Neural Models over Tree Structures

Mausam

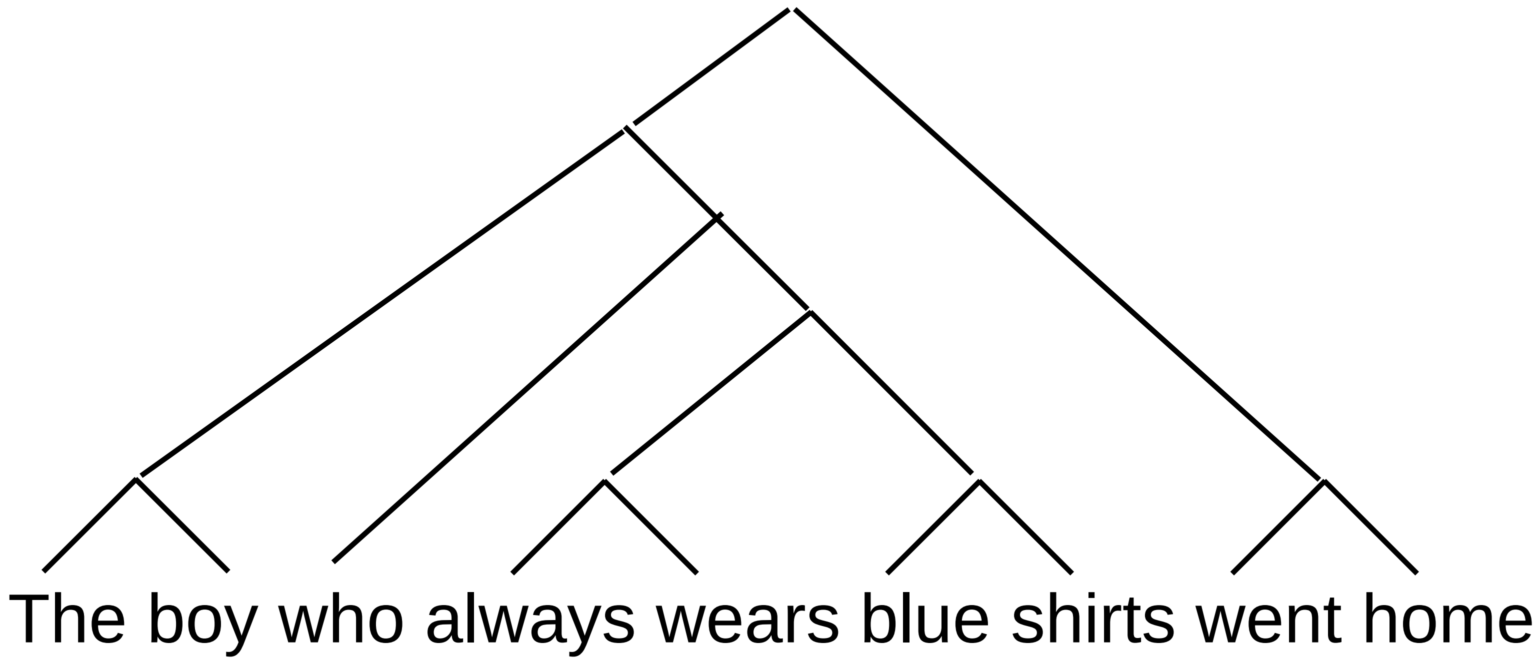
(Slides by Yoav Goldberg, Richard Socher, Daniel Perez)

Trees

- Sequences are nice.
- But when working with language, we often see tree structures.
- An RNN encodes a sequence as a vector.
- We would like to **encode a tree as a vector**

The boy who always wears blue shirts went home

(((The boy) (who (always wears) (blue shirts))) went home)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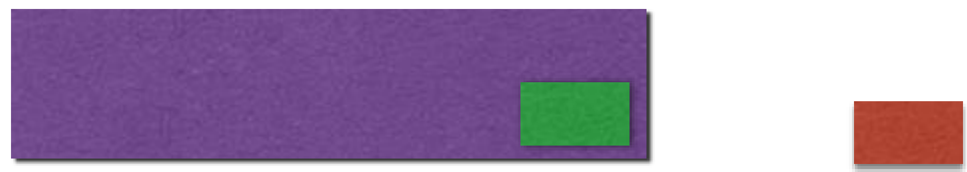

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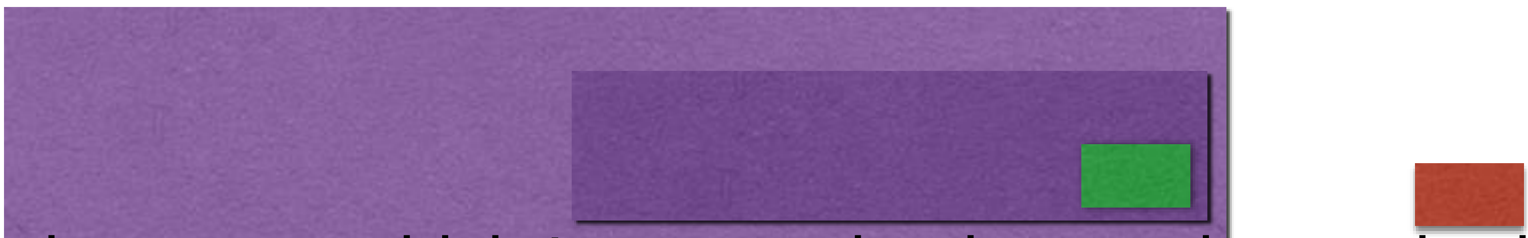

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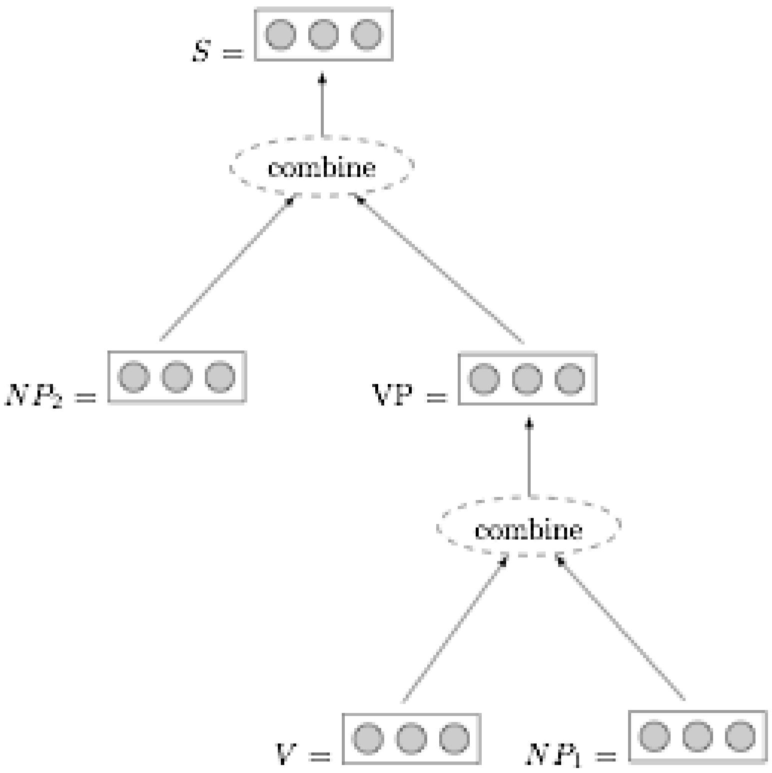
Recursive Neural Nets



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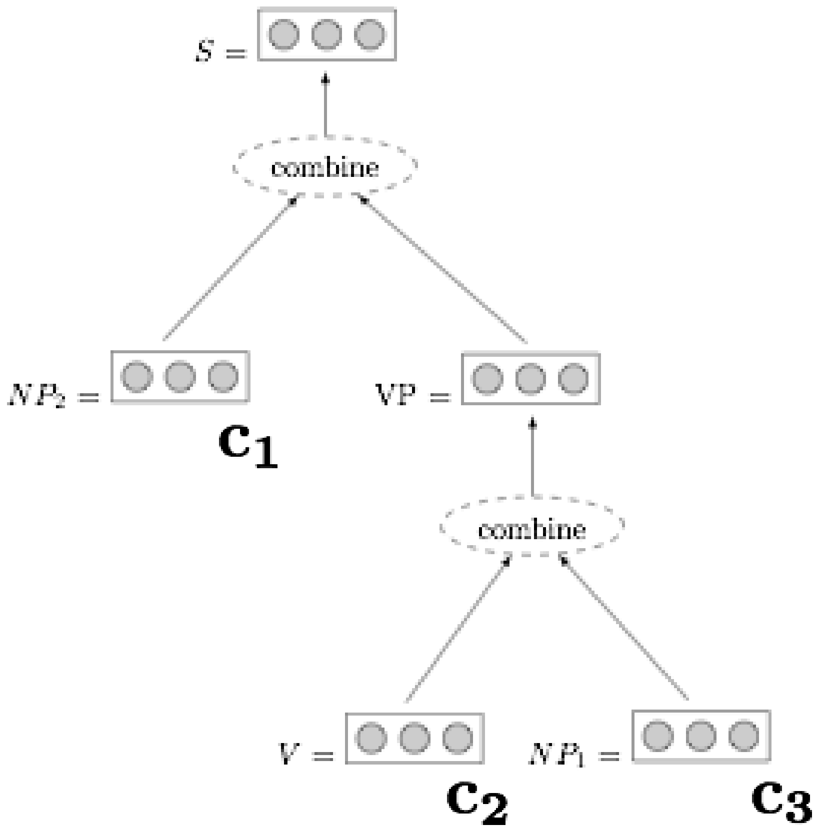

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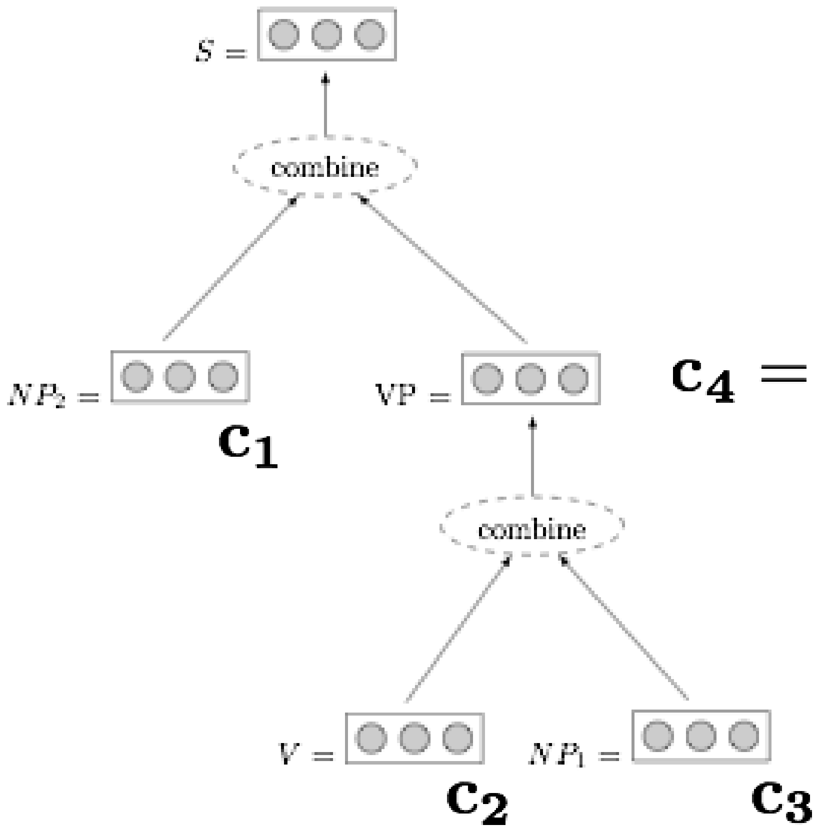

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Recursive Neural Nets

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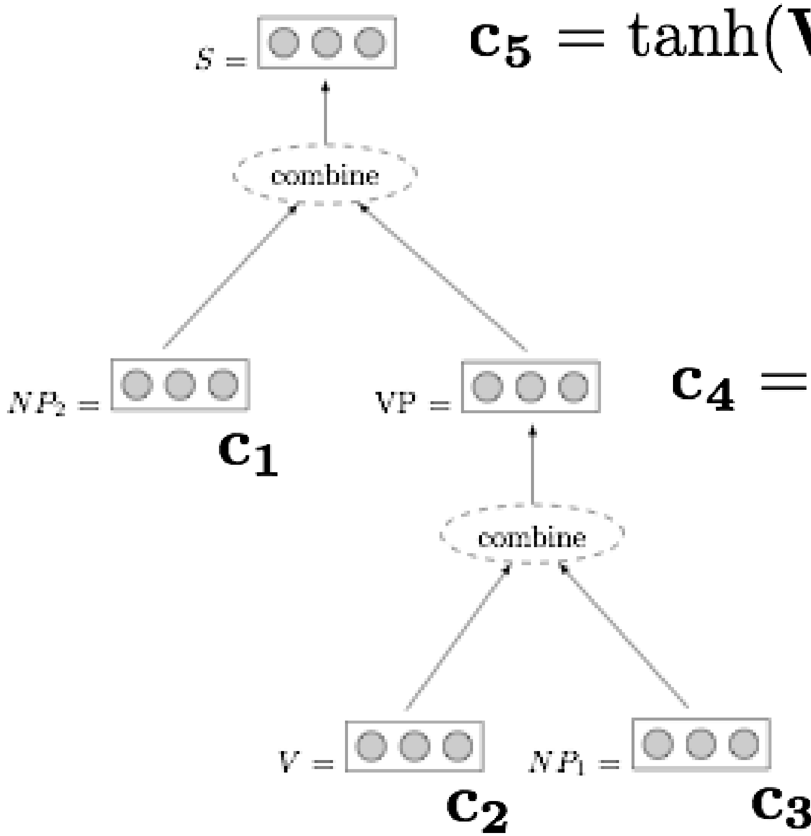
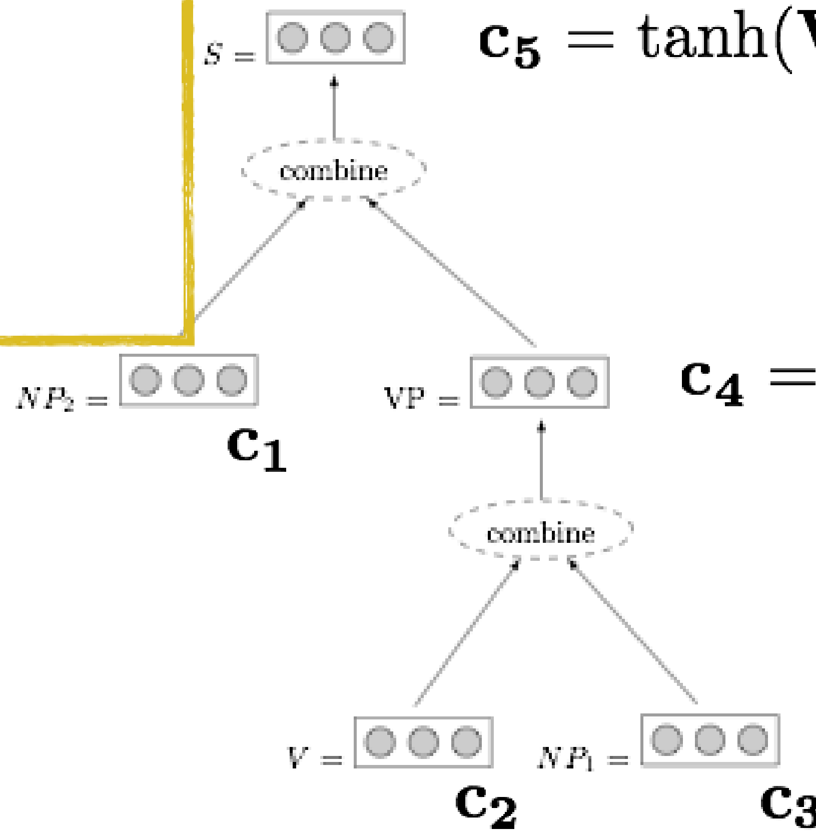


Recursive Neural Nets

Like recurrent nets:
we have **shared parameters** at nodes.
but structure is
no longer a sequence.



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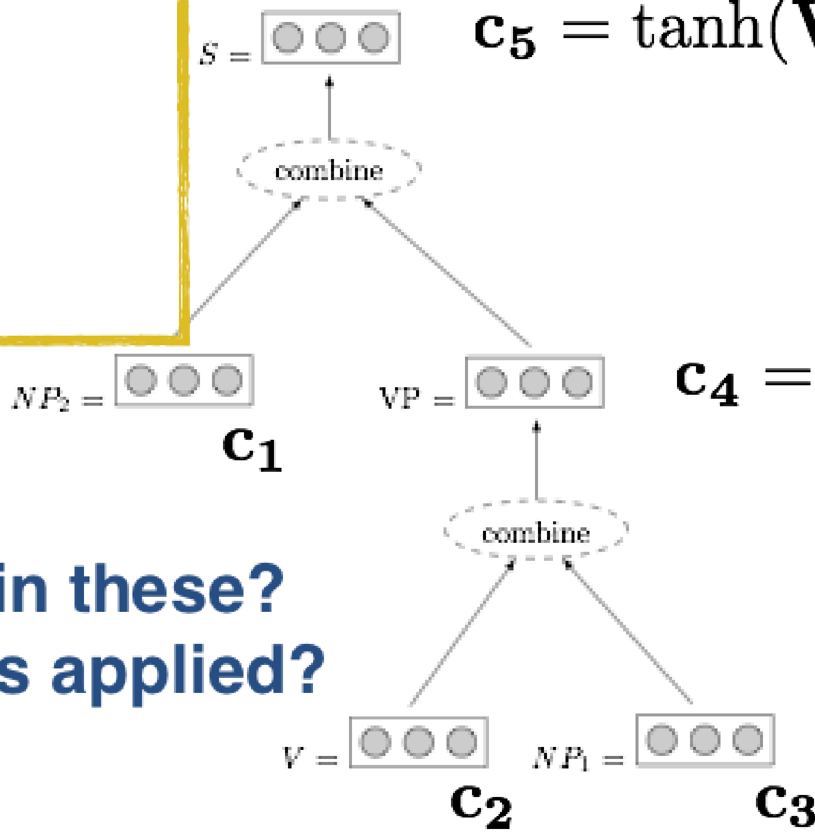
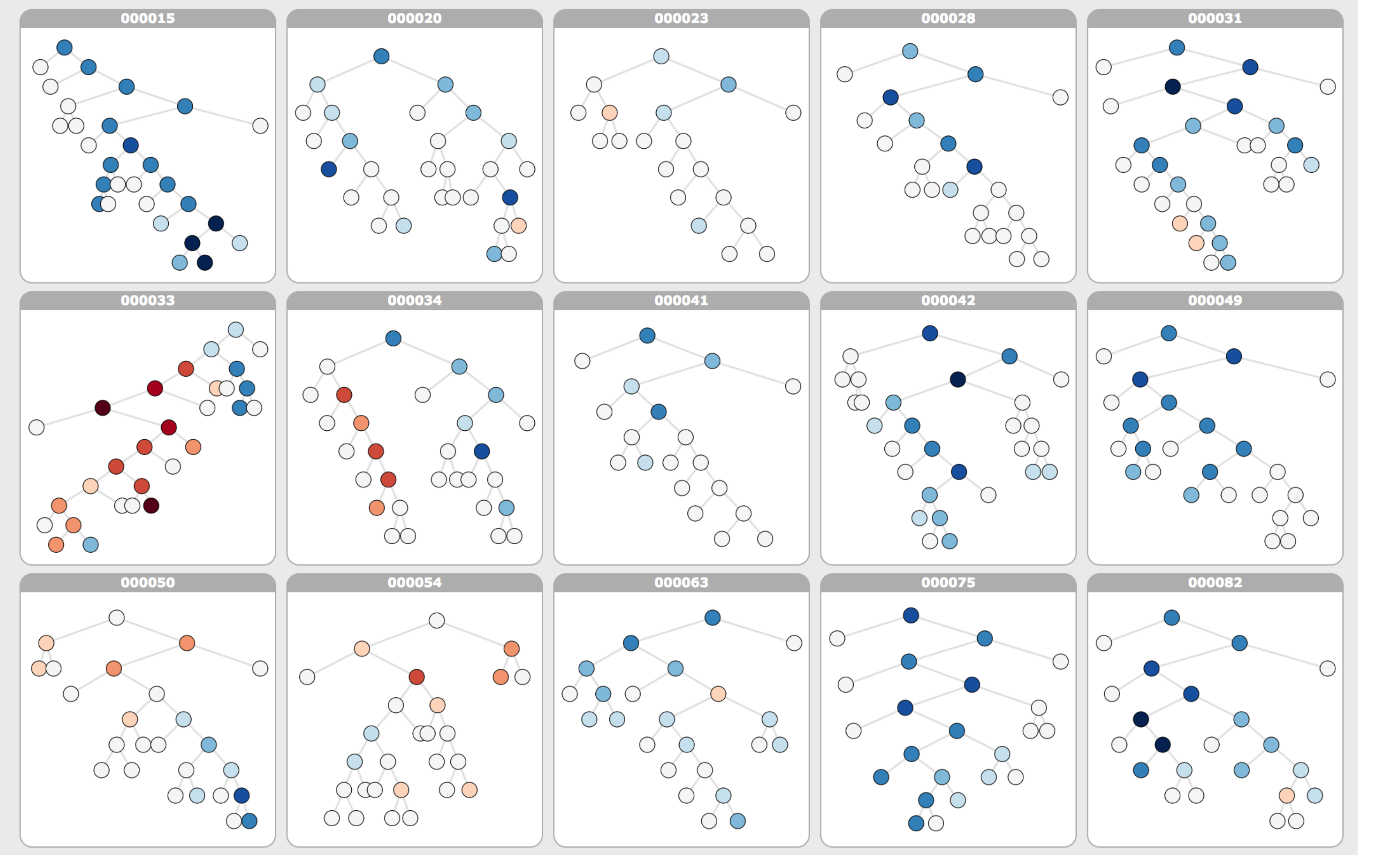


How do we train these?
where is the loss applied?

Stanford Sentiment Treebank

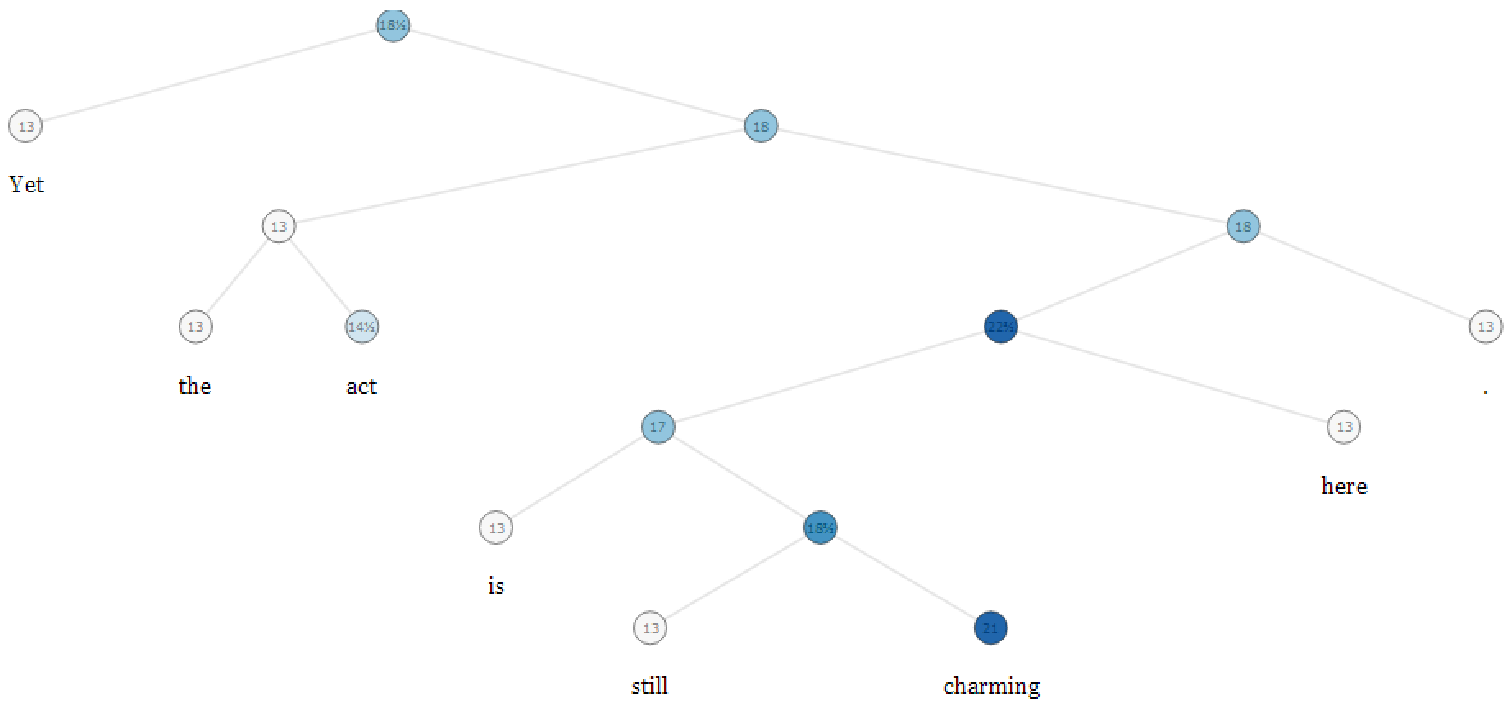


Need for a Sentiment Treebank

- Almost all work on sentiment analysis has used mostly word-order independent methods
- But many papers acknowledge that sentiment interacts with syntax in complex ways
- Little work has been done on these interactions because they're very difficult to learn
- Single-sentence sentiment classification accuracy has languished at ~80% for a long time

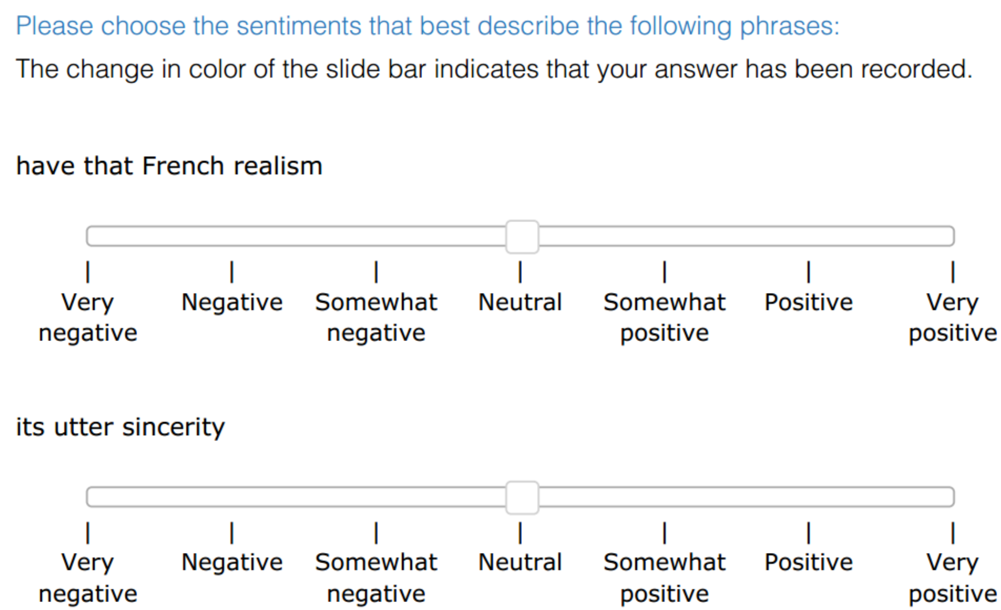
Goal of the Sentiment Treebank

- At every level of the parse tree, annotate the sentiment of the phrase it subsumes
- Use a 5-class scheme (--, -, 0, +, ++)



Construction of the Sentiment Treebank

- For 11,855 sentences, parse and break into phrases (215,154 total)
- The sentiment of each phrase is annotated with Mechanical Turk



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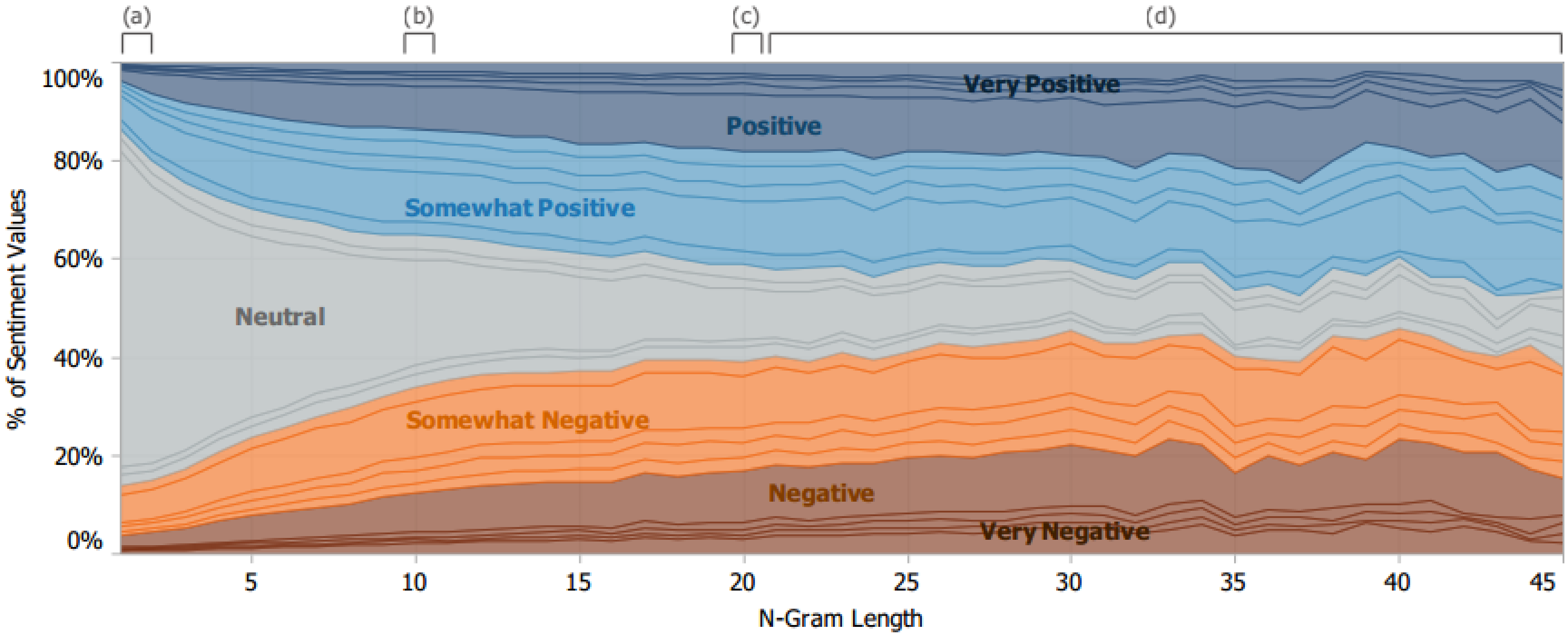
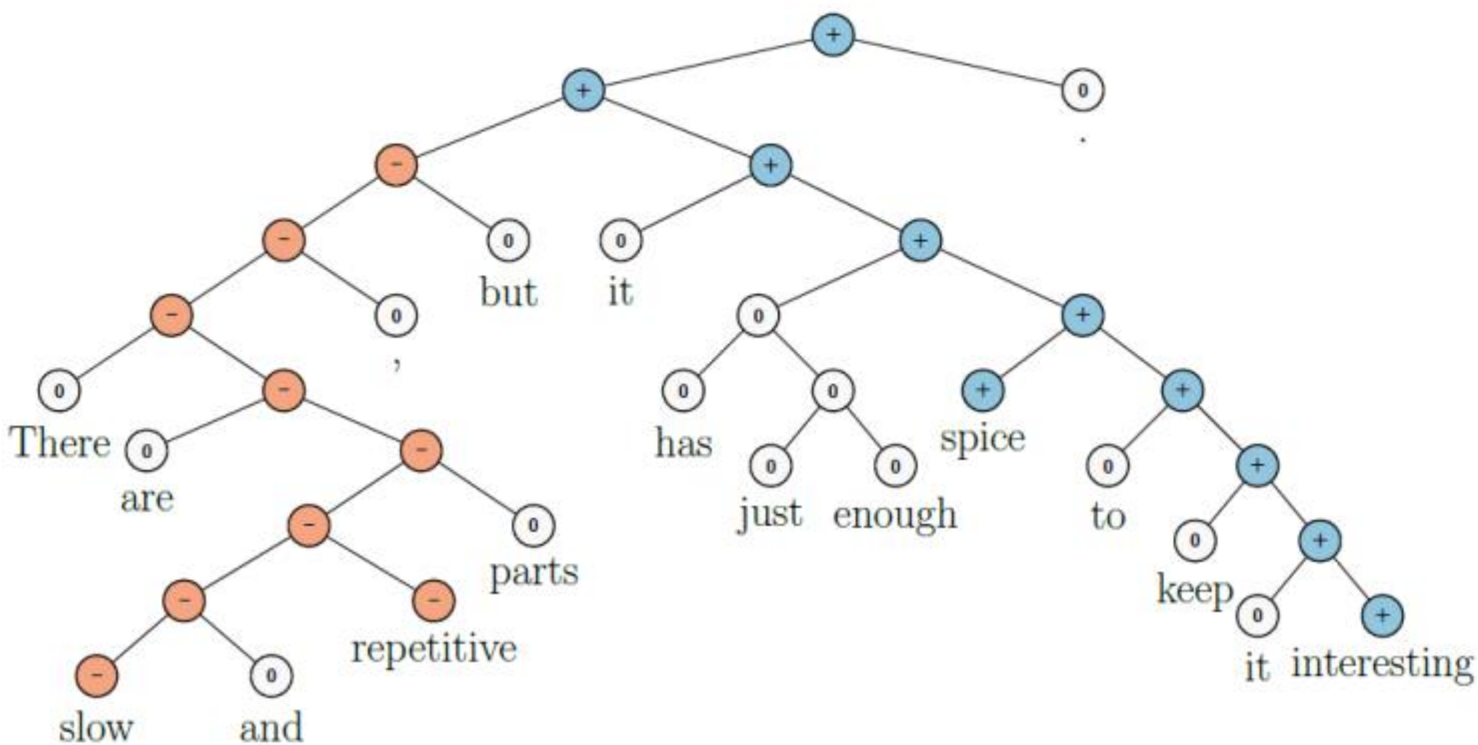


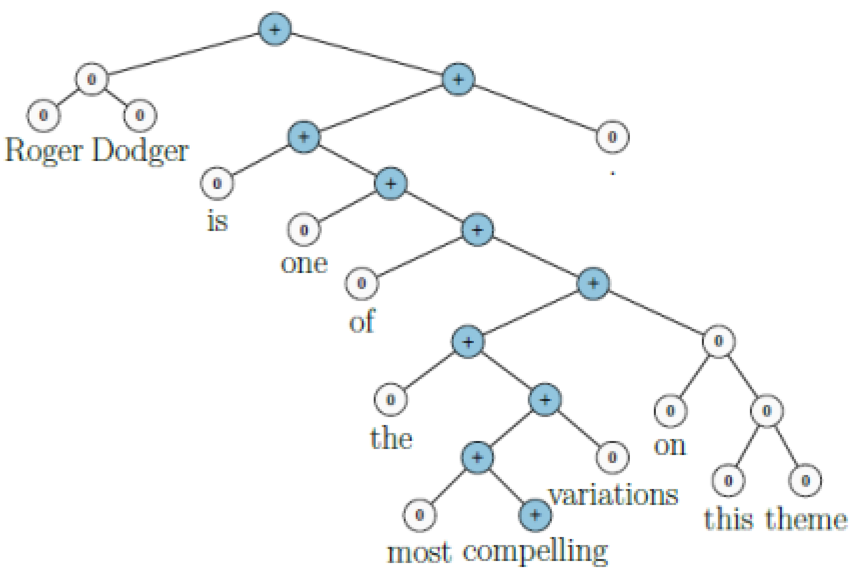
What is this model able to do?

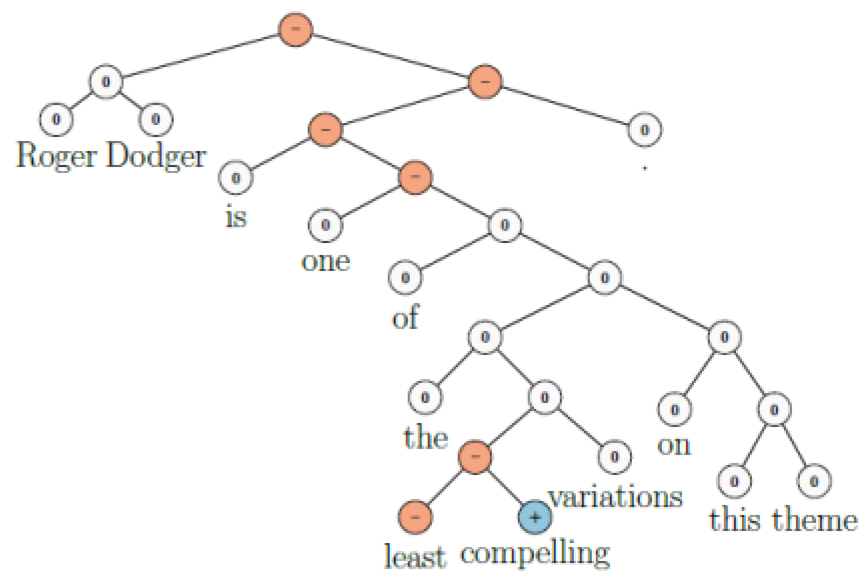
- Learns structures like "X but Y"



What is this model able to do?

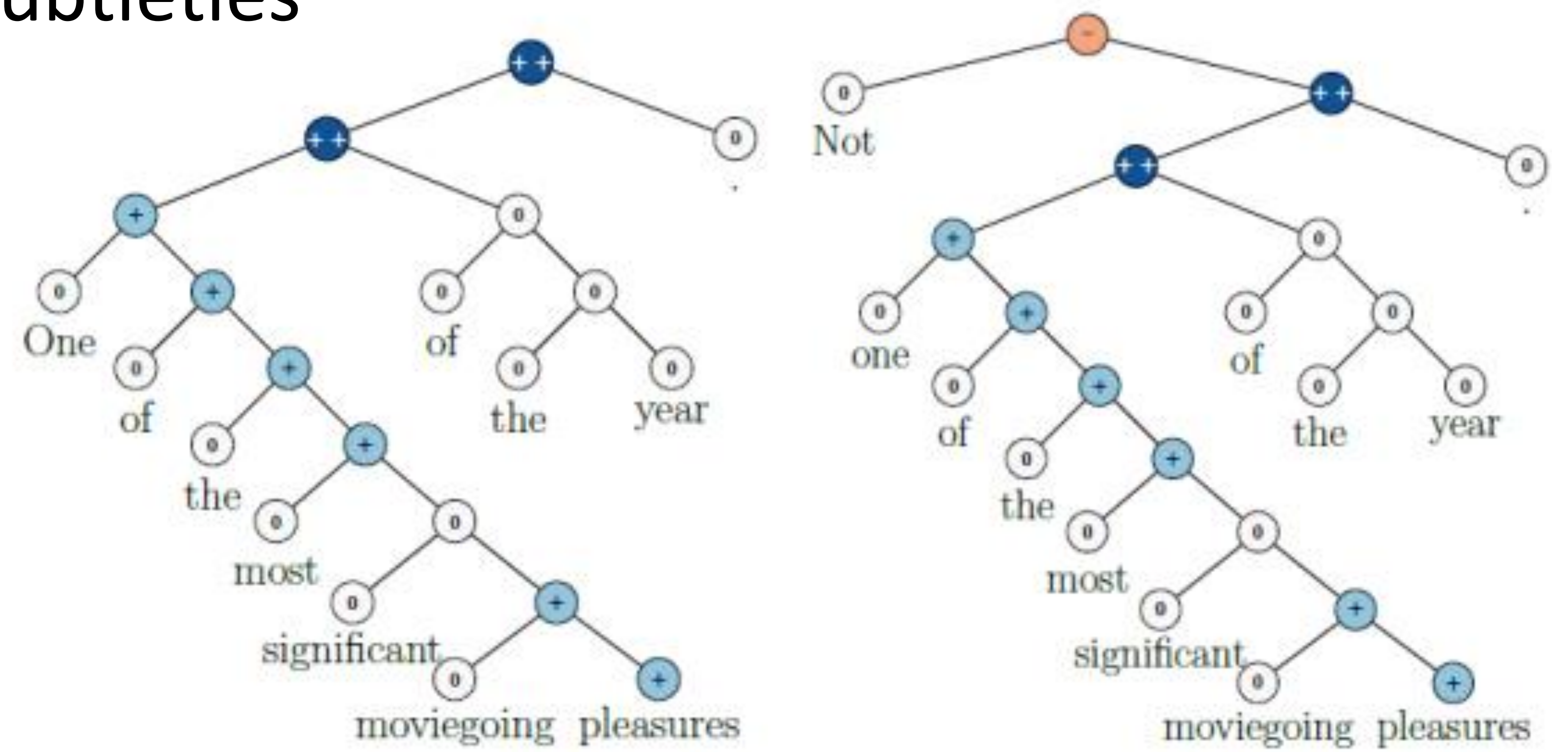
- Small changes are able to propagate all the way up the tree



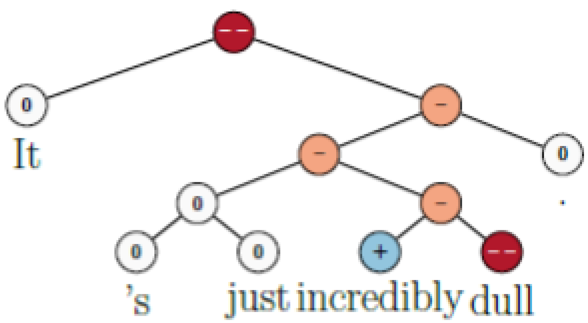


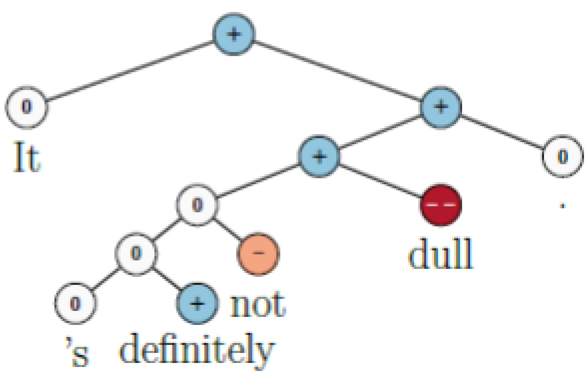
What is this model able to do?

- Learns how negation works, including many subtleties

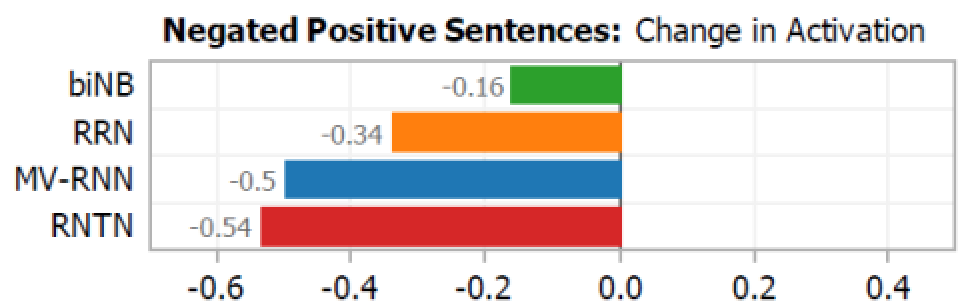


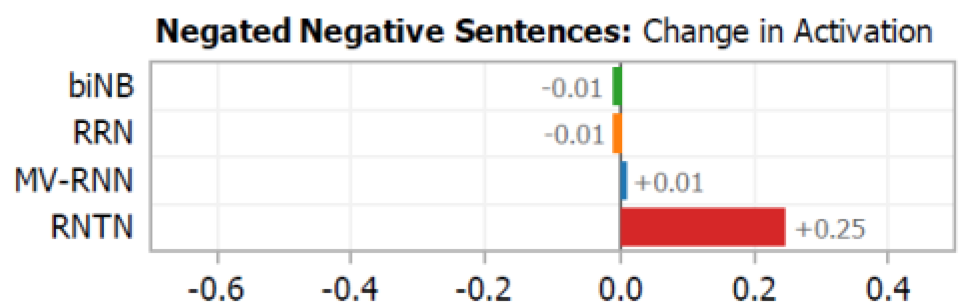
Negation Evaluation





Model	Accuracy	
	Negated Positive	Negated Negative
biNB	19.0	27.3
RNN	33.3	45.5
MV-RNN	52.4	54.6
RNTN	**71.4**	**90.9**

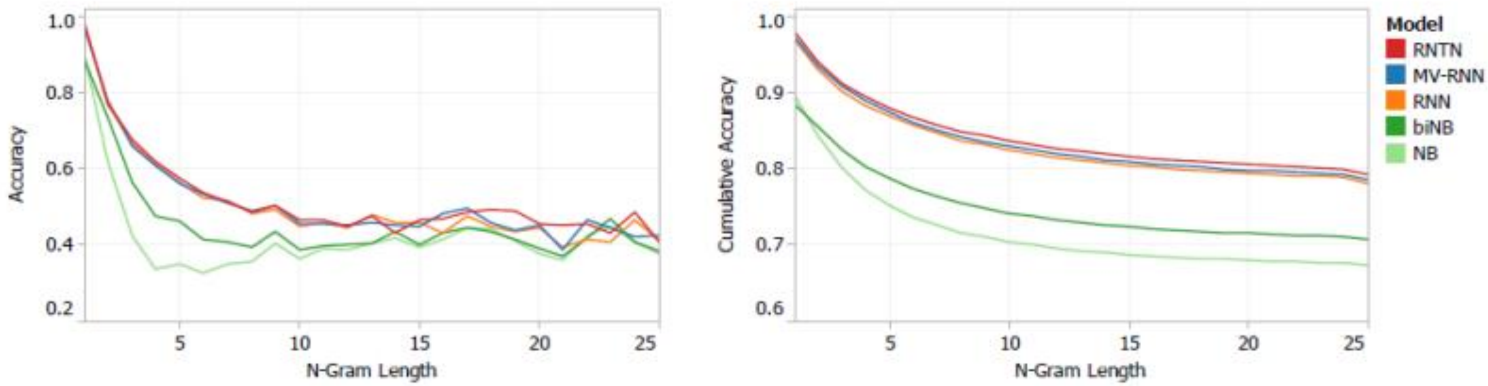




Positive and Negative N-grams

n	**Most positive n-grams**	**Most negative n-grams**
1	engaging ; best ; powerful ; love ; beautiful ; entertaining ; clever ; terrific ; excellent ; great ;	bad ; dull ; boring ; fails ; worst ; stupid ; painfully ; cheap ; forgettable ; disaster ;
2	excellent performances ; amazing performance ; terrific performances ; A masterpiece ; masterful film ; wonderful film ; terrific performance ; masterful piece ; wonderful movie ; marvelous performances ;	worst movie ; bad movie ; very bad ; shapeless mess ; worst thing ; tepid waste ; instantly forgettable ; bad film ; extremely bad ; complete failure ;
3	an amazing performance ; a terrific performance ; a wonderful film ; wonderful all-ages triumph ; A masterful film ; a wonderful movie ; a tremendous performance ; drawn excellent performances ; most visually stunning ; A stunning piece ;	for worst movie ; A lousy movie ; most joyless movie ; a complete failure ; another bad movie ; fairly terrible movie ; a bad movie ; extremely unfunny film ; most painfully marginal ; very bad sign ;
5	nicely acted and beautifully shot ; gorgeous imagery , effective performances ; the best of the year ; a terrific American sports movie ; very solid , very watchable ; a fine documentary does best ; refreshingly honest and ultimately touching ;	silliest and most incoherent movie ; completely crass and forgettable movie ; just another bad movie . ; drowns out the lousy dialogue ; a fairly terrible movie ... ; A cumbersome and cliche-ridden movie ; a humorless , disjointed mess ;
8	one of the best films of the year ; simply the best family film of the year ; the best film of the year so far ; A love for films shines through each frame ; created a masterful piece of artistry right here ; A masterful film from a master filmmaker , ; 's easily his finest American film ... comes ;	A trashy , exploitative , thoroughly unpleasant experience ; this sloppy drama is an empty vessel . ; a meandering , inarticulate and ultimately disappointing film ; an unimaginative , nasty , glibly cynical piece ; bad , he 's really bad , and ; quickly drags on becoming boring and predictable . ; be the worst special-effects creation of the year ;

Sentiment Analysis Evaluation



Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

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Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	**80.7**	**45.6**	**87.6**	**85.4**