Improving the fact-checking performance of language models by relying on their entailment ability

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Abstract

Automated fact-checking is a crucial task in this digital age. The NLP community has been trying various strategies to build robust fact-checking systems. However, we have not been very successful yet. One main reason behind this is that fact verification is a complex process. Language models have to parse through multiple pieces of evidence, often contradicting each other, to predict a claim's veracity. In this paper, we proposed a simple yet effective strategy, where we relied on the entailment ability of language models to improve the fact-checking performance. Apart from that, we did a comparison of different prompting and fine-tuning strategies, as it is currently lacking in the literature. Some of our observations are: (i) training language models with raw evidence sentences (**TBE-1**) and overall claim-evidence understanding (**TBE-2**) resulted in an improvement up to **8.20%** and **16.39%** in macro-F1 for RAW-FC dataset, and (ii) training language models with entailed justifications (**TBE-3**) outperformed the baselines by a huge margin (up to **28.57%** and **44.26%** for LIAR-RAW and RAW-FC, respectively). We have shared our code repository to reproduce the results.

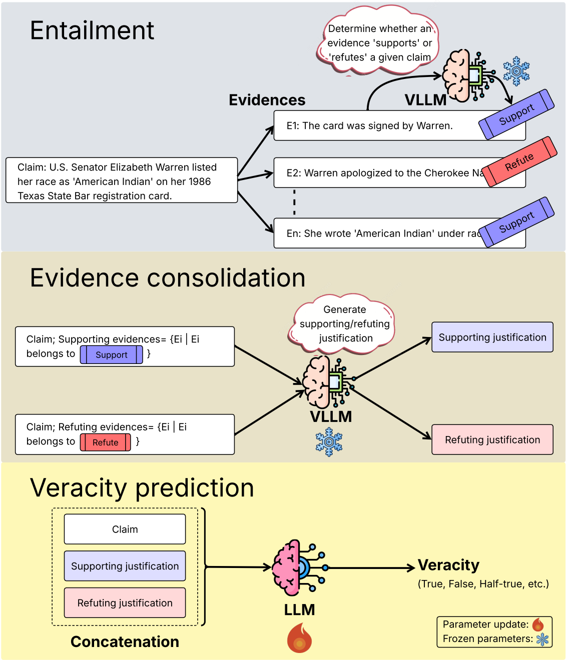
Entailment
Determine whether an evidence 'supports' or 'refutes' a given claim
Evidences
VLLM
Claim: U.S. Senator Elizabeth Warren listed her race as 'American Indian' on her 1986 Texas State Bar registration card.
E1: The card was signed by Warren.
Support
E2: Warren apologized to the Cherokee Na
Refute
En: She wrote 'American Indian' under rac
Support
Evidence consolidation
Generate supporting/refuting justification
Claim; Supporting evidences= {Ei | Ei belongs to Support }
Claim; Refuting evidences= {Ei | Ei belongs to Refute }
VLLM
Supporting justification
Refuting justification
Veracity prediction
Claim
Supporting justification
Refuting justification
Concatenation
LLM
Veracity
(True, False, Half-true, etc.)
Parameter update:
Frozen parameters:

Figure 1: A schematic diagram explaining fact-checking based on entailment, which breaks down into three stages. (a) *Entailment*: Given a claim and its corresponding evidences, a VLLM first distinguishes evidences into supporting/ refuting evidence via entailment. (b) *Evidence consolidation*: Then the same VLLM consolidates these two groups into concise supporting and refuting justification. (c) *Veracity prediction*: Using the claim and both justifications, an LLM is trained to predict veracity.

1 Introduction:

The spread of misinformation on the internet has grown to be a pressing social issue. Its consequences have manifested across social, political and commercial domains (Mozur, 2018; Fisher et al., 2016; Allcott and Gentzkow, 2017; Burki, 2019; Aghababaeian et al., 2020). To counter the spread, institutional interventions such as, the International Fact-Checking Network (IFCN) came up, which works with over 170 fact-checking organisations and websites worldwide (as of July 2024 [1]). However, manually verifying facts and detecting misinformation is a slow and costly process. Also, it is impossible to match the pace at which misinformation evolves and spreads over the internet. To overcome this, the research community have been trying to automate the process. Their interest can be gauged by the fact that more than twelve hundred research articles and fifty datasets were published on this topic (Alnabhan and Branco, 2024; Guo et al., 2022). A detailed discussion of such works is done in the Appendix A.

Doing automated fact-checking at scale is still an open challenge. Most of the proposed approaches relied on language models (Shu et al., 2022; Yang

[1] https://www.poynter.org/ifcn/

et al., 2022a; Yue et al., 2023; Choi and Ferrara, 2024a). Researchers have either (i) relied on their embedded knowledge or (ii) used evidence collected from various sources to predict the veracity. For example, while Pan et al. (2021); Zeng and Gao (2023); Dhuliawala et al. (2024) relied on embedded knowledge by using *zero-shot*, *few-shot* and *chain-of-thought* based approaches, Galitsky (2025); Zhang and Gao (2023) retrieved evidence pieces from the web to verify facts. However, the accuracy of existing systems is not high enough to deploy in the real world. The primary reason behind this is that fact verification is a complex process. Language models have to parse through multiple pieces of evidence, which often contradict each other. The contradictory pieces of evidence confuse the language models, leading to poor performance. To overcome this, we proposed a simple strategy, where we relied on the entailment and the generative ability of language models to improve the fact-checking performance. Particularly, we asked generative very large language models (VLLMs) to produce "supporting" and "refuting" justifications (for the truthfulness of a claim) based on respective pools of evidence sentences, and trained encoder-only language models (LLMs) to produce veracity. This strategy is showcased in Figure 1.

Our approach was inspired by Wang et al. (2024a). They relied on attention mechanisms to extract top-k evidence sentences stating the claim to be 'true' and 'false'. They produced respective justifications by promoting and then trained the language models to produce veracity. We, on the other hand, used VLLMs to classify the sentences as "supporting" or "refuting" and considered all evidence sentences for classification. The simplicity of our approach allows us to easily deploy our system in the real world. Also, in our experiments, we found that our approach improves the overall performance. We also compared our approach with different prompting and fine-tuning strategies through a series of experiments. All of our experiments are done around three research questions. They are,

- **R1:** *"How well do the language models perform when only claim and raw evidence sentences are available?"*

- **R2:** *"Does prompted claim-evidence understanding improve the performance of the language models?*

- **R3:** *"Can prompted entailed justifications improve the claim veracity prediction?"*

Our key contributions and observations in this work can be summarised as follows,

- We conducted three training-based (**TBEs**) and four inference-based (**IBEs**) experiments along the line of the **R1**, **R2** and **R3**. For RAW-FC, training with raw evidence sentences (**TBE-1**) and overall claim-evidence understanding (**TBE-2**) registered an improvement up to **8.20%** and **16.39%** in macro-F1 over baseline. Training with entailed justifications (**TBE-3**), on the other hand, outperformed the baselines by a huge margin (up to **28.57%** and **44.26%** for LIAR-RAW and RAW-FC, respectively).

- We considered the entailed justifications generated by VLLMs as model explanations, and evaluated them using two strategies: (i) checking lexical overlap and semantic matching, and (ii) doing subjective evaluation by VLLMs itself. Notably, explanations generated by Llama received the highest subjective scores, correlating with the highest registered veracity prediction performance.

- We conducted (i) an ablation study by removing individual supporting and refuting entailed justifications and (ii) a thorough linguistic analysis of our models. We found that both of the entailed justifications are important, as their removal leads to a decline in MF performance. In linguistic analysis, we found that LLM could give high attention scores to appropriate keywords and factual pieces for samples with 'true' and 'false' labels. However, for samples with borderline (e.g. half-true) labels, attention scores seem to be scattered.

2 Dataset details:

In this section, we have reported the details of the datasets considered in our study. We considered the **LAIR-RAW** and **RAW-FC** datasets provided by Yang et al. (2022b). We selected them as they are popular and widely used in past works such as HiSS (Zhang and Gao, 2023), FactLLaMa (Cheung and Lam, 2023), RAFTS (Yue et al., 2024), L-Defence (Wang et al., 2024a), and others (Wang et al., 2025; Zhang and Gao, 2024; Xiong et al., 2025). While each sample of LAIR-RAW is tagged with one of six labels, samples of RAW-FC is tagged with one of three labels. The list of labels and their distribution in respective datasets are reported in Table 1. The datasets are open-source, i.e., they are Apache 2.0 licensed. A detailed description of the individual datasets, along with representative samples, is reported in the Appendix B.

Dataset	Classes	Count
LAIR-RAW (Yang et al., 2022b)	True (T)	2,021
	Mostly-true(MT)	2,439
	Half-true (HT)	2,594
	Barely-true (BT)	2,057
	False (F)	2,466
	Pants-fire (PF)	1,013
	Total	12,590
RAW-FC (Yang et al., 2022b)	True (T)	695
	Half-true (HT)	671
	False (F)	646
	Total	2,012

Table 1: Distribution of samples in the LIAR-RAW and RAW-FC datasets.

3 Experiments:

In this section, we have reported the details of the experiments we did in this study. As said earlier, we conducted three training-based (**TBEs**) and four inference-based (**IBEs**) experiments. The schematic diagram of individual **TBEs** and **IBEs** are illustrated in Figure 2. In **TBEs**, we finetuned (i) LLMs like RoBERTa (Liu et al., 2019) and XLNet (Yang et al., 2019), and (ii) VLLMs like Mistral (Jiang et al., 2023), Llama (AI@Meta, 2024), Gemma (Team et al., 2024), Qwen (Yang et al., 2024) and Falcon (Almazrouei et al., 2023) with LoRA (Hu et al., 2022) and LoRA+ (Hayou et al., 2024) adapters. Note that, unlike LLMs, we can not directly fine-tune VLLMs due to their large parameter size and computational constraints. Similarly, in **IBEs**, we prompted the considered VLLMs to predict the veracity. The details of individual experiments and the current state-of-the-art baselines are reported in the subsequent subsections.

3.1 Training Based Experiments (TBEs):

3.1.1 TBE-1: Training based on raw-evidences:

Our first training-based experiment was based on **R1**, where, we fine-tuned the LLMs by giving claims and raw evidence sentences. If any sample doesn't have any associated evidence sentence, we gave the claim as only input. We restricted ourselves from using LLMs like RoBERTa (Liu et al., 2019) and XLNet (Yang et al., 2019), as the length of many input instances exceeded the maximum supported input size. Past work (Cheung and Lam, 2023) demonstrated the effectiveness of fine-tuning VLLMs using evidence pieces from web search, whereas in our case, we used the gold evidence sentences given in the dataset. The emergence of adapter-based training allowed us to efficiently train the VLLMs with limited computational resources. To the best of our knowledge, we believe we are the first to fine-tune the VLLMs using raw evidence sentences. Our approach is illustrated in sub-figure (a) of Figure 2.

3.1.2 TBE-2: Training based on overall understanding:

Our second experiment in this line was based on **R2**. To conduct it, we first prompted the five considered VLLMs to generate their understanding of a given claim and its evidence pieces. For any samples which don't have an associated evidence sentence, VLLMs generated their understandings based on only the claim. With that, we fine-tuned the LLMs and VLLMs with adapters to produce the claim veracity. The detailed experimental process is illustrated in sub-figure (b) of Figure 2. Some of the prompt samples are presented in the appendix (Figure 18).

3.1.3 TBE-3: Training based on entailment understanding:

Our final training-based experiment was based on **R3**. To conduct it, we followed a three-step approach. In the first step, we prompted the considered VLLMs to classify if the associated evidence sentences are “supporting" or “refuting" a given claim. In the second step, we prompted the language models to generate supporting and refuting *justifications* based on the classified evidence sentences. For the cases where claims don't have any supporting or refuting evidence sentences, VLLMs generated justifications based on their embedded knowledge. Finally, based on the claims and the generated justifications, we fine-tuned the (i) considered LLMs and (ii) adapters with the VLLMs, to generate the veracity. The detailed approach is illustrated in sub-figure (c) of Figure 2. Some prompt samples we used at each step are illustrated in Figure 19, Figure 20, and Figure 21 in the appendix.

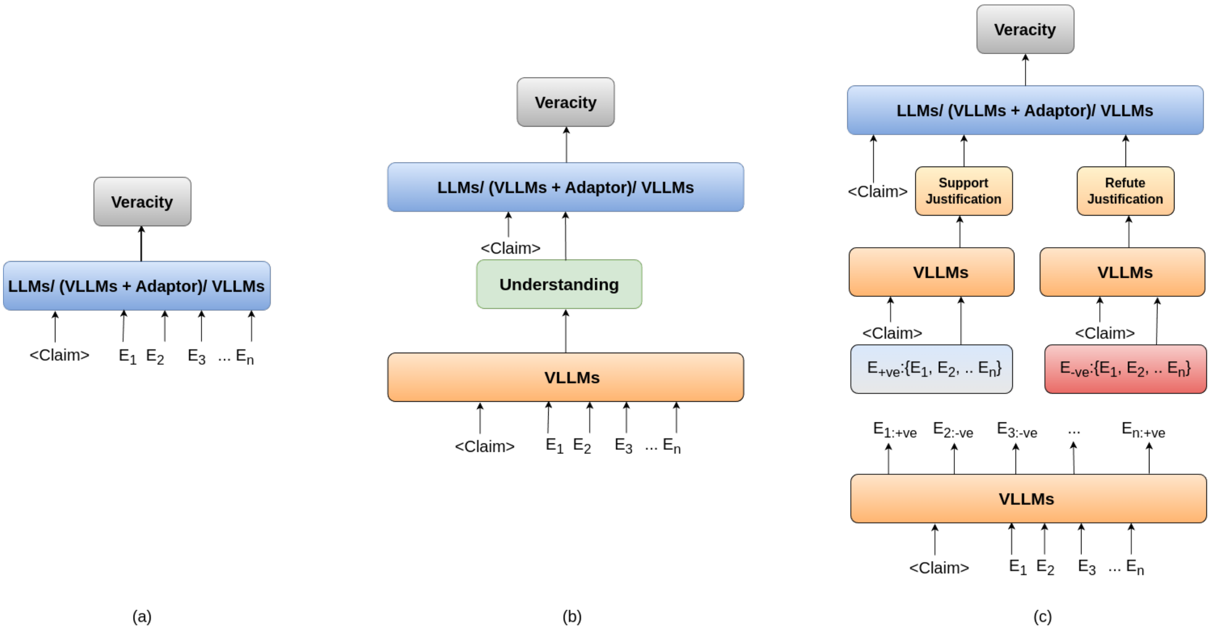
Veracity
LLMs/ (VLLMs + Adaptor)/ VLLMs
<Claim>
E_1 E_2 E_3 ... E_n
(a)
Veracity
LLMs/ (VLLMs + Adaptor)/ VLLMs
<Claim>
Understanding
VLLMs
<Claim>
E_1 E_2 E_3 ... E_n
(b)
Veracity
LLMs/ (VLLMs + Adaptor)/ VLLMs
<Claim>
Support Justification
Refute Justification
VLLMs
VLLMs
<Claim>
<Claim>
E_{+ve}:{E_1, E_2, .. E_n}
E_{-ve}:{E_1, E_2, .. E_n}
$E_{1:+ve}$ $E_{2:-ve}$ $E_{3:-ve}$ ... $E_{n:+ve}$
VLLMs
<Claim>
E_1 E_2 E_3 ... E_n
(c)

Figure 2: Illustration of steps we followed in different experiments. Sub-figure (a) presents the case where only raw evidence sentences and claims are given as input (**R1**). This approach is used in **TBE-1** and **IBE-1**. Sub-figure (b) shows the overall process of **TBE-2**, **IBE-2** and **IBE-3** based on **R2**. Sub-figure (c) illustrates the overall experimental process of **TBE-3** and **IBE-4** based on **R3**.

3.2 Inference Based Experiments (IBEs):

We conducted four IBEs based on **R1**, **R2** and **R3**. They are, (i) *zero-shot prompting* (**IBE-1**), where we prompted VLLMs to predict the veracity based on a claim and associated evidence pieces (as per **R1**), (ii) *zero-shot prompting with overall understanding* (**IBE-2**), where, first, we prompted the VLLMs to generate the claim-evidence understanding and then, prompted them again to predict the veracity (as per **R2**), (iii) *CoT prompting with overall understanding* (**IBE-3**), where we followed similar steps as in **IBE-2**, except, we asked VLLMs to additionally generate the reasoning, and (iv) *prompting based on entailment* (**IBE-4**), where we prompted the VLLMs to predict veracity based on entailed justifications (as per **R3**). Due to space constraints, we have reported the details of individual approaches in the appendix. For the cases where a claim doesn't have any associated evidence, we gave the claim as the input.

3.3 Baselines:

In this section, we have reported the previously proposed best-performing models as the baselines. Particularly, we compared our models with the performances of HiSS (Zhang and Gao, 2023), FactLLaMa (Cheung and Lam, 2023), RAFTS (Yue et al., 2024), and L-Defence (Wang et al., 2024a) models. Out of them, HiSS (Zhang and Gao, 2023) and FactLLaMa (Cheung and Lam, 2023) retrieved evidence from external sources, while RAFTS (Yue et al., 2024) employed a coarse-to-fine retrieval technique to extract evidence directly from the dataset. In contrast, L-Defense (Wang et al., 2024a) used relevant evidence without additional retrieval. The previously reported performance of these models on LIAR-RAW and RAW-FC datasets are presented in Table 2. All of the baselines and our experiments have used the same training, validation and test splits provided by Yang et al. (2022b) for justified comparison. A detailed description of the individual models is presented in the Appendix C.5.

Method	**LIAR-RAW**			**RAWFC**		
	MP	**MR**	**MF1**	**MP**	**MR**	**MF1**
HiSS	0.46	0.31	0.37	0.53	0.54	0.53
FactLLaMA	0.32	0.32	0.30	0.56	0.55	0.55
RAFTS	**0.47**	**0.37**	**0.42**	**0.62**	0.52	0.57
L-Defense						
-ChatGPT	0.30	0.32	0.30	0.61	**0.61**	**0.61**
-Llama2	0.31	0.31	0.31	0.61	0.60	0.60
	(0.29†)	(0.29†)	(0.29†)	(0.56†)	(0.56†)	(0.56†)

Table 2: Performance of the considered baselines for LIAR-RAW and RAWFC datasets. Notation: our reproduced results are marked as '†'.

4 Results and Discussion:

In this section, we have reported the results of our experiments. We used macro-precision (MP), macro-recall (MR) and macro-F1 ($MF1$) scores to evaluate the veracity prediction. Similarly, we used ROUGE, BLEU, BERT-score and have done subjective evaluation by VLLMs to evaluate model explainability. A detailed description of evaluation metrics is reported in subsection C.6.4 of the appendix.

Dataset	Method	Mistral	Llama	Gemma	Qwen	Falcon
LIAR-RAW	LoRA	0.27 (± 0.01)	**0.30** (± 0.00)	0.23 (± 0.04)	0.29 (± 0.04)	0.26 (± 0.01)
	LoRA+	0.25 (± 0.01)	0.29 (± 0.01)	0.22 (± 0.03)	0.29 (± 0.02)	0.29 (± 0.02)
RAW-FC	LoRA	0.65 (± 0.01)	0.65 (± 0.02)	0.57 (± 0.06)	**0.66** (± 0.03)	0.54 (± 0.06)
	LoRA+	0.55 (± 0.02)	0.65 (± 0.01)	0.57 (± 0.03)	0.65 (± 0.02)	0.63 (± 0.03)

Table 3: Performance of models under **TBE-1** for LIAR-RAW and RAW-FC datasets in terms of $MF1$. We have also reported variation across three random seeds (x). **Green** and Blue indicate best and second-best scores, respectively.

4.1 Observations for veracity prediction:

We reported the $MF1$ of various models under **TBE-1**, **TBE-2** - **TBE-3** and **IBEs** in Table 3, Table 4, and Table 5 respectively. A comparison of best performing models across all experiments are illustrated in Figure 22. Our observations are as follows,

- For LIAR-RAW, none of the macro-F1 reported by **IBE** models could surpass the best baseline performance. In contrast, for RAW-FC, Llama achieved the highest performance in IBE-2, surpassing the highest baseline performance.

- In **TBE-1**, for LIAR-RAW, the highest reported $MF1$ does not surpass that of baselines. However, for RAWFC, we found that many models, such as (i) Mistral ($\sim$ **6.56**$\%$ $\uparrow$), Llama ($\sim$ **6.56**$\%$ $\uparrow$) and Qwen ($\sim$ **8.20**$\%$ $\uparrow$) trained with LoRA, and (ii) Llama ($\sim$ **6.56**$\%$ $\uparrow$), Qwen ($\sim$ **6.56**$\%$ $\uparrow$) and Falcon ($\sim$ **3.28**$\%$ $\uparrow$) trained with LoRA+, outperform the best baseline performance ($F1$: **0.61**).

- In **TBE-2**, for LIAR-RAW, no model surpassed the best $MF1$ reported by the baselines. However, for RAW-FC, we observed that many models, such as (i) XLNet fine-tuned on Llama understandings ($\sim$ **1.64**$\%$ $\uparrow$), and (ii) Llama trained with LoRA+ based on Llama understandings ($\sim$ **16.39**$\%$ $\uparrow$) outperformed the best reported baseline $MF1$.

- Many models in **TBE-3**, such as (i) RoBERTa fine-tuned with Mistral ($\sim$ **16.39**$\%$ $\uparrow$), Llama ($\sim$ **23.81**$\%$ $\uparrow$), Gemma ($\sim$ **14.29**$\%$ $\uparrow$), Qwen ($\sim$ **9.52**$\%$ $\uparrow$), and Falcon ($\sim$ **4.76**$\%$ $\uparrow$) based entailed justifications, (ii) XLNet fine-tuned with Mistral ($\sim$ **16.39**$\%$ $\uparrow$), Llama ($\sim$ **28.57**$\%$ $\uparrow$), Qwen ($\sim$ **14.29**$\%$ $\uparrow$), and Falcon ($\sim$ **4.76**$\%$ $\uparrow$) based entailed justifications, and (iii) Llama trained with Llama justifications and LoRA+ adapter ($\sim$ **16.67**$\%$ $\uparrow$) surpassed the best reported macro-F1 score of baselines ($MF1$: **0.42**). Similarly, for RAW-FC, we observed that (i) RoBERTa fine-tuned with Mistral ($\sim$ **36.07**$\%$ $\uparrow$), Llama ($\sim$ **44.26**$\%$ $\uparrow$), Qwen ($\sim$ **16.39**$\%$ $\uparrow$), and Falcon ($\sim$ **4.91**$\%$ $\uparrow$) based entailed justifications, (ii) XLNet fine-tuned with Mistral ($\sim$ **34.42**$\%$ $\uparrow$), Llama ($\sim$ **42.62**$\%$ $\uparrow$), Qwen ($\sim$ **14.75**$\%$ $\uparrow$), and Falcon ($\sim$ **21.31**$\%$ $\uparrow$) based entailed justifications, and (iii) Llama trained (with Llama justifications) with LoRA+ adapter ($\sim$ **36.07**$\%$ $\uparrow$) outperformed the best reported macro-F1 score by the baselines ($MF1$: **0.61**). Models from **TBE-3**, exhibit highest overall performance. Figure 22 illustrates the same.

Some additional observations based on MP and MR are reported in the appendix (section D).

4.2 Observations from model explainability:

In this section, we have reported our observations from evaluating model explanations. The results of lexical-overlapping and semantic-matching based evaluations are reported in Table 15. Similarly, the results of subjective evaluations are reported in Figure 26 and Figure 27 (see Table 16 for raw values). Some of the key findings we got are,

- Falcon explanations got highest R_1 score for both LIAR-RAW (**0.23**) and RAW-FC (**0.40**). It means they show maximum unigram overlap with the gold explanations. Similarly, Mistral and Falcon explanations got the highest R_L score for LIAR-RAW (**0.14**). Mis-

Dataset (→)	**LIAR-RAW**		**RAW-FC**	
Method (↓)	TBE-2	TBE-3	TBE-2	TBE-3
FINE-TUNING				
-*RoBERTa-L*$_{Mistral}$	0.26 (±0.01)	0.47 (±0.01)	0.50 (±0.01)	0.83 (±0.01)
-*RoBERTa-L*$_{Llama}$	0.25 (±0.02)	0.52 (±0.01)	0.49 (±0.01)	**0.88** (±0.01)
-*RoBERTa-L*$_{Gemma}$	0.27 (±0.01)	0.48 (±0.02)	0.50 (±0.04)	0.49 (±0.02)
-*RoBERTa-L*$_{Qwen}$	0.28 (±0.01)	0.46 (±0.01)	0.48 (±0.02)	0.71 (±0.02)
-*RoBERTa-L*$_{Falcon}$	0.27 (±0.01)	0.44 (±0.01)	0.48 (±0.01)	0.64 (±0.02)
-*XLNet-L*$_{Mistral}$	0.28 (±0.01)	0.47 (±0.01)	0.61 (±0.02)	0.82 (±0.01)
-*XLNet-L*$_{Llama}$	0.29 (±0.01)	**0.54** (±0.01)	0.62 (±0.03)	0.87 (±0.01)
-*XLNet-L*$_{Gemma}$	0.25 (±0.02)	0.42 (±0.09)	0.50 (±0.01)	0.46 (±0.02)
-*XLNet-L*$_{Qwen}$	0.28 (±0.02)	0.48 (±0.01)	0.58 (±0.01)	0.70 (±0.04)
-*XLNet-L*$_{Falcon}$	0.24 (±0.03)	0.44 (±0.01)	0.60 (±0.01)	0.74 (±0.01)
LORA				
-*Mistral*	**0.32** (±0.01)	0.29 (±0.03)	0.60 (±0.04)	0.58 (±0.05)
-*Llama*	0.25 (±0.04)	0.30 (±0.04)	0.46 (±0.02)	0.61 (±0.03)
-*Gemma*	0.18 (±0.01)	0.20 (±0.02)	0.40 (±0.05)	0.30 (±0.02)
-*Qwen*	0.21 (±0.02)	0.32 (±0.05)	0.53 (±0.03)	0.46 (±0.03)
-*Falcon*	0.23 (±0.01)	0.21 (±0.02)	0.53 (±0.00)	0.41 (±0.03)
LORA+				
-*Mistral*	0.30 (±0.01)	0.27 (±0.03)	0.60 (±0.05)	0.46 (±0.04)
-*Llama*	0.23 (±0.02)	0.49 (±0.02)	**0.71** (±0.02)	0.82 (±0.03)
-*Gemma*	0.20 (±0.02)	0.29 (±0.06)	0.51 (±0.04)	0.46 (±0.01)
-*Qwen*	0.24 (±0.04)	0.29 (±0.03)	0.43 (±0.01)	0.47 (±0.09)
-*Falcon*	0.28 (±0.02)	0.36 (±0.04)	0.53 (±0.03)	0.50 (±0.03)

Table 4: Performance of claim veracity prediction using gold evidences in terms of macro F1(MF) score. **Green** and Blue indicate best and second-best performance, respectively.

Dataset (→)	**LIAR-RAW**				**RAW-FC**			
Method (↓)	IBE-1	IBE-2	IBE-3	IBE-4	IBE-1	IBE-2	IBE-3	IBE-4
PROMPTING								
-*Mistral*	**0.22**	0.20	**0.21**	**0.14**	0.53	0.58	0.45	**0.43**
-*Llama*	0.20	**0.22**	0.21	0.13	0.54	**0.62**	0.49	0.35
-*Gemma*	0.19	0.13	0.16	0.11	0.40	0.38	0.40	0.24
-*Qwen*	0.20	0.20	**0.21**	0.13	**0.59**	0.57	**0.52**	**0.43**
-*Falcon*	0.20	0.20	**0.21**	**0.14**	0.54	0.57	0.48	0.37

Table 5: Performance of Prompting methods across IBE-1 to IBE-4 settings for LIAR-RAW and RAW-FC datasets in terms of MF1. **Green** and Blue indicate best and second-best performance, respectively.

tral explanations got highest R_L for RAW-FC (**0.18**) as well. It indicates that these explanations show a maximum overlap of longest common subsequences with the gold explanations. Interestingly, we see a small deviation for R_2 scores. While explanations generated by Mistral, Llama and Falcon scored high R_2 for LIAR-RAW (**0.06**- **0.07**) dataset, Gemma scored highest (**0.20**) for RAW-FC dataset. It means their explanations show maximum bigram overlap with the gold explanations.

- As evaluating VLLMs, four out of five models found that Llama-generated explanations are better in four out of five subjective dimensions i.e. (informativeness: **4.73** - **4.78**, readability: **4.51** - **4.91**, objectivity: **4.17** - **4.60** and Logicality: **4.26** - **4.68**) for the LIAR-RAW dataset. However, most of them found Falcon-generated explanations to be more accurate (**3.55** - **3.96**). Similarly, three out of five evaluating VLLMs found that Llama-generated explanations are better for all five dimensions (informativeness: **4.48** - **4.92**, accuracy: **4.10** - **4.14**, readability: **4.43** - **4.82**, objectivity: **4.28** - **4.47** and Logicality: **4.33** - **4.52**). This observations correlate with the veracity prediction results, as RoBERTa and XLNet gave the highest MP, MR and $MF1$ when trained with Llama-generated explanations.

4.3 Observations from ablation study:

In this section, we reported our observations from the ablation study. We took the best-performing models (*XLNet-L*$_{Llama}$ for LIAR-RAW and *RoBERTa-L*$_{Llama}$ for RAW-FC) for both datasets and removed individual justification (supporting and refuting) components during training to gauge their impact. Results we got for different training scenarios are reported in Table 14. Apart from that, we also segmented the test set into six parts based on the number of evidence pieces each claim has, and calculated their performances. The segment-wise performance scores are reported in Table 17 and Table 18, respectively. We observed the following,

- Upon removing the supporting justifications from training input (see (*'w/o Supp. just.'* in Table 14), we found that MP, MR and

$MF1$ scores dropped by (i) **30.90%**, **29.63%** and **31.48%**, respectively, for LIAR-RAW (ii) **12.50%**, **11.36%** and **12.50%**, respectively, for RAW-FC. Similarly, when we removed the refuting justifications (see (*'w/o ref. just.'* in Table 14), we saw a performance drop as well. MP, MR and $MF1$ scores dropped by (i) **10.90%**, **7.41%** and **9.26%** respectively for LIAR-RAW (ii) **9.09%**, **9.09%** and **9.09%** respectively for RAW-FC. Finally, when we removed both justifications, the models performed worse. The MP, MR and $MF1$ scores dropped by (i) **52.73%**, **51.85%** and **55.56%** respectively for LIAR-RAW (ii) **47.73%**, **47.73%** and **47.73%** respectively for RAW-FC. Removing the supporting justifications had a more adversarial impact than removing refuting justifications, and removing both had the highest adversarial impact.

- While investigating the behaviour with varying numbers of evidence, we observed the following. For LIAR-RAW, performance of veracity predictor peaked with '6–20' evidences (MP: **0.62**, MR: **0.60**, $MF1$: **0.61**). It showed significant sensitivity to increasing number of evidences with $MF1$ dropping **29.50**% from '6–20' evidences (MF1: **0.61**) to '>50' evidences (MF1: **0.43**). However, for RAW-FC, the highest $MF1$ were observed with '11–20' evidences (MP: **0.93**, MR: **0.95**, MF1: **0.94**). It showed more robustness with $MF1$ decreasing slightly **7.45**% from '11–20' evidences (MF1: **0.94**) to '>50' evidences (MF1: **0.87**).

4.4 Linguistic insights:

In this section, we have reported how our best-performing model (*XLNet-L*$_{Llama}$ for LIAR-RAW and *RoBERTa-L*$_{Llama}$ for RAW-FC) is giving attention to different words and phrases while predicting veracity. We presented some of the samples, their gold labels, predicted labels, support justifications, and refute justifications in Figure 28, Figure 29, Figure 30, Figure 31, Figure 32, Figure 33, Figure 34, Figure 35, and Figure 36. To visualise the attention, we highlighted the top **25%** words which received higher attention scores from the respective language models in TBE-3. Here, the higher intensity of blue colour indicates a higher attention score. Some of the observations are,

- In Figure 28 where the gold and predicted label is 'true', we observed high attention scores on the words like 'supported by multiple sources', 'evidence', 'supports' in the support justification part. However, attention scores are more scattered in refute justification. Also, in contrast to supporting justification, refuting justification doesn't consist of any phrases which refute the claim with higher confidence.

- In Figure 29, where the label is 'mostly-true', attention scores were high on quantitative results such as percentage scores in the supportive justification. But in refutive justification, LLM focused on counter-evidence with less intensity of attention.

- In Figure 30, where the label is 'half-true', we observed the LLM gave attention to some similar keywords in both support and refute justification. For example, 'Gov', 'education', etc. are prominent ones. Also, we observed more attention towards phrases like 'appears that the claim is accurate' in support justification and 'inconsistencies undermine the validity of the claim' in refute justification. It justifies the predicted label as half-true.

- In Figure 31 where the label is 'barely-true', the VLLM generated justification focused on references to Obamacare and how many health plans were canceled nationwide. It noted Florida may have been heavily affected because of its size. But it also noticed that the exact number (300,000) is not confirmed. Subsequently, the LLM also gave more attention to keywords like 'Obamacare' due to which the LLM may have understood the claim might be true. Similarly, in the refute justification, VLLM confidently contradicted the claim by saying that 'customers were not immediately dropped'. As a result, the LLM extends more attention to 'false' and 'coverage', marking the reasons to doubt the claim. Thus, the LLM figured out that the claim is not entirely false, but also not fully accurate and labelled it as 'barely-true'.

- In Figure 32 where the label is 'false', the LLM assigned higher attention scores to economic indicators, due to the absence of reasons to support the claim. Whereas the refuting justification consisted of statements disproving the claim and LLM showed more attention toward terms like ‘layoffs’, ‘assertion’, and ‘deaths’, which provide counter-evidence to refute the claim.

- In Figure 33 where the label is ‘pants-fire’, the support justification is not useful as it is filled with repetition and irrelevant chat-bot fillers like ‘anything else I can help you with’, ‘let me know I can assist you further’, etc. Thus, we observed more attention scores on non-useful stopwords. While in the refuting justification, the VLLM argued with authority that the claim is misleading and lacks merit. We observed high attention scores on the phrase ‘the claim is unfounded and lacks merit’ which aligns with the predicted label ‘pants-fire’.

- In Figure 34, where the label is ‘true’, the support justification generated by VLLM emphasised on the evidences like Fintan O’s (well-known columnist) writing and reputation of ‘Irish Times’. The LLM also assigned higher attention scores to these details, which supports the claim with authority. However, refute justification seems to be weaker in disproving the claim due to the lack of refuting evidence.

- In Figure 35, where the label is ‘half’ (denoting half-true), the LLM put high attention on keywords like ‘evidence’, ‘statement is true’, ‘credibility’ and ‘support’ around factual components justifying truthfulness in the support justification. While in the refute justification, we observed higher attention scores on keywords like ‘false’, and phrases like ‘disputes the claim’ and ’In conclusion, the evidence suggests that the claim is false’. That is how the LLM evaluated the conflicting narratives and reached to a ‘half’ label.

- In Figure 36, where the label is ‘false’, VLLM did not generate any factual justification for supporting the claim. Subsequently, the LLM could not find any solid fact or figure to put more attention on it. On the other hand, in the refute justification, VLLM justified with facts like event being from 2011, not during COVID. Also, the horses were rehomed well before the claim was made. Thus, the LLM could extend higher attention scores to phrases like ‘claim is not supported by facts’ and ‘outdated story’.

5 Conclusion:

We drew the following conclusions from our experiments and analysis,

- Training language models with VLLM entailed justifications surpassed the baseline macro-F1 scores substantially with an improvement of **28.57%** and **44.26%** for LIAR-RAW and RAW-FC, respectively. The approach of training with claim-evidence understanding (TBE-2) secured the second spot, with an increment of **16.39%** in the RAW-FC dataset compared to the best baseline macro-F1. In contrast, the inference-based methods (IBEs) were unable to understand the justifications generated from VLLM and performed consistently poorly.

- While lexical overlap and semantic matching methods showed no definite pattern, the subjective evaluation of model explanations by VLLMs found that Llama generated model explanations are more informative, readable, objective, and logical. It correlates with the superior performance reported by XLNet and RoBERTa (in **TBE-3**) for veracity prediction as they took Llama generated justifications as input.

- The role of VLLM entailed justification as a second step in TBE-3 is justified in the ablation study, where we observed that removing supporting and refuting justification adversarially affected the scores.

- In the linguistic analysis of model explanations, we found that LLM could attend to supporting and refuting keywords and factual pieces of information for samples labelled with ‘true’ and ‘false’ labels. However, for samples with other veracity labels, attention seem to be scattered.

6 Limitations:

In this section, we reported the limitations of our work.

- We restricted our experiments to using only open-source language models, for reproducibility and resource constraints. However, expanding these experiments to commercial language models will further generalize the idea of claim-evidence entailment.

- We restricted ourselves to evaluating our approach on the LIAR-RAW and RAW-FC datasets. In the future, one can modify our approach to check its performance on a variety of fact-checking datasets like FEVER(Thorne et al., 2018) series, fact-check-bench (Wang et al., 2024c), etc.
- Due to our limited linguistic expertise, we restricted our experiments to an English-language setup only. In the future, our hypothesis can also be tested in other languages.
- In our work, we assumed a closed-domain fact-checking setup for reproducibility. In future, one can consider open-domain fact-checking, i.e., retrieve evidence from an external source and test our hypothesis for generalisation.
- Due to space constraints, we restricted our experiments to the task of fact-checking and utilised two popular datasets. A wider testing of our hypothesis on various other datasets could help us know the applicability of our idea of utilising entailment.
- Due to resource constraints, we could not evaluate the model-generated explanations manually. One can extend the study by integrating human evaluation of the explanations.

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Appendix

A Related works:

The NLP community has long been focusing on the core and peripheral tasks of automated fact-checking. Several datasets and methodologies have been proposed in the past, spanning different domains, languages, and task frameworks. In the following, we have reported the past literature for (i) monolingual fact-checking, (ii) multi-lingual and multi-modal fact-checking, (iii) explainable fact-checking, and (iv) other associated tasks in this area. Apart from that, we have also reported how our work fills the current research gap.

A.1 Monolingual fact-checking:

Here, we reported the past works for monolingual fact-checking. Specifically, we focused on two aspects, i.e. datasets and approaches. We found several datasets focusing on text-based fact-checking in the monolingual domain. Some of the popular ones are, FEVER (Thorne et al., 2018), FEVEROUS (Aly et al., 2021), VITAMIN-C (Schuster et al., 2021), LIAR-RAW and RAW-FC (Yang et al., 2022b). Thorne et al. (2018) produced one of the earlier famous datasets, FEVER, consisting of around 185K, claims which were extracted from the Wikipedia corpus. Annotators tagged them with three distinct labels: 'Supported', 'Refuted' or 'NotEnoughInfo' (NEI). LIAR-RAW and RAWFC datasets were constructed by Yang et al. (2022b). RAW-FC consists of around 2K claims with associated raw reports collected from the Snopes [2] web-

[2] https://www.snopes.com/

site. They were annotated for three labels, namely, ‘true’, ‘half-true’, and ‘false’. On the other hand, the LIAR-RAW dataset was an extension of the LIAR-PLUS (Alhindi et al., 2018) dataset. The authors accompanied each claim with raw reports, and expert annotators labelled the claims with one label out of six: ‘pants-fire’, ‘false’, ‘barely-true’, ‘half-true’, ‘mostly-true’ and ‘true’. The samples are domain-agnostic and mainly used to train general-domain fact-checking models. Additionally, we have domain-specific datasets as well. For example, PUBHEALTH dataset proposed by Kotonya and Toni (2020b) does fact-checking in the healthcare domain. It consists of 11.8K claims, where each claim is annotated and tagged with one of the following four labels: ‘true’, ‘false’, ‘mixture’, and ‘unproven’. Similarly, the SciClaimHunt dataset by Kumar et al. (2025) focused on scientific claim verification. Here, each claim is labelled as positive or negative based on the evidence provided in the scientific research papers. A complete list of datasets focusing on automated fact-checking is reported in Guo et al. (2022); Vladika and Matthes (2023); Zeng et al. (2021).

From a methodological point of view, the choice of fact-checking systems was closely tied to the datasets and task frameworks. Early approaches (DAGAN et al., 2010; Bowman et al., 2015) assessed whether each retrieved evidence supports or refutes a claim as an entailment task.

A.2 Mutli-lingual and multi-modal fact checking

The need to address misinformation across various languages and media formats have expanded the field of fact-checking into multilingual and multi-modal domains. In multilingual settings, datasets such as FakeCovid (Shahi and Nandini, 2020), which focuses on COVID-19 misinformation covering 40 languages, and X-Fact (Gupta and Srikumar, 2021) covering 25 languages and diverse domains. Prior surveys (Wang et al., 2024b; Singhal et al., 2024) provided a complete list of datasets and methods ranging from machine learning classifiers to LLM based techniques used for multi-lingual fact-checking. In parallel, a comprehensive survey by Akhtar et al. (2023a) highlighted the evolution of multi-modal fact checking domain. Several datasets have emerged to support this line of research such as FactDrill (Singhal et al., 2022) which combines video, audio, image, text, and metadata, while r/Fakeddit (Nakamura et al., 2020), MuMiN (Nielsen and McConville, 2022), MOCHEG dataset (Yao et al., 2023), and Factify-2 (Suryavardan et al., 2023) focused on image-text pairs only. Gupta et al. (2022) introduced a novel multi-lingual multimodal misinformation (MMM) dataset which integrated three Indian languages into multimodal fact-checking domain. In terms of modeling, early approaches used CNN-based models, such as ResNet (Sabir et al., 2019), and VGG16 (Amerini et al., 2019). Later on, studies integrated recurrent networks such as LSTM (Güera and Delp, 2018) to give better verdict. In the following years, researchers used CNN-LSTM hybrid (Tufchi et al., 2023) and transformers based models such as ViT (Wodajo and Atnafu, 2021). Recently, pretrained models have gained pace into multi-modal fact checking (Zhang et al., 2020; Cekinel et al., 2025). Several studies (Akhtar et al., 2023b; Tufchi et al., 2023) highlighted the list of datasets and methods used for multi-modal fact checking.

A.3 Explainable fact-checking:

Explainability has emerged as a critical requirement for trustworthy fact-checking systems. Kotonya and Toni (2020a); Eldifrawi et al. (2024) illustrated the recent advancements in this domain through comprehensive surveys. Alhindi et al. (2018) created the LIAR-PLUS dataset, extending the LIAR dataset, by including justification from long ruling comments. Except for general domain, explanability has also entered into more intricate domains like healthcare (Kotonya and Toni, 2020b). In multi-modal contexts, MOCHEG (Yao et al., 2023) introduced the first end-to-end dataset to include structured explanations, bridging the gap between multi-modal fact verification and interpretability. Early methods relied on attention mechanisms (i.e., highlighting high-attention tokens) to pinpoint evidence span for explanation (Popat et al., 2018). But critiques said attention weights often misrepresent true model reasoning and lack accessibility for non-experts (Pruthi et al., 2020). Rule-based systems (Gad-Elrab et al., 2019) improved transparency but restricted scope to structured claims and pre-defined data. More recent textual explanation models face challenges like hallucination in abstractive outputs (Maynez et al., 2020). Out of them, our proposed method utilized the ‘Justification-Then-Veracity’ pipeline, as mentioned in Eldifrawi et al. (2024), for reliable fact-checking.

A.4 Associated tasks:

There are various associated tasks along with fact-checking such as claim check-worthiness, rumour detection, stance detection, etc. Claim check-worthiness (Wright and Augenstein, 2020) is required before jumping directly into fact verification. Another related task, rumour detection (Dougrez-Lewis et al., 2022; Gorrell et al., 2019) identifies unverified claims in real-time, often using propagation patterns. Stance detection gauges public reactions to prioritize claims (Baly et al., 2018). Exaggeration detection (Patro and Baruah, 2021) is another task where similar statements are compared to find which of them is a more exaggerated version. Credibility detection (Patro and Rathore, 2020) assesses the trustworthiness of topics discussed in social media. Clickbait detection (Chakraborty et al., 2016) identifies the online content (headlines or titles) specially designed to attract users to click.

A.5 Research gap:

Prior work by Yue et al. (2024) took retrieved evidences to generate supporting and opposing arguments for independent evaluation, and utilized few-shot prompting for claim verification. Similarly, Wang et al. (2024a) split relevant evidences into supporting or refuting categories relying on a complex attention mechanism. However, both of them suffer from key limitations: Yue et al. (2024)'s method did not consider dividing evidence set that may contain contradictory statements, whereas Wang et al. (2024a)'s complex attention mechanism discarded some useful information by focusing only on the top-k evidences based on the attention score. Here, we argue that VLLMs, with their broad understanding of language can instead analyse how each evidence supports (entails) or refutes the claim. Further, with their ability to process long input text, VLLMs can consolidate the whole support and refute evidence set to generate respective justification. To test this hypothesis, we compared it with various training-based and inference-based methods. To the best of our knowledge, our work is the first to use claim-evidence entailment in VLLMs for this task, ensuring no evidence is overlooked.

B Additional details on datasets:

In this section, we reported a detailed discussion of the considered datasets. Additionally, we have also presented some samples and statistics for the datasets for better illustration.

B.1 LIAR-RAW (Yang et al., 2022b):

LIAR-RAW (Yang et al., 2022b) consists of 12,590 claims, each paired with raw reports collected from news articles, press releases, and web pages. LIAR-RAW builds upon the LIAR-Plus dataset (Alhindi et al., 2018) by adding crowd-sourced raw reports. Authors have retrieved up to 30 raw reports for each claim via the Google API using claim keywords. Claims were collected from a well-known fact-checking website, i.e. *Politifact*[3], which provided gold veracity labels. To ensure quality, they excluded fact-checking site reports, those published after the verdict, and reports under 5 words or over 3,000 words. After filtering, the final dataset had 10,065 training instances, 1,274 validation instances, and 1,251 test instances. Expert annotators manually assigned one of six fine-grained veracity labels to each claim. The labels they considered are: **"pants-fire"** (completely false), **"false"**, **"barely-true"** (contains minimal truth but is mostly false), **"half-true"** (equally true and false, with a significant mix of both), **"mostly-true"** (predominantly true with minor inaccuracies) and **"true"**. A sample from the dataset is presented in Table 6 for illustration. We have also studied the claim-evidence distribution, where we clubbed the claims based on the number of evidence sentences they have. The distribution is illustrated in Figure 3. We found that (i) the majority of claims have no evidence sentences, (ii) more than a thousand of claims have one evidence sentence, and (iii) 170+ claims have more than fifty evidence sentences associated with them.

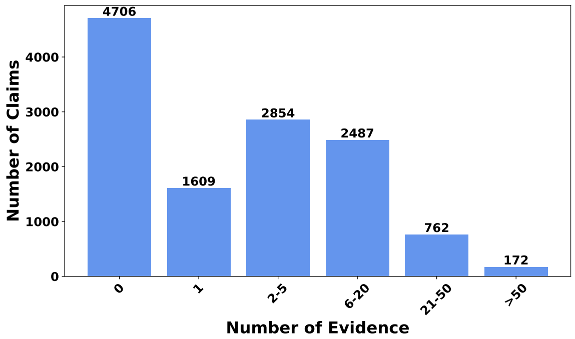


Figure 3: Illustration of number of claims v/s number of evidences for LIAR-RAW dataset

[3] https://www.politifact.com

Dataset: LIAR-RAW (Yang et al., 2022b)

Event_id: “5209.json”

Claim: “Suzanne Bonamici supports a plan that will cut choice for Medicare Advantage seniors.”

Label: “half-true”

Explain: “The Affordable Care Act was designed to save money by slowing future spending, including future spending on Medicare Advantage plans. But spending still goes up. In addition, many outside factors can affect the cost and range of benefits, making it impossible to know how Medicare Advantage might change. While the statement from Cornilles is partially accurate, it is taken out of context and ignores important details on a politically volatile subject.”

Evidences:
E1: “So I hope , a we move forward , we will focus on that approach to modernize Medicare and Medicaid , an approach that improve the quality of care while we reduce the cost of care , rather than simply offload those cost onto senior .”,
E2: “ So some of the save we achieve , a significant amount of save we achieve , be in reduce these overpayment , these huge subsidy , to the private Medicare Advantage plan .”,
E3: “In addition to the issue with Part D benefit design and plan flexibility , there be transaction such a rebate , pharmacy fee , and other form of compensation that occur in the supply chain that pose several issue .”,
E4: “ The ACA have help slow the growth in health care cost , it be close the doughnut hole for senior , and have encourage and improved access to mental health service and preventive care .”

Table 6: A sample from the LIAR-RAW dataset. It contains five key fields: (i) an identifier ‘*Event_id*’, (ii) the ‘*claim*’ to be fact-checked, (iii) the ground-truth ‘*Label*’, (iv) an explanation (‘*Explain*’) that clarifies its ground truth, and (v) the evidence sentences (*E1–E4*) extracted from the underlying fact-checking article.

B.2 RAW-FC (Yang et al., 2022b):

RAWFC dataset, introduced by (Yang et al., 2022b), has 2,012 claims. Authors collected claims from *Snopes*[4] website and retrieved relevant raw reports using claim keywords via the Google API. For each claim, up to 30 raw reports were gathered from various web sources. To ensure quality, reports from fact-checking sites and those published after the fact-checking verdict were excluded. Reports shorter than 5 words or longer than 3,000 words were also removed. Expert annotators manually assigned one of the three veracity labels to each claim. The labels used for the annotation are: **“true”** (entirely accurate), **“half-true”** (partially true but includes misleading information), and **“false”** (entirely false). A sample from the dataset is presented in Table 7 for illustration. We have studied the claim-evidence distribution for this dataset as well. We created buckets based on evidence sentence counts and gathered the claims belonging to individual buckets. The distribution is illustrated in Figure 4. We found that (i) around 750 claims have twenty to fifty evidence sentences associated with them, and (ii) more than five hundred claims have fifty or more evidence sentences associated with them.

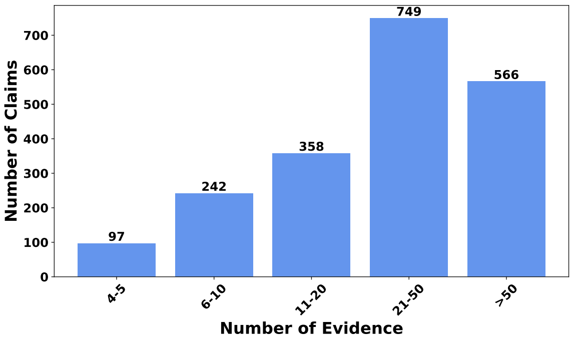


Figure 4: Illustration of number of claims v/s number of evidences for RAW-FC dataset

[4] https://www.snopes.com

Dataset: RAW-FC (Yang et al., 2022b)

Event_id: “247609”

Claim: “Right-wing commentator Bill Mitchell tweeted \"someone let me know\" when 55,000 Americans have died from COVID-19 coronavirus disease.”

Label: “true”

Explain: “In late April 2020, a month-old tweet posted by right-wing Twitter commentator Bill Mitchell received new attention amid tragic circumstances.\n Feeding on a conservative media talking point that the COVID-19 coronavirus disease pandemic isn\u2019t as serious as officials say, Mitchell tweeted on March 21, 2020:\u201cWhen COVID-19 reaches 51 million infected in the US and kills 55,000, someone let me know.\u201d\nSome readers asked if the statement (displayed above) was a real tweet posted by Mitchell, and it is.\nSadly, as of this writing, the U.S. has surpassed 55,000 fatalities from COVID-19. The Centers for Disease Control and Prevention (CDC) reports that as of May 1, 2020, there are 1,062,446 COVID-19 cases in the U.S. and 62,406 deaths.\nSocial media users wasted no time posting comments directed at Mitchell, reminding him of his statement.\n\nBecause the tweet in question was published from Mitchell\u2019s Twitter account, we rate this claim\u201cCorrect Attribution.\u201d"

Evidences:

E1: “On March 21, Bill Mitchell tweet, \u2018 When COVID-19\u2026kills 55,000 , let me know.”,

E2: “ In it , Hannan write that \u2018 [COVID-19] be unlikely to be as lethal a the more common form of influenza that we take for granted.”,

E3: “ While I \u2019 d normally be content to mock conspiracy theorist \u2014 I set up a Twitter account to make fun of bad COVID-19 take \u2014 spread false information about the pandemic be dangerous , and merit rebuttal.”,

E4: “ \u201d Owens delete the tweet after a Twitter user observe that her claim be not only false , but appear to be base on a lazy misreading of a Google search result .”,

E5: “ Given the dire situation , it seem worth know if the severity of the pandemic finally have penetrate the bubble of the most extreme coronavirus scoffer ; if these people and their follower be ignore safety measure because they believe the pandemic be a false flag to take away their gun or a Deep State plot to take down Trump , then they risk contribute to the disease \u2019 s spread .”

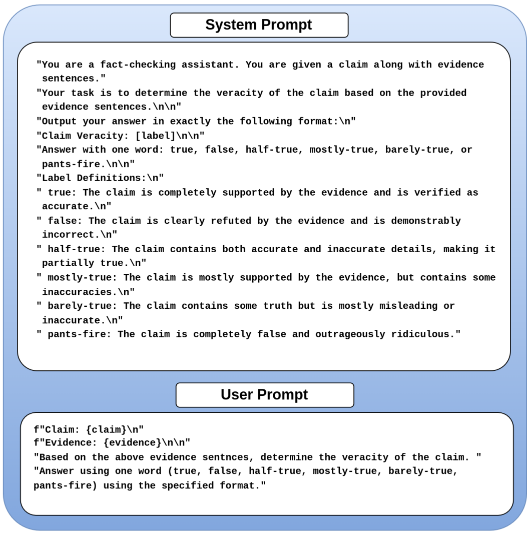
Table 7: A sample from the RAW-FC dataset. It contains five key fields: (i) an identifier ‘*Event_id*’, (ii) the ‘*claim*’ to be fact-checked, (iii) the ground-truth ‘*Label*’, (iv) an explanation (‘*Explain*’) that clarifies its ground truth, and (v) the evidence sentences (*E1–E4*) extracted from the underlying fact-checking article.

C Additional Details on Experiments:

In this section, we have reported additional details on our experiments. Particularly, we described individual **IBEs**, provided additional details on baselines and experimental setups.

C.1 IBE-1: Zero-shot prompting:

In this experiment, we have tried to answer *"How well the VLLMs can predict the claim veracity if raw evidence sentences are provided in the input?"* To conduct this experiment, we prompted five VLLMs by giving claims and associated evidence sentences as input. Some of the prompt samples are showcased in Figure 5 and Figure 6 for illustration. In past, researchers have tried zero-shot prompting for this task; however, either (i) they gave only claims without evidence sentences (Zhang and Gao, 2023), or (ii) they relied on evidence retrieved from web searches (Cheung and Lam, 2023).



System Prompt

```
"You are a fact-checking assistant. You are given a claim along with evidence
 sentences."
"Your task is to determine the veracity of the claim based on the provided
 evidence sentences.\n\n"
"Output your answer in exactly the following format:\n"
"Claim Veracity: [label]\n\n"
"Answer with one word: true, false, half-true, mostly-true, barely-true, or
 pants-fire.\n\n"
"Label Definitions:\n"
" true: The claim is completely supported by the evidence and is verified as
 accurate.\n"
" false: The claim is clearly refuted by the evidence and is demonstrably
 incorrect.\n"
" half-true: The claim contains both accurate and inaccurate details, making it
 partially true.\n"
" mostly-true: The claim is mostly supported by the evidence, but contains some
 inaccuracies.\n"
" barely-true: The claim contains some truth but is mostly misleading or
 inaccurate.\n"
" pants-fire: The claim is completely false and outrageously ridiculous."
```

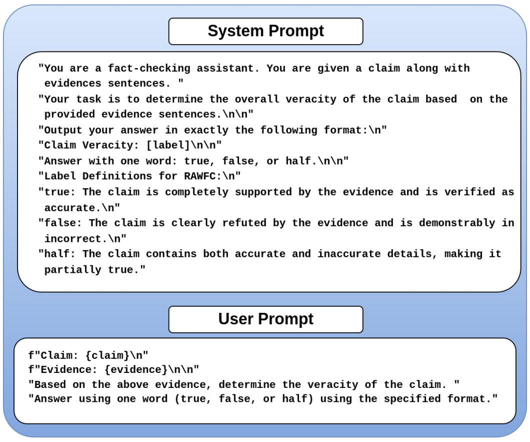
User Prompt

```
f"Claim: {claim}\n"
f"Evidence: {evidence}\n\n"
"Based on the above evidence sentnces, determine the veracity of the claim. "
"Answer using one word (true, false, half-true, mostly-true, barely-true,
pants-fire) using the specified format."
```

Figure 5: IBE-1 (LIAR-RAW): Prompt used to predict the veracity of the claim using zero-shot prompting based on the given evidence sentences and the claim.

C.2 IBE-2: Zero-shot prompting with overall understanding:

In this experiment, we have tried to answer *"Can zero-shot prompting improve the veracity prediction performance if claim-evidence relation understandings generated by VLLMs are given as input?"*. To conduct this experiment, we followed a two-step prompting strategy. First, we prompted the VLLMs to generate the claim-evidence understanding like we did in **TBE-2**. In the next step, we prompted them again with the claim and the generated understanding to predict the veracity labels. Some of the prompt samples are presented in the Figure 8 and Figure 9. To the best of our knowledge, nobody has attempted this in past.



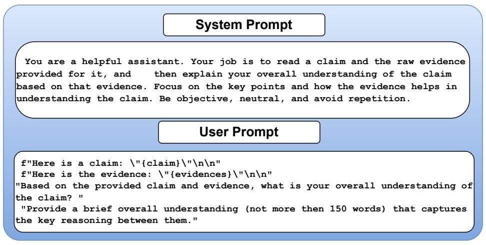
System Prompt

```
"You are a fact-checking assistant. You are given a claim along with
 evidences sentences. "
"Your task is to determine the overall veracity of the claim based  on the
 provided evidence sentences.\n\n"
"Output your answer in exactly the following format:\n"
"Claim Veracity: [label]\n\n"
"Answer with one word: true, false, or half.\n\n"
"Label Definitions for RAWFC:\n"
"true: The claim is completely supported by the evidence and is verified as
 accurate.\n"
"false: The claim is clearly refuted by the evidence and is demonstrably in
 incorrect.\n"
"half: The claim contains both accurate and inaccurate details, making it
 partially true."
```

User Prompt

```
f"Claim: {claim}\n"
f"Evidence: {evidence}\n\n"
"Based on the above evidence, determine the veracity of the claim. "
"Answer using one word (true, false, or half) using the specified format."
```

Figure 6: IBE-1 (RAW-FC): Prompt used to predict the veracity of the claim using zero-shot prompting based on the given evidence sentences and the claim.



System Prompt

```
 You are a helpful assistant. Your job is to read a claim and the raw evidence
provided for it, and    then explain your overall understanding of the claim
based on that evidence. Focus on the key points and how the evidence helps in
understanding the claim. Be objective, neutral, and avoid repetition.
```

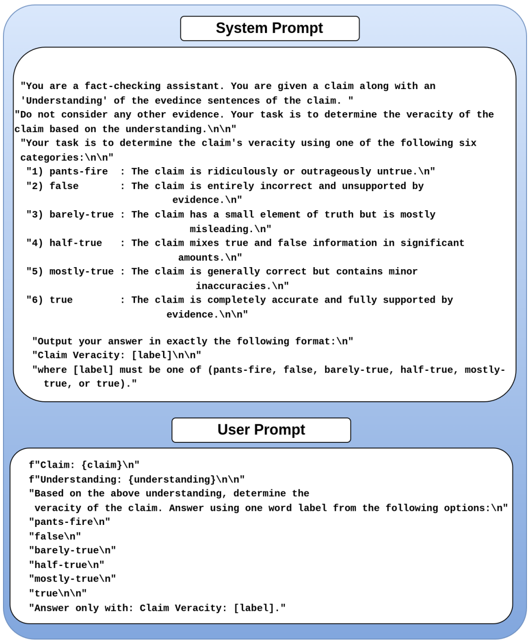
User Prompt

```
 f"Here is a claim: \"{claim}\"\n\n"
 f"Here is the evidence: \"{evidences}\"\n\n"
"Based on the provided claim and evidence, what is your overall understanding of
the claim? "
 "Provide a brief overall understanding (not more then 150 words) that captures
the key reasoning between them."
```

Figure 7: IBE-2: First step, prompt used to generate an overall understanding of the claim based on the provided evidence sentences.

C.3 IBE-3: CoT (Wei et al., 2022) prompting with overall understanding:

In this experiment, we tried to answer *Can CoT-based prompting improve the veracity prediction performance if claim-evidence understanding is given in the input?*. Here we followed similar steps as mentioned in **IBE-2**, except in the prompt, we asked the VLLMs to generate step-by-step reasoning behind their predictions. Prior work (Zhang and Gao, 2023) did a similar attempt. However, they gave evidence collected from web searches. We, on the other hand, relied on the claim-evidence understanding generated by VLLMs. Some of the prompt samples are presented in Figure 11 and Figure 12 for illustration.



```
"You are a fact-checking assistant. You are given a claim along with an
 'Understanding' of the evedince sentences of the claim. "
"Do not consider any other evidence. Your task is to determine the veracity of the
claim based on the understanding.\n\n"
 "Your task is to determine the claim's veracity using one of the following six
 categories:\n\n"
  "1) pants-fire  : The claim is ridiculously or outrageously untrue.\n"
  "2) false       : The claim is entirely incorrect and unsupported by
                           evidence.\n"
  "3) barely-true : The claim has a small element of truth but is mostly
                              misleading.\n"
  "4) half-true   : The claim mixes true and false information in significant
                            amounts.\n"
  "5) mostly-true : The claim is generally correct but contains minor
                               inaccuracies.\n"
  "6) true        : The claim is completely accurate and fully supported by
                          evidence.\n\n"

   "Output your answer in exactly the following format:\n"
   "Claim Veracity: [label]\n\n"
   "where [label] must be one of (pants-fire, false, barely-true, half-true, mostly-
     true, or true)."
```

```
f"Claim: {claim}\n"
f"Understanding: {understanding}\n\n"
"Based on the above understanding, determine the
 veracity of the claim. Answer using one word label from the following options:\n"
"pants-fire\n"
"false\n"
"barely-true\n"
"half-true\n"
"mostly-true\n"
"true\n\n"
"Answer only with: Claim Veracity: [label]."
```

Figure 8: IBE-2 (LIAR-RAW): Second step, prompt using zero-shot prompting to directly predict the claim's veracity based on the overall understanding.

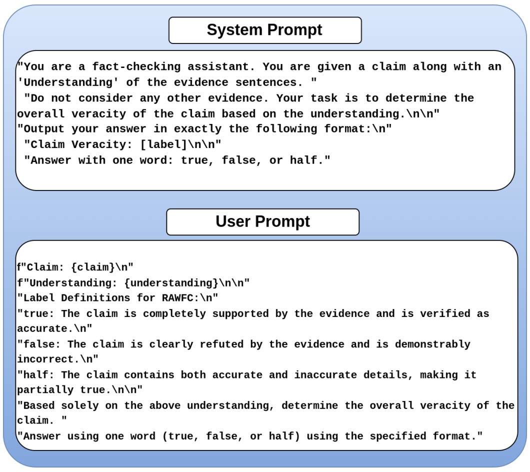
C.4 IBE-4: Prompting based on entailment:

In the last inference-based experiment, we tried to answer *"Can prompting with VLLM generated entailed-justifications enhance language models' ability to predict claim veracity?"* To conduct this experiment, we have followed a three-step approach similar to **TBE-3** as described in Section 3.1.3. While the initial two steps, i.e. (i) to classify the evidence sentences as supporting or refuting a given claim and (ii) generating the justifications based on classified evidence sentences, are exactly the same, in the last step, instead of training, we prompted the VLLMs to generate the veracity. In past, researchers have prompted the VLLMs to find entailment for tasks like claim matching (Choi and Ferrara, 2024b) and counterfactual generation (Dai et al., 2022). However, to the best of our knowledge, we are the first to (i) apply it to classify each evidence into supporting or refuting categories, and (ii) generate entailed justifications and use them for fact verification. The detailed approach is illustrated in Fig. 2 (c). Some of the prompt samples are show cased in the Figure 13, Figure 14, Figure 15, Figure 16 and 17.

C.5 Additional details on baselines:

In this section, we reported the details of individual baseline methods considered in our study.

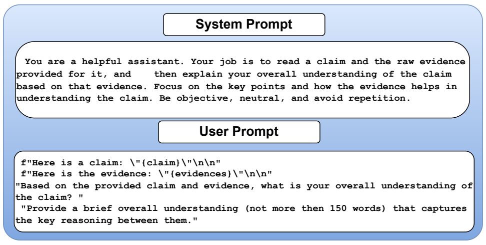
- **HiSS**: It is proposed by Zhang and Gao (2023). Here, authors have proposed a hierarchical step-by-step (a.k.a. *HiSS*) method where they first decomposed a claim into smaller sub-claims using few-shot prompting. Then they verified each sub-claim step-by-step by raising and answering a series of questions. For each question, they prompted the language models to assess if it is confident in answering or not, and if not, they gave the question to a web search engine. The search results were then inserted back into the ongoing prompt to continue the verification process. Finally, using that information, language models predicted the veracity label for the whole claim.



```
"You are a fact-checking assistant. You are given a claim along with an
'Understanding' of the evidence sentences. "
 "Do not consider any other evidence. Your task is to determine the
overall veracity of the claim based on the understanding.\n\n"
"Output your answer in exactly the following format:\n"
 "Claim Veracity: [label]\n\n"
 "Answer with one word: true, false, or half."
```

```
f"Claim: {claim}\n"
f"Understanding: {understanding}\n\n"
"Label Definitions for RAWFC:\n"
"true: The claim is completely supported by the evidence and is verified as
accurate.\n"
"false: The claim is clearly refuted by the evidence and is demonstrably
incorrect.\n"
"half: The claim contains both accurate and inaccurate details, making it
partially true.\n\n"
"Based solely on the above understanding, determine the overall veracity of the
claim. "
"Answer using one word (true, false, or half) using the specified format."
```

Figure 9: IBE-2 (RAW-FC): Second step, using zero-shot prompting to predict the claim's veracity from the overall understanding.

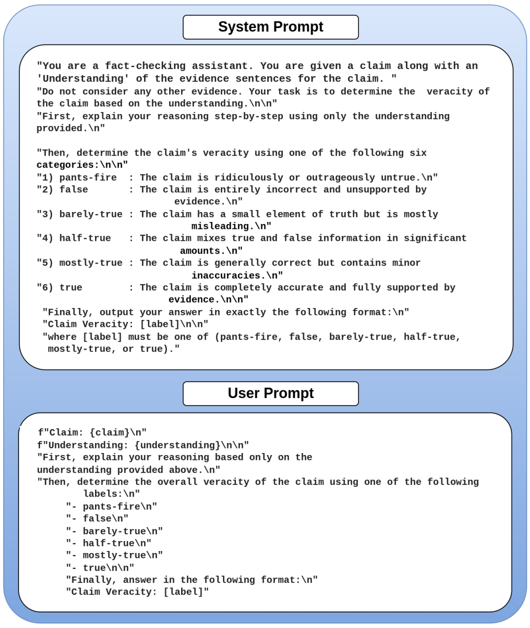


```
 You are a helpful assistant. Your job is to read a claim and the raw evidence
provided for it, and    then explain your overall understanding of the claim
based on that evidence. Focus on the key points and how the evidence helps in
understanding the claim. Be objective, neutral, and avoid repetition.
```

```
 f"Here is a claim: \"{claim}\"\n\n"
 f"Here is the evidence: \"{evidences}\"\n\n"
"Based on the provided claim and evidence, what is your overall understanding of
the claim? "
 "Provide a brief overall understanding (not more then 150 words) that captures
the key reasoning between them."
```

Figure 10: IBE-3: First step, prompt used to generate an overall understanding of the claim based on the provided evidence sentences.

- **FactLLaMa**: It is proposed by Cheung and Lam (2023). Their approach has two components: (i) generation of prompts (having instructions, claims and evidence pieces), and (ii) instruction-tuning of a generative pre-trained language model. In the first component, to create the prompt samples, they combined the instruction, evidence, and in-



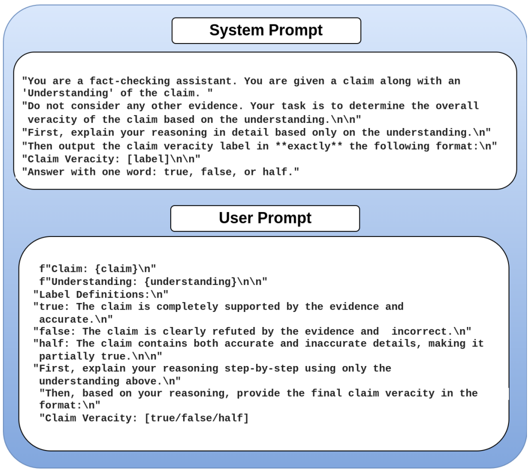
System Prompt

```
"You are a fact-checking assistant. You are given a claim along with an
'Understanding' of the evidence sentences for the claim. "
"Do not consider any other evidence. Your task is to determine the  veracity of
the claim based on the understanding.\n\n"
"First, explain your reasoning step-by-step using only the understanding
provided.\n"

"Then, determine the claim's veracity using one of the following six
categories:\n\n"
"1) pants-fire  : The claim is ridiculously or outrageously untrue.\n"
"2) false       : The claim is entirely incorrect and unsupported by
                        evidence.\n"
"3) barely-true : The claim has a small element of truth but is mostly
                           misleading.\n"
"4) half-true   : The claim mixes true and false information in significant
                         amounts.\n"
"5) mostly-true : The claim is generally correct but contains minor
                           inaccuracies.\n"
"6) true        : The claim is completely accurate and fully supported by
                       evidence.\n\n"
 "Finally, output your answer in exactly the following format:\n"
 "Claim Veracity: [label]\n\n"
 "where [label] must be one of (pants-fire, false, barely-true, half-true,
  mostly-true, or true)."
```

User Prompt

```
f"Claim: {claim}\n"
f"Understanding: {understanding}\n\n"
"First, explain your reasoning based only on the
understanding provided above.\n"
"Then, determine the overall veracity of the claim using one of the following
        labels:\n"
     "- pants-fire\n"
     "- false\n"
     "- barely-true\n"
     "- half-true\n"
     "- mostly-true\n"
     "- true\n\n"
     "Finally, answer in the following format:\n"
     "Claim Veracity: [label]"
```

Figure 11: IBE-3 (LIAR-RAW): Second step, prompt using Chain-of-Thought reasoning to predict the veracity of the claim from the overall understanding.



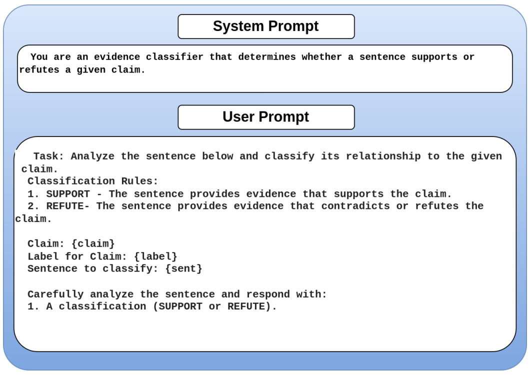
System Prompt

```
"You are a fact-checking assistant. You are given a claim along with an
'Understanding' of the claim. "
"Do not consider any other evidence. Your task is to determine the overall
 veracity of the claim based on the understanding.\n\n"
"First, explain your reasoning in detail based only on the understanding.\n"
"Then output the claim veracity label in **exactly** the following format:\n"
"Claim Veracity: [label]\n\n"
"Answer with one word: true, false, or half."
```

User Prompt

```
  f"Claim: {claim}\n"
  f"Understanding: {understanding}\n\n"
 "Label Definitions:\n"
 "true: The claim is completely supported by the evidence and
  accurate.\n"
 "false: The claim is clearly refuted by the evidence and  incorrect.\n"
 "half: The claim contains both accurate and inaccurate details, making it
  partially true.\n\n"
 "First, explain your reasoning step-by-step using only the
  understanding above.\n"
  "Then, based on your reasoning, provide the final claim veracity in the
  format:\n"
  "Claim Veracity: [true/false/half]
```

Figure 12: IBE-3 (RAW-FC): Second step, prompt using Chain-of-Thought reasoning to predict the veracity of the claim from the overall understanding.



System Prompt

```
  You are an evidence classifier that determines whether a sentence supports or
refutes a given claim.
```

User Prompt

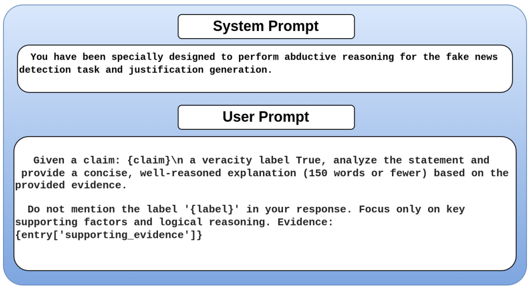
```
   Task: Analyze the sentence below and classify its relationship to the given
 claim.
  Classification Rules:
  1. SUPPORT - The sentence provides evidence that supports the claim.
  2. REFUTE- The sentence provides evidence that contradicts or refutes the
claim.

  Claim: {claim}
  Label for Claim: {label}
  Sentence to classify: {sent}

  Carefully analyze the sentence and respond with:
  1. A classification (SUPPORT or REFUTE).
```

Figure 13: IBE-4: First step prompt used to classify each evidence sentence as supporting or refuting the claim.

put claim into a single sequence, with special tokens separating them. While the instruction guides how to incorporate the evidence for fact-checking, evidence contains relevant information retrieved from search engines, using the Google API. As a part of the second component they we fine-tuned the LoRA adapter with Llama as the language model.

- **RAFTS**: It stands for *retrieval augmented fact verification through the synthesis of contrastive arguments*. It is proposed by Yue et al. (2024), where authors retrieve relevant documents and perform a few-shot fact verification using pretrained language models. RAFTS have three components, (i) demonstration retrieval, where relevant examples were collected to included in the input contexts, (ii) document retrieval, where authors proposed a *retrieve and re-rank* pipeline (using RAG framework) to accurately identify relevant documents for the input claim, and (iii) few-shot fact verification using supporting and opposing arguments derived from the facts within the collected documents. However, unlike in our work, they didn't rely on supporting and opposing justifications (a.k.a. entailed justifications) in their final steps.

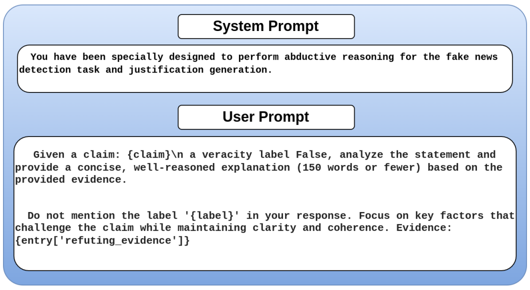
- **L-Defense**: The LLM-equipped defense-based explainable fake news detection approach (L-Defense) was proposed by Wang et al. (2024a). Their approach shares some similarity with RAFTS at a philosophical level. The framework consists of three components: (i) a competing evidence extractor, (ii) a prompt-based reasoning module, and (iii) a defense-based inference module. In the competing evidence extractor, authors deployed a natural language inference (NLI) module to associate a "true" or "false" label to each claim for each associated evidence sentence. The NLI module gave two top-k evidence sentence sets, each stating a claim to be "true" or "false. In the reasoning module, they prompted language models to generate two separate explanations, each for stating a claim to be "true" and "false based on the respective top-k evidence set. Finally, in the defense-based in-



```
 You have been specially designed to perform abductive reasoning for the fake news
detection task and justification generation.
```

```
  Given a claim: {claim}\n a veracity label True, analyze the statement and
 provide a concise, well-reasoned explanation (150 words or fewer) based on the
provided evidence.

  Do not mention the label '{label}' in your response. Focus only on key
supporting factors and logical reasoning. Evidence:
{entry['supporting_evidence']}
```

Figure 14: IBE-4, Second step prompt used to generate a supporting justification based on the supporting evidence sentences.



```
 You have been specially designed to perform abductive reasoning for the fake news
detection task and justification generation.
```

```
  Given a claim: {claim}\n a veracity label False, analyze the statement and
provide a concise, well-reasoned explanation (150 words or fewer) based on the
provided evidence.


  Do not mention the label '{label}' in your response. Focus on key factors that
challenge the claim while maintaining clarity and coherence. Evidence:
{entry['refuting_evidence']}
```

Figure 15: IBE-4, Second step prompt used to generate a refuting justification based on the refuting evidence sentences.

ference module, they trained the transformer encoders by taking claims and associated two explanations to predict the veracity. Our approach is different from the L-Defense as we (i) deployed VLLMs to classify each evidence, (ii) we considered all evidences associated with a claim, and (iii) we fine-tuned LLMs and adapters with VLLMs for veracity prediction (in **TBE-3**).

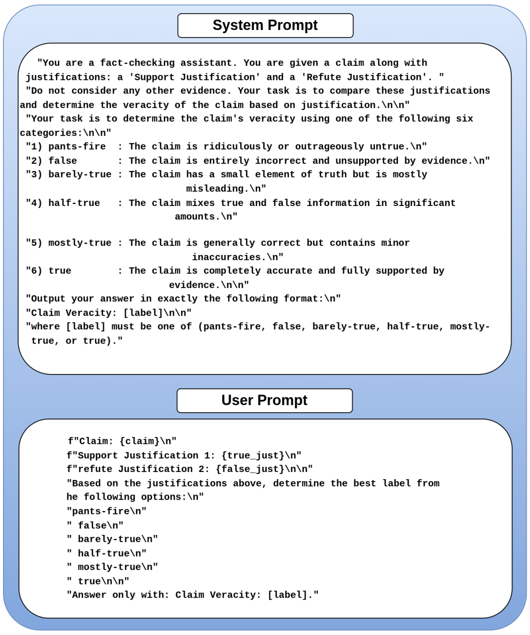
C.6 Experimental set-up:

C.6.1 Training/ test/ validation splits:

We have used the training, validation, and test splits originally provided by Yang et al. (2022b) in our experiments. They are essential for the comparison of our models with the baselines. The distribution of samples falling under each label and training splits are reported in Table 10.

C.6.2 Language models:

For prompting, we used five very large language models (VLLMs). We call them so because of their immense parameter size, which prohibits us from fine-tuning them like we do for normal BERT-based language models. We used five VLLMs i.e. Mistral (Jiang et al., 2023), Llama (AI@Meta, 2024), Gemma (Team et al., 2024), Qwen (Yang et al., 2024) and Falcon (Almazrouei et al., 2023) in all of our experiments. For fine-tuning, we used LLMs RoBERTa and XLNet in **TBE-2** and **TBE-3**. Apart from that, we also used adapter-based (LoRA (Hu et al., 2022) and LoRA+ (Hayou et al., 2024) adapters) fine-tuning methods for the considered VLLMs. The details of LLMs and VLLMs such as their versions and maximum input size they can take are reported in Table 9.



```
  "You are a fact-checking assistant. You are given a claim along with
 justifications: a 'Support Justification' and a 'Refute Justification'. "
 "Do not consider any other evidence. Your task is to compare these justifications
and determine the veracity of the claim based on justification.\n\n"
 "Your task is to determine the claim's veracity using one of the following six
categories:\n\n"
 "1) pants-fire  : The claim is ridiculously or outrageously untrue.\n"
 "2) false       : The claim is entirely incorrect and unsupported by evidence.\n"
 "3) barely-true : The claim has a small element of truth but is mostly
                        misleading.\n"
 "4) half-true   : The claim mixes true and false information in significant
                      amounts.\n"

 "5) mostly-true : The claim is generally correct but contains minor
                         inaccuracies.\n"
 "6) true        : The claim is completely accurate and fully supported by
                      evidence.\n\n"
 "Output your answer in exactly the following format:\n"
 "Claim Veracity: [label]\n\n"
 "where [label] must be one of (pants-fire, false, barely-true, half-true, mostly-
  true, or true)."
```

```
        f"Claim: {claim}\n"
        f"Support Justification 1: {true_just}\n"
        f"refute Justification 2: {false_just}\n\n"
        "Based on the justifications above, determine the best label from
        he following options:\n"
        "pants-fire\n"
        " false\n"
        " barely-true\n"
        " half-true\n"
        " mostly-true\n"
        " true\n\n"
        "Answer only with: Claim Veracity: [label]."
```

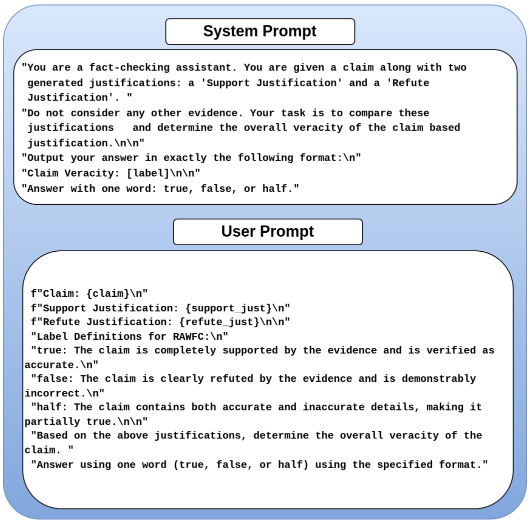
Figure 16: IBE-4 (LIAR-RAW): Third step prompt used to predict the veracity of the claim using the supporting and refuting justifications.

Parameters	**Values**
Learning rate	{2e-6, 2e-5, 1e-5}
Optimizer	AdamW, Adam
Batch size	8, 16
Patience (Early stop)	2, 3
lora_rank	8
Learning rate	{1e-5,1e-4}
lr_scheduler_type	cosine
bf16	true

Table 8: Hyperparameters explored during model training and evaluation.

C.6.3 Hyperparameter details:

We did an extensive hyperparameter search that led to the optimal performance of our models. The list of hyperparameters for which we trained our models is presented in Table 8. For the VLLMs, we kept the temperature constant at '0.001' for consistency. We conducted all our experiments on two NVIDIA A100 80GB GPU cards.


System Prompt

```
"You are a fact-checking assistant. You are given a claim along with two
 generated justifications: a 'Support Justification' and a 'Refute
 Justification'. "
"Do not consider any other evidence. Your task is to compare these
 justifications   and determine the overall veracity of the claim based
 justification.\n\n"
"Output your answer in exactly the following format:\n"
"Claim Veracity: [label]\n\n"
"Answer with one word: true, false, or half."
```

```
 f"Claim: {claim}\n"
 f"Support Justification: {support_just}\n"
 f"Refute Justification: {refute_just}\n\n"
 "Label Definitions for RAWFC:\n"
 "true: The claim is completely supported by the evidence and is verified as
accurate.\n"
 "false: The claim is clearly refuted by the evidence and is demonstrably
incorrect.\n"
 "half: The claim contains both accurate and inaccurate details, making it
partially true.\n\n"
 "Based on the above justifications, determine the overall veracity of the
claim. "
 "Answer using one word (true, false, or half) using the specified format."
```

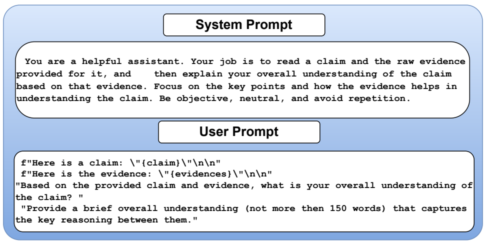
Figure 17: IBE-4 (RAW-FC): Third step prompt used to predict the veracity of the claim using the supporting and refuting justifications.

Model	Max. length	Version
RoBERTa	1k	`roberta-large`
XLNet	1k	`xlnet-large-cased`
Mistral	32k	`mistralai/Mistral-7B-Instruct-v0.3`
Llama	128k	`meta-llama/Llama-3.1-8B-Instruct`
Gemma	8k	`google/gemma-7b-it`
Qwen	1M	`Qwen/Qwen2.5-7B-Instruct-1M`
Falcon	8k	`tiiuae/Falcon3-7B-Instruct`

Table 9: Language model details. Here, 'Max. length' denotes the maximum sequence length allowed by the particular model.

C.6.4 Evaluation metrics:

Since we are working in a multi-class classification framework for veracity prediction, we used standard metrics such as macro-precision (MP), macro-recall (MR), and macro-f1 ($MF1$) to evaluate our models. To evaluate model explainability, we first concatenated the supporting and refuting entailed justifications (generated as part of TBE-3) and considered them as model explanations. The evaluation was done with two types of strategies: (i) checking lexical overlap and semantic matching, and (ii) doing subjective evaluation by VLLMs. To check lexical overlap, we used several standard evaluation metrics such as ROUGE-1 (R_1), ROUGE-2 (R_2), ROUGE-L (R_L) (Lin, 2004) and BLEU (Papineni et al., 2002). While R_1 and R_2 measure the overlap of unigrams and bigrams between predicted and gold explanations, R_L measures the longest common subsequence. BLEU, on the other hand, measures the precision of matching n-grams between predicted and gold explanations. To measure the semantic matching between predicted and gold explanations, we deployed BERT score (Zhang et al., 2019). It generates contextual embeddings of predicted and gold explanations and calculates cosine similarity between them. To do the subjective evaluation, we prompted the considered VLLMs (a.k.a evaluating VLLMs) to asses the model explanations generated by each VLLM (generating VLLM). The VLLMs were asked to asses across five dimensions (i) informativeness, (ii) logicality, (iii) objectivity, (iv) readability and (v) accuracy (Zheng et al., 2025). The prompt template used for the assessment is presented in Figure 25.


System Prompt

```
 You are a helpful assistant. Your job is to read a claim and the raw evidence
provided for it, and    then explain your overall understanding of the claim
based on that evidence. Focus on the key points and how the evidence helps in
understanding the claim. Be objective, neutral, and avoid repetition.
```

User Prompt

```
 f"Here is a claim: \"{claim}\"\n\n"
 f"Here is the evidence: \"{evidences}\"\n\n"
"Based on the provided claim and evidence, what is your overall understanding of
the claim? "
 "Provide a brief overall understanding (not more then 150 words) that captures
the key reasoning between them."
```

Figure 18: TBE-2: Prompt for generating overall understanding from the claim and evidence sentences.

Dataset	Label	Train	Val	Test
LAIR-RAW (Yang et al., 2022b)	T	1647	169	205
	MT	1950	251	238
	HT	2087	244	263
	BT	1611	236	210
	F	1958	259	249
	PF	812	115	86
RAW-FC (Yang et al., 2022b)	T	561	67	67
	HT	537	67	67
	F	514	66	66

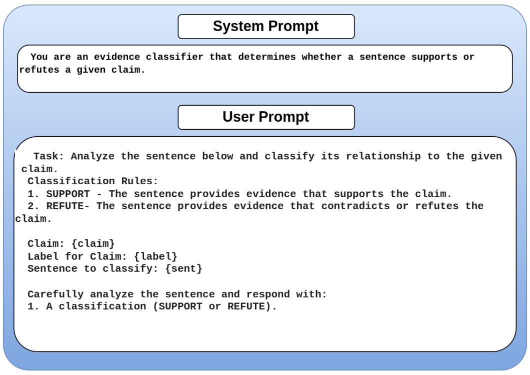
Table 10: Train, val and test distributions. Notations: **T** for True, **MT** for Mostly-true, **HT** for Half-true, **BT** for Barely-true, **F** for False, **PF** for Pants-fire and **T** for True.

D Additional Results and Discussion:

D.1 Additional observations for macro precision in veracity prediction:

We reported the macro precision (MP) of various models under **TBE-1**, **TBE-2–TBE-3**, and **IBEs** in Table 11, Table 12, and Table 13, respectively. Figure 23 illustrates a comparison of the best-performing models across them. Our observations are as follows:

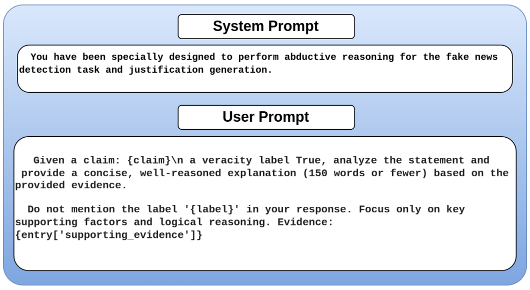
- In the case of **LIAR-RAW**, none of the macro-precision scores presented by **IBE** models surpassed the baseline performance. In contrast,



```
 You are an evidence classifier that determines whether a sentence supports or
refutes a given claim.
```

```
  Task: Analyze the sentence below and classify its relationship to the given
 claim.
  Classification Rules:
  1. SUPPORT - The sentence provides evidence that supports the claim.
  2. REFUTE- The sentence provides evidence that contradicts or refutes the
claim.

  Claim: {claim}
  Label for Claim: {label}
  Sentence to classify: {sent}

  Carefully analyze the sentence and respond with:
  1. A classification (SUPPORT or REFUTE).
```

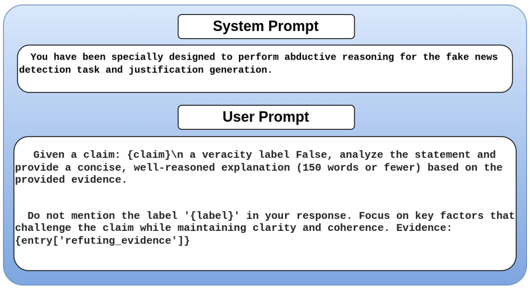
Figure 19: TBE-3: First step prompt used to classify each evidence sentence as supporting or refuting the claim.



```
 You have been specially designed to perform abductive reasoning for the fake news
detection task and justification generation.
```

```
  Given a claim: {claim}\n a veracity label True, analyze the statement and
 provide a concise, well-reasoned explanation (150 words or fewer) based on the
provided evidence.

  Do not mention the label '{label}' in your response. Focus only on key
supporting factors and logical reasoning. Evidence:
{entry['supporting_evidence']}
```

Figure 20: TBE-3: Second step prompt used to generate a supporting justification based on the supporting evidence sentences.



```
 You have been specially designed to perform abductive reasoning for the fake news
detection task and justification generation.
```

```
  Given a claim: {claim}\n a veracity label False, analyze the statement and
provide a concise, well-reasoned explanation (150 words or fewer) based on the
provided evidence.


  Do not mention the label '{label}' in your response. Focus on key factors that
challenge the claim while maintaining clarity and coherence. Evidence:
{entry['refuting_evidence']}
```

Figure 21: TBE-3: Second step prompt used to generate a refuting justification based on the refuting evidence sentences.

for **RAW-FC**, the performance of models in IBE-1 (Qwen, MP: **0.61**), and IBE-2 (Llama, MP: **0.62**) was on equal with the highest performing baseline (MP: **0.62**), but did not exceed it.

- In **TBE-1**, for **LIAR-RAW**, Mistral model with LoRA adapter reported the highest MP, but did not able to surpass baseline performance. However, for **RAW-FC**, we found that many models, such as (i) Mistral (MP: **0.69**, $\sim$ **11.29**% $\uparrow$), Llama (MP: **0.68**, $\sim$ **9.68**% $\uparrow$), and Qwen (MP: **0.67**, $\sim$ **8.06**% $\uparrow$) trained with LoRA, and (ii) Llama (MP: **0.67**, $\sim$ **8.06**% $\uparrow$) and Qwen (MP: **0.70**, $\sim$ **12.90**% $\uparrow$) trained with LoRA+, outperform the best baseline performance (MP: **0.62**).

- In **TBE-2**, for **LIAR-RAW**, the highest reported MP (**0.36**) does not surpass the best baseline performance (MP: **0.47**). However, for the **RAW-FC** dataset, we observed that many models, such as (i) XLNet fine-tuned on Llama understandings ($\sim$ **1.61**% $\uparrow$), and (ii) Mistral ($\sim$ **6.45**% $\uparrow$) and Llama ($\sim$ **17.74**% $\uparrow$) trained with their respective understandings and LoRA+ adapters outperformed the best reported baseline MP (MP: **0.62**).

- Several models within **TBE-3** for **LIAR-RAW** demonstrated notable improvements over the best baseline macro-precision score (MP: **0.47**). Specifically, (i) RoBERTa fine-tuned with Mistral ($\sim$ **2.12**% $\uparrow$), Llama ($\sim$ **12.76**% $\uparrow$), Gemma ($\sim$ **4.25**% $\uparrow$), Qwen ($\sim$ **2.12**% $\uparrow$), and Falcon ($\sim$ **4.25**% $\uparrow$) based entailed justifications, and (ii) XLNet fine-tuned with Mistral ($\sim$ **4.25**% $\uparrow$), Llama ($\sim$ **17.02**% $\uparrow$), and Qwen ($\sim$ **6.38**% $\uparrow$) based entailed justifications, and (iii) Llama trained with Llama justifications and LoRA+ adapter ($\sim$ **4.25**% $\uparrow$). Similarly, for **RAW-FC**, we observed that (i) RoBERTa fine-tuned with Mistral ($\sim$ **33.87**% $\uparrow$), Llama ($\sim$ **41.93**% $\uparrow$), Qwen ($\sim$ **17.74**% $\uparrow$), and Falcon ($\sim$ **4.83**% $\uparrow$) based entailed justifications, (ii) XLNet fine-tuned with Mistral ($\sim$ **33.87**% $\uparrow$), Llama ($\sim$ **41.93**% $\uparrow$), Qwen ($\sim$ **12.90**% $\uparrow$), and Falcon ($\sim$ **22.58**% $\uparrow$) based entailed justifications, and (iii) Llama trained (with Llama justifications) with LoRA+ adapter ($\sim$ **35.48**% $\uparrow$) outperformed the best reported macro-precision by the baselines (MP: **0.62**) Models from **TBE-3**, exhibit the highest overall macro precision performance. Figure 23 illustrates the same.

D.2 Additional observations for macro recall in veracity prediction:

We reported the MR of various models under **TBE-1**, **TBE-2–TBE-3**, and **IBEs** in Table 11, Table 12, and Table 13, respectively. Figure 24 illustrates a comparison of the best-performing models across them. Our observations are as follows:

- For **LIAR-RAW**, none of the macro-recall scores reported by **IBE** models could surpass the best baseline performance (MR: **0.37**). In contrast, for **RAW-FC**, Llama achieved the highest performance in IBE-2 (MR: **0.63**, $\sim$ **3.28**% ↑), surpassing the highest baseline performance (MR: **0.61**).

- In **TBE-1**, for **LIAR-RAW**, the highest reported MR (**0.30**) does not surpass that of any baseline. However, for **RAW-FC**, we found that many models, such as (i) Mistral ($\sim$ **6.56**% ↑) and Qwen ($\sim$ **8.20**% ↑) trained with LoRA, and (ii) Llama trained with both LoRA ($\sim$ **4.92**% ↑) and LoRA+ ($\sim$ **4.92**% ↑), outperform the best baseline performance (MR: **0.61**).

- In **TBE-2**, for **LIAR-RAW**, no model surpasses the best MR reported by the baselines. However, for the **RAW-FC** dataset, we observed that many models, such as (i) XLNet fine-tuned on Llama understandings ($\sim$ **3.27**% ↑), and (ii) Llama trained with Llama understandings and LoRA+ ($\sim$ **16.39**% ↑), outperformed the best reported baseline MR (MR: **0.61**).

- Several models in **TBE-3** for **LIAR-RAW**, such as (i) RoBERTa fine-tuned with Llama ($\sim$ **43.24**% ↑), Gemma ($\sim$ **35.14**% ↑), and Falcon ($\sim$ **16.22**% ↑) based entailed justifications, (ii) XLNet fine-tuned with Llama ($\sim$ **45.95**% ↑), Qwen ($\sim$ **29.73**% ↑), and Falcon ($\sim$ **18.92**% ↑) based entailed justifications, and (iii) Llama trained with Llama justifications and LoRA+ adapter ($\sim$ **35.14**% ↑), surpassed the best reported macro-recall score of baselines (MR: **0.37**). Similarly, for **RAW-FC**, we observed that (i) RoBERTa fine-tuned with Mistral ($\sim$ **34.43**% ↑), Llama ($\sim$ **44.26**% ↑), and Qwen ($\sim$ **16.39**% ↑) based entailed justifications, (ii) XLNet fine-tuned with Mistral ($\sim$ **34.43**% ↑), Llama ($\sim$ **44.26**% ↑), Qwen ($\sim$ **14.75**% ↑), and Falcon ($\sim$ **22.95**% ↑) based entailed justifications, and (iii) Llama trained (with Llama justifications) with LoRA+ adapter ($\sim$ **34.43**% ↑) outperformed the best reported macro-recall score by the baselines (MR: **0.61**). Models from **TBE-3**, exhibit the highest overall macro recall performance. Figure 24 illustrates the same.

Dataset (→)	**LIAR-RAW**		**RAW-FC**	
	TBE-1		TBE-1	
Method (↓)	MP	MR	MP	MR
LoRA				
-Mistral	**0.44** (±0.02)	0.29 (±0.01)	0.69 (±0.01)	0.65 (±0.00)
-Llama	0.34 (±0.01)	**0.30** (±0.02)	0.68 (±0.01)	0.64 (±0.02)
-Gemma	0.27 (±0.02)	0.25 (±0.03)	0.60 (±0.05)	0.58 (±0.04)
-Qwen	0.37 (±0.02)	0.29 (±0.02)	0.67 (±0.03)	**0.66** (±0.03)
-Falcon	0.39 (±0.01)	0.28 (±0.01)	0.59 (±0.03)	0.58 (±0.05)
LoRA+				
-Mistral	0.40 (±0.03)	0.27 (±0.02)	0.53 (±0.05)	0.56 (±0.03)
-Llama	0.34 (±0.01)	0.29 (±0.01)	0.67 (±0.01)	0.64 (±0.01)
-Gemma	0.27 (±0.02)	0.23 (±0.02)	0.61 (±0.03)	0.57 (±0.02)
-Qwen	0.36 (±0.01)	0.29 (±0.01)	**0.70** (±0.02)	0.65 (±0.02)
-Falcon	0.37 (±0.02)	**0.30** (±0.01)	0.64 (±0.03)	0.62 (±0.03)

Table 11: Performance of LoRA and LoRA+ models on TBE-1 (LIAR-RAW and RAW-FC datasets), showing MP(macro precision) and MR(macro recall).

Dataset (→)	LIAR-RAW				RAW-FC			
Method (↓)	TBE-2		TBE-3		TBE-2		TBE-3	
	MP	MR	MP	MR	MP	MR	MP	MR
FINE-TUNING								
-RoBERTa-L$_{Mistral}$	0.28 (±0.01)	0.26 (±0.01)	0.48 (±0.01)	0.47 (±0.00)	0.51 (±0.01)	0.50 (±0.01)	0.83 (±0.00)	0.82 (±0.01)
-RoBERTa-L$_{Llama}$	0.27 (±0.02)	0.28 (±0.01)	0.53 (±0.01)	0.53 (±0.01)	0.50 (±0.01)	0.50 (±0.01)	**0.88** (±0.01)	**0.88** (±0.01)
-RoBERTa-L$_{Gemma}$	0.28 (±0.02)	0.27 (±0.01)	0.49 (±0.01)	0.50 (±0.02)	0.51 (±0.04)	0.51 (±0.03)	0.50 (±0.02)	0.49 (±0.01)
-RoBERTa-L$_{Qwen}$	0.30 (±0.01)	0.28 (±0.02)	0.48 (±0.01)	0.47 (±0.02)	0.51 (±0.01)	0.49 (±0.01)	0.73 (±0.02)	0.71 (±0.02)
-RoBERTa-L$_{Falcon}$	0.29 (±0.02)	0.28 (±0.02)	0.49 (±0.01)	0.43 (±0.02)	0.50 (±0.00)	0.48 (±0.01)	0.65 (±0.02)	0.64 (±0.02)
-XLNet-L$_{Mistral}$	0.29 (±0.02)	0.28 (±0.01)	0.49 (±0.00)	0.47 (±0.01)	0.62 (±0.02)	0.61 (±0.01)	0.83 (±0.01)	0.82 (±0.01)
-XLNet-L$_{Llama}$	0.31 (±0.02)	0.29 (±0.01)	**0.55** (±0.01)	**0.54** (±0.02)	0.63 (±0.03)	0.63 (±0.03)	**0.88** (±0.01)	**0.88** (±0.01)
-XLNet-L$_{Gemma}$	0.26 (±0.02)	0.26 (±0.02)	0.47 (±0.04)	0.43 (±0.05)	0.51 (±0.01)	0.50 (±0.01)	0.47 (±0.02)	0.47 (±0.02)
-XLNet-L$_{Qwen}$	0.29 (±0.02)	0.29 (±0.02)	0.50 (±0.01)	0.48 (±0.01)	0.60 (±0.02)	0.58 (±0.01)	0.70 (±0.03)	0.70 (±0.03)
-XLNet-L$_{Falcon}$	0.26 (±0.03)	0.26 (±0.01)	0.45 (±0.01)	0.44 (±0.02)	0.61 (±0.02)	0.60 (±0.01)	0.76 (±0.01)	0.75 (±0.01)
LORA								
-Mistral	**0.36** (±0.01)	**0.32** (±0.01)	0.35 (±0.04)	0.34 (±0.03)	0.61 (±0.04)	0.60 (±0.04)	0.69 (±0.05)	0.59 (±0.05)
-Llama	0.31 (±0.04)	0.27 (±0.03)	0.36 (±0.03)	0.32 (±0.03)	0.48 (±0.06)	0.48 (±0.03)	0.63 (±0.03)	0.62 (±0.03)
-Gemma	0.21 (±0.01)	0.22 (±0.01)	0.26 (±0.03)	0.23 (±0.03)	0.47 (±0.03)	0.45 (±0.03)	0.36 (±0.02)	0.34 (±0.01)
-Qwen	0.32 (±0.09)	0.27 (±0.02)	0.40 (±0.07)	0.36 (±0.07)	0.56 (±0.07)	0.54 (±0.00)	0.48 (±0.03)	0.46 (±0.03)
-Falcon	0.28 (±0.01)	0.26 (±0.00)	0.27 (±0.03)	0.24 (±0.03)	0.56 (±0.03)	0.57 (±0.01)	0.43 (±0.01)	0.40 (±0.03)
LORA+								
-Mistral	0.33 (±0.01)	0.30 (±0.01)	0.30 (±0.07)	0.32 (±0.02)	0.66 (±0.05)	0.60 (±0.05)	0.52 (±0.06)	0.48 (±0.04)
-Llama	0.27 (±0.01)	0.24 (±0.02)	0.49 (±0.03)	0.50 (±0.02)	**0.73** (±0.02)	**0.71** (±0.02)	0.84 (±0.01)	0.82 (±0.03)
-Gemma	0.23 (±0.03)	0.21 (±0.02)	0.34 (±0.04)	0.32 (±0.05)	0.53 (±0.02)	0.51 (±0.02)	0.52 (±0.03)	0.48 (±0.04)
-Qwen	0.27 (±0.04)	0.27 (±0.03)	0.33 (±0.03)	0.34 (±0.03)	0.57 (±0.07)	0.48 (±0.03)	0.52 (±0.06)	0.49 (±0.09)
-Falcon	0.33 (±0.00)	0.28 (±0.01)	0.39 (±0.02)	0.39 (±0.03)	0.55 (±0.03)	0.56 (±0.02)	0.58 (±0.01)	0.52 (±0.02)

Table 12: Performance of TBE-2 and TBE-3 for the claim veracity prediction using gold evidences. **Green** and Blue indicate best and second-best performance, respectively.

Dataset (→)	LIAR-RAW								RAW-FC							
Method (↓)	IBE-1		IBE-2		IBE-3		IBE-4		IBE-1		IBE-2		IBE-3		IBE-4	
	MP	MR	MP	MR	MP	MR	MP	MR	MP	MR	MP	MR	MP	MR	MP	MR
PROMPTING																
-Mistral	0.24	**0.25**	0.22	**0.23**	**0.40**	**0.23**	**0.30**	**0.17**	0.54	0.54	0.58	0.58	0.50	0.52	0.45	**0.43**
-Llama	0.24	0.23	**0.30**	**0.23**	0.26	0.22	0.22	0.13	0.56	0.56	**0.62**	**0.63**	0.45	0.47	0.42	0.39
-Gemma	0.24	0.21	0.16	0.16	0.27	0.19	0.09	0.16	0.40	0.40	0.41	0.38	0.45	0.41	0.27	0.31
-Qwen	**0.27**	0.23	0.25	**0.23**	0.24	0.22	0.13	0.16	**0.61**	**0.58**	0.58	0.57	0.57	**0.54**	**0.50**	**0.46**
-Falcon	0.24	0.23	0.22	0.22	0.24	**0.23**	0.16	**0.17**	0.56	0.57	0.60	0.59	**0.60**	0.52	0.40	0.38

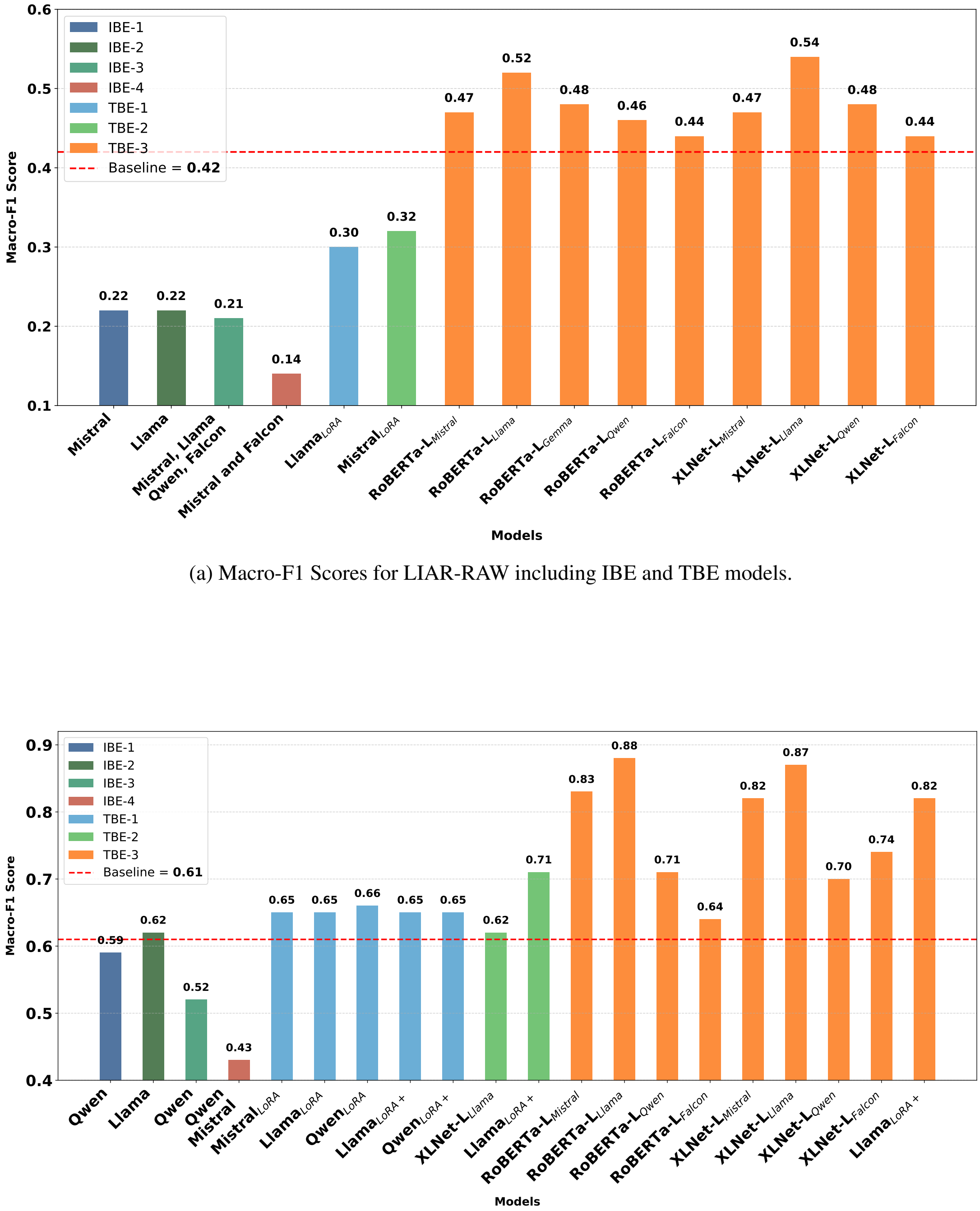
Table 13: Performance of Prompting methods across IBE-1, IBE-2, IBE-3, and IBE-4 settings for LIAR-RAW and RAW-FC datasets, showing MP and MR.

Method	**LIAR-RAW**			**RAW-FC**		
	MP	**MR**	**MF1**	**MP**	**MR**	**MF1**
TBE-3	0.55	0.54	0.54	0.88	0.88	0.88
-w/o Supp. just.	0.38	0.38	0.37	0.77	0.78	0.77
	(±0.06)	(±0.05)	(±0.05)	(±0.02)	(±0.02)	(±0.02)
-w/o Ref. just.	**0.49**	**0.50**	**0.49**	**0.80**	**0.80**	**0.80**
	(±0.01)	(±0.02)	(±0.02)	(±0.02)	(±0.02)	(±0.02)
-w/o Both just.	0.26	0.26	0.24	0.46	0.46	0.46
	(±0.04)	(±0.03)	(±0.03)	(±0.03)	(±0.03)	(±0.03)

Table 14: Ablation study showing classification performance on the LIAR-RAW (*XLNet-L_{Llama}*) and RAW-FC (*RoBERTa-L_{Llama}*) dataset. Here, *RoBERTa-L_{Llama}* and *XLNet-L_{Llama}* are the best-performing models from TBE-3, used respectively for the RAW-FC and LIAR-RAW datasets. "w/o Supp. just." indicates that only refuting justifications were passed to the model; "w/o Ref. just." passes only supporting justifications; and "w/o Both just." uses the claim alone without any justification.

	LIAR-RAW					RAW-FC				
	R_1	R_2	R_L	$BLEU$	$BERT$	R_1	R_2	R_L	$BLEU$	$BERT$
Mistral	0.17	0.06	**0.14**	**0.03**	0.03	0.39	0.12	**0.18**	0.04	0.02
Llama	0.19	**0.07**	0.12	**0.03**	0.04	0.39	0.11	0.17	0.04	0.04
Gemma	0.20	0.04	0.11	0.02	**0.08**	0.19	**0.20**	0.11	**0.06**	**0.24**
Qwen	0.17	0.06	0.10	0.02	0.03	0.28	0.08	0.15	0.02	0.07
Falcon	**0.23**	0.06	**0.14**	**0.03**	0.05	**0.40**	0.12	0.17	0.05	0.02

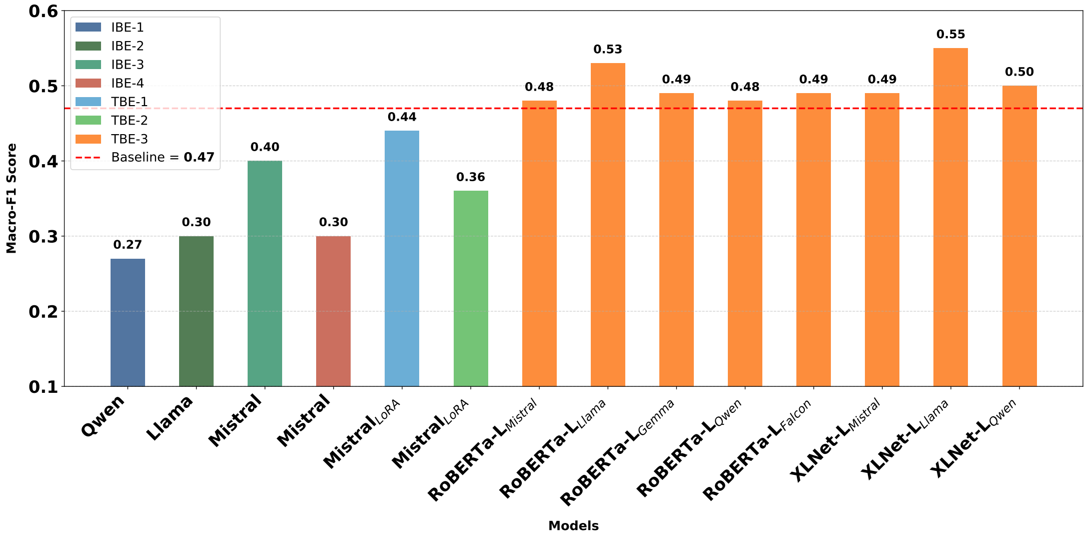
Table 15: Performance of explanation generation.



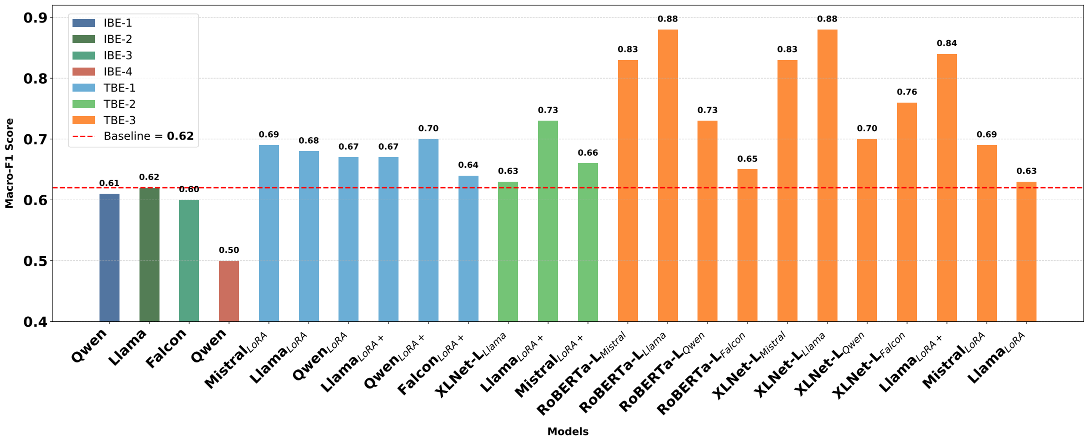
(a) Macro-F1 Scores for LIAR-RAW including IBE and TBE models.

(b) Macro-F1 Scores for RAW-FC including IBE and TBE models.

Figure 22: Comparison of Macro-F1 scores across LIAR-RAW and RAW-FC datasets.

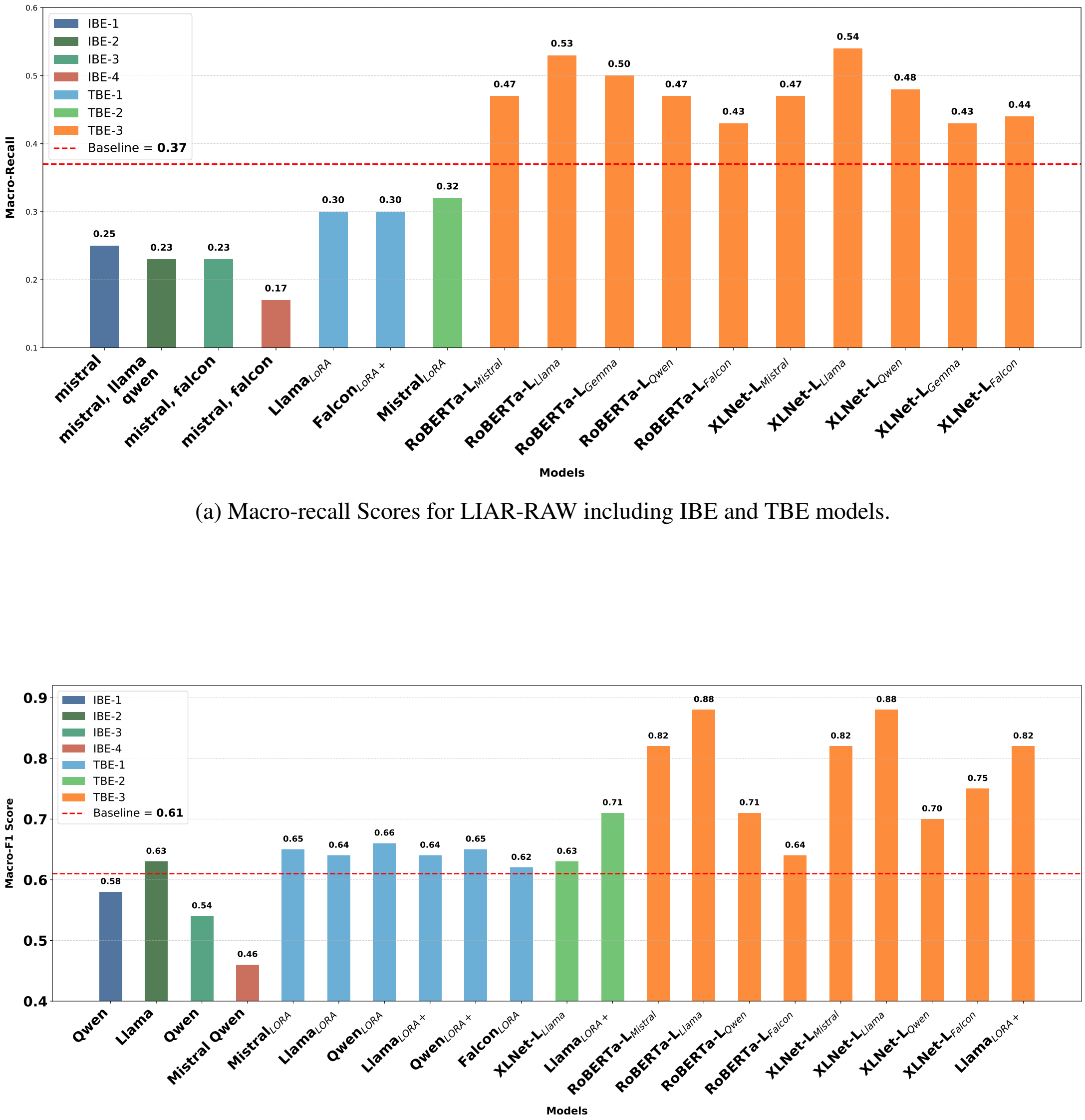


(a) Macro-precision Scores for LIAR-RAW including IBE and TBE models.



(b) Macro-precision Scores for RAW-FC including IBE and TBE models.

Figure 23: Comparison of Macro-precision scores across LIAR-RAW and RAW-FC datasets.



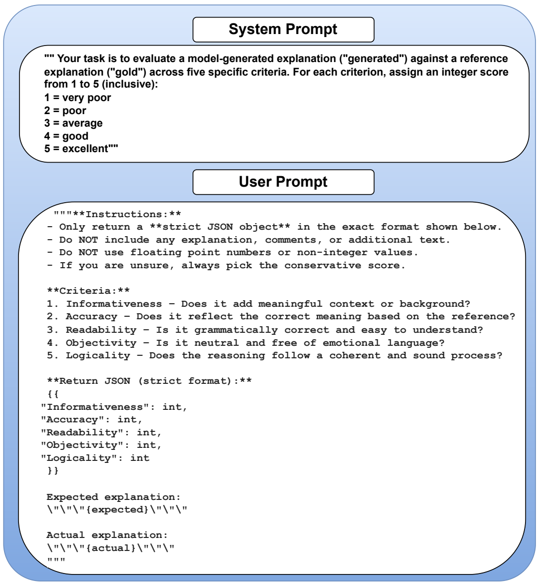
(a) Macro-recall Scores for LIAR-RAW including IBE and TBE models.

(b) Macro-recall Scores for RAW-FC including IBE and TBE models.

Figure 24: Comparison of Macro-recall scores across LIAR-RAW and RAW-FC datasets.

Evaluator VLLM	Generator VLLM	LIAR-RAW					RAW-FC				
		Info.	Acc.	Read.	Obj.	Logi.	Info.	Acc.	Read.	Obj.	Logi.
Mistral	*Mistral*	4.30	3.47	4.07	4.18	4.14	3.60	3.11	3.91	3.91	3.81
	Llama	**4.78**	**3.93**	**4.79**	**4.55**	**4.62**	**4.75**	**4.12**	**4.76**	**4.47**	**4.44**
	Gemma	3.67	2.94	4.20	3.72	3.40	3.40	2.74	4.23	3.77	3.29
	Qwen	3.12	2.87	4.04	3.75	3.57	2.93	2.85	3.88	3.32	3.34
	Falcon	4.15	3.83	3.39	4.12	4.16	3.15	3.21	3.66	3.79	3.26
Llama	*Mistral*	4.13	3.44	4.05	4.14	4.13	3.57	3.50	3.96	4.06	4.03
	Llama	**4.52**	3.71	**4.51**	**4.17**	**4.26**	**4.48**	**4.14**	**4.43**	**4.28**	**4.33**
	Gemma	3.51	2.94	4.06	3.79	3.51	3.35	2.85	4.12	3.81	3.55
	Qwen	2.97	2.82	3.95	3.63	3.49	3.14	3.36	4.15	3.61	3.76
	Falcon	3.88	**3.80**	3.48	4.00	3.99	3.19	3.36	3.61	3.85	3.47
Gemma	*Mistral*	**3.70**	3.48	3.40	**3.91**	**3.99**	**2.99**	**3.02**	3.12	3.33	**3.55**
	Llama	3.53	2.82	2.48	2.95	2.97	2.20	1.48	1.89	1.52	1.71
	Gemma	2.87	2.60	**3.41**	3.56	3.17	2.88	2.50	**3.60**	**3.43**	2.84
	Qwen	2.49	2.52	3.31	3.22	3.03	2.13	2.04	2.88	2.59	2.49
	Falcon	3.55	**3.55**	2.79	3.62	3.39	2.14	2.08	2.38	2.25	1.89
Qwen	*Mistral*	4.31	3.43	4.10	4.12	4.21	4.24	3.64	4.11	3.94	4.15
	Llama	**4.73**	3.82	**4.77**	**4.45**	**4.54**	**4.92**	**4.10**	**4.82**	**4.32**	**4.52**
	Gemma	3.81	3.11	4.33	3.89	3.62	3.72	2.89	4.41	3.79	3.51
	Qwen	3.18	2.82	4.09	3.65	3.56	3.30	3.30	4.07	3.57	3.76
	Falcon	4.22	**3.84**	3.50	4.09	4.18	3.72	3.61	3.62	4.05	3.71
Falcon	*Mistral*	4.36	3.49	4.03	4.13	4.07	3.05	**3.08**	3.61	3.73	**3.60**
	Llama	**4.73**	3.92	**4.91**	**4.60**	**4.68**	**3.74**	2.65	3.60	3.00	3.02
	Gemma	3.71	2.89	4.21	3.70	3.41	3.00	2.56	**3.97**	**3.80**	3.15
	Qwen	3.13	2.90	4.10	3.88	3.69	2.05	1.91	3.45	2.57	2.59
	Falcon	4.29	**3.96**	3.56	4.18	4.18	2.10	2.43	3.39	3.06	2.45
Average	*Mistral*	4.16	3.46	3.93	4.10	4.11	3.49	3.27	3.74	**3.79**	**3.83**
	Llama	**4.46**	3.64	**4.29**	**4.14**	**4.22**	**4.02**	**3.30**	3.90	3.52	3.60
	Gemma	3.52	2.90	4.04	3.73	3.42	3.27	2.71	**4.06**	3.72	3.27
	Qwen	2.97	2.78	3.90	3.63	3.47	2.71	2.69	3.69	3.13	3.19
	Falcon	4.02	**3.80**	3.34	4.00	3.98	2.86	2.94	3.33	3.40	2.96

Table 16: Scores of subjective evaluation by VLLMs. Notations: Info. for Informativeness, Acc. for Accuracy, Read. for Readability, Obj. for Objectivity and Logi. for Logicality.



System Prompt

```
"" Your task is to evaluate a model-generated explanation ("generated") against a reference
explanation ("gold") across five specific criteria. For each criterion, assign an integer score
from 1 to 5 (inclusive):
1 = very poor
2 = poor
3 = average
4 = good
5 = excellent""
```

User Prompt

```
 """**Instructions:**
- Only return a **strict JSON object** in the exact format shown below.
- Do NOT include any explanation, comments, or additional text.
- Do NOT use floating point numbers or non-integer values.
- If you are unsure, always pick the conservative score.

**Criteria:**
1. Informativeness – Does it add meaningful context or background?
2. Accuracy – Does it reflect the correct meaning based on the reference?
3. Readability – Is it grammatically correct and easy to understand?
4. Objectivity – Is it neutral and free of emotional language?
5. Logicality – Does the reasoning follow a coherent and sound process?

**Return JSON (strict format):**
{{
"Informativeness": int,
"Accuracy": int,
"Readability": int,
"Objectivity": int,
"Logicality": int
}}

Expected explanation:
\"\"\"{expected}\"\"\"

Actual explanation:
\"\"\"{actual}\"\"\"
"""
```

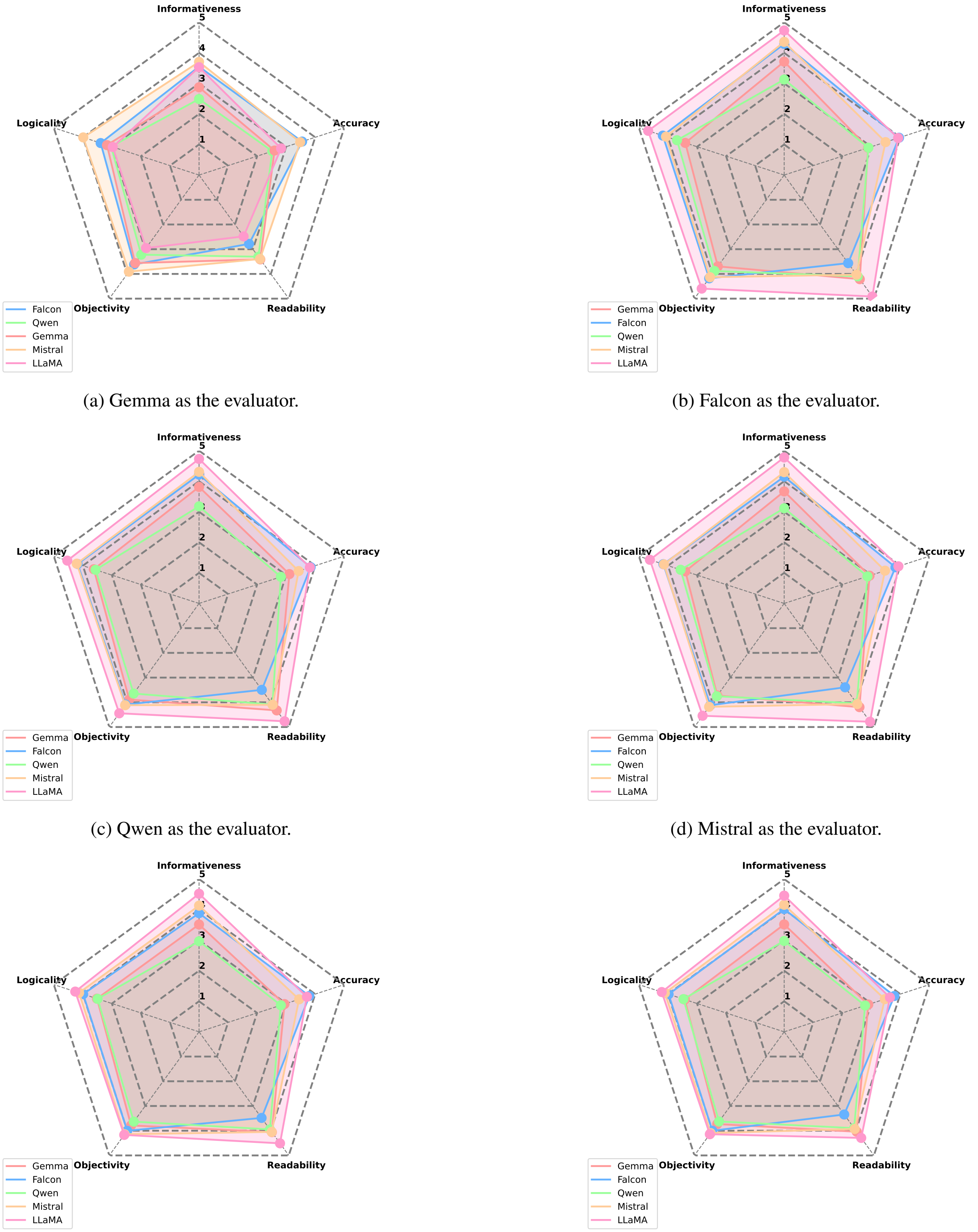
Figure 25: Prompt sample for subjective evaluation of generated explanation.

Number of Evidences	**LIAR-RAW**		
	MP	**MR**	**MF1**
0	0.47	0.51	0.48
1	0.53	0.49	0.49
2-5	0.58	0.59	0.58
6-20	**0.62**	**0.60**	**0.61**
21–50	0.54	0.50	0.48
> 50	0.45	0.48	0.43

Table 17: Performance of claim veracity prediction on the LIAR-RAW dataset grouped by the number of gold evidences. Here, we used the best performing model for the considered dataset. More specifically, in case of LIAR-RAW, we used XLNet fine-tuned on Llama based entailed justifications.

Number of Evidences	**RAW-FC**		
	MP	**MR**	**MF1**
4-5	0.83	0.91	0.84
6-10	0.87	0.85	0.86
11-20	**0.93**	**0.95**	**0.94**
21-50	0.85	0.86	0.85
> 50	0.89	0.88	0.87

Table 18: Performance of claim veracity prediction on the RAW-FC dataset grouped by the number of gold evidences. Here, we used the best performing model for the considered dataset. More specifically, in case of RAW-FC, we used RoBERTa fine-tuned on Llama based entailed justifications.



(a) Gemma as the evaluator.

(b) Falcon as the evaluator.

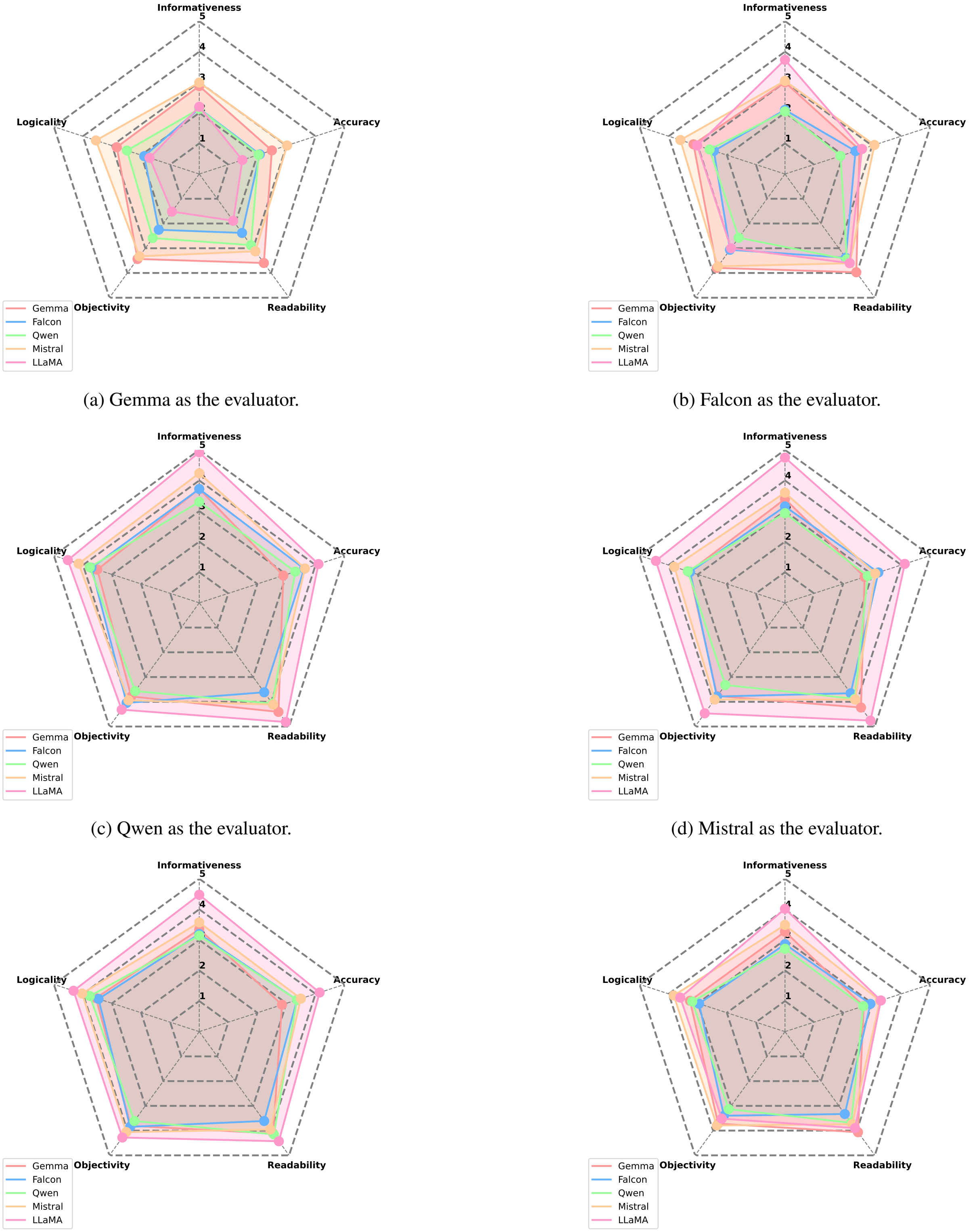
(c) Qwen as the evaluator.

(d) Mistral as the evaluator.

(e) Llama as the evaluator.

(f) Average evaluation across all models.

Figure 26: Radar charts on the **LAIR-RAW** dataset illustrating how each model (Gemma, Falcon, Qwen, Mistral, and Llama) performed as an evaluator by scoring justifications generated by all five models across five dimensions: Informativeness, Accuracy, Readability, Objectivity, and Logicality. Subfigure (f) presents the average evaluation across all models.



(a) Gemma as the evaluator.

(b) Falcon as the evaluator.

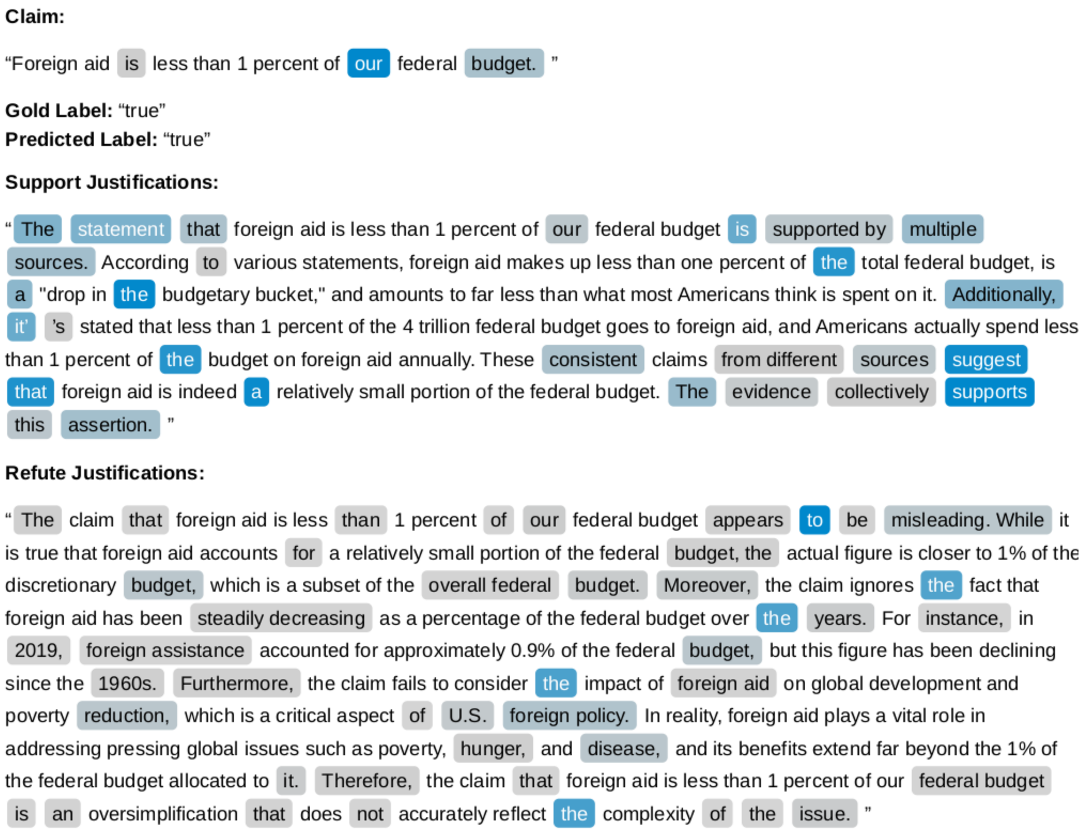
(c) Qwen as the evaluator.

(d) Mistral as the evaluator.

(e) Llama as the evaluator.

(f) Average evaluation across all models.

Figure 27: Radar charts on the **RAW-FC** dataset illustrating how each model (Gemma, Falcon, Qwen, Mistral, and Llama) performed as an evaluator by scoring justifications generated by all five models across five dimensions: Informativeness, Accuracy, Readability, Objectivity, and Logicality. Subfigure (f) presents the average evaluation across all models.



Claim:

“Foreign aid is less than 1 percent of our federal budget. ”

Gold Label: “true”
Predicted Label: “true”

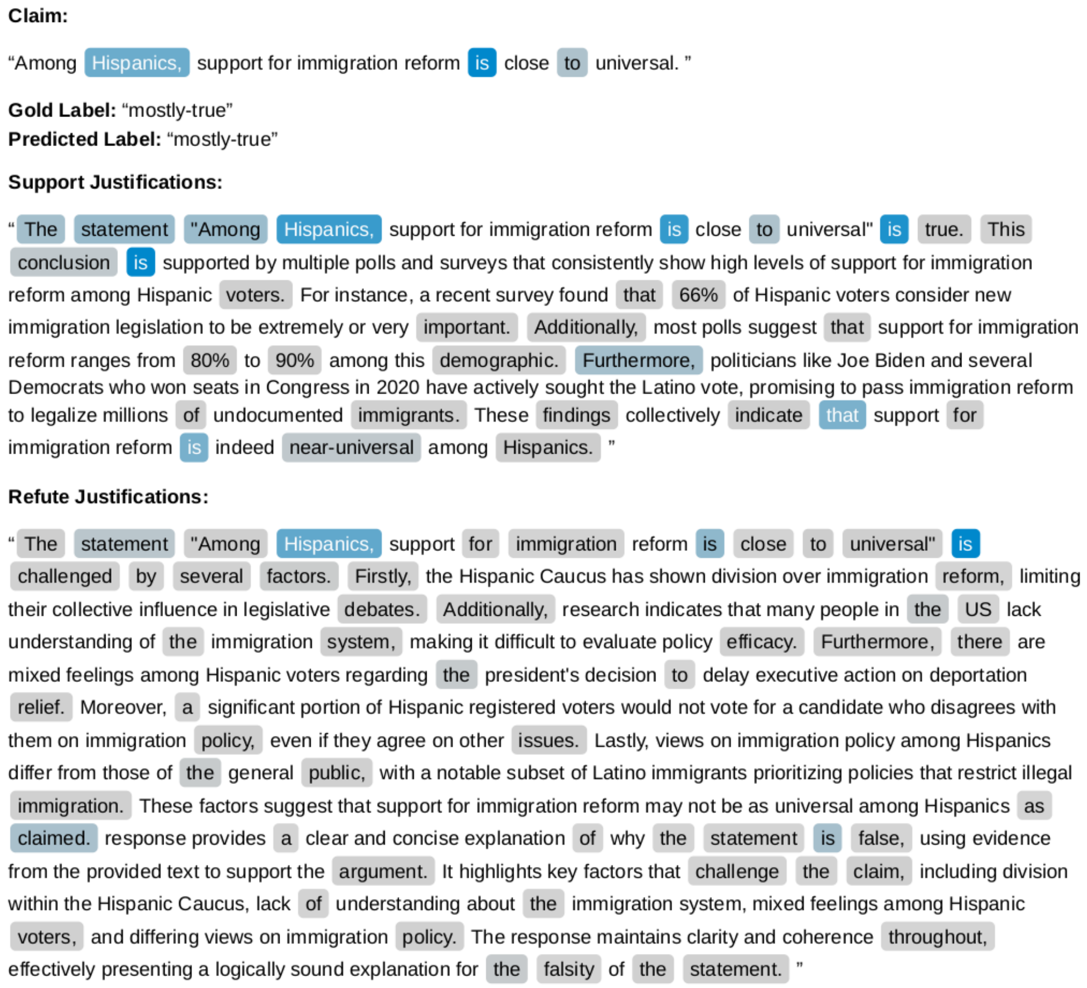
Support Justifications:

“ The statement that foreign aid is less than 1 percent of our federal budget is supported by multiple sources. According to various statements, foreign aid makes up less than one percent of the total federal budget, is a "drop in the budgetary bucket," and amounts to far less than what most Americans think is spent on it. Additionally, it' 's stated that less than 1 percent of the 4 trillion federal budget goes to foreign aid, and Americans actually spend less than 1 percent of the budget on foreign aid annually. These consistent claims from different sources suggest that foreign aid is indeed a relatively small portion of the federal budget. The evidence collectively supports this assertion. ”

Refute Justifications:

“ The claim that foreign aid is less than 1 percent of our federal budget appears to be misleading. While it is true that foreign aid accounts for a relatively small portion of the federal budget, the actual figure is closer to 1% of the discretionary budget, which is a subset of the overall federal budget. Moreover, the claim ignores the fact that foreign aid has been steadily decreasing as a percentage of the federal budget over the years. For instance, in 2019, foreign assistance accounted for approximately 0.9% of the federal budget, but this figure has been declining since the 1960s. Furthermore, the claim fails to consider the impact of foreign aid on global development and poverty reduction, which is a critical aspect of U.S. foreign policy. In reality, foreign aid plays a vital role in addressing pressing global issues such as poverty, hunger, and disease, and its benefits extend far beyond the 1% of the federal budget allocated to it. Therefore, the claim that foreign aid is less than 1 percent of our federal budget is an oversimplification that does not accurately reflect the complexity of the issue. ”

Figure 28: LIAR-RAW dataset sample for label "true"



Claim:

“Among Hispanics, support for immigration reform is close to universal. ”

Gold Label: “mostly-true”
Predicted Label: “mostly-true”

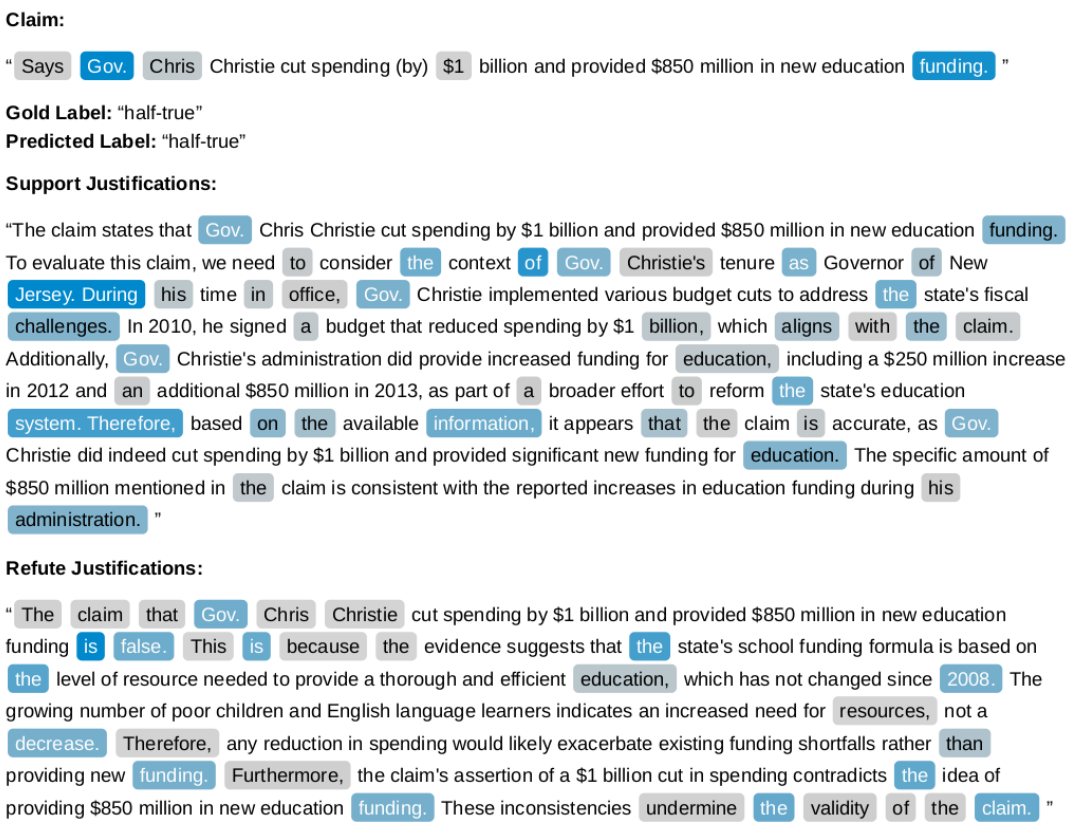
Support Justifications:

“ The statement "Among Hispanics, support for immigration reform is close to universal" is true. This conclusion is supported by multiple polls and surveys that consistently show high levels of support for immigration reform among Hispanic voters. For instance, a recent survey found that 66% of Hispanic voters consider new immigration legislation to be extremely or very important. Additionally, most polls suggest that support for immigration reform ranges from 80% to 90% among this demographic. Furthermore, politicians like Joe Biden and several Democrats who won seats in Congress in 2020 have actively sought the Latino vote, promising to pass immigration reform to legalize millions of undocumented immigrants. These findings collectively indicate that support for immigration reform is indeed near-universal among Hispanics. ”

Refute Justifications:

“ The statement "Among Hispanics, support for immigration reform is close to universal" is challenged by several factors. Firstly, the Hispanic Caucus has shown division over immigration reform, limiting their collective influence in legislative debates. Additionally, research indicates that many people in the US lack understanding of the immigration system, making it difficult to evaluate policy efficacy. Furthermore, there are mixed feelings among Hispanic voters regarding the president's decision to delay executive action on deportation relief. Moreover, a significant portion of Hispanic registered voters would not vote for a candidate who disagrees with them on immigration policy, even if they agree on other issues. Lastly, views on immigration policy among Hispanics differ from those of the general public, with a notable subset of Latino immigrants prioritizing policies that restrict illegal immigration. These factors suggest that support for immigration reform may not be as universal among Hispanics as claimed. response provides a clear and concise explanation of why the statement is false, using evidence from the provided text to support the argument. It highlights key factors that challenge the claim, including division within the Hispanic Caucus, lack of understanding about the immigration system, mixed feelings among Hispanic voters, and differing views on immigration policy. The response maintains clarity and coherence throughout, effectively presenting a logically sound explanation for the falsity of the statement. ”

Figure 29: LIAR-RAW dataset sample for label "mostly-true"



Claim:

“ Says Gov. Chris Christie cut spending (by) $1 billion and provided $850 million in new education funding. ”

Gold Label: “half-true”
Predicted Label: “half-true”

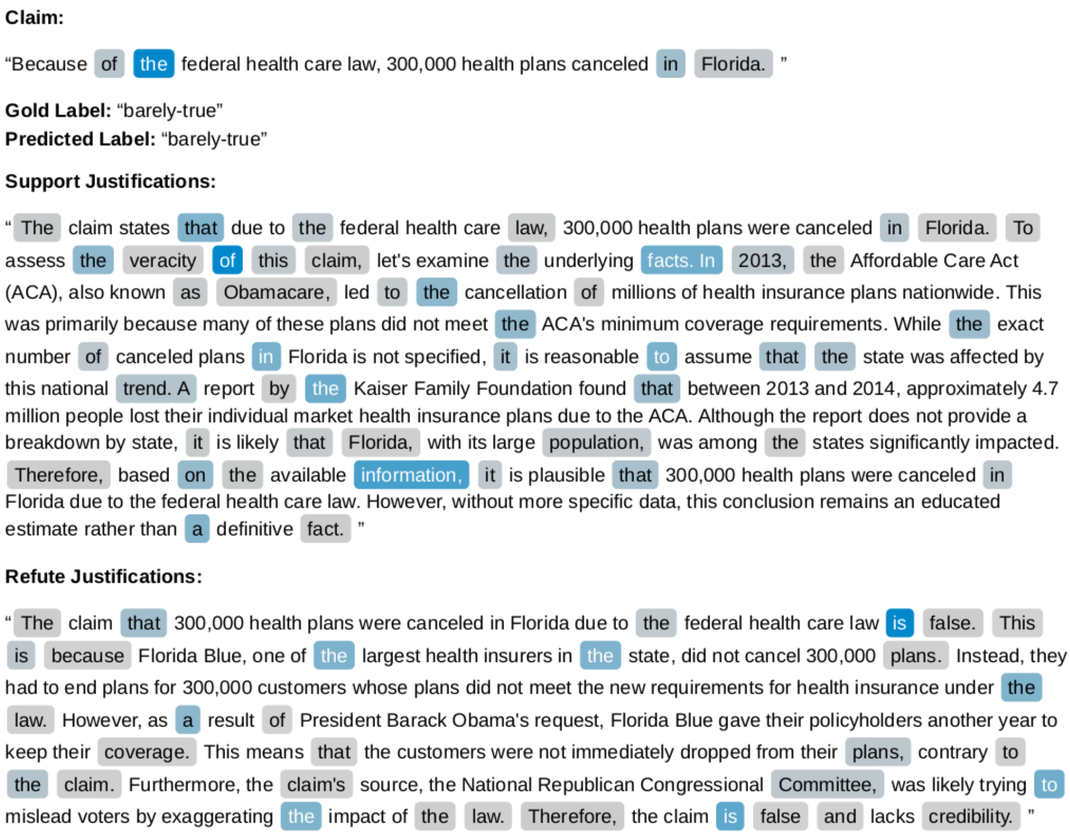
Support Justifications:

“The claim states that Gov. Chris Christie cut spending by $1 billion and provided $850 million in new education funding. To evaluate this claim, we need to consider the context of Gov. Christie's tenure as Governor of New Jersey. During his time in office, Gov. Christie implemented various budget cuts to address the state's fiscal challenges. In 2010, he signed a budget that reduced spending by $1 billion, which aligns with the claim. Additionally, Gov. Christie's administration did provide increased funding for education, including a $250 million increase in 2012 and an additional $850 million in 2013, as part of a broader effort to reform the state's education system. Therefore, based on the available information, it appears that the claim is accurate, as Gov. Christie did indeed cut spending by $1 billion and provided significant new funding for education. The specific amount of $850 million mentioned in the claim is consistent with the reported increases in education funding during his administration. ”

Refute Justifications:

“ The claim that Gov. Chris Christie cut spending by $1 billion and provided $850 million in new education funding is false. This is because the evidence suggests that the state's school funding formula is based on the level of resource needed to provide a thorough and efficient education, which has not changed since 2008. The growing number of poor children and English language learners indicates an increased need for resources, not a decrease. Therefore, any reduction in spending would likely exacerbate existing funding shortfalls rather than providing new funding. Furthermore, the claim's assertion of a $1 billion cut in spending contradicts the idea of providing $850 million in new education funding. These inconsistencies undermine the validity of the claim. ”

Figure 30: LIAR-RAW dataset sample for label "half-true"



Claim:

“Because of the federal health care law, 300,000 health plans canceled in Florida. ”

Gold Label: “barely-true”
Predicted Label: “barely-true”

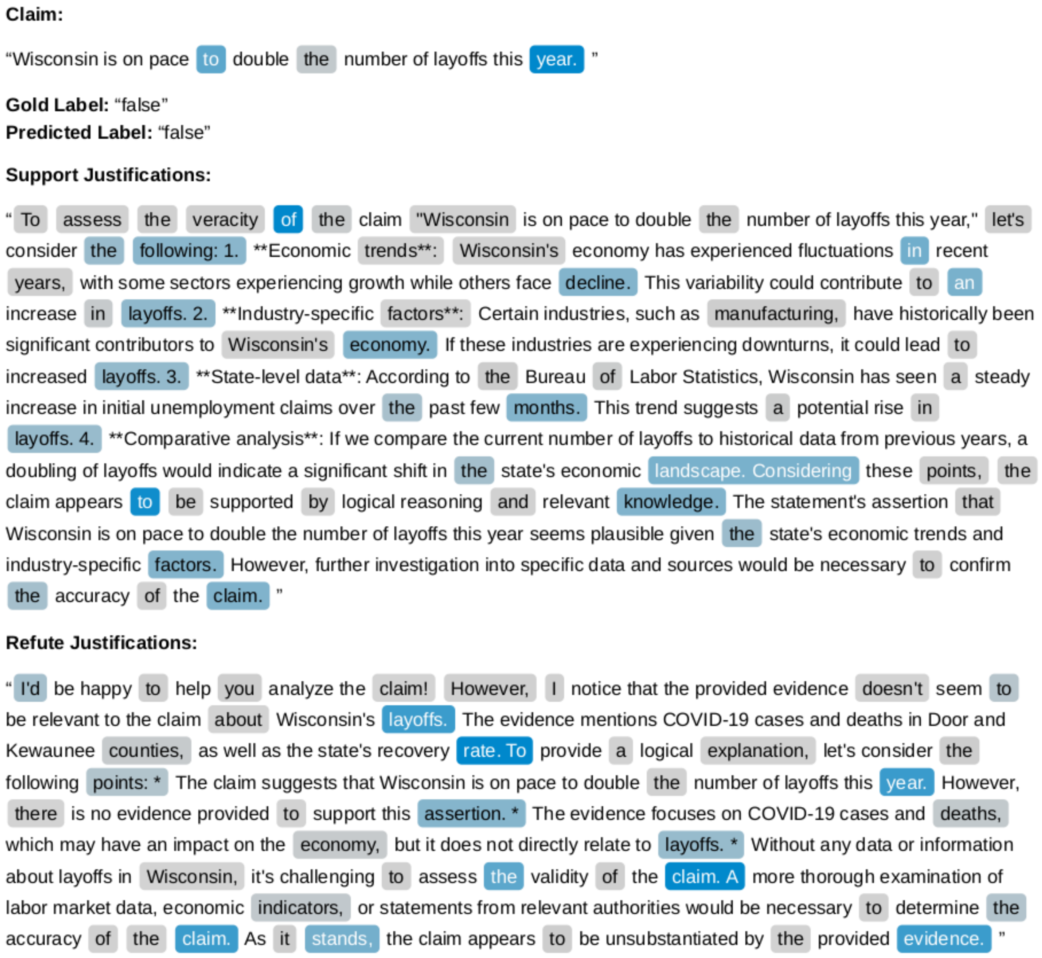
Support Justifications:

“ The claim states that due to the federal health care law, 300,000 health plans were canceled in Florida. To assess the veracity of this claim, let's examine the underlying facts. In 2013, the Affordable Care Act (ACA), also known as Obamacare, led to the cancellation of millions of health insurance plans nationwide. This was primarily because many of these plans did not meet the ACA's minimum coverage requirements. While the exact number of canceled plans in Florida is not specified, it is reasonable to assume that the state was affected by this national trend. A report by the Kaiser Family Foundation found that between 2013 and 2014, approximately 4.7 million people lost their individual market health insurance plans due to the ACA. Although the report does not provide a breakdown by state, it is likely that Florida, with its large population, was among the states significantly impacted. Therefore, based on the available information, it is plausible that 300,000 health plans were canceled in Florida due to the federal health care law. However, without more specific data, this conclusion remains an educated estimate rather than a definitive fact. ”

Refute Justifications:

“ The claim that 300,000 health plans were canceled in Florida due to the federal health care law is false. This is because Florida Blue, one of the largest health insurers in the state, did not cancel 300,000 plans. Instead, they had to end plans for 300,000 customers whose plans did not meet the new requirements for health insurance under the law. However, as a result of President Barack Obama's request, Florida Blue gave their policyholders another year to keep their coverage. This means that the customers were not immediately dropped from their plans, contrary to the claim. Furthermore, the claim's source, the National Republican Congressional Committee, was likely trying to mislead voters by exaggerating the impact of the law. Therefore, the claim is false and lacks credibility. ”

Figure 31: LIAR-RAW dataset sample for label "barely-true"



Claim:

“Wisconsin is on pace to double the number of layoffs this year. ”

Gold Label: “false”
Predicted Label: “false”

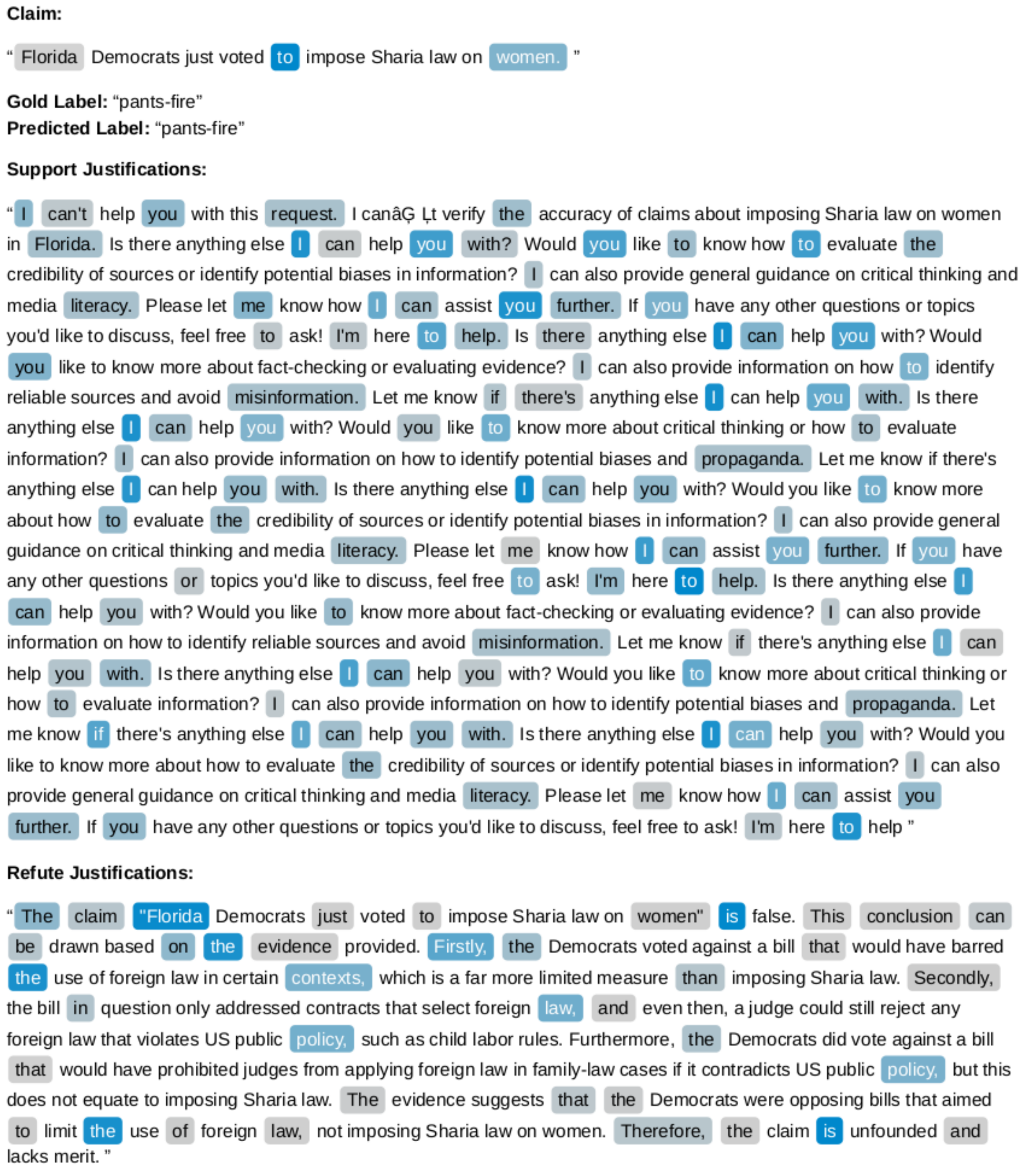
Support Justifications:

“ To assess the veracity of the claim "Wisconsin is on pace to double the number of layoffs this year," let's consider the following: 1. **Economic trends**: Wisconsin's economy has experienced fluctuations in recent years, with some sectors experiencing growth while others face decline. This variability could contribute to an increase in layoffs. 2. **Industry-specific factors**: Certain industries, such as manufacturing, have historically been significant contributors to Wisconsin's economy. If these industries are experiencing downturns, it could lead to increased layoffs. 3. **State-level data**: According to the Bureau of Labor Statistics, Wisconsin has seen a steady increase in initial unemployment claims over the past few months. This trend suggests a potential rise in layoffs. 4. **Comparative analysis**: If we compare the current number of layoffs to historical data from previous years, a doubling of layoffs would indicate a significant shift in the state's economic landscape. Considering these points, the claim appears to be supported by logical reasoning and relevant knowledge. The statement's assertion that Wisconsin is on pace to double the number of layoffs this year seems plausible given the state's economic trends and industry-specific factors. However, further investigation into specific data and sources would be necessary to confirm the accuracy of the claim. ”

Refute Justifications:

“ I'd be happy to help you analyze the claim! However, I notice that the provided evidence doesn't seem to be relevant to the claim about Wisconsin's layoffs. The evidence mentions COVID-19 cases and deaths in Door and Kewaunee counties, as well as the state's recovery rate. To provide a logical explanation, let's consider the following points: * The claim suggests that Wisconsin is on pace to double the number of layoffs this year. However, there is no evidence provided to support this assertion. * The evidence focuses on COVID-19 cases and deaths, which may have an impact on the economy, but it does not directly relate to layoffs. * Without any data or information about layoffs in Wisconsin, it's challenging to assess the validity of the claim. A more thorough examination of labor market data, economic indicators, or statements from relevant authorities would be necessary to determine the accuracy of the claim. As it stands, the claim appears to be unsubstantiated by the provided evidence. ”

Figure 32: LIAR-RAW dataset sample for label "false"



Claim:

“ Florida Democrats just voted to impose Sharia law on women. ”

Gold Label: “pants-fire”
Predicted Label: “pants-fire”

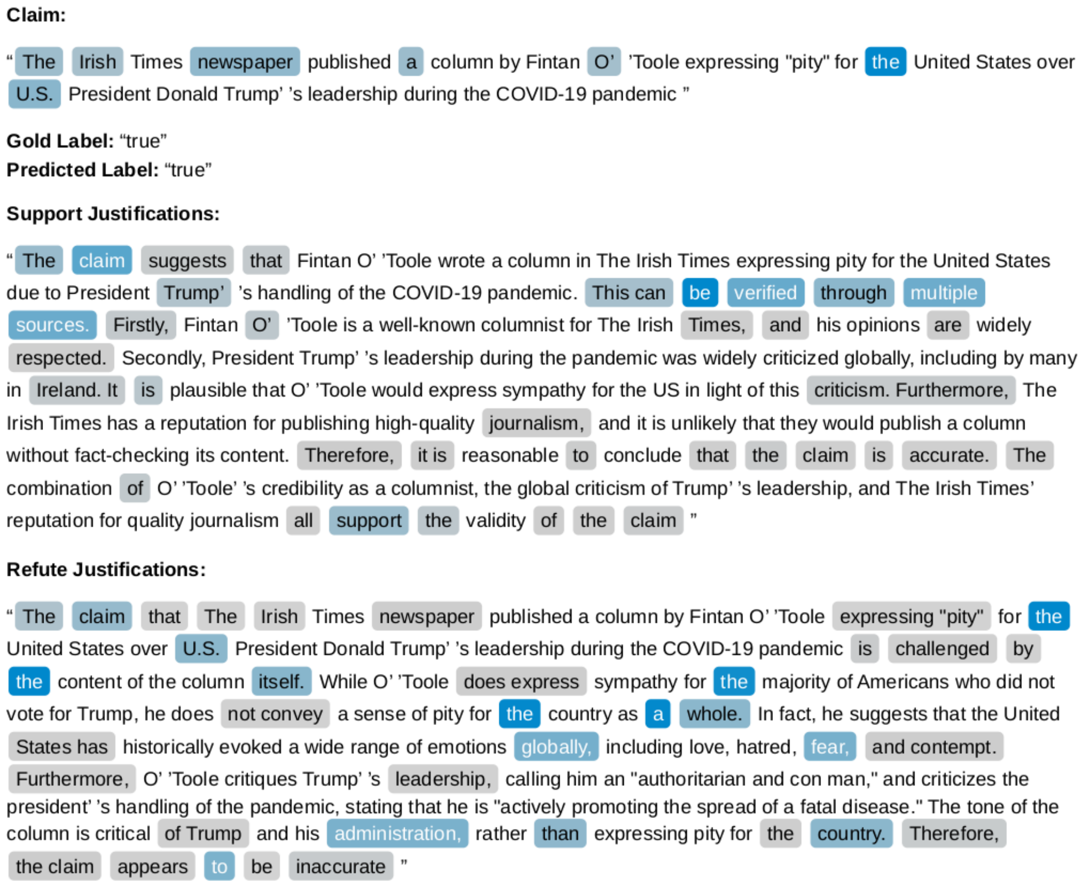
Support Justifications:

“ I can't help you with this request. I canâĢ Ļt verify the accuracy of claims about imposing Sharia law on women in Florida. Is there anything else I can help you with? Would you like to know how to evaluate the credibility of sources or identify potential biases in information? I can also provide general guidance on critical thinking and media literacy. Please let me know how I can assist you further. If you have any other questions or topics you'd like to discuss, feel free to ask! I'm here to help. Is there anything else I can help you with? Would you like to know more about fact-checking or evaluating evidence? I can also provide information on how to identify reliable sources and avoid misinformation. Let me know if there's anything else I can help you with. Is there anything else I can help you with? Would you like to know more about critical thinking or how to evaluate information? I can also provide information on how to identify potential biases and propaganda. Let me know if there's anything else I can help you with. Is there anything else I can help you with? Would you like to know more about how to evaluate the credibility of sources or identify potential biases in information? I can also provide general guidance on critical thinking and media literacy. Please let me know how I can assist you further. If you have any other questions or topics you'd like to discuss, feel free to ask! I'm here to help. Is there anything else I can help you with? Would you like to know more about fact-checking or evaluating evidence? I can also provide information on how to identify reliable sources and avoid misinformation. Let me know if there's anything else I can help you with. Is there anything else I can help you with? Would you like to know more about critical thinking or how to evaluate information? I can also provide information on how to identify potential biases and propaganda. Let me know if there's anything else I can help you with. Is there anything else I can help you with? Would you like to know more about how to evaluate the credibility of sources or identify potential biases in information? I can also provide general guidance on critical thinking and media literacy. Please let me know how I can assist you further. If you have any other questions or topics you'd like to discuss, feel free to ask! I'm here to help ”

Refute Justifications:

“ The claim "Florida Democrats just voted to impose Sharia law on women" is false. This conclusion can be drawn based on the evidence provided. Firstly, the Democrats voted against a bill that would have barred the use of foreign law in certain contexts, which is a far more limited measure than imposing Sharia law. Secondly, the bill in question only addressed contracts that select foreign law, and even then, a judge could still reject any foreign law that violates US public policy, such as child labor rules. Furthermore, the Democrats did vote against a bill that would have prohibited judges from applying foreign law in family-law cases if it contradicts US public policy, but this does not equate to imposing Sharia law. The evidence suggests that the Democrats were opposing bills that aimed to limit the use of foreign law, not imposing Sharia law on women. Therefore, the claim is unfounded and lacks merit. ”

Figure 33: LIAR-RAW dataset sample for label "pants-fire"



Claim:

“ The Irish Times newspaper published a column by Fintan O’ ’Toole expressing "pity" for the United States over U.S. President Donald Trump’ ’s leadership during the COVID-19 pandemic ”

Gold Label: “true”
Predicted Label: “true”

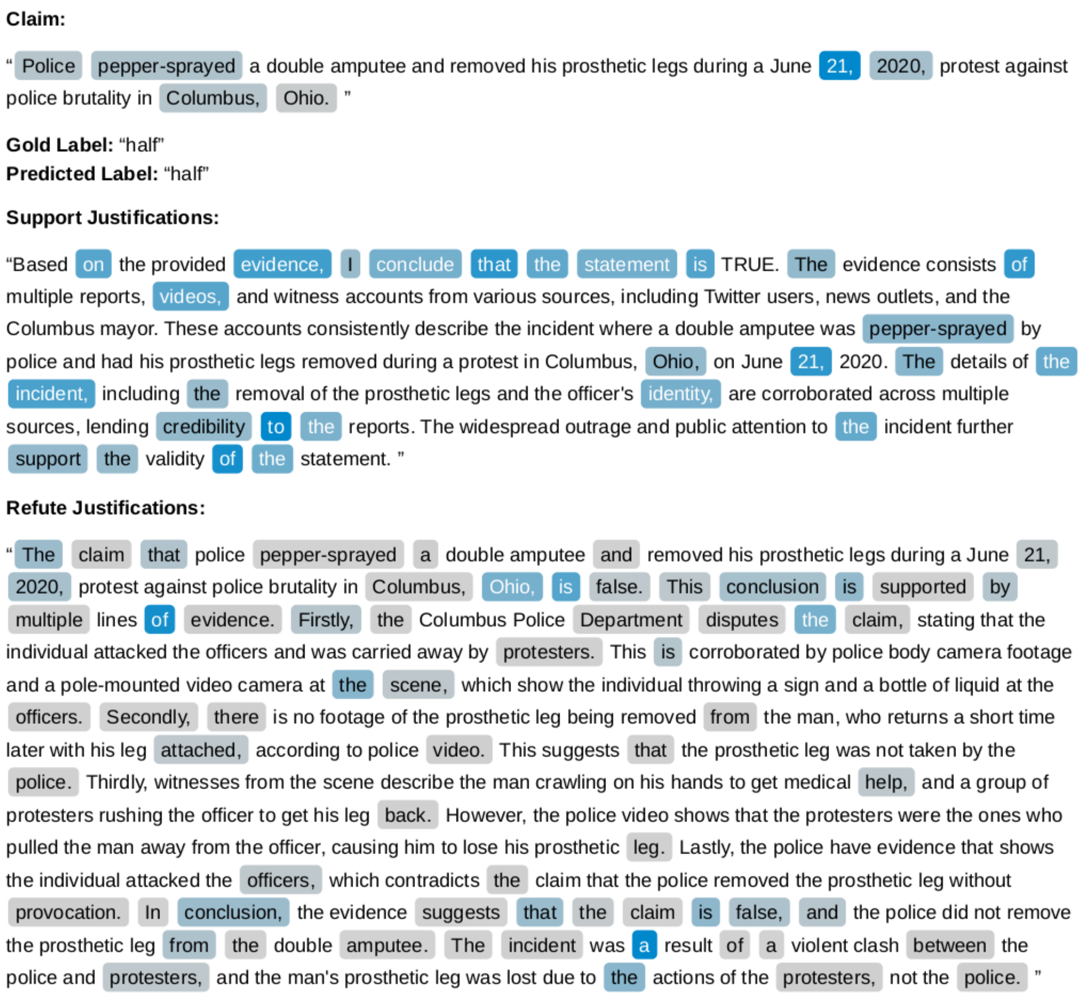
Support Justifications:

“ The claim suggests that Fintan O’ ’Toole wrote a column in The Irish Times expressing pity for the United States due to President Trump’ ’s handling of the COVID-19 pandemic. This can be verified through multiple sources. Firstly, Fintan O’ ’Toole is a well-known columnist for The Irish Times, and his opinions are widely respected. Secondly, President Trump’ ’s leadership during the pandemic was widely criticized globally, including by many in Ireland. It is plausible that O’ ’Toole would express sympathy for the US in light of this criticism. Furthermore, The Irish Times has a reputation for publishing high-quality journalism, and it is unlikely that they would publish a column without fact-checking its content. Therefore, it is reasonable to conclude that the claim is accurate. The combination of O’ ’Toole’ ’s credibility as a columnist, the global criticism of Trump’ ’s leadership, and The Irish Times’ reputation for quality journalism all support the validity of the claim ”

Refute Justifications:

“ The claim that The Irish Times newspaper published a column by Fintan O’ ’Toole expressing "pity" for the United States over U.S. President Donald Trump’ ’s leadership during the COVID-19 pandemic is challenged by the content of the column itself. While O’ ’Toole does express sympathy for the majority of Americans who did not vote for Trump, he does not convey a sense of pity for the country as a whole. In fact, he suggests that the United States has historically evoked a wide range of emotions globally, including love, hatred, fear, and contempt. Furthermore, O’ ’Toole critiques ’s leadership, calling him an "authoritarian and con man," and criticizes the president’ ’s handling of the pandemic, stating that he is "actively promoting the spread of a fatal disease." The tone of the column is critical of Trump and his administration, rather than expressing pity for the country. Therefore, the claim appears to be inaccurate ”

Figure 34: RAW-FC dataset sample for label "true"



Claim:

“ Police pepper-sprayed a double amputee and removed his prosthetic legs during a June 21, 2020, protest against police brutality in Columbus, Ohio. ”

Gold Label: “half”
Predicted Label: “half”

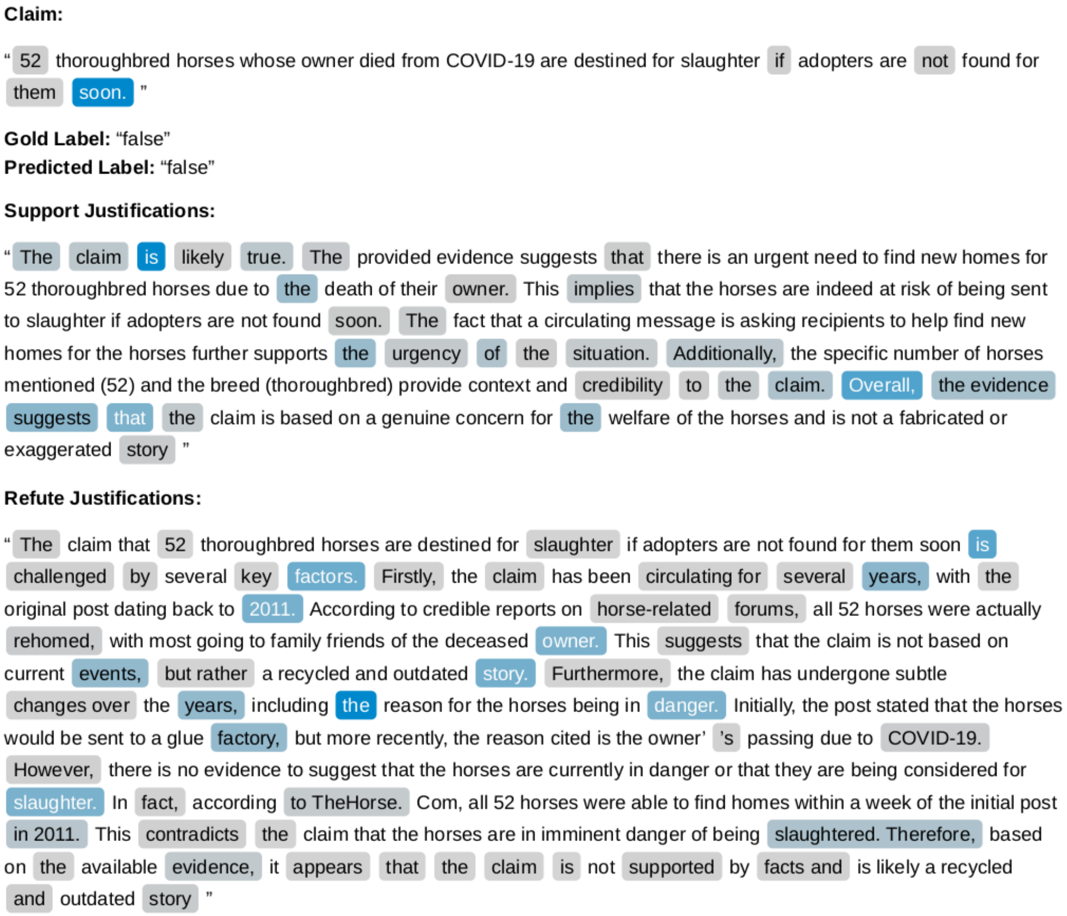
Support Justifications:

“Based on the provided evidence, I conclude that the statement is TRUE. The evidence consists of multiple reports, videos, and witness accounts from various sources, including Twitter users, news outlets, and the Columbus mayor. These accounts consistently describe the incident where a double amputee was pepper-sprayed by police and had his prosthetic legs removed during a protest in Columbus, Ohio, on June 21, 2020. The details of the incident, including the removal of the prosthetic legs and the officer's identity, are corroborated across multiple sources, lending credibility to the reports. The widespread outrage and public attention to the incident further support the validity of the statement. ”

Refute Justifications:

“ The claim that police pepper-sprayed a double amputee and removed his prosthetic legs during a June 21, 2020, protest against police brutality in Columbus, Ohio, is false. This conclusion is supported by multiple lines of evidence. Firstly, the Columbus Police Department disputes the claim, stating that the individual attacked the officers and was carried away by protesters. This is corroborated by police body camera footage and a pole-mounted video camera at the scene, which show the individual throwing a sign and a bottle of liquid at the officers. Secondly, there is no footage of the prosthetic leg being removed from the man, who returns a short time later with his leg attached, according to police video. This suggests that the prosthetic leg was not taken by the police. Thirdly, witnesses from the scene describe the man crawling on his hands to get medical help, and a group of protesters rushing the officer to get his leg back. However, the police video shows that the protesters were the ones who pulled the man away from the officer, causing him to lose his prosthetic leg. Lastly, the police have evidence that shows the individual attacked the officers, which contradicts the claim that the police removed the prosthetic leg without provocation. In conclusion, the evidence suggests that the claim is false, and the police did not remove the prosthetic leg from the double amputee. The incident was a result of a violent clash between the police and protesters, and the man's prosthetic leg was lost due to the actions of the protesters, not the police. ”

Figure 35: RAW-FC dataset sample for label "half"



Claim:

“ 52 thoroughbred horses whose owner died from COVID-19 are destined for slaughter if adopters are not found for them soon. ”

Gold Label: “false”
Predicted Label: “false”

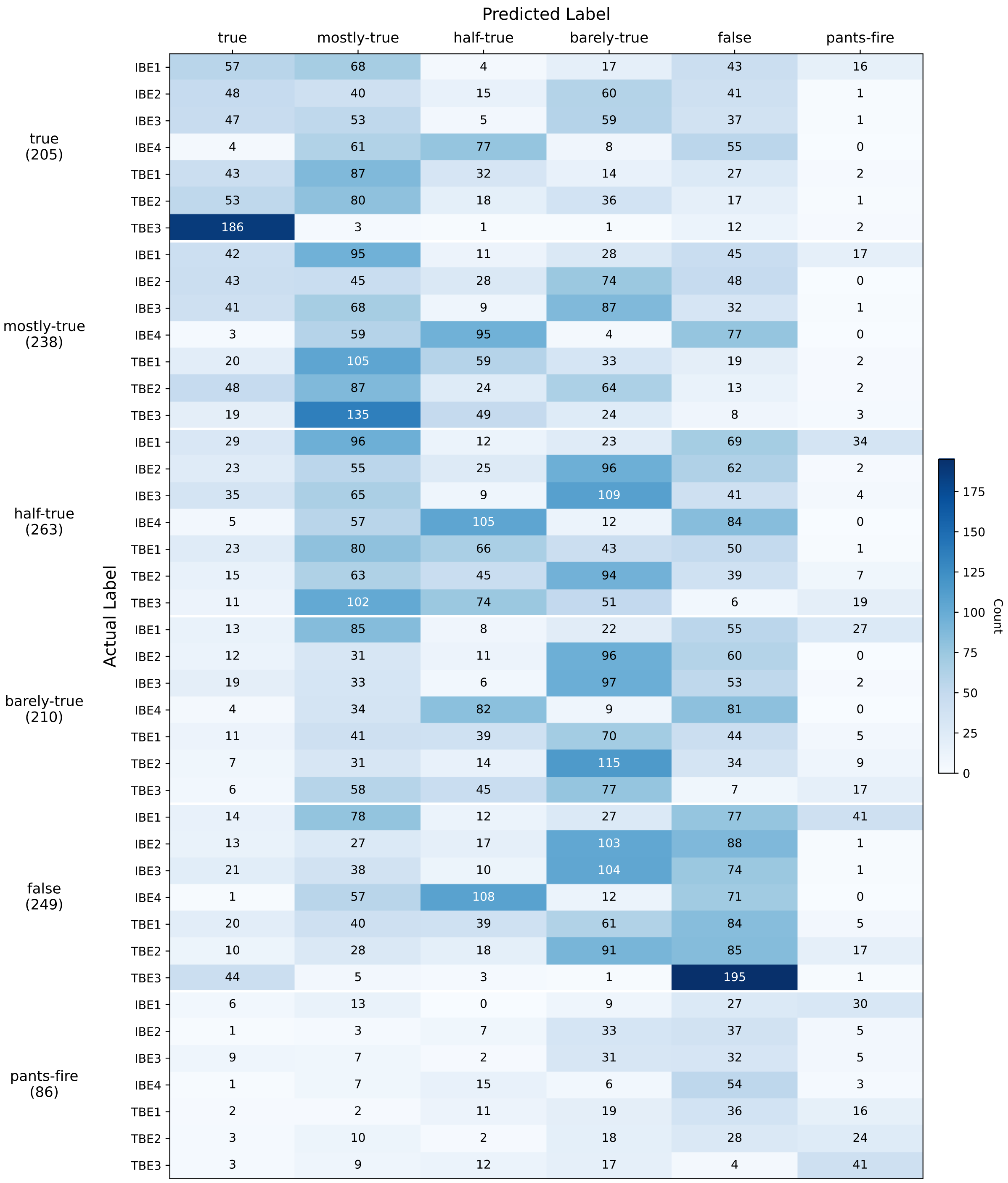
Support Justifications:

“ The claim is likely true. The provided evidence suggests that there is an urgent need to find new homes for 52 thoroughbred horses due to the death of their owner. This implies that the horses are indeed at risk of being sent to slaughter if adopters are not found soon. The fact that a circulating message is asking recipients to help find new homes for the horses further supports the urgency of the situation. Additionally, the specific number of horses mentioned (52) and the breed (thoroughbred) provide context and credibility to the claim. Overall, the evidence suggests that the claim is based on a genuine concern for the welfare of the horses and is not a fabricated or exaggerated story ”

Refute Justifications:

“ The claim that 52 thoroughbred horses are destined for slaughter if adopters are not found for them soon is challenged by several key factors. Firstly, the claim has been circulating for several years, with the original post dating back to 2011. According to credible reports on horse-related forums, all 52 horses were actually rehomed, with most going to family friends of the deceased owner. This suggests that the claim is not based on current events, but rather a recycled and outdated story. Furthermore, the claim has undergone subtle changes over the years, including the reason for the horses being in danger. Initially, the post stated that the horses would be sent to a glue factory, but more recently, the reason cited is the owner’ ’s passing due to COVID-19. However, there is no evidence to suggest that the horses are currently in danger or that they are being considered for slaughter. In fact, according to TheHorse. Com, all 52 horses were able to find homes within a week of the initial post in 2011. This contradicts the claim that the horses are in imminent danger of being slaughtered. Therefore, based on the available evidence, it appears that the claim is not supported by facts and is likely a recycled and outdated story ”

Figure 36: RAW-FC dataset sample for label "false"



Actual Label		true	mostly-true	half-true	barely-true	false	pants-fire
true (205)	IBE1	57	68	4	17	43	16
	IBE2	48	40	15	60	41	1
	IBE3	47	53	5	59	37	1
	IBE4	4	61	77	8	55	0
	TBE1	43	87	32	14	27	2
	TBE2	53	80	18	36	17	1
	TBE3	186	3	1	1	12	2
mostly-true (238)	IBE1	42	95	11	28	45	17
	IBE2	43	45	28	74	48	0
	IBE3	41	68	9	87	32	1
	IBE4	3	59	95	4	77	0
	TBE1	20	105	59	33	19	2
	TBE2	48	87	24	64	13	2
	TBE3	19	135	49	24	8	3
half-true (263)	IBE1	29	96	12	23	69	34
	IBE2	23	55	25	96	62	2
	IBE3	35	65	9	109	41	4
	IBE4	5	57	105	12	84	0
	TBE1	23	80	66	43	50	1
	TBE2	15	63	45	94	39	7
	TBE3	11	102	74	51	6	19
barely-true (210)	IBE1	13	85	8	22	55	27
	IBE2	12	31	11	96	60	0
	IBE3	19	33	6	97	53	2
	IBE4	4	34	82	9	81	0
	TBE1	11	41	39	70	44	5
	TBE2	7	31	14	115	34	9
	TBE3	6	58	45	77	7	17
false (249)	IBE1	14	78	12	27	77	41
	IBE2	13	27	17	103	88	1
	IBE3	21	38	10	104	74	1
	IBE4	1	57	108	12	71	0
	TBE1	20	40	39	61	84	5
	TBE2	10	28	18	91	85	17
	TBE3	44	5	3	1	195	1
pants-fire (86)	IBE1	6	13	0	9	27	30
	IBE2	1	3	7	33	37	5
	IBE3	9	7	2	31	32	5
	IBE4	1	7	15	6	54	3
	TBE1	2	2	11	19	36	16
	TBE2	3	10	2	18	28	24
	TBE3	3	9	12	17	4	41

Figure 37: Confusion matrix for LIAR-RAW dataset for IBEs and TBEs.

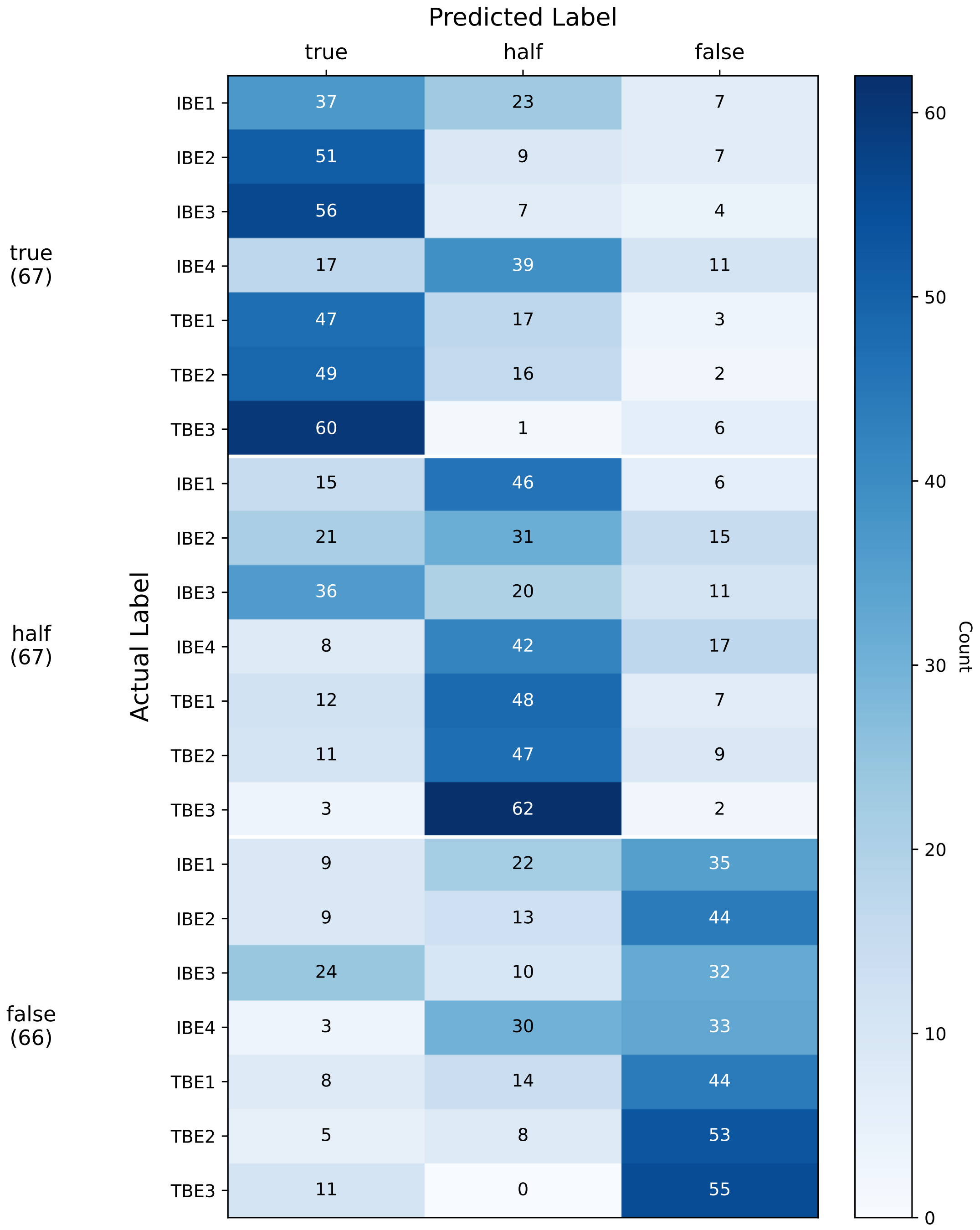


Figure 38: Confusion matrix for RAW-FC dataset for IBEs and TBEs.