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THERABOT an Artificial Intelligent Therapist at Your Fingertips

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Abstract: *Early study tries to use chatbot for counselling services. They changed drinking habit of who being consulted by leading them via intervene chatbot. However, the application did not concerned about psychiatric status through continuous conversation with user monitoring. Furthermore, they had no ethical judgment method that about the intervention of the chatbot. We argue that more reasonable and continuous emotion recognition will make better mental healthcare experiment. It will be more proper clinical psychiatric consolation in ethical view as well. This paper suggests a introduce a novel chatbot system for psychiatric counselling service. Our system understands content of conversation based on recent natural language processing (NLP) methods with emotion recognition. It senses emotional flow through the continuous observation of conversation. Also, we generate personalized counseling response from user input, to do this, we use additional constrains to generation model for the proper response generation which can detect conversational context, user emotion and expected reaction.*

Keywords— *conversational service; response generation; deep learning;*

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I. Introduction

The recent boom of AI has brought back a lot of attention to chat-oriented dialogue systems, commonly referred to as chatbots or conversational agents. Some early versions of these kinds of systems date back to the pioneering years of AI research. The most representative example of such early chatbots is the Eliza system [1], which impersonates a psychotherapist. While early systems were mainly rule-based and relied in a large repertory of handcrafted or semi-automatically collected rules that encoded the knowledge and intelligence of the system [2], [3], [4], the recent increase on computer resources and data availability have helped to the proliferation of data-driven systems.

On the other hand, different from traditional task-oriented dialogue, in which certain specific goals or tasks are to be accomplished (such as directory services, flight booking [2], or weather information [4]), conversational agents en-compass a broader scope of human-machine interaction in terms of user experience. Within this context, the perception of system intelligence by the human counterpart is of critical importance for delivering a good interaction experience and increasing the level of user engagement. In this manner, the affective and emotional dimensions of the human-machine interaction start playing a preponderant role with regards to system design, in addition to other traditional evaluation metrics such as objective-completion rates.

In this respect, beyond just constructing more efficient and useful conversational agents, the research community is also looking into making human-machine interaction more human-like in both behavioral and attitudinal terms. This paper gives some baby steps into this direction by analyzing a large movie dialogue dataset (currently used as knowledge source in some chatbot implementations) in terms of tonal polarity, affective bias and emotional bias. This analysis is conducted with the objective of developing resources for building conversational agents that are able to follow some specific personality and behavioral trends across these different dimensions. Future research is still needed to determine whether such a capability is actually beneficial from the user experience point of view.

The main objective of this paper is to evaluate how much information about these human-like attributes (tonal polarity, affective bias and emotional bias) is actually present in a typical dataset used for training chat-oriented conversational agents, and how much of this information can be actually exploited in the construction of chatbots with better defined personality trends.

The rest of the paper is structured as follows. Section II describes the specific dataset and tools used for the analysis. Section III describes and discusses the overall results of the analysis, showing some specific examples of data segments exhibiting the different considered orientations. Finally, Section IV concludes the work and discusses about the next steps that are needed to validate our basic assumptions on the utility of the generated resources.

II. Dataset And Tools

In this section we first describe MovieDiC [4], the dataset used for the analysis conducted in this work, along with a chat-oriented dialogue system developed with it. Second, we briefly described Crystal Emotion [12], the psycholinguistic analysis tool used to evaluate the dataset in terms of tonal polarity, affective bias and emotional bias.

A. The MovieDic Dataset

MovieDiC (Movie Dialogue Corpus) [3] is a dialogue data collection that has been semi-automatically extracted from movie scripts publically available in the Internet Movie Script Database (www.imsdb.com). It contains scripted dialogues from 16 different movie genres, including action, adventure, drama, etc. The original dataset contained over 760K dialogue turns extracted from 753 movie scripts. For this work, we use a revised version of the corpus, containing scripts from 615 movies. This revised dataset constitutes an improved version of the original collection, after performing some reprocessing and filtering out an important amount of noisy scripts. The total number of dialogue turns in it is 512,583.

Each dialogue in the data collection includes information about the character that speaks, the utterance spoken by the character and some additional contextual information related to the scene. The analysis will be conducted only over the utterance portion of the dataset, which mainly correspond to the segments spoken by the different characters in the movies.

Across the overall dataset, a huge variability of dialogues is observed. With an average of 175 dialogues per movie, there are movies with as few as 60 dialogues and movies with as much as 290 dialogues. Similarly, with an average of 5.78 turns per dialogue, there are few dialogues with more than 100 turns and a large amount of them with three or less turns. Regarding speakers per dialogue, i.e. the number of characters participating in a given dialogue, most of the dialogues are two-speaker sessions. However, there is also a large number of monologues (only one speaker), as well as a smaller but significant number of multi-party dialogues, including three and more (up to seven) speakers.

The MovieDiC dataset is the main knowledge resource for the data-driven conversational agent IRIS (Informal Response Interactive System) [4]. This chatbot uses an Information Retrieval approach to pull responses from the data collection based on the semantic similarity between the recent dialogue interaction with a user and the dialogues in the database. More specifically, it combines semantic information at both the utterance and the dialogue history levels in order to score and rank candidate responses. The ranking mechanism is of fundamental importance to the performance of the chatbot, and it can be used to incorporate different tonal, affective and emotional biases to generate different impersonations of IRIS.

B. The Crystal Emotion Tool

Crystal Emotion is an advanced psycholinguistic analysis tool developed at the Institute for High Performance Comput-ing (IHPC) in Singapore. It features a manually crafted lexicon, which is conceptualized and constructed with the guidance of linguistic principles and psychological knowledge. The tool is able to compute more than 100 word- and phrase-level features present in a given segment of text in terms of multiple affective and emotional dimensions, including valence-based, strength-based, intensity-based, psychological condition-based as well as basic emotion and fine-grained emotion features.

In their first application of Crystal Emotion in the context of sentiment analysis and sarcasm detection, Gupta and Yang described the initial development of the lexicon for three emotional dimensions (valence, strength, and intensity). They further presented experimental results indicating the lexicon's values in terms of providing novel features in enhancing the performance of SVM classifiers in sarcasm detection.

For this work, we sought to explore a subset of Crystal Emotion features in the context of characterizing movie dialogue corpus. Our focus is on the main indicators for the variations across tonal polarity, cognitive bias and affective bias, and basic emotional properties of movie dialogues. More specifically, the following dimensions are considered:

- Tonal Polarity Dimensions
  - Positive: favorable and positive comments
  - Negative: unfavorable and negative comments

- Cognitive-Affective Bias Dimensions
  - Cognitive: analytical and reasoning orientation
  - Affective: value and intuition orientation

- Emotional Bias Dimensions
  - Love: feeling of interpersonal affection
  - Joy: response to a pleasant observation o Surprise: response to unexpected events o Anger: response to perceived provocation o Sadness: feeling of loss and despair

o Fear: perceived danger or thread

A similar type of analysis has been already applied to agent-to-human negotiation theory [1], under the hypothesis that the perceived effectiveness of differently framed agent responses is influenced by the specific personality profile of the human counterpart interacting with the agent. In this work, we want to extend this proposition to the space of human-machine interaction by means of natural language. With this in mind, we aim at generating and evaluating resources that can be used to explore whether chatbot intelligence perception and chatbot rapport can be achieved by framing chatbot responses according to the specific personality profiles of the human counterparts interacting with the chatbot.

III. Results And Analysis

After using Crystal Emotion to score the utterances in MovieDiC, utterances with orientation towards the different dimensions described in the previous section have been identified. In the rest of this section, we present the basic statistics for utterance biases along the corresponding tonal, affective and emotional dimensions, as well as some of the most representative examples for each of those cases.

A. Tonal Polarity Dimensions

First, we analyzed the tonal polarity exhibited by the different utterances in the MovieDiC dataset. Table 1 presents the basic statistics for the two dimensions (positive and negative) of tonal polarity orientation.
As seen from the table, only about 30% of the total number of utterances in the dataset exhibits some sort of tonal polarity orientation. It is also interesting to observe that the number of utterances with positive polarity almost doubles in size the number of utterances with negative polarity. Finally, it can also be seen that a small percentage of utterances exhibit elements of both positive and negative polarity orientation.

TABLE 1: TONAL POLARITY DIMENSIONS

Dimension	Utterances	Percentage
Positive	92,983	18.14%
Negative	49,310	9.62%
Both	19,734	3.85%
None	350,556	68.39%

Table 2 presents some examples of utterances exhibiting each tonal polarity. More specifically, examples on similar topics, but with different tonal polarity, have been selected.

TABLE 2: EXAMPLES OF UTTERANCES WITH TONAL POLARITY

Dimension	Utterances
Positive	I'm well aware of how pleasant the weather is in Rome at the present time thank you.
Negative	Do you feel how cold it is? I'm freezing. I'm terribly cold.
Positive	I feel good. I feel great. I feel wonderful!
Negative	Oh, it was awful awful awful awful.

B. Affective Bias Dimensions

Next, we analyzed the affective bias of the utterances in the MovieDiC dataset. Table 3 presents the basic statistics for the two dimensions (affective and cognitive) of affective bias orientation, and Table 4 presents some examples of utterances exhibiting each orientation.

TABLE 3: AFFECTIVE BIAS DIMENSIONS

Dimension	Utterances	Percentage
Cognitive	38,392	7.49%
Affective	58,896	11.49%
Both	8,253	1.61%
None	407,042	79.41%

TABLE 4: EXAMPLES OF UTTERANCES WITH AFFECTIVE BIAS

Dimension	Utterances
Cognitive	Oh, thank you! Thank you! Thousand times, thank you!
Affective	I love you. I love you. I love you.
Cognitive	I want to be here. With you. What do you want.
Affective	Because I felt like it. What do you care?
Cognitive	Well well... I guess you have been around. I'm impressed.
Affective	I like it. I like it. I'm sorry I don't seem more appreciative.

As seen from Table 3, in this case, only about 20% of the total number of utterances in the dataset exhibits some sort of affective bias orientation. Although more balanced than the positive vs. negative distribution observed in Table 1, there is a significantly larger amount of utterances exhibiting affective bias orientation than those with cognitive bias orientation. Also, a small percentage of utterances exhibit elements of both cognitive and affective bias orientation.

Again, examples on similar topics with different cognitive vs. affective bias have been selected, which are presented in table 4. As seen from the table, cognitive oriented utterances are characterized by the use of rational verbs like “to guess”, “to want”. On the other hand, affective oriented utterances use more emotionally loaded verbs such as “to love”, “to feel” and “to like”.

C. Emotional Bias Dimensions

Finally, we analyzed the emotional bias of the utterances in the MovieDiC dataset. Table 5 presents the basic statistics for the six dimensions (love, joy, surprise, anger, sadness and fear) of emotional bias orientation.

TABLE 5: EMOTIONAL BIAS DIMENSIONS

Dimension	Utterances	Percentage
Love	46,696	9.11%
Joy	36,752	7.17%
Surprise	872	0.17%
Anger	15,070	2.94%
Sadness	21,836	4.26%
Fear	9,329	1.82%
Mixed	29,422	5.74%
None	352,606	68.79%

Table 6 presents specific examples of utterances exhibiting each of the six emotional dimension orientations encountered in the dataset.

TABLE 6: EXAMPLES OF UTTERANCES WITH EMOTIONAL BIAS

Dimension	Utterances
Love	I liked Florida. I liked having friends. I liked feeling normal.
Joy	I feel good. I feel great. I feel wonderful!
Surprise	Whoa-whoa-whoa. Mind telling me what […] is happening?
Anger	But mom! I'm not [...] addicted to […] bad language! I don't have a […] problem!

Sadness	I'm sorry. I'm sorry you lost your job. A beat.
Fear	If I let everything that should worry me, worry me, I'd be dead from worry.

IV. Conclusions And Future Work

Recent research in conversational agents looks for making human-machine interaction more human-like with regards to behavioral and attitudinal terms. Affect and emotion, as well as sentiment and tonal polarity, are inherent properties of human-human communication and interaction. These types of capabilities are still far beyond the reach of the current state-of-the-art in conversational agent technologies.

The main objective of this paper was to present some baby steps in the direction of developing affect and emotion resources for more human-like conversational agents. To this end, we analyzed a large dialogue dataset in terms of tonal, affective and emotional bias, with the objective of providing a valuable resource for developing and training data-driven conversational agents with discriminative power across such dimensions. Preliminary results of the conducted analysis demonstrate that only a relative small, although not negligible, percentage of the dialogue turns present clear orientation in any of the considered dimensions.

Future research is still needed to determine whether this proportion is enough for biasing system responses in order to create personality trends in conversational agents that are perceptible by humans when interacting with them. In these sense, our future research plan is to conduct an empirical validation of the usefulness of these generated resources to develop more human-like conversational agents. Our main experimental plan involves three basic steps:

- Step 1: subjects to conduct a personality test to determine their affective-cognitive orientation.
- Step 2: two different chatbots to be produced by biasing the affective-cognitive orientation of the responses using hypothesis ranking: chatbot 1 (affective biased), chatbot 2 (cognitive biased).
- Step 3: subjects to interact with both chatbots and indicate their preferred system.

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