Introduction to Machine Learning: Deep Supervised Learning

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Outline

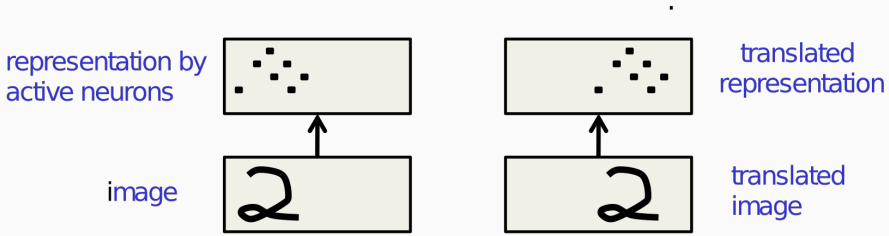
1. Convolutional Neural Networks (CNNs)
2. Recurrent Neural Networks (RNNs)
3. Long-Short Term Memory (LSTM)

What are CNNs?

- CNNs are a class of deep neural network that represents the deep learning framework for computer vision.
- They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on shared-weights architecture and translation invariance characteristics.
- They are powerful tools for image segmentation, object detection, object recognition

Why Object Recognition is difficult?

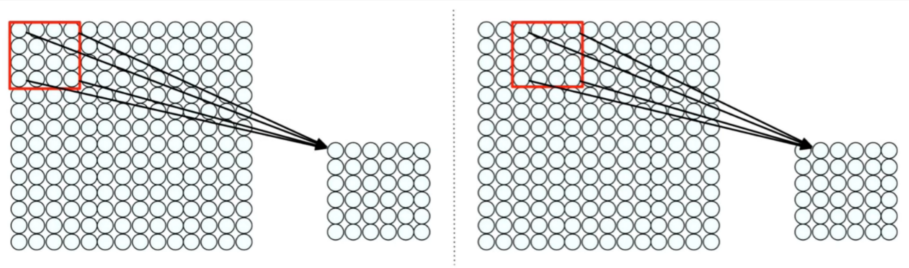
- Segmentation, Lighting, Deformation, Affordances
- Viewpoint (translation): changing the viewpoint would completely change the activation of the input layer in a multilayer perceptron



- Fully connected networks do not have spatial information and have plenty of parameters

How can we preserve spatial information?

Connect patches of inputs to neurons in hidden layers



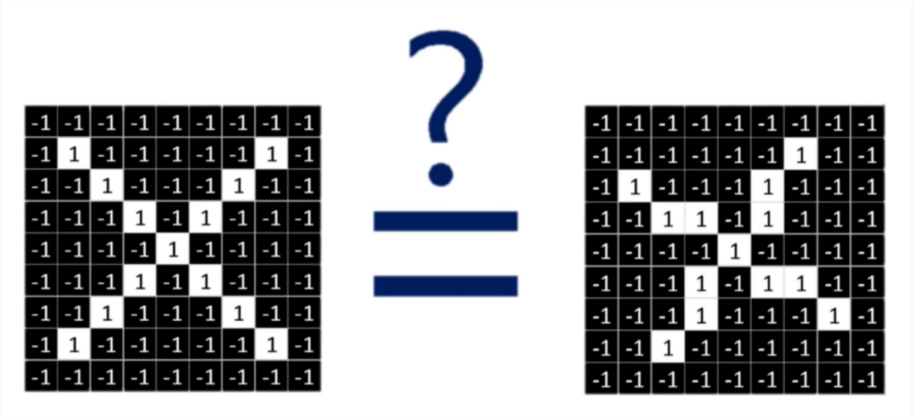
We want to have patches that are able to detect particular aspects of the image

Feature Extraction with Convolution

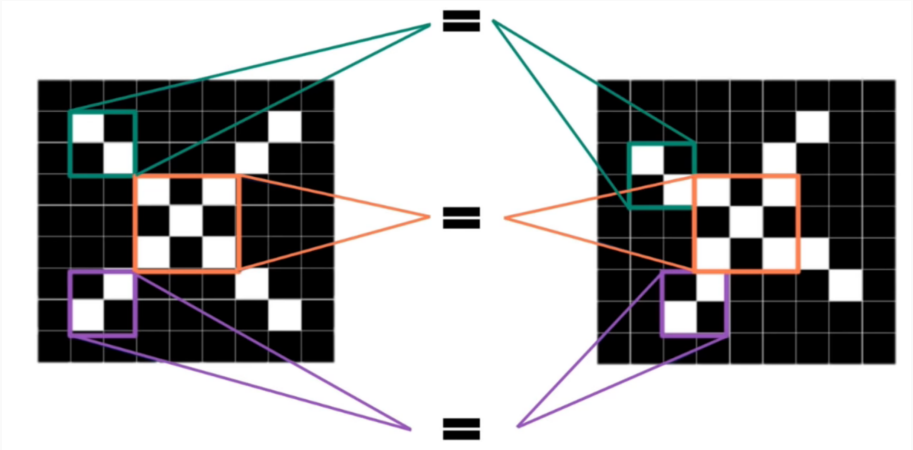
We want the following

1. Apply a filter to extract spatial information
2. Apply different filters in each convolutional layer
3. Learn each filter using shared parameters

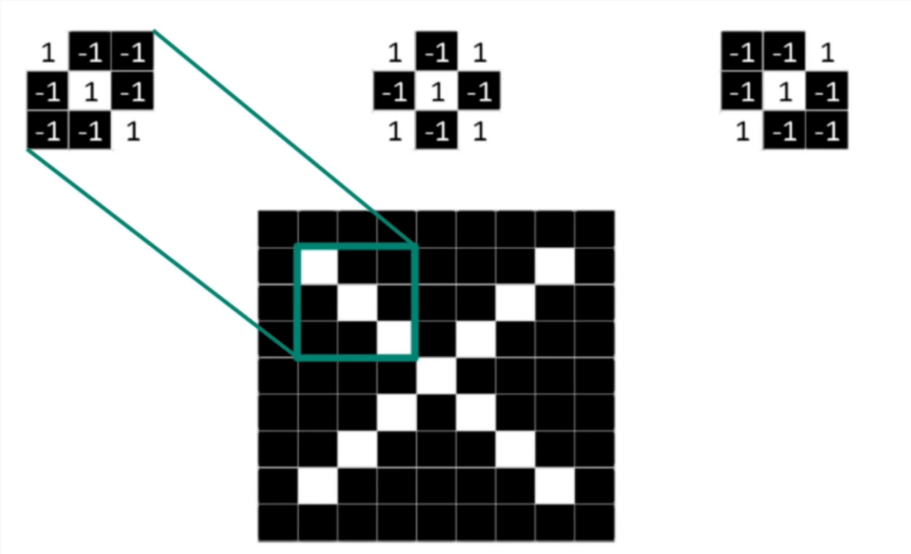
Relevant Features of a X



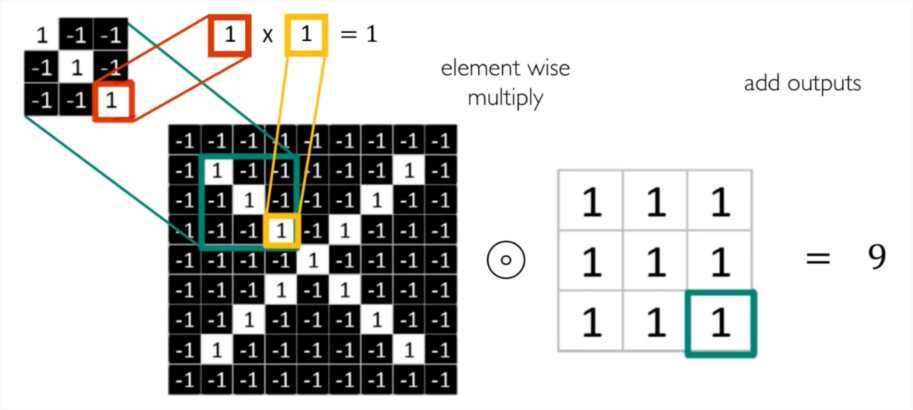
Relevant Features of a X



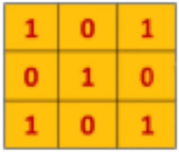
Relevant Features of a X



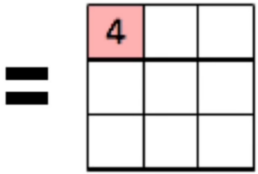
The Convolution Operation



The Convolution Operation

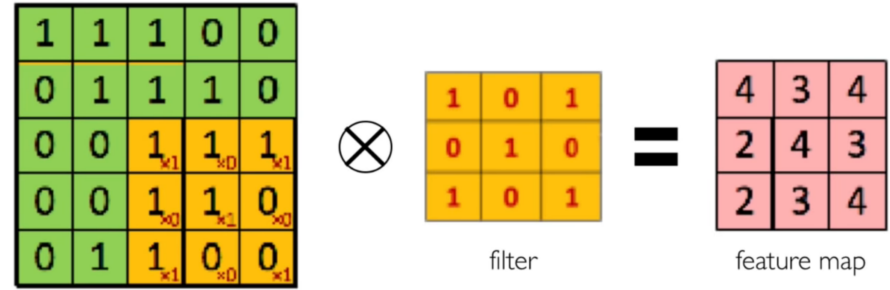


filter



feature map

The Convolution Operation

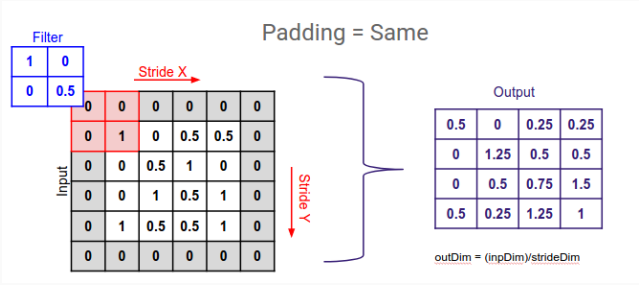


Padding before convolution

After convolution The dimension of the output O image (either height or width is):

$$O = \frac{W - K - 2P}{S} + 1 \tag{1}$$

where W = input dimension, K = filter size, P = padding, S = stride.



Without padding

1. Shrinking outputs
2. Loosing information on corners of the image

The Feature Maps

Original

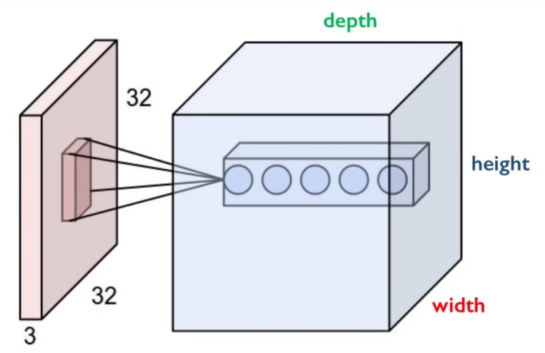
Sharpen

Edge Detect

"Strong" Edge Detect

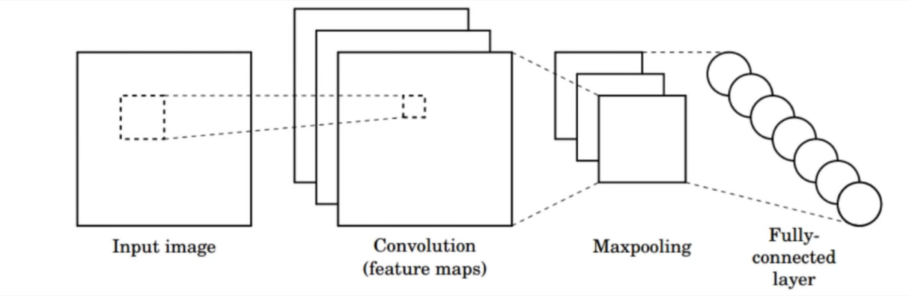
Spatial Arrangement of the Output Volume

- width and height depend on the input volume and on the filter size
- depth represents the number of weights



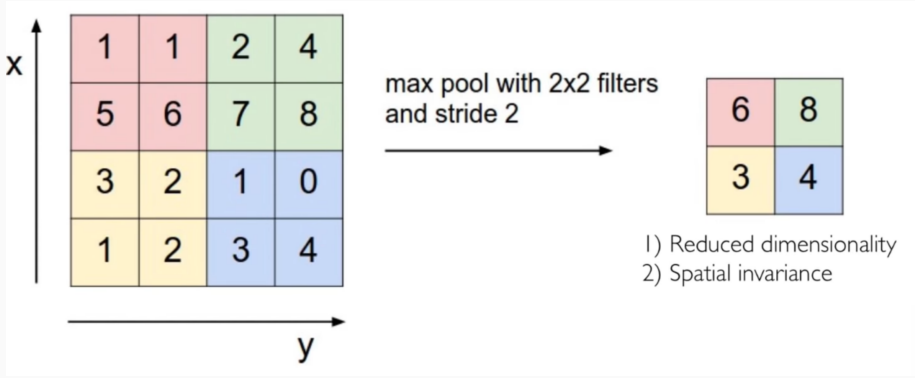
CNN for Classification

1. Multiple Convolutional Layers:
   - Apply a convolutional filter
   - Apply a non-linear function (ReLU)
   - Perform Maxpooling
2. Multiple Fullyconnected Layers
3. A softmax output

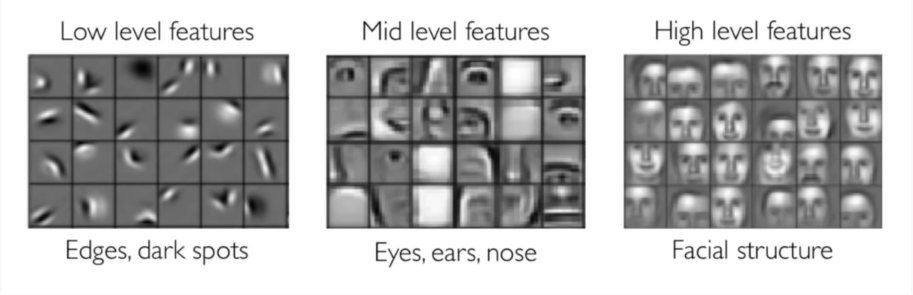


Pooling

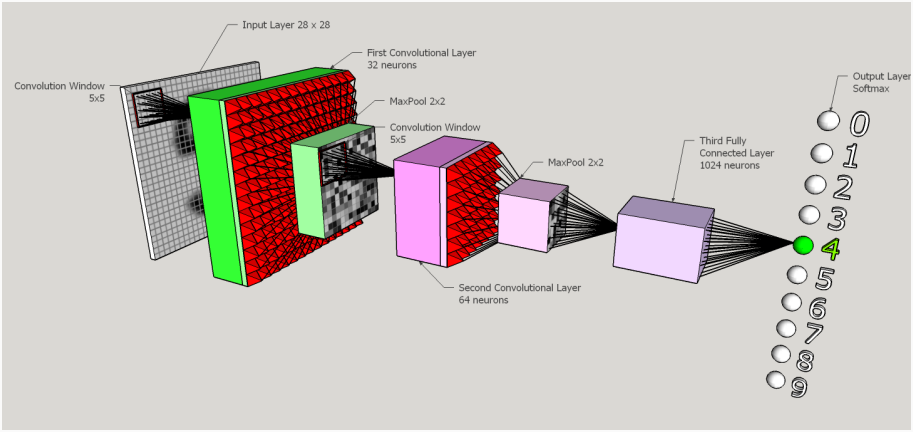
- Reduce dimensionality
- Preserve spatial invariance



Feature Map in CNNs



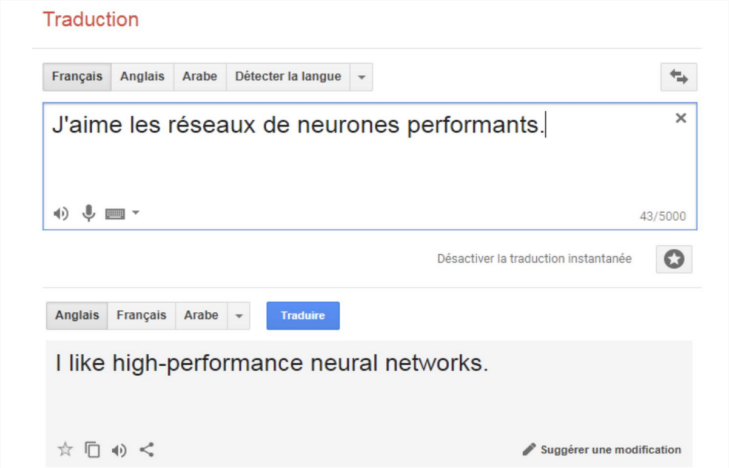
A CNN for the MNIST dataset



Why do we need RNNs?

To model sequential data (language model).

- Machine translation (text to text)



Why do we need RNNs?

To model sequential data (language model).

- Image captioning (image to text)

"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"girl in pink dress is jumping in air."

"black and white dog jumps over bar."

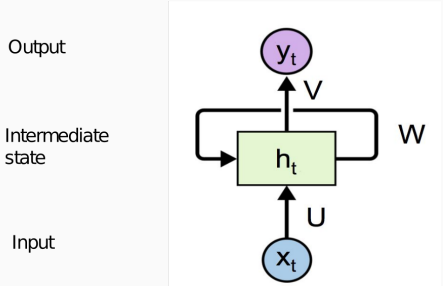
"young girl in pink shirt is swinging on swing."

What are RNNs?

Vanilla Recurrent Networks

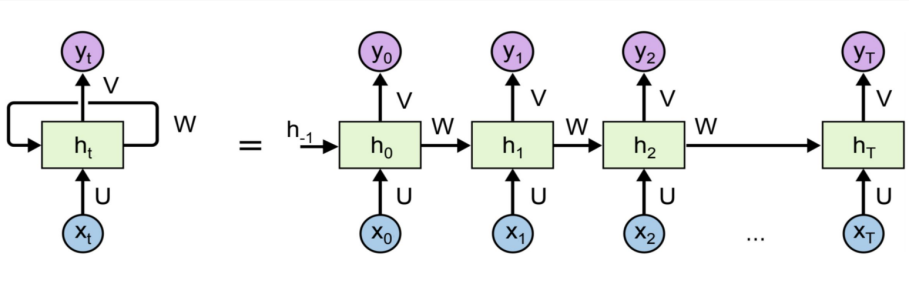
- The network is define by three sets of parameters: U, W, V
- The parameters are shared across time

$$h_t = \tanh(Ux_t + Wh_{t-1})$$
$$y_t = f(Vh_t)$$



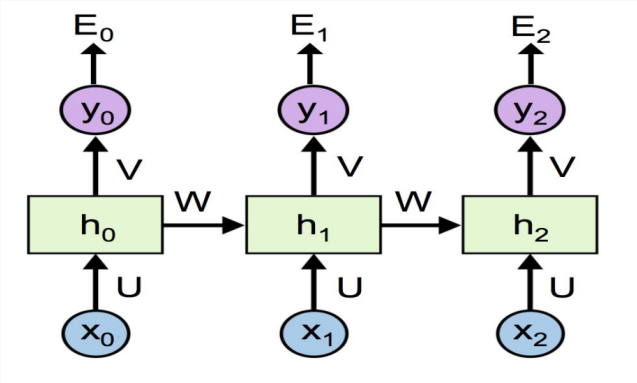
The unrolled network

Vanilla Recurrent Networks



Training RNNs

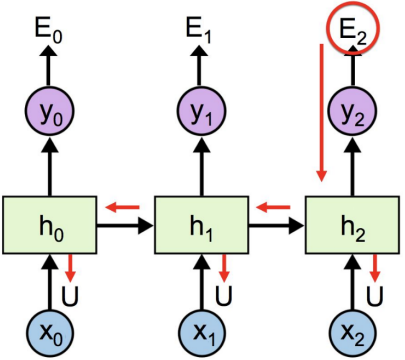
- The loss is: $E = \sum_{t=0}^{T} E_t$
- Do normal backpropagation using the loss E



Backpropagation through time (BPTT)

$$\frac{\partial E_2}{\partial U} = \frac{\partial E_2}{\partial h_2}\left(x_2^T + \frac{\partial h_2}{\partial h_1}\left(x_1^T + \frac{\partial h_1}{\partial h_0}x_0^T\right)\right)$$

mage from Christopher Olah's blog



Vanishing/Exploding gradient problem

$$\mathbf{h}_t = \boldsymbol{\theta}\boldsymbol{\phi}(\mathbf{h}_{t-1}) + \boldsymbol{\theta}_x \mathbf{x}_t$$
$$\mathbf{y}_t = \boldsymbol{\theta}_y \boldsymbol{\phi}(\mathbf{h}_t)$$

$$\frac{\partial E}{\partial \boldsymbol{\theta}} = \sum_{t=1}^{S} \frac{\partial E_t}{\partial \boldsymbol{\theta}}$$

$$\frac{\partial E_t}{\partial \boldsymbol{\theta}} = \sum_{k=1}^{t} \frac{\partial E_t}{\partial \mathbf{y}_t} \frac{\partial \mathbf{y}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \boldsymbol{\theta}}$$

[Yoshua Bengio et al]

Vanishing/Exploding gradient problem

$$\frac{\partial E_t}{\partial \boldsymbol{\theta}} = \sum_{k=1}^{t} \frac{\partial E_t}{\partial \mathbf{y}_t} \frac{\partial \mathbf{y}_t}{\partial \mathbf{h}_t} \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \frac{\partial \mathbf{h}_k}{\partial \boldsymbol{\theta}}$$

$$\frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} = \prod_{i=k+1}^{t} \frac{\partial \mathbf{h}_i}{\partial \mathbf{h}_{i-1}} = \prod_{i=k+1}^{t} \boldsymbol{\theta}^T \mathrm{diag}[\boldsymbol{\phi}'(\mathbf{h}_{i-1})]$$

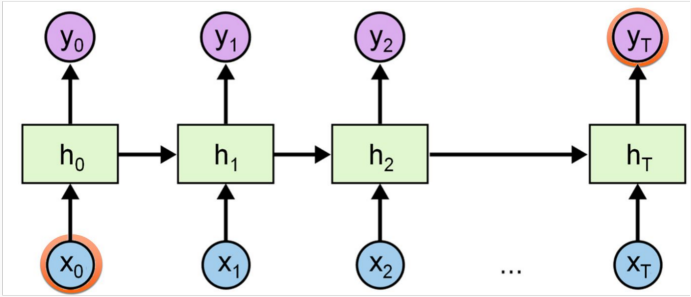
$$\left\| \frac{\partial \mathbf{h}_i}{\partial \mathbf{h}_{i-1}} \right\| \leq \|\boldsymbol{\theta}^T\| \|\mathrm{diag}[\boldsymbol{\phi}'(\mathbf{h}_{i-1})]\| \leq \gamma_\theta \gamma_\phi$$

$$\left\| \frac{\partial \mathbf{h}_t}{\partial \mathbf{h}_k} \right\| \leq (\gamma_\theta \gamma_\phi)^{t-k}$$

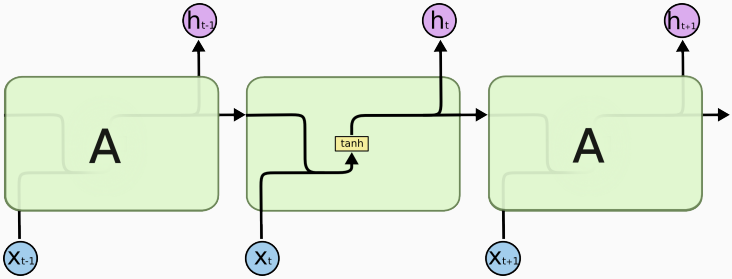
The gradient problem is problematic

Long term dependencies

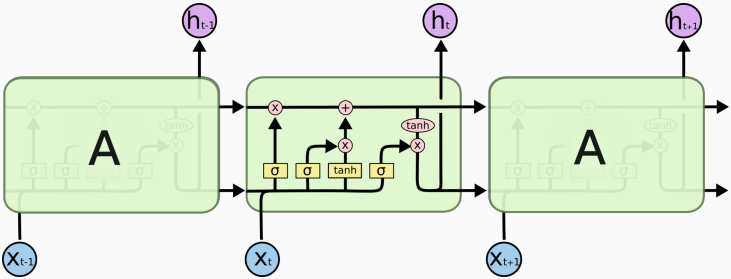
Who went to Paris?



Long short-term memory (LSTM)

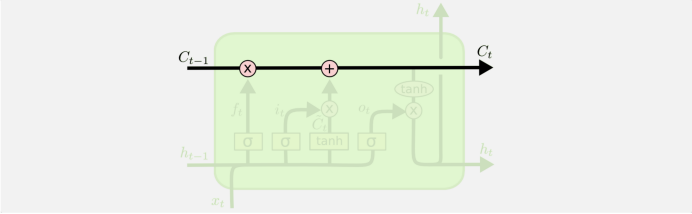


Long short-term memory (LSTM)



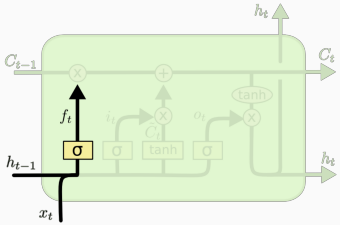
Long short-term memory (LSTM)

Introduce a cell state



Long short-term memory (LSTM)

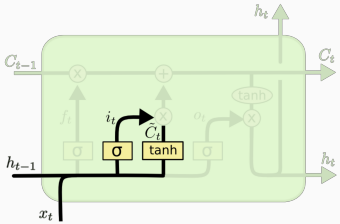
Introduce a forget gate (how much to keep in the cell state)



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Long short-term memory (LSTM)

Introduce an input gate (how much of the input is added to the cell state)

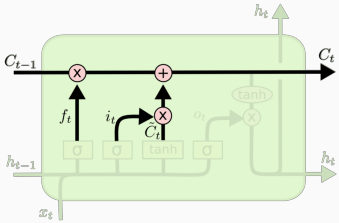


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Long short-term memory (LSTM)

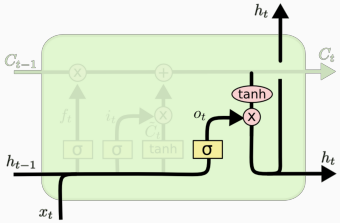
Update the cell state



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Long short-term memory (LSTM)

Produce an output



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$