# CS 6501: Deep Learning for Computer Graphics

# Convolutional and Recurrent Neural Networks

Connelly Barnes

# Outline

- Convolutional Neural Networks (“CNNs”, “ConvNets”)
  - Useful for images
- Recurrent Neural Networks (“RNNs”)
  - Useful for processing sequential data (e.g. text)

# Outline

- Convolutional Neural Networks
  - History
  - Convolutional layers
  - Downsampling: stride and pooling layers
  - Fully connected layers
  - Residual networks
  - Data augmentation
- Recurrent Neural Networks
- Deep learning libraries

# History

## A bit of history:

**Hubel & Wiesel**,

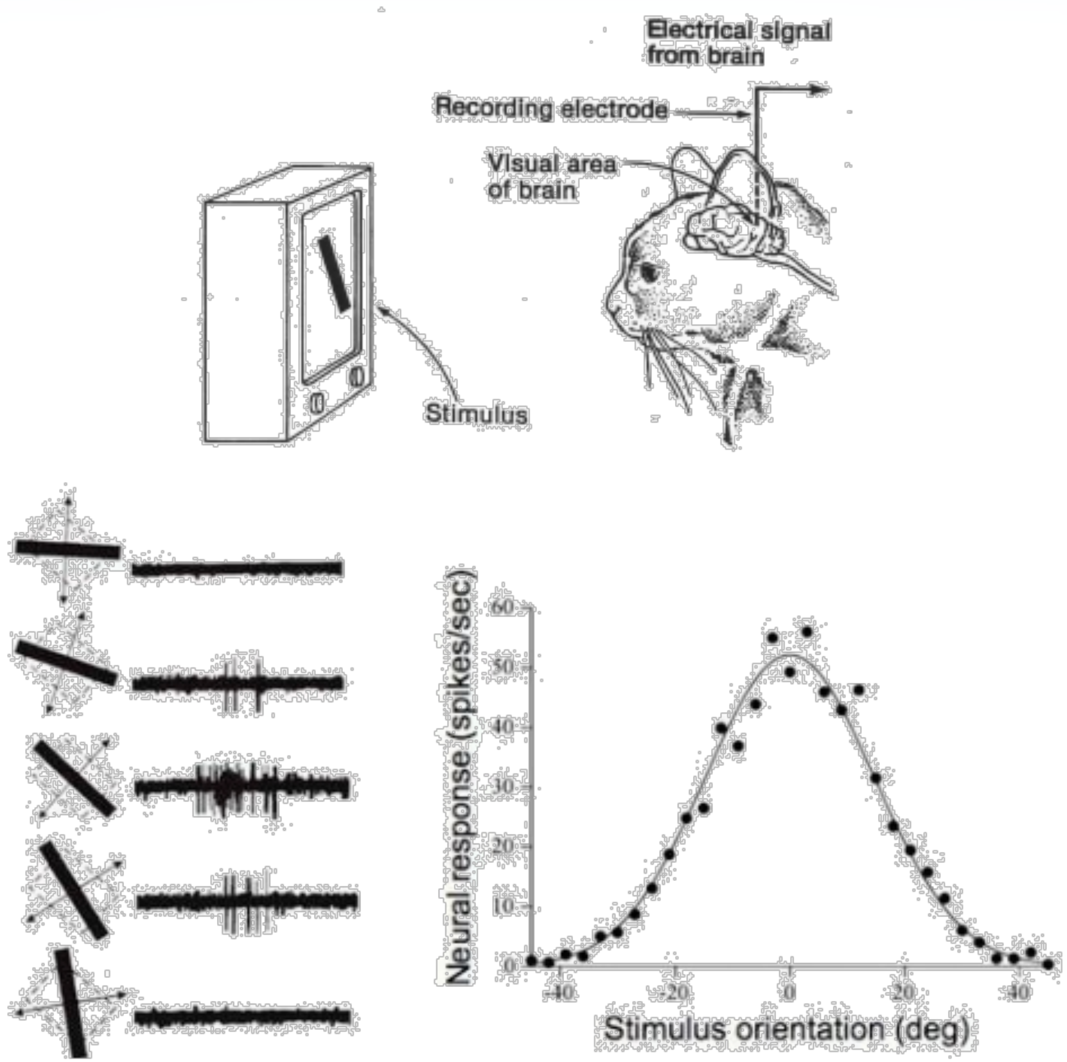
1959

RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX

1962

RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

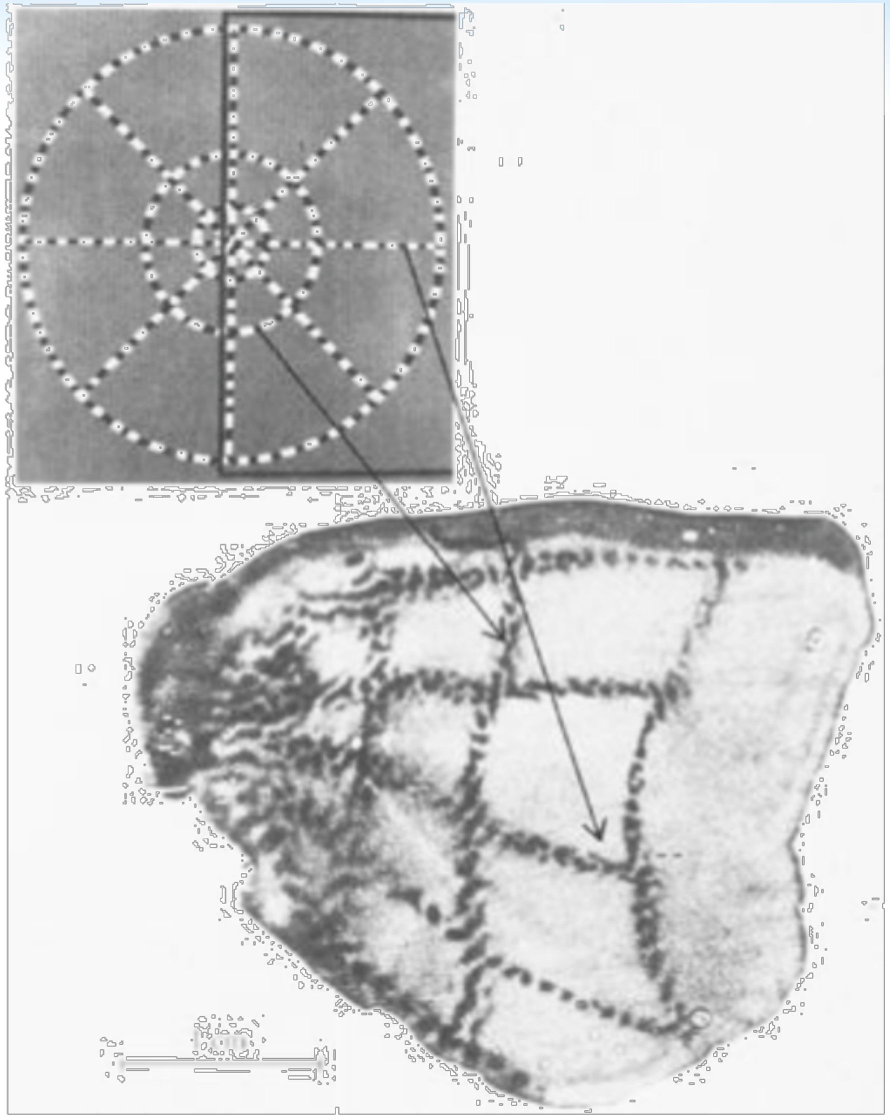
1968...




Slide from Stanford CS231N

# History

**Topographical mapping in the cortex:**
nearby cells in cortex represented
nearby regions in the visual field



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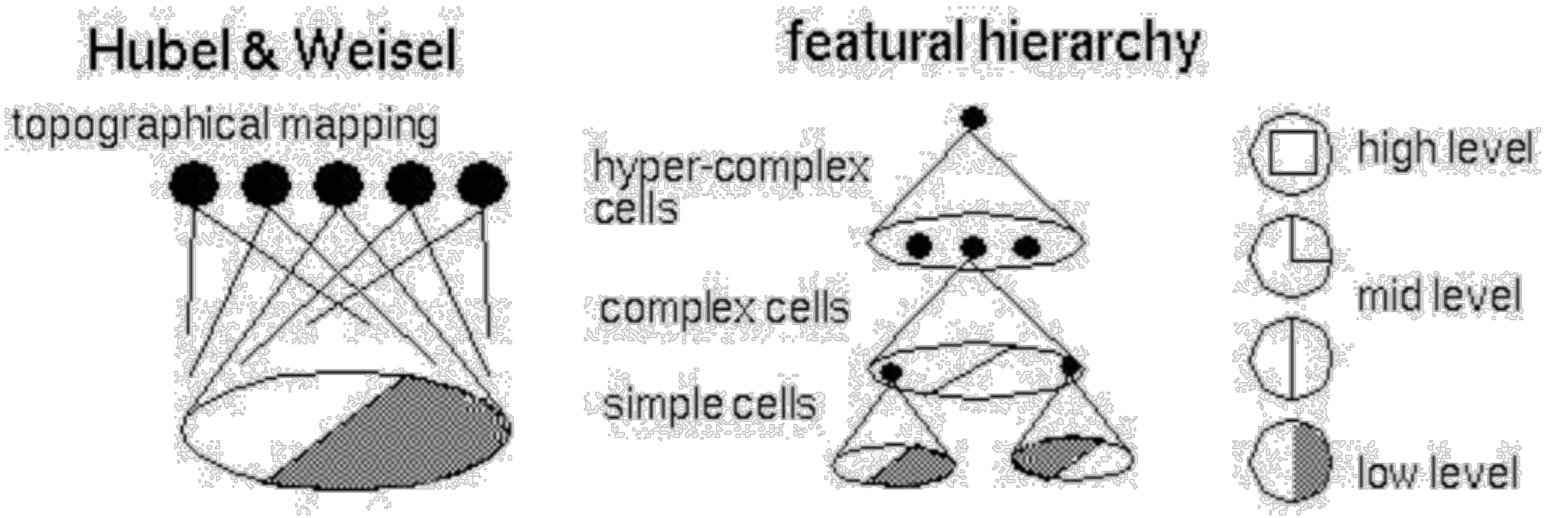
# History

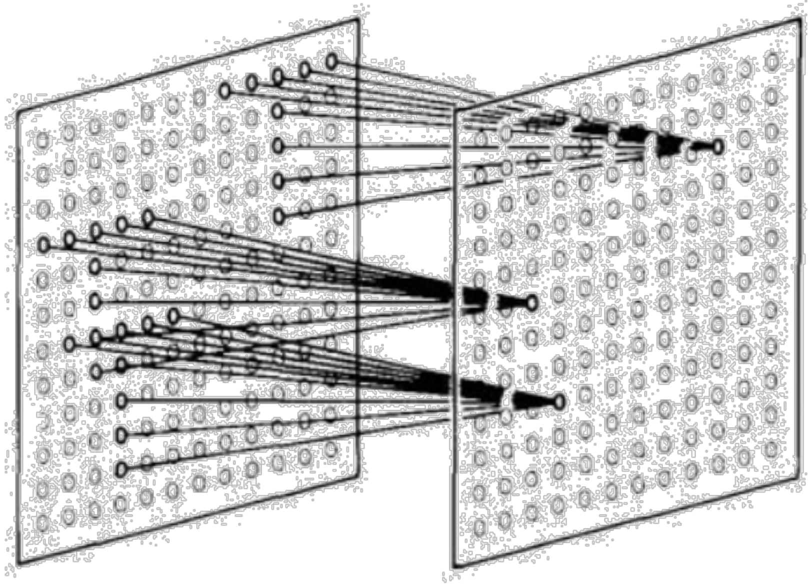
## Hierarchical organization

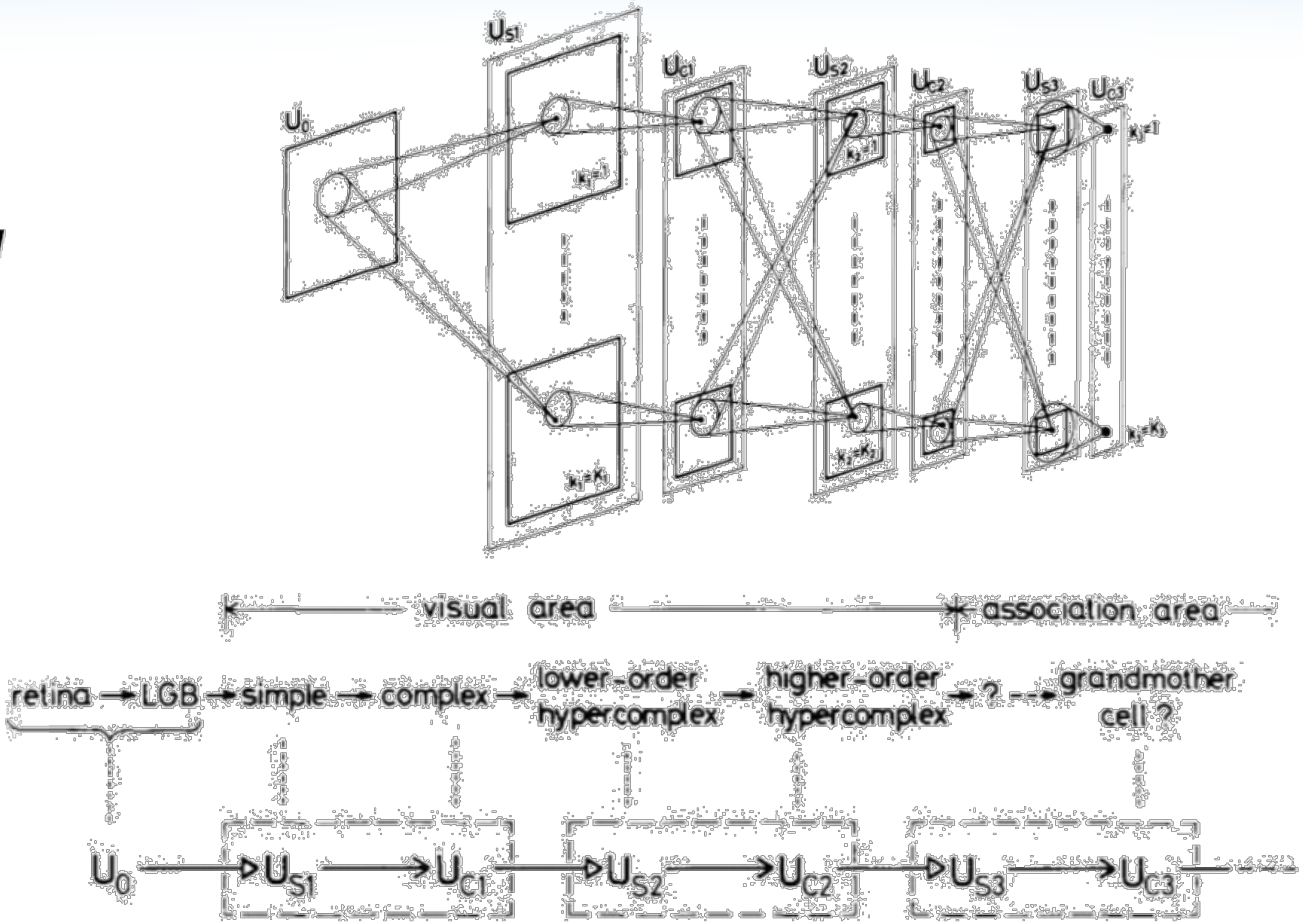


# History

"sandwich" architecture (SCSCSC...)
simple cells: modifiable parameters
complex cells: perform pooling

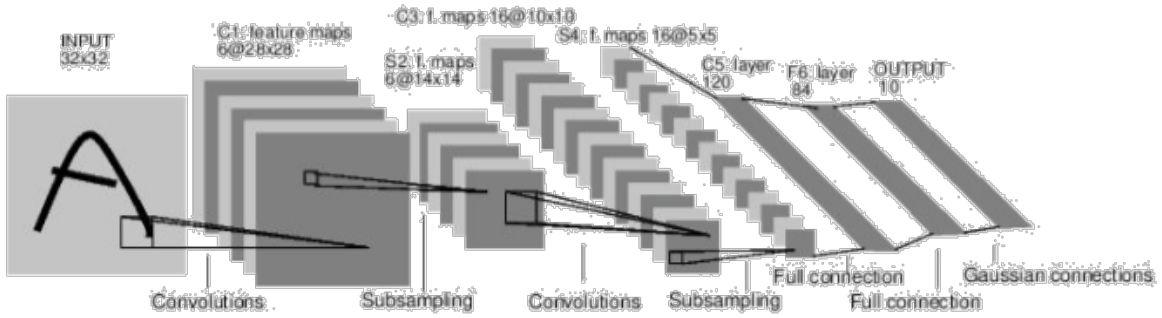
## Neurocognitron
*[Fukushima 1980]*



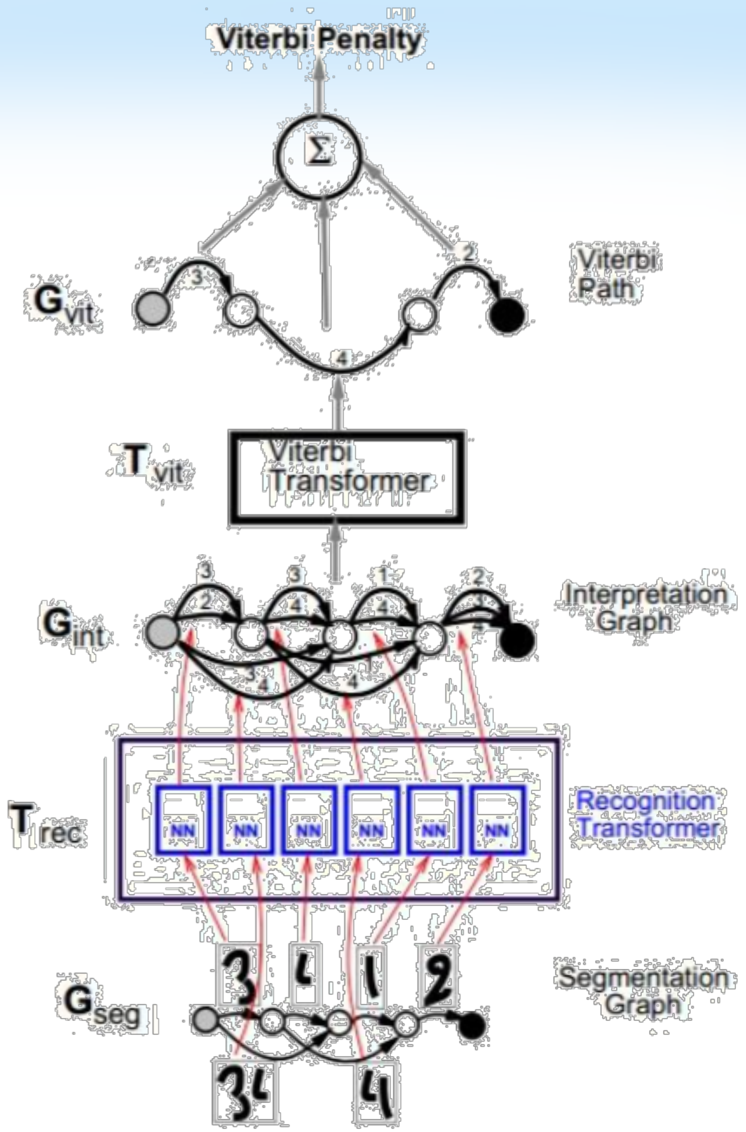


# History

**Gradient-based learning applied to document recognition**
*[LeCun, Bottou, Bengio, Haffner 1998]*

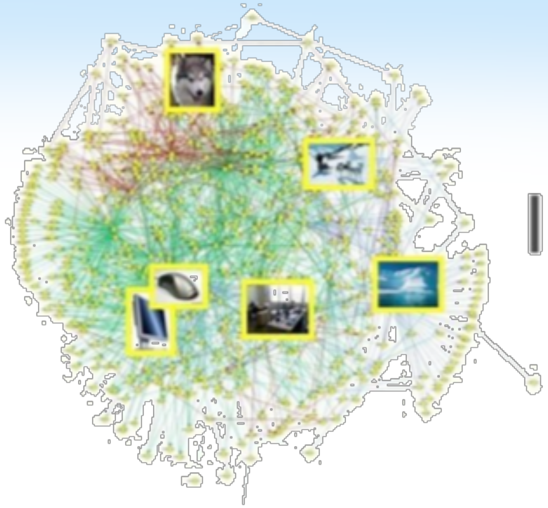


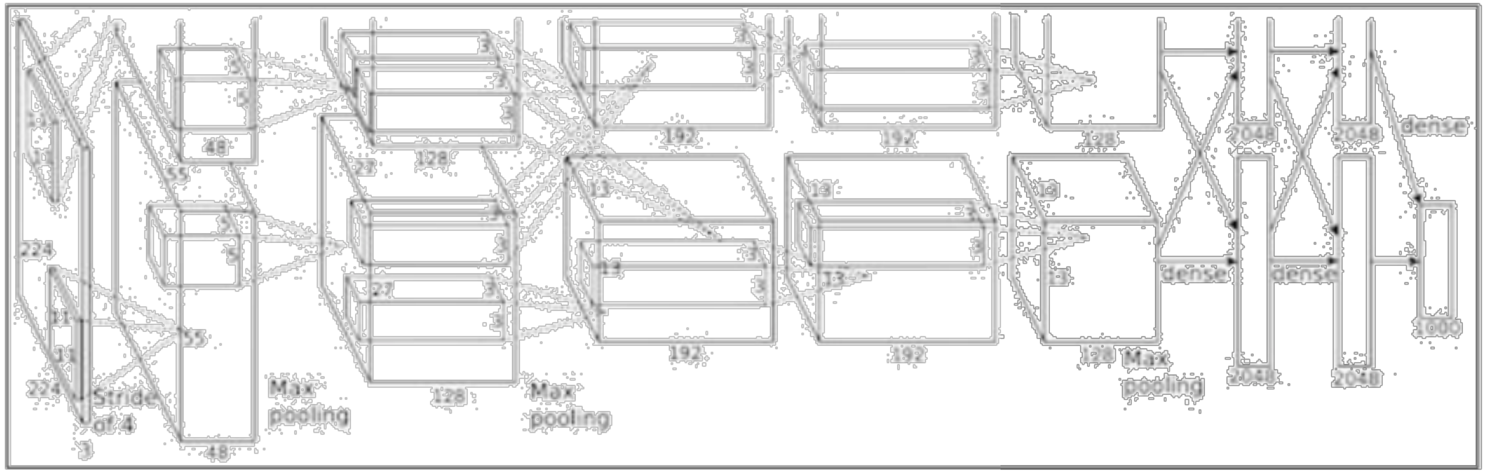

LeNet-5



# History

**ImageNet Classification with Deep Convolutional Neural Networks**
*[Krizhevsky, Sutskever, Hinton, 2012]*





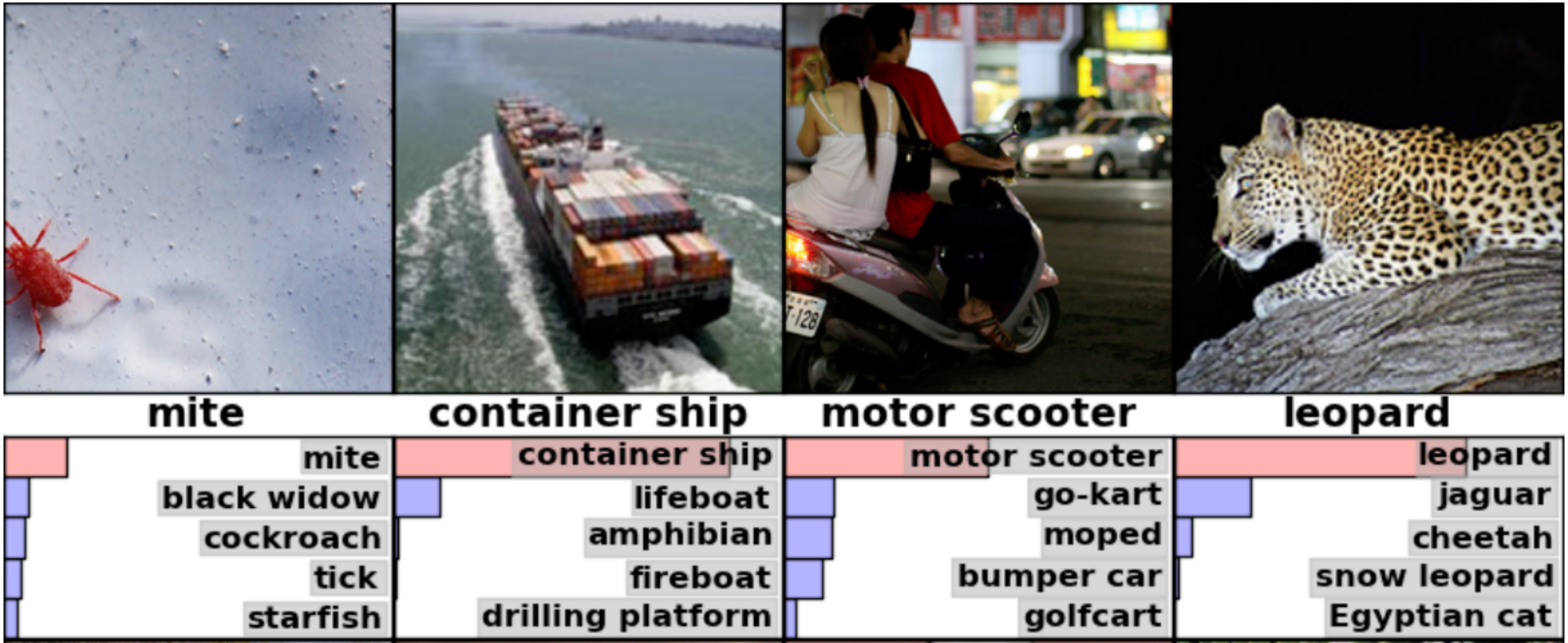

"AlexNet"

# Today: CNNs Widely Used

- [Self-driving cars]

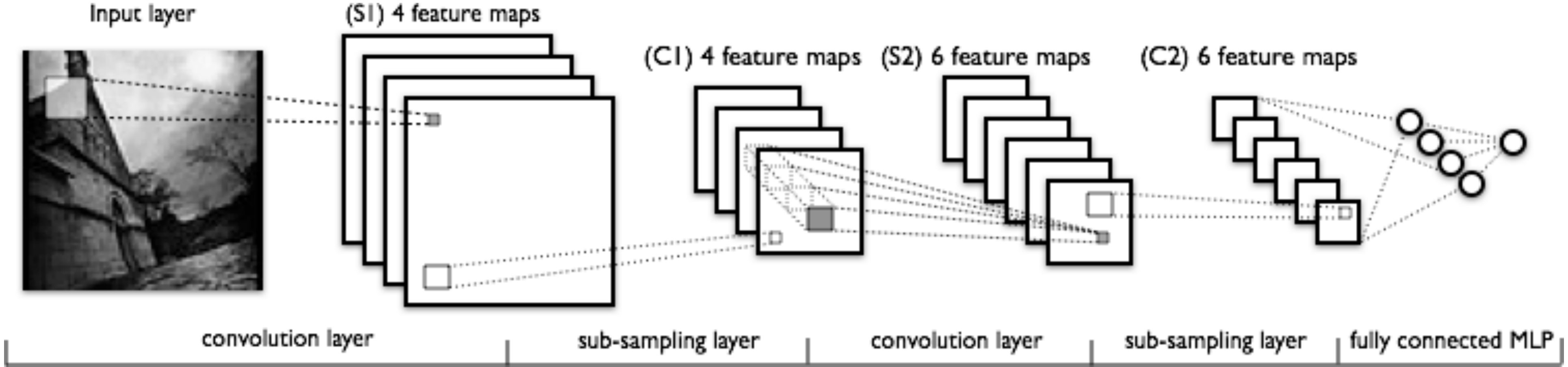
# Today: CNNs Widely Used

- Image Classification



# Convolutional Neural Networks

- Similar to multilayer neural network, but weight matrices now have a special structure (Toeplitz or block Toeplitz) due to convolutions.
- The convolutions typically sum over all color channels.



# Convolutional Neural Network Neuron Layout

- Input layer: RGB image
  - Centered, i.e. subtract mean over training set
  - Usually crop to fixed size (square) input image

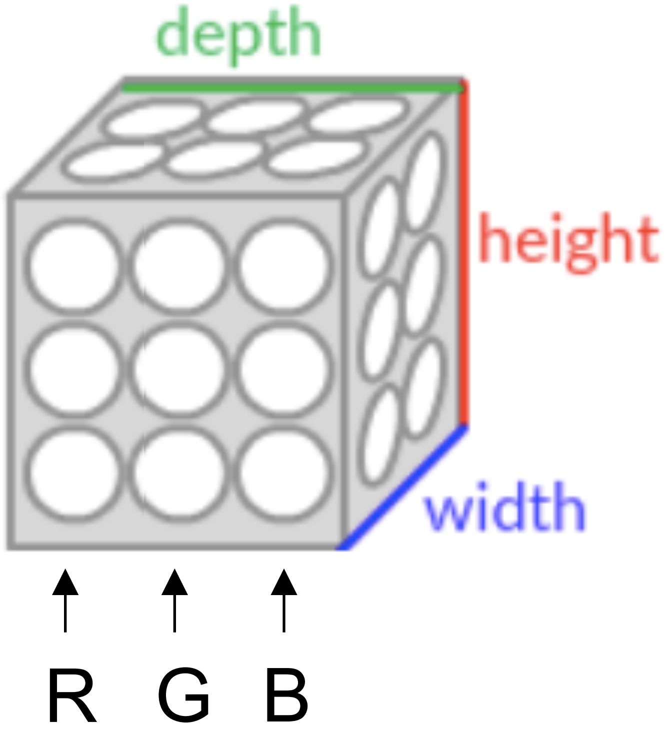



Image from Wikipedia

# Convolutional Neural Network Neuron Layout

- Hidden layer

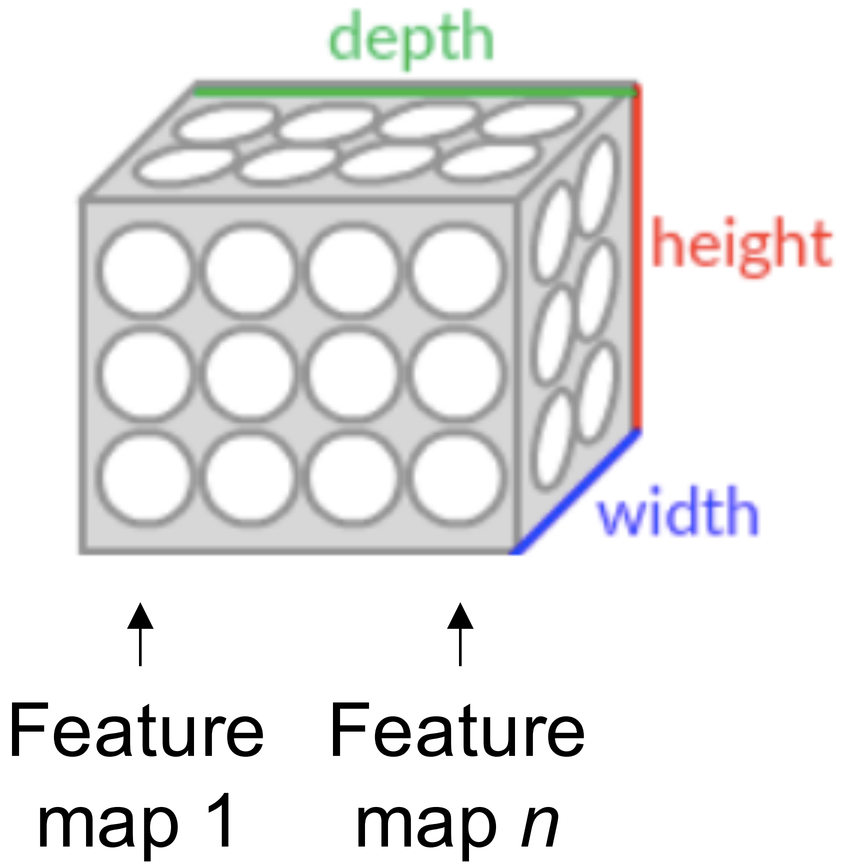



Image from [Wikipedia]

# Receptive Field

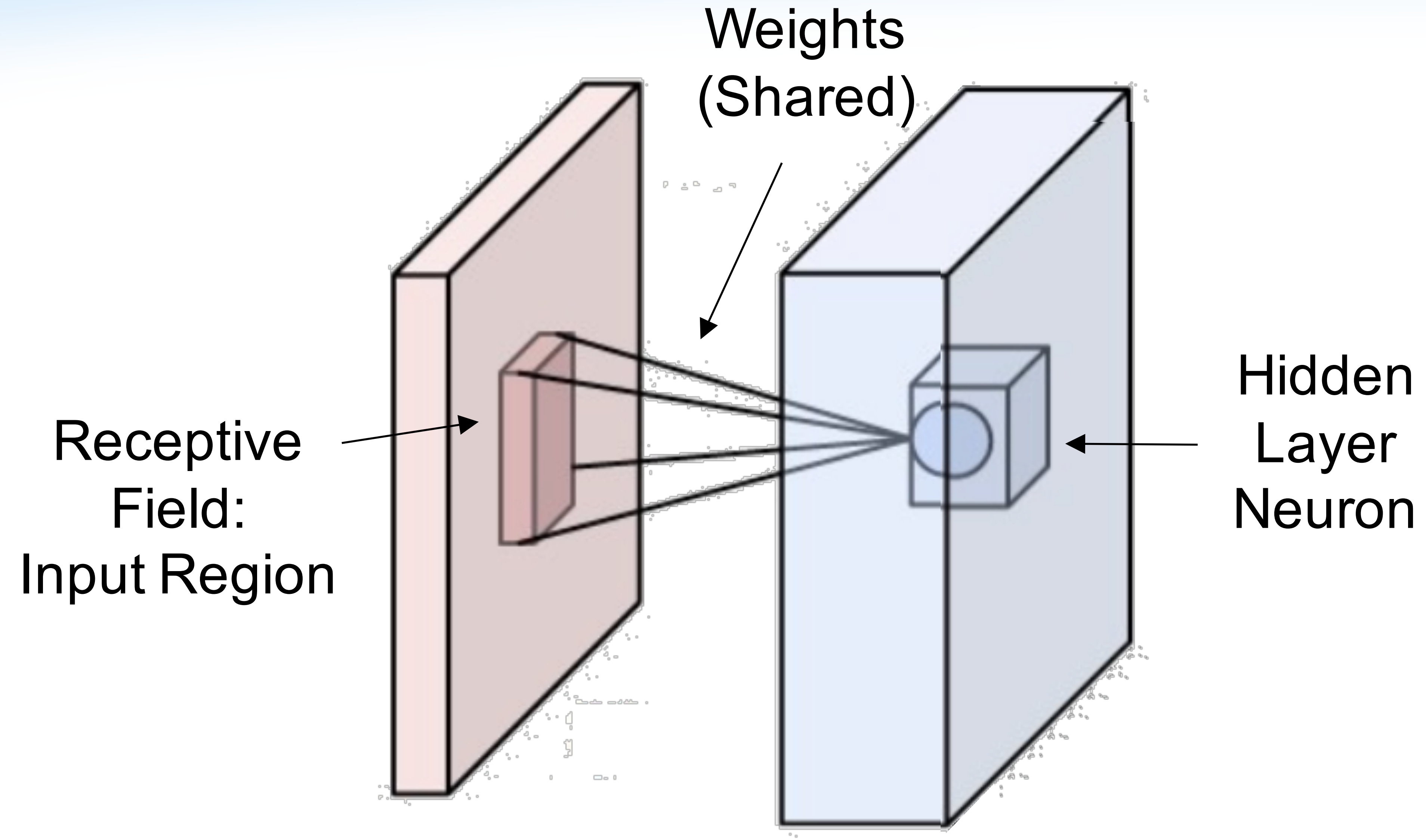



Image from [Wikipedia]

# Mathematically…

Activation Function

Weights for Feature Map 1

Weights for Feature Map *n*

Biases

$$\mathbf{L}_i = \varphi(\mathbf{L}_{i-1} * [\mathbf{W}_1, \mathbf{W}_2, \ldots \mathbf{W}_n] + [b_1, \ldots, b_n])$$

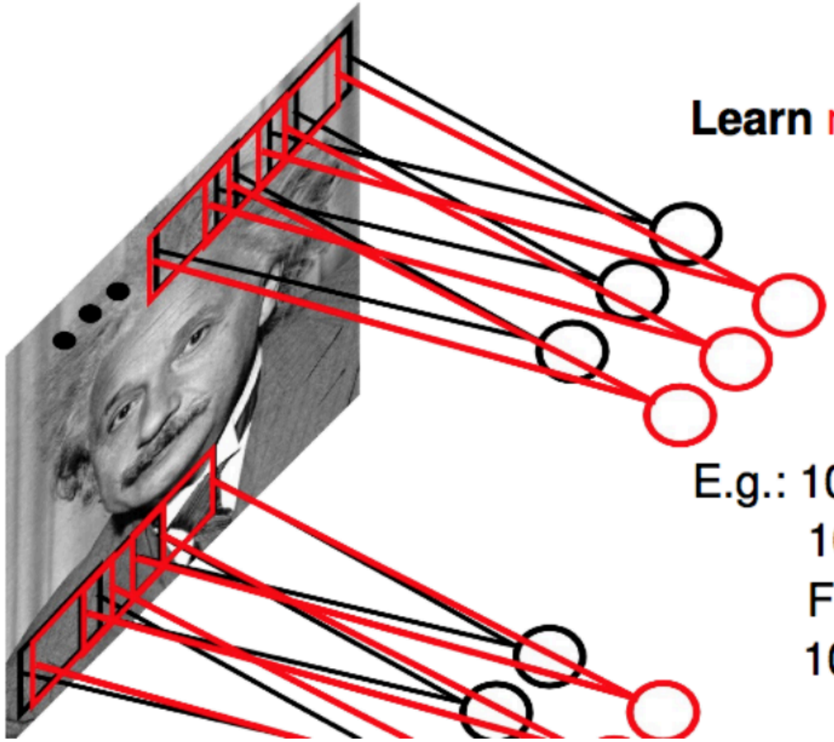
$h$ x $w$ x $d$ $\quad$ $k_1$ x $k_2$ x $d$

Current Layer Feature Maps

Previous Layer Feature Maps

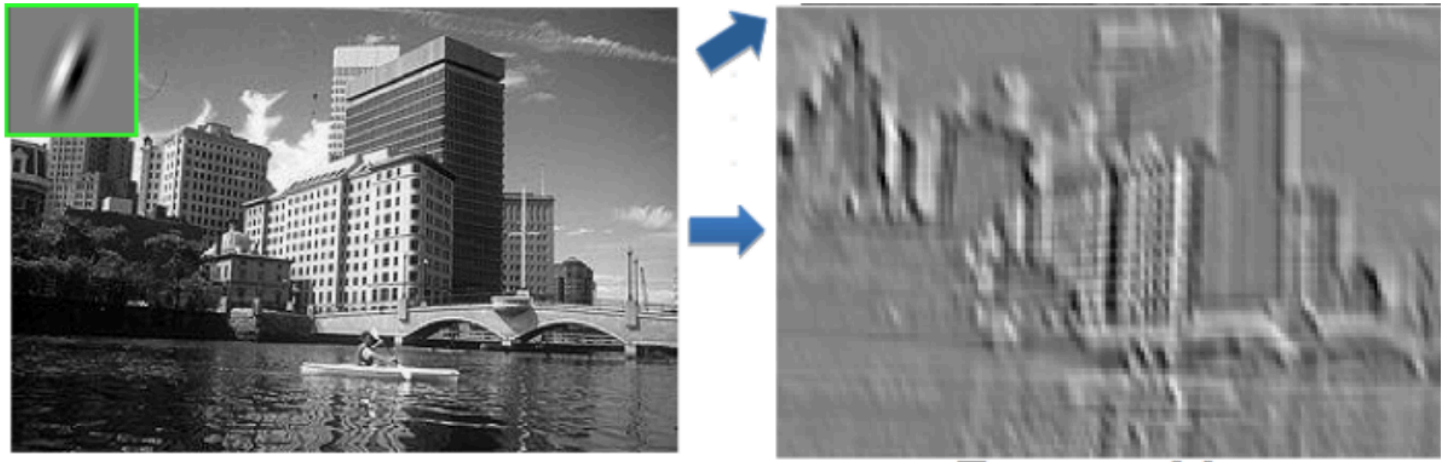
Convolution (Shares Weights Spatially)

# Convolutional / Filtering



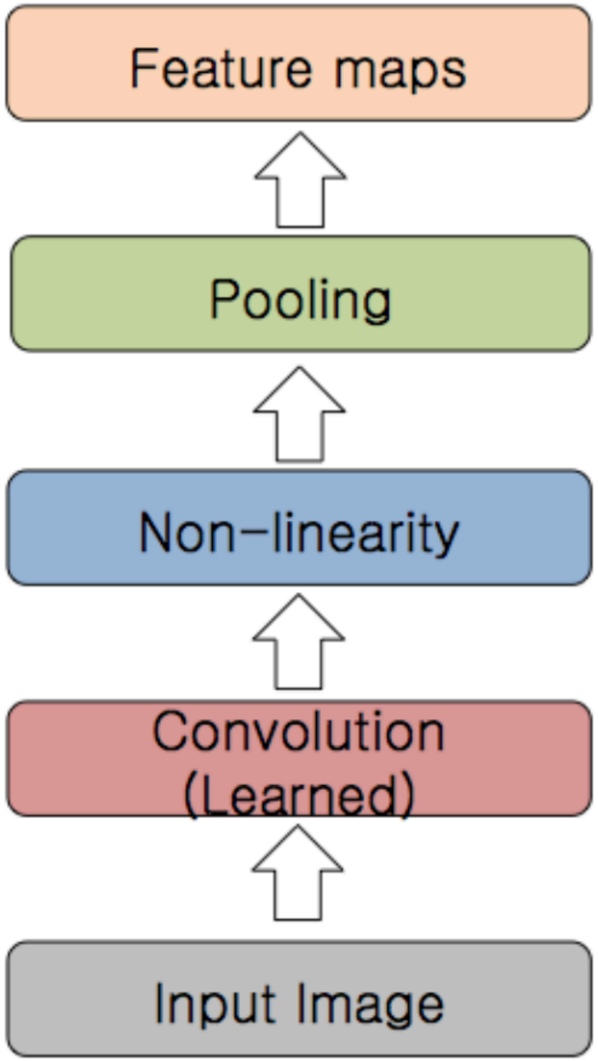
**Learn** multiple filters.

E.g.: 1000x1000 image
100 Filters
Filter size: 10x10
10K parameters



Input

Feature Map



# Outline

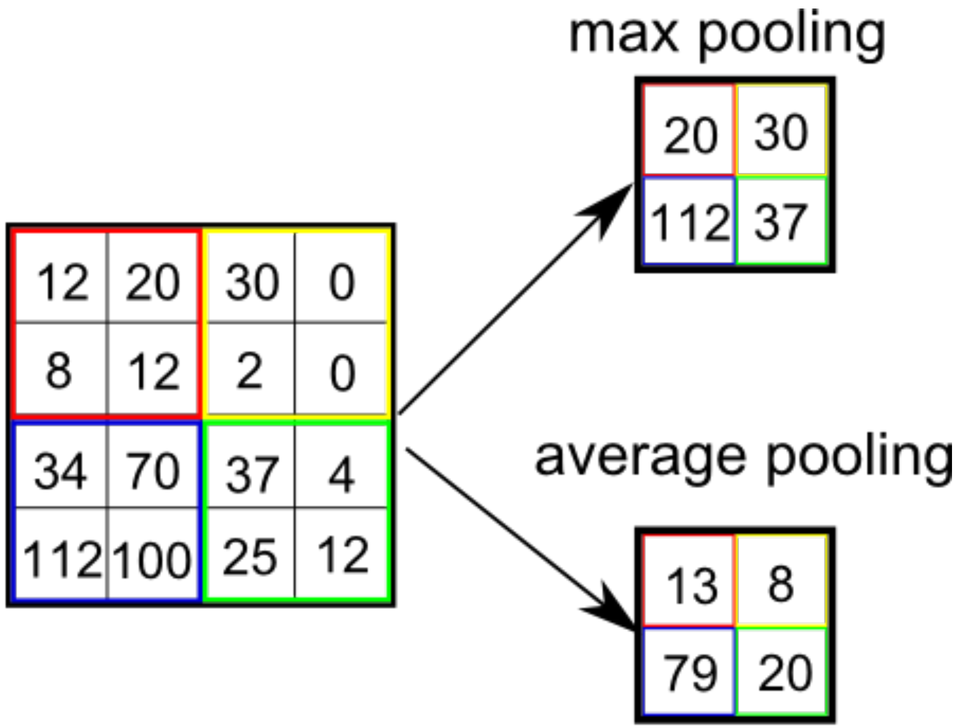
- Convolutional Neural Networks
  - History
  - Convolutional layers
  - **Downsampling: stride and pooling layers**
  - Fully connected layers
  - Residual networks
  - Data augmentation
- Recurrent neural networks
- Deep learning libraries

# Stride

- Stride *m* indicates that instead of computing every pixel in the convolution, compute only every *m*th pixel.

# Max/average pooling

- “Downsampling” using max() operator
- Downsampling factor *f* could differ from neighborhood size *N* that is pooled over.



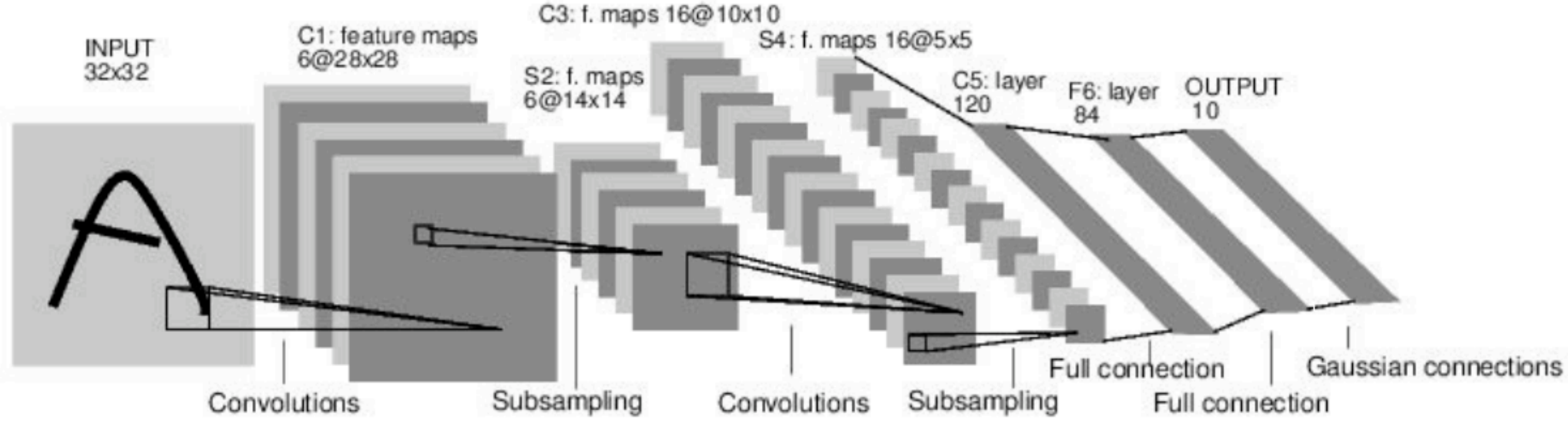
# Max/average pooling

- For max pooling, backpropagation just propagates error back to to whichever neuron had the maximum value.
- For average pooling, backpropagation splits error equally among all the input neurons.

# Fully connected layers

- Connect every neuron to every other neuron, as with multilayer perceptron.

[LeCun et al., 1998]



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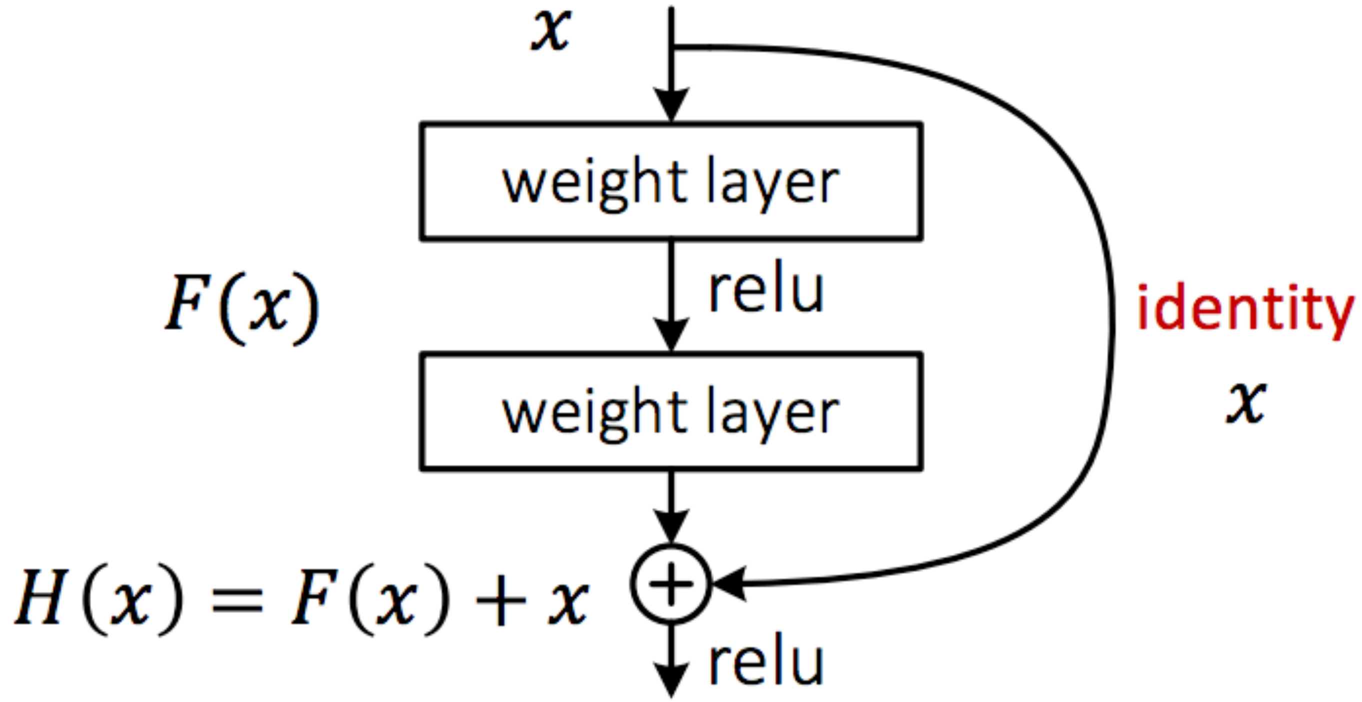
# Residual networks

- Make it easy to learn the identity function:
  - Network with all zero weights gives identity function.
- Helps with vanishing/exploding gradients.



# Outline

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# Data Augmentation

- Many weights to train
  - Often would be helpful to have more training data
- Fake having more training data
  - Random rotations
  - Random flips
  - Random shifts
  - Recolorings
  - etc

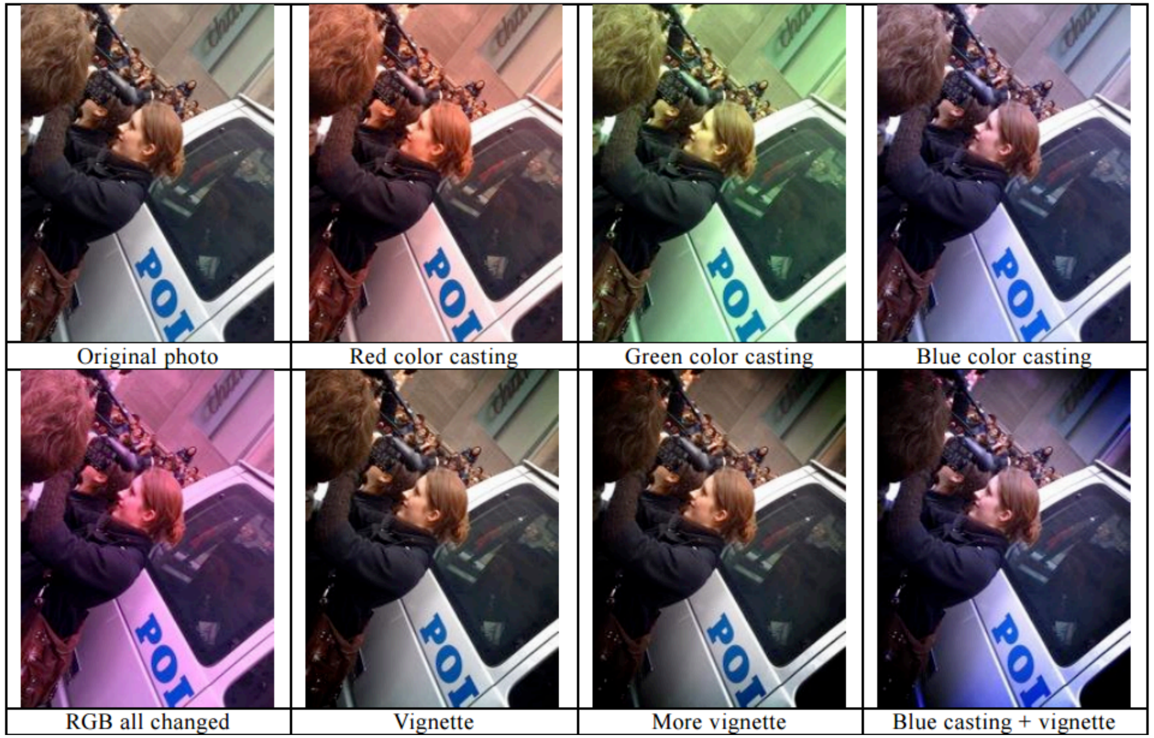



Figure from BaiduVision

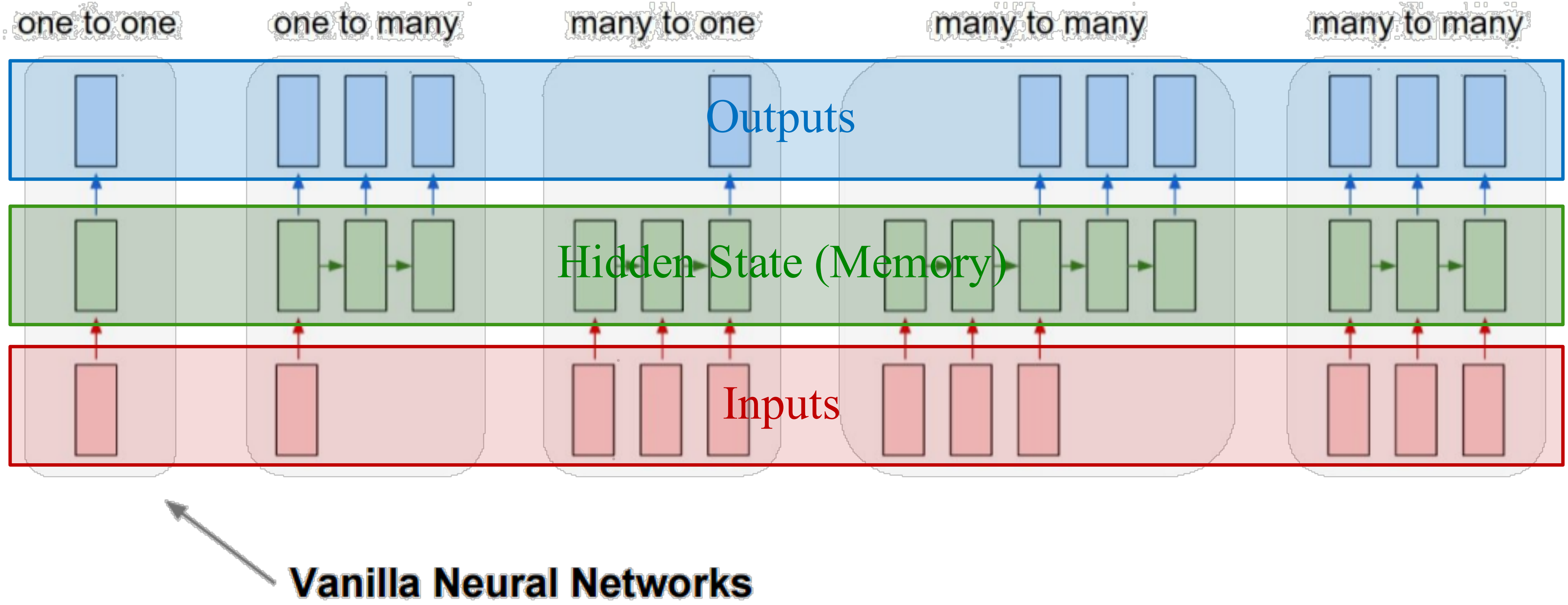
# Outline

- Convolutional Neural Networks
- **Recurrent Neural Networks**
  - Simple RNNs
  - LSTM, GRU
  - Applications
- Deep learning libraries

# Recurrent Neural Networks

- Feedforward neural networks have no *memory*: cannot remember the state of the world between one instant of time and the next
  - Cannot remember important events and recall them in the future
  - Cannot perform loops
  - Cannot implement arbitrary algorithms
- Recurrent networks help by adding memory to the computation

# Recurrent Neural Networks

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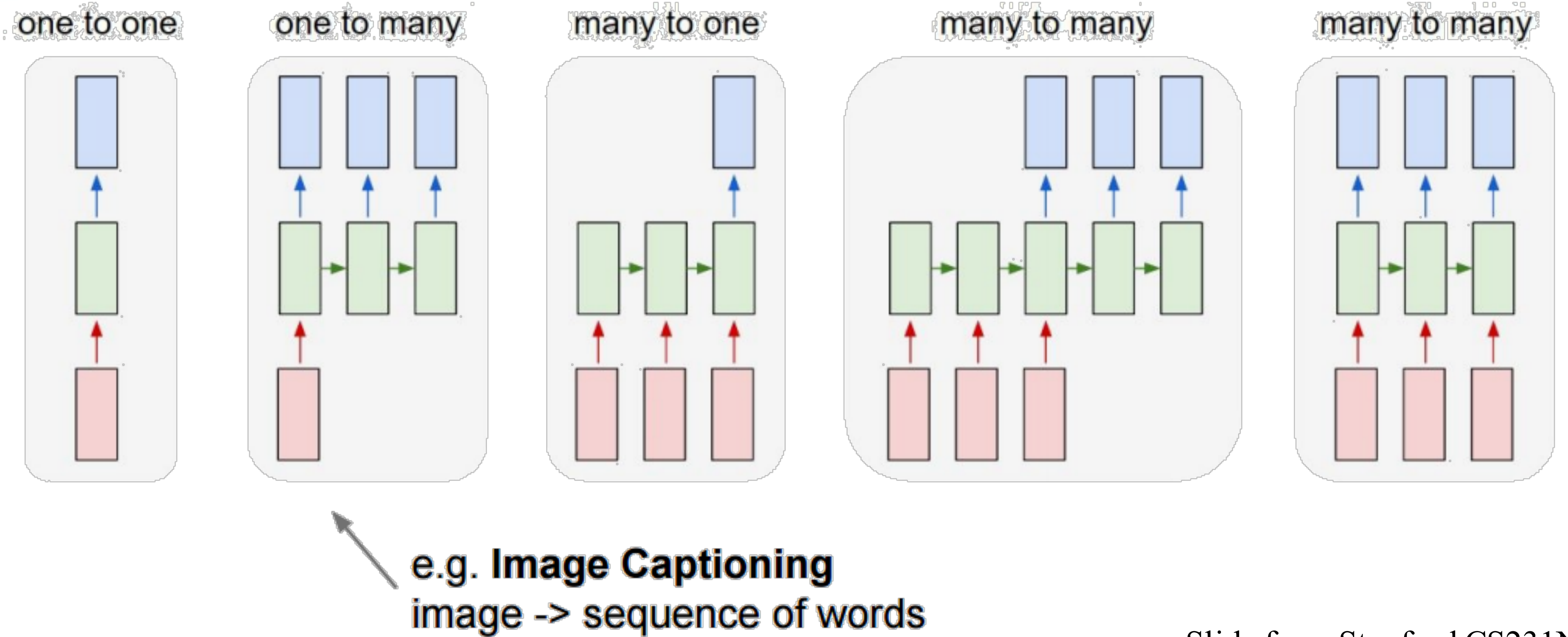
# Recurrent Neural Networks

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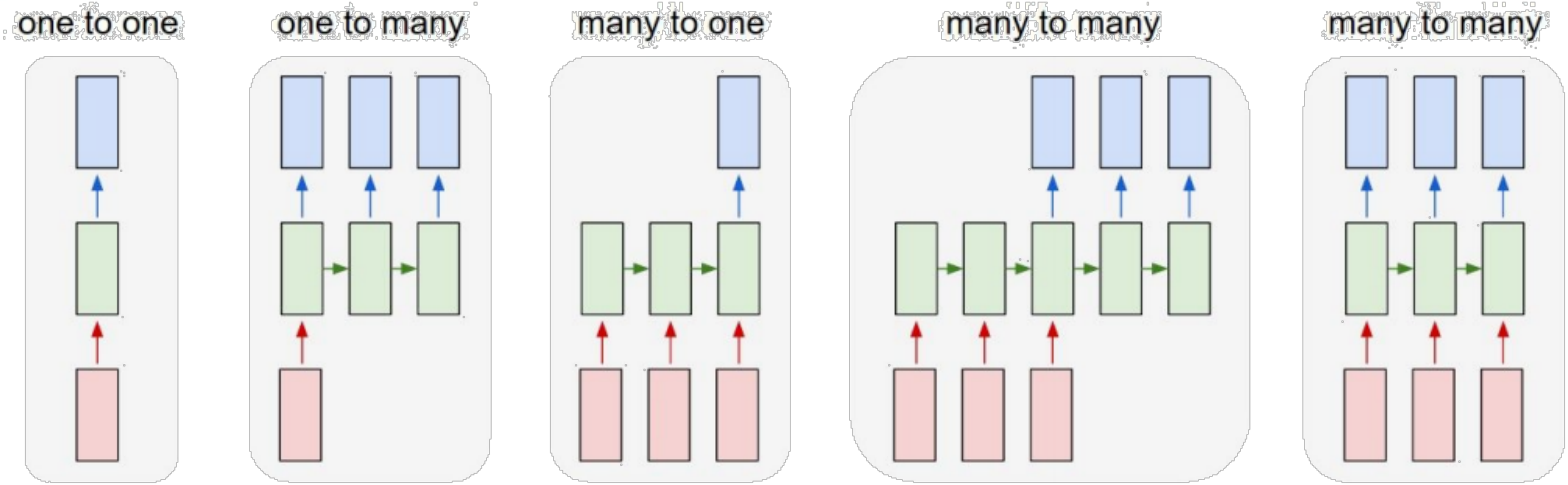
# Recurrent Neural Networks




e.g. **Sentiment Classification**
sequence of words -> sentiment

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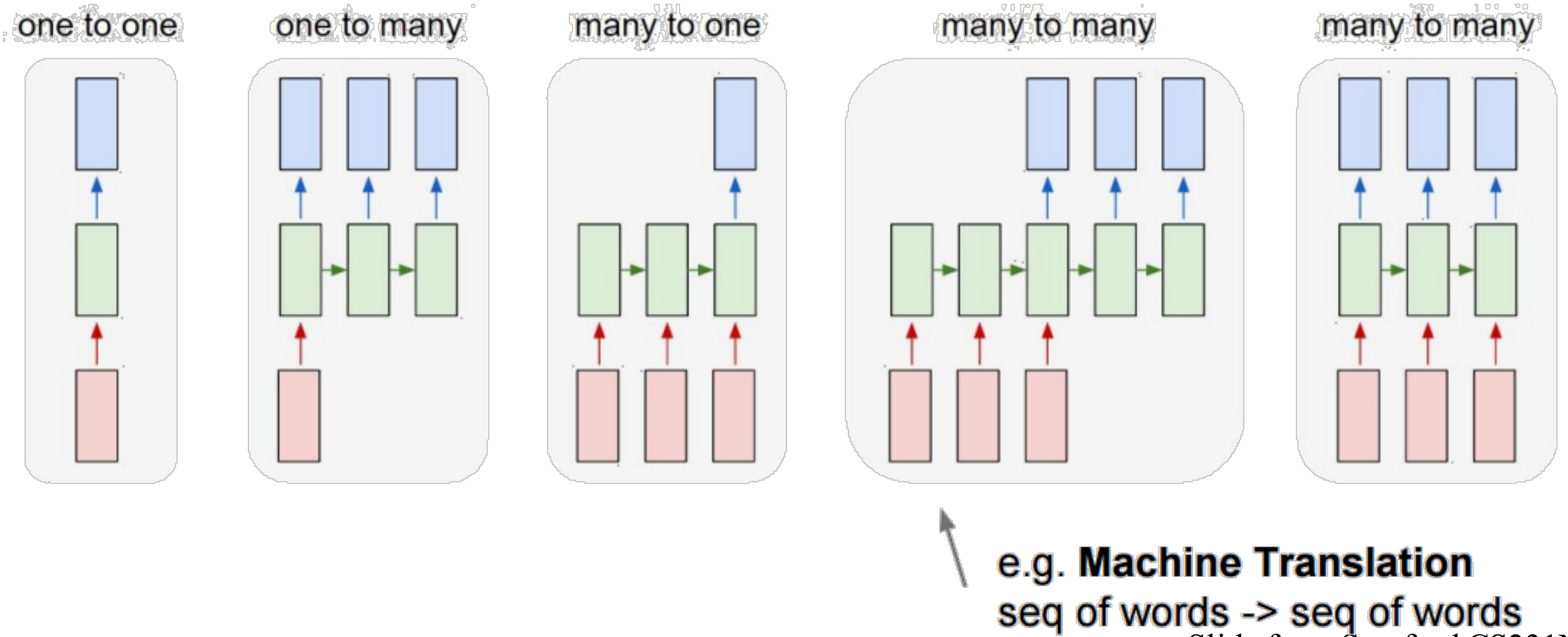
# Recurrent Neural Networks

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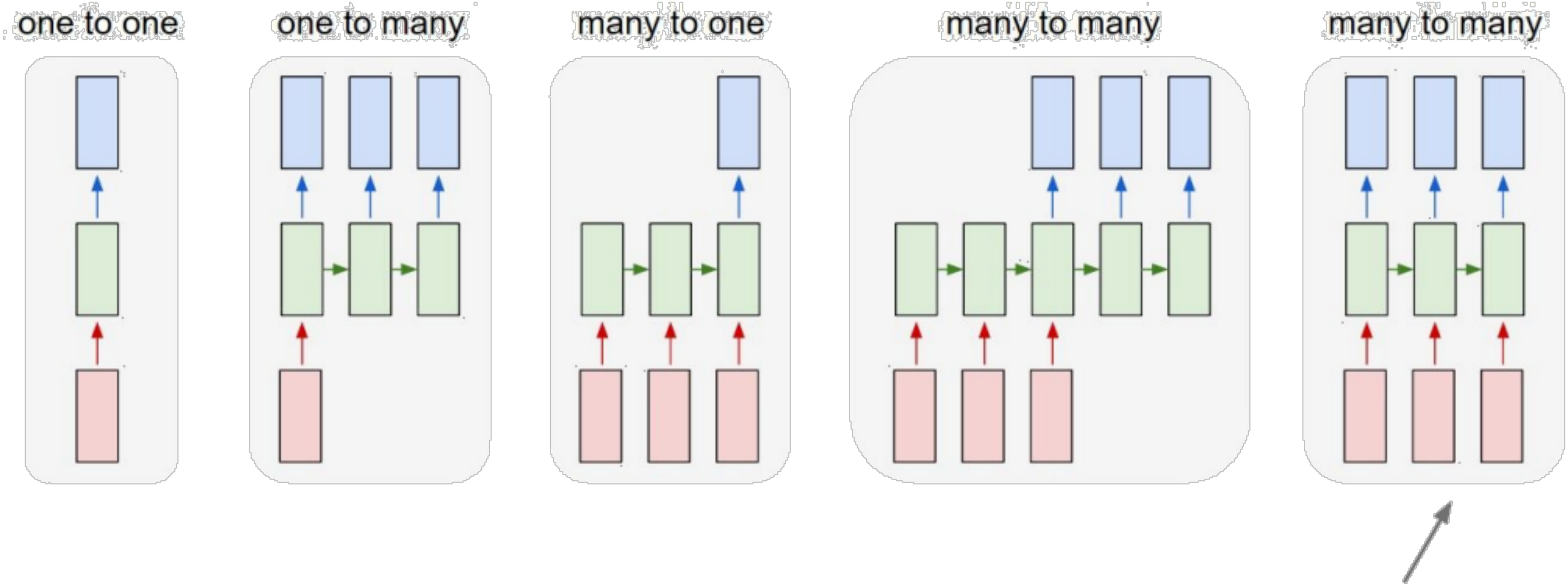
# Recurrent Neural Networks




e.g. **Video classification on frame level**

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# Simple Recurrent Neural Network

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

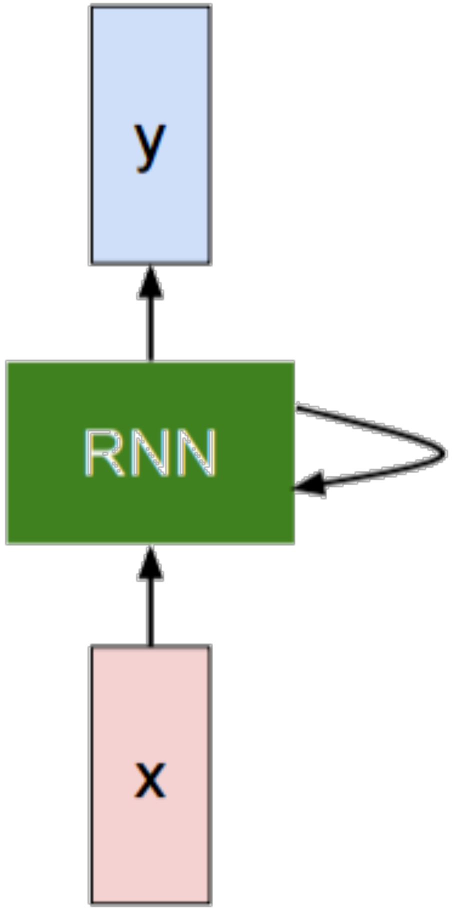
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W

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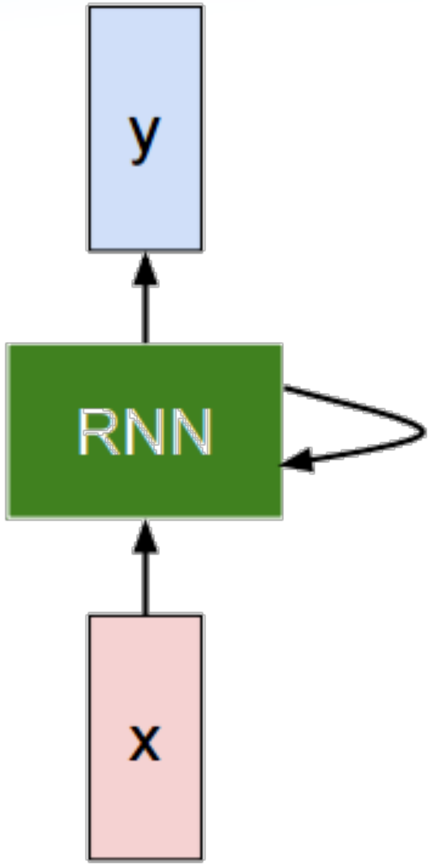
# Simple Recurrent Neural Network




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

Hidden state:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

Output:

$$y_t = W_{hy}h_t$$

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# How to Train?

- [Backpropagation through time]()

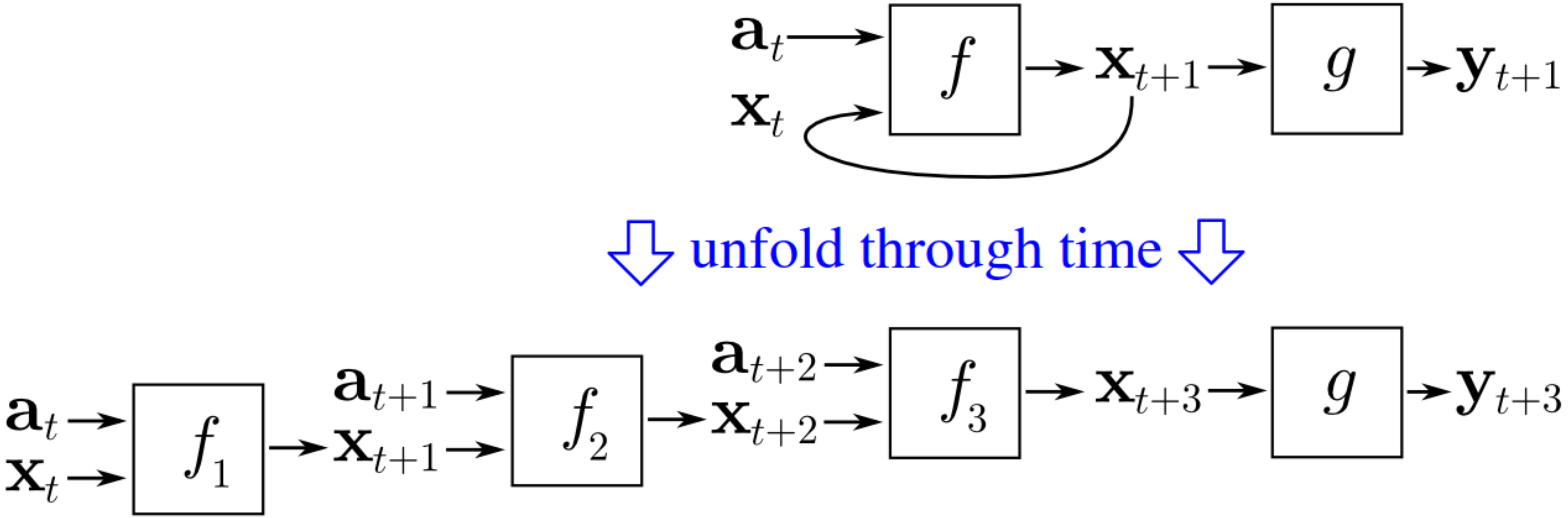
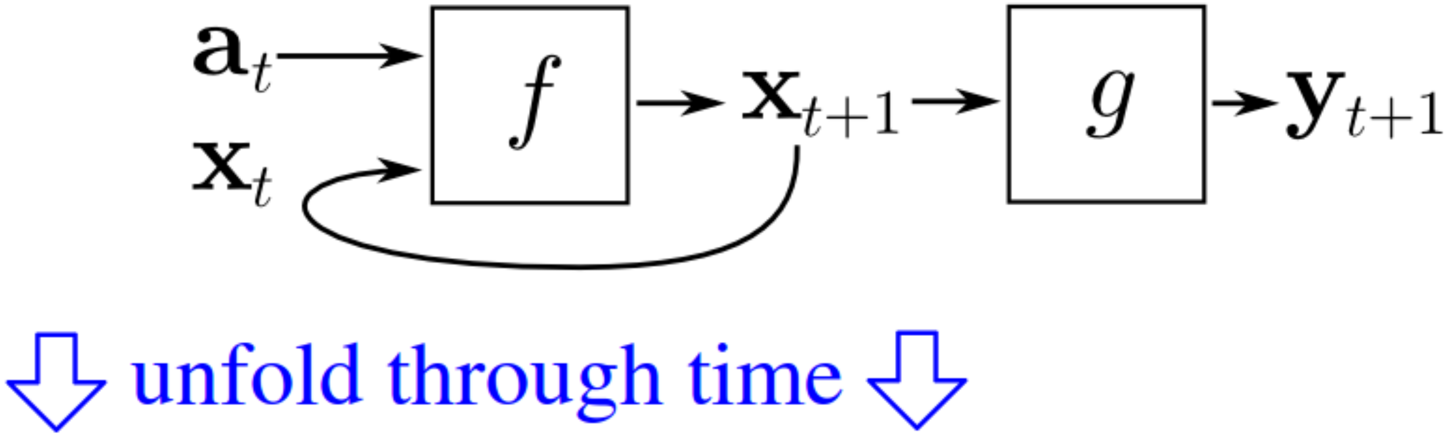


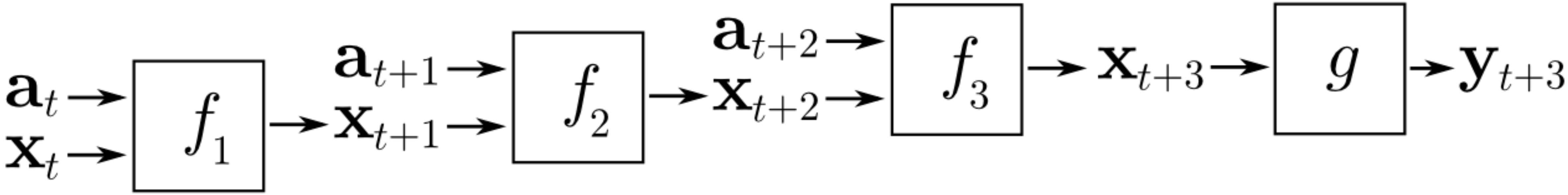

Image from [Wikipedia]()

# How to Train?

- More efficient: [Truncated backpropagation through time]()

(1) Only run backpropagation every $k_1$ time steps




(2) Limit number of times ($k_2$) unfolded

Image from [Wikipedia]()

# Application of Recurrent Neural Network

- Text synthesis (student presentation)

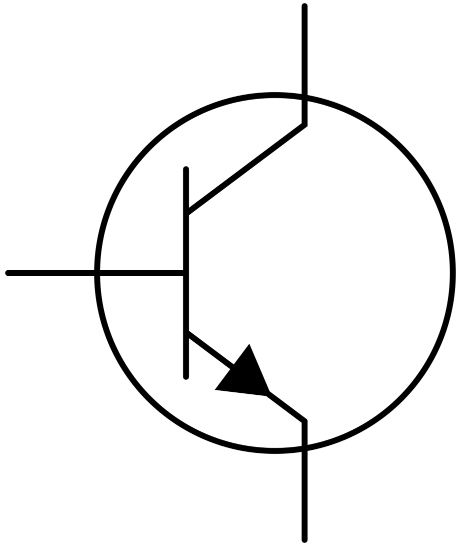
```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.
```

# Vanishing Gradients Revisited

- Suppose we want to “remember” an event at time 0 and use this in our model of the world at some later time *t*.
- Error gradients vanish exponentially quickly in the size of the time lag between these events.
- Fancier RNN models help with this problem:
  - Long Short Term Memory (LSTM)
  - Gated Recurrent Units (GRU)

# Long Short Term Memory

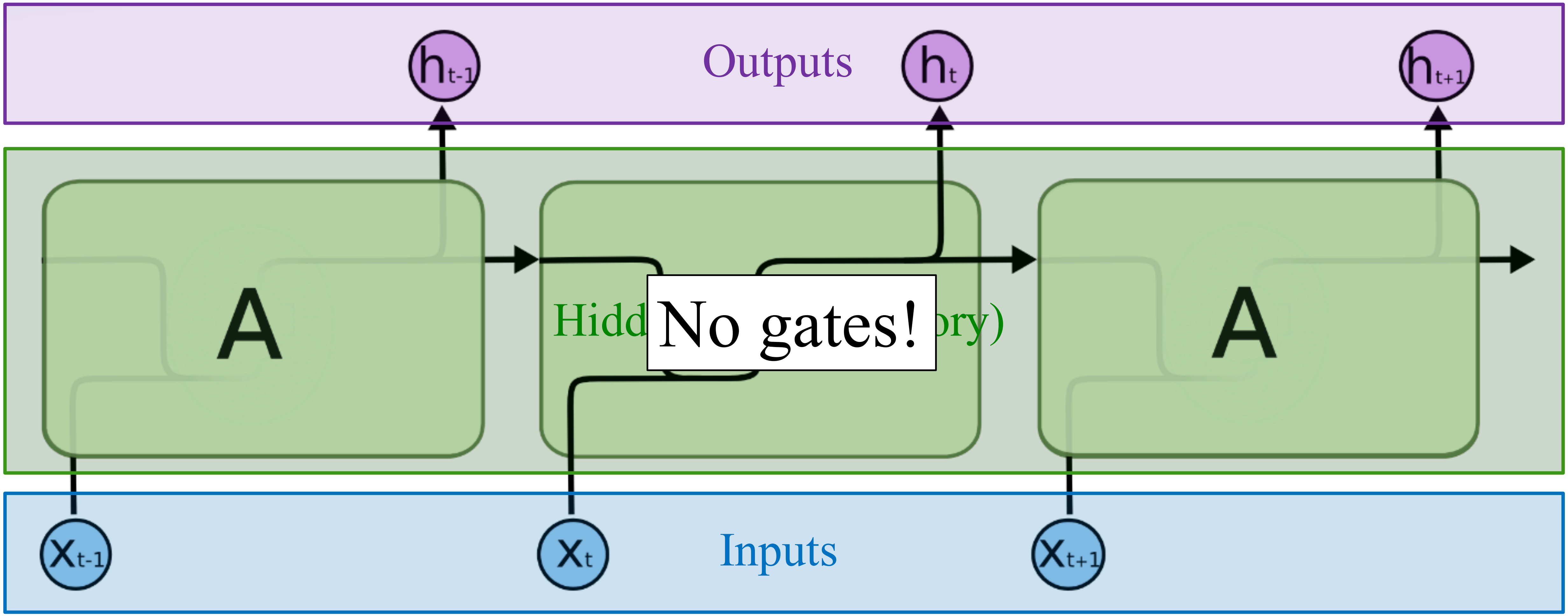
- How to better remember hidden state for a long time?
- Idea: use *gates* to create cells that can remember for a long time.



[Transistor diagram (from Wikipedia](https://en.wikipedia.org))

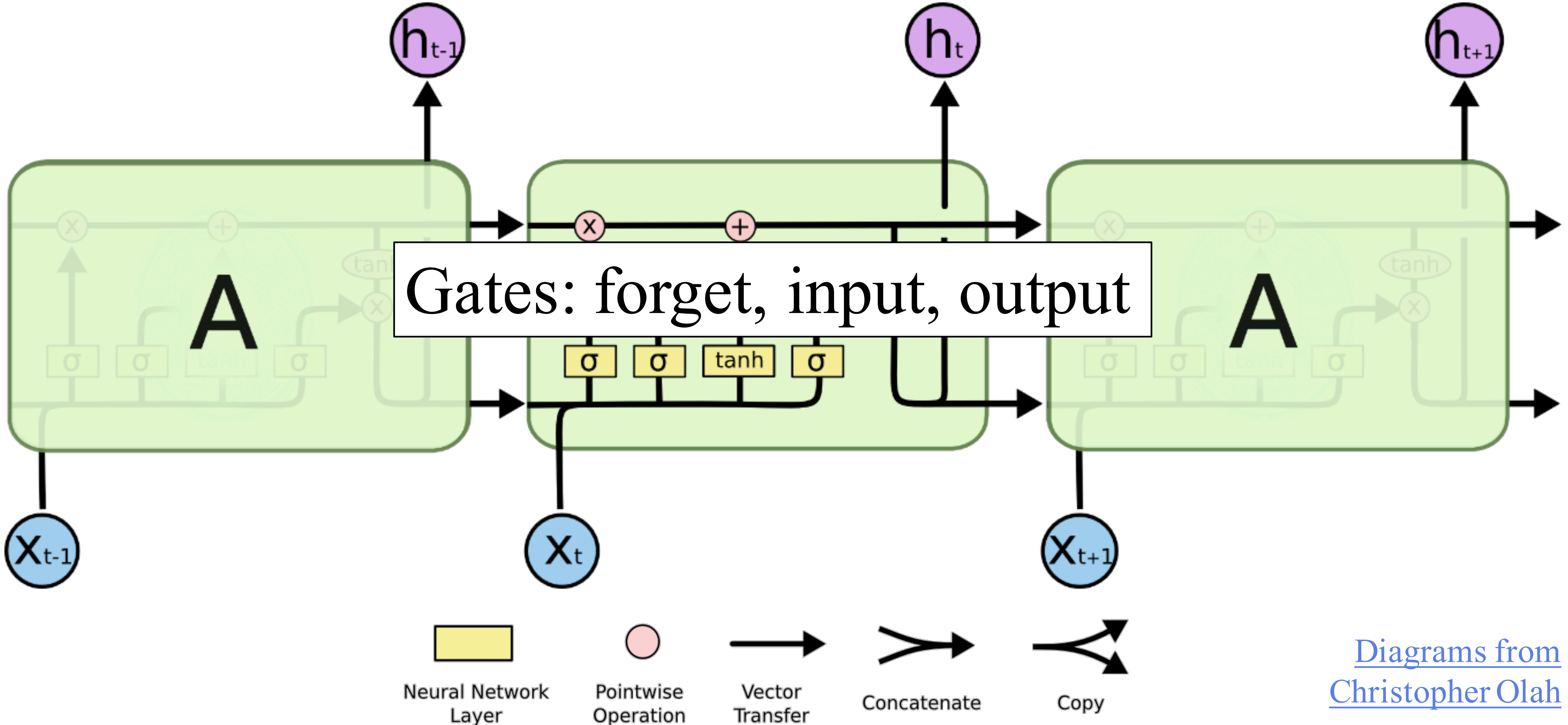
- Rough analogy: ternary logic gates used in transistors, AND, OR, …
- But use sigmoid activations so we have continuous values in [0, 1]

# Simple Recurrent Neural Network




[Diagrams from Christopher Olah]

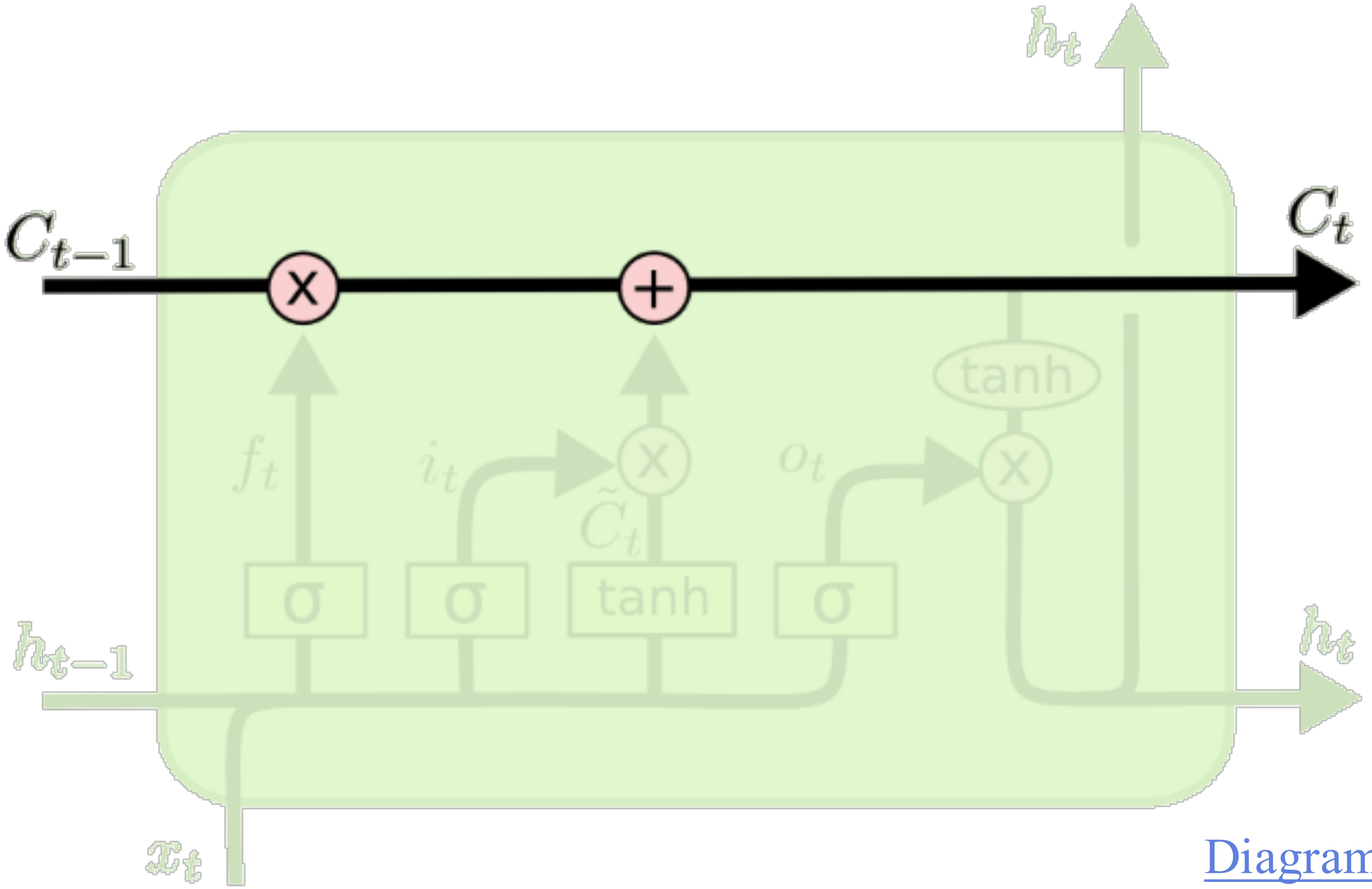
# Long Short Term Memory




[Diagrams from Christopher Olah]

# Long Short Term Memory

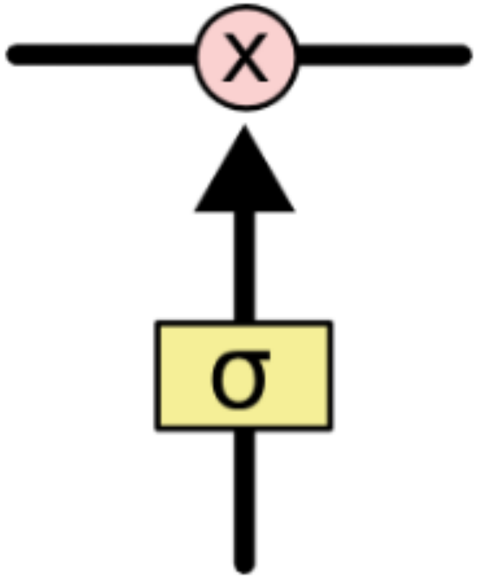
- Easy to have hidden state $C_t$ just flow through time, unchanged.




Diagrams from Christopher Olah

# Long Short Term Memory

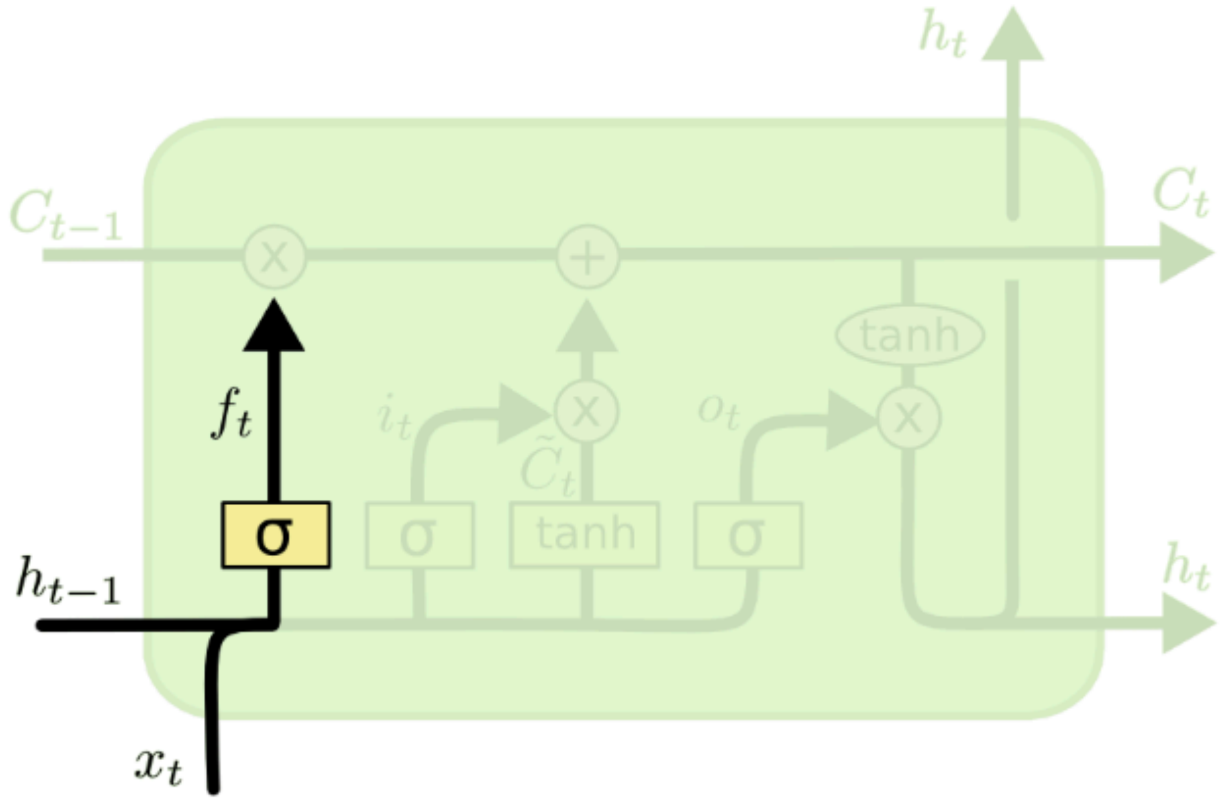
- Gate: pointwise multiplication.
- Multiply by zero: let nothing through.
- Multiply by one: let everything through.




Diagrams from Christopher Olah

# Long Short Term Memory

- Forget gate: conditionally discard previously remembered information.

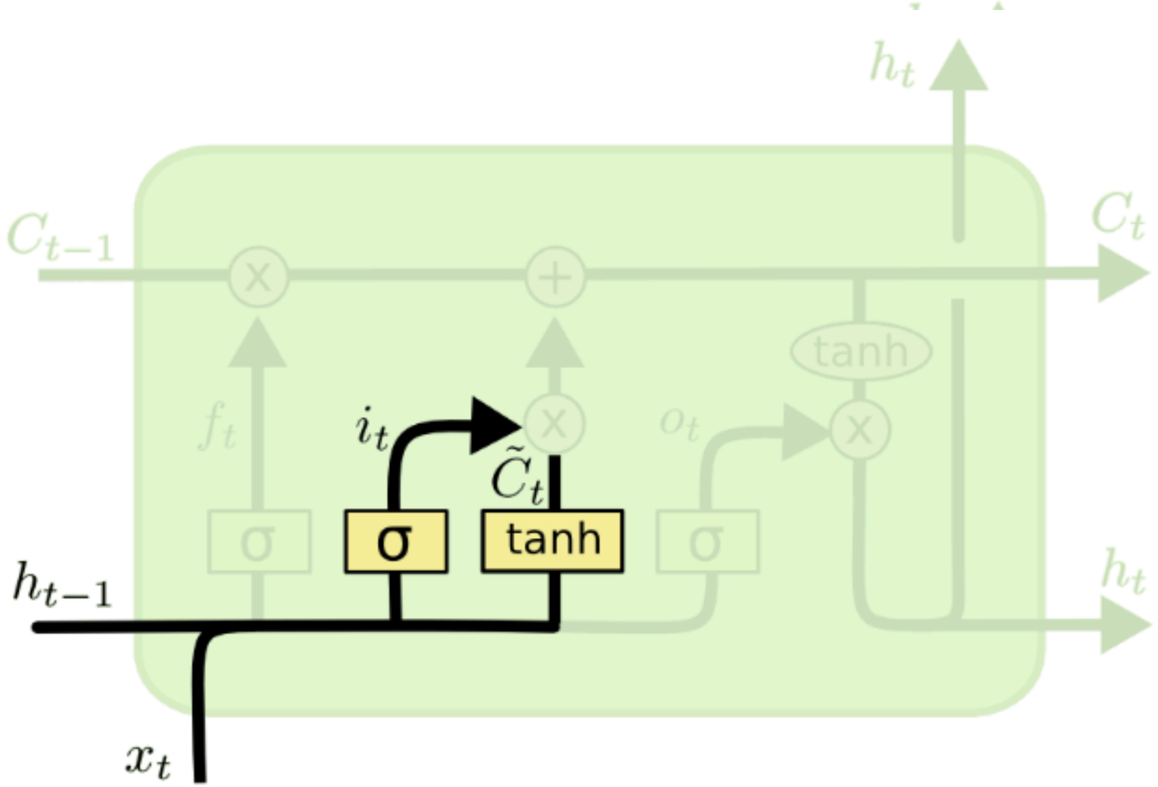



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

[Diagrams from Christopher Olah]

# Long Short Term Memory

- Input gate: conditionally remember new information.



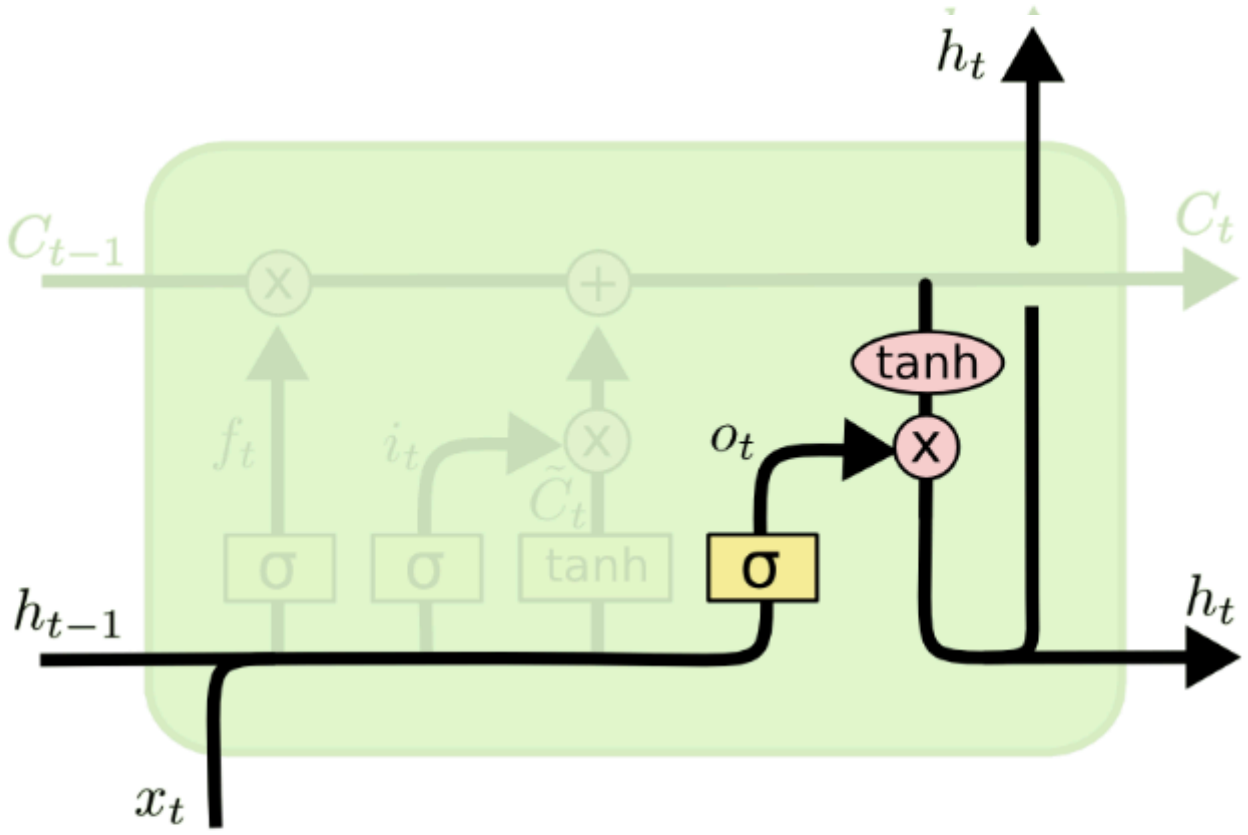

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

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

Diagrams from Christopher Olah

# Long Short Term Memory

- Output gate: conditionally output a relevant part of our memory.



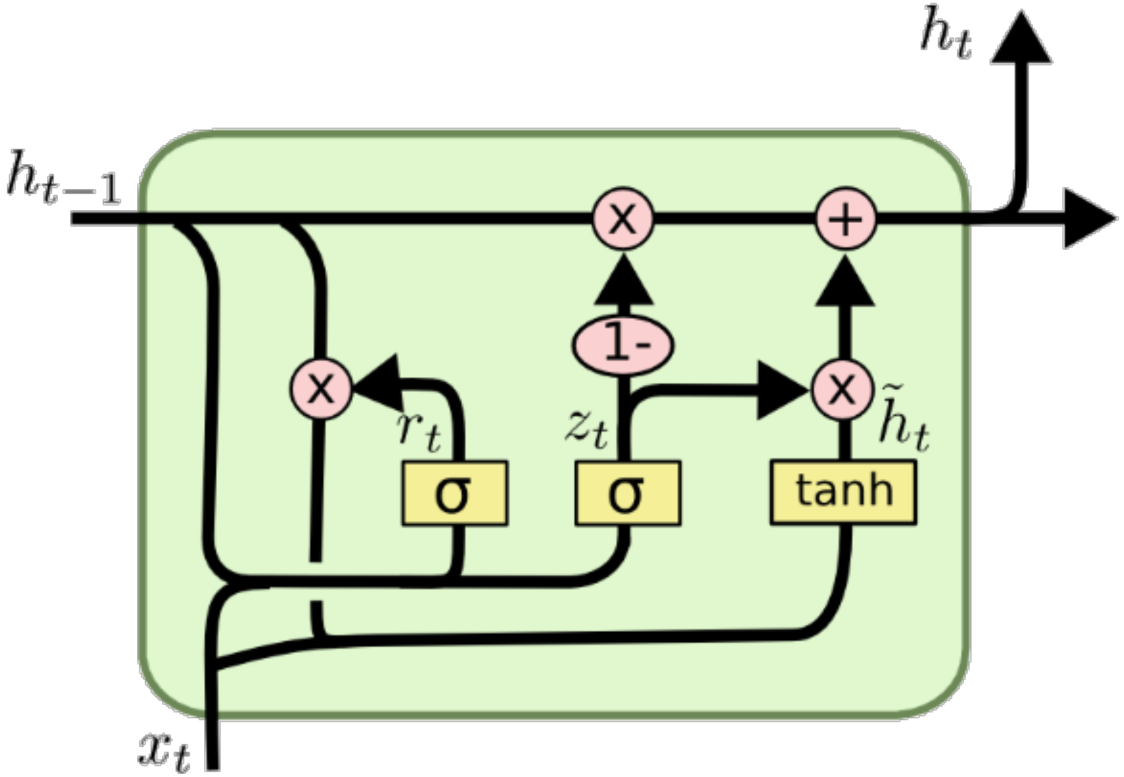

$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

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

Diagrams from Christopher Olah

# Gated Recurrent Units (GRUs)

- Merge input / forget units into a single “update unit.”
- Merge hidden states.




$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Diagrams from Christopher Olah

# Outline

- Convolutional Neural Networks
- Recurrent Neural Networks
- **Deep learning libraries**

# Libraries

- Deep learning:
  - Caffe (C++ with Python bindings),
  - Torch (Lua)
  - TensorFlow (C++ with Python bindings)
  - Python: Keras, built on Theano
- Recurrent networks (search for your framework + LSTM):
  - Caffe
  - Torch
  - TensorFlow
  - Keras