Towards Generalized and Explainable Long-Range Context Representation for Dialogue Systems

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Abstract
Long-range context modeling is crucial to both dialogue understanding and generation. The most popular method for dialogue context representation is to concatenate the last-$k$ previous utterances. However, this method may not be ideal for conversations containing long-range dependencies. In this work, we propose DialoGX, a novel encoder-decoder based framework for conversational response generation with a generalized and explainable context representation that can look beyond the last-$k$ utterances. Hence the method is adaptive to conversations with long-range dependencies. The main idea of our approach is to identify and utilize the most relevant historical utterances instead of the last-$k$ utterances in chronological order. We study the effectiveness of our proposed method on both dialogue generation (open-domain) and understanding (DST) tasks. DialoGX achieves comparable performance with the state-of-the-art models on DailyDialog dataset. We also observe performance gain in existing DST models with our proposed context representation strategy on MultiWOZ dataset. We justify our context representation through the lens of psycholinguistics and show that the relevance score of previous utterances agrees well with human cognition which makes DialoGX explainable as well.

1 Introduction
One of the key challenges in dialogue systems is modeling long-range context (Yan et al., 2022). Human conversations can be lengthy and may contain long-range dependencies among turns. While having a conversation, we often refer back to names, topics, or other information that was mentioned long before the current dialogue turn. For example, Table 1 shows an open-domain conversation from the DailyDialog (Li et al., 2017) dataset. We can observe that in Turn 11, “it” refers to the word “hats” which is mentioned only once in the first turn. Understanding such long-range dependencies is critical for long-range context modeling which can be beneficial for both dialogue generation and understanding.

The main challenge of dialogue context modeling comes from the fact that conversations can be arbitrarily long and complex in nature. To encode arbitrary long conversations, people started adapting hierarchical recurrent encoder framework that contains an utterance-level and a dialogue-level encoder (Sordoni et al., 2015a). However, this approach cannot fully leverage the benefits of the utterance-level features (discussed in Section 2.2). After the evolution of Transformers (Vaswani et al., 2017), the most popular approach of context modeling is to concatenate the history utterances and use a transformer decoder (or encoder-decoder) model to generate the response. As the sequence length of a transformer is limited, people generally use only the last-$k$ utterances according to memory limit. Despite its simplicity, this method has produced state-of-the-art results for almost all kinds of dialogue related tasks (Zhang et al., 2020; Heck et al., 2020; Kim et al., 2020a). Since the existing dialogue datasets have a scarcity of long-range dependencies among turns, looking only at last-$k$ turns is enough to generate a good aggregate level performance. Although this phenomenon of relying only on recent turns can be observed in short and simple real-world conversations, the same cannot be said for more complex scenarios.

Table 1: A sample conversation from DailyDialog
In this work we propose DialoGX, an open domain Dialogue system with Generalized and Explainable context representation. The primary objective of DialoGX is to enrich dialogue context modeling by addressing long-range dependencies such that arbitrarily long conversations can be handled in an easy and explainable way. The central idea of our approach is to find the relevant historical utterances along with a vector representation of the entire context that can guide the generation of a meaningful response. The main contributions of our work are as follows:

- We propose DialoGX, a novel dialogue generation framework that is capable of resolving long-range dependencies.

- The context representation method is able to handle arbitrary long conversations, and works even when the context for the current turn might have been presented much earlier in the conversation. The relevance scores over all the previous turns help to understand the long-range dependencies among dialogue turns which improves the generalization and explainability of the proposed approach.

- DialoGX achieves comparable performance with state-of-the-art models on DailyDialog dataset. Usage of relevant utterances in DST shows improvement in existing models.

- Detailed analysis of the proposed solution along with a psycholinguistic perspective.

2 Background and Related Works

The existing neural network approaches for context modeling can be broadly categorized into two classes: Concatenation-based Encoding, and Hierarchical Encoding.

2.1 Concatenation-based Encoding

In this approach, historical utterances are concatenated to represent the context. In pre-Transformer era, the concatenation-based encoding strategy was a go-to method to train an RNN based encoder-decoder (Sutskever et al., 2014; Cho et al., 2014; Bahdanau et al., 2015) for dialogue generation (Sordoni et al., 2015b). A major issue with this approach is that the concatenated utterances can be very long depending on the conversation. Moreover, modeling long-range dependencies with an RNN/LSTM is difficult. This is why people started switching to hierarchical encoders (Section 2.2) to handle long conversations. However, concatenation-based encoding again came to the forefront after the emergence of Transformer architecture (Vaswani et al., 2017). Most of the Transformer based dialogue models concatenate previous utterances and finetune the decoder on language modeling task (Wolf et al., 2019; Zhang et al., 2020; Bao et al., 2020; Li et al., 2021; Chen et al., 2022) to achieve state-of-the-art results on various dialogue datasets. Here one thing to be noted is that Transformers have a limit on maximum sequence length. This is why all these dialogue models can only take last-k previous utterances as input based on a pre-defined maximum sequence length. Hence, they are not able to look beyond last-k turns and thereby cannot capture very long-range dependencies among dialogue turns. There are variations of Transformer (like Big-Bird (Zaheer et al., 2020), Poolingformer (Zhang et al., 2021) etc.) that reduce computation complexity of self-attention operation from $O(n^2)$ to $O(n)$. This optimization enables the usage of longer sequence length. However, looking at more context does not necessarily solve the problem of long-range dependencies, as there might still exist dependencies beyond the concatenated context that could be passed according to the maximum allowed sequence length.

2.2 Hierarchical Encoding

In this strategy, encoding of arbitrary long conversations is achieved through a hierarchical encoder. Each utterance is first encoded using an utterance-level encoder. The encoded utterances are then fed to a dialogue-level encoder to get the final context representation. As discussed in Section 2.1, vanilla RNN-based encoder-decoder architecture cannot handle long conversations. To address this issue, researchers started adopting hierarchical recurrent encoders where two separate RNN/LSTM are employed as the utterance-level and dialogue-level encoders. Models like HRED (Sordoni et al., 2015a) and VHRED (Serban et al., 2017) fall under this category. There are few works that use BERT as an utterance-level encoder (Kim et al., 2020a). Li et al. (2019) proposed an Incremental Transformer for hierarchical recurrent encoding. DialogBERT (Gu et al., 2021) uses two separate BERT (Devlin et al., 2019) encoders to realize hierarchical encoding. Although DialogBERT can handle lengthy
conversations, theoretically the number of turns is limited by the maximum sequence length of BERT. The main advantage of hierarchical encoding is its ease of encoding long conversations. However, in human conversations, some words or information are often used directly from the context as it is. Since these methods are dependent only on the final context vector for response generation, it becomes difficult to re-generate those words/phrases with precision. On the contrary, the decoders of concatenation-based methods put attention on all the context tokens while generation. This is why most of the state-of-the-art results are reported using concatenation-based encoding even after not considering all the historical context. Models like HRAN (Xing et al., 2018) and ReCoSa (Zhang et al., 2019) try to address this issue by adding attention on utterance-level words/tokens. But doing so makes the dialogue generation dependent on context length which again brings back some of the limitations discussed in Section 2.1.

3 Methodology

In this section, we describe our proposed dialogue generation framework DialoGX. Let $D = \{u_1, u_2, u_3, \ldots\}$ be a multi-turn conversation where $u_i$ represents the utterance at turn $i$. The objective of dialogue generation is to generate $u_{t+1}$ given $D_{\leq t}$ i.e. $\{u_1, u_2, u_3, \ldots, u_t\}$. The main idea of our approach is to combine the advantages of both concatenation-based and hierarchical encodings and provide a generalized and explainable context representation for dialogue systems that is adaptive to long-range dependencies. The framework is based on an encoder-decoder architecture as shown in Fig. 1. The detailed description of the encoder and the decoder are as follows.

3.1 Encoder

DialoGX encoder is basically a hierarchical recurrent encoder with few added elements. At a given turn $t$, the encoder first predicts the encoding of the next response. This predicted encoding $(b'_{t+1})$ is then used to find a relevance score ($\alpha(t)$) for all the previous utterances. Finally, $\alpha(t)$ is used to compute a vector representation ($X_t$) of the entire context such that the prediction of ground-truth words/tokens is maximized.

Hierarchical Encoding: We use BERT (Devlin et al., 2019) and GRU (Gated Recurrent Unit) (Cho et al., 2014) as our utterance-level and dialogue-level encoders respectively. At each turn $t$, the utterance-level encoder ($f_\phi$) takes $u_t$ as input and outputs $b_t$. Here $f_\phi$ is defined as the mean of all the tokens of the second-to-last layer of the BERT model. The utterance-level encoding is then passed to the stacked GRU ($g_\psi$) with $l$ layers to generate the contextual representation $e_t$. The procedure of obtaining the contextual representation can be summarized as,

$$b_t = f_\phi(u_t) \in \mathbb{R}^d \quad (1)$$

$$e_t, h_t = g_\psi(b_t, h_{t-1}) \quad (2)$$

where $d$ is the dimension of BERT embedding, $e_t \in \mathbb{R}^d$ is the output of the GRU and $h_t \in \mathbb{R}^{l \times d}$ is the GRU hidden state. Initial hidden state $h_0$ is set to a zero matrix.

Next Utterance Prediction: After hierarchical encoding, we predict the encoding of the next utterance as $b'_{t+1} = \text{lin}_1(e_t)$ where $\text{lin}_1$ is a two layer feed-forward neural network with layer normalization (Ba et al., 2016). The key objective of DialoGX is to find the historical utterances that are relevant for generating the next utterance. Clearly, there is a requirement for computing a relevance score for all the previous utterances with respect to the next response. But to do so we need to know the ground-truth response which is not accessible during prediction time. For this reason, we approximate the next utterance using $b'_{t+1}$. Hence, we need $b'_{t+1}$ to be very close to utterance-level encoding of the next response i.e. $b_{t+1}$. To ensure that, we introduce a prediction loss ($\mathcal{L}_{\text{pred}}$) which is the distance between $b'_{t+1}$ and $b_{t+1}$. Since we are dealing with dialogue responses that have one-to-many nature, we choose L1 distance as it is robust to outliers.

Relevance Score and Context Vector: Next, we find the relevance scores for all the previous utterances using $b'_{t+1}$. Let $B = \{b_1, b_2, ..., b_t\} \in \mathbb{R}^{t \times d}$ be all the utterance-level encodings till turn $t$. Then we compute the relevance score as $\alpha(t) = \text{att}(B, b'_{t+1}) \in \mathbb{R}^t$ where $\text{att}$ is an additive attention function (Bahdanau et al., 2015). Finally, we compute a vector representation of the entire context till turn $t$ as $X_t = \sum_{i=1}^{t} \alpha_i b_i$. To learn a meaningful representation $X_t$, we introduce a Bag-of-Word (BoW) loss defined as,

$$p_t = \text{softmax}(\text{lin}_2(X_t)) \in \mathbb{R}^{|V|} \quad (3)$$

$$\mathcal{L}_{\text{bow}} = - \sum_{j=1}^{T} \log p_{t,j} \quad (4)$$
where $p_{t_j}$ is the probability of predicting the $j^{th}$ token in $u_{t+1}$, which is the next utterance in the ground-truth. $T$ is the total number of tokens in $u_{t+1}$, $lin_2$ is a feed-forward neural network, and $|V|$ is the vocabulary size of BERT tokens. Note that $L_{\text{bow}}$ helps to get a meaningful representation for $X_t$ by actually learning how to combine the previous contexts. Hence, the BoW loss plays an important role to learn the relevance score $\alpha^{(t)}$.

**Training Objective:** We train the encoder to jointly optimize $L_{\text{pred}}$ and $L_{\text{bow}}$. So, the final loss of the encoder ($L_{\text{enc}}$) is defined as,

$$L_{\text{enc}} = L_{\text{pred}} + L_{\text{bow}} \tag{5}$$

### 3.2 Decoder

The decoder of DialoGX is built on top of pretrained GPT-2 (Radford et al., 2018) with a language model head. For a given turn $t$, the decoder first takes $b_{t+1}^{(1)}, \alpha^{(t)}$, and $X_t$ as input from the encoder and selects the top-$k$ historical utterances using $\alpha^{(t)}$. Then a unified representation $Z_t$ is computed combining the past $(X_t)$ and predicted $(b_{t+1}^{(1)})$ contexts. Finally, $Z_t$ is concatenated with the encoding of top-$k$ relevant utterances and fed to GPT-2 to generate the reply.

**Construction of Decoder Context:** For a given turn $t$, we first combine $X_t$ and $b_{t+1}^{(1)}$ and compute the unified representation $Z_t$ as,

$$Z_t = lin_3([X_t; b_{t+1}^{(1)}]) \in \mathbb{R}^{d'} \tag{6}$$

where $lin_3$ is a feed-forward neural network with layer normalization, and $d'$ is the dimension of GPT-2 embedding. Similar to the encoder, we introduce a bag-of-word loss ($L_{\text{bow}}'$) for the decoder as well. Here, the tokens of $u_{t+1}$ is predicted conditioned on $Z_t$. We use the same method shown in Equations 3 and 4 to compute $L_{\text{bow}}'$ except we use $Z_t$ instead of $X_t$.

While giving a response during a conversation, we humans create an abstract/summary of the reply in our mind, based on what has been discussed so far and the way we want to respond to it. These two aspects are captured in $X_t$ and $b_{t+1}^{(1)}$ respectively. This abstract response, which can be considered to be represented by $Z_t$, guides the generation of the actual response. Hence, learning a meaningful representation of $Z_t$ is critical. The introduction of bag-of-word loss in the decoder serves this purpose.

To include the relevant utterances in the final context, we first choose the top-$k$ utterances based on the relevance scores $\alpha^{(t)}$. Let $R_t$ be the list of top-$k$ relevant utterances in chronological order. We tokenize each utterance in $R_t$ and concatenate them using a special token $[EOS]$ to get token-level encoding $Y_t \in \mathbb{R}^{m \times d'}$ where $m$ is the total number of tokens in $Y_t$. The final context is then represented as $C_t = [Z_t; Y_t] \in \mathbb{R}^{(m+1) \times d'}$. Representing the context in this manner enables to capture not only the entire context but also helps to focus on the important portions of the relevant utterances via self-attention while generating the response. We consider maximum $N$ tokens from each utterance in $R_t$. Hence, $m$ remains upper bounded by $kN$, where $k$ and $N$ can be set according to the requirement. On the contrary, existing concatenation-based encodings keep on adding previous utterances until the maximum token limit is exceeded. In other words, they use last-$k$ utterances as the context where $k$ may be different for different samples depending on the length of the individual utterances. Selection of the relevant past utterances in $R_t$ and ensuring none of them is left out while forming the context $C_t$ makes the proposed method generalized and explainable for long-range context representation.

**Training Objective:** The GPT-2 model takes...
$C_t$ as input and generates the next utterance. The language modeling loss ($\mathcal{L}_{LM}$) for generating $u_{t+1}$ given the context $C_t$ is defined as,

$$\mathcal{L}_{LM} = -\sum_{n=1}^{T} \log p(u_{t+1,n}|u_{t+1,<n}, C_t; \theta)$$  \hspace{1cm} (7)$$

where $T$ is the number of tokens in the generated response $u_{t+1}$, and $\theta$ denotes the parameters of the GPT-2 with language model head. We train the decoder to jointly optimize $\mathcal{L}_{bow}$ and $\mathcal{L}_{LM}$. The final loss of the decoder ($\mathcal{L}_{dec}$) is defined as follows,

$$\mathcal{L}_{dec} = \mathcal{L}_{LM} + \lambda \cdot \mathcal{L}_{bow}$$ \hspace{1cm} (8)$$

where $\lambda$ is a hyper-parameter to set the weightage of bag-of-word loss.

4 Experimental Setup

4.1 Dataset

We perform our experiments on DailyDialog (Li et al., 2017) and MultiWOZ 2.1 (Eric et al., 2020) for the generation and understanding task respectively. DailyDialog is a popular open-domain conversational dataset whereas MultiWOZ is one of the largest datasets for Dialogue State Tracking (DST). Both DailyDialog and MultiWOZ contain conversations with long-range dependencies where the next utterance often depends on multiple past utterances in the conversation, which may not be consecutive ones.

4.2 Implementation Details

In the encoder, we use a pre-trained bert-base-uncased model having embedding dimension $d = 768$ and a stacked GRU with 2 layers i.e. $l = 2$. Parameters of the BERT are not updated during training. For the decoder, we finetune pre-trained DialogPT (Zhang et al., 2020) instead of vanilla GPT-2. We specifically use DialoGPT-large with embedding size $d' = 1280$. In the decoder objective, the weight of the bag-of-word loss $\lambda$ is set to 0.5. We use dropout ratio of 0.2 and AdamW (Loshchilov and Hutter, 2019) optimizer with adam’s epsilon 1e-8. For the encoder, we use a learning rate of 5e-4 and maximum training epochs of 30 while the same values are set to 1e-5 and 10 respectively for the decoder. The encoder and decoder are trained separately as the end-end modeling is not straightforward due to the selection of relevant utterances.

The best model is selected based on minimum validation loss. For decoding, we use beam search with beam width 5, maximum sequence length 40, minimum sequence length 11, and 0.1 length penalty. The same decoding configuration is used to generate the results for the baseline models as well.

Since we are proposing to use top-$k$ relevant utterances, it may happen that the last turn may be excluded. Let’s say that we are at turn $t$, and trying to generate the next response for turn $(t+1)$. Then utterance $u_t$ may not be part of the top-$k$ relevant utterances. However, even if $u_t$ may not be important content-wise, it is important to maintain consistency and flow while generating the response. Moreover, note that we are fine-tuning DialoGPT which is trained using the concatenation of last-$k$ utterances as context. Hence, $u_t$ plays a key role in the generation in DialoGPT. This is why the exclusion of $u_t$ can break the consistency and result in the generation of inconsistent responses. To address this issue, we keep last-$m$ utterances as part of the context and pick top-$k$ from the remaining previous utterances where $k + m = c_{max}$. In this work, we use $c_{max} = 4$ i.e. we restrict ourselves to using up to 4 previous utterances to generate the next response. So, $m = 0$ is equivalent to using only top-$k$ relevant utterances whereas $m = c_{max}$ means only last-$m$ utterances are used as context. For simplicity, we call this model variation as DialoGX with context (top-$k$ + last-$m$). The main result is shown using $k = 2$ and $m = 2$.

4.3 Evaluation Metrics

For the generation task, we use five different metrics - BLEU (Papineni et al., 2002), NIST (Lin and Och, 2004), METEOR (Banerjee and Lavie, 2005), Diversity (Li et al., 2016), and Entropy (Zhang et al., 2018). In general, these metrics struggle to evaluate dialog responses because of the one-to-many nature of dialog (Liu et al., 2016; Yeh et al., 2021). As a result, dialog generation has to still rely on human evaluation. For the understanding task, we use Joint Goal Accuracy (Henderson et al., 2014; Wu et al., 2019) to evaluate DST.

4.4 Baseline Models

For DailyDialog, we use the large versions of DialoGPT (Zhang et al., 2020), DialoFlow (Li et al., 2021), and DialogVED (Chen et al., 2022) as baselines. Note that DialoGX becomes DialoGPT if we remove $Z_t$ and use only last-$k$ utterances as context. This is why we train DialoGPT with last 4 turns as
context in order to study the effect of architectural changes in DialoGX. However, no such changes are made in DialoFlow and DialogVED i.e. both these models use entire dialogue history as context (truncated by maximum sequence length). The results on MultiWOZ are shown using SOM-DST (Kim et al., 2020b) and Trippy (Heck et al., 2020). All the models are trained using the official codes publicly available.

5 Results

5.1 Dialogue Generation (DailyDialog)

Automated Evaluation: Table 2 shows the results of dialogue generation. We have the following observations from the main result (models 1-4). Firstly, DialoGX beats DialoGPT in all the metrics. This indicates that the add-on contexts ($Z_t$ and top-k relevant utterances) have successfully improved the performance of DialoGPT. Secondly, DialoGX performs better than DialoFlow on the BLEU and Diversity but falls short in NIST, METEOR, and Entropy. Thirdly, DialogVED outperforms all the models in BLEU, NIST, and METEOR. However, DialogVED performs worse than all the models in the Diversity and Entropy metric. The root cause of this behavior is the prediction of the next two future tokens while training DialoVED. This results in memorization of n-grams from training data, which hurts the diversity scores during the testing phase. Consequently, there is a boost in the performance of n-gram based metrics at the cost of lexical diversity. Later we show that DialogVED loses to DialoGX on human evaluation which restates the fact that automated metrics are not reliable for dialogue generation. Finally, note that DialoFlow and DialogVED use all the previous utterances as context. In contrast, DialoGX uses only limited context but still achieves comparable performance with both the models.

Human Evaluation: For human evaluation, we randomly picked 100 conversations from DailyDialog test data. For each conversation, we again randomly picked a turn $t$. We displayed the original conversation till turn $t$ and showed generated dialogue from two models (A and B) to the evaluator where A is always DialoGX. The evaluators were given four options as follows: a) A is better than B, b) B is better than A, c) Both are equally good, and d) Both are equally bad. We performed this experiment to compare DialoGX with all the other baselines on the same 100 conversations and context points. Hence, we had a total of 300 forms that were evaluated by 30 humans. Table 3 shows the result of human evaluation. We can observe that DialoGX has a clear edge on human evaluation in comparison to the other baselines.

| ID | Model | Context | Bleu-1 | Bleu-2 | Bleu-3 | Bleu-4 | Nist-2 | Nist-4 | Meteor | Div-1 | Div-2 | Entropy |
|----|-------|---------|--------|--------|--------|--------|--------|--------|--------|-------|-------|---------|
| 1  | DialoGPT | last-4  | 49.03  | 27.15  | 16.80  | 10.94  | 3.74   | 3.95   | 16.32  | 0.042 | 0.222 | 9.83    |
| 2  | DialoFlow | all     | 48.75  | 26.73  | 16.35  | 10.70  | 3.76   | 3.97   | 16.44  | 0.039 | 0.216 | 9.98    |
| 3  | DialogVED | all     | 50.50  | 28.95  | 18.38  | 12.29  | 3.94   | 4.18   | 16.90  | 0.037 | 0.204 | 9.82    |
| 4  | DialoGX (ours) | top-2 + last-2 | 49.13 | 27.25  | 16.88  | 11.07  | 3.76   | 3.98   | 16.40  | 0.043 | 0.223 | 9.88    |

Table 2: Dialogue generation result on DailyDialog dataset

| Comparison | %Win | %Lose | %Tie | %Bad |
|------------|------|-------|------|------|
| DialoGX vs DialoGPT | 35   | 31    | 27   | 7    |
| DialoGX vs DialoFlow | 36   | 31    | 27   | 6    |
| DialoGX vs DialogVED | 40   | 32    | 20   | 8    |

Table 3: Human Evaluation on DailyDialog
| ID | Model  | Context Strategy | Joint Acc. |
|----|--------|------------------|------------|
| 1  | Trippy | all              | 52.97%     |
| 2  | Trippy | last-4           | 51.91%     |
| 3  | Trippy | top-2 + last-2   | 52.67%     |
| 4  | SOM-DST| all              | 53.01%     |
| 5  | SOM-DST| last-4           | 52.39%     |
| 6  | SOM-DST| top-2 + last-2   | 52.82%     |

Table 4: Impact of relevant context on DST

point. In our case, the best performance is achieved using $k = 2$ and $m = 2$ which are used to report the main result of DialoGX as well as the human evaluation.

5.2 Dialogue Understanding (MultiWOZ)

We also study the effect of utilizing relevant utterances as context in existing DST models. To do so, we first train our DialoGX encoder on the MultiWOZ dataset. Next, we use the relevance score to compute the context as (top-2 and last-2) and feed it to existing DST models as dialogue history. We experiment with Trippy and SOM-DST which are BERT-based DST models having concatenation-based context encoding. We use the official code along with the default settings to train both the models and take the average of five runs to report the joint accuracies. Table 4 shows that (top-2+last-2) strategy performs better than last-4 for both the models. Moreover, the performance of (top-2+last-2) is close to the performance with all the previous utterances as dialogue history which correlates with the earlier observations from Table 2. Hence, the incorporation of relevant utterances help in dialogue understanding tasks as well.

6 Discussions

6.1 Nature of Context Representation

In this section, we discuss the nature of context representation in DialoGX. Due to the usage of hierarchical encoding on the encoder side, DialoGX can encode conversations of any length. However, as discussed, hierarchical encoding has its own limitations and because of that, it cannot beat the performance of concatenation-based methods. To mitigate this issue, we introduce the procedure of finding the previous utterances that are relevant for generating the next response. Our final context is represented as the concatenation of the context vector $Z_t$ and encoding of the relevant utterances ($Y_t$). This strategy of context representation has several advantages. Firstly, it is capable of handling arbitrary long conversations. Secondly, it looks only at the exclusive set of relevant turns at the decoding time which also resolves the long-range dependencies in an explainable way. Due to this property, it is adaptive to both short and long-range contexts. Hence, the context representation of DialoGX has better generalization than the earlier techniques. Thirdly, since we consider only a limited number of relevant turns, our representation limits the input sequence length (in number of tokens) for the decoder. Consequently, DialoGX can encode conversations of any length compactly while also keeping a check on the overall computational cost of the self-attention operations. With the growing popularity of dialogue systems, we can anticipate datasets with lengthy conversations and an abundance of long-range dependencies. DialoGX is already capable of handling such datasets due to its generalized context representation.

6.2 Explainability

In this section, we discuss the explainability of the context representation strategy of DialoGX. As discussed in Section 3, the final context of DialoGX is formed by concatenating the relevant utterances with the context vector $Z_t$. The top-$k$ relevant utterances can be interpreted as the extractive summary of the conversation whereas the context vector $Z_t$ can be viewed as the abstractive summary. In contrast, the concatenation-based strategies use a simple approximation of using only the last-$k$ turns as relevant context while hierarchical strategies only rely on the abstractive summary. Hence, DialoGX delivers a more meaningful context representation in comparison to earlier methods. In addition to that, the relevance scores provide insights into the selection of relevant utterances which makes the resolution of long-range dependencies explainable.

Let us now have a closer look at the actual predictions of DialoGX for a sample conversation. Table 5 shows the detailed prediction of DialoGX (top-2 + last-2) on a test instance of DailyDialog dataset. The conversation takes place between a customer (odd turns) and a hat seller (even turns). Firstly, we can observe that the model puts more weight on informative utterances. For example, while generating the response for Turn 10, maximum weight is assigned to turns 1, 3, 4, and 10 which essentially highlights the key dialogues till Turn 10. Moreover, since Turn 1 is considered as part of the decoder context, the word “hat” appeared in the generated response which makes it meaningful and consistent. Also, the predicted response expresses the same thing as the actual response given in Turn 11.
In this work, we analyze the usefulness and limitations of both concatenation-based and hierarchical context encodings for dialog context representation. To take advantage of both methods, we propose a novel conversation generation framework DialoGX with generalized and explainable context representation that is adaptive to long-range dependencies. We represent dialogue context as a combination of a context vector and relevant utterances. Performance of DialoGX is comparable with the state-of-the-models on DailyDialog dataset even with the usage of limited context. We also show performance gain in existing DST models with relevant dialogue history. We provide a detailed discussion on the nature of our proposed context representation strategy with a comprehensive example. We also justify the modeling of DialoGX from a psycholinguistic perspective.
perspective. In future work, we will explore the application of DialoGX on knowledge-grounded and other dialogue-related complex datasets.

8 Limitations

The limitations of this work are as follows-

• The end-end modeling of DialoGX is not straightforward. This is because of the relevant context selection step in the decoder. In this work, we have avoided this problem by training the encoder and decoder separately. However, end-end modeling will not be a problem if the annotations of relevant utterances to generate the next response are already available in the dataset.

• The experiments are performed with only two datasets. Studying the utility of our proposed context representation requires datasets with long-range context dependencies. Finding such datasets itself is challenging. This is why we restricted ourselves to DailyDialog (Li et al., 2017) and MultiWOZ (Budzianowski et al., 2018) where long-range dependencies can be easily observed.

• The improvements shown in Tables 2 and 4 are marginal. The primary objective of this work is to develop a context representation method that can not only handle arbitrary long conversations but also addresses long-range dependencies. We argued that our proposed solution contains both these properties which help us to achieve a generalized and explainable context representation. Even though DailyDialog and MultiWOZ contain long-range dependencies, the number of such conversation turns is very limited. Moreover, the average turn per conversation in both DailyDialog and MultiWOZ is around 8. This means that last-\textit{k} encoding will consider the entire context in most cases. This is why the improvements are marginal for both tasks.

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Appendix

A.1 Data Pre-processing

Data pre-processing for the DailyDialog dataset is minimal. All the dialogues are transformed into lower cased texts. While tokenizing the utterances for BERT/GPT-2, we consider a maximum of 64 tokens from each tokenized text i.e. tokenized texts having more than 64 tokens are truncated.
Turn | Utterance
-----|-----------------------
1 | oh , so many kinds of winter hats .
2 | what is your favorite color , miss ?
3 | red .
4 | here you are , it ’ s very attractive .
5 | may i try it on ?
6 | go ahead .
7 | is there a mirror around here ?
8 | right over here .
9 | does it suit me ?
10 | yes , you look very nice .
11 | how much is it ?

Table 6: A sample from DailyDialog multi-reference data.

### A.2 Multi-reference data for DailyDialog

To improve the quality of automatic evaluation for DailyDialog, Gupta et al. (2019) augmented the test set of DailyDialog with multiple references. To be more specific, four reference responses are augmented in addition to the original response in the test data. So, all five responses are used as references during the automatic evaluation.

### A.3 Post-processing of generated dialogues

The reference data of DailyDialog follows a specific format. Table 6 shows the formatting of the same example shown in Table 1. We can observe that apart from being lowercased, there are a few subtle formatting styles that the texts follow. For example, “,” is both preceded and succeeded by a space. Similarly, “.” is preceded by a space. Moreover, words like “it ’ s”, “do ’ nt” have particular formatting. Note that a space is added before ‘ which is not common. However, most of these issues are resolved by tokenizing the text using a word tokenizer followed by concatenating the tokenized text with spaces. In this work, we use the NLTK library for this purpose. However, this simple word tokenization trick is not sufficient to match the reference format completely. For example, the formatting of words like “it ’ s” and “do ’ nt” cannot be fully achieved using this trick. To address the issue, we manually found some frequently occurring mismatch patterns and applied a regex-based transformation to further approximate the reference format. These conversions are applied for all the generated conversations including the baselines. All the automated evaluation results are computed using the converted texts. Due to this reason, results of the baseline models on DailyDialog have a minor deviation from the results reported in the original papers. The post-processing script is shared with the code.

### A.4 Additional Dataset Details

The basic statistics of DailyDialog (Li et al., 2017) and MultiWOZ 2.1 (Eric et al., 2020) datasets are shown in Table 7.

### A.5 Additional Implementation Details

We implemented DialoGX using PyTorch and Huggingface (Wolf et al., 2020) libraries in Python 3.8. All the experiments are performed on a single device of Nvidia DGX server with 32GB of memory. The number of parameters in the encoder and the decoder is 33M and 840M respectively. Our current implementation of DialoGX is not parallelizable, so the batch size is fixed to 1. However, we use gradient accumulation and update the parameters after the training of every four conversations which makes the effective batch size around 28. The average training time of the encoder and decoder is 2.5 hours and 24 hours respectively. The loss values of the encoder and decoder are shown in Table 8 and Table 9 respectively.

### A.6 Analysis of Relevance Score on MultiWOZ dataset

In this section, we analyze the relevance score of the DialoGX encoder trained with the MultiWOZ dataset. Table 10 shows the predicted relevance score of the encoder on a test instance from the MultiWOZ dataset. Note that relevance scores predicted by this DialoGX encoder have been used to form the (top-2 + last-2) context of model 3.
| Turn | Speaker | Utterance | \( \alpha_1 \) | \( \alpha_2 \) | \( \alpha_3 \) | \( \alpha_4 \) | \( \alpha_5 \) | \( \alpha_6 \) | \( \alpha_7 \) | \( \alpha_8 \) | \( \alpha_9 \) | \( \alpha_{10} \) | \( \alpha_{11} \) | \( \alpha_{12} \) | \( \alpha_{13} \) | \( \alpha_{14} \) | \( \alpha_{15} \) | \( \alpha_{16} \) |
|------|---------|-----------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1    | User    | I need a train to stansted airport that leaves on Sunday. | 1.00 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 2    | System  | Did you have a time you would like to arrive or leave? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 3    | User    | I need to arrive by 14:30. | 0.65 | 0.21 | 0.14 | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 4    | System  | TR1665 will arrive at 14:38, would that work for you? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 5    | User    | That is perfect. I would like to make a booking for 6 people please. | 0.02 | 0.00 | 0.05 | 0.53 | 0.40 | - | - | - | - | - | - | - | - | - | - | - |
| 6    | System  | Booking was successful, the total fee is 48.48 GBP payable at the station. Your reference number is HF03UG02. Do you need assistance with anything else? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 7    | User    | I need to eat too. | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | - | - | - | - | - | - | - | - | - |
| 8    | System  | What type of restaurant and price range are you looking for? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 9    | User    | I'd like Catalan food. It needs to be in the centre and be expensive. | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.97 | - | - | - | - | - | - | - |
| 10   | System  | I'm sorry, there aren't any restaurants like that. Would you like something else? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 11   | User    | What about one that serves European food in the same side? | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.09 | 0.02 | 0.88 | - | - | - | - | - |
| 12   | System  | There are three European restaurants in the center of town. Would you like me to pick one? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 13   | User    | Yes please do and then make a reservation for 6 people at 10:15 on a Sunday. | 0.00 | 0.00 | 0.02 | 0.02 | 0.08 | 0.01 | 0.01 | 0.00 | 0.04 | 0.00 | 0.11 | 0.08 | 0.61 | - | - | - |
| 14   | System  | You have a table booked for Eraina and the reference number is T7255P985. Is there anything else I can do for you? is there anything else I can do for you? | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| 15   | User    | No, that's all. Thanks! | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.09 |
| 16   | System  | Have a great day | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |

Table 10: A comprehensive example from the MultiWOZ dataset showing the relevance score for each user turn. The underlined values indicate the turns that were considered to form the dialogue history using (top-2 + last-2) strategy.

(Trippy) and model 6 (SOM-DST) shown in Table 4. The sample conversation shown in Table 10 is basically task-oriented where a user converses with the system agent to book a train followed by a restaurant. In MultiWOZ, dialogue state predictions are made after each user turn. This is why we show the relevance scores only for the user turns. The score signifies the importance of the previous turns to generate the next system response.

Let us now analyze the relevance scores shown in Table 10. Firstly, we can observe that the relevance score of the current turn is significant for all the user turns. This shows that the model is capable to detect the importance of the last user turn which aligns with the conversations of the MultiWOZ dataset. Secondly, the model is able to understand the context switches. In Table 10, there are two context switches (Turns 7 and 15). In both cases, the model is able to put approx. 1 weightage on the current turn and nearly 0 on the rest of the turns.

Thirdly, in turn 11, we can observe that the user is referring to the word “centre” mentioned in turn 9. The model is able to capture this co-reference by putting the second highest (0.09) score on Turn 9. However, we reiterate that the relevance scores are not trained explicitly using annotated relevance scores. Due to this reason, it is better to consider the relevance score as a soft indicator of the importance of a given utterance towards generating the next response.

### A.7 Additional Details on Evaluation Metrics

We use five different metrics for the generation task - BLEU (Papineni et al., 2002), NIST (Lin and Och, 2004), METEOR (Banerjee and Lavie, 2005), Diversity (Li et al., 2016), and Entropy (Zhang et al., 2018). BLEU, NIST, and METEOR are word-overlapping based metrics that are standard automatic metrics for machine translation and other natural language generation tasks. On the other
hand, Diversity and Entropy give an idea about the lexical diversity of a generated text. For the evaluation of Dialogue State Tracking (DST), we use Joint Goal Accuracy. This is the primary metric for evaluating DST. Joint Goal Accuracy is computed as the fraction of turns where the predicted belief state exactly matches the ground-truth (Henderson et al., 2014; Wu et al., 2019).