Assisting the Human Fact-Checkers: Detecting All Previously Fact-Checked Claims in a Document

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Abstract

Given the recent proliferation of false claims online, there has been a lot of manual fact-checking effort. As this is very time-consuming, human fact-checkers can benefit from tools that can support them and make them more efficient. Here, we focus on building a system that could provide such support. Given an input document, it aims to detect all sentences that contain a claim that can be verified by some previously fact-checked claims (from a given database). The output is a re-ranked list of the document sentences, so that those that can be verified are ranked as high as possible, together with corresponding evidence. Unlike previous work, which has looked into claim retrieval, here we take a document-level perspective. We create a new manually annotated dataset for this task, and we propose suitable evaluation measures. We further experiment with a learning-to-rank approach, achieving sizable performance gains over several strong baselines. Our analysis demonstrates the importance of modeling text similarity and stance, while also taking into account the veracity of the retrieved previously fact-checked claims. We believe that this research would be of interest to fact-checkers, journalists, media, and regulatory authorities.

1 Introduction

Recent years have brought us a proliferation of false claims, which spread fast online, especially in social media; in fact, much faster than the truth (Vosoughi et al., 2018). To deal with the problem, a number of fact-checking initiatives have been launched, such as FactCheck, FullFact, PolitiFact, and Snopes, where professional fact-checkers verify claims. Yet, manual fact-checking is very time-consuming and tedious.

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Thus, automatic fact-checking has been proposed as an alternative (Li et al., 2016; Shu et al., 2017; Rashkin et al., 2017; Hassan et al., 2017; Vo and Lee, 2018; Lee et al., 2018; Li et al., 2018; Thorne and Vlachos, 2018; Lazer et al., 2018; Vosoughi et al., 2018; Zhang et al., 2020b; Alam et al., 2022; Nguyen et al., 2022). While it scales better and works faster, it lags behind in quality, credibility, transparency, and explainability.

Manual and automatic fact-checking can benefit from each other as automatic methods are trained data that human fact-checkers produce, while human fact-checkers can be assisted by automatic tools. A middle ground between manual and automatic fact-checking is to verify an input claim by finding a previously fact-checked claim that allows us to make a true/false judgment on the veracity of the input claim. This is the problem we will explore below.
Previous work has approached the problem at the sentence level: given an input sentence/tweet, produce a ranked list of relevant previously fact-checked claims that can verify it (Shaar et al., 2020a). However, this formulation does not factor in whether the factuality of the input sentence/tweet can be determined using the database of previously fact-checked claims, as it is formulated as a ranking task. For example, in a US presidential debate that has 1,300 sentences on average, only a small fraction would be verifiable using previously fact-checked claims from PolitiFact. Therefore, we target a more challenging reformulation at the document level, where the system needs to prioritize which sentences are most likely to be verifiable using the database of previously fact-checked claims. This is still a ranking formulation, but here we rank the sentences in the input document (by verifiability using the database of claims), as opposed to ranking database claims for one input sentence (by similarity with respect to that sentence).

In our problem formulation, given an input document, the system needs to detect all sentences that contain a claim that can be verified by a previously fact-checked claim (from a given database of such claims). The output is a re-ranked list of the document sentences, so that those that can be verified are ranked as high as possible, as illustrated in Figure 1. The system could optionally further provide a corresponding fact-checked claim (or a list of such claims) from the database as evidence. Note that we are interested in returning claims that would not just be relevant when fact-checking the claims in the input sentence, but also would be enough to decide on a verdict for its factuality.

This novel formulation of the problem would be of interest to fact-checkers not only when they are facing a new document to analyze, but also when they want to check whether politicians keep repeating claims that have been previously debunked, so that they can be approached for comments. It would also be of interest to journalists, as it could bring them a tool that can allow them to put politicians and public officials on the spot, e.g., during a political debate, a press conference, or an interview, by showing the journalist in real time which claims have been previously fact-checked and found false. Finally, media outlets would benefit from such tools for self monitoring and quality assurance, and so would regulatory authorities such as Ofcom.

Our contributions can be summarized as follows:

- We introduce a new real-world task formulation to assist fact-checkers, journalists, media, and regulators in finding which claims in a document have been previously fact-checked.

- We develop a new dataset for this task formulation, which consists of seven debates, 5,054 sentences, 16,636 target verified claims to match against, and 75,810 manually annotated sentence–verified claim pairs.

- We define new evaluation measures (variants of MAP), which are specifically tailored for our task.

- We address the problem using a learning-to-rank approach, and we demonstrate sizable performance gains over strong baselines.

- We offer analysis and discussion, which can facilitate future research.

- We release our data and code.¹

2 Related Work

Disinformation, misinformation, and “fake news” thrive in social media. See (Lazer et al., 2018) and (Vosoughi et al., 2018) for a general discussion on the science of “fake news” and the process of proliferation of true and false news online. There have also been several interesting surveys, e.g., Shu et al. (2017) studied how information is disseminated and consumed in social media. Another survey by Thorne and Vlachos (2018) took a fact-checking perspective on “fake news” and related problems.

More relevant to the present work, Nakov et al. (2021a) studied how AI technology can assist professional fact-checkers, and pointed to the following research problems: (i) identifying claims worth fact-checking, (ii) detecting relevant previously fact-checked claims, (iii) retrieving relevant evidence to fact-check a claim, and (iv) actually verifying the claim.

The vast majority of previous work has focused on the latter problem, while the other three problems remain understudied, even though there is an awareness that they are integral steps of an end-to-end automated fact-checking pipeline (Vlachos and Riedel, 2014; Hassan et al., 2017).

¹https://github.com/firojalam/assisting-fact-checking
This situation is gradually changing, and the research community has recently started paying more attention to all four problems, in part thanks to the emergence of evaluation campaigns that feature all steps such as the CLEF CheckThat! lab.

Shaar et al. (2020a) proposed a claim-focused task formulation, and released two datasets: one based on PolitiFact, and another one based on Snopes. They had a ranking formulation: given a claim, they asked to retrieve a ranked list of previously fact-checked claims from a given database of such claims; the database included the verified claims together with corresponding articles. One can argue that this formulation falls somewhere between (ii) detecting relevant previously fact-checked claims and (iii) retrieving relevant evidence to fact-check a claim. The same formulation was adopted at the CLEF CheckThat! lab in 2020, where the focus was on tweets, and in 2021-2022, which featured both tweets and political debates (Barrón-Cedeño et al., 2020; Shaar et al., 2020b; Barrón-Cedeño et al., 2020; Nakov et al., 2021b; Shaar et al., 2021; Nakov et al., 2022a,b).

The best systems at the CLEF CheckThat! 2021 lab used BM25 retrieval, semantic similarity using embeddings, and reranking (Chernyavskiy et al., 2021; Mihaylova et al., 2021; Pritzkau, 2021). A follow-up work used a batch softmax contrastive loss to better fine-tune BERT for the task (Chernyavskiy et al., 2022).

It has been further shown that it is important to match not only against the target claim, but also using the full text of the associated article that fact-checkers wrote to explain their verdict. Thus, in a follow-up work, Shaar et al. (2022) focused on modeling the context when checking an input sentence from a political debate, both on the source side and on the target side, e.g., by looking at neighboring sentences and using co-reference resolution.

Sheng et al. (2021) proposed a re-ranker based on memory-enhanced transformers for matching (MTM) to rank fact-checked articles using key sentences selected using lexical, semantic and pattern-based similarity. Si et al. (2021) modeled claim-matching using topic-aware evidence reasoning and stance-aware aggregation, which model semantic interaction and topical consistency to learn latent evidence representation. Kazemi et al. (2021) developed two datasets (one consisting of claim-like statements and the other one using annotation of claim similarity) covering four languages.

Jiang et al. (2021) used sequence-to-sequence transformer models for sentence selection and label prediction. Wan et al. (2021) proposed a deep Q-learning network, i.e., a reinforcement learning approach, which computes candidate pairs of precise evidence and their labels, and then uses post-processing to refine the candidate pairs.

Vo and Lee (2020) looked into multimodality. They focused on tweets that discuss images and tried to detect the corresponding verified claim by matching both the text and the image against the images in the verified claim’s article. They mined their dataset from pairs of tweets and corresponding fact-checking articles proposed by Twitter users as a response. Hardalov et al. (2022) used a similar crowd-checking idea, and further proposed how to learn from potentially noisy data.

Finally, the task was also addressed in a reverse formulation, i.e., given a database of fact-checked claims (e.g., a short list of common misconceptions about COVID-19), find social media posts that make similar claims (Hossain et al., 2020).

Unlike the above work, our input is a document, and the goal is to detect all sentences that contain a claim that can be verified by some previously fact-checked claim (from a given database).

### 3 Task Definition

We define the task as follows (see also Figure 1):

> **Given an input document and a database of previously fact-checked claims, produce a ranked list of its sentences, so that those that contain claims that can be verified by a claim from the database are ranked as high as possible. We further want the system to be able to point to the database claims that verify a claim in an input sentence.**

Note that we want the **Input** sentence to be verified as true/false, and thus we want to skip matches against Verified claims with labels of unsure veracity such as half-true. Note also that solving this problem requires going beyond stance, i.e., whether a previously fact-checked claim agrees/disagrees with the input sentence (Miranda et al., 2019). In certain cases, other factors might also be important, such as, (i) whether the two claims express the same degree of specificity, (ii) whether they are made by the same person and during the same time period, (iii) whether the verified claim is true/false or is of mixed factuality, etc. Table 1 shows some examples.
Table 1: Example sentences from Donald Trump’s interview with Fox and Friends on June 6, 2018.

| No. | Input Sentence                                                                 | Verified Claim                                                                 | Label & Date            | Stance | Verdict |
|-----|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|-------------------------|--------|---------|
| 1   | But the Democrats, by the way, are very weak on immigration.                   | Donald Trump: The weak illegal immigration policies of the Obama Admin, allowed bad MS 13 gangs to form in cities across U.S. We are removing them fast! | False, stated on April 18, 2017 | agree  | Unknown |
| 2   | ICE we’re getting MS13 out by the thousands.                                   | Donald Trump: Says of MS13 gang members, "We are getting them out of our country by the thousands." | Mostly-False, stated on May 15, 2018 | agree  | False   |
| 3   | ICE we’re getting MS13 out by the thousands.                                   | Donald Trump: I have watched ICE liberate towns from the grasp of MS13.        | False, stated on June 30, 2018   | agree  | Unknown |
| 4   | We have one of the highest business tax rates anywhere in the world, pushing jobs and wealth out of our country. | Barack Obama: “There are so many loopholes ... our businesses pay effectively one of the lowest tax rates in the world.” | Half-True, stated on September 26, 2008 | disagree | Unknown |

4 Dataset

4.1 Background

We construct a dataset using fact-checked claims from PolitiFact, which focuses on claims by politicians. For each fact-checked claim, there is a factuality label and an article explaining the reason for assigning that label. PolitiFact further publishes commentaries that highlight some of the claims made in a debate or speech, with links to fact-checking articles about these claims from their website. These commentaries were used in previous work as a way to obtain a mapping from Input sentences in a debate/speech to Verified claims. For example, Shaar et al. (2020a) collected 16,636 Verified claims and 768 Input–Verified claim pairs from 70 debates and speeches, together with the transcript of the target event. For each Verified claim, they released VerifiedStatement, TruthValue {Pants-on-Fire!, False, Mostly-False, Half-True, Mostly-True, True}, Title and Body.

The above dataset has high precision, and it is suitable for their formulation of the task: given a sentence (one of the 768 ones), identify the correct claim that verifies it (from the set of 16,636 Verified claims). However, it turned out not to be suitable for our purposes due to recall issues: missing links between Input sentences in the debate/speech and the set of Verified claims. This is because PolitiFact journalists were not interested in making an exhaustive list of all possible correct mappings between Input sentences and Verified claims in their database; instead, they only pointed to some such links, which they wanted to emphasize.

Moreover, if the debate made some claim multiple times, they would include a link for only one of these instances (or they would skip the claim altogether). Moreover, if the claims made in a sentence are verified by multiple claims in the database, they might only include a link to one of these claims (or to none).

However, we have a document-level task, where identifying sentences that can be verified using a database of fact-checked claims is our primary objective (while returning the matching claims is secondary), we need not only high precision, but also high recall for the Input–Verified claim pairs.

4.2 Our Dataset

We manually checked and re-annotated seven debates from the dataset of Shaar et al. (2020a) by linking Verified claims from PolitiFact to the Input sentences in the transcript. This includes 5,054 sentences, and ideally, we would have wanted to compare each of them against each of the 16,636 Verified claims, which would have resulted in a huge and very imbalanced set of Input–Verified pairs: 5,054 × 16,636 = 84,078,344. Thus, we decided to pre-filter the Input sentences and the Input–Verified claim pairs. The process is sketched in Figure 2 and described in more detail below.

4.3 Phase 1: Input Sentence Filtering

Not all sentences in a speech/debate contain a verifiable factual claim, especially when uttered in a live setting. In speeches, politicians would make a claim and then would proceed to provide the numbers and the anecdotes to emphasize and to create an emotional connection with the audience.
In our case, we only need to focus on claims. We also know that not all claims are important enough to be fact-checked. Thus, we follow (Konstantinovskiy et al., 2021) as guidance to define which Input sentences are worth fact-checking. Based on this definition, positive examples include, but are not limited to (a) stating a definition, (b) mentioning a quantity in the present or in the past, (c) making a verifiable prediction about the future, (d) referencing laws, procedures, and rules of operation, or (e) implying correlation or causation (such correlation/cause needs to be explicit). Negative examples include personal opinions and preferences, among others. In this step, three annotators independently made judgments about the Input sentences for check-worthiness (i.e., check-worthy vs. not check-worthy), and we only rejected a sentence if all three annotators judged it to be not check-worthy. As a result, we reduced the number of input sentences that need further manual checking from 5,054 to 700.

### 4.4 Phase 2: Generating Input–Verified Pairs

Next, we indexed the Verified claims and we queried with the Input sentence using BM25 to retrieve 15 Verified claims per Input sentence. As a result, we managed to reduce the number of pairs to check from $700 \times 16,636 = 11,645,200$ to just $700 \times 15 = 10,500$.

### 4.5 Phase 3: Input–Verified Pairs Filtering

Then, we manually went through the 10,500 Input–Verified pairs, and we filtered out the ones that were incorrectly retrieved by the BM25 algorithm. Again, we were aiming for high recall, and thus we only rejected a pair if all three out of the three annotators independently proposed to reject it. As a result, the final number of pairs to check got reduced to just 1,694.

### 4.6 Phase 4: Stance and Verdict Annotation

As in the previous phase, three annotators manually annotated the 1,694 Input–Verified pairs with stance and verdict labels using the following label inventory:

- **stance**: agree, disagree, unrelated, not-claim;
- **verdict**: true, false, unknown, not-claim.

The label for *stance* is agree if the Verified claim agrees with the Input claim, disagree if it opposes it, and unrelated if there is no agree/disagree relation (this includes truly unrelated claims or related but without agreement/disagreement, e.g., discussing the same topic).

The *verdict* is true/false if the Input sentence makes a claim whose veracity can be determined to be true/false based on the paired Verified claim and its veracity label; it is unknown otherwise. The veracity can be unknown for various reasons, e.g., (i) the Verified claim states something (a bit) different, (ii) the two claims are about different events, (iii) the veracity label of the Verified claim is ambiguous. We only need the verdict annotation to determine whether the Input sentence is verifiable; yet, we use the stance to construct suitable Input–Verified claim pairs.

### 4.7 Final Dataset

Our final dataset consists of 5,054 Input sentences, and 75,810 Input–Verified claim pairs. This includes 125 Input sentences that can be verified using a database of 16,663 fact-checked claims, and 198 Input–Verified claim pairs where the Verified claim can verify the Input sentence (as some Input sentences can be verified by more than one Verified claim). Table 2 reports some statistics about each claim inventory:

- **stance**: agree, disagree, unrelated, not-claim;
- **verdict**: true, false, unknown, not-claim.

The label for *stance* is agree if the Verified claim agrees with the Input claim, disagree if it opposes it, and unrelated if there is no agree/disagree relation (this includes truly unrelated claims or related but without agreement/disagreement, e.g., discussing the same topic).

The *verdict* is true/false if the Input sentence makes a claim whose veracity can be determined to be true/false based on the paired Verified claim and its veracity label; it is unknown otherwise. The veracity can be unknown for various reasons, e.g., (i) the Verified claim states something (a bit) different, (ii) the two claims are about different events, (iii) the veracity label of the Verified claim is ambiguous. We only need the verdict annotation to determine whether the Input sentence is verifiable; yet, we use the stance to construct suitable Input–Verified claim pairs.

### 4.8 Annotation and Annotators’ Agreement

Note that each Input–Verified claim pair was annotated by three annotators: one male and two females, with BSc and PhD degrees. The disagreements were resolved by majority voting, and, if this was not possible, in a discussion with additional consolidators. We measured the inter-annotator agreement on phase 4 (phases 1 and 3 aimed for high recall rather than agreement). We obtained a Fleiss Kappa ($\kappa$) of 0.416 for stance and of 0.420 for the verdict, both corresponding to moderate level of agreement.
Table 2: Statistics about our dataset: number of sentences in each transcript, and distribution of clear stance (agree + disagree) and clear verdict (true + false) labels. The number of topics was manually decided by looking at the keywords detected in each transcript. Sent. is the number of input sentences, and Sent.-Var. Pairs is the number of input sentences with top-15 verified claim pairs.

Table 3: Distribution of the labels: Input–Verified pairs with a true/false verdict vs. the TruthValue for Verified claim from PolitiFact.

5 Evaluation Measures

Given a document, the goal is to rank its sentences, so that those that can be verified (i.e., with a true/false verdict; Verdict-Input in Table 2) are ranked as high as possible, and also to provide a relevant Verified claim (i.e., one that could justify the verdict; Verdict-pairs in Table 2). This is a (double) ranking task, and thus we use ranking evaluation measures based on Mean Average Precision (MAP). First, let us recall the standard AP:

\[ AP = \frac{\sum_{k=1}^{n} P_r(k) \times rel(k)}{rel. \text{sentences}}, \]  

(1)

where \( P_r(k) \) is the precision at a cut-off \( k \) in the list, \( rel(k) \) is 1 if the \( k \)-th ranked sentence is relevant (i.e., has either a true or a false verdict), and \( rel. \text{sentences} \) is the number of Input sentences that can be verified in the transcript.

We define more strict AP measures, \( AP_{0.5} \), \( AP_{0.5}^t \), and \( AP_{0.5}^r \), which only give credit for an Input sentence with a known verdict, if also a corresponding Verified claim is correctly identified:

\[ AP_{0.5} = \frac{\sum_{k=1}^{n} P_r^t(k) \times rel(k)}{rel. \text{sentences}}, \]  

(3)

\[ AP_{0.5}^r = \frac{\sum_{k=1}^{n} P_r^r(k) \times rel(k)}{rel. \text{sentences}}, \]  

(4)

where \( P_m^t(k) \), is precision at cut-off \( k \), so that it increments by \( m \), if none of the relevant Verified claim was retrieved in the top-\( r \) Verified claim list; otherwise, it increments by 1.

Note that the simple AP can also be represented as \( AP_{1} \), as it increments by 1 regardless of whether a relevant Verified claim is in the top-\( r \) of the list of Verified claims.

We compute \( MAP \), \( MAP_{0.5}^t \), \( MAP_{0.5}^r \), and \( MAP_{0.5}^r \), by averaging \( AP \), \( AP_{0.5}^t \), \( AP_{0.5}^r \), and \( AP_{0.5}^r \), respectively, over the test transcripts.

We also compute \( MAP_{inner} \) by averaging the \( AP_{inner} \) on the Verified claims: we compute \( AP_{inner} \) for a given Input sentence, by scoring the rankings of the retrieved Verified claims as in the task presented in (Shaar et al., 2020a).

6 Model

The task we are trying to solve has two subtasks. The first sorts the Input sentences in the transcript in a way, so that the Input sentences that can be verified using the database are on top. The second one consists of retrieving a list of matching Verified claims for a given Input sentence. While we show experiments for both subtasks, our main focus is on solving the first one.

6.1 Input–Verified Pair Representation

In order to rank the Input sentences from the transcript, we need to find ways to represent them, so that we would have information about whether the database of Verified claims can indeed verify some claim from the Input sentence.
To do that, we propose to compute multiple similarity measures between all possible Input–Verified pairs, where we can match the Input sentence against the VerifiedStatement, the Title, and the Body of the verified claims’ fact-checking article in PolitiFact.

- **BM25** (Robertson and Zaragoza, 2009): These are BM25 scores when matching the Input sentence against the VerifiedStatement, the Title, and the Body, respectively (3 features);

- **NLI Score** (Nie et al., 2020): These are posterior probabilities for NLI over the labels {entailment, neutral, contradiction} between the Input sentence and the VerifiedStatement (3 features);

- **BERTScore** (Zhang et al., 2020a): F1 score from the BERTScore similarity scores between the Input sentence and the VerifiedStatement (1 feature);

- **Sentence-BERT (SBERT)** (Reimers and Gurevych, 2019): Cosine similarity for sentence-BERT-large embedding of the Input sentence compared to the embedding for the VerifiedStatement, the Title, and the Body. Since the Body is longer, we obtain the cosine similarity between the Input sentence vs. each sentence from the Body, and we only keep the four highest scores (6 features);

- **SimCSE** (Gao et al., 2021): Similarly to SBERT, we compute the cosine similarity between the SimCSE embeddings of the Input sentence against the VerifiedStatement, the Title, and the Body. Again, we use the top-4 scores when matching against the Body sentences (6 features: 1 from the VerifiedStatement + 1 from the Title + 4 from the Body).

### 6.2 Single-Score Baselines

Each of the above scores, e.g., SBERT, can be calculated for each Input–Verified claim pair. For a given Input sentence, this makes 16,663 scores (one for each Verified from the database), and as a baseline, we assign to the Input sentence the maximum over these scores. Then, we sort the sentences of the input document based on these scores, and we evaluate the resulting ranking.

| Experiment                           | MAP$_{inner}$ |
|--------------------------------------|---------------|
| BERTScore (F1) on VerifiedStatement  | 0.638         |
| NLI (Entl) on VerifiedStatement      | 0.574         |
| NLI (Neut) on VerifiedStatement      | 0.112         |
| NLI (Contr) on VerifiedStatement     | 0.025         |
| NLI (Entl+Contr) on VerifiedStatement| 0.553         |
| SimCSE on Title                      | 0.220         |
| SimCSE on VerifiedStatement          | 0.451         |
| SimCSE on Body                       | 0.576         |
| SBERT on Title                       | 0.165         |
| SBERT on VerifiedStatement           | 0.531         |
| SBERT on Body                        | 0.649         |
| BM25 on VerifiedStatement            | 0.316         |
| BM25 on Body                         | **0.892**     |
| BM25 on Title                        | 0.145         |

Table 4: Preliminary Verified Claim retrieval experiments on the annotations obtained from the PolitiFact dataset and the manually annotated pairs with agree or disagree stance.

### 6.3 Re-ranking Models

We performed preliminary experiments looking into how the above measures work for retrieving the correct Verified claim for an Input sentence for which there is at least one match in the Verified claims database. This corresponds to the sentence-level task of (Shaar et al., 2020a), but on our dataset, where we augment the matching Input–Verified pairs from their dataset with all the Input–Verified pairs with a stance of agree or disagree. The results are shown in Table 4. We can see that BM25 on Body yields the best overall MAP score, which matches the observations in (Shaar et al., 2020a).

**RankSVM for Verified Claim Retrieval** Since now we know that the best Verified claim retriever uses BM25 on Body, we use it to retrieve the top-$N$ Verified claims for the Input sentence, and then we calculate the above 19 similarity measures for each candidate in this top-$N$ list. Afterwards, we concatenate the scores for these top-$N$ candidates. Thus, we create a feature vector of size $19 \times N$ for each Input sentence. For example, a top-3 experiment uses for each Input sentence a feature vector of size $19 \times 3 = 57$, which represents each similarity measure based on the top-3 Verified claims retrieved by BM25 on Body. Then, we train a RankSVM model using this feature representation.

**RankSVM–Max** Instead of concatenating the 19-dimensional vectors for the top-$N$ candidates, we take the maximum over these candidates for each feature to obtain a new 19-dimensional vector. Then, we train a RankSVM model like before.
Table 5: Verdict experiments: Baseline and re-ranking experiments on the PolitiFact dataset. The results highlighted in **bold** are the best results for the particular sets of experiments. The *underlined* results are the best overall.

**RankSVM–Max with Skipping** Table 3 shows that almost all **Input–Verified** pairs for which the TruthValue of the **Verified** claim is Half–True eventually result in an **Input** sentence for which we cannot determine an actual verdict. This is to be expected as, if we cannot trust the veracity of the **Verified** claim, then even if the statement matches the **Input** sentence, we cannot determine its veracity. Thus, we further experiment with a variant of the **RankSVM–Max** model that skips any scores that belong to a Half–True **Verified** claim.

**7 Experiments and Evaluation**

We performed a 7-fold cross-validation, where we used 6 out of the 7 transcripts for training and the remaining one for testing. We first computed 19 similarity measures and then used them to test the baselines and to train pairwise learning-to-rank models. The results are shown in Table 5.
### Table 6: Ablation experiments for the verdict on the best model from Table 5: RankSVM with Top-5 scores from all measures while skipping half-true Verified claims.

| Experiment                              | MAP  | MAP\(_0\) | MAP\(_{0.5}\) | MAP\(_{0.5.5}\) | MAP\(_H\) | MAP\(_H\) |
|-----------------------------------------|------|------------|---------------|----------------|------------|------------|
| RankSVM–Max on Top-5 with Skipping      | 0.522| 0.379      | 0.501         | 0.451          | 0.512      | 0.316      |
| w/o BERTScore (F1)                      | 0.499| 0.376      | 0.480         | 0.437          | 0.489      | 0.313      |
| w/o NLI Score (E, N, C)                 | 0.475| 0.330      | 0.451         | 0.402          | 0.463      | 0.279      |
| w/o SimCSE                              | 0.511| 0.353      | 0.486         | 0.432          | 0.499      | 0.295      |
| w/o SBERT                               | 0.498| 0.381      | 0.481         | 0.440          | 0.490      | 0.308      |
| w/o BM25                                | 0.497| 0.343      | 0.473         | 0.420          | 0.485      | 0.287      |
| w/o scores on Title                     | 0.522| 0.369      | 0.501         | 0.445          | 0.511      | 0.308      |
| w/o scores on VerifiedStatement         | 0.311| 0.242      | 0.293         | 0.276          | 0.302      | 0.198      |
| w/o scores on Body                      | 0.444| 0.295      | 0.427         | 0.370          | 0.435      | 0.249      |

#### 7.2 RankSVM for Verified Claims Retrieval

We trained a RankSVM on the 19 similarity measures computed for the top-\(N\) retrieved Verified claims, according to BM25, the best system on Body. We can see from Table 5 that using the RankSVM on the 19 measures improves the scores by up to 10 MAP points absolute. Moreover, the best model achieves a MAP score of 0.404.

#### 7.3 RankSVM–Max

Using max-pooling instead of BM25-retrieved Verified claims yields huge improvements in MAP: from 0.404 to 0.491 using RankSVM on the top-10 scores from the 19 metrics.

A sizable improvement can be observed when we consider MAP\(_0\), MAP\(_{0.5}\), and MAP\(_H\) from RankSVM for Verified claims retrieval. Note that, since there is a max over each measure independently, we no longer have a unified Verified suggestion, which is required to compute MAP\(_0\), MAP\(_{0.5}\), and MAP\(_H\). Thus, to compute them, we use the best Verified claim retriever from Table 4, i.e., BM25 on Body.

#### 7.4 RankSVM–Max with Skipping

The highest MAP score, 0.522, is achieved by the RankSVM that uses the top-5 scores from each measure while skipping the Half–True Verified claim scores. We can also conclude by looking at the other variants of the MAP score, e.g., MAP\(_H\), that we can identify the Input sentences that need to be fact-checked and detect the correct Verified claims in the top-3 ranks.

#### 7.5 Ablation Experiments

We performed an ablation study for the best-performing model in Table 5, by removing one feature at a time. We also excluded all scores based on Title, VerifiedStatement, and Body. The results are shown in Table 6.

#### 8 Conclusion and Future Work

We introduced a new challenging real-world task formulation to assist fact-checkers, journalists, media, and regulatory authorities in finding which claims in a long document have been previously fact-checked. Given an input document, we aim to detect all sentences containing a claim that can be verified by some previously fact-checked claims (from a given database of previously fact-checked claims). We developed a new dataset for this task formulation, consisting of seven debates, 5,054 sentences, 16,636 target verified claims to match against, and 75,810 manually annotated sentence-verified claim pairs.

We further defined new evaluation measures (variants of MAP), which are better tailored for our task setup. We addressed the problem using learning-to-rank, and we demonstrated sizable performance gains over strong baselines. We offered analysis and discussion, which can facilitate future research, and we released our data and code.

In future work, we plan to focus more on detecting the matching claims, which was our second objective here. We also plan to explore other transformer architectures and novel ranking approaches such as multi-stage document ranking using monoBERT and duoBERT (Yates et al., 2021).
9 Limitations

We have developed a dataset and proposed and evaluated a model using data from PolitiFact, which consists of political statements. We have not evaluated our approach on other topics, e.g., factual claims appearing on social media, which is out of the scope of the present work.

Ethics and Broader Impact

Biases We note that there might be some biases in the data we use, as well as in some judgments for claim matching. These biases, in turn, will likely be exacerbated by the unsupervised models trained on them. This is beyond our control, as the potential biases in pre-trained large-scale transformers such as BERT and RoBERTa, which we use in our experiments.

Intended Use and Misuse Potential Our models can make it possible to put politicians on the spot in real time, e.g., during an interview or a political debate, by providing journalists with tools to do trustable fact-checking in real time. They can also save a lot of time to fact-checkers for unnecessary double-checking something that was already fact-checked. However, these models could also be misused by malicious actors. We, therefore, ask researchers to exercise caution.

Environmental Impact We would like to warn that the use of large-scale Transformers requires a lot of computations and the use of GPUs/TPUs for training, which contributes to global warming (Strubell et al., 2019). This is a bit less of an issue in our case, as we do not train such models from scratch; rather, we fine-tune them on relatively small datasets. Moreover, running on a CPU for inference, once the model is fine-tuned, is perfectly feasible, contributes much less to global warming.

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