Knowledge Aware Conversation Generation with Reasoning on Augmented Graph

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Abstract

Two types of knowledge, factoid knowledge from graphs and non-factoid knowledge from unstructured documents, have been studied for knowledge aware open-domain conversation generation, in which edge information in graphs can help generalization of knowledge selectors, and text sentences can provide rich information for response generation. Fusion of knowledge triples and sentences might yield mutually reinforcing advantages for conversation generation, but there is less study on that. To address this challenge, we propose a knowledge aware chatting machine with three components, augmented knowledge graph containing both factoid and non-factoid knowledge, knowledge selector, and response generator. For knowledge selection on the graph, we formulate it as a problem of multi-hop graph reasoning that is more flexible in comparison with previous one-hop knowledge selection models. To fully leverage long text information that differentiates our graph from others, we improve a state-of-the-art reasoning algorithm with machine reading comprehension technology. We demonstrate that supported by such unified knowledge and knowledge selection method, our system can generate more appropriate and informative responses than baselines.

1 Introduction

One of the key goals of AI is to build a machine that can talk with humans when given an initial topic. To achieve this goal, the machine should be able to understand language with background knowledge, recall knowledge from memory or external resource, reason about these concepts together, and finally output appropriate and informative responses. Lots of research efforts have been devoted to chitchat oriented conversation generation (Ritter et al., 2011; Shang et al., 2015). However, these models tend to produce generic responses or incoherent responses for a given topic, since it is quite challenging to learn semantic interactions merely from dialogue data (Ghazvininejad et al., 2018; Zhou et al., 2018) without help of background knowledge.

Recently, some previous studies have been conducted to introduce external knowledge in open-domain chitchat generation (Ghazvininejad et al., 2018; Liu et al., 2018; Vougiouklis et al., 2016; Young et al., 2018; Zhou et al., 2018). These models usually recall background knowledge from a source, either unstructured non-factoid knowledge base (Ghazvininejad et al., 2018; Vougiouklis et al., 2016) or structured factoid knowledge base (Liu et al., 2018; Young et al., 2018; Zhou et al., 2018), and then generate more informative responses conditioned on selected knowledge.

For factoid knowledge, e.g., facts about movies, triple attributes or graph edges provide high-quality candidates for knowledge selection decision, and these prior information can enhance generalization capability of knowledge selection models. But it suffers from information insufficiency for response generation since there is simply a single word or entity to facilitate generation. For non-factoid knowledge, e.g., comments about movies, the text sentences can provide rich information for generation, but its unstructured (e.g., document based) representation scheme demands strong capability for models to perform knowledge selection or attention from the list of knowledge texts. Fusion of knowledge triples (or graph based representation scheme) and text sentences might yield mutually reinforcing advantages for knowledge selection in conversation systems, but there is less study on that.

To bridge the gap between the two lines of studies on knowledge aware conversation generation, we present an augmented knowledge graph
based open-domain chatting machine (denoted as AKGCM), which consists of knowledge selector and response generator.

To construct augmented knowledge graph, we take a factoid knowledge graph (KG) as its backbone, and align unstructured sentences of non-factoid knowledge with the factoid KG by linking entities from these sentences to vertices (containing entities) of the KG. Thus we augment the factoid KG with non-factoid knowledge, and retain its structured representation. Then we use this augmented KG to facilitate knowledge selection and response generation, as shown in Figure 1.

Being operated on the graph, the knowledge selector first retrieves a vertex that matches an input message as a starting point, then learns to traverse the graph with multi-hop paths that may reflect conversation logic, and finally stops at an answer vertex with correct knowledge. Our graph differs from previous KGs in that: some vertices in ours contain long texts, not a single entity or word. To fully leverage this long text information, we improve a state of the art graph reasoning algorithm (Das et al., 2018) with machine reading comprehension (MRC) technology (Seo et al., 2017). For knowledge selection, to fully leverage long texts in vertices that differentiate our graph from others, we improve a state of the art graph reasoning algorithm (Das et al., 2018) with machine reading comprehension (MRC) technology (Seo et al., 2017).

2 Related Work

Conversation with Knowledge Graph There are growing interests in leveraging factoid knowledge (Han et al., 2015; Liu et al., 2018; Zhu et al., 2017) or commonsense knowledge (Young et al., 2018; Zhou et al., 2018) with graph based representation for generation of appropriate and informative responses. Compared with them, we augment previous KG with non-factoid knowledge and introduce multi-hop graph reasoning in conversational models. Wu et al. (2018) ever used document reasoning network for modeling of conversational contexts, but not for knowledge selection. Moreover, previous models cannot effectively utilize long texts from graph vertices since they simply use an embedding for representation of the whole vertex, without further text analysis.

Conversation with Unstructured Texts With availability of a large amount of knowledge texts from Wikipedia or user generated content websites, e.g., Reddit, some work focus on either modeling of conversation generation with unstructured texts (Ghazvininejad et al., 2018; Vougiouklis et al., 2016; Xu et al., 2017), or building benchmark dialogue data grounded on knowledge (Dinan et al., 2019; Moghe et al., 2018). In comparison with them, we adopt a graph based representation scheme for unstructured texts, which helps improve generalization of knowledge selection, as shown in our experiments.

Knowledge Graph Reasoning Previous studies on KG reasoning can be categorized into path-based models (Das et al., 2017a; Lao et al., 2011), embedding-based models (Bordes et al., 2013; Wang et al., 2014), and models in unifying embedding and path-based technology (Das et al., 2018; Lin et al., 2018; Xiong et al., 2017), which can predict missing links or entities for completion of KG. Our problem setting is different from and conducts more flexible multi-hop graph reasoning for knowledge selection. Supported by such knowledge and knowledge selection method, our system can respond more appropriately and informatively.

- For knowledge selection, to fully leverage long texts in vertices that differentiate our graph from others, we improve a state of the art graph reasoning algorithm (Das et al., 2018) with machine reading comprehension (MRC) technology (Seo et al., 2017).
their in that some vertices of our graph contain long texts, not limited to a single entity or word. It motivates us to improve previous reasoning models with machine reading technology to effectively leverage long text information.

**POMDP for Dialogue Modeling** POMDP based models have been extensively studied for policy learning, responsible for system action selection, in task oriented multi-turn conversational systems with pipelined architecture (Young et al., 2013). In this work, a POMDP based reasoning model is used for knowledge selection in a single turn, not for modeling of multi-turn dialogue. Moreover, our system is for open-domain chitchat, not task oriented dialogue.

**Fusion of KG triples and sentences** In the context of QA, combination of a KG and a text corpus has been studied with a strategy of late fusion (Gardner and Krishnamurthy, 2017; Ryu et al., 2014) or early fusion (Das et al., 2017b; Sun et al., 2018), which can help address the issue of low coverage to answers in KG based models. In this work, we conduct this fusion for conversation generation, not QA, and our model can select text span as answers, not restricted to entities as done in those QA models.

# 3 The Proposed Model

## 3.1 Problem Definition and Model Overview

Our problem is formulated as follows: Let $G = \{V, E, L^G\}$ denote an augmented KG, where $V$ is a set of vertices, $E$ is a set of edges, and $L^G$ is a set of edge labels (e.g., triple attributes, or vertex categories). Given an input message $X = \{x_1, x_2, \ldots, x_m\}$ and $G$, the goal is to generate a proper response $Y = \{y_1, y_2, \ldots, y_n\}$. Essentially, the system consists of two stages: (1) knowledge selection: we select the vertex that maximizes following probability as an answer, which is from vertices being connected to $v_X$:

$$v_Y = \arg \max_v P_{KS}(v|v_X, G, X).$$

(1)

$v_X$ is one of vertices retrieved from $G$ using the entity or words in $X$, and it is ranked as top-1 based on text similarity with $X$. Please see Equation 8 and 10 for computation of $P_{KS}(*)$; (2) response generation: it estimates the probability:

$$P_{RG}(Y|X, v_Y) = \prod_{t=1}^{n} P(y_t|y_{<t}, X, v_Y).$$

(2)

The overview of our augmented knowledge graph based chatting machine (AKGCM) is shown in Figure 2. The knowledge selector first takes as input a message $X = \{x_1, x_2, \ldots, x_m\}$ and retrieves a starting vertex $v_X$ from $G$ that is closely related to $X$, and then performs multi-hop graph reasoning on $G$ and finally arrives at a vertex $v_Y$ that has the knowledge being appropriate for response generation. The knowledge aware response generator produces a response $Y = \{y_1, y_2, \ldots, y_n\}$ with knowledge from $v_Y$. At each decoding position, it attentively reads the selected knowledge text, and then generates a word in the vocabulary or copies a span in the knowledge text.

For model training, each pair of [message, response] in training data is associated with ground-truth knowledge and its vertex ID (ground-truth vertex) in $G$ for knowledge grounding. These vertex IDs will be used as ground-truth for training of knowledge selector, while the pairs of [message, knowledge text, response] will be used for training of response generator.

## 3.2 Augmented Knowledge Graph

Given a factoid KG and related documents containing non-factoid knowledge, we take the KG as a backbone, where each vertex contains a single entity or word, and each edge represents an attribute or a relation. Then we segment the documents into sentences and align each sentence with entries of the factoid KG by mapping entities from these sentences to entity vertices of the KG. Thus we augment the factoid KG with non-factoid knowledge, and retain its structured representation.
the environment, and policy network.

3.3 Knowledge Selection on Graph

Task Definition We formulate knowledge selection on \( G \) as a finite horizon sequential decision making problem. It supports more flexible multi-hop walking on graphs, not limited to one-hop walking as done in previous conversation models (Han et al., 2015; Zhou et al., 2018; Zhu et al., 2017).

As shown in Figure 3, we begin by representing the environment as a deterministic partially observed Markov decision process (POMDP) on \( G \) built in Section 3.2. Our reinforcement learning (RL) based agent is given an input query of the form \((v_X, X)\). Starting from vertex \( v_X \) corresponding to \( X \) in \( G \), the agent follows a path in the graph, and stops at a vertex that it predicts as the answer \( v_y \). Using a training set of known answer vertices for message-response pairs, we train the agent using policy gradients (Williams, 1992) with control variates.

The difference between the setting of our problem and previous KG reasoning lies in that: (1) the content of our input queries is not limited to entities and attributes; (2) some vertices in our graph contain long texts, while vertices in previous KGs just contain a single entity or short text. It motivates us to make a few improvements on previous models, as shown in Equation (5), (6), and (7).

Next we elaborate the 5-tuple \((S, O, A, \delta, \mathcal{R})\) of the environment, and policy network.

States A state \( S_t \in S \) at time step \( t \) is represented by \( S_t = (v_t, v_X, X, v_{gt}) \) and the state space consists of all valid combinations in \( \mathcal{V} \times \mathcal{V} \times \mathcal{V} \), where \( v_t \) is current location of the RL agent, \( v_{gt} \) is the ground-truth vertex, and \( \mathcal{X} \) is the set of all possible \( X \).

Observations The complete state of the environment cannot be observed. Intuitively, the agent knows its current location \((v_t)\) and \((v_X, X)\), but not the ground-truth one \((v_{gt})\), which remains hidden. Formally, the observation function \( O : \mathcal{S} \times \mathcal{V} = \mathcal{X} \) is defined as \( O(S_t) = (v_t, v_X, X, v_{gt}) = (v_t, v_X, X) \).

Actions The set of possible actions \( A_{S_t} \) from a state \( S_t \) consists of all outgoing edges of the vertex \( v_t \) in \( G \). Formally \( A_{S_t} = \{(v_t, l_e, v_d) \in \mathcal{E} : S_t = (v_t, v_X, X, v_{gt}), l_e \in \mathcal{L}_e, v_d \in \mathcal{V}\} \cup \{(S_t, \emptyset, S_t)\} \).

It means an agent at each state has option to select which outgoing edge it wishes to take with the label of the edge \( l_e \) and destination vertex \( v_d \).

We limit the length of the action sequence (horizon length) up to a fixed number \((e.g., T)\) of time steps. Moreover, we augment each vertex with a special action called NO,OP which goes from a vertex to itself. This decision allows the agent to remain at a vertex for any number of time steps. It is especially helpful when the agent has managed to reach a correct vertex at a time step \( t < T \) and can continue to stay at the vertex for the rest of the time steps.

Transition The environment evolves deterministically by just updating the state to the new vertex according to the edge selected by the agent. Formally, the transition function \( \delta : S \times A \times S \) is defined by \( \delta(S_t, A) = (v_d, v_X, X, v_{gt}) \), where \( S_t = (v_t, v_X, X, v_{gt}) \) and \( A = (v_t, l_e, v_d) \). \( l_e \) is the label of an edge connecting \( v_t \) and \( v_d \), and \( v_d \) is destination vertex.

Rewards After \( T \) time steps, if the current vertex is the ground-truth one, then the agent receives a reward of \(+1\) otherwise \(0\). Formally, \( \mathcal{R}(S_T) = I\{v_T = v_{gt}\} \), where \( S_T = (v_t, v_X, X, v_{gt}) \) is the final state.

Policy Network We design a randomized non-stationary policy \( \pi = (d_0, d_1, \ldots, d_{T-1}) \), where \( d_t = P(A_{S_t}) \) is a policy at time step \( t \). In this work, for each \( d_t \), we employ a policy network with three components to make the decision of choosing an action from all available actions \( A_{S_t} \) conditioned on \( X \).

The first component is a history dependent feedforward network (FFN) based model proposed in (Das et al., 2018). We first employs a LSTM to encode the history \( H_t = (H_{t-1}, A_t, O_t) \) as a continuous vector \( h_t \in \mathbb{R}^{2d} \), where \( H_t \) is the sequence.
of observations and actions taken. It is defined by:

$$h_t = LSTM(h_{t-1}, [a_{t1}; o_t]),$$  \hspace{1cm} (3)$$

where \(a_{t1}\) is the embedding of the relation corresponding to the label of the edge the agent chose at time \(t1\) and \(o_t\) is the embedding of the vertex corresponding to the agent’s state at time \(t\).

Recall that each possible action represents an outgoing edge with information of the edge relation label \(l_e\) and destination vertex \(v_d\). So let \([l_e; v_d]\) denote an embedding for each action \(A \in \mathcal{A}_t\), and we obtain the matrix \(\mathbf{A}_t\) by stacking embeddings for all the outgoing edges. Then we build a two-layer feed-forward network with ReLU non-linearity which takes in the current history representation \(h_t\) and the representation of \(X (e_X^{new})\). We use another single-layer feed-forward network for computation of \(e_X^{new}\), which accepts the original sentence embedding (e.g., BERT based embedding) of \(X (e_X)\) as input. The updated FFN model for action decision is defined by:

$$P_{FFN}(\mathcal{A}_t) = A_t(W_2ReLU(W_1[h_t; o_t; e_X^{new}] + b_1) + b_2),$$  \hspace{1cm} (4)$$

$$e_X^{new} = ReLU(W_X e_X + b_X).$$ \hspace{1cm} (5)$$

Recall that in our graph, some vertices contain long texts, differentiating our graph from others in previous work. The original reasoning model (Das et al., 2018), MINERVA, cannot effectively exploit the long text information within vertices since it just learns embedding representation for the whole vertex, without detailed analysis of text in vertices. To fully leverage the long text information in vertices, we employ two models, a machine reading comprehension model (MRC) (Seo et al., 2017) and a bilinear model, to score each possible \(v_d\) from both global and local view.

For scoring from global view, (1) we build a document by collecting sentences from all possible \(v_d\), (2) we employ the MRC model to predict an answer span \((span_{aw})\) from the document, (3) we score each \(v_d\) by calculating a BLEU-1 score of \(v_d\)'s sentence with \(span_{aw}\) as the reference, shown as follows:

$$P_{MRC}(\mathcal{A}_{S_t}) = BLEU(Text(V_d), span_{aw}).$$ \hspace{1cm} (6)$$

Here, \(Text(\cdot)\) represents operation of getting text contents, and \(BLEU(\cdot)\) represents operation of calculating BLEU-1 score. We see that the MRC model can help to determine which \(v_d\) is the best based on global information from the whole document.

For scoring from local view, we use another bilinear model to calculate similarity between \(X\) and \(v_d\), shown as follows:

$$P_{Bi}(\mathcal{A}_{S_t}) = V_d W_B e_X.$$

Finally, we calculate a sum of outputs of the three above-mentioned models and outputs a probability distribution over the possible actions from which a discrete action is sampled, defined by:

$$P(\mathcal{A}_{S_t}) = \text{softmax}(\alpha P_{FFN}(\mathcal{A}_{S_t}) + \beta P_{Bi}(\mathcal{A}_{S_t}) + (1 - \alpha - \beta)P_{MRC}(\mathcal{A}_{S_t})), \hspace{1cm} (8)$$

$$A_t \sim \text{Sample}(P(\mathcal{A}_{S_t})), \hspace{1cm} (9)$$

$$P_{KS}(v_d|v_X, \mathcal{G}, X) = P(\mathcal{A}_{S_{T-1}}). \hspace{1cm} (10)$$

Please see Section 3.1 for definition of \(P_{KS}(\cdot)\). When the agent finally arrives at \(S_T\), we obtain \(v_T\) as the answer \(v_Y\) for response generation.

**Training** For the policy network \((\pi_\theta)\) described above, we want to find parameters \(\theta\) that maximize the expected reward:

$$J(\theta) = \mathbb{E}_{(v_0, X, v_{gt}) \sim D}[\mathbb{E}_{A_0, \ldots, A_{T1} \sim \pi_\theta} [R(S_T)|S_0 = (v_0, v_0, X, v_{gt})]], \hspace{1cm} (11)$$

where we assume there is a true underlying distribution \(D\), and \((v_0, X, v_{gt}) \sim D\).

### 3.4 Knowledge Aware Generation

Following the work of Moghe et al. (2018), we modify a text summarization model (See et al., 2017) to suit our knowledge aware response generation task.

In the summarization task, its input is a document and its output is a summary, but in our case the input is a [selected knowledge, message] pair and the output is a response. Therefore we introduce two RNNs: one is for computing the representation of the selected knowledge, and the other for the message. The decoder accepts the two representations and its own internal state representation as input, and then compute (1) a probability score which indicates whether the next word should be generated or copied, (2) a probability distribution over the vocabulary if the next word needs to be generated, and (3) a probability distribution over the input words if the next word needs
Table 1: The upper table shows statistics of the Reddit dataset and associated knowledge base. The lower table provides the detailed statistics of the two types of knowledge mentioned in utterances.

| Conversational Pairs | Augmented KG |
|-----------------------|---------------|
| #Train. pairs         | 34486         |
| #Valid. pairs         | 4388          |
| #Test pairs           | 4318          |
| #Vertices             | 117373        |
| #Relations             | 11            |
| #Triples              | 251138        |

| Factoid knowledge     | Non-factoid knowledge |
|-----------------------|-----------------------|
| #Total vertices       | 21028                 |
| #Total vertices       | 96345                 |
| #Vertices in utterances | 2740              |
| #Vertices in utterances | 31746            |

To be copied. These three probability distributions are then combined, resulting in $P(y_t | y_{<t}, X, v_Y)$, to produce the next word in the response.

4 Experiments and Results

4.1 Datasets

We adopt a publicly-available knowledge grounded multi-turn dialogue dataset for our experiments, the Reddit movie dataset released by (Moghe et al., 2018), since it contains conversations being grounded on both factoid and non-factoid knowledge. Other knowledge grounded datasets (Dinan et al., 2019; Liu et al., 2018) focus on a single type of knowledge, which are not applicable to our problem setting. The Reddit dataset contains movie chats wherein each response is explicitly generated by copying or modifying sentences from background knowledge such as triples about facts, plots, comments or reviews (from Reddit or IMDB) about movies. It consists of 9K conversation sessions containing a total of 90K utterances pertaining to about 921 movies. We follow their data split for training, validation and test. Then it is possible to make direct comparison with their reported results. Their statistics can be seen in Table 1. Non-factoid knowledge is more frequently involved in movie dialogue than factoid knowledge, indicating the importance of non-factoid knowledge.

4.2 Implementation Details

We implement our knowledge selection model based on the code by (Das et al., 2018) and that by (Moghe et al., 2018). We set the maximum reasoning length $T$ as 3. We use TransE (Bordes et al., 2013) to initialize vertex and relation representations in our augmented KG. The embedding size for TransE is set as 768 for compatibility with the setting of BERT (Devlin et al., 2018) embeddings. Here we use BERT to get the representations of input messages for knowledge selection model. We use BiDAF as our MRC module, shown in Equation (6), and we train the MRC module on the same training set for our knowledge selection model. $\alpha$ and $\beta$ in Equation (8) is set as 0.4 and 0.1 respectively. The embeddings of vertices and input messages is fixed during training process. We use Adam optimizer with a minibatch size of 32. The learning rate is 0.001. The model is ran at most 20 epochs. During preparation of $v_X$ for each $X$, if we cannot find any vertex for $X$, then we take its movie name vertex as $v_X$. This operation helps improve the recall of correct knowledge for $X$. We implement the knowledge aware generation model based on the code of GTTP released by (Moghe et al., 2018). The word embedding size is set to 300, the vocabulary size is limited to 30000, and for other parameter settings, we follow them. We will make the augmented KG and our code publicly available soon.

For baselines, including Seq2Seq, HRED, MemNet, and CCM, we initialize word embeddings with GloVe. We also follow the parameter setting in their original papers for model training.

4.3 Experiment Settings

We follow the existing work to conduct both automatic evaluation and human evaluation for our system. We also compare our system with a set of carefully selected baselines, shown as follows.

**Seq2Seq** We implement a sequence-to-sequence model (Seq2Seq) (Sutskever et al., 2014), which is widely used in open-domain conversational systems.

**HRED** We implement a hierarchical recurrent encoder-decoder model (Serban et al., 2016).

**MemNet** We implement an end-to-end knowledge-grounded generation model

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1We use the single-reference mixed-short test set for evaluation. Please see their paper for more details.

2https://github.com/shehzaadzd/MINERVA

3https://github.com/nikitacs16/Holl-E

4https://github.com/hanxiao/bert-as-service
| Model  | BLEU-4 (%) | ROUGE-2 (%) | ROUGE-L (%) |
|--------|------------|-------------|-------------|
| Seq2seq | 1.59       | 5.73        | 14.49       |
| HRED   | 2.80       | 13.45       | 23.45       |
| MemNet | 1.26       | 9.95        | 17.50       |
| GTTP   | 11.05      | 17.70       | 25.13       |
| BiDAF+G | 32.45     | 31.28       | 36.95       |
| CCM    | 2.54       | 4.40        | 15.25       |
| AKGCM  | 31.93      | 31.87       | 37.09       |

Table 2: Results of automatic evaluations. AKGCM outperforms all the baselines, except BiDAF+G, significantly (sign test, p-value < 2.2e-16) in terms of all the metrics.

| Model  | Appr. Win/Tie/Lose | Infor. Win/Tie/Lose |
|--------|---------------------|---------------------|
| Seq2seq| 0.63/0.28/0.09      | 0.76/0.16/0.08      |
| HRED   | 0.78/0.19/0.03      | 0.81/0.17/0.02      |
| MemNet | 0.67/0.28/0.05      | 0.78/0.17/0.05      |
| GTTP   | 0.49/0.36/0.15      | 0.49/0.34/0.17      |
| BiDAF+G| 0.20/0.68/0.12      | 0.20/0.67/0.13      |
| CCM    | 0.83/0.16/0.01      | 0.84/0.16/0.00      |

Table 3: Results of human evaluations. AKGCM outperforms all the baselines significantly (sign test, p-value < 0.005) in terms of the two metrics.

(Ghazvininejad et al., 2018), where top-k knowledge text candidates are selected by another retrieval model and then are stored into the memory units for generation.

**GTTP** It is an end-to-end text summarization model (See et al., 2017). We use the code released by Moghe et al. (2018), where they modify GTTP to suit the task of knowledge aware conversation generation, taking a message and a document containing all available knowledge as input.

**BiDAF+G** It is a Bi-directional Attention Flow based QA Model (BiDAF) (Seo et al., 2017). We use the code released by Moghe et al. (2018), where they use BiDAF to find the answer span from a knowledge document, taking the input message as the query. Moreover, we use a response generator (as same as ours) for NLG with the predicted knowledge span.

**CCM** It is an end-to-end commonsense conversational model (Zhou et al., 2018). We use the code released by the original authors and then modify our graph to suit their setting by selecting each content word from long text as an individual vertex to replace the original long-text vertices since their model cannot effectively process long texts in vertices.

**AKGCM** It is our two-stage system presented in Section 3. We use BiDAF as the MRC model.

### 4.4 Automatic Evaluations

**Metrics** Following the work of (Moghe et al., 2018), we adopt BLEU-4 (Papineni et al., 2002), ROUGE-2 (Lin, 2004) and ROUGE-L (Lin and Och, 2004) to evaluate how similar the output response is to the reference text.

**Results** As shown in Table 2, on the full task (both knowledge selection and response generation), AKGCM can obtain the highest scores on test set in terms of ROUGE-2 and ROUGE-L, and the second highest score in terms of BLEU-4, surpassing other models, except BiDAF, by a large margin. It indicates that AKGCM can generate more informative and grammatical responses.

### 4.5 Human Evaluations

**Metrics** We resort to a web crowdsourcing service for human evaluations. We randomly sample 200 messages from test set and run each model to generate responses, and then we conduct pair-wise comparison between the response by AKGCM and the one by a baseline for the same message. In total, we have 1,200 pairs since there are six baselines. For each pair, we ask five evaluators to give a preference between the two responses, in terms of the following two metrics: (1) appropriateness (Appr.), e.g., whether the response is appropriate in relevance, and logic, (2) informativeness (Infor.), whether the response provides new information and knowledge in addition to the input message, instead of generic responses such as “This movie is amazing.” Tie is allowed. Notice that system identifiers are masked during evaluation.

**Annotation Statistics** We calculate the agreements to measure inter-evaluator consistency. For appropriateness, the percentage of test instances that at least 3 evaluators give the same label (3/5 agreement) is 96%, and that for at least 4/5 agreement is 73%. For informativeness, the percentage for at least 3/5 agreement is 96% and that for at least 4/5 agreement is 75%.

**Results** In Table 3, each score for win/tie/lose is the percentage of messages for which AKGCM outperforms all the baselines significantly (sign test, p-value < 0.005) in terms of the two metrics.
Table 4: Results of ablation study for AKGCM on the full task (both knowledge selection and response generation). We also include results of the full model for comparison.

| Model variants                  | BLEU-4 (%) | ROUGE-2 (%) | ROUGE-L (%) |
|---------------------------------|------------|-------------|-------------|
| w/o non-factoid knowledge       | 0.61       | 0.84        | 1.52        |
| w/o Bilinear + MRC              | 6.71       | 4.69        | 12.47       |
| w/o MRC                         | 13.94      | 18.87       | 25.76       |
| w/o Bilinear                    | 28.83      | 28.24       | 34.04       |
| Full model                      | 31.93      | 31.87       | 37.09       |

Table 4: Results of ablation study for AKGCM on the full task (both knowledge selection and response generation). We also include results of the full model for comparison.

Table 5: Case study. Please refer to supplemental material for more cases.

4.6 Model Analysis and Case Study

AKGCM without (w/o) Non-factoid Knowledge

To verify contribution of non-factoid knowledge, we remove non-factoid knowledge from augmented KG in test procedure, and report the performance of our system with only factoid knowledge in Table 4. We see that without non-factoid knowledge, the performance of our system drops significantly in terms of BLEU and ROUGE. It indicates that non-factoid knowledge is essential for knowledge aware conversation generation.

AKGCM w/o the MRC Model or Bilinear One

For ablation study, we implement a few variants of our system without the bilinear model or MRC for knowledge selection. Results of these variants are reported in Table 4. If we compare the performance of our full model with its variants, we find that both MRC and the bilinear model can bring performance improvement to our system. It indicates that the full interaction between input message and knowledge texts by neural models is effective to knowledge selection.

Model Generalization

As shown in Figure 4, we gradually reduce the size of training data, and then AKGCM can still manage to achieve acceptable performance, even when given extremely small training data (around 3,400 u-r pairs at the x-axis point of 10%). But the performance of the two strongest baselines, BIDAF+G and GTTP, drops more dramatically in comparison with AKGCM. It indicates that our graph reasoning mechanism can effectively use the graph structure information for knowledge selection, resulting in better generalization capability of AKGCM.

Case Study

As shown in Table 5, given an input message talking about movie characters and scene, AKGCM can select appropriate knowledge text that is related to movie scene, and then produce more appropriate and informative response with the use of the selected knowledge, compared with other models. Furthermore, in comparison
with the high-quality responses by BiDAF+G and GTTP, AKGCM’s output is more similar to the ground-truth one. Moreover, Seq2seq and HRED generate comments of the movie, worse than other scene description related responses in terms of appropriateness and informativeness. MemNet and CCM fail to generate high-quality responses probably due to that the training data is too small (around 34,000 conversation pairs), significantly less than that in their original work.

5 Conclusion

In this paper, we propose an augmented knowledge graph based open-domain chatting machine (AKGCM) to facilitate conversation generation with the first attempt to unify both factoid and non-factoid knowledge as a graph, and then combine multi-hop graph reasoning with machine reading technology for knowledge selection. Results indicate that although the machine reading-based model (BiDAF+G) is a very strong baseline, AKGCM, supported by graph reasoning mechanism, can outperform it, especially when given extremely small training data.

This work may be viewed as a step towards knowledge-aware and interpretable neural conversational models. In the future, we may extend AKGCM to conduct multi-turn dialogue or expand our graph for more content coverage by incorporating data beyond background knowledge.

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