EMPATHETIC RESPONSE GENERATION WITH STATE MANAGEMENT

Yuhan Liu  Jun Gao  Jiachen Du  Lanjun Zhou*  Ruifeng Xu*

Harbin Institute of Technology (Shenzhen)
{yhanliu, jgao95} @stu.hit.edu.cn
{jacobvan199165, bluejade.zhou} @gmail.com
xuruifeng @hit.edu.cn

ABSTRACT

The goal of empathetic response generation is to enhance the ability of dialogue systems to perceive and express emotions in conversations. Current approaches to this task mainly focus on improving the response generation model by recognizing the emotion of the user or predicting a target emotion to guide the generation of responses. Such models only exploit partial information (the user’s emotion or the target emotion used as a guiding signal) and do not consider multiple information together. In addition to the emotional style of the response, the intent of the response is also very important for empathetic responding. Thus, we propose a novel empathetic response generation model that can consider multiple state information including emotions and intents simultaneously. Specifically, we introduce a state management method to dynamically update the dialogue states, in which the user’s emotion is first recognized, and then the target emotion and intent are obtained via predefined shift patterns with the user’s emotion as input. The obtained information is used to control the response generation. Experimental results show that dynamically managing different information can help the model generate more empathetic responses compared with several baselines under both automatic and human evaluations. Our code will be available at https://github.com/A-Rain/State_Management_EmpDialogue.

Index Terms— Natural Language Processing, Empathetic Dialogue

1. INTRODUCTION

Empathy plays a critical role in daily communication. Many researches have shown that endowing dialogue systems with empathy can improve the human-computer interaction experience [1]. In this work, we focus on empathetic response generation [2], whose goal is to enhance the ability of dialogue systems to perceive and express emotions in conversations. Though recent work on this task has achieved promising results, challenges still remain.

* Corresponding authors
ships and empathy through intent modeling. Thus, inspired by recent advance in state management from task-oriented dialogue [11], we argue that applying global state management can effectively control the model to generate more empathetic responses.

As shown in Figure [1] in the first turn, the listener shows a surprise feeling in consideration of speaker’s joyful emotion, and the listener expresses his empathy with two kinds of intents. The speaker’s emotion, the listener’s emotion, and the listener’s intent construct a triple. We define such triple as a state, and the response generation can be regarded as a state shift process.

To achieve this, we propose a novel empathetic chatbot which generates empathetic responses based on global guidance from state management. Specifically, we design a state manager to predict and extract the state feature and a response generator for response generation conditioned on the predicted state and dialogue history. We prove that the two sub-modules form an effective empathetic dialogue system. To sum up, the contributions of this work are: (1) We argue that empathetic response generation is controlled by several states and propose a novel empathetic dialogue model that can effectively generate high quality responses. (2) Experimental results show that the response generator and the state manager cooperate with each other very well, and our model outperforms other state-of-the-art baselines in both automatic and human evaluations.

2. METHODOLOGY

2.1. Preliminary

Given a dialogue history \( \{ s_0, l_0, s_1, l_1, \cdots, s_M \} \) where \( s_a \) and \( l_a \) represent utterances from speakers and listeners, the task goal is to generate proper empathetic response \( y = \{ y_1, \cdots, y_m \} \). Following previous works [3][2], we flatten the dialogue history into a sequence \( x = \{ x_1, \cdots, x_n \} \). We assume that the whole generation process is controlled by speaker emotion \( v_{s_a} \), listener emotion \( v_{l_a} \), and listener intent \( v_r \). Therefore, the problem can be optimized through maximizing the likelihood \( \prod_{i=1}^{n} P(y_i | y_{<i}; x; v) \).

Since the original dataset [2] does not contain emotion labels and intent labels for each utterance, we leverage several external datasets. Specifically, we first obtain an emotion prediction model by fine-tuning the BERT model [12] on a fine-grained emotion classification dataset, goEmotion [13]. The emotion prediction model is then used to annotate an emotion label for each utterance. The emotion prediction model achieved an accuracy of 70% on test set, indicating that it is reliable for emotion classification. The intent label of each utterance is obtained using the data proposed by [9], where each utterance is annotated with intent information.

As shown in Fig [2] our proposed model contains two parts: A State Manager (StatM) is used to predict the overall states and extract their features for further management and a Response Generator (RespG) is used to generate responses conditioned on dialogue context and the states.

2.2. State Manager

The StatM is based on a transformer [14] encoder. Given a dialogue history sequence \( x = \{ [CLS], x_1, \cdots, x_n \} \), the input representation for each word is the sum of its token embedding and position embedding, then they are fed into the transformer encoder to get a sequence of hidden outputs \( \{ h_{[CLS]_1}, h_{x_1}, \cdots, h_{x_n} \} \).

**Speaker Emotion Prediction.** We use the representation of \([CLS] \) token as the comprehensive representation of the dialogue context. The representation is then fed into a linear layer to obtain the speaker emotion probability distribution \( P(\varepsilon_s | x) = \text{softmax}(h_{[CLS]}^T V_\varepsilon) \). Specifically, the layer weights are shared with emotion state embedding \( V_\varepsilon \in \mathbb{R}^{N_e \times d} \). Here \( N_e \) is the number of emotion and \( d \) is the vector dimension.

**Listener Emotion Prediction.** It is crucial that strong emotion-emotion (emo-emo) shift pattern exists among conversations. We can use this prior knowledge to predict emotion as accurately as possible with only dialogue history context. Through normalizing the frequency that emotion \( i \) shifts to \( j \), we can compute the shift probabilities to build emo-emo prior matrix \( M_\varepsilon = \{ a_{i,j} \} \in \mathbb{R}^{N_e \times N_e} \) based on training and validation datasets. We can use the predicted speaker emotion to infer some clues about possible shift probabilities. According to the predicted label index \( k \), we can get the whole possible emotion shift probabilities \( m_{s,ft} = \{ a_{k,1}, \cdots, a_{k,N_e} \} \).

We multiply this prior distribution with the emotion state embedding \( V_e \) to get the representation \( v_{s,ft} = V_e^T m_{s,ft} \). Then we can obtain future emotion probability distribution \( P(\varepsilon_l | x, \varepsilon_s, M_\varepsilon) = \text{softmax}(W_\varepsilon [h_{[CLS]}; v_{s,ft}] + b_\varepsilon) \). Here
\( W_1 \) and \( b_1 \) are trainable parameters.

### Listener Intent Prediction
To accurately predict intent state, it is also necessary to use the emotion-intent (emoi) shift pattern as the prior knowledge. Similar to listener emotion prediction, we can build the emo-int entity prior matrix \( \mathcal{M}_r = [b_{ij}] \in \mathbb{R}^{N_r \times N_r} \). Here \( N_r \) is the number of intent. After that, we can get emotion-intent shift probabilities \( m_{sft} = [b_{k1}, ..., b_{kN_r}] \). We use \( m_{sft} \) an intent state embedding \( \hat{v}_{sft} = V_{\tau}^T m_{sft} \), which is similar to listener emotion prediction. Then we can predict intent probability distribution \( \mathcal{P}(\tau|\mathcal{M}_r) = \sigma(W_2[h_{CLS}; \hat{v}_{sft}] + b_2) \). Here we use sigmoid instead of softmax since there exist multiple intent labels in one response. \( W_2 \) and \( b_2 \) are trainable parameters.

### Optimization
The StatM can be optimized through a negative log likelihood (NLL) loss, where \( \alpha \) and \( \beta \) are hyper-parameters:

\[
L_U = \alpha \log \mathcal{P}(\varepsilon_S|x) + (1 - \alpha) \log \mathcal{P}(\varepsilon_I|x, \varepsilon_S, \mathcal{M}_r) + \beta \log \mathcal{P}(\tau|x, \varepsilon_S, \mathcal{M}_r)
\]  

#### 2.3. Response Generator
Our Response Generator (RespG) is based on a transformer decoder, which is used to generate empathetic responses given a dialogue context and the predicted states. We concatenate the special token [CLS], dialogue context \( \{x_1, x_2, ..., x_n\} \), and ground-truth response \( \{y_1, y_2, ..., y_m\} \) together and obtain their hidden outputs \( \{h_{CLS}, h_{x1}, ..., h_{ym}\} \) through the transformer decoder. In our RespG, we modify the original attention mask in the original transformer decoder to let [CLS] attend to the rightward history context for later usage.

During decoding, we fuse the hidden output \( h_{yi} \) of \( i \)-th step with the state feature predicted by StatM to control the generation process. Specifically, we first obtain speaker emotion state \( v_{es} \) and listener emotion state \( v_{el} \) from \( V_e \) according to predicted emotion labels where we can get them from \( \mathcal{P}(\varepsilon_I|x) \) and \( \mathcal{P}(\varepsilon_S|x, \varepsilon_S, \mathcal{M}_r) \) by argmax operation. Then we use the following approach to inject emotion state bias, where \( W_3 \) and \( W_4 \) are trainable parameters:

\[
h_{yi}^* = W_3(h_{yi} + v_{es}) + \text{tanh}(W_4 h_{yi}) v_{el}
\]

For intent states fusing, because the response may have multiple labels, we first get the intent state \( v_{\tau} \) from \( V_{\tau} \) with an average operation as in Eq(3) Then we inject intent features into token hidden outputs to provide control signals of intent:

\[
v_{\tau} = \hat{I}_{\tau} V_{\tau} / \sum_{l=1}^{\tau} \hat{I}_{\tau}^{(l)}
\]

\[
h_{yi}^* = v_{\tau} \odot h_{yi} + v_{\tau}
\]

Where \( \odot \) denotes element-wise multiplication and \( \hat{I}_{\tau} \) is the predicted multi-label vector. We can get it through applying argmax operation to each row of the intent probability distribution \( \mathcal{P}(\tau|x, \varepsilon_S, \mathcal{M}_r) \).

Now that two different kinds of state fused representations have been obtained, they are projected into vocabulary logit space. To effectively merge two distributions, we design a gate control layer to monitor the information flow. We pass [CLS] hidden output through a linear layer with sigmoid activation to obtain control value \( \gamma = \sigma(W_5 h_{CLS} + b_5) \). After that, we apply softmax to the merged logits to get final probabilities:

\[
\mathcal{P}(y_i|y_{<i}; x, v) = \text{softmax}(E_w^T (\gamma h_{yi}^* + (1 - \gamma) h_{yi}))
\]

Where \( W_5 \) and \( b_5 \) are trainable parameters and \( E_w \in \mathbb{R}^{V \times d} \) is the token embedding lookup table. For optimizing the RespG, we also adopt NLL loss for it.

### 3. EXPERIMENTS

#### 3.1. Experiment Setup
We conduct experiments on Empathetic Dialogue dataset [2], which consists of 25k one-to-one open-domain conversations with 8:1:1 train/validation/test split. We explore our models with two different initialization methods: the vanilla transformer and the pretrained language model, denoted as Ours(Ts) and Ours(LM) respectively. We first use the dataset to fine-tune the RespG backbone to learn some semantic features. Then we alternatively train the StatM and the RespG. For Ours(Ts), we train the model for 20 epochs, where the batch size and learning rate are set to 16 and 2e-4. For Ours(LM), we use BERT-base as StatM backbone and GPT2-small [15] as RespG backbone. We train the model for 10 epochs, where the batch size and learning rate are set to 16 and 5e-5. The value for \( \alpha \) and \( \beta \) are 0.6 and 0.5. We use AdamW [16] as the optimizer and apply the schedule sampling so that RespG can access true state feature with some probability. We choose the model where RespG performs best in the validation set for final evaluation. And top-k sampling [17] is adopted during inference.

Three kinds of automatic metrics are chosen: (1) BLEU: Following [6, 4, 3], we use BLEU-4 [18] to calculate n-gram overlap ratio. (2) \( F_{\text{BERT}} \): We use F1 BERTscore [19] to measure semantic similarity. (3) DIST: We use Dist-2 [20] computing the proportion of bigrams to get text diversity.

Two types of human evaluations are employed to verify the performance of different models: 1) Human rating: We randomly sample 100 dialogues and corresponding generated responses of each models. 5 professional annotators are required to give each response a rating score from \( \text{Relevance} \), \( \text{Fluency} \) aspect, and \( \text{Empathy} \) aspect. The score is 5-point scale (1: not at all, 3: somewhat, 5: very much). 2) Human A/B test: We rearrange the samples in an A-vs-B format, where A is our model and B is another baseline. Another 3 professional annotators are asked to choose the better response for each instance, or a TIE if both are good or bad.

#### 3.2. Baselines
Following baselines are compared: (1) MoEL [3]: the transformer-based model which softly combines the different decoder outputs according to emotion distribution. (2) MIME [4]: the transformer-based model, which introduces emotion grouping and sampling stochastically to generate responses. (3) EmpDG [6]: an adversarial model which
adopts multi-resolution emotion perception and exploits the user feedback. (4) MultiGPT: similar to [21][22], we re-implement a GPT2-based multi-task framework that does language modelling, speaker emotion prediction, and listener emotion prediction simultaneously. Ablation study is also conducted: (1) w/o emo: only intent state is predicted and fused. (2) w/o itt: only emotion state is predicted and fused. (3) Naive: only speaker emotion is predicted, and simply utilize prior shift matrix to get the other states for generation.

3.3. Main Results

| Models    | BLEU     | \(F_{\text{BERT}}\) | DIST     |
|-----------|----------|----------------------|----------|
| MoEL      | 1.592 ±0.001 | 0.133 ±0.003 | 0.076 ±0.005 |
| MIME      | 1.658 ±0.001 | 0.137 ±0.004 | 0.058 ±0.004 |
| EmpDG     | 1.318 ±0.002 | 0.108 ±0.008 | 0.072 ±0.018 |
| MultiGPT  | 1.448 ±0.001 | 0.169 ±0.001 | 0.209 ±0.003 |
| Ours(Trs) | 1.749 ±0.001 | 0.150 ±0.001 | 0.107 ±0.008 |
| Naive     | 1.511 ±0.002 | 0.142 ±0.002 | 0.114 ±0.008 |
| w/o emo   | 1.415 ±0.001 | 0.134 ±0.003 | 0.101 ±0.011 |
| w/o itt   | 1.486 ±0.001 | 0.138 ±0.003 | 0.138 ±0.024 |
| Ours(LM)  | 1.764 ±0.004 | 0.176 ±0.001 | 0.188 ±0.004 |
| Naive     | 1.255 ±0.002 | 0.158 ±0.003 | 0.214 ±0.017 |
| w/o emo   | 1.493 ±0.001 | 0.166 ±0.002 | 0.143 ±0.020 |
| w/o itt   | 1.716 ±0.002 | 0.171 ±0.003 | 0.178 ±0.010 |

Table 1: Automatic metric results. we repeat 5 runs with different seeds and average the results for each method. Standard deviations are given in the small text. \(\dagger\) means the results are statistically significant at \(p < 0.05\).

(a) Human rating results

| Models   | Relevance | Fluency | Empathy |
|----------|-----------|---------|---------|
| MoEL     | 2.70      | 3.81    | 2.62    |
| MIME     | 2.65      | 3.89    | 2.73    |
| EmpDG    | 2.74      | 3.71    | 2.65    |
| MultiGPT | 2.70      | 4.14    | 3.04    |
| Ours(Trs)| 2.87      | 3.82    | 2.94    |
| Ours(LM) | 3.70      | 4.37    | 3.67    |

(b) Human A/B test results.

Table 2: The Fleiss-Kappa of each three rating aspects and A/B test are 0.29, 0.14, 0.21, and 0.35, which indicate that the multiple annotators almost reach a fair agreement.

Automatic Evaluation. Table 1 illustrates the whole automatic metric results of different models. Comparing to other baselines, Ours(LM) and Ours(Trs) reaches the highest results in most metrics, indicating that our proposed methods can effectively learn expression patterns in the corpus. Although MultiGPT reaches the higher score in DIST, its \(F_{\text{BERT}}\) score is lower than Ours(LM), which shows that Ours(LM) has better semantic understanding and MultiGPT may generate some noise and unrelated words. Besides, For Ours(Trs), we achieves the best performances in all three metrics among vanilla transformer backbone based methods. Performance of both Ours(Trs) and Ours(LM) illustrate that our proposed method can generate more informative and empathetic responses.

Human Evaluation. The results of human ratings and A/B test are illustrated in Table 2. The results indicate that Ours(LM) obtains the highest rating score in all three rating aspects. In particular, our model exceeds MultiGPT about 0.5 points in both Relevance and Empathy, which shows the effective control from the overall states. For Ours(Trs), although the model performance is slightly worse than MultiGPT, we still achieve the best results comparing to other transformer based models. The human A/B test results also validate the conclusions mentioned above. Due to limited semantic mapping, Ours(Trs) model is not as good as Ours(LM) model. And the high winning percentage of Ours(LM) correlates with high human rating scores. Overall, the two evaluations together manifest that responses from our proposed model are more preferable and of better quality.

3.4. Further Analysis

Ablation Study. Ablation study results are presented in Table 1. For both Ours(LM) and Ours(Trs), performance of w/o-it is better than that of w/o-emo. Its DIST and \(F_{\text{BERT}}\) are higher than those of w/o-emo, which may indicate that emotion states can lead to generating more diverse and more semantic-related words. The emotion state may play a more crucial role in managing generation. Nevertheless, when we combine two states through gate control, the full model achieves the best metric results. This shows that both state feature can provide useful information from different views.

State Prediction Comparison. We evaluate the state prediction performance of the StatM. For Ours(LM), our proposed model achieves 88.32% and 52.67% accuracy (acc) in speaker emotion prediction and listener emotion prediction. Comparing to MultiGPT which get 87.61% and 51.81% acc, we get better results than it. We also achieve 55.60% averaged precision (AP) in intent prediction, which means our model has a good capability of predicting intent state. For Naive method, the speaker and listener emotion prediction acc are 87.67% and 42.69%, and the intent AP is 52.65%. This shows that simply using state shift statistics for prediction is not accurate, and our proposed StatM is more effective.

Gate Control. In the test set, for Ours(LM), gate control value \(\lambda\) ranges from 0.8536 to 0.8951. And for Ours(Trs), \(\lambda\) ranges from 0.2122 to 0.2588. For Ours(LM), it seems that more information is provided by emotion states, whereas intent states are also indispensable. For Ours(Trs), such a conclusion is opposite.

4. CONCLUSION

In this paper, we propose a novel empathetic response generation model by utilizing multiple state information to con-
trol the generation process. Experimental results and performance analysis demonstrate the effectiveness and rationality of our model. In the future, we will consider using some more powerful state management strategies to further improve the model performance.

5. REFERENCES

[1] Timo Partala and Veikko Surakka, “The effects of affective interventions in human–computer interaction,” Interacting with computers, vol. 16, no. 2, pp. 295–309, 2004.

[2] Hannah Rashkin, Eric Michael Smith, Margaret Li, et al., “Towards empathetic open-domain conversation models: A new benchmark and dataset,” in Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, July 2019, pp. 5370–5381.

[3] Zhaojiang Lin, Andrea Madotto, Jamin Shin, et al., “MoEL: Mixture of empathetic listeners,” in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Nov. 2019, pp. 121–132.

[4] Navonil Majumder, Pengfei Hong, Shanshan Peng, et al., “MIME: MIMicking emotions for empathetic response generation,” in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), Nov. 2020, pp. 8968–8979.

[5] Jun Gao, Yuhan Liu, Haolin Deng, Wei Wang, Yu Cao, Jiachen Du, and Ruifeng Xu, “Improving empathetic response generation by recognizing emotion cause in conversations,” in Findings of the Association for Computational Linguistics: EMNLP 2021, 2021, pp. 807–819.

[6] Qintong Li, Hongshen Chen, Zhaochun Ren, et al., “EmpDG: Multi-resolution interactive empathetic dialogue generation,” in Proceedings of the 28th International Conference on Computational Linguistics, Dec. 2020, pp. 4454–4466.

[7] Qintong Li, Piji Li, Zhumin Chen, and Zhaochun Ren, “Towards empathetic dialogue generation over multiple knowledge,” arXiv preprint arXiv:2009.09708, 2020.

[8] Lisong Qiu, Yingwai Shiu, Pingping Lin, et al., “What if bots feel moods?,” in Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 2020, SIGIR ’20, p. 1161–1170.

[9] Anuradha Welivita and Pearl Pu, “A taxonomy of empathetic response intents in human social conversations,” in Proceedings of the 28th International Conference on Computational Linguistics, Dec. 2020, pp. 4886–4899.

[10] Hao Zhou, Minlie Huang, Tianyang Zhang, et al., “Emotional chatting machine: Emotional conversation generation with internal and external memory,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2018, vol. 32.

[11] Tsung-Hsien Wen, David Vandyke, Nikola Mrkšić, et al., “A network-based end-to-end trainable task-oriented dialogue system,” in Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics, Apr. 2017, pp. 438–449.

[12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, et al., “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, June 2019, pp. 4171–4186.

[13] Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, et al., “GoEmotions: A dataset of fine-grained emotions,” in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, July 2020, pp. 4040–4054.

[14] Ashish Vaswani, Noam Shazeer, Niki Parmar, et al., “Attention is all you need,” in Proceeding of Advances in neural information processing systems, 2017, pp. 5998–6008.

[15] Alec Radford, Jeff Wu, Rewon Child, et al., “Language models are unsupervised multitask learners,” 2019.

[16] Ilya Loshchilov and Frank Hutter, “Decoupled weight decay regularization,” in Proceedings of International Conference on Learning Representations, 2019.

[17] Ari Holtzman, Jan Buys, Li Du, et al., “The curious case of neural text degeneration,” in Proceedings of International Conference on Learning Representations, 2020.

[18] Kishore Papineni, Salim Roukos, Todd Ward, et al., “Bleu: a method for automatic evaluation of machine translation,” in Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, July 2002, pp. 311–318.

[19] Tianyi Zhang, Varsha Kishore, Felix Wu, et al., “Bertscore: Evaluating text generation with bert,” in Proceedings of International Conference on Learning Representations, 2020.

[20] Jiwei Li, Michel Galley, Chris Brockett, et al., “A diversity-promoting objective function for neural conversation models,” in Proceedings of the 2016 Conference of the North American Chapter of the Association
for Computational Linguistics: Human Language Technologies, June 2016, pp. 110–119.

[21] Zhaojiang Lin, Peng Xu, Genta Indra Winata, et al., “Caire: An end-to-end empathetic chatbot,” CoRR, vol. abs/1907.12108, 2019.

[22] Rohola Zandie and Mohammad H Mahoor, “Emptransfo: A multi-head transformer architecture for creating empathetic dialog systems,” in Proceedings of The Thirty-Third International Flairs Conference, 2020.