# Week 4: Embeddings and Recurrent Neural Networks

Matthew Willetts - Alexander Camuto

# Outline

Embeddings

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Recurrent Neural Networks

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Recurrent Neural Networks

Long Short-term Memory Networks

# Embeddings

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- Notation: Symbol $s$ in vocabulary $V$

# One-hot representation

$$onehot(\text{'salad'}) = [0, 0, 1, \ldots, 0] \in \{0,1\}^{|V|}$$

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$$onehot(\text{'salad'}) = [0, 0, 1, \dots, 0] \in \{0, 1\}^{|V|}$$


- Sparse, discrete, large dimension $|V|$
- Each axis has a meaning
- Symbols are equidistant from each other:

euclidean distance = $\sqrt{2}$

# Embedding

$$embedding(\text{'salad'}) = [3.28, -0.45, \ldots 7.11] \in \mathbb{R}^d$$

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- Can represent a huge vocabulary in low dimension, typically: $d \in \{16, 32, \ldots, 4096\}$
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**Neural Networks compute transformations on continuous vectors**

# Implementation with Keras

Size of vocabulary $n = |V|$, size of embedding $d$

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# input: batch of integers
Embedding(output_dim=d, input_dim=n, input_length=1)
# output: batch of float vectors
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- $\mathbf{W}$ is typically **randomly initialized**, then **tuned by backprop**
- $\mathbf{W}$ are trainable parameters of the model

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## Euclidean distance

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## Cosine similarity

$cosine(x, y) = \frac{x \cdot y}{||x|| \cdot ||y||}$

- Angle between points, regardless of norm
- $\boldsymbol{cosine(x, y)} \in \boldsymbol{(-1, 1)}$
- Expected cosine similarity of random pairs of vectors is $\mathbf{0}$

# Distance and similarity in Embedding space

If $x$ and $y$ both have unit norms:

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Alternatively, dot product (unnormalized) is used in practice as a pseudo similarity

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## t-SNE

Visualizing data using t-SNE, L van der Maaten, G Hinton, *The Journal of Machine Learning Research*, 2008

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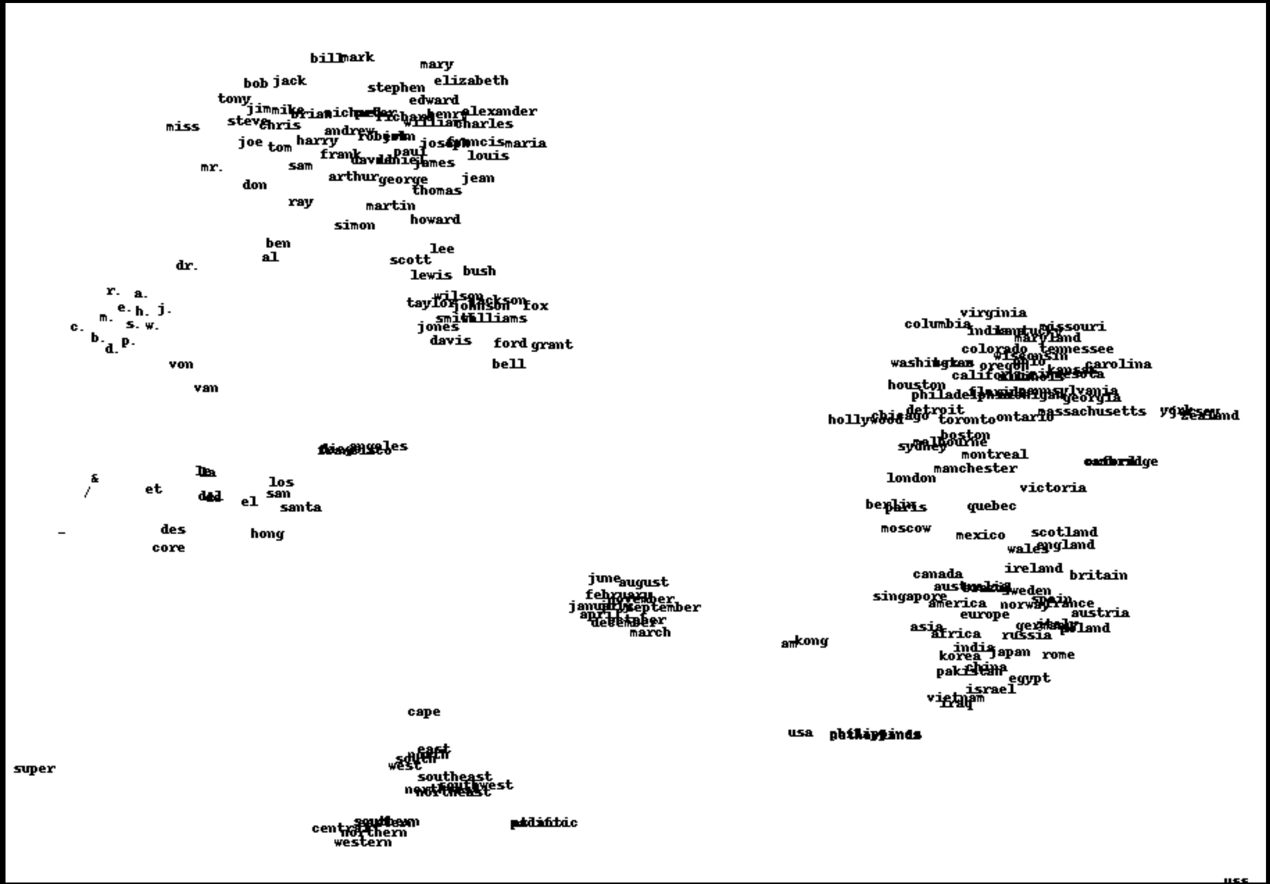
t-SNE projection is non deterministic (depends on initialization)

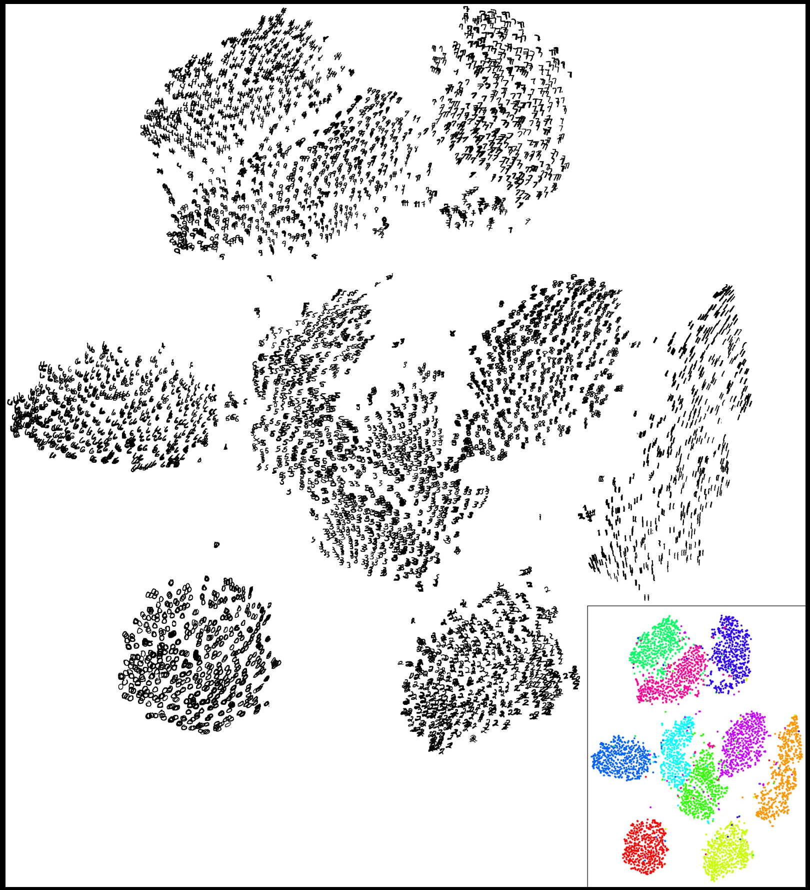
- Critical parameter: perplexity, usually set to 20, 30
- See [http://distill.pub/2016/misread-tsne/](http://distill.pub/2016/misread-tsne/)

# Example word vectors




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

# Visualizing Mnist



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**Deep Learning in NLP** has recently caught up with other domains such as computer vision and speech recognition - see Tranformer Networks like GPT and BERT

# 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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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:** $p(Target|Source)$

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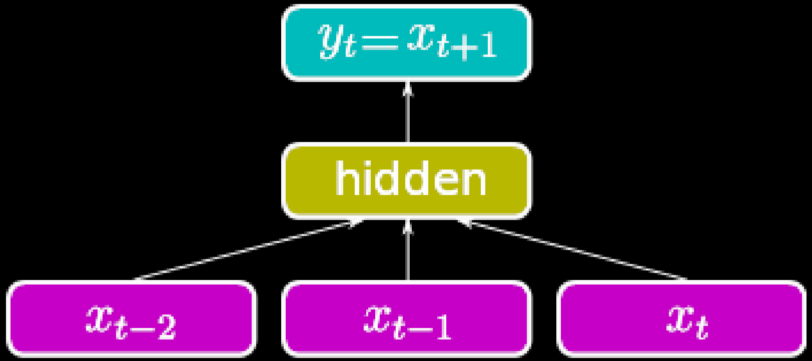
**Image Captionning:** $p(Caption|Image)$

- Instead of raw image, instead represent using activation of the penultimate layer of a CNN

# Simple Language Model



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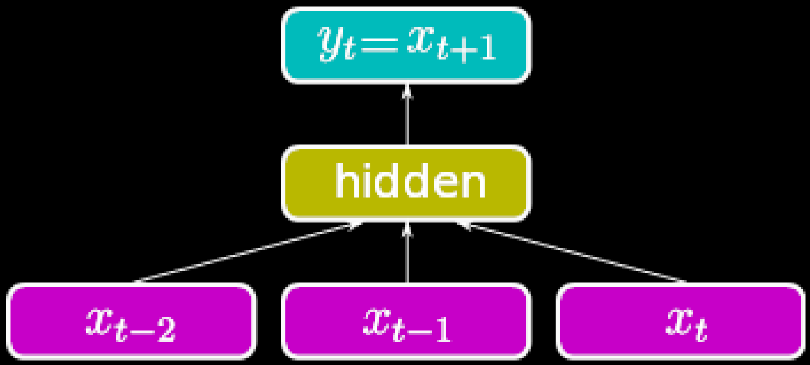


Fixed context size

Different modelling choices:

- **Average embeddings**: (same as CBoW) no sequence information, ie permutation invariant

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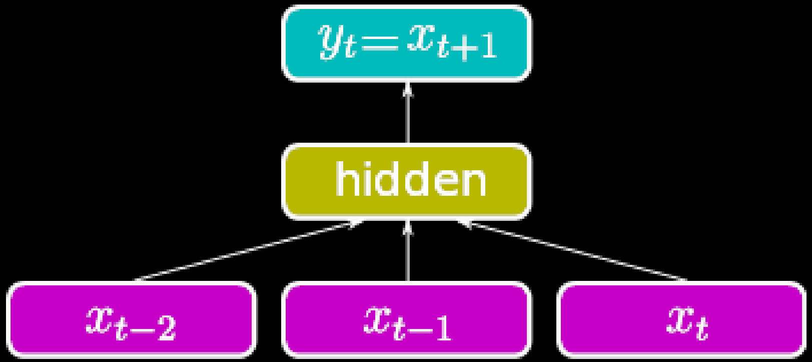


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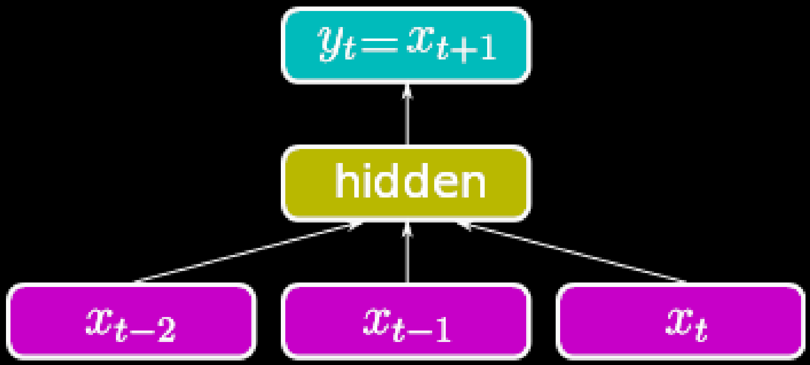


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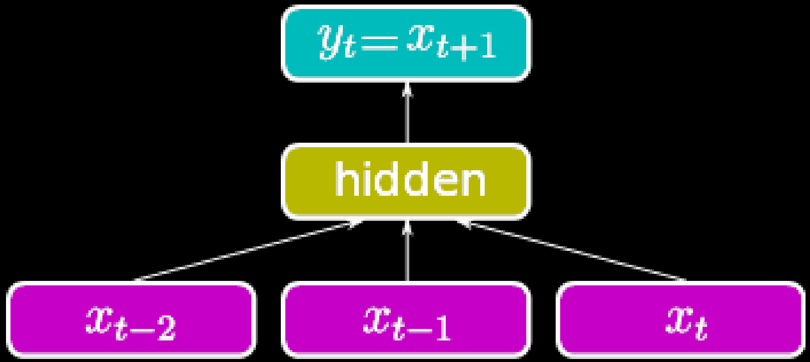


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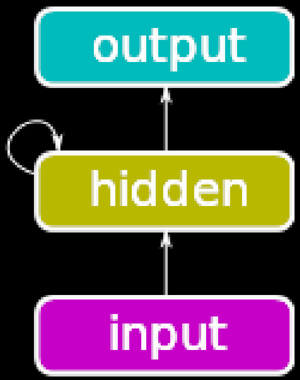
- Still does not take well into account varying sequence sizes and sequence dependencies

# Recurrent Neural Network



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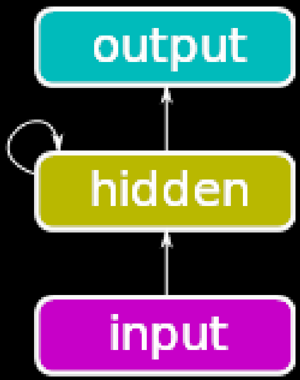
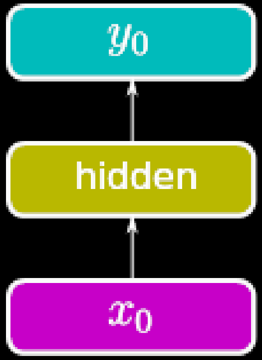



Unroll over a sequence $(x_0, x_1, x_2)$:



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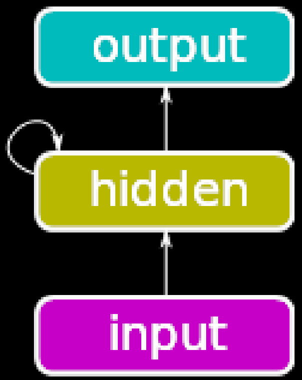


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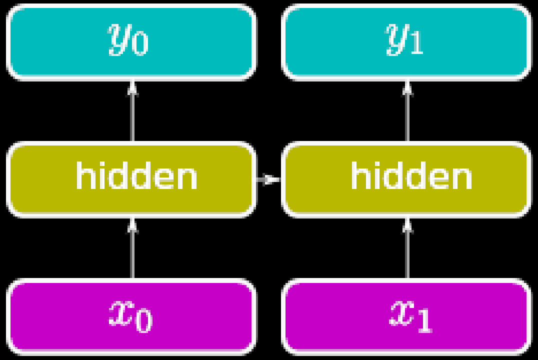

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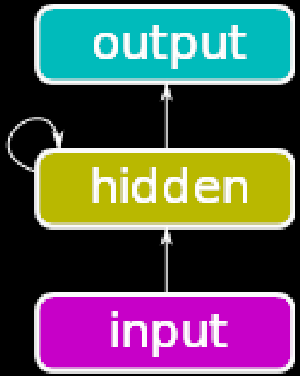


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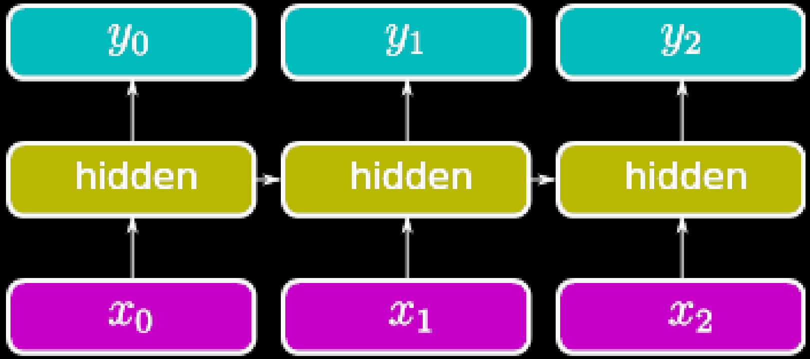
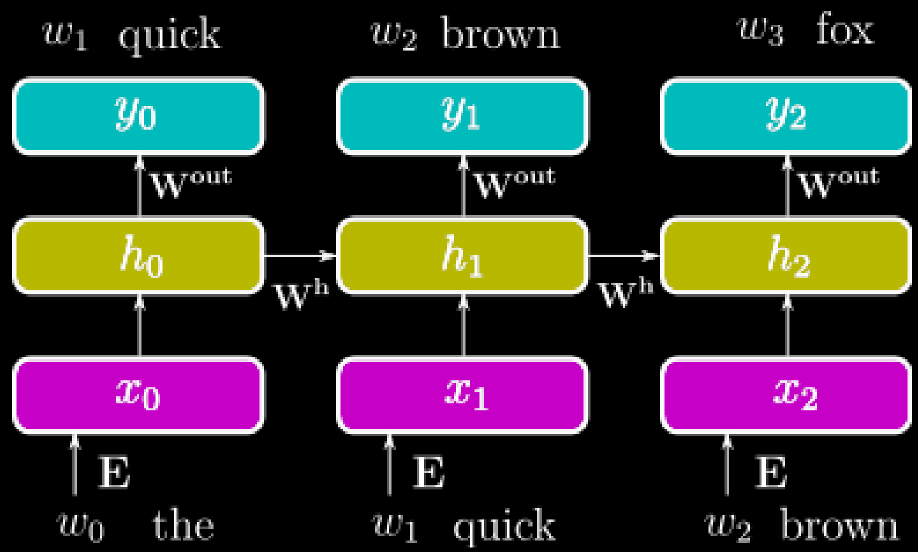


# Language Modelling




**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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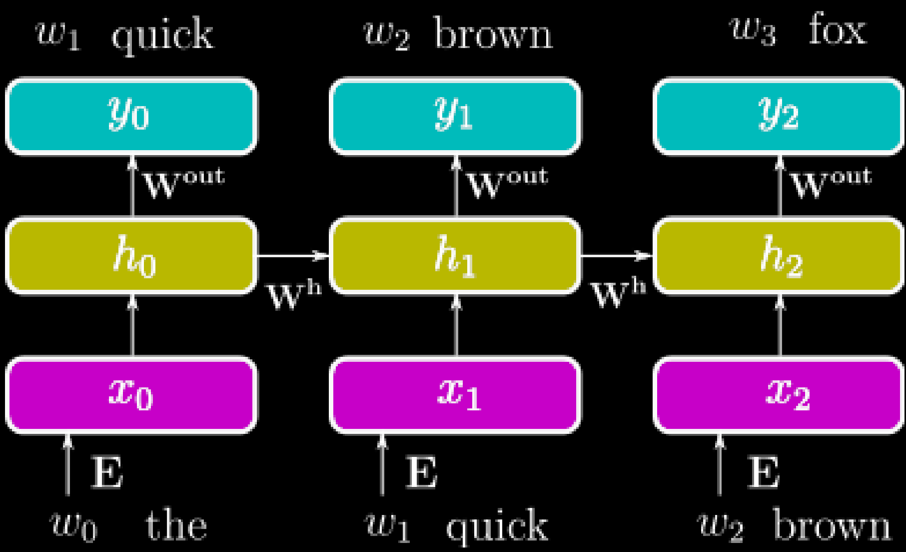


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input projection **H**

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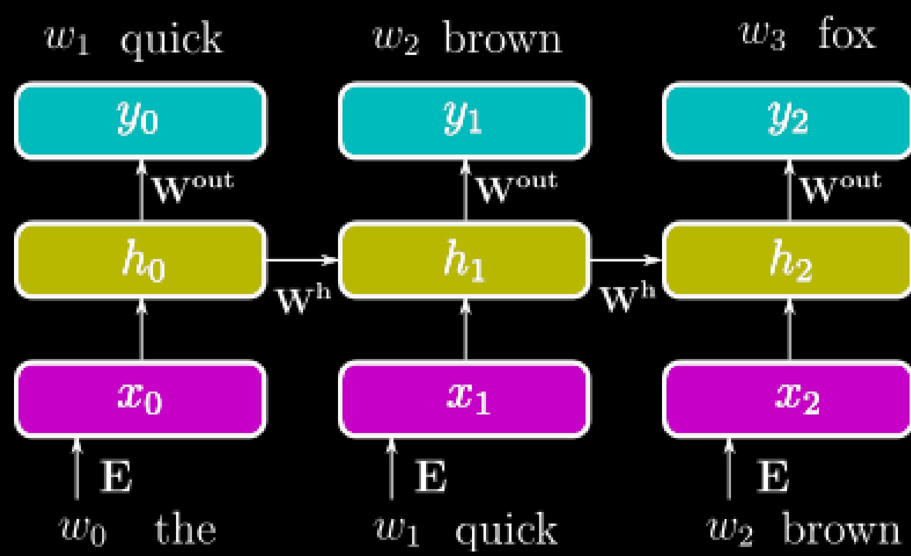


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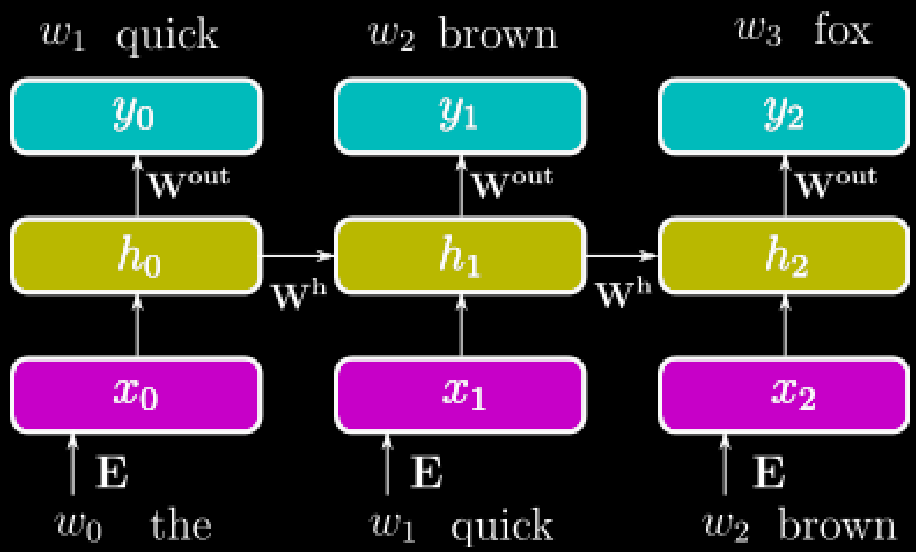


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$$y = \text{softmax}(\mathbf{W^o} h_t + b^o)$$

output projection K = |V|

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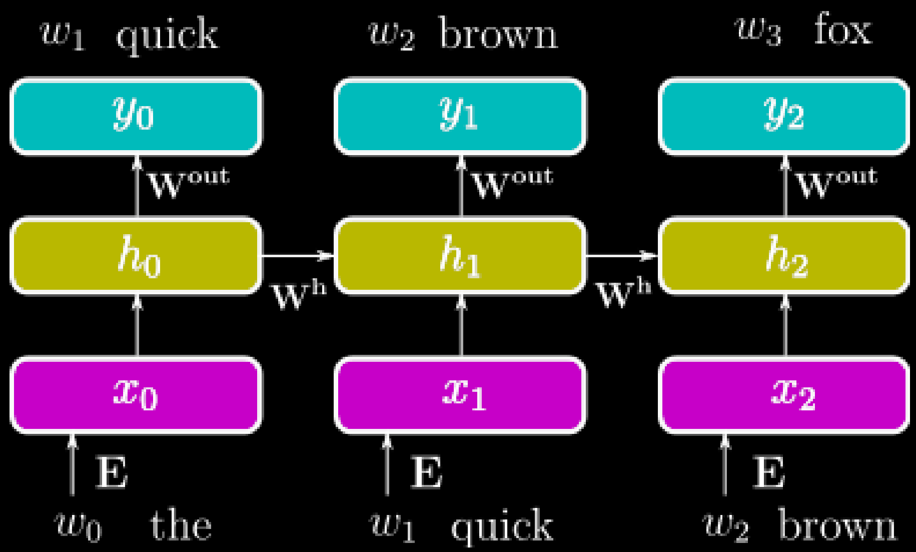


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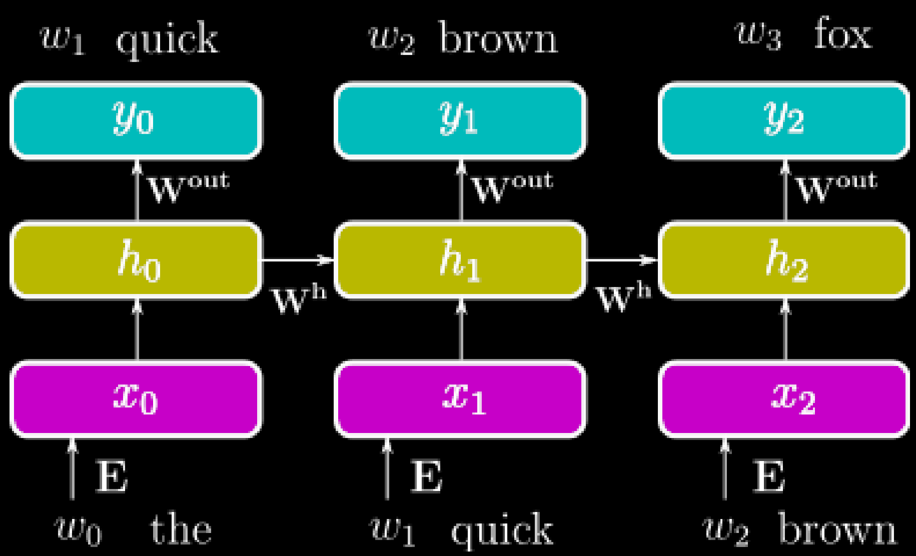


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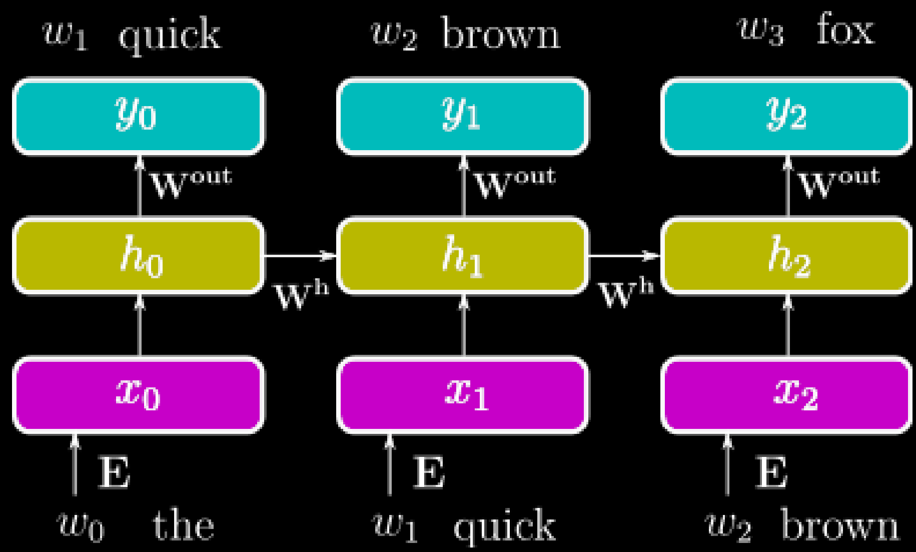


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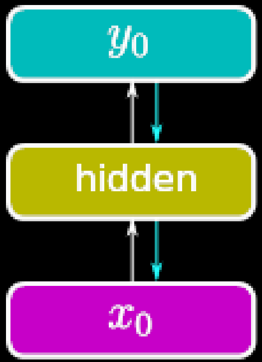
Output weights $\mathbf{W}^{\mathbf{out}}$

H x K = H x |V|

# Backpropagation through time

Similar as standard backpropagation on unrolled network



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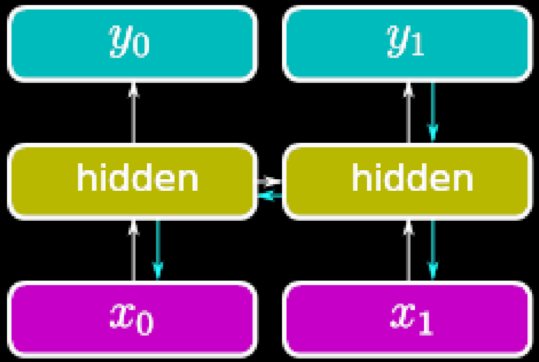

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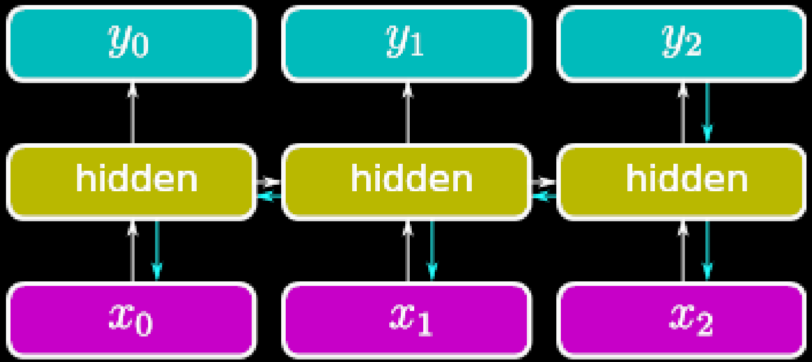

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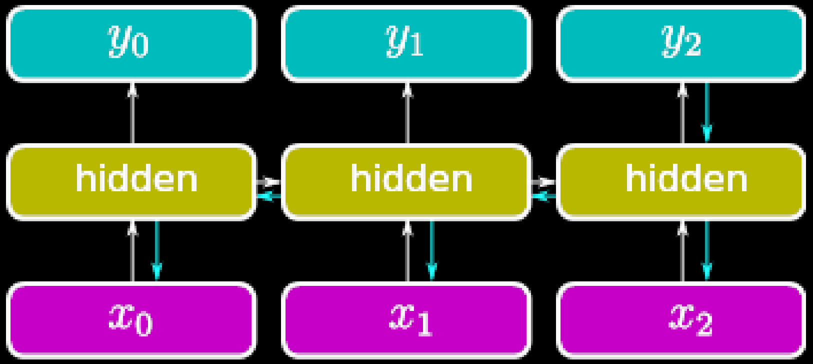


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- Example between $x_0$ and $y_2$: $W^h$ is used twice

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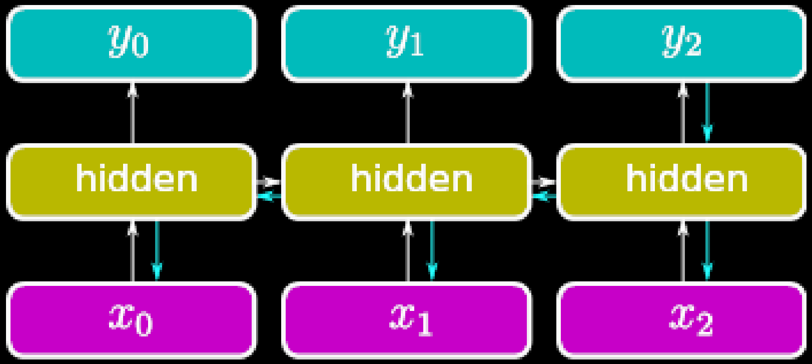


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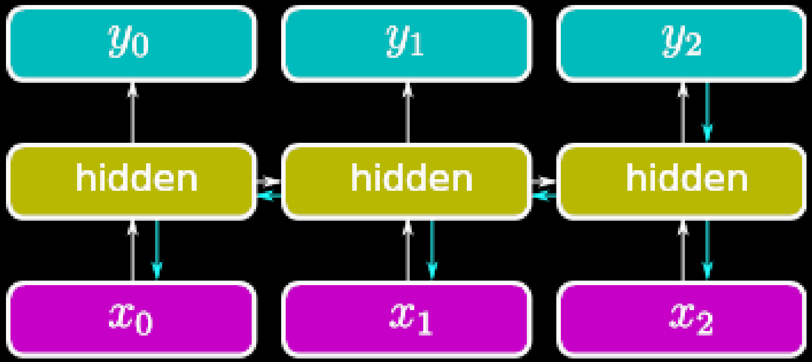


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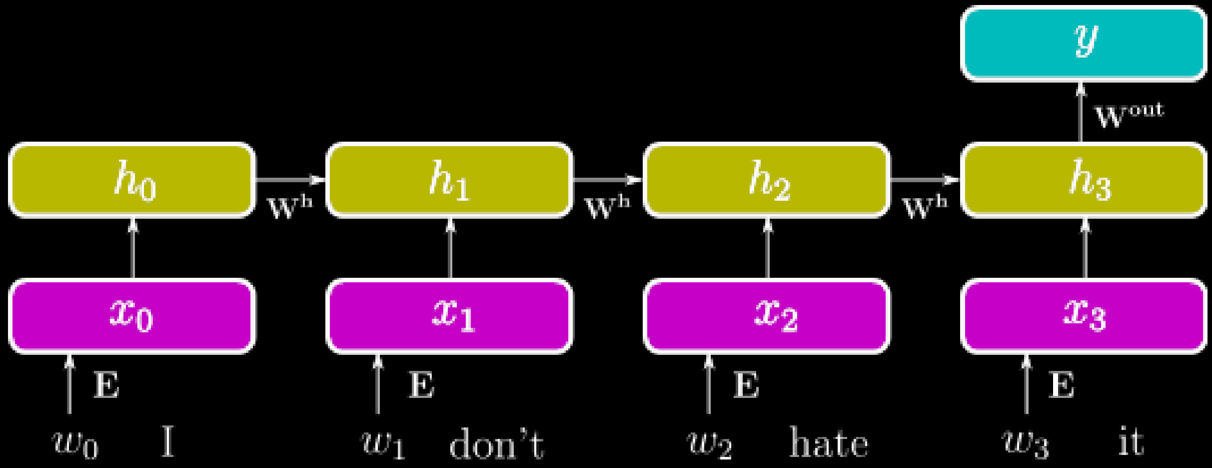
- Usually truncate the backprop after $T$ timesteps
- Difficulties to train long-term dependencies

# Other uses: Sentiment Analysis

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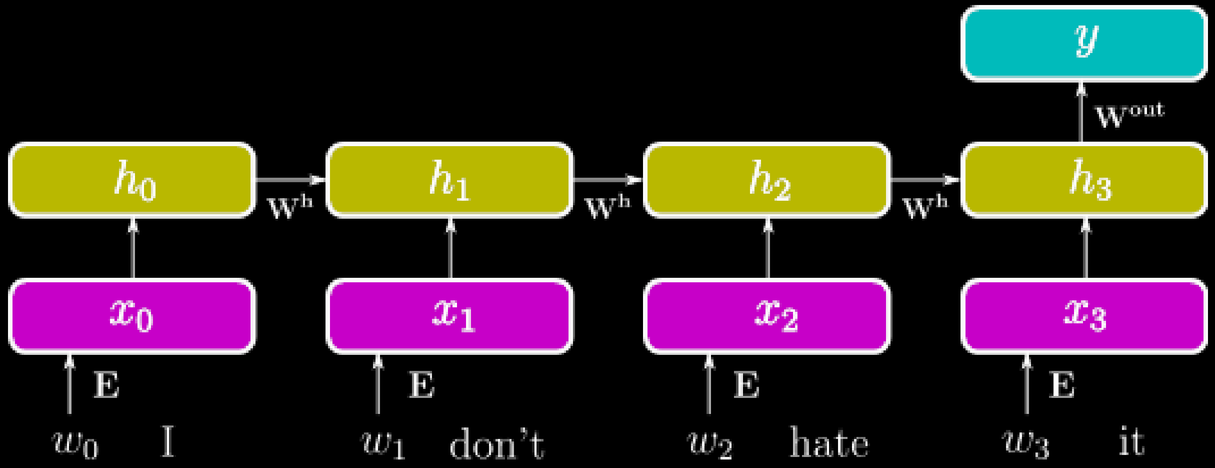


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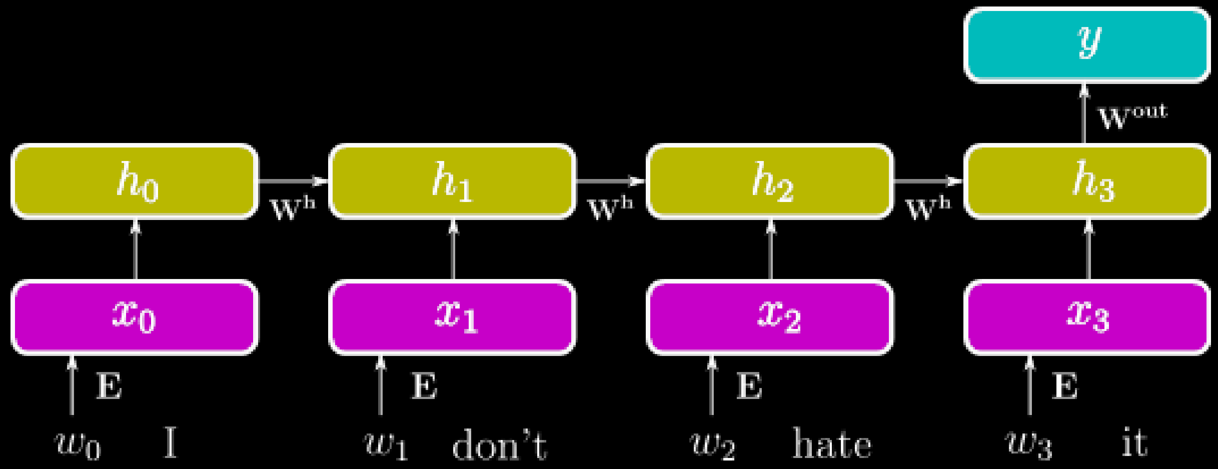


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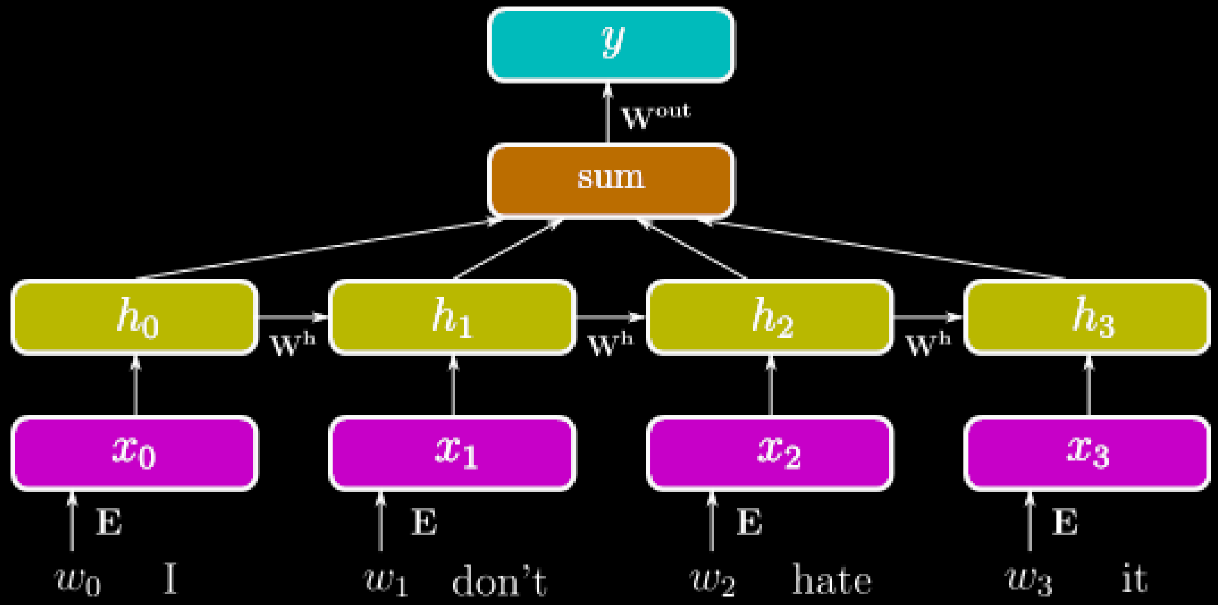


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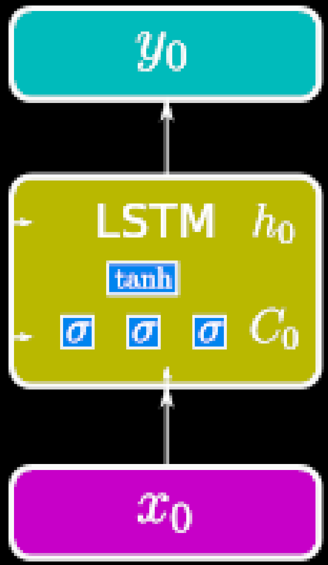
**Skip connections** in ResNet also alleviate a similar optimization problem.

# LSTM




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

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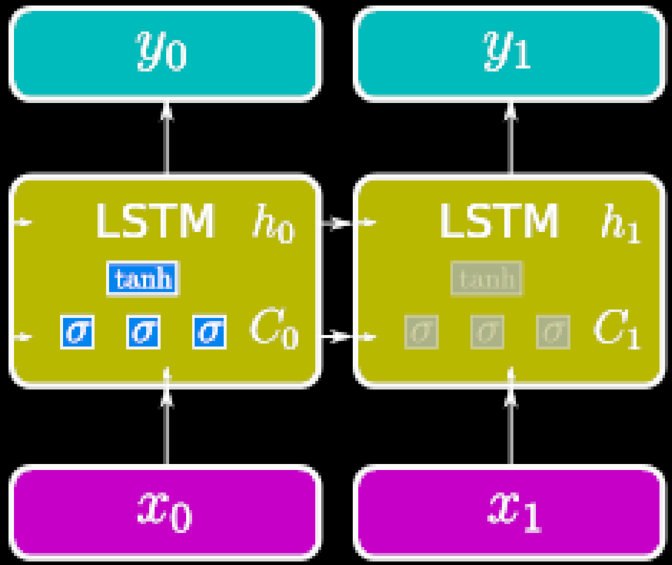


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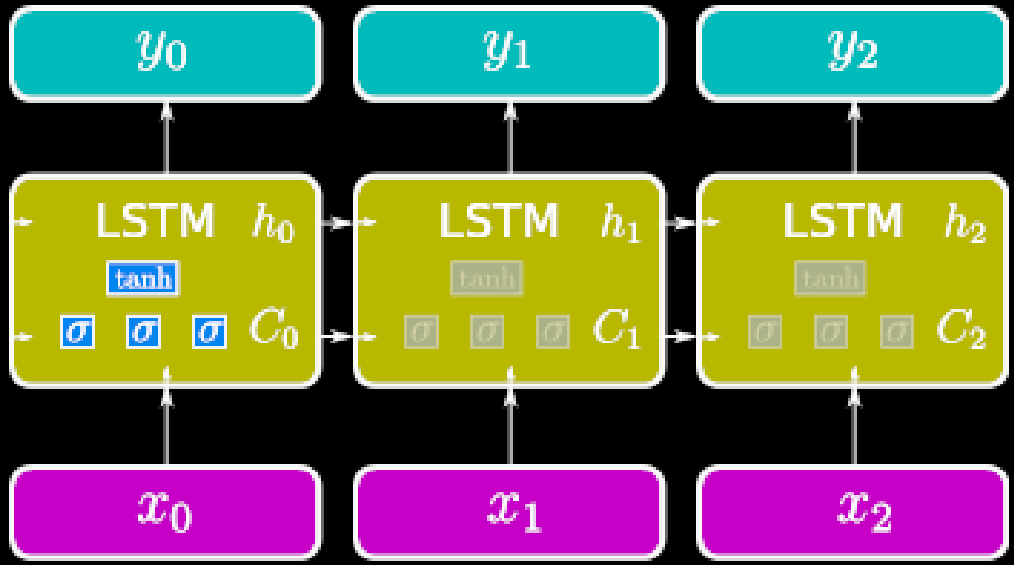


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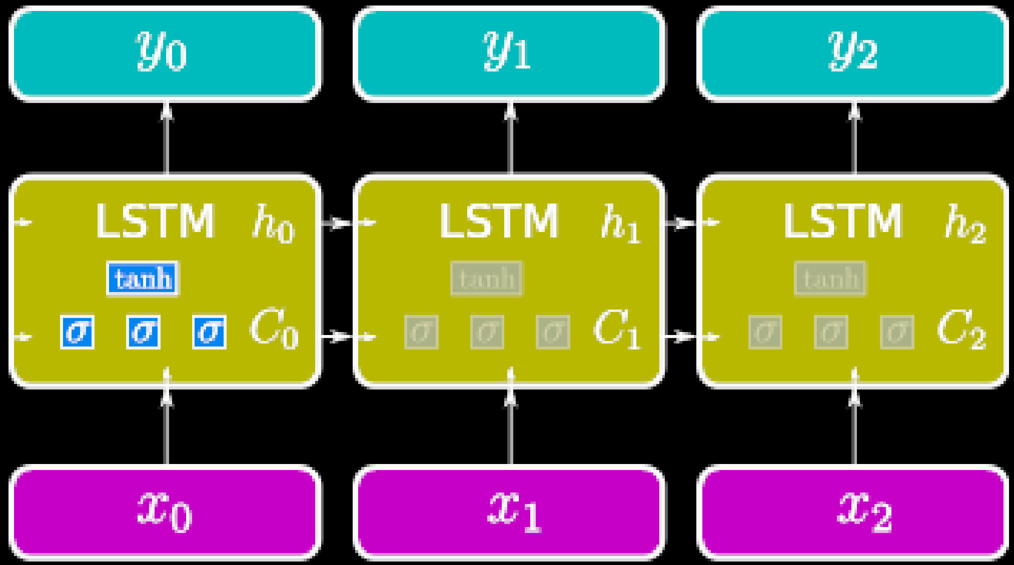


- 4 times more parameters than RNN

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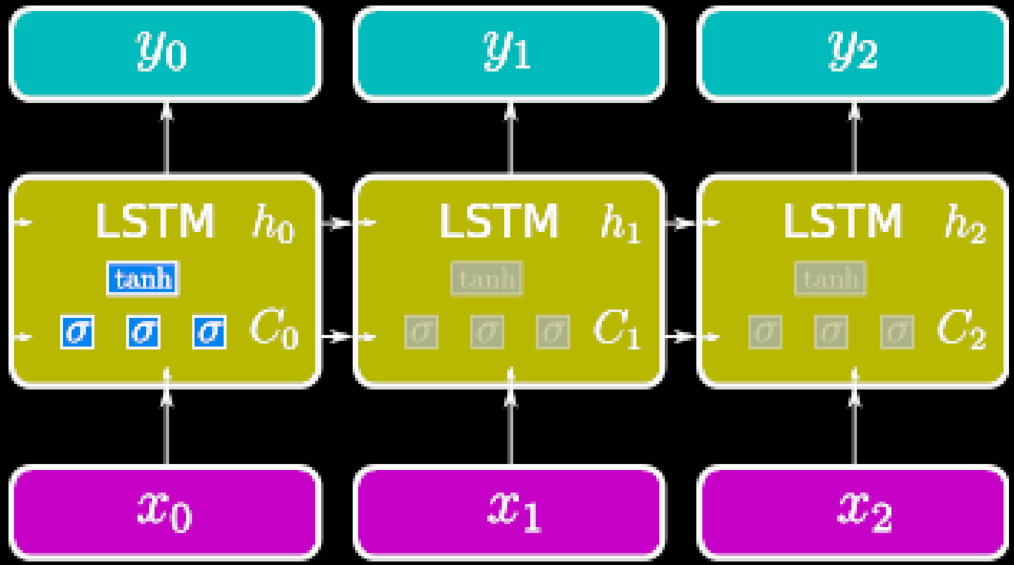


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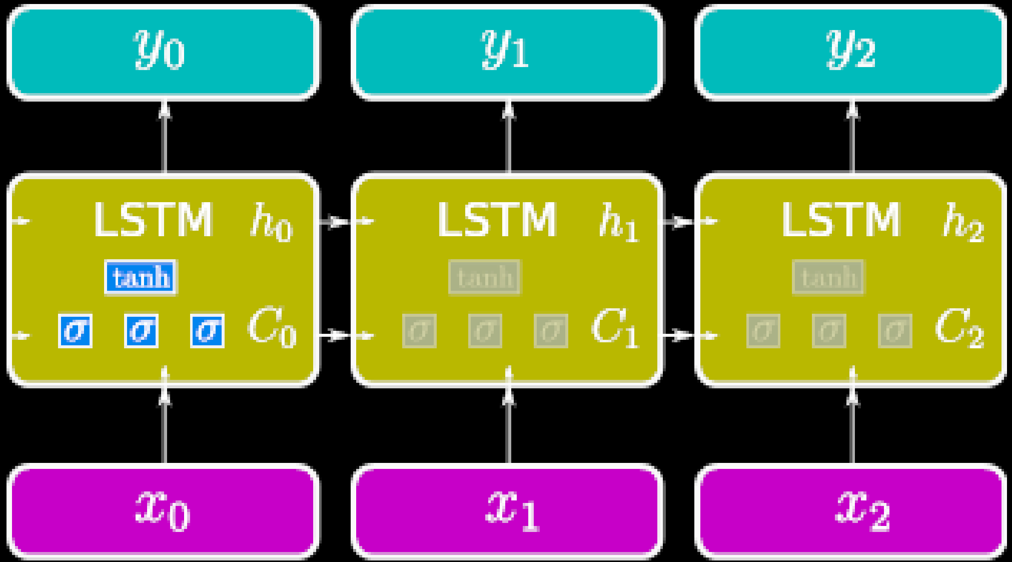


- 4 times more parameters than RNN
- Mitigates **vanishing gradient** problem through **gating**
- Widely used and (up until recently) SOTA in many sequence learning problems

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# 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

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In practice

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

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

# GPT-2: Current SOTA generation

–

```
I know that some people might be opposed to wearing
sneakers in a turtleneck, but I wanted to be true to myself,
so I went with a slim fitting turtleneck in a color more
similar to my favorite color of the day. Overall, it’s a
classic turtleneck, with nothing too flashy. I did swap my
shoes for these ASICS Tiger Killshots and I wish I hadn’t
did that. The shoe itself is very comfortable, however,
I found that wearing them in these sneakers made my
feet look a bit larger. I’d wear them with denim, chinos,
whatever, but would never recommend wearing them
alone. There are just too many variables involved.
```

# GPT-2: Current SOTA generation

–

```
Captain James J. Dall was born in Virginia in 1829 during
the Revolution and joined his father in the Army in 1836.
He served with the 2d Virginia Infantry until 1845, when
he went to the Western Reserve Regiment; and, on his
discharge, he reenlisted with Company I, 25th New York
Volunteers (which in 1845 numbered about 4,500 men).
One of his brothers, James, served with his company
in the same capacity in the same brigade. While the
regiment remained in Connecticut through 1846, Captain
Dall served with Company I at various times before
his discharge. A veteran of the Mexican War, he had
served two years on the staff of Brigadier General John J.
Sullivan at San Antonio. During the Peninsula Campaign
of 1863, he commanded a company of twenty-three and
was in charge of the battery of fifty-four heavy mortars
and the gunboat Pinta of the Battery, a gunboat and
several other boats. Captain Dall was on active duty with
Company I in the fall of 1865. Tw
```

# GPT-2: Current SOTA generation

–

```
Methinks I see her in her blissful dreams:
Or, fancy-like, in some mirage she lies,
Majestic yet majestic, and of seems
The image of the unconquerable skies.

Methinks I see her in her blissful dreams:
—Or, fancy-like, in some majestic cell,
Where lordly seraphs strew their balmy dreams
On the still night, or in their golden shell.

There, in the calm of some Platonic dream,
Sits she, and views the unclouded moon arise
Like a fair lady full of realms divine;

And, all at once, a stony face and bright
Glittering in moonlight, like the noon-tints of a night.
```

# Thanks to

Charles Ollion and Olivier Grisel, Paris-Saclay, for the slides

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