

Emotion Twenty Questions Dialog System for Lexical Emotional Intelligence

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Abstract—This paper presents a web-based demonstration of Emotion Twenty Questions (EMO20Q), a dialog game whose purpose is to study how people describe emotions. EMO20Q can also be used to develop artificially intelligent dialog agents that can play the game. In previous work, an EMO20Q agent used a sequential Bayesian machine learning model and could play the question-asking role. Newer transformer-based neural machine learning models have made it possible to develop an agent for the question-answering role.

This demo paper describes the recent developments in the question-answering role of the EMO20Q game, which requires the agent to respond to more open-ended inputs. Furthermore, we also describe the design of the system, including the web-based front-end, agent architecture and programming, and updates to earlier software used.

The demo system will be available to collect pilot data during the ACII conference and this data will be used to inform future experiments and system design.

An example of the demo system can be seen in Fig. 1 and the live system can be accessed at emo20q.org.

Index Terms—emotions, natural language processing, dialog systems, question-answering, EMO20Q, lexicon

I. INTRODUCTION

This demo system aims to use a dialog agent to collect question-answer data about human emotions. We use the emotion twenty questions game (EMO20Q) as the experimental setting. In EMO20Q, one player picks an emotion word and the other player tries to guess it in twenty or fewer turns. The player that picks the emotion word plays the *question-answering* role, because they answer questions about the emotion word that they picked. The player who tries to guess the emotion word plays the *question-asking* role, because they ask questions in order to identify the emotion word.

Both player roles for EMO20Q could be played by humans or computers. Past research collected data of humans playing both roles and then used this data to train dialog agents to play the question-asking role [1]. This past work used a sequential Bayesian probabilistic model for the question-asking role in the game [1]: the input was a sequence of question-answer pairs. The question set comes from human-human dialogs and

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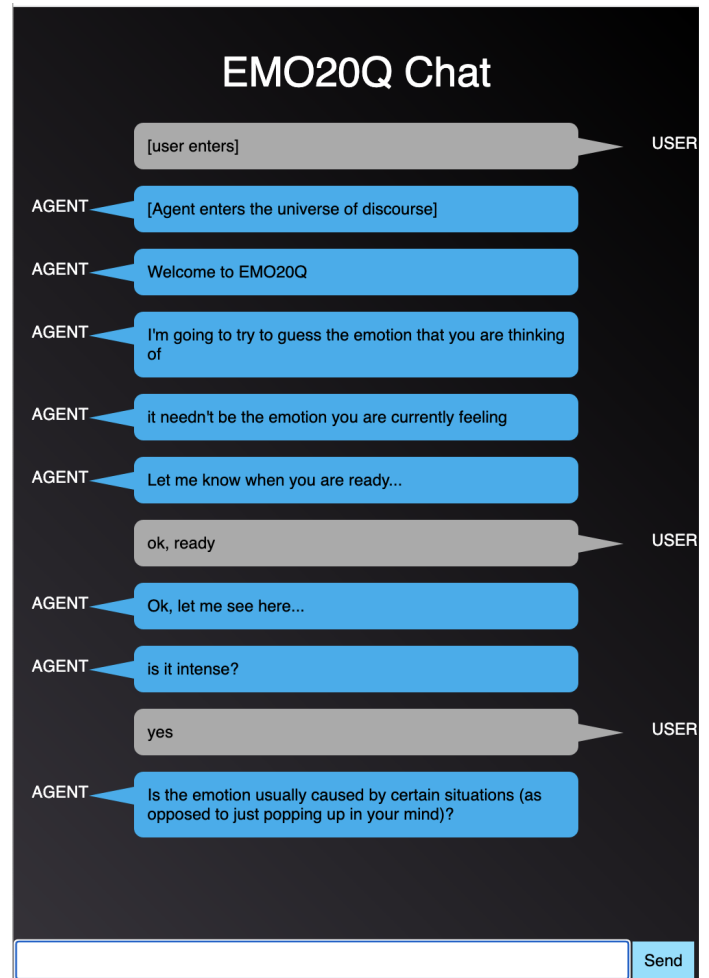


Fig. 1. Example of the web-based front end to the EMO20Q dialog system. the particular question that the agent asks is chosen based on the dialog history. The answers come from the user's corresponding responses. Posterior probabilities of the emotion words are updated based on these sequential question-answer inputs.

The current work aims to extend the approach to a dialog agent that can play the question-answering role. In this case, the agent picks the emotion word from words seen in previously collected data (167 words) and answers questions posed

by the user. In this case, the agent’s inputs are very open-ended: any possible yes/no questions about emotions. Many questions, especially earlier in the game, have been seen before (e.g., “is it a positive emotion?”, “is it a negative emotion?”, “is it an emotion that is directed at another person?”, “is it an emotion that lasts a long time?”), but in principle, any questions could be asked. In comparison, the inputs to the question-asking role are more limited. The question-asking agent asks questions from the set of questions seen in human-human data and its inputs are answers to these yes-no questions. The answers are not restricted to yes or no, but it is fairly trivial to bucket these responses into yes/no/other categories.

To deal with the open-ended question-answering task, we aim to leverage neural large language models (LLM), which encode linguistic knowledge from large pre-training datasets into neural networks, which can then be fine-tuned into task-specific models using relatively smaller datasets.

The goal for EMO20Q dialog system is to use dialog agents to test hypotheses about how well automated systems can understand language about emotions.

II. WEB FRONT END

To simply display the front end of the demo system, we used Flask, a lightweight Python web framework. Using the simple request-response interaction of a basic web server would have been an option, but it would require a page reload for every dialog turn and could result in slow response times, especially in cases where prediction requires beam search (the question-answering role). To prevent page reloads and response delays, we used WebSockets via the Socket.io library, which enables bidirectional communication between the browser and web server. Dialog events, i.e. turns from the user (via the browser) or agent (via the server), trigger updates to a typical speech bubble dialog display, as seen in Fig. 1.

III. DIALOG AGENT

The dialog agent was trained using a method inspired by wizard of Oz approaches [2] and games with a purpose [3]. First, non-expert human players played both roles of EMO20Q, which provided an initial set of training data. Then, we created automated agent for the question-asking role by finding the conditional probabilities of (question, answer) pairs given emotion words and using these to create a sequential Bayesian probabilistic model [1], which provided a further source of training data. The current work has focused on the question-answering role. This current work has benefited from recent trends in transfer-learned deep neural language models. In particular this demo uses BERT [4] to classify (emotion, question) pairs into “yes”, “no”, and “maybe” categories. Although our system achieves reasonable performance of about 72% accuracy on question-answering, we plan that the demo system will be an experimental tool to more fully evaluate this and other models.

The programming of the agent is based on a generalized pushdown automaton (GPDA) [5]. The abilities of a general

finite state automata are sufficient for most of the dialog behavior, but the pushdown stack is used to maintain contextual information that represents short-term/working memory in the question-asking role. The transition graph of the automaton is implemented with the NetworkX Python library.

IV. DISCUSSION AND FUTURE WORK

This paper presented an overview of a tool that we will use to test the abilities of automated systems to talk about emotions with human users. In this demo, we use BERT, an encoder-only model set up as a classification model to provide yes/no/maybe answers. This classification approach fits with the existing approaches used by the question-asking agent. Other transformer models that include decoders may allow for more fluent output and may be able to encompass the functionality currently covered by the dialog graph, so we anticipate that this will be an area of future testing.

Although the agent in our demo appears to the user as a single agent playing both roles, the design of the functionality of this single agent is currently implemented as two separate agents with different machine learning models built on the same data. One area of future research is to design a more unified approach where machine learning models are shared between the two EMO20Q roles. This approach could enable adversarial training scenarios where two automated agents play each other.

Another issue is the ordering of EMO20Q roles. Currently, the demo system makes the user play the question-answering role first, then the question-asking role. This order may induce experimental effects. For example, playing as question-answerer first may prime the human user to reuse the agent’s questions.

In conclusion, we demonstrate an automated system that plays EMO20Q using a web-based chat interface and a mix of older probabilistic models for the question-asking role and a fine-tuned BERT model for the question-answering role.

V. ETHICS STATEMENT

This research has been approved by the University of St. Thomas institutional review board (IRB). Data is not collected with personally identifiable information (PII) and the collected data will be examined again for PII before public dissemination.

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