Abstract

Existing benchmarks for open-domain question answering (ODQA) typically focus on questions whose answers are all in a single paragraph. By contrast, many natural questions, such as “What players were drafted by the Brooklyn Nets?” have a long list of answers extracted from multiple paragraphs. Answering such questions requires retrieving and reading many passages from a large corpus. We introduce QAMPARI, an ODQA benchmark, where answers are lists of entities, spread across many paragraphs. We created QAMPARI by (a) generating questions with multiple answers from Wikipedia’s knowledge graph and tables, (b) automatically pairing answers with supporting evidence in Wikipedia paragraphs, and (c) manually paraphrasing questions and validating each answer. Across a wide range of ODQA models, we find that QAMPARI is challenging in terms of both passage retrieval and answer generation, with models reaching an F1 score of 32.8 at best. We view QAMPARI as a valuable resource for ODQA research, which will aid to develop models that handle a broad range of question types, including single and multi-answer questions.

1 Introduction

Open-domain question answering (ODQA) is a core language understanding task concerned with answering factoid questions over large document collections (Voorhees and Tice, 2000; Brill et al., 2002). Due to its wide applicability, ODQA has received substantial attention in recent years (Chen et al., 2017; Lee et al., 2019; Karpukhin et al., 2020). Typically, systems tackling ODQA tasks follow the “retrieve-and-read” paradigm, where a retriever first retrieves a set of candidate passages, followed by a reader which receives the retrieved passages and produces the final answer.

The retrieve-and-read paradigm has been effective for benchmarks such as Natural Questions (NQ) (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017), where the answer is a single phrase from a single passage. However, in many cases, a question might have many answers, spread across multiple passages. Consider the example in Fig. 1. Eric Newman produced multiple movies, so finding them, along with their directors, requires incorporating information from many passages. Such questions pose two main challenges to retrieve-and-read systems. First, as there are multiple answers that can be far apart, the reader must reason over a long text sequence to generate all correct answers. Second, since the reader is computationally constrained to process at most K passages, the retriever must score all necessary passages at its top-K results, which is challenging and even impossible when the number of relevant passages exceeds K.

Nevertheless, research on multi-answer questions has largely been underexplored. While previous works proposed questions that involve reading multiple passages, the number of passages was quite small. AMBIGQA (Min et al., 2020) studied ambiguous questions from NQ with several answers. However, as 70% of its questions have at most two answers, retrieve-and-read models...
can be adapted to AMBIGQA. HOTPOTQA (Yang et al., 2018) focused on multi-hop reasoning, but its questions require no more than two passages to answer. WikiNLDDB (Thorne et al., 2021) is a benchmark for testing reasoning over multiple facts. However, WikiNLDDB restricted its text corpus to databases of 1,000 facts at most, making it significantly smaller than standard ODQA corpora. Moreover, these facts are model-generated utterances rather than natural language passages. Multi-answer questions are also rare in real-world user questions (Bajaj et al., 2016; Kwiatkowski et al., 2019), which can be attributed to the performance bias of existing systems. Namely, people mostly pose questions that they can successfully get answers to with current technology. This does not diminish the importance of multi-answer questions ("Which drugs are effective against skin cancer?"; ‘Which plants can be grown in an apartment?’), which constitute an important research challenge.

In this work, we present QAMPARI, a benchmark for Questions with many Answers over Multiple Paragraphs, Indeed. All questions in QAMPARI have at least 5 answers, with an average of 13 answers. Examples are semi-automatically generated using two data sources, Wikidata (Vrandečić and Krötzsch, 2014) and Wikipedia tables. We automatically generate multi-answer questions of the form “What/Who has [relation] with [entity]?" and convert these into pseudo-language using manually defined templates. Then, we verify that our questions are answerable from Wikipedia by automatically extracting evidence passages for all their answers. Finally, we use crowdsourcing to validate example correctness, and paraphrase questions into natural language (Wang et al., 2015). To further enrich our data we also generate composition questions, that compose two relations (as in Fig. 1), and intersection questions, such as “What movies were produced and directed by Clint Eastwood?”. Overall, QAMPARI contains 2K development and test questions and more than 60K training examples – see Tab. 1 for some examples.

We evaluate a large suite of baselines, including models from the retrieve-and-read family as well as a closed-book question answering model (Roberts et al., 2020), and find that they struggle on QAMPARI. In the retrieve-and-read setup, we experiment with both BM25 (Robertson and Zaragoza, 2009) and DPR (Karpukhin et al., 2020) retrievers, followed by either (a) a RAG-like reader (Lewis et al., 2020) that given each retrieved passage either decodes an answer or abstains, or (b) an FiD reader (Izacard and Grave, 2021) that takes the encoded representations of multiple passages and decodes the list of answers directly.

When training models on QAMPARI alone, or in a multi-task setup with NQ, we observe that QAMPARI is challenging in terms of both passage retrieval and answer generation. Namely, the best model reaches an F₁ score of 32.8. Moreover, models return more than 80% of the correct answers in only 31.2% of the test examples, well below performance on single-answer datasets like NQ.

To summarize, QAMPARI is a challenging benchmark for evaluating the ability of ODQA models to handle questions with many answers over multiple passages. We advocate to evaluate ODQA models not on QAMPARI alone, but alongside benchmarks such as NQ and TriviaQA. Such joint evaluation will test models’ ability to handle both single- and multi-answer questions, an evaluation that the community is currently lacking. The QAMPARI benchmark, models and relevant codebase are available at: https://anon/.

2 Dataset Construction

Each example in QAMPARI is a triple \((q, A, P)\), where \(q\) is a question, \(A\) is a set of answers and \(P\) is a set of passages from our target corpus. An answer \(a \in A\) has 1-2 evidence passages from \(P\) (see Fig. 1).

We define passages as consecutive sentences from our corpus (Wikipedia), that span on average 100 words. As our focus is multi-answer questions, examples in QAMPARI have \(|A| \geq 5\).

Overview We generate examples in two steps. First, we generate simple questions that involve a single entity and relation, e.g., “Who was drafted by the Brooklyn Nets?” (§2.1). Then, we expand such questions to generate complex questions with intersection and composition operations (§2.2).

To increase diversity, questions are generated from two data sources, Wikidata and Wikipedia tables. We first describe example generation over Wikidata, then briefly present the generation process from Wikipedia tables in §2.3. In both cases, we ensure answers can be derived from evidence passages in Wikipedia.\(^1\) Tab. 1 presents examples from each data source and question type.

\(^1\)Wikipedia dump: 2021-08-01
Notation  We introduce notation for formal queries over Wikidata to explain example generation. Wikidata is a knowledge graph, \( \mathcal{K} \), that can be viewed as a set of labeled edges \((e_1, r, e_2)\). Graph nodes \(e_1, e_2 \in \mathcal{E}\) are entities connected by an edge labeled by the relation \(r \in \mathcal{R}\). For example, a possible labeled edge is \((\text{Barack Obama}, \text{ReceivedAward}, 2009)\).

One can query \( \mathcal{K} \) by applying a relation \(r\) over an entity \(e\), resulting in a simple query \(r(e)\) whose denotation (answer set) is \(\{e_i \mid (e_i, r, e) \in \mathcal{K}\}\). Composition queries are formed by applying a relation over the result of a simple query. We denote a composition query by \(r_2(r_1(e))\), and its denotation is \(\{e_i \mid \exists e_j \text{ s.t. } (e_i, r_2, e_j) \in \mathcal{K} \land (e_j, r_1, e) \in \mathcal{K}\}\).

Last, an intersection query \(r_1(e_1) \cap r_2(e_2)\) corresponds to the intersection of two simple queries, \(\{e_i \mid (e_i, r_1, e_1) \in \mathcal{K} \land (e_i, r_2, e_2) \in \mathcal{K}\}\).

2.1 Simple Questions

Fig. 2 provides an overview of our procedure for creating simple question examples: (i) We manually define query templates, (ii) populate query templates using \( \mathcal{K} \) to create queries with a sufficiently large number of answers in \( \mathcal{K} \), (iii) automatically identify evidence passages for the answers and filter out noisy examples, (iv) map query templates to question templates to obtain pseudo-language questions, and (v) validate answers and paraphrase pseudo-language questions through crowdsourcing. Next, we describe each of these steps in detail.

Generating query templates  We manually select a set of 135 relations \( \bar{\mathcal{R}} \subset \mathcal{R} \), which will be used in our query templates. We select frequent relations from Wikidata for which denotations contain many entities (e.g., ReceivedAward). The list of relations is in App. A. For each relation, we manually write a template to map queries to pseudo-language questions. For example, the template for ReceivedAward is “Who received the award X?”

Some relations are underspecified – for example, LocatedIn can describe the location of buildings, geographical features, and cities. When generating synthetic questions, this leads to vague questions such as “What is located in Paris?”. To address this, we manually split these to typed relations that specify the semantic type of their answers/denotations. This is done using the type hierarchy given in Wikidata and given the type \(t\) of answer entities. We denote typed relations by \(r_t\), and the denotation of \(r_t(e)\) comprises all entities of type \(t\) returned by \(r(e)\). For example, the entity The Louvre has type cultural organization, and we can map the relevant query template to the pseudo-language question “Which cultural organization is located in Paris?”.

Simple question generation  We instantiate all possible simple queries using all \(r \in \bar{\mathcal{R}}\) and entities \(e\) in Wikidata. For a relation \(r\) (or \(r_t\)), we keep the query \(r(e)\) iff \(|r(e)| \geq 5\). We denote this set of instantiated simple queries by \(\mathcal{S}\), which contains 1,431,268 simple queries.
Finding evidence sentences For an ODQA benchmark, we must verify that every answer is found in our target corpus. We do this by identifying candidate evidence sentences from Wikipedia, and verifying they entail the answer, using a Natural Language Inference (NLI) model.

Specifically, every simple query-answer pair can be viewed as a triple \((e_1, r, e_2)\). We use a “distant supervision” approach (Mintz et al., 2009), similar to KELM (Agarwal et al., 2021), and define any sentence in the Wikipedia page of entity \(e_1\) that contains the entity \(e_2\), or one of its Wikidata aliases, as a candidate evidence sentence (and vice versa in the page of \(e_2\)). E.g., in Fig. 2, the bar for Barack Obama, ReceivedAward, NobelPeacePrize appears on the page Barack Obama, where ‘Nobel Peace Prize’ appears.

Aligning Wikipedia sentences to Wikidata can lead to false positives. E.g., for the triple (TheGoonies, HasScreenwriter, StevenSpielberg), most mentions of Spielberg in the page TheGoonies are not as a screenwriter. To account for this, we use an off-the-shelf NLI model. For every answer, we consider each candidate evidence sentence along with its two preceding sentences, and check whether they entail the hypothesis phrase describing the triple \((e_1, r, e_2)\). We use templates to phrase triples as short declarative sentences (“The Goonies has Steven Spielberg as screenwriter”). An answer is validated if there is an evidence sentence that entails the triple. Manual analysis shows this process eliminates 70% of false positives, while removing only 7.5% of the correct alignments.

Query filtering After finding evidence sentences, we only keep queries that at least 80% of their answers were validated and their number of validated answers is between 5 and 200. The resulting set contains 60,792 simple queries, where each query has a set of validated answers, \(A\), and of passages \(P\) that contain the identified evidence sentences.\(^3\)

2.2 Complex Questions
To increase diversity, we expand simple queries to composition and intersection queries, for which answers require reading two passages.

Intersection Intersection queries are generated by finding two simple queries such that the size of the intersection of their denotations is at least 5. To avoid improbable questions such as “Which competition was won by Manchester City and had Manchester City as a participant?”, we add a constraint that the denotation of one of the simple queries cannot be a subset of the other. Formally, the set of intersection queries are all queries \(\mathcal{R}_1 \cap \mathcal{R}_2\) such that \(|\mathcal{R}_1 \cap \mathcal{R}_2| \geq 5\), \(|\mathcal{R}_1| \nsubseteq |\mathcal{R}_2|\), and \(|\mathcal{R}_2| \nsubseteq |\mathcal{R}_1|\).

Pseudo-language questions are generated by heuristically combining the two simple questions, for example “Which television program had Chris Carter as screenwriter and had Frank Spotnitz as screenwriter?”. There is no need to perform answer validation since all of the underlying intersecting answers were already validated.

Composition To create composition queries, we manually handpick a set of 423 relations \(\mathcal{R}_{comp} \subset \mathcal{R}\) (list in our codebase), in a process similar to simple queries. Then, we generate all the possible composition queries \(\mathcal{R}_2(r_1(e))\) such that \(r_1(e) \in \mathcal{S}\), \(r_2 \in \mathcal{R}_{comp}\), and \(|\mathcal{R}_2(r_1(e))| \geq 5\). An example composition query is “What is the height of buildings located in Dubai?”.

Unlike intersection queries, in composition queries we need to validate that our new triples \((e_i, r_2, e_j)\), where \(e_j \in |\mathcal{R}_1(e)|\), are indeed supported by Wikipedia sentences. We use the same procedure to find evidence sentences for triples \((e_i, r_2, e_j)\), and consider an answer \(e_j\) as validated if both \((e_i, r_2, e_j)\) and \((e_j, r_1, e)\) can be aligned to Wikipedia. We keep all complex queries where 80% of the answers are validated. Finally, we manually define templates for relations in \(\mathcal{R}_{comp}\) to generate pseudo-language questions.

2.3 Questions from Wikipedia Tables
To further diversify QAMPARI, we create an analogous pipeline for generating simple and composition questions from Wikipedia tables, with more open-ended relations compared to Wikidata. We briefly describe this pipeline.

We look at all Wikipedia tables with title “List of X” that have at least 5 rows, in total, 1,897 tables. We find the “key” column, \(c_{\text{key}}\) in each table using the table classifier from Talmor et al. (2021), which outputs the column of entities that the table describes. For example, in the table List of nuclear whistle blowers, \(c_{\text{key}}\) is ‘name’ and specifies...
the whistle-blower names. This naturally creates simple questions of the form “Who or what is X?”. Simple questions are expanded to composition questions by looking at non-key columns, \( c_{\text{non-key}} \) and asking what rows in the table have the value \( v \) in column \( c_{\text{non-key}} \). For example, what is the value in the column ‘Year’ for nuclear whistle-blowers.

Questions from Wikipedia are validated using a procedure similar to Wikidata. For each answer entity \( e \), we validate that the Wikipedia page for \( e \) contains the relevant words that are part of the name of the table as well as the value (for composition questions), and only keep questions where 80% of the table rows are validated and the number of validated answers is at least 5. Overall, we generate 170 simple questions and 6,036 composition questions using this process.

2.4 Data Split

QAMPARi contains a training set, whose goal is to teach the model to handle multi-answer questions. However, we do not want the model to memorize how particular Wikidata relations map to text patterns. Consequently, we perform a relation split, randomly splitting the set \( \mathcal{R} \) into two equally-sized sets \( \mathcal{R}_{\text{train}} \) and \( \mathcal{R}_{\text{test}} \). Simple queries are assigned to the train/test set based on their relation, composition queries \( r_2(r_1(e)) \) are assigned to the test set iff either \( r_1 \) or \( r_2 \) are in \( \mathcal{R}_{\text{test}} \), and intersection queries \( r_1(e_1) \cap r_2(e_2) \) are placed in the test set iff both \( r_1 \) and \( r_2 \) are in \( \mathcal{R}_{\text{test}} \).

We now create the train/development/test split (Tab. 2). The main bottleneck in our example generation pipeline is validation of the test set through crowdsourcing (§2.5), since each question requires validating all of the answers. Thus, we pre-determine the test set to contain 1,000 simple questions (830 from Wikidata, 170 from Wikipedia tables) and 1,000 complex questions (400 Wikidata composition questions, 400 Wikidata intersection questions, 200 Wikipedia tables composition questions). For simple Wikidata questions, we sample 830 questions such that the distribution over relations from \( \mathcal{R}_{\text{test}} \) is roughly uniform. All Wikipedia tables simple questions are placed in the test set, and for complex questions we randomly sample the pre-determined number from the set of generated questions. Last, the test set is randomly split in half to a development set and test set. We also sub-sample training set examples, such that each relation appears in at most 1,000 examples.

2.5 Crowdsourcing

Correctness validation For every question and answer, we present a crowdsourcing worker with the question, the answer, and links to the Wikipedia page (or pages for complex questions) with the evidence passage. We ask the worker to check if the question can be answered from the given pages, using the text only (no infoboxes or tables).

Since the vast majority of examples are correct, we test worker performance by injecting wrong answers in 10% of the cases and reject workers that fail to identify wrong answers. Moreover, we manually verify 5% of examples marked as correct and all examples marked as incorrect, and again reject low-performing workers. Overall, 24 annotators validated 30,259 answers for an average pay of 12.5$ per hour. We find that our process for generating examples is accurate, with 96.6% of the answers validated. Non-validated questions were replaced until 2,000 questions were validated. A question is defined non-validated if its number of distinct answers goes below 5. Snapshots from the presented tasks are in App. C.

Paraphrasing Since our questions are in pseudo-language, we follow past work (Wang et al., 2015) and ask workers to re-phrase 3,000 questions in the training set and the entire development/test set. We restrict this task to US or UK workers who pass a qualification test. We randomly verified half of the paraphrases for each worker for quality assurance.

3 Dataset Analysis

QAMPARi contains 61,911 training examples, 1,000 development examples and 1,000 test examples. Tab. 1 provides example questions of each question type and data sources. We describe key statistics in Tab. 2. Test examples in QAMPARi have 13.23 answers on average and a median of 7 answers. For comparison, the number of answers per question is substantially higher than in AmbigQA (Min et al., 2020), where the median is 2. On average, simple questions have more answers than complex ones while being shorter in length. We note that since test and development questions were manually re-phrased by annotators they are generally shorter than the training questions.

Figure 3a presents a binned distribution of the number of answers per question in the development and test sets. Roughly half of the questions have 8 or more answers, with 20% having more than 15 answers and 3.5% with over 50 answers.
Table 2: QAMPARI questions breakdown by their type (Simple, Intersection or Composition questions) and underlying data source (WD for Wikidata, WP for Wikipedia tables).

![Figure 3](image-url)

(a) # answers  
(b) # added answers

Extended set: As discussed in §2.5, we manually validate each answer in QAMPARI is supported by sentences from Wikipedia. However, Wikipedia might contain additional correct answers. To alleviate this issue, we manually annotate additional gold answers for a subset of test questions, and name it the ExtendedSet. We randomly sampled 200 questions from the test set and had an author manually annotate as many additional answers as possible in 12 minutes per question. This process is not guaranteed to be complete, as it would require manually reviewing all of Wikipedia. Moreover, questions with hundreds of gold answers (“Who worked for Burton F. C?”) would incur hours of annotation, which is too expensive. This is similar to work in open information extraction (Vo and Bagheri, 2017), where creating the full gold set of triples is not feasible. Fig. 3 plots the number of added answers per question on the extended set. In 30% of the questions, we did not add any answer, and the median/average/maximum number of added answers are 2/3.13/16 respectively. Evaluation on the test set and the extended set in §4.3 shows that model precision on the extended set is somewhat higher, but does not alter model ranking, illustrating the reliability our test set.

4 Experimental Evaluation

4.1 Models

Retriever: For retrieval, we experiment with both sparse and dense retrieval models on Wikipedia. As discussed in §2, we chunk Wikipedia into passages of consecutive sentences, using NLTK’s sentence tokenizer, where each passage is 100 words on average. For all retrievers, we evaluate retrieval accuracy of the top-200 passages returned per question.

We use BM25 (Robertson and Zaragoza, 2009) as a strong sparse retrieval model. BM25 scores question-passage pairs based on their lexical similarity. It has been shown that BM25 is notoriously hard to beat using unsupervised retrieval methods (Izacard et al., 2021; Ram et al., 2022), and achieves comparable performance to that of supervised methods (Thakur et al., 2021). As our dense retriever we finetune on QAMPARI a DPR model (Karpukhin et al., 2020) trained on NQ. We finetune DPR in the typical contrastive manner (in-batch training), with one positive and one negative passage per question. Positives are sampled from the evidence passages, and negatives are sampled from the top-10 highest scoring passages, according to BM25, which do not contain the answer.

Reader: We experiment with two readers – a Passage-Independent Generator (PIG), which reads each passage independently (a-là RAG (Lewis et al., 2020)), and a Fusion-in-Decoder (FiD) model (Izacard and Grave, 2021), which reads multiple passages simultaneously.

PIG is an encoder-decoder model that takes each of the retrieved passages as input and decodes a single answer or outputs “Not Relevant” to indicate there is no answer. The final output is the union of all decoded answers across retrieved passages. We initialize PIG with T5-large (Raffel et al., 2019) and train with standard maximum likelihood. We use evidence passages as positive examples and the top scoring retrieved passage that is not an evidence passage and does not contain an answer (or its aliases) as a negative example.

FiD encodes each of the retrieved passages along with the input question. Its decoder then attends
to the encoded representation and outputs a list of answers. We initialize FiD using a pretrained T5-Large model (Raffel et al., 2019) and train with standard maximum likelihood.

FiD is computationally expensive, as its decoder attends to a large number of encoded tokens and the generated output is long. Thus, we can only fit the top-50 passages returned by the retriever on a single A100 GPU.

**Closed-book question answering** We also experiment with a closed-book setting, where the QA model generates answers from knowledge encoded in its parameters without any evidence passages. We initialize our closed-book QA model with T5-SSM with 3B parameters (Roberts et al., 2020), and train it with standard maximum likelihood — the question is provided as input, and the model is trained to generate the gold set of answers.

**Zero-shot** We test the zero-shot ability of OpenAI’s *text-davinci-003*, from the Instruct-GPT family (Ouyang et al., 2022). We use GPT-3 in: (a) closed-book QA setup; (b) as a multi-passage reader. In the closed-book setup, the model receives only the question and is asked to provide a list of answers. In the reader setup, the model gets the question and the 15 highest-ranking passages from BM25 (the maximal number that fits in the context) and is asked to output a list of answers.

### 4.2 Experimental Setup

We created QAMPAI as a benchmark to be evaluated alongside additional ODQA benchmarks, such as NQ. Since it is semi-automatically generated, one can develop models tailored for QAMPAI. However, our goal is to have a single model that performs well across a wide variety of question types. Thus, we train and test models in a multi-task setup, on both NQ and QAMPAI, in addition to a QAMPAI only setting. We also train our models on NQ only and evaluate them on QAMPAI, to verify QAMPAI’s training set indeed improves answering questions with many answers.

Our main metrics are recall, precision, and F1. Specifically, for test example \((q, P, A)\), and a predicted set of answers \(A_{\text{pred}}\), recall, precision, and F1 are standardly computed by comparing \(A\) and \(A_{\text{pred}}\) allowing for aliases (i.e., a gold answer is covered if it or one of its aliases are in \(A_{\text{pred}}\)). The model scores are averaged across examples. To get a sense of the average accuracy across examples, we measure the fraction of examples with F1 of at least 0.5 (%F1 ≥ 0.5) and the fraction with recall of at least 0.8 (%Recall ≥ 0.8). For NQ, we report the standard exact match (EM) metric.

We evaluate the retriever with Recall@K, that is, the fraction of answers that appear in the top-K retrieved passages, averaged across examples. This metric comes in two flavors: (a) Answer Recall@K (ARECALL@K); for every gold answer whether it or one of its aliases appear in the top-K retrieved passages. It is a loose metric since an answer can appear in a passage that does not provide any evidence to support the answer; (b) Evidence Recall@K (ERECALL@K): since we have evidence paragraphs for every answer, we consider for every gold answer the fraction of evidence passages in the top-K retrieved passages. This is a strict metric since an answer can sometimes be answered by passages other than the ones we identified.

### 4.3 Results

Tab. 3 presents passage retrieval results on QAMPAI test. Scores for ARECALL@200 for BM25 and DPR are 61.0% and 55.2%, respectively. As for ERECALL@K, results are unsurprisingly lower. BM25 retrieves 55.6% of the evidence passages with K=200, while DPR retrieves only 30.2% of evidence passages. Overall, DPR pretrained on NQ and finetuned on QAMPAI performs worse than BM25. This is in line with Sciavolino et al. (2021) who showed that, when tested on questions with rare entities, DPR performs worse than BM25. We hypothesize that rare entities in QAMPAI questions may account for DPR’s lower performance.

Tab. 4 lists results on the test sets of QAMPAI and NQ. Overall, performance on QAMPAI is low. FiD-DPR and PiG-DPR are more precision-oriented with FiD-DPR achieving precision of 41.3 and PiG-DPR a precision of 44.8. PiG-BM25 is recall-oriented, achieving recall of 47.9. Overall, PiG variants perform best, with small differences

| K   | BM25 ERECALL@K | DPR ERECALL@K |
|-----|---------------|---------------|
| K=10| 24.6          | 21.9          |
| K=25| 37.4          | 31.5          |
| K=50| 46.6          | 39.6          |
| K=100| 54.6        | 47.1          |
| K=200| 61.0        | 55.2          |

Table 3: Retriever test results.

---

4While ERECALL@K for DPR is substantially lower than BM25, observe that ARECALL@K is better correlated with QA metrics (Tab. 4), as DPR retrieves non-evidence passages that still lead to the correct answer.
Table 4: QAMPARI test results. **QO**: models trained on QAMPARI only; **NQO**: models trained on NQ only; **MT**: Multi-task training with NQ; **ZS**: Zero-shot setup.

When training on both NQ and QAMPARI (MT), performance on NQ (47.2 with BM25 and 53.1 with DPR) is similar to that reported by Izacard and Grave (2021) (44.1 with BM25 and 51.4 with DPR). When training on NQ only, results on QAMPARI are significantly lower than when training also on QAMPARI, showing that training on QAMPARI improves performance on multi-answer questions, as expected. The lower performance on QAMPARI compared to NQ, despite the fact that NQ’s EM evaluation metric is much more strict than the metrics used for QAMPARI, illustrates the challenge in answering multi-answer questions.

PIG-DPR has much higher recall than FiD-DPR, showing that going over 200 passages independently (PIG) leads to higher recall than jointly reasoning over 50 passages (FiD). Moreover, the solid performance of PIG-DPR indicates that QA performance is more correlated with ARecall@K than ERecall@K (Tab. 3).

Finetuned closed-book performance is low with an F1 of 2.6 for QAMPARI, which we attribute to the relation-based train/test split (§2.4). This guarantees that there is no overlap between train and test questions. Lewis et al. (2021) have shown that mitigating such train-test overlap causes a drop in QA performance, with a drastic drop being observed in closed-book models.

**Zero-shot results** The performance of zero-shot models is lower than finetuned retrieve-and-read models, as expected. However, text-davinci-003’s performance in the closed book setup is impressive and significantly better than finetuned T5-3B.

---

**ExtendedSet results** We report results for FiD and PIG on the ExtendedSet (see §3) in §F. As expected, considering additional correct answers improves the precision of all models. Since changes to recall are small, the overall F1 is higher when considering manual annotations. Importantly, ranking across models does not change, and the absolute performance remains low, suggesting that our test set can be safely used for evaluation.

**Oracle analysis** To disentangle retrieval from answer extraction, we run PIG and FiD in an oracle setup, where we assume a perfect retriever and run our readers on the gold evidence passages only. Performance of both models greatly improves in this setup, with larger gains for PIG. This shows that developing better retrieval mechanisms for multi-answer questions can greatly benefit QAMPARI. FiD’s recall is still limited (47.5), illustrating the challenge of reading a large number of documents. Full oracle results are in §G (Tab. §9).

5 Related work

ODQA tasks have largely been dedicated to single-answer questions (Berant et al., 2013; Joshi et al., 2017; Kwiatkowski et al., 2019). The same applies for most multi-hop ODQA tasks (Welbl et al., 2018; Yang et al., 2018; Trivedi et al., 2022a). While they require 2-4 paragraphs, the answer is a single phrase. Multi-answer questions were introduced in the TREC QA tracks (Voorhees, 2004, 2005). However, evaluation was on 50 questions. Trivedi et al. (2022b) introduced artificially generated multi-answer questions, but only for reading comprehension rather than ODQA. Concurrent to QAMPARI, Zhong et al. (2022) introduced RoMQA, a benchmark containing multi-answer questions generated using Wikidata. While their setup is closest to ours, they evaluate on a subset of Wikipedia that is aligned to a subset of Wikidata.

6 Conclusions

We release QAMPARI, a dataset targeting ODQA models ability to answer multi-answer questions, and show that it is challenging for current state-of-the-art models. QAMPARI will aid develop models that answer a wide range of question types, including single- and multi-answer questions.

**Limitations**

A key limitation of QAMPARI is that the gold set of answers is incomplete. Thus, predicted answers
might be correct but missing from the gold answer set. The ExtendedSet addresses this problem partially, allowing a more accurate model ranking, but even in this set all the correct answers are not part of the gold set. A second limitation is that our data generation process is mostly automatic and is thus amenable to reverse-engineering. Hence, we recommend evaluating models on QAMPAR1 along with additional benchmarks created with a different generation process. Last, our data generation process can only generate answers based on relations from Wikidata and relations that are in Wikipedia tables, and thus its scope does not generalize to arbitrary relations.

Acknowledgements

We want to thank Omer Bigi Amouyal, Levana Amouyal and Joseph McCrum for their help with the annotation verification process. We also want to thank Ori Ram for his helpful comments. This research was supported in part by The Yandex Initiative for Machine Learning, and The European Research Council (ERC) under the European Union Horizons 2020 research and innovation programme (grant ERC DELPHI 802800).

References

Oshin Agarwal, Heming Ge, Siamak Shakeri, and Rami Al-Rfou. 2021. Knowledge graph based synthetic corpus generation for knowledge-enhanced language model pre-training. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3554–3565, Online. Association for Computational Linguistics.

Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, Mir Rosenberg, Xia Song, Alina Stoica, Saurabh Tiwary, and Tong Wang. 2016. Ms marco: A human generated machine reading comprehension dataset.

Jonathan Berant, Andrew Chou, Roy Frostig, and Percy Liang. 2013. Semantic parsing on Freebase from question-answer pairs. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1533–1544, Seattle, Washington, USA. Association for Computational Linguistics.

Eric Brill, Susan Dumais, and Michele Banko. 2002. An analysis of the AskMSR question-answering system. In Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP 2002), pages 257–264. Association for Computational Linguistics.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1870–1879, Vancouver, Canada. Association for Computational Linguistics.

Jifan Chen and Greg Durrett. 2019. Understanding dataset design choices for multi-hop reasoning. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4026–4032, Minneapolis, Minnesota. Association for Computational Linguistics.

Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. 2021. Towards unsupervised dense information retrieval with contrastive learning. ArXiv preprint, abs/2112.09118.

Gautier Izacard and Edouard Grave. 2021. Leveraging passage retrieval with generative models for open domain question answering. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 874–880, Online. Association for Computational Linguistics.

Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1601–1611, Vancouver, Canada. Association for Computational Linguistics.

Vladimir Karpukhin, Barlas Ozgur, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6769–6781, Online. Association for Computational Linguistics.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Ilia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Lilian Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: A benchmark for question answering research. Transactions of the Association for Computational Linguistics, 7:452–466.

Kenton Lee, Ming-Wei Chang, and Kristina Toutanova. 2019. Latent retrieval for weakly supervised open domain question answering. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6086–6096, Florence, Italy. Association for Computational Linguistics.
Patrick Lewis, Pontus Stenetorp, and Sebastian Riedel. 2021. Question and answer test-train overlap in open-domain question answering datasets. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 1000–1008, Online. Association for Computational Linguistics.

Patrick S. H. Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-augmented generation for knowledge-intensive NLP tasks. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual.

Shayne Longpre, Kartik Perisetla, Anthony Chen, Nikhil Ramesh, Chris DuBois, and Sameer Singh. 2021. Entity-based knowledge conflicts in question answering. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5783–5797, Online. Association for Computational Linguistics.

Sewon Min, Julian Michael, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2020. AmbigQA: Answering ambiguous open-domain questions. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5783–5797, Online. Association for Computational Linguistics.

Mike Mintz, Steven Bills, Rion Snow, and Daniel Jurafsky. 2009. Distant supervision for relation extraction without labeled data. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP, pages 1003–1011, Suntec, Singapore. Association for Computational Linguistics.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Gray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. In Advances in Neural Information Processing Systems.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. ArXiv preprint, abs/1910.10683.

Ori Ram, Gal Shachaf, Omer Levy, Jonathan Berant, and Amir Globerson. 2022. Learning to retrieve passages without supervision. In North American Association for Computational Linguistics (NAACL).

Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How much knowledge can you pack into the parameters of a language model? In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 5418–5426, Online. Association for Computational Linguistics.

Stephen Robertson and Hugo Zaragoza. 2009. The probabilistic relevance framework: BM25 and beyond. Found. Trends Inf. Retr., 3(4):333–389.

Christopher Scialomino, Zexuan Zhong, Jinyuk Lee, and Danqi Chen. 2021. Simple entity-centric questions challenge dense retrievers. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6138–6148, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Alon Talmor, Ori Yoran, Amnon Catav, Dan Lahav, Yizhong Wang, Akari Asai, Gabriel Ilharco, Hannaneh Hajishirzi, and Jonathan Berant. 2021. Multimodalqa: complex question answering over text, tables and images. In 9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021. OpenReview.net.

Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. BEIR: A heterogeneous benchmark for zero-shot evaluation of information retrieval models. In Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2).

James Thorne, Majid Yazdani, Marzieh Saeidi, Fabrizio Silvestri, Sebastian Riedel, and Alon Halevy. 2021. Database reasoning over text. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 3091–3104, Online. Association for Computational Linguistics.

Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. 2022a. MuSiQue: Multi-hop questions via single-hop question composition. Transactions of the Association for Computational Linguistics, 10:539–554.

Harsh Trivedi, Niranjan Balasubramanian, Tushar Khot, and Ashish Sabharwal. 2022b. Teaching broad reasoning skills for multi-step qa by generating hard contexts.

Duc-Thuan Vo and Ebrahium Bagheri. 2017. Open information extraction. Encyclopedia with semantic computing and Robotic intelligence, 1(01):1630003.

Ellen Voorhees. 2004. Overview of the trec 2003 question answering track.

Ellen Voorhees. 2005. Overview of the trec 2004 question answering track.
A Simple Relations

In Tab. 5, we gathered all the 135 relations we used to create our simple questions. The 423 relations used to create our composition questions can be found in our code base.

B Composition template

Composition questions overall template is: **What is the** `<comp_property>` **of** `<subtype>` **who/which** `<base_property>` **?**. All the templates are in our code base.

C Crowdsourcing Validation

Fig. 4 shows two screenshots of the task crowdsourcing workers performed.

D Experimental setup details

For both readers (FiD and PIG), we used T5-large which has 770 million parameters. We used an A100 to train both of them, FiD with a batch size of 8 and PIG with a batch size of 32 for a single GPU. We trained each of them for around 48 hours on two GPUs.

For FiD, we concatenated the answers using # as a separator. At evaluation time, there is no importance to the order of the answers.

For both PIG and FiD, all aliases of a given gold entity provided by Wikidata are used as additional correct answers. When verifying whether our model predicted an answer A, we verify whether it predicted A or any of its aliases. We performed an hyper parameter search around the learning rate, the number of training steps, the ratio of positive to negative (for PIG) and the number of times an NQ example will appear in each epoch (for multi task).

Tab. 6 presents the parameters of the reported results.

We report the results of a single run with seed 0.

E Question type analysis

We break test performance of FiD-BM25 (MT) by question type (Tab. 7). Surprisingly, performance on simple questions is lower than complex questions, and intersection questions seem easiest. Possible explanations are: (a) simple questions have more answers (see Tab. 2), which makes them harder, and (b) models can predict the answer given just one evidence passage, due to “shortcuts” (Chen and Durrett, 2019), or parametric knowledge (Longpre et al., 2021).

F ExtendedSet Results

In Tab. 8 we present results analogous to those in Tab. 4 for the ExtendedSet with BM25. Precision improves by 5-6 points across models, while recall changes are smaller leading to an overall increase in F1. Nevertheless changes are not dramatic and model ranking remains constant, suggesting the full test set can be safely used.

G Development Set Results

In Tab. 9 we present results analogous to those in Tab. 4 for the development set.
Table 5: Simple relations

|                      | Learning rate | # steps | pos. to neg. | # NQ examples |
|----------------------|---------------|---------|--------------|---------------|
| FiD-BM25             | QO 0.00005    | 90k     | -            | -             |
|                      | MT 0.00005    | 190k    | -            | 2             |
| FiD-DPR              | QO 0.00005    | 85k     | -            | -             |
|                      | MT 0.00005    | 190k    | -            | 2             |
| PIG-BM25             | QO 0.000001   | 60k     | 1            | -             |
|                      | MT 0.000001   | 75k     | 1            | 1             |
| PIG-DPR              | QO 0.000001   | 60k     | 1            | -             |
|                      | MT 0.000001   | 75k     | 1            | 1             |
| Closed book          | QO 0.0001     | 95k     | -            | -             |

Table 6: Hyper parameters used for reported results.

|                      | Recall | Precision | F1 |
|----------------------|--------|-----------|----|
| Wikidata simple      | 21.3   | 30.7      | 23.1|
| Wikidata intersection| 37.0   | 47.1      | 40.0|
| Wikidata composition | 18.6   | 32.4      | 22.2|
| Wikipedia simple      | 9.1    | 20.6      | 11.5|
| Wikipedia composition| 31.2   | 37.4      | 32.7|

Table 7: Question type analysis of FiD-BM25, trained in MT setup on QAMPAR1 development set.
| Model             | Set   | Recall | Precision | QAMPARI          |
|------------------|-------|--------|-----------|------------------|
|                  |       | Recall |           |                  |
|                  |       | %Recall| %F1≥0.8  | F1≥0.5          |
| FiD-BM25 QO      | w.o. annotations | 20.5 | 34.6 | 24.3 | 4.0 | 19.6 |
| FiD-BM25 MT      | w. annotations  | 23.3 | 40.6 | 27.8 | 4.5 | 25.1 |
| FiD-DPR QO       | 22.8 | 37.0 | 26.8 | 4.5 | 20.6 |
| FiD-DPR MT       | 25.7 | 42.9 | 30.6 | 5.0 | 24.6 |
| PIG-BM25 QO      | w.o. annotations | 45.1 | 28.9 | 30.7 | 27.5 | 23 |
| PIG-BM25 MT      | w. annotations  | 42.7 | 33.6 | 32.8 | 24 | 29.5 |
| PIG-DPR QO       | 49.3 | 27.9 | 30.7 | 31.5 | 20.5 |
| PIG-DPR MT       | 47.1 | 33.1 | 33.2 | 27 | 26 |

Table 8: QAMPARI ExtendedSet results with (w.) and without (w.o.) the additional manual annotations. The best results with and without annotations are bolded. **QO**: models trained on QAMPARI only; **MT**: Multi-task training with NQ.

| Model             | Set   | Recall | Precision | QAMPARI          |
|------------------|-------|--------|-----------|------------------|
|                  |       | Recall |           |                  |
|                  |       | %Recall| %F1≥0.8  | F1≥0.5          |
| FiD-BM25 QO      | 23.3 | 35.6 | 26.3 | 5.9 | 22.7 |
| FiD-BM25 MT      | 23.9 | 34.2 | 26.3 | 6.0 | 22.4 |
| FiD-DPR QO       | 6.5  | 35.2 | 10.1 | 0 | 3.7 |
| FiD-DPR MT       | 7.2  | 39.8 | 11.4 | 0.0 | 2.8 |
| PIG-BM25 QO      | 41.4 | 26.4 | 28.0 | 25.3 | 21.0 |
| PIG-BM25 MT      | 43.7 | 26.9 | 28.9 | 26.6 | 22.0 |
| PIG-DPR QO       | 33.9 | 38.6 | 29.9 | 15.8 | 26.2 |
| PIG-DPR MT       | 31.7 | 42.2 | 29.6 | 14.3 | 26.3 |
| Closed book QO   | 2.4  | 7.2  | 3.1  | 0.1 | 0.7 |
| Closed book MT   | 47.5 | 62.7 | 51.2 | 18.4 | 56.1 |
| Closed book PIG  | 71.5 | 60.9 | 62.4 | 55.7 | 73.8 |

Table 9: QAMPARI development results. **QO**: models trained on QAMPARI only; **MT**: Multi-task training with NQ.
Figure 4: Screenshots from crowdsourcing task.