Zero-Shot Open-Book Question Answering

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Abstract

Open book question answering is a subset of question answering tasks where the system aims to find answers in a given set of documents (open-book) and common knowledge about a topic. This article proposes a solution for answering natural language questions from a corpus of Amazon Web Services (AWS) technical documents with no domain-specific labeled data (zero-shot). These questions can have yes-no-none answers, short answers, long answers, or any combination of the above. This solution comprises a two-step architecture in which a retriever finds the right document and an extractor finds the answers in the retrieved document. We are introducing a new test dataset for open-book QA based on real customer questions on AWS technical documentation. After experimenting with several information retrieval systems and extractor models based on extractive language models, the solution attempts to find the yes-no-none answers and text answers in the same pass. The model is trained on the The Stanford Question Answering Dataset - SQuAD (Rajpurkar et al., 2016) and Natural Questions (Kwiatkowski et al., 2019) datasets. We were able to achieve 49% F1 and 39% exact match score (EM) end-to-end with no domain-specific training.

Keywords:  
AWS technical documentation, extractive language models, information retrieval systems, zero-shot open-book question answering

1. Introduction

Question answering (QA) has been a major area of research in Artificial Intelligence and Machine Learning since the early days of computer science (Voorhees et al., 1999; Moldovan et al., 2000; Brill et al., 2002; Ferrucci et al., 2010). The need for a performant open-book QA solution was exacerbated by rapid growth in available information in niche domains, the growing number of users accessing this information, and the expanding need for more efficient operations. QA systems are especially useful when a user searches for specific information and does not have the time - or simply does not want - to peruse all available documentation related to their search to solve the problem at hand.

In this article, open-book QA is defined as the task whereby a system (such as a computer software) answers natural language questions from a set of available documents (open-book). These questions can have yes-no-none answers, short answers, long answers, or any combination of the above. In this work, we did not train the system on our domain-specific documents or questions and answers, a technique called zero-shot learning (Brown et al., 2020). The system should be able to perform with a variety of document types and question and answers without training. We defined this approach as “zero-shot open-book QA”. The proposed solution is tested on AWS Documentation dataset. However, as the
models within this solution are not trained on the dataset, the solution can be used in other similar domains such as finance and law.

Software technical documentation is a critical piece of the software development life cycle process. Finding the correct answers for one’s questions can be a tedious and time-consuming process. Currently, software developers, technical writers, and marketers are required to spend substantial time writing documents such as technology briefs, web content, white papers, blogs, and reference guides. Meanwhile, software developers and solution architects have to spend time searching for specific information they need. Our approach to QA aims to help them find it faster.

Our work’s key contributions are:

1. introduce a new dataset in open-book QA,
2. propose a two-module architecture to find answers without context,
3. experiment on ready-to-use information retrieval systems,
4. infer text and yes-no-none answers in a single forward pass once we find the right document.

The rest of the paper is structured as follows: First, related previous work is summarized. Then the dataset is described. Next, details on implementing the zero-shot open-book QA pipeline are provided. In addition, the experiments are explained, and finally the results along with limitations and next steps are presented.

2. Related work

There are a number of datasets in the literature for natural language QA (Rajpurkar et al., 2016; Joshi et al., 2017; Khashabi et al., 2018; Richardson et al., 2013; Lai et al., 2017; Reddy et al., 2019; Choi et al., 2018; Tafjord et al., 2019; Mitra et al., 2019), as well several solutions to tackle these challenges (Seo et al., 2016; Vaswani et al., 2017; Devlin et al., 2018; He and Dai, 2011; Kumar et al., 2016; Xiong et al., 2016; Raffel et al., 2019). The natural language QA solutions take a question along with a block of text as context and attempts to find the correct answer to the original question within the context. Open-book QA solutions take a question along with a set of documents that may contain the answer to the question, then the solution attempts to find the answer to the original question within the available set of documents. Open-book QA solutions have been explored by several research teams including Banerjee et al. (Banerjee et al., 2019), which performs QA using fine-tuned extractive language models, and the work of Yasunaga et al. (Yasunaga et al., 2021), which performs QA using GNNs.

In this paper, we propose an approach that differs from the previous body of work as we do not receive the context but assume that the answer lies in a set of readily available documents (open-book); In addition, we are not allowed to train our models on the given questions or set of documents (zero-shot). Our proposed solution attempts to answers questions from a set of documents with no prior training or fine-tuning (zero-shot open-book question answering).
3. Data

Real world open-book QA use cases require significant amounts of time, human effort, and cost to access or generate domain-specific labeled data. For our solution, we intentionally did not use any domain-specific labeled data and ran experiments on popular QA datasets and pre-trained models. We used feedback from customers to generate a set of 100 questions as the test dataset and used QA datasets, explained in section 3.2 and 3.3, for training.

3.1 AWS Documentation Dataset

Herein, we present the AWS documentation corpus \(^1\), an open-book QA dataset, which contains 25,175 documents along with 100 matched questions and answers. These questions are based on real customer questions on AWS services. There are two types of answers: text and yes-no-none answers. Text answers range from a few words to a full paragraph sourced from a continuous series of words in a document or from different locations within the same document. Yes-no-none (YNN) answers can be yes, no, or none for cases where the returned result is empty and does not lead to a binary answer (i.e., yes or no). All questions in the dataset have a valid answer within the accompanying documents. Table 1 shows a few examples from the dataset.

| Question                                                                 | Text Answer                                   | YNN Answer |
|-------------------------------------------------------------------------|-----------------------------------------------|------------|
| What is the maximum number of rows in a dataset in Amazon Forecast?     | 1 billion                                     | None       |
| Can I stop a DB instance that has a read replica?                       | You can’t stop a DB instance that has a read replica. | No         |
| Is AWS IoT Greengrass HIPAA compliant?                                  | Third-party auditors assess the security and compliance of AWS IoT Greengrass as part of multiple AWS compliance programs. These include SOC PCI FedRAMP HIPAA and others. | Yes        |

3.2 SQuAD Datasets

The Stanford Question Answering Dataset (SQuAD)\(^2\) is a reading comprehension dataset (Rajpurkar et al., 2016), including questions created by crowdworkers on Wikipedia articles. The answers to these questions is a segment of text from reading passages, or the question might be unanswerable. SQuAD1.1 comprises 100,000 question-answer pairs on more

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1. https://github.com/siagholami/aws-documentation
2. https://rajpurkar.github.io/SQuAD-explorer/
than 500 articles. SQuAD2.0 adds 50,000 unanswerable questions written adversarially by
crowdworkers to look similar to answerable ones.

3.3 Natural Questions Dataset
The Natural Questions (NQ) dataset \(^3\) includes 400,000 questions and answers created
on Wikipedia articles (Kwiatkowski et al., 2019). Questions consist of real queries which
answers can be long (a few sentences), short (a few words) if present on the page, or null if
no long or short answer is present.

4. Approach

Our approach consists of two high-level modules: retriever and extractor. Given a question,
the retriever tries to find a set of documents that contain the answer; Then, from these
documents, the extractor tries to find the answer. Figure 4 illustrates a high level workflow
of the solution, and Table 2 shows an example of the question, retrieved documents, and
extracted answers using the solution.

![High level workflow of the solution in one pass](Figure 1)

| Table 2: Our solution with an example |
|---------------------------------------|
| **Question:** | What are the Amazon RDS storage types? |
| **Retriever set of documents:** | CHAP_Storage.txt, CHAP_Limits.txt, CHAP_BestPractices.txt |
| **Extractor Text Answer:** | General Purpose, SSD, Provisioned IOPS, Magnetic |
| **Extractor Yes/No Answer:** | None |

4.1 Retrievers

Given a question with no context, our approach relies on the retriever to find the right
documents that contains the answer. The need for a retriever stems from the fact that our
extractors are fairly large models and it is time and cost prohibitive for the extractor to

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3. https://ai.google.com/research/NaturalQuestions
go through all available documents. For example in our AWS Documentation dataset from Section 3.1, it will take hours for a single instance to run an extractor through all available documents. We ran experiments with simple information retrieval systems with a keyword search along with deep semantic search models to list relevant documents for a question. We used precision at K ($P@K$) metric to evaluate our retrievers. Precision at K is the proportion of retrieved items in the top-k set that are relevant:

$$P@K = \frac{\text{number of retrieved documents that are relevant}}{\text{total number of retrieved documents}}$$

4.1.1 **Whoosh**

Whoosh$^4$ is a fast, pure Python search engine library. The primary design impetus of Whoosh is that it is pure Python and can be used anywhere Python is running, as no compiler or Java is required.

4.1.2 **Amazon Kendra**

Amazon Kendra$^5$ is a semantic search and question answering service provided by AWS for enterprise customers. Kendra allows customers to power natural language-based searches on their own AWS data by using a deep learning-based semantic search model to return a ranked list of relevant documents. Amazon Kendra’s ability to understand natural language questions enables it to return the most relevant passage and related documents.

4.2 **Extractors**

Given a question with no context, the retriever finds a set of documents. Then the output of the retriever will pass on to the extractor to find the right answer for a question. We created our extractors from a base model which consists of different variations of BERT (Devlin et al., 2018) language models and added two sets of layers to extract yes-no-none answers and text answers. Our approach attempts to find yes-no-none answers and text answers in the same pass. Our model takes the pooled output from the base BERT model and classifies it in three categories: yes, no, and none. Furthermore, our model takes the sequence output from the base BERT model and adds two sets of dense layers with sigmoid as activation. The first layer tries to find the start of the answer sequences, and the second layer tries to find the end of the answer sequences. There can be multiple starts and ends for a single text answer. Figure 4.2 illustrates the extractor model architecture.

For our base model, we compared BERT (tiny, base, large) (Devlin et al., 2018) along with RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019), and distillBERT (Sanh et al., 2019). We implemented the same strategy as the original papers to fine-tune these models. We also used the same hyperparameters as the original papers: L is the number of transformer blocks (layers), H is the hidden size, and A is the number of self-attention heads.

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4. https://whoosh.readthedocs.io/
5. https://aws.amazon.com/kendra/
4.2.1 Extractor Model

We define a training set datapoint as a four-tuple \((d, s, e, yn)\), where \(d\) is a document containing the answers, \(s, e\) are indices to the start and end of the text answer, and \(yn\) defines the yes-no-none answer. The loss of our model is:

\[
L = \log p(s, e, yn|d)
\]

\[
L = \frac{1}{3} (\log ps(s|d) + \log pe(e|d) + \log pyn(yn|d))
\]

where each probability \(p\) is defined as:

\[
ps(s|d) = \frac{1}{1 + \exp(-f_{\text{start}}(s, d; \theta))}
\]

\[
pe(e|d) = \frac{1}{1 + \exp(-f_{\text{end}}(e, d; \theta))}
\]

\[
pyn(yn|d) = \frac{\exp(-f_{yn}(yn, d; \theta))}{\sum yn' \exp(-f_{yn}(yn', d; \theta))}
\]
where \( \theta \) is the base model parameters and \( f_{\text{start}}, f_{\text{end}}, f_{\text{yn}} \) represent three outputs from the last layer of the model.

At inference, we pass through all text from each document and return all start and end indices with scores higher than a threshold. We used F1 and Exact Match (EM) metrics to evaluate our extractor models.

5. Experiments

In our experiments, we used pre-trained or ready-to-use information retrieval systems because these systems are readily available and building a custom retriever with better performance is not economical. Our experiments show that Amazon Kendra’s semantic search is far superior to a simple keyword search and that the bigger the base model (BERT-based), the better the performance. The retriever results are shown in Table 3.

| Retriever | P@1 | P@3 | P@5 | P@7 | P@9 | P@13 | P@22 | P@30 | P@40 | P@60 |
|-----------|-----|-----|-----|-----|-----|------|------|------|------|------|
| Whoosh    | .05 | .06 | .06 | .06 | .06 | .06  | .06  | .06  | .06  | .06  |
| Kendra    | .66 | .79 | .86 | .87 | .9  | .91  | .92  | .93  | .94  | .95  |

Regarding our extractors, we initialized our base models with popular pretrained BERT-based models as described in Section 4.2 and fine-tuned models on SQuAD1.1 and SQuAD2.0 (Rajpurkar et al., 2016) along with natural questions datasets (Kwiatkowski et al., 2019). We trained the models by minimizing loss \( L \) from Section 4.2.1 with the AdamW optimizer (Devlin et al., 2018) with a batch size of 8. Then, we tested our models against the AWS documentation dataset (Section 3.1) while using Amazon Kendra as the retriever. Our final results are shown in Table 4.

| Extractor | Base Model | Hyperparameters | F1  | EM  |
|-----------|------------|-----------------|-----|-----|
| BERT Tiny | L=2, H=128 |                 | .128| .09 |
| RoBERTa   | L=12, H=768|                 | .154| .09 |
| DistilBERT| L=12, H=768|                 | .158| .08 |
| ALBERT    | L=12, H=768|                 | .199| .11 |
| BERT      | L=12, H=768|                 | .245| .16 |
| BERT Large| L=24, H=1024|               | .247| .16 |
| ALBERT XXL| L=12, H=4096|               | .422| .39 |

6. Limitations and Future Work

Our solution has a number of limitations. Below we describe some of these and suggest directions for future work. We were able to achieve 49% F1 and 39% EM for our test dataset due to the challenging nature of zero-shot open-book problems. The performance
of the solution proposed in this article is fair if tested against technical software documentation. However, it needs to be improved before finding use in real-world software products. Additionally, more testing is needed if we want to further expand the applicability of this solution in other domains (e.g., medical corpus, laws and regulations). Furthermore, the solution performs better if the answer can be extracted from a continuous block of text from the document. The performance drops if the answer is extracted from several different locations in a document. Moreover, all questions had a clear answer in the AWS documentation dataset, which is not always the case in the real-world. As our proposed solution always returns an answer to any question, it fails to recognize if a question cannot be answered.

For future work, we plan to experiment with generative models such as GPT-2 (Radford et al., 2019) and GPT-3 (Brown et al., 2020) with a wider variety of text in pre-training to improve the F1 and EM score presented in this article.

7. Conclusion

In this paper, we presented a new solution for zero-shot open-book QA with a two-step architecture to answer natural language questions from an available set of documents. With this novel solution, we were able to achieve 49% F1 and 39% EM with no domain-specific labeled data. We hope this new dataset and solution helps researchers create better solutions for zero-shot open-book use cases in similar real-world environments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Sia Gholami: Conceptualization, Methodology, Software, Investigation, Writing - original draft. Mehdi Noori: Writing - review & editing.

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