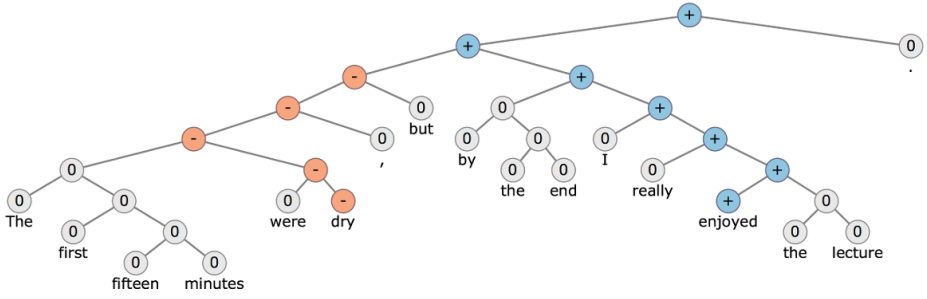
Natural Language Processing with Deep Learning

Charles Ollion - Olivier Grisel

Natural Language Processing

[Google Translate System - 2016]



[Socher 2015]

Natural Language Processing

- Sentence/Document level Classification (topic, sentiment)
- Topic modeling (LDA, ...)

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- Summarization

Recommended reading

A Primer on Neural Network Models for Natural Language Processing by Yoav Goldberg

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Useful open source projects

HUGGING FACE

Outline

Classification and word representation

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Word2Vec

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Language Modelling

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Recurrent neural networks

Word Representation and Word2Vec

Word representation

Words are indexed and represented as 1-hot vectors

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Large Vocabulary of possible words $|V|$

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Use of **Embeddings** as inputs in all Deep NLP tasks

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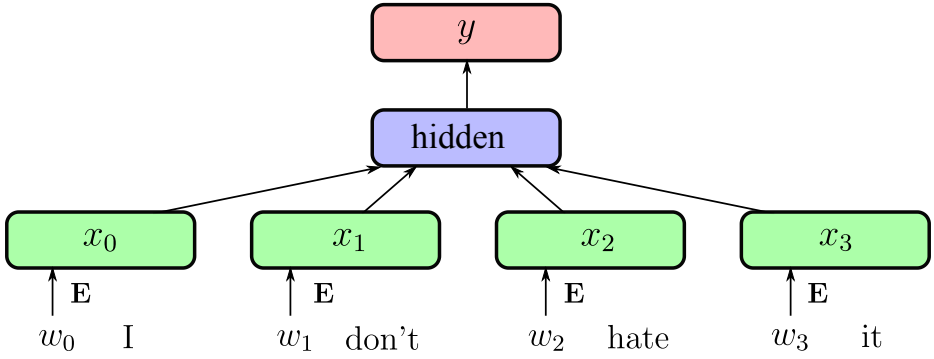
Use of **Embeddings** as inputs in all Deep NLP tasks

Word embeddings usually have dimensions 50, 100, 200, 300

Supervised Text Classification



Joulin, Armand, et al. "Bag of tricks for efficient text classification." FAIR 2016

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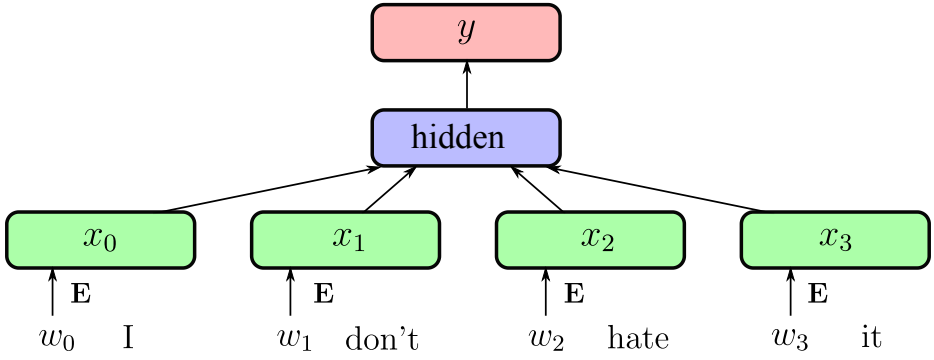

E embedding (linear projection) |V| x H

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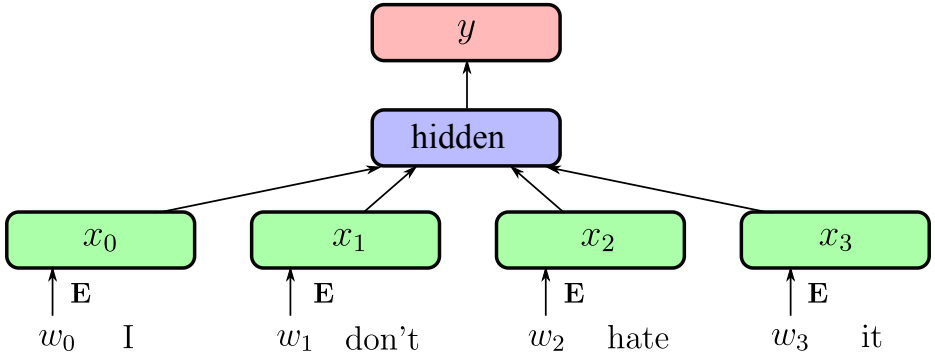

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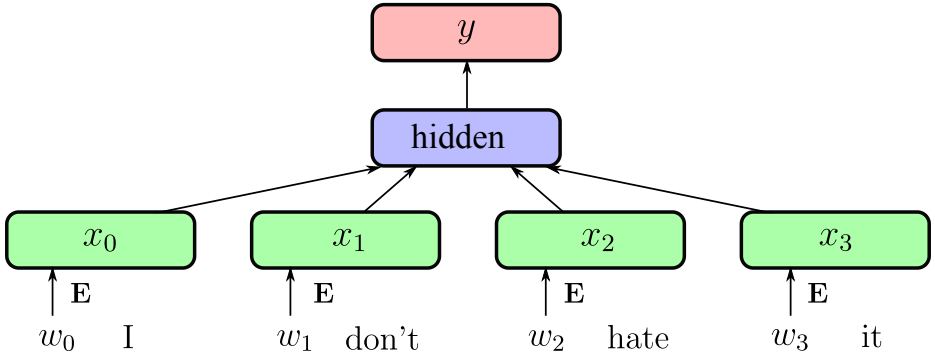

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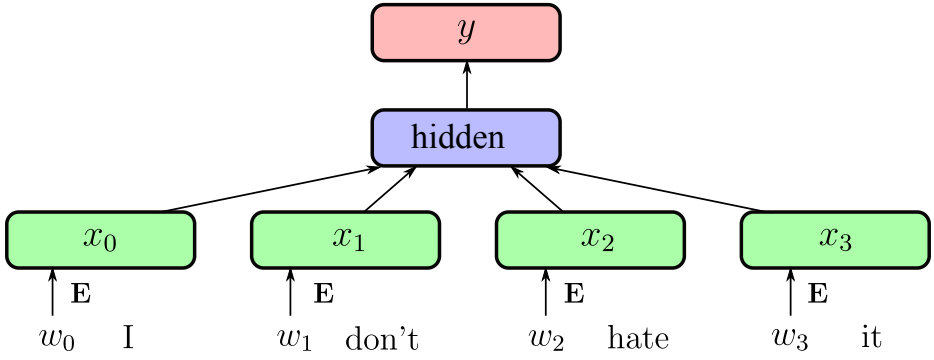

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Softmax and **cross-entropy** loss

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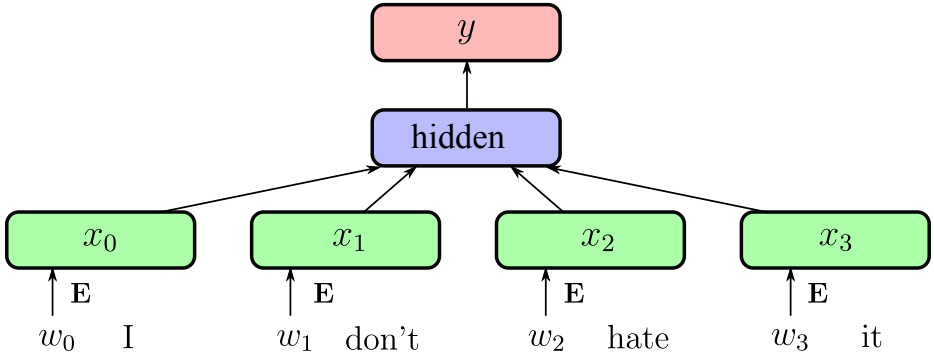

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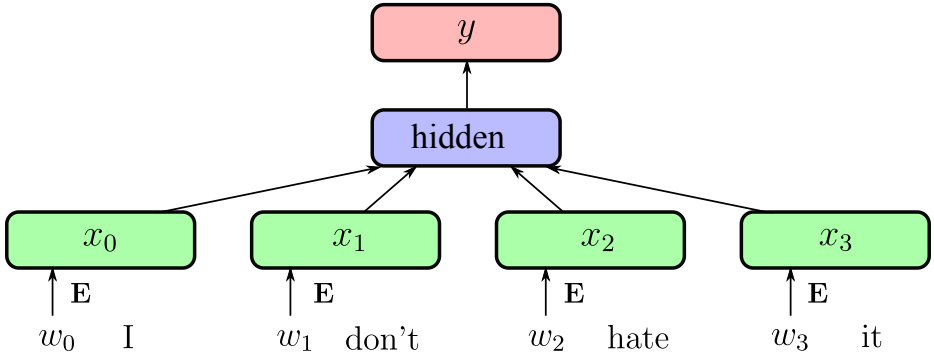

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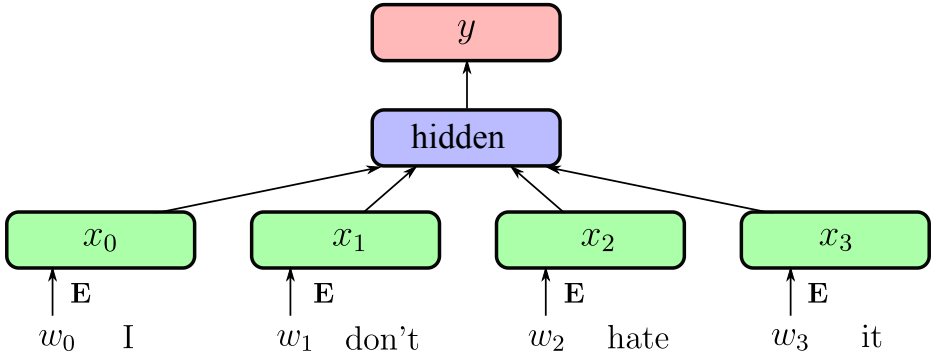

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- Little gains from depth

Transfer Learning for Text

Similar to image: can we have word representations that are generic enough to **transfer** from one task to another?

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Unsupervised / self-supervised learning of word representations

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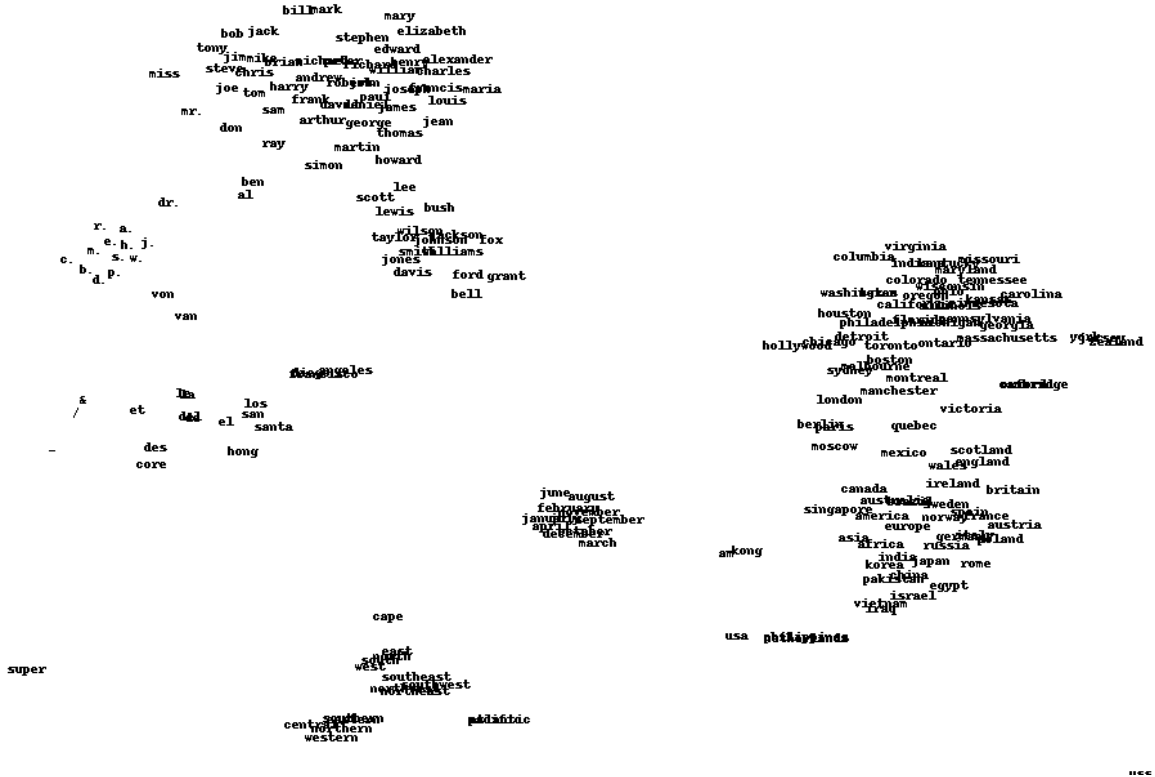
Unsupervised / self-supervised learning of word representations

Unlabelled text data is almost infinite:

- Wikipedia dumps
- Project Gutenberg
- Social Networks
- Common Crawl

Word Vectors



excerpt from work by J. Turian on a model trained by R. Collobert et al. 2008

Word2Vec

FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
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Colobert et al. 2011, Mikolov, et al. 2013

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Compositionality

Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

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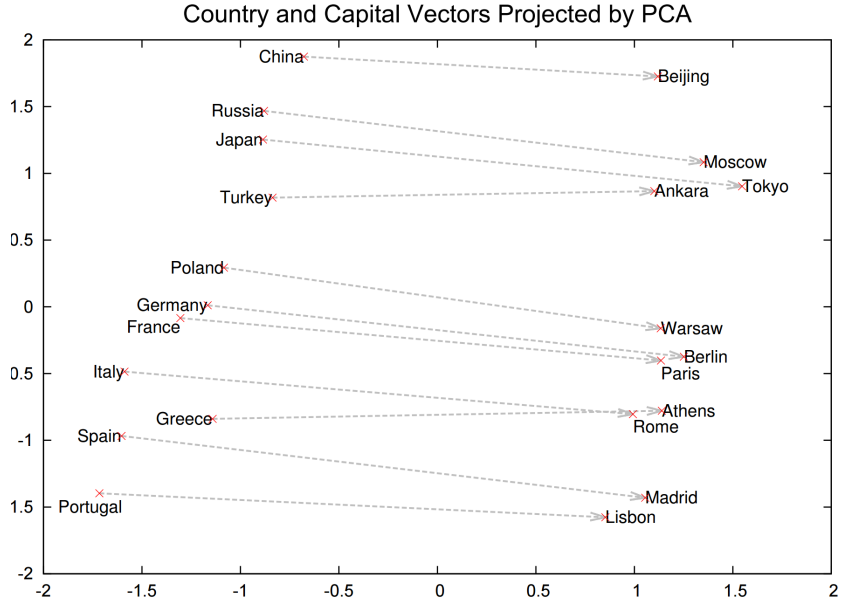
Word Analogies



Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." NIPS 2013

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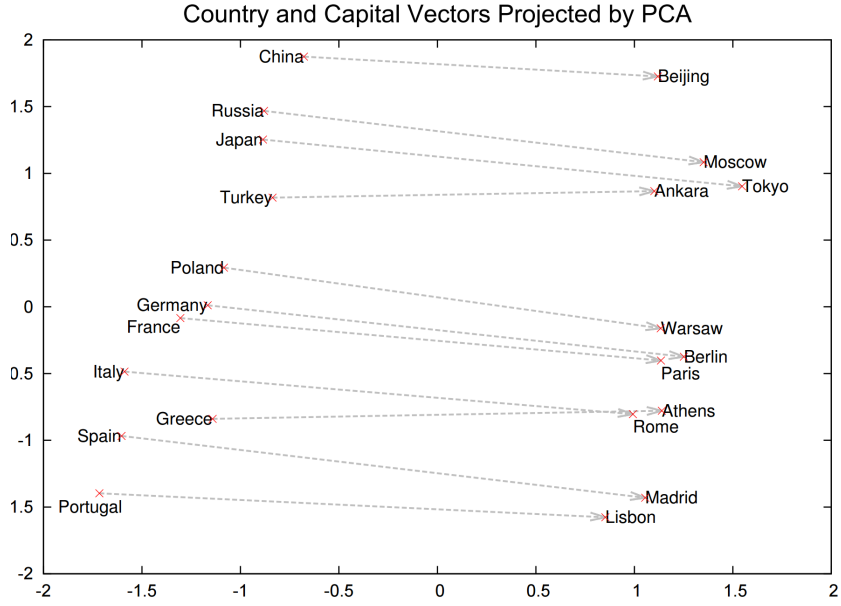

- Linear relations in Word2Vec embeddings

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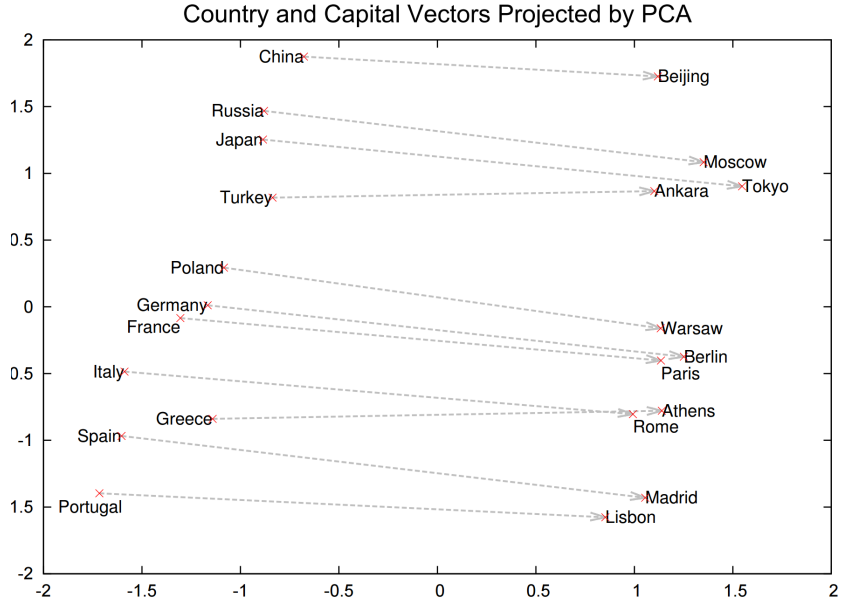

- Linear relations in Word2Vec embeddings
- Many come from text structure (e.g. Wikipedia)
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Self-supervised training

Distributional Hypothesis (Harris, 1954): *“words are characterised by the company that they keep”*

Main idea: learning word embeddings by **predicting word contexts**

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Main idea: learning word embeddings by **predicting word contexts**

Given a word e.g. “carrot” and any other word $w \in V$ predict probability $P(w \mid \text{carrot})$ that w occurs in the context of “carrot”.

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Given a word e.g. "carrot" and any other word $w \in V$ predict probability $P(w \mid \text{carrot})$ that w occurs in the context of "carrot".

- **Unsupervised / self-supervised**: no need for class labels.
- (Self-)supervision comes from **context**.
- Requires a lot of text data to cover rare words correctly.

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Word2Vec: CBoW

CBoW: representing the context as **Continuous Bag-of-Word**

Self-supervision from large unlabeled corpus of text: *slide* over an **anchor word** and its **context**:

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the carrot is a root vegetable, usually orange
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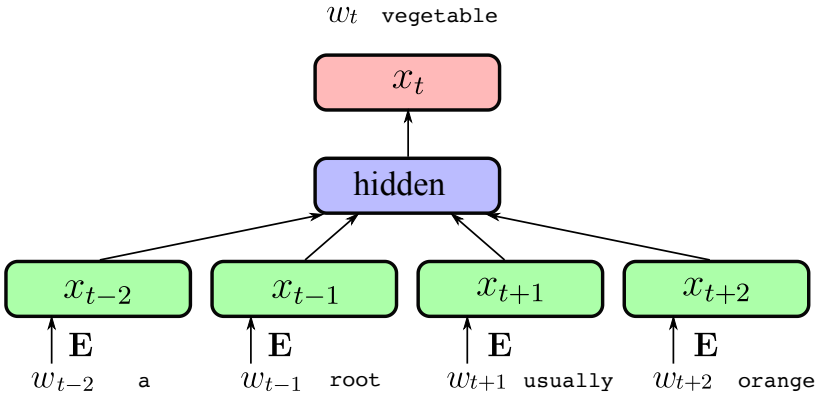

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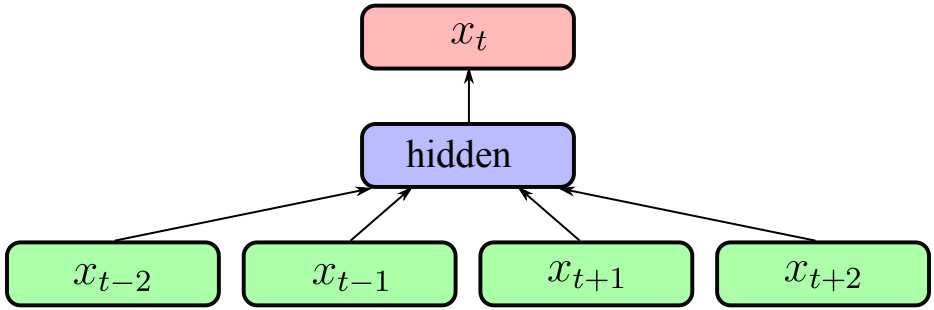

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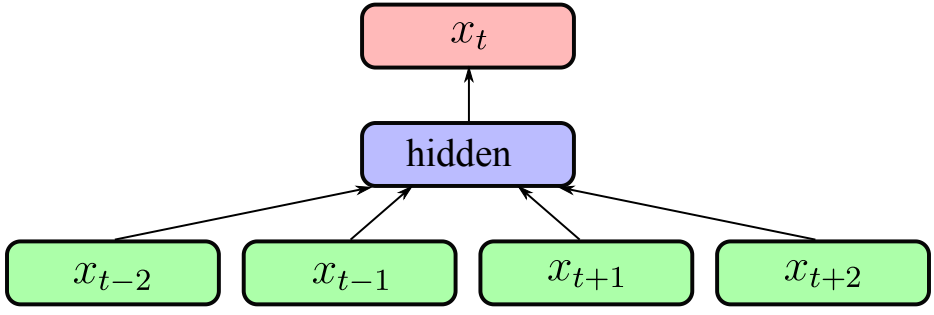

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- Use **Negative Sampling**: sample *negative* words at random instead of computing the full softmax. See:

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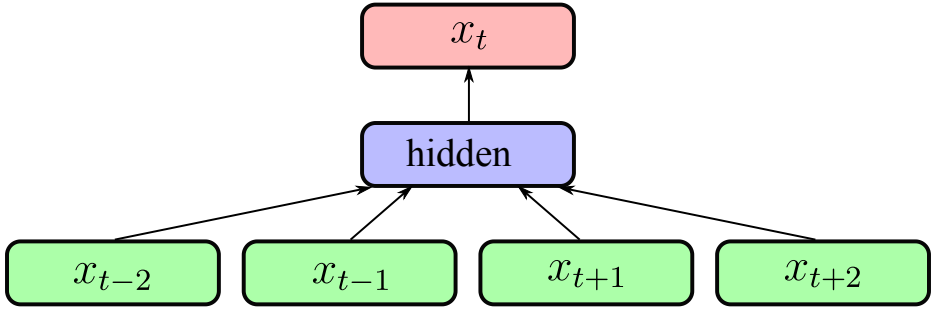

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- Large impact of **context size**

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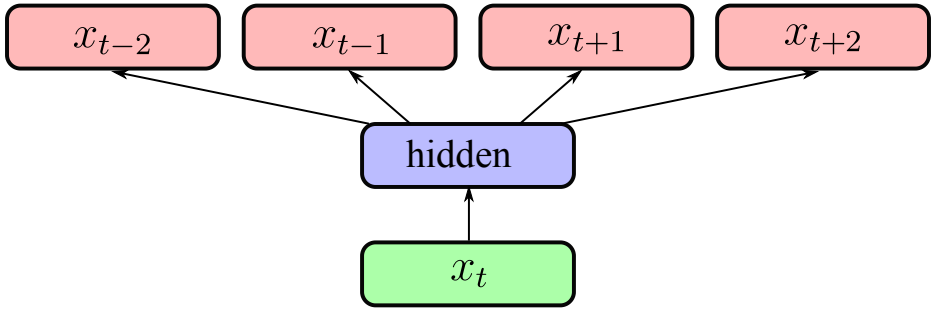
Word2Vec: Skip Gram

a



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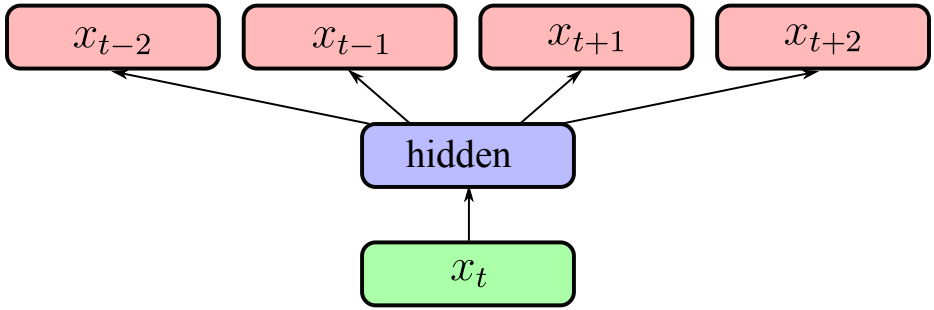

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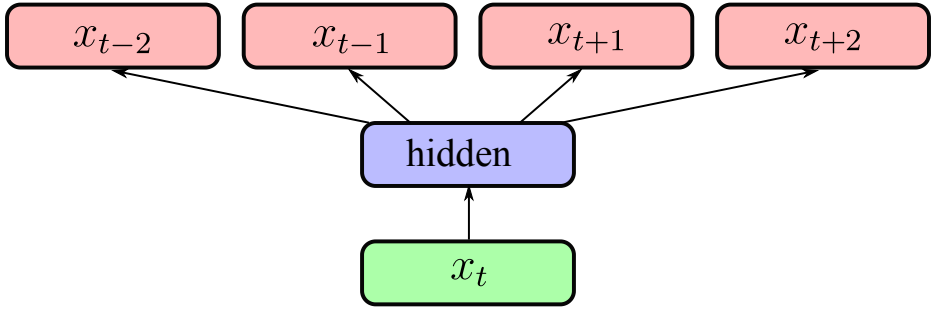

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- Again **Negative Sampling** is used as a cheaper alternative to full softmax.

Evaluation and Related methods

Always difficult to evaluate unsupervised tasks

- WordSim (Finkelstein et al.)
- SimLex-999 (Hill et al.)
- Word Analogies (Mikolov et al.)

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Other popular method: **GloVe** (Socher et al.)
http://nlp.stanford.edu/projects/glove/

Pennington, Jeffrey, Richard Socher, and Christopher D. Manning. "Glove: Global Vectors for Word Representation." EMNLP. 2014

Take Away on Embeddings

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Language Modelling and Recurrent Neural Networks

Language Models

Assign a probability to a sequence of words, such that plausible sequences have higher probabilities e.g:

- p("I like cats") > p("I table cats")
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$$p_\theta(w_0) \cdot p_\theta(w_1 \mid w_0) \cdot \ldots \cdot p_\theta(w_n \mid w_{n-1}, w_{n-2}, \ldots, w_0)$$

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p_θ is parametrized by a neural network.

The internal representation of the model can better capture the meaning of a sequence than a simple Bag-of-Words.

Conditional Language Models

NLP problems expressed as **Conditional Language Models**:

Translation: $p(Target \mid Source)$

- *Source*: "J'aime les chats"
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Conditional Language Models

Question Answering / Dialogue:

$p(Answer \mid Question, Context)$

- *Context*:
  - "John puts two glasses on the table."
  - "Bob adds two more glasses."
  - "Bob leaves the kitchen to play baseball in the garden."
- *Question*: "How many glasses are there?"
- *Answer*: "There are four glasses."

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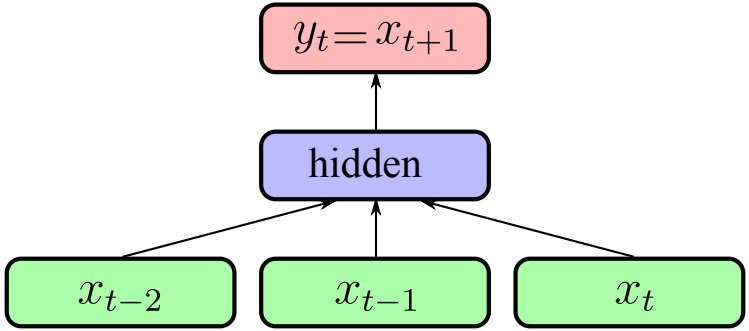
Image Captionning: $p(Caption \mid Image)$

- Image is usually the 2048-d representation from a CNN

Simple Language Model



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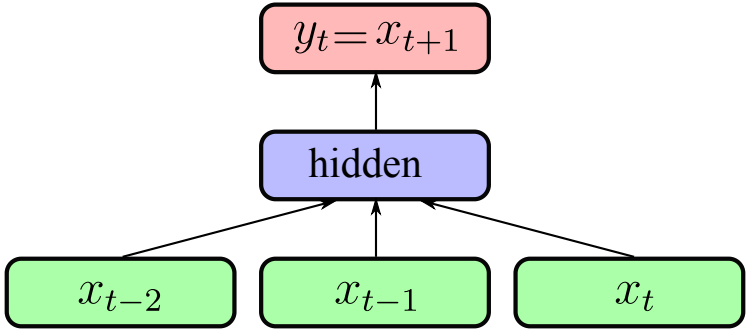
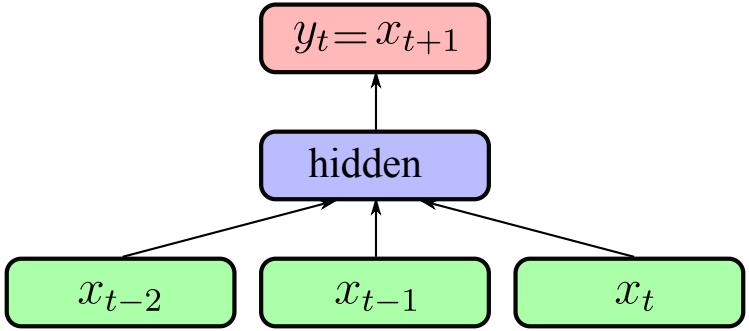


Fixed context size

- **Average embeddings**: (same as CBoW) no sequence information

Simple Language Model



Fixed context size

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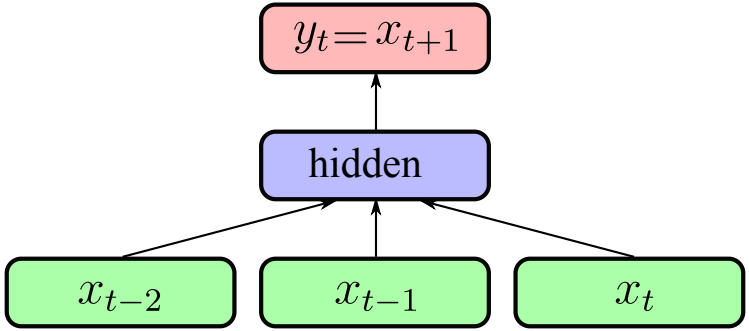
Simple Language Model



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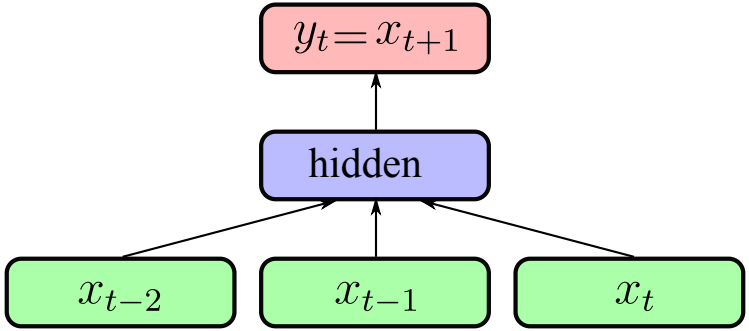

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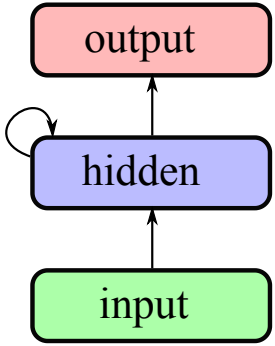
Recurrent Neural Network



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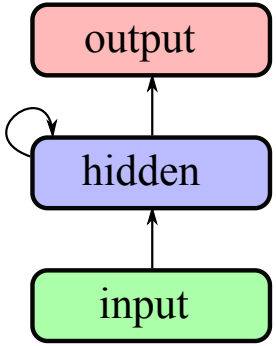
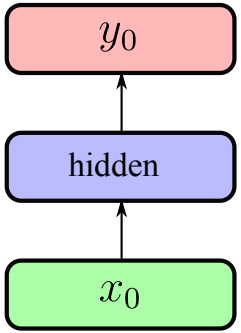
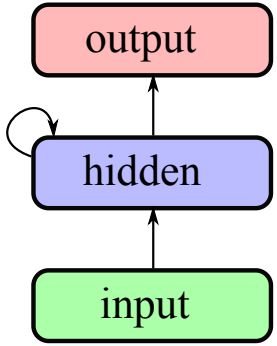


Unroll over a sequence (x_0, x_1, x_2):



Recurrent Neural Network



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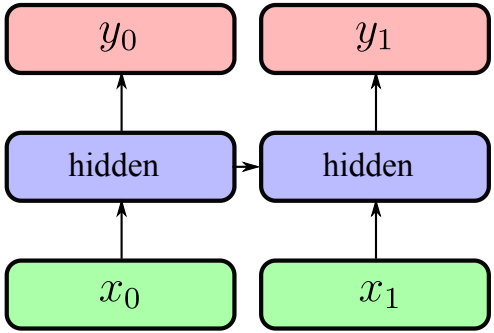

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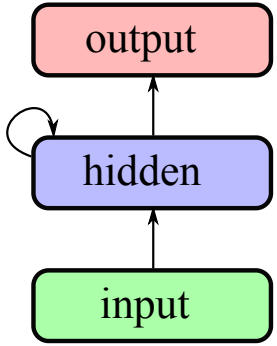

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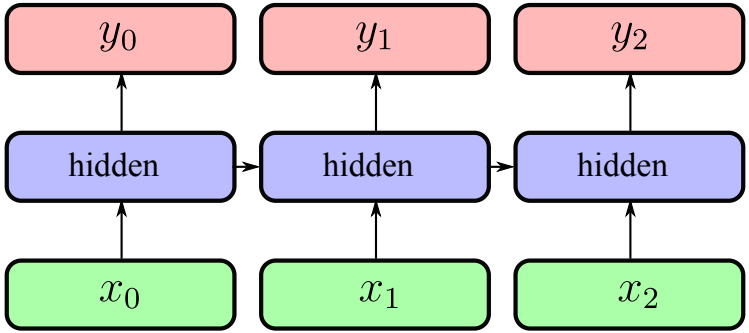
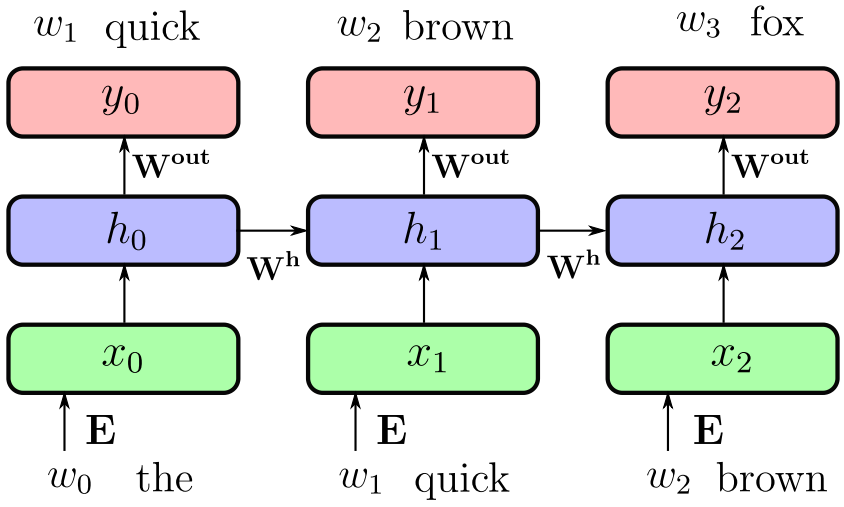


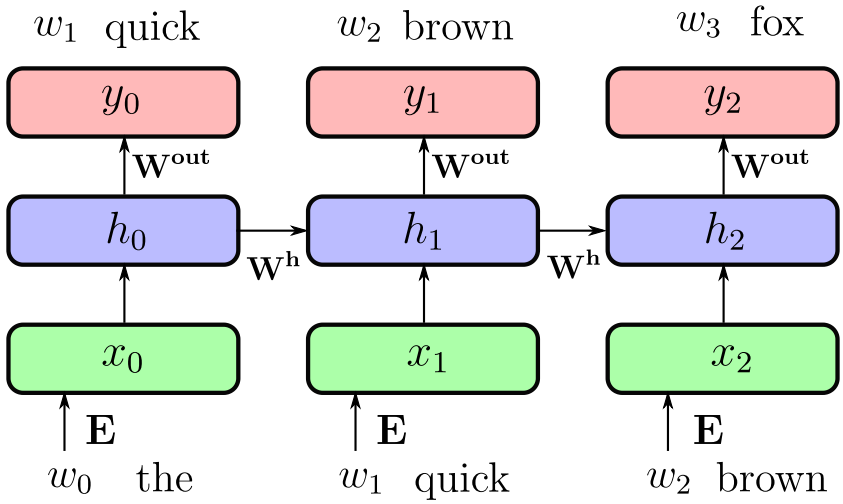
Language Modelling



input $(w_0, w_1, \ldots, w_t)$ sequence of words (1-hot encoded)

output $(w_1, w_2, \ldots, w_{t+1})$ shifted sequence of words (1-hot encoded)

Language Modelling



$x_t = \text{Emb}(w_t) = \mathbf{E}w_t$

input projection H

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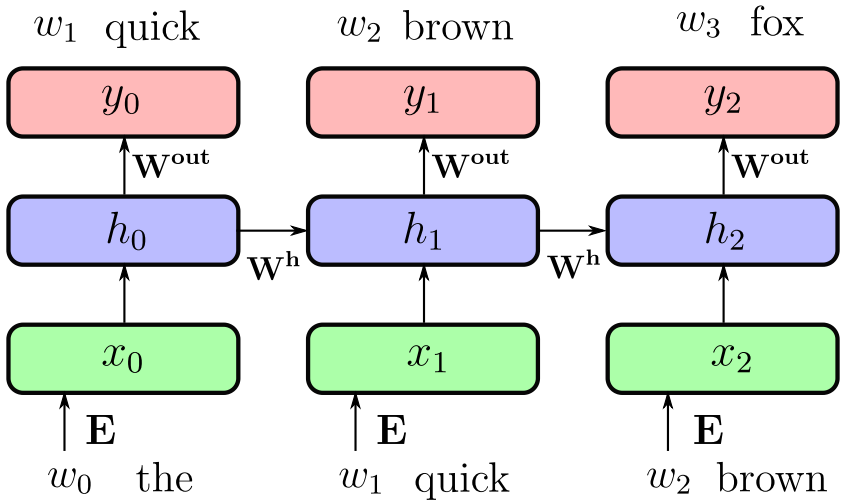

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recurrent connection H

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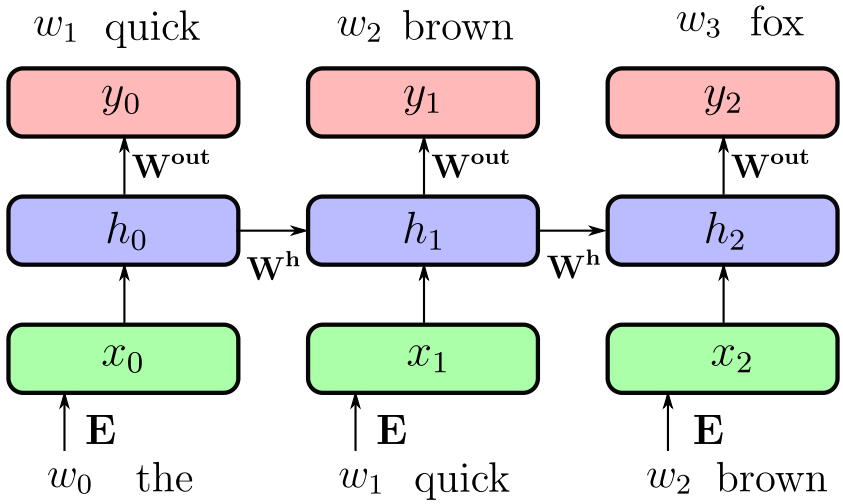
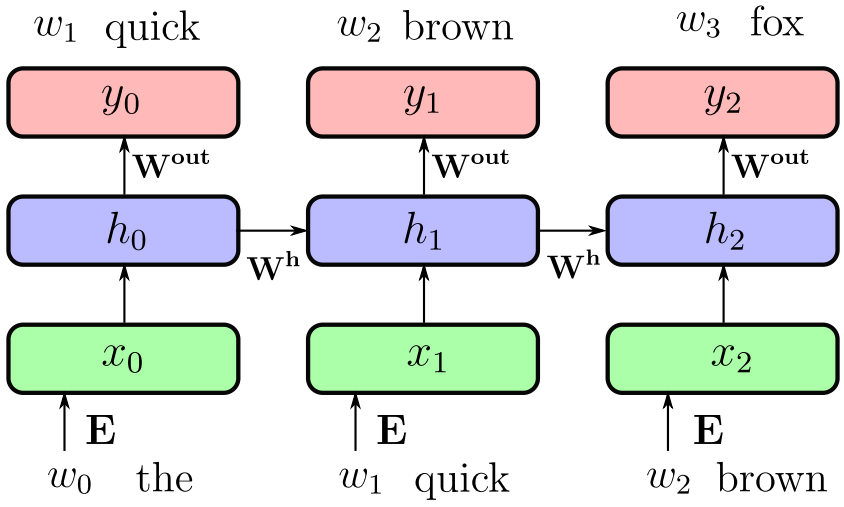


$$x_t = \text{Emb}(w_t) = \mathbf{E}w_t$$ input projection H

$$h_t = g(\mathbf{W^h}h_{t-1} + x_t + b^h)$$ recurrent connection H

$$y = \text{softmax}(\mathbf{W^o}h_t + b^o)$$ output projection K = |V|

Recurrent Neural Network



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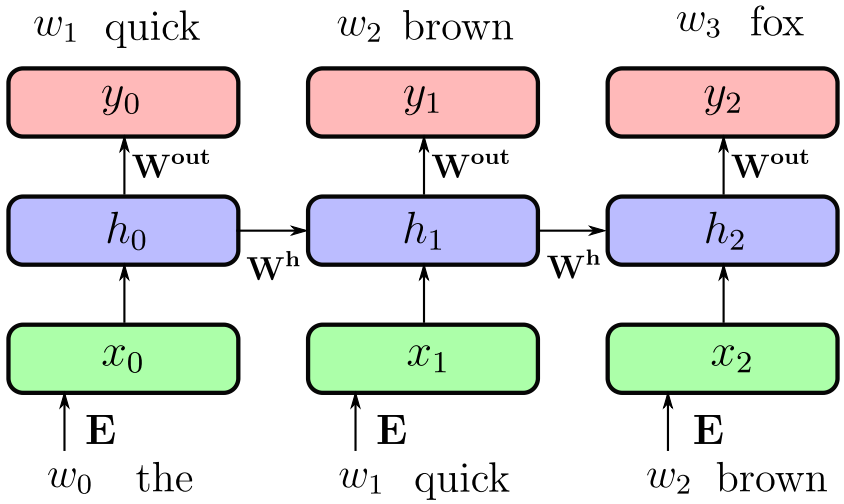

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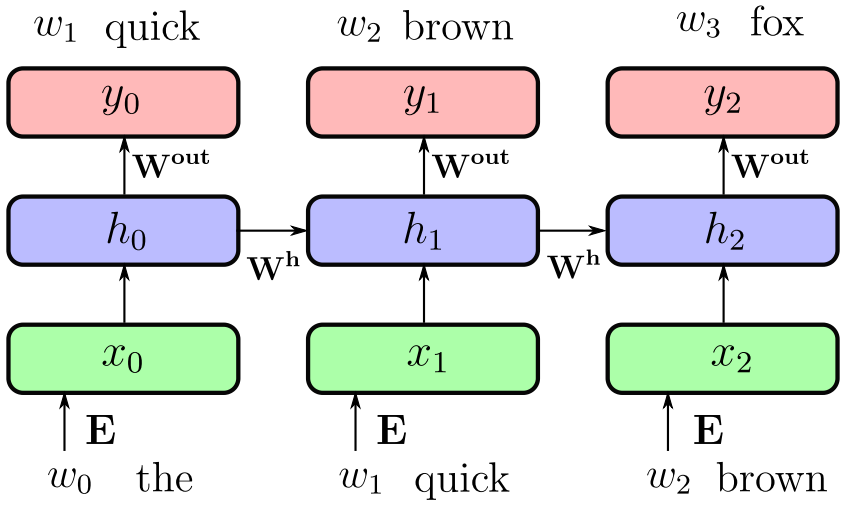


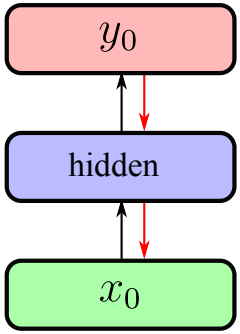
Input embedding $\mathbf{E}$ — `|V| x H`

Recurrent weights $\mathbf{W}^{\mathbf{h}}$ — `H x H`

Output weights $\mathbf{W}^{\mathbf{out}}$ — `H x K = H x |V|`

Backpropagation through time

Similar as standard backpropagation on unrolled network



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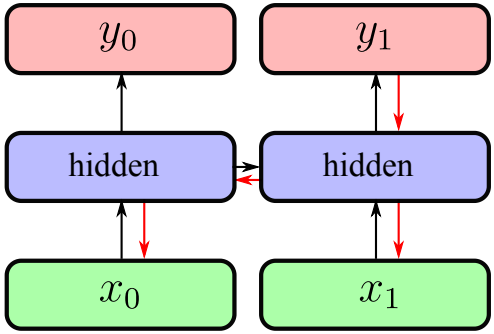

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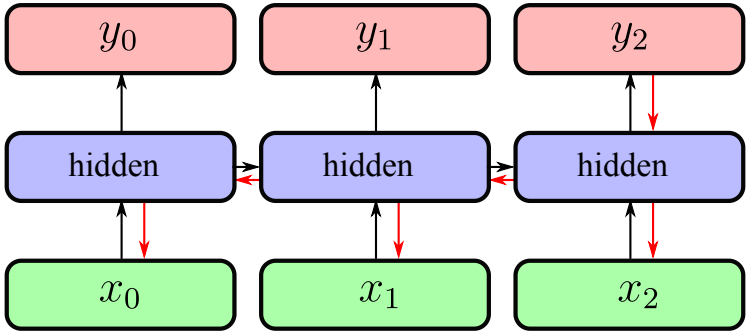

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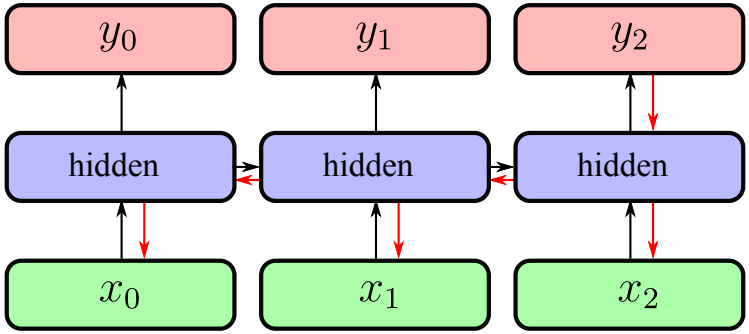

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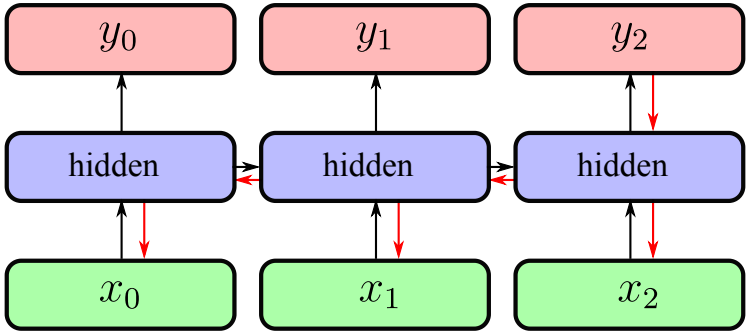

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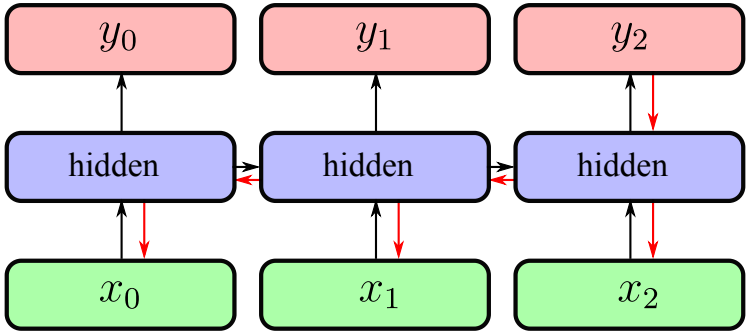
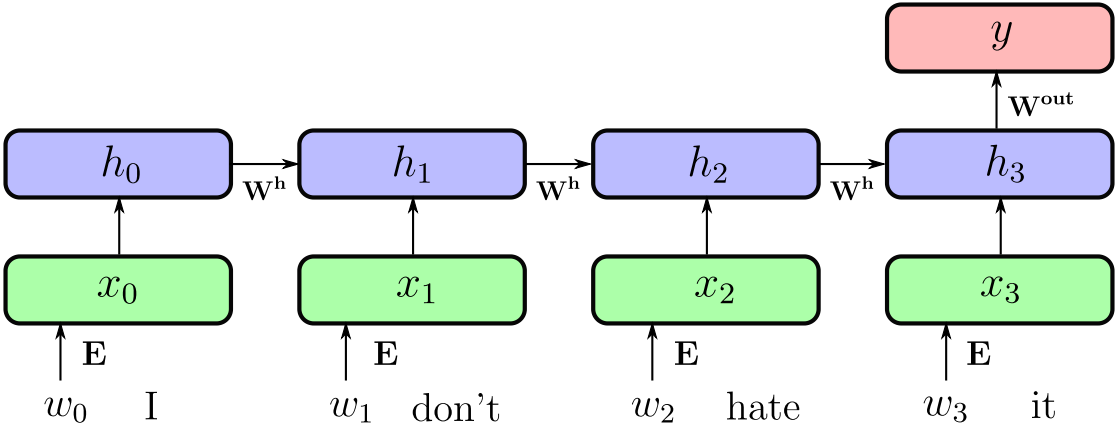


- Similar as training **very deep networks** with tied parameters
- Example between x_0 and y_2: W^h is used twice
- Usually truncate the backprop after T timesteps
- Difficulties to train long-term dependencies

Other uses: Sentiment Analysis



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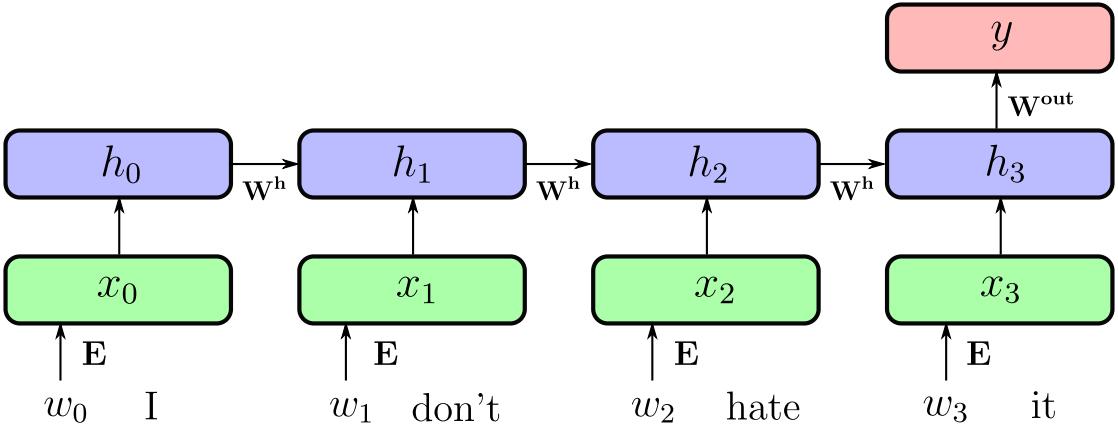

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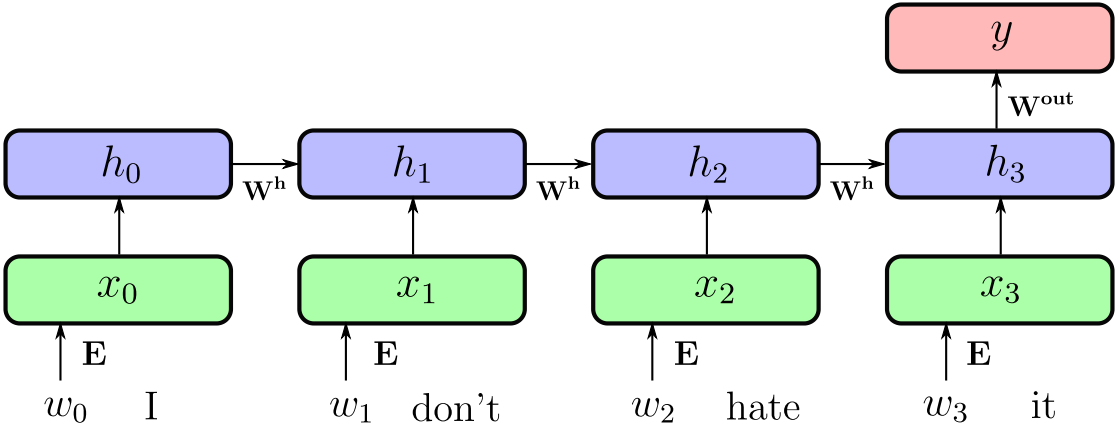

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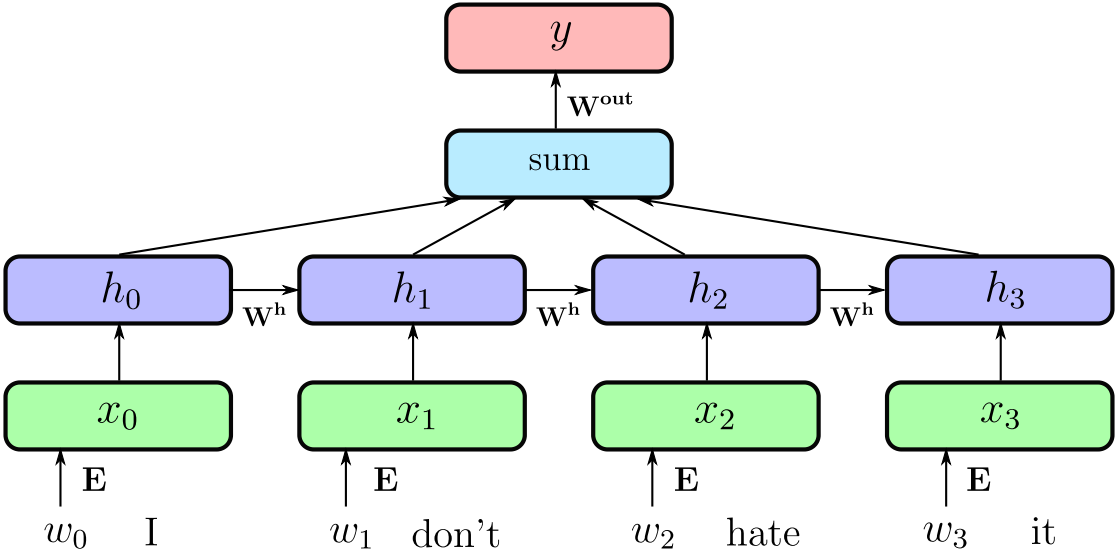

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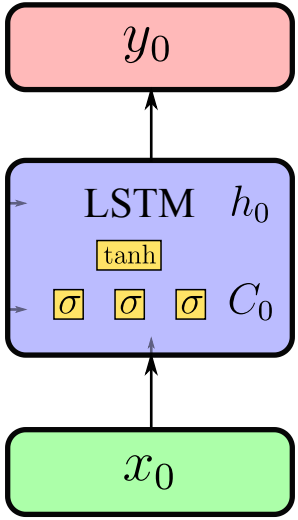
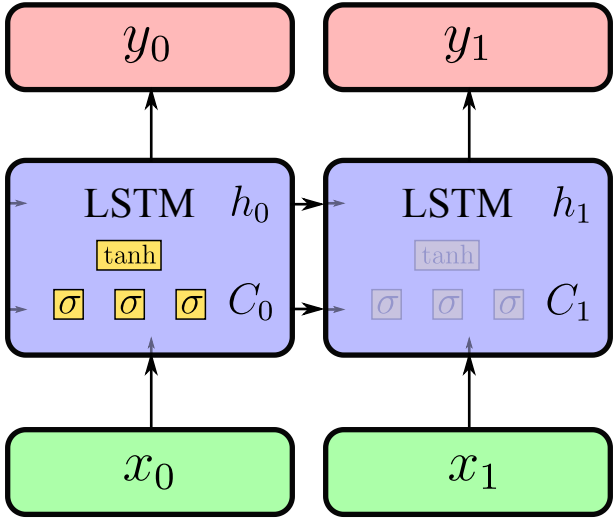
LSTM



Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 1997

LSTM



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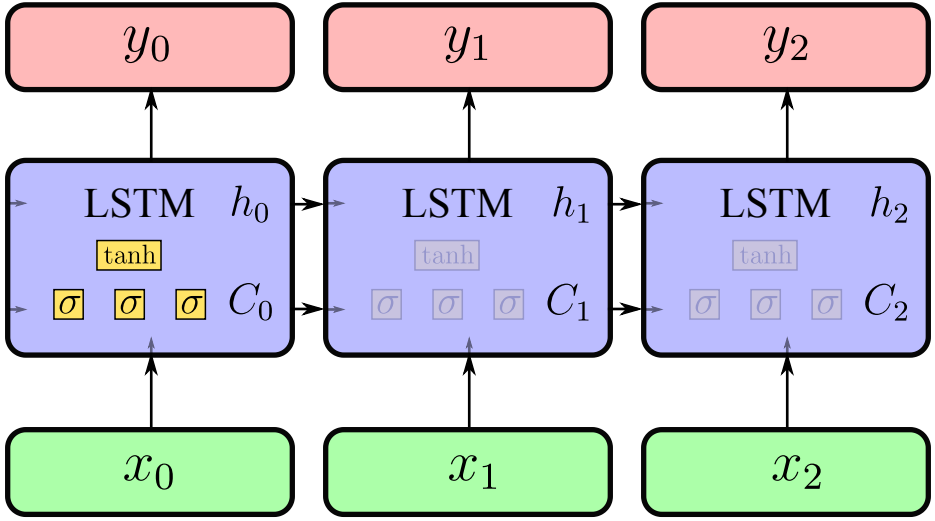

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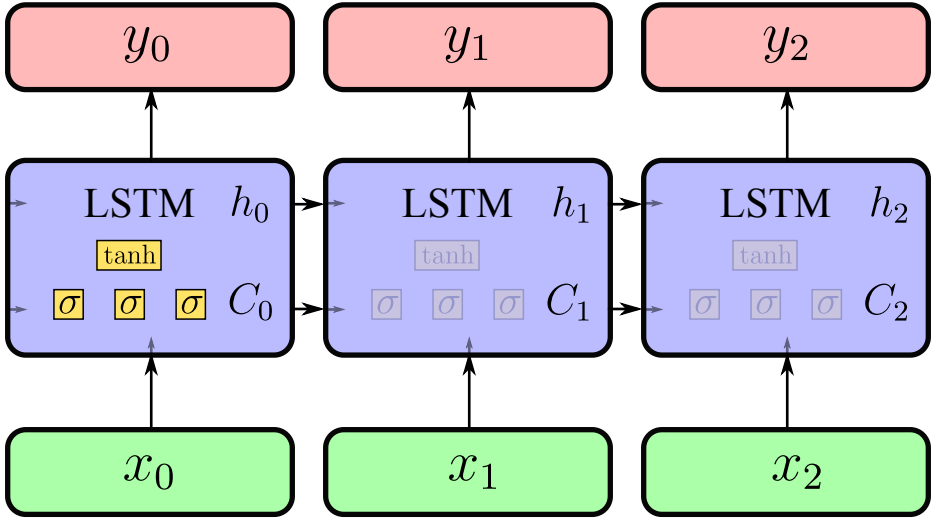

- 4 times more parameters than RNN

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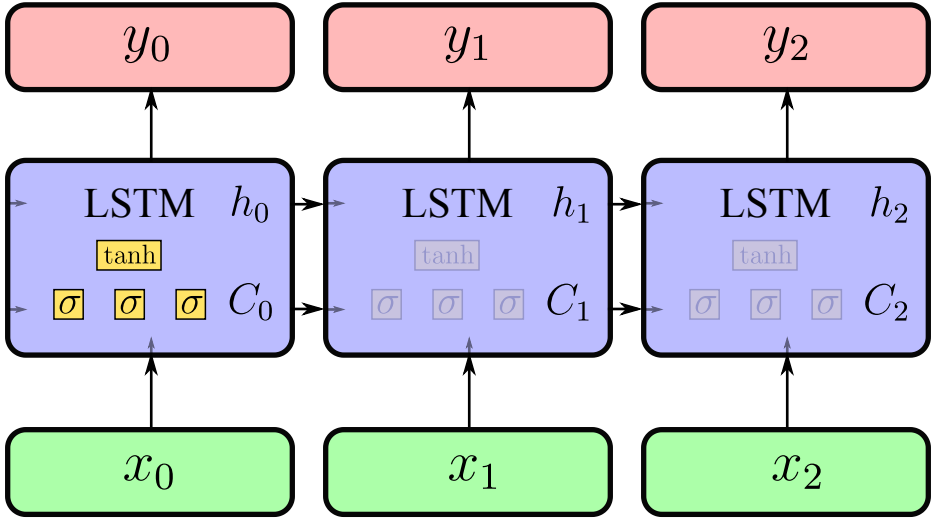

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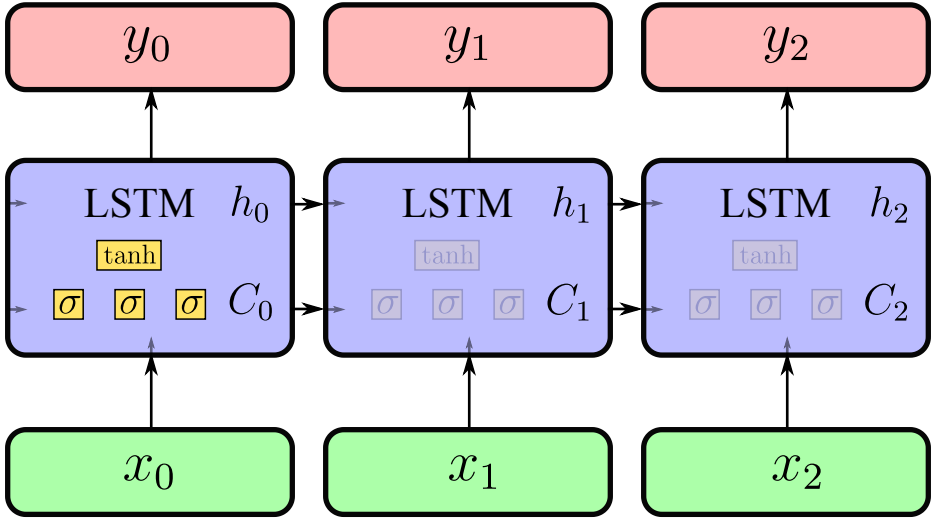

- 4 times more parameters than RNN
- Mitigates **vanishing gradient** problem through **gating**
- Widely used and SOTA in many sequence learning problems

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W^u, W^f, W^c, W^o Recurrent weights H x H

I^u, I^f, I^c, I^o Input weights N x H

Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." Neural computation 1997

GRU

Gated Recurrent Unit: similar idea as LSTM

- less parameters, as there is one gate less
- no "cell", only hidden vector h_t is passed to next unit

Chung, Junyoung, et al. "Gated Feedback Recurrent Neural Networks." ICML 2015

GRU

Gated Recurrent Unit: similar idea as LSTM

- less parameters, as there is one gate less
- no "cell", only hidden vector h_t is passed to next unit

In practice

- more recent, people tend to use LSTM more
- no systematic difference between the two

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Skip connections in ResNet also alleviate a similar optimization problem.

Lab 5: back here in 15 min!