Learning to Solve Complex Tasks by Talking to Agents

Tushar Khot  Kyle Richardson  Daniel Khashabi  Ashish Sabharwal

Allen Institute for AI, Seattle, WA, U.S.A.
{tushark,kyler,danielk,ashishs}@allenai.org

Abstract

Humans often solve complex problems by interacting (in natural language) with existing agents, such as AI assistants, that can solve simpler sub-tasks. These agents themselves can be powerful systems built using extensive resources and privately held data. In contrast, common NLP benchmarks aim for the development of self-sufficient models for every task. To address this gap and facilitate research towards “green” AI systems that build upon existing agents, we propose a new benchmark called COMMAQA that contains three kinds of complex reasoning tasks that are designed to be solved by “talking” to four agents with different capabilities. We demonstrate that state-of-the-art black-box models, which are unable to leverage existing agents, struggle on COMMAQA (exact match score only reaches 40pts) even when given access to the agents’ internal knowledge and gold fact supervision. On the other hand, models using gold question decomposition supervision can indeed solve COMMAQA to a high accuracy (over 96% exact match) by learning to utilize the agents. Even these additional supervision models, however, do not solve our compositional generalization test set. Finally the end-goal of learning to solve complex tasks by communicating with existing agents without relying on any additional supervision remains unsolved and we hope COMMAQA serves as a novel benchmark to enable the development of such systems.

1 Introduction

As tasks become more complex, humans usually break them down into manageable sub-tasks, solve them, and compose the results together. We often solve these sub-tasks by interacting—in natural language—with other people or automated agents whose respective skill-sets we are familiar with. Can AI systems learn to do the same?

To facilitate research in this direction, we propose a new reasoning challenge where, in addition to the usual end-task supervision, one has access to a set of pre-defined AI agents with examples of their natural language inputs.1 Importantly, the target end-task is designed to be sufficiently challenging for current models to learn based only on end-task supervision. The goal is instead to build models that learn to solve the target task by decomposing it into sub-tasks solvable by these agents, and interacting with these agents in natural language to do so.

As a motivating example, consider the interaction depicted in Figure 1 where the goal is to buy the book series with a certain property. We can break this goal down into using agent-1 (here Google Assistant) to identify the referenced book series, and then use agent-2 (here Amazon Alexa) to make the purchase.

1Our benchmark datasets and models are available at https://github.com/allenai/COMMAQA
purchase. While both of these agents interact with us in natural language, they have notably different skill sets, rely on private knowledge sources, and have been built at an enormous cost. At the same time, neither agent by itself is capable of accomplishing the original goal.

A common research avenue pursued these days is to rely on giant, monolithic language models with billions of parameters to solve all NLP and reasoning challenges. We could consider teaching all requisite sub-tasks and skills to such a black-box system, say via multi-task learning (Khashabi et al., 2020; Gupta et al., 2021). This, however, is not only inefficient and wasteful in terms of resources, but often also infeasible. For example, powerful agents such as Google Assistant and OpenAI GPT-3 use private knowledge resources and are computationally expensive to train even once. It would thus be nearly impossible to build a single system with the capabilities of both of these agents. In general, as tasks become more complex, a promising way forward is to decompose them into pre-defined sub-tasks solvable by existing agents where the internals of the agents or their training data aren’t always accessible or efficiently usable.

We note that agents do not have to be sophisticated AI assistants. An agent may simply be a previously developed question-answering (QA) model, a math module, a function that takes textual input, an image captioning system—anything we, as a community, already know how to build. The key question is, how can we learn to build upon existing agents to perform more complex tasks?

To help make progress towards this challenge, we formally define the minimal pre-requisites to build such a system – training data for the complex task, existing agents that together can solve the complex task and examples of valid questions that can be asked from these agents (capturing the agents capabilities). We develop a new benchmark dataset called COMMAQA (Communicating with agents for QA), containing three complex QA tasks and four input QA agents that can solve these tasks. We provide a set of input questions that define the capabilities of these agents. We use this dataset to demonstrate that black-box models can struggle to solve these complex tasks even when provided with auxiliary data. On the other hand, a compositional model (Khot et al., 2021) can achieve very high accuracy by utilizing the provided agents, but relies on the decomposition annotations. Additionally we release a compositional generalization test set that is not solved by any of these models. We hope that the COMMAQA dataset enables development of better approaches that do not rely on these additional annotations and generalize better.

**Contributions:**
1. Propose a new challenge task of learning to solve complex tasks by communicating with agents.
2. Develop a synthetic multi-hop QA dataset COMMAQA with three reasoning types and four QA agents.
3. Provide auxiliary training data and a compositional generalization test set to enable development of stronger models.
4. Demonstrate the challenging nature of this dataset for black-box models.
5. Show the value of compositional models that are able to learn to communicate with the agents in solving this task.

## 2 Related Work

We briefly review several related lines of research.

**Semantic Parsing** is typically focused on building models that can map language problems to executable symbolic representation based on predefined grammar (Roy and Roth, 2018; Krishna-murthy et al., 2017; Chen et al., 2020). This goal resembles ours in that both approaches seek to simplify complex problems into simpler executable forms, without relying on explicit intermediate annotations (Clarke et al., 2010; Berant et al., 2013). We, however, diverge from this line by seeking communications in free-form language that are not bound to any pre-specified set of operations or entities.

**Multi-hop QA** seeks to build models that can reason with collections of facts, often formulated as question answering tasks. This sub-field has seen tremendous activity in terms of datasets (Khashabi et al., 2018; Yang et al., 2018; Khot et al., 2020; Geva et al., 2021) and the development of new architectures (Min et al., 2019b; Pan et al., 2021; Fang et al., 2020). Despite this progress, existing benchmarks often contain many shortcuts (Trivedi et al., 2020; Min et al., 2019a), resulting in models being brittle (Gardner et al., 2020). Additionally these datasets contain sub-problems that may not be solvable by existing models, further disincentivising development of compositional models (Khot et al., 2021).

**Question Decomposition** has emerged out of the multi-hop QA research as the class of approaches for generating human-readable decom-
positions of a given question. Models using question decomposition (Talmor and Berant, 2018; Min et al., 2019b; Perez et al., 2020; Khot et al., 2021) are often dataset-specific, rely on decomposition annotations, and limited to one or two QA agents. To overcome this limitation, we propose a new task that covers three dataset types and four agents. Additionally, models are expected to learn to decompose the task by interacting with the agents, rather than rely on human annotations.

**Program Synthesis** has traditionally focused on constructing executable programs from high-level specifications (Manna and Waldinger, 1980) or intentions given input-output examples (Gulwani, 2011) and other pieces of evidence including natural language (Desai et al., 2016) (see Gulwani (2010)). While in practice many program synthesis problems and related problems in *programming by example* (Kurlander et al., 1993) involve executing programs across mixtures of sources (similar in spirit to our goal of modeling agent interaction), like with semantic parsing, such work is often limited to working with problems expressible in small and controlled domain specific languages, whereas we focus on a more open set of problems expressed in general natural language by building on the recent successes of pre-trained language modeling.

**Hard Reasoning Challenges** Given that recent advances in modeling have coincided with the discovery of serious shortcomings in existing benchmarks (Jia and Liang, 2017; Gururangan et al., 2018), including in multi-hop reasoning datasets as discussed above, there has been renewed interest in developing hard synthetic reasoning challenges (Lake and Baroni, 2018; Sinha et al., 2019; Ruis et al., 2020; Clark et al., 2020; Betz and Richardson, 2021) that help to more systematically identify model strengths and weaknesses and motivate new modeling approaches. Our new tasks are unique in this space, in that they focus on systematically simulating agent interaction and identifying the limitations of the information aggregation capacity of current pre-trained language models in a way that motivates decomposition-based modeling approaches.

## 3 Learning to Talk with Agents

We next describe the minimum pre-requisites to build a system that can learn to solve complex tasks by communicating with existing agents\(^2\) \{\(f_i\)\}. First, we must somehow convey to the system the capabilities of these agents and how they can be invoked, i.e., the space \(L_i\) of valid inputs for each \(f_i\). We assume that the space of valid inputs, when expressed in natural language, also captures the capabilities of the agent. For instance, “Buy the book ‘Harry Potter and the Sorcerer’s Stone’” captures the Alexa agent’s capability of buying books. Note that capabilities of complex agents can be difficult to define using a formal specification language. We believe natural language inputs provide a rich and convenient specification mechanism to capture agent capabilities.

Next, we need a target task \(T\) that can be solved by communicating with these agents, i.e., a complex task solvable via a composition of the capabilities of \(\{f_i\}\). Finally, to pose this as a machine learning problem, we need training data \(\{(x_k, y_k)\}\) for \(T\). Since collecting annotations for complex tasks can be generally difficult, this training dataset \(\{(x_k, y_k)\}\) would be relatively small in many real-world settings. Hence models for such complex tasks cannot rely on this end-task supervision alone; they should instead use these available agents.

Given these pre-requisites, we can define the goal of solving complex tasks by learning to talk to agents as follows:

**Challenge**: Learn a model to solve a complex task \(T\), given only:
- Training dataset \(D = \{(x_k, y_k)\}\) for \(T\);
- Agents \(\{f_1, \ldots, f_m\}\) that can be invoked to help solve \(T\);
- Examples \(\{u_{ij}\} \subseteq L_i\) of valid inputs for each agent \(f_i\) that captures its capabilities.

One example of such a task could be answering multi-hop questions, given two agents: an open-domain TextQA model \(f_1\) and an open-domain TableQA model \(f_2\). The TextQA model can use large textual corpora to answer questions such as “Who directed Kill Bill?” and “Who acted in Reservoir Dogs?” \(\{u_{1j}\}\). The TableQA model can use tables (e.g., Filmography tables in Wikipedia) to answer questions such as “List the movies directed by Quentin Tarantino” and “Which movies has Uma Thurman acted in?” \(\{u_{2j}\}\). Finally the training data for the complex task would contain examples such as (“What movies has the director of Kill

\(^2\)As mentioned earlier, we use agents to refer to models, assistants, or functions that take free-text as input and produce free-text as output.
Bill appeared in?”, [“Reservoir Dogs”, ....]). The goal of this work is to enable development of models that can learn to answer such multi-hop questions by talking to these agents which have already solved key and challenging sub-problems.

Apart from these minimal pre-requisites, in some cases we may also be able to obtain additional training supervision, or additional data about the internals of the agents. For example, it may be possible to annotate the ideal decomposition \( D_k \) of the complex task input \( x_k \) into valid inputs for various agents, or annotate the gold facts \( F_k \) that could be used to solve the task. Such annotation can then be used as intermediate supervision when training a model for the complex task.

Alternatively, when the agents are relatively simple, we may actually have access to the training data used to build these agents, or the underlying knowledge base \( K_i \) used by them (and possibly even a question-specific relevant subset \( K_{ik} \) of their knowledge). In the example above, \( K_i \) would be equivalent to the entire text corpora and table corpora used by the agents and \( K_{ik} \) could be the texts and tables relevant to the movie domain. Such information could be used as a substitute for actually invoking the agents, by first training the target model on the agents’ training data (as pre-training or multi-task training) or by supplying relevant knowledge directly to the target model. Such approaches, however, deviate from the kinds of models our dataset is designed to promote research on as they completely circumvent the agents. We nevertheless evaluate them and highlight their limits.

We thus have two kinds of potential auxiliary information:

- **Auxilliary Supervision (not always available):**
  - Gold Decomposition \( D_k \) for training examples
  - Gold Knowledge \( F_k \) for training examples

- **Auxilliary Data (generally not available):**
  - Training data \( D_{f_i} = \{(u_{ij}, v_{ij})\} \) for \( f_i \)
  - Complete knowledge resource \( K_i \) used by \( f_i \), or a manageable subset \( K_{ik} \subset K_i \) containing \( F_k \)

We emphasize that such auxiliary information may not always be available. A general-purpose system should therefore ideally learn to solve this challenge without relying on such additional information. However, this can be extremely difficult, as there are no existing methods that can be directly applied. Hence it’s acceptable for initial methods to rely on such auxiliary signals to develop narrower systems as stepping stones towards the more general challenge.

### 4 COMMAQA Benchmark

We next propose a new dataset COMMAQA, to enable development of models that can learn to communicate with existing agents. Specifically we provide a collection of three synthetic datasets for three variants of the multi-hop question answering task where each question is answerable by talking to simple QA agents. We focus on the QA task and use QA agents since the question-answer format can capture a broad range of tasks while also surface the capability of the agent (Gardner et al., 2019). For instance, the question “Does p entail h?” describes a capability of the invoked agent (namely, testing textual entailment) along with the inputs p and h.

#### 4.1 Complex Task: Multi-hop QA

We focus on the task of multi-hop question answering as it is naturally compositional—it is designed to make the system answer a sequence of single-hop questions in order to arrive at the final answer. Prior work (Welbl et al., 2018; Min et al., 2019b; Khot et al., 2021) has even decomposed multi-hop questions into questions answerable by a simple QA model, but these works have two limitations: they cover only single span answers and a small class of questions, and blackbox models performed competitively, if not better, than decomposition based models on the datasets they considered. In contrast, as we will show, state-of-the-art blackbox models struggle on COMMAQA. Further, our framework can be used to define future challenging datasets that focus on other complex reasoning tasks such as open-domain QA and multi-modal QA.

#### 4.2 Agents: QA models

We define and develop the multi-hop QA datasets using four QA agents that can answer simple questions given different underlying knowledge sources: (1) a TextQA agent that can answer questions based on textual knowledge; (2) a TableQA agent that uses tables; (3) a KBQA agent based on ConceptNet (Speer et al., 2017) relations; and (4) a MathQA agent that can perform arithmetic operations.

While this work focuses on the text modality, we do not fix the structure of the answers, e.g., to only a single span as is done in SQuAD (Rajpurkar
This work introduces a synthetic dataset, QA, designed to answer questions with similar variety of answer types. The dataset is intended to facilitate research on transformers to modify the output of QA agents. Additionally, we describe simple symbolic functions that query their corresponding knowledge resource. Since C\textsuperscript{OMMA}QA is a synthetic dataset with pre-determined language, we implement these agents as simple symbolic functions that query their corresponding knowledge resource. We hope this enables faster development of approaches that can learn to use these agents, without spending resources on running large-scale LMs for each agent. The specifics of the knowledge resource and the questions answerable by these agents are specific to the datasets and described in Sec. 4.5.

### 4.3 Composition Operators

Given the space of outputs from these agents (strings, lists, and maps), solving a complex task can often involve manipulating these data structures to produce valid inputs for invoking the next agent. To illustrate the complexity of this problem, consider the task of answering the following question from the DROP dataset ([Dua et al., 2019]: “Which player scored the most touchdowns?”). Given a TextQA agent \( f_1 \), one can start with: \( a_1 = f_1(c, "Who scored touchdowns?""). After, where \( a_1 = \{"Rodgers", "Adams"\} \) is the list of players that scored touchdowns. Next, the system needs to iterate over these players and find the number of touchdowns scored by each of them: \( a_2 = [(x, f_1("How many touchdowns did x score?")) \text{ for } x \in a_1] \). Since our TextQA agent cannot reason over a list of objects\(^3\), the system would need to learn such procedural composition operators to transform the list answer into a list of queries to the agent (i.e., iterating over all \( x \in a_1 \) and invoking \( f_1 \) on each).

Note that a TextQA agent may not even be able...
We next describe our approach to build the datasets. Values in a plates that can be answered by agent $f_i$ are sampled from a disjoint subset (based on the relation name) to base schema, we sample a set of facts $K_{ik}$. Given the space of entities and a knowledge base, we first sample entity names for each entity and assign $\arg\max$ to find the key with highest value in $a_2$. The agent then ground these templates (e.g. sample a valid entity for $f_1$) to create a complex question.

Here is a (truncated) example of the above question-generation process:

| $f_1$: TextQA | $f_2$: TableQA |
|----------------|-----------------|
| $K_{ik}$: directs("Spielberg", "Jaws"); directs("Spielberg", "ET");... |
| $K_{ik}$: released("Jaws", "1975"); released("ET", "1982");... |
| $u_{ij}$: "Which movies did Hithcock direct?"; "Who directed Kill Bill?";... |
| $u_{ij}$: "When was Jurassic Park released?"; "Which movies were released in 2020?";... |
| $x_k$: "When were movies directed by Spielberg released?" |

Theory:
$u_1$: select($f_1$, ... Which movies did Spielberg direct?)
$u_2$: project_keys($f_2$, $a_1$, When was __ released?)
$y_k$: ["1975", "1982"]

Note that sample inputs $\{u_{ij}\}$ are designed to never use the same entities as in the input complex question $x_k$. The system therefore cannot rely on simply memorizing these questions and is incentivized to extract a general pattern. Note that for brevity, the above example does not show the entire KB with other distractor entities and relations.

Constructing the dataset in this bottom-up fashion also makes it easy to generate auxiliary information for designing restricted systems as stepping stones towards the more general solution. Specifically, we run the questions in $\{u_{ij}\}$ against agent $f_i$ to obtain the training data for $f_i$. We verbalized the relations in the underlying knowledge base to generate the facts $K_i$ used by $f_i$. We use $f_i$ to additionally identify the facts in $K$ used to answer each question, thereby obtaining gold fact annotation. Finally, the theory itself can be directly used as gold decomposition supervision.

4.4 Building Examples

We next describe our approach to build the datasets in COMMAQA. At a high-level, we build a knowledge base, define the space of inputs for the QA agent, and create a complex question by applying composition operators over the agents’ input questions. Figure 2 describes our approach at a high-level. Given the space of entities and a knowledge base schema, we sample a set of facts $K_i$ and assign a disjoint subset (based on the relation name) to each agent $f_i$. We define a set of question templates that can be answered by agent $f_i$ over $K_{ik}$ (e.g. Who directed X?), and use this to generate examples of valid inputs $\{u_{ij}\}$ for $f_i$ by grounding them (e.g. Who directed Kill Bill?). We define a set of complex questions templates (e.g. What movies have people born in $1$ acted in?) and a corresponding sequence of operations (see Fig. 2) that can be used to answer each such question. We then ground these templates (e.g. sample a valid entity for $f_1$) to create a complex question.

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| $K_{ik}$: released("Jaws", "1975"); released("ET", "1982");... |
| $u_{ij}$: "Which movies did Hithcock direct?"; "Who directed Kill Bill?";... |
| $u_{ij}$: "When was Jurassic Park released?"; "Which movies were released in 2020?";... |
| $x_k$: "When were movies directed by Spielberg released?" |

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4.4.1 Details of Example Construction

We next describe our dataset construction in more detail. We first sample entity names for each entity type from a list of single-word names. To avoid any potential conflict with the knowledge that a LM may have obtained during pre-training, we create made-up entities using a GPT2 (Radford
We randomly assign the relations in our KB schema between these entities to create the knowledge base. Rather than building a static and very large KB for all the questions, we create a unique KB for a group of questions (similar to the reading-comprehension setting). This prevents any memorization of facts between the train and test splits as well as allows us to create a manageable KB size for the black-box model experiments. We also try to ensure that our dataset has sufficient distractor entities in this sampled KB.

We assign each relation to one of the agents and define the set of questions answerable by each agent based on these relations. E.g. we can assume that the "directs" relation is expressed in text and hence is answerable using the TextQA agent. However, it is possible that particular relations are expressed in a different knowledge resource for a different instance. So the same "directs" relation may be assigned to the TableQA agent in a different example. We define multiple questions for each agent and each relation, e.g. "Which movies has Spielberg directed?" and "What movies has Spielberg been the director of?" can both be part of $u_{ij}$ for TextQA and return the list of movies $\{y | \text{directs}("Spielberg", y) \in K_{ik}\}$.

For each sampled KB, we build a question group of $m$ questions ($m = 5$ in our experiments) by randomly selecting one of the pre-defined theories and a placeholder entity for the complex question (e.g. Spielberg in the example above). For simplicity, we ignore any questions that return in no answers or list answers that are too long ($\text{len}(y_k) \geq 5$). Since some theories may have fewer valid questions, they could end up being under-represented in the final dataset. To avoid this, we sample questions such that each theory has equal number of examples.

### 4.5 COMMAQA Dataset

In multi-hop QA, datasets have broadly focused on three different reasoning challenges—explicit decomposition (Yang et al., 2018; Trivedi et al., 2021), implicit decomposition (Mihaylov et al., 2018; Khot et al., 2020; Geva et al., 2021), and numeric reasoning (Dua et al., 2019; Ferguson et al., 2020). Inspired by these challenges, we use our framework to build the first multi-hop QA dataset with questions spanning all three classes.

**COMMAQA-E: Explicit Decomposition.** This dataset consists of multi-hop questions where the reasoning needed to answer the question is Explicitly described in the question itself (Yang et al., 2018; Ho et al., 2020; Trivedi et al., 2021). For example, "What awards have the movies directed by Spielberg won?". This dataset uses TextQA and TableQA agents designed for the movie domain. The underlying knowledge base has nine binary relations such as $\text{directed(movie,}$
person). We define six theories with two 2-hop compositions and four 3-hop compositions, and create complex questions using these theories. Refer to Figure 3 in the Appendix for the complete description of this dataset.

While these explicit decomposition questions clearly describe the needed reasoning steps, the knowledge needed for the steps might be split across different agents. For example, the movies directed by Spielberg might be listed in a text paragraph (and hence available to the TextQA agent) or in a table (and thus available to the TableQA agent). To emulate this behavior, we randomly assign certain predicates to the knowledge base of either the TextQA or TableQA agent within each question group. A successful system would therefore need to search for answers to individual reasoning steps against every potential agent, which makes the task challenging.

**COMMAQA-I: Implicit Decomposition.** This dataset consists of multi-hop questions where the reasoning needed is Implicit (Khot et al., 2020; Geva et al., 2021), for example, "Did Aristotle use a laptop?". Such questions do not explicitly describe the reasoning needed to answer the question (e.g., comparing Aristotle’s life’s time period with that of the invention of laptops). Inspired by such questions in StrategyQA (Geva et al., 2021), we create this dataset with just two question styles but with many possible ways to answer them: (1) "What objects has __ likely used?" and (2) "What objects has __ helped make?". We designed this dataset with a TextQA and a KBQA agent (with an associated textual and structured KB knowledge source, respectively).

As illustrated in Fig. 4 (in Appendix), the implicit reasoning strategy needed to answer this question can vary across examples. We define multiple reasoning strategies for each question type, but only one strategy is applicable for a given entity in the knowledge base. Note that this is a deliberate choice as similar sounding questions can have very different strategies in a real world setting. For example, "Did Steve Jobs help develop an Iphone?" needs a different answering strategy than "Did Edison help develop the television?".

**COMMAQA-N: Numeric Decomposition.** This dataset consists of Numeric (also referred to as discrete) reasoning questions requiring some mathematical operation, in addition to other types of inference. For example, "Who threw javelins longer than 5 yards?". We focus here on the sports domain and use three agents: TextQA, TableQA, and MathQA.

As illustrated in Fig. 5, the reasoning chains look much longer due to the presence of arithmetic operations, but these steps are generally much simpler (e.g., difference) than answering TextQA questions.

### 4.6 Final COMMAQA dataset

The final dataset consists of the three QA sub-datasets described above, whose key statistics are summarized in Table 4. We have equal number of examples in all the datasets with a 80%/10%/10% train/dev/test split. To ensure we have sufficient distractors in our KB, we need to sample a larger number of facts for COMMAQA-N and COMMAQA-I. For example, if we only have two entities belonging to the target answer type, there are only three non-empty subsets that can be valid answers for these datasets – making this effectively a 3-way multiple choice. For COMMAQA-N, we do not need as many distractors due to the numeric operations increasing the space of output answers. But the theories are much longer (as evidenced by the number of gold facts) in COMMAQA-N making it still a challenging dataset.

To generate the space of valid inputs $L_i$ for each agent $f_{ij}$, we define questions corresponding to each relation (in both directions) in the corresponding knowledge base, e.g., "Who all produced the movie __?" and "For which movies was __ the producer?". To emulate redundancy in natural language, we specify multiple phrasings for the same question. Similar to the construction of the COMMAQA dataset, we first sample a KB and then sample queries for each agent to generate $\{u_{ij}\} \subset L_i$.

As stepping stones towards solving the full challenge, we provide auxiliary information as part of the dataset. Specifically, COMMAQA includes the decompositions for all the questions in the same language as the underlying theory. Since we have multiple queries for the same KB relation, we randomly sample one of them to generate these decomposition annotations (see examples in Table 3).

To create the knowledge resource $K_{ij}$ associated with each question, we define modality-specific verbalizers that convert a KB relation into text. For example, the director(M, P) relation in a TextQA KB is converted into the fact "M was a movie directed by P", whereas the same relation a TableQA
Table 3: Sample Decomposition Annotations for example questions in COMMAQA. We denote the composition operators using the \([\text{operation}] <\text{agent}>\) format. Note that we simplify the \(\text{project\_values}\) operation to just \(\text{project}\) here.

| Question | Decomposition |
| --- | --- |
| **COMMAQA-E** | \(\text{select} <\text{TextQA}>\) Who were born in 1942? A: [“Flumph”, “Wetherality”] |
| What movies has #1 written? | \(\text{project\_flat\_unique} <\text{TextQA}>\) What movies has #1 written? A: [“Compressie”, “Sagali”, “Skirtscime”, “Tetroxidine”, “Coesestion”] |
| What objects has Teinteen likely used? | \(\text{project\_flat\_unique} <\text{TextQA}>\) Which objects are used by a #2? A: [“biopsie”, “jorrel”, “tenderhilskin”, “monovacuum”] |

Table 4: Average Statistics of COMMAQA.

| COMMAQA – | E | I | N |
| --- | --- | --- | --- |
| Total \#Qs | 10K | 10K | 10K |
| \#answer spans/question | 3.21 | 3.29 | 1.36 |
| \#entity types | 7 | 13 | 5 |
| \#relations | 11 | 16 | 4 |
| \#theories | 6 | 5 | 6 |
| \#uij templates | 41 | 68 | 24 |
| \#KB facts/KB | 169.4 | 175.7 | 80 |
| \#T5tokens/KB | 2252.9 | 2540.9 | 1513.4 |
| \#Gold facts/question | 7.5 | 6.9 | 15.4 |

We use the decomposition annotation to identify the relevant facts for each step and annotate them as the gold facts \(\mathcal{F}\). To create the auxiliary training data for each agent \(f_i\), we similarly sample KBs \(\mathcal{K}_{ij}\) and use the question templates to generate \((\{u_{ij}, \mathcal{K}_{ij}\}, v_{ij})\). We refer to this as the \(\text{COMMAQA}_{A + \mathcal{K}_{ij}}\).

5 Experiments

We next evaluate current state-of-the-art models on the COMMAQA dataset. Unfortunately there are no existing models that can be trained for the task of learning to talk to agents using only end-task supervision. Hence we focus on evaluating current models given one or more of the auxiliary data/supervision.

5.1 Models

Models with Access to Agent Knowledge:

Given access to the underlying knowledge \(\mathcal{K}_{ijk}\) associated with each complex question \(x_k\) and agent \(f_i\), one could treat the information in \(\mathcal{K}_{ijk}\) as a “context” for the question. This turns the problem into the commonly studied reading comprehension (RC) setting. We can now train standard black-box models to generate the answer given the question and the context containing verbalized facts.\(^5\)

We train a T5-Large and a T5-11B model on each of the three datasets to generate the answer given the question and facts in \(\mathcal{K}_{ijk}\).\(^6\) Since many

\(^5\)We reiterate that it is often unreasonable to expect access to \(\mathcal{K}_{ijk}\) and especially \(\mathcal{K}_{ijk}\). This model tries to solve COMMAQA without invoking agents, which deviates from the purpose of our benchmark dataset. Nevertheless, we conduct experiments in this setting for completeness and as a stepping stone towards solving the larger challenge.

\(^6\)We format the input sequence as \(<\text{concatenated facts}>\) Q: <question> A:
of the answers can be multiple spans, we sort\(^7\) and concatenate them into a single string with ‘+’ as the separator. As noted in Table 4, the verbalized facts can result in a context over 2K tokens long. We trained T5-Large models on A100 80G GPUs and T5-11B models on v3-32 TPUs to train on such a long context. Transformers designed for longer documents (Beltagy et al., 2020; Zaheer et al., 2020) would be able to handle such contexts more efficiently but generally under-perform due to sparse attention. Hence we don’t evaluate them here.

**Models with Fact Supervision:** If, in addition to access to the underlying knowledge \(K_{ik}\), we also have supervision for the gold facts \(F_k\) used by the agents for each training question \(x_k\), we can use this annotation to train a model to first identify relevant facts from \(K_{ik}\). We can then use this model to select the top-scoring facts to produce a shorter context for T5-Large and T5-11B model (same format as above). Note that such annotations are often very difficult to obtain, especially given large knowledge bases (Jansen et al., 2018). Further, the caveats of Footnote 5 also apply here.

We train a RoBERTa-Large model to classify the relevance of each fact independently given the input question. We select the top scoring facts such that \#tokens < 512 to create a smaller context.\(^8\) These smaller contexts reduce the amount of distractors (i.e., increase precision) to make the QA task easier, at the cost of sometimes dropping relevant facts (i.e., reducing recall). Generally with a limit of \#tokens < 512, we observe an average recall of around 0.9 on these datasets.

We also experimented with fine-tuning a T5-based UnifiedQA-large model (Khashabi et al., 2020) on this fact selected set, which has the advantage of having been additionally pre-trained on 7 benchmark QA tasks across several task formats. Given that this pre-training bears some resemblance to the structure of our tasks (and hence, potentially simulates some of the private data we assume our ideal agents would have been trained on), one goal is to test whether additional pre-training alone is an effective solution for obtaining high performance.

**Models with Decomposition Supervision:** None of the above models actually solve the problem of talking to agents—they circumvent it by directly interacting with the possibly private auxiliary data. Given decomposition supervision \(D_k\) for training questions \(x_k\), we can actually train a model that can then talk to these agents to solve the task.

Specifically, we train a T5-Large model to generate a decomposition (including the agent name and operation) given a complex question as input, and then ask the decomposed questions to appropriate agents. To this end, we use the Text Modular Network (TMN) framework (Khot et al., 2021) that trains a NextGen model to produce only the next question in the decomposition chain given the previous chain of questions and answers. Additionally they sample multiple questions at each step of the chain to search for a valid chains of reasoning. This framework is ideal for our dataset as some reasoning chains may lead to dead-ends, if the knowledge is not available to a given agent (e.g., in COMMAQA-E) or it is not the right strategy for this context (e.g., in COMMAQA-I).

### 5.2 Results

We compare these three classes of models on the COMMAQA dataset in Table 5.\(^9\)

**Black-box models struggle on COMMAQA:** Due to the large number of distractors, black-box models struggle to learn the task across all three datasets with average F1 below 30. The low performance on COMMAQA-E is especially notable as the reasoning needed to answer the question is explicit and described. While language models have shown to be successful on similar datasets (Yang et al., 2018) with fewer distractors, this shows that these models are not as powerful. The best performance of these models is on the COMMAQA-N dataset possibly due to two factors: the fact KB is smaller and some answers are single numbers instead of spans.

**Fact Annotations are helpful but insufficient:** The models trained on shorter context (by relying on fact annotations) are able to take advantage of the reduced #distractors and improve their F1 score. While the larger T5-11B struggled on the longer context, it was able to infer the reasoning patterns better with shorter contexts and outperform the T5-

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\(^{7}\)To ensure a deterministic order, we sort the answers in alphabetical order.

\(^{8}\)Tokens here are based on white-space splitting.

\(^{9}\)The Dev and Test numbers are identical. We report Dev numbers here.
Table 5: We train and evaluate all the models on the individual datasets and report their exact match (EM) / F1 score. We also compute the average EM and F1 across all three datasets (all three models weighed equally) to compute the aggregate EM and F1 score in the last column. Given the full KB, both black-box models struggle on this dataset. Using the additional fact supervision helps these models, but they still lag behind the TMN models that use the provided agents.

| Model          | Aux. Supervsn. | Aux. Data | Invokes Agents | COMMAQA-E EM / F1 | COMMAQA-I EM / F1 | COMMAQA-N EM / F1 | COMMAQA EM / F1 |
|----------------|----------------|-----------|----------------|-------------------|-------------------|-------------------|-----------------|
| T5-Large       | -              | \{K_{ik}\} | ×              | 0.8 / 30.0        | 0.1 / 15.5        | 33.9 / 37.7       | 11.6 / 27.7     |
| T5-11B         | -              | \{K_{ik}\} | ×              | 0.0 / 16.8        | 0.0 / 17.5        | 1.5 / 17.0        | 0.5 / 17.1      |
| T5-Large       | \mathcal{F}_k | \{K_{ik}\} | ×              | 38.8 / 72.6       | 20.4 / 47.9       | 30.5 / 35.3       | 29.9 / 51.9     |
| UnifiedQA-lrg  | \mathcal{F}_k | \{K_{ik}\} | ×              | 38.8 / 72.8       | 24.2 / 50.3       | 26.1 / 33.2       | 29.7 / 52.1     |
| T5-Large       | \mathcal{F}_k | \{K_{ik}\} | ×              | 43.8 / 76.0       | 20.9 / 50.24      | 57.9 / 58.1       | 40.9 / 61.5     |
| TMN, Greedy    | \mathcal{D}_k | -         | ✓              | 76.5 / 76.5       | 44.1 / 44.1       | 98.3 / 99.2       | 72.9 / 73.3     |
| TMN, Search    | \mathcal{D}_k | -         | ✓              | 96.1 / 96.1       | 99.4 / 99.4       | 100 / 100         | 98.5 / 98.5     |

Table 6: We evaluate the best-performing models on a compositional generalization test set. The EM scores for the black-box models are halved on the COMMAQA-E generalization set and completely fail to generalize on the COMMAQA-N set. TMNs observe a smaller drop in their EM score as they create semantically valid but out-of-scope questions.

| Model          | Aux. Info | COMMAQA-E | COMMAQA-N |
|----------------|-----------|-----------|-----------|
| T5-Large       | \{K_{ik}\}| 0.0 / 30.6 | 1.0 / 1.0 |
| T5-Large       | \mathcal{F}_k, \{K_{ik}\}| 15.0 / 61.8 | 1.0 / 1.0 |
| TMN search     | \mathcal{D}_k| 69.0 / 69.0 | 65.0 / 65.0 |

Large models.\textsuperscript{10} Relying on UnifiedQA and its additional pre-training doesn’t lead to any noticeable improvement over fine-tuning using T5-large.

**COMMAQA can be solved by talking to the agents:** While black-box models struggle on COMMAQA, a TMN model trained on the gold decomposition annotations can solve this task.\textsuperscript{11} Of course, such decomposition annotations could be impossible to obtain for real-world datasets. Nevertheless, this experiment shows that COMMAQA can be solved by a model that learns to talk to the agents (as designed). We also note that greedily selecting the next question, i.e., no search, results in much lower performance on COMMAQA-E and COMMAQA-I, the two datasets that have multiple decompositions for the same question.

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\textsuperscript{10}Larger contexts also required truncation of T5-11B models to 2048 tokens which could also explain their lower performance on longer contexts

\textsuperscript{11}The slightly lower numbers are primarily due to a limited search space. All errors were due to a failed search.

5.3 Compositional Generalization

We also create a compositional generalization test set for COMMAQA-E and COMMAQA-N to check the generalization ability of these models. Specifically, we create questions using novel composition of queries where each query has been seen during training but never together in this form. E.g. we create a new question "What awards have the directors of the __ winning movies received?", given that the model was trained on questions such as "What awards have the actors of the __ winning movies received?", "What movies have the directors from __ directed?", "What movies have people from the country __ acted in?".

As shown in Table 6, all models struggle on this test set. Even the strong TMN-Search model drops in score by about 30 F1 pts on this test set. We analyze the error cases and noticed that the model does capture the semantics of the new question correctly. However it uses language that is not in the space of valid inputs. For example, to answer the question "What awards have the directors of the XX winning movies received", it tries to find the list of directors of the XX-winning movies by asking "Who are the directors in the movie {}?". The model had basically learned to generalize the training sub-question: "Who are the actors in the movie {}?" to "Who are the directors in the movie {}?". But the space of valid inputs for the QA agents only includes: "Which movies has {} directed?" and "What movies has {} been the director of?". Adding constraints to respect the space of inputs or a model that detects potential violations would be helpful to ensure generalization of such systems.

6 Future Work

Currently the lexical diversity in our dataset is very limited and based on hand-authored patterns. Using language models to generate more semantically
equivalent statements as well as questions could introduce more diversity and make the task more challenging.

In this work, we assume that all models have a 100% accuracy and only answer questions that are within a narrow scope. When dealing with trained models, this will often not be the case. Models will make mistakes and even attempt to answer questions that are out of its scope. Emulating this behavior, and the type of noise that one would encounter in a more naturalistic datasets and settings, is one avenue of future work.

We did not include any boolean questions in this dataset as they have a high random-chance baseline making it hard to measure meaningful progress. Also they can be hard to train via end-task supervision only (Dasigi et al., 2019). Adding such boolean questions and other boolean operations can lead to an even harder dataset for compositional approaches.

7 Conclusion

In this work we motivate a new challenge task of solving complex task by communicating with existing AI agents. Developing approaches for this challenge, we argue, could allow for more generalizable, privacy-preserving and efficient models. Towards this goal, we introduce a new benchmark dataset COMMAQA which involves multi-hop questions with three multi-hop reasoning challenges, all solvable by composing four QA agents. Each agent has an internal knowledge base (similar to AI assistants or large LMs) that can be queried via natural language queries. Experiments with state-of-art language models indicated that they struggle to solve COMMAQA, even when provided with agents’ internal knowledge. In contrast, a model that is able to learn to communicate with the agents, albeit using annotated decompositions, is able to solve this task. This indicates the need and potential of such approaches to solve complex tasks. We hope this dataset will enable future work on learning to communicate with agents without relying on this additional supervision.

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Figure 3: Example KB, space of valid inputs and theory used to construct COMMAQA-E

Figure 4: Example KB, space of valid inputs and theory used to construct COMMAQA-I
Figure 5: Example KB, space of valid inputs and theory used to construct COMMAQA-N