Improving Conditional Sequence Generative Adversarial Networks by Stepwise Evaluation

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Abstract—Sequence generative adversarial networks (SeqGAN) have been used to improve conditional sequence generation tasks, for example, chit-chat dialogue generation. To stabilize the training of SeqGAN, Monte Carlo tree search (MCTS) or reward at every generation step (REGS) is used to evaluate the goodness of a generated subsequence. MCTS is computationally intensive, but the performance of REGS is worse than MCTS. In this paper, we propose stepwise GAN (StepGAN), in which the discriminator is modified to automatically assign scores quantifying the goodness of each subsequence at every generation step. StepGAN has significantly less computational costs than MCTS. We demonstrate that StepGAN outperforms previous GAN-based methods on both synthetic experiment and chit-chat dialogue generation.

Index Terms—Generative Adversarial Network, Sequence Generation

I. INTRODUCTION

Conditional sequence generation refers to the tasks in which machine generates a correspondent sequence given the input. Such applications include dialogue generation, question answering, machine translation and summarization. In these applications, the input-output pairs usually have one-to-many property. For example, in dialogue generation, given a specific input (“How was your day?”), there can be many acceptable responses (“It is good.”, “Very bad.”, etc.). One-to-many property makes it difficult to learn to generate high quality answers.

The sequence-to-sequence (seq2seq) based dialogue generation model was trained using maximum likelihood estimation (MLE) in the original work [1]. MLE achieved acceptable results in terms of coherence, but left space for improvement. According to previous studies [2]–[4], training a seq2seq model by MLE causes three main problems: (1) One directional KL divergence [4]. MLE only minimizes forward KL divergence (from target distribution to predicted distribution); ignoring backward KL divergence makes the predicted distribution unbounded. Therefore it cannot ensure the similarity between learned distribution (predicted distribution) and target one. (2) Exposure bias [2]. Target outputs and predicted outputs are taken as the inputs during training stage and inference stage respectively; (3) General Responses. Previous research [5] found that MLE often yields the models predicting general responses (e.g., “I don’t know.”). GANs have potential to solve the above three issues.

To tackle the issues of MLE, recently [6] and [7] proposed sequence generative adversarial networks (SeqGAN) for chit-chat dialogue generation. In SeqGAN, discriminator is used to evaluate the difference between the model responses and ground truths. This solves the problem of only one direction KL divergence. Additionally, exposure bias is eliminated because of using policy gradient [2] for optimization. As the result, SeqGAN generate more creative sentences by observation [6], [7].

SeqGAN uses policy gradient to solve the intractable back-propagation issue, but a common problem in reinforcement learning appears: sparse reward, that the non-zero reward is only observed at the last time step. The primary disadvantage of sparse reward is making the training sample inefficient. Sparse reward causes another problem to chit-chat chatbot. In chatting, an incorrect response and a correct one can share the same prefix. For example, “I’m John.” and “I’m sorry.” have the same prefix “I’m”. But for the input “What’s your name?”, the first response is reasonable and the second one is weak. The same prefix then receives opposite feedback. The phenomenon continuously happens during training; the training signals become highly variant. The training is therefore unstable [2], [6]–[8].

To deal with sparse reward, the original SeqGAN is trained with a stepwise evaluation method – Monte Carlo tree search (MCTS) [6]. MCTS stabilizes the training, but it is computationally intractable when dealing with large dataset. To meet the necessary of large dataset for chatbot, reward at every generation step (REGS) is proposed to replace MCTS but with worse performance [7]. According to all the previous attempts [6], [7], [9], [10], we know that stepwise evaluation affects the results remarkably, but it has not been thoroughly explored.

We propose an alternative stepwise evaluation method to replace MCTS called StepGAN. The motivation is to use discriminator to estimate immediate rewards without computing complex tree search. StepGAN only needs very little modification on discriminator, and has significantly less computational costs than MCTS. We compare different GAN-based sequence generation approaches on a synthetic task and chit-chat dialogue generation. StepGAN outperforms MCTS and REGS on the synthetic task, and generates more informative responses than other approaches in dialogue generation. Although we only apply StepGAN on dialogue generation in this paper, the proposed approach can be used in any tasks that can be considered as conditional sequence generation, for example, machine translation, summarization and video caption generation.

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II. RELATED WORKS

Neural based conditional sequence generation is first successfully studied by [11] and [1] using seq2seq model. The model is initially learned by MLE that minimizes the cross-entropy between the true data distribution and the model distribution. The method suffers from exposure bias, and thus beam search, scheduled sampling [12] and REINFORCE [2]. [13] are proposed to solve the problem. On the other hand, MLE also makes the model generate general responses, and thus mutual information [5] and adversarial learning [7] are used to make model generate creative sentences.

By providing a task-specific score (e.g., BLEU [14]), the reinforcement learning [15] based algorithm, REINFORCE [2], guides the seq2seq model to optimize the score. Further, MIXER [2] is proposed to integrate MLE and REINFORCE to reduce the exploration space for reinforcement learning. Other reinforcement learning methods are thereafter proposed to improve seq2seq model, including actor-critic architecture [8], off-policy learning [16] and deep reinforcement learning for multi-turns dialogue [17].

Recently, a study [18] verifies that BLEU score is weakly correlated with human prior knowledge. Therefore GANs, that can automatically assign scores to sentences, are applied to sequence modeling. The related researches include SeqGAN [6], MaliGAN [9], REGS [7], WGAN-GP [19], [20], TextGAN [21], RankGAN [22] and MaskGAN [10]. To conquer the intractable backpropagation through discrete sequences, policy gradient [6], Gumbel-softmax [23], soft-argmax [24] and Wasserstein distance [25] are applied. Among them, policy gradient is the most widely used. An early version of using policy gradient on sequence modeling is REINFORCE. As researchers have found that REINFORCE causes high variance during training, MCTS [6], [7], one of the stepwise evaluation methods, is used. MCTS stabilizes training, but suffers from high computational costs. To optimize computational costs, [7] and [10] propose alternatives to evaluate every subsequences, but their performances are still weaker than MCTS [7].

GAN has been applied on several tasks that can be formulated as conditional sequence generation. For dialogue generation, clear performance improvements on multiple metrics have been observed with SeqGAN using MCTS and REGS [7]. GAN improves machine translation models with different network architectures including RNNSearch [26], [27] and Transformer [27]. For abstractive summarization, GAN is able to generate more abstractive, readable and diverse summaries than conventional approaches [28]. Image captioning model trained with GAN produces captions which are diverse and match the statistics of human generated captions significantly better than the baseline models [29]–[31].

We observe that there is still no researches on comparing all the stepwise evaluation methods, even though many previous works [6], [7], [9], [10] have noted the importance. Therefore in this paper we study the influence of stepwise evaluation methods on conditional sequence generation, and propose StepGAN that preserves the property of MCTS but with computational efficacy. This is the first paper comparing the stepwise evaluation methods, and we also propose StepGAN to replace them.

III. CONDITIONAL SEQUENCE GENERATION

When the model learns to generate the target output sequence $y$ given input $x$, the task is called conditional sequence generation. Take chit-chat chatbot as example. Both $x$ and $y$ are word sequences that $x = \{x_1, x_2, \ldots, x_N\}$ and $y = \{y_1, y_2, \ldots, y_M\}$, where $x_i$ and $y_i$ are words in the vocabulary, and $N$ and $M$ are respectively the lengths of the input and output sequences.

A. Maximum Likelihood Estimation

The conditional sequence generator $G$ used in the paper is a recurrent neural network (RNN) based seq2seq model that consists of an encoder and a decoder. The encoder reads in the input sentence $x$ one token $x_i$ at a time. The decoder aims to generate output sentence $\hat{y}$ as close as possible to target sentence $y^*$. During inference, after the encoder reads the whole $x$, the decoder generates the first word distribution $P_G(y_1|x)$. The first word $\hat{y}_1$ is obtained by sampling or argmax from $P_G(y_1|x)$. As the decoder takes $\hat{y}_1$ as input, the distribution of the next word $y_2$, $P_G(y_2|x, \hat{y}_1)$, is generated. As the generation process stops when the token representing the end of the sentence is predicted, the output sequence $\hat{y}$ is completely generated. Because of using sampling in generation process, we can consider the generator as a distribution of $y$ given $x$: $P_G(y|x) = \prod_{t=1}^{N} P_G(y_t|x, y_{1:t-1})$, where $y_{1:t-1}$ represents the first $(t-1)$-th tokens in sequence $y$, or $y_{1:t-1} = \{y_1, y_2, \ldots, y_{t-1}\}$. For instance if argmax is used in the decoder, we can consider $P_G$ as a Kronecker delta function (or a very sharp distribution) that the probabilities are zeros everywhere except for the chosen sample.

The model is trained to maximize the likelihood of generating the ground-truth sequence $y^*$. The training method is called maximum likelihood estimation (MLE) [1]. The inconsistency of decoder inputs between training stage and inference stage leads to exposure bias [2], by which the generator might accumulate errors during inference.

B. Generative Adversarial Network

A generative adversarial network (GAN) consists of a generator $G$ and a discriminator $D$. When GAN is apply to sequence learning, it is called sequence GAN. Given an input sequence $x$, the discriminator learns to maximize score $D(x, y^*)$, while minimizing score $D(x, \hat{y})$; the generator learns to generate response $\hat{y}$ that maximizes the discriminator score $D(x, \hat{y})$,

$$\min_{G} \max_{D} \mathbb{E}_{(x, y^*) \sim P_R(x, y^*)} [\log D(x, y^*)] + \mathbb{E}_{x \sim P_R(x), \hat{y} \sim P_G(y|x)} [\log(1 - D(x, \hat{y}))],$$

(1)

where $P_R(x)$ and $P_R(x, y)$ are the probability distribution of $x$ and joint probability distribution of $(x, y)$ from the training data.

To overcome the intractable gradient computation because of the discrete nature of sequence generation, previous works
use policy gradient by taking sequence generation as a Markov decision process that is trainable by reinforcement learning [6]. The basic idea is that we consider the parameters of generator as the policy. The state at time step \( t \) is \( \{x, \hat{y}_{1:t-1}\} \). The action taken at each time step \( t \) is the \( t \)-th word in the output sequence \( \hat{y} \), namely \( \hat{y}_t \), which is taken according to the current policy and current state. The reward at each time step is set to zero except for the last action, and the discriminator score \( D(x, y) \) is taken as the reward at the last time step. The return is equivalent to \( D(x, y) \) because the rewards are always zeros except for the last time step. The intuition of training sequence GAN via policy gradient is that the generator maximizes the probability of generating words that get high expected return (i.e., \( D(x, y) \)) and minimizes the probability of words that get low expected return.

Given an input \( x \) from training data, an output sequence \( \hat{y} \) is sampled from the current generator, \( \hat{y} \sim P_G(y|x) \). Then we can approximate the gradient for updating generator as follows.

\[
\nabla_G = \sum_{t=1}^{M} D(x, \hat{y}) \nabla \log P_G(\hat{y}_t|x, \hat{y}_{1:t-1})
\]

In Equation 2, the gradients of the probabilities at all the generation steps are weighted by the same weight \( D(x, \hat{y}) \).

By using GANs, the generator learns to minimize the loss defined by discriminator instead of KL divergence; exposure bias is solved since the probabilities \( P_G(\hat{y}_t|x, \hat{y}_{1:t-1}) \) are conditioned on predicted subsequence \( \hat{y}_{1:t-1} \), the same as inference stage.

IV. STEPWISE EVALUATION APPROACH FOR SEQUENTIAL GANs

We propose a new stepwise evaluation method to improve sequence GAN by tackling both sparse reward and training instability. We call this method StepGAN. Borrowing the idea of Q-learning, StepGAN automatically estimates state-action value with very light computational costs, and the rewards are implicitly shaped into every time steps. Figure 1 illustrates the framework of StepGAN.

Algorithm 1 StepGAN

1: Initialize generator \( G \)
2: Pretrain generator \( G \) using MLE
3: Initialize discriminator \( D \), value network \( V \)
4: for number of training iterations \( \) do
5:   for \( i = 1 \) to D-iterations \( \) do
6:     Sample \( (x, y^*) \) from real data
7:     Sample \( \hat{y} \sim P_G(y|x) \)
8:     Update D using equation (5)
9:   end for
10: end for
11: \n12: for \( i = 1 \) to G-iterations \( \) do
13:   Sample \( x \) from real data
14:   Sample \( \hat{y} \sim P_G(y|x) \)
15:   Update \( G \) using equation (7)
16: end for

A. State-action Value

\( Q(s_t, a_t) \), the general form of Q-values depicted in Figure 1 is the state-action value which is the expected return of taking action \( a_t \) at state \( s_t \), and is often used in Q-learning to improve the training stability \([15], [32]–[34]\) of reinforcement learning.
learning. For conditional sequence generation by GANs, at each generation step, the input condition, \( x \), and the words that have been generated, \( \hat{y}_{1:t-1} \), form the state; the word to be generated, \( \hat{y}_t \), is the action. Therefore, the state-action pair is \((s_t, a_t) = (\{x, \hat{y}_{1:t-1}\}, \hat{y}_t)\), and thus the state-action value \( Q(s_t, a_t) = Q(x, \hat{y}_t) \). The definition of state-action value in conditional sequence GAN is as below:

\[
Q(x, \hat{y}_{1:t}) = \mathbb{E}_{z \sim P_G(x, \hat{y}_{1:t})} [D(x, \{\hat{y}_{1:t}, z\})].
\]

(3)

where \( z \) is a sequence of words generated by the current generator given input \( x \) and generated prefix \( \hat{y}_{1:t} \). Accordingly, the state-action value \( Q(x, \hat{y}_{1:t}) \) is the expected return of all the responses sharing the same prefix \( \hat{y}_{1:t} \).

To stabilize REINFORCE algorithm, the term \( D(x, \hat{y}) \) in Equation (3) is replaced with the term \( Q(x, \hat{y}_{1:t}) \), and the equation is modified as below:

\[
\nabla G = \sum_{t=1}^{M} Q(x, \hat{y}_{1:t}) \nabla \log P_G(\hat{y}_t|x, \hat{y}_{1:t-1})
\]

(4)

In Equation (4), each generation step is weighted by a step-dependent value, \( Q(x, \hat{y}_{1:t}) \). However, computing \( Q(x, \hat{y}_{1:t}) \) by Equation (3) is intractable. We propose an efficient approach to estimate \( Q(x, \hat{y}_{1:t}) \) for generator while training the discriminator in StepGAN.

B. Discriminator for StepGAN

In this paper, the discriminator is a seq2seq model that takes \( x \) as encoder inputs, and \( y \) (either \( \hat{y} \) or \( y^* \)) as decoder inputs. Although in Figure 1 the discriminator is only a native seq2seq model, any state-of-the-art seq2seq model, for example, attention-based model [35], CNN-based model [36], Transformer [37], etc., can be used here. As regular GANs, the discriminator is trained to maximize \( D(x, y^*) \) of ground-truth examples and minimize the \( D(x, \hat{y}) \) of generated response as below:

\[
\max_D \mathbb{E}_{(x, y^*) \sim P_R(x, y^*)} \left[ \log D(x, y^*) \right] + \mathbb{E}_{x \sim P_R(x), \hat{y} \sim P_G(y|x)} \left[ \log (1 - D(x, \hat{y})) \right].
\]

(5)

However, different from all the previous GAN-based sequence generation approaches, the definition of \( D(x, y) \) in StepGAN is designed to estimate the \( Q(x, \hat{y}_{1:t}) \). Instead of generating a scalar as the final discriminator score \( D(x, y) \) [6], we do some modification to the discriminator to automatically obtain the estimation of \( Q(x, \hat{y}_{1:t}) \). As shown in the upper block of Figure 1 after reading in the input sentence \( x \) and part of the response sequence \( \hat{y}_{1:t} \), discriminator generates a scalar \( \hat{Q}(x, \hat{y}_{1:t}) \).

The discriminator score \( D(x, y) \) is the average of all the scalars \( \hat{Q}(x, \hat{y}_{1:t}) \) throughout the generated sequence length \( M \).

\[
D(x, y) = \frac{1}{M} \sum_{t=1}^{M} \hat{Q}(x, \hat{y}_{1:t}),
\]

(6)

The term \( \hat{Q}(x, \hat{y}_{1:t}) \) in Equation (6) directly matches the role of \( Q(x, \hat{y}_{1:t}) \). Therefore, we take the scalars \( \hat{Q}(x, \hat{y}_{1:t}) \) as the approximation of state-action values \( Q(x, \hat{y}_{1:t}) \) to train the generator in Section IV-C. The theory behind the above approximation will be clear in Section IV-D.

C. Generator for StepGAN

The generator reads in the input sentence \( x \) and then predicts one token \( \hat{y}_t \) at a time based on the generated word sequence \( \hat{y}_{1:t-1} \). For stepwise evaluation, we update generator \( G \) by replacing \( Q(x, \hat{y}_{1:t}) \) with \( \hat{Q}(x, \hat{y}_{1:t}) \) in Equation (4).

As previous works [2, 7], we train a value network \( V \) to generate the value baseline for stabilizing policy gradient. The value network has the same structure as discriminator. It predicts the expected value \( V(x, \hat{y}_{1:t-1}) \) of the given state \( \{x, \hat{y}_{1:t-1}\} \). The value network is trained to approximate the predicted \( \hat{Q}(x, \hat{y}_{1:t}) \) for every previous states \( \{x, \hat{y}_{1:t-1}\} \). That is, \( V(x, \hat{y}_{1:t-1}) = \mathbb{E}_{\hat{y}}[\hat{Q}(x, \hat{y}_{1:t})] \).

With the value network, we train the generator as below.

\[
\nabla G = \sum_{t=1}^{M} \alpha_t (\hat{Q}(x, \hat{y}_{1:t}) - V(x, \hat{y}_{1:t-1})) \nabla \log P_G(\hat{y}_t|x, \hat{y}_{1:t-1})
\]

(7)

where \( \alpha_t \) is a weighting coefficient that is related to time \( t \). In uniform case, \( \alpha_t \) equals to 1 for all time \( t \). We also test increasing and decaying cases in the following experiments.

In Figure 1 the generator is a seq2seq model, but the proposed approach is independent to the network architecture of the generator. The complete training process of StepGAN is illustrated in Algorithm 1.

D. Theory behind StepGAN

StepGAN is based on a direct linking between \( D(x, y) \) and \( Q(x, \hat{y}_{1:t}) \) as below.

\[
\mathbb{E}_{\hat{y} \sim P_G(y|x)} [D(x, \hat{y})] = \frac{1}{M} \mathbb{E}_{\hat{y} \sim P_G(y|x)} \left[ \sum_{t=1}^{M} Q(x, \hat{y}_{1:t}) \right].
\]

(8)

The equation above suggests that we can decompose \( D(x, y) \) into \( M \) different scores for all the time steps \( t \) and take the decomposed scores as \( Q(x, \hat{y}_{1:t}) \). Because of Equation (8), we estimate state-action values \( Q(x, \hat{y}_{1:t}) \) by adding a simple component to the architecture of discriminator as shown in [6].

We can derive Equation (8) by following:

\[
\mathbb{E}_{\hat{y}_{1:M} \sim P_G(y|x)} \left[ \sum_{t=1}^{M} Q(x, \hat{y}_{1:t}) \right] = \mathbb{E}_{\hat{y}_{1:M} \sim P_G(y|x)} \left[ \sum_{t=1}^{M} \mathbb{E}_{z \sim P_G(z|x, \hat{y}_{1:t})} \left[ r_{ter}(x, \hat{y}_{1:t}, z) \right] \right].
\]

(9)

where \( z \) is sampled from \( P_G \) by given input \( x \) and partial prefix \( \hat{y}_{1:t} \), and \( r_{ter} \) is the reward of the whole sequence \( \{x, \hat{y}_{1:t}, z\} \). Based on GAN, the \( r_{ter} \) is estimated by discriminator score
The same equation can also be derived by substituting \( P \) for \( \hat{x} \) in the experiments. The equations are listed in Table I.

\[
\sum_{t=1}^{M} \sum_{z} \mathbb{E}_{x,y} [D(x, \hat{y}_{1:t+1:M})] = 1
\]

The two expectation \( \mathbb{E} \) can be combined:

\[
= \sum_{t=1}^{M} \sum_{z} \mathbb{E}_{x,y} [D(x, \hat{y}_{1:t+1:M})]
\]

Then we divide the above equations by \( M \) and obtain the equation below:

\[
\sum_{t=1}^{M} \sum_{z} \mathbb{E}_{x,y} [D(x, \hat{y}_{1:t+1:M})] = 1
\]

The same equation can also be derived by substituting \( P \) with \( P_{R} \) and substituting \( \hat{y} \) with \( y^{*} \). Equation (6) is therefore a sample estimation of Equation (12).

V. EXPERIMENTS: BASELINE APPROACHES

The following stepwise evaluation methods are used as the baselines in the experiments. The equations are listed in Table I.

**SegGAN** [6]. The discriminator predicts a final score \( D(x, y) \) after reading the entire pair of sentences \((x, y)\). The generator adopts 1-sample estimation, using \( D(x, y) \) as the multipliers for every time steps \( t \), for policy gradient updates.

**REGS** [7]. The discriminator optimizes a randomly selected score \( D(x, y) \sim \{\mathbb{Q}(x, y_{1:t})\}_{t=1}^{M} \). Every scores \( \mathbb{Q}(x, y_{1:t}) \) are taken as the multipliers for policy gradient.

**Monte-Carlo tree search (MCTS)** [6, 7, 9]. MCTS computes the estimated state-action value \( Q^*(s_t, a_t) \). Given input sentence and fixed prefix \((x, y_t)\), we roll out \( I \) suffixes \( y_{t+1:M} \) using the generator \( G \), where \( i \) is the index of suffix from 1 to \( I \), and each suffix has different lengths \( M_i \). Here \( \{y_{t+1:M_i}\} \) forms a full response whose first tokens are \( y_{1:i} \), and the rest tokens are \( y_{i+1:M_i} \). We average \( D(x, y) \) of the \( I \) responses obtained by roll-out, \( \frac{1}{I} \sum_{i=1}^{I} D(x, \{y_{1:i}, y_{i+1:M_i}\}) \), as the approximated state-action value \( Q^*(x, y_{1:i}) \). Monte-Carlo search would have high precision if \( I \) is very large but with very high computational costs.

**MaskGAN** [10]. The discriminator optimizes all scores \( D(x, y_{1:t}) \) for every time step \( t \); the generator takes each score \( D(x, y_{1:t}) \) as received reward, and estimates state-action value by summing future received rewards: \( Q^*(x, y_{1:t}) = \sum_{t=1}^{M} D(x, y_{1:t}) \).

VI. EXPERIMENTS: SYNTHETIC EXPERIMENT

To compare their performances accurately, we conducted experiments on synthetic data. This also help us understand how the StepGAN works. The source code is available at [GitHub](https://github.com/Pascalson/Conditional-Seq-GANs).

A. Task Description

We design a counting task that captures the one-to-many property of conditional sequence generation task. The counting task is that given an input sequence \( x = \{x_1, x_2, ..., x_t, ..., x_N\} \), a correct output sequence \( y = \{y_1, y_2, y_3\} \) obeys the following rules.

\[
\begin{align*}
k &\in \{1, 2, ..., N\} \\
y_1 &= k - 1 \\
y_2 &= x_k \\
y_3 &= N - k
\end{align*}
\]

where each token \( x_i \) is a digit selected from 0 to 9, and number \( N \) is the length of input.

Based on the above setup, given the same input sequence, several different output sequences are correct. For example, given an input sequence \( <1, 8, 3> \), the possible answers are \( <0, 1, 2> \), \( <1, 8, 1> \) and \( <2, 3, 0> \).

We generated 100,000 training examples, 10,000 validation examples and 10,000 testing examples according to the counting rule, and the length of the input sequence was set to 10 \((N = 10)\). We evaluated different sequence generation approaches based on GAN. All the GANs were trained upon
TABLE II: Results of synthetic experiment.

|        | BLEU | CoHS (%) | SHS (%) | LEN | GErr | General |
|--------|------|----------|---------|-----|------|---------|
| MLE    | 0.2580 | 50.52 | 42.6 | 5.765 | 32 | 115688 |
| SeqGAN | 0.2615 | 46.25 | 56.4 | 6.525 | 38 | 92273  |
| REGS   | 0.2540 | 48.43 | 59.5 | 7.000 | 124 | 107719 |
| StepGAN| 0.2394 | 44.96 | 60.4 | 7.335 | 24 | 51318  |
| StepGAN-W | 0.2394 | 44.96 | 60.4 | 7.335 | 24 | 51318  |

TABLE III: The results of chit-chat dialogue generation. CoHS (%) is coherence human score; SHS (%) is semantics human score. To make sure the reliability of human scores, we have measured their intraclass correlation coefficient (ICC) [38], [39], and they show substantially consistent.

a pretrained model trained by MLE until converged. All the GANs were trained with 64 minibatch size for 5,000 iterations.

B. Evaluation Metrics

In the synthetic experiments, given that we know all the possible answers to an input sentence, we can compute the precision and recall rates. Given each input \( x \), we used the generator \( G \) to generate one sample by \( \text{argmax} \) and 100 samples by sampling from the probability distribution of softmax outputs. Precision is how many the generated answers are correct; recall is how many possible answers are predicted.

\[
\text{precision} = \frac{N_{\text{True}}}{N_{\text{Gen}}} \\
\text{recall} = \frac{N_{\text{True}}}{N_{\text{All}}} 
\]

where the \( N_{\text{True}} \) is the number of correct generated answers, \( N_{\text{Gen}} \) is the number of all generated answers, and \( N_{\text{All}} \) is the number of possible answers. We evaluated three related indexes in Table II: (1) **Prec**, the precision of argmax outputs. It is not possible to evaluate recall for argmax because there is only one sample. (2) **SampP**, the precision of softmax outputs. (3) **SampR**, the recall of softmax outputs. They are intuitive indexes to test the performance of the models.

To have more insights of the models, we analyzed generator by evaluating both the forward KL divergence (FKLD) and inverse KL divergence (IKLD) between the conditional distribution of the generator, \( P_G(y|x) \), and the true distribution based on the counting rule, \( P_R(y|x) \). The definition of FKLD and IKLD are give as below.

\[
FKLD = \int_x \int_y P_R(y|x) \log \frac{P_R(y|x)}{P_G(y|x)} \\
IKLD = \int_x \int_y P_G(y|x) \log \frac{P_G(y|x)}{P_R(y|x)}
\]

(15)

All the above indexes are the benefits of the synthetic task. In real applications like dialogue generation, it is not possible to list all the correct responses, so precision and recall cannot be measured accurately. Additionally, the computations of FKLD and IKLD in most real applications are intractable; their computations in the synthetic task is tractable due to the finite number of answers.

C. Results

The results are shown in Table II. We compared StepGAN with other stepwise evaluation methods including REGS, MCST, MaskGAN. In addition, we performed weighted stepwise evaluation methods using StepGAN-W that we gave decaying weights for the policy gradient. The weights in Equation (7) were set as \( \alpha_t = M - t \), where \( M \) was the length of the generated outputs. We had tested both increasing and decaying cases, and found that increasing weights did not improve the training, so the results of increasing weights were not shown here.

**Precision and Recall.** Comparing to MLE, all GANs improve the precision of argmax outputs (the column labeled Prec in Table II). Specifically, SeqGAN improves the model by 0.94; previous stepwise evaluation methods improve the model by 1.19 ~ 3.68; our proposed approaches StepGAN and StepGAN-W improve the model by 3.87 and 5.97 respectively.

For sampled softmax outputs, the GANs have better precision (the column labeled SampP) and weaker recall (the column labeled SampR). Especially, the MaskGAN increases the precision the most but drops the recall significantly. It
means that MaskGAN overfits to a smaller portion of possible answers.

In Figure 2, we show the variance of the performance of the GAN-based approaches with different random parameter initialization. Each box represents the results of each model in Table II trained with different random initialization, and the green line represents the precision result of MLE. The results show that StepGAN-W not only achieves better performance than other approaches, it is also more stable with different parameter initialization.

**Forward and Inversed KL-Divergence.** Comparing to MLE, we observe that GANs increase FKLD (except SeqGAN) and decrease IKLD. This is reasonable because GANs do not minimize FKLD as MLE, but minimize other distance metrics. Because minimizing FKLD will cause the $P_G$ unbounded at where $P_R$ is almost zero (Equation (15)), and vise versa, we consider that FKLD and IKLD are equally important to measure true distance between two distributions. Hence, we add them together and get a score $FKLD+IKLD$ to check which model is overall good. The SeqGAN and previous stepwise evaluation methods improve $FKLD+IKLD$ score by $0.009 \sim 0.071$; our approaches StepGAN and StepGAN-W respectively improve this divergence score by 0.162 and 0.31, much better than previous methods.

The results show that GANs fine-tune a pretrained model that has converged to reach a better performance and reduce IKLD, and the precision scores are thus higher than the pretrained model. Furthermore, the stepwise evaluation methods can improve or maintain the model to generate as much as possible correct answers by showing comparable recall scores. Among them, stepGAN and stepGAN-W can reach better precision with little penalty of recall, and have more balanced results of $FKLD+IKLD$ scores.

**VII. EXPERIMENTS: CHIT-CHAT DIALOGUE GENERATION**

We trained chit-chat dialogue generation on OpenSubtitles [40], a collection of movies subtitles. After pretraining the generator by MLE, we fine-tuned the model for 1-epoch by three different stepwise evaluation methods: vanilla SeqGAN, REGS, and StepGAN. We choose to compare vanilla SeqGAN and REGS because they have been reported helpful on dialogue generation task [7]. We do not have the results of MCTS here because it costs too much computation which is not tractable on our machine.

**A. Experimental Setup**

We trained chit-chat dialogue generation on OpenSubtitles [40] and used the top 4000 most frequent words as the vocabulary. After pretraining the generator by MLE, we trained the model for 1-epoch by four different stepwise evaluation methods: vanilla SeqGAN, REGS, and StepGAN. All the discriminators were pre-trained on real data and generated data sampled from the pre-trained generator. To tune the parameters, grid search was used with optimization operation={SGD, Adam, RMSProp}, learning rate={1e-1, 1e-2, 1e-3, 1e-4}, discriminator iteration step={1, 5}, and batch size={32, 64}. All the generators and discriminators are 1 GRU layer with 512 dimension, which is an acceptable number of parameters on sentence generation [19], [20].

**B. Evaluation Metrics**

Currently, chit-chat dialogue generation still lack general rules for evaluation [18], therefore we use several different metrics to evaluate the generated responses.

**BLEU.** BLEU score [14] is an automatic evaluation metric that counts the appearance of n-grams. Although BLEU has been reported not consistent with the human evaluation [18] on dialogue, we reported it here as a reference.

**Coherence Human Score (CoHS) and Semantics Human Score (SHS).** We invited 5 judges to evaluate 200 examples. Because coherence is naturally binary (yes or no) and semantic is continuous, we asked judges to measure them by 0-1 test and...
Fig. 4: The average computation times for one training iteration (i.e., one mini-batch) of chit-chat dialogue generation (OpenSubtitles) and synthetic experiment (Counting).

ranking respectively. For CoHS, judges were asked to measure if each response is coherent to the input sentence (0 or 1); for SHS, they were asked to rank the information abundance of the given responses The ranking is then normalized to a score ranging from 0 to 1. Both CoHS and SHS are the higher the better.

LEN and GErr. LEN stands for length and is the average of length of generated responses; GErr stands for grammar error, and we measured it by an open source software https://github.com/languagetool-org/languagetool and calculated the number of violations of grammar rules.

General. This metric counts the number of generated general responses. Here we define the top 10% responses generated from the model learned by MLE as general responses. The top two general responses are “I don’t know” and “I’m sorry”. However, if a ground truth response happens to be belong to the top 10% responses, it would not be considered as general response. For instance, given input sentence “how much do you want?”, one of the possible answers included in OpenSubtitles is “i don’t know”. Hence, when the input is “how much do you want?”, the chat-bot would not be considered as generate a general response if it says “i don’t know”.

C. Results

All the results of our proposed evaluation metrics are listed in Table III. Generally, we found that on CoHS, MLE gets the highest score; on BLEU, SeqGAN is the highest; on metrics related to the quality of generated sentences (i.e., SHS, LEN, GErr, and General), StepGAN consistently gets the best scores.

We observed that all the three types of GANs can generate sentences with better semantic scores (SHS), longer lengths (LEN) and less general responses (General), but they do not equally lower GErr. Table III shows that among them, StepGAN is the most beneficial one, which yielded the highest semantic human score (SHS), longest generated sentences (LEN), the least grammatical errors (GErr) and the least general responses (General). This shows that the stepwise evaluation methods surely impact the results. The assumption that MLE easily results in general responses [5] can also be verified by the observation. Even MLE has the highest CoHS, it has relatively low SHS and LEN. This is probably because CoHS is more related to conditioning rather than sequence modeling.

In Table IV we present some generated examples of our trained dialogue generative models.

### D. CoHS and SHS Results

We asked 5 judges to evaluate 200 random selected examples. Each example consists of an input and 15 generated outputs by 5 different training algorithms and 3 inference methods. The training algorithms include MLE, SeqGAN, MaliGAN, REGS, and StepGAN; the inference methods include argmax, beam search, and MMI [5].

We can observe that by the two different inference methods (i.e., beam search and MMI), all the CoHSSs are higher but SHSs are lower.

### E. Analysis

1) discriminator outputs: To verify if the proposed stepwise evaluation method can estimate the state-action values, we analyzed the outputs of discriminators. Empirically, given the same response, the discriminator scores $D$ change frequently between the training iterations. This makes the values $\hat{Q}(x, y_{1:t})$ from $D$ unstable and thus difficult to be analyzed.

We proposed to measure the variance at each generation step throughout the training iterations. During training, $\hat{Q}(x, y_{1:t})$...
oscillates according to the performance of generator at that time. If at the generation step $t$, $Q(x,y_{-t})$ oscillates violently, the word generated at step $t$ is crucial to determine if a response is fake or real.

Four examples are shown in Figure 3. Figure 3a and 3b are respectively true response and wrong response given input sentence “how are you ?”; Figure 3c and 3d are true and wrong responses given input sentence “what ‘s your name ?”. The depth of the color is proportional to the variance at each generation step for MCTS, REGS and StepGAN.

We can observe that the variances of StepGAN and MCTS are similar, and the generation steps with large variance, that is, the critical words in the response, are consistent with human intuition. For example, when given “what ‘s your name ?”, they focus on the bold parts of “i ’m john .” in Figure 3c and “i ’m sorry .” in Figure 3d. People cannot identify if “i ’m” is good or bad, but can identify if the sentence is good or bad with more information. Besides, we found that the variances of StepGAN are even more reasonable for human than MCTS (e.g., (a) i ’m fine, ...... (c) i ’m john). The most possible reason is that the variances of StepGAN are directly an expectation of all the training examples; the variances of MCTS are average of $I = 5$ roll-out paths and highly depend on the number $I$. Figure 2 (a-d) also shows that REGS puts emphases on the last few steps, and the critical words do not meet human’s intuition.

2) computation: As demonstrated by Figure 4, StepGAN is much more computational efficiency than MCTS. The computational consumption of MCTS depends on the number of roll-out paths which is set to 5 in Figure 4. In synthetic task, SeqGAN, REGS, and StepGAN are twice faster than MCTS; in dialogue modeling, they are about five times faster than MCTS. For longer sequence length and larger number of roll-out paths, the time consumption of MCTS grows. MCTS is therefore intractable for large datasets.

In Figure 5 the MCTS results are calculated by using MCTS on SeqGAN model.

3) general responses: To see how the GANs learn from the training data, we first sorted the training data into input-outputs pairs – each input was paired with all the appeared outputs in training data. We then used the models trained by MLE, SeqGAN, REGS and StepGAN to generate responses, and counted how many responses are in the training data. The ratio of the number of appeared responses to the number of inputs is shown in Figure 5. The results verify that GANs learn more creative responses [6] that are not in training data. StepGAN especially generates the least non-creative ones.

VIII. CONCLUSION

This paper verifies that stepwise evaluation methods have notable impact on conditional sequence generation, and proposes a novel stepwise evaluation method – StepGAN that can directly estimate state-action value by discriminator. In experiments, we show that StepGAN can help conditional sequence generation. Compared to MCTS, it is computational efficient; compared to vanilla SeqGAN and REGS, it is more accurate on synthetic experiment and generates sentences with higher quality in dialogue generation.

REFERENCES

[1] O. Vinyals and Q. Le, “A neural conversational model,” arXiv preprint arXiv:1506.05869, 2015.
[2] M. Ranzato, S. Chopra, M. Auli, and W. Zaremba, “Sequence level training with recurrent neural networks,” arXiv preprint arXiv:1511.06732, 2015.
[3] I. Goodfellow; “NIPS 2016 tutorial: Generative adversarial networks,” arXiv preprint arXiv:1701.00160, 2016.
[4] M. Arjovsky and L. Bottou, “Towards principled methods for training generative adversarial networks,” arXiv preprint arXiv:1701.04862, 2017.
[5] J. Li, M. Galley, C. Brockett, J. Gao, and B. Dolan, “A diversity-promoting objective function for neural conversation models,” arXiv preprint arXiv:1510.03055, 2015.
[6] L. Yu, W. Zhang, J. Wang, and Y. Yu, “SeqGAN: Sequence generative adversarial nets with policy gradient,” in AAAI, 2017, pp. 2852–2858.
[7] J. Li, W. Monroe, T. Shi, A. Ritter, and D. Jurafsky, “Adversarial learning for neural dialogue generation,” arXiv preprint arXiv:1701.06547, 2017.
[8] D. Bahdanau, P. Brakel, K. Xu, A. Goyal, R. Lowe, J. Pineau, A. Courville, and Y. Bengio, “An actor-critic algorithm for sequence prediction,” arXiv preprint arXiv:1607.07086, 2016.
[9] T. Che, Y. Li, R. Zhang, R. D. Hjelm, W. Li, Y. Song, and Y. Bengio, “Maximum-likelihood augmented discrete generative adversarial networks,” arXiv preprint arXiv:1702.07983, 2017.
[10] W. Fedus, I. Goodfellow, and A. M. Dai, “MaskGAN: Better text generation via filling in the _,” arXiv preprint arXiv:1801.07736, 2018.
[11] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in Advances in neural information processing systems, 2014, pp. 3104–3112.
[12] S. Bengio, O. Vinyals, N. Jaitly, and N. Shazeer, “Scheduled sampling for sequence prediction with recurrent neural networks,” in Advances in Neural Information Processing Systems, 2015, pp. 1171–1179.
[13] R. J. Williams, “Simple statistical gradient-following algorithms for connectionist reinforcement learning,” Machine learning, vol. 8, no. 3-4, pp. 229–256, 1992.
[14] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “BLEU: a method for automatic evaluation of machine translation,” in Proceedings of the 40th annual meeting on association for computational linguistics. Association for Computational Linguistics, 2002, pp. 311–318.
[15] R. S. Sutton and A. G. Barto, Reinforcement learning: An introduction. MIT press Cambridge, 1998, vol. 1, no. 1.
[16] K. Kandasamy, Y. Bachrach, R. Tomioka, D. Tarlow, and D. Carter, “Batch policy gradient methods for improving neural conversation models,” arXiv preprint arXiv:1702.03334, 2017.
[17] J. Li, W. Monroe, A. Ritter, M. Galley, J. Gao, and D. Jurafsky, “Deep reinforcement learning for dialogue generation,” arXiv preprint arXiv:1606.01541, 2016.
[18] C.-W. Liu, R. Lowe, I. V. Serban, M. Noseworthy, L. Charlin, and J. Pineau, “How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation,” arXiv preprint arXiv:1603.08023, 2016.

[19] O. Press, A. Bar, B. Bogin, J. Berant, and L. Wolf, “Language generation with recurrent generative adversarial networks without pre-training,” arXiv preprint arXiv:1706.01399, 2017.

[20] S. Rajeswar, S. Subramanian, F. Dutil, C. Pal, and A. Courville, “Adversarial generation of natural language,” arXiv preprint arXiv:1705.10929, 2017.

[21] Y. Zhang, Z. Gan, K. Fan, Z. Chen, R. Henao, D. Shen, and L. Carin, “Adversarial feature matching for text generation,” arXiv preprint arXiv:1706.03850, 2017.

[22] K. Lin, D. Li, X. He, Z. Zhang, and M.-T. Sun, “Adversarial ranking for language generation,” arXiv preprint arXiv:1705.11001, 2017.

[23] M. J. Kusner and J. M. Hernández-Lobato, “GANS for sequences of discrete elements with the gumbel-softmax distribution,” arXiv preprint arXiv:1611.04051, 2016.

[24] Y. Zhang, Z. Gan, and L. Carin, “Generating text via adversarial training,” in NIPS workshop on Adversarial Training, vol. 21, 2016.

[25] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville, “Improved training of wasserstein GANs,” arXiv preprint arXiv:1704.00028, 2017.

[26] L. Wu, Y. Xia, L. Zhao, F. Tian, T. Qin, J. Lai, and T.-Y. Liu, “Adversarial neural machine translation,” in arXiv, 2017.

[27] Z. Yang, W. Chen, F. Wang, and B. Xu, “Improving neural machine translation with conditional sequence generative adversarial nets,” in NAACL, 2018.

[28] L. Liu, Y. Lu, M. Yang, Q. Qu, J. Zhu, and H. Li, “Generative adversarial network for abstractive text summarization,” in AAAI, 2018.

[29] R. Shetty, M. Rohrbach, L. A. Hendricks, M. Fritz, and B. Schiele, “Speaking the same language: Matching machine to human captions by adversarial training,” in ICCV, 2017.

[30] D. Li, Q. Huang, X. He, L. Zhang, and M.-T. Sun, “Generating diverse and accurate visual captions by comparative adversarial learning,” in arXiv, 2018.

[31] X. Liang, Z. Hu, H. Zhang, C. Gan, and E. P. Xing, “Recurrent topic-transition GAN for visual paragraph generation,” in arXiv, 2017.

[32] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, “Playing atari with deep reinforcement learning,” arXiv preprint arXiv:1312.5602, 2013.

[33] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, p. 529, 2015.

[34] M. Hausknecht and P. Stone, “Deep recurrent Q-Learning for partially observable MDPs,” CoRR, abs/1507.06527, 2015.

[35] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, and Y. Bengio, “Show, attend and tell: Neural image caption generation with visual attention,” in Proceedings of the 32nd International Conference on Machine Learning, 2015, pp. 2048–2057.

[36] J. Tiedemann and J. Cohen, “The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability.” Educational and psychological measurement, vol. 33, no. 3, pp. 613–619, 1973.

[37] J. J. Bartko, “The intraclass correlation coefficient as a measure of reliability,” Psychological reports, vol. 19, no. 1, pp. 3–11, 1966.

[38] J. Tiedemann, “News from OPUS - A collection of multilingual parallel corpora with tools and interfaces,” in Recent Advances in Natural Language Processing, N. Nicolov, K. Boncheva, G. Angelova, and R. Mitkov, Eds. Borovets, Bulgaria: John Benjamins, Amsterdam/Philadelphia, 2009, vol. V, pp. 237–248.
| Input | MLE | SeqGAN | REGS | StepGAN-W |
|-------|-----|--------|------|-----------|
| I'll send ya some more money. | that's a good idea. | that's a good idea. | that's a nice car, huh? | you're a good man, you know that? |
| I was so stupid to think that anything could ever change you. | I'm sorry. | I'm sorry, I'm sorry. | I don't want to be here anymore. | you're gonna be all right. |
| Fiona, my love, we gonna kiss away for our happily ever after. | oh, my god. | oh, my god. | oh, my god. | oh, i love you. |
| I had some girlfriends too, but all they wanted from me was weed and shit. | but, i don't know what to do. | i am sorry, but i'm not a doctor. | i was just kidding. | what's wrong with you, man? |
| Tell me how this ends. | I'm not going to be able to get you. | I'm not going to be able to get you. | I'm not going to be able to be a baby. | fine, you're good. |
| We gave it a thousand times more power. | I'm sorry. | I'm not a doctor. | I don't know what to do. | you were right. |
| I feel like a paris princess. | I know it. | I know that you're not there. | I can't see it. | you're not a child anymore. |
| I'm tired of all your questions. | I'm gonna have to ask you to come. | I'm gonna call you. | I'm going to have to ask you to come in | you're going to be a friend of you. |
| He's one of your own. | what? | what are you doing here? | he's not my father | what's your name, man? |
| What dance will you have? | I don't know | I'm not sure that i'm not going to. | I don't know. | good night, i'll tell you what's going on. |
| And so i realized this was what i had to do with my life. | I was going to be a good boy. | I was going to die. | I was going to be a good person | I was going to be a good guy with you. |
| I was just gonna tell you that your fly is down. | you're not gonna die. | you are not a liar. | you're not gonna die, but i don't have to. | you're gonna have to help me out. |
| Will you come on now, please? | I'm not going to let you go. | I can't hear you. | I can't believe it. | what's this all about? |

**TABLE V:** Examples of generated responses.