
FEVEROUS: Fact Extraction and VERification Over Unstructured and Structured information

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Abstract

Fact verification has attracted a lot of attention in the machine learning and natural language processing communities, as it is one of the key methods for detecting misinformation. Existing large-scale benchmarks for this task have focused mostly on textual sources, i.e. unstructured information, and thus ignored the wealth of information available in structured formats, such as tables. In this paper we introduce a novel dataset and benchmark, Fact Extraction and VERification Over Unstructured and Structured information (FEVEROUS), which consists of 87,026 verified claims. Each claim is annotated with evidence in the form of sentences and/or cells from tables in Wikipedia, as well as a label indicating whether this evidence supports, refutes, or does not provide enough information to reach a verdict. Furthermore, we detail our efforts to track and minimize the biases present in the dataset and could be exploited by models, e.g. being able to predict the label without using evidence. Finally, we develop a baseline for verifying claims against text and tables which predicts both the correct evidence and verdict for 18% of the claims.

1 Introduction

Interest in automating fact verification has been growing as the volume of potentially misleading and false claims rises [Graves, 2018], resulting in the development of both fully automated methods (see Thorne and Vlachos [2018], Zubiaga et al. [2018], Hardalov et al. [2021] for recent surveys) as well as technologies that can assist human journalists [Nakov et al., 2021]. This has been enabled by the creation of datasets of appropriate scale, quality, and complexity in order to develop and evaluate models for fact extraction and verification, e.g. Thorne et al. [2018], Augenstein et al. [2019]. Most large-scale datasets focus exclusively on verification against textual evidence rather than tables. Furthermore, table-based datasets, e.g. Chen et al. [2020a], assume an unrealistic setting where an evidence table is provided, requiring extensions to evaluate retrieval [Schlichtkrull et al., 2020].

*The author started working on this project whilst at Amazon.

<p>Claim: In the 2018 Naples general election, Roberto Fico, an Italian politician and member of the Five Star Movement, received 57,119 votes with 57.6 percent of the total votes.</p> <hr/> <p>Evidence:</p> <p>Page: wiki/Roberto_Fico e_1(Electoral history):</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th colspan="3">2018 general election: Naples -Fuorigrotta</th> </tr> <tr> <th>Candidate</th> <th>Party</th> <th>Votes</th> </tr> </thead> <tbody> <tr> <td>Roberto Fico</td> <td>Five Star</td> <td>61,819</td> </tr> <tr> <td>Marta Schifone</td> <td>Centre-right</td> <td>21,651</td> </tr> <tr> <td>Daniela Iaconis</td> <td>Centre-left</td> <td>15,779</td> </tr> </tbody> </table> <p>Verdict: Refuted</p>	2018 general election: Naples -Fuorigrotta			Candidate	Party	Votes	Roberto Fico	Five Star	61,819	Marta Schifone	Centre-right	21,651	Daniela Iaconis	Centre-left	15,779	<p>Claim: Red Sundown screenplay was written by Martin Berkeley; based on a story by Lewis B. Patten, who often published under the names Lewis Ford, Lee Leighton and Joseph Wayne.</p> <hr/> <p>Evidence:</p> <p>Page: wiki/Red_Sundown e_1(Introduction):</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <tr> <td colspan="2" style="text-align: center;">Red Sundown</td> </tr> <tr> <td>Directed by</td> <td>Jack Arnold</td> </tr> <tr> <td>Produced by</td> <td>Albert Zugsmith</td> </tr> <tr> <td>Screenplay by</td> <td>Martin Berkeley</td> </tr> <tr> <td>Based on</td> <td>Lewis B. Patten</td> </tr> <tr> <td colspan="2" style="text-align: center;">...</td> </tr> </table> <p>Page: wiki/Lewis_B._Patten e_2(Introduction): He often published under the names Lewis Ford, Lee Leighton and Joseph Wayne.</p> <hr/> <p>Verdict: Supported</p>	Red Sundown		Directed by	Jack Arnold	Produced by	Albert Zugsmith	Screenplay by	Martin Berkeley	Based on	Lewis B. Patten	...	
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Figure 1: FEVEROUS sample instances. Evidence in tables is highlighted in red. Each piece of evidence e_i has associated context, i.e. page, section title(s) and the closest row/column headers (highlighted in dark gray). Left: evidence consists of two table cells refuting the claim. Right: Evidence consists of two table cells and one sentence from two different pages, supporting the claim.

In this paper, we introduce a novel dataset and benchmark, FEVEROUS: Fact Extraction and VERIFICATION Over Unstructured and Structured information, consisting of claims verified against Wikipedia pages and labeled as supported, refuted, or not enough information. Each claim has evidence in the form of sentences and/or cells from tables in Wikipedia. Figure 1 shows two examples that illustrate the level of complexity of the dataset. A claim may require a single table cell, a single sentence, or a combination of multiple sentences and cells from different articles as evidence for verification. FEVEROUS contains 87,026 claims, manually constructed and verified by trained annotators. Throughout the annotation process, we kept track of the two- and three-way inter-annotator agreement (IAA) on random samples with the IAA kappa κ being 0.65 for both. Furthermore, we checked against dataset annotation biases, such as words present in the claims that indicate the label irrespective of evidence [Schuster et al., 2019], and ensured these are minimised.

We also develop a baseline approach to assess the feasibility of the task defined by FEVEROUS, shown in Figure 2. We employ a combination of entity matching and TF-IDF to extract the most relevant sentences and tables to retrieve the evidence, followed by a cell extraction model that returns relevant cells from tables by linearizing them and treating the extraction as a sequence labelling task. A RoBERTa classifier pre-trained on multiple NLI datasets predicts the veracity of the claim using the retrieved evidence and its context. This baseline substantially outperforms the sentence-only and table-only baselines. The proposed baseline predicts correctly both the evidence and the verdict label for 18% of the claims. The retrieval module itself fully covers 28% of a claims evidence. FEVEROUS is the first large-scale verification dataset that focuses on sentences, tables, and the combination of the two, and we hope it will stimulate further progress in fact extraction and verification and is publicly available online: <https://fever.ai/dataset/feverous.html>.

2 Literature Review

Datasets for fact verification often rely on real-world claims from fact-checking websites such as PolitiFact. For such claims, the cost of constructing fine-grained evidence sets can be prohibitive. Datasets therefore either leave out evidence and justifications entirely [Wang, 2017], rely on search engines which risk including irrelevant or misleading evidence [Popat et al., 2016, Baly et al., 2018, Augenstein et al., 2019], or bypass the retrieval challenge entirely by extracting evidence directly from the fact checking articles [Alhindi et al., 2018, Hanselowski et al., 2019, Kotonya and Toni, 2020b] or scientific literature [Wadden et al., 2020].

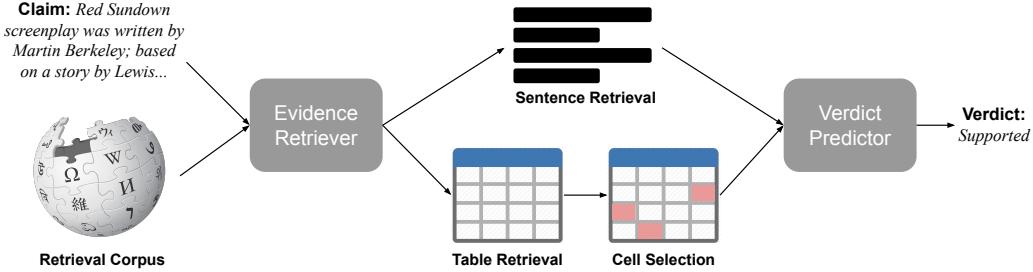


Figure 2: The pipeline of our FEVEROUS baseline.

The cost of curating evidence sets for real-world claims can be circumvented by creating artificial claims. Thorne et al. [2018] introduced FEVER, a large-scale dataset of 185,445 claims constructed by annotators based on Wikipedia articles. This annotation strategy was adopted to construct a similar dataset for Danish [Nørregaard and Derczynski, 2021], and adapted for real-world climate change-related claims [Diggelmann et al., 2021]. Jiang et al. [2020] extended this methodology to create a dataset of 26k claims requiring multi-hop reasoning. Other annotation strategies include Khouja [2020] who introduced a dataset of Arabic claims generating supported and unsupported claims based on news articles.

The datasets discussed so far have primarily focused on unstructured text as evidence during the annotation process. There is currently a small number of datasets that rely on structured information, primarily tables. TabFact [Chen et al., 2020a] and InfoTABS [Gupta et al., 2020] contain artificial claims to be verified on the basis of Wikipedia tables and infoboxes respectively, while SEM-TABFACTS [Wang et al., 2021] requires verification on the basis of tables from scientific articles. The latter is the only to also specify the location of the evidence in a table. Our proposed dataset is the first which considers both structured *and* unstructured evidence for verification, while explicitly requiring the retrieval of evidence.

In the related field of question answering [Bouziane et al., 2015], recent work also considered finding answers over both tables and text. Chen et al. [2020b] proposed HybridQA, a dataset consisting of multi-hop questions constructed by using Wikipedia tables and the introductory section of linked entities in the table, however, their dataset assumes the table as part of the input. Based on HybridQA, Chen et al. [2021] further required systems to retrieve relevant tables and texts by decontextualizing questions of HybridQA and adding additional questions to remove potential biases, resulting in a total of 45K question-answer pairs. The NaturalQA dataset [Kwiatkowski et al., 2019] is substantially larger (about 300K) with some questions requiring to retrieve answers from tables (17%). However, these tables are predominantly infoboxes and rarely require systems to combine information from both text and tables.

3 FEVEROUS Dataset and Benchmark

In FEVEROUS the goal is to determine the veracity of a claim c by: *i*) retrieving a set of evidence pieces E which can be either a sentence or a table cell, and *ii*) assigning a label $y \in \{\text{Supports}, \text{Refutes}, \text{Not Enough Info}\}$. The source of evidence is derived from the English Wikipedia (excluding pages and sections flagged to require addition references or citations), and consists of sentences and tables obtained as follows:

Sentence. Any sentence from a Wikipedia article’s text as well as special Wikipedia phrases referring to other articles (e.g. *See also: ...*, *X redirects here. For other uses, see ...*).

Table. A table consists of cells $c_{i,j}$, where i and j specify the row and column, respectively, and a caption q . Both cells and captions can take various formats like a single word, number or symbol, phrases, and entire sentences. In most datasets (e.g. Chen et al. [2020a]), headers are restricted to the first row of a table. However, tables in Wikipedia can have a more complex structure, including multi-level headers (see Figure 1 for an example). FEVEROUS maintains the diversity of Wikipedia tables, only filtering out those with formatting errors. For the purposes of annotation, a table caption q is considered to be a table cell and needs to be selected explicitly if it contains information relevant

to the claim. We also include Wikipedia infoboxes as tables, as well as lists. We consider the latter to be special tables where the number of items in the list yields the number of columns and the number of nested lists yields the number of rows. For example, $c_{1,5}$ represents the item of a nested list at depth 1 found at the fifth position of the main list.

The evidence retrieval in FEVEROUS considers the entirety of a Wikipedia article and thus the evidence can be located in any section of the article except the reference sections. The order between all elements in an article is maintained. We associate each candidate piece of evidence with its *context*, which consists of the article’s title and section titles, including the sub-sections the element is located in. For table cells, we also include the nearest row and column headers; if the element just before the nearest row/column is also a header, then it will be included in the context. Context adds relevant information to understand a piece of evidence, but it is not considered a piece of evidence by itself. Sentences and cells maintain their hyperlinks to other Wikipedia articles, if present.

Quantitative characteristics of FEVEROUS and most related fact-checking datasets (i.e. FEVER, TabFact, and Sem-Tab-Facts) are shown in Table 1. As seen, the average claim of FEVEROUS is more than twice as long as the other datasets. On average 1.4 sentences and 3.3 cells (or 0.8 Tables) are required as evidence per sample, higher than both FEVER and Sem-Tab-Facts *combined*. Looking into the evidence sets by type, we note that FEVEROUS is balanced, having almost an equal amount of instances containing, either exclusively text, tables, or both as evidence. Regarding the veracity labels, FEVEROUS is roughly balanced in terms of supported (56%) and refuted claims (39%), with only about 5% of claims being NotEnoughInfo.

Table 1: Quantitative characteristics of FEVEROUS compared to related datasets. Claim length is reported in tokens. Avg. *Evidence* is the average number of evidence pieces per claim in a dataset, while *Evidence Sets by type* reports the number of unique evidence sets by type. For FEVEROUS, *combined* measures the number of annotations that require evidence from both tables and sentences. The *Evidence Sets* can be used as *Evidence Source* for SEM-TAB-FACTS and TabFact, as explored by Schlichtkrull et al. [2020] for the latter.

Statistic	FEVEROUS	FEVER	TabFact	SEM-TAB-FACTS
Total Claims	87,026	185,445	117,854	5,715
Avg. Claim Length	25.3	9.4	13.8	11.4
Avg. Evidence	1.4 sentences, 3.3 cells (0.8 tables)	1.2 sentences	1 table	1.1 cells (1 table)
Evidence Sets by Type	34,963 sentences, 28,760 tables, 24,667 combined	296,712 sets	16,573 tables	1,085 tables
Size of Evidence Source	95.6M sentences, 11.8M tables	25.1M sentences,	16,573 tables	1,085 tables
Veracity Labels	49,115 Supported, 33,669 Refuted, 4,242 NEI	93,367 Supported, 43,107 Refuted, 48,973 NEI	63,723 Supported, 54,131 Refuted	3,342 Supported, 2,149 Refuted, 224 Unknown

3.1 Dataset Annotation

Each claim in the FEVEROUS dataset was constructed in two stages: 1) claim generation based on a Wikipedia article, 2) retrieval of evidence from Wikipedia and selection of the appropriate verdict label, i.e. claim verification. Each claim is verified by a different annotator than the one who generated it to ensure the verification is done without knowledge of the label or the evidence. A dedicated interface built on top of Wikipedia’s underlying software, Mediawiki (<https://www.mediawiki.org/wiki/MediaWiki>) to give annotators a natural and intuitive environment for searching and retrieving relevant information. The ElasticSearch engine, in particular the CirrusSearch Extension, allowed for more advanced search expressions with well-defined operators and hyperlink navigation, as well as a custom built page search functionality, enabling annotators to search for specific phrases in an article. This interface allows for a diverse generation of claims, as annotators can easily combine information from multiple sections or pages. See the supplementary material for screenshots of the interface and examples of its use. We logged all of the annotators’ interactions with the platform (e.g. search terms entered, hyperlinks clicked) and include them in the FEVEROUS dataset, as this information could be used to refine retrieval models with additional information on intermediate searches and search paths that led to relevant pages.

3.1.1 Claim Generation

To generate a claim, annotators were given a *highlight* of either four consecutive sentences or a table, located anywhere in a Wikipedia page; each page is used only once, i.e. only one set of claims is generated per page, to prevent the generation of claims that are too similar. This allowed us to control the information that annotators used and consequently the distribution of topics in the claims. Sentence highlights are restricted to sentences that have at least 5 tokens, whereas table highlights must have at least 5 rows and at most 50 rows. These bounds have been chosen based on previous work, with the rows upper bound being equal to TabFact’s and the lower bounds being equal to HybridQA’s. While TabFact does not use lower bounds, we noticed that it is infeasible to construct more complicated claims from tables with fewer than 5 rows.

The sentence versus table highlights ratio is 1:2. Annotators had the option to skip highlights if the sentences/tables had formatting issues or if the content enable the creation of verifiable, unambiguous, and objective claims (see supplementary material for the full list of requirements). For each highlight, annotators were asked to write three different claims with the specifications described below, each claim being a factual and well-formed sentence.

Claim using highlight only (Type I). This type of claim must use information exclusively from the highlighted table/sentences and their context (page/section titles or headers). For sentence highlights we did not allow claims to be paraphrases of one of the highlighted sentences, but to combine information from the four highlighted sentences instead. For claims based on a table highlight, annotators were asked to combine information from multiple cells if possible, using comparisons, filters, arithmetic and min-max operations. Only for the first claim we also specified the veracity of the generated claim, enforcing an equal balance between supported and refuted claims. This decision was motivated by the observation that annotators have a strong tendency to write supported claims as these are more natural to generate. For both Type II and III claims, annotators could freely decide to create either supported, refuted, or NEI claims, as long as they adhere to the claim requirements.

Claim beyond the highlight (Type II). This type of claim must be based on the highlight, but must also include information beyond it. Annotators could either modify the first claim they generated or create an unrelated claim that still included information from the highlight. Furthermore, we enforced with equal probability whether the claim had to use information exclusively from the same page or from multiple pages. For the latter, annotators were allowed to navigate Wikipedia using the search engine and page search tools previously described.

Mutated Claim (Type III). We asked annotators to modify one of the two claims previously generated using one of the following ‘mutations’: *More Specific*, *Generalization*, *Negation*, *Paraphrasing*, or *Entity Substitution*, with probabilities 0.15, 0.15, 0.3, 0.1, 0.3, respectively. These mutations are similar, but less restrictive than those used in FEVER (see supplementary material). Annotators were allowed to navigate Wikipedia freely to extract information for generating this claim.

For each generated claim, the annotators were also asked to specify the main challenge they expect a fact-checker would face when verifying that claim, selecting one out of six challenge categories: claims that require evidence from two or more sections or articles (*Multi-hop Reasoning*), combination of structured and unstructured evidence (*Combining Tables and Text*), reasoning that involves numbers or arithmetic operations (*Numerical Reasoning*), disambiguation of entities in claims (*Entity Disambiguation*), requiring search terms beyond entities mentioned in claim (*Search terms not in claim*), and *Other*.

3.1.2 Claim Verification

Given a claim from the previous annotation step, annotators were asked to retrieve evidence and determine whether a claim is supported or refuted by evidence found on Wikipedia. Each annotation may contain up to three possibly partially overlapping evidence sets, and each set leads to the same verdict independently. For supported claims, every piece of information has to be verified by evidence, whereas for refuted claims, the evidence only needs to be sufficient to refute one part of the claim. If the verification of a claim requires to include every entry in a table row/column (e.g. claims with universal quantification such as “highest number of gold medals out of all countries”), each cell of that row/column is highlighted. In some cases, a claim can be considered unverifiable (Not Enough Information; NEI) if not enough information can be found on Wikipedia to arrive at one of the two other verdicts. In contrast to FEVER dataset, we also require annotated evidence for NEI claims

capturing the most relevant information to verification of the claim, even if that was not possible. This ensures that all verdict labels are equally difficult to predict correctly, as they all require evidence.

Starting from the Wikipedia search page, annotators were allowed to navigate freely through Wikipedia to find relevant evidence. They were also shown the associated context of the selected evidence in order to assess whether the evidence is sufficient on its own given the context or whether additional evidence needs to be highlighted. Before submitting, annotators were shown a confirmation screen with the highlighted evidence, the context, and the selected verdict, to ensure that all required evidence has been highlighted and that they are confident in the label they have selected.

While we require information to be explicitly mentioned in the evidence in order to support a claim, we noticed that requesting the same for refuting claims would lead to counter-intuitive verdict labels. For example, “Shakira is Canadian” would be labelled as NEI when we consider the evidence “Shakira is a Colombian singer, songwriter, dancer, and record producer” *and* no mention of Shakira having a second nationality or any other relation to Canada. A NEI verdict in this case is rather forced and unnatural, as there is no reason to believe that Shakira could be Canadian given the Wikipedia article. To address these cases, we added a guideline question “Would you consider yourself misled by the claim given the evidence you found?”, so that, if answered yes (as in the above example), claims are labelled as Refuted, otherwise they are labelled NEI. This label rationale is different from FEVER for which explicit evidence is required to refute a claim. While it could be argued that, our approach to labelling claims leaves potentially more room for ambiguity as the decision partially depends on what the annotator expects to find on a Wikipedia page and whether a claim adheres to the Grice’s Maxim of Quantity (being as informative as possible, giving as much information as needed), our quality assessment shows that verdict agreement is very high when the annotated evidence is identical (see Section 3.2).

After finishing the verification of the given claim, annotators then had to specify the main challenge for verifying it, using the same six challenge categories as for the challenge prediction in section 7.9. Examples and quantitative characteristics on expected and actual challenges can be found in the supplementary material.

3.2 Quality Control

Annotators: Annotators were hired through an external contractor. A total of 57 and 54 annotators were employed for the claim generation and claim verification stages respectively. The annotations were supervised by three project managers as well as the authors of this paper. For claim generation, half of the annotators were native US-English speakers, while the other half were *language-aware* (an upper education degree in a language-related subject). English speakers from the Philippines, whereas the evidence annotators had to be language-aware native US-English speakers. The annotator candidates were screened internally by the external contractor to assess their suitability for this task. The screening followed a two-stage process. First, the candidates’ English proficiency was assessed through grammatical, spelling, and fluency tests. Second, the candidates were asked to give a sentence-long summary for a given paragraph that they would then be asked to mutate by means of negation or entity substitution, similarly to Section 7.9. The same screening procedure was used for both tasks, with the difference that the minimum score was set higher for the claim verification part. Details on the annotator demographics can be found in the supplementary material.

Calibration: Due to the complexity of the annotation, we used a two-phase calibration procedure for training and selecting annotators. For this purpose, highlights with generated claims annotated with evidence and verdicts were created by the authors to cover a variety of scenarios. While the first calibration phase aimed at familiarizing the annotators with the task, the second phase contained more difficult examples and special cases. Annotators had to annotate a total of ten highlights/claims in each calibration phase. Annotations for claim generation were graded by the project managers in a binary fashion, i.e. whether a claim adheres to the guideline requirements or not and whether the expected challenge is appropriate. For claim verification they were graded using the gold annotations by the authors using label accuracy, evidence precision/recall (see Section 5.1), the number of complete evidence sets, and selected verification challenge. Before continuing with the second calibration phase, annotators had to review the scores and feedback they received in the first phase. Based on the scores in both phases, the project managers approved or rejected each annotator, with an approval

rate of 40% for claim generation and 54% for claim verification, with a total of 141 and 100 claim generation and verification candidates, respectively.

Quality Assurance: Generated claims were quality checked by claim verification annotators who had to report those that did not adhere to the claim requirements, specifying the reason(s). 2534 claims were reported with the most common reason being *Ungrammatical, spelling mistakes, typographical errors*, followed by *Cannot be verified using any publicly available information*.

Around 10% of the claim verification annotations (8474 samples) were used for quality assurance. We measured two-way IAA using 66% of these samples, and three-way agreement with the remaining 33%. The samples were selected randomly proportionally to the number of annotations by each annotator. The κ over the verdict label was 0.65 both for two-way and three-way agreement. Duplicate annotations (and hence disagreements) due to measuring IAA are not considered for the dataset itself. These IAA scores are slightly lower than the ones reported for FEVER dataset (0.68), however the complexity of FEVEROUS is greater as entire Wikipedia pages with both text and tables are considered as evidence instead of only sentences from the introductory sections. TabFact has an agreement of 0.75, yet in TabFact the (correct) evidence is given to the annotators. If we only look at claims where annotators chose identical evidence, verdict agreement in FEVEROUS is very high (0.92), showing that most disagreement is caused by the evidence annotation. Pairs of annotators annotated the same evidence for 42% of the claims and partially overlapping evidence of at least 70% for 74% of them. In 27% of the claims the evidence of one annotator is a proper subsets of another, indicating that in some cases evidence might provide more information than required, e.g. identical information that should have been assigned to two different evidence set.

Further analysing the cases of disagreement, we observe that in a third of two-way IAA disagreement cases one annotator selected NEI, which is disproportionately high considering NEI claims make up only 5% of the dataset, again indicating that the retrieval of evidence is a crucial part of the verification task. For the other two-thirds, when annotators selected opposite veracity labels we identified four sources of disagreement: (i) numerical claims that require counting a large number of cells, so small counting errors lead to opposing labels (ii) long claims with a refutable detail that had been overlooked and hence classified erroneously (iii) not finding evidence that refutes/supports a claim due to relevant pages being difficult to find (e.g. when the article’s title does not appear in the claim) (iv) accidental errors/noise, likely caused by the complexity of the task. Looking into the IAA between every annotator pair shows an overall consistent annotation quality with a standard deviation of 0.07 and a total of 10 annotators with an average IAA of below 0.60, and 8 being higher than 0.70.

Dataset Artifacts & Biases: To counteract possible dataset artifacts, we measured the association between several variables, using normalized PMI throughout the annotation process. We found that no strong co-occurrence was measured between the verdict and the words in the claim, indicating that no claim-only bias [Schuster et al., 2019] is present in the dataset. We observed the following correlations: an evidence table/sentence being the first element on a page with supported verdict ($nPMI=0.14$) and after position 20 with NEI verdict ($nPMI=0.09$); words ‘which/who’ with Claim Type II as well as mutation type *More specific* and *Entity Substitution* ($nPMI=0.07$); Claim Type II with supported verdict ($nPMI=0.17$) and Claim Type III with refuted label ($nPMI=0.23$). The latter can most likely be attributed to the *Negation* and *Entity substitution* mutations. Since we do not release the claim-type correspondence, the association of words with claim types and mutations is not of concern.

We also developed a **claim-only baseline**, which uses the claim as input and predicts the verdict label. We opted to fine-tune a pre-trained BERT model [Devlin et al., 2019] with a linear layer on top and measured its accuracy using 5-fold cross-validation. This claim-only baseline achieves 0.58 label accuracy, compared to the majority baseline being 0.56. Compared to FEVER where a similar claim-only baseline achieves a score of about 0.62 over a majority baseline of 0.33 [Schuster et al., 2019], the artefacts in FEVEROUS appear to be minimal in this respect. Regarding the position of the evidence, we observed that cell evidence tends to be located in the first half of a table. For smaller tables, evidence is more evenly distributed across rows. Moreover, a substantial amount of claims require using entire columns as evidence, and thus the later parts of a table as well.

Finally, we trained a **claim-only evidence type model** to predict whether a claim requires as evidence sentences, cells, or a combination of both evidence types. The model and experimental setup were identical to the one used to assess claim-only bias. The model achieved 0.62 accuracy, compared to

0.43 using the majority baseline, suggesting that the claims are to some extent indicative of the type, but a strong system would need to look at the evidence as well.

4 Baseline Model

Retriever Our baseline retriever module is a combination of entity matching and TF-IDF using DrQA [Chen et al., 2017]. Combining both has previously been shown to work well, particularly for retrieving tables [Schlichtkrull et al., 2020]. We first extract the top k pages by matching extracted entities from the claim with Wikipedia articles. If less than k pages have been identified this way, the remaining pages are selected by Tf-IDF matching between the introductory sentence of an article and the claim. The top l sentences and q tables of the selected pages are then scored separately using TF-IDF. We set $k = 5$, $l = 5$ and $q = 3$.

For each of the q retrieved tables, we retrieve the most relevant cells by linearizing the table and treating the retrieval of cells as a binary sequence labelling task. The underlying model is a fine-tuned RoBERTa model with the claim concatenated with the respective table as input. When fine-tuning, we deploy row sampling, similar to Oguz et al. [2020], to ensure that the tables used during training fit into the input of the model.

Verdict prediction Given the retrieved evidence, we predict the verdict label using a RoBERTa encoder with a linear layer on top. Table cells are linearized to be used as evidence, following Schlichtkrull et al. [2020] who showed that a RoBERTa based model with the right linearization performs better than models taking table structure into account. Linearization of a table’s content enables cross-attention between cells and sentences by simply concatenating all evidence in the input of the model. For each piece of evidence, we concatenate its context ensuring that the page title appears only once, at the beginning of the evidence retrieved from it.

The verdict predictor is trained on labelled claims with associated cell and sentence evidence and their context. The FEVEROUS dataset is rather imbalanced regarding NEI labels (5% of claims), so we sample additional NEI instances for training by modifying annotations that contain both cell and sentence evidence by removing either a sentence or an entire table. We additionally explore the use of a RoBERTa model that has been pre-trained on various NLI datasets (SNLI [Bowman et al., 2015], MNLI [Williams et al., 2018], and an NLI-version of FEVER, proposed by Nie et al. [2020]).

5 Experiments

5.1 Dataset splits and evaluation

The dataset is split into a training, development and test split in a ratio of about 0.8, 0.1, 0.1. We further ensured that all three claims generated from a highlight are assigned to the same split to prevent claims in the development and test splits from being too similar to the ones in training data. Quantitative characteristics are shown in Table 2. Due to the scarcity of NEI instances, we maintained a rough label balance only for the test set. In all splits, the number of evidence sets with only sentences as evidence is slightly higher than sets that contain only cell evidence or sets that require a combination of different evidence types.

Table 2: Quantitative characteristics of each split in FEVEROUS.

	Train	Dev	Test	Total
Supported	41,835 (59%)	3,908 (50%)	3,372 (43%)	49,115 (56%)
Refuted	27,215 (38%)	3,481 (44%)	2,973 (38%)	33,669 (39%)
NEI	2,241 (3%)	501 (6%)	1,500 (19%)	4,242 (5%)
Total	71,291	7,890	7,845	87,026
$E_{Sentences}$	31,607 (41%)	3,745 (43%)	3589 (42%)	38,941 (41%)
E_{Cells}	25,020 (32%)	2,738 (32%)	2816 (33%)	30,574 (32%)
$E_{Sentence+Cells}$	20,865 (27%)	2,468 (25%)	2062 (24%)	25,395 (27%)

The evaluation considers the correct prediction of the verdict as well as the correct retrieval of evidence. Retrieving relevant evidence is an important requirement, given that it provides a basic justification for the label, which is essential to convince the users of the capabilities of a verification system and to assess its correctness [Uscinski and Butler, 2013, Lipton, 2016, Kotonya and Toni, 2020a]. Without evidence, the ability to detect machine-generated misinformation is inherently limited [Schuster et al., 2020]. The FEVEROUS score is therefore defined for an instance as follows:

$$Score(y, \hat{y}, \mathbb{E}, \hat{E}) = \begin{cases} 1 & \exists E \in \mathbb{E} : E \subseteq \hat{E} \wedge \hat{y} = y, \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

with \hat{y} and \hat{E} being the predicted label and evidence, respectively, and \mathbb{E} the collection of gold evidence sets. Thus, a prediction is scored 1 iff at least one complete evidence set E is a subset of \hat{E} and the predicted label is correct, else 0. The rationale behind not including precision in the score is that we recognise that the evidence annotations are unlikely to be exhaustive, and measuring precision would thus penalize potentially correct evidence that was not annotated. Instead, we set an upper bound on the number of elements to be allowed in \hat{E} to s table cells and l sentences. This distinction was made because the number of cells used as evidence is typically higher than the number of sentences. s is set to 25 and l to 5, ensuring that the upper bound covers the required number of evidence pieces for every instance E in both development and test set.

The FEVEROUS dataset was used for the shared task of the FEVER Workshop 2021 [Aly et al., 2021], with the same splits and evaluation as presented in this paper.

5.2 Results

Table 3 shows the results of our full baseline compared to a sentence-only and a table-only baseline. All baselines use our TF-IDF retriever with the sentence-only and table-only baseline extracting sentences and tables only, respectively. While the sentence-only model predicts the verdict label using only extracted sentences, the the table-only baseline only extracts the cells from retrieved tables with our cell extractor model and predicts the verdict by linearising the selected cells and their context. All models use our verdict predictor for classification. Our baseline that combines both tables and sentences achieves substantially higher scores than when focusing exclusively on either sentences or tables.

Table 3: FEVEROUS scores for the sentence-only, table-only, and full baseline for both development and test set. *Evidence* measures the full coverage of evidence (i.e. Eq. 1 without the condition on correct prediction $\hat{y} = y$).

Model	Dev		Test	
	Score	Evidence	Score	Evidence
Sentence-only baseline	0.13	0.19	0.12	0.19
Table-only baseline	0.05	0.07	0.05	0.07
Full baseline	0.19	0.29	0.18	0.29

Evidence Retrieval To measure the performance of the evidence retrieval module for retrieved evidence \hat{E} , we measure both the Recall@k on a document level as well as on a passage level (i.e. sentences and tables). Results are shown in Table 4. As seen for $k = 5$ the retriever achieves a document coverage of 69%. The top 5 retrieved sentences cover 53% of all sentences while the top 3 tables have a coverage of 56%, highlighting the effectiveness of our retriever to retrieve both sentences and tables. The overall passage recall is 0.55%. For comparison a TF-IDF retriever without entity matching achieves a coverage of only 49%.

Extracting evidence cells when the cell extraction model is given the gold table for the claim from the annotated data leads to a cell recall of 0.69, with a recall of 0.74 when a table contains only a single cell as evidence. Extracted cells from the retrieved tables in combination with the extracted sentences fully cover the evidence of 29% samples in the dev set.

Verdict prediction The right side of Table 4 shows oracle results (i.e. when given the correct evidence), as well as results without NEI sampling and without an NLI pre-trained model. Without the NEI sampling, the model is not able to recognise a single NEI sample correctly. NLI pre-training further increases results, resulting in a macro-averaged F_1 of 0.70.

Table 4: (left) Document and passage (sentence + tables) coverage for the retrieval module. (right) Verdict classification using gold evidence. *NLI* denotes pre-training on NLI corpora and *NEI* NEI sampling. Scores are reported in per-class F_1 . The overall score is reported using macro-averaged F_1 . All results are reported on the dev set.

top	Doc (%)	Sent (%)	Tab (%)	Model	Supported	Refuted	NEI	Overall
1	0.39	0.23	0.45	RoBERTa	0.89	0.87	0.05	0.53
2	0.49	0.37	0.54	+NLI	0.90	0.88	0.09	0.62
3	0.58	0.46	0.56	+NLI+NEI	0.89	0.87	0.34	0.70
5	0.69	0.53	-					

5.3 Discussion

Retrieval of structured information. While the verdict predictor combines information from both evidence types, our retrieval system extracts structured and unstructured information largely independently. However, tables are often specified and described by surrounding sentences. For instance [Zayats et al., 2021] enhance Wikipedia table representations by using additional context from surrounding text. Thus, sentences provide important context to tables to be understood and related to the claim (and vice versa). Moreover, we have ignored hyperlinks in our model, yet they are excellent for entity grounding and disambiguation, adding context to both tables and sentences.

Numerical Reasoning. An aspect currently ignored by our baseline is that a substantial number of claims in FEVEROUS require *numerical reasoning* (for about 10% of claims numerical reasoning was selected as the main verification challenge), ranging from simply counting matching cells to arithmetic operations. Dua et al. [2019] showed that reading comprehension models lack the ability to do simple arithmetic operations.

Verification of complex claims. Compared to previous datasets, the length of claims and number of required evidence is substantially higher. As a result, more pieces of evidence per claim need to be retrieved and related to each other. This opens opportunities to explore the effect of the order in which each part of a claim is being verified and how evidence is conditioned on each other. To facilitate research in this direction, FEVEROUS contains for each annotation a list of operations (e.g. searched ..., clicked on hyperlink ...) that an annotator used to verify a claim (see supplementary material).

Ecological Validity Incorporating information from both text and tables for fact-checking enables the verification of more complex claims than previous large-scale datasets, ultimately enhancing the practical relevance of automated fact-checking systems. However, FEVEROUS still simplifies real-world claims substantially, by controlling many variables of the claim generation process. For instance, it ignores the common strategy of biased evidence employed for generating misleading claims in the real world, also referred to as cherry picking, where facts which are true in isolation are being taken out of context, resulting in an overall false claim.

6 Conclusion

This paper introduced FEVEROUS, the first large-scale dataset and benchmark for fact verification that includes both unstructured and structured information. We described the annotation process and the steps taken to minimise biases and dataset artefacts during construction, and discussed aspects in which FEVEROUS differs from other fact-checking datasets. We proposed a baseline that retrieves sentences and table cells to predict the verdict using both types of evidence, and showed that it outperforms sentence-only and table-only baselines. With the baseline achieving a score of 0.18 we believe that FEVEROUS is a challenging yet attractive benchmark for the development of fact-checking systems.

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7 Supplementary Material

7.1 Access to the dataset

The FEVEROUS dataset can be accessed from the official website of the FEVER Workshop <https://fever.ai/dataset/feverous.html> and is hosted in an the same AWS S3 Bucket as the FEVER dataset, which has been publicly available since 2018. As the authors of this paper manage the workshop’s website they can ensure proper maintenance and access to the dataset. The hosting of the dataset includes a retrieval corpus, as well as each split of the dataset. At the time of this paper’s submission, the shared task is still ongoing with the unlabeled test set being kept hidden until the last week of the shared task. Elementary code to process the data from both annotations and the provided Wikipedia DB (e.g. extracting context for a given element, getting a table from a cell ID etc..) is publicly available on <https://github.com/Raldir/FEVEROUS>. The repository also contains the code of the annotation platform as well as the baseline’s code. The DOI for the FEVEROUS dataset is 10.5281/zenodo.4911508 and structured metadata has been added to the webpage.

The training and development data is hosted in Jsonlines format. Jsonlines contains a single JSON per line, encoded in UTF-8. This format allows to process one record at a time, and works well with unix/shell pipelines. Each entry consists of five fields: The training and development data contains 5 fields:

- id: The ID of the sample
- label: The annotated label for the claim. Can be one of SUPPORTS|REFUTES|NOT ENOUGH INFO.
- claim: The text of the claim.
- evidence: A list (at maximum three) of evidence sets. Each set consists of dictionaries with two fields (content, context).
 - content: A list of element ids serving as the evidence for the claim. Each element id is in the format "[PAGE ID]_[EVIDENCE TYPE]_[NUMBER ID]". [EVIDENCE TYPE] can be sentence, cell, header_cell, table_caption, item.
 - context: A dictionary that maps each element id in content to a set of Wikipedia elements that are automatically associated with that element id and serve as context. This includes an article’s title, relevant sections (the section and sub-section(s) the element is located in), and for cells the closest row and column header (multiple row/column headers if they follow each other).
- annotator_operations: A list of operations an annotator used to find the evidence and reach a verdict, given the claim. Each element in the list is a dictionary with the fields (operation, value, time).
 - operation: Any of the following

- * start, finish: Annotation started/finished. The value is the name of the operation.
- * search: Annotator used the Wikipedia search function. The value is the entered search term or the term selected from the automatic suggestions. If the annotator did not select any of the suggestions but instead went into advanced search, the term is prefixed with "contains..."
- * hyperlink: Annotator clicked on a hyperlink in the page. The value is the anchor text of the hyperlink.
- * Now on: The page the annotator has landed after a search or a hyperlink click. The value is the PAGE ID.
- * Page search: Annotator search on a page. The value is the search term.
- * page-search-reset: Annotator cleared the search box. The value is the name of the operation. Highlighting, Highlighting deleted: Annotator selected/unselected an element on the page. The value is ELEMENT ID.
- * back-button-clicked: Annotator pressed the back button. The value is the name of the operation.
- * value: The value associated with the operation.
- * time: The time in seconds from the start of the annotation.
- expected_challenge: The challenge the claim generator selected will be faced when verifying the claim, one out of the following: Numerical Reasoning, Multi-hop Reasoning, Entity Disambiguation, Combining Tables and Text, Search terms not in claim, and Other.
- challenge: The main challenge to verify the claim, one out of the following: Numerical Reasoning, Multi-hop Reasoning, Entity Disambiguation, Combining Tables and Text, Search terms not in claim, and Other.

The retrieval corpus is provided to annotators in either Jsonlines format, or as an SQLite3 database. The latter allows faster retrieval for articles by their name, which is helpful for instance when mapping annotation ids to their contents. Each Wikipedia article contains 2 base fields:

- title: The title of the Wikipedia article
- order: A list of elements on the Wikipedia article in order of their appearance. Elements can be: section, table, list, sentence.

Each element specified in order is a field. A sentence field contains the text of the sentence.

A section element is a dictionary with following fields:

- value: Section text
- level: The level/depth of the section.

A table element is a dictionary with following fields:

- type: Whether the table is an infobox or a normal table
- table: The content of the table. The table is specified as a list of lists. Each element in a list is a cell with the fields (id, value, is_header, row_span, column_span).
- caption: Only specified if the table contains a caption.

A list element consists of following fields:

- type: Whether the list is an ordered or unordered list
- list: A list of dictionaries, with fields being (id, value, level, type). level is the depth of the list item. The level increments with each nested list. type specifies type of a nested list, which is starting after the item specifying the type. Field is only specified if the next item is in a nested list. Hyperlinks in text are indicated with double square brackets. If an anchor text is provided, it is the text on the right hand side of a vertical bar in the square brackets

Example dataset and retrieval corpus entries can be found on <https://fever.ai/dataset/feverous.html>.

7.2 Ethics statement

The FEVEROUS dataset was collected with approval and following the practices outlined by the Ethics Committee of the Computer Lab of the University of Cambridge (reference number 1842). Furthermore, the external contractor has a well-outlined policy regarding their code of ethics to ensure the well-being of all annotators in our experiment. Their Code of Ethics consists of: Fair Pay, Inclusion, Crowd Voice (i.e. Feedback mechanisms), Privacy and Confidentiality, Communication, and Well-Being.

We anticipate that FEVEROUS will be used for the development of fact checking systems that might be applied in real world contexts to assign truth/false labels, similar to those on fact checking websites run by journalists. We use the labels supported/refuted (by evidence) instead of true/false to be clear that we do not make any judgements about the truth of a statement in the real-world, but only consider Wikipedia as the source of evidence to be used. And while Wikipedia is a great collaborative resource, it has mistakes and noise of its own similar to any encyclopedia or knowledge source. Thus we discourage users of FEVEROUS to make absolute statements about the claims being verified, i.e. avoid using it to develop truth-tellers. Finally, we require systems to predict when the evidence is not sufficient to make a judgement, in which case it would be useful to look beyond Wikipedia for evidence.

We did not collect personal data of the participants in any way. A participant is only identified using an identification number to access our online tool. Generated claims must only include information on Wikipedia or considered to be general world knowledge, while all evidence is taken from Wikipedia directly, thus not including any personally identifiable information or offensive content.

7.3 Data Statements

We follow the data statements structure of Bender and Friedman [2018] to give additional insights into the dataset and its construction.

Curation Rationale. In order to study fact extraction and verification on both unstructured and structured information, we use the entire English Wikipedia as the knowledge base. Wikipedia is a large-scale collaboratively created encyclopedia, covering a large extent of knowledge/topics and is as such considered to be a suitable testbed for our purpose. Only articles that have been flagged by Wikipedia to have issues, miss references and/or citations have been excluded. The rationale behind this decision is to compile a retrieval corpus with information that is consistent across pages. The entire content of an article is considered, with exception to sections that were flagged as aforementioned as well sections that are named 'References', 'Citations', 'Sources', 'Further reading', 'External links', 'Works', 'Gallery', 'Citations and references', 'Bibliography', or 'External links & References' as we consider these sections to be out-of-scope for our task. Sentence and Table highlights given to annotators were sampled randomly from the entire collection of English Wikipedia articles.

Language Variety. The extracted evidence aligns with English Wikipedia's characteristic on language variety. A section on this, describing the lack of standardization can be found here. For claim generation, half of the annotators were native US-English speakers, while the other half were English speakers from the Philippines. For claim verification, all annotators were native US-English speakers. The internal screening by the external contractor ensured that the variety of English used is very similar across annotators, being en-us.

Speech Situation. The retrieval corpus was compiled based on a December 2020 version of English Wikipedia. Wikipedia is a collaborative encyclopedia, and as such regularly edited. Wikipedia describes in detail the requirements and recommendation of texts in articles, which can be found for instance here, here, and here. Claims were generated between March and May 2021, with very detailed guidelines regarding content and structure. A claim is described in the guidelines as *a single well-formed sentence. It should end with a period; it should follow correct capitalization of entity names (e.g. 'India', not 'india'); numbers can be formatted in any appropriate English format (including as words for smaller quantities).* They further must not be subjective and be verifiable using publicly available information/knowledge. Claims further should be unambiguous as possible, and must not contain any idioms, figures of speech, similes, or verbose language (see Section 7.9).

Text characteristics. Since highlights were sampled randomly from Wikipedia articles, the distribution of topics of generated claims roughly corresponds to the underlying English Wikipedia distribution of articles (i.e. people, geography, history, and sports being the main topics). We restrict the topic in some instances, such as: *Claims should not be about contemporary political topics (e.g. contemporary Wars (from the second world war and onwards), or disputed topics).*

Annotator Demographic Annotator candidates were screened specifically for our task, with multiple screening and calibration-stages as described in the paper. This ensures that annotators are aware of the constraints and guidelines when generating claims and verifying them. All annotators were paid above their local minimum wage.

- Age: Claim generation: 11 people between 18-24 years, 20 people between 25-34 years, 8 people between 35-44 years, 6 people between 45-54, and 12 people unspecified. Claim verification: 4 people between 18-24 years, 17 people between 25-34 years, 9 people between 35-44 years, 12 people between 45-54, 5 people between 55-64, and 12 people unspecified.
- Gender: Claim generation: 11 male, 42 female, and 4 unspecified. Claim verification: 15 male, 36 Female, and 3 unspecified.
- Race/ethnicity: -
- Native language: Claim generation: 33 people are native en-us speakers, 24 annotators are native en-ph (English (Philippines)) speaker. Claim verification: All annotators are native en-us speakers.
- Socioeconomic status: -
- Training in linguistics/other relevant discipline: Claim generation: English speakers from the Philippines are language-aware (an upper education degree in a language-related subject). Claim verification: all annotators are language-aware.

7.4 Licensing

These data annotations incorporate material from Wikipedia, which is licensed pursuant to the Wikipedia Copyright Policy. These annotations are made available under the license terms described on the applicable Wikipedia article pages, or, where Wikipedia license terms are unavailable, under the Creative Commons Attribution-ShareAlike License (version 3.0), available at <http://creativecommons.org/licenses/by-sa/3.0/> (collectively, the “License Terms”). You may not use these files except in compliance with the applicable License Terms. Credits to the contents of a page go to the authors of the corresponding Wikipedia article. Since article names in the dataset are unchanged, the authors can be found on the respective article on Wikipedia (https://www.wikipedia.org/wiki + TITLE_ID). The associated code to FEVEROUS (i.e. annotation platform, baseline code) are licensed under Apache 2.0.

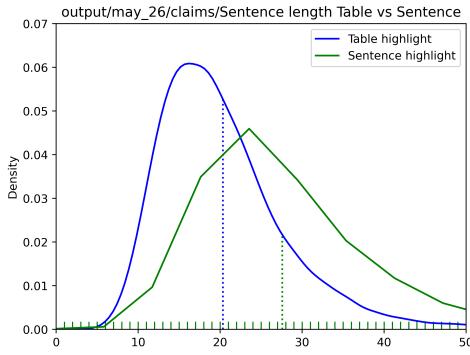
7.5 Detailed dataset and annotation statistics

7.5.1 Claim generation

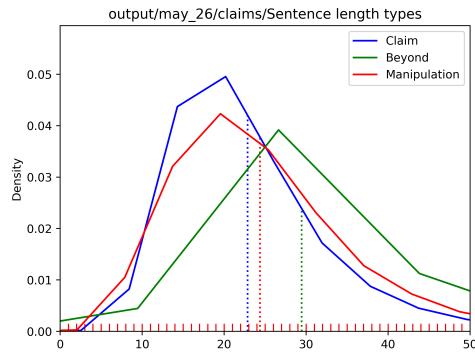
An average annotation (i.e. generating three claims) took an annotator 373 seconds. A total of 61058, and 32700 claims were created using table and sentence highlights, respectively. 47300 annotations were prompted to use information from the same page, and 46428 from different pages. The average length of a claim is 23, 29, and 24 for Type I, Type II and Type III, respectively. Annotators used on average 0.71 hyperlinks and 0.15 search queries. For Type II claims that require multiple pages, annotator used on average 1.2 hyperlinks and 0.2 searches. Sentence length by claim type is shown in figure 3a. Average sentence length for both table and sentence highlights is seen in figure 3b.

7.5.2 Claim verification

A single claim verification took on average 165 seconds. Claims are selected uniformly from the pool of different claim types, resulting in an claim verification set of about equal claims for each claim type. On average an annotation has 1.1 evidence sets, with a total of 7468 annotations having more than one evidence set. Annotators needed on average 1.34 search queries and 0.72 hyperlinks. On



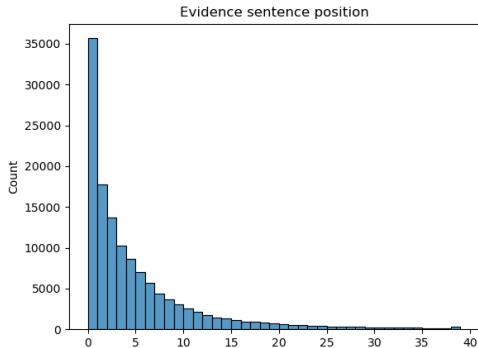
(a) Sentence length of claims given sentence versus table highlight.



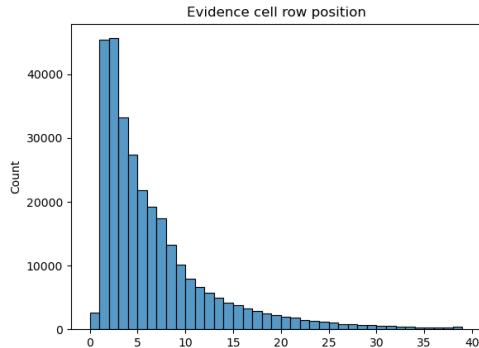
(b) Sentence length for different claim types.

average 0.1 advanced searches were used (i.e. searches for which no of the given page suggestions matches, so that annotators had to go to the advanced search page that uses 'in page' matches with Elasticsearch). In about 84% of claims do the pages from which evidence was retrieved directly match a word or phrase in the claim itself. 69% of all pieces of evidence are table cells, 29% are sentences, 1% are list items, and 1% are table captions.

Plot 4a and 4b show the evidences' sentence positions and row positions of cells in tables, respectively. Plot 5a shows the distribution of evidence numbers in the dataset. Plot 5b shows the section number where evidence is located, with -1 being the introduction section.



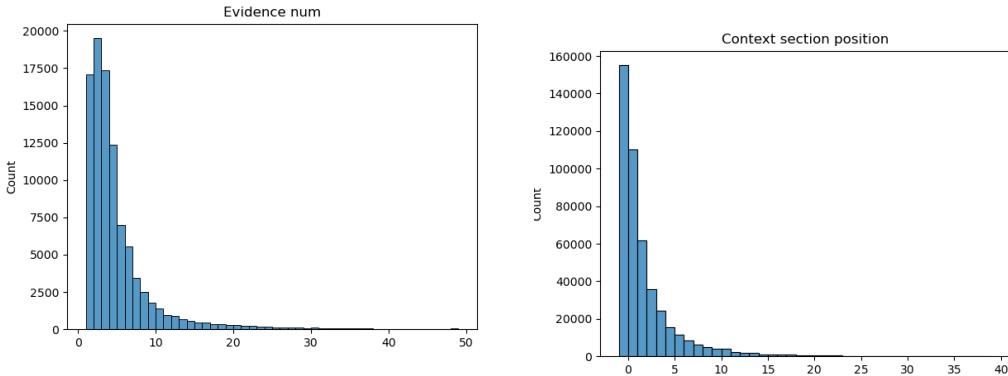
(a) Sentence position distribution in evidence.



(b) Row position of cells in tables in evidence.

7.5.3 Claim Verification Challenges

Table 5 shows the distribution of verification challenges in the FEVEROUS dataset, both the expected challenges as selected by the claim generators as well as the verification challenges by the verification annotators. The latter constitutes the actual distribution of challenges in FEVEROUS. As seen, the distribution is relatively similar across the splits, with about 10% of all claims having numerical reasoning, 16% multi-hop reasoning, 14% Combining Tables and text, 2% Entity Disambiguation, and 1.3% Search terms not in claim as their main verification challenge. Figure 6 shows the confusion matrix between expected and actual challenges, normalized along the x-axis. It is apparent that the claim generators overpredicted *Other* as the main challenge, indicating that the generators were frequently not aware of the challenge their claim poses when generating them. This particularly applies to *Entity Disambiguation* and *Search terms not in claim*, which have almost never been predicted correctly by the generators, most likely due to the generators not searching for the pages themselves, but are given a highlight on a page to generate their claim. Interestingly, there is also some discrepancy between numerical claims as well as claims that need both tables and text. This



(a) Distribution of number of evidence pieces in an evidence set.

(b) Section position of evidence pieces.

might be explained by information redundancy, having generated claims using both tables and text, not knowing that there is a sentence that contains the information of both. Further analyzing the challenges might lead to highly interesting insights on interactions and discrepancies between the expected difficulties from someone generating a claim and an annotator actually verifying it.

Following we show an example claim for each challenge category, taken from the dataset:

- **Numerical Reasoning** As of the 2011 Indian census, Nimbapur –located in the Indian state of Maharashtra, which is the second-most populous Indian state – has a population of 1903, with nearly half of the residents being non-workers. (*Calculation of the ratio between total population and residents who are non-workers*)
- **Multi-hop Reasoning** Belgium’s Léon Schots, a Belgian former long-distance runner who competed in track and cross country running competitions, was the fastest athlete in the senior men’s race (12.3km) at the 1977 IAAF World Cross Country Championships. (*Evidence to verify the claim are from two different articles*)
- **Entity Disambiguation** VUKOVI is a rock band from Scotland that plays pop rock, noise pop music and is formerly called Wolves. (*Disambiguation of the term Wolves*)
- **Search terms not in claim** In 2011, Evans signed with the Cincinnati Bengals after going undrafted in the NFL draft; but in November 2011, Evans was suspended for four games. (*To retrieve evidence, annotator first searched for any page containing "Evans signed with the Cincinnati Bengals", until finding the page for the entity's full name "DeQuin Evans".*)
- **Combining Tables and Text** Braeden Lemasters, an American actor, musician, and voice actor, appeared in six films since 2008 and also appeared in TV shows such as Six Feet Under where he starred as Frankie. (*Needing evidence from both tables and text*)
- **Other** Aquarion Logos is an anime series produced by Satelight which is a Japanese animation studio which serves as a division of pachinko operator Symphogear Group. (*Neither of the above five challenges apply*)

7.5.4 Details on QA statistics

In addition to the overall agreement, we measured the annotator agreement over evidence match ratios. As seen in Figure 7a, in the case of exact evidence match, the kappa agreement κ is 0.92, linearly decreasing with an agreement of 0.11 in the case of completely distinct evidence.

We further measured the annotation agreement sorted by annotator calibration score (more specifically the verdict accuracy) for the first 100 full-scale annotations of an annotator. As seen in Figure 7b, annotators with a calibration score of over 0.9 have an overall higher kappa score, of around 0.8 while annotators with a score of below 0.6 only achieved a kappa score of about 0.5. This indicates that the calibration score is indicative of the performance of annotators in the beginning. Looking at the score over all annotations, we however noticed, that annotators continue to align their annotations

Challenge Category	Train	Dev	Test	Total
Expected Challenges				
Numerical Reasoning	7798	1024	842	9664
Multi-hop Reasoning	17248	1871	2011	21130
Entity Disambiguation	826	143	77	1046
Combining Tables and Text	7775	975	769	9519
Search terms not in claim	405	57	90	552
Other	37239	3820	4056	45115
Verification Challenges				
Numerical Reasoning	7214	873	740	8827
Multi-hop Reasoning	11624	1281	1195	14100
Entity Disambiguation	1353	201	200	1754
Combining Tables and Text	10083	1035	940	12,058
Search terms not in claim	824	131	193	1148
Other	40193	4369	4577	49139

Table 5: Distribution of verification challenges in the FEVEROUS dataset. Top: Expected verification challenges, selected during claim generation. Bottom: Verification challenges, selected by annotator after a claim was verified.

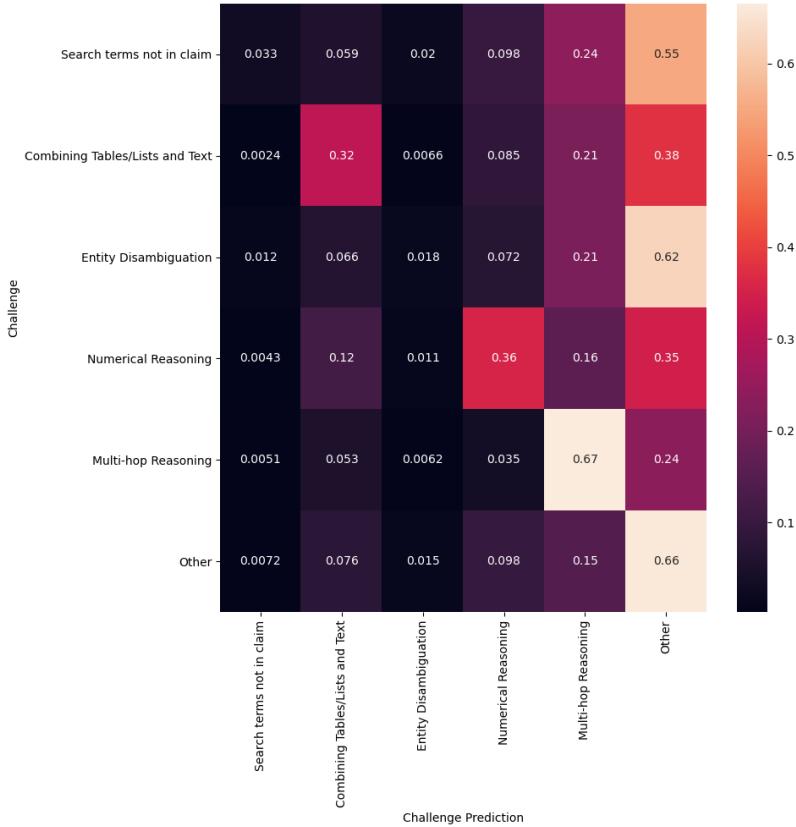
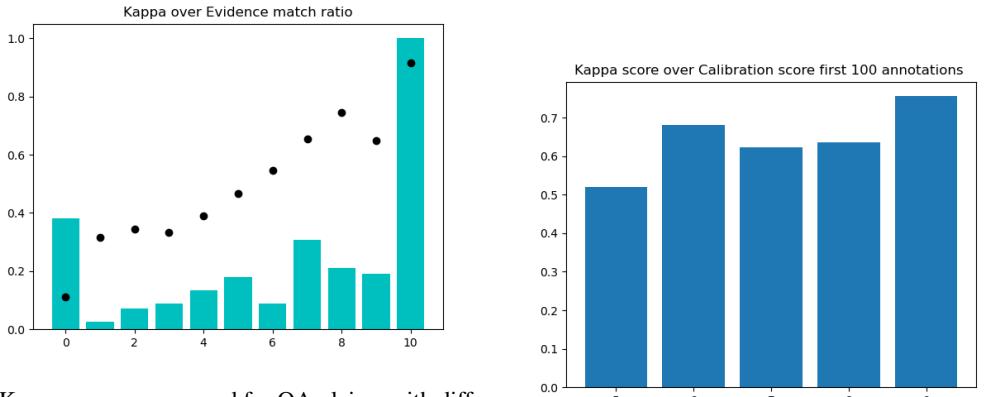


Figure 6: Confusion matrix for expected challenges versus actual challenges. Numbers are normalized across the x-axis.

with annotators having very similar agreement irregardless of calibration score (except annotators with very calibration score above 0.9 still having higher agreement).



(a) Kappa score κ measured for QA-claims with different evidence match ratio. Blue bars indicate the proportion of total annotations with that evidence match. The match is calculated as $\frac{2*|E_1 \cap E_2|}{|E_1|+|E_2|}$. Shown x-values 100 full-scale annotations. Shown x-values (calibration similarity) are multiplied by ten.

(b) Kappa agreement κ over calibration score for the first 100 annotations. Shown x-values (calibration scores) are multiplied by ten.

7.6 Dataset Processing & Implementation Details

7.7 Dataset Processing

Wikipedia articles were split into sentences using the NLTK unsupervised sentence tokenizer². We trained the unsupervised tokenizer on Wikipedia text to extract a large list of abbreviation words used on Wikipedia. These can be simply abbreviations of names (e.g. John F. Kennedy) or glossing abbreviations (for instance 'e.g.'.). Due to the extensive use of Wikipedia templates for tables and the difficulty in resolving/parsing them, we opted in extracting articles from Wikipedia directly. We used Scrapy for this³ and maintained a date stamp for each site. We limited the extracted tables to the classes 'wikitable' and 'infobox'. This restriction was set as there are contents of Wikipedia categorized as HTML tables while being highly specifically formatted, such as climate tables or tournament brackets. FEVEROUS maintains the diversity of Wikipedia tables/lists, only filtering ones out with formatting errors or that are empty (e.g. due to only containing images).

The FEVEROUS Wikipedia retrieval corpus was processed by keeping only hyperlinks with an associated article in the corpus. We replaced hyperlinks that are references to redirect pages with the respective page that the redirect page references to. URLs are replaced with a special token and text has been cleaned using the clean-text library⁴.

For the annotation platform, we populated a MediaWiki 1.31 database with the extracted articles as well as Wikipedia redirects. We installed the CirrusSearch extension⁵ to enable the search engine to use Elasticsearch as the back-end search. The annotations where stored in an SQL database using MariaDB.

7.7.1 Implementation & Evaluation Details

Retriever. We use Spacy⁶, specifically the en_core_web_sm model to extract entities from claims. We match extracted entities against all titles of our Wikipedida database and extract pages with an exact match. The TF-IDF part of our retriever is largely based on DrQA [Chen et al., 2017], computing the cosine similarity between the binned unigram and bigram TF-IDF vectors of claim and the introductory section of a Wikipedia article. The same TF-IDF approach is used to extract sentences and tables, however, restricted to the top k extracted pages. We excluded lists from the

²<https://www.nltk.org/api/nltk.tokenize.html>

³<https://scrapy.org/>

⁴<https://pypi.org/project/clean-text/>

⁵<https://www.mediawiki.org/wiki/Extension:CirrusSearch>

⁶<https://spacy.io/>

retrieval for our baseline to minimize computation time, considering that only 1% of annotated evidence is located in lists.

The cell retrieval model uses pre-trained RoBERTa_{base} from Huggingface⁷. Parts of the table that were longer than the maximum input length of RoBERTa were simply cut-off. To prevent this from happening during training we use row-sampling. We concatenate rows that contain relevant cell evidence first, before considering irrelevant rows.

The cell retrieval RoBERTa classifier was fine-tuned using binary cross-entropy. The batch-size was set to 16, with weight decay of 0.1, a learning rate of $5e^{-5}$, and a total of 1 training epochs. These hyperparameters are largely taken from recommendations [Devlin et al., 2019] and have not been further fine-tuned as the baseline’s purpose is not to achieve the highest possible scores, but rather to provide a working, intuitive model that motivates further exploration of the dataset. As such the models are not the main part of the paper.

Verdict predictor The verdict predictor uses RoBERTa_{large}, particularly the model pre-trained on multiple NLI datasets by Nie et al. [2020], which can be found here. Each piece of evidence is separated using </s>. We linearize cell evidence the following : [CONTEXT-HEADER] is [CELL], similar to [Schlichtkrull et al., 2020]. Our model is fine-tuned using a batch-size of 16, a weight decay of 0.01, a learning rate of $1e^{-5}$ for 1 epoch. Similar to the cell retrieval model, these values are largely taken from reference and have not been fine-tuned. Same rationale here as stated above.

Experiments using RoBERTa have been repeated twice and the average was reported, with very low variance (around $2e^{-5}$). All experiments were done in Python3.7. We fine-tuned all models on a single Quadro RTX 8000. Fine-tuning the cell extractor took around 1.5h, while fine-tuning the verdict predictor took around 4h. The TF-IDF retrieval needed around 10h on a Xeon Gold 5218 8 cores.

7.8 Annotation details

The annotation process to create FEVEROUS is visualized in Figure 8.

7.8.1 Annotation interfaces

Navigation To find relevant pages annotators can make use of the MediaWiki search functionality, a custom page search functionality, as well as hyperlinks. We aimed to create an ecosystem as realistic as possible, so annotators were motivated to approach this problem naturally: *How would you search for relevant information to check the truthfulness of a statement/claim given to you?* The search bar shows relevant articles to annotator’s search as soon as they start typing. They are further allowed to use the given recommendations and entering the main search page (i.e. clicking on ‘Containing ...’). There are three kinds of hyperlinks: i) Hyperlinks embedded in a sentence, table or list, ii) Hyperlinks in the content box of each Wikipedia article, iii) Hyperlinks below section headers that refer to the main article or to a more specialized article. Moreover, annotators had the option modify previous annotations.

Operating the search engine The search engine allows annotators to simply type in words or phrases that they are looking for. If they type in a query into the engine it will show them suggestions if a **title matches the query**. If it cannot find a matching title, they can start a “full text search” i.e. **searching through the actual content of a page by clicking on “containing...” on the very bottom of the suggestions**. Doing so redirects them to a search page, with suggestions and highlights in articles where the query could be (partially) matched. While queries can simply be words or phrases, annotators could further modify their search queries with some operators (see Annotation Guidelines, however, these have been used only very rarely).

⁷<https://huggingface.co/>

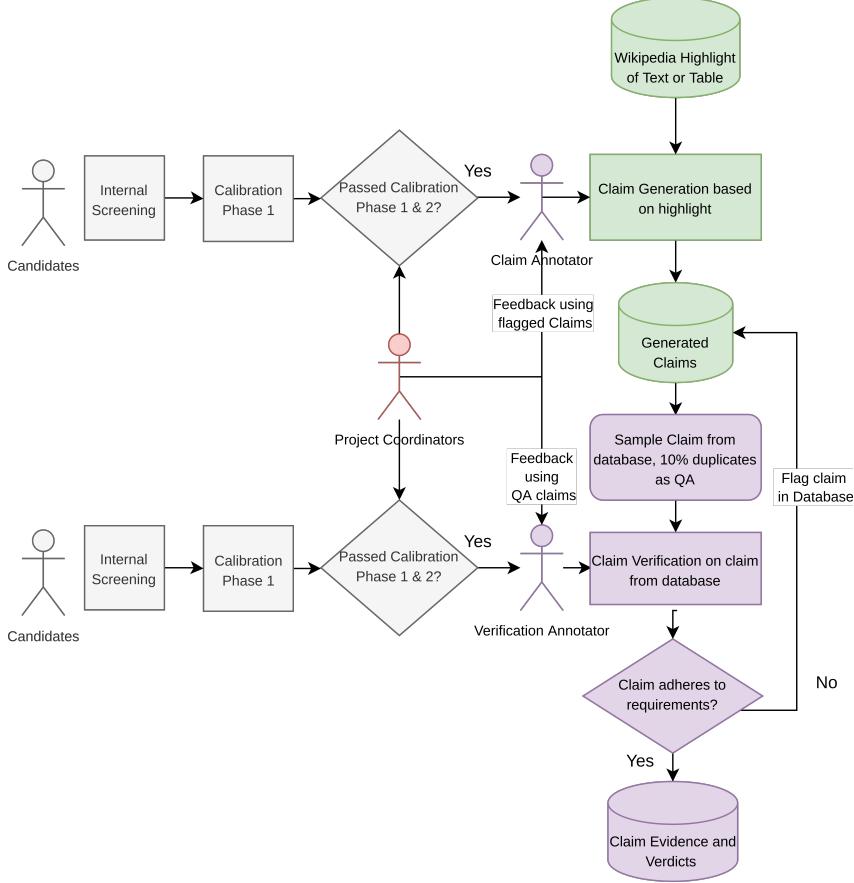


Figure 8: A schematic view on the annotation process of FEVEROUS. The claim generation phase is highlighted in green, the claim verification phase is noted in purple, and the screening of annotators is highlighted in gray.

7.9 Claim generation

7.9.1 Guidelines

Generating Claim using highlight (Type I) The first claim should **exclusively use information from the highlighted table/sentences**. Only the page title and/or section title the highlight is located might be used for the claim as well. The claim must either align with the contents in the highlight or contradict them, indicated on the tool (i.e. true and false claims). A claim should adhere to following requirements:

- A claim based on a table highlight should combine information of multiple cells if possible. This includes comparisons (e.g. *X scored higher/lower than Y*, or *While X was the son of Z, Y was the son of Q.*), superlatives (*X scored the highest/lowest*, or *X was the first Japanese supercomputer.*), filters (*X, Y and Z scored more than 10 points*, or *X, Y, Z are manufactured in Germany.*), and arithmetic operations (*5 teams scored more than 10 points*, or *X was born 2 years and 8 months before Y.*).
- A claim based on highlighted sentences should not simply paraphrase a highlighted sentence or concatenate sentences. Instead, information of multiple sentences must be combined. Information from at least two sentences must be used for generating the claim.
- A claim should be a single well-formed sentence. It should end with a period; it should follow correct capitalization of entity names (e.g. ‘India’, not ‘india’); numbers can be formatted in any appropriate English format (including as words for smaller quantities).

Figure 9: Claim generation interface. ① Menu bar with Access to User Information, Annotation Guidelines, and Logout. ② Title of current Wikipedia article. ③ Text field for writing claims. ④ Selection of expected challenges. ⑤ Buttons for i) Jumping back to the Wikipedia highlight, ii) submitting the written claims and selected challenges, iii) skip the current highlight. ⑥ Wikipedia article and navigation. ⑦ Article highlight to base the claims on. ⑧ Move between previously annotated claims.

Figure 10: claim verification Interface. ① Menu bar with Access to User Information, Annotation Guidelines, and Logout. ② Current claim to verify and retrieve evidence for. ③ Move between previously annotated evidence. ④ Management of selected evidence. ⑤ Specifying annotation challenges ⑥ Selection of the claims veracity (Supported, Refuted, NotEnoughInformation) ⑦ Button for submitting annotating/reporting claim ⑧ Search bars for i) navigating through Wikipedia articles, ii) information filtering within a Wikipedia page. ⑨ WikiMedia interface ⑩ Selected evidence (yellow highlighting) ⑪ Corresponding evidence context (lighter yellow highlighting).

- Generated claims must **not be subjective** and be **verifiable** using publicly available information/knowledge.

Don't: John Lennon was a more popular musician than Tommy Moore.

Do: John Lennon's discography sold two times as many box sets as Tommy Moore in 1997.

Don't: Sea Songs by Yadollah Royaei (born in 1932) is rich in symbolism and is deeply

inspired by Persian mysticism. *Do:* Sea Songs by Yadollah Royae (born in 1932) contains symbolism and is inspired by Persian mysticism.

- The claim should be **as unambiguous as possible** and avoid vague or speculative language (e.g. might be, may be, could be, rarely, many, barely or other indeterminate count words)
Don't: The Olympic Games have rarely taken places in Europe
Do: The Olympic Games were held three times in Europe. *Don't:* Michael Ballack scored the most goals.
Do: Michael Ballack scored the most goals in the Bundesliga 2004/2005 season.
- A claim must not contain any idioms, figures of speech, similes, or verbose language. *Don't:* The scientist Mary Lamb owned five sheep with fleece as black as coal, but they were not used in any of her experiments.
Do: The scientist Mary Lamb owned five sheep with black fleece, but they were not used in any of her experiments.
- The claim must be understood by itself (i.e. no pronouns) – *[Note: in the case where the highlighted text does not contain a mention of the entity at question, you should use the title of the page or the header of the section for that information].*
Don't: He played most of his football career for Chelsea.
Do: Didier Drogba played most of his football career for Chelsea.
- Claims should not be about contemporary political topics (e.g. contemporary Wars (from the second world war and onwards), disputed topics) – skip pages where the highlighted area only discusses such topics.
Don't: In 1974 Turkey had landed 30,000 troops on Cyprus and captured Kyrenia.
- In some cases highlighted Wikipedia information is not correct/consistent. These highlights are still valid for claim generation. For this workflow don't worry about the factual correctness of Wikipedia. If you think that the highlighted information is disputed, better skip it.
- Do not incorporate your own knowledge, beliefs or additional world knowledge into the claim. Focus only on the highlighted Wikipedia section given to you!

Generating Claim beyond the highlight (Type II) The second claim should be based on the highlight, but **must include information beyond the highlighted table/sentences**. You are free in deciding to modify the previously created claim that uses only the highlight or to create an unrelated one (that still includes information from the highlight). Either way, the new claim must still adhere to the requirements mentioned above. The new claim can either be supported or refuted. So in general, you should not worry whether the new claim preserves the truth value of the first claim. However, please keep in mind that we aim for having a similar number of positive vs negative claims. Information to include must either be on the same page or from other Wikipedia pages, indicated on the tool:

1. **Same page:** Include information outside of the highlight but on the same page.
2. **Multiple pages:** Include information from other Wikipedia page(s). You can search freely through Wikipedia using the search function, available hyperlinks on the pages, and the *Return to highlight* button.

Moreover, for this claim it is allowed to use information/knowledge that might not be available in Wikipedia but you assume to be general knowledge, e.g. that 90s refers to the timespan from 1990 to 1999. Similarly to the previous claim, the claim can either align with the used information or contradict it. We encourage you to create claims that are based on a combination of structured and unstructured information: tables, sentences, lists, captions, or section titles.

Example 1:

Claim using highlight: The Zuse Z3 was program-controlled by punched 35mm film stock.

Claim using more than highlight: Programs were executed on the Zuse Z3 by using punched 35mm film stock with manually entered initial values.

Example 2:

Claim using highlight: The player with the most number of total assists at Shrewsbury Town F.C in 2013 is Luke Summerfield.

Claim using more than highlight: The player with the most number of total assists at Shrewsbury Town F.C in 2013 also played for Liverpool.

Example 3:

Claim using highlight: Jeff Gordon had the most points at the 1998 Pepsi 400 stock car race.

Claim using more than highlight: Jeff Gordon's points at the end of the Winston cup in 1998 were higher than the points of all drivers at 1998 NAPA 500 combined.

Mutated Claim (Type III) We additionally ask the annotators to modify one of the two claims with one of the following *mutations types*: **More Specific, Generalization, Negation, Paraphrasing, Entity Substitution, Tense Shift**. Both the type of modification and which of the two claims to be modified are specified in the interface (see ③ in Figure 9). Similar to 'Claim beyond highlights', the modification can result in a claim that can either be supported or refuted. So in general, you should not worry whether the mutation will preserve the truth of the claim or not. Again, for this claim it is allowed to use information/knowledge that might not be available in Wikipedia but you assume to be general knowledge. Make sure that the new claim is still a single sentence! Here is an explanation for each mutation type:

1. **Generalization** Make the claim more general so that the new claim is a generalization of the original claim (by making the meaning less specific)
2. **More Specific** Make the claim more specific so that the new claim is a specialization (as opposed to a generalization) of the original claim (by making the meaning more specific).
3. **Negation** Negate the meaning of the claim. This is not to be confused with making claim false: negating the meaning of a claim could make a false claim true and vice versa!
4. **Paraphrasing** Rephrase the claim so that it has the same meaning
5. **Entity Substitution** Substitute an entity in the claim to alternative from either the same or a different set of things. If the object in the claim is an entity, replace this entity. Choose any entity in the claim otherwise.

Given the claim "*John E. Moss was a politician of the US Democratic party.*" Table 6 shows each modification for the example sentence, following table shows example modifications for each mutation type:

Type	Modified Claim
More specific	John E. Moss was a politician of the US Democratic party for California's 3rd congressional district.
Negation	John E. Moss has never ran for office.
Generalization	John E. Moss was a US American politician.
Paraphrase	John E. Moss was a US American politician of the Democratic party.
Entity Substitution	John E. Moss was a politician of the US Republican Party.

Table 6: Claim manipulation for the claim "*John E. Moss was a politician of the US Democratic party.*"

Expected Main Verification Challenge We want to know what you think is the main challenge for assessing the veracity and retrieving evidence for the claim you have created. You must select one of the given challenge categories you expect to be the main challenge: **Multi-hop Reasoning, Numerical Reasoning, Combining Text and Tables, Entity Disambiguation, and Search terms not in claim**. If the main challenge hasn't been any of these, select **Other**.

1. **Multi-hop Reasoning** Multi-hop reasoning expected to be the main challenge for verifying that claim, i.e. several pages/sections will be required for verification. e.g. "*The player who ranked 3rd at the US Open in 2010 played in the most populated city of Germany in 2014*".

2. **Numerical Reasoning** Numerical reasoning expected to be the main challenge to verify the claim, i.e. reasoning that involves numbers or arithmetic calculations. This also includes steps such as counting cells in tables. Example: Given a claim "A is older than B", and for both A and B only their birth dates are given, concluding the older person would require mathematical inference. Another example would be given the following scores in tennis '7-4', 2-6', and 6-1' to conclude that Player 1 won the match.
3. **Combining Tables and Text** Combining list(s)/table(s) with information from text (i.e. phrases, captions, sentences) outside tables is expected to be the main challenge, i.e. when the Text provides important context to Tables/List to be understood and vice versa (titles are excluded when talking about text in this challenge).
4. **Entity disambiguation** Disambiguating an entity is expected to be the main challenge for verifying a given claim. E.g. Adam Smith was a footballer for the Bristol Rovers (Wikipedia lists 4 Adam Smiths that played football).
5. **Search terms not in claim** The main challenge is expected to be finding relevant search terms to pages with required evidence to verify a given claim goes beyond searching for terms located in the claim itself, e.g. for the Claim "*Non college educated voters voted 67 percent for the democratic party in 1952*" the evidence is located on the page "New Deal Coalition" – challenging to deduce the page based on the claim. Evidence that can quickly be found by searching for an entity mentioned in the claim is most likely not a retrieval challenge (excluding entity mentions that could refer to many entities).
6. **Other** If none of the above challenges can be identified.

7.9.2 Examples

See Table 11 and 12 for examples.

<p>Warneford Place, also known as Sevenhampton Place, is a Grade II listed country house in Sevenhampton, south of Highworth, in Wiltshire, England.</p> <p>The main house is modern but is listed because it incorporates some features from the original 18th century mansion.</p> <p>Warneford Place dates back to at least the 17th century, and was home to the Warneford family.</p> <p>That family, although often impoverished, had been established in the area since around the 12th century and owned much of its land.</p> <p>The house was often empty and neglected.</p> <p>In 1902, there was an auction of the Warneford Place Estate and its contents.</p> <p>It has been grade II listed (as Warneford Place) since 1979.</p> <p>It was home to Frederick Banbury, 1st Baron Banbury of Southampton, who died there in 1936.</p> <p>In 1960, the James Bond author Ian Fleming bought the "demolished Warneford Place", and built a new house which he named Sevenhampton Place, incorporating some elements of the original building.</p> <p>He did not move in until the new house was completed in 1963 and spent little time there.</p> <p>He died in 1964, aged 56, and is buried in the Sevenhampton churchyard, along with his wife Ann and son Caspar.</p>	<table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th colspan="2" style="text-align: left;">Sevenhampton Place</th> </tr> <tr> <th colspan="2" style="text-align: left;">General information</th> </tr> </thead> <tbody> <tr> <td>Town or city</td> <td>Sevenhampton</td> </tr> <tr> <td>Country</td> <td>United Kingdom</td> </tr> <tr> <td>Coordinates</td> <td></td> </tr> <tr> <td>Completed</td> <td>17th century</td> </tr> <tr> <td>Renovated</td> <td>1963</td> </tr> <tr> <td>Owner</td> <td>Paddy McNally</td> </tr> </tbody> </table>	Sevenhampton Place		General information		Town or city	Sevenhampton	Country	United Kingdom	Coordinates		Completed	17th century	Renovated	1963	Owner	Paddy McNally
Sevenhampton Place																	
General information																	
Town or city	Sevenhampton																
Country	United Kingdom																
Coordinates																	
Completed	17th century																
Renovated	1963																
Owner	Paddy McNally																

Claim using Highlight (true): **Warneford Place is a country house in England that dates as far back as the 17th century.**

Challenge: Other

[Report Claim](#) 

Claim beyond Highlight: (Same page): **The Warneford Place was built in the 17th century in Wiltshire, England and neglected and rebuilt over the years and was owned for over 20 years by Ian Fleming who demolished the old house and rebuilt it.**

Challenge: Other

[Report Claim](#) 

Manipulation: (Second claim: Substitution): **The Warneford Place was built in the 18th century in Wiltshire, England and neglected and rebuilt over the years and was owned for over 20 years by Ian Fleming who demolished the old house and rebuilt it.**

Challenge: Other

[Report Claim](#) 

Figure 11: Example claim generation annotation, given a sentence highlight.

West Lothian Local Election Result 2017								
Party	Seats	Gains	Losses	Net gain/loss	Seats %	Votes %	Votes	+/-
SNP	13	0	-2	-2	39.39	37.29	23,218	
Labour	12	0	-4	-4	36.36	29.04	18,082	
Conservative	7	6	0	+6	21.21	23.21	14,449	
Independent	1	0	0	-	3.03	4.96	3,088	
Scottish Green	0	-	-	-	-	2.72	1,695	
Liberal Democrats	0	-	-	-	-	2.62	1,632	
TUSC	0	-	-	-	-	0.092	57	

Claim using Highlight (true): **The Labour Party lost the 2017 West Lothian Council election having only 29.04% (18,082) of total votes.**

Challenge: Other

[Report Claim](#)

Claim beyond Highlight: (Multiple pages): **The SNP Party (Scottish National Party) won the 2017 West Lothian Council election with a total of 37.29% (23,218) of all votes.**

Challenge: Multi-hop Reasoning

[Report Claim](#)

Manipulation: (Second claim: Paraphrasing): **A total of 37.29% (23,218) of all votes was accounted for the SNP (Scottish National Party), making them win the 2017 West Lothian Local Election.**

Challenge: Combining Tables/Lists and Text

[Report Claim](#)

Figure 12: Example claim generation annotation, given a table highlight.

7.10 Claim Verification

7.10.1 Guidelines

Evidence highlighting As soon as relevant information has been found in either *text (sentences or table captions), tables, or lists* you can add it as evidence to your annotation by clicking on it. For free text, the **entire sentence/phrase** will be selected as evidence. For tables, one **cell** is selected, and finally for lists, one **item** will be highlighted. Evidence from different Wikipedia can be freely combined – there are no restrictions. There is also no limitation in terms of evidence pieces required to validate a claim. However, an entire annotation for a single claim should not surpass **10 Minutes**. If it does, keep the already annotated evidence and submit it with the verdict *NotEnoughInformation*.

For every highlighted sentence/cell/list item some context is extracted automatically and shown to you in the interface. Article titles and sections (and subsections, subsubsections etc.) in which the evidence is located are always extracted. Additionally, if a cell has been highlighted the corresponding table headers are extracted as well. Due to the complexity and diversity in Wikipedia tables, it is possible that some additional table headers have not been highlighted automatically, but would still be needed to interpret the selected evidence correctly. **These headers need to be highlighted manually by you.**

You must apply common-sense reasoning to the evidence you read but avoid applying your own (world) knowledge. If possible, additional evidence should be highlighted which provides the missing information (e.g. that a *Democrat* is a politician of the Democratic Party, or that *60s* refers to the years 1960 – 1969). If this very general world knowledge cannot be found on Wikipedia you are nonetheless allowed to use it for the verdict or to find further evidence. Be careful that you do not use your knowledge to reach hasty conclusions, for instance given the evidence X is goalkeeper and the captain of Team Y, we do not have enough support that 'X' is the starting goalkeeper for Y'. While it is often the case that the first implies the second, it is not always true.

As a guide - you should ask yourself: **If I was given only the selected sentences, table cells, and list items shown in the evidence overview ③, do I have strong enough reason to believe the claim**

is supported or strong enough reason to believe the claim is refuted. If I'm not certain, what additional information do I have to add to reach this conclusion and can I find it on Wikipedia?

While claims that are *Supported* require evidence for each fact mentioned in that claim as far as possible, *Refuted* claims must only select evidence of the information that contradicts (parts of) the claim. If a refuted claim is partially supported, do not provide evidence for the partially supporting parts, unless it is necessary context for the refuting evidence, e.g. ensuring the correct entity is being referred to. If a claim is marked as *NotEnoughInformation* please still submit the evidence found in the process of reaching this verdict!

All your annotated evidence (excluding titles, and sections, but including table headers) is shown to you in the evidence overview ③, Figure 10. You initially see the ID of the annotated evidence, however, by clicking on the ID in the overview it will expand and show you the actual content of the element you selected. This way you can keep track of evidence from possibly multiple pages easily. If you change your mind and want to remove a piece of evidence simply click again on the now highlighted element.

Note!

- If the verification of a claim requires to include every entry in a table row/column (e.g. claims with universal quantification such as ‘highest number of gold medals out of all countries’), you must highlight each cell of that row/column (c.f. Example 4, 7).
- Content on Wikipedia that contains qualifier or hedges (e.g. probably, likely, might) should not be used as evidence. For instance, a sentence such as *Michael Mueller was likely not involved in the 2012 scandal* should not be considered as evidence for the given claim.
- If you are not able to find any evidence for the given claim, you are still required to submit the annotation. As mentioned above, select the verdict *Not enough Information* in this case and challenges (as described below)
- Make sure that you find evidence to support each fact mentioned in a claim when selecting *Supported*, especially for longer claims. For instance given the claim "The scientist Mary Lamb owned five sheep with black fleece, but they were not used in any of her experiments.", the claim can be broken down into five pieces of information that all need to be verified in order to select supported:
 1. There exists a person named Mary Lamb
 2. Mary Lamb is a scientist
 3. Mary Lamb owned five sheep
 4. Those sheep had black fleece
 5. The sheep that Mary owned were not used in any of her experiments
- Do not take possible motives of Wikipedia editors into account when assessing the evidence – take the evidence as it is.
- When highlighting cells in very large tables there could be a delay until the cell and the automated context are highlighted. This is because the table has to be processed before the correct context is identified.
- There exists no interaction between different claim verification annotators in the interface – do not worry about this!
- Even if entire sentences are located in tables or lists, the finest granularity remains the cell or item, respectively. Therefore, the entire content of the cell will be added which is fine!

Ambiguous & Misleading Claims In cases where you could find multiple ways of interpreting the claim which give rise to different verdicts, ask yourself the following question: *Would you consider yourself misled by the claim given the evidence you found?* For instance, take the claim "*Shakira is Canadian*". Even if the evidence only concludes that she is Colombian (not a direct contradiction to the claim), it is still okay to refute the claim as there is enough evidence to believe that the claim is misleading, according to common perception. Similar case with a claim "*Lamb owned five sheep*", given the sentence "*Lamb had a love of farming and owned many barnyard animals, including two hens and four sheep*", we can conclude that the claim is misleading and thus refuted.

If you have doubt regarding your assessment go with NEI, e.g. given the claim 'Shakira was diagnosed with Diabetes Type II' and the evidence that Shakira was diagnosed with Diabetes when she was 10, it is clear to someone with specialized knowledge that the claim is false, however as it goes beyond common perception it is NEI. Do not include any knowledge about how the claims are generated when evaluating how misleading a claim is, e.g. that this claim is likely to be a corrupted version of the claim "*Shakira is Colombian*".

Reporting a claim It is possible to report and skip a given claim. It might be appropriate to flag a claim if i) the claim is personal, implausible, not verifiable, not understandable by itself, or too ambiguous ii) does not meet other aspects of the guidelines from the Claim generation task (i.e. not containing idioms, figures of speech, similes, verbose language, and not be about contemporary political topics)*, iii) ungrammatical claims or typographical errors, spelling mistakes iv) required evidence is not displayed correctly. When reporting a claim select the appropriate action from the menu or write an individual text. Do not skip a claim if it is phrased similarly to another one you have already annotated. We explicitly include paraphrased claims for annotation as we want to gather claim verifications for these too.

Main Verification Challenge We are interested in gaining more insights into the main challenge the annotator had for finding evidence for the given claim. You must select one of the given challenge categories: **Multi-hop Reasoning**, **Numerical Reasoning**, **Combining Tables and Text**, **Entity Disambiguation**, and **Search terms not in claim**. If the main challenge hasn't been any of these, select **Other**.

1. **Multi-hop Reasoning** Multi-hop reasoning was the main challenge challenge for verifying that claim, i.e. several pages/sections will be required for verification. e.g. "*The player who ranked 3rd at the US Open in 2010 played in the most populated city of Germany in 2014*".
2. **Numerical Reasoning** Numerical reasoning was the main challenge when verifying the claim, i.e. reasoning that involves numbers or arithmetic calculations. This also includes steps such as counting cells in tables. Example: Given a claim "A is older than B", and for both A and B only their birth dates are given, concluding the older person would require mathematical inference. Another example would be given the following scores in tennis '7-4', 2-6', and 6-1' to conclude that Player 1 won the match.
3. **Combining Tables and Text** Combining list(s)/table(s) with information from text (i.e. phrases, captions, sentences) outside tables was the the main challenge, i.e. when the Text provides important context to Tables/List to be understood and vice versa (titles and sections are excluded when talking about text in this challenge).
4. **Entity disambiguation** Disambiguating an entity was the main challenge for verifying a given claim. E.g. Adam Smith was a footballer for the Bristol Rovers (Wikipedia lists 4 Adam Smiths that played football).
5. **Search terms not in claim** The main challenge was finding relevant search terms to pages with required evidence to verify a given claim goes beyond searching for terms located in the claim itself, e.g. for the Claim "*Non college educated voters voted 67 percent for the democratic party in 1952*" the evidence is located on the page "New Deal Coalition" – challenging to deduce the page based on the claim. Evidence that can quickly be found by searching for an entity mentioned in the claim is most likely not a retrieval challenge (excluding entity mentions that could refer to many entities).
6. **Other** If none of the above challenges can be identified.

7.10.2 Examples

In addition to Figure 1 in the main paper, two further examples are shown in Figure 13.

7.10.3 QA annotation interface

QA data was also used to recognise guidelines aspects that needed further clarification. Clarifications were communicated through updated guidelines as well as multiple FAQs. QA annotations were also used on an individual annotator level in combination with production reports, which measured

<p>Claim: Mike Ledwith (a professional baseball player) played one game in MLB and scored one run.</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th colspan="2" style="text-align: center; padding: 5px;">Evidence</th> </tr> </thead> <tbody> <tr> <td colspan="2" style="padding: 5px;">P: wiki/Mike_Ledwith</td> </tr> <tr> <td colspan="2" style="padding: 5px;">S0: Introduction</td> </tr> <tr> <td colspan="2" style="padding: 5px;">e₁: Michael Ledwith, was a professional baseball player who played catcher in one game for the 1874 Brooklyn Atlantics.</td> </tr> <tr> <td colspan="2" style="padding: 5px;">S0: Introduction</td> </tr> <tr> <td style="width: 15%;"> </td> <td style="width: 85%; padding: 5px;">Mike Ledwith</td> </tr> <tr> <td> </td> <td style="padding: 5px;">MLB statistics</td> </tr> <tr> <td style="padding: 5px;">e₂:</td> <td style="padding: 5px;">Games played 1</td> </tr> <tr> <td> </td> <td style="padding: 5px;">Runs scored 1</td> </tr> <tr> <td> </td> <td style="padding: 5px;">Hits 1</td> </tr> <tr> <td> </td> <td style="padding: 5px;">Batting average 0.250</td> </tr> </tbody> </table> <p>Verdict: Supported Expected Challenge: Combining Tables and Text Challenge: Combining Tables and Text</p>	Evidence		P: wiki/Mike_Ledwith		S0: Introduction		e₁: Michael Ledwith, was a professional baseball player who played catcher in one game for the 1874 Brooklyn Atlantics.		S0: Introduction			Mike Ledwith		MLB statistics	e₂:	Games played 1		Runs scored 1		Hits 1		Batting average 0.250	<p>Claim: Braeden Lemasters, an American actor, musician, and voice actor, appeared in six films since 2008 and also appeared in TV shows such as Six Feet Under where he starred as Frankie.</p> <table border="1" style="width: 100%; border-collapse: collapse;"> <thead> <tr> <th colspan="2" style="text-align: center; padding: 5px;">Evidence</th> </tr> </thead> <tbody> <tr> <td colspan="2" style="padding: 5px;">P: wiki/Braeden_Lemasters</td> </tr> <tr> <td colspan="2" style="padding: 5px;">S2: Filmography</td> </tr> <tr> <td colspan="2" style="padding: 5px;">e₁: Braeden Lemasters (born January 27, 1996) is an American actor, musician, and voice actor.</td> </tr> <tr> <td colspan="2" style="padding: 5px;">e₂:</td> </tr> <tr> <th style="width: 15%;">Year</th><th style="width: 85%;">Film</th><th style="width: 10%;">Role</th></tr> <tr> <td style="padding: 5px;">2008</td><td style="padding: 5px;">Beautiful Loser</td><td style="padding: 5px;">Jake</td></tr> <tr> <td style="padding: 5px;">2009</td><td style="padding: 5px;">The Stepfather</td><td style="padding: 5px;">Sean Harding</td></tr> <tr> <td style="padding: 5px;">2010</td><td style="padding: 5px;">Easy A</td><td style="padding: 5px;">8th Grade Todd</td></tr> <tr> <td style="padding: 5px;">2012</td><td style="padding: 5px;">A Christmas Story 2</td><td style="padding: 5px;">Ralphie Parker</td></tr> <tr> <td style="padding: 5px;">2017</td><td style="padding: 5px;">Totem</td><td style="padding: 5px;">Todd</td></tr> <tr> <td style="padding: 5px;">2017</td><td style="padding: 5px;">Flock of Four</td><td style="padding: 5px;">Joey Grover</td></tr> <tr> <td colspan="3" style="padding: 5px;">S1: Life and career</td></tr> <tr> <td colspan="3" style="padding: 5px;">e₃: In 2005, Braeden started his career at age 9, as Frankie, on the TV show Six Feet Under.</td></tr> <tr> <td colspan="3" style="padding: 5px;">Verdict: Supported Expected Challenge: Combining Tables and Text Challenge: Combining Tables and Text</td></tr> </tbody> </table>	Evidence		P: wiki/Braeden_Lemasters		S2: Filmography		e₁: Braeden Lemasters (born January 27, 1996) is an American actor, musician, and voice actor.		e₂:		Year	Film	Role	2008	Beautiful Loser	Jake	2009	The Stepfather	Sean Harding	2010	Easy A	8th Grade Todd	2012	A Christmas Story 2	Ralphie Parker	2017	Totem	Todd	2017	Flock of Four	Joey Grover	S1: Life and career			e₃: In 2005, Braeden started his career at age 9, as Frankie, on the TV show Six Feet Under.			Verdict: Supported Expected Challenge: Combining Tables and Text Challenge: Combining Tables and Text		
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Figure 13: Two examples from the FEVEROUS dataset that require both unstructured and structured information. The dataset contains both short, simple claims (left) and complex claims (right).

statistics such as the number of claims an annotator generated that have been reported by verification annotators, to identify error patterns and giving annotators further individual feedback. An interface was provided to annotators to see the annotations that have been quality checked and to allow them to maintain an overview on their performance.

Figure 14 shows the QA interface for project managers. QA annotations with only partial agreement or complete disagreement are highlighted in the interface in red. The QA interface for annotators looks similar, with ID’s being anonymized.

7.11 Author statement

The authors of this paper bear all responsibility in case of violation of copyrights associated with the FEVEROUS dataset.

Days of War is a first-person shooter game with a multiplayer mode, it is developed by Driven Arts. (31027)

Current Anno.	Anno ID: 45	Anno ID: 41						
Verdict: Supported Challenge: Other Evidence Set 1 <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 5px;"> Days of War_sentence_0 : Days of War is a multiplayer first-person shooter video game developed and published by Driven Arts. </div> <div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_1_1 : Driven Arts </div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_5_1 : First-person shooter </div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_6_1 : Multiplayer </div> <div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div>	Verdict: Supported Challenge: Combining Tables/Lists and Text Evidence Set 1 <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 5px;"> Days of War_sentence_0 : Days of War is a multiplayer first-person shooter video game developed and published by Driven Arts. </div> <div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px; background-color: #f0f0f0;"> <table border="1" style="width: 100%; border-collapse: collapse;"> <tr> <td style="width: 33%; padding: 2px;">War is a multiplayer first-person shooter video game developed</td> <td style="width: 33%; padding: 2px; text-align: center;">Days of War</td> <td style="width: 33%; padding: 2px; text-align: center;">Developer(s) Driven Arts</td> </tr> <tr> <td style="width: 33%; padding: 2px;">Publisher(s) Unreal</td> <td style="width: 33%; padding: 2px;"></td> <td style="width: 33%; padding: 2px;"></td> </tr> </table> </div>	War is a multiplayer first-person shooter video game developed	Days of War	Developer(s) Driven Arts	Publisher(s) Unreal			Verdict: Supported Challenge: Other Evidence Set 1 <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 5px;"> Days of War_sentence_0 : Days of War is a multiplayer first-person shooter video game developed and published by Driven Arts. </div> <div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_1_1 : Driven Arts </div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_5_1 : First-person shooter </div> <div style="border: 1px solid #ccc; padding: 5px; margin-top: 10px;"> Days of War_cell_0_6_1 : Multiplayer </div> <div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div>
War is a multiplayer first-person shooter video game developed	Days of War	Developer(s) Driven Arts						
Publisher(s) Unreal								
Evidence Set 2	Evidence Set 2	Evidence Set 2						
Days of War_sentence_0 : Days of War is a multiplayer first-person shooter video game developed and published by Driven Arts.	Days of War_cell_0_1_1 : Driven Arts	Days of War_cell_0_1_1 : Driven Arts						
Days of War_cell_0_5_1 : First-person shooter	Days of War_cell_0_5_1 : First-person shooter	Days of War_cell_0_5_1 : First-person shooter						
Days of War_cell_0_6_1 : Multiplayer	Days of War_cell_0_6_1 : Multiplayer	Days of War_cell_0_6_1 : Multiplayer						
<div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div>	<div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div>	<div style="background-color: #0072BD; color: white; text-align: center; padding: 2px 10px; border-radius: 5px; cursor: pointer; font-size: 0.8em;">Show Article</div>						
Evidence Set 3	Evidence Set 3	Evidence Set 3						

Figure 14: QA annotation interface for project managers. Interface for annotators looks similar, with ID's being anonymized