Towards Collaborative Question Answering: A Preliminary Study

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Abstract

Knowledge and expertise in the real-world can be disjointedly owned. To solve a complex question, collaboration among experts is often called for. In this paper, we propose CollabQA, a novel QA task in which several expert agents coordinated by a moderator work together to answer questions that cannot be answered with any single agent alone. We make a synthetic dataset of a large knowledge graph that can be distributed to experts. We define the process to form a complex question from ground truth reasoning path, neural network agent models that can learn to solve the task, and evaluation metrics to check the performance. We show that the problem can be challenging without introducing prior of the collaboration structure, unless experts are perfect and uniform. Based on this experience, we elaborate extensions needed to approach collaboration tasks in real-world settings.

1 Introduction

One of the fascinating aspects of human activity is collaboration: despite the limitations of our individual experience and knowledge, we can collaborate to solve a problem too challenging for any one person alone. In the context of this paper, we are interested in collaboration via rounds of questions and answers internal to a panel of experts responding to an external question. Forms of such activities have broadened into the realm of robots as well. For instance, customer service is automated with the backing of machine agents, each holding expert knowledge in a specific domain.

Figure 1 shows a hypothetical customer service example, where an AI agent is serving a customer who is about to place an order of a mask. Even though the agent has access to the features (e.g., ‘N95’) of the mask in its local database, it cannot answer the question “Can this mask protect me from \textit{COVID-19}?”. Instead of responding with “\textit{Sorry I don’t know}.” as most of the current QA systems do, it can reroute a new question “Can the N95 mask prevent the \textit{COVID-19}?” to a human expert.

We call this task CollabQA where a single agent (human or robot) cannot reason and respond to a complex question, but collectively they can. In other words, knowledge is not shared across agents, but the union contains the required reasoning path, which necessitates collaboration.

To solve the problem in its general form is hard. In this paper, we take a few steps forward by proposing 1) a simplified version of CollabQA task where one front-serving agent decomposes an external question into simple ones for the rest of the experts to answer, 2) a synthetic dataset of a large knowledge graph that can be distributed to experts, and 3) a set of baseline models and the associated evaluation metrics.
evaluation metrics.

Despite this very simple form, we show the problem can be very challenging. Our overall conclusion is that, even with such a simple setting where 1) knowledge is clearly decomposed, 2) collaboration is passive, and 3) questions and answers are formed with simple templates and node prediction, training a good collaboration policy remains challenging, unless we add a strong prior reflecting the collaboration structure, and assume collaborators that are both perfect and uniform. We use these experiences to reflect how to improve this task to gradually approach collaboration tasks with more real-world flavor.

The rest of the paper is organized as follows. Section 3 formally defines the CollabQA task setting and shows the toy dataset we synthesized for a preliminary study. Section 4 describes the approach we proposed to for the task. We show experimental results and their enlightenment in Section 5. Section 6 surveys related works to CollabQA and discuss the key differences. And Section 7 discusses some potential directions for future works.

2 Opening Remarks

This paper was initially submitted to the EMNLP 2020 on June 3, 2020. The reviewers’ primary concern about this paper was that it lacked real data experiments and rejected this paper. Since then, we thought we might have time to polish this paper further, but the research direction of our team changed to other fields. Therefore, we did not have the chance to go deeper in this direction. Some of the settings or discussions may be interesting to the community, so we decided to release this paper on the arxiv. Since 2020, we have noticed more related papers in this section. We list some of them for the readers’ reference and leave other parts of this paper almost unaltered to its initial version.

To make agents collaborate, we usually need to decompose a complex task into simpler ones so that different agents can tackle these simple tasks. Wolfson et al. (2020) defined several operators, and a complex question will be decomposed into several sub-queries so that each sub-query will have only one operator. Based on this principle, Wolfson et al. (2020) annotated a large dataset BREAK which can be served as a good starting point for Question Answering (QA) collaboration. He et al. (2017) proposed a dataset that requires two people, each with a distinct private list of friends, to find their mutual friends through talking. CEREALEXBAR proposed in (Suhr et al., 2019) is a collaborative game, which requires an instructor and a follower to collaborate to gather three cards in a virtual environment. The instructor can use natural language to pass messages to a follower, but not vice versa. The instructor has to learn to use better instructions to achieve better scores. Khot et al. (2021a) proposed to use natural language to make several existing QA models collaborate so that they together can solve a question that cannot be solved solely by any existing QA models. And they further proposed a synthetic benchmark COMMAQA which can facilitate the research of collaboration QA (Khot et al., 2021b).

3 The CollabQA Task

3.1 Notations and Settings

The general setting of CollabQA simulates a group of panelists \{P_i\}_{i=0}^n, out of which \(P_0\) is a special: it is the front-serving receptionist and the representative to the external world, it is also the moderator of the collaboration among \{P_i\}_{i=1}^n, who we term as the panelists. When \(P_0\) receives an external question \(Q\), it broadcasts an utterance \(q^{(1)}\) to the panelists and collects responses \(\{u^{(1)}_i\}_{i=1}^n\) from them. This process continues iteratively, each round is a tuple \((q^{(t)}, \{u^{(t)}_i\}_{i=1}^n)\), until a maximum of \(T\) turns, and/or when \(P_0\) is able to generate the final response which includes “UNK”, that means “I don’t know”. Notations used in this paper are listed in Table 1.

The panelists \(\{P_i\}_{i=1}^n\) owns a list of knowledge graphs, \(KG_1, KG_2, \ldots, KG_n\), and their union \(KG = \bigcup_{i=1}^n KG_i\) is the total graph. Questions are usually complex in the sense that they cannot be answered by one single agent. However, they are always answerable by KG. In other words, \(\tau(Q)\), the reasoning path of question \(Q\) can cut across

| Notations | Description |
|-----------|-------------|
| \(P_i\)   | The \(i\)-th panelist. |
| \(Q\)     | The external complex question. |
| \(q^t\)   | Utterance by \(P_t\) at \(t\)-th dialog turn. |
| \(u^{(t)}_i\) | Response of \(P_i\) at \(t\)-th dialog turn. |
| KG_i      | Knowledge graph owned by \(P_i\). |
| \(\tau(Q)\) | The reasoning path of \(Q\). |
| \(T\)     | Dialog turns. |
different graphs but is always contained within KG. As such, $P_0$ must generate multiple polls to the panelists to stitch together $\tau(Q)$. Our objective is to minimize the total number of turns while maximizing the success rate.

### 3.2 A Toy Task

Inspired by the bAbI task (Weston et al., 2015), we construct a CollabQA dataset, which contains a series of QA pairs and 3 supporting knowledge graphs.

We first construct KG\(_1\), KG\(_2\), KG\(_3\) consisting of fabricated \textit{person}, \textit{company} and \textit{city} entities and their relations. They stores the knowledge of $N_1$ persons, $N_2$ companies and $N_3$ cities respectively. The details of the three knowledge graphs are listed in Appendix A. They are assigned to the panelists $P_1$, $P_2$ and $P_3$ respectively as their knowledge.

Then we synthesize QA pairs from the knowledge graphs as well as the reasoning paths. Each question needs a cross-graph multi-hop reasoning. To illustrate the process of creating the dataset examples, we use an example to show how to create a 2-hop question: from a node “Person#1” in KG\(_1\), we follow a path with many-to-one or one-to-one types of relations, for example the “birthplace” relation and get a triplet (Person#1, birthplace, City#4); then we start from node “City#4” in KG\(_3\) to search a triplet (City#4, largest company, Company#4). Then we combine the two triplets into a reasoning path:

$$\text{Person#1} \xrightarrow{\text{birthplace}} \text{City#4} \xrightarrow{\text{largest company}} \text{Company#4} \quad (1)$$

so the final answer is the entity Company#4 in the end of the path. The question $Q$ asking about Company#4 following the reasoning path is “What is the largest company in the city where Person#1 was born?”, which is generated by templates. A more complex example is shown in the upper part of Figure 2.

The reason we use many-to-one or one-to-one types of relations during the search, is that it ensures the entities occurred in the path are unique, so that we can decompose the question into sub questions and each with unique answer. In general, to generate an $n$-hop question, we randomly pick an entity node and perform $n$-hop Depth First Search (DFS). Note that multiple edges may exist between a pair of entities (as in a person may live and die in the same city).

We limit the communications among the panelists are natural language. Therefore, $P_0$ needs to learn how to ask questions. To alleviate the burden of text generation, we pre-define a set of templates of sub questions. So, for $\tau(Q)$ in equation 1, the sub questions are “Which city was Person#1 born in?” for the first hop and “What is the largest company in City#4?” for the second hop. The bottom part of Figure 2 shows an ideal collaborative process.

Table 2 lists the overall statistics of the dataset.

| Statistics description               | Value     |
|-------------------------------------|-----------|
| Train set size                      | 66,800    |
| Dev set size                        | 8,350     |
| Test set size                       | 8,350     |
| # of templates of $Q$               | 49        |
| # of templates of simple questions  | 28        |

Table 2: Overall statistics of the CollabQA dataset.

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Figure 2: Illustration of Toy CollabQA Task: an example of QA pair and the ideal collaborative process.
3.3 Links to other QA Tasks

CollabQA can be regarded as an combination of several kinds of QA tasks: knowledge graph question answering (KGQA), multi-hop QA, multi-turn dialogue.

KGQA In CollabQA, each panelist is a KGQA system. KGQA assumes that each panelist can answer the questions according its own KG, though it may need one- or several-step reasoning.

Multi-hop QA In multi-hop QA, the supporting facts of a question are scattered in different sources. Most models for multi-hop QA assume they can access all the sources. Different from multi-hop QA, the supporting facts in CollabQA are separately owned by different panelists. Each supporting fact is not accessible except its owner. Therefore, panelists need communicate with each other to exchange information.

Multi-turn Dialogue The multi-turn dialogue usually occurs between human and agent. CollabQA aims to develop multi-turn interactions among several agents (panelists).

As such, CollabQA is more challenging than KGQA, multi-hop QA and multi-turn dialogue.

4 Proposed Approach

In our setting, panelists collaborate passively in that they respond with what they know or else with “UNK”. Therefore, $P_0$ leads the process of collaboration. Our general approach consists of two stages: 1) pre-train the panelists with supervised learning; 2) train the collaboration policy with reinforcement learning.

4.1 Panelists

Panelists share the same model architecture: a Graph Encoder that encode the knowledge graph into a graph representation matrix $H^{(KG)}$, a Question Encoder that encodes the incoming question $q^{(t)}$ into $h(q^{(t)})$, feeding both into a Node Selector then picks an entity the answer.

Graph Encoder Without ambiguity, we call each knowledge graph owned by expert agents KG = $(V, E)$. KG is a heterogeneous graph consisting of different types of entities $V$ and their relations $E$. The form of each relation is a triplet $\{(u, rel, v)\}$, where $u, v \in V$ and $rel \in R$ and $R$ is the set of relation types.

We come up with a modified version of Relational Graph Convolutional Network (R-GCN) (Schlichtkrull et al., 2018) as the graph encoder. R-GCN encodes the graph by aggregating the neighbor and edge information to the nodes. Given a node $v$ in KG, let $h_v^{(l)}$ denote its representation at the $l$-th layer of R-GCN, then

$$h_v^{(l+1)} = \delta \left( \sum_{r \in R, u \in N_v^{rel}} \frac{1}{c_{v, rel}} W_v^{(l)} h_u^{(l)} + W_r^{(l)} h_v^{(l)} \right),$$

where $\delta$ is an activation function, $N_v^{rel}$ denotes the neighbors of $v$ which have relation $r$ with $v$, $W_v^{(l)}$ is the weight matrix of relation $re$ at the $l$-th layer, and $\frac{1}{c_{v, rel}}$ is a normalization factor. After $L$ aggregations, the final representations of the nodes are $H^{(KG)}$.

However, R-GCN suffers from high GPU memory usage, making it hard to scale to large graphs. The reason is that computing the message includes a direct tensor operation that will produce a very large tensor, especially when number of relations is large. On the other hand, if we compute the messages with a for-loop, the speed of the aggregation will suffer. To get rid of this problem, we make modifications similar to (Vashishth et al., 2020) but simpler and sufficient for this task in CollabQA dataset: each relation is modelled by a trainable vector $h_{rel}$ instead of a matrix $W_{rel}$, then the aggregation process changes to:

$$h_v^{(l+1)} = \delta \left( \sum_{r \in R, u \in N_v^{rel}} MLP^{(l)}([h_u^{(l)}, h_v^{(l)}, h_{rel}^{(l)}]) \right),$$

In our experiments, we observe significant GPU memory saving. Our implementation leverages the DGL package for its superior GPU performance (Wang et al., 2019).

Question Encoder Similarly, we call the question to the expert agents $q$. The representation of a question $q$ is computed by BiLSTM (Hochreiter and Schmidhuber, 1997):

$$h(q) = BiLSTM(q),$$

Node Selector Node selector performs an attention operation with $h(q)$ on $H^{(KG)}$, and returns attention scores $\alpha^{(KG)}$ on $H^{(G)}$ as the likelihood of selecting each node as answer:

$$\alpha^{(KG)} = (H^{(KG)})^T W h(q)$$

then the answer is the value of the node which has the highest attention value.
4.2 Moderator and Collaboration Policy

$P_0$ coordinates collaboration according to a learned collaboration policy. At turn $t$, $P_0$ takes $a^{(t)}$ according to its current state $s^{(t)} = f_s(d^{(t)})$, where $d^{(t)}$ is the dialog history up to $t$, $d^{(t)} = [Q, q^{(1)}], \{u_i^{(1)}\}_{i=1}^n, \ldots, q^{(t-1)}, \{u_i^{t-1}\}_{i=1}^n$. The state encoder $f_s(\cdot)$ can be any neural model; here we use BiLSTM.

The action space includes asking a new sub question or returning the final answer. To alleviate the burden of text generation, $P_0$ generates sub question by selecting templates from a predefined set $\mathcal{U}$. To enable $P_0$ to determine whether to finish the collaboration and return the answer of $Q$, we add a special template in $\mathcal{U}$ which stands for “finish the collaboration”. Thus, we use a simple Multi-layer perceptron (MLP) to implement the collaboration policy $\pi(a^{(t)}|s^{(t)})$, which takes $s^{(t)}$ as input, outputs a probability distribution over the list of templates.

In CollabQA dataset, at each dialog turn, only one of the answers from the panelists is not “UNK”. So, once the template is selected, we fill in the placeholder with this answer and update $s^{(t)}$ to generate $q^{(t+1)}$ or the final answer.

**Reward** We use the number of correct answers for CollabQA as baseline reward. For each question, getting an correct answer within $T_{\max}$ turns leads to a reward $r = +1$; otherwise, the reward $r = -1$.

To alleviate the problem of reward sparsity, we assign the reward $r$ to all the actions in the trajectory. Besides, we add an entropy regularization term to encourage exploration (Haarnoja et al., 2018). We apply policy gradient method to train $P_0$. The gradient of the policy is

$$\nabla J = \mathbb{E}_{a \sim \pi} \left[ \sum_{t=1}^T r \nabla \theta \log \pi(a^{(t)}|s^{(t)}) + \nabla \theta \left( \max(0, C - H(\pi(|s^{(t)}|))) \right) \right],$$

(6)

where $T$ is the turns of dialogue, $C$ is a hyper-parameter, and $\theta$ stands for the parameters of the policy.

In our simple setting, we can introduce an inductive bias specifically tailored to improve the learning effects. Since experts do not share knowledge, and there shall be exactly one response that is not “UNK” in each turn, we add an extra negative reward $\beta(\beta < 0)$ if it’s not the case. Therefore, the reward $r$ are re-denoted as

$$r = \begin{cases} -1 + \beta, & \text{if not exactly one answer,} \\ -1, & \text{if wrong answer,} \\ +1, & \text{if right answer.} \end{cases}$$

(7)

where $\beta$ is a hyper-parameter. As we add prior information in this setting, we call it enhanced reward setting.

5 Experiments and Analysis

5.1 Experimental Setup

**Pre-training of the Panelists** We first train the $P_1, P_2, P_3$ with sub questions and their answers appeared in the training set. We fix the well trained panelists as the environment during training $P_0$. The performance of them are shown in Table 3.

|          | $P_1$ | $P_2$ | $P_3$ |
|----------|-------|-------|-------|
| Accuracy | 99.6  | 99.6  | 100   |

Table 3: Performance of the pre-trained panelists when asked one-hop questions on their domain knowledge.

The hyper-parameters of the model used in our experiments are listed in Table 4.

**Evaluation Metrics** We evaluate the performance of $P_0$ with two metrics:

1) **EMA**: exact match of the final answer;
2) **EMP**: the extracted reasoning path of $P_0$ exactly matches the ground-truth path.

5.2 Results and error analysis

The main results are shown in Table 5. In the top row, we show the performance for a random $P_0$.
| Hyper-parameter          | Value |
|-------------------------|-------|
| R-GCN Layer             | 1     |
| R-GCN hidden size       | 80    |
| Embedding dim.          | 40    |
| Bi-LSTM hidden size     | 40    |
| Number of Epoch         | 1000  |
| Batch size              | 500   |
| Optimizer               | Adam  |
| Learning rate           | 3e-3  |
| Entropy threshold $C$   | 0.1   |
| Prior penalty reward $\beta$ | -0.2 |

Table 4: The hyper-parameter used to learn the panelists and $P_0$.

|                | EMA | EMP |
|----------------|-----|-----|
| Random         | 0.0 | 0.0 |
| Baseline Reward| 68.8| 45.3|
| Enhanced Reward| 80.1| 52.6|

Table 5: Main results of the experiments on the test set.

who randomly picks one question to ask at each step. Its EMA is zero, which reveals that it is not easy to guess the right answer. The “baseline reward” row presents the results of using the Equation 6 as the gradient to optimize the model, and this model has one more termination action at each step (and it should pose the “termination” action only at the 4th turn.). The “enhanced reward” row is the additional penalty we give in Equation 7 (i.e. knowing exact number of turns and only one response is not “UNK”).

**Performance gap between two kinds of rewards**

The accuracy difference between the “baseline reward” row and the “enhanced reward” row is caused by that the “baseline reward” setting has one extra action, therefore it has the chance to terminate too early or fail to stop at the last turn. Based on our experiments, we found that this improper termination accounts for near 9% of the total errors. However, this kind error can be totally avoided in the “enhanced reward” setting. The left 2.3% performance lost may attribute to better training of “enhanced reward”. Another noticeable fact is that the EMP drop from “enhanced reward” to “baseline reward” is not as large as the EMA, this is because the wrong reasoning path in “enhanced reward” is also prone to terminate improperly. The training curves for “baseline reward” and “enhanced reward” are presented in Figure 3, the confidence interval is calculated from 5 experiments. From the figure, the accuracy for the EMA is quite stable, while the EMP is fluctuating. This is because the number of distinct samples are not very rich in our dataset, the variance should be innately small. However, because of the data bias which will be discussed in the following part, the EMP will fluctuate and without hurting the EMA.

**Fitting the data bias**

What is interesting is that a high answer accuracy (EMA) does not mean a high reasoning path accuracy (EMP); in both settings there is a large gap between the two accuracies.

To understand the reason behind the gap between answer accuracy and reasoning path accuracy, we compute the performance for each type of $Q$. We found that the model finds wrong reasoning path mostly on the questions that has sub questions “Which city does [PersonName] live in ?” and “Which city was [PersonName] born in ?”. It turns out that, in our dataset, nearly 99% of the time that a person’s “birthplace” and “live in place” are the same, and the model cannot distinguish the difference between them during training. We observe that nearly all the questions that need to be decomposed to “Which city does [PersonName] live in ?” have been decomposed to “Which city was [PersonName] born in ?” instead. One example can be viewed in Figure 4.

To further show how this overlap will have an impact on our results, we vary the overlap ratio, which is the probability one person has the same “live in place” and “birthplace”, in Figure 5. As the overlap ratio goes up, it will be harder for P0 to discern between “live in place” and “birthplace”, but the difficulty does not go up linearly, the EMP drops sharply after some point. However, the the drop of EMP does not have too much negative
affect on the EMA, since when the overlap ratio is high, it can still get the right answer with the wrong reasoning path.

In other words, the model settles on an approximate question decomposition that the final reward cannot distinguish. We note that similar data bias exist in the real world, and the model exploited it through exploration in our dataset. Fixing it means $P_0$ should inspect the semantic consistency between the sub questions and the original question, instead of blindly selecting templates.

Except for the data bias issue, there are numerous error cases. For instance, an imperfect expert can pick a wrong answer that are structurally correct (i.e. answer the birth city when the question is work location) that leads to a correct decomposition but wrong final answer. Note that our panelists are nearly perfect. Thus, small errors accumulate over the turns and greatly affect $P_0$’s performance.

The problem of group bias The data bias described above reminds us of another kind of bias, that during learning to collaborate, $P_0$ may fit the bias of the panelists. This is intuitive, since panelists are environment, any bias therein will lead to bias in $P_0$. What is more interesting in a collaboration setting is that such bias is per group.

To verify this assumption, we conduct experiments training 3 groups of panelists with different initialization, and we call them $Panel^{(1)}$, $Panel^{(2)}$, $Panel^{(3)}$. Each group has similar performance to those in Table 3. Then we train 3 versions of $P_0$ paired with different groups of panelist: $P_0^{(1)}$ trains with $Panel^{(1)}$. During testing, we pair each $P_0$ with different group of panelist. The the resulting answer accuracy are listed in Table 6.

The results show that there are always performance drop when $P_0$ is paired with panelists which is not trained with it.

6 Related work

KGQA In the simplified setting of CollabQA, each panelist is a simple KGQA system. The questions are either simple, or need one step reasoning to be reformulated into another simple question.

KGQA has been widely studied. The most common way of doing KGQA is by semantic parsing. Semantic parser maps a natural language question to a formal query such as SPARQL, $\lambda$-DCS (Liang et al., 2011) or FunQL (Liang et al., 2011). Previous works on KGQA can be categorized into classification based, ranking based and translation based methods (Chakraborty et al., 2019). The model of the panelists we proposed is most related to classification based methods. Classification based methods assume the target formal query has a fixed structure, and the task is to predict the elements in it. For example, in SimpleQuestions benchmark (Bordes et al., 2015), all the questions are factoid questions that need one-step reasoning. SimpleQuestions has been approached by various NN models (He and Golub, 2016; Dai et al., 2016; Yin et al., 2016; Yu et al., 2017; Lukovnikov et al., 2017; Mohammed et al., 2018; Petrochuk and Zettlemoyer, 2018; Huang et al., 2019).

Another line of KGQA approaches leverages knowledge graph embedding to make full use of the structural information of KGs (Huang et al., 2019).

Multi-hop QA To answer a multi-hopped question, multiple supporting facts are needed. WikiHop (Welbl et al., 2018) and HotpotQA (Yang et al., 2018) are recently proposed multi-hop QA datasets for text understanding. Different from multi-hop QA, the supporting facts in CollabQA are separately owned by different panelists. Each supporting fact is not accessible except its owner. Therefore, CollabQA is more challenging than multi-hop

|        | $P_0^{(1)}$ | $P_0^{(2)}$ | $P_0^{(3)}$ |
|--------|------------|------------|------------|
| Panel$^{(1)}$ | 81.7       | 82.5       | 76.4       |
| Panel$^{(2)}$ | 80.0       | 84.6       | 74.2       |
| Panel$^{(3)}$ | 80.8       | 83.6       | 81.9       |

Table 6: Results for pairing each $P_0$ with different group of panelist at testing time. Each column shows how a version of $P_0$ is paired with different panels; the diagonal entry is where $P_0$ pairs with the group it was trained on.
Multi-Agent Reinforcement Learning (MARL)
In this paper, panelists are passive and pre-trained, we just train the collaborative policy under single-agent RL setting. However, the general CollabQA should allow the panelists discuss with each other; therefore, each panelist has its own policy and can update the policy. Under this general setting, CollabQA naturally falls into the realm of MARL (Bușoniu et al., 2010; Foerster et al., 2016), which is a more challenging task.

7 Discussion
The task of CollabQA as it stands is very simple. Nevertheless, the experiences are helpful to drive towards an improved setting that is closer to real-world scenarios. To put it differently, if we were to design the task anew, what are the most important extensions? We examine three dimension: 1) the role and capability of participants, 2) the collaboration structure and 3) scaling to real-world problems.

(1) Role Definition In the current setting, the moderator $P_0$ assumes no knowledge of its own and its capacity is limited to breaking down a complex question. The panelists are domain experts whose knowledge do not overlap, and they can only respond with facts, without proactively ask questions, nor can they reveal any reasoning path. These are much simplified assumptions that do not reflect the reality. Relaxing these constraints is in general challenging; we list some of the issues below.

Consider the issue of common sense knowledge. Although inconsistencies among individuals do exist, it is nevertheless the foundation where collaboration among a collection of human experts can start. Often times, common sense is required to meaningfully decompose a complex question, whether the panelists are involved or not. Take the question “Does Person#1 work in the same city as Person#2 ?” as an example. $P_0$ needs to realize that the entities of the companies and their locations are key to solve this question. These missing steps, which are not obvious from the question itself, need to be inserted and it takes common sense to deduce them, since “working city” is not a relation readily available in our KG.

A debate is interesting when there are gaps between experts, not because they have non-overlapping knowledge but more often because they have different opinions on the same facts. As such we need to introduce overlapping knowledge imbeded with different certainty (or reliability). This, in turn, requires $P_0$ to have the capacity to arbitrate among parallel responses from different panelists.

(2) Collaboration Structure The overall structure of a moderator working together with a group of expert is not uncommon. Even with this broad structure, there can be other valid variations. For instance, instead of broadcast, the moderator can have pointed question to one panelist, or more generally a subset of the panelists. It is also possible that the final response needs a vote when the moderator cannot resolve a difference.

The constraint that panelists can only passively state facts is problematic when a question is ambiguous. Consider the question “Where does [PersonName] work ?” There are multiple legitimate responses (e.g. a company, a city, and/or a country). As such, a panelist should ask clarification question; drawing an exhaustive list from KG is a possibility, but an unnatural one. As a further extension, clarification questions can be generated and responded by any of the participants.

(3) Scale to Real World Scenario Despite its simplicity, our current setting is meaningful to approach real CollabQA tasks. In order to do so we believe there are few more necessary extensions.

Currently, we assume a complex question is the realization of a unique path. In general this is not true even when the reasoning does take a multi-hop path; multiple edges can exist between a pair of entities. A lazy (or unlucky) $P_0$ may learn to choose only one of them, if the only award is to get the final answer right. This is one problem we discussed in our experiments where “work_in” and “live_in” happen to overlap in the end nodes.

In general, reasoning can take a graph (thought we can consider a path as a degenerated graph, too). The earlier example (“Does Person#1 work in the same city as Person#2 ?”) can only be solved by a two-level tree with a Boolean comparison at the root. Booking an airline ticket with both pricing and timing constraints while the required information reside in different KGs is similar. As a result, to generate complex question there is a need to go beyond the perspective of a reasoning path.

In our current setting, $P_0$ selects template, and
panelists respond with the entity. As such, the action space of $P_0$ is constrained, and there is very low risk that communications get “lost in translation.” Ideally, such communication should take generated natural language. In other words, CollabQA needs natural language generation (NLG) as a component. However, doing so will be prohibitive expensive if we want to train from scratch. If there are $|V|$ valid words, the number of possible sentences for a $L$ length sequence will be $|V|^L$, and that is only for one turn. This will exponentially exacerbate the issue of sparse reward, making training difficult. Thus, we believe that this is not a fundamental problem. In other words, in the context of CollabQA, leaning what to ask is more important than how to ask. A more practical approach is using transfer learning to endorse the agents with NLG capability.

However, there should be surface realization diversity even for semantically identical questions. Doing so is not only a practically required, but will also make the system more robust. This can be easily accomplished by adding noises to templates, provided that the action space stays manageable.

8 Conclusion
The fact that knowledge are not shared gives rise to individual diversity and motivates collaboration. We believe natural-language based collaboration system is a domain that has practical implication and holds scientific values. The CollabQA task and dataset we proposed in this paper is a small step towards that direction.

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Figure 6: Structure and examples of entities in the three proposed knowledge graphs.

Appendices

A Details of the CollabQA dataset

Structures of the three KGs Figure 6 shows the structure and examples in our proposed knowledge graphs. $G_1$ contains a list of Person entities. The value of a property of the entity is randomly generated within a reasonable range. For example, the value of a person’s height is randomly sampled in the range $[160cm, 200cm]$. We add a series of constraints to make the KGs more realistic, such as a person who doesn’t have job gets no annual income; a person cannot be a mayor and be an employee in some company at the same time; the largest company of a city must be located in that city, and so on.

Statistics of the KGs The detailed statistics of the three KGs are shown in Table 7.
|                | $G_1$                          | $G_2$                                      | $G_3$                                      |
|----------------|-------------------------------|--------------------------------------------|--------------------------------------------|
| Overall        | Number of entities: 7541      | Number of entities: 7719                   | Number of entities: 1360                   |
|                | Number of relations: 24000    | Number of relations: 16000                 | Number of relations: 1500                  |
| Number of      | gender_value: 2               | CompanyName: 2000                          | CityName: 300                              |
| different node | PersonName: 3000              | date_value: 1862                           | area_value: 211                            |
| types          | height_value: 21              | number_value: 836                          | number_value: 259                          |
|                | weight_value: 31              | PersonName: 2600                           | PersonName: 285                            |
|                | date_value: 2597              | BusinessName: 20                           | BusinessName: 20                           |
|                | CityName: 300                 | CityName: 300                              | CompanyName: 300                           |
|                | CompanyName: 1559             | market_value: 101                          | StateName: 5                               |
|                | annual_income_value: 31       |                                           |                                           |
| Number of      | height: 3000                  | establish_date: 2000                       | area: 300                                  |
| different      | weight: 3000                  | number_of_employees: 2000                  | population: 300                            |
| relation types | birthday: 3000                | ceo: 200                                   | mayor: 300                                 |
|                | gender: 3000                  | founder: 2000                              | largest_company: 300                       |
|                | birthplace: 3000              | main_business: 2000                        | contained_by: 300                          |
|                | live_in: 3000                 | locate_in: 2000                            |                                           |
|                | work_in: 3000                 | has_service_in: 2000                       |                                           |
|                | annual_income: 3000           | chairman: 2000                             |                                           |
|                |                                | market_value: 2000                         |                                           |

Table 7: Statistics of three knowledge graphs used in our experiment.