Stress-Testing Neural Models of Natural Language Inference with Multiply-Quantified Sentences

Atticus Geiger  
Stanford Symbolic Systems Program  
atticusg@stanford.edu

Lauri Karttunen  
Stanford Linguistics  
laurik@stanford.edu

Ignacio Cases  
Stanford Linguistics  
_cases@stanford.edu

Christopher Potts  
Stanford Linguistics  
cgpotts@stanford.edu

Abstract

Standard evaluations of deep learning models for semantics using naturalistic corpora are limited in what they can tell us about the fidelity of the learned representations, because the corpora rarely come with good measures of semantic complexity. To overcome this limitation, we present a method for generating data sets of multiply-quantified natural language inference (NLI) examples in which semantic complexity can be precisely characterized, and we use this method to show that a variety of common architectures for NLI inevitably fail to encode crucial information; only a model with forced lexical alignments avoids this damaging information loss.

1 Introduction

Deep learning approaches to semantics hypothesize that it is feasible to learn fixed-dimensional distributed representations that encode the meanings of arbitrarily complex sentences. Well-known mathematical results show that this hypothesis is correct in terms of representational capacity (Cybenko, 1989), but it remains an empirical question whether a given model architecture can achieve the desired representations in practice. In addressing this question, researchers generally rely on corpora of naturalistic examples, using comparative performance metrics as a proxy for the underlying capacity of the models to learn rich meaning representations. However, these corpora rarely come with good independent measures for semantic complexity (but see Williams et al., 2018), so they too leave us guessing about precisely what has been learned by any given system.

This paper presents a method for generating artificial data sets in which the semantic complexity of individual examples can be precisely characterized. Our task is natural language inference (NLI). There are diverse, high-quality naturalistic corpora for this task, and a variety of architectures have been evaluated on them, with some clear success. However, the corpora themselves have been scrutinized and found to contain patterns that lower our confidence that the models are learning robust semantic representations (Rudinger et al., 2017; Poliak et al., 2018; Glockner et al., 2018; Gururangan et al., 2018; Tsuchiya, 2018).

We propose to pair these evaluations with ones conducted on our data sets to achieve a fuller picture. Our method is built around an interpreted formal grammar that generates sentences containing multiple quantifiers, modifiers, and negations. We constrain the open-domain vocabulary to ensure that all items neither entail nor exclude all others, to trivialize their contributions. This stresses models with learning interactions between logically complex function words. The sentences from this grammar are deterministically translated into first-order logic, and an off-the-shelf theorem prover is used to generate NLI examples. In this setting, we have control over all aspects of the generated data set and complete visibility into how different systems handle specific classes of example.

We evaluate a number of different architectures, including LSTM sequence models with attention, tree-structured neural networks (TreeNN), and a tree-structured neural network that processes aligned NLI examples (CompTreeNN). Our central finding is that only the CompTreeNN performs perfectly. Even the LSTM with attention, which has the space to learn lexical alignments, fails to find optimal solutions. What is special about the CompTreeNN is its ability to abstract away the identity of specific lexical items by computing and propagating lexical semantic relations. When stressed with even our small fragment of natural language’s complexity, the other models lose the identity of open-class lexical items as the sentence embeddings are recursively constructed. This re-
results in systematic errors, calling into question the viability of these models for semantics.

2 Data Generation

Our fragment $G$ consists of sentences of the form

$$Q_S \ Adj_S N_S \ Neg \ Adv \ V \ Q_O \ Adj_O \ N_O \ N_S$$

where $N_S$ and $N_O$ are nouns, $V$ is a verb, $Adj_S$ and $Adj_O$ are adjectives, and $Adv$ is an adverb. Neg is does not, and $Q_S$ and $Q_O$ can be every, not every, some, or no; in each of the remaining categories, there are 100 words. Additionally, $Adj_S$, $Adj_O$, $Adv$, and Neg can be the empty string, which is represented in the data by a unique token. Semantic scope is fixed by surface order, with earlier elements scoping over later ones.

For NLI, we define the set of premise–hypothesis pairs $S \subset G \times G$ such that $(s_p, s_h) \in S$ iff the non-identical non-empty nouns, adjectives, verbs, and adverbs with identical positions in $s_p$ and $s_h$ are mutually consistent (semantic independence). This constraint on $S$ trivializes the task of determining the lexical relations between adjectives, nouns, adverbs, and verbs, since the relation is equality where the two aligned elements are identical, otherwise independence. Furthermore, it follows that distinguishing contradictions from entailments is trivial. The only sources of contradictions are negation and the negative quantifiers no and not every. Consider $(s_p, s_h) \in S$ and let $C$ be the number of times negation or a negative quantifier occurs $s_p$ and $s_h$. If $s_p$ contradicts $s_h$, then $C$ is odd; if $s_p$ entails $s_h$, then $C$ is even.

Figure 1 summarizes the range of relations that can hold between aligned pairs of subconstituents given the constraints we impose on $S$. Even with the contributions of open-class lexical items trivialized, the level of complexity remains high, and all of it emerges from semantic composition, rather than from lexical relations.

Our corpora use the three-way labeling scheme of entailment, contradiction, and neutral. To assign these labels, we translate each premise–hypothesis pair into first-order logic and use Prover9 (McCune, 2005–2010). We assume no expression is empty or universal and encode these assumptions as additional premises. This label generation process implicitly assumes the relation between unequal artificial words is independence.

For NLI corpora, we create samples from $S$ in which, for a given example, every adjective–noun and adverb–verb pair across the premise and hypothesis is equally likely to have the relation equality, subset, superset, or independence. Without this balancing, any given adjective–noun and adverb–verb pair across the premise and hypothesis has more than a 99% chance of being in the independence relation. Even with this step, 98% of the pairs are neutral, so we again sample to create corpora that are balanced across the NLI labels.¹

¹Our data set generation code: https://github.com/atticusg/MultiplyQuantifiedData
cussed later.

3 Models

We consider five different model architectures:

- **CBoW** Premise and hypothesis are represented by the average of their respective word embeddings (continuous bag of words).

- **LSTM** Premise and hypothesis are processed as sequences of words using a recurrent neural network (RNN; Elman 1990) with LSTM cells (Hochreiter and Schmidhuber, 1997), and the final hidden state of each serves as its representation (Bowman et al., 2015a).

- **TreeNN** Premise and hypothesis are processed as trees, and the semantic composition function is a single layer feed forward network (Socher et al., 2011a, b). The value of the root node is the semantic representation in each case.

- **Attention LSTM** An LSTM RNN with word-by-word attention (Rocktäschel et al., 2015).

- **CompTreeNN** Premise and hypothesis are processed as a single aligned tree, as in figure 1. This model is inspired by research in natural logic (MacCartney, 2009; Icard and Moss, 2013; Bowman et al., 2015b).

For the first three models, the premise and hypothesis representations are concatenated. For the CompTreeNN and LSTM with attention, there is just a single representation of the pair. In all cases, the premise-hypothesis representation is fed through two hidden layers and a softmax layer.

All models are initialized with random 100-dimensional word vectors and optimized using Adam (Pennington et al., 2014; Kingma and Ba, 2014). A grid hyperparameter search was run over dropout values of [0, 0.1, 0.2] on the output and keep layers of LSTM cells, learning rates of $[1e-2, 3e-4, 1e-3]$, L2 regularization values of $[0, 1e-4, 1e-3]$ on all weights, and activation functions relu and tanh.

4 Results and Analysis

4.1 Overall Results

Table 1 summarizes the performance of each model trained on 500K examples and tested on a disjoint set of 10K examples. Figure 2 shows dev-set model performance by training epoch. The CBoW begins far behind all the other models and never catches up. The LSTM, Attention LSTM, and TreeNN both jump quickly to $\approx 94\%$, and slightly increase performance plateauing at very good but not perfect performance ($\approx 96\%$). When trained further, the train set is overfit and test performance declines to $\approx 94\%$. Only the CompTreeNN is able to perform perfectly.

4.2 A Shared Suboptimal Solution

We noted above that the LSTM, Attention LSTM, and TreeNN models get stuck at $\approx 94\%$ accuracy early in training. Because of the highly controlled way that we generate our data sets, we can pin-point exactly why this happens. These models find the same suboptimal solution: they learn the identity and order of quantifiers, the importance of negation, and whether or not adjectives and adverbs are empty, but they are unable to make use of the specific identity of non-empty nouns, verbs, adjectives, and adverbs. As a result, they make systematic errors on neutral examples that would be contradictions or entailments if aligned open-class lexical were equal (see Table 1). The following collapsing is performed:

- `Every Swiss baker madly rubs some rock` $\Rightarrow$ `every Adj S N S Adv V some N O`
- `Every wild baker sells some rock` $\Rightarrow$ `every Adj S N S V some N O`

As a result of this collapsing, this looks like an entailment relation, because the only difference is the deletion of the adverb, which expands the scope of the universal quantification.

For the Encoder LSTM and TreeNN models, there is a natural explanation for why these errors are made. These models separately bottleneck the information from the premise and hypothesis into
two 100-dimensional embeddings before a prediction is made using the concatenation of these embeddings. The function words are, like function words in natural data, very complex and very frequent as compared to open-class items. The stress of learning them seems to nullify the models’ ability to store the precise identity of up to six open-class items per example, each drawn from a lexicon of 100. Both these models make minor improvements on this solution to achieve ≈96%. The LSTM sometimes notices when object nouns and adjectives differ across the premise and hypothesis, and the TreeNN model is able to do so with subject nouns and adjectives. These are precisely the lexical items whose contributions to the sentence embeddings are most recent, emphasizing the architectural nature of this problem.

The performance of the Attention LSTM has a high variance. On some runs, it gets stuck at ≈94% test accuracy, and others it achieves ≈97%. This gives some hope for attention. However, in all runs, performance on examples with informative open-class lexical items is no higher than 60%, and the systematic errors remain. It is surprising that the Attention LSTM show this limitation, as it was designed to overcome the problem of representational bottlenecks by allowing interaction between the lexical items in the premise and hypothesis. However, Rocktäschel et al. (2015) anticipate this failure: “Word-by-word attention seems to work well when words in the premise and hypothesis are connected via deeper semantics or common-sense knowledge”, however “attention can fail, for example when two sentences and their words are entirely unrelated”. Our data sets pinpoint this weakness.

The CBow model also has a bottleneck, but actually performs better on examples with informative open-class lexical items than those without. However, this model performs very poorly on the overall task of learning complex interactions between function words, so its performance does not contradict our observation that learning such interactions results in systematic information loss.

The CompTreeNN avoids this bottleneck by design, since it mixes the premise and hypothesis via a strict word-by-word alignment. This makes its learning task much simpler: it need only determine these local relations and propagate them; we know from Bowman et al. (2015b) that the relational algebra that underlies this propagation can easily be learned by standard neural architectures.

### 4.3 The Problem is Architecture

These systematic errors are not an issue of low dimensionality; the trends by epoch and final results are virtually identical with 200-dimensional rather than 100-dimensions representations.

One might worry that these results represent a failure to optimize these models properly. We conducted fairly large hyperparameter searches (section 3), but perhaps more optimal settings lie outside of the space we searched. Figure 3 strong suggests that this is not the case. Here, we show the performance of the LSTM with a large sample of hyperparameter settings. There are two major groups of mostly indistinguishable runs, those that are completely stuck at the suboptimal solu-

| Model            | Train       | Dev         | Test        | Informative Open-class Subset |
|------------------|-------------|-------------|-------------|-------------------------------|
| CBow             | 69.18 ± 0.75| 69.91 ± 0.27| 69.66 ± 0.23| 82.30 ± 1.20                 |
| LSTM Encoder     | 96.05 ± 0.29| 95.83 ± 0.14| 95.61 ± 0.21| 26.90 ± 1.44                 |
| TreeNN           | 96.20 ± 0.17| 96.19 ± 0.15| 95.99 ± 0.11| 31.09 ± 2.91                 |
| Attention LSTM   | 97.50 ± 2.69| 95.98 ± 2.23| 95.82 ± 2.16| 35.69 ± 35.98                |
| CompTreeNN       | 99.85 ± 0.07| 99.87 ± 0.06| 99.85 ± 0.12| 98.05 ± 1.02                 |

Table 1: Mean accuracy of 5 runs, with 95% confidence intervals. ‘Informative Open-class Subset’ are the Test set examples labeled neutral solely due to the independence relation between open-class lexical items.
tation and those that partially overcome it. There is no indication that expanding the hyperparameter search would change the outcomes for this model and the patterns are the same for the others we consider. We are left with the conclusion that these models simply cannot learn to perform this task.

5 Conclusion

We defined a procedure for generating semantically challenging NLI data sets and showed that a range of neural models invariably learn suboptimal solutions that we can characterize based on the examples themselves. The CompTreeNN overcomes these limitations, which helps us diagnose the problem: the information bottleneck formed by learning separate premise and hypothesis representations. The CompTreeNN is a highly task-specific model, so its stand-out performance might be seen as more of a challenge than a victory for deep learning approaches to semantics.

Acknowledgements

This material is based in part upon work supported by the Stanford Data Science Initiative and by the NSF under Grant No. BCS-1456077.

References

Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. 2015a. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pages 632–642, Lisbon, Portugal. Association for Computational Linguistics.

Samuel R. Bowman, Christopher Potts, and Christopher D. Manning. 2015b. Recursive neural networks can learn logical semantics. In Proceedings of the 3rd Workshop on Continuous Vector Space Models and their Compositionality, pages 12–21. Association for Computational Linguistics.

George Cybenko. 1989. Approximation by superpositions of a sigmoidal function. Mathematics of Control, Signals and Systems, 2(4):303–314.

Jeffrey L. Elman. 1990. Finding structure in time. Cognitive Science, 14(2):179–211.

Max Glockner, Vered Shwartz, and Yoav Goldberg. 2018. Breaking nli systems with sentences that require simple lexical inferences. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 650–655. Association for Computational Linguistics.

Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A. Smith. 2018. Annotation artifacts in natural language inference data. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 107–112. Association for Computational Linguistics.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural Computation, 9(8):1735–1780.

Thomas F. Icard and Lawrence S. Moss. 2013. Recent progress on monotonicity. Linguistic Issues in Language Technology, 9(7):1–31.

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. CoRR, abs/1412.6980.

Bill MacCartney. 2009. Natural Language Inference. Ph.D. thesis, Stanford University.

Bill MacCartney and Christopher D. Manning. 2009. An extended model of natural logic. In Proceedings of the Eight International Conference on Computational Semantics, pages 140–156. Association for Computational Linguistics.

W. McCune. 2005–2010. Prover9 and Mace4. http://www.cs.unm.edu/~mccune/prover9/.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Adam Poliak, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. 2018. Hypothesis only baselines in natural language inference. In Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics, pages 180–191. Association for Computational Linguistics.

Tim Rocktäschel, Edward Grefenstette, Karl Moritz Hermann, Tomáš Kociský, and Phil Blunsom. 2015. Reasoning about entailment with neural attention. CoRR, abs/1509.06664.

Rachel Rudinger, Chandler May, and Benjamin Van Durme. 2017. Social bias in elicited natural language inferences. In Proceedings of the First ACL Workshop on Ethics in Natural Language Processing, pages 74–79. Association for Computational Linguistics.

Richard Socher, Jeffrey Pennington, Eric H. Huang, Andrew Y. Ng, and Christopher D. Manning. 2011a. Semi-supervised recursive autoencoders for predicting sentiment distributions. In Proceedings of the
Richard Socher, Jeffrey Pennington, Eric H. Huang, Andrew Y. Ng, and Christopher D. Manning. 2011b. Semi-supervised recursive autoencoders for predicting sentiment distributions. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP ’11, pages 151–161, Stroudsburg, PA, USA. Association for Computational Linguistics.

Masatoshi Tsuchiya. 2018. Performance impact caused by hidden bias of training data for recognizing textual entailment. CoRR, abs/1804.08117.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1112–1122. Association for Computational Linguistics.