

The Coadaptation Problem when Learning How and What to Compose

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RL and Parsing is Difficult
We Provide Two Promising Techniques

The original Catalan pyramid



Problem Statement

Can we use reinforcement learning to induce syntactically plausible parse trees?

Introduction

- We can learn to parse in a semi-supervised manner with SPINN and REINFORCE, using classification accuracy as the reward.
- When the model uses a consistent parsing strategy, the TreeLSTM composition function coadapts to this strategy. This can limit exploration of parsing strategies.
- By training the model in two alternating phases and sampling transitions from a novel prior distribution, we facilitate exploration of different parsing strategies early in training.

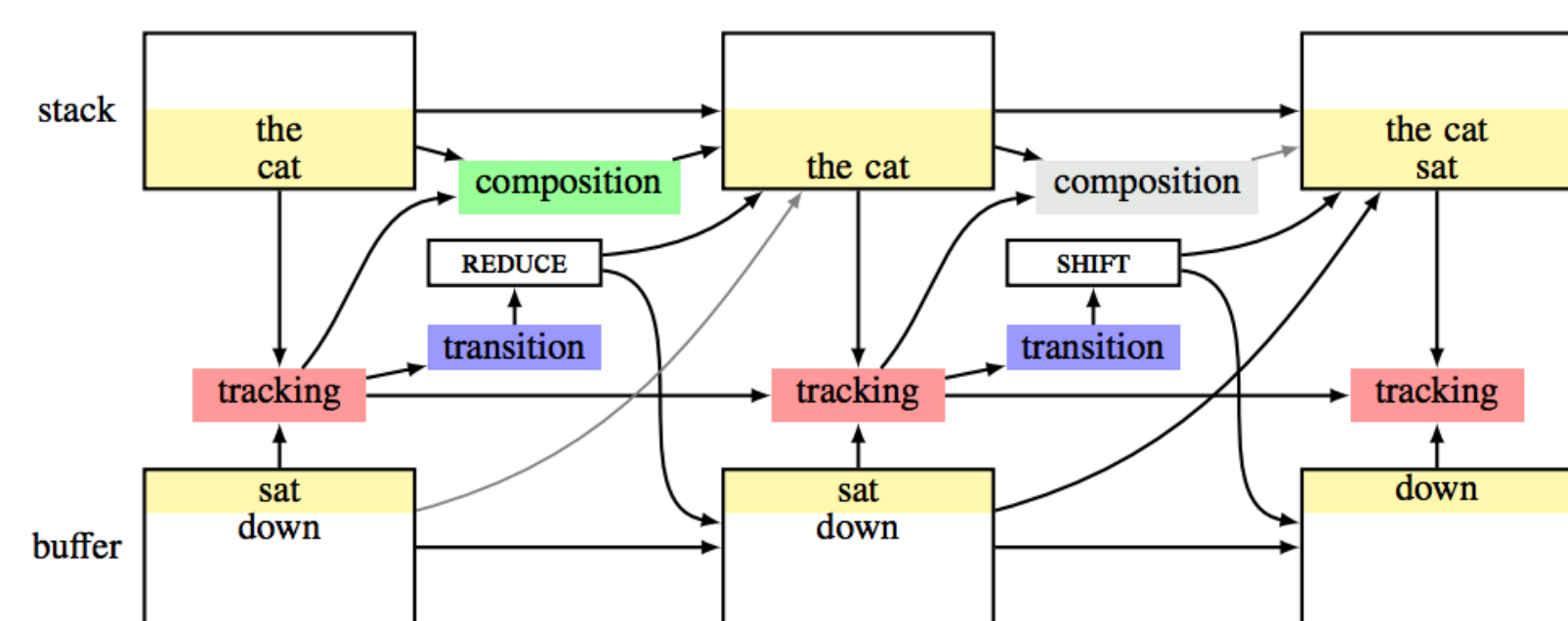


Figure 1: The SPINN model performing two transitions.

Temperature and Prior

$$\sigma(\vec{x}) = \frac{e^{\vec{x}}}{\sum_{\hat{x} \in \vec{x}} e^{\vec{x}}} \text{ softmax with temperature} \quad (1)$$

$$f(P, Q) = \frac{p \cdot q}{\sum p' \cdot q'} \text{ renormalized probabilities P with prior Q} \quad (2)$$

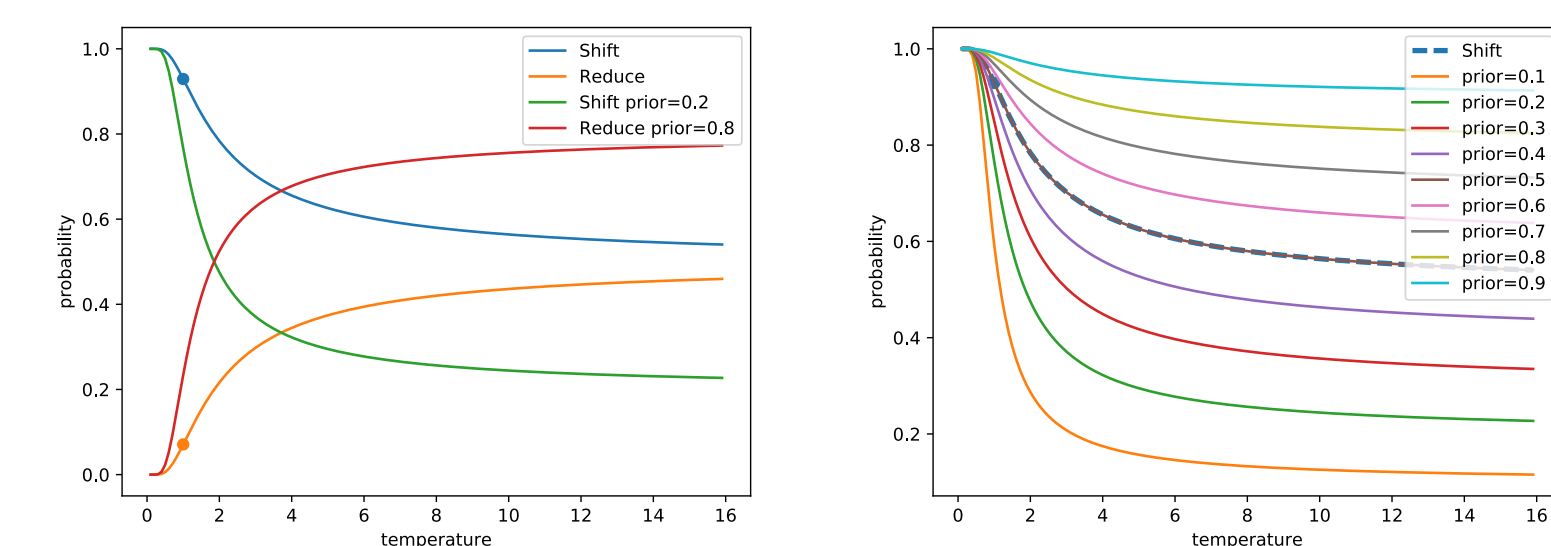


Figure 2: Normally, when using a softmax distribution with temperature, the probabilities of the variables would converge to uniform as temperature increases. When applying a prior as it's been defined above, the probabilities converge to the values of the prior as temperature increases.

Soft Wake Sleep

To prevent the model from becoming too closely tied to a specific parsing schedule early on, we oscillate between a random and predicted strategy.

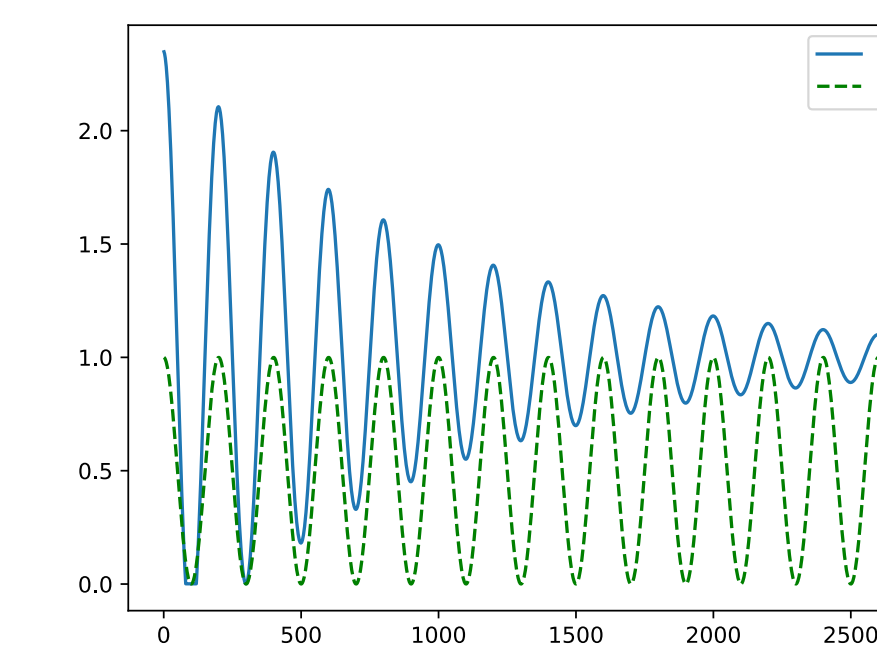


Figure 3: An example training schedule that interpolates between two phases with temperature annealed over time.

Bias when Sampling Binary Trees

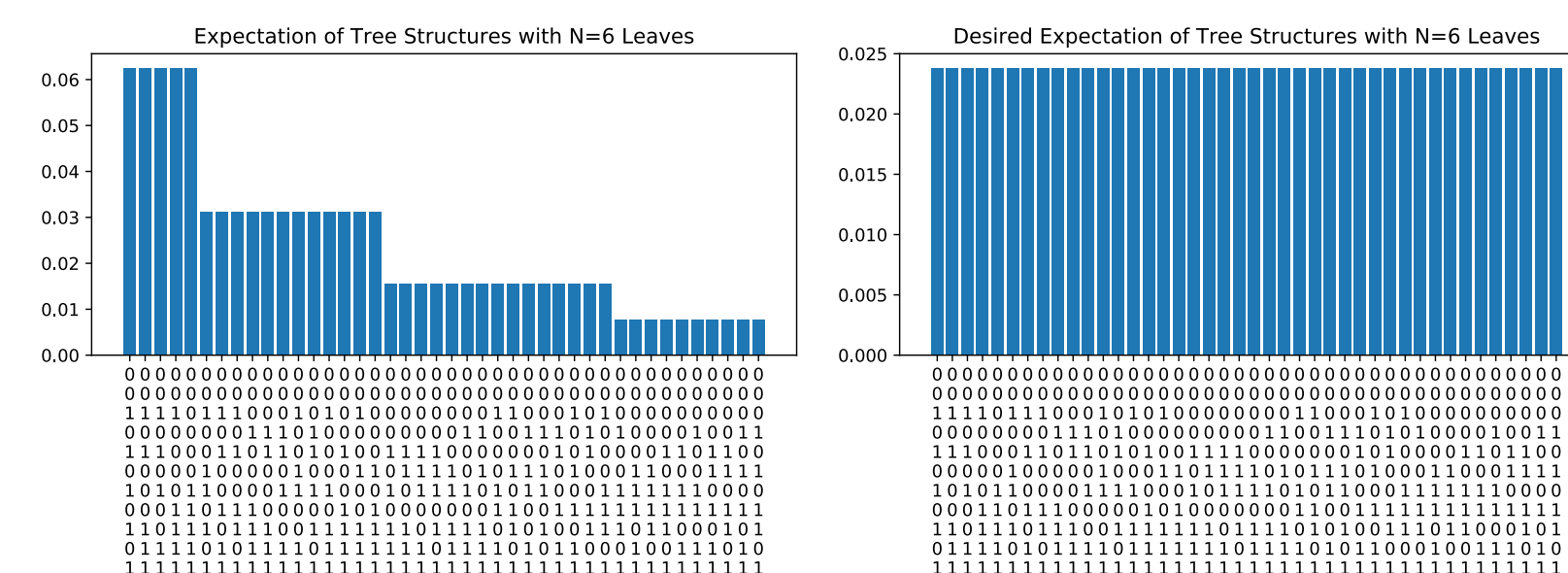


Figure 4: The expectation of different binary tree structures when sampling from a uniform prior over transitions (left) or using the novel Catalan pyramid distribution (right).

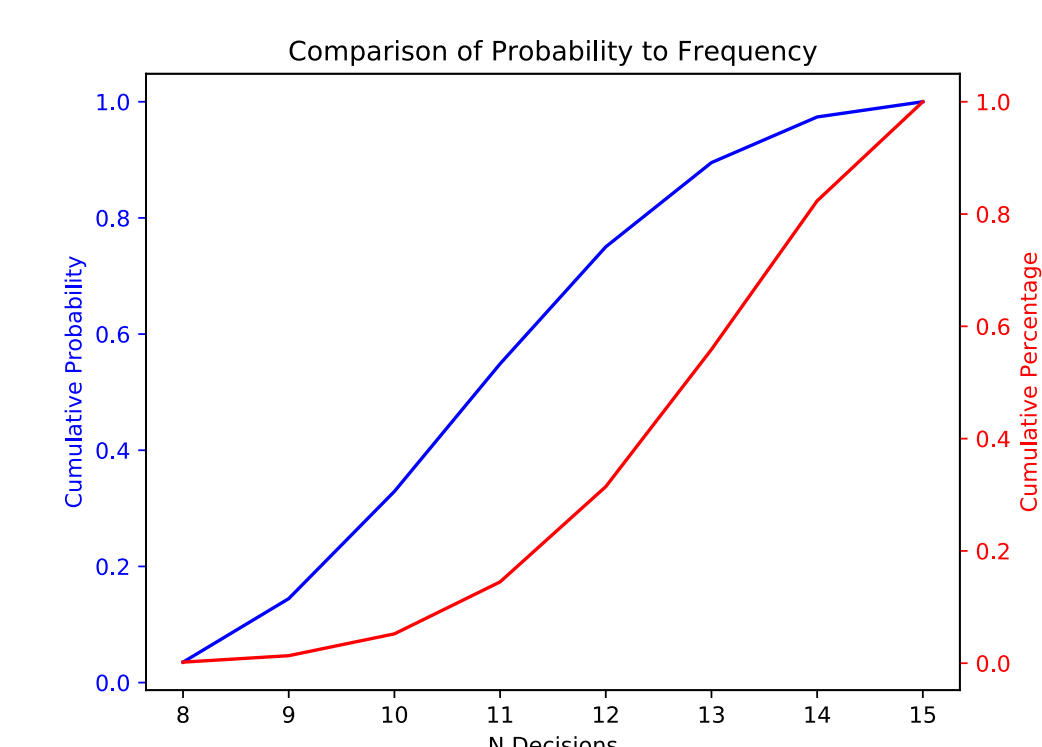


Figure 5: The probability of certain structures is higher than desired given their frequency among all possible trees.

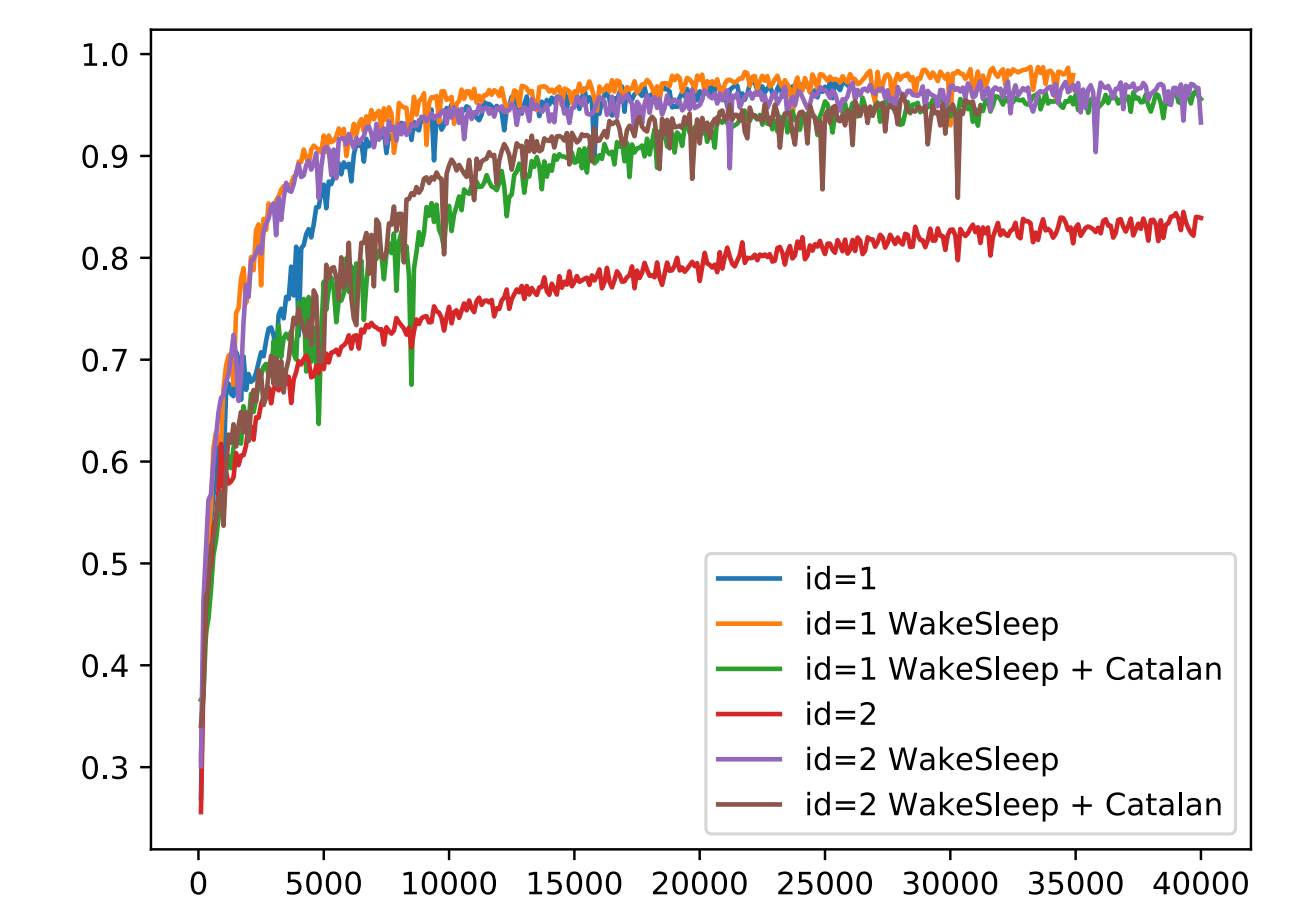
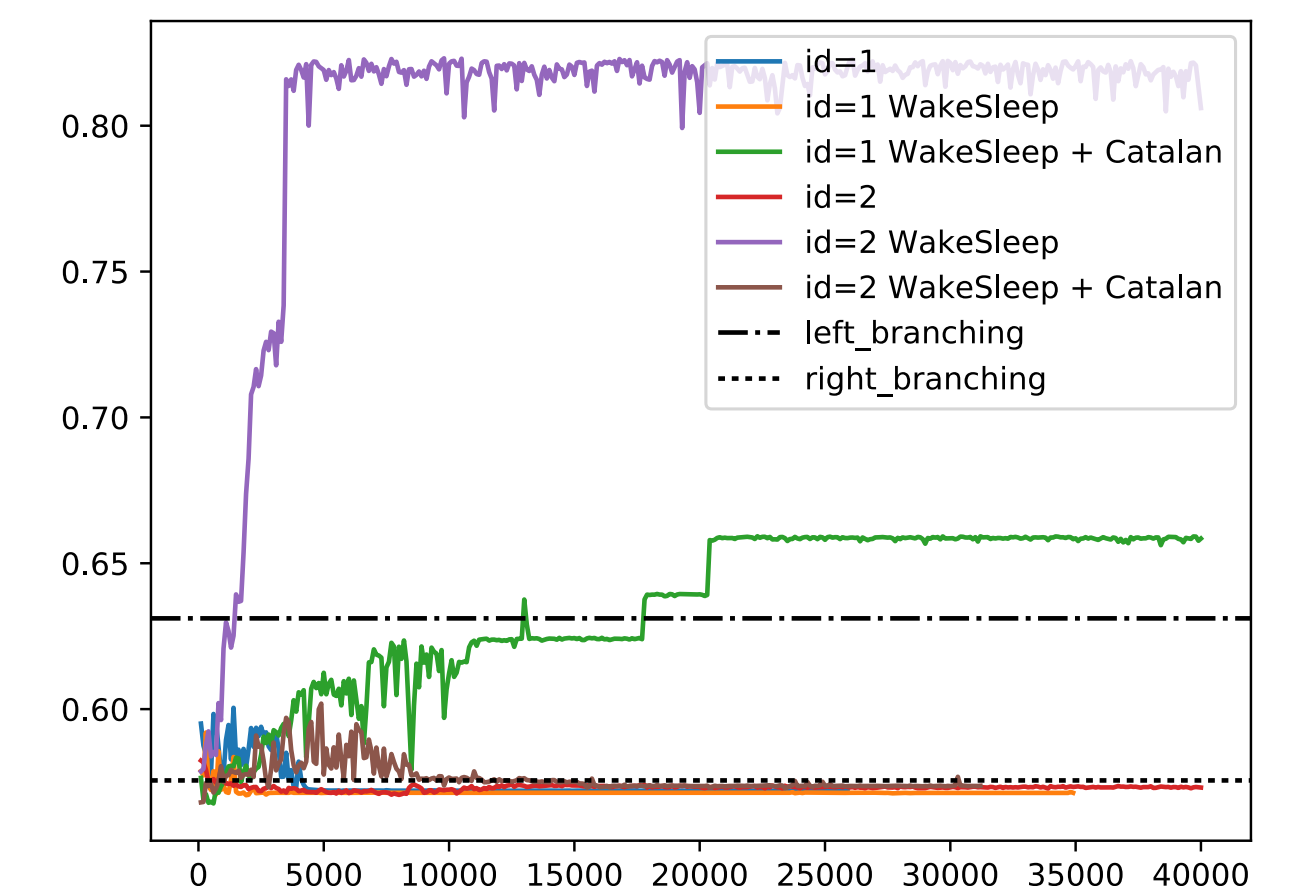


Figure 7: Transition Accuracy (top) and Classification Accuracy (bottom) on the development set of an artificial dataset meant to challenge tree-structure learning models.

Catalan Pyramid

For a sequence with N tokens, N*2 - 1 transitions, and N - 1 reduce transitions:

- 1 $row_{i,0,0} = 1$
- 2 $row_{i,0,1} = i + 2$
- 3 $row_{i,n_i-1,1} = Catalan(i + 2)$
- 4 $row_{i,n_i-1,0} = row_{i,n_i-1,1} - row_{i-1,n_i-2,1}$
- 5 $row_{i,j,0} = row_{i,j-1,1}$
- 6 $row_{i,j,1} = row_{i,j,0} + row_{i-1,j,1}$

	t=0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
r=0	1	1	297	165	75	27	7	1							
1			429	297	165	75	27	7							
2				1	90	48	20	6	1						
3					132	90	48	20	6	1					
4						1	28	14	5	1					
5							42	28	14	5	1				
6								1	9	4	1				
7									14	9	4	1			
8										1	3	1			
9											5	3	1		
10												1	2		
11														1	
12															1
13															
14															

Figure 6: Catalan Pyramid: Lookup table for shift probabilities. Empty slots indicate zero probability. This version is for a tree with 8 leaves.

Source Code

<https://github.com/nyu-ml1/spinn>