Tackling Multi-Answer Open-Domain Questions via a Recall-then-Verify Framework

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Abstract

Open-domain questions are likely to be open-ended and ambiguous, leading to multiple valid answers. Existing approaches typically adopt the rerank-then-read framework, where a reader reads top-ranking evidence to predict answers. According to our empirical analyses, this framework is faced with three problems: to leverage the power of a large reader, the reranker is forced to select only a few relevant passages that cover diverse answers, which is non-trivial due to unknown effect on the reader’s performance; the small reading budget also prevents the reader from making use of valuable retrieved evidence filtered out by the reranker; besides, as the reader generates predictions all at once based on all selected evidence, it may learn pathological dependencies among answers, i.e., whether to predict an answer may also depend on evidence of the other answers. To avoid these problems, we propose to tackle multi-answer open-domain questions with a recall-then-verify framework, which separates the reasoning process of each answer so that we can make better use of retrieved evidence while also leveraging the power of large models under the same memory constraint. Our framework achieves new state-of-the-art results on two multi-answer datasets, and predicts significantly more gold answers than a rerank-then-read system with an oracle reranker.

1 Introduction

Open-domain question answering (Voorhees, 1999; Chen et al., 2017) is a long-standing task where a question answering system goes through a large-scale corpus to answer information-seeking questions. Previous work typically assumes that there is only one well-defined answer for each question, or only requires systems to predict one correct answer, which largely simplifies the task. In practice, humans may lack sufficient knowledge or patience to frame very specific information-seeking questions, leading to open-ended and ambiguous questions with multiple valid answers. According to Min et al. (2020b), over 50% of a sampled set of Google search queries (Kwiatkowski et al., 2019) are ambiguous. Figure 1 shows an example with at least three interpretations. As can be seen from this example, the number of valid answers depends on both questions and relevant evidence, which challenges the ability of comprehensive exploitation of evidence from a large-scale corpus.

Existing approaches mostly adopt the rerank-then-read framework. A retriever retrieves hundreds or thousands of relevant passages which are later reranked by a reranker; a reader then predicts all answers in sequence conditioned on top-ranking passages. With a fixed memory constraint, there is a trade-off between the size of the reader and the number of passages the reader can process at a time. According to Min et al. (2021), provided that the reranker is capable of selecting a small

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set of highly-relevant passages with high coverage of diverse answers, adopting a larger reader can outperform a smaller reader using more passages. However, as shown by Section 4.4, this framework is faced with three problems: first, due to the small reading budget, the reranker has to balance relevance and diversity, which is non-trivial because it is often unknown beforehand how many or which relevant passages are sufficient for the reader to predict a particular answer; second, the reader has no access to more retrieved evidence that may be valuable but is filtered out by the reranker, while combining information from more passages was found to be beneficial to open-domain QA (Izacard and Grave, 2021b); third, as the reader predict answers in sequence all at once, the reader tends to under-generate answers partly due to high variance of the number of valid answers (Min et al., 2020b, 2021); the reader also seems to learn pathological dependencies among answers, i.e., whether to predict an answer may also depend on passages that cover some other answer(s), while ideally, prediction of a particular answer should depend on the soundness of associated evidence itself.

To avoid the problems above, we propose to tackle multi-answer open-domain questions with a recall-then-verify framework. Specifically, we first use an answer recaller to extract a possible answer from each retrieved passage. Not distracted by evidence of other answer(s), this can be done with high recall, even when using a weak answer predictor. However, due to insufficient evidence, these recalled answers are mostly invalid. We then aggregate retrieved evidence relevant to each answer candidate, and verify the answer with a large answer verifier. Through task reformulation, this framework can make better use of retrieved evidence under the same memory constraint.

Our contributions are summarized as follows:

- We empirically analyze the problems faced by the rerank-then-read framework when being used for multi-answer open-domain QA.
- To avoid the problems of the rerank-then-read framework, we propose to tackle multi-answer open-domain questions via a recall-then-verify framework, which makes better use of retrieved evidence while also leveraging the power of large models under the same memory constraint.
- We conducted experiments on two multi-answer QA datasets and achieved state-of-the-art results.

2 Related Work

Open-domain question answering requires question answering systems to answer factoid questions by searching for evidence from a large-scale corpus such as Wikipedia (Voorhees, 1999; Chen et al., 2017). The presence of many benchmarks has greatly promoted the development of this community, such as questions from real users like NQ (Kwiatkowski et al., 2019) and WEBQUESTIONS (Berant et al., 2013), and trivia questions like Quasar-T (Dhingra et al., 2017) and TriviaQA (Joshi et al., 2017). All these benchmarks either assume that each question has only one answer with several alternative surface forms, or only require a system to predict one valid answer. A typical question answering system is a pipeline as follows: an efficient retriever retrieves relevant passages using sparse (Mao et al., 2021; Zhao et al., 2021) or dense (Karpukhin et al., 2020; Xiong et al., 2021; Izacard and Grave, 2021a; Khattab et al., 2021) representations; an optional passage reranker (Asadi and Lin, 2013; Nogueira and Cho, 2019; Nogueira et al., 2020) further narrows down the evidence; an extractive or generative reader (Izacard and Grave, 2021b; Cheng et al., 2021) predicts an answer conditioned on retrieved or top-ranking passages. Nearly all previous work focused on locating passages covering at least one answer, or tried to predict one answer precisely.

However, both Kwiatkowski et al. (2019) and Min et al. (2020b) reported that there is genuine ambiguity in open-domain questions, resulting in multiple valid answers. To study the challenge of finding all valid answers for open-domain questions, Min et al. (2020b) proposed a new benchmark called AMBIGQA where each question is annotated with as many answers as possible. In this new task, the passage reranker becomes more vital in the rerank-then-read framework, particularly when only a few passages are allowed to feed a large reader due to memory constraints. This is because the reranker has to ensure that top-ranking passages are not only highly relevant, but also cover diverse answers. Despite state-of-the-art performance on AMBIGQA (Min et al., 2021), according to our empirical analyses, applying the rerank-then-read framework to multi-answer open-domain QA is faced with the following problems: balancing rel-
evance and diversity is non-trivial for the reranker due to unknown effect on the performance of the subsequent reader; using a large reader may prevent it from making good use of all retrieved evidence under memory constraints; as the reader generates all answers in sequence, it tends to suffer from high variance of the number of valid answers and learns pathological dependencies among answers. Therefore, we propose to tackle this task with a recall-then-verify framework, which leverages the power of large models while also making better use of retrieved evidence under the same memory constraint.

Some previous work argued that readers can be confused by similar but spurious passages, resulting in wrong predictions. Therefore, they proposed answer rerankers (Wang et al., 2018a,b; Hu et al., 2019; Iyer et al., 2021) to rerank top predictions from readers. Our framework is related to answer reranking but with two main differences. First, a reader typically aggregates available evidence and already does a decent job of answer prediction even without answer reranking; an answer reranker is introduced to filter out hard false positive predictions from the reader. By contrast, our answer recaller aims at finding all possible answers with high recall, most of which are invalid answers. Evidence focused on each answer is then aggregated and reasoned about by our answer verifier. It is also possible to introduce another model analogous to an answer reranker to filter out false positive predictions from our answer verifier. Second, answer reranking typically compares answer candidates to determine the most relevant one, while our answer verifier selects multiple valid answers mainly based on the soundness of their respective evidence but without comparisons among answer candidates.

3 Task Formulation

Multi-answer open-domain QA can be formally defined as follows: given an open-ended question $q$, a question answering system is required to make use of evidence from a large-scale text corpus $C$ and predict a set of valid answers $\{a_1, a_2, \ldots, a_n\}$. Questions and their corresponding answer sets are provided for training.

Evaluation To evaluate passage retrieval and reranking, we adopt the metric $\text{MRECALL}_k$ from (Min et al., 2021), which measures whether the top-$k$ passages cover at least $k$ distinct answers (or $n$ answers if the total number of answers $n$ is less than $k$). To evaluate question answering performance, we follow (Min et al., 2020b) to use F1 score between gold answers and predicted ones.

4 Rerank-then-Read Framework

In this section, we will briefly introduce the representative and state-of-the-art rerank-then-read pipeline from (Min et al., 2021) for multi-answer open-domain questions, and provide empirical analyses of this framework.

4.1 Passage Retrieval

Dense retrieval is widely adopted by open-domain question answering systems (Min et al., 2020a). A dense retriever measures relevance of a passage to a question by computing the dot product of their semantic vectors encoded by a passage encoder and a question encoder, respectively. Given a question, a set of most relevant passages, denoted as $B$ ($|B| < |C|$), is retrieved for subsequent processing.

4.2 Passage Reranker

To improve the quality of evidence, previous work (Nogueira et al., 2020; Gao et al., 2021) find it effective to utilize a passage reranker, which is more expressive than a passage retriever, to rerank retrieved passages, and select the $k$ best ones to feed a reader for answer generation ($k < |B|$). With a fixed memory constraint, there is a trade-off between the number of selected passages and the size of the reader. As shown by (Min et al., 2021), with good reranking, using a larger reader is more beneficial. To balance relevance and diversity of evidence, Min et al. (2021) proposed a passage reranker called JPR for joint modeling of selected passages. Specifically, they utilized T5 (Raffel et al., 2020) to encode retrieved passages following (Izacard and Grave, 2021b) and decode the indices of selected passages autoregressively. JPR is trained to seek for passages that cover new answers. To better balance relevance and diversity especially when there are less than $k$ answers for the question, Min et al. (2021) also proposed a tree-decoding algorithm, so that JPR has the flexibility to select more passages covering the same answer.

4.3 Reader

A reader takes as input the top-ranking passages, and predicts answers for the question. Min et al. (2021) adopted a generative encoder-decoder reader initialized with T5-3b (Raffel et al., 2020).
and used the fusion-in-decoder method from (Izacard and Grave, 2021b) which proves to efficiently aggregate and combine evidence from multiple passages. Specifically, each passage is concatenated with the question and is encoded independently by the encoder; the decoder then attends to the concatenation of the representations of all passages and generates all answers in sequence.

### 4.4 Empirical Analyses

To analyze performance of the rerank-then-read framework for multi-answer open domain questions, we built a system that resembles the state-of-the-art pipeline from (Min et al., 2021) but with two differences\(^2\). First, we used the retriever from (Izacard and Grave, 2021a). Second, instead of using JPR, we used an oracle passage reranker (OPR): a passage \(p\) is ranked higher than another passage \(p'\) if and only if 1) \(p\) covers some answer while \(p'\) covers none 2) or both \(p\) and \(p'\) cover or fail to cover some answer but \(p\) has a higher retrieval score. Following (Min et al., 2021), we retrieved \(|\mathcal{B}|=100\) Wikipedia passages, \(k=10\) of which were selected by the reranker. Table 2 shows model performance on the dev set of a representative multi-answer dataset called AMBIGQA (Min et al., 2020b). Compared with JPR, OPR is better in terms of reranking, with similar question answering results.

With the oracle knowledge of whether a passage contains an answer during reranking, OPR is probably still far from being a perfect reranker. Notably, we are not striving for a better rerank-then-read pipeline for multi-answer questions, but use OPR as a representative case to analyze the problems a rerank-then-read pipeline may face.

#### Trade-off between Relevance and Diversity

Though 3,670 diverse gold answers are covered by OPR, the reader predicts only 1,554 of them. We therefore investigate how well OPR balances relevance and diversity, using questions with multiple answers in the dev set of AMBIGQA, by comparing the supporting passages\(^3\) of missing gold answers and predicted gold answers.

Figure 1a and 1b show the distribution of supporting passages of missing answers but filtered out by the reranker. As shown by Figure 1c, OPR typically has a much lower level of evidence usage for missing answers than for predicted answers. A larger number of supporting passages of an answer is more likely to cover true positive evidence, which benefits question answering. However, as multiple answers share a small reading budget, it is inevitable that some answers are distributed with

\(^2\)Code and models from (Min et al., 2021) were not publicly available in the period of this work.

\(^3\)We abuse the use of supporting passages of an answer to refer to passages that cover the answer.

| Model          | Reranking MR@5 | Reranking MR@10 | QA MREC@5 | QA MREC@10 |
|----------------|----------------|-----------------|-----------|------------|
| JPR (Min et al., 2021) | 64.8/45.2 | 67.1/48.2 | 48.4/37.6 | 48.5/37.6 |
| OPR            | 67.7/46.5    | 70.3/51.2       | 46.5      | 51.2       |

Table 2: Reranking results and Question Answering results on the dev set of AMBIGQA using JPR and OPR. The two numbers in each cell are results on all questions and questions with multiple answers, respectively.
less supporting passages, which prevents the reader from making a better use of all retrieved evidence.

Judging from the widespread distribution of the number of supporting passages of predicted answers in Figure 1b, there may be cases where redundant false positive evidence is selected by the reranker and can be safely replaced with more evidence for missing answers to better balance relevance and diversity. However, it is non-trivial for the reranker to know beforehand whether a passage is false positive evidence, and how many or which supporting passages provide strong enough evidence for the reader.

**Dependencies among Answers** Ideally, whether to predict an answer should mainly depend on its associated evidence. However, under the rerank-then-read framework, a reader predicts all answers in sequence, conditioned on all selected passages, which makes it possible for the reader to learn pathological dependencies among answers, i.e., whether to predict an answer may also depend on passages that cover some other answer(s). We conjectured that these pathological dependencies also partly accounted for the large number of gold answers missed by the reader. For verification, we attacked OPR’s reader on the dev set of AMBIGQA as follows: a question is a target if and only if (1) it has a gold answer covered by OPR but missed by the reader and (2) it has a predicted gold answer whose supporting passages cover no other gold answers; a successful attack on a targeted question means that a missing answer is recovered after removing all supporting passages.

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4 Removed passages were replaced with the same number of top-ranking passages that cover no gold answer, so that the number of passages fed to the reader remained unchanged.

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Figure 2: Analysis of the pathological dependencies among answers learned by the reader (of a rerank-then-read pipeline, OPR being the reranker) on AMBIGQA. The horizontal axis is the number of diverse answers covered by OPR. The left axis shows the ratio of questions for which the reader recovers some originally missed gold answer after removing the supporting passages of some originally predicted gold answer.

of some predicted answer without removing any supporting passage of other gold answers.

There are 179 targeted questions; for 33.5% of them, we successfully recovered at least one missing gold answer per question, by eliminating the influence of evidence of some predicted gold answer. As shown by Figure 2, the success rate increases significantly when there are more answers covered by the reranker, indicating that predictions tend to be brittle on questions with many diverse supporting passages.

One possible explanation of the pathological dependencies is that the reader compares the validity of answer candidates and predicts the most likely ones. However, for 45.0% of successfully attacked questions, according to OPR, supporting passages of recovered missing answers are more relevant to the questions than those removed supporting passages of predicted answers. Notably, (Min et al., 2020b) also have a similar observation on another rerank-then-read pipeline, i.e., it is hard to argue that the predicted answers are more likely than the missing ones.

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5 Recall-then-Verify Framework

5.1 Overview

As shown by section 4.4, the rerank-then-read framework is faced with three problems when used for tackling multi-answer open-domain questions. First, to leverage the power of a large reader under a fixed memory constraint, a reranker should select only a few passages that are highly-relevant and also diverse enough to cover multiple answers. However, it is non-trivial for a reranker to know beforehand which answers can be safely distributed with less supporting passages and which ones should be distributed with more. Second, it is more likely for a reranker to cover true positive evidence with more supporting passages of an answer. However, as multiple answers share the small reading budget, most retrieved evidence, which is possibly valuable, is filtered out by the reranker and can not be used by the reader. Third, as the reader predicts answers all at once based on all selected passages, whether to predict an answer or not may pathologically depend on evidence of other answers.

To address the above problems, we propose a recall-then-verify framework, which separates the reasoning process of each answer so that answers...
We denote the set of recalled answer candidates \( \mathcal{A} = \{ a_1, a_2, \ldots, a_n \} \). Though a single passage may not contain strong enough evidence to support an answer, with some semantic clues, such as answer types, it is sufficient for even a weak model to predict possible answers with high recall. However, this is at the cost of low precision, which necessitates answer verification based on more evidence.

### 5.3 Evidence Aggregator

Our evidence aggregator aggregates evidence for each answer candidate from retrieved passages, which can be formulated as a reranking task, i.e., to rerank retrieved passages according to their relevance to a question-candidate pair, and select top-ranking ones for answer verification. We reuse the answer recaller as the evidence aggregator:

\[
\mathcal{E}_i = \text{top-}k_{p \in \mathcal{R}} P(a_i | q, p) \tag{2}
\]

where \( \mathcal{E}_i \) denotes the top-\( k \) relevant passages of the answer candidate \( a_i \).

### 5.4 Answer Verifier

Given an answer candidate \( a_i \) and its evidence \( \mathcal{E}_i \), our answer verifier, based on T5-3b, predicts whether \( a_i \) is valid, using the fusion-in-decoder method from (Izacard and Grave, 2021b). Each passage from \( \mathcal{E}_i \) is concatenated with the question and the answer candidate, and is encoded independently; the decoder then attends to the representations of all passages and is trained to produce the tokens “right” or “wrong” depending on whether the encoded answer candidate is valid or not. During inference, we compute the validity score of a candidate by taking the normalized probability assigned to the token “right”:

\[
P(a_i \text{ is valid}) = \frac{\exp(\text{logit}(\text{"right"}|q, a_i, \mathcal{E}_i))}{\sum_{l \in \{\text{"right"}, \text{"wrong"}\}} \exp(\text{logit}(l|q, a_i, \mathcal{E}_i))} \tag{3}
\]

Candidates with their validity scores higher than a pre-defined threshold \( \tau \) will be produced as final answers.
AMBIGQA (Min et al., 2020b) originates from NQ (Kwiatkowski et al., 2019), where questions are annotated with equally valid answers from Wikipedia.

| Dataset | # Question | # Answer |
|---------|------------|----------|
|        | Train      | Dev      | Test     | Avg. | Median |
| WEBQSP  | 2,752      | 245      | 1582     | 22.6 | 1.0    |
| AMBIGQA | 10,036     | 2,002    | 2,004    | 2.2  | 2.0    |

Table 3: Statistics of multi-answer QA datasets. The average and median number of answers are computed on the dev sets.

### 6.2 Baselines

We compare our recall-then-verify system with two state-of-the-art rerank-then-read systems.

**REFUEL** (Gao et al., 2021) selects 100 top-ranking passages from 1,000 retrieved passages, and predicts answers with a reader based on BART_large (Lewis et al., 2020). It also has a round-trip prediction mechanism, i.e., to generate disambiguated questions based on predicted answers, which are re-fed to the reader to recall more valid answers.

**JPR** (Min et al., 2021) is a passage reranker which jointly models selected passages. With improved reranking performance, Min et al. (2021) selected only 10 passages from 100 retrieved passages, and used a reader based on T5-3b which is much larger and more powerful than REFUEL’s reader, while requiring no more memory resources than REFUEL.

### 6.3 Implementation Details

Our retrieval corpus is the English Wikipedia from 12/20/2018, where articles are split into 100-word passages. The dense retriever is from (Izacard and Grave, 2021a) and is finetuned on each multi-answer QA dataset. The answer recaller and the answer verifier are initialized with T5-3b; both are pre-trained on NQ and then finetuned on each multi-answer dataset. We retrieve \(|B| = 100\) passages for a question, and verify an answer candidate with \(k = 10\) retrieved passages. The threshold \(\tau\) for verification is tuned on the dev set based on the sum of F1 scores on all questions and questions with multiple answers; the best \(\tau\) on WEBQSP and AMBIGQA are 0.7 and 0.75, respectively.

**Memory Constraint:** Min et al. (2021) considered a fixed hardware and trained a reader with the maximum number of passages. We follow this memory constraint, under which a reader based on T5-3b can encode up to \(k = 10\) passages each of length no longer than 360 tokens at a time.

### 6.4 QA Results

| System | WEBQSP | AMBIGQA |
|--------|--------|---------|
|        | Dev*   | Test    | Dev | Test |
| REFUEL | -      | -       | 48.3/37.3 | 42/33.3 |
| JPR    | 53.6/49.5 | 53.1/47.2 | 48.5/37.6 | 43.5/34.2 |
| Ours   | 54.4/48.5 | 54.9/48.2 | 51.2/40.2 | 44.9/35.9 |

Table 4: Question answering results on multi-answer datasets. The two numbers in each cell are F1 scores on all questions and questions with multiple answers, respectively. Note that results on the dev set of WEBQSP can not be directly compared, as we used a different train/dev split.

| System | \(k\) | T5 | Dev* | Test |
|--------|------|----|------|------|
| (Izacard and Grave, 2021a) | 100 | large | 51.9 | 53.7 |
| JPR    | 10 3b | 50.4 | 54.5 |
| Ours   | 10 3b | 51.9 | 54.5 |

Table 5: Exact match scores of different systems on NQ, which is a single-answer dataset. Izacard and Grave (2021a) used significantly more memory resources than JPR and our system for training.

Due to candidate-aware evidence aggregation and a fixed sufficient number of passages distributed to each candidate, our recall-then-verify framework can make use of most retrieved supporting passages (see our improvements over OPR in Figure 1c). With a higher level of evidence usage, our recall-then-verify system outperforms state-of-the-art rerank-then-read baselines on both multi-answer datasets, which is shown by Table 4.

Though our framework focuses on multi-answer questions, we also experimented on NQ to demonstrate that our framework is applicable to single-answer scenario without suffering from low precision. Specifically, for each question, we only output the answer candidate with the highest validity score. As shown by Table 5, our system slightly outperforms previous state-of-the-art rerank-then-read systems.

### 6.5 Ablation Study

#### 6.5.1 Can the Answer Recaller Do More than Guessing?

Our answer recaller is trained on only positive passages which cover some gold answer, thus not granted the capability of filtering out negative passages or negative answer candidates. As shown by Table 6, the performance of a recaller based on T5-base is close to that of a recaller based on T5-3b,
The answer recaller is likely to be trained on false positives, which may be misleading and make it over-conservative in filtering out hard negative passages. By contrast, using more evidence for verification is less likely to miss true positive evidence if there is any for a candidate, thus not prone to mislead the verifier.

### Reducing Answer Candidates

As shown by Table 6, training the answer recaller with a small ratio of negative passages helps reduce answer candidates without significantly lowering recall.

In summary, it is difficult for our recaller alone to tackle multi-answer open-domain questions, which necessitates answer verification based on more associated evidence. However, an answer recaller can be trained to shrink down the number of candidates, so that the burden on the verifier can be reduced.

#### 6.5.2 Effect of the Size of Evidence $k$

![Figure 4](image-url)

Figure 4: Performance on the dev set of AMBIGQA, with varying $k$ and $\tau$. In Figure (a), results with $k = 1$ are associated with the top and right axes, while the others are with the bottom and left axes. As $\tau$ increases ($\tau \in \{0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9\}$), points of the same color move from bottom right to top left.

Figure 4 shows the benefit of using more evidence for verification. As the number of passages $k$ increases from 1 to 10, there is a significant boost in F1 score and the number of predicted gold answers.

#### 6.5.3 Effect of the Validity Threshold $\tau$

As shown by Figure 4a, the balance between recall and precision can be controlled by varying $\tau$: a lower $\tau$ leads to higher recall and may benefit performance on questions with multiple-answers. When $k$ is set to 10, our recall-then-verify system outperforms the state-of-the-art rerank-then-read system JPR for a wide range of $\tau$. Under the best setups ($k = 10, \tau = 0.75$), our system predicts 25.0% and 25.7% more gold answers than OPR on all questions and questions with multiple answers, respectively.
## 6.6 Error Analyses

Among 3,206 recalled gold answers, the answer verifier misses 1,263 of them and outputs 1,316 wrong predictions. We manually analyzed 50 random samples, 25 of which are missed gold answers and 25 are wrong predictions. Table 7 reports our analysis. Our evidence aggregator aggregates true positive evidence for 80% of missing gold answers: 68% of missing ones actually have straightforward evidence, while verification for 12% of missing ones requires reasoning (e.g., multi-hop reasoning and numeric reasoning) on evidence or having necessary implicit knowledge. Notably, 84% of our “wrong” predictions turn out to be false negatives: 48% of “wrong” predictions are semantically equivalent to some annotated answer but are superficially different ([Si et al., 2021](#)); 36% of “wrong” predictions are unannotated false negatives. This demonstrates that it is indeed difficult to find all valid answers to an open-domain question ([Min et al., 2020b](#)) and that our system may be underrated.

### Table 7: Analysis of our predictions on the dev set of AMBIGQA. Examples are shown in Appendix.

| Missing Gold Answers                                      |   |
|-----------------------------------------------------------|---|
| Evidence is wrong                                         | 20%|
| Evidence is right and straightforward                     | 68%|
| Evidence is right but needs reasoning                     | 8% |
| Evidence is right but implicit                            | 4% |

| Wrong Predictions                                         |   |
|-----------------------------------------------------------|---|
| Predictions are true negatives                            | 16%|
| Predictions are superficially-different false negatives    | 48%|
| Predictions are unannotated false negatives               | 36%|

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53% of missing gold answers with straightforward evidence have validity scores higher than 0.5 but lower than the threshold.

To avoid these problems, we propose to tackle multi-answer open-domain questions with the recall-then-verify framework, which separates the reasoning process of each answer so that we can make better use of retrieved evidence with large models under the same memory constraint. Extensive experiments demonstrate the effectiveness of our framework.

## 7 Conclusion

In this paper, we empirically analyze the problems of the rerank-then-read framework for multi-answer open-domain questions. Using a large reader can benefit QA performance, but under a fixed memory constraint, it will force the reranker to select only a few passages that are relevant and also diverse enough to cover multiple answers. As a result, the reranker should deal with the non-trivial balance between relevance and diversity, and the reader fails to make use of retrieved evidence that is valuable but filtered out by the reranker. What’s more, as the reader predicts answers all at once based on all selected passages, whether to predict an answer may pathologically depend on evidence of other answers.

To avoid these problems, we propose to tackle multi-answer open-domain questions with the recall-then-verify framework, which separates the reasoning process of each answer so that we can make better use of retrieved evidence with large models under the same memory constraint. Extensive experiments demonstrate the effectiveness of our framework.

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Table 8 reports error analysis of our answer verifier.
### Missing Gold Answers > Evidence is wrong (20%)

**Question:** When was the last time Adelaide was in a grand final?

**Gold Answers:** 2016; 2017; 1998; 30 September 2017

**Prediction:** 2017

**Evidence:** ... in the home-and-away season in 2017, in Round 6, with Adelaide recording a 76-point ... Bookmakers installed Adelaide as the favourites to win the grand final ...

**Explanation:** Evidence is insufficient to infer whether the 2017 grand final was the last of Adelaide.

### Missing Gold Answers > Evidence is right and straightforward (68%)

**Question:** Who was the first person who discovered electricity?

**Gold Answers:** Ancient Egyptian; William Gilbert; Gilbert

**Prediction:** William Gilbert

**Evidence:** William Gilbert ... is credited as one of the originators of the term “electricity” ... the father of electrical engineering or electricity ...

### Missing Gold Answers > Evidence is right but needs reasoning (8%)

**Question:** Who plays James Corden’s sister in Gavin and Stacey?

**Gold Answers:** Sheridan Smith, OBE; Sheridan Smith

**Prediction:** Sheridan Smith

**Evidence:** (1) ... Gavin rushes to find Smithy with Smithy’s sister, Rudi (Sheridan Smith) ... (2) ... James Corden & Sheridan Smith performed ... as Smithy and Rudi ...

**Explanation:** Multi-hop reasoning is needed.

### Missing Gold Answers > Evidence is right but implicit (4%)

**Question:** Who did FSU beat for the 2013 championship?

**Gold Answers:** Duke; Duke Blue Devils; Auburn; Auburn Tigers

**Prediction:** Duke

**Evidence:** ... in the 2013 ACC Championship Game ... Duke lost to Florida State ...

**Explanation:** “FSU” is short for Florida State University, which is not mentioned.

### Wrong Predictions > Predictions are true negatives (16%)

**Question:** How many seasons of Shameless USA is there?

**Gold Answers:** ten; 10

**Prediction:** 9

**Evidence:** (1) ... Shameless (season 9) ... (2) ... The ninth series ... was reduced to 11 episodes, with the remaining 11 being turned into the tenth series.

### Wrong Predictions > Predictions are superficially-different false negatives (48%)

**Question:** Where did the Brown v Board of Education take place?

**Gold Answers:** U.S. Supreme Court; Topeka, KS

**Prediction:** United States Supreme Court

**Evidence:** “Brown v. Board of Education” ... was taken to the United States Supreme Court ...

### Wrong Predictions > Predictions are unannotated false negatives (36%)

**Question:** Who founded Jamestown in what is now Virginia?

**Gold Answers:** London Company; The Virginia Company of London; John Smith; Captain John Smith; Edward Maria Wingfield; Virginia Company of London; English settlement; the Virginia Company of London; Virginia Company of London

**Prediction:** Christopher Newport

**Evidence:** Virginia ... English settlement in the “New World”, Jamestown. Named for King James I, it was founded in May 1607 by Christopher Newport ...

Table 8: Analysis of predictions from our answer verifier. We display all annotated forms of gold answers, which are separated with semicolons.