Introduction to Deep Learning

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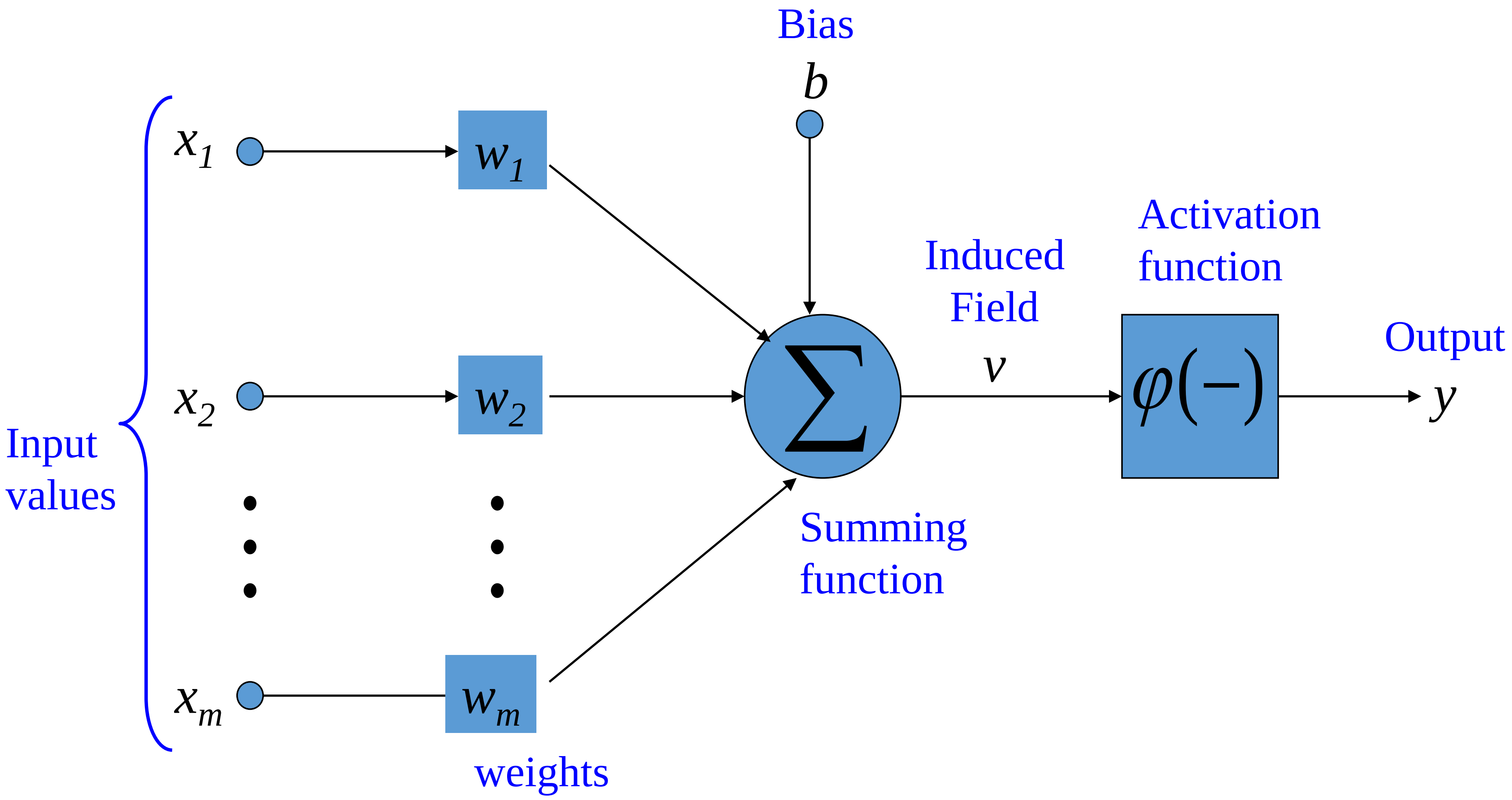
NSM Workshop on Accelerated Data Science

Deep Learning

- Based on neural networks
- Uses deep architectures

- Very successful in many applications

Perceptron


Bias
b
x1
x2
xm
w1
w2
wm
Induced
Field
v
Activation
function
φ(−)
Output
y
Input
values
Summing
function
weights

Neuron Models

- The choice of activation function φ determines the neuron model.

Examples:

- step function:

$$\varphi(v) = \begin{cases} a \ \text{ if } v < c \\ b \ \text{ if } v > c \end{cases}$$

- ramp function:

$$\varphi(v) = \begin{cases} a \ \text{ if } v < c \\ b \ \text{ if } v > d \\ a + ((v-c)(b-a)/(d-c)) \ \text{otherwise} \end{cases}$$

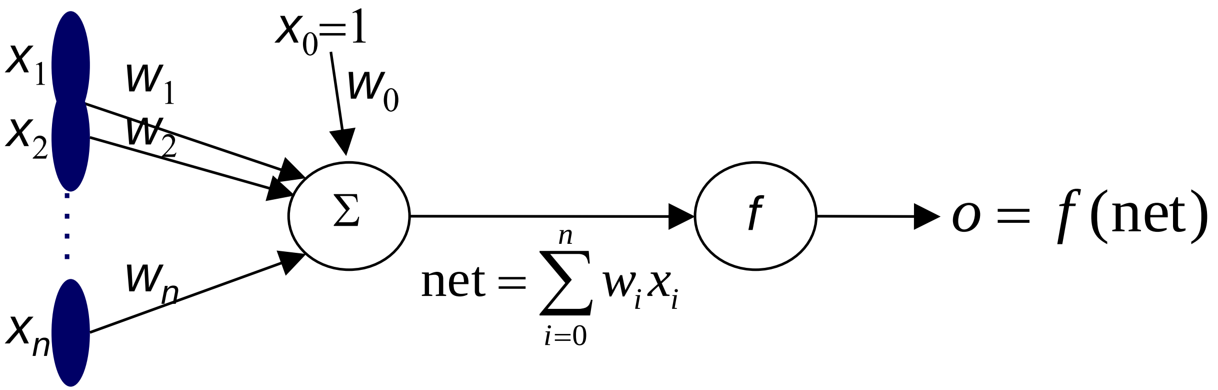
- sigmoid function with z,x,y parameters

$$\varphi(v) = z + \frac{1}{1 + \exp(-xv + y)}$$

- Gaussian function:

$$\varphi(v) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{v-\mu}{\sigma}\right)^2 \right)$$

Sigmoid unit



- f is the sigmoid function

$$f(x) = \frac{1}{1+e^{-x}}$$

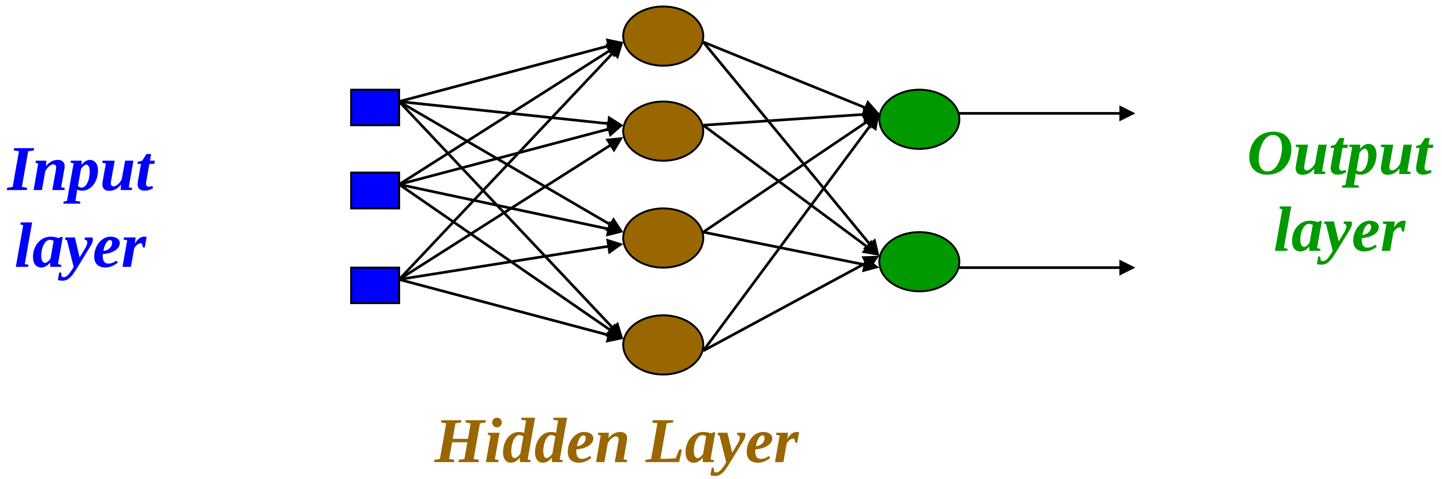
- Derivative can be easily computed:

$$\frac{df(x)}{dx} = f(x)\left(1 - f(x)\right)$$

- Logistic equation
  - used in many applications
  - other functions possible (tanh)
- Single unit:
  - apply gradient descent rule
- Multilayer networks: backpropagation

Multi layer feed-forward NN (FFNN)

- FFNN is a more general network architecture, where there are hidden layers between input and output layers.
- Hidden nodes do not directly receive inputs nor send outputs to the external environment.
- FFNNs overcome the limitation of single-layer NN.
- They can handle non-linearly separable learning tasks.



3-4-2 Network

Backpropagation

- Initialize all weights to small random numbers
- Repeat

  For each training example

  1. Input the training example to the network and compute the network outputs
  2. For each output unit k

     $$\delta_k \leftarrow o_k (1 - o_k)(t_k - o_k)$$

  3. For each hidden unit h

     $$\delta_h \leftarrow o_h (1 - o_h) \Sigma_{k \in \text{outputs}} w_{k,h} \delta_k$$

  4. Update each network weight $w_{j,i}$

     $$w_{j,i} \leftarrow w_{j,i} + \Delta w_{j,i}$$

   where $\Delta w_{j,i} = \eta \, \delta_j \, x_{j,i}$

NN DESIGN ISSUES

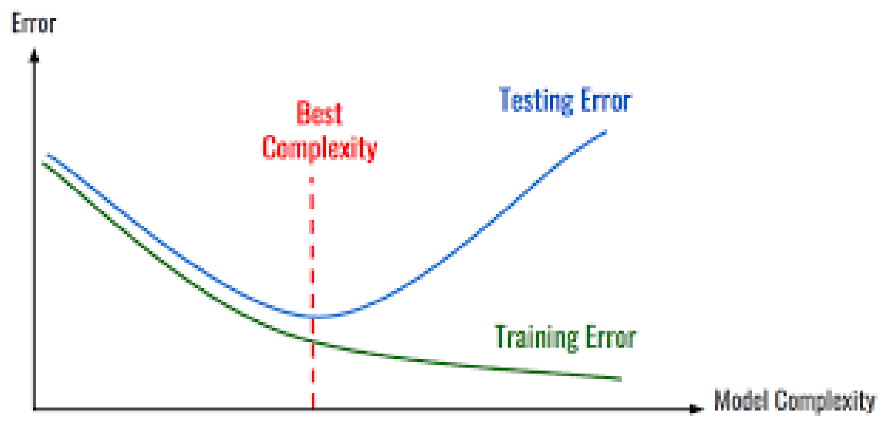
- Data representation
- Network Topology
- Network Parameters
- Training
- Validation

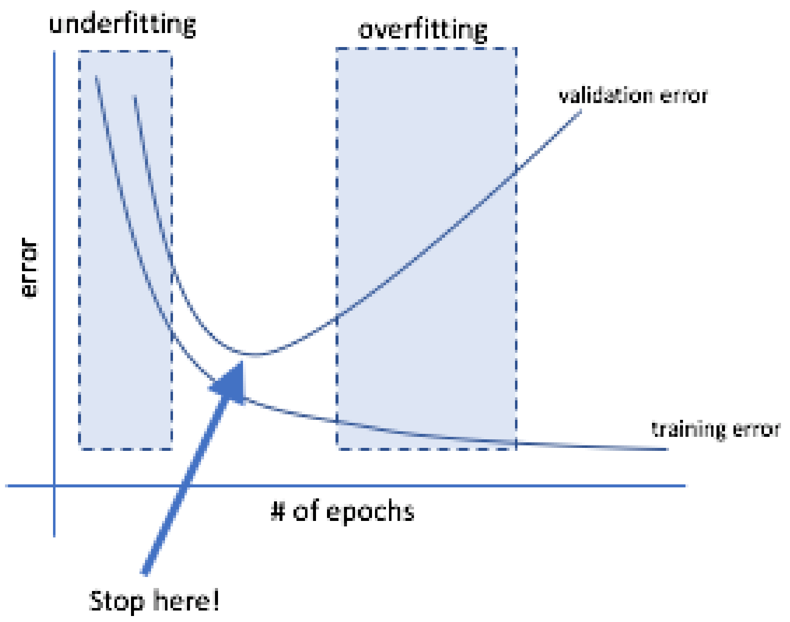
Expressiveness

- Every bounded continuous function can be approximated with arbitrarily small error, by network with one hidden layer (Cybenko et al ‘89)
  - Hidden layer of sigmoid functions
  - Output layer of linear functions
- Any function can be approximated to arbitrary accuracy by a network with two hidden layers (Cybenko ‘88)
  - Sigmoid units in both hidden layers
  - Output layer of linear functions

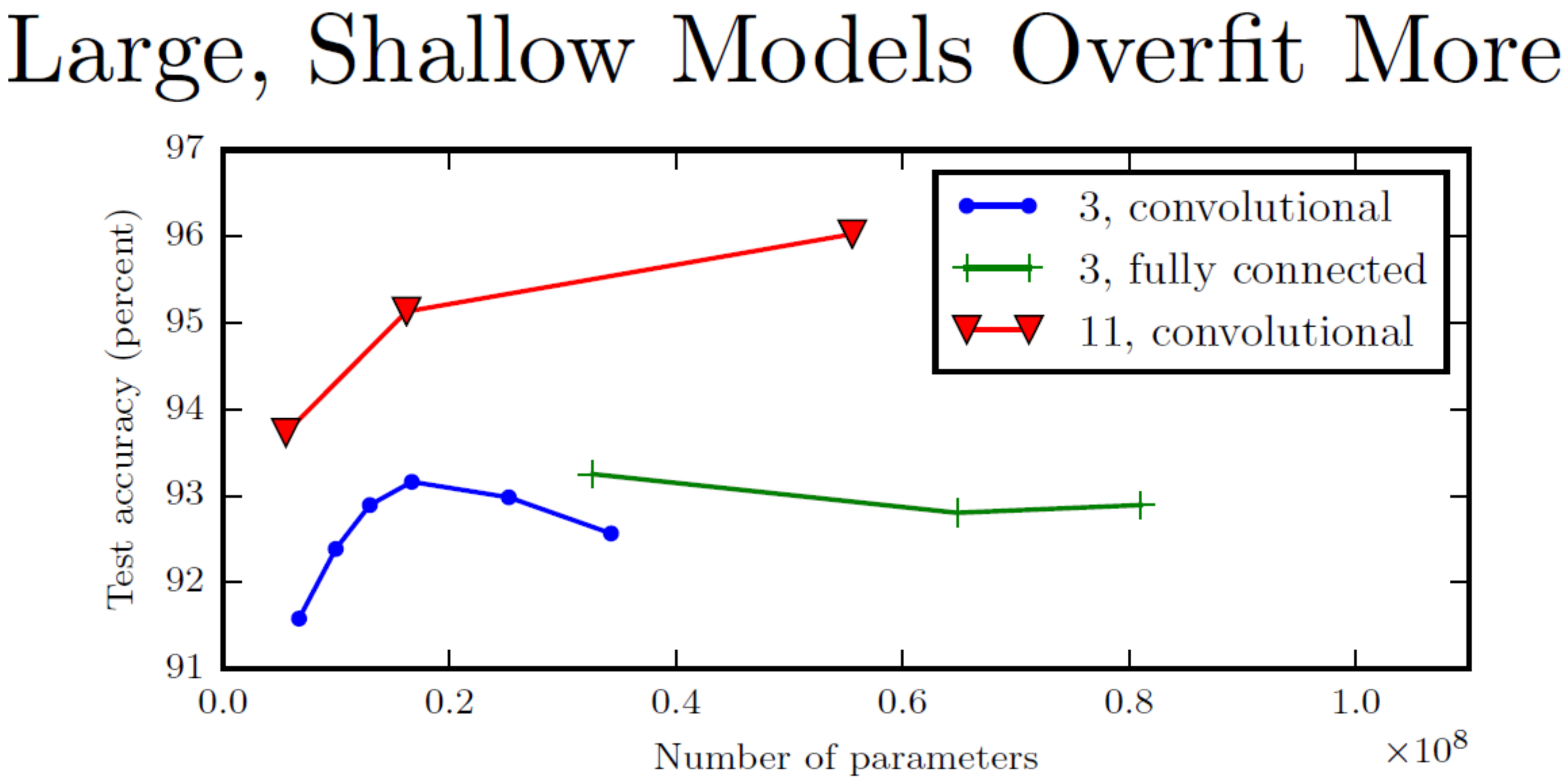
Choice of Architecture Neural Networks

- Training Set vs Generalization error

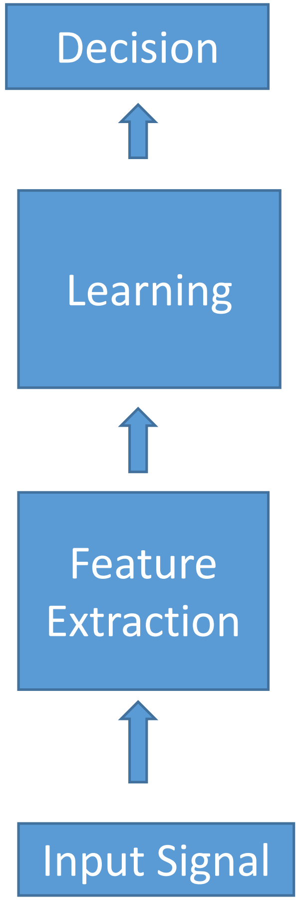


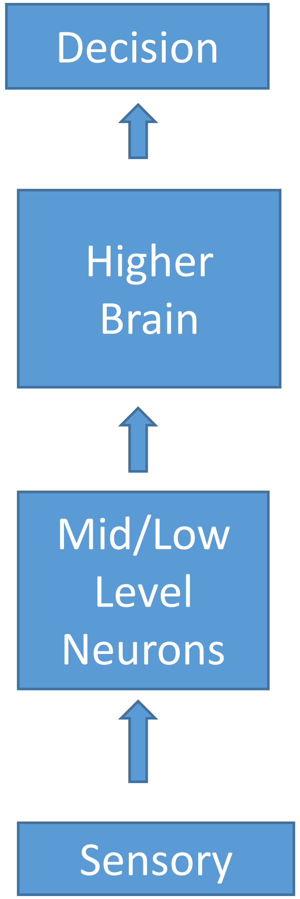


Motivation for Depth



Motivation: Mimic the Brain Structure





Neurons
Arranged
In Coupled
Layers

End-to-End
Neural
Architecture

Motivation

- Practical success in computer vision, signal processing, text mining
- Increase in volume and complexity of data
- Availability of GPUs

Convolutional Neural Network: Motivation

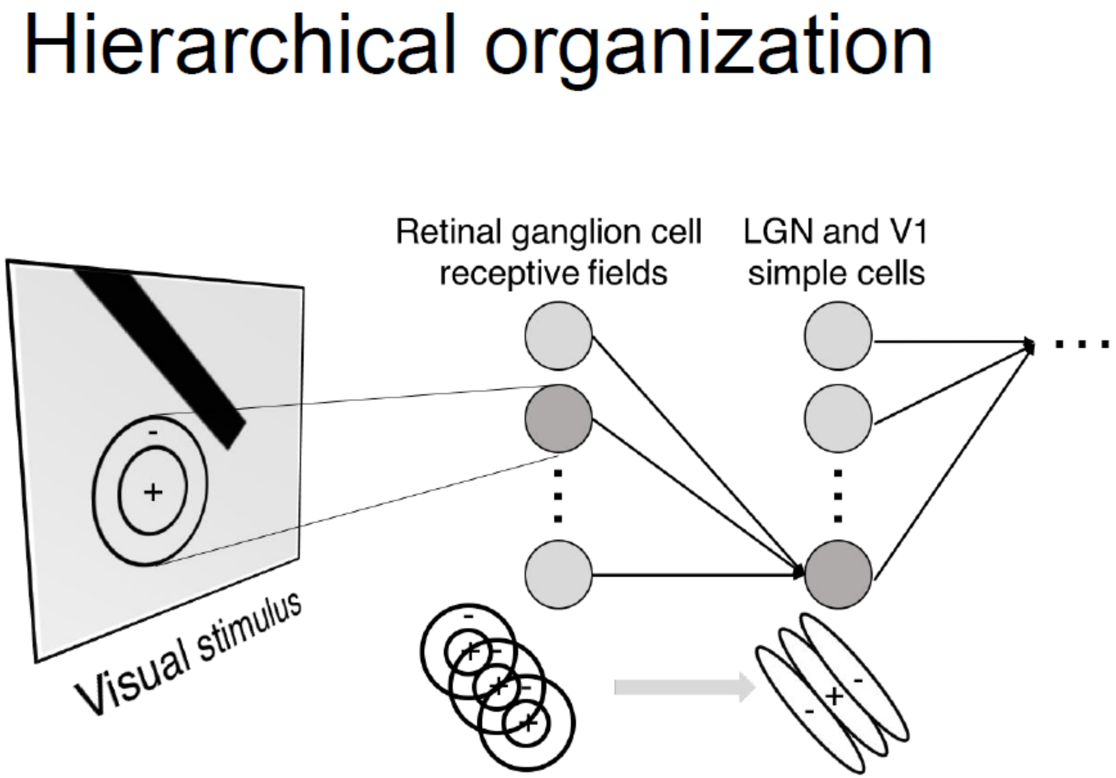
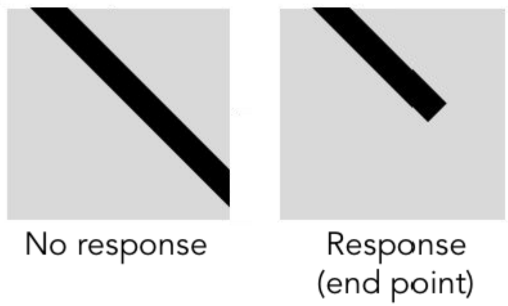


Illustration of hierarchical organization in early visual pathways by Lane McIntosh, copyright CS231n 2017

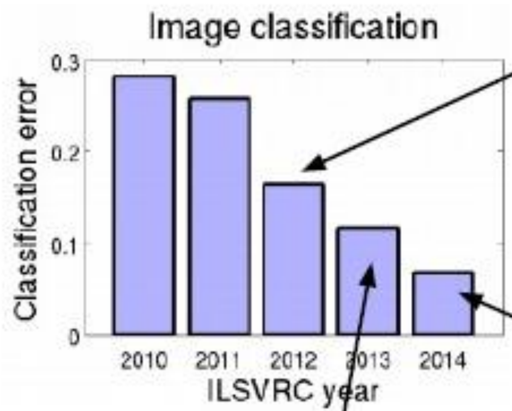
Simple cells:
Response to light orientation

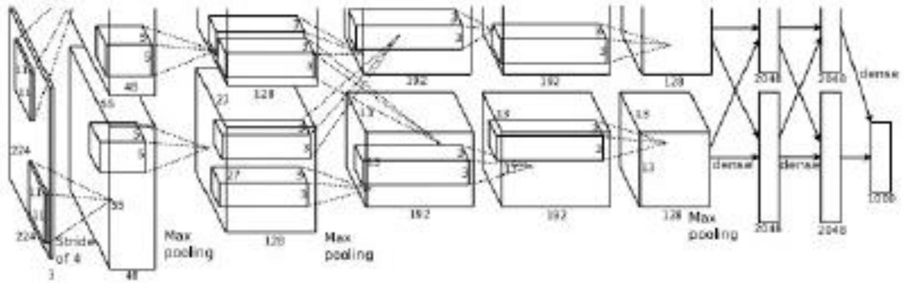
Complex cells:
Response to light orientation and movement

Hypercomplex cells:
response to movement with an end point



[Krizhevsky, Sutskever, Hinton. 2012] **16.4% error**





[Szegedy et al., 2014] **6.6% error**
[Simonyan and Zisserman, 2014] **7.3% error**

[Zeiler and Fergus, 2013] **11.1% error**

CNN

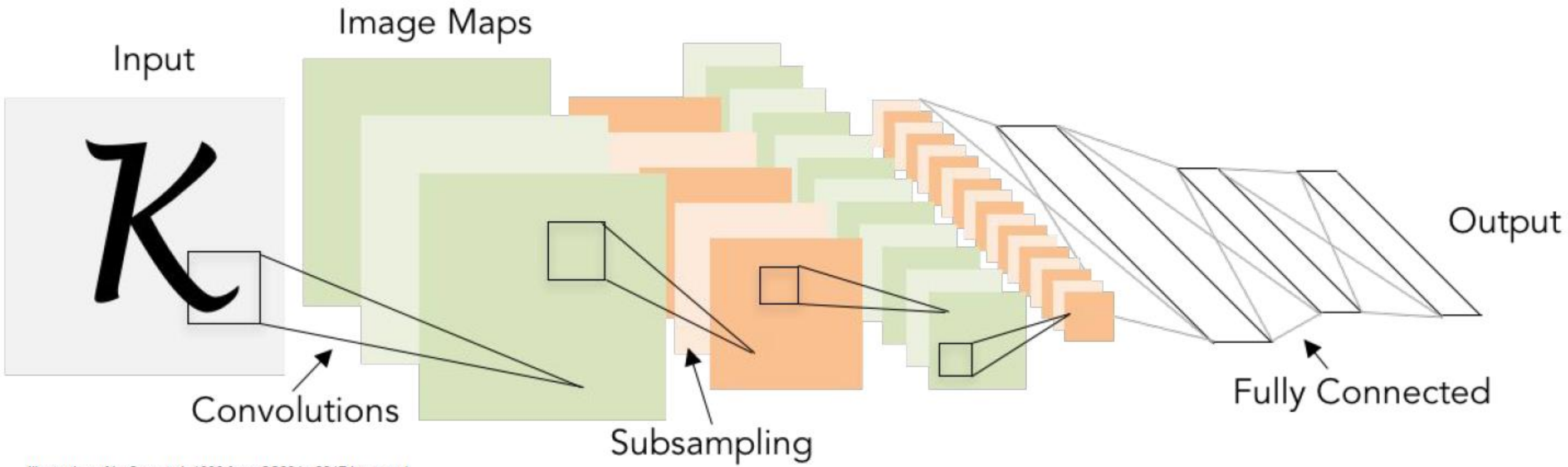
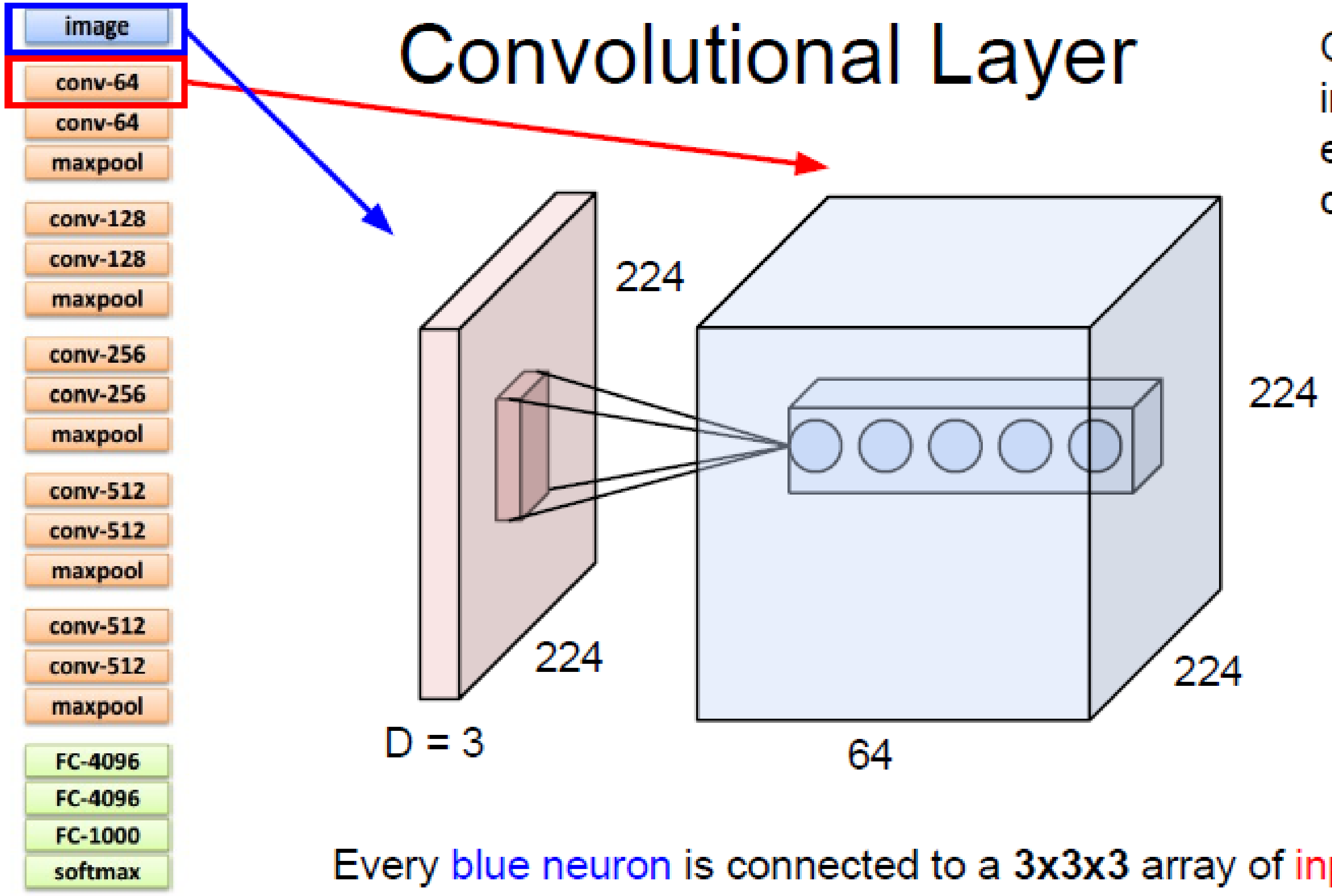


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

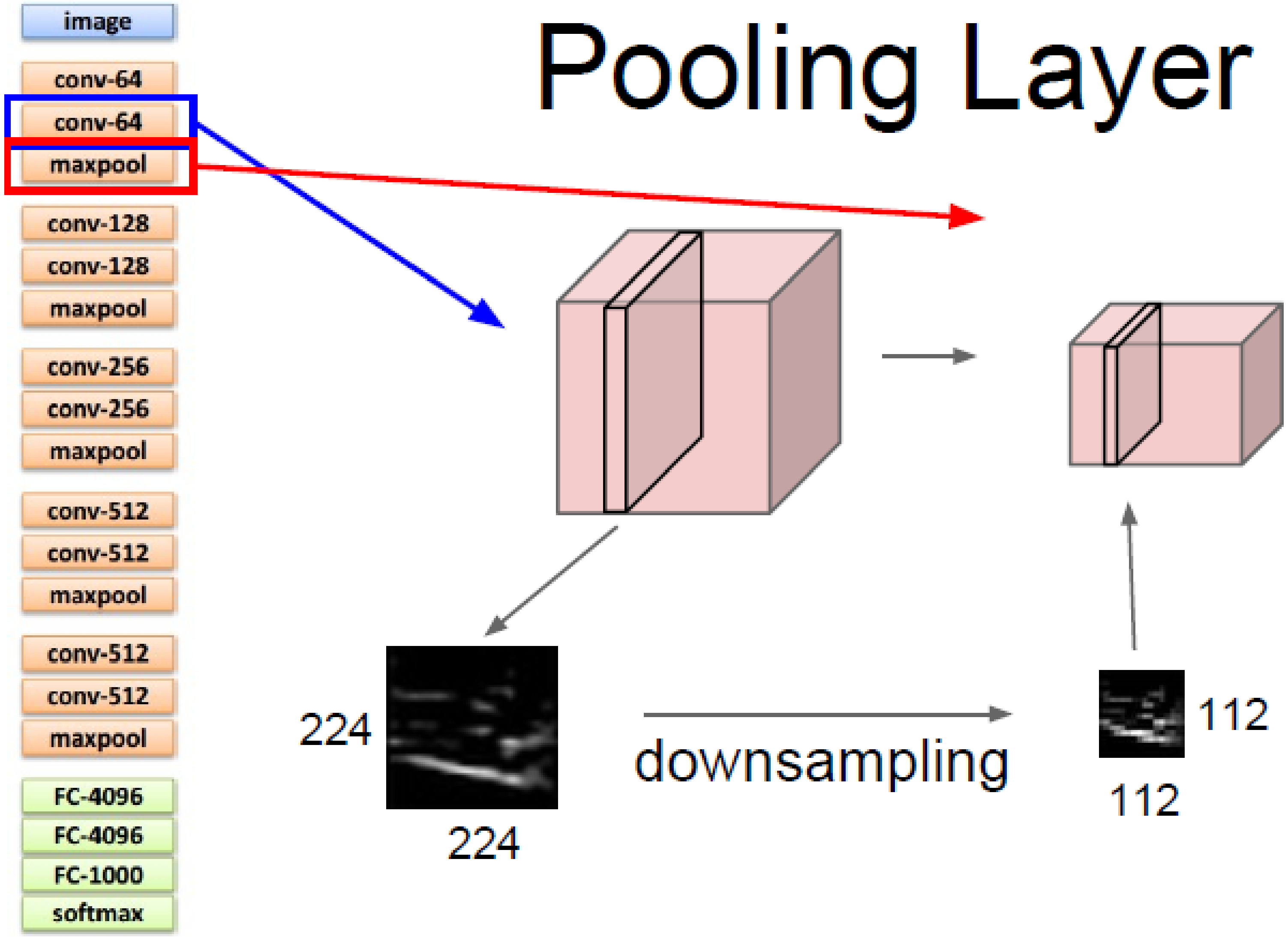
Convolutional Layer



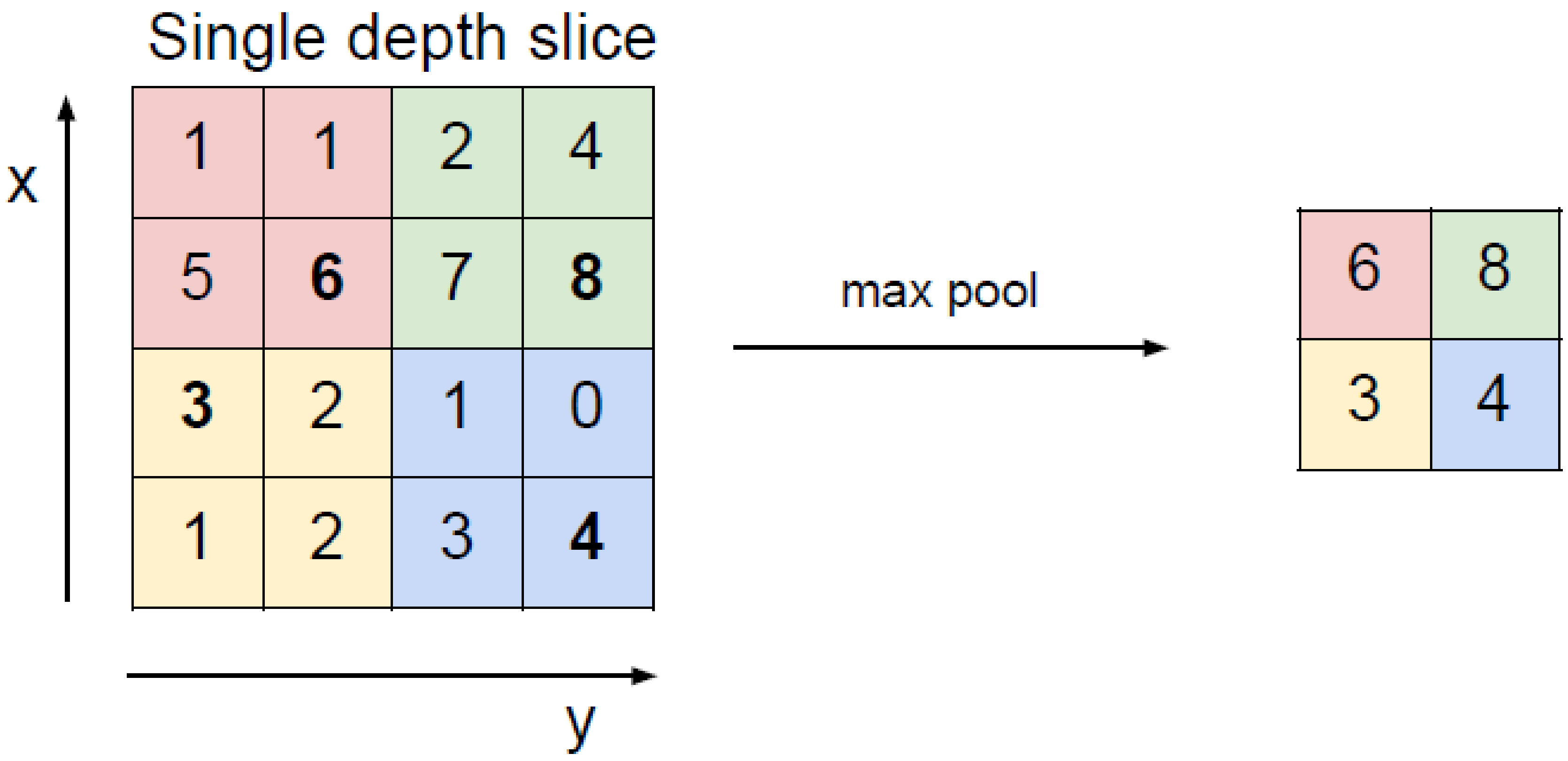
Can be implemented efficiently with convolutions

Every blue neuron is connected to a **3x3x3** array of inputs

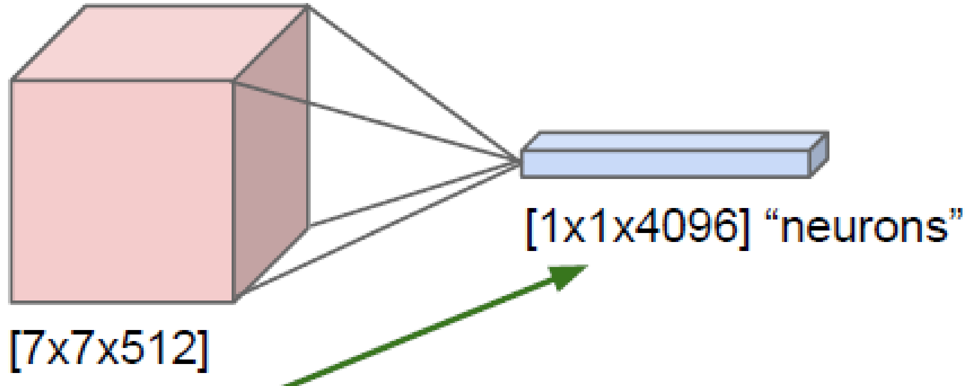
Pooling Layer



Max Pooling Layer



Fully Connected Layer

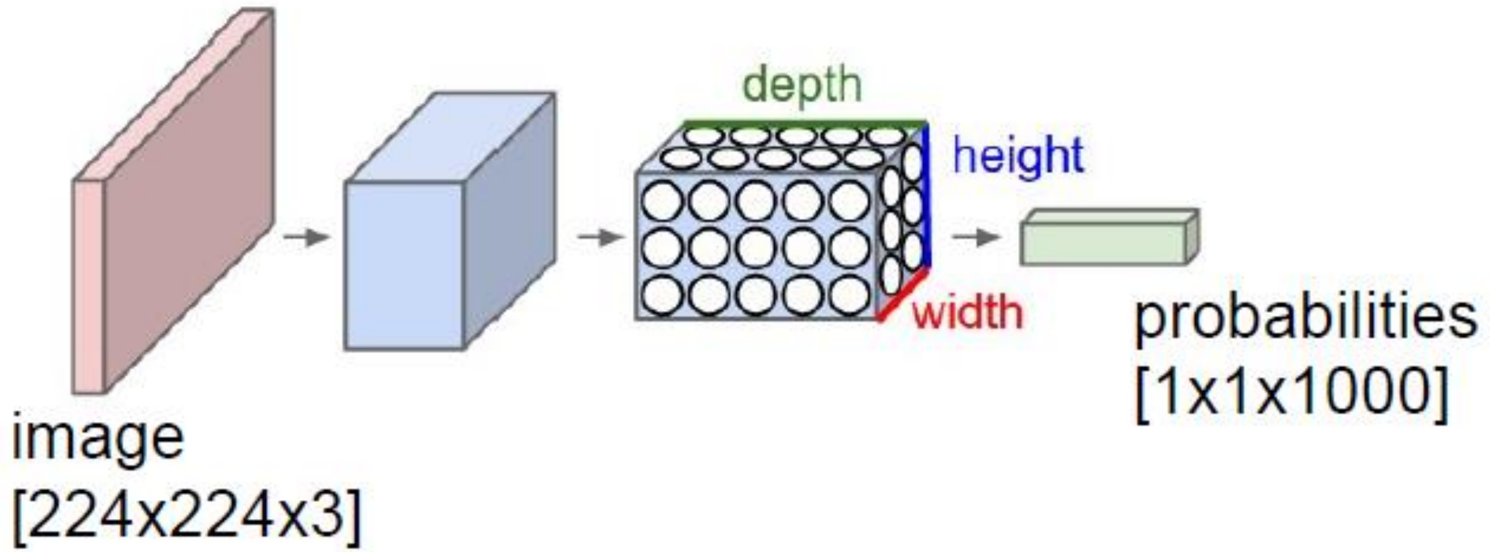


Every “neuron” in the output:

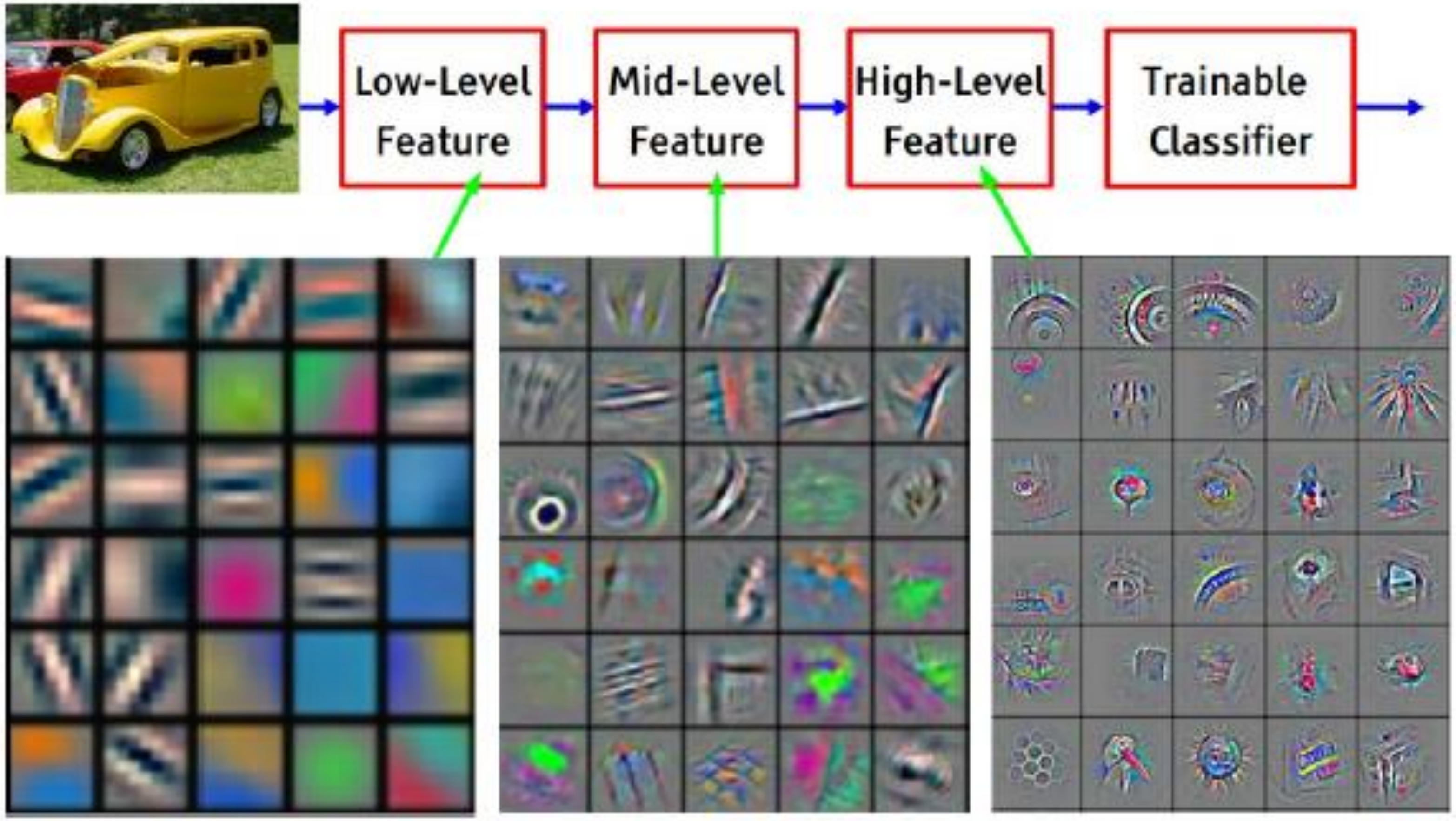
1. computes a **dot product** between the input and its weights $f = w^T x + b$
2. **thresholds** it at zero $f(x) = max(0, x)$

Every layer of a ConvNet has the same API:

- Takes a 3D volume of numbers
- Outputs a 3D volume of numbers
- Constraint: function must be **differentiable**

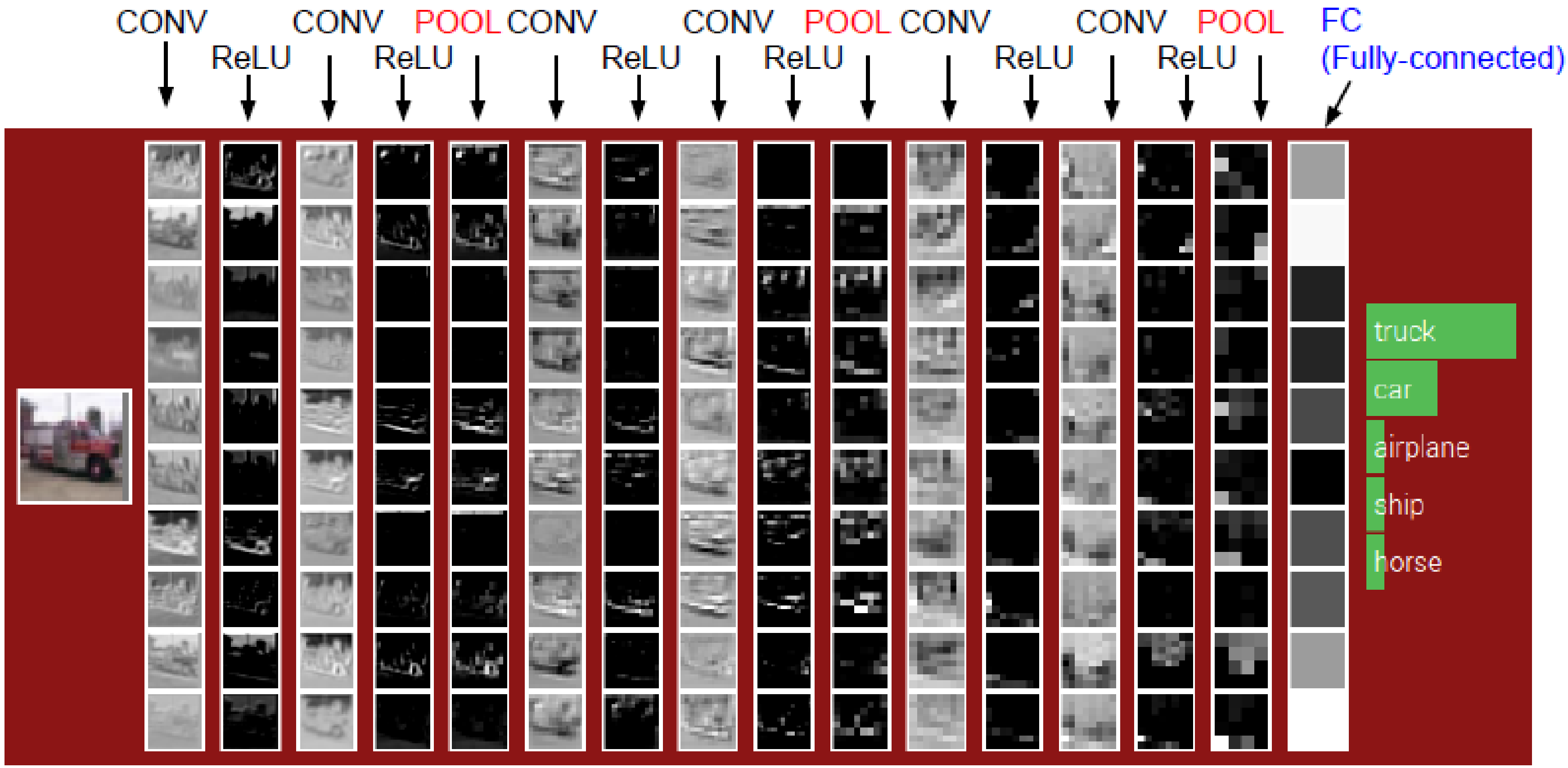


What do the neurons learn?



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

Example activation maps



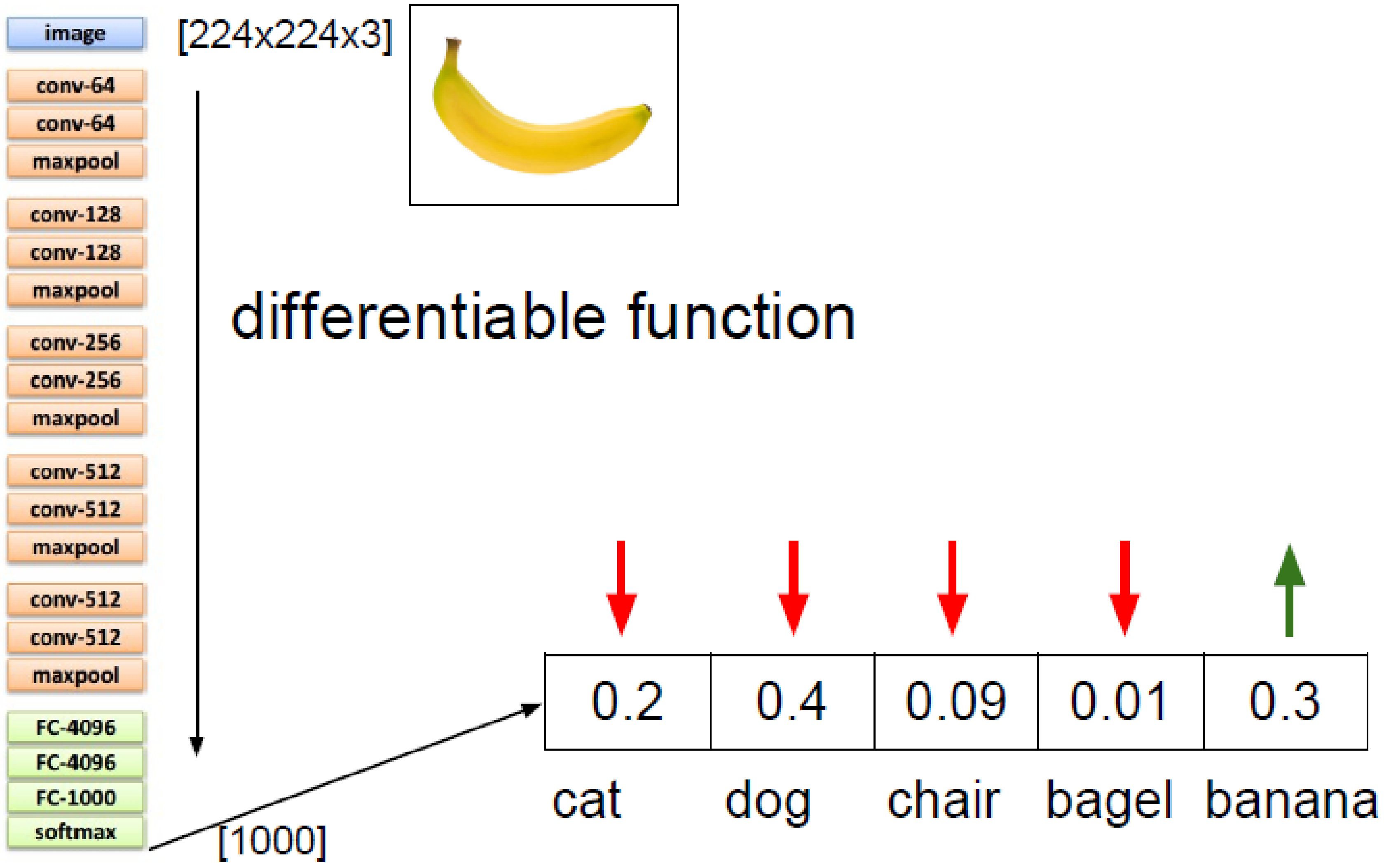


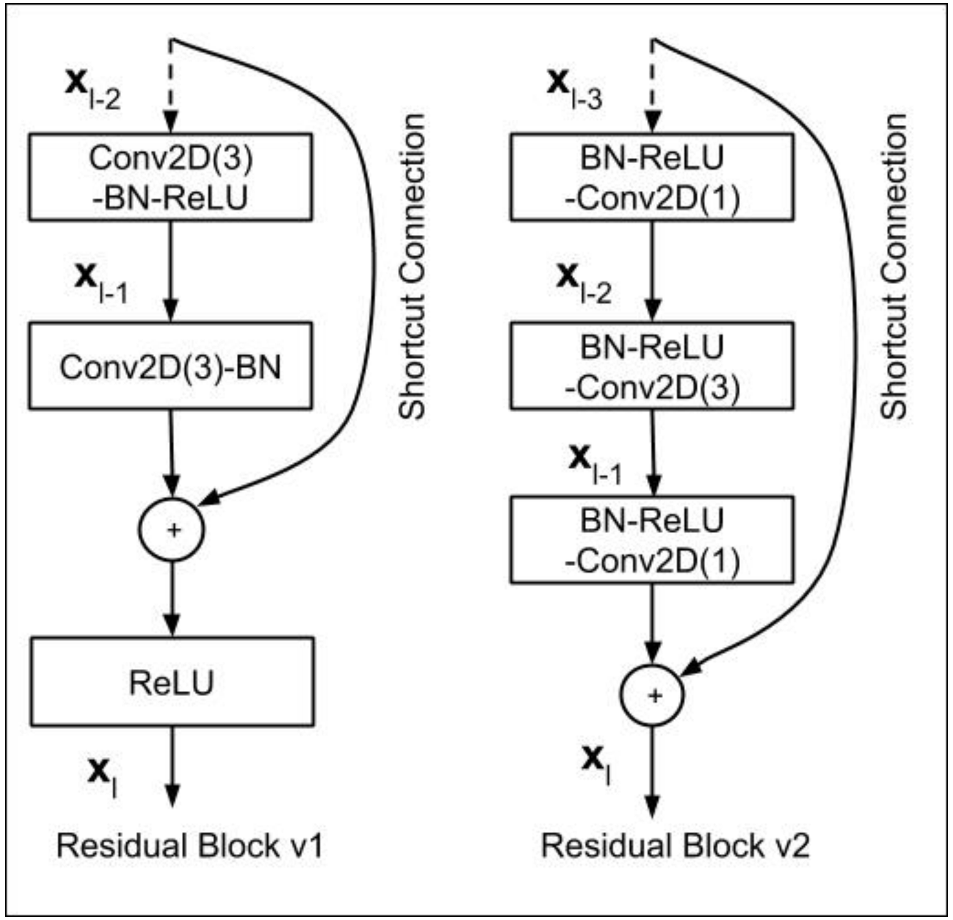
image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
FC-1000
softmax
[224x224x3]
differentiable function
[1000]
0.2
0.4
0.09
0.01
0.3
cat
dog
chair
bagel
banana

Training

Loop until tired:

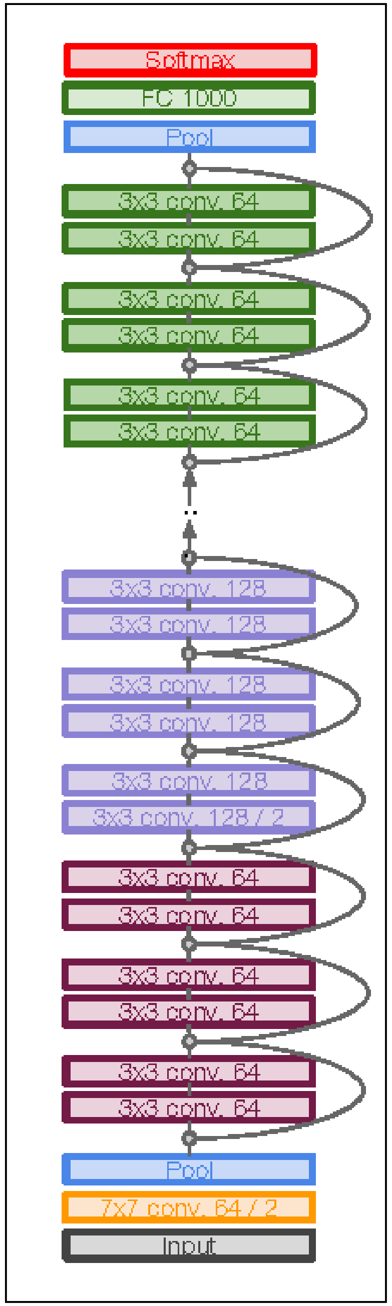
1. **Sample** a batch of data
2. **Forward** it through the network to get predictions
3. **Backprop** the errors
4. **Update** the weights

ResNet



CNN + Skip Connections

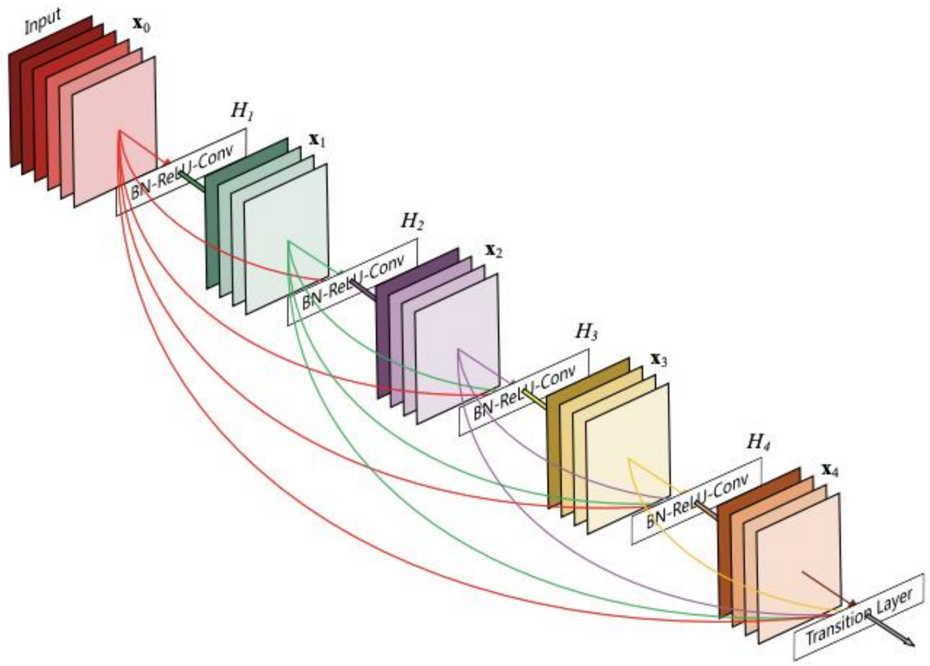
Pyramidal cells in cortex



Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (in each dimension)
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)

Densenet



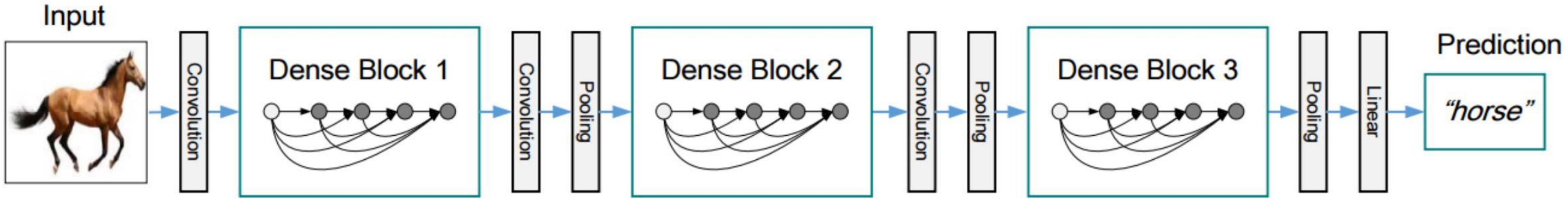


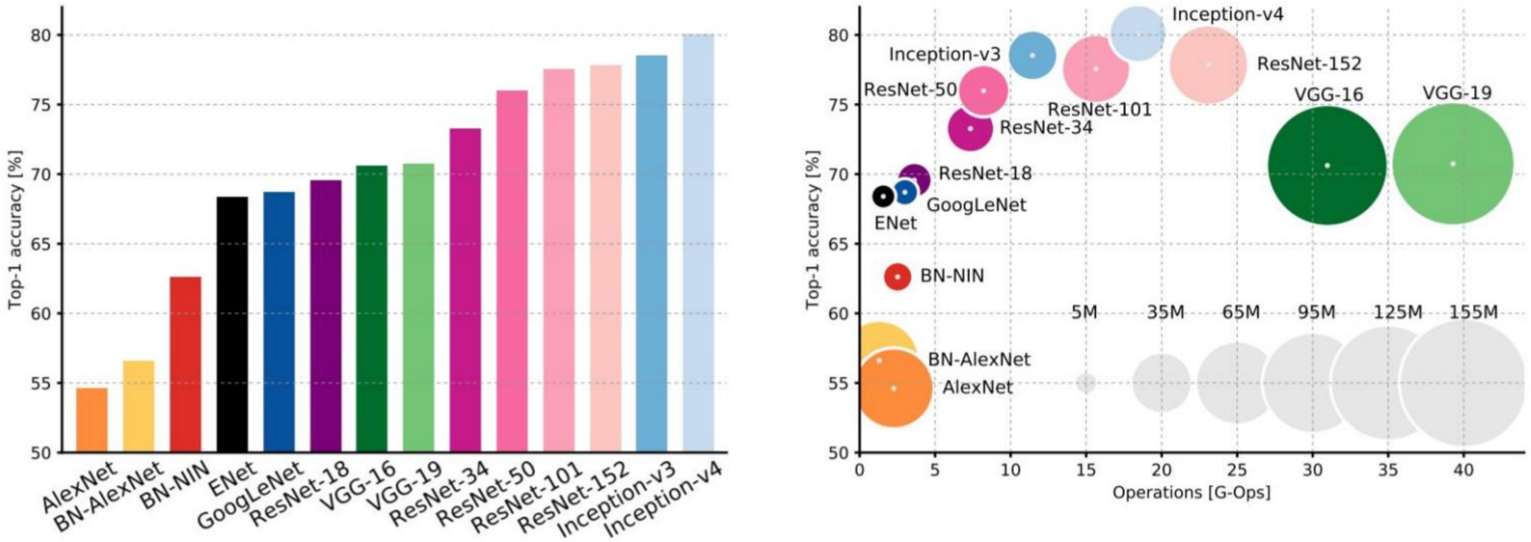
Figure 2. A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature map sizes via convolution and pooling.

Challenges of Depth

- Overfitting – dropout
- Vanishing gradient – ReLU activation
- Accelerating training – batch normalization
- Hyperparameter tuning

Computational Complexity

Comparing complexity...



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Types of Deep Architectures

- RNN, LSTM (sequence learning)

- Stacked Autoencoders (representation learning)

- GAN (classification, distribution learning)

- Combining architectures – unified backprop if all layers differentiable
  - Tensorflow, PyTorch

References

- Introduction to Deep Learning – Ian Goodfellow

- Stanford Deep Learning course