EVADE: LLM-Based Explanation Generation and Validation for Error Detection in NLI

Anonymous ACL submission

Abstract

High-quality datasets are critical for training and evaluating reliable NLP models. In tasks like natural language inference (NLI), human label variation (HLV) arises when multiple labels are valid for the same instance, making it difficult to separate annotation errors from plausible variation. An earlier framework VARIERR (Weber-Genzel et al., 2024) asks multiple annotators to explain their label decisions in the first round and flag errors via validity judgments in the second round. However, conducting two rounds of manual annotation is costly and may limit the coverage of plausible labels or explanations. Our study proposes a new framework, EVADE, for generating and validating explanations to detect errors using large language models (LLMs). We perform a comprehensive analysis comparing human- and LLM-detected errors for NLI across distribution comparison, validation overlap, and impact on model fine-tuning. Our experiments demonstrate that LLM validation refines generated explanation distributions to more closely align with human annotations, and that removing LLM-detected errors from training data yields improvements in fine-tuning performance than removing errors identified by human annotators. This highlights the potential to scale error detection, reducing human effort while improving dataset quality under label variation.

1 Introduction

Datasets are fundamental to research, yet annotation errors can undermine model reliability (Goswami et al., 2023), highlighting the need for high-quality data in trustworthy Natural Language Processing (NLP) systems (Klie et al., 2024; Nasution and Onan, 2024; Weber-Genzel et al., 2024). Human Label Variation (HLV, Plank 2022) refers to the plausible variation in annotation, where multiple labels can be assigned to a single instance. HLV has gained significant attention, particularly for Natural Language Inference (NLI) (Pavlick and Kwiatkowski, 2019; Nie et al., 2020), where multiple plausible labels (Entailment, Neutral, or Contradiction) can be valid for the same premise-hypothesis pair (Jiang and de Marneffe, 2022; Jiang et al., 2023; Jayaweera and Dorr, 2025). While HLV better reflects real-world ambiguities, it also introduces a challenge: annotation errors may be obscured within the variation.

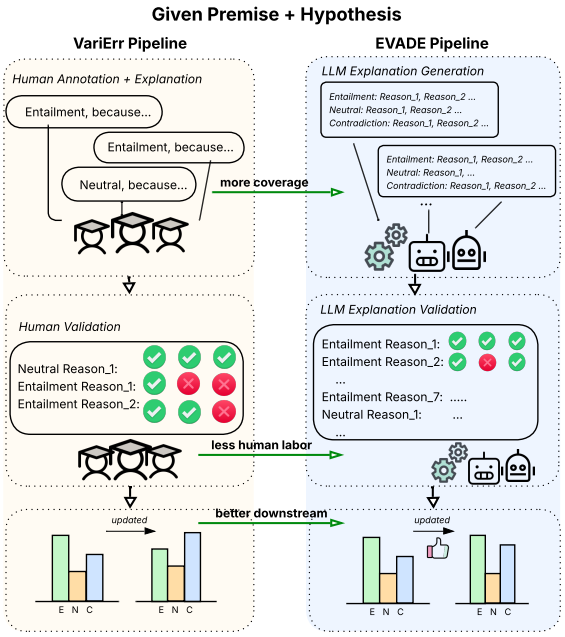

Figure 1: Overview of our LLM-based EVADE framework compared with the human-based VARIERR pipeline (Weber-Genzel et al., 2024). The first two modules, explanation generation and validation, are the core components. Compared with VARIERR, our EVADE framework provides broader explanation coverage, requires less human intervention, and delivers better downstream performance in predicting label distributions.

Many approaches for annotation error detection (AED) have been introduced in previous research (Klie et al., 2023; Weber and Plank, 2023; Weber et al., 2024; Bernier-Colborne and Vajjala, 2024),

but to our knowledge, Weber-Genzel et al. (2024) is the only work that explicitly focuses on separating errors from HLV. They propose a two-round error detection procedure in which expert annotators first provide labels with explanations and then reassess their reasoning after reviewing the full set of label and explanations from multiple annotators. For each annotated NLI label, if the annotators do not validate any of the supporting explanations in the second round, the label is considered erroneous. Previous studies typically introduce artificial noise by randomly flipping labels (Zheng et al., 2021; Jinadu and Ding, 2024), but these synthetic errors are often easily identifiable (Larson et al., 2019). In contrast, by leveraging self-validation, VARIERR captures naturally occurring errors and enables a more realistic evaluation of error detection.

However, a key limitation of this approach is its reliance on human experts to generate and validate explanations, both resource-intensive and difficult to scale. Fortunately, recent work (Chen et al., 2025) shows that LLM-generated explanations are comparable to humans in approximating label distributions in NLI, suggesting the potential to extend the VariErr framework to an LLM-based pipeline.

This paper presents EVADE, a LLM-driven method for error detection that leverages explanation generation and validation. Our main research questions are: **RQ1:** How effectively can LLM-generated explanations reflect valid HLV, and how do these compare to human-written explanations? **RQ2:** To what extent does LLM-validation enable reliable error detection compared to humans? **RQ3:** What is the impact of removing LLM-detected errors on downstream fine-tuning performance in terms of alignment with HLV?

Figure 1 presents the structure of EVADE. We first prompt LLMs to generate explanations given a premise–hypothesis pair and a candidate label. Subsequently, LLMs evaluate the explanations by assigning validity scores, indicating how effectively each explanation supports the assigned label (§3). To assess the effectiveness of our framework, we compare it with the human-driven pipeline from multiple perspectives, including explanation distribution, validated label overlap, linguistic similarity, and downstream task performance. Our findings demonstrate that EVADE aligns closely with human annotators in terms of label agreement, and can effectively identify errors, yielding annotations that more accurately reflect HLV (§4 & §5).

2 Related Work

Human label variation (HLV) refers to cases where annotators assign different but plausible labels to the same instance (Plank, 2022). HLV may arise from subjectivity (Cabitza et al., 2023), semantic ambiguity in the target instances (Aroyo and Welty, 2013, 2015) or guideline divergence (Peng et al., 2024), which challenges the assumption of a single ground truth in annotation. Aroyo and Welty (2013) propose the crowd truth, capturing subjective and diverse human interpretations.

HLV has been widely examined in the context of Natural Language Inference (NLI). Pavlick and Kwiatkowski (2019) show that NLI annotation disagreements are often systematic rather than noise. ChaosNLI (Nie et al., 2020) provides a human judgment distribution (HJD, Chen et al. 2024) by crowdsourcing 100 annotations per instance over a subset of MNLI (Williams et al., 2018), SNLI (Bowman et al., 2015), and αNLI (Bhagavatula et al., 2020) instances. LiveNLI (Jiang et al., 2023) and VariErrNLI (Weber-Genzel et al., 2024) supply ecologically valid explanations that verbalize different reasoning behind label decisions.

Annotation error detection (AED) is crucial in NLP, as many widely-used benchmarks contain annotation errors (Northcutt et al., 2021; Klie et al., 2023; Bernier-Colborne and Vajjala, 2024; Larson et al., 2020; Weber et al., 2024). Klie et al. (2023) conducted a comprehensive survey of error detection methods focusing on single-label tasks. However, annotation errors also arise when multiple labels are valid at the same time. To separate annotation error from HLV, VariErrNLI (Weber-Genzel et al., 2024) incorporates a second round of validity judgment to assess whether the provided explanations support the annotator's label decisions.

LLM-generated explanations are frequently used across a variety of tasks (Kunz and Kuhlmann, 2024), addressing whether they can approximate human reasoning. Within NLI, recent studies investigate how LLM-generated explanations can be leveraged to understand and model human annotation variations. Jiang et al. (2023) find that GPT-3 can generate fluent explanations, though not always aligned with the target label. Chen et al. (2025) prompt LLMs to generate explanations guided with human-annotated labels and achieve similar performance in approximating human judgment distribution as when using human-written explanations. Hong et al. (2025) propose a linguistic taxonomy

to further guide LLMs in generating more diverse explanations. The studies above highlight the potential of LLMs in generating explanations. Our paper addresses LLMs' ability to validate their explanation generation and detect annotation errors.

3 Generating and Validating Explanations Using LLMs

This section details our EVADE pipeline using LLMs. We introduce our dataset and model setups (§3.1), explanation generation and filtering process (§3.2), as well as validation scenarios (§3.3).

3.1 Setups

Dataset We experiment on the VARIERR dataset (Weber-Genzel et al., 2024), including NLI labels, explanations, and second-round validations from four human expert annotators. All 500 VARIERR instances are also in ChaosNLI (Nie et al., 2020), containing label distributions from 100 crowdworkers. This setup provides references for evaluating label distribution and explanation generation.

Models We select four state-of-the-art LLMs from two families due to their demonstrated capabilities in instruction following, critical in our generation and validation experiments: *Llama-3.1-8B-Instruct*, *Llama-3.3-70B-Instruct* (Grattafiori et al., 2024),[1] *Qwen2.5-7B-Instruct* and *Qwen2.5-72B-Instruct* (Team, 2024).

3.2 Explanation Generation and Filtering

Generation We follow Chen et al. (2025) to generate all distinct explanations for each label in a given premise-hypothesis pair to obtain a broad coverage. To maintain output validity, we adapted their prompt to allow LLMs to abstain if the label cannot be reasonably justified. Our prompt also explicitly prohibits introductory phrases or semantic repetitions. We kept all qualified explanation generations in our repository; thus, Chen et al. (2025)'s label-guided or label-free approaches in picking the longest or first explanations are irrelevant to this study. See Appendix A.1 Figure 3 for the template.

Filtering Despite explicit instructions, we still find two main issues with LLM-generated explanations: *fallback responses* and *formatting errors*, which would not occur in human-written explanations. Rather than omitting the output, Llama-72B model sometimes responds with fallback statements such as *"Note: Since the statement is not supported by the context, there are no explanations for why the statement is true."* These outputs do not contribute meaningful explanatory content. In addition, we observe formatting errors in the outputs of certain models, such as truncated outputs from Llama-8B caused by the default generation limit (256 tokens), and occasionally generated Chinese sentences from Qwen-7B, even all prompts are in English. As our framework aims not only to evaluate error detection performance but also to compare the alignment of LLM-generated explanations and relevant label distributions with human annotations, we manually deleted these low-quality explanations to ensure a cleaner distribution. In practice, we removed 37 incomplete outputs from LLaMA-8B, excluded 17 fallback generations from LLaMA-70B, and filtered out 6 explanations containing Chinese from Qwen-7B.

[1]At submission time, v3.1 is the most recent Llama-8B-Instruct model release and v3.3 for Llama-70B-Instruct.

Model	# Expl.	Avg. Length	# Label/Item	# Expl./Label
Llama-8B	**8845**	17.60	3.00	**5.90**
Llama-70B	4022	**22.35**	3.00	2.68
Qwen-7B	4047	16.19	2.87	2.82
Qwen-72B	3920	18.43	3.00	2.61
VariErr	1933	13.89	1.76	2.20

Table 1: Generation statistics on 500 VariErr examples. # Expl.: total number of explanations; Avg. Length: average number of words per explanation; # Label/Item: number of LLM-explained labels per instance; Expl./Label: average number of explanations per label.

Results We observe noticeable differences across model generation results in Table 1. Llama-8B generates nearly twice as many explanations as the others, suggesting potential redundancy between explanations, and Llama-70B yields the longest explanations (22.35 tokens on average) among all the models. These discrepancies become more evident when compared with human annotations in VARIERR. Human annotators generated much fewer explanations in quantity and, in general, much shorter explanations (13.89 tokens).

We then look at the average number of NLI labels that are supported by LLM-generated explanations per instance (#Label/Item), as well as the average number of explanations per label (#Expl./Label). VARIERR receives on average 1.76 explained labels. However, LLMs tend to produce explanations for every label (or almost all in the case of Qwen-7B), which is unlikely to reflect a re-

alistic human label variation. As for the number of generated explanations per label, LlaMA-8B still attains twice as many explanations as humans under each label, which is due to its extensive outputs. These LLM over-generations necessitate the explanation validation step in the EVADE framework.

3.3 Explanation Validation

To address the excessive generation of explanations, we instruct LLMs to validate their own explanations. Precisely, we ask an LLM to give validity judgments on whether each of its generated explanations supports the associated label, mirroring VARIERR's second-round self-validation process. We aim to align LLMs' explanations and label distribution more closely with human annotations and to demonstrate that LLMs can likewise be used for explanation validation and error detection.

Following Weber-Genzel et al. (2024), we prompt LLMs to assign a **validity score** (between 0.0 and 1.0) assessing how much each of its generated explanations justifies the corresponding label for the given premise–hypothesis pair. We consider an explanation as **validated** if its validity score p exceeds a predefined threshold τ; otherwise, it is **not-validated**. To determine whether a label is erroneous, we follow the criterion from VARIERR: a label is regarded as an "error" if the scores of all associated explanations fall below the threshold τ.

Prompts To systematically examine the role of context in LLM validation, we experiment with three prompting scenarios: (1) ***one-expl***: an LLM scores its generated explanations one at a time, without reference to other explanations; (2) ***one-llm***: an LLM scores each of its generated explanations in the context of all its generations; and (3) ***all-llm***: an LLM scores each of its generated explanations in the context of explanations generated by all four LLMs. When multiple explanations are in context, the LLM receives all explanations simultaneously and outputs a json file with set of scores in a single pass. Our prompts are adapted from Weber-Genzel et al. (2024); see Appendix A.2 Figures 4-5 for details.

Results Table 2 presents the average validation scores of different LLMs across the three validation scenarios. The *one-expl* setting consistently yields the highest validity, with most LLMs producing average validity scores above 0.8. This is the only prompt setup that does not provide contextual information from other candidate explanations, which

Model	*one-expl*	*one-llm*	*all-llm*
Llama-8B	0.8003 $_{0.1290}$	0.5009 $_{0.3134}$	0.5154 $_{0.3616}$
Llama-70B	**0.8456** $_{0.1126}$	0.6483 $_{0.2114}$	0.6439 $_{0.2333}$
Qwen-7B	0.7107 $_{0.1442}$	0.5675 $_{0.2628}$	0.3825 $_{0.3894}$
Qwen-72B	0.8299 $_{0.0780}$	**0.7279** $_{0.1352}$	**0.7006** $_{0.1835}$

Table 2: Average validation scores and standard deviations across three prompting scenarios for four LLMs.

most likely leads to models' over-confidence in the explanations' validity. When additional context is introduced in the *one-llm* and *all-llm* settings, models can review alternative explanations for the same instance. This broader perspective may result in more comprehensive evaluations. However, additionally providing contextual explanations generated by other LLMs (*all-llm* versus *one-llm*) only subtly changes the average validity score for all but the Qwen-7B model. We then turn to standard deviation (std), obtained by scoring each label within an instance and averaging across labels. *One-expl* scenario obtains the lowest std, reflecting more consistent scoring behavior with each label. However, this stability may reduce sensitivity to differences between valid and invalid explanations within the same label. In contrast, *one-llm* and *all-llm* appear to balance multiple explanations with higher std, and can thereby filter relatively more invalid explanations and yield refined distributions.

Moreover, smaller models tend to assign lower scores than large ones across all settings. The gap between differently sized models becomes particularly large in the *one-llm* and *all-llm* settings. One possible explanation could be that longer contextual inputs in these settings may overwhelm smaller models, reducing confidence when confronted with multiple competing explanations. For example, *all-llm* provides an average of approximately 41.7 explanations per instance, showing an extreme difference in average validity score between Qwen-7B (0.3825) and Qwen-72B (0.7006).

However, one should be cautious in assuming that differences in average validity scores directly indicate that one model is better or worse. To assess how well EVADE aligns with humans, we next examine whether the low validity scores correspond to genuine "errors" and analyze the overlap between LLM-validated labels and those approved by human annotators in VARIERR.

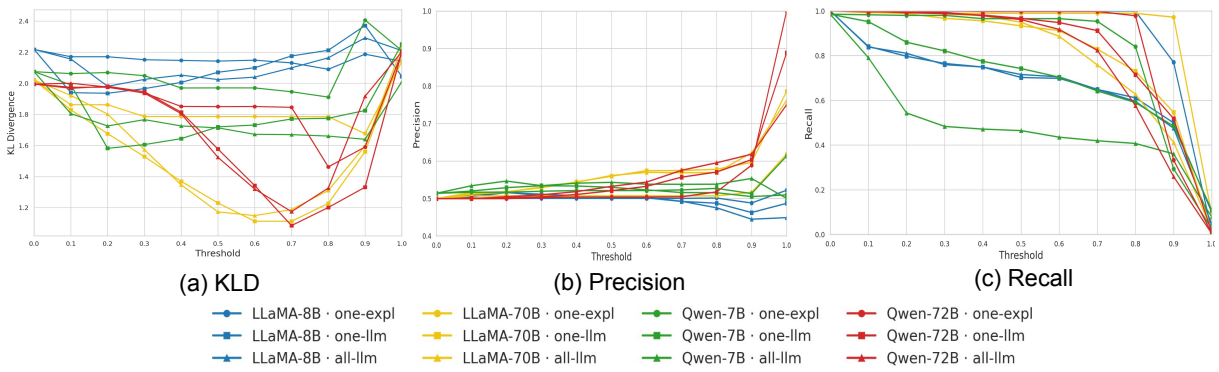

Figure 2: (a) shows the KLD curves between model distributions and ChaosNLI annotations across three prompting scenarios with validation threshold from 0.1 to 0.9. (b) and (c) present the precision and recall of the LLM-validated labels, computed against the VariErr-validated labels as ground truth, with validation thresholds from 0.1 to 0.9.

4 LLM versus Human Validation

After generation and validation, we compare the LLM-based (EVADE in this paper) and human-based error detection (VARIERR in Weber-Genzel et al. 2024) pipelines from different angles. We analyze the label distribution associated with LLM-generated explanations before and after LLM validation (§4.1) and examine the validated label overlap with those from human annotators (§4.2). Since VARIERR's validity judgments are binary and our LLM outputs range from 0.0 to 1.0, we also show in these sections how much the validity threshold τ affects our comparison. We last assess the semantic similarity between LLM-generated and human-written explanations, both before and after validation (§4.3).

4.1 Alignment with ChaosNLI Distribution

We compare the label distribution of model-generated explanations with human annotations from ChaosNLI (Nie et al., 2020), as the distribution aggregated from 100 annotators provides a softer representation that better reflects a reference "gold" distribution (Chen et al., 2024). Specifically, we examine model distributions before and after validation against the crowdworker distribution, in order to assess whether the validation step improves the alignment of model outputs with human consensus. We employ Kullback-Leibler Divergence (KLD, Kullback and Leibler 1951) following previous works (Chen et al., 2024, 2025) to measure the discrepancy between distributions.

An appropriate threshold has a substantial impact on the resulting distribution. To assess this effect, we compute the KLD between the model-validated distributions and the ChaosNLI annotations across three validation scenarios and diverse validation thresholds. Results are presented in Figure 2a. The point in the plot where the KLD curve is minimized corresponds to the validation threshold that yields the closest alignment with the ChaosNLI distribution. We observe a clear decreasing trend for most of the models with different prompting scenarios before the threshold reaches τ**=0.8**, with this effect being more pronounced for the two larger models. However, as the threshold further increases, the alignment to human distribution weakens. This suggests that while a high validation threshold can filter out invalid information, an overly strict threshold may also inadvertently discard correct information.

4.2 Comparing with Validated VARIERR

Given that LLMs generate substantially more explanations than humans and tend to provide explanations for every label, it is expected that LLMs identify more errors during validation, as their outputs may initially include a large number of inconsistent arguments. To obtain a more reliable comparison between LLM- and human-validation, we therefore focus on **the overlap of validated labels** rather than on the overlap of detected errors.

When comparing the overlaps, we observe strong similarity. The majority of human-validated labels are also confirmed by the LLM validation process. We thereby compute the precision and recall of LLM-validated labels by considering the VariErr labels as the gold standard, varying the validation threshold from 0.1 to 0.9.

Figures 2b-2c present the results. For precision, all models start around P=0.5 when τ=0. Larger models exhibit a generally increasing trend as the threshold rises, whereas smaller models show

Models	Lexical n=3↑	Syntactic n=3↑	Cosine↑	Euclidean↑
within-human	0.052	0.144	0.529	0.522
within-LLM				
Llama-8B	**0.103** / 0.101 / 0.097 / 0.099	**0.265** / 0.264 / 0.263 / 0.263	0.599 / 0.608 / **0.611** / 0.606	0.542 / **0.545** / **0.545** / 0.544
Llama-70B	0.030 / **0.031** / 0.029 / 0.029	0.201 / 0.201 / 0.200 / **0.202**	0.595 / 0.606 / 0.605 / **0.608**	0.535 / 0.539 / 0.538 / **0.540**
Qwen-7B	0.010 / **0.012** / 0.010 / 0.010	0.160 / 0.161 / 0.164 / **0.170**	0.533 / **0.548** / 0.536 / 0.536	0.517 / **0.521** / 0.518 / 0.518
Qwen-72B	**0.023** / **0.023** / 0.021 / 0.022	0.188 / 0.189 / 0.187 / **0.191**	0.578 / 0.583 / 0.583 / **0.584**	0.530 / **0.532** / 0.531 / **0.532**
LLM-vs-human				
Llama-8B	**0.020** / **0.020** / 0.019 / 0.018	0.116 / 0.116 / **0.117** / 0.116	0.450 / 0.452 / **0.453** / **0.453**	0.497 / **0.498** / **0.498** / **0.498**
Llama-70B	0.028 / 0.029 / 0.029 / **0.030**	0.129 / 0.131 / **0.132** / **0.132**	0.515 / 0.521 / 0.521 / **0.523**	0.514 / 0.516 / 0.516 / **0.517**
Qwen-7B	0.015 / **0.016** / 0.015 / 0.014	0.101 / **0.103** / 0.100 / 0.095	0.469 / **0.477** / 0.469 / 0.470	0.502 / **0.504** / 0.502 / 0.502
Qwen-72B	0.023 / **0.024** / 0.023 / **0.024**	0.125 / **0.127** / 0.126 / 0.126	0.502 / 0.506 / **0.507** / 0.504	0.511 / **0.512** / **0.512** / **0.512**

Table 3: Linguistic similarity (lexical, syntactic, semantic) of explanations across three evaluation regimes: *within-human*, *within-LLM*, and *LLM-vs-human*. Each cell lists scores orderly: before validation, after *one-expl* validation, after *one-llm* validation, and after *all-llm* validation. We underline lowest score(s) in each cell and **bold highest**.

more fluctuation and a noticeable decline when the threshold exceeds 0.6. This pattern suggests low thresholds effectively filter out low-confidence predictions and reduce false positives. Still, for smaller models, overly high thresholds begin to remove true positives as well, leading to a drop in precision. Regarding recall, all models across different validation scenarios exhibit a consistent decreasing trend as the threshold increases, with a particularly sharp decline beginning around 0.7. This occurs because higher thresholds exclude more true positive labels, thereby reducing the overall recall value. Among the three validation modes, *all-llm* is the most conservative: it validates substantially fewer labels and yields lower recall than the other two modes.

Overall, excessively low validation thresholds introduce numerous unreliable labels, while overly high thresholds risk discarding valid ones. An optimal threshold should balance precision and recall. Considering these metrics together with the KLD scores, we select the low KLD point that corresponds to relatively high precision and recall values as our final validation threshold (detailed in Appendix C Table 8). Interestingly, the selected thresholds closely align with the average validation scores reported in Table 2 across most models and prompting settings, supporting the calibration of validation scores as meaningful indicators where low scores generally correspond to genuine annotation errors. These thresholds are set to facilitate experiments and analyses in the following sections.

4.3 Explanation Similarity

We analyze the linguistic similarity between human and LLM-generated explanations before and after validation. Following Chen et al. (2025); Hong et al. (2025), we measure lexical, syntactic, and semantic similarity between explanations (Giulianelli et al., 2023), where lower scores indicate greater variation and the higher the more similar. We compare pairwise similarity within-VARIERR human explanations (*within-human*), within each LLM (*within-LLM*), and between each LLM and human explanations (*LLM-vs-human*). For each item, we compute pairwise scores among all explanations under the same label and average across labels. Table 3 reports results before validation and after three validation scenarios (*one-expl*, *one-llm*, and *all-llm*); more results are in Appendix D Table 9.

Firstly, when comparing similarity scores between LLM sizes, larger models more frequently exhibit higher similarity in both *within-LLM* and *LLM-vs-human* regimes. *Within-LLM* scores on Llama-7B explanations are an exception, scoring noticeably higher than Llama-70B on lexical and syntactic similarities. Moreover, Llama-8B attains the highest scores across lexical, syntactic, and semantic dimensions among all LLMs in the *within-LLM* regime, likely reflecting the greater volume and thus redundancy of its generated explanations.

Secondly, comparing *within-human* and *within-LLM* similarity scores, LLM generations exhibit greater lexical divergence (except for Llama-8B) while achieving higher syntactic and semantic similarity to each other than between human-written explanations, indicating that LLMs can generate lexically different outputs, while keeping syntactical structure and semantic meaning quite similar.

Thirdly, the similarity between LLM- and human-generated explanations (*LLM-vs-human*) is consistently lower than that observed *within-*

Model	Validation	# Expl.	# L/I	# E/L	AP	P@100	R@100
Llama-8B	*one-expl*	**7474**	**2.99**	**4.98**	**15.3**	**21.0**	**16.3**
	one-llm	5951	2.32	3.97	13.9	12.0	9.3
	all-llm	6283	2.35	4.19	13.9	14.0	10.9
Llama-70B	*one-expl*	**3354**	**2.82**	**2.24**	18.4	24.0	18.6
	one-llm	2931	2.38	1.95	22.6	26.0	20.2
	all-llm	2799	2.33	1.87	**26.8**	**31.0**	**24.0**
Qwen-7B	*one-expl*	**3282**	**2.73**	**2.19**	**16.4**	**19.0**	**15.3**
	one-llm	3157	2.44	2.10	13.6	15.0	12.1
	all-llm	1883	1.49	1.26	14.5	17.0	13.7
Qwen-72B	*one-expl*	**3286**	**2.83**	**2.19**	**18.8**	**26.0**	**20.2**
	one-llm	2878	2.45	1.92	16.7	21.0	16.3
	all-llm	2695	2.15	1.80	**18.8**	22.0	17.1
VariErr	self	1712	1.50	2.29	22.8	23.7	18.3

Table 4: Statistics after validation and performance of EVADE on the AED task. The AED values for VARIERR with mean Datamaps are copied from Weber-Genzel et al. (2024) for reference.

human/LLM, indicating that LLM generations still considerably diverge from human-written explanations, particularly in syntax and semantics.

Lastly, validation has minimal effects on similarity scores, frequently showing less than 0.010 difference before versus after validation. Even so, most (except for Llama-8B) similarity scores increase after validation, reflecting the objective of removing low-quality explanations.

4.4 Post-Validation Analyses

Statistics To assess the effectiveness of EVADE for automatic error detection (AED), Table 4 presents the statistics after each validation scenario. Compared with the pre-validation scores in Table 1, all numbers decrease, particularly under the *one-llm* and *all-llm* settings. This further indicates that a validation strategy with a higher standard deviation effectively removes a larger proportion of invalid explanations. LLMs exhibit a more radical filtering behavior than human. Even under the mildest validation prompt (*one-expl*), LLMs discard on average 16.8% of the generated explanations, compared to 11.4% for human validators. Interestingly, the number of explanations per label in VARIERR slightly increases after validation. The removal of explanations more directly translates into the rejection of labels, likely due to the VARIERR's sparsity that many labels, especially erroneous ones, are supported by only a single explanation.

Automatic Error Detection (AED) Following Weber-Genzel et al. (2024), we also compute the average validation score per label for each instance and then use these scores to rank labels' likelihood of being erroneous. We evaluate this ranking against the self-flagged errors identified by human annotators. We report standard ranking-based metrics: average precision (AP), as well as precision and recall at the top 100 predictions (P@100 and R@100) (Klie et al., 2023). We use the Datamaps (Swayamdipta et al., 2020) model as a baseline.

Overall, larger models achieve stronger AED performance. Among the validation strategies, *one-expl* consistently yields the highest scores, while *all-llm* with Llama-70B is the only configuration that surpasses the DM baseline. Nevertheless, this evaluation setup has limitations. Since these metrics rely solely on the ranking of numerical scores, they may underrepresent labels that receive low scores but are not explicitly ranked lower. For example, two instances with average scores of 0.75 and 0.05 would be classified as errors under a fixed threshold. We thus turn to fine-tuning experiments in §5 using the analyzed thresholds (cf. Table 8) that better preserve the numerical granularity.

5 EVADE for Fine-tuning

To assess whether EVADE benefits downstream fine-tuning experiments, we approximate human judgment distribution (HJD) in ChaosNLI (Nie et al., 2020), following Chen et al. (2024).

Setups We apply EVADE in two setups: (a) directly using EVADE labels before and after each validation scenario, and (b) using EVADE validations to remove LLM-detected errors from VARIERR Round 1 (R1) and then fine-tuning with pruned-VARIERR. This allows us to assess whether EVADE-validation is directly useful to modeling and whether it can help refine human annotations.

Baselines & Ceiling We consider two fine-tuning baselines: directly fine-tuning with VARIERR R1 (Round 1) annotations, and fine-tuning after removing human-identified errors in VARIERR R2 human validation. The latter investigates whether removing self-identified errors from VARIERR leads to improvements in HJD alignment.

Models We adopt two small pre-trained language models, **bert-base-uncased** (Devlin et al., 2019) and **roberta-base** (Liu et al., 2019) as backbones following Chen et al. (2024).

Fine-tuning Models are first fine-tuned on the large single-label MNLI training set (392k examples, Williams et al. 2018) and validated on the matched development set (9.8k examples) to learn the general structure of the NLI task. They are

Models	Validation	BERT F1 ↑	BERT KL ↓	RoBERTa F1 ↑	RoBERTa KL ↓
VariErr R1 *(baseline)*		*0.5842*	*0.1701*	*0.6248*	*0.1667*
VariErr R2 *(baseline)*		0.5500	0.2510	0.6125	0.2474
ChaosNLI *(ceiling)*		0.6526	0.0714	0.6990	0.0552
Fine-tuning with EVADE *labels*					
Llama-8B	*before*	0.4499	0.1181	0.3312	0.1188
	one-expl	0.4756	0.1172	0.5245	0.1170
	one-llm	**0.5911**	0.0971	0.5975	0.1218
	all-llm	0.5820	**0.0891**	**0.6088**	**0.0984**
Llama-70B	*before*	0.4499	0.1181	0.3312	0.1188
	one-expl	0.5219	0.1011	0.6119	0.0967
	one-llm	**0.6328**	0.0837	0.6151	0.0962
	all-llm	0.6210	**0.0716**	**0.6351**	**0.0818**
Qwen-7B	*before*	0.5074	0.1077	0.5406	0.1076
	one-expl	0.5519	0.1019	0.5624	0.1027
	one-llm	**0.6294**	**0.0783**	**0.5983**	**0.0772**
	all-llm	0.4984	0.2566	0.5172	0.2724
Qwen-72B	*before*	0.4499	0.1181	0.3312	0.1188
	one-expl	0.5310	0.1021	0.5570	**0.1001**
	one-llm	0.5125	0.0994	0.5579	0.1122
	all-llm	**0.6245**	**0.0807**	**0.6545**	0.1109
Using EVADE *to validate* VARIERR *R1 and then finetuning*					
Llama-8B	*one-expl*	**0.5939**	**0.1714**	0.6385	**0.1699**
	one-llm	0.6195	0.1938	**0.6617**	0.1907
	all-llm	0.5929	0.1916	0.6429	0.2042
Llama-70B	*one-expl*	0.5968	**0.1754**	0.6383	**0.1722**
	one-llm	0.5951	0.1924	0.6556	0.1903
	all-llm	**0.6096**	0.1915	**0.6762**	0.1805
Qwen-7B	*one-expl*	0.5892	0.1755	0.6294	0.1787
	one-llm	0.6232	**0.1704**	0.6654	**0.1588**
	all-llm	**0.6415**	0.2456	**0.6731**	0.2793
Qwen-72B	*one-expl*	0.5858	**0.1869**	0.6370	**0.1833**
	one-llm	0.5993	0.1920	0.6376	0.1939
	all-llm	**0.6228**	0.1954	**0.6614**	0.2099

Table 5: Results of directly fine-tuning with EVADE labels or using EVADE to validate VARIERR R1 labels and then finetuning.

then fine-tuned on the label distributions derived from EVADE validations. For each instance, we construct the label distribution by assigning equal probability to each of the candidate E/N/C labels if they appear in the set and normalizing the values accordingly. To evaluate the performance, we use the 1,099 ChaosNLI instances (Nie et al., 2020) that do not overlap with VARIERR, and split them into development and test sets, containing 549 and 550 instances, respectively. We use the label distributions of 100 crowdworkers in ChaosNLI as the gold standard and evaluate model performance in predicting soft labels using KLD and weighted F1. See Appendix B Tables 6-7 for hyper-parameters.

Results Table 5 presents the results. When comparing two VARIERR baselines, contrary to expectations, removing human-detected errors (R2) does not lead to improved alignment with HJD. For BERT and RoBERTa finetuning, both EVADE-informed setups improve when evaluated on F1. However, KL divergence is only moderately optimized when directly using EVADE labels. When comparing the EVADE validation scenarios, particularly on the improved weighted F1, we observe that *all-llm* delivers the best performance in most evaluations, followed by *one-llm*. This substantiates our hypothesis that LLM validation with additional labels and explanations as context benefits modeling. As for model sizes, the larger Llama-70B has an advantage over Llama-8B, but surprisingly, Qwen-7B beats Qwen-72B in BERT and RoBERTa finetuning on both F1 and KL in the EVADE-pruning setup. However, Qwen-7B significantly degrades when fine-tuned directly using *all-llm* validation. These outlying results echo Qwen-7B's noticeably lower number of explanations after *all-llm* validation reported in Table 4. Above all, our findings suggest that LLMs can effectively approximate HJD by validating their annotations using EVADE or by validating human ones.

6 Conclusion

In this paper, we introduce EVADE, an LLM-based explanation generation and validation framework designed to remove annotation errors from human label variation (HLV). Our findings show that LLMs produce more comprehensive explanations than human annotators. By analyzing explanation distributions before and after LLM-based validation, we demonstrate that LLM-generated explanations reliably signal valid instances of HLV, and that the validation process effectively refines these distributions to better capture human annotation variability. Larger context inputs and more capable models further yield more consistent and rational validation outcomes. Moreover, the validation process exhibits a high degree of consensus with human judgments in identifying valid labels, likely attributable to the broader range of candidate explanations considered by LLMs. Finally, we show that removing LLM-detected errors from the dataset yields superior fine-tuning performance compared to removing human-detected errors, underscoring the practical value of LLM-based validation for enhancing dataset quality.

Limitations

While our framework demonstrates that LLM-based explanation generation and validation can

effectively detect annotation errors from HLV in NLI tasks, several limitations remain. First, the current study is restricted to the NLI task and to the VARIERR dataset. Datasets that simultaneously provide HLV references and identified errors are scarce, which limits us to fully assess the robustness and generalizability of the framework across other tasks and domains. Second, VARIERR incorporates a peer-validation setup, where annotators evaluate not only their own explanations but also those of others. This setting potentially provides richer information for error detection, but it is not explored in the present study. Incorporating peer-validation signals through LLMs remains an important direction for future work. Lastly, our EVADE framework to use LLMs to detect errors is exploratory. LLM still over-generates explanations for almost all labels, which makes it challenging to use the same evaluation setup as evaluating natural human errors or synthetic errors.

Use of AI Assistants

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A Prompt Templates

This section presents the prompt templates used in this study for explanation generation (§A.1) and validation (§A.2).

A.1 Explanation Generation Prompt

Figure 3 shows the explanation generation prompt adapted from Chen et al. (2025), with additional instructions allowing the LLM to abstain when a label cannot be reasonably justified. The prompt also explicitly discourages introductory phrases and semantic redundancy.

```
EXPLANATION GENERATION PROMPT
"role": "system", "content":
You are an expert in Natural Language Inference
(NLI). List every distinct explanation for
why the statement is {relationship} given the
context below without introductory phrases.
If you think the relationship is false given
the context, you can choose not to provide
explanations. Do not repeat or paraphrase the
same idea in different words. End your answer
after all reasonable distinct explanations are
listed.
Format your answer as a numbered list (e.g.,
1., 2., 3.)

"role": "user", "content":
Context: {premise}
Statement: {hypothesis}
```

Figure 3: Explanation generation prompt.

A.2 Explanation Validation Prompts

Following the prompt design of Weber-Genzel et al. (2024) with with several modifications, Figure 4 presents the prompt for *one-expl* setting and Figure 5 illustrates the prompt for *one-llm* and *all-llm* settings. The latter one explicitly instructs the model to utilize the contextual information provided and to generate all validity scores together in a structured JSON format.

```
ORIGINAL VALIDATION PROMPT
You are an expert linguistic annotator.
We have collected annotations for an NLI
instance together with reasons for the labels.
Your task is to judge whether the reasons make
sense for the label. Provide the probability
(0.0-1.0) that the reason makes sense for the
label. Give ONLY the probability, no other
words or explanation.

For example:
Probability: <the probability between 0.0 and
1.0 that the reason makes sense for the label,
without any extra commentary whatsoever; just
the probability!>

Context: {premise}
Statement: {hypothesis}
Reason for label {label}: {reason_text()}
Probability:
```

Figure 4: Validation prompt for *one-expl* scenario.

```
ALL VALIDATION PROMPT
You are an expert linguistic annotator.
We have collected annotations for an NLI
instance together with explanations for
the labels. You will first be shown all
explanations together so that you understand
the overall context, and then your task is
to judge whether each reason makes sense for
the label. You must output a single JSON
object that maps each explanation's index
(1,2,3,...) to its probability in one time.
Provide the probability (0.0 - 1.0) that
each reason makes sense for the label. Give
ONLY the probability, no other words or
explanation.

Output example: {"1": 0.9, "2": 0.8, ...}

Context: {premise}
Statement: {hypothesis}
Reason {i} for label {label}: {reason_text()}
Reason {i} for label {label}: {reason_text()}
...

Now output the JSON object ONLY.
```

Figure 5: Validation prompt for *one-llm* and *all-llm* scenarios.

B Fine-Tuning Hyper-parameters

Hyper-parameter configurations for fine-tuning BERT and RoBERTa on the MNLI and VariErr dataset variants are summarized in Tables 6 and 7, respectively.

Hyper-parameter	Value
Learning Rate Decay	Linear
Weight Decay	0.0
Optimizer	AdamW
Max sequence length	128
Learning Rate	2e-5
Batch size	16
Num Epoch	3
Metric for best model	eval_accuracy

Table 6: Hyper-parameters used for fine-tuning BERT and RoBERTa on the MNLI dataset.

Hyper-parameter	Value
Learning Rate Decay	Linear
Weight Decay	0.0
Optimizer	AdamW
Learning Rate	2e-5
Batch size	4
Num Epoch	5
Metric for best model	eval_macro_F1

Table 7: Hyper-parameters used for further fine-tuning BERT and RoBERTa on the VARIERR dataset variants.

C Validation Threshold

Table 8 summarizes the optimal validation thresholds determined for each model and setting. These thresholds correspond to the points that best balance lower KL divergence with higher precision and recall when comparing LLM-validated labels against the human-validated VARIERR references, and are applied in all subsequent analysis.

	one-expl	*one-llm*	*all-llm*
Llama-8B	0.8	0.2	0.2
Llama-70B	0.9	0.6	0.6
Qwen-7B	0.7	0.2	0.2
Qwen-72B	0.8	0.7	0.7

Table 8: Validation threshold.

D Full Similarity Results

Table 9 reports full linguistic similarity results between human and LLM explanations across lexical (n-gram overlap), syntactic (POS n-gram overlap), and semantic (cosine and Euclidean) levels. For lexical and syntactic similarity, we compute n-gram overlaps with $n = 1, 2, 3$. Scores are shown for four stages: before validation, after *one-expl* validation, after *one-llm* validation, and after *all-llm* validation.

Models	Setting	Lexical			Syntactic			Semantic		AVG
		n = 1↓	n = 2↓	n = 3↓	n = 1↓	n = 2↓	n = 3↓	Cos.↓	Euc.↓	AVG ↓
within-human		0.313	0.118	0.052	0.713	0.323	0.144	0.529	0.522	0.339
within-LLM										
Llama-8B	before	0.382	0.191	0.103	0.841	0.483	0.265	0.599	0.542	0.426
	one-expl	0.382	0.189	0.101	0.840	0.483	0.264	0.608	0.545	0.427
	one-llm	0.378	0.183	0.097	0.842	0.484	0.263	0.611	0.545	0.425
	all-llm	0.380	0.186	0.099	0.842	0.483	0.263	0.606	0.544	0.425
Llama-70B	before	0.310	0.100	0.030	0.841	0.444	0.201	0.595	0.535	0.382
	one-expl	0.313	0.100	0.031	0.840	0.445	0.201	0.606	0.539	0.384
	one-llm	0.308	0.097	0.029	0.838	0.446	0.200	0.605	0.538	0.383
	all-llm	0.309	0.097	0.029	0.836	0.447	0.202	0.608	0.540	0.384
Qwen-7B	before	0.211	0.050	0.010	0.804	0.409	0.160	0.533	0.517	0.337
	one-expl	0.219	0.053	0.012	0.806	0.411	0.161	0.548	0.521	0.341
	one-llm	0.207	0.048	0.010	0.804	0.415	0.164	0.536	0.518	0.338
	all-llm	0.200	0.042	0.010	0.805	0.428	0.170	0.536	0.518	0.339
Qwen-72B	before	0.266	0.083	0.023	0.824	0.431	0.188	0.578	0.530	0.365
	one-expl	0.270	0.084	0.023	0.824	0.431	0.189	0.583	0.532	0.367
	one-llm	0.265	0.079	0.021	0.824	0.432	0.187	0.583	0.531	0.365
	all-llm	0.263	0.080	0.022	0.823	0.435	0.191	0.584	0.532	0.366
LLM-vs-human										
Llama-8B	before	0.233	0.062	0.020	0.742	0.308	0.116	0.450	0.497	0.303
	one-expl	0.234	0.062	0.020	0.739	0.307	0.116	0.452	0.498	0.303
	one-llm	0.233	0.061	0.019	0.742	0.310	0.117	0.453	0.498	0.304
	all-llm	0.233.	0.060	0.018	0.745	0.309	0.116	0.453	0.498	0.304
Llama-70B	before	0.257	0.079	0.028	0.754	0.322	0.129	0.515	0.514	0.325
	one-expl	0.262	0.081	0.029	0.755	0.325	0.131	0.521	0.516	0.328
	one-llm	0.262	0.082	0.029	0.756	0.326	0.132	0.521	0.516	0.328
	all-llm	0.263	0.083	0.030	0.753	0.326	0.132	0.523	0.517	0.328
Qwen-7B	before	0.207	0.052	0.015	0.727	0.293	0.101	0.469	0.502	0.296
	one-expl	0.213	0.054	0.016	0.728	0.296	0.103	0.477	0.504	0.299
	one-llm	0.206	0.052	0.015	0.725	0.293	0.100	0.469	0.502	0.295
	all-llm	0.199	0.048	0.014	0.716	0.288	0.095	0.470	0.502	0.291
Qwen-72B	before	0.245	0.072	0.023	0.749	0.323	0.125	0.502	0.511	0.319
	one-expl	0.248	0.074	0.024	0.748	0.324	0.127	0.506	0.512	0.320
	one-llm	0.247	0.073	0.023	0.747	0.324	0.126	0.507	0.512	0.320
	all-llm	0.247	0.073	0.024	0.745	0.324	0.126	0.504	0.512	0.319

Table 9: Full results comparing human and LLM explanations across lexical, syntactic, and semantic similarity. Each cell lists scores in the order: before validation, after *one-expl* validation, after *one-llm* validation, and after *all-llm* validation.