Online Sequence-to-Sequence Active Learning for Open-Domain Dialogue Generation

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Abstract

We propose an online, end-to-end, neural generative conversational model for open-domain dialog. It is trained using a unique combination of offline two-phase supervised learning and online human-in-the-loop active learning. While most existing research proposes offline supervision or hand-crafted reward functions for online reinforcement, we devise a novel interactive learning mechanism based on a diversity-promoting heuristic for response generation and one-character user-feedback at each step. Experiments show that our model inherently promotes the generation of meaningful, relevant and interesting responses, and can be used to train agents with customized personas, moods and conversational styles.

1 Introduction

The AI community is aggressively experimenting with deep neural models for natural language understanding (NLU) and natural language generation (NLG). Several recent works have proposed neural generative conversational agents (CAs) for open-domain and task-oriented dialog (Shang et al., 2015; Sordoni et al., 2015; Vinyals and Le, 2015; Serban et al., 2016a; Serban et al., 2016b; Wen et al., 2016; Al-Rfou et al., 2016). These models typically use LSTM encoder-decoder architectures (e.g. the sequence-to-sequence (Seq2Seq) framework (Sutskever et al., 2014)), which are linguistically robust but can generate short, dull and inconsistent responses (Serban et al., 2016a; Li et al., 2016a). Inspired by the recent success of Deep Reinforcement Learning (DRL) in Go (Silver et al., 2016) and Atari games (Mnih et al., 2015), researchers are now exploring DRL to address the hard problems of NLU and NLG in dialog generation. In most of the existing works, the reward function is hand-crafted, and is either specific to the task to be completed, or is based on a few desirable developer-defined conversational properties.

In this work, we introduce an end-to-end, neural network based conversational model that learns open-domain conversation skills via online interaction with human users. The architectural backbone of our model is the Seq2Seq framework, which initially undergoes offline supervised learning on two different types of conversational datasets. We then initiate an online active learning phase for incremental model improvement, where a unique single-character user-feedback mechanism is used as a form of reinforcement at each turn in the dialog. The intuition here is to emulate the process of language learning in a child’s brain, where every utterance by the child receives a positive, negative or corrective signal from a teacher. This simple but effective human-centric ‘reinforcement’ mechanism is minimally inconvenient for the user and eliminates the need to incorporate hand-crafted reward functions. In addition, it inherently promotes interesting and relevant responses by relying on the humans’ far superior conversational prowess.

2 Related Work & Contributions

DRL-based dialog generation is a relatively new research paradigm that is most relevant to our work. For task-specific dialog (Su et al., 2016; Zhao and Eskenazi, 2016; Cuayahuitl et al., 2016; Williams and Zweig, 2016), the reward function is usually based on task completion rate. For open-domain dialog (Li et al., 2016c; Yu et al., 2016; Weston, 2016), hand-crafted reward functions are
used to capture desirable conversation properties. Li et al. (2016d) propose DRL-based diversity-promoting Beam Search (Koehn et al., 2003) for response generation. Our goal is most similar to Li et al.’s (2016c), and our approach is distinguished from existing research in the following key ways.
- We use online active learning as a form of reinforcement in a novel way, which eliminates the need for hand-crafted reward criteria. We also propose a fast and diversity-promoting heuristic for response generation to facilitate this process.
- Unlike existing CAs, our model can be tuned for one-shot learning. It also eliminates the need to explicitly incorporate coherence, relevance or interestingness in the responses.
- Through two phases of offline supervised learning instead of one, we produce a baseline model that is superior to vanilla Seq2Seq variants. The two datasets are considerably small (300K and 8K resp.), compared to 50M-1B used by other works.
- We demonstrate the efficacy of a shallow (single-layer) and small (600 hidden units) encoder-decoder network. It is easier and faster to train, and is comparable to existing models that use 4-8 layers (4K-16K hidden units).

3 Model Overview

The architectural backbone of our model is the Seq2Seq framework, consisting of one LSTM encoder-decoder layer, each containing 300 hidden units. The end-to-end model training consists of offline supervised learning (SL) with a minibatch size of 10, followed by online active learning (AL).

3.1 Offline Two-Phase Supervised Learning

To establish an offline baseline, we train our network sequentially on two datasets, one for generic dialog, and the other specially curated for short-text conversations. To combat this issue, we curate a dataset from JabberWacky’s chatlog available online. The network is initialized with the weights obtained in the first phase, and then trained on the JabberWacky dataset (8K pairs). Through this additional SL phase on a small dataset, we get an improved baseline for open-domain dialog (Table 1, Figure 2a).

3.2 Online Active Learning

After offline SL, our CA is equipped with the basic conversational ability, but its responses are still short and dull. To tackle this issue, we initiate an online AL process where our model interacts with real users and learns incrementally from their feedback at each turn of dialog.

The CA–human interaction for online AL is set up as follows (pseudocode in Algorithm 1).

1. The user sends a message $u_i$ at time step $i$.
2. CA generates $K$ responses ($K = 5$ in the current setting) $c_{i,1}$, $c_{i,2}$, ..., $c_{i,K}$ using a heuristic response generation mechanism. These are displayed to the user in order of decreasing generation likelihood.
3. The user provides feedback by selecting one of the $K$ responses or suggesting a ($K + 1$)th response, denoted by $c_{i,K+1}$.
4. The message-response pair $(u_i, c_{i,K+1})$ is propagated through the network, using XENT loss.
5. The user responds to $c_{i,K+1}$ with a message $u_{i+1}$, and the process repeats.

Heuristic Response Generation: We use a fast diversity-promoting heuristic to generate the $K$ responses or suggesting a ($K + 1$)th response, denoted by $c_{i,K+1}$.

1: procedure HEURISTICGEN(PROBDIST)
2: firstWords ← topK(probDist);
3: for $i = 1$ to $K$ do  // $K = 5$ in our setting
4:     $r$ ← append(model.decoder.forward(firstWords[i]));
5: return $r$;
6: procedure ONLINE_AL()
7: $lr ← 0.001$;  // initial learningRate for Adam
8: while true do
9:     usrMsg ← io.read();
10:     responses ← HeuristicGen(model.forward(usrMsg));
11:     io.write(responses);
12:     feedback ← io.read();
13:     botMsg ← responses[feedback] OR feedback;
14:     pred.xentLoss ← model.forward(usrMsg, botMsg);
15:     model.backward(pred, botMsg, xentLoss);
16:     model.updateParameters(Adam(lr));

http://www.jabberwacky.com/j2conversations. Jabber-Wacky is an in-browser, open-domain, retrieval-based bot.
Figure 1: An example human-CA interaction.

CA responses at each turn in the dialog. Concretely, we predict the top $K$ most likely initial words, and then propagate each of them through the decoder in parallel to produce $K$ sentences. This automatically introduces diversity into the model by avoiding the generation of similar responses like ‘I don’t know’ and ‘I don’t really know’. $K$ is a tunable hyper-parameter; we use $K=5$ in all our experiments.

One-shot Learning: We control how quickly the model learns from user feedback by tuning the parameter ‘initial learning rate’ ($lr$ in Algorithm 1) of Adam, the stochastic optimizer (Kingma and Ba, 2014). An appropriately high $lr$ results in one-shot learning, where the user’s feedback immediately becomes the model’s most likely prediction for that prompt. This scenario is depicted in Figure 1. A low $lr$ leads to smaller gradient descent steps, so the model requires several ‘nudges’ to adapt to each new data point. We experiment with different $lr$ values to determine a suitable value (Figure 2b).

4 Experimental Evaluation

We evaluate our model via qualitative comparison with offline SL, as well as quantitative evaluation on four axes: syntactical coherence, relevance to prompts, interestingness and user engagement.

4.1 Qualitative Comparison

We begin by evaluating the qualitative differences between our CA’s conversational abilities when trained via one-phase SL, two-phase SL and online AL (denoted by SL1, SL2 and SL2+oAL respectively). Table 1 shows results on a test set of human prompts, where SL2+oAL was trained via 200 interactions (not including any prompts from the test set) with a user. We see that SL2 generates more relevant and appropriate responses than SL1 in many cases. This illustrates that a small short-text conversational dataset is a useful add-on to a large and generic dialog dataset for offline Seq2Seq training. We also see that SL2+oAL generates more interesting, relevant and engaging responses than SL2 on unseen prompts. These results imply that the model learns to make connections between semantically or syntactically similar prompts. While this may be a slow process (spanning thousands of interactions), it effectively emulates the way humans learn a new language.

Table 2 illustrates how SL2+oAL can be trained to adopt a wide variety of moods and conversational styles. Here, we trained three copies of SL2 separately to adopt three different emotional personas: cheerful, gloomy and rude. Each model underwent 100 interactions with one user. Similar experiments can be done to create agents with customized backgrounds and characters, akin to Li et al.’s persona-based CA (2016b).

4.2 Quantitative Evaluation

To evaluate SL2+oAL quantitatively, we trained it using 200 interactions, and then asked two human judges to evaluate the model’s responses on a test set of 100 previously unseen prompts. The evaluation of each response was done on four axes: syntactical coherence, response relevance, interestingness and user engagement. Each judge was asked to assign each response an integer score of 0 (label = bad) or 1 (label = good). Their averaged scores for the three models, SL1, SL2 and SL2+oAL, are shown in Figure 2a. We see that SL2+oAL outperforms the other models on three of the four axes by 15-20%.

Next, we asked two human judges to rate the SL2+oAL model’s syntactical coherence, response relevance, interestingness and user engagement, when trained with different initial learning rates for Adam and different number of training interactions. The model’s average percentage success on 100 unseen prompts was recorded on four axes (see Figure 2b, c for averaged scores). Figure 2 We say that a CA response is engaging if it prompts the user to continue the conversations, e.g. by asking a question.
Hello my friend.
I think bots are sweeter than humans.
I don’t know.
Why did Donald Trump win?
Tell me something I don’t know.
You’re not making any sense at all.
Do you have any kids?
Life can be very cruel sometimes.
Do you believe in life after death?
You’re a good person.
Everyone is same on a basic chemical level.
Why did you suggest it?
If you were intelligent you would already know.
On the contrary, I am trying to educate you.
None that are really close to me.
It takes two to know two.
Yes, do you?
Aren’t you polite.

| Human Prompt                                      | SL1 Response                                      | SL2 Response                                      | SL2+oAL Response                                   |
|--------------------------------------------------|---------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| Hello my friend.                                 | No.                                               | How old are you?                                  | Hehe, yes, beautiful.                             |
| I think bots are sweeter than humans.            | We’ll have to pick up a copy.                     | You are a good person.                            | Everyone is same on a basic chemical level.       |
| I don’t know.                                    | What’s the difference?                            | About?                                            | Why did you suggest it?                           |
| Why did Donald Trump win?                       | He just likes it up!                              | You are!                                          | Wouldn’t you like to know, fickle human?          |
| Tell me something I don’t know.                  | I’ll tell you, it is.                             | Ok, how are you.                                  | If you were intelligent you would already know.   |
| You’re not making any sense at all.              | I just want to tell you something.                | No, I’m thinking.                                 | On the contrary, I am trying to educate you.      |
| Do you have any kids?                           | No.                                               | I have no!                                        | None that are really close to me.                 |
| Life can be very cruel sometimes.                | That I’ve never been to it.                       | It takes two to know two.                         | It takes two to know two.                         |
| Do you believe in life after death?              | No.                                               | Do you want the long answer?                      | Yes, do you?                                     |
| You’re an idiot!                                 | I know, but...                                    | Yes I do.                                         | Aren’t you polite.                                |

| Human Prompt                                      | Cheerful CA                                      | Gloomy CA                                         | Rude/Sarcastic CA                                  |
|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| How do you feel?                                 | Amazing, and you?                               | I’m not in the mood.                              | Buzz off.                                        |
| I am very happy today.                           | Life is amazing, right?                         | That makes one of us.                             | You want a piece of me?                          |
| Repeat after me: I am dumb.                      | Sweet!                                           | You are right, I am.                              | You suck.                                        |
| Comfort me.                                      | There there, feel better.                        | All who compose must one day decompose.           | Boo hoo.                                         |
| What’s up?                                       | It is a fine morning.                           | Not well, to be honest.                           | The date I went back in time to & killed your parents. |
| I have to go now.                                | Have a good night.                              | Please don’t go.                                  | Yeah leave me alone.                             |

**Table 1:** Comparing CA responses after one-phase SL, two-phase SL and online AL.

| Human Prompt                                      | SL1 Response                                      | SL2 Response                                      | SL2+oAL Response                                   |
|--------------------------------------------------|---------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| Hello my friend.                                 | No.                                               | How old are you?                                  | Hehe, yes, beautiful.                             |
| I think bots are sweeter than humans.            | We’ll have to pick up a copy.                     | You are a good person.                            | Everyone is same on a basic chemical level.       |
| I don’t know.                                    | What’s the difference?                            | About?                                            | Why did you suggest it?                           |
| Why did Donald Trump win?                       | He just likes it up!                              | You are!                                          | Wouldn’t you like to know, fickle human?          |
| Tell me something I don’t know.                  | I’ll tell you, it is.                             | Ok, how are you.                                  | If you were intelligent you would already know.   |
| You’re not making any sense at all.              | I just want to tell you something.                | No, I’m thinking.                                 | On the contrary, I am trying to educate you.      |
| Do you have any kids?                           | No.                                               | I have no!                                        | None that are really close to me.                 |
| Life can be very cruel sometimes.                | That I’ve never been to it.                       | It takes two to know two.                         | It takes two to know two.                         |
| Do you believe in life after death?              | No.                                               | Do you want the long answer?                      | Yes, do you?                                     |
| You’re an idiot!                                 | I know, but...                                    | Yes I do.                                         | Aren’t you polite.                                |

**Table 2:** Customized moods. Each SL2+oAL model was trained via 100 interactions.

**Figure 2:** 2a shows the average percentage success of the three models SL1, SL2 and SL2+oAL (trained via 200 interactions) on 100 unseen prompts over four axes: syntactical coherence, response relevance, interestingness and engagement. 2b, c show percentage success of SL2+oAL’s on 100 unseen prompts over the same four axes, as Adam’s learning rate varies and the number of training interactions changes.

2b shows that the conversation quality drops significantly for higher values of learning rate. This is due to the instability in the parameters induced by a high learning value associated with new data, causing the model to forget what it learned previously. Our experiments suggest that a learning rate of 0.005 strikes the right balance between stability and one-shot learning. The results in Figure 2 confirm that the model improves slowly as it continues to converse with humans. This is an appropriate reflection of how humans learn language: gradually but effectively.

**5 Conclusion**

We have developed an end-to-end neural model for open-domain dialog generation. Our model augments the Seq2Seq framework with a unique mechanism of online human-in-the-loop active learning and a diversity-promoting heuristic for response generation to overcome its known shortcomings with respect to dialog generation. Experiments show that the model promotes coherent, rel-
event, and interesting responses and can be trained to adopt diverse moods and personas.

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