An Approach to Incorporate Emotions in a Chatbot with Seq2Seq Model

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Thesis Abstract

This master thesis project has focused on the development of an open-domain generative model for chatbots. In particular, we target one of the under-studied aspects in the existing chatbots, which is the emotion modelling of the natural language. The motivation of introducing emotions in a chatbot is to improve the communication quality by making the chatbot more human-like — the chatbot acts as an artificial companion that is able to generate emotional responses. Such a functionality is accomplished by following an emotion model which enables us to customize emotional content in generated sentences.

The proposed model as shown in **Fig. 1** is associated with two types of text representations: affective representation (SenticNet [1]) and semantic representation (GloVe [2]). It follows a two-fold process: first, we represent the input-output pairs by the concepts and their emotion scores which are provided by the SenticNet. Concepts are terms that contain conceptual and affective information of the text; emotion scores are two-dimensional values that correspond to the valence and arousal levels of the emotion. Given the emotion scores of the texts, the emotion model utilizes a fully connected neural network to learn the emotion relations between the input and output in a common conversation. Second, we apply a Seq2Seq (Sequence-to-Sequence) [3] model as a basic structure for text generation, and modify the model to integrate the emotion relations learned by the emotion model. The modified Seq2Seq model takes word vectors from GloVe to represent the input, and combines the GloVe representation with the intended emotion score of the output generated by the emotion model. The rest of the network remains the same with the basic Seq2Seq model which applies recurrent neural networks with long short-term memory (LSTM) cells as used in [3].

In the experiment, we used 10,000 dialogs from Cornell Movie-Dialogs Corpus [4] to train the emotion model, and another 10,000 dialogs to train the modified Seq2Seq model. We take the GloVe representation of the outputs from the basic and the modified Seq2Seq models, and compare the vectors dimension-wise. The representation reflects that the two models generate different responses given certain inputs. The difference can be interpreted from two aspects: one is from the network itself which causes minor shifts in the vector representation, and the other is from the emotional component added in the input. Instead of

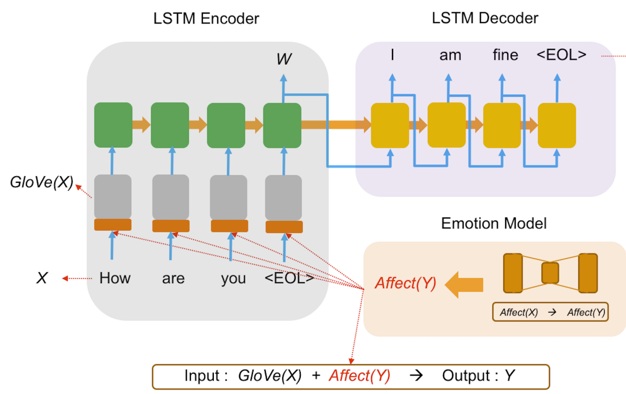

Fig. 1. The modified Seq2Seq model with emotion components, where X denotes the input, *Affect(X)* and *GloVe(X)* are the affective and semantic representations of X respectively, Y is the generated response, and *Affect(Y)* is the affective representation of the output produced by the emotion model given the current *Affect(X)*.

using the movie-dialogs extracted from the corpus randomly, the proposed model is able to offer a finer-tuned emotion status while training with movie-dialogs from a specific category. Such a selection of the categories can be manipulated by the end-user as well in order to enrich the functionality of a chatbot, and to lengthen the conversation by increasing the user's interest. In this thesis project, we have performed a preliminary test for integrating emotion component with Seq2Seq model, and comprehensive comparisons are planned for the next stage due to the time constraints. For future research, such a chatbot can be extended to provide a companionship that personalizes the user experience as in [5].

References

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