A Rose by Any Other Name: LLM-Generated Explanations Are Good Proxies for Human Explanations to Collect Label Distributions on NLI

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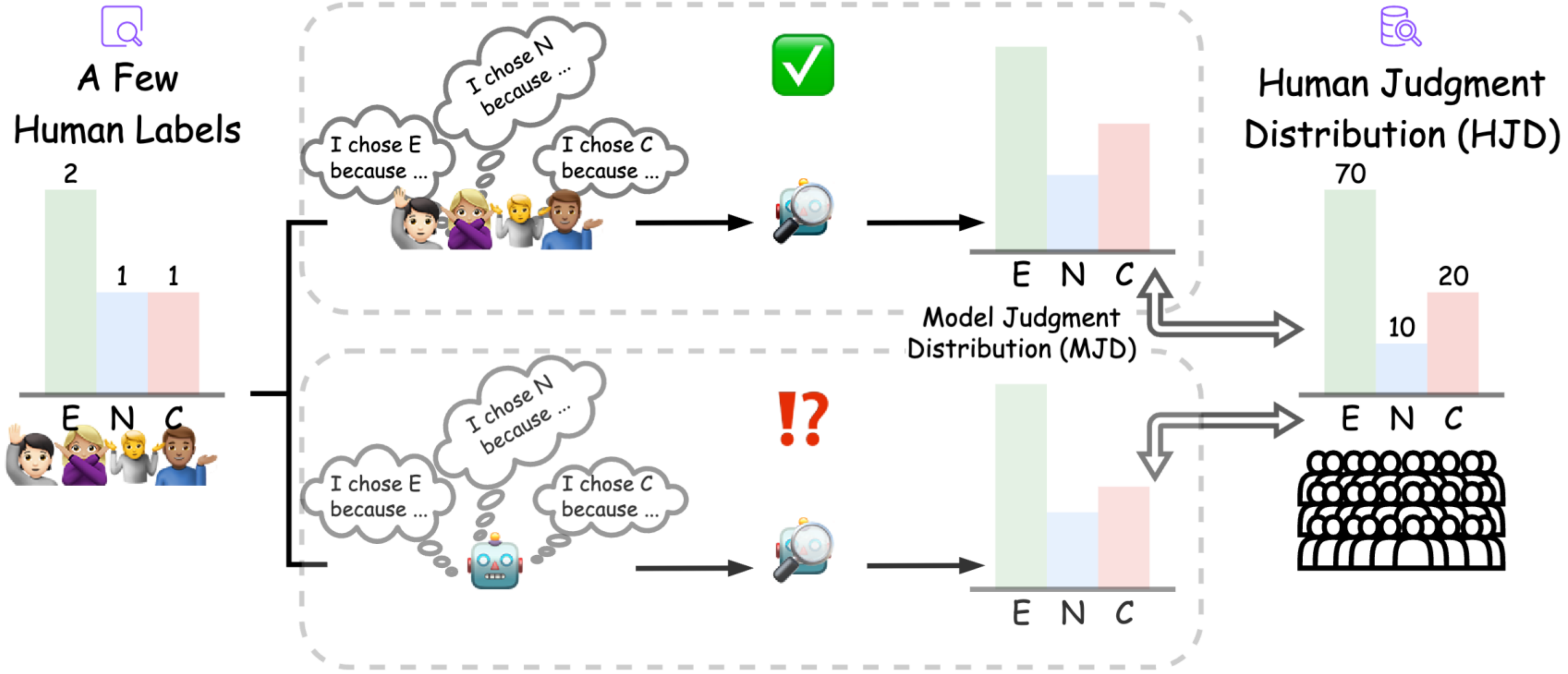
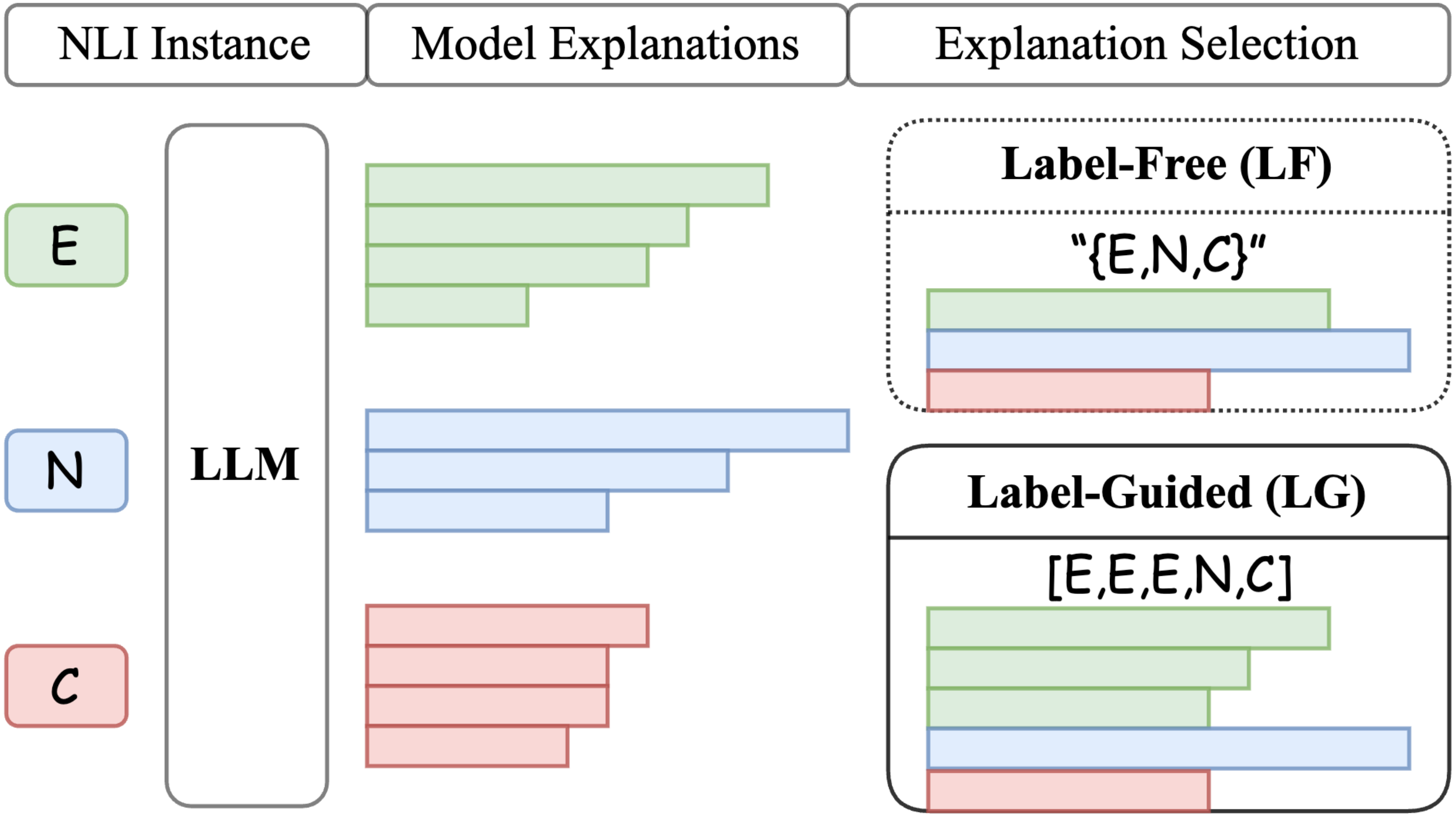
Outline

- **Introduction & Method**
- Can Model Explanations Help LLMs Approximate HJD as Humans Do?
- Can Model-EX Enhance Performance on OOD ANLI Test Set?
- Human versus Model: Are They Different and Does It Matter?
- Can Human Preference Lead to Better Explanation Selection?
- Conclusion

Introduction & Method



Introduction & Method



Introduction & Method

Dataset Name	Number of Instances	Annotations per Instance	Explanations	Valid Overlap
MNLI (Williams et al., 2018)	433K total, 40K multi-label	1 or 5	No	341
ChaosNLI (Nie et al., 2020a)	1.5K from each of αNLI, SNLI, MNLI	100	No	341
VariErr NLI (Weber-Genzel et al., 2024)	500	4	1 per label	341
ANLI test (Nie et al., 2020a)	1K (R1), 1K (R2), 1.2K (R3)	1	Yes (Rationale)	0

HLV: human label variation

HJD: human judgment distribution

MJD: model judgment distribution

LF / LG: label-free / label-guided

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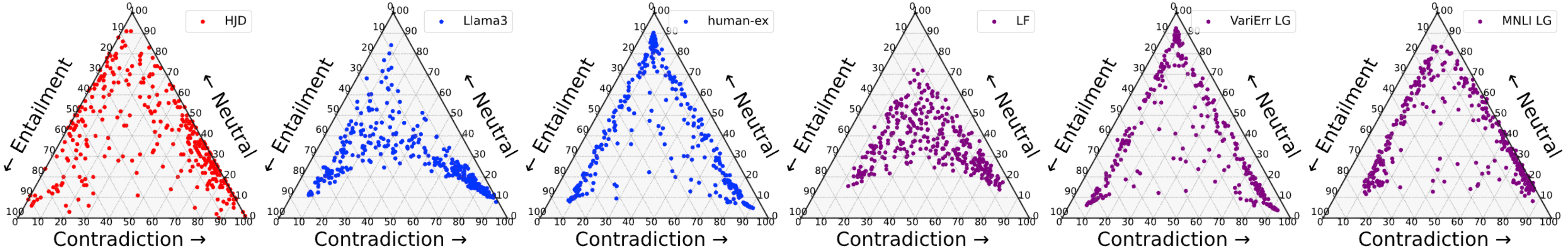
Can Model Explanations Help LLMs Approximate HJD as Humans Do?

Distributions	Dist. Comparison			BERT Fine-Tuning Comparison (dev/test)			RoBERTa Fine-Tuning Comparison (dev/test)			Global
	KL ↓	JSD ↓	TVD ↓	KL ↓	CE Loss ↓	Weighted F1 ↑	KL ↓	CE Loss ↓	Weighted F1 ↑	D.Corr ↑
ChaosNLI HJD	0.000	0.000	0.000	0.073 / 0.077	0.967 / 0.974	0.645 / 0.609	0.062 / 0.060	0.933 / 0.922	0.696 / 0.653	1.000
VariErr dist.	3.604	0.282	0.296	0.177 / 0.179	1.279 / 1.279	0.552 / 0.522	0.166 / 0.173	1.246 / 1.261	0.616 / 0.594	0.688
MNLI dist.	1.242	0.281	0.295	0.104 / 0.100	1.062 / 1.042	0.569 / 0.555	0.101 / 0.093	1.052 / 1.020	0.625 / 0.607	0.795
Llama3 MJD	0.259	0.262	0.284	0.099 / 0.101	1.045 / 1.044	0.516 / 0.487	0.094 / 0.096	1.030 / 1.031	0.545 / 0.522	0.689
+ human-ex	0.238	0.250	0.269	0.098 / 0.099	1.043 / 1.039	0.575 / 0.556	0.091 / 0.092	1.021 / 1.019	0.641 / 0.616	0.771
+ LF model-ex	0.295	0.278	0.310	0.106 / 0.107	1.066 / 1.063	0.539 / 0.533	0.103 / 0.105	1.059 / 1.058	0.581 / 0.571	0.744
+ VariErr LG model-ex	**0.234**	**0.247**	**0.266**	0.097 / 0.098	1.041 / 1.037	0.558 / 0.544	**0.089** / **0.091**	**1.016** / **1.014**	0.633 / 0.626	0.760
+ MNLI LG model-ex	0.242	0.251	0.275	**0.096** / **0.097**	**1.037** / **1.034**	**0.589** / **0.580**	0.090 / 0.092	1.019 / 1.018	**0.657** / **0.645**	**0.849**
GPT-4o MJD	0.265	0.263	0.289	0.103 / 0.096	1.059 / 1.029	0.526 / 0.517	0.093 / 0.092	1.027 / 1.018	0.525 / 0.521	0.703
+ human-ex	**0.187**	**0.207**	**0.223**	0.093 / 0.098	1.027 / 1.036	**0.570** / **0.552**	**0.079** / **0.080**	**0.986** / **0.987**	0.617 / **0.617**	**0.769**
+ LF model-ex	0.252	0.242	0.275	0.101 / 0.102	1.052 / 1.047	0.537 / 0.545	0.157 / 0.167	1.220 / 1.244	0.587 / 0.561	0.752
+ VariErr LG model-ex	0.192	0.209	0.226	**0.092** / **0.093**	**1.026** / **1.022**	0.554 / 0.551	0.088 / 0.089	1.013 / 1.008	**0.618** / 0.598	0.761



(a) (b) (c) (d) (e) (f)

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Can Model-EX Enhance Performance on OOD ANLI Test Set?

Trained Classifiers	BERT ANLI Test			RoBERTa ANLI Test		
	R1 ↑	R2 ↑	R3 ↑	R1 ↑	R2 ↑	R3 ↑
Zero-shot-LM	0.170	0.176	0.197	0.167	0.167	0.168
MNLI-FT-LM	0.220	0.269	0.293	0.292	0.262	0.257
ChaosNLI HJD	0.268	0.289	0.332	0.357	0.331	0.338
VariErr dist	0.302	0.259	0.319	0.402	0.311	0.321
MNLI dist	0.229	0.260	0.279	0.317	0.275	0.281
Llama3 MJD	0.246	0.276	0.306	0.304	0.297	0.304
+ human-ex	0.296	0.289	0.349	0.400	**0.330**	**0.344**
+ LF model-ex	0.292	**0.295**	0.328	0.314	0.262	0.323
+ VariErr LG model-ex	**0.305**	0.285	**0.349**	**0.411**	0.324	0.319
+ MNLI LG model-ex	0.284	0.283	0.321	0.339	0.287	0.307
GPT-4o MJD	0.258	0.263	0.295	0.309	0.282	0.302
+ human-ex	**0.351**	**0.294**	**0.332**	**0.393**	**0.324**	**0.325**
+ LF model-ex	0.285	0.283	0.315	0.350	0.282	0.310
+ VariErr LG model-ex	0.341	0.293	0.330	0.393	0.324	0.323

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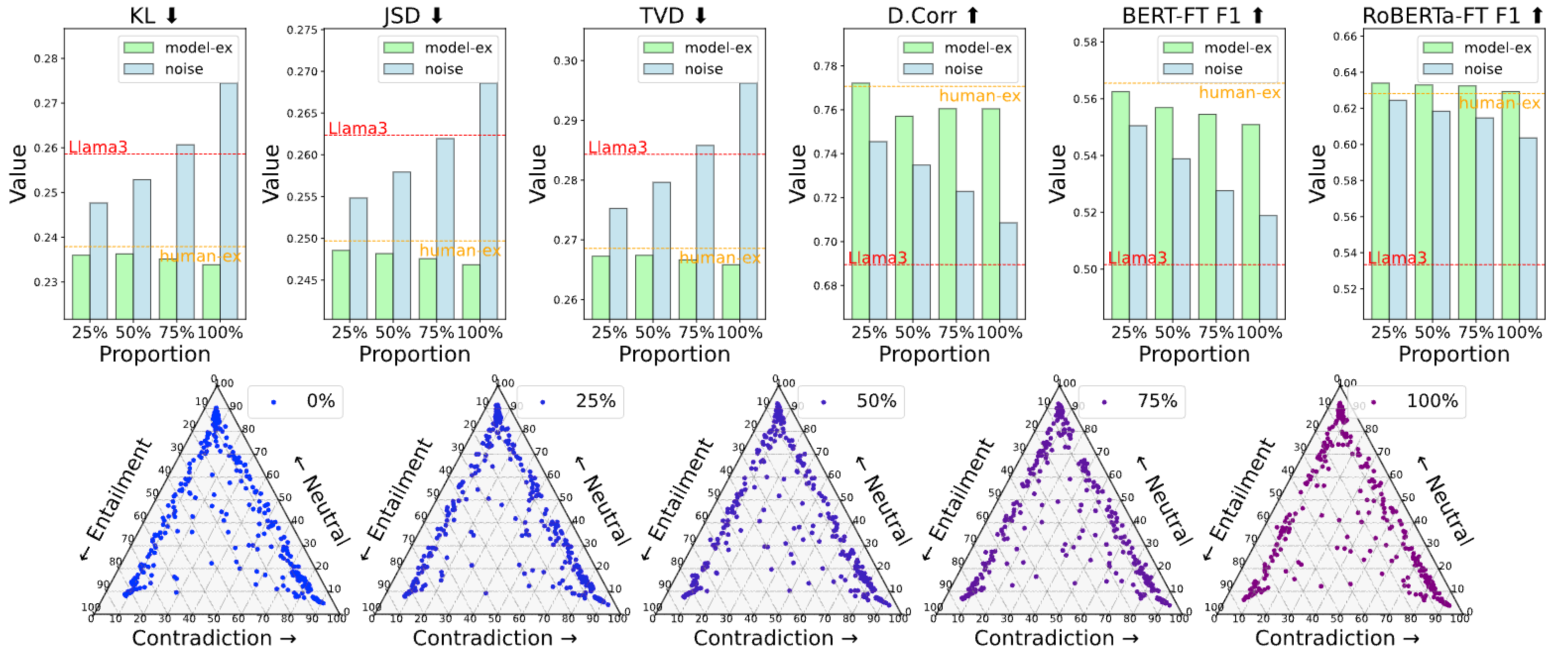
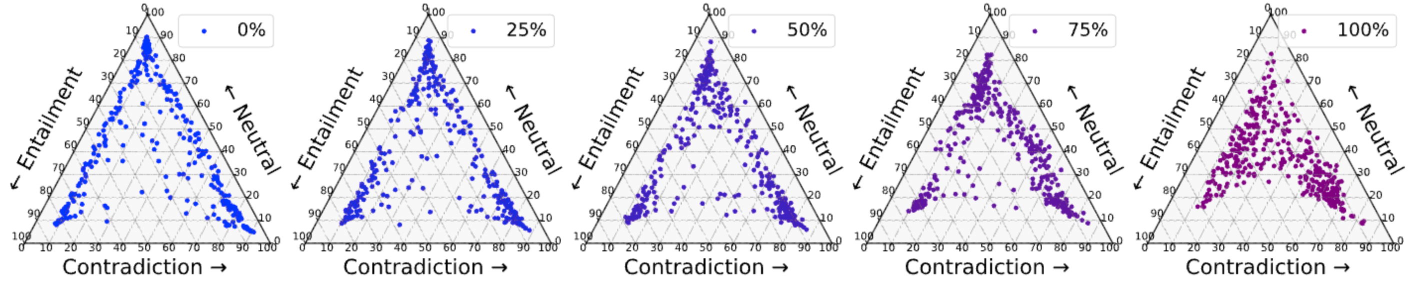
Human versus Model: Are They Different and Does It Matter?



(a) Gradually *replaced* by **model** explanations.



(b) Gradually *replaced* by **noise** explanations.

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Can Human Preference Lead to Better Explanation Selection?

Distributions	Dist. Comparison			RoBERTa Fine-Tuning Comparison(dev/test)			Global
	KL ↓	JSD ↓	TVD ↓	KL ↓	CE Loss ↓	Weighted F1 ↑	D.Corr ↑
Llama3 MJD	0.258	0.261	0.286	0.092 / 0.095	1.025 / 1.026	0.531 / 0.512	0.684
+ human ex	0.240	0.249	0.275	0.089 / 0.091	1.014 / 1.015	0.618 / 0.597	0.750
+ replace *preferred* model ex							
greedy 75.75%	0.241	0.248	0.274	0.088 / 0.090	1.013 / 1.013	0.619 / 0.594	0.733
representative 55.25%	0.240	0.248	0.274	0.088 / 0.091	1.013 / 1.014	0.619 / 0.597	0.739
+ replace *unpreferred* model ex							
greedy 68.5%	0.239	0.247	0.273	**0.087** / 0.090	**1.011** / 1.012	**0.623** / 0.599	0.752
representative 63.25%	**0.237**	**0.246**	**0.271**	0.088 / **0.090**	1.011 / **1.012**	0.621 / **0.607**	**0.761**

Datasets	Lexical			Syntactic			Semantic		AVG
	n = 1↓	n = 2 ↓	n = 3↓	n = 1↓	n = 2↓	n = 3↓	Cos.↓	Euc.↓	AVG ↓
human-ex	0.335	0.098	0.042	0.767	0.341	0.140	0.528	0.520	0.428
replaced *preferred* model ex									
greedy	0.416	0.157	0.082	0.874	0.488	0.233	0.540	0.532	0.474
represent.	0.392	0.149	0.089	0.835	0.426	0.205	0.542	0.541	0.466
replaced *unpreferred* model ex									
greedy	0.387	0.130	0.069	0.841	0.432	0.196	0.527	0.528	0.457
represent.	0.378	0.130	0.073	0.837	0.426	0.195	0.534	0.532	**0.455**

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Conclusion

- Model explanations are comparable to humans in approximating HJD on NLI, and can be scaled up from a few annotations of datasets without explanations.
- Modeling HLV information can improve NLI classifiers' performance, and MJDs generated by our method are robust on OOD datasets w/o labels or explanations.
- Model and human explanations result in similar performance, while noise replacement clearly hurts, indicating that the relevant contents of explanations are crucial.
- The potential of *variability* as a metric for measuring the model explanations.
- Experiments show that MJDs from LLMs and model explanations result in comparable scores with MJDs from LLM and human explanations — A rose by any other name would smell as sweet.
- Notably, our approach generalizes to explanation-free datasets and remains effective in challenging out-of-domain test sets. Results indicate that LLM-generated explanations can significantly reduce annotation costs, making it a scalable and efficient proxy for capturing human label variation.

Thank you !!!

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Resource:

Paper

Code

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