Beyond Fact Verification: Comparing and Contrasting Claims on Contentious Topics

Miyoung Ko

Ingyu Seong

Hwaran Lee

Joonsuk Park

Minsuk Chang

Minjoon Seo

KAIST

Korea University

NAVER AI Lab

University of Richmond

Google Research

{miyoungko, minjoon}@kaist.ac.kr
dlssrb7777@korea.ac.kr
hwaran.lee@navercorp.com
park@joonsuk.org
minsukchang@google.com

Abstract

As the importance of identifying misinformation is increasing, many researchers focus on verifying textual claims on the web. One of the most popular tasks to achieve this is fact verification, which retrieves an evidence sentence from a large knowledge source such as Wikipedia to either verify or refute each factual claim. However, while such problem formulation is helpful for detecting false claims and fake news, it is not applicable to catching subtle differences in factually consistent claims which still might implicitly bias the readers, especially in contentious topics such as political, gender, or racial issues. In this study, we propose ClaimDiff, a novel dataset to compare the nuance between claim pairs in both a discriminative and a generative manner, with the underlying assumption that one is not necessarily more true than the other. This differs from existing fact verification datasets that verify the target sentence with respect to an absolute truth. We hope this task assists people in making more informed decisions among various sources of media.

1 Introduction

With an ever-increasing amount of textual information on the web, many researchers have focused on detecting misinformation from diverse sources, such as detecting fake news (Potthast et al., 2018) and rumor tweets (Zubiaga et al., 2016; Kochkina et al., 2018). In particular, the fact verification task (Thorne et al., 2018; Aly et al., 2021) has become popular due to its utility and the availability of reliable datasets such as FEVER (Thorne et al., 2018).

For contentious topics, however, fact verification alone is not sufficient; comparing and contrasting claims from the opposing sides is necessary to gain an unbiased understanding of the topic. Note that this observation is not limited to subjective claims. Even objective claims can be used to bolster subjective opinions of the author by means of framing and selective presentation of relevant facts. For example, consider claims A and B in Figure 1 which are extracted from news articles by the Washington Post and CBS, respectively. Each claim, though seemingly objective, presents a biased view of the topic favoring a particular side: About the copyright dispute between Google and Oracle, claim A favors Oracle while claim B assists Google’s side.

In this paper, we present ClaimDiff, a novel dataset consisting of 2,204 pairs of claims extracted from news articles on 137 contentious topics.¹ The dataset is designed to support two tasks, determining whether a claim strengthens (ClaimDiff-S) or weakens (ClaimDiff-W) another claim. ClaimD-

¹The articles were collected from allsides.com, licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.
iff focuses on recognizing the relationship and comparison between two claims on a topic; this is distinguished from existing tasks such as fact verification—verifying the veracity of a claim using evidence sentences/documents—and stance detection—identifying the stance of a claim toward a topic. Also, while ClaimDiff targets sentence-level relations, models trained on it can be used to conduct document-level analyses as shown in Figure 2.

As an initial study on ClaimDiff, we present fine-tuned BERT / T5 (Devlin et al., 2019; Raffel et al., 2020), prompt-tuned T5 (Lester et al., 2021), and zero-shot T0 (Sanh et al., 2021) as baselines. We further investigate the rationale generation abilities of fine-tuned rationale baselines.

Contributions of our work as follows:

• We present ClaimDiff, a novel dataset for comparing claims on contentious topics. This complements existing work focused on the factuality and the verification of claims.

• We present competitive baselines for the dataset, leveraging fine-tuned, prompt-tuned, and zero-shot approaches. Existing models fail to reach the human performance, with the F1 gaps of 13% (ClaimDiff-S) and 32% (ClaimDiff-W). ClaimDiff further provides stance labels with rationales that help to build explainable models.  

• We extend the ClaimDiff to document-level to compare two news articles. This can be further applicable to building an assistant system for readers to obtain information from diverse views in an efficient and unbiased way.

2 Related Works

Dealing with Misinformation With a massive amount of information on the web, detecting and avoiding misinformation received intense interest. Existing works introduced benchmarks with a broad spectrum of sources, including rumors in social media (Potthast et al., 2018; Kochkina et al., 2018) and fake news (Zubiaga et al., 2016). Other researchers focus on dealing with an exploding amount of misinformation on global events, such as the COVID-19 pandemic (Saakyan et al., 2021; Jiang et al., 2021; Alam et al., 2021). While many previous benchmarks aim to detect the wrong information on unverified sources, our work targets subtle differences in verified sources, leading to biased views on contentious topics.

Claim Verification Claim verification or fact verification verifies the factuality of the target sentence with respect to an absolute truth from verified sources. Automatic claim verification shows remarkable progress with the introduction of rich claim verification datasets (Vlachos and Riedel, 2014; Thorne et al., 2018; Hanselowski et al., 2019; Aly et al., 2021; Khan et al., 2022). Existing claim verification datasets introduce many variants, including shift in domains and languages of claims; claims from political sources (Wang, 2017), scientific claims (Wadden et al., 2020), climate change-related claims (Leippold and Diggelmann, 2020), Arabic claims (Baly et al., 2018; Alhindi et al., 2021), and Danish claims (Nørregaard and Derczynski, 2021). Our assumption is different from claim verification in that one claim is not necessarily more true than the other, resulting the need for comparison between claims rather than verification.

Stance Detection Stance detection aims to predict the stance of a claim toward a specific topic between agreeing or opposing perspectives. Mohammad et al. (2016) propose SemEval challenges to predict the stance of tweets toward target keywords. Derczynski et al. (2017) further presents a sub-challenge to detect the stance of corresponding threads of rumor tweets. Many other benchmarks are introduced with diverse challenges, such as claim-based stance detection (Ferreira and Vlachos,
Table 1: Statistics of ClaimDiff dataset. Test-full indicates raw test dataset over whole article, including neutral claims.

2016; Bar-Haim et al., 2017), stance detection with evidence (Chen et al., 2019), and stance detection over political domains (Li et al., 2021).

3 ClaimDiff

This section formally defines ClaimDiff task (Section 3.1) and then describes how the dataset is constructed (Section 3.2). We also provide the statistics and the analysis of the resulting dataset in Section 3.3 and 3.4.

3.1 Task Description

ClaimDiff consists of two sub-tasks: (1) classifying the relation between the given pair of claims into whether one strengthens or weakens the other, and (2) generating the rationale for the relation. For instance, as shown in Figure 1, claim A and claim B are both about the copyright dispute of codes in the Android operating system. Claim A argues that it is problematic, while claim B argues it is fair use. We want to classify this case into weakens as claim A weakens the other’s argument (claim B). Although, in this case, claim B weakens claim A as well, note that the relation is not guaranteed to be the same in the opposite direction in general.

More formally, given a claim pair \((c_1, c_2)\), the first goal of ClaimDiff is to correctly answer the questions asking whether the difference exists. It is composed of two questions; (i) whether \(c_1\) strengthens \(c_2\) and (ii) whether \(c_1\) weakens \(c_2\) or not. We call each question as ClaimDiff-S and ClaimDiff-W, respectively. Both questions are solved as binary classification tasks. If contents of \(c_1\) strengthen the subjectivity of \(c_2\) or \(c_1\) shares the stance with \(c_2\), the answer for ClaimDiff-S becomes positive. When \(c_1\) weakens the subjectivity of \(c_2\) or \(c_1\) has opposing stance with the other, the result for ClaimDiff-W becomes positive. If \(c_2\) and \(c_1\) do not affect the subjectivity of each other, both become negative. Note that for a single claim pair, either one of ClaimDiff-S or ClaimDiff-W can be positive.

For positive pairs in ClaimDiff-S and ClaimDiff-W, the next goal is rationale generation, which generates the phrases that support the relation. We consider phrases in each claim as rationales, and a single example can have multiple rationales. For instance, in Figure 1, a rationale for ClaimDiff-W is ‘Google stole when it was creating its Android operating system’. The above phrase weakens the perspective claim A, about the view that copying the code was long-settled and good for technical progress.

3.2 Constructing ClaimDiff Dataset

Raw Data Collection We first collected a group of news articles from AllSides\(^3\) headlines. In AllSide headlines, there are groups of news articles about the same topics with different media press. The article groups have a wide political spectrum; each belongs to one of (left, center, and right) political stances. We crawl the headline pages uploaded from 2012-06-01 to 2021-11-21, covering more than 180 media sources. We choose two articles with left and right labels if possible.

To construct the claim pairs, we filtered the sentences from each article. As most claim pairs do not provide overlapping contents, a large proportion of pairs are not related. We apply an additional filtering process using human evaluators\(^4\) to collect the overlapping claim pairs. Each annotator answered the question, ‘Does target sentence overlap with a given sentence?’, where each sentence is from two different articles. Given a single example, three annotators made a response. We collected the pairs if at least two annotators answered given pairs are overlapping.

Annotation Process After the filtering process, we conducted a labeling process with 15 in-house expert annotators to obtain the final data. Given a pair of claims, the annotators were requested to determine the stance among strengthen, weaken and no effect. If they choose strengthen or weaken, the annotators had to choose the phrases that strengthen or weaken the other claim. The overall interface for the data collection process is shown in Appendix.

From three to five participants submitted their responses for each single claim pair. We collected the responses and converted the relation options to scaled values. We first consider strengthen as 1, weaken as -1, and no effect as 0 and av-

\(^3\)https://www.allsides.com/unbiased-balanced-news/
\(^4\)https://www.mturk.com/
average the choices after conversion. We filtered out the pairs with the absolute average values between (0, 0.5), whose relations are ambiguous. The pairs with positive values are mapped into strengthening claims (1 for ClaimDiff-S), and the pairs with negative values are mapped into weakening claims (1 for ClaimDiff-W). If the resulting values are exactly 0, the claims become 0 for both ClaimDiff-S and ClaimDiff-W. We measure the average inner-annotation agreement by Krippendorff’s alpha (Hayes and Krippendorff, 2007) of 0.46 on ClaimDiff-S and 0.47 of ClaimDiff-W.

### Constructing Test-full Dataset
To encounter the real-world distribution over whole articles, we provide an additional test dataset, Test-full, following the distribution over whole article pairs. Test-full can be considered as an unfiltered test dataset, resulting in a high ratio of not related pairs. We collect the negative claim pairs obtained from the previous filtering step, given a set of articles in the test dataset. Over 70% of the claim pairs from article pairs are not related, resulting in a highly skewed distribution. We combine filtered out claim pairs with standard test dataset to construct final Test-full dataset.

### 3.3 Dataset Statistics
As shown in Table 1, ClaimDiff dataset provides overall 1,857 examples, extracted from 274 articles with 137 topics. We extract the pairs from a group of articles sharing the same topic, released by multiple presses. The diverse views on contentious topics can be obtained by collecting the claims written by different authors and presses. Finding the weakening claim pairs is challenging, resulting in less than 8% positive examples in the test-full environment.

### 3.4 Dataset Analysis
This part analyzes strengthening and weakening claim pairs in ClaimDiff. We first provide the subjectivity analysis over claims with positive labels in ClaimDiff-S and ClaimDiff-W. ClaimDiff includes both subjective and objective claims, indicating the proposed task defines more general relation between claims than fact verification. We further present prediction results of the natural language inference (NLI) and fact verification (FEVER) models, showing that previous models do not cover the understanding of nuances.

#### Subjectivity Analysis
To analyze the subjectivity of claims, we randomly sample 50 positive examples from each ClaimDiff-S and ClaimDiff-W test dataset. We manually label each claim in a pair between subjective and objective. The results are shown in Figure 3 (a). Both tasks include subjective and objective claims, while ClaimDiff-W includes a relatively higher proportion of subjective claims. We expect at ClaimDiff-W is more challenging because of not only the skewed distribution but also more diverse composition of claims.

#### Prediction Results of NLI / FEVER Model
To compare the ClaimDiff with previous sentence pair classification tasks such as NLI and FEVER tasks, Figure 3 (b) and (c) present the prediction results of transformer-based models trained on NLI and FEVER. We trained RoBERTa-large (Liu et al.,
2019) on each MNLI(Williams et al., 2018) and FEVER(Thorne et al., 2018), resulting in F1 of 90.2% (MNLI) and 70.1% (FEVER). Note that we only provide the prediction results of positive claim pairs, having strengthens or weakens relation in the test dataset. The MNLI model predicts most claims as neutral pairs on both ClaimDiff-S and ClaimDiff-W, while the FEVER model predicts them as supporting claims. This failure might come from multiple reasons, including the domain shift in claims and the different goals of each task. Figure 3 (c) shows a large ratio of supporting claims in both tasks, indicating the objectivity of given pairs is already verifiable. Strengthen and weaken relations are defined over objectively verified pairs, showing fact verification is not sufficient to catch the proposed differences.

4 Task 1 - S / W Classification

4.1 Experimental Setup

We provide the following baselines according to the learning strategies: (1) fine-tuning pre-trained language models, (2) prompt-tuning, and (3) zero-shot baselines. Implementation details of each model are described in Appendix.

Fine-tuning Baselines We fine-tune pre-trained language models for the sentence classification tasks. Each model takes a pair of claims as inputs and predicts whether the first claim strengthens/weakens the other. We construct the development data by sampling 25% of topics from training data. To measure the test performance, we select hyperparameters and thresholds based on development results. We train two types of pre-trained language models, BERT-base (Devlin et al., 2019) and T5-base (Raffel et al., 2020), on ClaimDiff-S and ClaimDiff-W, respectively.

Prompt-tuning Baselines As the number of training examples is not as large as previous fact verification datasets, we further measure the performance of prompt-tuned models. We train T5(Raffel et al., 2020) based on prompt-tuning method on training data. Following Lester et al. (2021), we concatenate 100 prompt token embeddings and optimize the embeddings while freezing the models. To evaluate the models with a limited number of data, we train the models on 100 positive and negative examples extracted from ClaimDiff-S and ClaimDiff-W, respectively. Like fine-tuned baselines, thresholds are determined by the F1 results on the development split, which is also composed of 100 positive and negative examples. We train T5 models by increasing the size, T5-base, T5-large, and T5-3B.

Zero-shot Baselines We further present the zero-shot performance of large language models, T0 (Wei et al., 2021). We use the same input formats as in prompt-tuned baselines, except for the additional prompt tokens. Unlike previous baselines, the thresholds for both ClaimDiff-S and ClaimDiff-W are 0.5 to test the zero-shot environment.

4.2 Evaluation on ClaimDiff Test

Human Evaluation Following Rajpurkar et al. (2016), we evaluate human performance on ClaimDiff based on the human annotation results. As each example has at least three responses, we randomly sample one response as prediction and leave others as ground truth answers. We follow the same procedures as in Section 3.2. The resulting human performance is shown in Table 2, indicating human is capable to detecting both types of relation, resulting in a significant gap between human and model performance. Even for more challenging ClaimDiff-W, readers can figure out more than half of the weakening nuances while maintaining

| Model       | F1  | Precision | Recall |
|-------------|-----|-----------|--------|
| ClaimDiff-S |     |           |        |
| Random      | 52.50 | 49.23    | 56.26  |
| Human Evaluation | 86.27 | 95.34    | 78.77  |
| BERT-base*  | 73.12 | 58.19    | 98.37  |
| T5-base*    | 72.21 | 56.61    | 99.67  |
| T5-base†    | 69.18 | 57.38    | 86.64  |
| T5-large‡   | 69.03 | 56.55    | 88.60  |
| T0‡         | 61.44 | 69.78    | 54.89  |
| ClaimDiff-W |     |           |        |
| Random      | 30.71 | 22.35    | 49.14  |
| Human Evaluation | 68.29 | 81.01    | 58.56  |
| BERT-base*  | 33.87 | 22.87    | 65.27  |
| T5-base*    | 32.46 | 23.13    | 54.39  |
| T5-base†    | 35.90 | 21.96    | 98.32  |
| T5-large‡   | 35.44 | 21.79    | 94.98  |
| T0‡         | 20.50 | 15.32    | 30.96  |

Table 2: Performance on ClaimDiff test dataset. Human represents the human performance evaluated on test dataset. Each symbol represents: * fine-tuned baselines, † prompt-tuned baselines, and ‡ zero-shot baselines.

Following (Nie et al., 2019), we convert FEVER into NLI-style task, predicting only the labels among Support, Refute, and Not enough info given query and context.
Table 3: Performance measured on Test-full dataset. AP represents the average precision, and P@50 / P@80 represents precision at fixed recall of 50 / 80, respectively.

81.01% of precision.

**Main Results** The overall evaluation results are presented in Table 2. We measure the random performance by randomly sampling the prediction from the uniform distribution. Except for human evaluation, BERT-base results the best F1 on ClaimDiff-S, while prompt-tuned T5 achieves the best results on ClaimDiff-W. T0 performs worst, showing a lower F1 than random predictions on ClaimDiff-W, which might be due to the non-optimal form of prompts. We are still working on finding the optimal prompts for the zero-shot baseline. When comparing with human results, ClaimDiff-W shows a significant gap between humans and models. The possible reasons for the failure are the difficulty of ClaimDiff-W and non-optimal configurations. Solving ClaimDiff-W is more challenging because of a low appearance rate of weakening examples and a more diverse composition of subjective / objective claims.

### 4.3 Evaluation on ClaimDiff Test-full

Test-full represents the distribution of the whole articles, having a high ratio of non-overlapping claims. In the case of Test-full, the critical goal is to detect the informative claim pairs, which have strengthening or weakening relations. We provide additional metrics for Test-full: Average precision (AP), P@50, and P@80. AP measures the area under the precision-recall curve (PR curve), while P@50 and P@80 report the precision of the points whose recall is 50 and 80. All three metrics present the number of how well the model retains the precision while detecting a different amount of positive examples.

We evaluate the same baselines as in Section 4.2 on Test-full. Note that we do not provide human performance on Test-full, as obtaining human annotation over whole articles is costly. T0 results the best F1 on ClaimDiff-S with the highest precision among baselines. Comparing fine-tuned and prompt-tuned baselines, fine-tuned baseline works better with the same number of parameters (T5-base). However, due to the small size of the dataset, fine-tuning larger models on ClaimDiff is challenging, which easily overfits to wrong predictions (e.g., always predicting 0). Although prompt-tuned T5-large is optimized on only 200 examples, it shows the competitive performance with fine-tuned T5-base, showing the effectiveness of bigger models.

### 5 Task 2 - Rationale Generation

We perform rational generation over related pairs, whose relation is positive for one of ClaimDiff-S and ClaimDiff-W. Unlike S / W Detection, we train a single model to generate rationales for both tasks. The performance is also measured on combined sets of ClaimDiff-S and ClaimDiff-W.

#### 5.1 Models

**T5** Since prior works (Narang et al., 2020; Lakhotia et al., 2021) on extractive rationale generation showed strong performance on several ERASER (DeYoung et al., 2020) tasks, we fine-tune the pre-trained T5 model to sequentially generate rationales in a token-by-token fashion. Formally, given claim pairs \((c_1, c_2)\) and the relation label \(r\), our goal is to obtain rationale phrases \(\{e_k\}_{k=1}^K\), \(e_k \in c_1\), that supports the relation. Specifically, the model takes input as “explain claimdiff claim1: \(c_1\) claim2: \(c_2\), and is trained to generate the target sequence represented as “explanation: \(e_1\) ··· explanation: \(e_k\)”. In the case of \(\text{w/ label}\) in Table 4, we additionally append “relation: \(r\)” to the input text, where \(r\) is strengthen or weaken.
Table 4: Rationale generation performance measured on test set. We fine-tuned T5 on two different settings: when strengthen / weaken labels are given as inputs (w/ label) and labels are not given (w/o label).

|                  | Perplexity | TF1    | IOU F1 |
|------------------|------------|--------|--------|
| **w/o label**    |            |        |        |
| T5-base          | 1.65       | 74.08  | 64.57  |
| T5-large         | 1.46       | 75.05  | 65.26  |
| **w/ label**     |            |        |        |
| T5-base          | 1.58       | 68.77  | 60.40  |
| T5-large         | 1.50       | 75.18  | 65.01  |

5.2 Evaluation Metrics

**Perplexity** We report the per-token perplexity of rationales which measures how well the language model predicts the tokens in each rationale. Perplexity is defined as the exponentiated average negative log-likelihood of a sequence. Formally, given tokenized sequence $X = \{x_1, x_2, ..., x_t\}$, the perplexity of $X$ is defined as

$$\text{PPL}(X) = \exp \left\{ -\frac{1}{t} \sum_{i} \log p_{\theta}(x_i|x_{<i}) \right\}$$  (1)

**Token F1 (TF1)** Following Lakhotia et al. (2021), we compute the TF1 scores between ground-truth rationales and generated rationales. TF1 calculates the token-level F1 score, which measures the number of overlapping tokens between two rationales. Following DeYoung et al. (2020), we use spaCy tokenizer\(^6\) to compute the F1 score.

**Intersection over Union F1 (IOU F1)** IOU F1, present by DeYoung et al. (2020), computes the F1 score on matched predictions. IOU F1 first checks whether predicted rationales match ground-truth rationales by calculating the intersection of union (IOU). IOU is the value that computes the number of overlapping tokens divided by the union of tokens. If IOU is larger than the threshold, the predicted explanation becomes a matched prediction. In this work, we set the threshold as 0.5.

5.3 Results

In table 4, we show the results of fine-tuned T5 model trained on rationale generation. Following DeYoung et al. (2020), we report extractive measures (TF1 and IOUF1), as the ground-truth rationales are extracted phrases from each claim. We further measure the generative score (perplexity) over the generated rationales. Note that we choose perplexity because rationales are in the form of phrases rather than complete sentences. T5-large consistently provides better results than T5-base for both w/ label and w/o label settings. The injection of labels degrades the performance of T5-base, while the T5-large shows a slight improvement. The increasing number of parameters is also beneficial for incorporating additional label information.

6 Conclusion

This paper introduces ClaimDiff, a dataset for comparing claims on contentious topics in a discriminative and generative manner. When dealing with contentious topics, even the objective claims might lead the subjective views of events. To catch these subtle differences, we need to compare two claims rather than verify the objectivity. We experiment with pre-trained language model baselines with fine-tuned, prompt-tuned, and zero-shot approaches. The results show a significant room for improvement with over 30% gap between human and model performance. We further provide document-level ClaimDiff and demo with document-level baselines.\(^2\) We hope this work to be an initial study for providing a service for readers to obtain an unbiased understanding of contentious topics.

References

Firoj Alam, Shaden Shaar, Fahim Dalvi, Hassan Sajjad, Alex Nikolov, Hamdy Mubarak, Giovanni Da San Martino, Ahmed Abdelali, Nadir Durrani, Kareem Darwish, Abdulaziz Al-Homaid, Wajdi Zahouani, Tommaso Caselli, Gijs Danoe, Friso Stolk, Britt Brunink, and Preslav Nakov. 2021. Fighting the COVID-19 infodemic: Modeling the perspective of journalists, fact-checkers, social media platforms, policy makers, and the society. In Findings of the Association for Computational Linguistics: EMNLP 2021, pages 611–649, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Tariq Alhindi, Amal Alabdulkarim, Ali Alshehri, Muhammad Abdul-Mageed, and Preslav Nakov. 2021. AraStance: A multi-country and multi-domain dataset of Arabic stance detection for fact checking. In Proceedings of the Fourth Workshop on NLP for Internet Freedom: Censorship, Disinformation, and Propaganda, pages 57–65, Online. Association for Computational Linguistics.

Rami Aly, Zhijiang Guo, Michael Sejr Schlichtkrull, James Thorne, Andreas Vlachos, Christos
\(^6\)https://spacy.io/
\(^2\)We will upload the link for the demo.
Ramy Baly, Mitra Mohtarami, James Glass, Luís Machado, Alessandro Moschitti, and Preslav Nakov. 2018. Integrating stance detection and fact checking in a unified corpus. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 21–27, New Orleans, Louisiana. Association for Computational Linguistics.

Roy Bar-Haim, Indrajit Bhattacharya, Francesco Dinuzio, Amrita Saha, and Noam Slonim. 2017. Stance classification of context-dependent claims. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 251–261, Valencia, Spain. Association for Computational Linguistics.

Si Shao Chen, Daniel Khashabi, Wenpeng Yin, Chris Callison-Burch, and Dan Roth. 2019. Seeing things from a different angle: discovering diverse perspectives about claims. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 542–557, Minneapolis, Minnesota. Association for Computational Linguistics.

Leon Derczynski, Kalina Bontcheva, Maria Liakata, Rob Procter, Geraline Wong Sak Hoi, and Arkaitz Zubiaga. 2017. SemEval-2017 task 8: RumourEval: Determining rumour veracity and support for rumours. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 69–76, Vancouver, Canada. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Jay DeYoung, Sarthak Jain, Nazneen Fatema Rajani, Eric Lehman, Caiming Xiong, Richard Socher, and Byron C. Wallace. 2020. ERASER: A benchmark to evaluate rationalized NLP models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4443–4458, Online. Association for Computational Linguistics.

William Ferreira and Andreas Vlachos. 2016. Emergent: a novel data-set for stance classification. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1163–1168, San Diego, California. Association for Computational Linguistics.

Andreas Hanselowski, Christian Stab, Claudia Schulz, Zile Li, and Iryna Gurevych. 2019. A richly annotated corpus for different tasks in automated fact-checking. In Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL), pages 493–503, Hong Kong, China. Association for Computational Linguistics.

Andrew F. Hayes and Klaus Krippendorff. 2007. Answering the call for a standard reliability measure for coding data. Communication Methods and Measures, 1(1):77–89.

Ye Jiang, Xingyi Song, Carolina Scarton, Ahmet Aker, and Kalina Bontcheva. 2021. Categorising fine-to-coarse grained misinformation: An empirical study of covid-19 infodemic. arXiv preprint arXiv:2106.11702.

Kashif Khan, Ruizhe Wang, and Pascal Poupart. 2022. WatClaimCheck: A new dataset for claim entailment and inference. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1293–1304, Dublin, Ireland. Association for Computational Linguistics.

Elena Kochkina, Maria Liakata, and Arkaitz Zubiaga. 2018. All-in-one: Multi-task learning for rumour verification. In Proceedings of the 27th International Conference on Computational Linguistics, pages 3402–3413, Santa Fe, New Mexico, USA. Association for Computational Linguistics.

Kushal Lakhota, Bhargavi Paranjape, Asish Ghoshal, Scott Yih, Yashar Mehdad, and Sriniv Iyer. 2021. FiD-ex: Improving sequence-to-sequence models for extractive rationale generation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 3712–3727, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Markus Leippold and Thomas Diggelmann. 2020. Climate-fever: A dataset for verification of real-world climate claims. In NeurIPS 2020 Workshop on Tackling Climate Change with Machine Learning.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 3045–3059, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Yingjie Li, Tiberiu Sosea, Aditya Sawant, Ajith Jayaraman Nair, Diana Inkpen, and Cornelia Caragea.
Arkadiy Saakyan, Tuhin Chakrabarty, and Smaranda Muresan. 2021. COVID-fact: Fact extraction and verification of real-world claims on COVID-19 pandemic. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2116–2129, Online. Association for Computational Linguistics.

Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. 2021. Multitask prompted training enables zero-shot task generalization. arXiv preprint arXiv:2110.08207.

James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. FEVER: a large-scale dataset for fact extraction and VERification. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 809–819, New Orleans, Louisiana. Association for Computational Linguistics.

Andreas Vlachos and Sebastian Riedel. 2014. Fact checking: Task definition and dataset construction. In Proceedings of the ACL 2014 Workshop on Language Technologies and Computational Social Science, pages 18–22, Baltimore, MD, USA. Association for Computational Linguistics.

David Wadden, Shanchuan Lin, Kyle Lo, Lucy Lu Wang, Madeleine van Zuylen, Arman Cohan, and Hannaneh Hajishirzi. 2020. Fact or fiction: Verifying scientific claims. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7534–7550, Online. Association for Computational Linguistics.

William Yang Wang. 2017. “liar, liar pants on fire”: A new benchmark dataset for fake news detection. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 422–426, Vancouver, Canada. Association for Computational Linguistics.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2021. Finetuned language models are zero-shot learners. arXiv preprint arXiv:2109.01652.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.

Arkaitz Zubiaga, Maria Liakata, Rob Procter, Geraldine Wong Suk Hoi, and Peter Tolmie. 2016. Analysing how people orient to and spread rumours in social media by looking at conversational threads. PloS one, 11(3):e0150989.