Spatio-Temporal Deep Neural Networks for Extreme Event Detection

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Image and Signal Processing - ISP

IPL Image Processing Laboratory

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XAIDA

XAIDA Summer School 2022
21st June 2022

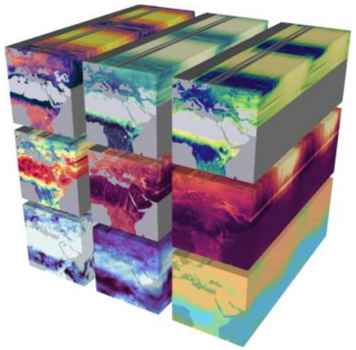
Contents

PyTorch

1. Extreme Event Detection using DNNs

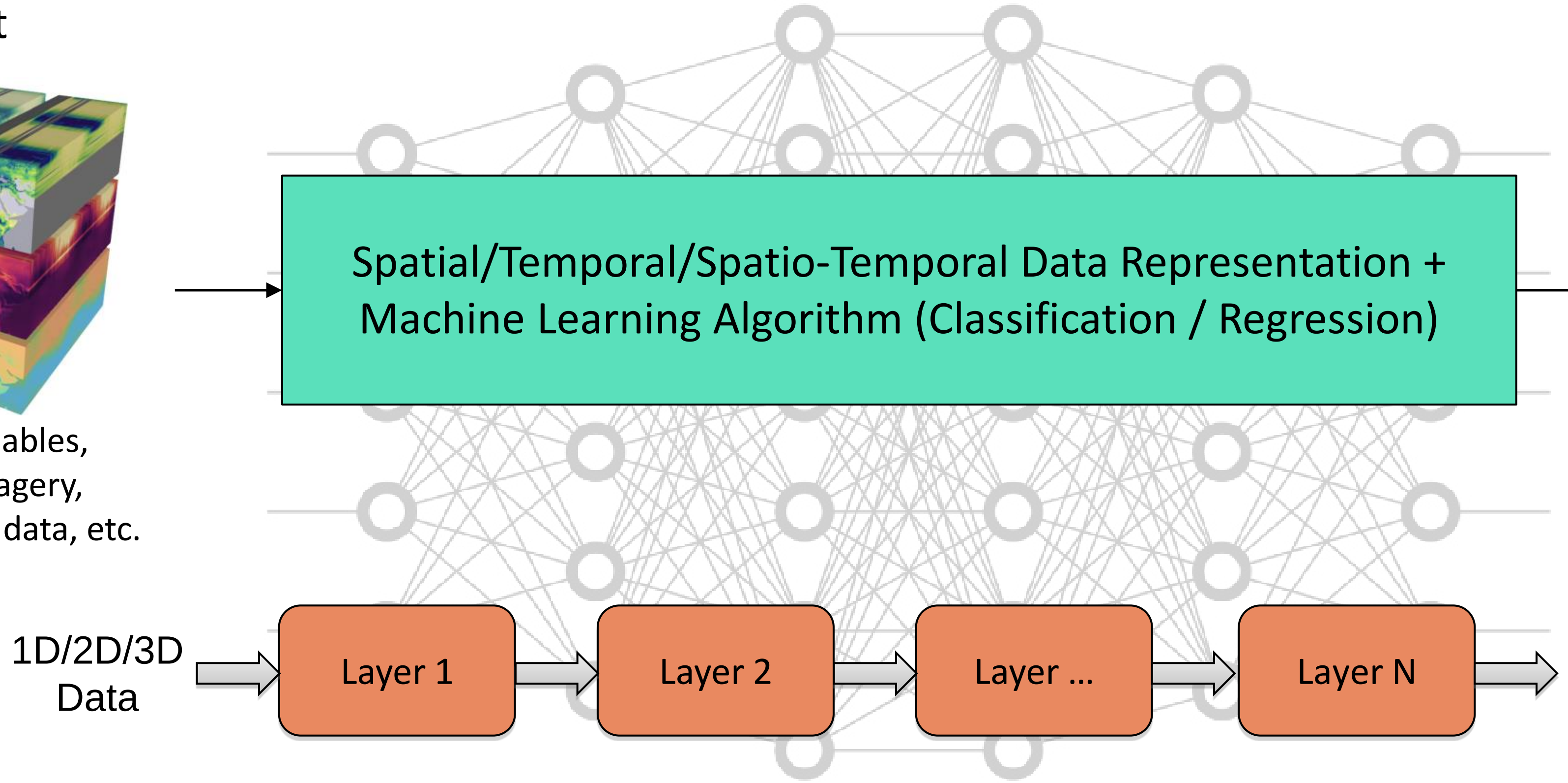
Extreme Event Detection using DNNs

Input

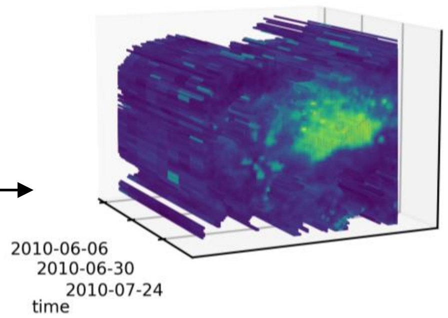


Source: Mahecha et al., 2020

Climate variables,
satellite imagery,
location-aware data, etc.



Output



Extreme event detection

- From classical Machine Learning/Computer Vision to Deep Learning

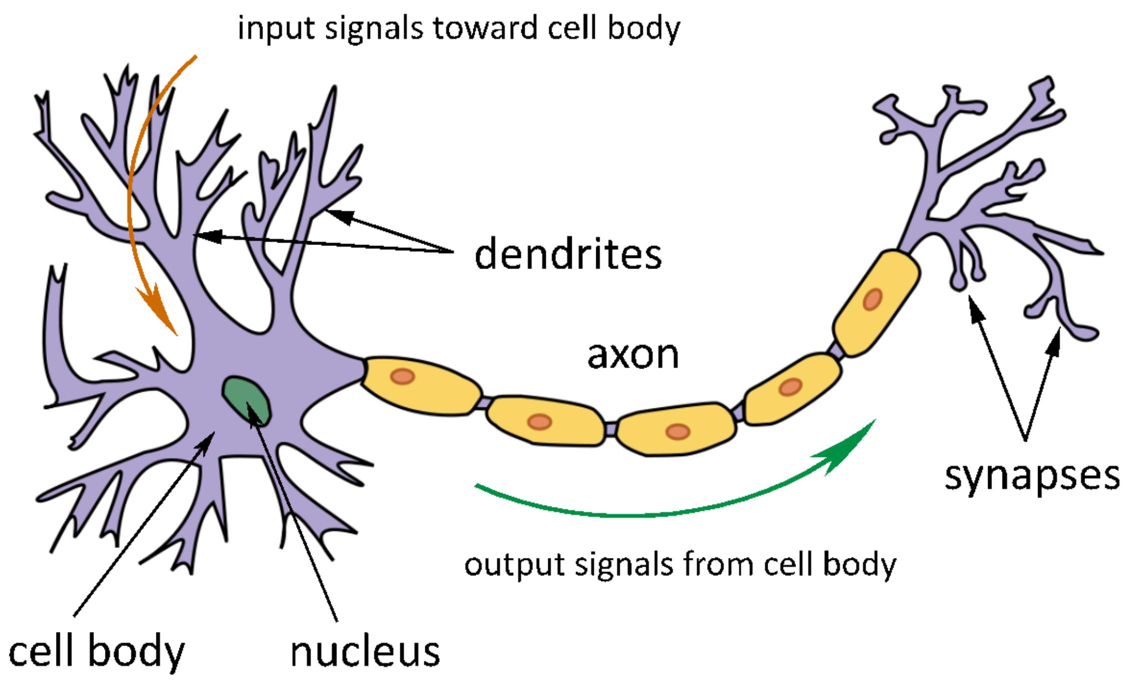
→ From feature engineering (extraction + selection) to feature learning

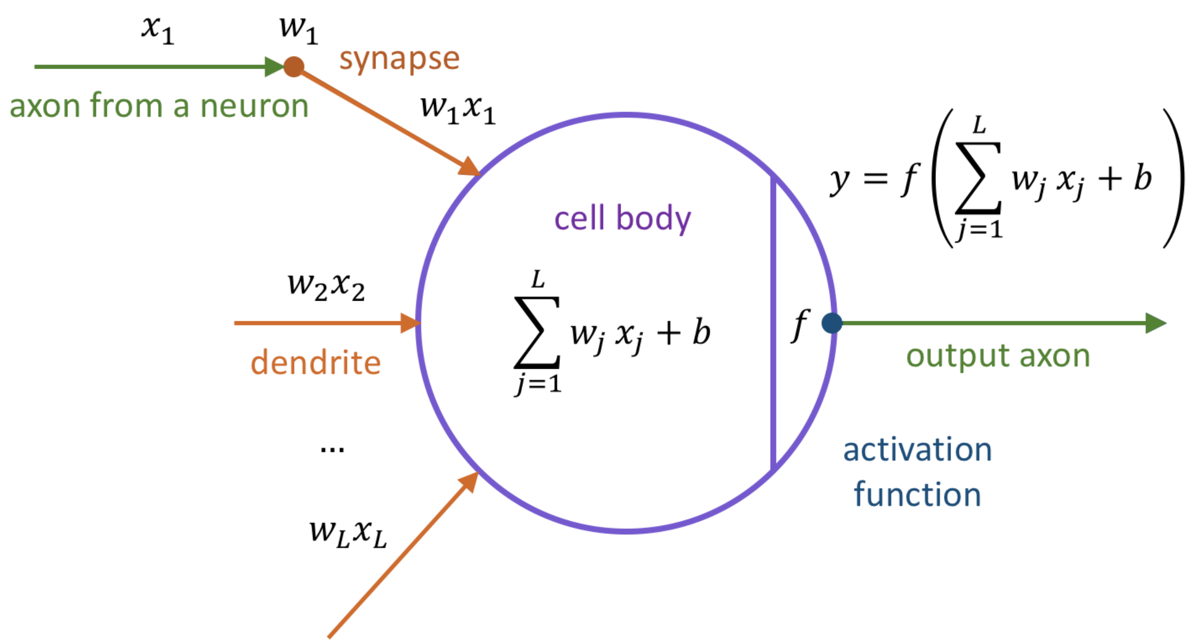
- Spatial/temporal/spatio-temporal hierarchical representations from 1D/2D/3D data to classifier/regressor.
- Each layer extract features from the output of the previous layer.
- End-to-End Learning: Train all layers jointly.

2. Deep Neural Networks (DNNs)

Deep Neural Networks (DNNs)

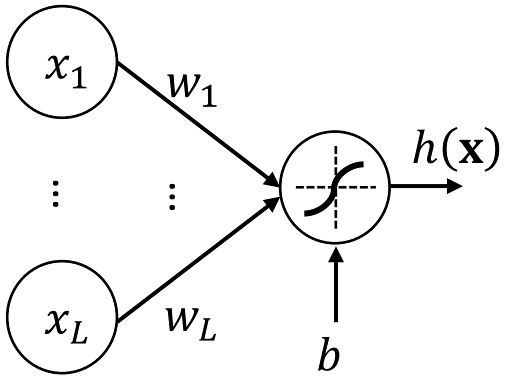
Neuron Model: Biological vs. Computational Neuron





From Linear Regression to Neural Networks

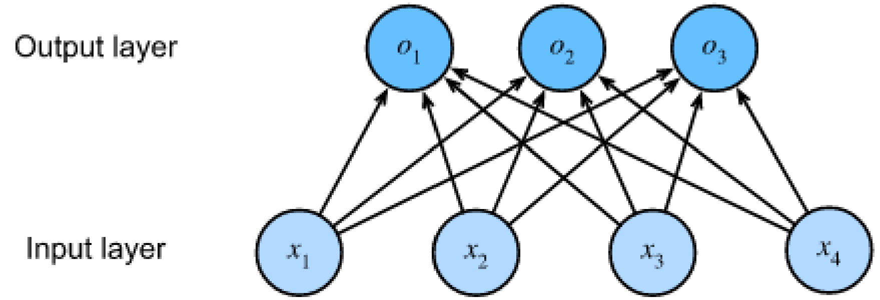
- **Linear regression: Single-layer neural network**



  - Pre-activation: $a(\mathbf{x}) = \sum_i w_i \, x_i + b = \mathbf{w}^T\mathbf{x} + b$
  - Activation: $h(\mathbf{x}) = g\big(a(\mathbf{x})\big) = g(\sum_i w_i x_i + b)$
  - Fully-connected/dense layer: Every input connected to every output

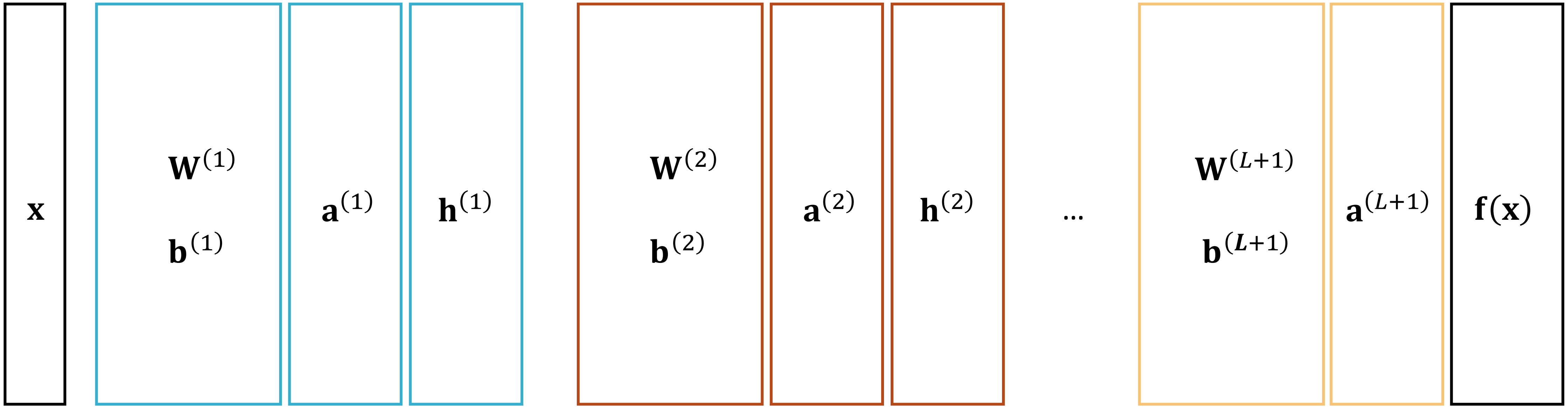
- **Classification/Softmax regression: Single-layer neural network**

$\hat{\boldsymbol{y}} = softmax(\mathbf{Wx} + \mathbf{b}) \quad \boldsymbol{y} \in \mathbb{R}^C, \mathbf{x} \in \mathbb{R}^L, \mathbf{W} \in \mathbb{R}^{C\times L}, \mathbf{b} \in \mathbb{R}^C$



  - L features or descriptors $\mathbf{x}$
  - C classifiers, one per category, evaluated in parallel
  - Objective: Given training set, learn $\boldsymbol{W}$ (weights or parameters) and $\mathbf{b}$ (bias term)
  - Once weights are learned, the set of training data can be discarded
  - Predicted scores for each class $\hat{\boldsymbol{y}}$

Multi-layer Neural Network – Feedforward Propagation



$$\mathbf{a}^{(1)}(\mathbf{x}) = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}$$

$$\mathbf{a}^{(2)}(\mathbf{x}) = \mathbf{W}^{(2)}\mathbf{h}^{(1)}(\mathbf{x}) + \mathbf{b}^{(2)}$$

$$\mathbf{a}^{(L+1)}(\mathbf{x}) = \mathbf{W}^{(L+1)}\mathbf{h}^{L}(\mathbf{x}) + \mathbf{b}^{(L+1)}$$

$$\mathbf{h}^{(1)}(\mathbf{x}) = \mathbf{g}\left(\mathbf{a}^{(1)}(\mathbf{x})\right)$$

$$\mathbf{h}^{(2)}(\mathbf{x}) = \mathbf{g}\left(\mathbf{a}^{(2)}(\mathbf{x})\right)$$

$$\mathbf{f}(\mathbf{x}) = \mathbf{o}\left(\mathbf{a}^{(L+1)}(\mathbf{x})\right)$$

Why Deep Neural Networks?

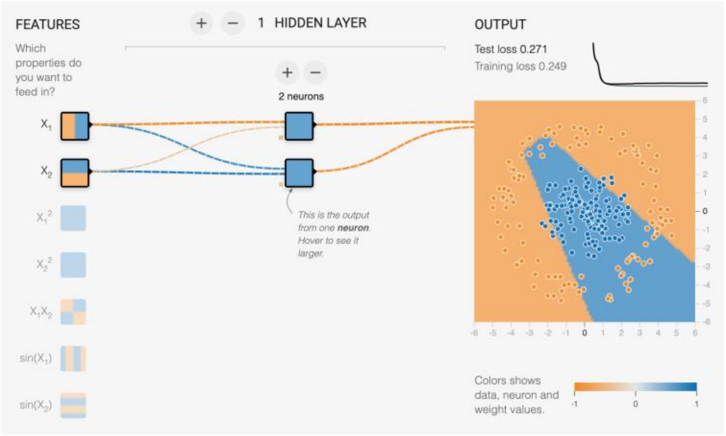
- There are functions you can compute with “deep” NNs that shallower NNs would require exponentially more hidden units
- More layers, less hidden units per layer
- Hierarchical representations: From less to more abstract concepts

`torch.nn.Linear`

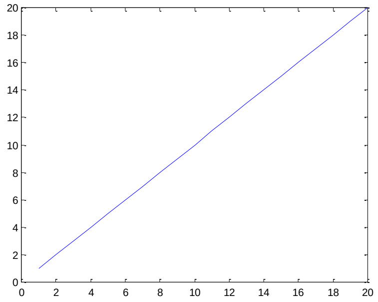
Activation Functions

`nn.Sigmoid | nn.Tanh | nn.ReLU`

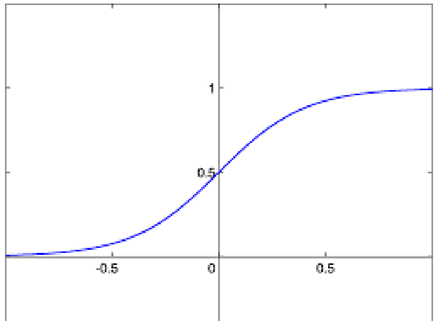
- A Neural Network Playground: https://playground.tensorflow.org/
- A neural network solves linear problems
- Non-linear problems
  - Designing more suitable features (e.g. polynomial features).
  - Building more complex networks, combining several neurons.
  - Activation functions



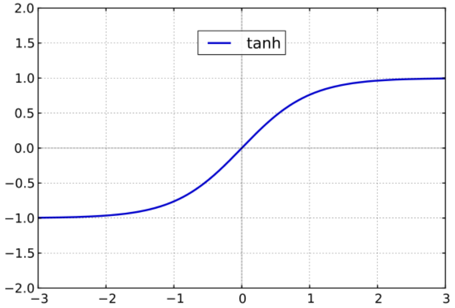
Linear
$g(x) = x$



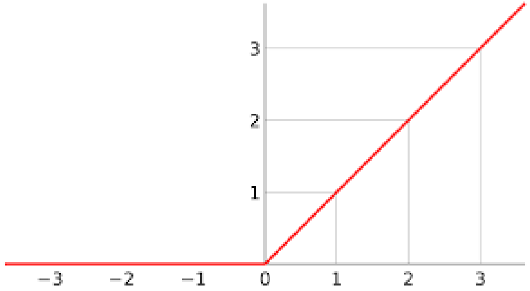
Logistic or Sigmoid
$$g(x) = \frac{1}{1 + e^{-x}}$$



Hyperbolic tangent
$g(x) = \tanh(x)$



RELU
$g(x) = max(0, x)$



Binary classification, Multi-class classification → Softmax

Most hidden layers

“How to Train your (Deep) Neural Network”

Loss Function, cost function, objective l

- Quantitatively determines how accurate the output of the model is.
- Objective: Minimize empirical risk $J(\boldsymbol{\theta})$:

$$\arg\min_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \arg\min_{\boldsymbol{\theta}} \frac{1}{N} \sum_{i} l(f(\mathbf{x}_i; \boldsymbol{\theta}), y_i)$$

  - $N \equiv$ Number of training samples
  - $x_i \equiv$ Input *i* features or descriptors
  - $y_i \equiv$ Ground-truth (GT) value, label for input *i*
  - $\theta \equiv$ Network architecture weights

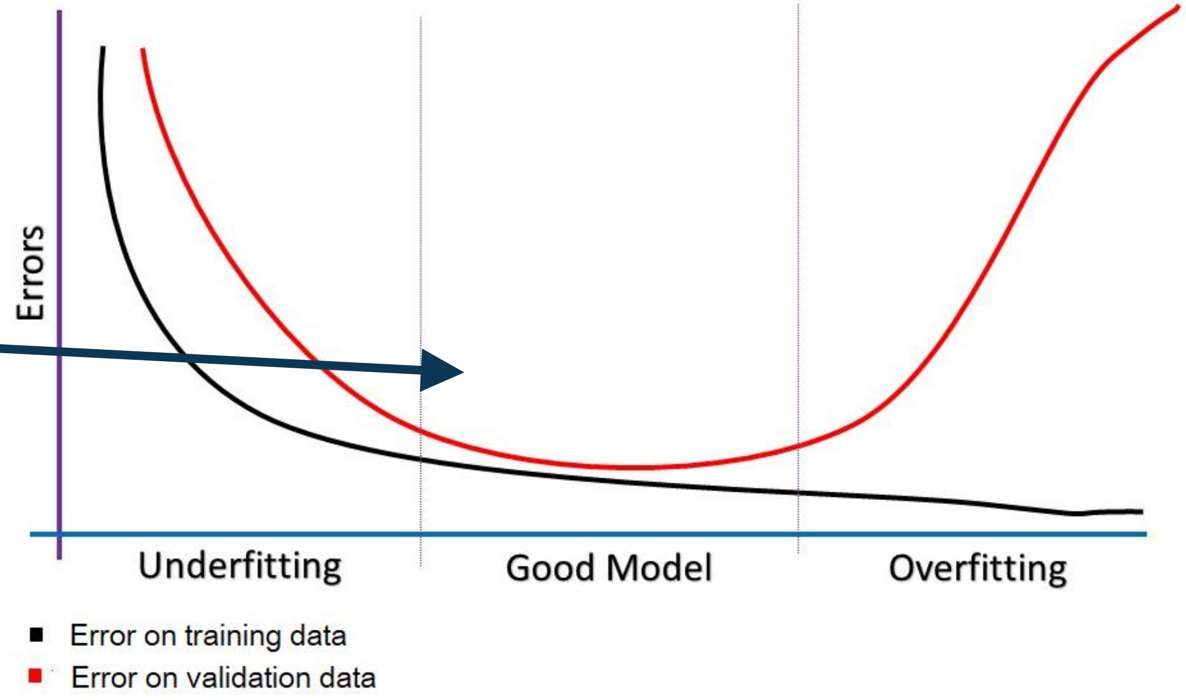
- Some well-known loss functions:
  - Classification: Cross-Entropy Loss, Hinge Loss (Support Vector Machine)
  - Regression: L1 Norm or Mean Absolute Error, L2 or Mean Squared Error

```
torch.nn.CrossEntropyLoss | torch.nn.MultiMarginLoss
torch.nn.L1Loss | torch.nn.MSELoss
```

“How to Train your (Deep) Neural Network”

Regularization Techniques

- L2 regularization: $\Omega(\boldsymbol{\theta}) = \|\mathbf{w}\|_2^2$
- L1 regularization: $\Omega(\boldsymbol{\theta}) = \|\mathbf{w}\|_1$
- Data Augmentation
- Early Stopping
- Dropout



“How to Train your (Deep) Neural Network”

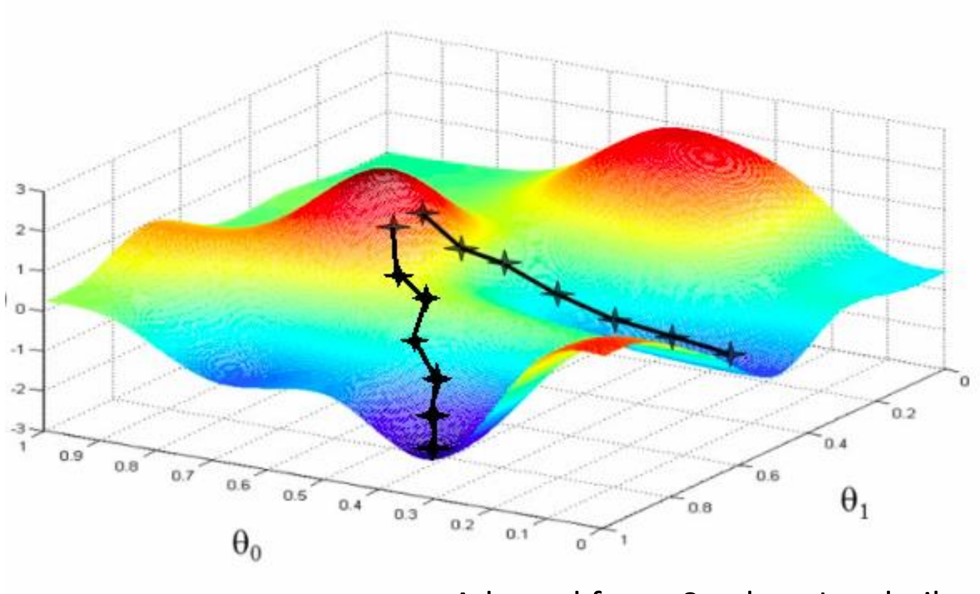
Optimization and Backpropagation

- Optimization: Find network weights q to minimize the error between true and estimated labels of training examples:

$$J(\theta) = \frac{1}{T}\sum_{t} l\left(f\left(\mathrm{x}^{(t)};\theta\right), y^{(t)}\right)$$

- Backpropagation:
  - Compute the gradient of the loss function w.r.t. parameters, from output to input layers
  - Update weights by gradient descent:

$$\theta \leftarrow \theta - \alpha\frac{\partial J}{\partial \theta} \qquad \alpha \equiv Learning\ rate$$

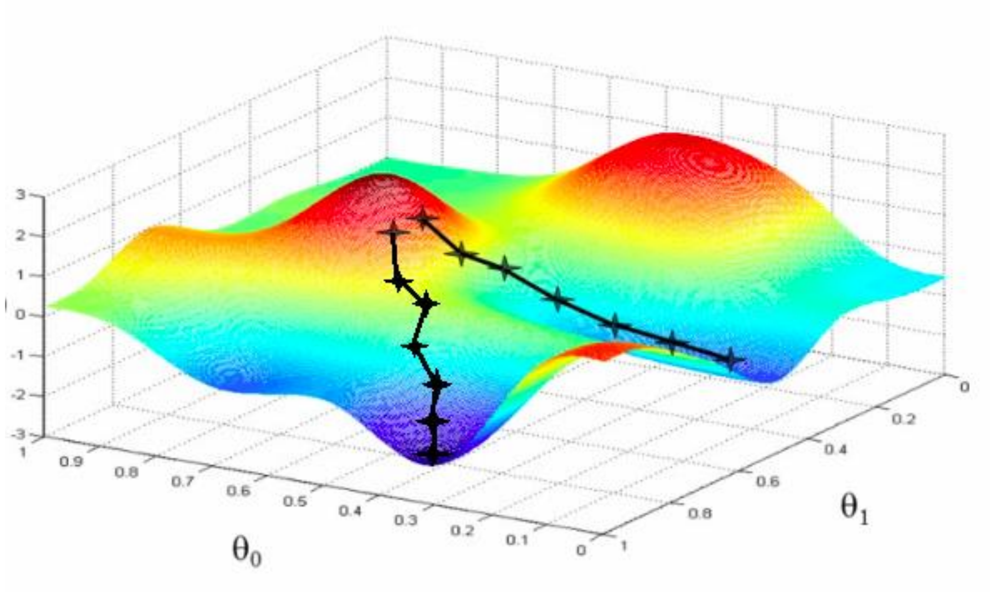


Adapted from: Svetlana Lazebnik

“How to Train your (Deep) Neural Network”

Optimization and Backpropagation

- Learning rate:
  - A learning rate α that is too large can cause the model to converge too quickly to a suboptimal solution…
  - whereas a learning rate that is too small can cause the process to get stuck
- Stochastic Gradient Descent (SGD):
  - Compute the weight update w.r.t. one training example at a time…
  - or a small batch of examples: Mini-batch SGD
  - Cycle through training examples in random order in multiple epochs

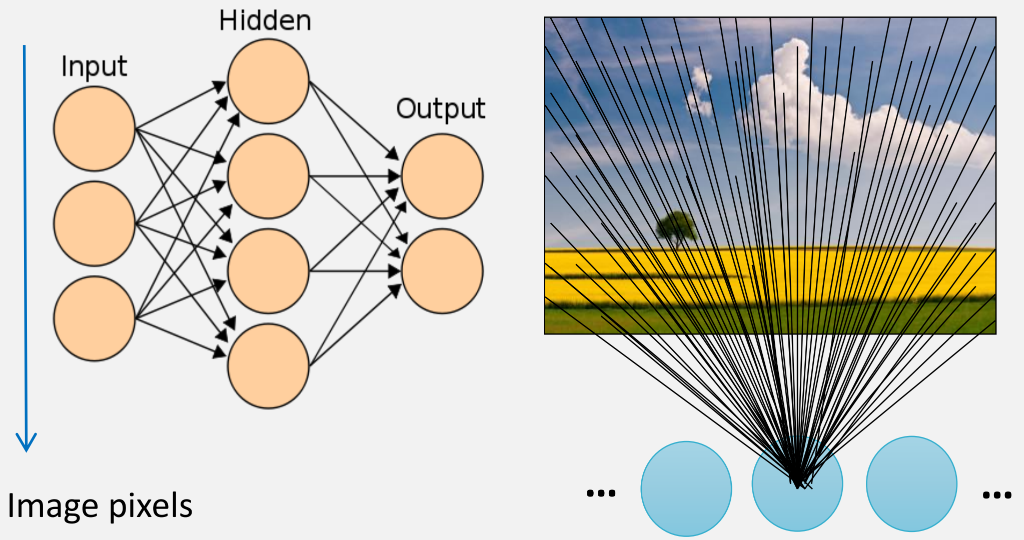


Adapted from: Svetlana Lazebnik

`torch.optim.SGD | torch.optim.RMSprop | torch.optim.Adam | ...`

3. Space: Convolutional Neural Networks (CNNs)

Space: Convolutional Neural Networks (CNNs)



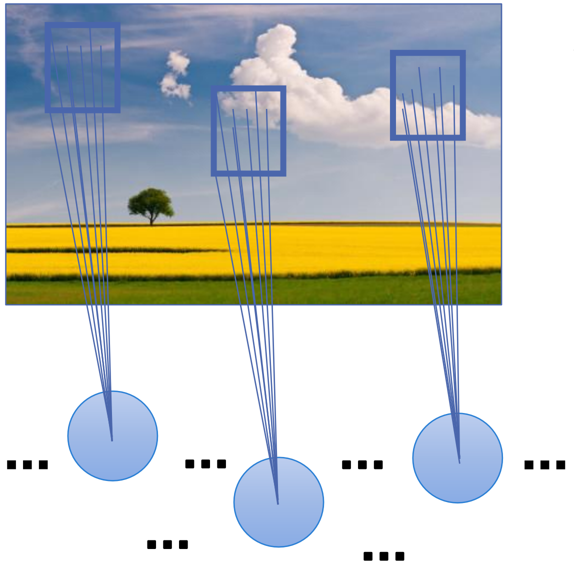
Fully Connected NNs

Example: 100x100px images
- 1 fully connected hidden layer: 10k neurons (1 per pixel)
- 1 fully connected output.

Complexity: ~100M parameters

Example: 100x100px images
- Spatial correlation/filtering is local
- 1 locally connected hidden layer with a filterbank:
  - Spatial filter size 10x10
  - 100-1000 filters
- 1 fully connected output layer

Complexity: ~10k-100k parameters, more efficient!!



- The number of parameters does not depend on the input size! (less prone to overfitting)
- Inspired by Hubel and Wiesel (1962): *Neurons are sensitive to simple patterns of light (oriented edges, color blotches)*

CNN Architecture Design

Input → A×[B×[CONV → ReLU] → POOL?] → C×[FC → ReLU] → FC → Output

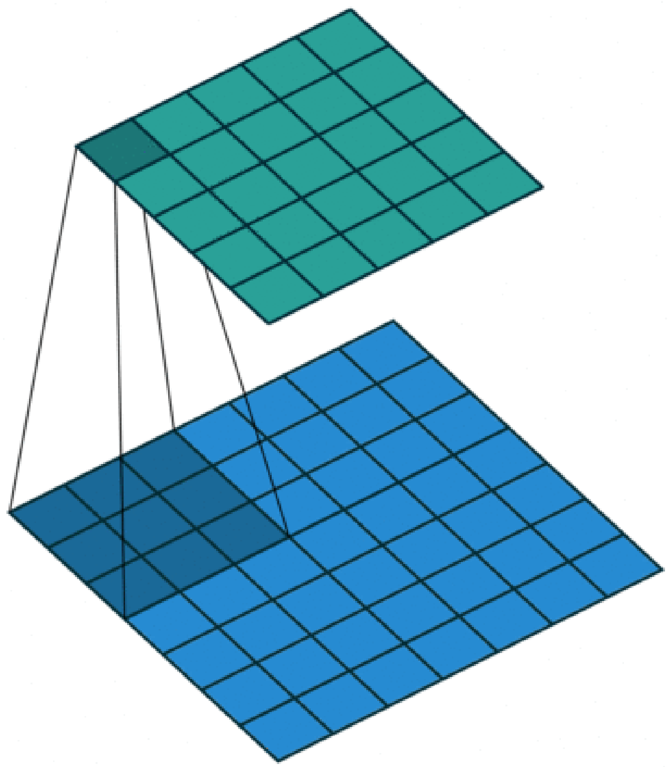
- Input
- Sequence of **A blocks** of **B** CONV layers with ReLU (or other) activations, sometimes followed by a POOL layer.
- Stack of **C** FC layers.
- Last FC layer holds the output predicted values.
- Output

`torch.nn.Conv2d | torch.nn.MaxPool2d | torch.nn.ReLU | torch.nn.Linear`

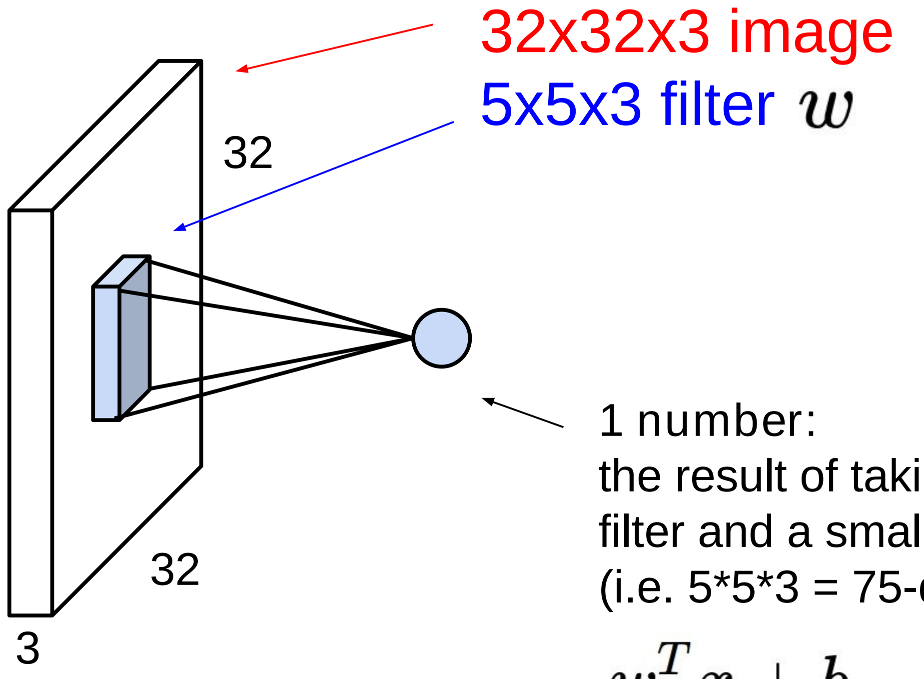
Convolutional Layer (CONV)

`torch.nn.Conv2d`

- Input: 3D volume (width, height and depth)
- Set of filters with learnable weights
  - Spatially slided along width and height of channels or spatial maps stacked on depth
- Filter or kernel size *F* → Receptive field of the neuron
- Output: 3D volume
  - Number of filters *U*
    → Depth or number of output channels
  - Stride *S* or down-sampling factor
    → Spatial size of the output
    - Bigger strides, smaller output volumes
  - Zero-padding to vary the output spatial size



Convolutional Layer (CONV)

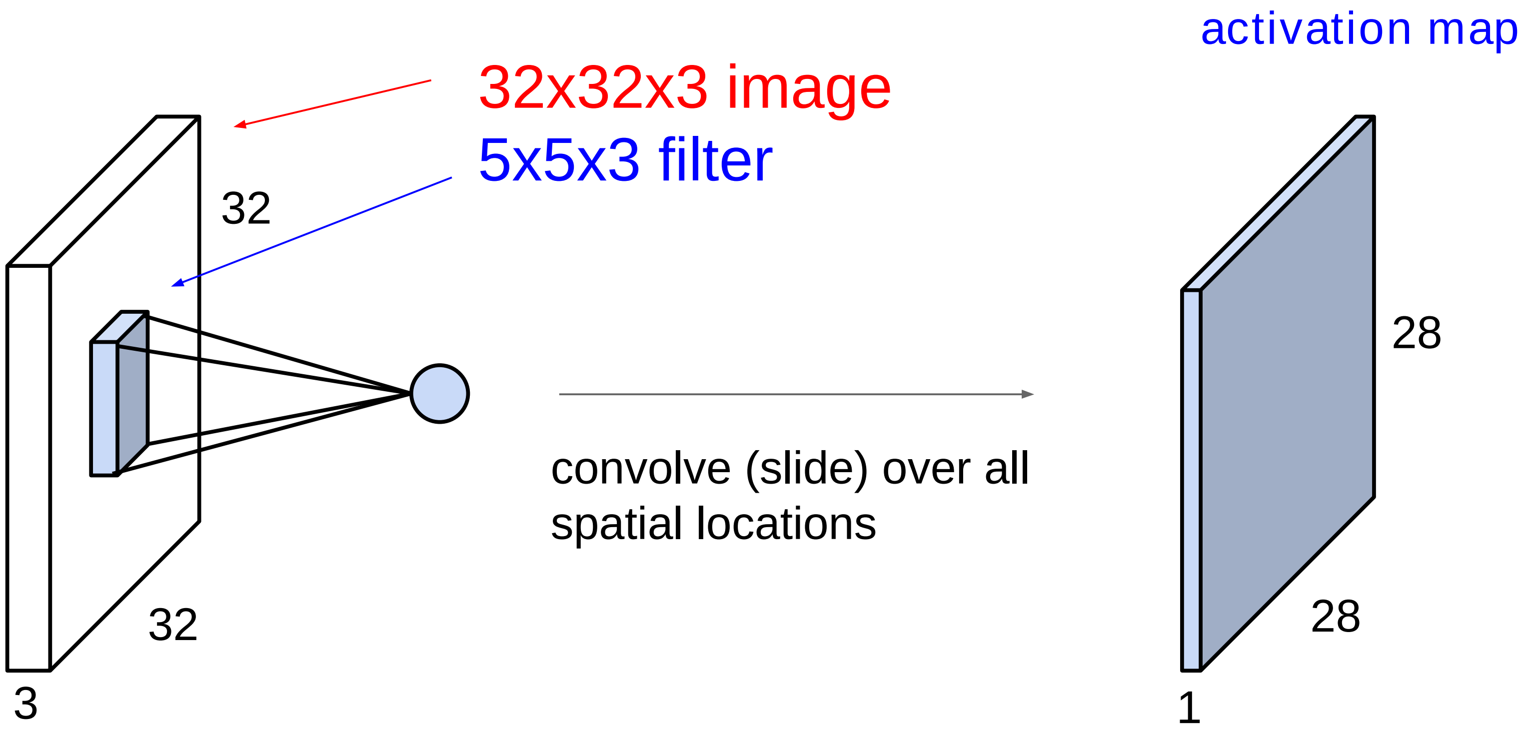


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

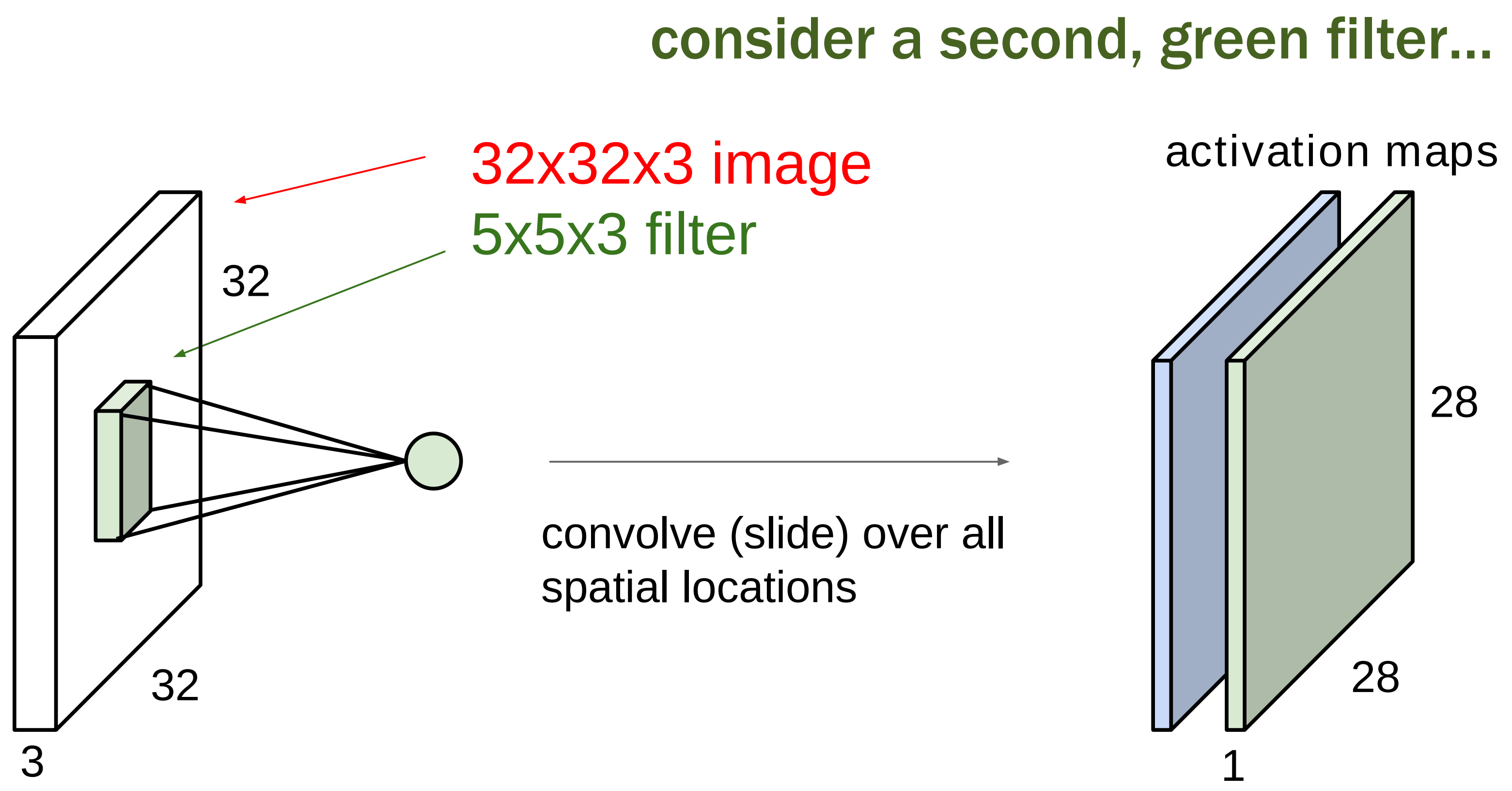
Source: CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University

Convolutional Layer (CONV)



Source: CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University

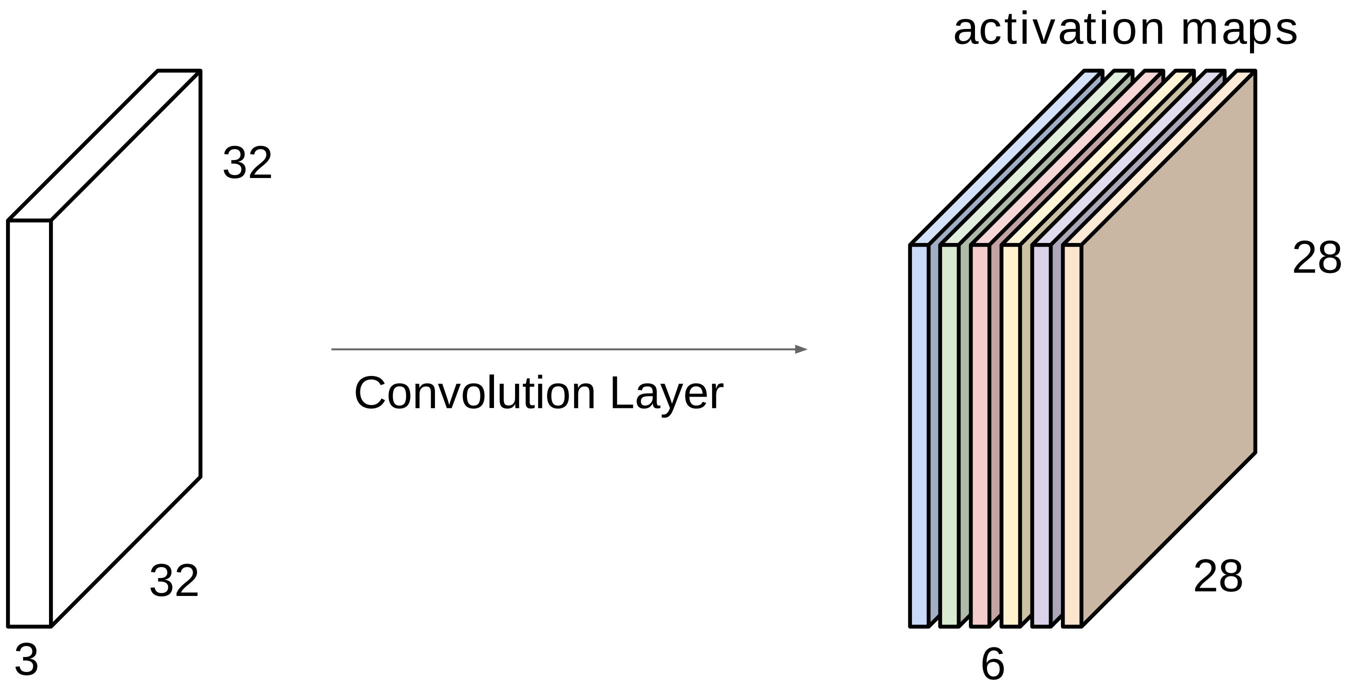
Convolutional Layer (CONV)



Source: CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University

Convolutional Layer (CONV)

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

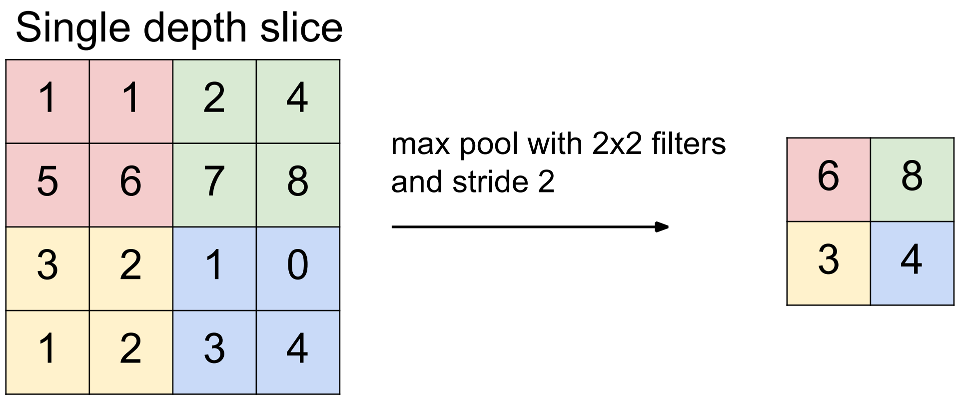
Source: CS231n: Convolutional Neural Networks for Visual Recognition, Stanford University

Pooling Layer (POOL)

```
torch.nn.MaxPool2d
torch.nn.AvgPool2d
```

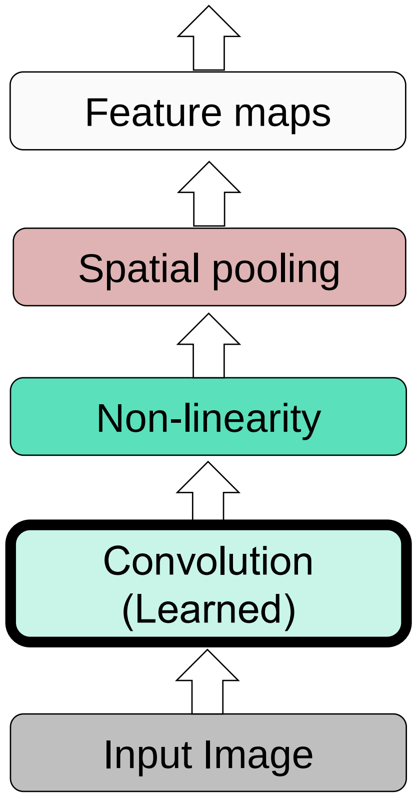
- Pooling: Fusing information from nearly locations
- Types:
  - Max pooling: Stimuli competition, only the strongest survives. In bottom/medium layers
  - Average pooling: Used more in top layers
- Invariance against small translations/shifts
- No parameters!

MAX POOLING

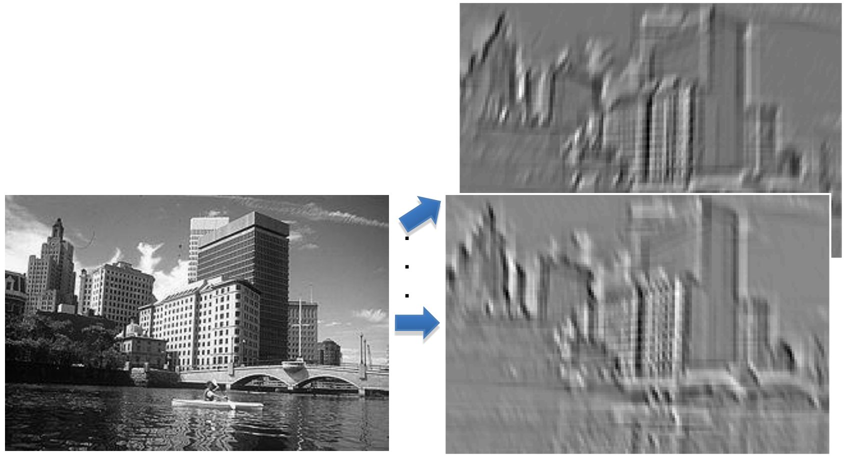


Summary: CNN Pipeline

`torch.nn.Conv2d`



Source: R. Fergus, Y. LeCun

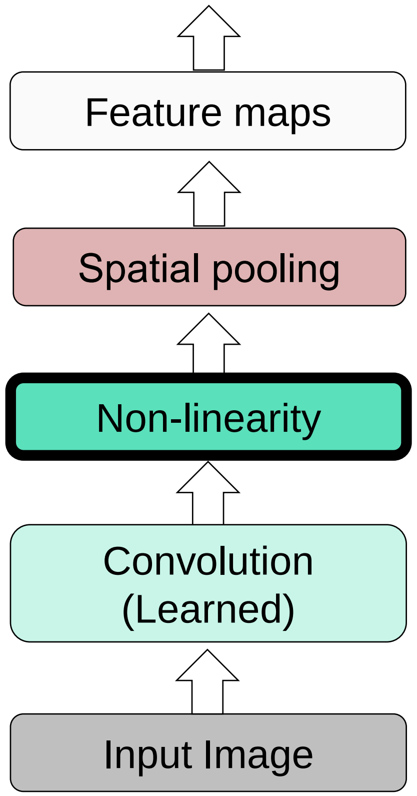


Input

Feature Map

Summary: CNN Pipeline

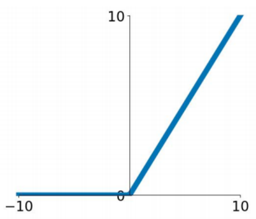
`torch.nn.ReLU`



Source: R. Fergus, Y. LeCun

ReLU

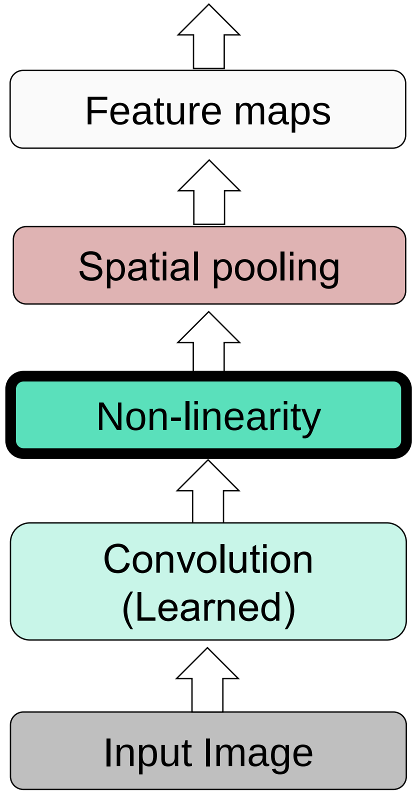
$$\max(0, x)$$



Source: [Stanford 231n]

Summary: CNN Pipeline

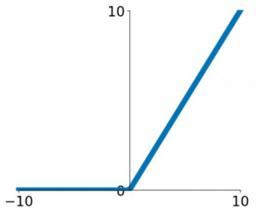
`torch.nn.LeakyReLU`
`torch.ELU`



Source: R. Fergus, Y. LeCun

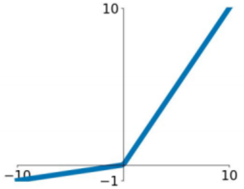
ReLU

$$\max(0, x)$$



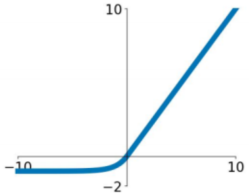
Leaky ReLU

$$\max(0.1x, x)$$



ELU

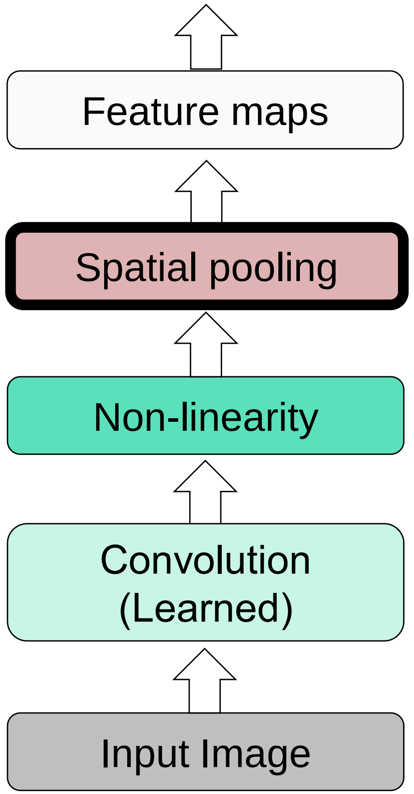
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



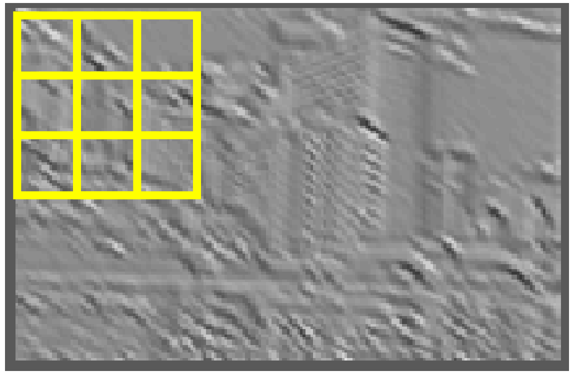
Source: [Stanford 231n]

Summary: CNN Pipeline

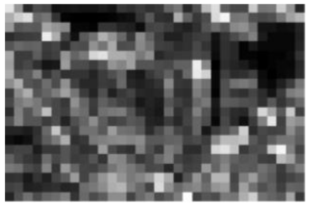
```
torch.nn.MaxPool2d
Torch.nn.AvgPool2d
```



Source: R. Fergus, Y. LeCun



Max
(or Avg)



Source: [Stanford 231n]

Summary: CNN Pipeline

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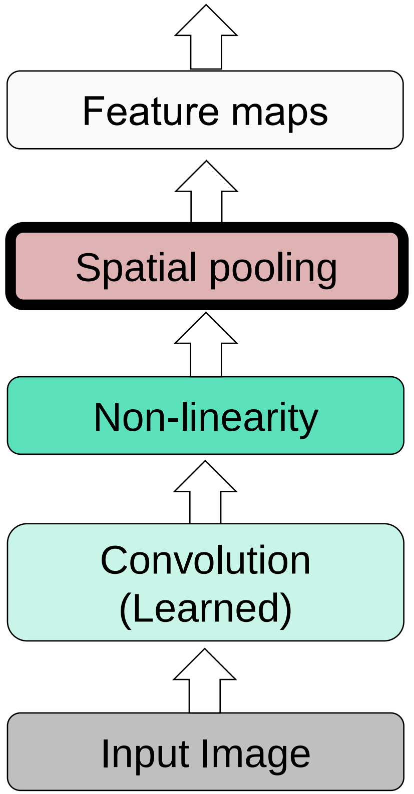
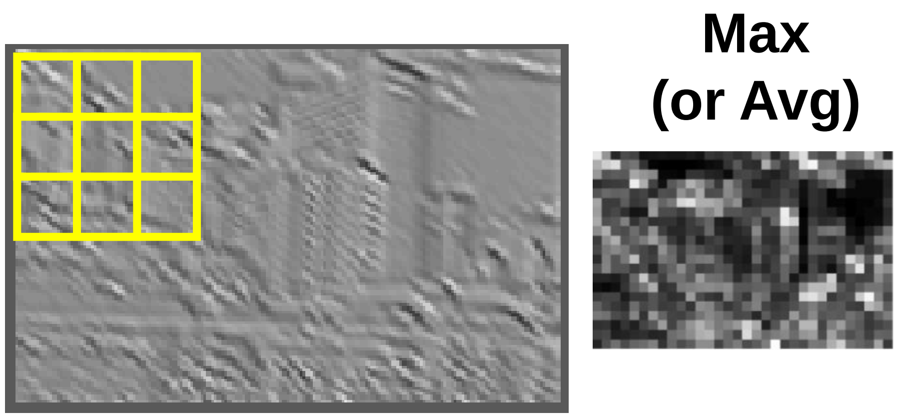
torch.nn.MaxPool2d
Torch.nn.AvgPool2d
```



Source: R. Fergus, Y. LeCun

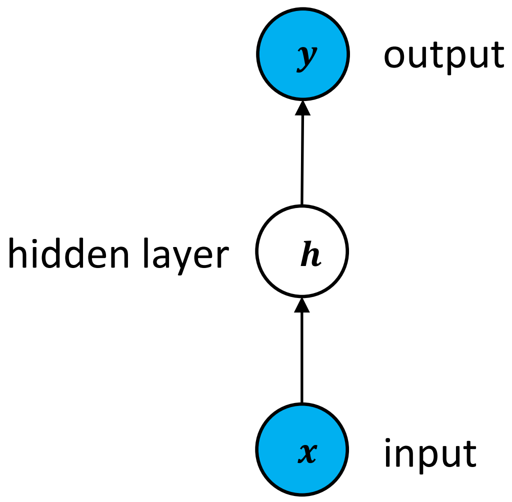


Source: [Stanford 231n]

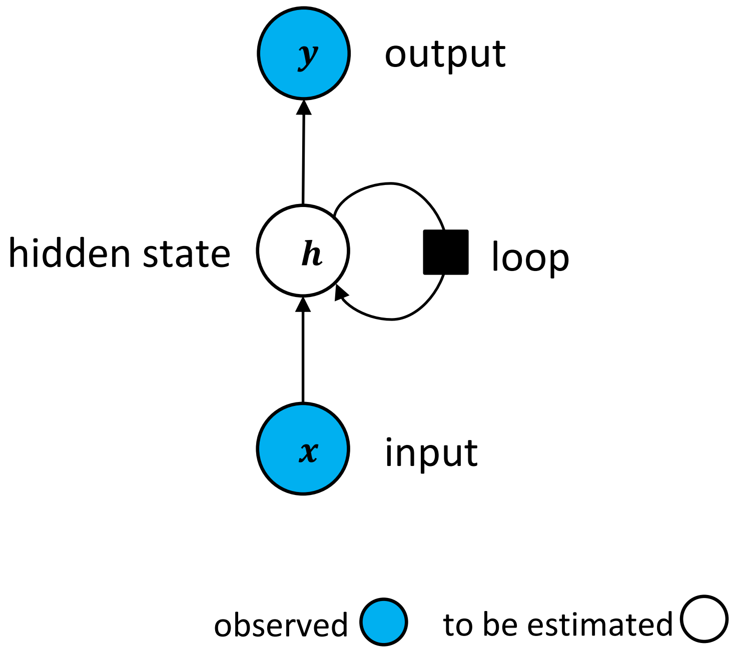
4. Time: Recurrent Neural Networks (RNNs)

Time: Recurrent Neural Networks (RNNs)

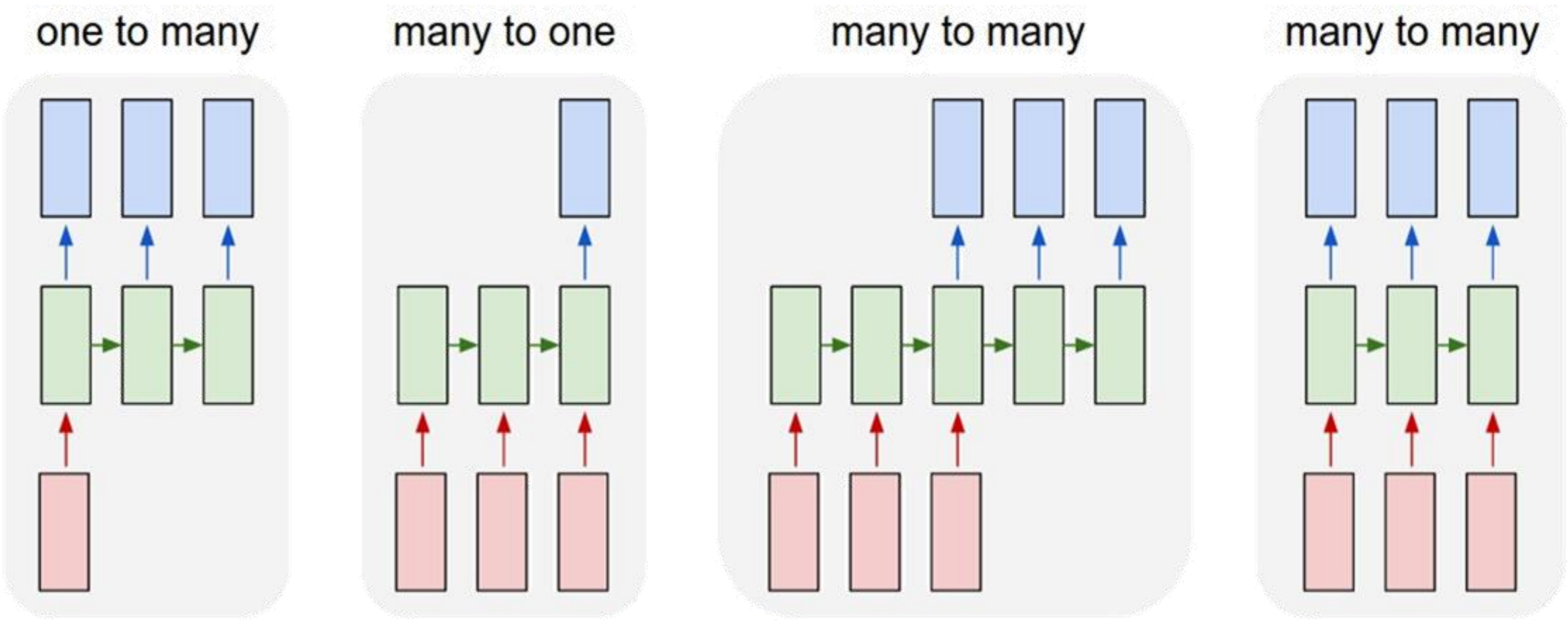
Neural Networks (NNs)



Recurrent Neural Networks (RNNs)



Types of Recurrent Neural Networks



1 input, N outputs	N inputs, 1 output	N inputs, M outputs	N inputs, N outputs

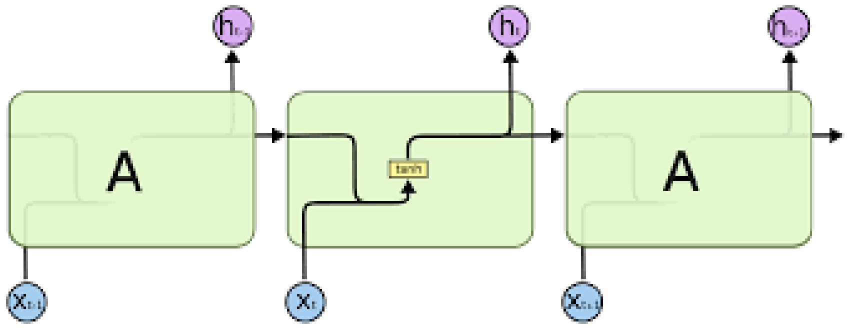
e.g. **Event description**
Image/Feature map
→ Sequence of words

e.g. **Event recognition**
Time/Space-time series
→ Class(es)

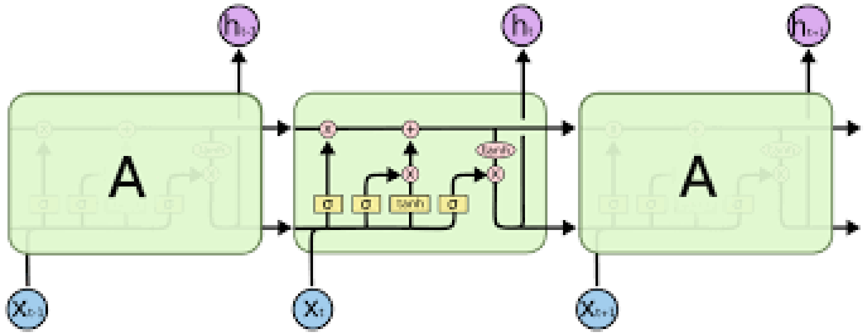
e.g. **Event detection/forecasting**
Time/Space-time series
→ Time/Space-time series for event detection/forecasting

The Problem of Long-Term Dependencies

Recurrent Neural Networks (RNNs)



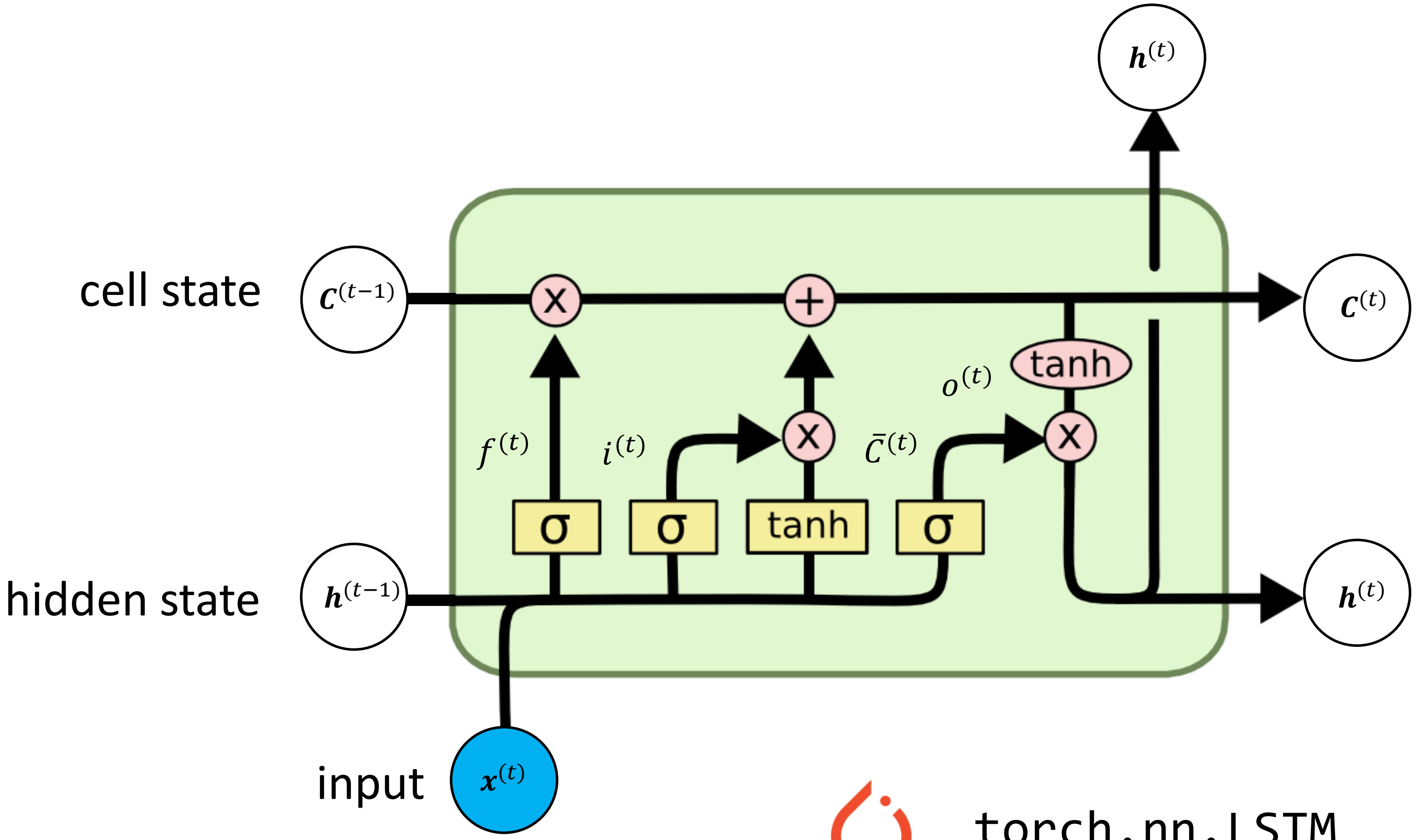
Long Short-Term Memory (LSTM) Networks



Designed to alleviate the problem of vanishing and exploding gradients

Source: Colah’s Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

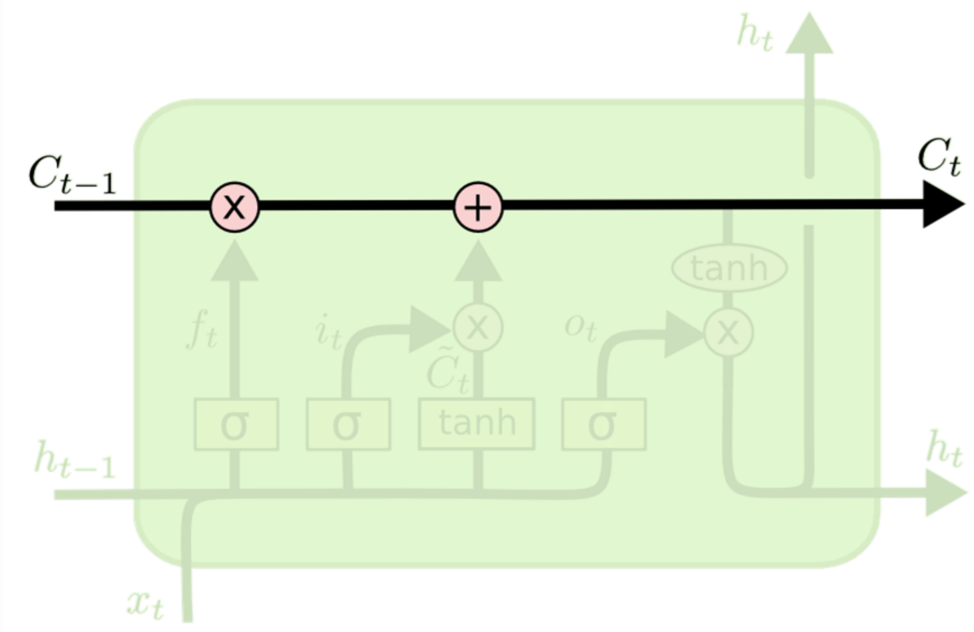
Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



torch.nn.LSTM

Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

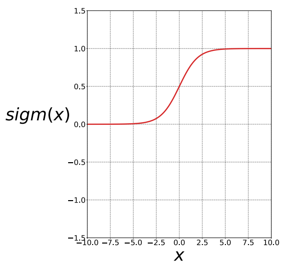
Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

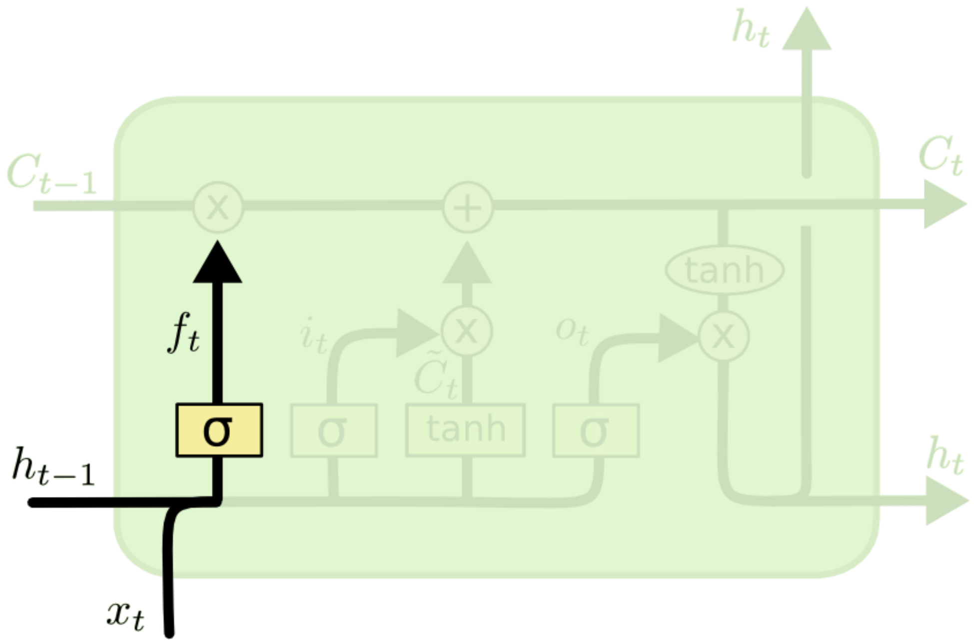
Cell state

- "Conveyor belt"
- Uninterrupted gradient flow
- LSTMs add or remove info to cell state.
- Info is regulated by gates.
- Gate: sigmoid + pointwise multiplication operation



`torch.nn.LSTM`

Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



Forget gate layer

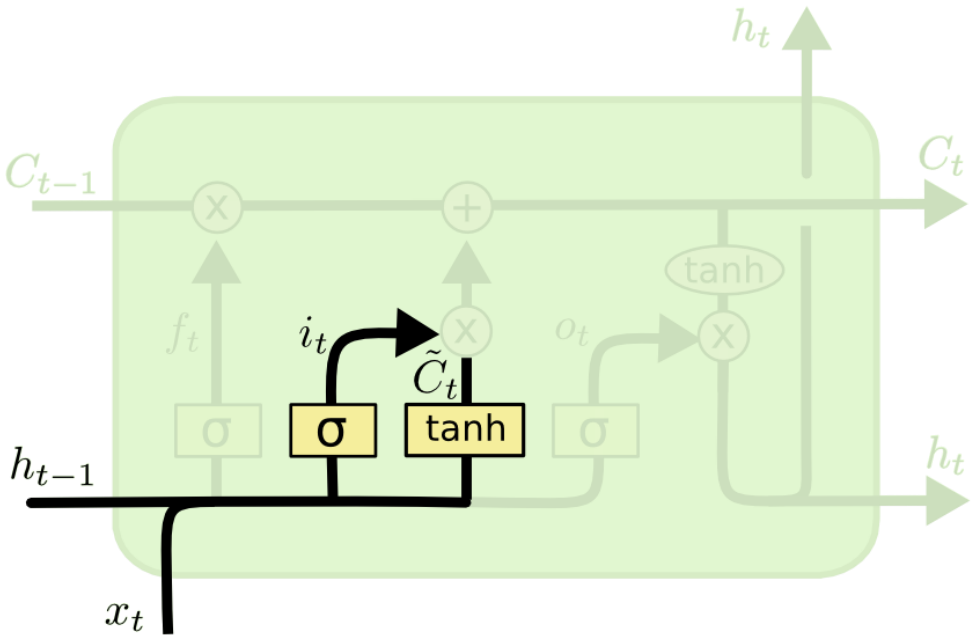
What info to remove?

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

`torch.nn.LSTM`

Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



Input gate layer

What info to add?

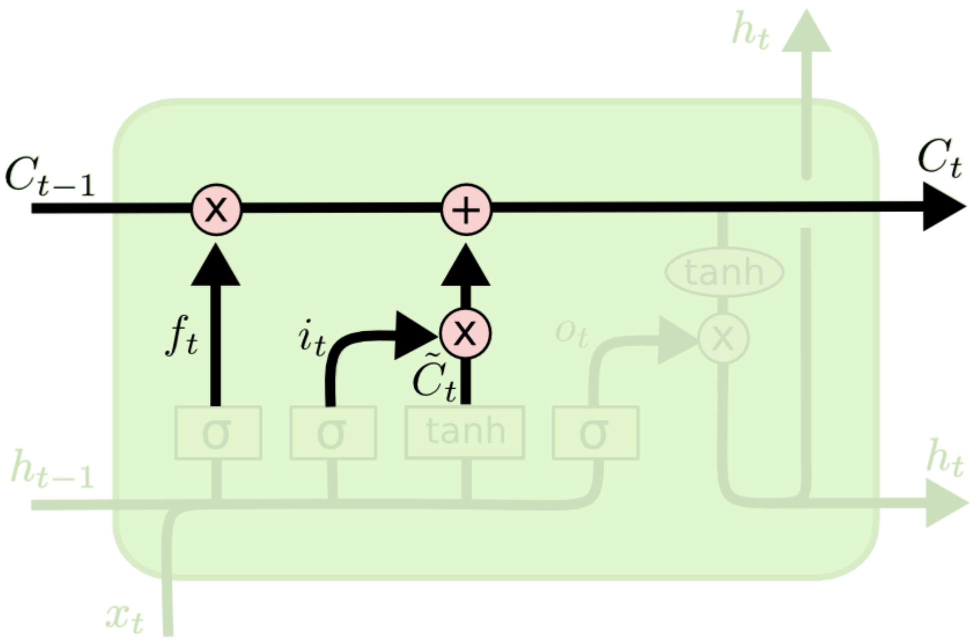
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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

`torch.nn.LSTM`

Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



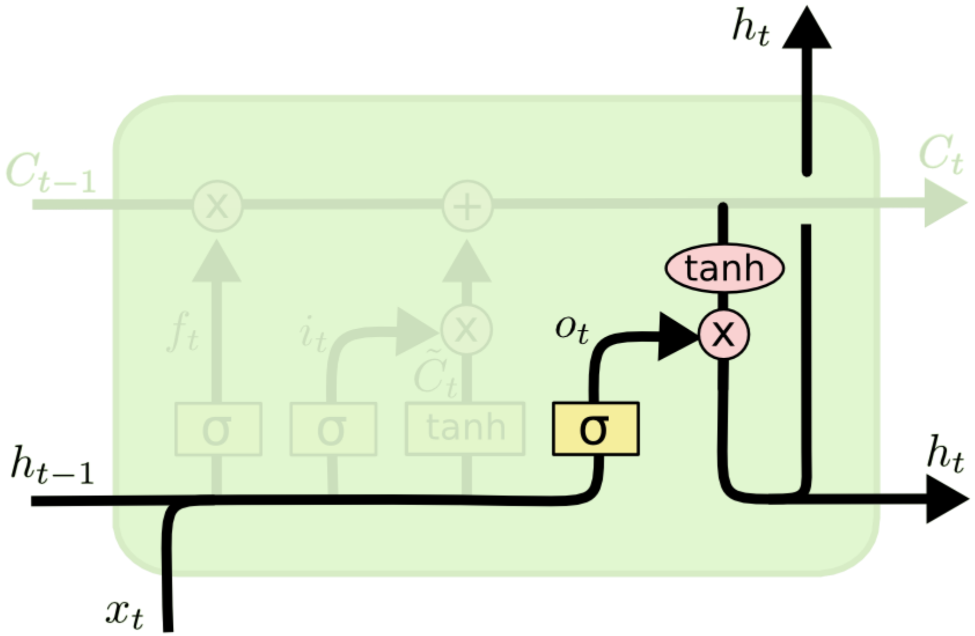
Old cell state update

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

`torch.nn.LSTM`

Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-Term Memory (LSTM) Networks [Hochreiter et al., 1997]



Output

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

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

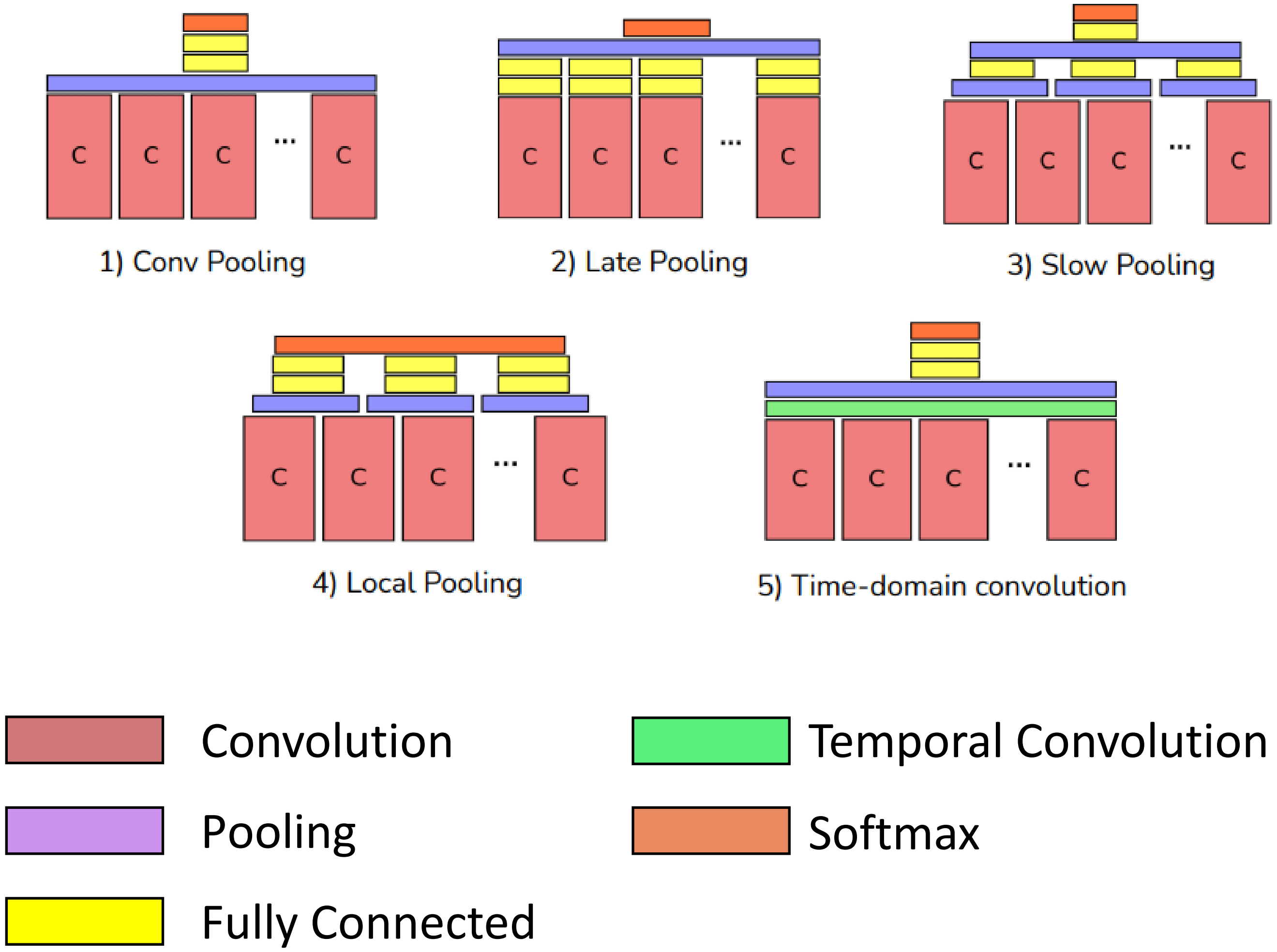
`torch.nn.LSTM`

Source: Colah's Blog, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

5. Spatio-Temporal DNNs

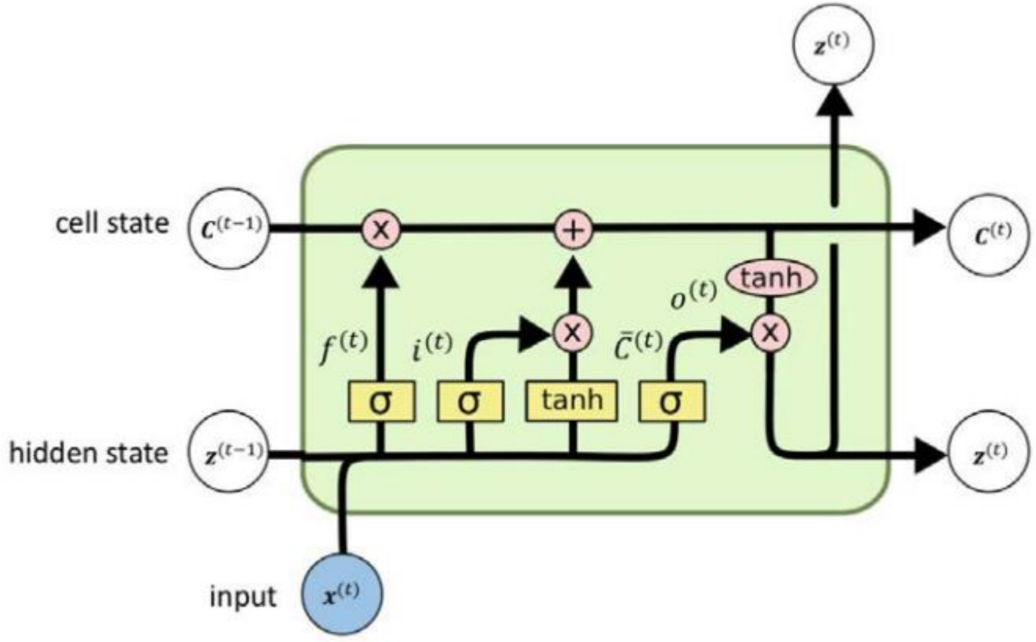
Spatio-Temporal DNNs: CNN+RNN

- Multi-frame features are temporally local (e.g. 10 frames)
- Hypothesis: A global description would be beneficial
- Challenge: Model variable length sequences with a fixed number of parameters
- Design choices:
  - Modality:
    1) RGB
    2) Motion estimation (e.g. optical flow)
    3) RGB + motion estimation
  - Features:
    1) Hand-crafted
    2) Extracted using CNN
  - Temporal aggregation:
    1) Temporal feature pooling
    2) RNN (e.g. LSTM, GRU)

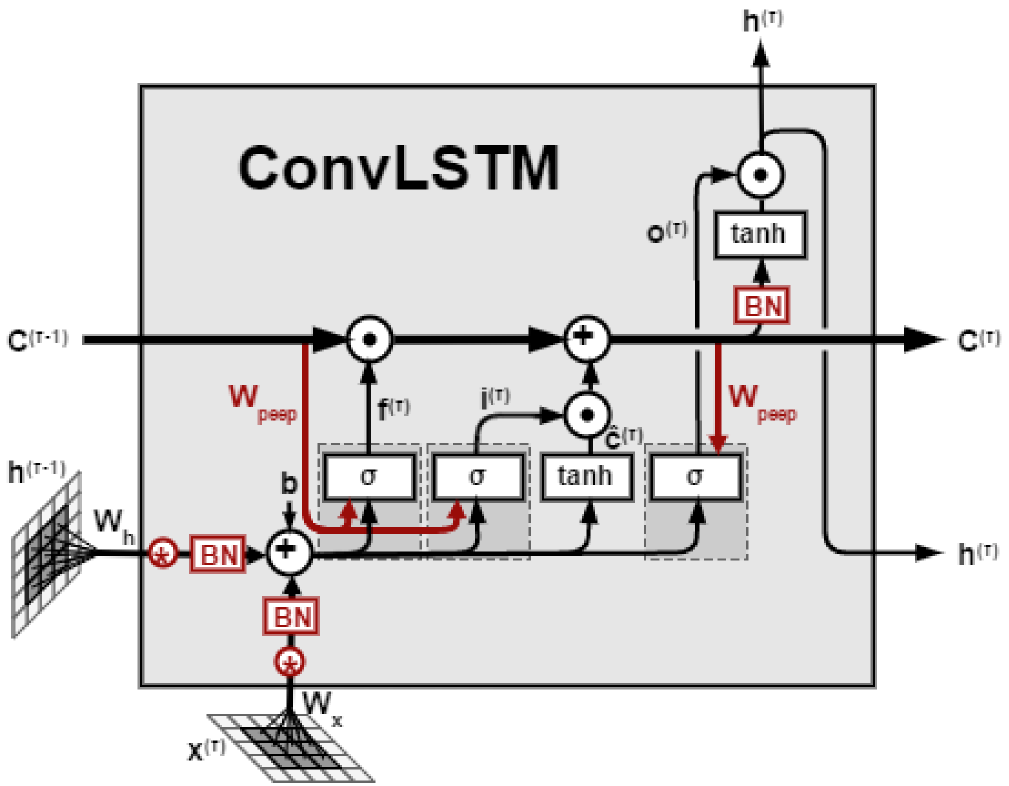


Convolutional LSTM [Shi et al., 2015]

LSTM cell



ConvLSTM cell



Source: https://medium.com/neuronio/an-introduction-to-convlstm-55c9025563a7

Convolutional LSTM [Shi et al., 2015]

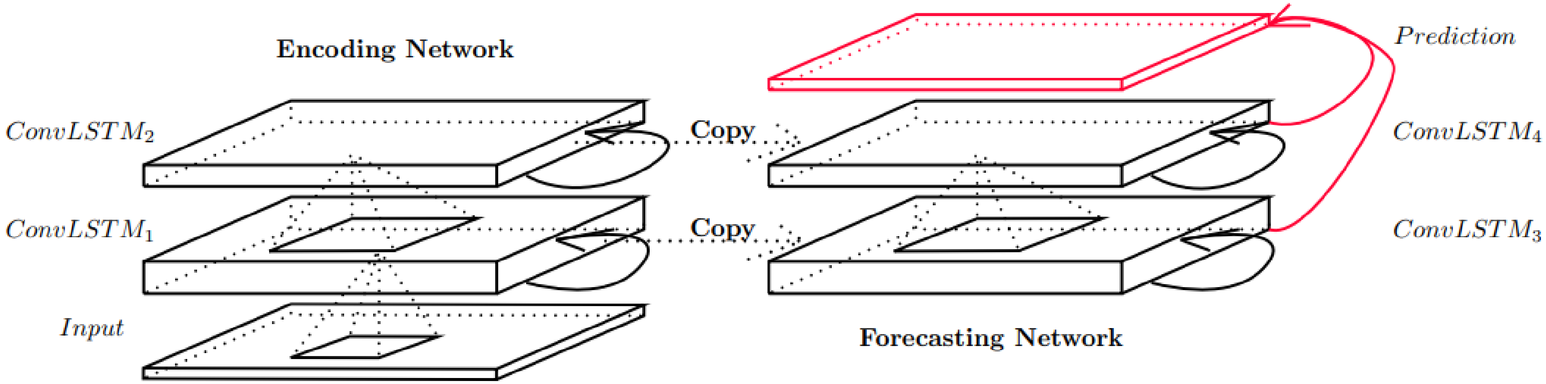


Figure 3: Encoding-forecasting ConvLSTM network for precipitation nowcasting

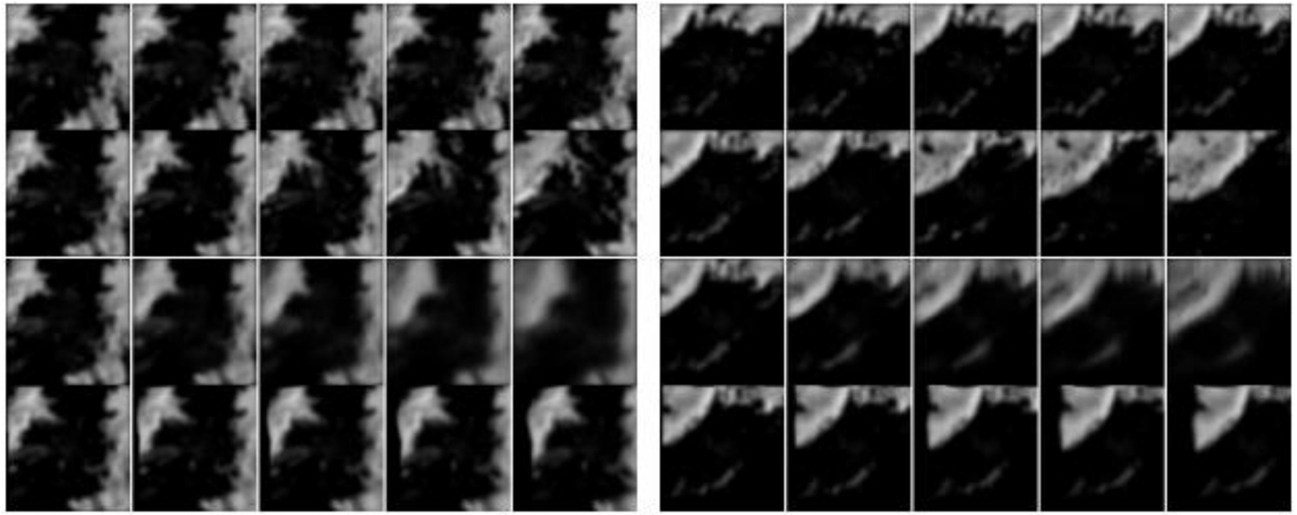
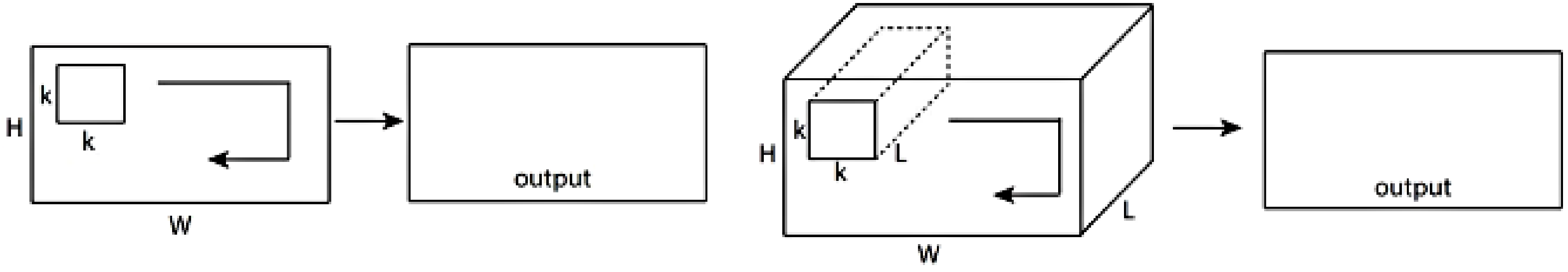


Figure 8: **(Larger Version) Two prediction examples for the precipitation nowcasting problem.** All the predictions and ground truths are sampled with an interval of 3. From top to bottom: input frames; ground truth; prediction by ConvLSTM network; prediction by ROVER2.

3D Convolution: Embed Temporal Dimension to CNN

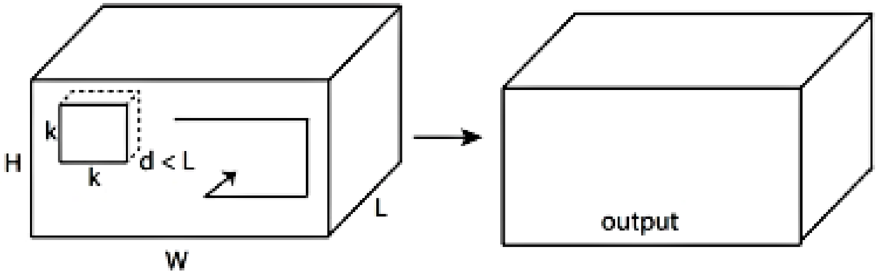
Previous work: 2D convolutions collapse temporal information



(a) 2D convolution

(b) 2D convolution on multiple frames

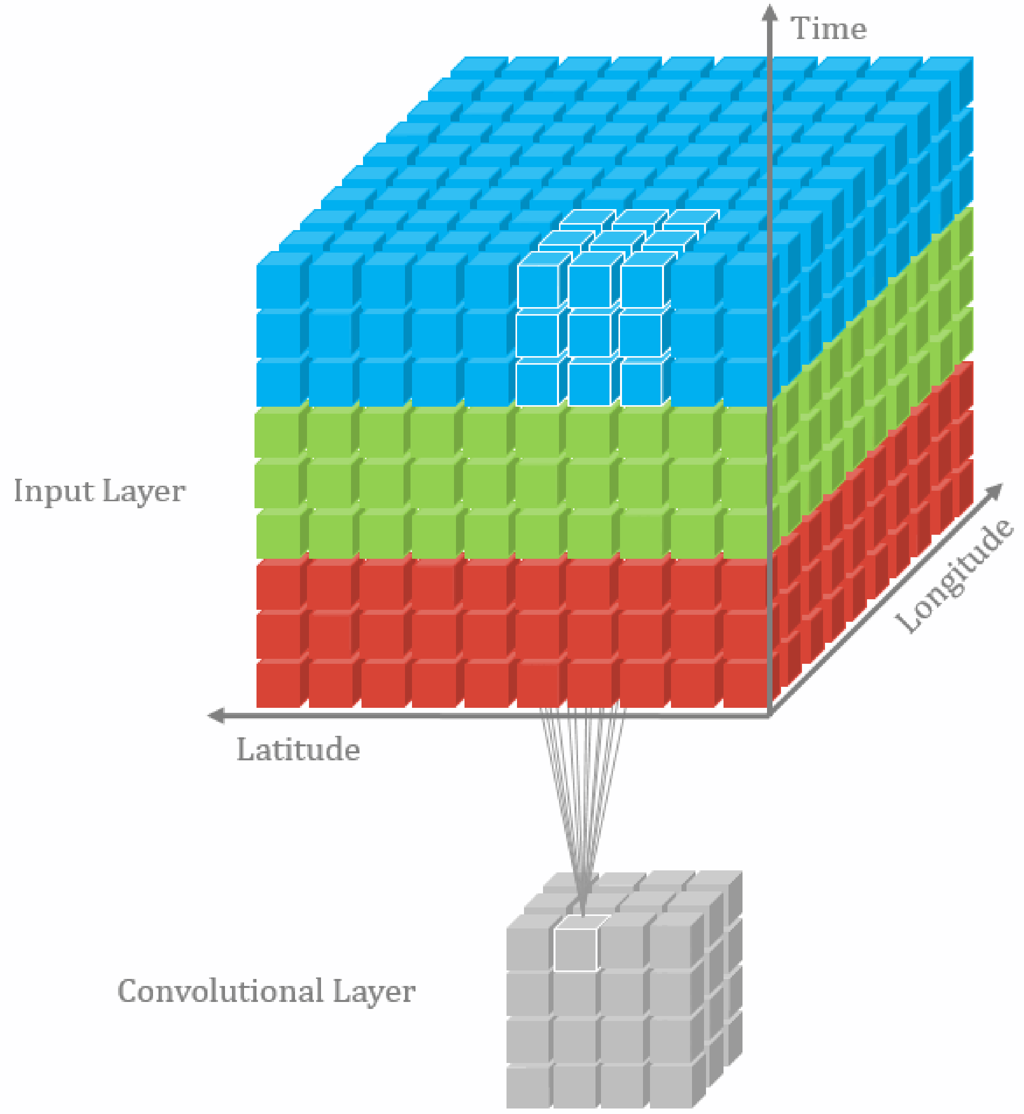
Proposal: 3D convolution → learning features that encode temporal information



(c) 3D convolution

3D Convolution

```
torch.nn.Conv3d
torch.nn.MaxPool3d
torch.nn.AvgPool3d
```



Source: Resuly's Blog, http://resuly.me/

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Spatio-Temporal Deep Neural Networks for Extreme Event Detection

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