LiTEx: A Linguistic Taxonomy of Explanations for Understanding Within-Label Variation in Natural Language Inference

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TL;DR:

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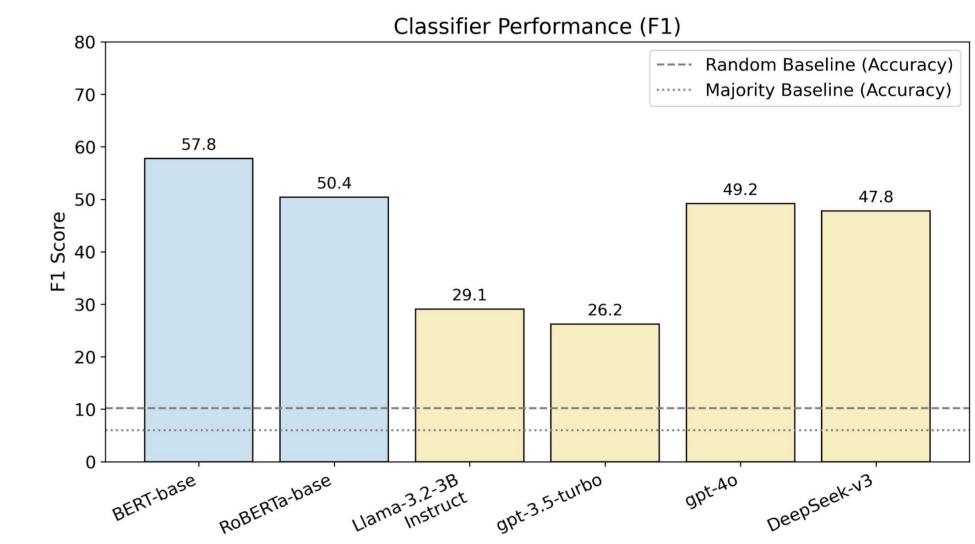
We introduce **LiTEx**, a linguistic taxonomy for categorizing NLI explanations, to analyze **within-label variation**. By annotating e-SNLI and validating the taxonomy, we show that LiTEx reveals how explanations relate to labels, and improves explanation generation to better match human reasoning.

INTRODUCTION

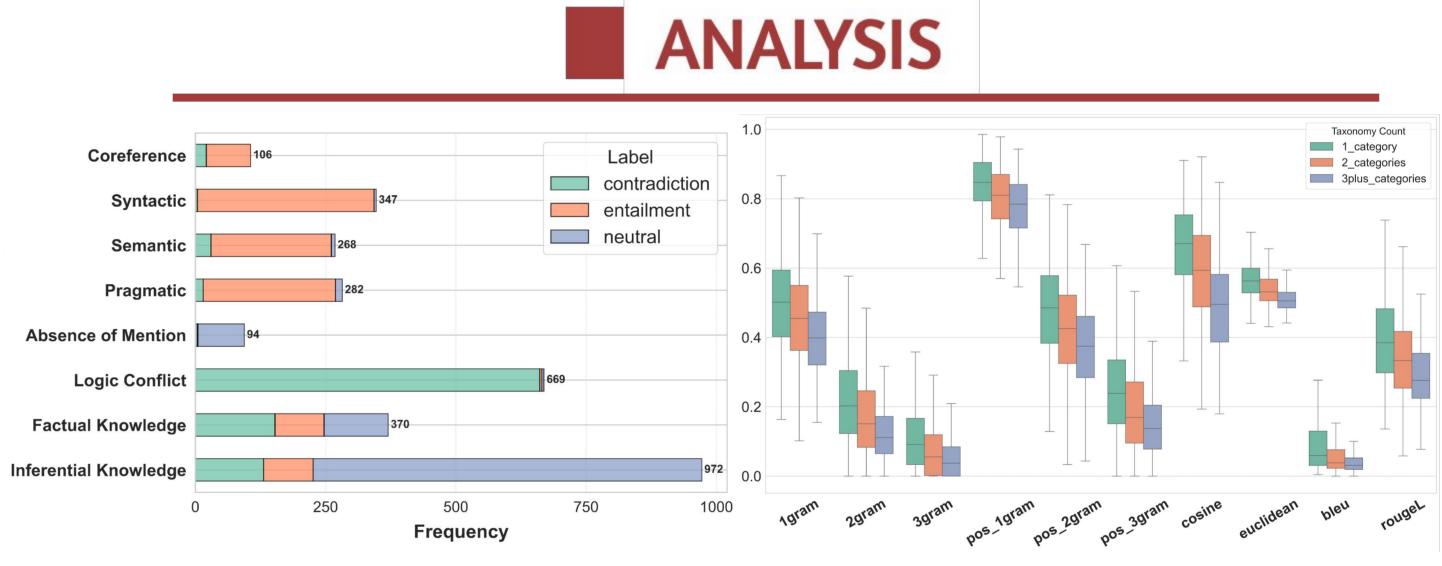
Highlight **Taxonomy** Example A Premise: A crowd is watching a group of men in suits Coreference with briefcases walk in formation down the street led by a woman holding a sign. Hypothesis: The sign the woman is holding states that **Syntactic** 'Freedom is free'. Reasol Different highlights Semantic Explanation 1: it doesn't tell you what the sign says. Explanation 2: There's no explanation that the sign the woman is holding state that "Freedom is free". **Pragmatic** Same explanation Absence of Mention **Example B** Premise: A man in an Alaska sweatshirt stands behind a counter. **Logic Conflict** Hypothesis: The man is wearing a tank top. wledge Same highlight Factual Knowledge Explanation 1: The man cannot simultaneously be wearing a sweatshirt and a tank top. rd-Kno Son Explanation 2: A man in Alaska would typically not be Inferential wearing a tank top, as it is rather cold there most times Knowledge of the year. ŏ M Different explanations

VALIDATION

- IAA on subset: Cohen's k of 0.862
- Model classification:

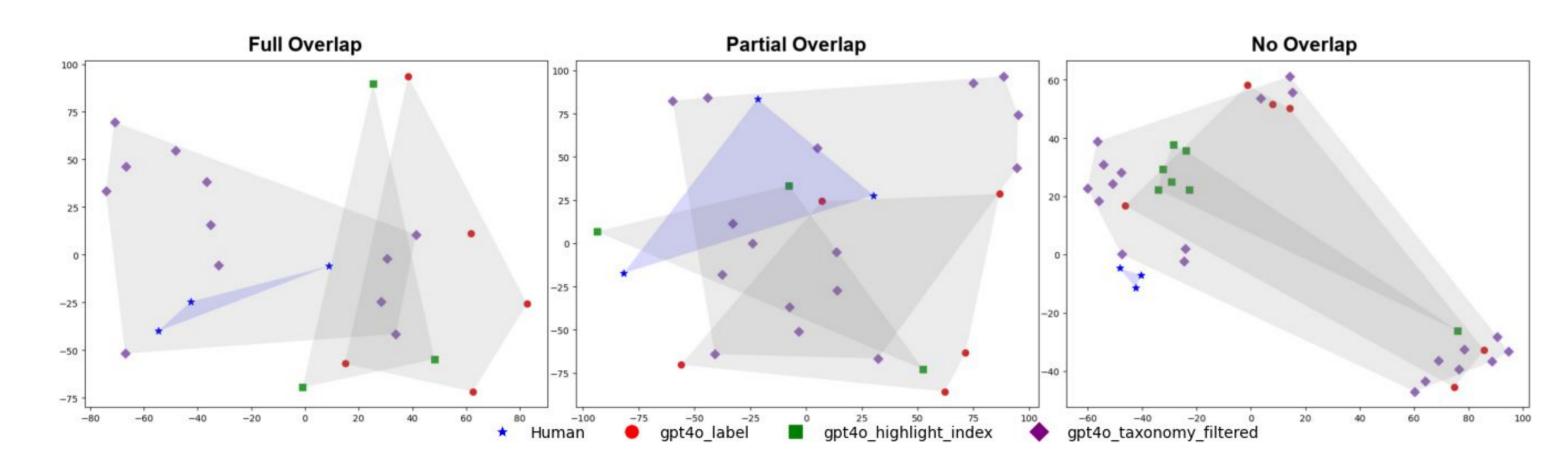


- ★ Consistent taxonomy assignment across annotators
- ★ Learnable by fine-tuned and prompted models



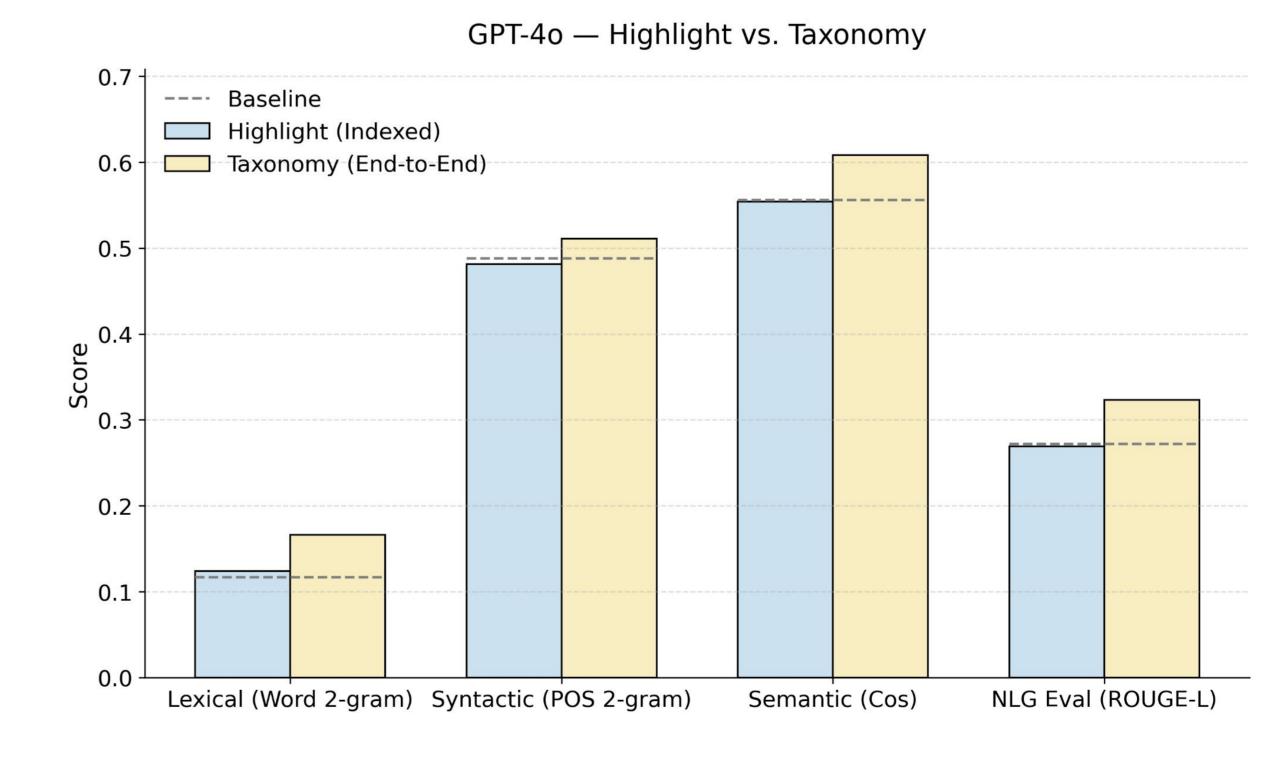
- ★ Distribution of taxonomy categories across NLI labels reflects expected patterns.
- ★ Greater reasoning diversity corresponds to lower similarity.

RESULTS



Mode (GPT40)	Coverage		Area	
	Full	Partial	Rec	Prec
baseline	1.9	21.6	16.5	5.7
highlight-guided	1.1	13.5	10.0	4.7
taxonomy-guided	10.7	56.1	49.3	5.6

- Models: GPT4o, DeepSeek-v3, Llama-3.3-70B
- Prompting Paradigms: Baseline, Highlight-guided, Taxonomy-guided



- ★ Taxonomy-based prompting approaches consistently produce higher similarity scores
- * Taxonomy-guided outputs cover more of the human explanation space.

CONCLUSION





- Taxonomy-guided generation produces richer, more human-like explanations.
- Enhanced e-SNLI dataset with fine-grained taxonomy labels, offering a new resource.







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