How to Train Your Fact Verifier: Knowledge Transfer with Multimodal Open Models

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Abstract

Given the growing influx of misinformation across news and social media, there is a critical need for systems that can provide effective real-time verification of news claims. Large language or multimodal model based verification has been proposed to scale up online policing mechanisms for mitigating spread of false and harmful content. While these can potentially reduce burden on human fact-checkers, such efforts may be hampered by foundation model training data becoming outdated. In this work, we test the limits of improving foundation model performance without continual updating through an initial study of knowledge transfer using either existing intra- and inter-domain benchmarks or explanations generated from large language models (LLMs).

We evaluate open multimodal foundation models on twelve public benchmarks covering fact-checking, misinformation, toxicity and stance detection. Our results on two recent and widely used multi-modal fact-checking benchmarks, Mocheg and Fakeddit, indicate that knowledge transfer strategies can improve Fakeddit performance over the state-of-the-art by up to 1.7% and Mocheg performance by up to 2.9%. The code, model checkpoints, and dataset are available: `https://github.com/given131/fact-verifier-knowledge-transfer`.

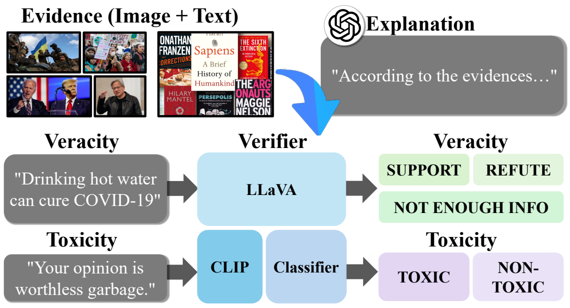

Figure 1: Visualization of our fact verification pipeline. Textual and visual evidence is embedded using a multimodal model, e.g. CLIP (Radford et al., 2021), before passing through a classifier. Alternatively, a vision-language model such as LLaVA (Liu et al., 2024) can also be utilized. An external explanation generation model can be used to augment the input. Here we show a true claim from the Mocheg dataset. (Yao et al., 2022).

1 Introduction

Top news stories rapidly go out-of-date and are replaced, e.g. during political election cycles. A recent study of Google Trends[1] in 2018 found that popular news stories tend to stay relevant for a lifespan of only 7 days. The actual observed behavior of the general public seems incongruous with the current paradigm of automated fact-checking, which relies on static resources. Fact-checking organizations are increasingly turning to open pretrained language models like BERT (Devlin et al., 2019) to scale up content moderation efforts (Morrish, 2023; Abels, 2022). These systems, trained on fixed knowledge bases, are not guaranteed to remain relevant as media narratives shift over time.

Motivated by previous approaches that have shown transformer-based models can effectively learn task-specific and linguistic reasoning skills from unified pretraining, e.g. for QA (Khashabi et al., 2020) and small-scale text-only misinformation detection (Lee et al., 2021), we conduct a large-scale study of transfer learning across diverse text-only and multimodal datasets to boost reasoning capabilities of misinformation detection systems. We consider *intra-domain transfer* from 6 misinformation detection and fact-checking datasets, as well as *inter-domain transfer*, where a fact verification model is jointly trained across other content moderation tasks (e.g. hate speech detection) to overcome brittleness to biases of fact-checking

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[1]https://www.newslifespan.com/

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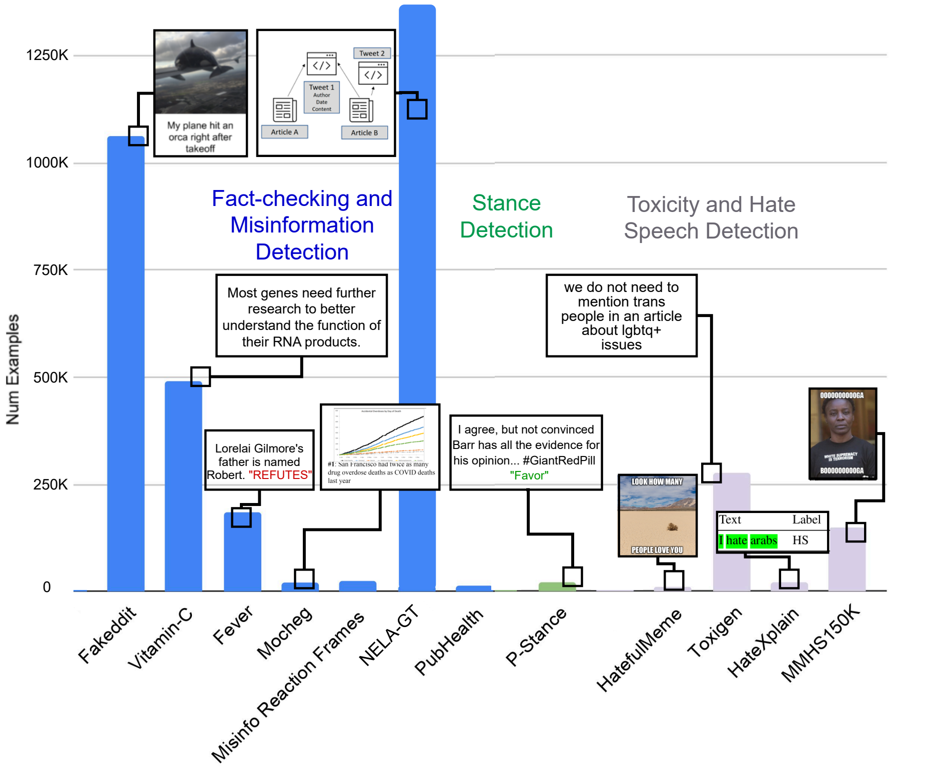


Figure 2: Finetuning and evaluation datasets considered in this work, with a breakdown by dataset scale and domain (misinformation detection, stance detection or toxicity detection). Fakeddit (Nakamura et al., 2020), Mocheg (Yao et al., 2022), HatefulMemes (Kiela et al., 2020) and MMHS150K (Gomez et al., 2019) are all multi-modal datasets.

datasets. We also consider the impact of parametric knowledge transfer from larger-scale closed models like GPT-3.5-turbo (OpenAI, 2022) and GPT-4 (OpenAI, 2023) through generated explanations for a specific veracity label. We also address how transfer learning impacts a model generalization issue known as *covariate shift* (Shimodaira, 2000), when the test data distribution diverges from the training distribution despite consistency in labeling procedures. A very tangible example of this is when evaluated news topics change entirely from training data due to a major unforeseen event like the Covid-19 pandemic.

Given a claim like *"The FBI warned that smart TVs can 'spy' on their owners,"* Figure 1 shows how our full verification pipeline can be used to predict the reliability of a social media claim. The system consists of (1) a unified fact verification model M_{FC} that predicts the veracity or potential harm (e.g. toxicity) of multi-modal inputs, and (2) an explanation model M_{EG} prompted to generate explanations of claim veracity. Following from theories of human cognition and language interpretation, which relies not only on continuous learning of facts but on commonsense world understanding (e.g, Newell, 1973; Fillmore, 1976), as well as recent work showing the effectiveness of LLM explanations for countering misinformation (Hsu et al., 2023; Chen and Shu, 2023; Wan et al., 2024; Gabriel et al., 2024), we seek to supervise verifier training with examples of correct and noisy fact verification reasoning using M_{EG}.

We evaluate our verification pipeline on 12 existing text-only and multi-modal fact verification, hate speech and stance detection benchmarks. Our results confirm that fact verification models trained on common benchmarks are extremely brittle to distribution shift and indicate data diversity is an important factor in high-performing fact verifiers over scale alone. Our best intra-domain mixture improves Fakeddit results by 1.7% F1, leading to a performance of 93.42% F1. We also find that knowledge distillation through GPT-4o and GPT-3.5-turbo explanations can boost Mocheg performance over the state-of-the-art by 2.9%. Beyond fact-checking, our study has implications for other important content moderation domains like hate speech detection, where we find knowledge transfer from fact-checking data can boost performance by 13.65%.

In summary, our contributions are as follows:

1. We address the task of fact verification using various knowledge transfer approaches, including (a) intra-domain, (b) inter-domain, and (c) explanation-based approaches.

2. We evaluate on extensive datasets, specifically 12 public benchmark datasets, covering misinformation detection and related tasks such as stance detection and toxicity/hate speech detection.

3. We achieve state-of-the-art scores on modern multimodal benchmark, including Mocheg (+2.9%) and Fakeddit (+1.7%).

To encourage further research on robust fact verification, we release our code, model checkpoints, and dataset at `https://github.com/given131/fact-verifier-knowledge-transfer`.

2 Motivation & Related Work

Automated Fact-Checking. Given the rapid proliferation of misinformation on social media, there is a critical need for automatic tools that can assist human fact-checkers (Nakov et al., 2021). Much of the earlier work in this area relied on linguistic cues or social media network features (e.g., Wang, 2017; Rashkin et al., 2017; Pérez-Rosas et al., 2017; Yang et al., 2019). Later work on detection of mis- and disinformation has considered transformer-based approaches, notably (Zellers et al., 2019). Most similar to our work is (Lee et al., 2021), which also does unified misinformation detection on a much smaller scale by training a model on various unimodal misinformation detection corpora. Seperately, a body of prior work also explores fact-checking explanations (e.g., Atanasova et al., 2020), and prior to us, Angeli and Manning (2014) draws a connection between claim verification and the natural logical inference underlying commonsense acquisition.

Robustness in Fact-Checking. Prior work has highlighted challenges to automated fact-checking like insufficient evidence (Atanasova et al., 2022) or spurious correlations used for evidence retrieval (Asai et al., 2022). We address these knowledge gaps by exploring the use of machine-generated explanations to aid in fact verification. This is similar to the motivation behind the VITAMIN-C dataset (Schuster et al., 2021), however VITAMIN-C only considers Wikipedia revisions and is not multi-modal. Most recently, (Caramancion, 2023; Cao et al., 2023; Guan et al., 2023) have delved into the limitations of LLMs for fact verification, noting that while the ability of LLMs to verify inputs surpasses their ability to generate factual content, they are still far less reliable than human fact-checkers.

3 Transfer Learning Strategies

In this section, we first describe the basic experimental setup for multimodal fact-checking. We then describe transfer learning methodologies based on whether knowledge is being distilled from more diverse sources within the same domain, transfer of knowledge across domains (e.g. misinformation detection and toxicity detection), or from parametric knowledge through LLM-generated explanations.

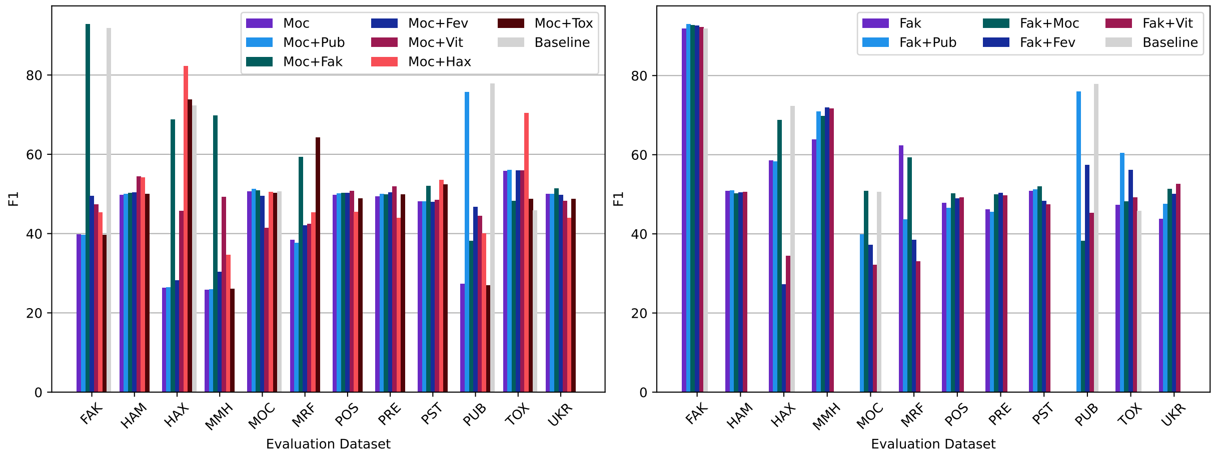
3.1 Base Verification Architecture

Our base verification model M_{FC} is implemented using the vision-and-language classification model introduced by Yao et al. (2022). This model jointly encodes a textual claim, text evidence and image evidence using CLIP-base (Radford et al., 2021). This representation is then used for the intermediate task of predicting the stance of the evidence towards the claim. The output stance representations are aggregated to predict the claim veracity using a final linear classification layer. We modify the base architecture with several larger embedding models: CLIP-large, CLIP-large-336 and 7B LLaVA-NeXT (Liu et al., 2024) which we will refer to as LLaVA.

3.2 Dataset Mixtures

Figure 2 shows the 12 datasets considered in this work, along with their 3 respective domains (fact checking / misinformation detection, toxicity / hate speech detection and stance detection).[2]
For intra-domain analysis, misinformation and fact-checking datasets are normalized to have a shared label space (*supported*, *refuted*, *nei*). All results are reported using gold image and text evidence.

[2]For Mocheg, we use the original training/val/test splits described in `https://arxiv.org/abs/2205.12487v1`.



(a) 2-dataset mixtures, Mocheg.

(b) 2-dataset mixtures, Fakeddit.

Figure 3: Transfer learning results for both intra- and inter-domain 2-dataset mixtures used to train our largest multimodal model (CLIP-large-336). Due to the large size and computational demands of Fakeddit, we only evaluate intra-domain mixtures. Baseline results are shown for Fakeddit, Hateful Memes, Mocheg, PubHealth and Toxigen eval sets in light gray.

3.3 LLM Explanations

For the explanation generation model M_{EG}, we use GPT-3.5-turbo or GPT-4o (OpenAI, 2023) with text-only inputs. We instruct the model to provide an explanation for why a claim x has a specific label y using the following system and user prompts:

> **System Prompt**:
>
> *You are an AI assistant skilled in fact-checking. Your role is to generate justifications for relationships between claims and evidence. Analyze the information provided and explain why the evidence supports or refutes the claim based on the labeled relationship.*
>
> **User Prompt**:
>
> *Here is the information:*
>
> *Claim: {claim}*
>
> *Evidence: {evidence}*
>
> *Relationship: {label}*
>
> *# Task*
>
> *Please generate a explanation that justifies the specified relationship between the claim and the evidence*
>
> *# Requirements*
>
> *- You should provide explanation without expressing the relationship explicitly.*
>
> *- You should be concise and clear.*
>
> *- The answer should be less than 100 words.*

On the Mocheg dataset, GPT-3.5-turbo achieves 45.17% F1 and GPT-4o achieves 65.85% F1. Despite the strong performance of GPT-4o, we include the older GPT-3.5-turbo model in experimentation given that GPT-4o's predictive abilities may be partly explained by dataset leakage of Mocheg in GPT-4's training set.

4 Experimental Setup

4.1 Model Training

We used publicly open models from Huggingface. Specifically, (1) openai/clip-vit-base-patch32 , (2) openai/clip-vit-large-patch14, (3) openai/clip-vit-large-patch14-336, and (4) llava-hf/llava-v1.6-mistral-7b-hf were used.

CLIP-based Verifiers. All the CLIP-based verifiers were trained with 2048 batch size using grad-accumulation with minibatch size of 256. The models were trained with 50 epochs without early stopping. Adam optimizer was used. The learning rate was 1e-3. Models were trained on RTX3090, RTX4090, RTX8000, A6000, A100, and H100 GPUs.

LLaVA-based Verifiers. LLaVA models were trained using LoRA(rank=64, lora alpha=16, dropout=0.05), targeting all linear layers. For precision, bfloat16 was adopted. The max sequence length was 2048. The batch size was 32, using grad

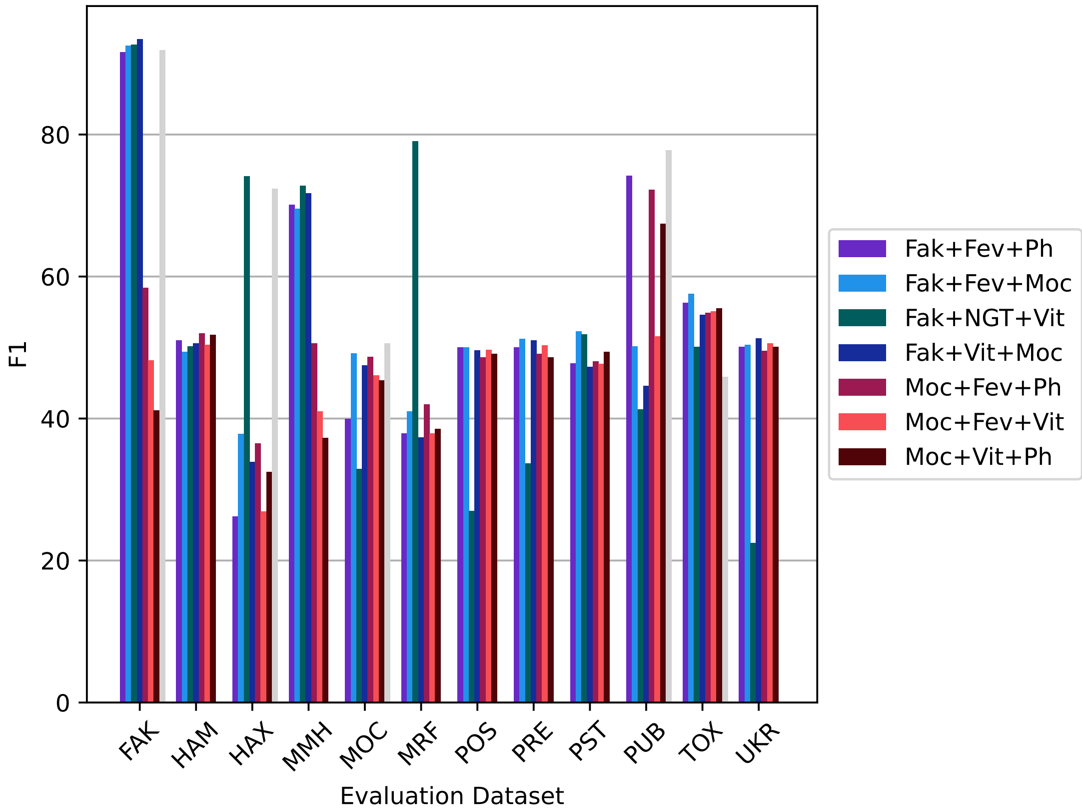


Figure 4: Transfer learning results for intra-domain 3-dataset mixtures used to train our largest multimodal CLIP model (CLIP-large-336).

accumulation with the minibatch size of 1. AdamW was used for the optimizer, with the learning rate of 2e-5. For the scheduler, cosine-annealing learning rate scheduler was used. Models were trained on A100 and H100.

Other Details. All datasets are primarily in English and publicly available for research purposes. For all results, we report a single run. We use most recent version of NLTK and SciPy packages for pre-processing and analysis.

5 Evaluation Details

We evaluate claim verification, toxicity detection and stance detection performance using F1. For three-label dataset mixtures evaluated on two-label datasets, we map labels 0 and 1 between the datasets (e.g. supports → benign, and refutes → toxic). If the predicted label is 2, we determine $\hat{y}$ for the two-label dataset from the model output probability distribution by finding the most probable label from 0,1. We consider 12 evaluation sets: Fakeddit (fak), HatefulMemes (ham), HateXplain (hax), MMHS150K (mmh), Mocheg (moc), Misinfo Reaction Frames (mrf), 3 temporal Nela-GT subsets (pre, pos, ukr) described in the next section, P-Stance (pst), PubHealth (ph), and Toxigen (tox).

5.1 Temporal Shift Evaluation

To test the robustness of misinformation detection systems to temporal shift, we consider three different filters on the NELA-GT 2020-2022 dataset (Gruppi et al., 2021, 2023) which can be used to partition eval examples as in-distribution or out-of-distribution depending on the training cut-off of the underlying model. We relate these partitions to notable recent historical events, with *pre* representing news before the first vaccine release in December 2020, *pos* representing news from 2021 after the vaccine release, and *ukr* representing recent news from 2022 relating to the Ukraine-Russia war. Each evaluation set contains 1000 randomly sampled claims from the relevant subsets of NELA-GT.

6 Learning from Dataset Mixtures

In Figures 3 and 4,[3] we show that the transfer learning mixture substantially impacts the in-

[3]We omit results from Fakeddit on Mocheg and PubHealth in Figure 3b since Fakeddit lacks nei labels.

distribution and out-of-distribution performance of CLIP-large-336 trained on fact-checking and toxicity detection benchmarks. While some mixtures (e.g. *Mocheg* + *Fakeddit* + *PubHealth*) actually decrease fact-checking benchmark performance of multimodal models, others (e.g. *Mocheg* + *PubHealth* for Mocheg, *Mocheg* + *Vitamin-C* + *Fakeddit* for Fakeddit) improve by up to 1.56% F1 over single dataset baseline results. For Fakeddit, we achieve the state-of-the-art performance with the mixture of *Mocheg* + *Vitamin-C* + *Fakeddit*, resulting in 93.42% F1.[4]

We also find that fact-checking mixtures can lead to strong performance at hate speech detection (up to 72.75% F1 for MMHS and 82.22% F1 for HateXplain). In the next few sections, we discuss in-depth how model performance and generalization capabilities are affected by our dataset mixtures.

6.1 Learning within Domain

Shown in Figures 3 and 4, fact-checking models are particularly brittle to domain shift. Dataset mixtures get close to random performance on temporal evaluation sets *pre*, *pos* and *ukr*.

Improvements from PubHealth Mixtures. For PubHealth, no mixtures improve over the single dataset baseline (77.81% F1), though including PubHealth in 2-dataset mixtures improves performance for other fact-checking/misinformation evaluation sets: Fakeddit (+1.09% F1), Mocheg (+0.61% F1). Figure 3a shows that Fakeddit + Mocheg consistently outperforms or is comparable to other out-of-distribution mixtures.

Data Diversity Over Scale. Notably, from Figure 3b Fakeddit does not generalize well on its own despite being significantly larger than other training datasets (1,063,106 samples), indicating there is still benefit from data diversity introduced by mixtures over a single large-scale dataset.

In-distribution Performance. For fact-checking, unsurprisingly the strongest performance on a given eval set comes from mixtures including the associated training set. Interestingly, this is not always true for toxicity/hate speech benchmarks. We discuss this in the next section, and full results can be found in the Appendix.

[4]To assess statistical significance, we conduct McNemar's test (McNemar, 1947), which yields a p-value of 5e-53.

6.2 Learning across Domains

From Figure 3, we do not find that inter-domain knowledge transfer from toxicity/hate speech detection aids in fact-checking. This indicates that it may be most critical for future work to focus on development of diverse, high-quality fact-checking datasets rather than cross-task learning. However, inter-domain transfer from fact-checking datasets does improve toxicity/hate speech detection. For example, the Mocheg + HateXplain mixture improves HateXplain performance by 13.65% and also performs better than HateXplain alone (by 9.97%) on Toxigen, another hate speech detection dataset.

6.3 Discussion

For both intra- and inter-domain mixtures, discrepancies in the structure and label space of the datasets may harm generalization capabilities. For example, we observe that adding evidence-less datasets to mixtures including fact-checking datasets with *nei* labels leads to over-prediction of *nei*. A potential solution is dataset normalxization, but this requires evidence retrieval. Our next section is motivated by this issue, where we explore effects of knowledge transfer from GPT-4o generated veracity explanations on Mocheg performance. This could be used to close the gap between evidence-augmented and evidence-less datasets.

7 Learning from Explanations

In the next section, we explore the use of GPT-4o and GPT-3.5-turbo explanations as silver evidence.

7.1 Explanation Scenarios

We consider 8 different scenarios which assume different levels of access to gold labels, and compare against baseline results without explanations. We evaluate with the following scenarios that assume knowledge of the gold label:

- **Oracle**: We use the gold claim labels for generating explanations. This acts as an upper-bound on explanation performance.
- **Opposite**: We generate explanations arguing for the opposite label to the gold label if the gold label is true/false. This tests the model's ability to learn from contradictory information.

The next 6 scenarios are more realistic, and do not assume knowledge of the gold claim labels:

Scenario	CLIP-base $\Delta F1_{4o}$	CLIP-base $\Delta F1_{3.5}$	CLIP-large $\Delta F1_{4o}$	CLIP-large $\Delta F1_{3.5}$
Random	+ 1.39	+ 0.29	+ 0.45	+ 0.17
Opposite	+ 0.16	+ 4.38	+ 1.48	+ 1.03
Always Supports	+ 2.79	- 1.02	+ 1.60	- 0.69
Always Refutes	+ 1.39	+ 0.21	- 0.90	+ 0.04
Always NEI	+ 2.87	- 0.20	- 0.86	+ 1.72
All	+ 1.39	- 0.78	- 0.69	- 0.86
Guided	+ 1.84	+ 1.35	+ 1.15	+ 0.41
Oracle	+ 10.03	+ 11.51	+ 10.89	+ 12.49

Scenario	LLaVA $\Delta F1_{4o}$	LLaVA $\Delta F1_{3.5}$
Random	- 1.35	- 1.03
Guided	+ 1.84	- 0.70
Oracle	+ 30.38	+ 23.67

Table 1: Mocheg test F1 after augmenting the training set with LLM explanations. $\Delta F1_{4o}$ denotes the difference between F1 results from the GPT-4o augmented model and the baseline F1, while $\Delta F1_{3.5}$ denotes the difference from the GPT-3.5-turbo augmented model and the baseline model. Here we can consider Oracle as an upperbound on performance. The left table shows CLIP results and the right table shows LLaVA results.

- **Random**: We generate explanations using randomly selected labels for each claim.
- **All**: We use explanations for all three possible claim labels.
- **Always Supports**: We always use *supports* as the label to generate explanations.
- **Always Refutes**: We always use *refutes* as the label to generate explanations.
- **Always NEI**: We always use *nei* as the label to generate explanations.
- **Guided**: We use the explanation generation model's zero-shot predicted claim labels to generate explanations.

7.2 Verification Results

Table 1 shows effect on baseline Mocheg results (49.18% F1 for CLIP-base, 50.49% F1 for CLIP-large and 63.23% F1 for LLaVA) from training models on the Mocheg dataset and GPT4-o generated explanations. The smaller CLIP models always benefit from guided explanations with improvements of 0.41-1.84% F1, even though the accuracy of GPT-3.5-turbo is lower than Mocheg finetuned CLIP-large. We note that explanations generated using random labels also improve results slightly. Results for explanations generated using a single label are mixed, and will potentially be influenced by label distributions. Using explanations generated for every label was generally not beneficial, possibly because of information being ignored when considering the longer context.

Following our findings with CLIP, we see if these performance gains hold for LLaVA, a recent state-of-the-art vision-and-language model. While LLaVA results do not improve using GPT-3.5-turbo explanations, we do find that GPT-4o explanation augmented models consistently outperform the LLaVA baseline, leading to state-of-the-art open model results[5] (65.07% F1) on Mocheg.[6]

7.3 Quality of Explanations

Evaluation Setup. We conduct a human evaluation on the Amazon Mechanical Turk crowdsourcing platform[7] to assess how multimodal models may learn from GPT-4o and GPT-3.5-turbo generated explanations. We randomly sample 36 claims from the Mocheg eval set and consider pairs of GPT-4o and GPT-3.5-turbo explanations arguing for the same random label (*supports*, *refutes* or *nei*) for each claim. We then ask participants the following 6 questions to measure the reasoning capabilities of the two explanation generation models:

- **Q1**: Does the AI explanation use inaccurate reasoning to prove the claim is true or false? (yes/no)
- **Q2**: Does the AI explanation use commonsense reasoning to prove the claim is true or false? (yes/no)
- **Q3**: Does the AI explanation use knowledge of specific events to prove the claim is true or false? (yes/no)

[5]To the best of our knowledge.
[6]We obtain a p-value of 5e-2 from McNemar's test.
[7]https://www.mturk.com/

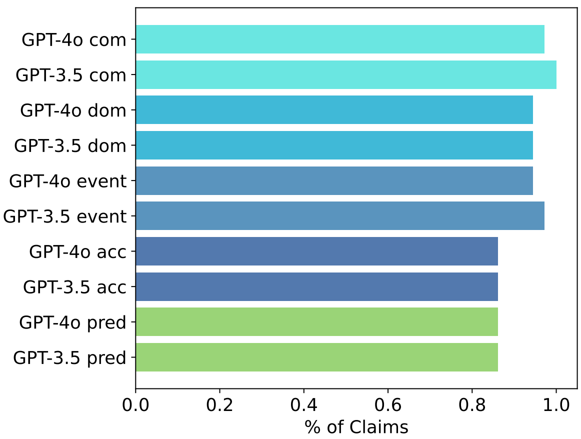


Figure 5: Human evaluation questions 1-5 for explanation quality. We measure use of commonsense reasoning (com), use of domain knowledge (dom), use of event knowledge (event), accuracy of reasoning (acc) and label predictability (pred).

- **Q4**: Does the AI explanation use domain knowledge (e.g. scientific or legal knowledge) to prove the claim is true or false? (yes/no)
- **Q5**: Can you predict the claim label from the explanation? (the label is true, the label is false, the label is unprovable, no)
- **Q6**: What is the overall quality of the explanation ? (1-5 scale)

We explicitly instruct the participants that they can make use of external sources (e.g. Google Search) when verifying explanation quality. Each explanation is assessed by 5 participants, who have prior experience working on misinformation detection tasks and have passed basic attention checks. We filter annotators who contribute to low inter-annotator agreement based on Fleiss' κ for judgments of explanation quality. We observe fair agreement of Fleiss' κ = 0.276 for GPT-4 explanation quality. For each claim and evaluation question except predictability, we take a majority vote over participant responses to determine the answer. For predictability, we check if at least 1 participant could identify the correct explanation label.

Results. As shown by Figure 5, explanations use a combination of commonsense reasoning and domain-specific knowledge, as well as evidence retrieval from known events. Explanations were generally found to be accurate (86.11% of explanations for both models). Participants struggled to predict the label used to generate a given explanation, with the majority of participants able to predict the correct label in less than half of cases. When we consider cases where at least one participant could identify the correct explanation label, we find that GPT-4o explanation labels and GPT-3.5-turbo explanations have equal predictability. Quality is comparable between the models (4.00 for GPT-4o vs. 4.04 for GPT-3.5-turbo).

8 Conclusion

In conclusion, we test three different transfer learning strategies to measure impact on multimodal fact-checking performance and improve results on two widely used benchmarks. We also discuss future steps for robust fact verification, such as using closed LLMs to expand reasoning capabilities of open foundation models. We show that explanations generated from powerful LLMs like GPT-4o and GPT-3.5-turbo can boost performance of smaller models.

9 Ethics Statement & Limitations

Given our findings, we urge caution in selection of fact verification models. Even more so than other content moderation domains like hate speech detection, our study suggests that strong in-distribution performance of fact verifiers is not indicative of strong general performance. Users and researchers should bear this in mind when deploying out-of-the-box fact verifiers on unseen data.

While we provide a preliminary study on knowledge transfer from dataset mixtures and LLM-generated explanations, future work may expand upon this by considering an even broader range of datasets and tasks. Another future direction may be use of visual information in explanation generation.

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A Appendix

A.1 ChatGPT Usage

ChatGPT has been used for writing simple scripts, including normalizing datasets into common schemas or merging different tsv files into a single file.

A.2 Human Evaluation Details

Annotators were paid $0.20 per explanation evaluation, which we judged to be a fair wage based on estimated time required to complete the task. Full instructions given to annotators are shown in Figures 6 and 7. We obtained the appropriate IRB exemption approval for the study.

A.3 Supplementary Results

Instructions

Summary | **Detailed Instructions** | Examples

Detailed Instructions

Read each AI explanation carefully, then answer the following 6 questions. You can make use of external sources (e.g. Google Search) if you're uncertain of the content in the claim.

Questions:

1. Does the AI explanation use inaccurate reasoning to prove the claim is true or false?

2. Does the AI explanation use commonsense reasoning to prove the claim is true or false?

3. Does the AI explanation use knowledge of specific events to prove the claim is true or false?

4. Does the AI explanation use domain knowledge to prove the claim is true or false?

5. Can you predict the claim label from the explanation?

6. What is the overall quality of the explanation (1-5)?

Figure 6: Full Instructions for Amazon Mechanical Turk Task.

Summary | Detailed Instructions | **Examples**

Good examples	**Bad examples**
For Q1, a good explanation should either use self-contained reasoning or bring in valid external evidence.	For Q1, even if the explanation is arguing for a label that you believe is correct, check if the argument itself is valid. Make sure there are not errors, for example using evidence that is made up or not related to the claim.
For Q2, a good explanation uses reasoning that anyone can innately understand without needing external or domain knowledge.	For Q2, if the explanation is entirely dependent on external evidence (e.g. knowledge of a specific event), then it is not using commonsense reasoning.
For Q3, a good explanation uses actual retrieved knowledge of a specific event (e.g. something a political figure said) to prove the claim is true or false.	For Q3, if the explanation does not rely on knowledge of any prior events then the answer is no.
For Q4, if the claim requires domain knowledge like knowledge of specific laws and the explanation uses this, then the answer is yes.	For Q4, if the explanation does not use any domain-specific knowledge (e.g. scientific or legal knowledge) then the answer is no.
For Q5, if you think you can guess the claim label that the explanation is arguing for, please provide the appropriate answer.	For Q5, if the explanation is vague, confusing or otherwise poor quality it may be hard to predict the label it is arguing for. Please state no in this case.
For Q6, rate what you think the quality of the explanation is from very bad (1) to very good (5). A good explanation should be coherent, clear about which label it is arguing for, not contain any invalid references or evidence, and should be convincing.	For Q6, a bad explanation (less than 3) may be difficult to read, incorrect, confusingly stated, or contain some logical gaps.

Figure 7: Explanations for Answering Amazon Mechanical Turk Questions.

Dataset Mixture	MC	FK	PH	Pre-V	Post-V	U-R	MRF	HX	MMHS	TX	HM	PS
FK	54.87	89.31	43.36	52.70	44.80	53.50	57.77	54.89	65.77	49.15	50.00	47.98
FK + PH	39.23	88.73	76.16	43.30	44.30	44.60	60.86	63.77	63.80	47.55	50.00	51.65
FV	38.25	60.76	60.66	49.40	48.00	50.40	47.92	38.62	52.70	54.04	48.40	50.12
FV + FK	36.69	87.99	59.01	49.80	50.30	48.70	41.92	38.72	63.44	52.55	50.40	49.24
FV + FK + PH	38.78	88.07	74.61	48.40	49.90	49.90	39.01	28.33	62.30	57.77	52.80	47.47
FV + NGT	32.88	60.33	52.23	35.30	24.20	17.20	74.16	70.32	74.06	53.62	50.20	51.97
FV + NGT + FK	36.16	90.72	63.08	41.90	32.60	23.70	69.82	72.45	69.19	50.11	51.60	52.80
FV + NGT + MC	46.03	60.41	56.59	35.40	25.90	18.70	78.55	72.25	39.28	50.21	50.00	52.20
FV + NGT + PH	32.27	60.37	72.19	32.70	24.40	16.90	75.19	68.24	74.02	54.79	50.00	53.41
FV + NGT + VC	29.36	60.37	34.01	32.80	25.60	16.10	74.47	70.06	74.01	52.23	50.00	52.25
FV + PH	37.80	59.29	74.61	60.30	59.20	60.00	44.16	32.07	71.92	51.81	50.20	42.10
FV + VC	35.50	39.70	48.64	50.00	50.40	49.80	37.62	26.20	25.89	55.53	50.00	47.57
FV + VC + FK	35.42	89.11	37.98	49.30	45.30	51.30	49.57	48.49	66.31	51.38	51.20	51.09
FV + VC + PH	39.03	39.45	64.92	50.10	50.30	50.10	35.20	26.35	26.50	55.85	49.60	47.43
HX	57.61	60.46	42.25	48.50	47.60	46.40	65.56	80.67	43.83	54.89	48.80	53.92
MC	49.18	39.66	35.95	50.00	50.00	50.00	37.75	26.20	25.88	56.28	50.00	47.84
MC + FK	47.87	87.34	32.66	44.70	45.60	46.50	57.55	69.39	58.01	55.96	51.00	52.43
MC + FK + PH	49.63	89.22	73.06	48.10	50.40	51.60	59.70	68.04	64.61	49.04	51.40	50.72
MC + FV	45.13	62.18	47.58	47.40	50.60	49.00	48.32	41.53	48.82	58.09	48.20	45.34
MC + FV + FK	46.56	89.01	47.97	49.30	49.80	49.60	38.69	28.90	64.18	56.38	51.40	48.08
MC + FV + PH	48.81	39.71	76.55	50.10	50.10	50.10	38.47	26.51	25.88	56.17	50.00	47.84
MC + FV + VC	46.23	40.30	40.99	49.90	49.90	50.00	37.80	26.51	25.94	56.17	49.80	47.94
MC + HX	49.06	40.53	41.18	40.00	44.90	44.60	64.53	80.15	26.84	58.30	49.60	59.99
MC + PH	47.50	39.69	76.16	50.00	50.00	50.00	37.75	26.20	25.98	56.28	49.60	47.84
MC + TX	49.84	40.38	32.56	44.90	51.20	44.80	64.89	73.96	30.83	50.43	49.20	53.36
MC + VC	45.74	48.48	43.02	49.50	48.80	49.50	41.78	28.69	33.52	54.68	51.00	47.57
MC + VC + FK	43.00	89.45	36.34	48.50	49.30	52.70	38.42	31.86	67.58	56.60	51.00	48.22
MC + VC + PH	45.41	46.22	68.02	50.00	49.30	50.00	37.89	26.40	33.57	56.49	51.80	47.66
PH	37.88	55.78	76.36	50.00	50.10	49.00	62.11	73.39	48.60	43.83	48.80	52.11
TX	48.90	60.54	52.79	49.30	48.90	48.70	39.72	57.90	62.56	70.43	49.00	53.41
VC	35.38	57.84	41.09	50.60	51.00	50.40	37.04	28.38	36.70	56.17	50.60	47.24
VC + FK	35.22	89.40	39.83	46.30	51.70	50.20	46.04	38.88	66.61	50.32	51.40	45.11
VC + NGT + FK	33.33	89.22	31.01	41.40	31.80	23.30	56.92	52.60	62.82	48.83	50.00	51.69
VC + NGT + MC	44.55	62.78	38.37	34.70	25.20	19.50	71.20	65.85	64.11	52.77	52.40	53.13
VC + NGT + PH	36.69	62.17	70.45	31.90	25.60	19.80	72.59	65.28	62.61	54.04	49.20	53.36
VC + PH	34.73	60.45	65.79	49.50	49.10	50.20	37.98	26.20	73.93	56.06	49.80	47.66
VC + PH + FK	38.37	88.43	70.45	45.50	51.30	49.30	58.49	56.91	60.92	53.40	51.20	49.79

Table 2: The results from the CLIP-based verifier are shown above. Abbreviations include: **FK** - Fakeddit, **FV** - Fever, **HM** - HatefulMemes, **HX** - HateXplain, **MC** - Mocheg, **MMHS** - MultiModal Hate Speech 150k, **MRF** - Misinformation Reaction Framework, **NGT** - NelaGT2022, **PH** - PubHealth, **PS** - PStance, **TX** - Toxigen, **VC** - VitaminC.

Dataset Mixtures	MC	FK	PH	Pre-V	Post-V	U-R	MRF	HX	MMHS	TX	HM	PS
FK	57.13	91.41	46.10	50.90	47.90	49.40	61.71	72.71	70.36	44.36	51.20	51.65
FK + PH	39.35	91.21	72.48	40.30	42.50	36.90	59.43	65.12	64.37	47.66	52.00	48.86
FV	38.41	39.66	58.91	49.40	52.90	48.30	47.83	48.65	25.88	42.45	50.00	46.96
FV + FK	36.69	91.37	59.59	49.50	49.60	49.80	38.83	27.44	65.82	55.64	50.40	48.40
FV + FK + PH	38.17	92.27	75.39	49.10	49.50	49.70	38.83	30.04	70.92	55.74	50.20	48.22
FV + NGT	37.26	39.41	57.56	31.00	22.40	16.10	76.18	69.70	26.99	52.02	49.80	52.53
FV + NGT + FK	36.45	92.32	62.50	32.50	26.60	17.80	79.98	72.61	70.18	53.19	50.80	52.43
FV + NGT + MC	48.28	58.93	60.95	28.30	22.30	17.60	76.62	68.50	48.23	53.94	50.60	52.39
FV + NGT + PH	40.50	39.68	76.65	31.40	22.40	16.00	77.03	69.70	25.88	51.60	49.80	51.55
FV + NGT + VC	35.14	52.80	36.82	31.10	23.90	18.10	74.07	71.83	40.54	48.40	51.20	51.32
FV + PH	40.66	39.66	74.42	50.30	50.00	50.00	62.16	73.80	25.88	43.94	50.00	52.16
FV + VC	34.93	39.66	32.85	51.70	50.80	49.20	42.68	42.67	25.92	52.45	50.00	44.51
FV + VC + FK	35.71	91.81	40.21	54.30	48.20	52.00	37.84	28.59	67.61	56.38	51.80	47.52
FV + VC + PH	39.84	39.66	67.64	50.10	50.00	49.60	40.62	30.15	25.88	53.94	50.00	47.61
HX	57.43	39.66	50.96	44.90	46.50	43.80	49.75	81.44	25.88	65.11	50.00	55.49
MC	50.49	48.52	41.96	50.00	50.00	50.00	62.25	73.80	44.73	43.72	48.60	52.16
MC + FK	48.16	91.44	36.92	49.50	49.20	49.10	38.11	27.81	64.63	56.38	50.60	47.89
MC + FK + PH	50.08	92.46	73.84	49.50	49.60	49.90	38.47	35.86	71.82	56.60	50.80	50.02
MC + FV	49.02	43.25	42.44	50.00	48.60	49.90	42.59	28.79	29.68	56.91	53.20	48.31
MC + FV + FK	47.05	92.10	53.68	50.00	50.00	49.90	37.80	26.25	69.55	56.28	51.20	47.89
MC + FV + PH	50.86	61.18	74.81	50.90	49.60	51.00	46.62	31.86	51.11	55.43	49.80	47.52
MC + FV + VC	42.30	49.27	43.31	51.20	50.20	50.60	50.56	43.97	33.40	52.55	49.80	48.86
MC + HX	50.04	55.27	35.37	49.30	48.30	49.10	68.25	75.94	59.49	48.30	51.00	53.41
MC + PH	51.68	43.53	75.97	50.00	50.00	50.10	37.80	26.40	28.22	56.17	50.60	47.57
MC + TX	49.26	39.87	32.66	50.00	48.00	48.90	64.44	73.80	26.50	51.49	51.60	52.76
MC + VC	43.61	46.90	53.20	50.60	45.40	49.60	47.56	60.50	47.16	56.60	52.00	52.11
MC + VC + FK	47.75	91.94	41.96	43.00	43.90	47.50	63.14	62.73	68.07	54.36	51.00	52.39
MC + VC + PH	46.52	43.66	70.93	48.50	47.80	49.90	39.54	33.16	39.01	54.79	52.60	48.77
PH	41.40	39.66	76.45	50.70	46.60	52.70	66.32	68.04	25.88	53.94	50.00	47.66
TX	59.99	39.66	46.71	49.10	49.70	50.60	62.61	73.91	25.88	46.60	50.00	52.85
VC	35.79	39.66	36.82	50.30	51.50	51.50	44.74	41.74	25.87	52.34	50.00	48.77
VC + FK	33.70	92.27	35.47	49.00	50.00	49.50	38.78	28.27	70.61	56.49	51.20	49.61
VC + NGT + FK	34.81	91.95	37.89	34.90	27.50	22.70	68.61	63.36	69.35	49.68	50.60	51.60
VC + NGT + MC	46.52	45.32	42.34	33.30	28.20	18.30	74.88	66.53	39.40	51.91	52.40	53.27
VC + NGT + PH	37.76	39.65	68.22	32.30	24.50	17.70	73.26	67.62	25.88	54.36	50.00	53.08
VC + PH	37.84	39.88	69.19	48.60	50.10	49.60	43.48	32.90	28.72	55.43	49.00	47.61
VC + PH + FK	36.57	91.13	71.80	43.70	45.10	46.50	52.40	35.65	71.64	56.91	51.00	50.16

Table 3: The results from the CLIP-large verifier are shown above. Abbreviations are same as Table 2.

Dataset Mixtures	MC	FK	PH	Pre-V	Post-V	U-R	MRF	HX	MMHS	TX	HM	PS
FK	58.10	91.87	49.75	46.20	47.80	43.80	62.38	58.58	63.78	47.34	50.80	50.86
FK + PH	39.84	92.96	75.97	45.50	46.50	47.50	43.62	58.26	70.90	60.43	51.00	51.23
FV	37.59	39.66	58.62	48.00	52.70	46.40	42.32	48.18	25.88	46.49	50.00	45.57
FV + FK	37.26	92.63	57.36	50.30	49.00	50.10	38.42	27.18	71.95	56.17	50.40	48.35
FV + FK + PH	39.93	91.62	74.22	50.00	50.00	50.10	37.89	26.20	70.13	56.28	51.00	47.80
FV + NGT	37.71	39.89	55.23	33.80	23.90	17.20	69.28	63.20	25.99	53.09	50.00	52.85
FV + NGT + FK	34.68	92.34	61.05	31.30	23.80	17.70	79.85	72.40	72.19	51.17	50.00	53.41
FV + NGT + MC	48.85	44.45	56.69	31.70	22.10	15.40	75.91	69.49	31.95	53.40	50.60	52.20
FV + NGT + PH	40.21	39.66	74.13	32.00	24.80	17.90	73.58	61.49	25.88	54.15	50.00	52.76
FV + NGT + VC	35.54	44.78	33.53	31.00	27.50	15.10	74.12	67.31	30.46	51.17	50.80	53.41
FV + PH	39.56	40.35	75.00	48.40	53.00	50.00	40.53	26.77	25.94	55.32	50.00	48.49
FV + VC	36.73	39.66	39.63	51.10	50.10	49.90	41.42	33.58	25.89	56.06	50.00	47.15
FV + VC + FK	33.58	92.22	32.17	51.50	47.80	45.80	41.24	45.63	69.84	53.83	50.80	49.42
FV + VC + PH	39.80	39.66	70.25	50.50	50.00	50.50	39.50	29.11	25.88	55.32	50.00	47.20
HX	59.44	39.66	43.26	48.10	48.10	49.40	38.42	72.35	25.88	64.04	50.00	49.10
MC	50.61	39.78	27.33	49.40	49.70	50.00	38.42	26.35	25.86	55.74	49.80	48.08
MC + FK	50.82	92.80	38.18	49.90	50.20	51.40	59.34	68.81	69.78	48.19	50.20	51.97
MC + FK + PH	47.83	91.66	74.03	50.50	51.40	50.30	38.51	38.46	68.78	57.02	51.40	47.94
MC + FV	49.47	49.47	46.71	50.40	50.30	49.70	42.10	28.17	30.28	55.96	50.40	47.94
MC + FV + FK	49.18	92.49	50.19	51.20	50.00	50.40	41.02	37.84	69.54	57.55	49.40	52.25
MC + FV + PH	48.69	58.42	72.19	49.10	48.60	49.50	42.01	36.49	50.58	54.89	52.00	48.08
MC + FV + VC	46.11	48.21	51.55	50.30	49.70	50.60	37.89	26.92	40.99	55.11	50.40	47.71
MC + HX	50.45	45.31	40.02	43.90	45.40	43.90	45.32	82.22	34.60	70.43	54.20	53.55
MC + PH	51.23	39.71	75.68	50.00	50.10	50.00	37.62	26.46	25.90	56.06	50.00	48.08
MC + TX	50.20	39.68	26.94	49.90	48.90	48.70	64.17	73.86	26.06	48.72	50.00	52.43
MC + VC	41.40	47.31	44.48	51.90	50.80	48.20	42.45	45.69	49.21	55.96	54.40	48.45
MC + VC + FK	47.46	93.42	44.57	51.00	49.60	51.30	37.35	33.89	71.73	54.57	50.60	47.24
MC + VC + PH	45.37	41.18	67.44	48.60	49.10	50.10	38.56	32.48	37.28	55.53	51.80	49.42
PH	41.52	39.66	77.81	50.20	50.20	50.10	66.23	72.40	25.88	47.98	50.00	50.86
TX	60.05	39.66	43.26	49.10	49.60	50.20	62.70	73.80	25.88	45.85	50.00	52.57
VC	35.38	39.43	34.40	51.00	47.90	48.30	52.35	65.44	27.17	45.74	50.60	51.65
VC + FK	32.15	92.19	45.25	49.70	49.20	52.60	33.05	34.46	71.72	49.15	50.60	47.38
VC + NGT + FK	32.92	92.67	41.28	33.70	27.00	22.50	79.09	74.12	72.75	50.11	50.20	51.88
VC + NGT + MC	44.88	55.55	49.61	35.70	25.00	18.90	68.20	61.80	52.28	54.89	55.20	52.16
VC + NGT + PH	39.11	39.67	67.64	29.40	21.40	16.50	75.41	63.62	25.92	54.68	50.00	52.90
VC + PH	39.39	39.66	70.25	49.50	47.30	48.80	49.71	46.57	25.88	51.81	50.00	51.18
VC + PH + FK	39.15	91.95	68.51	47.20	47.10	45.50	45.45	41.68	69.15	53.51	49.20	48.22

Table 4: The results from the CLIP-large-336 verifier are shown above. Abbreviations are same as Table 2.

Model	Method	F1-Score
CLIP-base	Baseline	49.18
CLIP-base	Random	49.47
CLIP-base	Opposite	53.56
CLIP-base	All	48.40
CLIP-base	Always Supports	48.16
CLIP-base	Always Refutes	49.39
CLIP-base	Always NEI	48.98
CLIP-base	Guided	50.53
CLIP-base	Oracle	60.69
CLIP-large	Baseline	50.49
CLIP-large	Random	50.66
CLIP-large	Opposite	51.52
CLIP-large	All	49.63
CLIP-large	Always Supports	49.80
CLIP-large	Always Refutes	50.45
CLIP-large	Always NEI	52.21
CLIP-large	Guided	50.90
CLIP-large	Oracle	62.98
CLIP-large-336	Baseline	50.98
CLIP-large-336	Random	52.09
CLIP-large-336	Opposite	51.72
CLIP-large-336	All	52.99
CLIP-large-336	Always Supports	50.66
CLIP-large-336	Always Refutes	52.33
CLIP-large-336	Always NEI	51.35
CLIP-large-336	Guided	51.64
CLIP-large-336	Oracle	62.69

Table 5: The Mocheg results with CLIP models with explanations generated by GPT-3.5-turbo.

Model	Method	F1-Score
CLIP-base	Baseline	49.18
CLIP-base	Random	50.57
CLIP-base	Opposite	49.34
CLIP-base	All	50.57
CLIP-base	Always Supports	51.97
CLIP-base	Always Refutes	50.57
CLIP-base	Always NEI	52.05
CLIP-base	Guided	51.02
CLIP-base	Oracle	59.21
CLIP-large	Baseline	50.49
CLIP-large	Random	50.94
CLIP-large	Opposite	51.97
CLIP-large	All	49.8
CLIP-large	Always Supports	52.09
CLIP-large	Always Refutes	49.59
CLIP-large	Always NEI	49.63
CLIP-large	Guided	51.64
CLIP-large	Oracle	61.38
CLIP-large-336	baseline	50.98
CLIP-large-336	Random	50.04
CLIP-large-336	Opposite	53.07
CLIP-large-336	All	45.54
CLIP-large-336	Always Supports	53.77
CLIP-large-336	Always Refutes	51.23
CLIP-large-336	Always NEI	51.64
CLIP-large-336	Guided	54.22
CLIP-large-336	Oracle	62.61

Table 6: The Mocheg results with CLIP models with explanations generated by GPT-4o.

Model	Dataset	P-value	Etc
CLIP-Large-336	Mocheg + VitaminC + Fakeddit	5e-53	state-of-the-art for Fakeddit
CLIP-Large-336	GPT-4o Guided	1e-2	
LLaVA	GPT-4o Guided	5e-2	state-of-the-art for Mocheg
LLaVA	GPT-4o Golden	8e-182	
LLaVA	GPT-3.5 Guided	4e-1	
LLaVA	GPT-3.5 Golden	4e-113	

Table 7: P-value from McNemar's test.

Task	Dataset	0	1	2
Misinformation Detection, Fact-checking	Fakeddit	0	1	N/A
	Vitaminc	REFUTES	SUPPORTS	NOT ENOUGH INFO
	Fever	REFUTES	SUPPORTS	NOT ENOUGH INFO
	Mocheg	refuted	supported	NEI
	Misinfo Reaction Framework	misinfo	real	N/A
	Nela-GT	0	1	2
	PUBHEALTH	false	true	unproven
Stance Detection	P-Stance	AGAINST	FAVOR	N/A
Toxicity / Hate Speech Detection	Hateful-Memes	0	1	N/A
	ToxiGen	toxicity_ai ≥ 3 || toxicity_human ≥ 3	toxicity_ai < 3 && toxicity_human < 3	N/A
	HateXplain	1 exists in the sentence	1 does not exist in the sentence	N/A
	MMHS150k	label ≠ [0,0,0]	label == [0,0,0]	N/A

Table 8: Label mappings for intra/inter-domain experiments. The table describes how each dataset's labels are mapped for dataset mixture and evaluation.