Ranking Enhanced Dialogue Generation

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ABSTRACT

How to effectively utilize the dialogue history is a crucial problem in multi-turn dialogue generation. Previous works usually employ various neural network architectures (e.g., recurrent neural networks, attention mechanisms, and hierarchical structures) to model the history. However, a recent empirical study by Sankar et al. has shown that these architectures lack the ability of understanding and modeling the dynamics of the dialogue history. For example, the widely used architectures are insensitive to perturbations of the dialogue history, such as words shuffling, utterances missing, and utterances reordering. To tackle this problem, we propose a Ranking Enhanced Dialogue generation framework in this paper. Despite the traditional representation encoder and response generation modules, an additional ranking module is introduced to model the ranking relation between the former utterance and consecutive utterances. Specifically, the former utterance and consecutive utterances are treated as query and corresponding documents, and both local and global ranking losses are designed in the learning process. In this way, the dynamics in the dialogue history can be explicitly captured. To evaluate our proposed models, we conduct extensive experiments on three public datasets, i.e., bAbI, PersonaChat, and JDC. Experimental results show that our models produce better responses in terms of both quantitative measures and human judgments, as compared with the state-of-the-art dialogue generation models. Furthermore, we give some detailed experimental analysis to show where and how the improvements come from.

CCS CONCEPTS

 \bullet Computing methodologies \to Discourse, dialogue and pragmatics; Natural language generation.

KEYWORDS

Dialogue Generation; Dialogue History; Multi-turn Dialogue; Learning-to-rank

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1 INTRODUCTION

With the development of deep learning techniques and the acquisition of a massive amount of chat data, multi-turn dialogue generation systems have achieved great progress, and many technology companies have launched their chat-bots, such as Microsoft Xiaoice, Cortana, and Apple Siri. As the dialogue goes on, the number of its turns increases, accompanying with the emotion changing [20, 29], topic drifting [8, 32], and task switching [6, 30]. Therefore, the dialogue history embodies the high-level dynamics, and how to effectively use the dialogue history becomes crucial yet a big challenge in the task of multi-turn dialogue system.

Most recent neural dialogue generation methods are based on the Seq2Seq [24] framework, which can be mainly categorized into two groups. The first group treats the whole history as a sequence of text [28]. The historical utterances are directly concatenated in chronological order before the encoding process to generate a dialogue history representation. Typically, recurrent neural network [17] and Transformer neural network [27] are used to aggregate all the dialogue history to a single vector, and the outputs of the encoder are treated as the input representation for response generation. The second group treats the dialogue history hierarchically [22, 23, 25, 33, 34]. Each history utterance is encoded separately, and then another encoder is applied on these encoded utterances sequentially to generate the historical representation. Both word-level encoder and utterance-level encoder are modeled by either recurrent neural network or Transformer neural network, hence both words in utterance and utterances in the dialogue history are captured. However, Sankar et al. point out that neither the recurrent neural network nor Transformer neural network in the Seq2Seq framework can fully capture the dynamics. As previous models focus more on the generative loss, the dynamics are often modeled simply and implicitly by the recurrent structure or the positional embeddings, which is insufficient for thoroughly using the useful information implicated in dynamics.

To further enhance their understanding to the history, we propose to explicitly model the dynamics for multi-turn dialogue generation. Specifically, in multi-turn dialogue, dynamics can be represented as the flow of the semantic information in history utterances, for example, task steps in task-oriented dialogue or topic drifting

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in chit-chat. In most of the time, the history utterance follows the consistency attribute, that the next utterance can be predicted by the former utterances. As an initial step of modeling dynamics in dialogue, we ignore the special cases, while assuming that if the next utterance can be selected from candidates using the former utterances, the dynamic flow will be captured by the generation model. Thus, we introduce a Ranking Enhanced Dialogue generation framework (RED) to explicitly model the internal utterance order in the dialogue history.

The RED framework mainly consists of three modules. Despite the traditional utterance representation module and response generation module, an additional ranking enhanced module is introduced to explicitly model the dynamics of the dialogue histories. Referring to the definition of ranking task in information retrieval, for each utterance in dialogue history, the former utterances can be treated as a query, in the meanwhile, the consecutive utterance right behind the query can be treated as the most relevant document. The suitability of the dynamic flow between them can be treated as relevance in information retrieval. In other words, the utterance ranking task aims to identify the next utterance from the candidates, given the former utterances as a query, where the candidates can be selected from the utterances after the query. So the target of the ranking enhanced module is to evaluate the relevance between the query and documents, by making use of the ranking technique which has been well-explored in information retrieval [14]. We design both local ranking loss and global ranking loss to capture such dynamics, by using local or global information for utterance ranking. Our proposed RED framework is general and can be easily incorporated with most of the recent dialogue generation models.

To demonstrate the effectiveness of our proposed RED framework, we conduct experiments on three public datasets to compare with two types of state-of-the-art neural dialogue generation models. Experimental results show that the proposed models outperform existing ones, by incorporating the ranking enhanced module. The detailed analysis further proves that explicitly learning the dynamics of the dialogue history does help response generation. Moreover, it gives some explanations on where and how the improvements come from.

2 RELATED WORKS

In this section, we first describe the general form of the multi-turn dialogue generation task. Then, two categories of recent models that make use of dialogue history are introduced.

2.1 Multi-turn Dialogue Generation Task

The multi-turn dialogue generation task provides a context that contains the history utterances of a conversation, while recent single turn dialogue only provides the nearest one, called the post. Therefore, the multi-turn dialogue generation task naturally satisfies a two-level hierarchy: a sequence of sub-sequences, and sub-sequences of tokens. In particular, a dialogue is modeled as a sequence of utterances (subsequences), with each utterance being a sequence of words. Formally, suppose that we are given a collection of dialog history and its corresponding response pairs, where the collection $\mathcal{D} = \{(H_i, r_i)\}_{i=1}^N$ contains N history-response pair instances. Each dialogue history H_i contains M utterances,

 $H_i = [h_1, h_2, \ldots, h_M]$ and each utterance $h_j \in H_i$ composites by a sequence of words with length K, denotes as $h_j = [w_1, w_2, \ldots, w_K]$. The $r_i = [v_1, v_2, \ldots, v_L]$ denotes the response sentence of the i-th instance. In a Seq2Seq framework, neural generation models are trained on the given collection, which parameterizes a probability distribution P, governed by parameters θ , over the set of all possible dialogues of arbitrary lengths. The probability of generating the response r can be defined as:

$$P_{\theta}(r) = \prod_{l=1}^{L} P_{\theta}(v_l|v_{< l}, H), \tag{1}$$

where $v_{< l} = [v_1, v_2, \ldots, v_{l-1}]$ denotes the words before v_l in the response. The task is analogous to language modeling, with the critical difference that dialogue generation is conditioned on history H. Sampling from the model can be performed as in standard language modeling: sampling one word at a time from the conditional distribution $P_{\theta}(v_l|v_{< l}, H)$ given the previously sampled words.

2.2 Multi-turn Dialogue Generation Models

Using the dialogue history effectively is vital for generating coherent and meaningful responses. Existing studies can be mainly separated into two categories, sequential way and hierarchical way depending on the different network structures for encoding the dialogue history information.

In a sequential way, it treats all dialogue history as a whole sequence of text, where the words in each utterance are directly concatenated in its chronological order. This category merely applies single turn dialogue generation models in the multi-turn settings, just treating current dialogue history as a longer post. Vinyals and Le [28] first applies the recurrent neural network to the dialogue generation task, which considers all previous utterances equivalently. To summarize all the past information up to the last token representation suffers from the vanishing gradient effect. Therefore the short-term goals will dominate the output distribution [3]. In particular, for sequences with high variability, the models are likely to favor short-term predictions as opposed to long-term predictions. Bahdanau et al. [1] introduces the attention mechanism into a recurrent neural network to tackle this problem. For simplification, a pure attention-based approach is proposed, namely Transformer [27]. By eschewing recurrence and instead relying entirely on attention mechanism, Transformer draws global dependencies between input and output which makes it more parallelizable than RNNs. However, all of the sequential models ignore the two-level hierarchy structure of the multi-turn dialogue generation task, which provides rich information during the encoding part.

In a hierarchical way, Serban et al. [22] first propose the hierarchical recurrent encoder-decoder architecture (HRED), they use an utterance level RNN to get the embedding of each history utterance, and use an inter-utterance level RNN to get the final embedding of the whole history by feeding the embedding of each history utterance as the inputs. Considering that treating all history turns indiscriminately is not proper as the response is only usually related to some certain previous history turns, Tian et al. [25] proposed a weighted sequence (WSeq) attention model for HRED, using the cosine similarity to measure the degree of the relevance between the utterance of the current turn and each of utterance of the previous

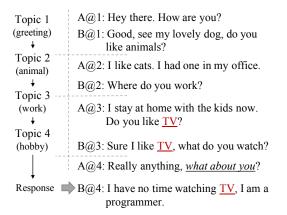


Figure 1: An example of dynamics in multi-turn dialogue.

history turns. Xing et al. [33] extend the HRED with the attention mechanism [1] to attend to important parts within and among utterances with word-level attention and utterance-level attention. Zhang et al. [34] propose a Transformer based model named Re-CoSa to HRED, they use history turns self-attention to strengthen the encoder and use history-response attention to extract and use the relevant history turns for response generation.

However, the aforementioned works solely concentrate on exploring new network structures for modeling dialogue history, expecting the dynamic flow can be captured by well-designed network structures implicitly.

3 MOTIVATION

Previous studies [12, 15] take their effort to construct multi-turn dialogue datasets, expecting that richer contextual information can facilitate selecting and generating the next utterance [36]. It is inspired by the behavior that human-generated responses are heavily dependent on the previous dialogue segments at different granularities (words, phrases, sentences, etc), both semantically and functionally, over multiple turns rather than one turn [10, 26]. As we can see in Figure 1, the post (A@4) is a general question 'what about you?', thus dialogue history, such as 'TV' entity plays an important role in generating the response. In a typical multi-turn dialogue, there are several kinds of dialogue flows in the history dialogue to sustain the conversation, 1) the task-oriented conversation has a clear purpose which required to fulfill specific steps in order, 2) speaker can change from information-provider to informationseeker in turns, for example asking follow-up questions (B@1), 3) speakers often have different views about a topic (A@3), and by exchanging different proposals, they persuade and influence the other. The above-described dialogue flows embed the dynamics inside, such as topic drifting in Figure 1, from general to specific, from public to private. Therefore, each utterance in history is predictable.

Recent works implicitly model the dynamics in history dialogue using the predefined network structures, such as recurrent neural network and transformer neural network. Recurrent neural network processes tokens step by step in history dialogue. Therefore, the output representation of the current token is a combination of previous token output representation and the current token input

representation. Similarly, the Transformer structure utilizes positional embeddings to keep the order of utterance in mind. These model structures proposed for the sequential data assume to capture the dynamics implicitly. Nevertheless, Sankar et al. [21] point out that neither the recurrent neural network nor the Transformer neural network in the Seq2Seq framework fully captures the dynamic flow in the dialogue history. In their study, authors make the perturbations to the dialogue history, but surprisingly find a marginal hurt to the generation performance. The increases to the perplexity of the generated response is too small, even though using drastic and unnatural modifications, including shuffling or reversing every utterance in the dialogue history. Such observations suggest that the well-known sequential model structures use far from all the information in the dialogue history that is available to them, not order information, let alone other complex dynamics.

Therefore, in this paper, we argue that the dynamics in history dialogue should be modeled explicitly. As we have seen in Figure 1, the order of utterances reflects the simplest dynamic flow structure, any change of the dialogue history (A@1 - A@4) will destroy the dynamic flow in this conversation. In order to force utterances in order, predicting the next utterance using previous utterances is a good way which can be treated as a ranking problem. The previous utterance can be treated as a query and the next utterance can be treated as the most relevant document to the given query, while the other utterances are not as relevant as it. Thus we propose a ranking enhanced dialogue generation approach, in order to utilize dialogue history effectively.

4 OUR APPROACHES

This section first introduces the architecture and major components involved in the proposed RED framework. As shown in Figure 2, the RED framework mainly consists of three components: utterance representation module, response generation module, and ranking enhanced module. The former two modules are derived from traditional dialogue generation models, while the additional ranking enhanced module is the core part in RED distinguishing to them.

Utterance representation module: Given the dialogue history $H = [h_1, h_2, \dots, h_M]$, where M is the number of history utterances. Each utterance is composited of words. We first get the word embedding for each word in all history utterances. For sequential models, the whole sequence of word embeddings are fed into an RNN encoder or a Transformer encoder according to the structure of different models. The encoder then outputs the representation for each word. We use the average of word representations for each history utterance as its representation. For hierarchical models, the word embeddings for each history utterance are first fed into an utterance level RNN encoder. The outputs of the utterance level RNN encoder are then fed into an inter-utterance level RNN encoder or Transformer encoder. We use the output of inter-utterance level encoder for each history utterance as its representation. The final representations of the dialogue history is denoted as $U = [u_1, u_2, ..., u_M]$.

Response generation module: A typical decoding module in the Seq2Seq framework. In the training, our goal is to maximize the response probability defined in Equation 1. It takes the history dialogue and previously generated response words as the conditions,

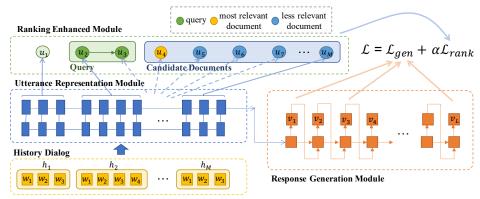


Figure 2: Overview architecture of RED model, RED with 2-order as an example.

then maximizes the probability of choosing the next right response word. In the testing, one common way is to generate response word by word, and greedy pick the word with the highest probability at each time step.

Ranking enhanced module: Directly constructed upon the utterance representation module, and shares the representations with the response generation module, as shown in the top of Figure 2. The goal of ranking enhanced module is to make sure that the next utterance can be predicted by the utterances before, thereby maintaining the dynamic structure of dialogue history. To achieve this goal, we introduce a ranking perspective in this module, then construct the query, the most relevant document and less relevant documents using history utterances (the circles with different colors in Figure 2). Therefore, the degree of learning dynamic flow can be evaluated by utilizing a list-wise ranking loss.

4.1 Ranking Enhanced Module

Assuming that simplest dynamic flow in dialogue history can be regarded as the chronological order between utterances, for the purpose of keeping all history utterances in order, we introduce a ranking perspective on the dialogue history. Recalling that the top-1 relevant document ranking task in information retrieval defines a standard ranking framework. Given a query q represents the user's information need and a set of n documents $D = \{d_1, d_2, \ldots, d_n\}$, where $d_r \in D$ represents the most relevant document. The goal of ranking is to maximize the probability $P(d_r|q)$. Specifically, in the case of multi-turn dialogue generation, former utterances can be treated as query q, and the consecutive utterance right after the query can be treated as the most relevant document, while the others are less or not relevant. Note that the query is constructed by multiple former utterances (Section 4.1.1) and the relevant document is exactly the next utterance (Section 4.1.2).

4.1.1 Query Construction. There are two approaches to construct the ranking query, i.e., local and global query construction. Within both ranking methods, a sequential structure LSTM is adopted to aggregate former utterances, in order to obtain a fixed-dimensional query representation. Despite the common structure, the scope of selecting former utterances is the main difference between the two ranking approaches.

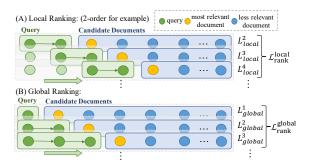


Figure 3: Two types of ranking enhanced module.

Query construction for local ranking It is often the case that locally consecutive utterances belong to the same topic, or have a gradual and smooth topic drifting to keep coherence. To meticulously capture such local dynamic flow, we design the local query for ranking. Consider the utterance u_i in a dialogue history, for constructing a k-order query in the local ranking method, the top k-1 former utterances closest to u_i and the u_i itself are used to construct the query. More precisely, the query representation q_i is defined as,

$$q_i = \text{LSTM}(u_{i-k+1}, \dots, u_i), i \in [k, M-1].$$
 (2)

where u_i is the representation of the i-th utterance in dialogue history, LSTM is a function generating the last hidden state of the LSTM encoder. As index i varies from k to M-1 in the history H, we can construct M-k queries in total. The M-k k-order queries can be obtained in a sliding window, where the window size is k. For example, as shown in Figure 3 (A), the first query is constructed from utterances $[u_1, u_2]$, exactly fulfill the first window with size 2. When the window slides one step to the right, a new query $[u_2, u_3]$ is generated. When the window slides to the end, we get the last query $[u_{M-2}, u_{M-1}]$.

Note that in this work, k is set to be 1, 2, 3, denote as 1-order query, 2-order query, and 3-order query, respectively. Note that when k = 1, only u_i itself is used to construct the 1-order query.

Query construction for global ranking To effectively utilize the previous dynamic flow till this history position and better modeling the global dynamic flow, different from using a fixed number of former utterances near the *i*-th utterance, the global ranking

method uses all former utterances before the i-th utterance and the i-th utterance itself to construct the query. We call this type of query as full-order query, the representations q_i of which is then constructed as follows:

$$q_i = \text{LSTM}(u_1, \dots, u_i), i \in [1, M - 1].$$
 (3)

Similar to the local ranking query, M-1 queries can be constructed by using the different length of history, as in Figure 3 (B).

4.1.2 Documents Construction. Given the dialogue history utterance representations $U = [u_1, u_2, \ldots, u_M]$, for the i-th query q_i , the utterance u_{i+1} is the most relevant document. Thus, the candidate document set contains all of the utterances after the i-th utterance, denoted as $U_{>i} = \{u_{i+1}, \ldots, u_M\}$. That is to say, each utterance in the candidate set can be seen as a unique document, and the query is used to rank the candidate documents according to their relevance with the query. The relevance here can be viewed as a certain type of manifestation for proper dynamic flow. Specifically, (q_i, u_{i+1}) is the most relevant pair, while $\{(q_i, u_j), j > i + 1\}$ are treated as less relevant or irrelevant pair.

4.1.3 Ranking. For the local ranking method, the utterances in a sliding window described in 4.1.1 are used for constructing the query, all of the utterances after those utterances are candidate documents. For the local ranking methods using the k-order query, we can construct M-k query-documents pairs. For the global ranking method, dialogue history can be simply divided into two consecutive parts, the former part is the query and the following part is the candidate documents, thus we construct M-1 query-document pairs.

Within each query-document pair, the Topk-ListMLE [31] is designed for correct ranking at the top-k positions in information retrieval. In our ranking task, given former utterances, we only need to rank the next utterance correctly at the top-1 position without taking the ranking position among utterances after the next utterance into account, because all of them are less relevant than the next utterance. Thus, we use Top1-ListMLE loss in the RED framework for our ranking task.

Specially, in our ranking case, for the i-th query-documents pair, its query is q_i , its candidate document set is $U_{>i} = \{u_{i+1}, \ldots, u_M\}$ and the ground-truth labels are $\{1,0,\ldots,0\}$. We firstly get the ranking score for each element u_t in the $U_{>i}$ by a ranking function f_r . The f_r function is implemented in the following steps. Firstly, we concatenate q_i with each element in the $U_{>i}$ and get a sequence of concatenated representations, $\{[q_i,u_{i+1}],[q_i,u_{i+2}],\ldots,[q_i,u_{M-i}]\}$, where $[\cdot,\cdot]$ represents the function that concatenates two vectors.

Secondly, for the utterance u_t in $U_{>i}$, we use a fully connected layer to get its final ranking score. This layer takes the concatenated representation $[q_i, u_t]$ as the inputs and then outputs a real-value score for the utterance u_t . $f_r(u_t)$ can be formalized as,

$$f_r(u_t) = W^r \cdot [q_i, u_t] + b^r, \tag{4}$$

where W^r and b^r are the parameters of the fully connected layer. After getting the ranking score for each utterance in the candidate documents, the Top1-ListMLE loss L^i is defined as,

$$L^{i}(U_{>i}; f_{r}) = -\log \frac{\exp(f_{r}(u_{i+1}))}{\sum_{t=i+1}^{M} \exp(f_{r}(u_{t}))}.$$
 (5)

For the ranking task, we design local ranking loss and global ranking loss for capturing the local and global dynamics implied in dialogue history turns. For the local ranking method, the local ranking loss for the i-th query-documents pair is denoted as L^i_{local} . For the global ranking method, the global ranking loss for the i-th query-documents pair is denoted as L^i_{qlobal} .

Given a single history-response pair, the RED model whose query is k-order query designed for capturing local dynamics, the local ranking loss $\mathcal{L}_{rank}^{local}$ is defined as,

$$\mathcal{L}_{rank}^{local} = \frac{1}{M-k} \sum_{i=k}^{M-1} L_{local}^{i}(U_{>i}; f_r), \tag{6}$$

and the RED model whose query is full_order query designed for capturing global dynamics, the global ranking loss $\mathcal{L}_{rank}^{global}$ is defined as,

$$\mathcal{L}_{rank}^{global} = \frac{1}{M-1} \sum_{i=1}^{M-1} L_{global}^{i}(U_{>i}, f_{r}). \tag{7}$$

4.2 Objective Function and Training

The RED framework appends ranking enhanced module to the original dialogue generation models, so the objective function contains two parts, including a traditional sequence generation loss, denotes as \mathcal{L}_{gen} and a newly proposed ranking loss, denotes as \mathcal{L}_{rank} . The overall loss function is a linear combination of these two losses:

$$\mathcal{L} = \mathcal{L}_{qen} + \alpha \mathcal{L}_{rank}, \tag{8}$$

where α is a hyper-parameter that control the ratio of two losses. Moreover, the generative loss \mathcal{L}_{gen} for response generation module is defined as,

$$\mathcal{L}_{gen} = -\log(\prod_{l=1}^{L} P(v_l|v_{< l}, H))$$
 (9)

where H is the given dialogue history and the target response is represented as $r = \{v_1, v_2, \ldots, v_L\}$. The ranking loss \mathcal{L}_{rank} can be set to either $\mathcal{L}_{rank}^{local}$ or $\mathcal{L}_{rank}^{global}$, to complete a local ranking task or a global ranking task, and can be seen as a regular type. We jointly train the response generation module and the ranking enhanced module by sum up the generation loss and the ranking loss with a parameter α , then we get the final loss function \mathcal{L} .

The training for generation is a type of supervised training, and the training for ranking is indeed a type of self-supervised learning. We train the RED models with joint training loss using batched Stochastic Gradient Descent (SGD) with Adam [9].

5 EXPERIMENTS

Experiments are conducted on three public multi-turn dialogue datasets, i.e., bAbI, PersonaChat and JDC, including task-oriented datasets and open domain datasets in multiple languages, e.g English and Chinese, in order to thoroughly evaluate our proposed RED framework. In this section, we first introduce experimental settings including dataset statistics, evaluation metrics and baselines description. Result evaluations, then, proposed in order to demonstrate the effectiveness and generalization of our RED framework. Furthermore, empirical analysis is conducted to show where and how the improvements come from.

Table 1: Descriptive statistics of datasets, including the number of dialogues in train/valid/test sets, the total number of history-response pairs, the average number of turns, the average number of words per turn and vocabulary size

Dataset	#Train	#Valid	#Test	#History-Response Pairs	#Avg. Turns	#Avg. Words	# Vocabulary
PersonaChat	8939	1000	968	162064	14.86	14.24	18745
JDC bAbI dialog	99944 1000	1549 1000	1565 1000	980023 110390	9.51 36.8	15.86 7.02	113503 1109

5.1 Experimental Settings

5.1.1 Datasets. We conduct experiments on three multi-turn dialogue datasets with different styles, they are the bAbI dialog [4], the PersonaChat [35] and the Chinese customer service dataset (JDC) [34] respectively. Each dataset is split into train/valid/test sets according to the previous works [21, 34]. Note that each multi-turn dialogue in the three datasets is processed to many history-response pairs with different history lengths. Table 1 provides descriptive statistics about the three datasets.

PersonaChat is an open domain dataset with multi-turn chitchat conversations between turkers who are each assigned a "persona" at random. It comprises 10.9k dialogs with an average of 14.86 turns per dialog.

JDC The Chinese customer service dataset, named JDC, consists of 103058 dialogues published by the JD multi-turn dialogue challenge. This dataset is a collection of multi-turn dialogues between customer and customer service in the JD E-commerce platform. The average turns per dialogue is 9.51.

bAbI Dialog is a synthetic goal-oriented multi-turn dialogue dataset consisting of 5 different tasks for restaurant booking with increasing levels of complexity. We consider Task 5 in our experiments since it is the hardest and is a union of all four tasks. The average turns per dialogue is 36.8.

5.1.2 Evaluations. We use both quantitative metrics and human judgments for evaluation in our experiments. Considering that BLEU [19] and other word-overlap metrics correlate poorly with human judgments of response quality [13], we use per-word perplexity (PPL) [2] and Distinct [11] as automatic metrics for quantitative comparisons. The traditional metric PPL describes how well our trained probabilistic model (denoted as p) predicts the expected ground-truth responses. Given an utterance $u = \{w_1, w_2, \ldots, w_n\}$, the PPL is defined as the exponentiation of the word entropy,

$$PPL(u) = \exp(H[p(u)]) = \exp(-\sum_{i=1}^{N} p(w_i) \log p(w_i)).$$

The smaller the PPL, the closer the generated probabilistic distribution is to the ground-truth distribution. The metric PPL has been widely used in NLP and multi-turn dialogue generation [5, 25, 33] to evaluate the quality of generated responses. We use Distinct to evaluate the degree of diversity of the generated responses by calculating the number of distinct unigrams and bigrams in the generated responses. The two numbers are scaled by the total number of generated tokens and then denoted as dist-1 and dist-2. The larger the distinct values indicates the more informative and diverse the generated responses.

What's more, we also conduct a human evaluation to evaluate the ability of the models to generate good responses. Given

200 randomly sampled dialogue history turns, we choose the standard Transformer and ReCoSa, and their corresponding ranking enhanced RED1 and REDfull models (which model local and global dynamics respectively) to generate responses for each of the 200 sampled cases. We then invite 3 CS annotators to judge the quality of responses generated by the 6 representative models. Each of them is required to give the comparison between our proposed ranking enhanced models and the baseline standard models, e.g., win, loss, and tie, based on the informativeness, fluency and relevance with history. For example, the "win" label means that the generated response of model A is more proper than model B. Notably, the order of the responses is shuffled randomly.

5.1.3 Baselines and Our Models. We compare 5 baseline models, Seq2Seq, Seq2Seq with attention (SeqAtt), Transformer, HRED and ReCoSa, with those models applied our RED framework.

For sequential models:

- Seq2Seq: The RNN based sequence to sequence model uses LSTM for both encoder and decoder.
- SeqAtt: The se2seq with attention. It introduces the attention mechanism to the RNN-based Seq2Seq model.
- **Transformer** [27]: The standard Transformer model which takes all of the history turns as a whole sequence of words.

The above three models are provided by the ParlAI [18] framework which is identical to the experiments in Sankar's empirical study [21]. The hyperparameters are exactly the same as which provided by their work for fair comparison on the bAbI and PersonaChat

For hierarchical models:

- HRED [22]: The basic hierarchical model which uses a twolevel hierarchical encoder to encode the history turns.
- ReCoSa [34]: The state of the art hierarchical model which uses Transformer as the inter-utterance level encoder.

We implement HRED and ReCoSa in the ParlAI framework by ourselves, to reuse the standard components and the common process provided by the framework.

REDx_y: The prefix 'RED' denotes our Ranking Enhanced Dialogue generative models, and the **x** in 1,2,or 3 denotes all of the ranking enhanced methods whose query are 1 order, 2 order or 3 order respectively. We set **x** to symbol 'full' to denote ranking method who use all the history utterances as a query. The **y** denotes the baseline models from Seq2Seq, SeqAtt, Transformer, HRED or ReCoSa. For example, RED2_Transformer denotes the Transformer model with 2 order local ranking enhanced module.

The query is constructed using a single LSTM layer with 64 hidden size, and followed a fully connected layer with the hidden size of 128 in all RED based models. The hyperparameter α set to be 0.01 in loss function \mathcal{L} . For the bAbI dialog and the PersonaChat

Table 2: Human evaluation on the PersonaChat dataset.

	Informativeness		Fluency		Relevance	
Models v.s. Transformer	Win/Tie/Loss	Kappa	Win/Tie/Loss	Kappa	Win/Tie/Loss	Kappa
- RED1_Transformer - REDfull_Transformer	50.13/44.73/5.14 51.30/39.51/10.19	0.493 0.482	23.02/56.31/20.67 35.62/44.06/20.32	0.578 0.569	25.47/54.04/20.49 35.32/59.48/5.20	0.589 0.510
Models v.s. ReCoSa	Win/Tie/Loss	Kappa	Win/Tie/Loss	Kappa	Win/Tie/Loss	Kappa
- RED1_ReCoSa - REDfull_ReCoSa	35.79/34.38/30.63 35.62/44.77/20.61	0.477 0.515	32.90/39.58/28.52 25.15/54.71/22.14	0.623 0.596	16.90/69.31/14.79 21.29/59.60/19.11	0.497 0.524

Table 3: Examples of responses generated by baselines and RED models on the PersonaChat dataset.

Multi-turn Dialogue History	Generated Responses		
A: Hi . Just chilling to john denver after my work out . How about you ? B: Hi , just studying for my college exam . Hows it going	Transformer: I am a cashier at the local department . RED1_Transformer: I like music . I love rap music . REDfull_Transformer: I love country music . I love country music .		
A: Good . What are you taking in college ? B: What kind of music do you like to listen to ? A: John Denver . How about you ?	ReCoSa: I am from georgia . I am in the navy . RED1_ReCoSa: I am a fan of 60s and 70s music . REDfull_ReCoSa: I like all kinds of music . I love all kinds of music .		
A: Scotch goes good with meat B: Scotch goes good with anything lol . A: I have a brother who likes scotch	Transformer: I have a brother , he is a detective . RED1_Transformer: I have a cat named after my daughter REDfull_Transformer: I have a cat named gizmo . He is a big cat .		
B: I am an only child . A: I have just the one brother and 3 sisters B: Do you have any pets ? I am scared of dogs .	ReCoSa: I do not have any pets, I have a dog and a dog RED1_ReCoSa: I do not have any pets REDfull_ReCoSa: I have a dog, I love dogs		

Table 4: Performance of queries of different order for five models on the PersonaChat dataset. The best score is bolded.

	Model	PPL	Dist-1	Dist-2
	Seq2Seq	43.04	0.0035	0.0081
Seq2Seqs	RED1_Seq2Seq	42.90	0.0042	0.0110
	RED2_Seq2Seq	43.01	0.0039	0.0099
	RED3_Seq2Seq	42.70	0.0040	0.0098
	REDfull_Seq2Seq	43.03	0.0034	0.0080
	SeqAtt	40.98	0.0111	0.0385
C A + + -	RED1_SeqAtt	40.81	0.0115	0.0411
SeqAtts	RED2_SeqAtt	40.92	0.0102	0.0362
	RED3_SeqAtt	40.56	0.0107	0.0400
	REDfull_SeqAtt	40.96	0.0097	0.0334
	Transformer	40.48	0.0138	0.0559
Transformers	RED1_Transformer	39.49	0.0103	0.0352
Transformers	RED2_Transformer	39.45	0.0104	0.0380
	RED3_Transformer	39.54	0.0106	0.0401
	REDfull_Transformer	39.46	0.0121	0.0426
	HRED	44.96	0.0040	0.0105
IMED	RED1_HRED	44.02	0.0044	0.0116
HREDs	RED2_HRED	44.01	0.0043	0.0123
	RED3_HRED	44.46	0.0036	0.0093
	REDfull_HRED	44.40	0.0033	0.0093
	ReCoSa	38.27	0.0066	0.0174
ReCoSas	RED1_ReCoSa	37.89	0.0072	0.0204
KeCoSas	RED2_ReCoSa	37.57	0.0095	0.0281
	RED3_ReCoSa	37.76	0.0091	0.0272
	REDfull_ReCoSa	38.07	0.0073	0.0202

Table 5: Performance of queries of different order for five models on the JDC dataset and the bAbI dialog dataset.

	,		U		
JDC Dataset					
	Models	PPL	Dist-1	Dist-2	
Seq2Seqs	Seq2Seq	12.72	0.0035	0.0101	
	REDfull_Seq2Seq	11.82	0.0037	0.0110	
SeqAtts	SeqAtt REDfull_SeqAtt	11.70 11.68	0.0086 0.0051	0.0311 0.0178	
Transformers	Transformer	10.40	0.0014	0.0027	
	REDfull_Transformer	10.28	0.0051	0.0140	
HREDs	HRED	10.90	0.0087	0.0376	
	REDfull_HRED	10.80	0.0091	0.0396	
ReCoSas	ReCoSa	10.44	0.0015	0.0029	
	REDfull_ReCoSa	9.43	0.0111	0.0465	
bAbI Dataset					
Models PPL Dist-1 Dist-2					
Seq2Seqs	Seq2Seq	1.21	0.0007	0.0015	
	REDfull_Seq2Seq	1.172	0.0007	0.0016	
SeqAtts	SeqAtt	1.032	0.0007	0.0020	
	REDfull_SeqAtt	1.025	0.0007	0.0020	
Transformers	Transformer	1.026	0.0007	0.0020	
	REDfull_Transformer	1.023	0.0007	0.0020	
HREDs	HRED REDfull_HRED	1.027 1.026	0.0007 0.0007	0.0020 0.0019	
ReCoSas	ReCoSa	1.024	0.0007	0.0019	
	REDfull_ReCoSa	1.019	0.0007	0.0020	

datasets, in Seq2Seq, SeqAtt and their RED versions, the encoder and decoder components are 2-layer LSTM with 128 hidden size. For Transformer, we use 300 dimensional embeddings and hidden size, 2 layers and 2 attention heads. For HRED and related ranking enhanced models, we use a 2-layer LSTM with hidden size 128 as its utterance level encoder and use another 2-layer LSTM with hidden size 128 for both inter-utterance level encoder and decoder. For Re-CoSa and related ranking enhanced models, we use a 2-layer LSTM with hidden size 300 as its utterance level encoder, the hidden size/layers/attention heads for both inter-utterance level Transformer encoder and Transformer decoder are 300/2/2 respectively. For the JDC dataset, except for the LSTM encoder for constructing queries representations and the following fully connected layer in RED framework, all of the models on JDC use 512-dimensional hidden units and 512-dimensional word embedding both for LSTMs and Transformers. Additionally, the LSTM components reduce to a single-layer LSTM and the layers and attention heads for Transformers are 6 and 8 respectively.

Adam [9] is utilized for optimization, and the learning rate is set to be 0.005 for Seq2Seq/SeqAtt/HRED and their related ranking enhanced models, 0.001 for Transformer/ReCoSa and their related ranking enhanced models. We use early stopping with a patience of 10 on the validation set to obtain the best models.

The source code and all of the experiments can be found in https://github.com/ying-A/RED

5.2 Experimental Results

Metric-based Evaluation We do comparative experiments on the three datasets to observe the differences of quantitative metrics between the baseline models and our ranking enhanced models. Specifically, we calculate PPL and distinct on the test datasets to compare the generative ability of different models fairly. Results are shown in Tables 4 and 5. On the three datasets, all RED models outperform baselines in PPL. For the bAbI dataset, the gaps in PPL are small, mainly because the task is relatively simpler compared with the other two datasets, even the basic Seq2Seq model can achieve a nearly perfect PPL close to 1. Thus the RED models also achieve almost the same distincts with baselines. For the JDC dataset and the PersonaChat dataset, our improvements on PPL are significant and the vast majority of RED models get higher distincts than baselines. Take the results on the PersonaChat dataset for example. For PPL, all of the RED models in the five groups achieve lower PPL than their related baseline models. It reveals that by additionally learning a task of ranking history utterances, the generated probabilities of the generative module can be closer to the ground-truth distribution in the probability distribution space. For distinct, we find that the highest distinct values are all got by our RED models except for models in Transformer groups. It shows that the RED models are better for generating diverse responses by explicitly modeling dynamics in history turns.

Moreover, RED3_Seq2Seq, RED3_SeqAtt, RED2_Transformer, RED2_HRED and RED2_ReCoSa achieve the lowest PPL in each of their related group, REDfull_Transformer and REDfull_HRED achieve the second-lowest PPL in each of their related group. It shows that both local ranking methods and global ranking methods are helpful for improving generative performance. We also find

what matters most for improving generative performance is the ability to model sequential order information for original baseline models. As the ability to model the sequential dynamic flow for original baseline models becomes weaker and weaker, the performance improvements (PPL decreases) brought by RED models become bigger and bigger. The largest PPL decreases for baselines Seq2Seq(0.34), SeqAtt(0.42), ReCoSa(0.7), HRED(0.95), Transformer(1.03) respectively. Take a deep look into the phenomenon, RNN structures are inherently capable to model sequential order. Seq2Seq and SeqAtt use fully RNN structures to model word order information. Hierarchical models HRED and ReCoSa also use an utterance level RNN to model word order information, however, the word order information is separately modeled in each individual utterance. While the Transformer only uses a weak positional embedding to keep order information, thus the improvements for Transformer are larger than other baselines.

Human Evaluation and Case Study For qualitative evaluation, we use human evaluation to compare responses generated by different models. The results are shown in Table 2. The percentage of win, loss and tie, as compared with the baselines in terms of informativeness/fluency/relevance, are given to evaluate the quality of generated responses by RED models. The results show that all of the RED models achieve better performances (#win – #loss) in the three aspects, which reveals that our RED models generate responses with higher quality than baselines. Kappa [7] values are presented to demonstrate the consistency of different annotators.

Table 3 presents two samples generated by RED models and baselines. For the first example, person A first answer that he likes the music by 'John Denver', and ask what B likes by an elliptical sentence 'how about you'. We can see that baselines Transformer and ReCoSa only care about the utterance 'how about you' without correctly understanding the logical relationship between it and its previous history utterances, and thus generate wrong answers. However, our RED models generate coherent answers concentrating on the current dialogue topic music. For the second example, the utterance of the last history turn is about pets and dogs. Transformer gives its reply by the word 'brother' that appeared twice in past history utterances, and ReCoSa generates two sentences with inconsistent logic. Our RED models generate informative responses about the pets. The two examples show that baselines ignore the dynamic logical information in history turns, while RED models give appropriate answers by learning the dynamic history structure.

5.3 Empirical Analysis

We conducted additional experiments to analyze the reasons that the RED framework outperforms the baselines. The analysis was conducted using the results on the PersonaChat dataset as examples. The similar phenomenon is also observed on the other two datasets.

5.3.1 Where does the improvement comes from. To identify where the improvement for RED models comes from, we split the dialogue history into three groups of similar size according to their lengths, including length less than 11, between 11 and 15, and longer than 15 utterances. The 968 multi-turn conversation instances in the PersonaChat dataset can be constructed into 6544 history-response pairs in total, in this way, three groups contain 1937/2431/2176

Table 6: PPL of queries of different order for Transformer
on PersonaChat split dataset with different history length.

Model	History Length	PPL	ΔPPL
	<11	35.82	
	11-15	40.37	-
Transformer	>15	45.78	
	all	40.48	
	<11	35.36	-0.46
	11-15	39.63	-0.74
RED1_Transformer	>15	43.83	-1.95
	all	39.49	-0.99
	<11	35.72	-0.10
_	11-15	39.47	-0.90
RED2_Transformer	>15	43.44	-2.34
	all	39.45	-1.03
	<11	35.67	-0.15
_	11-15	39.41	-0.96
RED3_Transformer	>15	43.88	-1.90
	all	39.54	-0.94
	<11	35.33	-0.49
	11-15	39.52	-0.85
REDfull_Transformer	>15	43.88	-1.90
	all	39.46	-1.02

instances respectively. The Transformer and its RED enhanced versions are evaluated on these new divided data partitions, and the results are shown in Table 6. For each model on each data partitions, we calculate their PPL and ΔPPL metrics, where ΔPPL is the difference between each RED model and original Transformer model under a specific history length. For example, ΔPPL in the 5-th row equals to PPL in the 5-th row minus PPL in the 1-st row. ΔPPL indicates the improvement of each RED model compares to the baseline under different history length data partitions.

As shown in Table 6, in each block, PPL increases along with the increasing of history length for all models, reflecting that generating the response with longer history utterance is more difficult than the shorter one. Longer dialogue history brings not only more informative signals, but also more complex dynamics, which makes it harder for response generation. As for the ΔPPL in each RED model, e.g., RED1_Transformer, the values decrease along with the increasing of history length, e.g., from -0.46, -0.74 to -1.95. The phenomenon reveals that the RED framework, regardless of query orders, is more helpful for the instance with longer dialogue history by modeling the order of the utterances explicitly. It makes RED able to capture the dynamic flow easier than the original Transformer, especially for longer dialogue history which is a tougher part in the multi-turn dialogue generation task.

5.3.2 How does the improvement comes from. The ranking loss for RED models is indeed a type of regularization, and it demands the models learn to rank by learning better utterance representations. Meanwhile, the enhanced representations can help generation module effectively use the dynamic information encoded in them and generate better responses. To study whether RED

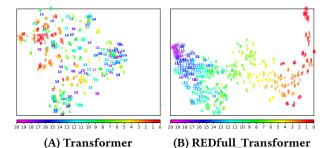


Figure 4: t-SNE embeddings of representations learned by the models for utterances from the PersonaChat test set. Embeddings are color coded by the position of the utterance in the dialogue history it appears.

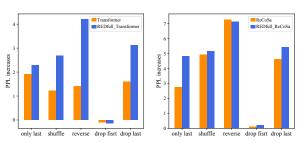


Figure 5: PPL increases for 4 models (Left: Transformer and REDfull_Transformer, Right: ReCoSa and REDfull_ReCoSa) when applying 5 kinds of perturbations.

representations encoded dynamics well, we analyze the learned utterance representations for RED models and baseline models.

Without loss of generality, we use the trained Transformer and REDfull_Transformer as our two comparison models, and analyze the representations of utterances on the PersonaChat test dataset. For each model, we random sample 1000 representations of utterances with different positional-indexes (1 to max history length) in the history. After that, an off-the-shelf technique - t-SNE [16] is used to reduce the representation dimensions for further visualization. Specifically, we reduce the representations to 2-dimensional vectors and draw them with positional-indexes in an x-y coordinate.

It is evident that in REDfull_Transformer, see Figure 4(B), the vectors with the same positional-index gather in a tight cluster. The clusters form a clear sense of hierarchy according to their positional orders, vividly showing a scene of dynamic flow. However, such structure information is not illustrated in Transformer as in Figure 4(A), where variant labeled vectors are scattered everywhere. It indicates that RED learned the high-level dynamic structures by encoding this information in the utterance representations, while traditional models do not have sufficient ability to do that.

What's more, we also do utterance perturbation experiments on the PersonaChat test set as implemented in Sankar's empirical study[21]. We first get the PPL for different models on the test set. Then we perturb the dialogue history and record the PPL on the perturbed test set. The PPL increases after perturbations for all of the models are calculated and shown in Figure 5. Results show that all of the REDfull models get larger PPL increases in most kinds of perturbations than origin models and thus more sensitive to

history utterance perturbations. It proves that the dynamic (order) information is more effectively used by RED models according to the premise in [21] that the more sensitive the model to perturbations, the stronger ability for it of modeling dynamics.

6 CONCLUSION

In this paper, we proposed a Ranking Enhanced Dialogue generation framework, namely RED, to explicitly capture the dynamics in the dialogue history. RED consists of the regular representation encoder module and response generation module, that have been used in the original dialogue generation models, and an additionally novel ranking enhanced module. In the ranking module, a learning-to-rank task is designed for ranking dialogue history, where the former utterance is treated as a query, and the consecutive utterances after the query are treated as the documents. RED is a general framework that can easily cooperate with most of the recent multiturn dialogue generation models. With the help of RED, we observe the improvement in terms of both quantitative metrics and human evaluations. Further empirical analysis demonstrates that the RED is especially good at tackling longer dialogue history, by encoding history dynamics into the utterance representations.

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