Examining Single Sentence Label Leakage in Natural Language Inference Datasets

Michael Saxon, Xinyi Wang, Wenda Xu, William Yang Wang
University of California, Santa Barbara
Department of Computer Science
saxon@ucsb.edu, xinyi_wang@ucsb.edu, wendaxu@ucsb.edu, william@cs.ucsb.edu

Abstract
Many believe human-level natural language inference (NLI) has already been achieved. In reality, modern NLI benchmarks have serious flaws, rendering progress questionable. Chief among them is the problem of single sentence label leakage, where spurious correlations and biases in datasets enable the accurate prediction of a sentence pair relation from only a single sentence, something that should in principle be impossible. This leakage enables models to cheat rather than learn the desired reasoning capabilities, and hasn’t gone away since its 2018 discovery. We analyze this problem across 10 modern NLI datasets, and find that new datasets have a single sentence accuracy of 8% over chance at best and 19% on average. We examine how regular NLI models cheat on this data and discuss how to ameliorate this.

1 Introduction
Natural language inference (NLI) is a fundamentally pairwise task, wherein a logical relation between two statements is predicted. Progress on NLI benchmarks is an important part of tracking advancements of machine reasoning in language. Unfortunately many modern NLI datasets exhibit single sentence label leakage—models can predict the pairwise relation using only one of the sentences at alarmingly high rates (Poliak et al., 2018). This is a serious problem for any dataset intended to capture reasoning ability, as single sentence label leakage, in principle, contradicts the pairwise nature of NLI as a task.

NLI is formalized as predicting a relation \( r \in \{\text{neutral, entail, contradict}\} \) from a pair of sentences (premise \( s_1 \) and hypothesis \( s_2 \)). An ideal NLI benchmark without single sentence label leakage will have distribution of \( r \) that is conditionally dependent on the pair of sentences, but independent from either sentence individually (Wang et al., 2021c). In practice this is difficult to achieve, particularly when constructing usefully large datasets.

Most large-scale NLI datasets are produced by first sourcing seed sentences from an existing text population to serve as initial premises or hypotheses. Then they can either be assigned other seed sentences, and labelled with relations by annotators, or assigned a relation, which a crowdworker uses to write a new elicited sentence that satisfies the desired relation relative to the seed. Many elicited datasets assign seeds to either exclusively be premises, or exclusively be hypotheses.

In this condition, eliminating leakage from the seed sentence distribution is trivially easy—simply produce three elicited sentences for each seed, one for each relation. However, this approach tends to produce undesired side-information about the relation in the elicited sentences. Systematic, shared
biases in the words, sentence structures, or ideas that crowdworkers consider when instructed to generate a sentence given a logical relation drive this relation leakage (Gururangan et al., 2018). For example, a slight preference for non-sequitur topics for neutral sentences, or words like “not,” “isn’t,” and “doesn’t” when given contradict as opposed to entail, might become leakage features in training sets which lead to brittle NLI models. Simple heuristics inspired by these findings can produce challenging test sets that hobble models trained on these biased datasets (McCoy et al., 2020).

These “leakage features” encoded in the elicited sentences are visible to NLI models (Zhang et al., 2019), enabling them to “cheat” instead of replicating logical reasoning, calling into question the appropriateness of NLI datasets as benchmarks for language understanding (Bowman and Dahl, 2021).

In this work we rigorously analyze this problem of single sentence relation leakage in both popular and recent NLI datasets using novel techniques to enable targeted interventions and create higher quality future resources.

Further NLI datasets have been proposed to tackle these problems using machine-in-the-loop adversarial sentence elicitation, (Nie et al., 2019), counterfactual augmentation (Kaushik et al., 2020), and learning dynamic-based debiasing (Wu et al., 2022). These datasets are purported to provide more challenging generalization scenarios for NLI models to better test logical reasoning capabilities. One big question remains—have these techniques actually eliminated relation leakage biases?

In this work, we demonstrate the following:

- **Label leakage remains a problem.** We compare elicited-only performance for 10 modern NLI datasets (including those previously assessed by Poliak et al. (2018)) using a simple transformer baseline, finding that single sentence relation leakage remains a severe problem for NLI.

- **NLI models still use these features to cheat.** We analyze the datasets using output decision agreement and input token importance statistics between models for in the elicited-only and normal conditions to demonstrate this.

- **Automated leakage bias detection is feasible.** We introduce a novel model-based metric and dataset analysis tool, the Progressive Evaluation of Cluster Outliers (PECO) (Figure 1), for examining the degree of single sentence relation leakage and potentially eliminating it in future datasets.¹

### 2 Quantifying NLI Dataset Bias

An ideal NLI benchmark is neither saturated nor biased. **Saturated** benchmarks are datasets for which current approaches already achieve high accuracy. They are “solved” and have limited utility in tracking future progress (Bowman and Dahl, 2021). **Biased** NLI benchmarks exhibit significant single-sentence relation leakage for at least one sentence class.

According to these two characteristics we analyze 10 datasets containing a total of 14 test or validation sets in which this bias can be analyzed, across 17 conditions of either premise-only ($s_1$) or

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¹Code at github.com/michaelsaxon/DatasetAnalysis
hypothesis-only ($s_2$) biased single sentence conditions. Table 1 provides an overview of this information along with statistics such as train/dev/test set size, and which sentence population is potentially unbalanced.

Each dataset $D$ is composed of $(s_1, s_2, r)$ tuples. We use the standard notation $(X, Y) \leftarrow D$ to describe the samples, as depending on whether the training condition is standard two-sentence or single sentence, each $X_i$ can be $(s_{1i}, s_{2i})$, $s_{1i}$, or $s_{2i}$. Models trained in condition $c$ are referred to as $f_c$.

### 2.1 Saturation and Bias Scoring

We assess accuracy on the test set (or val set when no labeled test set is available) for each dataset in standard and single-sentence conditions.

**Saturation (Accuracy):** We report state-of-the-art (SOTA) model performance results using publicly available benchmark tracking sites.

$$A_{SOTA}(D) = P(f_{SOTA}(X_{test}) = Y_{test}); \quad X, Y \in D \quad (1)$$

Additionally, we train our own transformer-based replication models using a simple procedure described in Sec. 2.4 to assess replication accuracy,

$$A_{Ours}(D) = P(f_{Ours}(X_{test}) = Y_{test}); \quad X, Y \in D \quad (2)$$

**Biased Cond. Accuracy:** For each potential single-sentence label leakage population (biased condition) we train a model $f_{bias}$ according to the procedure described in Sec. 2.4.2

$$A_{bias}(D) = P(f_{bias}(X_{test}) = Y_{test}); \quad X, Y \in D \quad (3)$$

Table 2 shows current SOTA models and results for the 10 datasets, as well as our replication model performance and the relevant training hyperparameters (more detail in Sec. 2.4). Figure 2 shows bias condition accuracy against replication (standard NLI condition) accuracy for each dataset. Datasets that exhibit higher biased condition accuracy have worse single sentence relation leakage, and are thereby questionable in their ability to capture reasoning abilities. Ideally, an optimal benchmark for NLI will both have low maximum biased condition accuracy and low maximum replication accuracy (room for future model growth).

These absolute measures of dataset bias and sat-
We assess two relative dataset bias scores. These results clearly show that each dataset exhibits significant single-sentence relation leakage across the 17 biased condition tests on the 14 splits for the 10 NLI datasets. These results clearly show that each dataset exhibits significant single-sentence relation leakage for at least one condition. The comparison columns replication test recovery (%R_R) and biased condition improvement over the chance majority guessing strategy (Δ_maj) are all computed using the single-sentence condition accuracy and the standard NLI two-sentence condition SOTA and replication accuracy values in Table 2.

2.4 Model Training

We additionally perform a grid search over learning rates in {5e–7, 1e–6, 5e–6, 1e–5, 5e–5}. For each dataset in the standard two-sentence NLI classification condition, we select a batch size for maximum GPU utilization. We obtain separate fine-tuning checkpoints from the pretrained models consistently to all datasets. We fine-tune three different language-specific pretrained transformer checkpoints^2 from HuggingFace (Wolf et al., 2019) using Pytorch Lightning. All models were trained on NVIDIA A-100 GPUs. All models are the HuggingFace xForSequenceClassification with num_classes=3 and no other modifications. All models are trained using the Adam optimizer with cross entropy loss.

We find that this procedure produces broadly near-SOTA performance models, with a maximum relative accuracy difference of 8%, and a 92% Pearson’s correlation coefficient (PCC) between SOTA and replication accuracy across the datasets (Figure 3). Our replications are a reasonable proxy to SOTA for comparative dataset analysis.

2.4.1 Replication Training Details

| Dataset  | Cond. | Biased | %R_R | Δ_maj |
|----------|-------|--------|------|-------|
| SICK     | s2    | 60.0   | 68.3 | 4.0   |
| SNLI     | s2    | 71.6   | 79.0 | 37.8  |
| MNLI-b   | s2    | 59.8   | 67.4 | 24.2  |
| MNLI-u   | s2    | 60.9   | 69.0 | 24.4  |
| XNLI     | s2    | 55.0   | 74.6 | 21.7  |
| FEVER    | s1    | 63.5   | 85.0 | 30.2  |
| ANLI     | s2    | 48.2   | 89.3 | 14.7  |
| ~A1      | s2    | 67.5   | 82.4 | 17.6  |
| ~A2      | s2    | 82.1   | 96.2 | 14.7  |
| ~A3      | s2    | 90.1   | 96.6 | 14.6  |
| OCNLI    | s2    | 61.5   | 85.7 | 24.7  |
| CAugNLI  | s1    | 41.9   | 49.5 | 8.0   |
|          | s2    | 39.0   | 46.0 | 7.1   |
| SNLI_debiased | s1 | 45.3   | 45.3 | 2.9   |
|          | s2    | 65.3   | 68.3 | 29.8  |
| MNLI_debiased | s1 | 34.0   | 35.6 | -2.2  |
|          | s2    | 57.1   | 58.9 | 20.9  |

Table 3: For each NLI dataset and potential leakage-exhibiting single-sentence condition (Cond.) we report test accuracy in the single sentence condition (Biased), and three derived metrics from Sec. 2.1. SOTA test accuracy recovery (%R_R), replication test recovery (%R_R), and biased condition improvement over the chance majority guessing strategy (Δ_maj).

We find that this procedure produces broadly near-SOTA performance models, with a maximum relative accuracy difference of 8%, and a 92% Pearson’s correlation coefficient (PCC) between SOTA and replication accuracy across the datasets (Figure 3). Our replications are a reasonable proxy to SOTA for comparative dataset analysis.

2.4.1 Replication Training Details

Hyperparameters For each dataset in the standard two-sentence NLI classification condition, we select a batch size for maximum GPU utilization. We additionally perform a grid search over learning rates in {5e–7, 1e–6, 5e–6, 1e–5, 5e–5}.

Single Dataset Fine-tuning We obtain separate fine-tuning checkpoints from the pretrained models.

Figure 3: Test set accuracy for SOTA models vs our universal replication procedure models for each dataset, with a trendline (PCC=0.97) and y = x line.
for each dataset to enable clean analysis of one dataset at a time. We do not accumulate fine-tuning passes across multiple datasets.

2.4.2 Biased Condition Training
To train each dataset’s corresponding bias condition(s) model, we use the same setup as the replication model but follow Poliak et al. (2018)’s formulation of fine-tuning the chosen classification model on only the bias condition sentence, premise only or hypothesis only.

FEVER exhibits bias in the premise distribution, and CAugNLI, SNLI\textsubscript{debiased}, and MNLI\textsubscript{debiased} exhibit imbalance in both (Table 1). For the datasets that have imbalanced distributions in both conditions, we separately train bias models for both hypothesis-only and premise-only.

3 Analyzing NLI Dataset Bias
In this section we introduce quantification techniques for more accurately characterizing the extent of these bias problems in the aforementioned NLI datasets, analyze how they interact with the observable bias itself, and develop tools for producing future NLI benchmarks that more closely resemble the ideal benchmark.

3.1 Sample-level Model Behavior
We are particularly interested in understanding the degree to which models trained in the normal and biased conditions “reason” similarly. For this section we use the notations \( f(X_{\text{test}}), Y_{\text{test}} \) to denote the \((1 \times N)\) column vectors of model output decisions and labels for a test set of \(N\) samples, and a simple agreement function \(Ag(Y_1,...,Y_n)\) as the ratio of elements that are identical across all \(Y_i\) to the vector size \(N\). In other words,

\[
Ag(f(X_{\text{test}}), Y_{\text{test}}) = P(Y_{\text{test}} = f(X_{\text{test}})) \quad (6)
\]

Normal-Bias Agreement: The total number of samples for which the biased and normal models agree over the total number of samples in the set:

\[
\text{NBA} = \frac{Ag(f_{\text{bias}}(X_{\text{test}}), f_{\text{Ours}}(X_{\text{test}}))}{|X_{\text{test}}|} \quad (7)
\]

Normal-Bias Recovery: The total number of samples for which the biased and normal models agree, and both classify correctly over the total number of samples they agree on:

\[
\text{NBR} = \frac{Ag(f_{\text{bias}}(X_{\text{test}}), f_{\text{Ours}}(X_{\text{test}}), Y_{\text{test}})}{Ag(f_{\text{bias}}(X_{\text{test}}), f_{\text{Ours}}(X_{\text{test}}))} \quad (8)
\]

Token Relevance Agreement: For a single sentence \(X\) with length \(n\), we compute the gradient of the classification output respect to each token embedding \(emb(w)\). We take the 2-norm of the each gradient vector and normalized it over the entire sequence to produce a normalized local explanation vector \(m(f(X))\) (Sundararajan et al., 2017):

\[
m(f,X) = \left[\frac{\|\nabla_{\text{emb}}(f(\text{emb}(w)))\|_2}{\sum_{j=1}^n \|\nabla_{\text{emb}}(f(\text{emb}(w)))\|_2}\right]^{n} \quad (9)
\]

To compare “reasoning” similarity between the two models, we compute the samplewise input token relevance agreement can be computed using cosine similarity:

\[
\text{TRA}(X_i) = \frac{m(f_{\text{Ours}}, X_i) \cdot m(f_{\text{bias}}, X_i)}{||m(f_{\text{Ours}}, X_i)|| ||m(f_{\text{bias}}, X_i)||} \quad (10)
\]

As the bias condition model only considers a single sentence, we pad the bias condition importance vector for \(m(f_{\text{bias}}(X_i))\) with zeros either prepended or postpended (depending on if the bias condition is hypothesis- or premise-only) to make the two local explanation map vectors of equal length. The dataset-level token relevance agreement is the average of samplewise TRA.

3.2 Cluster-based Bias Evaluation
We are interested in investigating how the biased distributions of the elicited sentences in NLI datasets are captured in the learned representation spaces of models trained on them. In particular, we are interested in answering this question: is elicited sentence label leakage captured semantically in regions of latent space?

To answer this we produce dimensionality-reduced elicited sentence embeddings for the test set, using the normal condition replication models, then fit a high-\(k\) KNN clustering to this collection of embeddings. This will allow us to analyze how the local distribution of labels varies over the elicited sentence embedding space. By comparing the L2-divergence of the label distribution within each cluster and the global label distribution, we can compute the Progressive Evaluation of Cluster Outliers (PECO) score (Figure 4).

Elicited Sentence Embeddings: To embed the elicited sentences as they’re learned by a model in the standard condition, we feed the elicited sentences \(s_e\) through the normal replication fine-tuned
Figure 4: An overview of the approach to computing the PECO score from a collection of elicited population sentences $s_{\text{elicited}}$ and their corresponding Labels $r$. When a fixed threshold is chosen, the Hypothesis embeddings can be dimensionality-reduced using T-SNE to produce plots like Figure 1.

NLI model encoder. We extract the latent codes produced at the output very last fully connected layer of the model before the linear classifier to collect latent codes for every $s_i$ in the test set. We then embed these codes into their 30 principal components to produce the embeddings (Figure 4 (a)).

Clustering: We fit a high-k (in this case, $k = 50$) k-means clustering over the distribution of elicited sentence embeddings to provide a set of local bins for analysis. For each cluster, we count the relation labels its samples contain, to produce a set of 50 cluster-label distributions (Figure 4 (b)).

Computing Cluster Divergences: For each cluster label distribution $p_i = P(Y|\text{cluster} = i)$, we assess the L2 divergence between it and the global label distribution $p_G$ to produce divergence scores $s_i$:

$$s_i = \frac{1}{3} \sum_{j=1}^{3} (P(Y = j) - P(Y = j|\text{cluster} = i))^2$$  \hspace{1cm} (11)

This step is depicted in Figure 4 (c).

Progressive Evaluation: Finally, we compute the PECO score for this collection of cluster divergences as the area under the curve produced by counting the number clusters with divergence $s_i$ over some threshold $t$ for the range of $s_i$.

$$\text{PECO} = \int_{\text{min}(s)}^{\text{max}(s)} \text{count}(s_i > t) dt$$  \hspace{1cm} (12)

Generality of PECO: These same techniques could be applied to a wide variety of potential leakage features on the input to analyze a wide variety of correlation types. For example, input sentence words could be shuffled to test for word order invariance, or word classes could be specifically masked to test for spurious vocabulary correlations.

4 Results

As discussed above, ideal NLI benchmarks are neither saturated nor biased. Unfortunately, as Table 3 demonstrates, none of the NLI datasets tested thus far satisfy this condition. This is more clearly illustrated in Figure 2. Two questions remain: to what extent do current models cheat and how can we make less biased, less saturated datasets? Table 4 contains experimental results intended to answer these two questions. The “agreement metrics” as introduced in Sec. 3.1, Normal-Bias Agreement (NBA) and Recovery (NBR), Token Relevance Agreement (TRA) and the Progressive Evaluation of Cluster Outliers (PECO) score.

Table 4: Metrics comparing the behavior of our replication and single-sentence condition models on each dataset using the metrics introduced in Secs. 3.1, 3.2: Normal-Bias Agreement (NBA) and Recovery (NBR), Token Relevance Agreement (TRA) and the Progressive Evaluation of Cluster Outliers (PECO) score.

![Figure 5: Model-wise output agreement vs Bias accuracy recovery (\%R$^2$). As the replication normal condition model and the biased condition model agree more often for a given dataset, their performances in the two conditions tends to converge. (PCC=0.69)](image-url)
4.1 Result-Metric Correlations

We find that normal-biased model output agreement (NBA) and bias recovery rate \( R^2 \) are positively correlated with a PCC of 0.69 (Figure 5). In other words, the more the models in the biased single-sentence condition and the standard two-sentence NLI condition agree for a dataset, the narrower the performance gap between the relation prediction accuracy of these two models is.

On its own, this result is vaguely suggestive of reasoning similarities between models in the two conditions, but it has limitations. \( R^2 \) takes the ratio between two variables (bias condition accuracy and replication condition accuracy) that are both ideally low. Relying on this ratio alone is thus problematic because relatively desirable datasets (low bias, low saturation) and undesirable ones (high bias, high saturation) can both have similar \( R^2 \) ratios. Additionally, models agreeing more frequently on their output values (NBA) do not necessarily arrive at the same conclusions for the same reasons. To disentangle this phenomenon, we compare token relevance agreement (TRA) with biased condition accuracy directly.

We find that TRA and single sentence biased condition accuracy are also positively correlated with a PCC of 0.57 (Figure 6). This result demonstrates that for a single dataset, similar reasoning patterns for the single sentence condition and standard sentence pair condition are strongly correlated to single-sentence relation leakage. In other words, standard condition NLI models trained on biased (high leakage) datasets tend to cheat. This result strengthens Gururangan et al. (2018)'s finding that models rely on annotation artifacts in NLI datasets to achieve high accuracy, and demonstrates that this continues to be a problem in newer NLI datasets, in spite of mitigation attempts. How can we use this knowledge to build better benchmarks?

Figure 7 depicts the relationship between PECO score and bias recovery (%\( R^2 \)). We find the two are positively correlated with a PCC of 0.64. This result is fairly intuitive: the more uneven the distribution of labels is in the single-sentence latent spaces (and thus, the higher the area under the PECO curve), the more bias condition performance approaches the standard two-sentence condition performance for a given NLI dataset. This suggests PECO-reducing interventions may be able to target debiasing efforts.

5 Discussion

Relation Leakage Remains a Problem.

Elicited sentence relation leakage is a problem for all evaluated NLI datasets, including the newer ones intended to fix it. Even datasets that have gone undiscussed in prior NLI debiasing work, such as XNLI, FEVER, and OCNLI, exhibit high absolute bias condition performance over majority (\( \Delta_{maj} > 20 \)).

Although ANLI (Nie et al., 2020) and CAugNLI (Kaushik et al., 2020) are improvements over the others in terms of \( \Delta_{maj} \), with CAugNLI shining particularly in this regard, none eliminate the relation leakage problem entirely, as even CAugNLI still has \( \Delta_{maj} = 8.0 \), an 8% performance over chance in the single sentence condition.

SNLI\(_{debiased}\) and MNLI\(_{debiased}\), which were designed to not contain single sentence label leakage,
still contain significant amounts (29.8% and 20.9% over chance respectively). This might be because while their production (Wu et al., 2022) does eliminate bias originally present in SNLI and MNLI, it fails to prevent the introduction of new bias in the data generation pipeline.

**Some examples are only correctly classified in the single-sentence condition.** A common assumption to discussions of cheating features in machine learning is that they play a role in inflated classification accuracy when present. However, ANLI R3 provides an interesting counterexample. For this dataset, the hypothesis sentence only model achieves a biased condition accuracy of 48.1%, and the replication model achieves 49.8% (a %R of 90%), and SOTA achieves 53%. Despite this overall score similarity, the samples which the two conditions are able to actually classify correctly vary surprisingly. With an A3 NBR of 58.5%, only approximately 27% of test samples are correctly classified by both the single and two sentence condition models. This means that around 21% of samples in A3 test are only correctly classified by the single-sentence model.

Perhaps unsurprisingly, ANLI exhibits the lowest TRA out of all datasets tested, indicating that it is somewhat of an outlier in having the biased and normal condition models reason differently on it.

**XNLI demonstrates the cross-lingual and semantic nature of single-sentence leakage.** While previous work has focused on finding words, phrases, patterns, and heuristics in the surface form of the data, our study of XNLI provides an interesting opportunity to investigate the potential for the influence of underlying semantics as a leakage feature. XNLI consists exclusively of 14 language test and val sets, manually translated from MNLI examples. Our XNLI replication and bias condition models are thus trained on MNLI alone, using the multilingual xlm-roberta checkpoint.

This produces a natural experiment wherein surface form biases present in the training data are completely eradicated in the test set (as only the 14 non-English languages Table 1 are present), while the underlying meanings encoded by those words remain. In Table 3 we indeed find that XNLI and MNLI exhibit very similar result comparisons. The models on both datasets have a $\Delta_{\text{max}} \approx 20\%$ and $\%R_S \approx 65\%$. These leakage feature results, being robust to manual translation into 14 different languages, seem to indicate that there is a strong fundamental semantic component to the human biases driving the elicited sentence relation leakage.

**Cluster approaches are promising for future debiasing efforts.** Figure 1 shows how the PECO-derived cluster-bias T-SNE plots can be used directly to visualize, analyze, and “debug” biased datasets. In the plot, SNLI clearly has considerably more high-biased clusters taking up a considerable portion of the latent space as compared to CAugNLi, for the bias threshold of 0.2.

An intervention could be performed on identified bias regions in the distribution by having human annotators create new premise sentences from the given hypotheses, thereby forcing the PECO-based bias metrics to reduce. This idea is further backed up by the PCC of 35.8 that we find between PECO and %R, suggesting that producing datasets of lower PECO score will naturally lead to lower recovered performance in the biased condition, and thus less elicited sentence relation leakage.

### 6 Related Work

Huang et al. (2020) have already demonstrated that the counterfactual augmentation process alone is not sufficient to produce models that generalize better than unaugmented dataset. Multi-task learning (such as by larger, more diverse NLI datasets) can improve model robustness to fitting to spurious features (Tu et al., 2020), by essentially overwhelming model capacity to fit to all the various bias patterns available. However, significant single sentence label leakage in the NLI benchmarks these are being demonstrated on render claimed progress on the desired reasoning capability questionable (Poliak et al., 2018). Other techniques for studying issues of dataset bias include geometric complexity and n-Gram entropy (McKenna et al., 2020), dataset cartography (Swayamdipta et al., 2020), and producing difficult test sets (Gururangan et al., 2018; Saxon et al., 2021).

### 7 Conclusion

In the four years since (Poliak et al., 2018) single sentence relation leakage bias has proven to remain a difficult issue. Efforts to debias NLI have led to datasets that merely exhibit different kinds of bias than those shown before, or less saturated benchmarks that continue to exhibit cheating features. Future work must prioritize reducing observable bias directly using a model-driven approach.
8 Ethics and Limitations

In the short term, progress toward better natural language inference does not appear to lead to significant social risks in its broader impacts. While “underclaiming” progress in natural language processing tasks (e.g. exaggerating the scope or severity of failures of specific models on specific tasks) (Bowman, 2021) may be enabled by this work in the future, our focus on directly quantifiable and observable single sentence leakage, use of SOTA-like models (fine-tuned transformers) for analysis, and our side-by-side comparison of our model implementations with SOTA all ensure that our criticisms of current NLI benchmarks are well-founded. All data and tools we utilized were freely distributed for unlimited research use in the academic context.

Our work is limited primarily by the PECO’s reliance on test-set classification. To successfully analyze the train set-only datasets of SNLI debiased and MNLI debiased, we had to generate our own train/test splits over the data by sampling. Luck in split selection may play a role in the level of observable bias in cases like these. Furthermore, this reliance on observing held-out samples to understand bias in general means that interventions to reduce single sentence label leakage must apply costly multi-fold splitting and analysis, consuming more significant compute resources than would otherwise be needed for other model-driven approaches.

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A Detailed Dataset Info

SICK Sentences Involving Compositional Knowledge (Marelli et al., 2014) was produced by instructing annotators to label existing sourced pairs from 8K ImageFlickr data set (Young et al., 2014) and SemEval 2012 STS MSR-Video Description data set (Agirre et al., 2012). The dataset is in English. Each sentence pair was annotated for relatedness and entailment by means of crowdsourcing techniques.

SNLI The Stanford NLI dataset was produced using (Bowman et al., 2015). The corpus contains content from the Flickr 30k Corpus (Young et al., 2014), VisualGenome corpus (Krishna et al., 2017) and Gururangan et al. (2018). The corpus is in English. The dataset is collected through human-written English sentence pairs.

MNLI The Multi-genre NLI Corpus (Williams et al., 2018) is modeled on the SNLI corpus (Bowman et al., 2015) but it differs in the range of genres of spoken and written English text supporting cross-genre evaluation.

XNLI The Cross-Lingual NLI Corpus (Conneau et al., 2018) consists of manually-translated dev and test samples from MNLI in 14 languages: French, Spanish, German, Greek, Belgian, Russian, Turkish, Arabic, Vietnamese, Thai, Chinese, Hindi, Swahili, and Urdu. It is interesting for analysis because on a high level the semantics of the data follow MNLI. The corpus is made to evaluate the inference in any language when only English data is presented at training time.

FEVER NLI-style FEVER (Nie et al., 2019) is an NLI reformulation of the FEVER claim verification dataset (Thorne et al., 2018). The original dataset was collected by eliciting annotators to write fact sentences that are supported, refuted, or unverifiable relative source passages drawn from Wikipedia. This is converted into an NLI task by treating the elicited sentences as premises and the source passages as NLI pairs with relations entail, contradict, or neutral respectively. This dataset is unique in that the premises were elicited from seed hypotheses, meaning it has a balanced hyp. distribution but potentially biased prem. distribution.

ANLI The adversarial NLI corpus (Nie et al., 2020) is collected through crowdworkers and the purpose of this dataset creation is to make the state-of-art results fail in this dataset. The sentences are selected from the Wikipedia and manually curated HotpotQA training set (Yang et al., 2018). The
language is in English. It contains three partitions of increasing complexity and size, which we refer to hereafter as A1, A2, and A3. Detailed data statistics are in Table 1.

**OCNLI** The Original Chinese NLI corpus was collected following MNLI-procedures but with strategies intended to produce challenging inference pairs (Hu et al., 2020). No translation was employed in producing this data; the source premise sentences and elicited hypotheses are original.

**CAugNLI** Kaushik et al. (2020) produced counterfactually augmented datasets for NLI and sentiment analysis using human annotators, instructing them to make minimal changes to the sentences beyond those necessary to change the label. It extends the work of Maas et al. (2011) and Bowman et al. (2015). They find that a BiLSTM classifier achieves negligible performance over chance when trained on hypothesis only. However, since their dataset includes elicited modified sentences in both the premise and hypothesis populations, there are opportunities for bias on both.

**CAugNLI** was produced by having human annotators minimally modify either the premise or hypothesis of 2,500 samples drawn randomly from SNLI so as to produce new samples with similar structure and word distributions but different meanings. These modifications are intended to reduce spurious correlations, in particular by roughly equalizing the distribution of relation labels with respect to word-level and semantic-level patterns in the elicited hypothesis sentences.

**SNLI debiased and MNLI db** are augmentations of the SNLI and MNLI train sets produced by training GPT-2 (Radford et al., 2019) generators on them, and then generating samples which they check for accuracy using a pretrained RoBERTa NLI classifier, and then reject if they exhibit spurious correlations including samplewise hypothesis-only model classifiability (Wu et al., 2022). To do this they first train static hypothesis-only SNLI and MNLI models, and reject all generated samples that can be successfully classified hypothesis-only by them. However, beyond this test under a static hypothesis-only distribution they do not attempt to assess if their generator models introduce new leakage features in the sentence distributions as a result of their accuracy filtering process. To test this we create test splits on the data (as they provide train sets only) which contain no sentence overlap with the train sets through random sampling.