Neural Network Training: Old & New Tricks

Old: (80's)

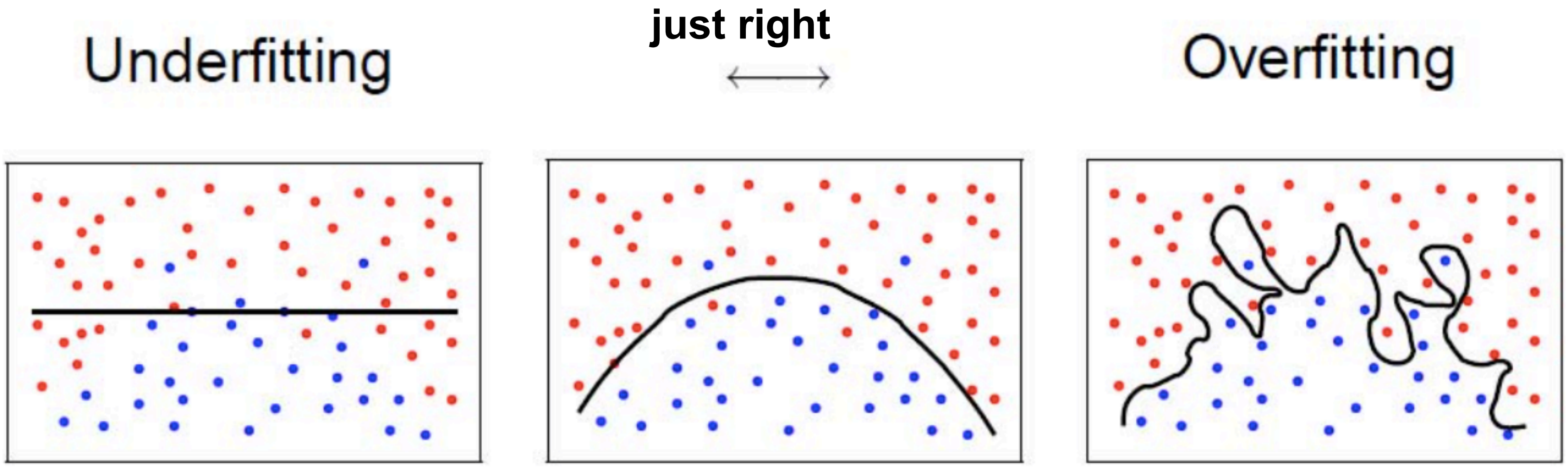
- Stochastic Gradient Descent, Momentum, "weight decay"

New: (last 5-6 years)

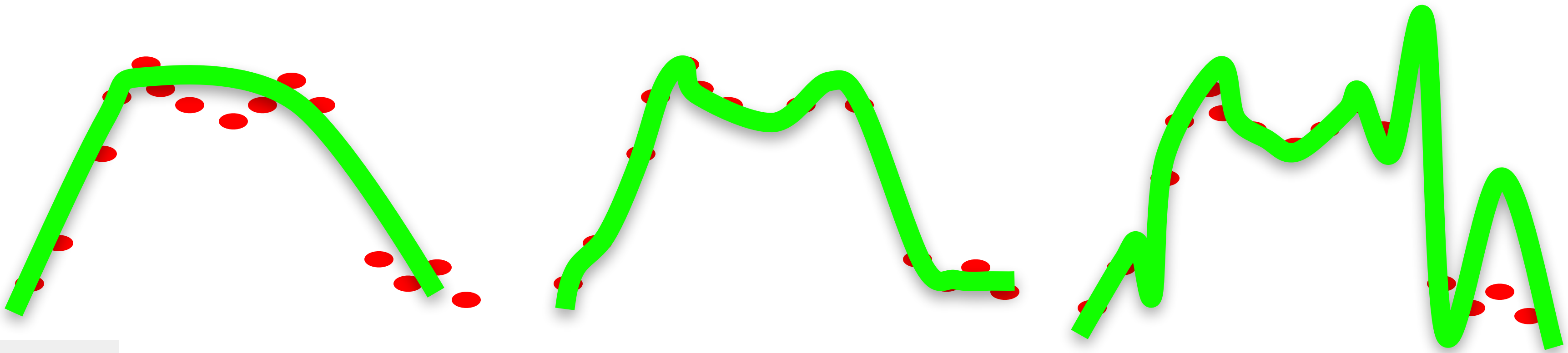
- Dropout
- ReLUs
- Batch Normalization

Reminder: Overfitting, in images

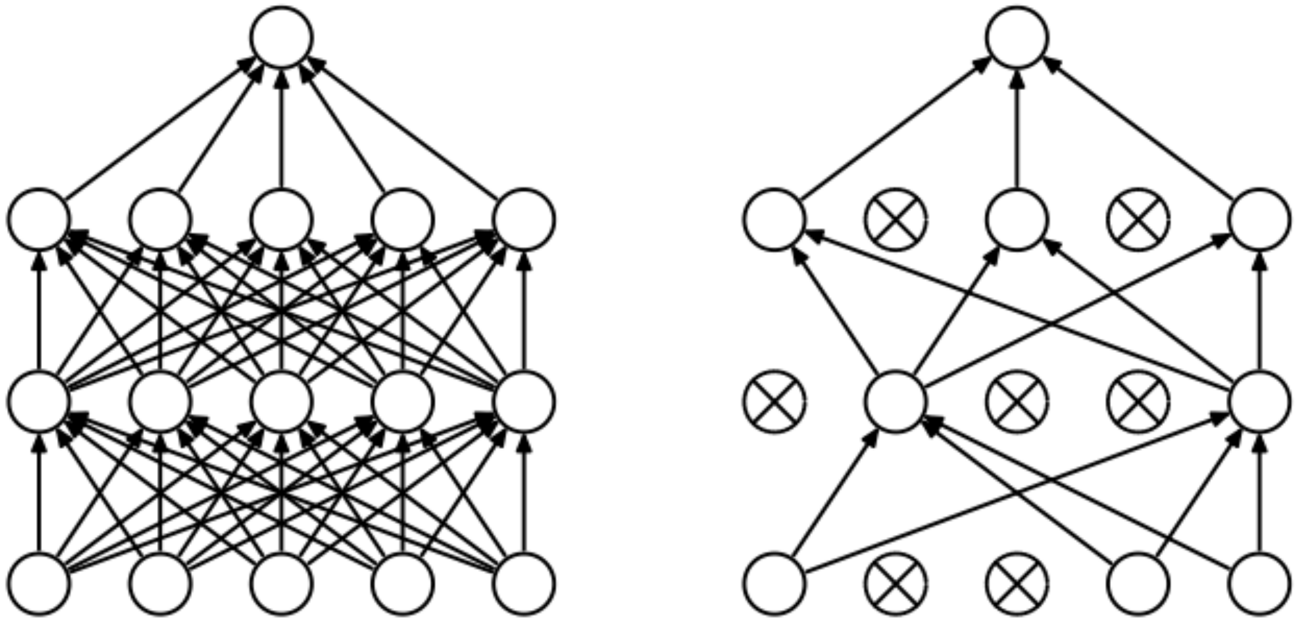
Classification



Regression



Dropout

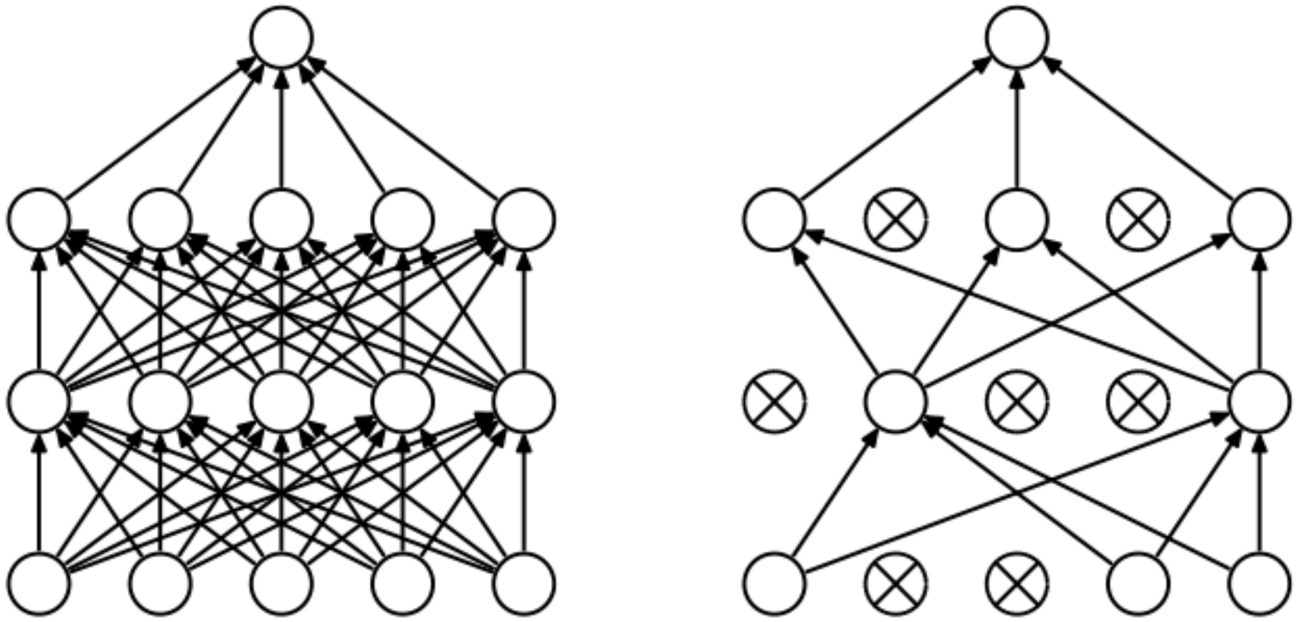


(a) Standard Neural Net

(b) After applying dropout.

Each sample is processed by a 'decimated' neural net

Dropout



(a) Standard Neural Net

(b) After applying dropout.

Each sample is processed by a 'decimated' neural net

Decimated nets: distinct classifiers

But: they should all do the same job

Dropout Performance

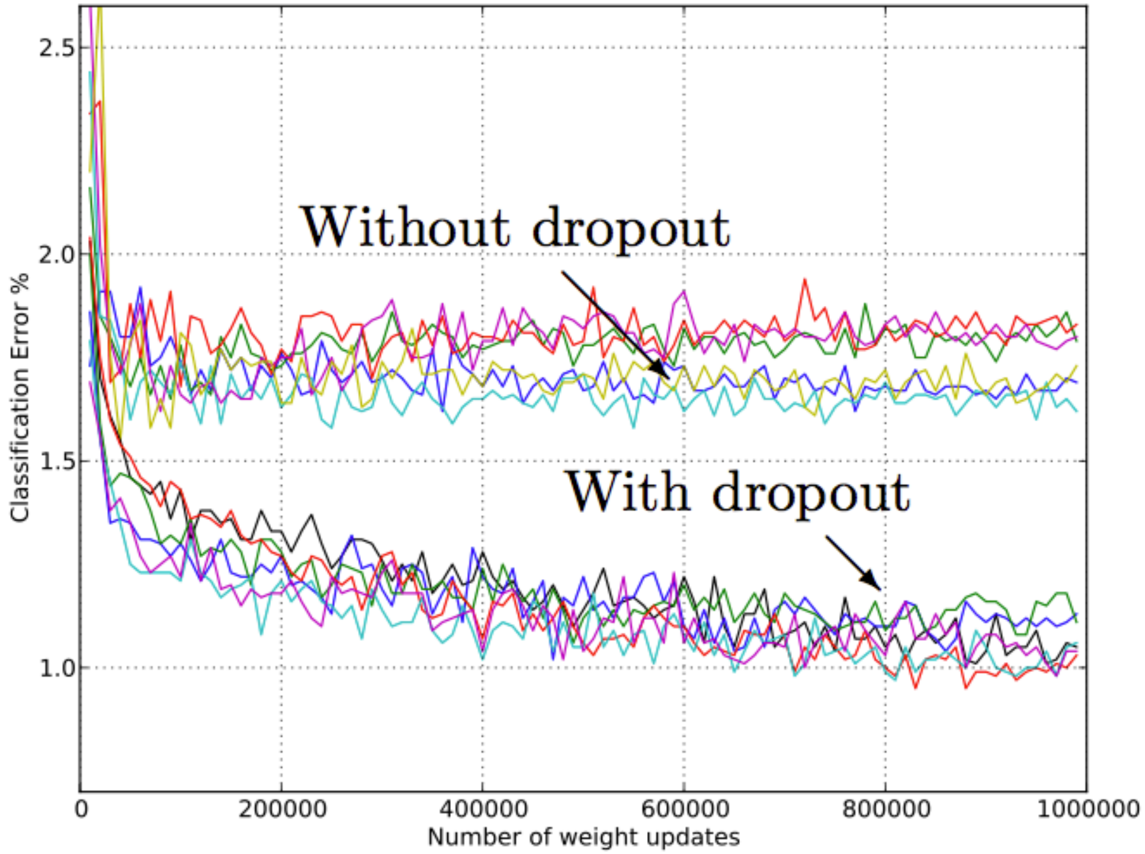


Figure 4: Test error for different architectures with and without dropout. The networks have 2 to 4 hidden layers each with 1024 to 2048 units.

Neural Network Training: Old & New Tricks

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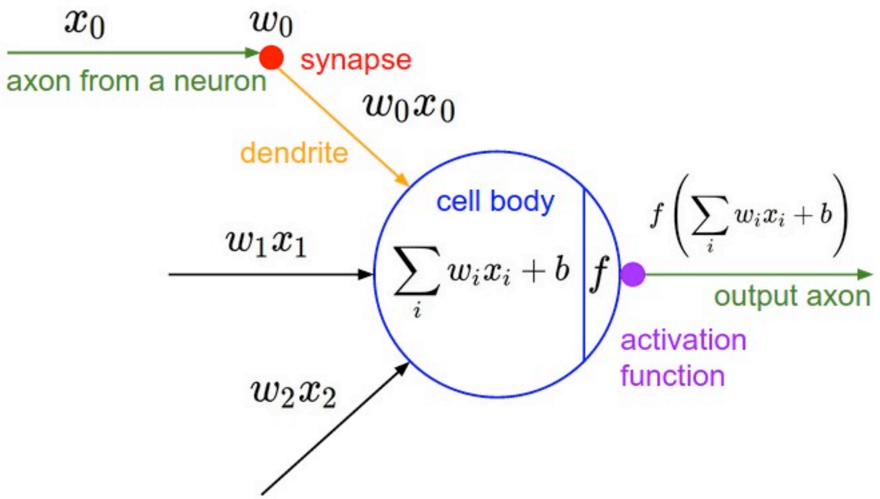
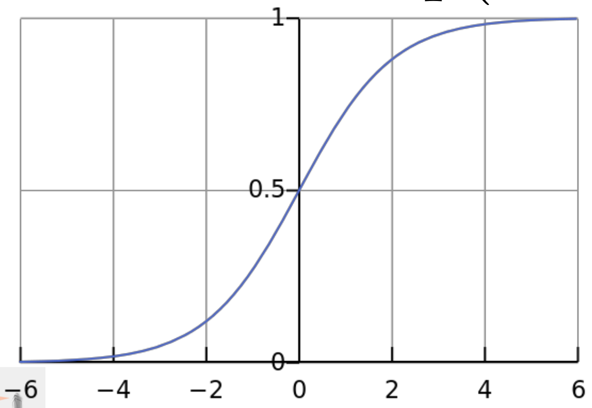
Batch Normalization

‘Neuron’: Cascade of Linear and Nonlinear Function



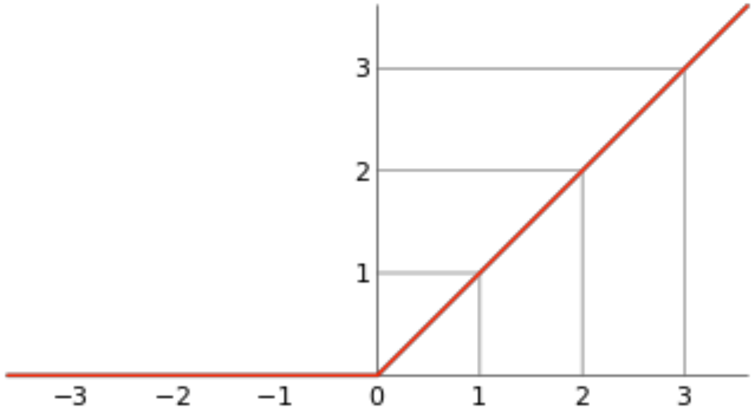
Sigmoidal (“logistic”)

$$g(a) = \frac{1}{1 + \exp(-a)}$$



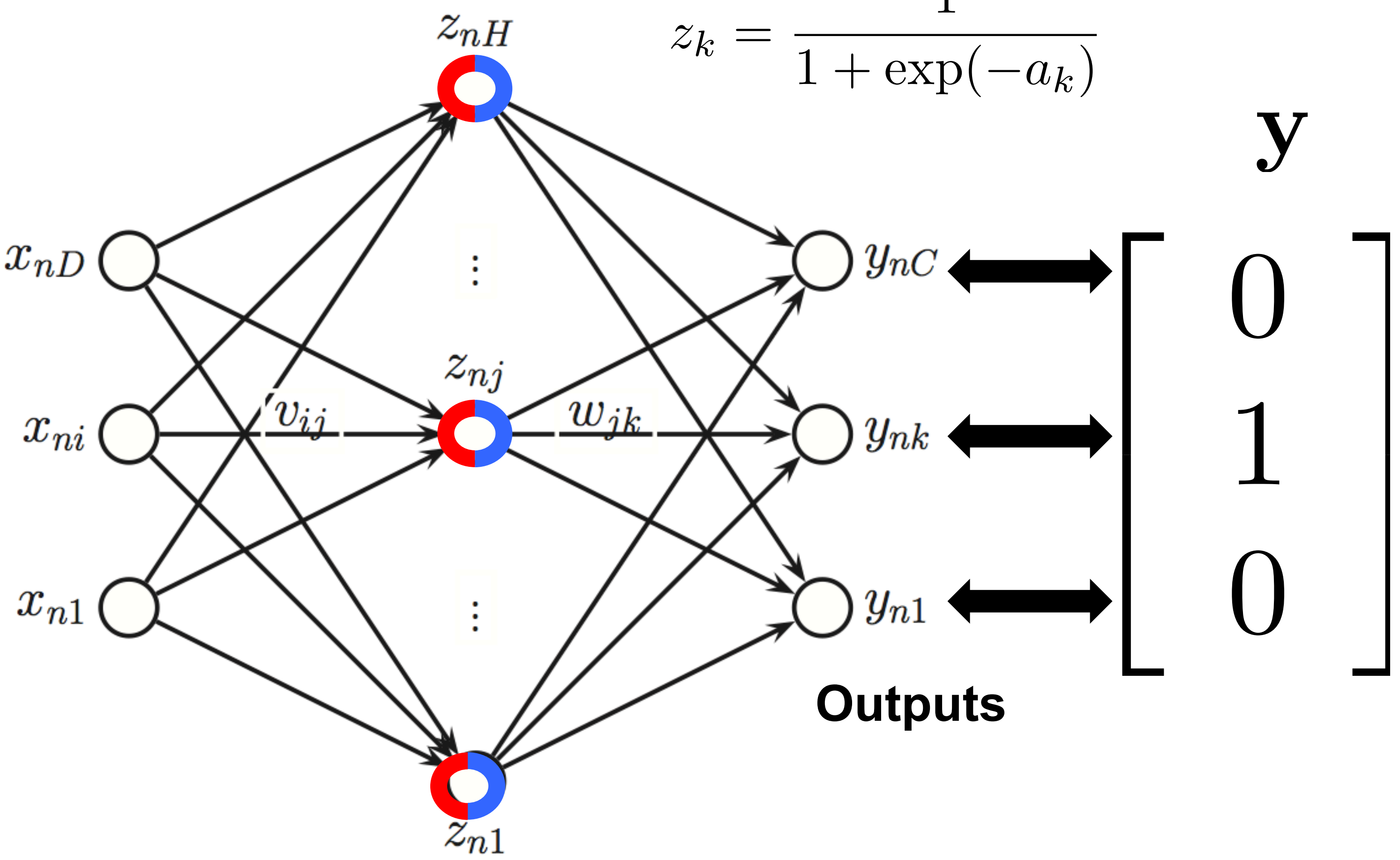
Rectified Linear Unit (RELU)

$$g(a) = \max(0, a)$$



Reminder: a network in backward mode

$$z_k = \frac{1}{1+\exp(-a_k)}$$



$$\frac{\partial l}{\partial a_k} = \sum_m \frac{\partial l}{\partial z_m}\frac{\partial z_m}{\partial a_k} = \frac{\partial l}{\partial z_k} g'(a_k) = \frac{\partial l}{\partial z_k} g(a_k)(1-g(a_k))$$

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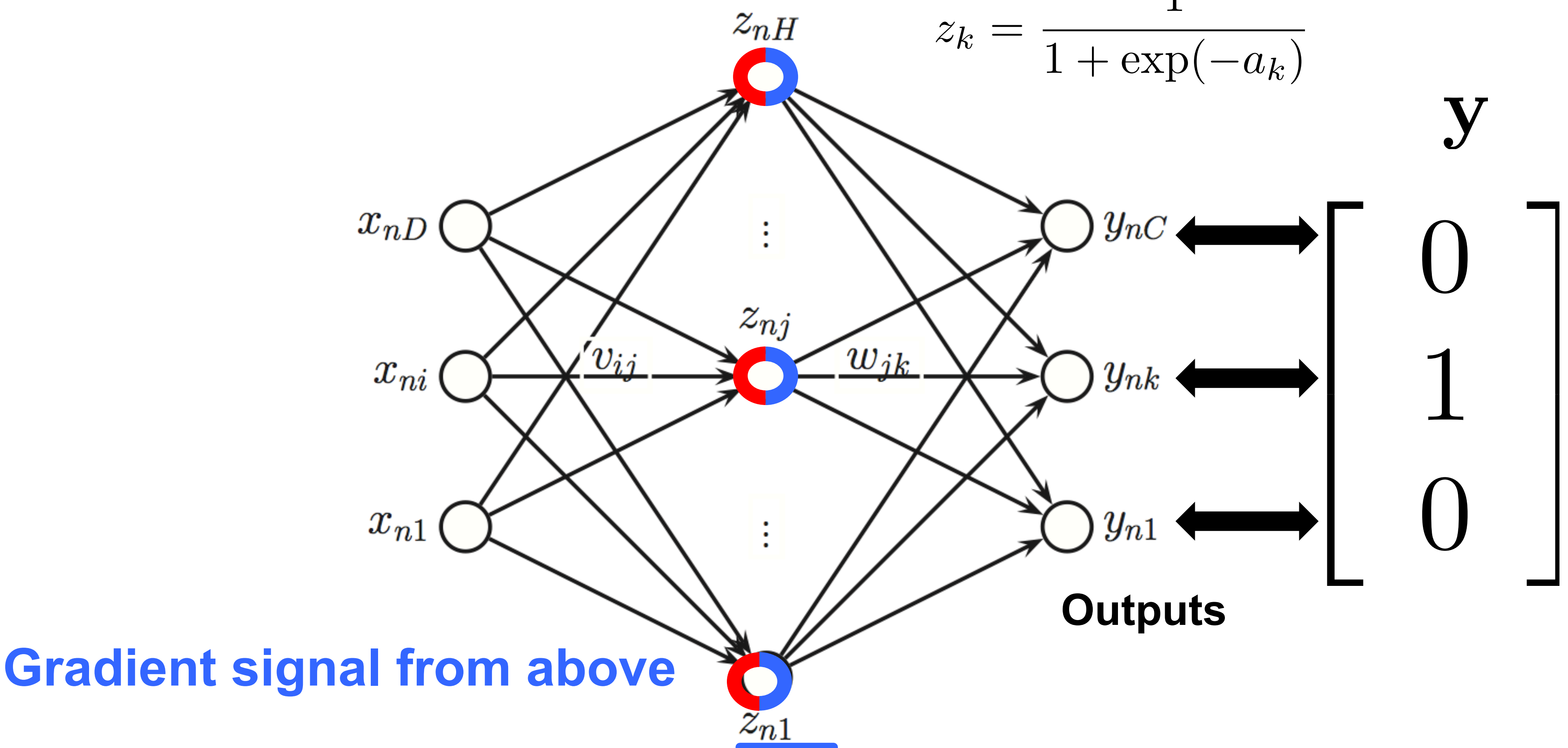

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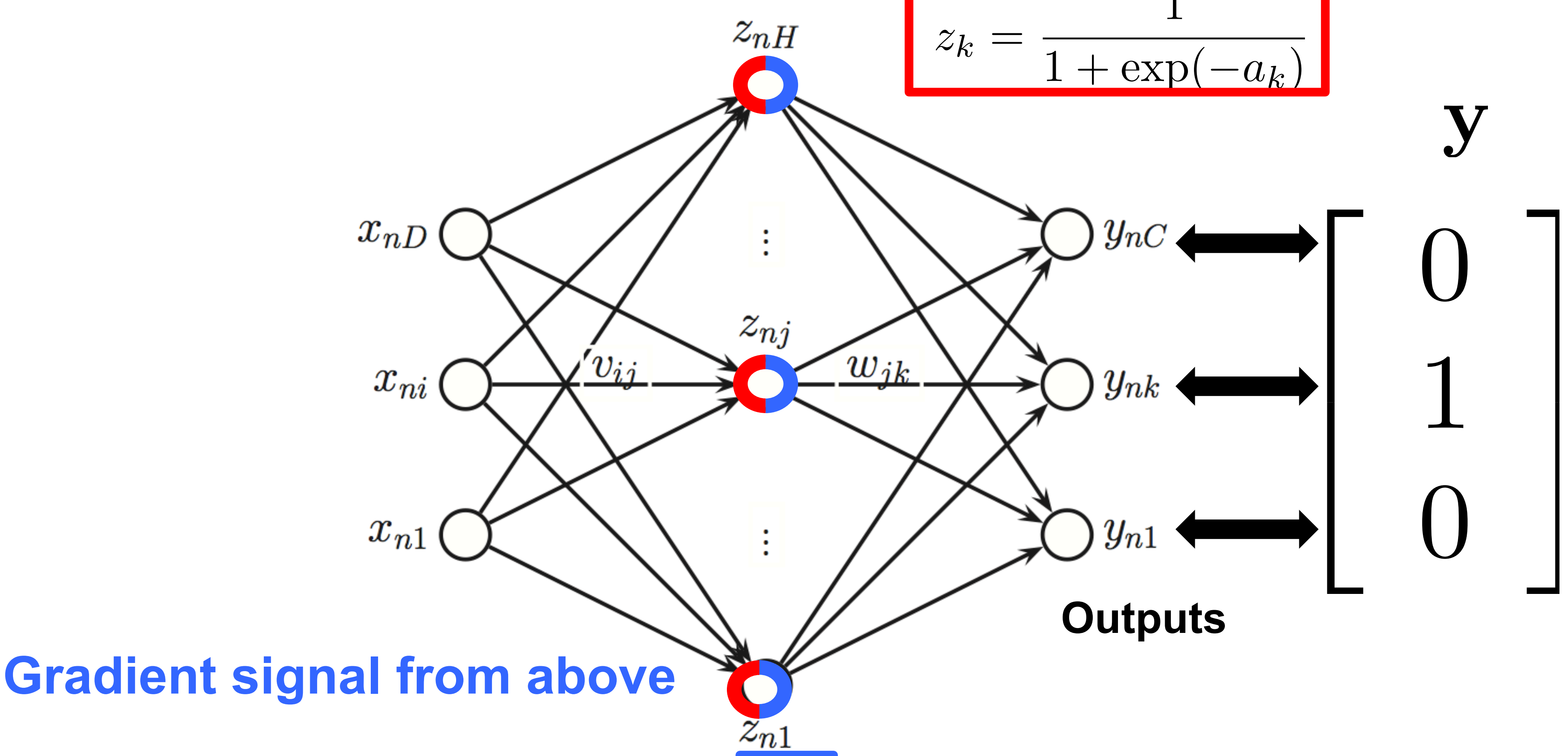

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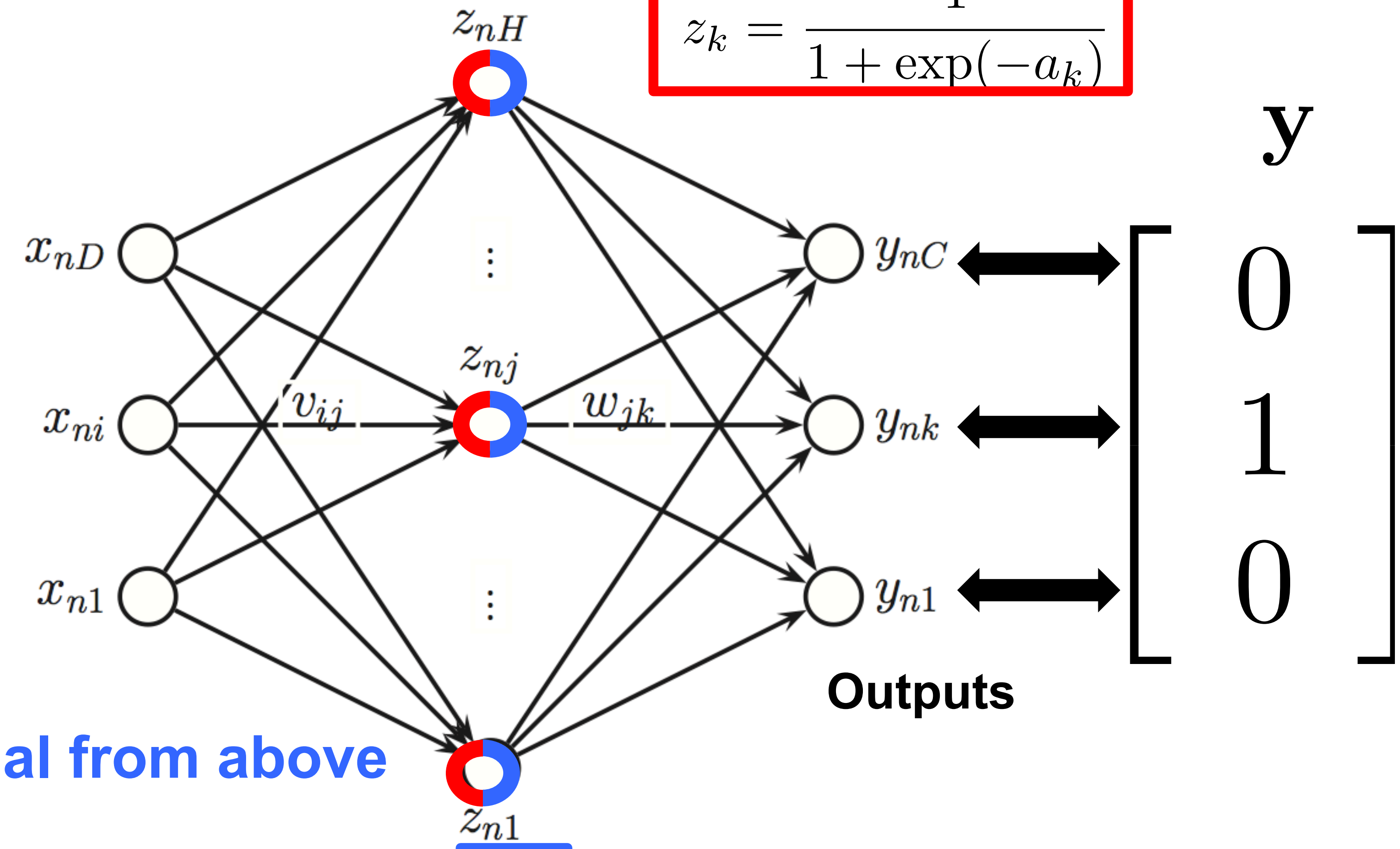

Outputs

Gradient signal from above

$$\frac{\partial l}{\partial a_k} = \sum_m \frac{\partial l}{\partial z_m}\frac{\partial z_m}{\partial a_k} = \boxed{\frac{\partial l}{\partial z_k}}\,\boxed{g'(a_k)} = \frac{\partial l}{\partial z_k}\boxed{g(a_k)(1-g(a_k))}$$

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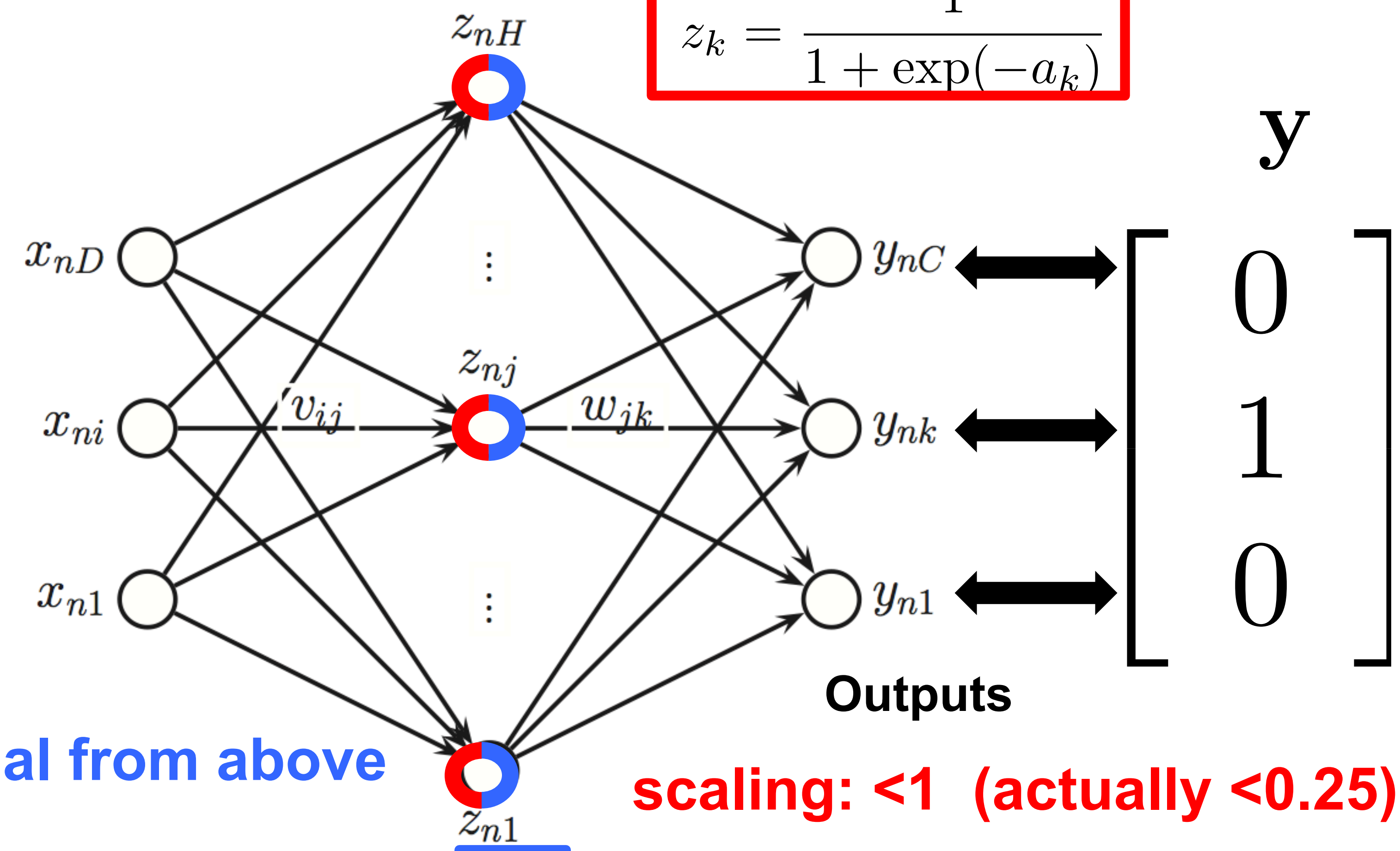

Gradient signal from above

scaling: <1 (actually <0.25)

$$\frac{\partial l}{\partial a_k} = \sum_m \frac{\partial l}{\partial z_m}\frac{\partial z_m}{\partial a_k} = \boxed{\frac{\partial l}{\partial z_k}}\,\boxed{g'(a_k)} = \frac{\partial l}{\partial z_k}\boxed{g(a_k)(1-g(a_k))}$$

Vanishing Gradients Problem

Gradient signal from above

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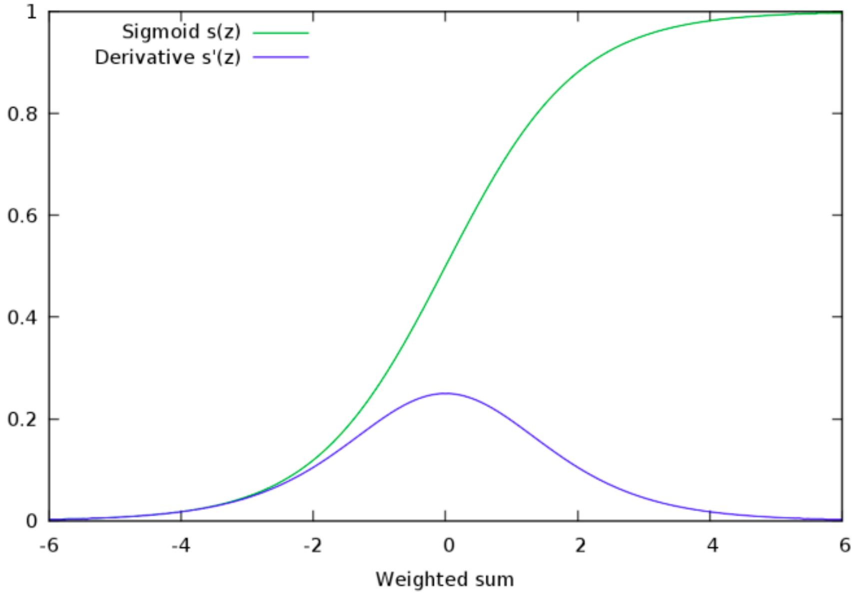

Vanishing Gradients Problem

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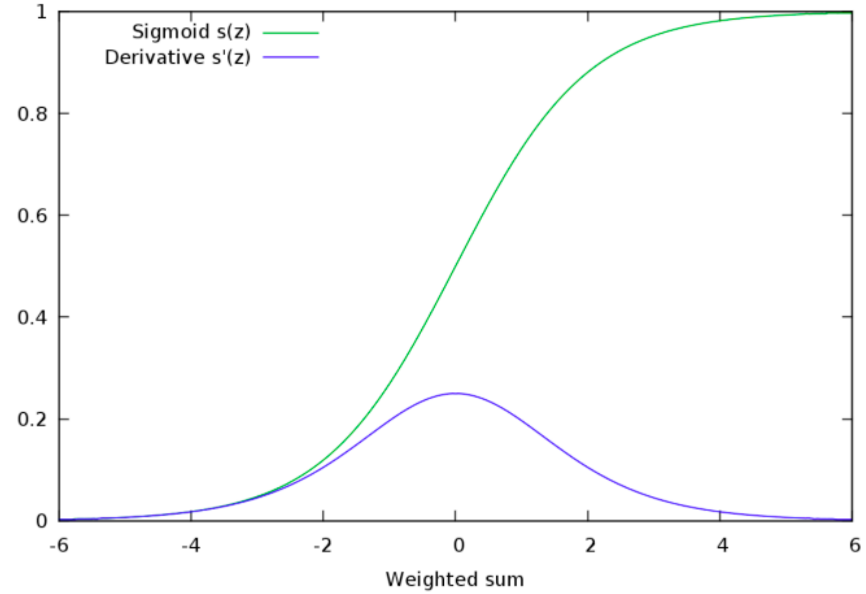
Do this 10 times: updates in the first layers get minimal

Top layer knows what to do, lower layers “don’t get it”

Sigmoidal Unit: Signal is not getting through!



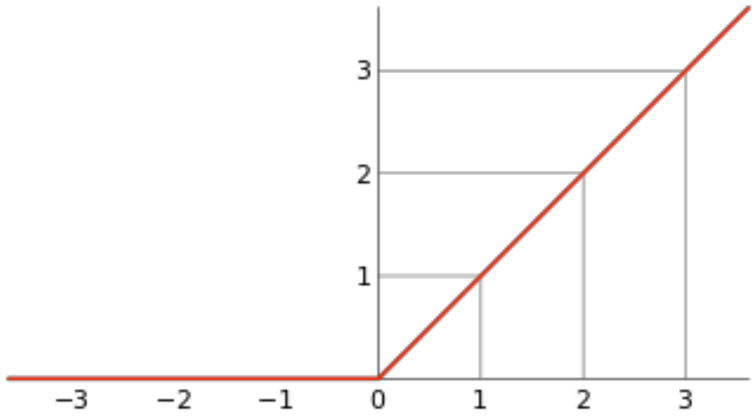
Vanishing Gradients Problem: ReLU Solves It

Gradient signal from above

Scaling: {0,1}

$$\frac{\partial l}{\partial a_k} = \sum_m \frac{\partial l}{\partial z_m} \frac{\partial z_m}{\partial a_k} = \boxed{\frac{\partial l}{\partial z_k}} \boxed{g'(a_k)}$$

$$g(a) = \max(0, a)$$



$$g'(a) = \begin{cases} 1 & a > 0 \\ 0 & a < 0 \end{cases}$$

Activation Functions: ReLU & Co

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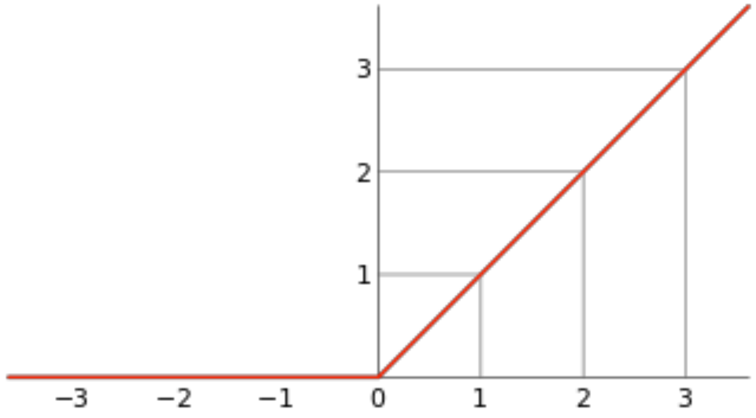

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Great! But… no gradient for negative half-space

Activation Functions: ReLU & Co

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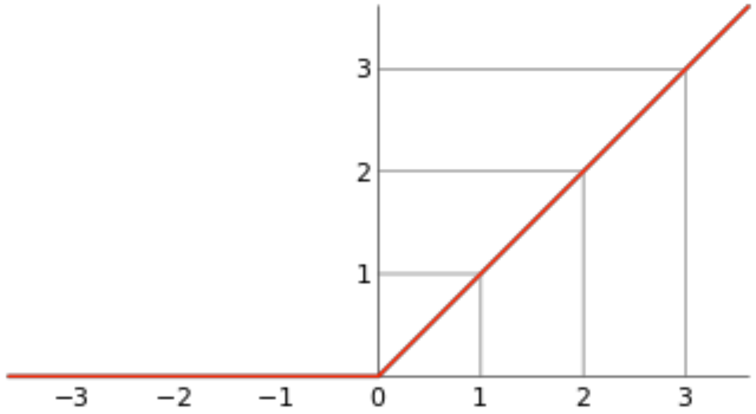

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Great! But… no gradient for negative half-space

Lots of follow up work: LeakyReLU, eLU, etc.

Can improve results, but typically fine-tuning only

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- ReLUs
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External Covariate Shift: your input changes

10 am

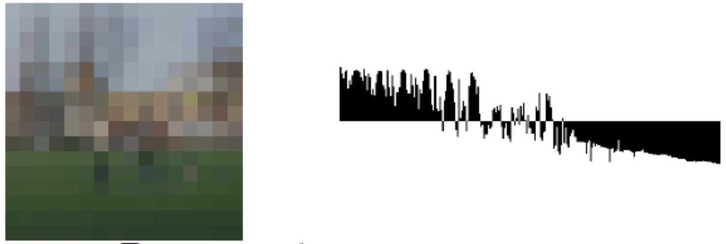
2pm

7pm

“Whitening”: Set Mean = 0, Variance = 1

Photometric transformation: $I \rightarrow a\,I + b$


Original Patch and Intensity Values


Brightness Decreased


Contrast increased,

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- Make each patch have zero mean:

Photometric transformation: $I \rightarrow a\,I + b$

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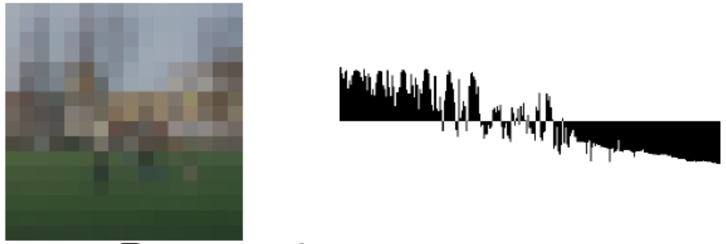

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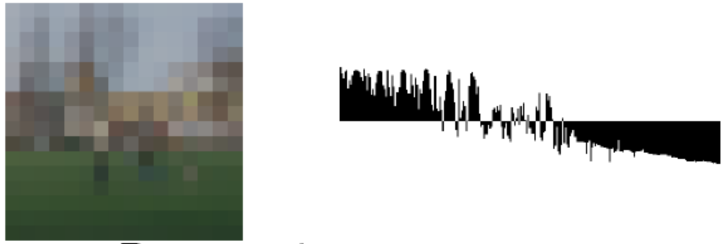

Brightness Decreased

Contrast increased,

$$\mu = \frac{1}{N}\sum_{x,y} I(x,y)$$

$$Z(x,y) = I(x,y) - \mu$$

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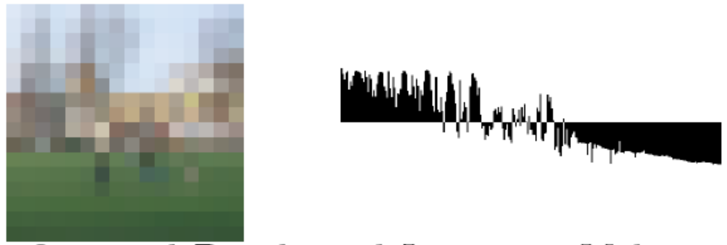

- The

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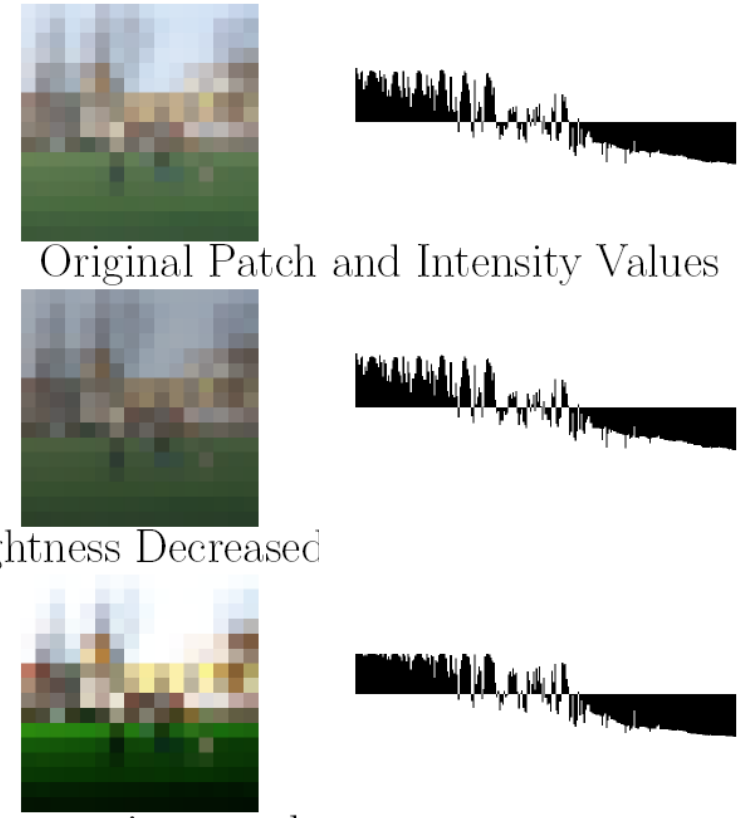

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- The ance:

$$\sigma^2 = \frac{1}{N}\sum_{x,y} Z(x,y)^2$$

$$ZN(x,y) = \frac{Z(x,y)}{\sigma}$$

Batch Normalization

Whiten-as-you-go:

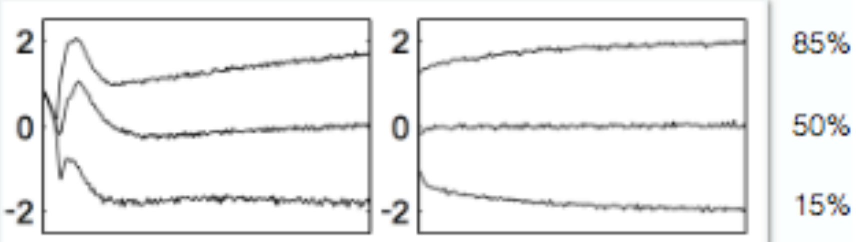
- Normalize the activations in each layer within a mini-batch.
- Learn the mean and variance (γ, β) of each layer as parameters

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

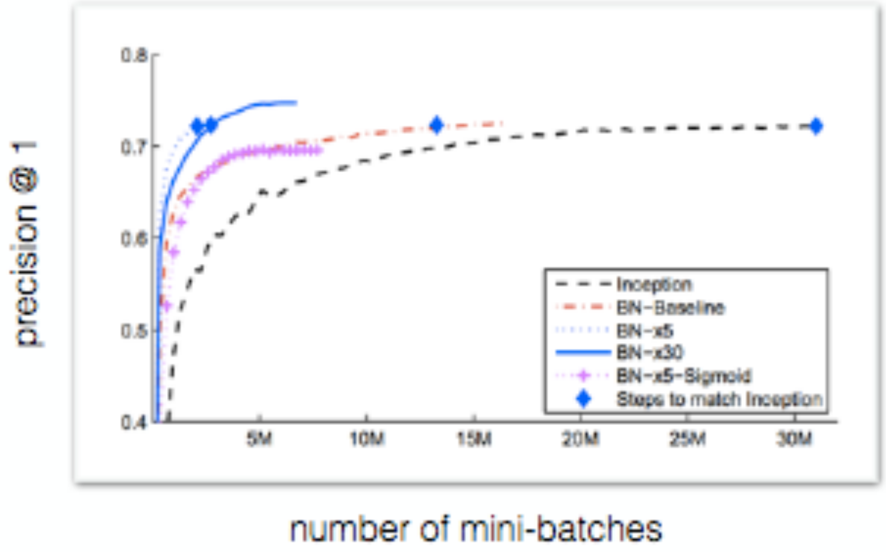


(b) Without BN (c) With BN

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift
S Ioffe and C Szegedy (2015)

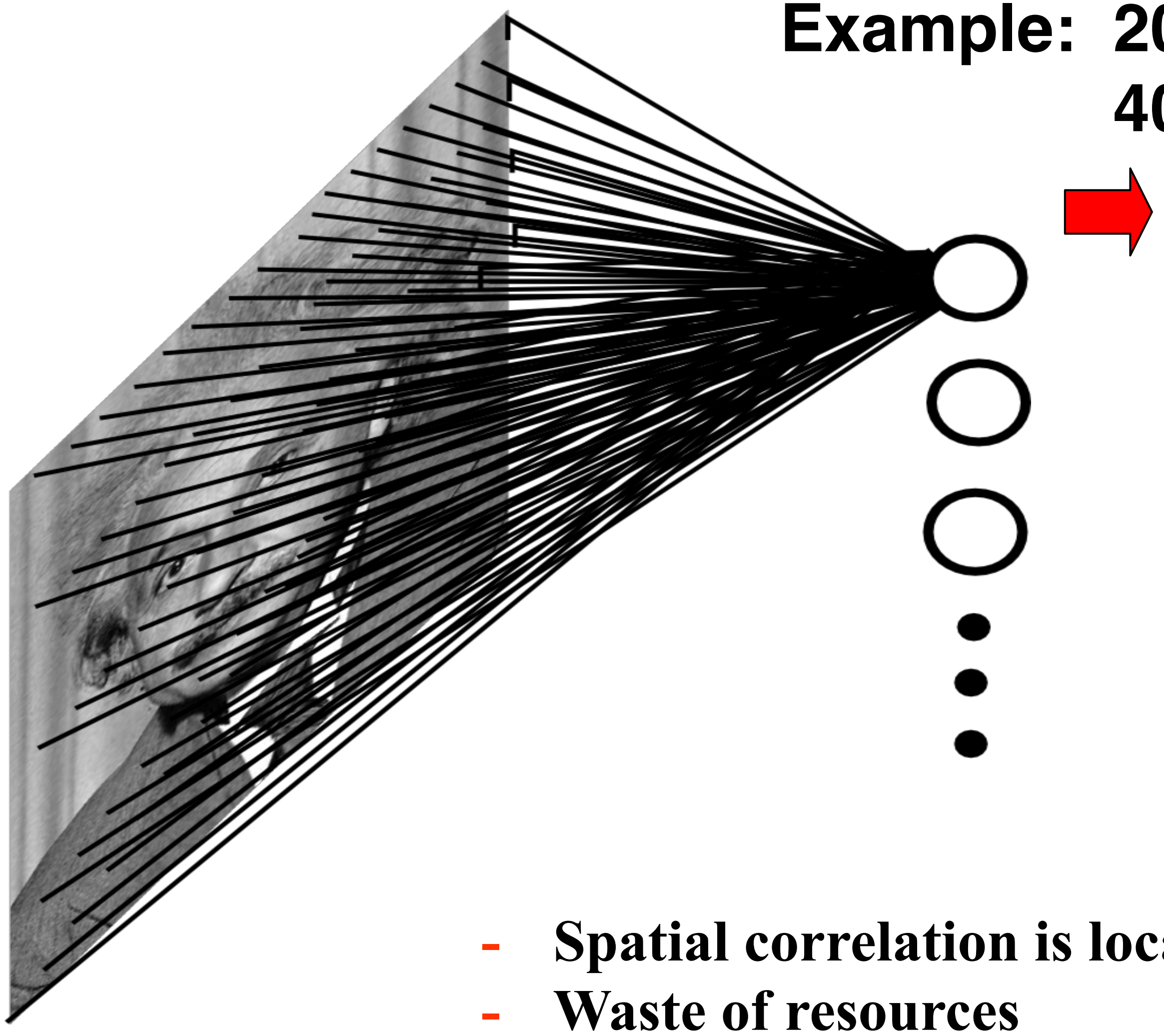
Batch Normalization: Used in all current systems

- Multi-layer CNN's train faster with fewer data samples (15x).
- Employ faster learning rates and less network regularizations.
- Achieves state of the art results on ImageNet.



Convolutional Neural Networks

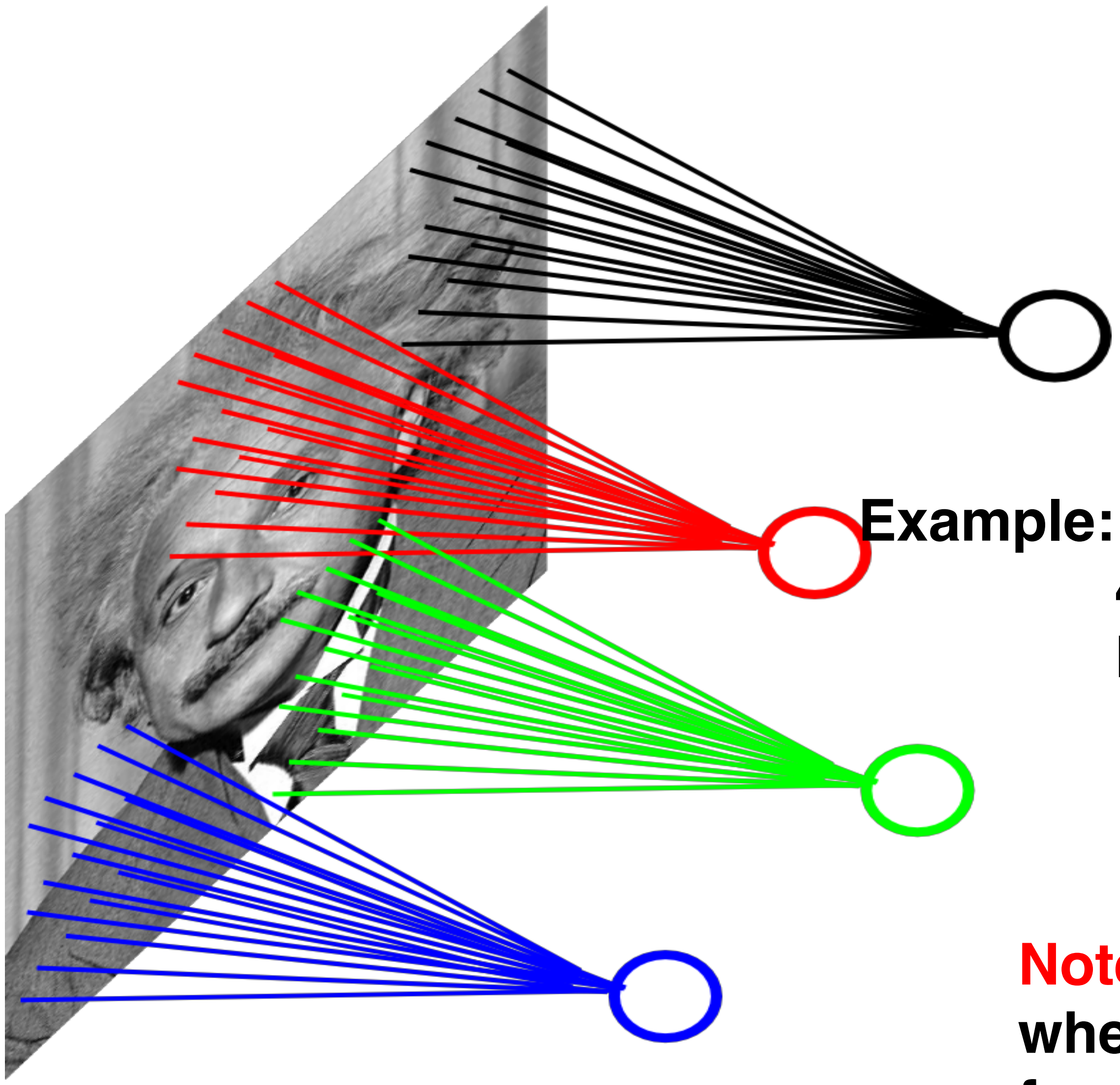
Fully-connected Layer



Example: 200x200 image
40K hidden units
~1.6B parameters!!!

- Spatial correlation is local
- Waste of resources
- We don't have enough training samples anyway…

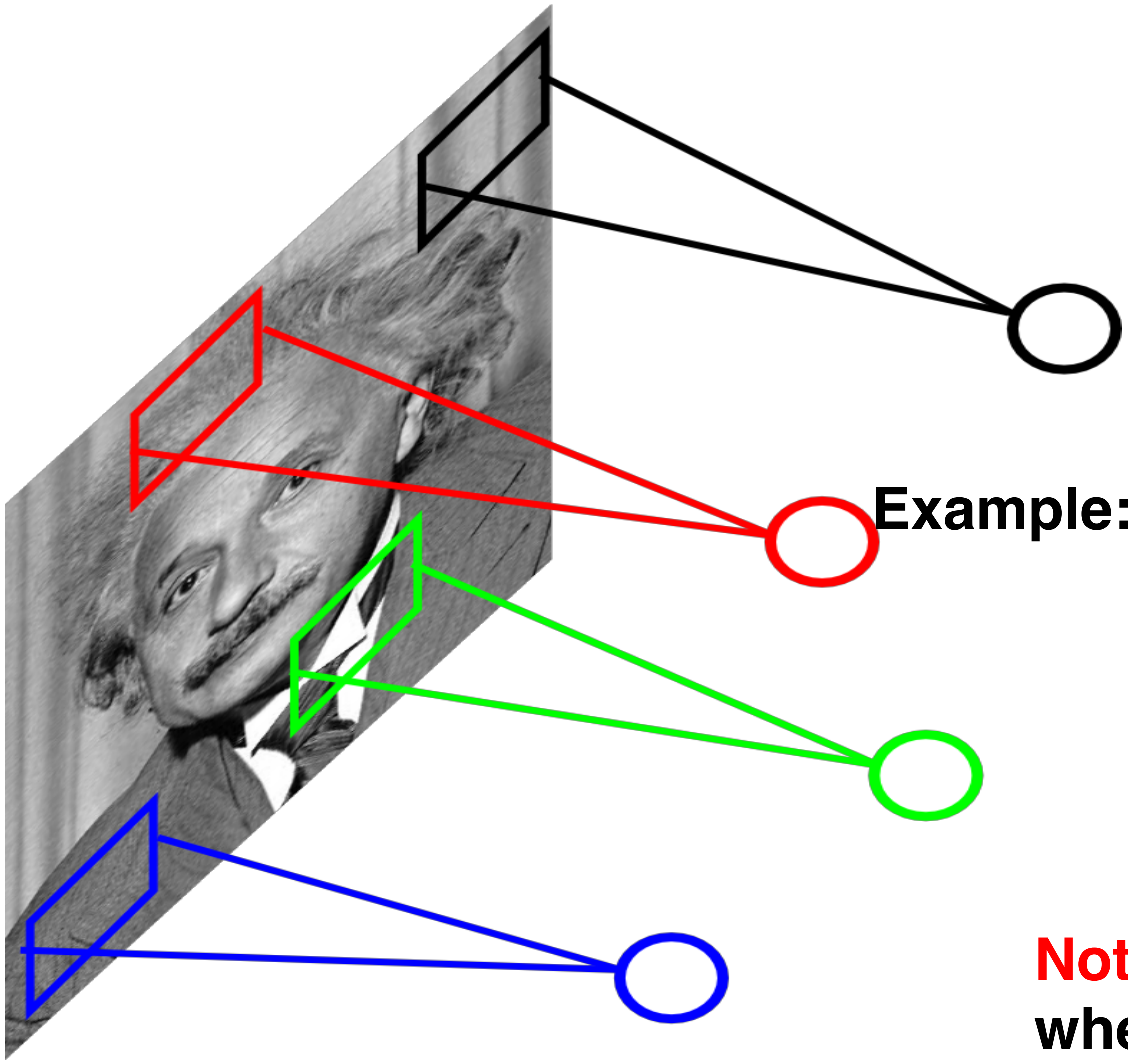
Locally-connected Layer



Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

Locally-connected Layer



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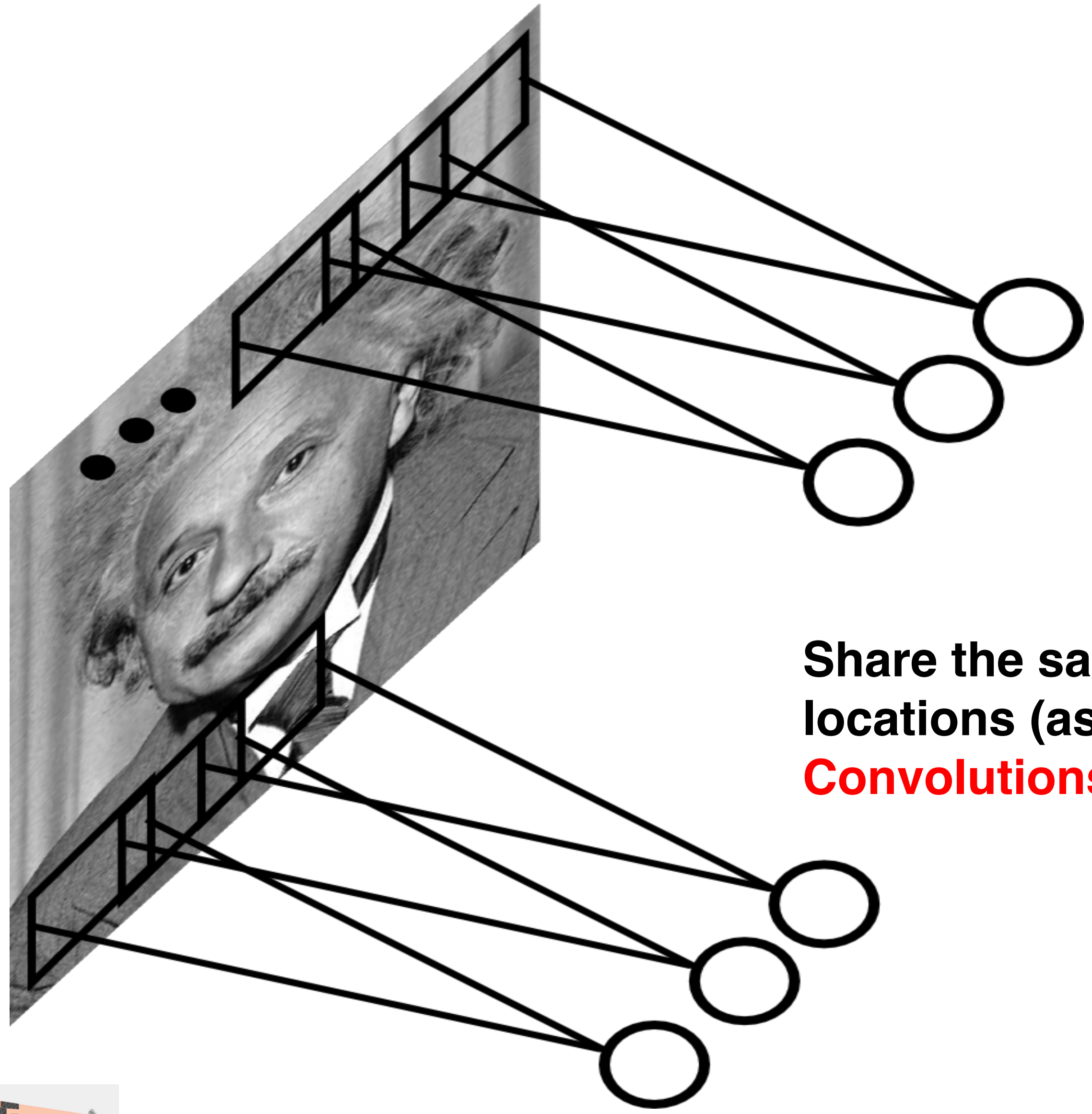
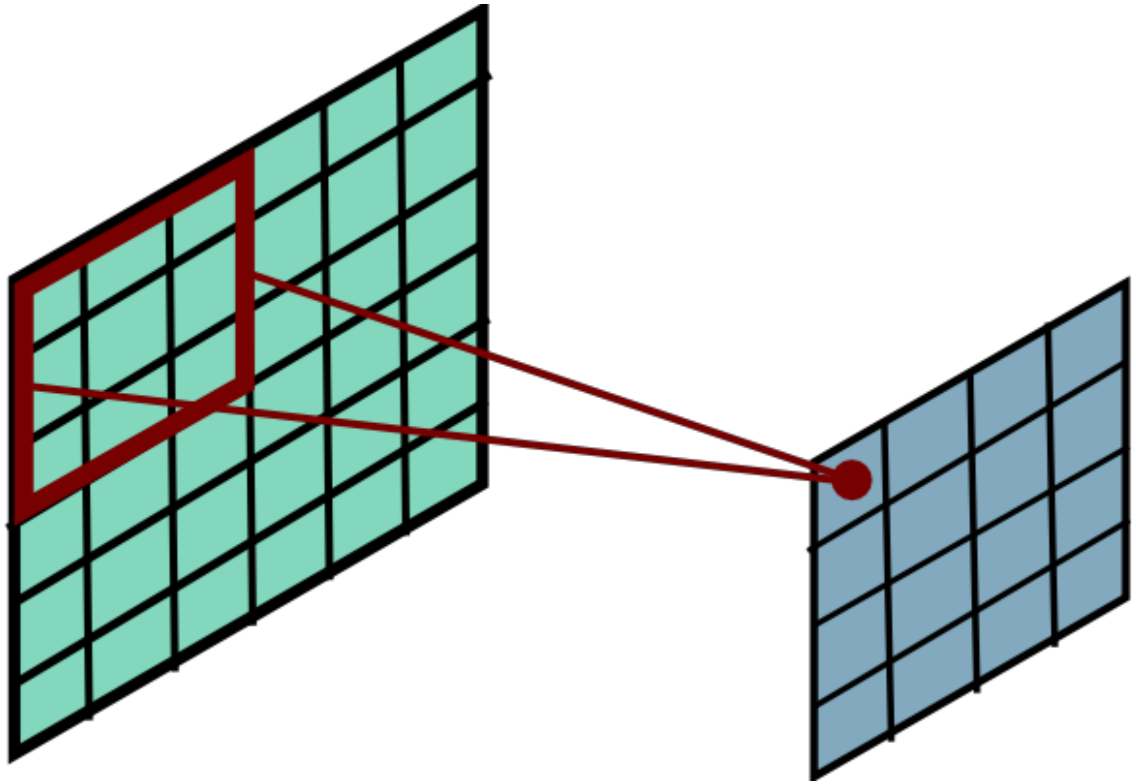
Convolutional Layer

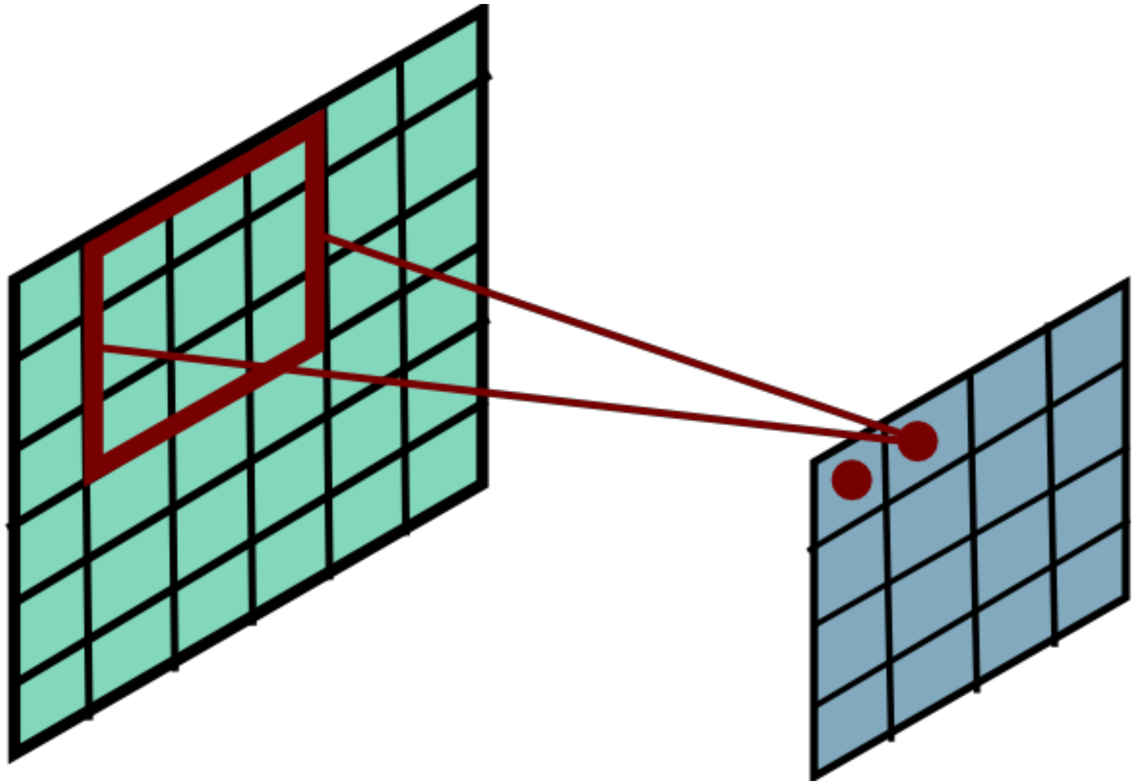


Share the same parameters across different locations (assuming input is stationary):
Convolutions with learned kernels

Convolutional Layer



Convolutional Layer



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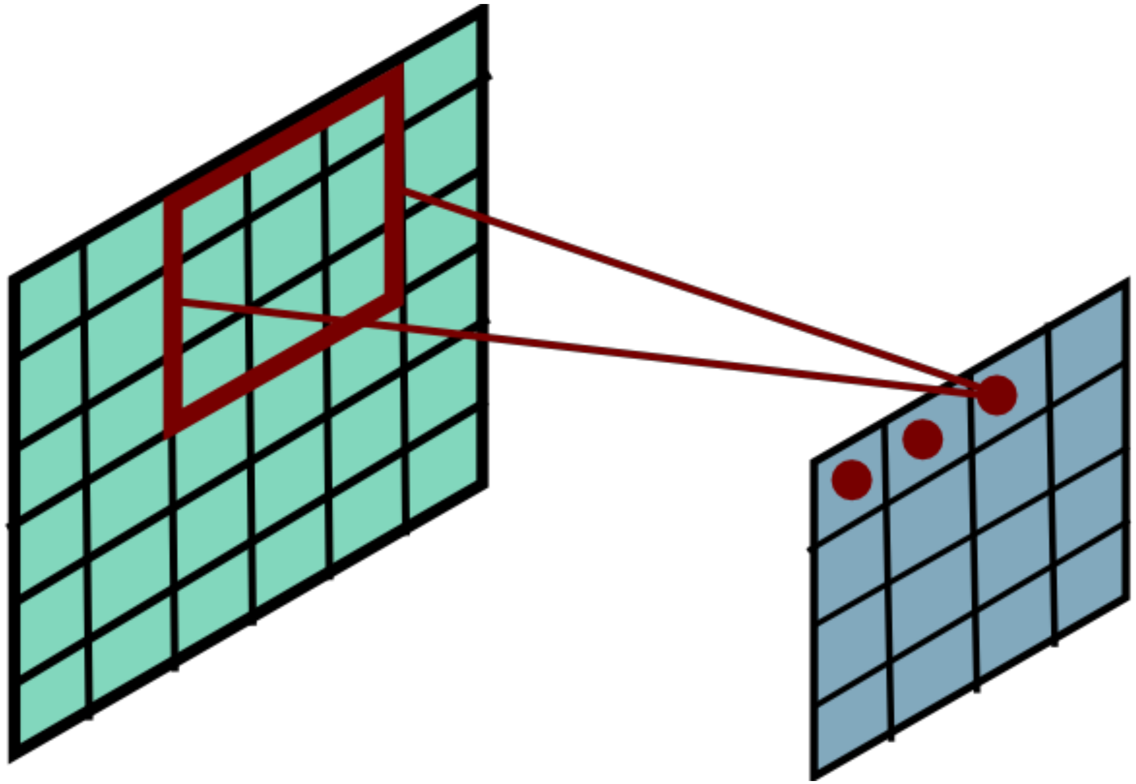

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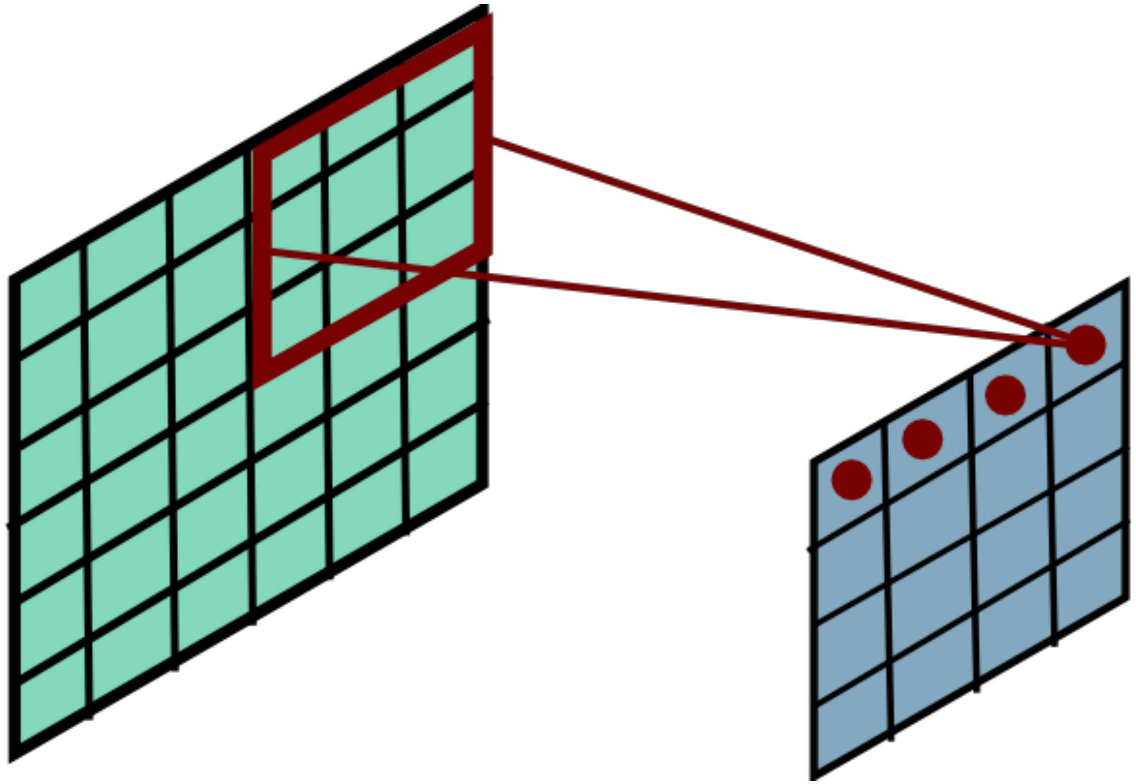

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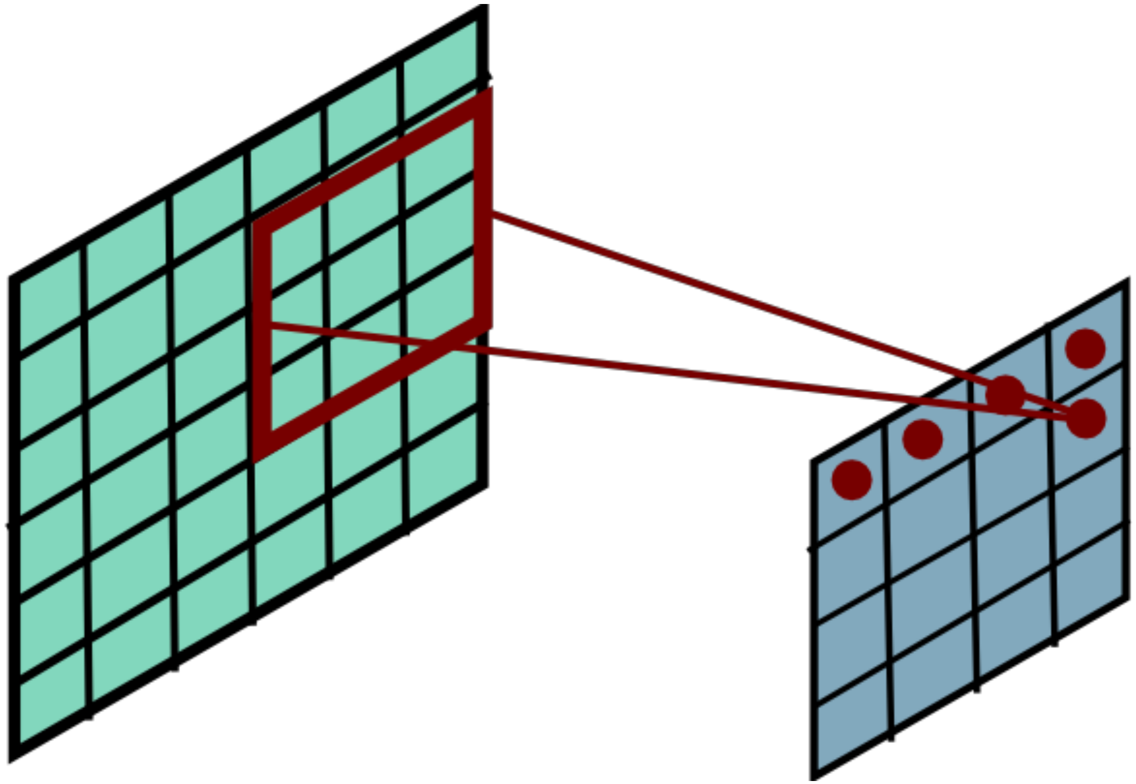

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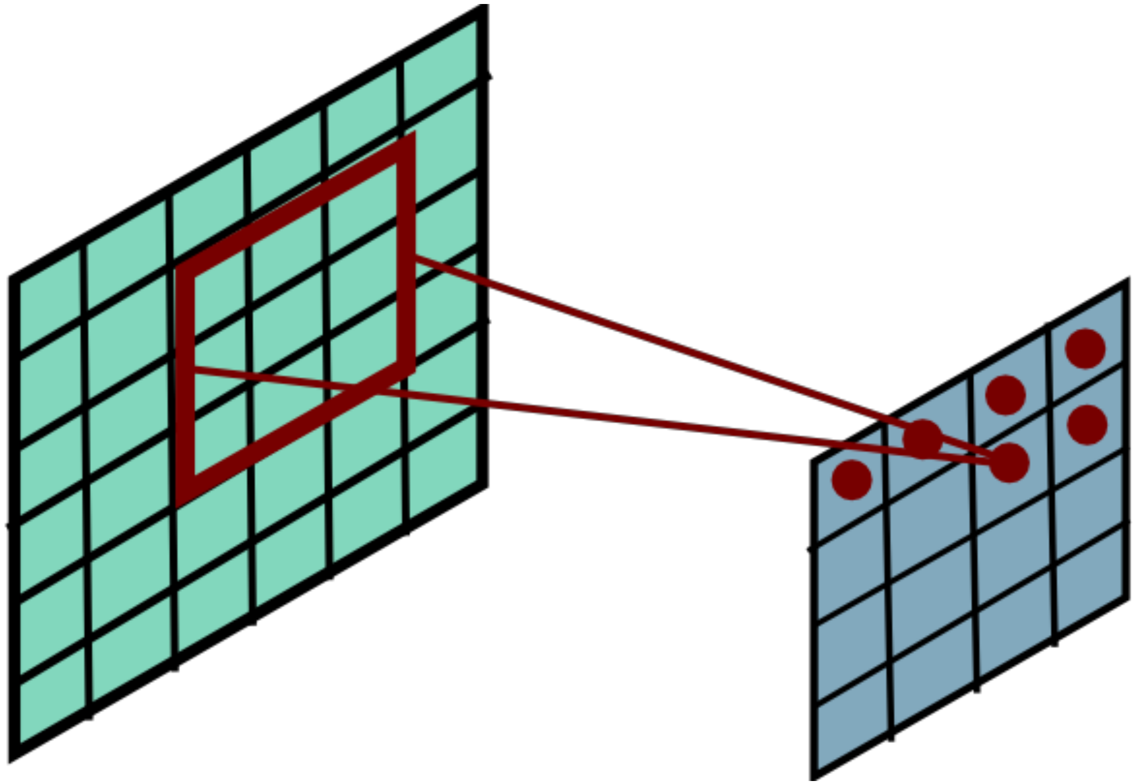

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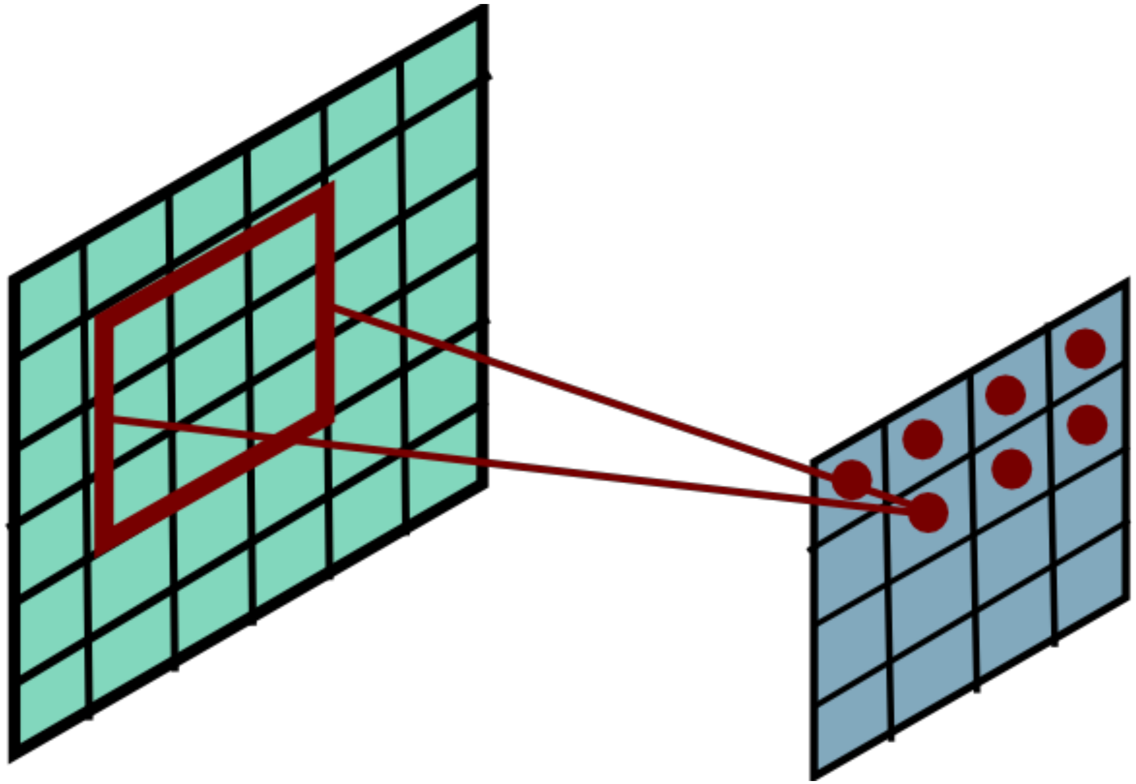

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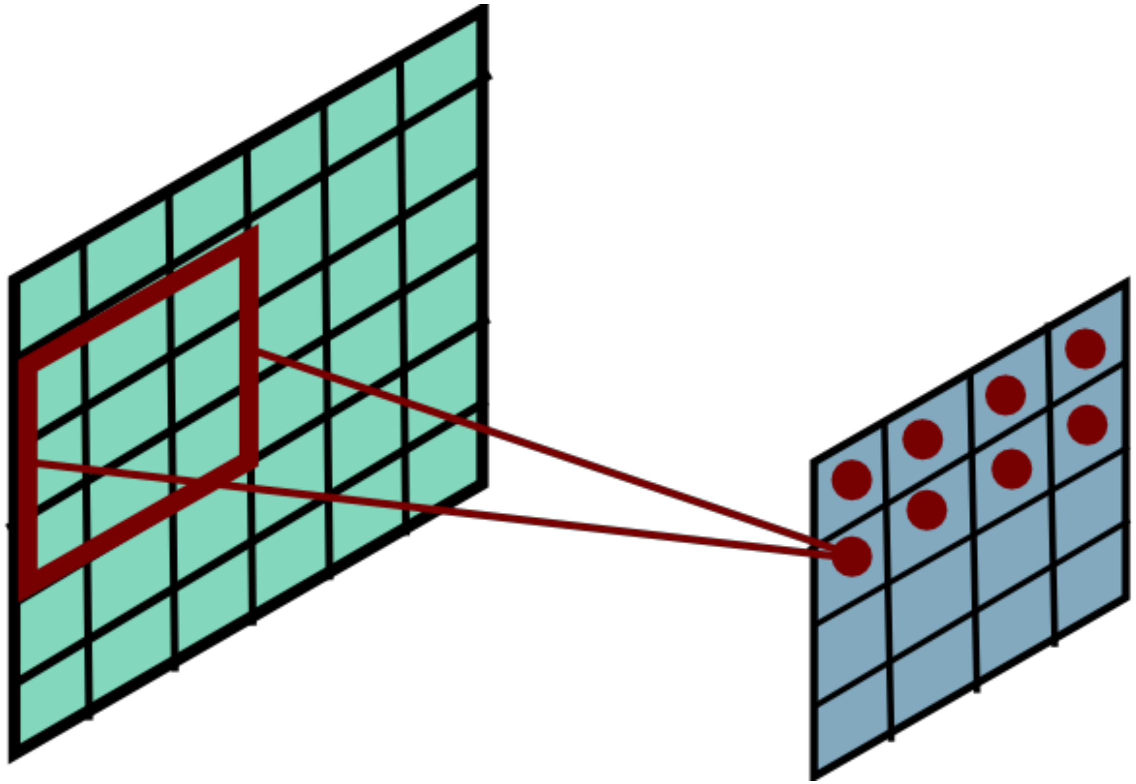

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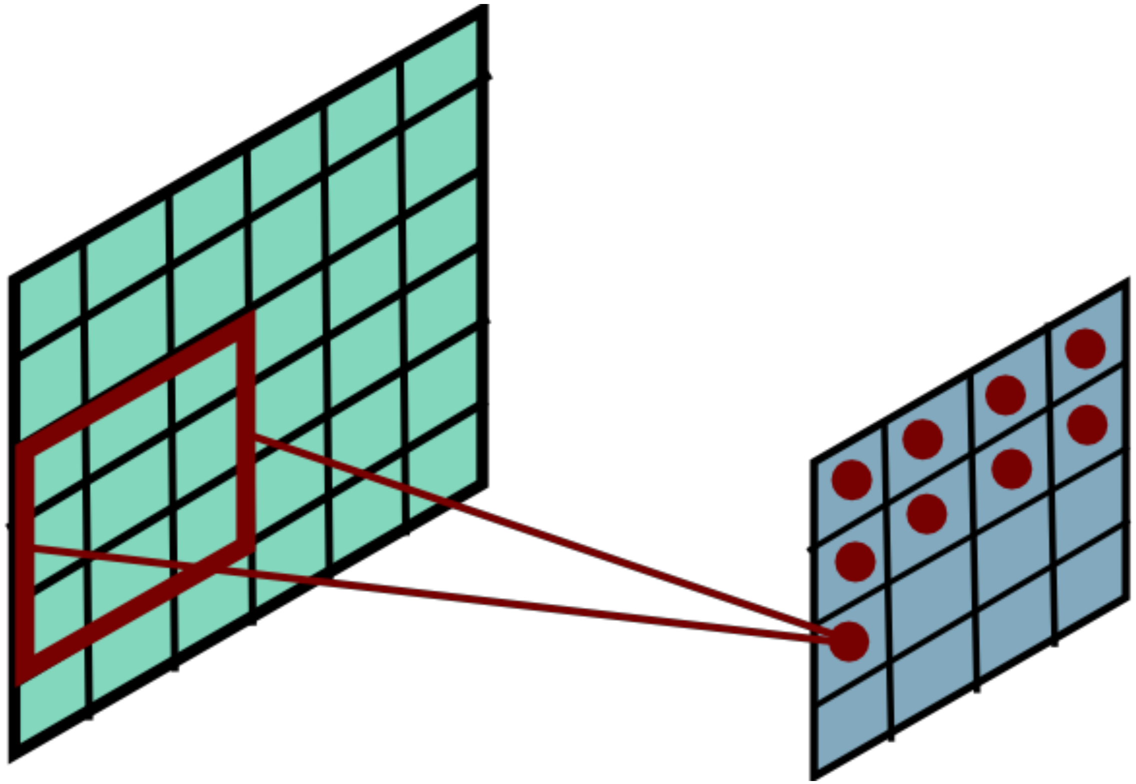

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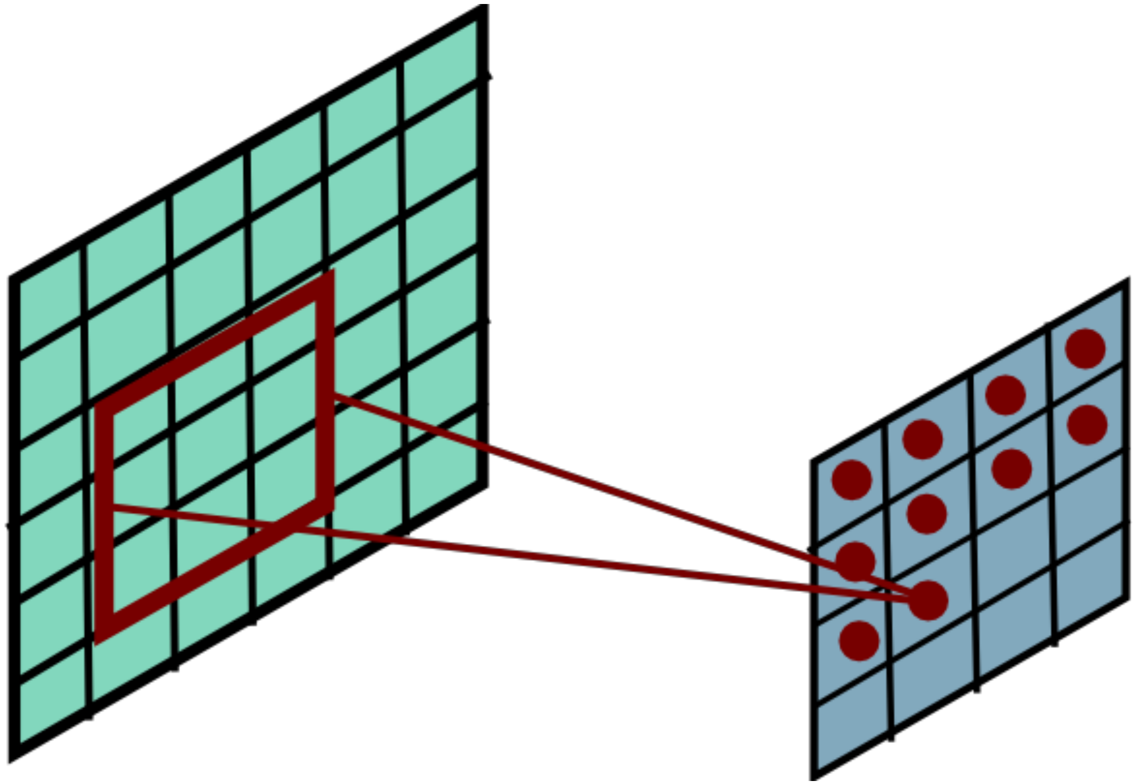

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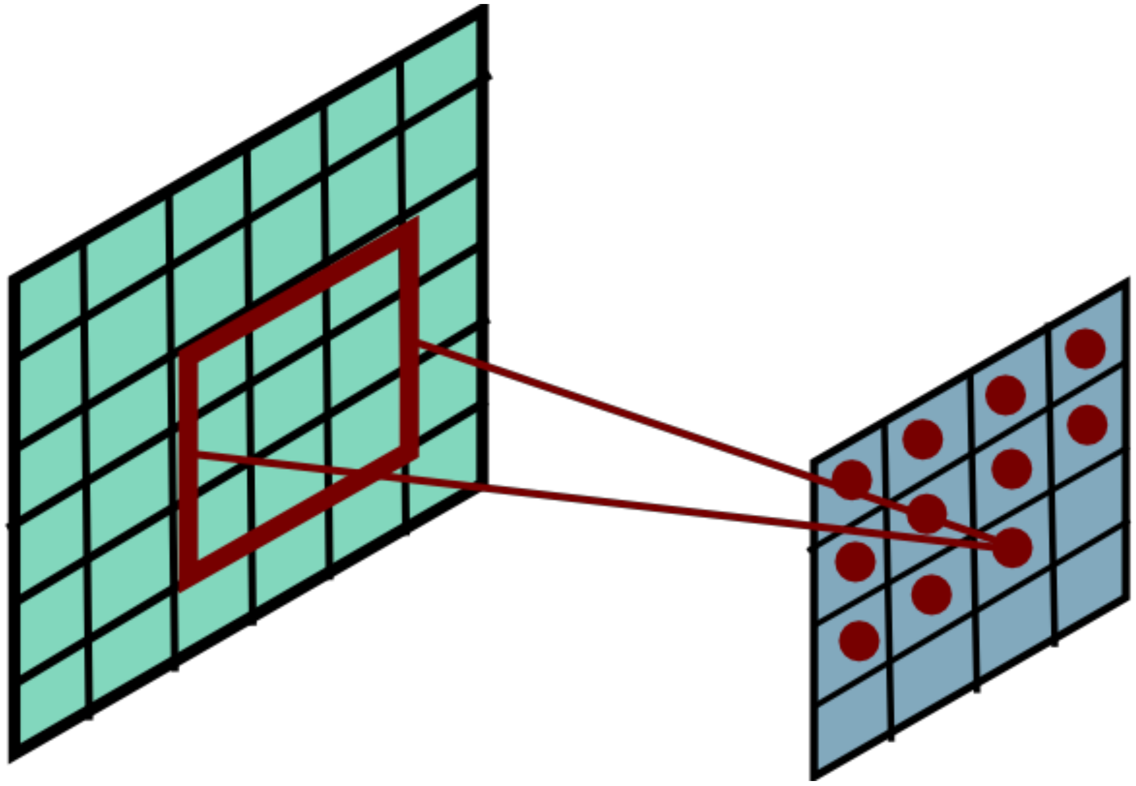

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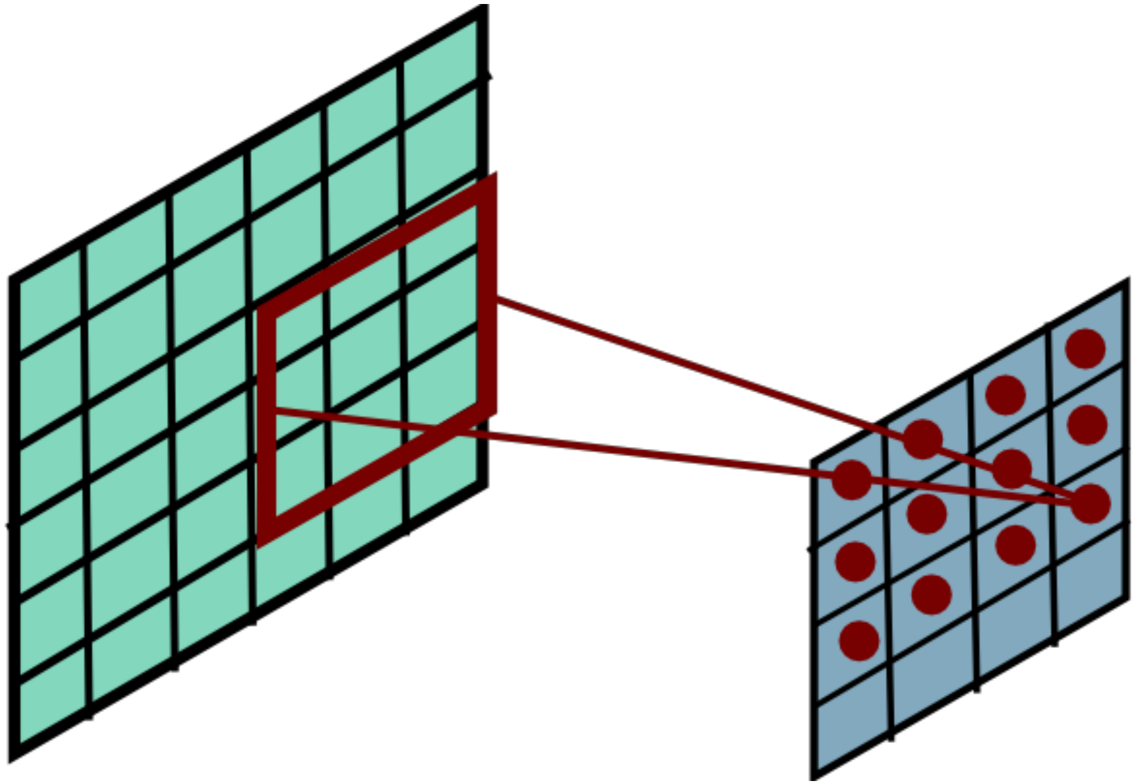

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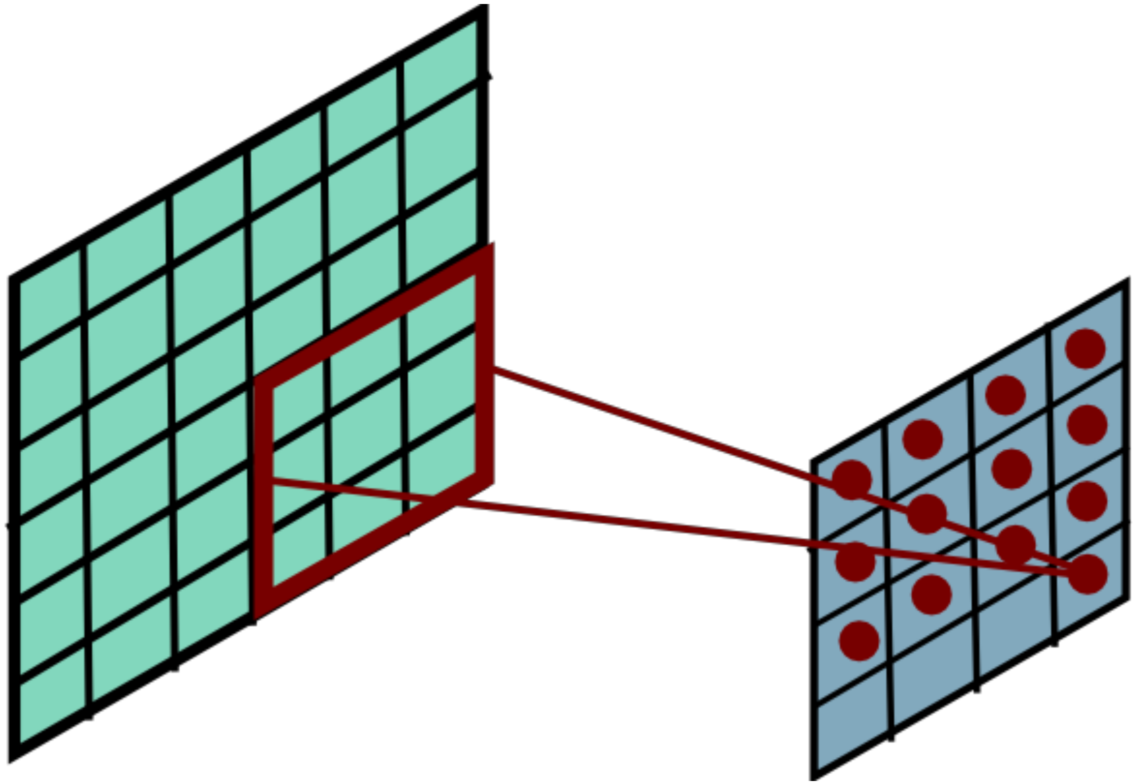

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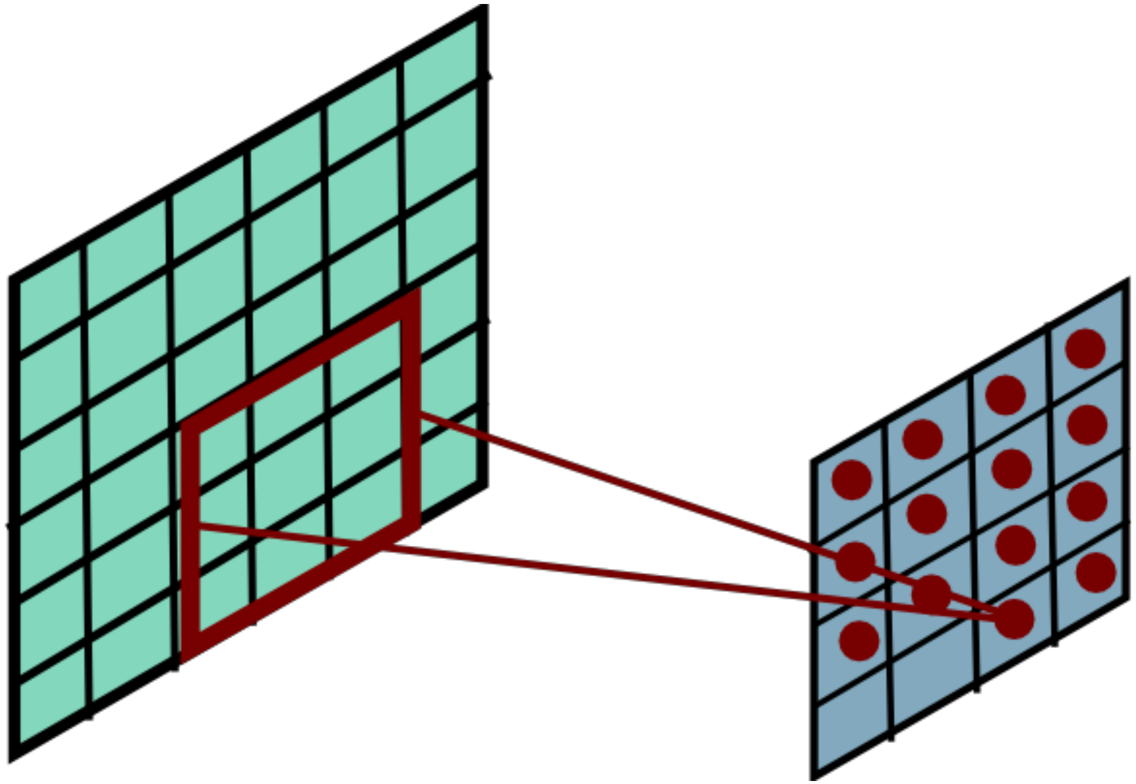

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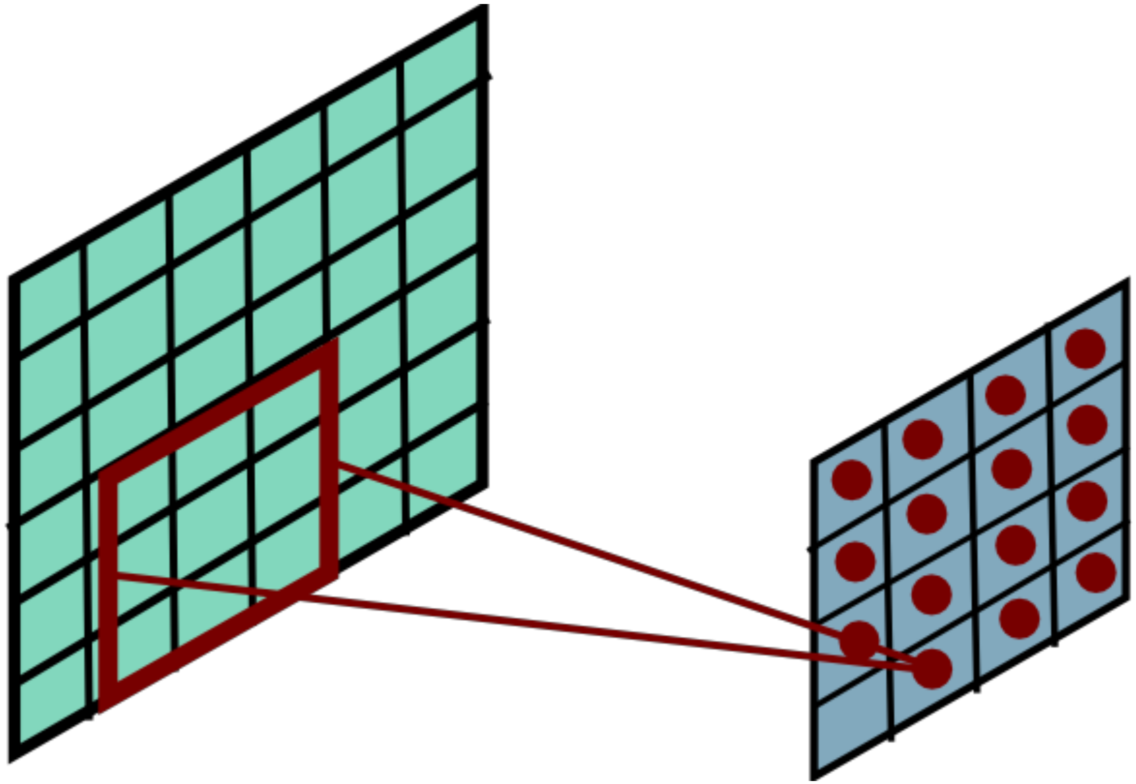

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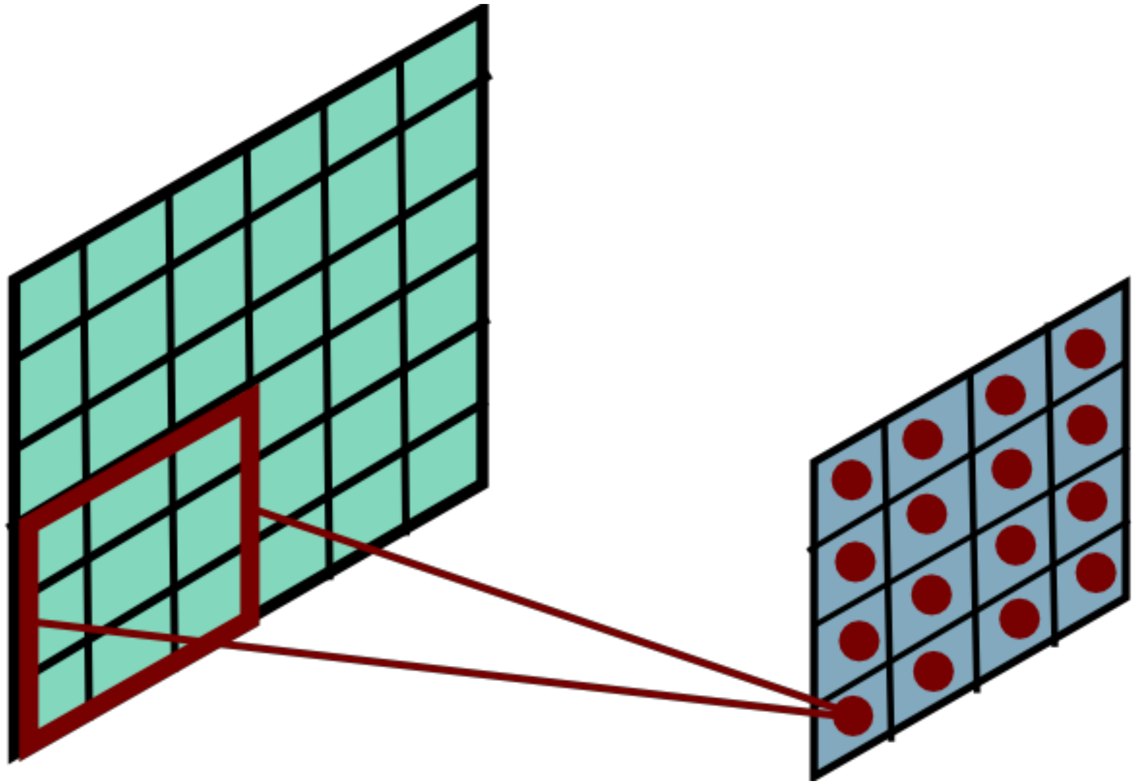
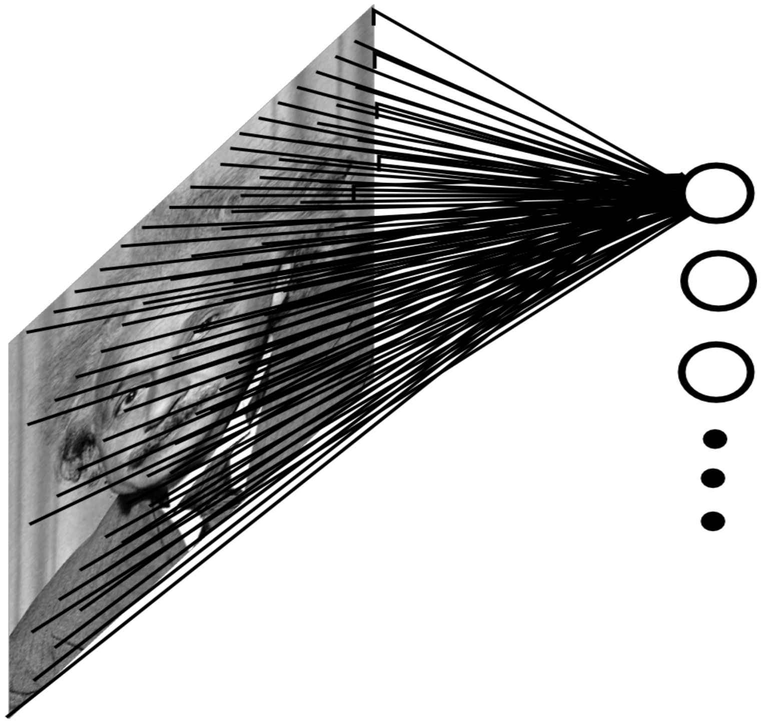


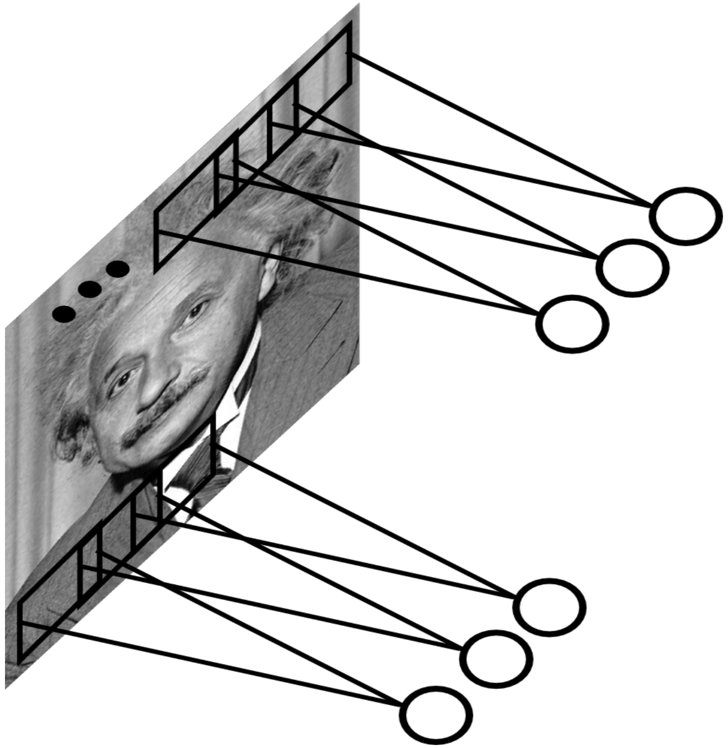
Fully-connected layer



#of parameters: K²

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} & w_{1,4} & \dots & w_{1,K} \\ w_{2,1} & w_{2,2} & w_{2,3} & w_{2,4} & \dots & w_{2,K} \\ w_{3,1} & w_{3,2} & w_{3,3} & w_{3,4} & \dots & w_{3,K} \\ w_{4,1} & w_{4,2} & w_{4,3} & w_{4,4} & \dots & w_{4,K} \\ & & \vdots & & & \\ w_{K,1} & w_{K,2} & w_{K,3} & w_{K,4} & \dots & w_{K,K} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \\ x_K \end{bmatrix}$$

Convolutional layer

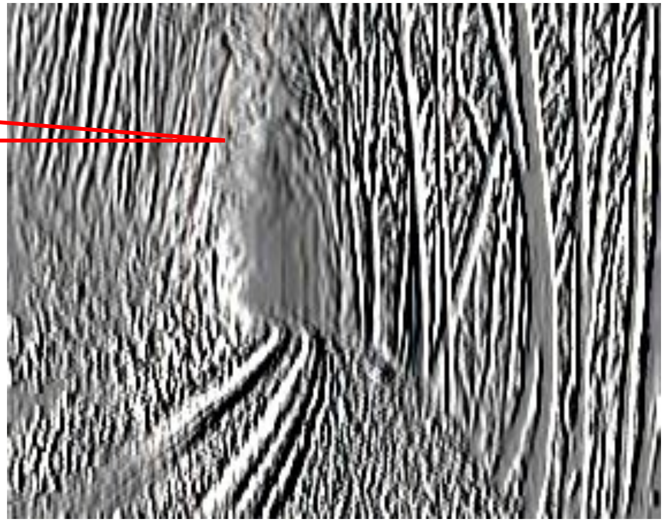


#of parameters: size of window

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} w_0 & w_1 & w_2 & 0 & \dots & 0 \\ 0 & w_0 & w_1 & w_2 & \dots & 0 \\ 0 & 0 & w_0 & w_1 & \dots & 0 \\ 0 & 0 & 0 & w_0 & \dots & 0 \\ & & \vdots & & & \\ 0 & 0 & 0 & 0 & \dots & w_0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ \vdots \\ x_K \end{bmatrix}$$

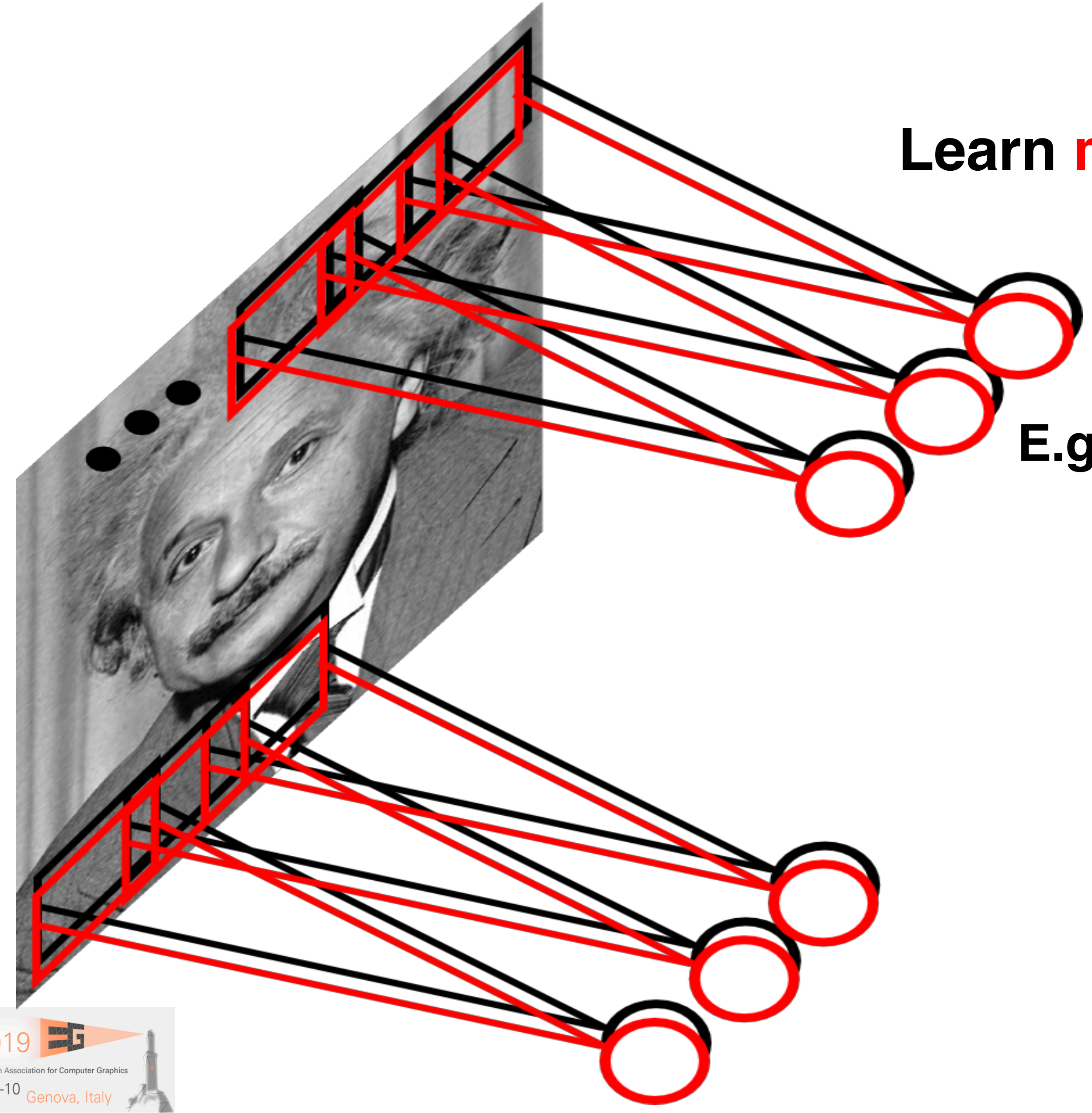
Convolutional layer

$$* \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} =$$



Learning an edge filter

Convolutional layer



Learn **multiple filters.**

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters

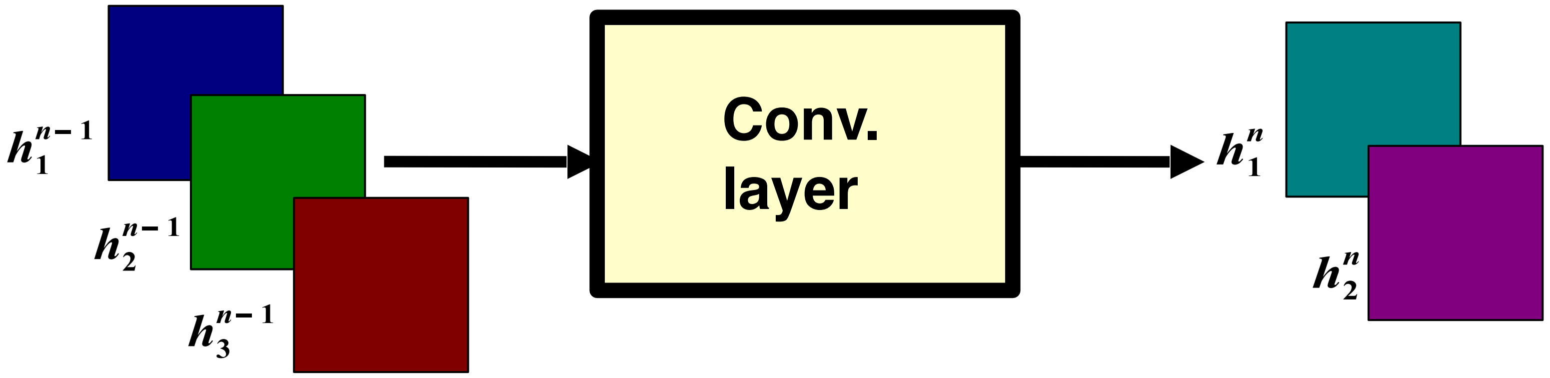
Convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n \right\}$$

output feature map

input feature map

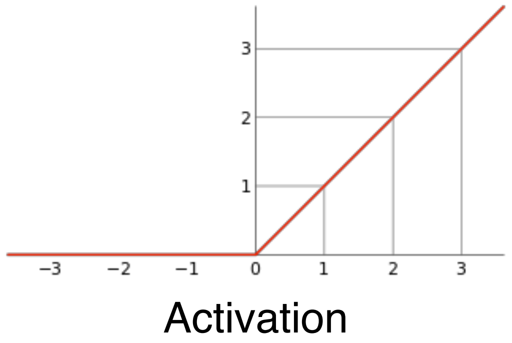
kernel

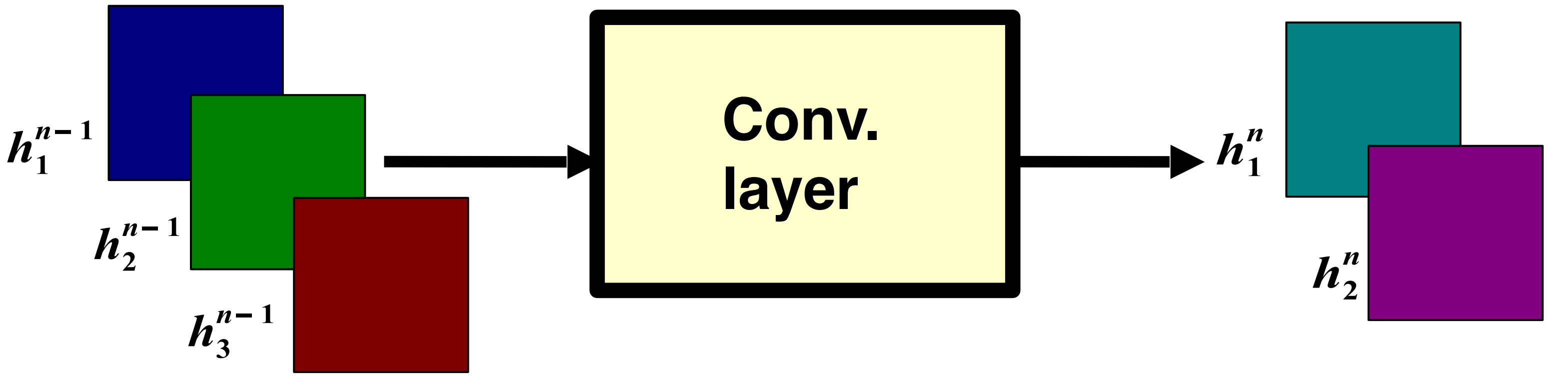


Convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n\right\}$$

output feature map **ReLU** **input feature map** **kernel**





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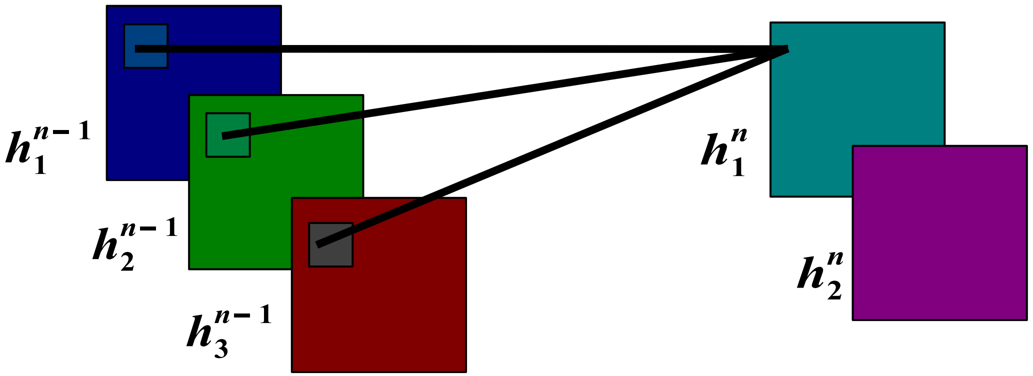

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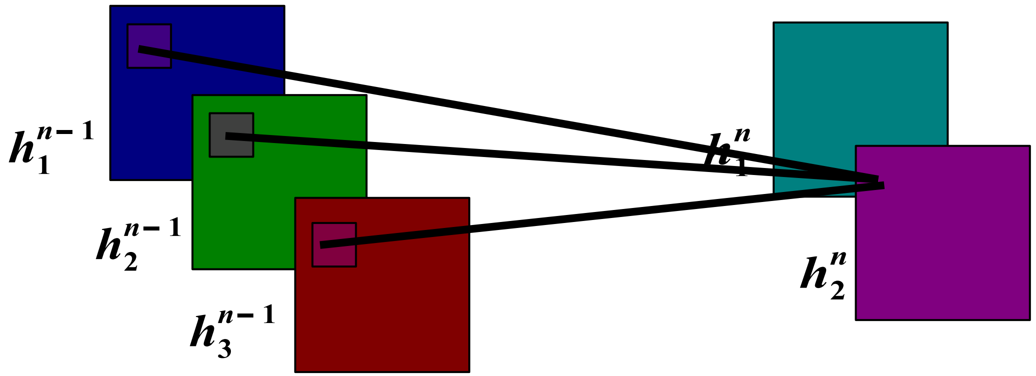
output feature map

input feature map

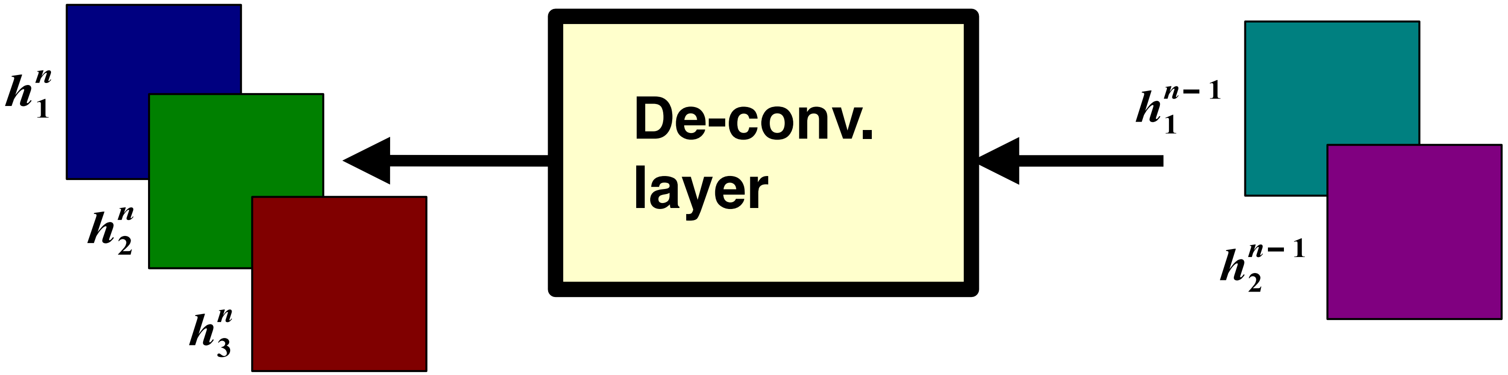
kernel



De-convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n\right\}$$

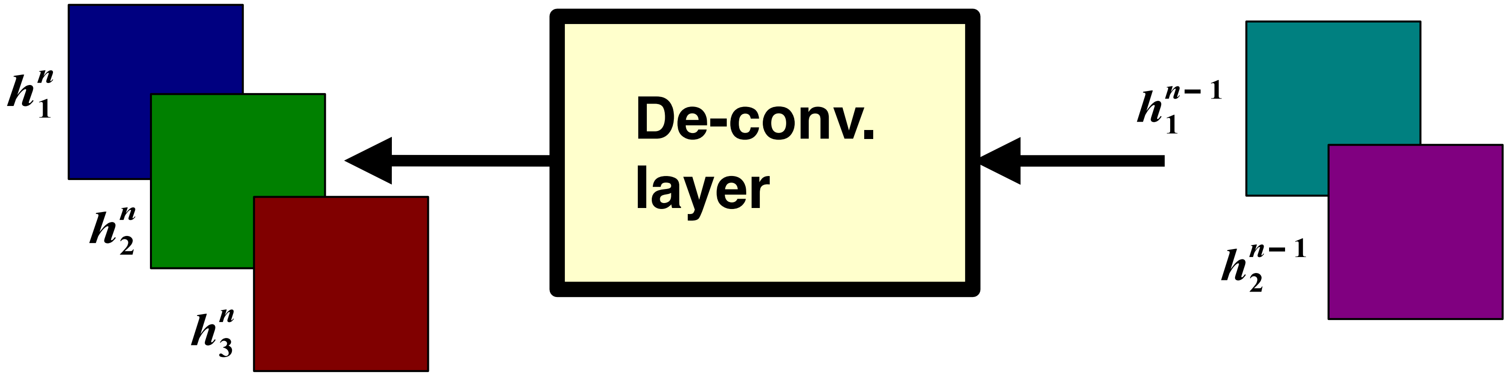
Still holds, same structure



De-convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n\right\}$$

Still holds, same structure

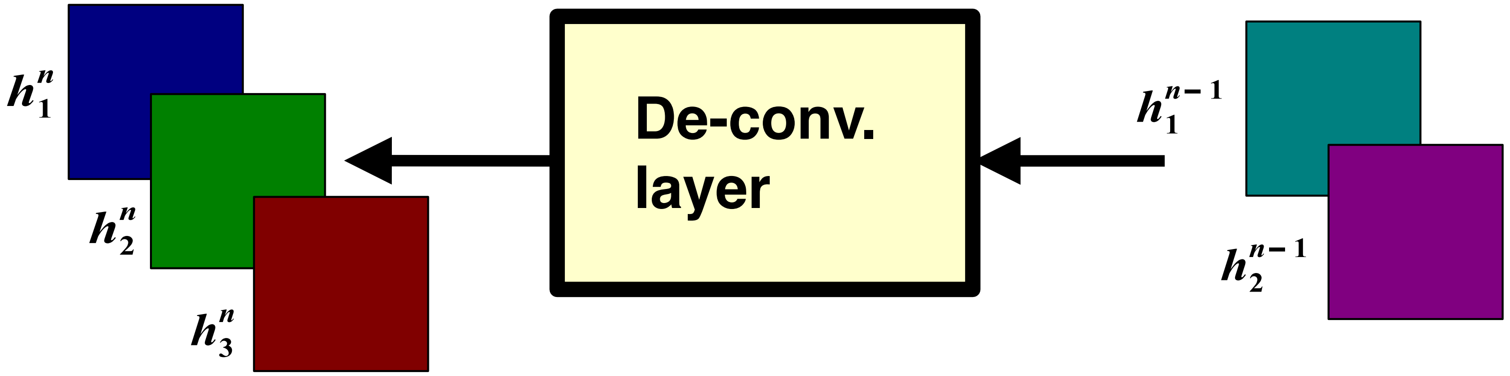


No real inverse - but convolutions can easily go the other way

De-convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n\right\}$$

Still holds, same structure



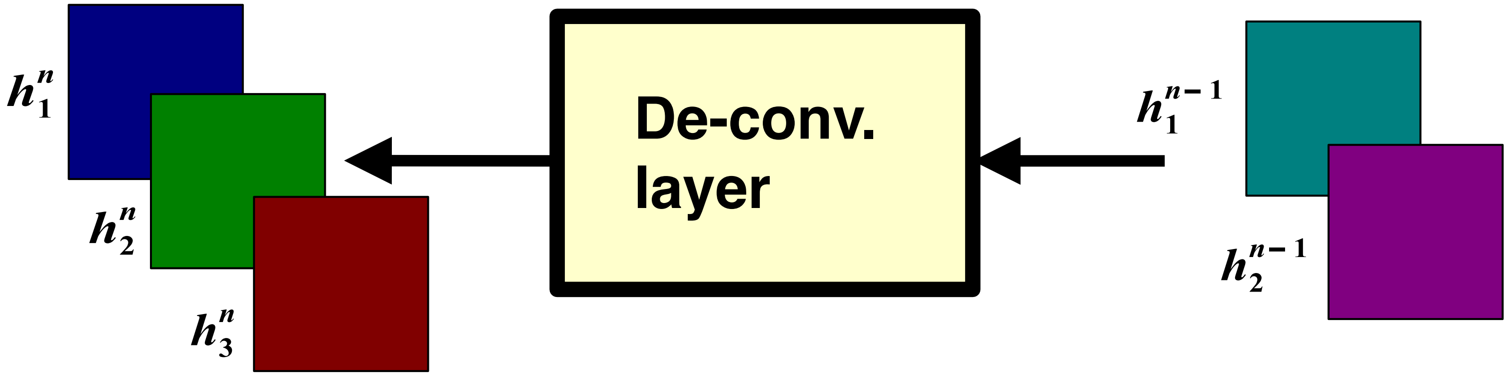
No real inverse - but convolutions can easily go the other way

"De-convolution" or "Transposed convolution"

De-convolutional layer with ReLU activation

$$h_i^n = \max\left\{0, \sum_{j=1}^{\#\text{input channels}} h_j^{n-1} * w_{ij}^n\right\}$$

Still holds, same structure

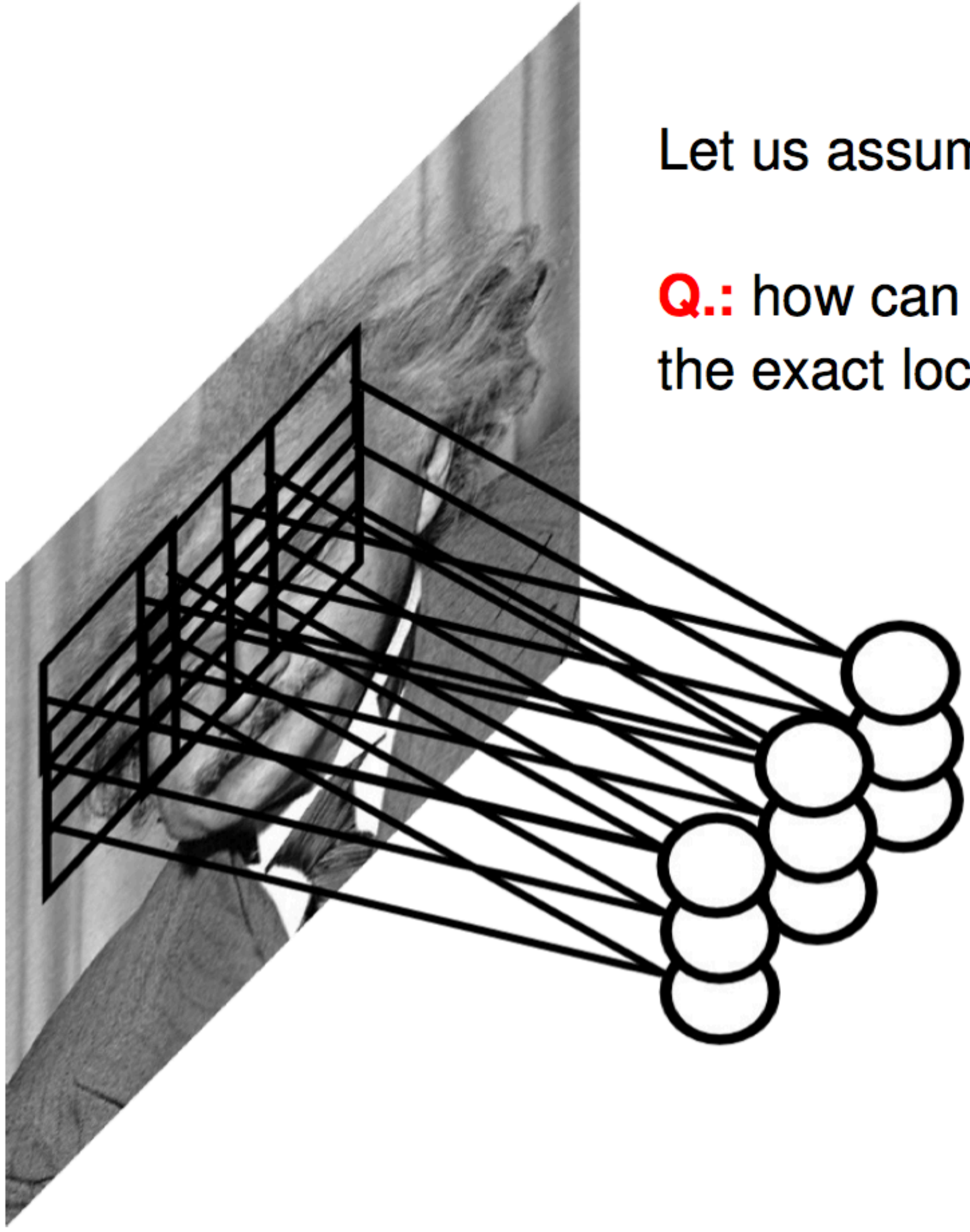


No real inverse - but convolutions can easily go the other way

“De-convolution” or “Transposed convolution”

Also a convolution with transposed weight tensor

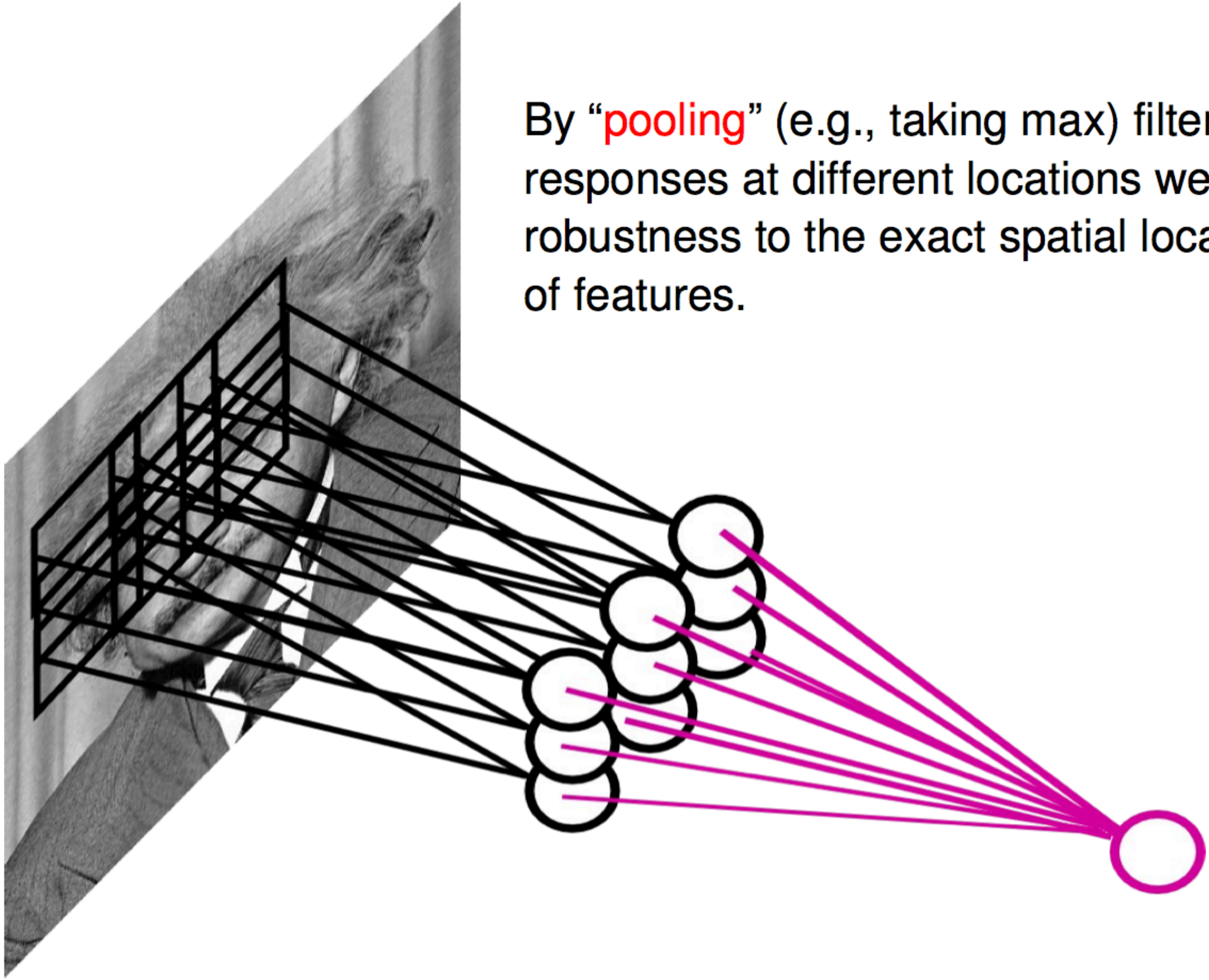
Pooling layer



Let us assume filter is an “eye” detector.

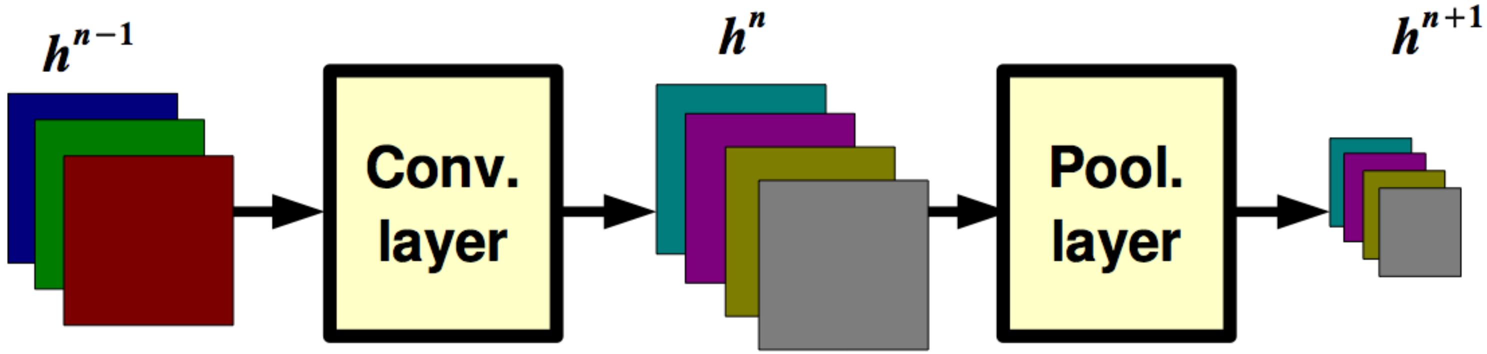
Q.: how can we make the detection robust to the exact location of the eye?

Pooling layer

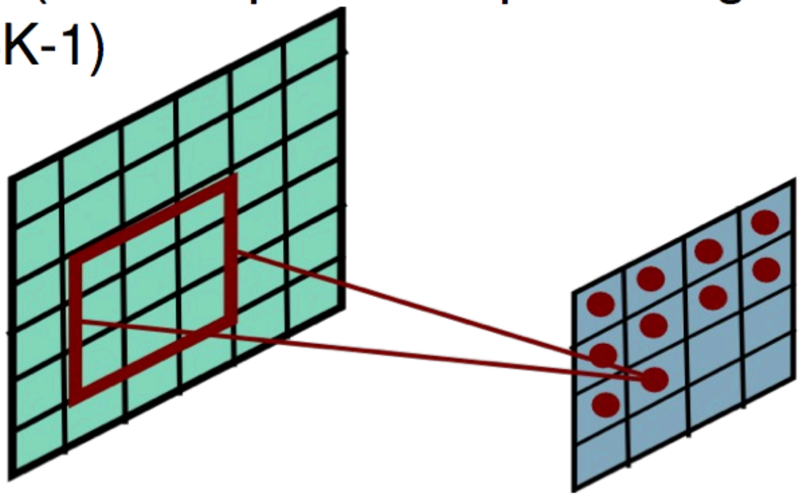


By “pooling” (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.

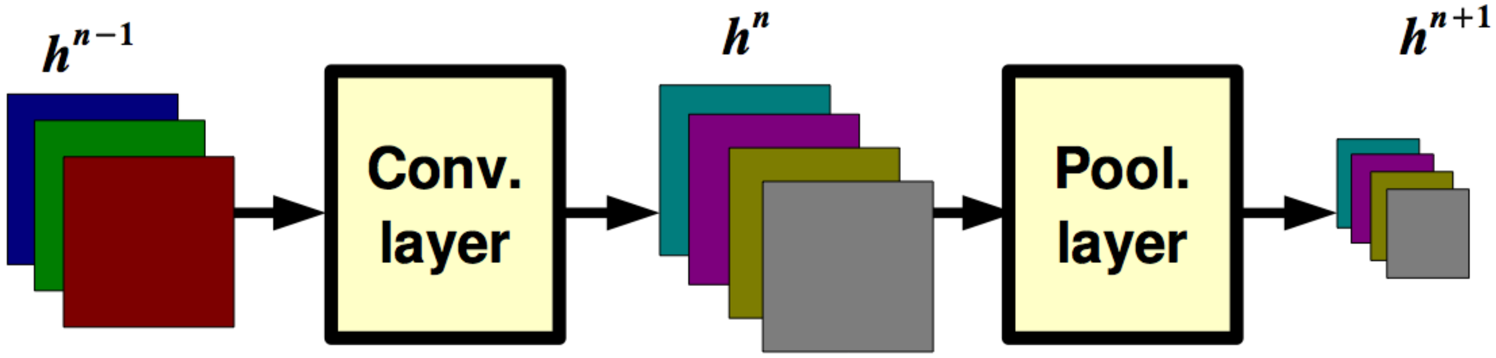
Pooling layer: receptive field size



If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: (P+K-1)x(P+K-1)



Pooling layer: receptive field size



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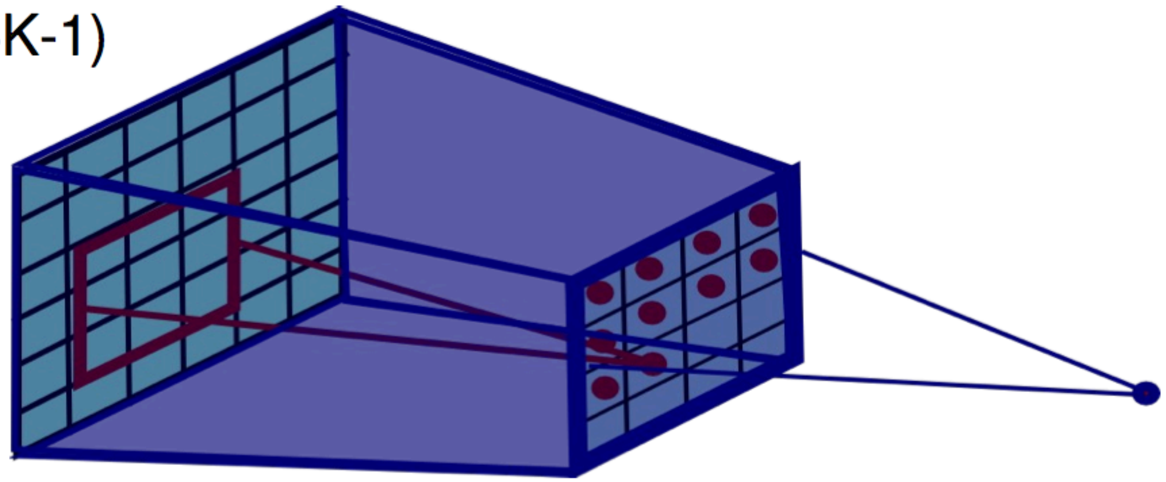


Receptive field

Receptive field: layer 1

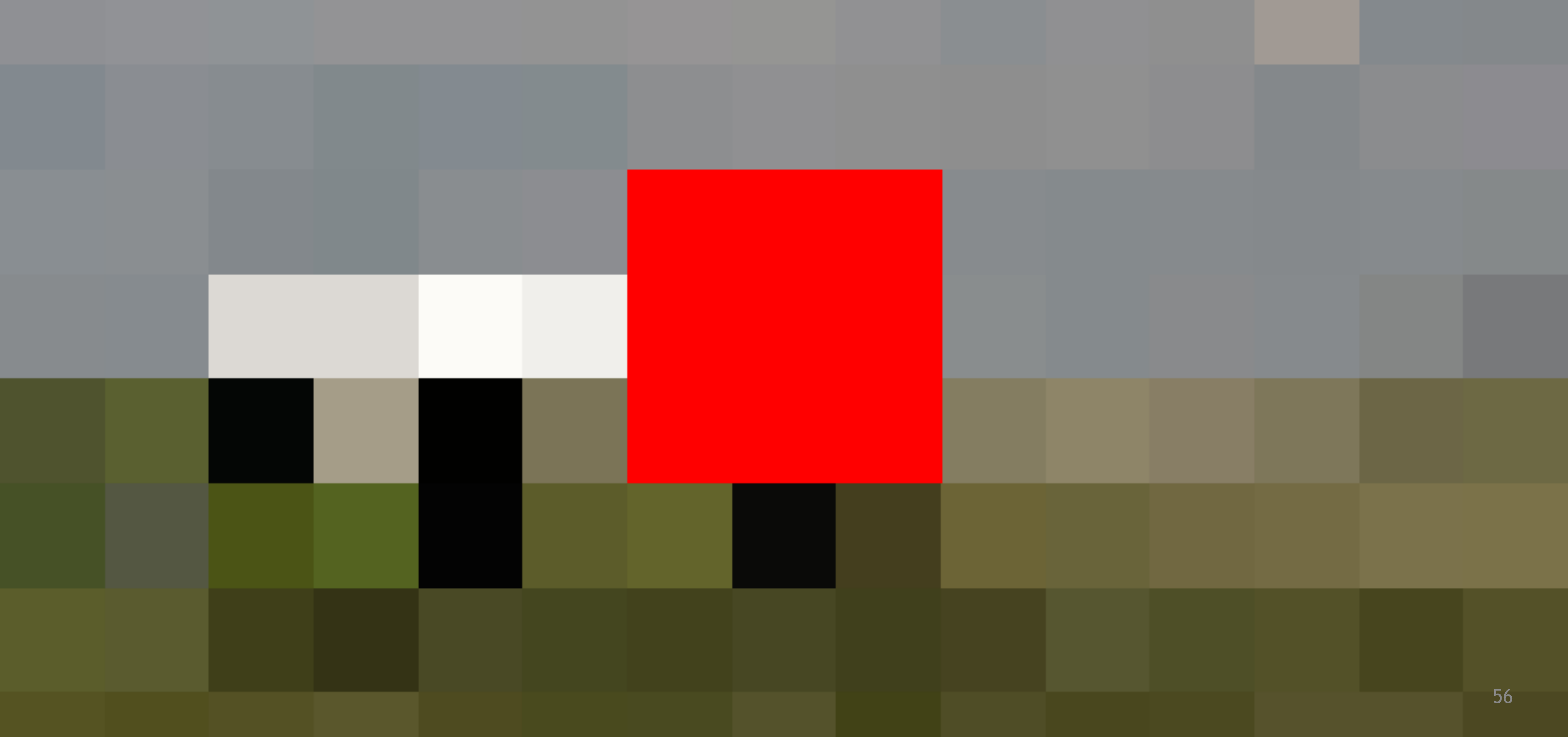
Receptive field: layer 2

Receptive field: layer 3

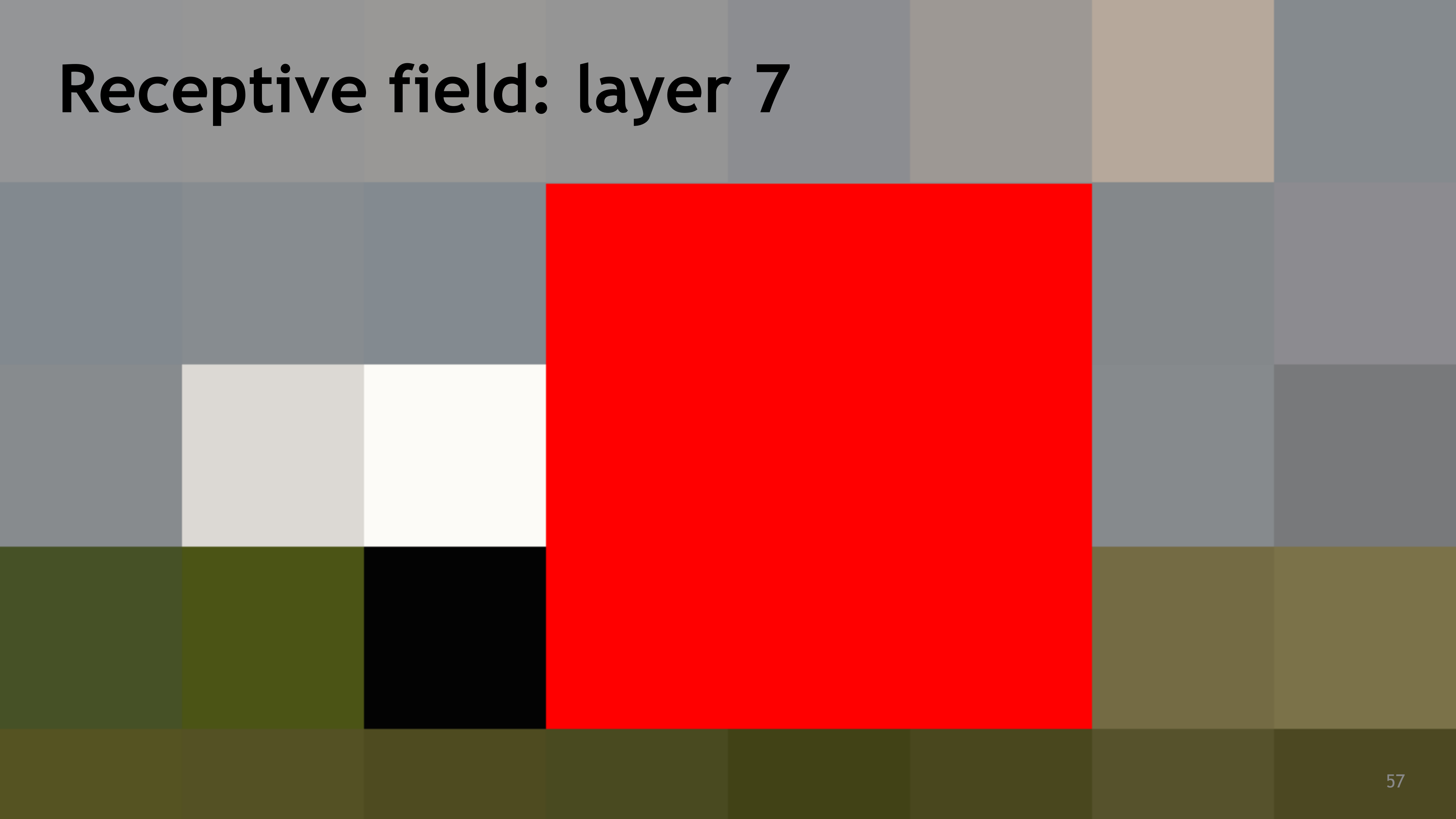
Receptive field: layer 4

Receptive field: layer 5

Receptive field: layer 6



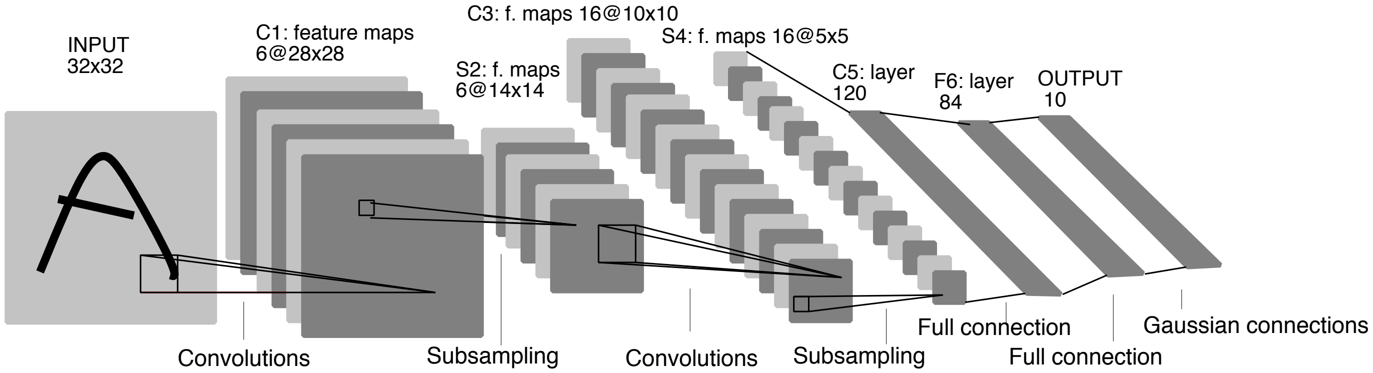
Receptive field: layer 7



Receptive field: layer 8

Modern Architectures

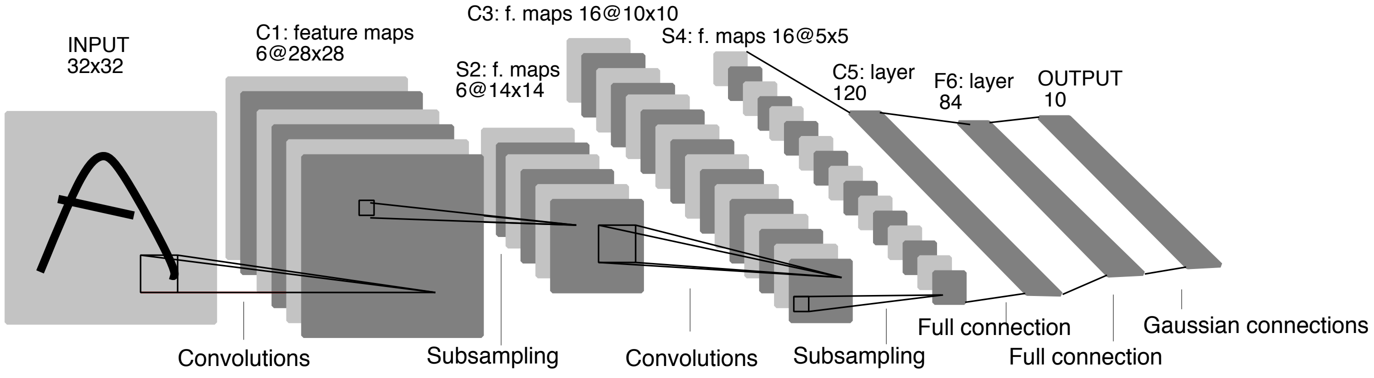
CNNs, late 1980's: LeNet



https://www.youtube.com/watch?v=FwFduRA_L6Q

Gradient-based learning applied to document recognition,
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, 1998.

CNNs, late 1980's: LeNet



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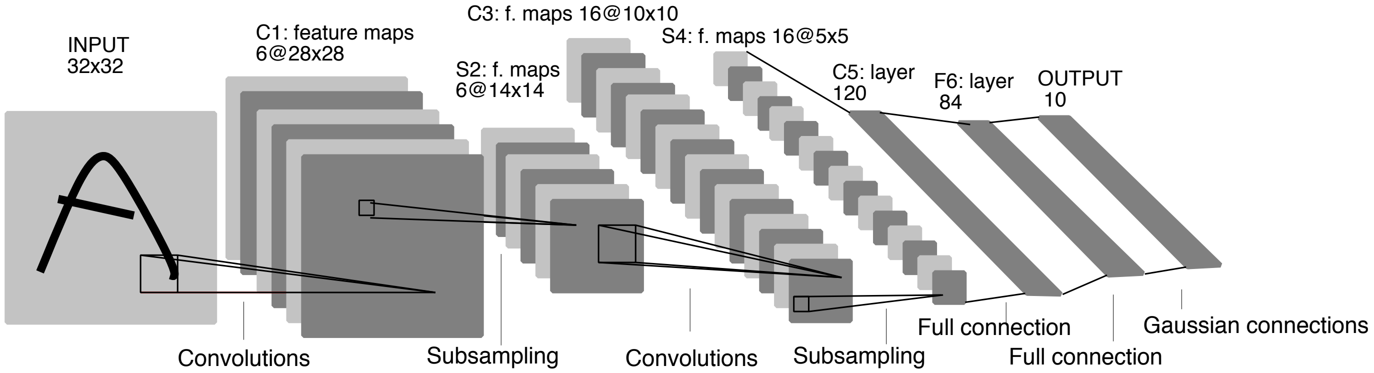

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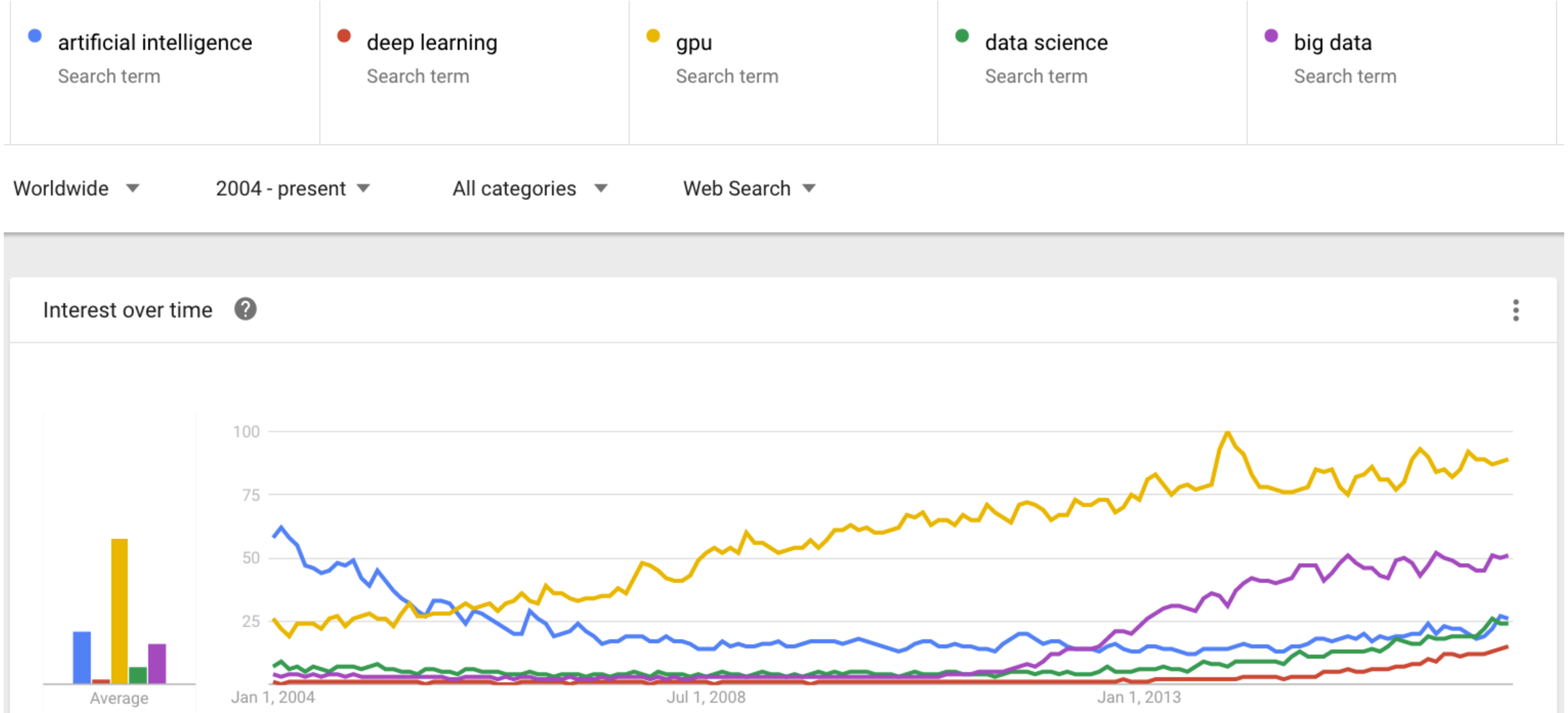
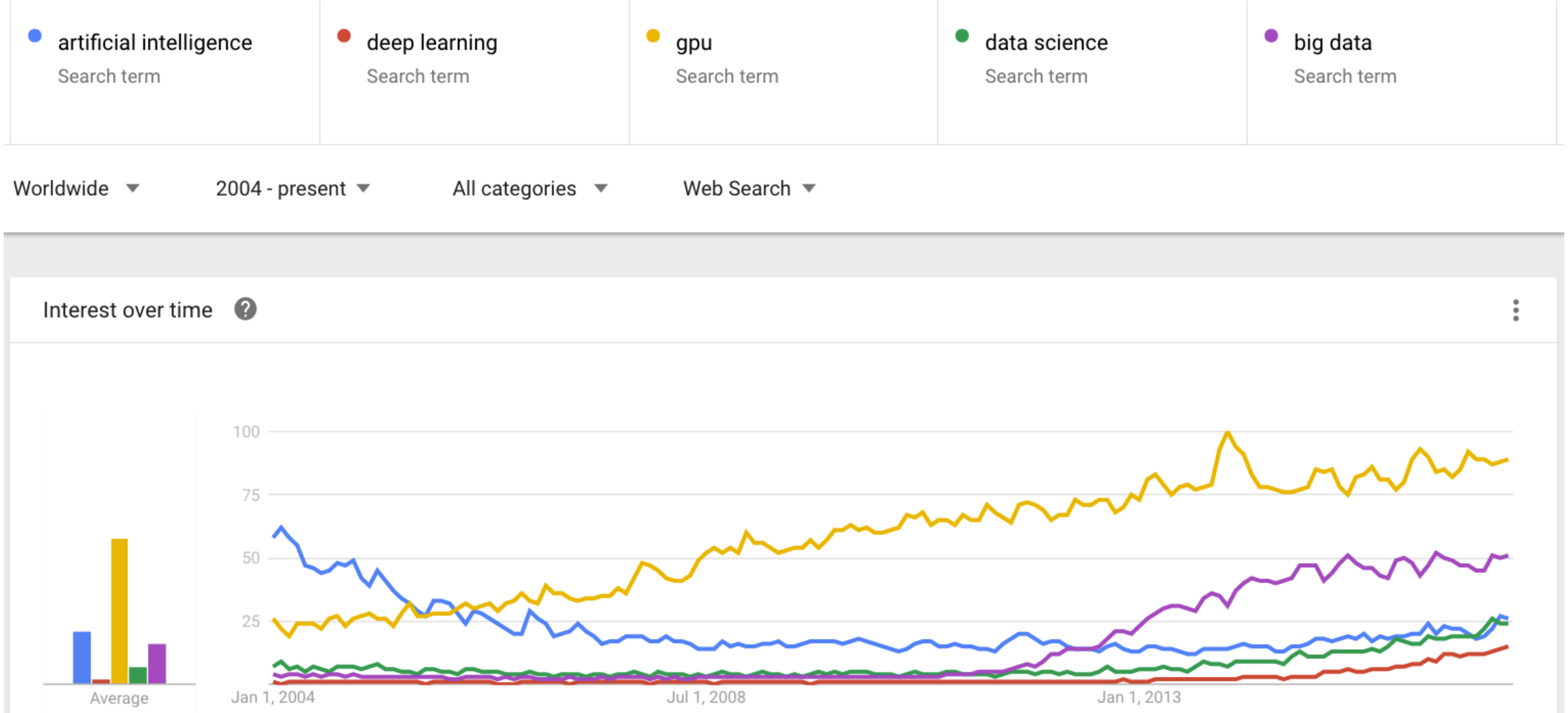
Gradient-based learning applied to document recognition,
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, 1998.

What happened in between?

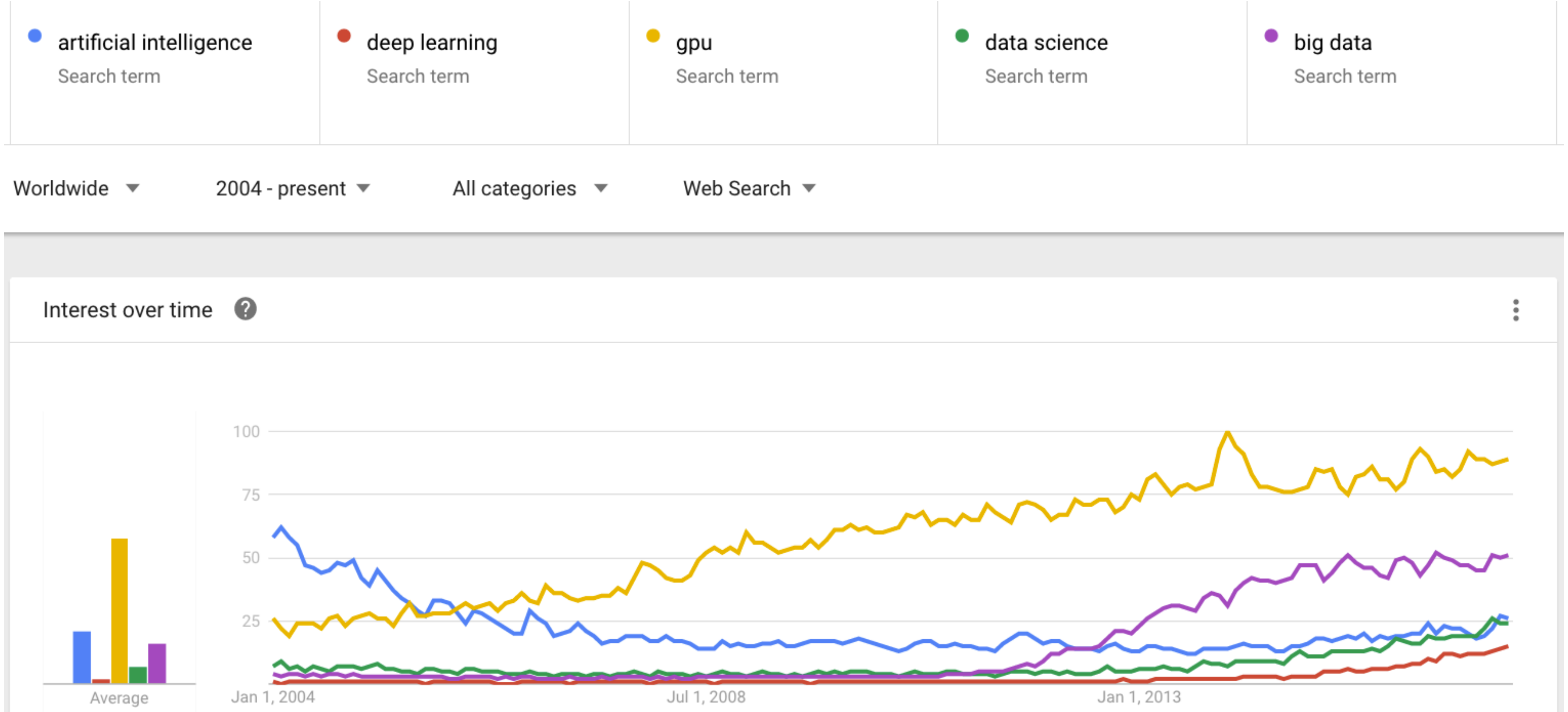


What happened in between?



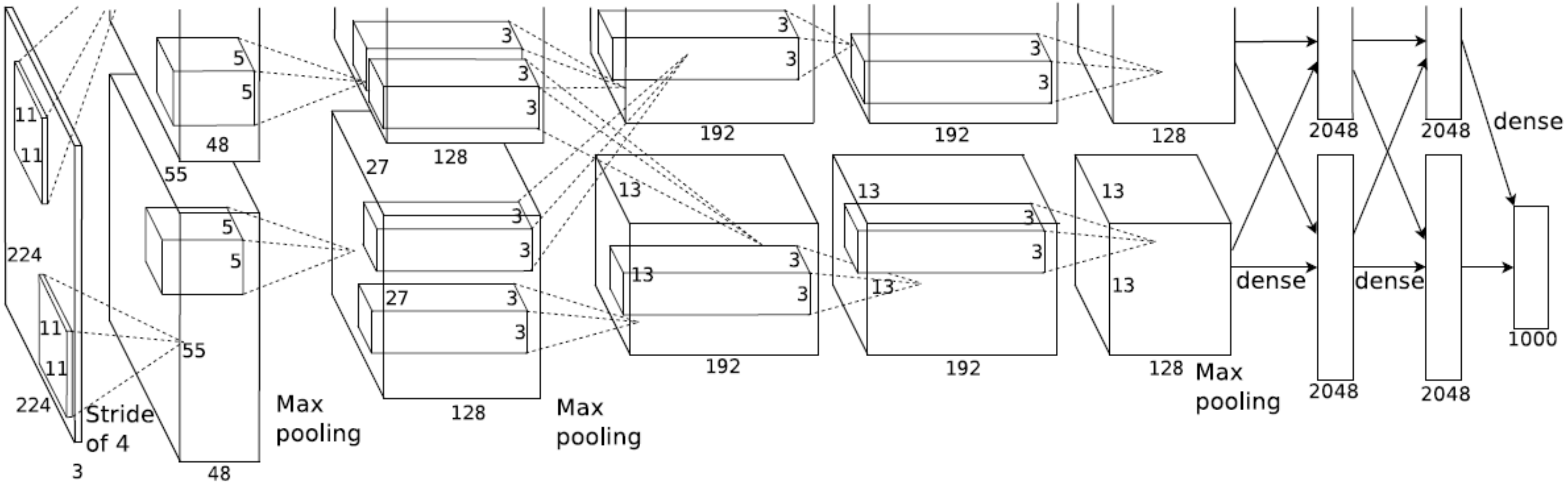
deep learning = neural networks (+ big data + GPUs)

What happened in between?



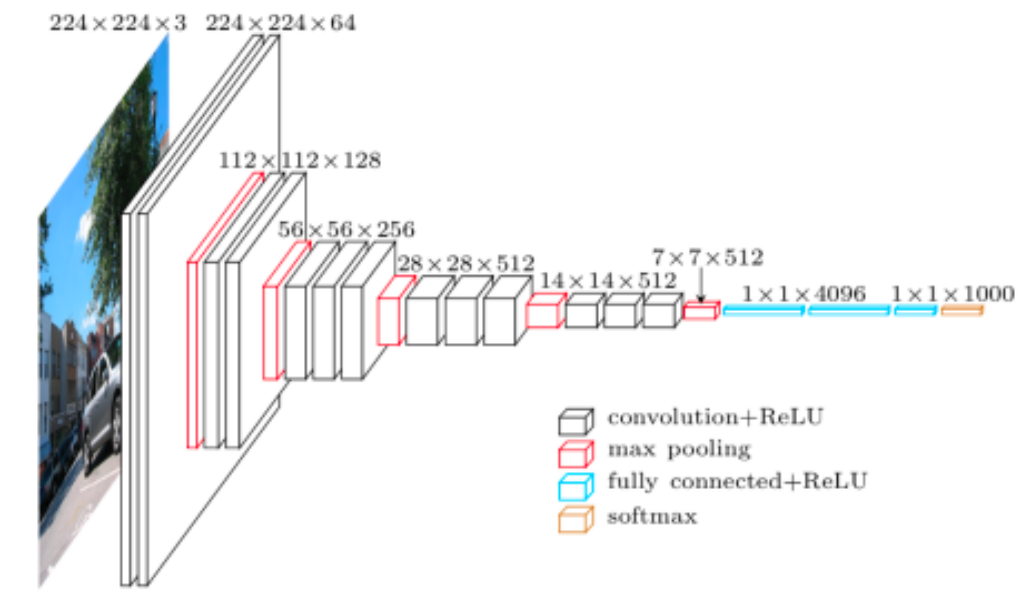
deep learning = neural networks (+ big data + GPUs) **+ a few more recent tricks!**

CNNs, 2012



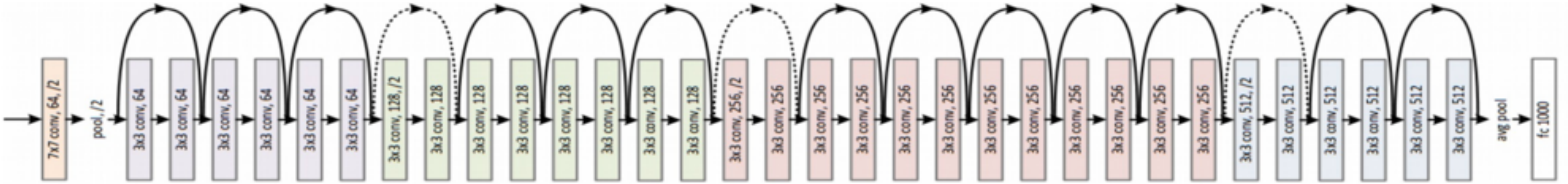
AlexNet
Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton: ImageNet classification with deep convolutional neural networks. Commun. ACM 60(6): 84-90 (2017)

CNNs, 2014: VGG



VGG
Karen Simonyan, Andrew Zisserman (=Visual Geometry Group)
Very Deep Convolutional Networks for Large-Scale Image Recognition, arxiv, 2014.

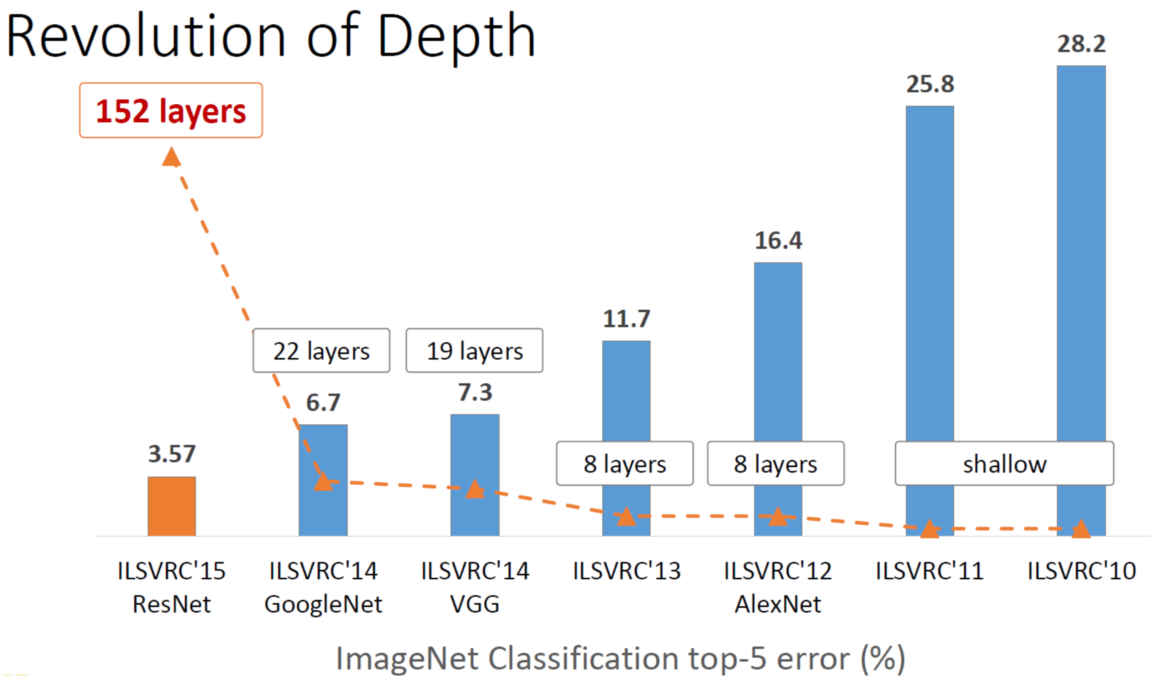
CNNs, 2015: ResNet



ResNet
Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun,
Deep Residual Learning for Image Recognition, CVPR 2016.

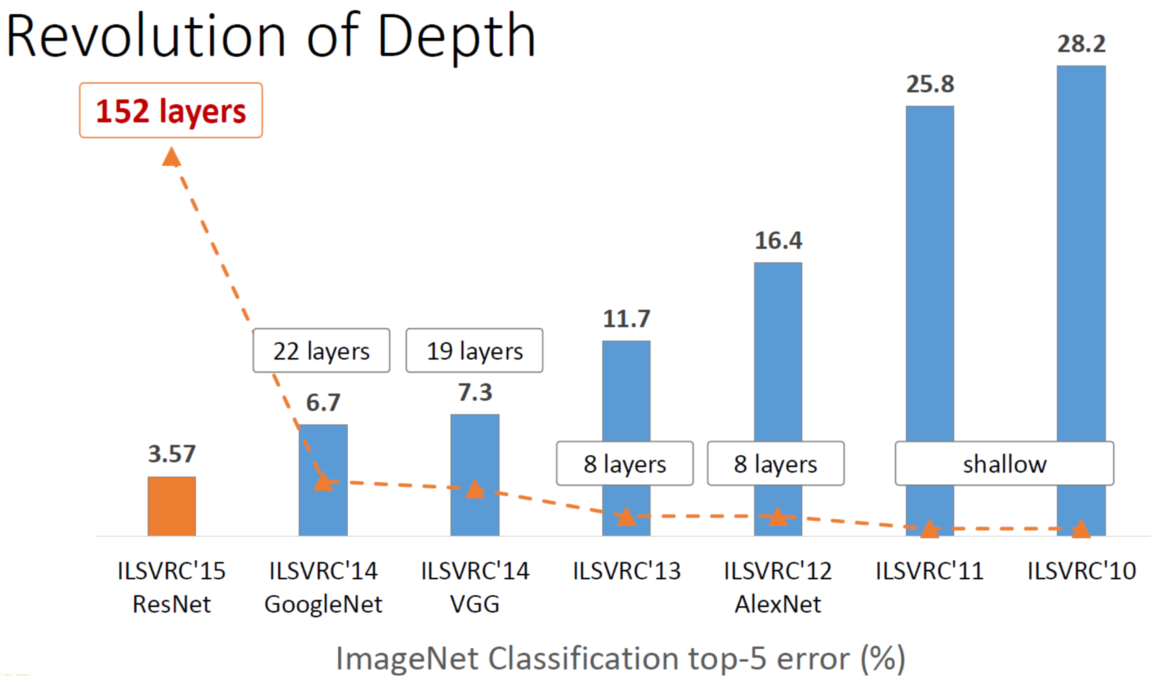
Going Deeper - The Deeper, the Better

- Deeper networks can cover more complex problems
  - Increasingly large receptive field size & rich patterns



Going Deeper

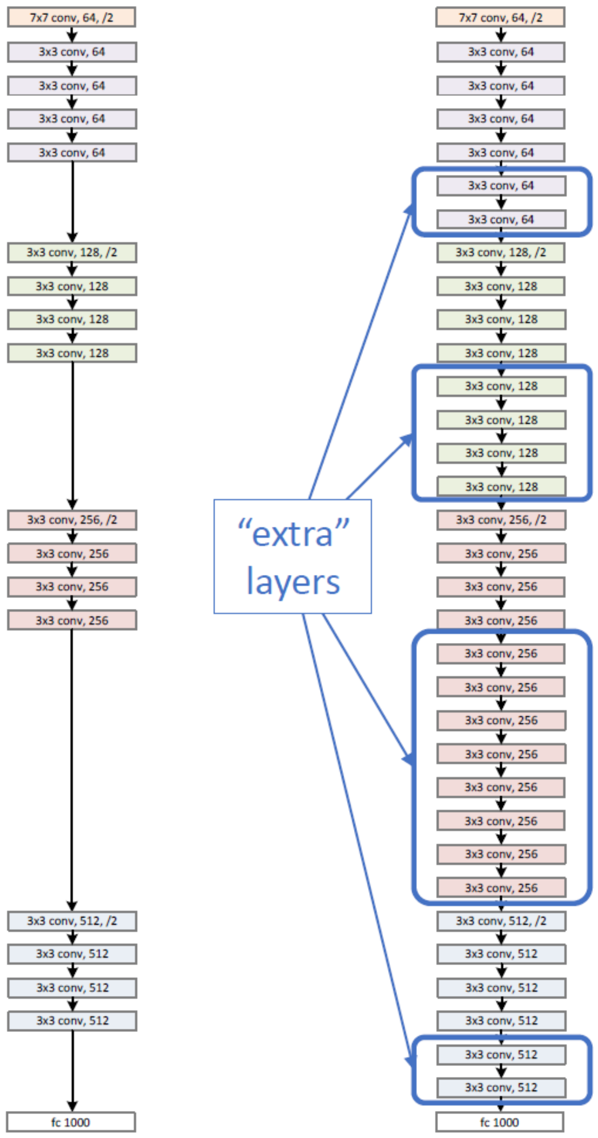
- From 20 to 100/1000
  - Residual networks



Residual Network

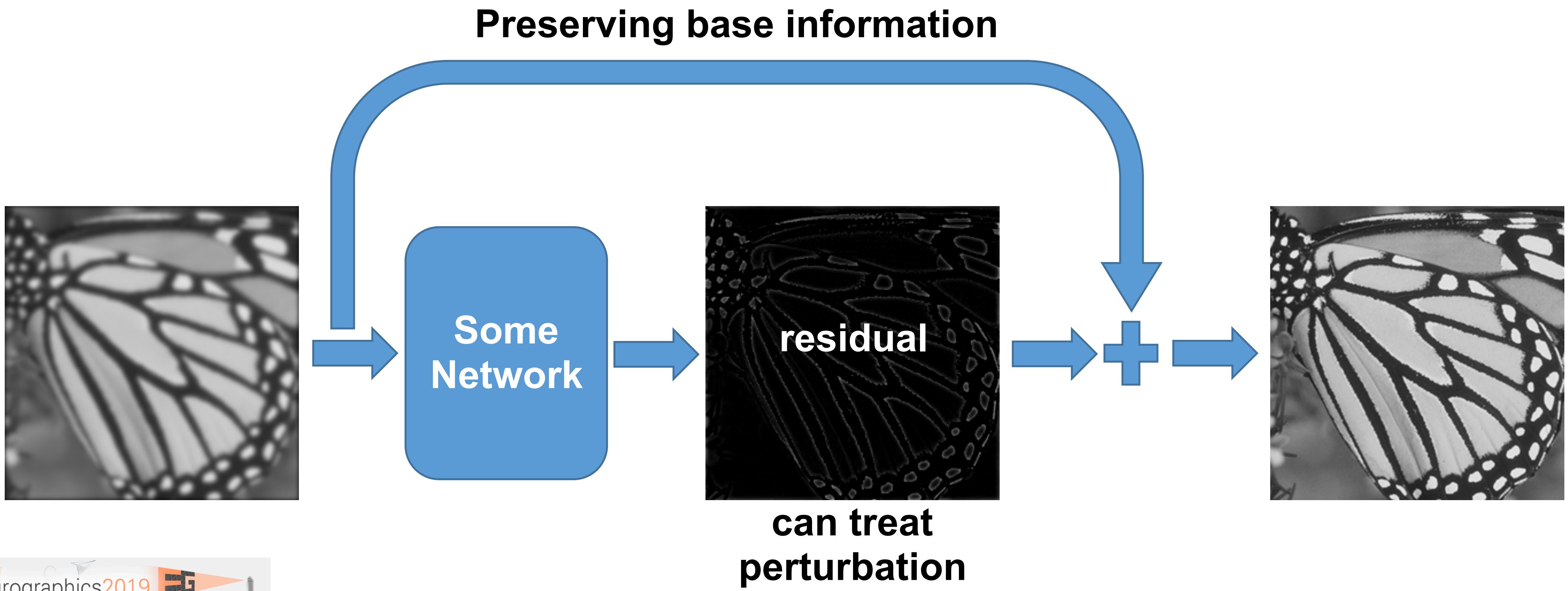
Naïve solution

- If extra layers are an identity mapping, the not increase



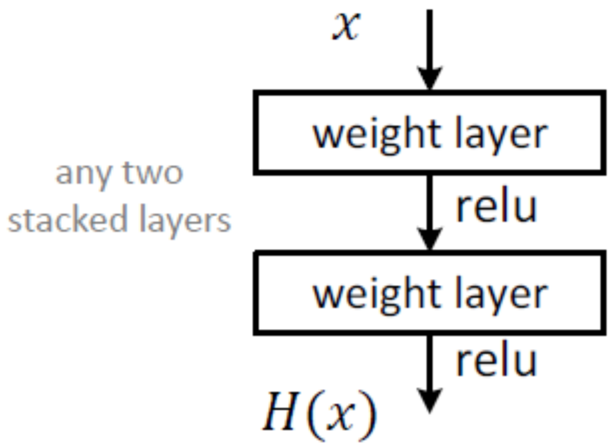
Residual Modelling: Basic idea in image processing

- Goal: estimate update between an original image and a changed image



Residual Network

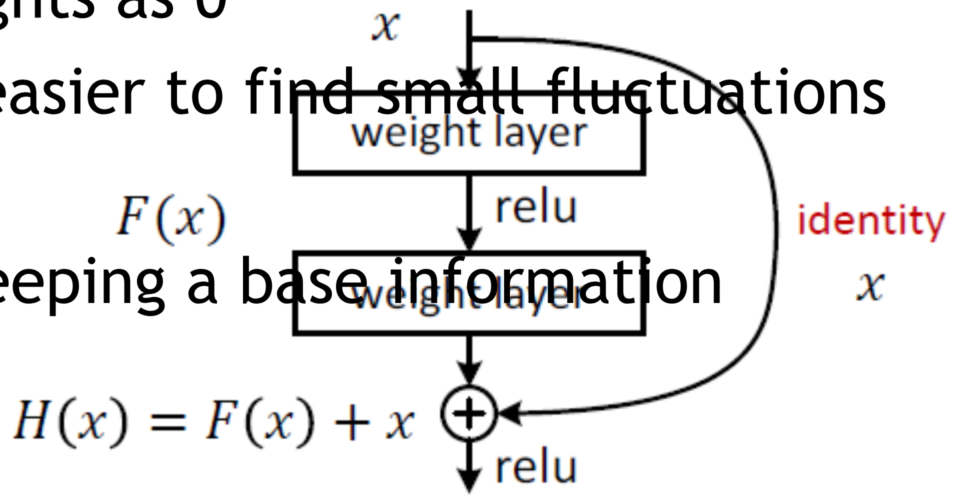
- Plain block
  - Difficult to make identity mapping because of multiple non-linear layers



Residual Network

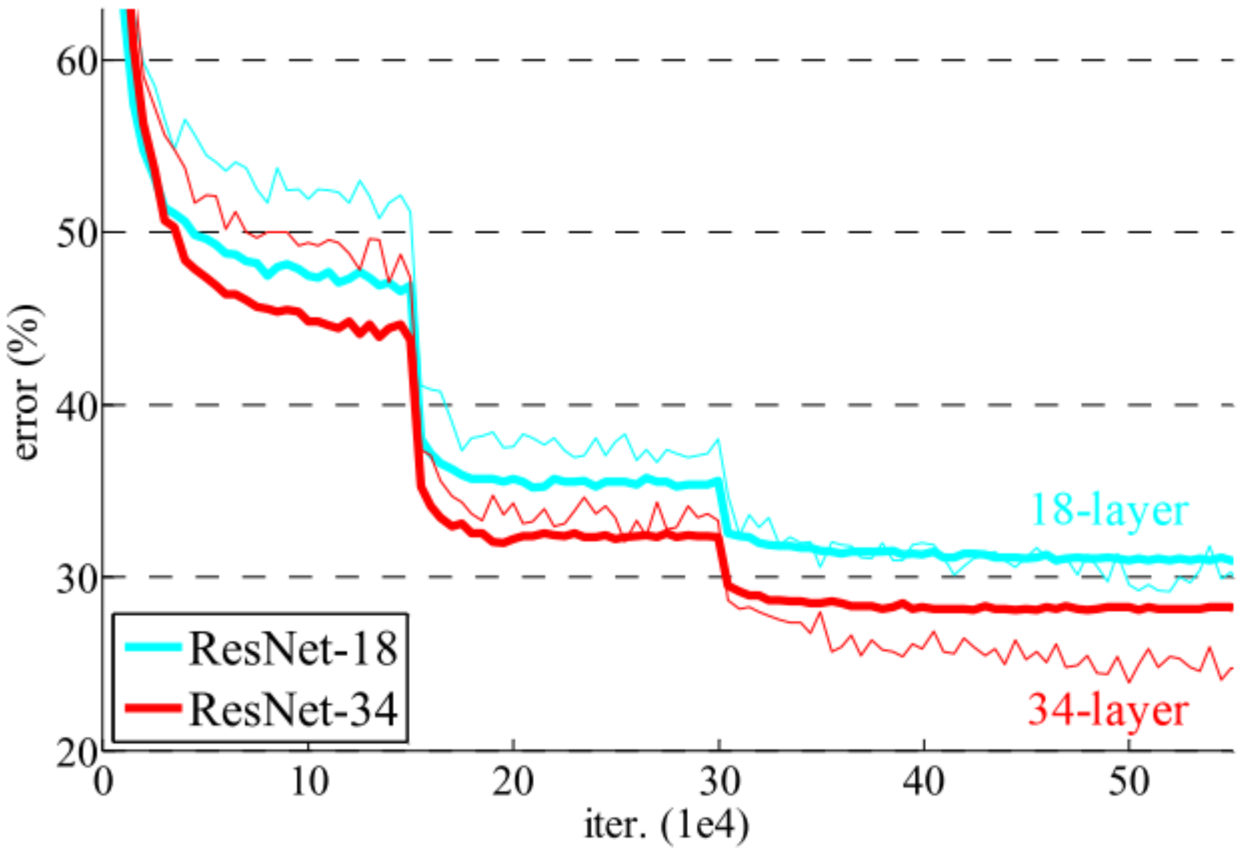
- Residual block
  - If identity were optimal, easy to set weights as 0
  - If optimal mapping is closer to identity, easier to find small fluctuations

Appropriate for treating perturbation as keeping a base information

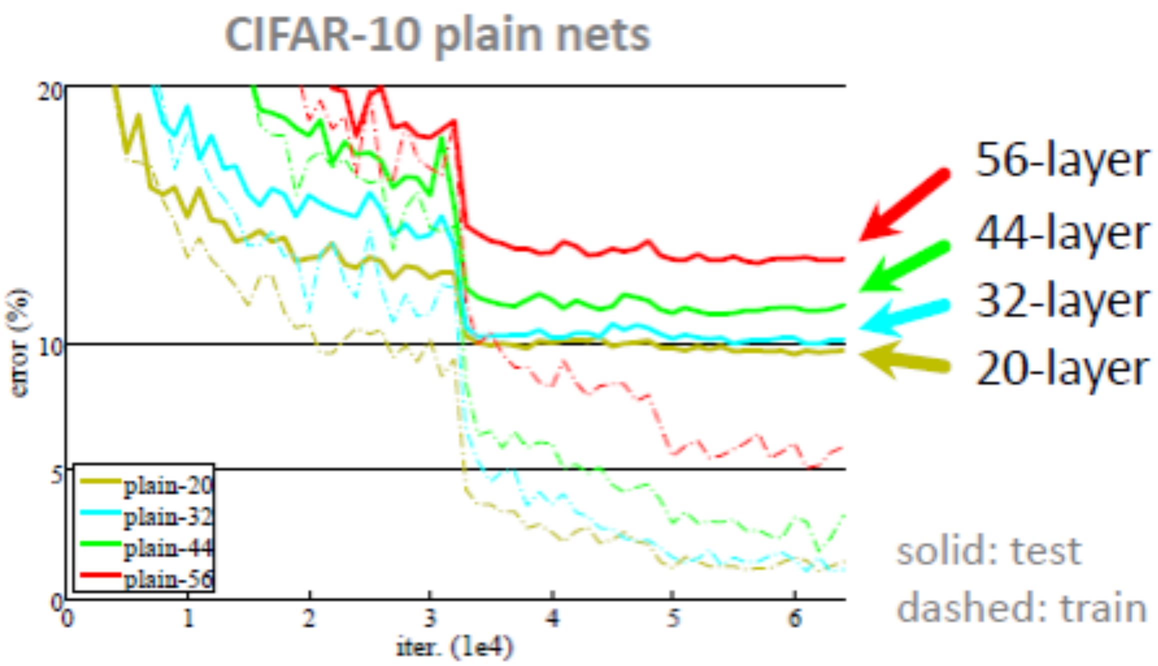


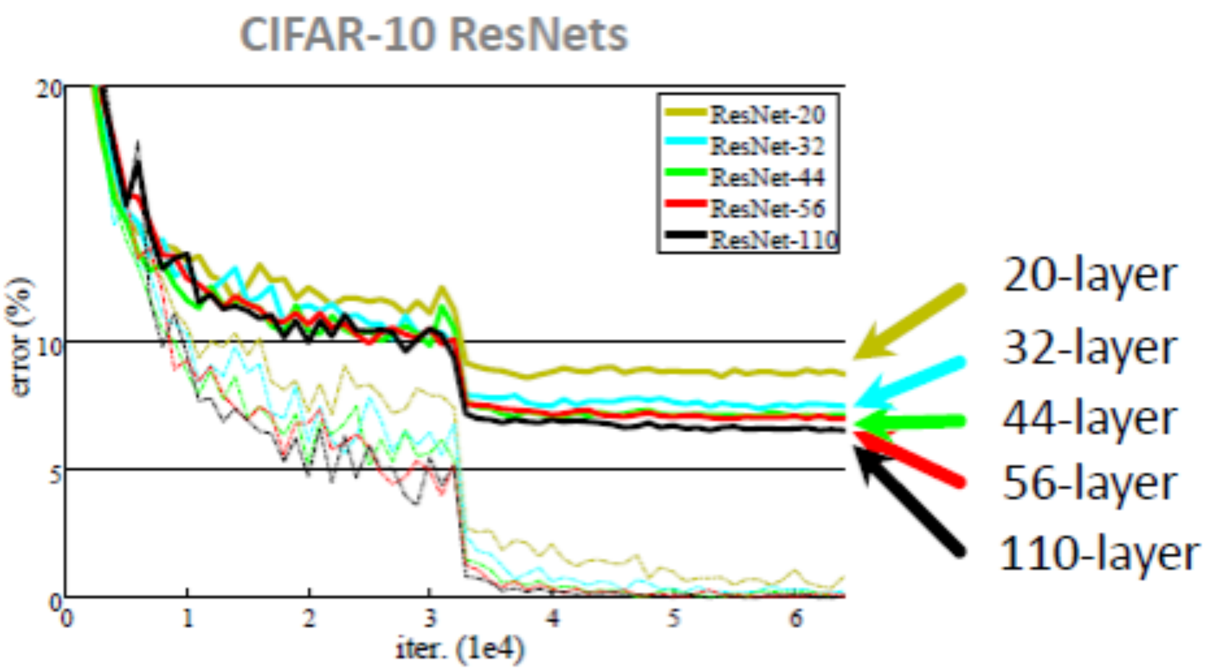
Residual Network: Deeper is better

- Deeper ResNets have lower training error



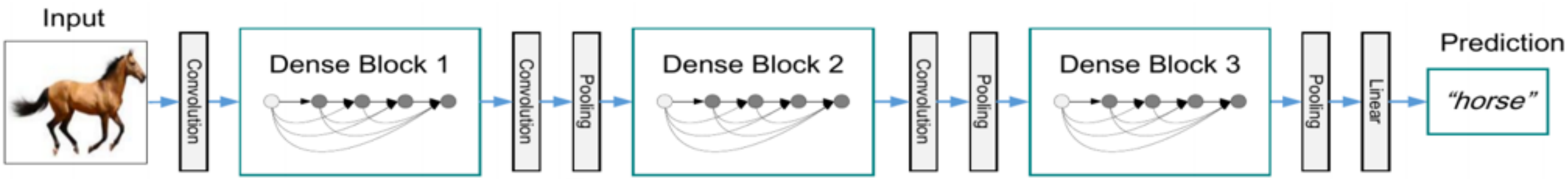
Residual Network: Deeper is better



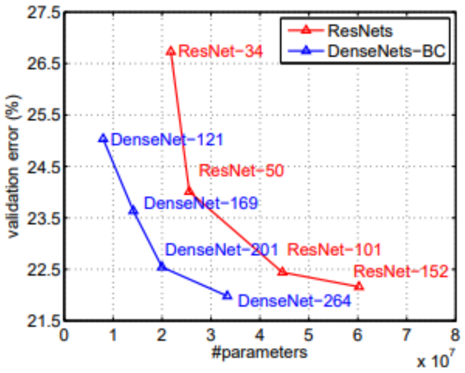


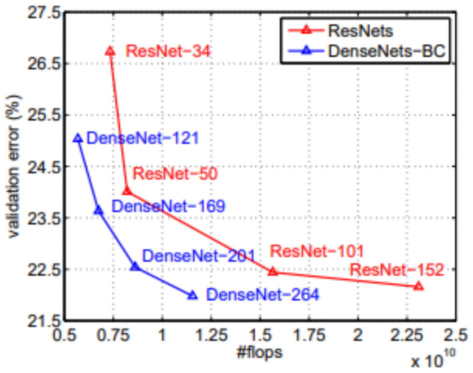
CNNs, 2017: DenseNet

Densely Connected Convolutional Networks, CVPR 2017
Gao Huang, Zhuang Liu, Laurens van der Maaten, Kilian Q. Weinberger



Recently proposed, better performance/parameter ratio





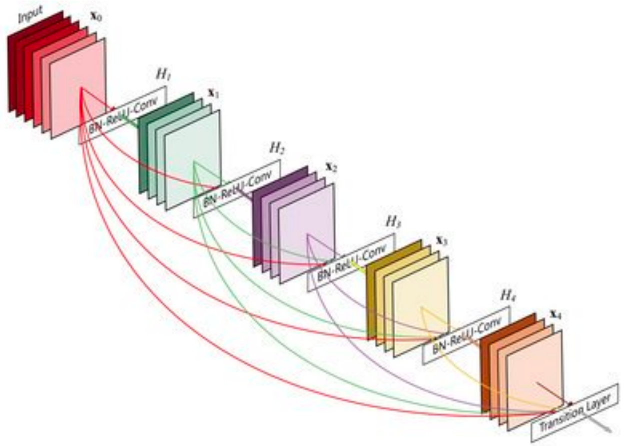
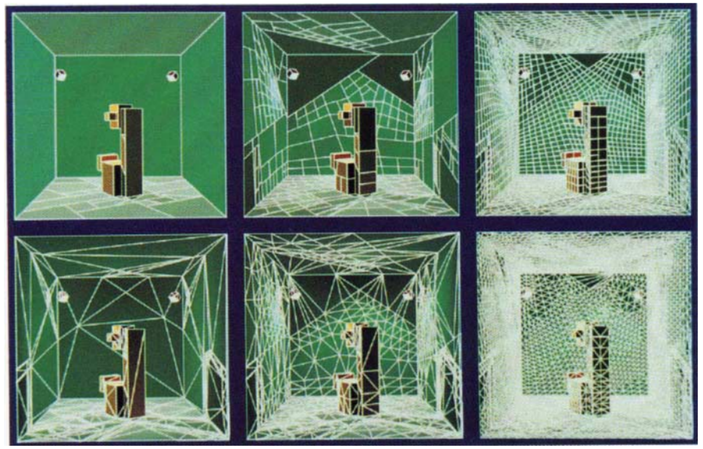
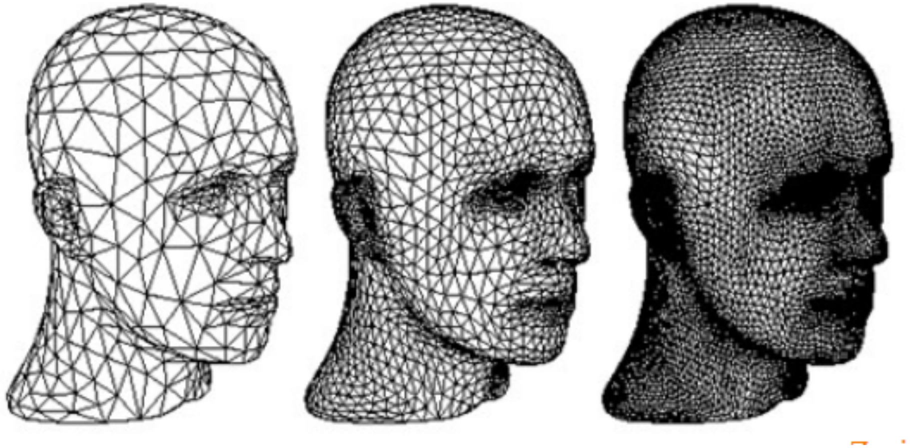
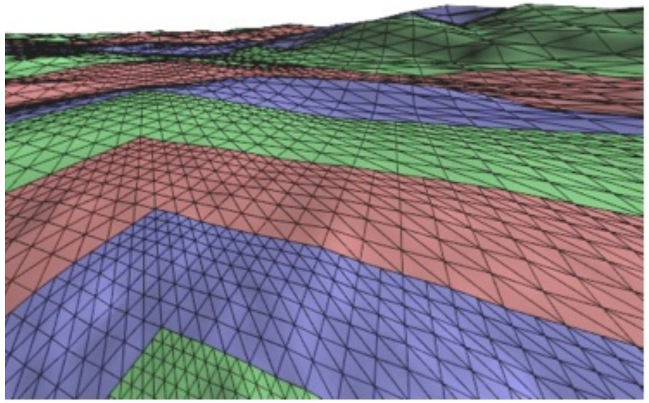


Image-to-Image

Graphics: Multiresolution







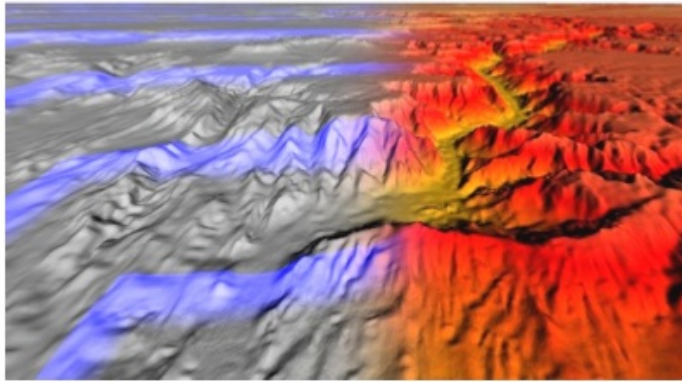
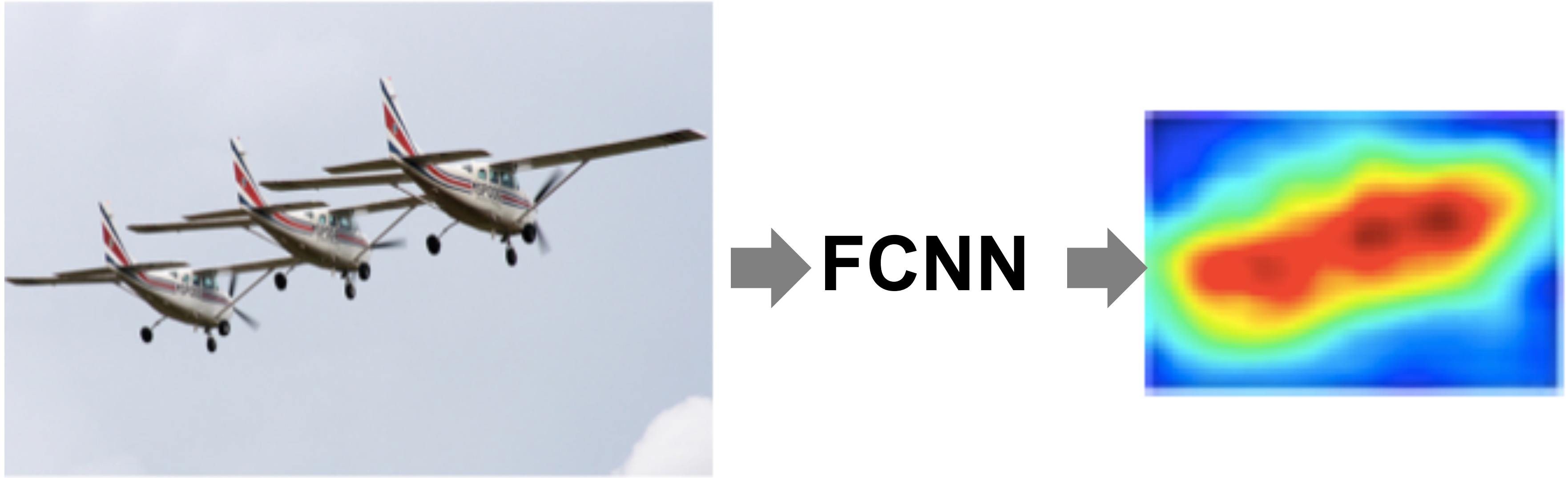


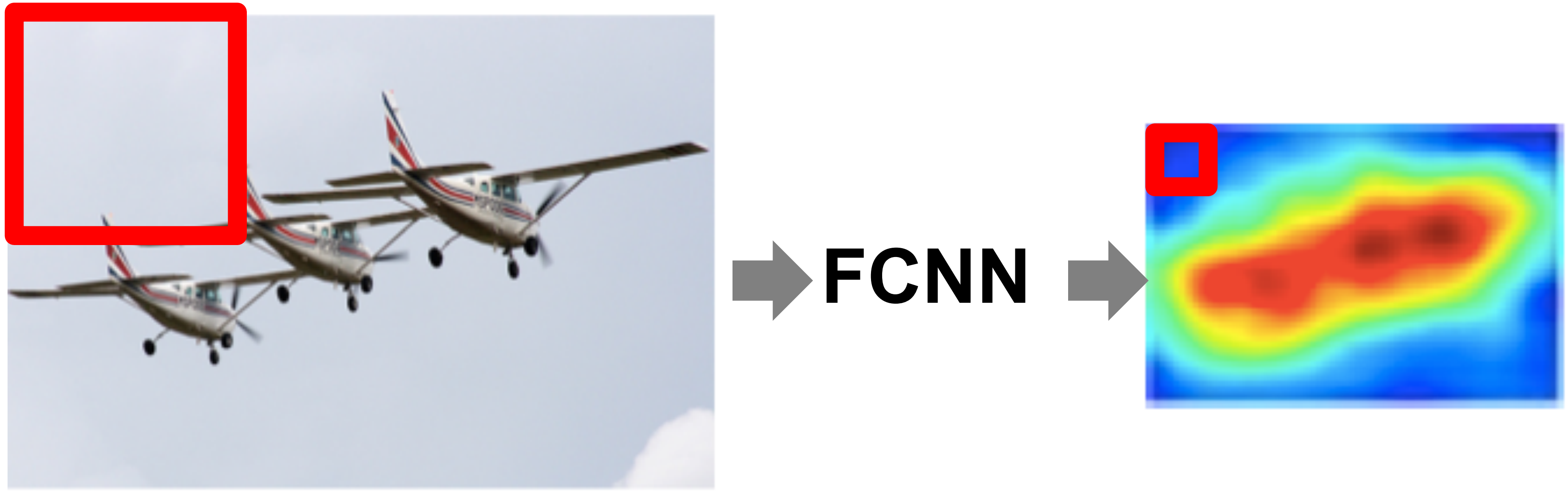
Image-to-image

- So far we mapped an image image to a number or label
- In graphics, output often is "richer":
  - An image
  - A volume
  - A 3D mesh
  - …
- Note: "*image*" just placeholder name here for any Eulerian data
- **Architectures**
  - Fully convolutional
  - Encoder-Decoder
  - Skip connections

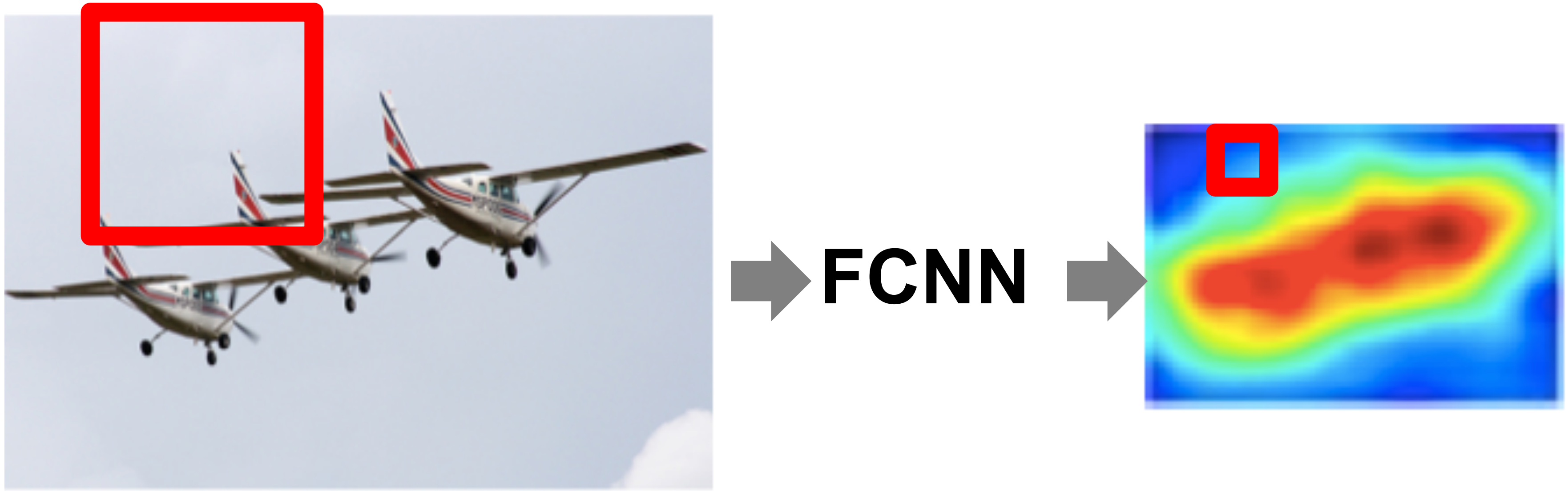
Fully-convolutional Neural Networks



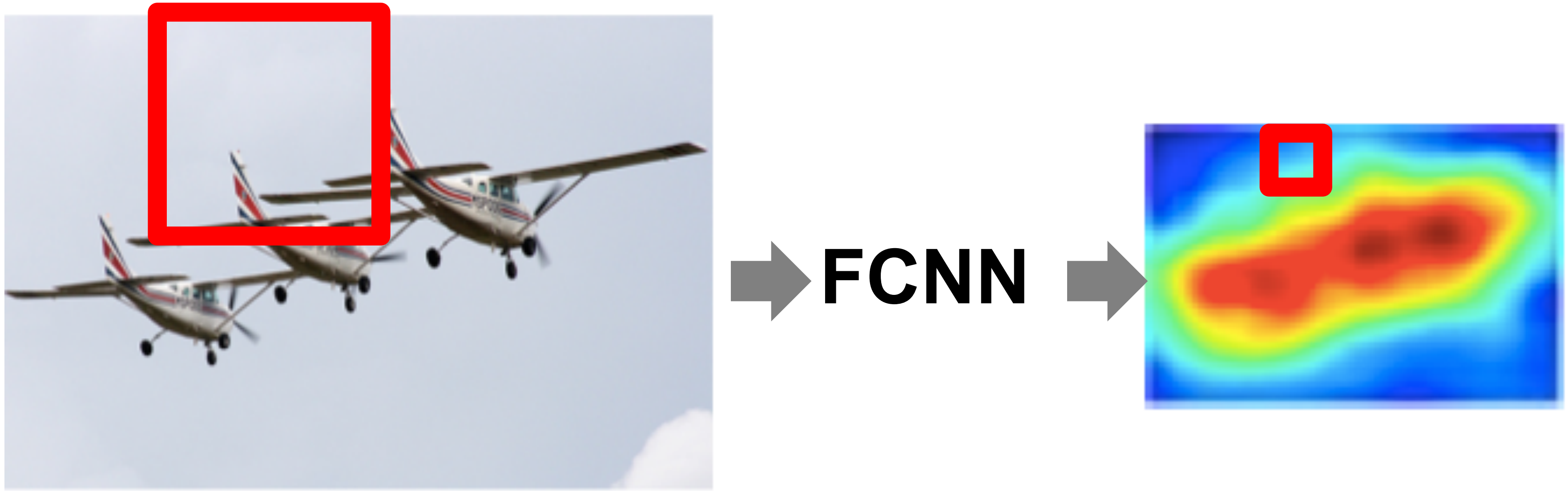
Fully-convolutional Neural Networks



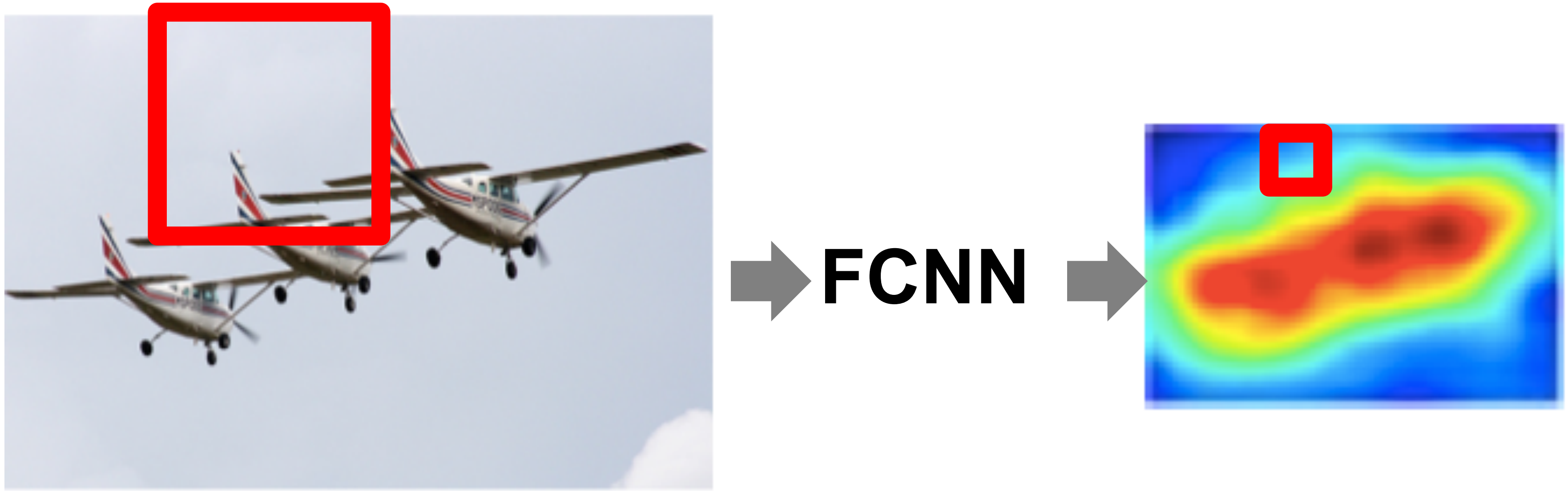
Fully-convolutional Neural Networks



Fully-convolutional Neural Networks



Fully-convolutional Neural Networks

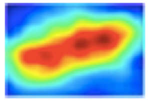


Flexible - works with varying input sizes

Fully Convolutional Neural Networks in Practice

32-fold decimation
224x224 to 7x7

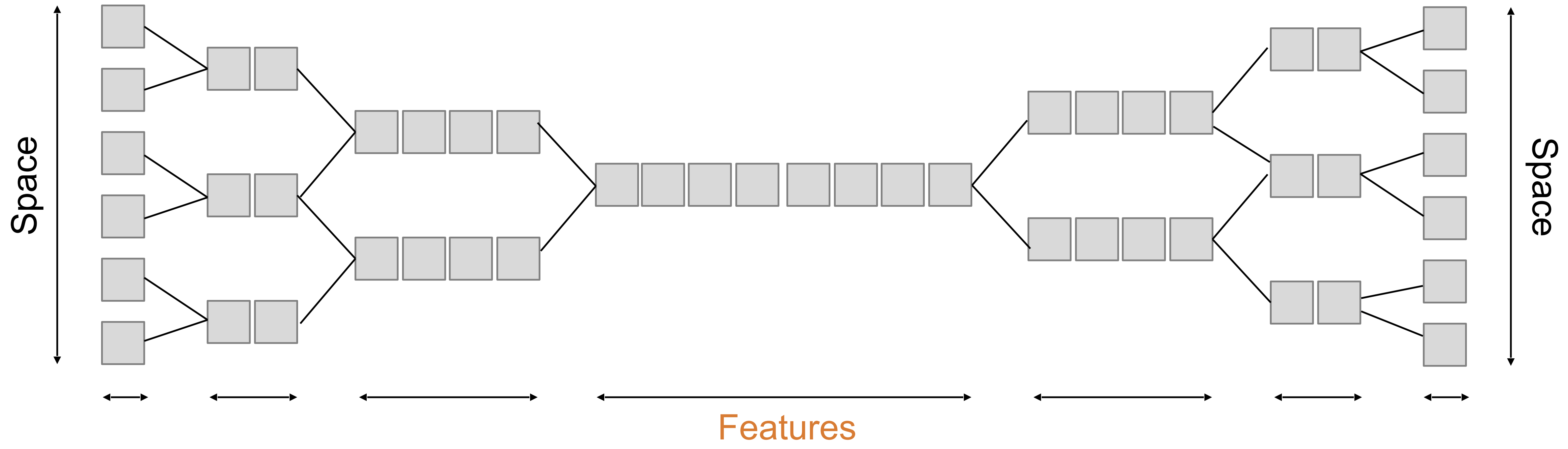
FCNN



Flexible - works with varying input sizes

Typically reduces input by fixed factor

Encoder-Decoder

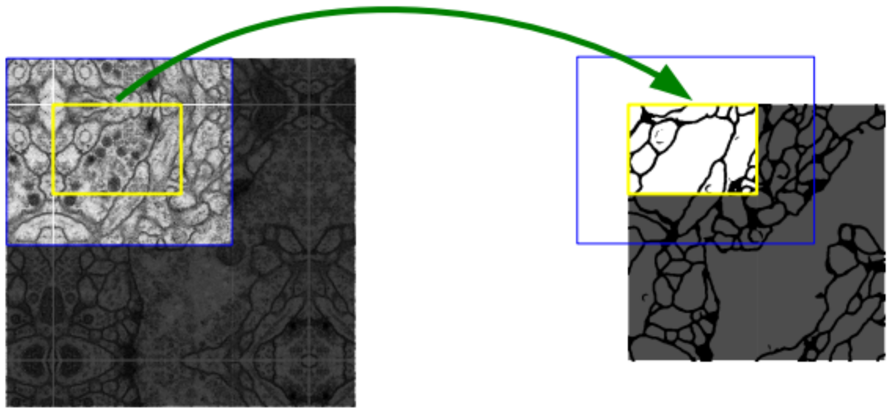


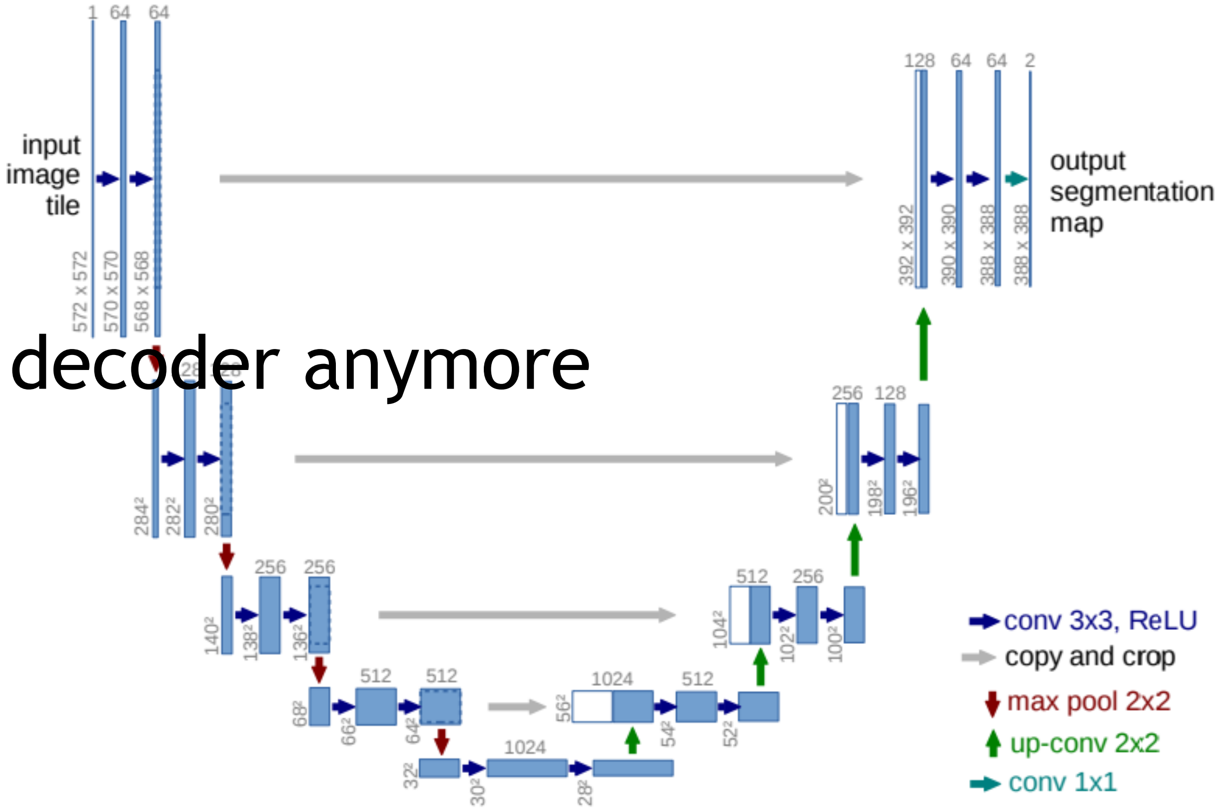
Interpretation

- Encoder: turns data set (e.g. image) into vector
- This vector is a very compact and abstract "code"
- Lives in the "latent space" of the neural network
- Decoder: turns code back into image

Encoder-decoder + Skip connections

- 1st: Reduce resolutions as before
- 2nd: Increase resolution
- Transposed convolutions
- Preserves information
- But cannot be split into en- and decoder anymore

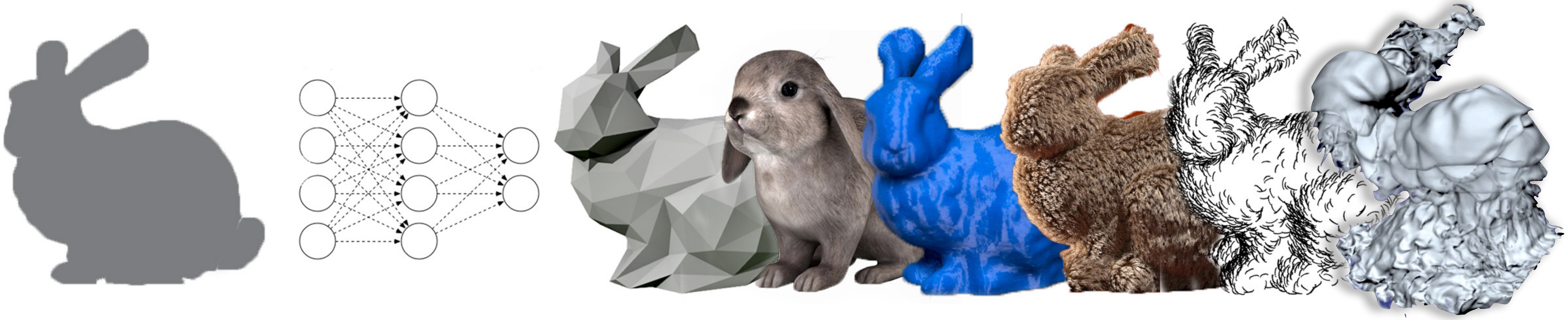




U-Net: Convolutional Networks for Biomedical Image Segmentatio. Ronneberger et al. 2015

Thank you!

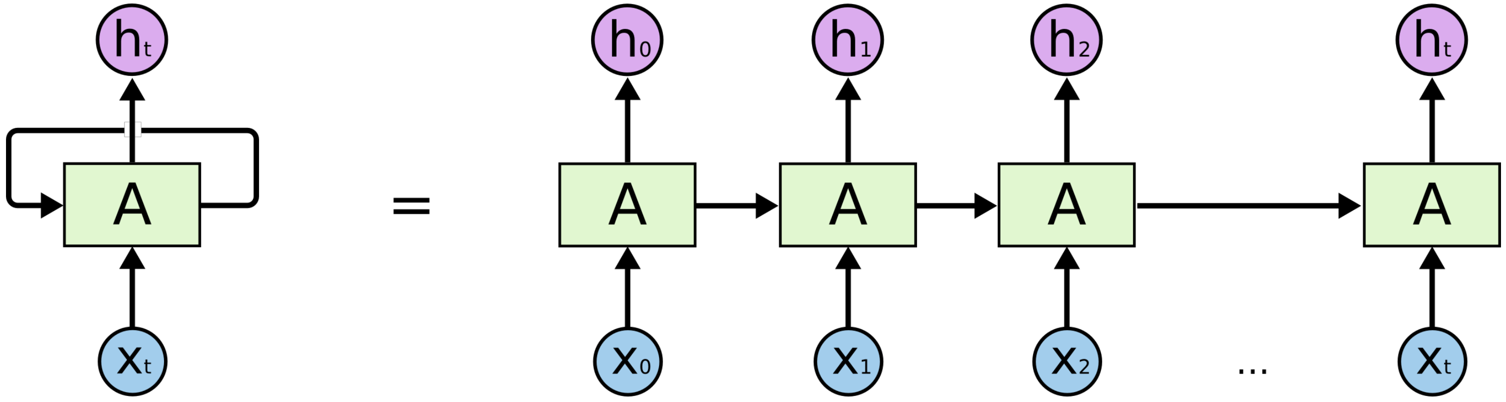
http://geometry.cs.ucl.ac.uk/creativeai/



Recurrent Neural Networks

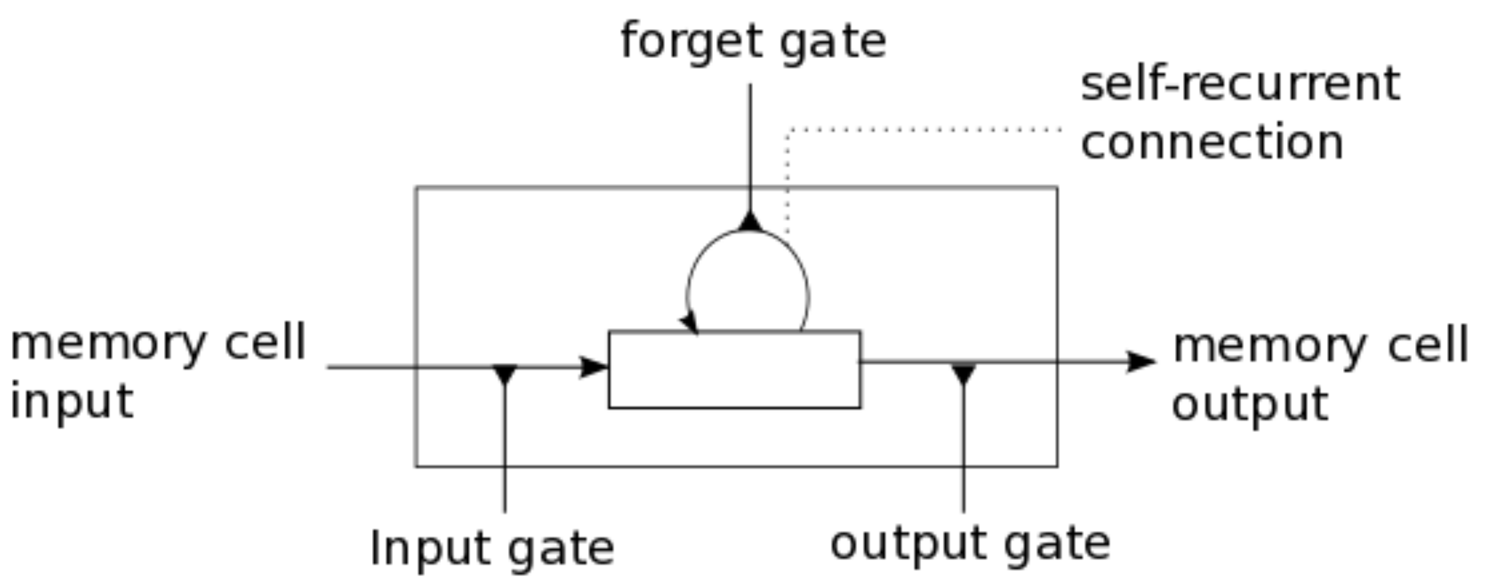
Recurrent Neural Networks

- Time dependent problems: repeated evaluations with internal “state”
- State x_t at time t, depends on previous times
- Recurrent Neural Networks (RNNs)
- Specialized back-prop possible: Back-propagation through time (BPTT)
- Unrolled:



Common Building Block: LSTM Units

- *Long short term memory* (LSTM) networks
- Three internal states: input, output, forget



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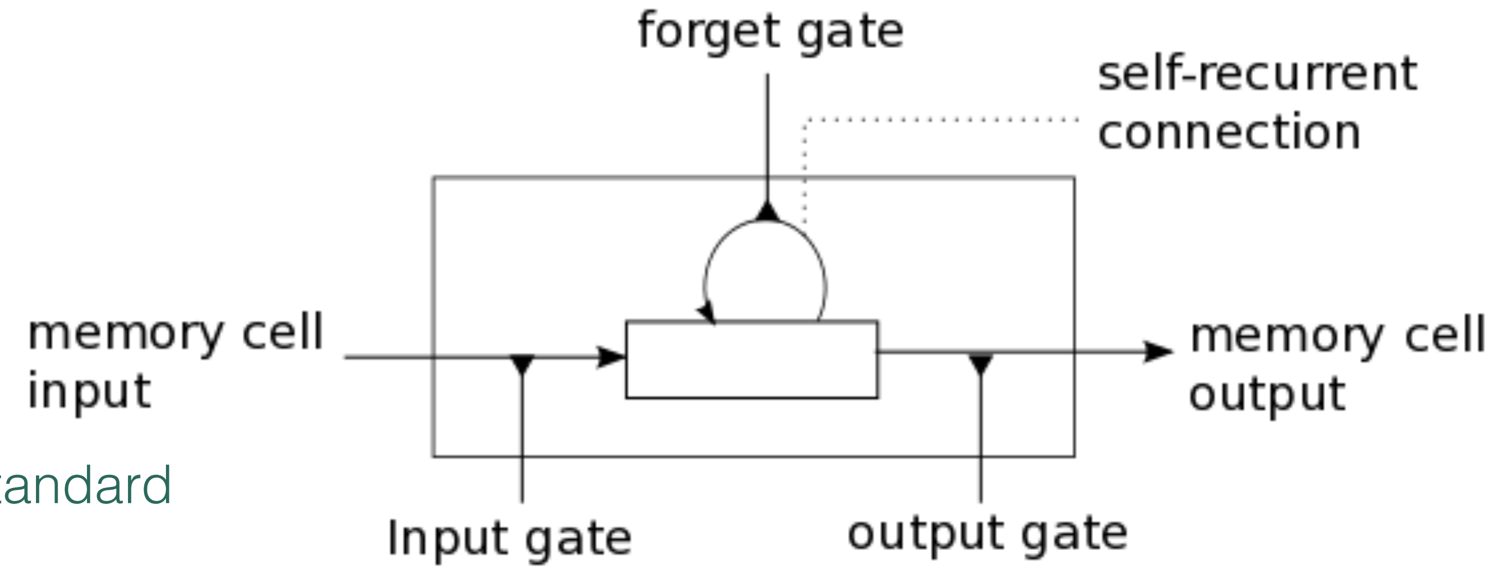

standard

Common Building Block: LSTM Units

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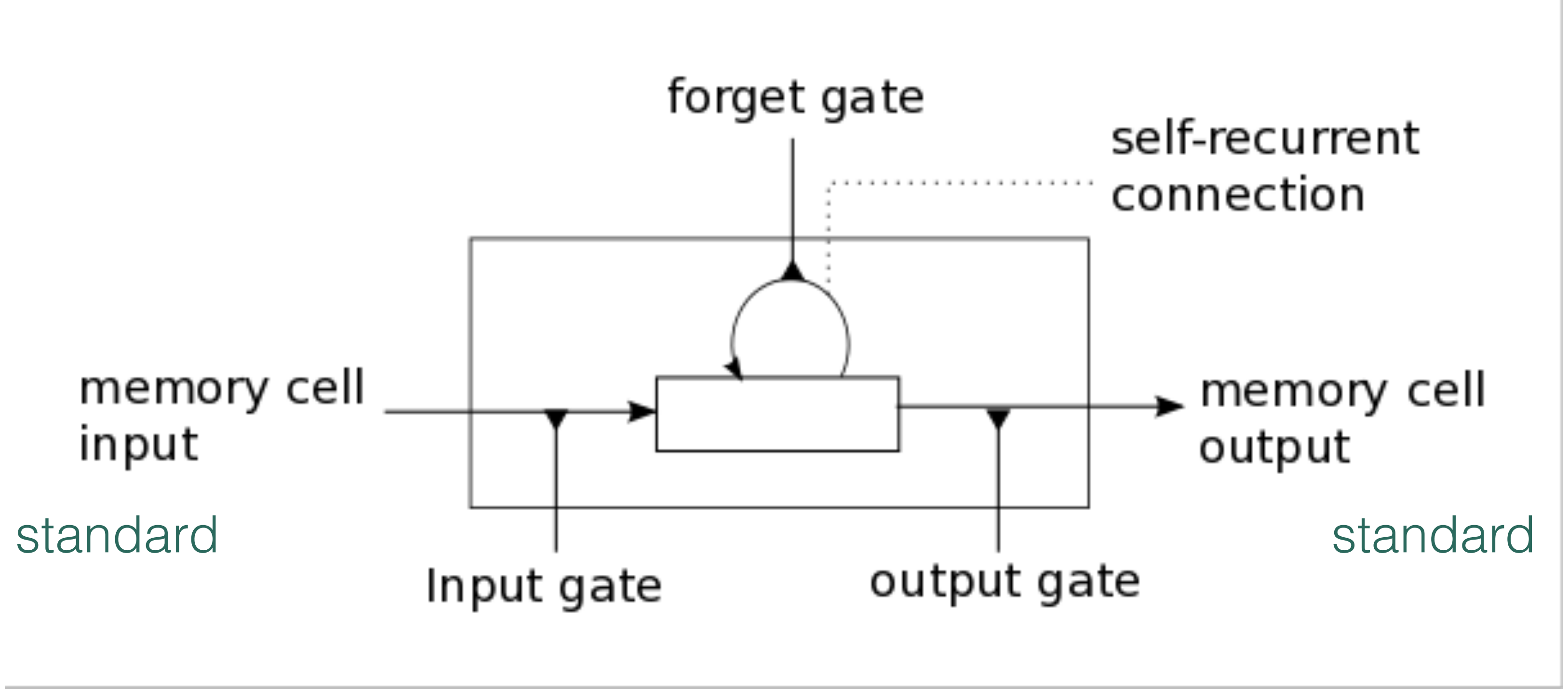
- Three internal states: input, output, forget



Common Building Block: LSTM Units

- *Long short term memory* (LSTM) networks
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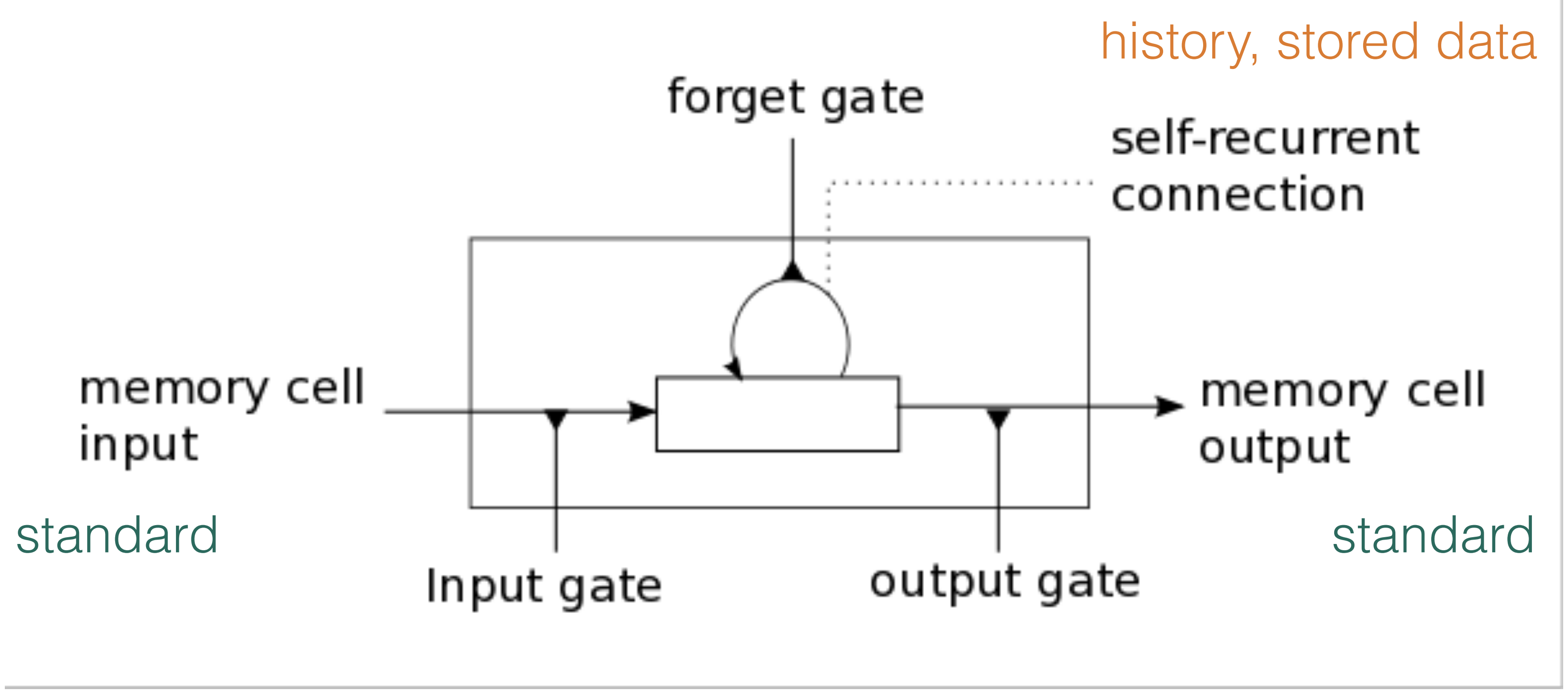

Common Building Block: LSTM Units

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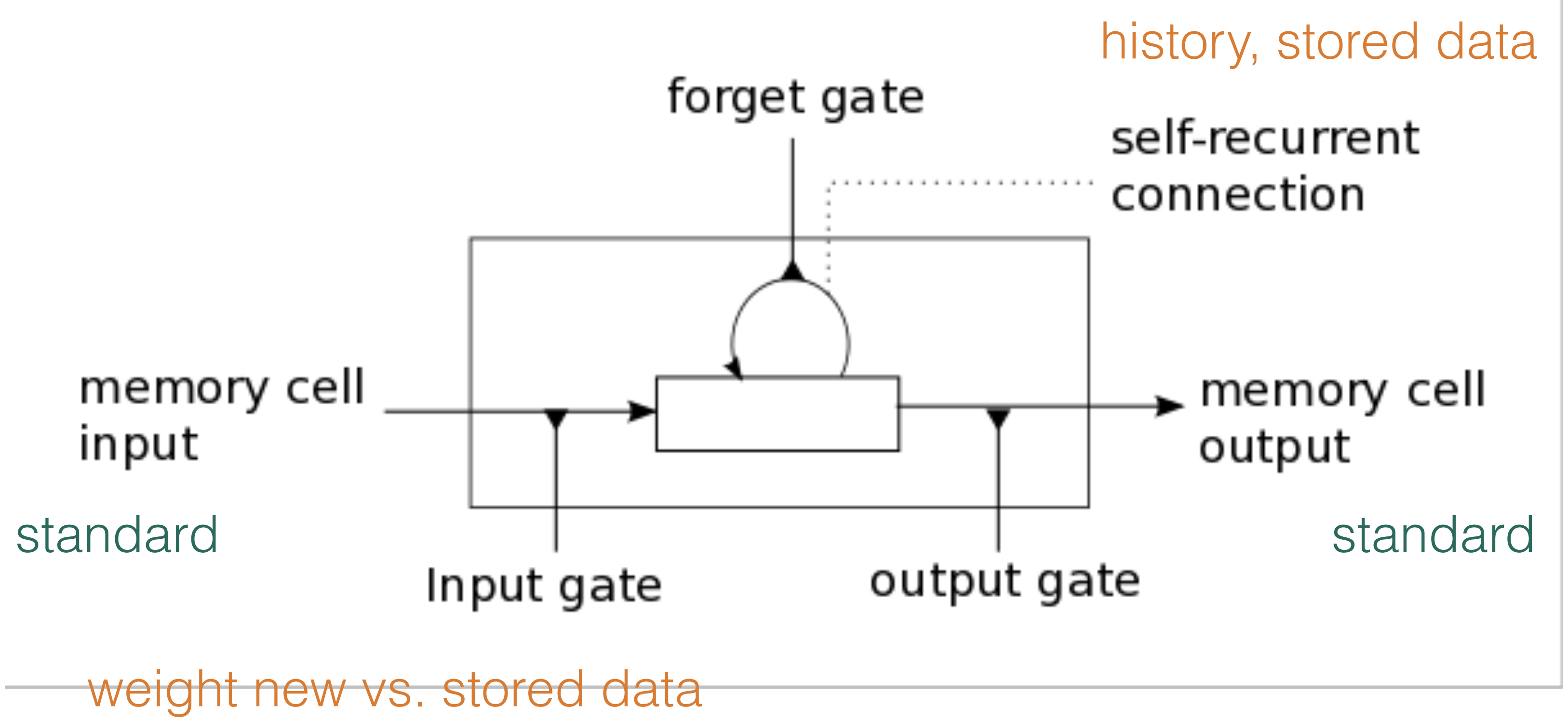

Common Building Block: LSTM Units

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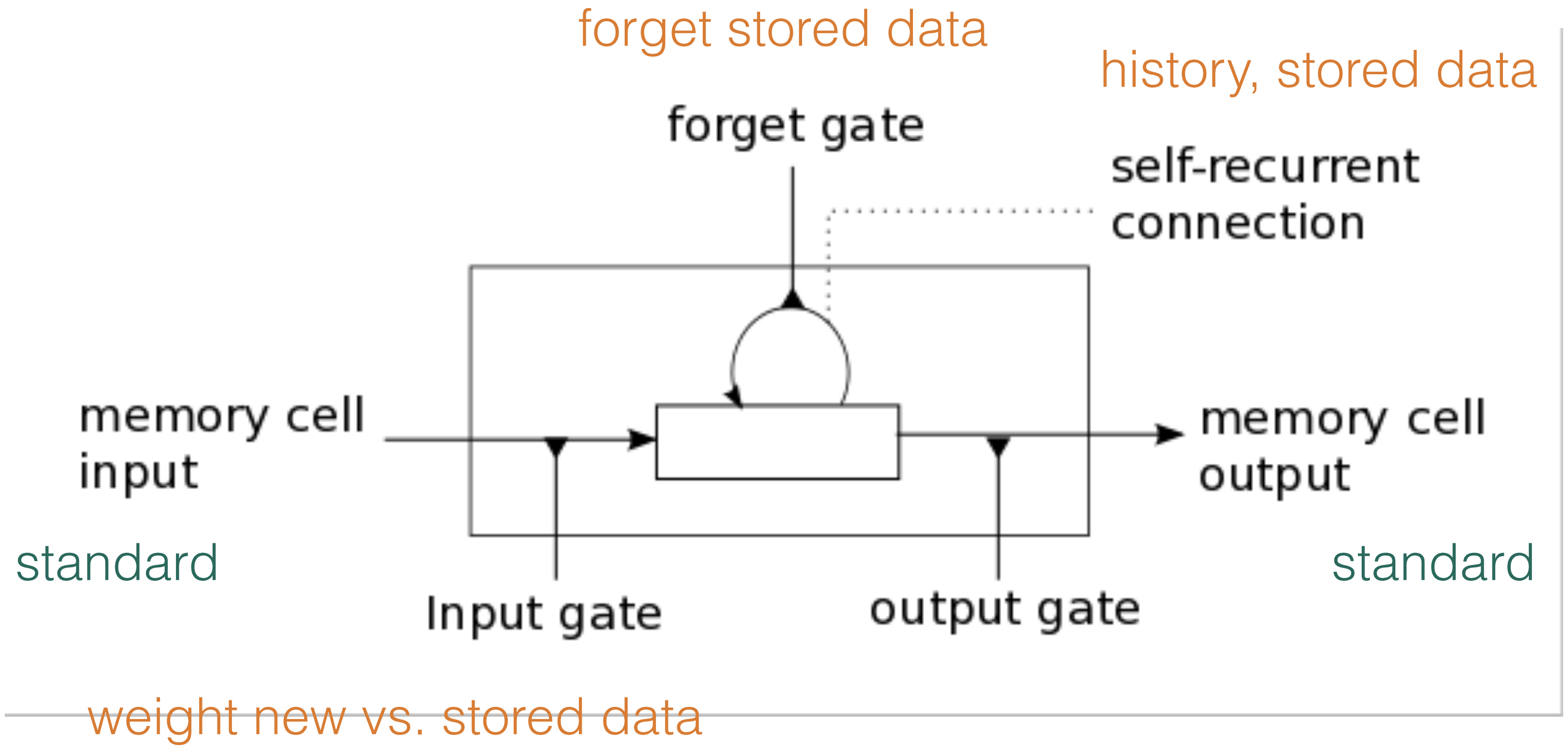
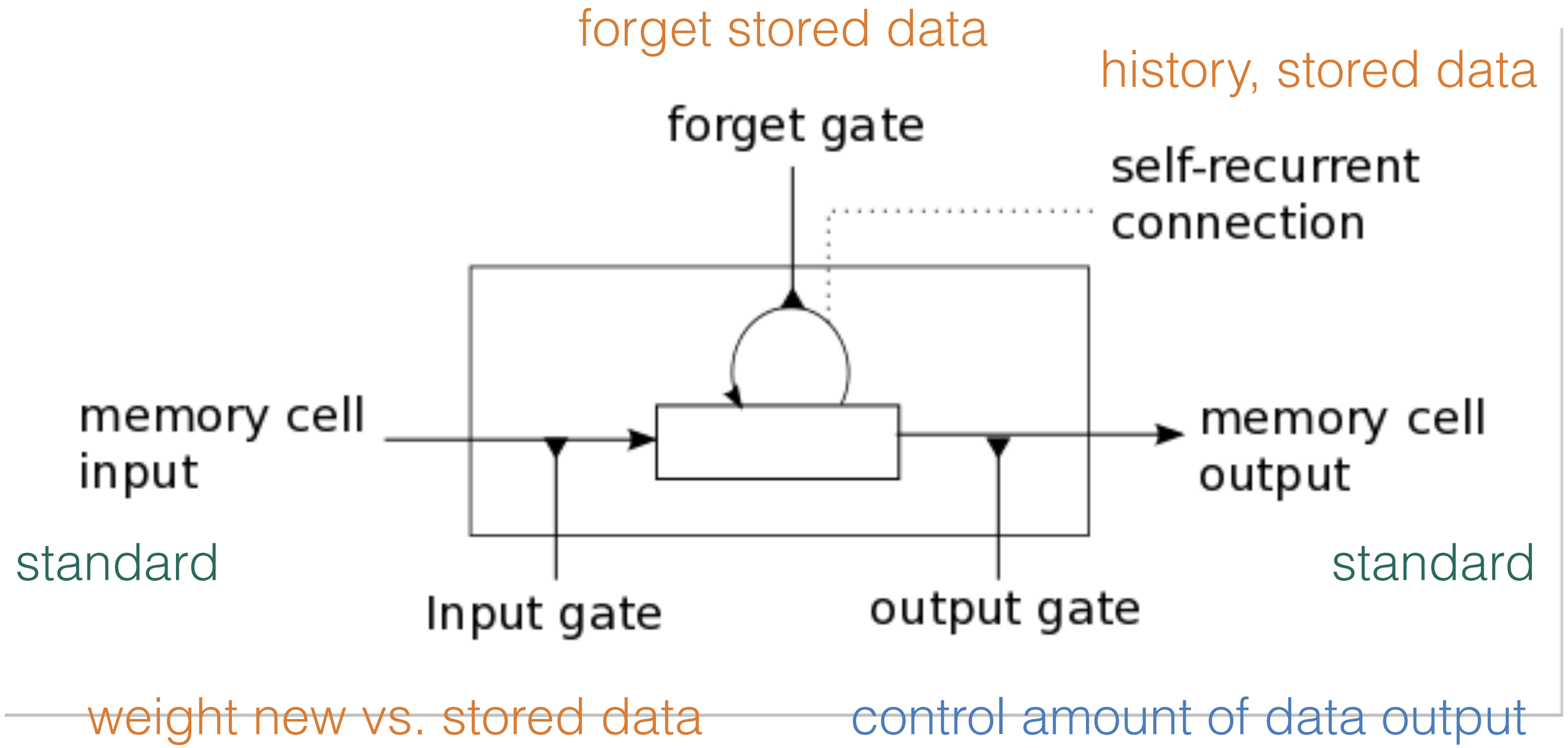


Common Building Block: LSTM Units

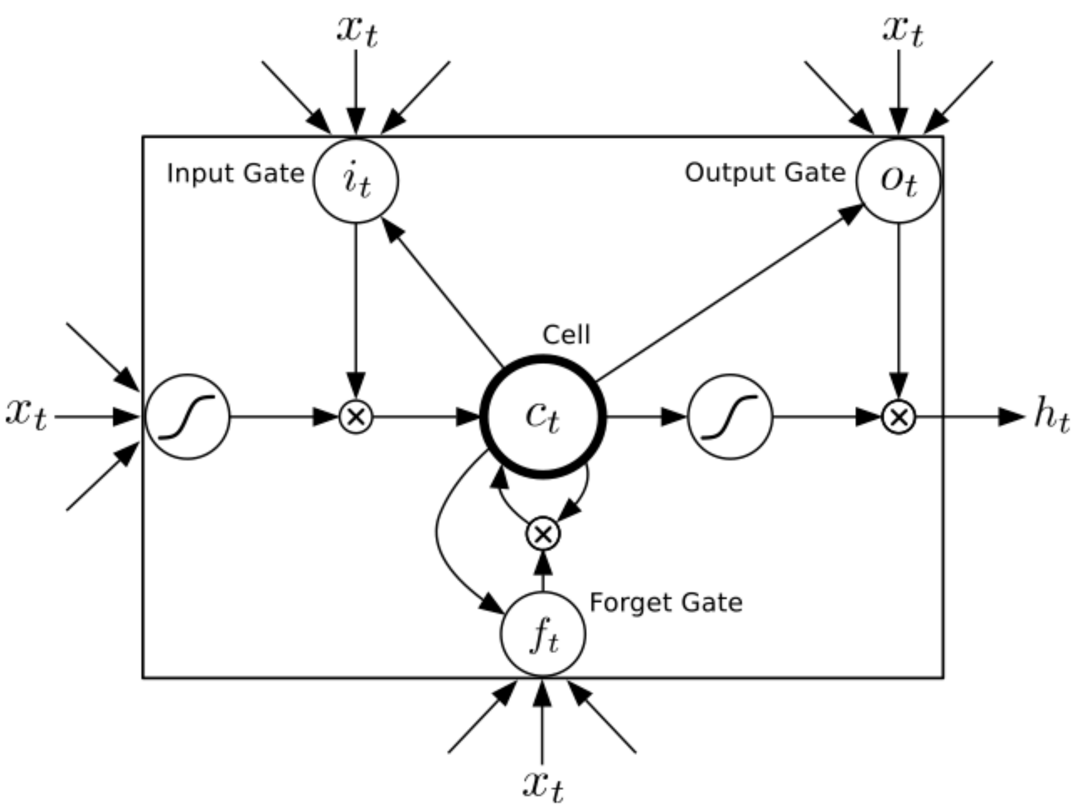
- *Long short term memory* (LSTM) networks
- Three internal states: input, output, forget



Common Building Block: LSTM Units

- *Long short term memory* (LSTM) networks
- In equation form:

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right)$$
$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right)$$
$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right)$$
$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right)$$
$$h_t = o_t \tanh(c_t)$$



[Sutskever et al., “Sequence to Sequence Learning with Neural Networks”, 2014]

Recurrent Neural Networks

- LSTM networks powerful tool for sequences over time
- Alternatives:
  - Gated Recurrent Units (GRUs)
  - Time convolutional networks (TCNs)
  - …

[Chung et al., "Empirical evaluation of gated recurrent neural networks on sequence modeling",2014]

[Bai et al., "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling", 2018]

Deep Learning Frameworks

Main frameworks

TensorFlow™

(Python, C++, Java)

Keras

(Python, backends support other languages)

PYTORCH

(Python)

Caffe

(C++, Python, Matlab)

Currently less frequently used

Chainer

(Python)

theano

(Python)

Caffe2

(Python, C++)

Microsoft CNTK

(Python, C++, C#)

MATLAB

(Matlab)

DL4J

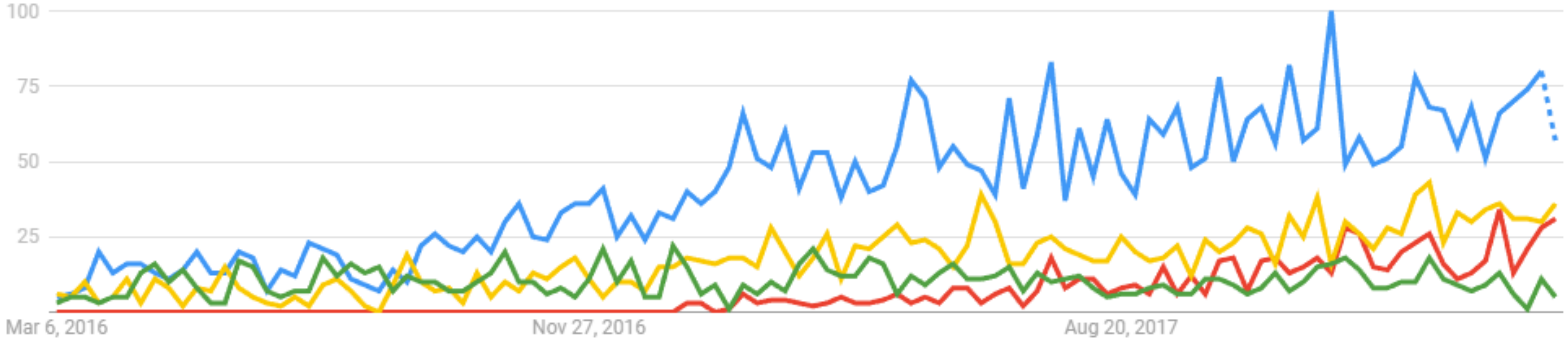
(Python, Java, Scala)

mxnet •••

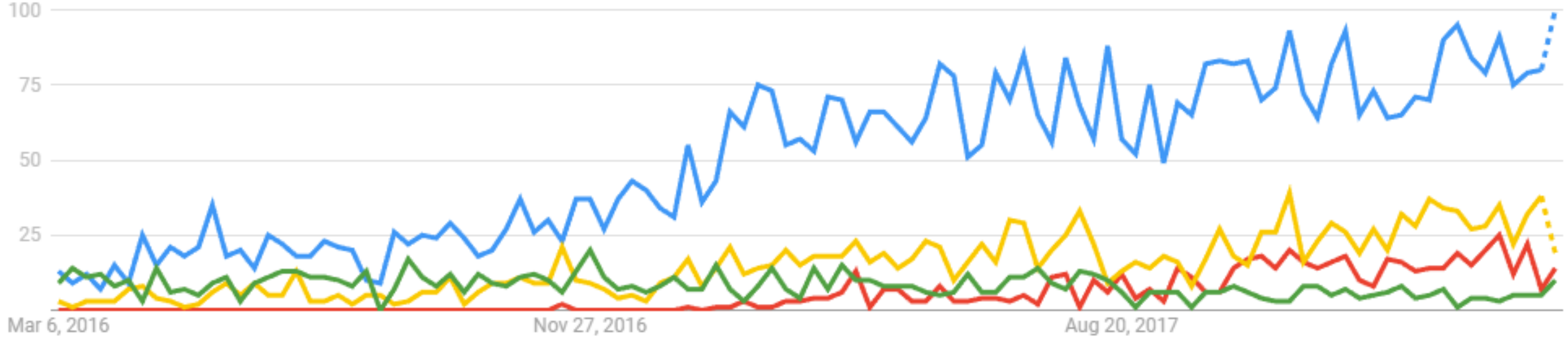
(Python, C++, and others)

Popularity

Google Trends for search terms: “[name] github”



Google Trends for search terms: “[name] tutorial”



TensorFlow
Keras
PYTORCH
Caffe

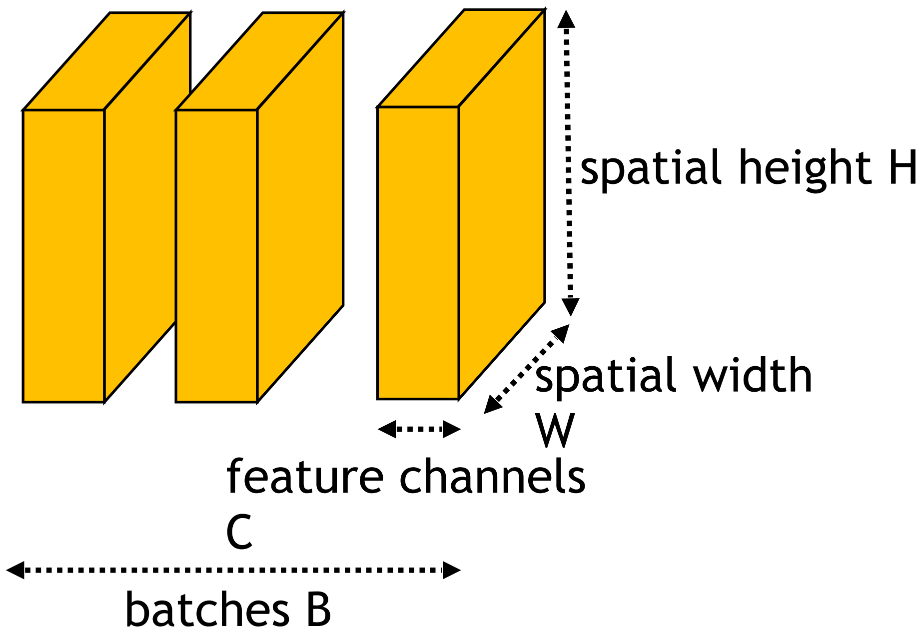
Typical Training Steps

```
for i = 1 .. max_iterations

    input, ground_truth = load_minibatch(data, i)

    output = network_evaluate(input, parameters)

    loss = compute_loss(output, ground_truth)

    # gradients of loss with respect to parameters
    gradients = network_backpropagate(loss, parameters)

    parameters = optimizer_step(parameters, gradients)
```

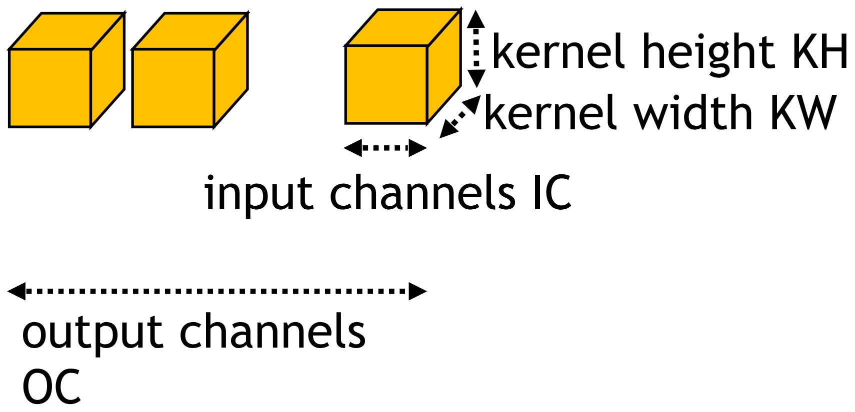
Tensors

- Frameworks typically represent data as tensors
- Examples:

4D input data: B x C x H x W



4D convolution kernel: OC x IC x KH x KW



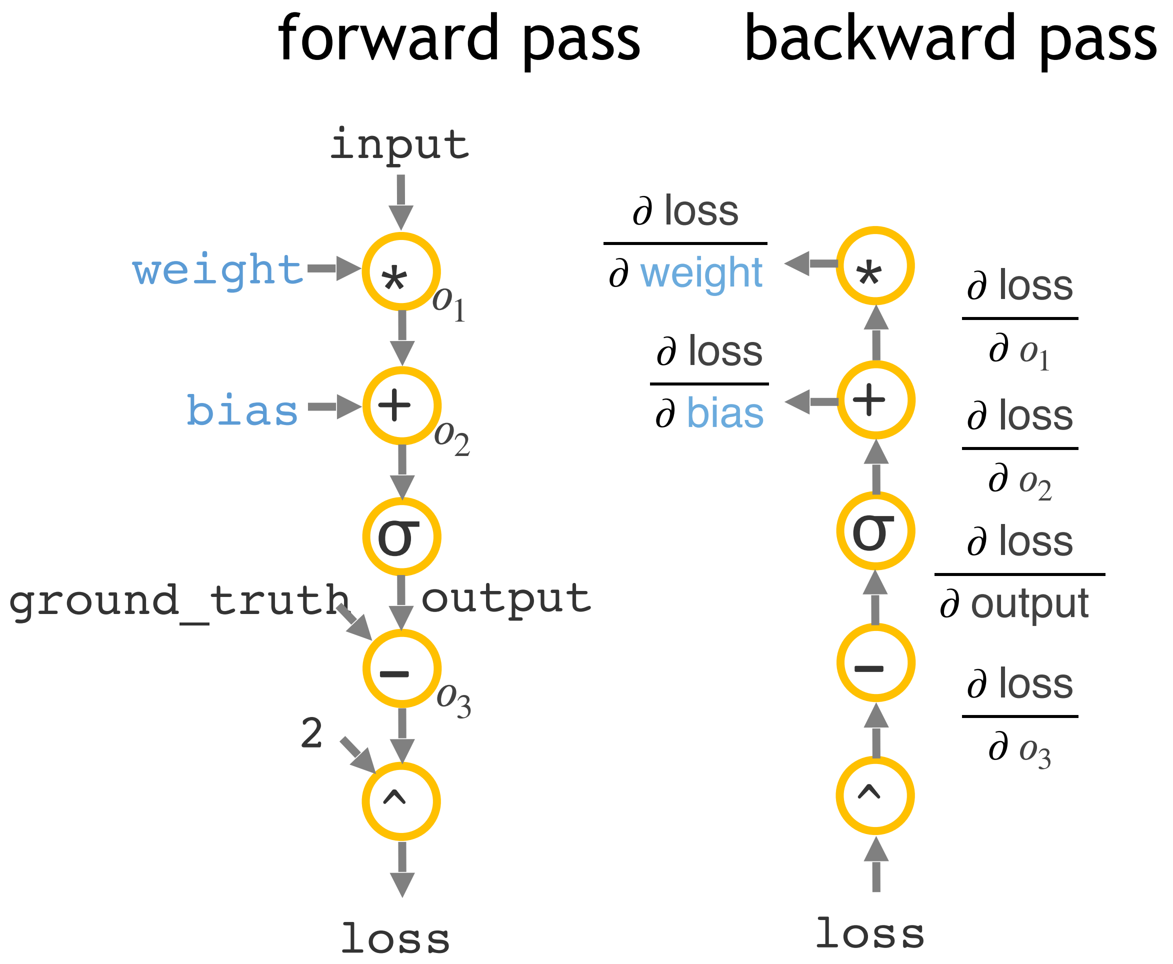
What Does a Deep Learning Framework Do?

- Tensor math
- Common network operations/layers
- Gradients of common operations
- Backpropagation
- Optimizers
- GPU implementations of the above
- usually: data loading, network parameter saving/loading
- sometimes: distributed computing

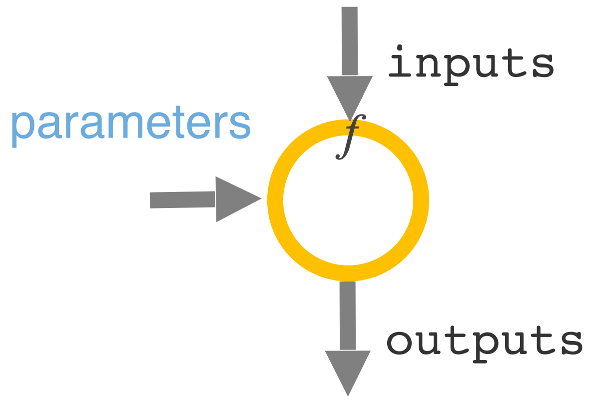
Automatic Differentiation & the Computation Graph

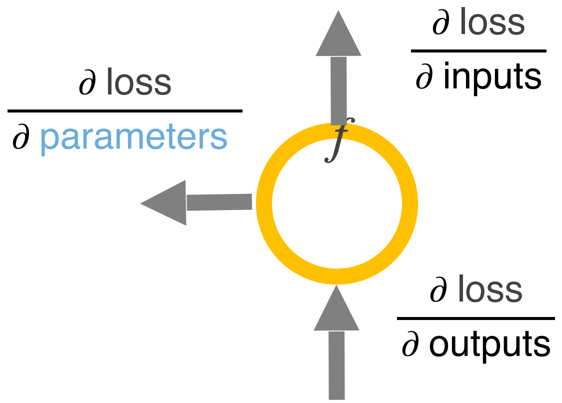
```
parameters = (weight, bias)

output = σ(weight * input + bias)

loss = (output - ground_truth)^2

# gradients of loss with respect to parameters
gradients = backpropagate(loss, parameters)
```

Since loss is a scalar, the gradients are the same size as the parameters



Automatic Differentiation & the Computation Graph






```
outputs = forward(inputs, )
```

```
 ,    = backward()
```

Static vs Dynamic Computation Graphs

- Static analysis allows optimizations and distributing workload
- Dynamic graphs make data-driven control flow easier
- In static graphs, the graph is usually defined in a separate ‘language’
- Static graphs have less support for debugging

define once,
evaluate during training

Static

```
x = Variable()
loss = if_node(x < parameter[0],
    x + parameter[0],
    x - parameter[1])

for i = 1 .. max_iterations
    x = data()
    run(loss)
    backpropagate(loss, parameters)
```

define implicitly by running operations,
a new graph is created in each evaluation

Dynamic

```
for i = 1 .. max_iterations
    x = data()
    if x < parameter[0]
        loss = x + parameter[0]
    else
        loss = x – parameter[1]
    backpropagate(loss, parameters)
```

Tensorflow

- Currently the largest community
- Static graphs (dynamic graphs are in development: Eager Execution)
- Good support for deployment
- Good support for distributed computing
- Typically slower than the other three main frameworks on a single GPU

PyTorch

PYTORCH

- Fast growing community
- Dynamic graphs
- Distributed computing is in development (some support is already available)
- Intuitive code, easy to debug and good for experimenting with less traditional architectures due to dynamic graphs
- Very Fast

Keras

- A high-level interface for various backends (Tensorflow, CNTK, Theano)
- Intuitive high-level code
- Focus on optimizing time from idea to code
- Static graphs

Caffe

Caffe

- Created earlier than Tensorflow, PyTorch or Keras
- Less flexible and less general than the other three frameworks
- Static graphs
- Legacy - to be replaced by Caffe2: focus is on performance and deployment
  - Facebook’s platform for Detectron (Mask-RCNN, DensePose, …)

Converting Between Frameworks

- Example: develop in one framework, deploy in another
- Currently: a large range of converters, but no clear standard
- Standardized model formats are in development

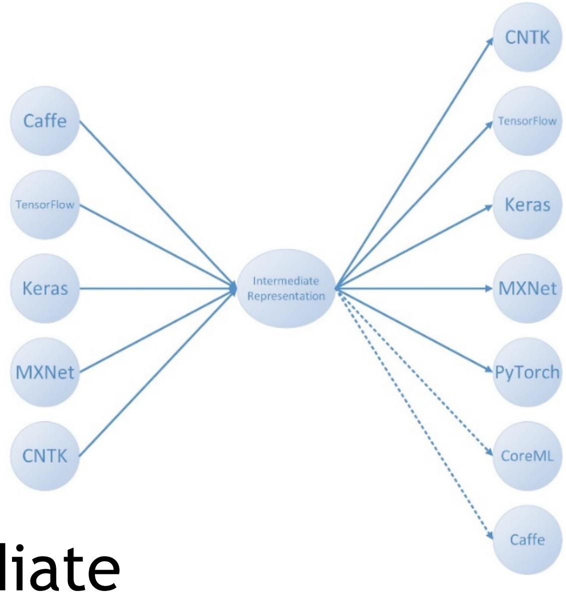
from https://github.com/ysh329/deep-learning-model-convertor

convertor	tensorflow	pytorch	keras	caffe	caffe2	CNTK	chainer	mxnet
tensorflow	-	pytorch-tf/ MMdnn	model-converters/ nn_toolsconvert-to-tensorflow/MMdnn	MMdnn/ nn_tools	None	crosstalk/MMdnn	None	MMdnn
pytorch	pytorch2keras (over Keras)	-	Pytorch2keras/ nn-transfer	Pytorch2caffe/ pytorch-caffe-darknet-convert	onnx-caffe2	ONNX	None	None
keras	nn_tools /convert-to-tensorflow/ keras_to_tensorflow/ keras_to_tensorflow/ MMdnn	MMdnn/ nn-transfer	-	MMdnnnn_tools	None	MMdnn	None	MMdnn
caffe	MMdnn/nn_tools/ caffe-tensorflow	MMdnn/ pytorch-caffe-darknet-convert/ pytorch-resnet	caffe_weight_converter / caffe2keras/nn_tools/ kerascaffe2keras/ Deep_Learning_Model_Converter/MMdnn	-	CaffeToCaffe2	crosstalkcaffe/ CaffeConverterMMdnn	None	mxnet/tools/ caffe_converter/ ResNet_caffe2mxnet/ MMdnn
caffe2	None	ONNX	None	None	-	ONNX	None	None
CNTK	MMdnn	ONNX MMdnn	MMdnn	MMdnn	ONNX	-	None	MMdnn
chainer	None	chainer2pytorch	None	None	None	None	-	None
mxnet	MMdnn	MMdnn	MMdnn	MMdnn/MXNet2Caffe/ Mxnet2Caffe	None	MMdnn	None	-

ONNX

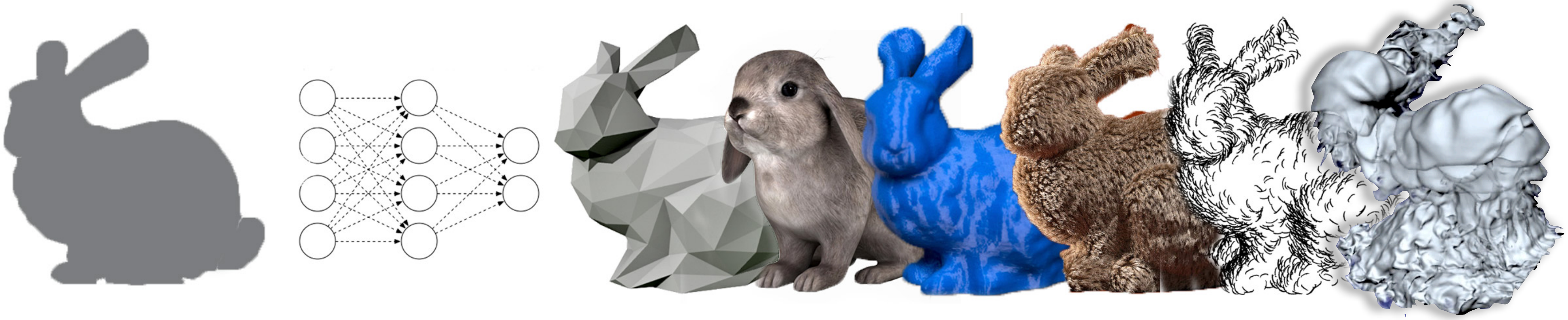
- Standard format for models
- Native support in development for Pytorch, Caffe2, Chainer, CNTK, and MxNet
- Converter in development for Tensorflow

MMdnn



- Converters available for several frameworks
- Common intermediate representation, but no clear standard

Thank you!



http://geometry.cs.ucl.ac.uk/creativeai/