Unsupervised Natural Language Inference Using PHL Triplet Generation

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Abstract

Transformer-based models have achieved impressive performance on various Natural Language Inference (NLI) benchmarks, when trained on respective training datasets. However, in certain cases, training samples may not be available or collecting them could be time-consuming and resource-intensive. In this work, we address this challenge and present an explorative study on unsupervised NLI, a paradigm in which no human-annotated training samples are available. We investigate NLI under three challenging settings: PH, P, and NPH that differ in the extent of unlabeled data available for learning. As a solution, we propose a procedural data generation approach that leverages a set of sentence transformations to collect PHL (Premise, Hypothesis, Label) triplets for training NLI models, bypassing the need for human-annotated training datasets. Comprehensive experiments show that this approach results in accuracies of 66.75%, 65.9%, 65.39%, in PH, P, NPH settings respectively, outperforming all existing baselines. Furthermore, fine-tuning our models with as little as ~0.1% of the training dataset (500 samples) leads to 12.2% higher accuracy than the model trained from scratch on the same 500 instances.

1 Introduction

Natural Language Inference (NLI) is the task of determining whether a “hypothesis” is true (Entailment), false (Contradiction), or undetermined (Neutral) given a “premise”. State-of-the-art models have matched human-level performance on several NLI benchmarks such as SNLI (Bowman et al., 2015), Multi-NLI (Williams et al., 2018), and Dialogue NLI (Welleck et al., 2019). This high performance can be partially attributed to the availability of large training datasets; SNLI (570k), Multi-NLI (392k), and Dialogue-NLI (310k). For new domains, collecting such training data is time-consuming and can require significant resources. What if no training data was available at all?

In this work, we address the above question and explore Unsupervised NLI, a paradigm in which no human-annotated data is provided for learning the task. We study three different unsupervised settings: PH, P, and NPH that differ in the extent of unlabeled data available for learning. PH-setting corresponds to learning from unlabeled premise-hypothesis pairs i.e data without ground-truth labels. P-setting corresponds to learning from a set of premises only i.e. unlabeled partial inputs. The third setting NPH does not provide access to any training dataset (unlabeled or partial), and thus is the hardest among the three unsupervised settings considered in this work.

We propose to solve these unsupervised settings via a procedural data generation approach. Given a sentence, our approach treats it as a premise (P) and generates multiple hypotheses (H) corresponding to each label (L = Contradiction, Entailment,
and Neutral) using a set of rule-based sentence transformations as illustrated in Figure 1. This results in creation of (Premise-Hypothesis-Label) PHL triplets that can be used for training the NLI model. In the P and PH settings, we directly apply the sentence transformations over the available premises to generate PHL triplets. However, in the NPH setting, premises are not provided. We tackle this challenge by incorporating a premise generation step that extracts sentences from various raw text corpora such as Wikipedia, short stories, etc. We use these sentences as the premises to generate PHL triplets. Figure 2 compares the four settings (supervised and three unsupervised) and summarizes our approach to solve each setting.

Through comprehensive experiments on several NLI datasets, we evaluate the efficacy of our approach in each unsupervised setting. We show that in the hardest setting (NPH) where no training data is provided, BERT model trained on our procedurally generated PHL triplets achieves an accuracy of 65.39% on the SNLI dataset. In the P and PH settings, we further improve over this and achieve 65.9% and 66.75% respectively, outperforming the existing unsupervised NLI approaches by ~13%.

We also conduct experiments in low-data regimes where a few labeled instances are provided. We show that further fine-tuning our models (trained in unsupervised settings) with the provided labeled instances achieves considerably higher performance than their counterpart models fine-tuned from scratch. Specifically, in presence of just 500 labeled instances, our models achieve 8.4% and 10.4% higher accuracy on SNLI and MNLI datasets respectively. Finally, we show that using adversarial examples (examples on which the unsupervised model fails) from the training dataset instead of randomly sampled instances further improves the accuracy. With 500 adversarial instances, our models achieve 12.2% and 10.41% higher accuracy on SNLI and MNLI datasets.

In summary,
1. We explore three unsupervised settings for NLI and propose a procedural data generation approach that outperforms the existing approaches by ~13% and raises the state-of-the-art unsupervised performance to 66.75% on the SNLI dataset.
2. We also conduct experiments in low-data regimes where a few labeled instances are provided and demonstrate that further fine-tuning our models (trained in unsupervised settings) with the provided instances achieves 8.4% and 10.4% higher accuracy on SNLI and MNLI datasets respectively.
3. We show that using adversarial examples (examples on which the unsupervised model fails) from the training dataset instead of randomly sampled instances further improves the accuracy by 12.2% and 10.41% on the SNLI and MNLI datasets.
4. Finally, we conduct a comprehensive analysis of our approach and release the code to procedurally generate PHL triplets.

We hope that our work will encourage development of models that do not solely rely on expensive human-annotated data for learning a task and will draw attention towards efficient ways of crowd-sourcing high-quality data, an important-yet-understudied field in NLP.
2 Related Work

Unsupervised QA: In NLP, the unsupervised paradigm where no human-annotated data is provided for learning has mostly been explored for the Question Answering (QA) task. The prominent approach involves synthesizing QA pairs and training a model on the synthetic data. Lewis et al. (2019); Dhingra et al. (2018); Fabbri et al. (2020) propose a template-based approach, while Puri et al. (2020) leverage generative models such as GPT-2 (Raffel et al., 2019) to generate QA pairs. Banerjee and Baral (2020) propose knowledge triplet learning and create synthetic graphs for commonsense and scientific knowledge to solve the zero-shot QA task. Banerjee et al. (2021a) propose a ‘test-time learning’ method that operates directly on a single test context, uses self-supervision to train models on synthetically generated question-answer pairs, and then infers answers to unseen human-authored questions for this context. Banerjee et al. (2021b) present a method to generate QA pairs from image captions for Visual Question Answering. Wang et al. (2021) leverage few-shot inference capability of GPT-3 (Brown et al., 2020) to synthesize training data for SuperGLUE (Wang et al., 2019) tasks.

Unsupervised NLI: Cui et al. (2020) propose to solve the unsupervised NLI task via task-agnostic multimodal pretraining. They use multimodal aligned contrastive decoupled learning (MACD) to train a BERT-based text encoder. For the NLI task, they compute cosine similarity between the representations of premise and hypothesis learned by their text encoder and assign the label (Entailment, Contradiction, or Neutral) based on the range in which the cosine similarity lies. Our approach differs from MACD as it incorporates a procedural data generation step based on several sentence transformations and does not leverage data from other modalities. We use MACD as one of the baselines in our experiments.

Template-based Data Generation: Shen et al. (2021) propose a Masked Noun-Phrase Prediction strategy to synthesize data for pronoun resolution tasks. Gokhale et al. (2020) propose to augment VQA datasets with questions containing logical compositions using a template-based approach. Gokhale et al. (2021) utilize a set of linguistic transformations in a distributed robust optimization setting for vision-and-language models.

Adversarial Training & Data Collection: Pereira et al. (2021) present an adversarial training algorithm that introspects current mistakes and prioritize adversarial training steps to where the model errs the most. Glockner et al. (2018) propose an adversarial dataset for testing robustness of NLI models. Nie et al. (2020); Kiela et al. (2021) present a data collection strategy that involves human-and-model-in-the-loop technique.

3 Unsupervised NLI

In the NLI task, a premise-hypothesis pair \((P, H)\) is provided as input and the system needs to determine the relationship \(L \in \{\text{Entailment, Contradiction, Neutral}\}\) between \(P\) and \(H\). In the supervised setting, a labeled dataset \(D_{\text{train}} = \{(P_i, H_i), L_i\}_{i=1}^{M}\) consisting of \(M\) instances which are usually human-annotated is available for training. However in the unsupervised setting, labels \(L_i\) are not available, thus posing a significant challenge for training NLI systems. Along with this standard unsupervised setting (referred to as PH), we consider two novel unsupervised settings (P and NPH) that differ in the extent of unlabeled data available for learning:

**PH-setting:** It corresponds to the standard unsupervised setting where an unlabeled dataset of PH pairs \(\{(P_i, H_i)\}_{i=1}^{M}\) is provided.

**P-setting:** In this setting, only premises from \(D_{\text{train}}\), i.e \(\{(P_i)\}_{i=1}^{M}\) are provided. It is an interesting setting as the large-scale NLI datasets such as SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018) have been collected by presenting only the premises to the crowd-workers and asking them to write hypotheses corresponding to each of Entailment, Contradiction, and Neutral. Furthermore, this setting presents a harder challenge for training NLI systems than the PH-setting as only partial inputs are provided.

**NPH-setting:** Here, no datasets (even with partial inputs) are provided. Thus, it corresponds to the hardest unsupervised NLI setting considered in this work. This setting is of interest in scenarios where we need to make inferences on a test dataset but its corresponding training dataset is not available in any form.

From the above formulation, it can be inferred that the hardness of the task increases with each successive setting (PH→P→NPH) as lesser and lesser information is made available. In order to
address the challenges of each setting, we propose a two-step approach that includes a pipeline to procedurally generate PHL triplets from the limited information provided in each setting (Section 4), followed by training an NLI model using this procedurally generated data (Section 5). Figure 2 highlights the differences between four NLI settings (one supervised and three unsupervised) and summarizes our approach to solve each setting.

4 PHL Triplet Generation

To compensate for the absence of labeled training data, we leverage a set of sentence transformations and procedurally generate PHL triplets that can be used for training the NLI model. In P and PH settings, we apply these transformations on the provided premise sentences. In the NPH setting where premises are not provided, we extract sentences from various raw text corpora and apply these transformations on them to generate PHL triplets.

4.1 P: Premise Generation

We extract sentences from raw text sources, namely, COCO captions (Lin et al., 2014), ROC stories (Mostafazadeh et al., 2016), and Wikipedia to compile a set of premises for the NPH setting. We use these text sources as they are easily available and contain a large number of diverse sentences from multiple domains.

ROC Stories is a collection of short stories consisting of five sentences each. We include all these sentences in our premise pool. MS-COCO is a dataset consisting of images with five captions each. We add all captions to our premise pool. From Wikipedia, we segment the paragraphs into individual sentences and add them to our premise pool.

We do not perform any sentence filtration during the premise collection process. However, each transformation (described in subsection 4.2) has its pre-conditions such as presence of verbs/adjectives/nouns that automatically filter out sentences from the premise pool that can not be used for PHL triplet generation.

4.2 T: Transformations

Now, we present our sentence transformations for each of the three NLI labels: Entailment, Contradiction, and Neutral. Table 1 illustrates examples of PHL triplets generated from these transformations.

4.2.1 Entailment:

In NLI, the relationship between a premise-hypothesis pair is classified as entailment when the hypothesis must be true if the premise is true.

Paraphrasing (PA): Paraphrasing corresponds to restating the meaning of a text using different words. We use a recently introduced Pegasus (Zhang et al., 2019) tool to generate up to 10 paraphrases of a sentence and use them as hypothesis with the original sentence as the premise. It is an effective way of creating entailment examples as the hypothesis which is simply a paraphrased version of the premise is always entailed

Extracting Snippets (ES): We use dependency parse tree to extract meaningful snippets from a sentence and use them as hypothesis with the original sentence as the premise. Specifically, we extract sub-trees that form a complete phrase or a sentence. For example, from the sentence “A person with red shirt is running near the garden”, we create entailing hypotheses “A person is running near the garden”, “A person is running”, “A person is near the garden”, etc. We implement 10 such extracting techniques using spacy (Honnibal et al., 2020).

Hypernym Substitution (HS): A hypernym of a word is its supertype, for example, “animal” is a hypernym of “dog”. We use WordNet (Miller, 1995) to collect hypernyms and replace noun(s) in a sentence with their corresponding hypernyms to create entailment hypothesis. For example, from the premise “A black dog is sleeping”, we create “A black animal is sleeping”. Note that swapping the premise and hypothesis in this case gives us another PH pair that has a Neutral relationship.

Pronoun Substitution (PS): Here, we leverage Part-of-Speech (POS) tagging of spacy to heuristically substitute a noun with its mapped pronoun. For example, substituting “boy” with “he” in the sentence “boy is dancing in arena” results in an entailing hypothesis “he is dancing in arena”.

Counting (CT): Here, we count nouns in a sentence with common hypernyms and use several templates to generate hypotheses such as

“There are {count} {hypernym}s present”,

“More than {count’} {hypernym}s are present” where count’ is < count, etc.

1 Further details are in Supplementary Section A
Table 1: Illustrative examples of PHL triplets generated from our proposed transformations. E, C, and N correspond to the labels Entailment, Contradiction, and Neutral respectively.

4.2.2 Contradiction:

The relationship between a premise-hypothesis pair is classified as contradiction when the hypothesis can never be true if the premise is true. Note that contradiction also includes PH pairs that describe two completely different events as defined in (Bowman et al., 2015). For example, P: “Ruth Bader Ginsburg was appointed to the US Supreme Court” and H: “I had a sandwich for lunch today”.

Contradictory Words (CW): In this transformation, we replace noun(s) and/or adjective(s) (identified using spacy POS tagging) with their corresponding contradictory words. For example, replacing the word “big” with “small” in the sentence “He lives in a big house” results in a contradictory hypothesis “He lives in a small house”. For contradictory adjectives, we collect antonyms from wordnet and for contradictory nouns, we use the function ‘most_similar’ from gensim (Rehurek and Sojka, 2011) library that returns words close (but distinct) to a given word. For instance, it returns words like ‘piano’, ‘flute’, ‘saxophone’ when given the word ‘violin’.

Contradictory Verb (CV): We collect contradictory verbs following the aforementioned contradictory noun collection strategy using gensim and create hypothesis in the following two ways: (i) Replacing verb in a sentence with the contradictory verb, for example, from the sentence “A girl is walking in the park”, we create a contradictory hypothesis “A girl is driving in the park”. (ii) Selecting other sentences from the premise pool that have the same subject as the original sentence but have contradictory verbs, for example, sentences like “A young girl is driving fast on the street”, “There is a girl skiing with her mother”, etc. The second approach adds diversity to our synthetically generated PHL triplets.

Subject Object Swap (SOS): Here, we swap the subject and object of a sentence to create a contradictory hypothesis. For example, from the sentence “A clock is standing on top of a concrete pillar”, we create a contradictory hypothesis “a pillar is standing on top of a concrete clock”.

Negation Introduction (NI): Here, we simply introduce negation into the original sentence to obtain a contradictory hypothesis. For example, from the sentence “Empty fog covered streets in the night amongst traffic lights”, we create “Empty fog did not cover streets in the night amongst traffic lights” as a contradictory hypothesis.

Number Substitution (NS): Here, we replace numbers (tokens with dependency tag ‘nummod’ in the parse tree) in the original sentence resulting in a contradictory hypothesis. For example, we create a hypothesis “More than seven traffic lights in the city are damaged” from the sentence “Four traffic lights in the city are damaged”.

Irrelevant Hypothesis (IrH): We select sentences that have different subjects and objects (other nouns) than the premise sentence as contradictory hypotheses. For example, for the premise “Sign for an ancient monument on the roadside”, we sample “A man goes to strike a tennis ball” as a contradictory hypothesis.

4.2.3 Neutral:

A hypothesis H is neutral with respect to a premise P, if P does not provide enough information to classify it as either entailment or contradiction.
4.3 Data Validation

Here, we use ConceptNet (Con) to randomly generated PHL triplets, we validate accordingly modifying the label. For instance, from the sentence “A car parked near the fence”, we insert a randomly selected modifier for the noun ‘car’ from the list ['colored', 'rental', 'silver', 'dark', 'elegant', ...] and create a neutral hypothesis “A silver car parked near the fence”.

From ConceptNet (Con): Here, we use ConceptNet (Speer et al., 2017) to add additional but relevant information to a sentence in order to create a neutral hypothesis. Specifically, we use ConceptNet relations AtLocation, DefinedAs, etc. and insert the node connected by these relations to the sentence resulting in a neutral hypothesis. For instance, from the sentence “Bunch of bananas are on a table”, we create a hypothesis “Bunch of bananas are on a table at kitchen” using the AtLocation relation.

Same Subject but Non-Contradictory Verb (SSNCV): Here, we utilize the contradictory verbs dictionary (described in CV) and select sentences from the premise pool that have the same subject as the original sentence but contain additional noun(s) and do not contain contradictory verbs as neutral hypothesis. For instance, from a sentence “A small child is sleeping in a bed with a bed cover”, we sample “A child laying in bed sleeping with a chair near by” as a neutral hypothesis.

We further create examples by swapping premise and hypothesis of collected PHL triplets and accordingly modifying the label. For instance, swapping $P$ and $H$ in HS, ES, HS, etc. results in neutral examples, swapping $P$ and $H$ in AM, Con results in entailment examples, etc. Furthermore, we note that transformations ES, HS, PS, SOS, NI result in PH pairs with high word overlap between premise and hypothesis sentences, whereas, transformation PA, CV, IrH, SSNCV, etc. result in PH pairs with low word overlap. In order to add more diversity to the examples, we use composite transformations on the same sentence such as $PA + ES \quad (L = E)$, $PA + CW \quad (L = C)$, etc. as shown in Table 1.

4.3 Data Validation

In order to measure the correctness of our procedurally generated PHL triplets, we validate randomly sampled 50 instances for each transformation. We find that nearly all the instances get correct label assignments in case of $PA$, HS, PS, NI, NS, IrH, AM transformations. While transformations CW, Con, SSNCV result in a few mislabeled instances. Specifically, SSNCV transformation results in the maximum errors (5). Supplementary Section B provides examples of such instances. While it is beneficial to have noise-free training examples, doing so would require more human effort and increase the data collection cost. Thus, in this work, we study how well we can do using our procedurally generated data without investing human effort in either creating instances or eliminating noisy instances.

5 Method

In this section, we describe our approach to develop NLI models for each unsupervised setting. Table 13 (supplementary) shows sizes of the generated PHL datasets for each setting.

5.1 NPH-Setting

We use the Premise Generation function ($P$) over raw-text sources, namely, COCO captions, ROC stories, and Wikipedia i.e., $P(COCO)$, $P(ROC)$ and $P(Wiki)$ to compile a set of premises and apply the transformations ($T$) over them to generate PHL triplets. We then train a transformer-based 3-way classification model (Section 6.1) using the generated PHL triplets for the NLI task.

5.2 P-Setting

In this slightly relaxed unsupervised setting, premises of the training dataset are provided. We directly apply the transformation functions ($T$) on the given premises and generate PHL triplets. Similar to the NPH setting, a 3-way classification model is trained using the generated PHL triplets.

5.3 PH-Setting

In this setting, access to the unlabeled training data is provided. We present a 2-step approach to develop a model for this setting. In the first step, we create PHL triplets from the premises and train a model using the generated PHL triplets same as done for the P-setting. In the second step, we pseudo-label the unlabeled PH pairs using the model trained in Step 1.

Here, a naive approach to develop NLI model would be to train using this pseudo-labeled dataset. This approach is limited by confirmation bias i.e
Table 2: Comparing performance of models in the PH-setting. C (COCO), R (ROC), and W (Wikipedia) correspond to the various premise sources used for PHL triplet generation.

| Model     | SNLI | MNLI | MULI | DNLI | BNLI |
|-----------|------|------|------|------|------|
| SNLI      |      |      |      |      |      |
| MNLI      |      |      |      |      |      |
| BERT*     | 35.09 | - | - | - | - |
| LXMERT*   | 39.03 | - | - | - | - |
| VilBert*  | 43.13 | - | - | - | - |
| MACD*     | 52.63 | - | - | - | - |
| \(T(P)\)  | 65.72 | 49.56 | 50.00 | 43.27 | 67.78 |
| \(T(P)(C)\) | 65.36 | 49.91 | 49.24 | 46.25 | 70.07 |
| \(T(P)(R)\) | 65.90 | 48.53 | 48.36 | 44.97 | 66.43 |

Table 3: Comparing accuracy of various approaches in the P-Setting. Results of approaches marked with * have been taken from (Cui et al., 2020). Note that we utilize the premises of the SNLI training dataset only but evaluate on SNLI (in-domain), and MNLI, DNLI, BNLI (out-of-domain).

| Approach | SNLI | MNLI | MULI | DNLI | BNLI |
|----------|------|------|------|------|------|
| From Scratch MaxProbFilt | 66.67 | 53.37 | 55.17 |      |      |
| From Scratch MaxProbFilt+ \(T(P)\) | 66.75 | 50.22 | 50.37 |      |      |
| Finetune P-model MaxProbFilt | 65.60 | 52.97 | 53.44 |      |      |

Table 4: Comparing accuracy of our proposed approaches in the PH-Setting. Note that the models are evaluated on MNLI (out-of-domain) dataset.

| Model     | SNLI | MNLI | MULI | DNLI | BNLI |
|-----------|------|------|------|------|------|
| SNLI      |      |      |      |      |      |
| MNLI      |      |      |      |      |      |
| BERT*     | 35.09 | 31.0 | 34.8 | 40.0 | 51.7 |
| LXMERT*   | 39.03 | 33.9 | 37.6 | 42.8 | 54.1 |
| VilBert*  | 43.13 | 37.3 | 41.2 | 46.4 | 58.2 |
| MACD*     | 52.63 | 46.5 | 46.2 | 50.8 | 62.8 |
| \(T(P)(C)\) | 63.52 | 50.5 | 53.1 | 57.5 | 69.8 |
| \(T(P)(R)\) | 68.43 | 52.3 | 52.5 | 56.7 | 70.0 |
| \(T(P)(C+R)\) | 67.92 | 52.4 | 54.3 | 57.5 | 71.7 |
| \(T(P)(C+R+W)\) | 70.00 | 53.7 | 55.4 | 58.7 | 73.4 |
| Training Dataset | Method       | 100 | 200 | 500 | 1000 | 2000 |
|------------------|--------------|-----|-----|-----|------|------|
|                  | **SNLI**     | **MNLI** | **SNLI** | **MNLI** | **SNLI** | **MNLI** | **SNLI** | **MNLI** | **SNLI** | **MNLI** |
| SNLI             | BERT         | 44.62 | 37.36 | 48.97 | 34.71 | 58.54 | 44.01 | 65.36 | 37.24 | 72.51 | 45.59 |
|                  | NPH (Random) | 64.82 | 49.72 | 65.06 | 50.48 | 66.97 | 52.33 | 70.61 | 56.75 | 73.7 | 59.0 |
|                  | NPH (Adv.)   | 68.21 | 51.93 | 69.23 | 56.55 | 70.85 | 58.46 | 73.62 | 59.47 | 74.31 | 60.43 |
| MNLI             | BERT         | 35.12 | 36.01 | 35.14 | 36.58 | 46.16 | 47.1 | 47.64 | 56.21 | 60.42 | 62.89 |
|                  | NPH (Random) | 63.87 | 52.85 | 63.87 | 53.61 | 64.23 | 57.47 | 65.62 | 60.42 | 66.87 | 63.3 |

Table 5: Comparing performance of various methods on in-domain and out-of-domain datasets in low-data regimes (100-2000 training instances). ‘BERT’ method corresponds to fine-tuning BERT over the provided instances from SNLI/MNLI, ‘NPH (Random)’ corresponds to further fine-tuning our NPH model with the randomly sampled instances from SNLI/MNLI, ‘NPH (Adv.)’ corresponds to further fine-tuning our NPH model with the adversarially selected instances from SNLI/MNLI.

premises outperforms ROC and Wikipedia models on all datasets. We attribute this superior performance to the short, simple, and diverse sentences present in COCO that resemble the premises of SNLI that were collected from Flickr30K (Plummer et al., 2015) dataset. In contrast, Wikipedia contains lengthy and compositional sentences resulting in premises that differ from those present in SNLI, MNLI, etc. Furthermore, we find that combining the PHL triplets of COCO and ROC leads to a slight improvement in performance on SNLI (65.39%), and BNLI (77.37%) datasets.

**P-Setting:** Cui et al. (2020) presented MACD that performs multi-modal pretraining using COCO and Flickr30K caption data to solve the unsupervised NLI task. It achieves 52.63% on the SNLI dataset. Our approach outperforms MACD and other single-modal and multi-modal baselines by ~13% on SNLI as shown in Table 3. We also experiment by adding PHL triplets generated from COCO and ROC to the training dataset that further improves the accuracy to 65.90% and establish a new state-of-the-art performance in this setting.

**PH-Setting:** In this setting, we first train an NLI model following the P-Setting approach and then pseudo-label the given unlabeled PH pairs using that model. From this pseudo-labeled dataset, we select instances based on the maximum softmax probability as described in section 5.3. We refer to this set of selected instances as MaxProbFilt dataset. This approach results in accuracy of 66.67% on the SNLI dataset as shown in Table 4. We further investigate two more approaches of training the NLI model in this setting. In the first approach, we add the PHL triplets generated in the P-Setting to the MaxProbFilt dataset and train a model using the combined dataset. In the second approach, we fine-tune the same model used for pseudo-labeling with MaxProbFilt dataset. We find that the first approach slightly improves the accuracy to 66.75%. This also represents our best performance across all the unsupervised settings. Furthermore, we observe improvement in the Out-of-domain datasets also. Specifically, we achieve 53.37% and 55.17% on MNLI matched and mismatched datasets respectively.

### 6.3 Low-Data Regimes

We also conduct experiments in low-data regimes where a few labeled instances are provided. We select these instances from the training dataset of SNLI/MNLI using two strategies:

**Random Selection:** Here, we randomly select instances from the corresponding training dataset. Further fine-tuning our NPH model with the selected labeled instances achieves higher performance than the models fine-tuned from scratch as shown in Table 5. Specifically, in presence of just 500 SNLI instances, our models achieve 8.4% and 8.32% higher accuracy on SNLI (in-domain) and MNLI (out-of-domain) datasets respectively. Furthermore, in presence of just 500 MNLI instances, our models achieve 10.37% and 18.07% higher accuracy on MNLI (in-domain) and SNLI (out-of-domain) datasets respectively.

**Adversarial Selection:** Here, we select those instances from the training dataset on which the NPH model makes incorrect prediction. This is similar to the adversarial data collection strategy (Nie et al., 2020; Kiela et al., 2021) where instances that fool the model are collected. Here, we do not simply fine-tune our NPH model with the adversarial examples as it would lead to catastrophic forgetting (Carpenter and Grossberg, 1988). We tackle this
### Analysis

#### Ablation Study
We conduct ablation study to understand the contribution of individual transformations on NLI performance. Table 6 shows the performance drop observed on removing PHL triplets created using a single transformation in the NPH-Setting. We find that Contradictory Words (CW) and Contradictory Verbs (CV) lead to the maximum drop in performance of 5.88% and 3.07% respectively. In contrast, Pronoun Substitution (PS) transformation doesn’t impact the performance significantly. Note that this does not imply that this transformation is not effective, it means that the evaluation dataset (SNLI) does not contain instances requiring this transformation.

#### NC and RS Evaluation
We evaluate our model on NER-Changed (NC) and Roles-Switched (RS) datasets presented in (Mitra et al., 2020) that test ability to distinguish entities and roles. Our model achieves high performance on these datasets. Specifically, 84.22% on NC and 75.39% on SNLI-NC as shown in Table 7.

#### Label-Specific Analysis
Table 8 shows the precision and recall values achieved by our model under each unsupervised setting. We observe that our models achieve better precision and recall values on Entailment and Contradiction than Neutral examples. This suggests that neutral examples are relatively more difficult as models trained on procedurally generated data tend to achieve lower performance on them. We provide examples of instances where our model makes incorrect predictions in the supplementary.

### Discussion
We explored three different settings in unsupervised NLI and proposed a procedural data generation approach that outperformed the existing approaches by \(\sim 13\%\). We showed that fine-tuning our models (trained only on procedurally generated data) with a few human-authored labeled instances leads to a considerable improvement in performance. We also showed that selecting adversarial instances for this fine-tuning step further improves the performance. Specifically, in presence of just 500 adversarial instances, we achieved 70.85% accuracy on SNLI, 12.2% higher than the model trained from scratch on the same 500 instances. This improvement in performance suggests an alternative strategy of crowdsourcing high-quality task-specific datasets. Recently, there has been an interest in model-in-the-loop data collection strategies (Nie et al., 2020; Kiela et al., 2021; Li et al., 2021; Sheng et al., 2021) where humans are asked to create samples that fool the model. However, these approaches require a large training dataset that a model needs to be trained on before further adversarial sample collection. In contrast, adopting our method, a dataset designer can first develop some simple heuristics, train a model on procedurally generated data using those heuristics, and then ask crowd-workers to adversarially attack this model to collect non-trivial samples.

| Approach      | Δ Accuracy |
|---------------|------------|
| NPH model     | 64.8%      |
| - CV          | -5.88%     |
| - CW          | -3.07%     |
| - SSNCV       | -2.63%     |
| - Neg         | -0.70%     |
| - IrH         | -0.50%     |
| - PS          | -0.00%     |

Table 6: Ablation Study of transformations in the NPH-Setting. Each row corresponds to the drop in performance on the SNLI dataset when trained without PHL triplets created using that transformation.

| Setting | Metric | Label |
|---------|--------|-------|
| NPH     | Precision | 0.65  | 0.71  | 0.6  |
|         | Recall   | 0.68  | 0.77  | 0.51 |
| P       | Precision | 0.66  | 0.72  | 0.58 |
|         | Recall   | 0.67  | 0.78  | 0.52 |
| PH      | Precision | 0.64  | 0.74  | 0.60 |
|         | Recall   | 0.73  | 0.77  | 0.50 |

Table 8: Precision and Recall values achieved by our models under each unsupervised setting.

| NC     | RS      | SNLI-RS | SNLI-NC |
|--------|---------|---------|---------|
| 84.22  | 50.07   | 58.59   | 75.39   |

Table 7: Performance of our NPH model on Names-Changed (NC) and Roles-Switched (RS) adversarial test sets (Mitra et al., 2020).
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A Transformations

In this section, we provide details about the proposed sentence transformations.

A.1 Entailment

Table 9 shows examples of our transformations.

Paraphrasing (PA): Since the Pegasus tool is trained for abstractive text summarization, it often removes some information from the original sentence while paraphrasing. For instance, a paraphrase of the sentence “A boy is playing with a red ball” could be “Boy is playing with a ball”. This restricts us from using the paraphrased sentence as the premise with the original sentence as the hypothesis as the formed PH pair does not represent an entailment scenario (neutral in this case). It is non-trivial to detect such instances in an automated way. Hence, in order to avoid noisy examples, we only use the original sentence as premise and paraphrased sentences as hypothesis. We also explore back-translation (Sennrich et al., 2016) but it often results in noisy outputs and provides less diversity than the Pegasus tool. Hence, we use only the Pegasus tool for generating paraphrases of sentences.

Extracting Snippets (ES): Here, we provide details of the techniques used for extracting snippets from a text. Note that we use dependency parse tree of the sentence to select/skip the tokens to create the hypothesis.

(i) We skip modifiers (tokens with dependency amod) that have no children in the parse tree. For example, from the sentence “The male surfer is riding a small wave”, we create “The surfer is riding a small wave”, “The male surfer is riding a wave”, and “The surfer is riding a wave” as entailing hypotheses.

(ii) Similar to the previous technique, we skip adverb modifier (advmod). For example, from the sentence “A very beautiful girl is standing outside the park”, we create an entailment hypothesis “A beautiful girl is standing outside the park”.

(iii) We skip adjectives that do not have dependency token conj and also have 0 children in the parse tree. For example, from the sentence “A middle-aged man in a beige vest is sleeping on a wooden bench.”, we create “A middle-aged man in a vest is sleeping on a bench.”.

(iv) In another technique, we select the root token and all the tokens to the left of it. If this results in selection of at least 3 tokens and if one of them is a verb then we consider it to be a valid sentence and use it as an entailment hypothesis. For example, from the sentence “The male surfer is riding a small wave”, we create “surfer is riding”.

Hypernym Substitution (HS): Examples of hypernyms:

‘alcohol’: ['beverage’, ‘drink’]
‘apple’: ['fruit']
‘axe’: ['edge tool']
‘banana’: ['fruit']

Pronoun Substitution (PS): For words in the list ['man’, 'boy’, 'guy’, 'lord’, 'husband’, 'father’, 'boyfriend’, 'son’, 'brother’, 'grandfather’, 'uncle’], we use ('he'/ 'someone'/ ‘they’, etc.) and for words in the list ['woman’, 'girl’, 'lady’, 'wife’, 'mother’, 'daughter’, 'sister’, 'girlfriend’, 'grandmother’, 'aunt’], we use ‘she'/ 'someone'/ ‘they’, etc.). In other cases, we use the pronoun ‘they’ or ‘someone’ or ‘somebody’.

Counting (CT): We provide examples of templates we use to create counting hypotheses:

“There are {count} {hypernym} present”,
“{count} {hypernym} are present”,
“Several {hypernym} present”,
“There are multiple {hypernym} present”,
Table 9: Illustrative examples of entailment transformations.

| Category   | Original Sentence (Premise) | Hypothesis                          |
|------------|-----------------------------|-------------------------------------|
| PA         | Fruit and cheese sitting on a black plate. | There is fruit and cheese on a black plate. |
| ES         | Person relaxes at home while holding something. | Person relaxes while holding something. |
| HS         | A girl is sitting next to a blood hound. | A girl is sitting next to an animal. |
| PS         | People are walking down a busy city street. | They are walking down a busy city street. |
| CT         | A man and woman setup a camera. | Two people setup a camera. |
| Composite  | A large elephant is very close to the photographic equipment. | Elephant is close to the photographic equipment. |

“There are more than {count'} {hypernym} present”,
“There are at least {count'} {hypernym} present”,

We also substitute the hypernym in the original sentence directly to create hypotheses as shown in Table 9.

A.2 Contradiction

Table 10 shows examples of our transformations.

Contradictory Words (CW): In order to filter out the inflected forms of the same word or its synonyms from the list returned by most_similar function, we remove words that have high STS with the given word. This step removes noisy contradictory word pairs to a large extent. Here, we provide examples of contradictory words:

- ‘stove’: ['heater']
- ‘cucumber’: ['onion', 'carrot', 'melon', 'turnip', 'eggplant', 'watermelon', 'radish']
- ‘motorcycle’: ['truck', 'scooter', 'car']
- ‘kitchen’: ['bedroom', 'bathroom', 'toilet']

Contradictory Verb (CV): We provide examples of contradictory verbs:

- ‘stand’: ['sprint', 'cycle', 'drive', 'jump', 'sit', etc.]
- ‘play’: ['sleep', 'cry', 'fight', 'drink', 'hunt', etc.]
- ‘smile’: ['cry', 'anger', 'frown', etc.]

A.3 Neutral

Table 11 shows examples of our transformations.

Adding Modifiers (AM): We provide examples of modifiers collected using our approach:

- ‘metal’: ['large', 'circular', 'galvanized', 'heavy', 'dark', etc.]
- ‘vegetable’: ['steamed', 'cruciferous', 'green', 'uncooked', 'raw', etc.]

‘park’: ['quiet', 'neglected', 'vast', 'square', 'crowded', etc.]

etc.

B Data Validation

Table 12 shows examples of mis-labeled instances generated by our transformations.

C Training NLI Model

Table 13 shows sizes of the generated PHL datasets for each setting.
### Table 10: Illustrative examples of contradiction transformations.

| Category | Original Sentence (Premise) | Hypothesis |
|----------|-----------------------------|------------|
| CW-noun  | A small bathroom with a sink under a cabinet. | a small kitchen with a sink under a cabinet. |
| CW-adj   | A young man is doing a trick on a surfboard. | A old man is doing a trick on a surfboard. |
| CV       | A couple pose for a picture while standing next to a couch. | A couple sit in a chair on laptops |
| SOS      | A man is flying a kite on the beach. | a beach is flying a kite on the man |
| NS       | Two green traffics lights in a European city. | nine green traffics lights in a European city |
| NI       | A boy with gloves on a field throwing a ball. | a boy with gloves on a field not throwing a ball |
| Composite| A woman holding a baby while a man takes a picture of them | a kid is taking a picture of a male and a baby. |

### Table 11: Illustrative examples of neutral transformations.

| Category | Original Sentence (Premise) | Hypothesis |
|----------|-----------------------------|------------|
| AM       | two cats are eating next to each other out of the bowl | two cats are eating next to each other out of the same bowl |
| SSNCV    | A man holds an electronic device over his head. | man is taking photo with a small device |
| FCon     | a food plate on a table with a glass. | a food plate on a table with a glass which is made of plastic. |
| Composite| two dogs running through the snow. | The big dogs are outside. |

### Table 12: Examples of mis-labeled PHL triplets generated by our transformations.

| Trans. | Premise | Hypothesis | Assigned Label | True Label |
|--------|---------|------------|----------------|------------|
| PS     | Two dogs on leashes sniffing each other as people walk in a outdoor market | Two dogs on leashes sniffing each other as they walk in a market | E | N |
| CT     | Adult woman eating slice of pizza while standing next to building | There are 2 humans present | E | C |
| CW     | Meal with meat and vegetables served on table | There is a meal with cheese and vegetables | C | N |
| SSNCV  | A person riding skis down a snowy slope | A person riding skis in a body of water | N | C |
| SSNCV  | A person on a skateboard jumping up into the air | A person jumping up in the air on a snowboard | N | C |
| CV     | A male surfer riding a wave on the ocean | A surfer is surfing in the ocean near some swimmers | C | N |
Transformation $\mathcal{T}$

| NPH-Setting | P-Setting |
|-------------|-----------|
| $\mathcal{T}(P(C))$ | $\mathcal{T}(P(R))$ | $\mathcal{T}(P(W))$ | $\mathcal{T}(SNLI)$ |
| Raw Sentences | 591 | 490 | 600 | 548 |
| PA | 5083 | 3072 | 273 | 475 |
| ES | 2365 | 196 | 87 | 516 |
| PS | 37 | 41 | 137 | 38 |
| CT | 25 | 8 | 2 | 43 |
| Neg. | 1175 | 1175 | 2053 | 990 |
| CW | 978 | 119 | 116 | 265 |
| CV | 1149 | 63 | 5 | 505 |
| NS | 73 | 16 | 224 | 91 |
| SOS | 428 | 180 | 229 | 76 |
| AM | 1048 | 125 | 535 | 327 |
| SSNCV | 1363 | 2 | 7 | 405 |

Table 13: Sizes of PHL triplet datasets generated by our transformations for the unsupervised settings. All numbers are in thousands. C, R, W denote COCO, ROC Stories, and Wikipedia respectively. For P-Setting, we show stats for SNLI dataset. We do not include PH-Setting in this table because we leverage the PHL triplets generated using the P-Setting to solve it as described in Section 5.3.