GRAPHFLOW: Exploiting Conversation Flow with Graph Neural Networks for Conversational Machine Comprehension

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Abstract

Conversational machine reading comprehension (MRC) has proven significantly more challenging compared to traditional MRC since it requires better utilization of conversation history. However, most existing approaches do not effectively capture conversation history and thus have trouble handling questions involving coreference or ellipsis. We propose a novel graph neural network (GNN) based model, namely GRAPHFLOW, which captures conversational flow in the dialog. Specifically, we first propose a new approach to dynamically construct a question-aware context graph from passage text at each turn. We then present a novel flow mechanism to model the temporal dependencies in the sequence of context graphs. The proposed GRAPHFLOW model shows superior performance compared to existing state-of-the-art methods. For instance, GRAPHFLOW outperforms two recently proposed models on the CoQA benchmark dataset: FLOWQA by 2.3% and SDNet by 0.7% on F1 score, respectively. In addition, visualization experiments show that our proposed model can better mimic the human reasoning process for conversational MRC compared to existing models.

1 Introduction

Recent years have observed a surge of interest in conversational machine reading comprehension (MRC). Unlike the traditional setting of MRC that requires answering a single question given a passage (aka context), the conversational MRC task is to answer the current question in a conversation given a passage and the previous questions and answers. The goal of this task is to mimic real-world situations where humans seek information in a conversational manner.

Despite the success existing works have achieved on traditional MRC (e.g., SQuAD (Rajpurkar et al., 2016)), conversational MRC has proven significantly more challenging when the conversations are incorporated into the MRC task. It has been observed that in those human-to-human conversations (Reddy et al., 2018; Choi et al., 2018), the starting turns tend to focus on the beginning chunks of the passage and as the conversation progresses, the focus shifts to the later chunks. Moreover, the turn transitions are usually smooth, with the focus often remaining in the same chunk or moving to a neighboring chunk. Lastly, many questions refer back to the conversation history via either coreference or ellipsis. Therefore, one hopes to develop a model that can capture these shifts of focus during a conversation. We model conversation flow as a sequence of latent states in the dialog and learn important latent states associated with these shifts of focus.

To cope with the above challenges, many methods have been proposed to effectively utilize conversation history, including previous questions and/or previous answers. Most existing approaches, however, simply prepend the conversation history to the passage (Choi et al., 2018; Yatskar, 2018), and treat the task as a single-turn MRC while ignoring the important information from the conversation flow. (Huang et al., 2018) assumed that the hidden representations generated during the previous reasoning processes potentially capture important information for answering the previous questions, and thus provide additional clues for answering the current question. They proposed an Integration-Flow (IF) mechanism to first process sequentially in passage, in parallel of question turns and then process sequentially in question turns, in parallel of passage words. Their
FLOWQA model achieves strong empirical results on two benchmarks (i.e., CoQA and QuAC) (Reddy et al., 2018; Choi et al., 2018).

However, the IF mechanism is not quite natural since it does not mimic how humans perform reasoning. This is because when humans execute such a task, they typically do not first perform reasoning in parallel for each question, and then refine the reasoning results across different turns. This may partially explain why this strategy is inefficient because the results of previous reasoning processes are not incorporated into the current reasoning process. As a result, the reasoning performance at each turn is only slightly improved by the hidden states of the previous reasoning process, even though they use stacked IF layers to try to address this problem.

To address the aforementioned issues, we propose GRAPHFLOW, a Graph Neural Network (GNN) based model for conversational MRC. As shown in Fig. 1, GRAPHFLOW consists of three components, Encoding layer, Reasoning layer, and Prediction layer. The Encoding layer encodes conversation history and the context text that aligns question embeddings. The Reasoning layer dynamically constructs a question-aware context graph at each turn, and then applies GNNs to process the sequence of context graphs. In particular, the graph node embedding outputs of the reasoning process at the previous turn are used as a starting state when reasoning at the current turn.

2 Graph-Flow Approach

2.1 Encoding Layer

The task of conversational MRC is to answer a question given the context and conversation history. We denote the context as $C$ which consists of a sequence of words $\{c_1, c_2, \ldots, c_m\}$ and the question at the $i$-th turn as $Q_i$ which consists of a sequence of words $\{q_1^{(i)}, q_2^{(i)}, \ldots, q_n^{(i)}\}$. The details of encoding the question and context are given next.

Pretrained word embeddings We use 300-dim GloVe (Pennington et al., 2014) embeddings as well as 1024-dim BERT (Devlin et al., 2018) embeddings to embed each word in the context and the question. Following (Zhu et al., 2018), we pre-compute BERT embeddings for each word using a weighted sum of BERT layer outputs.

Aligned question embeddings Following (Lee et al., 2016) and recent work, for each context word $c_j$ at the $i$-th turn, we incorporate an aligned question embedding $f_{\text{align}}(c_j^{(i)}) = \sum_k a_{j,k}^{(i)} g_k^Q$, where $g_k^Q$ is the GloVe embedding of question word $q_k^{(i)}$ and $a_{j,k}^{(i)}$ is an attention score between context word $c_j$ and question word $q_k^{(i)}$. Here we define the attention score $a_{j,k}^{(i)}$ as,

$$a_{j,k}^{(i)} \propto \exp(\text{ReLU}(W g_j^C)^T \text{ReLU}(W g_k^Q))$$

where $W \in \mathbb{R}^{d \times 300}$ is a trainable model parameter, $d$ is the hidden state size, and $g_j^C$ is the GloVe embedding of context word $c_j$. To simplify notation, we denote the above attention mechanism as $\text{Align}(A, B, C)$, meaning that an attention matrix is computed between two sets of vectors $A$ and $B$, which is later used to get a linear combination of vector set $C$. Hence we can reformulate the above alignment as $f_{\text{align}}(C^{(i)}) = \text{Align}(g_j^{C^{(i)}}, g_k^{Q^{(i)}}, g_k^{Q^{(i)}})$.

Manual features For each context word, we also encode manual features to a vector $f_{\text{man}}(c_j^{(i)})$ concatenating 12-dim POS (part-of-speech) embed-
dicing, 8-dim NER (named entity recognition) embedding and a 3-dim exact matching vector indicating whether the context word appears in $Q_i$.  

**Conversation history** Following (Choi et al., 2018), we utilize conversation history by concatenating a feature vector $f_{ans}(c_j)$ encoding previous $N$ answer locations to the context word embeddings. In addition, we also prepend previous $N$ answer embeddings. In addition, we also prepend previous $N$ question-answer pairs to the current question. When prepending conversation history, previous methods usually separate the current question from conversation history using some special tokens, which is not a good strategy in practice as observed by (Choi et al., 2018). We instead concatenate a 3-dim relative turn marker embedding $f_{turn}(q_k^{(i)})$ to each word vector in the augmented question to indicate which turn it belongs to (e.g., $i$ indicates the previous $i$-th turn). We find this strategy works better in practice.

In summary, at the $i$-th turn in a conversation, each context word $c_j$ is encoded by a vector $w_{c_j}^{(i)}$ which is a concatenation of $g_j^{C}$, BERT$_j^C$, $f_{align}(c_j^{(i)})$, $f_{man}(c_j^{(i)})$ and $f_{ans}(c_j^{(i)})$. And each question word $q_k^{(i)}$ is encoded by a vector $w_k^{Q_i}$ which is a concatenation of $g_k^{Q_i}$, BERT$_k^{Q_i}$ and $f_{turn}(q_k^{(i)})$. We denote $W_{C}^{(i)}$ and $W_{Q}$ as a sequence of context word vectors $w_{c_j}^{(i)}$ and question word vectors $w_k^{Q_i}$, respectively at the $i$-th turn.

### 2.2 Reasoning Layer

#### 2.2.1 Question Understanding

For each question $Q_i$, we apply a BiLSTM (Hochreiter and Schmidhuber, 1997) to the raw question embeddings $W_{Q}^{(i)}$ to obtain contextualized embeddings $Q_i \in \mathbb{R}^{d \times n}$.

$$Q_i = q_1^{(i)}, \ldots, q_n^{(i)} = \text{BiLSTM}(W_{Q}^{(i)})$$  \hspace{1cm} (2)

Each question is then represented as a weighted sum of word vectors in the question via a simple self attention mechanism.

$$\hat{q}^{(i)} = \sum_k a_k^{(i)} q_k^{(i)}, \text{ where } a_k^{(i)} \propto \exp(w^T q_k^{(i)})$$ \hspace{1cm} (3)

where $w$ is a $d$-dim trainable weight.

Finally, we encode question history sequentially in question turns with a LSTM to generate history-aware question vectors.

$$p_1, \ldots, p_T = \text{LSTM}((\hat{q}^{(1)}, \ldots, \hat{q}^{(T)}))$$ \hspace{1cm} (4)

The output hidden states of the LSTM network $p_1, \ldots, p_T$ will be used for predicting answers.

#### 2.2.2 Graph Learner

We dynamically build a weighted graph to model semantic relationships among context words at each turn in a conversation. We claim that the process of building such a context graph is supposed to depend on not only the semantic meanings of context words, but also on the question being asked, as well as the conversation history, so as to help better answer the question.

To this end, we first apply an attention mechanism to the context representations $W_{C}^{(i)}$ (which additionally incorporate both question information and conversation history as described in Section 2.1) at the $i$-th turn to compute an attention matrix $A_{C}^{(i)}$, serving as a weighted adjacency matrix for the context graph, defined as,

$$A_{C}^{(i)} = \text{ReLU}(UW_{C}^{(i)})^T \text{ReLU}(UW_{C}^{(i)})$$ \hspace{1cm} (5)

where $U$ is a $d \times d_c$ trainable weight and $d_c$ is the embedding size of $w_{c_j}^{(i)}$. 

![Figure 1: Overall architecture of the proposed model. Best viewed in color.](image-url)
Considering that a fully connected context graph is not only computationally expensive but also makes little sense for reasoning, we then proceed to extract a sparse graph from $A_C^{(i)}$ via a KNN-style strategy where we only keep the $K$ nearest neighbors (including itself) for each context node and apply a softmax function to these selected adjacency matrix elements to get a sparse and normalized adjacency matrix $\tilde{A}_C^{(i)}$.

$$\tilde{A}_C^{(i)} = \text{softmax}(\text{topk}(A_C^{(i)})) \quad (6)$$

### 2.2.3 Graph-Flow

Given the context graphs constructed by the Graph Learner, we propose a novel Graph-Flow (GF) mechanism to sequentially process a sequence of context graphs. Readers can think that it is analogous to an RNN-style structure where the main difference is that each element in a sequence is not equivalent to an RNN-style structure where the main mechanism as $C^{(i)}_l = \text{Graph-Flow}(C^{(i)}_{l-1}, \tilde{A}_C)$ which takes as input the old graph node embeddings $C^{(i)}_{l-1}$ and the normalized adjacency matrix $\tilde{A}_C$, and updates the graph node embeddings.

### 2.2.4 Multi-level Graph Reasoning

While a GNN is responsible for modeling the global interactions among context words, modeling local interactions among consecutive context words is also important for the task. Therefore, before feeding the context word representations to a GNN, we first apply a BiLSTM to the context words, that is, $C^{(i)}_l = \text{BiLSTM}(W_C^{(i)})$, and then use the output $C^{(i)}_l$ as the initial context node embedding. Inspired by recent work (Wang et al., 2018) on modeling the context with different levels of granularity, we choose to apply one GF layer on low level representations of the context and another GF layer on high level representations of the context, as formulated in the following.

$$\begin{align*}
C^1 &= \text{Graph-Flow}(C^0, \tilde{A}_C) \\
H^C_1 &= [C^1; g^C; \text{BERT}^C] \\
H^Q_1 &= [Q_0; g^Q; \text{BERT}^Q] \\
\alpha^2_{align}(C^{(i)}) &= \text{Align}(H^C_1, H^Q_1, Q_0) \\
C^1_i &= \text{BiLSTM}(C^1_{i-1}, \alpha^2_{align}(C^{(i)})) \\
C^2 &= \text{Graph-Flow}(C^1, \tilde{A}_C)
\end{align*} \quad (9)$$

### 2.3 Prediction Layer

Following (Huang et al., 2018; Zhu et al., 2018), we predict answer spans by computing the start and end probabilities $P^S_{ij}$ and $P^E_{ij}$ of the $j$-th context word for the $i$-th question, formulated as,

$$\begin{align*}
P^S_{ij} &\propto \exp(c_{ij}^2 \cdot T \cdot W_S p_i) \\
p^E_{ij} &\propto \exp(c_{ij}^2 \cdot T \cdot W_E \tilde{p}_i)
\end{align*} \quad (10)$$

where $W_S$ and $W_E$ are $d \times d$ trainable weights and GRU is a Gated Recurrent Unit (Cho et al., 2014).

We additionally train a classifier to handle unan-
swerable questions or questions whose answers are not text spans in the context. We design different classifiers for the two benchmarks CoQA and QuAC as CoQA contains questions with abstractive answers but QuAC does not. For the CoQA benchmark, we train a multi-class classifier which classifies a question into one of the four categories including “unknown”, “yes”, “no” and “other”. We do text span prediction only if the question type is “other”. For the QuAC benchmark, we train three separate classifiers to handle three question classification tasks including a binary classification task (i.e., “unknown”) and two multi-class classification tasks (i.e., “yes/no” and “followup”). The classifier is defined as, 

\[ \text{L}_{\text{CoQA}}^C = - \sum_i t_i^C \log P_i^C + (1 - t_i^C) \log (1 - P_i^C) \]

where \( t_i^C \) indicate the ground-truth labels of the “unknown”, “yes/no” and “followup” prediction tasks for \( i \)-th question, and \( P_i^Y \) and \( P_i^F \) are the corresponding probability predictions.

Thus, the training losses for CoQA and QuAC are \( L_S + L_{\text{CoQA}}^C \) and \( L_S + L_{\text{QuAC}}^C \), respectively.

### 2.3.2 Prediction

During inference, for CoQA, we do text span prediction only if span probability is the largest; otherwise, the answer is “unknown”, “yes” or “no” depending on which one has the largest probability. For QuAC, we do text span prediction only if \( P_i^C \) is no larger than a certain threshold; otherwise, the question is unanswerable.

### 3 Experiments

In this section, we conduct an extensive evaluation of our proposed model against state-of-the-art conversational MRC models. We use two popular benchmarks, described below. The implementation of the model will be publicly available soon.

### 3.1 Data and Metrics

**CoQA** CoQA contains 127k questions with answers, obtained from 8k conversations. In CoQA, answers are in free-form and hence are not necessarily text spans from the context (i.e., 33.2% of the questions have abstractive answers). Although this calls for a generation approach, following previous work (Yatskar, 2018; Huang et al., 2018; Zhu et al., 2018), as detailed in Section 2.3, we adopt an extractive approach with additional question type classifiers to handle non-extractive questions. The average length of questions is only 5.5 words (i.e., 70% questions have coherence or ellipsis), which means conversation history is important for better understanding those questions. The average number of turns per dialog is 15.2. Notably, in the testing set, there are two out-of-domain datasets which are reserved for testing only.

**QuAC** QuAC contains 98k questions with answers, obtained from 13k conversations. Unlike
Table 1: Model and human performance (% in F1 score) on the CoQA test set.

| Model          | Child. | Liter. | Mid-High. | News | Wiki | Reddit | Science | Overall |
|----------------|--------|--------|-----------|------|------|--------|---------|---------|
| PGNet          | 49.0   | 43.3   | 47.5      | 47.5 | 45.1 | 38.6   | 38.1    | 44.1    |
| DrQA           | 46.7   | 53.9   | 54.1      | 57.8 | 59.4 | 45.0   | 51.0    | 52.6    |
| DrQA+PGNet     | 64.2   | 63.7   | 67.1      | 68.3 | 71.4 | 57.8   | 63.1    | 65.1    |
| BiDAF++        | 66.5   | 65.7   | 70.2      | 71.6 | 72.6 | 60.8   | 67.1    | 67.8    |
| FLOWQA         | 73.7   | 71.6   | 76.8      | 79.0 | 80.2 | 67.8   | 76.1    | 75.0    |
| SDNet          | 75.4   | 73.9   | 77.1      | 80.3 | 83.1 | 69.8   | 76.8    | 76.6    |
| GRAPHFLOW      | 77.1   | 75.6   | 77.5      | 79.1 | 82.5 | 70.8   | 78.4    | 77.3    |
| Human          | 90.2   | 88.4   | 89.8      | 88.6 | 89.9 | 86.7   | 88.1    | 88.8    |

Table 2: Model and human performance (in %) on the QuAC test set.

| Model          | F1   | HEQ-Q | HEQ-D |
|----------------|------|-------|-------|
| BiDAF++        | 60.1 | 54.8  | 4.0   |
| FLOWQA         | 64.1 | 59.6  | 5.8   |
| GRAPHFLOW      | 64.9 | 60.3  | 5.1   |
| Human          | 80.8 | 100   | 100   |

CoQA, all the answers in QuAC are text spans from the context. The average length of questions is 6.5 and there are on average 7.2 questions per dialog. The average length of QuAC context is 401 which is longer than that of CoQA which is 271. The average length of QuAC answers is 14.6 which is also longer than that of CoQA which is 2.7.

The main evaluation metric is F1 score which is the harmonic mean of precision and recall at word level between the predicted answer and ground truth. In addition, for QuAC the Human Equivalence Score (HEQ) is used to judge whether a system performs as well as an average human. HEQ-Q and HEQ-D are model accuracies at question level and dialog level, respectively. Please refer to (Reddy et al., 2018; Choi et al., 2018) for details of these metrics.

### 3.2 Model Settings

We keep and fix the GloVe vectors for those words that appear more than 5 times in the training set. The size of all hidden layers is set to 300. When constructing context graphs, the neighborhood size is set to 10. The number of GNN hops is set to 5 for CoQA and 3 for QuAC. During training, we apply dropout after the embedding layers (0.3 for GloVe and 0.4 for BERT). A dropout rate of 0.3 is also applied after the output of all RNN layers. We use Adamax (Kingma and Ba, 2014) as the optimizer and the learning rate is set to 0.001. We reduce the learning rate by a factor of 0.5 if the validation F1 score has stopped improving every one epoch. We stop the training when no improvement is seen for 10 consecutive epochs. We clip the gradient at length 10. We batch over dialogs and the batch size is set to 1. When augmenting the current turn with conversation history, we only consider the previous two turns. When doing text span prediction, the span is constrained to have a maximum length of 12 for CoQA and 35 for QuAC. All these hyper-parameters are tuned on the development set.

### 3.3 Model Comparison

**Baseline methods** We compare our approach with the following baseline methods: PGNet (See et al., 2017), DrQA (Chen et al., 2017), DrQA+PGNet (Reddy et al., 2018), BiDAF++ (Yatskar, 2018), FLOWQA (Huang et al., 2018) and SDNet (Zhu et al., 2018). We will discuss the details of these methods in Section 4.1.

**Results** As shown in Table 1 and Table 2, our model consistently outperforms these state-of-the-art baselines in terms of F1 score. In particular, GRAPH-FLOW yields improvement over all existing models on both datasets by at least +0.7% F1 on CoQA and +0.8% F1 on QuAC, respectively. Compared with FLOWQA which is also based on the flow idea, our model improves F1 by 2.3% on CoQA and 0.8% on QuAC, which demonstrates the superiority of our Graph-Flow mechanism over the Integration-Flow mechanism. Compared with SDNet which relies on sophisticated inter-attention and self-attention mechanisms, our model improves F1 by 0.7% on CoQA.²
Q1: Who went to the farm? -> Q2: Why?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner, Billy’s mom was also very happy.

Figure 2: The highlighted part of the context indicates the QA model’s focus shifts between consecutive question turns.

|                  | F1  |
|------------------|-----|
| GraphFlow (2-His)| 78.3|
| - PreQues        | 78.2|
| - PreAns         | 77.7|
| - PreAnsLoc      | 76.6|
| - BERT           | 70.2|
| - GF             | 68.8|
| - TempConn       | 69.9|
| GraphFlow (1-His)| 78.2|
| GraphFlow (0-His)| 76.7|

Table 3: Ablation study: model performance (in %) on the CoQA dev. set.

### 3.4 Ablation Study

We conduct an extensive ablation study to further investigate the performance impact of different components in our model. Here we briefly describe ablated systems: TempConn removes temporal connections between consecutive context graphs, GF removes the GF layer, PreQues does not prepend previous questions to the current turn, PreAns does not prepend previous answers to the current turn, PreAnsLoc does not mark previous answer locations in the context, and BERT removes pretrained BERT embeddings. We also show the model performance with no conversation history GraphFlow (0-His) or one previous turn of the conversation history GraphFlow (1-His).

Table 3 shows the contributions of the above components on the CoQA development set. We find that the pretrained BERT embedding has the most impact on the performance, which again demonstrates the power of large-scale pretrained language models. Our proposed GF mechanism also contributes significantly to the model performance (i.e., improves F1 score by 1.4%). In addition, within the GF layer, both the GNN part (i.e., 1.1% F1) and the temporal connection part (i.e., 0.3% F1) contribute to the results. We also notice that explicitly adding conversation history to the current turn helps the model performance by comparing GraphFlow (2-His), GraphFlow (1-His) and GraphFlow (0-His). We can see that the previous answer information is more crucial than the previous question information. And among many ways to use the previous answer information, directly marking previous answer locations seems to be the most effective. We conjecture this is partially because the turn transitions in a conversation are usually smooth and marking the previous answer locations helps the model better identify relevant context chunks for the current question.

### 3.5 Interpretability Analysis

Here we visualize the memory bank (i.e., an \( m \) by \( d \) matrix) which stores the hidden representations (and thus reasoning output) of the context throughout a conversation. While directly visualizing the hidden representations is difficult, thanks to the flow-based mechanism introduced into our model, we instead visualize the changes of hidden representations of context words between consecutive turns. We expect that the most changing parts of the context should be those which are relevant to the questions being asked and therefore should probably be able to indicate shifts of the focus in a conversation.

Following (Huang et al., 2018), we visualize this by computing the cosine similarity of the hidden representations of the same context words at consecutive turns, and then highlight the

\[ \text{They did not report the results on QuAC.} \]
words that have small cosine similarity scores (i.e., change more significantly)\(^3\). Fig. 2 highlights the most changing context words between consecutive turns in a conversation from the CoQA dev. set. As we can see, the hidden representations of context words which are relevant to the consecutive questions are changing most and thus highlighted most. We suspect this is in part because when the focus shifts, the model finds out the context chunks relevant to the previous turn become less important but those relevant to the current turn become more important. Therefore, the memory updates in these regions are the most active. Obviously, this makes the model easier to answer follow-up questions. As we observe in our visualization experiments, in conversations extensively involving coreference or ellipsis, our model can still perform reasonably well. We refer the interested readers to the supplementary material for complete visualization examples.

4 Related Work

4.1 Conversational MRC

Many methods have been proposed to utilize conversation history in the literature of conversational MRC. (Reddy et al., 2018; Zhu et al., 2018) concatenate previous questions and answers to the current question. (Choi et al., 2018) concatenate a feature vector encoding the turn number to the question word embedding and a feature vector encoding previous N answer locations to the context embeddings. However, as claimed by (Huang et al., 2018), these methods ignore previous reasoning processes performed by the model when reasoning at the current turn. Instead, they propose the idea of Integration-Flow to allow rich information in the reasoning process to flow through a conversation.

Another challenge of this task is how to handle abstractive answers. (Reddy et al., 2018) propose a hybrid method DrQA+PGNet, which augments a traditional extractive RC model with a text generator. (Yatskar, 2018) propose to first make a Yes/No decision, and output an answer span only if Yes/No was not selected.

4.2 Graph Neural Networks

Over the past few years, graph neural networks (GNNs) (Kipf and Welling, 2016; Gilmer et al., 2017; Hamilton et al., 2017; Li et al., 2015; Xu et al., 2018a) have drawn increasing attention since they extend traditional Deep Learning approaches to non-euclidean data such as graph-structured data. Recently, GNNs have been applied to various question answering tasks including visual question answering (VQA) (Teney et al., 2017; Norcliffe-Brown et al., 2018), knowledge base question answering (KBQA) (Sun et al., 2018) and MRC (De Cao et al., 2018; Song et al., 2018; Xu et al., 2018c), and have shown advantages over traditional approaches. For tasks where the graph structure is unknown, (De Cao et al., 2018; Song et al., 2018; Xu et al., 2018b) construct a static graph where entity mentions in a passage are nodes of this graph and edge information is determined by coreferences of entity mentions. (Norcliffe-Brown et al., 2018) dynamically construct a graph which contains all the visual objects appearing in an image. In parallel to our work, (Liu et al., 2018) also dynamically construct a graph of all words from free text.

5 Conclusion

We proposed a novel GNNs-based model, namely GRAPHFLOW, for conversational MRC which carries over the reasoning output throughout a conversation. On two recently released conversational MRC benchmarks, our proposed model achieves superior results over previous approaches. Interpretability analysis shows that the model can better mimic the human reasoning process for conversational MRC compared to existing models.

In the future, we would like to investigate more effective ways of automatically learning graph structures from free text and modeling temporal connections between sequential graphs.

\(^3\)For better visualization, we apply an attention threshold of 0.3 to highlight only the dramatically changing context words.
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A Supplemental Material

A.1 Visualization of the Flow Operation

More visualization examples on detecting the most changing parts in the context. (Starts on next page.)
Q1: Who went to the farm? -> Q2: Why?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q2: Why? -> Q3: For what?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q3: For what? -> Q4: How many cows did he see there?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q4: How many cows did he see there? -> Q5: Did they have spots?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q5: Did they have spots? -> Q6: What color?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.
Q6: What color? -> Q7: What were they doing?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q7: What were they doing? -> Q8: Where?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q8: Where? -> Q9: How did the spots look to him?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.

Q9: How did the spots look to him? -> Q10: Did he move closer?

Billy went to the farm to buy some beef for his brother’s birthday. When he arrived there he saw that all six of the cows were sad and had brown spots. The cows were all eating their breakfast in a big grassy meadow. He thought that the spots looked very strange so he went closer to the cows to get a better look. When he got closer he also saw that there were five white chickens sitting on the fence. The fence was painted blue and had some dirty black spots on it. Billy wondered where the dirty spots had come. Soon he got close to the chickens and they got scared. All five chickens flew away and went to eat some food. After Billy got a good look at the cows he went to the farmer to buy some beef. The farmer gave him four pounds of beef for ten dollars. Billy thought that it was a good deal so he went home and cooked his brother dinner. His brother was very happy with the dinner. Billy’s mom was also very happy.