Deep Learning

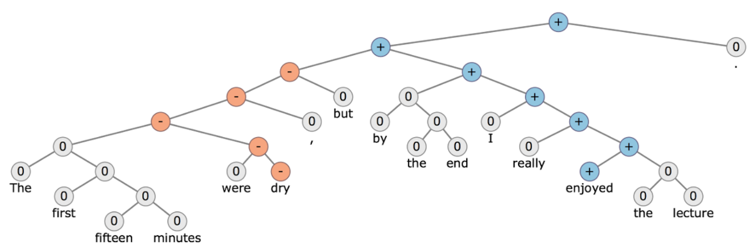
Natural Language Processing with Deep Learning

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)

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- Topic modeling (LDA, ...)

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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

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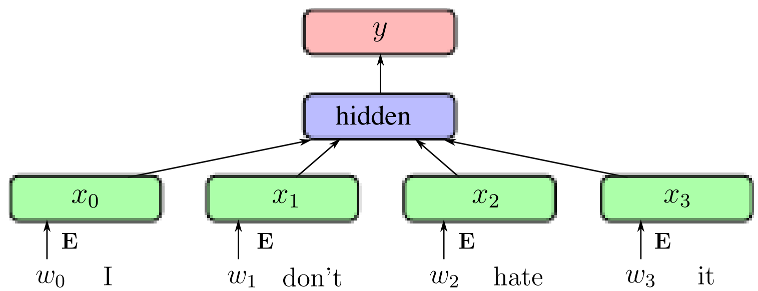
Use of **Embeddings** as inputs in all Deep NLP tasks

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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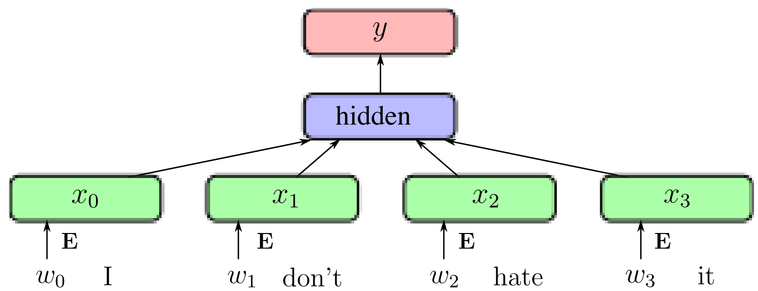

E embedding (linear projection) |V| x H

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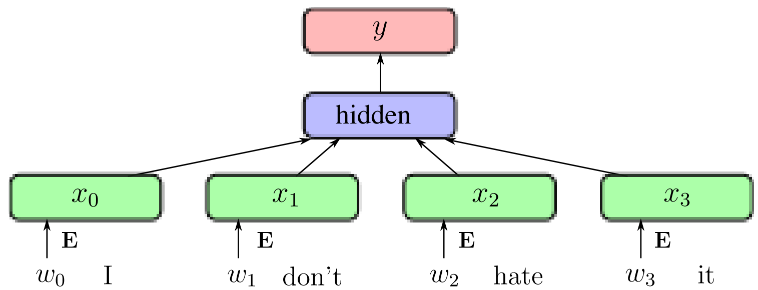

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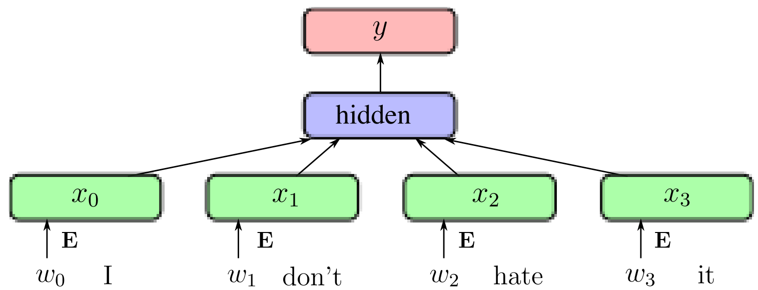

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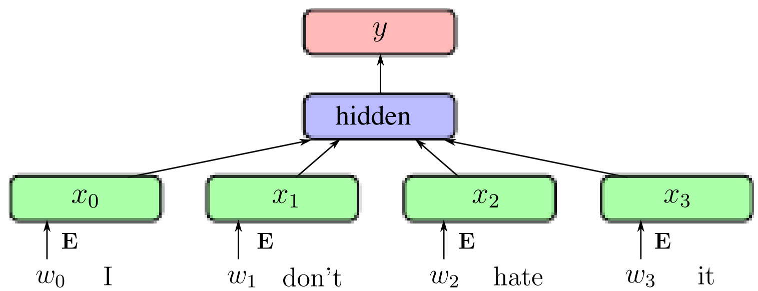

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Softmax and **cross-entropy** loss

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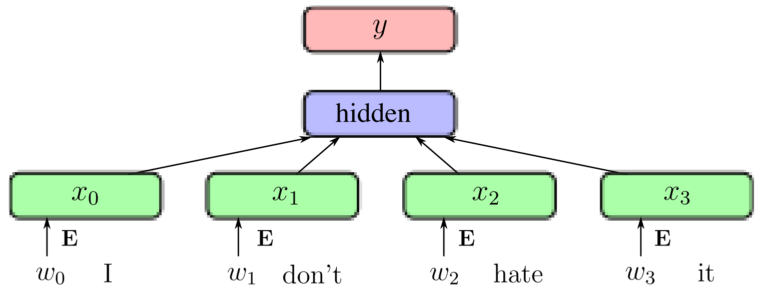

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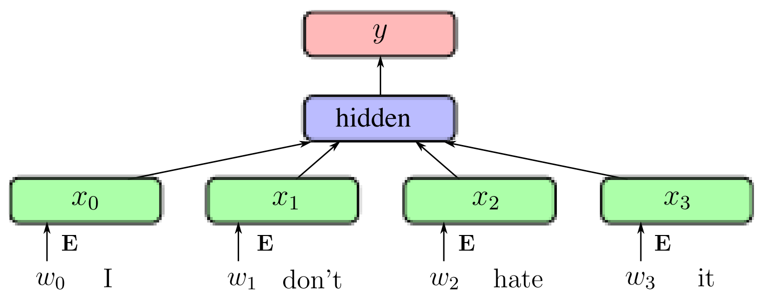

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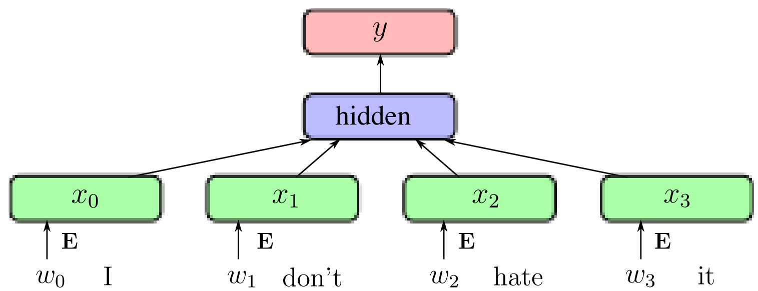

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- State-of-the-art (or close to) on several classification, when adding **bigrams/ trigrams**
- Little gains from depth

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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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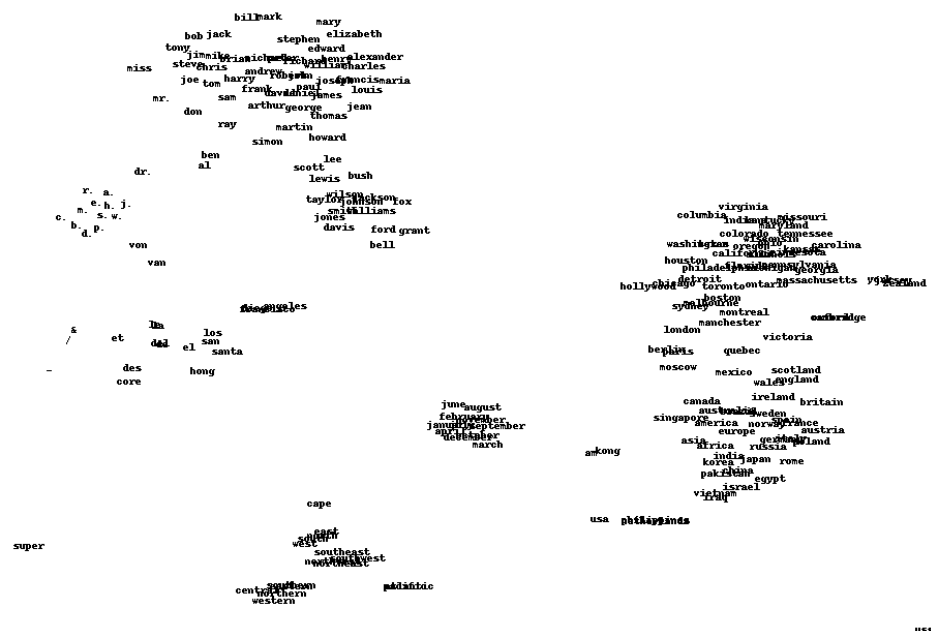
Unsupervised / self-supervised learning of word representations

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
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAYISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
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Colobert et al. 2011, Mikolov, et al. 2013

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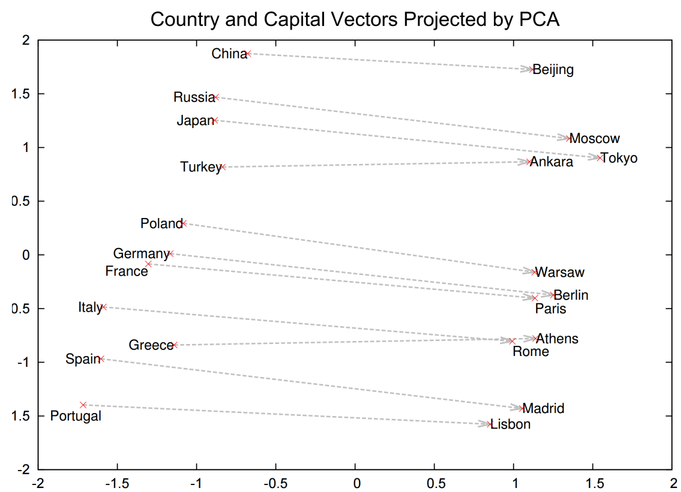
Compositionality

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

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

Word Analogies



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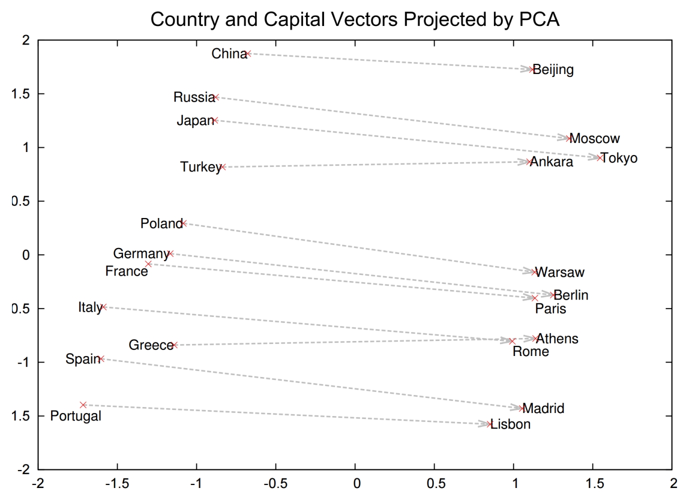

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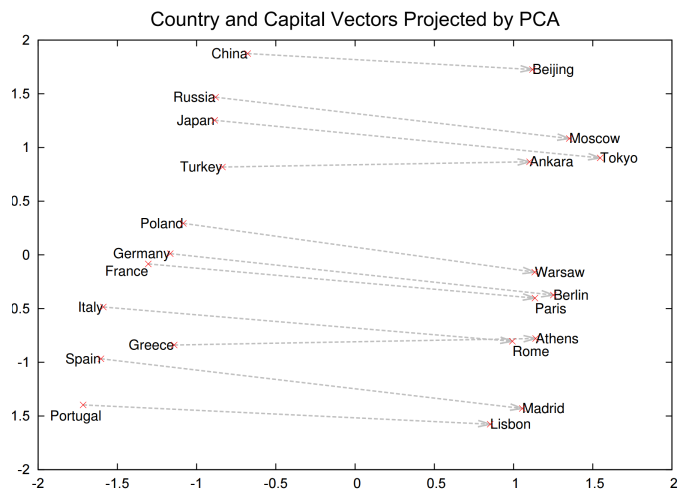

- Linear relations in Word2Vec embeddings
- Many come from text structure (e.g. Wikipedia)

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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-Words**

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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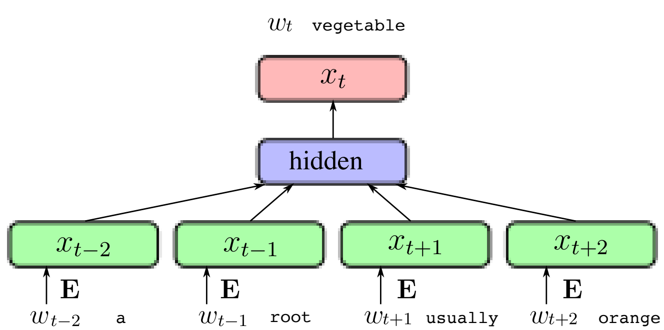

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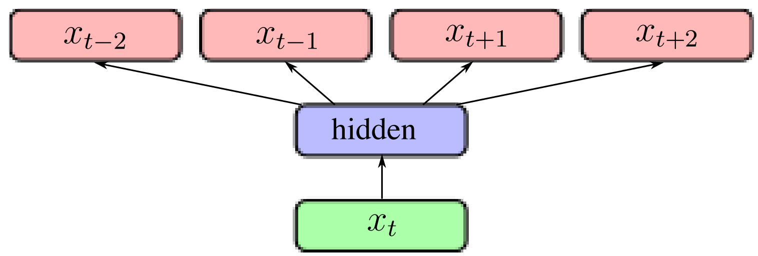
Word2Vec: Skip Gram



- Given the central word, predict occurence of other words in its context.

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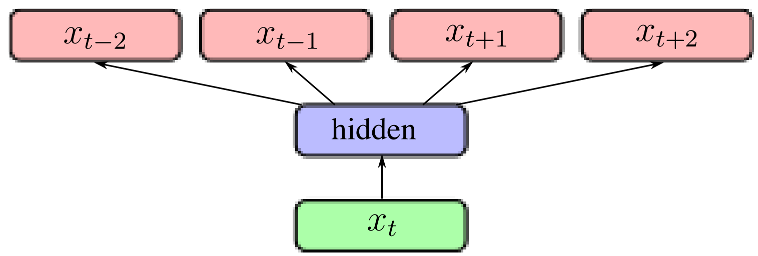

- Given the central word, predict occurence of other words in its context.
- Widely used in practice

Word2Vec: Negative Sampling

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- For the sentence "The quick brown fox jumps over the lazy dog":
- "quick" and "fox" are positive examples (if context window is 2)
- "quick" and "apple" are negative examples
- By sampling negative examples, we don't just bring similar words' embeddings closer, but also push away dissimilar words' embeddings.

Transformer-based methods

- **Attention** mechanism: more recent and more powerful than Word2Vec
- **BERT** (Bidirectional Encoder Representations from Transformers) allows for **contextual embeddings** (different embeddings for the same word in different contexts)
- For example, "bank" in "river bank" and "bank account" will have different embeddings
- This means converting a word to a vector is no longer a simple lookup in a table, but a function of the entire sentence

Transformer-based methods

- **Sub-word tokenization**: BERT uses a sub-word tokenization, which allows it to handle out-of-vocabulary words better than Word2Vec
- For example, "unbelievable" can be split into "un" and "believable"

- This means that the model can guess the meaning of words it has never seen before, based on the meanings of their parts

- OpenAI tokenization example: https://platform.openai.com/tokenizer

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- word2vec uses **Bag-of-Words** (BoW): they **ignore the order** in word sequences
- Depth & non-linear activations on hidden layers are not that useful for BoW text classification.

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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Language Models

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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"
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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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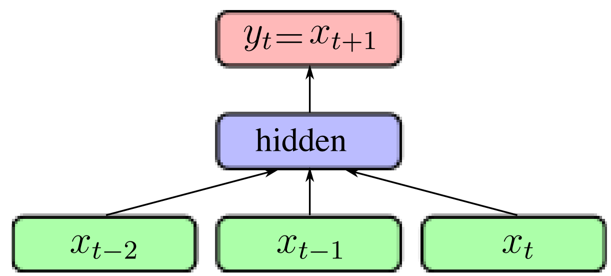
Image Captionning: $p(Caption|Image)$

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

Simple Language Model



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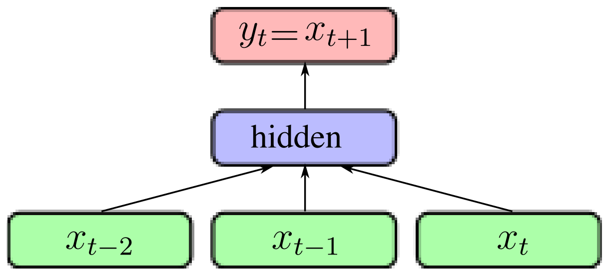

Fixed context size

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

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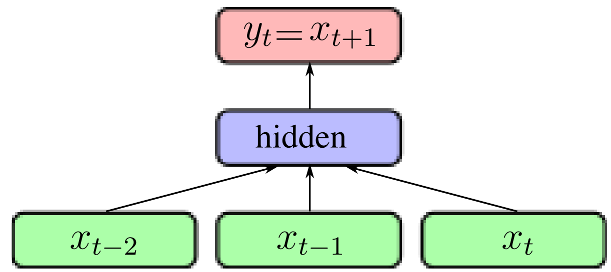

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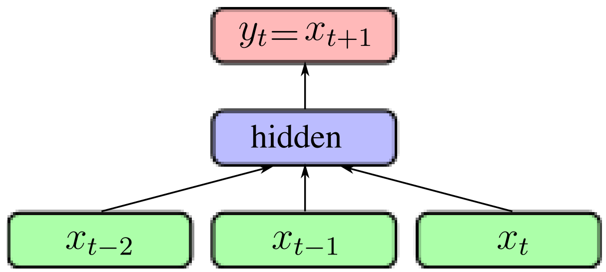

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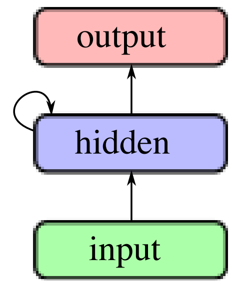
- **Concatenate embeddings**: introduces many parameters
- Still does not take well into account varying sequence sizes and sequence dependencies

Recurrent Neural Network



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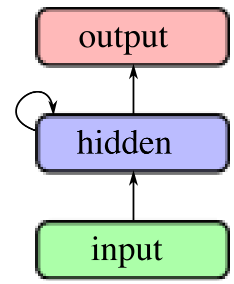
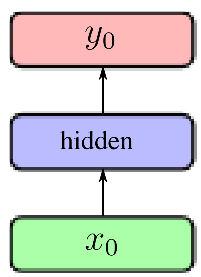


Unroll over a sequence (x_0, x_1, x_2):



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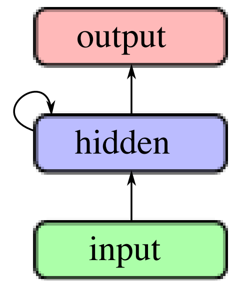

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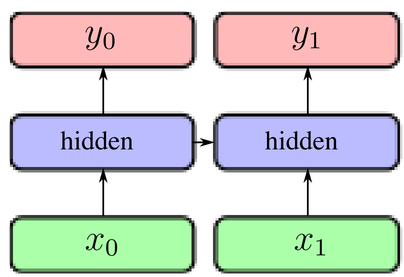

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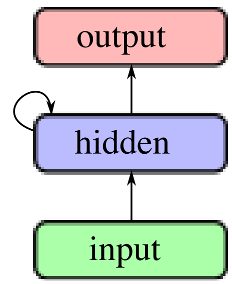

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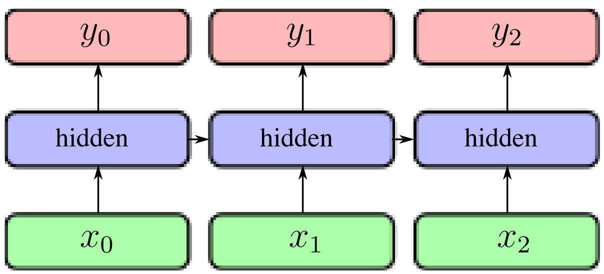
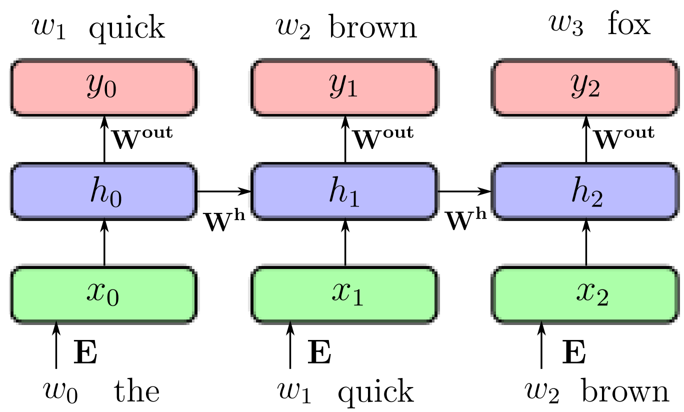


Language Modelling



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)

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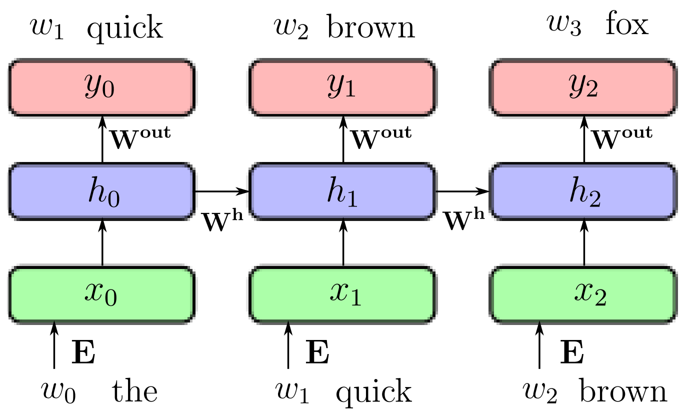

$x_t = \mathrm{Emb}(w_t) = \mathbf{E}w_t$ input projection H

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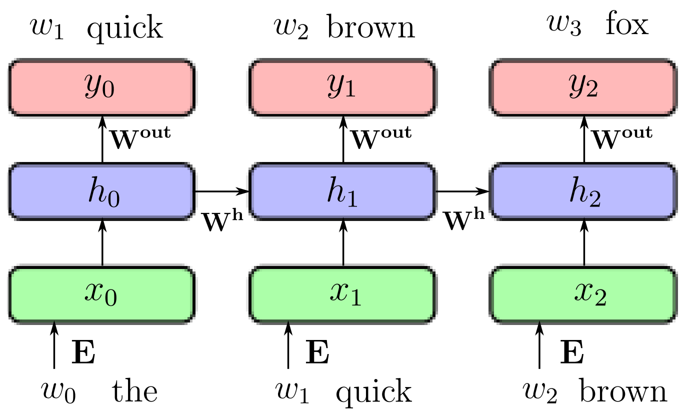

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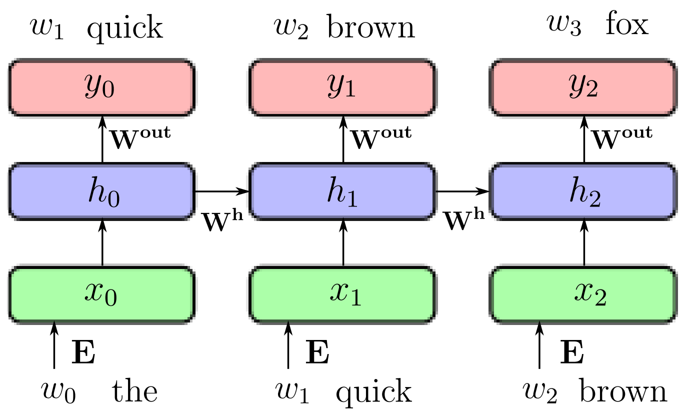
$$h_t = g(\mathbf{W^h} h_{t-1} + x_t + b^h)$$ recurrent connection H

Language Modelling



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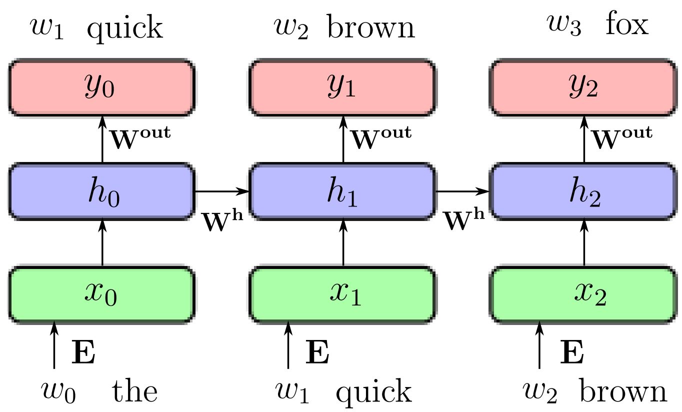
Recurrent Neural Network



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

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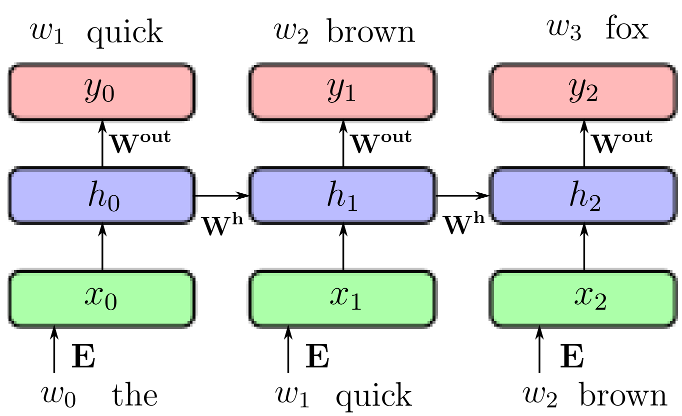

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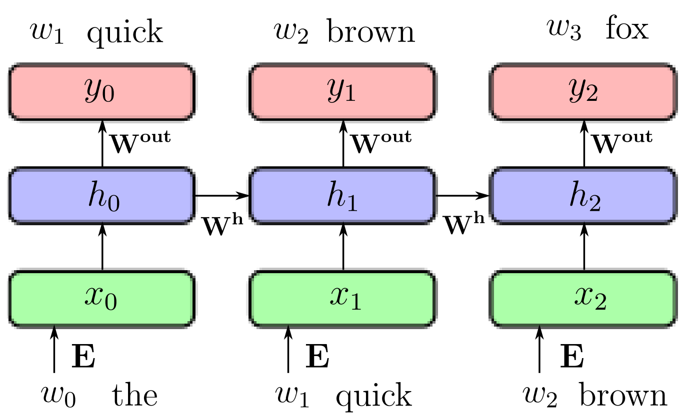
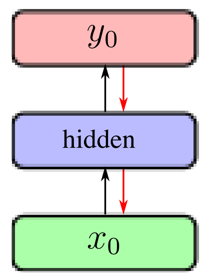


Input embedding $\mathbf{E}$	|V| x H
Recurrent weights $\mathbf{W}^{\mathbf{h}}$	H x H
Output weights $\mathbf{W}^{\mathbf{out}}$	H x K = H x |V|

Backpropagation through time

Similar as standard backpropagation on unrolled network



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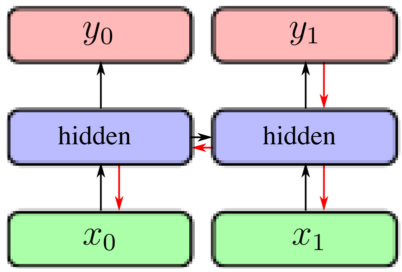

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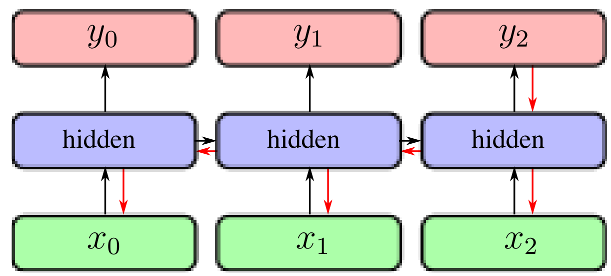

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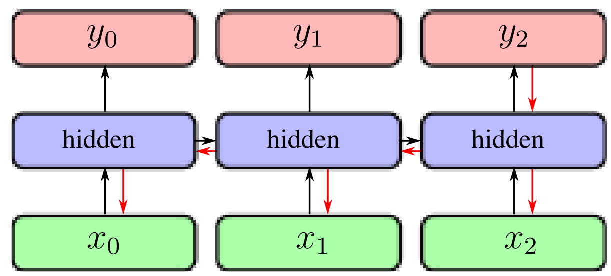

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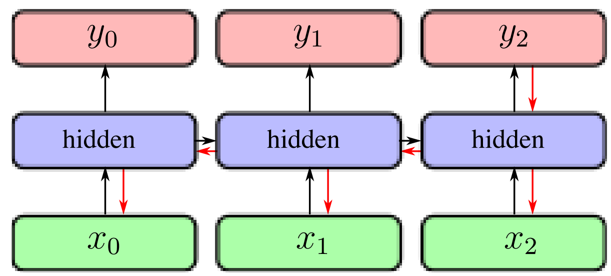

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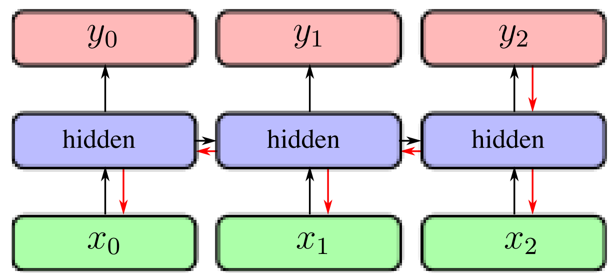

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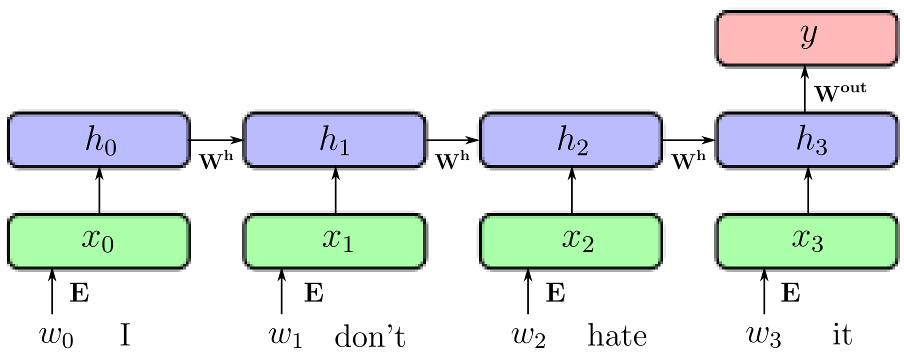
- Difficulties to train long-term dependencies

Other uses: Sentiment Analysis



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

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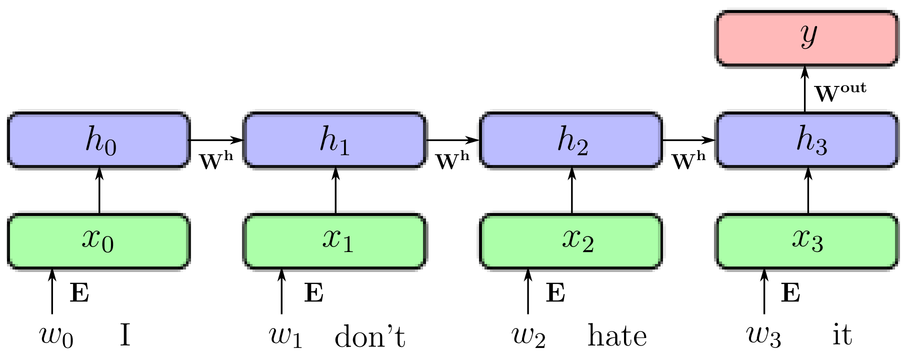

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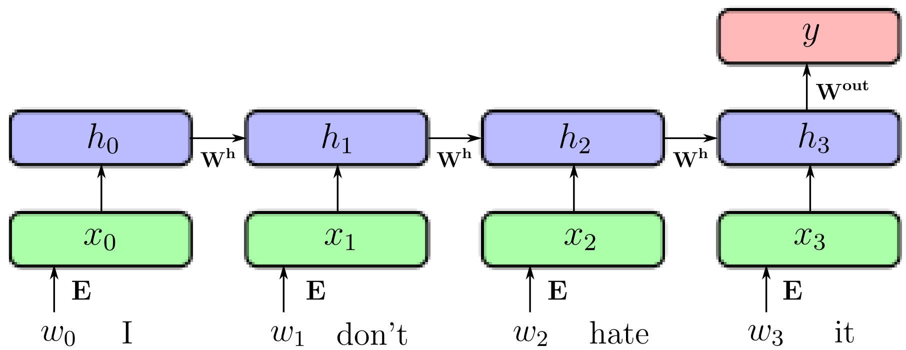

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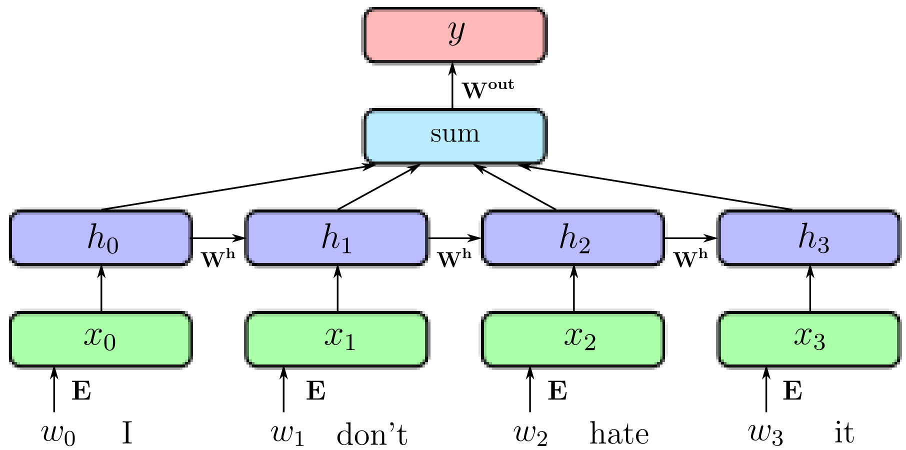

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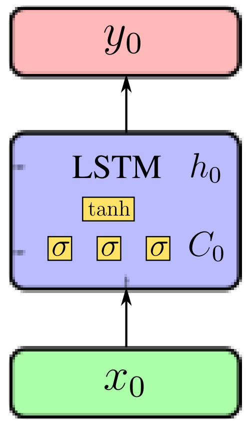
LSTM



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

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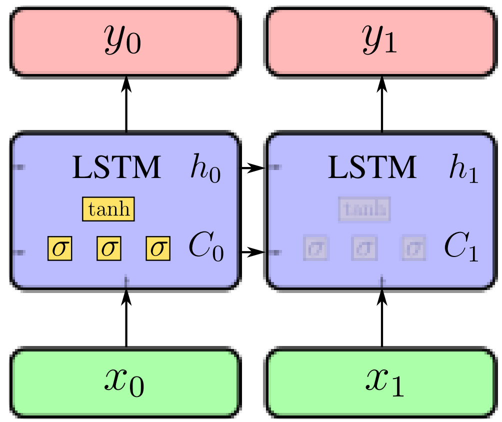

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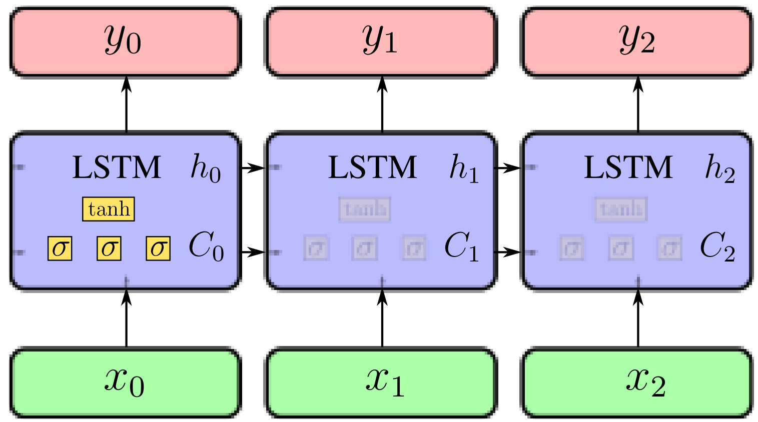

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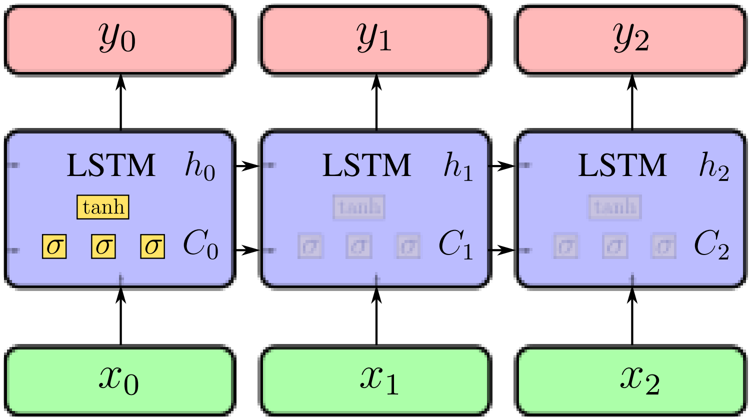

- 4 times more parameters than RNN

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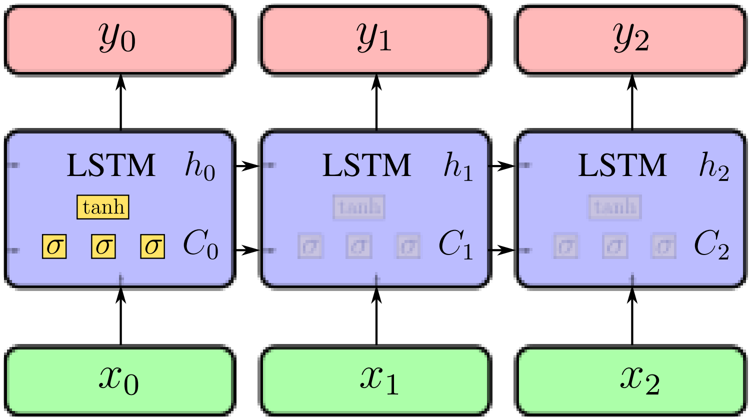

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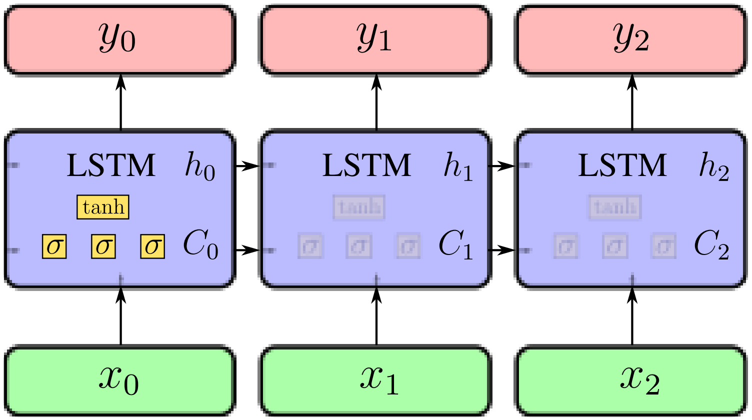

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- Mitigates **vanishing gradient** problem through **gating**
- Widely used and SOTA in many sequence learning problems

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Skip connections in ResNet also alleviate a similar optimization problem.

Next: Lab 6!