Nested-Wasserstein Self-Imitation Learning for Sequence Generation

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Abstract

Reinforcement learning (RL) has been widely studied for improving sequence-generation models. However, the conventional rewards used for RL training typically cannot capture sufficient semantic information and therefore render model bias. Further, the sparse and delayed rewards make RL exploration inefficient. To alleviate these issues, we propose the concept of nested-Wasserstein distance for distributional semantic matching. To further exploit it, a novel nested-Wasserstein self-imitation learning framework is developed, encouraging the model to exploit historical high-rewarded sequences for enhanced exploration and better semantic matching. Our solution can be understood as approximately executing proximal policy optimization with Wasserstein trust-regions. Experiments on a variety of unconditional and conditional sequence-generation tasks demonstrate the proposed approach consistently leads to improved performance.

1 Introduction

Sequence generation is an important research topic in machine learning, covering a wide range of applications, including machine translation \cite{bahdanau2015neural,cho2014learning}, image captioning \cite{anderson2017neural,vinyals2015show,xu2015show}, and text summarization \cite{paulus2017summarizing}. Standard sequence generation follows an auto-regressive model design under maximum likelihood estimation (MLE) learning \cite{huszar2015neural,sutskever2014sequence,wiseman2016scalable}. That is, models are trained to maximize the expected log-likelihood of the next word conditioned on its preceding ground-truth partial sentence. However, when testing, the generated partial sequence is fed to the generator to draw the next token. Such a discrepancy between training and testing, commonly known as exposure bias, leads to accumulated approximation errors along the sequence-generation trajectory \cite{bengio2015scheduled,ranzato2016sequence}.

To address exposure bias, reinforcement learning (RL) techniques have been introduced \cite{ranzato2016sequence}. Unlike MLE, which only leverages training examples, RL can also exploit samples drawn from the current policy. Improvements are gained from reinforcing the training towards more-plausible generations, typically based on a user-specified reward function \cite{ranzato2016sequence,yu2017improved}. However, the manually designed rewards often target specific desirable properties in sequence generation (e.g., matching n-gram overlap between generated sequences and ground-truth references), which unintentionally induces extra bias and is often criticized as a bad proxy for human evaluation \cite{wang2018addressing,hu2019self}. Concerns have also been raised w.r.t. efficient exploration in sequence generation. In existing RL-based methods for sequence generation \cite{bahdanau2017actor,ranzato2016sequence,remie2016actor}, all experiences are treated as equivalent. However, merely relying on policy samples to explore often leads to forgetting a high-reward trajectory, unless it can be re-sampled frequently \cite{liang2018behavior}. This problem becomes severe in the sparse-reward setting in sequence generation, i.e., the reward is only available after the whole sentence is generated.

Motivated by the above observations, we present a novel nested-Wasserstein Self-Imitation Learning (WSIL) framework for sequence generation. Specifically, we propose the nested-Wasserstein distance, a generalization of the Wasserstein distance, and exploit it to measure distance between the behavior policy and the artificial policy defined by the replay buffer to encourage self-imitation. The nested-Wasserstein distance is well suited for distributional semantic matching be-
tween two (sequence) distributions whose samples are still discrete distributions, as in the case of sequence generation. The proposed WSIL is inspired by and derived from the policy optimization with Wasserstein trust-regions [Zhang et al. 2018]. It provides a novel reward function to match the generated sequences with the high-reward sequences in the replay buffer, encouraging distributional semantic matching rather than simple n-gram overlapping.

The main contributions of this paper are summarized as follows. (i) A novel nested-Wasserstein self-imitation learning framework is developed for sequence generation, exploiting historical good explorations for better future exploration. (ii) A novel nested-Wasserstein distance is introduced for sequence generation via distributional semantic matching, effectively alleviating the model training bias imposed by conventional rewards. (iii) Extensive empirical evaluation is performed on both unconditional and conditional text generation tasks, demonstrating consistent performance improvement over existing state-of-the-art approaches.

2 Background

Sequence-generation model We consider the problem of discrete sequence generation, which learns to generate a sequence \( Y = (y_1, \ldots, y_T) \in \mathcal{Y} \) of length \( T \), possibly conditioned on context \( X \). Here each \( y_t \) is a token from vocabulary \( A \). Pairs \((X, Y)\) are used for training a sequence-generation model. We are particularly interested in applications to text generation, where \( Y \) is a sentence and each \( y_t \) is a word. Starting from the initial state \( s_0 \), a recurrent neural network (RNN) produces a sequence of states \((s_1, \ldots, s_T)\) given an input sequence-feature representation \((e(y_1), \ldots, e(y_T))\), where \( e(\cdot) \) denotes a word embedding mapping a token to its \( d\)-dimensional feature representation. The states are recursively updated with a function known as the cell: \( s_t = h_\theta(s_{t-1}, e(y_t)) \), where \( \theta \) denotes the model parameters. Popular implementations include Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber 1997] and the Gated Recurrent Unit (GRU) [Cho et al. 2014]. In order to generate sequence \( Y^* \) from a (trained) model, one iteratively applies the following operations:

\[
y_{t+1}^* \sim \text{Multi}(\text{softmax}(g(s_t))),
\]

\[
s_t = h(s_{t-1}, e(y_t)),
\]

with deterministic state transition and sparse reward. It can be formulated as a Markov decision process (MDP) \( \mathcal{M} = (\mathcal{S}, \mathcal{A}, P, r) \), where \( \mathcal{S} \) is the state space, \( \mathcal{A} \) is the action space, \( P \) is the deterministic environment dynamics and \( r(s, a) \) is a reward function. The policy \( \pi_\theta \), parameterized by \( \theta \), maps each state \( s \in \mathcal{S} \) to a probability distribution over \( \mathcal{A} \). The objective is to maximize the expected reward, defined as:

\[
J(\pi_\theta) = \mathbb{E}_{Y \sim \pi_\theta} [r(Y)] = \sum_{t=1}^{T} \mathbb{E}_{(s_t, y_t) \sim \pi_\theta} [r(s_t, y_t)],
\]

where \( Y \equiv (s_1, y_1, \ldots, s_T, y_T) \) is a trajectory from policy \( \pi_\theta \) with \( y_t \in A \), and \( r(Y) \) represents the reward for a sentence \( Y \), and \( r(s_t, y_t) \) is the step-wise reward. RL seeks to learn an optimal policy, that maximizes the expected total reward \( J(\pi_\theta) \).

Optimal transport on discrete domains The optimal transport (OT) distance \( W_1(\mu, \nu) \) is a discrepancy score that measures the distance between two probability distributions \( \mu(\cdot) \) and \( \nu(\cdot) \) w.r.t. a cost function \( c(\cdot, \cdot) \). Specifically, we consider two discrete distributions \( \mu \equiv \sum_{i=1}^{n} u_i \delta_{z_i} \) and \( \nu \equiv \sum_{j=1}^{m} v_j \delta_{z_j} \) with \( \delta_z \) the Dirac delta function centered on \( z \). The weight vectors \( u = \{u_i\}_{i=1}^{n} \in \Delta_n \) and \( v = \{v_j\}_{j=1}^{m} \in \Delta_m \) respectively belong to the \( n \) and \( m \)-dimensional simplex, i.e., \( \sum_{i=1}^{n} u_i = \sum_{j=1}^{m} v_j = 1 \). Accordingly, Wasserstein distance is equivalent to solving the following minimization problem:

\[
W_1(\mu, \nu) = \min_{\mathbf{T} \in \Gamma(\mu, \nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} T_{ij} \cdot c(z_i, z_j) \ ,
\]

where \( \sum_{i=1}^{n} T_{ij} = \frac{1}{m} \) and \( \sum_{i=1}^{m} T_{ij} = \frac{1}{n} \) are the constraints, \( \langle \cdot, \cdot \rangle \) represents the Frobenius dot-product, and \( \mathbf{C} \) is the cost matrix defined by \( C_{ij} = c(z_i, z_j) \). Intuitively, the OT distance is the minimal cost of transporting mass from \( \mu \) to \( \nu \).

3 Distributional Semantic Matching

We first consider evaluating the sentence from syntactic and semantic perspectives. Conventional metric rewards (e.g., BLEU) can capture the syntactic structure better, where the exact matching of words (or short phrases) to the reference sequences is encouraged, which induces strong bias in many cases. As such, we focus on the semantic matching and propose the nested-Wasserstein distance, which defines the distance between two sequence distributions. Nested-Wasserstein distance provides a natural way to manifest semantic matching compared with the conventional rewards used in existing RL-based sequence models. Alternatively, we can train a discriminator to learn the reward model, but empirically it only rewards high-quality generations, even though they may be characterized by mode
Table 1: Comparison of different rewards in terms of the sequence-level (higher is better). The top figure illustrates the Wasserstein reward of comparing two candidate sentences with a reference sentence, which will automatically match semantically similar words. Dominant edges are shown in dark blue, determined by the optimal transport matrix $T$.

| Candidate 1 (C1): There are six freshmen reading papers. | Candidate 2 (C2): Six freshmen are playing soccer. |
|----------------------------------------------------------|----------------------------------------------------------|
| Reference: There are six freshmen playing football.       | Reference: There are six freshmen playing football.       |

| BLEU | ROUGE-L | CIDEr | Naive | Wasserstein |
|------|---------|-------|-------|-------------|
| C1   | 36.8    | 50.0  | 163.7 | 84.1        | 76.3        |
| C2   | 0.0     | 35.8  | 55.9  | 42.5        | 80.1        |

Nested-Wasserstein distance

Our ultimate goal is to measure distance between two policy distributions instead of sequence pairs. Given two sets of sequences from two policies, one aims to incorporate the semantic information between sentences into the distance measure. To this end, we propose the nested-Wasserstein distance in Definition 2. Figure 1 illustrates the nested-Wasserstein, considering both word- and sequence-level matching with Wasserstein distance.

Definition 2 (Nested-Wasserstein Distance)

Consider two sets of sequences $Y = \{Y_i\}_{i=1}^K$ and $Y' = \{Y'_i\}_{i=1}^{K'}$ drawn from two sequence distributions $\mathbb{P}_Y$ and $\mathbb{P}_{Y'}$, where $K$ and $K'$ are the number of sequences in $Y$ and $Y'$. The nested-Wasserstein distance, denoted as $W_{nc}(\mathbb{P}_Y, \mathbb{P}_{Y'})$, is a metric measuring the distance between $\mathbb{P}_Y$ and $\mathbb{P}_{Y'}$ defined in a nested manner:

$$W_{nc}(\mathbb{P}_Y, \mathbb{P}_{Y'}) = \min_{T'} \sum_{i=1}^{K} \sum_{j=1}^{K'} T'_ij W_c(p_y, p_{y'}) , \tag{5}$$

where $T'_ij \geq 0$ satisfies $\sum_i T'_ij = \frac{1}{K}$ and $\sum_j T'_ij = \frac{1}{K'}$; and $W_c(\cdot, \cdot)$ denotes the $c$-Wasserstein distance defined in [1].

Remark 1

The word “nested” comes from the definition in [5], which essentially consists of two nested levels of Wasserstein distances. The proposed nested-Wasserstein distance brings in the semantic information via the distance measure $W_c$ in the first level distance. Note that we have omitted the expectation over samples in [5] for simplicity, as we essentially use a single set of samples to approximate $W_{nc}(\cdot, \cdot)$ in algorithms.

Sample-based estimation of nested-Wasserstein distance

Computing the exact Wasserstein distance is computationally intractable [Arjovsky et al., 2017; Genevay et al., 2018; Salimans et al., 2018], let alone the proposed nested-Wasserstein distance. Fortunately, we can employ the recently proposed IPOT algorithm [Xie et al., 2018] to obtain an efficient approximation. Specifically, IPOT considers the following proximal gradient descent to solve the optimal transport matrix $T$ via iterative optimization, i.e.,

$$T^{(t+1)} = \text{arg min}_{T \in \Pi(\mu, \nu)} \left\{ (T, C) + \gamma \cdot D_{KL}(T, T^{(t)}) \right\} ,$$

where $C$ is the word ground metric; $W_c$ is the sequence ground metric.

Figure 1: Illustration of nested-Wasserstein distance ($W_{nc}$) over distributions of sequences ($\mathbb{P}_Y$), showing how the distance is defined in a nested manner to measure distance of sequence distributions. $c_{cos}$ is the word ground metric; $W_c$ is the sequence ground metric.
1/γ > 0 is the generalized step size and the
generalized KL-divergence \( D_{\text{KL}}(\mu, \nu) = \sum_{i,j} T_{ij} \log \frac{T_{ij}}{T_{ij}^{(t)}} - \sum_{i,j} T_{ij} + \sum_{i,j} T_{ij}^{(t)} \) is used
as the proximity metric. Standard Sinkhorn iterations [Cuturi, 2013] are used to solve the above sub-problem.
The IPOT was designed to approximately calculate the
standard Wasserstein distance. Here we extend it to
calculate the nested-Wasserstein distance by applying
IPOT twice in a nested manner, i.e., in the sequence
and distribution levels, respectively. The full approach
of IPOT is summarized as Algorithm 2 in Appendix B.

4 Nested-Wasserstein Self-Imitation Learning

Purely adopting the nested-Wasserstein distance as the
reward in a standard policy-gradient method is not effective, because the syntactic information is missing. Specifically, we consider sequences generated from a conditional behavior policy \( \pi_{\theta,Y} \), parameterized by \( \theta \) with the conditional variable \( X \). For example, in
image captioning, each sequence is generated conditioned
on a given image. For unconditional generation, the conditional variable is empty. Instead of combining
the rewards with different weights [Liu et al., 2017] Pa-
sumuru et al. [2017], we present the nested-Wasserstein
Self-Imitation Learning (WSIL) framework, which provides
a novel way of leveraging both syntactic (metric) and semantic (Wasserstein) information.

The overall idea of the proposed nested-Wasserstein self-
imitation learning is to define a Wasserstein trust-region between the current policy (a.k.a. behavior policy) and the artificial policy defined by the replay buffer. Intuitively, the Wasserstein trust-region encourages the self-imitation of historical high-reward sequences, which provides semantic signals to guide training, in addition to the stabilizing effect from trust-region optimization. Furthermore, a replay buffer is used to store high-
reward historical sequences, whose induced conditional policy is denoted \( \pi_{B,X} \). Our new objective function with a Wasserstein trust-region is defined as:

\[
J(\pi_{\theta}) = \mathbb{E}_{X \sim p_d} \left[ \mathbb{E}_{Y^s \sim \pi_{\theta,X}} [r(Y^s)] - \lambda \cdot W_{nc}(\pi_{\theta,X}, \pi_{B,X}) \right],
\]

where \( W_{nc} \) is the nested-Wasserstein distance defined in Definition 2 and \( r(\cdot) \) can be a metric reward between \( Y^s \) and the ground-truth references \( Y \). With a little abuse of notation, but for conciseness, we use \( \pi_{\theta} \) to denote both the policy and the distribution over the sequences. Distinct from classic trust-region policy optimization, which defines the trust region based on KL-divergence Schulman et al. 2015, WSIL defines the trust region based on the nested-Wasserstein distance between the behavior policy \( \pi_{\theta,X} \) and the artificial policy \( \pi_{B,X} \). Note when \( K = K' = 1 \), the nested Wasserstein distance degenerates to the definition of Wasserstein distance between two sequences.

Remark 2 Unconditional Generation: By considering samples (features) themselves as discrete distributions, we replace the mean square difference over features of sequence pairs, i.e., Euclidean norm, with the Wasserstein distance. Then for the distributions of sequences, we again adopt the Wasserstein distance as in WGAN Arjovsky et al. 2017 but in the discrete domain. Thus, the Wasserstein distance is defined in a nested manner.

Remark 3 Conditional Generation: We replace the exact matching of sequence pairs with metric rewards in RL training, with the Wasserstein distance. In this case, we are matching two conditional distributions with Wasserstein distance, instead of matching the generated sentence with all reference sentences by average. This is a more suitable way as a generated sentence does not necessarily need to match all the references.

For simplicity, we sometimes omit the first expectation \( \mathbb{E}_{X \sim p_d} \). With the proposed nested Wasserstein distance, we propose the Wasserstein self-imitation scheme in [6], as illustrated in Figure 2. We seek to use historical high-
reward sequences to define a “self-imitation” reward function, which is then combined with the original reward function to update the generator with policy gradient methods. Intuitively, higher self-imitation rewards are achieved when the generated sequences are close to historical high-reward sequences. Thus the generator is guided to perform self imitation and we call this method indirect nested-Wasserstein self-imitation learning (WSIL-I). The word “indirect” comes from the mechanism that historical sequences interact with the policy indirectly via the self-imitation reward.

WSIL-I incorporates a self-imitation reward, denoted as \( r_s(Y^s, Y^b) \), into the objective function. Here \( Y^b \)
denotes a sample from the replay buffer and \(Y^s\) denotes a sample from the current policy. To this end, we replace the Wasserstein distance \(W_e\) in the nested-Wasserstein distance with \(r_s(Y^s, Y^b)\) in the general objective \(J_1\). Specifically, we define the two sets of sample sequences from \(\pi_{\theta,X}\) and \(\pi_{B,X}\) to be \(Y^s = \{Y^s_i\}_{i=1}^K\) and \(Y^b = \{Y^b_j\}_{j=1}^{K'}\), respectively. Here \(Y^s_i \sim \pi_{\theta,X}\) and \(Y^b_j \sim \pi_{B,X}\), \(\forall j\). \(\{X_i\}_{i=1}^K\) and \(Y^b\) will be used in calculating the nested-Wasserstein distance. Let \(r_{ns}(Y^s, Y^b) \equiv \sum_j T^n_j r_s(Y^s_i, Y^b_j)\) be the nested-Wasserstein reward, with \(T^n = \{T^n_j\}\) the optimal weights in distribution-level. Based on (6), the objective of WSIL-I is adapted to be:

\[
J_1(\pi_\theta) \triangleq \mathbb{E}_{X \sim p_d} \mathbb{E}_{Y^s \sim \pi_{\theta,X}} \left[ r(Y^s) + \lambda r_{ns}(Y^s, Y^b) \right], \\
(7)
\]

where \(r\) is the original RL reward; \(r_{ns}\) is the nested-Wasserstein reward. Since not all historically explored samples are helpful for updating the current policy, we only consider a subset of the high-reward sequences when performing self-imitation. Using \(K\) trajectories sampled i.i.d. from \(\pi_\theta\) and introducing a baseline \(b\), the gradient estimate of WSIL-I is expressed as:

\[
\nabla_\theta J_1(\pi_\theta) \approx - \sum_{k=1}^K \left[ (r(Y^s_k) - b) \nabla_\theta \log \pi_\theta(Y^s_k) \right] \\
+ \lambda r_{ns}(Y^s_k, Y^b) \nabla_\theta \log \pi_\theta(Y^s_k)]. \\
(8)
\]

In practice, if \(\mathbb{E}[r(Y^b) > r(Y^s)]\) will be combined with the nested-Wasserstein rewards, where \(\mathbb{E}[\cdot] = 1\) if the condition is satisfied, and 0 otherwise; \(b\) is the baseline to stabilize training. If the reward of a historical high-reward sequence is greater than the current one (i.e., \(r(Y^b) > r(Y^s)\)), the generator learns to imitate this high-reward sequence. Otherwise, the update based on the historical sequence is not performed due to the \(\mathbb{E}[\cdot]\) operator. This encourages the agent to only imitate its good historical explorations. We have also developed another way to implement (direct) WSIL (WSIL-D) as discussed in the Appendix A. Algorithm 1 describes the general implementation procedure of the WSIL.

**Algorithm 1** Nested-Wasserstein Self-Imitation.

**Require:** Generator policy \(\pi_\theta\); a sequence dataset \(D = \{Y_1, \ldots, Y_N\}\); a possibly empty condition \(\mathcal{X} = \{X\}\).

**Initialize** \(\pi_\theta\) and replay buffer \(B\).

**Pretrain** generator \(\pi_\theta\) with MLE.

**repeat**

**Generate** \(K\) sequences \(Y^s = \{Y^s_k\}_{k=1}^\cdot\), where \(Y^s_k \sim \pi_\theta\).

**Update** replay buffer \(B\) using \(Y^s\).

**if** Self-Imitation **then**

Sample \(K'\) sequences \(Y^b = \{Y^b_j\}_{j=1}^{K'}\), where \(Y^b_j \sim \pi_B\).

Estimate the OT matrix \(T^n\) via IPOT.

Update \(r_{ns}(Y^s_k, Y^b)\) and update \(\pi_\theta\) with (8).

**else**

Update the generator \(\pi_\theta\) with \(\mathbb{E}\) using \(Y^s\).

**end if**

**until** Algorithm \(\pi_\theta\) converges

**Figure 3:** Exploration space of different methods. Circle: ground truth; Star: high-reward sequences.

**Increasing Self-Imitation** According to the theory of Wasserstein gradient flows [Villani 2008], \(1/\lambda\) can be interpreted as a generalized decaying learning rate. With more explorations, \(\lambda\) becomes larger, and the algorithm should focus more on the self-imitation learning, providing a guideline to balance the standard RL training and self-imitation learning. More details are provided in Appendix B. Practically, nested-Wasserstein provides weak supervision focusing on semantic matching, which is reasonable since the historical high-reward sequences contain some noises.

**5 Related Work**

**Optimal transport** Kusner et al. [2015] proposed the *word mover’s distance* (WMD) and first applied optimal transport (OT) to NLP; OT has also been employed to improve topic modeling [Huang et al., 2016]. The transportation cost is usually defined as Euclidean distance, and OT distance is approximated by solving a Kantorovich-Rubinstein dual [Gulrajani et al., 2017] or a less-accurate lower bound [Kusner et al., 2015]. Yurochkin et al. [2019] proposed a hierarchical OT representation for document, but the hierarchy was in word- and topic-level based on the WMD. Our work considers nested-Wasserstein distance, presenting an efficient IPOT-based implementation for OT distance approximation [Xie et al., 2018] successfully using it to guide sequence generation.
Self-Imitation Learning Experience replay has been widely considered in RL. Deterministic policy gradient [Silver et al., 2014, Lillicrap et al., 2016] performs experience replay, but is limited to continuous control. Actor-critic approaches [Konda and Tsitsiklis, 2000] can also utilize a replay buffer to improve performance. Prioritized experience replay [Schaul et al., 2015] samples trajectories based on the time-difference error, and we adopt it in our implementation. These approaches indiscriminately buffer all experiences, while the approach proposed here only buffers high-reward experience. Further, episodic control [Lengyel and Dayan, 2008] can be regarded as an extreme way of exploiting past experience, trying to reproduce its best past decisions, but retrieving states leads to poor efficiency and generalization in testing. Self-imitation learning was first applied in Atari games and Mujoco [Oh et al., 2018, Gangwani et al., 2018], reporting performance improvement w.r.t. sparse rewards. Compared with that work, our solution considers a novel self-imitation learning scheme in the context of sequence generation.

RL for Sequence Generation RL techniques have been explored in detail for sequence generation. For example, a Seq2Seq model can be trained by directly optimizing BLEU/ROUGE scores via policy gradient [Ranzato et al., 2016, Bahdanau et al., 2017]. Furthermore, Rennie et al. [2016] baselines the actor with the reward of a greedy-decoding sequence for the REINFORCE method. Model-based RL and hierarchical RL have also been studied for sequence generation [Zhang et al., 2018a, Huang et al., 2019]. Further, a learned discriminator (or, critic) can also be used to provide sequence-level guidance. By constructing different objectives, previous work [Yu et al., 2017, Lin et al., 2017, Guo et al., 2017, Fedus et al., 2018] combines the policy-gradient algorithm with the original GAN training procedure. However, mode-collapse problems make the training of these methods challenging. By contrast, we propose the use of self-imitation learning, and maintain a replay buffer to exploit past good explorations.

6 Experiments

We evaluate the proposed method on both unconditional and conditional text-generation tasks, considering standard benchmark datasets. Our approach achieves state-of-the-art results on unconditional text generation and video captioning. We also observed improved performance on image captioning though relying on much simpler features compared to prior state-of-the-art methods. We also perform ablation studies to understand the improvements brought by self-imitation and Wasserstein rewards individually. Details of the datasets, experimental setup and model architectures are provided in Appendix C.

Figure 4: Demonstration of nested-Wasserstein distance in word-level (left) and sentence-level (right).

Figure 5: An example of image captioning. The right generated sentence is better but given a lower CIDEr.

Implementation Details A few key techniques are required for successful model training. (i) The reward from a greedy-decoding sentence is used as the baseline [Rennie et al., 2016] in conditional text generation; in unconditional text generation, a constant baseline is used. (ii) A single large replay buffer is maintained for unconditional generation, and multiple replay buffers are maintained for different conditions in conditional generation. (iii) For each pair of sentences, the shorter one should be padded to the same length as the longer one for a balanced optimal transport, which is a key implementation technique.

Demonstration of nested-Wasserstein Figure 4 shows the optimal matching in word-level (T) and sentence-level (T*). It is interesting to see that all similar words (e.g., bike and cycle) are matched with each other (higher weights), which cannot be achieved via exact hard-matching metrics. At the distribution-level, we show an example in captioning tasks, where we have five reference and hypothesis sentences. Traditional methods will match a hypothesis sentence to each of the references and average over them; while our method performs distributional semantic matching, i.e., only matching similar references instead of all of them. For example, the third hypothesis is almost matched with the fifth reference, because they are more similar. This is reasonable, because the references are usually very different, and equivalently matching with all of them is confusing for the generator. As shown in Figure 5, CIDEr focuses more on the locality fluency and equivalent matching with all references, while nested-Wasserstein performs distributional semantic matching. More examples are provided in the Appendix.
6.1 Unconditional Text Generation

We compare our approach with a number of related RL-based GAN models for unconditional text generation \cite{Guo2017, Lin2017, Yu2017, Zhang2017}. Our implementation is developed based on the LeakGAN model, by incorporating Wasserstein self-imitation learning. All baseline experiments are performed on the textygen platform \cite{Zhu2018}. The corpus-level BLEU score is employed to evaluate the generated sentences. Specifically, we follow the strategy in Yu et al. \cite{2017} and adopt the BLEU score, referenced by test set (test-BLEU) and themselves (self-BLEU) to evaluate the quality of generated samples. Test-BLEU evaluates the goodness of generated samples, and self-BLEU measures their diversity. The BLEU scores for 1000 generated sentences are averaged to obtain the final score for each model. A good generator should achieve both a high test-BLEU score and a low self-BLEU score.

Analysis Compared with other methods, LeakGAN, WSIL-D and WSIL-I achieve comparable test-BLEU scores, demonstrating high-quality generated sentences. However, LeakGAN tends to over-fit on training data, leading to much higher (worse) self-BLEU scores. Our proposed methods, by contrast, show good diversity of the generated text with lower self-BLEU scores. Other baselines obtain both low self-BLEU and test-BLEU scores, leading to more random generations.

Ablation Study We conduct ablation studies on EMNLP2017 WMT News to investigate the improvements brought by each part of WSIL. First, we test the benefits of using two types of self-imitation schemes. We compare RL training with (i) self-imitation (SIL-D and SIL-I), where only a replay buffer and conventional matching (features extracted from a neural network) are employed; and (ii) Wasserstein self-imitation (WSIL-D and WSIL-I). Results are shown in Table 3. We observe that the self-imitation strategy, with specific replay buffer construction, can alleviate the discrepancies between reward model bias and conventional rewards (e.g., self-BLEU). Without Wasserstein rewards, we achieve lower self-BLEU at the sacrifice of test-BLEU. When combining with Wasserstein rewards, WSIL-D and WSIL-I show superior performance relative to the baselines. The random generated samples in Appendix D and human evaluations further validate this.

Sweep the Temperature To better evaluate the proposed method, we follow Caccia et al. \cite{2018} to evaluate the trade-off between the quality and diversity. We use the F1-BLEU score as a metric, which considers both quality and diversity, and is defined as the geometry average of BLEU score and 1−Self-BLEU:

\[
F1\text{-BLEU} = \frac{2 \times \text{BLEU} \times (1-\text{Self-BLEU})}{\text{BLEU} + (1-\text{Self-BLEU})}
\]
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Table 4: Video captioning results on MSR-VTT.

| Method       | BLEU-4 | METEOR | ROUGE-L | CIDEr  |
|--------------|--------|--------|---------|--------|
| MLE          | 39.2   | 27.9   | 69.8    | 46.6   |
| MIXER        | 40.2   | 27.9   | 69.8    | 50.3   |
| SCST         | 40.7   | 27.9   | 61.6    | 51.3   |
| SIL-D        | 42.5   | 29.0   | 62.4    | 52.1   |
| WSIL-D       | 41.6   | 28.4   | 62.0    | 52.2   |
| WSIL-I       |        |        |         |        |

Table 6: Results of human evaluation.

| Methods  | MLE | LeakGAN | SIL-D | SIL-I |
|----------|-----|---------|-------|-------|
| Human scores | 2.97±0.05 | 2.63±0.05 | 2.54±0.05 | 2.55±0.05 |
| Methods  | Real | WSIL-D | WSIL-I |
| Human scores | 4.11±0.04 | 3.49±0.05 | 3.41±0.05 | -     |

Figure 6: F1-BLEU-4 on sweeping temperature on unconditioned generation; CIDEr scores of Video Captioning on validation set.

Human Evaluation  Simply relying on the above metrics is not sufficient to evaluate the proposed method [Caccia et al., 2018]. Following previous work [Guo et al., 2017], we performed additional human evaluation on the EMNLP2017 WMT News dataset using Amazon Mechanical Turk. We require all the workers to be native English speakers, with approval rate higher than 95% and at least 100 assignments completed. Previous work has shown higher scores of LeakGAN compared with other baselines [Guo et al., 2017], therefore we mainly focus on the comparison of our methods with LeakGAN. We randomly sampled 200 sentences from each model, and asked 5 different workers to score each sentence on a scale of 1 to 5, considering its readability and meaning. Results are shown in Table 6, which indicates better performance of the proposed WSIL.

6.2 Conditional Text Generation

Video Captioning We conduct experiments on the MSR-VTT dataset [Xu et al., 2016] for video captioning. The MSR-VTT is a large-scale video dataset, consisting of 20 video categories. The dataset was split into 6513 and 3487 clips in the training and testing sets. Each video is annotated with about 20 captions. For each video, we sample at 3 fps and extract Inception-v4 [Szegedy et al., 2017] features from these sampled frames. We report BLEU-4 [Papineni et al., 2002], CIDEr [Vedantam et al., 2015], and METEOR [Banerjee and Lavie, 2005] scores. Results are summarized in Table 4. Consistent improvements are observed with the WSIL framework. WSIL-D performs slightly better than WSIL-I, both yielding much higher optimized CIDEr and METEOR scores than SCST. This indicates that Wasserstein self-imitation can improve the semantic matching between generated sentences and their references, while achieving reasonable exact-matching-based metric scores.

Image Captioning We consider image captioning using the COCO dataset [Lin et al., 2014], which contains 123,287 images in total, each of which is annotated with at least 5 captions. Following with Karpathy’s split [Karpathy and Fei-Fei, 2015], 113,287 images are used for training and 5,000 images are used for validation and testing. We follow the implementation of the SCST approach [Rennie et al., 2016], and use extracted image tags [Gan et al., 2017] as image features (encoder). We report BLEU-4 (k from 1 to 4) [Papineni et al., 2002], CIDEr [Vedantam et al., 2015], and METEOR [Banerjee and Lavie, 2005] scores. Results are summarized in Table 5. Compared with the MLE baseline, RL-based methods significantly increase the overall performance under all evaluation metrics. We choose CIDEr as the optimizing metric, since it performs best [Rennie et al., 2016]. Our proposed WSIL shows improvement on most metrics compared with the SCST baseline. Examples of generated captions are provided in Appendix E.

7 Conclusions

We have proposed a novel Wasserstein self-imitation learning framework for sequence generation, to alleviate the sparse-rewards problem of RL methods, and model-training bias imposed by conventional rewards. This is done by encouraging self imitation and semantic matching in policy learning. Further, our method can be approximately interpreted as policy optimization with Wasserstein trust-regions. Experiments on unconditional and conditional text generation demonstrate consistent performance improvement over strong baselines. For future work, the proposed method has the potential to be applied on other interesting sequence-generation tasks such as program synthesis [Liang et al., 2018].
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References

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and vqa. In CVPR, 2017.

Martin Arjovsky, Soumith Chintala, and Léon Bottou. Wasserstein generative adversarial networks. In ICML, 2017.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In ICLR, 2015.

Dzmitry Bahdanau, Philemon Brakel, Kelvin Xu, Anirudh Goyal, Ryan Lowe, Joelle Pineau, Aaron Courville, and Yoshua Bengio. An actor-critic algorithm for sequence prediction. In ICLR, 2017.

Santanjeev Banerjee and Alon Lavie. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In ACL Workshop, 2005.

Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. Scheduled sampling for sequence prediction with recurrent neural networks. In NeurIPS, 2015.

Massimo Caccia, Lucas Caccia, William Fedus, Hugo Larochelle, Joelle Pineau, and Laurent Charlin. Language gans falling short. arXiv:1811.02549, 2018.

Liqun Chen, Shuyang Dai, Chenyang Tao, Haichao Zhang, Zhe Gan, Dinghan Shen, Yizhe Zhang, Guoyin Wang, Ruiyi Zhang, and Lawrence Carin. Adversarial text generation via feature-mover’s distance. In NeurIPS, 2018.

Liqun Chen, Yizhe Zhang, Ruiyi Zhang, Chenyang Tao, Zhe Gan, Haichao Zhang, Bai Li, Dinghan Shen, Changyou Chen, and Lawrence Carin. Improving sequence-to-sequence learning via optimal transport. In ICLR, 2019.

Kyunghyun Cho, Bart Van Merriënoorder, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. In EMNLP, 2014.

Marco Cuturi. Sinkhorn distances: Lightspeed computation of optimal transport. In NeurIPS, 2013.

William Fedus, Ian Goodfellow, and Andrew M Dai. Maskgan: Better text generation via filling in the _. In ICLR, 2018.
Maté Lengyel and Peter Dayan. Hippocampal contributions to control: the third way. In NeurIPS, 2008.

Chen Liang, Mohammad Norouzi, Jonathan Berant, Quoc Le, and Ni Lao. Memory augmented policy optimization for program synthesis with generalization. In NeurIPS, 2018.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, et al. Continuous control with deep reinforcement learning. In ICLR, 2016.

Kevin Lin, Dianqi Li, Xiaodong He, Zhengyou Zhang, and Ming-Ting Sun. Adversarial ranking for language generation. In NeurIPS, 2017.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In ECCV, 2014.

Siqi Liu, Zhenhai Zhu, Ning Ye, Sergio Guadarrama, and Kevin Murphy. Improved image captioning via policy gradient optimization of spider. In ICCV, 2017.

Jiasen Lu, Caiming Xiong, Devi Parikh, and Richard Socher. Knowing when to look: Adaptive attention via a visual sentinel for image captioning. In CVPR, 2017.

Tom Salimans, Han Zhang, Alec Radford, and Dimitris Metaxas. Improving GANs using optimal transport. In ICLR, 2018.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, et al. Continuous control with deep reinforcement learning. In ICLR, 2016.

Kevin Lin, Dianqi Li, Xiaodong He, Zhengyou Zhang, and Ming-Ting Sun. Adversarial ranking for language generation. In NeurIPS, 2017.
Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron C Courville, Ruslan Salakhutdinov, Richard S Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In ICML, 2015.

Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher Pal, Hugo Larochelle, and Aaron Courville. Describing videos by exploiting temporal structure. In CVPR, 2015.

Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. Seqgan: Sequence generative adversarial nets with policy gradient. In AAAI, 2017.

Mikhail Yurochkin, Sebastian Claici, Edward Chien, Farzaneh Mirzazadeh, and Justin Solomon. Hierarchical optimal transport for document representation. In NeurIPS, 2019.

Ruiyi Zhang, Changyou Chen, Zhe Gan, Wenlin Wang, Liqun Chen, Dinghan Shen, Guoyin Wang, and Lawrence Carin. Sequence generation with guider network. arXiv preprint arXiv:1811.00696, 2018a.

Ruiyi Zhang, Changyou Chen, Chunyuan Li, and Lawrence Carin. Policy optimization as wasserstein gradient flows. In ICML, 2018b.

Yizhe Zhang, Zhe Gan, Kai Fan, Zhi Chen, Ricardo Henao, Dinghan Shen, and Lawrence Carin. Adversarial feature matching for text generation. In ICML, 2017.

Yaoming Zhu, Sidi Lu, Lei Zheng, Jiaxian Guo, Weinan Zhang, Jun Wang, and Yong Yu. Texygen: A benchmarking platform for text generation models. In SIGIR, 2018.
A More Details about WSIL

Direct nested-Wasserstein Self-Imitation Learning

Direct nested-Wasserstein self-imitation learning (WSIL-D) weights the original rewards with outputs from the behavior policy for sequences in the replay buffer $B$. The sequences from the replay buffer are directly used as pseudo-samples to update the generator [Liang et al., 2018]. Similarly, define $r_{ns}(Y^s, Y) \triangleq \sum_j T_j \hat{r}_s(Y^s, Y_j)$, with $T^i = \{T_j^i\}$ the optimal weights, to be the nested-Wasserstein reward between the sequence $Y^s$ and ground-truth references $Y$. The general objective is then extended to be the objective for WSIL-D, as

$$J_D(\pi_\theta) \triangleq \mathbb{E}_{Y^s \sim \pi_\theta, X} \left[ r(Y^s) \right] + \lambda \mathbb{E}_{Y^s \sim \pi_\theta, X} \left[ r_{ns}(Y^b, Y) \pi_\theta(Y_b^b) \right],$$

where $r$ is the original RL reward; $r_{ns}$ is the nested-Wasserstein reward. Based on the objective of (11), we update the generator with standard RL loss and the self-imitation loss alternatively, with a hyperparameter $\lambda$ that controls the update frequency:

$$\nabla_\theta J_D(\pi_\theta) \approx -\sum_{k=1}^K \left[ (r(Y_k^s) - b) \nabla_\theta \log \pi_\theta(Y_k^s) \right] - \lambda \sum_{k=1}^K \left[ (r_{ns}(Y_k^b, Y) - b_b) \nabla_\theta \log \pi_\theta(Y_b^b) \right]$$

where $(\cdot)_+ = \max(\cdot, 0)$ and $b$ and $b_b$ are the baselines to reduce the variance of gradient estimates. In practice, $(\cdot)_+$ means that WSIL-D only imitates the sequences in the replay buffer with the higher rewards. Intuitively, direct self-imitation implicitly imposes larger weights on good simulated data for training, to exploit good historical explorations. The main difference between WSIL-D and its indirect counterpart is that sequences from the replay buffer are not used to compute the self-imitation rewards, but used to evaluate the policy. Intuitively, WSIL-D changes the data distribution to explore the good history more efficiently.

B Implementation Details

Replay Buffer Construction

In our algorithm, a metric is required to be designed to select high-reward history demonstrations, which will be stored in the replay buffer $D$. There are different ways for evaluating sentences:

$$J_D(\pi_\theta) \triangleq \mathbb{E}_{Y^s \sim \pi_\theta, X} \left[ r(Y^s) \right] + \lambda \mathbb{E}_{Y^s \sim \pi_\theta, X} \left[ r_{ns}(Y^b, Y) \pi_\theta(Y_b^b) \right],$$

where $r$ is the original RL reward; $r_{ns}$ is the nested-Wasserstein reward. Based on the objective of (11), we update the generator with standard RL loss and the self-imitation loss alternatively, with a hyperparameter $\lambda$ that controls the update frequency:

$$\nabla_\theta J_D(\pi_\theta) \approx -\sum_{k=1}^K \left[ (r(Y_k^s) - b) \nabla_\theta \log \pi_\theta(Y_k^s) \right] - \lambda \sum_{k=1}^K \left[ (r_{ns}(Y_k^b, Y) - b_b) \nabla_\theta \log \pi_\theta(Y_b^b) \right]$$

where $(\cdot)_+ = \max(\cdot, 0)$ and $b$ and $b_b$ are the baselines to reduce the variance of gradient estimates. In practice, $(\cdot)_+$ means that WSIL-D only imitates the sequences in the replay buffer with the higher rewards. Intuitively, direct self-imitation implicitly imposes larger weights on good simulated data for training, to exploit good historical explorations. The main difference between WSIL-D and its indirect counterpart is that sequences from the replay buffer are not used to compute the self-imitation rewards, but used to evaluate the policy. Intuitively, WSIL-D changes the data distribution to explore the good history more efficiently.

ii) For unconditional generation with real data, since we will use Test BLEU score and Self BLEU score for evaluating generated sentences, we maintain a single large replay buffer with BLEU-F1 score as the selection criteria to evaluate quality and diversity trade-off [Gu et al., 2019]. F1-BLEU score is defined as the geometry average of BLEU score and $1 -$ Self-BLEU

$$F1_{\text{BLEU}} = \frac{2 \times \text{BLEU} \times (1 - \text{Self-BLEU})}{\text{BLEU} + (1 - \text{Self-BLEU})}. \quad (13)$$

iii) For conditional generation with captioning task, we maintain a small ($K' = 5$ sequences) replay buffer for each conditional input; the replay buffer seems large, but we only need to store sequences of indexes, which is very efficient. Here we use the nested Wasserstein rewards as the metric.

iv) For conditional generation with non-parallel style transfer, we maintain a large replay buffer storing successfully transferred pairs, and we define a metric which considers both the accuracy and content preservation: $p(\text{Right Style}) \times \text{BLEU}$.
as generalized decaying learning rate. With more explorations, $\lambda$ becomes larger, and the algorithm should focus more on the self-imitated learning. In practice, we do one self-imitated learning update with every 10 RL training updates, and as training proceeds, we increase the frequency of self-imitation, and finally update the generator with one-step self-imitation followed with one-step standard RL training.

### The trick of soft-argmax

Recall that in sequence generation, one first samples a token based on the policy, then feeds its token embedding into the RNN to compute the logits of the next token, and repeat the above process based on the logits again until the stop token is generated. Instead of using the embedding of a sampled token, the soft-argmax trick feeds the RNN with the weighted average of the embeddings of most-likely tokens. In particular, let $E$ be the word embedding matrix, $g_t$ be the logits under the current policy and $s_t$ be the hidden state of the policy $\pi_\theta$. With the soft-argmax trick, the state vector is updated by

$$
\tilde{y}_t = E \cdot \text{softmax}(g_t / \beta),
$$

$$
\tilde{s}_t = h(\tilde{s}_{t-1}, e(\tilde{y}_t)),
$$

where $0 < \beta < 1$ is the annealing factor, and in practice, we set $\beta = 0.01$.

### Discriminator implementation

In unconditional generation, instead of using policy gradient and the output of the discriminator as rewards, we use the soft-argmax trick [Hu et al., 2017]. Since the policy gradient is not stable enough and soft-argmax trick gives us better performance (See our extensive experiments).

### Nested-Wasserstein rewards implementation

In conditional generation, the Wasserstein rewards is implemented based on COCO test tools, and we use the fasttext [Mikolov et al., 2018] as the fixed word embedding to compute the reward. In practice, we use $K = 5$ with a hyper-parameter search from $\{3, 5, 8, 10\}$. We will release this code, which is easy to use as other metrics. For unconditional generation, we use the fixed learned word embedding via stop its gradient, where the embedding and the Wasserstein trust region are jointly optimized.

We conduct experiments on synthetic data similar to [Yu et al., 2017], where our implementation is based on LeakGAN. The result is shown in Figure 3, where WSIL-I and WSIL-D show better performance than LeakGAN. Specifically, LeakGAN is not stable in the training and the Negative log-likelihood increases after 150 epochs. Compared with LeakGAN, WSIL-I and WSIL-D are more stable.

### Experimental Setup

#### Conditional text generation

We consider image captioning using the COCO dataset [Lin et al., 2014], which contains 123,287 images in total, each of which is annotated with at least 5 captions. Following Karpathy’s split [Karpathy and Fei-Fei, 2015], 113,287 images are used for training and 5,000 images are used for validation and testing. We follow the implementation of the SCST approach [Rennie et al., 2016], and use extracted image tags [Gan et al., 2017, Wang et al., 2019] as image features (encoder). The learning rate of the generator is 0.0002, the maximum length of sequence is set to 25. For video captioning, the learning rate of the generator is 0.0001, the maximum length of sequence is set to 30. We use fixed image features and do not finetune the image encoder following previous work. A one-layer LSTM with 1024 units is used as the decoder. The word-embedding dimension is set to 512.

#### Unconditional text generation

We use the COCO dataset [Lin et al., 2014], in which most sentences are of length about 10. Since we consider unconditional text generation, only image captions are used as the training data. After preprocessing, the training dataset consists of 27,842 words and 417,126 sentences. We use 120,000 random sample sentences as the training set, and 10,000 as the test set. For the COCO dataset, the learning rate of the generator is 0.0002, the learning rate of the manager is 0.0002 (we follow the LeakGAN work), and the maximum length of sequence is set to 25.

Following Zhu et al., 2018, we use the News section in the EMNLP2017 WMT4 Dataset as our training data, which consists of 646,459 words and 397,726 sentences. After preprocessing, the training dataset contains 5,728 words and 278,686 sentences. The learning rate of the generator is 0.0002, the learning rate of the manager is 0.0002, and the maximum length of sequence is set to 50. The number of hidden units used in both the LSTM for the generator and the manager are set to 128. The dimension of the word embedding is 300. The discriminator is a CNN with its structure specified in Table 7.

#### Settings of human evaluation

We perform human evaluation using Amazon Mechanical Turk, evaluating the text quality based on readability and meaningfulness (whether sentences make sense). We ask the worker to rate the input sentence with scores scaling from 1 to 5, with criterion listed in Table C. We require all the workers to be native English speakers, with approval rate higher than 95% and at least 100 assignments completed.
Nested-Wasserstein Self-Imitation Learning for Sequence Generation

| Sequence to a scalar value |
|-----------------------------|
| Input 300× Seq. Length Sequences |
| (Kernel Size: Num(×300), Kernel Numbers) |
| (1, 100),(2, 200),(3, 200),(4, 200),(5, 200) |
| (6, 100),(7, 100),(8, 100),(9, 100),(10, 100) |
| (16, 160),(20, 160),(30, 160),(40, 160) |
| MLP output 1, ReLU |

Table 7: Architecture of the discriminator.

| Scores | Criterion |
|--------|-----------|
| 5 (Best) | It is consistent, informative, grammatically correct. |
| 4 | It is grammatically correct and makes sense. |
| 3 | It is mostly meaningful and with small grammatical error. |
| 2 | It needs some time to understand and has grammatical errors. |
| 1 (Worst) | Meaningless, not readable. |

Table 8: Human evaluation rating criterion.

| Dataset                  | Train  | Test  | Vocabulary | Average Length |
|--------------------------|--------|-------|------------|----------------|
| Synthetic                | 10,000 | 10,000| 5,000      | 20             |
| COCO captions            | 120,000| 10,000| 27,842     | 11             |
| WMT News                 | 278,686| 10,000| 5,728      | 28             |

Table 9: Brief description of the datasets used in unconditional text generation.

D Generated Samples of Unconditional Text Generation

We show the generated samples of EMNLP NEWS2017 in Table 10, Table 11 and MS COCO in Table 12. Please Note all the samples are randomly selected from the generated sentences, without any human selection. It is obvious to see the diversity of LeakGAN is very poor in MSCOCO Captions, since it keeps generating sentences started with ‘a’. Our proposed methods are more similar to the real data.

E Generated Samples of Image Captioning

We show the generated samples of Image Captioning in Figure 7. We compares WSIL-D with SIL-D. We highlight benefits of using Wasserstein rewards, and put scores of each candidate.
| Methods | Generated Examples |
|---------|-------------------|
| **Real Data** | But public opposition to the policy has been growing in other countries, and Austria on Wednesday announced an overall limit over the next four years of 130, 000 - or the equivalent of 1. 5 per cent of the population. Company is that the government will put the draft to a referendum, which is expected in July though no date has been fixed. I feel that sometimes the people accept me the way I am and other times they don’t accept me at all. For years the state told us we were crazy, that our water was safe, which wasn’t true. It provides less accommodation of companies engaged in high - cost development and more reward for those that can lower their cost structures. When you win a title you gain confidence, and the supporters love you, because they want to win things as well. The combined value of the contracts is about $ 8 . 3 million but could nearly double once additional funding is provided. He also imposed conditions on a release on bond that include being placed on an electronic monitor, drug testing and reporting weekly to authorities. Only then would a discussion begin within the Justice Department over whether to pursue any legal action against Clinton or anyone else involved in the matter. Andy Hall, an advocate for migrants who advised defence lawyers in the case, said the defence requested additional DNA-related documents from the prosecution but they were not provided. Wales put tickets for its three home matches - versus Scotland, France and Italy - on general sale back in October, with Scotland tickets now completely sold out. |
| **LeakGAN** | It’s not easy but I have to be with the fact that the problem is probably: “I like me,” he said. "This is the lie that Ted’s campaign is built on," Rubio said of his fellow challenge as the EU to vote for prime minister. The new rules mean that international companies will have to tell the country they operate in what they make in up companies do just over their year as they have a very high out. The team of Ohio State researchers set out to determine what they had been "more "head of an "a "country or seven, according to the public of the incident. As a result, most people believed they were voting for his voice is only going to get the data right when he is there. The main thing for us is to keep it as a long - term - wide range of travel, that their calls for students or twice - and - she said. The committee also said some people decide to move as many as the highest - child coalition can get the little of better - and - have done in the attacks, at the point when they are having the best chance of the victory. The report, however, was a child’s first child in the ISIS commander, the second half since the past seven years, it has been No on the family who do not have a gun control. |
| **WSIL-D** | A report from Kings College London last year revealed that members of the UK armed forces are twice as likely to develop depression or anxiety than members of the general working population. We need to identify with him on a human level, to understand whatever he does in his job in Afghanistan he’s also affected by stuff that happens at home. She said she was in the car park when Campbell climbed into the driver’s seat of a vehicle, prompting her to offer him £ 20 to get a taxi instead. A report published by NHS England found it had failed to investigate hundreds of deaths over four months before the 2020 election and they did not want to even more common if they are. You need to be absolutely totally clear about which customers you are going to see a lot of people out. In the UK, parents, local authorities, charities, the media and politicians have all bought into the schools - can - fix - it narrative. The annual report, on behalf of the Welsh government, also found more people than ever are being treated. In his view, although he can be seen with a £ three million to expand its annual million to income out 4 per cent. It was the first day I fell in with the first year I’ve ever been playing for a long - term plan for 45 per cent. And then I ran into him out a few months later and we started hanging out and now we are in a relationship with that we all. A decision from the ACT on the dispute between the national energy regulator and the power networks was due by December 22, but the ACT advised before Christmas it could be up to three months late. |
| **WSIL-I** | He said he was using his executive powers as president because the US Congress has failed to address the problem. When I would make my meals for my family, I would double it and bring a meal of the year’s heart,” she says, at the time. We accept all the recommendations for the Ministry of Justice in this report and are already taking action to implement them. This has been a dream scared, but for the long - term goal would stay be from class - to - the - quarter down. The Trump campaign will air the ad in the early - voting states of Iowa, New Hampshire, and South Carolina. Both winners said the crowds at this year’s event seemed similar to last year, although official numbers found the four-day crowd was slightly smaller at just over 100,000. But the one good thing we can take from this is it’s happened quite early in the wet season and, what more people are. It’s nice to know that I am wanted. I have lost a lot of confidence in myself over the last two days,” he said. The president responded that those criminals illegally purchase weapons from others who should’ve been subject to background checks. I’ve got worse since this started, I’ve isolated myself even more over the last couple of months. According to Swedish Radio, police want up to 2, 500 more officers and 1, 600 new civilian workers by the year 2020. I don’t know what the truth is and I don’t, as a regular citizen, know how to find that information out. We might think we know where we’re going, but the way ahead, and the path behind, when the show was to work out. He was told that he didn’t even think he could have had information but to the evidence to make a couple of weeks. It’s great that we hold ourselves back and we know about every January we had the best of the season we’ll have just as to be the best in the world. |

Table 10: Generated examples on EMNLP2017 WMT.
Methods | Generated Examples
--- | ---
SeqGAN | Following the few other research and asked for " based on the store to protect older, nor this. But there, nor believe that it has reached a the person to know what never - he needed. The trump administration later felt the alarm was a their doctors are given. We have been the time of single things what people do not need to get careful with too hurt after wells then. If he was waited same out the group of fewer friends a more injured work under it. It will access like the going on an " go back there and believe. Premier as well as color looking to put back on a his is. So, even though: " don ' t want to understand it at an opportunity for our work. I was shocked, nor don ' t know if mate, don ' t have survived, So one point like ten years old, but a sure, nor with myself more people substantial. And if an way of shoes of crimes the processes need to run the billionaire. Now that their people had trained and people the children live an actor, nor what trump had. However, heavily she been told at about four during an innocent person.

MLE | Two separate officials are making a statement for comment, and people believe that the technology had started the act with several thousand in a million new location. It ' s just that this attack is not used to the water there ' s been a lot to gain in the middle of their water, she said on Monday. It is the first time the media science shows that women are here to be married, but this will never be forgotten. I wouldn ' t have made it down for my money, but I ' m happy to stay on, he says. They think much is really the most important place to do with that, because the educational situation will be on the way forward. I had a long time and investigators have said that it will be the wrong decision to establish cases, he said. We will be trying to work with both of us to vote for the, for the next cabinet to get to the bottom of the negotiations, he said. He had no a proper question I thought I was going to host over such a long time, he added. We ' ve become more competitive, because it ' s a great year and we ' re going to do that. You therefore have to understand the way our response goes the light we will on on this, the source said.

SIL-D | He had a couple of clear, he had to be able to lead to be after he was seen as a result from the kind of type of involvement of both. The company has said the final phase in its special group will be the police, they have to believe it. But instead of helping her 15 years, but the most of permission down from some of the Republicans, he said, and he wants to be an all one to the next in - one - a Republican debate. Go out and share the main entry of all the Syrian civil war, should to confirm the difficult, make response to the wrong end of the financial crisis.

SIL-I | To have a good group of quality quality abuse is a route - and is still there to yourself health, and how to feel is going to put on the roads a day, it ' s fine. At some point it is, he has come to work hard for a few minutes to get the right up and they ' re not going. He thought that at the time she had done to take a couple of hours again before she ' s emails. The most recent trade numbers had 3. 4 percent of one in the national sector in the first few months. He said: ' It is entirely possible that there ' s some people who are going to get to earn it up," he said. I think my business is very good very talented, and you are, and that the things that you can ' t teach, you ' re going to be fair - you need to.

Table 11: Generated examples on EMNLP2017 WMT.
| Method       | Generated Examples                                                                                                                                 |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------|
| **Real Data**| a surfer a woman and a child walk on the beach .  
a few people sit on a dim transportation system .  
a person protected from the rain by their umbrella walks down the road .  
the bathroom with a toilet has an interesting sink .  
two women preparing food in a kitchen one at the sink and one at the table .  
a white kitchen in a home with the light on .  
a cat stuck in a car with a slightly opened window .  
two bicycles and a woman walking in front of a shop .  
green tiled backsplash highlighted by low overhead lighting .  
a bicycle is parked by a bench at night .  
a brown horse is grazing grass near a red house . |
| **LeakGAN**  | a bike parked in a bunch of grass on a sidewalk in front of a yellow and a yellow bus on a road .  
a dog is jumping high in the air .  
the bathroom is clean and ready for us to use .  
a woman in a bikini rides a skateboard .  
a bathroom with a mirror and a picture on the wall above .  
a bathroom with a toilet and a shower .  
a cat sitting on the roof of an old car .  
a bathroom with a toilet and a bathtub .  
a couple of people walking across a street holding an umbrella .  
a man sitting in front of a laptop computer on a counter . |
| **WSIL-D**   | a large bathroom with a long marble shower .  
a bath and sink in a room with a large mirror .  
there is a woman that is sitting in the sink while the photo of a dog .  
white glass table sitting on top of a living room .  
woman in a blue dress sitting on a city street talking on a telephone .  
a person is taking a flash photo in a mirror .  
a bathroom sink with a mirror just above it .  
two guys are talking in a field with a blue bike in front of it as a train car .  
a nice bathroom with a standalone shower and a shower curtain .  
the corner of a rest room with toilet paper .  
a boy holding some yellow umbrella next to a street .  
some tables in a small wooden kitchen area . |
| **WSIL-I**   | cat standing in sink and another woman in black tiled floor .  
a bathroom with tiled walls has a mirror on the wall .  
a black and white cat in a bathroom sink .  
the man is standing on his bike with the beach behind him .  
a person riding a long board down a road in front of a parked car .  
a bicycle and some pictures on the street corner with the car .  
the bathroom tub with ceramic tub has a glass door .  
a large modern lighted space with bath tub .  
the kitchen is preparing an elaborate appliances it .  
a guy jumping high in the air with people in around around .  
this family a man talks on his cell phone .  
a public toilet with the seat up in a bathroom .  
this kitchen with white cupboards and stainless steel oven in someones home . |

Table 12: Generated examples on COCO.
| Images | References | Hypothesis |
|--------|------------|------------|
| ![Image](image1.png) | 1. young man on a skateboard trying simple tip up stunt 2. young skateboarder displaying skills on sidewalk near field 3. a person on a skateboard on a street 4. a young boy is *performing tricks* on a skateboard 5. a little boy that is jumping a skateboard | a man riding a skateboard on a ramp CIDEr: 1.2375203331 Wasserstein: 64.5707599929 |
| ![Image](image2.png) | 1. tennis player holding a tennis racket on a court 2. two people playing a match of tennis on a court 3. a man with a tennis racket walks from the net of a tennis court 4. a man standing on a tennis court holding a racquet 5. a man in shorts and a long sleeve shirt playing tennis | a man doing a trick on a skateboard on a ramp CIDEr: 1.0138281793 Wasserstein: 65.7397472556 |
| ![Image](image3.png) | 1. a fire hydrant on a sidewalk near a street 2. there is a fire hydrant on the side of the road 3. a fire hydrant sitting on the side of a road 4. a *green* fire hydrant sitting by a yellow pole 5. a fire hydrant that is on a sidewalk | a fire hydrant on the side of a street CIDEr: 3.45013175762 Wasserstein: 76.402286692 |
| ![Image](image4.png) | 1. a full plate full of delicious food sets on top of the table 2. plate with dinner items on it on a white table cloth 3. a plate with *chicken scallops* pasta and other food items 4. a plate of food and a fork on a table 5. a white plate topped with *chicken coleslaw and potatoes* | a plate of food on a table with an CIDEr: 1.15756194919 Wasserstein: 66.016523321 |
| ![Image](image5.png) | 1. one man rides a skateboard down an empty pool while another man watches 2. two men in a drained pool one on a skateboard the other holding a skateboard 3. two guys are skateboarding in an empty pool 4. some teenage boys skateboard inter he park 5. a person on a skateboard on a ramp | a man riding a skateboard on a skate park CIDEr: 0.959694148787 Wasserstein: 61.8797805118 |
| ![Image](image6.png) | 1. a giraffe that is laying on the ground 2. giraffe lays down in an enclosure 3. some giraffes dirt trees fence and a building 4. a giraffe sitting down while another giraffes eats on branches 5. three giraffes one seated on some dirt the other two standing | a group of giraffes standing next to a giraffe CIDEr: 1.0495772431 Wasserstein: 57.070483353 |

Figure 7: Image captioning examples on COCO. Top: SIL-D; Bottom: WSIL-D. The examples are shown to highlight the benefits given by the Wasserstein rewards. As a gram-based hard-matching metric, CIDEr rewards focus more on the locality fluency and may render incomplete sentences. Wasserstein rewards focus more on semantic matching. WSIL provides a natural way to combine both benefits.