

TREE-STRUCTURED DECODING WITH DOUBLY-RECURRENT NEURAL NETWORKS

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ABSTRACT

We propose a neural network architecture for generating tree-structured objects from encoded representations. The core of the method is a *doubly* recurrent neural network that models separately the width and depth recurrences across the tree, and combines them inside each cell to generate an output. The topology of the tree is explicitly modeled, allowing the network to predict both content and topology of the tree when decoding. That is, given only an encoded vector representation, the network is able to *simultaneously* generate a tree from it and predict labels for the nodes. We test this architecture in an encoder-decoder framework, where we train a network to encode a sentence as a vector, and then generate a tree structure from it. The experimental results show the effectiveness of this architecture at recovering latent tree structure in sequences and at mapping sentences to simple functional programs.

1 INTRODUCTION

Recurrent neural networks have become extremely popular for modeling structured data. Key to their success is their ability to learn long-range temporal dependencies, their flexibility, and ease of customization. These architectures are a natural choice for modeling sequences; the notion of *time*—consecutive, linear inputs—in intrinsic to their design (Williams & Zipser, 1995; Hochreiter & Schmidhuber, 1997). Indeed, it is for sequential data that these architectures have achieved greater success, with groundbreaking performance in language modeling (Zaremba et al., 2015), machine translation (Sutskever et al., 2014) and conversational agents (Vinyals & Le, 2015), among other applications.

Although sequences are easy to manipulate and arise frequently in practice, they are by no means the only kind of structured data. Certain objects are more naturally modeled as trees or graphs, such as natural language parses, programs and hierarchical structures in bioinformatics. Even in tasks where the data is apparently sequential, there might be an underlying hierarchical structure that guides the generation. Language, for example, is known to be *compositional*: the meaning of a sentence is composed from the individual meanings of its parts Frege (1892). Thus, methods that construct sentences compositionally have the potential of generating language more naturally and efficiently than their sequential counterparts.

The flexibility and success of recurrent neural networks in modeling and generating sequential data has prompted efforts to adapt them to non-sequential data. Recent work has pioneered the application of neural architectures to hierarchical structures, albeit in limited settings. Most of this work has assumed that either the full tree structure is given (Socher et al., 2012; Tai et al., 2015) or at least the nodes are (Socher & Lin, 2011; Chen & Manning, 2014; Kiperwasser & Goldberg, 2016). In the former scenario, the network must simply aggregate the node information in a manner that is coherent with the tree structure, while in the latter, generation essentially becomes an attachment problem: deciding which pairs of nodes to join with an edge until a tree is formed.

Full *decoding with structure*, that is, generating a tree-structured object from nothing more than a vector representation, is a much harder problem and was until very recently mostly unexplored. Clearly, the main challenge of this paradigm lies in the fact that both the topology and the content (node and/or edge labels) of the tree must be generated. That is, without knowing in advance its

size, node degree or depth, one must generate a tree that is both topologically feasible and whose predicted node labels are coherent. There have been efforts to adapt RNNs to this context too. In fact, most current approaches to structured decoding rely on extensions and variations of sequential architectures. Since there is no obvious way to *de-sequentialize* these, previous work has relied on artifacts to simulate depth, such as padding trees with special tokens (Dong & Lapata, 2016) or using alternating RNNs coupled with external classifiers to predict branching (Zhang et al., 2016).

In this work, we propose a novel architecture tailored specifically to tree-structured decoding. At the heart of our approach is a *doubly-recurrent* (breadth and depth-wise recurrent) neural network which separately models the flow of information between parent and children nodes, and between siblings. Each of these relationships is modeled with a recurrent module whose hidden states are updated upon observing node labels. Every node in the tree receives two hidden states, which are then combined and used to predict a label for that node. Besides maintaining separate but simultaneous *fraternal* and *paternal* recurrences, the proposed architecture departs from previous methods in that it explicitly models tree topology. Each node in the network has modules that predict, based on the cell state, whether the node is terminal, both in terms of depth and width. Decoupling these decisions from the label prediction allows for a more concise formulation, which does not require artificial tokens to be added to the tree to simulate branching.

We test this novel architecture in various encoder-decoder frameworks, coupling it with sequential encoders to predict tree structure from encoded vector representations of sequences. The experimental results show the effectiveness of this approach at recovering latent structure in flattened string representations of trees (Section 4.1) and at mapping from natural language descriptions of simple programs to abstract syntax trees (Section 4.2). In addition, we show that even for sequence-to-sequence tasks such as machine translation, the proposed architecture exhibits desirable properties, such as invariance to structural changes and coarse-to-fine generation (Section 4.3).

To summarize, the main contributions of this paper are as follows:

- We propose a novel neural network architecture specifically tailored to tree-structured decoding, which maintains separate depth and width recurrences states and combines them to obtain hidden states for every node in the tree.
- We equip this novel architecture with a mechanism to predict tree topology *explicitly*, as opposed to *implicitly* by adding nodes with special tokens.
- We show experimentally that the proposed method is capable of recovering trees from encoded representations and that it outperforms state-of-the-art methods in a task consisting of mapping sentences to simple functional programs.

2 RELATED WORK

Recursive Neural Networks. Recursive neural networks (Socher & Lin, 2011; Socher et al., 2012) were proposed to model data with hierarchical structures, such as parsed scenes and natural language sentences. Though they have been most successfully applied to encoding objects when their tree-structured representation is given (Socher et al., 2013), their original formulation by Socher & Lin (2011) also showed how they can be used to *predict* the structure (edges), albeit for the case where nodes are given. Thus, besides their limited applicability due to their assumption of binary trees, recursive neural networks are not useful for *fully* generating trees from scratch.

Tree-structured encoders. The Tree-LSTM of Tai et al. (2015) is a generalization of long short-term memory networks (Hochreiter & Schmidhuber, 1997) to tree-structured inputs. Their model constructs a sentence representation bottom-up, obtaining at every step the representation of a node in the tree from the representations of its children. In this sense, this model can be seen as a generalization of recursive neural networks to trees with degree potentially greater than two, with the additional long-range dependency modeling provided by LSTMs. They propose two methods for aggregating the states of the children, depending on the type of underlying tree: N-ary trees or trees with unknown and potentially unbounded branching factor. TreeLSTMs have shown promising results for compositional encoding of structured data, though by construction they cannot be used for decoding, since they operate on a given tree structure.

Tree-structured decoders. Proposed only very recently, most tree-structured decoders rely on stacked on intertwined RNNs, and use heuristic methods for topological decisions during generation. Closest to our method is the Top-down Tree LSTM of Zhang et al. (2016), which generates a tree from an encoded representation. Their method relies on 4 independent LSTMs, which act *in alternation*—as opposed to simultaneously in our approach—yielding essentially a standard LSTM which changes the weights it uses based on the position of the current node. In addition, in their method children are faced with *asymmetric parent input*: “younger” children receive information from the parent state only through the previous sibling’s state. Though most of their experiments focus on the case where the nodes are given, they mention how to use their method for full prediction by introducing additional binary classifiers which predict which of the four LSTMs is to be used. These classifiers are trained in isolation after the main architecture has been trained. Contrary to this approach, our method can be trained end-to-end in only one pass, has a simpler formulation and explicitly incorporates topological prediction as part of the functioning of each neuron.

A similar approach is proposed by Dong & Lapata (2016). They propose SEQ2TREE, an encoder-decoder architecture that maps sentences to tree structures. For the decoder, they rely on hierarchical use of an LSTM, similar to Tai et al. (2015), but in the opposite direction: working top-down from the root of the tree. To decide when to change levels in the hierarchy, they augment the training trees with nonterminal nodes labeled with a special token $\langle n \rangle$, which when generated during decoding trigger the branching out into a lower level in the tree. Similar to our method, they feed nodes with hidden representations of their parent and sibling, but they do so by concatenating both states and running them through a single recurrent unit, as opposed to our method, where these two sources of information are handled separately. A further difference is that our method does not require artificial nodes with special tokens to be added to the tree, which results in smaller trees.

Hierarchical Neural Networks for Parsing. Neural networks have also been recently introduced to the problem of natural language parsing (Chen & Manning, 2014; Kiperwasser & Goldberg, 2016). In this problem, the task is to predict a parse tree over a given sentence. For this, Kiperwasser & Goldberg (2016) use recurrent neural networks as a building block, and compose them recursively to obtain a tree-structured encoder. Starting from the leaves (words) they predict a parse tree with a projective bottom-up strategy, which sequentially updates the encoded vector representation of the tree and uses it to guide edge-attaching decisions. Though conceptually similar to our approach, their method relies on having access to the nodes of the tree (words) and only predicts its topology, so—similar to recursive neural networks—it cannot be used for a fully generative decoding.

3 DOUBLY RECURRENT NEURAL NETWORKS

Generating a tree-structured object from scratch using only an encoded representation poses several design challenges. First, one must decide in which order to generate the tree. If the nodes on the decoder side were given (such as in parsing), it would be possible to generate a tree bottom-up from these nodes (e.g. as Kiperwasser & Goldberg 2016 do). In the setting we are interested in, however, not even the nodes are known when decoding, so the natural choice is a top-down decoder, which starting from an encoded representation generates the root of the tree and then recursively generates the children (if any) of every node.

The second challenge arises from the asymmetric hierarchical nature of trees. Unlike the sequence-to-sequence setting where encoding and decoding can be achieved with analogous procedures, when dealing with tree-structured data these two involve significantly different operations. For example, an encoder that processes a tree bottom-up using information of a node’s children to obtain its representation cannot be simply reversed and used as a decoder, since when generating the tree top-down, nodes have to be generated before their children are.

An additional design constraint comes from deciding what information to feed to each node. For sequences, the choice is obvious: a node should receive information from the node preceding or succeeding it (or both), i.e. there is a one-dimensional flow of information. In trees, there is an evident flow of information from parent to children (or vice-versa), but when generating nodes in a top-down order it seems unnatural to generate children in isolation: the label of one of them will likely influence what the other children states might be. For example, in the case of parse trees, generating a verb will reduce the chances of other verbs occurring in that branch of children.

With these considerations in mind, we propose an architecture tailored to tree decoding from scratch: top-down, recursive and *doubly-recurrent*, i.e. where both *ancestral* (parent-to-children) and *fraternal* (sibling-to-sibling) flow of information is modeled with recurrent modules. Thus, the building block of a *doubly recurrent neural network* (DRNN) is a cell with two types of input states, one coming from its parent, updated and passed on to its descendants, and another one received from its *previous* sibling,¹ updated and passed on to the next one. We model the flow of information in the two directions with separate recurrent modules.

Formally, let $\mathcal{T} = \{\mathcal{V}, \mathcal{E}, \mathcal{X}\}$ be a connected labeled tree, where \mathcal{V} is the set of nodes, \mathcal{E} the set of edges and \mathcal{X} are node labels.² Let g^a and g^f be functions which apply one step of the two separate RNNs. For a node $i \in \mathcal{V}$ with parent $p(i)$ and previous sibling $s(i)$, the ancestral and fraternal hidden states are updated via

$$\mathbf{h}_i^a = g^a(\mathbf{h}_{p(i)}^a, \mathbf{x}_{p(i)}) \quad (1)$$

$$\mathbf{h}_i^f = g^f(\mathbf{h}_{s(i)}^f, \mathbf{x}_{s(i)}) \quad (2)$$

where $\mathbf{x}_{s(i)}$, $\mathbf{x}_{p(i)}$ are the vectors representing the previous sibling’s and parent’s values, respectively. Once the hidden depth and width states have been updated with these observed labels, they are combined to obtain a *predictive hidden state*:

$$\mathbf{h}_i^{(pred)} = \tanh\left(\mathbf{U}^f \mathbf{h}_i^f + \mathbf{U}^a \mathbf{h}_i^a\right) \quad (3)$$

where $\mathbf{U}^f \in \mathbb{R}^{n \times D_w}$ and $\mathbf{U}^a \in \mathbb{R}^{n \times D_d}$ are learnable parameters. This state contains combined information of the node’s neighborhood in the tree, and is used to predict a label for it. In its simplest form, the network could compute the output of node i by sampling from distribution

$$\mathbf{o}_i = \text{softmax}(\mathbf{W} \mathbf{h}_i^{(pred)}) \quad (4)$$

In the next section, we propose a slight modification to (4) whereby topological information is included in the computation of cell output. After the node’s output symbol \mathbf{x}_i has been obtained by sampling from \mathbf{o}_i , the cell passes \mathbf{h}_i^a to all its children and \mathbf{h}_i^f to the next sibling (if any), enabling them to apply Eqs (1) and (2) to realize their states. This procedure continues recursively, until termination conditions (explained in the next section) cause the procedure to halt.

3.1 TOPOLOGICAL PREDICTION

As mentioned before, the central issue with free-form tree construction is to predict the topology of the tree. When constructing the tree top-down, for each node we need to decide: (i) whether it is a leaf node (and thus it should not produce offspring) and (ii) whether there should be additional siblings produced after it. Answering these two questions for every node allows us to construct a tree from scratch and eventual stop growing it.

Sequence decoders typically rely on special tokens to terminate generation (Sutskever et al., 2014). The token is added to the vocabulary and treated as a regular word. During training, the examples are padded with this token at the end of the sequence, and during testing, generation of this token signals termination. These ideas have been adopted by most tree decoders (Dong & Lapata, 2016). There are two important downsides of using a padding strategy for topology prediction in trees. First, the size of the tree can grow considerably. While in the sequence framework only one stopping token is needed, a tree with n nodes might need up to $O(n)$ padding nodes to be added. This can have important effects in training speed. The second reason is that a single stopping token selected competitively with other tokens requires one to continually update the associated parameters in response to any changes in the distribution over ordinary tokens so as to maintain topological control.

Based on these observations, we propose an alternative approach to stopping, in which topological decisions are made *explicitly* (as opposed to implicitly, with stopping tokens). For this, we use the

¹Unlike the “ancestral” line, the order within sibling nodes is ambiguous. While in abstract trees it is assumed that there is no such ordering, we assume that for the structures we are interested in learning there is always one: either chronological (the temporal order in which the nodes were generated) or latent (e.g. the grammatical order of the words in a parse tree with respect to their sentence representation).

²We assume throughout that these values are given as class indicators $\mathbf{x}_i \in \{1, \dots, N\}$.

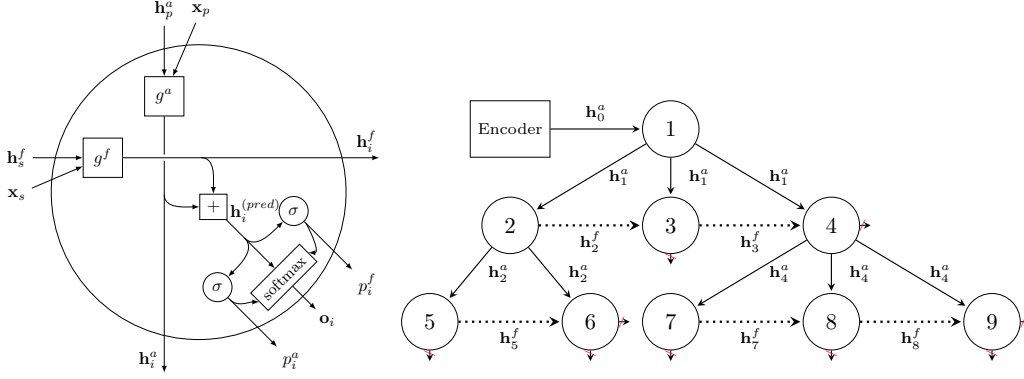


Figure 1: **Left:** A cell of the doubly-recurrent neural network corresponding to node i with parent p and sibling s . **Right:** Structure-unrolled DRNN network in an encoder-decoder setting. The nodes are labeled in the order in which they are generated. Solid (dashed) lines indicate ancestral (fraternal) connections. Crossed arrows indicate production halted by the topology modules.

predictive hidden state of the node $\mathbf{h}^{(pred)}$ with a projection and sigmoid activation:

$$p_i^a = \sigma(\mathbf{u}^a \cdot \mathbf{h}_i^{(pred)}) \quad (5)$$

The value $p_i^a \in [0, 1]$ is interpreted as the probability that node i has children. Analogously, we can obtain a probability of stopping *fraternal* branch growth after the current node as follows:

$$p_i^f = \sigma(\mathbf{u}^f \cdot \mathbf{h}_i^{(pred)}) \quad (6)$$

Note that these stopping strategies depart from the usual padding methods in a fundamental property: the decision to stop is made *before* instead of *in conjunction* with the label prediction. The rationale behind this is that the label of a node will likely be influenced not only by its context, but also by the type of node (terminal or non-terminal) where it is to be assigned. This is the case in language, for example, where syntactic constraints restrict the type of words that can be found in terminal nodes. For this purpose, we include the topological information as inputs to the label prediction layer. Thus, (4) takes the form

$$\mathbf{o}_i = \text{softmax}(\mathbf{W}\mathbf{h}_i^{(pred)} + \alpha_i \mathbf{v}^a + \varphi_i \mathbf{v}^f) \quad (7)$$

where $\alpha_i, \varphi_i \in \{0, 1\}$ are binary variables indicating the topological decisions and $\mathbf{v}^a, \mathbf{v}^f$ are learnable offset parameters. During training, we use gold values in (7), i.e. $\alpha_i = 1$ if node i has children and $\varphi_i = 1$ if it has a succeeding sibling. During testing, these values are obtained from p^a, p^f by sampling or beam-search. A schematic representation of internal structure of a DRNN cell and the flow of information in a tree are shown in Figure 1.

3.2 TRAINING DRNNs

We train DRNNs with (reverse) back-propagation through structure BPTS (Goller & Kuechler, 1996). In the forward pass, node outputs are computed in a top-down fashion on the structure-unrolled version of the network, following the natural³ dependencies of the tree. We obtain error signal at the node level from the two types of prediction: label and topology. For the former, we compute cross entropy loss of \mathbf{o}_i with respect to the true label of the node \mathbf{x}_i . For the topological values p_i^a and p_i^f we compute binary cross entropy loss with respect to gold topological indicators $\alpha_i, \varphi_i \in \{0, 1\}$. In the backward pass, we proceed in the reverse (bottom-up) direction, feeding into every node the gradients received from child and sibling nodes and computing internally gradients with respect to both topology and label prediction. Further details on the backpropagation flow are provided in the Appendix.

³The traversal is always breadth-first starting from the root, but the order in which sibling nodes are visited might depend on the specific problem. If the nodes of the tree have an underlying order (such as in dependency parse trees), it is usually desirable to preserve this order.

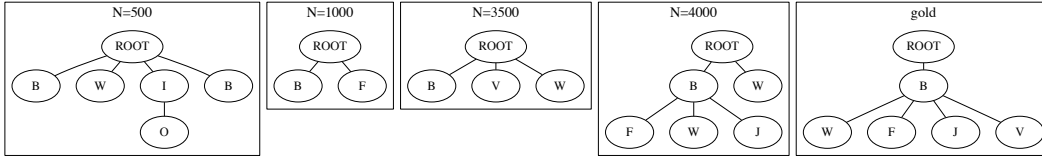


Figure 2: Trees generated by the DRNN decoder trained on subset of size N of the synthetic dataset, for a test example with description “ROOT B W F J V”.

Note that the way BPTS is computed for implies and underlying decoupled loss function

$$\mathcal{E}(\hat{\mathbf{x}}) = \sum_{i \in \mathcal{V}} \mathcal{L}^{label}(\mathbf{x}_i, \hat{\mathbf{x}}_i) + \mathcal{L}^{topo}(\mathbf{p}_i, \hat{\mathbf{p}}_i) \quad (8)$$

The decoupled nature of this loss allows us to weigh these two objectives differently, to emphasize either topology or label prediction accuracy. Investigating the effect of this is left for future work.

As is common with sequence generation, during training we perform *teacher forcing*: after predicting the label of a node and its corresponding loss, we replace it with its gold value, so that children and siblings receive the correct label for that node. Analogously, we compute the probabilities p^a and p^f , obtain a loss with respect to actual values, and replace these for ground truth variables α_i, φ_i for all downstream computations. Addressing this *exposure bias* by mixing ground truth labels with model predictions during training (Venkatraman et al., 2015) or by incremental hybrid losses (Ranzato et al., 2016) is left as an avenue for future work.

4 EXPERIMENTS

4.1 SYNTHETIC TREE RECOVERY

In our first set of experiments we evaluate the effectiveness of the proposed architecture to recover trees from flattened string representations. For this, we first generate a toy dataset consisting of simple labeled trees. To isolate the effect of label content from topological prediction, we take a small vocabulary consisting of the 26 letters of the English alphabet. We generate trees in a top-down fashion, conditioning the label and topology of every node on the state of its ancestors and siblings. For simplicity, we use a Markovian assumption on these dependencies, modeling the probability of a node’s label as depending only on the label of its parent and the last sibling generated before it (if any). Conditioned on these two inputs, we model the label of the node as coming from a multinomial distribution over the alphabet with a dirichlet prior. To generate the topology of the tree, we model the probability of a node having children and a next-sibling as depending only on the label of the node and the depth of the tree. For each tree we generate a string representation by traversing it in breadth-first preorder, starting from the root. The labels of the nodes are concatenated into a string in the order in which they were visited, resulting in a string of $|\mathcal{T}|$ symbols. We create a dataset of 5,000 trees with this procedure, and split it randomly into train, validation and test sets (with a 80%,10%,10% split). Further details on the construction of this dataset are provided in the Appendix.

The task consists of learning a mapping from strings to trees, and using this learned mapping to recover the tree structure of the test set examples, given only their flattened representation. To do so, we use an encoder-decoder framework, where the strings are mapped to a fixed-size vector representation using a recurrent neural network. For the decoder, we use a DRNN with LSTM modules, which given the encoded representation generates a tree. We choose hyper-parameters with cross-validation. Full training details are provided in the Appendix.

Measuring performance only in terms of exact recovery would likely yield near-zero accuracies for most trees. Instead, we opt for a finer-grained metric of tree similarity that gives partial credit for correctly predicted subtrees. Treating tree generation as a retrieval problem, we evaluate the quality of the predicted tree in terms of the precision and recall of recovering nodes and edges present in the gold tree. Thus, we penalize both missing and superfluous components. As baseline, we induce a probabilistic context-free grammar (PCFG) on the full training data and use it to parse the test

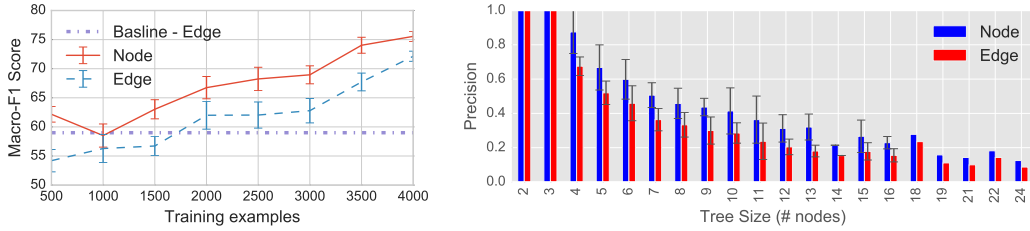


Figure 3: **Left:** F1-Score for models trained on randomly sampled subsets of varying size, averaged over 5 repetitions. **Right:** Node (first column) and edge (second) precision as a function of tree size.

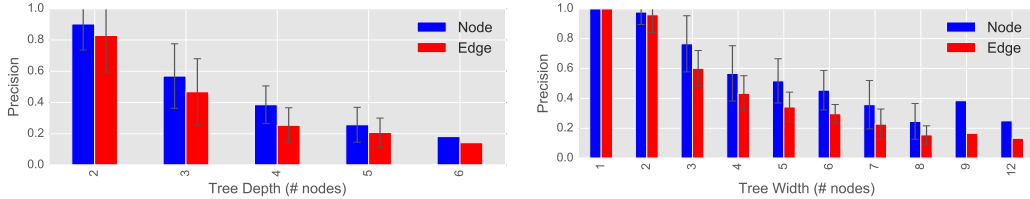


Figure 4: Node and edge precision as a function of tree depth (left figure) and width (right).

sentences. Note that unlike the DRNN, this parser has direct access to the sentence representation and thus its task is only to infer the tree structure on top of it, so this is indeed a strong baseline.

Figure 3 shows the results on the test set. Training on the full data yields node and edge retrieval F1-Scores of 75% and 71%, respectively, the latter considerably above the baseline.⁴ This 4% gap can be explained by correct nodes being generated in the wrong part of the tree, as in the example in Figure 2. The second plot in Figure 3 shows that although small trees are recovered more accurately, precision decays slowly with tree size, with depth accounting for the largest effect (Figure 4).

4.2 MAPPING SENTENCES TO FUNCTIONAL PROGRAMS

Tree structures arise naturally in the context of programs. A typical compiler takes human-readable source code (expressed as sequences of characters) and transforms it into an executable abstract syntax tree (AST). Source code, however, is already semi-structured. Mapping natural language sentences directly into executable programs is an open problem, which has received considerable interest in the natural language processing community (Kate et al., 2005; Branavan et al., 2009).

The IFTTT dataset (Quirk et al., 2015) is a simple testbed for language-to-program mapping. It consists of if-this-then-that programs (called *recipes*) crawled from the IFTTT website⁵, paired with natural language descriptions of their purpose. The recipes consist of a trigger and an action, each defined in terms of a channel (e.g., “Facebook”), a function (e.g., “Post a status update”) and potentially arguments and parameters. An example of a recipe and its description are shown in Figure 5. The data is user-generated and extremely noisy, which makes the task significantly challenging.

We approach this task using an encoder-decoder framework. We use a standard RNN encoder, either an LSTM or a GRU (Cho et al., 2014), to map the sentence to a vector representation, and we use a DRNN decoder to generate the AST representation of the recipe. We use the original data split, which consists of 77,495 training, 5,171 development and 4,294 test examples. For evaluation, we use the same metrics as Quirk et al. (2015), who note that computing exact accuracy on such a noisy dataset is problematic, and instead propose to evaluate the generated AST in terms of F1-score on the set of recovered productions. In addition, they compute accuracy at the channel level (when both channels are predicted correctly) and at the function level (both channels *and* both functions predicted correctly).

⁴Since the PCFG parser has access to the nodes by construction, node accuracy for the baseline method is irrelevant and thus omitted from the analysis.

⁵www.ifttt.com

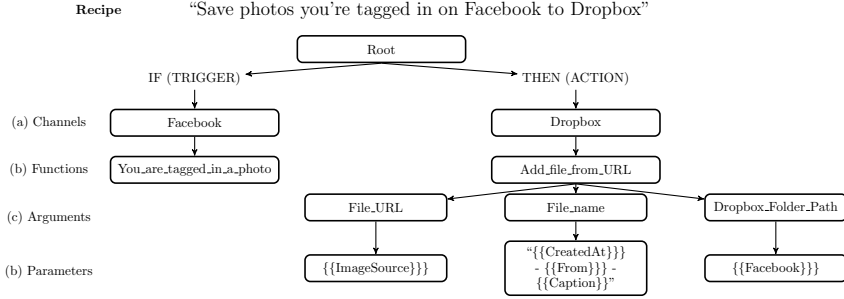


Figure 5: Example recipe from the IFTTT dataset. The description (above) is a user-generated natural language explanation of the if-this-then-that program (below).

Table 1: Results on the IFTTT task. **Left:** non english and unintelligible examples removed (2,262 recipes). **Right:** examples for which at least 3+ turkers agree with gold (758 recipes).

Method	Channel	+Func	F1
retrieval	36.8	25.4	49.0
phrasal	27.8	16.4	39.9
sync	26.7	15.4	37.6
classifier	64.8	47.2	56.5
posclass	67.2	50.4	57.7
SEQ2SEQ	68.8	50.5	60.3
SEQ2TREE	69.6	51.4	60.4
GRU-DRNN	70.1	51.2	62.7
LSTM-DRNN	74.9	54.3	65.2

Method	Channel	+Func	F1
retrieval	43.3	32.3	56.2
phrasal	37.2	23.5	45.5
sync	36.5	23.5	45.5
classifier	79.3	66.2	65.0
posclass	81.4	71.0	66.5
SEQ2SEQ	87.8	75.2	73.7
SEQ2TREE	89.7	78.4	74.2
GRU-DRNN	89.9	77.6	74.1
LSTM-DRNN	90.1	78.2	77.4

We compare our methods against the various extraction and phrased-based machine translation base-lines of Quirk et al. (2015) and the the methods of Dong & Lapata (2016): SEQ2SEQ, a sequence-to-sequence model trained on flattened representations of the AST, and SEQ2TREE, a token-driven hierarchical RNN. Following these two works, we report results on two noise-filtered subsets of the data: one with all non-english and unintelligible recipes removed and the other one with recipes for which at least three humans agreed with the gold AST. The results are shown in Table 1. In both subsets, DRNNs perform on par or above previous approaches, with LSTM-DRNN achieving significantly better results. The improvement is particularly evident in terms of F1-score, which is the only metric used by previous approaches that measures global tree reconstruction accuracy. To better understand the quality of the predicted trees beyond the function level (i.e. (b) in Figure 5), we computed node accuracy on the arguments level. Our best performing model, LSTM-DRNN, achieves a Macro F1 score of 51% (0.71 precision, 0.40 recall) over argument nodes, which shows that the model is reasonably successful at predicting structure even beyond depth three. The best performing alternative model, SEQ2TREE, achieves a corresponding F1 score of 46%.

4.3 MACHINE TRANSLATION

In our last set of experiments, we offer a qualitative evaluation of the performance of DRNNs in a machine translation task. Obtaining good results in such a task requires highly-optimized architectures and vast amounts of data. Our goal here is not to compare against the state-of-the-art, but rather to investigate whether decoding with structure can bring benefits to a task traditionally approached as a sequence-to-sequence problem. For this reason, we consider a setting with a restricted dataset: a subset of the WMT14 dataset consisting of about 50K english \leftrightarrow french sentence pairs (see the Appendix for details) along with dependency parses of the target (English) side.

We train a sequence-to-tree model using an LSTM encoder and a DRNN decoder as in the previous experiments, with a slight modification: we distinguish left and right children in the tree, using two symmetric width-modules g_L^f, g_R^f that produce children from the parent outwards. With this, chil-

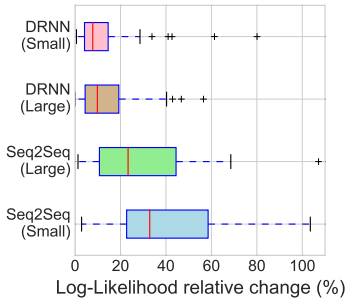


Figure 6: Likelihood change under target structural perturbation.

Source	“ produit différentes réponses qui changent avec le temps selon nos expériences et nos relations ”	“ je ne sais jamais quoi dire dans ces cas là ”
SEQ2SEQ:		
$l = 1$	a	I
$l = 4$	with the different actions	I do
$l = 8$	with the different actions who change with	I do not know what to say
DRNN:		
$d = 1$	answers	know
$d = 2$	different answers change	but i do not know
$d = 3$	product the different answers change .	but i do not know to say

Table 2: Translations at different resolutions (size constraints imposed during decoding) for two example sentences.

dren are lexically ordered, and therefore trees can be easily and un-ambiguously projected back into sentences. We compare our model against a sequence-to-sequence architecture of similar complexity (in terms of number of parameters) trained on the same data with the highly optimized OpenNMT library (Klein et al., 2017). For decoding, we use a simple best-of-k sampling scheme for our model and beam search for the SEQ2SEQ models.

First, we analyze the quality of the translations as a function of the maximum allowed target sentence “size” (defined as *length* for the sequence decoder and *depth* for DRNN). Two such examples are shown in Table 2. Having been trained to generate dependency parses top-down, the DRNN decoder first generates the fundamental aspects of the sentence (verb, nouns), leaving less important components to deeper down in the tree. The sequence decoder, on the other hand, is trained for left-to-right sequential production, and thus produces less informative translations when restricting output length. In our second experiment we investigate the robustness of the models over structural perturbation of the output. A desirable property of a decoder in an MT system is that it scores similarly sentences having the same semantic content but different grammatical structure. One way to assess this invariance is to compare the likelihood assigned by a model to the gold target sentence and to a paraphrase of it. To test this, we take 50 examples from the WMT test split and manually generate paraphrases with various types of structural alterations (see details in the Appendix). For each system, we measure the relative change in log-likelihood after this perturbation. All the models we compare have similar standard deviation (40 ± 20) of log-likelihood scores over these examples, so the relative changes are directly comparable. For each architecture we train two models of different size, with models of the same category having a similar number of parameters. The results in Figure 6 show that DRNN’s are significantly more robust to structural perturbations than their SEQ2SEQ counterparts.

5 DISCUSSION AND FUTURE WORK

We have presented *doubly recurrent neural networks*, a natural extension of (sequential) recurrent architectures to tree-structured objects. This architecture models the information flow in a tree with two separate recurrent modules: one carrying ancestral information (received from parent and passed on to offspring) and the other carrying fraternal information (passed from sibling to sibling). The topology of the tree is modeled explicitly and separately from the label prediction, with modules that given the state of a node predict whether it has children and siblings.

The experimental results show that the proposed method is able to predict reasonable tree structures from encoded vector representations. Despite the simple structure of the IFTTT trees, the results on that task suggest a promising direction of using DRNNs for generating programs or executable queries from natural language. On the other hand, the results on the toy machine translation task show that even when used to generate sequences, DRNN’s exhibit desirable properties, such as invariance over structural modifications and the ability to perform coarse-to-fine decoding. In order to truly use this architecture for machine translation, the approach must be scaled by resorting to batch processing in GPU. This is possible since forward and backward propagation are computed sequentially along tree traversal paths so that inputs and hidden states of parents and siblings can be grouped into tensors and operated in batch. We leave this as an avenue for future work.

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A VARIATIONS ON TOPOLOGY PREDICTION

Besides the proposed topology prediction presented in Section 3.1, we experimented with two additional variations of the proposed doubly-recurrent neuron: (i) using tokens to trigger both depth and width termination (i.e. no explicit topology prediction) and (ii) using tokens for width-stopping decision, but predict explicitly depth termination (single topology prediction). Recall that in the model proposed in Section 3.1 both decisions are explicit (double topology prediction). The neurons in each of these alternative formulations are depicted in Figure 7. In order to train these two alternative models, we add special stopping tokens to the vocabulary, and we pad the trees during training with additional nodes labeled with a this token. Besides requiring larger trees and resulting in slower training, we empirically observed alternatives (i) and (ii) to result in worse performance. We hypothesize that this has to do with the fact that when using token-based stopping, topological and label prediction decisions are confounded, which results in less efficient learning.

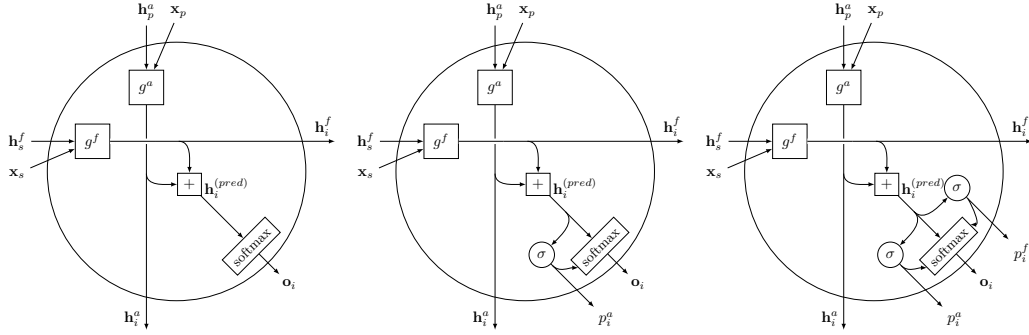


Figure 7: A single unit in each of the three alternative versions of the doubly-recurrent neural network, for node i with parent p and sibling s . **Left:** No explicit topology prediction, **Middle:** single (ancestral) topology prediction, **Right:** double (ancestral and fraternal) topology prediction. The top (left) incoming arrows represent the input and state received from the parent node (previous node, respectively).

B TRAINING DETAILS

B.1 BACKPROPAGATION WITH DRNN’S

For every example tree during training, we do the forward pass in breadth first preorder, feeding into every node an ancestral and a fraternal state. Before passing on the ancestral state the offspring, we update it through the RNN using the current node’s label, so as to avoid repeating this step for every child node. After the forward pass is complete, we compute label (cross-entropy) and topological (binary cross entropy) loss for every node. In the backward pass, we compute in this order:

1. Gradient of the current node’s label prediction loss with respect to softmax layer parameters $\mathbf{W}, \mathbf{v}^a, \mathbf{v}^f$: $\nabla_{\theta} \mathcal{L}(\mathbf{x}_i, \hat{\mathbf{x}}_i)$.
2. Gradients of topological prediction variable loss with respect to sigmoid layer parameters: $\nabla_{\theta} \mathcal{L}(p_i^a, t_i^a)$ and $\nabla_{\theta} \mathcal{L}(p_i^f, t_i^f)$.
3. Gradient of predictive state layer parameters with respect to $\mathbf{h}^{(pred)}$.
4. Gradient of predicted ancestral and fraternal hidden states with respect to g^f and g^a ’s parameters.

The gradients of the input ancestral and fraternal hidden states are then passed on to the previous sibling and parent. When nodes have more than one child, we combine gradients from multiple children by averaging them. This procedure is repeated until the root node is reached, after which a single (ancestral state) gradient is passed to the decoder.

B.2 MODEL SPECIFICATION AND TRAINING PARAMETERS

The best parameters for all tasks are chosen by cross-validation on the validation sets. We do early stopping based on the validation loss. For the IFTTT task, we initialize word embeddings with pre-trained GloVe vectors (Pennington et al., 2014). For both tasks we clip gradients when the absolute value of any element exceeds 5. We regularize with a small penalty ρ on the l_2 norm of the parameters. We train all methods with ADAM (Kingma & Ba, 2014), with initial learning rate chosen by cross-validation. The parameter configurations that yielded the best results and were used for the final models are shown in Table 3. Details about the four models used for the machine translation task are shown in Table 4.

Table 3: Hyperparameter choice for DRNNs in the synthetic and IFTTT tasks

Task	Encoder	Dim	Batch	Learning Rate	Regularization ρ
synthetic	LSTM	50	20	0.05	1×10^{-5}
IFTTT	GRU	150	35	0.06	1×10^{-4}
IFTTT	LSTM	150	35	0.05	5×10^{-4}

Table 4: Models used in the machine translation task.

Model	Encoder	Decoder	Dim	RNN Layers	Batch
SEQ2SEQ (Small)	LSTM	LSTM	150	1	64
SEQ2SEQ (Large)	LSTM	LSTM	300	3	64
DRNN (Small)	LSTM	DRNN-GRU (Left-Right)	150	1	32
DRNN (Large)	LSTM	DRNN-GRU (Left-Right)	150	1	32

C DATASET DETAILS

C.1 SYNTHETIC TREE DATASET GENERATION

We generate trees in a top-down fashion, conditioning the label and topology of every node on the state of its ancestors and siblings. For simplicity, we use a Markovian assumption on these dependencies, modeling the probability of a node’s label as depending only on the label of its parent and the last sibling generated before it (if any). Conditioned on these two inputs, we model the label of the node as coming from a multinomial distribution over the alphabet:

$$P(w_i | \mathcal{T}) = P(w | w_{p(i)}, w_{s(i)}) \sim \text{Multi}(\theta_{w_{p(i)}, w_{s(i)}}) \quad (9)$$

where $\theta_{w_{p(i)}, w_{s(i)}}$ are class probabilities drawn from a dirichlet prior with parameter α_v . On the other hand, we denote by b_i^a the binary variable indicating whether node i has descendants, and by b_i^f that indicating whether it has an ensuing sibling. We model these variables as depending only on the label of the current node and its position in the tree:

$$\begin{aligned} P(b_i^a | \mathcal{T}) &= P(b_i^a | w_i, D_i) = \text{Bernoulli}(p_{w_i}^a \cdot g^a(D_i)) \\ P(b_i^f | \mathcal{T}) &= P(b_i^f | w_i, W_i) = \text{Bernoulli}(p_{w_i}^f \cdot g^f(W_i)) \end{aligned}$$

where D_i is the depth of node i and W_i its width, defined as its position among the children of its parent $p(i)$. Intuitively, we want to make $P(b_i^a = 1 | \mathcal{T})$ decrease as we go deeper and further along the branches of the tree, so as to control its growth. Thus, we model g^a and g^f as decreasing functions with geometric decay, namely $g^a a = (\gamma^a)^D$ and $g^f f = (\gamma^f)^W$, with $\gamma^a, \gamma^f \in (0, 1)$. For the label-conditioned branching probabilities $P(b_i^a | w_i)$ and $P(b_i^f | w_i)$, we use Bernoulli distributions with probabilities drawn from beta prior with parameters (α^a, β^a) and (α^f, β^f) , respectively.

In summary, we use the following generative procedure to grow the trees:

1. For each $w_i \in V$, draw $p_{w_i}^a \sim \text{Beta}(\alpha^a, \beta^a)$ and $p_{w_i}^f \sim \text{Beta}(\alpha^f, \beta^f)$
2. For each pair (w_i, w_j) draw $\theta_{w_i, w_j} \sim \text{Dir}(\alpha^V)$
3. While there is an unlabeled non-terminal node i do:
 - Sample a label for i from $w^* \sim P(w|w_{p(i)}, w_{s(i)}) = \text{Multi}(\theta_{w_{p(i)}, w_{s(i)}})$.
 - Draw $b_a \sim P(b^a|w^*, D) = \text{Bernoulli}(\gamma_a^D p_{w(i)}^a)$, where D is the current depth. If $b^a = 1$, generate an node k , set $p(k) = i$, and add it to the queue.
 - Draw $b_f \sim P(b^f|w^*, D) = \text{Bernoulli}(\gamma_f^W p_{w(i)}^f)$, where W is the current width. If $b^f = 1$, generate an node k , set $s(k) = i$, and add it to the queue.

Note that the generative process above does create a dependence between the topology and content of the trees (since the variables b^a and b^f depend on the content of the tree via their dependence on the label of their corresponding node). However, the actual process by which labels and topological decision is generated relies on separate mechanisms. This is natural assumption which is reasonable to expect in practice.

The choice of prior parameters is done drawing inspiration from natural language parse trees. We want nodes to have low but diverse probability of generating children, so we seek a slow-decaying distribution with most mass allocated in values close to 0. For this, we use $(\alpha^a, \beta^a) = (0.25, 1)$. For sibling generation, we use $(\alpha^f, \beta^f) = (7, 2)$, which yields a distribution concentrated in values close to 1, so that nodes have on average a high and similar probability of producing siblings. Since we seek trees that are wider than they are deep, we use decay parameters $\gamma_a = 0.6, \gamma_f = 0.9$. Finally, we use a $\alpha_v = 10 \cdot 1$ for the parent-sibling probability prior, favoring non-uniform interactions. Using this configuration, we generate 5000 sentence-tree pairs, which we split into training (4000 examples), validation (500) and test (500) sets. The characteristics of the trees in the dataset are summarized in Table 5.

Table 5: Synthetic tree dataset statistics. Tree size is measured in number of nodes, depth is the largest path from the root node to a leaf and width is the maximum number of children for any node in the tree. The values reported correspond to means with one standard deviation in parentheses.

Fold	Examples	Size	Depth	Width
train	4000	3.94 (3.38)	1.42 (0.66)	2.89 (1.71)
dev	500	4.13 (3.21)	1.46 (0.67)	2.91 (1.76)
test	500	3.64 (3.21)	1.32 (0.61)	2.80 (1.71)

C.2 IFTTT

The IFTTT dataset comes with a script to generate the data by crawling a parsing the recipes. Unfortunately, by the time we ran the script many recipes had been removed or changed. We therefore requested the original dataset used by (Quirk et al., 2015). We converted these recipes into our tree format, assigning a node to each element in the first three levels (channels, functions and arguments, see figure 5). For the parameters level, many recipes have sentences instead of single tokens, so we broke these up creating one node per word. The last two layers are therefore the most topologically diverse, whereas the structure of the first two layers is constant (all trees have channels and functions). A small fraction of trees that could not be parsed into our format was excluded from the dataset.

Table 6 shows various statistics about the topological characteristics of the recipes in the IFTTT dataset. The middle columns show percentage of trees that contain nonempty arguments and parameters in trigger (IF) and action (THEN) branches. Almost all recipes have none empty arguments and parameters (and thus depth 4, excluding the root), and a lower percentage –but still a majority– has arguments and parameters of the trigger side too. The last two columns show tree statistics pertaining to the complexity of trees after conversion to our format. Most trees contain somewhere between 4 and 30 nodes, with a small tail to larger examples (see Figure 8).

Table 6: IFTTT dataset statistics. The middle columns show percentage of trees that contain nonempty arguments and parameters in trigger (IF) and action (THEN) branches. The last column shows average (with standard deviation) tree size and depth.

Fold	Examples	Has args. (%)		Has params. (%)		Tree Size	
		Trigger	Action	Trigger	Action	# Nodes	Depth
train	67,444	69.10	98.46	65.47	96.77	16.93 (31.71)	3.99 (.13)
dev	4,038	69.44	98.46	66.42	96.31	16.55 (8.75)	3.99 (.11)
test	3,725	68.38	98.66	65.64	97.50	16.43 (8.18)	3.99 (.12)

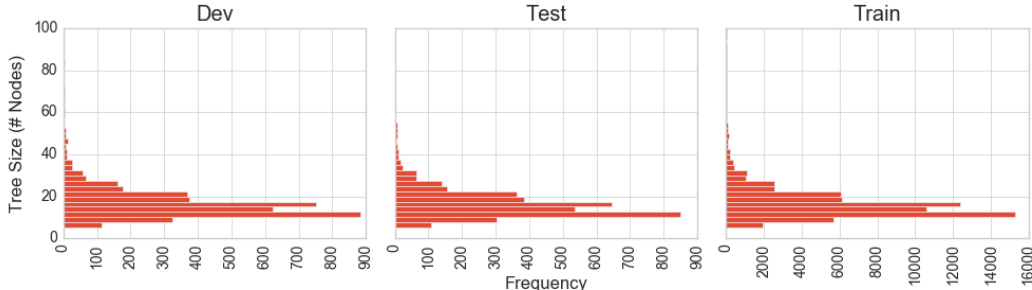


Figure 8: Tree size distribution in the IFTTT dataset.

Regarding the content of the trees, the labels of the nodes in the first two levels (channels and functions) come from somewhat reduced vocabularies: 111 and 434 unique symbols for the trigger branch, respectively, and 157 and 85 for the action branch. The lower layers of the tree have a much more varied vocabulary, with about 60K unique tokens in total. On the source side, the description sentences have a very diverse vocabulary too, with about 30K unique tokens. The average sentence size is 6.07, with 80% of the sentences having at most 12 tokens.

C.3 MACHINE TRANSLATION

Starting from a preprocessed⁶ 2% sub-selection of the english-french section of the WMT14 dataset, we further prune down the data by keeping only sentences of length between 5 and 20 words, and for which every word is within the 20K most frequent. The reason for this is to simplify the task by keeping only common words and avoiding out-of-vocabulary tokens. After this filtering, we are left with 53,607, 918 and 371 sentences for train, validation and test sets. After tokenizing, we obtain dependency parses for the target (English) sentences using the Stanford CoreNLP toolkit (Manning et al., 2014).

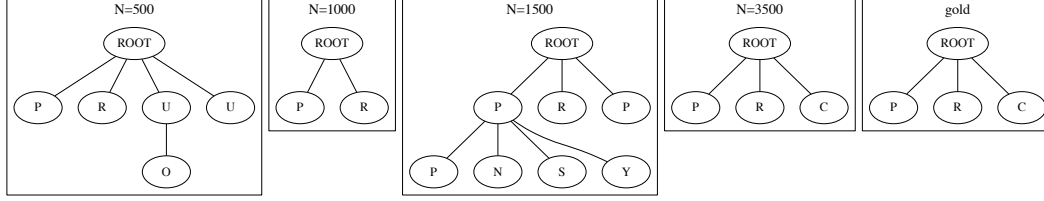
For the perturbation experiments, we randomly selected 50 sentences from the test that could be easily restructured without significantly altering their meaning. The type of alterations we perform are: subordinate clause swapping, alternative construction substitution, passive/active voice change. In doing this, we try to keep the number of added/deleted words to a minimum, to minimize vocabulary-induced likelihood variations. When inserting new words, we verify that they are contained in the original vocabulary of 20K words. In Table 7 we show a few examples of the source, (original) target and perturbed target sentences.

⁶http://www-lium.univ-lemans.fr/~schwenk/csml_joint_paper/

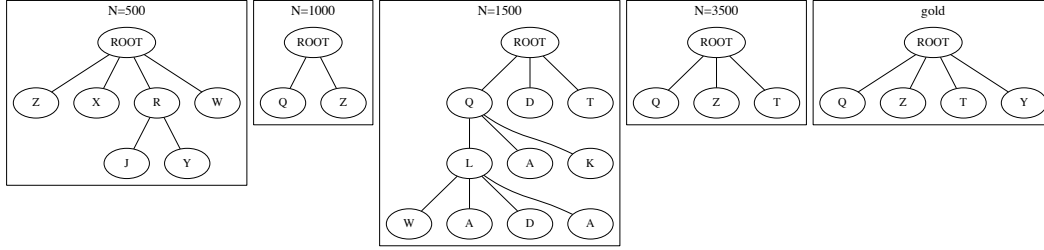
Table 7: Example structural perturbations for likelihood robustness experiments.

source	“après un accord de paix signé en 1992 elle est devenue un parti d opposition.”
target	“after a 1992 peace deal it became an opposition party.”
perturbation	“it became an opposition party after a 1992 peace deal.”
source	“cela représente environ 9 milliards de grains de maïs.”
target	“that’s about 9 billion individual kernels of corn.”
perturbation	“this amounts to about 9 billion kernels of corn.”
source	“l’exercice de fonctions publiques est une question de service public.”
target	“public office is about public service.”
perturbation	“the exercise of public functions is a matter of public service.”
source	“nous avons ainsi effectué depuis la fin de l’hiver dernier 64 interventions.”
target	“hence we have carried out 64 operations since last winter.”
perturbation	“we have therefore carried out 64 operations since last winter.”
source	“on estime qu’un enfant sur 2000 nés chaque année n’est ni un garçon ni une fille.”
target	“an estimated one in 2000 children born each year is neither boy nor girl.”
perturbation	“it is estimated that one in every 2000 children born every year is neither a boy nor a girl.”

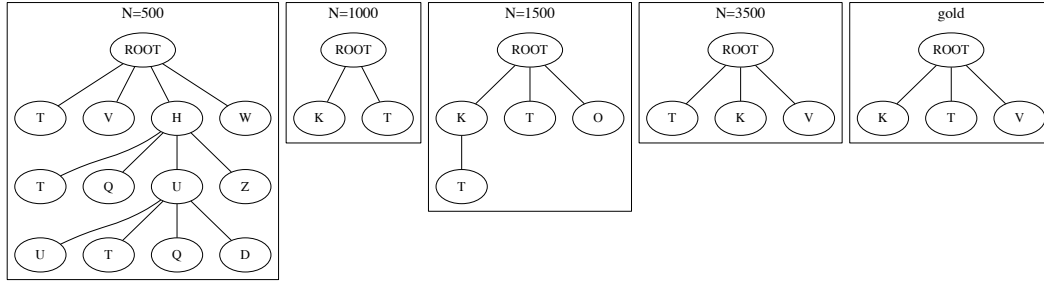
D ADDITIONAL EXAMPLE GENERATED TREES



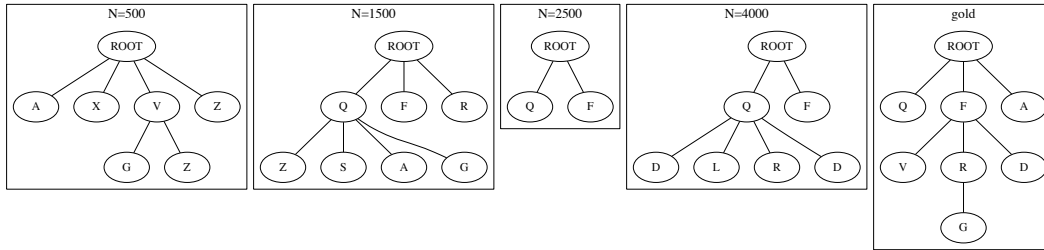
(a) Encoder sentence input: "ROOT P R C"



(b) Encoder sentence input: "ROOT Z T Y Q"



(c) Encoder sentence input: "ROOT K T V"



(d) Encoder sentence input: "ROOT Q F V R G D A"

Figure 9: Example trees generated by the DRNN decoder from vector-encoded descriptions for test examples of the synthetic tree dataset. Trees in the same row correspond to predictions by models trained on randomly sampled subsets of size N of the training split. We present both cases for which the prediction is accurate (a,c) and cases for which it is not (b,d). Note how in (d) the model gets high accuracy on label prediction, but confuses some of the dependencies (edges) in the tree.