Evidence-based Verification for Real World Information Needs

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Abstract

Claim verification is the task of predicting the veracity of written statements against evidence. Previous large-scale datasets model the task as classification, ignoring the need to retrieve evidence, or are constructed for research purposes, and may not be representative of real-world needs. In this paper, we introduce a novel claim verification dataset with instances derived from search-engine queries, yielding 10,987 claims annotated with evidence that represent real-world information needs. For each claim, we annotate evidence from full Wikipedia articles with both section and sentence-level granularity. Our annotation allows comparison between two complementary approaches to verification: stance classification, and evidence extraction followed by entailment recognition. In our comprehensive evaluation, we find no significant difference in accuracy between these two approaches. This enables systems to use evidence extraction to summarize a rationale for an end-user while maintaining the accuracy when predicting a claim’s veracity. With challenging claims and evidence documents containing hundreds of sentences, our dataset presents interesting challenges that are not captured in previous work—evidenced through transfer learning experiments. We release code and data\textsuperscript{1} to support further research on this task.

1 Introduction

Automated claim verification has received considerable attention from the Natural Language Processing community in recent years. The task is to identify evidence for a claim, a short sentence of unknown veracity, from a corpus of documents and predict whether the claim is supported or refuted by this evidence. The growth in this discipline has been driven by the introduction of many datasets and task variants (Wang et al., 2017; Karadzhov et al., 2017; Baly et al., 2018; Thorne et al., 2018; Chen et al., 2019; Augenstein et al., 2019; Hanselowski et al., 2019; Chen et al., 2020; Wadden et al., 2020; Diggelmann et al., 2020; Schuster et al., 2021, inter alia) that have enabled the development of new models and methods for machine reading and comprehension.

One of the challenges involved when building large-scale datasets is to balance being representative of real-world information needs, but simple enough to gain high quality and consistent annotations that systems can learn from. The largest claim verification dataset, FEVER (Thorne et al., 2018), contains 185,000 claims which were manually constructed; annotated with evidence supporting or refuting them from the introductory sections of Wikipedia pages. In contrast, MultiFC (Augenstein et al., 2019) contains real-world claims collected from multiple fact-checking websites with scraped web page snippets that support modelling
verification through stance classification. While stance classification considers whether claims are supported or refuted by evidence, unlike FEVER, it does not involve document retrieval or evidence extraction. However, identifying which (parts of) documents are evidence is important for interpretability of the model predictions and still presents a challenge for real-world fact-checking.

In this paper, we introduce a new dataset that allows direct comparison between stance classification and evidence extraction methods for claim verification. Unlike FEVER, our data is derived from real-world information needs, captured in the questions of the BoolQ dataset (Clark et al., 2019) (a subset of natural questions (Kwiatkowski et al., 2019) where instances have a yes or no answer). We use human annotators to rewrite these questions as claims, without modifying the information content, and verify them against evidence from Wikipedia. Our task definition mandates that systems identify evidential sentences from pre-selected articles that support or refute the claim. We release a dataset containing 10,987 annotated claims with evidence from 62,999 passages and 659,595 sentences. For all claims where evidence is present, we complete 5-way annotation and resolve label disagreements using MACE (Hovy et al., 2013). Our dataset considers the entire Wikipedia article, with a median of 48 sentences per claim and a 90th percentile of 124 sentences per claim.

Our experiments, which use a RoBERTa model (Liu et al., 2019), indicate no significant difference in accuracy using either stance classification or a pipeline of evidence extraction and entailment recognition (attaining 65.5% and 66.0% respectively). Furthermore, transfer experiments from FEVER to our data highlight the challenging nature of verifying real-world information needs from larger documents: a model trained on FEVER, attaining 75.4% F1 for evidence extraction, has an evidence extraction F1 of 19.8% on our task.

| Dataset | Number of claims | Stance classification | Evidence extraction | Domain |
|---------|------------------|-----------------------|---------------------|--------|
| This work | 10,987 | yes | yes | Wikipedia (user queries) |
| (Vlachos and Riedel, 2014) | 106 | yes | no | Fact checking websites |
| (Derczynski et al., 2017) | 330 | yes | no | Twitter |
| (Baly et al., 2018) | 442 | yes | no | News + fact checking websites |
| (Thorne and Vlachos, 2018) | 185,445 | no | yes | Wikipedia (constructed claims) |
| (Chen et al., 2019) | 1,000 | yes | no | Debate websites |
| (Augenstein et al., 2019) | 36,534 | yes | no | Fact checking websites |
| (Hanselowski et al., 2019) | 6,422 | yes | yes | Fact checking websites |
| (Wadden et al., 2020) | 1,409 | no | yes | Scientific articles |
| (Diggelmann et al., 2020) | 1,535 | no | yes² | Wikipedia (Climate change) |

Table 1: Most previous works consider either stance classification or evidence extraction, but not both.

2 Related Work

Progress in evidence-based verification of claims has been supported through a number of datasets. The key aspects for comparison are the evidence collection strategy, the domain of the claims undergoing verification, and whether the claims are derived from real-world sources. The most relevant works to ours are compared in Table 1.

Evidence  The use of evidence in fact verification allows the task to be modeled as recognizing textual entailment (Dagan et al., 2009) – predicting whether a claim can be supported or refuted from evidence. Without evidence, the task signature reduces to sentence classification where linguistic features alone provide an indication to a claim’s veracity, which has limitations (Schuster et al., 2020).

Two common approaches for fact verification against evidence are stance classification (Ferreira and Vlachos, 2016), labelling whether a paragraph of text supports or refutes a claim, and to consider individual sentences of evidence extracted from a large corpus (Thorne et al., 2018). Assuming that evidence is pre-selected, similar model architectures can be applied to both settings. However, in FEVER (Thorne et al., 2018), CLIMATE-FEVER² (Diggelmann et al., 2020) and ²⁵ retrieved evidence candidates are annotated
SciFact (Wadden et al., 2020), individual evidence sentences must be retrieved from a corpus (such as Wikipedia). These evidence sentences were manually labelled and form part of the scoring protocol for the task. For stance classification in Karadzhov et al. (2017) and Baly et al. (2018), the use of evidence isn’t incorporated into the scoring protocol, making it difficult to discern whether the claim, or the interaction between the evidence and the claim is influencing the label predicted by the model. The MultiFC dataset (Augenstein et al., 2019) contains search results related to the claims rather than manually labeled evidence.

The fact-checking dataset released by Hanselowski et al. (2019) contains evidence annotated for claims collected from the Snopes fact-checking website. Evidence is scraped from URLs linked from the published fact-checking reports and the stance is annotated with respect to the claim. While these could be used to support a pipeline of retrieval and fact-checking similar to FEVER, some of the evidence sources are secondary sources reporting the event, inducing language biases that may give away a claim’s veracity. Furthermore, the wide variety of claims and evidence yielded low scores in accuracy for the baseline models.

**Domain and Construction** The majority of existing fact-verification and fake news detection datasets operate over political claims (Wang, 2017), fact checking reports (Baly et al., 2018; Augenstein et al., 2019; Hanselowski et al., 2019), websites (Diggelmann et al., 2020) and debates (Chen et al., 2019). These provide claims over a vast range of topics and, for humans, would require complex reasoning and application of world knowledge to verify. In contrast, FEVER (Thorne et al., 2018), and SciFact (Wadden et al., 2020) operate over claims written during dataset construction with greater control than the naturally occurring statements.

One potential risk of using scraped claims is that linguistic cues (Rashkin et al., 2017) provide indication to a claim’s veracity without the need to use textual evidence (Wang, 2017). Even where evidence is provided, claim only models can outperform those that incorporate evidence (Augenstein et al., 2019, Table 4). Even when manually constructing claims, making meaning-altering changes may allow the veracity to be predicted without evidence (Schuster et al., 2019) due to subconscious patterns introduced by annotators.

### 3 Fact Verification Task Definition

Fact verification is the task of predicting the veracity of a claim $c$ against evidence $E$ – whether it be pre-selected (as in the case of stance classification tasks) or retrieved (denoted $\hat{E}$). Variants of the task that require extraction or retrieval of evidence do so in two stages: retrieving related documents $\hat{D} \subset D$, and selecting relevant sentences from this set of documents, $\hat{E} = \text{Extract}(\hat{D})$, in a process we refer to as evidence extraction. Veracity prediction, $p(\hat{y}|c, E)$ or $p(\hat{y}|c, \hat{E})$, is a function of whether the claim is SUPPORTED or REFUTED by this evidence. For example, the claim “the legal drinking age is 18” would yield different veracity labels considering evidence about the USA or UK. For evidence extraction, we assume that relevant documents can be found for two reasons: ensuring annotation completeness over multiple documents is intractable, and secondly, contemporary systems for document retrieval identify relevant documents $D$ with a high recall (De Cao et al., 2020; Petroni et al., 2020).

**Stance Classification vs Evidence Extraction Pipeline** Stance classification for fact checking (Ferreira and Vlachos, 2016; Karadzhov et al., 2017) assumes the evidence $E$ is provided as a passage of text $P = E$. This provides fewer mechanisms to explain the prediction. Evidence extraction (Thorne et al., 2018) filters passages $\hat{E} \subseteq P$ to find a minimal subset of sentences that act as evidence which can be returned to the user as a rationale. To allow comparison between both methods, our dataset contains labels as both passage-level and sentence-level veracity annotations (where passages are entire sections from Wikipedia). With the exception of Hanselowski et al. (2019), discussed in Section 2, previous works only consider one, not both of these tasks, precluding direct comparison.

### 4 Data Collection Procedure

We used crowd-workers to collect both the claims and evidence compiled in this paper in a two-step procedure yielding instances as demonstrated in Figure 2. In the first step (question rewriting Section 4.1), questions with yes-or-no answers from the BoolQ dataset (Clark et al., 2019) underwent surface-level rewrites to change the questions into assertive statements. The second step (evidence selection Section 4.2) was to annotate all sentences and sections from the reference page from BoolQ for evidence that supports or refutes the claim.
Example

**BoolQ query:**
Is sweet Italian sausage the same as mild?

**Generated Claim:**
Sweet Italian sausage is the same as mild.

**Selected Evidence:**
The most common varieties marketed as “Italian sausage” in supermarkets are hot, sweet, and mild. The difference between mild and sweet is the addition of sweet basil in the latter.

4.1 Question Rewriting

The claims in our dataset were generated by rewriting questions from the BoolQ dataset as assertive statements. BoolQ (Clark et al., 2019) is a subset of the Natural Questions (Kwiatkowski et al., 2019) dataset of questions with yes-or-no answers. The questions which we use to generate the claims from arise from a real world information need. Each question from BoolQ was paraphrased into a claim by two different annotators using Mechanical Turk. In contrast to the FEVER dataset (Thorne et al., 2018), where annotators needed to use their imagination to generate meaning altering perturbations to the claims, workers for our task were instructed to retain as many tokens from the question as possible when writing the claims – mitigating potential biases of synthesized claims identified by Schuster et al. (2019).

**Quality Controls** Each question was re-written as a claim by two separate annotators. Annotators produced different strings in 28 occurrences – differences were due to how negation was rewritten. In this case, both instances were added to the dataset. All claims were manually reviewed by the authors and minor typographical errors were corrected.

Annotators with an acceptance rate of 95% were eligible to complete this task. All crowd-workers underwent a qualification round which used manual evaluation. 20% of the HITs were used for worker qualification and training and 80% formed the final dataset. 512 unique annotators contributed to this task. To mitigate effects where models are coupled to patterns used by annotators (Geva et al., 2019), the train and test splits of BoolQ were annotated by different pools of annotators. However due to leakage between the train and test set, identified by Lewis et al. (2021), we did not retain the original dataset split from BoolQ and instead split the dataset to be disjoint by Wikipedia page.

4.2 Evidence Selection

Evidence for the claims was selected by annotators through a separate crowd-sourced data annotation process on Mechanical Turk. Annotators were asked to highlight any sentence from a section of Wikipedia page sufficient to persuade them a claim is true or false and their overall verdict given the whole section. The Wikipedia pages were those listed in the BoolQ dataset as those which answered the question. The article text we used for this task was collected from the Wikipedia API on 1st May 2020. Unlike the data annotation process from FEVER (Thorne et al., 2018) (which only considers the introductory sections of Wikipedia), our annotation considers the evidence from the full Wikipedia page. To mitigate the bias of the prior knowledge or selecting content from the top of the page, and to prevent annotator fatigue, we split the page into multiple annotation tasks which were assigned in random order. Each annotation task was less than 20 sentences in length pertaining to a contiguous span of text from a section, or paragraph. The mean section length was 10 sentences over 2 paragraphs. For each annotation task, annotators were provided context of the page and section they were annotating, but asked not to use any external resources, linked pages or world knowledge.

**Quality Controls** Annotation of natural language inference depends on human judgement and is subject to disagreement (Pavlick and Kwiatkowski, 2019; Nie et al., 2020). To mitigate the biases arising from any one annotator, we collect verdicts from multiple annotations for evidence from each section. All sections initially had two annotations. For each section where annotators found supporting or refuting evidence, we performed three further annotations, yielding 5 annotations in total for all sections containing evidence. While 63,201 section annotation tasks had perfect label agreement, 20,366 had disagreement between supported and neutral, 10,778 had disagreement between refuted and neutral, and 6,248 had disagreement between supported and refuted. The Fleiss $\kappa$ score was 0.361, highlighting the difficulty of interpreting users’ intentions and information.
Table 2: Dataset statistics. We report the number of claims associated with different Wikipedia pages.

|                | Train | Dev  | Test |
|----------------|-------|------|------|
| Claims         | 8,723 | 1,088| 1,086|
| Wiki pages     | 4,214 | 526  | 528  |
| Claim Sections | 50,902| 5,832| 6,265|
| Claim Sentence | 535,649| 61,842| 62,104|

| Sections / Claim | 5.8 | 5.4 | 5.8 |
|------------------|-----|-----|-----|
| Supporting Sections | 25.8% | 27.1% | 27.8% |
| Refuting Sections  | 12.3% | 12.4% | 13.0% |
| Neutral Sections   | 62.0% | 60.5% | 59.2% |

| Sentences / Section | 10.5 | 10.6 | 9.9 |
|---------------------|------|------|-----|
| Supporting Sentences | 8.1%  | 8.6% | 8.9% |
| Refuting Sentences  | 3.8%  | 3.9% | 4.5% |
| Neutral Sentences   | 88.2% | 87.5% | 86.6% |

Figure 3: Distribution of claim categories on a random sample of 500 claims.

needs, finding evidence, and subsequently reaching a verdict. The low information density beyond the introduction section exacerbated difficulty in finding information: Fleiss $\kappa$ for the introduction was 0.522 but was lower for subsequent sections. To generate ground-truth labels, we resolved disagreements using MACE (Hovy et al., 2013), retaining 95% of the annotations with the lowest entropy. We further only keep sections if MACE resolved a label for all sentences in that section. The authors manually verified a sample of 466 ground truth labels to ensure consistency.

Annotators underwent a 3-stage approval process consisting of a qualification quiz, manual review of their first 100 HITs and continuous manual review. Errors made by annotators were communicated to them and used to provide formative feedback. For the continuous manual review, we sampled a batch of claims every day for which annotation was running. 12,137 HITs (5.2% of all annotation tasks) were manually reviewed by the authors and accepted, and corrections were offered for a further 400 HITs (indicating an error rate of 3.2% where annotators didn’t follow guidelines (i.e. not because their opinion differed to the authors’)). The number of HITs reviewed for each annotator was proportional to the annotator’s error rate and the number of annotations submitted. Annotation times (median was 23 seconds per paragraph) were used to calibrate the median hourly pay at $22.

5 Dataset Statistics and Bias Analysis

After resolving ground truth labels with MACE, we were left with evidence for 10,897 claims. Training, development and test splits were constructed to be disjoint by Wikipedia page (5,268 unique pages).

The number of claims and the evidence sizes are reported in Table 2. For each claim a mean of 5.4–5.8 sections from Wikipedia were annotated with evidence. The distribution of labels over these sections is predominantly neutral; with supported sections being labeled twice as often as refuted ones. Interestingly, in 15% of cases claims have both supported and refuted labeled sections. This occurred when claims had different verification outcomes depending on the context, which occurred with geographical information or time. For example, a claim about the legal age of drinking being 18 would be true for the UK, but false for the USA. Within the sections, annotators individually labeled sentences: 11.3% (1852) of all supporting and 23.1% of all refuting sections contain both supporting and refuting evidence sentences, similar to the example shown in Figure 1.

Claim category and domain 500 claims were randomly sampled and annotated by the authors for the type of information being checked as well as the domain. Claims fell into one of 6 categories, examples are given in parentheses: general knowledge (the world cup stays with the winner), comparison (tomato sauce is the same as passata), existence (there is a place where 4 states meet), possibility (a computer can beat a human at poker), rules and constraints (it is illegal to jaywalk in New York), and entity properties (The Cubs and White Sox share a stadium). The distribution over these categories is plotted in Figure 3. For the domain of the claims: 27% were about laws and expected behaviour; 23% were about movies; 14% about geography; 11% about sports, 10% about spoilers in TV shows and books, 10% about science, and 4% of claims were about food.
5.1 Claim-Only Bias

Stance classification and fact verification can be modeled as a classification of a claim given evidence. This task signature is similar to that of Natural Language Inference (NLI) where models are trained to predict whether a hypothesis is entailed by a premise. Manually constructed NLI datasets exhibit biases that allow the label to be accurately predicted using only the hypothesis sentence (Gururangan et al., 2018; Poliak et al., 2018). This issue is also known to affect fact-verification (Schuster et al., 2019; Thorne and Vlachos, 2021) where workers are tasked with modifying the information content of claims. In contrast, the claims in this dataset are derived from questions in response to real-world information needs. Our hypothesis is that rewriting the questions into claims will mitigate potential biases from being introduced by annotators subconsciously introducing patterns with high correlation with the veracity label.

Even though the data we collected originated from real-world information needs, there may still be naturally occurring correlations between tokens in the claims and whether the claim was labelled as supported, refuted or neutral by the annotator given evidence. Following (Schuster et al., 2019), we measure this phenomenon by computing local mutual information (LMI) (Evert, 2005) between the veracity label, $l$, claim bigrams, $w$, with more than 50 occurrences. LMI $\text{LMI}(p(w,l) \cdot \log \frac{p(|w|)}{p(l)})$ is a product of the joint bigram-label probability and point-wise mutual information which highlights both frequent and highly correlated bigrams. To better understand how the biases change through the annotation process, we use LMI to identify bigrams with the highest impact on the dataset (in terms of skew or frequency), and report bias towards the supported or refuted class using the entropy of the label distributions.

Our rewriting process maintains the uncertainty of frequent bigrams, such as the same, is the, is a and there is. These 4 most-frequent bigrams in BoolQ collectively account for 1/4 of instances in the dataset. Their LMI is high, because they occur frequently rather than providing giveaway cues. Our annotation process introduced an additional label (moving from a binary annotation, to 3-way annotation that also considers the neutral class). This increased the label entropy for these bigrams from 0.99 bits, 0.91 bits, and 0.86 bits (out of a maximum of $\log_2 3 = 1.58$ bits) maintaining the uncertainty of these common patterns. Our rewriting process, introduced bigrams with high LMI, such as there is (which occurs in about 10% of instances) which was a common pattern for supported claims (supported/refuted entropy = 0.86 bits). Most of the high LMI bigrams from BoolQ were retained with no new frequent bigrams with low entropy. In BoolQ, low entropy for bigrams such as is possible, can get and has never was observed and also retained by our rewrites. However, these instances collectively account for less than 2% of the dataset.

Following (Poliak et al., 2018), we trained a classifier to predict claim veracity without evidence. Using a BERT classifier, attained 71.7% accuracy for supported/refuted classification (majority baseline is 68.6%). Considering the neutral class, too, models attained 62.2% accuracy (majority baseline is 60.5%). While there are some signals that the model can exploit, predicting veracity without evidence remains a challenging task – especially in comparison to previous datasets where models attain higher accuracies without evidence (Thorne and Vlachos, 2021, Appendix 1).

5.2 Positional Bias in Evidence Annotation

Our dataset consists of both, section-level and sentence-level annotations, taken over the entire Wikipedia page. The first (introductory) sections contain 2,918 neutral, 4,632 supporting and 2,345 refuting annotations. This proportion differs from the average dataset proportions in Figure 2 and are reflected in the high KL divergence in Figure 4b. Subsequent sections (shown in Figure 4a) contain diminishing evidence, reflected by a large number of neutrally labeled sections appearing later within the document. KL divergence in the subsequent sections increases as these contain proportionally more neutral annotations.

Considering sentence-level evidence, Figure 4e shows the cumulative proportion of claims that can be verified with the first $k$ sentences of each section. Within the sections, the claims can be verified as supported or refuted using the first sentence in one quarter of cases, whereas in FEVER, the first sentence was evidence in 41% of claims. In both datasets, the first 10 sentences are sufficient to verify approximately 80% of the claims. With the exception of the first sentence of each passage, the proportion of supporting, refuting and neutral
labels remains stable for the first 20 sentences (Figure 4c). For sections containing more than 20 sentences, the later sentences contain mostly neutral annotations, resulting in a higher divergence compared to the dataset average (Figure 4d).

6 Experiments

Our experiments evaluate two component tasks for fact verification which are captured in our dataset:

Evidence Extraction (T1): Given a claim $c$ and Wikipedia section $S = \{s_1, \ldots, s_n\}$, the system selects which sentences $s_i \in S$ are ground truth evidence: $E \subseteq S$. We evaluate this using $F_1$.

Veracity Prediction (T2): Given a claim $c$ and a Wikipedia section $S$, the system predicts the veracity for $c$ given $S$. STANCE-classification predicts the veracity of $c$ using all sentences within $S$ directly and we compare this to using a PIPELINE of extracted evidence $E$ from T1. We report label accuracy and macro $F_1$.

Conditional Scoring of T2 given T1 Similar to FEVER-score (Thorne et al., 2018), we require models to correctly predict the evidence and veracity label. The FEVER score optimizes for recall and allows a superset of any of the minimal evidence sets to be submitted. Our dataset, however, contains complete rather than minimal annotations. Furthermore, the recall-only aspect of FEVER can be easily gamed by systems as it does not penalize returning evidence for neutral instances. We, instead, opt for the point-wise product of the evidence F1 with the accuracy of the veracity label $(y)$, averaged over all instances in the dataset.

6.1 Implementation

All our models use the HuggingFace implementation (Wolf et al., 2020) of RoBERTa-base (Liu et al., 2019). Our code is adapted from the fact checking system VERISci released by Wadden et al. (2020):

Training All models are trained for six epochs with a learning rate of $2e^{-5}$ and a batch size of 32. These hyper-parameter choices were found by maximizing the accuracy of T2 on an early version of the dataset. The evidence extraction model (T1) is trained to predict either a binary (evidence or not) or 3-way (supporting, refuting or neutral) label over the concatenation of the claim and a single sentence from the Wikipedia section.

For veracity prediction (T2), the model is either trained with the entire section $S$ for STANCE or with the evidence sentences $E \subseteq S$ that constitute the ground truth for PIPELINE. To build resilience to false-positive extracted evidence in the PIPELINE, we randomly sample up to two neutral sentences from the section. Due to the abundance of neutral sections we only sample such neutral evidence sentences from sections without evidence. Our sampling strategy slightly differs to the sam-
### Table 3: Comparison of PIPELINE with STANCE models over all tasks. C indicates that the classifier corrects (removes) the selected evidence sentences if neutral was predicted.

| Pipeline System | Evidence Veracity | Evidence (T1) F1 Score | Veracity (T2) Accuracy | Conditional Score (T1+T2) Accuracy | Conditional Score (T1+T2) F1 macro |
|-----------------|------------------|------------------------|------------------------|-------------------------------------|-----------------------------------|
| oracle majority | 100              | 91.0 ± 1.1             | 85.4 ± 0.5             | 85.4 ± 0.5                          | 81.1 ± 0.5                        |
| oracle classifier | 100              | 85.4 ± 0.5             | 77.5 ± 0.6             | 77.5 ± 0.6                          | 75.2 ± 0.7                        |
| oracle classifier C | 93.2 ± 0.6                     | 57.9 ± 1.7             | 58.9 ± 0.9             | 48.3 ± 0.5                          | 42.9 ± 1.3                        |
| tf-idf classifier | 33.8 ± 0.8        | 65.9 ± 2.3             | 67.4 ± 2.3             | 67.4 ± 2.3                          | 57.7 ± 2.1                        |
| tf-idf classifier C | 36.2 ± 0.8                    | 57.9 ± 1.7             | 58.9 ± 0.9             | 48.3 ± 0.5                          | 42.9 ± 1.3                        |
| 3-way majority | 40.0 ± 1.1        | 70.4 ± 0.9             | 62.2 ± 0.9             | 48.3 ± 0.5                          | 33.8 ± 0.6                        |
| 3-way classifier | 40.0 ± 1.1        | 75.5 ± 0.7             | 65.5 ± 1.0             | 48.3 ± 0.5                          | 42.9 ± 1.3                        |
| 3-way classifier C | 46.8 ± 1.4                     | 65.5 ± 1.0             | 57.9 ± 0.6             | 51.8 ± 0.6                          | 48.3 ± 0.5                        |
| binary classifier | 50.4 ± 1.5        | 75.2 ± 0.5             | 65.4 ± 0.3             | 48.3 ± 0.5                          | 42.9 ± 1.3                        |
| binary classifier C | 48.6 ± 1.6                     | 75.2 ± 0.5             | 65.4 ± 0.3             | 51.8 ± 0.6                          | 48.3 ± 0.5                        |

**Stance**

| Evidence Veracity | Evidence (T1) F1 Score | Veracity (T2) Accuracy | Conditional Score (T1+T2) Accuracy | Conditional Score (T1+T2) F1 macro |
|------------------|------------------------|------------------------|-------------------------------------|-----------------------------------|
| Stance           | -                      | 75.0 ± 0.8             | 66.0 ± 0.8                          | -                                 | -                                 |

7 Results

We first report the outcome of evidence extraction (T1), veracity prediction (T2) and the conditional veracity prediction (T1+T2) in Table 3. In Section 7.1 we evaluate the transfer capabilities between our dataset and FEVER. All results report the mean and standard deviation over three independent runs with different random seeds.

**Baselines**

An upper bound using majority voting on gold-standard information (oracle), outperformed the RoBERTa-based counterpart. Using retrieved evidence, classifiers were more robust to noise than majority voting, reflected in higher scores for T2.

Using TF-IDF for evidence extraction yielded low precision (23.3%) and recall (51.1%), resulting in an F1 of 33.8%. Poor evidence negatively impacted veracity prediction (T2). This result is similar to that reported by Thorne et al. (2018) for sentence selection for FEVER. The reduction in false positives after applying the correction rule C almost doubled the conditional veracity (T1+T2).

**Binary vs 3-way Evidence Extraction**

For both schemes, the downstream accuracy and F1 on the veracity prediction exhibited no significant difference (unpaired t-test, p=0.42 in accuracy). We observed similar findings with the conditional scoring metric (T1+T2). In 3-way labeling, evidence selection was marginally more precise (57.3%) at the expense of recall (43.0%) compared to binary (precision=56.4%, recall=46.2%). This improved the accuracy on T2 for the neutral class (see Table 4), which is the most-common label.
| Model       | Our Dataset (F1) | FEVER (F1) | Δ T1 |
|------------|-----------------|------------|------|
|            | T1 supporting   | refuting   | T1 supporting | refuting |         |
| 3-way O    | 49.0 ± 1.3      | 44.2 ± 0.4 | 28.6 ± 2.0 | 54.8 ± 1.1 | 44.3 ± 1.3 | 36.0 ± 4.3 | +5.7 |
| 3-way O    | 47.7 ± 0.7      | 41.1 ± 0.8 | 29.2 ± 0.7 | 41.5 ± 1.7 | 30.1 ± 1.6 | 35.3 ± 0.8 | -0.2 |
| 3-way F    | 48.0 ± 0.7      | 42.3 ± 0.9 | 28.7 ± 2.2 | 63.3 ± 0.2 | 55.6 ± 0.4 | 55.3 ± 1.6 | +15.2 |
| 3-way O > F| 19.8 ± 2.8      | 19.6 ± 2.4 | 6.6 ± 2.0  | 75.4 ± 0.2 | 73.5 ± 0.3 | 66.8 ± 0.6 | -55.6 |
| binary O   | 25.5 ± 1.3      | 24.8 ± 0.6 | 11.4 ± 2.0 | 75.7 ± 0.5 | 73.2 ± 0.2 | 67.3 ± 0.1 | -50.2 |
| binary O   | 50.4 ± 1.5      | -          | -          | 53.5 ± 6.1 | -          | -          | +3.1 |
| binary O   | 48.5 ± 1.2      | -          | -          | 41.0 ± 0.4 | -          | -          | -7.5 |
| binary O   | 51.0 ± 1.2      | -          | -          | 62.3 ± 2.1 | -          | -          | +1.4 |
| binary O   | 23.7 ± 1.9      | -          | -          | 75.7 ± 0.2 | -          | -          | -52.0 |
| binary O   | 25.8 ± 3.8      | -          | -          | 75.3 ± 0.5 | -          | -          | -49.6 |

Table 4: Evidence Extraction (T1) on our dataset and FEVER. O or F indicate that the model was trained on our dataset or FEVER. F > O indicates that the model was finetuned on FEVER before finetuning on our dataset. Δ T1 shows the difference in F1 (T1) between the performance on the fine-tuned dataset vs. the other respectively. We down-sample the number of neutral sentences for models marked with S.

**Stance vs Pipeline** There was no significant difference on T2 using either method for accuracy (unpaired t-test, p=0.36), or considering macro F1 (unpaired t-test, p=0.54). The correction rule C was helpful in all cases for (T1+T2), increasing the conditional accuracy by 6% which was significant (p<0.01). With C, performance on T1 was harmed by removing evidence for claims incorrectly predicted as neutral. Applying C also prevent a model from reaching a perfect score on T1 as 10.3% of neutral sections contain partially supporting/refuting sentences.

**7.1 Transfer to/from FEVER**

**7.1.1 Evidence Extraction**

**Pre-training** We a pre-trained a RoBERTa classifier on FEVER before fine-tuning on our dataset (indicated by F > O in Table 4) and vice-versa. In both cases, the improvements gained by pre-training are marginal. Pre-training on FEVER for binary evidence selection yielded the highest evidence F1 score on our dataset. When pre-training using our dataset before FEVER, 3-way evidence extraction yielded higher evidence F1 on FEVER.

We observe that information gained from pre-training on our dataset is almost entirely lost after fine-tuning on FEVER, performing only 5.7 (3-way) or 2.1 (binary) points better than its counterpart without pre-training. Models pretrained on FEVER and fine-tuned on our dataset, however, preserved much the learned information and outperformed their counterparts without pre-training by a large margin.

**Zero Shot** Models trained only on our dataset performed better on FEVER than on our dataset without ever seeing a single FEVER sample, suggesting that our dataset captures many of challenges within FEVER. This trend is reversed when only training on FEVER. The average recall for refuting sentences was of 3.6% indicating that FEVER captures different patterns to our data.

**Down-sampling** To lower the impact of neutral evidence, we down-sampled the number of neutral sentences during training,3 indicated by S. Down-sampling resulted in a slight decrease in F1, trading recall for precision. The 3-way model reached on average 57.3/43.0 and 34.9/75.4 in precision/recall without and with sampling respectively, the binary model 56.4/46.2 and 36.6/72.4.

**7.1.2 Veracity Prediction**

We show the conditional performance (T1+T2) of models including pre-training on FEVER in Table 5. Since FEVER only provides evidence containing documents, our task definition is not applicable for evaluations on FEVER.

The PIPELINE using binary evidence extraction that is fully pre-trained on FEVER reached the overall best performance. Independent from the evidence extraction, all veracity models benefited from pre-training for the detection of refuted claims, which constitutes the least frequent class in our dataset. The S models performed slightly worse for the evidence extraction (see Table 4) as

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3We limit the number of neutral sentences to either the number of supporting sentences, that constitute the majority of evidence sentence labels (for 3-way), or evidence sentences (for binary).
| Evidence | System Veracity | Weighted Acc. | $F_{\text{macro}}$ | Weighted F1 supporting | Weighted F1 refuting | Weighted F1 neutral |
|----------|----------------|---------------|-------------------|------------------------|---------------------|---------------------|
| oracle | classifier $O \ C$ | 81.1 ± 0.5 | 75.2 ± 0.7 | 78.7 ± 1.1 | 60.7 ± 1.5 | 86.3 ± 0.3 |
| oracle | classifier $F \ C$ | 81.2 ± 0.6 | 75.6 ± 0.6 | 78.0 ± 1.9 | 62.2 ± 1.9 | 86.7 ± 0.1 |
| 3-way $O$ | classifier $O \ C$ | 64.2 ± 0.4 | 51.8 ± 0.6 | 46.7 ± 1.4 | 31.8 ± 0.4 | 76.9 ± 0.3 |
| S 3-way $O$ | classifier $O \ C$ | 58.8 ± 1.2 | 50.3 ± 0.6 | 45.6 ± 1.2 | 31.0 ± 0.1 | 74.2 ± 1.1 |
| 3-way $F \ C$ | classifier $F \ C$ | 63.7 ± 0.4 | 51.8 ± 0.8 | 45.8 ± 1.3 | 33.0 ± 1.4 | 76.7 ± 2.0 |
| 3-way $F \ C$ | classifier $F \ C$ | 63.2 ± 0.6 | 51.2 ± 1.0 | 45.9 ± 1.4 | 32.5 ± 1.5 | 76.5 ± 2.2 |
| binary $O$ | classifier $O \ C$ | 64.1 ± 0.5 | 52.2 ± 0.4 | 47.5 ± 0.3 | 32.3 ± 1.4 | 76.9 ± 0.2 |
| S binary $O$ | classifier $O \ C$ | 59.9 ± 0.4 | 50.8 ± 0.2 | 46.0 ± 0.9 | 31.2 ± 0.3 | 75.2 ± 0.4 |
| binary $F \ C$ | classifier $F \ C$ | 63.8 ± 0.6 | 52.6 ± 0.4 | 47.4 ± 0.2 | 33.5 ± 1.1 | 77.0 ± 0.4 |

Table 5: Veracity Prediction on our dataset with pre-training on FEVER.

8 Error Analysis

We analyse the confusion of the veracity prediction component (T2) for PIPELINE systems under different evidence conditions. We first consider the effect of the retriever: under ideal conditions (oracle), binary classification (evidence or not), and 3-way classification (supports, refutes, neutral) and report breakdowns when evidence consists of sentences with all one label (denoted S or R for supported or refuted) and with sentences with mixed labels (denoted S+R). For this breakdown by gold evidence type (denoted Gold Ev. in Table 6), the number of labeled sections for S+R is 209 (for both gold veracity labels), 1,528 for S and 607 for R.

The label confusion for the test set predictions are reported in Table 6. For refuted claims, the model was less accurate. Mixed evidence (S+R) induces the greatest number of errors, and is most prevalent when using oracle evidence. The ratio of predicting the wrong label on sections with mixed evidence is more than two times higher sections with evidence of the same label. This issue was less apparent when using retrieved evidence due to the noise induced by the retrieval system. These results indicate that (a) models are indeed sensitive to the provided evidence during veracity prediction, yet (b) in many cases struggle to aggregate evidence with mixed stances to a correct veracity label.

9 Conclusions

We present a novel large-scale dataset for fact verification on claims arising from real-world information needs by rewriting users’ search engine queries and annotating evidence. This construction method addressed limitations from previous work by mitigating the risk of introducing linguistic biases – decoupling the claim generation procedure from the evidence. Annotating evidence is inherently challenging and we found this problem was exacerbated for our claims, which by nature were under-specified and annotated against Wikipedia sections with low information density. These challenges were further highlighted when evaluating transfer learning from models trained on FEVER (Thorne et al., 2018), which had nearly zero recall for refuting evidence for our task.

Our dataset contains both sentence-level and section-level evidence annotations from entire Wikipedia articles and allows direct comparison between stance classification and a pipeline of evidence extraction followed by veracity classification.
tion. Extracting evidence provides a mechanism to explain the veracity decision to an end user, summarizing the key rationale, and could further support human fact-checkers in this time-consuming task. In a direct comparison between these two approaches, we found no significant difference in accuracy – indicating that label accuracy may be maintained while returning a usable rationale.

We hope that the resources we release with this paper inspire further progress in verification for more complex topics and enable better understanding of how to reason over topics that real-world users have a need to find information for.

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A Appendix

A.1 Data statement

A. CURATION RATIONALE We took BoolQ questions and asked annotators to rewrite them as a claim and give feedback in case they found any anomalies such as grammar issues, typos, not a Boolean question or any other. Each question was rephrased by two different annotators and. At the end of the data gathering, one of the authors and another curator cleaned the obtained annotations, integrating workers’ comments and correcting typos to keep consistency among annotators. They also discarded not rephrased questions and bad quality annotations, resulting on about 27k claims, produced by 510 crowdworkers in total.

B. LANGUAGE VARIETY The corpus is an English collection of language on the web. However, due to the use of anonymized questions from an existing dataset, we do not have available information about the variety of the language. Nevertheless, taking into account different topics of the queries, we can infer that originally the corpus contains queries in among other US, Australian Canadian and British English. However, this does not exclude the possibility of having other varieties of English in our collection.

C. SPEAKER DEMOGRAPHIC This dataset was built out of the existing BoolQ dataset. The Original paper mentions anonymized data, which implies that we cannot retrieve any demographic information of the users, protecting search engine user’s privacy.

D. ANNOTATOR DEMOGRAPHIC AMT annotators, in total 510, formulated claims from given queries. During data collection we did not constrain crowdworkers’ location in advance, taking into account that native speakers do not necessarily live in their origin countries. This allows us to keep a wide variety of workers and different formulations for each query. We kept evaluating quality while creating a white-list working group. Hence, this results in not available data regarding annotators’ demographics.

E. SPEECH SITUATION We asked annotators to reformulate search engine queries into claims. Our assumption is that these queries cover a near-spontaneously uttered language, either written or spoken. We define the type of language as informal web language, user-machine interaction. Regarding claims, annotators were asked to keep all relevant elements from the query. This leads to keeping the language situation from the queries i.e. human-machine interaction and informal cyber, but elicited speech.

F. TEXT CHARACTERISTICS The corpus contains user queries issued to the Google search engine and rewritten in a claim form. Since these queries come from actual users, we mitigate biases annotators that might introduce. In Section 5, we depict categories and their percentage distribution in the collection. We created these categories by clustering claims embeddings extracted using spaCy and mini-batch k-means with k = 8 after trying several values for k. One of the authors reviewed the clusters and gave them a name. We observed that the dataset has a variety of topics, with movie details, allowance and geography being the most popular.

G. RECORDING QUALITY N/A.

H. OTHER Curators of the query transformation process were two female graduate students at a German institution. They are between 20 and 35 years old and Spanish and German native speakers.

I. PROVENANCE APPENDIX Please refer to the BoolQ paper (Clark et al., 2019) and the dataset itself for further information about the questions.

4https://github.com/google-research-datasets/boolean-questions