Unsupervised Dialogue Spectrum Generation for Log Dialogue Ranking

Xinnuo Xu†, Yizhe Zhang‡, Lars Liden†, Sungjin Lee‡
†The Interaction Lab, Heriot-Watt University, Edinburgh
xx6@hw.ac.uk
‡Microsoft Research, Redmond, WA, USA
Yizhe.Zhang, Lars.Liden, sule@microsoft.com

Abstract

Although the data-driven approaches of some recent bot building platforms make it possible for a wide range of users to easily create dialogue systems, those platforms don’t offer tools for quickly identifying which log dialogues contain problems. This is important since corrections to log dialogues provide a means to improve performance after deployment. A log dialogue ranker, which ranks problematic dialogues higher, is an essential tool due to the sheer volume of log dialogues that could be generated. However, training a ranker typically requires labelling a substantial amount of data, which is not feasible for most users. In this paper, we present a novel unsupervised approach for dialogue ranking using GANs and release a corpus of labelled dialogues for evaluation and comparison with supervised methods. The evaluation result shows that our method compares favorably to supervised methods without any labelled data.

1 Introduction

Task-oriented dialogue systems provide a natural interface to accomplish various daily-life tasks such as restaurant finding and flight booking. Data-driven approaches offered by common bot building platforms (e.g. Google Dialogflow, Amazon Alexa Skills Kit, Microsoft Bot Framework) make it possible for a wide range of users to easily create dialogue systems with a limited amount of data in their domain of interest. Typically, the development process of a dialogue system based on data-driven approaches (Williams et al., 2017; Bordes et al., 2016) goes around an operational loop in Figure 1: (1) The cycle begins with a developer creating a training dataset with seed dialogues. (2) A dialogue system is trained and deployed. (3) Real users interact with the system and generate log dialogues. (4) The developer reviews the logs to identify which log dialogues contain problems. (5) The developer updates the training dataset to fix the problems. (6) The cycle repeats from step 2). Of all steps, (4) is the most significant in slowing down the loop, because of the sheer volume of log dialogues that can be generated and the need to manually inspect each. Thus, it is essential to support tools that help developers quickly identify problematic log dialogues. To achieve this goal, we propose a neural dialog ranker whose goal is to place problematic dialogues higher in the rank.

However, training a ranker typically requires labelling a substantial amount of data, which is not feasible for most developers. Furthermore, one might have to repeat this process whenever a significant change is made to the system’s behavior. This motivates us to explore a set of unsupervised approaches to reduce the prohibitive cost. The core idea of these methods is that we learn a generative model to produce problematic dialogue examples as positive examples and train a ranker with seed dialogues used as negative examples. Specifically, we propose a novel dialogue generator using Generative Adversarial Networks (GANs) and train the generator with a curriculum learning scheme. Another possible avenue is to leverage off-the-shelf dialogue quality classifiers which are trained on open-domain corpora such as
One turn consists of a pair of system and user utterances. Formally, given a dialogue $D = \{S_1, U_1, S_2, \cdots, U_{n-1}, S_n\}$, a dialogue ranker $\psi$ produces a score of $D$ being problematic where $S_i$ and $U_i$ are the system and user utterance in $i^{th}$ turn, respectively. To train the dialogue ranker $\psi$, we formulate the ranking task as binary classification where problematic and normal dialogues correspond to positive and negative classes, respectively. We optimize the cross-entropy objective:

$$L_{\text{sent}} = \frac{1}{N} \sum_{i=1}^{N} [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]$$

where $\hat{y}_i = 1/(1 + \exp(-\psi(D_i)))$ and $y_i = 1$ for positive class and 0 otherwise.

We design a deep neural ranking model for $\psi$ to automatically learn salient features as illustrated in Figure 2. We first use a bi-directional LSTM (Bi-LSTM) to encode each utterance in dialogue $D$:

$$D_{\text{emb}} = \{S_{1\text{emb}}, U_{1\text{emb}}, S_{2\text{emb}}, \cdots, U_{n\text{emb}}, S_{n\text{emb}}\}$$

where $S_{i\text{emb}} = \text{Bi-LSTM}(S_i)$ and $U_{i\text{emb}} = \text{Bi-LSTM}(U_i)$. Then, we calculate attention embeddings for each utterance with a multi-head self-attention mechanism (Vaswani et al., 2017):

$$D_{\text{attn}} = \text{softmax}\left(\frac{D_{\text{emb}}D_{\text{emb}}^\top}{\sqrt{d}}\right)D_{\text{emb}}$$

where $d$ is the dimension of the embedding and $D_{\text{attn}} = \{c_{1\text{attn}}, U_{1\text{attn}}, \cdots, c_{n\text{attn}}, U_{n\text{attn}}\}$. Now, we apply a feed-forward network (FFN) to the concatenation of utterance embeddings $D_{\text{emb}}$ and their corresponding attentive embeddings $D_{\text{attn}}$ to yield context-sensitive utterance embeddings:

$$D_{\text{ctx}} = \{S_{1\text{ctx}}, U_{1\text{ctx}}, \cdots, U_{n\text{ctx}}, S_{n\text{ctx}}\}$$

where $S(U)_{i\text{ctx}} = \text{FFN}([S(U)_{i\text{emb}}, S(U)_{i\text{attn}}])$ and $[\cdot, \cdot]$ denotes a concatenation operator. After that, we apply another FFN followed by a sigmoid activation to each pair of utterances to measure the consistency of adjacency pairs:

$$A_i = \text{sigmoid}(\text{FFN}([X_{i\text{ctx}}, Y_{i\text{ctx}}]))$$

where $(X_{i\text{ctx}}, Y_{i\text{ctx}})$ is either $(S_{i\text{ctx}}, U_{i\text{ctx}})$ or $(U_{i\text{ctx}}, S_{i+1\text{ctx}})$. Finally, the ranker $\psi$ produces a ranking score for the dialogue based on the consistency scores and a set of manually crafted features:

$$\psi(D) = \text{FFN}([A_1, \cdots, A_{n-1}, f_1, \cdots, f_m])$$

where $f_i$ denotes a set of manual features. In this study, we use a single manual feature to consider redundant turns:

$$f = \frac{\text{Num (distinct utterances)}}{\text{Num (all utterances)}}$$
Each instance of FFNs has separate parameters and consists of two linear layers with a ReLU activation in between:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

3 Unsupervised Approach

Training a ranker typically requires labelling a substantial amount of data and one might have to repeat this process whenever a significant change is made to the system’s behavior. This is not feasible for most developers and motivates us to explore a set of unsupervised approaches. The core idea is that we learn a generative user simulator and have it talk with the bot to produce problematic dialogues. We then train a ranker with seed dialogues used as normal examples. A straightforward approach for problematic dialogue generation is to train the generative user simulator on a dialogue corpus collected from a wide range of different domains, dubbed as MultiDomain. However, this approach can only produce obvious problematic dialogues where the simulated user mimics users who barely know what the bot is for.

To generate more relevant dialogues, one can fine-tune the MultiDomain model on the seed dialogues, dubbed as FineTune. But this approach gains an improved relevance at the cost of decreased diversity and it is a formidable task to adjust fine-tuning to strike the right balance between relevance and diversity.

We observe that, in most cases, a dialogue follows a natural course until a problem occurs and the dialogue subsequently gets off track. Table 1 shows a problematic dialogue. To bring this to our problematic dialogue generation, we introduce a novel stepwise fine-tuning approach, called StepFineTune. The idea is that we fine-tune the MultiDomain model only up to $l$-th turn to generate dialogues in which it normally unfolds up to $l$-th turn and starts seeing problems afterward. As we fine-tune the model in this stepwise fashion from $l = 1$ to $n$, we accumulate all the dialogues that we generate at each step. This allows us to produce a spectrum of diverse problematic dialogues while controlling relevance.

However, it is widely known that the typical MLE training scheme often generates bland and generic responses (Li et al., 2016). To alleviate this problem and generate naturally diverse dialogues, we propose a novel stepwise GAN training scheme, dubbed as StepGAN. StepGAN differs from StepFineTune in that it conducts GAN training instead of the simple MLE fine-tuning for each step. As we cast the dialogue ranking task as binary classification in Section 2, the dialogue ranking model $\psi$ lends itself well to discriminating real dialogues from simulated ones. In the rest of this section, we describe StepGAN in detail.

3.1 StepGAN overview

Figure 3 shows the overall pipeline of the StepGAN approach. A dialogue generator consists of a user simulator and the bot, and have them talk with each other. We start off by pre-training a generative user simulator on a large corpus of dialogues collected from multiple domains which teaches the simulator basic language skills and helps learn diverse out-of-domain behavior. We use the pre-trained user simulator to produce problematic dialogues and pre-train a discriminator with seed dialogues used as normal dialogues.

We then begin stepwise GAN training. At each step, starting from the user simulator of turn $l-1$ and the pre-trained discriminator, we further train them using GAN to make the first $l$ turns of a generated dialogue less distinguishable from the seed dialogues, as listed in Algorithm 1. To achieve this goal, we truncate both seed and generated dialogues up to length $l$ when we train the user simulator and discriminator. Once the GAN training is done, we generate a set of problematic dialogues $D^l_{pos}$ using the trained user simulator. Note that we don’t truncate these dialogues so that they may follow a normal course up to $l$-th turn and start seeing problems afterward. When we finish the final step $L$, we collect all the problematic dialogues generated from each step and construct a

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2 A dialogue ends either when the system or user terminates or when the pre-set maximum length is reached.
Algorithm 1 GAN training at step l

Require: Problematic dialogues $D_{pos}$
1: $D_{seed}^l$ ← seed dialogues truncated at turn $l$
2: $g'$ ← user simulator from turn $l - 1$
3: $d^l$ ← pre-trained discriminator
4: while not convergent do
5: $d^l$ ← Train_d($D_{seed}^l$, $D_{gen}^l$)
6: $g'$ ← Train_g($D_{gen}^l$, $d^l$)
7: end while
8: $D_{pos}^l$ ← Generate($g'$)

In Eq 2 and 3, $N_u$ is the number of tokens in $U_i$ and $M$ is the vocabulary size. $p_\theta(u^m_j | D^{<i}, u^{<j})$ is the conditional distribution over the vocabulary at time step $j$ in the generation of $U_i$. Since Eq 1 is not differentiable, we adopt the REINFORCE algorithm (Williams, 1992) for gradient updates:

$$\nabla_\theta J(\theta) \propto d^l(U_i, D^{<i}) \sum_{i=0}^l \nabla_\theta \log p_\theta(U_i | D^{<i}) + \sum_{i=0}^l \nabla_\theta H_\theta(U_i | D^{<i})$$

To stabilize the learning process, we employ two common techniques: 1) a baseline: we take the average of rewards in each training batch 2) teacher forcing: we occasionally draw a random dialogue from the seed dialogues with $d^l(\cdot)$ set to return 1. To increase the diversity of the output of the user simulator, during inference, we combine sampling with beam search. At each time step $j$, instead of choosing the top beam_size terms, we sample beam_size terms according to the probability distribution $p_\theta(u_j | D^{<i}, u^{<j})$.

Since we cast the dialogue ranking task as binary classification, we use the same architecture as the dialogue ranking model in Section 2 to discriminate seed dialogues from simulated ones. The only difference is that seed and generated dialogues now correspond to positive and negative classes, respectively.

3.2 GAN training details

Based on our empirical study, we choose to use a sequence-to-sequence model with attention for our user simulator. With GAN, at the $l$-th iteration, we optimize the following objective which basically adjusts the user simulator to fool the discriminator:

$$J(\theta) = E_{p_\theta(D)} \left[ d^l(D^{<i}, U_i) \right] + \lambda \sum_{i=0}^l H_\theta(U_i | D^{<i})$$

(1)

where $D$ denotes a generated dialogue and $D^{<i} = [S_i, U_1, \ldots, U_{i-1}, S_i]$. $d^l(\cdot)$ denotes the discriminator being trained at the $l$-th iteration and returns the probability of $D^{<i}$ being real, as reward for training the generator. $\theta$ is the parameters for the user simulator and $H(\cdot)$ is the entropy penalty (Pereyra et al., 2017) for increasing the generation diversity:

$$H_\theta(U_i | D^{<i}) = \sum_{j=0}^{N_u} H_\theta(u_j | D^{<i}, u^{<j})$$

(2)

where,

$$H_\theta(u_j | D^{<i}, u^{<j}) = - \sum_{m=0}^M p_\theta(u^m_j | D^{<i}, u^{<j}) \cdot \log p_\theta(u^m_j | D^{<i}, u^{<j})$$

(3)

4 Datasets

In this work, we build a log dialogue ranker for the restaurant inquiry bot offered by the PyDial platform. The task for the bot is to search for restaurants based on user’s requirements in a multi-turn natural language communication. Three main corpora are introduced: (1) log dialogues with labels, (2) seed dialogues for the restaurant domain, (3) a large corpus of dialogues collected from multiple domains (Lee et al., 2019).

Log dialogues with labels

To collect log dialogues, we deployed the Pydial restaurant bot via the Amazon Mechanical Turk (AMT) platform.

http://www.camdial.org/pydial/

We use the data collection toolkit offered by ParlAI

http://www.parl.ai/static/docs/tutorial_mturk.html.
restaurants that satisfy automatically generated requirements, such as food type, location and price range, by chatting with the restaurant bot. To make the conversation natural, we encourage turkers to speak in natural utterances and do not allow any turkers to carry out more than 20 dialogues in total. At the end of each task, turkers are required to answer a questionnaire whether they found restaurants meeting their requirements, and whether they experienced contextually unnatural turns in the conversation. We control the quality of a turker’s judgements by checking if a turker judges correctly for some obvious cases that we can automatically identify.

From the collected dialogues, we label successful dialogues without any contextually unnatural turns as 0 (normal dialogue), and the rest as 1 (problematic dialogue). Table 2 shows the number and average length of log dialogues. Examples are shown in Table 1.

We split the corpus as shown in Table 3. Note that, the training and validation sets are used only for supervised training, whereas the test set is used for evaluating all approaches.

Seed dialogues
The corpus of seed dialogues has two use cases: 1) we use it to fine-tune the user simulator for the FineTune and StepFineTune approaches, 2) StepGAN takes it as input to the discriminator training and teacher forcing process. Since the restaurant bot does not have associated seed dialogues, we collect 100 seed dialogues by having the bot talk with the agenda-based user simulator that Pydial offers. 5

Multi-domain dialogues
The multi-domain corpus has two use cases: 1) we use it for training the user simulator for the MultiDomain approach, 2) we pretrain the simulator for the StepFineTune and StepGAN approaches. The multi-domain corpus consists of around 40,000 dialogues with 11 turns on average. Each dialogue is a task-oriented conversational interaction between two real speakers over 51 domains and 242 tasks, collected by crowd-sourcing in which one turker is simulating a user and the other one is simulating a chatbot. We preprocess dialogues into training pairs for the sequence-to-sequence model learning. A training pair consists of a dialogue context and the corresponding response. We consider three consecutive turns as dialogue context and the following turn as response. The number of dialogues in train/val/test sets are 38000/1000/1000 and the training pairs are 394821/10411/10370.

5 Experiments
We describe a set of experimental settings in Section 5.1 and evaluation metrics in Section 5.2.

5.1 Experimental settings
We present three experiments to demonstrate the efficacy of our approaches.

- StepGAN vs. other unsupervised approaches: To compare the StepGAN against other unsupervised approaches introduced in Section 3:
  - MultiDomain: We train the user simulator on the multi-domain corpus.
  - FineTune: We fine-tune the user simulator on the seed dialogues.
  - StepFineTune: We fine-tune the user simulator in a stepwise fashion.

We train dialogue rankers for each approach on a balanced dataset, consisting of 1000 problematic dialogues generated by each approach and 1000 normal dialogues oversampled from the seed dialogues to balance the class distribution. We evaluate two additional models:

- DBDC3: We use the off-the-shelf CRF model trained on open-domain dialogue corpora for the dialogue breakdown detection challenge (Higashinaka et al., 2017). Since the DBDC3 model operates at the utterance level, we aggregate the utterance scores to obtain a dialogue-level score. Based on our experiments, we choose to use a model trained on the collection of four challenge datasets (CIC_115, IRIS_100, TKTK_100, YL_100) and aggregate the utterance scores through summation.

- PlainMultiDomain: Instead of training a user simulator, we simply take the entire multi-domain corpus (38,000 dialogues) as problematic dialogues and train the ranker with the same number of normal dialogues oversampled from the seed dialogues.

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5 We collected 100 seed dialogues based on our observations that most developers start training their bots with a seed dialogue corpus on a similar scale.

6 The multi-domain corpus (MetaLWOz) will be made available through a DSTC8 track (Lee et al., 2019).

7 https://github.com/dbd-challenge/dbdc3
One normal example in the labelled corpus
SYS: hello, welcome to the restaurant finding system. how may i help you?
USER: hi i ’ m looking for a restaurant.
SYS: what part of town do you have in mind?
USER: the east part of town please.
SYS: what kind of food would you like?
USER: i’d like chinese food please.
SYS: yu garden is a nice place, it serves chinese food and it is in the east part of town.
USER: what is the phone number?
SYS: yu garden is a nice place their phone number is 0 1223 248882.
USER: what is the address?
SYS: yu garden is a nice place their address is 529 newmarket road fen ditton.
USER: thank you
SYS: thank you, goodbye.

One problematic example in the labelled corpus
SYS: hello, welcome to the restaurant finding system. how may i help you?
USER: hello i would really like to eat some cheap indian tonight
SYS: what part of town do you have in mind?
USER: i would really like to eat in the centre of town
SYS: i am sorry but there is no place, in the expensive price range, serving corsica food and in the area of centre.
USER: i would really like so indian thats cheap in the centre of town
SYS: the gandhi is a nice place, it is in the cheap price range, it is in the centre of town and it serves indian food.
USER: thats great, have you got a contact number?
SYS: what part of town do you have in mind?
USER: the centre of town
SYS: efes restaurant is a nice place, it is in the centre of town, it is in the moderate price range and it serves turkish food.
USER: i want to eat at the gandhi have you got the address?
SYS: the gandhi is a nice place their address is 72 regent street city centre.
USER: thank you, have you got a phone number for the gandhi?
SYS: the gandhi is a nice place their phone number is 0 1223 353942.
USER: thanks
SYS: chiquito bar is a nice place, it serves mexican food in the expensive price range and it is in the south part of town.
USER: quit

Table 1: One normal and one problematic examples in the labelled corpus.

| Normal dials | Problematic dials |
|--------------|-------------------|
| Num of dials | 1621              |
|              | 1329              |
| Avg length   | 5.87 turns        |
|              | 8.28 turns        |

Table 2: The number of dialogues and average dialogue length in the log dialogue corpus.

|                   | Train | Val | Test |
|-------------------|-------|-----|------|
| Normal dialogues  | 1321  | 100 | 200  |
| Problematic dialogues | 1029  | 100 | 200  |

5.2 Evaluation metrics

We use ranking metrics for evaluation:
- $P@K$ – Precision at $k$, corresponds to the number of problematic dialogues in the top $k$ ranked options.
- $R@K$ – Recall at $k$, corresponds to the number of problematic dialogues in the top $k$ ranked options against the number of all problematic dialogues in the test set (i.e. 200). Note that we modified the standard of Recall at $k$ to get monotonic increase with respect to $k$.

6 Results and Discussion

In this section, we first present the results for the experimental settings in Section 5.1 that we de-
Figure 4: Precision@k StepGAN vs. other unsupervised approaches.

Figure 5: Precision@k StepGAN with different training size vs. supervised approach.

Figure 6: Precision@k of semi-supervised StepGAN vs. supervised settings.

Figure 7: Average length of generated dialogues in each training step.

Figure 8: Success rates of generated dialogues in each training step.

Figure 9: Average score of generated dialogues in each training step.

Table 4: Evaluation results. DB, PM, MD, FT, SF and SG stand for the DBDC3, PlainMultiDomain, MultiDomain, FineTune, StepFineTune and StepGAN approach, respectively. The Sup denotes the supervised approach trained on the balanced labelled dialogues.

| Model     | DB   | PM   | MD   | FT   | SF   | SG   | Sup  |
|-----------|------|------|------|------|------|------|------|
| P@10      | .700 | .750 | .911 | .767 | .844 | .889 | .850 |
| P@20      | .800 | .777 | .867 | .794 | .850 | .900 | .870 |
| P@30      | .800 | .777 | .811 | .807 | .859 | .896 | .887 |
| P@40      | .825 | .763 | .792 | .814 | .867 | .886 | .878 |
| P@50      | .800 | .738 | .762 | .800 | .836 | .864 | .870 |
| P@100     | .720 | .617 | .680 | .758 | .758 | .773 | .827 |
| P@200     | .655 | .499 | .612 | .688 | .702 | .708 | .765 |
| R@10      | .035 | .038 | .046 | .038 | .042 | .044 | .043 |
| R@20      | .080 | .077 | .087 | .079 | .085 | .090 | .087 |
| R@30      | .120 | .117 | .122 | .121 | .129 | .134 | .133 |
| R@40      | .165 | .153 | .158 | .163 | .173 | .177 | .176 |
| R@50      | .200 | .185 | .191 | .200 | .209 | .216 | .218 |
| R@100     | .360 | .308 | .340 | .379 | .379 | .387 | .414 |
| R@150     | .535 | .391 | .481 | .551 | .553 | .562 | .600 |
| R@200     | .655 | .499 | .612 | .688 | .702 | .708 | .765 |

6.1 Comparative results

**StepGAN vs. other unsupervised approaches:**

Figure 4 shows that StepGAN outperforms other unsupervised approaches by a large margin. The only exception is MultiDomain when $k = 10$. One noteworthy observation is made by comparing MultiDomain with FineTune. MultiDomain is more effective than FineTune when $k$ is small, less than 30 in this case. This is because most turns are contextually wrong or unnatural when we look into the most problematic dialogues (e.g. $k < 10$) and MultiDomain generates exactly such dialogues. On the contrary, as $k$ increases, generated dialogues gradually resemble normal ones with less wrong turns and FineTune essentially generates this type of dialogues.

This observation indicates that a high-quality model should be able to generate a spectrum of dialogues, ranging from obvious dialogues to subtle ones. That is why we introduced a stepwise training scheme and thus StepFineTune shows a significantly improved performance. Furthermore, StepGAN employs the GAN training procedure to generate more natural and diverse dialogues and almost always outperforms all other unsupervised approaches. The fact that StepGAN outperforms DBDC3 and PlainMultiDomain highlights that the StepGAN's capability of generating domain-relevant problematic dia-
logues is crucial in obtaining high performance. **StepGAN vs. supervised approach:** In Figure 5, StepGAN2000, StepGAN4000 and StepGAN6000 denote ranking models trained on 2000, 4000, 6000 balanced datasets generated by StepGAN respectively. Sup stands for a ranker trained on 2000 balanced labelled dialogues. Interestingly, StepGAN performs even better than the supervised approach when \( k < 50 \). Even though the supervised approach yields higher performance when \( k \) is large, StepGAN still compares favorably and the gap is narrower if more dialogues are generated. Note that having developers review a large number of log dialogues (over 100) induces a significant cognitive load. Thus, the higher performance of StepGAN in the small \( k \) regime can offer more practical value.

**Semi-supervised learning attempts:** In Figure 6, Sup500 and Sup2000 denote supervised dialogue rankers trained on randomly sampled 500 and 2000 balanced labelled dialogues, respectively. StepGAN+Sup500 and StepGAN+Sup2000 denote semi-supervised approaches trained on the 500 and 2000 labelled datasets plus 6000 simulated dialogues generated by StepGAN, respectively. The higher performance of the semi-supervised approaches compared to the supervised counterparts highlights that our unsupervised approach can bring additional generalization by simulating a wide range of dialogues that are not covered by labelled data. As expected, the performance gain increases as we move to a smaller data regime, e.g. 500 labelled dialogues.

6.2 Analysis on generated dialogues
To investigate how generated dialogues move toward normal dialogues, we examine dialogues generated at each step of StepGAN training in terms of three quantitative metrics: average dialogue length, task success rate and ranking score produced by the supervised ranker. Figure 7, 8 and 9 clearly show that as training progresses, the characteristics of generated dialogues are getting more similar to normal dialogues – average dialogue length of generated dialogues is decreasing while task success rate and average ranking score are increasing. In Table 5, we show example dialogues generated by StepGAN after two different training steps to qualitatively examine generated dialogues. The generated dialogues clearly show that StepGAN manages to follow a normal course up to the training-step turn and then start to get off track. For the full dialogue examples generated by different generative models, refer to Supplemental Material A.

7 Related Work
In contrast to conventional approaches (Jokinen and McTear, 2009), end-to-end neural models have been recently investigated for task-oriented dialogue systems which allows for directly learning dialogue systems from human-human dialogue data (Wen et al., 2016; Bordes et al., 2016; Williams et al., 2017). For such approaches, our proposed dialogue ranking method can help developers quickly go over log dialogues to improve their dialogue systems. There are prior studies on dialogue quality assessment. Walker et al. (1997); Engelbrecht et al. (2009) investigate automatic ways of dialogue evaluation. Walker et al. (2002); Herm et al. (2008); Kim (2007); Higashinaka et al. (2010, 2016) focus on dialogue breakdown detection during the dialogue. Ultes et al. (2012); Su et al. (2016) estimate dialogue quality to improve dialogue policy. However, none has directly dealt with log dialogue ranking task and offered unsupervised approaches to reduce labelling cost. For automatic error handling, Clark (1996); Bohus and Rudnicky (2005); Higashinaka et al. (2015) examined different types of errors. Whereas, for our work, it suffices to rank problematic dialogues higher than normal ones so that developers may take appropriate measures based on the goal of their bots, e.g., adding new slots or system actions to handle previously uncovered scenarios.

8 Conclusions and Future Work
We proposed unsupervised approaches for the task of log dialogue ranking and provided comprehensive experimental results. StepGAN outperforms other unsupervised approaches and compares favorably with the supervised approach. Moreover, StepGAN improves upon the supervised approach in semi-supervised settings. Finally, we release the labelled dialogue corpus and seed dialogues. Future work includes 1) in-depth human evaluation on the quality of generated dialogues, 2) testing StepGAN on a broader range of tasks 3) performing dialogue clustering before ranking to reduce redundant workload for developers.
Table 5: Dialogues simulated by the StepGAN approach in different training steps.

| StepGAN training at step 1 |
|-----------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: hi, i want to book a table |
| SYS: what part of town do you have in mind? |
| USER: boston. |
| SYS: what part of town do you have in mind? |
| USER: part is going up in colorado. |
| SYS: what part of town do you have in mind? |
| USER: i do not want to book a movie price range and in the usa in the west of town. |
| SYS: i am sorry but there is no place, serving north american food and in the area of west. |
| USER: alright, that’s understandable, can you tell me more? |
| SYS: i am sorry but there is no place, in the area of west and serving north american food. |
| USER: that’s sound great. oh that’s the limit. that is all i need as well though, can you help |
| SYS: thank you, goodbye. |

| StepGAN training at step 3 |
|-----------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: i need another restaurant. |
| SYS: what part of town do you have in mind? |
| USER: i want a venue in the moderate price range and in the north of town. |
| SYS: what kind of food would you like? |
| USER: i need a indian venue. |
| SYS: the nirala is a nice place, it is in the moderate price range, it serves indian food and it is in the north part of town. |
| USER: i am not looking for this. please change. |
| SYS: the nirala is a nice place, it is in the moderate price range, it serves indian food and it is in the north part of town. |
| USER: the account 555 - venue is great. i am in the moderate price range and i am going at town. |
| SYS: the nirala is a nice place, it serves indian food, it is in the moderate price range and it is in the north part of town. |
| USER: well, i want a venue in the business site. please do, i am going to get a brief globe. |
| SYS: the nirala is a nice place, it serves indian food, it is in the moderate price range and it is in the north part of town. |
| USER: that doesn’t matter. |
| SYS: the nirala is a nice place, it is in the north part of town, it is in the moderate price range and it serves indian food. |
| USER: okay, thanks for the help me book |
| SYS: thank you, goodbye. |

| StepGAN training at step 6 |
|-----------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: i need a european restaurant. |
| SYS: what part of town do you have in mind? |
| USER: it doesn’t matter. |
| SYS: what part of town do you have in mind? |
| USER: it doesn’t matter. |
| SYS: what part of town do you have in mind? |
| USER: i want a venue in the expensive price range and in the centre of town. |
| SYS: what kind of food would you like? |
| USER: i need a european venue. |
| SYS: michaelhouse cafe is a nice place, it is in the centre of town, it is in the expensive price range and it serves european food. |
| USER: what is the phone number of the restaurant? |
| SYS: michaelhouse cafe is a nice place their phone number is 0 1223 309147. |
| USER: thanks for your help, goodbye. |
| SYS: thank you, goodbye. |

| StepGAN training at step 9 |
|-----------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: i need a european restaurant. |
| SYS: what part of town do you have in mind? |
| USER: i prefer a venue in centre. |
| SYS: would you like something in the cheap, moderate, or expensive price range? |
| USER: i want a venue in the expensive price range. |
| SYS: michaelhouse cafe is a nice place, it is in the expensive price range, it is in the centre of town and it serves european food. |
| USER: what is the address of michaelhouse cafe? |
| SYS: michaelhouse cafe is a nice place their address is st. michael’s church trinity street city centre. |
| USER: thanks for your help, goodbye. |
| SYS: thank you, goodbye. |
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Supplemental Material

A Dialogues simulated by unsupervised approaches

| Dialogues simulated by the MultiDomain approach |
|------------------------------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: i am looking for cheap french cuisine |
| SYS: i’m having trouble understanding what you want. could you please rephrase it? |
| USER: i want a champagne without a different tables |
| SYS: midsummer house restaurant is nice |
| USER: where is the restaurant? |
| SYS: rajmahal is nice |
| USER: how about champagne’s? |
| SYS: the good luck chinese food takeaway is nice |
| USER: ooh okay. that’s the problem! i really i’m craving midsummer vegas. |
| SYS: what part of town do you have in mind? |
| USER: the galleria vegas adventure |
| SYS: galleria is a nice place it is in the centre of town. |
| USER: awesome, i’ll go with that topic to serve, need else |
| SYS: galleria is a nice place it is in the moderate price range. |
| USER: , my account is very good i guess |
| SYS: galleria is a nice place it serves european food. |
| USER: i will thanks anyways |
| SYS: thank you, goodbye. |

| Dialogues simulated by the FineTune approach |
|------------------------------------------------|
| SYS: hello, welcome to the restaurant finding system. how may i help you? |
| USER: hi, i want to book a table |
| SYS: what part of town do you have in mind? |
| USER: i prefer a venue in south. |
| SYS: what kind of food would you like? |
| USER: i need a chinese venue. |
| SYS: would you like something in the cheap, moderate, or expensive price range? |
| USER: it doesn’t matter. |
| SYS: would you like something in the cheap, moderate, or expensive price range? |
| USER: i want a venue in the expensive price range. |
| SYS: the good luck chinese food takeaway is a nice place, it is in the south part of town, it is in the expensive price range and it serves chinese food. |
| USER: thanks for your help, goodbye. |
| SYS: thank you, goodbye. |

Table 6: Dialogues simulated by the MultiDomain approach/FineTune approach.
Dialogues simulated by the StepFineTune approach in different training steps

| StepFineTune training at step 1 |
|---------------------------------|
| **SYS**: hello, welcome to the restaurant finding system. how may i help you? |
| **USER**: i need another restaurant. |
| **SYS**: what part of town do you have in mind? |
| **USER**: i need another restaurant. |
| **SYS**: what part of town do you have in mind? |
| **USER**: washington dc. |
| **SYS**: what kind of food would you like? |
| **USER**: i want a table |
| **SYS**: what kind of food would you like? |
| **USER**: i need another restaurant. |
| **SYS**: what kind of food would you like? |
| **USER**: i want restaurant in centre. |
| **SYS**: what kind of food would you like? |

| StepFineTune training at step 3 |
|---------------------------------|
| **SYS**: hello, welcome to the restaurant finding system. how may i help you? |
| **USER**: i want a restaurant in the moderate price range. |
| **SYS**: what part of town do you have in mind? |
| **USER**: i prefer a venue in west. |
| **SYS**: what kind of food would you like? |
| **USER**: i need a venue in south. |
| **SYS**: what kind of food would you like? |
| **USER**: i need an international venue. |
| **SYS**: i am sorry but there is no place, serving international food, in the area of south and in the moderate price range. |
| **USER**: no, i am not looking for this. please show me another one. |
| **SYS**: i am sorry but there is no place, serving international food, in the area of south and in the moderate price range. |
| **USER**: no, i need a venue in south. |
| **SYS**: i am sorry but there is no place, serving international food, in the area of south and in the moderate price range. |
| **USER**: what about the venue in south? |
| **SYS**: i am sorry but there is no place, in the moderate price range, in the area of south and serving international food. |
| **USER**: thanks for the help, goodbye. |
| **SYS**: thank you, goodbye. |

| StepFineTune training at step 6 |
|---------------------------------|
| **SYS**: hello, welcome to the restaurant finding system. how may i help you? |
| **USER**: hi, i want to book a table |
| **SYS**: what part of town do you have in mind? |
| **USER**: i prefer a venue in south. |
| **SYS**: what kind of food would you like? |
| **USER**: i need an asian oriental venue. |
| **SYS**: would you like something in the cheap, moderate, or expensive price range? |
| **USER**: i want a venue in the expensive price range. |
| **SYS**: saigon city is a nice place, it serves asian oriental food, it is in the north part of town and it is in the expensive price range. |
| **USER**: what is the phone number of the restaurant? |
| **SYS**: saigon city is a nice place their phone number is 0 1223 356555. |
| **USER**: thanks for your help, goodbye. |
| **SYS**: thank you, goodbye. |

| StepFineTune training at step 9 |
|---------------------------------|
| **SYS**: hello, welcome to the restaurant finding system. how may i help you? |
| **USER**: hi, i want to book a table |
| **SYS**: what part of town do you have in mind? |
| **USER**: i prefer a venue in south. |
| **SYS**: what kind of food would you like? |
| **USER**: i need an chinese venue. |
| **SYS**: would you like something in the cheap, moderate, or expensive price range? |
| **USER**: i need a restaurant in the expensive price range. |
| **SYS**: the good luck chinese food takeaway is a nice place, it is in the south part of town, it serves chinese food and it is in the expensive price range. |
| **USER**: thanks for your help, goodbye. |
| **SYS**: thank you, goodbye. |

Table 7: Dialogues simulated by the StepFineTune approach in different training steps.