Abstract

Compositional reasoning tasks like multi-hop question answering, require making latent decisions to get the final answer, given a question. However, crowdsourced datasets often capture only a slice of the underlying task distribution, which can induce unanticipated biases in models performing compositional reasoning. Furthermore, discriminatively trained models exploit such biases to get a better held-out performance, without learning the right way to reason, as they do not necessitate paying attention to the question representation (conditioning variable) in its entirety, to estimate the answer likelihood. In this work, we propose a generative context selection model for multi-hop question answering that reasons about how the given question could have been generated given a context pair. While being comparable to the state-of-the-art answering performance, our proposed generative passage selection model has a better performance (4.9% higher than baseline) on adversarial held-out set which tests robustness of model’s multi-hop reasoning capabilities.

1 Introduction

Recently many reading comprehension datasets like HotpotQA (Yang et al., 2018) and WikiHop (Welbl et al., 2018) that require compositional reasoning over several disjoint passages have been introduced. This style of compositional reasoning, also referred to as multi-hop reasoning, first requires finding the correct set of passages relevant to the question and then the answer span in the selected set of passages. Most of these dataset are often collected via crowdsourcing, which makes the evaluation of such models heavily reliant on the quality of the collected held-out sets.

Crowdsourced datasets often present only a partial picture of the underlying data distribution. Learning complex latent sequential decisions, like multi-hop reasoning, to answer a given question under such circumstances is marred by numerous biases, such as annotator bias (Geva et al., 2019), label bias (Dua et al., 2020; Gururangan et al., 2018), survivorship bias (Min et al., 2019; Jiang and Bansal, 2019), and ascertainment bias (Jia and Liang, 2017). As a result, testing model performance on such biased held-out sets becomes unreliable as the models exploit these biases and learn shortcuts to get the right answer but without learning the right way to reason.

Consider an example from HotpotQA in Figure 1, where the latent entity “Virginia Commonwealth University” can be used by the model (Jiang and Bansal, 2019) to bridge the two relevant passages (highlighted in green) from the original dev set and correctly predict the answer “1838”. However, upon adding an adversarial context (high-
lighted in pink) to the pool of contexts, the model prediction changes to “1938” implying that the model did not learn the right way to reason. This is because the discriminatively trained passage selector exploits lexical cues like “founded” in the second passage and does not pay attention to the complete question. The absence of such adversarial contexts at training allows the model to find incorrect reasoning paths.

In this work, we propose a generative context pair selection model, which tries to reason through the data generation process of how a specific question could have been constructed from a given pair of passages. We show that our proposed model is comparable in performance to the state-of-the-art systems, with minimal drop in performance on the adversarial held-out set. Our generative passage selector shows an improvement of 4.9% in Top-1 accuracy as compared to discriminatively trained passage selector on the adversarial dev set.

2 Generative Passage Selection

Given a set of contexts $C = \{c_0, c_1, ... c_N\}$, the goal of multi-hop question answering is to combine information from multiple context passages to identify the answer span $a$ for a given question $q$. In single-hop QA, the goal is to identify the pair of contexts, from all possible pairs $\psi = \{(c_i, c_j) : c_i \in C, c_j \in C\}$, that is appropriate for answering the question.

Existing models for multi-hop question answering (Tu et al., 2020; Chen et al., 2019) consist of two components: a discriminative passage selection and an answering model. Passage selection identifies which pairs of contexts are relevant for answering the given question, i.e. estimates $p(c_{ij}|q, \psi)$. This is followed by the answering model to extract the answer span given a context pair and the question ($p(a|q, c_{ij})$). These are combined as follows:

$$p(a, q|\psi) = \sum_{c_{ij}} p(a|q, c_{ij})p(c_{ij}|q, \psi)$$

(2)

First, a prior, $p(c_{ij}|\psi)$, over the context pairs establishes a measure of compatibility between passages in a particular dataset. Then, a conditional generation model, $p(q|c_{ij})$, establishes the likelihood of generating the given question from a selected pair of passages. Finally, a standard answering model, $p(a|q, c_{ij})$, estimates the likely answer distribution given a question and context pair. The first two terms (prior and conditional generation) can be seen as a generative model that chooses a pair of passages from which the given question could have been constructed. The answering model can be instantiated with any existing state-of-the-art model, such as a graph neural network (Tu et al., 2020; Shao et al., 2020), entity-based chain reasoning (Chen et al., 2019), etc.

The process at test time is identical to that with discriminative passage selection, except that the context pairs are scored by taking the entire question into account, $c_{ij}^*$ = argmax$_{c_{ij}} p(q|c_{ij})p(c_{ij}|\psi)$.

2.1 Model Description

We propose a joint question-answering model which learns $p(a, q|\psi)$ instead of $p(a|q, \psi)$. This joint question-answer model can be factorized into a generative passage selector and a standard answering model as:

$$p(a, q|\psi) = \sum_{c_{ij}} p(a|q, c_{ij})p(q|c_{ij})p(c_{ij}|\psi)$$

(2)

In other words, we use passage selection to pick the best context pair $c_{ij}^*$, which is used by the answering module to get the answer, $a^* = \text{argmax}_{c_{ij}} p(a|q, c_{ij})$.

2.2 Model Learning

We use a pre-trained T5 (Raffel et al., 2019) based encoder-decoder model for obtaining contextual representations, which are further trained to estimate all individual probability distributions.

For learning the generative model, we train the prior, $p(c_{ij}|\psi)$ and the conditional generation model $p(q|c_{ij}, \psi)$ jointly. First, the prior network projects the concatenated contextualized representation, $r_{ij}$, of starting and ending token of concatenated contexts $(c_i; c_j)$, from the encoder to obtain un-normalized scores, which are then normalized across all context-pairs via softmax operator. The

$\text{Summing over all context pairs, or maintaining a beam of highly ranked pairs, did not yield much higher performance, in particular, not worth the additional computation cost.}$
We experiment with two popular multi-hop passage selection accuracy: 73.5 all EM are 74.5 performance. The generative selector on end-to-end model performance has a comparable performance to SOTA answering models to illustrate the effect that has a comparable performance to SOTA passage selector (Table 1).

We use an existing adversarial set (Jiang and Bansal, 2019) for HotpotQA to test the robustness of model’s multi-hop reasoning capabilities given a confusing passage. This helps measure, quantitatively, the degree of biased correlations learned by the model. In Table 2, we show that the standard discriminative passage selector has a much higher performance drop (−4%) as compared to the generative selector (−1%) on adversarial dev set (Jiang and Bansal, 2019), showing that generative selector is less biased and less affected by conservative changes (Ben-David et al., 2010) to the data distribution. We can also see in Table 2 that SOTA models (Tu et al., 2020; Fang et al., 2019), which use the standard passage selector, also have a larger F1 drop when applied to the adversarial set. Table 3 shows that the generator was able to generate multi-hop style questions using both the contexts.

### 3.1 Adversarial Evaluation

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### 3.2 Context pairs vs. Sentences

Some context selection models for HotpotQA use a multi-label classifier that chooses top-k sentences (Fang et al., 2019; Clark and Gardner, 2017) which result in limited inter-document interaction than context pairs. To compare these two input types, we construct a multi-label sentence classifier \( p(s|q, C) \) that selects relevant sentences. This classifier projects a concatenated sentence and question representation, followed by a sigmoid, to predict if the sentence should be selected. This model has a better performance over the context-pair selector but is more biased (Table 4).

We performed similar experiments with the generative model. Along with the passage selection model, we train a generative sentence selection model by first selecting a set of sentences with gumbel softmax and then generating the question.
The America East Conference is a collegiate athletic conference affiliated with the NCAA Division I, whose members are located mainly in the Northeastern United States. The conference was known as the Eastern College Athletic Conference-North from 1979 to 1988 and the North Atlantic Conference from 1988 to 1996.

The Vermont Catamounts men’s soccer team represents the University of Vermont in all NCAA Division I men’s college soccer competitions. The team competes in the America East Conference.

Table 3: Sample questions generated by using the question generation decoder with top-k sampling show that the generative model is able to construct (reason about) possible multi-hop questions given a context-pair.

| Model | Original | Adversarial |
|-------|----------|-------------|
| **Discriminative Selectors** | | |
| Passage, \(p(c_{ij}|q, \psi)\) | 95.3 | 96.3 |
| Sentence, \(p(s|q, C)\) | 97.6 | 90.9 |
| **Generative Selectors** | | |
| Passage, \(p(q|c_{ij}, \psi)p(c_{ij}|\psi)\) | 97.5 | 96.3 |
| Sentence, \(p(q|s, C)p(s|C)\) | 90.6 | 89.2 |
| Multi-task, \(p(q, s|c_{ij}, \psi)p(c_{ij}|\psi)\) | 98.1 | 97.2 |

Table 4: **Passages vs Sentences**: Passage selection accuracy for models with different context inputs on the development and adversarial set of HotpotQA.

given the set of sentences. Given that the space of set of sentences is much larger than context pairs, the generative sentence selector does not have good performance (Table 4). To further improve the performance of the generative selector, we add an auxiliary loss term that predicts the relevant sentences in the context pair, \(p(q, s|c_{ij}, \psi)\), along with selecting the context pair in a multi-task setting. We see slight performance improvements by using relevant sentences as an additional supervision signal.

## 4 Related work

Most passage selection models for HotpotQA and Wikihop’s distractor style setup employ a RoBERTA based context selectors given the question (Tu et al., 2020; Fang et al., 2019). In an ideal scenario, the absence of latent entity in the question should not allow selection of all oracle passages. However, the high performance of these systems can be attributed to existing bias in HotpotQA (Jiang and Bansal, 2019; Min et al., 2019).

Another line of work dynamically updates the working memory to re-rank the set of passage at each hop (Das et al., 2019). With the release of datasets like SearchQA (Dunn et al., 2017), TriviaQA (Joshi et al., 2017), and NaturalQuestions (Kwiatkowski et al., 2019), lot of work has been done in open-domain passage retrieval, especially in the full Wikipedia setting. However, these questions do not necessarily require multi-hop reasoning. A series of work has tried to match a document-level summarized embedding to the question (Seo et al., 2018; Karpukhin et al., 2020; Lewis et al., 2020) for obtaining the relevant answers. In generative question answering, a few works (Lewis and Fan, 2018; dos Santos et al., 2020) have used a joint question answering approach on single context.

## 5 Conclusion

We have presented a generative formulation of context pair selection in multi-hop question answering models. By encouraging the context selection model to explain the entire question, it is less susceptible to bias, performing substantially better on adversarial data than existing methods that use discriminative selection. Our proposed model is simple to implement and can be used with any existing (or future) answering model; we will release code to support this integration.

Since context pair selection scales quadratically with the number of contexts, it is not ideal for scenarios that involve a large number of possible contexts. However, it allows for deeper inter-document interaction as compared to other approaches that use summarized document representations. With more reasoning steps, selecting relevant documents given only the question becomes challenging, increasing the need for inter-document interaction.
6 Ethical Considerations
This paper focuses on biases found in question answering models that make its reasoning capabilities brittle. It uses an existing method of testing model performance on adversarial held-out set as an evaluation metric. This work does not deal with any social impacts of biases in natural language processing systems.

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