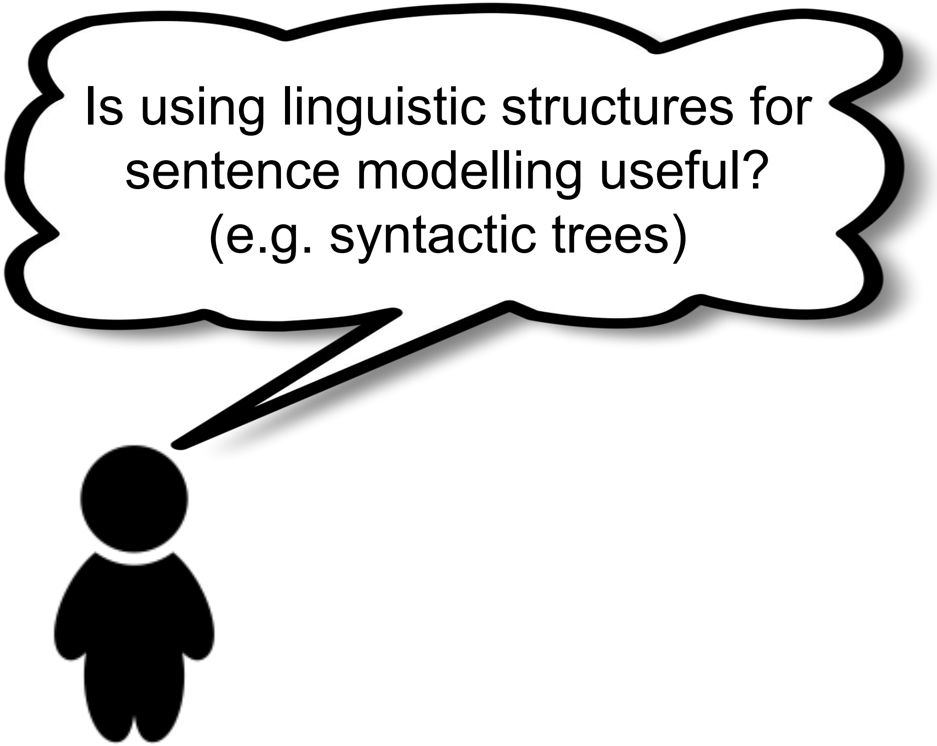
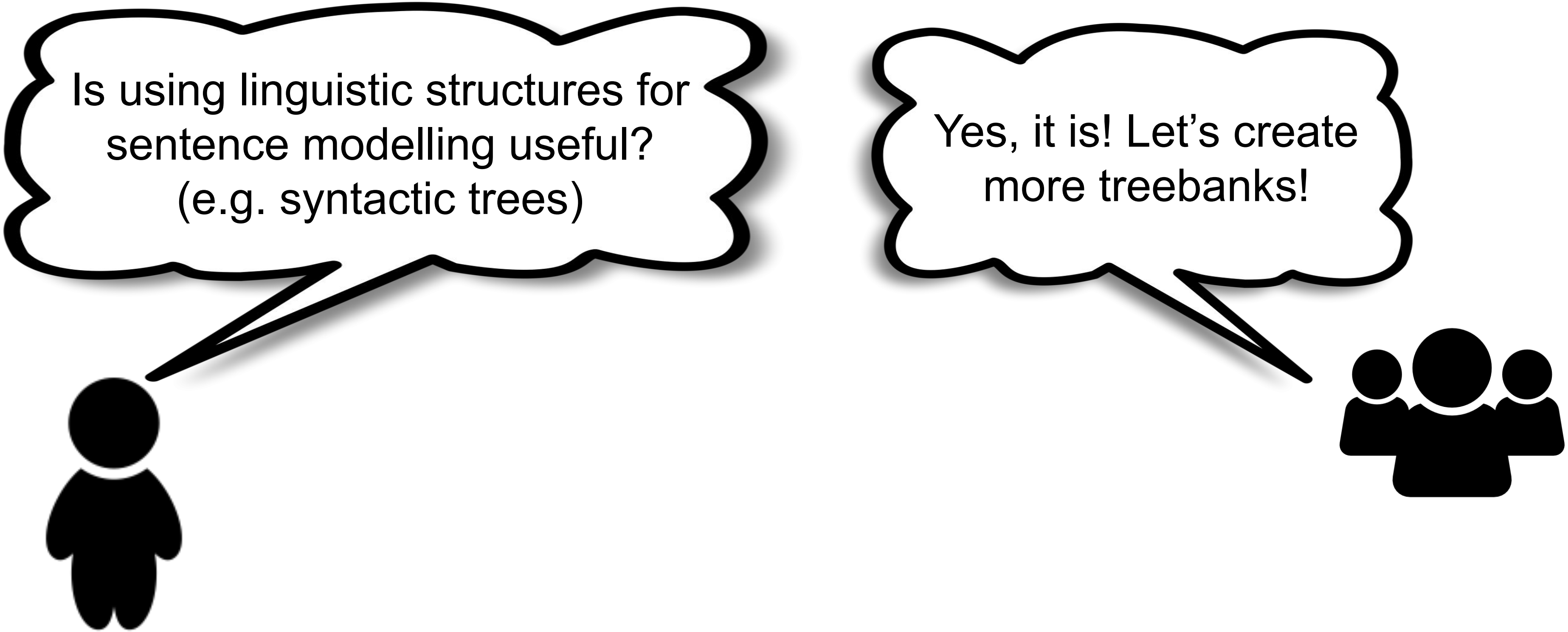
Cooperative Learning of Disjoint Syntax and Semantics

Serhii Havrylov

Germán Kruszewski
Armand Joulin


Is using linguistic structures for
sentence modelling useful?
(e.g. syntactic trees)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Yes, it is! Let’s create more treebanks!

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Yes, it is! Let’s create more treebanks!

No! Annotations are expensive to make.
Parse trees is just a linguists’ social construct.
Just stack more layers and you will be fine!

Recursive neural network

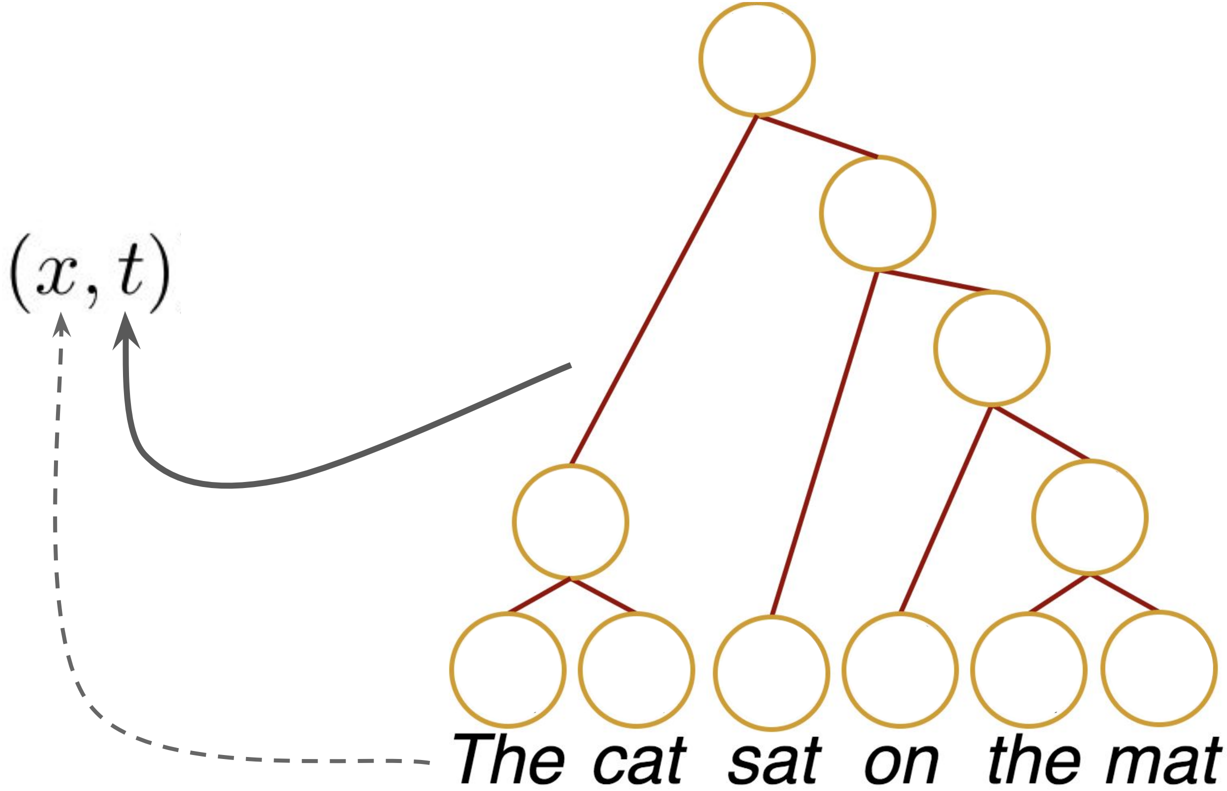
The cat sat on the mat

Recursive neural network

x

The cat sat on the mat

Recursive neural network



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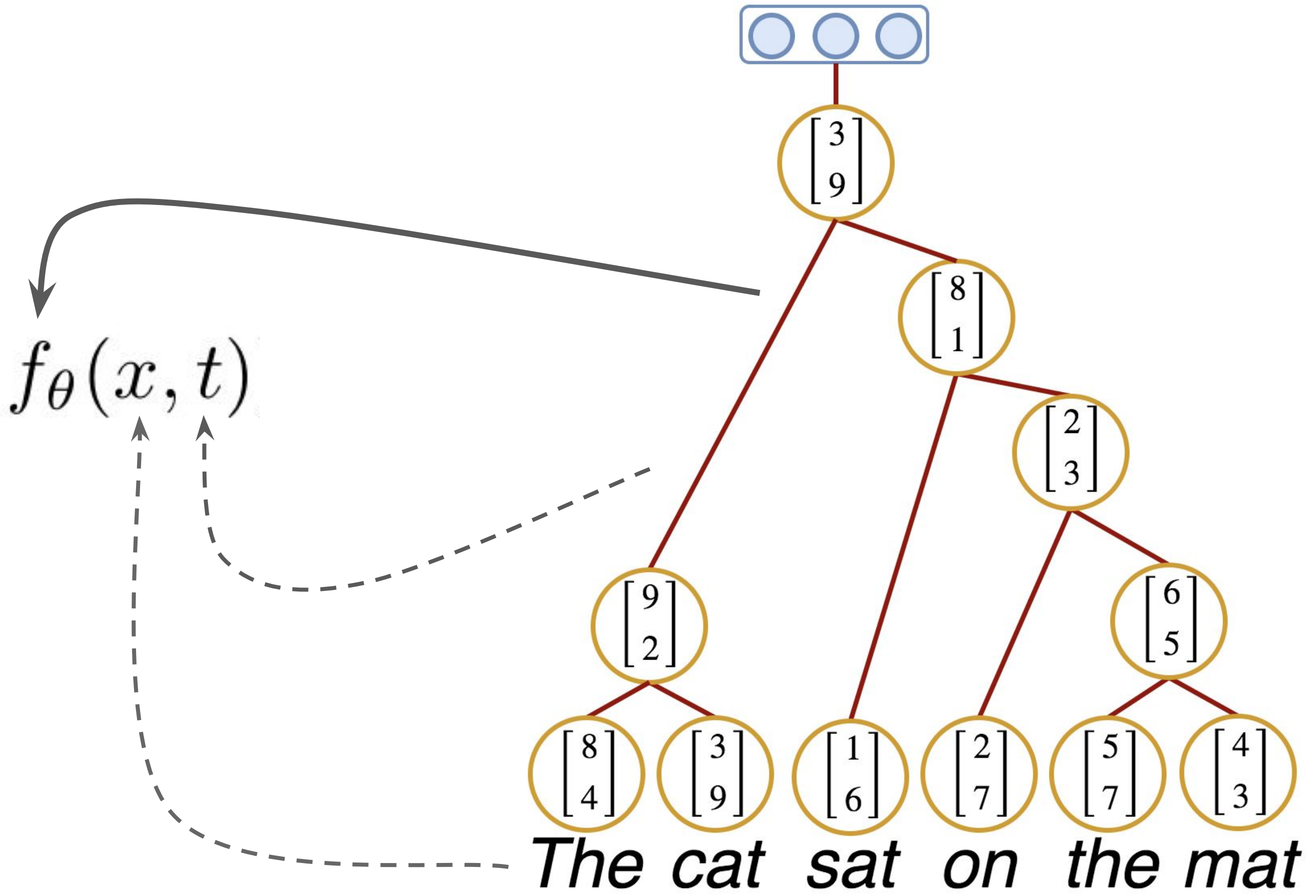
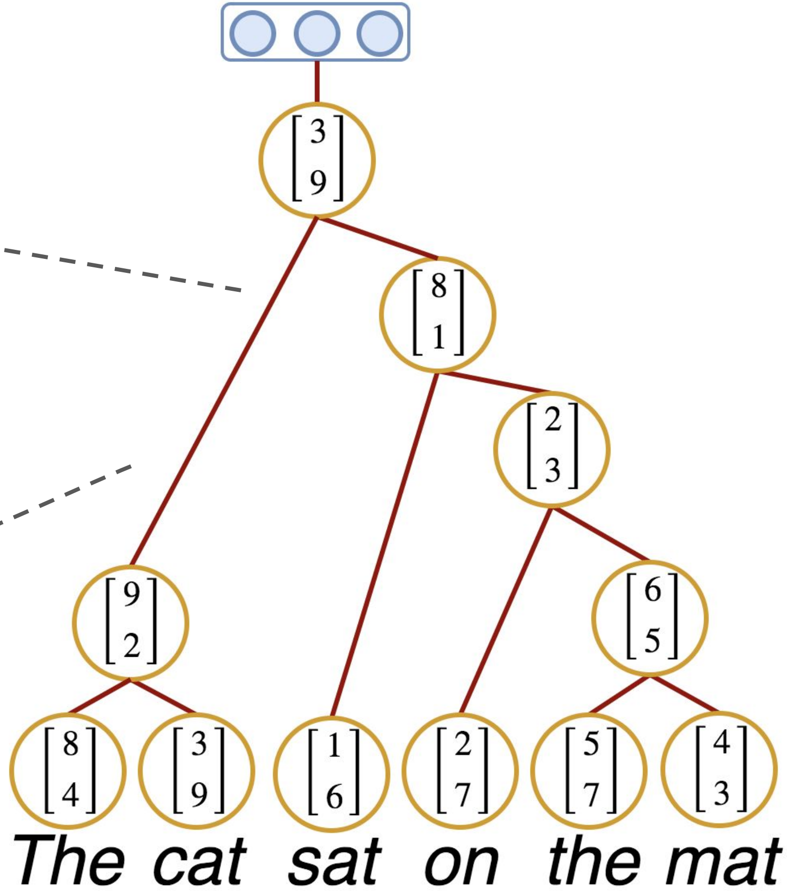


Recursive neural network

$$(y, f_\theta(x, t))$$

neutral



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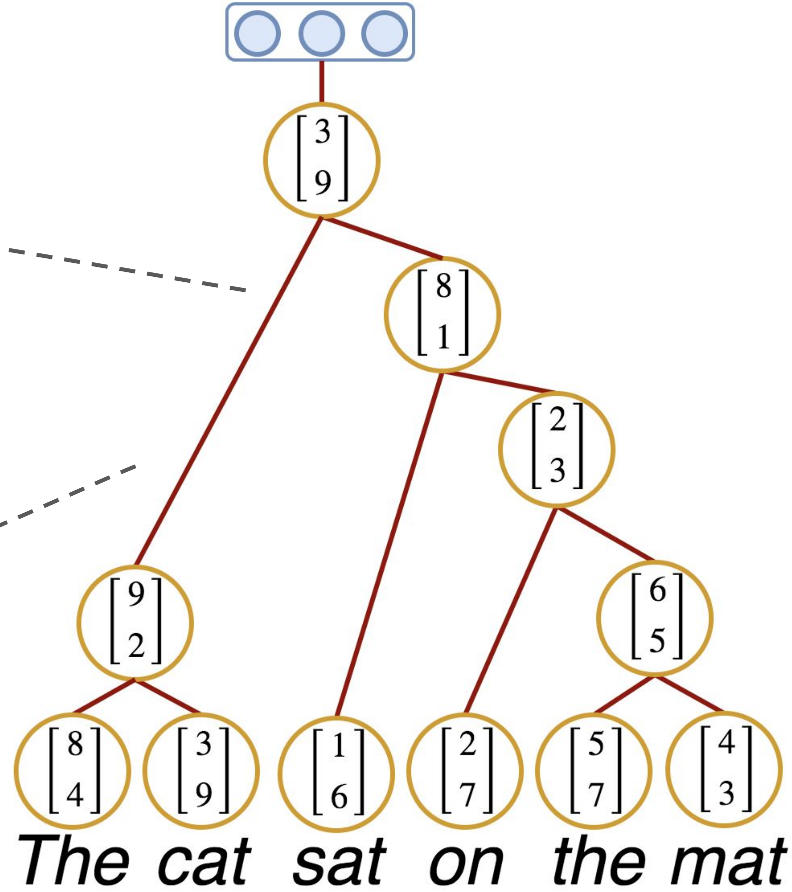

Latent tree learning

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$$\mathbb{E}_{p_\phi(t|x)}[\ell(y, f_\theta(x,t))]$$

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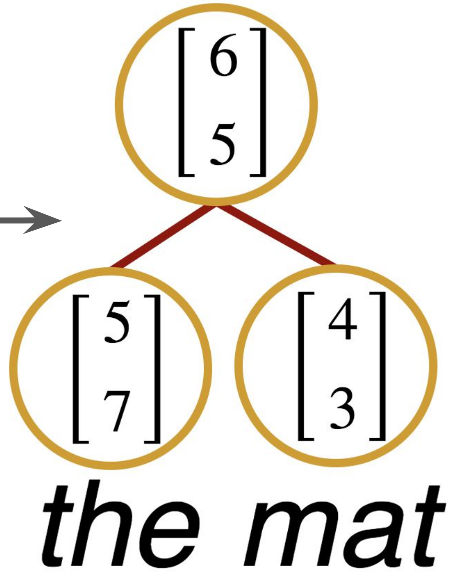

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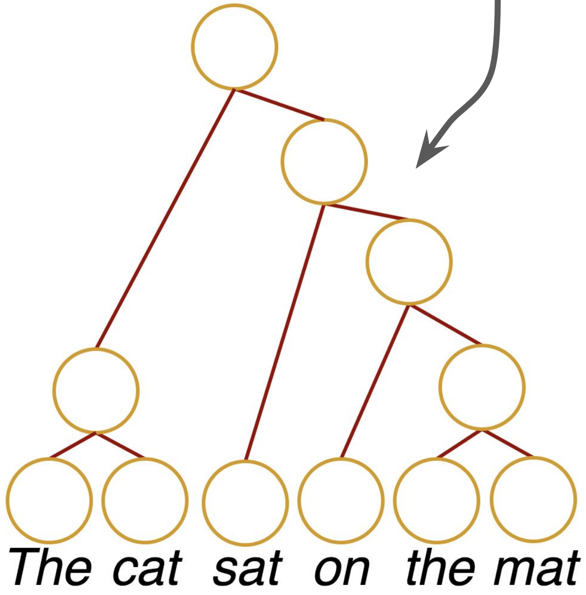

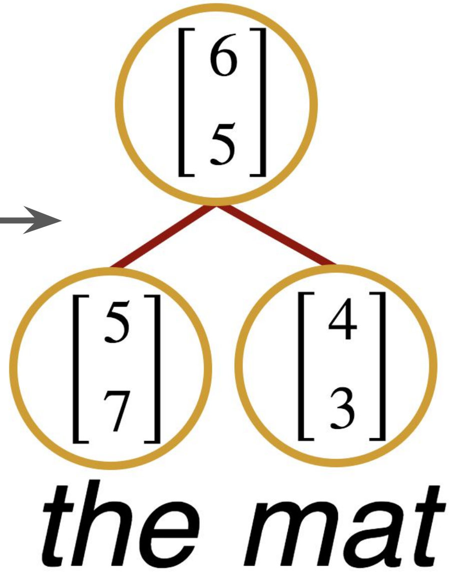

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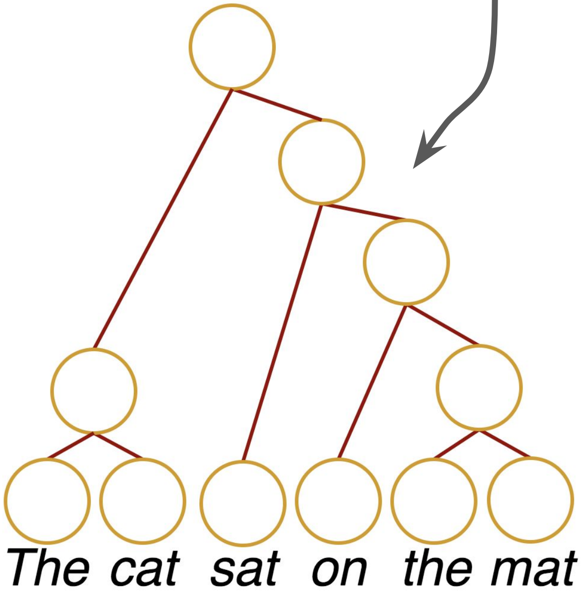

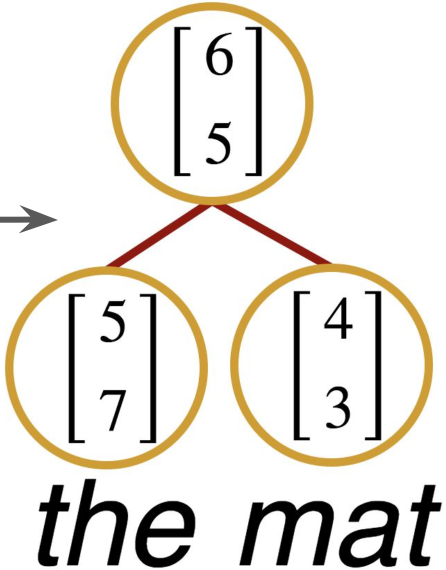

Latent tree learning

- RL-SPINN: Yogatama et al., 2016
- Soft-CYK: Maillard et al., 2017
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Recent work has shown that:

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- Trees **do not resemble** any semantic or syntactic formalisms (Williams et al. 2018).
- Parsing strategies **are not consistent** across random restarts (Williams et al. 2018).
- These models **fail to learn the simple context-free grammar** (Nangia et al. 2018).

ListOps (Nangia, & Bowman (2018))

[MIN 1 [MAX [MIN 9 [MAX 1 0] 2 9 [MED 8 4 3]] [MIN 7 5] 6 9 3]]

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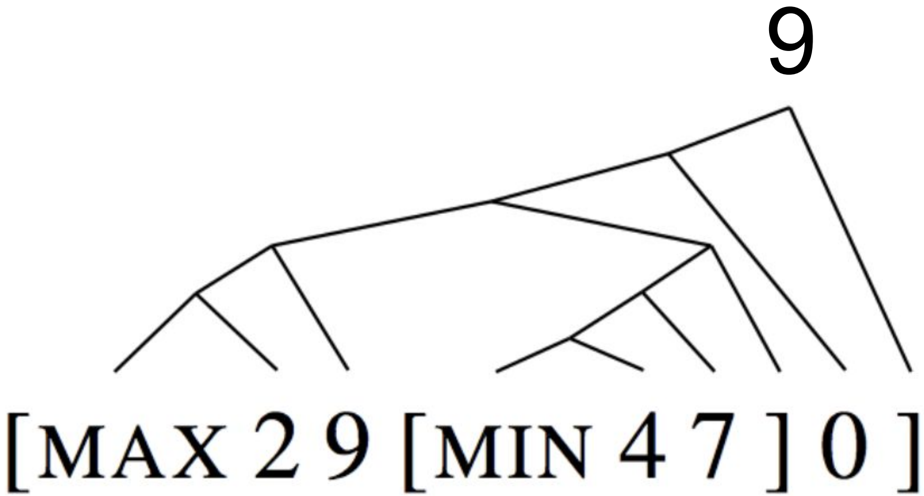

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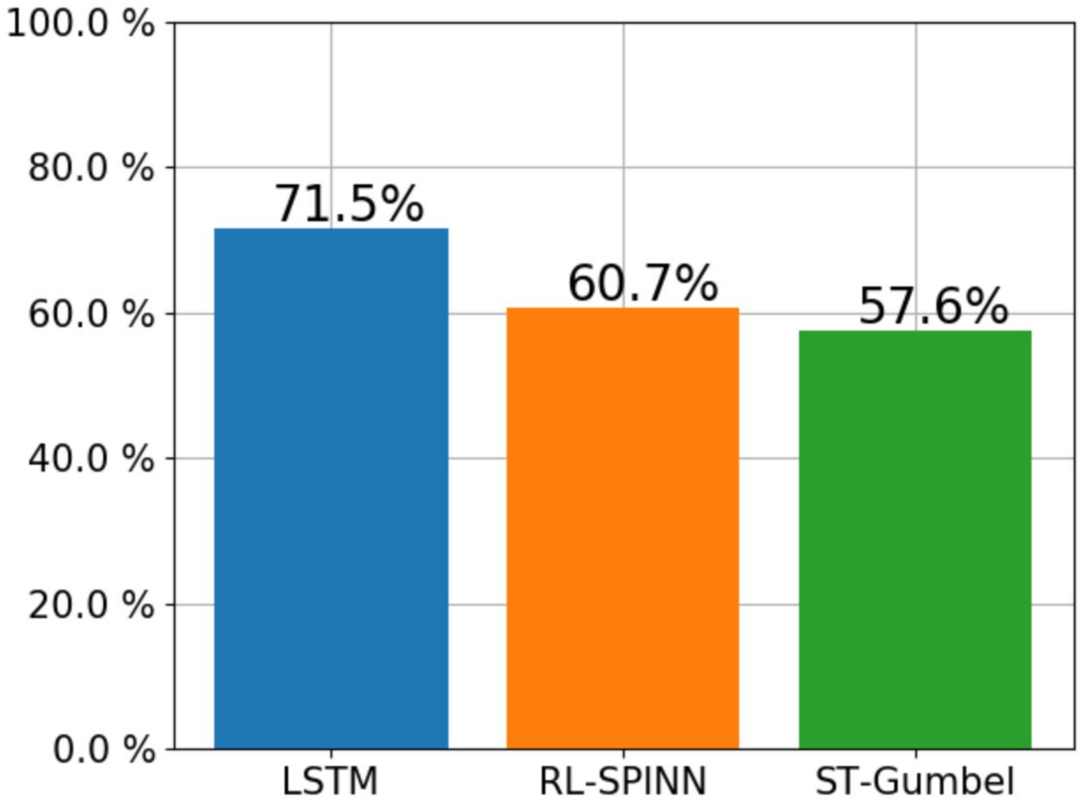

Tree-LSTM parser (Choi et al., 2018)

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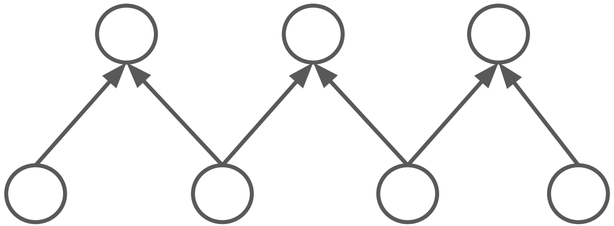
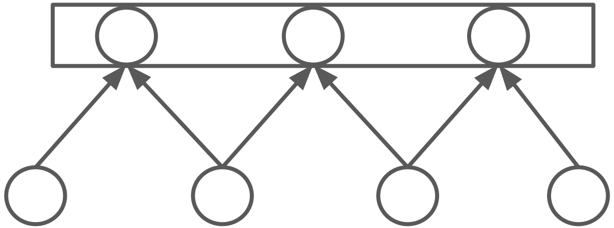


$$\mathbf{r}_i^{k+1} = \texttt{Tree-LSTM}(\mathbf{r}_i^k, \mathbf{r}_{i+1}^k)$$

Tree-LSTM parser (Choi et al., 2018)

$$s_k(i) = \langle \mathbf{q}, \mathbf{r}_i^{k+1} \rangle$$



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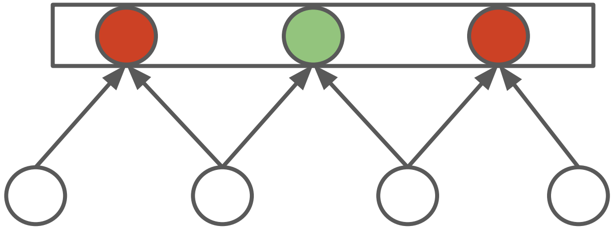

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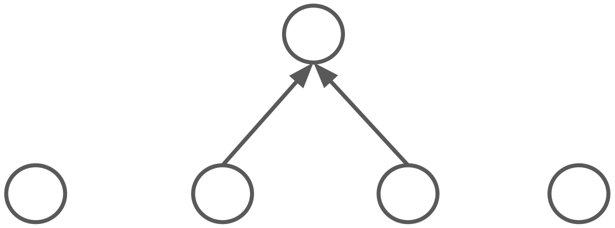

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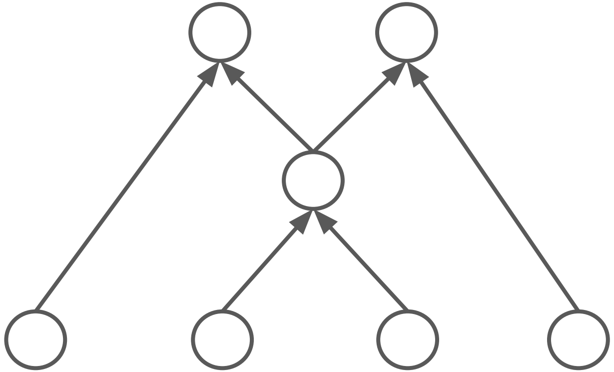

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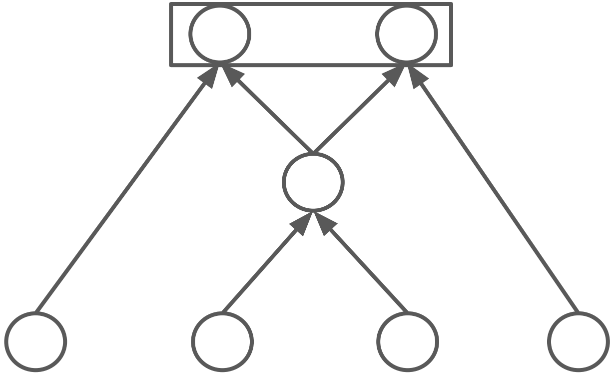

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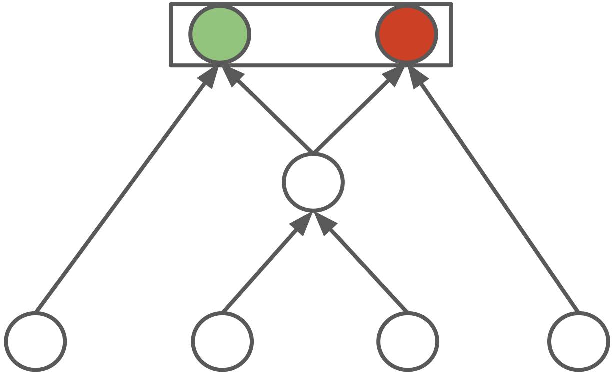

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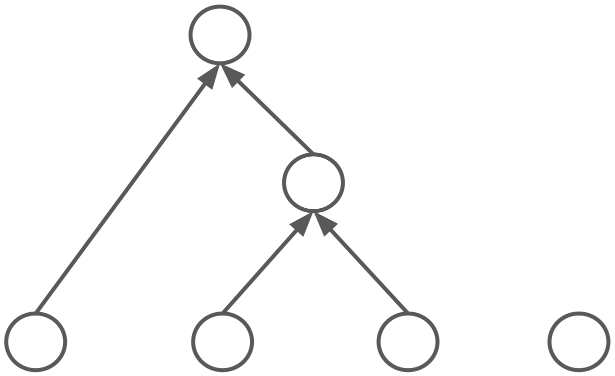

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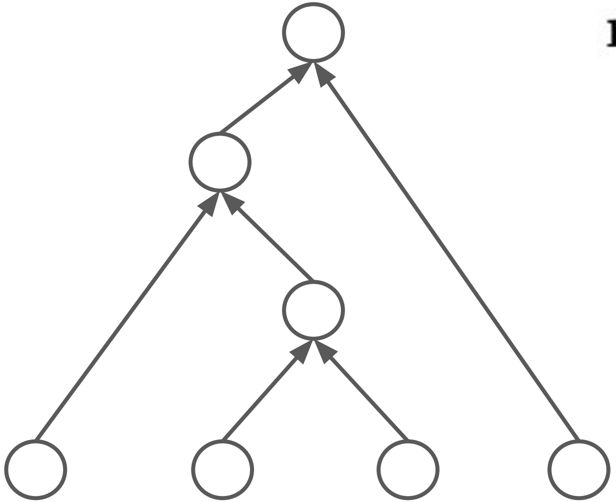

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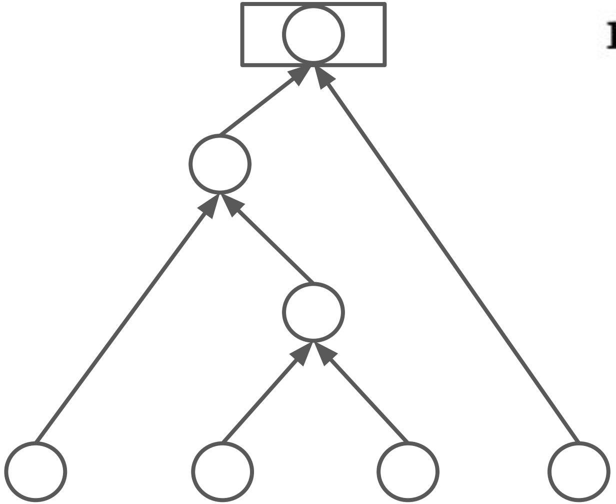

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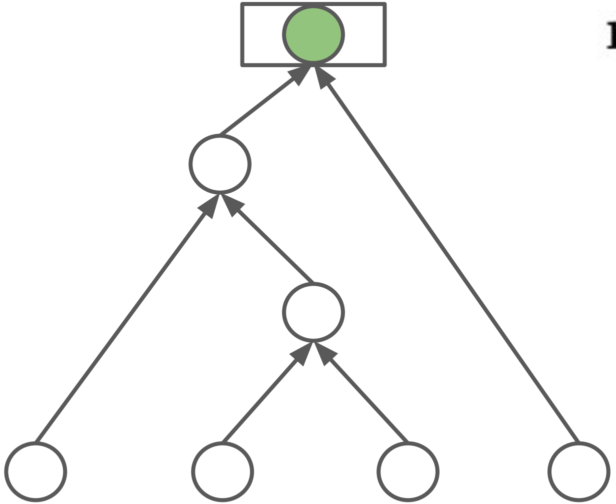

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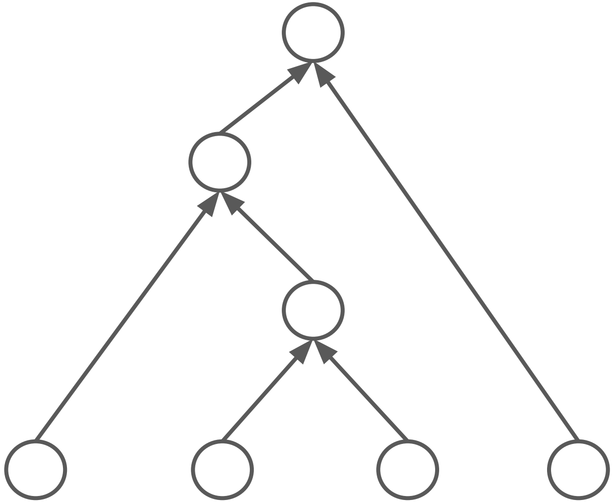
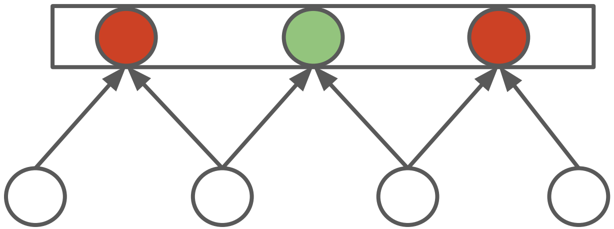


Separation of syntax and semantics

Parser ϕ

$$s_k(i) = \langle \mathbf{q}, \texttt{Tree-LSTM}(\mathbf{r}_i^k, \mathbf{r}_{i+1}^k) \rangle$$



Compositional Function θ

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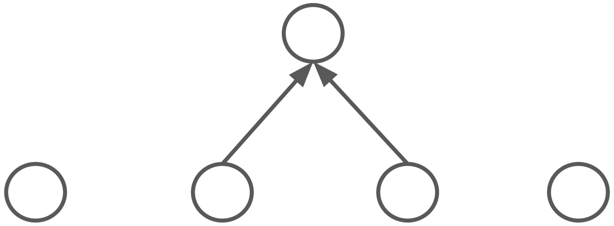
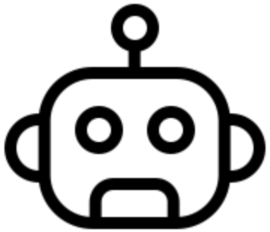
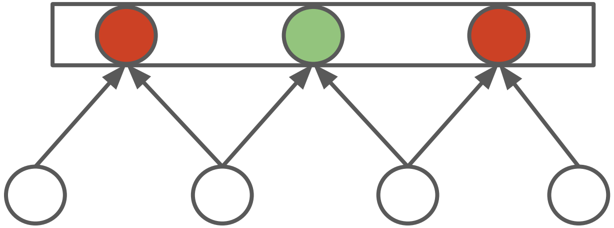


Parsing as a RL problem

Parser ϕ

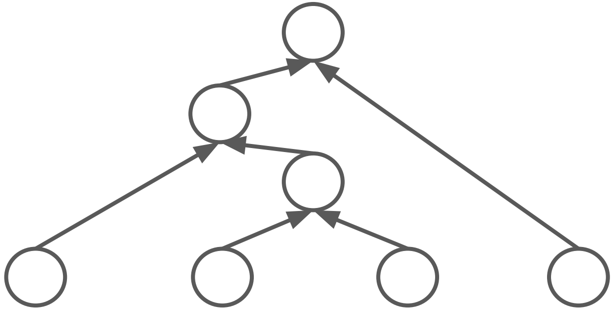


$$p_\phi(t|x) = \prod_{k=0}^{K} \pi_\phi(a_k^i|\mathbf{r}^k)$$



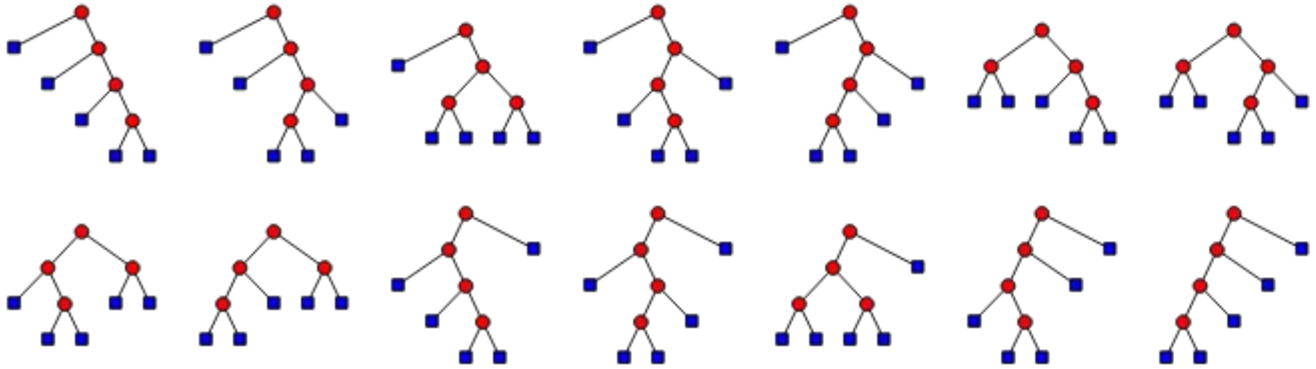
Compositional Function θ

$$\ell(f_\theta(x,t),y)$$



Optimization challenges

Size of the search space is $$C_n \sim \frac{4^n}{n^{3/2}\sqrt{\pi}}$$



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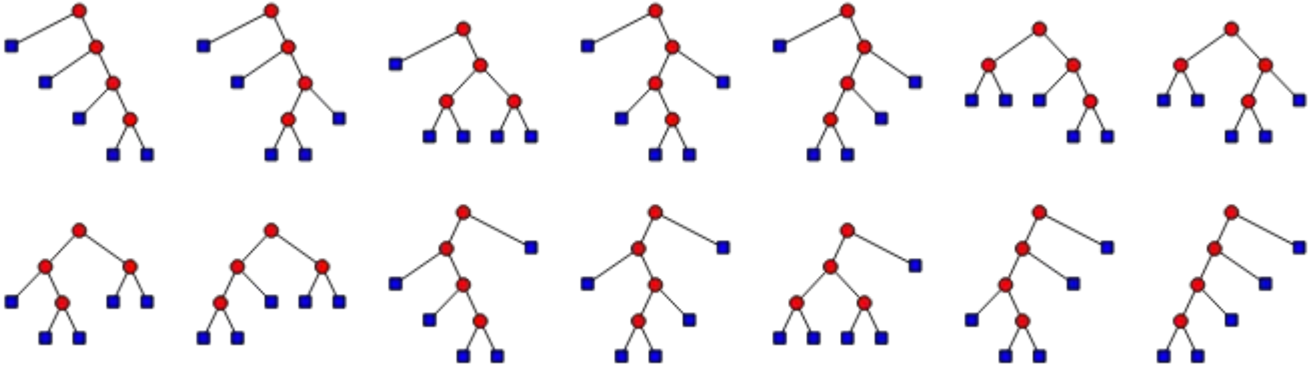

For a sentence with 20 words, there are **1_767_263_190** possible trees.

Optimization challenges

Syntax and semantic has to be learnt simultaneously

model has to infer from examples that `[MIN 0 1] = 0`

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– nonstationary environment (i.e the same sequence of actions can receive different rewards)

Optimization challenges

Typically, the ***compositional function*** θ is learned faster than the ***parser*** φ.

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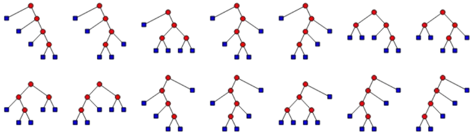
This fast coadaptation limits the exploration of the search space to parsing strategies similar to those found at the beginning of the training.

Optimization challenges

- High variance in the estimate of a parser's gradient ∇_{φ} has to be addressed.



- Learning paces of a parser θ and a compositional function φ have to be levelled off.

Variance reduction

$$\nabla_\phi \mathcal{L} \approx \ell(f_\theta(x,t),y)\frac{\partial \log p_\phi(t|x)}{\partial \phi}.$$

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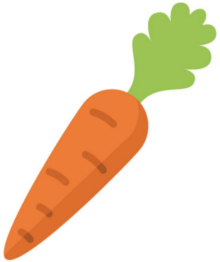

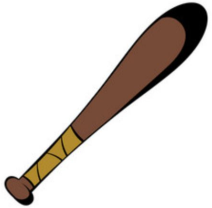

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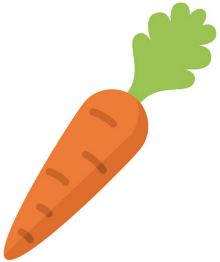

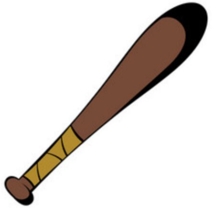

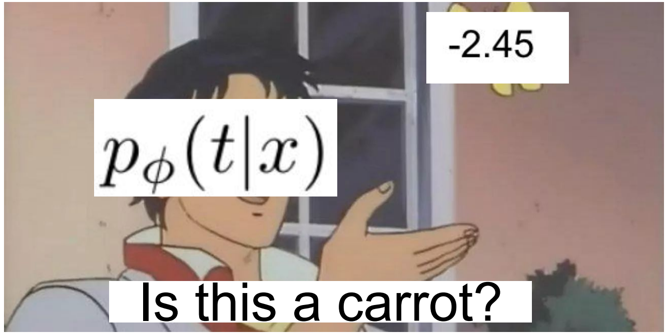

Variance reduction

$$\nabla_\phi \mathcal{L} \approx \ell(f_\theta(x,t),y)\frac{\partial \log p_\phi(t|x)}{\partial \phi}.$$

the moving average of recent rewards

$$\nabla_\phi \mathcal{L} \approx \underbrace{(\ell(f_\theta(x,t),y) - c)}_{\textbf{new reward}}\frac{\partial \log p_\phi(t|x)}{\partial \phi}.$$

Variance reduction

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self-critical training (SCT) baseline Rennie et al. (2017)

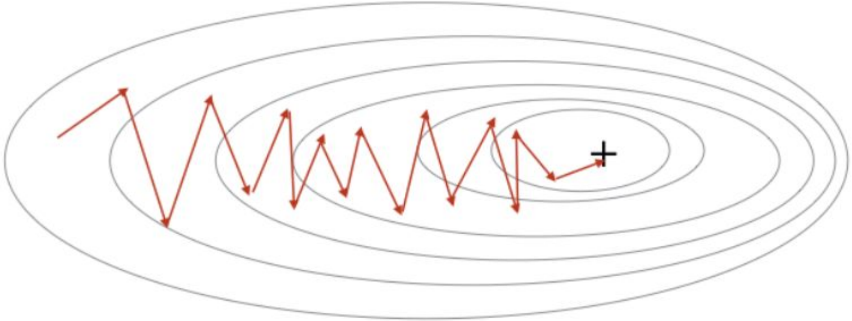
$$c(x) = \ell(f_\theta(x,\hat{t}),y)$$

$$\hat{t} = \arg\max p_\phi(t|x)$$

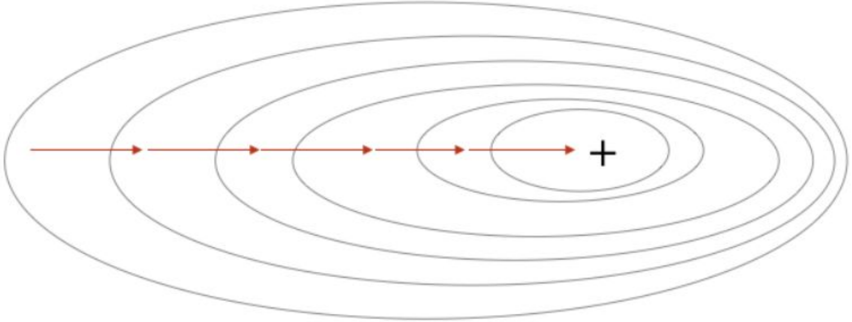
Synchronizing syntax and semantics learning

Syntax  $p_\phi(t|x)$

Semantics  $f_\theta(x, t)$



ϕ



θ

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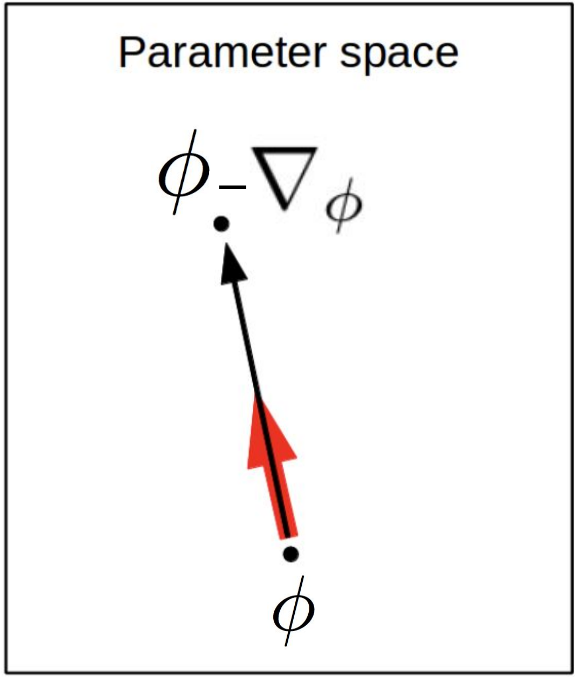

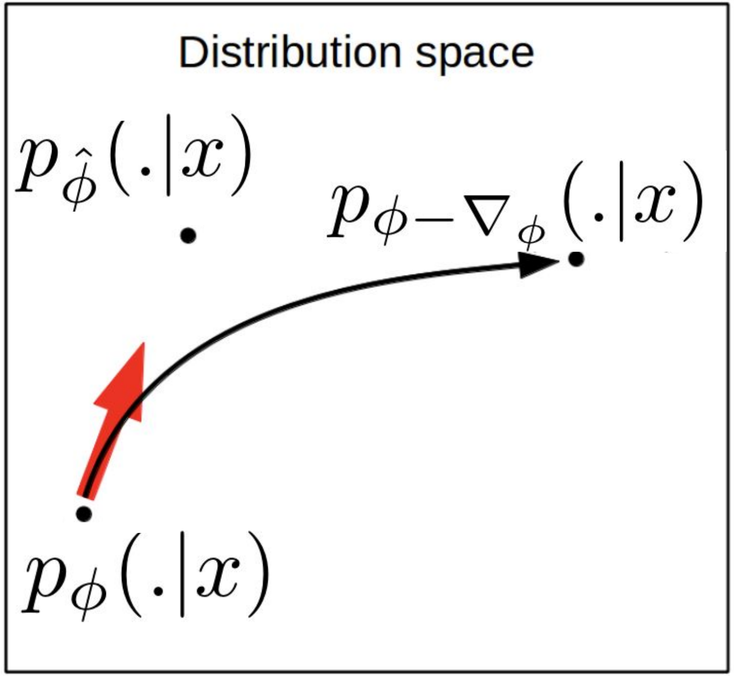

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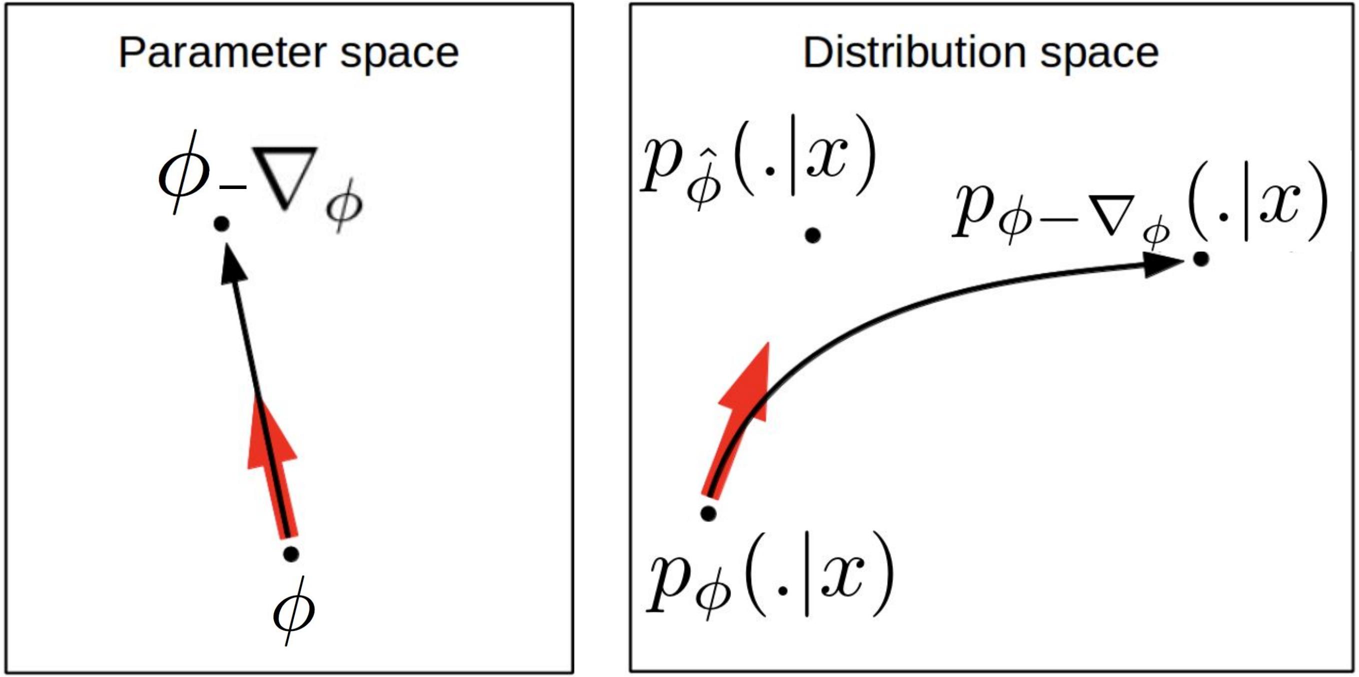
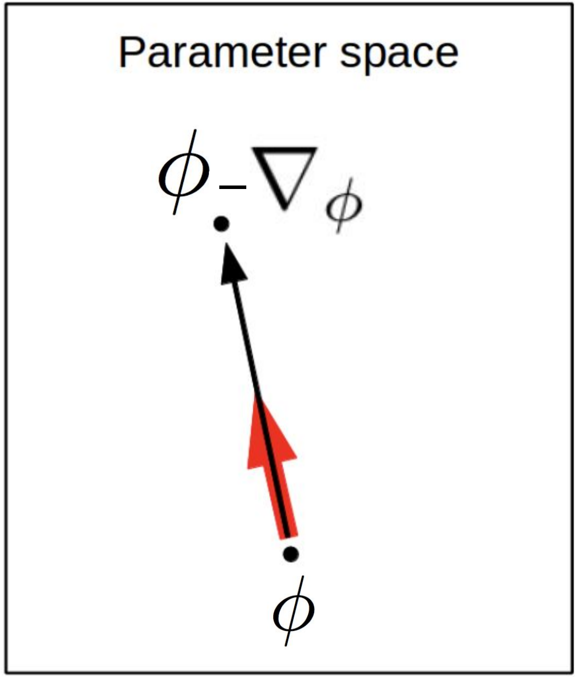
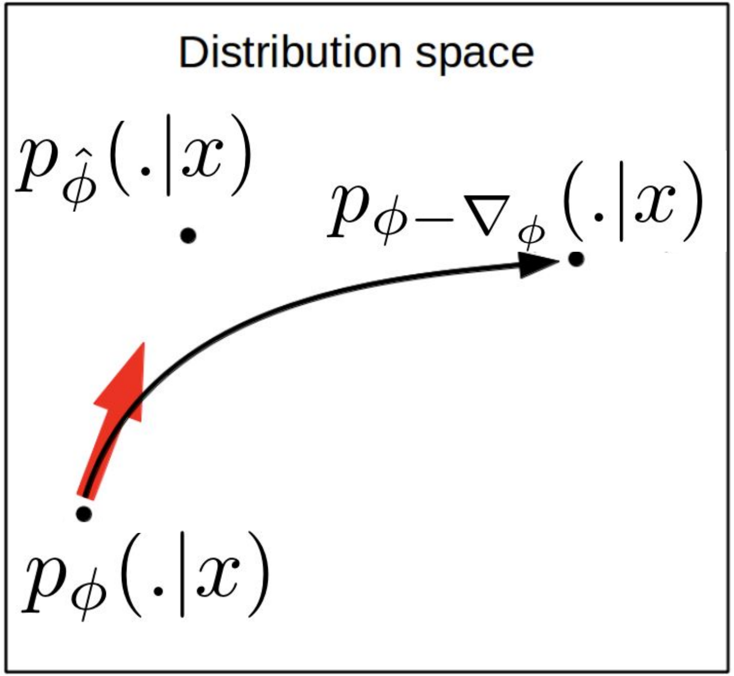


$$\frac{p_\phi(t|x)}{p_{\phi_{\text{old}}}(t|x)} \in [1-\epsilon; 1+\epsilon]$$

Synchronizing syntax and semantics learning

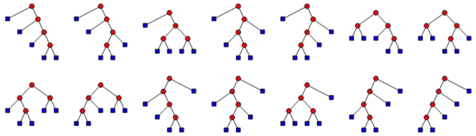




Proximal Policy Optimization (PPO) of Schulman et al. (2017)

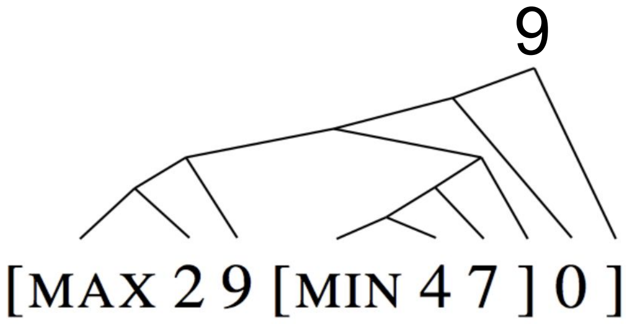
Optimization challenges

- High variance in the estimate of a parser's gradient ∇_{φ} is addressed by using **self-critical training** (SCT) baseline of Rennie et al. (2017).



- Learning paces of a parser φ and a compositional function θ is levelled off by controlling parser's updates using **Proximal Policy Optimization** (PPO) of Schulman et al. (2017).

ListOps results



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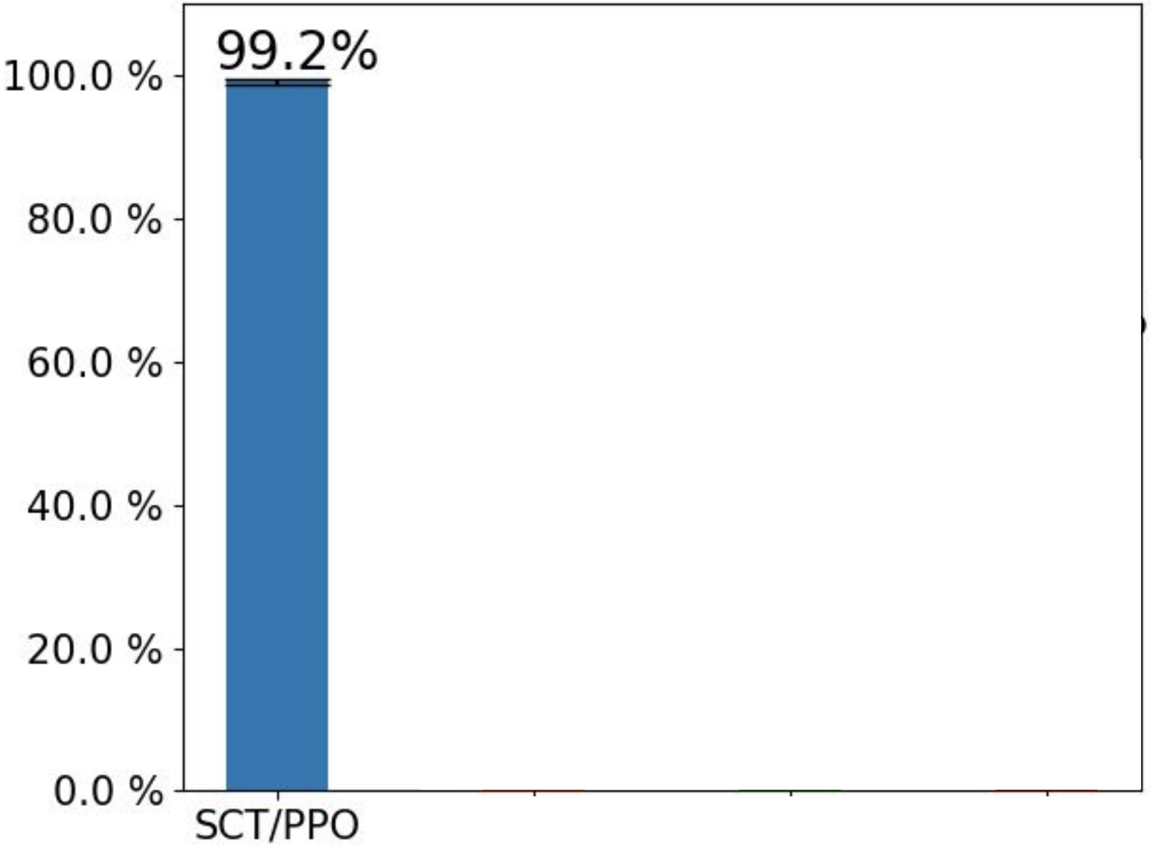
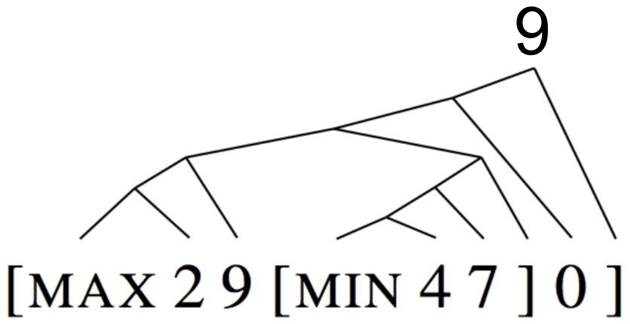
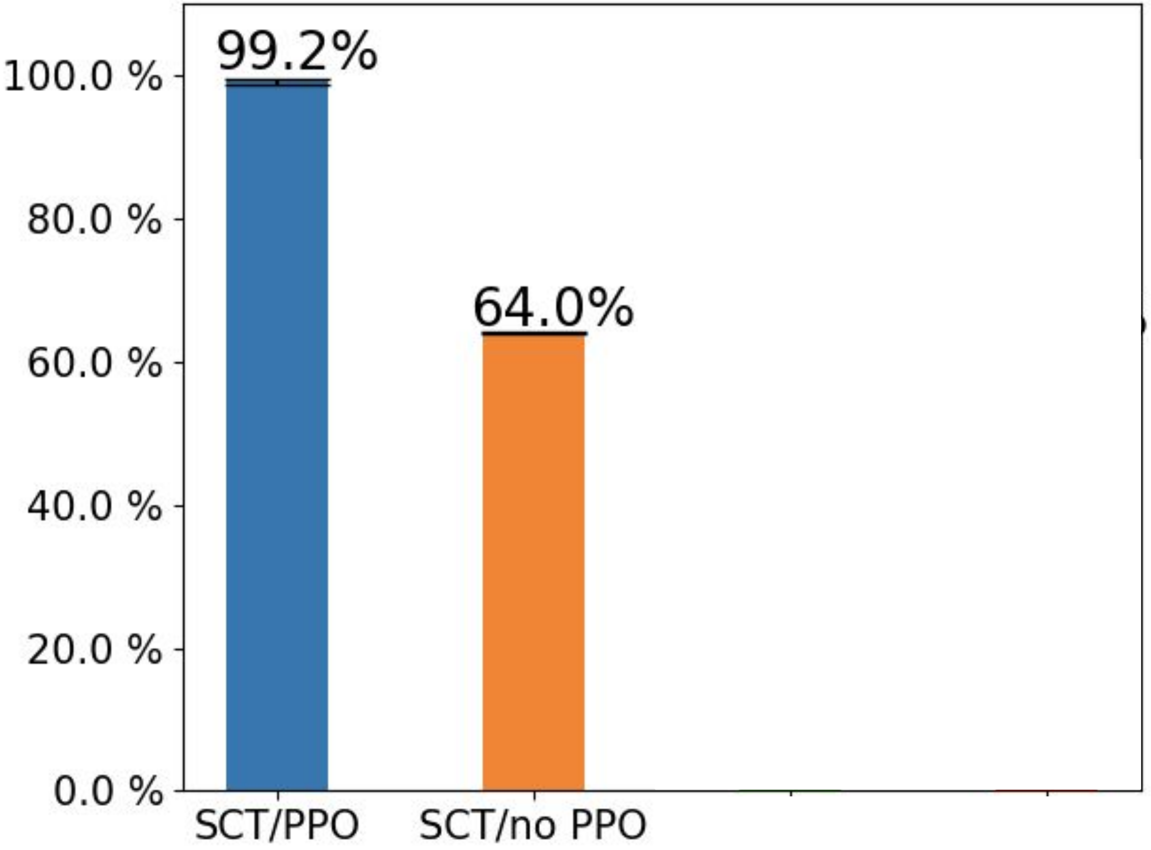
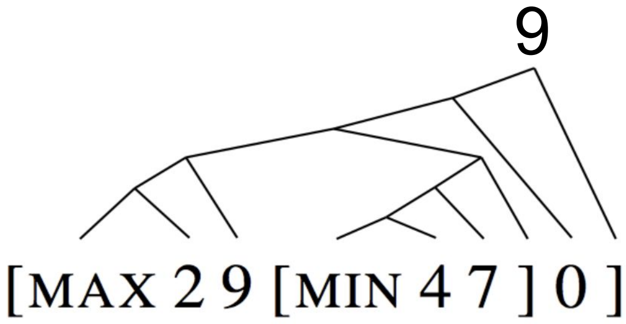


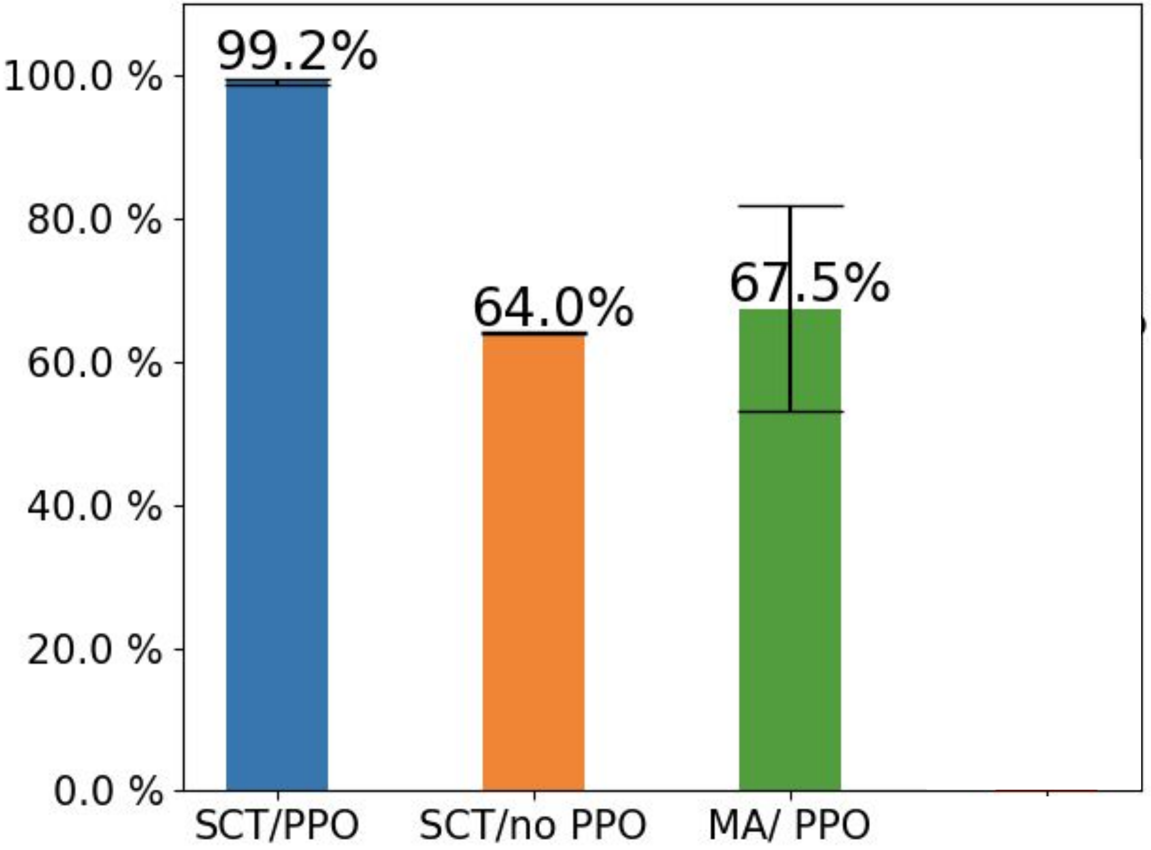


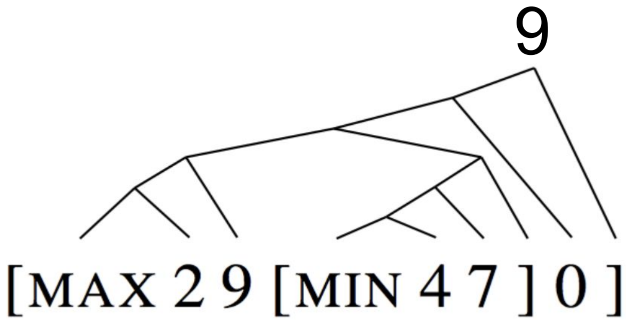
ListOps results



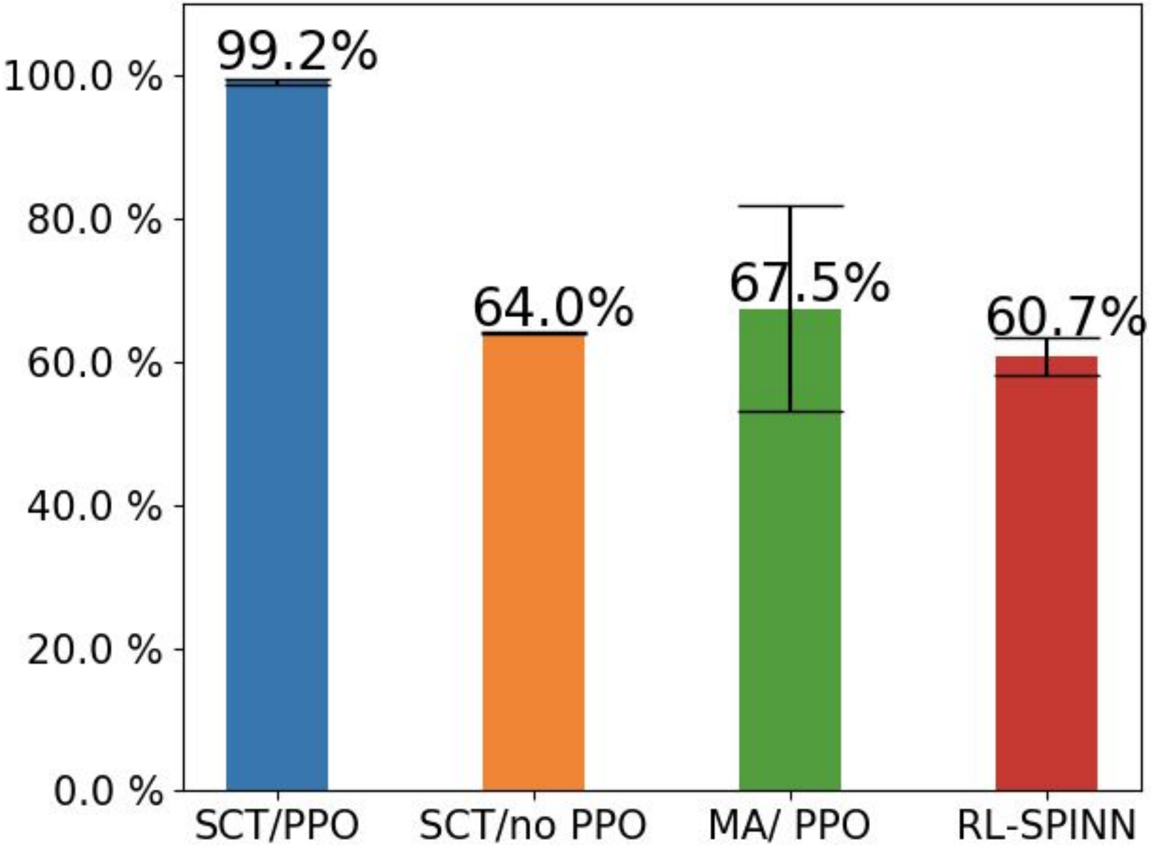


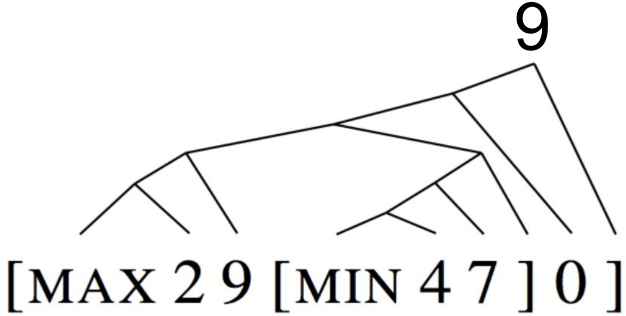
ListOps results



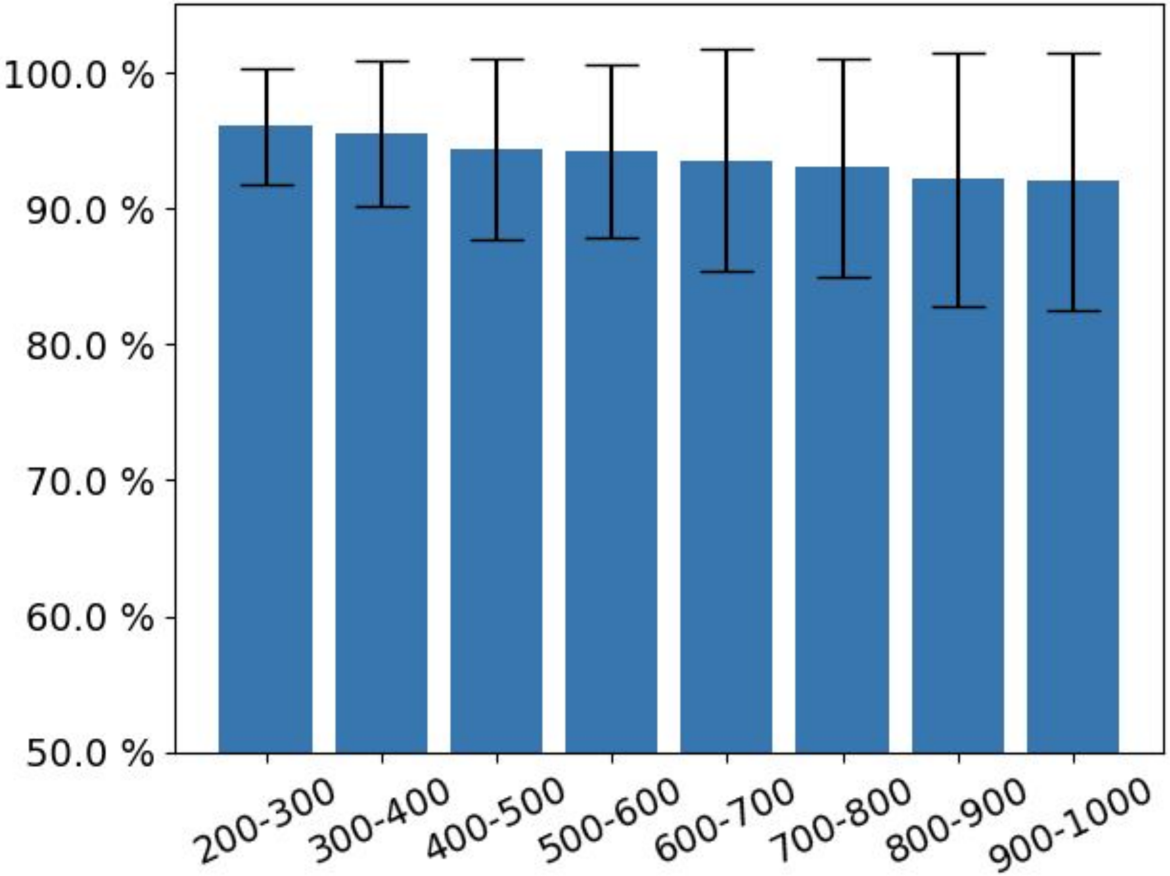


ListOps results

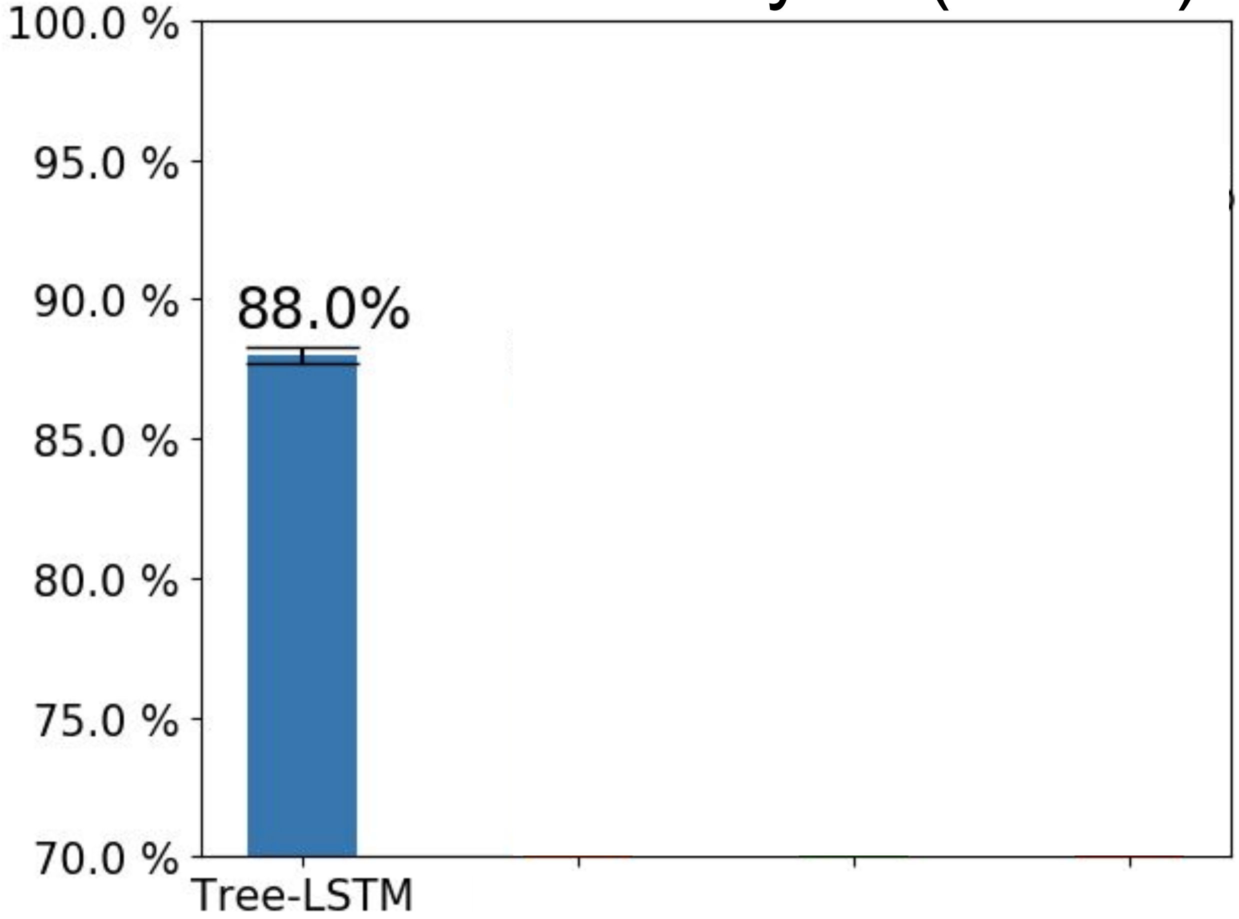




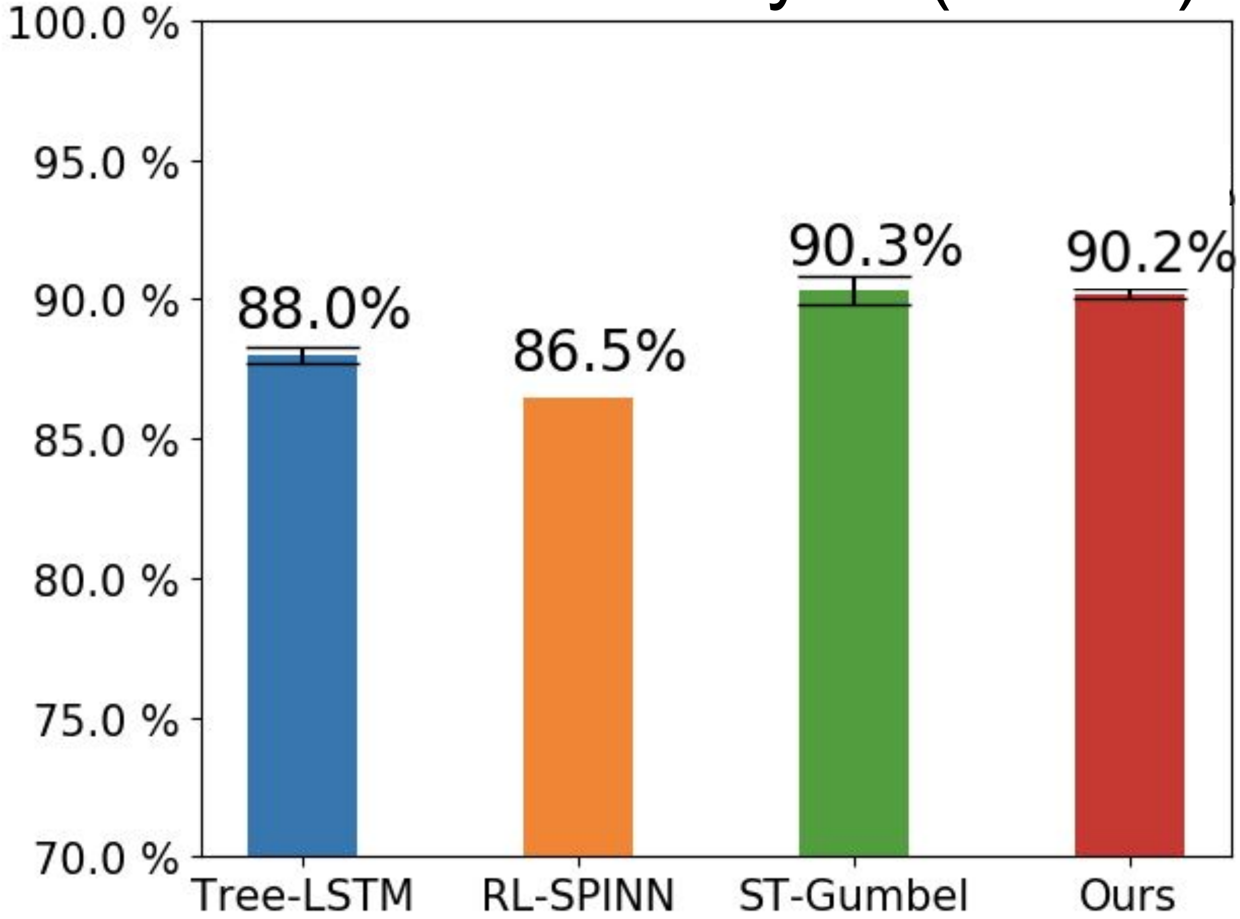
Extrapolation



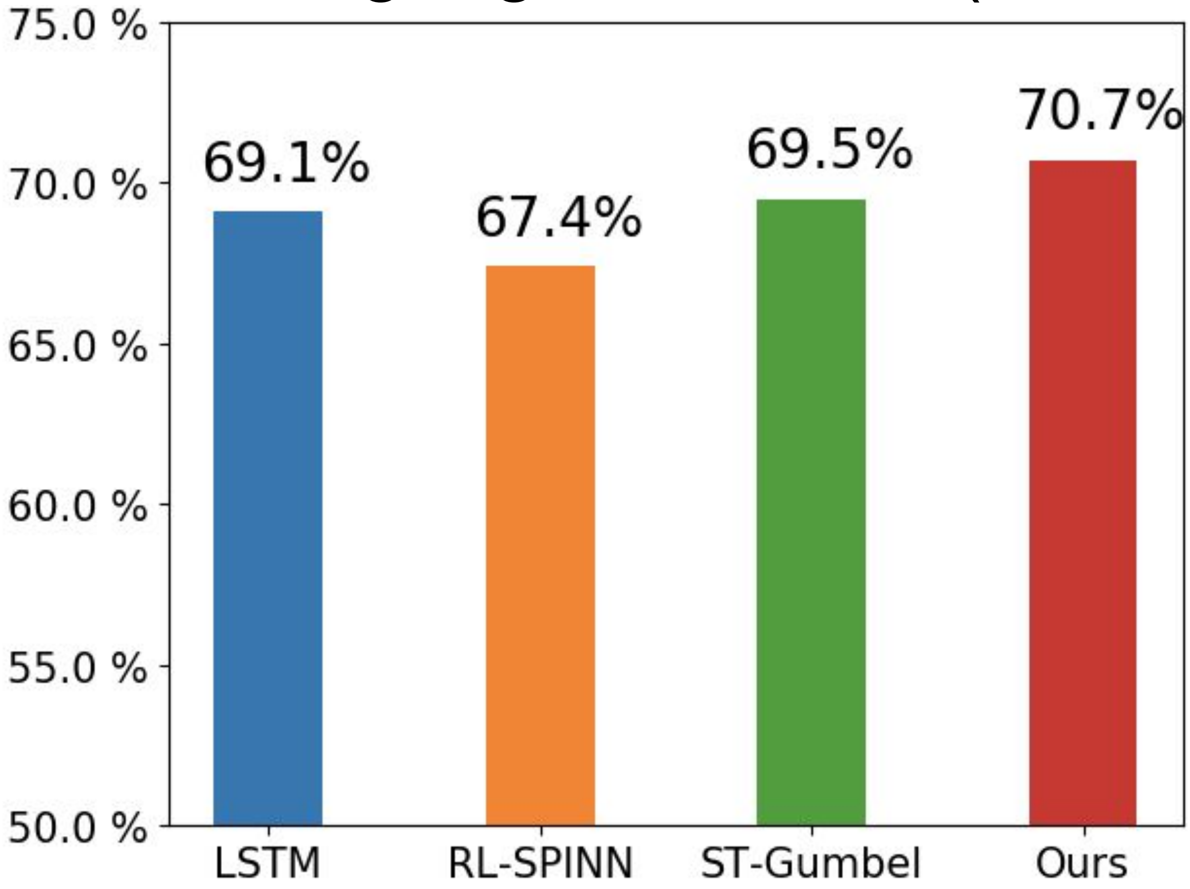
Sentiment Analysis (SST-2)



Sentiment Analysis (SST-2)



Natural language inference (MultiNLI)



Time and Space complexities

Method	Time complexity	Space complexity	ListOps
RL-SPINN: Yogatama et al., 2016	$O(nd^2)$	$O(nd^2)$	✗
Soft-CYK: Maillard et al., 2017	$O(n^3d+n^2d^2)$	$O(n^3d)$	✗
Gumbel Tree-LSTM: Choi et al., 2018	$O(n^2d+nd^2)$	$O(n^2d)$	✗
Ours	$O(Knd^2)$	$O(nd^2)$	✓

n – sentence length
d – tree-LSTM dimensionality
K – number of updates in PPO

Conclusions

- The *separation* between syntax and semantics allows **coordination** between optimisation schemes for each module.
- Self-critical training **mitigates credit assignment** problem by *distinguishing* “hard” and “easy” to solve datapoints.
- The model **can recover** a simple context-free grammar of mathematical expressions.
- The model **performs competitively** on several real natural language tasks.

github.com/facebookresearch/latent-treelstm