Natural Language Understanding

Lecture 17: Distributed Representations for Documents

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1. Introduction
   - Sentences
   - Documents
2. Li and Hovy's Model
3. Other Models

Reading: Li and Hovy (EMNLP, 2014)

Representations for Sentences

1. Vector addition/multiplication
2. Convolutional Neural Networks (CNNs)
3. Sequential language models (RNNs, LSTMs)
4. Recursive neural networks

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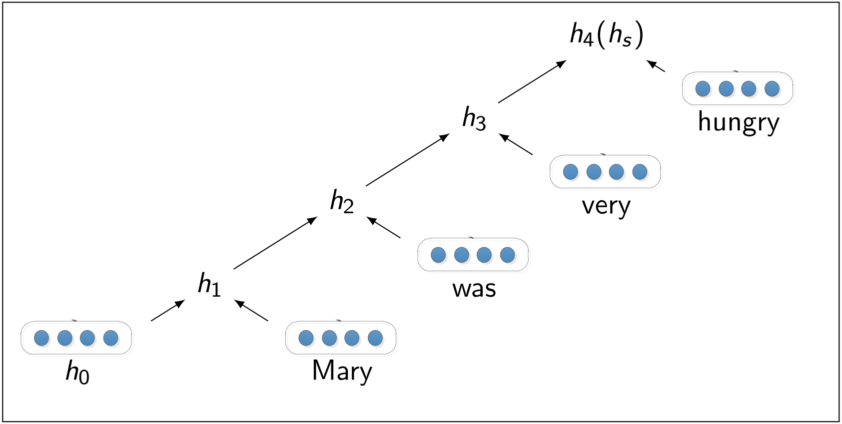
4. Recursive neural networks
   - structure $\approx$ binary trees
   - learn representations for linguistic units

Representations for Documents

- We have to first decide how to represent sentences.
- Then, we compose sentences into a document representation.
- Many classes of models are possible!



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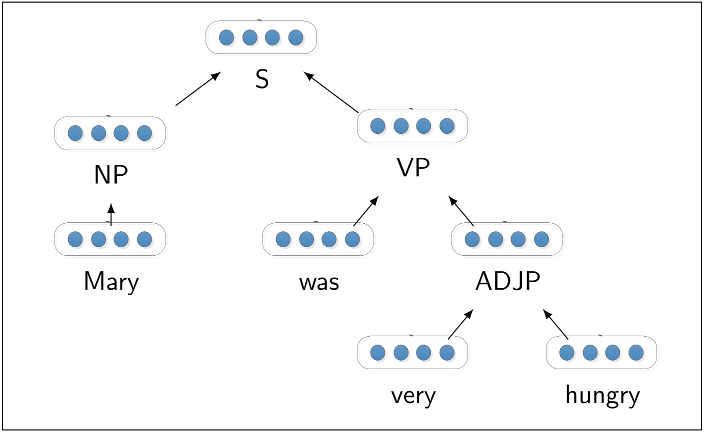

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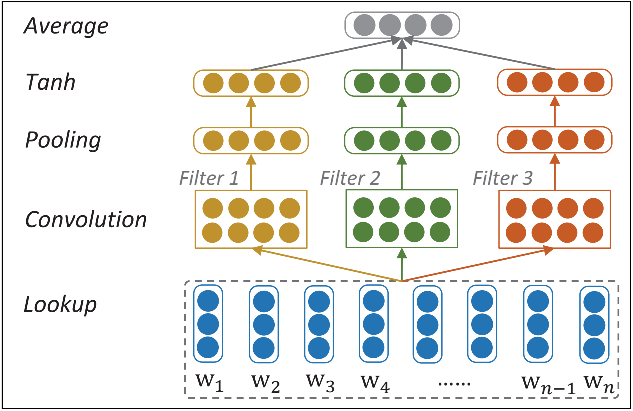

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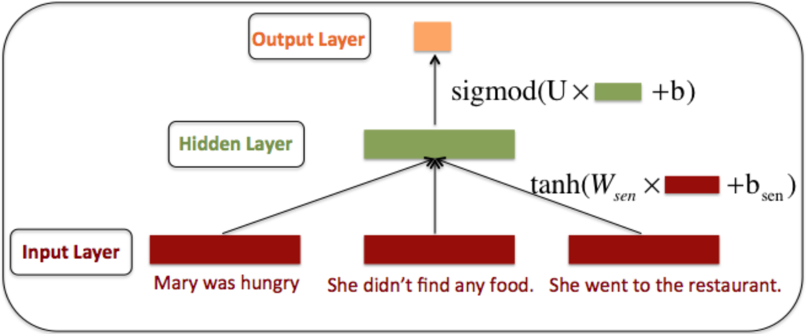
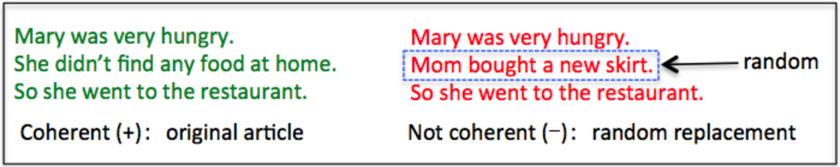


- Model is trained with a classification task in mind.
- Hidden layer learns document representation.
- We will see how this can be used for coherence modeling.

More Formally

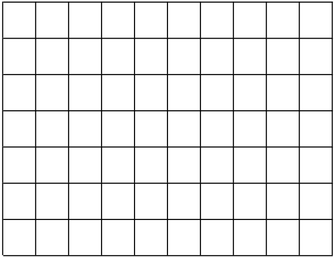
- Let clique C denote a window of sentences
- Each clique has a label $y_C \in 1$ if C coherent and 0 otherwise.
- How are labels generated?



More Formally

Mary was hungry
She didn't find any food at home
So she went to the restaurant
She had a prawn cocktail
It smelled funny
When she went home, she felt sick
She had food poisoning!

$d = 10$



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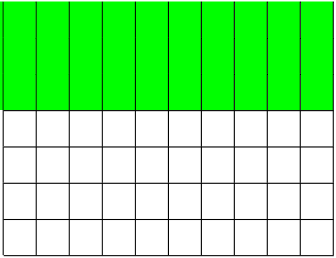

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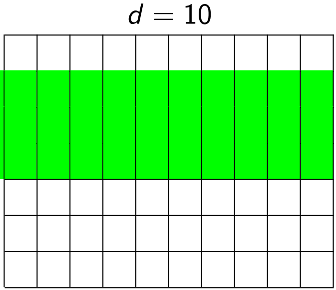

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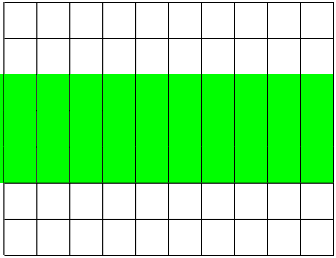

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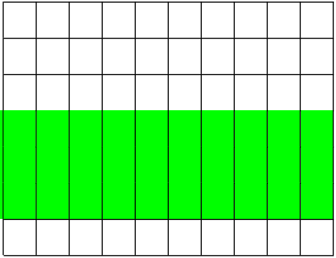

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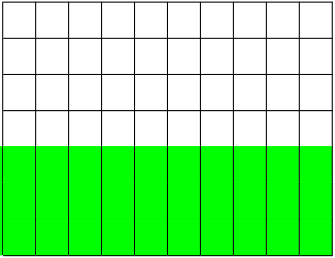

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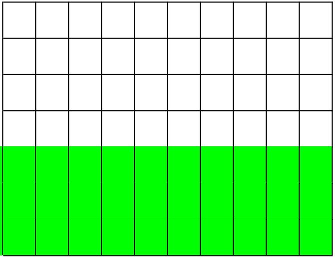

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More Formally

- Let $h_C = [h_{s1}, h_{s2}, \ldots, h_{sL}]$ denote concatenation of sentences.
- Each clique C takes as input a $L \times K$ vector h_C (L is the sentence window size, K dimensionality input sentence)
- Hidden layer H takes h_C as input and performs convolution using non-linear function:

$$q_C = \tanh(W_{sen} \times h_C + b_{sen})$$

- Output layer takes q_C and generates a scalar using linear function; sigmoid projects value to [0,1] probability space:

$$p(y_C = 1) = \text{sigmoid}(U^T q_C + b)$$

Training Objective

$$
\begin{aligned}
J(\Theta) \quad = \quad & \frac{1}{M} \sum_{C \in trainset} \{-y_C \log[p(y_C = 1)] \\
& - (1 - y_C) \log[1 - p(y_C = 1)]\} + \frac{Q}{2M} \sum_{\theta \in \Theta} \theta^2
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- Collection of M labeled training cliques C

Training Objective

$$J(\Theta) = \frac{1}{M} \sum_{C \in trainset} \{-y_C \log[p(y_C = 1)] - (1 - y_C) \log[1 - p(y_C = 1)]\} + \frac{Q}{2M} \sum_{\theta \in \Theta} \theta^2$$

- Collection of M labeled training cliques C
- Error for one clique C with label y_C

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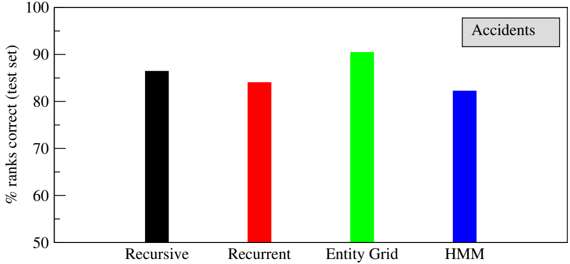
- Collection of M labeled training cliques C
- Error for one clique C with label y_C
- $\Theta = [W_{Recurrent}, W_{sen}, U_{sen}]$
- Regularization parameter

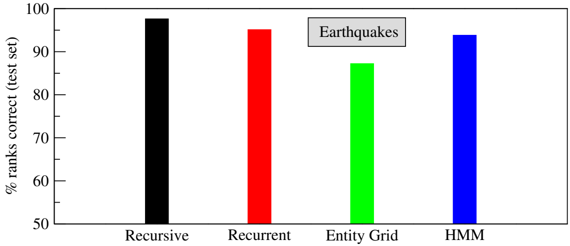
Coherence Rating

- Let S_d denote coherence score for document d
- d consists of sequence of sentences $d = \{s_1, s_2, \dots, s_{N_d}\}$
- The coherence score for a given document S_d is the probability that all cliques within d are coherent:

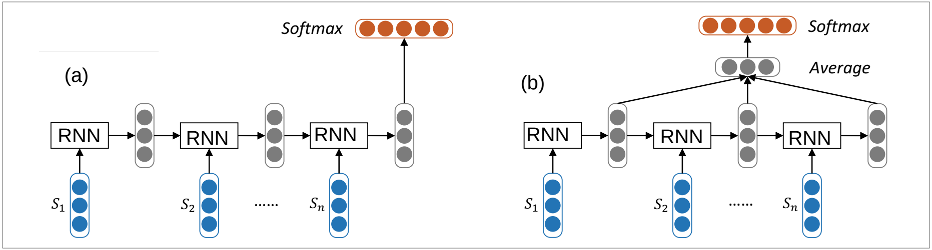
$$S_d = \prod_{C \in d} p(y_C = 1)$$

Results: Ordering





Hierarchical RNNs



Hierarchical CNNs

Document Embedding

Vectorisation

Stackable Layers
- Pooled representation
- K-max pooling
- Feature map
- Wide convolution

Sentence Embedding - Document Matrix

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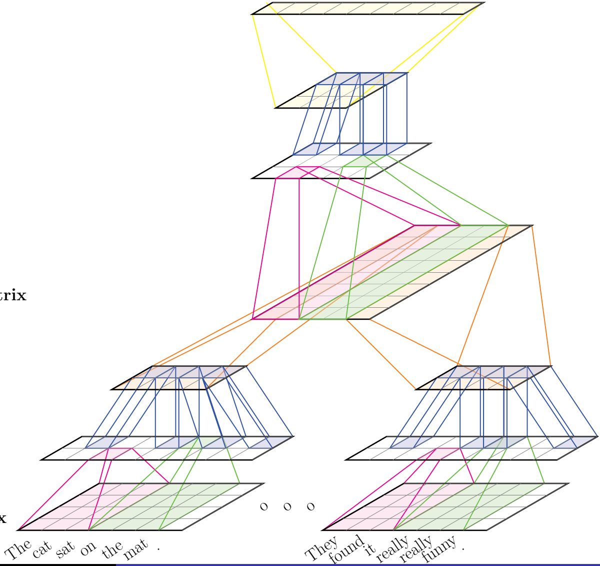
Word Embedding - Sentence Matrix



Conclusions

- Techniques for sentence modeling transfer to documents
- Different classes of models depending on choice of composition model for sentences/documents
- Is it reasonable to compress the meaning of a document in a single vector?
- Choice is motivated by computational reasons.

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