text generation, implementing Maximum Likelihood Estimation (MLE) with autoregressive structure gains great success [3-5]. This method uses ground truth as input during training, but reads previously generated tokens during inference. The discrepancy between training and inference causes the exposure bias problem [6-8]. This problem affects the quality of generated sentences and grows the needs of exploring other alternatives in text generation. Generative Adversarial Networks (GANs) [9] are central in many image generation success stories [10, 11]. GANs can tackle the exposure bias problem by providing a consistent generation manner in training and inference.

However, the non-differentiable sampling operations in text generators stop gradients from passing through to generators, which limit the direct applications of GANs in text generation [13]. Currently, many researchers tackle this problem by REINFORCE [14] or continuous relaxations [15, 16]. REINFORCE is an unbiased but high variance estimator [17], whereas continuous relaxations are low variance but bias estimators [18]. The inherent limitations of these two methods lead the fragile training of GANs to be more unstable, so existing language GANs rely on either MLE pre-training or pre-trained embedding to be comparable with MLE [17, 19].

Methods based on REINFORCE or continuous relaxations explicitly model word distributions, so we denote them as Distribution Modeling Methods (DMMs). Another type of methods is to firstly transform words into representations, and then train generators to model these representations. We denote these methods as Representation Modeling Methods (RMMs). Research on RMMs is...
extremely limited, due to the unsatisfactory performance in previous attempts [18, 20]. However, such methods should be a promising research line, since they contain neither non-differentiable operations nor bias estimators. The discrepancy between theoretical feasibility and unexpected poor performance prompts us to conduct an in-depth analysis of its reasons, based on which two problems are found as responsible for the poor performance of RMMs.

The first one is invalid sampling method. RMMs do not have word distributions that can be sampled. Injecting random noise into generators is also demonstrated to be ineffective in autoregressive structure [21, 22]. Generators with an invalid sampling method will generate samples in high similarities. It not only leads to the mode collapse problem but also brings the potential of training fails. Another problem is unhealthy gradients. RMMs update generators based on gradients from discriminators. Compared with other sequence models [23], more layers are stacked to build the discriminator and the generator, so RMMs place higher demands on healthy gradients. Gradient vanishment is more severe in LSTM [24], for the output gate there further narrows down the gradients from other layers. Unhealthy gradients will directly influence the performance of generators.

To tackle the first problem, we introduce a simple but effective sampling method: dropout sampling. Unlike injecting random noise, it provides a non-negligible random factor by masking a certain number of dimensions in input. This method improves both diversity and quality of generated samples by relieving the mode collapse problem.

We solve the second problem by proposing a new variant of LSTM: fully normalized LSTM. Our theoretical analyses show that incorporating layer normalization [25] in the calculation of hidden state can relieve gradient vanishment by providing an additional augmentation term in its derivative. This operation, however, is omitted in the existing combination of layer normalization and LSTM (LayerNorm LSTM) [25]. Fully normalized LSTM makes up for this shortcoming to simultaneously obtain strong sequence modeling capabilities and healthier gradients.

Language GANs can theoretically get satisfactory performance without any pre-training techniques (MLE pre-training or pre-trained embedding). In this work, we propose InitialGAN to echo this significant goal in text generation. The contributions of this work can be summarized as follows:

- We analyze and tackle two main limitations in representation modeling methods. For the invalid sampling method, we introduce dropout sampling which is a simple but effective sampling method to improve both the quality and diversity of generated samples. For the unhealthy gradients, we propose a fully normalized LSTM which can relieve gradient vanishment by making use of layer normalization to provide an augmentation term.
- Based on the above two techniques, we put forward InitialGAN which has three models: aligner, generator and discriminator. The aligner transforms words into representations, and the generator tries to model word representations; the discriminator uses these representations as input and identify whether the representations are from the aligner or the generator. Different from existing language GANs which are based on pre-training techniques, all the parameters in InitialGAN are initialized randomly.
- Observing that the existing embedding level metric is not sensitive to the change of sample quality, we propose a new metric: Least Coverage Rate, which can better identify the differences among different models. The experimental results show that InitialGAN outperforms both MLE and other compared models. To the best of our knowledge, it is the first time a language GAN can outperform MLE without using any pre-training techniques. It also demonstrates that RMMs denote a promising research line for language GANs.

2 Related Work

Currently, most of text generative models implement Maximum Likelihood Estimation (MLE) by combining cross entropy and autoregressive structure [3–5]. However, this method uses true tokens as input during training, and predicts based on previously generated tokens during inference. Mistakes from previous generation will lead the model to be in the state space that it has never seen during training, so they will be amplified quickly and lead to a sharp decrease of sentence quality [6]. This problem is denoted as exposure bias [7,8].

To tackle this problem, researchers try to incorporate GANs [9] into text generation. When modeling word distributions, there are two popular methods to process the non-differentiable sampling operation:
Figure 1: Effects of Dropout Sampling. (a) The real distribution. (b) The distribution learned by a sub-model (blue area). (c) The distribution learned by the complete model.

REINFORCE [26,28] and continuous relaxations [29,30]. REINFORCE makes use of rewards from discriminators to update generators. This method is an unbiased but high variance estimator [17]. A number of methods are proposed to give more reasonable and stable rewards [31], such as: obtaining rewards with Monte Carlo Search [13], changing the discriminator into a ranker [32] and training the generator by filling blank [33]. Continuous relaxations like Gumbel-Softmax trick [15,16] allow gradients pass through to generators directly. It is a low-variance but bias estimator, so more complex model structures like Relation Networks [34] are adopted to provide a more informative signal [35].

The methods mentioned above all rely on MLE pre-training. Even so, their performance still remains gaps comparing with MLE [36]. Recently, researchers try to build language GANs without MLE pre-training [17,18]. These attempts are comparable with MLE with the help of pre-trained embeddings which are learned from additional large scale corpus, so they are still based on pre-training techniques.

The dependence on pre-training techniques reveal the inherent limitations in existing language GANs. In this work, we focus on Representation Modeling Methods (RMMs), which should be a promising line. However, previous attempts on RMMs either list it as a failure approach [18], or show it can only generate sentences that are poor in both quality and diversity [20].

3 Model

In this section, we firstly present dropout sampling and fully normalized LSTM which can tackle invalid sampling method and unhealthy gradients, respectively. Then, we introduce our proposed model, InitialGAN which is based on these two techniques.

3.1 Dropout Sampling

An effective sampling method plays a crucial role in training GANs. Once we choose to model representations, we can no longer sample words from word distributions directly. Although we can sample results by feeding random noise into generators as a part of input, previous work [21,22] shows that generators with autoregressive structure tend to ignore those additional input. As a result, these generators will give samples in high similarities. The discriminator can easily identify these samples from real data. It may prompt generated samples to change between unreal modes rather than becoming indistinguishable ones. Thus, invalid sampling method not only leads to the mode collapse problem but also brings the potential of training fails.

Ever since, Dropout [37] was introduced in 2014, it has been widely used in training neural networks. Previous work [38] also adopts dropout to be random noises in image GANs. Using dropout in both training and inference as a sampling method is extremely suitable in representation modeling methods because it provides a non-negligible random factor.

However, the distribution provided by dropout sampling is decided by the input which is always trainable embeddings. It leads the distribution to keep changing during training and may cause the training process to be unstable. Thus, we concatenate the input with random noise to increase the robustness of the model. The complete method is described in the following:

\[ z_t = \text{Dropout}(E(\hat{x}_{t-1}) \oplus \epsilon, \rho) \]
where $z_t$ is the $t$-th latent variable, $x_{t-1}$ is the word generated in the last timestep, $E(\cdot)$ is a function to transform words into embeddings, $\epsilon$ is random noise sampled from a pre-defined distribution and $\rho$ is the dropout rate. Dropout can be viewed as the selection of sub-models. Given a real distribution in Figure 1(a), each sub-model may still suffer from mode collapse as shown in Figure 1(b). However, different sub-models can cover different modes, so the distribution given by the complete model is closer to the real data distribution (as shown in Figure 1(c)).

Dropout sampling will slow down the convergence of generators, since the parameters are updated less frequently. To speed up the training process, we suggest to use imbalanced batch size. Suppose $bs_d$ is the batch size of discriminator’s training, setting the batch size of the generator’s training as $bs_g = bs_d/(1 - \rho)$ can bridge the gap in update frequency.

3.2 Fully Normalized LSTM

When building representation modeling based language GANs, generators update their parameters based on the gradients from discriminators. Compared with other sequence models [23], representation modeling methods place higher demands on healthy gradients, since they need to stack more layers to build discriminators and generators.

In language GANs, generators make predictions based on previous output in both training and inference. It limits the use of Transformer [5] whose computational speed is extremely slow without parallel computation. Instead, LSTM [24] is more popular in language GANs [18]. When using LSTM to build a representation modeling method, we need to care about possible gradient vanishment among both different timesteps and different layers. This time, the gated mechanism in LSTM cuts both ways. It can relieve gradient vanishment among different timesteps, but it narrows down the output of LSTM which directly aggravates gradient vanishment among layers.

The problem gets worse when we stack several LSTM layers to build the generator and the discriminator. Unhealthy gradients will exist throughout the whole training process and affect model performance directly. Thus, we need to find a method to relieve the gradient vanishment problem.

Layer normalization [25] is a widely used technique in neural networks [5]. Previous work [39] shows that layer normalization helps stabilize training by reducing the variance of gradients. We further find that layer normalization has potential to relieve gradient vanishment. A common understanding is that it can shift and scale input into a more reasonable interval to avoid the interval whose gradients are small. However, layer normalization does more than that. According to our analyses, it provides an addition term to augment gradients when the deviation of the normalized term is smaller than 1:

$$x_l = \left(\text{LayerNorm}\left(y_l \cdot W_l x + b_l\right)\right)$$

where $y_l$ is the $l$-th layer in a model, $y_l$ is the input of the $l$-th layer and also the output from the $(l-1)$-th layer. Adopting layer normalization in the input (i.e., $y_{l+1} = F_l(LN(y_l))$) provides an addition term when calculating the partial derivative of $y_{l+1}$ with respect to $y_l$. This term can augment the gradients when the deviation of $y_l$ is smaller than 1.

In LSTM, the output of LSTM is the element-wise product of the output gate (which is in $(0, 1)$) and cell state (which is in $(-1, 1)$). Its deviation must be smaller than 1, which can meet the conditions of Theorem 1. Thus, we have:

**Theorem 1** Suppose $y_{l+1} = F_l(y_l)$ is the $l$-th layer in a model, $y_l$ is the input of the $l$-th layer and also the output from the $(l-1)$-th layer. Adopting layer normalization in the input (i.e., $y_{l+1} = F_l(LN(y_l))$) provides an addition term when calculating the partial derivative of $y_{l+1}$ with respect to $y_l$. This term can augment the gradients when the deviation of $y_l$ is smaller than 1.

In LSTM, the output of LSTM is the element-wise product of the output gate (which is in $(0, 1)$) and cell state (which is in $(-1, 1)$). Its deviation must be smaller than 1, which can meet the conditions of Theorem 1. Thus, we have:

**Corollary 1** Adopting layer normalization when calculating the hidden state in LSTM provides a scaler factor to its gradients. This factor can augment the gradients, thereby mitigating the gradient vanishment between different layers in LSTM.

The proofs of Theorem 1 and Corollary 1 can be found in Appendix A.1 and A.2 respectively. Based on our analyses, we propose a fully normalized LSTM which is calculated as follows:

$$\begin{align*}
\begin{pmatrix}
    f_t \\
    i_t \\
    o_t \\
    c_t
\end{pmatrix}
&= LN(W_h h_{t-1}) + LN(W_x x_t) + b \\
\begin{pmatrix}
    c_t \\
    h_t
\end{pmatrix}
&= LN(f_t(f_t) \circ c_{t-1} + f_t(i_t) \circ f_h(c_t)) \\
&= LN(f_t(o_t) \circ f_h(c_t))
\end{align*}
$$

where $\circ$ is the element-wise product, $f_t(\cdot)$ is sigmoid function and $f_h(\cdot)$ is tanh. Fully normalized LSTM is based on LayerNorm LSTM [25] whose effectiveness has been shown by various tasks [18].
The main difference is that the fully normalized LSTM adopts layer normalization when calculating the hidden state, so as to offset the influence from the output gate. Thus, it can obtain both strong sequence modeling capabilities and healthier gradients.

3.3 Model Structure

Based on the above-introduced techniques, in the following, we put forward InitialGAN which has three components in InitialGAN: aligner, discriminator and generator. The aligner maps words into representations and the generator models word representations. The discriminator uses these representations as input to identify whether the representations are from the generator or not.

We use the encoder in Transformer [5] to construct the aligner. The training objective is based on which is

\[
\mathcal{L} = \mathbb{E}_{x \sim \mathcal{P}_x}[D(G(z))] + \frac{\lambda_d}{2}\mathbb{E}_{r_m \sim \mathcal{P}_r}[\max\{0, ||\nabla D(r_m)||_2 - 1\}]^2
\]

where \( \lambda_d \) is a hyperparameter. The first two terms consist of the original objective in VAE. The last term provides a penalization to the variance, which controls the size of the representation region directly. This objective can help keep the regions of different words in similar size by giving more penalization to the variance of high frequency words.

Both the discriminator and the generator are constructed based on the fully normalized LSTM. Dropout sampling is adopted in both training and inference stage of the generator. The generator uses the same linear transformation \( F_{LT} \) in the aligner to transform representations back into words. We adopt Wasserstein distance as training objective [42], and use Lipschitz penalty [43] to regularize the discriminator. The loss functions of the discriminator \( L_D \) and the generator \( L_G \) are:

\[
L_D = -\mathbb{E}_{x \sim \mathcal{P}_x}[D(G(z))] + \mathbb{E}_{z \sim \mathcal{P}_z}[D(r_m)] + \lambda_d\mathbb{E}_{r_m \sim \mathcal{P}_r}[\max\{0, ||\nabla D(r_m)||_2 - 1\}]^2
\]

\[
L_G = -\mathbb{E}_{z \sim \mathcal{P}_z}[D(G(z))]
\]

where \( z \) is from dropout sampling, \( r_m \) is sampled uniformly along straight lines between pairs of representations from the aligner and the generator, and \( r_d \) is the word representation from the aligner, which is \( \mu_{x_i} \) in this work. More details about InitialGAN can be found in Appendix C.

4 Experiment

In this section, we firstly introduce the evaluation metrics, datasets and compared models. Then, we demonstrate the experimental results with our analyses.

4.1 Evaluation Metrics

For the token level metrics, we use BLEU [44] to evaluate fluency and Self-BLEU [45] to evaluate diversity. Caccia et al. [36] propose to tune temperature in the softmax to draw a curve so as to evaluate fluency and diversity together. However, InitialGAN does not model the word distribution directly, so we can not use this method to evaluate the performance. Instead, we find Inverse BLEU is a good choice for evaluating the overall performance in both fluency and diversity. Inverse BLEU uses sentences in test sets as inference and generated sentences as references. Sentences in test sets are fluency and diverse, so the generated sentences can get high Inverse BLEU only when they have good performance in terms of both two aspects. When calculating token level metrics, all of them are calculated up to 5 grams and the size of each set is set to be 5,000.
For the embedding level metrics, we use Fréchet Embedding Distance (FED) [18] which is indicated to Fréchet inception distance (FID) [46] except for the encoding model. Although it can evaluate the global similarity of two distributions, previous work [17, 18] shows that its values are extremely small. We find FED is not sensitive to the changes of sample quality. When models get similar FED, it does not mean they get close performance. To further identify the differences of compared models, we propose a new metric, Least Coverage Rate (LCR). It is calculated as follows:

\[
S_{ij} = \text{Sim}(\mathbf{E}(x^a_i), \mathbf{E}(x^b_j))
\]

\[
R_a = \frac{1}{n} \sum_{i=1}^{n} \delta(\sum_{j=1}^{m} S_{ij} \geq \tau), \quad R_b = \frac{1}{m} \sum_{j=1}^{m} \delta(\sum_{i=1}^{n} S_{ij} \geq \tau)
\]

\[
LCR(X_a, X_b) = \min(R_a, R_b)
\]

(5)

where \(x^a_i \) and \(x^b_j \) are the \(i\)-th and \(j\)-th sentences from sentence sets \(X_a\) and \(X_b\), respectively. \(\mathbf{E}(\cdot)\) is the model to transform sentences into embeddings, \(\tau\) is a hyperparameter, \(\text{Sim}(\cdot)\) is a similarity function and \(\delta(\cdot)\) is a function return to 1 if input is higher than 0 and 0 for others. \(R_a\) and \(R_b\) are the coverage rates of \(X_a\) and \(X_b\), respectively. LCR uses minimum value between \(R_a\) and \(R_b\) as final result, so it can be aware of two common cases: 1) a majority of generated samples are out of real distribution; 2) generated samples are real-like but in high similarities. LCR compares the similarity of two distributions in a fine-grained level, so it is more sensitive to the changes in samples. More explanations and comparisons between FED and LCR can be found in Appendix B.

When adopting these two embedding level metrics, we select 10,000 sentences in each set and use Universal Sentence Encoder [47] to encode them into embeddings. For the similarity function in LCR, we use cosine similarity suggested by the Universal Sentence Encoder [47].

4.2 Experiment Setup

We use two datasets in our experiment: COCO Image Caption Dataset [48] and EMNLP 2017 News Dataset [3]. For the COCO Image Caption Dataset, we choose 50,000 sentences as training set. For the EMNLP 2017 News Dataset, we choose 200,000 sentences as training set.

We compare the performance of InitialGAN with MLE and other language GANs. For REINFORCE methods, we choose SeqGAN [13], RankGAN [32], MaliGAN [49], LeakGAN [31] and ScratchGAN [18]. For continuous relaxation methods, we choose RelGAN [35]. All these methods except ScratchGAN rely on MLE pre-training, while ScratchGAN is based on pre-trained embeddings—GloVe [50]. InitialGAN is the only language GAN whose parameters are initialized completely randomly. More experimental details can be found in Appendix D.

4.3 Experimental Results

Figure 2 reports FED of different models. On COCO Image Caption Dataset, MLE, ScratchGAN and InitialGAN can significantly outperform other compared models. The differences among these
Figure 3: Evaluation Results in Least Coverage Rate (LCR). Higher is better. (a) LCR with different $\tau$ on COCO Image Caption Dataset. (b) LCR on EMNLP 2017 News Dataset ($\tau = 0.45$).

Table 1: Evaluation Results in Token Level Metrics (S-BLEU: Self-BLEU, I. BLEU: Inverse BLEU).

| Model     | COCO Image Caption |           | EMNLP 2017 News |           |
|-----------|---------------------|-----------|-----------------|-----------|
|           | BLEU ↑ | S-BLEU ↓ | I. BLEU ↑       | BLEU ↑ | S-BLEU ↓ | I. BLEU ↑       |
| Training Data | 34.99 | 34.80 | 35.36 | 20.50 | 20.47 | 20.62 |
| MLE       | 32.59 | 37.15 | 32.03 | 16.66 | 17.21 | 16.97 |
| SeqGAN    | 34.68 | 69.85 | 22.34 | 9.01  | 27.89 | 9.90  |
| RankGAN   | 37.32 | 73.30 | 22.10 | 10.35 | 56.77 | 10.37 |
| MaliGAN   | 26.49 | 53.47 | 25.95 | 12.23 | 21.34 | 13.11 |
| LeakGAN   | 33.14 | 56.88 | 29.43 | 27.61 | 50.55 | 11.59 |
| ScratchGAN | 30.98 | 35.72 | 30.76 | 17.54 | 19.04 | 17.19 |
| ReLGAN    | 54.04 | 73.70 | 29.53 | 30.95 | 57.48 | 14.74 |
| InitialGAN | 34.87 | 39.06 | **33.06** | 19.40 | 25.74 | **17.74** |

To better compare the performance among these three models, we further compare their performance in LCR. The results are shown in Figure 3. We explore the effectiveness of the threshold $\tau$ in LCR on Image COCO Caption Dataset. The results are demonstrated in Figure 3 (a). Although the values change significantly with different $\tau$, the rankings of different models are kept when $\tau$ is in a reasonable interval. According to Figure 3 (a), ScratchGAN is slightly inferior to MLE while InitialGAN can outperform the other two models. Figure 3 (b) shows LCR on EMNLP 2017 News Dataset. InitialGAN gets the highest LCR among all the models. Unlike on Image COCO Caption Dataset, ScratchGAN can also outperform MLE on this dataset. EMNLP 2017 News Dataset consists of long sentences and its distribution is more complicated. The exposure bias problem in MLE is more likely to happen, which leads to the poor performance on this dataset.

The evaluation results in token level evaluation metrics are shown in Table 1. We firstly analyze the results on COCO Image Caption Dataset. Except for ScratchGAN and InitialGAN, most of language GANs tend to get very high Self-BLEU. Sentences generated by these models have high similarities, which indicates the mode collapse problem in these models. ScratchGAN can tackle this problem, and get better result in Inverse BLEU. However, it still remains a gap comparing with MLE even with the help of pre-trained embeddings. InitialGAN is the only language GAN which can outperform MLE when considering fluency and diversity together.

Similar results can be found on EMNLP 2017 News Dataset. The difference is that ScratchGAN can slightly outperform MLE in terms of Inverse BLEU. It is consistent with the results in LCR. When generating long sentences, MLE is more likely to meet exposure bias, so MLE gets lower BLEU which means these sentences are lack of local consistency. Besides, the Self-BLEU shows sentences generated by MLE are more diverse than training data. It indicates a number of generated sentences are out of the real distribution. Thus, MLE can only get unsatisfactory performance on this dataset.
Besides, we further explore the performance of ScratchGAN without pre-trained embeddings, and show the results in Figure 4(b). Once we remove the pre-trained embeddings, ScratchGAN can no longer outperform MLE in terms of Inverse BLEU, and the gap between ScratchGAN and InitialGAN becomes larger. It reflects the dependence of ScratchGAN on pre-trained embeddings.

Figure 4(b) shows the experimental results of the ablation study about dropout sampling and fully normalized LSTM. The performance decreases a lot after removing dropout sampling, and the situation gets worse if we further remove the fully normalized LSTM. These results demonstrate that the importance of dropout sampling and fully normalized LSTM to the performance of InitialGAN. Additional experiments on COCO Image Caption Dataset are conducted to further explore these two proposed techniques. The results are shown in Figure 5.

In Figure 5(a), we show the influence of dropout rate to FED. The curve shows a rough symmetry. We suppose it comes from the symmetry of combinations. Given a $d$-dimension vector, the number of possible combinations of masking $\rho \cdot d$ dimensions is the same as the number of masking $(1 - \rho) \cdot d$ dimensions ($\rho$ is the dropout rate). In Figure 5(b), we show the change of FED on the validation set during the training process. LayerNorm LSTM, the original combination of LSTM and layer normalization [25], can outperform LSTM, while our fully normalized LSTM can further speed up convergence and get better FED. It shows the effectiveness of our design.

LCR uses the minimum values among two coverage rates as the final results, but analyzing these two coverage rates can also help us to better understand models (more explanations about it can be found in Appendix B). We train MLE and InitialGAN with different random seeds on COCO Image Caption Dataset, and show their average coverage rates with the standard deviations in Figure 6(a). InitialGAN gets higher coverage rates and its standard deviation is slightly smaller than MLE. It shows InitialGAN can get consistently better result with different random seeds. Besides, MLE gets lower coverage rate in inference set. We regard the exposure bias as the cause leading MLE to generate sentences out of the real distribution, so its coverage rate of inference set is lower.
Figure 6: (a) Coverage Rate of MLE and InitialGAN ($\tau = 0.65$). (b) Sentence length distribution.

InitialGAN gets higher coverage rate on inference set, so further work needs to be done to relieve the mode collapse problem. We also show the sentence length distributions in Figure 6 (b). Compared with MLE, sentences generated by InitialGAN have a closer distribution to the training data. More experimental results and generated samples can be found in Appendix E and G, respectively.

5 Conclusion and Limitation

In this work, we conduct an in-depth study about constructing language GANs based on representation modeling. We analyze two main problems which limit the performance of representation modeling methods: invalid sampling method and unhealthy gradients. For the invalid sampling method, we introduce dropout sampling, a simple but effective method. For the unhealthy gradients, we make use of our analyses to layer normalization and present the fully normalized LSTM. Armed with these two techniques, we propose InitialGAN, a language GAN with completely random initialization. Besides, we find that FED is not sensitive to the change of sample quality, so we propose Least Coverage Rate (LCR) which can help us better identify the differences among different models. We conduct experiments on two widely used datasets, and the experimental results show that InitialGAN can outperform both MLE and other compared models. To the best of our knowledge, it is the first time that a language GAN can outperform MLE without using any pre-training techniques. This work also demonstrates that RMMs denote a promising research line for language GANs.

Although language GANs can tackle the exposure bias problem, their training speed is one of the most urgent limitations which must be tackled. Language GANs need to use previously generated tokens as input in both training and inference, so its training speed can not be improved by parallel computation structures like Transformer. It limits the applications of current language GANs on large datasets. How to improve the training speed is the key problem that needs to be solved before we apply it in more complicated scenarios.

Broader Impact

In this work, we study text generative models—fundamental components in various tasks, so all the tasks related to text generation have the possibility to benefit from this work. Our model is a data-driven model which learns the distribution of datasets, so it may have the chance to generate sentences with biased content. Additional filters should be adopted before presenting generated sentences to public. Furthermore, it is also possible to use this technique to implement applications that may be detrimental to society (e.g., generating fake news). The applications of this technique should be under public scrutiny so as to relieve the possible negative impacts.

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A Theoretical Analyses

A.1 Proof of Theorem 1

Suppose $F$ is a non-linear transformation in a model. We investigate the effects of layer normalization by analyzing two different implementations:

\begin{align}
    y_l^{(a)} &= F_a(y_l) \\
    y_l^{(b)} &= F_b(LN(y_l))
\end{align}

where $LN(\cdot)$ is layer normalization. These two implementations are both based on $y_l$, which is the output from the previous layer. The difference is that Eq. 6 does not use layer normalization in the input, while Eq. 6 uses it. The gradients of output to input are:

\begin{align}
    \frac{dy_l^{(a)}}{dy_{l+1}} &= F'_a(y_l) \\
    \frac{dy_l^{(b)}}{dy_{l+1}} &= F'_b(LN(y_l)) \cdot LN'(y_l)
\end{align}

There are two differences in Eq. 8 and Eq. 9. $y_l$ is normalized when calculating $F'_b(\cdot)$. It can prevent input from lying in an interval whose gradients are extremely small. Another difference is the additional term $LN'(y_l)$ in Eq. 9. To simplify the notations, we use $x$ to represent $y_l$. Layer normalization is related to the mean and standard deviation among all the dimensions of $x$. We start the analyses from the $i$-th dimension in $x$, which is denoted as $x_{[i]}$.

\begin{align}
    LN'(x_{[i]}) &= \frac{[x_{[i]} - \mu_x]}{\sigma_x} = \frac{([x_{[i]} - \mu_x]' \cdot \sigma_x) - ((x_{[i]} - \mu_x) \cdot \sigma_x')}{\sigma^2_x} \\
    \text{The derivative of } [x_{[i]} - \mu_x]' &= d(x_{[i]} - \frac{1}{H} \sum_{j=1}^H x_{[j]})/dx_{[i]} = 1 - \frac{1}{H}
\end{align}
where $H$ is the dimension of $x$. Besides, the derivative of $\sigma_x$ is:

$$
\sigma'_x = \frac{d\mathbb{E}(x^2 - \mathbb{E}^2(x))^{1/2}}{dx[1]} \\
= \frac{1}{2} \mathbb{E}[x^2 - \mathbb{E}^2(x)]^{-1/2} \cdot |\mathbb{E}(x^2) - \mathbb{E}^2(x)|' \\
= \frac{1}{2\sigma_x} \left( \frac{2x[1]}{H} - \frac{2\mathbb{E}(x)}{H} \right) \\
= \frac{x[1] - \mu_x}{H \cdot \sigma_x}
$$

(12)

Considering Eq. 10, 11 and 12 we have:

$$
LN'(x[i]) = \frac{(1 - \frac{1}{H}) \cdot \sigma_x - \frac{(x[i] - \mu_x)^2}{H \cdot \sigma_x}}{\sigma_x^2} \\
= -\frac{1}{H} \sigma_x^2 + \frac{\sigma_x^2 - \frac{(x[i] - \mu_x)^2}{H}}{\sigma_x^3} \\
= -\frac{\sigma_x^2}{H} + \frac{\sum_{j \neq i}(x[j] - \mu_x)^2}{H} \\
= -\frac{\sigma_x^2}{H} + \frac{1}{H - 1} \sigma_x^3
$$

(13)

When $H$ is large enough, we can adopt the law of large numbers to obtain the following relation:

$$
\frac{1}{H - 1} \sum_{j \neq i}(x[j] - \mu_x)^2 \approx \sigma_x^2
$$

(14)

Thus, Eq. 13 can be further transformed as:

$$
LN'(x[i]) \approx -\frac{\sigma_x^2}{H} + \frac{H - 1}{H} \sigma_x^2 = H - \frac{2}{H} \frac{1}{\sigma_x} \approx (1 - \frac{2}{H}) \frac{1}{\sigma_x}
$$

(15)

We can regard $1 - \frac{2}{H} \approx 1$ when $H$ is large enough, so we have:

$$
LN'(x[i]) \approx \frac{1}{\sigma_x}
$$

(16)

If the deviation of $x$ is smaller than 1, this term will be a scaler factor larger than 1. In this time, it can help augment gradients and relieve gradient vanishment problem.

### A.2 Proof of Corollary 1

LSTM is calculated as follows:

$$
\begin{pmatrix}
  f_t \\
  i_t \\
  o_t \\
  \hat{c}_t
\end{pmatrix} = W_h h_{t-1} + W_x x_t + b
$$

(17)

$$
\begin{align*}
  c_t &= f_s(f_t) \odot c_{t-1} + f_s(i_t) \odot f_h(\hat{c}_t) \\
  h_t &= f_s(o_t) \odot f_h(c_t)
\end{align*}
$$

(18)

To simplify analyses, we discuss the influence of the output gate to gradients using following functions:

$$
\begin{align*}
  y_{t+1}^{(c)} &= F_c(o_t \odot c_t) \\
  y_{t+1}^{(d)} &= F_d(LN(o_t \odot c_t))
\end{align*}
$$

(20)
where $o_t$ can be regarded as the output gate in LSTM, so its values are in $(0, 1)$. And $c_t$ can be regarded as the cell state whose values are in $(-1, 1)$. The gradients of these functions are:

$$\frac{dy^{(c)}}{dc_t} = F'_c(o_t \circ c_t) \cdot diag(o_t)$$  \hspace{1cm} (22)$$

$$\frac{dy^{(d)}}{dc_t} = F'_d(LN(o_t \circ c_t)) \cdot LN'(o_t \circ c_t) \cdot diag(o_t)$$  \hspace{1cm} (23)$$

where $diag(\cdot)$ represents a diagonal matrix.

Both Eq. 22 and Eq. 23 contain $o_t$, which is in $(0, 1)$. The gradients related to the calculation of $c_t$ are all scaled down. However, in Eq. 23, we have an additional term $LN'(o_t \circ c_t)$. And the variance of $o_t \circ c_t$ is:

$$Var(o_t \circ c_t) = \mathbb{E}[(o_t \circ c_t)^2] - \mathbb{E}^2(o_t \circ c_t)$$  \hspace{1cm} (24)$$

Consider $o_t \in (0, 1)$ and $c_t \in (-1, 1)$, we have $\mathbb{E}[(o_t \circ c_t)^2] < 1$. $\mathbb{E}^2(o_t \circ c_t)$ is a non-negative term, which means $\mathbb{E}^2(o_t \circ c_t) \geq 0$, so we have $Var(o_t \circ c_t) < 1$ and its deviation is also smaller than 1. According to Theorem 1, $LN'(o_t \circ c_t)$ is now an augmentation factor which can offset the influence from $o_t$. This augmentation factor is an adaptive factor. The lower $o_t$ is, the higher the factor.

When we stack several fully normalized LSTM layers to build a model, the normalized output from the previous layer needs to be normalized again after a linear transformation. One can adopt fully normalized LSTM in the last layer of the model and use LayerNorm LSTM in the remaining layers to avoid high frequent normalization operation. However, we still suggest to use fully normalized LSTM in all the layers. Given two matrices $A$ and $B$, the standard deviation of $AB$ is very likely to be higher than the ones of $A$ and $B$. Thus, the scale factor has high probability to be reduced after linear transformation. More detailed analyses can be found in the following.

### A.3 Standard Deviation in Linear Transformation

Suppose we have two matrices $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times k}$, which are:

$$A = \begin{pmatrix} \hat{a}_1 \\ \hat{a}_2 \\ \vdots \\ \hat{a}_m \end{pmatrix}, \text{ where } \hat{a}_i = (a_{i1}, a_{i2}, \ldots, a_{in})$$

$$B = (\hat{b}_1, \hat{b}_2, \ldots, \hat{b}_k), \text{ where } \hat{b}_i = (b_{i1}, b_{i2}, \ldots, b_{in})$$  \hspace{1cm} (25)$$

We denote the standard deviation of $AB$ as $\sigma_{AB}$, then we will discuss the relations between $\sigma_{AB}$, $\sigma_A$ and $\sigma_B$. The sum of all the elements in $AB$ is:

$$S_{AB} = \sum_{1 \leq i \leq m, 1 \leq j \leq k} (\hat{a}_i \hat{b}_j) = \sum_{i=1}^{m} \hat{a}_i \sum_{j=1}^{k} \hat{b}_j$$  \hspace{1cm} (26)$$

And the mean value of all the elements is

$$\frac{1}{mk} S_{AB} = \frac{\sum_{i=1}^{m} \hat{a}_i}{m} \cdot \frac{\sum_{j=1}^{k} \hat{b}_j}{k}$$  \hspace{1cm} (27)$$

We denote $\bar{a} = \frac{\sum_{i=1}^{m} \hat{a}_i}{m}$ and $\bar{b} = \frac{\sum_{j=1}^{k} \hat{b}_j}{k}$, the variance of $AB$ can be represented as:

$$Var(AB) = \frac{1}{mk} \sum_{1 \leq i \leq m, 1 \leq j \leq k} (\hat{a}_i \hat{b}_j)^2 - \left(\frac{1}{mk} S_{AB}\right)^2$$

$$= \frac{1}{mk} \sum_{1 \leq i \leq m, 1 \leq j \leq k} (\hat{a}_i \hat{b}_j)^2 - (\bar{a} \bar{b})^2$$  \hspace{1cm} (28)$$
We suppose the square norms $\dot{a}_i$ and $\dot{b}_j$ as $\theta_{ij} \in [0, \pi]$, and we have:

$$(\dot{a}_i \dot{b}_j)^2 = \dot{a}_i^2 \dot{b}_j^2 \cos^2 \theta_{ij} = \frac{1}{2} \dot{a}_i^2 \dot{b}_j^2 (1 + \cos 2\theta_{ij})$$

(30)

We suppose the square norms $\dot{a}_i^2$ and $\dot{b}_j^2$ are independent of the angle $\theta_{ij}$. Considering Eq. 28, Eq. 29 and 30, we have:

$$Var(AB) = \frac{1}{mk} \left( \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \frac{1}{2} \dot{a}_i^2 \dot{b}_j^2 \cos 2\theta_{ij} \right)$$

$$= \frac{1}{2mk} \left( \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \dot{a}_i^2 \dot{b}_j^2 \cos 2\theta_{ij} \right) + \frac{1}{2} \cdot \frac{1}{mk} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} (\dot{a}_i^2 \dot{b}_j^2) \cdot \frac{1}{mk} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \cos 2\theta_{ij}$$

(31)

Suppose the angle $\theta_{ij}$ follows a uniform distribution from $[0, \pi]$, we can regard all the angles as a continuous curve. Then, we have:

$$\frac{1}{mk} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \cos 2\theta_{ij} = \frac{1}{\pi} \int_0^\pi \cos 2\theta d\theta$$

(32)

Combining (31) and (32), we can get:

$$Var(AB) = \frac{1}{2} \frac{1}{mk} \left( \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \dot{a}_i^2 \dot{b}_j^2 \right) + \frac{1}{2} \cdot \frac{1}{mk} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} (\dot{a}_i^2 \dot{b}_j^2) \cdot \frac{1}{\pi} \int_0^\pi \cos 2\theta d\theta$$

$$= \frac{1}{2} \frac{1}{mk} \left( \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} \dot{a}_i^2 \dot{b}_j^2 \right) + \frac{1}{2} \cdot \frac{1}{mk} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq k} (\dot{a}_i^2 \dot{b}_j^2) \cdot \frac{1}{\pi} \cdot \frac{1}{2} \sin 2\theta \bigg|_0^\pi$$

(33)

Beside, $Var(A)$ and $Var(B)$ are:

$$Var(A) = \frac{1}{mn} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq n} \dot{a}_{ij}^2 - \left( \frac{1}{mn} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq n} \dot{a}_{ij} \right)^2$$

(34)

$$Var(B) = \frac{1}{nk} \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq k} \dot{b}_{ij}^2 - \left( \frac{1}{nk} \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq k} \dot{b}_{ij} \right)^2$$

(35)
Since we have supposed $A$ and $B$ are centered around 0, Eq. 34 and 35 can be further transformed as:

$$\text{Var}(A) = \frac{1}{mn} \sum_{1 \leq i \leq m} \sum_{1 \leq j \leq n} a_{ij}^2$$ (36)

$$\text{Var}(B) = \frac{1}{nk} \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq k} b_{ij}^2$$ (37)

Combining Eq. 33, 36 and 37, we have:

$$\text{Var}(AB) = \frac{(mn \cdot \text{Var}(A))(nk \cdot \text{Var}(B))}{2} = \frac{n^2 \cdot \text{Var}(A) \text{Var}(B)}{2}$$ (38)

Thus, their standard deviations have the following relation:

$$\sigma_{AB} = \frac{\sqrt{2}}{2} n \cdot \sigma_A \sigma_B$$ (39)

This relation is also satisfied when multiplying a vector and a matrix. In practice, $n$ is always set to be a large number (e.g., 512 or 1024), so $\sigma_{AB}$ is very likely to be higher than both $\sigma_A$ and $\sigma_B$.

### B Supplementary Explanations about Least Coverage Rate (LCR)

Least Coverage Rate (LCR) has following features:

- It compares two distributions in a fine-grained level. Given two sets of sentences, LCR computes the similarity of every two sentences in the two sets to make sure whether specific modes are covered or not. Thus, it can be more sensitive to the change of sample quality.
- The minimum operation in LCR helps it be sensitive to two common problems in generative models: 1) generating samples out of real distributions; 2) generating samples in high similarities. The coverage rates on test sets ignore the samples out of real distribution, while the coverage rates on inference sets is not aware to the mode collapse problem.
- It better makes of sentence encoders. Most of sentence encoders are designed to compare sentence similarities with a pre-defined method (e.g., cosine similarity). FED only considers the mean and covariance of two sets, and does not make use of this feature directly.
- It is efficient to compute. Although it needs to compute the similarity of every two sentences in the two sets, it can be implemented in a high efficiency way. For example, if we use Universal Sentence Encoder to transform sentences into embeddings, we can easily implement the calculation of cosine similarity in a parallel way.

We also conduct an experiment to explore the effectiveness of Least Coverage Rate. We explore the sensitivity of Least Coverage Rate (LCR) and Fréchet Embedding Distance (FED) to data changes by replacing words in sentences with random ones in a certain probability. The experimental results are shown in Figure 7.
Generally, the changes of FED are not obvious even when replacing 10% of words with random words. In the early stage, we nearly cannot observe any changes in FED. It shows that FED is not sensitive to the changes of sample quality. Different with FED, LCR is a much more sensitive evaluation metric. Even minor changes can be reflected in LCR. LCR decreases from around 0.75 to less than 0.5 when 10% of words are replacing with random words. This result shows that LCR can be a good compliment when the compared model gets close performance in FED.

Least coverage rate uses the minimum value among the coverage rates of test sets and inference sets as result. In practice, we can give more detailed analyses about these two coverage rates to reveal the problems hidden in models. When the coverage rate of the inference set is higher, it shows the model tends to generate samples out of real distributions. If the coverage rate of the test set is higher, it demonstrates the mode collapse problem in the model.

C Model Details of InitialGAN

The structure of InitialGAN is shown in Figure 8. There are three models in InitialGAN: aligner, generator and discriminator. The aligner is based on the encoder in Transformer [5]. We train the aligner based on the strategy of BERT [51]. More specifically, 15% of words in training data will be randomly selected as the word needs to be predicted. The replacing words having 80% of the time are replaced with [MASK] token, 10% of time are replaced with random tokens, and 10% of time are unchanged. In the training objective of the aligner, we propose to add an additional term to penalize $\sigma_x^2$. It should be noted that vanilla VAE needs to calculate $\sigma_x^2$ to update the KL divergence term in the objective, so there is nearly no additional computational cost in the new training objective.

After the training of the aligner is finished, all its parameters are fixed and the transformation layer which transforms representations back into words will be shared with the generator. In practice, we use a linear transformation to implement the transformation layer. We train the discriminator to identify whether a specific representation in the $t$-th timestep is from the aligner or the generator based on the previous $(t-1)$ representations:

$$c_t = D_{\psi}(r_t|r_{t-1},...,r_1)$$

where $r_t$ is the $t$-the representation from the aligner or the generator. For the generator, we use dropout sampling to get the latent input $z_t$. Then, the generated representation and its corresponding word of each timestep is calculated as:

$$r^{(t)}_g = G_{\phi}(z_t|z_{t-1},...,z_0)$$

$$\hat{x}_t = F_{LT}(r^{(t)}_g)$$
Algorithm 1: Training of InitialGAN

Input: Initial parameters of Variational Aligner \( \phi_0 \), Discriminator \( \psi_0 \), and Generator \( \varphi_0 \). Batch size \( m \) and imbalanced batch size \( m' \).

// Training the aligner
while \( \phi \) has not converged do
  for \( i = 1 \) to \( m \) do
    Sample real data \( x \sim P_x \)
    \( \mu_x, \sigma^2_x \leftarrow A_\phi(x) \)
    \( \hat{\epsilon} \sim \mathcal{N}(0, 1) \)
    \( \hat{z} \leftarrow \hat{\epsilon} \circ \sigma_x + \mu_x \)
    \( L_A^i \leftarrow -\mathbb{E}_{z \sim q(z|x)} (\log p(x|\hat{z})) + KL(q(z|x)||p(z)) + \lambda_a \log (\sigma^2_x) \)
  end
  \( \phi \leftarrow \text{AdamW} \left( \nabla \phi \frac{1}{m} \sum_{i=1}^{m} L_A^i, \phi \right) \)
end
// Training the discriminator and the generator
while \( \varphi \) has not converged do
  for \( i = 1 \) to \( m \) do
    Sample real data \( x \sim P_x \), latent variable \( z \sim P_z \), random number \( \epsilon' \sim \text{Uniform}[-0.1, 0.1] \).
    \( \mu_x, \sigma^2_x \leftarrow A_\phi(x) \)
    \( r_d \leftarrow \mu_x \)
    \( r_g \leftarrow G_\phi(z) \)
    \( r_m \leftarrow \epsilon' \cdot r_d + (1 - \epsilon') \cdot r_g \)
    \( L_D^i \leftarrow D_\psi(r_g) - D_\psi(r_d) + \lambda_d \max \{0, ||\nabla_{r_m} D_\psi(r_m)||_2 - 1\}^2 \)
  end
  \( \psi \leftarrow \text{AdamW} \left( \nabla \psi \frac{1}{m} \sum_{i=1}^{m} L_D^i, \psi \right) \)
  Sample a batch of latent variables \( \{z(i)\}_{i=0}^{m'} \sim P_z \)
  \( \varphi \leftarrow \text{Adam} \left( \nabla \varphi - \frac{1}{m'} \sum_{i=1}^{m'} D_\psi(G_\varphi(z(i))), \varphi \right) \)
end

where \( r^{(t)}_g \) is the \( t \)-th representation and \( F_{LT}(\cdot) \) is the transformation layer from the aligner. Its parameters are fixed during the training of generator. When implementing dropout sampling, dropout is adopted in all the layers of the generator, and the input is the concatenation of word embeddings and \( \epsilon \sim \text{Uniform}(-0.1, 0.1) \). The full training process of InitialGAN is described in Algorithm 1.

D Experiment Details

The hyperparameters of InitialGAN are:

- Batch size: 128
- Maximum epoch of the aligner training: 200
- Maximum epoch of the adversarial training: 3,000 for COCO, 2,000 for EMNLP
- Embedding size: 512
- Feature size in the aligner: 512
- Feature size in the discriminator: 1024
- Feature size in the generator: 512
- Dimension of random noise: 128
- Layer number of the aligner: 4
- Layer number of the discriminator: 2
- Layer number of the generator: 2
- Head number of the aligner: 8
- Dropout rate for the aligner: 0.5
- Dropout rate in dropout sampling: 0.75
- Learning rate of the aligner: 0.0001
- Learning rate of the discriminator: 0.0004 for COCO, 0.0002 for EMNLP
- Learning rate of the generator: 0.0001
- $\lambda_a$ in the aligner loss: 0.1
- $\lambda_d$ in the discriminator loss: 50
- Optimizer of the aligner: AdamW ($\beta_1 = 0.9, \beta_2 = 0.999$, weight decay=0.00001)
- Optimizer of the discriminator: AdamW ($\beta_1 = 0.5, \beta_2 = 0.9$, weight decay=0.00001)
- Optimizer of the generator: Adam ($\beta_1 = 0.5, \beta_2 = 0.9$)

We save the model after every epoch, and select the best model based on FED on validation sets. We follow the settings of the previous work [45] to implement MLE except for the layer number and feature size which are set to be same with the generator in InitialGAN. It not only leads the model to be more comparable, but also improves its performance. We obtain the results of other language GANs by running the public code.

We implement InitialGAN based on Tensorflow 2 [52]. It is trained on NVIDIA GeForce RTX 3090 with around 12G RAM. The training needs to take 10 to 20 days depending on the dataset.

### E Supplementary Experimental Results

![Gradient Norm](image)

According to our analyses, fully normalized LSTM can relieve the gradient vanishment by providing an augmentation term. We train models with different variants of LSTM, and show their average gradient norms of first 100 training batches in Figure 9 (a). These norms are calculated based on the gradients of the input linear transformation matrix in the last layers of generators. LayerNorm LSTM can slightly augment the gradient norm, while fully normalized LSTM can obtain more obvious augmentation. The experimental results are consistent with our theoretical analyses.

In the aligner, we map words into distributions instead of specific embeddings. We show the FED and LCR ($\tau = 0.65$) of these two mapping methods on Image COCO Caption Dataset in Figure 9 (b). Aligner trained by cross entropy, which maps words into specific points, is inferior to the one trained by our proposed loss function in both FED and LCR. Cross entropy does not provide confirmed mapping relations when the generated representations are away from the real representations. Minor errors in the generated representations may lead them to be mapped into totally irrelevant words. It adds noise to training and increases instability in inference.

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4 [https://github.com/geek-ai/Texygen](https://github.com/geek-ai/Texygen) (MIT license)
5 [https://github.com/deepmind/deepmind-research/tree/master/scratchgan](https://github.com/deepmind/deepmind-research/tree/master/scratchgan) (Apache-2.0 license)
6 [https://github.com/weilinie/RelGAN](https://github.com/weilinie/RelGAN) (MIT license)
In the training objective of the aligner, we add a penalization term to constraint words in different frequency having the regions in similar size. We also explore the effectiveness of this penalization term. We firstly compare its influence to Inverse BLEU on Image COCO Caption Dataset. As shown in Figure 10 (a), the penalization term helps the model to get better Inverse BLEU. Besides, we also try to evaluate the size of different word regions directly. Thus, we randomly select the representations of two words and use linear interpolation to get 100 points between these two representations. Then, we use the transformation layer to transform these representations back into words. We denote the times that a word is mapped as mapping times. If the size of the two regions are similar, the mapping times of the two words should be generally same, i.e., close to 50, so we design a balance error to evaluate the size of the regions:

\[
\text{balance_error} = \frac{1}{n} \sum_{i=1}^{n} |\text{times}_i - \text{exp\_times}|
\]

where \(\text{times}_i\) is the mapping times of a word in the \(i\)-th word pair (choosing any of the word in the pair will give same result), and \(\text{exp\_times}\) is the expected mapping times which is 50 in our experiments. We randomly select 1,000 word pairs to conduct this experiment and the results are shown in Figure 10 (b). Penalization term helps the model gets lower balance error. It means the regions of different words are more balanced after penalization. We also show two cases of mapping times in Figure 10 (c). The mapping times of these words are all closer to 50 after penalization. These experiments show the effectiveness of the penalization term.

F Unsuccessful Attempts

We show some attempts that do not bring improvements in our experiments so as to provide a reference for future work:

- Using Bi-LSTM to build the discriminator. It does not get improvements.
- Using spectral normalization to regularize the discriminator. It is unsuccessful.
- Using Hinge loss as the training objective. It is unsuccessful when adopting either spectral normalization or gradient penalty.
- In addition to the original loss, adding next word prediction or part-of-speech (POS) prediction to train the discriminator by making use of multi-task learning. It is unsuccessful.
- Using dropout in the discriminator. It can not get improvements.
- Adding random noise in each layer of the discriminator and the generator. It is unsuccessful.
- Using AdamW as the optimizer of the generator. Mode collapse is found.
- Prompt the model to firstly learn first few words and adds the number of words gradually. It is unsuccessful.
- Learning rates of the discriminator and the generator are decayed during training process. It is unsuccessful.
### G Generated Samples

We demonstrate generated samples given by the models trained on COCO Image Caption Dataset and EMNLP 2017 News Dataset in Table 2 and Table 3 respectively.

| Table 2: Samples Generated by Models Trained on COCO Image Caption Dataset |
|--------------------------------------------------|
| **MLE**                                          |
| - a living room has no parking watch a chair.    |
| - a man is playing wii in a home hand.           |
| - two groups of skiers are hanging around the large business park. |
| - bikes outside by a big bridge.                  |
| - a white plate topped with lots of chinese food. |
| **SeqGAN**                                       |
| - there is a basket in the small bathroom with a white sink, and bathroom. |
| - the side of a small dog is sitting next to it.  |
| - there is sitting in his hand up in the water.   |
| - the side of a pole has a building is in the rear view mirror. |
| - three donuts on the plate of broccoli are in the green. |
| **RankGAN**                                      |
| - a black and white photo of a toiletry shelf in a room. |
| - a black cat watches a city from the corner of a room. |
| - a street with a white and yellow motorcycle next to a street. |
| - the zebra stands on a grass covered mountain.   |
| - a cart holding a note on a ground.             |
| **MaliGAN**                                      |
| - a row of traffic lights showing off the side of an intersection. |
| - a man walks behind them in high chair with a wii remote in her hands in a nursery room. |
| - a row of pink fire trucks parked outside by a row in the corner of the head of a window. |
| - a row up on a bus driving over a city park pair of scissors in a donut. |
| - a city is floating in the sky.                  |
| **LeakGAN**                                      |
| - a man in a small corner on a counter and a table. balcony. |
| - a man and a baseball and a photograph of wine. word throw a wave. |
| - a man is on a busy city street with a pink. choices on the beach. & sam. |
| - a man riding a horse track with lots of items on a wooden desk. slot. |
| - a man riding a skateboard while holding a tennis racket. describing is on it. lined up. dancer |
| **ScratchGAN**                                   |
| - people and standing in a large yard playing frisbee. |
| - a device with smaller sandwiches rusted between one hair. |
| - a person sitting on on the park looking at two pairs seductive. |
| - a grasses sticking his head over a train on the tracks. |
| - a 2 machine is cutting into the air a ride.     |
| **RelGAN**                                       |
| - a woman sitting on a bench next to a man.      |
| - a woman holding up a smart phone in front of a man. |
| - two women sitting on the beach with two horses. |
| - a man in a black and white cat lays on a corner. |
| - a man in an orange and white cat laying on a carpet of a sink. |
| **InitialGAN**                                   |
| - a man walks down the street holding a surfboard. |
| - a man in a jacket playing with his frisbee in his hand. |
| - a baby elephant in the grass with a toy zoo.    |
| - a cute teddy bear is wearing a red shirt.       |
| - a dog playing a game of baseball on a sunny day. |
| Models          | Samples Generated by Models Trained on EMNLP 2017 News Dataset |
|----------------|---------------------------------------------------------------|
| MLE            | - this year bbc 11 key travel power has been released an enemy and those we reached , and if they weren ’ t going to have her - best service and back there is fair and they might have worn data .  
- the court heard is as unfair than ever became resulting to ensure it is the high school .  
- " i told the shops and cold anything about the day ’ s eight years ago , " a single feature for that possibility talk to it without streaming treatment .  
- some would have taken at least nine offences in the future on saturday morning on the highway out in the quarter and she has slipped back .  
- they can ” s resources ” the sunday vote but the citizens have been an early in and started . |
| SeqGAN         | - and the event has been for a much more equal third .  
- we would say .  
- a bottle of women who is the first , so .  
- it just want to create and maintenance .  
- that top . |
| RankGAN        | - we can ’ t come in the i manhattan ‘ , ruling .  
- if he was sent as they ’ ve been consistently unable to down into trouble .  
- it comes to supporters of the liberal ruling , fleet , in a question of their children .  
- it is to have been as long as a question for anyone who i would .  
- it ’ s the ruling , responsibility and we ’ re not going on a reason for a question of the liberal ruling , and , like to improve them . |
| MaliGAN        | - “ this “ isn ‘ t the third ‘ best , we ’ ve got a “ this message “ year ’ s going to , they are a nation to bringing a truck on a book  
- there was especially down , i ’ ve got to see that and i ’ ve been arrested years old , carson , the chancellor ’ s attacks carried out - like news keeping an inquiry have  
- the best mark in domestic days , but people she ’ s leading the prosecutor ’ s going - it ’ s somewhere her par decided more out that thousands were called an additional cell and hope  
- “ i ’ d need an nfl club border when is very expensive to seeing me politics of opportunities , and not my players were always wrong , not coming back and operated a comparison to the - its people , also used to wayne to you up , it ’ s all those primary , money to escape it - at pace . |
| LeakGAN        | - i think the reason why the war is a “ state “ and they are talking about the coming , and the potential loss against a l last year . ad , the us government has  
- “ as a result of the bbc , “ he said . roll trauma for the most part , the people , they are more likely to stay toward $ 3 . 5 million viewers .  
- if we have to be a little bit nervous that much more than ever appeared to be honest to do that to take us to do something that i ’ ve been a lot of times for  
- “ they are the same one of the most important . edwards this week is a problem in texas , “ she said in a fox news interview . grass . completely .  
- “ after that , it ’ s going to be named , i actually have to be a lot of the timing to the position of a boost for the first time : “ i think a |
| ScratchGAN     | - men even fewer than 0 they didn ’ t have to wait until their baby pick up : from last month .  
- the website does not live same , and move , in another statement , to improving video images of data and volume 2019 , said donations .  
- even though it is , because of apparently take it , have no symptoms if respond to a high level as far as the decision to ensure .  
- the anyway will carry too quickly , but might not have trouble with a specific eye on your mental health system .  
- at the time this year - on their own balance , it is not below the cost of free benefits . |
| ReIGAN         | - but there will be no difference between donald trump ’ s shock , whether you can win this .  
- but we don ’ t know if any storm there will be a lot of problems here . |
- as you don’t know what to say about this difficult conversation in the new year, “he said.
- her, who has stayed in the street and talk about what’s anyone young people to do on the street, ’ she said.
- the right now, i was trying to create an overall pick in the year and have to keep going open to my team.

- “I’m working hard in 2008 and come into my message to win the program,” the republican player said during his post.
- “We’re not getting the same one coming here for our budget and we are doing what again this time,” he said.
- “It was only the case where they got older schools and arrived that happening had moved the program,” she continued.
- as i was in new york, it actually help us and enjoy my interview on those with friends, i’m not talking to them.
- and if you continue to do it, she can tell the girls that you don’t think or about the reason things in the right side.