OptiGAN: Generative Adversarial Networks for Goal Optimized Sequence Generation

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Abstract—One of the challenging problems in sequence generation tasks is the optimized generation of sequences with specific desired goals. Existing sequential generative models mainly generate sequences to closely mimic the training data, without direct optimization according to desired goals or properties specific to the task. In this paper, we propose OptiGAN, a generative GAN-based model that incorporates both Generative Adversarial Networks and Reinforcement Learning (RL) to optimize desired goal scores using policy gradients. We apply our model to text and sequence generation, where our model is able to achieve higher scores out-performing other GAN and RL models, while not sacrificing output sample diversity.

Index Terms—Sequence Data, Generative Models, GAN, Reinforcement Learning, Policy Gradients.

I. INTRODUCTION

Learning to generate realistic sequences from existing data is essential to many artificial intelligence applications, including text generation, drug design, robotics, and music synthesis. In these applications, a generative model learns to generate sequences of different data types according to each task. For instance, natural language and speech are sequences of words or utterances, in robot motion planning, a trajectory is an action sequence learned from experiences or sensory data. Recently, there has been a growing interest in deep models for sequence generation following the success of Generative Adversarial Networks (GANs) [1] and Variational Autoencoders (VAEs) [2] in image generation tasks [3], [4], [5], [6], [7].

However, realizing the full potential of these models in aforementioned applications has many challenges, and one of these key challenges is the absence of mechanisms to optimize the generated outputs according to certain metrics or useful properties. Most of current work on generative sequence models mainly learn to “resemble” the data, meaning to generate outputs that are close to the real distribution. However, in many applications, we are not only interested in generating data similar to the real ones, but we need them to have specific useful properties or attributes. For example, in drug design, useful properties include solubility and ease of synthesis [8], [9]. In music generation, we might want the music to have specific pitch or tempo, or in text applications, the user might be interested in generating sentences according to certain sentiment or tense [10]. Therefore, the lack of optimization mechanisms in current models hinders their practical use in a wide range of real world applications.

In this paper, we propose a new sequential generative framework, named OptiGAN [1] that can generate sequences resembling those in a given dataset and achieving high scores according to an optimized goal (e.g., solubility and ease of synthesis in drug design). Our proposed framework leverage GAN for mimicking real data and policy gradient reinforcement learning (RL) [11] for optimizing a score of interest. It is very well-known that although GANs can resemble real data, they face the mode collapsing problem [12], [13], [14], [15], [16], hence leading to generate less diverge examples. To tackle this issue in the context of sequence generation, we propose to leverage maximum likelihood and GAN principles elegantly (see Section IV-A) in which we prove that in the final optimization problem, Kullback-Leibler (KL) and Jensen-Shannon (JS) divergences between real data distribution and generated data distribution are simultaneously maximized, hence relieving the mode collapsing problem, concurring with what found in the paper [13]. The proposed model is then leveraged with gradient policy RL for optimizing a score of interest according to a goal (see Section IV-B). We observe that when incorporating policy gradient RL to our current framework which bases on GAN and maximum likelihood, the variance in estimating gradient is very high, hence leading to unstable training. To resolve this issue, we resort the Monte Carlo rollout in [17] with a slight modification (see Section IV-C).

We demonstrate the capacity of our OptiGAN in two applications: text generation (discrete data nature) and air combat trajectory generation (real-valued data nature). For text generation task, we aim to generate sentences resembling real sentences in a given text corpus, while optimizing the BLEU [18] score for obtaining better sentences from human justification. For aircraft trajectory generation task, we aim to generate a trajectory plan for air-combat maneuver scenario between two aircrafts and optimize the McGrew score [19] which reflects the tactic quality of aircraft trajectories in an air combat [19]. In both applications, we show that we can generate high quality outputs and achieve higher scores than current related models thanks to the RL component, while preserving the diversity of generated outputs thanks to our new maximum likelihood GAN.

The main contributions of our paper include:

• We propose OptiGAN which has the following advantages: (i) an end-to-end generative framework with in-

1Our code is available here: https://github.com/mahossam/OptiGAN
corporated goal optimization, (ii) general formulation that can be used for wide variety of different goals and models, and (iii) achieve higher desired goal scores while preserving sample diversity.

- We investigate the problems of interest comprehensively and our findings would advance the understanding of the behaviors when incorporating a generative model and a RL component, hence useful for the community. Specifically, we empirically found that if we apply pure RL component to maximize a score of interest, we might obtain generated examples with high scores but poor diversity. For instance, in the case of text generation, the model somehow cheats the BLEU score by generating sentences in which a few words repeated all the times. In contrast, if we apply only a generative model to resemble real data, we cannot achieve higher values for the score of interest. Our workaround is to leverage both generative model and RL to simultaneously obtain realistic diverse examples with good scores. In addition, to obtain diverse examples, the applied generative model must be able to avoid the mode collapsing problem, aided by our proposed maximum likelihood GAN.

II. BACKGROUND AND RELATED WORK

A. Background

Generative Adversarial Networks (GAN): Generative Adversarial Networks (GAN) [11] use adversarial training between two players to learn the density function of input data. The goal of the first player, the generator $G$, is to get very good at generating data that is very close to the real data distribution $p_d(x)$. The goal of the second player, the discriminator $D$, is to distinguish real data from fake data generated by the generator.

The standard GAN objective to optimize is the minimax game between $D$ and $G$ is:

$$\min_G \max_D \left( \mathbb{E}_{x \sim p_d} \log D(x) + \mathbb{E}_{z \sim p_z} \log (1 - D(G(z))) \right),$$

(1)

where $z$ is the random noise inputted to $G$ and $p_z$ is the prior distribution of the $z$. After the training is finished, the generator is used to generate data from any random input $z$.

Reinforcement Learning using Policy Gradients: Reinforcement learning [20] is a general learning and optimization framework that finds approximate solutions to combinatorial problems using actions, state and rewards system. Rewards received by the agent encourage it to learn a policy close to the desired behavior to increase accumulated rewards (the returns) over time.

Policy gradients [20] are group of methods in reinforcement learning that enable optimizing future returns by direct optimization of the policy. The objective is to maximize the return rewards over an episode of $T$ time steps $J(\theta) = \mathbb{E}_\pi [U_t]$ , where $\pi$ is the “policy” and $U_t$ specifies the accumulative reward of an episode which is defined as follows:

$$U_t = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \cdots + \gamma^{T-t} R_T,$$

where $\gamma$ is a discount factor, and $R_t$ is the reward received from the environment.

A policy could be parameterized by some parameters $\theta$ and be directly optimized through taking the gradient of $J(\theta)$ with respect to $\theta$. This method is called policy gradients. A well-known policy gradients algorithm is REINFORCE [11], a Monte Carlo algorithm to find the optimal policy $\pi$. The model is updated via gradient ascent with:

$$\nabla J(\theta) = \mathbb{E}_\pi [U_t \nabla_\theta \log \pi (a_t | s_t, \theta)],$$

(2)

where $a_t$ is an action chosen at time step $t$ by the agent’s policy $\pi$ given the current state of the environment $s_t$.

B. Related work

In general, sequential deep generative models are either based on the variational approximation of maximum likelihood (like Variational Autoencoders VAE [2]) or on GANs [11]. Models based on variational approximation [21], [22], [23], [24] are mainly based on autoregressive models like Long Short-Term Memory (LSTM) [25], incorporated into VAE training framework. These models were applied to many sequence generating tasks including handwriting and music generation. However, training VAE based models with autoregressive networks suffers from the problem of “posterior collapse”, where the latent variables are often ignored, especially when trained for discrete data like text [26].

The other group of models based on GANs are mainly focused on discrete data like text. There are two main approaches for these models; they either use reinforcement learning techniques [17], [27], or a fully differentiable GAN [28], [29], [30], [31]. The first approach uses policy gradients [11] in an adversarial training framework. The other approach however, employs a fully differentiable GAN network, where they use Gumbel-Softmax trick [32], [33] or distance measure on feature space [29] to overcome the non-differentiability problem for discrete data.

Some recent work tried to address the goal optimized generation problem. In [34], authors used convolutional GAN or autoregressive VAE to generate music with specific pitch and timbre. For text generation, [10] uses semi-supervised VAE approach to generate text based on sentiment and tense. Interest is growing as well in the biological sequences and drug design applications [35], where VAE latent space or GAN based model with reinforcement learning are used for molecular design. However, these models either optimize using a RL objective or employ feature learning in the generative VAE or GAN model. There is not much work on using RL to guide GAN learning for goal optimization, combining benefits of GAN unsupervised learning with goal optimization. MolGAN [8], is a recent work in that direction, that uses both GAN and RL for optimized graph generation. However, MolGAN uses a different RL technique than ours, that restricts it to use a separate network per each objective, thus susceptible to increase in network parameters in case of multi-goal optimization.

III. PROBLEMS OF INTEREST

We demonstrate the capacity of our proposed framework in two applications of interest: text generation and air combat trajectory generation. For each application, our task is
to generate sequences that achieve two concurrent goals: i) mimicking those in a given dataset and ii) obtaining high scores specified by an optimized goal which might be varied for specific tasks.

A. Text generation

We need to generate sentences that are similar to real sentences in a given text corpus and have high quality from human justification. One of well-known score used to justify the quality of generated sentences is BLEU score [18]. Specifically, the BLEU score for each sentence computes the ratio of n-grams generated from the model that matches with a true ground truth, called reference sentences and is defined as follows:

\[
\text{BLEU}(N) = \sum_{n=1}^{N} \frac{\text{Count}(\text{Model generated n-grams} \cap X_{\text{test-n-grams}})}{\text{Count}(\text{Model generated n-grams})}
\]

In our proposed model, beside generating realistic sentences, we also aim to maximize the BLEU score of generated sentences. As shown later, we utilize the BLEU score as reward function in our RL inspired framework.

B. Air combat trajectory generation

For air combat missions, pilots are trained to conduct certain maneuvers according the combat situation they face. There are well known maneuvers that the pilots are trained on, either defensive, offensive, or neutral. We consider a specific air combat maneuver between two fighters called “Stern Conversion” maneuver [36]. In this maneuver, the opponent (the red aircraft) flies in a straight and level line, and does not detect the blue aircraft, while the blue aircraft, on the other hand, tries to get behind the opponent aircraft, in order to increase the chance to engage it (see Fig. 1). In this specific task, in addition to generate realistic trajectories, we also need to maximize the McGrew score [19], which measures the score of how well an aircraft was doing relative to another aircraft in an attempt to get behind the other aircraft (refer to [19] for more detail). Due to security restrictions, we cannot access the real trajectories sensory data. Instead, we use ACE-Zero [37] air combat flight simulator to generate the training data. This simulator was developed by domain experts to imitate the real aircraft trajectories. As demonstrated in the experiments section, our model can generate novel trajectories with high McGrew score close to the average scores for ACE-Zero trajectories.

IV. PROPOSED FRAMEWORK

In what follows, we present the technical detail of our proposed framework. We employ a neural autoregressive model \(G\) (e.g., Bi-RNN or RNN) as a generator to map from a noise \(z \sim p_z\) to a sequence that can mimic those in a given dataset and achieve high score corresponding to a goal optimized. In term of modeling, we start from the maximal likelihood (ML) principle and then propose to incorporate adversarial learning to the learning process in a principled way. The coupling of ML and adversarial learning principles helps us to generate realistic sequences being ‘able to imitate those in a given dataset. Moreover, to reach those with high scores according to a given optimized goal, we propose to leverage reinforcement learning in which policy gradient allows us to train our models end-to-end. Finally, to stabilize the training process, we apply a technique to reduce the variance when training with policy gradient. The final model is named OptiGAN whose overview architecture is shown in Fig. 2.

A. Maximum likelihood and adversarial training

A sample \(X\) in our setting is defined as a sequence of \(T\) tokens denoted by \(X = [x_1, x_2, ..., x_T]\), where we assume that all samples have length \(T\). For our autoregressive model with model parameters \(\theta\), the log-likelihood can be written as:

\[
\log p_G(X | \theta) = \sum_{i=2}^{T} \log p_G(x_i | h_{i-1}, \theta) + \log p_G(x_1 | \theta),
\]

This is the default neural autoregressive model formulation. Now we start introducing an adversarial learning framework for this model by introducing a latent variable \(z\) to the autoregressive model, where we rewrite \(\log p(x_1 | \theta)\) as marginalization over the \(z\):

\[
\log p_G(x_1 | \theta) = \log \sum_{z} p_G(x_1, z | \theta) \geq -I_{KL}(q(z | x_1, \phi) || p(z)) + \mathbb{E}_{q(z|x_1,\phi)}[\log p_G(x_1 | z, \theta)],
\]

where \(I_{KL}\) is Kullback–Leibler divergence, \(q(z | x_1, \phi)\) is an approximation of the posterior \(p(z | x_1, \theta)\) and \(p(z)\) is a prior distribution to \(z\). The right hand side of Eq. (3) is a lower bound for \(\log p_G(x_1 | \theta)\). We can then write \(\log p_G(X | \theta)\) in terms of a lower bound as:

\[
\log p_G(X | \theta) \geq \sum_{i=2}^{T} \log p_G(x_i | h_{i-1}, \theta) - I_{KL}(q(z | x_1, \phi) || p(z)) + \mathbb{E}_{q(z|x_1,\phi)}[\log p_G(x_1 | z, \theta)].
\]

We propose to incorporate adversarial learning to autoregressive sequential model in a principled way. One generator \(G(z)\) and one discriminator \(D(X)\) are employed to create a game like in GAN while the task of the discriminator is to discriminate true data and fake data and the task of the generator is to generate fake data that maximally make the discriminator confused. In addition, the generator \(G\) is already available which departs from a noise \(z \sim p_z\), uses the conditional distribution \(p(x_1 | z, \theta)\) to generate \(x_1\), and follows the autoregressive model to consecutively generate \(x_{2:T}\). We come with the following minimax problem:

\[
\max_G \min_D \left[ \mathbb{E}_{X \sim p_d} [\log p_G(X | \theta)] - \mathbb{E}_{X \sim p_d} [\log D(X)] - \mathbb{E}_{z \sim p_z} [\log [1 - D(G(z))]\right],
\]
where the generator $G$ consists of the decoder $p (x_1 \mid z, \theta)$, the autoregressive model, hence $G$ is parameterized by $(\theta, \phi)$, and $\log p_G (x \mid \theta)$ is substituted by its lower bound in Eq. (4). We can theoretically prove that the minimax problem in Eq. (5) is equivalent to the following optimization problem (see the proof in Appendix A):

$$\min_G I_{KL} (P_d \parallel P_G) + I_{JS} (P_d \parallel P_G),$$

(6)

where $I_{JS}$ is Jenshen-Shannon divergence and $P_G$ is the generative distribution. The optimization problem in Eq. (6) reveals that at the Nash equilibrium point the generative distribution $P_G$ is exactly the data distribution $P_d$, thus overcoming the mode-collapse issue caused by original GAN formulation.

To train our model, we alternatively update $G$ and $D$ with relevant terms. We note that in the optimization for updating $G$ regarding $\log p_G (X \mid \theta)$, we maximize its lower bound in Eq. (4) instead of the likelihood function.

**Training procedure.** Likewise GAN, to train our proposed Adversarial Autoregressive Network (ARN), we alternatively update the discriminator and generator:

- **Update $D$:**
  $$\max_D E_{X \sim p_d} [\log D (X)] + E_{z \sim p_z} [\log [1 - D (G (z))]].$$

- **Update $G$:**
  $$\max_G E_{X \sim p_d} [\log p (X \mid \theta)] - E_{z \sim p_z} [\log [1 - D (G (z))]]$$
  $$= \max_G E_{X \sim p_d} [\log p (X \mid \theta)] + E_{z \sim p_z} [\log D (G (z))].$$

(7)

It is worth noting that for discrete data (e.g. text), we define the likelihood $p(x_i \mid h_i) = \text{softmax}(W_oh_i)$ where $W_o$ is the output weight matrix. In addition, to allow end to end training, we apply Gumbel softmax trick for the discrete case, and fix start token to $p(x_1 \mid z) = 0$, as we depend on Gumbel Softmax for random output sampling. For real-valued data (e.g. air combat trajectory), we employ $p(x_i \mid h_i) = N (W_oh_i, \sigma^2)$ where $\sigma$ is the standard deviation parameter.

**B. Optimizing score corresponding to a goal with reinforcement learning**

To incorporate the ability to model the data to maximize rewards from the environment, we use policy gradient to learn a policy that maximizes the total rewards from environment. Following [20], the learning objective to maximize the return rewards over an episode from $t = [0, 1, ..., T - 1, T]$ is:

$$J(\theta) = E_{\pi} [U_t \log \pi (A_t | S_t, \theta)] ,$$

where $\pi$ is the “policy”, or the probability distribution of actions given states of environment, $A_t$ and $S_t$ are the action and state at time $t$, $\theta$ are the parameters of $\pi$ and $U_t$ is “the return rewards” at time $t$.

In our model, the policy is the generator $G$, and the state at time $t$ is the hidden state of the generator $h_t$. Thus the objective becomes:

$$J(\theta) = E_{X \sim p_d} [U_t \log p (X \mid h_t, \theta)] .$$

We simply use the REINFORCE algorithm [11] to find the optimum parameters for policy $G$ by gradient ascent of the gradient of $J$ as

$$\nabla J(\theta) = E_{X \sim p_d} [U_t \nabla_{\theta} \log p (X \mid h_t, \theta)] ,$$

where $U_t$ is computed as

$$U_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots + \gamma^{(T-t-1)} R_T$$

where $R_t$ is the reward value from the environment at time $t$, $\gamma \in [0, 1]$ is the “discount factor” of future rewards. Note that for the text generation task, we use the BLEU score as reward value and for the air combat trajectory generation task, we use the McGrew score as reward value.
Total loss. The final total loss to train the generator \( G \) with adversarial training and policy gradients is:

\[
\max_G \mathbb{E}_{X \sim p_d} \left[ \log p(X | \theta) + \lambda \mathbb{E}_{z \sim p_z} [ \log D(G(z))] \right] + \alpha \mathbb{E}_{X \sim p_d} \left[ U_t \log p(X | h_t, \theta) \right],
\]

where \( \lambda \) and \( \alpha \) are hyper-parameters that control how much the effect of adversarial training and policy gradients are on the total loss.

C. Reducing policy gradients variance

In order to reduce the variance of policy gradients, we use an algorithm similar to the Monte Carlo rollout in [17] with a slight modification. We generate few complete sentences at each time step onward, and take their average as \( U_t \) at that time step. Instead of getting the reward value from a discriminator as in [17], we directly compute the reward according to the chosen score.

In addition, to further reduce the variance of the policy gradients and to help policy gradients converge faster toward optimal solution, we use policy gradients with baseline [20], where policy gradient is defined as:

\[
\nabla J(\theta) = \mathbb{E}_s \left[ \left( U_t - b(s_t) \right) \nabla_{\theta} \log p \left( \theta | h_t, S_t \right) \right] = \mathbb{E}_s \left[ \left( U_t - b(h_t) \right) \nabla_{\theta} \log p \left( X | h_t, \theta \right) \right],
\]

where \( b(s_t) \) is a baseline, a function that can be estimated or learned during training. The use of a baseline does not change the gradient expected value, but in practice, reduces its variance. In our experiments, \( b(s_t) \) is a value equivalent to the average of computed rewards over training time.

V. EXPERIMENTAL STUDIES

A. Baselines

We evaluate our proposed model for both discrete (in our case, text generation) and real-valued data (air-craft trajectory generation), summarized in Table I

| TABLE I | COMPARISON BASELINES |
|---------|-----------------------|
|         | Discrete Data (Text) | Real Valued Data (Trajectories) |
| SeqGAN  | ✓                     | –                     |
| LSTM    | –                     | ✓                     |
| OptiGAN-OnlyRL | ✓ | – | |
| OptiGAN-OnlyGAN | ✓ | ✓ | |
| OptiGAN | ✓                     | ✓                     |

1) SeqGAN [17]: is a well-known baseline for sequential generative models that uses a discriminator as a reward signal for training the generator in a reinforcement learning framework.

2) OptiGAN-OnlyRL: This model is the vanilla reinforcement learning using policy gradients. For fairness, we implement it by using our own model with GAN component canceled, by zeroing out the GAN loss part.

3) OptiGAN-OnlyGAN: The sequence GAN with LSTM and discrete relaxation nodes, without any policy gradient component. We implement it using our model with RL component canceled, by zeroing out the policy gradient loss.

The GAN network implementation of our model is based on RELGAN with same hyperparameters and temperature scheduling, but using LSTM unit instead of relational memory.

For trajectory generation, we implement two different models to compare with: LSTM (The LSTM component of our model without adversarial training) and OptiGAN-OnlyGAN (our model without RL component), and we study the effect of the RL component on optimizing the goal metric.

B. Text generation

1) Evaluation Metrics: We use both BLEU score and negative log-likelihood (NLL) mentioned below to evaluate the quality of our model.

BLEU Score: As discussed in Section III-A BLEU score [18] is well-known text quality score in machine translation and text generation tasks.

The higher the BLEU score is, the more the number of matching n-grams with the test set. In practice, and as discussed later, the BLEU score can be easily cheated by repeating few matching n-grams in one sentence, or by generating only one or few high quality sentences from the model after training. This situation implies low output quality and diversity from the model.

Negative Log-Likelihood (NLL): Since BLEU score cannot measure the diversity of the model, we need to add another metric. We use the negative log-likelihood of the generator [28] to measure diversity, defined as:

\[
\text{NLL}_{\text{gen}} = -\mathbb{E}_{x_1:T \sim p_d} \log P_{G_{\theta}} (x_1, \cdots, x_T)
\]

where \( p_d \) and \( P_{G_{\theta}} \) are the real data and generated data distributions, respectively. The lower the value, the closer the model distribution is to the empirical data distribution.

2) Datasets: Two text datasets were used in our experiments for text generation are

- The MS-COCO image captions dataset [38] includes 4,682 unique words with the maximum sentence length 37. Both the training and test data contain 10,000 text sentences.
- The EMNLP2017 WMT News dataset [39] consists of 5,119 unique words with the maximum sentence length 49 after using first 10,000 sentences from [28]. Both the training and test data contain 10,000 sentences.

3) Experimental settings and results: For MS-COCO dataset, we use policy gradient baseline value of 2.5 and \( \alpha \) value of 2.0 for both Vanilla-RL and our model. The number of Mone Carlo samples we use during training is 3. For EMNLP News, we use baseline value of 2.0 and 16 Monte Carlo samples.

In all experiments, we use gradient clipping value of 10.0 for the generator. In Tables III and IV we report the means and standard deviations of test BLEU scores and training negative likelihoods values of our model compared to other baselines.
Quality and diversity discussion
Tables II and III show that, except for the OptiGAN-OnlyRL special case, our model outperforms the baselines in BLEU scores on MS-COCO dataset and all but BLEU-2 for EMNLP News dataset. Our model also achieves a competitive NLL value with the best model, OptiGAN-OnlyGAN. This means that our model does not sacrifice the diversity of generated output when optimizing for the given score. We find that SeqGAN suffers the worst NLL score, even when compared to OptiGAN-OnlyRL. Since SeqGAN modified generator objective does not encourage matching the model distribution to data distribution, it can be susceptible to diversity collapse. On the other hand, GANs that use Gumbel-Softmax to keep objective does not encourage matching the model distribution to data distribution, it can be susceptible to diversity collapse. In the case of OptiGAN-OnlyRL, we find that pure reinforcement learning can achieve a higher BLEU score than other models (with very high variance). However, it has worse NLL values, which means it has worse diversity than our model. Fig. 3 shows that OptiGAN-OnlyRL fails to converge to low NLL, unlike our model, which has competitive NLL values with OptiGAN-OnlyGAN.

Moreover, although pure reinforcement learning can reach high BLEU scores, the sentences mostly are not realistic. We show in Table IV sentences from OptiGAN-OnlyRL, where we find that many of the generated sentences are unrealistic repetitions of certain n-grams in the test set. In the case of MS-COCO dataset, the generated sentences lengths are shorter than the average length of the dataset. This behavior possibly means that in the absence of the GAN objective part of the loss, pure reinforcement learning does not have incentive to generate sentences close to the real data distribution. In this case, the model only has to achieve high BLEU score to reduce the optimization loss.

Sentences quality of OptiGAN
Table V shows generated sentences of OptiGAN. The sentences generally look meaningful, structured and diverse, hence showing the capacity of OptiGAN in generating good and diverse sentences.

C. Air-Combat Trajectory Generation

1) Evaluation metrics: We use the McGrew score[19] which measures how good is the aircraft positioned in an attempt to get behind the other aircraft. McGrew score is well-known by domain experts in air-combat maneuvers.

2) Datasets: For trajectory generation task, we used simulated data from ACE-Zero simulator [37]. We created simulated trajectory data for the Stern Conversion maneuver [36] (Fig. I) with two fighters; the blue and the red. We created 6,000 trajectories under this scenario[2]. Each trajectory contains 16 features for each of the two fighters.

3) Experimental settings and results: In all of our experiments, we use 40 simulation time steps (tokens) for each fighter trajectory. We use 256 units hidden layer for LSTM unit with 2 hidden layers. For the VAE part of the model, we use

All trajectory data is available at [https://bit.ly/33k1Akt](https://bit.ly/33k1Akt)
TABLE V
GENERATED SAMPLE SENTENCES FROM OUR MODEL

| Samples from MS-COCO |
|----------------------|
| a group of men and women selling lots of antique items on a conference table. |
| a bathroom with a mirror and shower curtain. |
| a woman wearing a backpack standing next to a person talking on a man in a window. |
| a group of people riding motorcycles down a highway. |
| a man slices meat and his bicycle with his cell phone behind a picture. |
| a multi-colored airplane makes its way through the corner. |
| a long wall lined kitchen with stainless double sinks, paint, shower and there are |
| a kitten is sitting in a bathroom mirror looking out towards multiple plants in it |

but we find a great school, and i feel like maybe i do it .
and i mean i am desperate to get seen, so it ' s a mental trials that they would do .
only reason that the law with particular evidence is a chance to do it .
in the station was cocaine, in the agenda of state .
i want to work here for democrats , and then have said a starting point of →
→ companies , is a matter of the 2016 election .

12 hidden units and latent dimension of size 10. We pretrained the generator for 80 epochs before starting the adversarial and policy gradients training. In all experiments we set \( \sigma = 0 \) for sampling \( x_t \). We show samples of the training data trajectories and generated trajectories by our model in supplementary materials. We can see from the generated trajectories is that the model is able to capture the correct behavior, were the blue trajectory tries to get behind the red aircraft.

TABLE VI
BLUE FIGHTER ENGAGEMENT SCORES (MCGRew Score)

| \( \lambda \) | \( \alpha \) | McGrew Score |
|----------|----------|--------------|
| SeqGAN\(^*\) | – | N/A |
| LSTM | – | 6.21 |
| OptiGAN-OnlyGAN | 1.0 | 7.34 |
| OptiGAN | 0.2 | 0.75 | **8.41** |

\(^*\)SeqGAN works only with discrete data, not real-valued data

TABLE VII
EFFECT OF HYPER-PARAMETER \( \lambda \) FOR GAN-ONLY TRAINING

| \( \lambda \) | McGrew Score |
|----------|--------------|
| OptiGAN-OnlyGAN | 1.0 | 7.34 |
| 0.2 | **6.79** |

Score optimization

We want the generated trajectories to be more optimized towards better engagement position against the red fighter. The desired outcome is a higher McGrew score, which means better engagement positions along the generated trajectory. We evaluate the effect of using policy gradients on the McGrew score of the blue aircraft and show the results in Table VII. In all experiments, we use \( \gamma = 0.9 \).

We compare with three baselines, Our model for real-valued data without adversarial training or policy gradients (LSTM), GAN without policy gradients (OptiGAN-OnlyGAN), and the average McGrew score of the training data (from simulator).

In all baselines, we generate 6,000 trajectories. We can see that full OptiGAN model with the policy gradients achieve higher McGrew scores than other baselines, and closest to the real physics simulator. Although the GAN without policy gradients was able to achieve a slightly less score, the policy gradient model was run with adversarial \( \lambda = 0.2 \), which is very low. This means that the adversarial training did not contribute to the high score achieved by policy gradients model, rather it was mainly the effect of policy gradients. As shown in Table VII, GAN with no PG model with \( \lambda = 0.2 \) did not achieve the same score as the the one with \( \lambda = 1.0 \).

**Trajectories quality of OptiGAN**

Fig. 4 shows the trajectories generated by OptiGAN compared to real trajectories. It can be observed that OptiGAN can generate high-quality trajectories resembling real data.

![Generated Trajectories](image)

**VI. CONCLUSION**

In this paper we presented a sequential deep generative model, OptiGAN, that integrates both generative adversarial networks and reinforcement learning for goal optimized generation. In many applications, goal optimization is a useful mechanism to give desired properties to generated outputs. We applied our model to text and air-combat trajectory generation tasks, and showed that the model generated high quality sentences with higher desired scores. In addition, OptiGAN preserves the diversity of outputs close to the real data. Our model serves as a general framework, that can be used for any GAN model to enable it to directly optimize a desired goal according to the given task.

In future work, we plan to learn the baseline function using a value network to automate the choice of hyperparameters. In addition, we intend to incorporate a latent space in the discrete case, which can be leveraged to guide the generation process along learned disentangled features of the data.

**REFERENCES**

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A. Proof of final objective function

Consider this optimization problem:

\[
\max_G \min_D \left[ \mathbb{E}_{X \sim p_d} \left[ \log p_G (X | \theta) \right] - \mathbb{E}_{X \sim p_d} \left[ \log D (X) \right] - \mathbb{E}_{z \sim p_z} \left[ \log \left[ 1 - D (G(z)) \right] \right] \right].
\]  

Given a generator \( G \), the optimal \( D^* (\cdot) \) is determined as:

\[
D^*_G (X) = \frac{p_d (X)}{p_G (X) + p_d (X)}
\]

where \( p_G (X) \) is the distribution induced from \( G (X) \) where \( X \sim p_d (X) \).

Substituting \( D^*_G \) back to Eq. \ref{eq:objective_function}, we obtain the following optimization problem regarding \( G \):

\[
\max_G \left( \mathbb{E}_{p_d} \left[ \log p_G (X) \right] - \mathbb{I}_{JS} (P_d || P_G) \right).
\]

The objective function in Eq. \ref{eq:objective_function} can be written as:

\[
\mathbb{E}_{p_d} \left[ \log p_G (X) \right] = \mathbb{I}_{JS} (P_d || P_G) - \mathbb{I}_{KL} (P_G || P_d) - \mathbb{E}_{p_d} \left[ \log p_d (X) \right] = \mathbb{I}_{JS} (P_d || P_G) - \mathbb{I}_{KL} (P_G || P_d) + \text{const}.
\]

Therefore, the optimization problem in Eq. \ref{eq:objective_function} is equivalent to:

\[
\min_G \left( \mathbb{I}_{JS} (P_d || P_G) + \mathbb{I}_{KL} (P_G || P_d) \right).
\]

At the Nash equilibrium point of this game, we hence obtain: \( p_G (X) = p_d (X) \).

APPENDIX

A. Proof of final objective function

Consider this optimization problem:

\[
\max_G \min_D \left[ \mathbb{E}_{X \sim p_d} \left[ \log p_G (X | \theta) \right] - \mathbb{E}_{X \sim p_d} \left[ \log D (X) \right] - \mathbb{E}_{z \sim p_z} \left[ \log \left[ 1 - D (G(z)) \right] \right] \right].
\]  

Given a generator \( G \), the optimal \( D^* (\cdot) \) is determined as:

\[
D^*_G (X) = \frac{p_d (X)}{p_G (X) + p_d (X)}
\]

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Substituting \( D^*_G \) back to Eq. \ref{eq:objective_function}, we obtain the following optimization problem regarding \( G \):

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\[
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\]

Therefore, the optimization problem in Eq. \ref{eq:objective_function} is equivalent to:

\[
\min_G \left( \mathbb{I}_{JS} (P_d || P_G) + \mathbb{I}_{KL} (P_G || P_d) \right).
\]

At the Nash equilibrium point of this game, we hence obtain: \( p_G (X) = p_d (X) \).