

# MultiVerS

Improving scientific claim verification with weak supervision and full-document context

**CS221.O12.KHCL**

*Instructor: PhD. Nguyen Thi Quy*

**Group 15**

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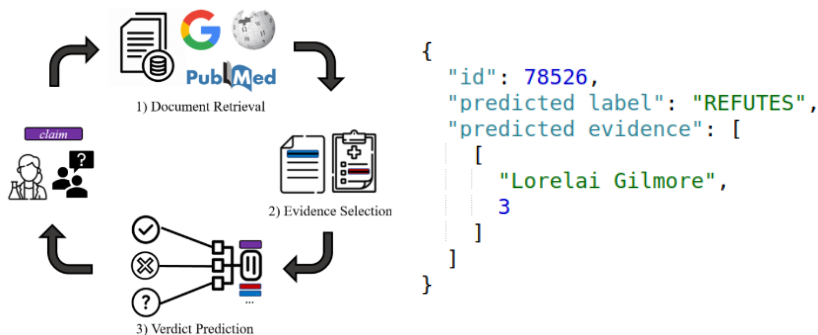
December 17, 2023

## Definition of scientific claim verification from the SCIFACT task:

Given a claim  $c$  and a *candidate abstract*  $a$ .

Label  $y(c, a) \in \{SUPPORTS, REFUTES, NEI\}$ .

Identify rationales  $R(c, a) = \{r_1(c, a), \dots, r_n(c, a)\}$ .



**Claim:**

Advil (ibuprofen) worsens  
COVID-19 symptoms

**Evidence abstract:****Covid-19 and avoiding  
Ibuprofen.**

...

Increased risk of COVID-19  
infection was feared with  
ibuprofen use

...

At this time, there are no  
findings discouraging the use  
of ibuprofen

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## Task Outputs

- 1 Fact-checking label

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- ① Fact-checking label
- ② Rationales justifying the label

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**Rationale**

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**Label: Refuted**

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Context required

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## Claim:

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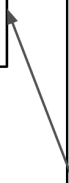
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# Prior work: Extract-then-label

## Claim:

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## Drawbacks of extract-then-label:

- ① Rationales may lack context
- ② Requires rationale supervision during training

## These models make predictions in 2 steps:

Predict rationales  $\hat{R}(c, a) = \{\hat{r}_1(c, a), \dots, \hat{r}_n(c, a)\}$

Then, make a label prediction  $\hat{y}(c, f_R(\hat{R}(c, a)))$

Given a claim  $c$  and candidate abstract  $a$

## A multitask system for full-context scientific claim verification

- Predict  $\hat{y}(c, a)$  directly based on an encoding of the entire claim and abstract.
- Enforce consistency of  $\hat{R}(c, a)$  with  $\hat{y}(c; a)$  during decoding.

## Long document encoding:

A claim  $c$  and candidate abstract  $a$  consisting of title  $t$  and sentences  $s_1, \dots, s_n$ .

The  $\langle /s \rangle$  token following each sentence  $s_i$  is notated as  $\langle /s \rangle_i$ .

$$\langle s \rangle \ c \ \langle /s \rangle \ t \ \langle /s \rangle \ s_1 \ \langle /s \rangle_1 \ \dots s_n \ \langle /s \rangle_n$$

Global attention is assigned to  $\langle s \rangle$  token, all tokens in  $c$  and all  $\langle /s \rangle$  tokens.

## Claim

Advil (ibuprofen)  
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symptoms

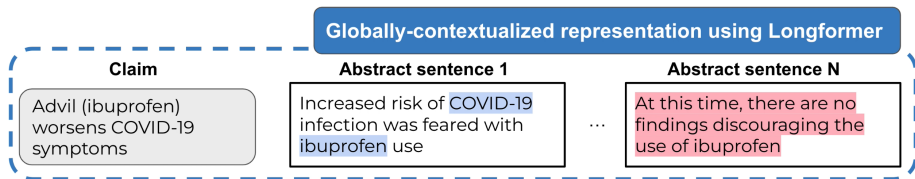
## Abstract sentence 1

Increased risk of COVID-19  
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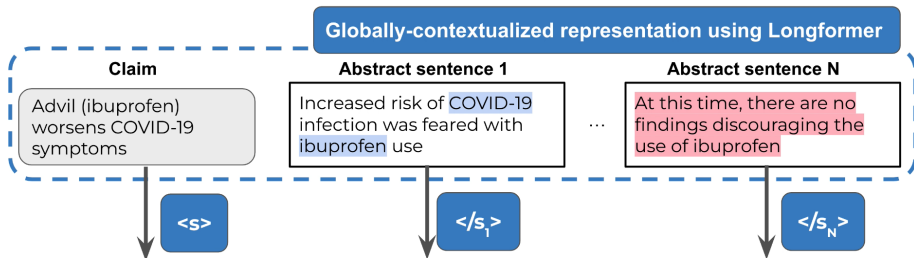
...

## Abstract sentence N

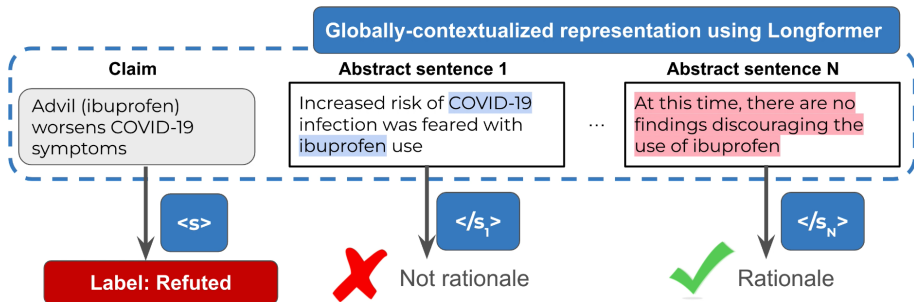
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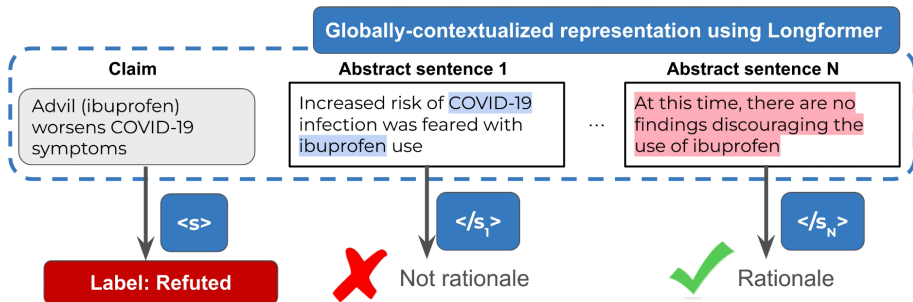


**Rationale Prediction:** The model analyzes each sentence's ending  $</s>$  to decide if it justifies the claim, using a binary classification.



**Label Prediction:** A special  $\langle s \rangle$  token captures the essence of both the claim and the abstract through "global attention".

→ Enabling accurate fact-checking label prediction for the abstract.



$$\mathcal{L} = \mathcal{L}_{label} + \lambda_{rationale} \mathcal{L}_{rationale}$$

## Benefits of multitask approach:

- ① Incorporates all relevant context
- ② Can train on instances with no rationale annotations

# Experiments

Dataset	Domain	Claim source	Open	Has NEI	Claim complexity	Negation method	Train claims	Eval claims	> 512 tokens
HealthVer	COVID	TREC-COVID	✗	✓	Complex	Natural	1,622	230	14.9%
COVIDFact	COVID	Reddit	✗	✗	Complex	Automatic	903	313	12.4%
SCIFACT	Biomed	Citations	✓	✓	Atomic	Human	1,109	300	27.4%
FEVER	Wiki	Wikipedia	-	✓	Atomic	Human	130,644	-	33.2%
PUBMEDQA	Biomed	Paper titles	-	✓	Complex	Automatic	58,370	-	12.1%
EVIDENCEINFERENCE	Biomed	ICO prompts	-	✓	Atomic	Automatic	7,395	-	42.7%

Table: Summary of datasets used in experiments

# Experiments

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- HealthVer
- COVID-Fact
- SciFact

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## Traning procedure:

- **Stage 1:** Train on a combination of *labeled out of domain data* and *weakly-labeled in-domain data*.
- **Stage 2:** Continue training on data from each target dataset.

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## Domain adaptation settings:

- **Zero-shot:** Stage 1 training only.
- **Few-shot:** 45 instances from target datasets.
- **Full-supervised:** All target data.



# Data: Stage 1

**Supervised** out-of-domain  
data (FEVER)

LeBron James was born in  
Ohio

Label: Supported

LeBron James is an American  
basketball player. He was born  
in Akron, Ohio.

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## Supervised out-of-domain data (FEVER)

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## Weakly-supervised in-domain data

**Diabetes increases risk of depression**

Abstract

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} Claim: Paper title

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Claim: Paper title

**Rationales** likely to appear in abstract, but are not annotated

MultiVerS can train on these examples, even though no rationale annotations are provided

## Abstract-level evaluation:

- Identifying abstracts that SUPPORT or REFUTE each claim.
- Predicting the correct label  $y(c, a)$  is sufficient

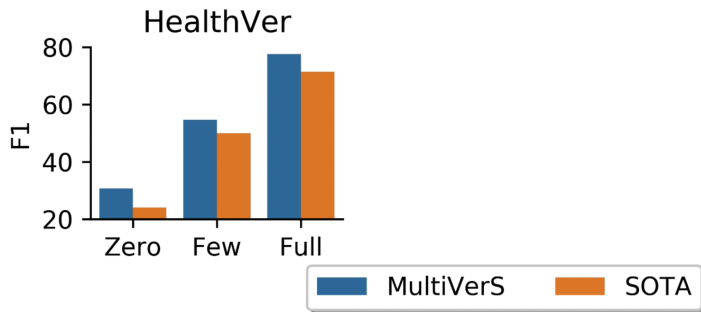
## Sentence-level evaluation:

- It combines the accuracy of abstract-level label prediction with the precision of rationale identification.

Setting	Model	HealthVer						COVIDFact						SciFact					
		Abstract			Sentence			Abstract			Sentence			Abstract			Sentence		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Zero	PARAGRAPHJOINT	72.3	14.4	24.0	22.9	2.7	4.9	51.3	37.9	43.6	31.5	16.0	21.3	52.9	32.4	40.2	36.4	14.9	21.1
	MULTIVERs	60.6	20.5	<b>30.7</b>	25.0	4.6	<b>7.8</b>	48.8	45.7	<b>47.2</b>	32.7	18.5	<b>23.6</b>	49.0	44.6	<b>46.7</b>	39.0	21.6	<b>27.8</b>
Few	PARAGRAPHJOINT	62.7	41.6	50.0	46.0	29.3	<b>35.8</b>	73.3	60.6	66.3	44.3	30.6	36.2	44.4	51.4	47.6	33.0	35.1	34.0
	MULTIVERs	63.6	47.9	<b>54.7</b>	41.9	31.0	35.7	71.3	68.1	<b>69.7</b>	39.5	35.4	<b>37.4</b>	76.4	54.1	<b>63.3</b>	51.7	40.3	<b>45.3</b>
Full	VERT5ERINI	71.3	74.0	72.6	65.6	61.2	63.3	76.6	52.7	62.4	44.8	27.2	33.9	64.0	73.0	68.2	60.6	66.5	63.4
	PARAGRAPHJOINT	75.0	68.3	71.5	69.9	60.6	64.9	71.5	68.1	69.8	41.4	40.3	40.8	75.8	63.5	69.1	68.9	54.6	60.9
	MULTIVERs	78.9	76.3	<b>77.6</b>	71.4	67.0	<b>69.1</b>	77.3	77.3	<b>77.3</b>	41.5	46.1	<b>43.7</b>	73.8	71.2	<b>72.5</b>	67.4	67.0	<b>67.2</b>

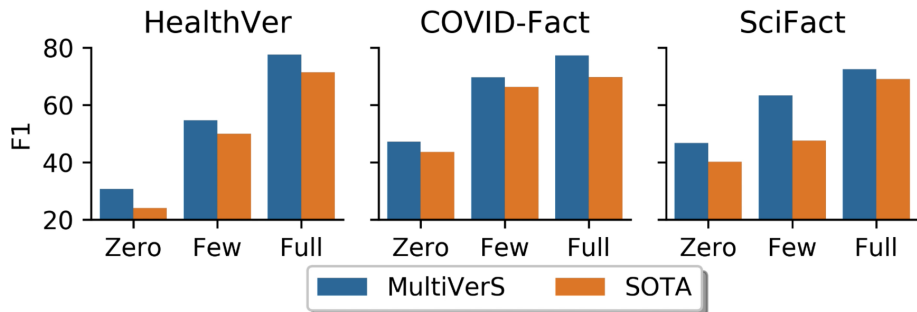
Table 2: Performance of MultiVerS and baselines.

# Results



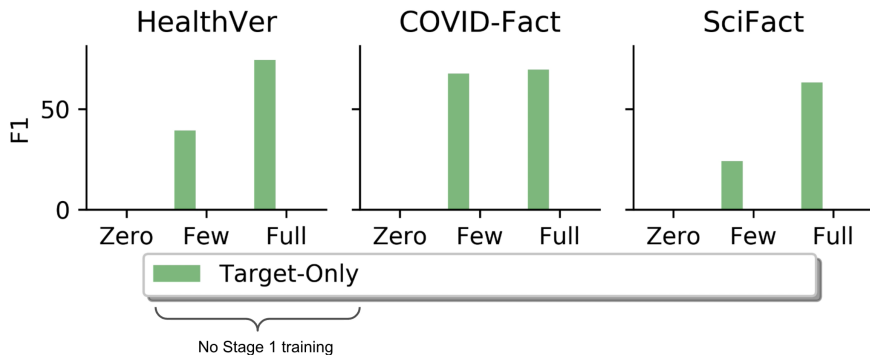


# Results

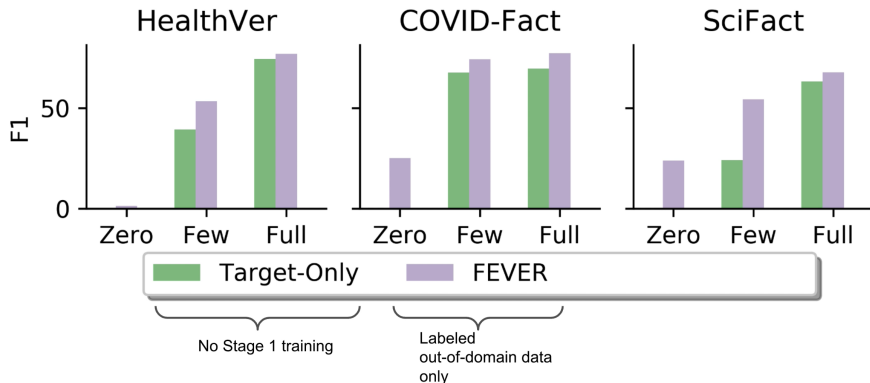


MultiVerS outperforms SOTA on all datasets

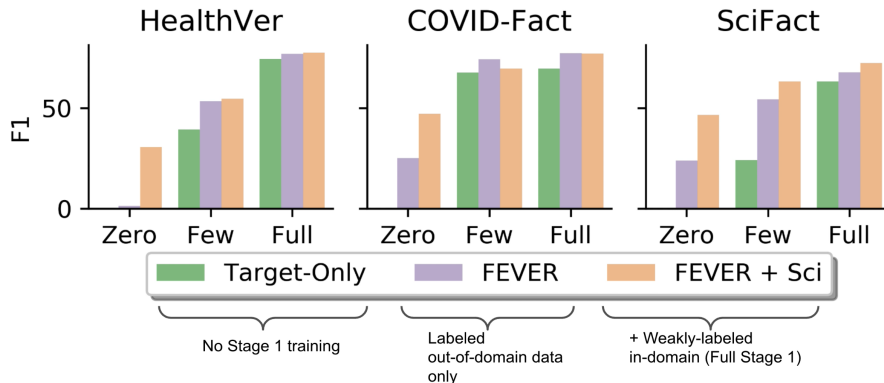
# Ablations: Training strategy



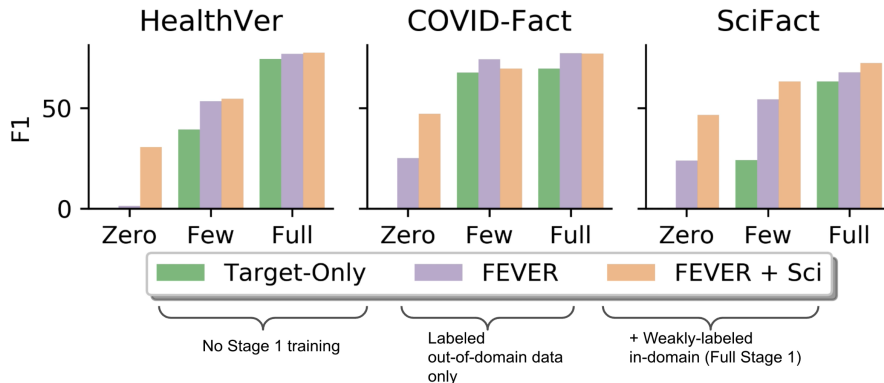
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Pretraining with weakly-supervised in-domain data improves few / zero shot performance.

# Reference



MULTIVERS: Improving scientific claim verification with weak supervision and full-document context



Scientific Fact-Checking: A Survey of Resources and Approaches  
Juraj Vladika and Florian Matthes



Longformer: The Long-Document Transformer  
Iz Beltagy, Matthew E. Peters and Arman Cohan



[Code and model checkpoints for the MultiVerS model](#)  
[dwadden/multivers](#)

# Thanks for listening!

## Q&A section