Deep Learning

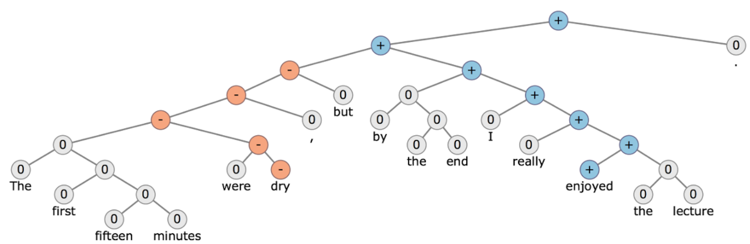
Natural Language Processing with Deep Learning

Alex Olson

Adapted from material by 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

gensim spaCy

scikit learn

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

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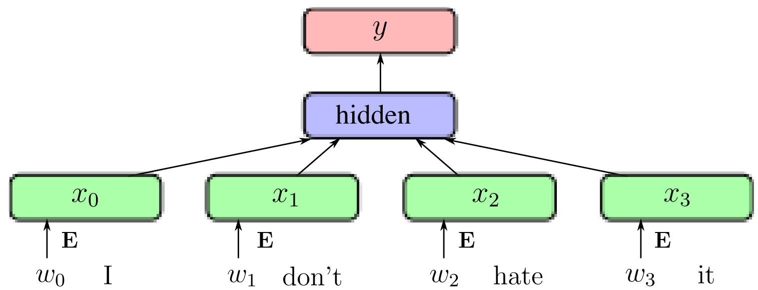
Use of **Embeddings** as inputs in all Deep NLP tasks

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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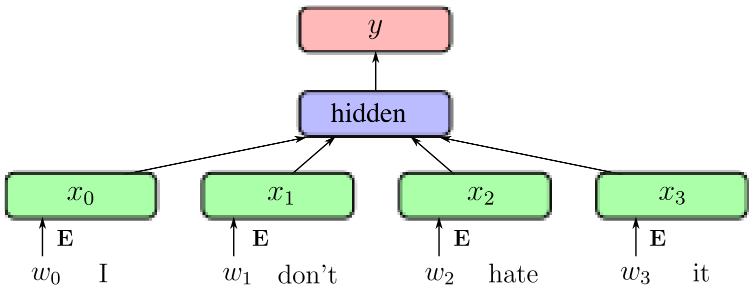

E embedding (linear projection) |V| x H

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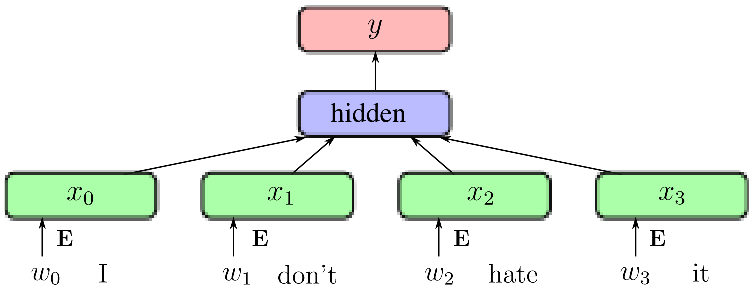

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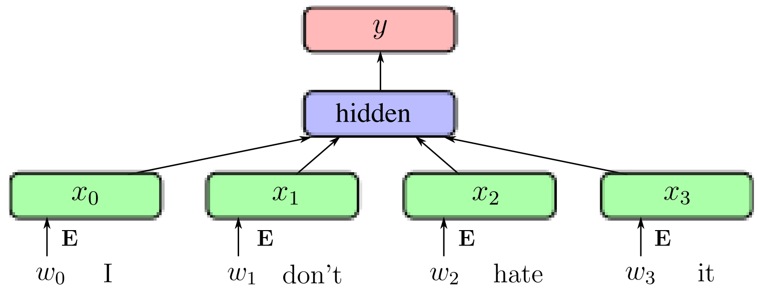

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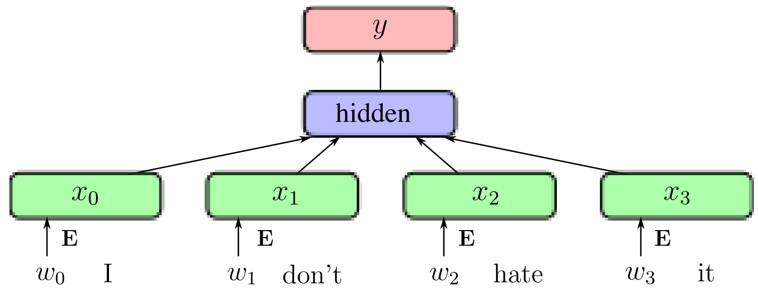

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Softmax and **cross-entropy** loss

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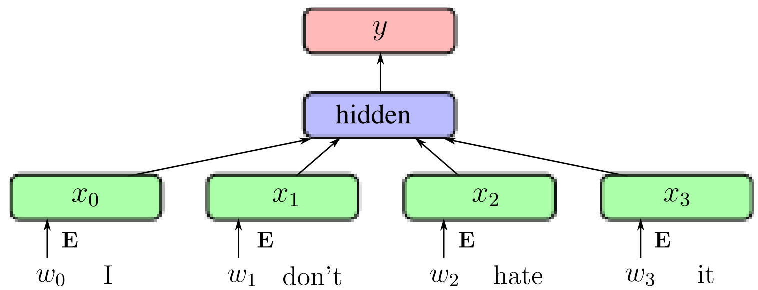

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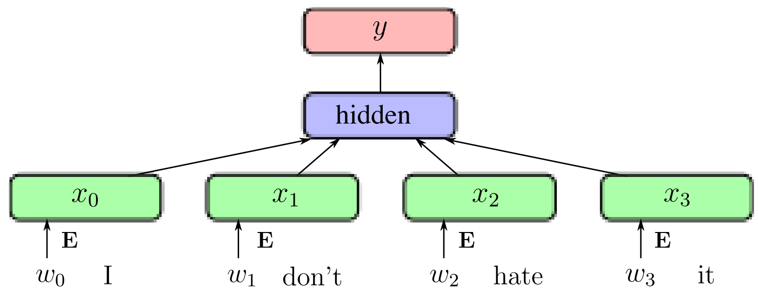

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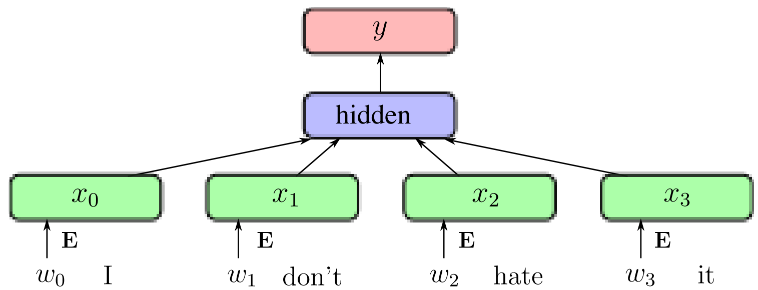

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- Little gains from depth

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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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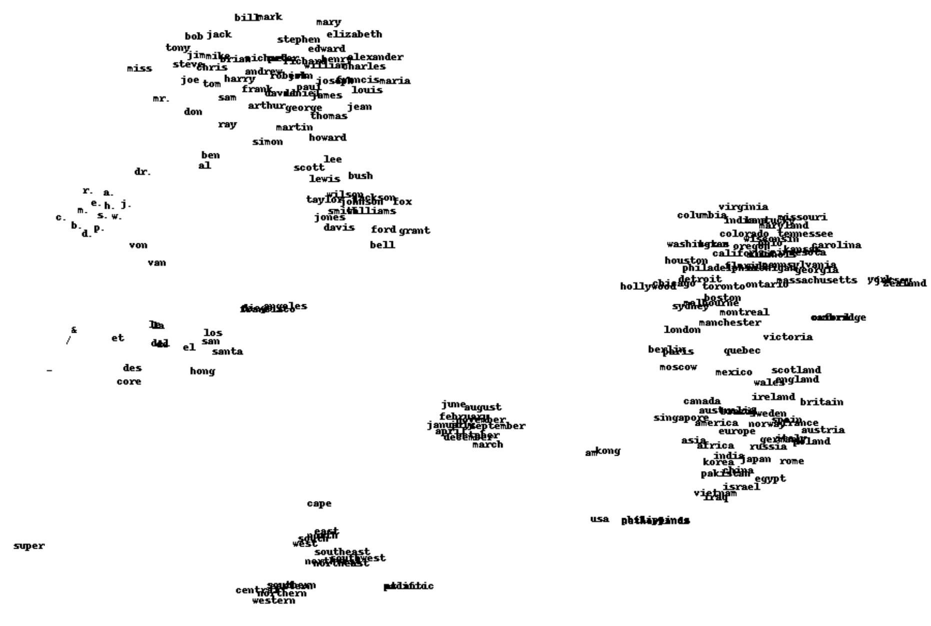
Unsupervised / self-supervised learning of word representations

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
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
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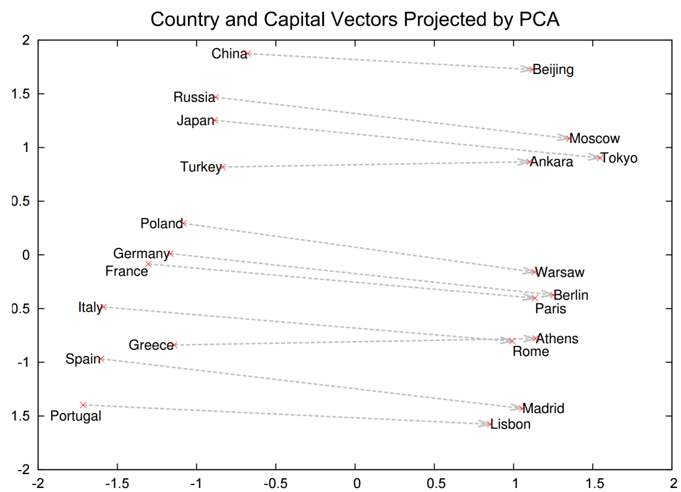
Compositionality

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

Colobert et al. 2011, Mikolov, et al. 2013

Word Analogies



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

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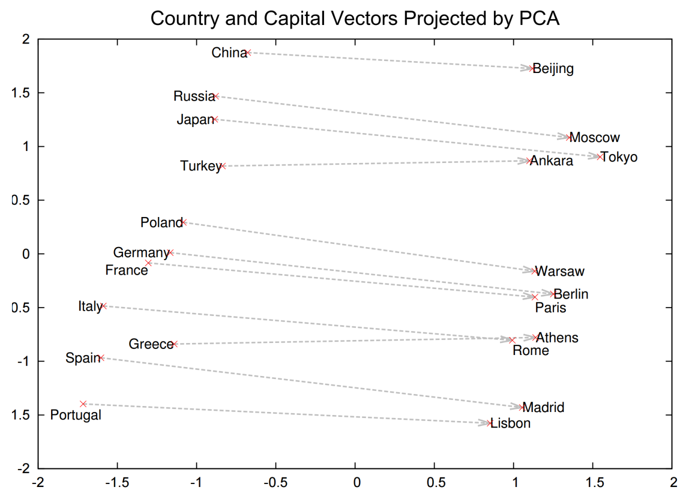

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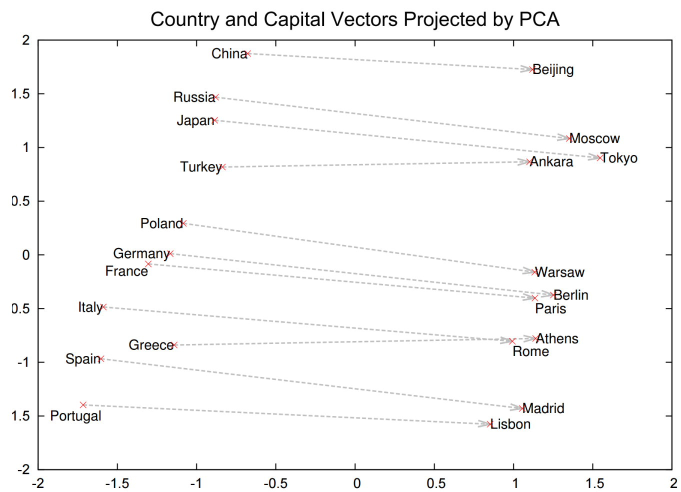

- Linear relations in Word2Vec embeddings
- Many come from text structure (e.g. Wikipedia)

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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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Given a word e.g. "carrot" and any other word $w \in V$ predict probability $P(w|\text{carrot})$ 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 $P(w|\text{carrot})$ 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**:

`the carrot is a root vegetable, usually orange`

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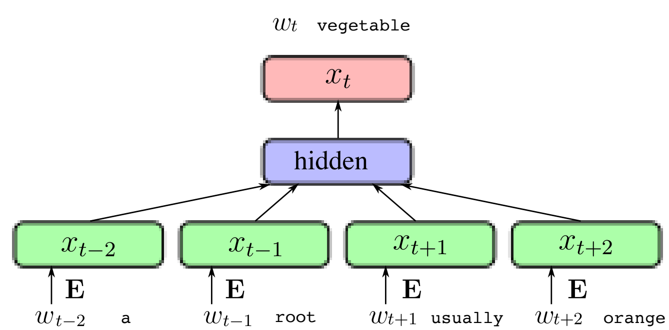

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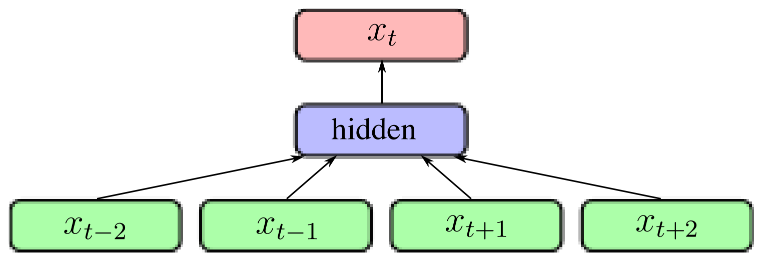
Word2Vec: Details



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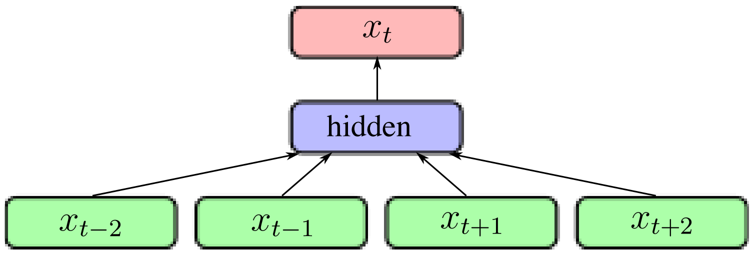

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- Use **Negative Sampling**: sample *negative* words at random instead of computing the full softmax. See: http://sebastianruder.com/word-embeddings-softmax/index.html

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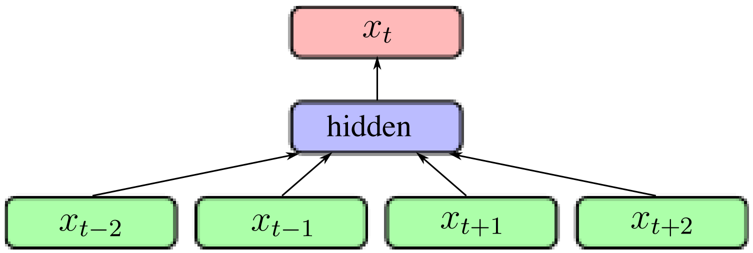

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- Large impact of **context size**

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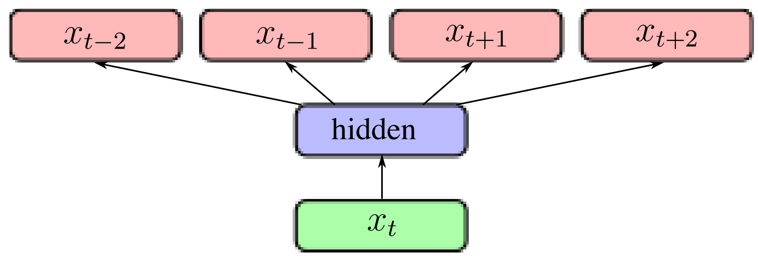
Word2Vec: Skip Gram

a



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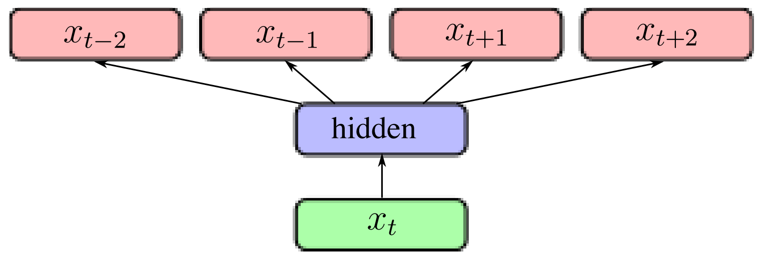

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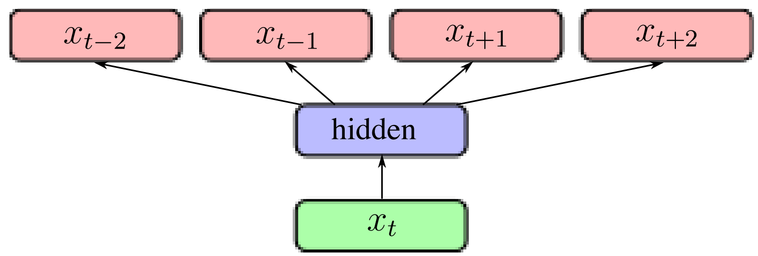

- Given the central word, predict occurence of other words in its context.
- Widely used in practice
- Again **Negative Sampling** is used as a cheaper alternative to full softmax.

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

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Word Embeddings no long state of the art for NLP tasks: BERT-style pretraining of deep transformers with sub-word tokenization is now used everywhere.

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:

- $p(\text{"I like cats"}) > p(\text{"I table cats"})$
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$p_\theta(w_0)$

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$$p_\theta(w_0) \cdot p_\theta(w_1 | w_0) \cdot \ldots \cdot p_\theta(w_n | w_{n-1}, w_{n-2}, \ldots, w_0)$$

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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: $p(Target|Source)$

- *Source*: "J'aime les chats"
- *Target*: "I like cats"

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Conditional Language Models

Question Answering / Dialogue:

$p(Answer|Question, Context)$

- *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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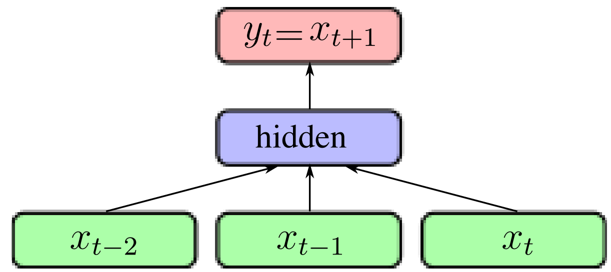
Image Captionning: $p(Caption|Image)$

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

Simple Language Model



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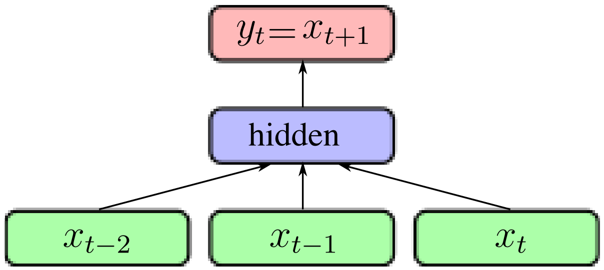

Fixed context size

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

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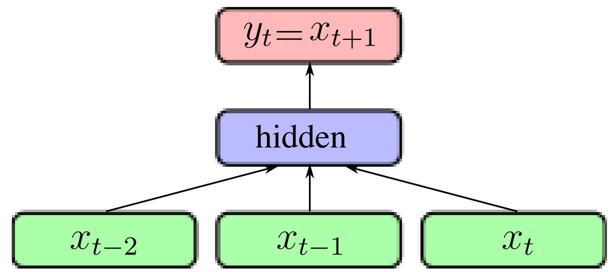

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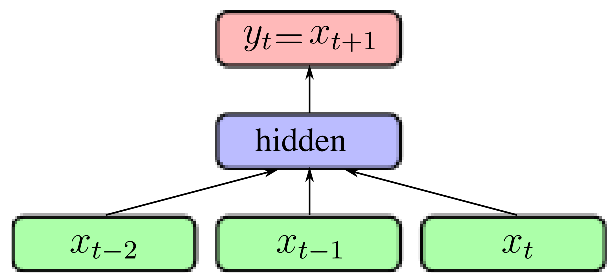

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- **1D convolution**: larger contexts and limit number of parameters

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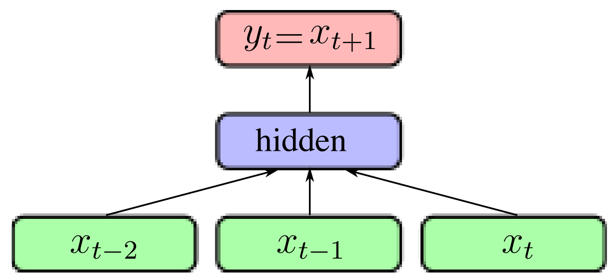

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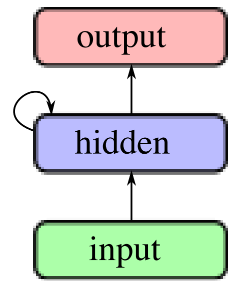
- **1D convolution**: larger contexts and limit number of parameters
- Still does not take well into account varying sequence sizes and sequence dependencies

Recurrent Neural Network



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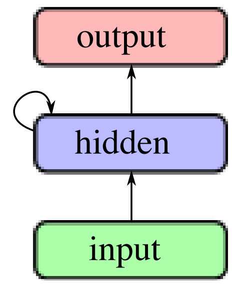
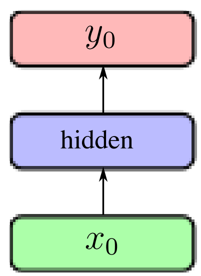
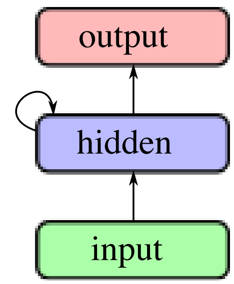


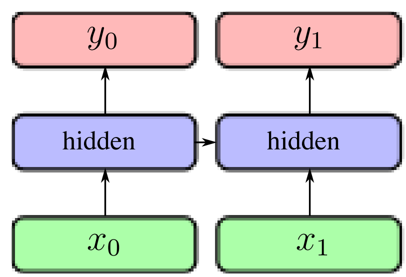
Unroll over a sequence (x_0, x_1, x_2):



Recurrent Neural Network



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



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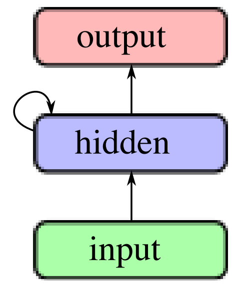

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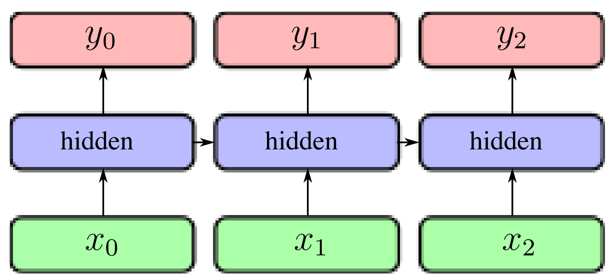
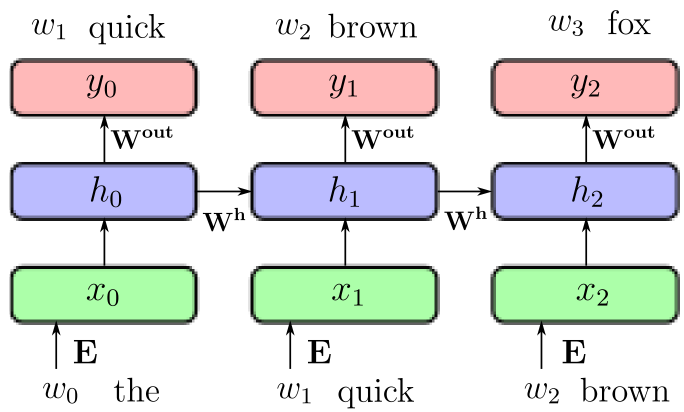
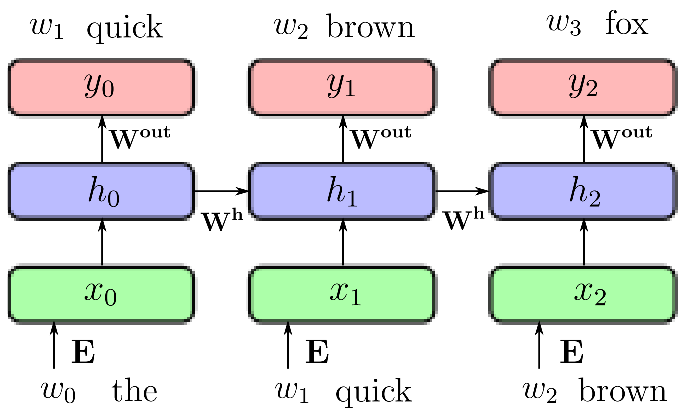


Language Modelling



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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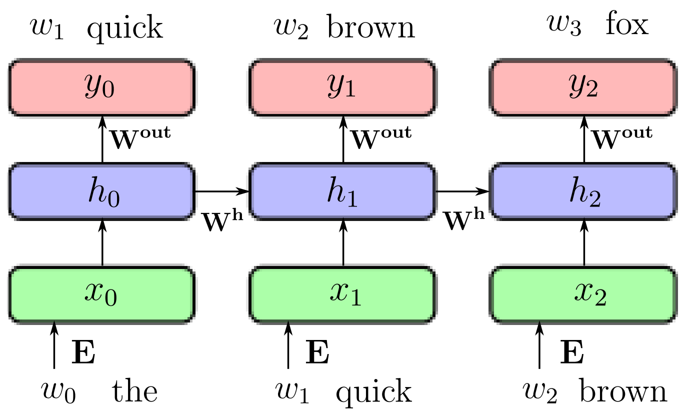

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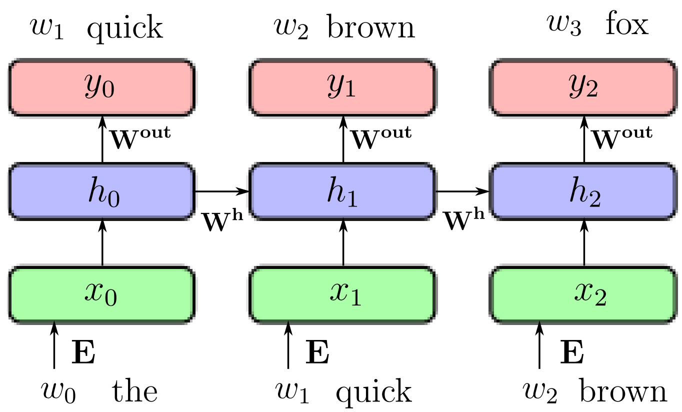

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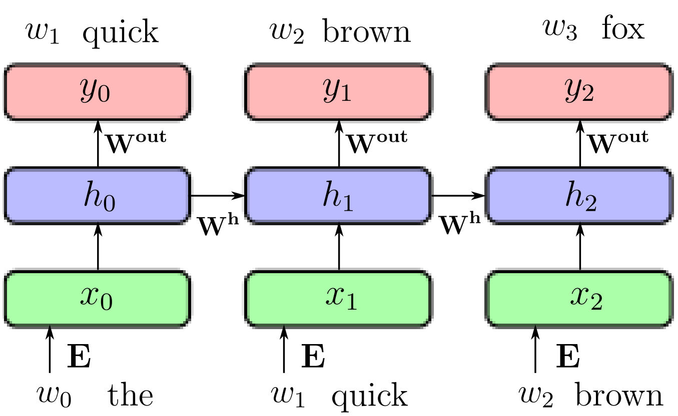
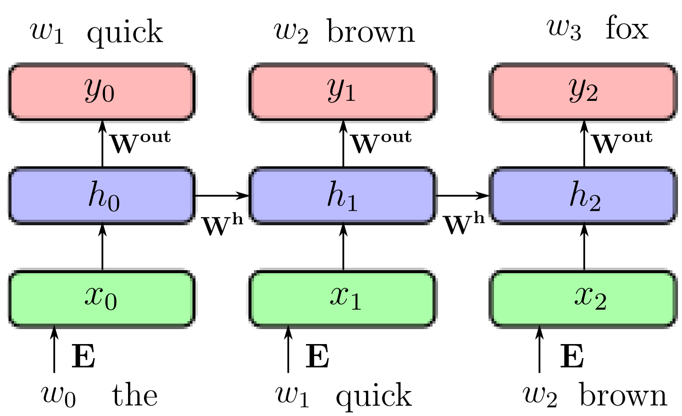
$y = \mathrm{softmax}(\mathbf{W^o} h_t + b^o)$ output projection K = |V|

Recurrent Neural Network



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

Recurrent Neural Network



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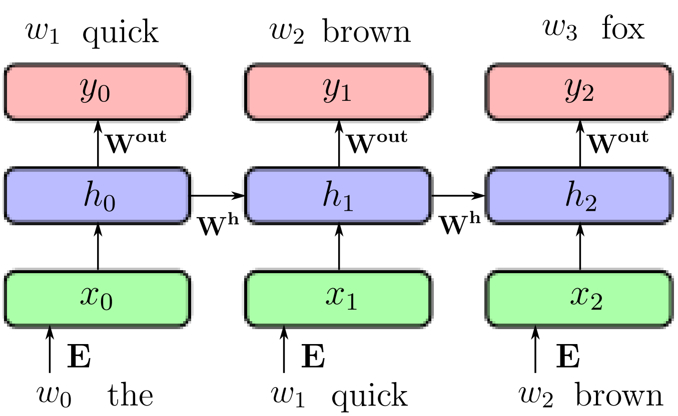
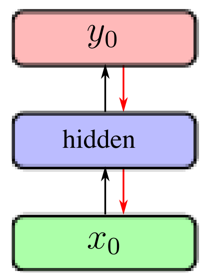
Recurrent Neural Network



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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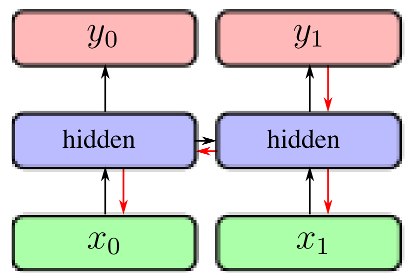

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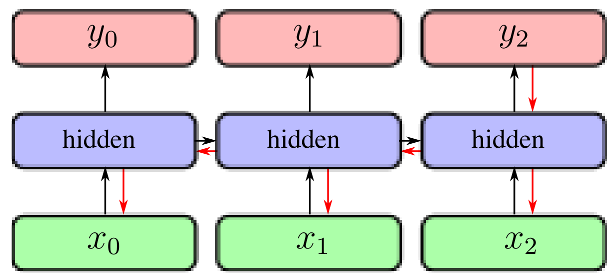

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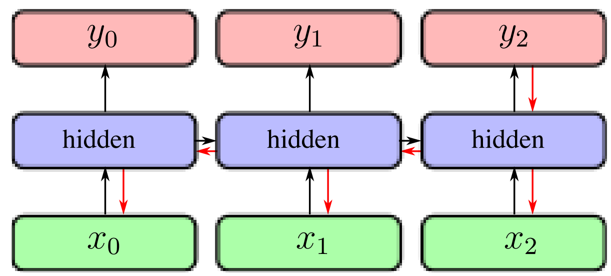

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- Example between x_0 and y_2: W^h is used twice

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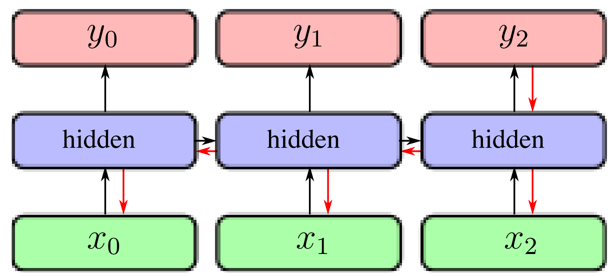

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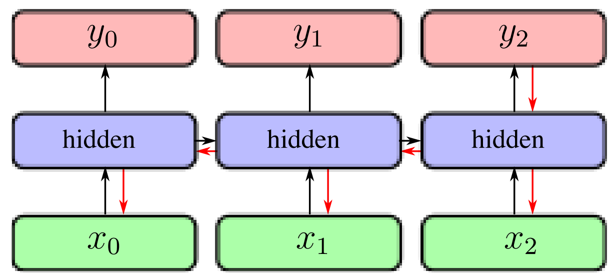

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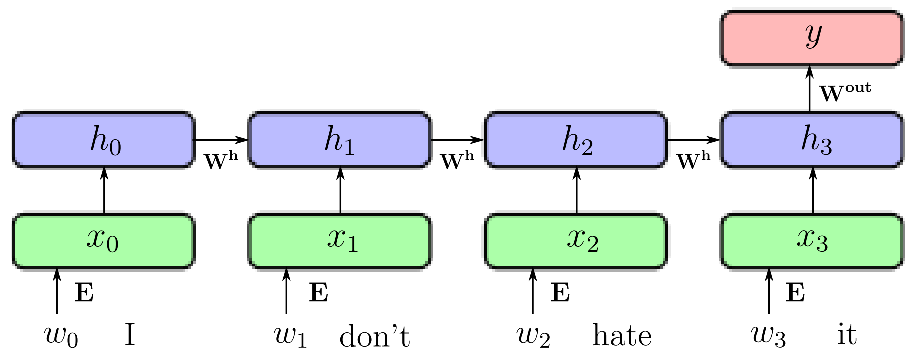
- Example between x_0 and y_2: W^h is used twice
- Usually truncate the backprop after T timesteps
- Difficulties to train long-term dependencies

Other uses: Sentiment Analysis



- Output is sentiment (1 for positive, 0 for negative)

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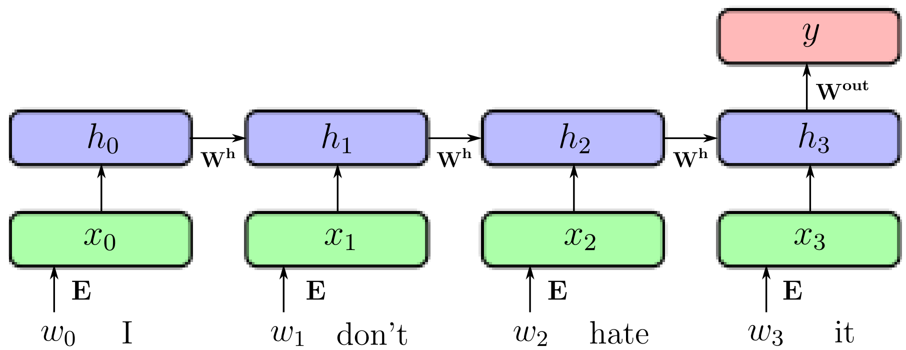

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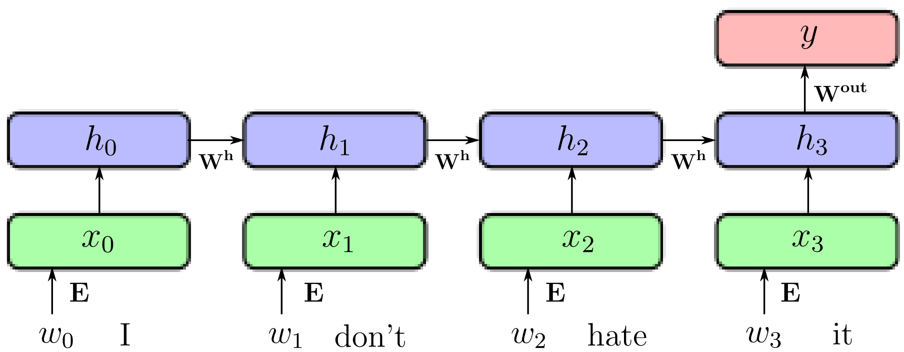

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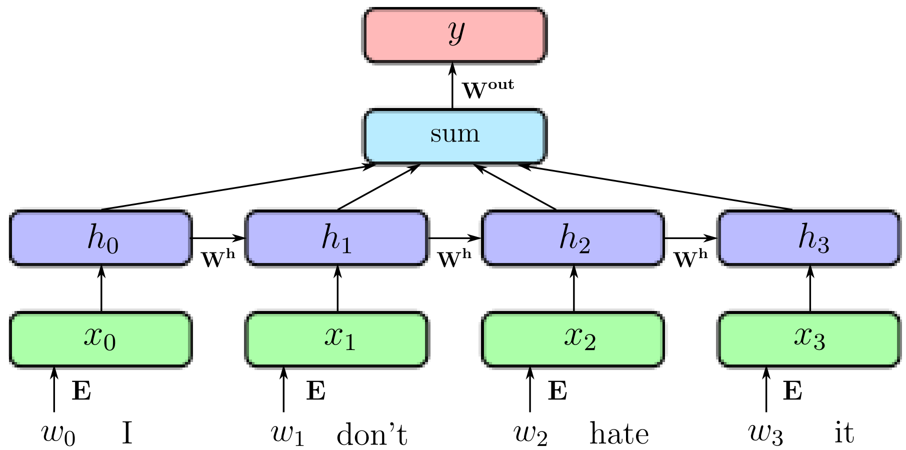

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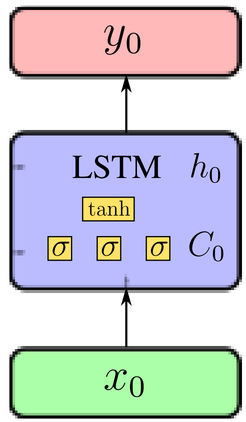
LSTM



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

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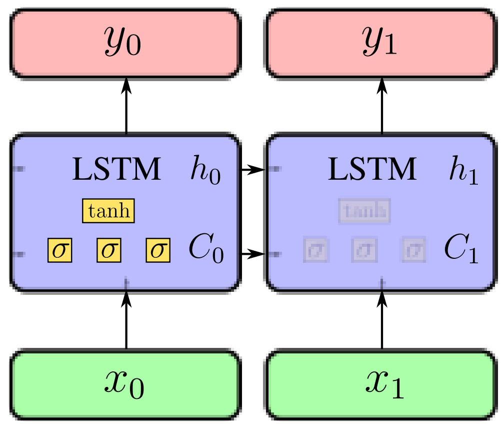

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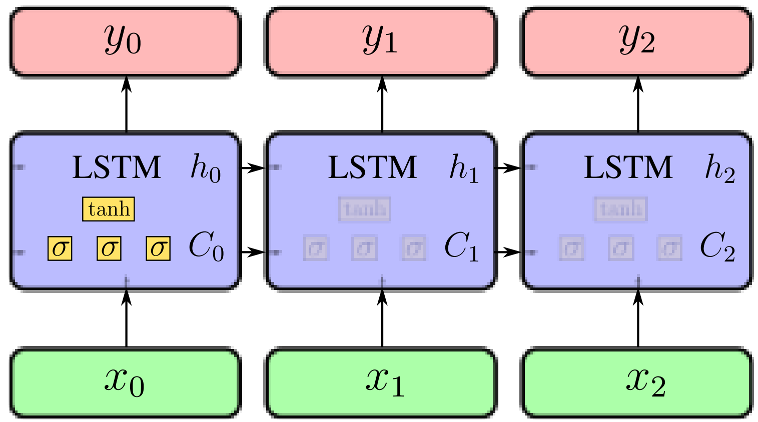

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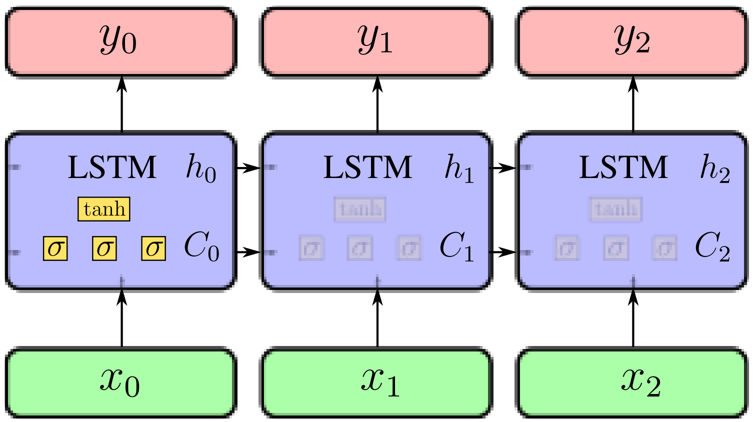

- 4 times more parameters than RNN

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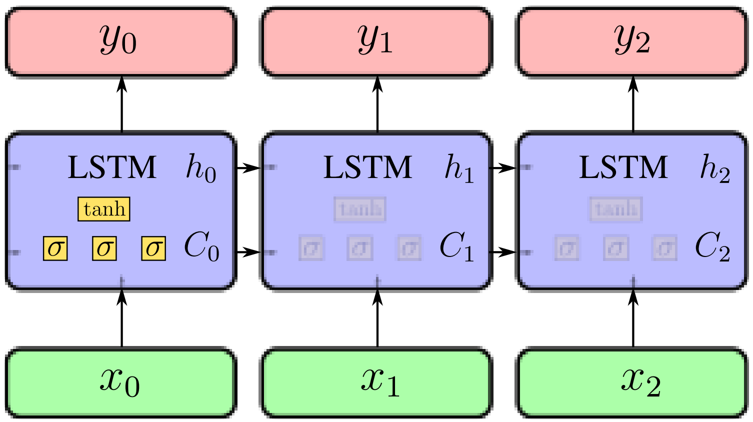

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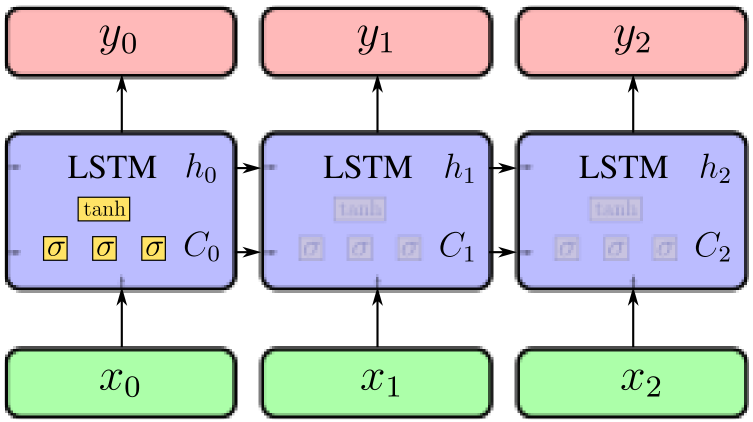

- 4 times more parameters than RNN
- Mitigates **vanishing gradient** problem through **gating**
- Widely used and SOTA in many sequence learning problems

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Vanishing / Exploding Gradients

Passing through t time-steps, the resulting gradient is the **product** of many gradients and activations.

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Skip connections in ResNet also alleviate a similar optimization problem.

Next: Lab 6!