

Natural Language Processing with Deep Learning

CS224N/Ling284



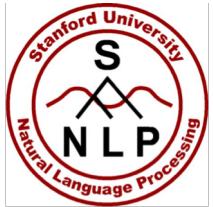
Christopher Manning

Lecture 18: Tree Recursive Neural Networks,
Constituency Parsing, and Sentiment

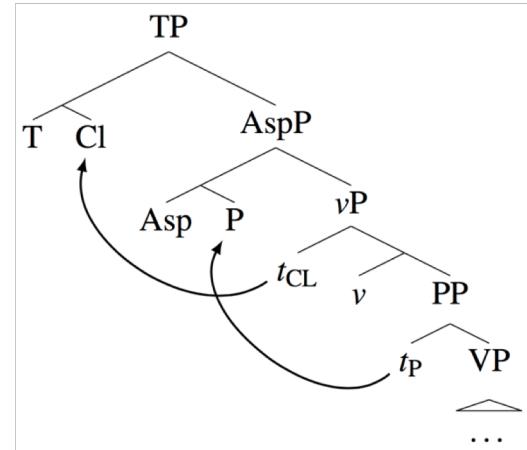
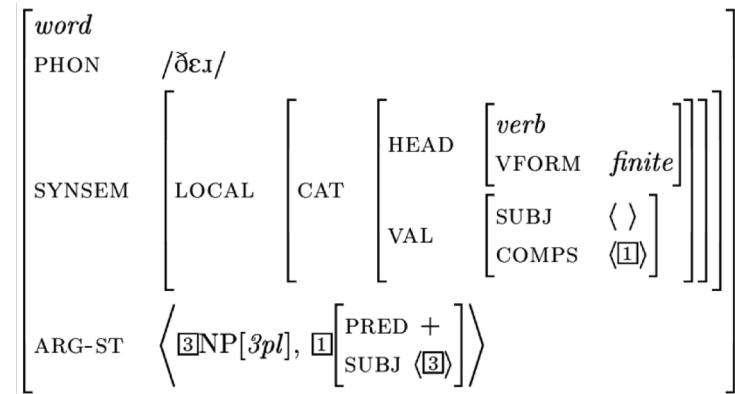
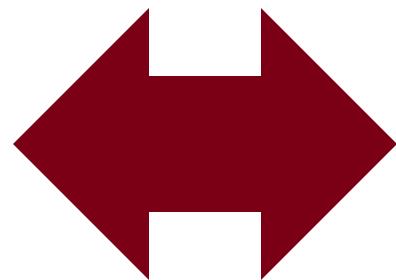
Lecture Plan:

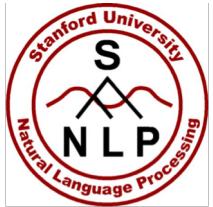
Lecture 18: Tree Recursive Neural Networks, Constituency Parsing, and Sentiment

1. Motivation: Compositionality and Recursion (10 mins)
2. Structure prediction with simple Tree RNN: Parsing (20 mins)
3. Backpropagation through Structure (5 mins)
4. More complex TreeRNN units (35 mins)
5. Other uses of tree-recursive neural nets (5 mins)
6. Institute for Human-Centered Artificial Intelligence (5 mins)



1. The spectrum of language in CS





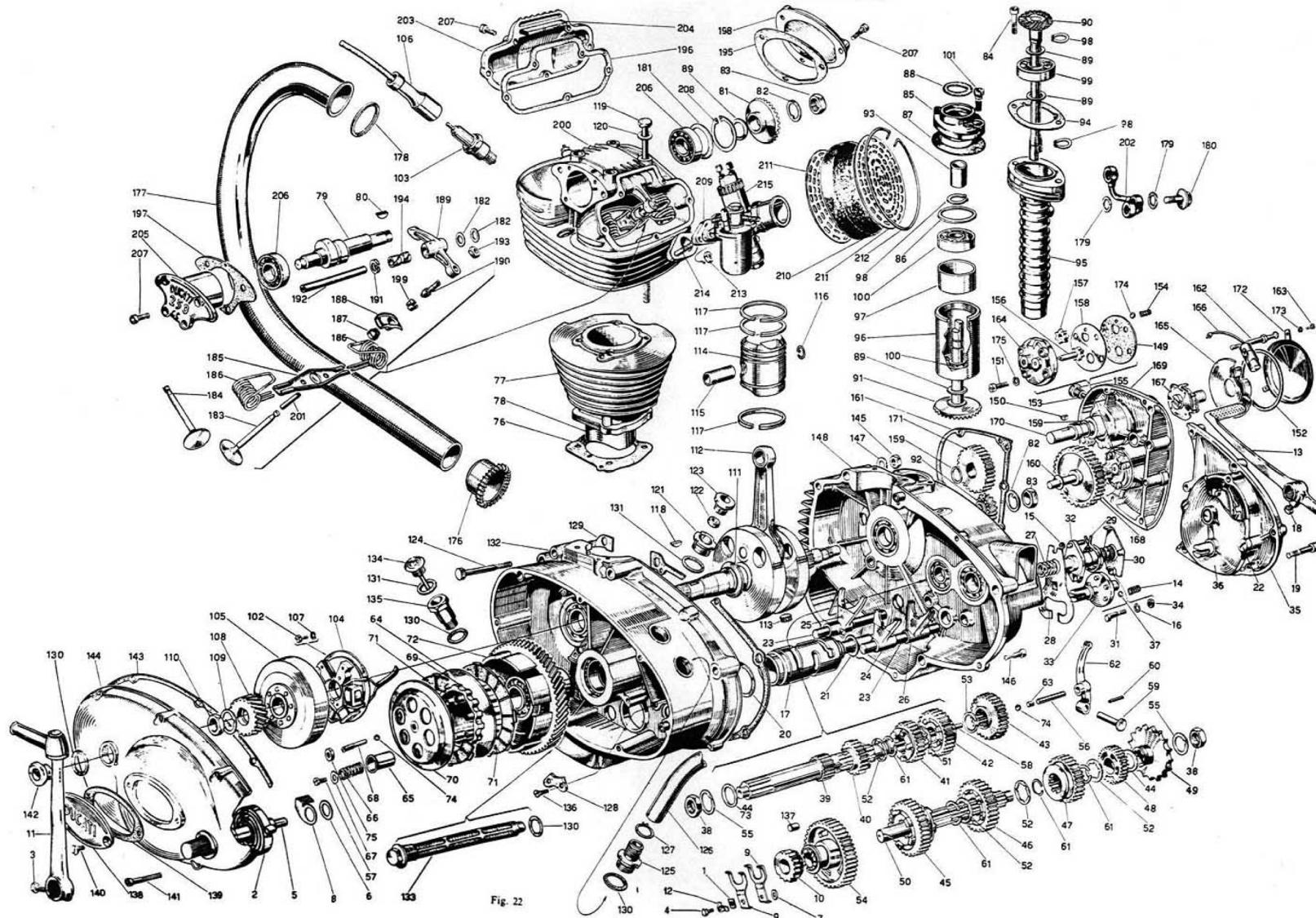
Semantic interpretation of language – Not just word vectors

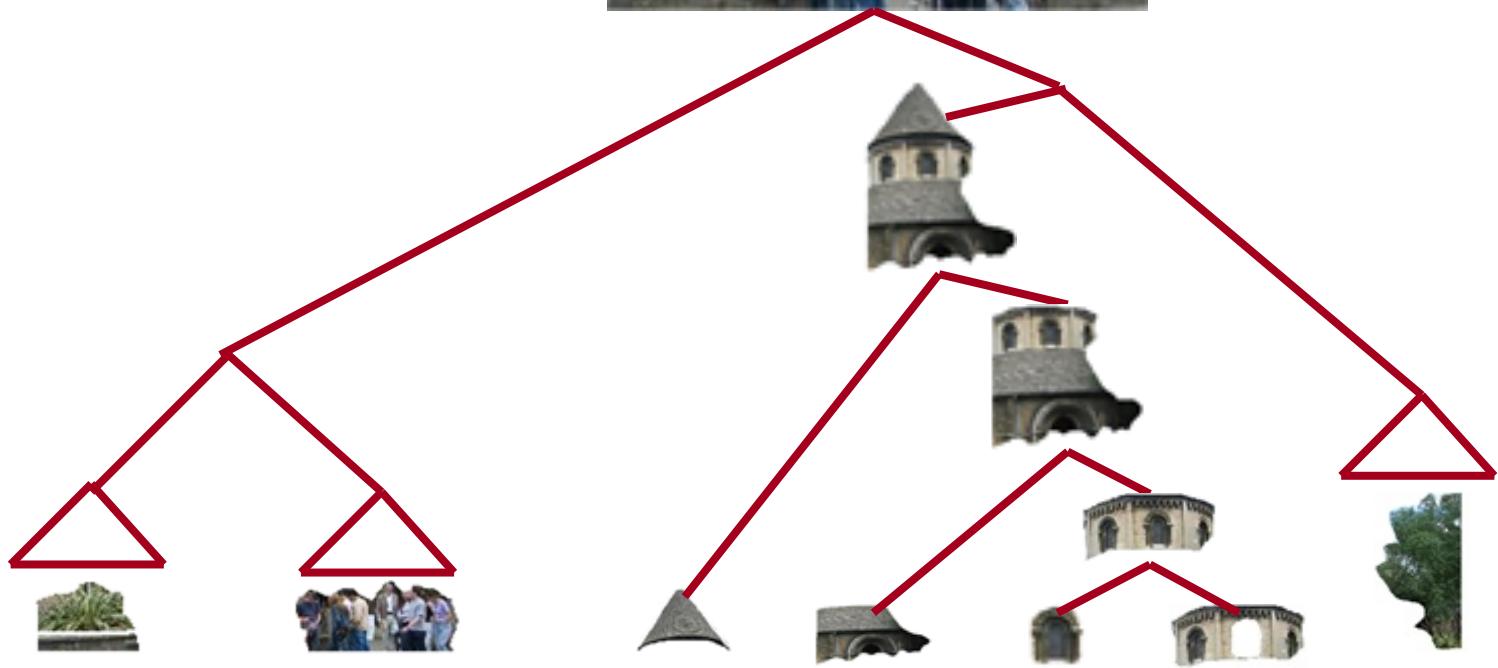
How can we work out the meaning of larger phrases?

- *The snowboarder is leaping over a mogul*
- *A person on a snowboard jumps into the air*

People interpret the meaning of larger text units – entities, descriptive terms, facts, arguments, stories – by **semantic composition** of smaller elements

Compositionality







Language understanding -
\$ Artificial Intelligence - requires
being able to understand bigger
things from knowing about smaller
parts



The Faculty of Language: What Is It, Who Has It, and How Did It Evolve?

Marc D. Hauser,^{1*} Noam Chomsky,² W. Tecumseh Fitch¹

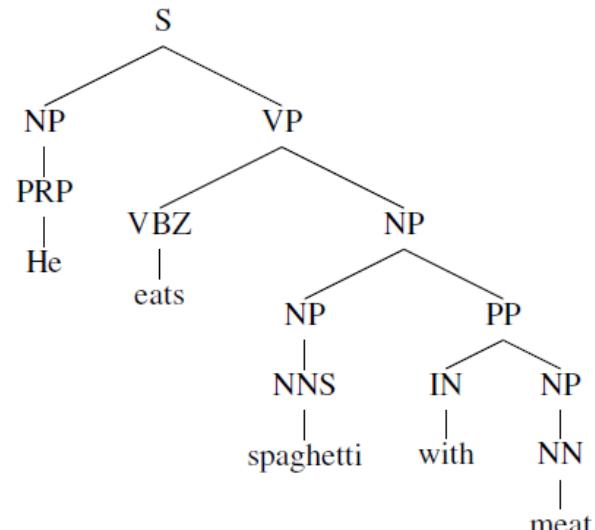
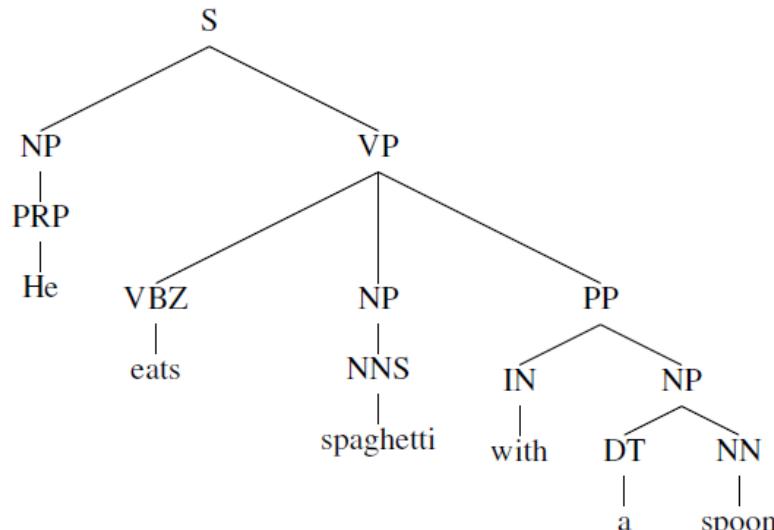
We argue that an understanding of the faculty of language requires substantial interdisciplinary cooperation. We suggest how current developments in linguistics can be profitably wedded to work in evolutionary biology, anthropology, psychology, and neuroscience. We submit that a distinction should be made between the faculty of language in the broad sense (FLB) and in the narrow sense (FLN). FLB includes a sensory-motor system, a conceptual-intentional system, and the computational mechanisms for recursion, providing the capacity to generate an infinite range of expressions from a finite set of elements. We hypothesize that FLN only includes recursion and is the only uniquely human component of the faculty of language. We further argue that FLN may have evolved for reasons other than language, hence comparative studies might look for evidence of such computations outside of the domain of communication (for example, number, navigation, and social relations).

If a martian graced our planet, it would be struck by one remarkable similarity among Earth's living creatures and a key difference. Concerning similarity, it would note that all

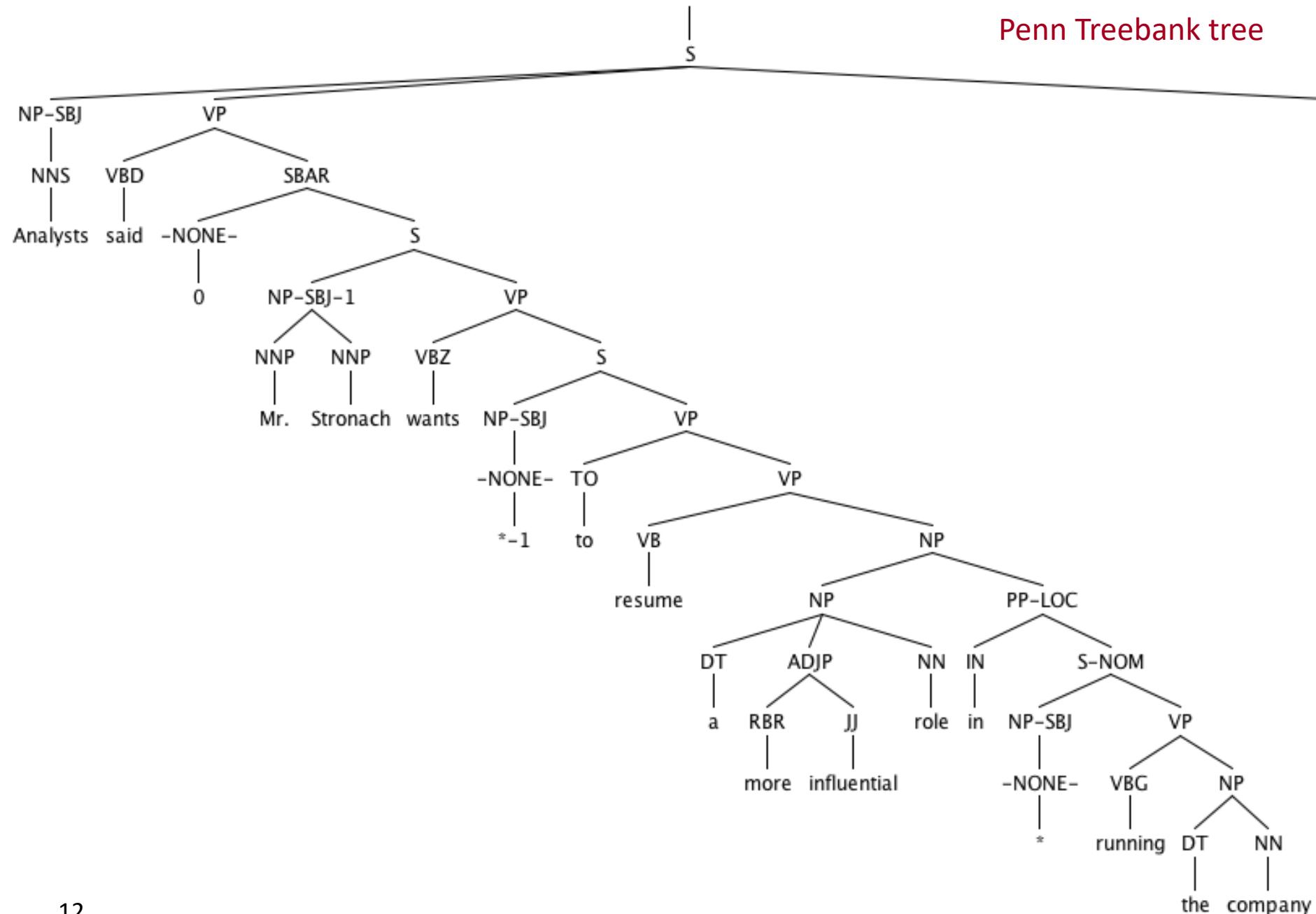


Are languages recursive?

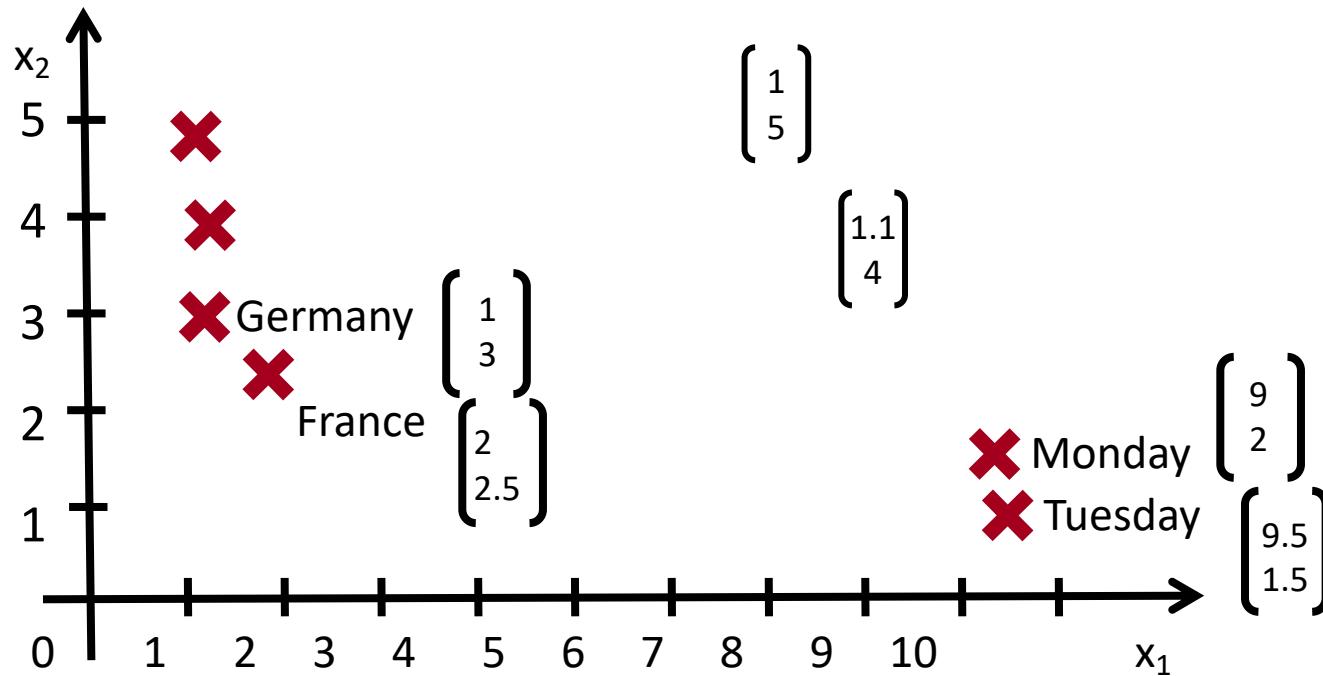
- Cognitively somewhat debatable (need to head to infinity)
- But: recursion is natural for describing language
 - *[The person standing next to [the man from [the company that purchased [the firm that you used to work at]]]]*
 - noun phrase containing a noun phrase containing a noun phrase
- It's a very powerful prior for language structure



Penn Treebank tree



2. Building on Word Vector Space Models



the country of my birth
the place where I was born

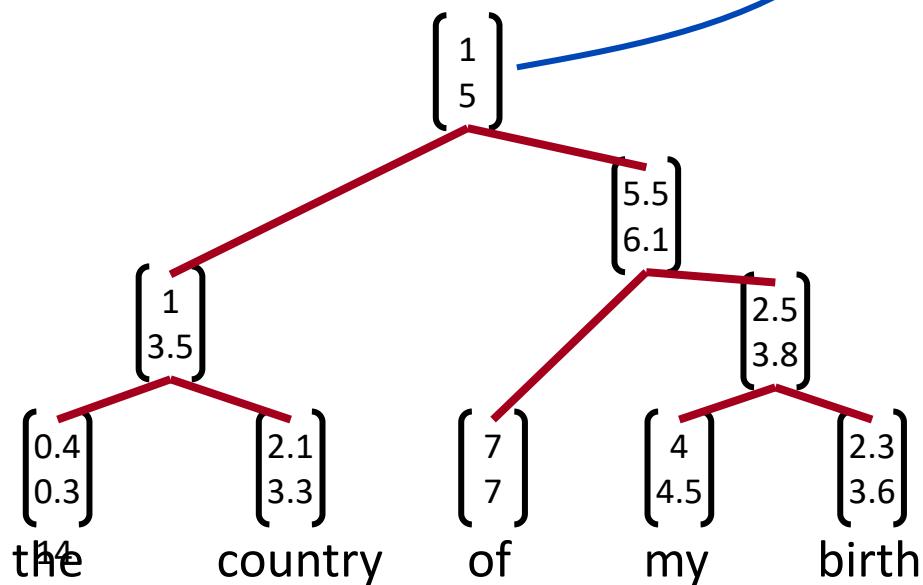
How can we represent the meaning of longer phrases?
By mapping them into the same vector space!

How should we map phrases into a vector space?

Use principle of compositionality

The meaning (vector) of a sentence is determined by

- (1) the meanings of its words and
- (2) the rules that combine them.

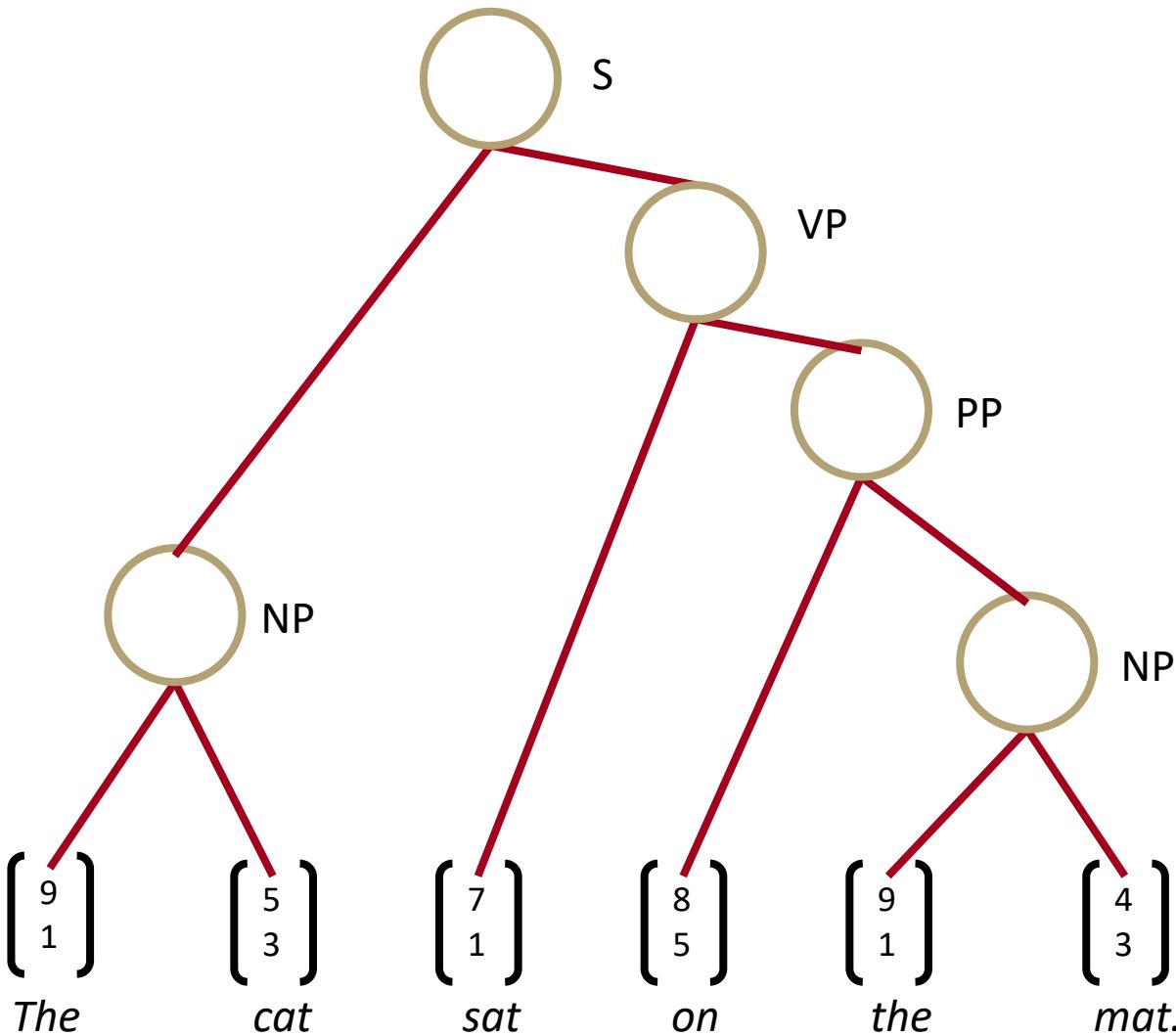


Socher, Manning, and Ng. ICML, 2011

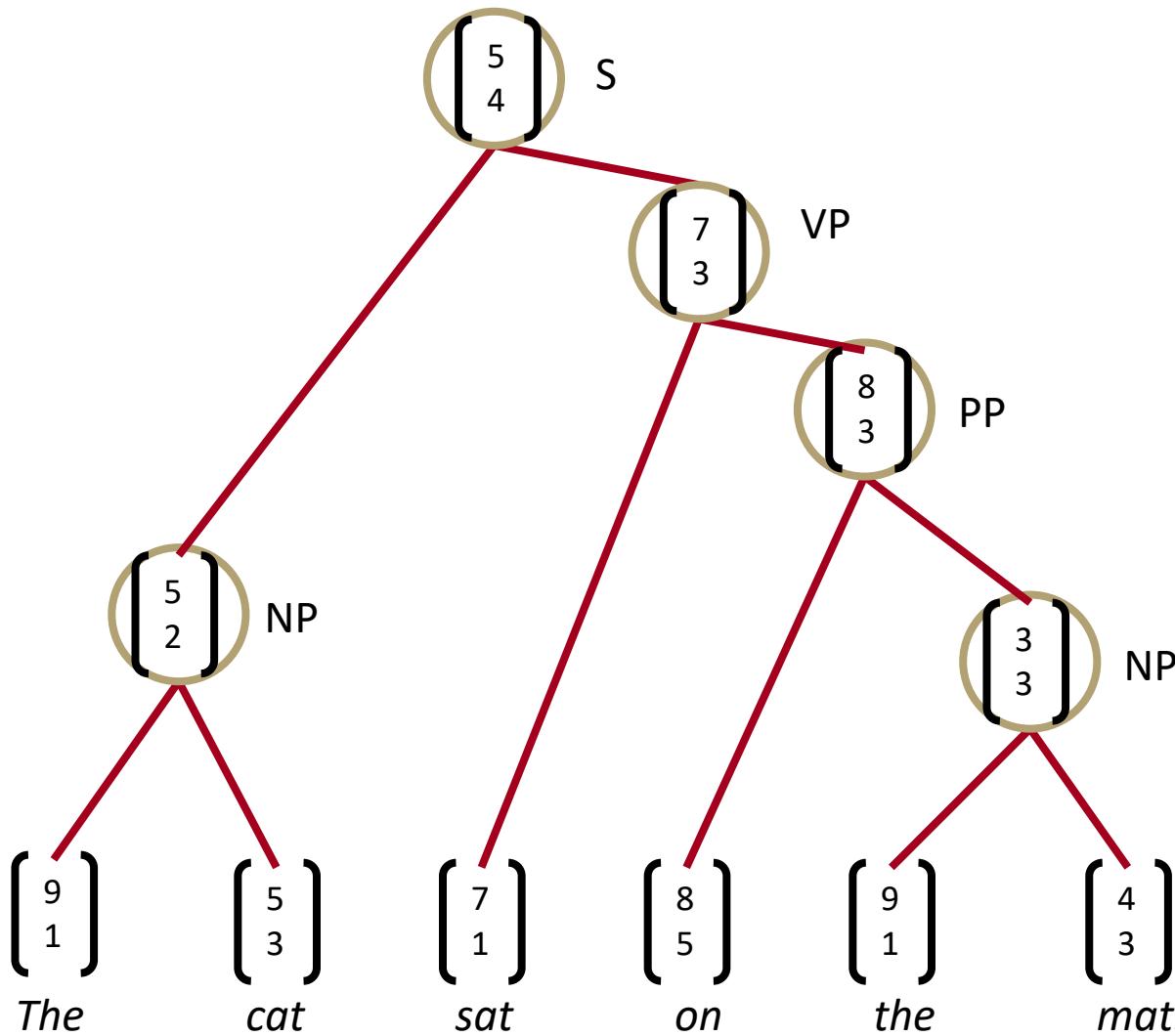


Models in this section can jointly learn parse trees and compositional vector representations

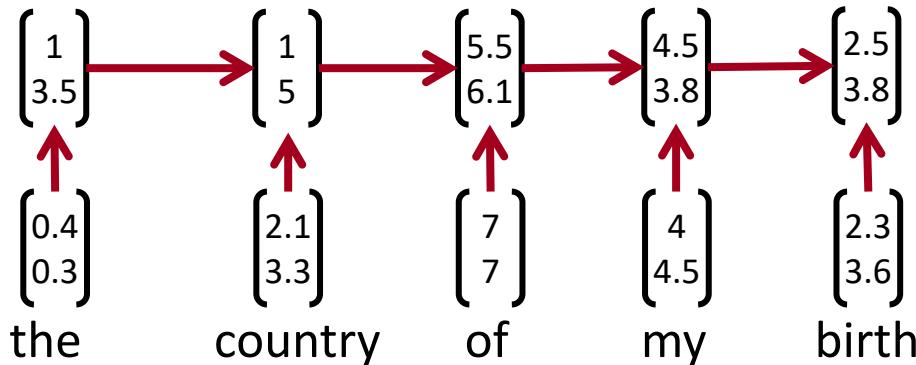
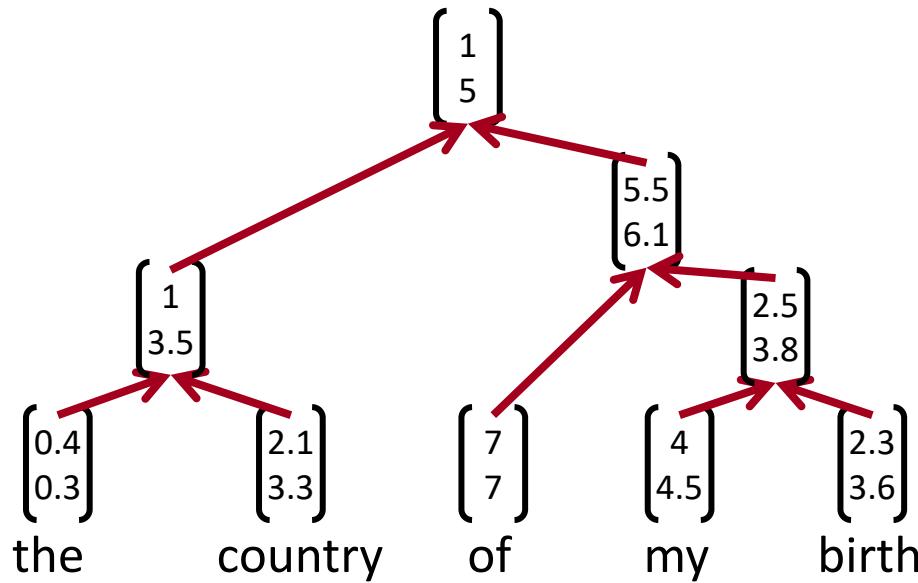
Constituency Sentence Parsing: What we want



Learn Structure and Representation

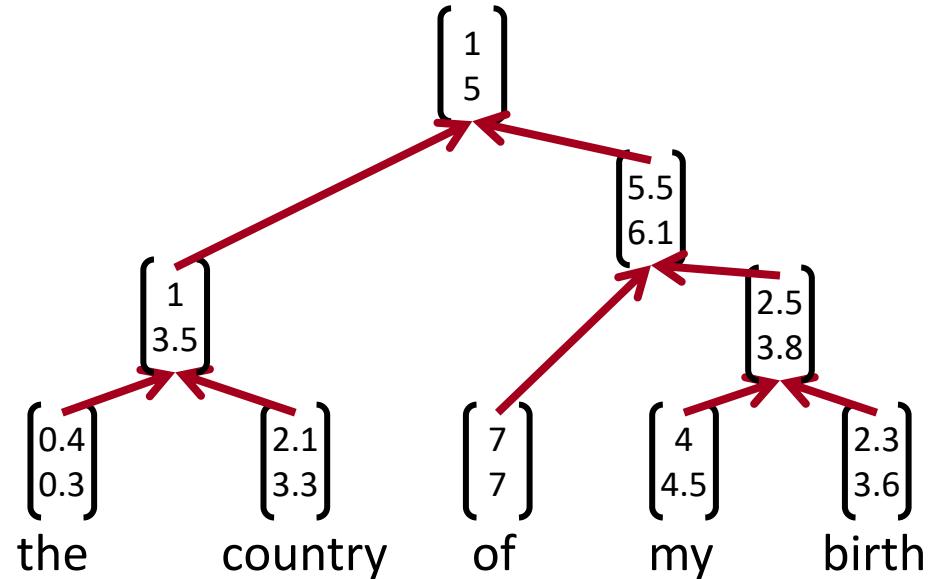


Recursive vs. recurrent neural networks

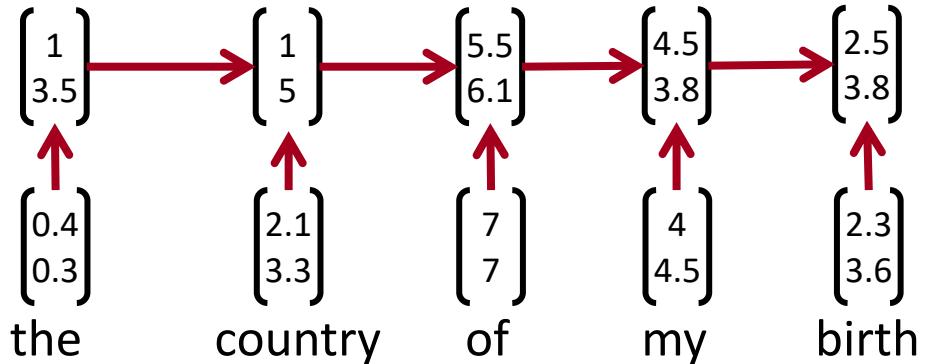


Recursive vs. recurrent neural networks

- Recursive neural nets require a tree structure



- Recurrent neural nets cannot capture phrases without prefix context and often capture too much of last words in final vector

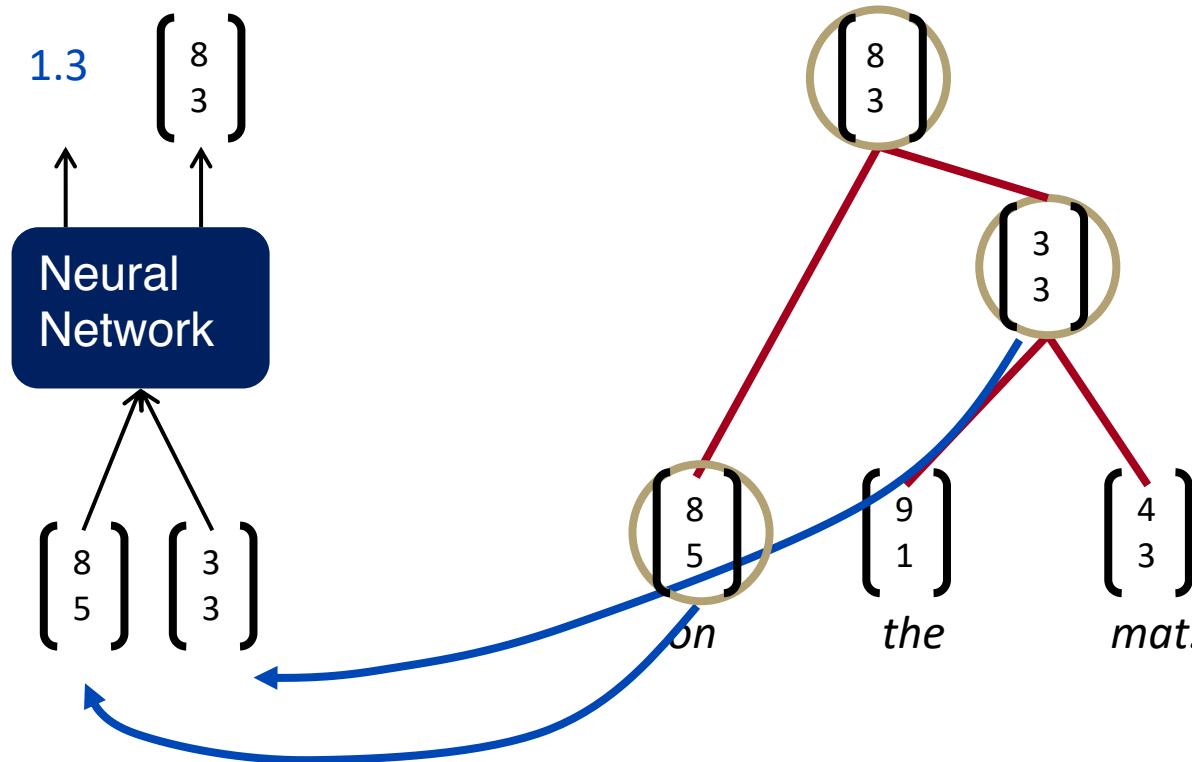


Recursive Neural Networks for Structure Prediction

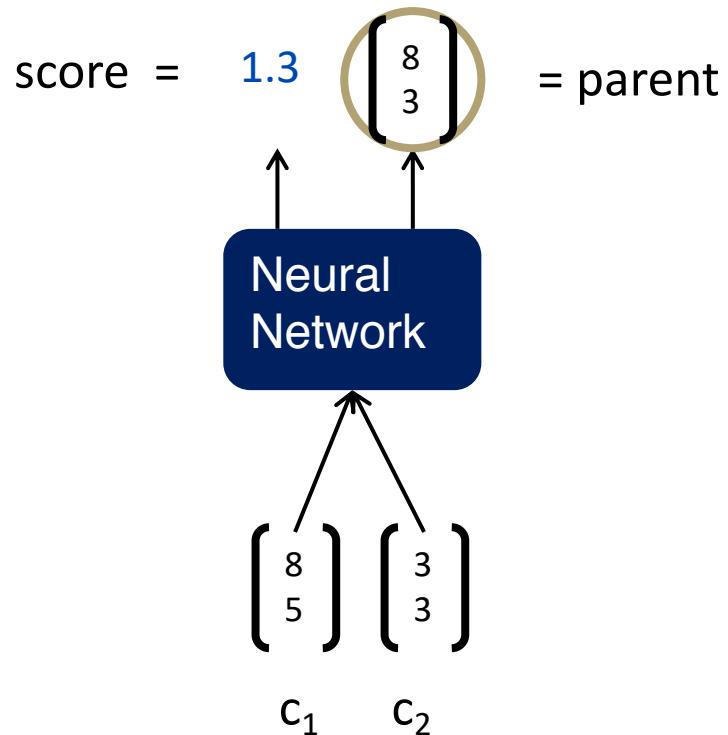
Inputs: two candidate children's representations

Outputs:

1. The semantic representation if the two nodes are merged.
2. Score of how plausible the new node would be.

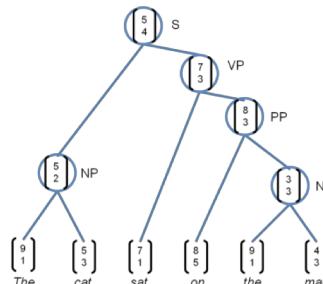


Recursive Neural Network Definition

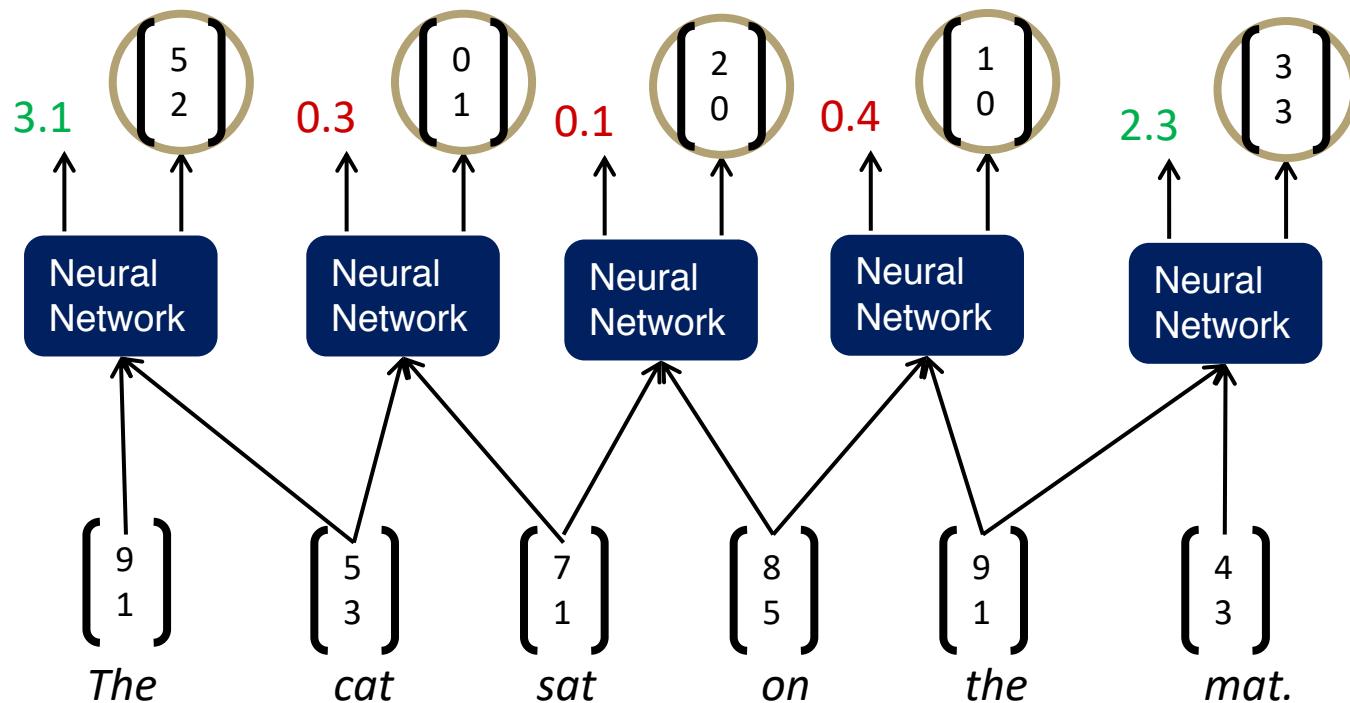


$$\left. \begin{aligned} \text{score} &= U^T p \\ p &= \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right), \end{aligned} \right\}$$

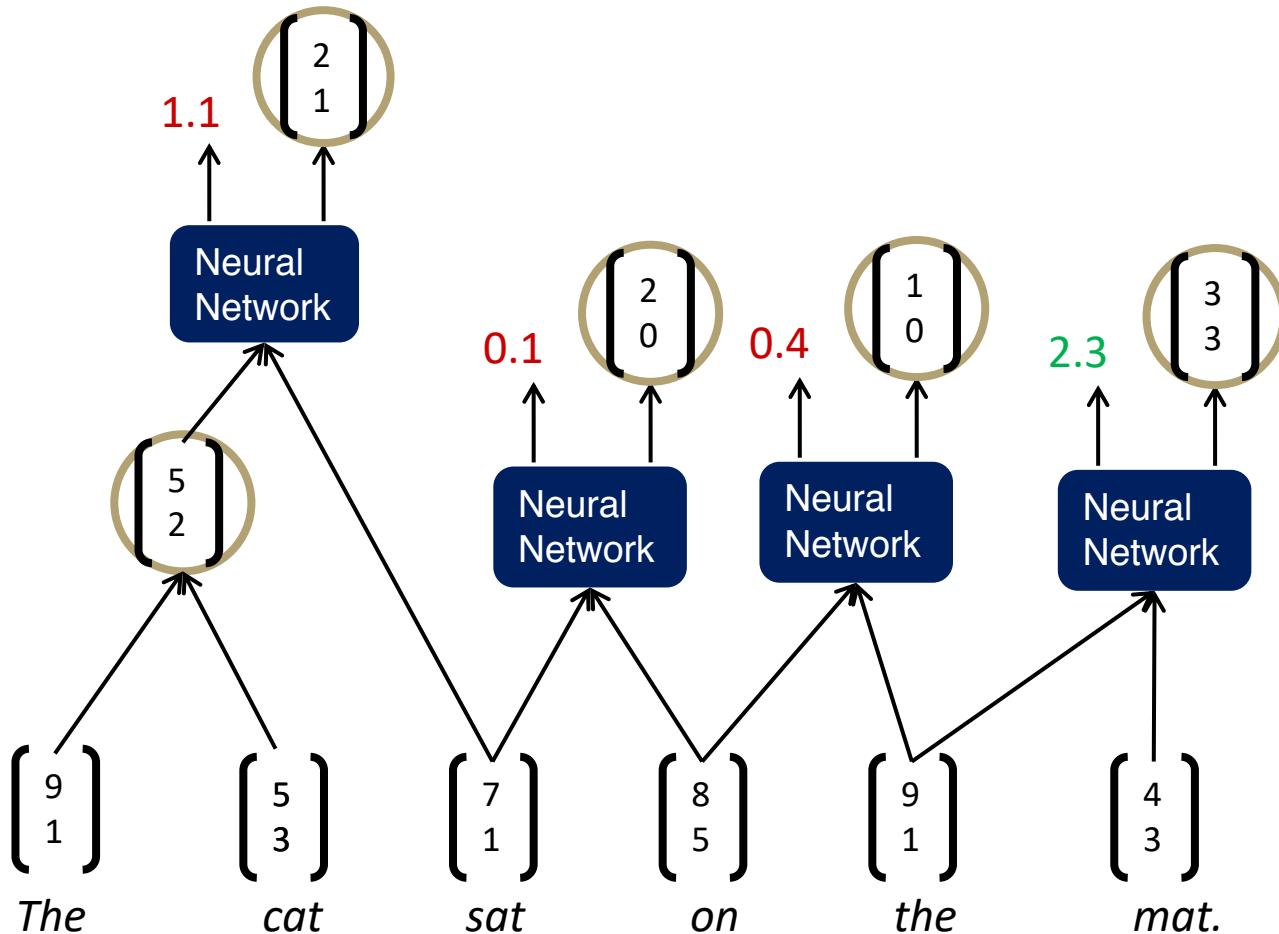
Same W parameters at all nodes of the tree



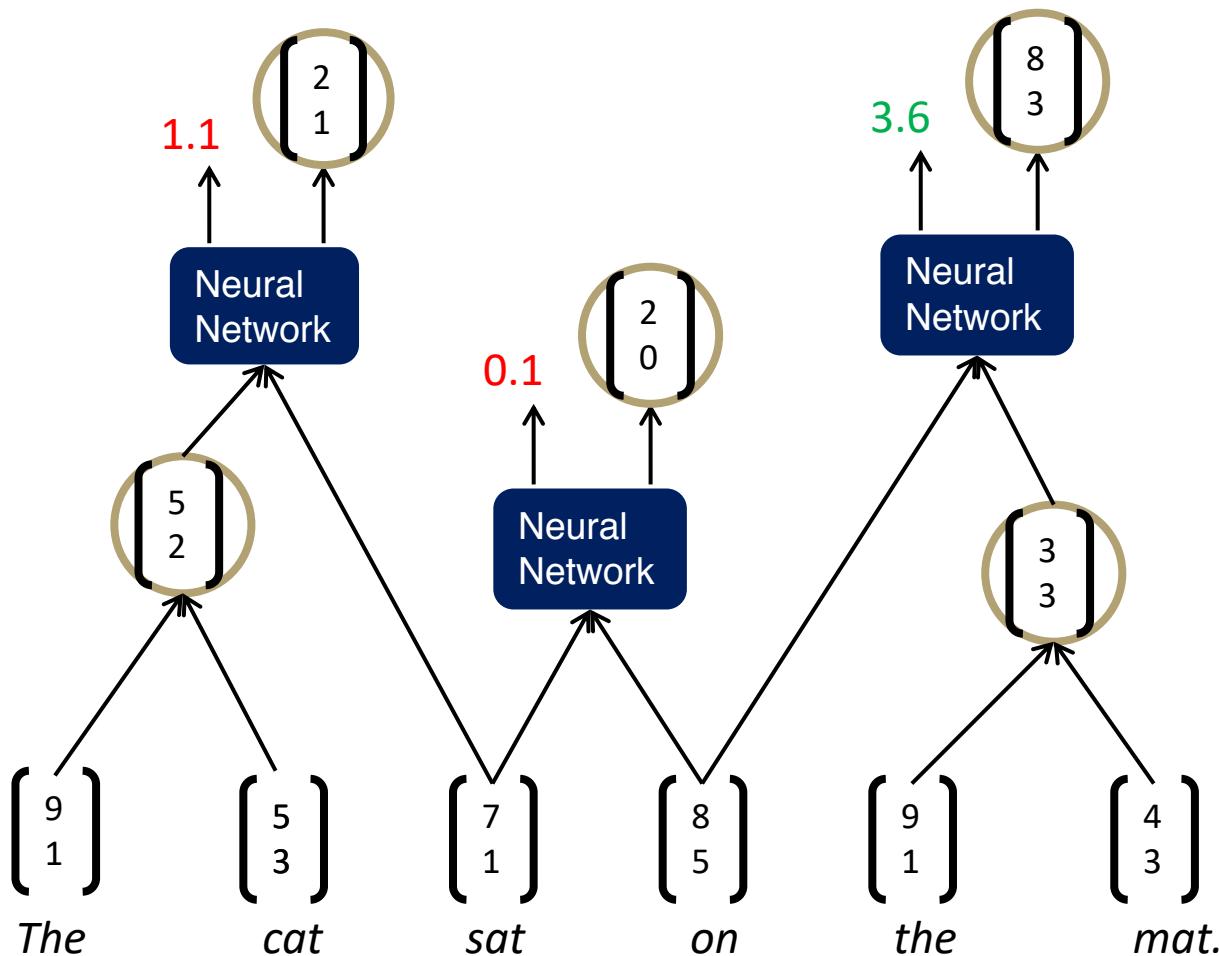
Parsing a sentence with an RNN (greedily)



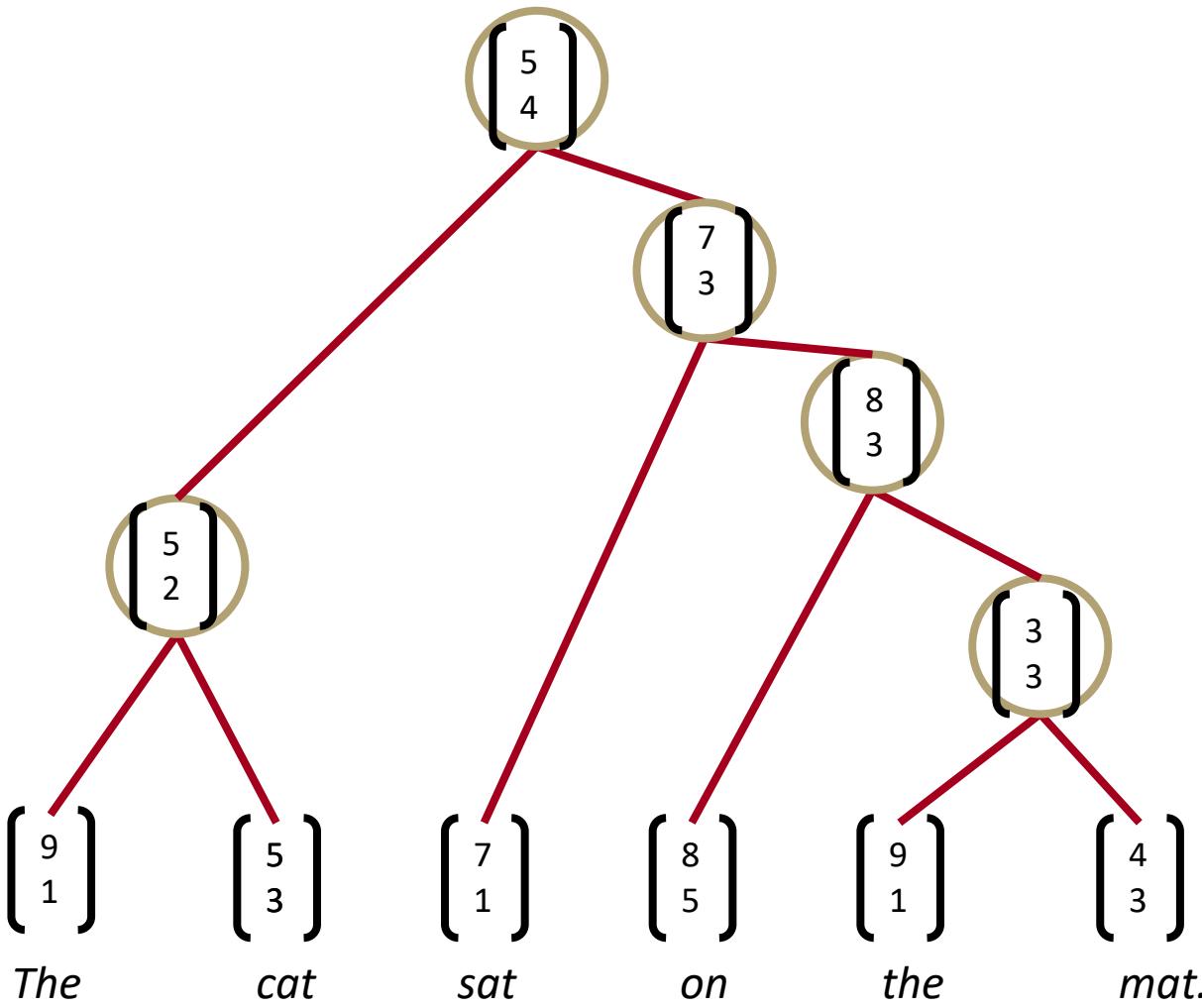
Parsing a sentence



Parsing a sentence



Parsing a sentence



Max-Margin Framework - Details

- The score of a tree is computed by the sum of the parsing decision scores at each node:

$$s(x, y) = \sum_{n \in \text{nodes}(y)} s_n$$



- x is sentence; y is parse tree

Max-Margin Framework - Details

- Similar to max-margin parsing (Taskar et al. 2004), a supervised max-margin objective

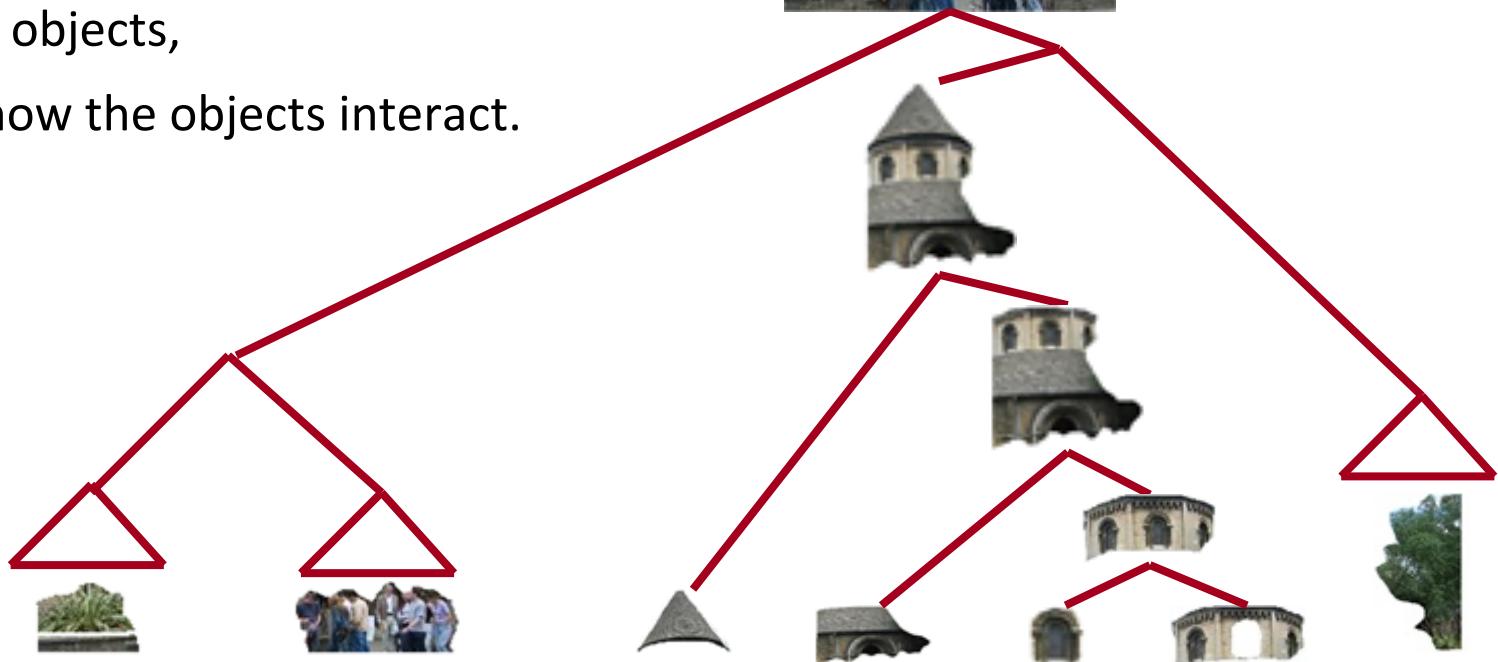
$$J = \sum_i s(x_i, y_i) - \max_{y \in A(x_i)} (s(x_i, y) + \Delta(y, y_i))$$

- The loss $\Delta(y, y_i)$ penalizes all incorrect decisions
- Structure search for $A(x)$ was greedy (join best nodes each time)
 - Instead: Beam search with chart

Scene Parsing

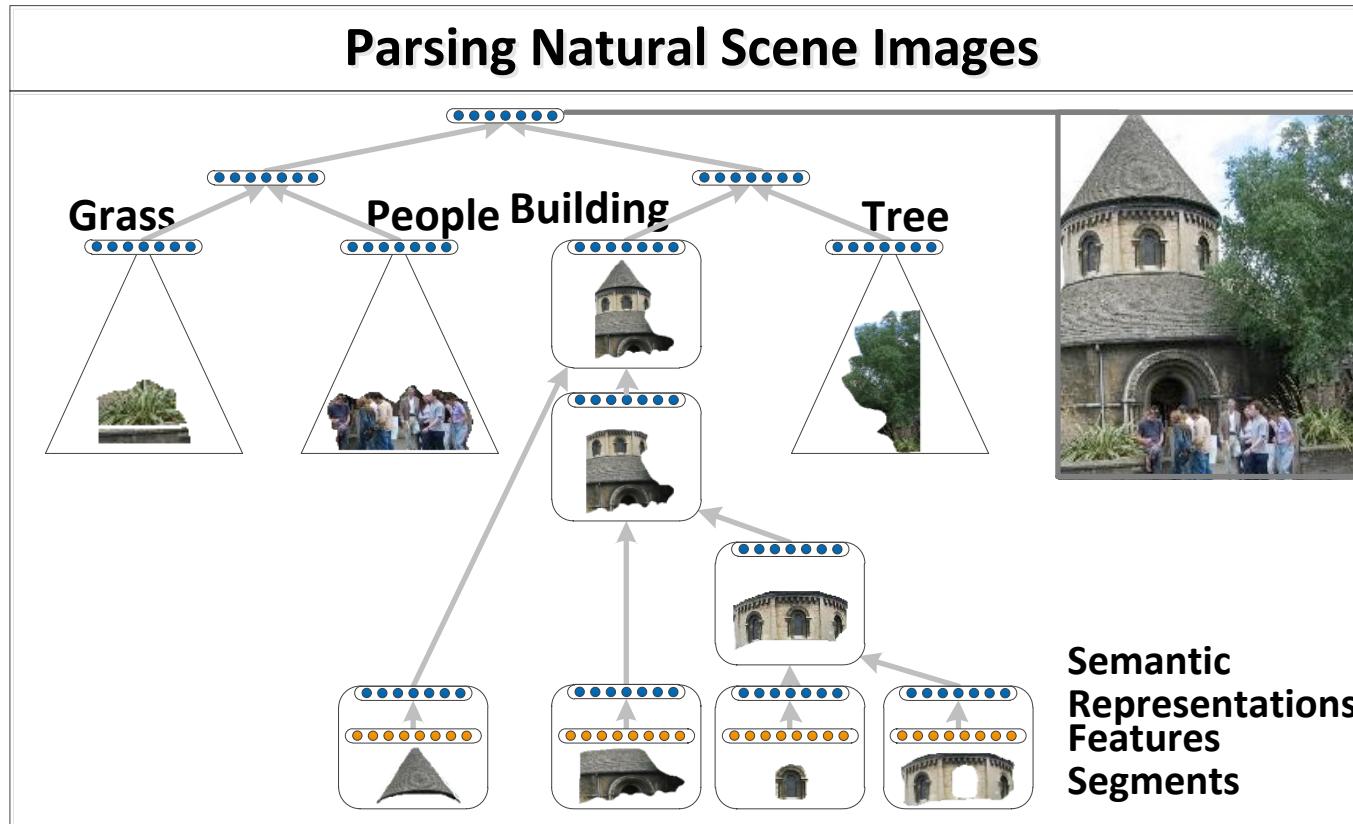
Similar principle of compositionality.

- The meaning of a scene image is also a function of smaller regions,
- how they combine as parts to form larger objects,
- and how the objects interact.



Algorithm for Parsing Images

Same Recursive Neural Network as for natural language parsing!
(Socher et al. ICML 2011)



Multi-class segmentation



sky tree road grass water bldg mtn fg obj.

Method	Accuracy
Pixel CRF (Gould et al., ICCV 2009)	74.3
Classifier on superpixel features	75.9
Region-based energy (Gould et al., ICCV 2009)	76.4
Local labelling (Tighe & Lazebnik, ECCV 2010)	76.9
Superpixel MRF (Tighe & Lazebnik, ECCV 2010)	77.5
Simultaneous MRF (Tighe & Lazebnik, ECCV 2010)	77.5
Recursive Neural Network	78.1

3. Backpropagation Through Structure

Introduced by Goller & Küchler (1996)

Principally the same as general backpropagation

$$\delta^{(l)} = \left((W^{(l)})^T \delta^{(l+1)} \right) \circ f'(z^{(l)}),$$

$$\frac{\partial}{\partial W^{(l)}} E_R = \delta^{(l+1)} (a^{(l)})^T + \lambda W^{(l)}$$

Calculations resulting from the recursion and tree structure:

1. Sum derivatives of W from all nodes (like RNN)
2. Split derivatives at each node (for tree)
3. Add error messages from parent + node itself

BTS: 1) Sum derivatives of all nodes

You can actually assume it's a different W at each node

Intuition via example:

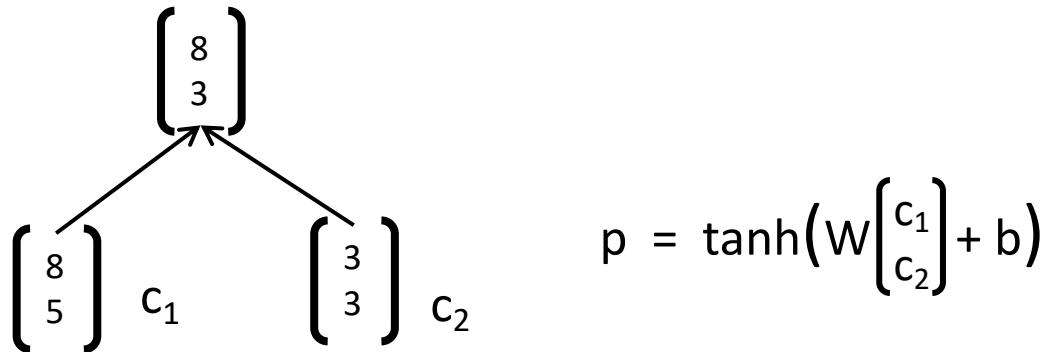
$$\begin{aligned} & \frac{\partial}{\partial W} f(W(f(Wx))) \\ = & f'(W(f(Wx))) \left(\left(\frac{\partial}{\partial W} W \right) f(Wx) + W \frac{\partial}{\partial W} f(Wx) \right) \\ = & f'(W(f(Wx))) (f(Wx) + W f'(Wx)x) \end{aligned}$$

If we take separate derivatives of each occurrence, we get same:

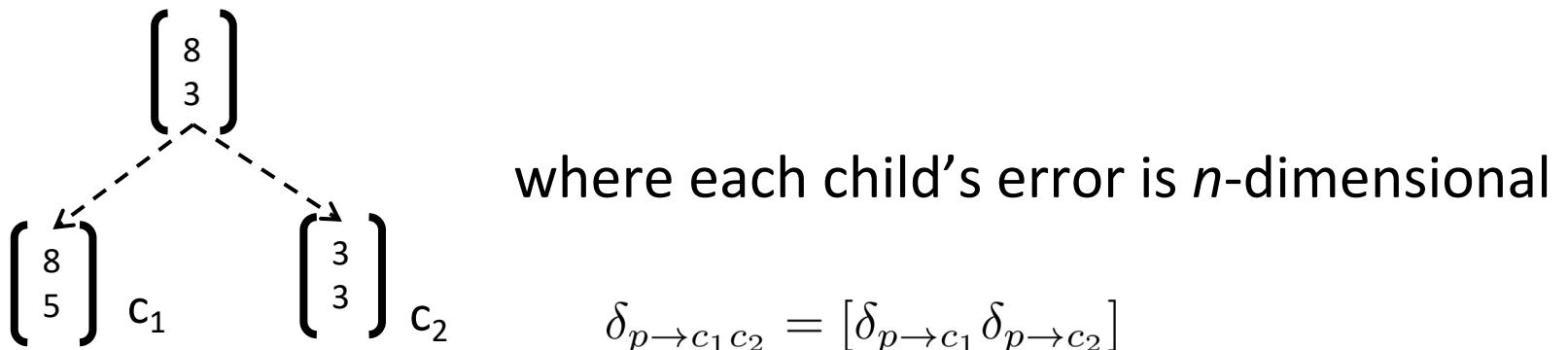
$$\begin{aligned} & \frac{\partial}{\partial W_2} f(W_2(f(W_1x))) + \frac{\partial}{\partial W_1} f(W_2(f(W_1x))) \\ = & f'(W_2(f(W_1x))) (f(W_1x)) + f'(W_2(f(W_1x))) (W_2 f'(W_1x)x) \\ = & f'(W_2(f(W_1x))) (f(W_1x) + W_2 f'(W_1x)x) \\ = & f'(W(f(Wx))) (f(Wx) + W f'(Wx)x) \end{aligned}$$

BTS: 2) Split derivatives at each node

During forward prop, the parent is computed using 2 children

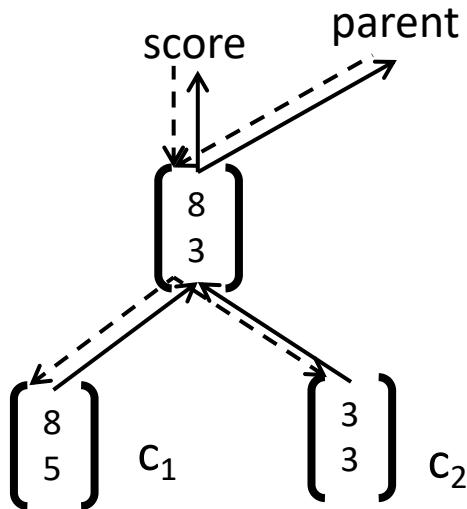


Hence, the errors need to be computed wrt each of them:



BTS: 3) Add error messages

- At each node:
 - What came up (fprop) must come down (bprop)
 - Total error messages = error messages from parent + error message from own score



BTS Python Code: forwardProp

```
def forwardProp(self,node):
    # Recursion
    ...

    # This node's hidden activation
    node.h = np.dot(self.W,np.hstack([node.left.h, node.right.h])) + self.b
    # Relu
    node.h[node.h<0] = 0

    # Softmax
    node.probs = np.dot(self.Ws,node.h) + self.bs
    node.probs -= np.max(node.probs)
    node.probs = np.exp(node.probs)
    node.probs = node.probs/np.sum(node.probs)
```

BTS Python Code: backProp

```
def backProp(self, node, error=None):
    # Softmax grad
    deltas = node.probs
    deltas[node.label] -= 1.0
    self.dWs += np.outer(deltas, node.h)
    self.dbs += deltas
    deltas = np.dot(self.Ws.T, deltas)

    # Add deltas from above
    if error is not None:
        deltas += error

    # f'(z) now:
    deltas *= (node.h != 0)

    # Update word vectors if leaf node:
    if node.isLeaf:
        self.dL[node.word] += deltas
        return

    # Recursively backprop
    if not node.isLeaf:
        self.dW += np.outer(deltas, np.hstack([node.left.h, node.right.h]))
        self.db += deltas
        # Error signal to children
        deltas = np.dot(self.W.T, deltas)
        self.backProp(node.left, deltas[:self.hiddenDim])
        self.backProp(node.right, deltas[self.hiddenDim:]))

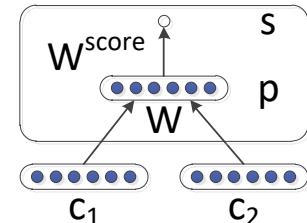

```

$$\delta^{(l)} = \left((W^{(l)})^T \delta^{(l+1)} \right) \circ f'(z^{(l)}),$$

$$\frac{\partial}{\partial W^{(l)}} E_R = \delta^{(l+1)} (a^{(l)})^T + \lambda W^{(l)}$$

Discussion: Simple TreeRNN

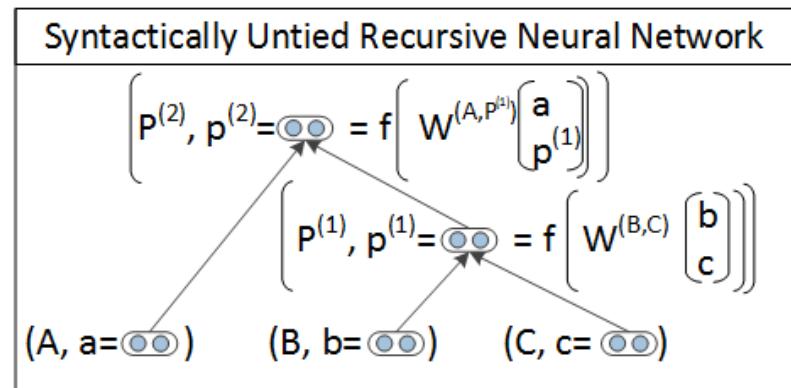
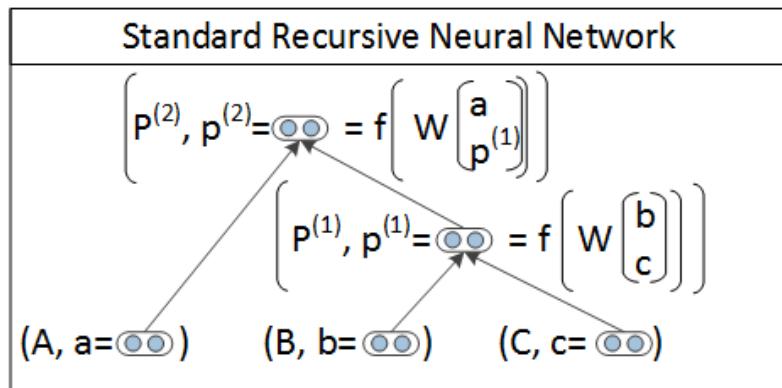
- Decent results with single matrix TreeRNN
- Single weight matrix TreeRNN could capture some phenomena but not adequate for more complex, higher order composition and parsing long sentences
- There is no real interaction between the input words
- The composition function is the same for all syntactic categories, punctuation, etc.



4. Version 2: Syntactically-Untied RNN

[Socher, Bauer, Manning, Ng 2013]

- A symbolic Context-Free Grammar (CFG) backbone is adequate for basic syntactic structure
- We use the discrete syntactic categories of the children to choose the composition matrix
- A TreeRNN can do better with different composition matrix for different syntactic environments
- The result gives us a better semantics



Compositional Vector Grammars

- Problem: Speed. Every candidate score in beam search needs a matrix-vector product.
- Solution: Compute score only for a subset of trees coming from a simpler, faster model (PCFG)
 - Prunes very unlikely candidates for speed
 - Provides coarse syntactic categories of the children for each beam candidate
- Compositional Vector Grammar = PCFG + TreeRNN

Related Work for parsing

- Resulting CVG Parser is related to previous work that extends PCFG parsers
- Klein and Manning (2003a) : manual feature engineering
- Petrov et al. (2006) : learning algorithm that splits and merges syntactic categories
- Lexicalized parsers (Collins, 2003; Charniak, 2000): describe each category with a lexical item
- Hall and Klein (2012) combine several such annotation schemes in a factored parser.
- CVGs extend these ideas from discrete representations to richer continuous ones

Experiments

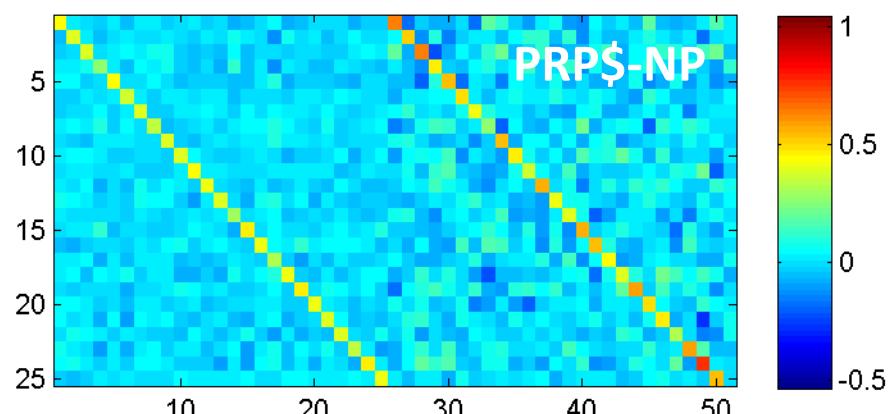
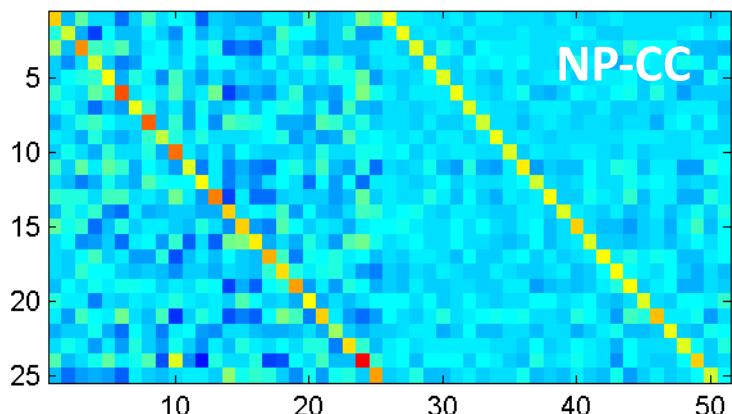
- Standard *WSJ* split, labeled F1
- Based on simple PCFG with fewer states
- Fast pruning of search space, few matrix-vector products
- 3.8% higher F1

Parser	Test, All Sentences
Stanford PCFG, (Klein and Manning, 2003a)	85.5
Stanford Factored (Klein and Manning, 2003b)	86.6
Factored PCFGs (Hall and Klein, 2012)	89.4
Collins (Collins, 1997)	87.7
SSN (Henderson, 2004)	89.4
Berkeley Parser (Petrov and Klein, 2007)	90.1
CVG (RNN) (Socher et al., ACL 2013)	85.0
CVG (SU-RNN) (Socher et al., ACL 2013)	90.4
Charniak - Self Trained (McClosky et al. 2006)	91.0
Charniak - Self Trained-ReRanked (McClosky et al. 2006)	92.1

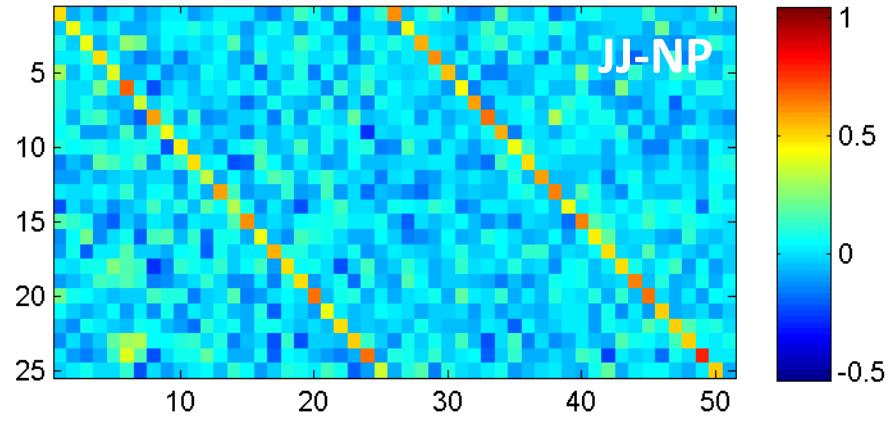
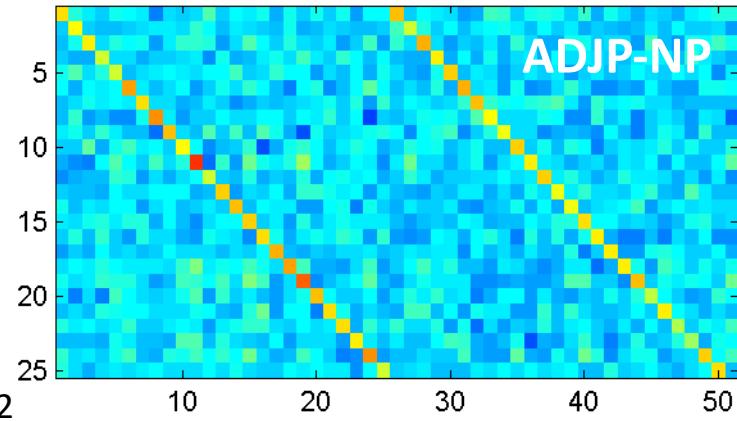
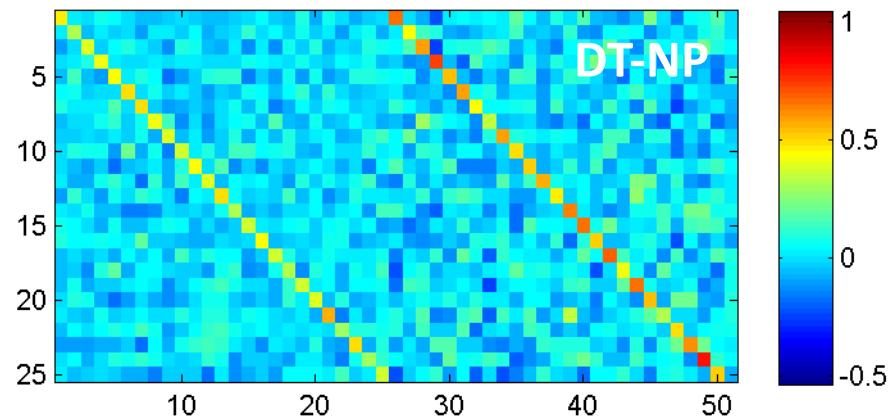
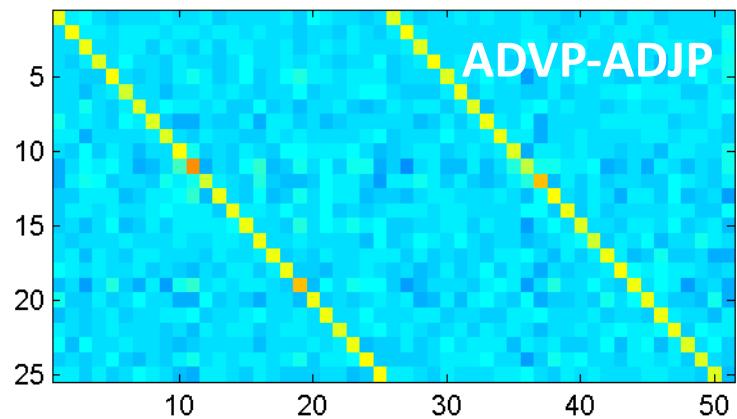
SU-RNN / CVG [Socher, Bauer, Manning, Ng 2013]

Learns soft notion of head words

Initialization: $W^{(\cdot)} = 0.5[I_{n \times n} I_{n \times n} 0_{n \times 1}] + \epsilon$



SU-RNN / CVG [Socher, Bauer, Manning, Ng 2013]



Analysis of resulting vector representations

All the figures are adjusted for seasonal variations

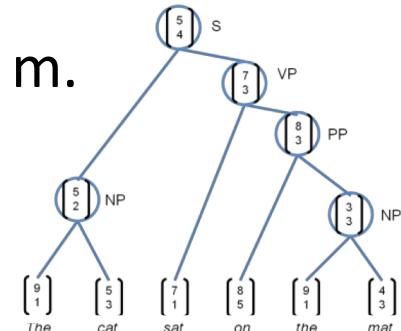
1. All the numbers are adjusted for seasonal fluctuations
2. All the figures are adjusted to remove usual seasonal patterns

Knight-Ridder wouldn't comment on the offer

1. Harsco declined to say what country placed the order
2. Coastal wouldn't disclose the terms

Sales grew almost 7% to \$UNK m. from \$UNK m.

1. Sales rose more than 7% to \$94.9 m. from \$88.3 m.
2. Sales surged 40% to UNK b. yen from UNK b.



Version 3: Compositionality Through Recursive Matrix-Vector Spaces

[Socher, Huval, Bhat, Manning, & Ng, 2012]

Before:

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

One way to make the composition function more powerful was by untying the weights W

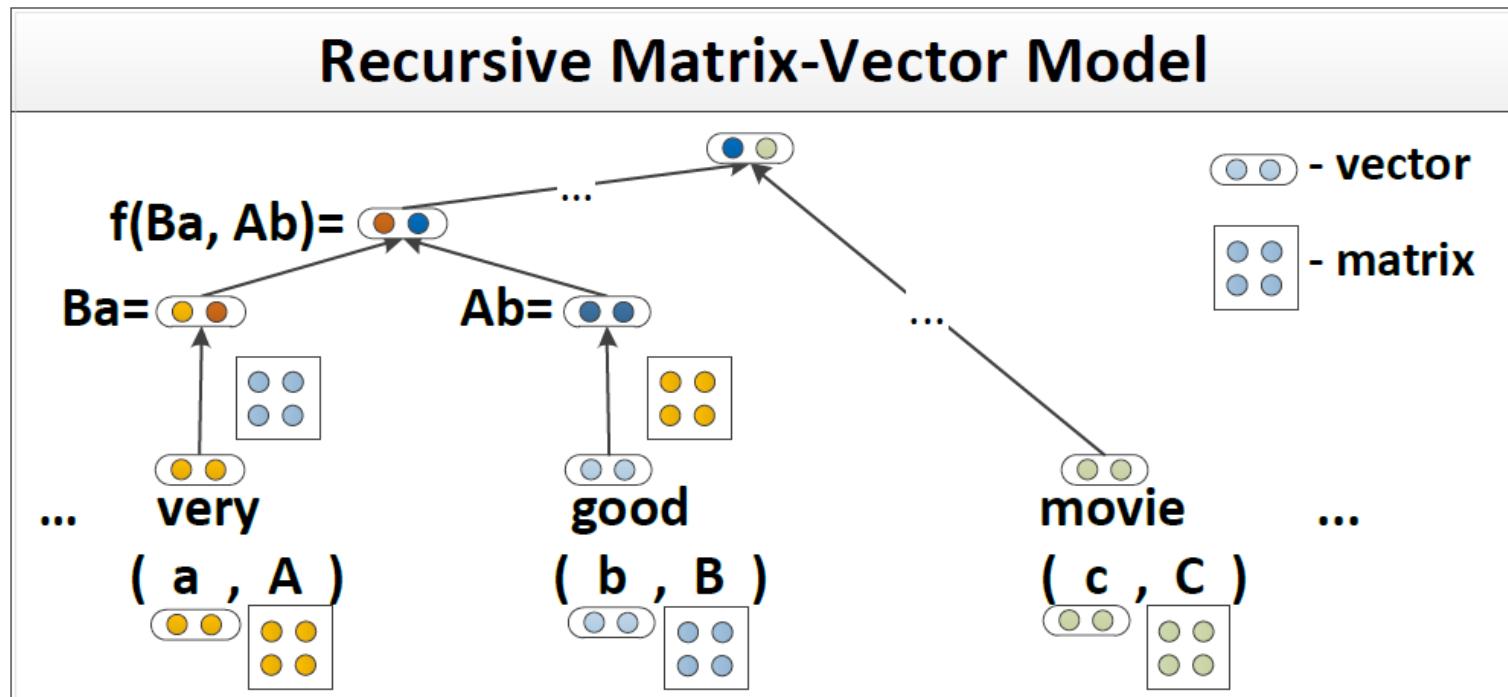
But what if words act mostly as an operator, e.g. “very” in
very good

Proposal: A new composition function

Compositionality Through Recursive Matrix-Vector Recursive Neural Networks

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right)$$

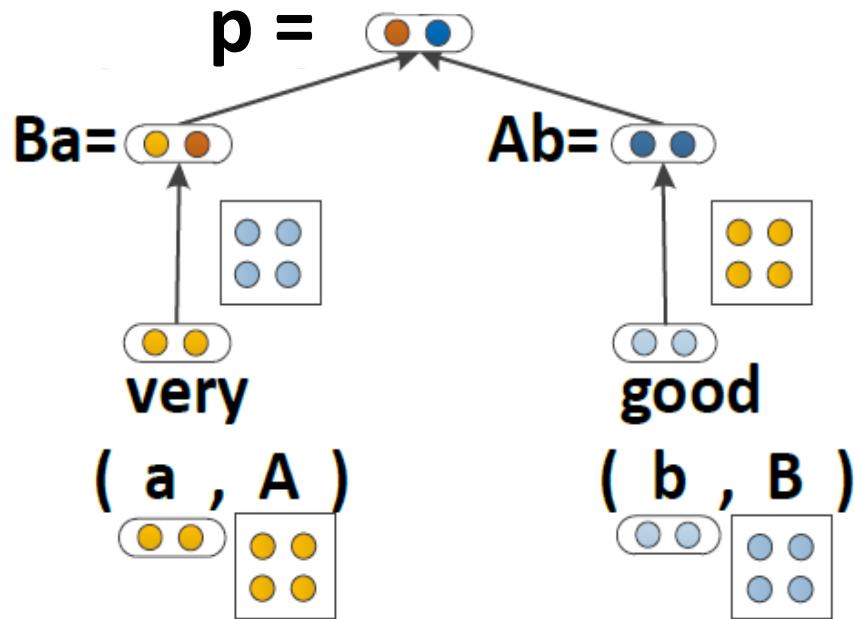
$$p = \tanh\left(W \begin{bmatrix} c_2 c_1 \\ c_1 c_2 \end{bmatrix} + b\right)$$



Matrix-vector RNNs

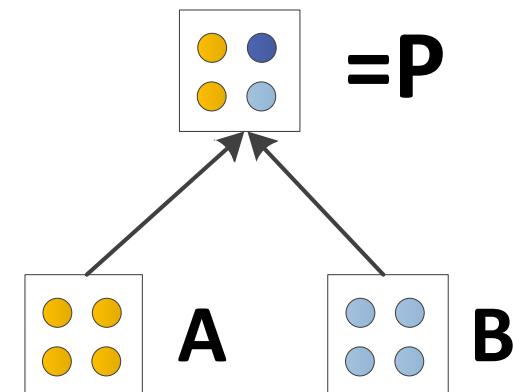
[Socher, Huval, Bhat, Manning, & Ng, 2012]

$$p = f \left(W \begin{bmatrix} Ba \\ Ab \end{bmatrix} \right)$$



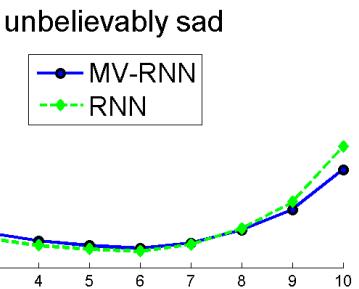
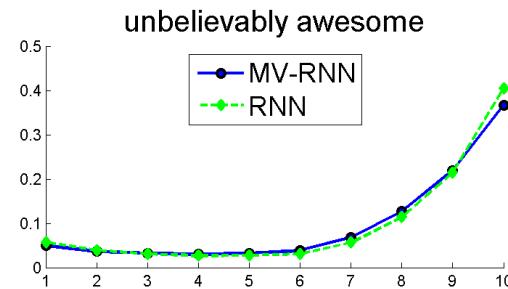
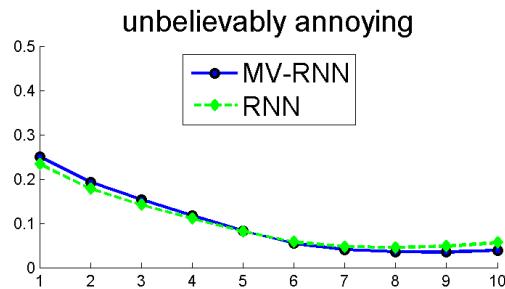
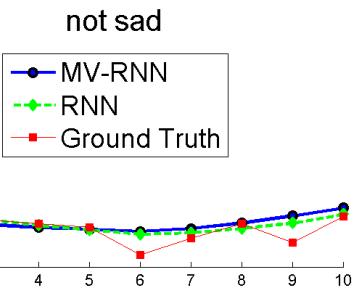
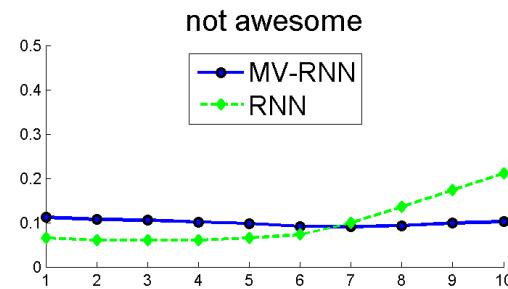
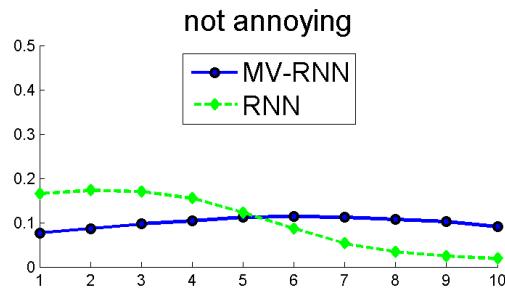
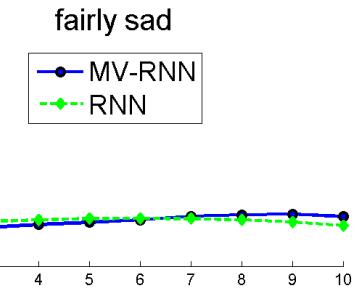
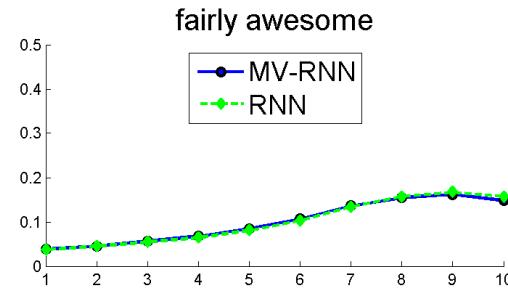
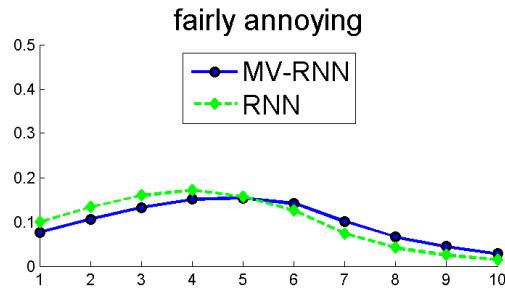
$$P = g(A, B) = W_M \begin{bmatrix} A \\ B \end{bmatrix}$$

$$W_M \in \mathbb{R}^{n \times 2n}$$



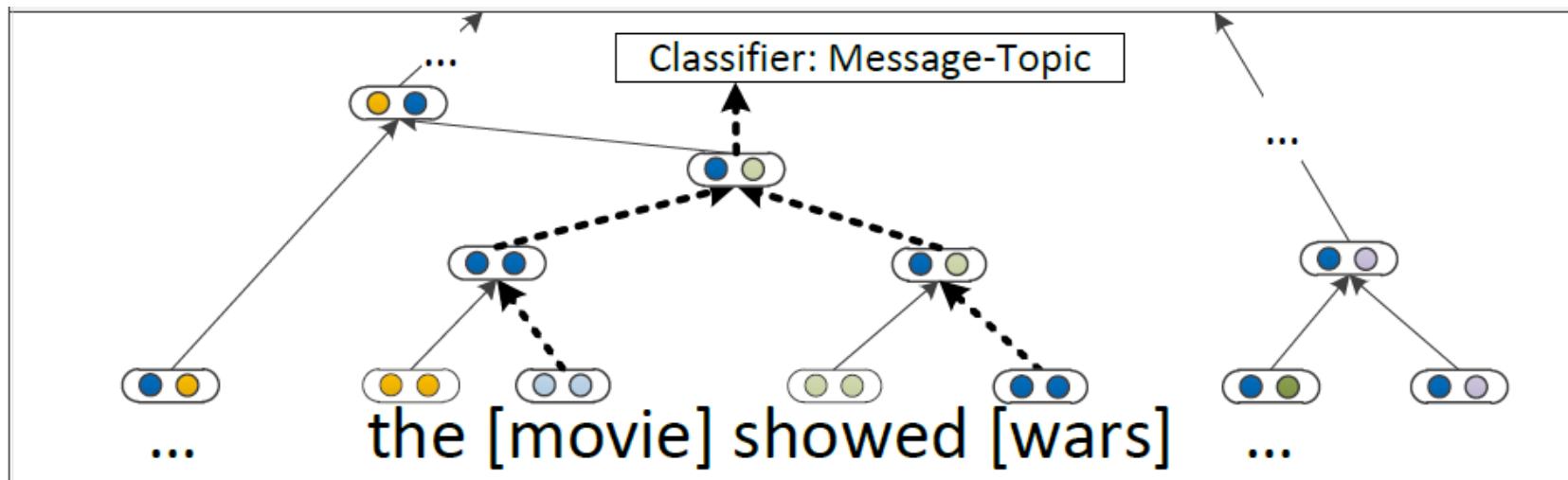
Predicting Sentiment Distributions

Good example for non-linearity in language



Classification of Semantic Relationships

- Can an MV-RNN learn how a large syntactic context conveys a semantic relationship?
- My [apartment]_{e1} has a pretty large [kitchen]_{e2}
→ component-whole relationship (e2,e1)
- Build a single compositional semantics for the minimal constituent including both terms



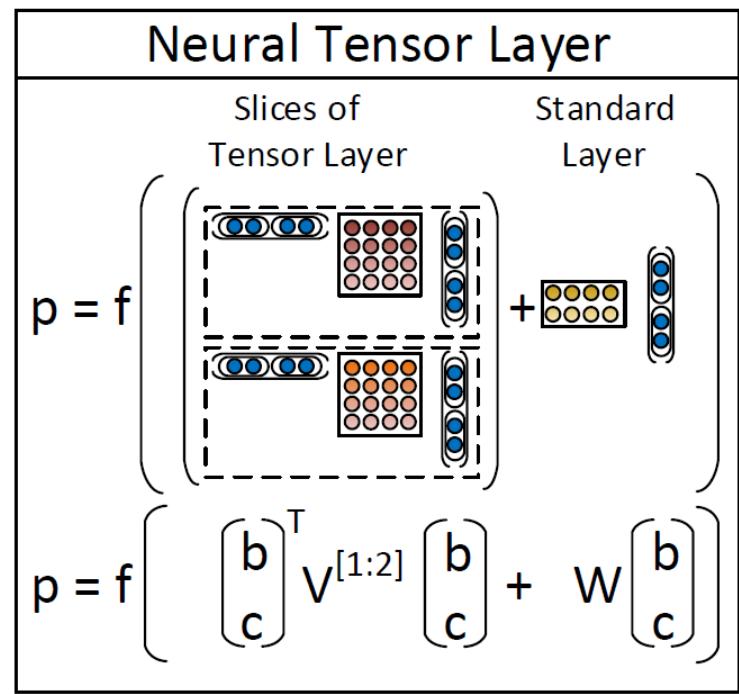
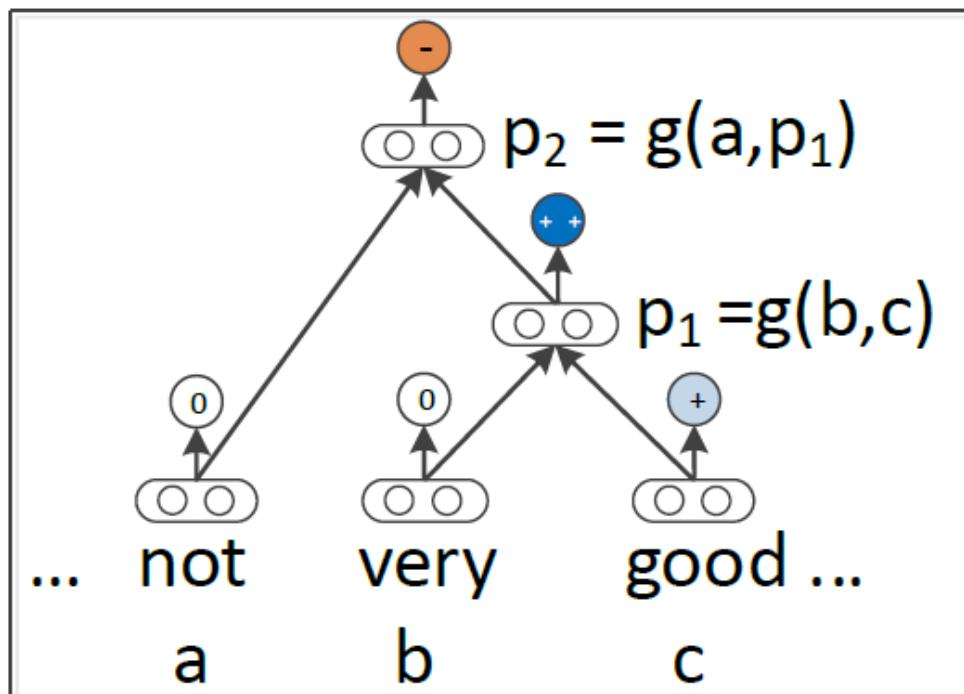
Classification of Semantic Relationships

Classifier	Features	F1
SVM	POS, stemming, syntactic patterns	60.1
MaxEnt	POS, WordNet, morphological features, noun compound system, thesauri, Google n-grams	77.6
SVM	POS, WordNet, prefixes, morphological features, dependency parse features, Levin classes, PropBank, FrameNet, NomLex-Plus, Google n-grams, paraphrases, TextRunner	82.2
RNN	—	74.8
MV-RNN	—	79.1
MV-RNN	POS, WordNet, NER	82.4

Version 4: Recursive Neural Tensor Network

Socher, Perelygin, Wu, Chuang, Manning, Ng, and Potts 2013

- Less parameters than MV-RNN
- Allows the two word or phrase vectors to interact multiplicatively



Beyond the bag of words: Sentiment detection

Is the tone of a piece of text positive, negative, or neutral?

- Sentiment is that sentiment is “easy”
- Detection accuracy for longer documents ~90%, BUT

... ... loved great impressed
... marvelous

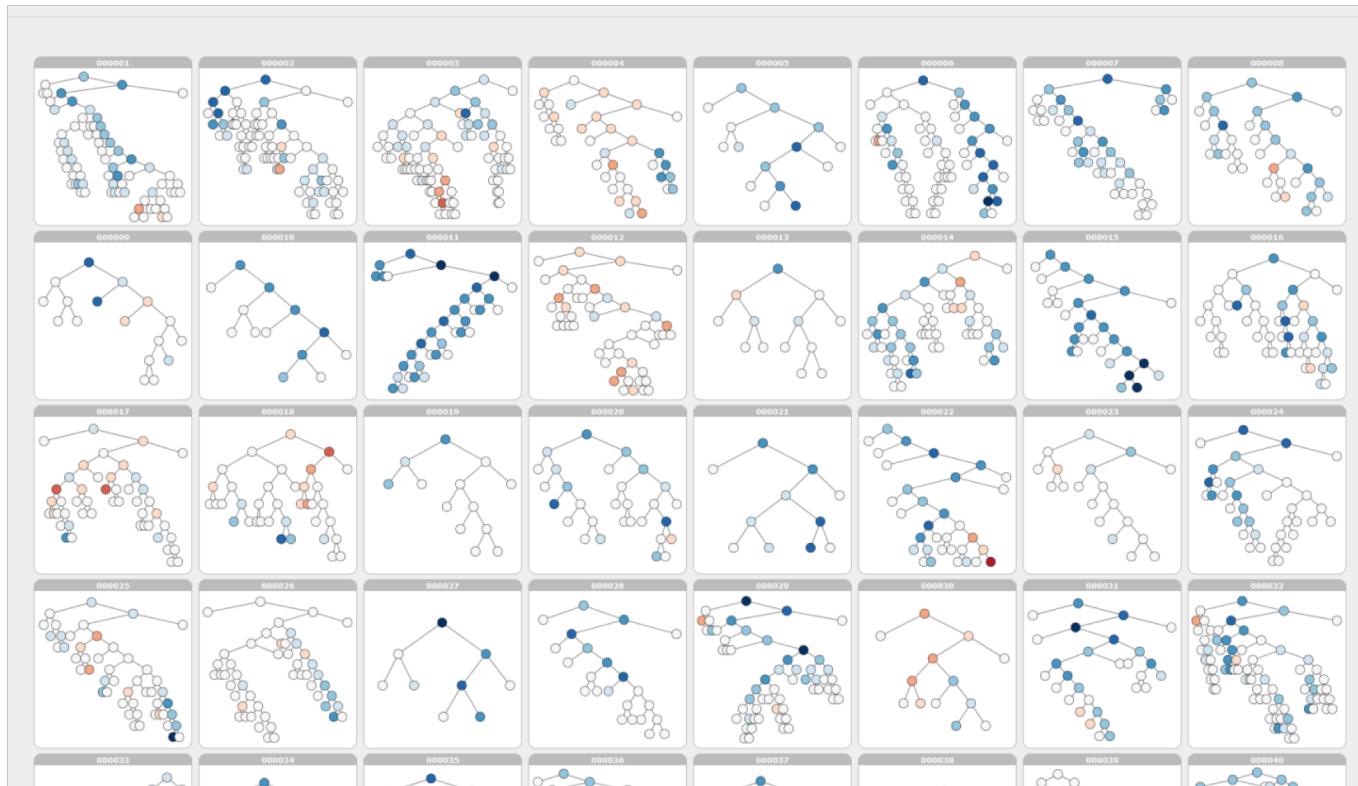


With this cast, and this subject matter, the movie should have been funnier and more entertaining.



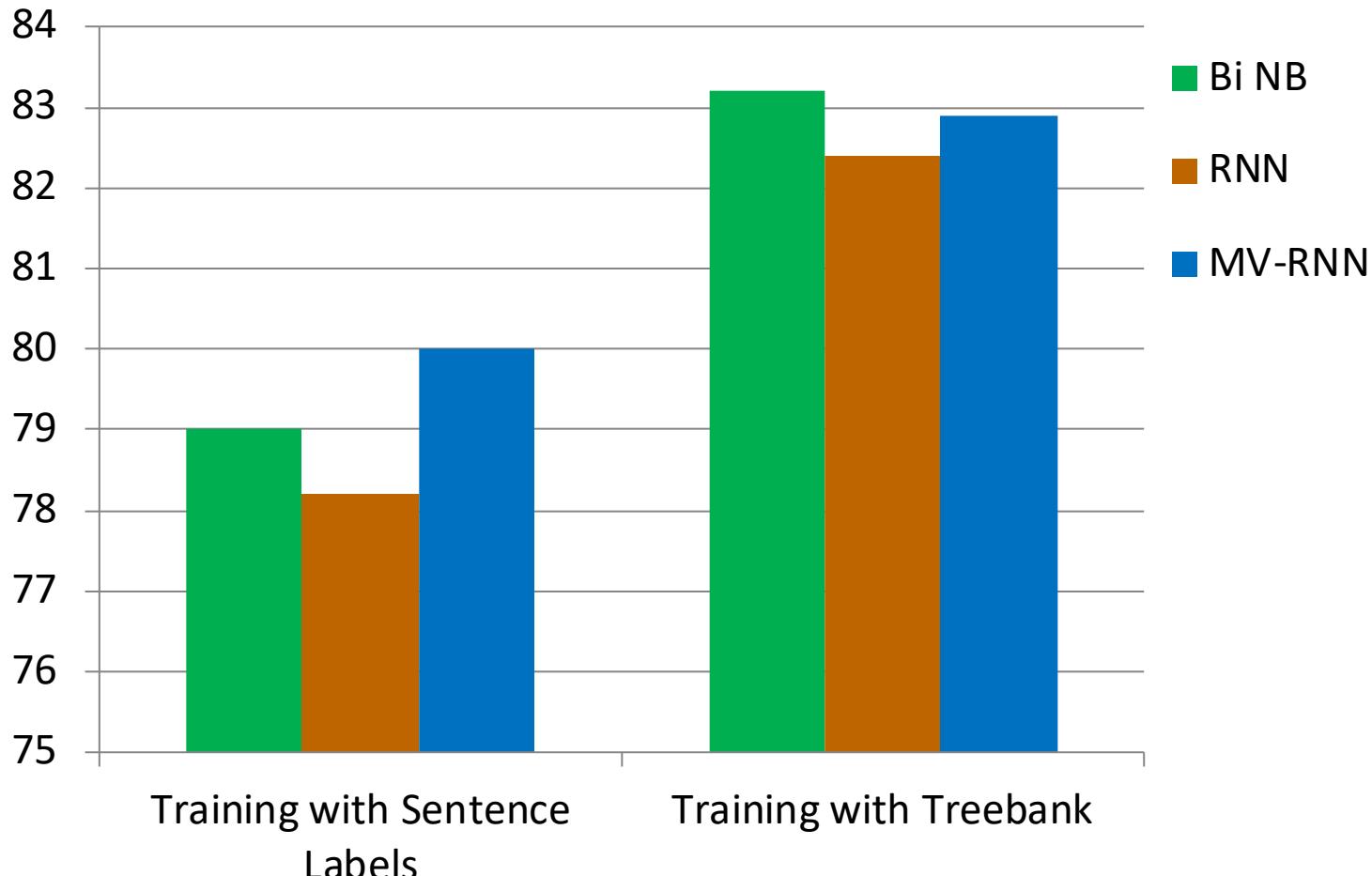
Stanford Sentiment Treebank

- 215,154 phrases labeled in 11,855 sentences
- Can actually train and test compositions



<http://nlp.stanford.edu:8080/sentiment/>

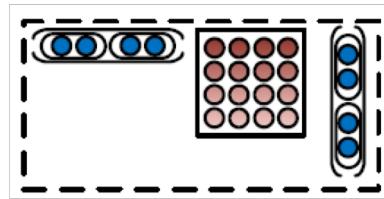
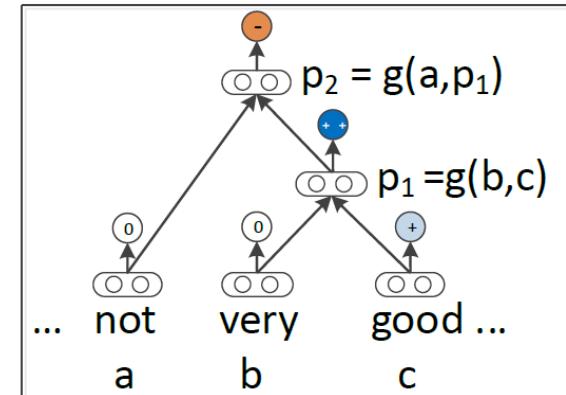
Better Dataset Helped All Models



- Hard negation cases are still mostly incorrect
- We also need a more powerful model!

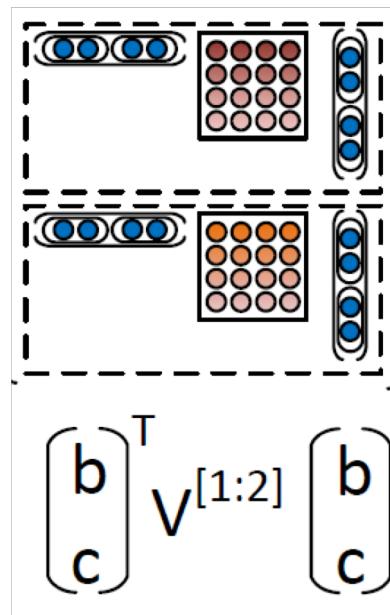
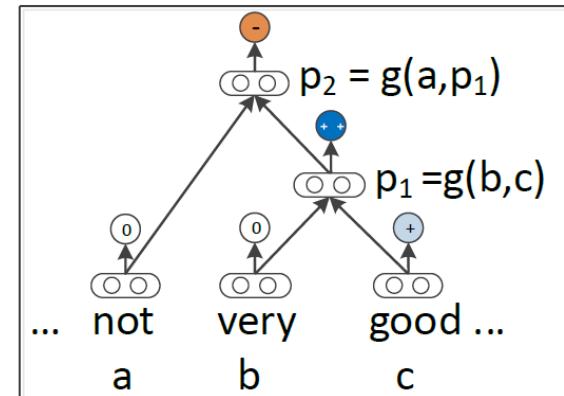
Version 4: Recursive Neural Tensor Network

Idea: Allow both additive and mediated multiplicative interactions of vectors

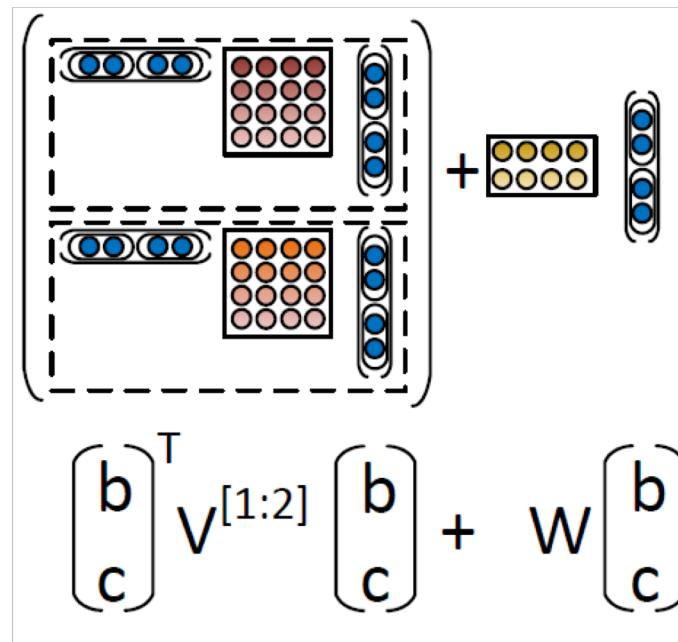
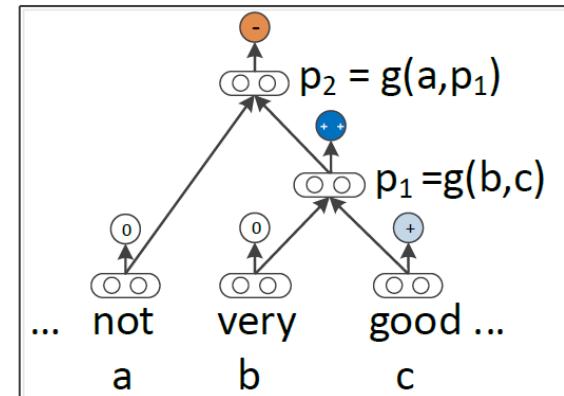


$$\begin{bmatrix} b \\ c \end{bmatrix}^T V \quad \begin{bmatrix} b \\ c \end{bmatrix}$$

Recursive Neural Tensor Network

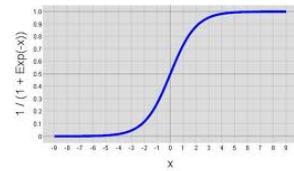
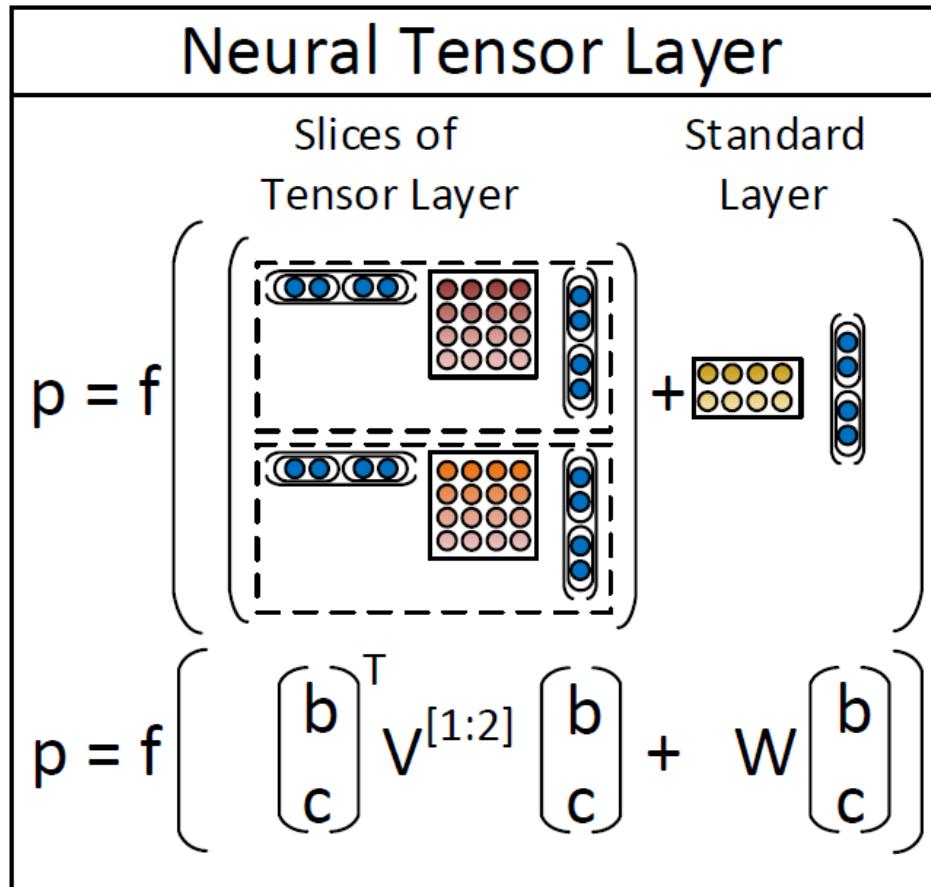
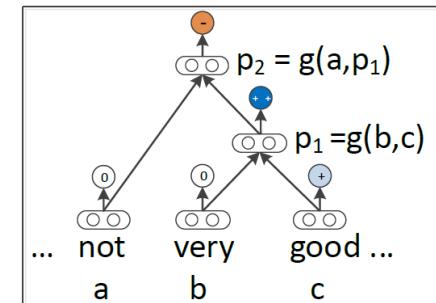


Recursive Neural Tensor Network



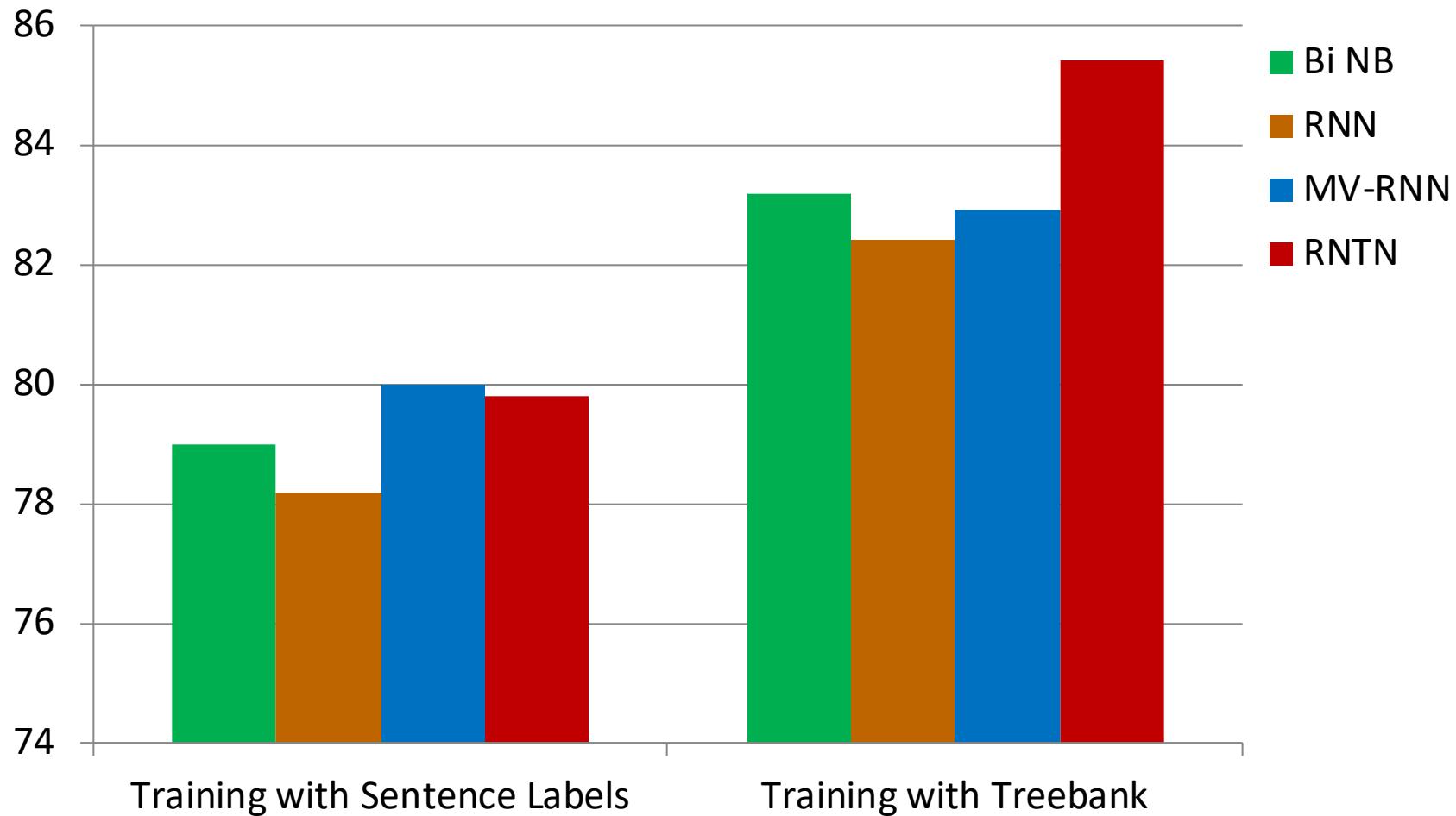
Recursive Neural Tensor Network

- Use resulting vectors in tree as input to a classifier like logistic regression
- Train all weights jointly with gradient descent



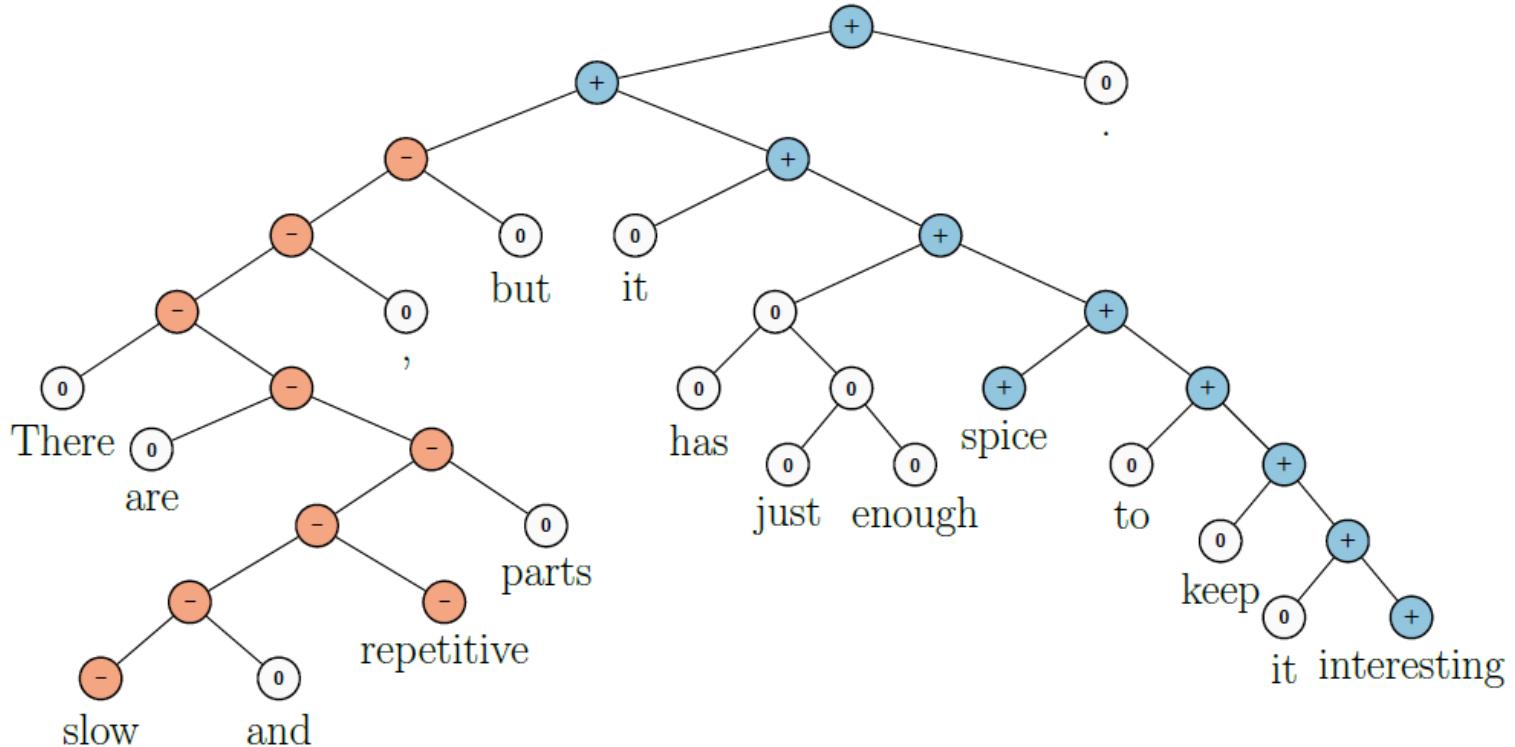
Positive/Negative Results on Treebank

Classifying Sentences: Accuracy improves to 85.4



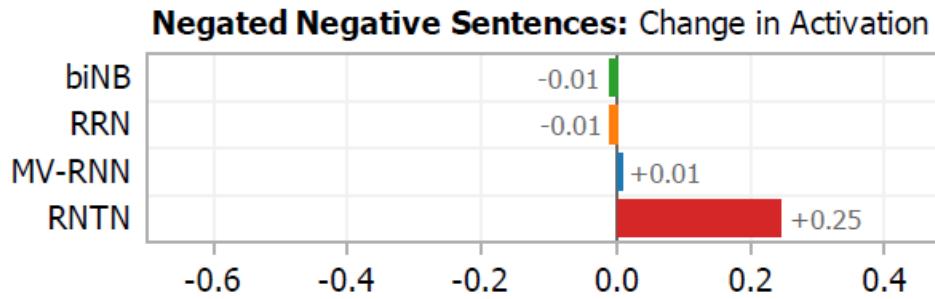
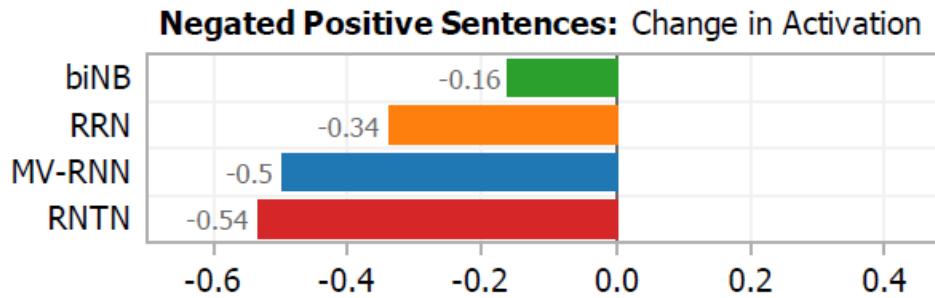
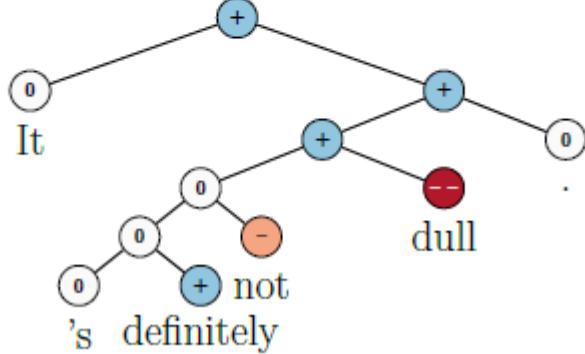
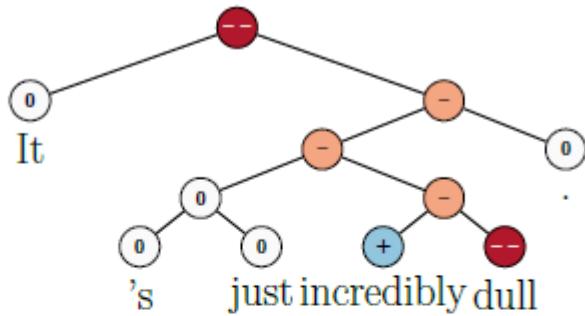
Experimental Results on Treebank

- RNTN can capture constructions like *X but Y*
- RNTN accuracy of 72%, compared to MV-RNN (65%), biword NB (58%) and RNN (54%)



Negation Results

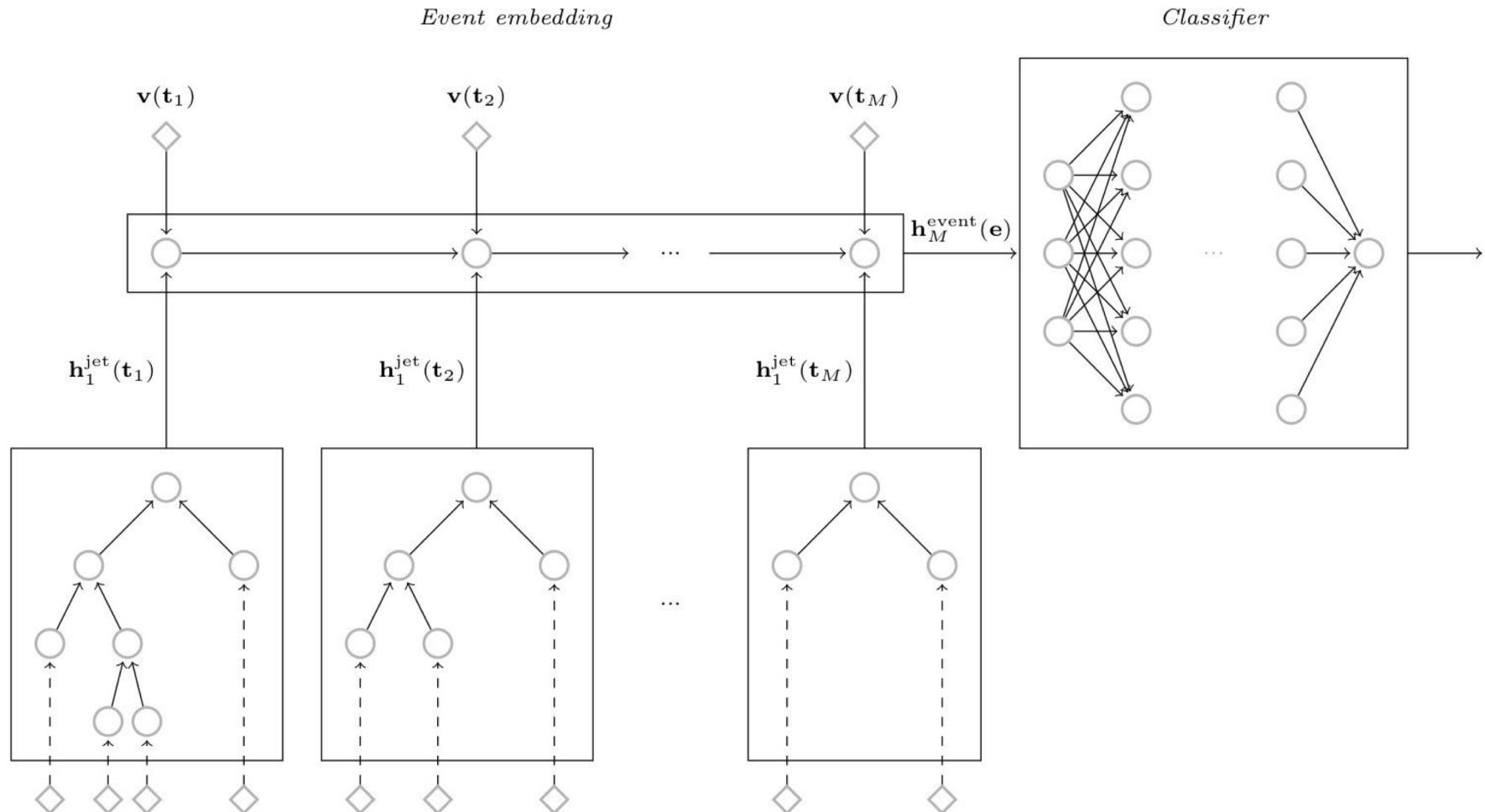
When negating negatives, positive activation should increase!



Demo: <http://nlp.stanford.edu:8080/sentiment/>

5. QCD-Aware Recursive Neural Networks for Jet Physics

Gilles Louppe, Kyunghun Cho, Cyril Becot, Kyle Cranmer (2017)



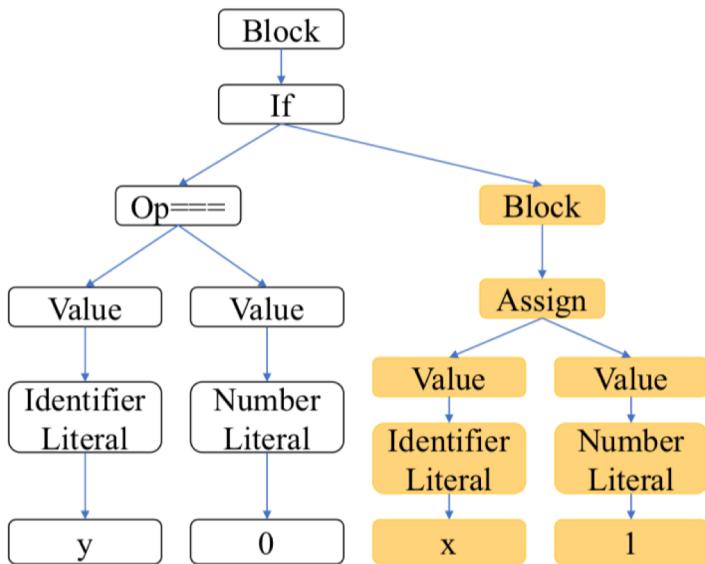
Tree-to-tree Neural Networks for Program Translation

[Chen, Liu, and Song NeurIPS 2018]

- Explores using tree-structured encoding and generation for translation between programming languages
- In generation, you use attention over the source tree

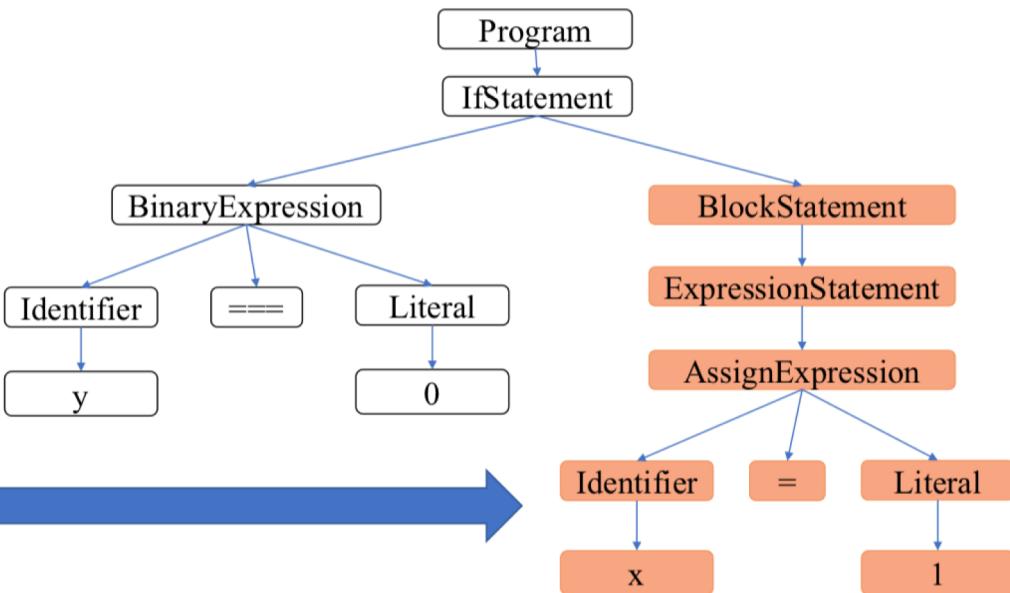
CoffeeScript Program: `x=1 if y==0`

Parse Tree



JavaScript Program: `if (y === 0) { x = 1; }`

Parse Tree



Tree-to-tree Neural Networks for Program Translation

[Chen, Liu, and Song NeurIPS 2018]

	Tree2tree			Seq2seq				Seq2tree		Tree2seq	
	T→T	T→T (-PF)	T→T (-Attn)	P→P	P→T	T→P	T→T	P→T	T→T	T→P	T→T
CoffeeScript to JavaScript translation											
CJ-AS	99.57%	98.80%	0.09%	90.51%	79.82%	92.73%	89.13%	86.52%	88.50%	96.96%	92.18%
CJ-BS	99.75%	99.67%	0%	97.44%	16.26%	98.05%	93.89%	91.97%	88.22%	96.83%	78.77%
CJ-AL	97.15%	71.52%	0%	21.04%	0%	0%	0%	80.82%	78.60%	82.55%	46.94%
CJ-BL	95.60%	78.61%	0%	19.26%	9.98%	25.35%	42.08%	76.12%	76.21%	83.61%	26.83%
JavaScript to CoffeeScript translation											
JC-AS	87.75%	85.11%	0.09%	83.07%	86.13%	73.88%	86.31%	86.86%	86.99%	71.61%	86.53%
JC-BS	86.37%	80.35%	0%	80.49%	85.94%	69.77%	85.28%	85.06%	84.25%	66.82%	85.31%
JC-AL	78.59%	54.93%	0%	77.10%	77.30%	65.52%	75.70%	77.11%	77.59%	60.75%	75.75%
JC-BL	75.62%	44.40%	0%	73.14%	73.96%	61.92%	74.51%	74.34%	71.56%	57.09%	73.86%

Tree-to-tree Neural Networks for Program Translation

[Chen, Liu, and Song NeurIPS 2018]

	Tree2tree	J2C#	1pSMT	mppSMT
		Reported in [22]		
Lucene	72.8%	21.5%	21.6%	40.0%
POI	72.2%	18.9%	34.6%	48.2%
Itext	67.5%	25.1%	24.4%	40.6%
JGit	68.7%	10.7%	23.0%	48.5%
JTS	68.2%	11.7%	18.5%	26.3%
Antlr	31.9% (58.3%)	10.0%	11.5%	49.1%

Stanford Institute for Human-Centered Artificial Intelligence (HAI)



Stanford

Human-Centered Artificial Intelligence

Artificial intelligence is poised to transform economies and societies, change the way we communicate and work, reshape governance and politics, and challenge the international order

HAI's mission is to advance AI research, education, policy, and practice to improve the human condition



Developing AI
technologies
inspired by
human
intelligence

Guiding and
forecasting
the human and
societal impact
of AI

Designing AI
applications that
augment human
capabilities