Neural architectures

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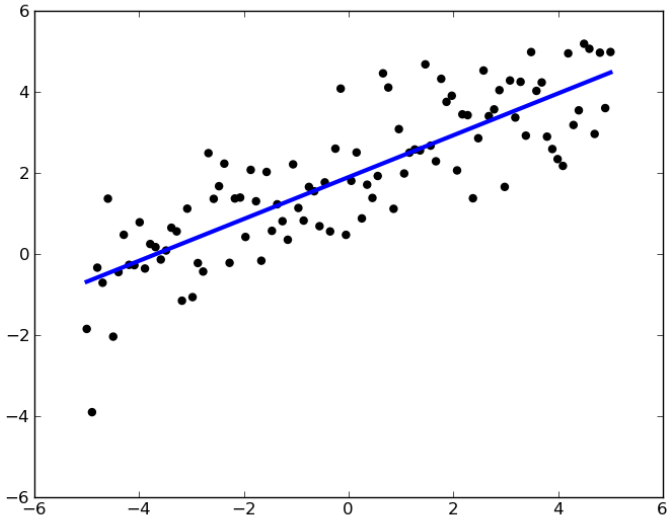
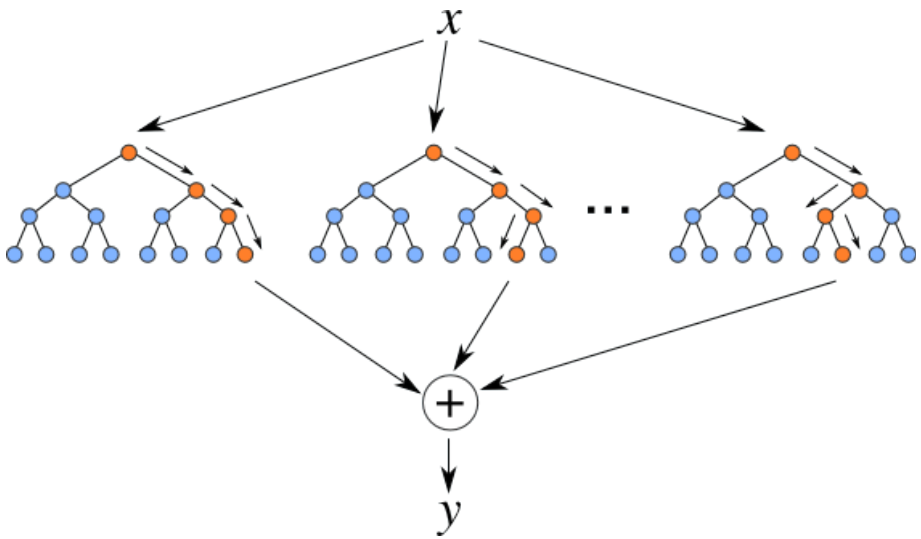
Deep|Bayes

Machine learning models

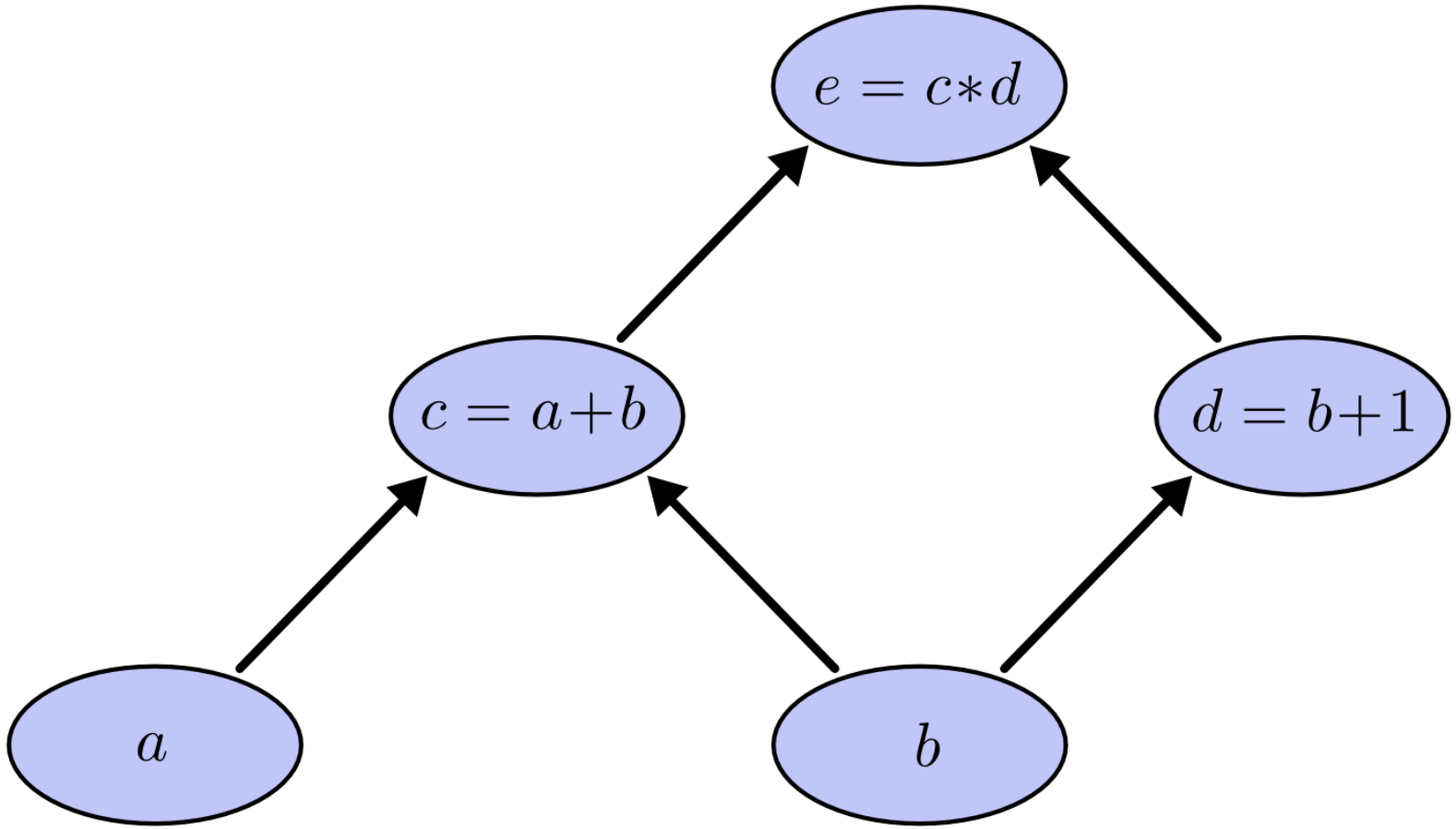
Linear models



Decision trees and ensembles

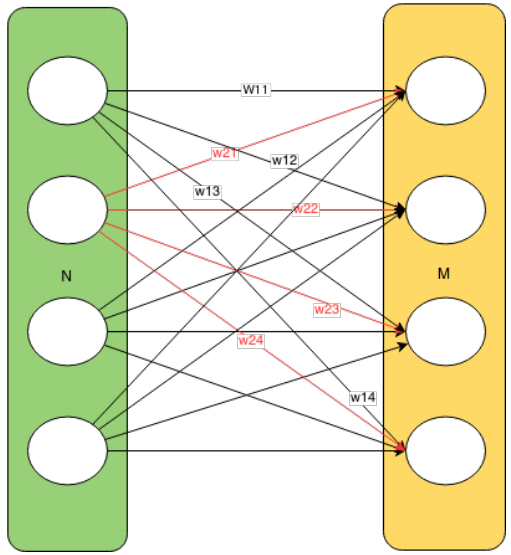


Computational graphs

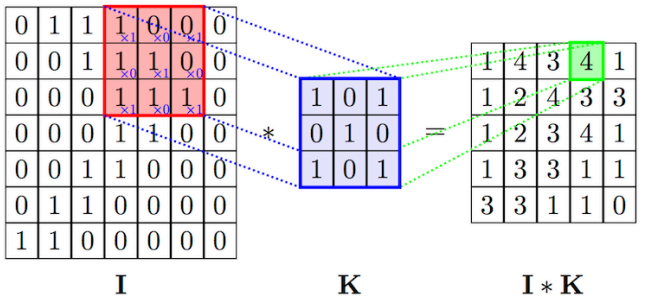


Examples

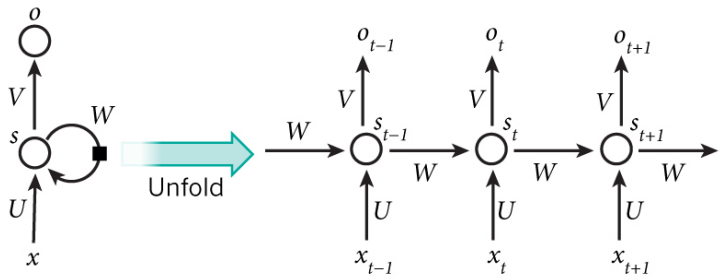
Fully connected layer



Convolutional layer



Recurrent layer



Examples

Dropout layer

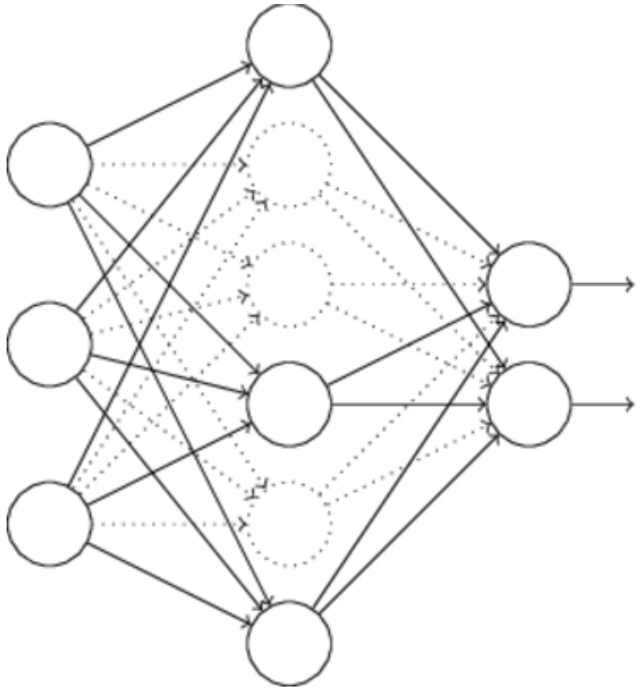
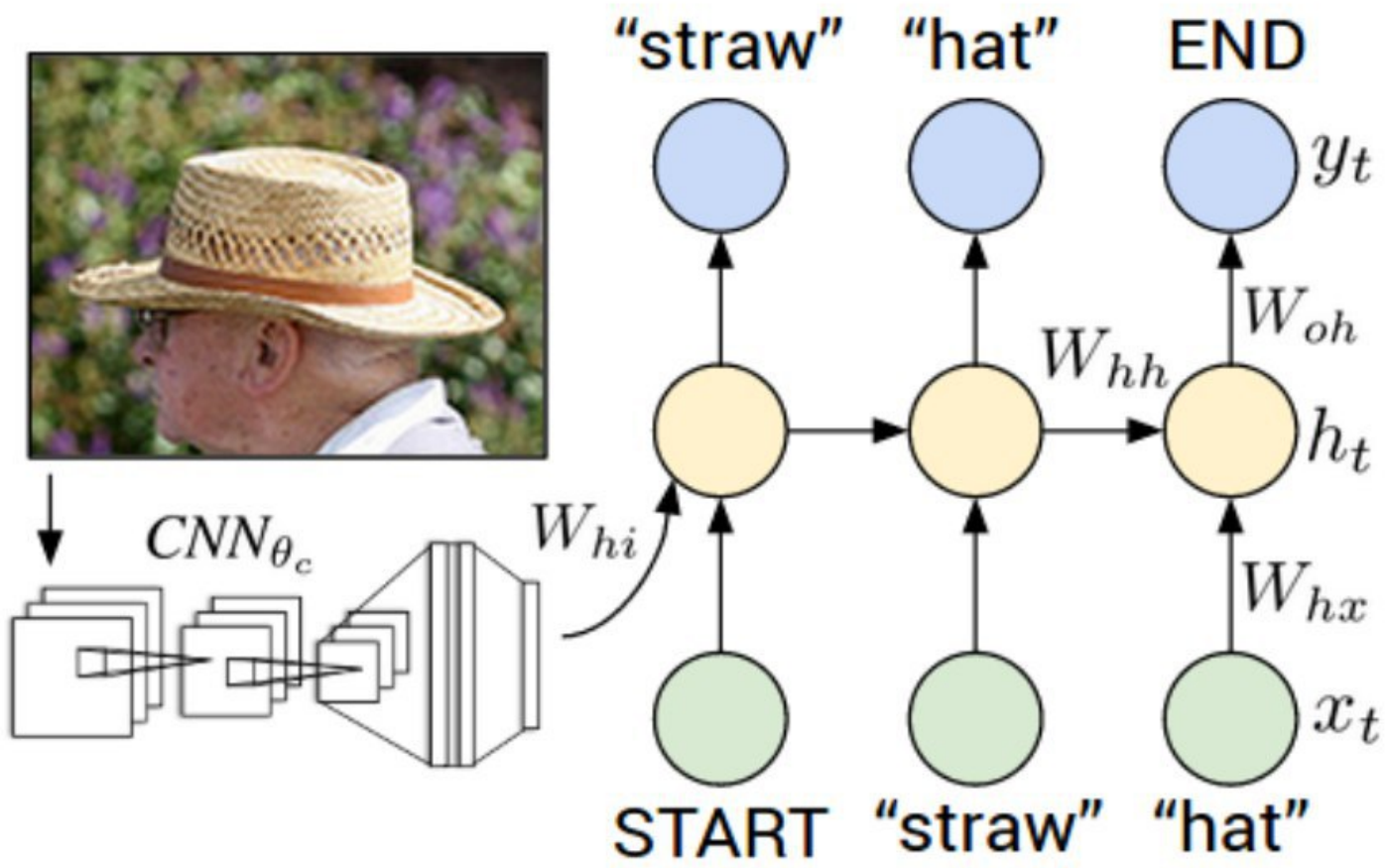


Image captioning example



Computational graphs

- State-of-the-art quality for many computer vision and NLP problems
- Sometimes even superhuman performance!
- Key components are:
  - Computational power and GPUs
  - Lots of data (or transfer learning)
  - Stochastic optimization
  - Regularization techniques

Universal approximation theorem

Let $\varphi(\cdot)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Let I_m denote the *m*-dimensional unit hypercube $[0,1]^m$. The space of continuous functions on I_m is denoted by $C(I_m)$. Then, given any $\varepsilon > 0$ and any function $f \in C(I_m)$, there exist an integer N, real constants $v_i, b_i \in \mathbb{R}$ and real vectors $w_i \in \mathbb{R}^m$, where $i = 1, \cdots, N$, such that we may define:

$$F(x) = \sum_{i=1}^{N} v_i \varphi\left(w_i^T x + b_i\right)$$

as an approximate realization of the function f where f is independent of φ; that is,

$$|F(x) - f(x)| < \varepsilon$$

for all $x \in I_m$. In other words, functions of the form $F(x)$ are dense in $C(I_m)$.

Deep architectures are better

- Deep nets can be trained and regularized effectively
- Deep nets can achieve better performance with same number of parameters
- Deep architectures are more intuitive and can be interpreted as a sequence of simple data transformations

Training computational graphs

- $f_j(x, w_j)$ — j-th layer of the network
- $v_j(x) = f_j(v_{j-1}(x), w_j)$
- $a(x, w) = v_n(x)$ — output
- Optimization problem:

$$Q(w) = \sum_{i=1}^{\ell} L(y_i, a(x_i; w)) \to \min_w$$

Backpropagation

$$\frac{\partial Q}{\partial w_i} = \frac{\partial Q}{\partial f_{i+1}} \frac{\partial f_{i+1}}{\partial f_i} \frac{\partial f_i}{\partial w_i}$$

Comes from previous steps

Easy for differentiable layers

$$\frac{\partial Q}{\partial f_{ij}} = \sum_k \frac{\partial Q}{\partial f_{i+1,k}} \frac{\partial f_{i+1,k}}{\partial f_{ij}}$$

$$\frac{\partial Q}{\partial w_{ij}} = \sum_k \frac{\partial Q}{\partial f_{i,k}} \frac{\partial f_{i,k}}{\partial w_{ij}}$$

Backpropagation

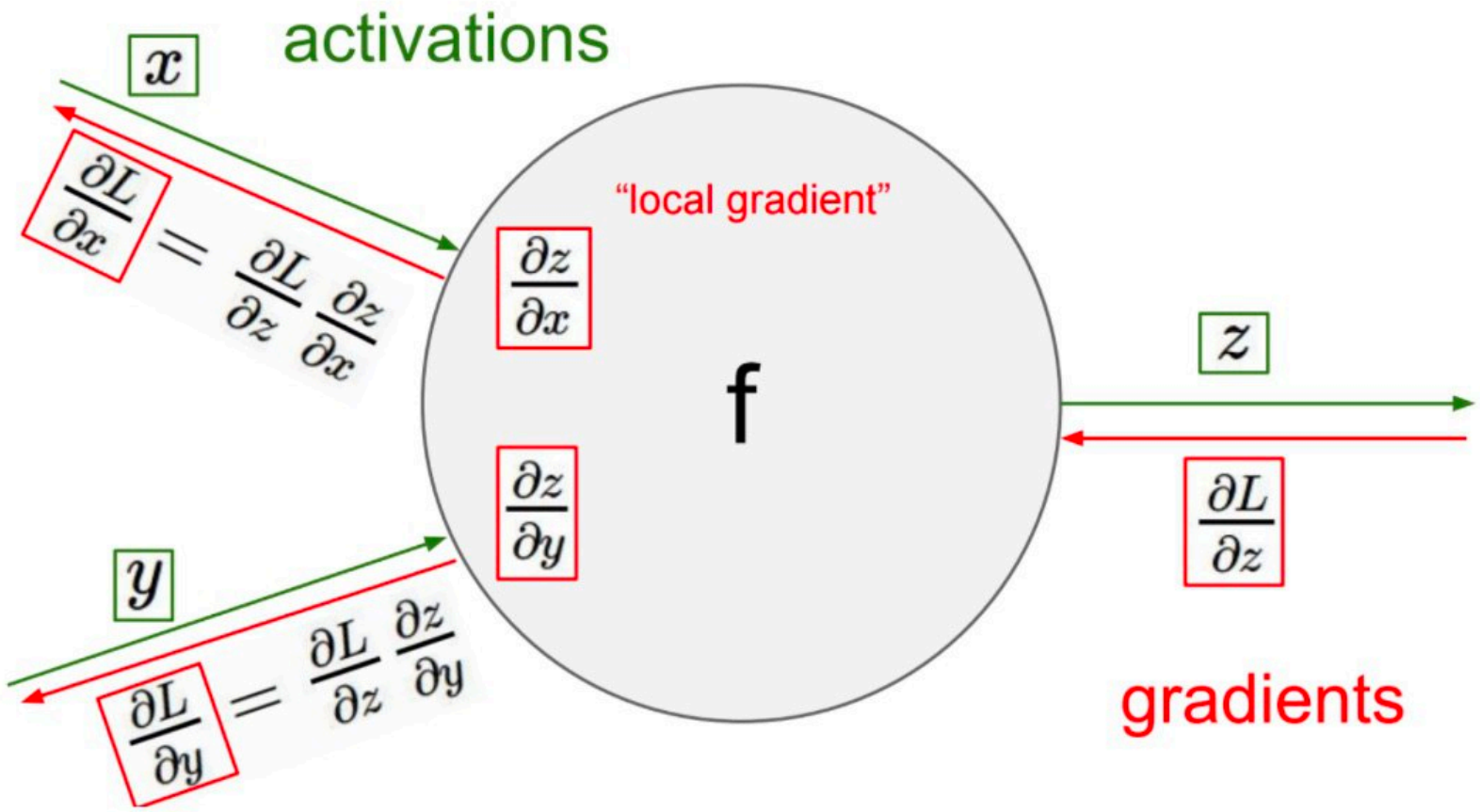
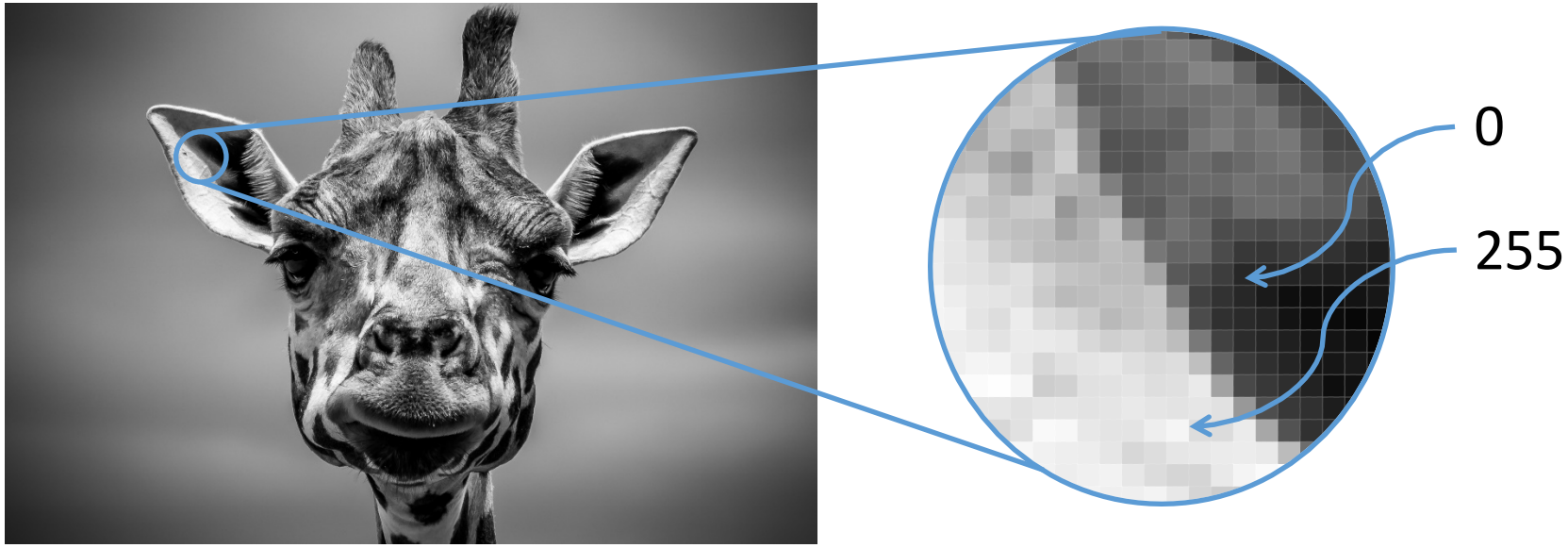


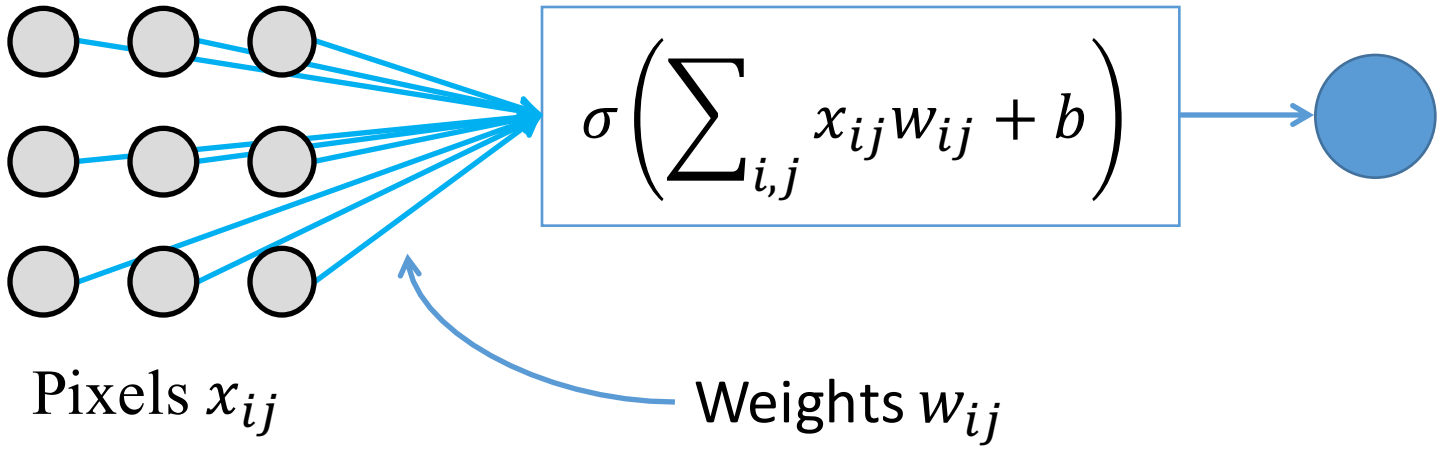
Image representation

- Each pixel stores its brightness (or **intensity**) ranging from 0 to 255, 0 intensity corresponds to black color:
- Color images store pixel intensities for 3 channels: red, green and blue

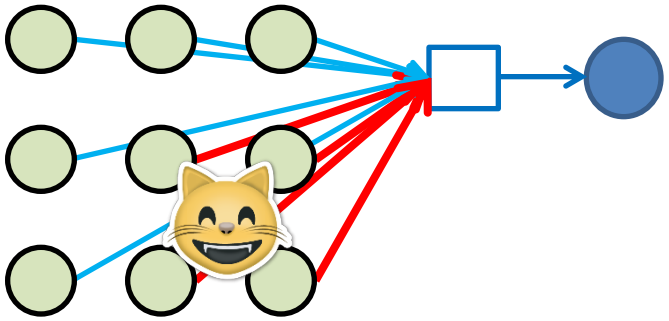


Multilayer perceptron for image classification

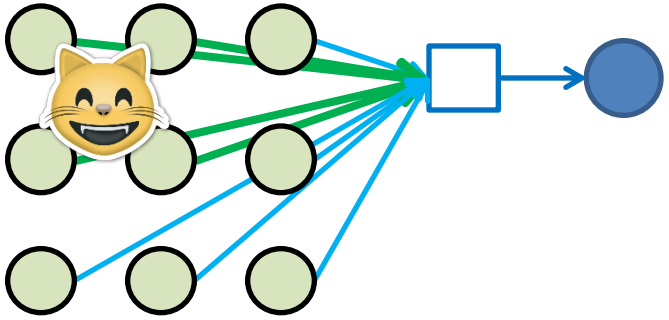
- Normalize input pixels: $x_{norm} = \frac{x}{255} - 0.5$
- Maybe MLP will work?



Multilayer perceptron for image classification



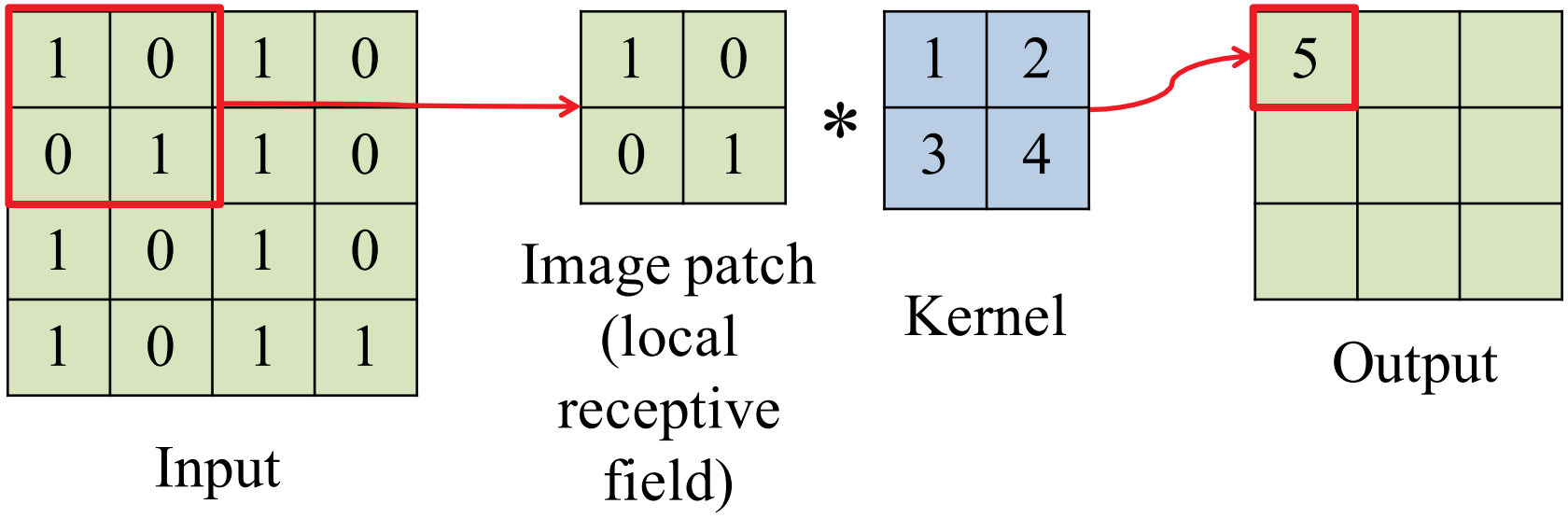
On this training image red weights w_{ij} will change a little bit to better detect a cat



On this training image green weights w_{ij} will change…

Convolutions

Convolution is a dot product of a **kernel** (or filter)
and a patch of an image (**local receptive field**) of the same size



Convolutions

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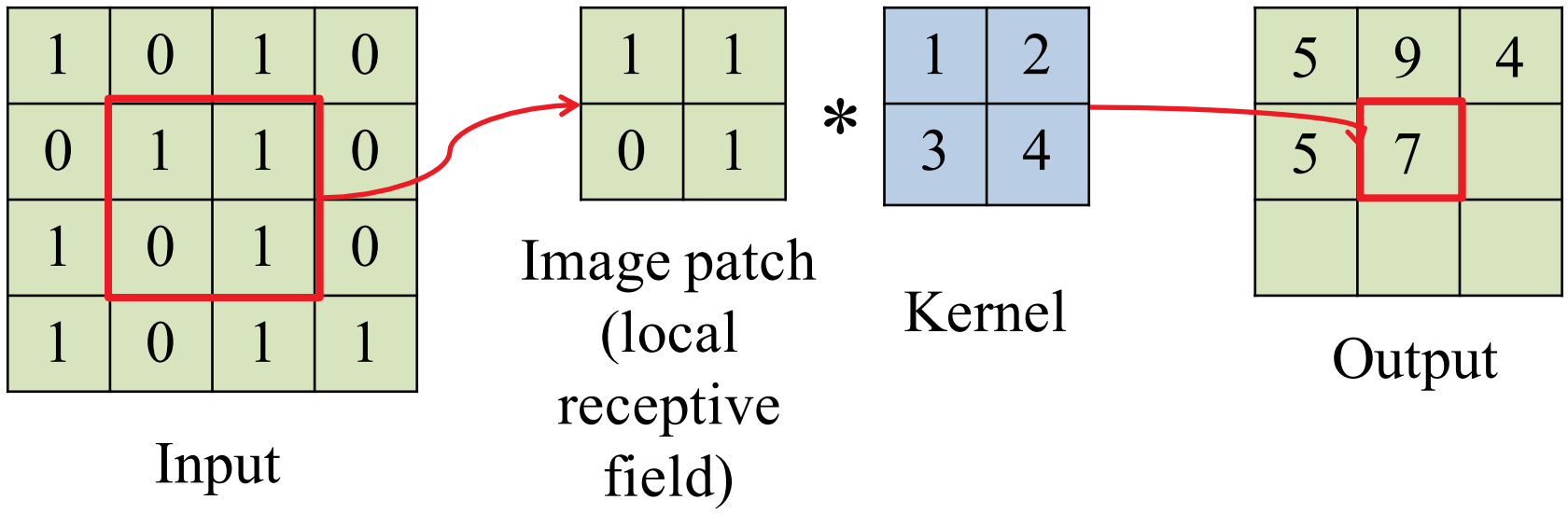
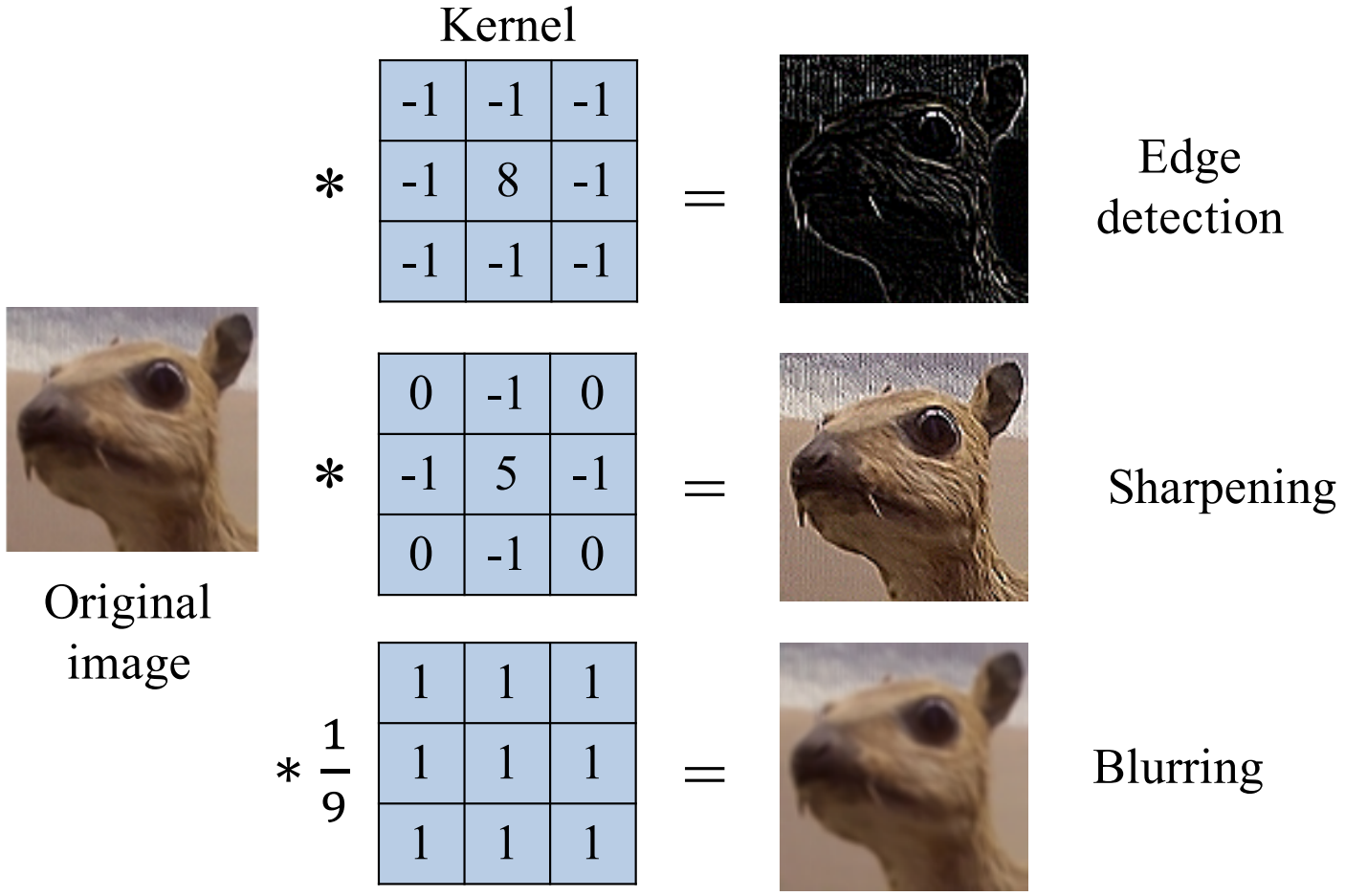
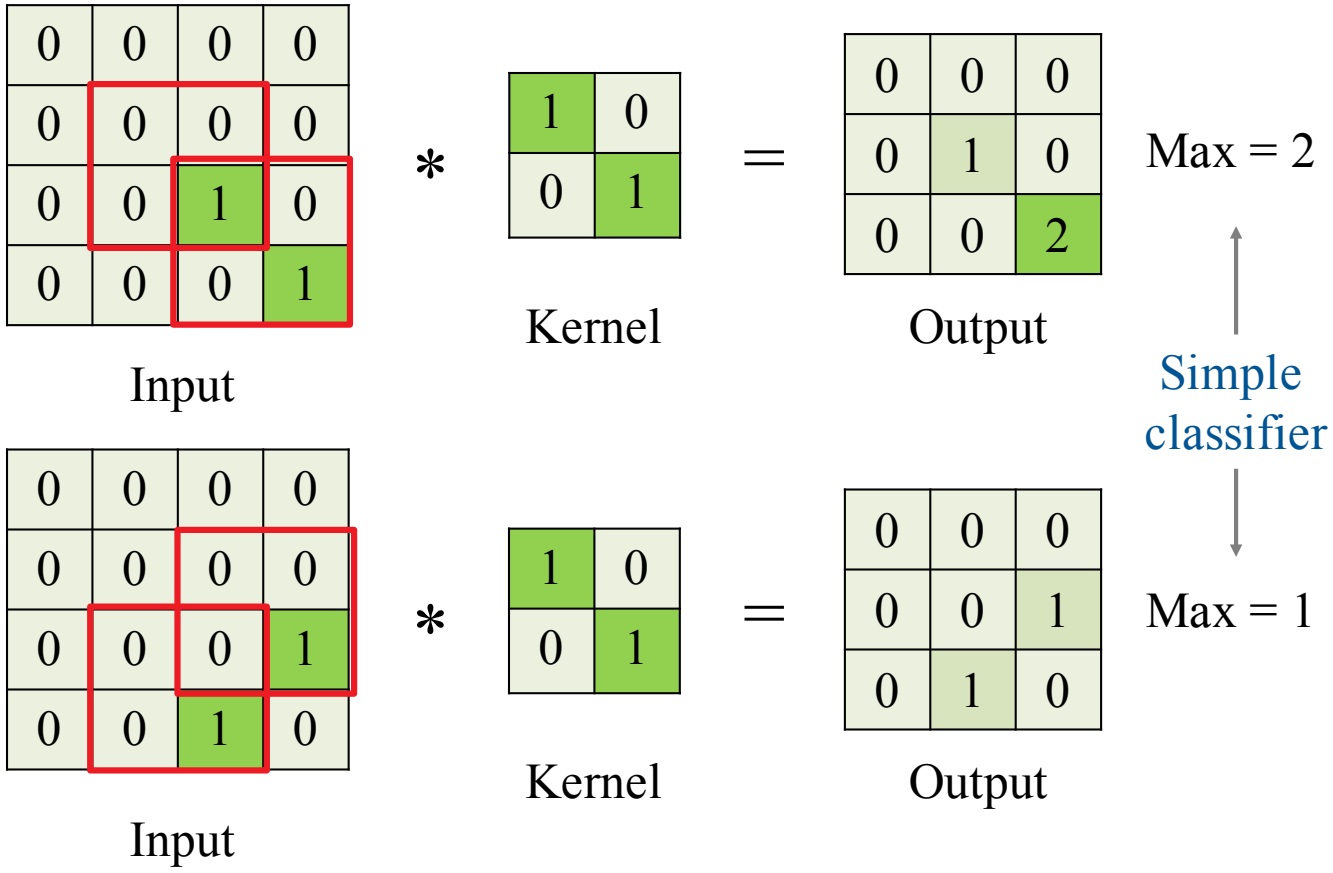


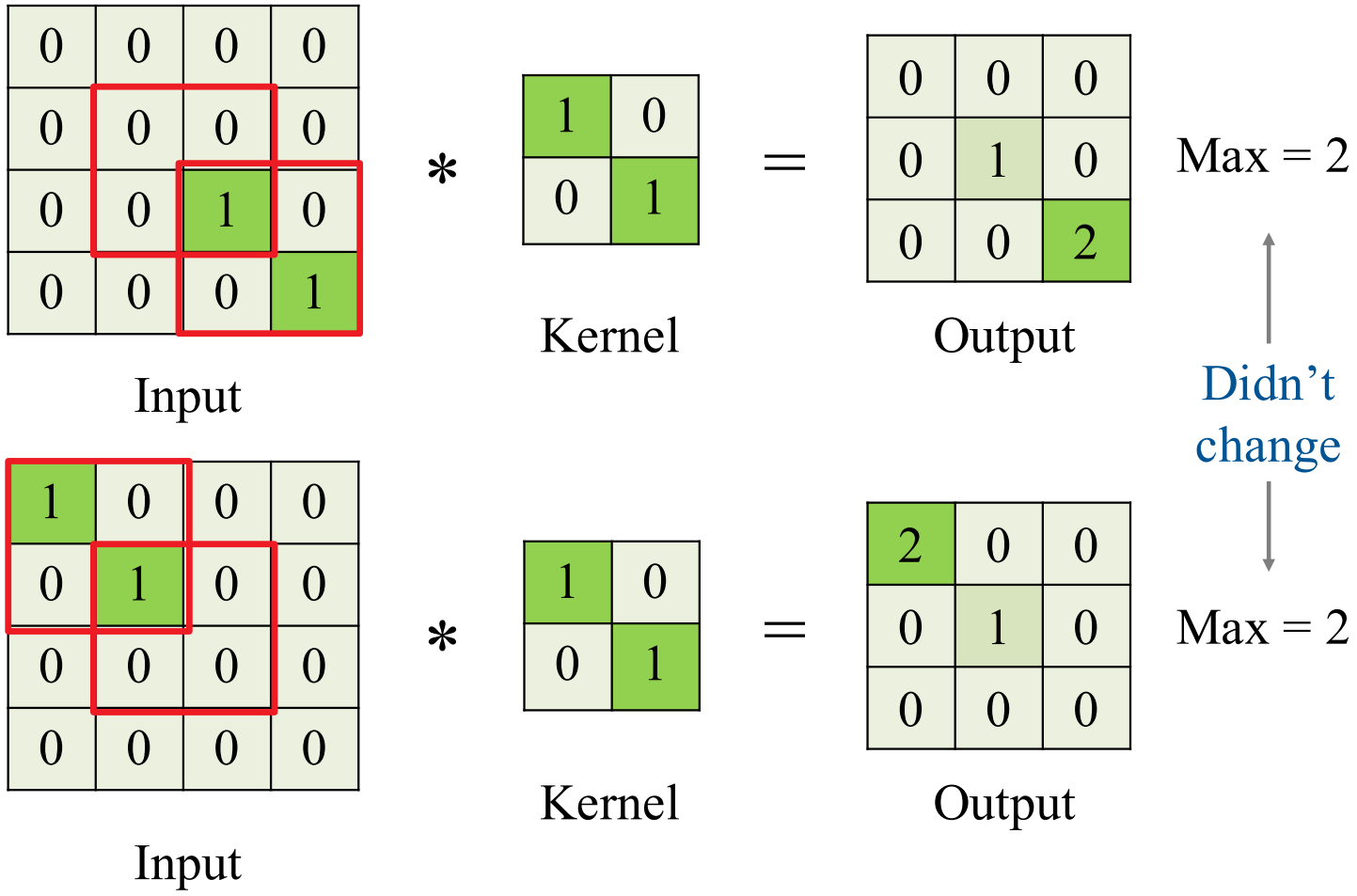
Convolutions have been used for a while



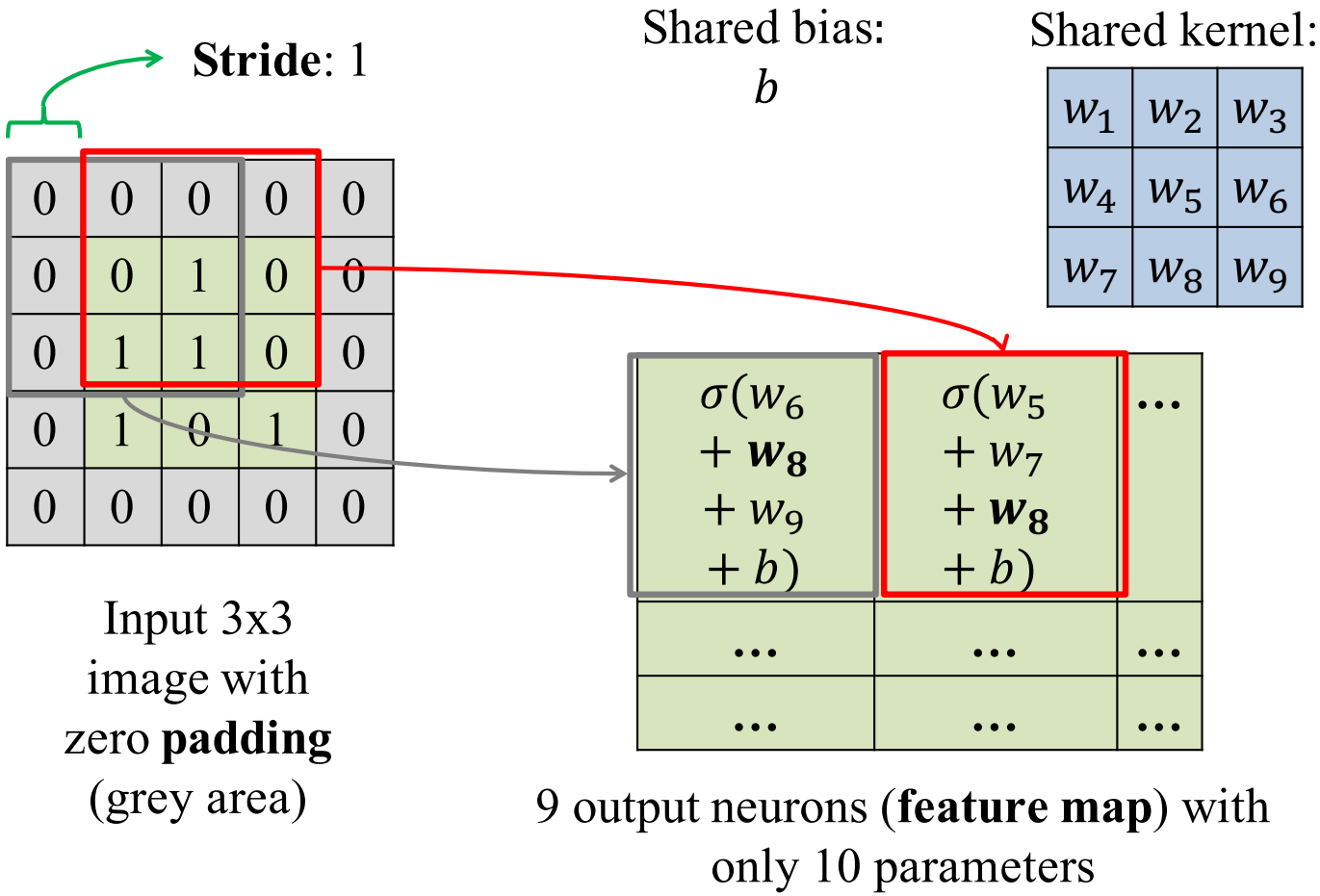
Convolution is similar to correlation



Convolution is translation invariant



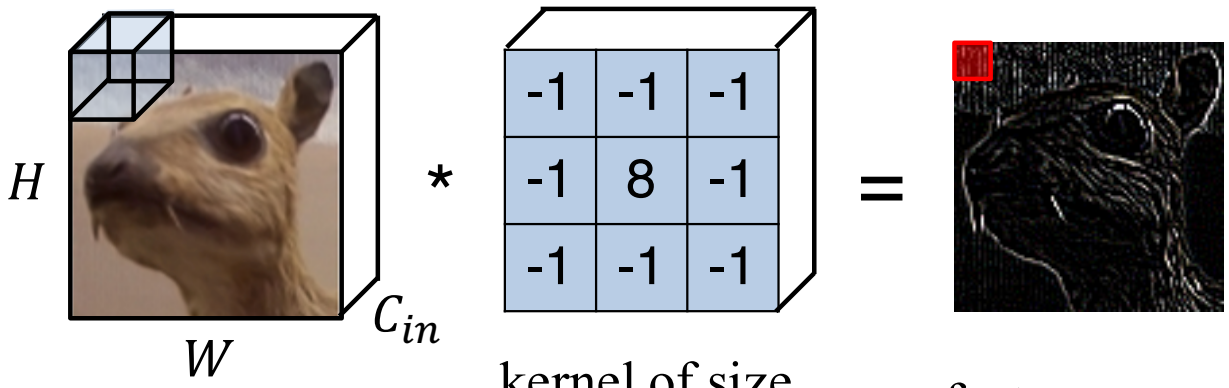
Convolutional layers



Convolutional layer

Let's say we have a color image as an input, which is W× H×C_{in} **tensor** (multidimensional array), where

- W – is an image width,
- H – is an image height,
- C_{in} – is a number of input channels (e.g. 3 RGB channels).

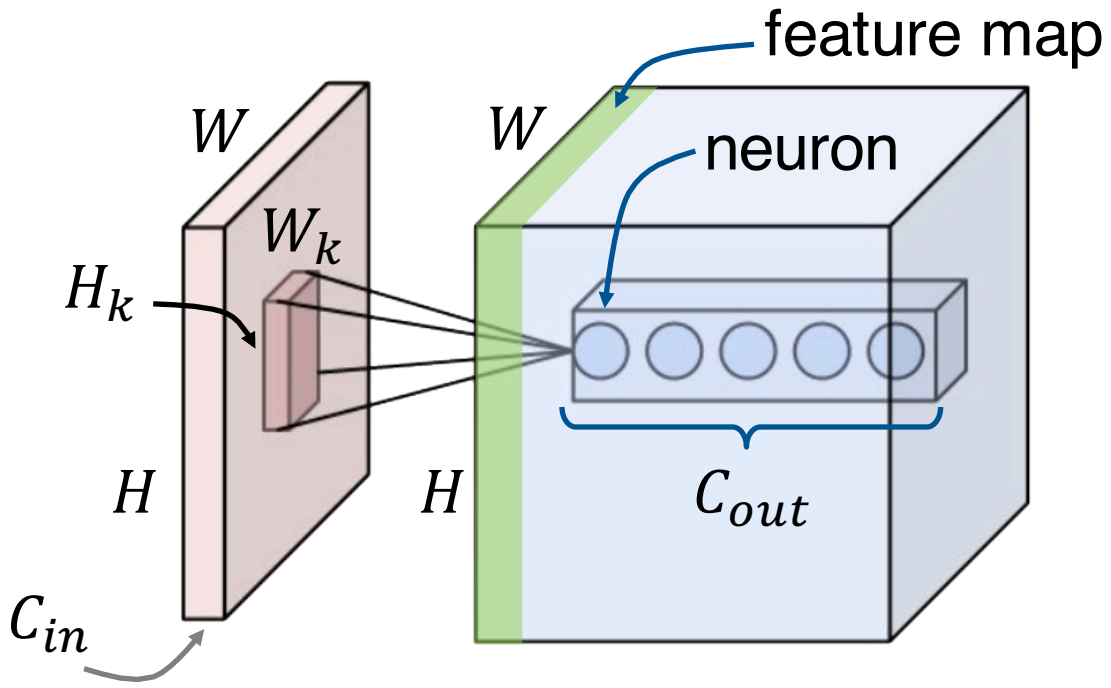


kernel of size W_k× H_k×C_{in}

feature map

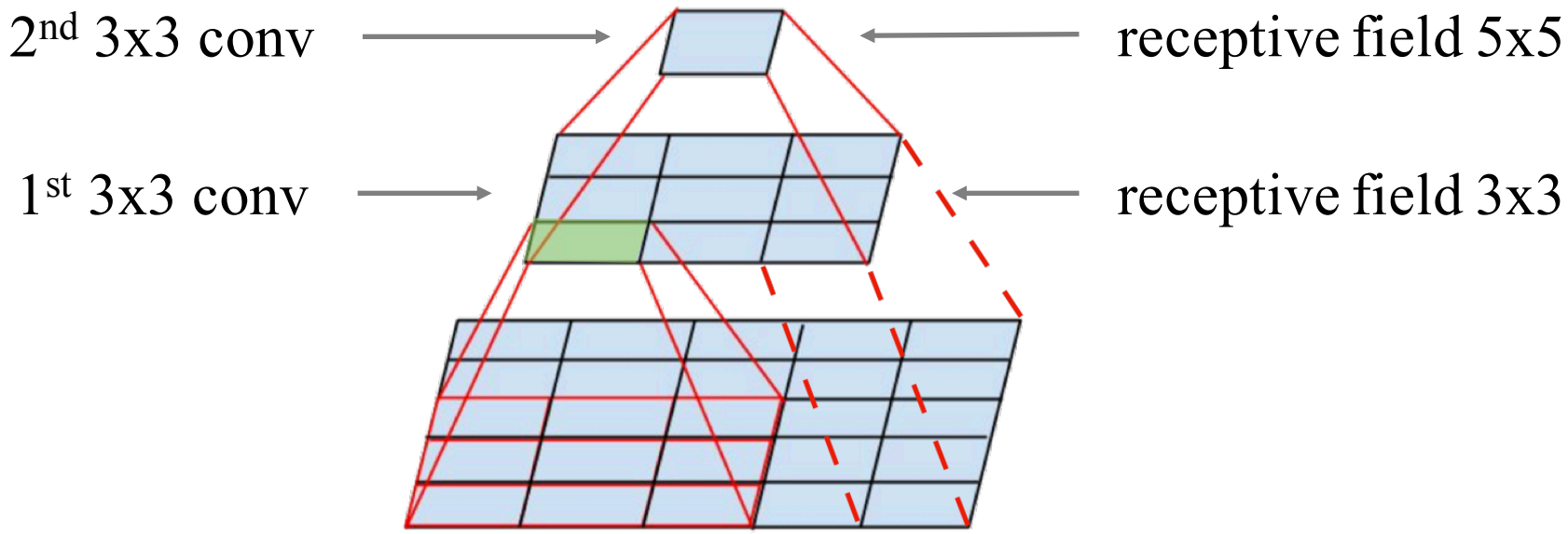
Convolutional layer

- We want to train C_{out} kernels of size $W_k \times H_k \times C_{in}$.
- Having a stride of 1 and enough zero padding we can have $W \times H \times C_{out}$ output neurons.



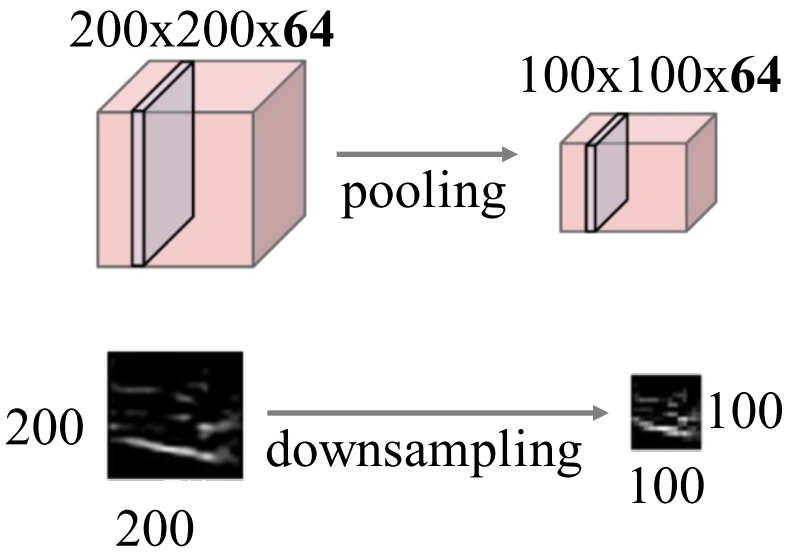
One convolutional layer is not enough!

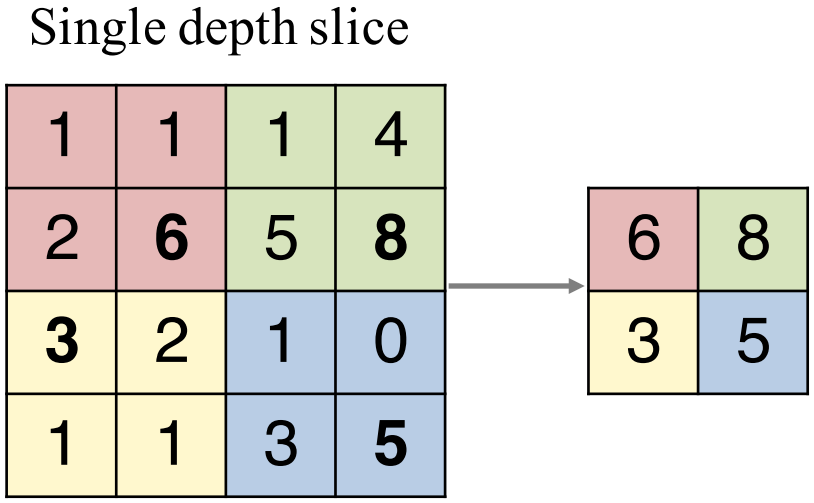
- Let's say neurons of the 1st convolutional layer look at the patches of the image of size 3x3.
- What if an object of interest is bigger than that?
- We need a 2nd convolutional layer on top of the 1st!



Pooling layer

- This layer works like a convolutional layer but doesn't have kernel, instead it calculates **maximum** or **average** of input patch values.

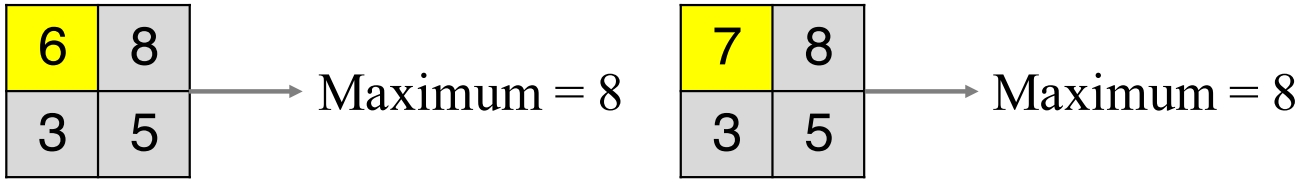




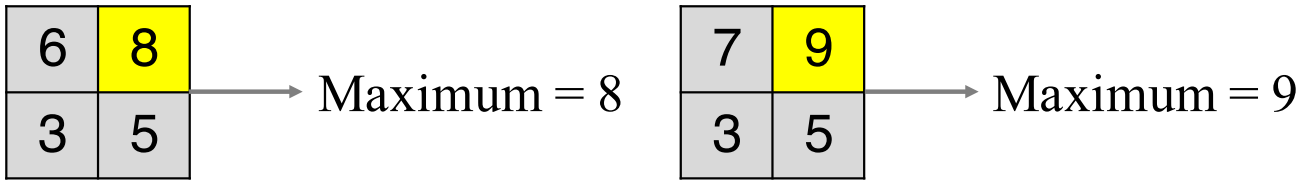
2x2 **max pooling** with stride 2

Pooling layer

Strictly speaking: maximum is not a differentiable function!

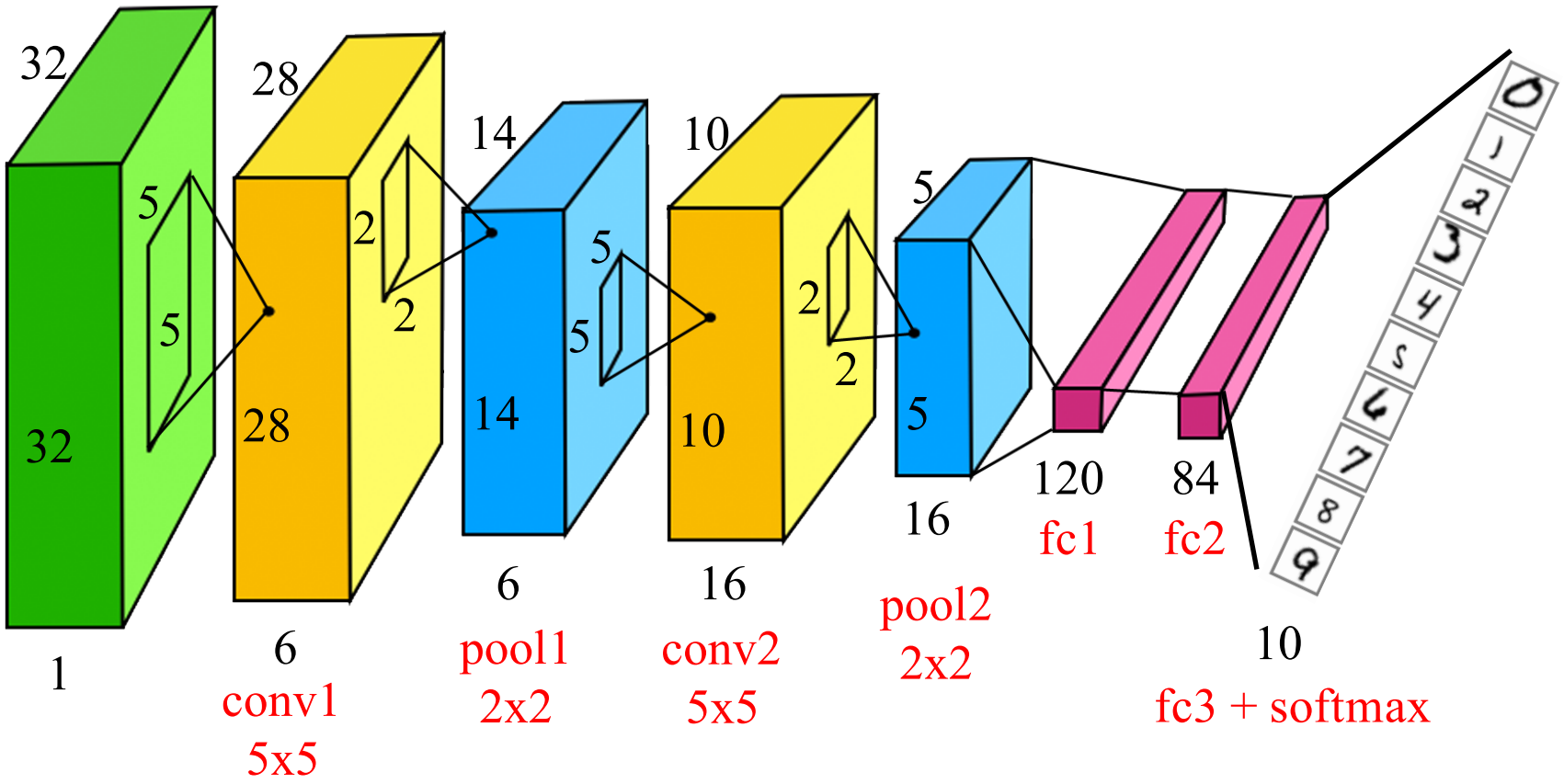


There is no gradient with respect to non maximum patch neurons,
since changing them slightly
does not affect the output.



For the maximum patch neuron we have a gradient of 1.

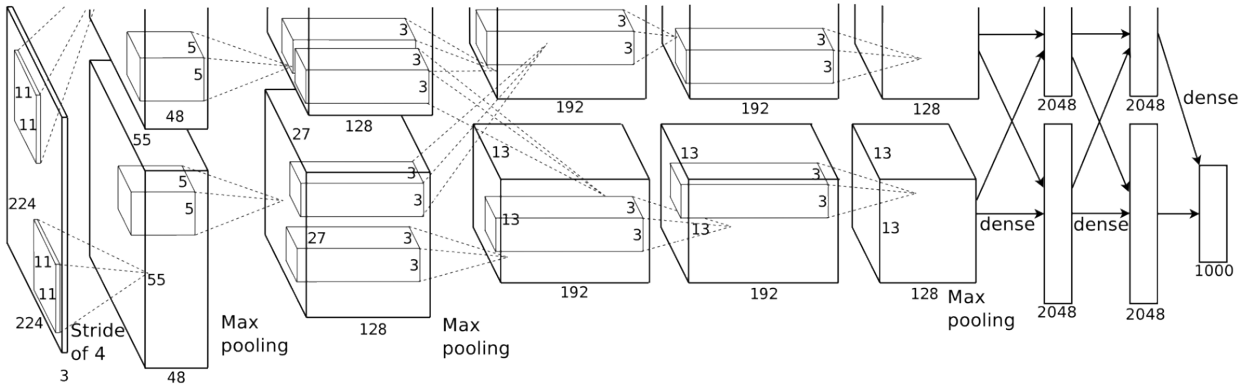
Convolutional network



http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf

AlexNet (2012)

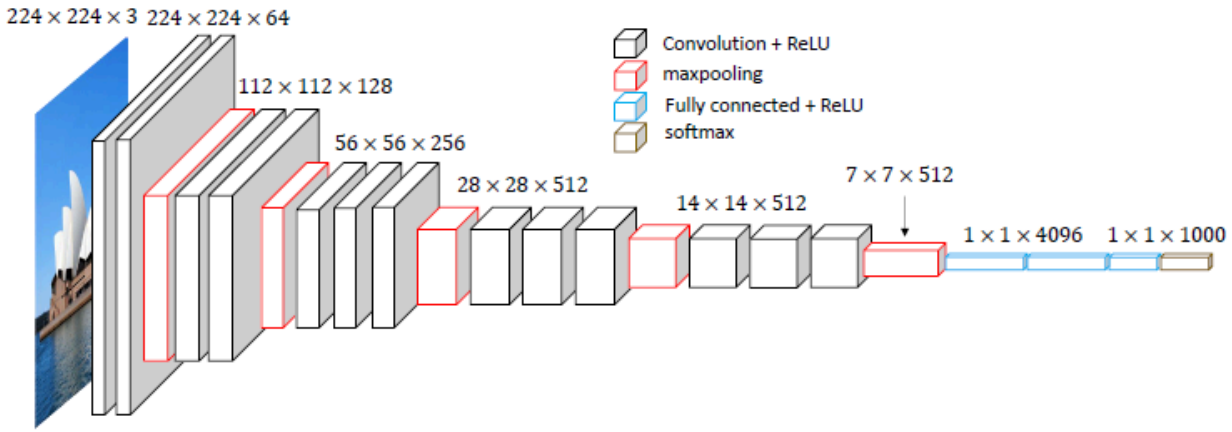
- First deep convolutional neural net for ImageNet
- Significantly reduced top 5 error from 26% to 15%



- 11x11, 5x5, 3x3 convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum
- 60 million parameters
- Trains on 2 GPUs for 6 days

VGG (2015)

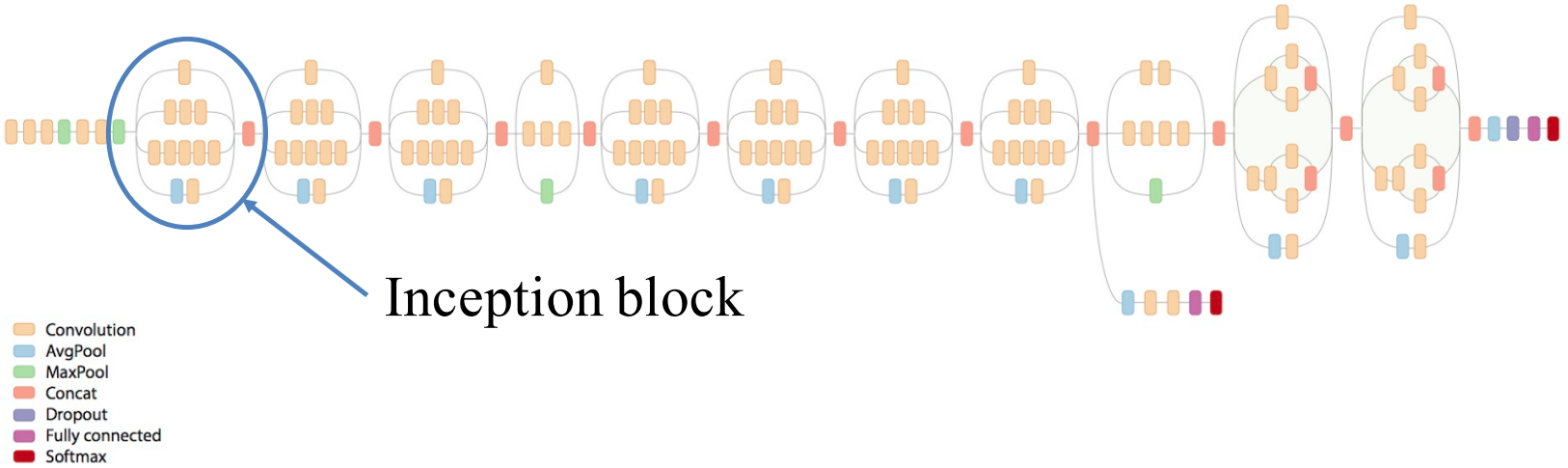
- Similar to AlexNet, only 3x3 convolutions, but lots of filters!
- ImageNet top 5 error: 8.0% (single model)



- Training similar to AlexNet with additional multi-scale cropping.
- 138 million parameters
- Trains on 4 GPUs for 2-3 weeks

Inception V3 (2015)

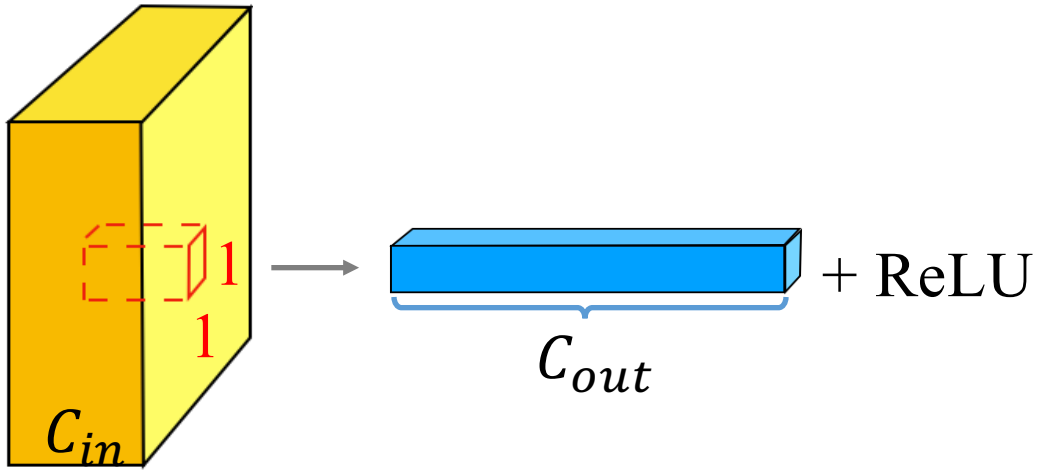
- Similar to AlexNet? Not quite, uses Inception block introduced in GoogLeNet (a.k.a. Inception V1)
- ImageNet top 5 error: 5.6% (single model), 3.6% (ensemble)



- Batch normalization, image distortions, RMSProp
- 25 million parameters!
- Trains on 8 GPUs for 2 weeks

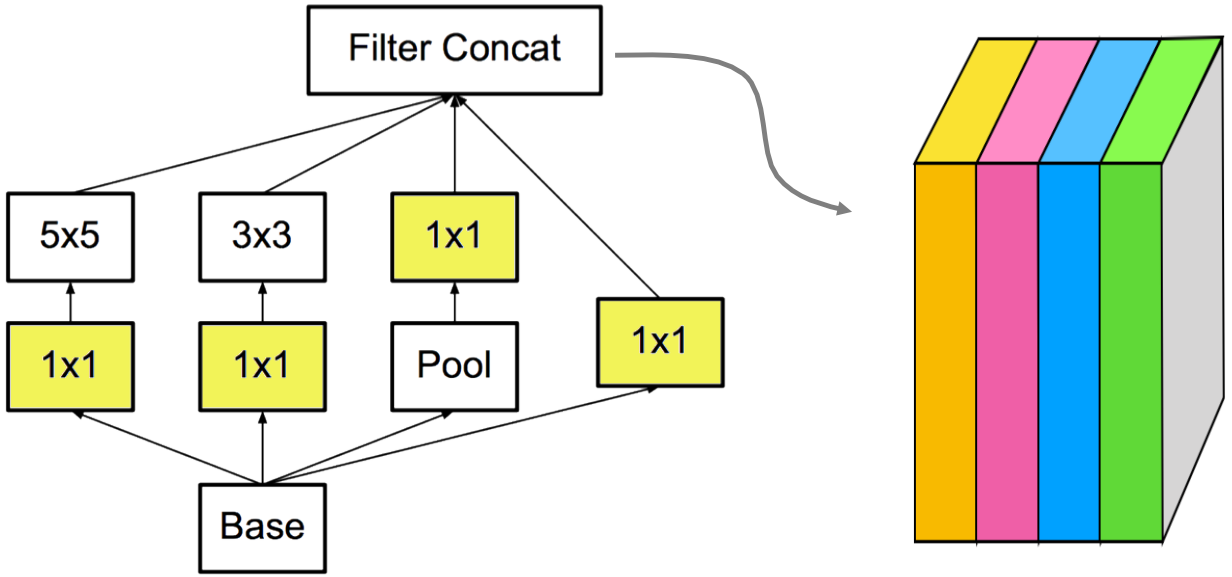
1x1 convolution

- Such convolutions capture interactions of input channels in one “pixel” of feature map
- They can reduce the number of channels not hurting the quality of the model, because different channels can correlate
- Dimensionality reduction with added ReLU activation



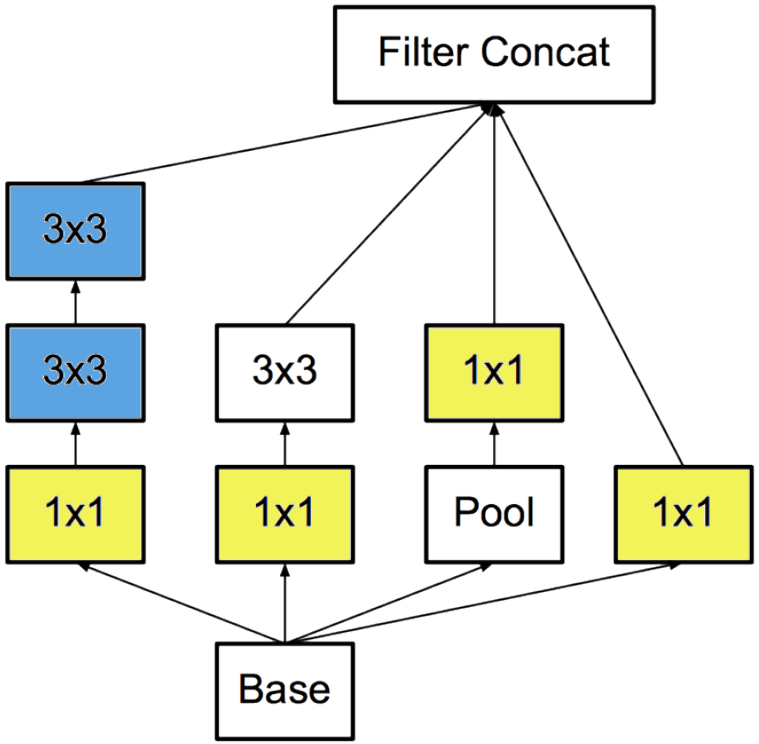
Inception block

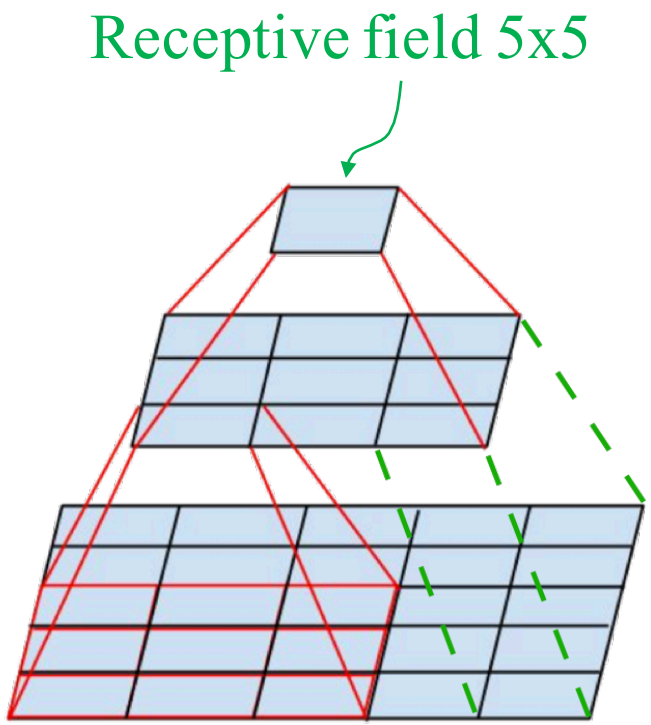
- All operations inside a block use stride 1 and enough padding to output the same spatial dimensions ($W \times H$) of feature map.
- 4 different feature maps are concatenated on depth at the end



Christian Szegedy, https://arxiv.org/pdf/1512.00567.pdf

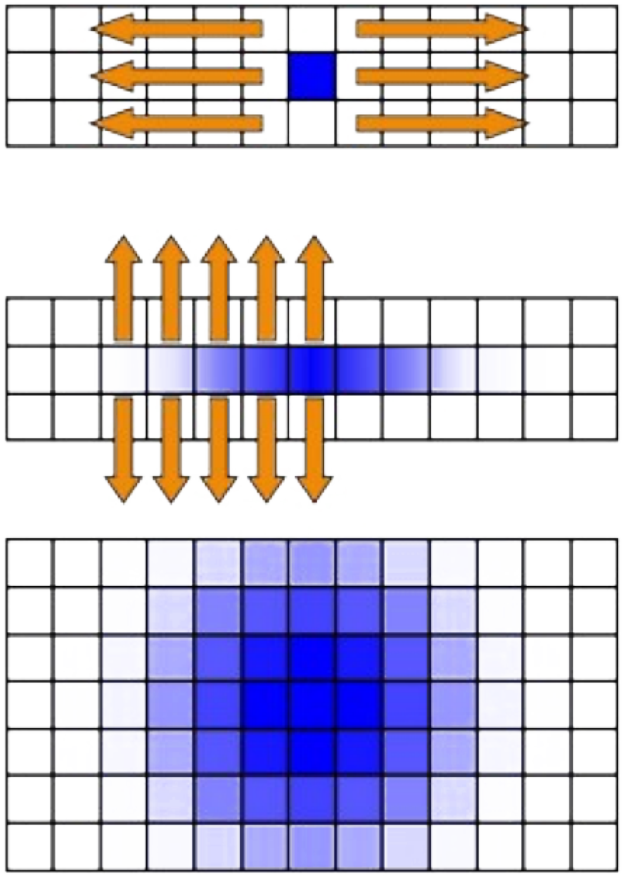
Replacing 5x5 convolutions





Christian Szegedy, https://arxiv.org/pdf/1512.00567.pdf

Filter decomposition

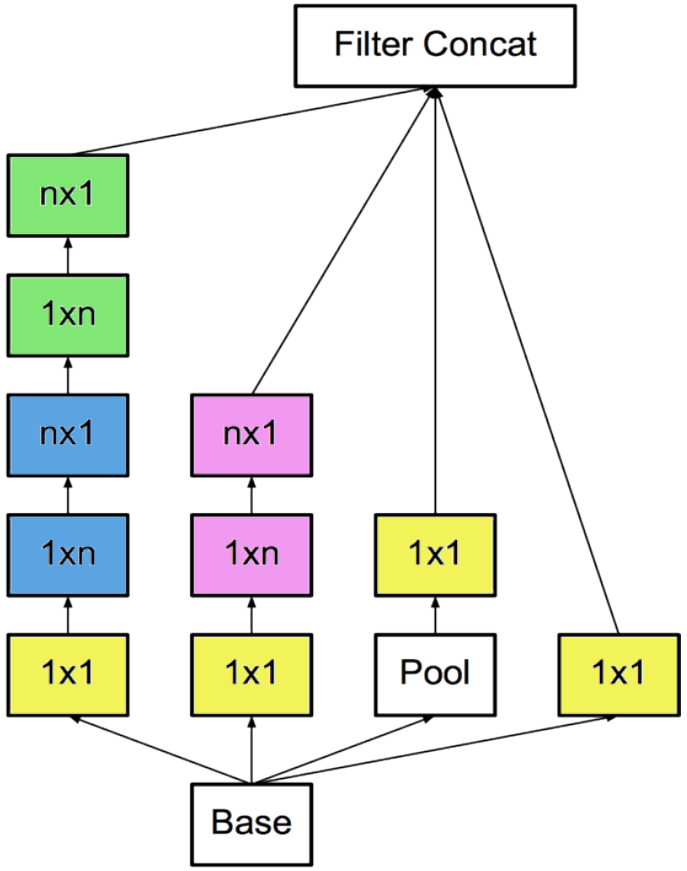


Blur the source horizontally

Blur the blur verticaly

Result

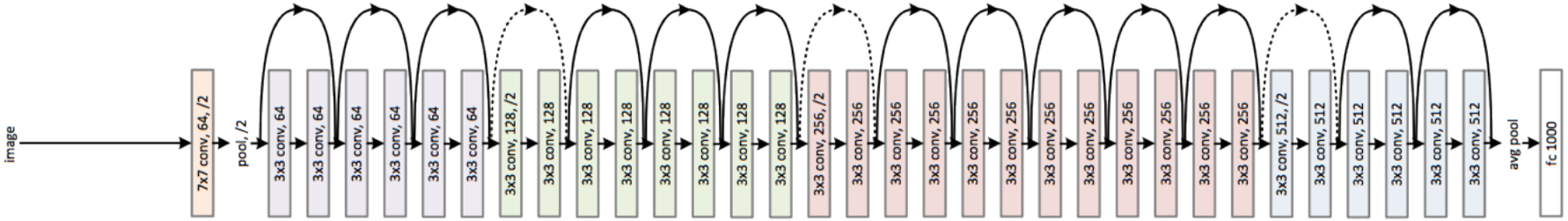
Inception block



Christian Szegedy, https://arxiv.org/pdf/1512.00567.pdf

ResNet (2015)

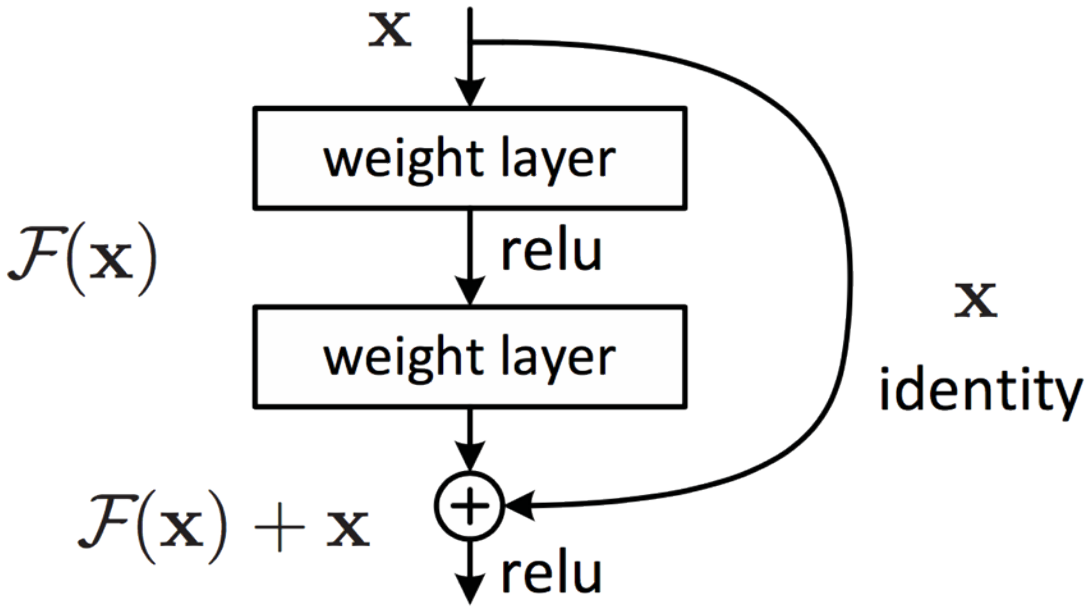
- Introduces residual connections
- ImageNet top 5 error: 4.5% (single model), 3.5% (ensemble)



- 152 layers, few 7x7 convolutional layers, the rest are 3x3, batch normalization, max and average pooling.
- 60 million parameters
- Trains on 8 GPUs for 2-3 weeks.

Residual connections

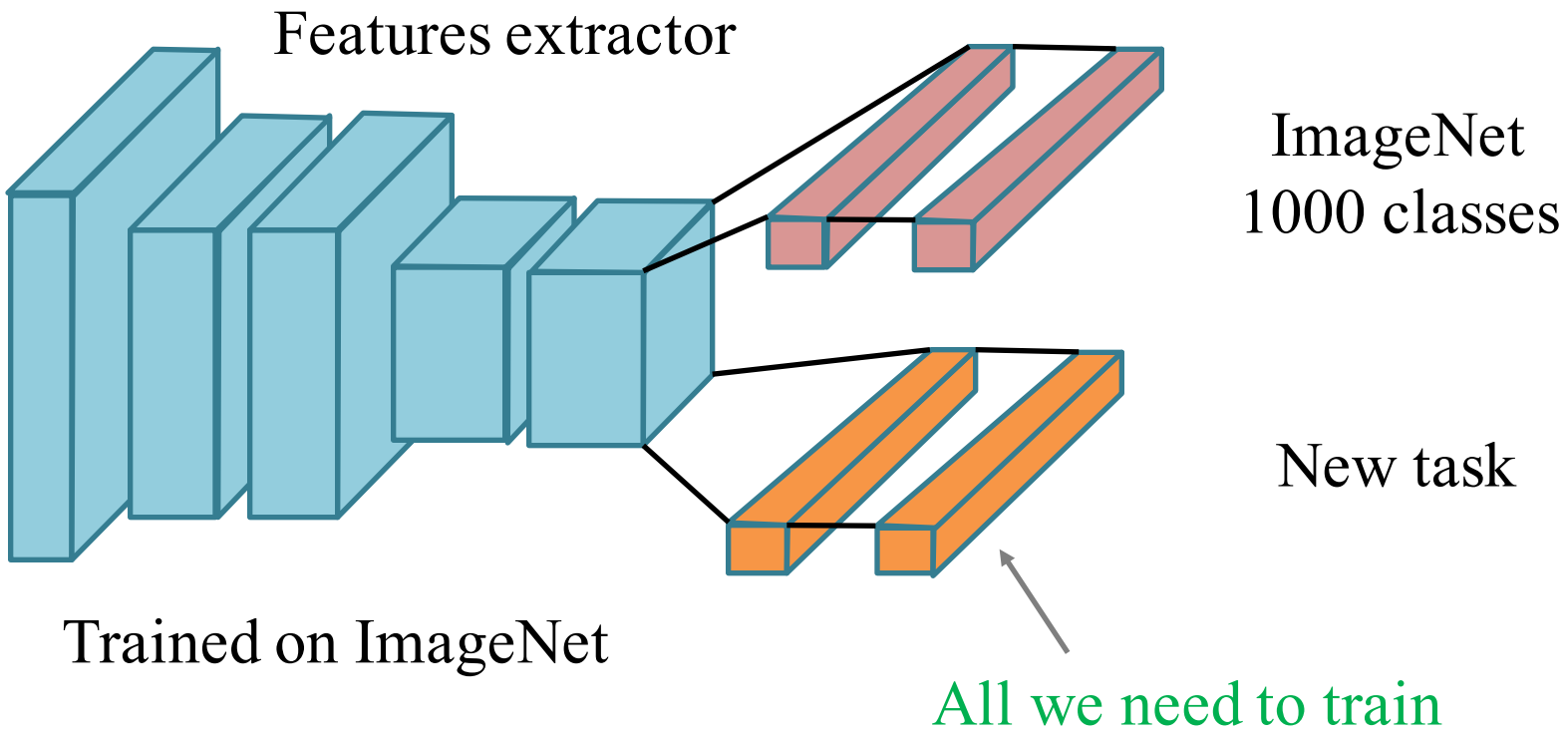
- We create output channels adding a small delta $F(x)$ to original input channels x:



- This way we can stack thousands of layers and gradients do not vanish thanks to residual connections

Transfer learning

- Deep networks learn complex features extractor, but we need lots of data to train it from scratch!
- What if we can reuse an existing features extractor for a new task?

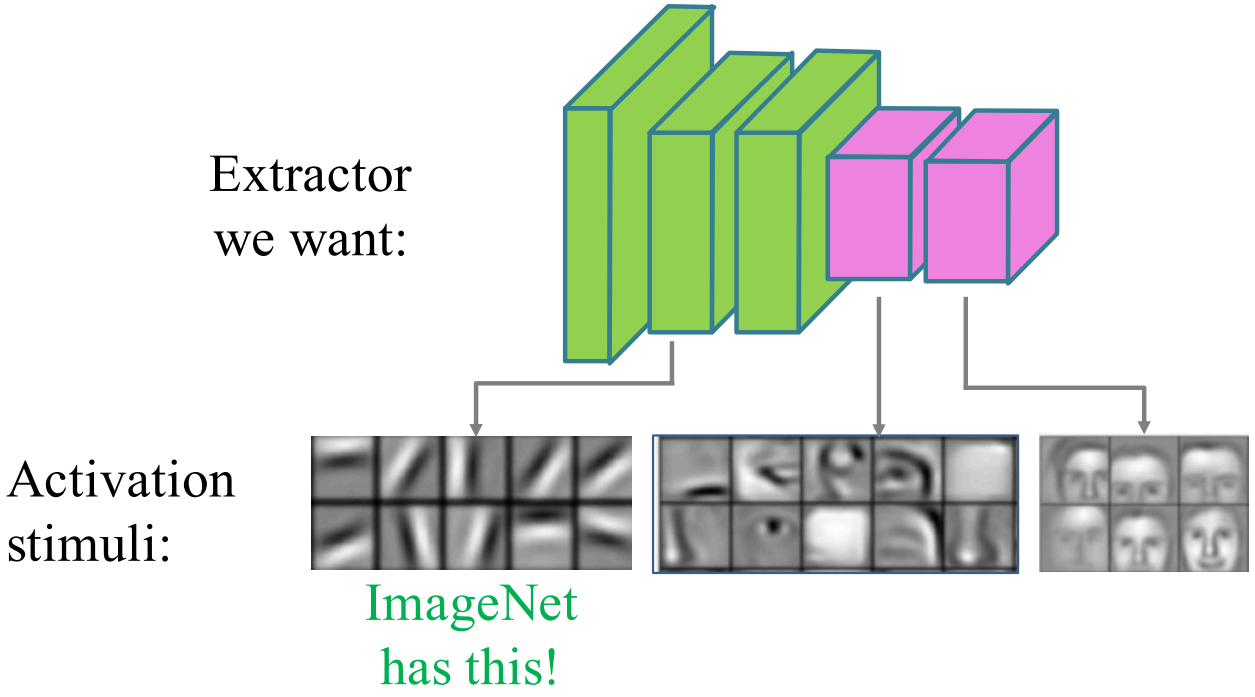


Transfer learning

- You need less data to train (for training only final MLP)
- It works if a domain of a new task is similar to ImageNet's
- Won't work for human emotions classification,
  ImageNet doesn't have people faces in the dataset!

Transfer learning

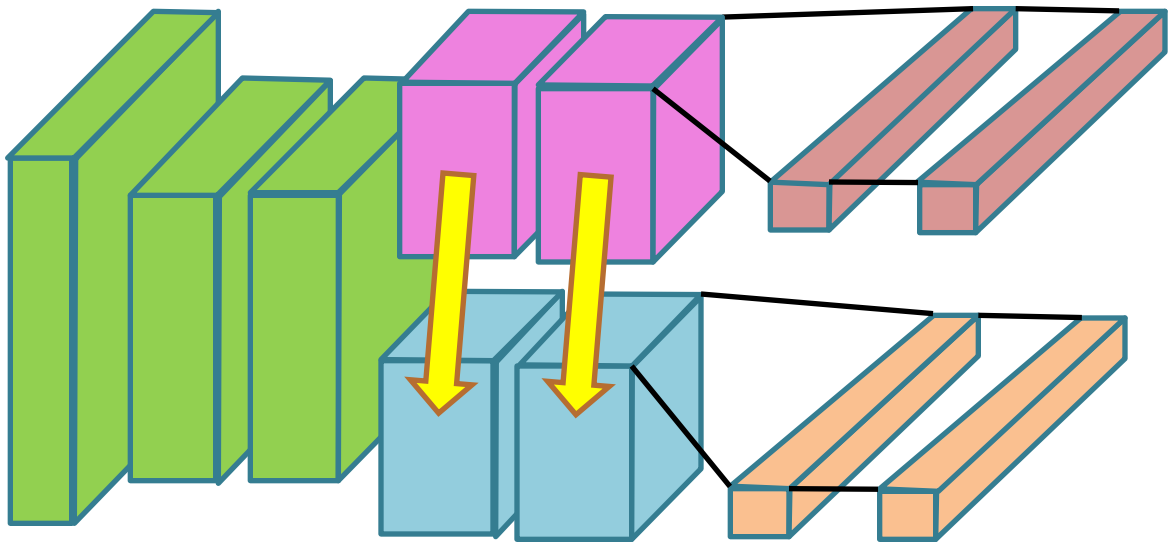
- But what if we need to classify human emotions?
- Maybe we can partially reuse ImageNet features extractor?



Honglak Lee, http://web.eecs.umich.edu/~honglak/icml09-ConvolutionalDeepBeliefNetworks.pdf

Transfer learning

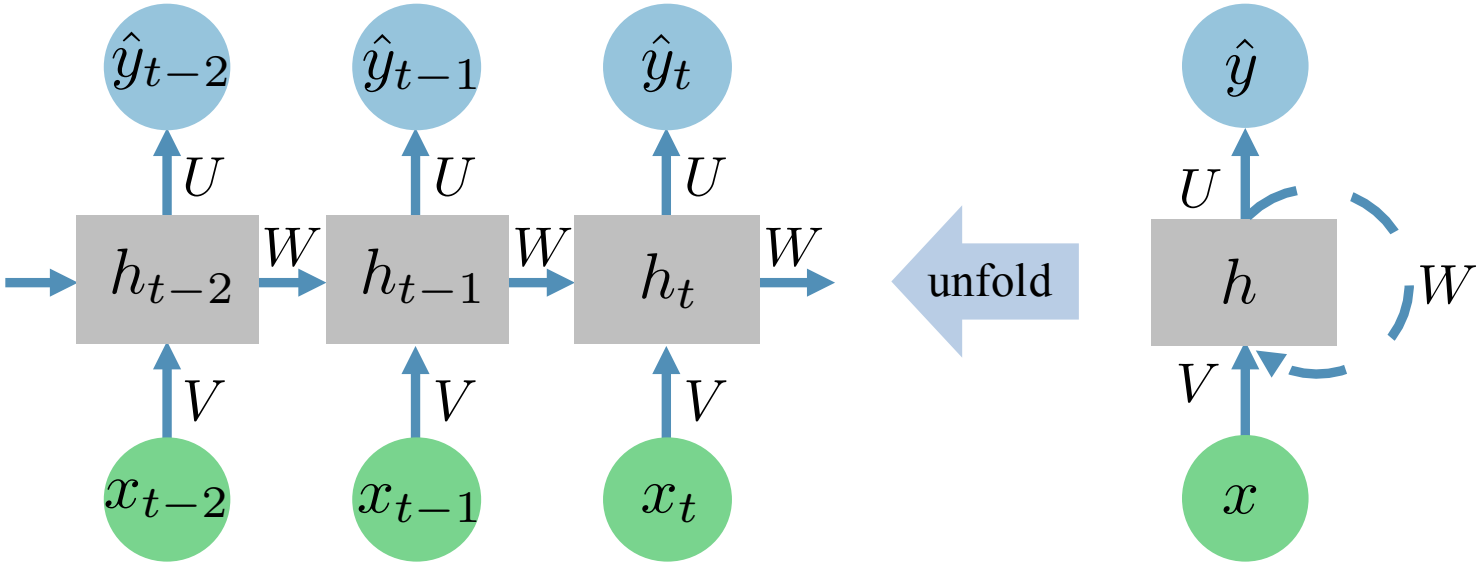
- You can initialize deeper layers with values from ImageNet.
- This is called **fine-tuning**, because you don't start with a random initialization.
- Propagate all gradients with smaller learning rate.



ImageNet
1000 classes

New task

Recurrent neural networks



x - input

$\hat{y}$ - output (prediction)

h - hidden state

$$h_t = f_h(Vx_t + Wh_{t-1} + b_h)$$

$$\hat{y}_t = f_y(Uh_t + b_y)$$

Conclusions

- Simple differentiable computational blocks can be combined into graphs and still efficiently trained
- Convolutional architectures achieve superhuman performance in some vision problems
- Graphs trained on large datasets can be reused for other tasks
- Recurrent neural networks are quite efficient for sequential data