Contextualized Word Embeddings

CS114B Lab 12

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April 28, 2022

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Source 1

Source 2

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Source 3

Distributed Representations of Words

- Representations of (contexts of) words as embeddings in some vector space
- Two approaches to distributed, distributional representations (Baroni et al. 2014):
  - Count-based
    - Count occurrences of words in contexts, optionally followed by some mathematical transformation (e.g. tf-idf, PPMI, SVD)
  - Prediction-based
    - Given some context vector(s) $\mathbf{c}$, predict some word $\mathbf{x}$ (or vice versa)
    - a.k.a. language modeling-based

Language Models

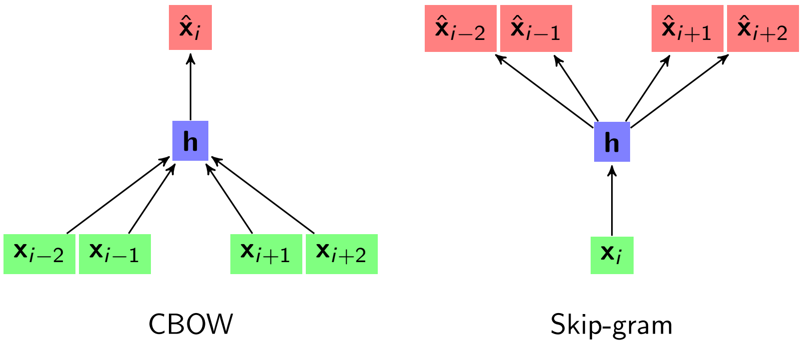
- Given some context vector(s) $\mathbf{c}$, predict some word $\mathbf{x}$ (or vice versa)
- Two approaches to language models:
  - Generative models
    - Model the joint probability distribution $P(\mathbf{x}, \mathbf{c})$
    - Examples: n-gram language models
      - Unigram: predict $P(\mathbf{x}_i)$
      - Bigram: predict $P(\mathbf{x}_i | \mathbf{x}_{i-1})$
      - Trigram: predict $P(\mathbf{x}_i | \mathbf{x}_{i-2}, \mathbf{x}_{i-1})$

Language Models

- Given some context vector(s) $\mathbf{c}$, predict some word $\mathbf{x}$ (or vice versa)
- Two approaches to language models:
  - Discriminative models
    - Predict the conditional probability $P(\mathbf{x}|\mathbf{c})$ (or $P(\mathbf{c}|\mathbf{x})$) directly
    - Examples: neural network language models
      - Feedforward: word2vec (Mikolov et al. 2013a, 2013b)
      - Recurrent:  (Peters et al. 2018)
      - Transformer:  (Devlin et al. 2019)

word2vec

- Based on a feedforward neural network language model



- Continuous bag of words (CBOW): use context to predict current word
- Skip-gram: use current word to predict context

word2vec

- Input layer: one-hot word vectors
- Hidden (projection) layer: identity activation function, no bias
  - Input $\rightarrow$ hidden $=$ table lookup (in weight matrix)
- Output layer: softmax activation function

word2vec

- Skip-gram model: for each word, word2vec learns two word embeddings
  - Target word vector $\mathbf{w}$ (row of $\mathbf{W}$, $=$ output of hidden layer)
  - "Context" word vector $\mathbf{c}$ (column of $\mathbf{C}$)

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  - Add $\mathbf{w} + \mathbf{c}$
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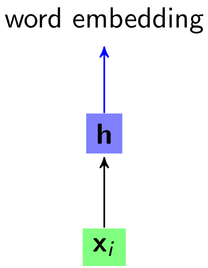

word2vec

- Two issues with word2vec:

word2vec

- Two issues with word2vec:
  - One vector per word type

word2vec

- Two issues with word2vec:
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    - Limited (fixed-length) context

Polysemy

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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?

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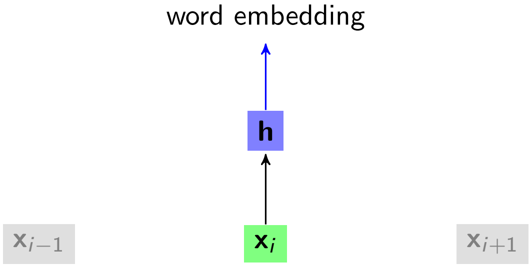
- How can we distinguish between mouse^1 and mouse^2?
  - Context!

Word Embeddings



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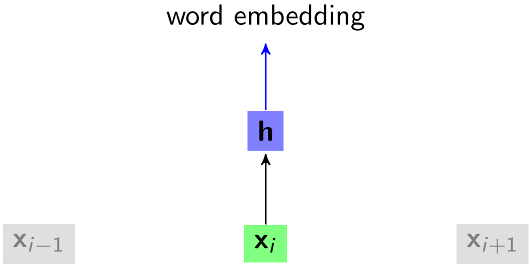

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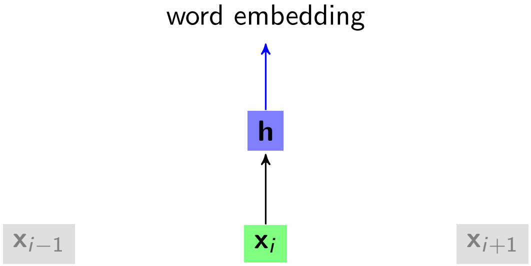

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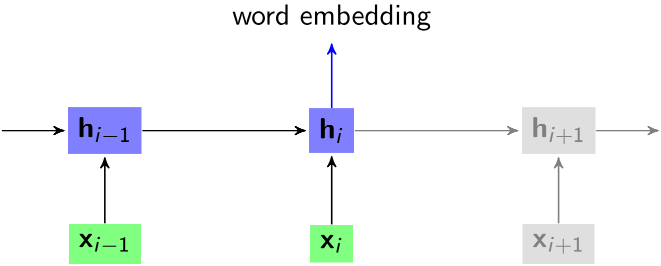

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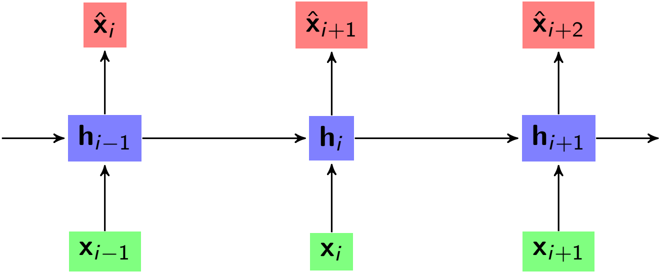
Recurrent Neural Networks



- Neural networks in which the output of a layer in one time step is input to a layer in the next time step

Recurrent Neural Networks

- RNNs allow for contextualized word embeddings

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- RNNs allow for contextualized word embeddings
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  - Arbitrary-length context
- Is this enough?

Context and Long-Distance Dependencies

- $\mathbf{h}_{i-1}$ encodes the context $\mathbf{x}_1, ..., \mathbf{x}_{i-1}$

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  - But mostly $\mathbf{x}_{i-1}$, less $\mathbf{x}_{i-2}$, even less $\mathbf{x}_{i-3}$, ..., very little $\mathbf{x}_1$

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- Context is local

Context and Long-Distance Dependencies

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- The flights the airline was cancelling (was/were) full.

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    - Very little “flights”

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    - At each time step, the model explicitly computes which other words to pay attention to

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    - At each time step, the model explicitly computes which other words to pay attention to
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- Embeddings from Language Models

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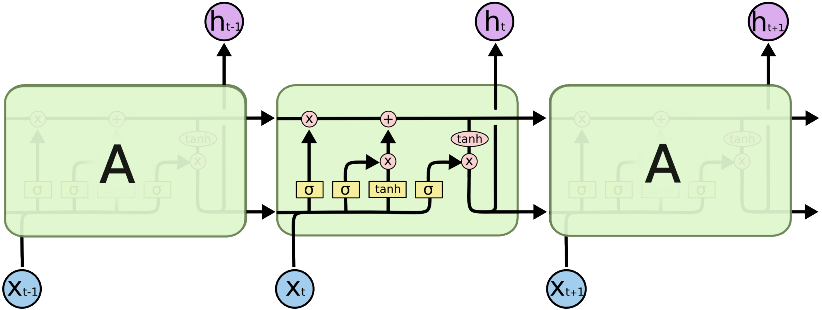
- Based on a bidirectional long short-term memory (LSTM) language model

Long Short-Term Memory



Source

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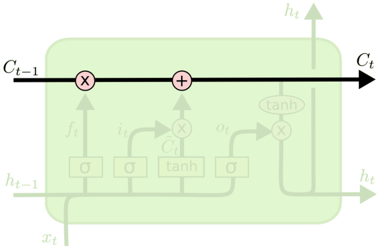

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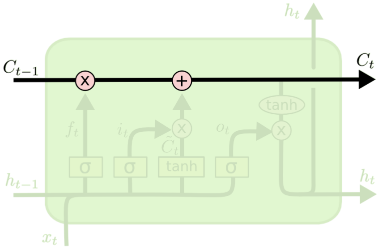
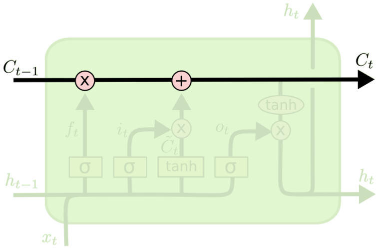


Source

- Separate memory (cell) state

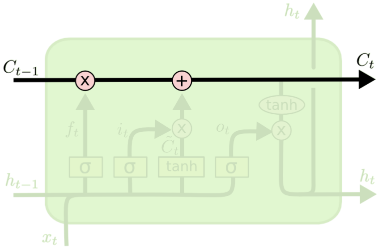
Long Short-Term Memory



Source

- Separate memory (cell) state
  - Reading from and writing to memory controlled by gates

Long Short-Term Memory



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    - Each gate contains one or two neural network layers

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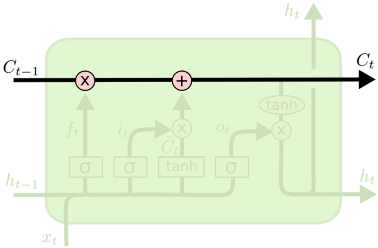

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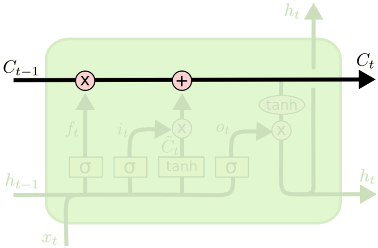

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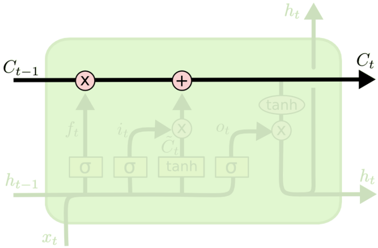

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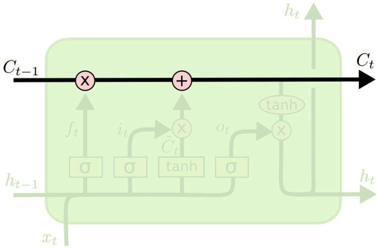

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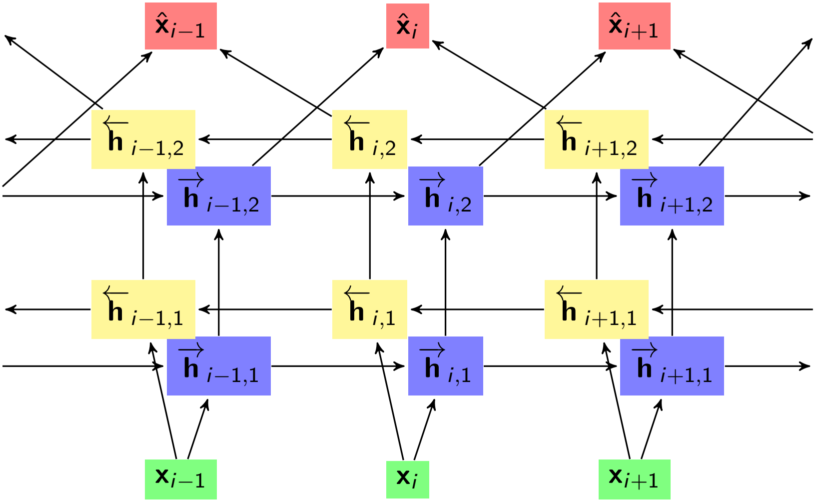
- See Christopher Olah's Understanding LSTM Networks for more details!



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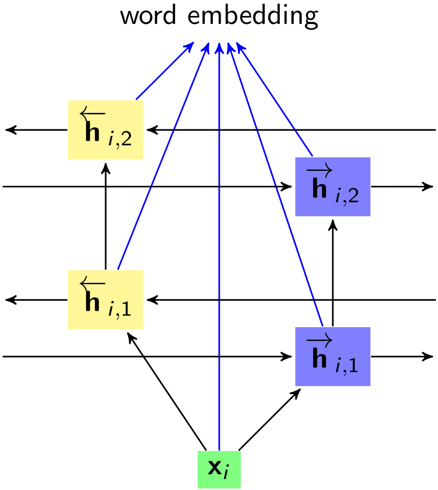
- Word embeddings: weighted sum of outputs of input and LSTM layers (task dependent)


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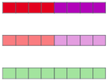
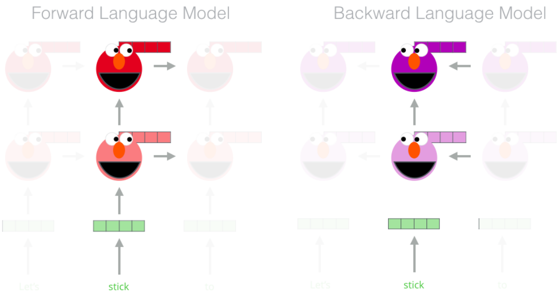
$\overrightarrow{\mathbf{h}}_{i,1}$
$\mathbf{x}_i$

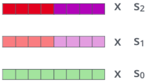
Embedding of “stick” in “Let’s stick to” - Step #2

1- Concatenate hidden layers





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



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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- Based on a transformer ("attention is all you need") model

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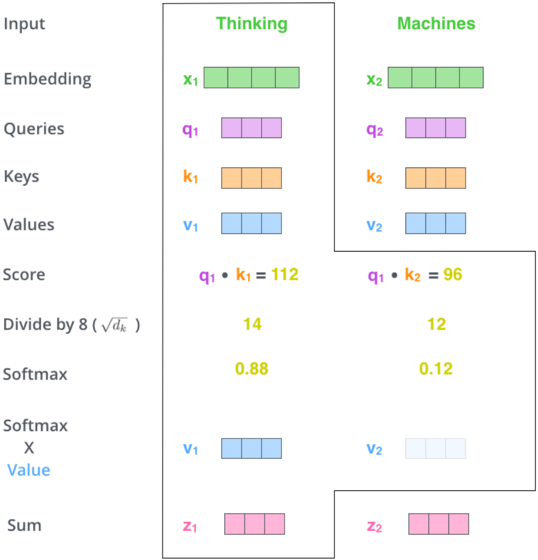
  4. Softmax
  5. Compute the weighted sum of values v_j for each word j
     - Weights = softmax output from previous step

Attention



Source

Attention

- Output: weighted sum of value vectors (modulo some more advanced topics)

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  - Positional encodings
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- See Jay Alammar's The Illustrated Transformer for more details!

Transformers

- "Attention Is All You Need" (Vaswani et al. 2017)

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  - Recurrent neural networks are inherently sequential, processing one word at a time
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    - More efficient, especially on GPUs
    - Also scores better on many NLP tasks

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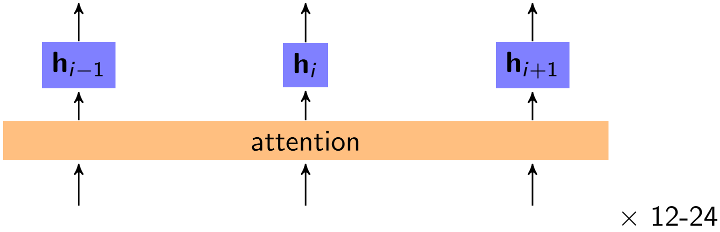

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    - Mask 15% of input tokens at random, predict masked words
  - NSP (Next Sentence Prediction)
    - Given sentences A and B, does B follow A?

- Word embeddings: combinations of outputs of encoder layers

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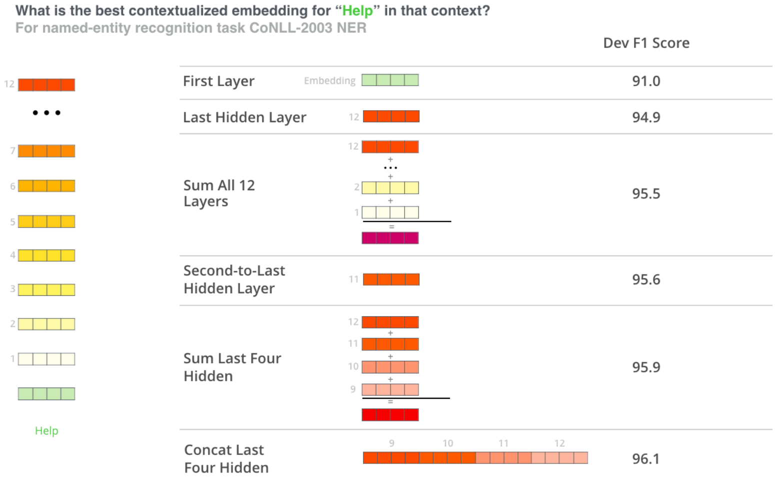

Source

References

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