

MERGE: Minimal Expression-Replacement GEneralization Test for Natural Language Inference

Mădălina Zgreabă¹ Tejaswini Deoskar¹ Lasha Abzianidze¹

¹Utrecht Institute of Linguistics OTS, Utrecht University, The Netherlands
 {b.m.zgreaban, t.deoskar, l.abzianidze}@uu.nl

Abstract

In recent years, many generalization benchmarks have shown language models' lack of robustness in natural language inference (NLI). However, manually creating new benchmarks is costly, while automatically generating high-quality ones, even by modifying existing benchmarks, is extremely difficult. In this paper, we propose a methodology for automatically generating high-quality variants of original NLI problems by replacing open-class words, while crucially preserving their underlying reasoning. We dub our generalization test as MERGE (Minimal Expression-Replacements GEneralization), which evaluates the correctness of models' predictions across reasoning-preserving variants of the original problem. Our results show that NLI models' perform 4–20% worse on variants, suggesting low generalizability even on such minimally altered problems. We also analyse how word class of the replacements, word probability, and plausibility influence NLI models' performance.

1 Introduction

Generalizability is models' ability to reliably adapt to new scenarios, especially important in real-life deployment (Hupkes et al., 2023; Budnikov et al., 2025; Dutt et al., 2024; Yang et al., 2023). To evaluate it, held-out test sets – e.g. *in-distribution* evaluation – might be insufficient, as they still might contain similar heuristics the models learned during training (Gardner et al., 2020; Hupkes et al., 2023; Dutt et al., 2024). Better options are *out-of-distribution* (OOD) benchmarks which introduce different **text genres** or slightly changed training data items (Hupkes et al., 2023). For example, for tasks like Natural Language Inference (NLI), where models classify the entailment between a premise (P) and a hypothesis (H), OOD benchmarks with either adversarial items (ANLI, Nie et al., 2019) or *minimally* changed training items (Verma et al., 2023) have

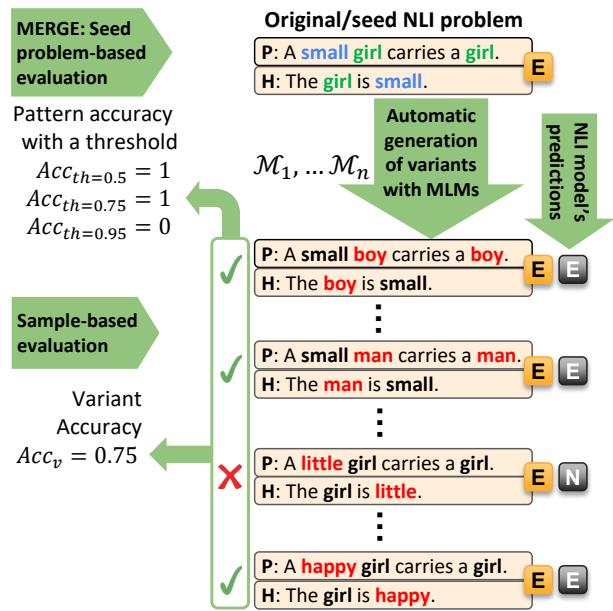


Figure 1: MERGE vs. standard sample-based evaluations: while in the former each variant is an independent example, in MERGE performance is measured as the proportion of correctly classified variants for an NLI seed problem, i.e. whether a model classifies at least x amount of variants (the threshold number) for each NLI problem.

shown models' poor generalization more effectively than traditional in-distribution ones such as SNLI (Bowman et al., 2015) or MNLI (Williams et al., 2018). However, previous OOD NLI benchmarks have confounds: building them by extensive modifications can shift data distributions and can cause decreased performance by breaking well-known model-used heuristics (e.g., (inverse) word overlap, Rajae et al., 2022), rather than for true reasoning failures. Thus, new OOD NLI benchmarks are needed, but according to previous accounts, constructing them presupposes a trade-off (Gardner et al., 2020) between ensuring the correctness of their entailments (done manually) or their efficiency and scalability (done automatically).

We propose the Minimal Expression-

Replacement GEneralization (MERGE) test for NLI, a methodology with which we test generalization by **reliably** and **automatically** altering NLI problems (henceforth named *seed* problems) to actually create **minimally** changed variants of them, henceforth named *variants*. As shown in [Figure 1](#), we construct these variants by automatically replacing open-class words shared between P and H – usually irrelevant for the seed problems’ underlying reasoning in NLI datasets – with *contextually probable* replacements suggested by masked language models (MLMs). As variants preserve (i) the underlying reasoning of the seed problem; and ii) model exploited-heuristics such as sentence lengths and word overlap size ([Naik et al., 2018](#); [McCoy et al., 2019](#); [Bernardy and Chatzikyriakidis, 2019](#); [Rajaee et al., 2022](#)), our generalization test should enable strong model performance by allowing them to leverage these well-known shortcuts, provided they have good reasoning skills. We also automatically filter out replacements considering strict quality criteria to ensure highly plausible variants, without requiring large-scale human validation, further preventing score changes from implausibility artifacts.

Importantly, as shown in [Figure 1](#), generalizability is evaluated on amounts of variants rather than on individual ones ([Abzianidze et al., 2023](#); [Srikanth et al., 2024](#)).

We aim to answer the following questions:

1. Are NLI models robust against minimal variants of NLI problems?
2. How reliable is our methodology for **automatically** obtaining variants of NLI problems?
3. Do factors such as the likelihood, word class, semantic plausibility, or the MLM of replacement words influence performance?

Our contributions are the following:

1. We present a model- and dataset-agnostic methodology to test generalizability using the simplest, model-friendliest minimal changes to create reasoning-preserving NLI variants.
2. We evaluate multiple models on our variants, with results of poor generalization and oversensitivity to label-preserving minimal changes.
3. We show that data generation with MLMs does not favor the same NLI models when

evaluated, and that the number of unique variants in a variant dataset affects models’ scores more than other quality control criteria.

We review previous works in §2, while presenting our methodology in §3, experiments -in 4, and results in §5. The conclusions are in §6.

2 Related Work

Generalizability in NLI OOD benchmarks obtained by minimal alterations (or *contrasts sets* in [Petrov, 2025](#); [Li et al., 2020](#)) suggest models severely lack NLI generalization abilities, given their decreased performance ([Li et al., 2020](#); [Gardner et al., 2020](#); [Kaushik et al., 2020](#), among others). We review previous NLI variant datasets studies, considering aspects such as their *modification strategy*, and the *(non)automatic* approach for creating variants.

Modification Strategy To construct variant datasets, previous studies have used various modification strategies, such as **replacing** words, **decomposing**, or **paraphrasing** problems, or a combination of **multiple** operations, described in the Column *Strategy* in [Table 1](#).

Creation Type Operations were achieved **automatically**, **manually**, or by using a **mix** of automatic and manual methods, shown in Column *Creation* in [Table 1](#).

Validation The variants have been either validated by i) human validation, namely **partially** ($HVal_p$), **fully** ($HVal_f$), or **combined** ($HVal_{pf}$) where only a randomly chosen subset, the full set, or a combination thereof are manually validated; ii) by a **mix** of automatic and manual validation methods (Mix.); or iii) not validated at all (*N/A*), described under Column *Validation*.

Meaning, Reasoning, Word Overlap and Syntax The meaning (M), underlying reasoning (R), syntax (s), or word overlap (WO) of P & H ¹ can be **preserved** (Y), **changed** (N), or a **mix** of both, shown in Columns M , R , S and WO of [Table 1](#).

Modified Sentence The *update*² (U), *premise* (P) and the *hypothesis* (H), both of them separately (P/H), and both of them together ($P\&H$) can be

¹Note that word overlap preservation requires modifying $P\&H$ at the same time.

²Some NLI datasets evaluate how new information, i.e., updates, might change the entailment label between P & H .

Study	Strategy	Creation	Val.	Sentence Mod.	M	R	S	WO	Evaluation	Dataset
Li et al. (2020)	Multiple	Auto.	HVal _p	P	Mix.	Mix.	N	N	Vs-G; Vs-O	SNLI; MNLI
Glockner et al. (2018)	Replace	Auto.	HVal _f	H	N	Mix.	Y	N	V-G	SNLI
Verma et al. (2023)	Paraphrase	Auto.	HVal _f	P/H; P&H	Y	Y	N	N	Vs-O	Pascal RTE1-3 (Dagan et al., 2005)
Srikanth et al. (2024)	Paraphrase	Mix.	HVal _{pf}	H; U	Y	Y	N	N	Vs-Vs; Vs-G	α -NLI (Bhagavatula et al., 2020); δ -NLI (Rudinger et al., 2020)
Arakelyan et al. (2024)	Paraphrase	Auto.	HVal _p	H	Y	Y	N	N	V-O	SNLI; MNLI; ANLI
Petrov (2025)*	Multiple	Auto.	N/A	H	N	N	N	N	V-G	SNLI
Kaushik et al. (2020)	Multiple	Man.	HVal _f	P; H	N	N	N	N	V-G	SNLI
Srikanth and Rudinger (2025)	Decompose	Auto.	Mix.	H	Y	Y	N	N	V-G; Vs-O	SNLI; δ -NLI
MERGE	Replace	Auto.	LMVal	P&H	N	Y	Y	Y	V-G; Vs-G	SNLI

Table 1: Overview of minimal generalizability tests. **Strategy:** *Replacing* words, *Paraphrasing*, *Decomposing* sentences, or a combination of *Multiple* operations; **Creation:** *Auto.* – automatic; *Man.* – manual; *Mix.* – mixing methods; **Val.:** *HVal_p* – a subset, *HVal_f* – the full set, or a combination *HVal_{pf}* of variants is human-validated; *Mix* – automatic and human validation; *LMVal* – LM validated. **Sentence Mod:** only the premise (*P*), hypothesis (*H*), or update (*U*); or both *P* and *H* at the same time (*P&H*) or separately (*P/H*) are modified; **M/R/S/WO:** meaning, reasoning, syntax, or word overlap between *P&H* are (*Y*), or are not (*N*) preserved, or a mix of these two (*Mix.*); **Eval.:** *individual comparison* – the gold label (*V-G*) or prediction of the original problem (*V-O*) vs. the variant; *group comparison* – the gold label (*Vs-G*), prediction of original sentence (*Vs-O*), or other variants (*Vs-Vs*) vs. variants. **Dataset:** modified dataset(s); * in **Study** column: variant datasets used for fine-tuning models. All studies use labels: *entailment*, *contradiction*, *neutral*.

modified, shown under Column *Sentence Mod.* in Table 1.

Evaluation Predictions on variants are evaluated by comparing them (i) individually — with the **gold label** (*V-G*) or the prediction of the original NLI problem (*V-O*); (ii) as a group — with the prediction on the original NLI problem (*Vs-O*), the gold label (*Vs-G*), or with each other (*Vs-Vs*). See column *Eval.* in Table 1 for their classification.

Results of previous studies Models were shown to overall decrease in performance on variant datasets with 14 to 30% (Kaushik et al., 2020; Petrov, 2025; Glockner et al., 2018), being as inconsistent as changing their original NLI predictions in 10-16% of variants (Verma et al., 2023; Arakelyan et al., 2024).

Shortcomings of previous variant datasets Overall, previous lower scores of models on variant datasets cannot be attributed fully to poor generalizability, as they could also be due to: i) new syntactic constructions – syntactic **non-preserving** changes might be more challenging for models (Li et al., 2020); or ii) changed lexical overlap of *P&H* – caused by *paraphrased* or *decomposed* NLI problems. Preserving the word overlap of *P&H* by using *replacement* words has been partially explored previously (Glockner et al., 2018) but with non-preserving label changes, where variants’ plausibility was prioritized at the expense of their lexical diversity. Other shortcomings of previ-

ous studies concern their creation type, with automatic methods having been criticized due to their potential (i) to bias variants in favor of models deployed (Li et al., 2020; Gardner et al., 2020), with some authors arguing for full manual creation of new datasets to prevent data contamination (Gardner et al., 2020); and (ii) to construct implausible variants (Dutt et al., 2024). However, manual creation is time-consuming, and cannot be faster than the rate at which new models might learn variants.

MERGE automatically creates **plausible** variants by replacing shared words of *P&H* with felicitous alternatives. Thus, the lexical overlap of *P&H*, their syntax, and underlying logical reasoning are preserved, while avoiding the implausibility of constructed variants, unlike in previous studies (Arakelyan et al., 2024; Srikanth et al., 2024; Verma et al., 2023). Lexical diversity is not fixed but can also be increased, for instance, by considering more suggestions from more MLMs, unlike in previous list-restricted replacement studies (Abzianidze et al., 2023; Glockner et al., 2018).

3 Methodology

For a seed NLI problem $\langle P, H, l \rangle$ and a label l , open-class words w shared between P and H , $w \in P \cap H$, are replaced with new words to obtain variant NLI problems $\langle P_i, H_i, l \rangle$.

The new words are collected from a set of MLMs $\mathcal{M} = \{M_1, \dots, M_n\}$, as follows: for a sentence $S = (s_1, \dots, s_k)$, an MLM M_j , and a word posi-

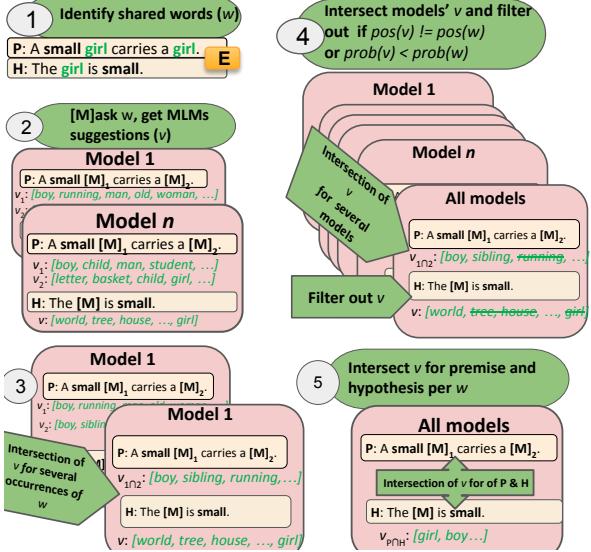


Figure 2: Generating NLI problem variants with MLMs. The suggestions of a shared word between $P \& H$ are excluded if they have different *classes* (*teen* for *little*) than w_i , or if they are already part of the problem (*girl*).

tion $1 \leq i \leq k$, where s_i is an open-class word, $W_j(S, i_{>}^c)$ is the set of words that (i) are more probable than s_i , under M_j , in the masked context $S[s_i := \text{MASK}]$, marked with $>$; (ii) do not occur in S_l and (iii) belong to the same word class³ as s_i in S , marked with c .

With constraints (i) and (iii), suggested words are more felicitous than the original w_i , while preserving syntactic structure and WO. For instance, ‘girl’ from Figure 2 as a replacement for ‘running’ results in an implausible variant, with different syntax, and a possible non-preserved original label. Similarly, low probability suggestions might affect fluency and cause a similar effect of non-preserving the original label. (ii) excludes potential cases in which substituting a shared word like *boy* with one like *dog* in ‘two dogs and a boy swim’, changes the initial entailment relation from entailing ‘only one boy swims’ to contradicting it.⁴

Note that the suggestion set from M_j for a word w , with multiple occurrences in S , is defined as:

$$W_j(S, w_{>}^c) = \bigcap_{\substack{1 \leq i \leq k \\ s_i = w}} W_j(S, i_{>}^c)$$

where the suggested words should comply with

³The possible word classes are nouns, verbs, adjectives, or adverbs; note that if s_i is not part of the M_j vocabulary, the set of suggestions will be empty.

⁴However, variants with incorrect inference labels are still possible, although improbable. For example, replacing ‘boy’ with ‘animal’ in the aforementioned sentence results in an incorrect entailment label.

constraints (i), (ii), (iii) at each occurrence position of w in S . When considering a set of MLMs \mathcal{M} , we define their suggestions set for a word w in S as:

$$W_{\mathcal{M}}(S, w_{>}^c) = \bigcup_{M_j \in \mathcal{M}} W_j(S, w_{>}^c)$$

where suggested words should be validated by the same MLM at each occurrence position of w in S . Finally, for an NLI problem $\langle P, H, l \rangle$ and $w \in P \cap H$, we define a set of suggestions from a set of MLMs \mathcal{M} as:

$$W_{\mathcal{M}}(\langle P, H \rangle, w_{>}^c) = \bigcap_{S \in \{P, H\}} W_{\mathcal{M}}(S, w_{>}^c) \quad (1)$$

and the variant NLI problems $\langle P_{ij}, H_{ij}, l \rangle$ are obtained by replacing the original shared words $w_i \in P \cap H$ with corresponding suggested words $v_{ij} \in W_{\mathcal{M}}(\langle P, H \rangle, w_{i>}^c)$:

$$P_{ij} = P[w_i/v_{ij}], H_{ij} = H[w_i/v_{ij}]$$

We will use $W^{d=m}$ to denote a random subset of size m of the suggestion set W . We call d a degree of inflation. If there are k words shared between P and H , and for each word we have a set of suggestions with the inflation degree of d , then the total number of generated variants will be $k \times d$.

4 Experimental Setup

We will now describe the various experimental choices made in building our variant dataset.

Suggestion generation For all shared nouns, verbs, adverbs and adjectives between $P \& H$ from SNLI test problems, illustrated in Table 4, we generated 200 suggestions v_i with the following MLMs: BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019), Electra (Clark et al., 2020), and BART (Lewis et al., 2019). Their sizes, fully described in Table 5, were base and large, except for ALBERT (base and xxl).

Suggestion filtering Suggestions were kept if they were: i) same *class* as the original w_i ; ii) higher probability than w_i ; iii) different from words already in $P \& H$, w_i included; iv) validated by at least one model; vi) word tokens (i.e. excluding punctuation marks or subwords). Across open-classes, v_i had more often the same class as w_i (40-80% of v_i) than a bigger probability (10% of v_i), as shown in the Appendix Table 6.

We also excluded SNLI test problems that had

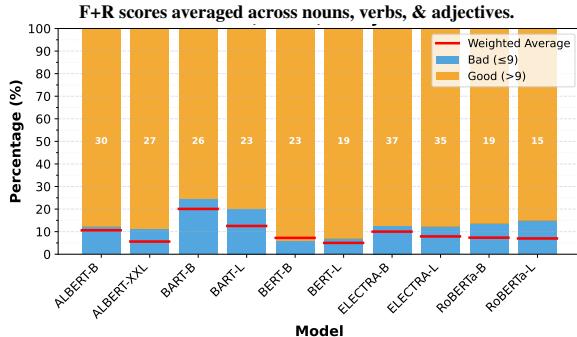


Figure 3: Averaged Fluency and Reasoning scores with normalized counts for 100 random variants for Nouns, Verbs, and Adjectives. The red lines are the bar plots weighted considering the distribution of classes in the seed NLI problems ($N=67\%$, $V=23\%$, $ADJ=10\%$). Good variants have a score of $F + R \geq 9$.

fewer than 20^5 v_i suggestions ($d = 20$) after filtering, from all their summed w_1 , meaning each remaining seed problem had to yield at least 20 potential variants.

Variants Manual Annotation We formed variants by replacing w_1 with v_i^6 , which we partially annotated manually by checking 100 randomly subsampled variants per class. The variants were annotated by two authors independently on a scale from 1–5 (1 – good; 5 – poor) considering their: a) replacement’s plausibility; and b) preservation of the original seed label, with subsection A.2 showing the full annotation guidelines. Good variants had $a + b \geq 9$, with few variants (5%) receiving scores lower than 3 on b) due to ungrammaticalities and one lack of label preservation.⁷. In Figure 3 we show the proportions of good and bad variants per model averaged across classes. Given BART models had more bad scores assigned, they were excluded, which led to a minor reduction of 318 seed problems. The confusion matrix in Figure 9, showing model-specific suggestions on the diagonal, also supports the inclusion of all models’ sizes as they generated more unique than overlapping suggestions, with only some (e.g., BERT, Electra) showing nearly equal proportions of both. To check

⁵Number more interpretable for evaluating across variants (e.g., 95% correct variants of 20 is 19 vs. 9.5 out of 10).

⁶We limit the replaced classes to nouns, verbs, and adjectives, as few seed problems were sharing adverbs between P & H .

⁷Due to the replacement ‘short’ in ‘The short player is tall’ which changed the problem to contradiction from neutral. Despite SNLI having grammatical errors that might justify accepting some in our variants, we penalized any that could

Class	Seed	Average	N(%)	C(%)	E(%)	Uni
N _{Var}	1808	90.8	29.4	20.2	50.3	4121
V _{Var}	506	86.8	30.6	18.6	50.8	1115
A _{Var}	259	77.6	32.8	22.4	44.8	460
ALL_{Var}	2222	77.4	30.0	20.4	49.5	5781

Table 2: Total number of variants after filtering across classes: **Seed** – number of seed problems; **Averaged** – number of variants per seed problem across classes, not computed as **Subs/Seed**, since variant counts vary by the latter; **N/C/E (%)** – percentages per label across seed problems: *neutral*, *contradiction*, and *entailment*; **Uni** – average of unique variants subsampled 10 times, i.e. variants that appear in only one subsample.

the final quality level of our variants, we manually annotate again variants post-BART exclusion with 100 randomly chosen ones across all classes out of which 91% had a good score, plotted in Figure 10.

Final Variant Dataset For each seed problem we randomly selected 20 of all its variants per class, to balance variants across seed problems, repeating subsampling 10 times to reduce randomization artifacts. We refer to this dataset as All_{Var}. Table 2 shows the overall distribution of variants across classes, their seed counts and labels. As some problems share more than one word with different classes, e.g. the *P&H* in Figure 2 share both the noun ‘girl’ and adjective ‘small’, the total seed count is non-summative.

Evaluation Metrics To capture models’ generalizability across variants we used two metrics: 1) standard accuracy – hereby referred to as Sample Accuracy (SA); and 2) Pattern Accuracy (PA) (Abzianidze et al., 2023) – a problem $\langle P, H \rangle$ is correct only if at least an x threshold amount of its variants $\langle P_{ik}, H_{ik} \rangle$ are as well (i.e. the Accuracy threshold). For All_{Var}, each reported PA score for a threshold is the average of the corresponding threshold score across all subsamples, with models being expected to get at least 90%⁸ of variants correctly (i.e. the quality threshold, QT). See Figure 1 for a visualization of the differences between the two metrics.

NLI Models We evaluated several models finetuned for NLI: BERT, RoBERTa, DeBERTa (He et al., 2021), BART, ALBERT, Electra, XLNet (Yang et al., 2019), OPT (Zhang et al., 2022) and

affect reasoning.

⁸While 91% of variants are qualitative, we use 90% for interpretability (e.g. 90% is 18 of 20 variants).

GPT-2 (Radford et al., 2019), with the sizes and training datasets from Table 3, and model cards shown in Table 8 of the Appendix. Note that we examined models trained on a different number of NLI datasets (only SNLI or more) to test whether broader NLI training improves performance.

5 Results

5.1 Are models robust against variants?

Models’ SA scores on $\text{SNLI}_{\text{test}}$, ALL_{Seed} , and ALL_{Var} in Table 3 were further compared via a paired t-test, which resulted in a significant difference between the last two datasets, where the latter was rendered more difficult than the former. At QT, scores decrease by 4–9% (Column QT), and continue to decrease thereafter (see Figure 4). Most importantly, obtaining PA scores on All_{Var} comparable to the SA scores on ALL_{Seed} requires setting the accuracy threshold for most models at around 60% (see Column MT in Table 3).

Overall, models’ scores decrease considerably after the 80% accuracy threshold, showing less generalization the more variants are considered (see the full Figure 11 in the Appendix). To investigate if the observed differences between models’ PA scores are significant at QT, we conducted a paired t-test. While initially BERT-L-S performs worst and OPT-1-3b-S among the best, beyond the 86% threshold OPT-1-B drops to the lowest rank, with BERT scoring significantly better at QT. In line

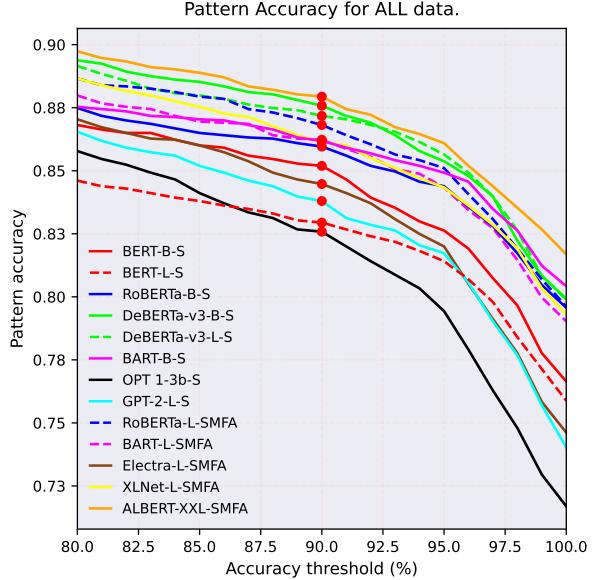


Figure 4: PA scores of models on ALL_{Var} from 80% threshold on. The red dots are PA scores at QT of ALL_{Var} (90%).

with previous studies (Li et al., 2020; Srikanth and Rudinger, 2025), both RoBERTa NLI models significantly outperform BERT, though only RoBERTa-L-SMFA surpasses both of its versions. Partially consistent with the findings of the aforementioned studies are also the scores of RoBERTa-B-S which are significantly worse than DeBERTa-v3-L-S. Note that RoBERTa-L-SMFA even has the highest thresholds in Column MT, suggesting its degradation in generalizability is slower.

In terms of best-performing models, ALBERT-XXL-SMFA scores significantly better than the other models at QT, except DeBERTa, being also the model with the highest scores on ALL_{Seed} . Models trained on more NLI data tend to do better, as generally they rank among the highest-performing models with the exception of Electra-L-SMFA. We also tested if they improve given the majority label, similar to Madaan et al. (2024), by replacing variant labels with the majority baseline in ALL_{Seed} . However, models scores decrease to $\approx 50\%$ on QT, indicating a weaker majority baseline on variants than in previous studies.

Overall, such results indicate models are sensitive to minimal word-level changes that are irrelevant for reasoning, in line with previous studies showing their lack of robustness and generalizability to variant datasets (Verma et al., 2023; Arakelyan et al., 2024; Glockner et al., 2018, etc.).

Model	SNLI _{Test}	ALL _{Seed}	ALL _{Var}	QT	MT
BERT-B-S	90.5	89.6	88.9	-4.9	59
BERT-L-S	87.1	87.2	87.4	-4.5	47
RoBERTa-B-S	90.1	90.1	89.2	-4.5	47
DeBERTa-v3-B-S	91.7	92.1	90.7	-4.9	58
DeBERTa-v3-L-S	91.7	91.9	91.0	-4.9	54
BART-B-S	90.6	90.2	89.4	-4.3	57
OPT-1-3b-S	91.0	90.5	89.1	-8.6	58
GPT-2-L-S	90.9	90.9	89.5	-7.7	55
RoBERTa-L-SMFA	91.8	91.4	90.5	-5.0	59
BART-L-SMFA	92.0	91.9	90.5	-6.0	55
Electra-L-SMFA	91.1	90.6	90.0	-6.5	56
XLNet-L-SMFA	91.7	91.4	90.6	-5.4	55
ALBERT-XXL-SMFA	91.9	92.2	91.2	-4.8	57

Table 3: SA scores of models on $\text{SNLI}_{\text{test}}$, seed problems (ALL_{Seed}) and their variants (ALL_{Var}). First acronym of models— their size; second acronym— NLI datasets used for fine-tuning, i.e. S – only SNLI; SMFA – SNLI, MNLI, FEVER (Thorne et al., 2018), and ANLI. QT: SA on ALL_{Seed} — PA on ALL_{Var} at threshold 90; MT: nearest matching threshold where PA on $\text{All}_{\text{Var}} \approx \text{SA}$ on All_{Seed} .

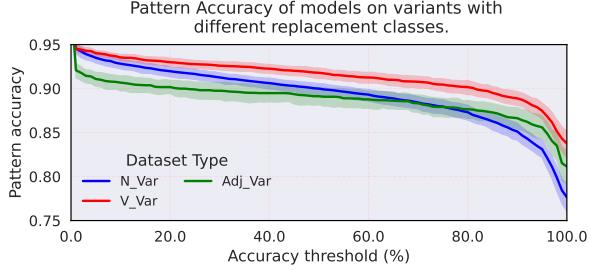


Figure 5: Averaged PA scores on N_{Var} , V_{Var} , and A_{Var} .

5.2 Which word classes are more difficult?

We test models on the ALL_{Var} and its classes from [Table 2](#): N_{Var} , V_{Var} , and A_{Var} , to observe their effect on models’ scores. [Figure 5](#) shows averaged model scores across classes. Until around the 80% threshold, adjectives (in green) are the hardest, after which nouns become most difficult (in blue). Verbs remain the easiest throughout (in red), as indicated by their higher scores. To test the significance of such differences, we conduct an individual t-test⁹ across the class datasets at QT, which shows only nouns to be significantly different than verbs.

To better isolate the effect of classes from their imbalanced number of seed problems shown in [Table 2](#), we only select variants of those seed problems that share at least two out of the three open-class words¹⁰.

For example, the seed problem ‘A small girl carries a girl’ is sharing both an adjective and a noun across $P\&H$. The averaged scores across models are plotted in [Figure 6](#), where dataset names indicate by their first letter which variants from the two classes were considered, e.g. V_N – includes variants formed only by replacing verbs in seeds sharing at least a verb and a noun. In the figure, nouns are initially easier when compared to verbs (in red), similarly to adjectives (in green). On very high accuracy thresholds, nouns and adjectives become more difficult than verbs, with the nouns being most difficult. However, when considering their differences at QT, none of the datasets is significantly different than the others.

5.3 Do MLMs favor the same NLI models?

We averaged the scores of NLI models with a MLM-base counterpart (i.e. BERT-B-S, BERT-L-S, RoBERTa-B-S, RoBERTa-L-SMFA, Electra-L-SMFA, and ALBERT-XXL-SMFA) to test whether

⁹We chose here an individual t-test given the seed problems across class datasets are different.

¹⁰Sharing $N-V=202$; $N-A = 130$, and $V-A = 46$.

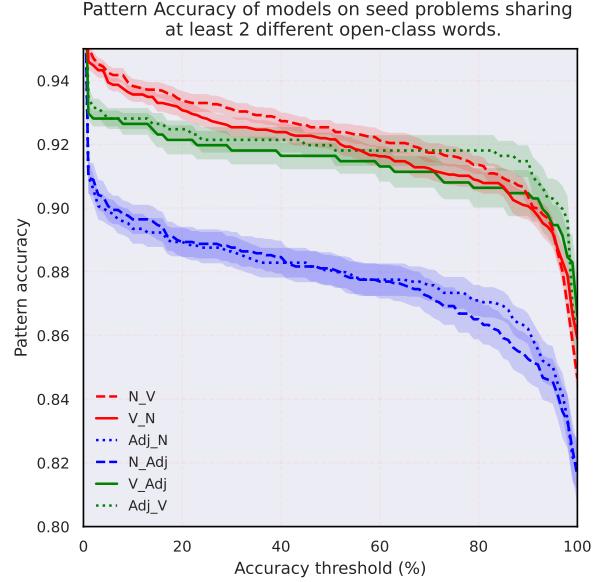


Figure 6: Averaged PA curves of all models on variants of seed problems sharing at least two out of the three open-class words.

NLI models perform better on variants generated by their corresponding MLM (suggested previously by [Li et al., 2020](#); [Gardner et al., 2020](#)), which we plotted in [Figure 7](#). Dataset names reflect averaged NLI scores on variants validated by: 1) Equiv-MLM – the same MLM; 2) Size-MLM — a MLM of similar architecture, but different size (e.g., BERT-B-S evaluated on BERT-L-generated variants); 3) Multi-MLM – any two MLMs, potentially including the evaluated model; 4) Arch-MLM – a model of different architecture¹¹. Models’ performance stays constantly good on Equiv-MLM and Size-MLM. Comparatively, higher scores are achieved on Multi-MLM and Arch-MLM until around the 70% accuracy threshold (blue and black curves), which decrease after the 80% accuracy threshold. Thus, Multi-MLM variants indicate that size of the dataset might influence models’ scores more, as their lower scores on the QT threshold are on variants they have also possibly validated.

5.4 Which filtering criteria matter?

To test if different filtering criteria for v_{ij} affect NLI models’ scores, we selected new variants for the seed problems of ALL_{Var} forming datasets with: i) v_{ij} of the union of $P\&H$, instead of their intersection in [Equation 1](#) – $P \cup H$; ii) v_{ij} only having

¹¹MLMs can contribute with variants to both Equiv-MLM and Size-MLM (e.g., scores on BERT-B are averaged in Equiv-MLM for BERT-B-S and in Size-MLM for BERT-L-S). Also note that the Multi-MLM dataset is disproportionately bigger than others, shown in [Table 9](#).

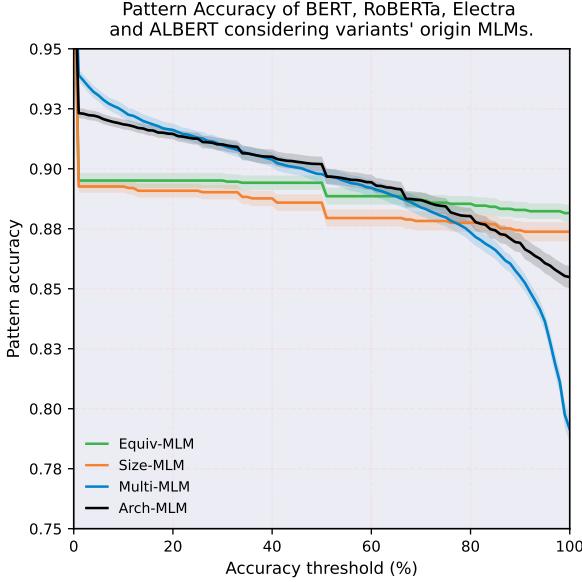


Figure 7: Averaged PA curves for BERT, RoBERTa, Electra and ALBERT, all sizes tested, on variants divided by their origin MLM.

$w^c - \text{pos}$; iii) v_{ij} only having $w_{i>} - \text{Prob}$; iv) v_{ij} of any class or probability – None ; v) v_{ij} with their letters randomly scrambled – Scr . Except for Scr , the datasets are more diverse given the less strict filtering, while still excluding punctuation signs and v_{ij} already part of $P \& H$. We plot the averaged PA scores of all models in Figure 8, highest performance being achieved on Scr , followed by ALL_{Var} , Prob , Pos , None , and $P \cup H$.

While Scr starts as the lowest curve (in green), it ends up as the one with the highest scores on very high thresholds. The other variant datasets seem to follow a constant downward trend where the more variants are considered, the lower the scores get. Out of these, $P \cup H$, Pos , and None have the lowest scores, which might be caused by the higher number of unique variants¹² per dataset, which enlarges its overall lexical diversity. Thus, the number of variants seems more important than controlling for factors such as probability, or plausibility.

5.5 What the hard NLI problems look like

We analyzed how successfully on average the NLI models classified the NLI original seed problems (2222). We found that 1.4% (31) problems had no variants classified correctly by any NLI model. After careful inspection, we found out that only 29% of them have a correct gold inference label (see the problems in Table 10), adding evidence to the

¹²All three datasets have around $\approx 380k$ unique variants each, while each of the others have $\approx 190k$.

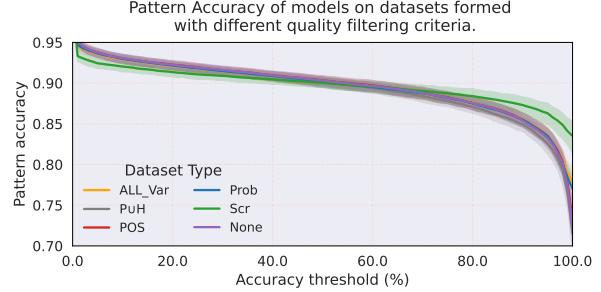


Figure 8: Averaged PA curves of all models on datasets formed with v_{ij} having any class or probability – None , being scrambled – Scr , with higher probability than the original word – Prob , with the same class – Pos , suggested in either P and H – $P \cup H$, and ALL_{Var} .

well-known issue of annotation variation in NLI (Pavlick and Kwiatkowski, 2019; Weber-Genzel et al., 2024). If we consider problems that were classified with $< 5\%$ average accuracy by all models, we found that out of these 32 problems, only 6 had a correct gold label. For variants of correctly predicted seed problems, models score 93 on average at the 90% threshold, compared to only 0.01 for variants of incorrectly predicted seed, showing they are more consistent in the case of the first, a well-known trend remarked by previous studies (Miralles-González et al., 2025). Occasionally, models do correctly predict variants of originally misclassified seeds (an average of 90 seed problems per model). In such cases, for models only trained on SNLI, the replacement words of correct variants occurred, on average, about 2,000 times more often in the SNLI train dataset than the original replaced words, pointing out to a link between models’ prediction and the frequency of tokens in their training data (Razeghi et al., 2022).

6 Conclusions

We presented MERGE, a methodology for minimal generalization testing that automatically constructs variants of NLI problems, while preserving reasoning and word overlap. Its strength lies in minimal, controlled replacements: through quality filters for fluency and consistency, MERGE tests models under the simplest generalization conditions.

We show models do not generalize well even under the best conditions, as they drop with 4–6% one the quality level of our variant dataset to be 90%, and by up to $\approx 20\%$ in high accuracy thresholds. Even more, achieving a pattern accuracy comparable to that obtained on the seed problems entails lowering the accuracy threshold by 60% for most

models, indicating their generalizability extends only this far. Our results also show variants formed from replacing nouns are more difficult than those from verbs, while NLI models are not favored by the use of any MLM to achieve higher scores. In fact, we have highlighted how the overall unique variant number might affect models’ scores more. When it comes to important filtering criteria for suggestions, them being equally plausible in both the premise and the hypothesis seems to be the most important one.

Given we have developed MERGE to create minimally altered variants of sentences, this strategy can be extended to test generalizability in other NLI benchmarks and NLU tasks (e.g. reading comprehension), especially as many can be framed as NLI (Demszky et al., 2018), which we are planning to do in the future.

Limitations

One limitation of our methodology is the lack of account for original words that are split into subwords by tokenizers, which we are excluding by default. Additionally, our suggestions are obtained by masking one occurrence of a word at a time. However, when one occurrence is masked, the other ones are still part of the sentence, which might bias the suggestions of models. Future studies could also consider evaluating prompt-based models, to observe if different prompt strategies might help the models perform better on variants.

Acknowledgments

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References

- Lasha Abzianidze, Joost Zwarts, and Yoad Winter. 2023. [SpaceNLI: Evaluating the consistency of predicting inferences in space](#). In *Proceedings of the 4th Natural Logic Meets Machine Learning Workshop*, pages 12–24, Nancy, France. Association for Computational Linguistics.
- Erik Arakelyan, Zhaoqi Liu, and Isabelle Augenstein. 2024. [Semantic sensitivities and inconsistent predictions: Measuring the fragility of NLI models](#). In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 432–444, St. Julian’s, Malta. Association for Computational Linguistics.
- Jean-Philippe Bernardy and Stergios Chatzikyriakidis. 2019. [What kind of natural language inference are nlp systems learning: Is this enough?](#) In *ICAART (2)*, pages 919–931.
- Chandra Bhagavatula, Ronan Le Bras, Chaitanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Scott Wen tau Yih, and Yejin Choi. 2020. [Abductive commonsense reasoning](#). *Preprint*, arXiv:1908.05739.
- Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015. [A large annotated corpus for learning natural language inference](#). *Preprint*, arXiv:1508.05326.
- Mikhail Budnikov, Anna Bykova, and Ivan P Yamshchikov. 2025. [Generalization potential of large language models](#). *Neural Computing and Applications*, 37(4):1973–1997.
- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. [Electra: Pre-training text encoders as discriminators rather than generators](#). *Preprint*, arXiv:2003.10555.

- Ido Dagan, Oren Glickman, and Bernardo Magnini. 2005. *The pascal recognising textual entailment challenge*. In *Machine learning challenges workshop*, pages 177–190. Springer.
- Dorottya Demszky, Kelvin Guu, and Percy Liang. 2018. *Transforming question answering datasets into natural language inference datasets*. *ArXiv*, abs/1809.02922.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. *BERT: pre-training of deep bidirectional transformers for language understanding*. *CoRR*, abs/1810.04805.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. *Bert: Pre-training of deep bidirectional transformers for language understanding*. *Preprint*, arXiv:1810.04805.
- Ritam Dutt, Sagnik Ray Choudhury, Varun Venkat Rao, Carolyn Rose, and V.G.Vinod Vydiswaran. 2024. *Investigating the generalizability of pretrained language models across multiple dimensions: A case study of NLI and MRC*. In *Proceedings of the 2nd GenBench Workshop on Generalisation (Benchmarking) in NLP*, pages 165–182, Miami, Florida, USA. Association for Computational Linguistics.
- Matt Gardner, Yoav Artzi, Victoria Basmova, Jonathan Berant, Ben Bogin, Sihao Chen, Pradeep Dasigi, Dheeru Dua, Yanai Elazar, Ananth Gottumukkala, Nitish Gupta, Hanna Hajishirzi, Gabriel Ilharco, Daniel Khashabi, Kevin Lin, Jiangming Liu, Nelson F. Liu, Phoebe Mulcaire, Qiang Ning, Sameer Singh, Noah A. Smith, Sanjay Subramanian, Reut Tsarfaty, Eric Wallace, Ally Zhang, and Ben Zhou. 2020. *Evaluating models’ local decision boundaries via contrast sets*. *Preprint*, arXiv:2004.02709.
- Max Glockner, Vered Shwartz, and Yoav Goldberg. 2018. *Breaking NLI systems with sentences that require simple lexical inferences*. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 650–655, Melbourne, Australia. Association for Computational Linguistics.
- Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. 2021. *Deberta: Decoding-enhanced bert with disentangled attention*. *Preprint*, arXiv:2006.03654.
- Dieuwke Hupkes, Mario Giulianelli, Verna Dankers, Mikel Artetxe, Yanai Elazar, Tiago Pimentel, Christos Christodoulopoulos, Karim Lasri, Naomi Saphra, Arabella Sinclair, et al. 2023. *A taxonomy and review of generalization research in nlp*. *Nature Machine Intelligence*, 5(10):1161–1174.
- Divyansh Kaushik, Eduard Hovy, and Zachary C. Lipton. 2020. *Learning the difference that makes a difference with counterfactually-augmented data*. *Preprint*, arXiv:1909.12434.
- Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. *ALBERT: A lite BERT for self-supervised learning of language representations*. *CoRR*, abs/1909.11942.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. *Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension*. *Preprint*, arXiv:1910.13461.
- Chuanrong Li, Lin Shengshuo, Zeyu Liu, Xinyi Wu, Xuhui Zhou, and Shane Steinert-Threlkeld. 2020. *Linguistically-informed transformations (LIT): A method for automatically generating contrast sets*. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 126–135, Online. Association for Computational Linguistics.
- 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*. *Preprint*, arXiv:1907.11692.
- Lovish Madaan, David Esiobu, Pontus Stenetorp, Barbara Plank, and Dieuwke Hupkes. 2024. *Lost in inference: Rediscovering the role of natural language inference for large language models*. *Preprint*, arXiv:2411.14103.
- R. Thomas McCoy, Ellie Pavlick, and Tal Linzen. 2019. *Right for the wrong reasons: Diagnosing syntactic heuristics in natural language inference*. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3428–3448, Florence, Italy. Association for Computational Linguistics.
- Pablo Miralles-González, Javier Huertas-Tato, Alejandro Martín, and David Camacho. 2025. *Pushing the boundary on natural language inference*. *Preprint*, arXiv:2504.18376.
- Aakanksha Naik, Abhilasha Ravichander, Norman Sadeh, Carolyn Rose, and Graham Neubig. 2018. *Stress test evaluation for natural language inference*. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 2340–2353, Santa Fe, New Mexico, USA. Association for Computational Linguistics.
- Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2019. *Adversarial nli: A new benchmark for natural language understanding*. *arXiv preprint arXiv:1910.14599*.
- Ellie Pavlick and Tom Kwiatkowski. 2019. *Inherent disagreements in human textual inferences*. *Transactions of the Association for Computational Linguistics*, 7:677–694.

- Daniel Petrov. 2025. *From superficial patterns to semantic understanding: Fine-tuning language models on contrast sets*. *arXiv preprint arXiv:2501.02683*.
- Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. *Language models are unsupervised multitask learners*.
- Sara Rajaei, Yadollah Yaghoobzadeh, and Mohammad Taher Pilehvar. 2022. *Looking at the overlooked: An analysis on the word-overlap bias in natural language inference*. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 10605–10616, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yasaman Razeghi, Robert L. Logan IV, Matt Gardner, and Sameer Singh. 2022. *Impact of pretraining term frequencies on few-shot reasoning*. *Preprint*, arXiv:2202.07206.
- Rachel Rudinger, Vered Shwartz, Jena D. Hwang, Chandra Bhagavatula, Maxwell Forbes, Ronan Le Bras, Noah A. Smith, and Yejin Choi. 2020. *Thinking like a skeptic: Defeasible inference in natural language*. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4661–4675, Online. Association for Computational Linguistics.
- Neha Srikanth, Marine Carpuat, and Rachel Rudinger. 2024. *How often are errors in natural language reasoning due to paraphrastic variability?* *Transactions of the Association for Computational Linguistics*, 12:1143–1162.
- Neha Srikanth and Rachel Rudinger. 2025. *Nli under the microscope: What atomic hypothesis decomposition reveals*. *Preprint*, arXiv:2502.08080.
- James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. *FEVER: a large-scale dataset for fact extraction and VERification*. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 809–819, New Orleans, Louisiana. Association for Computational Linguistics.
- Dhruv Verma, Yash Kumar Lal, Shreyashee Sinha, Benjamin Van Durme, and Adam Poliak. 2023. *Evaluating paraphrastic robustness in textual entailment models*. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 880–892, Toronto, Canada. Association for Computational Linguistics.
- Leon Weber-Genzel, Siyao Peng, Marie-Catherine de Marneffe, and Barbara Plank. 2024. *Varierr nli: Separating annotation error from human label variation*. *Preprint*, arXiv:2403.01931.
- Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. *A broad-coverage challenge corpus for sentence understanding through inference*. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana. Association for Computational Linguistics.
- Linyi Yang, Yaoxian Song, Xuan Ren, Chenyang Lyu, Yidong Wang, Jingming Zhuo, Lingqiao Liu, Jindong Wang, Jennifer Foster, and Yue Zhang. 2023. *Out-of-distribution generalization in natural language processing: Past, present, and future*. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 4533–4559, Singapore. Association for Computational Linguistics.
- Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. 2019. *Xlnet: Generalized autoregressive pretraining for language understanding*. *CoRR*, abs/1906.08237.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuhui Chen, Christopher Deewani, Mona Diab, Xian Li, Xi Victoria Lin, Todor Miaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. *Opt: Open pre-trained transformer language models*. *Preprint*, arXiv:2205.01068.

A Appendix

A.1 Variant Creation

Word Class	T	N(%)	C(%)	E(%)
Nouns	7363	33.4	28.7	37.8
Verbs	3780	31.8	28.2	40.0
Adjectives	1067	33.6	23.7	42.6
Adverbs	76	26.3	13.2	60.5

Table 4: Number of seed problems and label distributions for open-class word categories from the SNLI test set. T: seed problems shared between P and H ; N/C/E: percentage of *neutral*, *contradiction*, and *entailment* labels.

MLMs For the MLMs, we used the models enumerated in Table 5, from which BART was excluded given its suggestions were of lower quality, as shown in Figure 3. In addition to the models described in the table, we also tried including DeBERTa, which was too noisy to use for suggestion generation.

Class Filtering Suggestions of different classes than the original word w_i were excluded by tagging each suggestion v_i in the context of its corresponding sentence using the spaCy model en_core_web_sm. We calculated the average of excluded suggestions after tagging per model, which is shown in the table in 6.

Model	Size	Architecture	Vocabulary
BERT (Devlin et al., 2018) google-bert/bert-base-cased	B	E	28,996
BERT (Devlin et al., 2018) google-bert/bert-large-cased	L	E	28,996
RoBERTa (Liu et al., 2019) FacebookAI/roberta-base	B	E	50,265
RoBERTa (Liu et al., 2019) FacebookAI/roberta-large	L	E	50,265
BART (Lewis et al., 2019) facebook/bart-base	B	E-D	50,265
BART (Lewis et al., 2019) facebook/bart-large	L	E-D	50,265
ALBERT (Lan et al., 2019) albert/albert-base-v2	B	E	30,000
ALBERT (Lan et al., 2019) albert/albert-xxlarge-v2	XXL	E	30,000
ELECTRA (Clark et al., 2020) google/electra-base-generator	B	E	30,522
ELECTRA (Clark et al., 2020) google/electra-large-generator	L	E	30,522

Table 5: Overview of selected pretrained MLMs used for suggestion generation. Column **Size**: Size **Base**, **Large**, or **XXLarge**; Column **Architecture**: the model is **Encoder**, **Decoder** or **Encoder-Decoder**. The vocabulary size of the models is shown in the last column.

Probability Filtering We obtained the probability of each v_{ij} of w_i in P or H from the MLM that suggested it, and we excluded those of lower probability. MERGE validates variants by assuming that replacements as likely as the w_i are less likely to be semantically implausible. Original words w_i that were not part of the model’s vocabulary were also automatically excluded. Also note that both probability and class filtering are important, as highly probable suggestions might not have the correct class and vice versa. Table 6 shows the percentages of excluded suggestions for having lower probability than the replaced word under Column **Prob. Fil.**.

A.2 Annotation

We annotated variants in terms of how much they change the fluency and the original logical label of the NLI problems, which we considered to be correct. The scores used were: 1 – **poor**, 2 – **mostly poor**, 3 – **uncertain**, 4 – **mostly good**, 5 – **good**. Table 7 shows how we annotated certain variants, and their attributed fluency and reasoning scores, alongside an explanation for them. Variants were classified as **poor** if they were: 1) ungrammatical; 2) had missing arguments; 3) nonsense; or 4) logic non-preserving. Aspects 1) and 2) were chosen given they directly hinder the evaluation of fluency and reasoning.

The instructions in the annotation guidelines are

Model	POS	POS Fil.		Prob. Fil.	
		P	H	P	H
ALBERT-B	A	45.7	48.4	87.6	80.4
	N	7.2	7.8	88.4	79.9
	V	26.5	29.3	91.1	87.1
ALBERT-XXL	A	45.3	48.4	87.8	78.1
	N	6.1	6.7	89.6	75.9
	V	24.5	24.5	92.1	84.5
BART-B	A	63.9	65.8	90.2	84.2
	N	28.3	26.6	91.3	84.8
	V	38.7	37.2	90.0	88.5
BART-L	A	64.0	65.9	89.4	83.4
	N	30.6	30.8	91.5	83.3
	V	37.2	38.1	88.7	87.6
BERT-B	A	45.1	48.7	93.5	89.6
	N	10.6	11.6	92.2	85.8
	V	26.4	28.6	92.5	90.4
BERT-L	A	44.4	47.4	94.5	91.0
	N	10.4	12.3	94.0	87.9
	V	28.9	29.7	94.5	92.6
Electra-B	A	45.4	48.4	89.6	84.9
	N	11.0	11.3	88.2	82.4
	V	27.6	27.5	88.3	88.9
Electra-L	A	45.6	49.0	91.1	86.2
	N	10.7	10.7	90.9	85.0
	V	25.5	26.5	90.5	89.5
RoBERTa-B	A	49.2	52.3	93.9	89.1
	N	7.7	8.2	94.2	88.3
	V	31.1	33.8	95.0	91.8
RoBERTa-L	A	47.7	50.9	95.2	91.3
	N	7.7	8.1	95.7	90.2
	V	33.2	32.3	96.6	93.6

Table 6: Average percentages of suggestions with other POS Categories (Pos Fil.) and lower probabilities (Prob Fil.). The percentages under *Premise* and *Hypothesis* show how many suggestions, on average, out of 200 had a different class or lower probability than the original masked word.

provided below with the demo examples in Table 7:

The NLI problems are assessed on the fluency (grammaticality and sensibility) and reasoning. The reasoning component focuses on the relation between the meaning of P and H rather than their fluency. However, poor fluency can negatively affect the reasoning part. For example, "Colorless green ideas sleep furiously" entailing "Green thoughts is angrily sleeping" should be assessed with fluency 1 and reasoning 5, in short F1-R5.

The original SNLI problems could

suffer from fluency and reasoning; however, the obtained NLI problem variants should be assessed with respect to the original NLI problems. Annotation should assess the fluency and reasoning of the variants while assuming that the fluency and reasoning of the original NLI problems are fine. That’s why variant NLI problems are provided with the origin word that helps to reconstruct the original SNLI problem.

Below are several examples to demonstrate different combinations of fluency and reasoning. The scale 1-5 should be interpreted as: poor, mostly poor, uncertain, mostly good, good.

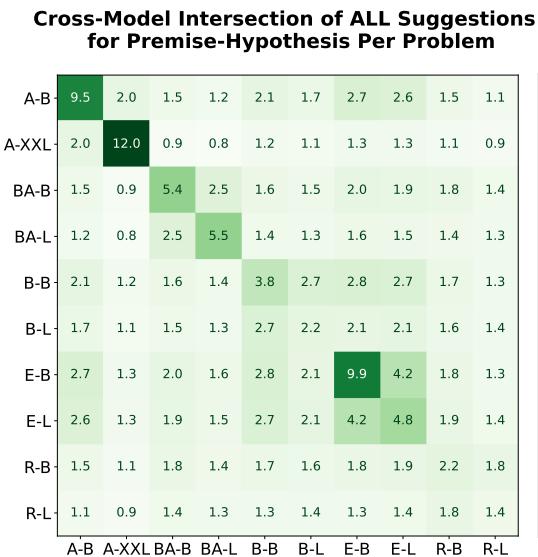


Figure 9: Confusion matrix showing how models’ suggestions intersect on average, across problems, with the diagonal being the averaged number of original or model-specific suggestions a model generates. For instance, in the problem ‘A small girl carries a girl’, a suggestion like ‘bear’ counts on the diagonal if unique to one model, or in the other cells if shared between models.

Evaluated NLI Models The NLI models we evaluated alongside with their model cards are in Table 8.

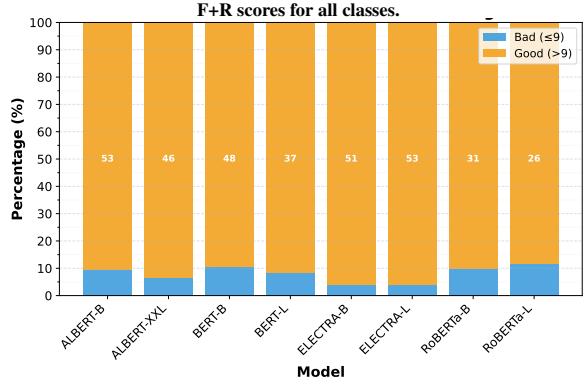


Figure 10: Fluency and Reasoning scores for 100 randomly sampled variants and their normalized counts, from all pos tags, and the models that validated them, after exclusion of suggestions from BART. Note that 91 out of the 100 examples evaluated had $F + R \Rightarrow 9$.

Model	Model Card
ALBERT-XXL-SMFA	ynie/albert-xxlarge-v2-snli_mnli_fever_anli_R1_R2_R3-nli
BART-B-S	varun-v-rao/bart-base-snli-model1
BART-L-SMFA	ynie/bart-large-snli_mnli_fever_anli_R1_R2_R3-nli
BERT-B-S	textattack/bert-base-uncased-snli
BERT-L-S	varun-v-rao/bert-large-cased-lora-1.58M-snli
DeBERTa-v3-B-S	pepa/deberta-v3-base-snli
DeBERTa-v3-L-S	pepa/deberta-v3-large-snli
Electra-L-SMFA	ynie/electra-large-discriminator-snli_mnli_fever_anli_R1_R2_R3-nli
GPT-2-L-S	varun-v-rao/gpt2-large-snli-model3
OPT-1.3b-S	utahnlp/snli_facebook_opt-1.3b_seed-3
RoBERTa-B-S	pepa/roberta-base-snli
RoBERTa-L-SMFA	ynie/roberta-large-snli_mnli_fever_anli_R1_R2_R3-nli
XLNet-L-SMFA	ynie/xlnet-large-cased-snli_mnli_fever_anli_R1_R2_R3-nli

Table 8: NLI evaluated models and their Hugging Face model cards.

Model	Avg	Avg Other
BERT-B	473.7	9572.0
ALBERT-B	2085.8	4073.9
Electra-L	700.1	7445.4
BERT-L	228.0	9572.0
ALBERT-XXL	4114.0	4073.9
Electra-B	2128.2	7445.4
RoBERTa-B	355.9	9729.8
RoBERTa-L	188.0	9729.8
Both	41186.3	10273.7

Table 9: Average entries per subsample corresponding to each MLM. The **Avg Other** is the **average** of all **other** variants coming from different architectures for one MLM model, excluding those from the same model family and those that are validated by at least two models.

Pattern Accuracy for ALL data.

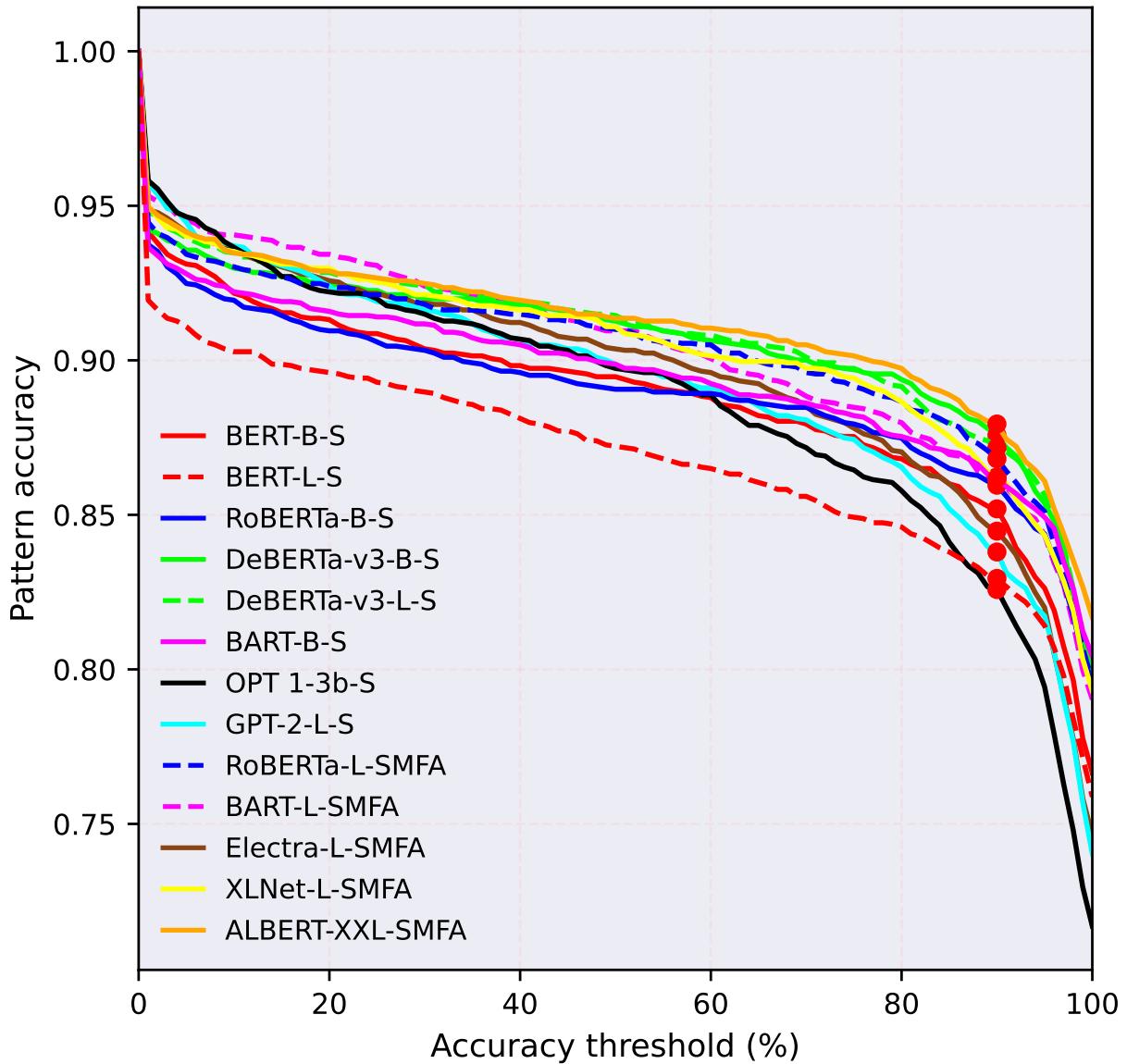


Figure 11: PA scores from threshold 0% for all models on ALL_{Var}. The red dots are PA scores at QT on ALL_{Var}.

Premise	Hypothesis	Label	Original	Suggested	F	R	Explanation
A man in a black shirt, in a detached kitchen, holding up meat he took out of a bag.	A woman in a black shirt, in a detached kitchen, holding up meat he took out of a bag.	C	commercial	detached	5	5	Good: the variant is fluent and preserves reasoning.
A teenage dog is running in a field near a mountain.	A teenage dog is running outdoors.	E	yellow	teenage	5	5	Good: the variant is fluent and preserves reasoning.
A man driving while at a restaurant eating.	A man driving while at a restaurant eating.	N	laughing	driving	4	5	Mostly good: the variant might be likely in a certain scenario (e.g. there might be a restaurant where tables are like cars).
A man is celebrating his victory while smiling and wearing champagne in the air with his teammate.	A man is happily celebrating his victory while smiling and wearing champagne in the air	N	shooting	wearing	3	5	Uncertain: the variant might be likely in a certain scenario (e.g. the man is wearing a champagne-shaped costume), but a less likely one.
A man slung into the ear wearing a striped shirt in a small boat filled with many people.	A man is slung into the ear and wearing a light striped shirt.	N	pointing	slung	2	5	Mostly poor: the scenario is very unlikely, e.g. a man being forced to hear something.
clutched to her ear, a woman bends forward at the side of a busy street.	clutched to her ear, a woman bends forward	E	Phone	clutched	1	5	Poor: the variant is ungrammatical, thus making it difficult to verify its fluency, i.e. missing the theme of 'clutched'.
A hole is on a cherry picker in a palm tree.	A hole falls out of a tree.	C	worker	hole	1	5	Poor: the variant is not fluent, until we consider a very specific metaphorical context, i.e. a hole cannot be have agency.
A shirt booth with a man got a shirt.	The man is got some pants.	C	printing	got	1	4	Mostly Good: the variant is still fluent, despite it being metaphorical, and it is still likely to preserve the initial inference label, despite the ungrammaticality of the hypothesis.
This child is took a pedicure.	Child took a manicure.	C	getting	took	1	3	Uncertain: the ungrammaticality of the premise makes it difficult to assess its fluency, however the main source of the contrast giving the contradiction (i.e. <i>pedicure</i> vs. <i>manicure</i>) is kept.
A brown dog wearing a collar is chasing and running on a red broom.	There is an animal running a broom.	E	biting	running	4	2	Very Poor: Even though 'running a broom' might be running <i>with</i> a broom, running <i>on</i> something does not entail running <i>with</i> X.
Two construction workers produced the steel ribbed exterior of a new building at their work site.	Two workers are produced a building	N	climbing	produced	1	1	Poor: the hypothesis is hard to understand given its ungrammaticality, while the subject of 'produced' is unclear, which makes reasoning impossible to assess.

Table 7: Examples of annotation scores for NLI variants, considering their fluency (**F**) and the preservation of the original NLI label (**R**), alongside explanations for their scores. Note that the labels under Column *Label* are Neutral, Entailment, and Contradiction.

- P:** A man pushing a hand-truck of boxes is bending over to pick up a pear.
H: A happy man is picking up a pear.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A man in a colorful shirt and a lady in a white blouse sign copies of books for people.
H: Two people sign copies of their latest novel.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A black dog is swimming with a ball in his mouth.
H: A black dog found a ball in the water and is bring it back to its owner.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A wet child stands in chest deep ocean water.
H: The child s playing on the beach.
Gold label: E Correct label: N Annotations: E(3) N(1) C(1) Avg rate: 0.00
- P:** A young boy runs across a road in front of a sky blue building with barred windows.
H: A boy runs across a road in front of an abandoned building.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** The man in the brown shirt is holding the hand of the long-haired child in front of a painting.
H: A male has clothes on with his hand holding another young male in front of a painting.
Gold label: N Correct label: N Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** A mom and her boy are riding in a bumper car.
H: The mom and boy are at an amusement park.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A man wearing a blue apron and long rubber boots is dragging a flotation device from a long row of flotation devices.
H: A man in rubber boots and a work apron is rubbing his face in between pulling floating objects.
Gold label: E Correct label: N Annotations: E(3) N(1) C(1) Avg rate: 0.00
- P:** A boy dressed for summer in a green shirt and kahki shorts extends food to a reindeer in a petting zoo.
H: A boy alien dressed for summer in a green shirt and kahki shorts
Gold label: E Correct label: N Annotations: E(3) N(1) C(1) Avg rate: 0.00
- P:** A boy dressed for summer in a green shirt and kahki shorts extends food to a reindeer in a petting zoo.
H: A boy dressed for summer in a tight green shirt and kahki shorts
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A cowboy is showing off his mule next to a horse hauling trailer.
H: A man is showing off his prize winning mule.
Gold label: E Correct label: N Annotations: E(4) N(1) C(0) Avg rate: 0.00
- P:** A female gymnast flies off of the lower bar and is suspended in the air with her feet pointed upward.
H: A gymnast is in mid air.
Gold label: N Correct label: E Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** Two women stand in the street both wearing matching outfits with police like jackets that say Polotie.
H: Two women are dancing in the street wearing dresses.
Gold label: N Correct label: N Annotations: E(0) N(3) C(2) Avg rate: 0.00
- P:** One girl sips a soda while another looks on, standing on a street in front of a bunch of bicycles.
H: A girl drinks a soda on the street in front of people
Gold label: N Correct label: N Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** people standing at a beach with Cameras.
H: A group of people standing at a beach filled with cameras.
Gold label: N Correct label: E Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** A young woman with red-hair is adjusting a blue bracelet on an older woman with short hair.
H: A redhead is putting a bracelet on an old woman.
Gold label: N Correct label: E Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** A person is sitting in front of a graffiti covered wall.
H: A person is sitting outside
Gold label: N Correct label: N Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** A woman holds a newspaper that says "Real change".
H: a woman on a street holding a newspaper that says "real change"
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A happy woman quite stands in front of a business that displays a closed sign and looks very animated.
H: A woman stands by a business.
Gold label: N Correct label: E Annotations: E(2) N(3) C(0) Avg rate: 0.00
- P:** A small child dressed for winter stares across a lake while leaning on a mesh fence in a scenic park setting.
H: A small child dressed for winter stares across a large lake while leaning on a mesh fence
Gold label: E Correct label: N Annotations: E(4) N(1) C(0) Avg rate: 0.00
- P:** Bearded black dressed male performer is displaying his skill by swinging a fire line in each hand in arcs.
H: A sideshow man in a black costume is performing a trick with fire for the audience.
Gold label: E Correct label: N Annotations: E(4) N(1) C(0) Avg rate: 0.00
- P:** Two women competing in a roller derby with several teammates and referee in the background.
H: Two roller derby competitors skate quickly ahead of teammates.
Gold label: E Correct label: N Annotations: E(3) N(2) C(0) Avg rate: 0.00
- P:** A young man blew up balloons to craft into animals for the seven excited children that looked on.
H: The children watch the man make dogs and giraffes out of balloons

Gold label: E	Correct label: N	Annotations: E(3) N(2) C(0)	Avg rate: 0.00
P: The man is trying to make a pottery that he can market soon.			
H: An old man is making pottery to sell.			
Gold label: E	Correct label: E	Annotations: E(3) N(2) C(0)	Avg rate: 0.00
P: Two dirt bike riders, one wearing green and the other wearing blue and white, are jumping a hill.			
H: Two dirt bike riders are outside			
Gold label: N	Correct label: N	Annotations: E(2) N(3) C(0)	Avg rate: 0.00
P: A train conductor in coveralls is standing in the door of the train.			
H: The conductor is walking in a field.			
Gold label: N	Correct label: N	Annotations: E(0) N(3) C(2)	Avg rate: 0.00
P: An older gentleman looks at the camera while he is building a deck.			
H: An older gentleman in overalls looks at the camera while he is building a stained red deck in front of a house.			
Gold label: E	Correct label: N	Annotations: E(3) N(2) C(0)	Avg rate: 0.00
P: Children, including one with a painted face, pet tiny turtles that are crawling in the green grass.			
H: Turtles are crawling in the white grass.			
Gold label: E	Correct label: N	Annotations: E(3) N(0) C(2)	Avg rate: 0.00
P: A young man waits on a bench with his bag behind a few advertisements in London.			
H: A young man waits outdoors in London on a bench.			
Gold label: N	Correct label: N	Annotations: E(2) N(3) C(0)	Avg rate: 0.00
P: A group of people are in a rowboat in the ocean surrounded by seagulls.			
H: A bunch of people are in a wooden object on the water.			
Gold label: N	Correct label: N	Annotations: E(2) N(3) C(0)	Avg rate: 0.00
P: A man in a hard hat looks intimidated.			
H: He is working in a potentially dangerous field that requires a hard hat.			
Gold label: E	Correct label: N	Annotations: E(4) N(1) C(0)	Avg rate: 0.00

Table 10: The original SNLI Problems whose variants were most poorly classified by the NLI models. **Avg rate** represents the average accuracy of NLI models across all variants per seed/original problem. **Annotations** reports the annotation labels of 5 annotators from the SNLI data, where the gold label is selected based on the majority voting. **Corrected label** is an inference label the authors think is correct. We are aware of the inherent disfigurements in NLI labeling (Pavlick and Kwiatkowski, 2019), especially in SNLI, but we dub our corrected labels as the most likely label.