Defending Against Misinformation Attacks in Open-Domain Question Answering

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Abstract

Recent work in open-domain question answering (ODQA) has shown that adversarial poisoning of the search collection can cause large drops in accuracy for production systems. However, little to no work has proposed methods to defend against these attacks. To do so, we rely on the intuition that redundant information often exists in large corpora. To find it, we introduce a method that uses query augmentation to search for a diverse set of passages that could answer the original question but are less likely to have been poisoned. We integrate these new passages into the model through the design of a novel confidence method, comparing the predicted answer to its appearance in the retrieved contexts (what we call Confidence from Answer Redundancy, i.e. CAR). Together these methods allow for a simple but effective way to defend against poisoning attacks that provides gains of nearly 20% exact match across varying levels of data poisoning/knowledge conflicts.

1 Introduction

Open-domain question answering (ODQA) is the task of answering a given question, based on evidence from a large corpus of documents. In order to do so, a system generally first retrieves a smaller subset of documents (typically between 5-100) and then answers the question based on those documents. Previous research in ODQA has resulted in many well-curated datasets that evaluate a model's ability to answer questions on a wide array of topics (Kwiatkowski et al., 2019; Joshi et al., 2017; Dunn et al., 2017; Yang et al., 2015).

However, most internet users search across lesscarefully curated sources, where malicious actors are able to affect articles that may be used by an ODQA system (Figure 1). Furthermore, even in curated knowledge sources like Wikipedia, we fre-



Figure 1: An example of a poisoning attack on an opendomain question answering (ODQA) pipeline with our method (Lower) vs a standard system (Upper). The passages have been adversarially poisoned to replace Obama's correct birthplace to be incorrect. Our proposed defense method uses query augmentation to find new contexts that are less likely to be poisoned (#4 and #5). It then uses a novel confidence-based aggregation method (CAR) to predict the correct answer.

quently see attacks (e.g. malicious edits/fake pages) that have even impacted production QA systems.¹

Recent work has recognized the potential for bad actors to influence automated knowledge-intensive NLP systems that involve retrieval: Du et al. (2022) explored how poisoned information affects automated fact verification systems using sparse nonneural information retrieval systems, while Chen et al. (2022) and Longpre et al. (2021) have studied the role that knowledge conflicts play in ODQA

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¹For examples of disinformation attacks on popular entities that motivate our approach see Appendix A or the "Reliability of Wikipedia" or "Vandalism on Wikipedia" pages.

pipelines, mainly for the sake of understanding how these models use parametric vs non-parametric knowledge rather than in the context of data poisoning. Although these papers (see Appendix D for more) highlight the vulnerability of existing methods, the problem of defending against data poisoning or knowledge conflicts is still understudied, with limited to no published efforts in the area.

Thus, we seek to show the effects of data poisoning and propose a simple but effective defense. Building on the intuition that information is usually available in multiple places and that it is unlikely that all sources (or pages) will be poisoned, we propose a novel query augmentation scheme to gather a larger set of diverse passages. We also propose a new confidence method to decide when to use the newly gathered contexts vs the original, which we call *Confidence from Answer Redundancy* (CAR).

Our proposed approach involves no gradient updates, can easily be applied to existing frameworks, and uses a simple resolution approach to arrive at the predicted answer. Together, our methods can provide gains of nearly 20 points in exact match, helping to reduce the negative effects of data poisoning and disinformation attacks on ODQA.

2 Experimental Details

We seek to mimic realistic disinformation attacks on a curated knowledge source; thus, for our experiments we use Wikipedia as the knowledge collection for both original and augmented queries, and simulate an attack on each question independently. We follow Du et al. (2022) and poison the most relevant articles returned by searching with the question. We vary the amount of poisoned articles from 1 to 100, as 100 passages are given to the models.² Note that we do not poison the entire corpus, as poisoning millions of documents is beyond the scope of common disinformation attacks.

2.1 Data

For our experiments we use Natural Questions (NQ) (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017), two popular datasets for opendomain question answering. Furthermore, previous research on conflicts in ODQA has used these datasets in their experiments (Chen et al., 2022). The Natural Question dataset was gathered by collecting real-user queries typed into Google Search, while TriviaQA was collected by scraping question and answer pairs from trivia websites, and then matching the answers to Wikipedia passages.

We simulate the data poisoning through the code available from Longpre et al. (2021), which introduced the problem of knowledge conflicts in ODQA. Instead of simply providing conflicts for model analysis, we use them as adversarial poisoning strategies as they provide realistic fake answers to the question. This method uses the answers to the questions to suggest an entity of the same type, using SpaCY NER (Honnibal and Montani, 2017), which is then used to replace the correct answer in the text. This allows for entity substitutions that keep the semantic order of the context, such as replacing dates with dates, people with people, etc.

2.2 Models

We use Fusion-in-Decoder (FiD), an encoderdecoder architecture that generates an answer by first retrieving and encoding N passages and then concatenating them before passing them through the decoder (Izacard and Grave, 2021). This model uses the DPR bi-encoder architecture for retrieval (Karpukhin et al., 2020). We also use the Atlas model (Izacard et al., 2022), which is currently the state-of-the-art model on Natural Questions and TriviaQA. This model also uses fusion in the decoder and has a T5 backbone, but trains both the question answering and retrieval end-to-end. For detailed hyperparameters see Appendix B.

3 Proposed Method

3.1 Query Augmentation

We hypothesize that in cases of conflicting evidence in large corpora for *factoid* based questions, there will generally be more evidence for the correct answer than for incorrect ones. As an example, imagine the question "Where was Barack Obama born?" with a corresponding attack to his Wikipedia page (see Figure 1). Since there exists redundant information throughout Wikipedia, alternate questions that find contexts on other pages (such as his mother's page, *Ann Dunham*) will still be able to find the correct answer.

To create these alternate questions that will still find the correct answer but with more diverse passages, we propose a query augmentation scheme that has similarities to classical query expansion in information retrieval (IR) (Singhal et al., 2001; Carpineto and Romano, 2012). We generate these

²We also experimented with poisoning random passages and found similar results (Appendix E)



Figure 2: Number of new passages retrieved per augmented question (e.g., a question in the 100 bin would have 100 new contexts not retrieved by the original). Natural Questions is on top and TriviaQA on bottom.

new questions for each original question by prompting GPT-3 (davinci-002) from Brown et al. (2020). Note that these query augmentations are not necessarily paraphrases as they strive to be as different as possible while still leading to the correct answer. They are also not identical to classic query expansion from IR either, as they do not intend to solely broaden the query scope but rather to find diverse contexts from questions of any scope.

For each query in the dataset, we prompt GPT-3 with the following: "Write 10 new wildly diverse questions with different words that have the same answer as {Original Question}", thus generating approximately 10 augmented questions per original question (c.f. Table 1 for three examples of generations). Finally, we retrieve the 100 most relevant contexts for those augmented questions.³

When we compare these newly retrieved passages to the passages retrieved by the original question we find that they do provide a more diverse set of passages. Figure 2 shows the distribution of new passages retrieved, with almost all retrieving at least 20 or more new passages and a substantial amount having an entirely new set of 100 passages. When was the last time anyone was on the moon?

When was the last time anybody walked on the moon? When was the last manned mission to the moon? When was the last time a human was on the moon?

In which year did Picasso die?

When did Picasso die?
How old was Picasso when he died?
What was Picasso's cause of death?

What is the largest city in Turkey?

What city in Turkey has the most people? What is the most populous city in Turkey? What is the most urbanized city in Turkey?

Table 1: Examples of the question augmentation generation (Section 3.1) with the original question on top.

3.2 Confidence from Answer Redundancy

In order to identify the best augmented queries with their corresponding new passages, we derive a novel method, CAR, for measuring ODQA confidence. CAR measures how often the predicted answer string occurs in the retrieved contexts (usually 100 contexts). For example, if the predicted answer appears only once in all 100 contexts, this may mean that the retriever was not able to find many documents relevant to the query, especially as popular entities (those asked about in NQ and TriviaQA) are generally found in many articles. Overall, the more frequently the predicted answer appears in the contexts, the more likely that the retrieval was both successful and plentiful (e.g. redundant).

In practice, given a set of documents D, we set a hyperparameter k to determine the cutoff for CAR (in practice we use k = 5, found by tuning on the dev set). If the model retrieves more than k unique passages that contain the predicted answer string, we classify the model as confident and vice versa. We use this as part of our resolution method below.

3.3 Answer Resolution

We use the following methods to combine (or not combine) the original question with the augmented questions, with their shortened names in italics: (1) use the *original* question only, e.g. the baseline (2) *random*ly pick one new augmented question (3) take a *majority vote* of the augmented question's predictions or (4) use answer *redundancy*, described in the following paragraph. See Appendix J for details on other methods we tried that underperformed and are excluded for clarity.

Our new method for answer resolution, *redundancy*, uses CAR to effectively combine both the original question and the new augmented questions.

³Note if searching with the augmented questions retrieves a passage from an article designated as poisoned we swap the original text for the poisoned text following Du et al. (2022).



Figure 3: Main results showing the effect of data poisoning and various defense strategies using FiD (see Appendix C for ATLAS). Left shows TriviaQA while right shows Natural Questions. C stands for context.

We use CAR to decide whether to choose the original question's prediction, and if not, use a majority vote over the predictions from the augmented questions that are confident (filtered using CAR). By doing so, we retain performance from the original question and passage set when confident, while otherwise backing off to the augmentation.

All methods except *original* can use either the original (*Original C*) or new (*New C*) contexts. Further, *majority vote* and *redundancy* can use either the new or original questions during inference (we use original, after tuning c.f. Appendix B).

4 **Results**

Figure 3 highlights our key findings using the FiD model (ATLAS results are similar, see Appendix C). Following (Longpre et al., 2021; Chen et al., 2022), all results are filtered by those that the model originally predicted correctly, thus making the original method have by definition 100% EM at the 0-article poisoning level. As expected, as the amount of poisoned data given to the model increases, performance decreases. We see that resolution methods that use the new contexts (New C) outperform those that use the original contexts, confirming the intuition behind our proposed method. Furthermore, we see that the *redundancy* resolution strategy outperforms all other strategies, by up to 19.4% in the TriviaQA setting (33.2% at 100 poisoned articles vs 13.8% baseline). Scores on NQ are lower than TriviaQA, even with no poisoning, but still improves up to 14% EM using our methods.

However, how many of these augmented questions are needed for this approach to work well? To answer this, we include Figure 4 in Appendix F with the overall trend being that as the number of augmented queries increases, so does the performance. Furthermore, it shows that even one augmented query has gains over the baseline method, allowing for a more compute efficient method at the expensive of several points of performance.

We also explore why performance is non-zero when the number of poisoned articles is equal to the number of contexts the model receives. We manually annotated 20 examples on TriviaQA that FiD got correct at the 100-article poisoning setting. We found that it is due to the model using its parametric knowledge to correctly answer (65% of the time), as the correct answer was not present in any of the input documents, or due to answer aliases (35%) that were not part of the answer set. Examples of cases can be found in Appendix G.

5 Conclusion

Our work defends against data poisoning attacks in open-domain question answering through two novel methods: (1) the use of query augmentation to find diverse passages that still correctly answer the question and (2) the use of answer redundancy as a strategy for model confidence in its prediction. Our proposed methods do not involve *any* gradient updates and provide a significant performance improvement. Thus, our work shows the effect of data poisoning on state-of-the-art open-domain question-answering systems and provides a way to improve poisoned performance by almost 20 points in exact match. We hope that this work encourages future work in defending against poisoning attacks.

6 Limitations

Our work focuses on the TriviaQA and Natural Questions benchmarks, which include questions about popular entities in Wikipedia. As discussed in Appendix A, our approach simulates real-world common attacks which are the most frequent type of attacks. However, for entities that appear less often in the knowledge source (and are less likely to be attacked), our approach will not be as effective.

We leave attacks on less-popularity entities to future work, as we focus on the most frequently and higher impact attacks, while also using datasets that are standard in existing literature, e.g. Natural Questions and TriviaQA.

Our work shows the impact that disinformation attacks could have on Wikipedia and provides an initial attempt to help remedy those attacks. We note that our strategy does not have perfect accuracy and is still susceptible to attacks, e.g. if there is no correct information in any context to be found, it will be very difficult for ODQA systems to give the correct answer. We welcome additional research to improve the resistance of ODQA systems to adversarial attacks.

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A Realism of Proposed Setting

We focus on data poisoning attacks to high to medium popularity entities, as included in TriviaQA and Natural Questions. But such attacks realistic and have they happened before?

Due to the way that search engines work, any data poisoning done at the time of indexing is able to effect system performance until the data is reindexed. Thus, if one were to change a Wikipedia page (or a personal website that was included in an index) and that change was indexed, the data would be poisoned until re-indexing.



Figure 4: An ablation on the number of augmented queries used for the *redundancy* resolution method on Natural Questions 5-article poisoning setting. Note that as the number of augmented queries increases, so does the performance. Baseline performance is 17.5%.

Furthermore, because of the popularity of the entities, data poisoning attacks are more common (see "Vandalism on Wikipedia"). There have even been many high profile attacks on popular entities that have been reflected in production systems (e.g. this is not hypothetical). One such entity who has been frequently attacked is Donald Trump, whose Wikipedia page was changed to include critical text and inappropriate images, returned by Siri to real user queries. The Wikipedia page on vandalism include many such examples of famous politicians, musicians, athletes and other popular entities being subject to attacks on Wikipedia that were propagated to users via Google or various news outlets (e.g. Thomas Edison's page describing him as a "douchebag", famed swimmer Chad Le Clos's page edited to say he literally "died at the hands of Michael Phelps" when losing a race, etc.).

These attacks are just the tip of the iceberg for disinformation, as attacks to Wikipedia are the easiest to trace. Since production search engines index the web and then answer questions about them, any personal or company page can be used for attacks (see this humorous attack for QA to Bing Chat about Mark Reidl). And as the people directing disinformation campaigns are likely motivated to attack well-known entities rather than unknown entities (for political or economic reasons), our proposed setting of defending against popular entities is well-motivated and is a serious problem affecting current production systems today.



Figure 5: Main results showing the effect of data poisoning and various defense strategies on ATLAS. Left shows TriviaQA while right shows results on Natural Questions. Q and C stand for question and context respectively.

B Hyperparameters

For all our experiments we use a cluster of V100 GPUs, with each job running on a 4 to 8 GPU node and taking approximately 12-24 hours depending on the model. We use the models as provided by the original authors with default retriever hyperparameters. We use ATLAS'S XL version.

Following previous work in question answering, we report Exact Match (EM) in all of our experiments. We take the data from Longpre et al. (2021) and split into equal dev and test sets. We use the dev set to tune the CAR method's hyperparameters and use K = 5 for our experiments.

Along with the *New C* and *Original C* options, the *redundancy* and *majority vote* methods also have hyperparameters for using either the augmented questions or the original question for the final prediction (after generating and searching for new contexts). Our tuning on the dev set indicated that using the original question and the new contexts from searching with the augmented question provides slightly higher performance (which makes sense, since the original question is the most important to answer). Thus, the process is first generating augmented questions, then searching with those, then doing inference with the original questions and the newly retrieved contexts (and finally CAR, if using the redundancy method).

C Results with ATLAS

We also show similar results using the ATLAS model in Figure 5. These results suggest the same conclusion as in the main paper (up to 14.7% EM improvement on Natural Questions and up to 18.8%

EM improvement on TriviaQA). A minor difference is that ATLAS performs higher in terms of absolute scores compared to FiD, and thus our methods also scores higher in absolute terms. This suggests that our methods will continue to work well even with newer and better models.

D More Related Work

As a larger section of related work did not have space in the main paper, we include more related work here.

Data Poisoning Attacks Data poisoning attacks in NLP have a long history, with several prominent works appearing in recent years including (Wallace et al., 2019a, 2020; Schwarzschild et al., 2021) focusing on various NLP tasks such as machine translation, language modeling, etc. However, in the question answering space most adversarial work is focused on making harder questions, rather than simulating a real attack (Wallace et al., 2019b; Lee et al., 2019). Those that do focus on human attacks focus on the machine reading setting (Bartolo et al., 2021).

As mentioned in the main text, a nascent line of work has focused on knowledge conflicts in opendomain question answering (Chen et al., 2022; Longpre et al., 2021). These works' main motivation is to explore how ODQA models operate under the influence of conflicts, mostly in the context of non-parametric vs parametric knowledge. We extend these works by using their methods as simulated attacks on a knowledge source and proposing efforts to defend against these attacks. **Open-Domain Question Answering** Our work builds off of recent advances in ODQA, such as using Fusion-in-Decoder (Izacard and Grave, 2021). Other work such as DPR (Karpukhin et al., 2020) showed promising results but has been improved upon by models that encode a large number of contexts into a single reader model.

Query Augmentation Query augmentation is a traditional information retrieval technique to augment a given query to find a better set of documents (Singhal et al., 2001; Carpineto and Romano, 2012). In classical terms, the strategy is usually to expand the query, spelling out acronyms or adding synonyms. Recently, work has begun to use neural models to generate these expansions (Wang et al., 2021; Claveau, 2021). In our work, we use a similar strategy to create new queries that will gather a diverse set of passages.

Confidence and Calibration of QA Many works have focused on calibrating QA models so that they correctly reflect probabilities that equal their actual correct answer rate (Clark and Gardner, 2017; Kamath et al., 2020; Si et al., 2022; Jiang et al., 2021). Our proposed confidence method is similar in that it measures when the model will be more likely to be correct, however, it does not do calibration in the sense of calibrated probabilities, instead giving a single value of "confident" or "not confident."

Answer redundancy has been studied before in other NLP contexts, such as Downey et al. (2006) in the information extraction task. We apply a similar intuition of answer redundancy to the novel context of document inputs for open-domain question answering.

E Alternate Poisoning Attacks

In the main section of the paper, we used poisoning attacks based on articles. However, one could attack a system directly by going after its retrieved results, either randomly poisoning N% or poisoning the top N%. We note that we tried both settings and found similar results, with the main difference that model performance declines slower (as randomly picking contexts to poison is less likely to impact the model until higher levels of poisoning).

F Number of Augmented Queries

In Figure 4 we see the results for how the number of augmented queries affects performance. Over-



Figure 6: An ablation on Confidence from Answer Redundancy (CAR) compared to their exact match scores on the NQ 1-article poisoned setting. Those in the True bar have greater than 5 unique passages that contain the predicted answer string.

all, one query provides strong performance (above the baseline original performance at 17.5% EM) and multiple questions continue to show gains. We note that this figure uses Natural Questions and the 5-article poisoning setting with FiD, but other settings showed roughly the same results. As including more queries only seems to increase the score, it's possible that generating more than 10 augmented queries would show even better results.

G Why is performance not 0% at 100 poisoned documents?

To explore this question, we conducted a manual analysis of 20 pairs of question and 100 document passages on TriviaQA using FiD. We found that 65% of cases were due to the model's parametric knowledge, as there was no such answer string in the input text. However, the answer was generally very obvious, like "In which country is Dubrovnik?" which is generally easier for the model to predict (e.g. "Croatia"). In 35% of cases there was a missing alias from the answer string set, such as "What dance craze was named after a city in South Carolina?" with an answer string set of "Charleston rhythm", "Charleston (dance)", "Charleston (dance move)", "Charleston dance", and "The Charleston". FiD predicted "Charleston" from the text, since "Charleston" was not in the answer string set so it was not poisoned in the text. Future work on data poisoning could improve on



Figure 7: The number of poisoned *passages* given the article poisoning level. Notice that TriviaQA (*tqa*, right) has more passages to poison and a more gradual slope of poisoning than Natural Questions (*nq*, left).

this category by developing more robust poisoning techniques to aliases.

H Number of Poisoned Passages

In our experiments, we poisoned at the article level, as an attacker might do to a specific entity. However, each Wikipedia article corresponds to more than one *passage* which are what is used for retrieval. When we poison at the article level we poison all passages in the article, so oftentimes many passages are poisoned even when poisoning one article. Furthermore, passages can only be poisoned if the answer is present in the passage (and thus available to be replaced).

How many passages are poisoned at each articlepoisoning level? Figure 7 answers this question and shows the number of poisoned passages vs the article-poisoning level. We find that the number of articles poisoned is much higher on TriviaQA, which means that TriviaQA had a much higher number of passages with the answer to begin with.

I Confidence from Answer Redundancy

We compare the confidence from answer redundancy (CAR) to the actual exact match score (using the 1-article poisoning setting on Natural Questions) to show the effectiveness of this heuristic. In Figure 6 we see the large gap between queries that do not meet CAR and those that do (around 65% absolute exact match). Error bars indicate a 95% confidence interval.

J Alternate Answer Resolution Strategies

Due to space and clarity for figures, we do not include all possible answer resolution strategies in the main figures. Some potential alternate resolution stratgies we tried included:

- Using the new augmented questions with CAR alone, without using them as a backup for the original question. This is equivalent to the majority vote method but using CAR to filter the question that get to vote. Although this method performed well it consistently underperformed our *redundancy* method and thus we do not include it
- Using a majority vote over both the original question's prediction *and* and augmented question's predictions. This performed nearly identically to the standard majority vote method, hence we leave it out for clarity.
- Taking the difference between the the CAR values of the original and augmented questions. This again greatly underperformed the *redundancy* method and is therefore not included

We encourage others who have new ideas for answer resolution strategies to use our code as a start to develop their method.

K Compute Cost of our Proposed Method

Our method requires the addition of 1 call to GPT-3's API and 10 instances of additional search and inferences of the ODQA model. As GPT-3 and other large language models become more available and cheaper (as they have already started to be) this will become cheaper to do with time. Furthermore, retrieval takes milliseconds with modern indexes and methods adding only a negligible overhead to standard ODQA pipelines. Thus, the biggest overhead for our proposed method is the additional inference steps after the retrieval steps which, as mentioned in Appendix F, can be reduced to only one and still see large gains.