Deep Learning

743.

Compositionality

and Recursive Neural Networks

Non-compositionality

- BLACK CAT = BLACK + CAT
- BLACK MARKET $\neq$ BLACK + MARKET

Compositional Semantics

- Given:
  - Vector representations of individual words
- Needed:
  - Representations of units such as phrases, sentences
- Early work:
  - Pointwise sum, multiplication
  - Mitchell and Lapata 2010, Blacoe and Lapata 2012
- Neural methods:
  - Tree RNN, etc.

Recursive Neural Tensor Networks (RNTN)

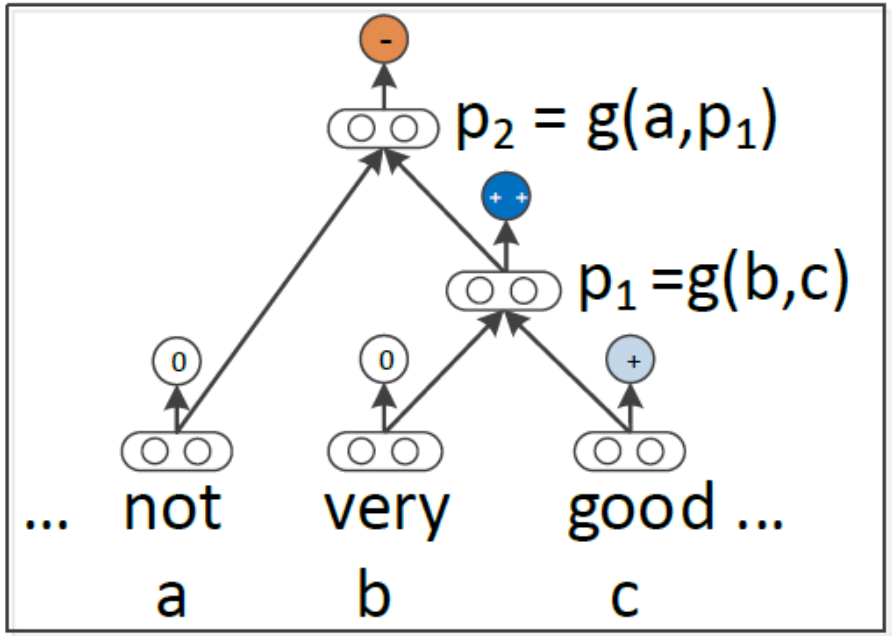
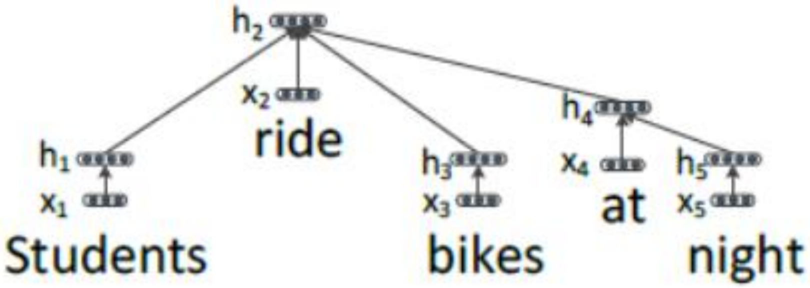


Figure 4: Approach of Recursive Neural Network models for sentiment: Compute parent vectors in a bottom up fashion using a compositionality function g and use node vectors as features for a classifier at that node. This function varies for the different models.



[Socher et al. 2013, 2014]

Recursive Neural Tensor Networks

Socher et al. (2013)
Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

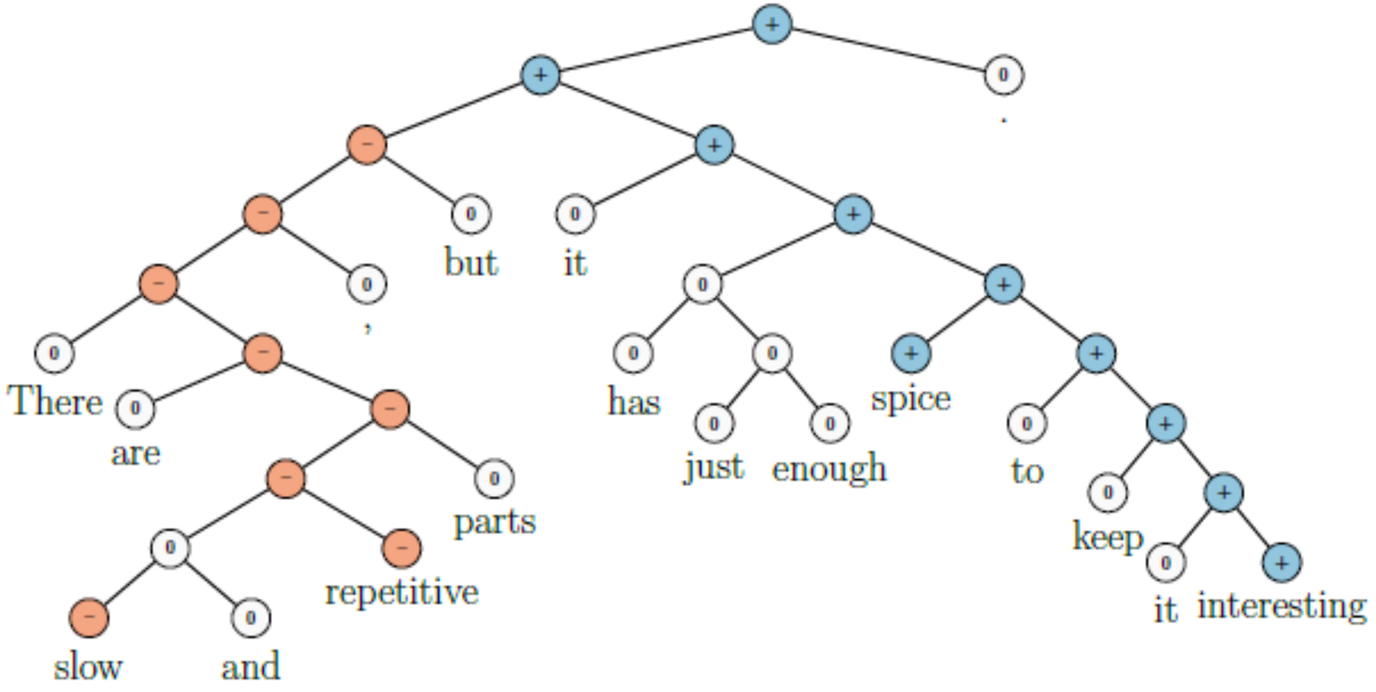
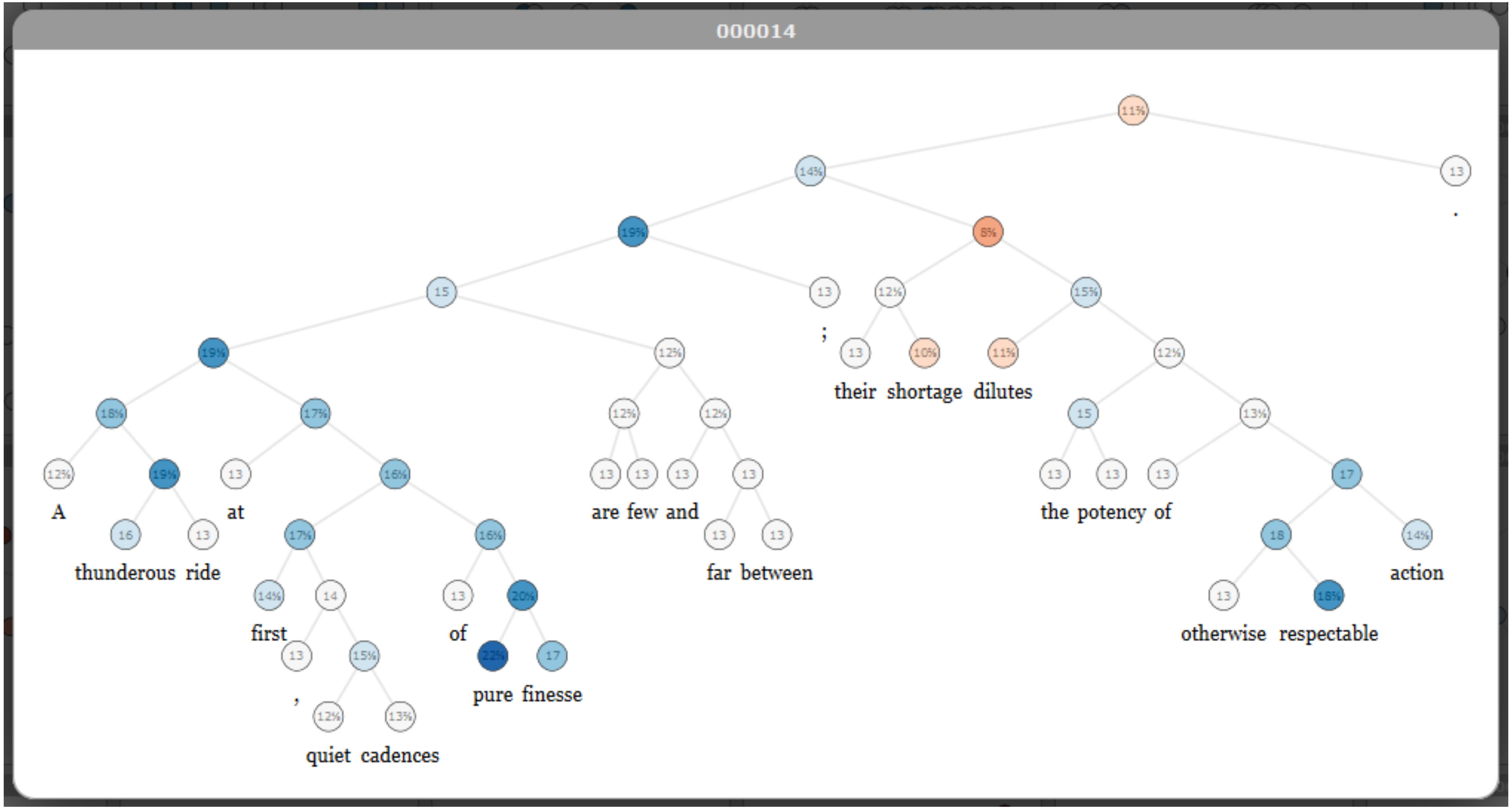
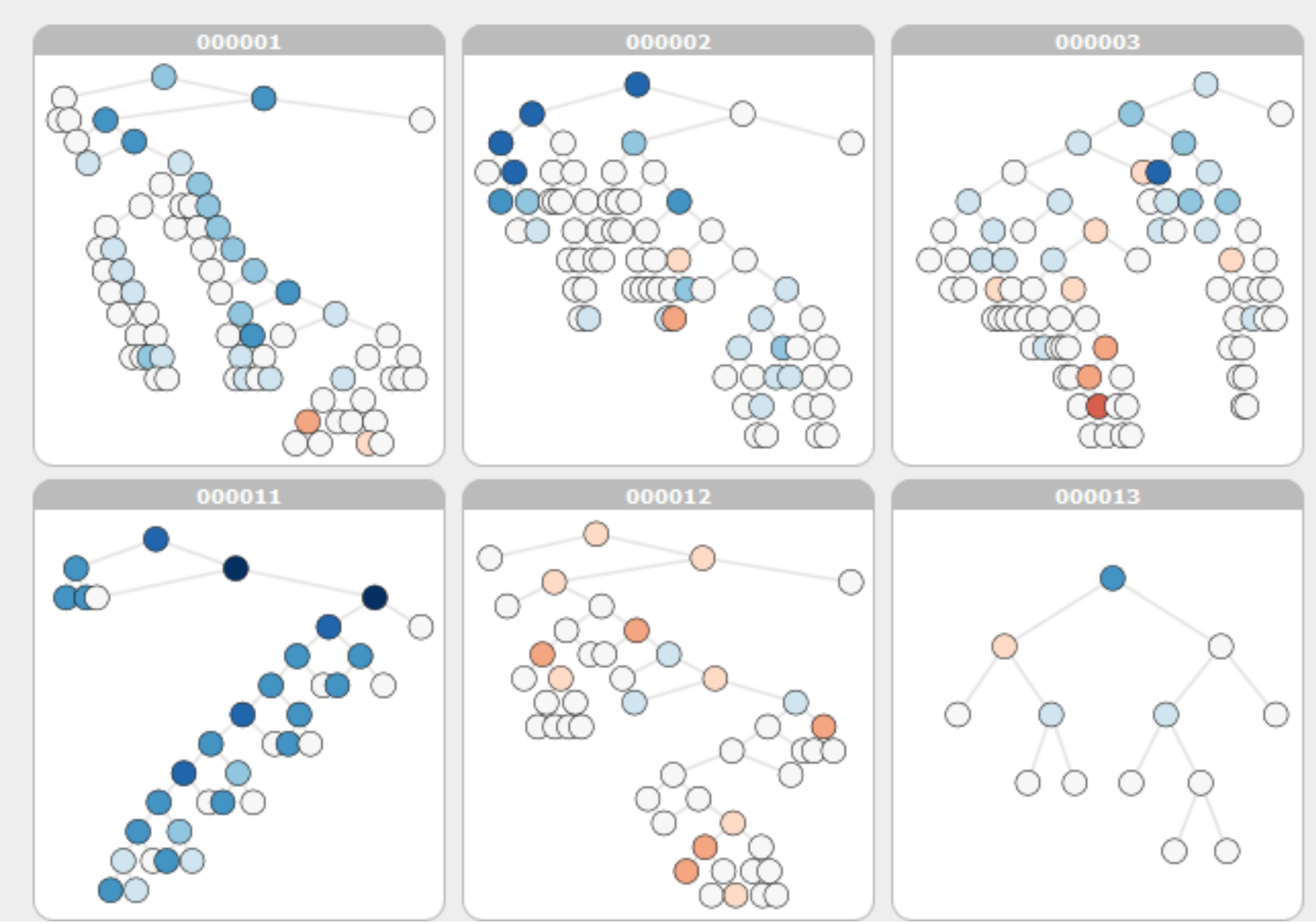


Figure 7: Example of correct prediction for contrastive conjunction X *but* Y.

Stanford Sentiment Treebank



Stanford Sentiment Treebank



https://nlp.stanford.edu/sentiment/treebank.ht
ml

Stanford Sentiment Treebank

The *Stanford Sentiment Treebank* is the first corpus with fully labeled parse trees that allows for a complete analysis of the compositional effects of sentiment in language. The corpus is based on the dataset introduced by Pang and Lee (2005) and consists of 11,855 single sentences extracted from movie reviews. It was parsed with the Stanford parser (Klein and Manning, 2003) and includes a total of 215,154 unique phrases from those parse trees, each annotated by 3 human judges. This new dataset allows us to analyze the intricacies of sentiment and to capture complex linguistic phenomena.

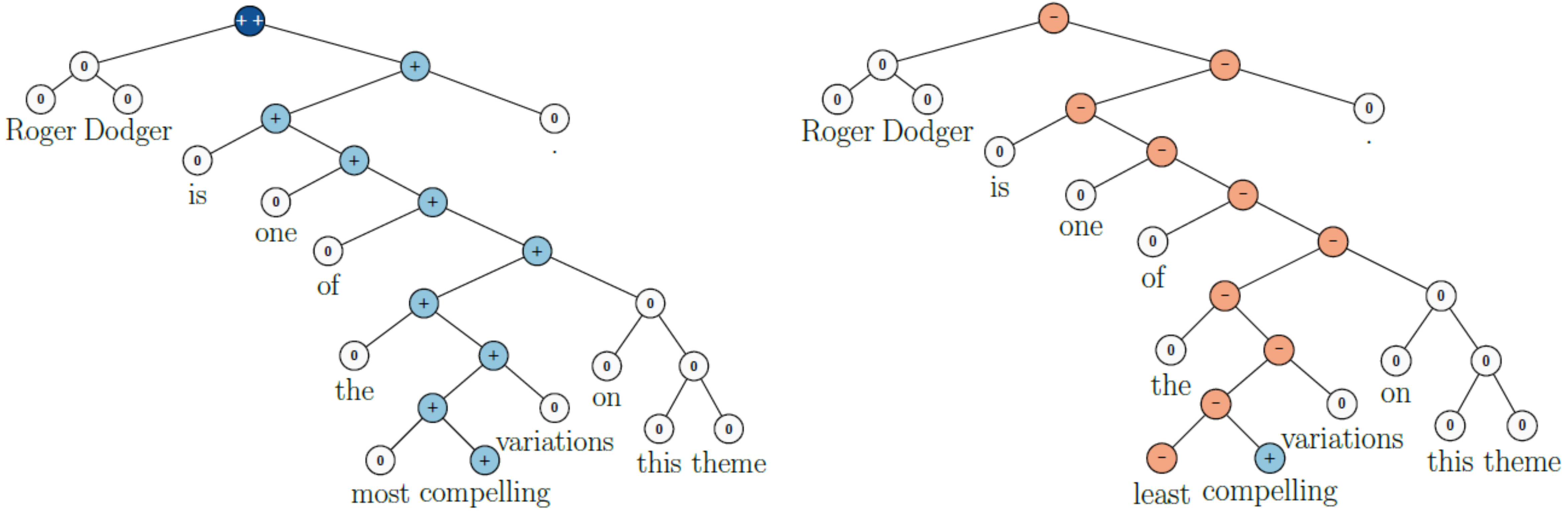
Recursive Neural Networks

Socher et al. (2013)
Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

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**	**45.7**	**87.6**	**85.4**

Table 1: Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes.

Dealing with Negation



[Socher et al. 2013]

Dealing with Negation

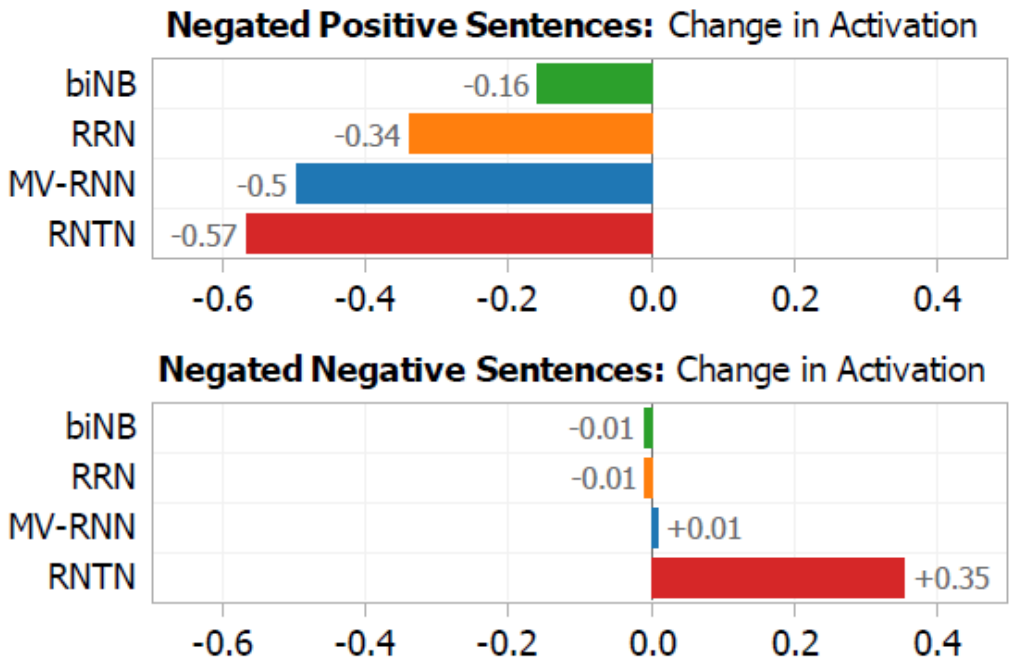


Figure 8: Change in activations for negations. Only the RNTN correctly captures both types. It decreases positive sentiment more when it is negated and learns that negating negative phrases (such as *not terrible*) should increase neutral and positive activations.

[Socher et al. 2013]

Dealing with Negation

n	Most positive n-grams	Most negative n-grams
1	engaging; best; powerful; love; beautiful	bad; dull; boring; fails; worst; stupid; painfully
2	excellent performances; A masterpiece; masterful film; wonderful movie; marvelous performances	worst movie; very bad; shapeless mess; worst thing; instantly forgettable; complete failure
3	an amazing performance; wonderful all-ages triumph; a wonderful movie; most visually stunning	for worst movie; A lousy movie; a complete failure; 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; refreshingly honest and ultimately touching	silliest and most incoherent movie; completely crass and forgettable movie; just another bad movie. A cumbersome and cliche-ridden movie; a humorless, disjointed mess
8	one of the best films of the year; A love for films shines through each frame; created a masterful piece of artistry right here; A masterful film from a master filmmaker,	A trashy, exploitative, thoroughly unpleasant experience ; this sloppy drama is an empty vessel.; quickly drags on becoming boring and predictable.; be the worst special-effects creation of the year

Table 3: Examples of n-grams for which the RNTN predicted the most positive and most negative responses.

[Socher et al. 2013]