CSCI-567 Machine Learning (Spring 2021) Special Topics: Representation Learning and Time-series Processing with Neural Networks

Nitin Kamra

University of Southern California

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Acknowledgements

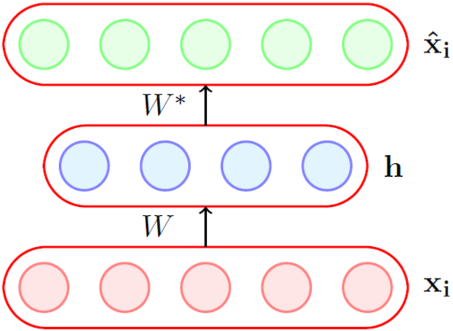
The materials borrow *heavily* from the following sources:

- Chris Olah's blog post on LSTMs: `http://colah.github.io/posts/2015-08-Understanding-LSTMs/`
- Dr. Nasim Zolaktaf's UBC lecture on recurrent neural networks: `https://www.cs.ubc.ca/labs/lci/mlrg/slides/rnn.pdf`
- Dr. Mitesh M. Khapra's lectures on Deep Learning: `https://www.cse.iitm.ac.in/~miteshk/CS7015/Slides/Teaching/pdf/Lecture7.pdf`

Outline

1. Autoencoders
2. Recurrent Neural Networks

Introduction to Autoencoder



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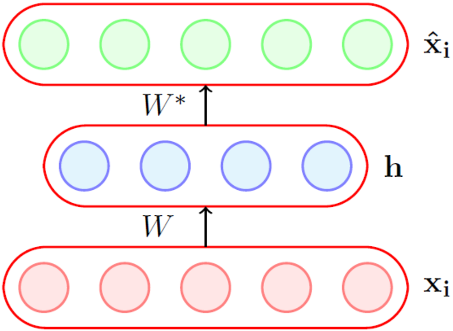

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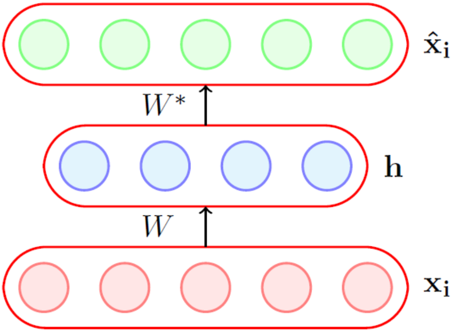

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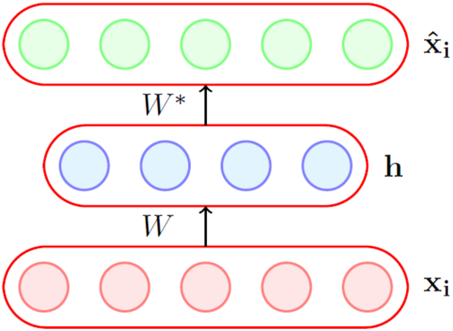

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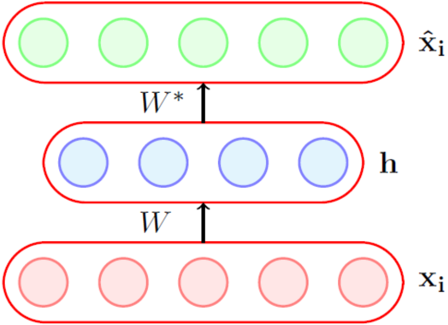

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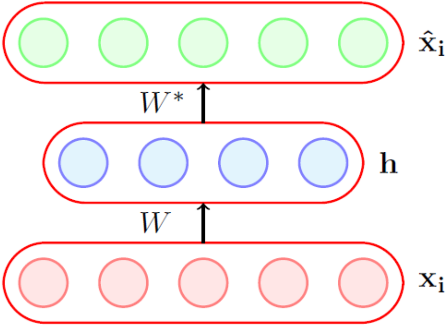

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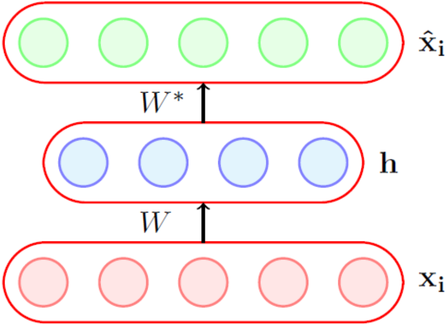

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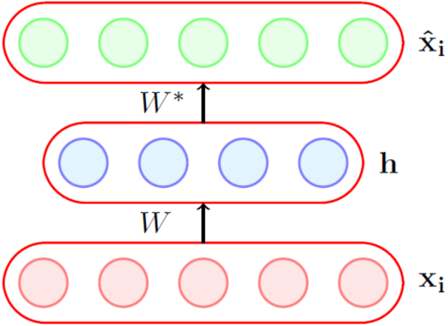

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- If dim$(\boldsymbol{h}) <$ dim$(\boldsymbol{x_i})$, then the neural network will have to encode maximum information from $\boldsymbol{x_i}$ into $\boldsymbol{h}$ for an accurate reconstruction!

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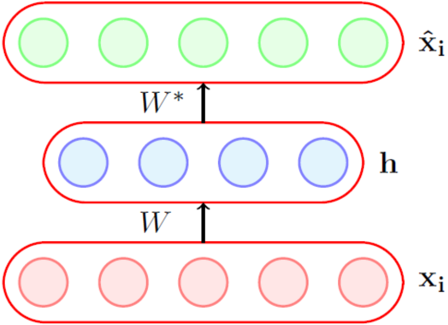

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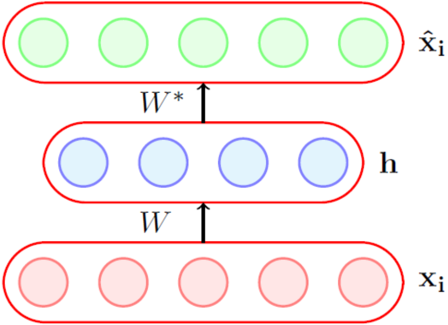
Hence, one can use autoencoders for:

- Representation learning
- Dimensionality reduction
- Finding hidden structure in data
- Data compression
- Clustering
- Anomaly detection

Choice of f and g



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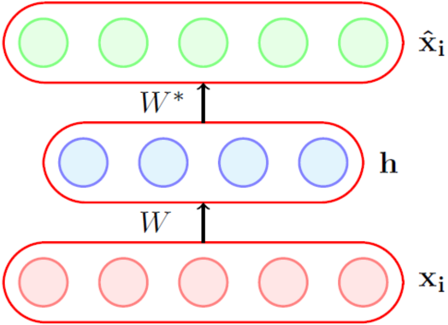

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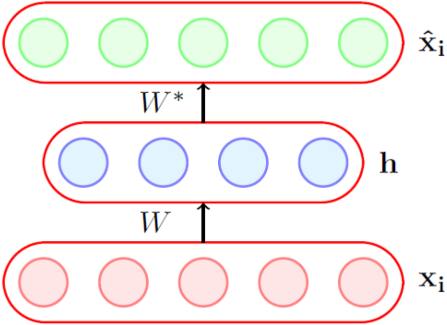

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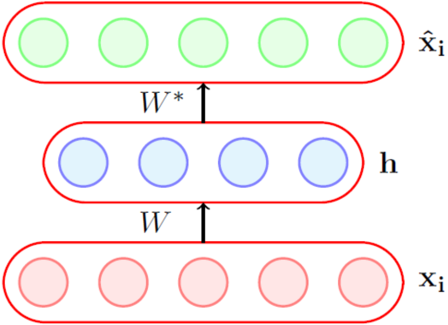

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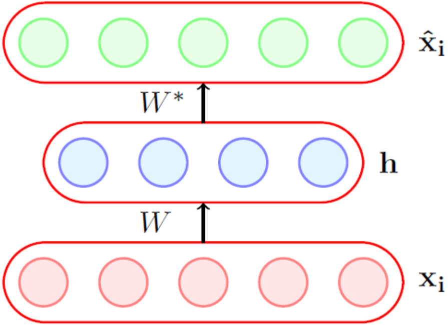

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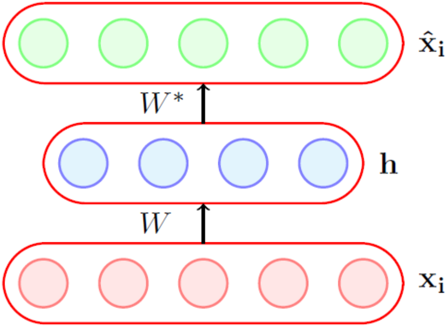

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What should be the choice for encoder activation g?

Answer: Typically, g is chosen as the sigmoid or tanh function to keep embedding values ($\boldsymbol{h}$) bounded and introduce non-linearity.

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Homework question: What if the inputs were binary-valued?

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- center the input by subtracting column-wise means

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- **Sparse autoencoders**: Use a sigmoid function for g and include a sparsity penalty on the hidden representations in the loss function.

Outline

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2 Recurrent Neural Networks

Sequential Data

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  - Text generation
  - Stock price prediction

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  - Hard to represent patterns with more than a few words (possible patterns increases exponentially)
- Simple solution: Neural networks?
  - Fixed input/output size
  - Fixed number of steps

Recurrent Neural Networks

- **Recurrent neural networks (RNNs)** are networks with loops, allowing information to persist [Rumelhart et al., 1986].

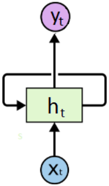
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

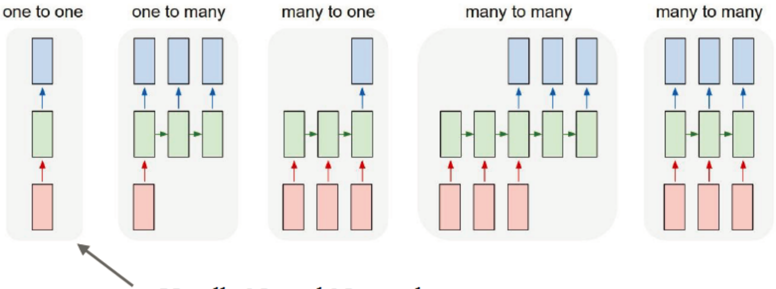
some function with parameters W



- Have **memory** that keeps track of information observed so far
- Maps from the entire history of previous inputs to each output
- Handle sequential data

Adapted from: *N. Cinbis and C. Olah*

Recurrent Networks Offer a Lot of Flexibility



Vanilla Neural Network

fixed-sized input -> fixed-size output

e.g. image classification

Adapted from: *A. Karpathy*

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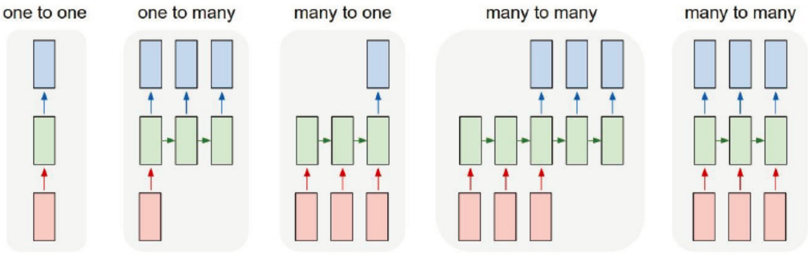

sequence output

e.g. image captioning

image -> sequence of words

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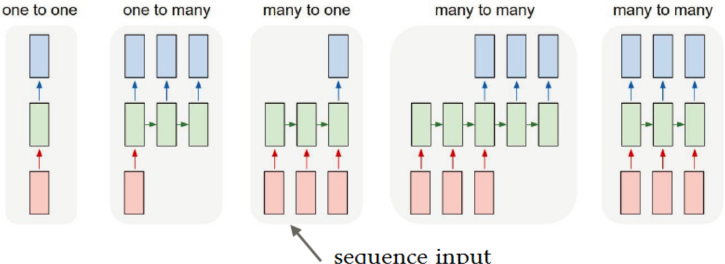

sequence input

e.g. sentiment classification

sequence of words -> sentiment

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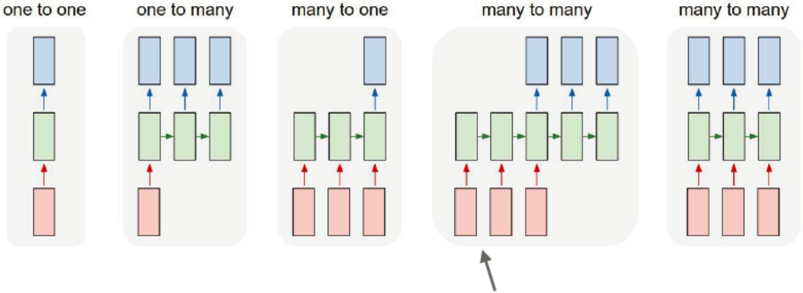

sequence input and sequence output

e.g. machine translation

seq of words -> seq of words

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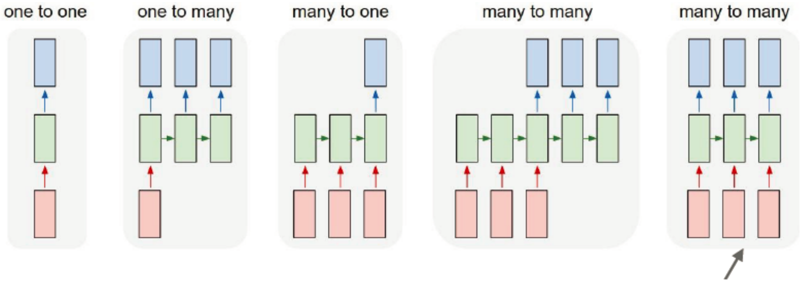

synced sequence input and output

e.g. video classification on frame level

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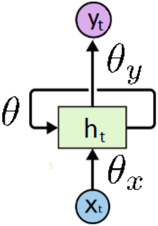
Recurrent Neural Networks

$$\mathbf{h}_t = \theta\phi(\mathbf{h}_{t-1}) + \theta_x \mathbf{x}_t$$

$$\mathbf{y}_t = \theta_y \phi(\mathbf{h}_t)$$

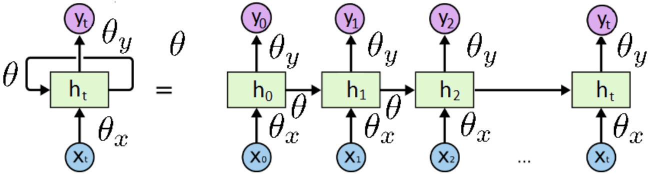


- $\mathbf{x}_t$ is the **input** at time t.
- $\mathbf{h}_t$ is the **hidden state** (memory) at time t.
- $\mathbf{y}_t$ is the **output** at time t.
- θ, θ_x, θ_y are distinct **weights**.
  - weights are the same at all time steps.

Adapted from: *C. Olah*

Recurrent Neural Networks

- RNNs can be thought of as multiple copies of the same network, each passing a message to a successor.

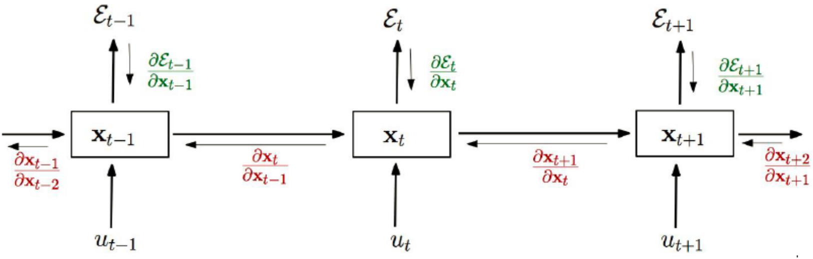


- The same function and the same set of parameters are used at every time step.
    - Are called recurrent because they perform the same task for each input.

Adapted from: *C. Olah*

Back-Propagation Through Time (BPTT)

- Using the generalized back-propagation algorithm one can obtain the so-called **Back-Propagation Through Time** algorithm.
- The recurrent model is represented as a multi-layer one (with an unbounded number of layers) and backpropagation is applied on the unrolled model.



$\mathcal{E}_{t-1}$
$\frac{\partial \mathcal{E}_{t-1}}{\partial \mathbf{x}_{t-1}}$
$\mathcal{E}_t$
$\frac{\partial \mathcal{E}_t}{\partial \mathbf{x}_t}$
$\mathcal{E}_{t+1}$
$\frac{\partial \mathcal{E}_{t+1}}{\partial \mathbf{x}_{t+1}}$
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$\frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_{t-1}}$
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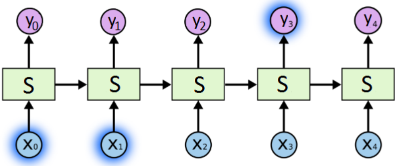
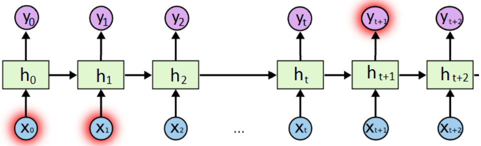
$\frac{\partial \mathbf{x}_{t+2}}{\partial \mathbf{x}_{t+1}}$
u_{t-1}
u_t
u_{t+1}

The Problem of Long-term Dependencies

- RNNs connect previous information to present task:
  - may be enough for predicting the next word for ”the clouds are in the sky”



  - may not be enough when more context is needed: ”I grew up in France ... I speak fluent French”



Adapted from: *C. Olah*

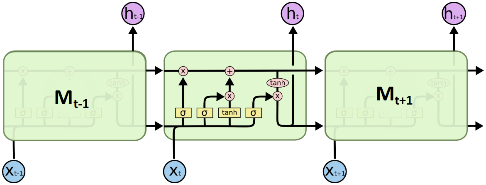
Vanishing/Exploding Gradients

- In RNNs, during the gradient back propagation phase, the gradient signal can end up being multiplied many times.
- If the gradients are large
    - Exploding gradients, learning diverges
    - Solution: clip the gradients to a certain max value.
- If the gradients are small
    - Vanishing gradients, learning very slow or stops
    - Solution: introducing memory via LSTM, GRU, etc.

Adapted from: *N. Cinbis*

Long Short-Term Memory Networks

- **Long Short-Term Memory (LSTM) networks** are RNNs capable of learning **long-term dependencies** [Hochreiter and Schmidhuber, 1997].



- A **memory** cell using logistic and linear units with multiplicative interactions:
  - Information **gets** into the cell whenever its **input gate** is on.
  - Information is **thrown away** from the cell whenever its **forget gate** is off.
  - Information can be **read** from the cell by turning on its **output gate**.

Adapted from: *C. Olah*

LSTM Overview

- We define the LSTM unit at each time step t to be a collection of vectors in $\mathbb{R}^d$:
  - **Memory cell** $\mathbf{c}_t$

    $\widetilde{\mathbf{c}}_t = \text{Tanh}(W_c.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)$ **vector of new candidate values**

    $$\mathbf{c}_t = \mathbf{f}_t * \mathbf{c}_{t-1} + \mathbf{i}_t * \widetilde{\mathbf{c}}_t$$
  - **Forget gate** $\mathbf{f}_t$ in [0, 1]: scales old memory cell value (**reset**)

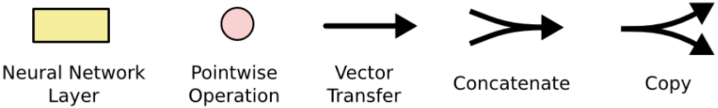
    $$\mathbf{f}_t = \sigma(W_f.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f)$$
  - **Input gate** $\mathbf{i}_t$ in [0, 1]: scales input to memory cell (**write**)

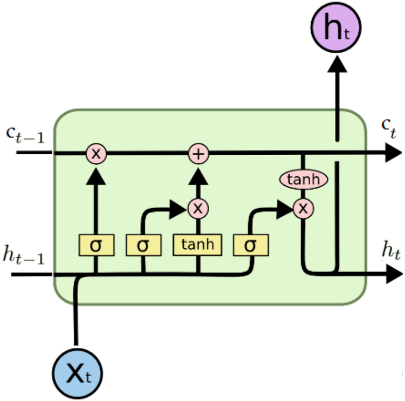
    $$\mathbf{i}_t = \sigma(W_i.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)$$
  - **Output gate** $\mathbf{o}_t$ in [0, 1]: scales output from memory cell (**read**)

    $$\mathbf{o}_t = \sigma(W_o.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o)$$
  - **Output** $\mathbf{h}_t$

    $$\mathbf{h}_t = \mathbf{o}_t * \text{Tanh}(\mathbf{c}_t)$$

Notation

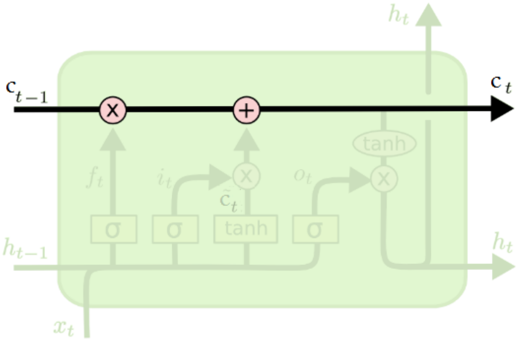




Adapted from: *C. Olah*

The Core Idea Behind LSTMs: Cell State (Memory Cell)

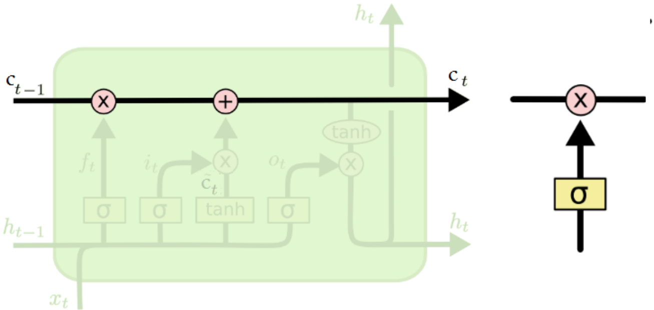
- Information can flow along the **memory cell unchanged**.
- Information can be **removed** or **written** to the **memory cell**, regulated by gates.



Adapted from: *C. Olah*

Gates

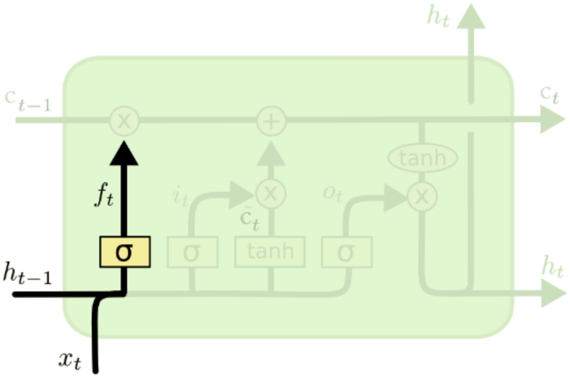
- **Gates** are a way to optionally let information through.
  - A **sigmoid layer** outputs number between 0 and 1, **deciding** how much of each component should be let through.
  - A pointwise multiplication operation applies the decision.



Adapted from: *C. Olah*

Forget Gate

- A **sigmoid** layer, **forget gate**, **decides** which values of the **memory cell** to **reset**.

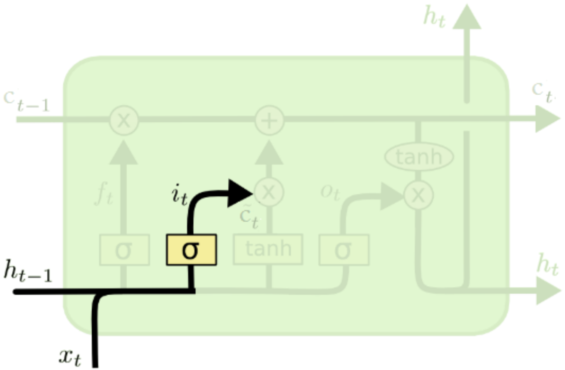


$$\mathbf{f}_t = \sigma(W_f.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f)$$

Adapted from: *C. Olah*

Input Gate

- A **sigmoid** layer, **input gate**, **decides** which values of the **memory cell** to **write** to.

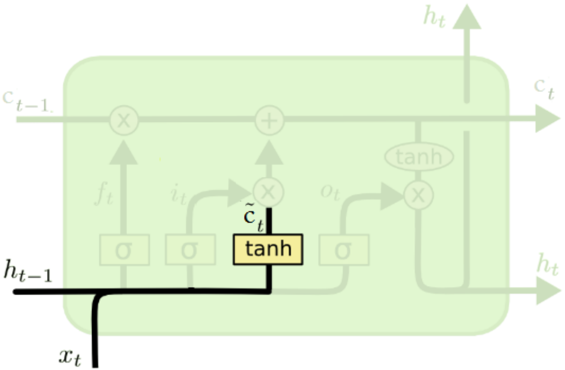


$$\mathbf{i}_t = \sigma(W_i.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)$$

Adapted from: *C. Olah*

Vector of New Candidate Values

- A **Tanh** layer creates a **vector of new candidate values** $\widetilde{c}_t$ to **write** to the **memory cell**.

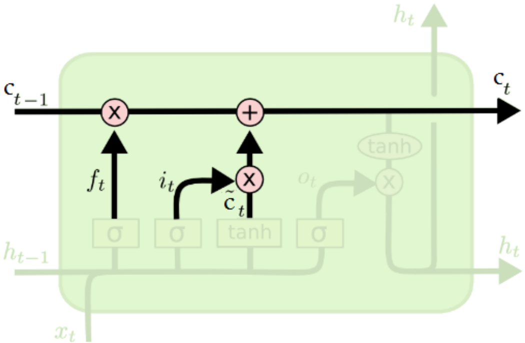


$$\widetilde{\mathbf{c}}_t = \text{Tanh}(W_c.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)$$

Adapted from: *C. Olah*

Memory Cell Update

- The previous steps decided which values of the **memory cell** to **reset** and **overwrite**.
- Now the LSTM **applies the decisions** to the **memory cell**.

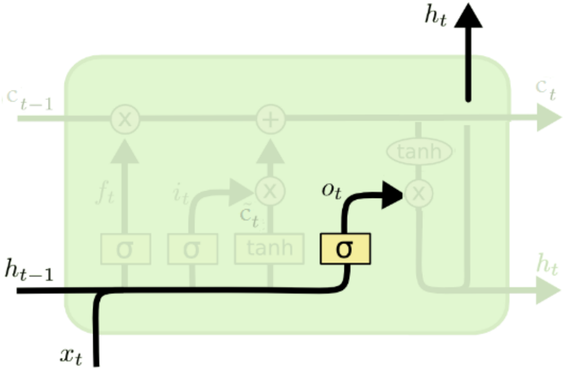


$$\mathbf{c}_t = \mathbf{f}_t * \mathbf{c}_{t-1} + \mathbf{i}_t * \widetilde{\mathbf{c}}_t$$

Adapted from: *C. Olah*

Output Gate

- A **sigmoid** layer, **output gate**, **decides** which values of the **memory cell** to **output**.

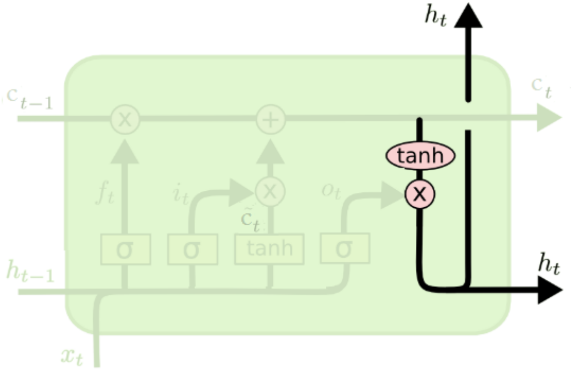


$$\mathbf{o}_t = \sigma(W_o.[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o)$$

Adapted from: *C. Olah*

Output Update

- The **memory cell** goes through **Tanh** and is multiplied by the **output gate**.



$$\mathbf{h}_t = \mathbf{o}_t * \text{Tanh}(\mathbf{c}_t)$$

Adapted from: *C. Olah*

Variants on LSTM

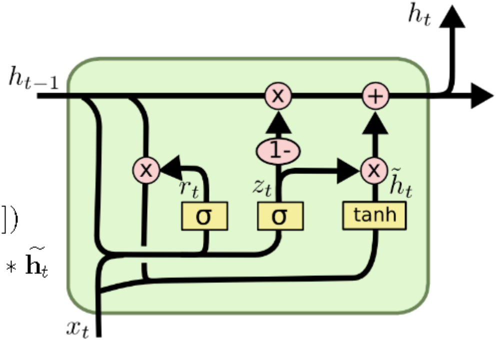
- Gated Recurrent Unit (GRU) [Cho et al., 2014]:
  - Combine the **forget** and **input** gates into a single **update** gate.
  - **Merge the memory cell and the hidden state**.
  - ...

$$z_t = \sigma(W_z.[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

$$r_t = \sigma(W_r.[\mathbf{h}_{t-1}, \mathbf{x}_t])$$

$$\widetilde{\mathbf{h}_t} = \text{Tanh}(W.[r_t * \mathbf{h}_{t-1}, \mathbf{x}_t])$$

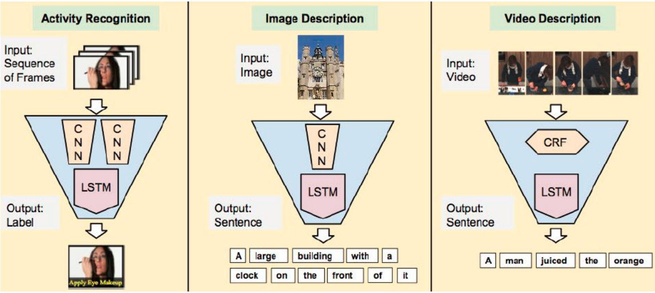
$$\mathbf{h}_t = (1 - z_t) * \mathbf{h}_{t-1} + (z_t) * \widetilde{\mathbf{h}_t}$$



Adapted from: *C. Olah*

Applications

- Cursive handwriting recognition
  - https://www.youtube.com/watch?v=mLxsbWAYIpw
- Translation
  - Translate any signal to another signal, e.g., translate English to French, translate image to image caption, and songs to lyrics.
- Visual sequence tasks



Adapted from: *Jeff Donahue et al. CVPR15*