LONGCHECKER: Improving scientific claim verification by modeling full-abstract context

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Abstract

We introduce the LONGCHECKER system for scientific claim verification. Given a scientific claim and an evidence-containing research abstract, LONGCHECKER predicts a veracity label and identifies supporting rationales in a multitask fashion based on a shared encoding of the claim and abstract. We perform experiments on the SCIFACT dataset, and find that LONGCHECKER achieves state-of-the-art performance. We conduct analysis to understand the source of this improvement, and find that identifying the relationship between a claim and a rationale reporting a scientific finding often requires understanding the context in which the rationale appears. By making labeling decisions based on all available context, LONGCHECKER achieves better performance on cases requiring this type of understanding. In addition, we show that LONGCHECKER is able to leverage weakly-supervised in-domain data to facilitate few-shot domain adaptation for scientific claim verification.†

1 Introduction

The task of scientific claim verification requires a system to assess the veracity of a scientific claim against a corpus of documents. The proliferation of mis- and dis-information on the web – particularly as it relates the COVID-19 pandemic – has spurred the development of new datasets and modeling approaches for this task.

In this work, we focus on the SCIFACT task and dataset (Wadden et al., 2020). Substantial modeling progress has been made on SCIFACT since its release, facilitated by techniques like neural re-ranking for document retrieval (Pradeep et al., 2021), and methods that incorporate document-level context for rationale selection (Li et al., 2021; Zhang et al., 2021). One important commonality among existing models is that they make label predictions by first selecting a small number of rationales (i.e. sentences reporting results that entail or contradict the claim) from a larger document context, and then predict a veracity label based on the selected rationales. In contrast, the model we present in this work predicts fact-checking labels based on an encoding of the full context of the evidence-containing title and abstract when predicting fact-checking labels.

Our approach offers two advantages. First, scientific writing makes heavy use of acronyms, qualifiers, coreference, and anaphora (Nye et al., 2020; Barnett and Doubleday, 2020). As a result, the relationship between a claim and a sentence reporting a scientific finding is often only clear when the finding is interpreted in its original context; Figure 1 provides an example. A manual analysis of a collection of claims from the SCIFACT dataset indicates that this situation occurs in roughly two-thirds of claim / evidence pairs in SCIFACT.

Second, while fact-checking annotations in the scientific domain are expensive and require expert annotators, unlabeled scientific papers are ex-

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Figure 1: A claim from the SCIFACT dev set, supported by a research abstract. The sentence in green reports a finding that SUPPORTS the claim, but this finding cannot be interpreted properly without the context in blue. LONGCHECKER incorporates the full context of the evidence-containing title and abstract when predicting fact-checking labels.

### Claim:

Macrolides do not protect against heart attack

### Evidence abstract:

**OBJECTIVE:** To determine whether previous use of antibiotics decreases the risk of heart attack. …… No effect was found for previous use of macrolides.

### Label: SUPPORTS

1 Our code and model checkpoints are available at [https://github.com/dwadden/longchecker](https://github.com/dwadden/longchecker).
tremely plentiful. In addition, it is possible to devise simple heuristics to weakly label documents that SUPPORT or REFUTE a given claim – for instance, a paper abstract is likely to SUPPORT a claim made in its title. LONGCHECKER can be trained directly on these weakly-supervised claim / abstract pairs, whereas models which first select rationales as inputs for label prediction would require some additional form of supervision to identify the rationales.

We make the following contributions:

1. We introduce the LONGCHECKER model. LONGCHECKER verifies claims against scientific research abstracts by encoding the full claim, title, and abstract together, and then predicts a veracity level and identifies rationales in a multitask fashion.

2. We find that LONGCHECKER establishes a new state-of-the-art on the SciFact task.

3. We perform analysis to understand the source of this improvement, and find that it is due primarily to LONGCHECKER’s better performance on instances requiring abstract-level context.

4. We demonstrate that LONGCHECKER can leverage weakly-labeled in-domain data during training, facilitating zero-shot and few-shot domain adaptation for scientific fact-checking.

5. We find that both LONGCHECKER— as well as two other strong baselines on SciFact — achieve performance close to the “upper bound” set by human agreement, suggesting the need for more challenging datasets for scientific claim verification.

2 Related work

We review literature on fact-checking and claim verification in the scientific domain.

2.1 Datasets for scientific claim verification

Since 2020, a number of datasets have been released to facilitate the development of models for scientific claim verification. PUBHEALTH (Kotonya and Toni, 2020) collects public health claims from fact-checking websites like Snopes, and verifies them against information in news articles and fact-checking websites.

COVID-Fact (Saakyan et al., 2021) collects claims about COVID-19 scraped from a COVID-19 subreddit, and verifies them against linked scientific papers, as well as documents retrieved via Google search. HealthVer (Sarrouti et al., 2021) also focuses on COVID-related claims, which are obtained by re-writing answers to questions from TREC-COVID (Voorhees et al., 2020), and verifies them against documents retrieved from the CORD-19 corpus (Wang et al., 2020). Both COVID-Fact and HealthVer are formatted as entailment-style tasks, pairing claims with the rationales that entail or contradict them.

The SciFact dataset collects claims by re-writing citation sentences appearing in scientific articles, and verifies them against the abstracts of the articles mentioned in each citation (Wadden et al., 2020). The SciFact dataset includes the full abstracts which SUPPORT and REFUTE each claim, annotated with the rationales reporting the findings which entail each label (in the context of the abstract). In this work, we focus on SciFact because it (1) focuses on verifying claims about scientific findings against primary research literature, and (2) includes the full context associated with each fact-checking label.

2.2 Models for the SciFact task

Substantial modeling progress has been made on the SciFact task since its introduction, driven in part by a shared task (called SciVer) and leaderboard (Wadden and Lo, 2021). The two strongest systems on the shared task were VERT5ERINI (Pradeep et al., 2021) and PARAGRAPHJOINT (Li et al., 2021), which we describe in detail in §5.1. More recently, ARSJJOIN (Zhang et al., 2021) achieved performance competitive with these top two systems.

These models all employ a three-stage approach consisting of (1) abstract retrieval, (2) rationale selection, and (3) label prediction using the selected rationales. They differ in how they select rationales. While VERT5ERINI makes rationale selection decisions for each sentence independently, PARAGRAPHJOINT and ARSJJOIN encode all sentences in the source abstract (truncating as necessary to fit within model limits), and use pooling and self-attention to produce sentence representations used for rationale selection.

Our proposed system, LONGCHECKER, uses a document-level encoding approach like PARAGRAPHJOINT and ARSJJOIN. Unlike those systems, it uses this encoding to make label predictions directly, rather than using it to select evidence to serve as downstream inputs for label prediction.
It also uses a long-document transformer, Longformer (Beltagy et al., 2020), to avoid the need for abstract truncation. Long-document transformers have been used for general-domain fact-checking on the FEVER dataset (Thorne et al., 2018): Stammbach (2021) uses Big Bird (Zaheer et al., 2020) to encode Wikipedia articles for token-level evidence selection.

3 Scientific claim verification

We briefly review the scientific claim verification task as defined in SciFACT. For more details, see Wadden et al. (2020).

Task definition Given a claim \( c \) and a corpus of scientific research abstracts \( \mathcal{A} \), the scientific claim verification task consists of identifying all evidence abstracts \( \mathcal{E} \subseteq \mathcal{A} \) relevant to \( c \), and for each abstract \( a \in \mathcal{E} \) predicting a label \( y(c, a) \) which indicates the relationship (either SUPPORTS or REFUTES) of \( a \) to \( c \). All abstracts \( a' \in \mathcal{E} \) that do not contain relevant evidence are labeled \( y(c, a') = \text{NEI} \) (Not Enough Info). The system must also identify rationales which report the findings sufficient to justify each label, in the context of the abstract.

Evaluation metrics We perform two styles of evaluation. Abstract-level evaluation is similar to the FEVER score (Thorne et al., 2018): it measures a model’s ability to identify evidence-containing abstracts, and label their relationship (SUPPORTS or REFUTES) relative to a claim. The label-only variant of this evaluation only requires a model to predict the correct veracity label, whereas the label+rationale variant requires the model to also select supporting rationales; this latter metric rewards high recall in selecting rationales. Sentence-level evaluation, on the other hand, rewards high precision in selecting rationales. The selection-only variant measures the model’s ability to identify rationales, while the selection+label variant requires that the model also predict the correct veracity label.

Retrieval settings We evaluate models in two settings: in the oracle abstract setting, models are provided with “gold” evidence-containing abstracts. In the open setting, models must first retrieve relevant documents from the corpus \( \mathcal{A} \), which consists of 5,183 abstracts.

What counts as a rationale? Gold rationales include all sentences containing a statement of a result that entails or contradicts the claim. However, they may not contain all context necessary to interpret the result; for instance, context outside the rationales may be required to resolve coreferential expressions or acronyms, or may contain qualifiers specifying experimental context or study population. This convention is consistent with related tasks in rationalized NLP for biomedical literature, such as Lehman et al. (2019); DeYoung et al. (2020). We will explore this issue further in §6.

4 LONGCHECKER: Modeling full abstracts

We develop a model for full-abstract claim verification, which consists of two stages: (1) retrieval of relevant abstracts, and (2) multitask prediction of labels and rationales.

4.1 Retrieval

In the open retrieval setting, models must first retrieve documents likely to contain evidence. To accomplish this, we use the retrieval model from the VERT5ERINI (Pradeep et al., 2021) system, the top-performing retrieval system on SciVER. This model first retrieves abstracts using BM25 (Robertson and Zaragoza, 2009), then refines the predictions using a neural re-ranker based on Nogueira et al. (2020), which is trained on the MS MARCO passage dataset (Campos et al., 2016). \(^2\)

4.2 Multi-task label prediction and rationale selection

Prior work on related tasks involving long-document context – such as question answering over NLP papers (Dasigi et al., 2021) and multi-hop QA (Beltagy et al., 2020) – has demonstrated that models can benefit from shared representations learned on the tasks of (1) predicting a final, document-level label or answer and (2) identifying the relevant information necessary to arrive at the final label. Motivated by this observation, we develop LONGCHECKER, which cross-encodes a given claim and candidate document (both title and abstract), and uses this representation to make label and rationale predictions in a multitask fashion.

Long-document encoding Since many abstracts in our corpus exceed the 512-token length limit

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\(^2\)We performed some exploratory experiments using DPR trained on FEVER (Karpukhin et al., 2020), but found that the two-stage model enjoyed better performance. This is consistent with the findings from (Thakur et al., 2021).
common to many transformer-based language models like BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), we leverage the Longformer model (Beltagy et al., 2020) to cross-encode the claim, title, and abstract.³

Given a claim \( c \), title \( t \), and abstract \( a \) consisting of sentences \( s_1, \ldots, s_n \), we concatenate the inputs separated by \(<s>\) tokens. The \(<s>\) token following each sentence \( s_i \) is notated as \(<s>_i\) :

\[
<s> c <s> t <s> s_1 <s>_1 \ldots s_n <s>_n
\]

We encode this sequence using Longformer, assigning global attention to the \(<s>\) token, as well as all tokens in the claim \( c \) and all \(<s>_i\) tokens.

**Multi-task prediction and loss** We predict a label \( \hat{y}(c, a) \in \{ \text{SUPPORTS}, \text{REFUTES}, \text{NEI} \} \) by adding a classification head over the encoding of the \(<s>\) token, consisting of two feedforward layers followed by a three-way softmax. We predict whether sentence \( s_i \) is a rationale by adding a similar two-way classification head on top of \(<s>_i\).

During training, we compute the cross-entropy losses for the label and rationale predictions, and train to minimize the multitask loss:

\[
L = L_{\text{label}} + \lambda_{\text{rationale}}L_{\text{rationale}},
\]

where \( \lambda_{\text{rationale}} \) is tuned on the dev set.

### 4.3 Two-stage finetuning for domain adaptation

Collecting fact-checking annotations in scientific domains like biomedicine or public health is challenging and time-consuming, even for expert annotators with domain expertise. Given the availability of large general-domain fact-checking datasets like FEVER (Thorne et al., 2018), domain adaptation techniques to shift these models to new domains with minimal in-domain annotations could facilitate the development of fact-checking models for new subfields of science, or other specialized domains.

With this motivation in mind, we develop a two-stage finetuning procedure. In Stage 1, we finetune Longformer on a combination of one human-labeled, out-of-domain fact verification dataset, and two weakly-labeled in-domain datasets. In Stage 2, we continue finetuning on the S2IFACT dataset, using additional “hard” negatives also obtained from S2ORC. In §5, we conduct ablations to assess the benefits of incorporating weakly-labeled in-domain data into Stage 1 finetuning.

**Stage 1: Finetuning on out-of-domain and weakly-labeled in-domain data** We finetune LONGCHECKER on a combination of 136,564 supervised, out-of-domain claims from the FEVER fact-checking dataset, together with two sources of weakly-supervised in-domain data derived from the EVIDENCEINFER and PUBMEDQA datasets.

The EVIDENCEINFER dataset (Lehman et al., 2019; DeYoung et al., 2020) was released to facilitate the development of systems capable of extracting results from clinical trial reports. Clinical trial reports are a specific type of research paper, which examines the effect of an intervention on an outcome, relative to a comparator (or baseline). This dataset contains annotations consisting of “ICO” (intervention / comparator / outcome) prompts paired with (1) labels indicating whether the outcome increased or decreased as a result of the intervention, and (2) rationales justifying each label. We use rule-based heuristics to convert these prompts into claims (see Figure 2 for an example). This process yields 7,395 weakly-labeled claims.

We also use the PQA-A subset of PUBMEDQA (Jin et al., 2019), a large collection of biomedical abstracts with “claim-like” titles – for instance, “Vitamin B6 supplementation increases immune responses in critically ill patients.” We treat the paper titles as claims and the corresponding abstracts as the evidence sources. Since abstracts presumably contain evidence supporting their titles, we generate additional contradictory claims by identifying titles featuring a negation and removing the negation words (e.g. replacing “does not” with “does”). In total, PQA-A provides us with an additional 58,375 claims. Since these instances are not annotated with rationales, existing models for scientific

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³We use a Longformer-large checkpoint pretrained on the S2ORC corpus (Lo et al., 2020).

![Figure 2: An example showing how an evidence inference prompt (top) can be converted into a claim (bottom) using templates. A refuted claim could be generated by substituting “increases” for “decreases” in the prompt text.](image-url)
claim verification cannot utilize them for training without first generating weakly-labeled rationales. Using a multitask approach eliminates this requirement; we simply set $\lambda_{\text{rationale}} = 0$ in our multitask loss function when training on these instances.

**Stage 2: Finetuning on SciFact** We continue finetuning on the claim / evidence pairs from the SciFact dataset. Based on the findings from Li et al. (2021), we train on additional negative examples – i.e. claim / abstract pairs that do not have any relationship. We create a search index from 500K abstracts randomly selected from the biomedical subset of the S2ORC corpus. For each claim, we obtain “hard” negative abstracts by using the retrieval system from §4.1 to retrieve the top-1000 most-similar abstracts from this index, removing abstracts that are annotated as containing evidence, and randomly sampling 20 abstracts to be used as negatives during training.

5 Experiments

We conduct the following experiments: (1) We evaluate the performance of LongChecker on the SciFact test set, relative to two state-of-the-art baselines on SciFact. (2) We assess the performance of LongChecker and the baselines relative to the “upper bound” imposed by human agreement. (3) We examine the “zero-shot” and “few-shot” generalization performance of LongChecker when trained on Fever alone, compared to its performance when also trained on weakly-labeled in-domain data as described in §4.3.

5.1 Baseline systems

We compare LongChecker to the two models which achieved the best performance on the SciVer shared task.

**Vert5Erini** Pradeep et al. (2021) uses BM25 followed by neural re-ranking step for retrieval. For rationale selection, it makes a separate decision for each sentence, conditioned on the claim $c$ but not the surrounding abstract context. The selected rationales are used as inputs to make a final label decision. As T5-3B is used as both the rationale selection and label prediction models, this system has roughly 10x as many parameters as LongChecker.

**ParagraphJoint** Li et al. (2021) performs retrieval using representations derived from BioSentVec (Chen et al., 2019). Then, it uses RoBERTa-large to encode the title and abstract, truncating sentences as necessary to fit the 512-token limit. Rationale labels are predicted for each sentence based on the sentence’s encoding in the context of the abstract. As with Vert5Erini, the selected rationales are given as input to another RoBERTa-large model which makes the final label decision. This model has roughly the same number of parameters as LongChecker.

5.2 Results

**LongChecker establishes a new state-of-the-art on SciFact** Table 1a shows the performance of LongChecker and the two baselines on the original SciFact task. We present results in both the “oracle” setting where gold abstracts are provided as inputs, and the original SciFact setting, where evidence must be retrieved from a corpus of 5K abstracts. In both retrieval settings, LongChecker outperforms previous systems (including Vert5Erini, which is an order of magnitude larger) as measured by both “sentence-level” and “abstract-level” evaluation. We explore the source of this improvement in Section 6.

**LongChecker and baselines achieve near human-level performance** During the collection of the SciFact dataset, 151 claim-evidence pairs were independently annotated by two different SciFact annotators. We obtain an estimate of “human-level” performance by treating the first annotator’s results as “gold”, and the second annotator’s results as predictions. The results in Table 1a show that, as measured by sentence-level evaluation, existing systems surpass human agreement when “oracle” abstracts are provided, and match it with retrieved abstracts. For abstract-level evaluation, human agreement still exceeds the best systems, but the gap is only 5.5 F1 in the “oracle abstract” setting. It is understandable that human agreement is lower on sentence-level evaluation, since the task of selecting rationales is inherently more subjective than that of assigning an overall label. Collectively, these results suggest that existing models are capable of very strong performance on the fact verification sub-task of predicting whether an abstract (or collection of rationales) Supports or Refutes a claim, given that the abstract is known to contain relevant information (i.e. given oracle retrieval). Saakyan et al. (2021) and Sarrouti et al. (2021) report similarly strong
Table 1: Performance on the SciFact task.

| Retrieval | Model        | Sentence-Level | Abstract-Level |
|-----------|--------------|----------------|----------------|
|           |              | Selection-Only | Label-Only     |
|           |              | Selection+Label| Label+Rationale|
| Oracle    | VERT5ERINI   | P 87.9 R 68.6  F1 77.1 | P 87.9 R 68.6  F1 81.7 |
|           | PARAGRAPHP空前| P 68.6 R 77.1  F1 70.5 | P 64.4 R 74.1  F1 84.8 |
|           | LONGCHECKER  | P 84.0 R 80.5  F1 75.4 | P 74.1 R 80.9  F1 73.3 |
| Human     |              | P 90.7 R 74.3  F1 87.4 | P 85.9 R 73.9  F1 79.4 |
| Open      | VERT5ERINI   | P 81.7 R 87.4  F1 71.6 | P 82.6 R 72.0  F1 71.6 |
|           | PARAGRAPHP空前 | P 71.6 R 84.0  F1 72.0 | P 72.0 R 84.9  F1 76.0 |
|           | LONGCHECKER  | P 88.7 R 84.0  F1 75.4 | P 84.9 R 74.9  F1 76.0 |

(a) LONGCHECKER establishes a new state-of-the-art on the SciFact task. In the “oracle abstract” setting where gold abstracts are provided, state-of-the-art models surpass human performance as measured by sentence-level evaluation, and approach human performance for abstract-level evaluation. For human agreement, sentence-level precision and recall are (coincidentally) identical.

(b) Zero-shot and few-shot experiments on SciFact. We present results in the “Open retrieval” setting; the results in the “Oracle” setting are qualitatively similar. Models are pre-trained either on FEVER, or FEVER combined with EVIDENCEINFER and PUBLMEDQA for domain adaptation (indicated as “FEVER + Adapt”). In the “zero-shot” setting, models are not finetuned on any SciFact examples, while in the “few-shot” setting, they are finetuned on 45 examples from SciFact.

Table 1: Performance on the SciFact task.

| Setting     | Data       | Sentence-Level | Abstract-Level |
|-------------|------------|----------------|----------------|
|             | Selection-Only | P 77.4 R 6.5  F1 12.0 | P 83.9 R 11.7  F1 19.9 |
| Zero-shot   | FEVER + Adapt | P 23.6 R 13.8  F1 62.8 | P 31.3 R 19.8  F1 29.2 |
| Few-shot    | FEVER + Adapt | P 42.3 R 46.8  F1 44.0 | P 61.4 R 61.3  F1 52.9 |
|             | FEVER + Adapt | P 47.4 R 46.8  F1 44.0 | P 61.4 R 61.3  F1 52.9 |

6 Analysis

To determine the source of LONGCHECKER’s performance improvements over previous systems, as well as to identify potential areas for further model development, we annotate 128 claim / evidence pairs from the SciFact test set to understand the specific linguistic and reasoning challenges associated with verifying scientific claims.

Weakly-labeled in-domain training data facilitates domain adaptation We examine the effectiveness of our strategy to leverage weakly-labeled in-domain data to improve few-shot generalization. In particular, we compare two variants of Stage 1 finetuning from §4.3: one in which we finetune only on FEVER, and one in which we finetune on FEVER, along with weakly-supervised in-domain data from EVIDENCEINFER and PQA-A. We evaluate these models in two settings. In the “zero-shot” setting, we do not finetune on any SciFact data (i.e. we skip Stage 2 finetuning from §4.3), while in the “few-shot” setting we finetune on 45 SciFact examples.

The results are shown in Table 1b. We find that pre-training on weakly-supervised in-domain data improves performance in both the zero-shot and few-shot settings. This improvement is particularly substantial in the zero-shot setting, leading to relative performance improvements of 73% and 60% on sentence-level and abstract-level F1, respectively. One important factor contributing to this improvement is that classification thresholds learned on FEVER tend to be poorly-calibrated for scientific fact-checking, yielding high precision at the expense of very low recall. Pretraining on in-domain data (even lacking any gold labels) appears to improve calibration. Finally, we observe that the performance gap between the few-shot and complete-data settings remains substantial, indicating that there is ample room for improvement on domain adaptation for scientific claim verification.
**Category Example**

**Context (Acronym)**

Claim: Hematopoietic stem cells segregate their chromosomes randomly.
Context: we tested these hypotheses in hematopoietic stem cells (HSCs)...
Evidence: ...indicated that all HSCs segregate their chromosomes randomly.
Explanation: HSCs is an acronym for Hematopoietic stem cells.

**Context (Coreference)**

Claim: Errors in peripheral IV drug administration are most common during bolus administration
Context: OBJECTIVES: To determine the incidence of errors in the administration of intravenous drugs...
Evidence: ...Most errors occurred when giving bolus doses
Explanation: The evidentiary sentence reporting the finding does not specify the type of error.

**Background**

Claim: Silencing of Bcl2 slows the progression of tumors.
Evidence: Eliminating BCL-2 yielded rapid loss of leukemic cells
Explanation: Leukemic cells contribute to tumor progression.

**Numerical**

Claim: 1/2000 in UK have abnormal PrP positivity.
Evidence: Of the 32,441 appendix samples, 16 were positive for abnormal PrP
Explanation: Verifying the claim requires recognizing that 16 / 32,441 is roughly 1 / 2000.

Table 2: Example claim-evidence pairs demonstrating a type of modeling capability.

| Category       | Claim:                                                                 | Evidence:                                                                 | Explanation:                                      |
|----------------|------------------------------------------------------------------------|--------------------------------------------------------------------------|---------------------------------------------------|
| Context        | Hematopoietic stem cells segregate their chromosomes randomly.         | we tested these hypotheses in hematopoietic stem cells (HSCs)…            | HSCs is an acronym for Hematopoietic stem cells.   |
| Context        | Errors in peripheral IV drug administration are most common during bolus administration | OBJECTIVES: To determine the incidence of errors in the administration of intravenous drugs… | The evidentiary sentence reporting the finding does not specify the type of error. |
| Background     | Silencing of Bcl2 slows the progression of tumors.                    | Eliminating BCL-2 yielded rapid loss of leukemic cells                    | Leukemic cells contribute to tumor progression.    |
| Numerical      | 1/2000 in UK have abnormal PrP positivity.                             | Of the 32,441 appendix samples, 16 were positive for abnormal PrP         | Verifying the claim requires recognizing that 16 / 32,441 is roughly 1 / 2000. |

Table 3: Breakdown of performance for claims / evidence pairs requiring different modeling capabilities. \( \Delta_{\text{LONGCHECKER}} \) indicates the difference between the average of the two LONGCHECKER models, and the two baseline systems; higher values indicate better relative performance of LONGCHECKER.

| Category       | Difficulty | Count | PARAGRAPHTABLE | VERTSERINI | LONGCHECKER | \( \Delta_{\text{LONGCHECKER}} \) |
|----------------|------------|-------|----------------|-------------|-------------|----------------------------------|
| Context        | No         | 43    | 85.0           | 85.4        | 78.0        | -7.1                             |
|                | Yes        | 85    | 71.7           | 72.5        | 77.1        | 5.0                              |
| Background     | No         | 106   | 78.1           | 75.4        | 80.0        | 3.3                              |
|                | Yes        | 22    | 68.4           | 85.0        | 65.0        | -11.7                            |
| Numerical      | No         | 106   | 74.9           | 76.4        | 77.1        | 1.4                              |
|                | Yes        | 22    | 84.2           | 80.0        | 79.1        | -3.0                             |
| All            | All        | 128   | 76.4           | 77.1        | 77.4        | 0.7                              |

**Verifying scientific claims poses distinct modeling challenges**

We identify three major challenges. The first, and most frequent, is context. As mentioned in §3, SciFact follows the convention that sentences from an abstract \( a \) are annotated as rationales if they report a result that entails or contradicts the claim, in the context of the abstract. We find that these rationales would entail the claim in isolation in only 43 / 128 cases. In the other 85 cases, context is required to clarify the meaning of an acronym, resolve a coreference link, or otherwise specify qualifiers or conditions necessary for the rationale to entail the claim. Examples of this phenomenon are provided in Table 2. This challenge has previously been observed in the context of understanding clinical trial reports. For instance, Nye et al. (2020) observe that the conditions of an experiment (e.g. the population being studied, intervention, etc) are often reported early in the abstract, while the results are often reported at the end.

The two remaining challenges—reasoning over background knowledge not explicitly expressed in the abstract, and recognizing or reasoning over numerical expressions—are less common; both occur in 22 / 128 of our annotated instances. Examples are provided in Table 2.

**LONGCHECKER performs strongly on examples requiring abstract-level context**

Table 3 shows the performance of LONGCHECKER and the two baselines on each of the modeling challenges just described. The results indicate that LONGCHECKER improves over previous baselines because of its superior performance on instances where context outside the rationales is required to make a correct label prediction. In particular, LONGCHECKER exhibits essentially equal performance on claims that do and do not require additional context, while PARAGRAPHTABLE
and VerTeR5EINI suffer performance drops of 13.3 F1 and 12.9 F1, respectively. Interestingly, LongChecker does the worst on instances where no additional context is required—presumably because making a classification decision is more challenging when given unnecessary context as input.

On claims requiring background knowledge, VerTeR5EINI strongly outperforms the other two systems, consistent with observations indicating that larger language models are able to store more knowledge in their parameters (Raffel et al., 2020). Interestingly, none of the systems seem to struggle with instances involving numerical or statistical statements. Due to the small number of examples, it is difficult to determine whether the systems are actually interpreting numerical statements correctly, or using other signals in the evidence to produce verdicts.

7 Conclusion and future work

In this work, we developed a new model for scientific claim verification that incorporates all available context when predicting fact-checking labels. We found that this modeling approach improved performance on the SciFact task, and facilitated domain adaptation via finetuning on weakly-labeled in-domain data.

Our work points toward a number of promising future directions. The observation that existing systems achieve roughly human-level performance on the entailment portion of scientific fact-checking suggests the need for newer, and more realistic, versions of the scientific fact-checking task. This could involve predicting more fine-grained labels than a simple SUPPORTS / REFUTES, or requiring models to verify claims against much larger research corpora. Domain adaptation represents another area with substantial room for improvement, as the few-shot models in this work still exhibit a large performance gap relative to their fully-supervised counterparts. We hope that our models and findings will facilitate progress on these research challenges.

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