Mitigating False-Negative Contexts in Multi-document Question Answering with Retrieval Marginalization

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Abstract

Question Answering (QA) tasks requiring information from multiple documents often rely on a retrieval model to identify relevant information from which the reasoning model can derive an answer. The retrieval model is typically trained to maximize the likelihood of the labeled supporting evidence. However, when retrieving from large text corpora such as Wikipedia, the correct answer can often be obtained from multiple evidence candidates, not all of them labeled as positive, thus rendering the training signal weak and noisy. The problem is exacerbated when the questions are unanswerable or the answers are boolean, since the models cannot rely on lexical overlap to map answers to supporting evidences. We develop a new parameterization of set-valued retrieval that properly handles unanswerable queries, and we show that marginalizing over this set during training allows a model to mitigate false negatives in annotated supporting evidences. We test our method with two multi-document QA datasets, IIRC and HotpotQA. On IIRC, we show that joint modeling with marginalization on alternative contexts improves model performance by 5.5 F1 points and achieves a new state-of-the-art performance of 50.6 F1. We also show that marginalization results in 0.9 to 1.6 QA F1 improvement on HotpotQA in various settings.

1 Introduction

Multi-document question answering refers to the task of answering questions that require reading multiple documents, extracting relevant facts, and reasoning over them. Systems built for this task typically involve retrieval and reasoning components that work in tandem. The retrieval component needs to extract information from the documents that is suitable for the reasoning model to perform the end-task effectively. Recent advances in reading comprehension have resulted in models that have been shown to answer questions requiring complex reasoning types such as bridging, comparison (Asai et al., 2020; Tu et al., 2020) or even arithmetic (Ran et al., 2019; Gupta et al., 2020), given adequate context. However, when the context needs to be retrieved from a large text corpus (e.g., Wikipedia), the performance of such reading comprehension models is greatly affected by the quality of the retrieval model. Given supervision at

An Example in IIRC:
Q: How many other Cardinals participated in the 2005 papal conclave with Policarpo?
A: 115
From article "2005 papal conclave":
Snippet 1: After accepting his election, he took the pontifical name of Benedict XVI.
Snippet 2: Of the 117 eligible members of the College of Cardinals ... all but two attended.
Snippet 3: With 115 cardinals electors participating ...

An Example in HotpotQA:
Q: What languages did the son of Sacagawea speak?
A: French, English, German, Spanish, Shoshone and other western American Indian languages
From article "Charbonneau, Oregon":
Snippet 1: The development was named for Jean Baptiste Charbonneau, the son of Sacagawea.
From article "Museum of Human Beings":
Snippet 2: ... which delves into the heart-rending life of Jean-Baptiste Charbonneau, the son of Sacagawea.
From article "Jean Baptiste Charbonneau":
Snippet 2: ... He spoke French and English, and learned German and Spanish during his six years in Europe from 1823 to 1829. He spoke Shoshone, his mother tongue, and other western American Indian languages.

Figure 1: Examples of alternative contexts in multi-document QA. Equivalent information is marked in blue, and only the snippets with "✓" are annotated as gold evidence. The HotpotQA example is from Xiong et al. (2020).
all stages (i.e., document, supporting evidence and answer), it is common to build retrieval and reasoning models independently and connect them as a pipeline at test time. In this case, the retrieval and reasoning models are usually trained to maximize the likelihood of labeled supporting evidences and the answer given the gold context respectively.

However, in a multi-document QA setting, it is common to have some relevant snippets not marked as gold. Two such examples are shown in Fig. 1. In the first example, only snippet 2 is marked as gold evidence thus snippet 1 and 3 are usually treated as negative examples during retrieval. This is problematic because unlike snippet 1 which is actually irrelevant, snippet 3 is not only useless, but provides an even more direct way to derive the correct answer since it does not require a subtraction. Similarly, in the second example two evidence snippets from different documents contain the same information, thus at least two contexts can be used to answer this question, yet only one of them is labeled as being a positive example for the training objective. We define these contexts that contain non-gold snippets and can still be used to answer the questions as alternative contexts. These alternative contexts are considered false negatives during training and lead to noisy and weak learning signal, even with this "fully-supervised" setup. Due to the size of such corpus, it is prohibitively expensive to exhaustively annotate all possible contexts, thus the presence of false-negative contexts is inevitable.

We design a training procedure for handling these false negatives, as well as cases where retrieval should fail (i.e., when the question is unanswerable). Specifically, we assign probabilities to documents, evidence candidates, and potential answers with parameterized models, and marginalize over a set of potential alternative contexts by combining top retrieved evidences from each document, allowing the model to score false negatives highly. To make the marginalization feasible, we decompose the retrieval problem into document selection and evidence retrieval and show how we can still model contexts as sets. To evaluate our model on two multi-document QA datasets: IIRC (Ferguson et al., 2020) and HotpotQA (Yang et al., 2018). Our method improves the final QA F1 performance by 0.9 to 4.8 points from the traditional pipeline approaches across different datasets and settings. Our final result of 50.6 F1 on IIRC represents a new state-of-the-art.

| Total questions # | 44 |
| Total documents # | 50 |
| Documents w/ at least one alternative context | 27 |
| Avg. # alternative evidence per document | 1.14 |
| Question w/ at least one alternative context | 28 |

Table 1: Alternative evidence/context in IIRC. Analysis is done on a small subset of the training set.

2 Multi-Document QA

Here we formally describe the multi-document QA setting and highlight the two main challenges in this setting that our work attempts to address.

Problem Definition Multi-document question answering measures both the retrieval and reasoning abilities of a QA system. Given a question \( q \) and a set of documents \( D = \{d^1, d^2, ..., d^n\} \), each document containing a set of evidences \( d^i = \{s^i_1, s^i_2, ..., s^i_{n_i}\} \), the goal of the model is to output the correct answer \( a \). This task is typically modeled with a retrieval step, which locates a set of evidences \( C = \{s^1_{j_1}, s^2_{j_2}, ..., s^{k_h}\} \) to formulate a context, and a reasoning step to derive the answer from such context \( C \). Though such models can be learned with or without annotations on supporting evidences, we focus on the fully-supervised setting and assume supervision for all stages. It is also common for such documents to have some internal structure (e.g., hyperlinks in Wikipedia, citations for academic papers), which can be used to constrain the space of retrieval.

Inevitable False-negatives in Context Retrieval Annotations Even when supporting evidence is annotated, we claim that the learning signal provided by those labels may be weak and noisy when retrieving from a large corpus such as Wikipedia. This is due to the redundancy of information in such large corpora: it is common to have multiple sets of supporting evidences that can answer the same question, as in Fig. 1. To quantify how often alternative contexts exist for the multi-document QA problem, we analyzed IIRC (Ferguson et al., 2020), an information seeking multi-document QA dataset. We sampled 50 answerable questions with labeled with a retrieval step, which locates a set of alternative contexts exist for the multi-document QA setting and highlight the two main challenges in this setting that our work attempts to address.
not labeled as supporting evidence, in the same document. From Tab. 1, we can see that more than half of the questions have at least one alternative context, and on average there is more than one sentence we can find in the same document that contains the same information as the gold evidence. Note that it is also possible to have alternative evidence in a different document, which would further increase the frequency of questions with alternative contexts.

Due to the prevalence of such false-negative evidences and contexts, simply training the retrieval model to maximize the likelihood of the labeled supporting evidences would result in the models ignoring or even being confused by other unlabeled relevant information that could benefit the reasoning process. The problem is more severe when considering questions with boolean answers or those that are unanswerable since the answers have no lexical overlap with corresponding evidence making it harder to identify unlabeled yet relevant evidence snippets. Such false-negative context annotations are also inevitable in the data creation process, since the annotators will have to exhaustively search for evidences from all relevant documents, which is rather unpractical. As solving this problem is not typically feasible during data collection, we instead deal with it during learning.

### Learning to Reason with Noisy Context

Given retrieved supporting evidence as context, the second step of the problem is reading comprehension. Recently proposed models have shown promise in answering questions that require multi-hop (Nishida et al., 2019; Asai et al., 2020; Tu et al., 2020) or even numerical (Ran et al., 2019; Gupta et al., 2020) reasoning given small and sufficient snippets as contexts. However, the performance of such models degenerates rapidly when they are evaluated in a pipeline setup and attempt to reason with retrieved contexts that are potentially noisy and incomplete. For instance, Ferguson et al. (2020) found that the performance of reasoning models can drop 39.2 absolute F1 when trained on gold contexts and evaluated on retrieved contexts. This is mainly because the model is exposed to much less noise at training time than at test time.

### Handling Retrieval for Unanswerable Questions

It is especially challenging when we consider questions to be unanswerable since it is possible to have documents that are obviously relevant but the answer might not appear in any of its sentences. Take IIRC (Ferguson et al., 2020) as an example, where the questions annotators are given initial paragraphs to generate questions, and they may label some links to other documents to be relevant but the answer annotators might override them after reading the linked documents by marking the question as unanswerable when the relevant information is not present. Thus it raises the question of how to make use of such learning signal and correctly model the retrieval step for unanswerable questions.

### 3 Learning with Marginalization over Retrieval

To address these challenges, we decompose the retrieval problem into document selection and evidence retrieval, leaving the handling of unanswerable questions entirely to the evidence retrieval component. These two components together produce a probability distribution over sets of retrieved contexts, which we marginalize over during training to account for false negatives.

#### 3.1 Modeling Multi-Document Retrieval

As described in § 2, the end product of retrieval for multi-document QA should be a set of evidences from different documents \(\{s_{i1}^{1}, s_{i2}^{1}, ..., s_{ik}^{1}\}\) which are combined to be the reasoning context \(C\). When a question is not answerable, \(C\) is empty, and supervision of the model is not entirely straightforward. The decision of where to look for evidence is separate from whether the necessary information is present, and a naive supervision that nothing should be retrieved risks erroneously telling the model that the place it chose to look was incorrect, possibly leading to spurious correlations between question artifacts and answerability judgments. For this reason, we separate document selection from evidence retrieval, and we leave answerability determinations entirely to the evidence retrieval step.

#### Document selection

Given the question \(q\) and a set of documents \(D = \{d_1, d_2, ..., d_n\}\), to evaluate the relevance of each document \(d^r\) and the question \(q\), we first jointly encode them with a (dataset-dependent) transformer-based model \(T\). To model...
the selection of documents as a set variable, a Sigmoid function ($\sigma$) is used to compute the document probability:

$$x_{d_i} = T(d_i^t, q)$$
$$P(d_i^t|q) = \sigma(w_d^T \cdot x_{d_i} + b_d)$$

For simplification, we assume the selection of each document being independent, thus the joint probability of selecting a set of document $D = \{d^1, d^2, ..., d^k\}$, $D \subseteq D$ can be computed with:

$$P(D|q) = \prod_{d^i \in D} P(d^i|q) \cdot \prod_{d^i \in D-D} (1 - P(d^i'|q))$$

(1)

**Evidence retrieval** Given the set of selected documents $D$, the goal for the evidence retrieval model is to select the evidences $s_j^i \in d^i$ that are relevant to question $q$ for each document $d^i \in D$. To model the relevance between an evidence snippet and the question, we first use pretrained language models to obtain a joint embedding of the concatenated question-evidence input. To simplify the problem while approximating the set of evidences as context, we only take one evidence from each document. Moreover, to give more flexibility to our retrieval model, we allow the evidence retrieval model to retrieve nothing from a document by predicting NULL, which is artificially added to the end of every document. Thus we model the probability of an evidence being retrieved given its document as:

$$x_{s_j} = \text{Encode}([s_j||q])$$
$$P(s_j^i|d^i) = \frac{\exp(w_{s_j}^T \cdot x_{s_j}^i + b_s)}{\sum_{s_j^i \in d_i} \exp(w_{s_j}^T \cdot x_{s_j}^i + b_s)}$$

Here we can derive the joint probability of a set of evidences $C = \{s_{j_1}^1, s_{j_2}^2, ..., s_{j_k}^k\}$ being retrieved as context:

$$P(D, C|q) = P(D|q) \cdot P(C|D, q)$$

(2)

$$= P(D|q) \prod_{s_{j_i}^i \in C, j_i \in d_i, d_i \in D} P(s_{j_i}^i|d_i^t, q)$$

3.2 Joint Modeling with Marginalization

With the retrieved context $C$, the final step is to predict the answer. For this part, we use existing reading comprehension models that take a question and relatively small context and output a probability distribution its answer predictions. The retrieved sentences in the context are simply concatenated and treated as context for the reading comprehension model (RC). Given the context $C$ and question $q$, the probability of the answer is defined as:

$$P(a|q, D, C) = \text{RC}(q, [s_{j_1}^1||s_{j_2}^2||...||s_{j_k}^k])$$

(3)

Now we can derive the joint probability of the answer and the retrieved context:

$$P(a, D, C|q) = P(a|D, C, q) \cdot P(D, C|q)$$

$$= P(D|q) \prod_{s_{j_i}^i \in C, j_i \in d_i, d_i \in D} P(a|D, C) \cdot P(s_{j_i}^i|d_i^t, q)$$

With the objective to maximize the likelihood of the training set with supervision on gold $C$, $\bar{D}$ and $\bar{a}$, the loss function is as in Eq. 4:

$$\max_\theta \mathcal{G}_D + \mathcal{G}_C + \mathcal{G}_a$$

(4)

where

$$\mathcal{G}_D = \sum_{d_i \in D} \log P(d_i^t|q)] + \sum_{d_i^t \in D-D} \log(1 - P(d_i^t'|q))$$

$$\mathcal{G}_C = \sum_{d_i \in D} \sum_{s_{j_i}^i \in d_i} \log P(s_{j_i}^i|d_i^t, q)$$

$$\mathcal{G}_a = \log P(\bar{a}|\bar{D}, C, q)$$

Marginalization over Retrieved Evidences

As mentioned in § 2, the learning signals for $\{\mathcal{G}_D, \mathcal{G}_C, \mathcal{G}_a\}$ may be noisy and weak because the objectives in Eq. 4 assumes that given a question-answer pair $(q, a)$ there is only one set of gold context $\bar{C}$ that can serve as the supporting evidence. To augment the learning signal, we propose to add the weakly-supervised objective with marginalization over a set of alternative context $S = \{(C_1, D_1'), (C_2, D_2'), ..., (C_m, D_m')\}$ given the selected documents $D$:

$$\max_\theta \mathcal{G}_M = \max_\theta \log P(\bar{a}|q)$$

(5)

$$= \max_\theta \log \sum_{(C_i', D_i') \in S} P(\bar{a}, C_i', D_i'|q)$$

Ideally, we want the marginalization set $S$ to be all possible combinations of sentences in different documents, but it is infeasible for a large text corpora. So here, we approximate the marginalization set by: 1) using only the top-ranked document set $D$, and 2) selecting only the top $m$ contexts from each $d_i$ in $D$. However, not all of the contexts in the top $m$
set $S$ are good alternative contexts, especially when the retrieval model is under-trained and performs poorly. We use a set of answer-type-dependent heuristics to determine whether a context $C$ is valid, which is described in more detail in § 4.2.4. Using these heuristics, we can divide the top $m$ retrieved context $S$ into two subsets $S_1, S_2 \subseteq S$, where $S_1$ contains all valid contexts while the contexts in $S_2$ are invalid.

**Auxiliary Loss for Invalid Context** Because contexts in $S_2$ are not valid alternative contexts for obtaining the correct answer, we do not marginalize over contexts in this set. We can still use them during training, however, by formulating an auxiliary loss that encourages the RC model to predict the NULL answer $a_N$ given these invalid contexts:

$$G_{a_N} = \max_{\theta_a} \sum_{(C^*, D^*) \in S_2} \log P(a_N|C^*, D^*, q)$$

(6)

Note that here we do not use joint probability $P(a_N, C^*, D^*|q)$ since doing so would also encourage the retrieval models to retrieve irrelevant context for answerable questions. In this way, this auxiliary loss can also be viewed as augmenting the dataset with extra unanswerable question-context pairs for the RC model.

Our final learning objective of the joint modeling is the result of combining the objectives in Eq. 4, Eq. 5 and Eq. 6:

$$\max_{\theta} (G_D + G_C + G_a) + G_M + \alpha \cdot G_{a_N}$$

(7)

The only weight we tune in the objective is $\alpha$ to regulate the contribution of the loss from the invalid contexts the RC model encounters at training time.

4 Experiments

4.1 Datasets

We test our method on two multi-document question answering datasets: IIRC and HotpotQA.

**IIRC** (Ferguson et al., 2020) is a dataset consisting of 13K information-seeking questions generated by crowdworkers who had access only to single Wikipedia paragraphs and the list of hyperlinks to other Wikipedia articles, but not the articles themselves. Given an initial paragraph, a model needs to retrieve missing information from multiple linked documents to answer the question. Since the question annotators can only see partial context, the questions and contexts containing the answers have less lexical overlap. The questions in IIRC may have one of four types of answers: 1) span; 2) number (resulting from discrete operations); 3) yes/no; 4) none (when the questions are unanswerable).

**HotpotQA** (Yang et al., 2018) consists of 113K questions and the contexts for answering those questions are a pair of Wikipedia paragraphs. This dataset provides two settings, a distractor setting where the 2 gold paragraphs are mixed with 8 bi-gram TF-IDF retrieved "distractors" that the retrieval models need to distinguish from. The other setting which is more challenging from the retrieval part is the fullwiki setting, in which the models will need to retrieve the two paragraphs from a subset of Wikipedia which contains about 5.2M paragraph candidates. The answers are either spans in the contexts, “yes” or “no”.

4.2 Implementation Details

Since the two datasets where we conduct our experiments are different in terms of document length and structure, reasoning types from questions and possible answer types, here we describe the dataset-specific implementation details for IIRC and HotpotQA.

4.2.1 Pretrained Language Models

Transformer-based pretrained language models are used to generate contextualized embeddings for retrieval and reasoning in our experiments. To be as comparable to previous methods as possible, we use roberta-base for IIRC, bert-base for HotpotQA distract and bert-large-wwm for HotpotQA fullwiki.

4.2.2 Document Selection

Though IIRC and both settings from HotpotQA can be seen as multi-document QA problems, the structure between the documents are largely different. To make full use of these structure, we handle the document selection part differently, namely using different $T$ functions mentioned in section § 3.1. But note that the outputs are all a set of documents (or paragraphs for HotpotQA) with their probabilities so other parts of the framework remains the same.

**Link prediction for IIRC.** For IIRC, an initial paragraph $p$ is given and we need to follow certain links in it, so the document selection problem can be translated into a link prediction problem given
and \( q \). So for IIRC, we define \( T \) as the BERT embedding of the concatenated question-paragraph sequence at the position of the link \( l_i \) to the document \( d_i \):

\[
T_{\text{IIRC}}(d^i, q) = \text{BERT}_{[l_i]}([q]||p])
\]

For IIRC, since we do not know how many links needs to be followed to answer the questions, we use \( P(d^i|q, p) = 0.5 \) as a threshold for document selection.

**HotpotQA distractor.** For the distractor setting of HotpotQA, we simply concatenate the question and the first 64 tokens of the candidate paragraph \( d^i \), run it through BERT and take the embedding of the separation token:

\[
T_{\text{Hotpot}}(d^i, q) = \text{BERT}_{[\text{SEP}]}([q]||d^i])
\]

Here we take the top-2 documents (paragraphs) predicted by the model for each question.

**HotpotQA fullwiki.** For this setting, we follow (Asai et al., 2020) and apply their trained recurrent retriever to retrieve a small subset of relevant paragraphs \( D' \) with the highest score. We choose to use this model because they are the best performing model on HotpotQA fullwiki setting with public code. For a better learning signal, we manually add the paragraphs marked as gold if they are not already included in \( D' \) but we only use \( D' \) at test time for a fair comparison under the fullwiki setting. For marginalization, here we consider the top-3 paragraphs, and the other modeling setups are the same with the distractor setting above.

### 4.2.3 Reading Comprehension Models

We use existing reading comprehension models for both IIRC and HotpotQA. NumNet+ (Ran et al., 2019) is used for IIRC since it can handle numerical reasoning. We augment the model by adding binary and unanswerable as two additional question types to its question type classification model and further introduce a binary classification model for outputting "Yes" and "No" when a question is classified as binary type. For HotpotQA, to handle questions with binary answers, we append "yes or no" to the start of the retrieved context to transform its reasoning part to a pure span-prediction problem. Then we follow Devlin et al. (2019) and append two linear layers to the contextualized embeddings from transformer-based language models, and they are used to separately model the starting and ending position of the span.

### 4.2.4 Identifying Alternative Context for IIRC

Depending on the answer types, we use different heuristics to identify valid contexts for answering the question. For span types, we judge by whether the context has at least one span that matches the gold answer string. As for numbers as answers, we check if the answer can be derived from the numbers in the context with the arithmetic operations supported by our RC model, or if it is a span in the context. Lastly, with binary and unanswerable questions, all contexts are considered valid.

### 4.3 Evaluation Metrics

We consider the following evaluation metrics with the main goal of improving the QA performance, which is best measured by QA F1:

- **QA F1**: This is F1 score on the predicted answer.
- **QA exact match (EM)**: This is used in both IIRC and HotpotQA as a 0-1 metric of whether the predicted answer exactly matches the gold answer;
- **Overall retrieval recall (Rt-Recall)**: Here we measure the retrieval ability of the overall retrieval system given the annotated set of supporting evidences;
- **Document selection F1 (Doc-F1)**: This is used to measure the performance of the document retrieval model given the documents marked as gold;

### 4.4 Training Settings

In the formulation of the evidence retrieval model, all sentences must be embedded with BERT or RoBERTa to determine the most relevant one, which is very inefficient during training. So for IIRC, we downsample the negative examples to 7 for evidence retrieval during training. We do the same for HotpotQA, but further downsample it to 3 negative examples. For IIRC, we take \( m = 4 \) for the top \( m \) context marginalization and take \( m = 3 \) for HotpotQA. For the weight for invalid context loss, we use 0.5 for IIRC and 0 for HotpotQA since it does not have unanswerable questions. To be more memory and storage efficient, our joint model performs parameter sharing by using the
same pretrained language models across different components. We evaluate and discuss the effect of this for a fair comparison with the pipeline models which cannot perform such parameter sharing in § 5.1. The models are trained for 30 epochs for IIRC and 10 epochs for both of the settings in HotpotQA. Our most expensive experiment takes about 2.5 days to run on two RTX 8000 (48GB) GPUs or one A100 (40GB) GPU, while a typical experiment takes about half of that computing power.

5 Main Results on IIRC

Tab. 2 shows our main results on IIRC. We can see that our proposed joint model with marginalization outperforms the pipeline model by 5.2 and 4.8 points for QA exact match and F1 score, respectively. While the 17.6 point improvement over the baseline system seems large, the correct point of comparison for our contribution in this work is our pipeline system, which is simply an improved version of the pipeline used by the baseline system.

Another comparison worth noticing is that despite the large improvement on the QA side, the retrieval performance is slightly lower than its pipeline counterpart. Our hypothesis is that our trained joint model with marginalization can better utilize the alternative contexts that are not marked as gold and derive the correct answers based on them. Since the retrieval performance is compared with the evidences that are annotated, the gain from alternative contexts will not be reflected in these numbers. We explore this hypothesis in § 5.1.

To further understand the effectiveness of joint modeling with marginalization comparing to the pipeline model, we breakdown the QA performance by different answer types and show it in Tab. 3. Our proposed method yields big gain of performance on binary, numerical and unanswerable questions. As we discussed in § 2, since those questions enjoy less lexical overlap between question, context and the correct answer, it is harder for the retrieval model to learn from the false negatives and the reasoning model trained in a pipeline is more susceptible to noise of the retrieved context. We also notice that the QA F1 on span-type question drops 1.2 points; we think this is because the auxiliary loss we have on invalid contexts slightly altered the distribution to favor the unanswerable questions. To confirm this, we removed the auxiliary loss and its QA F1 on span questions went back up to 48.7 points.

5.1 Analysis

Here we conduct some analysis on our proposed method on IIRC and show the results in Tab. 4.

Effectiveness of retrieval marginalization

Tab. 4 shows that training with marginalization improve the final QA F1 performance by 2.7 points, while doing slightly worse in terms of retrieving annotated context. To go beyond pure numbers and explain why modeling with retrieval marginalization results in better final QA performance, we analyzed 50 questions where the model with marginalization correctly answered a question that the model without marginalization missed, and 50 questions where the opposite was true. We found that in 24% of the cases where the marginalization model was correct, it relied on non-gold evidence to make its prediction, while this was only true 4% of the time for the model...
Table 4: Marginalization and other ablations on IIRC. Note that the removal of parts from the full model is accumulative\(^5\).

| Model                        | Doc-F1 | Rt-Recall | QA F1 |
|------------------------------|--------|-----------|-------|
| Full Model                   | 87.3   | 62.0      | 50.6  |
| w/o invalid context loss     | 87.5   | 62.5      | 49.2  |
| w/o Marginalization          | 87.8   | 62.2      | 47.9  |
| w/o Joint Modeling           | 87.8   | 62.4      | 45.1  |

Effectiveness of invalid context loss Without the auxiliary loss on the subset of invalid contexts during marginalization, we observe a 1.4 points decrease in the QA performance. On further inspection, we found that the main reason was the performance on the unanswerable questions, which decreases 8.9 points in F1 (not shown in the table).

Effectiveness of joint modeling We also explore the setting where both marginalization and joint modeling are taken away from our model. This is similar to the pipeline setting but all three models are jointly optimized by summing up their losses and the pretrained language model weights are shared. The difference between row 3 and 4 in Tab. 4 illustrates the performance improvements from joint modeling alone, which is 2.8 QA F1. We believe this is largely due to the fact that when the model is jointly trained, the reasoning model is dynamically adapting to the noisy retrieval results, which makes it more resilient to noise at test time.

6 Results on HotpotQA

Tab. 5 compares our proposed method with and without marginalization on both the distractor and fullwiki settings of HotpotQA. For the distractor setting, marginalization improves 1.0 and 1.1 points on QA EM and F1 score and the gap is slightly larger on the fullwiki setting, where the model with marginalization has 1.4 points EM and 1.6 points F1 advantage by comparison.

Comparing the two settings of HotpotQA, the non-gold distractor paragraphs in the distractor setting is retrieved with bigram TF-IDF (Chen et al., 2017), a rather weak retrieval method, while the non-gold paragraphs we use in the fullwiki setting are the outputs of the trained retrieval model from Asai et al. (2020), which is much stronger. Thus in our experiments, it is more likely to have alternative contexts in the non-gold paragraphs for the fullwiki setting than the distractor setting. We also observe lower improvements with retrieval marginalization on HotpotQA than IIRC. The reason by our hypothesis is that each link refers to a full document (i.e., Wikipedia article) in IIRC while typically only the introductory paragraphs are considered for the HotpotQA fullwiki setting. Based on the assumption that it is easier to find alternative evidence in the same article than the same paragraphs, larger improvements with marginalization on IIRC than HotpotQA are expected. It is also worth noting that HotpotQA lacks unanswerable questions, a category that our framework explicitly handles and yields most improvements on, with IIRC.

We also compare our proposed method to previous work on HotpotQA in Tab. 5. The main purpose of these experiments is to show the effectiveness of our proposed retrieval marginalization to mitigate the false negatives which also exist in HotpotQA, but not to compete with the state-of-the-art. In fact, the individual models in our joint framework are significantly simpler than the proposed by the prior work (e.g. RNN-based retrieval multi-task QA models in Asai et al. (2020), Graph Neural Networks in Tu et al. (2020) and Qiu et al. (2019) etc.).

7 Related Work

In terms of dealing with false negatives in retrieved texts for question answering, the most similar prior
work to ours is by Clark and Gardner (2017). However, they focused only on span-type answers while we apply similar methods to more complex reasoning types. More recent work such as Lee et al. (2019); Karpukhin et al. (2020) focus on modeling retrieval for question answering, but focus more on an open-reading setting where the biggest challenge is to scale up models to let them retrieve from large corpora. Work from Xiong et al. (2020) focuses on retrieval for multi-hop question answering, they note in their error analysis that a large portion of the retrieval errors were actually alternative contexts. Some recent works also investigate the possibility of modeling retrieval as a latent task and enabling end-to-end training. Guu et al. (2020) used a neural retriever to augment language models with external knowledge for question answering, while Lewis et al. (2020) adopted a similar method for sequence generation tasks. Finally, our work leverages marginalization over latent variable to deal with weak and noisy supervision signal, which is reminiscent of using maximum marginal likelihood for training weakly supervised semantic parsers (Berant et al., 2013; Krishnamurthy et al., 2017, among others).

8 Conclusion

We proposed a new probabilistic model for retrieving set-valued contexts for multi-document QA and show that training the QA model with marginalization over this set can help mitigate the false negatives in evidence annotations. Experiments on IIRC and HotpotQA show that our proposed marginalization method can learn to retrieve unlabeled alternative contexts and improves QA F1 from 0.9 to 2.7 points.

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