Multi-turn Dialogue Response Generation in an Adversarial Learning Framework

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Abstract

We propose an adversarial learning approach to the generation of multi-turn dialogue responses. Our proposed framework, hredGAN, is based on conditional generative adversarial networks (GANs). The GAN’s generator is a modified hierarchical recurrent encoder-decoder network (HRED) and the discriminator is a word-level bidirectional RNN that shares context and word embedding with the generator. During inference, noise samples conditioned on the dialogue history are used to perturb the generator’s latent space to generate several possible responses. The final response is the one ranked best by the discriminator. The hredGAN shows major advantages over existing methods: (1) it generalizes better than networks trained using only the log-likelihood criterion, and (2) it generates longer, more informative and more diverse responses with high utterance and topic relevance even with limited training data. This superiority is demonstrated on the Movie triples and Ubuntu dialogue datasets in terms of perplexity, BLEU, ROUGE and Distinct n-gram scores.

1 Introduction

Recent advances in deep neural network architectures have enabled tremendous success on a number of difficult machine learning problems. Deep recurrent neural networks (RNNs) in particular are achieving impressive results in a number of tasks involving the generation of sequential structured outputs, including language modeling [1], machine translation [2,3], image tagging [4], visual and language question and answering [5], speech recognition [6], and so on. While these results are impressive, producing a deployable neural network–based conversation model that can engage in open domain discussion still remains elusive. A dialogue system needs to be able to generate meaningful and diverse responses that are simultaneously coherent with the input utterance and the overall dialogue topic. Unfortunately, earlier conversation models trained with naturalistic dialogue data suffered greatly from limited contextual information [7,8] and lack diversity [9]. These problems often leads to generic and safe utterance in response to varieties of input utterance.

Serban et al. [10] and Xing et al. [11] proposed the Hierarchical Recurrent Encoder-Decoder (HRED) network to capture long temporal dependencies in multiturn conversations to address the limited

*Use footnote for providing further information about author (webpage, alternative address)—not for acknowledging funding agencies.

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contextual information but the diversity problem remained. On the other hand, some HRED variants such as variational [12] and multiresolution [13] HREDS attempt attempt to alleviate the diversity problem by injecting noise at the utterance level and by extracting additional context to condition the generator on. While these approaches achieve certain measures of success over the basic HRED, generated responses are still mostly generic since they do not control the generator’s output. Li et al. [9], on the other hand, consider diversity promoting training objective but their model is for single turn conversations, cannot be trained end-to-end and therefore achieves little.

The generative adversarial network (GAN) [14] seems to be an appropriate solution to this problem of exposure bias. GAN matches data from two different distributions by introducing an adversarial game between a generator and a discriminator. Much recent work, [15-19] except for Li et al. [16] has explored this idea for unconditional sequence generation, which has no control on the modes of the data being generated. This cannot be used for dialogue generation because generated responses should be consistent with the dialogue input and overall topic.

In order to solve this problem, we turn to the conditional GAN [20-23]. We explore hredGAN: conditional GANs for multiturn dialogue models with HRED generator and discriminator. hredGAN combines both generative and retrieval-based multi-turn dialogue systems to improve their individual performances. This is achieved by sharing the context and word embedding between the generator and the discriminator allowing for joint end-to-end training using back-propagation. To the best of our knowledge, no existing work has applied conditional GANs to multiturn dialogue models and especially with HRED generators and discriminators. We demonstrate the effectiveness of hredGAN for dialogue modeling with evaluations on the Movie triples and Ubuntu technical support datasets.

### 2 Model

#### 2.1 Adversarial Framework for Mult-turn Dialogue Response Generation

Consider a dialogue consisting of a sequence of $N$ utterances, $X = (X_1, X_2, \ldots, X_N)$, where each utterance $X_i = (X_i^1, X_i^2, \ldots, X_i^{|M_i|})$ contains a variable-length sequence of $|M_i|$ word tokens such that $X_i^j \in V$ for vocabulary $V$. At any time step $i$, the dialogue history is given by $X_i = (X_1, X_2, \ldots, X_i)$. The dialogue response generation task can be defined as follows: Given a dialogue history $X_i$, generate a response $Y_i = (Y_i^1, Y_i^2, \ldots, Y_i^{T_i})$, where $T_i$ is the number of generated tokens. We also want the distribution of the generated response $P(Y_i)$ to be indistinguishable from that of the ground truth $P(X_{i+1})$ and $T_i = |M_{i+1}|$. Given the conditioning of response generation on dialogue history and the need to match the estimated and ground truth response distributions, we propose a conditional GAN as a solution. Conditional GAN learns a mapping from an observed dialogue history, $X_i$, and a sequence of random noise vectors, $Z_i$ to a sequence of output tokens, $Y_i$. $G : (X_i, Z_i) \rightarrow Y_i$. The generator $G$ is trained to produce output sequences that cannot be distinguished from the ground truth sequence by an adversarially trained discriminator $D$ that is trained to do well at detecting generator’s fakes. The distribution of the generator output sequence

| Item | $D(G(\cdot))$ | Utterance |
|------|---------------|-----------|
| **MFC** | Context_0 NA | perhaps <person> had a word with the man upstairs. |
|       | Context_1 NA | a word ? i`m sure by now he `s engineered a hostile takeover |
|       | Response_0 0.996 | <person>, i know what you`re saying <person>, that` s not what i`m saying |
|       | Response_1 0.991 | <person>, i know i was just about to help the guy |
|       | Response_2 0.315 | <person>, i`m sorry |
|       | Response_3 0.203 | <person>, i`m a little out |
| **UDC** | Context_0 NA | says he wanted food <person>, he wanted the gold |
|       | Context_1 NA | how`s he going to want the gold? he couldn`t even know we had it |
|       | Response_0 0.998 | <person>, i know but it` s not him, it` s the only way he` s got it all figured |
|       | Response_1 0.981 | <person>, i know but i have to tell you these things are really stupid and you think i was wrong? |
|       | Response_2 0.690 | <person>, i`m sure he did |
|       | Response_3 0.314 | <person>, i`m not sure |
|       | Response_4 0.003 | you a. 1.1.1.1.1.1.unk. deb |
| **MTC** | Context_0 NA | perhaps <person> had a word with the man upstairs |
|       | Context_1 NA | a word? i`m sure by now he` s engineered a hostile takeover |
|       | Response_0 0.996 | <person>, i know what you`re saying <person>, that` s not what i`m saying |
|       | Response_1 0.991 | <person>, i know i was just about to help the guy |
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|       | Response_2 0.315 | <person>, i`m sorry |
|       | Response_3 0.203 | <person>, i`m a little out |

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Table 1: Example of Discriminator Re-ranking with hredGAN_w
can be factored by the product rule:

\[ P(Y_i|X_i) = P(Y_i^1) \prod_{j=2}^{T_i} P(Y_i^j|Y_i^{j-1}, X_i) \]  

(1)

\[ P(Y_i^j|Y_i^{j-1}, X_i) = P_{\theta_G}(Y_i^{j-1}, X_i) \]  

(2)

where \( Y_i^{j-1} = (Y_i^1, \ldots, Y_i^{j-1}) \) and \( \theta_G \) are the parameters of the generator model. \( P_{\theta_G}(Y_i^{j-1}, X_i) \) is an autoregressive generative model where the probability of the current token depends on the past generated sequence. Training the generator \( G \) is unstable in practice, and therefore the past generated sequence is substituted with the ground truth, a method known as teacher forcing [24], i.e.,

\[ P(Y_i^j|Y_i^{\leq j-1}, X_i) \approx P_{\theta_G}(X_i^{j-1}, X_i) \]  

(3)

Using (3) in relation to GAN, we define our fake sample as the teacher forcing output with some input noise \( Z_i \)

\[ Y_i^j \sim P_{\theta_G}(X_i^{j-1}, X_i, Z_i) \]  

(4)

and the corresponding real sample as ground truth \( X_i^{j+1} \). With the GAN objective, we can match the noise distribution, \( P(Z_i) \) to the distribution of the ground truth response, \( P(X_i^{j+1}|X_i) \). Varying the noise input then allows us to generate diverse responses to the same dialogue history. Furthermore, the discriminator is used during inference to rank the generated responses, providing a means of controlling the generator output.

### 2.1.1 Objectives

The objective of a conditional GAN can be expressed as

\[ \mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{X_i, X_{i+1}}[\log D(X_{i+1}, X_i)] + \mathbb{E}_{X_i, Z_i}[1 - \log D(G(X_i, Z_i), X_i)] \]  

(5)

where \( G \) tries to minimize this objective against an adversarial \( D \) that tries to maximize it:

\[ G^*, D^* = \arg\min_G \arg\max_D \mathcal{L}_{cGAN}(G, D). \]  

(6)

Previous approaches have shown that it is beneficial to mix the GAN objective with a more traditional loss such as cross-entropy loss [18] [15]. The discriminator’s job remains unchanged, but the generator is tasked not only to fool the discriminator but also to be near the ground truth \( X_{i+1} \) in the cross-entropy sense:

\[ \mathcal{L}_{MLE}(G) = \mathbb{E}_{X_i, X_{i+1}, Z_i}[-\log P_{\theta_G}(X_{i+1}, X_i, Z_i)]. \]  

(7)

Our final objective is,

\[ G^*, D^* = \arg\min_G \arg\max_D (\lambda_G \mathcal{L}_{cGAN}(G, D) + \lambda_M \mathcal{L}_{MLE}(G)). \]  

(8)

It is worth mentioning that, without \( Z_i \), the net could still learn a mapping from \( X_i \) to \( Y_i \), but would produce deterministic outputs and fail to match any distribution other than a delta function [22]. This is one key area where our work is different from Lamb et al.’s and Li et al.’s. The schematic of the proposed hredGAN is depicted at the right hand side of Figure [1].

### 2.1.2 Generator

We adopted an HRED dialogue generator similar to [10] [13] [12] [11]. The HRED contains three recurrent structures, unlike Seq2Seq [3], which has two. The HRED consists of the encoder (\( eRNN \)), context (\( cRNN \)), and decoder (\( dRNN \)) RNN. The conditional probability modeled by the HRED per output word token is given by

\[ P_{\theta_G}(Y_i^j|X_{i+1}^{j-1}, X_i) = dRNN(E(X_{i+1}^{j-1}), h_{i+1}^{j-1}, h_i) \]  

(9)

where \( E(.) \) is the embedding lookup, \( h_i = cRNN(eRNN(E(X_i), h_{i-1}), eRNN(.) \) maps a sequence of input symbols into fixed-length vector, and \( h \) and \( h \) are the hidden states of the decoder and context RNN, respectively.
**Figure 1:** Right: The hredGAN architecture - The generator makes predictions conditioned on the dialogue history, $h_i$, attention, $A^j_i$, noise sample, $Z^j_i$, and ground truth, $X^j_{i+1}$. The discriminator conditioned on $h_i$ distinguishes between the generated output $\{Y^j_M\}_{j=1}^{M_i+1}$ and ground truth $\{X^j_{i+1}\}_{j=1}^{M_i+1}$.

Left: RNN-based discriminator that discriminates bidirectionally at the word level.

**Figure 2:** The HRED generator with local attention - The attention RNN ensures local relevance while the context RNN ensures global relevance. Their states are combined to initialize the decoder RNN and the discriminator BiRNN.

In the multi-resolution HRED, [13], high-level tokens are extracted and processed by another RNN to improve performance. We circumvent the need for this extra processing by allowing the decoder to attend to different parts of the input utterance during response generation [2, 25]. We introduce a local attention into (9) and encode the attention memory differently from the context through an attention encoder RNN ($aRNN$), yielding:

$$P_{th}(Y^j_i|X^j_{i+1}^{j-1}, X^j_i) = dRNN(E(X^j_{i+1}^{j-1}), h^j_i, A^j_i, h_i)$$ (10)

where $A^j_i = \sum_{m=1}^{M_i} \alpha^j_m \exp(\alpha^j_m) h^j_i, h^m_i = aRNN(E(X^j_i), h^m_i), h^m_i$ is the hidden state of the attention RNN and $\alpha^j_m$ is either a logit projection of $\langle h^j_{i-1}, h^m_i \rangle$ in the case of [2] or $\langle h^j_{i-1} \rangle^T \cdot h^m_i$ in the case of [25]. The modified HRED architecture is shown in Figure 2.

**Noise Injection:** We inject Gaussian noise at the input of the decoder RNN. Noise samples could be injected at the utterance or word level. With noise injection, the conditional probability of the decoder output becomes

$$P_{th}(Y^j_i|X^j_{i+1}^{j-1}, Z^j_i, X^j_i) = dRNN(E(X^j_{i+1}^{j-1}), h^j_i, A^j_i, Z^j_i, h_i)$$ (11)

where $Z^j_i \sim N_i(0, I)$ for utterance-level noise and $Z^j_i \sim N_i^j(0, I)$, for word-level noise.
2.1.3 Discriminator

The discriminator shares context and word embedding with the generator and can discriminate at the word level [18]. The word-level discrimination is achieved through a bidirectional RNN and is able to capture both syntactic and conceptual differences between the generator output and the ground truth. The aggregate classification of an input sequence, \( \chi \), can be factored over word-level discrimination and expressed as

\[
D(X_i, \chi) = D(h_i, \chi) = \left[ \prod_{j=1}^{J} D_{RNN}(h_i, E(\chi^j)) \right]^{\frac{1}{2}} \tag{12}
\]

where \( D_{RNN}(\cdot) \) is the word discriminator RNN, \( h_i \) is an encoded vector of the dialogue history \( X_i \) obtained from the generator’s CRNN(\( \cdot \)) output, and \( \chi^j \) is the \( j \)th word or token of the input sequence \( \chi \). \( \chi = Y_i \) and \( J = T_i \) for the case of generator’s decoder output, \( \chi = X_{i+1} \) and \( J = M_{i+1} \) for the case of ground truth. The discriminator architecture is depicted on the left hand side of Figure [1].

2.2 Adversarial Generation of Multi-turn Dialogue Response

In this section, we describe the generation process during inference. The generation objective can be mathematically described as

\[
Y_i^* = \arg \max _i \{ P(Y_i, i | X_i) + D^*(X_i, Y_i, i) \}^{L}_{l=1} \tag{13}
\]

where \( Y_{i,l} = G^*(X_i, Z_{i,l}), Z_{i,l} \) is the \( l \)th noise samples at dialogue step \( i \), and \( L \) is the number of response samples. Equation (13) shows that our inference objective is the same as the training objective [5], combining both the MLE and adversarial criteria. This is in contrast to existing work where the discriminator is usually discarded during inference.

The inference described by Equation (13) is intractable due to the enormous search space of \( Y_{i,l} \). Therefore, we turn to an approximate solution where we use greedy decoding (MLE) on the first part of the objective function to generate \( L \) lists of responses based on noise samples \( \{Z_{i,l}\}^{L}_{l=1} \). In order to facilitate the exploration of the generator’s latent space, we sample a modified noise distribution, \( Z_{i,l}^* \sim N_{i,l}(0, \alpha I) \), or \( Z_{i,l}^* \sim N_{i,l}(0, \alpha I) \) where \( \alpha > 1.0 \), is the exploration factor that increases the noise variance. We then rank the \( L \) lists using the discriminator score, \( \{D^*(X_i, Y_{i,l})\}^{L}_{l=1} \). The response with the highest discriminator ranking is the optimum response for the dialogue context.

3 Related Work

Our work is related to end-to-end neural network–based open domain dialogue models. Most neural dialogue models use transduction frameworks adapted from neural machine translations [7][2]. The architecture is an encoder-decoder recurrent network (Seq2Seq) and is used to learn the source-to-target relationship between an input utterance and the output response. There are many works in the area of open domain dialogue, including [26][28][9][9][30]. These networks are trained end-to-end with MLE criteria using large corpora of human-to-human conversation data. Other conversation Seq2Seq models are trained with the GAN framework alone [16] or in conjunction with MLE [18], otherwise known as professor forcing. Others use GAN’s discriminator as a reward function in a reinforcement learning framework [15] and in conjunction with MLE [16][17]. Zhang et al. [19] explored the idea of GAN with a feature matching criterion.

Still, Seq2Seq models are limited in their ability to capture long temporal dependencies in multi-turn conversation. Hence, the introduction of HRED models [10][14][12][11] for modeling dialogue response in multi-turn conversation. However, these HRED models suffer from lack of diversity since they are trained with only MLE criteria. On other hand, adversarial system has been used for evaluating open domain dialogue models [31][32]. Our work, hredGAN is closest to the combination of HRED generation models [10] and adversarial evaluation [32].

4 Training of hredGAN

We trained both the generator and the discriminator simultaneously as highlighted in Algorithm [1] with \( \lambda_G = \lambda_M = 1 \). GAN training is prone to instability due to competition between the generator and the discriminator. We need to keep the discriminator from becoming too good at discrimination,
making the adversarial loss useless to the generator. At the same time, we have to make sure that the discriminator is not returning very poor loss to the generator. Therefore, parameter updates are conditioned on the discriminator performance \[18\]. To achieve this, the discriminator is only updated when its accuracy is less than \(acc_{Dth}\). If the discriminator accuracy is less than \(acc_{Gth}\), the generator is updated using only the gradients from the MLE loss. Otherwise, it is updated with gradients from the combined MLE and adversarial losses.

The **generator** consists of four RNNs with different parameters, that is, \(aRNN, eRNN, cRNN,\) and \(dRNN\). \(aRNN\) and \(eRNN\) are both bidirectional, while \(cRNN\) and \(dRNN\) are unidirectional. Each RNN has 3 layers, and the hidden state size is 512. The \(dRNN\) and \(aRNN\) are connected using an additive attention mechanism [2].

The **discriminator** shares \(aRNN, eRNN,\) and \(cRNN\) with the generator. \(D_{RNN}\) is a stacked bidirectional RNN with 3 layers and a hidden state size of 512. The \(cRNN\) states are used to initialize the states of \(D_{RNN}\). The output of both the forward and the backward cells for each word are concatenated and passed to a fully-connected layer with binary output. The output is the probability that the word is from the ground truth given the past and future words of the sequence.

**Others:** All RNNs used are gated recurrent unit (GRU) cells [3]. The word embedding size is 512 and shared between the generator and the discriminator. The initial learning rate is 0.5 with decay rate factor of 0.99, applied when the adversarial loss has increased over two iterations. We use a batch size of 64 and clip gradients around 5.0. As in [18], we find \(acc_{Dth} = 0.99\) and \(acc_{Gth} = 0.75\) to be good enough. All parameters are initialized with Xavier uniform random initialization [33]. The vocabulary size \(V\) is 50,000. Due to the large vocabulary size, we use sampled softmax loss [34] for MLE loss to expedite the training process. However, we use full softmax for evaluation. The model is trained end-to-end using the stochastic gradient descent algorithm. Finally, the model is implemented, trained, and evaluated using the TensorFlow deep learning framework.

### Algorithm 1 Adversarial Learning of hredGAN

**Require:** A generator \(G\) with parameters \(\theta_G\).

**Require:** A discriminator \(D\) with parameters \(\theta_D\).

**for** number of training iterations **do**

1. Initialize \(eRNN\) to zero state, \(h_0\)
2. Compute the generator output using [17].
3. Sample a corresponding mini batch of utterance \(Y_i\), \(Y_i \sim P_{\theta_D}(Y_i | Z_i, X_i)\)
4. **for** \(i = 1\) to \(N - 1\) **do**
   1. Compute the discriminator accuracy \(\Delta_{acc}\) over \(N - 1\) utterances \(\{Y_i\}_{i=1}^{N-1}\) and \(\{X_{i+1}\}_{i=1}^{N-1}\)
   2. If \(\Delta_{acc} < acc_{Gth}\) then
      1. Update \(\theta_G\) with gradient of the discriminator loss.
      2. \(\sum_i |\nabla_{\theta_D} \log D(h_i, X_{i+1}) + \nabla_{\theta_D} \log (1 - D(h_i, Y_i))|\)
   3. Else
      1. Update \(\theta_G\) with both adversarial and MLE losses.
      2. \(\sum_i |\nabla_{\theta_D} \log D(h_i, Y_i) + \lambda M \nabla_{\theta_D} \log P_{\theta_G}(Y_i | Z_i, X_i)|\)

**end if**

**end**

### 5 Experiments and Results

We consider the task of generating dialogue responses conditioned on the dialogue history and the current input utterance. We compare the proposed hredGAN model against some alternatives on publicly available datasets.

#### 5.1 Datasets

**Movie Triples Corpus**, (MTC) dataset [10]. This dataset was derived from the Movie-DiC dataset by Banchs et al. [35]. Although this dataset spans a wide range of topics with few spelling mistakes, its small size of only about 240,000 dialogue triples makes it difficult to train a dialogue model, as pointed out by Serban et al. [10]. We thought that this scenario would really benefit from the proposed adversarial generation.

**Ubuntu Dialogue Corpus**, (UDC) dataset [12]. This dataset was extracted from the Ubuntu Relay Chat Channel. Although the topics in the dataset are not as diverse as in the MTC, the dataset is very large, containing about 1.85 million conversations with an average of 5 utterances per conversation.
We split both MTC and UDC into training, validation, and test sets, using 90%, 5%, and 5% proportions, respectively. We performed minimal preprocessing of the datasets by replacing all words except the top 50,000 most frequent words by an UNK symbol.

5.2 Evaluation Metrics

Accurate evaluation of dialogue models is still an open challenge. There are no well-established automatic evaluation metrics, and human evaluation is expensive. Nevertheless, we employed some of the automatic evaluation metrics that are used in probabilistic language and dialogue models [1,10] and statistical machine translation [36,38]. Although these metrics may not correlate well with human judgment of dialogue responses [39], they provide a good baseline for comparing dialogue model performance.

**Perplexity** - For a model with parameter \( \theta \), we define perplexity as:

\[
\exp \left( -\frac{1}{NW} \sum_{k=1}^{K} \log P_\theta(Y_1, Y_2, \ldots, Y_{N_k-1}) \right)
\]

where \( K \) is the number of conversations in the dataset, \( N_k \) is the number of utterances in conversation \( k \), and \( NW \) is the total number of word tokens in the entire dataset. The lower the perplexity, the better. The perplexity measures the likelihood of generating the ground truth given the model parameters. While a generative model can generate a diversity of responses, it should still assign a high probability to the ground truth utterance. Therefore, perplexity seems to be a good measure of the model’s ability to account for the syntactic structure of the dialogue.

**BLEU** - The BLEU score, [36] provides a measure of overlap between the generated response (candidate) and the ground truth (reference) using a modified n-gram precision. According to Liu et. al. [39], BLEU-2 score is fairly correlated with human judgment for non-technical dialogue (such as MTC).

**ROUGE** - The ROUGE score, [38] is similar to BLEU but it is recall oriented instead. It is used for automatic evaluation of text summarization and machine translation. To compliment the BLEU score, we use ROUGE-N with \( N = 2 \) for our evaluation.

**Distinct n-gram** - This is the fraction of unique n-grams in the generated responses. It provides a measure of diversity. Models with higher number of distinct n-grams tend to produce more diverse responses [9]. For our evaluation, we use 1- and 2- grams.

**Normalized Average Sequence Length (NASL)** - This measures the average number of words in model generated responses normalized by the average number of words in the groundtruth.

5.3 Baseline

We compare the performance of our model to (V)HRED [10, 12], since they are the closest to our approach in implementation and are the current state of the art in open-domain dialogue models. HRED is very similar to our proposed generator, but without the input utterance attention and noise samples. VHRED introduces a latent variable to the HRED between the \( cRNN \) and the \( dRNN \) and was trained using the variational lower bound on the log-likelihood. The VHRED can generate multiple responses per context like hredGAN, but has no specific criteria for selecting the best response.

The HRED and VHRED models are both trained using the Theano-based implementation obtained from [https://github.com/julianser/hed-dlg-truncated](https://github.com/julianser/hed-dlg-truncated). The training and validation sets used for UDC and MTC dataset were obtained directly from the authors of (V)HRED. For model comparison, we use a test set that is disjoint from the training and validation sets.

5.4 Results

We have two variants of hredGAN based on the noise injection approach, i.e., hredGAN with utterance-level (hredGAN_u) and word-level (hredGAN_w) noise injections. We compare the performance of these two variants with HRED and VHRED models.

\(^2\)UDC was obtained from [http://www.iulianserban.com/Files/UbuntuDialogueCorpus.zip](http://www.iulianserban.com/Files/UbuntuDialogueCorpus.zip) and the link to MTC was obtained privately.
Table 2: Generation and Discrimination Performance

| Model     | Perplexity   | $-\log D(G(.)$ | 
|-----------|--------------|----------------|
| MTC       | 31.92/36.00  | NA             |
| VHRED     | 42.61/44.97  | NA             |
| hredGAN_u | 23.57/23.54  | 6.85/6.81      |
| hredGAN_w | 24.20/24.14  | 13.35/13.40    |
| UDC       | 69.39/86.40  | NA             |
| VHRED     | 98.50/105.20 | NA             |
| hredGAN_u | 56.82/57.32  | 10.09/10.08    |
| hredGAN_w | 47.73/48.18  | 8.37/8.36      |

Table 3: Autoregressive Inference Performance

| Model     | BLEU-2      | ROUGE-2      | DISTINCT-1/2 | NASL |
|-----------|-------------|--------------|--------------|------|
| MTC       |             |              |              |      |
| VHRED     | 0.0474      | 0.0384       | 0.0026/0.0056| 0.535|
| hredGAN_u | 0.0493      | 0.2416       | 0.0167/0.1306| 0.884|
| hredGAN_w | 0.0613      | 0.3244       | 0.0179/0.1720| 1.540|
| UDC       |             |              |              |      |
| VHRED     | 0.0177      | 0.0483       | 0.0203/0.0466| 0.892|
| hredGAN_u | 0.0137      | 0.0716       | 0.0260/0.0847| 1.379|
| hredGAN_w | 0.0216      | 0.1168       | 0.0516/0.1821| 1.098|

**Perplexity:** The average perplexity per word performance of all the four models on MTC and UDC datasets (validation/test) are reported in the first column on Table 2. The table indicates that both variants of the hredGAN model perform better than the HRED and VHRED models in terms of the perplexity measure. However, using the adversarial loss criterion (Eq. (8)), the hredGAN_u model performs better on MTC and worse on UDC. Note that, for this experiment, we run all models in teacher forcing mode.

**Generation Hyperparameter:** For adversarial generation, we perform a linear search for $\alpha$ between 1 and 20 at an increment of 1 using Eq. (13), with sample size $L = 64$. We run the models in autoregressive mode to reflect performance in actual deployment. The $\alpha$ value that gives the lowest average discriminator loss per word of the generator output ($-\log D(G(.)$) over the validation set is chosen as the optimum. The optimum values of $\alpha$ for hredGAN_u and hredGAN_w for UDC are 7.0 and 9.0 respectively. The values for MTC are not convex, probably due to small size of the dataset, so we use the same $\alpha$ values as UDC. We however note that for both datasets, any integer value between 3 and 10 (inclusive) works well in practice.

**Quantitative Generator Performance:** We run autoregressive inference for all the models (using optimum $\alpha$ values for hredGAN models and selecting the best of $L = 64$ responses using a discriminator) with dialogue contexts from a unique test set. Also, we compute the average BLEU-2, ROUGE-2(f1), DISTINCT-1/2 and normalized average sequence length (NASL) scores for each model and summarize the results in Table 3. DISTINCT-1/2 largely agrees with the perplexity score. Most scores, similar to the perplexity, indicate that hredGAN models perform better than (V)HRED on both datasets. However, on the UDC and MTC, ROUGE and BLUE, respectively scores VHRED slightly better than hredGAN_u but still worse than hredGAN_w.

A good dialogue model should find the right balance between precision (BLEU) and diversity. We strongly believe that our adversarial approach is better suited to solving this problem. As hredGAN generators explore diversity, the discriminator ranking gives hredGAN an edge over (V)HRED because it helps detect responses that are out of context and the natural language structure (Table 1). Also, the ROUGE(f1) performance indicates that hredGAN_w strikes a better balance between precision (BLEU) and diversity than the rest of the models. This is also obvious from the quality of generated responses. Therefore, we recommend hredGAN_w for multi-turn dialogue response generation.

**Qualitative Generator Performance:** In addition to the quantitative analysis of the performance, looking at the actual samples from the generator outputs in Table 4 shows that hredGAN especiallyhredGAN_w performs better than (V)HRED. While other models produce short and generic utterances, hredGAN_w mostly yields informative responses. For example, in the first dialogue in Table 4 when the speaker is sarcastic about "the man upstairs", hredGAN_w responds with the most coherent utterance with respect to the dialogue history. We see similar behavior across other samples. We also note that although hredGAN_u’s responses are the longest on Ubuntu (in line with the NASL score), the responses are less informative compared to hredGAN_w. We reckon this might be due to a mismatch between utterance-level noise and word-level discrimination or lack of capacity to capture the data distribution using single noise distribution. We hope to investigate this further in the future.
While this is a good starting point, we recognize the need to explore further improvements to the proposed adversarial framework: In the future, we hope to: explore which noise level works with the generator outputs, using an HRED-derived generator and discriminator. The proposed framework outperforms existing state-of-the-art (V)HRED models for generating responses in multi-turn dialogue with respect to perplexity and automatic evaluation metrics. Our analysis also concludes that the generator can produce rarer utterances that will be scored high by the discriminator.

### Discriminator Performance:

Although only hredGAN uses a discriminator, the observed discriminator behavior is interesting. We observe that the discriminator score is generally reasonable with longer, more informative and more persona-related responses receiving higher scores as shown in Table 1. It worth to note that this behavior, although similar to the behavior of a human judge is learned without supervision. Moreover, the discriminator seems to have learned to assign average score to more frequent or generic responses such as “I don’t know”, “I’m not sure” and so on, and high score to rarer answers. That’s why we sample a modified noise distribution during inference so that the generator can produce rarer utterances that will be scored high by the discriminator.

### 6 Conclusion and Future Work

In this paper, we have introduced an adversarial learning approach that addresses response diversity and control of generator outputs, using an HRED-derived generator and discriminator. The proposed system outperforms existing state-of-the-art (V)HRED models for generating responses in multi-turn dialogue with respect to perplexity and automatic evaluation metrics. Our analysis also concludes that the word-level noise injection seems to perform better in general.

While this is a good starting point, we recognize the need to explore further improvements to the proposed adversarial framework: In the future, we hope to: explore which noise level works with which discrimination level; consider a multi-resolution discriminator with combined word- and utterance-level discriminations; and explore further tuning of the generator and discriminator models.

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