Introduction to Statistical Learning and Machine Learning

Chap 7 - Neural Network

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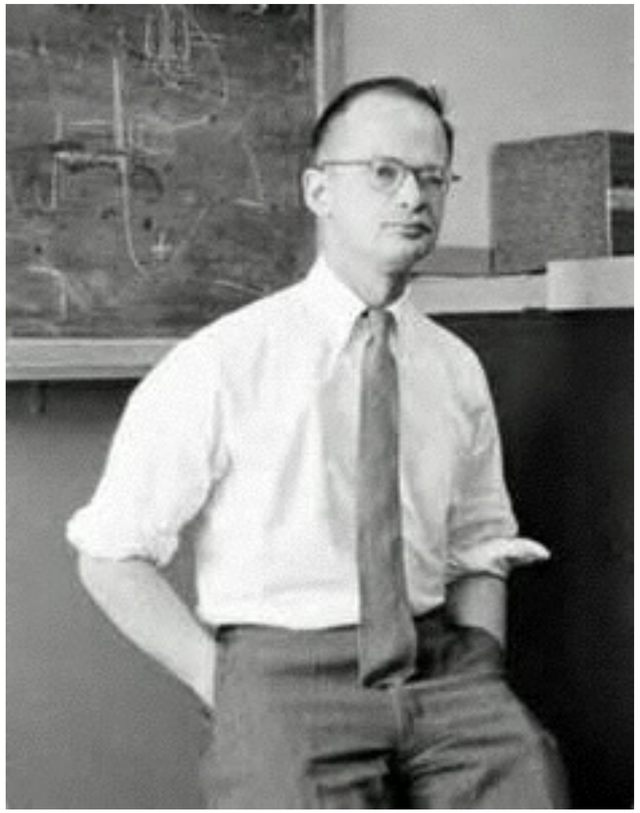
Chap 7 - Neural Network

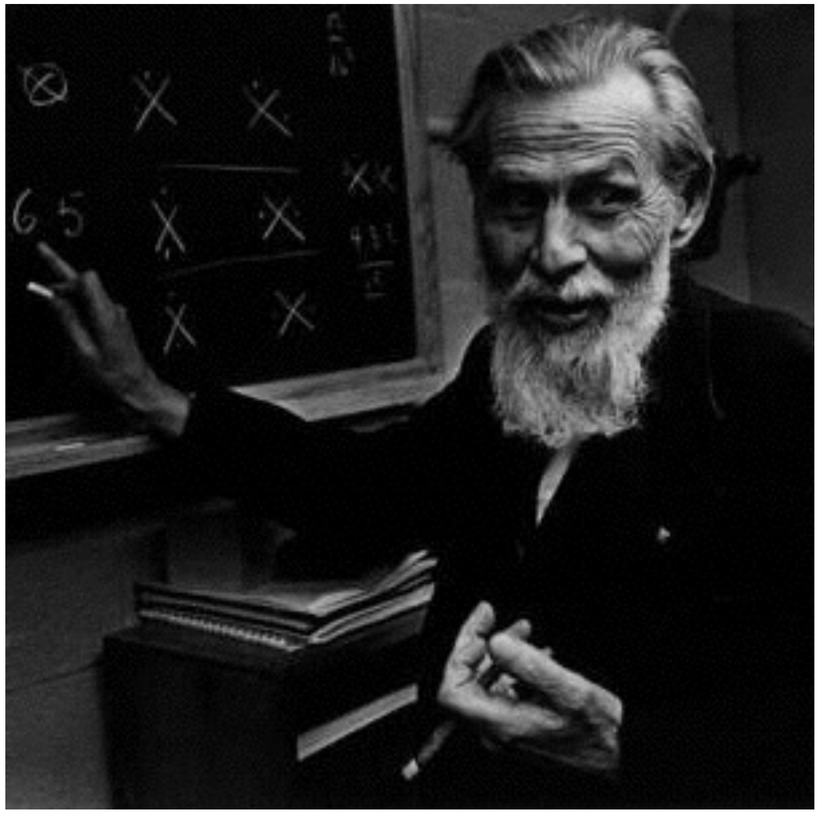
Main Content:

1. Regularization, Error Back-propagation;
2. Loss function and Optimization;
3. Feed-forward neural networks (Multi-layer perception, Convolutional neural networks);

History

神经元进入计算领域的视野





BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

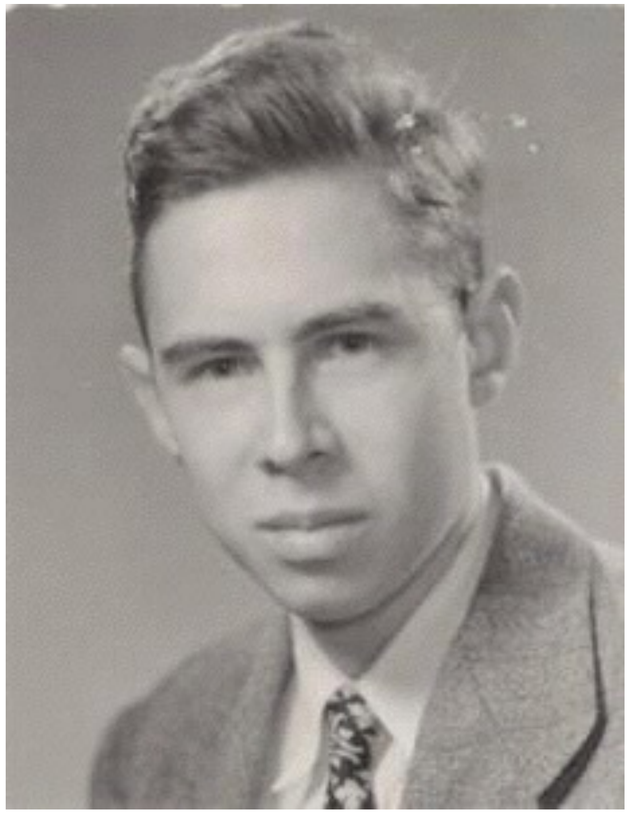
FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

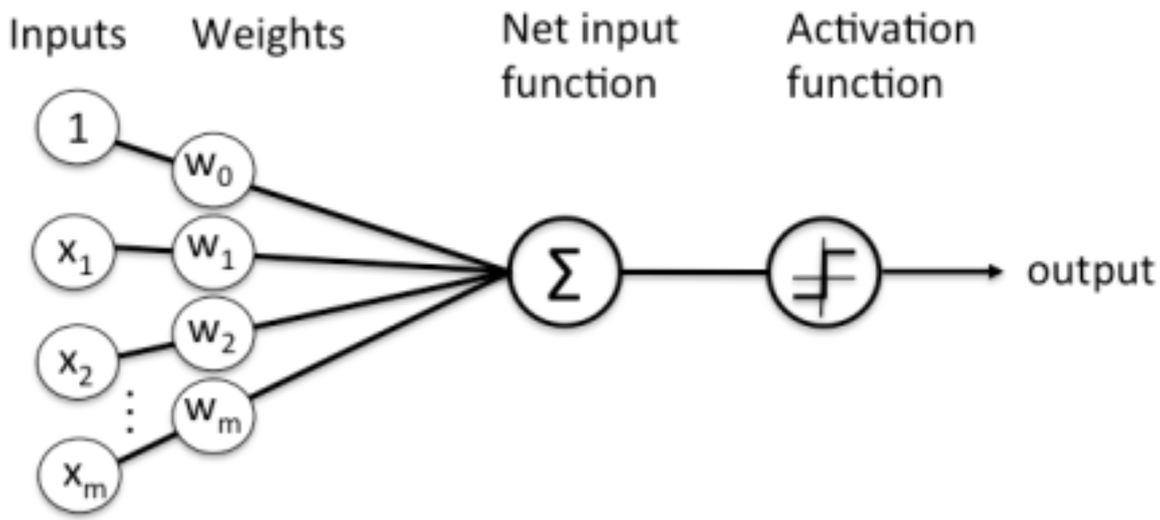
Walter Pitts
(1923-1969)

Warren McCulloch
(1898-1969)

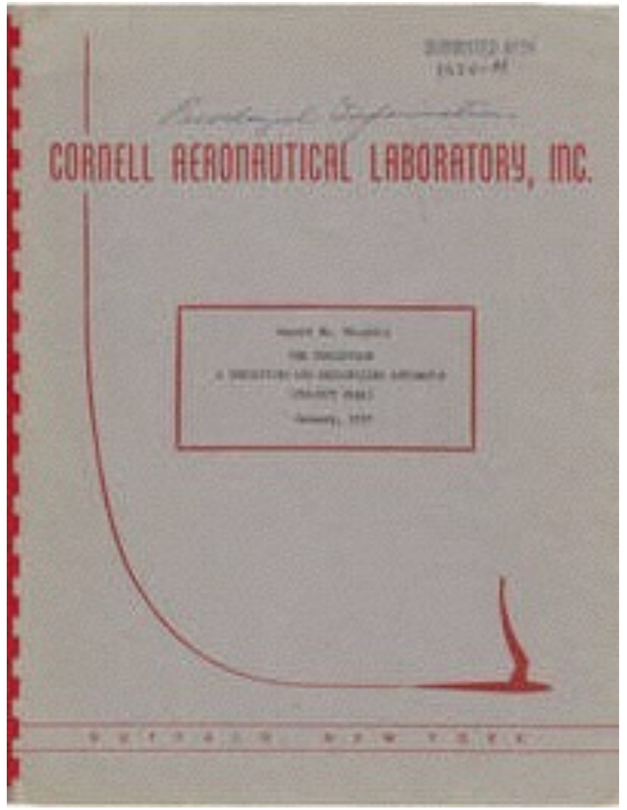
引入感知机（Perceptron）概念



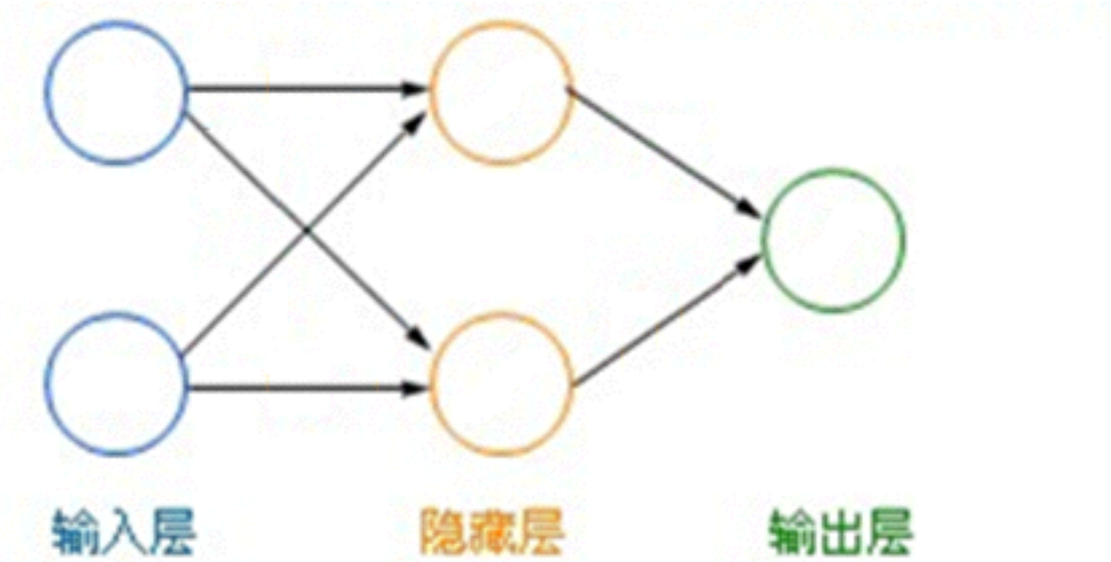
Frank Rosenblatt
(1923-1971)



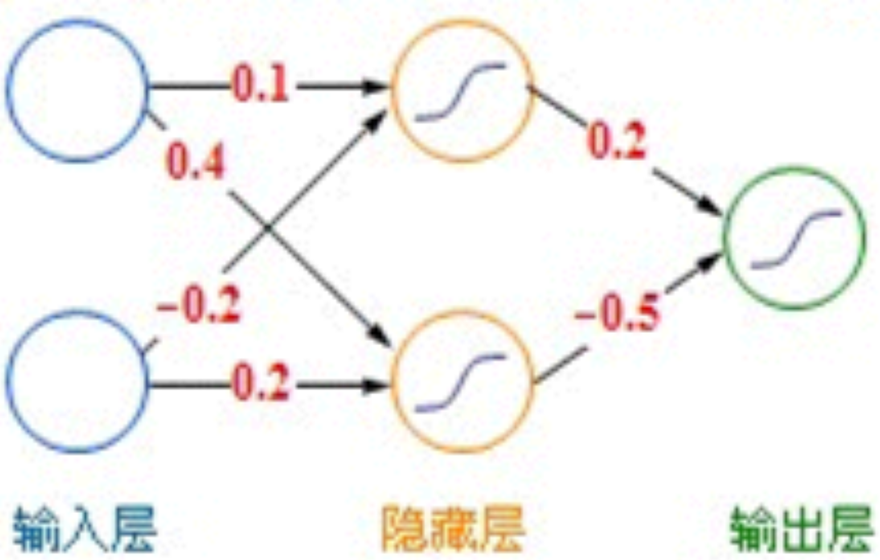
The perceptron, a perceiving and recognizing automaton Project Para. Cornell Aeronautical Laboratory, 1957



神经网络基础模型

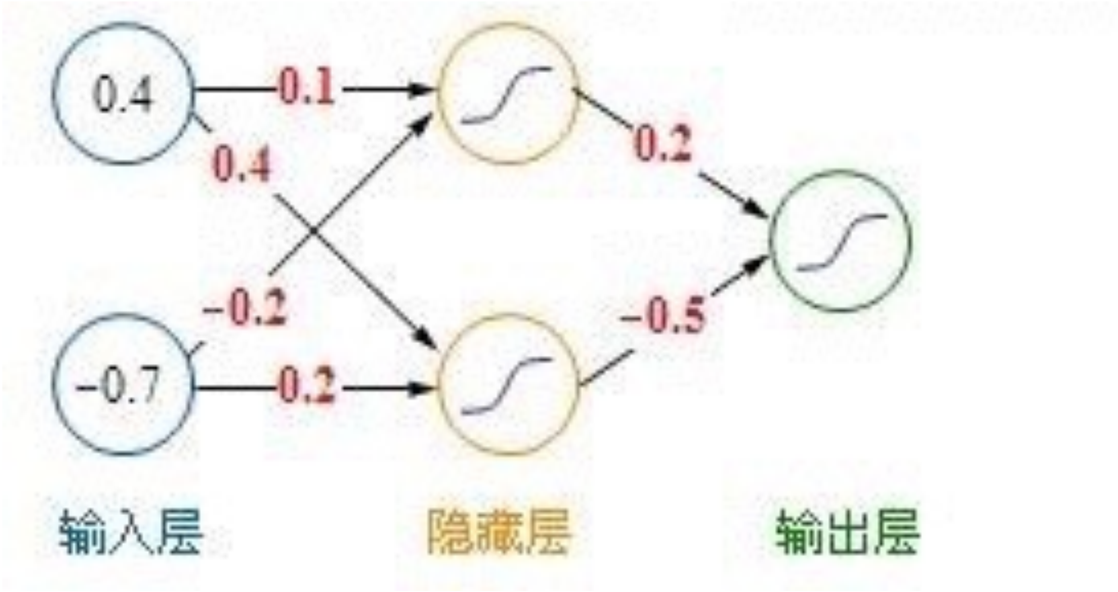


神经网络基础模型

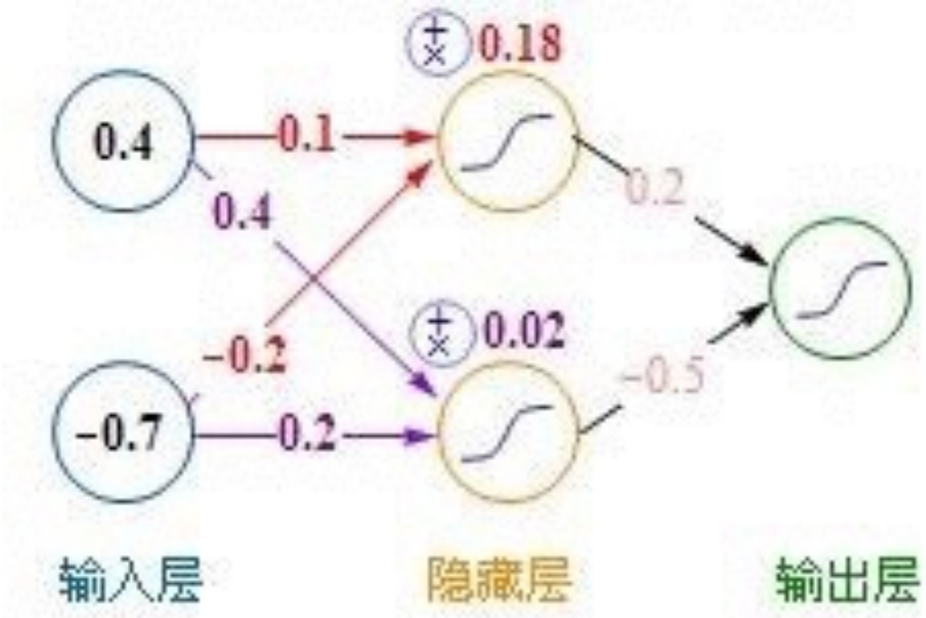


$$y = \text{logsig}(x) = \frac{1}{1 + e^{-x}}$$

神经网络基础模型



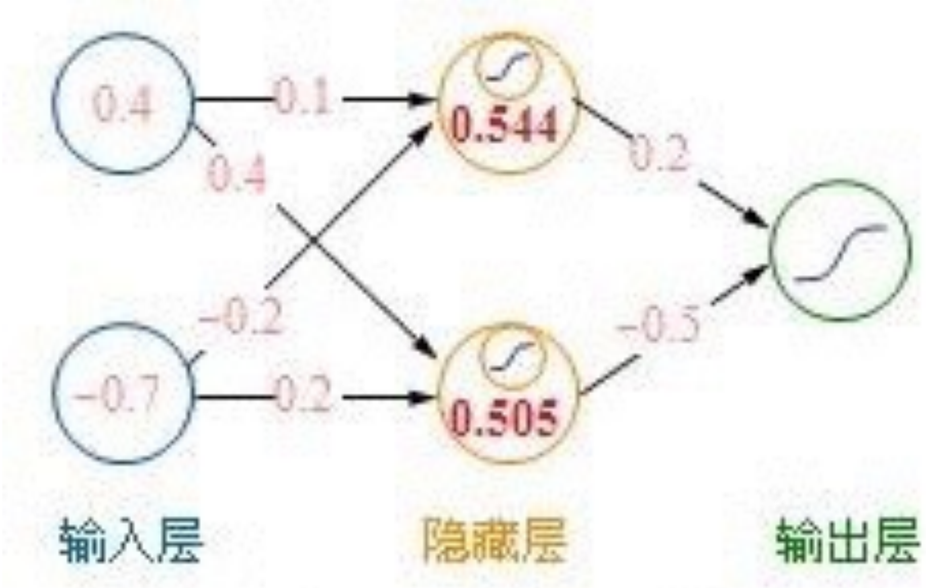
神经网络基础模型



$0.4\times0.1+(-0.7)\times(-0.2)=0.18$

$0.4\times0.4+(-0.7)\times(0.2)=0.02$

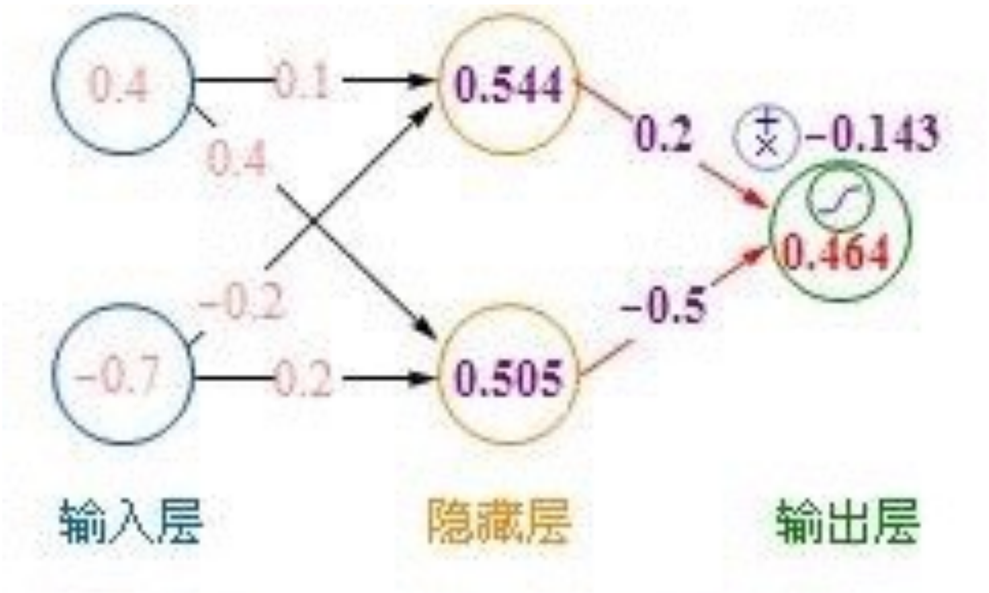
神经网络基础模型



$$\text{logsig}(0.18)=\frac{1}{1+e^{-0.18}}=0.544$$

$$\text{logsig}(0.02)=\frac{1}{1+e^{-0.02}}=0.505$$

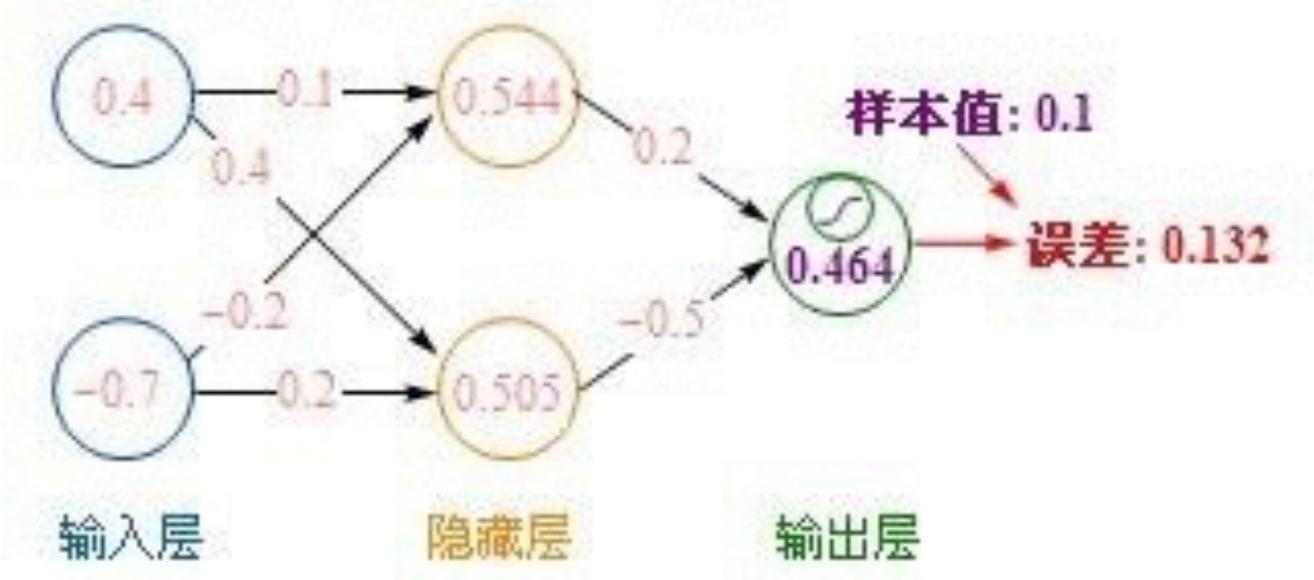
神经网络基础模型



$$0.544\times0.2+0.505\times(-0.5)=-0.143$$

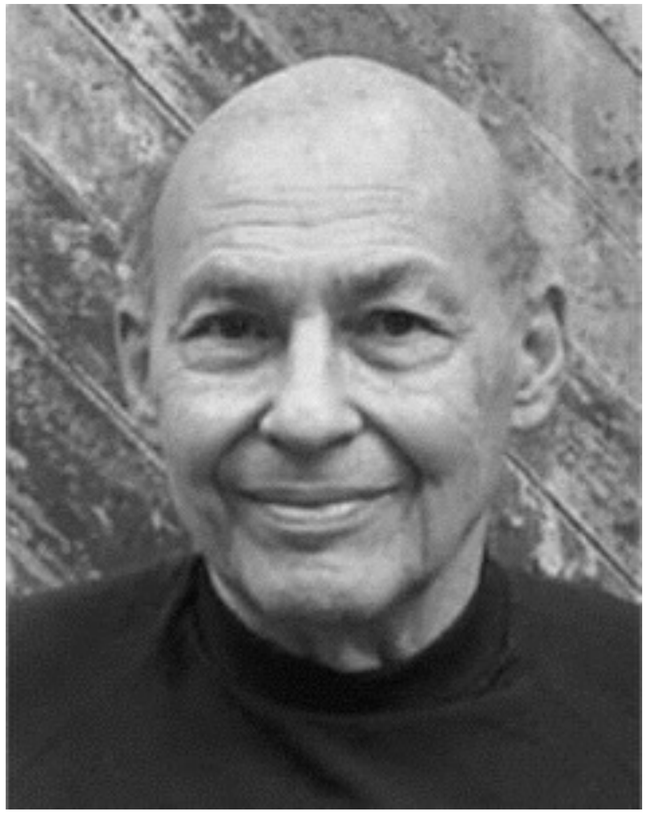
$$\text{logsig}(-0.143)=\frac{1}{1+e^{0.143}}=0.464$$

神经网络基础模型

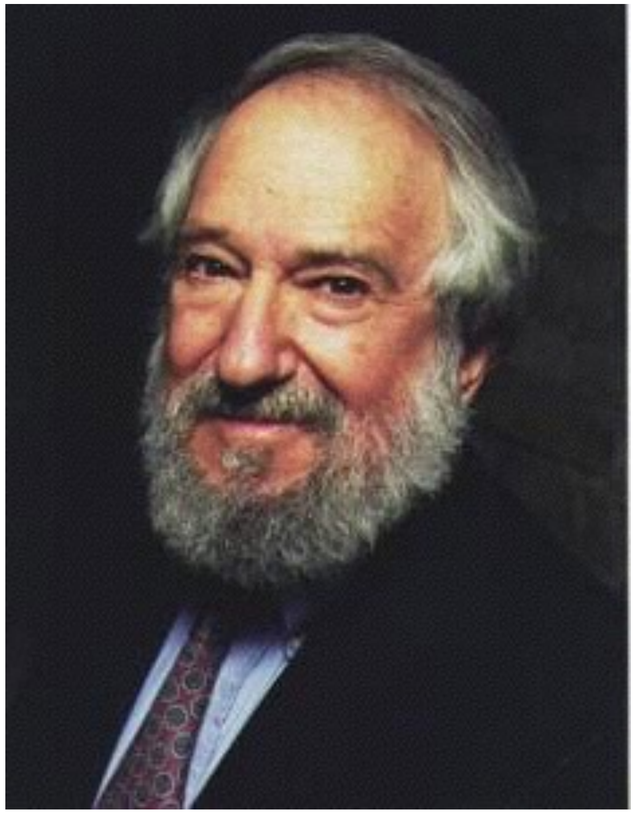


误差=(0.464 - 0.1)²=0.132 (误差<0.0001,可以收敛)

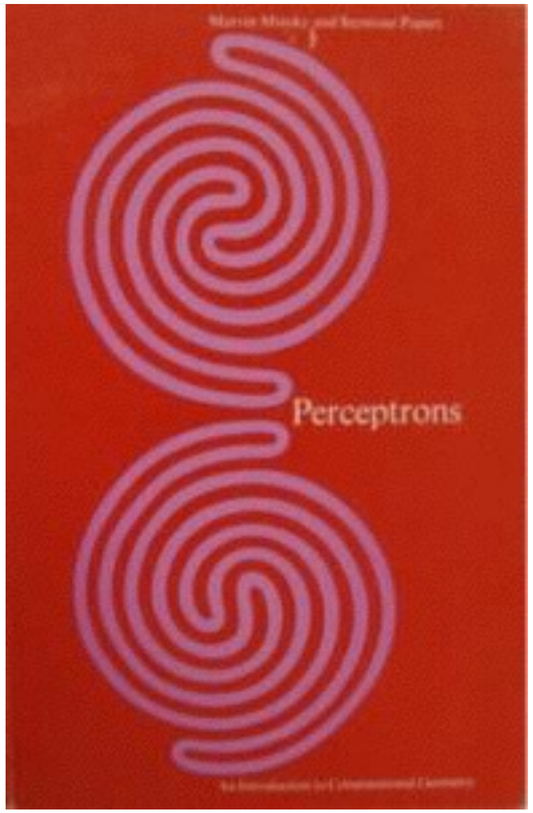
神经网络的第一次寒冬

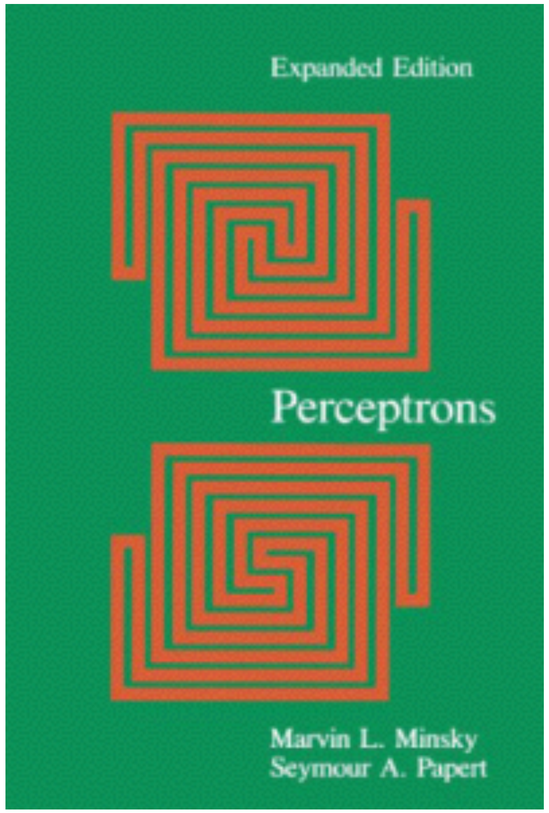


Marvin Minsky (1927-2016)



Seymour Papert (1928-)



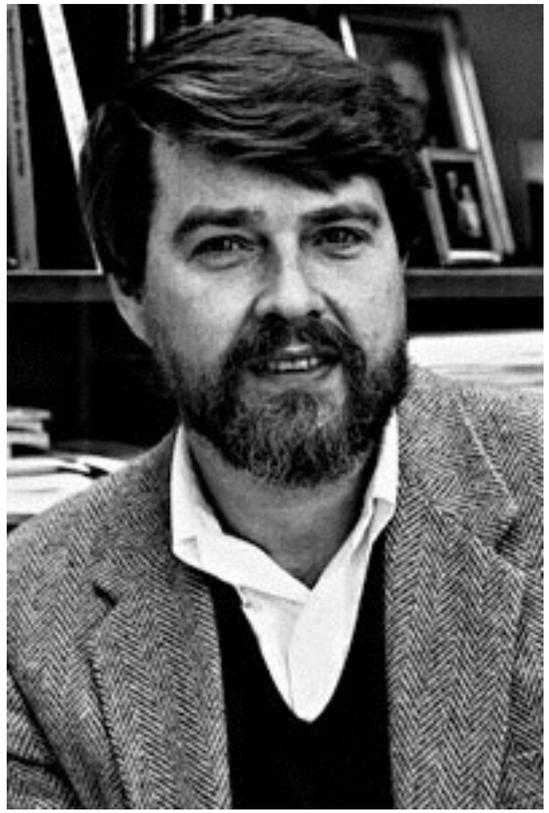


1969年出版《Perceptrons》一书，认为仅靠局部连接的神经网络无法有效开展训练

以及很多被后来的读者们以讹传讹的观点

反向传播算法（BP）的提出

Geoffrey Hinton (1947-)



David Rumelhart (1942-2011)

Learning representations by back-propagating errors

David E. Rumelhart*, Geoffrey E. Hinton† & Ronald J. Williams*

* Institute for Cognitive Science, C-015, University of California, San Diego, La Jolla, California 92093, USA
† Department of Computer Science, Carnegie-Mellon University, Pittsburgh, Philadelphia 15213, USA

1986年发表在Nature上的文章将BP算法用于神经网络模型，极大降低了计算量（$O(n^2)$->$O(n)$）

当时的计算机普及率、计算能力也远胜60年代

“首个”重要应用：手写数字识别

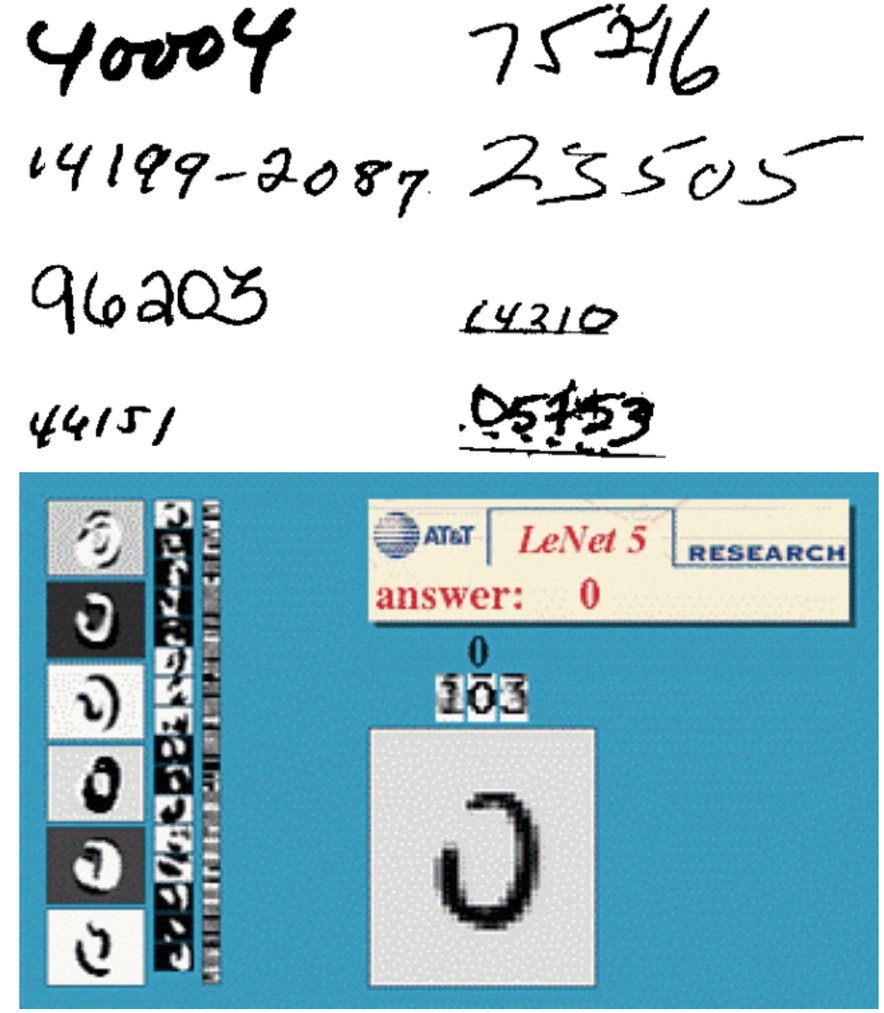
Yann LeCun (1960-)

Handwritten Digit Recognition with a Back-Propagation Network

Y. Le Cun, B. Boser, J. S. Denker, D. Henderson,
R. E. Howard, W. Hubbard, and L. D. Jackel
AT&T Bell Laboratories, Holmdel, N. J. 07733

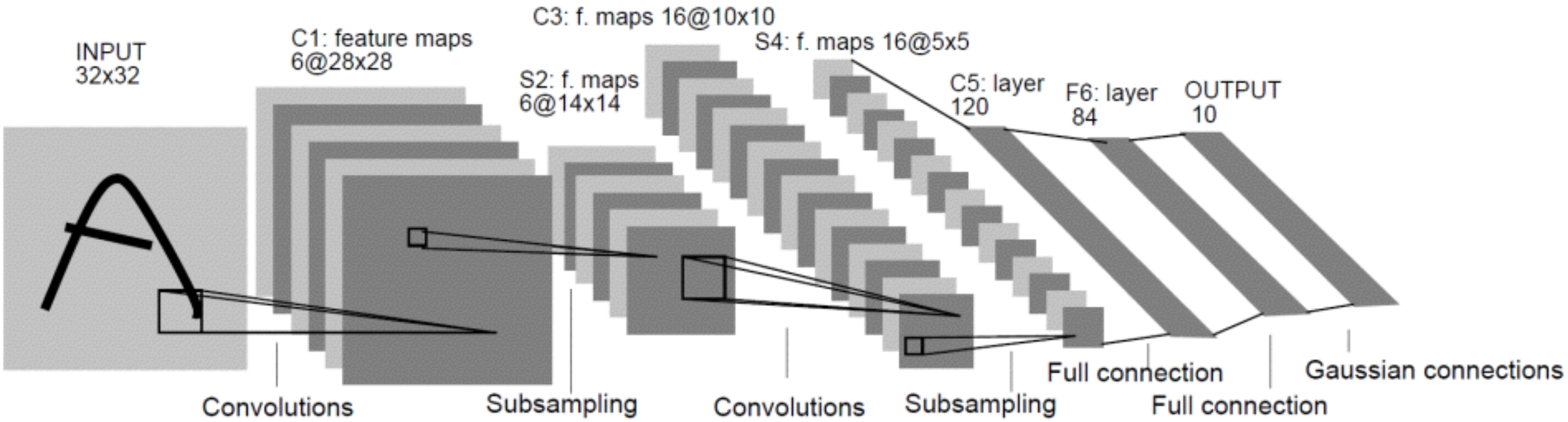
ABSTRACT

We present an application of back-propagation networks to handwritten digit recognition. Minimal preprocessing of the data was required, but architecture of the network was highly constrained and specifically designed for the task. The input of the network consists of normalized images of isolated digits. The method has 1% error rate and about a 9% reject rate on zipcode digits provided by the U.S. Postal Service.



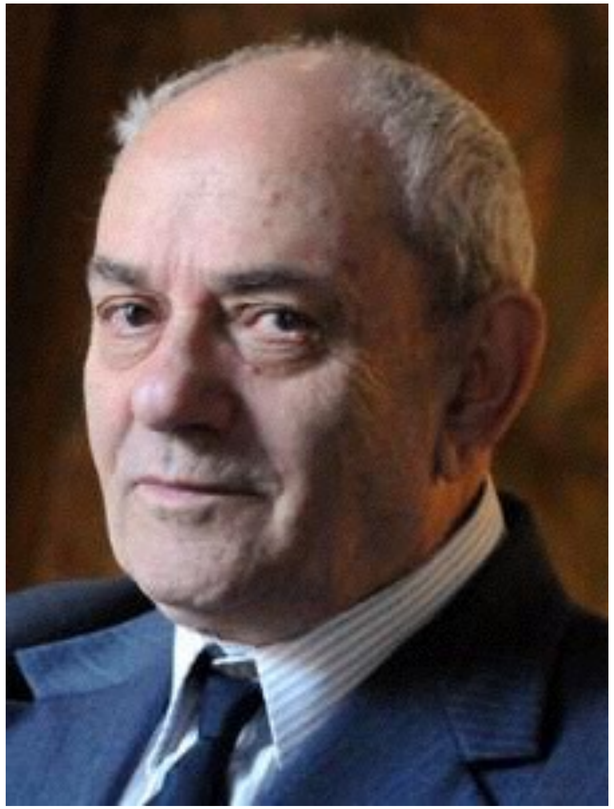
到上世纪九十年代末，超过10%的美国支票识别采用了相关技术

LeNet-5

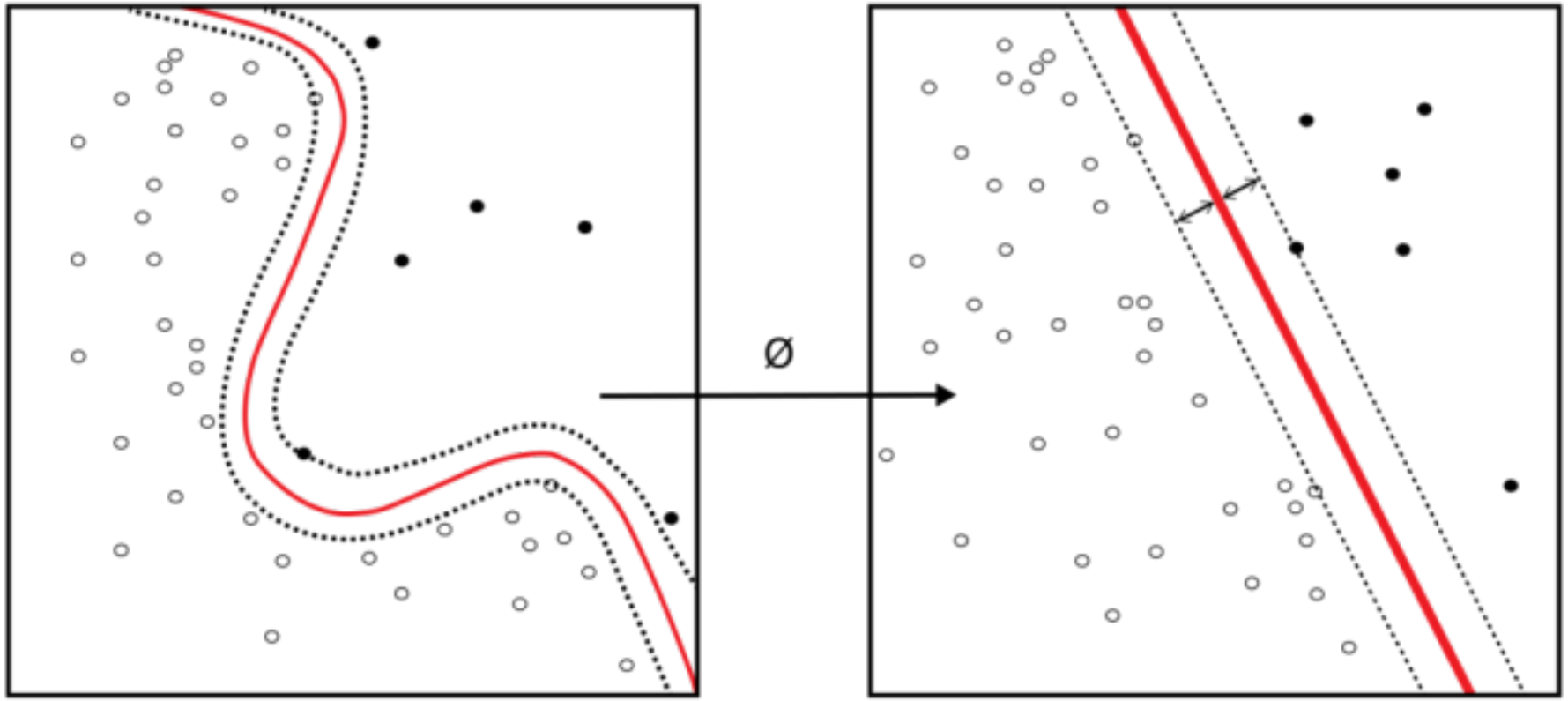


1998年发表的Gradient-based learning applied to Document Recognition一文中提出了LeNet-5
已是Convolutional Neural Network的基本框架

神经网络的第二次寒冬



Vladmir Vapnik (1936-)

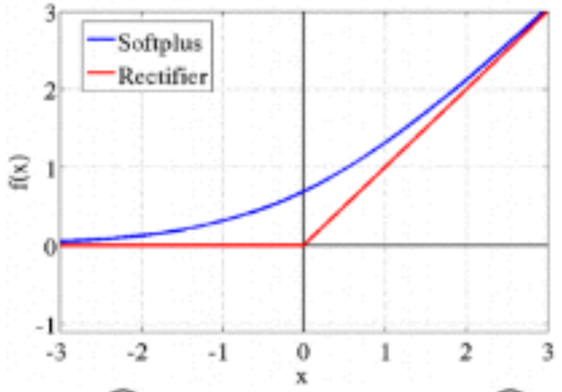


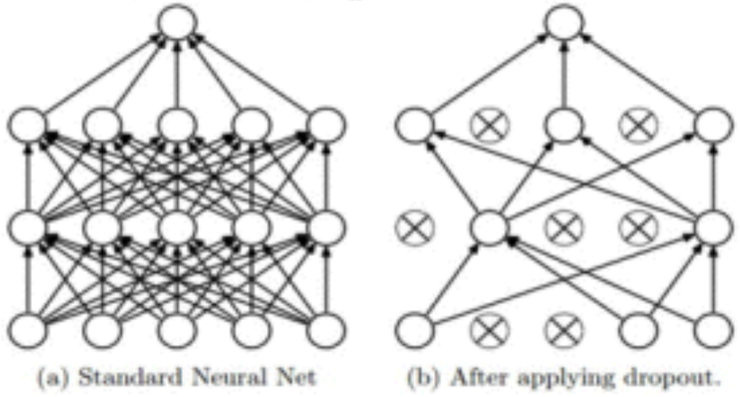
在1963年发表的论文中即提出Support Vector Machine的概念
在2002年左右，不断改进的SVM方法将手写数字识别的错误率降到了0.56%
不需要大量样本（事实上也难以支撑大量样本），速度相对可以接受

卷土重来的（深度）神经网络

优化策略

梯度弥散问题通过ReLU、Dropout、Deep Residual Learning等方法得到缓解

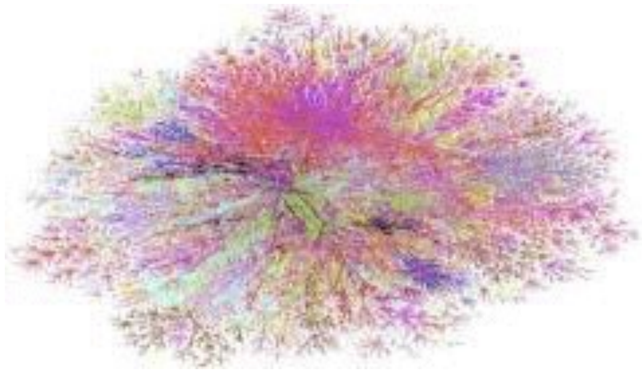




数据规模

真正意义上的大数据出现

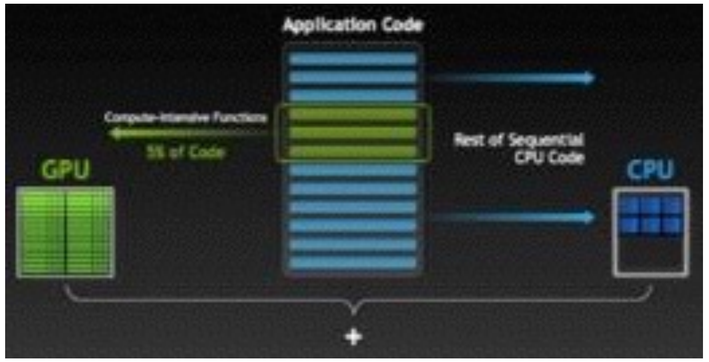
社会标注机制



计算能力

CPU、GPU的长足进步

共享权值



AlexNet

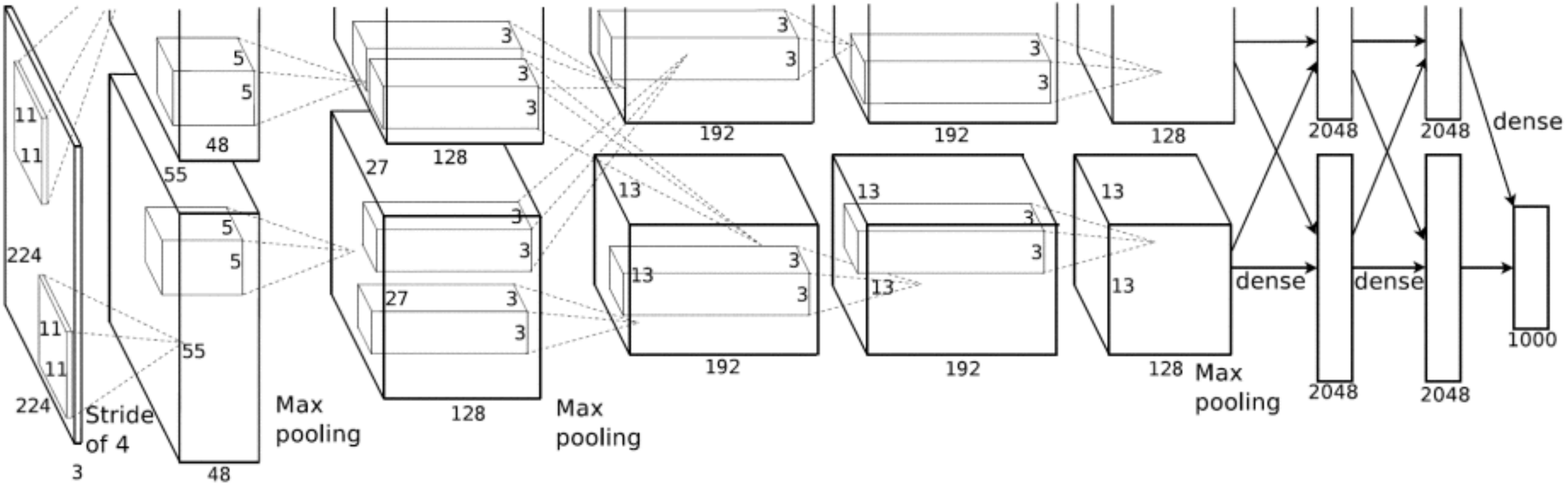
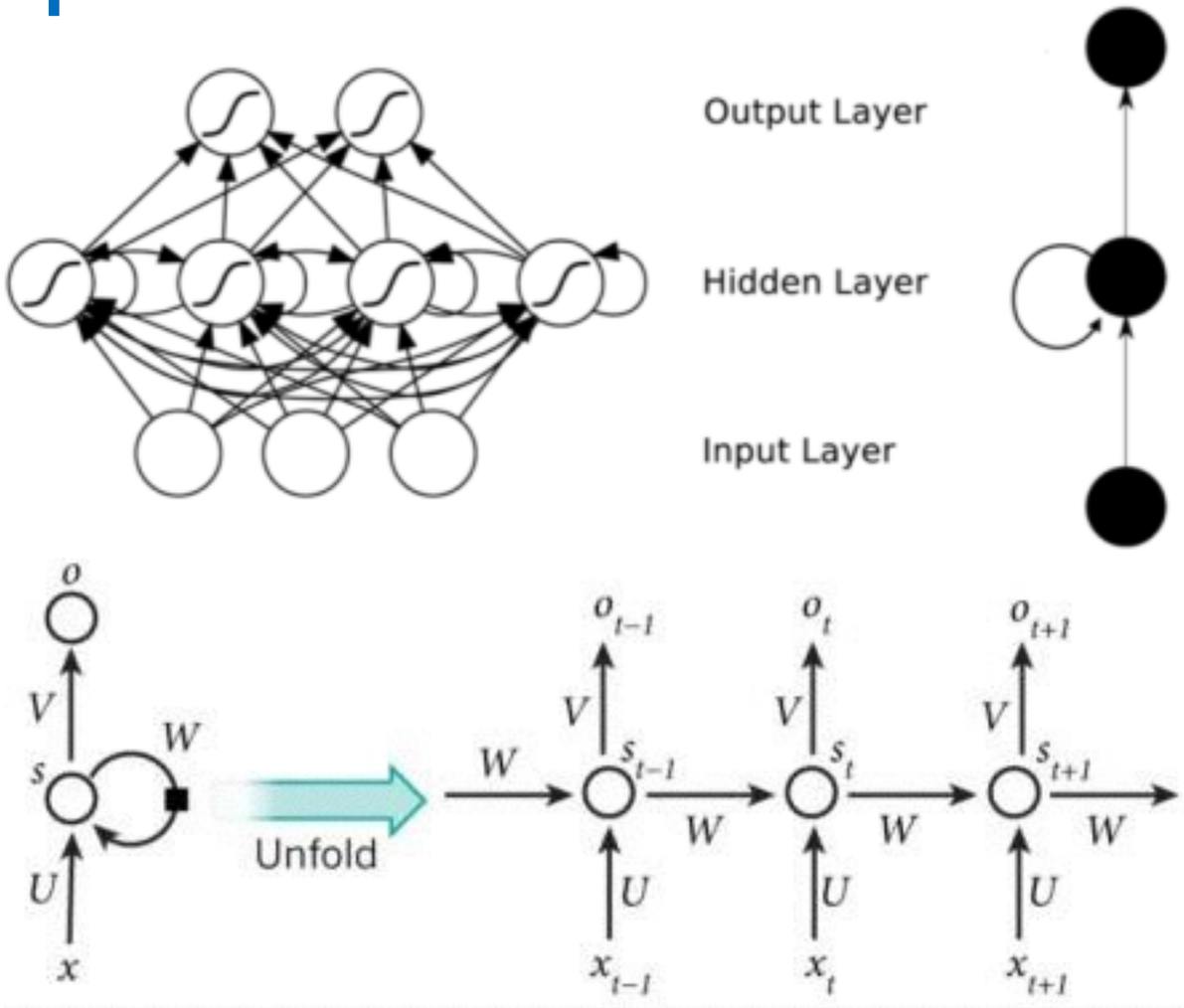


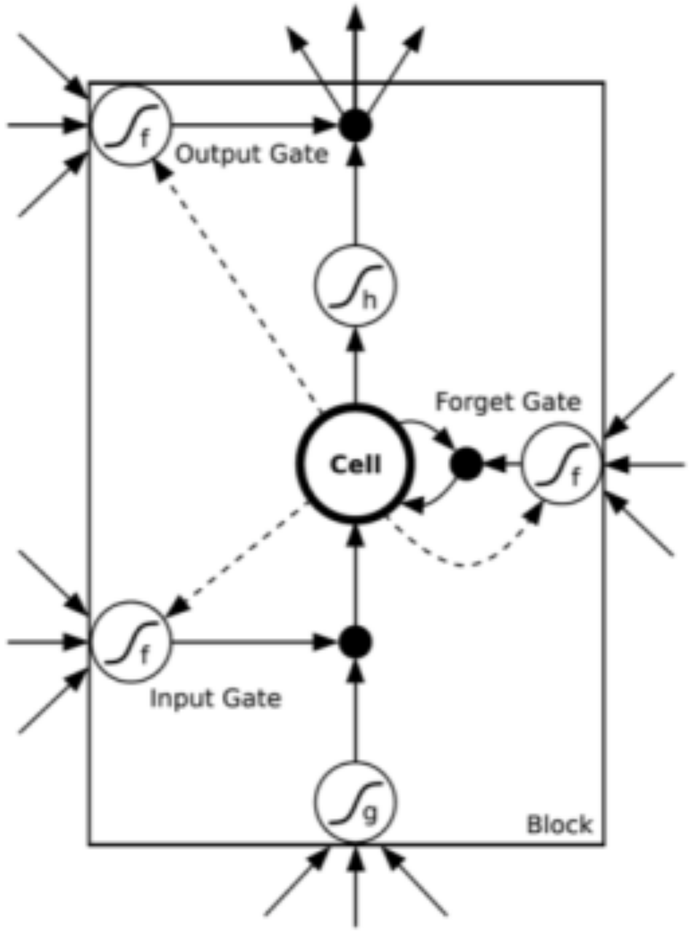
Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

可处理时序数据的深度学习机制

Recursive Neural Networks



Long Short Term Memory



大型企业不同于以往的密切关注

开源框架

名称	基本语言	是否支持多GPU	速度	应用领域
TensorFlow	Python、C++	是	★★☆	通用
Caffe	C++	是	★★★☆	图像分类
Torch	Lua	是	★★☆	通用
Theano	Python	默认为否	★★★☆	通用
IBM DL Platform	SystemML等	是	?	通用

Details of the History of neural network (1)

- Pioneering work on the mathematical model of neural networks
  - McCulloch and Pitts 1943;
  - Include recurrent and non-recurrent (with “circles”) networks;
  - Use thresholding function as nonlinear activation; No learning
- Early works on learning neural networks
  - Starting from Rosenblatt 1958;
  - Using thresholding function as nonlinear activation prevented computing derivatives with the chain rule, and so errors could not be propagated back to guide the computation of gradients
- Backpropagation was developed in several steps since 1960
  - The key idea is to use the chain rule to calculate derivatives;
  - It was reflected in multiple works, earliest from the field of control
- Standard backpropagation for neural networks
  - Rumelhart, Hinton, and Williams, Nature 1986: Clearly appreciated the power of backpropagation and demonstrated it on key tasks, and applied it to pattern recognition generally
  - In 1985, Yann LeCun independently developed a learning algorithm for three-layer networks in which target values were propagated, rather than derivatives. In 1986, he proved that it was equivalent to standard backpropagation
- Prove the universal expressive power of three-layer neural networks
  - Hecht-Nielsen 1989

- Convolutional neural network
  - Introduced by Kunihiko Fukushima in 1980
  - Improved by LeCun, Bottou, Bengio, and Haffner in 1998
- Deep belief net (DBN)
  - Hinton, Osindero, and Tech 2006
- Auto encoder
  - Hinton and Salakhutdinov 2006 (Science)
- Deep learning
  - Hinton. Learning multiple layers of representations. Trends in Cognitive Sciences, 2007.
  - Unsupervised multilayer pre-training + supervised fine-tuning (BP)
- Large-scale deep learning in speech recognition
  - Geoff Hinton and Li Deng started this research at Microsoft Research Redmond in late 2009.
  - Generative DBN pre-training was not necessary
  - Success was achieved by large-scale training data + large deep neural network (DNN) with large, context-dependent output layers
- Unsupervised deep learning from large scale images
  - Andrew Ng et al. 2011
  - Unsupervised feature learning
  - 16000 CPUs
- Large-scale supervised deep learning in ImageNet image classification
  - Krizhevsky, Sutskever, and Hinton 2012
  - Supervised learning with convolutional neural network
  - No unsupervised pre-training

Motivation

The biological metaphor

- Our neural system is composed of 100 billion computing units (neurons) and 10^{15} connections (synapses).
- How can a system composed of many simple interconnected units give rise to highly complex activities?
- Emergence: complex systems arise out of a multiplicity of relatively simple *interacting* units.

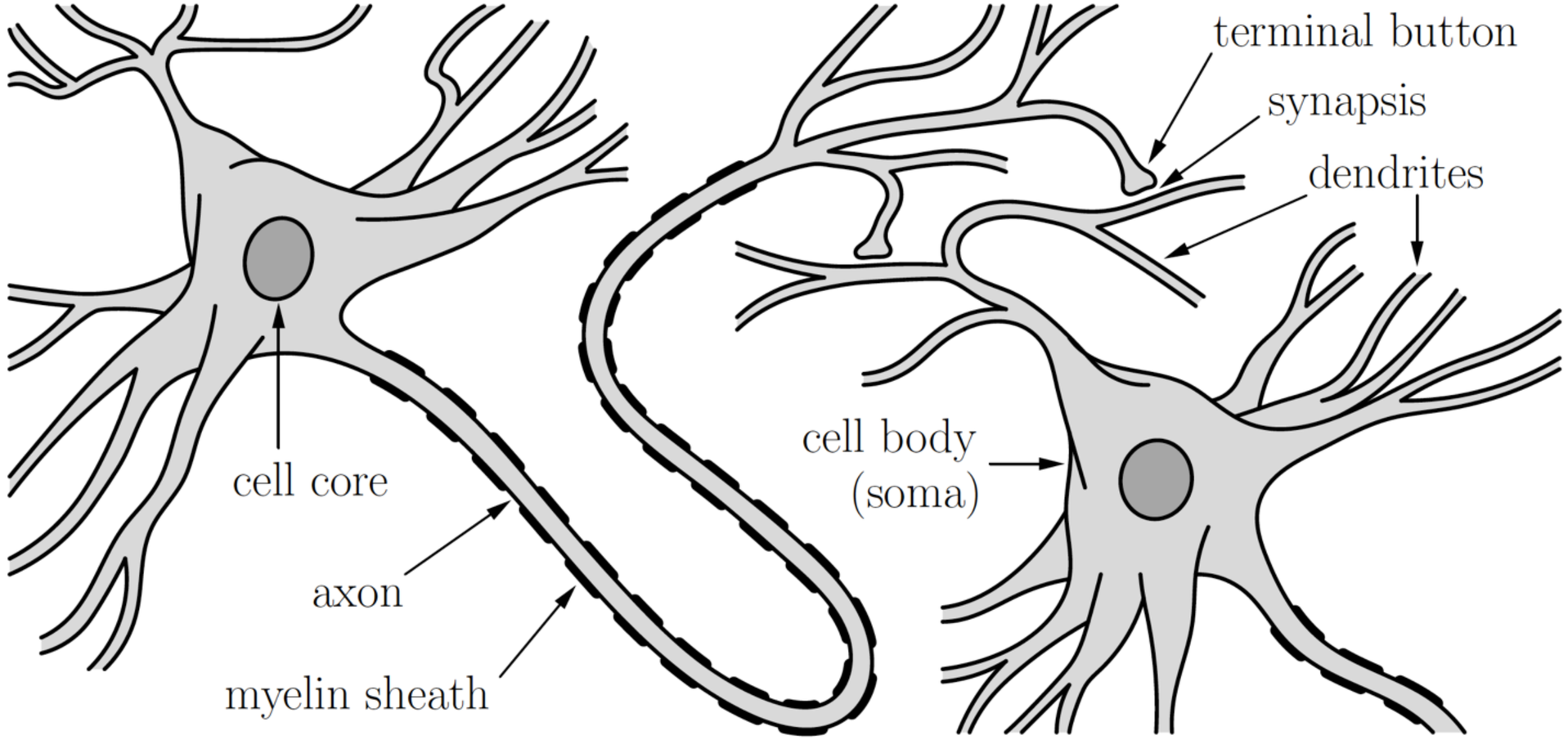
Symbolic vs. sub-symbolic paradigm

- ”Standard” sequential computers operate in cycles, fetching items from memory, applying mathematical operations and writing results back to memory.
- The *intelligence* of biological brains is different, it lies in the interconnection strengths, learning occurs by modifying connections (**dynamical systems**)
- Neural networks **do not separate memory and processing** but operate via the flow of signals through the network connections.

Biological Background

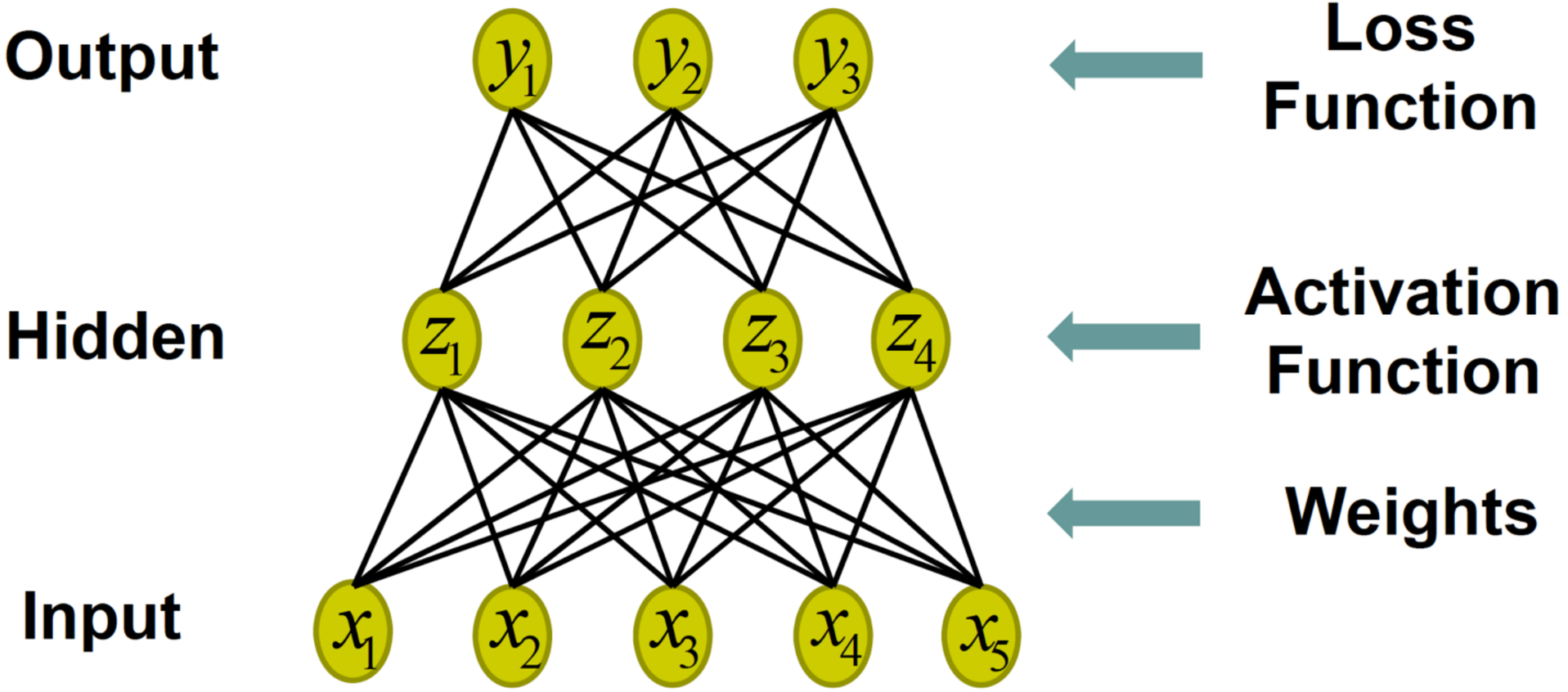
Optional subtitle

Structure of a prototypical biological neuron



Neural Network In General

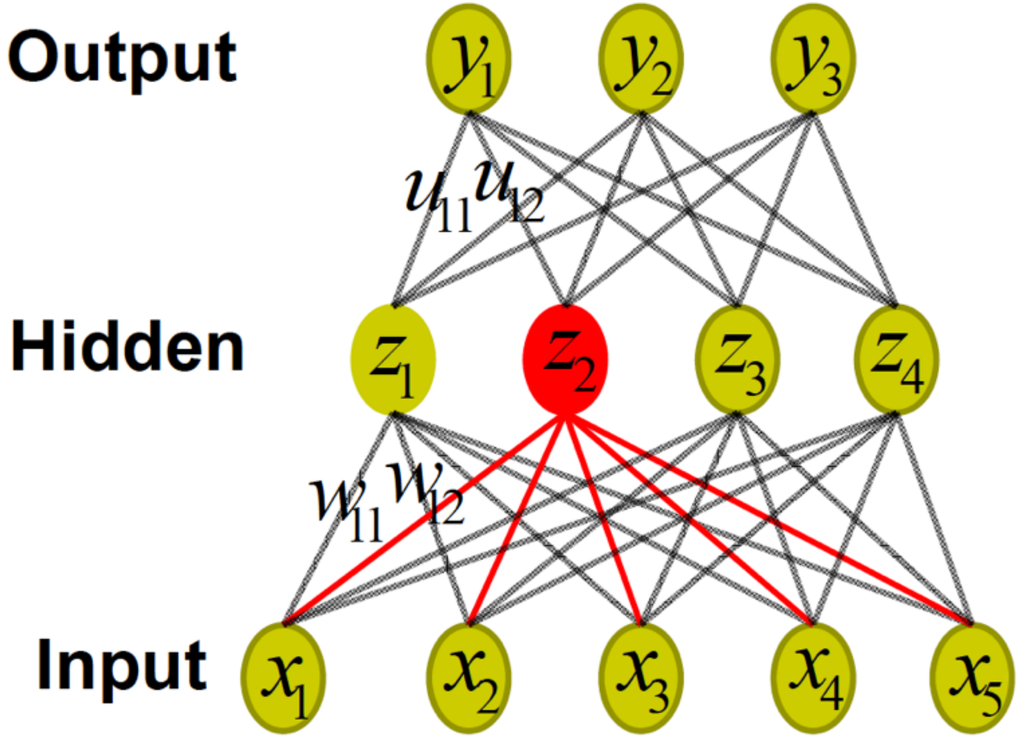
Neural Network



Local Computation At Each Unit

Optional subtitle

Linear Combination + Nonlinear Activation



Activation Function

units in the lower layer

$$z_2 = \sigma\left(\sum_{i=1}^{5} w_{2i} x_i\right)$$

Weights connecting to units in the lower layer

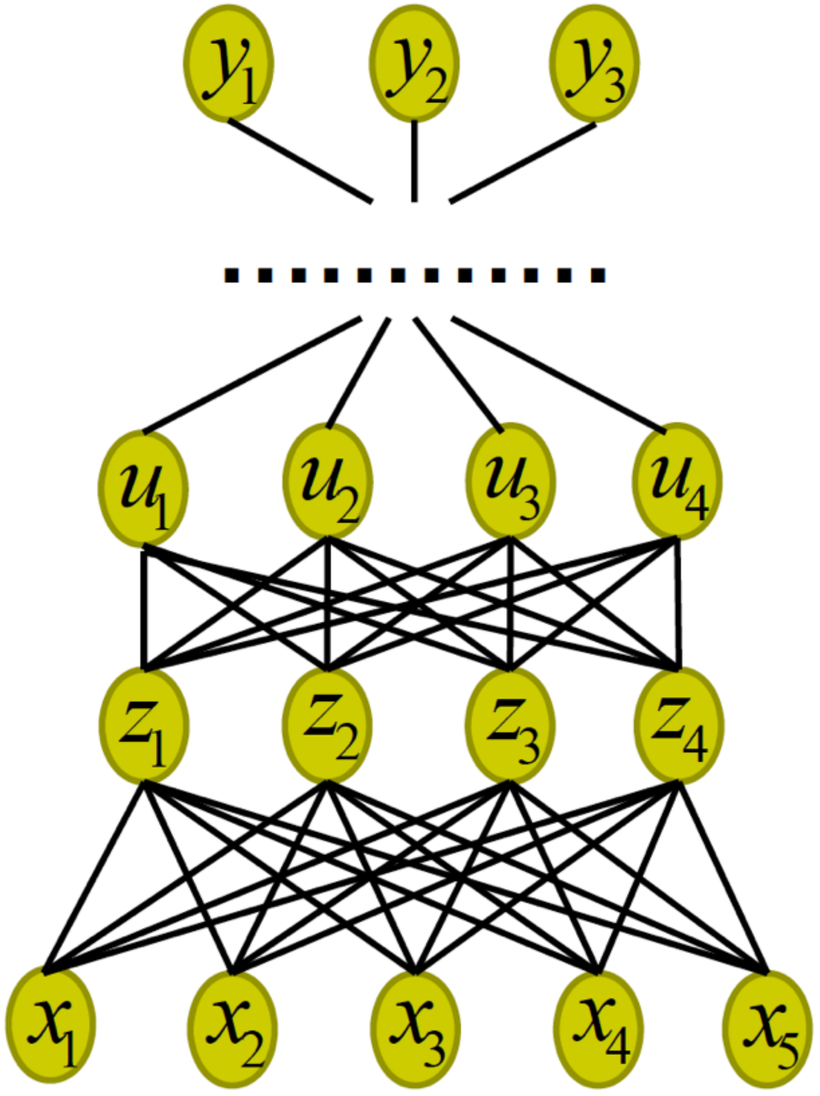
Deep Neural Network

Optional subtitle

Output

More Hidden Layers

Input

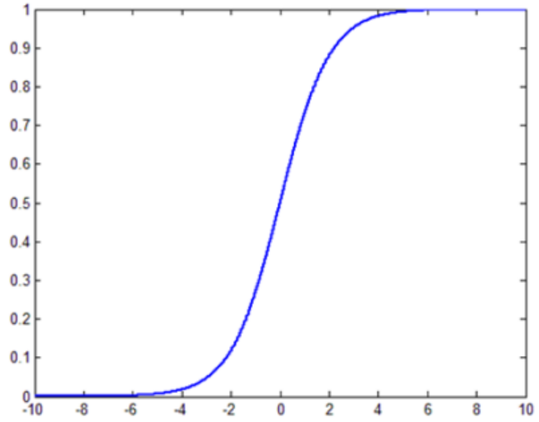


Activation Functions

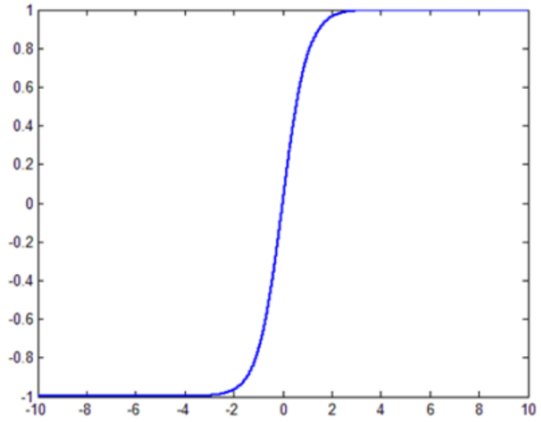
Optional subtitle

- Applied on the hidden units
- Achieve nonlinearity
- Popular activation functions

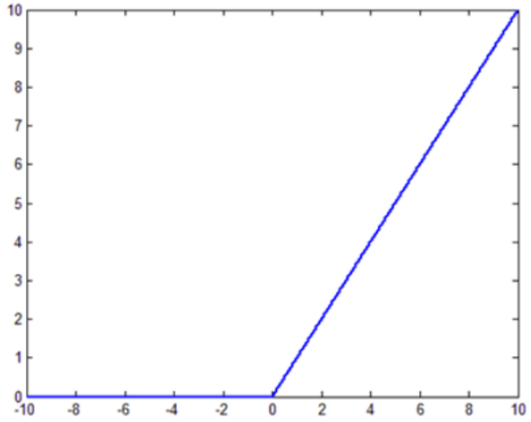
Sigmoid



Tanh



Rectified Linear



More Activation functions

Popular choice of f (·)

- Sigmoid function $f(s) = \frac{1}{1+e^{-s}}$
- Tanh function (shift the center of Sigmoid to the origin) $f(s) = \frac{e^{s}-e^{-s}}{e^{s}+e^{-s}}$
- Hard thanh $f(s) = \max(-1, \min(1, x))$
- Rectified linear unit (ReLU) $f(s) = \max(0, x)$
- Softplus: smooth version of ReLU $f(s) = \log(1+e^{s})$
- Softmax: mostly used as output non-linearrity for predicting discrete probabilities

$$f(s_k) = \frac{e^{s_k}}{\sum_{k'=1}^{C} e^{s_{k'}}}$$

- Maxout: it generalizes the rectifier assuming there are multiple netactivations

$$f(s_1, \ldots, s_n) = \max_i(s_i)$$

Loss Functions

Optional subtitle

- Squared loss for regression

$$(y - t)^2$$

Prediction　　True value

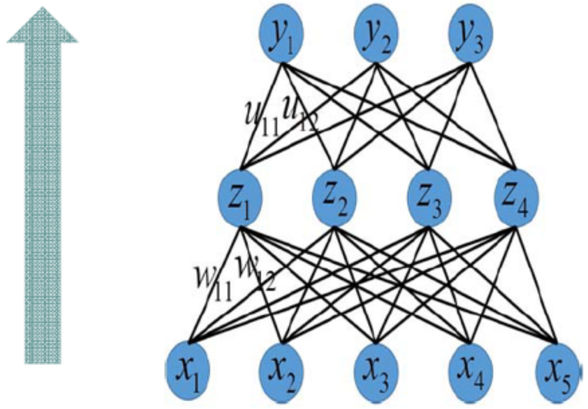
- Cross entropy loss for classification

$$-\sum_{k=1}^{K} t_k \ln a_k \qquad a_k = \frac{\exp(y_k)}{\sum_{j=1}^{K} \exp(y_j)}$$

Class label　　Prediction

Neural Network Prediction

- Compute unit values layer by layer in a forward manner



- Prediction function

Activation Function

Input

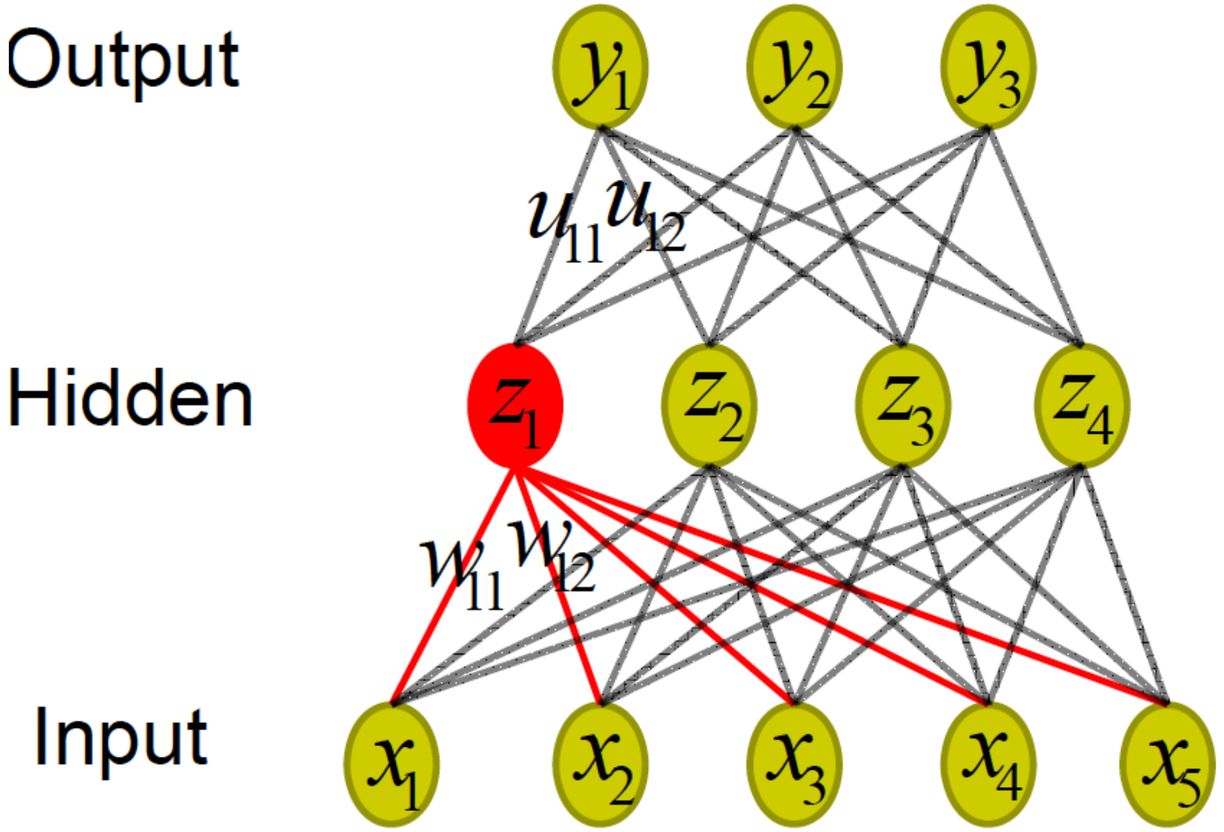
$$y_k = \sum_{j=1}^{4} u_{kj}\sigma\left(\sum_{i=1}^{5} w_{ji}x_i\right)$$

Output

Weights

Neural Network Prediction

Optional subtitle

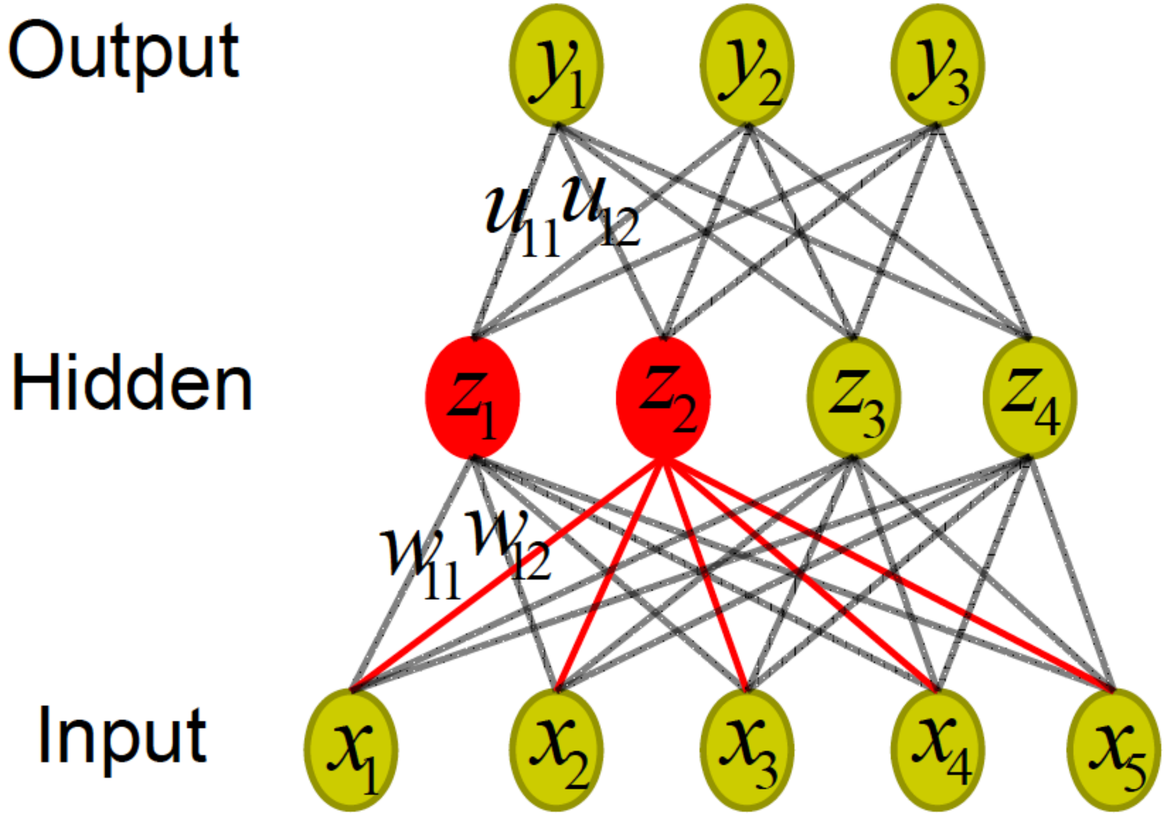


$$z_1 = \sigma\left(\sum_{i=1}^{5} w_{1i} x_i\right)$$

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

Neural Network Prediction

Optional subtitle

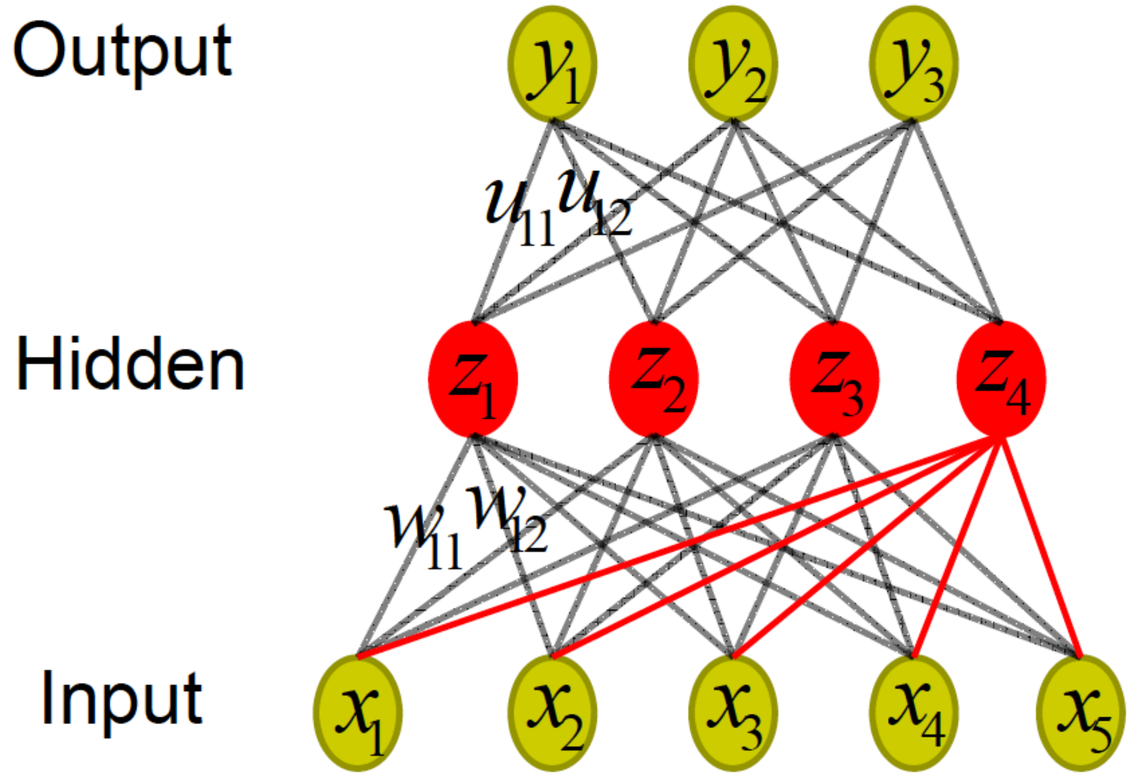


$$z_2 = \sigma\left(\sum_{i=1}^{5} w_{2i} x_i\right)$$

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

Neural Network Prediction

Optional subtitle

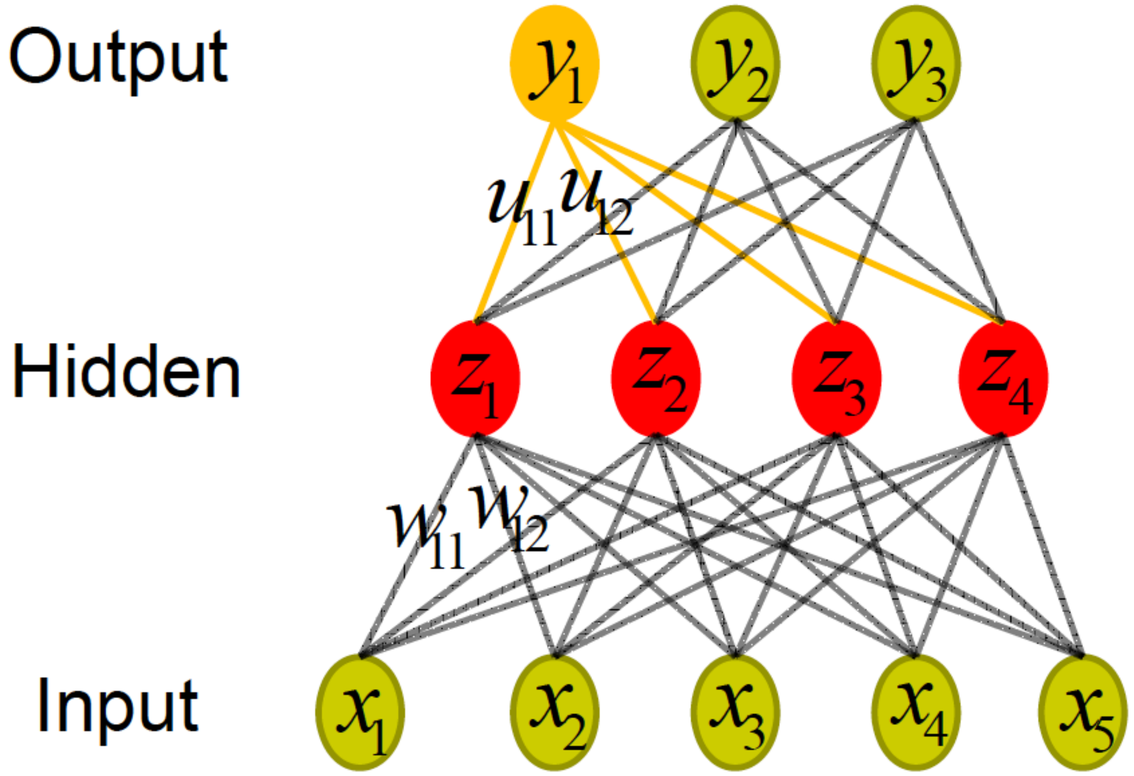


$$z_4 = \sigma\left(\sum_{i=1}^{5} w_{4i} x_i\right)$$

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

Neural Network Prediction

Optional subtitle

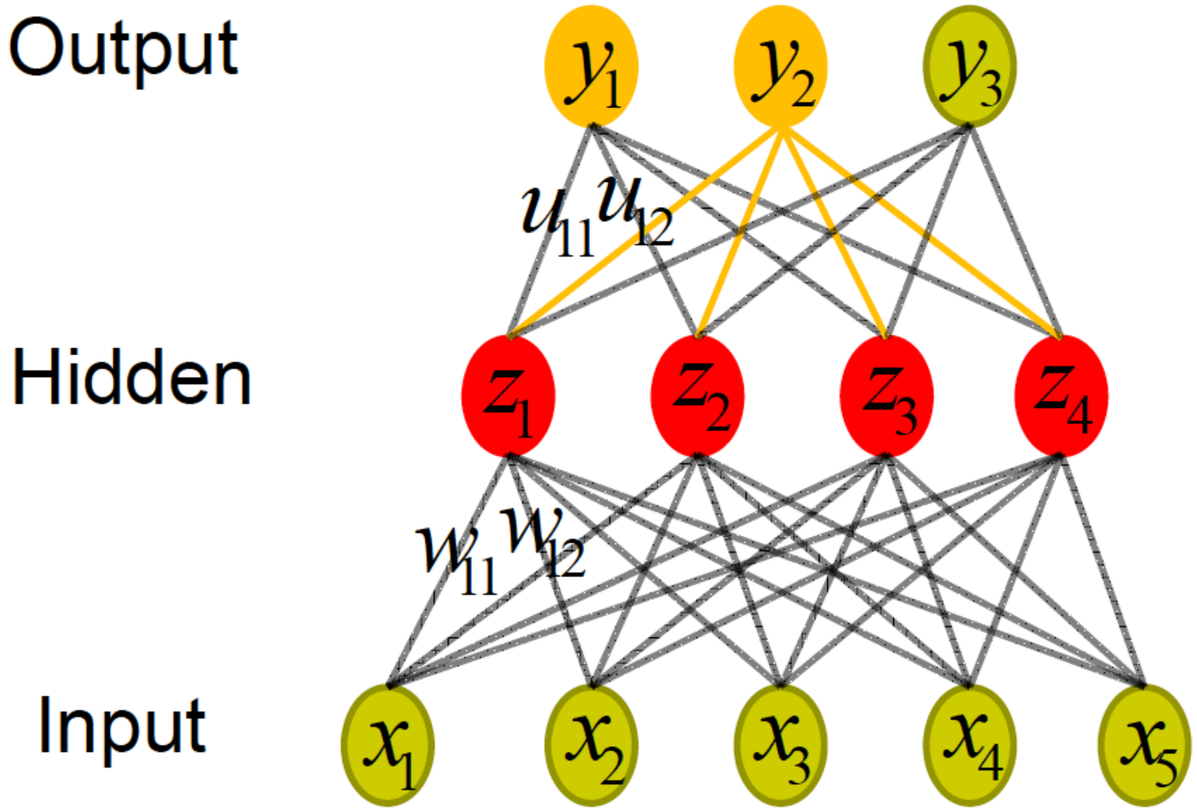


$$y_1 = \sigma\left(\sum_{i=1}^{4} u_{1i} z_i\right)$$

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

Neural Network Prediction

Optional subtitle

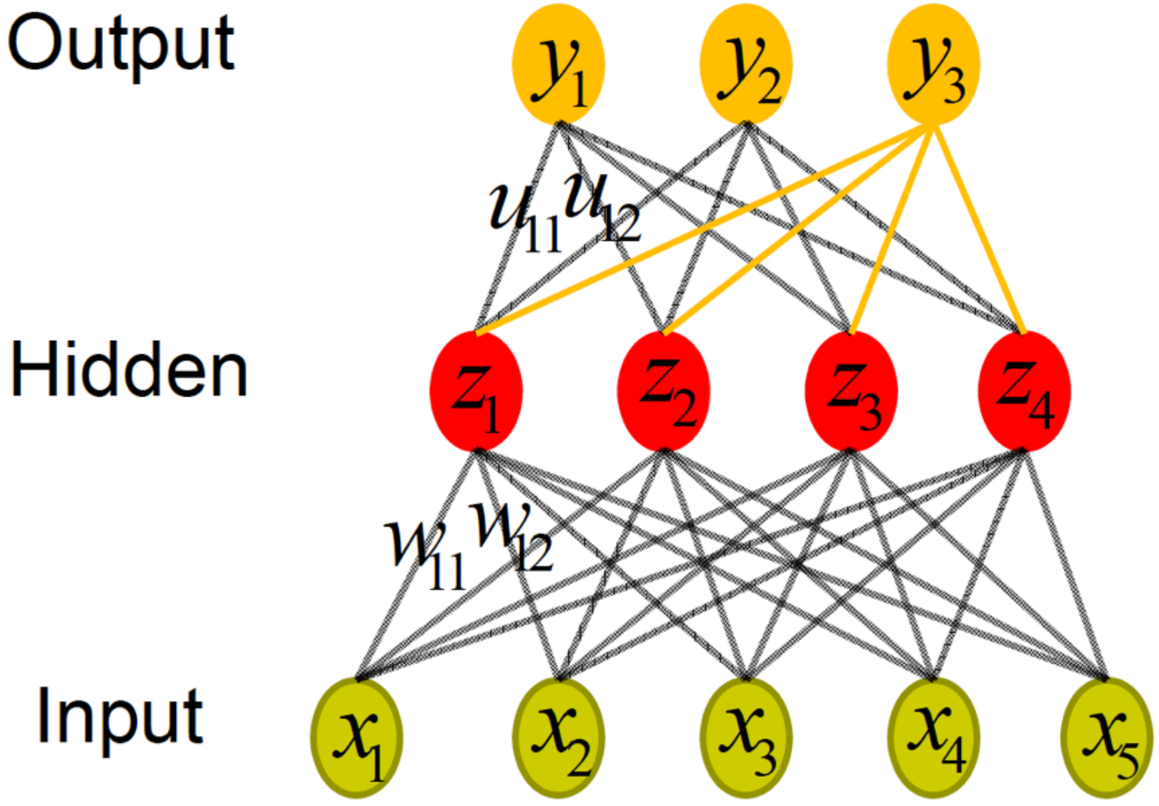


$$y_2 = \sigma\left(\sum_{i=1}^{4} u_{2i} z_i\right)$$

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

Neural Network Prediction

Optional subtitle



$$y_3 = \sigma\left(\sum_{i=1}^{4} u_{3i} z_i\right)$$

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

Neural Network Training

- Goal: compute gradient

$$\frac{\partial L}{\partial w_{ij}}$$

$\frac{\partial L}{}$ ← Training loss

∂w_{ij} ← Weight between unit i and j

- Apply chain rule

$$\frac{\partial L}{\partial w_{ji}} = \frac{\partial L}{\partial a_j}\frac{\partial a_j}{w_{ji}}$$

← Linear combination value $a_j = \sum_i w_{ji} z_i$

$$\boxed{\frac{\partial L}{\partial a_j}} = \sum_k \boxed{\frac{\partial L}{\partial a_k}}\frac{\partial a_k}{a_j}$$

Called error, computed recursively in a backward manner

Neural Network Training

Optional subtitle

- Apply chain rule (cont'd)

$$\frac{\partial a_j}{w_{ji}} = z_i$$ ← Derivative of activation function

$$\frac{\partial a_k}{\partial a_j} = \frac{\partial a_k}{\partial z_j}\frac{\partial z_j}{\partial a_j} = w_{kj}\sigma'(a_j)$$

gradient=$\frac{\partial L}{\partial w_{ji}} = \frac{\partial L}{\partial a_j}\frac{\partial a_j}{w_{ji}}$=backward error x forward activation

- Pseudo code of BP

While not converge

1. compute forward activations
2. compute backward errors
3. compute gradients of weights
4. perform gradient descent

Pretraining

Optional subtitle

- A better initialization strategy of weight parameters
  - Based on Restricted Boltzmann Machine
  - An auto-encoder model
  - Unsupervised
  - Layer-wise, greedy
- Useful when training data is limited
- Not necessary when training data is rich

Multilayer Perceptrons (MLPs) are universal approximators.

- MLPs are very flexible models: they can approximate any smooth input-output transformation. Really?!!
- Most widely used pattern recognition models (such as SVM, boosting, and KNN) can be approximated as neural networks with one or two hidden layers. They are called models with **shallow architectures**.
- Shallow models divide the feature space into regions and match templates in local regions. O(N) parameters are needed to represent N regions.
- **Deep architecture**: the number of hidden nodes can be reduced exponentially with more layers for certain problems. (1000-Layer ResNet)

Multilayer Perceptrons (MLPs) are universal approximators

Optional subtitle

An MLP with one hidden layer can approximate any smooth function to any desired accuracy, subject to a sufficient number of hidden nodes. [1]

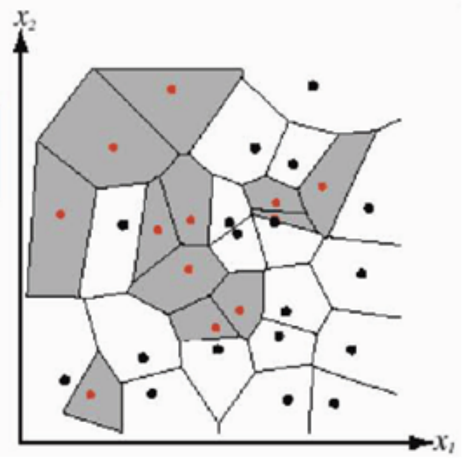
[1] K. Hornik, M.Stinchcombe, and H.White. Multilayer feedforward networks are universal approximations. Neural Networks, 1989.

That's a very interesting result: neural-like architectures composed of simple units (linear summation and squashing sigmoidal transfer functions), organised in layers with at least a hidden layer are what we need to model arbitrary smooth input-output transformations.

Expressive power of a three-layer neural network

Optional subtitle

KNN

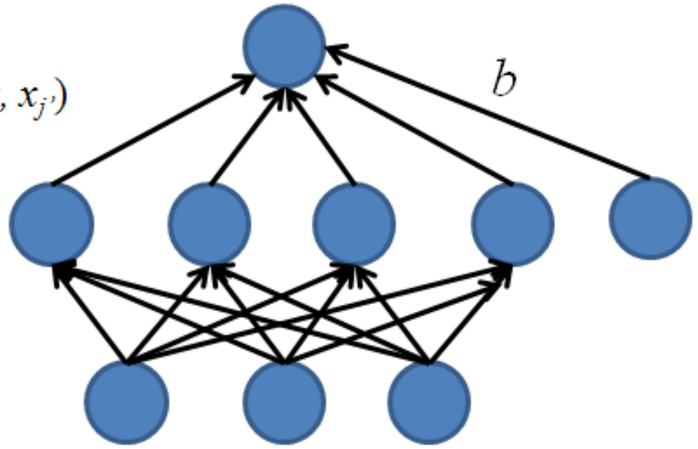


output $g(x) = label_j$

$j = \text{argmin}_{j'} d(x, x_{j'})$

hidden $d(x, x_j)$

input x

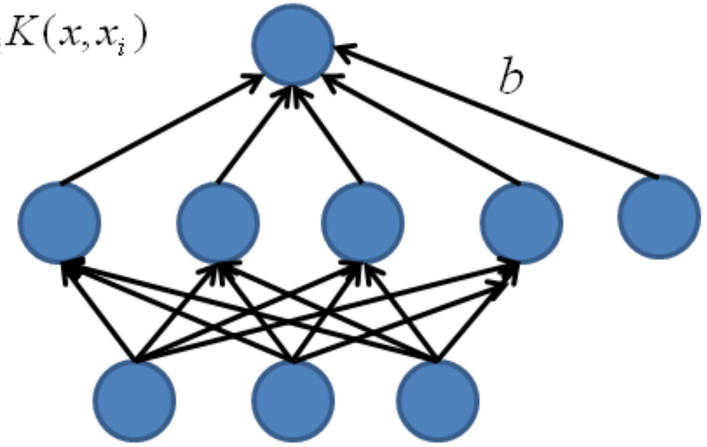


SVM

output $g(x) = b + \sum_i \alpha_i K(x, x_i)$

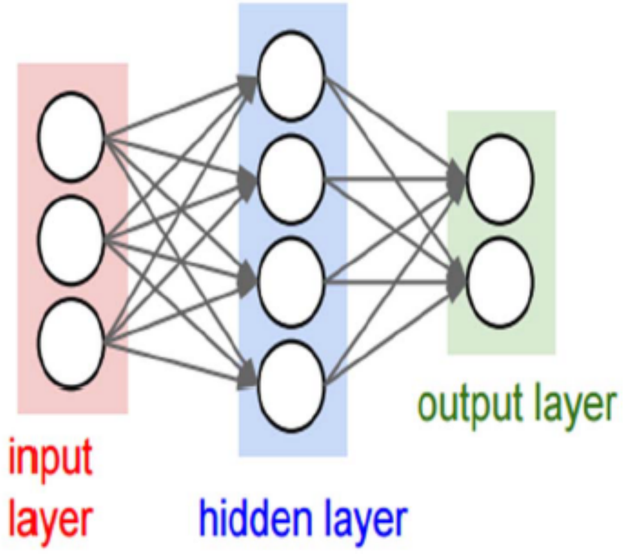
hidden $K(x, x_j)$

input x

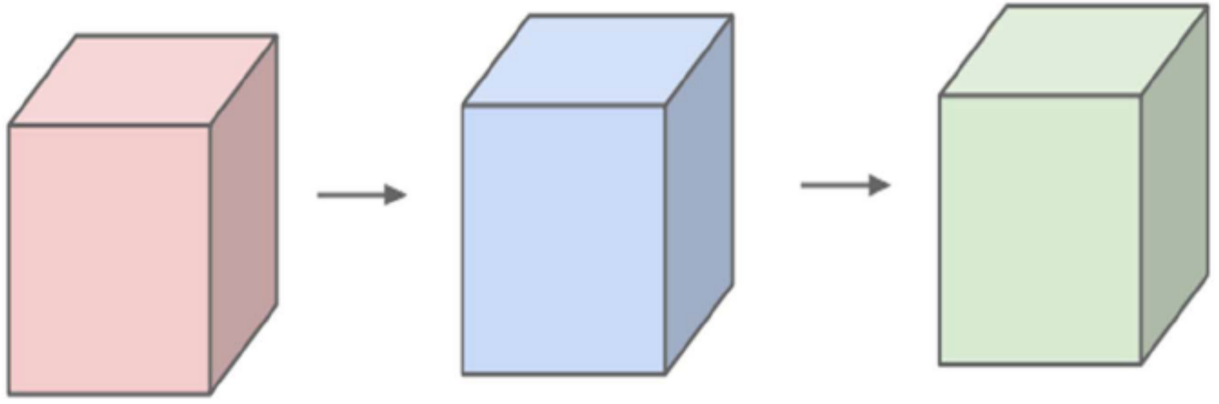


Convolutional Neural Network(CNN)

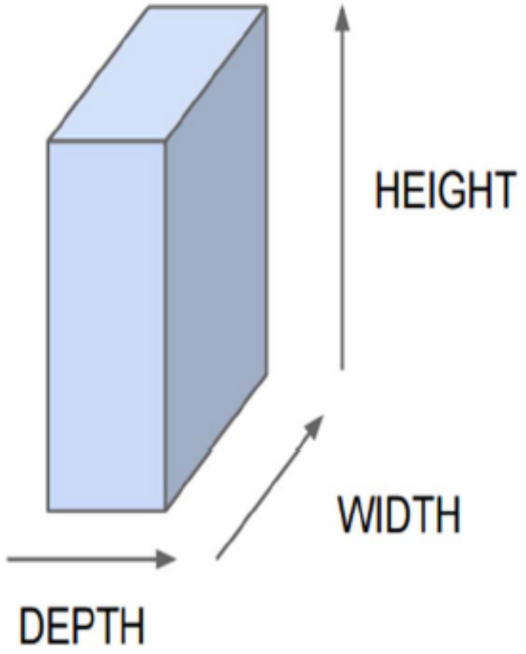
Ordinary Neural Network



Now



All Neural Net activations arranged in 3 dimensions



For example, a CIFAR-10 image is a 32*32*3 volume: 32 width, 32 height, 3 depth (RGB)

Local connectivity

Optional subtitle

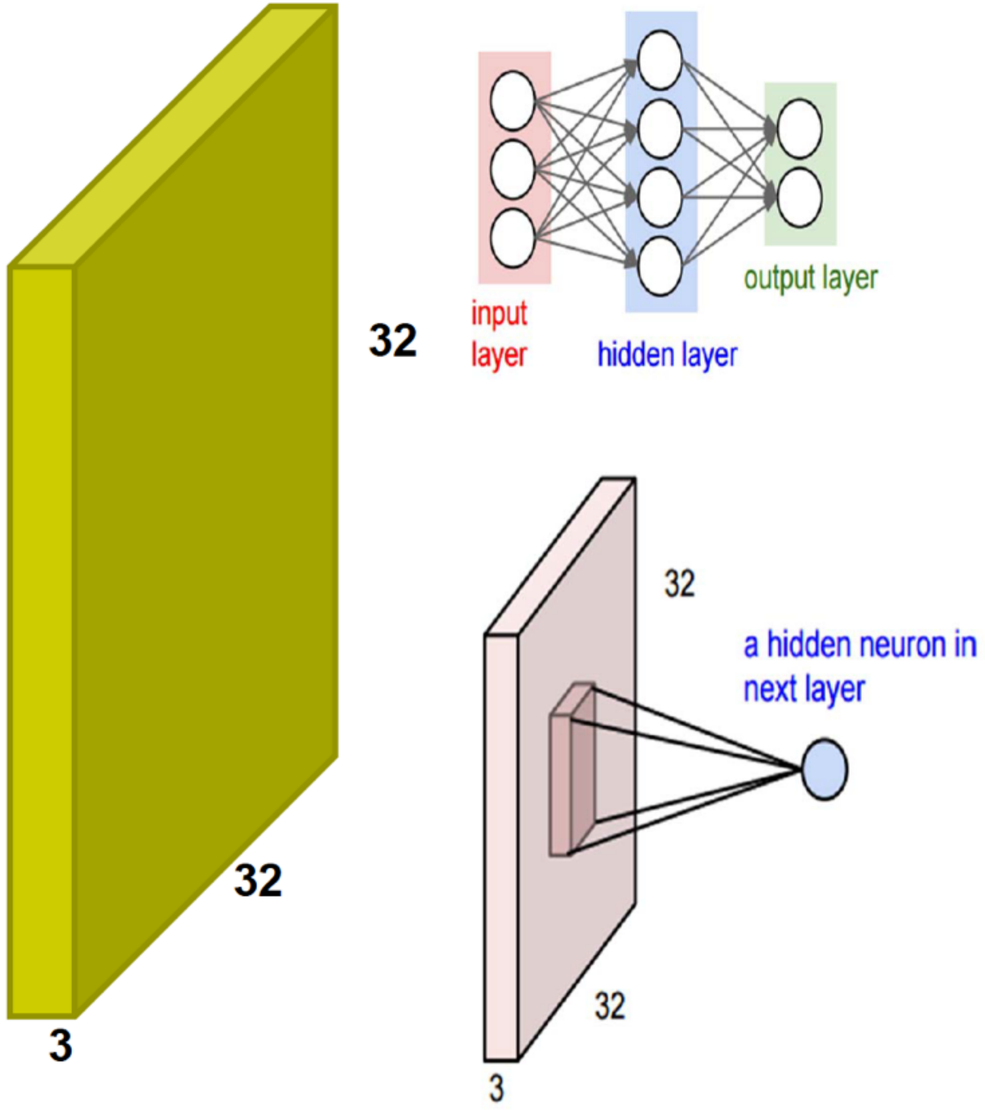


image: 32 * 32 * 3 volume

before: full connectivity: 32 * 32 * 3 weights for each neuron

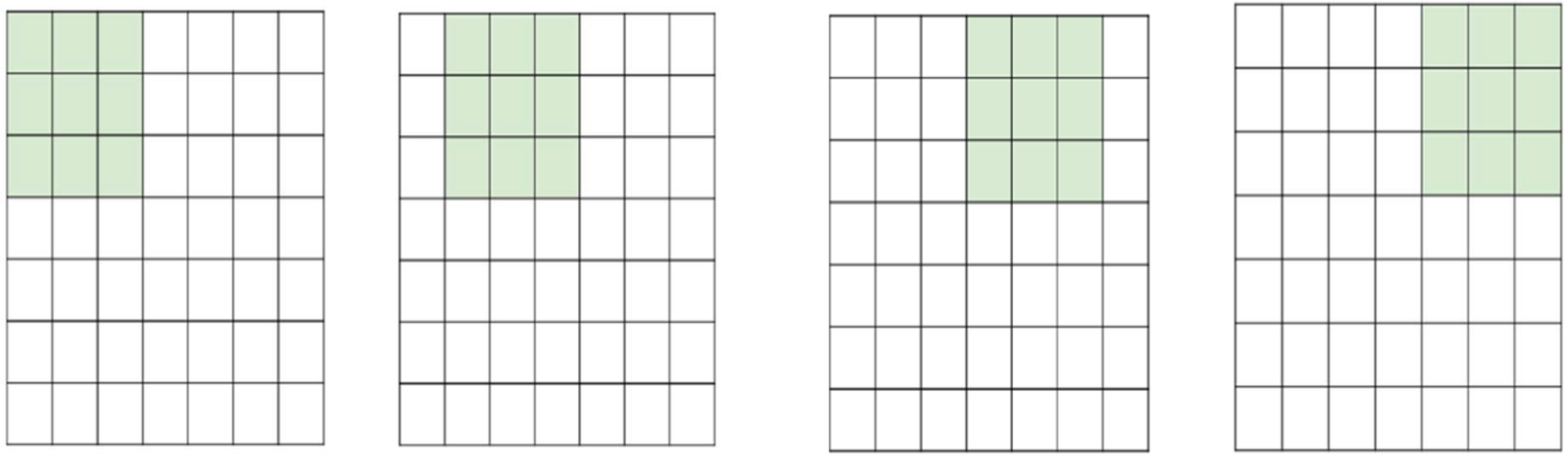
now: one unit will connect to, e.g. 5*5*3 chunk and only have 5*5*3 weights

Note the connectivity is:

- **local in space**
- **full in depth**

Convolution

- One local region only gives one output
- Convolution: Replicate the column of hidden units across space, with some stride



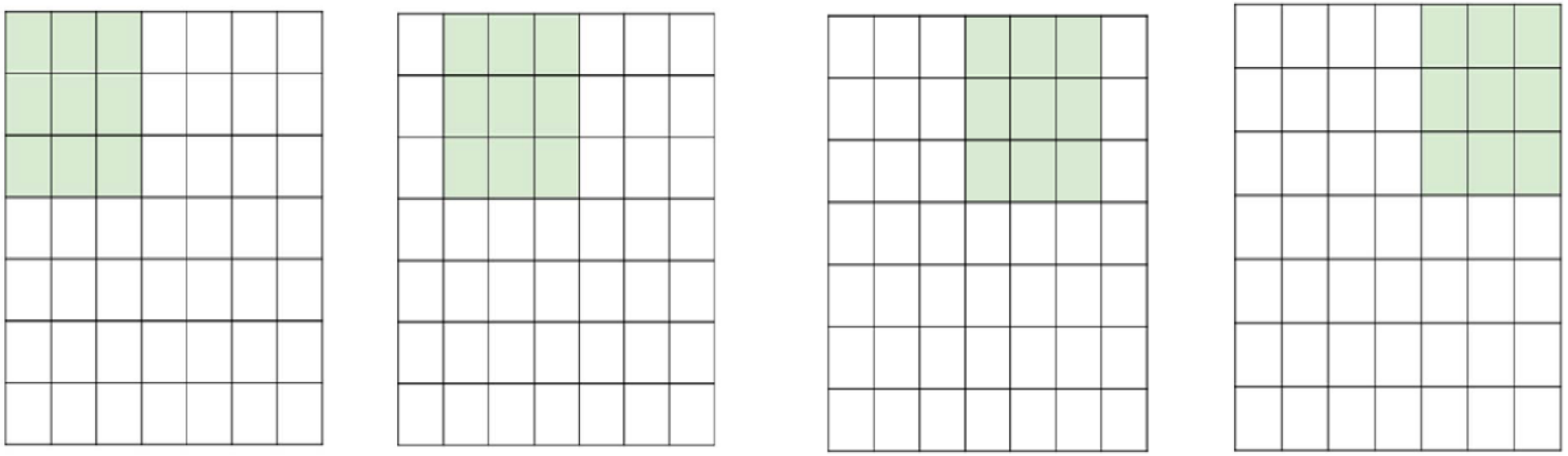
- 7 * 7 Input
- Assume 3*3 connectivity, stride = 1

- Produce a map
- What's the size of the map? 5 * 5

Convolution

Optional subtitle

- One local region only gives one output
- Convolution: Replicate the column of hidden units across space, with some stride



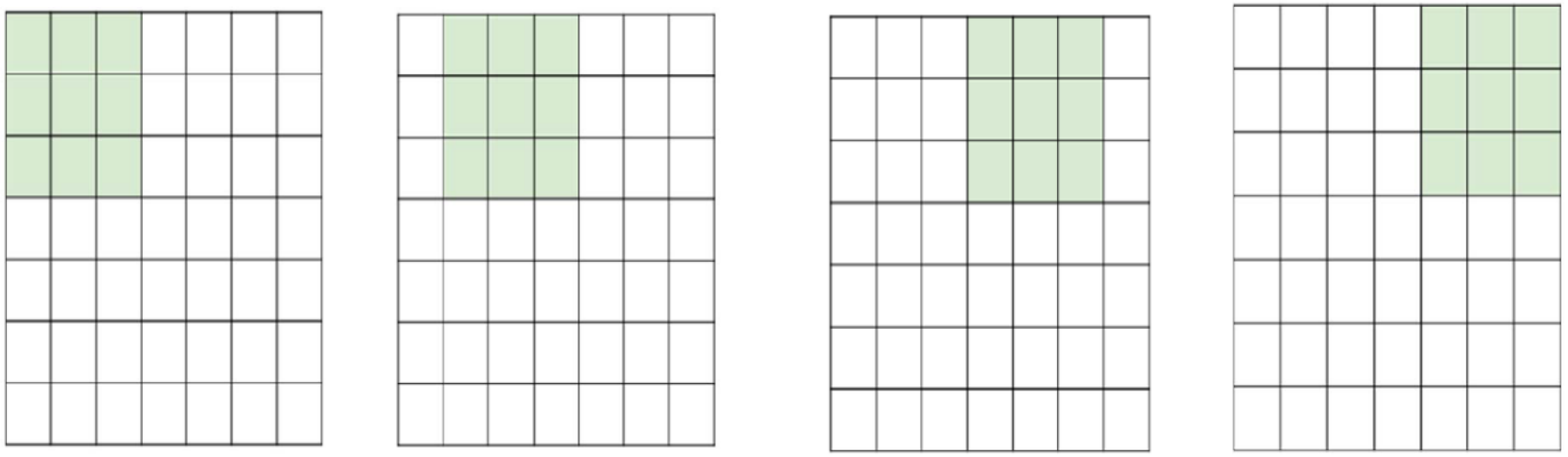
- 7 * 7 Input
- Assume 3*3 connectivity, stride = 1

- What if stride = 2?

Convolution

Optional subtitle

- One local region only gives one output
- Convolution: Replicate the column of hidden units across space, with some stride



- 7 * 7 Input
- Assume 3*3 connectivity, stride = 1

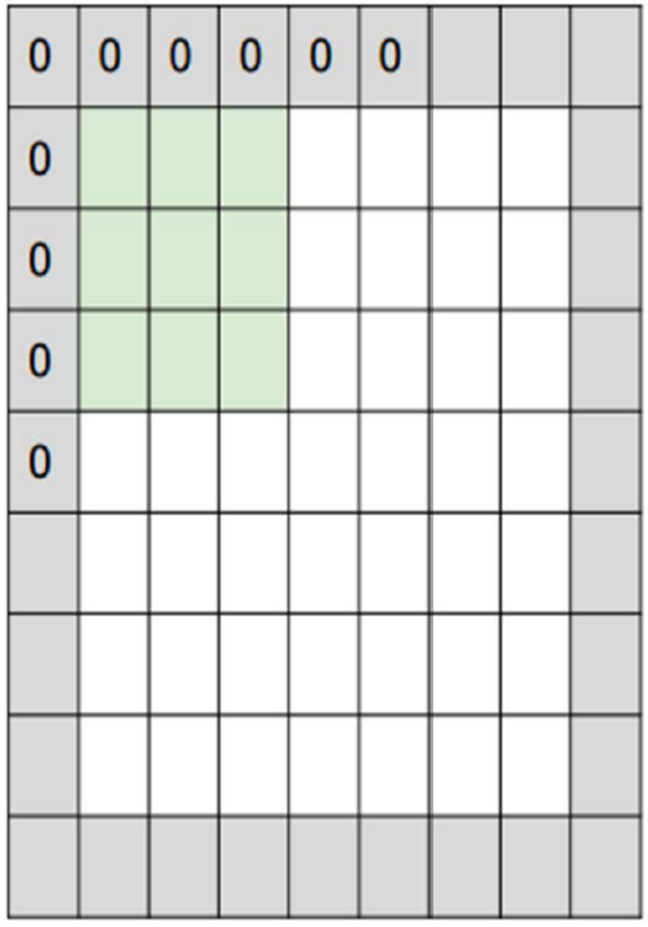
- What if stride = 3?

Convolution: In Practice

Optional subtitle

- Zero Padding
  - Input size: 7 * 7
  - Filter Size: 3*3, stride 1
  - Pad with 1 pixel border

- Output size?
  - 7 * 7 => preserved size!



Convolution: Summary

- Zero Padding
  - Input volume of size [W1 * H1 * D1]
  - Using K units with receptive fields F x F and applying them at strides of S gives

    Output volume: [W2, H2, D2]

- W2 = (W1 – F)/S + 1
- H2 = (H1 - F) / S + 1
- D2 =k

Convolution: Problem

Optional subtitle

- Assume input [32 * 32 * 3]
- 30 units with receptive field 5 * 5, applied at stride 1/pad 1

  => Output volume: [30 * 30 * 30]

At each position of the output volume, we need 5 * 5 * 3 weights

=> Number of weights in such layer: 27000 * 75 = 2 million ☹

Idea:
Weight sharing!

Learn one unit, let the unit convolve across all local receptive fields!

Convolution: Problem

Optional subtitle

- Assume input [32 * 32 * 3]
- 30 units with receptive field 5 * 5, applied at stride 1/pad 1

  => Output volume: [30 * 30 * 30] = 27000 units

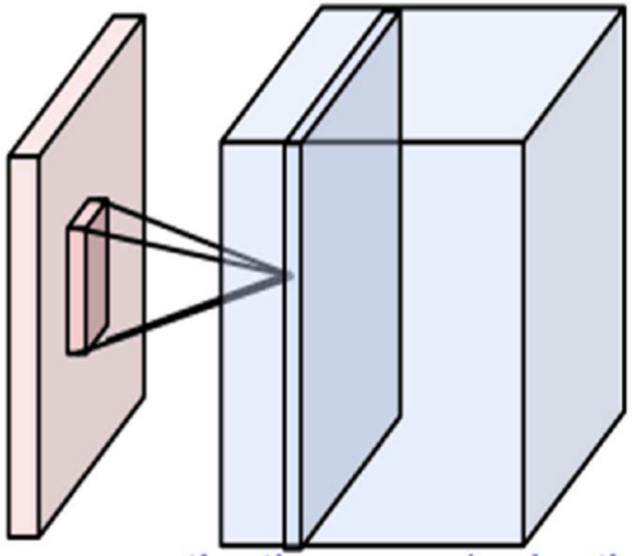
Weight sharing

  => Before: Number of weights in such layer: 27000 * 75 = 2 million ☹

  => After: weight sharing: 30 * 75 = 2250 ☺

Convolutional Layers

- Connect units only to local receptive fields
- Use the same unit weight parameters for units in each “depth slice” (i.e. across spatial positions)



one activation map (a depth slice), computed with one set of weights

Can call the units “**filters**”

We call the layer convolutional because it is related to convolution of two signals

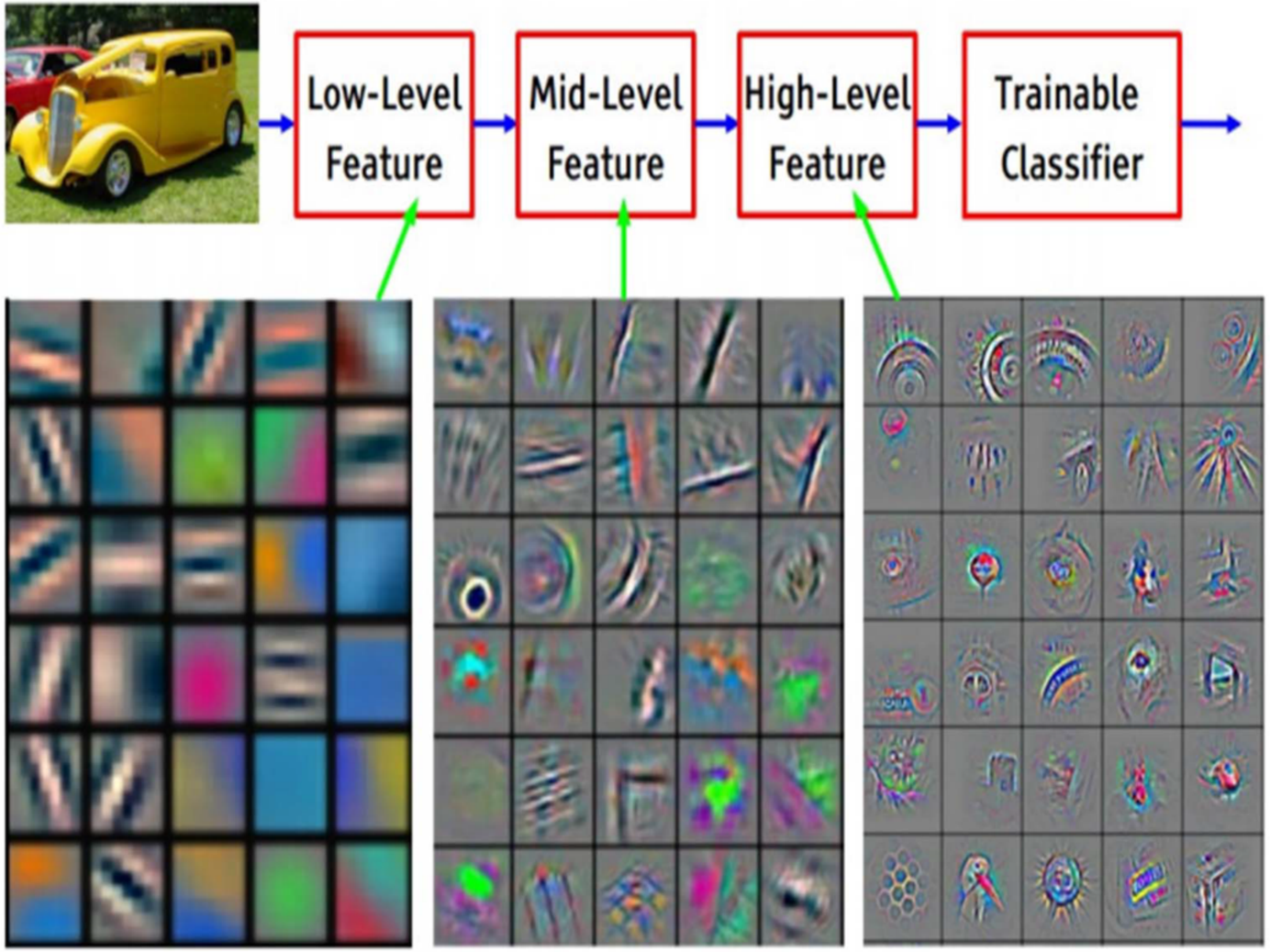
$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

Sometimes we also add a bias term b, y = Wx + b, like what we have done for ordinary NN

Short question: Will convolution layers introduce nonlinearity?

Stacking Convolutional Layers

Optional subtitle

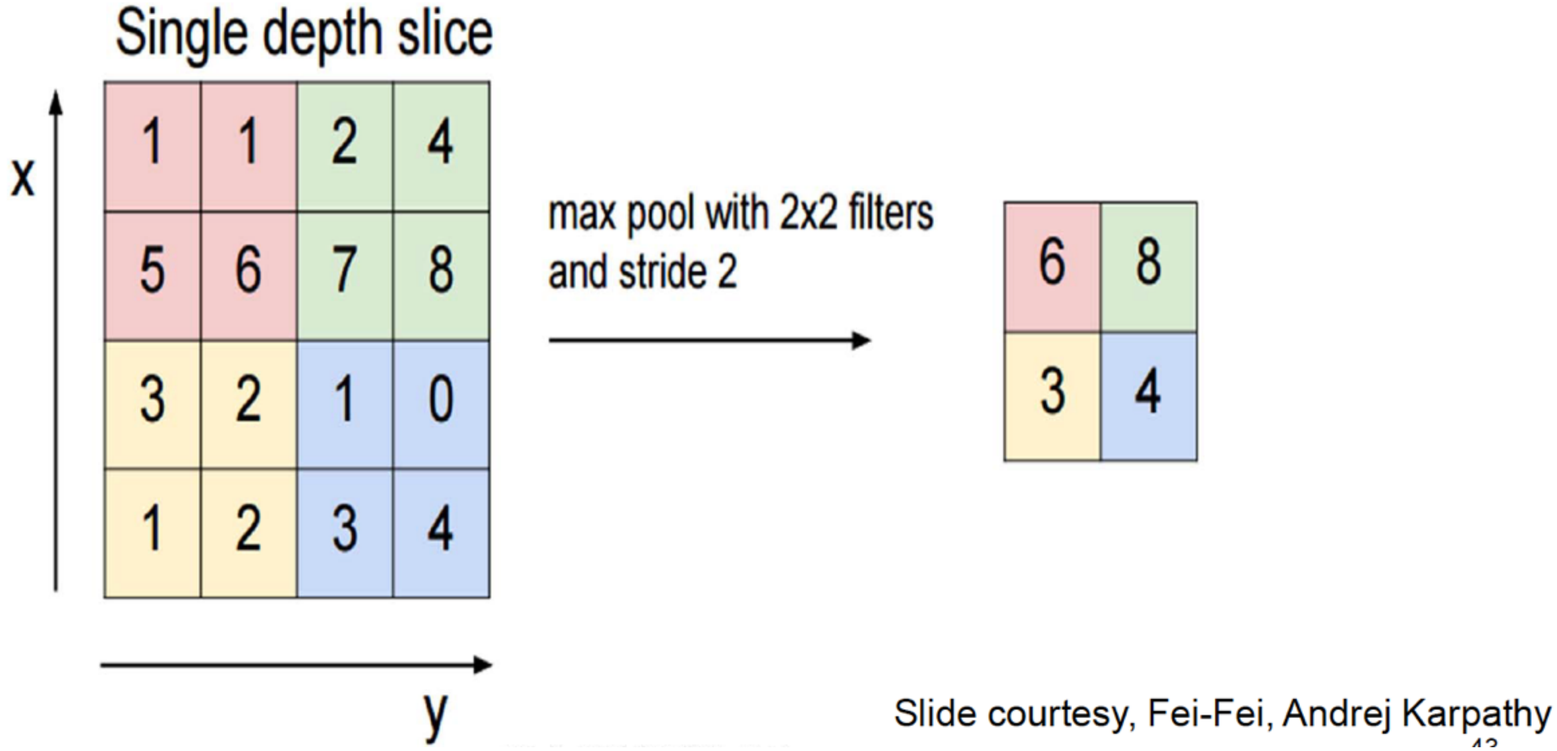


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Pooling Layers

Optional subtitle

- In ConvNet architectures, Conv layers are often followed by Pool layers
  - makes the representations smaller and more manageable without losing too much information. Computes MAX operation (most common)



Slide courtesy, Fei-Fei, Andrej Karpathy

Pooling Layers

Optional subtitle

- In ConvNet architectures, Conv layers are often followed by Pool layers
  - makes the representations smaller and more manageable without losing too much information. Computes MAX operation (most common)
- Input volume of size [W1 x H1 x D1]
- Pooling unit receptive fields F x F and applying them at strides of S gives
- Output volume: [W2, H2, D1]: depth unchanged!

$$W2 = (W1-F)/S+1,$$

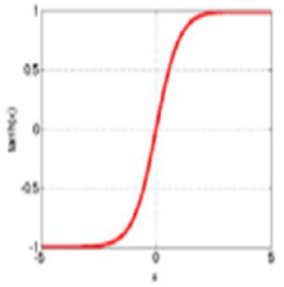
$$H2 = (H1-F)/S+1$$

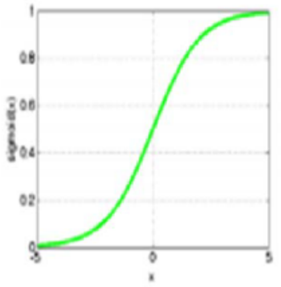
Short question: Will pooling layer introduce nonlinearity?

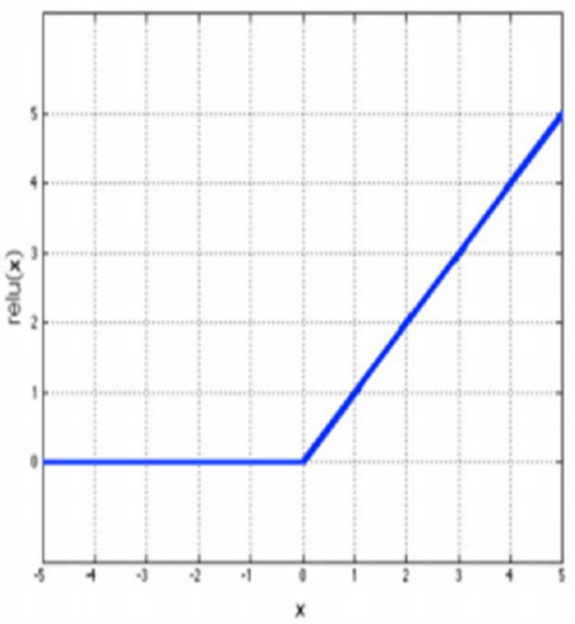
Nonlinerity

Optional subtitle

- Similar to NN, we need to introduce nonlinearity in CNN
  - Sigmoid
  - Tanh
  - RELU: Rectified Linear Units -
    - Simplifies backpropagation
    - Makes learning faster
    - Avoids saturation issues



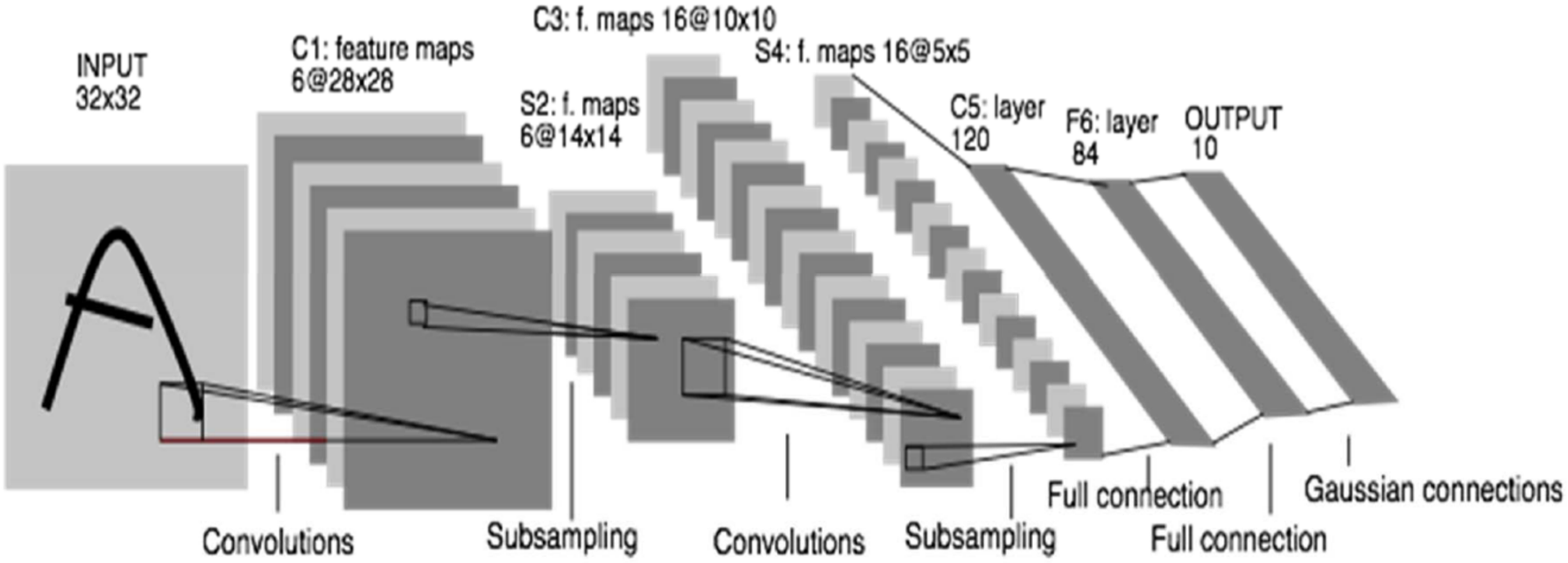




Slide courtesy, Yan Lecun

Convolutional Networks: 1989

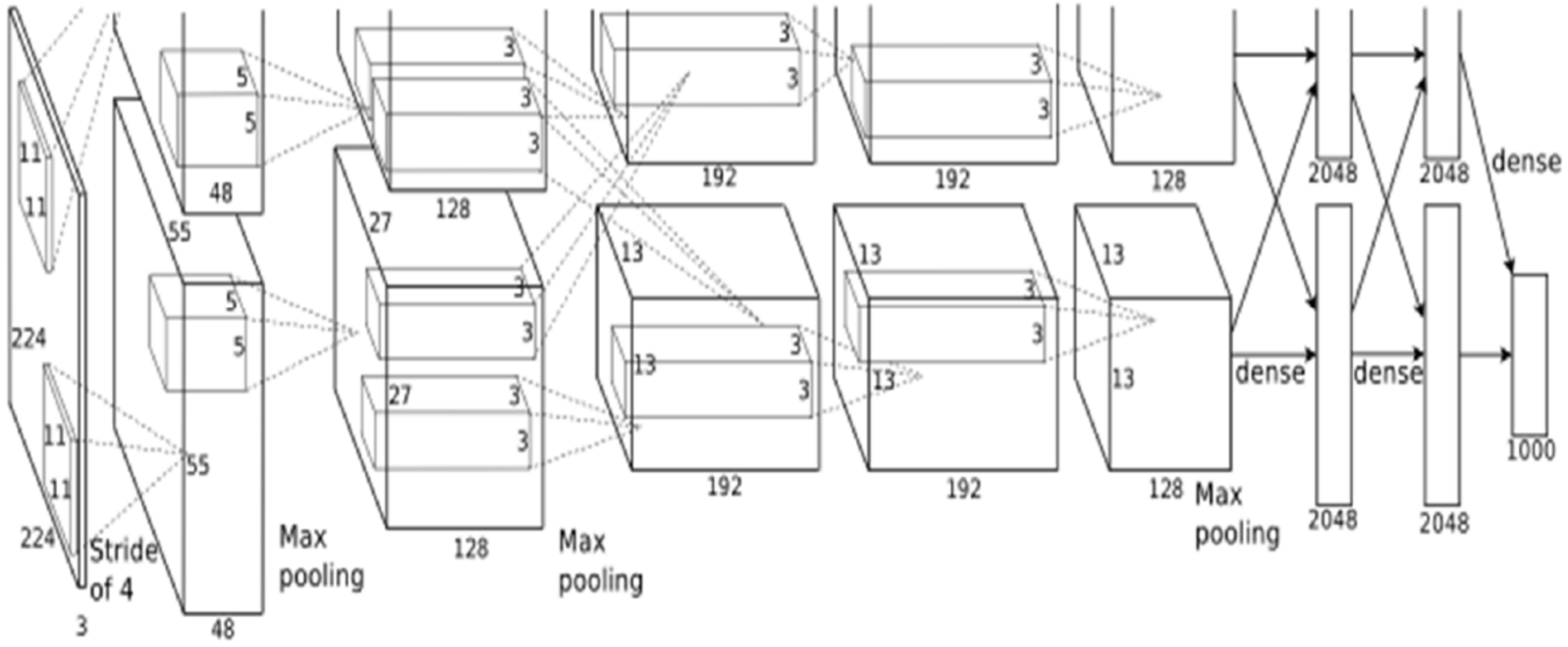
Optional subtitle



LeNet: a layered model composed of convolution and subsampling operations followed by a holistic representation and ultimately a classifier for handwritten digits.
[LeNet]

Convolutional Nets: 2012

Optional subtitle



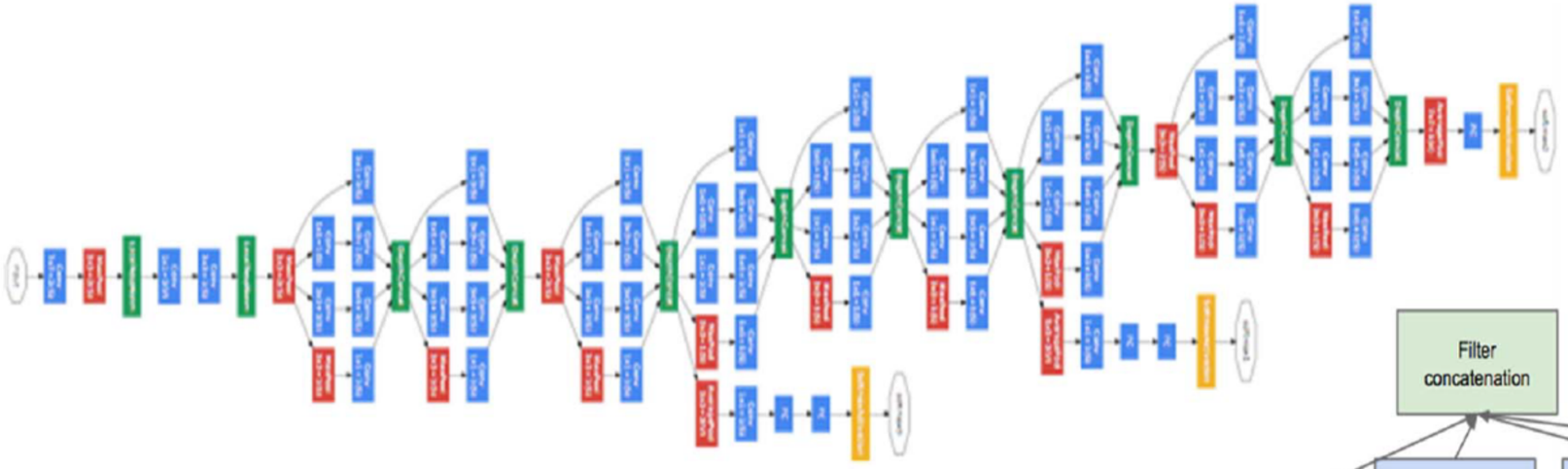
AlexNet: a layered model composed of convolution, subsampling, and further operations followed by a holistic representation and all-in-all a landmark classifier on ILSVRC12. [AlexNet]

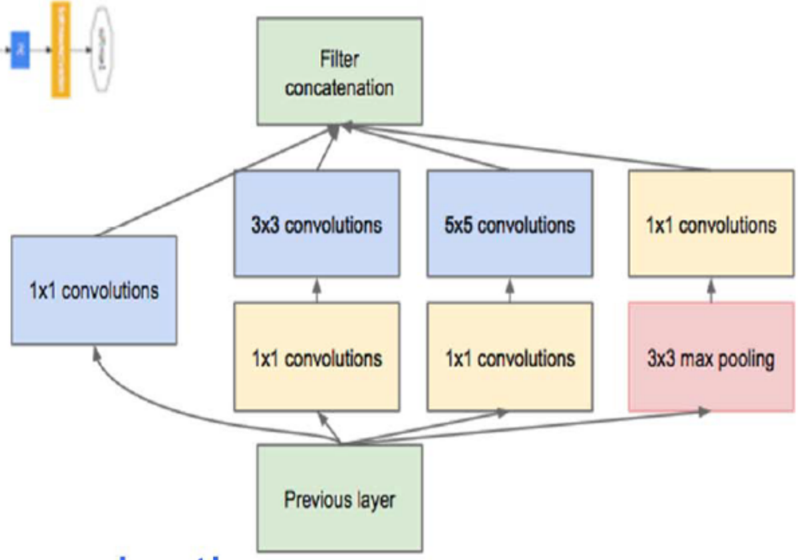
+ data
+ gpu
+ non-saturating nonlinearity
+ regularization

Slide courtesy Yangqing Jia

Convolutional Nets: 2014

Optional subtitle





ILSVRC14 Winners: ~6.6% Top-5 error

- GoogLeNet: composition of multi-scale dimension-reduced modules (pictured)
- VGG: 16 layers of 3x3 convolution interleaved with max pooling + 3 fully-connected layers

+ depth
+ data
+ dimensionality reduction

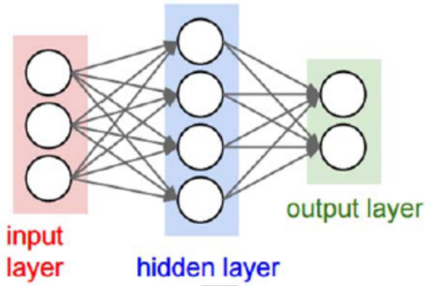
Slide courtesy Yangqing Jia

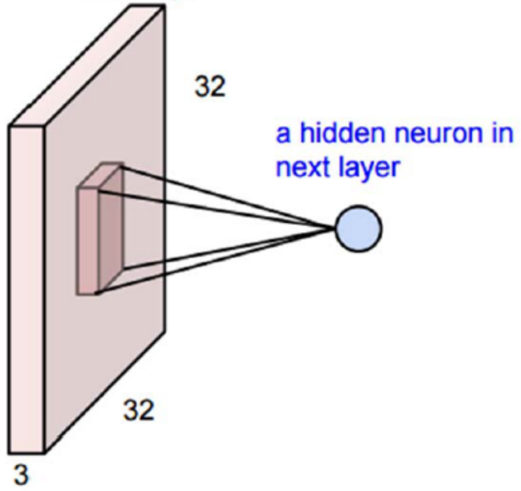
Training CNN: Use GPU

- Convolutional layers
  - Reduce parameters BUT Increase computations
- FC layers
  - each neuron has more weights
  - but less computations
- Conv layers
  - each neuron has less weights
  - but more computations. Why?

because

it will

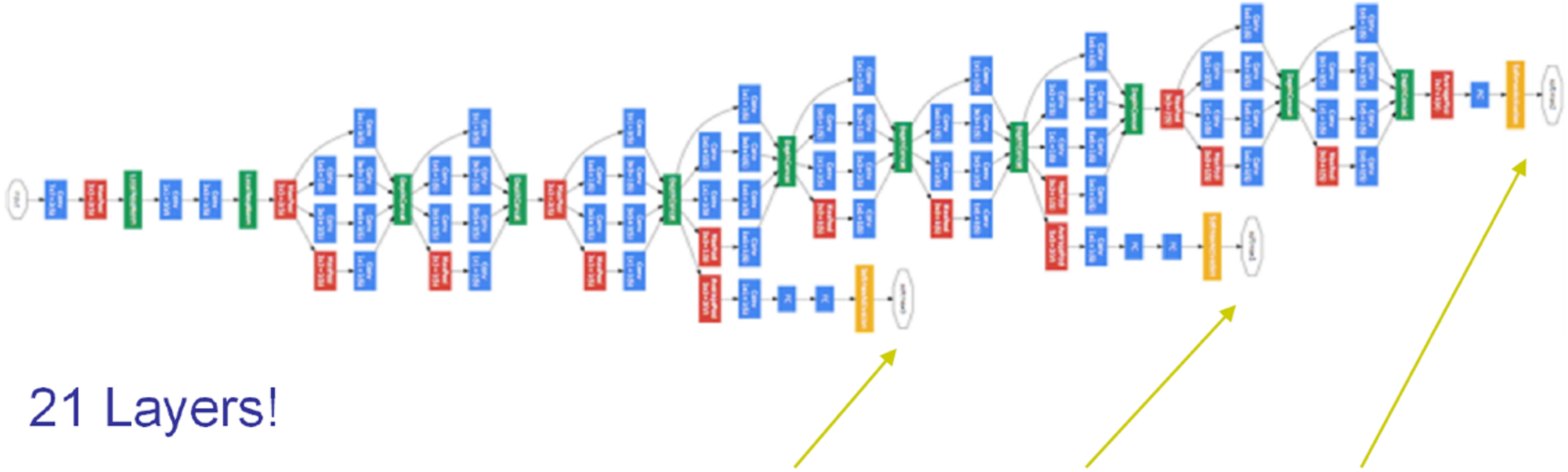




GPU is good at convolution!

Training CNN: depth cares!

Optional subtitle

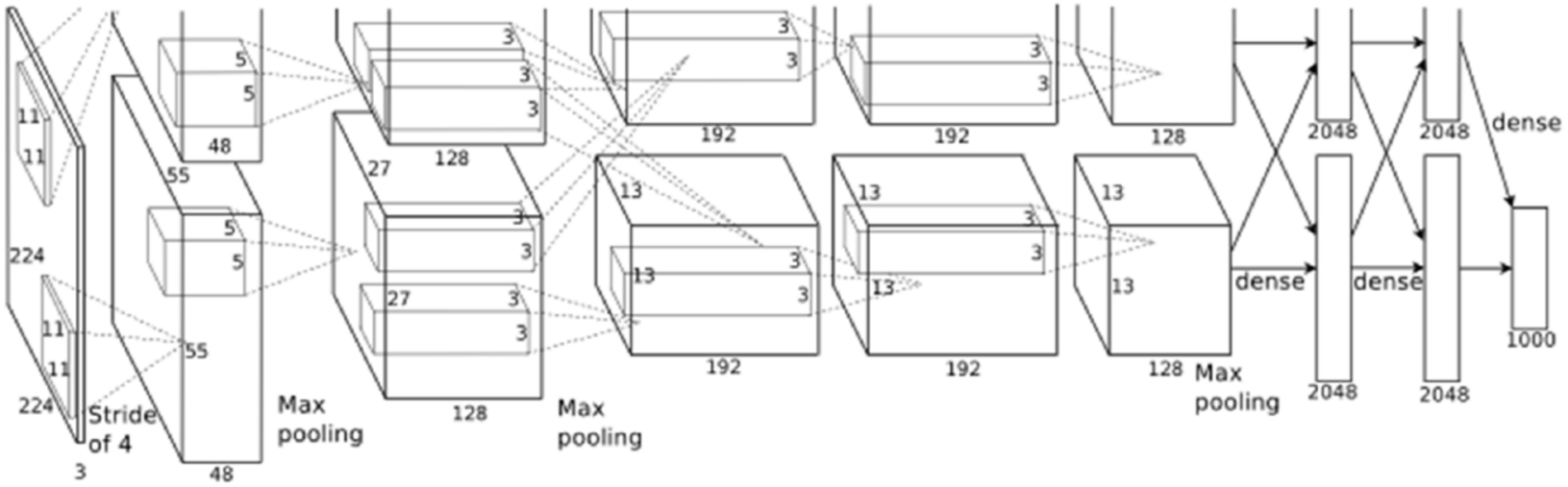


- 21 Layers!
- Gradient vanishes when the network is too deep: Lazy to learn!

- Add intermediate loss layers to produce error signals!
- Do contrast normalization after each conv layer!
- Use ReLU to avoid saturation!

Training CNN: Huge model needs more data!

Optional subtitle



IMAGENET

- Only 7 layers, 60M parameters!
- Need more labeled data to train!
- Data augmentation: crop, translate, rotate, add noise!

Training CNN: highly nonconvex objective

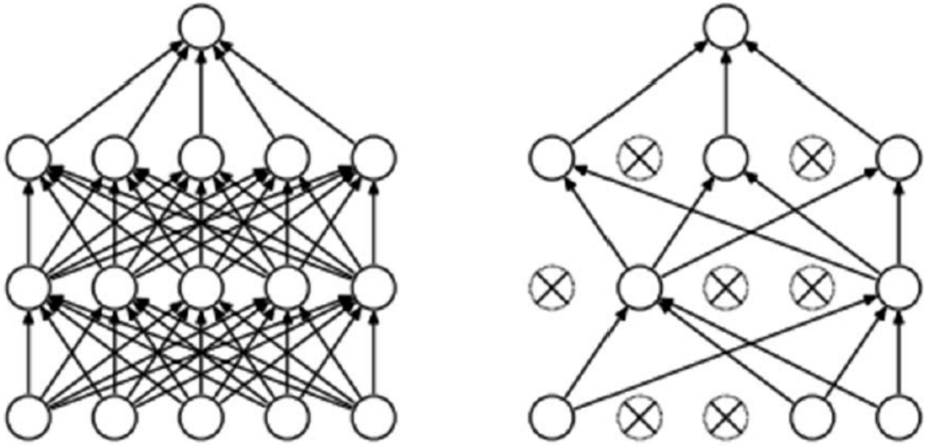
Optional subtitle

- Demand more advanced optimization techniques
  - Add momentum as we have done for NN
  - Learning rate policy
    - decrease learning rate regularly!
    - different layers use different learning rate!
    - observe the trend of objective curve more often!
  - Initialization really cares!
    - Supervised pretraining
    - Unsupervised pretraining

Training CNN: avoid overfitting

Optional subtitle

- More data are always the best way to avoid overfitting
  - data augmentation
- Add regualizations: recall what we have done for linear regression
- Dropout

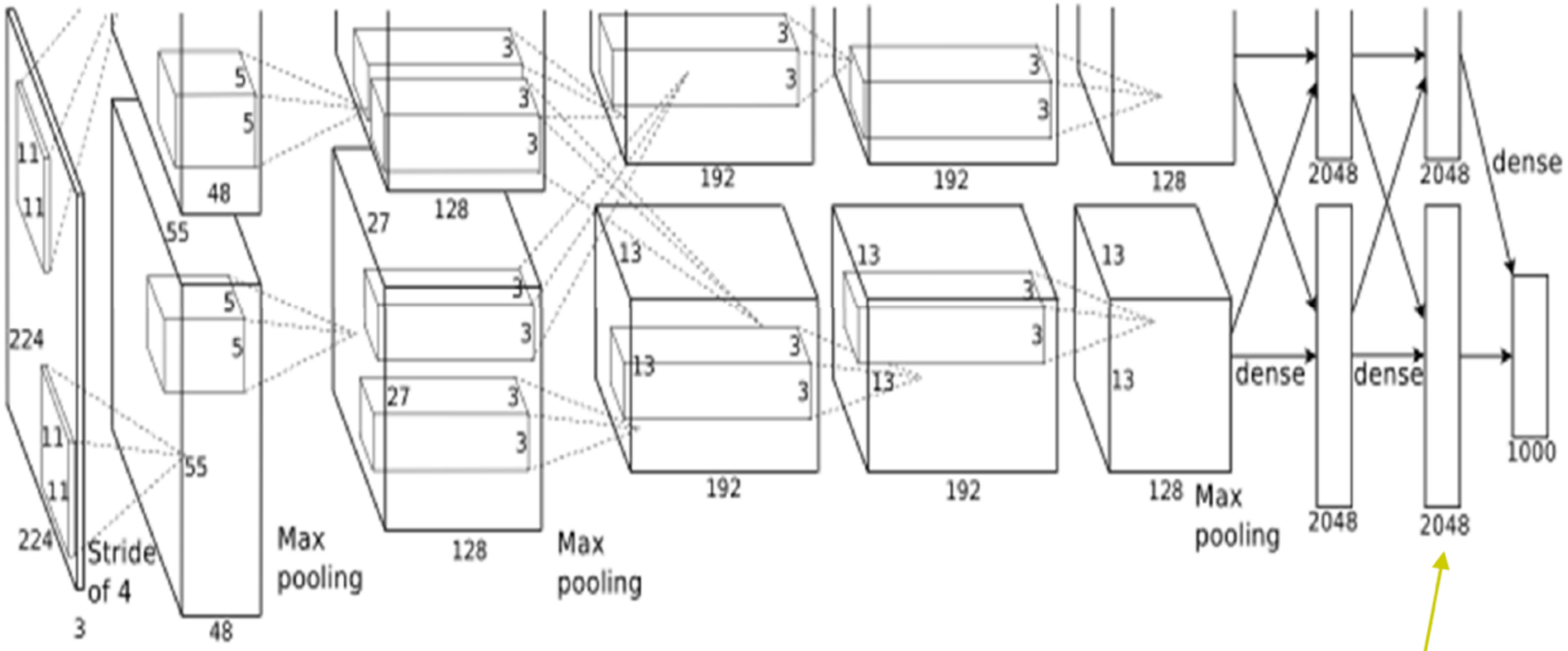


(a) Standard Neural Net

(b) After applying dropout.

Visualize and Understand CNN

Optional subtitle

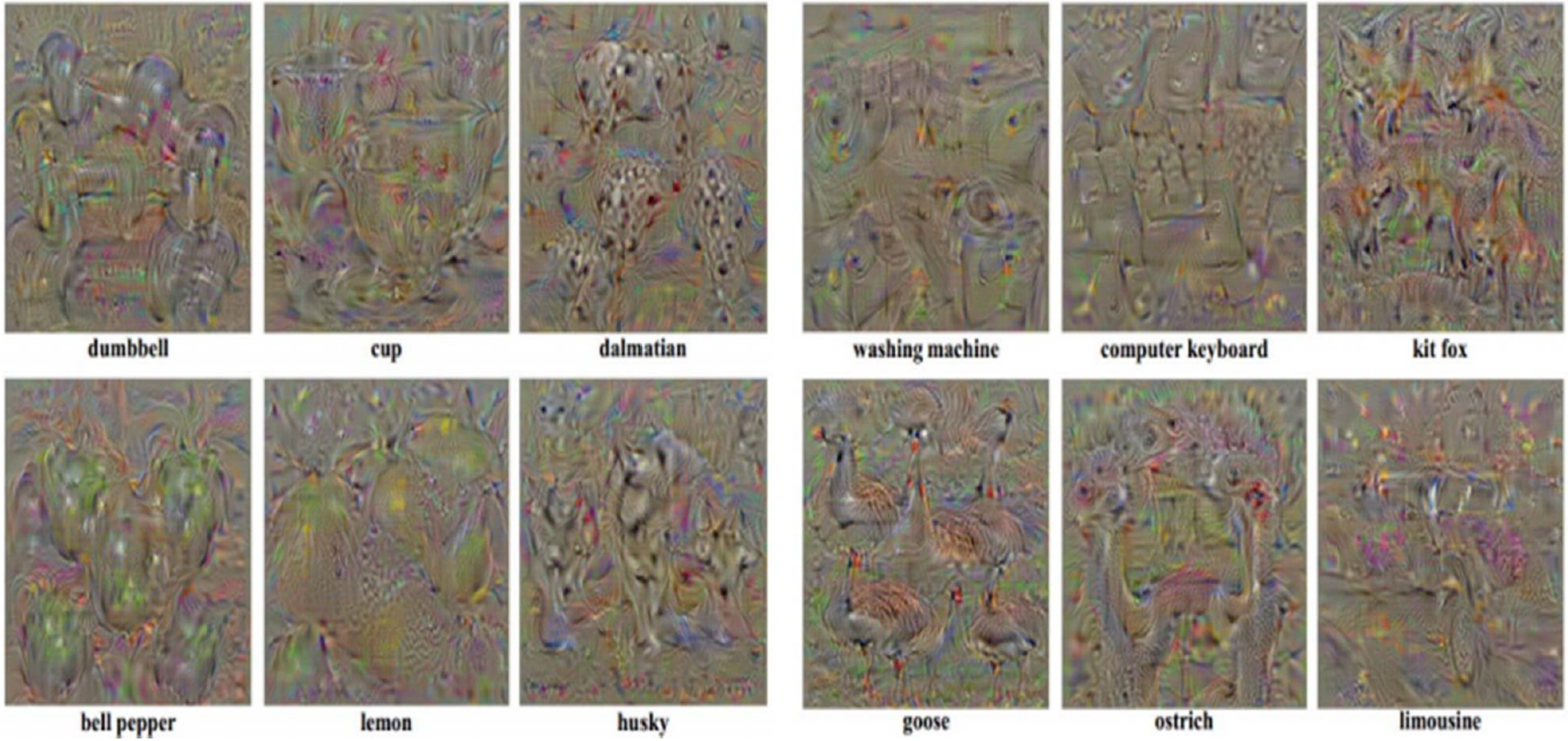


A CNN transforms the image to 4096 numbers that are then linearly classified.

Visualize and Understand CNN

Optional subtitle

- Find images that maximize some class score:



Limitations

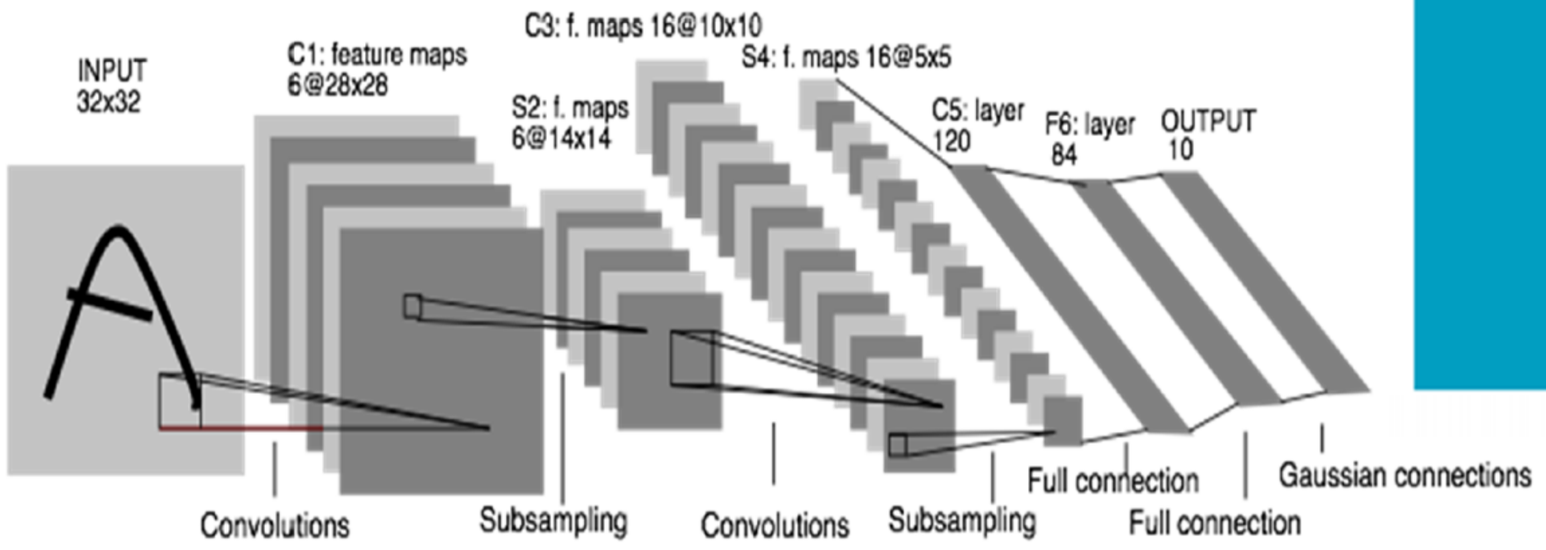
Optional subtitle

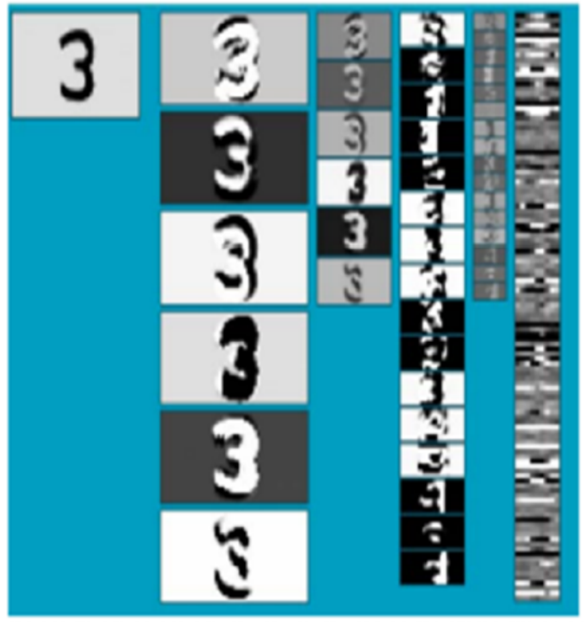
- Supervised Training
  - Need huge amount of labeled data, but label is scarce!
- Slow Training
  - Train an AlexNet on a single machine need one week!
- Optimization
  - Highly nonconvex objective
- Parameter tuning is hard
  - The parameter space is so large…

Summary

Optional subtitle

- 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

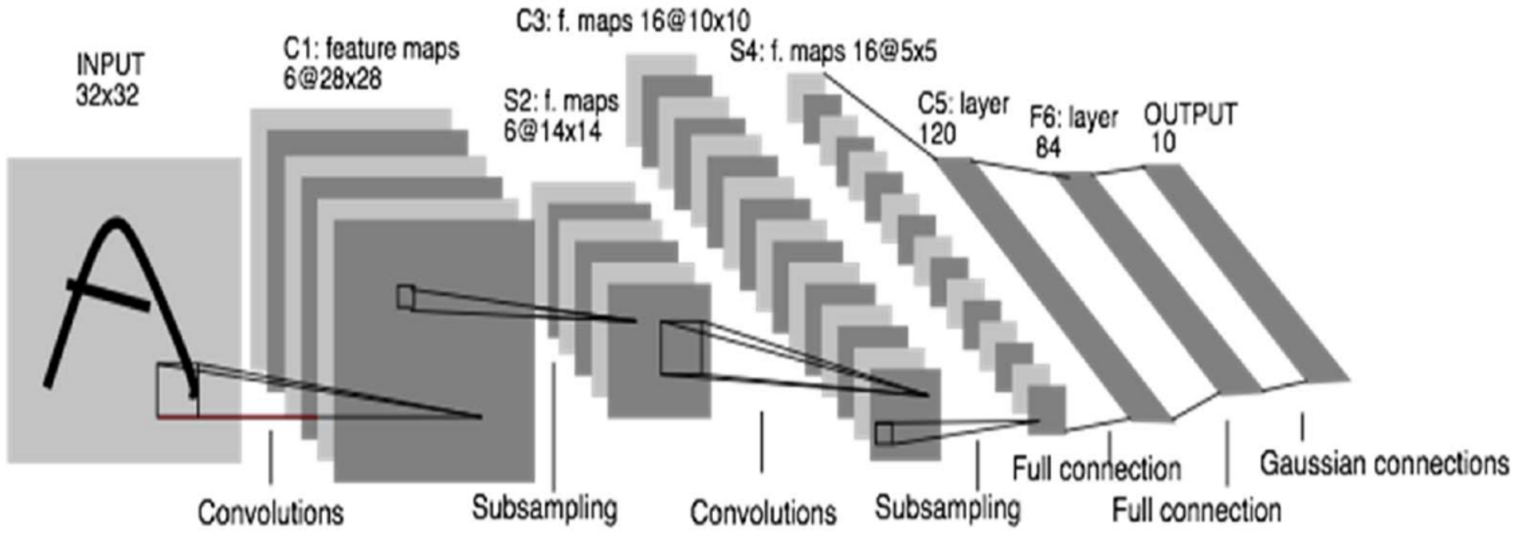


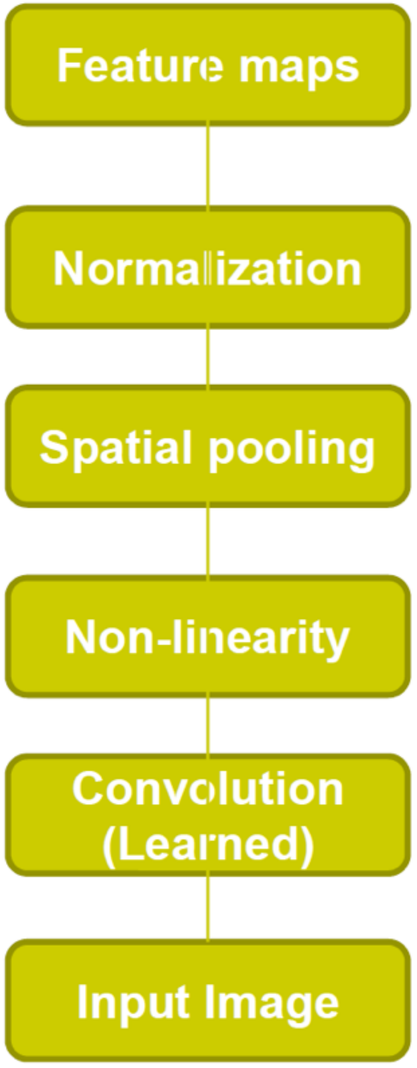


Summary

Optional subtitle

- Feed-forward
  - Convolve input
  - Non-linearity (rectified linear)
  - Pooling (local max, mean)
- Supervised
- Train convolutional filter s by back-propagation classification error at the end





Further reading

Optional subtitle

- Andrej Karpathy: The Unreasonable Effectiveness of Recurrent Neural Networks
  - (http://karpathy.github.io/2015/05/21/rnn-effectiveness)
- Recurrent Neural Networks Tutorial
  - (http://www.wildml.com/2015/09/recurrent-neural-networkstutorial-part-1-introduction-to-rnns)

http://ufldl.stanford.edu/wiki/index.php/UFLDL教程

Appendix

AI的产生与发展

1. 孕育期（1943年—1955年）

1943年Warren McCulloch 和Walter Pitts:人工神经元模型(MP model)

1946年美国人毛奇莱(Mauchly)和艾克特(Eckert):世界上第一台电子计算机ENIAC

1945年冯诺依曼(John Von Neumann): 冯诺依曼结构。

1948年维纳(N.Wiener）：创立了控制论。控制论向人工智能的渗透，形成了行为主义学派。

1951年Marvin Minsky 和Dean Edmonds:神经元网络计算机

1950年Alan Turing: Computer Machinery and Intelligence

AI的产生与发展

2. AI的诞生（1956年）

AI诞生于一次历史性的聚会

时间：1956年夏季

地点：达特莫斯 (Dartmouth) 大学

目的：为使计算机变得更“聪明”，或者说使计算机具有智能

发起人：

麦卡锡(J.McCarthy），Dartmouth的年轻数学家、计算机专家，后为MIT教授

明斯基(M.L.Minsky），哈佛大学数学家、神经学家，后为MIT教授

洛切斯特(N.Lochester)， IBM公司信息中心负责人

香农(C.E.Shannon)，贝尔实验室信息部数学研究员

参加人：

莫尔(T.more)、塞缪尔(A.L.Samuel)， IBM公司

塞尔夫里奇(O.Selfridge)、索罗蒙夫(R.Solomonff)， MIT

纽厄尔(A.Newell)，兰德(RAND)公司

西蒙(H.A.Simon)，卡内基(Carnagie)工科大学

会议结果：

由麦卡锡提议正式采用了“Artificial Intelligence”这一术语

人工智能三大学派

1956年，美国的达特茅斯
历史意义的会议，标志着人工智能的正式诞生。
McCarthy——“人工智能之父”

符号主义（以数理逻辑和知识为核心）
联结主义（如人工神经网络）
行为主义（控制论等）

Acknowledgement

Some slides come from the course of “deep learning”, Prof. Xiaoyang Wang.