COMMUNITYNOTES:
A Dataset for Exploring the Helpfulness of Fact-Checking Explanations

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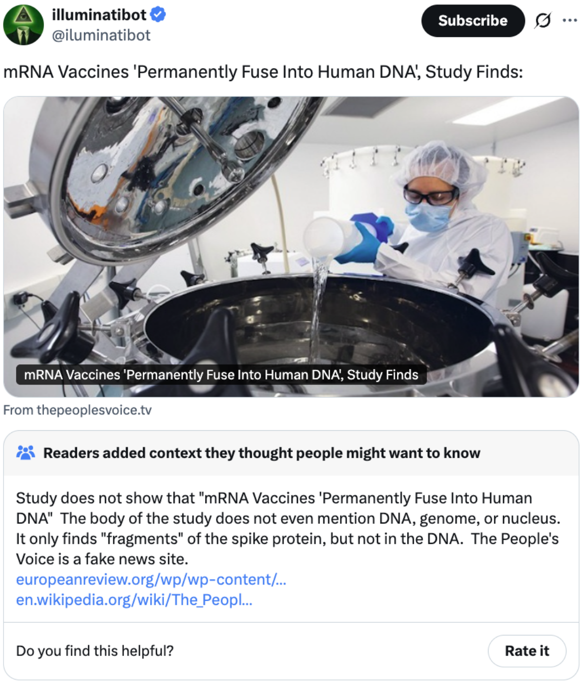
Abstract

Fact-checking on major platforms, such as X, Meta, and TikTok, is shifting from expert-driven verification to a community-based setup, where users contribute explanatory notes to clarify why a post might be misleading. An important challenge here is determining whether an explanation is helpful for understanding real-world claims and the reasons why, which remains largely underexplored in prior research. In practice, most community notes remain unpublished due to slow community annotation, and the reasons for helpfulness lack clear definitions. To bridge these gaps, we introduce the task of predicting both the helpfulness of explanatory notes and the reason for this. We present COMMUNITYNOTES, a large-scale multilingual dataset of 104k posts with user-provided notes and helpfulness labels. We further propose a framework that automatically generates and improves reason definitions via automatic prompt optimization, and integrate them into prediction. Our experiments show that the optimized definitions can improve both helpfulness and reason prediction. Finally, we show that the helpfulness information is beneficial for existing fact-checking systems. The code and the data are available at https://github.com/ruixing76/Helpfulness-FCExp.

1 Introduction

Beyond simple verification, fact-checking systems should provide explanations that clarify why a claim is misleading (Atanasova et al., 2020; Xing et al., 2022; Russo et al., 2023; Warren et al., 2025). Explanations not only strengthen user trust in fact-checking decisions, but also help mitigate common pitfalls of fact-checking, e.g., backfire effect, where exposure to corrections can paradoxically reinforce false beliefs rather than hinder them (Lewandowsky et al., 2012; Guo et al., 2022; Xing et al., 2025).



illuminatibot
@iluminatibot

mRNA Vaccines 'Permanently Fuse Into Human DNA', Study Finds:

mRNA Vaccines 'Permanently Fuse Into Human DNA', Study Finds

From thepeoplesvoice.tv

Readers added context they thought people might want to know

Study does not show that "mRNA Vaccines 'Permanently Fuse Into Human DNA" The body of the study does not even mention DNA, genome, or nucleus. It only finds "fragments" of the spike protein, but not in the DNA. The People's Voice is a fake news site.
europeanreview.org/wp/wp-content/...
en.wikipedia.org/wiki/The_Peopl...

Do you find this helpful?

Figure 1: An example of X Community Notes. The potential misleading tweet states, "mRNA Vaccines Permanently Fuse Into Human DNA". The user-generated note appears under *Readers added context* and provides an explanation for the tweet.

Typically, fact-checking explanations are produced by expert organizations. Yet the ecosystem is currently shifting, and platforms are increasingly experimenting with community-based fact-checking, where contributors collaboratively provide explanatory notes on claims (Augenstein et al., 2025). This crowd-sourcing process distributes the labor of verification and offers diverse perspectives from the community. A representative example is *Community Notes*[1] on X (formerly Twitter), which allows users to attach notes to explain potentially misleading posts. As illustrated in Figure 1, the user-generated note appears under *Readers added context* and provides an explanation for the tweet.

[1] https://communitynotes.x.com/guide/

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Critically, for a note to become visible or formally published, it must receive a sufficient number of ratings from a diverse set of users (De et al., 2025). A key challenge in this process is determining whether an explanation is helpful for understanding real-world claims, as well as identifying why it is helpful, a question that remains largely underexplored in prior research on fact-checking explanations (Atanasova et al., 2020; Guo et al., 2022; Russo et al., 2023; Eldifrawi et al., 2024). In practice, this lack of clarity makes it difficult for contributors to write effective notes and for raters to assess them consistently.

This process is slow on *Community Notes*: notes can take hours or even days to appear, and the vast majority (over 90%) never become visible, despite contributor efforts (De et al., 2025). Moreover, although the platform provides reasons for judging notes as helpful or unhelpful, these reasons lack clear definitions, leaving both contributors and raters unclear about the underlying evaluation criteria (De et al., 2025; Augenstein et al., 2025). This opacity hinders the efficiency, scalability, and explainability of the crowd-sourced fact-checking. Motivated by these challenges, we explore the idea of simplifying and making the helpfulness annotation process more explicit. Our contributions of this paper are as follows:

- We introduce the task of predicting the helpfulness of an explanatory note and the reasons underlying this judgment, given the note and the original X post.

- We present `COMMUNITYNOTES`, a large-scale dataset for explanation helpfulness, containing over 104K potentially misleading posts with corresponding user-provided notes.

- We propose a framework that automatically generates and optimizes reason label definitions via prompt optimization, and integrates these definitions into helpfulness and reason predictors to improve their performance.

- We apply explanation helpfulness prediction to the evidence sufficiency task (Atanasova et al., 2022) and further incorporate it as an auxiliary signal into automated fact-checking on `CLIMATE-FEVER` (Diggelmann et al., 2020), demonstrating its potential to enhance current existing automated fact-checking systems.

2 Related Work

Community-Based Fact-Checking The proliferation of misinformation has become a growing societal concern, posing significant risks to areas such as public health, science, and politics (Borenstein et al., 2025). Misleading claims can spread rapidly online, shaping public opinion and undermining trust in institutions. To address this challenge, fact-checking has emerged as a central strategy for mitigating the spread of false or misleading information, by evaluating claims and providing corrective context to users (Guo et al., 2022; Nakov et al., 2021; Xie et al., 2025).

Traditionally, fact-checking has been carried out by professional third-party organizations that assess claim veracity through expert analysis. However, as a result, recent years have seen a paradigm shift toward more decentralized, community-based approaches (Renault et al., 2024; Augenstein et al., 2025). Major social media platforms have increasingly adopted this paradigm. X's *Community Notes* is the most prominent example, allowing their users to collaboratively annotate and assess online content by attaching contextual notes to potentially misleading posts. Following this trend, Meta ended its partnerships with professional fact-checkers[2] in favor of a similar community-driven system, while TikTok has also introduced a comparable feature.[3]

Empirical evidence suggests that community-based fact-checking can be highly effective in countering misinformation at scale. Studies have shown that the presence of a Community Note can reduce the rate of retweets by nearly half (Renault et al., 2024), while displaying such notes on misleading posts has been found to decrease their spread by an average of 61% (Chuai et al., 2024). Moreover, authors of posts flagged by community notes are up to 80% more likely to delete their content, and such posts generally exhibit markedly lower virality (Drolsbach and Pröllochs, 2023; Renault et al., 2024). These findings highlight the potential of community-based explanations in debunking online misinformation.

Despite these benefits, *Community Notes* often require a long time to accumulate sufficient contributor ratings to determine helpfulness. In addition, the absence of reason definitions further undermines the trustworthiness of the mechanism.

[2] Meta is ending its third-party fact-checking partnership with US partners. Here's how that program works.

[3] Testing a New Feature to Enhance Content on TikTok.

Label Definitions Recent work has shown that providing models with explicit definitions of labels can lead to substantial improvements in classification. Khatuya et al. (2025) used predefined label descriptions and trained the model to generate these descriptions based on the input text, achieving sizable improvements in multi-label classification. Similarly, Gao et al. (2023) demonstrated that curating a small dictionary of terms for label description can improve zero-shot accuracy by 17-19% absolute, while also increasing the robustness to prompts. Peskine et al. (2023) showed improvements when using label definitions with GPT-3 zero-shot classification on the challenging task of fine-grained conspiracy theory detection.

Automatic Prompt Optimization Prompt engineering has become essential to many Natural Language Processing (NLP) tasks; yet, manual trial-and-error approaches remain a barrier to effective use. Automatic Prompt Optimization (APO) methods address this challenge by systematically searching for high-performing prompts (Ramnath et al., 2025). These approaches explore the large instruction space using diverse strategies: PROMPTBREEDER evolves task-specific prompts across generations using optimized mutation strategies (Fernando et al., 2024); PROMPTAGENT applies Monte Carlo Tree Search (MCTS) with feedback reflection to guide exploration (Wang et al., 2024); and SCULPT represents prompts as trees, enabling targeted refinements while preserving overall structure—especially useful for long or complex prompts (Kumar et al., 2025).

3 Predicting Whether an Explanation is Helpful and Why

3.1 Task Definition

Given a post P that contains potentially misleading information and a note N that provides an explanation about that post, the task is to predict two types of labels: a **helpfulness label** $L_{helpful}$, indicating whether the note is helpful in explaining the misleading nature of the post, and a **reason label** L_{reason}, specifying why the note is (un)helpful. The helpfulness prediction is formulated as a binary classification task with the label space $\{Helpful, Unhelpful\}$. The reason prediction is a multi-label classification task, where the predefined label set includes eight reasons for helpful notes and ten reasons for unhelpful ones (see Appendix Table 15 for detailed reason labels).

Language	Train	Dev	Test	Total
English	40,994	5,858	11,717	58,569
Other languages	32,478	4,638	9,281	46,397
Total	73,472	10,496	20,998	104,966

Table 1: COMMUNITYNOTES data split statistics for English and Other languages.

Text Type	Mean	Median	Min	Max
Post	57.44	42	0	5,072
Note	87.05	70	1	1,402

Table 2: Token length statistics for claims and notes. Texts are tokenized by OpenAI's tiktoken v0.11.0.

3.2 Data Collection and Pre-processing

We collected all our data from X's official *Community Notes* platform between January 2021 and December 2024, combining all publicly available releases. Because ratings are provided in multiple shards, we merge them and join them with the remaining components to obtain complete note–rating pairs. We then apply the official note-ranking algorithm to compute the aggregated helpfulness and reason labels. For helpfulness prediction, we remove entries labeled NEED_MORE_RATINGS, resulting in a binary label space–CURRENTLY_RATED_HELPFUL or CURRENTLY_RATED_NOT_HELPFUL. The reason annotation is multi-label, covering 18 predefined categories. Finally, we retrieve tweet content and metadata via the X API and web crawling (Borenstein et al., 2025), linking each post with its corresponding notes to create the final dataset. See Appendix A.2 for details of the preprocessing.

Table 1 provides the data distribution. Our final dataset contains 104,966 posts, including 58,569 posts in English and 46,397 in other languages. Note that each post may be associated with one or more notes. We perform stratified partitioning with a ratio of 7:1:2 for training, development, and testing sets, maintaining separate splits for English and other language data. Henceforth we will refer to this dataset as COMMUNITYNOTES.

3.3 Dataset Statistics

We inspected multiple aspects of our entire COMMUNITYNOTES dataset. Table 2 shows the token length distribution for posts and notes correspondingly. The median token numbers are 42 for posts and 70 for notes, which suggests most posts and notes are short text snippets in our dataset.

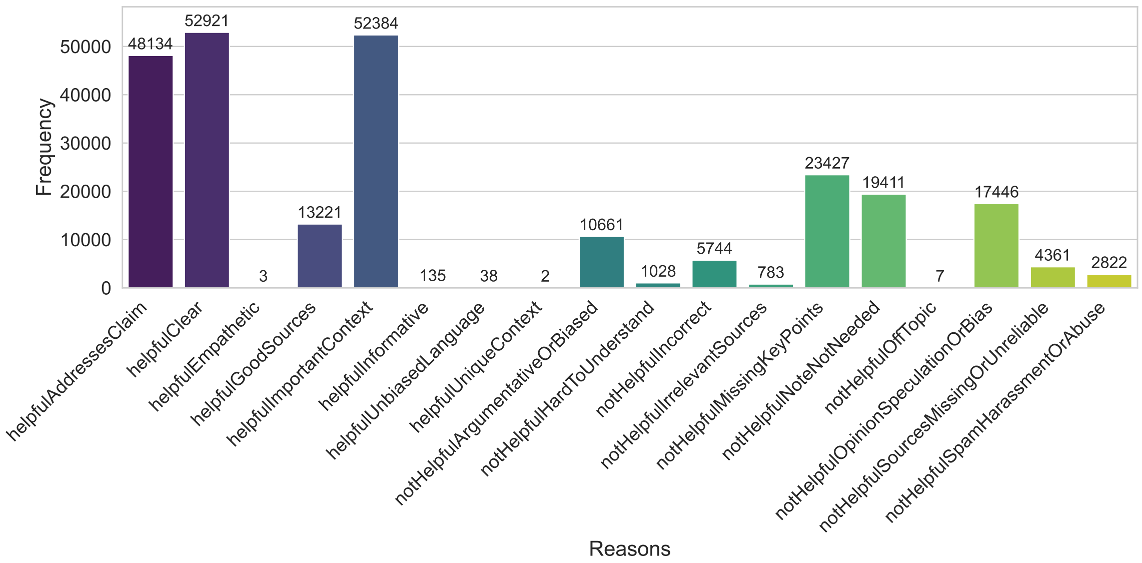

Figure 2: The histogram of the *Note Reason* label distribution. COMMUNITYNOTES contains 18 reason categories—8 corresponding to helpful notes and 10 to not helpful notes.

Notes per Post	Count (%)
1	84.74%
2	11.84%
3	2.43%
4	0.65%
5	0.18%
6	0.08%
7	0.03%
8	0.01%
≥9	<0.02%

Table 3: Distribution of the number of notes per post. The majority of posts have only one associated note.

In Table 3, we observe that 84.74% of posts have only one note, 11.84% have two notes, and the remaining posts contain three or more notes. Table 4 shows that 64.36% of posts have notes that are all rated as helpful, 31.30% have only unhelpful notes, and the remaining 4.34% include notes with mixed ratings. There are eight predefined reasons for a note being rated as helpful and ten reasons for being rated as unhelpful. The most common helpful reasons are `helpfulAddressClaim`, `helpfulImportantContext`, and `helpfulClear`, whereas `nothelpfulArgumentativeOrBiased` and `nothelpfulMissingKeyPoints` are the most frequent unhelpful reasons.

We present the distribution of helpfulness reasons in COMMUNITYNOTES in Figure 2. The most frequent helpful reason categories are `helpfulClear`, `helpfulImportantContext` and `helpfulAddressClaim`. They account for the majority of helpful instances in our dataset.

Post Type	Count	Percentage
All helpful notes	67,558	64.36%
All unhelpful notes	32,851	31.30%
Mixed helpful / unhelpful notes	4,557	4.34%

Table 4: Distribution of posts by helpfulness composition of their associated notes.

The most frequent not helpful reasons in our dataset are `notHelpfulNoteNotNeeded`, `notHelpfulMissingKeyPoints`, and `notHelpfulOpinionSpeculationOrBias`. They form a distinct middle tier in COMMUNITYNOTES. The remaining categories form a long tail with substantially lower frequencies.

Beyond note level statistics, we also examine the popularity of the posts targeted by notes in Figure 3. We measure popularity using the number of replies, likes, and retweets. These posts receive a median of approximately 3k likes, 300 replies, and 700 retweets, indicating that notes are frequently attached to already popular content. As shown in Figure 3, The mean reaction counts are substantial (e.g., ≈ 1,200 replies, ≈ 2,800 retweets, and ≈ 20,000 likes), indicating that posts in the dataset receive great public attention on average. However, the median for all three metrics is near zero. This large gap between the mean and median confirms the existence of a long tail of highly viral tweets. Given that such posts are flagged as potentially misleading, this highlights the importance of providing clear and helpful explanations at scale.

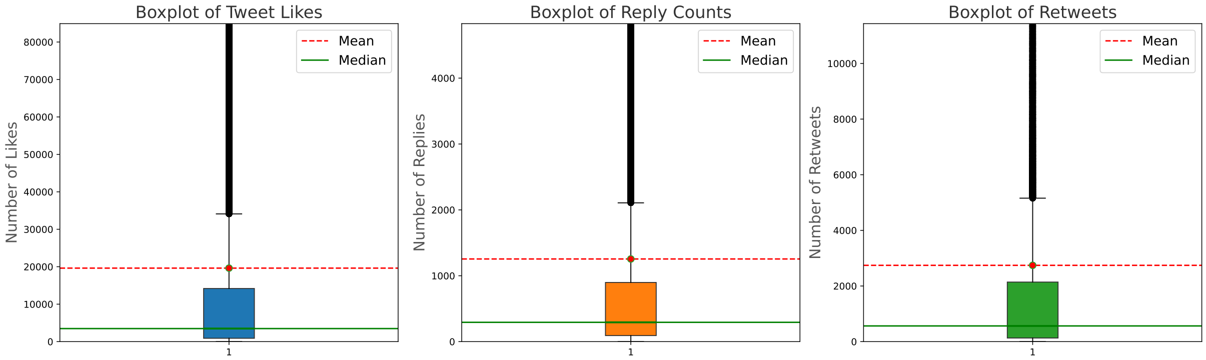

Figure 3: Boxplot of tweet post reactions in COMMUNITYNOTES. We measure popularity using the number of replies, likes, and retweets. These posts receive a median of approximately 3k likes, 300 replies, and 700 retweets, indicating that notes are frequently attached to already popular content.

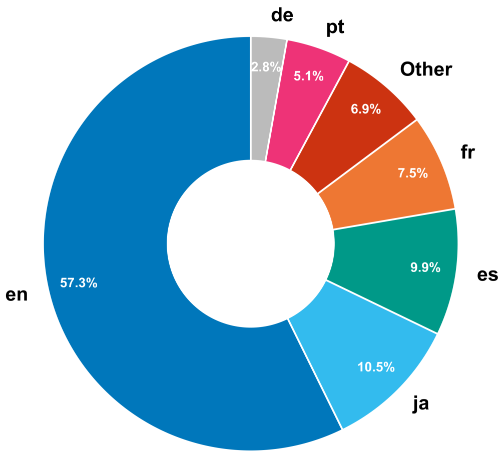

Figure 4: The language distribution of COMMUNITYNOTES: en=English, fr=French, es=Spanish, ja=Japanese, pt=Portuguese, de=German, Other=languages that appear less than 1,000 times.

Figure 4 illustrates the language distribution of COMMUNITYNOTES. English is the dominant language, accounting for 57.3% of all notes, followed by Japanese (10.5%) and Spanish (9.9%). This indicates that our final dataset effectively captures the multilingual nature of crowd-sourced explanations.

3.4 Benchmarking

Experimental Setup To establish a baseline for understanding the model performance in predicting the note helpfulness on COMMUNITYNOTES, we conducted a comprehensive set of experiments using both Small Language Models (SLMs) (BERT-style encoder-only architectures in our paper) and decoder-only Large Language Models (LLMs). This setup provides a clear view of how different model architectures and capacities affect performance on our helpfulness evaluation task.

For SLMs, we formulate the task as multi-task classification, jointly predicting: (1) a binary helpfulness label; and (2) a multi-label reason classification, across 18 predefined categories. Inputs are constructed as a concatenated sequence in the format "[CLS] Claim: {claim} [SEP] Note: {note_text}". For LLMs, we fine-tune using LoRA fine-tuning (Hu et al., 2022) (see Appendix Table 15 for detailed prompts).

We partitioned our experiments by model and language setting. For English, we experimented with SLMs including BERT (Devlin et al., 2019), ModernBERT (Warner et al., 2025), RoBERTa (Liu et al., 2019) and DeBERTa (both base and large) (He et al., 2023), For multilingual evaluation, we used BERT-base-multilingual (mBERT) and XLM-RoBERTa. We also evaluated LLMs including Llama3.1-8B (Dubey et al., 2024) and Mistral-7B (Jiang et al., 2023) for both English and multilingual settings on COMMUNITYNOTES.

Results and Analysis As shown in Table 5, models perform well on helpfulness prediction, with most of them achieving F1 above 0.88. This suggests that this task is relatively easy. In contrast, reason prediction is much more challenging, as reflected by substantially lower F1 for all models, which consistently fall below 0.70.

Comparing SLMs to LLMs: Table 5 shows that LLMs such as Llama3.1-8B and Mistral-7B outperform smaller SLMs on helpfulness prediction. In paticular, Mistral-7B achieves the highest F1 score (0.920), demonstrating the advantages of larger models. However, LLMs perform worse than SLMs in reason prediction, with F1 remaining comparable to those of the best-performing SLMs such as DeBERTa-large.

Language	Model	Helpfulness F1	Reason P	Reason R	Reason F1
English	BERT-base	0.866	0.549	0.742	0.631
	BERT-large	0.874	0.553	0.758	0.640
	RoBERTa-base	0.876	0.546	0.783	0.643
	RoBERTa-large	0.890	0.581	0.772	0.663
	ModernBERT-base	0.871	0.545	0.755	0.633
	ModernBERT-large	0.888	0.576	0.752	0.652
	DeBERTa-base	0.886	0.541	**0.810**	0.650
	DeBERTa-large	0.896	0.589	0.759	**0.665**
	Llama3.1-8B	0.919	**0.640**	0.640	0.640
	Mistral-7B	**0.920**	0.620	0.620	0.620
Other	mBERT	0.873	0.562	0.799	0.659
	XLM-RoBERTa-base	0.882	0.584	0.798	0.674
	XLM-RoBERTa-large	0.894	0.603	**0.815**	**0.693**
	Llama3.1-8B	**0.928**	**0.653**	0.652	0.653
	Mistral-7B	0.926	0.647	0.647	0.647

Table 5: Benchmark results for helpfulness and reasons prediction. *Helpfulness* means the binary classification of notes helpfulness. *Reason* means multi-label classification of helpfulness reasons. *P* is Precision and *R* is Recall.

Within the SLM families (BERT, RoBERTa, DeBERTa), larger models consistently outperform their base-sized counterparts. For example, RoBERTa-large achieves better scores than RoBERTa-base across all metrics. This highlights the importance of model capacity for capturing the nuances required for this complex task. The table also shows that DeBERTa models generally perform at or near the top among the SLMs, particularly for the reasons task, with the highest F1 Score of 0.665 among all SLMs.

The multilingual part show a similar trend: larger models achieve strong performance in Helpfulness prediction while smaller models like mBert and XLM-RoBERTa exhibit better performance on the reason prediction. Among all models, XLM-RoBERTa-large achieves the highest Reason F1 of 0.693. This indicates that these models are effective at generalizing across different languages.

4 Enhancing Helpfulness Prediction with Reason Definitions

Preliminary analysis shows that predicting why a particular explanation is (un)helpful is often subjective across instances, largely due to the lack of unified or official definitions. This subjectivity poses a barrier to model performance and limits the explainability of community-based fact-checking platforms. Prior work has demonstrated that providing clear label definitions can significantly improves the classification performance (Gao et al., 2023; Peskine et al., 2023; Khatuya et al., 2025).

Given the large number of notes with annotated reasons available, we aim to automatically generate and optimize reason label definitions based on data. To this end, we introduce a pipeline that leverages Automatic Prompt Optimization (APO) to generate and improve helpfulness reason definitions, which are then integrated with notes for reason prediction. Since the majority of notes are written in English, we focus on **English** data for the remainder of our experiments. Figure 5 illustrates the overall pipeline of our approach.

4.1 Automatically Optimizing Helpfulness Reason Definition

We automatically generate and optimize reason definitions following the first two steps in Figure 5: (1) *Seed reason definition generation*; and (2) *Reason definition optimization*. In the first step, we follow Peskine et al. (2023) and randomly sample 40 instances per helpfulness reason category. We then prompt the GPT-4o model[4] to generate an initial "seed" version of the definitions based on the sampled candidate instances (see Appendix Table 14 for detailed prompts to generate seed definitions).[5] In the second step, we employ PROMPTAGENT (Wang et al., 2024), a Monte Carlo Tree Search (MCTS)-based automatic prompt optimization framework, to refine the initial definitions.

[4] Detailed model version: gpt-4o-2024-08-06.

[5] Since a single sample may have multiple reason labels, we perform an additional check to ensure that each sample appears only within the same category to encourage diversity.

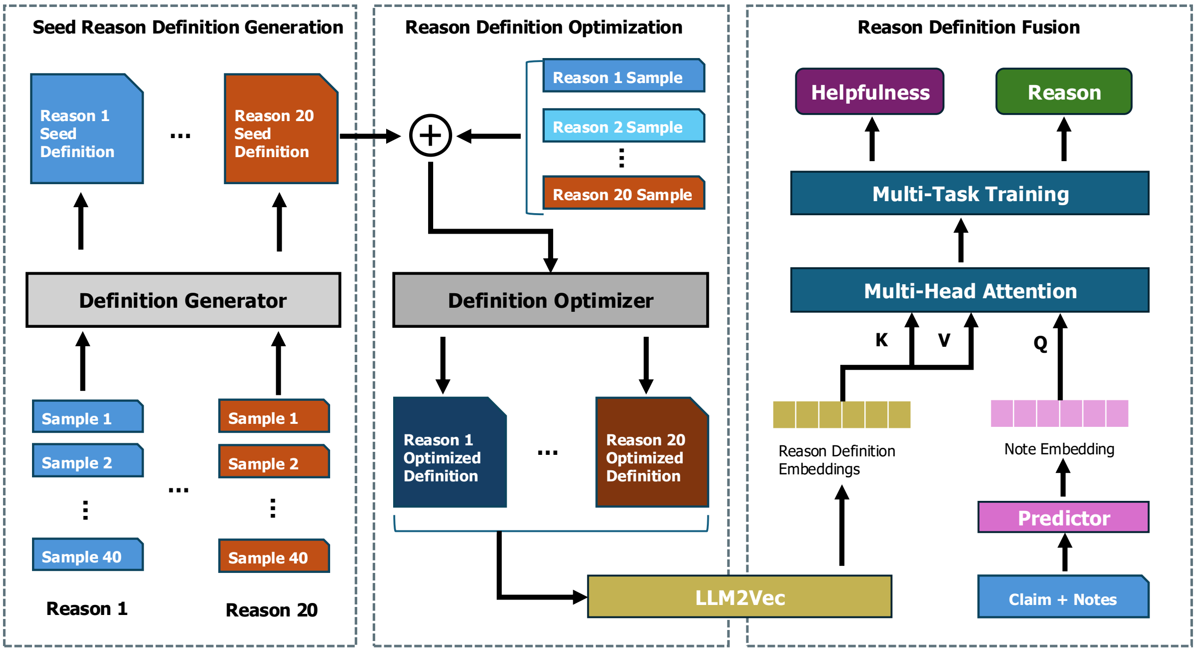

Figure 5: Our framework for automatic reason definition generation and optimization. (1) Seed reason definitions are generated from sampled post-note pairs. (2) The definitions are refined via PROMPTAGENT. (3) The optimized definitions are embedded and fused with note representations for joint helpfulness and reason prediction.

PROMPTAGENT adopts an iterative refinement process that emulates how human experts strategically craft effective prompts, using an MCTS-based planning mechanism. Each refined prompt corresponds to a new state in the search space, obtained by the refiner agent model through feedback collected from the feedback agent model. PROMPTAGENT relies on the MCTS state–action value function to estimate the reward of each state. MCTS iteratively performs four key operations—selection, expansion, simulation, and backpropagation—until a predefined number of iterations is reached. The highest-reward trajectory is then selected to produce the final refined prompt. We initialize the process with the seed definitions obtained from step (1) in Figure 5 and run adapted PROMPTAGENT using a definition-refinement feedback loop.

To evaluate the impact of incorporating generated definitions, we perform zero-shot prompting with Llama3.1-8B and Mistral-7B for both helpfulness and reason prediction. Table 6 reports results for the vanilla setting, as well as for models integrated with seed and optimized definitions. We observe substantial F1 improvements in both helpfulness and reason prediction when adding seed definitions (on average around 15%), with further gains after definition optimization, indicating that refined definitions provide additional benefits.

Model	Helpfulness F1	Reason F1
Llama3.1-8B-ins	0.636	0.126
Llama3.1-8B-ins-seed	0.783	0.304
Llama3.1-8B-ins-opt	**0.785**	**0.344**
Mistral-7B-ins	0.761	0.135
Mistral-7B-ins-seed	0.776	0.257
Mistral-7B-ins-opt	**0.786**	**0.324**

Table 6: Zero-shot prediction performance for LLMs w/o adding reason definitions on our COMMUNITYNOTES test set. *No suffix* means the vanilla model prediction performance. *seed* means definitions are generated by GPT-4o on randomly sampled cases. *opt* means that the definitions are further optimized by PROMPTAGENT.

For Llama3.1-8B, both seed and optimized definitions yield large improvements. Although Mistral-7B starts stronger than Llama3.1-8B in the vanilla setting, it still benefits notably from incorporating definitions, particularly in reason F1. These results suggest that incorporating reason definition information substantially enhances model performance—not only in predicting whether a given explanation note is helpful, but also in identifying the underlying reason with respect to the claim. (See detailed seed definition in Table 18 and optimized reason definition in Table 19 in the Appendix).

Model	Helpfulness F1	Reason F1
RoBERTa-base	0.876	0.643
RoBERTa-base-MHA	**0.887**	**0.652**
RoBERTa-large	0.890	0.663
RoBERTa-large-MHA	**0.899**	**0.672**
ModernBERT-base	0.871	0.633
ModernBERT-base-MHA	**0.874**	**0.644**
ModernBERT-large	0.888	0.652
ModernBERT-large-MHA	**0.898**	**0.662**
DeBERTa-base	0.886	0.650
DeBERTa-base-MHA	**0.887**	**0.668**
DeBERTa-large	0.896	0.665
DeBERTa-large-MHA	0.896	**0.677**

Table 7: Reason prediction performance comparison of base SLMs versus fusing optimized reason definition with the Multi-Head Attention module.

4.2 Training with Reason Definition Fusion

After obtaining the optimized helpfulness reason definitions, we proceed to the third step in Figure 5, where we incorporate this information into the training SLM predictors for helpfulness and reason prediction. The core idea is that the predictor should attend more strongly to the most relevant helpfulness reasons for a given claim–note pair.

We obtain note embeddings E_{note} from the base predictors and reason embeddings E_{reason} from the optimized reason definitions using LLM2Vec (BehnamGhader et al., 2024).[6] We then apply a Multi-Head Attention (MHA) mechanism, using E_{note} as the query (Q) and E_{reason} as the key (K) and value (V), to fuse the reason information into the note representation. Finally, we adopt a multi-task learning objective that jointly optimizes helpfulness prediction and multi-label reason classification for our experiments.

Table 7 shows that integrating optimized reason definitions via MHA consistently improves performance across all SLMs. For example, RoBERTa-large-MHA achieves a Helpfulness F1 of 0.899 and a Reason F1 of 0.669, outperforming its vanilla counterpart (0.890 and 0.663, respectively). Similar trends hold for ModernBERT and DeBERTa, with DeBERTa-large-MHA achieving the highest Reason F1 score of 0.677.

Overall, these results demonstrate that attention-based fusion of reason definitions effectively enhances SLMs for both helpfulness and reason prediction on COMMUNITYNOTES.

Predictors	NEI P	NEI R	NEI F1
RoBERTa-base-FT	0.869	0.920	0.894
RoBERTa-base-notes	0.742	0.521	0.612
RoBERTa-large-FT	0.882	**0.935**	**0.908**
RoBERTa-large-notes	0.731	0.676	0.702
ModernBERT-base-FT	0.845	0.843	0.844
ModernBERT-base-notes	0.770	0.779	0.774
ModernBERT-large-FT	0.902	0.906	0.904
ModernBERT-large-notes	0.808	0.807	0.808
DeBERTa-base-FT	0.912	0.855	0.882
DeBERTa-base-notes	0.746	0.553	0.635
DeBERTa-large-FT	**0.919**	0.890	0.905
DeBERTa-large-notes	0.736	0.774	0.755

Table 8: Predictor generalization performance on evidence sufficiency task. *notes* stands for models for original communitynotes predictors. *FT* means **F**ine**T**uned models on evidence sufficiency task. **NEI** means **N**ot **E**nough **I**nformation label.

5 Generalization of the Explanation Helpfulness

In this section, we assess the generalization and the utility of our helpfulness predictors beyond community notes. A key challenge is that most existing datasets lack explicit annotations for explanation of helpfulness. Therefore, we explore two key scenarios in automated fact-checking. First, we evaluate whether helpfulness prediction can generalize to evidence sufficiency prediction, which is an important subtask in fact-checking (Atanasova et al., 2022). Second, we explore the effect of incorporating evidence helpfulness in automated fact-checking (Xing et al., 2025).

5.1 Generalization to Evidence Sufficiency

Evidence sufficiency is a task that decides whether the information in the evidence is sufficient for predicting the veracity of a claim. Automated fact-checking models can make veracity predictions only when there is enough evidence (Atanasova et al., 2022). In this scenario, we would like to explore whether our helpfulness predictors can predict the sufficiency of an evidence (since a helpful evidence must be "sufficient"). We adopted *Sufficient Fact* (Atanasova et al., 2022), a diagnostic fact-checking dataset to detect when evidence with omitted information is (in)sufficient. To adapt our prediction, we treat sufficient evidence (*EI-ENOUGH INFO*) as helpful and insufficient evidence (*NEI-NOT ENOUGH INFO*) as unhelpful. Table 8 shows the model performance on the evidence sufficiency task, focusing on the *NEI* label.

[6] Specifically, we use the following model: LLM2Vec-Meta-Llama-31-8B-Instruct-mntp-supervised.

As expected, fine-tuned (FT) models outperform the original notes predictors, with RoBERTa-large-FT achieving the best *NEI* F1 of 0.908. Nevertheless, the notes models show competitive performance: for example, ModernBERT-large-notes achieves a *NEI* F1 of 0.808, only about 10% lower than its FT counterpart. Across all predictors, the top predicted reason is `notHelpfulMissingKeyPoints`, which closely corresponds to the *NEI* label, as both signify the absence of critical information. This indicates that helpfulness prediction carries transferable signal for evidence sufficiency.

Still, helpfulness and sufficiency are not the same: even sufficient evidence could be predicted as unhelpful for other reasons such as `notHelpfulArgumentativeOrBiased`, which may account for the observed performance gap in our experiments.

5.2 Incorporating Evidence Helpfulness in Automated Fact Checking

In this part, we further investigate whether predicted evidence helpfulness can enhance automated fact-checking. Helpfulness scores provide auxiliary signals for assessing evidence quality, with the potential to help models prioritize informative evidence during prediction. We adopted `CLIMATE-FEVER` (Diggelmann et al., 2020), a real-world dataset for verifying climate change–related claims. Each claim is associated with multiple evidence sentences, to which we apply our predictors to assign helpfulness scores and reasons. To perform fact-checking, we use Llama3.1-8B to perform fact-checking (see detailed prompt in Appendix Table 20) prompting the model with both the claim and its associated evidence.

We compare the F1 with and without the evidence helpfulness information and report results in Table 9. Overall, incorporating helpfulness improves fact-checking performance, with ModernBERT-base achieving 0.537 accuracy and ModernBERT and RoBERTa-base improving performance by around 2%. While ModernBERT demonstrates major gains, DeBERTa and RoBERTa yield smaller, non-significant improvements. Interestingly, this pattern mirrors their performance drop in cross-domain evidence sufficiency evaluation in Section 5.1 (despite strong in-domain results in Table 5). One possible explanation is that models overfit `COMMUNITYNOTES` and generalize less effectively to other domains.

Predictors	F1	+Helpfulness F1
RoBERTa-base	0.517	**0.521**
RoBERTa-large	0.519	0.521
ModernBERT-base	0.521	**0.535**
ModernBERT-large	0.517	**0.535**
DeBERTa-base	0.517	0.519
DeBERTa-large	0.518	0.519

Table 9: Automated fact-checking performance of Llama3.1-8B on the `CLIMATE-FEVER` dataset. *F1* stands for Accuracy. *+Helpfulness F1* means accuracy incorporating helpfulness information. Numbers in bold represents the gap between *+Helpfulness* and basic prediction accuracy is statistically significant (using a two-tailed t-test with $p < 0.05$).

6 Conclusion

In this paper, we introduced the novel task of predicting the helpfulness of explanations and their underlying reasons for a given claim. To support this task, we constructed `COMMUNITYNOTES`, a large-scale post–note helpfulness dataset based on X's *Community Notes*, and established benchmarks with pretrained language models.

While existing models perform reasonably well on overall helpfulness, they struggle to identify underlying reasons. To address this limitation, we proposed a framework that automatically generates and optimizes reason definitions, which, when reintegrated, greatly improves reason prediction. We further demonstrated that helpfulness prediction can help predict evidence sufficiency and enhance automated fact-checking systems.

Beyond performance gains, our findings highlight the importance of making evaluation criteria for explanation helpfulness more explicit and structured. We hope that our dataset and framework can serve as a foundation for building stronger helpfulness predictors capable of assigning prior labels to real-time community notes, thereby streamlining the community-based fact-checking process. Additionally, the automatically generated and optimized reason definitions may enhance the explainability and trustworthiness of automated fact-checking models and could be extended to improve other classification tasks beyond this domain.

In future work, we plan to extend our framework to multilingual and multimodal settings and evaluate it in more advanced end-to-end fact-checking systems and real-world applications.

Limitations

While our study provides new insights into the helpfulness of crowd-sourced fact-checking explanations, several limitations remain.

First, the inherently subjective nature of community-based annotations introduces potential noise and inconsistency in the helpfulness and reason labels. Despite our efforts to aggregate ratings through official mechanisms, differences in annotator interpretation and cultural context may still influence the results.

Second, our automated definition generation and optimization pipeline has thus far been evaluated primarily on English. Although our dataset includes multilingual content, we did not systematically validate the quality or transferability of the generated definitions across languages. Future work should explore multilingual adaptation and cross-lingual alignment of reason definitions.

Third, while our experiments show improved model performance when integrating optimized reason definitions, the evaluation is limited to classification metrics. Further human-centered evaluation is necessary to assess whether these improvements translate to greater interpretability and practical usefulness in real-world fact-checking workflows.

Finally, our study focuses on publicly available *Community Notes* data, which may reflect platform-specific norms and biases. For a broader generalization to other fact-checking ecosystems (e.g., Meta's or TikTok's community moderation systems), we need further investigation.

Ethics and Broader Impact

Our work aims to improve the transparency, explainability, and scalability of community-based fact-checking systems. By modeling and predicting the helpfulness of user-generated explanations, we hope to assist both contributors and platforms in identifying notes that are more informative, balanced, and useful for the public discourse.

Bias and Fairness. Community-based ratings may reflect social, cultural, or political biases that influence which notes are deemed "helpful." Our models inevitably inherit such biases from the underlying data. We would like to emphasize that model predictions should not be directly used to automatically moderate or suppress user content. Instead, they should be interpreted as auxiliary signals to guide human review.

Responsible Use. While our framework can help prioritize potentially helpful notes, it is not intended to replace human judgment. Automated systems that assign helpfulness or credibility labels at scale may affect content visibility, user reputation, and online discourse. We encourage incorporating fairness-aware and interpretable mechanisms before deployment.

Positive Societal Impact. Despite these caveats, our dataset and models can help combat misinformation by improving the quality, trustworthiness, and accessibility of community fact-checking. Making helpfulness definitions explicit and machine-interpretable supports more transparent and accountable information verification.

Data Collection and Licenses All data that we used in this work originated from the publicly available *X Community Notes* dataset,[7] which was released under the X platform's open data policy. The dataset contains user-generated notes, associated posts, and helpfulness and reason labels, without any personally identifiable information. We release only anonymized text and aggregated statistics in compliance with the X platform's terms of service. The dataset is multilingual, with English, Japanese, and Spanish being the best represented languages. Any future release of derived data will follow ACL data ethics guidelines with appropriate documentation, to enable transparent, reproducible research in NLP and computational social science.

Security Implication Our study introduces no direct security risks, but models trained on user-generated content may be vulnerable to misuse, such as large-scale manipulation or suppression of dissent. To mitigate these risks, we release only aggregated and anonymized data and emphasize that our models are intended for research use, not automated moderation or deployment without human oversight. Future work should address adversarial attacks, bias exploitation, and model inversion risks when integrating such models into live platforms.

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[7] https://communitynotes.x.com/guide/en/under-the-hood/download-data

References

Pepa Atanasova, Jakob Grue Simonsen, Christina Lioma, and Isabelle Augenstein. 2020. Generating fact checking explanations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, ACL 2020, pages 7352–7364, Online. Association for Computational Linguistics.

Pepa Atanasova, Jakob Grue Simonsen, Christina Lioma, and Isabelle Augenstein. 2022. Fact checking with insufficient evidence. *Transactions of the Association for Computational Linguistics*, 10:746–763.

Isabelle Augenstein, Michiel Bakker, Tanmoy Chakraborty, David Corney, Emilio Ferrara, Iryna Gurevych, Scott Hale, Eduard Hovy, Heng Ji, Irene Larraz, Filippo Menczer, Preslav Nakov, Paolo Papotti, Dhruv Sahnan, Greta Warren, and Giovanni Zagni. 2025. Community moderation and the new epistemology of fact checking on social media. *ArXiv preprint*, abs/2505.20067.

Parishad BehnamGhader, Vaibhav Adlakha, Marius Mosbach, Dzmitry Bahdanau, Nicolas Chapados, and Siva Reddy. 2024. LLM2Vec: Large language models are secretly powerful text encoders. In *Proceedings of the First Conference on Language Modeling*, COLM 24, Philadelphia, PA, USA.

Nadav Borenstein, Greta Warren, Desmond Elliott, and Isabelle Augenstein. 2025. Can community notes replace professional fact-checkers? In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics*, ACL 2025, pages 535–552, Vienna, Austria. Association for Computational Linguistics.

Yuwei Chuai, Moritz Pilarski, Thomas Renault, David Restrepo-Amariles, Aurore Troussel-Clément, Gabriele Lenzini, and Nicolas Pröllochs. 2024. Community-based fact-checking reduces the spread of misleading posts on social media. *ArXiv preprint*, abs/2409.08781.

Soham De, Michiel A. Bakker, Jay Baxter, and Martin Saveski. 2025. Supernotes: Driving consensus in crowd-sourced fact-checking. In *Proceedings of the ACM on Web Conference 2025*, WWW 25, page 3751–3761, Sydney NSW, Australia. Association for Computing Machinery.

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

Thomas Diggelmann, Jordan Boyd-Graber, Jannis Bulian, Massimiliano Ciaramita, and Markus Leippold. 2020. CLIMATE-FEVER: A dataset for verification of real-world climate claims. *ArXiv preprint*, abs/2012.00614.

Chiara Patricia Drolsbach and Nicolas Pröllochs. 2023. Diffusion of community fact-checked misinformation on Twitter. In *Proceedings of the ACM on Human-Computer Interaction*, New York, USA. Association for Computing Machinery.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, and 8 others. 2024. The Llama 3 herd of models. *ArXiv preprint*, abs/2407.21783.

Islam Eldifrawi, Shengrui Wang, and Amine Trabelsi. 2024. Automated justification production for claim veracity in fact checking: A survey on architectures and approaches. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics*, ACL 2024, pages 6679–6692, Bangkok, Thailand. Association for Computational Linguistics.

Chrisantha Fernando, Dylan Banarse, Henryk Michalewski, Simon Osindero, and Tim Rocktäschel. 2024. PromptBreeder: Self-referential self-improvement via prompt evolution. In *Proceedings of Forty-first International Conference on Machine Learning*, ICML 2024, Vienna, Austria. OpenReview.net.

Lingyu Gao, Debanjan Ghosh, and Kevin Gimpel. 2023. The benefits of label-description training for zero-shot text classification. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, EMNLP 2023, pages 13823–13844, Singapore. Association for Computational Linguistics.

Zhijiang Guo, Michael Schlichtkrull, and Andreas Vlachos. 2022. A survey on automated fact-checking. *Transactions of the Association for Computational Linguistics*, 10:178–206.

Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2023. DeBERTaV3: Improving DeBERTa using ELECTRA-style pre-training with gradient-disentangled embedding sharing. In *Proceedings of The Eleventh International Conference on Learning Representations*, ICLR 2023, Kigali, Rwanda. OpenReview.net.

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. LoRA: Low-rank adaptation of large language models. In *Proceedings of the Tenth International Conference on Learning Representations*, ICLR 2022, Virtual Event. OpenReview.net.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. *ArXiv preprint*, abs/2310.06825.

Subhendu Khatuya, Shashwat Naidu, Saptarshi Ghosh, Pawan Goyal, and Niloy Ganguly. 2025. Label-semantics aware generative approach for domain-agnostic multilabel classification. In *Findings of the Association for Computational Linguistics: ACL 2025*, ACL 2025, pages 22286–22298, Vienna, Austria. Association for Computational Linguistics.

Shanu Kumar, Akhila Yesantarao Venkata, Shubhanshu Khandelwal, Bishal Santra, Parag Agrawal, and Manish Gupta. 2025. SCULPT: Systematic tuning of long prompts. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics*, ACL 2025, pages 14996–15029, Vienna, Austria. Association for Computational Linguistics.

Stephan Lewandowsky, Ullrich K. H. Ecker, Colleen M. Seifert, Norbert Schwarz, and John Cook. 2012. Misinformation and its correction: Continued influence and successful debiasing. *Psychological Science in the Public Interest*, 13(3):106–131. PMID: 26173286.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized BERT pretraining approach. *ArXiv preprint*, abs/1907.11692.

Cameron Martel and David G. Rand. 2024. Fact-checker warning labels are effective even for those who distrust fact-checkers. *Nature Human Behaviour*, 8:1957 – 1967.

Preslav Nakov, David P. A. Corney, Maram Hasanain, Firoj Alam, Tamer Elsayed, Alberto Barrón-Cedeño, Paolo Papotti, Shaden Shaar, and Giovanni Da San Martino. 2021. Automated fact-checking for assisting human fact-checkers. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence*, IJCAI 2021, pages 4551–4558, Montreal, Canada.

Youri Peskine, Damir Korenčić, Ivan Grubisic, Paolo Papotti, Raphael Troncy, and Paolo Rosso. 2023. Definitions matter: Guiding GPT for multi-label classification. In *Findings of the Association for Computational Linguistics*, EMNLP 2023, pages 4054–4063, Singapore. Association for Computational Linguistics.

Kiran Ramnath, Kang Zhou, Sheng Guan, Soumya Smruti Mishra, Xuan Qi, Zhengyuan Shen, Shuai Wang, Sangmin Woo, Sullam Jeoung, Yawei Wang, Haozhu Wang, Han Ding, Yuzhe Lu, Zhichao Xu, Yun Zhou, Balasubramaniam Srinivasan, Qiaojing Yan, Yueyan Chen, Haibo Ding, and 2 others. 2025. A systematic survey of automatic prompt optimization techniques. *ArXiv preprint*, abs/2502.16923.

Thomas Renault, David Restrepo-Amariles, and Aurore Troussel. 2024. Collaboratively adding context to social media posts reduces the sharing of false news. HEC Research Papers Series 1519, HEC Paris.

Daniel Russo, Serra Sinem Tekiroğlu, and Marco Guerini. 2023. Benchmarking the generation of fact checking explanations. *Transactions of the Association for Computational Linguistics*, 11:1250–1264.

Xinyuan Wang, Chenxi Li, Zhen Wang, Fan Bai, Haotian Luo, Jiayou Zhang, Nebojsa Jojic, Eric P. Xing, and Zhiting Hu. 2024. PromptAgent: Strategic planning with language models enables expert-level prompt optimization. In *Proceedings of the International Conference on Learning Representations*, ICLR 2024, Vienna, Austria. OpenReview.net.

Benjamin Warner, Antoine Chaffin, Benjamin Clavié, Orion Weller, Oskar Hallström, Said Taghadouini, Alexis Gallagher, Raja Biswas, Faisal Ladhak, Tom Aarsen, Griffin Thomas Adams, Jeremy Howard, and Iacopo Poli. 2025. Smarter, better, faster, longer: A modern bidirectional encoder for fast, memory efficient, and long context finetuning and inference. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics*, ACL 2025, pages 2526–2547, Vienna, Austria. Association for Computational Linguistics.

Greta Warren, Irina Shklovski, and Isabelle Augenstein. 2025. Show me the work: Fact-checkers' requirements for explainable automated fact-checking. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, CHI 2025, Yokohama, Japan. Association for Computing Machinery.

Stefan Wojcik, Sophie Hilgard, Twitter Cortex, Nick Judd, Delia Mocanu, Stephen Ragain, M.B. Fallin Hunzaker, Keith Coleman Twitter Product, and Jay Baxter. 2022. Birdwatch: Crowd wisdom and bridging algorithms can inform understanding and reduce the spread of misinformation. *ArXiv preprint*, abs/2210.15723.

Zhuohan Xie, Rui Xing, Yuxia Wang, Jiahui Geng, Hasan Iqbal, Dhruv Sahnan, Iryna Gurevych, and Preslav Nakov. 2025. FIRE: Fact-checking with iterative retrieval and verification. In *Findings of the Association for Computational Linguistics*, NAACL 2025, pages 2901–2914, Albuquerque, New Mexico. Association for Computational Linguistics.

Rui Xing, Timothy Baldwin, and Jey Han Lau. 2025. Evaluating evidence attribution in generated fact checking explanations. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies*, NAACL 2025, pages 5475–5496, Albuquerque, New Mexico. Association for Computational Linguistics.

Rui Xing, Shraey Bhatia, Timothy Baldwin, and Jey Han Lau. 2022. Automatic explanation generation for climate science claims. In *Proceedings of the 20th Annual Workshop of the Australasian Language Technology Association*, ALTA 2022, pages 122–129, Adelaide, Australia.

A Appendix

A.1 Extended Background of X Community Notes Program

Origin X *Community Notes* originated from the Birdwatch (Wojcik et al., 2022) program which was launched by X (formerly Twitter) in 2021.[8] Participants, known as contributors, write "notes" that clarify or contextualize claims made in posts, and other users rate these notes for helpfulness and accuracy. Notes receiving broad agreement across diverse raters are surfaced publicly beneath the corresponding posts. This community-driven system aims to promote transparency and provide multiple perspectives in addressing misinformation on social media (Augenstein et al., 2025). Initially limited to U.S. users, the program gained wider attention in 2022 during major misinformation events such as the Russian invasion of Ukraine and the COVID-19 pandemic. Birdwatch was rebranded as *Community Notes* and expanded globally in November 2022. As of November 2023, the program had over 133,000 contributors, with notes reportedly viewed tens of millions of times per day, reflecting its growing role in mitigating misinformation in online social media.

Advantages and Challenges *Community Notes* introduces a promising new paradigm for fact-checking. It democratizes content moderation by enabling the public to collectively determine whether a note should be added to a post, offering a less intrusive alternative to traditional expert-based fact-checking systems that often rely on explicit warning labels. This community-driven approach also accelerates the detection of misinformation, offering better scalability. However, *Community Notes* also faces several challenges. The community can still favor popularity over truth, similar to the echo-chamber effects often seen on social media. While its scalability and faster operation are promising, studies show that its performance still lags behind expert-based fact-checking in many cases (Martel and Rand, 2024). In addition, helpful notes often appear too late—after a post has already received significant engagement—reducing their effectiveness in correcting misinformation and changing user beliefs (Augenstein et al., 2025; De et al., 2025; Borenstein et al., 2025).

A.2 `COMMUNITYNOTES` Pre-processing Details

Raw Data Community notes data are publicly available on the official website.[9] The data is released in several following separate files:

- **Notes:** This table contains all notes and their attributes. Core attributes include *tweetId*, which identifies the tweet the note is associated with, and *classification*, indicating whether the tweet is considered misleading. It also includes several attributes describing potential types of misinformation (e.g., *misleadingFactualError*); however, these fields are not directly related to note ratings and are excluded from this study.

- **Ratings:** This table includes all user ratings of notes. Our helpfulness label scheme is derived from this table, where attributes prefixed with *helpful-* and *notHelpful-* correspond to the helpfulness reasons used in our `COMMUNITYNOTES` experiments.

- **Note Status History:** This table contains metadata about notes, including their status updates and timestamps. We use the *currentStatus* attribute to determine each note's final helpfulness label.

- **User Enrollment:** This table provides metadata on each user's enrollment status in the Community Notes program. Since it does not contain information related to note helpfulness, we exclude it from our experiments.

- **Note Requests:** This table records all requests submitted by X users for a Community Note. It was added after our data collection period, so it is not used in this study.

We first construct the full dataset by joining all data files on the *noteID* column. We then remove empty notes and merge the duplicated helpfulness reasons `notHelpfulOpinionSpeculation` and `notHelpfulOpinionSpeculationOrBias` into a single reason category which is `notHelpfulOpinionSpeculationOrBias`.
Finally, we exclude notes that are labeled as `notHelpfulOther`, as their reasons are unclear and uninformative.

[8] Introducing Birdwatch, a community-based approach to misinformation, By Keith Coleman, Monday, 25 January 2021.

[9] `https://x.com/i/communitynotes/download-data`

Phase	#	Step Description
Prescoring	1.	Pre-filter Data: Include only raters ($\geq$ 10 ratings) & notes ($\geq$ 5 ratings). Coalesce similar raters.
	2.	Initial Model Fit: Fit matrix factorization (MF) models for each scorer. Assign intermediate note status based on intercept thresholds.
	3.	Calculate & Filter Helpfulness: Compute Author/Rater Helpfulness Scores from the initial MF results. Filter out low-helpfulness raters.
	4.	Refine Score: Fit a tag-consensus MF model on the helpfulness-filtered data and update all helpfulness scores.
Scoring	1.	Load & Refresh Data: Load prescoring outputs. Re-run the pre-filtering step on the newest available data.
	2.	Re-fit Main Models: Re-fit the main MF models (for all scorers) using the helpfulness-filtered ratings.
	3.	Fit Diligence Model: Fit the note diligence MF model.
	4.	Compute Confidence Bounds: Add pseudo-ratings and re-fit models to get upper/lower confidence bounds for note intercepts.
	5.	Reconcile & Finalize Status: Generate a final status for each note from all scorer results. Stabilize status for notes older than two weeks.
	6.	Assign Explanation Tags: Assign the top two matching explanation tags. If two such tags are not found, revert status to `NEED_MORE_RATINGS`.

Table 10: Overview of the X *Community Notes* note ranking Algorithm pipeline.

Language	Before Processing			After Processing		
	Train	Dev	Test	Train	Dev	Test
English	41,102	5,872	11,744	40,994	5,858	11,717
Other	32,520	4,646	9,292	32,478	4,638	9,281
Total	73,622	10,518	21,036	73,472	10,496	20,998

Table 11: Comparison of dataset sizes before and after processing for English and other language subsets.

Note Ranking Algorithm Table 10 summarizes the ranking algorithm used by *Community Notes*. Contributors submit notes for potentially misleading posts, which are rated by other users and aggregated to assign one of three statuses — `CURRENTLY_RATED_HELPFUL`, `CURRENTLY_RATED_NOT_HELPFUL`, or `NEED_MORE_RATINGS` — determining public visibility. All notes initially receive the `NEED_MORE_RATINGS` and remain unpublished until they accumulate at least five ratings.

The ranking algorithm is based on a Matrix Factorization (MF) model trained on a sparse note–rater matrix, producing a continuous *Note Helpfulness Score* for each note. A note is assigned `CURRENTLY_RATED_HELPFUL` if its score exceeds 0.40; currently, only notes associated with potentially misleading posts and meeting this threshold are shown publicly. Conversely, a note is assigned `CURRENTLY_RATED_NOT_HELPFUL` if its score falls below $-0.05 - 0.8 \times |\text{noteFactorScore}|$, or if its upper confidence bound is smaller than -0.04. Notes with scores between these thresholds remain at `NEED_MORE_RATINGS` state until additional ratings are collected. Table 11 presents data size statistics for English and other language subsets before and after processing in `COMMUNITYNOTES`.

Reason Category	**Support**	**F1**
Top 3 Predicted Reasons		
helpfulAddressesClaim	6,630	0.794
helpfulImportantContext	5,222	0.713
notHelpfulArgumentativeOrBiased	1,454	0.658
Bottom 3 Predicted Reasons		
notHelpfulIncorrect	780	0.345
notHelpfulHardToUnderstand	156	0.306
notHelpfulIrrelevantSources	84	0.096

Table 12: DeBERTa-large F1 broken down.

A.3 Further Analysis of SLM performance

As reason prediction is much more challenging compared with helpfulness prediction, in order to better understand the task, we further analyze model F1 scores across different reason categories. We chose DeBERTa, which achieves the best reason prediction performance in the benchmark results (Table 5). We report the top and bottom five reason categories by F1 in Table 12. The model achieves its highest F1 scores on frequent categories such as `helpfulAddressesClaim` (0.794) and `helpfulImportantContext` (0.713). Conversely, it struggles with sparse categories such as `helpfulEmpathetic` and `helpfulInformative` (both 0.00 F1), highlighting a long-tail challenge where the model fails to generalize to infrequent reasons with limited training examples. Notably, there is systematic confusion among `helpfulClear`, `helpfulImportantContext`, and `helpfulAddressesClaim`. This suggests that while the model can reliably identify whether a note is helpful, it often struggles to distinguish fine-grained semantic differences between closely related reason categories.

Model	Training Epoch	Batch Size
BERT-base	19	64
BERT-large	8	32
RoBERTa-base	16	64
RoBERTa-large	10	32
ModernBERT-base	6	32
ModernBERT-large	5	16
DeBERTa-base	10	32
DeBERTa-large	8	16
XLM-RoBERTa-base	20	64
XLM-RoBERTa-large	10	32
mBERT	11	64

Table 13: Training Epoch and Batch Size for all SLMs used in our experiments on COMMUNITYNOTES.

A.4 Experimental Details

We report the best training epochs and batch sizes for SLMs in Table 13. To reduce overfitting, we use smaller batch sizes and fewer epochs for base models, and larger ones for their large counterparts. For LLMs, we apply LoRA fine-tuning with a rank of 16, alpha of 32, and applied to all linear modules. We train with a batch size of 4, gradient accumulation of 1 step, for 3 epochs, using a cosine learning rate scheduler with a warmup ratio of 0.1. The training takes between 32 and 46 GPU hours on 2 NVIDIA RTX6000 Ada Generation GPUs (48GB GPU RAM). All open source models are directly adopted from the Hugging Face Hub, including SLMs (BERT,[10] RoBERTa,[11] DeBERTa,[12] ModernBERT,[13] mBERT,[14] XLM-RoBERTa[15]) and LLMs (Llama3.1-8B,[16] Mistral-7B[17]).

We reimplemented the complete ranking algorithm on a 64-core Intel(R) Xeon(R) Gold 6448H CPU with 500 GB of RAM to recover aggregated helpfulness labels and reason annotations for each note in *Community Notes*.[18]

A.5 Prompts

In this section, we provided detailed prompts used in our COMMUNITYNOTES experiments. Table 14 shows the prompt for initial reason generation. Table 15 presents the prompt for LLM to predict Helpfulness and Reasons. Table 16 shows English prompts used for helpfulness and reason prediction on COMMUNITYNOTES with seed definition. Table 17 shows the same task with optimized definition for LLM predictions. Table 18 provides the seed definition generated using GPT-4o over random samples. Table 19 is the detailed reason definition optimized using PROMPTAGENT. Table 20 shows the prompt we used for LLM to perform fact checking on CLIMATE-FEVER dataset.

[10] https://huggingface.co/docs/transformers/en/model_doc/bert

[11] https://huggingface.co/docs/transformers/en/model_doc/roberta

[12] https://huggingface.co/docs/transformers/en/model_doc/deberta

[13] https://huggingface.co/docs/transformers/en/model_doc/modernbert

[14] https://huggingface.co/google-bert/bert-base-multilingual-cased

[15] https://huggingface.co/docs/transformers/en/model_doc/xlm-roberta

[16] https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct

[17] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

[18] https://github.com/twitter/communitynotes

Initial reason generation

You will be given a set of samples, each sample contains CLAIM, their corresponding NOTE to explain the CLAIM. All samples provided are ${helpful_label} in explaining the CLAIM and associated with the same REASON. Your task is to conclude the definition of the REASON.
Here are samples: ${samples}
The REASON for above samples being ${helpful_label} is ${reason_label}. After checking these samples, the definition of this REASON is:

Table 14: Prompt for initial reason generation.

Original Prompt

Given a potentially misleading CLAIM and an associated NOTE, your task is to determine whether the NOTE is helpful in clarifying the CLAIM and identify two reasons from the predefined reason set explaining why it is helpful or not helpful.

The predefined reason set is:’helpfulAddressesClaim’, ’helpfulClear’, ’helpfulEmpathetic’, ’helpfulGoodSources’, ’helpfulImportantContext’, ’helpfulInformative’, ’helpfulUnbiasedLanguage’, ’helpfulUniqueContext’, ’notHelpfulArgumentativeOrBiased’, ’notHelpfulHardToUnderstand’,’notHelpfulIncorrect’, ’notHelpfulIrrelevantSources’, ’notHelpfulMissingKeyPoints’, ’notHelpfulNoteNotNeeded’, ’notHelpfulOffTopic’, ’notHelpfulOpinionSpeculationOrBias’, ’notHelpfulSourcesMissingOrUnreliable’, ’notHelpfulSpamHarassmentOrAbuse’

Output in the following JSON format only, no extra output: {"helpfulness": helpful or non_helpful,"reasons":"reason1;reason2"} CLAIM: ${claim}
NOTE: ${note}
Answer:

Table 15: Original English prompt for note helpfulness and reason prediction.

Prompt with seed defininion

Given a potentially misleading CLAIM and an associated NOTE, your task is to determine whether the NOTE is helpful in clarifying the CLAIM and identify two reasons from the predefined reason set explaining why it is helpful or not helpful.

Here are reasons and their definitions: ${reason definitions}
Output in the following JSON format only, no extra output: {"helpfulness": helpful or non_helpful,"reasons":"reason1;reason2"}
CLAIM: ${claim}
NOTE: ${note}
Answer:

Table 16: English prompt with seed definition for note helpfulness and reason prediction.

Optimized Prompt

For each claim-note pair below, select exactly two reasons (from the provided list) that most accurately explain whether and why the note is helpful or not helpful for understanding or resolving the claim.

Continued on next page

Optimized Prompt

High-Level Criteria

1. Prioritizing Central, Accurate Clarification

- Assign a “helpful” reason only if the note is factually accurate, well-supported, and directly clarifies, corrects, or provides essential context for the main assertion, a key factual sub-claim, or the foundational evidence of the claim. Peripheral or partially related details are insufficient.
- If the note’s chief function is to correct a specific fact, figure, identity, date, source, or a significant misattribution or misconception central to the claim, this counts as clarification or correction (use “helpfulClear” and/or “helpfulAddressesClaim”).
- Never assign any “helpful” reason if the note contains substantive factual errors, misrepresentations, speculation, or bias regarding any key claim point or related evidence—regardless of any attempt to clarify.

2. “Helpful” Reason Prioritization

- helpfulClear and helpfulAddressesClaim take precedence over other “helpful” reasons when a note offers a direct factual correction or explicit clarification for the claim’s core point or supporting evidence.
- helpfulGoodSources should only be selected in addition if the note’s correction is fundamentally grounded in clearly cited, authoritative, and faithfully summarized sources (not just the presence of a source).
- helpfulImportantContext is used when the note supplies background or context without which the claim would be misunderstood or misinterpreted, and this context is not a direct factual correction but provides essential interpretive clarity.
- Use helpfulUnbiasedLanguage or helpfulEmpathetic only in conjunction with a substantive clarification or correction and if the neutrality or tone of the explanation is materially helpful. When both direct correction and crucial context are present, prefer (b) helpfulClear or (a) helpfulAddressesClaim as primary, paired with (e) helpfulImportantContext as secondary only if context is indispensable and not redundant with the correction.
- helpfulGoodSources never substitutes for correction—pick it only if the faithful use of sources is a main reason for helpfulness.

3. “NotHelpful” Reason Selection

- Assign “notHelpfulIncorrect” if there is any inaccuracy, factual misstatement, or misleading claim regarding the main point or evidence.
- Assign “notHelpfulMissingKeyPoints” if the note avoids or omits addressing the core issue or supporting fact, no matter how detailed its peripheral info.
- Use “notHelpfulNoteNotNeeded” if the note is trivial, redundant, or supplies information already evident and non-essential for claim comprehension.
- “notHelpfulSourcesMissingOrUnreliable” or “notHelpfulIrrelevantSources” apply if sources are not credible, are misrepresented, or are irrelevant to the core of the claim.
- If tone, personal opinion, bias, speculation, or argumentativeness blocks any clarification, use one of the corresponding “notHelpful” reasons that best fits the limitation.
- For unclear, incomplete, or confusing notes, use “notHelpfulHardToUnderstand.” “notHelpfulOther” and “notHelpfulOffTopic” only if none of the above describe the problem or the note is wholly irrelevant.

Reason Definitions:${Reason Definitions}

Continued on next page

Optimized Prompt

Decision Process Checklist

1. Is the note factually accurate and not misleading about any major point or evidence?

- If no, assign “notHelpfulIncorrect” and another as fits.
- If yes, proceed.

2. Does the note directly clarify, correct, or critically contextualize the main assertion, a key factual sub-claim, or any central supporting evidence?

- If yes, select the most specific “helpful” reason(s) per above priority order.
- If its primary value is sources, include “helpfulGoodSources” only if the sourcing itself is decisive.
- Do not select “helpfulImportantContext” unless the info is both necessary for accurate interpretation and not primarily a direct correction.
- If note only offers peripheral detail, trivia, or sidesteps the key issue, use “notHelpfulMissingKeyPoints” and/or “notHelpfulNoteNotNeeded.”

3. Is the note clear, neutral, and respectful in tone?

- If so in addition to being factually helpful, pair with “helpfulUnbiasedLanguage” or “helpfulEmpathetic” as needed.
- If tone, speculation, or bias prevents meaningful clarification, pick the corresponding “notHelpful” reason.

4. Is the note hard to understand, incomplete, or not addressing the claim?

- Assign “notHelpfulHardToUnderstand” or “notHelpfulOffTopic” as required.

5. Would a typical, reasonably attentive reader gain essential, accurate insight into the claim’s truth, context, or credibility—including debunking of misused/incorrect supporting evidence—because of this note?

- If yes, “helpful” reasons most fitting the note’s substance.
- If no, most directly explanatory “notHelpful” reasons.

Output in the following JSON format only, no extra output: {"helpfulness": helpful or non_helpful,"reasons":"reason1;reason2"}
CLAIM: ${claim}
NOTE: ${note}
Answer:

Table 17: Optimized English prompt for note helpfulness and reason prediction.

Seed Definitions

Helpful Reasons

- "helpfulClear": "**HelpfulClear** refers to the practice of validating and clarifying claims by providing accurate context or corrections through credible evidence and expert opinion. It involves critically examining information to dispel misinformation, address misconceptions, and ensure that communications are both accurate and informative. The aim is to enhance understanding, promote informed decision-making, and prevent the spread of false or misleading narratives.",
- "helpfulGoodSources": "**HelpfulGoodSources** refers to reliable, fact-based information that clarifies, corrects, or disproves misleading or false claims. It encompasses various forms of authoritative references, including government reports, scientific studies, expert opinions, and credible news articles. The purpose of these sources is to provide accuracy and context to statements made in public discourse, aiding in the dissemination of factual knowledge and supporting informed decision-making.",
- "helpfulAddressesClaim": "**HelpfulAddressesClaim** is a concept that refers to the clarification or correction of claims made in various contexts by providing accurate information, context, or details that counter or explain the original assertion. This often involves highlighting misconceptions, providing factual evidence, or referencing authoritative sources to support the revised understanding of the claim, ultimately helping to prevent misinformation and promoting informed discourse.",
- "helpfulImportantContext": "The REASON, defined as ḧelpfulImportantContext,r̈efers to the provision of essential background information that clarifies or corrects claims presented in various statements. This context is crucial for understanding the accuracy, validity, or implications of the claims made, by offering factual corrections, historical context, or relevant comparisons to ensure a more informed and nuanced comprehension of the situation or assertion being discussed.",
- "helpfulInformative": "The definition of the REASON ḧelpfulInformativeïs that it refers to explanations or notes provided in response to claims, which serve to clarify, correct inaccuracies, or provide essential context and background information. These notes help the reader better understand the claims by presenting factual evidence, linking to credible sources, and addressing misunderstandings, thereby enhancing the overall comprehension of the topic at hand.",
- "helpfulUnbiasedLanguage": "The definition of the REASON ḧelpfulUnbiasedLanguageïs the use of clear, neutral, and factual language that provides context and clarification to claims without introducing bias or misinformation. It seeks to present information in an objective manner, ensuring that the audience receives accurate and relevant details to better understand the claims being made. This approach emphasizes transparency and factual integrity, allowing for informed discussions and assessments.",
- "helpfulEmpathetic": "**Helpful Empathetic**: This reason reflects the intention to provide accurate and clarifying information in response to claims that are misleading or false. It embodies a commitment to enhancing understanding by offering factual corrections and context that reveal the truth, thereby enabling informed discussion. The goal is to support others in recognizing discrepancies or inaccuracies in claims, fostering a more informed perspective while acknowledging the importance of factual accuracy."

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Seed Definitions

Unhelpful Reasons

- "notHelpfulArgumentativeOrBiased": "The REASON "notHelpfulArgumentativeOrBiased" can be defined as follows: This classification refers to comments or notes that fail to provide constructive or relevant context to the accompanying claims. Instead, they tend to be argumentative, inflammatory, or biased, often lacking factual support or logical reasoning. Such responses may attempt to undermine the original claim without addressing its merits, focusing instead on personal attacks, irrelevant comparisons, or emotional appeals that detract from a rational discussion. In essence, they do not foster an understanding of the claim and instead perpetuate division or misinformation.",
- "notHelpfulMissingKeyPoints": "The definition of the REASON n̈otHelpfulMissingKeyPointsïs: The notes provided do not adequately address or clarify the claims made. Instead, they often introduce unrelated information or misconstrue the context, leaving significant gaps in understanding the primary arguments presented in the claims.",
- "notHelpfulNoteNotNeeded": "The definition of the REASON n̈otHelpfulNoteNotNeededïs that the provided notes fail to contribute meaningful or relevant information to clarify, support, or contradict the claims made. Instead, they either introduce unrelated details, emphasize inaccuracies without addressing the core of the claim, or illustrate a lack of factual backing, thus rendering them ineffective in providing substantiated context or understanding regarding the claims.",
- "notHelpfulIncorrect": "The definition of the REASON n̈otHelpfulIncorrectïs as follows: This category refers to claims that are supported by notes or explanations that are factually inaccurate, misleading, or irrelevant to the initial claim. The notes do not effectively clarify, substantiate, or provide accurate context for the claims, thereby failing to contribute meaningful information to the discussion. Instead, they may promote misinformation, misunderstandings, or misinterpretations of the original assertions.",
- "notHelpfulSourcesMissingOrUnreliable": "The REASON for the samples being non-helpful is defined as **the presence of sources that are unreliable, lack credibility, or do not substantiate the claims made**. This includes situations where evidence is anecdotal, opinion-based, or referencing non-verifiable documents, thereby failing to provide the necessary backing to support the claims.",
- "notHelpfulSpamHarassmentOrAbuse": "The definition of the REASON n̈otHelpfulSpamHarassmentOrAbuseïs content that is either unconstructive, irrelevant, or disrespectful in nature, often resorting to personal attacks, derogatory language, or baseless accusations. Such comments fail to provide meaningful engagement or contribute to the discussion, instead serving to provoke or demean individuals, typically lacking in factual or supportive content.",
- "notHelpfulIrrelevantSources": "The REASON n̈otHelpfulIrrelevantSourcesc̈an be defined as follows: NotHelpfulIrrelevantSources refers to a category of information where the claims being made are accompanied by explanations, notes, or sources that do not provide pertinent or factual support to validate the claims. This includes instances where the sources cited are either misleading, unrelated to the claim, or factually incorrect, resulting in a lack of credible evidence that would otherwise substantiate the assertions made. Essentially, information categorized under NotHelpfulIrrelevantSources fails to enhance understanding or clarify the claims due to its inaccuracy or irrelevance.",
- "notHelpfulOther": "The definition of the REASON n̈otHelpfulOtherïs that the provided notes do not effectively contribute to or clarify the claims made. Instead, they often reference unrelated information or distract from the central claim, failing to provide direct support, context, or factual information pertinent to understanding or verifying the claim.",
- "notHelpfulHardToUnderstand": "The REASON for the above samples being non-helpful is that the notes provided do not effectively clarify or support the claims made. They often lack relevant information, context, or clarity, making it difficult for readers to comprehend the claims or understand their significance. This results in a communication gap where the intended message is obscured or misunderstood.",
- "notHelpfulOpinionSpeculationOrBias": "The definition of the REASON n̈otHelpfulOpinionSpeculationOrBiasïs as follows: This reason applies to statements or claims that are influenced by subjective views, personal opinions, speculation, or perceived biases rather than presenting objective facts or useful information. Such claims often lack substantiation and do not contribute constructively to the discourse, focusing instead on emotional responses or distorted interpretations of events or behaviors."

Table 18: Detailed seed definitions that explain why notes are helpful and unhelpful.

Optimized Definitions

Helpful Reasons

- helpfulClear: The note delivers an accurate, unambiguous correction or direct clarification targeting a central claim or supporting fact/evidence. Use when the note dispels a major misconception, corrects a key number, identifies a misattributed element, or plainly states the essential fact needed to resolve or accurately interpret the claim.
- helpfulAddressesClaim: The note explicitly and accurately responds to or explains the principal assertion, central factual sub-claim, or foundational evidence of the claim. Includes refuting an implied mechanism or performing a core fact check that settles the claim's credibility.
- helpfulGoodSources: The note cites sources that are authoritative, reputable, and faithfully, directly, and unambiguously support its factual correction or clarification. Pick only if sourcing is integral—don't select if other reasons are more fundamental to helpfulness.
- helpfulImportantContext: The note supplies indispensable, targeted background or context needed for the reader to assess the claim or its evidence correctly (such as revealing regulatory nuance, historical policies, deception/fraud, or other context that transforms meaning or evaluation).
- helpfulInformative: The note gives essential factual explanation or contextualization directly linked to dispelling misunderstanding about the claim's main point. Don't use if the note merely provides general or background info.
- helpfulUnbiasedLanguage: The note's language is clear, objective, and neutral while providing a substantive correction or clarification. Use only paired with a direct factual "helpful" label.
- helpfulEmpathetic: The note enhances the factual correction by presenting it in a manner that increases reader trust and comprehension through clarity and respect.
- helpfulUniqueContext: The note delivers information not widely available, central to correctly interpreting the claim or core evidence.

Unhelpful Reasons

- notHelpfulArgumentativeOrBiased: Hostile, inflammatory, or overtly biased language dominates and no factual clarification or relevant context is given.
- notHelpfulMissingKeyPoints: The note wholly fails to clarify, correct, or address the main assertion, supporting fact, or evidence, OR it focuses solely on peripheral, partial, or unrelated points.
- notHelpfulNoteNotNeeded: The note adds no meaningful, fresh, or essential clarification—it is trivial, redundant, tangential, or consists of widely-known facts non-essential for comprehending the claim.
- notHelpfulIncorrect: Contains factual errors, misleading/unsupported claims, or confuses main assertions or evidence.
- notHelpfulSourcesMissingOrUnreliable: Sources are missing, non-credible, don't support the note's claim, or are misrepresented.
- notHelpfulSpamHarassmentOrAbuse: Contains spam, personal attacks, or offensive/unrelated content.
- notHelpfulIrrelevantSources: Sources in the note do not substantiate or clarify any main aspect of the claim or are not relevant to its core.
- notHelpfulOther: Any failure to clarify or support the claim not captured by the above categories.
- notHelpfulHardToUnderstand: The note is so unclear, incomplete, or poorly written that its meaning regarding the claim cannot be determined.
- notHelpfulOpinionSpeculationOrBias: Personal views, speculation, or bias present to such a degree that no clarification on the main claim or evidence is possible.
- notHelpfulOffTopic: The note is wholly unrelated to any claim feature or its main supporting facts/evidence.

Table 19: Detailed optimized definitions that explain why notes are helpful and unhelpful.

Prompt for Fact Checking Climate Fever claims
Direct Prompt Fact-check the following claim using provided evidence: Claim: ${claim} Evidence: ${evidence_text} Classify the claim as *SUPPORTS*, *REFUTES*, *NOT_ENOUGH_INFO* or *DISPUTED*. Format: Classification: [YOUR_ANSWER] Brief reason: **Incorporating Helpfulness Information** Fact-check this claim using the evidence and the helpfulness information of the evidence, if the evidence is not helpful, take less weight of the evidence. Claim: ${claim} Evidence: ${evidence_text_with_helpfulness_information} Classify the claim as *SUPPORTS*, *REFUTES*, *NOT_ENOUGH_INFO* or *DISPUTED*. Format: Classification: [YOUR_ANSWER] Brief reason:

Table 20: Prompt for fact-checking CLIMATE-FEVER claims.