Project Survey: Data-driven dialogue generation in therapy

Leili Tavabi
Institute for Creative Technologies
University of Southern California

Abstract
Data-driven conversational dialogue generation has recently been brought to researchers attention and effort, with the purpose of generating human-like conversations that are engaging to the user. Conversational open-domain dialogue is different from task-oriented dialogues whose main purpose is task completion, often in narrow and specific domains. The goal of this project is to train a conversational backbone, which can be transferred to therapy dialogues with a specific focus on generating follow-up questions relevant to the context. Therapeutic dialogues tend to have a pattern of relatively long monologues by the patient followed by considerably shorter responses of a therapist. This pattern highlights the importance of gaining an understanding of the patient's monologue content in order to generate the appropriate response, which will be part of this project.

1 Introduction
In this project, an initial model will be trained to learn a conversational backbone using a large open-domain conversation corpus, leveraging a seq2seq model inspired by the existing work. To represent the input sequence, pretrained phrase embeddings will be experimented with additional features obtained from extracted relations of the monologue input. It is expected for the added relational features to increase the model's performance, especially for imbalanced dialogues such as therapy, due to the relatively long and complicated patient input sequence. Initial training on a separate corpus is necessary due to the abundance of available conversational data which would not be accessible in therapy. This will provide a conversational backbone that we can adapt for the domain of therapy with a relatively smaller dataset.

After building the conversational backbone, it is intended to use transfer learning to adjust the model for imbalanced therapy dialogues. The goal would be to generate short phrases that are follow-ups to the patient input to encourage more disclosure related to the previous topic of attention. Generation of follow-up questions and statements relevant to the context and conversation history, will therefore be the primary focus of this work and hence its novelty and contribution.

Although recent papers have worked on data-driven open-domain conversational dialogue, to my knowledge there is no fully generative model focusing on therapy.

The main focus of this survey will be on data-driven models for generation of open-domain dialogue, trained and tested on offline datasets. Although many prior works have focused on Partially Observable Markov Decision Processes(POMDPs) or Reinforcement Learning(RL) for training their dialogue models, this survey intentionally avoids extensive discussion of these models, because of the infeasibility of adopting such methods based on the current focus and resources of the project.

2 Related Work
(Sordoni et al., 2015) uses large quantities of unstructured Twitter conversations to train their Recurrent Neural Network Language Model(RLM) for context-sensitive response generation. They use continuous embeddings of words and phrases to compactly encode semantic and syntactic similarity, arguing for these representations ability to model the transitions between consecutive utterances while capturing long-term dependencies.

(Serban et al., 2016) builds an end-to-end model using Recurrent Neural Networks(RNN) and n-grams. They adopt the Hierarchical Recurrent
Encoder-Decoder (HRED) along with pretrained word embeddings to demonstrate competitiveness with other models in literature. 

(Xing et al., 2017) proposes a topic aware sequence-to-sequence (TA-Seq2Seq) model. Their model utilizes topics to simulate prior human knowledge that guides them to form informative and interesting responses in conversation, and leverages topic information in generation by a joint attention mechanism and a bias generation probability. The joint attention mechanism summarizes the hidden vectors of the input as context vectors by input attention, and topic vectors by topic attention from the topic words obtained by a pretrained LDA model.

(Ghazvininejad et al., 2018) generalizes the seq-to-seq model to incorporate the conversational dialogue with external facts by conditioning the responses on both conversation history and the external facts. They use multi-task learning to combine informal exchanges (e.g., a response to hi, how are you) with conversational data that is naturally associated with external data (e.g., discussions about restaurants, etc.). They initially train their model on 3-turn twitter exchanges to build a conversational backbone and in order to infuse the response with factual information, they use a knowledge-grounded model architecture where they have a large collection of world facts (e.g., a collection of raw text entries from Foursquare, Wikipedia, or Amazon reviews) indexed by named entities as keys. Then, given a conversational history, they identify the focus which is the text span, based on which they form a query to link to the facts.

(Garg et al., 2018) proposes a dialogue modeling framework using binary hashcodes as compact text representations, allowing for efficient similarity search, and a lower bound on mutual information between the hashcodes of the two dialogue agents. This serves as a model selection criterion toward optimizing the representations for better alignment between the two participants responses. Their model is applicable to domains with smaller amounts of data, which is their models advantage in comparison with data hungry neural network architectures.

They train their model on two separate datasets focusing on imbalanced dialogue: 1) Interviews from Larry King Live, and 2) therapy sessions. Although their work is similar to the goal of this project, their model is not completely generative and is very different in its approach. 

(Li et al., 2017) uses adversarial learning for open-domain dialogue generation. They cast the task as a reinforcement learning (RL) problem where they jointly train two systems where the generator (a neural seq2seq model) produces response sequences and the output of the discriminator is used as rewards for the generative model. The discriminator is analogous to the human evaluator in the Turing test.

(Li et al., 2016) argues that the current dialogue generations ignore their influence on future outcomes and are therefore shortsighted. They propose a solution using a reinforcement learning generation method, which can optimize long-term rewards designed by system developers.

(Lowe et al., 2017) proposes an evaluation model for dialogue responses, which is a challenging problem in the domain of dialogue generation. They formulate dialogue evaluation as a learning problem and provide a model (ADEM) that learns to predict human-like scores to input responses. They show that their model has a high correlation with human judgment outperforming metrics such as BLEU and word overlap statistics. ADEM learns distributed representations of the context, model response, and reference response using a hierarchical RNN encoder.

3 Conclusion

This project will leverage the prior model architectures in open-domain dialogue described above (specifically seq2seq models), toward data-driven generation of contextually relevant conversations. The trained model will then be adapted for the domain of therapeutic dialogue focusing on follow-up questions that are relevant to the context of the patient’s monologue along with the conversation history, with the intention to increase disclosure by the patient. The primary evaluation of the model will be done through a combination of the metrics provided in prior work about relevance, diversity and coherency along with metrics of patient’s disclosure at each utterance.

References

Sahil Garg, Guillermo Cecchi, Irina Rish, Shuyang Gao, Bhavana Bhaskar, Greg Ver Steeg, Palash Goyal, and Aram Galstyan. 2018. Dialogue model-


