Towards dynamic computation graphs via sparse latent structure

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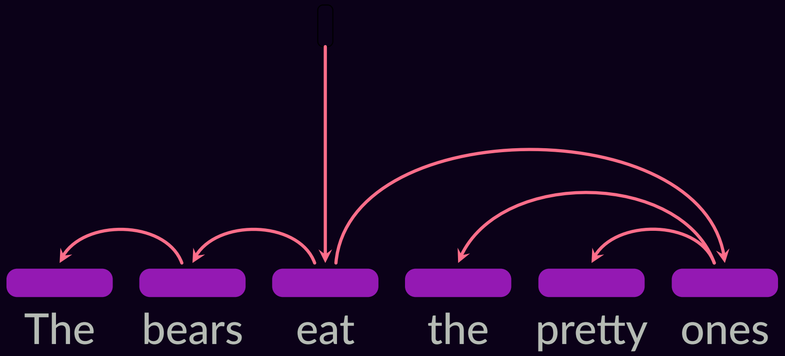
github.com/vene/sparsemap @vnfrombucharest

Dependency TreeLSTM

Dependency TreeLSTM



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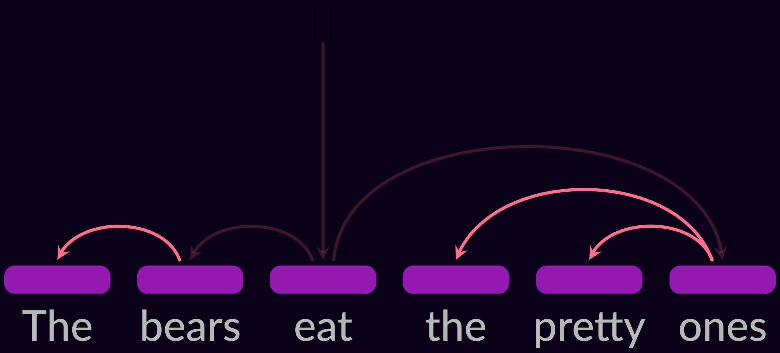

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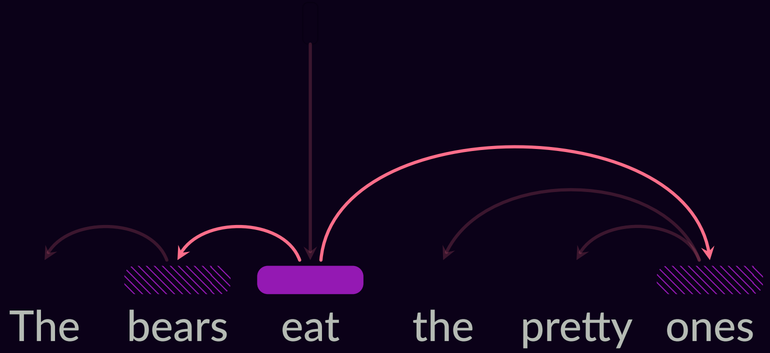

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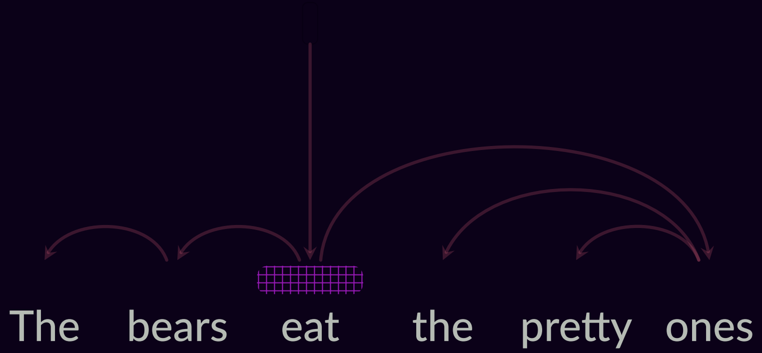

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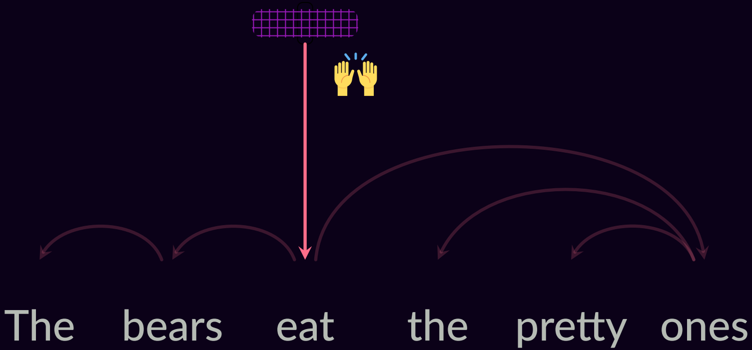
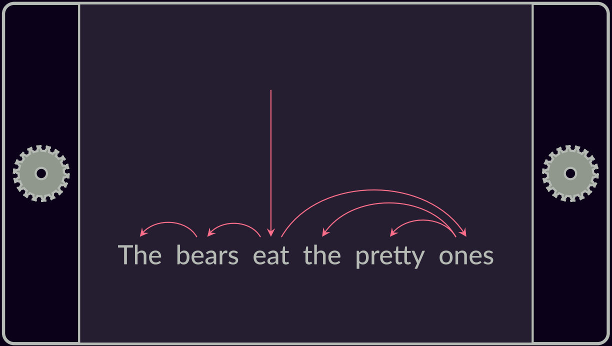


Latent Dependency TreeLSTM

input

x

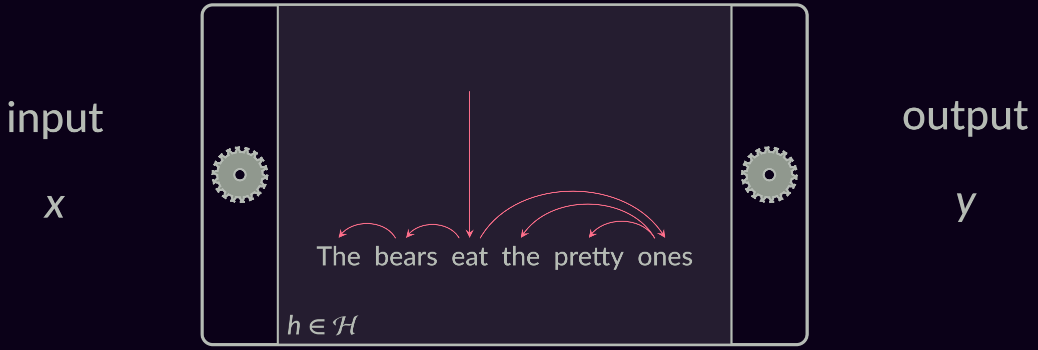


output

y

Latent Dependency TreeLSTM

$$p(y|x) = \sum_{h \in \mathcal{H}} p(y \mid h, x)\, p(h \mid x)$$



Structured Latent Variable Models

$$p(y \mid x) = \sum_{h \in \mathcal{H}} p \quad (y \mid h, x)\, p \quad (h \mid x)$$

Structured Latent Variable Models

$$p(y \mid x) = \sum_{h \in \mathcal{H}} p_{\boldsymbol{\phi}}(y \mid h, x)\, p_{\boldsymbol{\pi}}(h \mid x)$$

Structured Latent Variable Models

e.g., a TreeLSTM defined by h

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parsing model,
using some $\mathrm{score}_{\boldsymbol{\pi}}(h; x)$

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sum over
all possible trees

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Exponentially large sum!

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How to define $\boldsymbol{p_{\pi}}$?

idea 1

idea 2

idea 3

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$$\sum_{h \in \mathcal{H}} \frac{\partial p(y \mid x)}{\partial \boldsymbol{\pi}}$$

idea 1 $p_{\boldsymbol{\pi}}(h \mid x) = 1$ if $h = h^\star$ else 0 argmax

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😊

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idea 3		SparseMAP	😊	😊

SparseMAP Inference

(Niculae et al, ICML 2018)

 = .7  + .3 

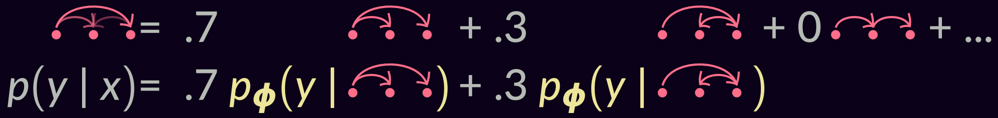
SparseMAP Inference

(Niculae et al, ICML 2018)

 $= .7$  $+ .3$  $+ 0$  $+ \ldots$

SparseMAP Inference

(Niculae et al, ICML 2018)



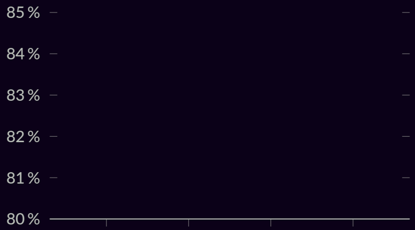
SparseMAP Inference

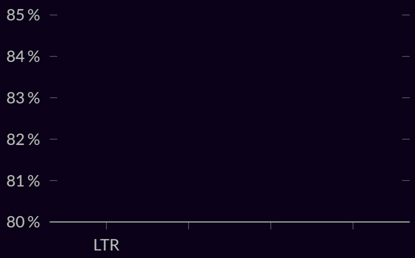
(Niculae et al, ICML 2018)

 $= .7$  $+ .3$  $+ 0$  $+ \dots$

$p(y \mid x) = .7\, p_{\phi}(y \mid$  $) + .3\, p_{\phi}(y \mid$  $)$

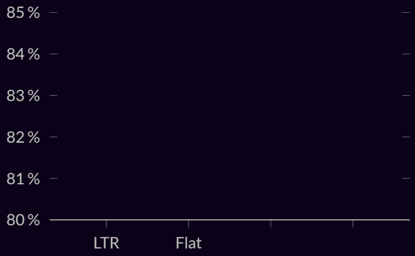
 is not a tree itself: $p(y \mid x) \neq p_{\phi}(y \mid$  $)$!

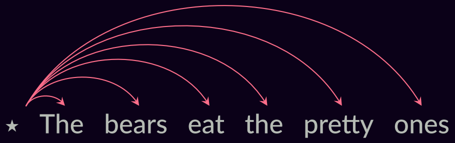

85 %
84 %
83 %
82 %
81 %
80 %



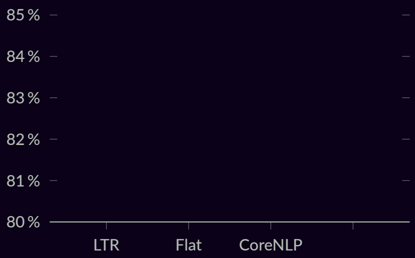
★ The bears eat the pretty ones

Left-to-right: regular LSTM

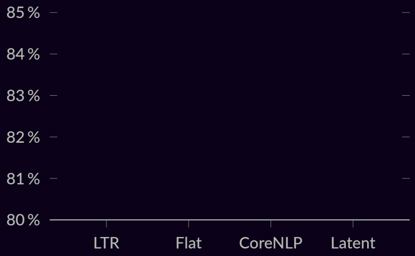


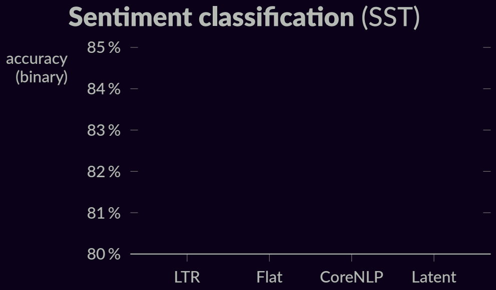


Flat: bag-of-words–like



CoreNLP: off-line parser


85 %
84 %
83 %
82 %
81 %
80 %
LTR
Flat
CoreNLP
Latent


Sentiment classification (SST)
accuracy
(binary)
85 %
84 %
83 %
82 %
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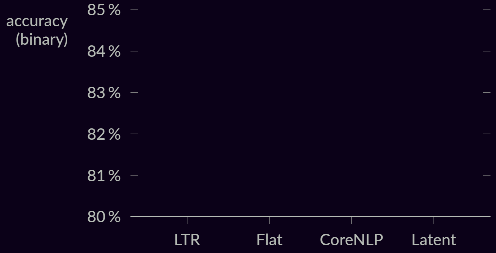
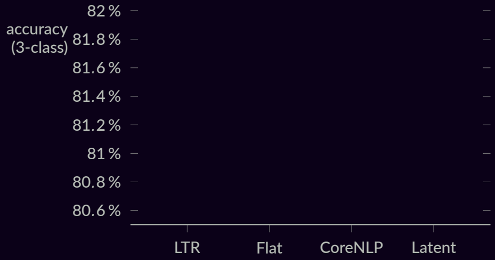


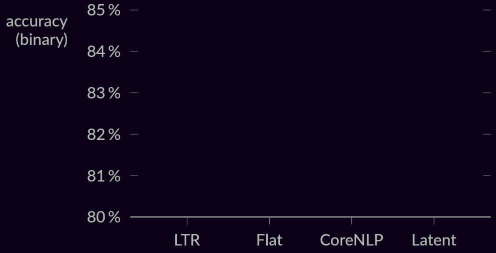
Natural Language Inference (SNLI)



Sentence pair classification (P, H)

$$p(y \mid P, H) = \sum_{h_P \in \mathcal{H}(P)} \sum_{h_H \in \mathcal{H}(H)} p_{\boldsymbol{\phi}}(y \mid h_P, h_H)\, p_{\boldsymbol{\pi}}(h_P \mid P)\, p_{\boldsymbol{\pi}}(h_H \mid H)$$

Sentiment classification (SST)



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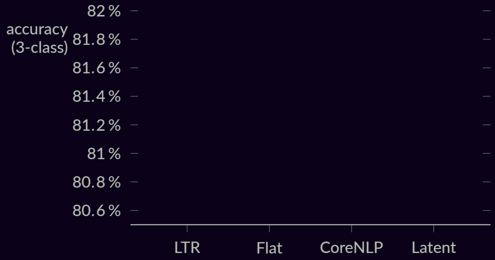
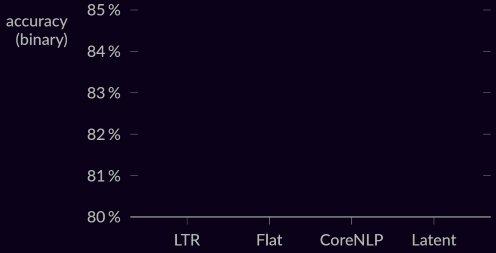


Reverse dictionary lookup

given word description, predict word embedding (Hill et al, 17)

instead of $p(y \mid x)$, we model $\mathbb{E}_{p_{\boldsymbol{\pi}}} \boldsymbol{g}(x) = \sum_{h \in \mathcal{H}} \boldsymbol{g}(x; h)\, p_{\boldsymbol{\pi}}(h \mid x)$

Sentiment classification (SST)



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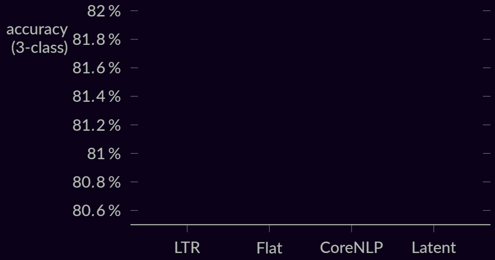
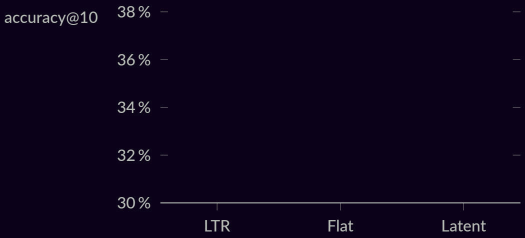
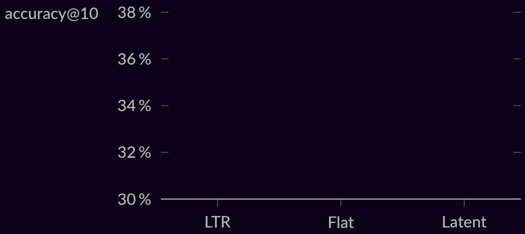


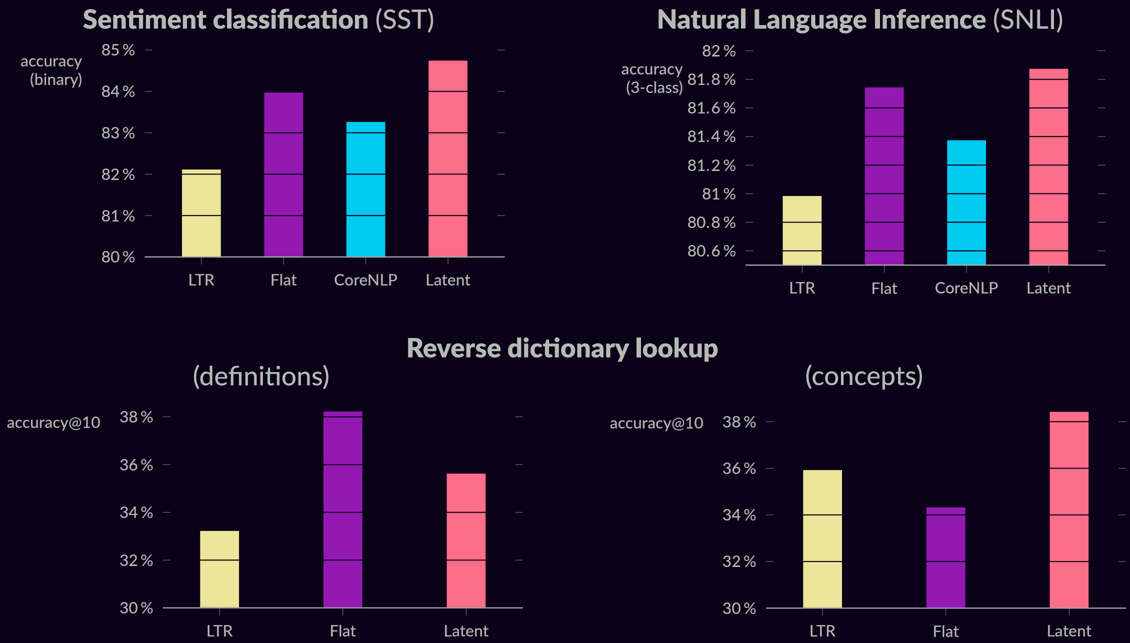
Reverse dictionary lookup

(definitions)



(concepts)




Sentiment classification (SST)
accuracy (binary)
85 %
84 %
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81 %
80 %
LTR
Flat
CoreNLP
Latent
Natural Language Inference (SNLI)
accuracy (3-class)
82 %
81.8 %
81.6 %
81.4 %
81.2 %
81 %
80.8 %
80.6 %
LTR
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CoreNLP
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Reverse dictionary lookup
(definitions)
accuracy@10
38 %
36 %
34 %
32 %
30 %
LTR
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Latent
(concepts)
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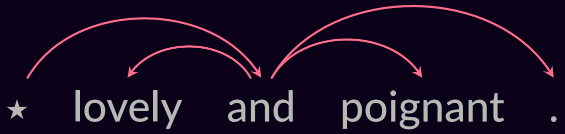
Syntax vs. Composition Order

CoreNLP parse, $p = 21.4\%$

★ lovely and poignant .

Syntax vs. Composition Order

$p = 22.6\%$



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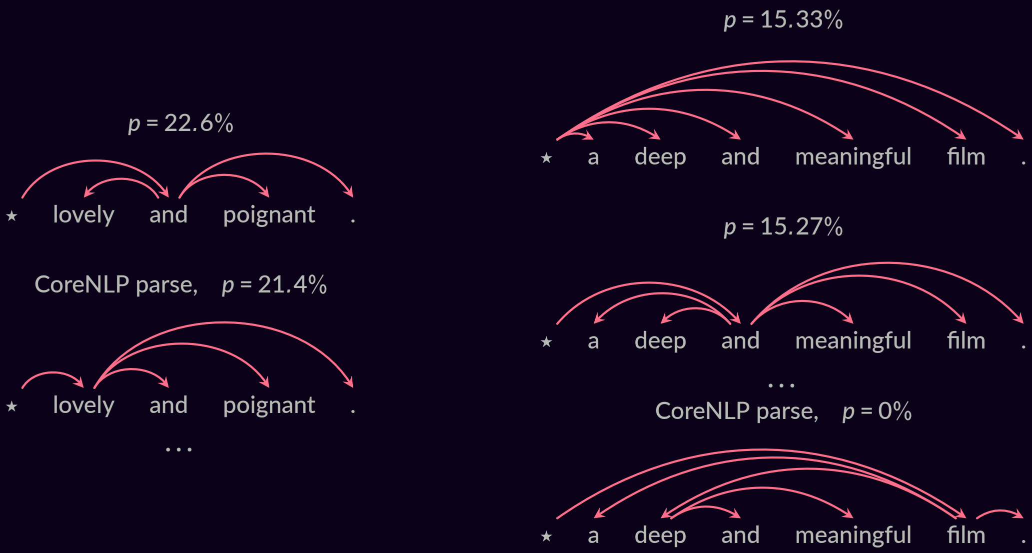
. . .

Syntax vs. Composition Order

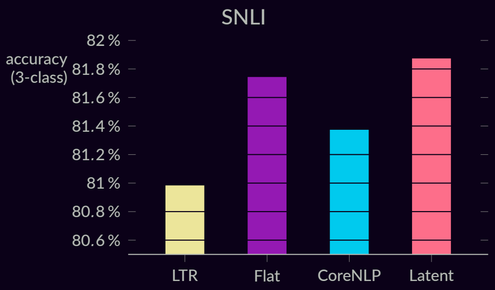


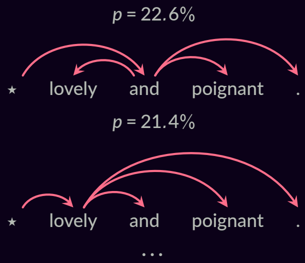
Conclusions

Latent structured variables for uncertainty & compositionality

Tractable marginalization via SparseMAP inference

Flexible model: arbitrary function of discrete latent structures





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