ORCHARD: A Benchmark For Measuring Systematic Generalization of Multi-Hierarchical Reasoning

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Abstract
The ability to reason with multiple hierarchical structures is an attractive and desirable property of sequential inductive biases for natural language processing. Do the state-of-the-art Transformers and LSTM architectures implicitly encode for these biases? To answer this, we propose ORCHARD, a diagnostic dataset for systematically evaluating hierarchical reasoning in state-of-the-art neural sequence models. While there have been prior evaluation frameworks such as ListOps or Logical Inference, our work presents a novel and more natural setting where our models learn to reason with multiple explicit hierarchical structures instead of only one, i.e., requiring the ability to do both long-term sequence memorizing, relational reasoning while reasoning with hierarchical structure. Consequently, backed by a set of rigorous experiments, we show that (1) Transformer and LSTM models surprisingly fail in systematic generalization, and (2) with increased references between hierarchies, Transformer performs no better than random.

1 Introduction
Sequential models like the Long-Short Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) and Transformer (Vaswani et al., 2017) have achieved state-of-the-art (SOTA) performance on a myriad of NLP tasks, such as language modeling (Melis et al., 2019), machine translation (Edunov et al., 2018), summarization (Yan et al., 2020) and document classification (Adhikari et al., 2019). Language is hierarchical in nature, where documents are composed of sentences, and in turn composed of words. These hierarchical structures are intricately cross-referencing, with words referencing others in different sentences or even paragraphs. For example, if we use the term ‘aforementioned SOTA models’ in this sentence, the reader needs to relate it to the terms ‘LSTM’ and ‘Transformer’ in the first sentence of this paragraph. In our paper, we ask this central question: Do these SOTA models exploit the ubiquitous relational hierarchies in NLP? Our experiments show they do not, and surprisingly fail to reason with multiple hierarchies when tested on systematic generalization of our proposed task. Transformer does no better than random chance with larger hierarchies.

We study these models’ ability of capturing hierarchical structure without explicit parse trees, by evaluating the bi-directional LSTM with attention and the Transformer models on a novel multi-hierarchical reasoning task. To mitigate effects of spurious correlations and annotation artifacts in natural language datasets (Niven and Kao, 2019), we propose Operating Relational-Cum-Hierarchical Arithmetic Reasoning Dataset (ORCHARD), a dataset comprising sequences of numbers and nested mathematical operators. The task is as follows: Given two trees with values 0-9 and operators \{FIRST, LAST, MIN, MAX, COPY\}, evaluate both trees at their roots. An example is illustrated in Figure 1.

Figure 1: Example parse of an ORCHARD sequence showing the ground truth parse tree. Correct output is 0, 8. Blue arrows indicate the referencing done by COPY operators in the second tree.

1.1 Contributions
Diagnostic dataset We design a sequence-to-sequence dataset\(^1\) for measuring relational reasoning on hierarchical sequences. We evaluate six variants of the ORCHARD tasks, where models resolve

\(^1\)https://github.com/billptw/Orchard
the values of increasingly nested mathematical operations of different types, with explicit parses in the form of parenthesized lists.

**Model analysis and generalization tests** We perform experimental evaluation on Transformer and attentional Bi-LSTM architectures, and show that these models perform surprisingly badly on systematic generalization, i.e. when trained on a train set of depths 3 to 6, and tested on separate bins of depth 3 to 12, the model performance degrade significantly beyond depth 7. We show that the LSTM model is better able to systematically generalize to larger depths than the Transformer.

2 Related Work

Learning to induce hierarchical structures from sequential data has shown tremendous potential in many recent works (Wang et al., 2019; Shen et al., 2019, 2018, 2017; Yogatama et al., 2016; Choi et al., 2018; Drozdov et al., 2019; Jacob et al., 2018). After all, many forms of sequential data, especially language, are intrinsically hierarchical in nature.

ListOps (Nangia and Bowman, 2018), subje...
Hence, in the generation of the tree, the left and right children of each operator node have an equal probability of being assigned a branching operator node or a terminal node. Terminal nodes are nodes with a COPY operator, or with only integer values.

4 Experiments

4.1 Tasks

To examine the effects of hierarchical reasoning versus relational reasoning, we run three difficulty variants on two permutations of operators used. We generate a train, validation and test set of 500k, 50k and 50k sequences respectively. The train and validation set comprises depths of tree from 3 to 6 in equal proportions, and test on bins of depths 3 to 12 individually for generalization.

**Difficulty** To vary the difficulty of the relational reasoning required by the models, we vary the number of COPY operators in the second sentence of each input sequence in the dataset. When generating a sequence, each terminal node has a probability $c$ of being assigned the COPY operator, or otherwise be assigned one or two integer values ranging from 0 to 9. We vary $c$ in the second tree for each difficulty variant of the task, choosing from $c \in \{0, 0.5, 1\}$ to generate ORCHARD-easy, ORCHARD-medium and ORCHARD-hard tasks respectively. Hence the second tree an each sequence of the ORCHARD-hard dataset references the first tree fully, containing no integer values in the raw parse.

**Operators Used** The purpose of the ORCHARD task is to test the model’s ability to reason hierarchically, and not its ability to approximate mathematical operations. Hence, we minimized the number and type of operations used per task. For each of the three ORCHARD difficulty levels, we trained models on two variants of the ORCHARD dataset. The FIRST-LAST variant requires only positional and relational operators \{FIRST, LAST, COPY\}, while the MIN-MAX variant requires only comparative and relational operators \{MIN, MAX, COPY\}.

4.2 Experimental Details

**Models Examined** We train both Transformers of 44.3M parameters and bi-directional attentional LSTM of 6.2M parameters on the tasks, using the Fairseq\(^2\) framework to conduct the experiments. We minimize the sum of log probabilities of the correct character via the Adam optimizer (Kingma and Ba, 2014). For both models, we use a batch size of 128 split across 4 NVIDIA RTX 2080 GPUs, trained for 500 epochs using floating-point 16 precision. This results in an average training time of 18 hours. We then generate the output classification using beam search evaluated using the model checkpoint with the best validation accuracy, saved every 50 epochs. We include more hyper-parameter details in the appendix.

![Figure 2: Percentage accuracy for classification on both trees in ORCHARD tasks comprising only MIN-MAX task. Dashed lines for Transformer model.](image)

![Figure 3: Percentage accuracy for classification on both trees in ORCHARD tasks comprising only FIRST-LAST task. Dashed lines for Transformer model.](image)

5 Analysis

**ORCHARD Variants** From figures 2 and 3, we empirically verify the increased difficulty of ranging the amount of cross-tree referencing through the COPY operator. This is shown by the drop in performance from ORCHARD easy, medium to
hard for both MIN-MAX and FIRST-LAST experiments, on both LSTM and Transformer models. Comparing the comparative MIN-MAX operators with the positional FIRST-LAST task, we see that both models perform better on the FIRST-LAST dataset for ORCHARD-med and ORCHARD-hard. This suggests that reasoning with position within the level of the tree is relatively easy.

**Depths of Tree** As the depth of tree N increases, the performance of both models greatly decreases. From figures 2 and 3, we see that both models perform well for depths of tree within the training set (i.e. 3-6). Overall, we see that both models are unable to generalize well. From figures 4 and 5, we see that for the ORCHARD-hard task, the models can generalize well for the first tree classification. However, the classification score for both trees are held back by poor performance in classifying the second tree, highlighting the difficulty of hierarchical reasoning required in evaluating the COPY operator. These results suggest that the models are unable to relationally reason with hierarchical structures, as the task should be trivial to solve otherwise. Without a successful hierarchical parsing strategy, the difficulty of the ORCHARD task increases exponentially as the depth of tree increases, as the memory required to store the values of long sequences exceed the hidden state size if the model does not learn to resolve sub-trees in correct hierarchical order.

**Transformer vs LSTM** The Transformer model outperforms LSTM for ORCHARD-med and ORCHARD-hard for depths of tree within the training set (i.e. 3-6). However, the LSTM far outperforms Transformers when generalizing for greater depths of tree (≥ 9). From figures 4 and 5, we see that LSTM generalizes very well when evaluating the value of the first tree at depth 12, obtaining an accuracy of 86.7% and 88.7%, whereas the Transformer model scored 54.1% and 48.3%, on MIN-MAX and FIRST-LAST ORCHARD-hard tasks respectively. At depth of tree 12, the performance by the Transformer model degrades to random chance at 10%. These results suggest that LSTM is able to successfully reason hierarchically, generalizing well when parsing the first tree. However, both models are unable to generalize when doing relational reasoning, which is required when evaluating the COPY operator to successfully classify the second tree, leading to poor performance on the overall task.

### 6 Conclusion

Natural language is structured hierarchically with multiple references between hierarchies, where words from one sentence recursively refer to words or phrases in other sentences. How do SOTA models fare on the natural setting of reasoning between multiple hierarchies in an input sequence? To answer this, we introduce ORCHARD, a diagnostic dataset involving reasoning with multiple hierarchical structures. We empirically show that LSTM and Transformer models are unable to generalize on this setting, despite a small vocabulary of 10 numbers and 3 operators of the task, as the multi-hierarchical inductive bias is not implicitly captured.
References

Ashutosh Adhikari, Achyudh Ram, Raphael Tang, and Jimmy Lin. 2019. Rethinking complex neural network architectures for document classification. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4046–4051.

Samuel R Bowman, Christopher D Manning, and Christopher Potts. 2015. Tree-structured composition in neural networks without tree-structured architectures. arXiv preprint arXiv:1506.04834.

Jihun Choi, Kang Min Yoo, and Sang-goo Lee. 2018. Learning to compose task-specific tree structures. In Thirty-Second AAAI Conference on Artificial Intelligence.

Andrew Drozdov, Pat Verga, Mohit Yadav, Mohit Iyyer, and Andrew McCallum. 2019. Unsupervised latent tree induction with deep inside-outside recursive autoencoders. arXiv preprint arXiv:1904.02142.

Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. Understanding back-translation at scale. arXiv preprint arXiv:1808.09381.

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

Athul Paul Jacob, Zhouhan Lin, Alessandro Sordoni, and Yoshua Bengio. 2018. Learning hierarchical structures on-the-fly with a recurrent-recurssive model for sequences. In Proceedings of The Third Workshop on Representation Learning for NLP, pages 154–158.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Tal Linzen, Emmanuel Dupoux, and Yoav Goldberg. 2016. Assessing the ability of lstms to learn syntax-sensitive dependencies. Transactions of the Association for Computational Linguistics, 4:521–535.

Gábor Melis, Tomáš Kočiský, and Phil Blunsom. 2019. Mogrifier lstm. arXiv preprint arXiv:1909.01792.

Nikita Nangia and Samuel R Bowman. 2018. Listops: A diagnostic dataset for latent tree learning. arXiv preprint arXiv:1804.06028.

Timothy Niven and Hung-Yu Kao. 2019. Probing neural network comprehension of natural language arguments. arXiv preprint arXiv:1907.07355.

Yikang Shen, Zhouran Lin, Chin-Wei Huang, and Aaron Courville. 2017. Neural language modeling by jointly learning syntax and lexicon. arXiv preprint arXiv:1711.02013.

Yaushian Wang, Hung-Yi Lee, and Yun-Nung Chen. 2019. Tree transformer: Integrating tree structures into self-attention. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1061–1070, Hong Kong, China. Association for Computational Linguistics.

Yu Yan, Weizhen Qi, Yeyun Gong, Dayiheng Liu, Nan Duan, Jiusheng Chen, Ruofei Zhang, and Ming Zhou. 2020. Prophetnet: Predicting future n-gram for sequence-to-sequence pre-training. arXiv preprint arXiv:2001.04063.

Dani Yogatama, Phil Blunsom, Chris Dyer, Edward Grefenstette, and Wang Ling. 2016. Learning to compose words into sentences with reinforcement learning. arXiv preprint arXiv:1611.09100.