HappyBot: Generating Empathetic Dialogue Responses by Improving User Experience Look-ahead

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Abstract

Recent neural conversation models that attempted to incorporate emotion and generate empathetic responses either focused on conditioning the output to a given emotion, or incorporating the current user emotional state. While these approaches have been successful to some extent in generating more diverse and seemingly engaging utterances, they do not factor in how the user would feel towards the generated dialogue response. Hence, in this paper, we advocate such look-ahead of user emotion as the key to modeling and generating empathetic dialogue responses. We thus train a Sentiment Predictor to estimate the user sentiment look-ahead towards the generated system responses, which is then used as the reward function for generating more empathetic responses. Human evaluation results show that our model outperforms other baselines in empathy, relevance, and fluency.

1 Introduction

Despite the success of neural conversation models in generating fluent and relevant responses, optimizing the maximum likelihood tends to promote *generic* and *dull* responses (Li et al., 2016). In part, this is because human-to-human social conversations naturally involve sharing of feelings and emotions that are not normally incorporated into the objective function. Hence, this brings our attention to the task of *empathetic* dialogue response generation which is to understand the user's current emotional state and respond *appropriately* (Bertero et al., 2016).

Tackling this problem, several recent works have been successful in controlling and conditioning the generated responses to certain sentiments, emotions, and emojis (Hu et al., 2017; Wang and Wan, 2018; Zhou and Wang, 2018; Zhou et al., 2018). Meanwhile, others have

Dialogue Context

SPEAKER: I just froze when it was my turn to get on the tycoon rollar coaster at disney world.

Seq2Seq

LISTENER: That sounds so fun! What kind of coaster was it?

MultiSeq

LISTENER: Oh no! I bet that was a very scary movie!

RL Current

LISTENER: That sounds like a lot of fun!

RL Look-ahead (ours)

LISTENER: Oh wow! I bet you were scared.

GOLD

LISTENER: Do roller coasters scare you

Table 1: Generated dialogue responses from different models. Our method (RL Look-ahead) produces the most empathetic and relevant response.

worked on more data-driven approaches by training a model to jointly predict the current emotional state and generate a response (Lubis et al., 2018; Rashkin et al., 2018). However, controlling the response to be empathetic assumes we know the appropriate response emotion prior to the generation, while the second line of work assumes that the model will implicitly learn to respond appropriately, from the empathetic dialogue data and its understanding of the "current" emotional state of the user.

On the other hand, as an empathetic response would naturally improve the "future" user experience, we ask the following research question: whether we can generate more empathetic dialogue responses by conditioning on future user experience. Hence, we offer a new perspective to this task which is to incorporate the future emotional impact of our response in the generation process. To elaborate, hypothesizing that sentiment is a good approximation of user experience, we propose to learn how to generate an empathetic

response by improving the *user sentiment look-ahead*, which is a task that an empathetic person would do well.

In this paper, we draw on Reinforcement Learning (Williams, 1992) to encourage a pre-trained conversation agent to explore the action space with the reward being the user sentiment lookahead towards the sampled response. We compare our proposed method with baselines considering only "current" emotional states. Our experiments show that our *look-ahead* approach outperforms the baselines in human evaluations on empathy, relevance, and fluency, confirming our hypothesis.

2 Methodology

Considering a conversation between a user and the system, we can represent a dialogue as an alternating sequence between the two as such: $[u_1, s_1, u_2, s_2, \cdots, u_t, s_t]$, where u and s denote the utterances from the user and system, respectively. Our policy model, the Seq2Seq generator (Sutskever et al., 2014) takes flattened dialogue context of 2 turns, $[s_i; u_{i+1}]$ as input and outputs response s_{i+1} . Then the reward function predicts the sentiment of the next user utterance u_{i+2} , and reinforces the policy based on the score. In short, our model consists of a policy model which is a pre-trained Seq2Seq generator, and a pre-trained sentiment predictor as the reward model.

We denote the flattened dialogue input as $x = [w_1, w_2, w_3, \cdots, w_M]$, and the corresponding response as $y^* = [y_1^*, y_2^*, y_3^*, \cdots, y_T^*]$, where M is the length of the input and T is the length of the response.

2.1 Policy Model: Seq2Seq with Attention

We choose the Bi-directional Gated Recurrent Unit (Bi-GRU) as our encoder and GRU (Chung et al., 2014) with dot product attention (Luong et al., 2015) as our generator. Firstly, the tokens of input w_i are fed into the encoder one-by-one and the encoder generates a sequence of hidden states h_i . For each decoding step t, the decoder receives the embedding for each token of a response as input, and updates its hidden states m_t . The attention mechanism is

calculated as in Luong et al. (2015)

$$e_i^t = h_i^T m_t \tag{1}$$

$$a^t = \operatorname{softmax}(e^t) \tag{2}$$

$$c_t = \sum_{i} a_i^t h_i \tag{3}$$

$$m_t^* = \tanh(W_c([c_t; m_t])) \tag{4}$$

where c_t is the context vector and W_c is a trainable parameter. m_t^* is used to predict the next word.

$$P_{\text{vocab}} = \operatorname{softmax}((Vm_t^* + b)/\tau) \tag{5}$$

where V, b are parameters to train, and τ is temperature.

2.2 Reward Function: Sentiment Predictor

As the sentiment predictor is of vital importance to our generator and BERT (Devlin et al., 2018) has shown state-of-the-art performance on many NLP tasks, including Sentiment Analysis, we choose to use BERT as sentiment predictor. More specifically, given a flattened dialogue context $[u_i; s_i]$, we fine-tune a pre-trained BERT model to predict the sentiment of the next user turn u_{i+1} , which has been labeled by our previous Sentiment Classifier. Details of training is in Section 3.1.

2.3 Hybrid Training

The empathetic dialogue generation model can be trained with Maximum Likelihood Estimation (MLE), Reinforcement Learning (RL), or a combination of both MLE and RL, where MLE training is to minimize the negative log likelihood of the gold responses. We feed y^* into the decoder word by word and maximize the likelihood of y^* . The loss function for MLE becomes

$$L_{\text{MLE}} = -\frac{1}{T} \sum_{t=1}^{T} \log P(y_t^*)$$
 (6)

For RL training, we choose the REINFORCE algorithm (Williams, 1992). In the training phase, after encoding an input, a response $y^s = [y_1^s, y_2^s, y_3^s, \cdots, y_T^s]$ is obtained by sampling from P(w) from our generator, and then a reward is calculated from sentiment predictor. We employ the baseline reward \hat{R}_t to reduce the variance of the reward, similar to Ranzato et al. (2016). Specifically, a linear model is deployed to estimate the baseline reward \hat{R}_t based on m_t for each time-step t. The parameters of the linear model are trained

by minimizing the mean square loss between R and \hat{R}_t :

$$\hat{R}_t = W_r m_t + b_r \tag{7}$$

$$L_b = \frac{1}{T} \sum_{t=1}^{T} |R - \hat{R}_t|^2$$
 (8)

where W_r and b_r are trainable parameters. Our loss function for RL becomes

$$L_{\rm RL} = -\frac{1}{T} \sum_{t=1}^{T} (R - \hat{R}_t) \log P(w_t) \qquad (9)$$

A mixed training method has shown to be effective in many generation tasks (Paulus et al., 2018; Zhou and Wang, 2018) by including MLE training to mitigate the issues of readability caused RL. We thus combine RL and MLE training and the loss function becomes:

$$L_{\text{mixed}} = \lambda L_{\text{RL}} + (1 - \lambda) L_{\text{MLE}} \qquad (10)$$

where λ is the hyper-parameter to decide the weight of the RL.

3 Experiments

3.1 Training Details

To train the policy model, we use three different open-domain dialogue datasets: DailyDialog (DD) (Li et al., 2017), PersonaChat (PC) (Zhang et al., 2018), and EmpatheticDialogues (ED) (Rashkin et al., 2018) ¹. This setting has been organized to promote diversity of the response generation, as the ED dataset mainly contains empathetic responses. For training the reward model, we use SST-2 (Socher et al., 2013) and the situation texts from ED.

Furthermore, in order to train the reward model, we first train a high-performing Sentiment Classifier by fine-tuning the pretrained BERT (Devlin et al., 2018) on SST-2 (Socher et al., 2013) and situation texts from ED (by mapping the emotions to sentiments) and achieve ~91% accuracy. We then use this Sentiment Classifier to label the user sentiments, and train the Sentiment Predictor, which reaches around 71% accuracy. Specific details on hyper-parameters are in the Appendix A.2.

3.2 Baselines

We implement and compare the following models:

	BLEU	Empathy	Relevance	Fluency
Gold	-	3.651	3.752	3.718
Seq2Seq	2.29	3.013	3.173	2.967
MultiSeq	2.45	2.979	3.25	2.952
RL Current	2.31	3.18	3.187	3.14
RL Look-ahead	2.32	3.327	3.593	3.327

Table 2: Comparison between our proposed methods and baselines. RL Look-ahead model achieves the highest score for all three aspects: Empathy, Relevance, and Fluency. MultiSeq model achieves highest BLEU score, but not significant.

Seq2Seq The Seq2Seq model is trained by minimizing L_{MLE} in Equation 6.

MultiSeq The MultiSeq model is the multi-task model trained as in (Rashkin et al., 2018) by using the Bi-GRU encoder to jointly predict the emotion of context x. We add a softmax layer to the Bi-GRU for prediction and the loss incurred here is simply added to Equation 6 for optimization.

RL Current The RL Current model is trained by minimizing L_{mixed} in Equation 10 using the sentiment of the y^s as the reward. The reason we experiment with this baseline is to show whether improving sentiment itself is helpful or not.

RL Look-ahead (ours) The RL Look-ahead model is trained by minimizing L_{mixed} in Equation 10 using the score of y^s from Sentiment Predictor as the reward.

3.3 Evaluation

We compare the performance of the baselines and our model in two-folds: automatic and human evaluation. For automated metrics, we measure the BLEU (Papineni et al., 2002) scores of the generated samples. For human evaluation, we randomly sample 50 dialogues with their corresponding generations, and randomly assign, for each sample, three crowd-workers on Amazon Mechanical Turk to annotate the quality of generation from the range of 1 to 5 for Empathy, Relevance, and Fluency as in Rashkin et al. (2018). Details of questions asked can be found in Appendix A.1.

4 Results

4.1 Analysis of Automated Metric

From the BLEU scores in Table 2, we can see that although *MultiSeq* has the highest BLEU score, all models have similar BLEU scores and the difference is not that significant. Note that these

¹both PC and ED are obtained from ParlAI.

LISTENER	Ugh! I hate it when stuff like that happens. Were you able to get a refund on your tickets?	Nice. What was dinner?	
SPEAKER	No. We went ahead and went on. It actually	Surprisingly enough, a pizza from the	
SPEAKEK	turned out to be a great trip with zero incidents.	bowling alley. I never said that I was picky!	
Seq2Seq	I would be too! I would have been so scared.	That sounds like a great time.	
MultiSeq	That 's so bad . I hope you get it fixed .	That sounds like a great time.	
RL Current	I can understand that . I hope you get a refund and the next one .	Sounds like a fun time .	
RL Look-ahead	I bet that was a good surprise!	That sounds delicious . I love pizza .	
Gold	Awesome!!	I have nt met a pizza I did nt like yet.	

Table 3: Generated responses from different models. RL Look-ahead model understands the dialogue and gives the most appropriate responses.

automated results are lower than those reported in Rashkin et al. (2018) mainly because the difference in base model architecture (Vaswani et al., 2017), the size of pre-training data, and the use of beam search.

4.2 Analysis of Human Evaluation

The usefulness of BLEU in open-domain dialogue has been questioned many times (Galley et al., 2015; Liu et al., 2016; Li et al., 2016), so we turn to human evaluation for a more precise measure of dialogue quality (Liu et al., 2016). We can clearly notice from human evaluations shown in Table 2 that our model, *RL Look-ahead*, outperforms all of the others in all three evaluated categories. Furthermore, the results of *MultiSeq* shows to be similar as *Seq2Seq* for Empathy.

To confirm that our gains come from the modeling of future emotional impact, we further evaluate another baseline that reinforces the improvement of the current sentiment of the generated response (RL Current), using, as reward function, the BERT Sentiment Classifier that was used to label the data as explained in Section 3.1. It is clear that our model outperforms RL Current, but improving the current sentiment also helps the model to generate more empathetic responses. This is because the model generally encourages higher sentiment responses which is beneficial when the answer is supposed to be positive. On the other hand, considering the future reward also allows our model to generate empathetic responses even when the answer is not necessarily positive as shown in the example from Table 1.

4.3 Case Study

To further understand how our model generates empathetic and natural responses, we conduct a qualitative analysis using examples from Table 3. Given the dialogue setup in the second column, Seq2Seq and MultiSeq models generate negative responses with words like "scared" or "bad", as they do not understand the "great trip with zero incidents" from the user side of the dialogue (Speaker). RL Current model outputs less negative responses, but still does not understand the dialogue correctly. Meanwhile, RL Look-ahead model gets the most appropriate and natural responses by referring to the trip as "a good surprise", which naturally will encourage the user to share their happy story during the great trip. On the other hand, the example in the third column shows our model generates more emotional and vivid words, such as "delicious" and "love pizza".

5 Related Work

Recognizing sentiment and emotion has been a relatively well understood and researched task (Socher et al., 2013; Felbo et al., 2017; McCann et al., 2017; Xu et al., 2018) that has been deemed necessary for generating empathetic dialogues (Fung et al., 2016; Bertero et al., 2016; Chatterjee et al., 2019a,b; Winata et al., Taking this further, Hu et al. (2017); 2019). Wang and Wan (2018); Zhou and Wang (2018); Zhou et al. (2018) successfully introduce a framework of controlling the sentiment and emoji of the generated response, while Zhou and Wang (2018) released a new Twitter conversation dataset distantly supervised with emojis. Meanwhile, Lubis et al. (2018); Rashkin et al. (2018) also introduce new datasets for empathetic dialogues and train multi-task models on it. Finally, Deep RL has gained popularity for the ability to optimize non-differential metrics in summarization (Ranzato et al., 2016; Paulus et al., 2018),

dialogue (Li et al., 2016), and emotional chatbot (Zhou and Wang, 2018).

6 Conclusion

In this paper, we propose *look-ahead* of user experience as the key to generating empathetic responses. We train a Sentiment Predictor to predict the sentiment look-ahead of the user given the dialogue setup, and the predicted score is utilized as the reward under a reinforcement learning framework to encourage more empathetic responses. The empirical results confirm that our approach is an effective way to generate more empathetic responses compared to models that condition on current user emotional state, or maximize the sentiment of the generated response itself.

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A Appendices

A.1 Human Evaluation

We ask the human judges to evaluate each of the following categories from a 1 to 5 scale, where 5 is the best score.

- Empathy / Sympathy: Did the responses from the LISTENER show understanding of the feelings of the SPEAKER talking about their experience?
- Relevance: Did the responses of the LIS-TENER seem appropriate to the conversation? Were they on-topic?
- Fluency: Could you understand the responses from the LISTENER? Did the language seem accurate?

A.2 Hyper-parameters

In addition, we report the hyper-parameters and heuristics we use for training our model. We used pre-trained FastText (Bojanowski et al., 2017) embeddings of dimension size 300, and for each GRU cell in both encoder and decoder, we also use a hidden size of 300. This has been done so that we can tie the weights of the embeddings and the output layer of the decoder as in Merity et al. (2018). For the BERT model, we use the pre-trained *base* model. Finally, we use learning rate in [1e-3, 1e-4], softmax temperature τ of 0.4, and hybrid training ratio λ of 0.25. Note that for all our models, we use greedy decoding for evaluation.