Automatically Identifying Semantic Bias in Crowdsourced Natural Language Inference Datasets

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Abstract

Natural language inference (NLI) is an important task for producing useful models of human language. Unfortunately large-scale NLI dataset production relies on crowdworkers who are prone to introduce biases in the sentences they write. In particular, without quality control they produce hypotheses from which the relational label can be predicted, without the premise, better than chance. We introduce a model-driven, unsupervised technique to find “bias clusters” in a learned embedding space of the hypotheses in NLI datasets, from which interventions and additional rounds of labeling can be performed to ameliorate the semantic bias of the hypothesis distribution of a dataset.

1 Introduction

Natural language inference (NLI) is an important task for producing useful models of human language. The NLI task is to, given a pair of sentences, typically referred to as the premise $s_1$ and hypothesis $s_2$, infer $r \in \{\text{neutral, entail, contradict}\}$, the logical relationship between the two sentences. Ideally, examples in an NLI dataset are drawn from a distribution where $r$ is conditionally dependent on the pair of sentences, but independent from either sentence individually (1).

$$p(r|s_1, s_2) = p(r) = p(r|s_2) = p(r|s_1)$$ (1)

Large-scale NLI datasets are typically produced by first sampling a large set of premise sentences, and then for each premise producing a hypothesis for each possible relation label using crowdworkers. Unfortunately, this process tends to produce datasets with quality issues, in particular hypothesis-relation bias, where sufficient information to accurately predict the relational label is carried in the hypotheses alone, as in Eqn (2).

$$p(r|s_2) \neq p(r)$$ (2)

SNLI (Bowman et al., 2015a) is a prominent large-scale NLI dataset that is known to have this bias issue. Several mechanisms to quantify and resolve bias during the data creation process have been proposed, and employed in producing high-quality NLI datasets such as MNLI (Williams et al., 2018a) and ANLI (Nie et al., 2020a). Furthermore, work on robustifying models against this bias at train time have been fruitful.

Zhang et. al (Zhang et al., 2019) identified a series of leakage features that capture ways that selection bias and production bias is characterized for the aforementioned NLI datasets as well as the related Kaggle Quora Question Pairs paraphrase detection task.

Figure 1: A T-SNE projection of our method applied on the SNLI test set, showing a clear separation of clusters in the hypothesis embedding space in which entailment, contradiction, and neutral labels dominate. Small dots are used as markers within low-bias clusters ($L2$-distance to $[0.33, 0.33, 0.33] < .25$) and large X’s are used as markers within high-bias clusters. The chart clearly shows that lobes containing majority entailment, majority contradiction, and majority neutral examples are present.

The hypothesis sentence (Wang et al., 2021).

$$p(r|s_2) \neq p(r)$$ (2)
It is widely thought that systematic, shared biases in the types of words, sentence structures, or ideas that crowdworkers tend to choose when prompted with a logical relation drive this leakage of the label in the hypothesis sentence (Gururangan et al., 2018; Zhang et al., 2019). For example, crowdworkers might slightly tend toward choosing certain non-sequitur topics when asked to write a neutral sentence, or occasionally not-invert the premise when given contradict, while avoiding using the word “not” when given entail.

In this work we demonstrate how problematic clusters of samples exhibiting this bias can be found using a straightforward model-driven approach.

1.1 Approach

Two popular neural network architectures in text classification tasks in general, and NLI in particular, are BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019). BERT is trained on a large-scale language modeling task, wherein the models are trained on cloze tasks to fill in missing words in example sentences, and next sentence prediction tasks, where they are trained to identify whether two sentences belong to the same document or not. Given a large enough corpus of training data, and the use of enough compute time, this leads to a sophisticated contextual model of written language, which is adaptable to downstream tasks.

Figure 2 shows the high-level essentials of our approach. We pre-train RoBERTa (Liu et al., 2019) for NLI by using the training partitions from the SNLI, MNLI, and ANLI datasets. We then use this hypothesis embeddings for each example in the dataset partition to be evaluated.

1.2 Data

We study the following popular NLI datasets: Stanford Natural Language Inference (SNLI) (Bowman et al., 2015b), Multi Natural Language Inference (MNLI) (Williams et al., 2018b) and Adversarial Natural Language Inference (ANLI) (Nie et al., 2020b) which 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.

| Dataset | #train | #dev | #test |
|---------|--------|------|-------|
| A1      | 16,946 | 1,000| 1,000 |
| A2      | 45,460 | 1,000| 1,000 |
| A3      | 100,459| 1,200| 1,200 |
| ANLI    | 162,865| 3,200| 3,200 |
| SNLI    | 550,152| 10,000| 10,000|
| MNLI    | 392,702| 20,000| 20,000|

Table 1: NLI datasets statistics. ‘ANLI’ refers to ‘A1+A2+A3’.

To provide a better view of the datasets, we give one example for each dataset below:

**ANLI:**

Premise: The Parma trolleybus system (Italian: "Rete filoviaria di Parma") forms part of the public transport network of the city and “comune” of Parma, in the region of Emilia-Romagna, northern Italy. In operation since 1953, the system presently comprises four urban routes.

Hypothesis: The trolleybus system has over 2 urban routes.

**SNLI:**

Premise: A man splashes playfully in a lake.

Hypothesis: A man trying to coax his girlfriend into the lake.

**MNLI:**

Premise: What was this complication of a will?

Hypothesis: What complication did the will have?

1.3 Producing hypothesis embeddings

The hypothesis embedding process involves three steps: first the input sequence of test sentence pair wordpiece tokens is lesioned using attention masking, then the latent codes corresponding to it from the fully connected layer in the classification output head of the RoBERTa model. Finally, we embed the latent codes with 30 principal components.
Lesioning. We mask all tokens from the premise sentence \( s_1 \) in the model input sequence by replacing premise \( s_1 \) sentence tokens with \([\text{MASK}]\) and applying attention mask \( m \) s.t.

\[
m_i = \begin{cases} 
0 & 0 < i \leq |s_1| \\
1 & \text{else}
\end{cases}
\]

For BERT we then take the output embedding of this lesioned sentence pair on the \( [\text{CLS}] \) token, and use this as the BERT sentence embedding. For RoBERTa the sentence tokens are then pooled as usual and passed through the final fully connected (FC) layer to produce an output lesioned hypothesis sentence embedding.

1.4 Producing a Clustering

As a final step we perform principal component analysis (PCA) to reduce the dimensionality of the sentence embeddings to 30 principal vectors. Following this dimensionality reduction we fit a high-\( k \) (in this case, \( k = 50 \)) \( k \)-means clustering over the distribution of reduced-dim sentence embeddings. Then, each individual cluster can be analyzed in terms of the distribution of relation labels within it, as a perfectly balanced dataset (i.e., the distribution of premises w.r.t.

2 Cluster-based Bias Analysis

Using these clusters, we can hunt for bias by simply comparing the distribution of labels within each cluster to the global distribution (even)= \([0.33, 0.33, 0.33]\) of labels in the dataset. For example, by applying some threshold to the L2 distance between the label distribution within a cluster and the global label distribution, we can find clusters exhibiting outlier distributions. It turns out that these clusters clearly identify continuous regions of bias in the 2d t-SNE embedding space of samples, as shown in Figure 1.

2.1 Analyzing hypothesis-label distributions

After a full set of hypothesis embeddings are extracted for a dataset, we move to analyze the distribution of labels in the hypothesis embedding space. To enable this, we first perform a \( k \)-nearest neighbors (KNN) clustering on the set of embeddings. We find that \( k = 30 \) is a sufficiently large number of clusters for our purposes. For each cluster, we then analyze the L2 distance \( d \) between the cluster-wise label distribution and the global label distribution.

Finding outliers. For every cluster the label distribution distance \( d \in [0, 1] \) captures how “unbalanced” the collection of labels in the cluster is relative to the uniform distribution. We can choose any outlier threshold \( t \in (0, 1) \), which allows us to determine the outlier clusters for which \( d > t \).

Progressive evaluation. At \( t = 0 \), all \( k \) clusters will be classified as outliers, for all datasets. However, as \( t \) varies from 0 to 1, the number of outlier clusters will decrease, until eventually reaching 0, drawing the progressive evaluation of cluster out-
liers (PECO) curve. We hypothesize that datasets exhibiting a greater degree of hypothesis-label bias will have PECO curves that reach 0 later than others, and thus the area under the PECO curve will be greater for more biased NLI datasets.

2.2 Cluster as pseudoclassification

We can also test the extent to which the clusters partition the samples along relation label by assigning the majority label within each cluster as a “pseudoclass” and test how accurate a classifier that simply uses the 50 cluster IDs as the only input feature performs.

3 Results

In this section, we demonstrate our experiment results and discuss the effect of different choices of experimental settings.

3.1 Comparing Bias Level between Datasets

Using the progressive evaluation of cluster outliers (PECO) curve we can visualize how datasets are differently biased. Figure 3 shows how the RoBERTa-based PECO curve for SNLI in particular exhibits significantly more bias.

| Dataset | BERT (n,c) | (n,e) | (e,c) | RoBERTa (n,c) | (n,e) | (e,c) | Average |
|---------|-----------|-------|-------|---------------|-------|-------|---------|
| A1      | 59%       | 64%   | 57%   | 60%           | 66%   | 60%   | 61%     |
| A2      | 61%       | 71%   | 61%   | 63%           | 71%   | 62%   | 65%     |
| A3      | 57%       | 61%   | 56%   | 59%           | 65%   | 64%   | 60%     |
| MNLI    | 55%       | 56%   | 55%   | 56%           | 63%   | 65%   | 58%     |
| SNLI    | 58%       | 57%   | 60%   | 69%           | 67%   | 68%   | 63%     |

Table 2: The pairwise training pseudoaccuracy of the KNN-cluster partitions.

3.3 Visualizing and Ameliorating Bias

Figure 4 shows how the cluster-bias T-SNE plots can be used directly as a visualization tool for analyzing and “debugging” biased datasets. For example, 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.

4 Future Directions

We hope to further apply these techniques to analyze a wider array of different sentence-pair classification tasks generated from crowdworkers, and design interventions for producing datasets with less opportunity for cheating features by applying the cluster bias identification techniques to find amelioration steps in the loop as future datasets are created.

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