Analyzing and Mitigating Dataset Artifacts in Natural Language Inference through Adversarial Filtering

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Abstract

Pre-trained language models often achieve impressive performance on benchmark datasets, but recent work suggests they may be exploiting spurious correlations—dataset artifacts—rather than learning genuine semantic reasoning. We investigate this phenomenon in the Stanford Natural Language Inference (SNLI) dataset using ELECTRA-small. Through hypothesis-only baseline analysis, we discover that models can achieve 68.4% accuracy on SNLI without ever seeing the premises, revealing significant artifacts in the dataset. We identify specific word-level artifacts (e.g., "there" for entailment, "sitting" for contradiction) and propose an adversarial filtering approach that removes artifact-driven examples by training on a hard subset where the hypothesis-only model fails. Our approach successfully reduces artifact reliance—we observe 52-68% reductions in attention to artifact words through saliency map analysis—and improves reasoning on critical cases. We evaluate on both SNLI and MultiNLI to assess in-domain and cross-domain performance.

1 Introduction

Natural Language Inference (NLI) requires models to determine whether a hypothesis can be logically inferred from a premise. Models achieve impressive accuracy on benchmark datasets like SNLI (Bowman et al., 2015), but recent work suggests they may exploit dataset artifacts—spurious correlations between surface-level features and labels—rather than learning genuine semantic reasoning (Poliak et al., 2018).

The hypothesis-only baseline provides striking evidence: Poliak et al. (2018) showed that a model trained only on hypotheses (with premises removed) can achieve high accuracy on SNLI. In our experiments, this baseline achieves 68.4% accuracy—well above random chance (33%)—suggesting that many examples can be solved using hypothesis-only heuristics.

In this work, we investigate and mitigate dataset artifacts in SNLI. We analyze word-level patterns that serve as shortcuts, then propose an adversarial filtering approach: we train a hypothesis-only model to identify artifact-driven examples, and remove those examples from our training set, forcing the model to learn from a "hard subset" that requires genuine premise-hypothesis reasoning.

Our contributions are: (1) we analyze word-level artifacts in SNLI, identifying top artifact words for each label class; (2) we propose an adversarial filtering approach that removes examples solvable by hypothesis-only baselines, reducing the training set by 68%; (3) we provide comprehensive evaluation using quantitative metrics and gradient-based saliency maps, showing that our approach successfully reduces artifact reliance and improves reasoning on critical cases.

2 Related Work

Poliak et al. (2018) first demonstrated the hypothesis-only baseline phenomenon, showing that models can achieve substantial accuracy by learning patterns in hypotheses alone. Gardner et al. (2020) introduced contrast sets to evaluate model robustness, while Ribeiro et al. (2020) proposed CheckList, a behavioral testing framework for identifying model failures.

Our approach uses adversarial filtering, identifying and removing artifact-driven examples from training data. This is conceptually related to dataset cartography but uses hypothesis-only model failures as a direct proxy for genuine reasoning requirements.

3 Methodology

3.1 Baseline Model

We begin by establishing a strong baseline model. We fine-tune ELECTRA-small (Clark et al., 2020)

on the full SNLI training set (549,367 examples) for 3 epochs using the HuggingFace Transformers library. We use a batch size of 32, learning rate of 2e-5, maximum sequence length of 128 tokens, and standard AdamW optimizer with linear warmup. The model achieves 87.6% accuracy on the SNLI validation set (9,842 examples), which is comparable to reported baselines and confirms that the model is learning effectively from the training data.

However, as we will show, this high accuracy may be misleading—the model may be learning shortcuts rather than genuine reasoning.

3.2 Artifact Analysis

3.2.1 Hypothesis-Only Baseline

To identify artifacts, we train what we call a "hypothesis-only" model. This model is identical to our baseline in architecture and hyperparameters, but during both training and evaluation, we replace all premises with empty strings. The model sees only hypotheses, yet it must still predict the correct label. This is a diagnostic tool: if the model can achieve high accuracy without seeing premises, it must be learning patterns in the hypotheses themselves that correlate with labels—these are the artifacts we seek to identify.

The results are striking: this hypothesis-only model achieves 68.4% accuracy on SNLI validation. This is well above random chance (33% for three classes) and alarmingly close to the full model's performance. This confirms that a substantial portion of SNLI examples can be solved using hypothesis-only heuristics, suggesting that models trained on full premise-hypothesis pairs may be learning these shortcuts rather than true inference capabilities.

3.2.2 Word-Level Artifact Identification

To understand what specific patterns the hypothesis-only model is learning, we analyze the most frequent words in hypotheses for each label class. We tokenize all hypotheses, filter out common stop words (e.g., "a", "the", "is", "are"), and count word frequencies separately for Entailment, Neutral, and Contradiction labels. Table 1 shows the top artifact words:

Label	Top Artifact Words
Entailment	people, outside, there, men, an
Neutral	for, people, his, her, men
Contradiction	people, sitting, his, men, girl

Table 1: Top artifact words by label class in SNLI hypotheses

These words serve as powerful shortcuts. For example, the word "there" appears frequently in entailment hypotheses, making it a strong signal for entailment. Similarly, "sitting" is strongly associated with contradictions, creating a strong association. The word "people" appears frequently across all classes, suggesting it's less discriminative, but still appears in the top words due to its overall frequency.

Interestingly, we see some words appearing across multiple classes (e.g., "people", "men", "his"), which suggests that context matters—the same word can serve as an artifact in different ways depending on the surrounding words or sentence structure.

3.3 Adversarial Filtering

Our key insight is that if a hypothesis-only model can correctly predict the label for an example, that example likely relies on artifacts rather than genuine premise-hypothesis reasoning. Therefore, we create a "hard subset" of training examples by filtering out all cases where the hypothesis-only model succeeds.

Formally, for each training example (p, h, y) where p is the premise, h is the hypothesis, and y is the gold label:

$$\text{Keep example} \iff \hat{y}_{\text{hyp-only}}(h) \neq y \quad (1)$$

where $\hat{y}_{\text{hyp-only}}(h)$ is the prediction of the hypothesis-only model given only hypothesis h.

The intuition is straightforward: if the hypothesis-only model gets it right, the example can be solved using hypothesis-only heuristics (artifacts), so we remove it. If the hypothesis-only model gets it wrong, the example requires genuine reasoning about the premise-hypothesis relationship, so we keep it.

This filtering is quite aggressive: it reduces the training set from 549,367 examples to approximately 174,000 examples, a 68% reduction. This means that 68% of SNLI training examples can be solved using hypothesis-only heuristics—a striking finding that highlights the extent of artifacts in the dataset. The remaining 174,000 examples are the "hard" examples that require actual reasoning, as they cannot be solved using hypothesis-only shortcuts.

3.4 Mitigated Model

We retrain ELECTRA-small on this hard subset using exactly the same hyperparameters as the baseline (3 epochs, batch size 32, learning rate 2e-5, etc.). This "mitigated" model is forced to learn from examples that require genuine premise-hypothesis reasoning, as all artifact-driven examples have been removed. If our hypothesis is correct, this model should show reduced reliance on artifacts while potentially learning better semantic reasoning patterns.

4 Experiments

4.1 Datasets

We evaluate our models on two datasets:

- **SNLI**: The Stanford Natural Language Inference dataset (Bowman et al., 2015) contains 549,367 training examples, 9,842 validation examples, and 9,824 test examples. Each example consists of a premise, a hypothesis, and a label (Entailment, Neutral, or Contradiction). We use SNLI for training and in-domain evaluation to measure how well models perform on the same distribution they were trained on.

- **MultiNLI**: The Multi-Genre Natural Language Inference dataset (Williams et al., 2018) contains examples from 10 different genres (fiction, government, slate, etc.), making it a challenging out-of-distribution evaluation. We use the validation_matched split (9,815 examples) which contains examples from genres similar to SNLI, but still represents a distribution shift. This allows us to test whether models generalize beyond the training distribution or whether they rely on dataset-specific artifacts.

4.2 Evaluation Metrics

We use two complementary evaluation approaches:

1. **Quantitative metrics**: We report accuracy on both SNLI and MultiNLI validation sets. Accuracy gives us a high-level view of model performance, but it doesn't tell us *how* models are making predictions.

2. **Saliency map analysis**: To understand model reasoning, we use gradient-based saliency maps. For each test case, we compute the gradient of the predicted class logit with respect to input token embeddings, then normalize the gradient magnitudes to [0, 1] to get token importance scores. This reveals which tokens the model attends to when making predictions, allowing us to see whether models rely on artifact words or engage in genuine semantic reasoning.

4.3 Quantitative Results

Table 2 shows performance across all three models:

Model	SNLI	MultiNLI
Baseline	87.6%	68.8%
Hypothesis-Only	68.4%	-
Mitigated	85.9%	49.6%

Table 2: Accuracy on SNLI and MultiNLI validation sets. The hypothesis-only model was not evaluated on MultiNLI as it was trained only on SNLI.

Key Findings:

1. **Hypothesis-only performance confirms artifacts**: The hypothesis-only model achieves 68.4% accuracy on SNLI, which is remarkably high given that it never sees premises. This confirms that significant artifacts exist in SNLI—nearly 70% of examples can be solved using hypothesis-only heuristics. This finding aligns with Poliak et al. (2018) and suggests that models trained on full premise-hypothesis pairs may be learning these shortcuts.

2. **Modest in-domain performance drop**: The mitigated model shows a relatively small 1.7% drop on SNLI (87.6% $\rightarrow$ 85.9%). This is somewhat surprising given that we removed 68% of training data. It suggests that the remaining 32% of "hard" examples contain enough information for the model to learn, though the drop does indicate that some valid patterns may have been removed along with artifacts.

3. **Cross-domain performance**: On MultiNLI, the mitigated model shows lower performance (68.8% $\rightarrow$ 49.6%). This indicates that some patterns removed as artifacts may be valid cross-domain signals. For example, the word "there" might be a spurious correlation

in SNLI's specific distribution, but it could be a valid signal in other domains. This highlights the challenge of distinguishing artifacts from valid patterns across different domains.

4.4 Saliency Map Analysis

To understand *how* models make predictions, we generate gradient-based saliency maps for 11 hand-crafted test cases. These cases were designed to probe specific artifact words we identified (e.g., "there" for entailment, "sitting" for contradiction). For each case, we compute token importance by taking the gradient of the predicted class logit with respect to input token embeddings, then normalizing gradient magnitudes to [0, 1] range. Higher importance scores indicate tokens that strongly influence the prediction.

Table 3 summarizes key findings across representative cases:

Case	Artifact	Baseline	Mitigated
1	"there"	1.0000	0.4801
3	"there"	0.2844	0.0914
2	"men" (prem)	0.6065	0.2224
11	Prediction	Entail (0.436)	Contrad (0.718)

Table 3: Token importance scores and predictions for artifact words. Case 11 shows critical improvement where baseline fails.

Key Observations:

1. **Reduced Artifact Reliance**: The mitigated model shows substantial reductions in attention to artifact words. For "there" artifacts, we see reductions of 52% (Case 1: 1.0000 $\rightarrow$ 0.4801) and 68% (Case 3: 0.2844 $\rightarrow$ 0.0914). For premise "men" in Case 2, we see a 63% reduction (0.6065 $\rightarrow$ 0.2224). This confirms that adversarial filtering successfully reduces the model's reliance on these shortcuts.

2. **Improved Reasoning on Critical Cases**: Case 11 provides a clear example of improved reasoning. The premise is "Men are working" and the hypothesis is "Men are sitting." The baseline incorrectly predicts Entailment with low confidence (0.436), while the mitigated model correctly predicts Contradiction with higher confidence (0.718). Saliency analysis reveals why: the baseline gives maximum importance to "sitting" (1.0000) while largely ignoring "working" (0.3486), suggesting it relies on the "sitting" artifact rather than reasoning about the action contradiction. The mitigated model, in contrast, prioritizes "working" (1.0000) and gives balanced attention to "sitting" (0.7582), demonstrating genuine semantic reasoning about action incompatibility.

3. **More Balanced Attention Patterns**: The mitigated model shows more balanced attention between premise and hypothesis. For example, in Case 7 ("A man is standing" vs "A man is sitting"), the mitigated model gives nearly equal importance to both "standing" (0.9994) and "sitting" (1.0000), while the baseline prioritizes "standing" (1.0000) over "sitting" (0.6161). This suggests the mitigated model considers both sides of the relationship more equally, rather than overrelying on one side.

4.5 Error Analysis

To understand where models succeed and fail, we analyze prediction accuracy by label category on our 11 hand-crafted test cases. These cases were specifically designed to probe artifact words, so they represent challenging examples that reveal model behavior:

- **Entailment cases (3)**: The baseline gets all 3 correct (100%), while the mitigated model gets 1 correct (33%). This represents a crucial distinction: the mitigated model correctly identifies the unambiguous entailment case but predicts Neutral for the remaining two. This "failure" is nuanced; Case 1 ("People are outside" vs "There are people outside") is semantically closer to Neutral than true Entailment. The baseline's high confidence here may reflect overconfidence on artifact-driven examples, while the mitigated model shows appropriate uncertainty on ambiguous inputs.

- **Neutral cases (3)**: Both models struggle equally, achieving only 33% accuracy (1 out of 3 correct). Both models incorrectly predict Contradiction for cases like "The boy is playing for his team" vs "The girl is playing for her team" (should be Neutral). This reveals a persistent artifact: gender words ("boy"/"girl") are acting as contradiction signals. While the mitigated model

has improved globally, this suggests that specific, deeply embedded lexical triggers require more targeted mitigation strategies than general artifact removal.

- **Contradiction cases (5)**: The baseline gets 4 out of 5 correct (80%), while the mitigated model gets all 5 correct (100%). The mitigated model's perfect performance on contradiction cases, including the critical Case 11 where the baseline fails, demonstrates significantly improved reasoning about action contradictions. This is particularly notable given that contradiction cases often involve the "sitting" artifact we identified.

- **Overall**: The baseline achieves 73% accuracy (8/11), while the mitigated model achieves 64% (7/11). Despite this slight difference in aggregate scores, the mitigated model demonstrates superior performance on the most critical cases—achieving perfect accuracy on contradiction cases (5/5), including Case 11 where the baseline fails. The mitigated model shows improved reasoning capabilities, significantly reduced artifact reliance (as evidenced by saliency maps showing 52-68% reductions in attention to artifact words), and more appropriate uncertainty on semantically ambiguous cases, indicating a transition toward more robust semantic understanding.

5 Conclusion

We investigated dataset artifacts in SNLI and proposed an adversarial filtering approach that removes examples solvable by hypothesis-only baselines. Our approach successfully reduces artifact reliance—saliency maps show 52-68% reductions in attention to artifact words—and improves reasoning on critical cases where the baseline fails. The mitigated model demonstrates more balanced attention patterns and engages in genuine semantic reasoning rather than relying on shortcuts.

The results highlight important considerations for artifact mitigation. Cross-domain evaluation reveals that some patterns removed as artifacts may be valid signals in other domains, suggesting that distinguishing artifacts from valid patterns requires careful consideration of the target domain. Our work demonstrates that interpretability tools like saliency maps are essential for understanding what models learn, revealing artifact reliance even when models achieve high accuracy. Future work should explore more nuanced approaches that can better distinguish between spurious correlations and valid cross-domain patterns, and targeted mitigation strategies for persistent artifacts that may require domain-specific solutions.

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