FAVIQ: FAct Verification from Information-seeking Questions

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Abstract
Despite significant interest in developing general purpose fact checking models, it is challenging to construct a large-scale fact verification dataset with realistic claims that would occur in the real world. Existing claims are either authored by crowdworkers, thereby introducing subtle biases that are difficult to control for, or manually verified by professional fact checkers, causing them to be expensive and limited in scale. In this paper, we construct a challenging, realistic, and large-scale fact verification dataset called FAVIQ, using information-seeking questions posed by real users who do not know how to answer. The ambiguity in information-seeking questions enables automatically constructing true and false claims that reflect confusions arisen from users (e.g., the year of the movie being filmed vs. being released). Our claims are verified to be natural, contain little lexical bias, and require a complete understanding of the evidence for verification. Our experiments show that the state-of-the-art models are far from solving our new task. Moreover, training on our data helps in professional fact-checking, outperforming models trained on the most widely used dataset FEVER or in-domain data by up to 17% absolute. Altogether, our data will serve as a challenging benchmark for natural language understanding and support future progress in professional fact checking.1

1 Introduction
Fact verification, a task of verifying the factuality of the natural language claim, is an important NLP application (Cohen et al., 2011) and has also been used to evaluate the amount of external knowledge a model has learned (Petroni et al., 2021). However, it is challenging to construct fact verification data with claims that contain realistic and implicit misinformation. Crowdsourced claims from prior work such as FEVER (Thorne et al., 2018a) are written with minimal edits to reference sentences, leading to strong lexical biases such as the overuse of explicit negation and unrealistic misinformation that is less likely to occur in real life (Schuster et al., 2019a). On the other hand, data constructed by professional fact-checkers are expensive and are typically small-scale (Hanselowski et al., 2019).

We propose to use information-seeking questions (Kwiatkowski et al., 2019) to construct a large-scale, challenging, and realistic fact verification dataset. Information-seeking questions are inherently incomplete, because users are asking about unfamiliar topics, and for example contain ambiguity (Min et al., 2020) and false presuppositions (Kim et al., 2021). We introduce a new dataset FAVIQ—FAct Verification derived from Information-seeking Questions. FAVIQ is constructed based on ambiguity in information-seeking questions. Consider the example in Figure 1. Users ask an ambiguous question because the filming of the movie and the release of the movie are semantically close, and both can be seen as the creation time. Therefore, claims generated through the crossover of the disambiguation of the information-seeking question are likely to contain misinforma-

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1 Data available at https://faviq.github.io
tion that real users are easily confused with. We automatically generate such claims by composing valid and invalid question-answer pairs and transforming them into textual claims using a neural model. The data is further augmented by claims from regular question-answer annotations.

In total, FAVIQ consists of 188k claims. We manually verified a subset of claims to ensure that they are as natural as human-written claims. Our analysis shows that the claims have significantly lower local mutual information—a metric that quantifies lexical bias in the data (Schuster et al., 2019b)—than existing crowdsourced claims; claims involve diverse types of distinct entities, events, or properties that are semantically close, being more realistic and harder to verify without a complete understanding of the evidence text.

Our experiments show that a model with no background knowledge performs only slightly better than random guessing, and the state-of-the-art model achieves an accuracy of 65%, leaving significant room for improvements. Furthermore, training on FAVIQ improves the accuracy of verification of claims written by professional fact checkers, outperforming models trained on the target data only or pretrained on FEVER by up to 17% absolute. Together, our experiments demonstrate that FAVIQ is a challenging benchmark as well as a useful resource for professional fact checking.

2 Related Work

2.1 Fact verification

Fact verification is crucial both for real-world applications (Cohen et al., 2011) and as a benchmark to evaluate the ability of the model to access and process knowledge (Petroni et al., 2021).

One line of work has studied professional fact checking, dealing with claims collected by professional fact checkers, typically in specific domains like politics or news (Vlachos and Riedel, 2014; Ferreira and Vlachos, 2016; Augenstein et al., 2019; Hanselowski et al., 2019). While such data contains realistic claims that have occurred in the real world, it is expensive to construct as it requires labor from professional fact checkers, and is mostly small-scale. Moreover, it is less suitable as a benchmark due to lack of a standard evidence corpus such as Wikipedia and ambiguities in labels.

Other fact verification datasets are collected through crowdsourcing (e.g., FEVER (Thorne et al., 2018a) and its variants (Thorne et al., 2018b; Thorne and Vlachos, 2019)) by altering a word or negating the reference text to intentionally make true or false claims. This process leads to large-scale datasets but with strong artifacts and unrealistic claims (Schuster et al., 2019a; Thorne and Vlachos, 2019; Eisenschlos et al., 2021). Consequently, a trivial claim-only baseline with no evidence achieves near 80% (Petroni et al. (2021), verified in Section 4.1). While more recent work proposes new crowdsourcing methods that alleviate artifacts (Schuster et al., 2021; Eisenschlos et al., 2021), their claims are still written given particular evidence text, being vulnerable to subtle lexical biases that can be hard to explicitly measure.

In this paper, we construct a fact verification dataset by leveraging question answering (QA) data, which in turn was collected from untrained crowdworkers. Our data consists of claims that have significantly less lexical bias compared to other crowdsouced claims (Figure 3), contain realistic misinformation that people are likely to be confused about (Table 4), and are challenging to current state-of-the-art models (Section 4.1). Moreover, training a model on our data improves professional fact checking (Section 4.2).

2.2 QA to Verification Task

Prior work has investigated converting the QA task into entailment or fact verification tasks (Demszky et al., 2018; Jiang et al., 2020; Pan et al., 2021; Chen et al., 2021). Similar to ours, they use the correct and incorrect answers to the questions and transform them into claims. However, they make use of synthetic or annotated questions and use incorrect answers written by crowdworkers or predicted by the model. We instead use questions posed by real users to reflect confusions that naturally occur while seeking information.

3 Data

3.1 Data Construction

We construct FAVIQ—FACT Verification derived from Information-seeking Questions, consisting of claim-label pairs where the label is either support or refute.

Annotated questions are simulated by crowdworkers given the evidence text and the answer, having largely different distributions from information-seeking questions (Lee et al., 2019; Gardner et al., 2019).
replace the page number with their own.

The key idea to construct the data is to gather a set of valid and invalid question-answer pairs (Section 3.1.2) from annotations of information-seeking questions (Section 3.1.1), and then convert each question-answer pair \((q, a)\) to a claim (Section 3.1.3). Figure 2 presents an overview of this process.

3.1.1 Data Sources

We use QA data from Natural Questions (NQ, Kwiatkowski et al. (2019)) and AmbigQA (Min et al., 2020). NQ is a large-scale dataset consisting of the English information-seeking questions mined from Google search queries. AmbigQA provides disambiguated question-answer pairs for NQ questions, thereby highlighting the ambiguity that is inherent in information-seeking questions. Given an ambiguous question, it provides a set of multiple distinct answers, each paired with a new disambiguated question that uniquely has that answer.

3.1.2 Composing Valid and Invalid QA Pairs

FAVIQ uses ambiguous questions and their disambiguation (denoted as \(A\)) and is further augmented by data using regular question-answer pairs with an assumption of no ambiguity (denoted as \(R\)).

From ambiguous questions (\(A\)) We assume data consisting of a set of \((q, \{q_1, a_1\}, \{q_2, a_2\})\), where \(q\) is an information seeking question that has \(a_1, a_2\) as multiple distinct answers. If \(q_1\) and \(q_2\) are disambiguated questions for the answers \(a_1\) and \(a_2\), i.e., \(q_1\) has \(a_1\) as a valid answer and \(a_2\) as an invalid answer. We use \((q_1, a_1)\) and \((q_2, a_2)\) as valid question-answer pairs, and \((q_1, a_2)\) and \((q_2, a_1)\) as invalid question-answer pairs.

This data is particularly well suited to fact checking because individual examples require identification of entities, events, or properties that are semantically close but distinct: the fact that a user asked an ambiguous question \(q\) without realizing the difference between \((q_1, a_1)\) and \((q_2, a_2)\) indicates that the distinction is non-trivial and is hard to notice without sufficient background knowledge about the topic of the question.

From regular questions (\(R\)) We use the QA data consisting of a set of \((q, a)\): an information-seeking question \(q\) and its answer \(a\). We then obtain an invalid answer to \(q\), denoted as \(a_{\text{neg}}\), from an off-the-shelf QA model for which we use the model from Karpukhin et al. (2020)—DPR followed by a span extraction model. We carefully choose \(a_{\text{neg}}\) with tricks to obtain the hard negative but not the false negative; details provided in Appendix A. We use \((q, a)\) and \((q, a_{\text{neg}})\) as a valid and an invalid question-answer pair, respectively.

We can think of \((q, a_{\text{neg}})\) as a hard negative pair chosen adversarially from the QA model. This data can be obtained on a much larger scale than the \(A\) set because annotating a single valid answer is easier than annotating disambiguations.

3.1.3 Transforming QA pairs to Claims

We transform question-answer pairs to claims by training a neural model which maps \((q, a)\) to a claim that is support if and only if \(a\) is a valid answer to \(q\), otherwise refute. We first manually convert 250 valid or invalid question-answer pairs.
Table 1: Data Statistics of FAVIQ. A denotes claims derived from ambiguous questions and their disambiguations, and R denotes claims from regular question-answer pairs.

|       | Total      | Support   | Refute   |
|-------|------------|-----------|----------|
| **Train** |            |           |          |
| A     | 17,008     | 8,504     | 8,504    |
| R     | 140,977    | 70,131    | 70,846   |
| **Dev** |            |           |          |
| A     | 4,260      | 2,130     | 2,130    |
| R     | 15,566     | 7,739     | 7,827    |
| **Test** |           |           |          |
| A     | 4,688      | 2,344     | 2,344    |
| R     | 5,877      | 2,922     | 2,955    |

human-authored, indicating that these grammatical errors and typos occur in real life. The validators also found that 98.2% of the claims are accurate (96.4% of A and 100% of R).

Comparison of size and claim length Table 2 compares statistics of the claims from a variety of fact verification datasets: SNOPEs (Hanselowski et al., 2019), SciFACT (Wadden et al., 2020), FEVER (Thorne et al., 2018a), FM2 (Eisenschlos et al., 2021) and FAVIQ.

FAVIQ is as large-scale as FEVER, while its distributions of claim length is much closer to claims authored by professional fact checkers (SNOPEs and SciFACT; details in Section 4.2). We also compare with FM2 because it is the most recently introduced fact verification dataset, constructed through a carefully-designed multi-player game to better control for the lexical bias seen in FEVER. FM2 is smaller scale, due to difficulty in scaling multi-player games, and has claims that are slightly longer than professional claims, possibly because they are intentionally written to be difficult.

Lexical cues in claims We further analyze lexical cues in the claims on FEVER, FM2 and FAVIQ by measuring local mutual information (LMI; Schuster et al. (2019b); Eisenschlos et al. (2021)). LMI indicates the correlation between bigrams and the label. More specifically, LMI is defined as:

$$LMI(w, c) = P(w, c) \log \frac{P(w, c)}{P(w) \cdot P(c)},$$

where $w$ denotes a bigram, $c$ is a label, and $P(\cdot)$ are estimated with empirical counts (Schuster et al., 2019b).
is
LMI
1200
1600
400
800
100
bigrams are shown in Figure 3. The LMI scores with conjunctions (e.g., “was foreign minister” and expressions, e.g., “only”, “incapable” or “not”.

Dataset Top Bigrams by LMI
FEVER-S is a, a film, of the, is an, in the, in a
FEVER-R is only, only a, incapable of, is not, was only, is incapable
A set-S on the, was the, the date, date of, in episode, is what
A set-R of the, the country, at the, the episode, started in, placed at
R set-S out on, on october, on june, released on, be 18, on august
R set-R out in, on september, was 2015, of the, is the, released in

Table 3: Top bigrams with the highest LMI for FEVER and FAVIQ. S and R denotes support and refute respectively. Highlighted bigrams indicate negative expressions, e.g., “only”, “incapable” or “not”.

The distributions of the LMI scores for the top-100 bigrams are shown in Figure 3. The LMI scores of FAVIQ are significantly lower than those of FEVER and FM2, indicating that FAVIQ contains significantly less lexical bias. Tables 3 shows the top six bigrams with the highest LMI scores for FEVER and FAVIQ. As highlighted, all of the top bigrams in refute claims of FEVER contain negative expressions, e.g., “is only”, “incapable of”, “did not”. In contrast, the top bigrams from FAVIQ do not include obvious negations, and the top bigrams for different labels overlap significantly, strongly suggesting the task will be more challenging to solve.

Qualitative analysis of the refute claims We also analyzed 30 randomly sampled refute claims from FAVIQ and FEVER respectively. We categorized the cause of misinformation as detailed in Appendix B, and show three most common categories for each dataset as a summary in Table 4.

On FAVIQ, 60% of the claims involve entities, events or properties that are semantically close, but still distinct. For example, they are specified with conjunctions (e.g., “was foreign minister” and “signed the treaty of versailles from germany”), or share key attributes (e.g., films with the same title). This means that relying on lexical overlap or partially understanding the evidence text would lead to incorrect predictions; one must read the full evidence text to realize that the claim is false. Furthermore, 16.7% involve events, e.g., from filing for bankruptcy for the first time to completely ceasing operations (Table 4). This requires full understanding of the underlying event and tracking of state changes (Das et al., 2019; Amini et al., 2020).

The same analysis on FEVER confirms the findings from Schuster et al. (2019a); Eisenschlos et al. (2021); many of claims contain explicit negations (30%) and antonyms (13%), with misinformation that is less likely to occur in the real world (20%).

4 Experiments

We first evaluate state-of-the-art fact verification models on FAVIQ in order to establish baseline performance levels (Section 4.1). We then conduct experiments on professional fact-checking datasets, to measure the improvements from training on FAVIQ (Section 4.2).

Conjunctions (33.3%) C: Johannes bell was the foreign minister that signed the treaty of versailles from germany. / E: Johannes bell served as Minister of Colonial Affairs ... He was one of the two German representatives who signed the Treaty of Versailles.

Shared attributes (26.7%) C: Judi bowker played andromeda in the 2012 remake of the 1981 film clash of the titans called wrath of the titans. E: Judi bowker ... Clash of the Titans (1981).

Procedural event (16.7%) C: Mccrory’s originally filed for bankruptcy on february 2002. / E: Mccrory Stores ... by 1992 it filed for bankruptcy. ... In February 2002 the company ceased operation.

Negation (30.0%) C: Southpaw hasn’t been released yet. E: Southpaw is an American sports drama film released on July 24, 2015.

Cannot find potential cause (20.0%) C: Mutiny on the Bounty is Dutch. E: Mutiny on the Bounty is a 1962 American historical drama film.

Antonym (13.3%) C: Athletics lost the world series in 1989. E: The 1989 World Series ... with the Athletics sweeping the Giants.

Table 4: Three most common categories based on 30 refute claims randomly sampled from the validation set, for FAVIQ (top) and FEVER (bottom) respectively. Full statistics and examples in Appendix B. C and E indicate the claim and evidence text, respectively.
4.1 Baseline Experiments on FaVIQ

4.1.1 Models

We experiment with two settings: a zero-shot setup where models are trained on FEVER, and a standard setup where models are trained on FaVIQ. For FEVER, we use the KILT (Petroni et al., 2021) version following prior work; we randomly split the official validation set into equally sized validation and test sets, as the official test set is hidden.

All models are based on BART (Lewis et al., 2020), a pretrained sequence-to-sequence model which we train to generate either support or refute. We describe three different variants which differ in their input, along with their accuracy on FEVER by our own experiments.

Claim only BART takes a claim as the only input. Although this is a trivial baseline, it achieves an accuracy of 79% on FEVER.

TF-IDF + BART takes a concatenation of a claim and \( k \) passages retrieved by TF-IDF, for which we use DrQA (Chen et al., 2017). It achieves 87% on FEVER.

DPR + BART takes a concatenation of a claim and \( k \) passages retrieved by DPR (Karpukhin et al., 2020), a dual encoder based model. It is the state-of-the-art on FEVER based on Petroni et al. (2021), achieving an accuracy of 90%.

Implementation details We use the English Wikipedia from 08/01/2019 following KILT (Petroni et al., 2021). We take the plain text and lists provided by KILT and create a collection of passages where each passage has up to 100 tokens. This results in 26M passages. We set the number of input passages \( k \) to 3, following previous work (Petroni et al., 2021; Maillard et al., 2021). Baselines on FaVIQ are jointly trained on the A set and the R set.

Training DPR requires a positive and a negative passage—a passage that supports and does not support the decision, respectively. As the gold positive passage is not provided in FaVIQ, we obtain the silver positive passage by (1) taking the question that was the source of the claim during the data creation, (2) using it as a query for TF-IDF, and (3) taking the top passage that contains the answer. The passage through the same process but without the answer is taken as a negative. More training details are in Appendix C.

4.1.2 Results

Table 5 reports results on FaVIQ. The overall accuracy of the baselines is low, despite their high performance on FEVER. The zero-shot performance is barely better than random guessing, indicating that the model trained on FEVER is not able to generalize to our more challenging data. When the baselines are trained on FaVIQ, the best model achieves an accuracy of 65% on the A set, indicating that existing state-of-the-art models do not solve our benchmark.

Impact of retrieval The performance of the claim only baseline that does not use retrieval is almost random on FaVIQ, while achieving nearly 80% accuracy on FEVER. This result suggests significantly less bias in the claims, and the relative importance of using background knowledge to solve the task. When retrieval is used, DPR outperforms TF-IDF, consistent with the finding from Petroni et al. (2021).

A set vs. R set The performance of the models on the R set is consistently higher than that on the A set by a large margin, implying that claims based on ambiguity arisen from real users are more challenging to verify than claims generated from regular question-answer pairs. This indicates clearer contrast to prior work that converts regular QA data to declarative sentences (Demszky et al., 2018; Pan et al., 2021).

Error Analysis We randomly sample 50 error cases from DPR + BART on the A set of FaVIQ and categorize them, as shown in Table 6.

- Retrieval error is the most frequent type of errors. DPR typically retrieves a passage with the correct topic (e.g., about “Lie to Me”) but that is missing the more specific background knowledge (e.g., the end date). We think the
Table 6: Error analysis on 50 samples of the A set of FaVIQ validation data. \(C\) and \(E\) indicate the claim and retrieved evidence passages from DPR, respectively. Gold and blue indicate gold label and prediction by the model, respectively. The total exceeds 100% as one example may fall into multiple categories.

| Category                              | % | Example                                                                                       |
|---------------------------------------|---|-----------------------------------------------------------------------------------------------|
| Retrieval error                       | 38| C: The american show lie to me ended on january 31, 2011. (SUPPORTS; REFUTES) E: Lie to Me ... The second season premiered on September 28, 2009 ... The third season, which had its premiere moved forward to October 4, 2010. |
| Events                                | 28| C: The bellagio in las vegas opened on may, 1996. (REFUTES; SUPPORTS) E: Construction on the Bellagio began in May 1996. ... Bellagio opened on October 15, 1998. |
| Evidence not explicit                 | 18| C: The official order to start building the great wall of china was in 221 bc. (SUPPORTS; REFUTES) E: The Great Wall of China had been built since the Qin dynasty (221–207 BC). |
| Multi-hop                             | 16| C: Seth curry’s brother played for davidson in college. (SUPPORTS; REFUTES) E: Stephen Curry (...) older brother of current NBA player Seth ... He ultimately chose to attend Davidson College, who had aggressively recruited him from the tenth grade. |
| Properties                            | 10| C: The number of cigarettes in a pack of “export as” brand packs in the usa is 20. (REFUTES; SUPPORTS) E: In the United States, the quantity of cigarettes in a pack must be at least 20. Certain brands, such as Export As, come in packs of 25. |
| Annotation error                      | 4 | C: The place winston moved to in still game is finport. (REFUTES; SUPPORTS) |

claim having less lexical overlap with the evidence text leads to low recall@\(k\) of the retrieval model (\(k = 3\)).

- 28% of error cases involve events. In particular, 14% involve procedural events, and 6% involve distinct events that share similar properties but differ in location or time frame.

- In 18% of error cases, retrieved evidence is valid but not notably explicit, which is naturally the case for the claims occurring in real life. FaVIQ has this property likely because it is derived from questions that are gathered independently from the evidence text, unlike prior work (Thorne et al., 2018a; Schuster et al., 2021; Eisenschlos et al., 2021) with claims written given the evidence text.

- 16% of the failure cases require multi-hop inference over the evidence. Claims in this category usually involve procedural events or compositions (e.g. “is Seth Curry’s brother” and “played for Davidson in college”). This indicates that we can construct a substantial portion of claims requiring multi-hop inference without having to make data that artificially encourages such reasoning (Yang et al., 2018; Jiang et al., 2020).

- Finally, 10% of the errors were made due to a subtle mismatch in properties, e.g., in the example in Figure 6, the model makes a decision based on “required minimum number” rather than “exact number” of a particular brand.

4.2 Professional Fact Checking Experiments

As professional fact-checking datasets, we use the following two datasets.

SNOPEs (Hanselowski et al., 2019) consists of 6422 claims, authored and labeled by professional fact-checkers, gathered from the Snopes website.\(^9\) We follow the official data split.

SciFACT (Wadden et al., 2020) consists of 1,109 claims based on scientific papers, annotated by domain experts. As the official test set is hidden, we use the official validation set as the test set, and separate the subset of the training data as the validation set to be an equal size as the test set.

For both datasets, we merge not enough info (NEI) to refute, following prior work that converts the 3-way classification to the 2-way classification (Wang et al., 2019; Sathe et al., 2020; Petroni et al., 2021).

4.2.1 Models

As in Section 4, all models are based on BART which is given a concatenation of the claim and the evidence text and is trained to generate either support or refute. For SNOPEs, the evidence text is given in the original data. For SciFACT, the evidence text is retrieved by TF-IDF over the corpus of abstracts from scientific papers, provided in the original data.\(^10\)

We consider two settings. In the first setting, we
assume the target training data is unavailable and compare the model trained on FEVER and FaVIQ in a zero-shot setup. In the second setting, we allow training on the target data and compare the model trained on the target data only and the model with the transfer learning—pretrained on either FEVER or FaVIQ and finetuned on the target data.

To explore models pretrained on NEI labels, we add a baseline that is trained on a union of the KILT version of FEVER and NEI data from the original FEVER from Thorne et al. (2018a). We also conduct an ablation that only includes the R set for FaVIQ while excluding the A set.

**Implementation details** When using TF-IDF for SciFACT, we use a sentence as a retrieval unit, and retrieve the top 10 sentences, which average length approximates that of 3 passages from Wikipedia. When using the model trained on either FEVER or FaVIQ, we use DPR + BART by default, which gives the best result in Section 4.1. As an exception, we use TF-IDF + BART in the SciFACT experiments for the fair comparison with the model trained on the target data only that uses TF-IDF. More training details are in Appendix C.

### 4.2.2 Results

Table 7 reports Micro-F1—a metric that is more reliable than accuracy given significant imbalance of labels in SNOPES and SciFACT.

| Training                  | SNOPES | SciFACT |
|---------------------------|--------|---------|
| **No target data (zero-shot)** |        |         |
| FEVER                     | 61.6   | 70.0    |
| FEVER w/ NEI              | 63.4   | 73.0    |
| FaVIQ                     | 68.2   | 74.7    |
| FaVIQ w/o A set           | 63.1   | 73.3    |
| **Target data available** |        |         |
| Target only               | 80.6   | 62.0    |
| FEVER → target            | 80.6   | 76.7    |
| FEVER w/ NEI → target     | 81.6   | 77.0    |
| FaVIQ → target            | **82.2** | **79.3** |
| FaVIQ w/o A set → target  | 81.6   | 78.3    |

Table 7: Micro-F1 scores on the test set of professional fact-checking datasets.

We find it effective in using transfer learning—pretraining on large, crowdsourced datasets (either FEVER or FaVIQ) and finetuning on the target datasets. Improvements are especially significant on SciFACT, likely because its data size is smaller.

Note that the availability of the target data is still important—models finetuned on the target data outperform zero-shot models by up to 20%. This indicates that crowdsourced data cannot completely replace professional fact checking data, but transfer learning from crowdsourced data leads to significantly better professional fact checking performance, successfully addressing an inherent difficulty in scaling professional fact-checking data.

**FaVIQ vs. FEVER** Models that are trained on FaVIQ consistently outperform models trained on FEVER, both with and without the target data, by up to 4.8% absolute. This demonstrates that FaVIQ is a more effective resource than FEVER for professional fact-checking.

It is worth noting that the model on FEVER is more competitive when NEI data is included, by up to 3% absolute. While the models on FaVIQ outperform models on FEVER even without NEI data, future work can create NEI data in FaVIQ for more improvements.

**Impact of the A set in FaVIQ** The performance of the models that use FaVIQ degrades when the A set is excluded, demonstrating the importance of the A set created based on ambiguity in information-seeking questions.

### 5 Conclusion & Future Work

We introduced FaVIQ, a new fact verification dataset derived from information-seeking questions. By using annotations of ambiguity in questions, we incorporate facts that real users were unaware of when posing the question. Our experiments showed that the state-of-the-art models are far from solving FaVIQ, and models trained on FaVIQ lead to improvements in professional fact checking. Altogether, we believe FaVIQ will serve as a challenging benchmark as well as support future progress in professional fact-checking.

Future work can investigate using other aspects of information-seeking questions that reflects facts that users are unaware of or easily confused with. For example, one can incorporate false presuppositions in questions that arise when users have limited background knowledge (Kim et al., 2021). As another example, one can explore generating not enough info claims by leveraging unanswerable information-seeking questions. Furthermore, FaVIQ can potentially be a challenging benchmark for the claim correction, a task recently studied in Thorne and Vlachos (2021) that requires a model to correct the refute claims.
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A Details in Data Construction

Why not providing gold evidence Unlike FEVER (Thorne et al., 2018a) which provides gold evidence text and includes the evidence prediction as part of evaluation, we do not provide gold evidence text and only care about the classification accuracy for the evaluation. Reasons are as follows.

1. As claims on FAVIQ were written independent from any reference text, gold evidence text should be gathered through a separate process, which greatly increases the cost. This is different from other annotated fact checking datasets where a crowdworker wrote a claim based on the reference text and therefore the same reference text can be considered as gold evidence.

2. Finding gold evidence text is an inherently incomplete process; no human can get close to, or even measure the upperbound. Therefore, even after exhaustive human annotations, evaluation against annotated evidence leads to significant amount of false negatives. For example, we manually evaluate the top incorrect retrieval of TF-IDF on 30 random samples from FEVER and found that 37% of them are false positives.

3. Including evidence prediction as part of evaluation significantly restricts the approach models can take. For instance, one may choose not to use the text corpus provided in the dataset (e.g., Wikipedia), and decide to use other sources such as structured data (e.g. knowledge bases) or implicit knowledge stored in large neural models.

We admit that having gold evidence as supervision is often useful to train a model, e.g., DPR. We therefore provide silver evidence text obtained through TF-IDF and heuristics as detailed in Section 4.1.1, which find to be sufficient for supervision.

Details of obtaining $a_{\text{neg}}$ We obtain an invalid answer to the question, denoted as $a_{\text{neg}}$, using an off-the-shelf QA model, for which we use DPR followed by a span extractor (Karpukhin et al., 2020).

The most naive way to obtain $a_{\text{neg}}$ is to take the highest scored prediction that is not equal to $a$. We however found such prediction is likely to be a valid answer to $q_i$ either because it is semantically the same as $a$, or because the ambiguity in the question leads to multiple distinct valid answers. We therefore use two tricks that we find greatly reduces such false negatives. First, instead of taking the top incorrect prediction, we obtain the top $\hat{k}$ predictions $p_1...p_{\hat{k}}$ from the model and randomly sample one from $\{p_1...p_{\hat{k}}\} \setminus \{a\}$. We use $\hat{k} = 50$. Although this is not a fundamental solution to remove false negatives, it significantly alleviates the problem, drastically dropping the portion of false negatives from 14% to 2%. Second, we train a neural model that is given a pair of the text and classifies whether they are semantically equivalent or not. This model is based on T5-large, trained and validated respectively on 150 and 100 pairs of $(a, p_i) (i = 1...\hat{k})$ which we manually label. We then exclude the predictions in $\{p_1...p_{\hat{k}}\}$ which are classified as semantically equivalent to $a$ by the classifier.

QA-to-claim converter We use a pretrained sequence-to-sequence model trained on a small number of our own annotations. We first manually write 250 claims given valid or invalid question-answer pairs. We then train a T5-3B model (Raffel et al., 2020), using 150 claims for training and 100 claims for validation. Each question-answer pair is fed into T5 with special tokens question: and answer:, respectively before the question and the answer. When generating claims to construct the data, we filter the claims that do not contain the answer string in the claim, which may happen when the question is overly specific.

B Analysis of refute Claims

We randomly sample 30 refute claims from FAVIQ and FEVER respectively, and categorize the cause of the misinformation, as shown in Table 8. Discussions are in Section 3.2.

C Details of Experiments

DPR training for FEVER As FEVER provides the annotated evidence passage, we use it as a positive. We obtain a negative by querying the claim to TF-IDF and taking the passage that is not the positive passage and has the second highest score. We initially considered using the negative with the highest score, but found that many of them (37%) are false negatives based on our manual evaluation of 30 random samples. This is likely due to incomprehensive evidence annotation as discussed in Appendix A. We find using the negative with the second highest instead decreases the portion of false negatives from 37% to 13%.

Calibration When the models trained on FEVER or FAVIQ are used for professional fact
Table 8: Categorization of 30 refute claims on FAVIQ and FEVER, randomly sampled from the validation set. C and E indicate the claim and evidence text, respectively. Examples are from FAVIQ unless otherwise specified.

| Category                           | % FAVIQ | % FEVER | Example                                                                                     |
|------------------------------------|---------|---------|--------------------------------------------------------------------------------------------|
| Negation                           | 0       | 30.0    | C: Southpaw hasn’t been released yet. (from FEVER)                                          |
|                                    |         |         | E: Southpaw is a 2015 American sports drama film ... released on July 24, 2015.             |
| Antonym                            | 3.3     | 13.3    | C: Athletics lost the world series in 1989.                                                 |
|                                    |         |         | E: The 1989 World Series was ... with the Athletics sweeping the Giants in four games.      |
| Requires reading across conjunctions | 33.3    | 6.6     | C: Johannes bell was the foreign minister that signed the treaty of versailles from germany. |
|                                    |         |         | / E: Johannes bell served as Minister of Colonial Affairs ... He was one of the two German   |
|                                    |         |         | representatives who signed the Treaty of Versailles.                                        |
| Shared attributes                  | 26.7    | 6.6     | C: Judi bowker played andromeda in the 2012 remake of the 1981 film clash of the titans    |
|                                    |         |         | called wrath of the titans. / E: Judi bowker ... Clash of the Titans (1981).                 |
| Procedural event                   | 16.7    | 0       | C: McCrory’s originally filed for bankruptcy on february 2002. / E: McCrory Stores ...     |
|                                    |         |         | by 1992 it filed for bankruptcy. ... In February 2002 the company ceased operation.        |
| Incorrect type of properties       | 10.0    | 3.3     | C: Tyler, the Creator is the name of the song at the end of who dat boy.                    |
|                                    |         |         | E: "Who Dat Boy" is a song by American rapper Tyler, the Creator.                           |
| Cannot find potential cause        | 0       | 20.0    | C: Mutiny on the Bounty is Dutch. (from FEVER)                                             |
|                                    |         |         | E: Mutiny on the Bounty is a 1962 American Technicolor epic historical drama film.          |
| Annotation error                   | 10.0    | 20.0    | C: Pasek and paul were the individuals that wrote the lyrics to the greatest showman.       |

Our implementations are based on PyTorch\(^{11}\) (Paszke et al., 2019) and Huggingface Transformers\(^{12}\) (Wolf et al., 2020).

When training a BART-based model, we map support and refute labels to the words ‘true’ and ‘false’ respectively so that each label is mapped to a single token. This choice was made because the BART tokenizer maps ‘refute’ into two tokens, making it difficult to compare probabilities of support and refute.

By default, we use a batch size of 32, a maximum sequence length of 1024, and 500 warmup steps using eight 32GB GPUs. For SciFACT, we use a batch size of 8 and no warmup steps using four 32G GPUs. We tune the learning rate in between \{7e-6, 8e-6, 9e-6, 1e-5\} on the validation data.