Advanced Machine Learning
Lecture 13

Convolutional Neural Networks

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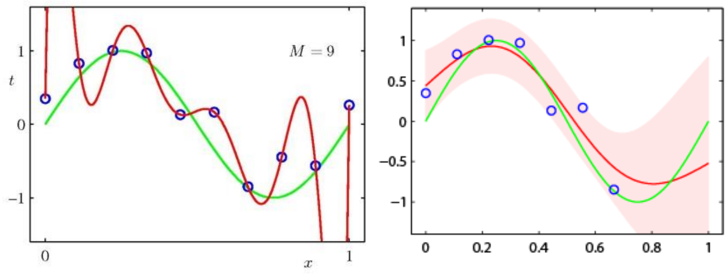
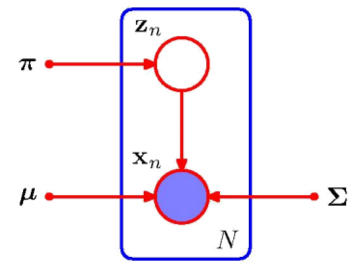
This Lecture: *Advanced Machine Learning*

$$f : \mathcal{X} \rightarrow \mathbb{R}$$

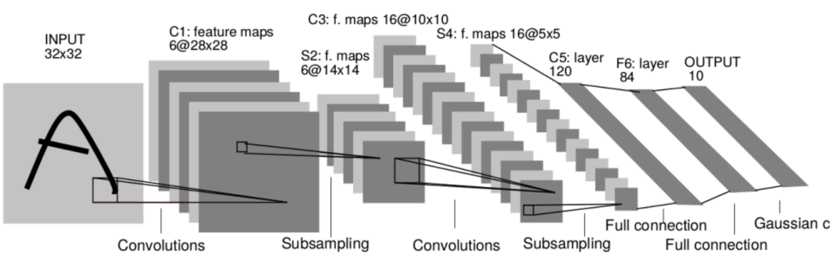
- Regression Approaches
  - Linear Regression
  - Regularization (Ridge, Lasso)
  - Kernels (Kernel Ridge Regression)
  - Gaussian Processes



- Approximate Inference
  - Sampling Approaches
  - MCMC



- Deep Learning
  - Linear Discriminants
  - Neural Networks
  - Backpropagation & Optimization
  - CNNs, RNNs, ResNets, etc.



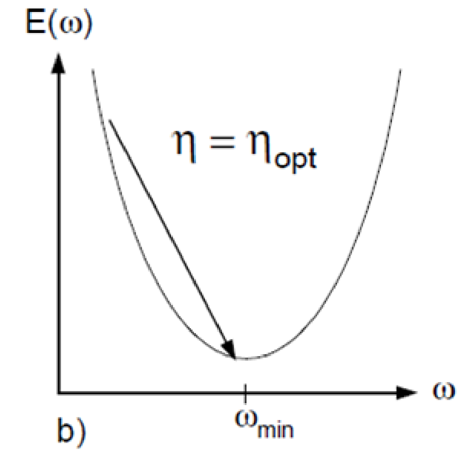
Topics of This Lecture

- Tricks of the Trade
  - Recap
- Convolutional Neural Networks
  - Neural Networks for Computer Vision
  - Convolutional Layers
  - Pooling Layers
- CNN Architectures
  - LeNet
  - AlexNet
  - VGGNet
  - GoogLeNet

Recap: Choosing the Right Learning Rate

- **Convergence of Gradient Descent**
  - **Simple 1D example**

$$W^{(\tau-1)} = W^{(\tau)} - \eta \frac{\mathrm{d}E(W)}{\mathrm{d}W}$$



  - **What is the optimal learning rate η_{opt}?**
  - **If E is quadratic, the optimal learning rate is given by the inverse of the Hessian**

$$\eta_{\text{opt}} = \left(\frac{\mathrm{d}^2 E(W^{(\tau)})}{\mathrm{d}W^2} \right)^{-1}$$

  - **Advanced optimization techniques try to approximate the Hessian by a simplified form.**
  - ***If we exceed the optimal learning rate, bad things happen!***

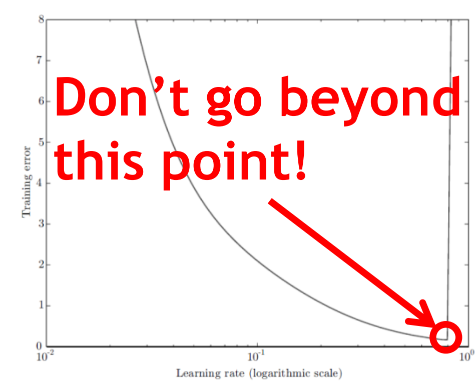
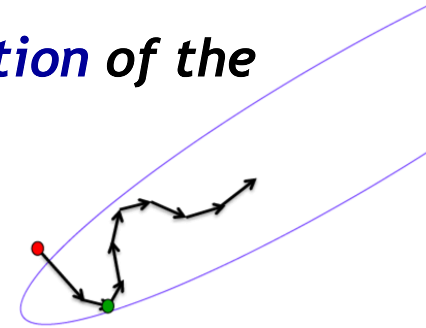


Image source: Yann LeCun et al., Efficient BackProp (1998)

Recap: Advanced Optimization Techniques

- Momentum
  - *Instead of using the gradient to change the position of the weight "particle", use it to change the velocity.*
  - Effect: dampen oscillations in directions of high curvature



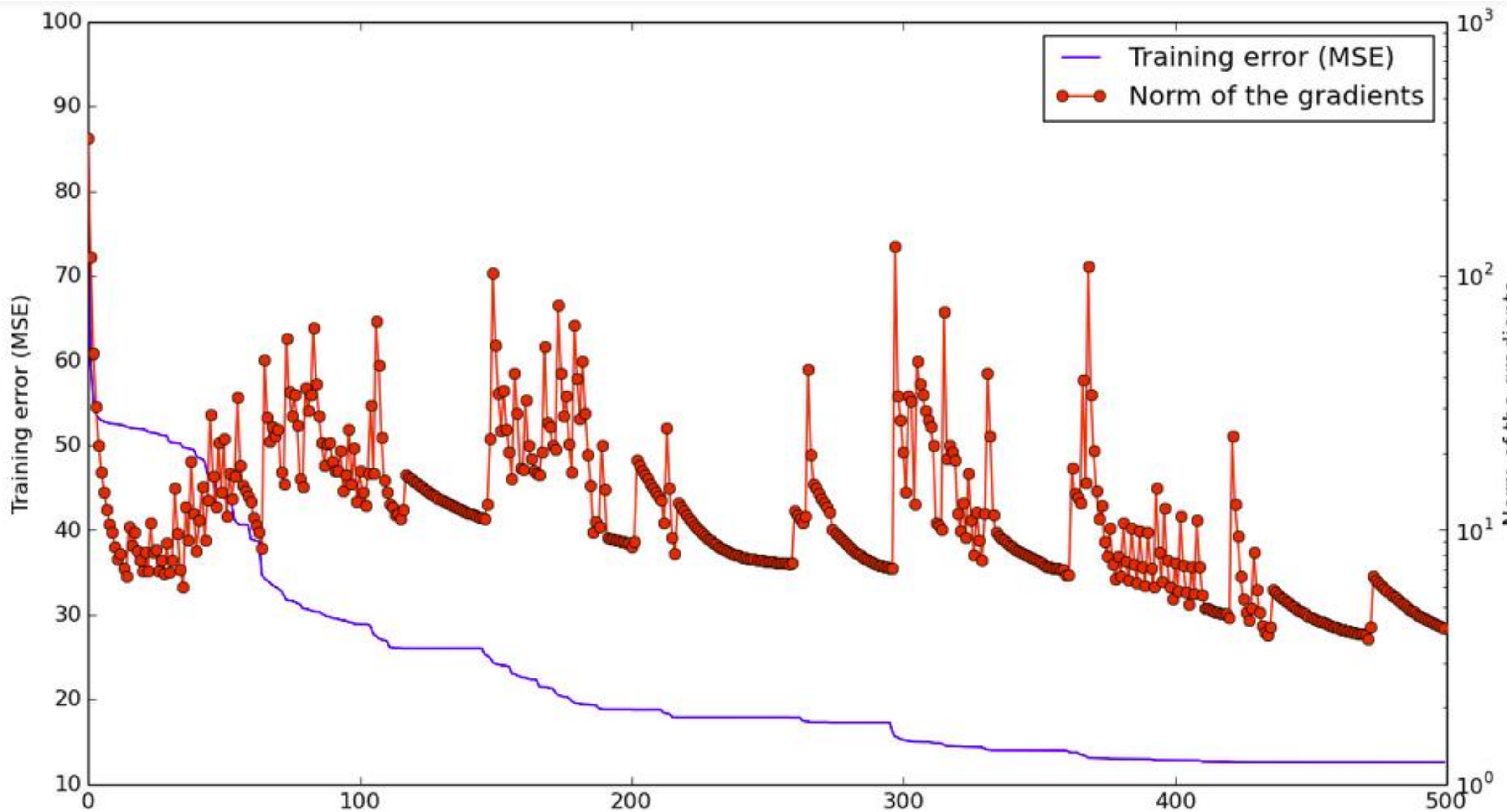
  - Nesterov-Momentum: Small variation in the implementation
- RMS-Prop
  - *Separate learning rate for each weight: Divide the gradient by a running average of its recent magnitude.*
- AdaGrad
- AdaDelta
- Adam

Some more recent techniques, work better for some problems. Try them.

Image source: Geoff Hinton

Trick: Patience

- **Saddle points dominate in high-dimensional spaces!**

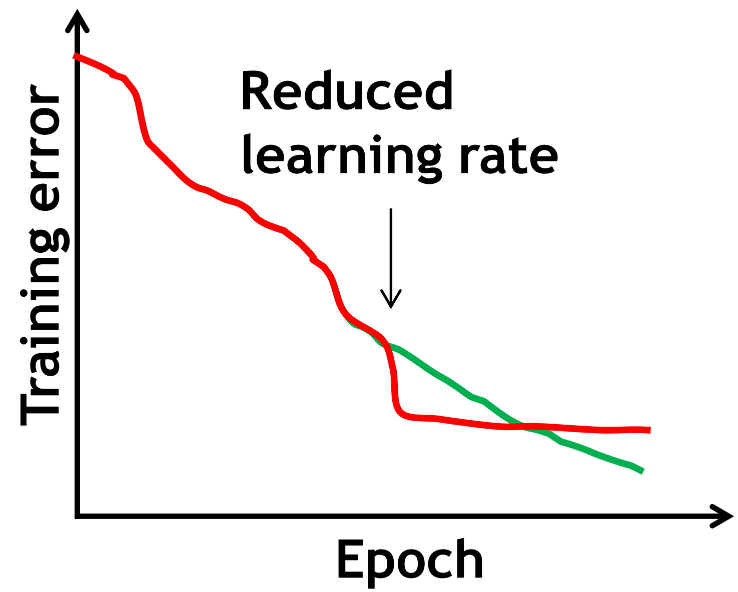


⇒ **Learning often doesn't get stuck, you just may have to wait...**

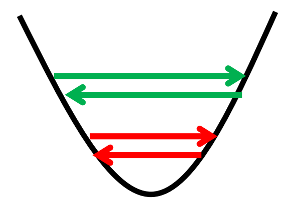
Image source: Yoshua Bengio

Recap: Reducing the Learning Rate

- Final improvement step after convergence is reached
  - Reduce learning rate by a factor of 10.
  - Continue training for a few epochs.
  - Do this 1-3 times, then stop training.



- Effect
  - Turning down the learning rate will reduce the random fluctuations in the error due to different gradients on different minibatches.



- *Be careful: Do not turn down the learning rate too soon!*
  - Further progress will be much slower after that.

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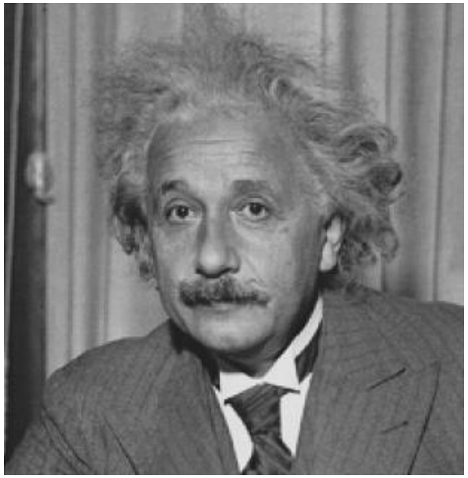
  - VGGNet
  - GoogLeNet

Neural Networks for Computer Vision

- How should we approach vision problems?



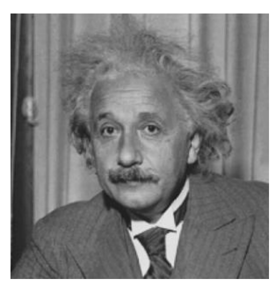
$\longrightarrow$ Face Y/N?

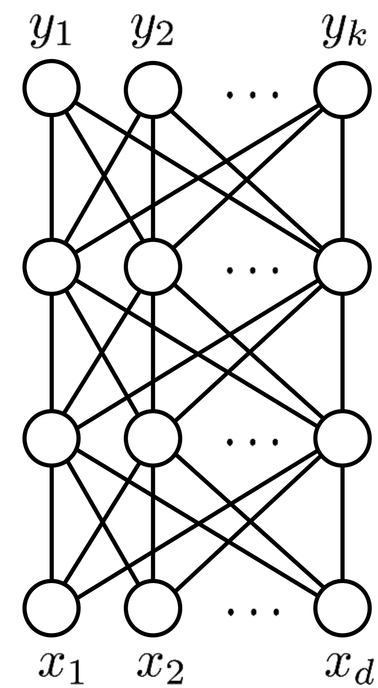
- Architectural considerations
  - Input is 2D $\Rightarrow$ 2D layers of units
  - No pre-segmentation $\Rightarrow$ Need robustness to misalignments
  - Vision is hierarchical $\Rightarrow$ Hierarchical multi-layered structure
  - Vision is difficult $\Rightarrow$ Network should be deep

Why Hierarchical Multi-Layered Models?

- **Motivation 1: Visual scenes are hierarchically organized**

Object	Face
↑	↑
Object parts	Eyes, nose, ...
↑	↑
Primitive features	Oriented edges
↑	↑
Input image	Face image

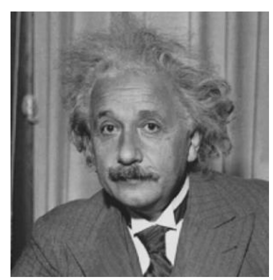




Why Hierarchical Multi-Layered Models?

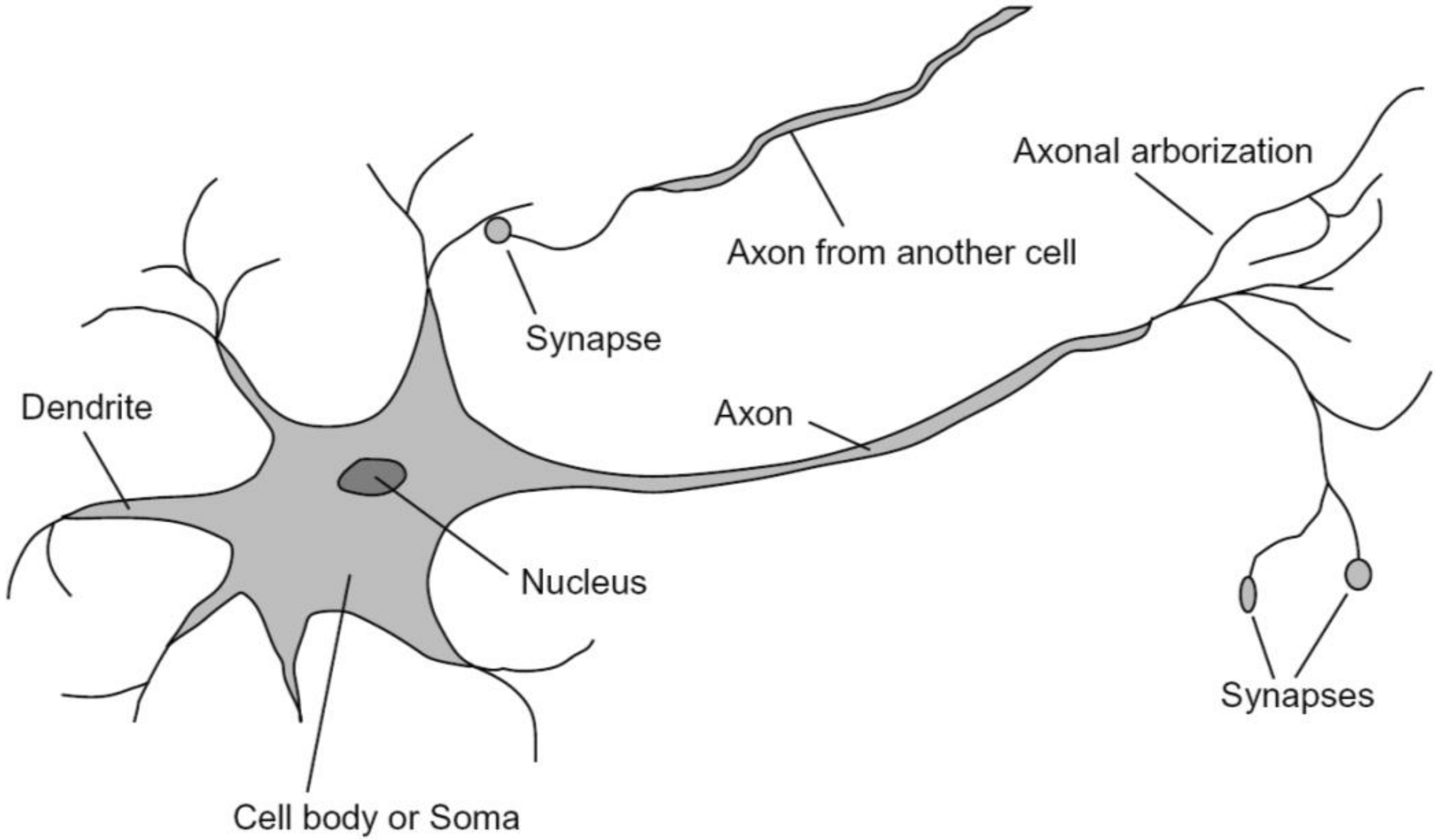
- Motivation 2: *Biological vision* is hierarchical, too

Object	Face	Inferotemporal cortex
↑	↑	
Object parts	Eyes, nose, ...	V4: different textures
↑	↑	
Primitive features	Oriented edges	V1: simple and complex cells
↑	↑	
Input image	Face image	Photoreceptors, retina



Slide adapted from Richard Turner

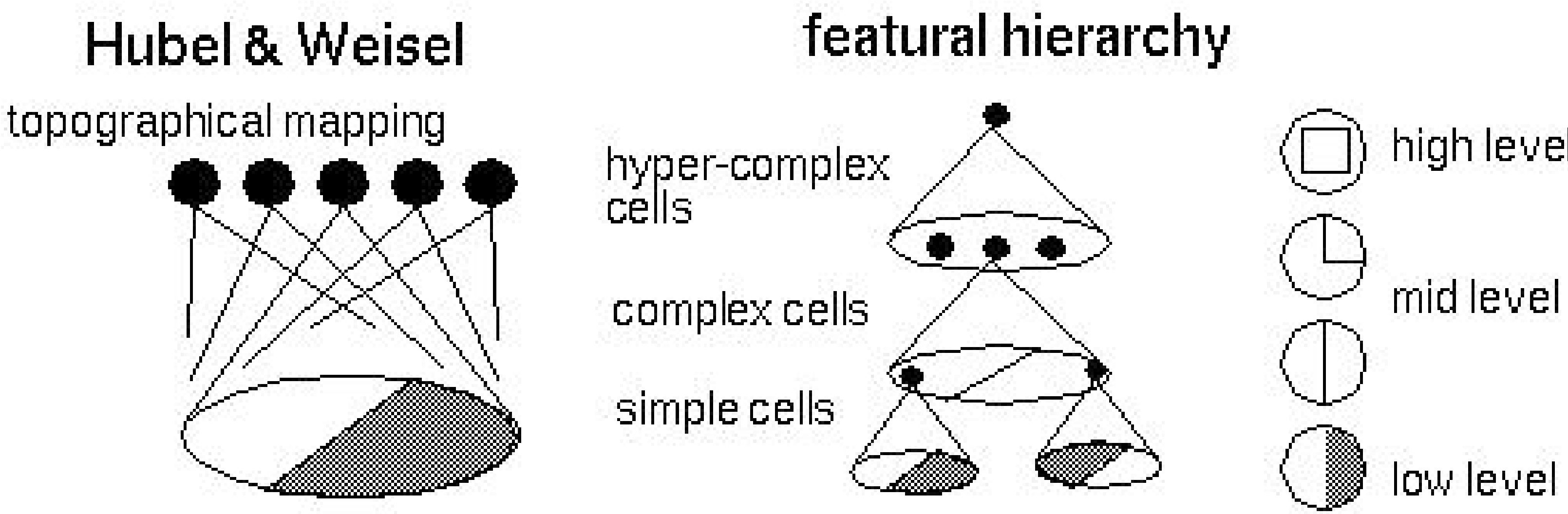
Inspiration: Neuron Cells



Slide credit: Svetlana Lazebnik, Rob Fergus

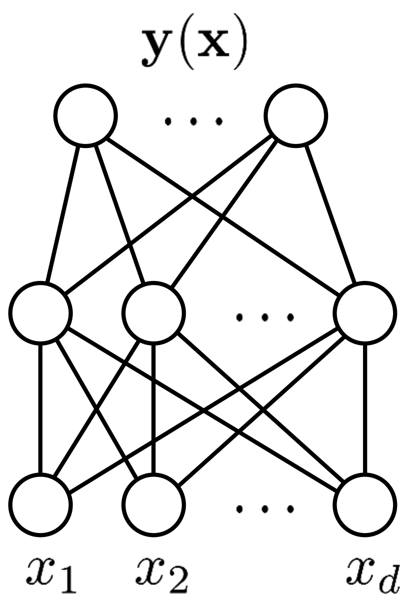
Hubel/Wiesel Architecture

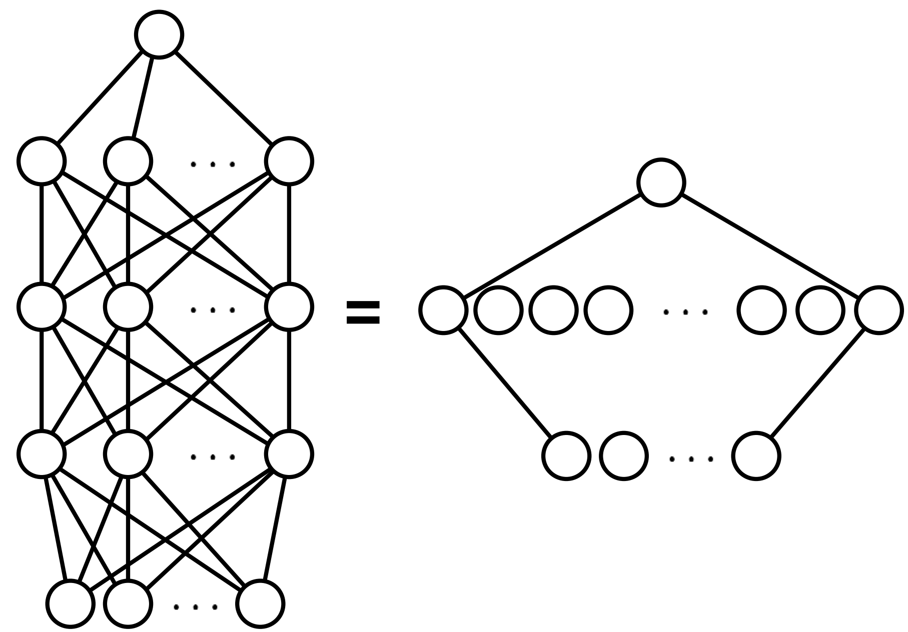
- **D. Hubel, T. Wiesel (1959, 1962, Nobel Prize 1981)**
  - **Visual cortex consists of a hierarchy of *simple*, *complex*, and *hyper-complex* cells**



Why Hierarchical Multi-Layered Models?

- **Motivation 3: Shallow architectures are inefficient at representing complex functions**





An MLP with 1 hidden layer can implement *any* function (universal approximator)

However, if the function is deep, a very large hidden layer may be required.

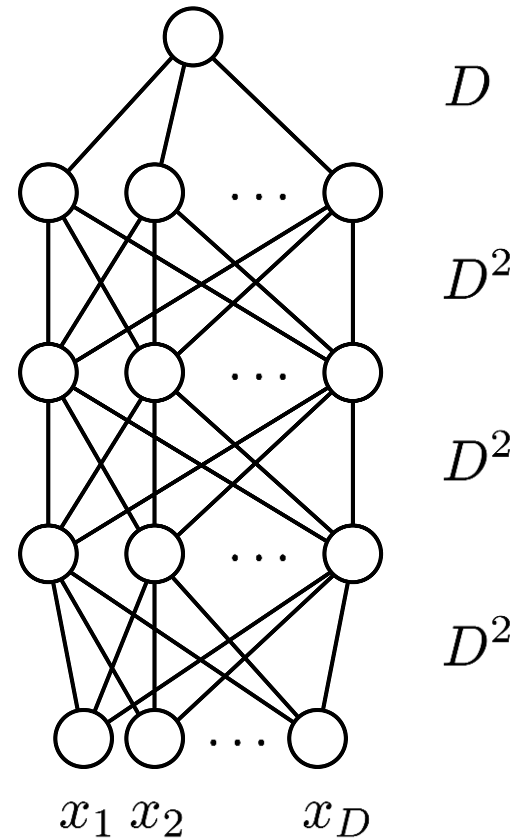
What's Wrong With Standard Neural Networks?

- Complexity analysis
  - How many parameters does this network have?

$$|\theta| = 3D^2 + D$$

  - For a small 32×32 image

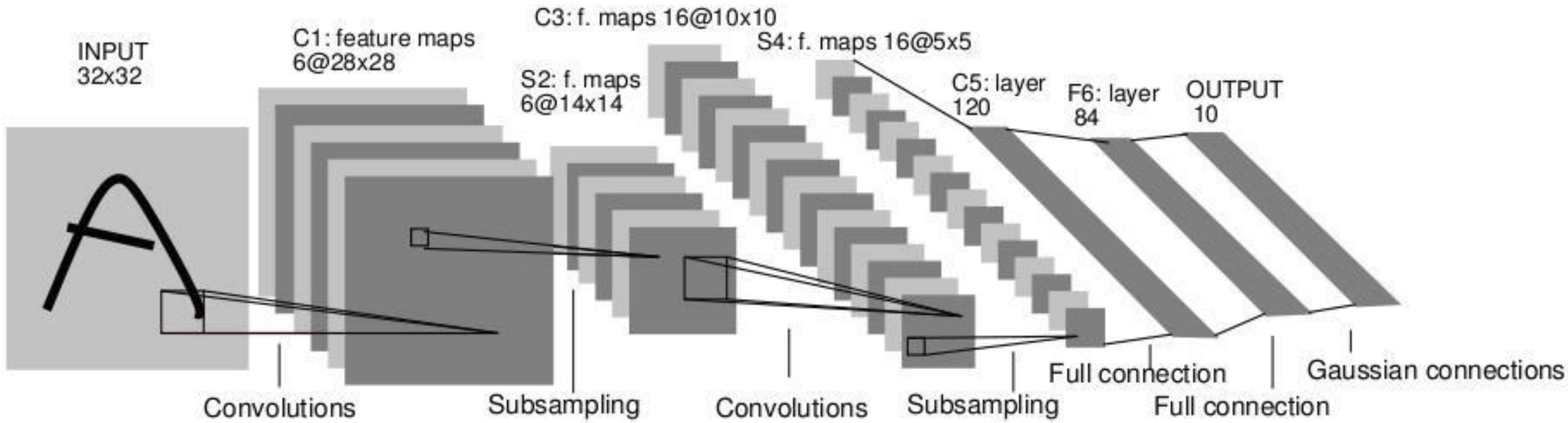
$$|\theta| = 3 \cdot 32^4 + 32^2 \approx 3 \cdot 10^6$$



- Consequences
  - Hard to train
  - Need to initialize carefully

  - *Convolutional nets reduce the number of parameters!*

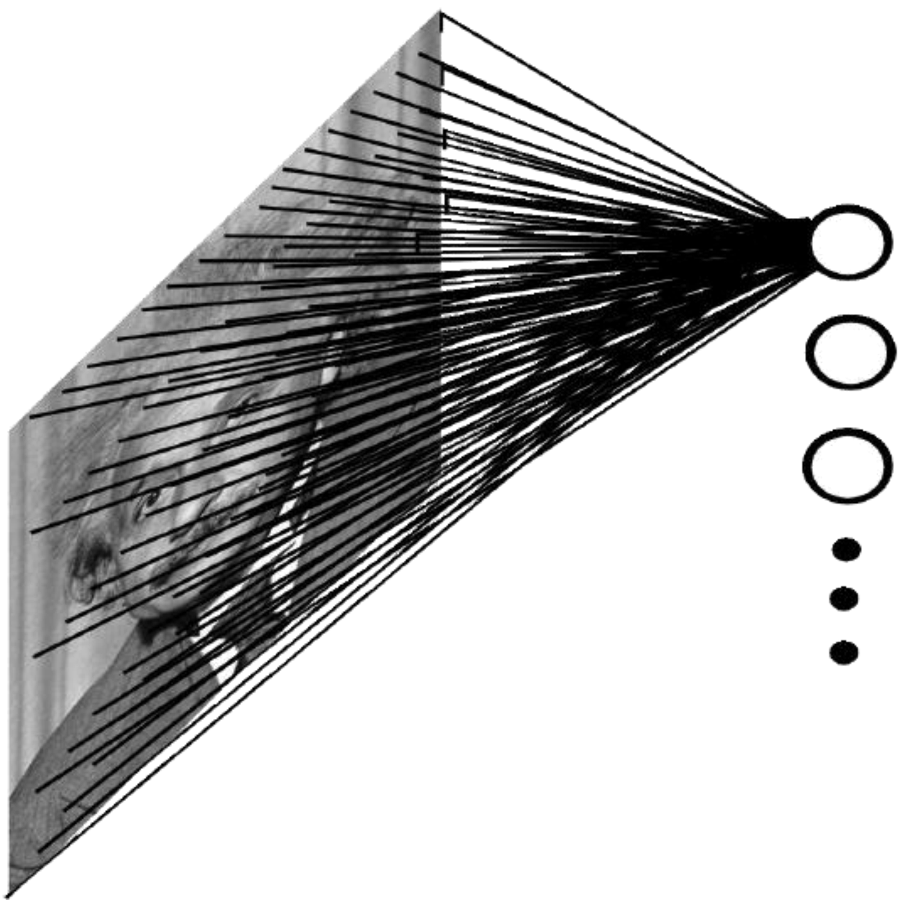
Convolutional Neural Networks (CNN, ConvNet)



- Neural network with specialized connectivity structure
  - Stack multiple stages of feature extractors
  - Higher stages compute more global, more invariant features
  - Classification layer at the end

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Convolutional Networks: Intuition



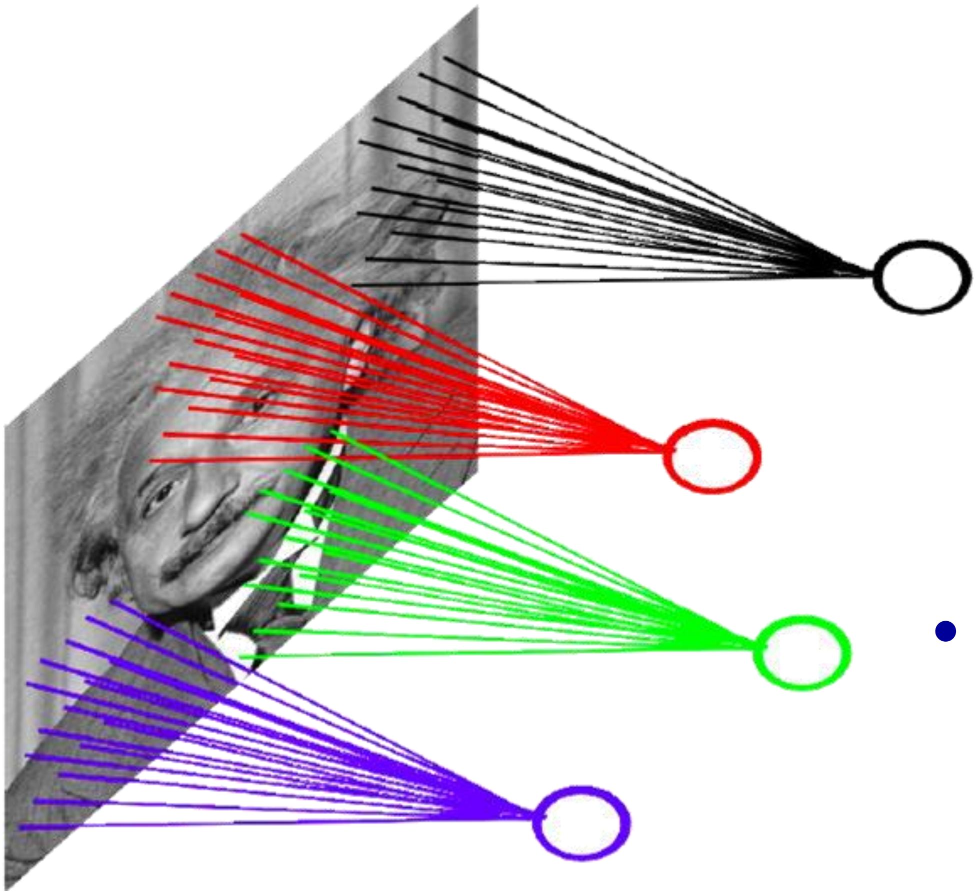
- Fully connected network
  - E.g. 1000×1000 image
    1M hidden units

  $\Rightarrow$ 1T parameters!

- Ideas to improve this
  - Spatial correlation is local

Image source: Yann LeCun

Convolutional Networks: Intuition

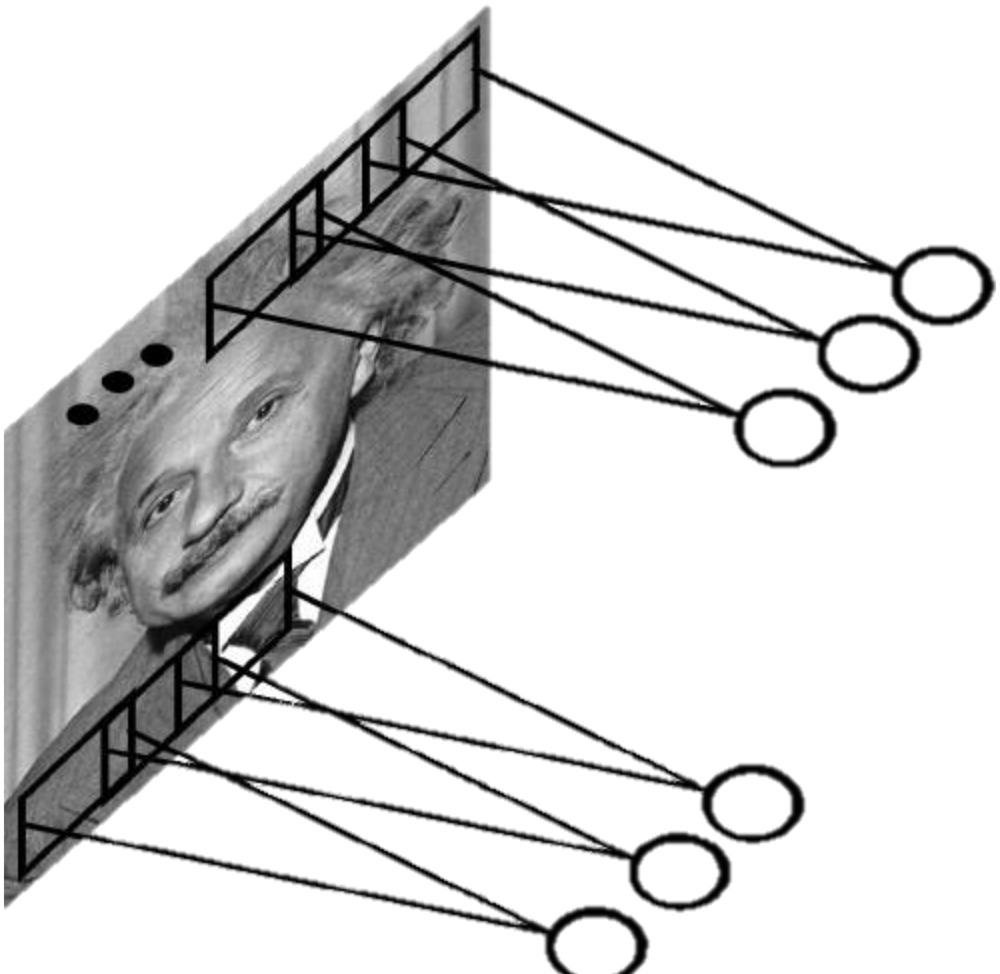


- Locally connected net
  - E.g. 1000×1000 image
    1M hidden units
    10×10 receptive fields
  - ⇒ 100M parameters!

- Ideas to improve this
  - Spatial correlation is local
  - Want translation invariance

Image source: Yann LeCun

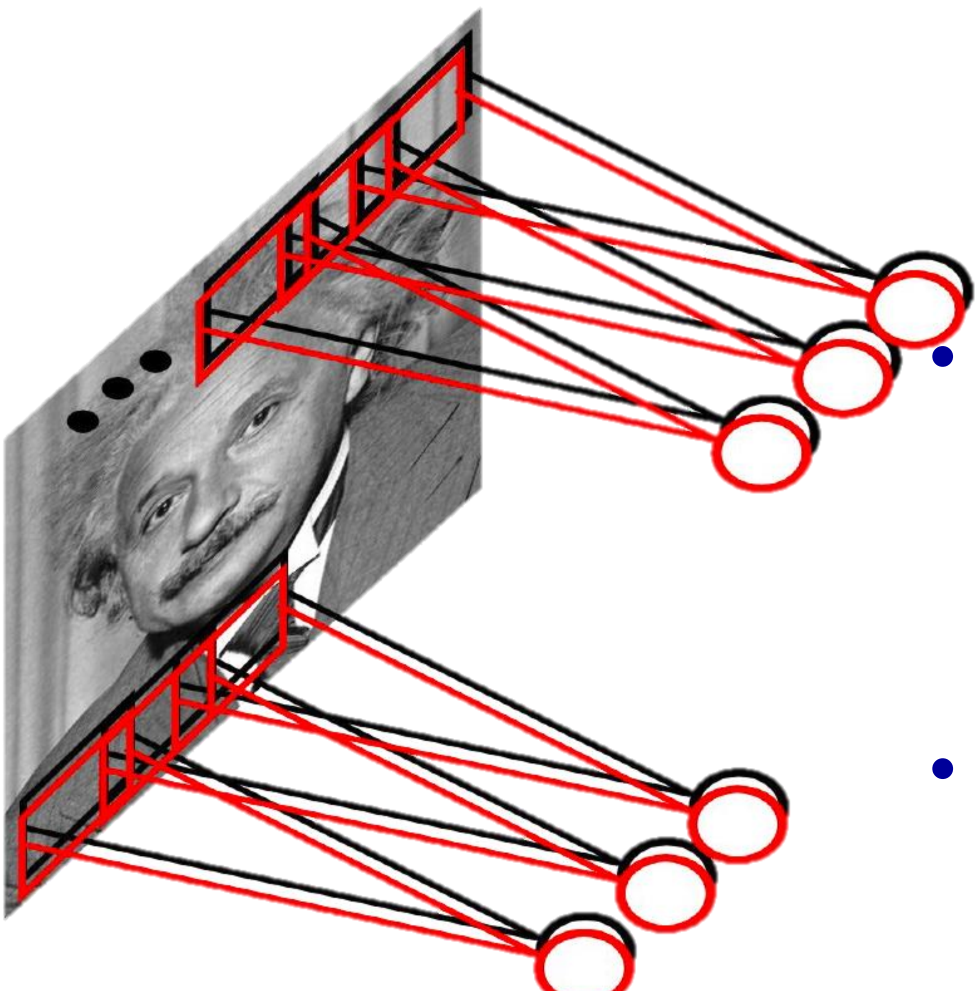
Convolutional Networks: Intuition



- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels

Image source: Yann LeCun

Convolutional Networks: Intuition



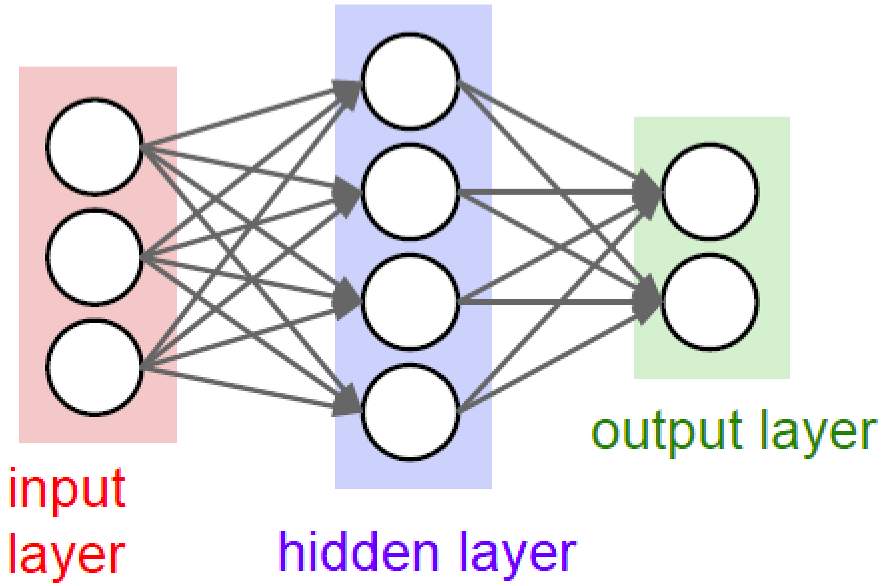
- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels
- Learn *multiple* filters
  - E.g. 1000×1000 image
    100 filters
    10×10 filter size

  ⇒ 10k parameters
- Result: Response map
  - size: 1000×1000×100
  - Only memory, not params!

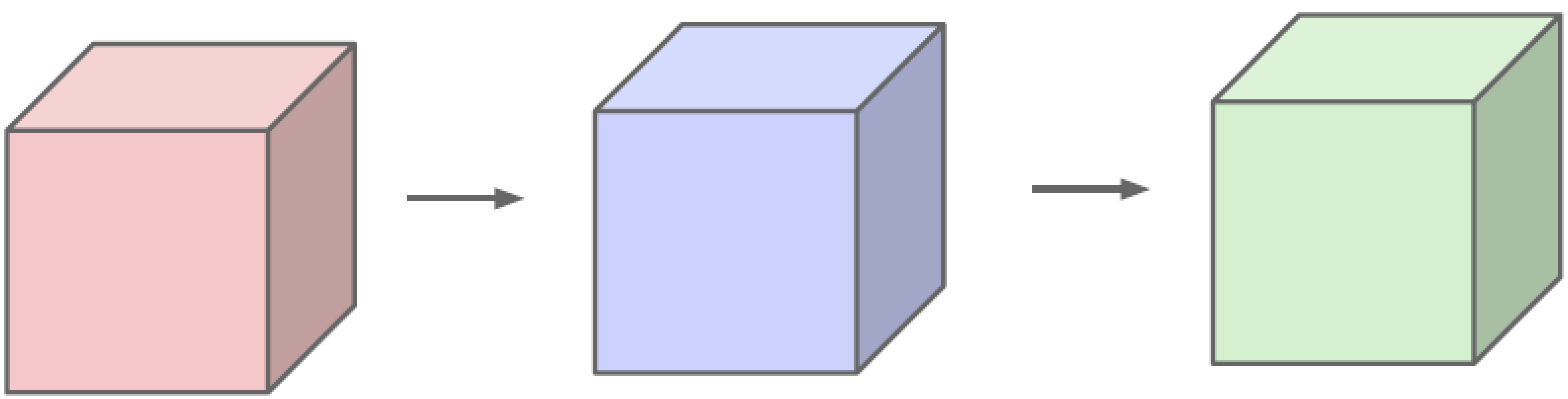
Image source: Yann LeCun

Important Conceptual Shift

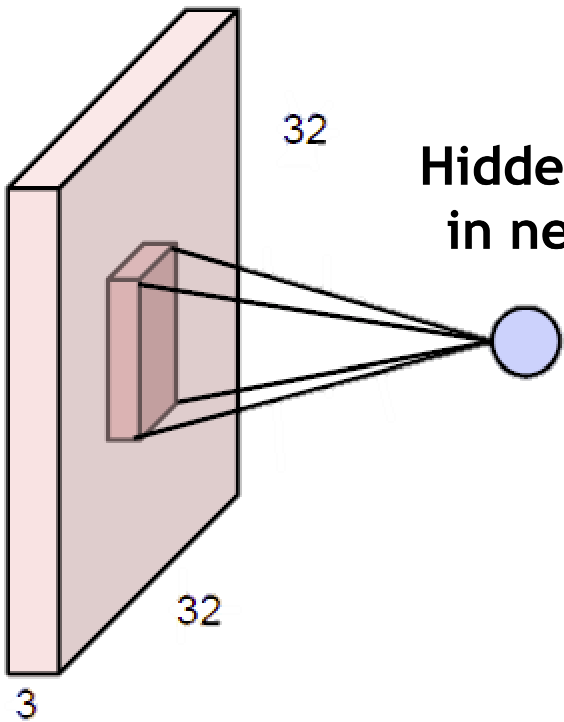
- **Before**



- **Now:**



Convolution Layers



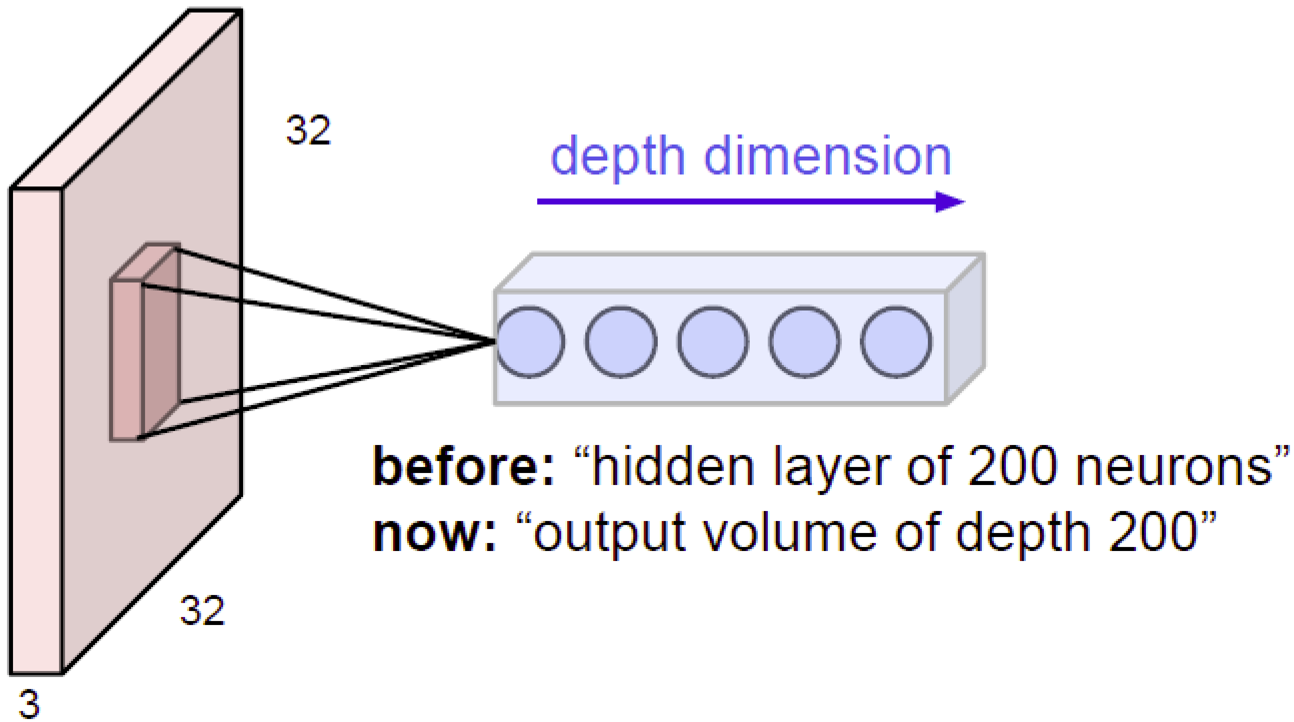
Example
image: 32×32×3 volume

Before: Full connectivity
32×32×3 weights

Now: Local connectivity
One neuron connects to, e.g.,
5×5×3 region.
⇒ Only 5×5×3 **shared weights**.

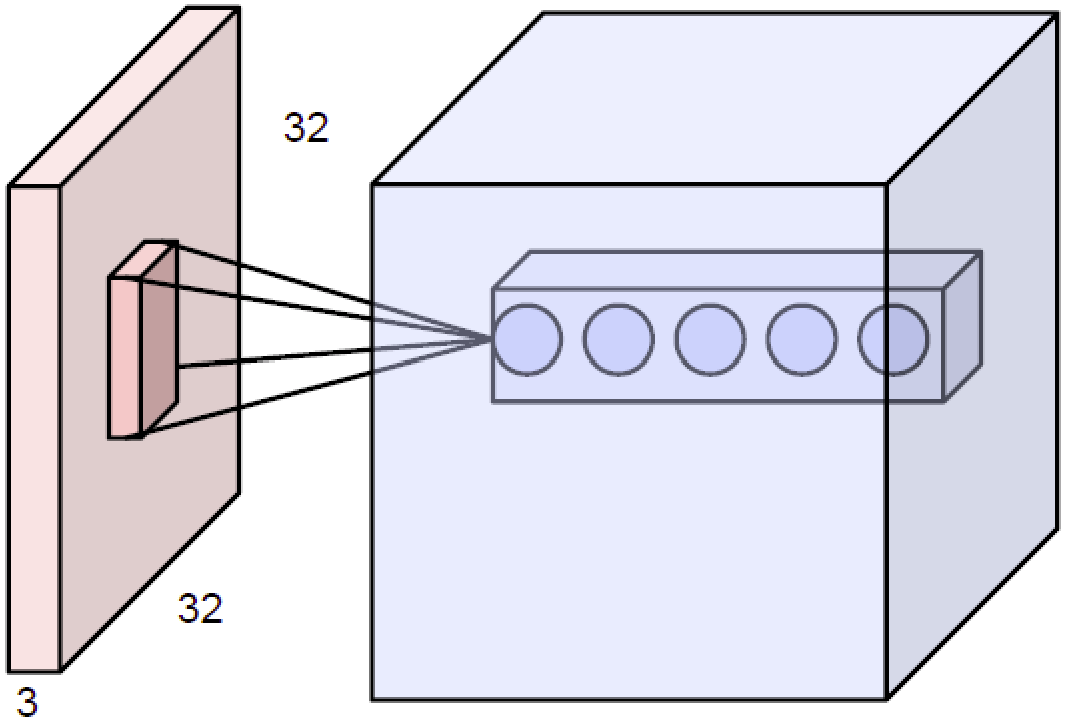
- Note: Connectivity is
  - Local in space (5×5 inside 32×32)
  - But full in depth (all 3 depth channels)

Convolution Layers

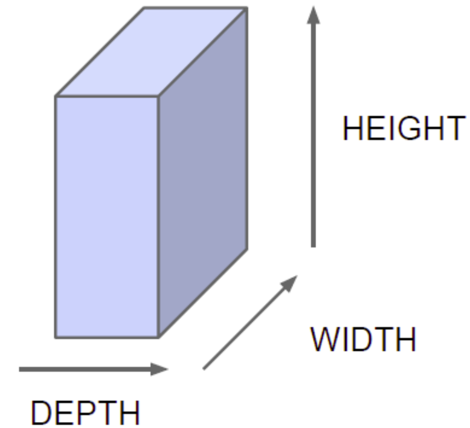


- **All Neural Net activations arranged in 3 dimensions**
  - **Multiple neurons all looking at the same input region, stacked in depth**

Convolution Layers

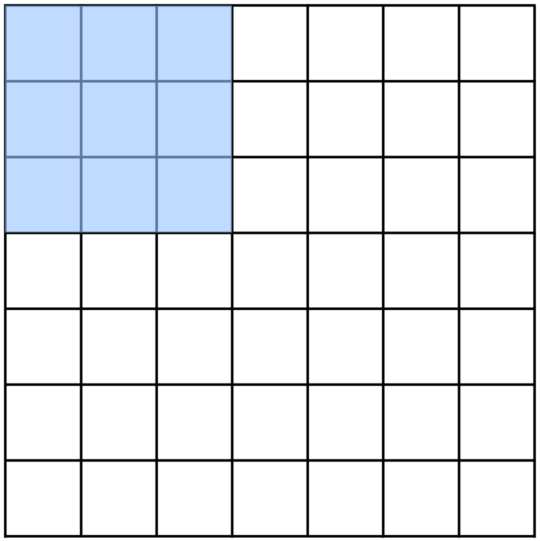


Naming convention:



- All Neural Net activations arranged in 3 dimensions
  - Multiple neurons all looking at the same input region, stacked in depth
  - Form a single [$1\times1\times$depth] depth column in output volume.

Convolution Layers

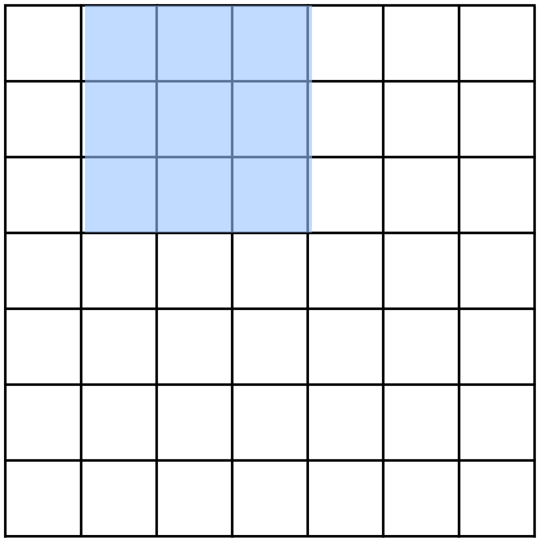


Example:
7×7 input
assume 3×3 connectivity
stride 1

- Replicate this column of hidden neurons across space, with some stride.

Slide credit: FeiFei Li, Andrej Karpathy

Convolution Layers



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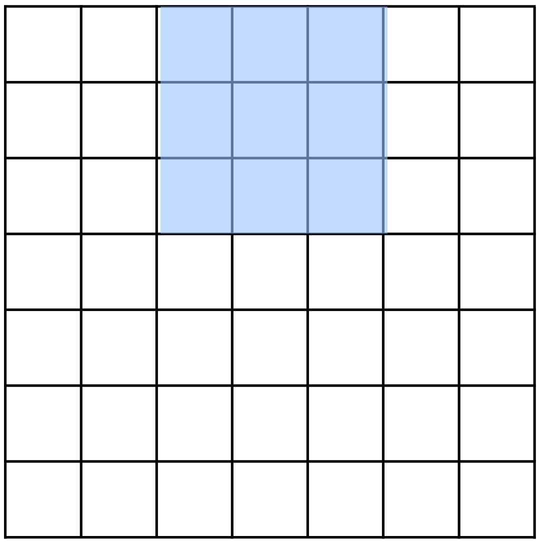

Example:
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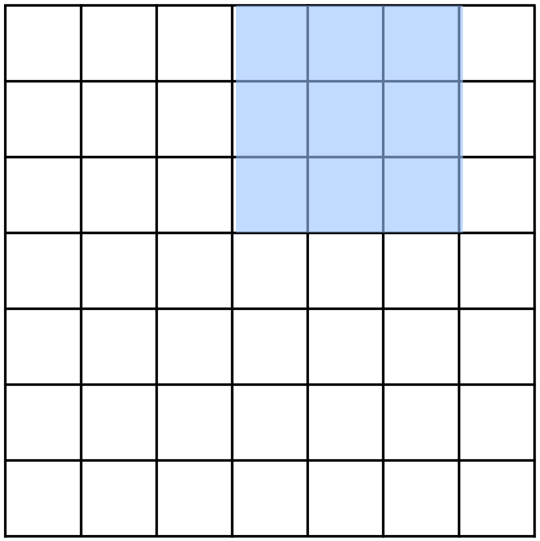
- **Replicate this column of hidden neurons across space, with some stride.**

Convolution Layers



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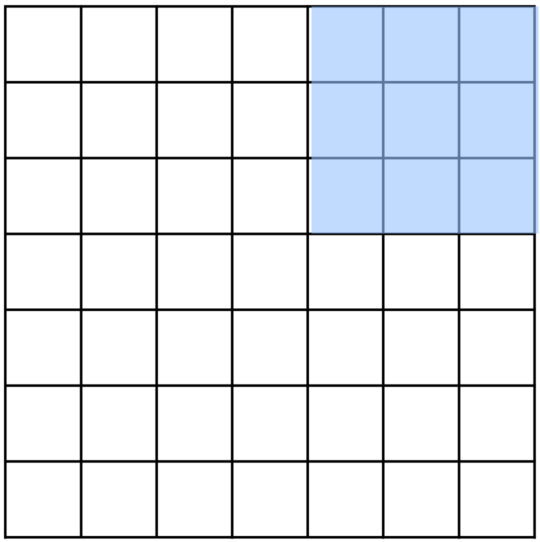
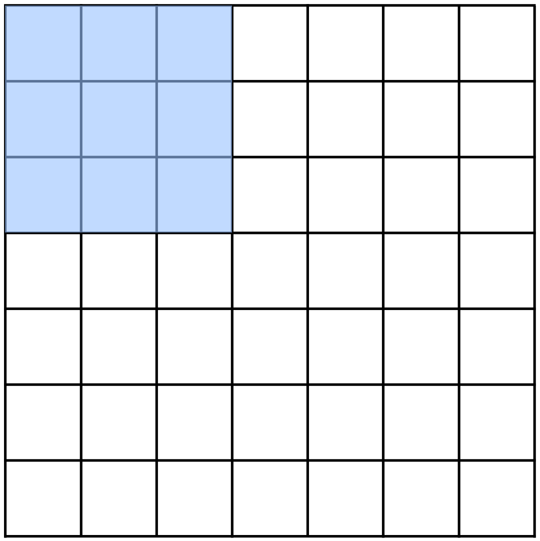
Convolution Layers



Example:
7×7 input
assume 3×3 connectivity
stride 1
⇒ 5×5 output

- Replicate this column of hidden neurons across space, with some stride.

Convolution Layers

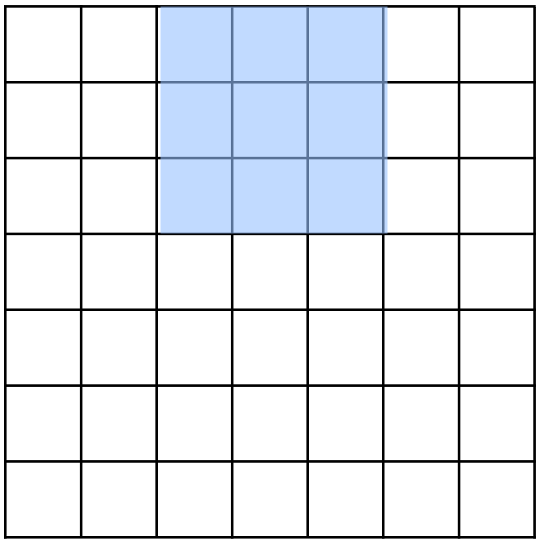


Example:
7×7 input
assume 3×3 connectivity
stride 1
$\Rightarrow$ 5×5 output

What about stride 2?

- Replicate this column of hidden neurons across space, with some stride.

Convolution Layers



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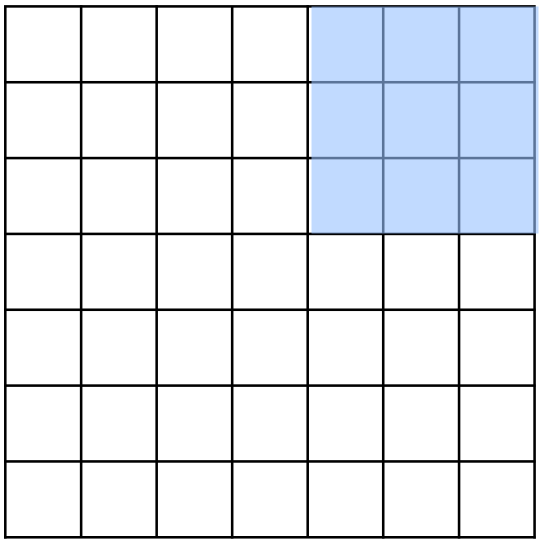
Convolution Layers

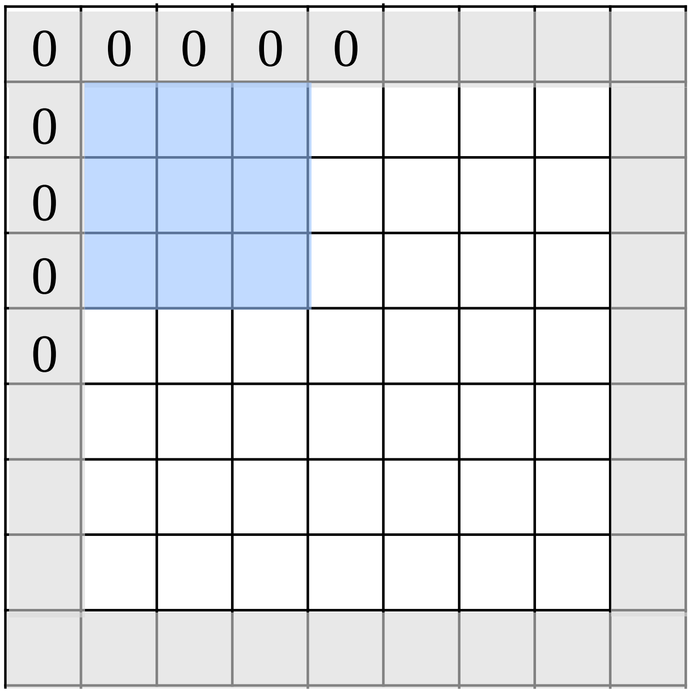


Example:
7×7 input
assume 3×3 connectivity
stride 1
$\Rightarrow$ 5×5 output

What about stride 2?
$\Rightarrow$ 3×3 output

- Replicate this column of hidden neurons across space, with some stride.

Convolution Layers



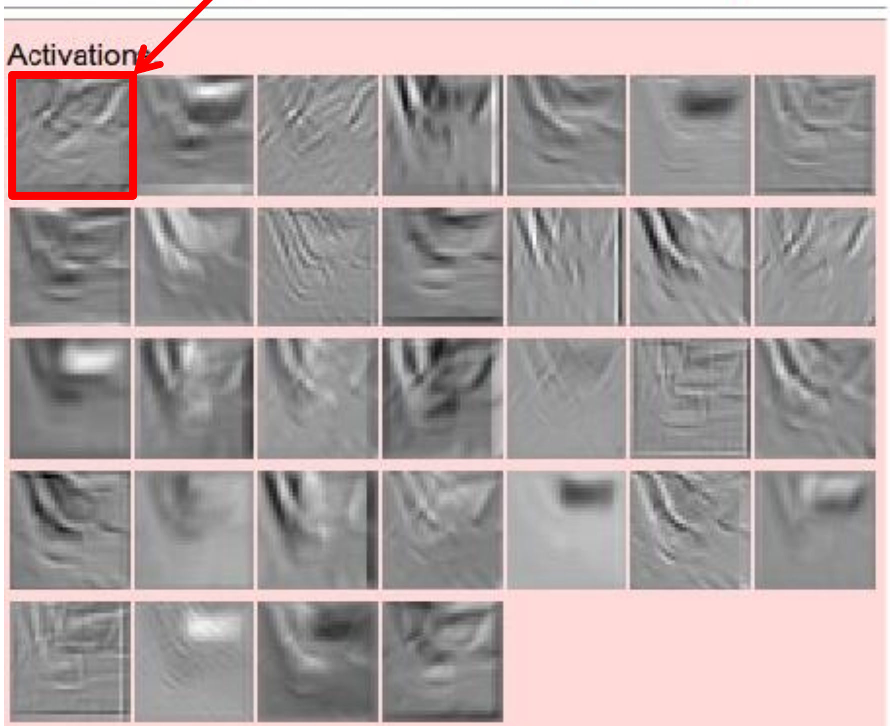
Example:
7×7 input
assume 3×3 connectivity
stride 1
$\Rightarrow$ 5×5 output

What about stride 2?
$\Rightarrow$ 3×3 output

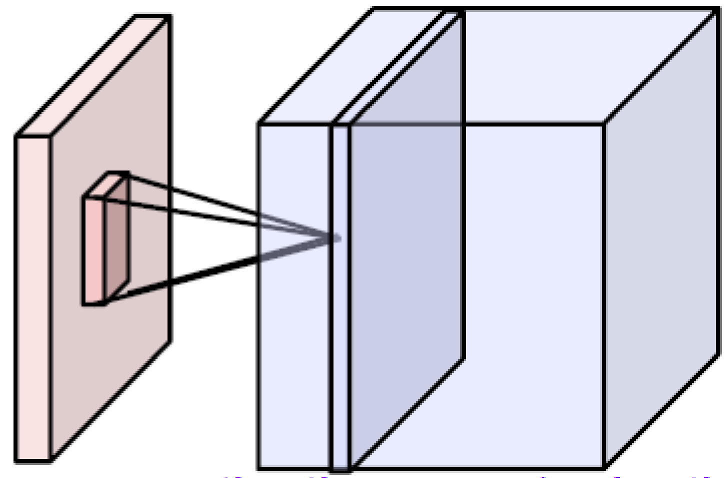
- Replicate this column of hidden neurons across space, with some stride.
- In practice, common to zero-pad the border.
  - Preserves the size of the input spatially.

Activation Maps of Convolutional Filters

5×5 filters

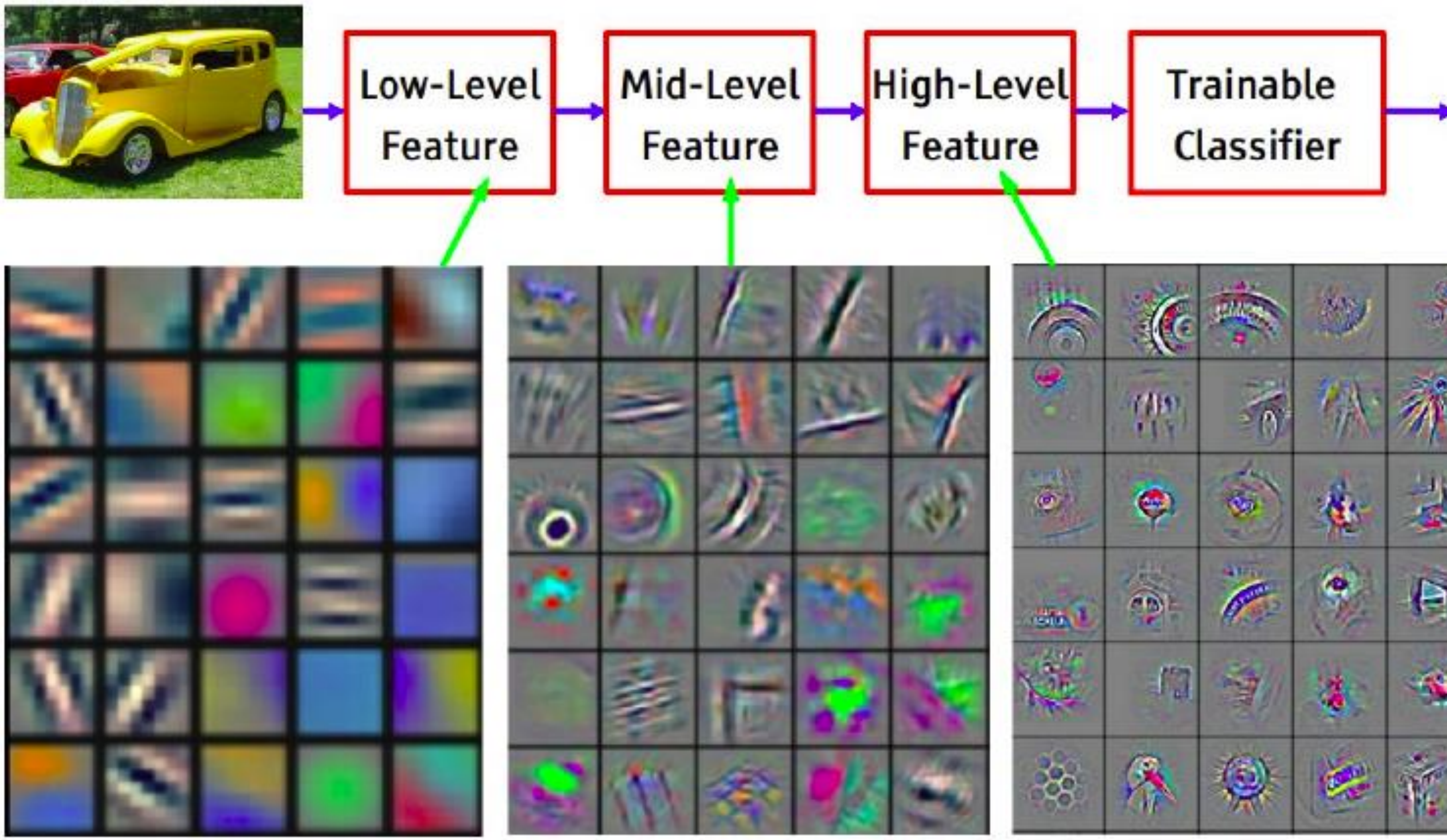


Activation maps



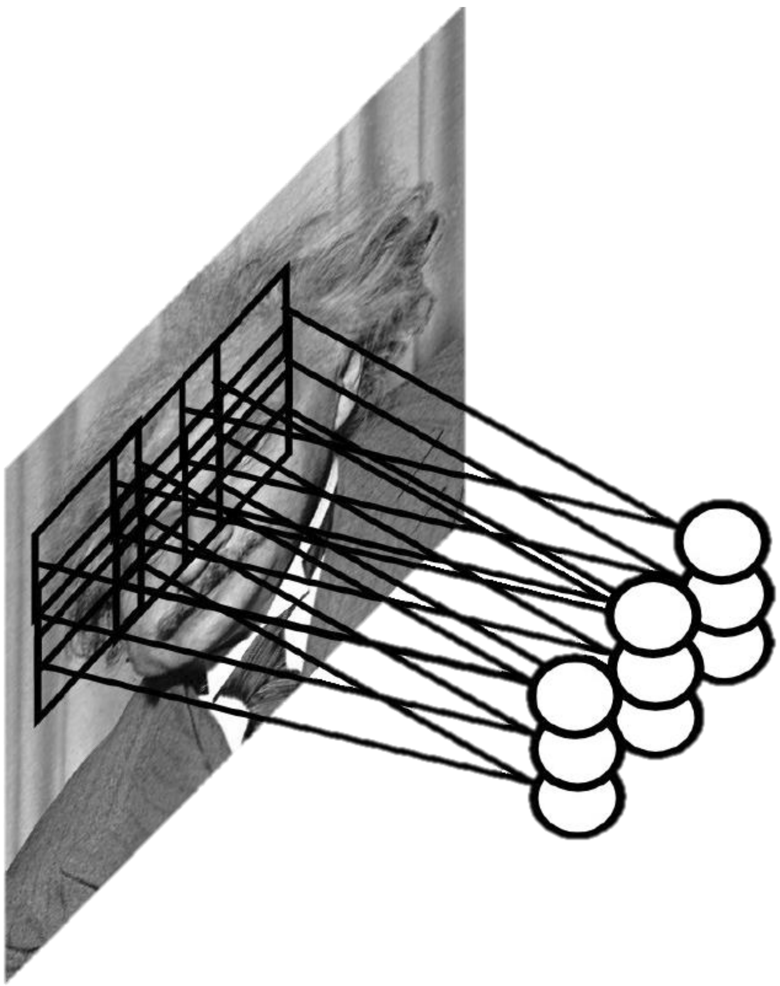
Each activation map is a depth slice through the output volume.

Effect of Multiple Convolution Layers



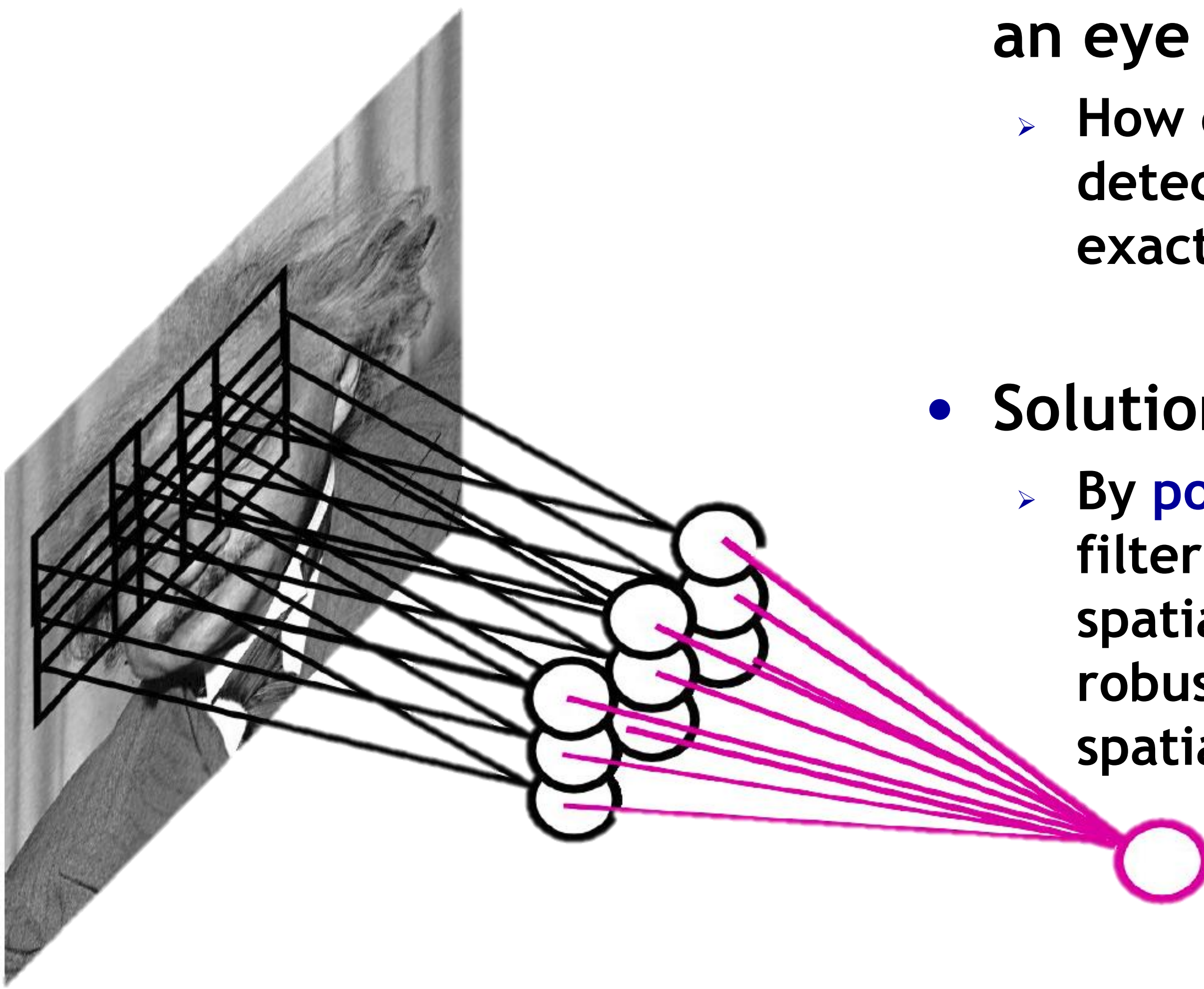
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Convolutional Networks: Intuition



- Let's assume the filter is an eye detector
  - How can we make the detection robust to the exact location of the eye?

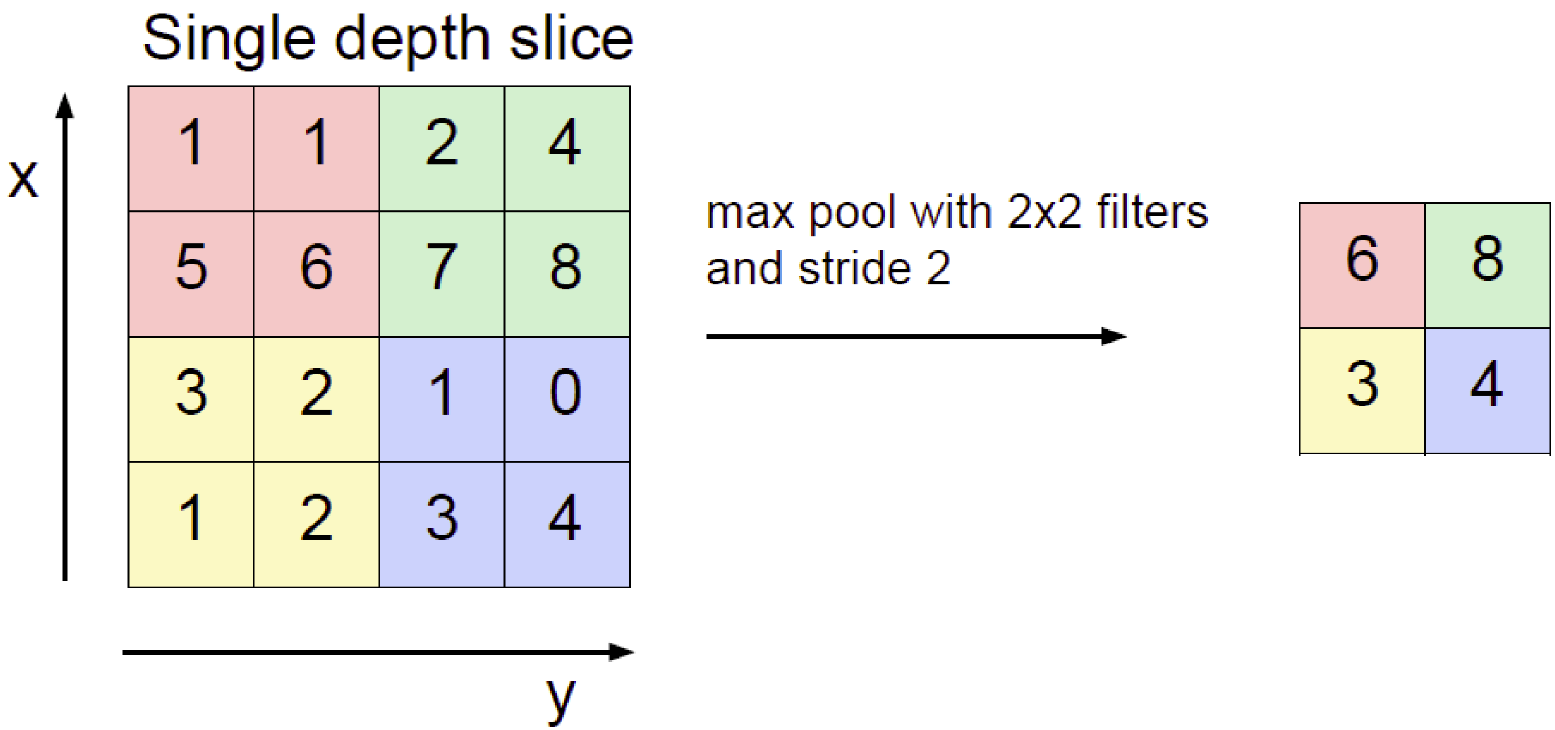
Convolutional Networks: Intuition



- **Let's assume the filter is an eye detector**
  - How can we make the detection robust to the exact location of the eye?
- **Solution:**
  - By pooling (e.g., max or avg) filter responses at different spatial locations, we gain robustness to the exact spatial location of features.

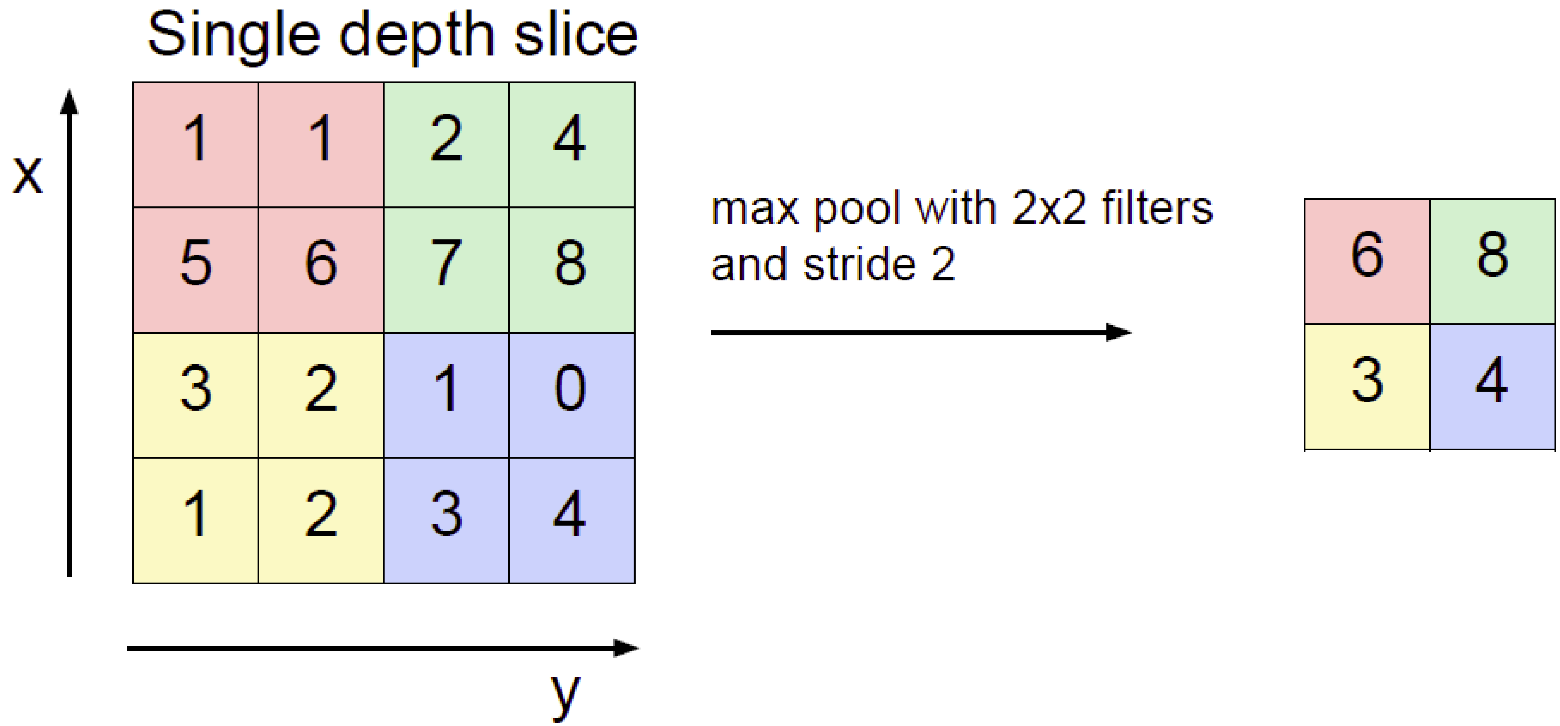
Image source: Yann LeCun

Max Pooling



- **Effect:**
  - **Make the representation smaller without losing too much information**
  - **Achieve robustness to translations**

Max Pooling



- **Note**
  - **Pooling happens independently across each slice, preserving the number of slices.**

CNNs: Implication for Back-Propagation

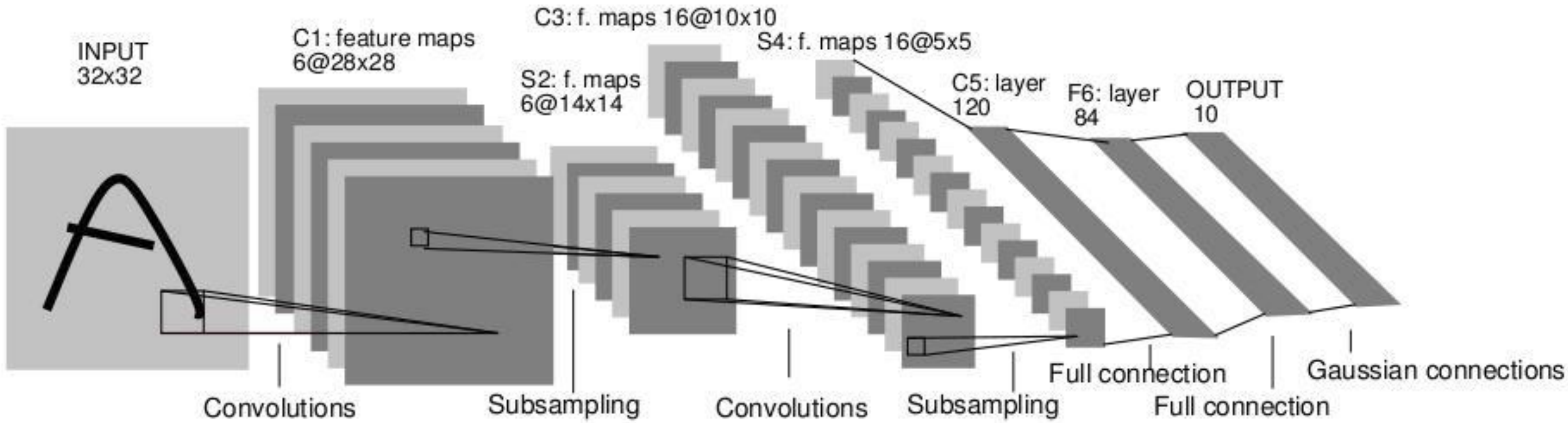
- Convolutional layers
  - Filter weights are shared between locations

  $\Rightarrow$ Gradients are added for each filter location.

Topics of This Lecture

- Tricks of the Trade
  - Recap
- Convolutional Neural Networks
  - Neural Networks for Computer Vision
  - Convolutional Layers
  - Pooling Layers
- **CNN Architectures**
  - LeNet
  - AlexNet
  - VGGNet
  - GoogLeNet

CNN Architectures: LeNet (1998)



- Early convolutional architecture
  - 2 Convolutional layers, 2 pooling layers
  - Fully-connected NN layers for classification
  - Successfully used for handwritten digit recognition (MNIST)

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

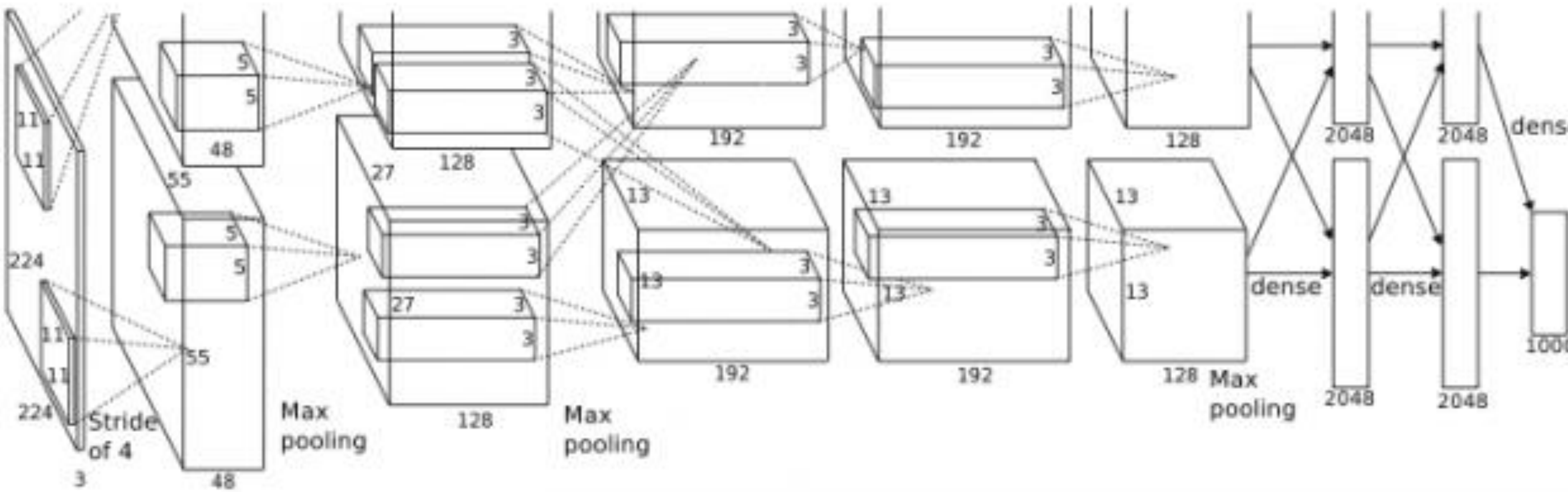
ImageNet Challenge 2012

- ImageNet
  - ~14M labeled internet images
  - 20k classes
  - Human labels via Amazon Mechanical Turk

[Deng et al., CVPR'09]

- Challenge (ILSVRC)
  - 1.2 million training images
  - 1000 classes
  - Goal: Predict ground-truth class within top-5 responses
  - Currently one of the top benchmarks in Computer Vision

CNN Architectures: AlexNet (2012)

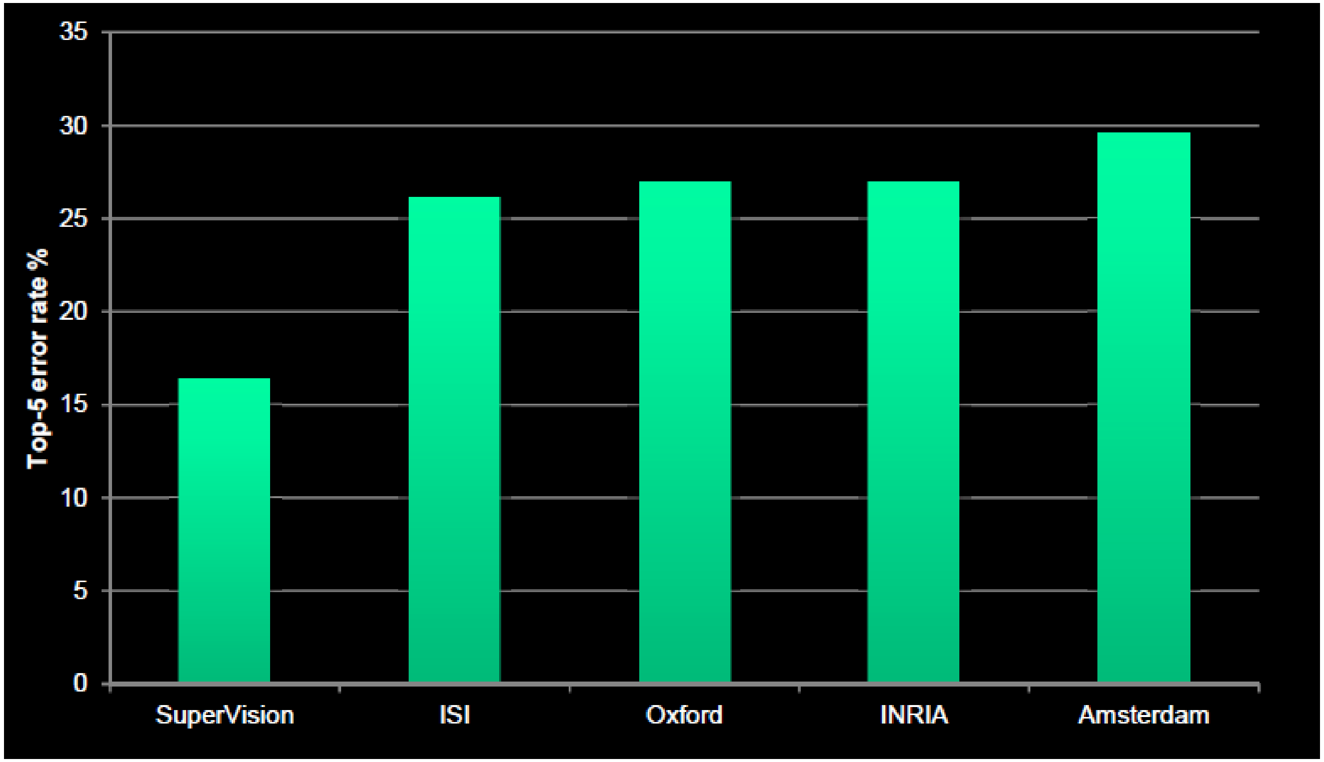


- **Similar framework as LeNet, but**
  - **Bigger model (7 hidden layers, 650k units, 60M parameters)**
  - **More data (10^6 images instead of 10^3)**
  - **GPU implementation**
  - **Better regularization and up-to-date tricks for training (Dropout)**

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

ILSVRC 2012 Results



- AlexNet almost halved the error rate
  - 16.4% error (top-5) vs. 26.2% for the next best approach

  $\Rightarrow$ A revolution in Computer Vision
  - Acquired by Google in Jan '13, deployed in Google+ in May '13

AlexNet Results

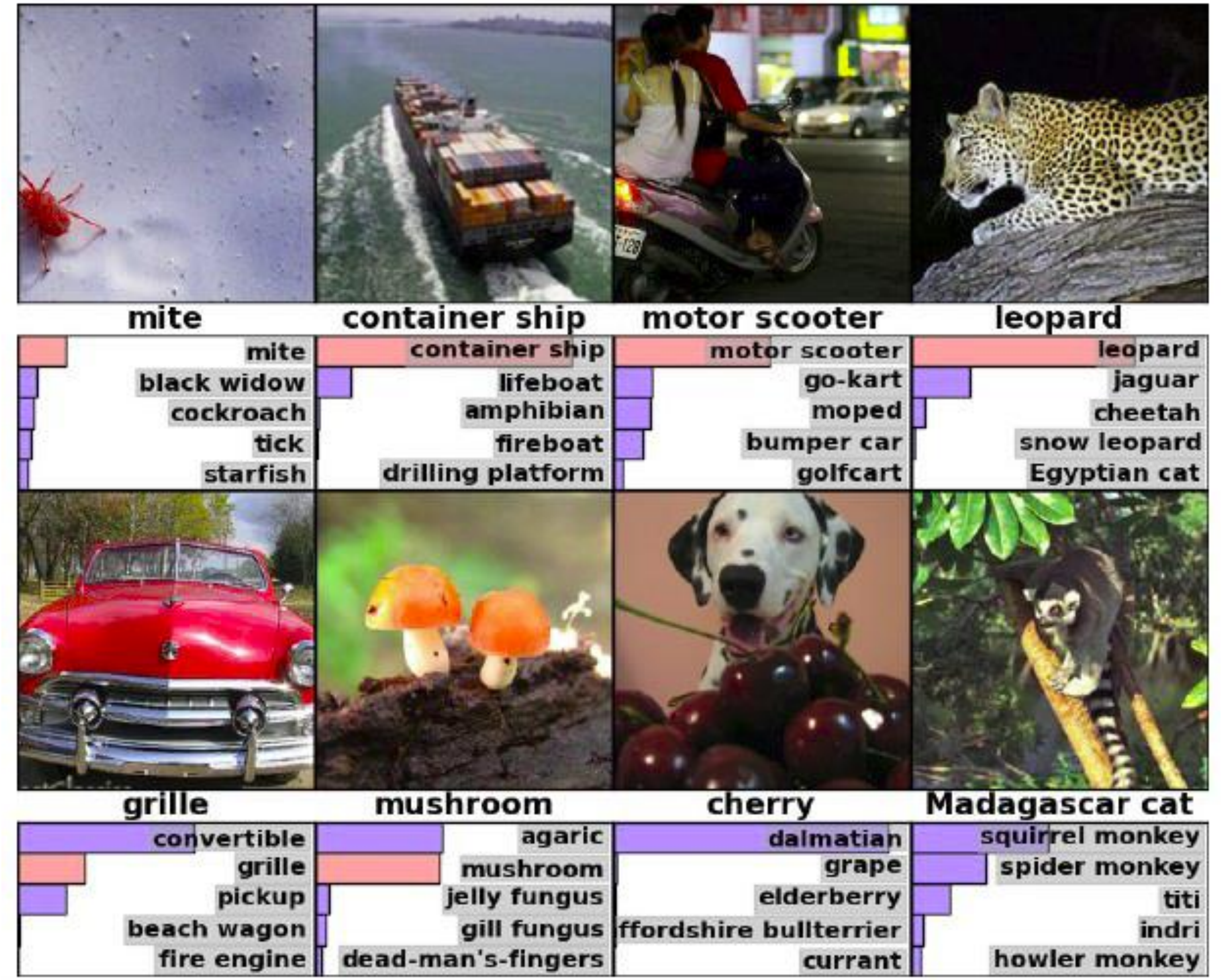


Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

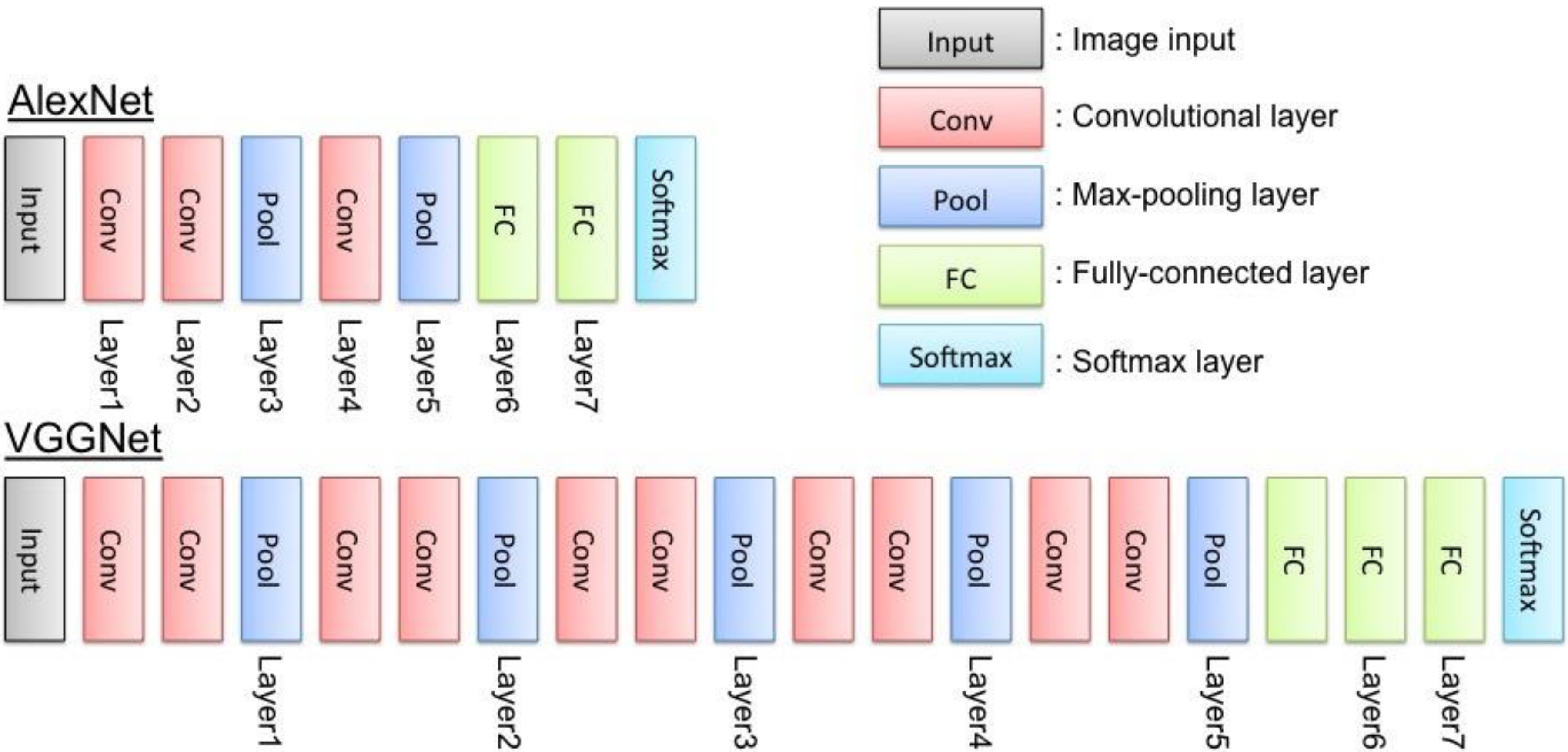
AlexNet Results

Test image

Retrieved images

Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

CNN Architectures: VGGNet (2014/15)



K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015

Image source: Hirokatsu Kataoka

CNN Architectures: VGGNet (2014/15)

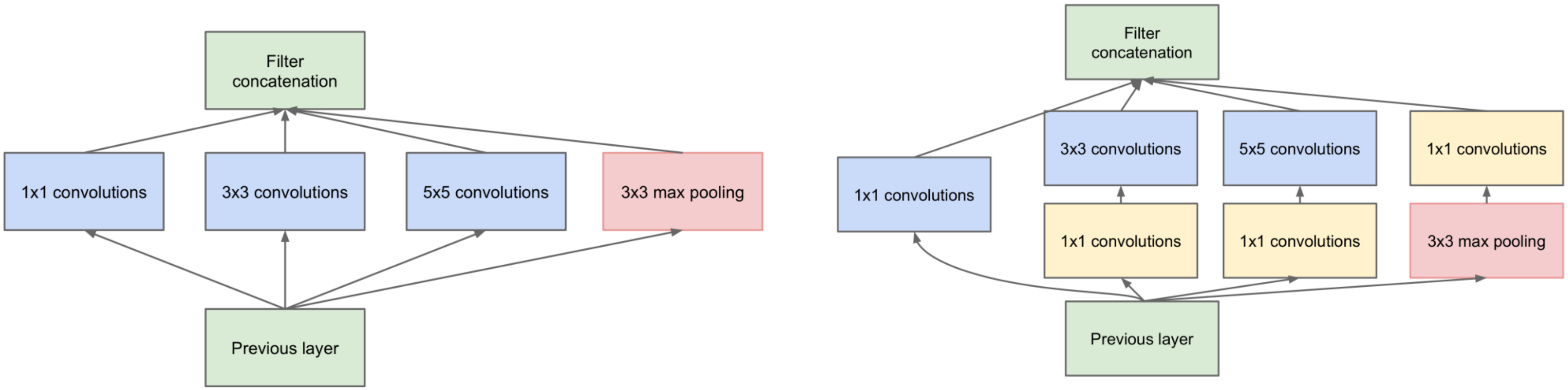
- **Main ideas**
  - Deeper network
  - Stacked convolutional layers with smaller filters (+ nonlinearity)
  - Detailed evaluation of all components
- **Results**
  - Improved ILSVRC top-5 error rate to 6.7%.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Mainly used

Image source: Simonyan & Zisserman

CNN Architectures: GoogLeNet (2014)



(a) Inception module, naïve version

(b) Inception module with dimension reductions

- **Main ideas**
  - **"Inception" module as modular component**
  - **Learns filters at several scales within each module**

C. Szegedy, W. Liu, Y. Jia, et al, Going Deeper with Convolutions, arXiv:1409.4842, 2014.

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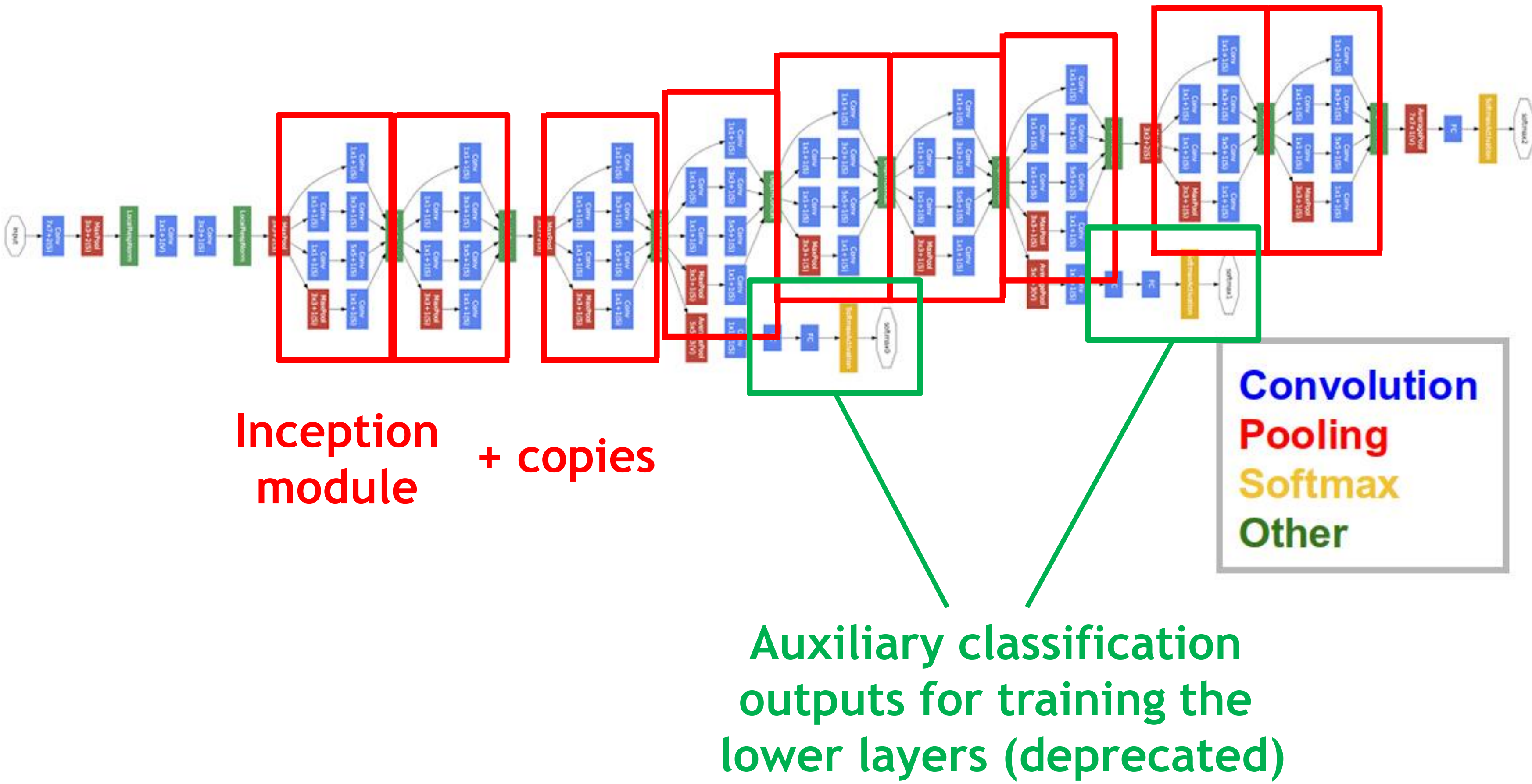
GoogLeNet Visualization



Results on ILSVRC

Method	top-1 val. error (%)	top-5 val. error (%)	top-5 test error (%)
VGG (2 nets, multi-crop & dense eval.)	**23.7**	**6.8**	**6.8**
VGG (1 net, multi-crop & dense eval.)	24.4	7.1	7.0
VGG (ILSVRC submission, 7 nets, dense eval.)	24.7	7.5	7.3
GoogLeNet (Szegedy et al., 2014) (1 net)	-	7.9	
GoogLeNet (Szegedy et al., 2014) (7 nets)	-	**6.7**	
MSRA (He et al., 2014) (11 nets)	-	-	8.1
MSRA (He et al., 2014) (1 net)	27.9	9.1	9.1
Clarifai (Russakovsky et al., 2014) (multiple nets)	-	-	11.7
Clarifai (Russakovsky et al., 2014) (1 net)	-	-	12.5
Zeiler & Fergus (Zeiler & Fergus, 2013) (6 nets)	36.0	14.7	14.8
Zeiler & Fergus (Zeiler & Fergus, 2013) (1 net)	37.5	16.0	16.1
OverFeat (Sermanet et al., 2014) (7 nets)	34.0	13.2	13.6
OverFeat (Sermanet et al., 2014) (1 net)	35.7	14.2	-
Krizhevsky et al. (Krizhevsky et al., 2012) (5 nets)	38.1	16.4	16.4
Krizhevsky et al. (Krizhevsky et al., 2012) (1 net)	40.7	18.2	-

Image source: Simonyan & Zisserman

References and Further Reading

- **LeNet**
  - Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.
- **AlexNet**
  - A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.
- **VGGNet**
  - K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015
- **GoogLeNet**
  - C. Szegedy, W. Liu, Y. Jia, et al, Going Deeper with Convolutions, arXiv:1409.4842, 2014.

References

- ReLu
  - X. Glorot, A. Bordes, Y. Bengio, Deep sparse rectifier neural networks, AISTATS 2011.
- Batch Normalization
  - S. Ioffe, C. Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, ArXiV 1502.03167, 2015.