Contextualized Word Embeddings

CS114 Lab 12

Kenneth Lai

April 24, 2020

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Source 1

Source 2

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Source 1

Source 3

Word Embeddings

- Distributed representations of words

Word Embeddings

- Distributed representations of words
  - What is the difference between distributed and distributional representations?

Word Embeddings

- Sparse vectors

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  - One-hot, tf-idf, PPMI, etc.

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Word Embeddings

- Sparse vectors
  - One-hot, tf-idf, PPMI, etc.
- Dense vectors
  - SVD, word2vec, etc.

word2vec

- Based on a feedforward neural network language model

word2vec

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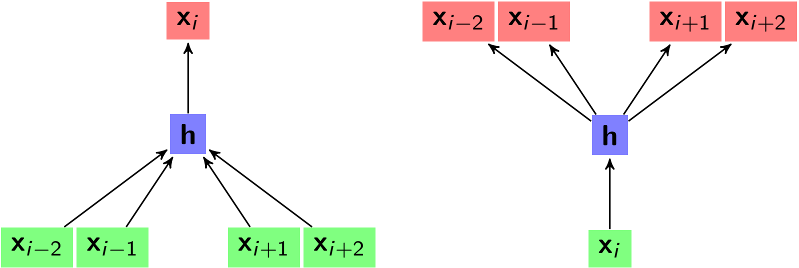

CBOW　　　　Skip-gram

word2vec

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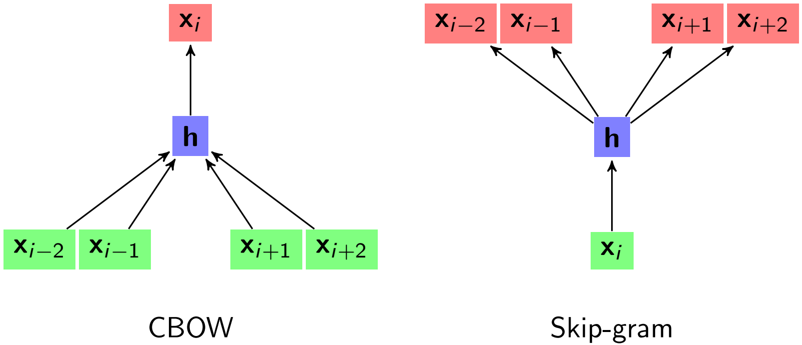

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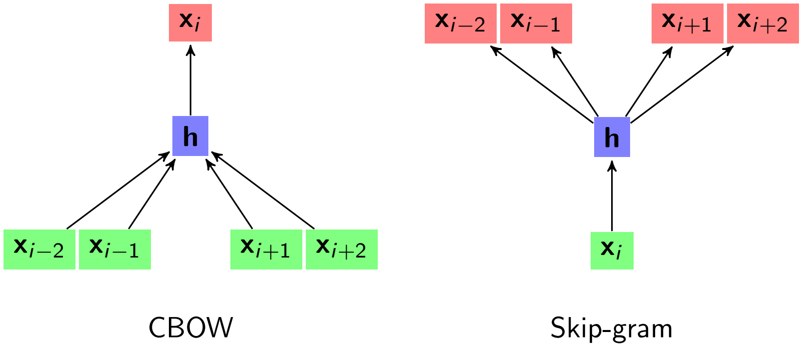

- CBOW: use context to predict current word
- Skip-gram: use current word to predict context

word2vec

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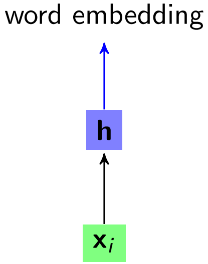

Polysemy

- One vector per word type

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- But words have multiple senses

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  - a mouse[1] controlling a computer system in 1968

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    - Syntagmatic association between mouse^1 and computer

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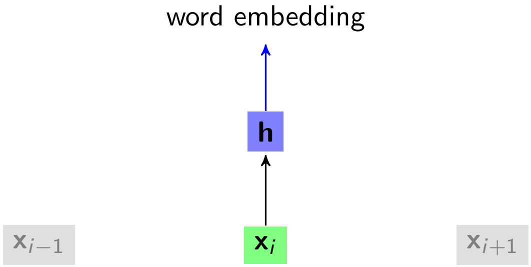
- How can we distinguish between mouse^1 and mouse^2?
  - Context!

Word Embeddings



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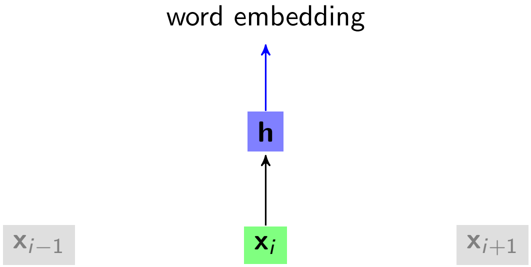

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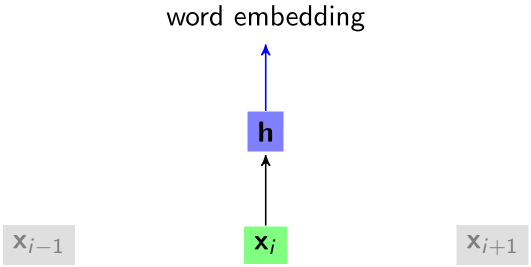

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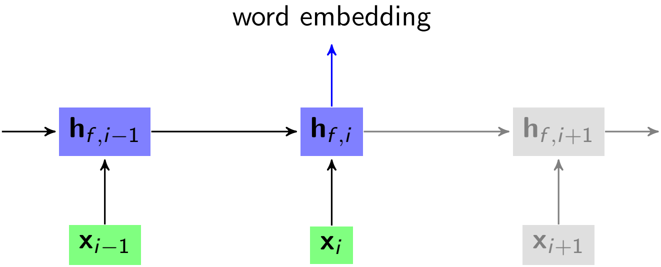

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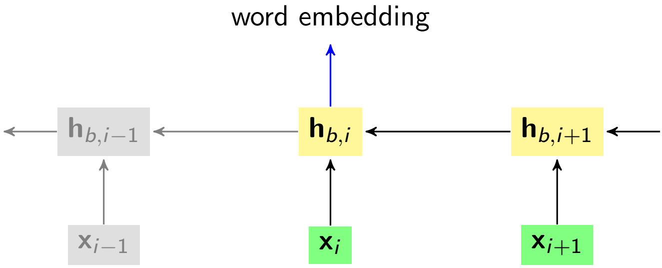

- **h** is an embedding of $\mathbf{x}_i$ only
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- Embeddings from Language Models

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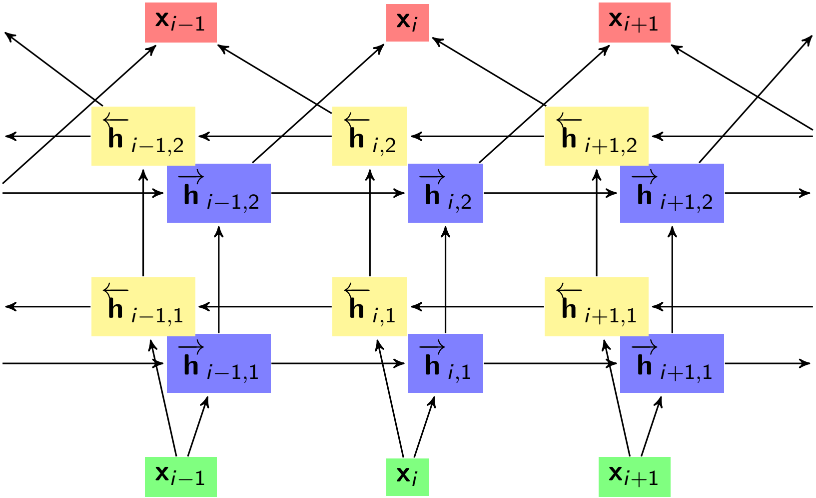
- Based on a bidirectional recurrent neural network language model


$\mathbf{x}_{i-1}$
$\mathbf{x}_{i}$
$\mathbf{x}_{i+1}$
$\overleftarrow{\mathbf{h}}_{i-1,2}$
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$\overleftarrow{\mathbf{h}}_{i+1,2}$
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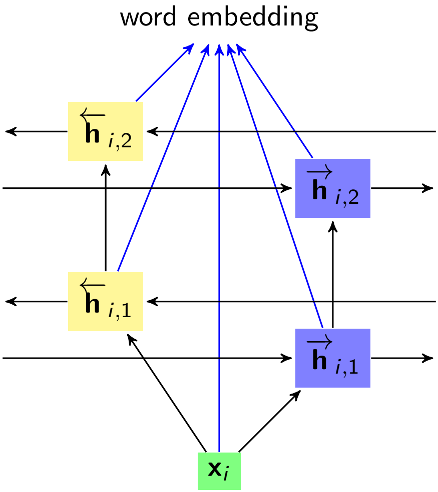
- Word embeddings: weighted sum of outputs of input and LSTM layers (task dependent)


word embedding
$\overleftarrow{\mathbf{h}}_{i,2}$
$\overrightarrow{\mathbf{h}}_{i,2}$
$\overleftarrow{\mathbf{h}}_{i,1}$
$\overrightarrow{\mathbf{h}}_{i,1}$
$\mathbf{x}_i$

Embedding of “stick” in “Let’s stick to” - Step #2

1- Concatenate hidden layers

2- Multiply each vector by a weight based on the task

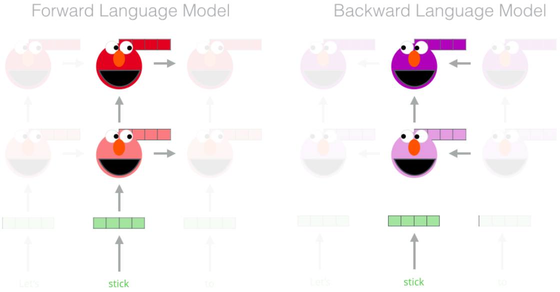
x s_2

x s_1

x s_0

3- Sum the (now weighted) vectors

ELMo embedding of “stick” for this task in this context



Source

- Bidirectional Encoder Representations from Transformers

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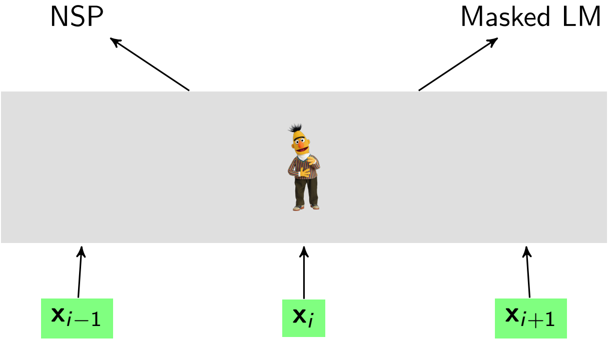

Transformers

- An encoder-decoder architecture with attention

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- Encoders take a sequence as input, output sequence representation
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- Useful for machine translation, among other things
- BERT only uses the encoder part

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- Result: the output for each input i contains information about the whole sequence
  - More information about more relevant parts of the sequence
- Useful for long-distance dependencies, among other things

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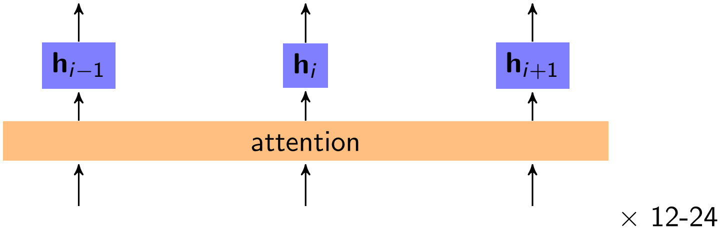

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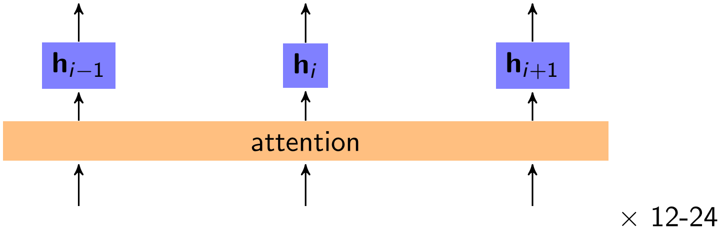

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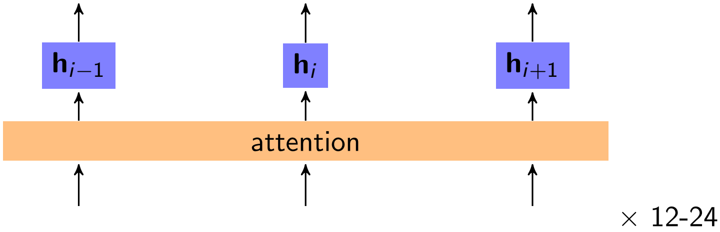

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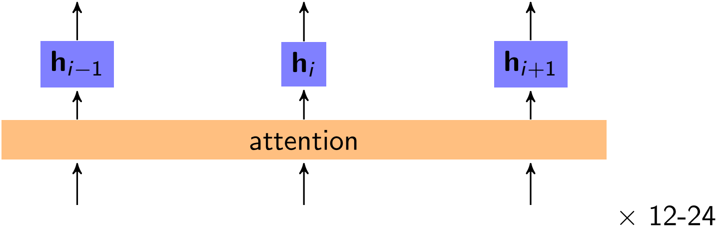

- Output layer: 2 pre-training tasks
  - Masked LM (Cloze)
  - NSP (Next Sentence Prediction)

Masked LM

- Mask 15% of input tokens at random

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- Predict masked words

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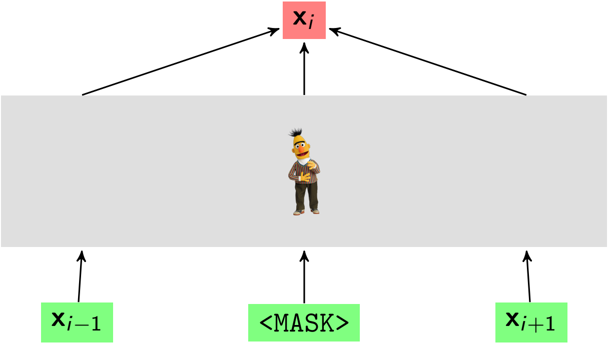

NSP

- Given sentences A and B, does B follow A?

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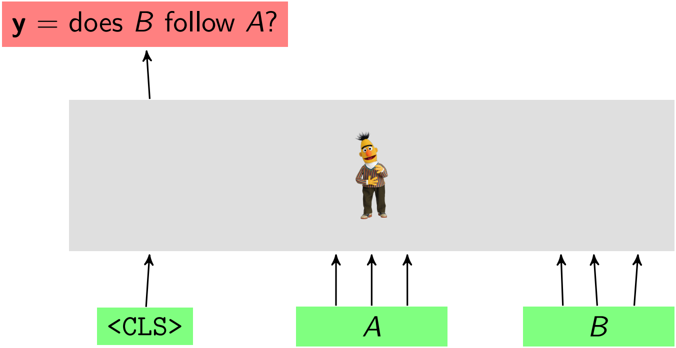

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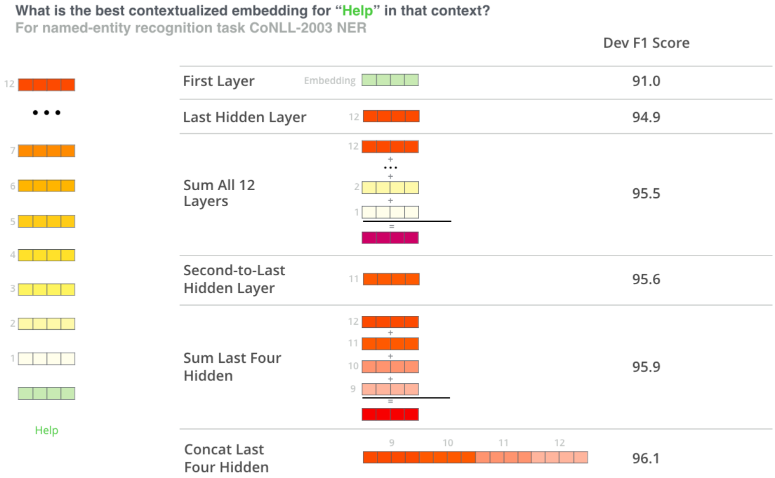

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