Domain Aware Neural Dialog System

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Abstract

We investigate the task of building a domain aware chat system which generates intelligent responses in a conversation comprising of different domains. The domain in this case is the topic or theme of the conversation. To achieve this, we present DOM-Seq2Seq, a domain aware neural network model based on the novel technique of using domain-targeted sequence-to-sequence models (Sutskever et al., 2014) and a domain classifier. The model captures features from current utterance and domains of the previous utterances to facilitate the formation of relevant responses. We evaluate our model on automatic metrics and compare our performance with the Seq2Seq model.

1 Introduction

With the advent of personal assistants such as Siri and Alexa, there has been a renewed focus on dialog systems, specifically those which can hold open-domain conversations. Readily available conversations from social media such as Reddit 1 have facilitated the use of data driven models to generate open domain responses. A recurrent neural network-based sequence-to-sequence model has been successfully applied to generating responses for conversational tasks (Vinyals and Le, 2015).

Though these models generate responses that are fluent and natural, they often fail to produce domain-specific responses since they are trained on a single general data-set. Moreover, these models tend to capture information solely based on previous words in a single utterance and fail to acknowledge switching of domains in a multi-turn conversation. Recent research has aimed at solving these problems and has shown promising results. Topic-aware neural networks (Xing et al., 2017) seek to incorporate topic information in their model to generate responses relevant to the topic words in the query. However, the context inherent in the previous utterances is not taken into account. On the other hand, hierarchical neural networks (Serban et al., 2016, 2017) model the interactive structure of a conversation in order to output more contextual responses. Though these models try to capture the context of previous utterances in a conversation, the responses generated might lack domain-specific relevance.

We hypothesize that each utterance in a conversation belongs to a domain and that during a conversation, participants tend to switch between domains. Moreover, sometimes the domain of an utterance might be ambiguous, but incorporating the previous domains of the conversation might be helpful in inferring the precise domain. For instance in Figure 1, the first utterance by speaker A lies in the sports domain. The domain for A’s second utterance is ambiguous and could lie in ei-

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1https://www.reddit.com/
ther sports or music. Since the previous domains referenced by the participants is sports, it is highly probable that the exchange is about playing “tennis” rather than playing a song named “tonight”. When B is a chatbot, this utterance might be misinterpreted as a request for playing a song. We address the above problems by modelling a conversation and taking into account the domain of the current utterance as well as domains of the previous utterances.

In this paper, we describe a novel domain aware dialog system, DOM-Seq2Seq, consisting of three main components: 1) Domain Classifier, 2) Domain specific response generators (Seq2Seq), and 3) Re-ranker to combine responses of the above two models.

2 Model

2.1 Overview

In order to maintain a smooth conversation within the domain as well as during switching of domains in a conversation, we built a model consisting of a domain classifier and a set of response generators. The overview of the model is depicted in Figure 2. An utterance is fed into the domain classifier as well as multiple response generators which are trained separately on domain-specific data. The output domain (d) predicted by the domain classifier and all the generated responses (r1, r2, r3) are then fed to the re-ranker. Re-ranker outputs the final predicted domain(d′) and response(r′). The final predicted domain(d′) is fed back to the domain classifier to be used in subsequent predictions.

2.2 Domain classifier

Domain classification predicts the domain of an utterance. Firstly, we used a tf-idf based supervised SVM to capture utterance level word features. Subsequently, we employed two ways to combine predicted domain from SVM and previous set of domains in the conversation.

2.2.1 Ensemble based Domain Classifier

We applied a logistic regression model to capture the sequence of domains in the conversation. While training the model, three previous actual domains (dt−1, dt−2, dt−3) are taken into consideration, where dt−1 is the domain of the previous utterance and so on. Along with this, the domain predicted by the SVM model (dtSV M) is also included as a feature. Hence, this model optimizes the cost function,

\[ p(y|dt−1, dt−2, dt−3, dtSV M) \]  (1)

where y is the actual label (domain) of the utterance in the conversation.

2.2.2 RNN based Domain Classifier

Our previous approach (2.2.1) is based on the assumption that the last three domains in the conversation are sufficient to predict the current domain. However, capturing long term dependencies on domains is more beneficial for this task instead of relying only on the last few domains. The best way to capture this information is to use an RNN model with one hot input vector representation of subsequent domains. This is depicted in Figure 3. The state at time step t for an RNN is represented as \( s_t = f(d_t, s_{t−1}) \) where \( s_t \) is the hidden state of the RNN at \( t^{th} \) time step and \( d_t \) is the domain at the same time step. Thus, at each time step, the state modifies itself based on its previous state and the current input. In our case, RNN is fed with the sequence of domains. The last hidden state (vt) captures all the necessary information about the sequence of domains. The SVM model’s prediction is also represented in a vector form (vd). These two vectors are concatenated and fed to a softmax classifier to get a probability distribution over the domains as in Equation 2.

\[ p(dt|d_{<t}, v_d) = Softmax(W * [v_t | v_d] + b) \]  (2)
Figure 3: RNN Based Domain Classifier: The vector representation of the output from SVM tf-idf ($v_d$) is concatenated with the last hidden state of RNN. These are then fed to softmax classifier.

2.3 Response Generators

For generating the output response, we used an LSTM based Seq2Seq model with attention mechanism (Bahdanau et al., 2014). Seq2Seq consists of two recurrent neural networks: encoder and decoder. An encoder compresses the input sentence into a fixed length vector, which is then passed to the decoder. The decoder then generates the output response word at a time. Thus a candidate response is output for each domain. During testing phase, the output of the decoder at time step $t$ is fed to the input of decoder at time step $t+1$; it outputs the logit at each time step. We extract the output logit $l$ from the last time step of the decoder and apply sigmoid function to limit its value between 0 and 1. The value of $\sigma(l) = \frac{1}{1+e^{-l}}$ is used in the re-ranker stage to combine it with the output of the domain classifier.

2.4 Re-ranker

The output scores from the the generators and the domain classifier are fed into a re-ranker which implements soft classification to figure out the best response from the set of candidate responses. Equation 3 returns the index of the response with the highest multiplied score. So,

$$\text{final response index} = \arg \max_i \{p(d_i) \times p(r_i)\},$$

where $p(d_i)$ is the probability that the utterance belongs to $i^{th}$ domain and $p(r_i)$ is the $i^{th}$ domain’s decoder probability which was calculated from its output logit.

3 Experiments

In this section, we describe the experiments performed for our proposed models. We present the quantitative results of our evaluations and compare them with the those of the Seq2Seq model. We also put forward some qualitative examples of conversation snippets tested on our models. Our experiments were restricted to three domains namely Movies, Gaming and Out of Domain to aid in data collection and evaluation. We introduced Out Of Domain to manage utterances that do not lie in either Movies or Gaming.

3.1 Data Sets

We collected data from the social discussion website Reddit for training our models. We gathered 1,334,119, and 542,594 query-response pairs from the Movies and Gaming Reddit categories respectively for training two Seq2Seq models. Furthermore, for responding to Out of Domain queries, we trained Seq2Seq using 301,812 query-response pairs from twitter.

The SVM classifier for the domain classifier was trained and tested on 544,630 posts from Reddit categories of Movies, Gaming and tweets from Twitter combined. We made sure that there was no overlap with the data used for training of Seq2Seq models.

Tagging Conversational Data with Domains

Conversations extracted from Reddit IAmu were used as data for the model. Reddit IAmu threads specially suited our purposes, as they are already tagged with a flair, which is essentially the category of the conversation. We found that participants often switch categories during the conversations as these are of the type “ask me anything”. Each utterance of conversation was labelled automatically. Latent Dirichlet Allocation (Blei et al., 2003) was used to learn topics from the conversation and to label each utterance with a topic corresponding to a domain if the topic proportion for that domain was above the threshold of 0.5. We replaced any domains outside of Movies and Gaming by Out Of Domain. Finally, we weighted the previous domains with exponentially decaying weights and took an average of these to incorporate the effect of previous domains. We amassed 947 conversations.

3.2 Experimental Setup

Response Generators

We used a Seq2Seq model with 3 layers of LSTM each consisting of 1024 hidden units as encoder and decoder. The vocabulary size for the Seq2Seq
Table 1: Qualitative comparisons of responses from the Seq2Seq baseline and DOM-Seq2Seq.

| Model            | Domain Classifier Accuracy | Word Embedding Greedy |
|------------------|---------------------------|-----------------------|
| Seq2Seq          | N/A                       | 0.760                 |
| RNN-DOM-Seq2Seq  | 67.8%                     | 0.797                 |
| En-DOM-Seq2Seq   | **77.57%**                | **0.801**             |

Table 2: Results for evaluation of Seq2Seq, RNN based DOM-Seq2Seq (RNN-DOM-Seq2Seq), and Ensemble based DOM-Seq2Seq model (En-DOM-Seq2Seq).

5 Conclusion

We proposed an original technique for building a domain-aware chat system that can generate more relevant responses. We put forth two models to achieve this: an ensemble that considers a fixed number of previous domains and the current utterance to generate an appropriate response, and an RNN based classifier that models the switching of domains during a conversation. The methods described here can be extended to model a user’s conversation pattern (domain shifts) and personalize the responses of the chat system.
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