BERTs of a feather do not generalize together: Large variability in generalization across models with similar test set performance

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Abstract

If the same neural architecture is trained multiple times on the same dataset, will it make similar linguistic generalizations across runs? To study this question, we fine-tuned 100 instances of BERT on the Multi-genre Natural Language Inference (MNLI) dataset and evaluated them on the HANS dataset, which measures syntactic generalization in natural language inference. On the MNLI development set, the behavior of all instances was remarkably consistent, with accuracy ranging between 83.6% and 84.8%. In stark contrast, the same models varied widely in their generalization performance. For example, on the simple case of subject-object swap (e.g., knowing that the doctor visited the lawyer does not entail the lawyer visited the doctor), accuracy ranged from 0.00% to 66.2%. Such variation likely arises from the presence of many local minima that are equally attractive to a low-bias learner such as a neural network; decreasing the variability may therefore require models with stronger inductive biases.

1 Introduction

Generalization is a crucial component of learning a language. No training set can contain all possible sentences, so learners must be able to generalize to sentences that they have never encountered before. We differentiate two types of generalization:

1. **In-distribution generalization**: Generalization to examples which are novel but which are drawn from the same distribution as the training set.

2. **Out-of-distribution generalization**: Generalization to examples drawn from a different distribution than the training set.

The standard evaluation procedure in natural language processing uses test sets that were generated in the same way as the training set, therefore testing only in-distribution generalization. Current neural architectures perform very well at this type of generalization. For example, on the natural language understanding tasks in the GLUE benchmark (Wang et al., 2019), several Transformer-based models (Liu et al., 2019b,a; Yang et al., 2019) have surpassed the human baselines established by Nangia and Bowman (2019).

An alternative evaluation approach is to test models on targeted datasets designed to illuminate how the models handle some particular linguistic phenomenon. In this line of investigation, which tests out-of-distribution generalization, the results are more mixed. Some works have found successful handling of subtle linguistic phenomena such as subject-verb agreement (Gulordava et al., 2018) and filler-gap dependencies (Wilcox et al., 2018). Other works, however, have illuminated surprising failures even on seemingly simple types of examples (McCoy et al., 2019). Such results make it clear that there is still much room for improvement in how neural models perform on syntactic structures that are rare in training corpora.

In this work, we investigate whether the linguistic generalization behavior of a given neural architecture is consistent across multiple instances of that architecture. This question is important because, in order to tell which types of architectures generalize best, we need to know whether successes and failures of generalization should be attributed to aspects of the architecture or to random luck in the choice of the model’s initial weights.

We investigate this question using the task of natural language inference (NLI) by fine-tuning 100 instances of BERT (Devlin et al., 2019) on the MNLI dataset (Williams et al., 2018). These 100 instances differed only in (i) the initial weights of the classifier trained on top of BERT and (ii) the order in which examples were sampled during training. All other aspects of training, including
the initial weights of BERT, were held constant. We evaluated these 100 instances on both the in-distribution MNLI development set and also on the out-of-distribution HANS evaluation set (McCoy et al., 2019), which was designed to evaluate syntactic generalization in NLI models.

We find that these 100 instances were remarkably consistent on in-distribution generalization, with all accuracies on the MNLI development set falling in the range 83.6% to 84.8%. In contrast, these 100 instances varied dramatically in their out-of-distribution generalization performance; for example, on one of the thirty categories of examples in the HANS dataset, accuracy ranged from 7% to 77%. These results show that, when assessing the linguistic generalization of neural models, it is important to consider multiple training runs of each architecture, since models can differ vastly in how they perform on examples drawn from a different distribution than the training set, even when they perform similarly on an in-distribution test set.

2 Background

2.1 In-distribution generalization

Several past works have noted that the same architecture can perform very differently across random restarts (Reimers and Gurevych, 2017, 2018). Most relevantly for our work, the original BERT paper (Devlin et al., 2019) noted that fine-tuning of BERT is unstable for some datasets, such that some random restarts achieve state-of-the-art results while others perform poorly; this instability has further been noted in Phang et al. (2018). However, this observation only applies to in-distribution generalization, while we focus on out-of-distribution generalization.

2.2 Out-of-distribution generalization

There have also been several past works that included a focus on how different runs of the same architecture can have different out-of-distribution generalization. Weber et al. (2018) trained 50 instances of a sequence-to-sequence model on a simple symbol replacement task and found that all 50 instances achieved over 99% accuracy on the in-distribution test set but had highly variable performance on out-of-distribution generalization sets; for example, in the most variable case, accuracy ranged from close to 0% to over 90%, with a standard deviation of 20.6%. Similarly, McCoy et al. (2018) trained 100 instances for each of 6 types of sequence-to-sequence recurrent neural networks, using a synthetic training set that was ambiguous between two generalizations. Some of these models were highly consistent across instances in terms of which generalization they learned, but others varied considerably, with some instances of a given architecture strongly preferring one of the two generalizations while other instances strongly preferred the other generalization. Finally, Liška et al. (2018) trained 5000 instances of recurrent neural networks on the synthetic lookup tables task and found that most failed on compositional generalization but that a small number did display strong compositional generalization.

All of these past works that studied variation in out-of-distribution generalization used simple, synthetic tasks with training sets carefully designed to have certain types of examples withheld. Our work extends this area of inquiry to models trained on natural language, which is noisier and does not have such explicit constraints, to see if models are still as variable even in more practical cases where the training set is not adversarially designed to be ambiguous.

2.3 Linguistic analysis of BERT

Many recent papers have sought a deeper understanding of BERT, whether to assess its encoding of sentence structure (Lin et al., 2019; Hewitt and Manning, 2019; Chrupała and Alishahi, 2019; Jawahar et al., 2019; Tenney et al., 2019b); its representational structure more generally (Abnar et al., 2019); its handling of specific linguistic phenomena such as subject-verb agreement (Goldberg, 2019), negative polarity items (Warstadt et al., 2019), function words (Kim et al., 2019), or a variety of psycholinguistic phenomena (Ettinger, 2019); or its internal workings (Coenen et al., 2019; Tenney et al., 2019a; Clark et al., 2019). The novel contribution of this work is the focus on variability across a large number of fine-tuning runs; previous works have generally used models without fine-tuning or have used only a small number of fine-tuning runs (usually only one fine-tuning run, or at most five fine-tuning runs).

3 Method

3.1 Task and datasets

We used the task of natural language inference (NLI; also known as Recognizing Textual Entail-
Heuristic Definition Example

Lexical overlap Assume that a premise entails all hypotheses constructed from words in the premise. The doctor was paid by the actor. The doctor paid the actor.

Subsequence Assume that a premise entails all of its contiguous subsequences. The doctor near the actor danced. The actor danced.

Constituent Assume that a premise entails all complete subtrees in its parse tree. If the artist slept, the actor ran. The artist slept.

Figure 1: The heuristics targeted by the HANS dataset, along with examples of incorrect entailment predictions that these heuristics would lead to. (Figure from McCoy et al. (2019).)

ment), which involves giving a model two sentences, called the premise and the hypothesis. The model must then output a label of entailment if the premise entails (i.e., implies the truth of) the hypothesis, contradiction if the premise contradicts the hypothesis, or neutral otherwise. For training, we used the training set of the MNLI dataset (Williams et al., 2018), examples from which are given below:

(1) a. Premise: One of our number will carry out your instructions minutely.
   b. Hypothesis: A member of my team will execute your orders with immense precision.
   c. Label: entailment

(2) a. Premise: but that takes too much planning
   b. Hypothesis: It doesn’t take much planning.
   c. Label: contradiction

(3) a. Premise: He turned and smiled at Vrenna.
   b. Hypothesis: He smiled at Vrenna who was walking slowly behind him with her mother.
   c. Label: neutral

To test models’ in-distribution generalization, we evaluated their performance on the MNLI matched development set, which was generated in the same way as the MNLI training set. To test out-of-distribution generalization, we used the HANS dataset (McCoy et al., 2019), which contains NLI examples designed to require understanding of syntactic structure. More specifically, the HANS dataset targets three structural heuristics that models trained on MNLI are likely to learn. These heuristics are defined in Figure 1, along with examples of cases where the heuristics make incorrect predictions.

To assess whether a model has learned these heuristics, the HANS dataset contains examples where each heuristic makes the right predictions (i.e., where the correct label is entailment) and examples where each heuristic makes the wrong predictions (i.e., where the correct label is non-entailment). A model that has adopted one of the three heuristics will output entailment for all examples targeting that heuristic, even the examples for which the correct answer is non-entailment.

3.2 Models and training

All of our models consisted of BERT with a linear classifier on top of it outputting labels of entailment, contradiction, or neutral. We fine-tuned this model on MNLI using the MNLI fine-tuning code available on the BERT GitHub repository. We initialized the BERT component of the model with the pre-trained bert-base-uncased weights from the BERT GitHub repository; these weights were obtained by training BERT on a large quantity of natural text. All of our instances of fine-tuning used these same initial BERT weights, but they all used different, random initial weights for the classifier. The fine-tuning process then modified the weights of both the BERT component and the classifier. We ran 100 instances of this fine-tuning. Following Devlin et al. (2019), we varied only two things across fine-tuning runs: (i)

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1We used the development set rather than the test set because the test set labels are not available to the public. This development set was not used in any way during training, making it effectively a test set.

2https://github.com/google-research/bert
4 Results

4.1 In-distribution generalization

The 100 instances performed remarkably consistently on in-distribution generalization, with all models achieving an accuracy between 83.6% and 84.8% on the MNLI development set (Figure 2).

4.2 Out-of-distribution generalization

On the HANS evaluation set, performance was much more variable. This evaluation set consists of 6 main categories of examples, each of which can be further divided into 5 subcategories. Performance was reasonably consistent on five of the six categories, but on the sixth category—the non-entailed lexical overlap category—performance varied dramatically, ranging from 6% accuracy to 54% accuracy (Figure 3). Given that this is the most variable case, we focus on it for the rest of the analysis of the HANS results.

The non-entailed lexical overlap category encompasses examples for which the correct label is non-entailment (i.e., either contradiction or neutral) and for which all the words in the hypothesis also appear in the premise but not as a contiguous subsequence of the premise. This category can be broken down into five subcategories; examples for these subcategories, along with the distribution of the instances’ performance on each subcategory, are in Figure 4. Chance performance on HANS is 50%; on all of the subcategories except for passive sentences, accuracies range from far below chance to modestly above chance. At least some of these subcategories seem intuitively simple, yet models still vary considerably on them; for example, the subject-object swap examples could be handled with only rudimentary knowledge of syntax (in particular, knowledge of the distinction between subjects and objects), yet models still range in accuracy on this subcategory from 0% to 66%, indicating that, although these models performed very consistently on the in-distribution test set, they have nevertheless learned strikingly variable representations of syntax.

5 Discussion

We have found that models that vary only in their initial weights and the order of training examples can vary substantially in their out-of-distribution linguistic generalization. We found this variation even with the vast majority of initial weights held constant (i.e., all the weights in the BERT component of the model), suggesting that models might display an even greater degree of variability if the pre-training step used to initialize the weights of the BERT component were also redone across instances. These results underscore the importance of evaluating models on multiple random restarts, as conclusions drawn from a single instance of a model might not hold across instances. Further, these results also highlight the importance of evaluating models on out-of-distribution generalization; given that all 100 of our instances displayed similar in-distribution generalization, only their performance on out-of-distribution generalization actually illuminates the substantial differences in what these models have learned.
| Category              | Example                                                                 | Accuracy distribution |
|-----------------------|-------------------------------------------------------------------------|-----------------------|
| Subject-object swap   | The doctor visited the lawyer. → The lawyer visited the doctor.         | ![Accuracy distribution](image1) |
| Preposition           | The judges by the manager saw the artists. → The artists saw the manager| ![Accuracy distribution](image2) |
| Relative clause       | The actors advised the author who the tourists saw. ← The author advised the tourists | ![Accuracy distribution](image3) |
| Passive               | The senators were recommended by the managers. ← The senators recommended the managers | ![Accuracy distribution](image4) |
| Conjunction           | The doctors advised the presidents and the tourists. ← The presidents advised the tourists | ![Accuracy distribution](image5) |

Figure 4: Results on the various subcategories within the non-entailed lexical overlap examples of the HANS dataset. We do not include the other 25 subcategories of the HANS dataset in this figure as there was little variability across instances for those subcategories.

The high degree of variability shown by these models likely reflects the presence of many local minima in the loss surface, all of which are equally attractive to our models, making the choice of the particular minimum that the model settles on essentially arbitrary and easily affected by random variations in initial weights and the order of training examples. To reduce this variability, therefore, it will likely be necessary to use models with stronger inductive biases that can help distinguish between these many local minima. In stark contrast to the models we have looked at—which generalized in highly variable ways despite being trained on the same set of examples—humans tend to converge to remarkably similar linguistic generalizations despite major differences in the linguistic input that they encounter as children (Chomsky, 1965, 1980). This fact suggests that humans have stronger inductive biases than these models, leading to more robustly similar generalization in humans than we have observed with our re-runs of BERT. This suggests that reducing the generalization variability of NLP models is desirable as a step toward bringing models closer to human performance in one of the major areas where they still dramatically lag behind humans, namely in out-of-distribution generalization.

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