Target Guided Emotion Aware Chat Machine

WEI WEI†, Cognitive Computing and Intelligent Information Processing (CCIIP) Laboratory, School of Computer Science and Technology, Huazhong University of Science and Technology.
JIAYI LIU†, Cognitive Computing and Intelligent Information Processing (CCIIP) Laboratory, School of Computer Science and Technology, Huazhong University of Science and Technology
XIANLING MAO, School of Computer Science and Technology, Beijing Institute of Technology
GUIBING GUO, Software College, Northeastern University
FEIDA ZHU, School of Information Systems, Singapore Management University
PAN ZHOU, School of Computer Science and Technology, Huazhong University of Science and Technology
YUCHONG HU, School of Computer Science and Technology, Huazhong University of Science and Technology
SHANSHAN FENG, Inception Institute of Artificial Intelligence Abu Dhabi, UAE

The consistency of a response to a given post at semantic-level and emotional-level is essential for a dialogue system to deliver human-like interactions. However, this challenge is not well addressed in the literature, since most of the approaches neglect the emotional information conveyed by a post while generating responses. This article addresses this problem by proposing a unified end-to-end neural architecture, which is capable of simultaneously encoding the semantics and the emotions in a post and leverage target information for generating more intelligent responses with appropriately expressed emotions. Extensive experiments on real-world data demonstrate that the proposed method outperforms the state-of-the-art methods in terms of both content coherence and emotion appropriateness.

CCS Concepts: • Computing methodologies → Natural language generation; Natural language processing; Discourse, dialogue and pragmatics.

Additional Key Words and Phrases: Dialogue generation; emotional conversation; emotional chatbot

1 INTRODUCTION

Dialogue systems in practice are typically built for various purposes like emotional interaction, customer service or information acquisition, which can be roughly categorized into three classes, i.e., chit-chat chatbot, task-oriented chatbot and domain-specific chatbot. For example, a task-specific chatbot can serve as a customer consultant, while a chit-chat chatbot is commonly designed for convincingly simulating how a human would respond as a conversational partner. In fact, most recent work on response generation in chitchat domain can be summarized as follows, i.e., retrieval-based, matching-based, or statistical machine learning based approaches [13, 31, 45, 48]. Recently, with the increasing popularity of deep learning, many research efforts have been dedicated to employing an encode-decoder architecture i.e., Sequence-to-sequence (Seq2seq) models [3, 38], to map a post to the corresponding response with little hand-crafted features or domain-specific

†Corresponding author: weiw@hust.edu.cn; liujiayi7@hust.edu.cn.

An earlier version of this article was presented at CIKM 2019, titled: "Emotion-aware Chat Machine: Automatic Emotional Response Generation for Human-like Emotional Interaction".

Authors’ addresses: Wei Wei† Cognitive Computing and Intelligent Information Processing (CCIIP) Laboratory, School of Computer Science and Technology, Huazhong University of Science and Technology.; Jiayi Liu†Cognitive Computing and Intelligent Information Processing (CCIIP) Laboratory, School of Computer Science and Technology, Huazhong University of Science and Technology; Xianling MaoSchool of Computer Science and Technology, Beijing Institute of Technology; Guibing GuoSoftware College, Northeastern University; Feida ZhuSchool of Information Systems, Singapore Management University; Pan ZhouSchool of Computer Science and Technology, Huazhong University of Science and Technology; Yuchong Hu School of Computer Science and Technology, Huazhong University of Science and Technology; Shanshan FengInception Institute of Artificial Intelligence Abu Dhabi, UAE.
| Post | ECM responses | EACM response | TG-EACM response |
|------|---------------|---------------|------------------|
| 厉害啊，咖啡还有这作用。 | 这是什么牌子的咖啡？ What brand of coffee is this? (Like) | 这到底是什么东西啊？! What on earth is this thing? | 喝的时候也有这样的感觉， | 非常好 I also have such feeling while drinking. This is really great. |
| This is amazing that coffee actually has such effect. | 我也是，怎么喝的啊 Me too, how did you drink it (Sad) |  |  |
| 这是什么咖啡啊？求解 Which kind of coffee is this, I wonder. (Disgust) | 什么书啊？?! What book is it?!! (Angry) |  |  |
| 哈哈，我也喝过! Haha, I’ve also tasted that! (Happy) |  |  |  |

Fig. 1. Conversation examples generated by ECM, EACM and TG-EACM. ECM is able to generate multiple responses when giving different pre-defined emotions, and thus is called semi-auto response generation. As comparison, EACM and TG-EACM are automatic generation models, and the accuracy of emotion prediction of TG-EACM is higher than that of EACM, such as in Fig.1 TG-EACM choose an optimal emotion (like), while EACM choose (angry).

Despite the great progress made in neural dialogue generation, a general fact is that few work has been reported to automatically incorporate emotional factors for dialogue systems. In fact, several empirical studies have proven that chatbots with the ability of emotional communication with humans are essential for enhancing user satisfaction [2, 22, 29]. To this end, it is highly valuable and desirable to develop an emotion-aware chatbot that is capable of perceiving/expressing emotions and emotionally interacting with the interlocutors. In literature, Zhou et al. [53] successfully build an emotional chat machine (ECM) that is capable of generating emotional responses according to a pre-defined emotion category, and several similar efforts are also made by [11, 26]. Besides, [57] proposed by Zhou et al. utilizes emojis to control the emotional response generation process within conditional variational auto-encoder (CAVE) framework.

Nevertheless, these mentioned approaches cannot work well owing to the following facts: (i) These approaches solely generate the emotional responses based on a pre-specified label (or emoji) as shown in Figure 1, which is unrealistic in practice as the well-designed dialogue systems need to wait for a manually selected emotion category for response generation; (ii) The generation process apparently divided into two parts would significantly reduce the smoothness and quality of generating responses; and (iii) As shown in Figure 1, some emotionally-inappropriate responses (even conflicts) might apparently affect the interlocutor’s satisfaction. Thereby, here we argue that fully exploiting the information of the given post and leveraging the guidance from the target to supervise the generating process is definitely beneficial for automatically generating responses with the optimal emotion (rf. “TG-EACM response” generated by our method shown in Figure 1).

Previous methods greatly contribute to emotion-expressing conversation generation problem, however, they are insufficient and several issues emerge when trying to fully-address this problem. **First**, it is not easy to model human emotion from a given sentence due to the semantic sparsity in natural language. Psychological studies [27, 28] demonstrate that human emotion is quite complex and one sentence may contain multi-types of emotions with different intensities. For example, a hotel guest might write a comment like “The environment is not bad, however the location is too remote.” As such, solely using the post’s emotion label is insufficient and we need to facilitate

---

Wei, et al.
the model with helpful guidance from the target. **Second**, it is difficult for a model to decide the optimal response emotion for generation, and it is also not reasonable to directly map the post’s emotion label to the response’s emotion label, as the emotion selection process is determined not only by the post’s emotion but also by its semantic meaning. **Third**, it is also problematic to design a unified model that can generate plausible emotional sentence without sacrificing grammatical fluency and semantic coherence [53]. Hence, the response generation problem faces a significant challenge: that is, how to effectively leverage handy information from the post as well as the target to automatically learn the emotion interaction mode for emotion-aware response generation within a unified model.

In this paper, we propose a innovative Target-Guided Emotion-Aware Chat Machine (named TG-EACM for short), which is capable of perceiving other interlocutor’s feeling (i.e., post’s emotion) and generating plausible response with the optimal emotion category (i.e., response’s emotion). Specifically, TG-EACM is based on a unified Seq2seq architecture with a self-attention enhanced emotion selector and an emotion-biased response generator, to simultaneously modeling the post’s emotional and semantic information for automatically generating appropriate response. Targets (i.e., responses in the training data) are used as guidance to boost the learning ability of the emotion interaction pattern. Experiments on the public datasets demonstrate the effectiveness of our proposed method, in terms of two different types of evaluation metrics, i.e., automatic metric, which is used to measure the diversity of words in the generated sentences, and human evaluation, which is used to decide whether the generated responses’ emotions are appropriate according to human annotations. The main contributions of this research are summarized as follows:

1. It advances the current emotion conversation generation problem from a new perspective, namely emotion-aware response generation, by taking account of the emotion interactions between interlocutors.
2. It also proposes an innovative generation model (i.e., TG-EACM) that is capable of extracting post’s emotional and semantic information and leveraging guidance from the targets in order to generate intelligible responses with appropriate emotions. In specific, we use a prior network and a posterior network (which is not used in the original model) for mitigating the gap between the training part and the testing one, as the posterior network can learn a better intermedia encoder both from the post and the given response, which can effectively guide the model to learn the emotion transition between the post and response, and then the prior network can help more accurately modeling the post’s semantic and emotion information during testing, and in the ablation study, we shows that the proposed method can significantly improve the evaluation performance in terms of automatic metric and human evaluation.
3. It conducts extensive experiments on a real-word dataset, which demonstrate the proposed approach outperforms the state-of-the-art methods at both semantic-level and emotional-level.

## 2 RELATED WORKS

**General model.** The early work on conversational models is initially proposed by Joseph in 1960s, called ELIZA [47], which primarily builds a dialogue system based on the handcrafted templates and heuristic rules. However, the manual process is subjective, time-consuming and tedious, and thus making it difficult for large-scale conversation generation problem. Recently, with the exponential growth of available human-to-human conversation data, many data-driven approaches are proposed for the conversation generation task, which generally falls into two categories, i.e., retrieval-based and generation-based.

**Retrieval-based** methods aim at choosing an appropriate response from the historical data via measuring the matching degree between the post and the candidate response. There already exist
several efforts dedicated to research on single-turn response selection where the input is a single post [9, 20, 46]. Later, many deep learning based approaches are proposed for multi-turn response selection problem via calculating context-response matching score, such as dual LSTM model [19], deep learning to respond architecture [51], sequential matching network (SMN) [49], multi-view matching model [55], deep attention matching network (DAM) [56] and multi-representation fusion network (MRFN) [40].

With advances in deep learning, generation-based models have become the most promising solution to many conversation generation tasks, through regarding the conversation generation as a monolingual translation task that encodes a post into a fixed-length vector from which a decoder generates a response, such as chit-chat or domain-specific conversation [52]. The mainstream of representative methods are usually based on Sequence-to-sequence (Seq2seq) architecture with attention mechanism [34, 37, 44], as its strong ability in effectively addressing the sequence mapping issues [1, 3, 38]. Several variants of Seq2seq model are also proposed, such as hierarchical recurrent model [32, 33] or topic-aware model [50].

Besides, there also exist several lines of studies on different aspects of conversation generation problem, such as: (i) Context-consistency, which aims to endow the chatbots with particular personality traits for addressing the context-consistency problem, e.g., persona-based model [15] and identity-coherent model [30]; (ii) Diversity, the goal of which is to enhance the diversity and informativeness of generated responses, e.g., Maximum Mutual Information (MMI) based model [14] or enhanced beam-search based model [16, 42]; and (iii) Commonsense Knowledge, which takes account of static graph attention to incorporate commonsense knowledge for chatbots [54]. In addition, Zhang et al. [52] also propose different solutions for two classical conversation scenarios, i.e., chit-chat and domain-specific conversation. However, all of these methods do not consider emotion factor for emotion-aware conversation generation as we do in this work.

**Emotion-aware model.** The methods of emotion-aware conversation generation aims at perceiving other interlocutor’s feeling (i.e., post’s emotion) and generating plausible response with the optimal emotion category (i.e., response’s emotion). Ghosh et al. [7] propose affect language model to generate texts conditioned on a specified affect categories with controllable affect strength. Hu et al. [10] present a combination of Variational Auto-Encoder (VAE) and holistic attribute discriminators to generate sentences with certain types of sentiment and tense, and which is however mainly built for emotional text generation task. However, they are not designed for emotion-aware conversation generation problem.

In recent years, several proposals [11, 53, 57] approach the problem of generating more intelligent responses with appropriately expressed emotions towards a given post, which is of great significance for successfully building human-like dialogue systems. Zhou et al. [53] develop an Emotional Chat Machine (ECM) model composed of three different mechanisms (i.e., emotion embedding, internal memory and external memory) for response generation, according to a designated emotion category. Similarly, Zhou et al. [57] propose a reinforcement learning based approach with Conditional Variational Auto-Encoder (CVAE) architecture to generate responses conditioned on several given emojis. In [11], Huang et al. consider emotion factors for response generation via different emotion injecting methods. And more recently, in [36] Song et al. propose to leverage lexicon-based attention mechanism to encourage expressing emotion words. However, all of such models are designed based on a semi-automatic architecture that needs to pre-define an optimal response emotion category for generation. Besides, they also ignore the post’s emotion information during generation process, which easily leads to an insufficient and inhumane response. In contrast, our proposed model is able to automatically learn the emotion interaction mode within a unified
framework for more human-like (emotion-aware) response generation, through effectively and explicitly making use of the emotional and semantic information from the given post.

**Others.** Indeed, there also exist numerous attempts to extend the basic encoder-decoder architecture for improving the performance of *Seq2seq* model. For example, Bahdanau et al. [1] extend a Bi-directional Long Short-Term Memory (Bi-LSTM) network with attention mechanism for long-sentence generation, which is able to automatically predict the target word by (soft-)searching for relevant parts in the context, rather than explicitly modeling such parts as a hard segment. Luong et al. [21] thoroughly evaluate the effectiveness of different types of attention mechanisms, *i.e.*, global/local attention with different alignment functions. Furthermore, several studies employ the techniques from machine translation domain for improving performance, *e.g.*, self-attention mechanism [17, 41], which has been proven that can yield large gains in terms of BLEU [25], as compared to the state-of-the-art methods. Jean et al. [12] utilize large vocabularies and back-off dictionaries to address the out-of-vocabulary (OOV) problem, and achieve the encouraging results by using a sampled soft-max method for tackling the increasing complexity during decoding (caused by large-scale vocabularies). Though these works have successfully build a solid foundation for future studies based on the optimized *Seq2seq* model, the purposes of such approaches are different from our current work.

### 3 Proposed Model

#### 3.1 Preliminary: *Seq2Seq* with Attention Model

Recently, generation-based methods have received a considerable amount of attention in dialogue generation domain, *e.g.*, *Seq2seq*-attention model [1], as proven in many studies [1, 3, 38], which can promote the quality of generated sentences via dynamically attending on the key information of the input post during decoding. As *Seq2seq*-attention architecture is a widely-adopted solution for response generation problem, therefore our approach is also mainly based on it to generate responses. Next, we firstly illustrate this basic model in principle.

The *seq2seq*-attention model is typically a deep RNN-based architecture with an encoder and a decoder. The encoder takes the given post sequence \( x = \{x_1, x_2, \cdots, x_T\} \) (\( T \) is the length of the post) as inputs, and maps them into a series of hidden representations \( h = (h_1, h_2, \cdots, h_T) \). The decoder then decodes them to generate a word sequence, *i.e.*, \( y = \{y_1, y_2, \cdots, y_{T'}\} \), where \( T' \) is the length of the output sequence, and it may differ from \( T \).

In more detail, the context representation \( c_t \) of the post sequence \( x \) is computed by parameterizing the encoder hidden vector \( h \) with different attention scores [1], that is,

\[
c_t = \sum_{j=1}^{T} \alpha(s_{t-1}, h_j) \cdot h_j, \tag{1}
\]

where \( \alpha(\cdot, \cdot) \) is a weighted coefficient estimated by each encoder token’s contribution to the target word \( y_t \). The decoder iteratively updates its state \( s_t \) using previously generated word \( y_{t-1} \), namely,

\[
s_t = f(s_{t-1}, y_{t-1}, c_t), \quad t = 1, 2, \cdots, T', \tag{2}
\]

where \( f(\cdot, \cdot, \cdot) \) is a non-linear transformation of RNN cells (*e.g.*, LSTM [8] or GRU [3]).

Then, the probability of generating the \( t \)-th word \( y_t \) conditioned on the input sequence \( x \) and the previous predicted word sequence \( y_{1:t-1} \) is computed by

\[
Pr(y_t|y_{1:t-1}, x) = g(y_{t-1}, s_t, c_t), \tag{3}
\]

where \( g(\cdot, \cdot, \cdot) \) is a function (*e.g.*, softmax) to produce valid probability distribution for sampling the next word of the output sequence.
| Notation | Definition |
|----------|------------|
| **Input** |            |
| $x$      | Post utterance, $x = \{x_1, x_2, \ldots, x_T\}$; |
| $y$      | Response utterance, $y = \{y_1, y_2, \ldots, y_{T'}\}$; |
| $e_p$    | Post’s emotion label denoted by a multi-hot vector, e.g., $(0, 1, 1, 0, 0)$; |
| $e_r$    | Response’s emotion label denoted by a multi-hot vector, e.g., $(1, 1, 0, 0, 0)$; |
| $e_r^*$  | The selected response’s emotion over emotion categories, denoted by a multi-hot vector, e.g., $(0.1, 0.3, 0.5, 0, 1)$; |
| **Latent Variable** |            |
| $h_{tp}$, $h_{te}$, $h_{tr}$ | Hidden states of prior encoder, intermediate encoder and recognition encoder at $t$-th step; |
| $\overline{h}_{pe}, \overline{h}_{re}$ | Fused representation of prior network and recognition network; |
| $\hat{e}_p, \hat{e}_r, \hat{e}_r'$ | Estimated post’s emotion vector based on prior encoder; and response’s emotion vectors from the prior network and the recognition network, respectively; |
| $c_t$    | Context vector for the generator calculated by attention mechanism at step $t$; |
| $s_t$    | Hidden states of the generator at step $t$; |
| $V_e$    | Embedded response emotion vector; |
| **Loss Function** |            |
| $L_p, L_r, L_r'$ | Cross entropy loss over post’s emotion label; and response emotion label from the prior network and the recognition network, respectively; |
| $L_{KL}$ | Kullback-Leibler divergence loss between the prior network and the recognition network; |
| $L_{NLL}$ | Negative log likelihood loss for generated response. |

### 3.2 Problem Definition and Overview

In this paper, our task is to perceive the emotion involved in the input post and incorporate it into the generation process for automatically producing both semantically reasonable and emotionally appropriate response. Hence, our conversation generation problem is formulated as follows: Given a post $x = \{x_1, \ldots, x_T\}$ and an emotion category $e_p$ for a responder, the problem of automatic emotion-aware response generation aims to generate a corresponding response sequence $y = \{y_1, y_2, \ldots, y_{T'}\}$ with proper emotion $e_r$. To tackle the problem, we first need to answer two key questions as follows. For ease of reference, some notations and their definitions are listed in Table 1.

- **1.** How to automatically select an appropriate response emotion for generation according to the emotion and semantic information derived from the given post, which can be defined as

  $$e_r^* \leftarrow \arg \max_{e_r \in \mathcal{E}_c} \Pr(e_r | x, e_p), \quad (4)$$

  where $\mathcal{E}_c$ is the $K$-dimensional vector space of the emotions ($K$ represents the number of emotions); and $e_r^*$ is the generated emotion distribution over emotion categories (ref. Fig. 2).

- **2.** How to generate an emotion-aware response via the obtained emotion $e_r^*$ and the input post $x$, namely, the problem is how to estimate the probability of the response sequence $y$ with a standard LSTM-LM formulation given the encoded post sequence $x$ with the selected
emotion $e_r^*$.

$$
\Pr(y|x, e_r^*) = \Pr(y_1, y_2, \cdots, y_T|x, e_r) = \prod_{t=1}^{T} \Pr(y_t|y_{t-1}, x, e_r^*)
$$

Therefore, the problem is transformed to estimate the probability of predicting the target word $y_t$ by given the previous word sequence $y_{1:t-1}$, the given post $x$ and the optimal response emotion $e_r^*$, i.e.,

$$
y_t^* \leftarrow \arg \max \Pr(y_t|y_{1:t-1}, x, e_r^*).
$$

To address the above two problems, we propose a novel approach named Target-Guided Emotion-Aware Chat Machine (i.e., TG-EACM) within an unified framework presented in Fig. 2, which primarily consists of two subcomponents, i.e., emotion selector and response generator. More concretely, the emotion selector is in charge of the emotion selection process, i.e., yielding an emotion distribution over $E_c$, which is use for response generator to generate a corresponding response based on the input post. We will detail them in the following sections, respectively.

**Remark.** Actually, previous methods usually assume the emotion of the generated response is derived from an unique emotion category and is thus denoted by a one-hot vector, where the corresponding emotion is labeled with 1, and 0 for others. However, we observe that emotions of responses are more complicated in practice, that is, there are no simple emotion mappings between the post and the response (i.e., not 1-1 mapping). For example, a response may be “The location is good, but the price is too expensive.”, which contains two different types of emotions. As such, we use a emotion probability distribution over $E_c$ to model the emotion of a response, rather than directly mapping it into a single emotion category. Need to note that we follow academical conventions to distinguish the word “sentiment” and “emotion”, and in our paper “sentiment” is defined as the effect of “emotion”, and thus such as “happy”, “anger” and “love”, which are defined as emotions and the sentiments like “positive”, “negative” and “neutral” are defined as sentiments.

---

1Here we follow the work [53] to use ESTC dataset with the emotion category (i.e., {Angry, Disgust, Happy, Like, Sad, Other}) for experimental comparison.
3.3 Target Guided Emotion Selector

3.3.1 Overview. Given an input post $x$ with its emotion label $e_p$, one way to infer the response emotion is to approximately estimate the conditional probability over a emotional distribution by using a simple RNN-based architecture. But as mentioned in Section 3.2, there are no simple emotion mappings between the post and the response (i.e., not one-to-one mapping).

To address the problem, we propose a novel approach named Target-Guided Emotion Selector (TG-ES) to model the emotional interaction by approximately estimating the posterior probability conditioned on the post and its response within a prior-recognition architecture (as shown in Fig. 2), which consists of three sub-components, i.e., prior network, recognition network and fusion network\(^2\). Hereinafter, Eq. (4) can be transformed to approximately estimate the response emotion probability distribution conditioned on post $x$ and response $y$, namely,

$$e^*_r \leftarrow \arg \max_{e_r \in E} \Pr(e_r | x, y).$$

(7)

Specifically, here the recognition network is used to calculate the posterior distribution conditioned on the post and the corresponding response, to incorporate the target (i.e., response) information as a guidance for prior network for more accurately modeling the emotional interaction. Then, the fusion network is used to balance the contributions derived from different types of information (e.g., the semantic and the emotional information of the post), and finally a prediction network is employed to generate the optimal emotion vector over the fusion information. Additionally, it is worth noting that the discrepancy between the prior distribution and the posterior distribution makes the model hard to train, and we thus utilize Kullback-Leibler (KL) loss to minimize the difference between the prior network and the recognition network, which will be detailed in the following section (rf. Section 3.3.4).

3.3.2 Self-Attention Based Encoder. To model the emotion interaction during selection process, we propose a novel self-attention based encoder to explicitly extract the semantic and emotional information of the post and the response for representation. In fact, there are three different types of encoders in our model, i.e., prior encoder, recognition encoder and intermediate encoder, which are used to encode post’s emotional and semantic information, as well as the response’s emotional information, respectively. It is worth noting that the intermediate encoder is simultaneously used in the prior network and the recognition network, as it is used to make the emotion distribution of the posterior network and the prior network consistent.

Specifically, these encoders are firstly implemented through GRU cells for extracting auxiliary information from post sequence $x = (x_1, x_2, \cdots, x_T)$ and response sequence $y = \{y_1, y_2, \cdots, y_{T'}\}$.

\(^2\)Note that we label the different components with different color for better distinction in Fig. 2.
and map them into hidden representations using the following formulas:

\[ h^t_p = \text{GRU}(h^{t-1}_p, x_t), \]  
\[ h^t_e = \text{GRU}(h^{t-1}_e, x_t), \]  
\[ h^t_r = \text{GRU}(h^{t-1}_r, y_t). \]

where \( h^t_p \), \( h^t_e \) and \( h^t_r \) denote the hidden states of the prior encoder, the intermediate encoder and the recognition encoder at \( t \)-th time step, respectively.

To enhance the representation power of the hidden states, we introduce self-attention mechanism [17] to enable such encoders to attend to information-rich words in the utterances, and then obtain the attended hidden states \( e\h^t_p \), \( e\h^t_e \) and \( e\h^t_r \) by calculating:

\[ e\h^t_p = \sum_{i=1}^{T} a^p_i h^i_p, \]
\[ e\h^t_e = \sum_{i=1}^{T} a^e_i h^i_e, \]
\[ e\h^t_r = \sum_{i=1}^{T} a^r_i h^i_r, \]

where \( a^p_i, a^e_i, a^r_i \) are the weights of the \( i \)-th hidden states of different encoders (i.e., \( h_p, h_e, h_r \)), which are calculated by feeding \( h^i_p, h^i_e \) and \( h^i_r \) into a multi-layer perceptron with a softmax layer to ensure that the sum of all the weights equals to 1,

\[ a^p_i = \text{softmax}(V_p \tanh(W_p (h^i_p)^T)), \]
\[ a^e_i = \text{softmax}(V_e \tanh(W_e (h^i_e)^T)), \]
\[ a^r_i = \text{softmax}(V_r \tanh(W_r (h^i_r)^T)). \]

Differentiate from the prior encoder and the recognition encoder, the intermediate encoder aims to ensure the post’s prior emotional distribution is consistent with the post’s posterior emotional distribution. As such, let \( L_p \) be a loss function that imposes a cross entropy loss on the top of the emotion hidden state \( e\h_p \), namely, passing the emotion hidden state through a linear layer and a sigmoid layer to project it into an emotion distribution over \( E_c \), and the cross entropy loss is calculated as follows,

\[ e_p = \sigma(W_p e_p + b), \]
\[ L_p = -e_p \log(e_p), \]

where \( e_p \) is a multi-hot representation of the post’s emotion vector (e.g., \( (0, 1, 1, 0) \)) since it may contain multiple emotions.

3.3.3 Emotional and Semantic Word Embedding. To force the emotion selector to focus on different aspects of the post’s auxiliary information, we consider to use the recognition encoder and the intermediate encoder for semantic embedding, as well as the prior encoder for emotional embedding, respectively.

Most of existing traditional word embedding approaches (e.g., word2vec [23]) usually only model the syntactic context of words for making the words with similar syntactic context close, which may result in mapping words with totally opposite sentiment polarity to neighboring word vectors, e.g., good and bad. As such, here we consider to employ SSWE [39] for emotional embedding, which has been proven that is effective in learning sentiment-specific word embedding by incorporating
the supervision from sentiment polarity of text to encode sentiment information in the continuous representation of words, which is capable of mapping words with similar sentiment polarity to neighboring word vectors, such as good and beautiful. As such, here we consider to make use of SSWE and word2vec for emotional embedding and semantic embedding in our model, respectively.

Based on such embedding settings, the prior network (i.e., prior encoder and intermediate encoder) can learn to extract from both the post’s emotional and semantic information, and the recognition network (i.e., recognition encoder and intermediate encoder) is able to offer the semantic guidance from both the post and the response, and the prior-recognition network can work interactively to effectively supervise the modeling of the emotion interaction during selection process.

3.3.4 Fusion and Prediction Network. Simply mapping \( \hat{e}_p \) to the response emotion category \( e_r \) is insufficient to model the emotion interaction process between partners, as we cannot choose emotion category only based on post’s emotion category under some circumstances. In fact, some posts expressing negative feelings like sad are inappropriate to be replied with the same emotion, such as “It’s a pity you can’t come with us” or “I’m so sad that you broke my heart”. Therefore, we not only consider the post’s emotional information, but also take into account its semantic meaning by combining the hidden states from the prior encoder and intermediate encoder (i.e., \( \tilde{h}_p \) and \( \tilde{h}_e \)).

We consider to use a fusion network to balance the contributions derived from different types of information, and employ a prediction network to select the response emotion categories based on such mixed information. Specifically, we concatenate the obtained \( \tilde{h}_p \) and \( \tilde{h}_e \) and feed them into a sigmoid layer to yield a trade-off weight:

$$w = \sigma([\tilde{h}_p; \tilde{h}_e]),$$  \hspace{1cm} (19)

The final representation is a weighted sum of the non-linear transformed hidden states of two encoders:

$$\tilde{h}_p = \tanh(\tilde{h}_p),$$  \hspace{1cm} (20)

$$\tilde{h}_e = \tanh(\tilde{h}_e),$$  \hspace{1cm} (21)

$$\tilde{h}_{pe} = w \otimes \tilde{h}_p + (1 - w) \otimes \tilde{h}_e,$$  \hspace{1cm} (22)

where \( \otimes \) indicates element-wise multiplication. The final representation is fed into a prediction network to produce an emotion vector for generation, which is passed through MLP and then mapped into a probability distribution over the emotion categories:

$$\hat{e}_r = \sigma(W_r \tilde{h}_{pe} + b),$$  \hspace{1cm} (23)

$$L_r = -e_r \log(\hat{e}_r),$$  \hspace{1cm} (24)

where \( e_r \) is the multi-hot representation of the response emotion vector. \( \hat{e}_r \) is the final response emotion vector generated through the proposed emotion selector, which is then passed to the generator for emotional response generation.

However, during the first several training epochs, we noticed that the model can not effectively learn to predict the response’s emotion. This may due to the fact that a post can be respond in multiple response (a.k.a., the one-to-many mapping problem). Hence, we assume that with the guidance from the target, it is easier for the emotion selector to find the optimal responding emotion and learn the emotion interaction pattern better. We exploit the guidance from the target by using the recognition network, which is composed of the recognition encoder and the intermediate encoder, and we apply the same method of a fusion-prediction network to obtain \( \tilde{h}_{re} \) and \( L_r' \).
In training stage, we optimize both the prior and recognition network, but only feed the emotion vector predicted from the recognition network into the response generator. As the target is not available in testing stage, prior network serve the purpose of predicting the emotion vector, and recognition network is no longer used in such time. An intuitive idea of minimizing the discrepancy between training and testing stage is to apply Kullback-Leibler divergence loss between the two predicted emotion vectors:

\[
\mathcal{L}_{KL} = \sum_{i=1}^{K} p(e_{r} = e_{i}|x, y) \log \frac{p(e_{r} = e_{i}|x, y)}{p(e_{r} = e_{i}|x, e_{p})}.
\]  

(25)

However, as the emotion vectors are already restrained by cross-entropy loss, instead of optimizing Eqn. 25 here we apply KL-divergence on the hidden states of \( \hat{h}_{pe} \) and \( h_{re} \) to reduce the distribution divergence in hidden space:

\[
\mathcal{L}_{KL} = KL(\sigma(W_{k1}\hat{h}_{pe} + b)||\sigma(W_{k1}h_{re} + b)).
\]  

(26)

Note that the intermediate encoder is used in both prior network and recognition network because the asymmetry in their network would widen the gap between them, adding more trouble into optimizing the whole neural network.

Intuitively, the recognition network provides rich guidance from the target to choose the optimal responding emotion and fusion network can adaptively determine the weight between different type of information, ensuring accurate prediction of response’s emotion.

3.4 Emotion-Biased Response Generator

To construct the generator, we consider to use an emotion-enhanced seq2seq model that is capable of balancing the emotional part with the semantic part and generate intelligible responses.

Thereby, we first generate the response emotion embedding \( V_{e} \) by multiplying \( \hat{e}_{r} \) with a randomly initialized matrix:

\[
V_{e} = W_{e}\hat{e}_{r},
\]  

(27)

where \( W_{e} \) is the emotion category embedding matrix, which is a high-level abstraction of emotion expressions. Note that we follow Plutchik’s assumptions [27] about the complicated nature of human emotion and believe it is possible that response sentence contains several diverse emotions. Thus here we do not use a softmax on \( \hat{e}_{r} \) to only pick only ONE optimal emotion category for generation. As such, we call it as soft-emotion injection procedure, which is used to model the diversity of response emotions.

By following the work [43], we use a new encoder to encode \( x \) for obtaining a sequence of hidden states \( h = (h_{1}, h_{2}, \cdots, h_{T}) \) through a RNN network, and then generate the context vector \( c_{t} \) for decoding the current hidden state \( s_{t} \), via applying attention mechanism to re-assign an attended weight to each encoder hidden state \( h_{i} \).

\[
u_{t}^{i} = v^{T} \tanh(W_{1}h_{i} + W_{2}s_{t}), \]

(28)

\[
a_{t}^{i} = \text{softmax}(u_{t}^{i}), \]

(29)

\[
c_{t} = \sum_{i=1}^{T} a_{t}^{i}h_{i}. \]

(30)

At each time step \( t \), the context vector encoded with attention mechanism enable our model to proactively search for salient information which is important for decoding over a long sentence. However, it neglects the emotion (\( V_{e} \)) derived from the response during generation, and thus we
Table 2. Details of ESTC dataset.

|                | Posts          | Responses      |
|----------------|----------------|----------------|
|                | 219,162        |                |
| Training       |                |                |
| No Emotion     | 1,586,065      |                |
| Single Emotion | 2,792,339      |                |
| Dual Emotion   | 53,545         |                |
| Validation     | 1,000          |                |
| Testing        | 1,000          |                |

propose an emotion-biased attention mechanism to rewritten Eq.(28),

\[ u'_t = \mathbf{v}^T \tanh(\mathbf{W}_1 \mathbf{h}_t + \mathbf{W}_2 \mathbf{s}_t + \mathbf{W}_3 \mathbf{V}_e). \]  

(31)

The context vector \( c_t \) is concatenated with \( s_t \) and forms a new hidden state \( s'_t \):

\[ s'_t = \mathbf{W}_4 [s_t; c_t], \]  

(32)

from which we make the prediction for each word; \( s_t \) is obtained by changing Eq. (2) into:

\[ s_t = \text{GRU}(s'_{t-1}, [y_{t-1}; \mathbf{V}_e]), \]  

(33)

which fulfills the task of injecting emotion information while generating responses. To be consistent with previous conversation generation approaches, here we consider to use cross entropy to be the loss function, which is defined by

\[ \mathcal{L}_{\text{NLL}}(\theta) = -\log P(y|x) \]

\[ = -\sum_{t=1}^{T'} \log P(y_t | y_1, y_2, \cdots, y_{t-1}, c_t, \mathbf{V}_e), \]  

(34)

where \( \theta \) denotes the parameters.

### 3.5 Loss Function

The loss function of our model is a weighted summation of the semantic loss and emotional loss:

\[ \mathcal{L}_{\text{TG-EACM}}(\theta) = \alpha \mathcal{L}_e + (1 - \alpha) \mathcal{L}_{\text{NLL}}, \]  

(35)

where \( \alpha \) is a balance factor, and \( \mathcal{L}_e \) denotes the emotional loss, namely,

\[ \mathcal{L}_e = \mathcal{L}_p + \mathcal{L}_r + \mathcal{L}_{r'} + \mathcal{L}_{KL}. \]  

(36)

### 4 EXPERIMENTAL RESULTS

#### 4.1 Dataset

A large-scale publicly available dataset, i.e., Emotional Short-Text Conversation (ESTC), is used in the experiments to evaluate the performance of the models. This dataset is derived from STC [34] and contains over four million real-world conversations collected from Chinese Weibo, a social media platform. The raw dataset contains 4,433,949 post-comment pairs, from which 1,000 pairs are extracted for validation and another 1,000 pairs are used for testing. Details of this dataset are illustrated in Table 2.

**Preprocessing.** As the raw dataset (STC) does not have emotion labels, we follow the work [53] to train an emotion classifier for assigning emotional labels to the sentences in the dataset. Specifically,
we train an emotion classifier based on BERT [4] model over two different datasets, i.e., NLPCC 2013[^3] and NLPCC 2014[^4] emotion classification datasets, which contain 29,417 manually annotated data in total, and every piece of sentence in these datasets is marked with two emotional labels, namely, a primary label and a secondary one. We preprocess the labels over the mentioned emotion categories, i.e., (like, disgust, sad, angry, happy, other) and rare emotion categories like fear are removed. Note that here “other” indicates no emotion. Actually, unlike [53] solely using the primary label for classification, we consider both the primary and the secondary emotion labels and thus regard it as a multi-label classification task. Under such circumstances, there are three cases appearing in the label sets, i.e., sentences with no emotion labeled with (other, other), the ones with one emotion (emo1, other) and those with two emotions (emo1, emo2), respectively. Ultimately, we train the BERT model on the pre-processed dataset and obtain the best performance (accuracy) of 72.57% at step 19,635. We will leave it for future work to study how the classification errors influence the emotion selection process.

To evaluate the emotion perception ability of different approaches over the emotion categories, we build an emotion-rich dialogue test set for a fair empirical comparison. Specifically, we randomly choose 1,000 pairs whose primary emotion label is among the (like, disgust, sad, angry or happy) categories, with 200 pairs for each emotion, respectively. In addition, we also present an in-depth analysis the emotion interaction pattern (EIP) over conversations, in which each EIP is defined as a \((e_p, e_r)\) pair for each conversation to reflect the transition pattern from the post’s emotion to the response’s emotion. Figure 4 shows a heatmap depicting the number of EIP occurrences in the dataset, and each row (or column) indicates the post’s emotion \(e_p\) (or the response’s emotion \(e_r\)). The darker each grid is, the more \((e_p, e_r)\) pairs appearing in the dataset. From the figure we can observe that: (1) Only 25 distinctive combinations of (primary label, secondary label) are discovered in the dataset as some combinations like (happy, sad) are invalid in practice; (2) The second heat map is sparse because we’ve presented both primary emotional and secondary emotion label for post and response in one heatmap (4 dimensions), and for more intelligibility we reduce the 4 dimensions to 2 dimensions by permutating and combining the primary and secondary emotion in Fig 4.(b). Some permutation is not even shown in the dataset, so the heatmap provided in the paper is rather coarse. For better understanding, here we provide another heatmap (matrix) ONLY containing the primary emotion labels for post and responses in Fig 4.(a), which is rather dense. (3)

[^3]: http://tcci.ccf.org.cn/conference/2013/
[^4]: http://tcci.ccf.org.cn/conference/2014/
For each post emotion category, it is easy to find the most frequent responding emotion category according to this heatmap. These analyses will be useful for testing our baselines.

Moreover, we also utilize “Weibo Sentiment Dataset” provided by Shujutang\textsuperscript{5} to train the sentiment-specific word embeddings (SSWE), which consists of two million Weibo sentences with sentiment labels, and we remove some extra domain-specific punctuations like “@user” and “URLs”.

4.2 Evaluation Metric

Automatic evaluation for generation models still remains as a challenge, as is argued in [18], and some of the existing metrics correlates weakly with human judgements in terms of the response quality. Nevertheless, it is necessary to have automatic metrics to objectively assess the models, and thus we adopt distinct-1, distinct-2 \cite{14}, BLEU-1 and BLEU-2 \cite{25} to automatically evaluate our baselines. In addition, we also carry out a manual evaluation to evaluate the performance of the models at both emotional-level and semantic-level with human intuition, and then the response quality is calculated by combining such two results from different levels for integrally assessing these models.

**Automatic Evaluation.** As mentioned, we consider to use distinct-1, distinct-2 \cite{14}, BLEU-1 and BLEU-2 \cite{25} to be our automatic evaluation metric. Distinct-n measures the degree of diversity by computing the number of distinct n-grams in the generated responses and can indirectly reflect the degree of emotion diversity, as the generated sentence containing diverse emotions is more likely to have more abundant words in principle. BLEU-n is a referenced metric which calculates the n-gram word overlap between the generated response and the target. It reflects how well the model can learn to respond from the training set.

**Human Evaluation.** We randomly sampled 200 posts from the test set, and then aggregate the corresponding responses returned by each to-be-evaluated method, then three graduate students (whose research research focus is not in text processing area) are invited for labeling. Each generated response is labeled from two different aspects, i.e., emotional aspect and semantic aspect. Specifically, from emotional perspective, each generated response is labeled with (score 0) if its emotion is apparently inappropriate (namely evident emotion collision, e.g., angry-happy) to the given post, and (score 1) otherwise. From semantic perspective, we evaluate the generated results using the scoring metrics as follows. Note that if conflicts happen, the third annotator determines the final result.

- 1: If the generated sentence can be obversely considered as a appropriate response to the input post;
- 0: If the generated sentence is hard-to-perceive or has little relevance to the given post.

To conduct an integral assessment of the models at both emotional-level and semantic-level, we measure the response quality by using the formula as follows,

$$Q_{\text{response}} = S_{\text{emotion}} \land S_{\text{semantics}},$$

where $Q_{\text{response}}$ reflects the response quality and $S_{\text{emotion}}, S_{\text{semantics}}$ denote the emotional score and semantic score, respectively. The response quality of each case is equal to 1 if and only if both of its emotion score and semantic score are scored as 1.

4.3 Baselines

We compare our model (TG-EACM) with the following baselines.

\textsuperscript{5}http://www.datatang.com/data/45439
**Seq2seq** [38, 43]. The canonical seq2seq model with attention mechanism.

**ECM** [53]. As mentioned, ECM model is improper to directly be as the baseline since it cannot automatically select an appropriate emotion label to the respond. Thereby, we manually designate a most frequent response emotion to ECM for fair comparison. Specifically, we train a post emotion classifier to automatically detect post’s emotion, and then choose the corresponding response emotion category using the most frequent response’s emotion to the detected post’s emotion over EIPs, which is easy to find according to Figure 3.

**Seq2seq-emb** [11, 53]. Seq2seq with emotion embedding (Seq2seq-emb) is also adopted in the same manner. This model encodes the emotion category into an embedding vector, and then directly utilizes it as an extra input when decoding (i.e., hard emotion injection).

Intuitively, the generated responses from ECM and Seq2seq-emb can be viewed as the indication of the performance of simply incorporating the EIPs for modeling the emotional interactions among the conversation pairs. Moreover, in order to evaluate the impact of recognition network, which brings target into training process, and directly investigate whether the guidance information from the ground truth can facilitate the whole selection-generation process, we also compare our model with EACM by removing the recognition network from TG-EACM (i.e., solely using the prior network).

### 4.4 Implementation Details

For all approaches, each encoder and decoder with 2-layers GRU cells containing 256 hidden units, and all of the parameters are not shared between such two different layers. The vocabulary size is set as 40,000, and the OOV (out-of-vocabulary) words are replaced with a special token UNK. The size of word embeddings is 200, which are randomly initialized. The emotion category embedding is a $6 \times 200$-dimensional matrix (if used). The parameters of inmemory and ememory in ECM are the same as the settings in [53]. We use stochastic gradient descent (SGD) with mini-batch for optimization when training, and the batch size and the learning rate are set as 128 and 0.5, respectively. The greedy search algorithm is adopted for each approach to generate responses. Additionally, for speeding up the training process, we leverage the well-trained Seq2seq model to initialize other methods.

For our proposed method, the parameters are empirically set as follows: SSWE is trained by following the parameter settings in [39], where the length of hidden layer is set at 20 and window size at 3, and AdaGrad [5] is used to update the trainable parameters with the learning rate of 0.1. The size of emotional embedding and semantic embedding are both set at 200. In particular, the Word2vec embedding is used based on Tencent AI Lab Embedding\(^6\), which is pre-trained over 8 million high-quality Chinese words and phrases by using directional skip-gram method [35]. We use jieba\(^7\) for word segmentation during the evaluation process.

### 4.5 Results and Discussion

In this section, we evaluate the effectiveness of generating emotional responses by our approach as comparison to the baseline methods.

**Automatic Evaluation.** From Table 3, we can observe that: (i) ECM performs worse than Seq2seq, the reason might be that the generation process is a two-stage process, i.e., post emotion detection process and response generation process, which would significantly reduce the diversity and quality of emotion response generation due to the errors of emotion classification and the one-to-one

---

\(^6\)https://ai.tencent.com/ailab/nlp/embedding.html

\(^7\)https://github.com/fxsjy/jieba
mapping of emotional interaction pattern. In particular, the emotion category (other, other) is more likely to be chosen than other emotion categories. We will present an in-depth analysis in Section 4.7. (ii) Our proposed TG-EACM consistently outperforms all of the baselines in terms of all the metrics and the improvements are statistically significant (2-tailed t-test, with p value < 0.05). The results demonstrate that our target-guided emotion selection process is really effective in enhancing the ability of generating more diverse words and high-quality responses. Deep and thorough analysis between TG-EACM and EACM will be presented in Section 4.6.

| Models      | Distinct-1 | Distinct-2 | BLEU-1 | BLEU-2 |
|-------------|------------|------------|--------|--------|
| Seq2seq     | 0.0666     | 0.2147     | 0.2429 | 0.1589 |
| Seq2seq-emb | 0.0691     | 0.2426     | 0.2229 | 0.1470 |
| ECM         | 0.0603     | 0.2070     | 0.2316 | 0.1525 |
| EACM        | 0.0819     | 0.2840     | 0.2305 | 0.1518 |
| TG-EACM     | 0.0839     | 0.4070     | 0.2708 | 0.1832 |

Table 3. Automatic evaluation: distinct-n and BLEU-n

| Models      | $S_{\text{semantics}}$ | $S_{\text{emotion}}$ | $Q_{\text{response}}$ |
|-------------|------------------------|----------------------|------------------------|
| Seq2seq     | 0.390                  | 0.815                | 0.360                  |
| Seq2seq-emb | 0.280                  | 0.795                | 0.250                  |
| ECM         | 0.355                  | 0.870                | 0.310                  |
| EACM        | **0.415**              | 0.885                | **0.390**              |
| TG-EACM     | 0.410                  | **0.910**            | **0.390**              |

Table 4. Human evaluation: averaged semantic score, emotional score and response quality.

**Human Evaluation.** Results for human evaluation are listed in Table 4. Here, we calculated inter-rater agreement among the three annotators with the Fleiss’ kappa [6]. The Fleiss’ kappa for semantics and emotion is 0.492 and 0.823, indicating “Moderate agreement” and “Substantial agreement”, respectively. Besides, from Table 4 we can observe that: Seq2seq-emb provides the worst performance as expected, this is because the generation process’s apparently interrupted by injecting the emotion category embedding, which would significantly reduce the quality of generated responses and thus generate some hard-to-perceive sentences; ECM achieves a relatively better result, as it models the dynamic emotional expressing process using (i.e., internal memory), which alleviates the problem brought by hard emotion injection. In addition, we can see an apparent increase of emotion score for ECM model over Seq2seq and Seq2seq-emb, because the ECM model guarantees the emotional accuracy of generated response by further assigning different generation probabilities to emotional/generic words using external memory; Our proposed model TG-EACM sees improvements over the baseline methods at both semantic level and emotional level (p-value ≤ 0.05). For example, TG-EACM outperforms seq2seq model by 5.12%, 11.7% and 8.3% in terms of semantic score, emotion score and response quality, respectively. Also, as the response quality result shows our model is able to balance the emotion selecting process and generating process within a unified model, and thus generating plausible responses with appropriately expressed emotion.
The reason might be the fact that **TG-EACM** is capable of simultaneously encoding the semantics and the emotions in a post and is good at gaining expressing skills from the guidance of the target. Note that comparing to the **EACM**, there’s a minor increase in emotion score, which also proves that the target helps the model to select correct emotion. We will do an ablation study to prove the efficacy of our method in the next section.

| Method       | 1-1 | 1-0 | 0-1 | 0-0 |
|--------------|-----|-----|-----|-----|
| Seq2seq      | 36.0| 45.5| 3.0 | 15.5|
| Seq2seq-emb  | 25.0| 54.5| 3.0 | 17.5|
| ECM          | 31.0| 56.0| 4.5 | 8.5 |
| EACM         | 39.0| 49.5| 2.5 | 9.0 |
| TG-EACM      | 39.0| 52.0| 2.0 | 7.0 |

The percentage of the emotional-semantic scores under the human evaluation is shown in Table 5. For **ECM**, the percentage of (0-0) declines while the percentage of (1-0) increases as opposed to **Seq2seq**, which suggests that simply using EIP, i.e., the most frequent response emotions, has lower probability in causing emotional conflicts and improves emotional satisfaction to a certain extent. However, this amelioration comes at a price, as the percentage of (1-1) decreases because of the fact that directly using EIPs to model emotion interaction process is insufficient for complex human emotions. In comparison, **TG-EACM** reduces the percentage of generating responses with wrong emotion and correct semantics (i.e., 0-1) while increase the percentage of (1-1) correspondingly, which demonstrates that **TG-EACM** is capable of successfully modeling the emotion interaction pattern among human conversations and meanwhile can guarantee the semantic correctness in sentences. Moreover, it can be concluded that the information from the target help enhance emotion selecting ability, as the percentage of (1-0) increases when comparing **TG-EACM** with **EACM** model.

### 4.6 Ablation Study

We also carry out ablation study to prove the effectiveness of different parts of the proposed model.

#### 4.6.1 Effectiveness of the guidance from the target

As is explained above, our hypothesis is that better prediction of emotion lead to stronger ability of approximating the data distribution and finally generating more appropriate responses. In order to verify such assumption, we first evaluate the emotion predicting accuracy for **TG-EACM** and **EACM** model to prove that with the guidance from the target, the model is better at predicting the optimal emotion. And then we compare the overall performance using automatic metrics and human evaluation over the generated responses from the two models, in order to show that such method is effective in practice.

The emotion predicting accuracy result is shown in Fig 5. The X-axis represents the training steps (for every thousand steps) and the Y-axis represents the emotion prediction accuracy. For the **TG-EACM** model we assess both the prior network and recognition network. From the figure we can come to the following conclusions: (1) At about 100k training steps the recognition network gradually converges and the prior network reaches its local lowest point; (2) After 100k training steps, the recognition network fluctuates around 0.49 ACC and now the prior network starts to learn from the recognition network and finally reaches its peak value at 0.4389 ACC. (3) Prediction from the **EACM** network surpasses the prior network of **TG-EACM** at the beginning, but gradually loses its advantage and is finally overtaken by the prior network of **TG-EACM**. The peak value of...
The emotion prediction accuracy for TG-EACM and EACM. The X-axis denotes number of thousand training steps. Prior network in TG-EACM is able to learn from recognition network and achieves better performance compared with EACM.

The automatic evaluation and human evaluation results are already shown in Table 3 and Table 4. For more clear.

From the result we can conclude that utilizing the target do help the model learn better about how to express and generate more interesting and diverse responses.

We also provide an further illustration of the sampled response emotion distributions from the prior network and the recognition network in the validation set with 500 samples. We perform dimensionality reduction with Principal Components Analysis (PCA) algorithm over the emotional distributions, and the results from different training steps are shown in Figure 6. With the constraint from the KL-loss and emotional cross-entropy loss, we can see that the prior distribution is getting really close to the posterior distribution as the optimization continues, which indicates the efficacy of our prior-recognition network.

### 4.6.2 Effectiveness of pre-training and word embeddings

We also perform an extra experiment to test the impact of the diverse word embeddings (i.e., SSWE embedding and Word2Vec embedding) as well as the pre-training operation. We test the performance over KL-divergence and emotional accuracy in the training period. The results are depicted in Figure 7 and Figure 8, where the base model represents the TG-EACM model without pre-training from seq2seq and applied randomly-initialized word embeddings for all the encoder and decoders. From Figure 7 we can conclude that the SSWE embedding and Word2Vec embedding would make the peak point appear ahead of time with a much higher peak value, and using well trained seq2seq model parameters to initialize our
4.7 Case Study

In this section, we present an in-depth analysis of emotion-aware response generation results of our proposed approach. We select three samples (with the input posts and their corresponding responses) generated by different methods are shown in Figure 9, as can be seen:

**Case 1.** The response generated by TG-EACM and Seq2seq are both emotionally and semantically correct. Only a few responses generated by ECM achieved this goal, *i.e.*, (Like, other) and (Happy, other) emotion, which indicates that ECM model needs humans to manually select these emotions to respond in practice. Besides, the responses with (Sad, other) emotion generated by ECM is
obviously improper in such situation and may cause conflict between the interlocutors. Seq2seq-emb fails to catch the semantic meaning of the post and generate some irrelevant responses. This case demonstrates the efficacy of our target guided emotion aware chat machine on automatically generating optimal emotional response.

Case 2. In this case, the post expresses a sad feeling and ask the other person to comfort her, but only TG-EACM model could recognize such mood and generate a response which shows great empathy. In addition, Seq2seq cannot detect the emotion and thus generates an irrelevant response. All of ECM with different emotions seems improper for response (especially for ECM with (Happy, other)), which reflects directly using a designated emotion for generation might be a unreasonable way for modeling the emotion interaction pattern. Moreover, the most frequent emotion to (Sad, other) should never be (Happy, other) when referring to the EIPs, and thus simply using EIPs would fail to achieve the task.

Case 3. The emotion in the case is (Sad, other), however the responses provided by ECM and Seq2seq-emb with (Sad, other) are just repeating the post. Note that the responses genereated by ECM with (Angry, other) is semantically correct, but the response provided by TG-EACM is much better due to its more empathetic attitude.

5 CONCLUSION

In this paper, we propose an target guided emotion-aware chat machine (TG-EACM) to address the emotional response generation problem, which is composed of an emotion selector and a response generator. Specifically, the prior/recognition network is used to combine the emotional and semantic information from the post and the guidance information from the target, in order to predict emotion vector which is used to supervise the emotional response generation process. Extensive experiments conducted on a public dataset demonstrate the effectiveness of our proposed method as compared to baselines at both semantic-level and emotional-level, in terms of automatic evaluation and human evaluation metrics.

REFERENCES

[1] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In ICLR.

[2] Zoraida Callejas, David Griol, and Ramón López-Cózar. 2011. Predicting user mental states in spoken dialogue systems. EJASP (2011), 6.

, Vol. x, No. x, Article x. Publication date: x 2020.
| Case | Posts | Seq2seq | Seq2seq-emb | ECM | TG-EACM |
|------|-------|---------|-------------|-----|---------|
| 1    | 她有你们真幸福<br>She is blessed to have you guys. (Like, other) | "What a happy family!" (Happy, other) |  |  |  |
|      |  | 超好吃了！（Like, other） | 可爱的小猫咪，好可爱 | 这个味道，我很喜欢。 | 她太幸福了！有木有！ |
|      |  |  |  | This is a lovely girl, and she is so happy | She is so happy! Aren't they sweet! (Like, other) |
| 2    | 那你要怎么安慰我呢……<br>How are you going to comfort me…? (Sad, other) | "What a lovely cat. So adorable." (Like, other) |  |  |  |
|      |  | 可爱的小猫咪，可爱 | 可爱的小猫咪，很可爱 | 非常可爱！这是什么动物啊？ |  |
|      |  |  |  | Which kind is this dog? (Like, other) |  |
| 3    | 可怜的孩子……！<br>These poor children…! (Sad, other) | "What a lovely dog. So adorable." (Like, other) |  |  |  |
|      |  | 可怜的孩子，可怜的孩子 | 可怜的孩子，可怜的孩子 | 这是狗吗？ | 孩子是不是太辛苦了？ |
|      |  | Poor children. Poor children. (Sad, other) | Poor children. Poor children. (Sad, other) | Which one of their numbers is this? | Are these children working too hard? (Sad, other) |
| 4    | 我还记得当初的我是 00 后的<br>I still remember that I was post-90s then. | "I still remember my childhood." (Happy, other) |  |  |  |
|      |  | 怀念，我最爱<br>Missing then, it is my favorite food. (Like, other) | 怀念我的童年。 | 怀念啊，我的童年呢！ | 还行，我曾经的童年就是这个味道！ |
|      |  |  |  | I’m very missing this! This is my childhood! (Sad, other) | Not really! This course tastes exactly the same as that in my childhood! |

Fig. 9. Case Study. Three Samples (with the given posts and the corresponding responses) generated by Seq2seq, Seq2seq-emb, ECM and TG-EACM. Words that express appropriate emotion in responses are highlighted in red, along with their posts’ corresponding emotion words, while those expressing inappropriate emotion are bold in black.
[3] Kyunghyun Cho, Bart Van Merrienboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. In EMNLP.

[4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv (2018).

[5] John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. JMLR 12, 7 (2011), 257–269.

[6] Joseph L. Fleiss and Jacob Cohen. 1973. The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. Educational and psychological measurement 33, 3 (1973), 613–619.

[7] Sayan Ghosh, Mathieu Chollet, Eugene Laksana, Louis-Philippe Morency, and Stefan Scherer. 2017. Affect-lm: A neural language model for customizable affective text generation. arXiv (2017).

[8] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9, 8 (1997), 1735–1780.

[9] Baotian Hu, Zhengdong Lu, Hang Li, and Qingcai Chen. 2014. Convolutional neural network architectures for matching natural language sentences. In NIPS. 2042–2050.

[10] Zhiting Hu, Zichao Yang, Xiaodan Liang, Ruslan Salakhutdinov, and Eric P Xing. 2017. Toward controlled generation of text. In ICML.

[11] Chenyang Huang, Osmar Zaiane, Amine Trabelsi, and Nouha Dziri. 2018. Automatic Dialogue Generation with Expressed Emotions. In NAACL. 49–54.

[12] Sébastien Jean, Kyunghyun Cho, Roland Memisevic, and Yoshua Bengio. 2014. On using very large target vocabulary for neural machine translation. arXiv (2014).

[13] Zongcheng Ji, Zhengdong Lu, and Hang Li. 2014. An information retrieval approach to short text conversation. arXiv (2014).

[14] Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2015. A diversity-promoting objective function for neural conversation models. In NAACL.

[15] Jiwei Li, Michel Galley, Chris Brockett, Georgios P Spithourakis, Jianfeng Gao, and Bill Dolan. 2016. A persona-based neural conversation model. In ACL.

[16] Jiwei Li, Will Monroe, and Dan Jurafsky. 2016. A simple, fast diverse decoding algorithm for neural generation. arXiv (2016).

[17] Zhouhan Lin, Minwei Feng, Cicero Nogueira dos Santos, Mo Yu, Bing Xiang, Bowen Zhou, and Yoshua Bengio. 2017. A structured self-attentive sentence embedding. arXiv (2017).

[18] Chia-Wei Liu, Ryan Lowe, Iulian V Serban, Michael Noseworthy, Laurent Charlin, and Joelle Pineau. 2016. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. In EMNLP.

[19] Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. 2015. The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems. arXiv (2015).

[20] Zhengdong Lu and Hang Li. 2013. A deep architecture for matching short texts. In NIPS. 1367–1375.

[21] Minh-Thang Luong, Hieu Pham, and Christopher D Manning. 2015. Effective approaches to attention-based neural machine translation. In EMNLP.

[22] Bilyana Martinovski and David Traum. 2003. Breakdown in human-machine interaction: the error is the clue. In ISCA tutorial and research workshop. 11–16.

[23] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. arXiv (2013).

[24] Lili Mou, Yiping Song, Rui Yan, Ge Li, Lu Zhang, and Zhi Jin. 2016. Sequence to backward and forward sequences: A content-introducing approach to generative short-text conversation. In COLING.

[25] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: a method for automatic evaluation of machine translation. In ACL. 311–318.

[26] Yehong Peng, Yizhen Fang, Zhiwen Xie, and Guangyou Zhou. 2019. Topic-enhanced emotional conversation generation with attention mechanism. KBS 163 (2019), 429–437.

[27] Robert Plutchik. 1980. A general psychoevolutionary theory of emotion. In Theories of emotion. Elsevier, 3–33.

[28] Robert Plutchik. 2001. The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. American scientist 89, 4 (2001), 344–350.

[29] Helmut Prendinger, Junichiro Mori, and Mitsuru Ishizuka. 2005. Using human physiology to evaluate subtle expressivity of a virtual quizmaster in a mathematical game. IJHCS (2005), 231–245.

[30] Qiao Qian, Minlie Huang, Haizhou Zhao, Jingfang Xu, and Xiaoyan Zhu. 2017. Assigning personality/identity to a chatting machine for coherent conversation generation. arXiv (2017).

[31] Alan Ritter, Colin Cherry, and William B Dolan. 2011. Data-driven response generation in social media. In EMNLP. 583–593.
[32] Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C Courville, and Joelle Pineau. 2016. Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models. In AAAI. 3776–3784.

[33] Iulian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron Courville, and Yoshua Bengio. 2017. A hierarchical latent variable encoder-decoder model for generating dialogues. In NAACL.

[34] Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. Neural responding machine for short-text conversation. In ACL.

[35] Yan Song, Shuming Shi, Jing Li, and Haisong Zhang. 2018. Directional Skip-Gram: Explicitly Distinguishing Left and Right Context for Word Embeddings. In NAACL. 175–180.

[36] Zhenqiao Song, Xiaoqing Zheng, Lu Liu, Mu Xu, and Xuan-Jing Huang. 2019. Generating responses with a specific emotion in dialog. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 3685–3695.

[37] Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. arXiv (2015).

[38] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. In NIPS. 3104–3112.

[39] Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, and Bing Qin. 2014. Learning sentiment-specific word embedding for twitter sentiment classification. In ACL. 1555–1565.

[40] Chongyang Tao, Wei Wu, Can Xu, Wenpeng Hu, Dongyan Zhao, and Rui Yan. 2019. Multi-representation fusion network for multi-turn response selection in retrieval-based chatbots. In WSDM. 267–275.

[41] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS. 5998–6008.

[42] Ashwin K Vijayakumar, Michael Cogswell, Ramprasath R Selvaraju, Qing Sun, Stefan Lee, David Crandall, and Dhruv Batra. 2018. Diverse beam search: Decoding diverse solutions from neural sequence models. In AAAI.

[43] Oriol Vinyals, Łukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, and Geoffrey Hinton. 2015. Grammar as a foreign language. In NIPS. 2773–2781.

[44] Oriol Vinyals and Quoc Le. 2014. A neural conversational model. In ICML Deep Learning Workshop.

[45] Richard Wallace. 2003. The elements of AIML style. Alice AI Foundation (2003).

[46] Hao Wang, Zhengdong Lu, Hang Li, and Enhong Chen. 2013. A dataset for research on short-text conversations. In EMNLP. 935–945.

[47] Joseph Weizenbaum. 1966. ELIZA—a computer program for the study of natural language communication between man and machine. Commun. ACM 9, 1 (1966), 36–45.

[48] Bruce Wilcox. 2011. Beyond Façade: Pattern matching for natural language applications. GamaSutra. com (2011).

[49] Yu Wu, Wei Wu, Chen Xing, Ming Zhou, and Zhoujun Li. 2016. Sequential matching network: A new architecture for multi-turn response selection in retrieval-based chatbots. arXiv (2016).

[50] Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. 2017. Topic Aware Neural Response Generation. In AAAI. 3351–3357.

[51] Rui Yan, Yiping Song, and Hua Wu. 2016. Learning to respond with deep neural networks for retrieval-based human-computer conversation system. In SIGIR. 55–64.

[52] Hainan Zhang, Yanyan Lan, Jiaoyan Suo, Xin Chen, and Xueqi Cheng. 2018. Tailored Sequence to Sequence Models to Different Conversation Scenarios. In ACL. 1479–1488.

[53] Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. 2018. Emotional chatting machine: Emotional conversation generation with internal and external memory. In AAAI.

[54] Hao Zhou, Tom Young, Minlie Huang, Haizhou Zhao, Jingfang Xu, and Xiaoyan Zhu. 2018. Commonsense Knowledge Aware Conversation Generation with Graph Attention. In IJCAI. 4623–4629.

[55] Xiangyang Zhou, Daxiang Dong, Hua Wu, Shiqi Zhao, Dianhai Yu, Hao Tian, Xuan Liu, and Rui Yan. 2016. Multi-view response selection for human-computer conversation. In EMNLP. 372–381.

[56] Xiangyang Zhou, Lu Li, Daxiang Dong, Yi Liu, Ying Chen, Wayne Xin Zhao, Dianhai Yu, and Hua Wu. 2018. Multi-turn response selection for chatbots with deep attention matching network. In ACL. 1118–1127.

[57] Xianda Zhou and William Yang Wang. 2017. Mojitalk: Generating emotional responses at scale. arXiv (2017).