Emily: Developing An Emotion-affective Open-Domain Chatbot with Knowledge Graph-based Persona

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Abstract

In this paper, we describe approaches for developing Emily, an emotion-affective open-domain chatbot. Emily can perceive a user’s negative emotion state and offer supports by positively converting the user’s emotion states. This is done by finetuning a pretrained dialogue model upon data capturing dialogue contexts and desirable emotion states transition across turns. Emily can differentiate a general open-domain dialogue utterance with questions relating to personal information. By leveraging a question-answering approach based on knowledge graphs to handle personal information, Emily maintains personality consistency. We evaluate Emily against a few state-of-the-art open-domain chatbots and show the effects of the proposed approaches in emotion affecting and addressing personality inconsistency.

1 Introduction

Developing dialogue systems capable of responding to human emotions has emerged as a major research stream to enhance human engagements in conversation. These research works focused on developing conversational agents perceiving and expressing emotions, for example, “empathetic listeners/chatbots” (Lin et al., 2019, 2020), and “emotional chatting machines” (Zhou et al., 2018). While the studies mentioned above focused on generating empathetic responses from the system side, another stream of research works relating to emotion elicitation commenced exploring the effects of the agent’s responses on users’ emotion states (Lubis et al., 2018, 2019; Li et al., 2020). A concurrent research work addressing negative human emotions in dialog systems has recently coined the notion of “Emotional Support Conversation (ESC)” (Liu et al., 2021), in which a task framework of ESC is defined. In this paper, we describe approaches for developing Emily, an emotion-affective open-domain chatbot built by finetuning a pretrained dialogue model upon data capturing dialogue contexts and desirable emotion states transition across turns.

Another major issue associated with open-domain chatbots is the lack of consistent personality (Vinyals and Le, 2015; Li et al., 2016). Despite the ongoing efforts in incorporating persona information into dialogue generation, the issue remains unsolved due to a lack of control over the decoding process (Li et al., 2016; Zhang et al., 2018; Song et al., 2020). In order to reduce the discrepancy between personalized information and the responses from a chatbot, we replace dialogue generation with a retrieval-based approach when addressing personality-related questions. We leverage a question-answering (QA) approach based on knowledge graphs (KGQA) to retrieve personal information embedded as attribute graphs. Emily first classifies users’ utterances to identify the personalized questions which is subsequently handled by the KGQA model resulting in more accurate responses. In addition, Emily is equipped with a world celebrity knowledge graph to offer answers relating to celebrities.

Besides presenting the way developing Emily, which is an emotion-affective open-domain chatbot, the contributions of this work are as follows:

• We produce a dataset allowing for modeling users’ positive emotion state transitions;
• We further develop a KGQA approach to address personality inconsistency between personal information and the responses;
• We evaluate Emily against a few state-of-the-art (SOTA) open-domain chatbots and show the effects of proposed approaches in emotion affecting and providing personality consistency.
Table 1: The data used to train the utterance classifier.

|               | Persona-related | General |
|---------------|----------------|---------|
| Training Data | 150,000        | 150,000 |
| Validation Data | 10,000        | 10,000  |
| Test Data     | 10,000         | 10,000  |

2 Methodology

Figure 1 shows the way Emily is constructed. Emily consists of three key components: the utterance classifier, the emotion-affective module, and the Embedded KGQA persona module, depicted in the following subsections.

2.1 Utterance Classifier

The utterance classifier is designed to identify a persona-related question that the Embedded KGQA persona module handles to ensure consistency. The emotion-affective module deals with the general non-persona-related utterances. The classifier is built by finetuning the pretrained language model “Roberta” (Liu et al., 2019) on the data with statistics depicted in Table 1.

The probability is computed as follows during inference:

\[ P(z|x) = \text{softmax}(WQ) \] (1)

where \( Q \) is the vector representation of the question encoded by “Roberta” and the \( W \) is the parameter of the classifier. The model uses the cross-entropy loss function to calculate the classification loss. The utterance classifier can achieve an accuracy of 99.5%.

2.2 Emotion-affective Modelling

2.2.1 Data Preparation

We collect data from Twitter and Empathetic data set available from Li et al. (2020) and Rashkin et al. (2019). We remove the symbol “@user”, quotation marks, and hashtags from the Twitter dataset to normalize the data. As for the Twitter dataset, 58 common emojis are used to label the emotion states (positive, neutral, negative), consistent with the selection rules mentioned in “MOJITALK” (Zhou and Wang, 2018). When multiple types of emojis appear in the dialogue sentence, we choose the most frequent emoji to represent the emotion state of the sentence.

It is critical to classify the Twitter data to produce valid emotion labels. The following steps are performed:

1. We train an emotion classifier for states (positive, neutral, and negative) by finetuning BERT (Devlin et al., 2019) on the Google Play Store Apps review data available from Kaggle;
2. The classifier is used to identify the emotion states of each dialogue sentence;
3. The sentence is also tagged with the above-mentioned emoji labeling method;
4. The intersection of the classification result and the emoji label is used to produce the final result of the emotion state of the sentence.

As for the empathetic dataset, we also map 32 evenly distributed emotion labels for the empathetic dataset into the three categories mentioned above. We subsequently perform a data filtering process in which only dialogue turns with positive users’ emotion state transitions are selected from the two data sources mentioned above.

2.2.2 Finetuning Pretrained Dialogue Response Generation Model

The emotion-affective chatbot is developed based on the DialoGPT-large architecture (Zhang et al., 2020), initialized with DialoGPT-large model parameters of 762M. The base model is finetuned with the filtered data mentioned in Section 2.2.1 until it converges. In addition to the model parameters, we also learn the word embeddings of the tokens with a size of 1,280. The size of the vocabulary is 50,257.

The maximum mutual information (MMI) score function (Zhang et al., 2020) is implemented to regulate generation in removing uninformative responses.

2.3 Developing Embedded KGQA-based Persona

2.3.1 Embedded KGQA

The KGQA module is based on the work of Embedded KGQA (Saxena et al., 2020). The Knowledge Graph \( G \) consists of a series of triples, each represented as \((h, r, t)\) that indicates a relation \( r \) from a head entity \( h \) to a tail entity \( t \). Knowledge Graph Embedding (KGE) targets at learning a low-dimensional vector representation for entities and relations denoted as \( E \) and \( R \) respectively and the \( i \)th entity and \( j \)th relationship are denoted as \( E_i \) and \( R_{ij} \) respectively.

1https://www.kaggle.com/lava18/google-play-store-apps
and $R_j$. ComplEx (Trouillon et al., 2016) embeds entities and relations in complex space and defines a scoring function as:

$$\phi(h, r, t) = Re(<E_h, R_r, E_t>)$$

\[= Re(\sum_{k=1}^{d} E_{hk}, R_{rk}, E_{tk})
\]

\[=< Re(E_h), Re(R_r), Re(E_t) > + < Im(E_h), Im(R_r), Im(E_t) > + < Im(E_h), Re(R_r), Im(E_t) > - < Im(E_h), Im(R_r), Re(E_t) > \tag{2}\]

$E_h \in C^d, R_r \in C^d, E_t \in C^d$ represent the head entity vector, the relation vector and the conjugate of the tail entity vector respectively, while $d$ represents the dimension of a vector. $Re()$ is a function to obtain the real part of a complex vector and $Im()$ extracts the imaginary part. For a score of a true triplet in KG greater than 0, it can be represented as $\phi(h, r, t) > 0$. $\phi(h, r, t) < 0$ is used to describe a negative triplet which a tail entity $t$ is randomly replaced by another entity $\bar{t}$. As shown in Figure 1, for each natural language question $q$, we use the maximum string matching method to obtain the topic entity and map it to the representation $E_h \in C^d$. And the model embeds the question to a 768-dimensional vector by “Roberta” and then converts the vector to a fixed dimension vector $Q_q \in C^d$ by a feed-forward neural network. While the question is embedded, the answer $a \in A$ is mapped to a fixed dimension vector $E_a \in C^d$, where $A$ are the answer entities set of question.

$$\phi(h, q, a) = \begin{cases} Re(<E_h, Q_q, E_a>) > 0, & a \in A \\ Re(<E_h, Q_q, E_a>) < 0, & a \notin A \end{cases} \tag{3}\]

At the training stage, the scoring function is calculated with all the entities in KG to produce the predicted score distributions. Kullback-Leibler divergence (Kullback and Leibler, 1951) loss function is used to measure the distance from the predicted distributions to the true answer distributions.

2.3.2 Data Preparation

Knowledge Graph-based Persona: We construct a knowledge graph about Emily along with some celebrities whose information are collected from the website \(^2\). As shown in Table 2, the persona information contains a number of personality settings (i.e., “Name”, “Birthday”).

Question Answering Dataset: For training the QA model, we build a dataset based on the knowledge graph. Following the way that MetaQA (Zhang et al., 2017) is generated, we design about 10 question templates for each relationship in KG.

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\(^2\)https://www.thefamouspeople.com/
| Personalized Key | Personalized Value |
|------------------|-------------------|
| Name             | Emily             |
| Birthday         | Privacy           |
| Nationality      | World             |
| Age              | Forever Young     |
| Gender           | Privacy           |
| Born Country     | China             |
| Famous as        | AI                |
| City             | shenzhen          |

Table 2: Persona information for Emily.

| KG-based | Triplet | Entity | Relation |
|----------|---------|--------|----------|
| Persona  | 187,116 | 59,672 | 23       |

| QA pairs | Train | Validation | Test |
|----------|-------|------------|------|
|          | 143,776 | 20,000 | 20,000 |

Table 3: The data used in Embedded KGQA Module.

and perform stratified random sampling from them when generating questions. For example, we design the question templates such as “How old are the NE” and “Tell me NE’s age” for the relation “Age”. The “NE” can be replaced by a specific person’s name, while the age value would be the answer. To increase the robustness of the data, we apply the back-translation (Sennrich et al., 2016) approach using a pretrained neural machine translation model for data enhancement. Entities are guaranteed to be kept in the paraphrased question. The statistics of the dataset are shown in Table 3.

3 Experiments and Evaluation

In this section, we describe a range of experiments comparing Emily with two SOTA open-domain chatbots, Blender (Roller et al., 2020) and PLATO-2 (Bao et al., 2021), on related metrics. It should be bear in mind that Emily and other open-domain chatbots are designed for different purposes; the results only indicate the effectiveness of Emily in emotion affecting and maintaining personality consistency.

3.1 Automatic Evaluation

3.1.1 Evaluation Metrics

We adopt three well-accepted automatic evaluation metrics to compare Emily with Human (reference data), Blender and PLATO-2.

- **Context:** We measure the context correlation between the responses produced by the dialogue model and the queries, similar to a metric used in Pang et al. (2020).

- **Fluency:** Fluency is often measured using a language model. It indicates the negative perplexity of generated responses. We adopt the calculation method proposed by Pang et al. (2020) to produce the fluency score.

3.1.2 Automatic Evaluation Results

We randomly sample 100 dialogues from an empathetic dialogue test dataset (Rashkin et al., 2019). The corresponding response generations are produced by Emily, Blender, and PLATO-2. Then we visualize the distribution of results on each evaluation metric.

The distribution of context is shown in Figure 2(a). It is clearly shown that Emily (the blue histogram/distribution) achieves a higher context correlation with human judgments (the red histogram/distribution) than those recorded for Blender and PLATO-2. In addition, Figure 2(b) demonstrates that Emily achieves competitive results in comparison to those of Blender and PLATO-2.

3.2 Human Evaluation Results

To further measure the emotion-affective effect of the generated responses, we conduct human evaluations on empathetic dialogue test dataset (Rashkin et al., 2019) for Human (reference data), Emily, and Blender. Following an approach mentioned in Lin et al. (2019), we randomly select 100 dialogues and their corresponding responses. We ask a human evaluator to blind review the systems mentioned above on three metrics: Empathy, Relevance, and Fluency, all rated on a Likert scale of 1 to 5 (1: not at all, 3: somewhat, 5: very much):

- **Empathy:** The metric of empathy is used to measure whether the system can perceive users’ emotion states and to elicit positive emotions subsequently;

- **Relevance:** We ask a human evaluator to judge whether the responses are relevant to the user’s topics;

- **Fluency:** We utilize fluency to estimate whether the human evaluator can understand the system-generated responses and whether the responses are correct in grammar.
Figure 2: Distribution results on the automatic evaluation metrics.

| Model    | Empathy | Relevance | Fluency |
|----------|---------|-----------|---------|
| Human    | 4.05    | 4.51      | 4.76    |
| Emily    | 3.93    | 4.23      | 4.72    |
| Blender  | 3.96    | 3.99      | 4.84    |

Table 4: Human evaluation results are mean scores from blind-reviewing the generated responses for Emily, Blender, and Human (the reference data).

| Question                                      | Answer |
|-----------------------------------------------|--------|
| May I know your name please?                  | Emily  |
| Could you tell me your name?                  | Emily  |
| Hello! What’s your name?                      | Emily  |
| your name, please                            | Emily  |
| Would you mind telling me your name?          | Emily  |
| May I make bold to ask your name?             | Emily  |
| How shall I call you?                         | Emily  |
| I like to know your name please               | Emily  |
| How shall I address you?                      | Emily  |

Table 5: Building variations of persona-related questions into Emily.

The evaluation results are shown in Table 4. Emily achieves an equivalent empathy score to those of human reference data and Blender. It can be observed from Table 4 that Emily scores higher than Blender in the relevance metric. It is interesting to find out Blender is able to produce a fluency score higher than that of reference data, probably due to the prevalence of texting-induced unconventional English in the reference data.

3.3 Embedded KGQA Evaluation

We describe the performance of Emily in addressing persona-related questions via Embedded KGQA (Saxena et al., 2020). As mentioned before, the personal information and celebrity-related knowledge are organized as knowledge graphs. The entities in the graph are the answers to the questions. For this task, we use hit@1, hit@3, and hit@10 to evaluate the performance of the model, as shown in Table 6.

| Embedded KGQA | hit@1 | hit@3 | hit@10 |
|----------------|-------|-------|--------|
|                | 0.9778| 0.9898| 0.9925 |

Table 6: Evaluation of the Embedded KGQA on personal information relating to Emily and celebrities.

4 Related Work

4.1 Emotion-affective Dialog System

Emotion-aware chatbot has become an emerging area of research in recent years. Zhou et al. (2018) first addressed the emotion factor in large-scale dialog generation using an end-to-end framework to generate contents and emotions. Zhou and Wang (2018) proposed a sophisticated CVAE-based model called “MOJITALK”, which used emoji to control the emotion and sentiment of the generated responses. Lin et al. (2020) presented an empathetic chatbot “CAiRE” which fine-tunes a large-scale pretrained language model with multiple objectives aiming at detecting dialogue emotion and generating empathetic responses. Rashkin et al. (2019) focused on empathetic dialogue generation
and released a novel empathetic dialogue dataset as a benchmark. Shin et al. (2019) trained a sentiment predictor with a reinforcement learning framework to encourage more empathetic responses. Lin et al. (2019) introduced a novel dialogue system named “MoEL” to perceive the users’ feelings and respond accordingly by learning specific listeners for each emotion state.

Lubis et al. (2018) utilized many examples of human appraisal in spoken dialogue to elicit a positive emotional impact throughout the interaction. Lubis et al. (2019) built a chat-oriented dialogue system that can dynamically mimic affective human interaction and generate more natural responses aiming at eliciting a more positive emotional impact. Li et al. (2020) proposed a variational model EmoElicitor to generate responses that can elicit users’ specific emotions with the help of a pre-trained language model. Liu et al. (2021) defined a task framework for developing ESC to reduce users’ emotional distress via a three-stage procedure (exploration, comforting, and action) and supporting strategies.

4.2 Personality Consistency

The first attempt to model persona can be seen in Li et al. (2016) where a speaker model is used to capture individual characteristics. Qian et al. (2017) designed a model to decide whether a post should be responded to based on pre-specified agent profiles. To solve the user-sparcity problem and the issue w.r.t. meaningless responses (Zhang et al., 2018; Song et al., 2020), new persona models and high-quality data have been introduced. Zhang et al. (2018) introduced a Persona-Chat dataset and proposed two generative models to handle persona-related information. Zheng et al. (2019) contributed a multi-turn dialogue dataset containing various traits from a large number of speakers. A human-annotated dataset with single-turn conversations and key-value attribute profiles were created by (Song et al., 2020).

To address factoid questions based on incomplete KG, Sun et al. (2018, 2019) drew answers from topic entity-related corpora and from knowledge-based sources. Huang et al. (2019) and Saxena et al. (2020) leveraged the knowledge graph embedding (KGE) to deal with the problem of sparse graphs. KGE is used to learn a low-dimensional vector representation for each entity and relation to preserve the original structure, for example in TransE (Bordes et al., 2013), ComplEx (Trouillon et al., 2016). Unlike Huang et al. (2019) focusing on simple questions, Saxena et al. (2020) proposed an “EmbedKGQA” model performing multi-hop KGQA over sparse KG.

5 Conclusion

In this work, we present approaches for developing an emotion-affective open-domain chatbot Emily. Emily is designed to generate emotion affecting responses in response to a negative emotion state. This is performed by finetuning a pretrained dialogue model upon data capturing dialogue contexts and desirable user emotion states transition. Leveraging an utterance classifier and Embedded KGQA module, Emily can handle persona-related questions in a consistent way. Experimental results demonstrate Emily’s effectiveness in emotion affecting and addressing personality inconsistency. Future work will focus on enhancing the emotion affecting capability and benchmark the results in more extensive experiment settings.

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