iEval: Interactive Evaluation Framework for Open-Domain Empathetic Chatbots

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Abstract

Building an empathetic chatbot is an important objective in dialog generation research, with evaluation being one of the most challenging parts. By empathy, we mean the ability to understand and relate to the speakers’ emotions, and respond to them appropriately. Human evaluation has been considered as the current standard for measuring the performance of open-domain empathetic chatbots. However, existing evaluation procedures suffer from a number of limitations we try to address in our current work. In this paper, we describe iEval, a novel interactive evaluation framework where the person chatting with the bots also rates them on different conversational aspects, as well as ranking them, resulting in greater consistency of the scores. We use iEval to benchmark several state-of-the-art empathetic chatbots, allowing us to discover some intricate details in their performance in different emotional contexts. Based on these results, we present key implications for further improvement of such chatbots. To facilitate other researchers using the iEval framework, we will release our dataset consisting of collected chat logs and human scores.¹

1 Introduction

Development of open-domain chatbots endowed with social and emotional intelligence is a crucial task in natural language research (Rashkin et al., 2019). Empathetic chatbots are expected to engage in a conversation with the users and demonstrate understanding and appropriate handling of users’ feelings. While many strategies for generating empathetic responses have been described, there is still little consensus on their evaluation. For dialog generation, automatic metrics do not show consistency in correlations with human judgement (Liu et al., 2016; Tao et al., 2018), leading to their limited adoption. Therefore, most of existing works rely on human evaluation. It may happen in either static or interactive setting (Adiwardana et al., 2020). In the former case, a human judge rates chatbot’s responses, generated from a fixed set of

¹Our annotated dataset is publicly accessible at https://github.com/Sea94/ieval.
contexts. In the latter case, dialogs for evaluation are collected as humans’ multi-turn chats with the model.

Recently, two comprehensive approaches based on interactive multi-turn human evaluation were proposed. Adiwardana et al. (2020) described a metric called Sensibleness and Specificity Average, which measures these two aspects of chatbot’s responses. Human judges give Likert-type scores to each chatbot’s turn in a dialog, which are further averaged to obtain a final score. As Likert-type scores may exhibit differing bias and variance per annotator, associated with the lack of sensitivity, Li et al. (2019) suggested an alternative evaluation strategy based on pairwise comparisons. According to their method, human judges indicate their preference of one chatbot over another by comparing two dialog logs with these chatbots. This procedure is more robust, but become very costly when the number of compared models goes up.

Both of these approaches differentiate humans who interact with the models and humans who judge them. They probably opt for this design choice due to such considerations as workers’ fatigue. However, according to findings in cognitive psychology, our emotional experiences are highly subjective. Barrett et al. (2007) points out that only the experiencers can reveal the full complexity of emotions that they feel. For example, if a client complains about a hotel room being too cold, a third-party observer might underestimate the gravity of the issue, especially if he enjoys indoor coolness. This fact argues for the necessity of a new evaluation approach of chatbots, which would ensure that both emotional interaction and evaluation of a chatbot are accomplished by the same human actor. To help these humans share their emotional experiences, asking them to role-play a relatable scenario is a frequently used procedure in social sciences (Walther et al., 2005; Hancock et al., 2007).

In this work, we introduce iEval, an interactive evaluation framework for open-domain empathetic chatbots, which mitigates the issue of separating an experiencer and an evaluator. To combine the benefits of Likert scales, allowing to evaluate many chatbots in a single stretch of time, and pairwise comparisons, offering greater reliability and cross-experiment robustness, we propose a novel ranking-based approach. According to iEval, a human first converses with all chatbots, having all chats grounded in an emotional scenario (Figure 1 (a)). Then, the same human ranks the models by dragging-and-dropping them into corresponding categories (Figure 1 (b)). Our experiments demonstrate that iEval can reveal subtle but significant differences in chatbots’ performance across emotional contexts.

Overall, our contributions include the following. 1) We describe a new evaluation framework to measure chatbots’ abilities to respond appropriately in sensitive contexts. 2) We demonstrate a rigorous procedure for preparing grounding scenarios for the given evaluation task. 3) We benchmark several state-of-the-art empathetic chatbots, which have never been compared before. 4) Based on the analysis of the benchmark results, we discuss implications for the future development of empathetic chatbots. 5) Finally, we release the data from our experiments to facilitate future research endeavors.

2 Related Work

Most works focusing on the development of empathetic chatbots couple automatic evaluation with human judgement. Automatic metrics usually include perplexity, approximating the model’s language modeling ability (Roller et al., 2021; Xie and Pu, 2021; Li et al., 2020), and may incorporate other scores, depending on the specific focus of the work. Some frequently used examples are BLEU score (Lin et al., 2019; Majumder et al., 2020), diversity metrics (Xie and Pu, 2021; Li et al., 2020), and F-1 score or accuracy of emotion detection (Lin et al., 2019; Xie and Pu, 2021; Li et al., 2020).

Since the appropriateness of automatic metrics for open-domain dialog is still ambiguous, all works de facto rely on human judgement. Most commonly, researchers employ single-turn static evaluation, where a fixed emotionally-colored context is shown to a judge along with the responses generated by different chatbots. The judges are asked to rate how empathetically appropriate the responses are, and the assessment may come either as Likert-type scores (Hu et al., 2018; Lin et al., 2019; Majumder et al., 2020; Li et al., 2020) or ranking (Xie and Pu, 2021). Although this approach is widespread due to the ease of implementation, it fails to capture issues emerging in multi-turn chats, such as repetitiveness or deterioration of semantic coherence in long-range contexts (See et al., 2019).

Few works that focus on integrating empathetic abilities into chatbots started adopting interactive evaluations. Roller et al. (2021) employed ACUTE-
Eval (Li et al., 2019) framework based on pairwise comparisons to assess engaginess and humanness of their models. Ghandeharioun et al. (2019) defined their own evaluation protocol to collect Likert-type scores for a series of dimensions measuring chatbot’s performance. However, in both of these studies, the evaluated data points were open-ended chats that began with a generic greeting. Based on the provided examples of conversations, these exchanges generally developed as light small-talk, maintaining neutral or positive sentiments. Therefore, it remains unclear how well the collected scores reflect empathetic abilities of the chatbots, which should ideally succeed over a range of emotions. Our framework addresses this limitation by grounding the chats in diverse emotional scenarios.

3 Method: iEval

To compare empathetic abilities of several chatbots, iEval suggests that at first a human makes an emotionally-grounded conversion with each bot in a randomized order. If necessary, fine-grained Likert-type assessments of specific chatbot’s performance aspects may be collected after each conversation. As the next step, the same human is asked to rank the chatbots according to her experience with them. An example of this flow is given in Figure 1. Finally, appropriate statistical instruments should be applied to compare the chatbots.

3.1 Emotionally-grounded Chats

To make sure that humans experience the full extent of chatbots’ empathetic abilities, we condition each conversation with a short emotional scenario, instructing the humans to imagine themselves feeling a particular emotion in a given situation. They are further asked to role-play a character in this scenario and chat about it with the models. The first dialog turn is provided to the humans to facilitate the process of their getting into the assigned role.

Careful conditioning of the experiment is essential to ensure that it adequately represents chatbots’ abilities in a vast range of topics and emotions. We noticed that some dialogs from the EmpatheticDialogues dataset (Rashkin et al., 2019), a popular dataset for building empathetic models, form large clusters in terms of the similarity of discussed situations (see Appendix A). It may lead to models’ shifted performance on specific topics. Therefore, one should control for topical diversity when defining conditioning scenarios for iEval.

Besides, previous results pointed out that the same model may receive different appraisals depending on the emotional polarity of the chats (Ma jämder et al., 2020). This may be linked to the existing difference between humans’ empathetic responding in positive and negative scenarios (Aue et al., 2021), and hence difference in expectations. Thus, we argue for the importance of balancing and studying the role of emotional polarity within iEval.

Finally, ensuring sufficient interaction experience with the models is necessary before asking humans for their judgements. Previous works required between 3 and 14 chatbot’s turns per dialog. We find 3 turns to be enough, given that the dialog starts with a specific input.

3.2 Ranking

The concluding step of iEval requests a human to recall the conversations with the chatbots and rank them by assigning the bots into three categories: Bad, Okay, and Good. Several chatbots can be assigned to the same category, indicating equal rank. This approach allows moving away from inter-annotator variability associated with Likert scales (Li et al., 2019; Kulikov et al., 2019), while preserving the benefits of relative comparisons. To obtain the final standing of the chatbots, we propose converting the resulting rank into an ordinal rating (Bad → 1, Good → 3) and running non-parametric ANOVA to compare the mean ratings.

3.3 Annotation Quality

According to iEval framework, one human should chat with and evaluate several models. As human’s short-term mental storage capacity is limited to several informational chunks, we recommend keeping the number of evaluated models between 3 and 7, giving preference to lower values (Cowan, 2001).

To meet the requirements of randomized controlled experiments, it is also advisable to allow each human to complete only one evaluation task to eliminate anchoring effects. For the same reason, the order in which humans interact with the chatbots should be randomized and counterbalanced across tasks. To distinguish different models without revealing their names to the humans, we suggest color-coding them to avoid any fixation effects which could be caused by aliases that reflect order.

Finally, we use crowdsourcing for our experiment. To decrease the probability of encountering
fraudulent or inattentive workers, human intelligent task design and configuration should follow the quality control recommendations of the platform in combination with other attention checks.

4 Experiment

To demonstrate how iEval works in practice, we apply the framework to benchmark several state-of-the-art empathetic chatbots, which have never been compared against each other in an interactive setting. The details and analysis are outlined below.

4.1 Measures

We use the final ranking of the chatbots, converted into ordinal ratings, as our main metric. To better understand which factors play a principal role in defining overall ranking, we also ask human workers for fine-grained Likert-type scores to a number of chatbots’ qualities on a 1-5 scale. These questions were derived as a combination of the established key qualities for conversational chatbots (Svikhnushina and Pu, 2021) and other critical aspects related to their language modeling abilities (See et al., 2019). We measured chatbots’ perceived politeness, empathy, likability, repetitiveness, and whether their responses make sense.

4.2 Models

We benchmarked four models, as this corresponds to an average number of informational chunks that humans can store in short-term memory (Cowan, 2001). We chose between the top-performing chatbots available at the moment of preparing our experiment in Q4 2021. We selected the models, which use distinct approaches for generating empathetic responses. Only one of them participated in an interactive setting previously, but it was not targeted at its empathetic skills. The four models with assigned color-codes are as follows.

**Blender** is a large model employing a standard Seq2Seq Transformer architecture with ≈90M parameters (Roller et al., 2021). Blender was pre-trained on ≈1.5B comments from Reddit discussions and fine-tuned on EmpatheticDialogues dataset (Rashkin et al., 2019).

**MIME** is a relatively small model with ≈18M parameters also based on Seq2Seq Transformer with additional stochastic emotion grouping and mimicry mechanism (Majumder et al., 2020). Without pretraining, MIME was directly initialized with GloVe embeddings (Pennington et al., 2014) and fine-tuned on EmpatheticDialogues.

**MEED** is a middle-size Seq2Seq Transformer-based model with ≈40M parameters, which incorporates extra controllability of response generation achieved through modeling fine-grained empathetic intents. The model was pre-trained on ≈1M dialogs from OpenSubtitles (Lison and Tiedemann, 2016) and fine-tuned on EmpatheticDialogues.

**Plain** is a basic Seq2Seq Transformer-based model with ≈40M parameters, which followed the same training pipeline as MEED. Plain serves as a baseline in our experiment.

All models were adapted to operate in an interactive setting so that for generating each next response, all previous dialog history was passed to the models as input.

4.3 Grounding Scenarios

As EmpatheticDialogues (Rashkin et al., 2019) is the mainly used benchmarking dataset for empathetic chatbots, we employed its test set to create grounding scenarios. This dataset contains 24,850 dialogs associated with emotional contexts (out of which 2,547 dialogs comprise the test set). To create the dataset, (Rashkin et al., 2019) connected two types of crowdworkers, speakers and listeners, to have conversations with each other. Speakers first had to select one of the 32 emotional labels (e.g., sad, joyful, proud) and describe a situation when they felt that way. Then they proceeded to have a conversation with the listeners using the outlined situations as guiding prompts. We utilized these attributes (32 emotional labels and prompts describing the speakers’ situations) to describe our grounding scenarios and kept the first turn from each selected dialog as a starting turn for the worker in our evaluation task.

To ensure comprehensibility of the task for crowdworkers, this selection of grounding prompts and opening utterances was organized very carefully. Firstly, we selected dialogs where the length of the associated prompt falls between the first and third quantiles in terms of the number of tokens to ensure it provides sufficient details about the speaker’s situation. Secondly, we computed Vader sentiment scores (Hutto and Gilbert, 2014) of the first utterance in each dialog and only kept those that had a clear emotional coloring. These steps produced 527 data points, which we finally proofread and annotated with emotional polarity labels (negative or positive). Note that we used the
original 32 emotional labels to show them to crowd-workers to ground their interaction with the chatbots, while the polarity labels were needed for the analysis part. We further narrowed the set of 527 data points down to 480 prompts with utterances to meet our experimental design requirements (§4.4). The discarded data points were chosen manually in order to diversify the topics in the main set. The distribution of emotional labels in the resulting evaluation set is shown in Figure 8 in Appendix B. Some examples of grounding scenarios (emotional labels and prompts) are provided in Figures 4, 5, and 6.

4.4 Experiment Design
We aimed at evaluating the performance of the participating chatbots, while also contrasting their abilities in negative and positive emotional contexts. To maintain a manageable number of human intelligence tasks (HIT), we decided to ask each crowdworker to interact with all chatbots in both conditions. Therefore, our experiment was a $2 \times 4$ within-subject factorial design. By designing our study as a factorial experiment, we were able to examine both main effects and interactions among chatbots and emotional contexts. We used G*Power software to estimate the required sample size to achieve “medium” effect size (Faul et al., 2007). As the recommended sample size was about 200, we ran 240 experimental tasks to achieve a full counterbalance of the order of chatbots and emotional contexts across subjects. We analyzed ranking of the chatbots using the nonparametric Aligned Rank Transform (ART) procedure (Wobbrock et al., 2011). Quartile-quartile plots of the fitted residuals of our the model showed that they were normally distributed, indicating the appropriateness of this model for our analysis.

4.5 Running the Experiment
We ran our experiment on Amazon Mturk, requiring one US-based worker per each of the 240 HITs. Our workers spent on average 20.6 minutes to complete a HIT and their reward was $2.5 per HIT, which agrees with the US minimum wage standards. Following Mturk recommendations,\(^2\) we required the workers to have 98% approval rate and 10,000 approved HITs. We further rejected the workers whose average HIT completion time,

\(^2\)https://blog.mturk.com/qualifications-and-worker-task-quality-best-practices-886f1f4e03fc

Figure 2: Benchmarking results of the four chatbots.

length of chat responses, or number of contradictory responses to reverse-scaled questions in the Likert-type questionnaire stood out as outliers.

5 Analysis of Results
Below, we describe the eventual ranking of the models and consider the aspects that likely explain the observed results.

5.1 Benchmarking of Empathetic Chatbots
We used the nonparametric ART procedure to analyze ranking of the chatbots. As described above (§3.2), for this analysis we converted the resulting rank into an ordinal rating for more straightforward interpretation (the higher, the better). Results show a main effect of chatbot ($F_{3,1673} = 257.92, p < 0.001$) and of emotional context ($F_{1,1673} = 43.17, p < 0.001$) on the rating, and of their interaction ($F_{1,1673} = 9.80, p < 0.001$) as illustrated in the lower right subplot of Figure 2. Interaction results revealed several interesting relationships. Blender is consistently rated significantly higher than the other three chatbots, and it also performs significantly better in positive contexts ($p < 0.01$). MIME is rated the lowest, while for MEED and Plain a shift in the ratings emerges depending on emotional context. MEED significantly outperforms Plain in positive contexts ($p < 0.05$) while the diametrically opposite result manifests for negative contexts ($p < 0.05$).

5.2 Aspects Explaining the Ranking
We fitted an ordinal regression model to identify which of the factors measured by our Likert-type questionnaire correlate strongest with the assigned
ratings (McFadden’s pseudo-$R^2 = 0.37$). The statistical model was chosen due to the ordinal nature of the dependent variable. All evaluated qualities exhibit significant influence on chatbots’ ratings. Making sense ($\beta = 1.01, p < 0.001$), empathy ($\beta = 0.35, p < 0.001$), and repetitiveness ($\beta = -0.32, p < 0.001$) are the strongest predicting factors, followed by politeness ($\beta = 0.21, p < 0.01$) and likability ($\beta = 0.18, p < 0.05$) (Figure 3).

The leading factor suggests that the language modeling abilities of the chatbots define their ranking at large. This is understandable as language fluency is essential for the comprehensive handling of emotions in chat. Blender, being a massive model pre-trained on a dataset that is 1000-time larger than the one for MEED or Plain, is capable of generating considerably longer fluent responses than any other chatbot (Figure 9 in Appendix C), which ensures its highest rank. Meanwhile, MIME is the smallest model, which did not undergo any pre-training. It responds reasonably well to the first speaker’s utterance, but as context gets longer its ability to produce semantically coherent responses quickly deteriorates (Figure 4), causing its poor performance regardless of the emotional context.

For chatbots with better language modeling skills, the next most decisive factors bring about curious shift in chatbots’ rankings, depending on the emotional polarity of conversations. We analyze these phenomena in the next section, focusing on empathy and repetitiveness (diversity) revealed in chatbots’ responses. While considering empathy of the models, we pay special attention to the role of questions that they ask as it has been established to be the most prominent intent of human empathetic listeners (Welivita and Pu, 2020). Moreover, question mark appears in the top-15 most frequent tokens in the responses of all models studied in our experiment (Table 3 in Appendix C).

### 5.3 Analysis of Interaction Effects

#### 5.3.1 Intricacies between MEED and Plain

Both MEED and Plain have moderate language modeling abilities compared to the other two counterparts. To reason about why these models’ rankings swapped depending on the emotional polarity, we make two noteworthy observations. First, even though the gap in scores is not huge, Plain is rated significantly more repetitive than MEED (Figure 2). Second, as it can be seen from Table 1, both chatbots actively ask questions in their responses, but MEED asks significantly more questions than Plain in negative contexts (independent t-test $p < 0.01$).

It is expected that MEED establishes greater diversity and poses questions as it models multiple listeners’ empathetic intents, where questioning makes up the largest class. However, as we observed during qualitative inspection of the dialog logs, MEED falls into a typical trap of neural-
At a turn-level perspective, bots (MEED vs. Plain) had different strategies depending on the context: positive or negative. During positive conversations, bots were more effective in delivering meaningful emotional regulation (Svikhnushina et al., 2022), showing extended engagement via more question-answer sequences. In contrast, in negative conversations, bots were more successful in delivering repetitive responses. It suggests a plausible explanation that human speakers are more forgiving when chatbots do not align perfectly with their context. In positive contexts, they are more forgiving even if the chatbot’s response is slightly misaligned with the context (Pearson’s $r = -0.42$ ($p < 0.001$)) than in positive (Pearson’s $r = -0.51$ ($p < 0.001$)).

We further combined these observations with the fact that correlation between these chatbots’ repetitiveness scores and overall ratings is slightly lower in negative scenarios (Pearson’s $r = -0.42$ ($p < 0.001$)) than in positive (Pearson’s $r = -0.51$ ($p < 0.001$)). It suggests one plausible explanation to the observed phenomenon. In positive contexts, human speakers value chatbots’ diversity and active engagement demonstrated via questioning, and are more forgiving even if the chatbot’s response is slightly misaligned with the context. In negative scenarios, speakers feel much more vulnerable and
expect greater attention. Consequently, they prefer a generic, but safe response over the one which is somewhat unrelated or diverting attention from the speaker’s emotional state. Figure 5 provides examples illustrating these observations.

5.3.2 Decline of Blender in Negative Contexts

To study the possible reasons of Blender’s lower performance in negative contexts, we started with qualitative inspection of dialog logs. While Blender asks fewer questions than MEED or Plain, they still appear frequently in its responses (Table 1) and the same issue of asking overly general questions, failing to address speaker’s emotional needs in negative contexts, preserves also for this chatbot.

More interestingly, we observed that Blender is the only chatbot in our experiment that persistently shares its own experiences and views with the speakers. To get a better idea of this behavior, we randomly sampled 50 chat logs (25 per emotional polarity) for each chatbot and annotated how many of their responses were oriented towards the speaker (other), reflecting the chatbot’s own experience (self), or both. Blender is the only chatbot, for whom the amount of responses oriented towards self and both largely exceeds zero in the later dialog turns, almost reaching the proportion of purely other-oriented responses (Table 2 in Appendix C).

Self-disclosure is frequent in peer support discussion forums (Barak and Gluck-Ofri, 2007). This likely explains Blender’s tendency to share own perspective as it was pre-trained on Reddit conversations, where peer support is actively practiced. However, human attitude to chatbot’s sharing about self is unclear, especially in negative scenarios. Even in human-human interaction, positive disclosure is appreciated more than negative (Caltabiano and Smithson, 1983). Moreover, in counselling practice, therapist self-disclosure is usually portrayed as a mistake (Henretty and Levitt, 2010). We could not find studies about users’ preferences for the degree of chatbot’s self-oriented responses, but some previous findings about embodied computer agents reveal that their empathetic other-oriented emotions lead to more positive ratings of the agent (Brave et al., 2005). We, therefore, hypothesize that pulling attention to self too quickly in negative conversations might have resulted in Blender’s poorer performance in this emotional polarity, which is demonstrated with an example in Figure 6.

6 Discussion

6.1 Implications for Chatbot Development

Most of the chatbots in our experiment were trained to model short-context conversations and did not support the interactive chat mode by default, which also applies to other dialog models, e.g. (Hu et al., 2018; Lin et al., 2019). Nevertheless, being able to maintain continuous engaging conversation is an ultimate goal for empathetic chatbots. Thus, more attention should be paid to adapting training procedures and architectures to track longer-term dialog history and evolution of speaker’s emotions.

Our findings demonstrate that users’ emotional needs differ in positive and negative scenarios, and that they do not necessarily expect a strong emotional reaction to their inputs. Raising a question may be an appropriate response. According to our results, chatbots should dwell longer on speakers’ negative situations, employing meaningful questioning strategies, which can possibly be achieved by modeling fine-grained empathetic questioning
intents (Svikhnushina et al., 2022). In addition, more research on the amount of chatbots’ self-disclosure would further help tailor chatbots’ responses to users’ expectations.

6.2 Next Steps

While human evaluation is the current standard to assess chatbots’ performance, developing an automated metric to approximate human judgement is an important milestone that would considerably facilitate the developmental cycle. Some attempts towards this goal have been made (Yeh et al., 2021), but very few of these metrics try to capture empathetic abilities of chatbots. Our analysis suggests that all dimensions evaluated in our Likert-type questionnaire constitute significant predictors of the overall human satisfaction (§5.2). Therefore, to develop a stronger automatic proxy for human evaluation, we consider creating rationale heuristics approximating those dimensions and identifying a meaningful way to combine them into a single score. The dataset of collected chat logs and human scores from our experiment should streamline the construction and calibration of such a metric.

7 Limitations

In our work, we applied iEval framework to benchmark four empathetic agents. We did not compare them against human-human interaction, as synchronizing two crowdworkers for conducting several chats between each other entails more logistical difficulties. More importantly, we were mainly interested in measuring how existing chatbots address users’ emotional needs, rather than checking if they are indistinguishable from human interlocutors.

Our results show that bigger models rank higher in the evaluation task. It raises the subsequent question about to what extent the proposed framework measures differences in models’ empathetic abilities compared to their underlying language model performances. We believe that iEval is an effective framework for evaluating chatbots’ empathy as it succeeded in registering intricate differences in the performances of MEED and Plain, two models of comparable sizes and pre-training pipelines, as well as distinguishing the performance of Blender in emotional contexts of different polarity. To further disentangle the role of language modeling and empathetic abilities, one can consider running the iEval evaluation experiment to compare equal-size models with and without fine-tuning for empathetic response generation (e.g., Blender, which was only pre-trained on Reddit, and Blender, which was further fine-tuned on the EmpatheticDialogues dataset). However, this was not the main objective of our study and we leave it for future work.

Finally, we propose to use ranking as a way of expressing the appraisals of the chatbots, as it affords advantages of both Likert scales and pairwise comparisons. Ranking may be less robust for comparing results across experiments with mismatched sets of chatbots. Applying rank aggregation techniques can be useful to tackle such cases (Sculley, 2007).

8 Conclusion

Our paper introduced iEval, a novel evaluation framework for open-domain chatbots that can detect humans’ personal perceptions of social interaction, manifesting in emotional dialogs. We used iEval to benchmark four recent empathetic chatbots. Further analysis revealed several limitations in empathetic response generation approaches of these models, which came out due to their uneven abilities in handling positive and negative conversational scenarios. Based on our findings, we formulated implications informing future efforts in the development and evaluation of such chatbots. We also publicly release the data from our experiment to expedite future research in these directions.

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A Topic Clusters in EmpatheticDialogues

While working with the EmpatheticDialogues dataset (Rashkin et al., 2019), we noticed that many dialogues appear repetitive in terms of the situational scenarios brought up by the speakers. To examine it more closely, we used Sentence Transformers framework (Reimers and Gurevych, 2019) to compute vector embeddings of first speakers’ turns in all dialogues and cluster them according to cosine-similarity. Figure 7 shows the empirical cumulative distribution function of topic cluster sizes in the train set of EmpatheticDialogues. From the figure, it can be seen that clusters with between 30 and 130 similar situation descriptions per cluster comprise almost 20% of the training data.

![ECDF of cluster sizes in train set](image)

Figure 7: Empirical cumulative distribution function of topical cluster sizes in the train set of EmpatheticDialogues dataset (Rashkin et al., 2019).
Table 2: Counts of orientation of chatbots’ responses (other-, self-, or both) in 50 sampled chat logs (25 for positive and 25 for negative contexts). Prefixes “Pos” and “Neg” stand for positive and negative contexts respectively.

### B Emotion Distribution in Grounding Scenarios

Figure 8 shows the distribution of original emotional labels from the EmpatheticDialogues dataset (Rashkin et al., 2019) in 480 grounding scenarios used for our benchmarking experiment. To demonstrate the even coverage of the whole emotional spectrum, we mapped 32 emotions from the dataset to 14 emotions from Plutchik’s wheel (Plutchik, 1991) (8 basic and 6 intermediate emotions) and color-coded the bars in Figure 8 according to these 14 categories.

### C Additional Details about Chatbots’ Responses

Figure 9 depicts the average number of tokens in chatbots’ responses over three dialog turns.

Table 3 shows the top-15 most frequent tokens for each of the four chatbots. As it can be noticed, question marks appear in the list of tokens of each model, pinpointing their tendency to ask questions.

Figure 9: Counts of average number of token in chatbots’ responses over three dialog turns with 95% confidence intervals.

Table 2 demonstrates the counts of orientation of chatbots’ responses (other-, self-, or both) in 50 sampled chat logs (25 positive and 25 negative) over the dialog turns.

Table: Counts of orientation of chatbots’ responses (other-, self-, or both) in 50 sampled chat logs (25 for positive and 25 for negative contexts). Prefixes “Pos” and “Neg” stand for positive and negative contexts respectively.

|        | Pos: Other t-1 | Pos: Other t-2 | Pos: Other t-3 | Pos: Self t-1 | Pos: Self t-2 | Pos: Self t-3 | Pos: Both t-1 | Pos: Both t-2 | Pos: Both t-3 | Neg: Other t-1 | Neg: Other t-2 | Neg: Other t-3 | Neg: Self t-1 | Neg: Self t-2 | Neg: Self t-3 | Neg: Both t-1 | Neg: Both t-2 | Neg: Both t-3 |
|--------|----------------|----------------|----------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| MEED   | 25             | 24             | 24             | 0             | 0             | 0             | 1             | 1             |               | 25            | 25            | 25            | 0             | 0             | 0             | 0             | 0             | 0             |
| Blender| 22             | 16             | 11             | 0             | 3             | 4             | 3             | 6             | 10            | 24            | 14            | 15            | 0             | 4             | 6             | 1             | 7             | 4             |
| MIME   | 22             | 22             | 20             | 2             | 1             | 1             | 1             | 2             | 4             | 25            | 24            | 22            | 0             | 0             | 1             | 0             | 1             | 2             |
| Plain  | 24             | 20             | 20             | 1             | 4             | 4             | 0             | 1             | 1             | 25            | 24            | 23            | 0             | 0             | 2             | 0             | 1             | 0             |

Figure 8: Distribution of emotional labels from EmpatheticDialogues dataset in grounding scenarios. The legend shows the mapping between the colors and 14 emotional categories from Plutchik’s wheel (Plutchik, 1991) (8 basic and 6 intermediate emotions).
| MEED | Blender | MIME | Plain |
|------|---------|------|-------|
| ?    | .       | that | i     |
| you  | i       | i    |       |
| that | you     | .    | you   |
| .    | to      | is   | ?     |
| what | that    | you  | that  |
| of   | it      | a    | to    |
| it   | ’s      | to   | !     |
| !    | a       | ?    | sorry |
| a    | of      | am   | so    |
| i    | do      | !    | it    |
| ’s   | ?       | good | hear  |
| kind | !       | what | what  |
| did  | have    | have | did   |
| is   | the     | do   | am    |
| sounds | ’m   | ,    | of    |

Table 3: Top-15 most frequent tokens for each chatbot in order of decreasing frequency.