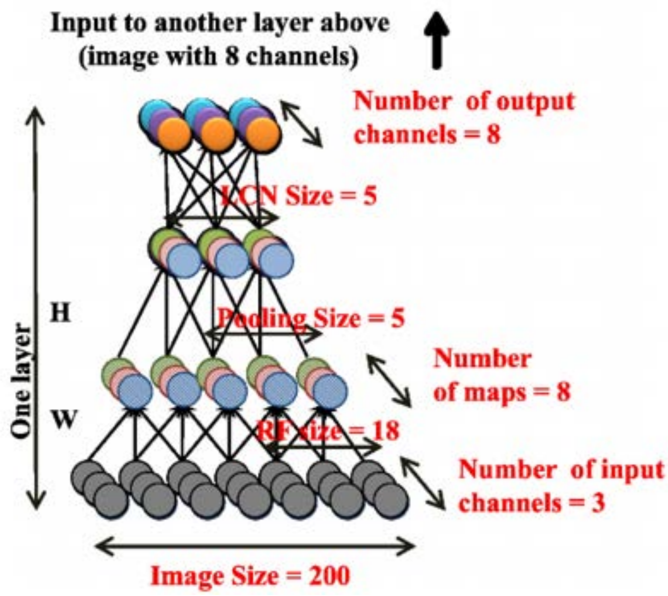
DEEP LEARNING CRASH COURSE

- Single Layer Perceptron
- Multiple Layer Perceptron
- Convolutional Neural Net



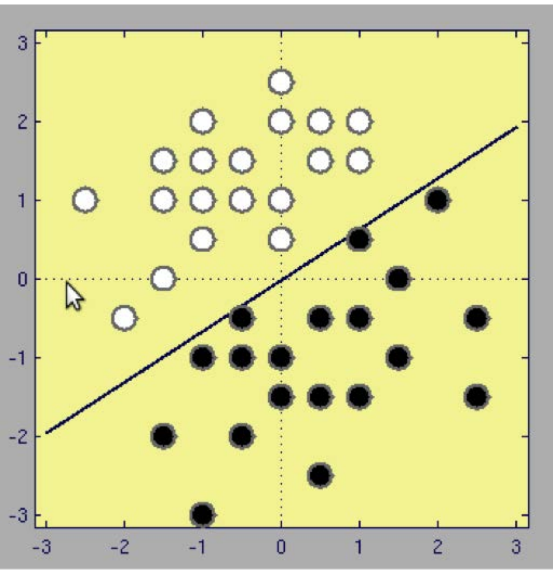
M.A. Nielsen. Neural Networks and Deep Learning, 2015
http://neuralnetworksanddeeplearning.com/

ARTIFICAL INTELLIGENCE

1997: Deep Blue beats chess World Champion

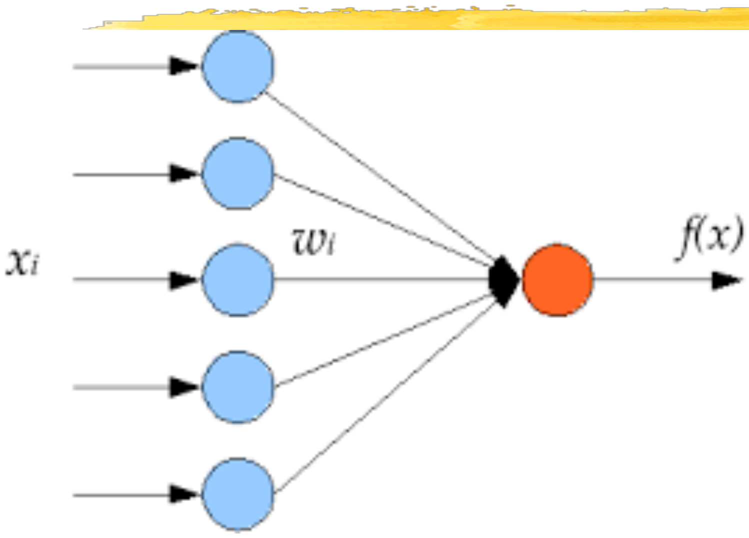
2016: AlphaGo beats go world champion

LINEAR CLASSIFICATION



$$f(\mathbf{x}) = \begin{cases} 1 \text{ if } \mathbf{w} \cdot \mathbf{x} + \mathbf{b} \geq 0, \\ 0 \text{ otherwise.} \end{cases}$$

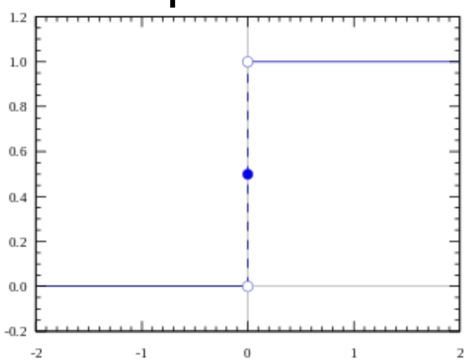
SINGLE LAYER PERCEPTRON



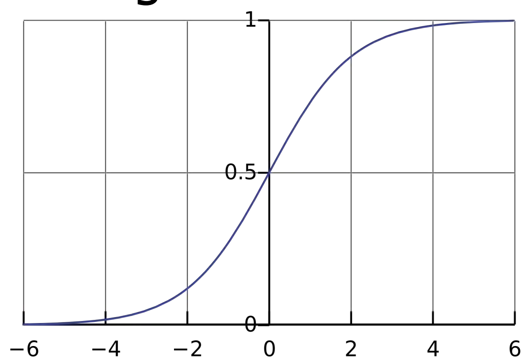
$$f(\mathbf{x}) = \sigma(\mathbf{w} \cdot \mathbf{x} + \mathbf{b})$$

σ:

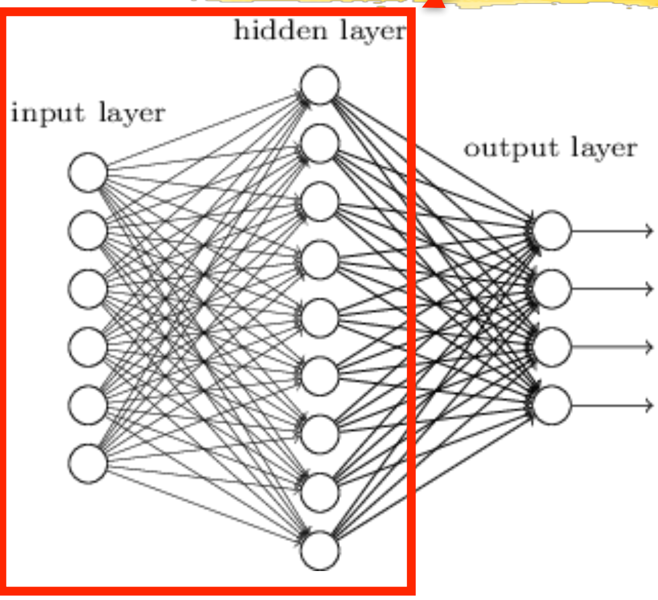
Step function



Sigmoid function



MULTILAYER PERCEPTRON



$$\boxed{\mathbf{f}(\mathbf{x}) = \sigma(\mathbf{W} \cdot \mathbf{x} + \mathbf{B})}$$

For each node j in layer l,

$$a_j^l = \sigma\left(b_j^l + \sum_k w_{j,k}^l a_k^{l-1}\right) ,$$

where a is the activation of the node.

- The network can be trained to produce a desired output given a specific input.
- In practice, this means learning the b and w parameters by minimizing a loss function on a training set.
- Often done on GPUs, which are much faster.

BINARY LOSS FUNCTION

In the binary case,

$$L(\mathbf{w}, \mathbf{b}) = -\frac{1}{N} \sum_{1}^{N} [y_n \log(\hat{y}_n) + (1 - y_n) \log(1 - \hat{y}_n)]$$

where $\hat{y}_n = f_{\mathbf{w},\mathbf{b}}(x_n)$.

MULTICLASS LOSS FUNCTION

In the multiclass case, the probability that input vector $\mathbf{x}$ belongs to class i can be written as

$$P(Y = i|\mathbf{x}, \mathbf{w}, \mathbf{b}) = \frac{f_i(\mathbf{x})}{\sum_j f_j(\mathbf{x})}$$

The class assigned to vector $\mathbf{x}$ is taken to be

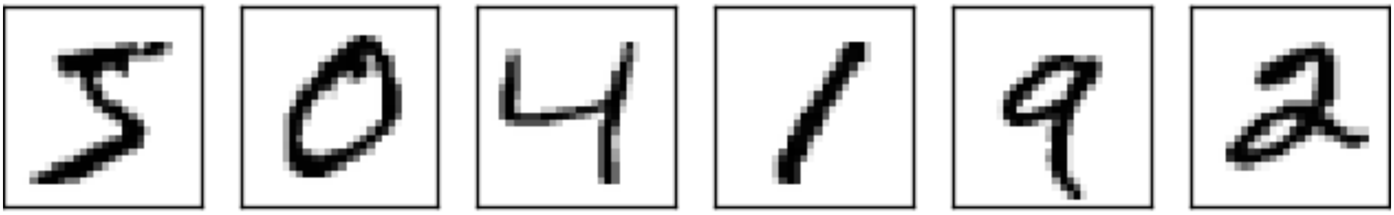
$$\hat{y} = \arg\max_i P(Y = i|\mathbf{x}, \mathbf{w}, \mathbf{b})$$

Given a set of N training samples $(\mathbf{x}_n, y_n)_{1 \leq n \leq N}$, the loss function can be written as

$$L(\mathbf{w}, \mathbf{b}) = \sum_n \log(P(Y = y_n|\mathbf{x_n}, \mathbf{w}, \mathbf{b}))$$

–> L is a differentiable function of $\mathbf{w}$ and $\mathbf{b}$ and can be optimised using *back propagation*, that is, gradient descent.

MNIST

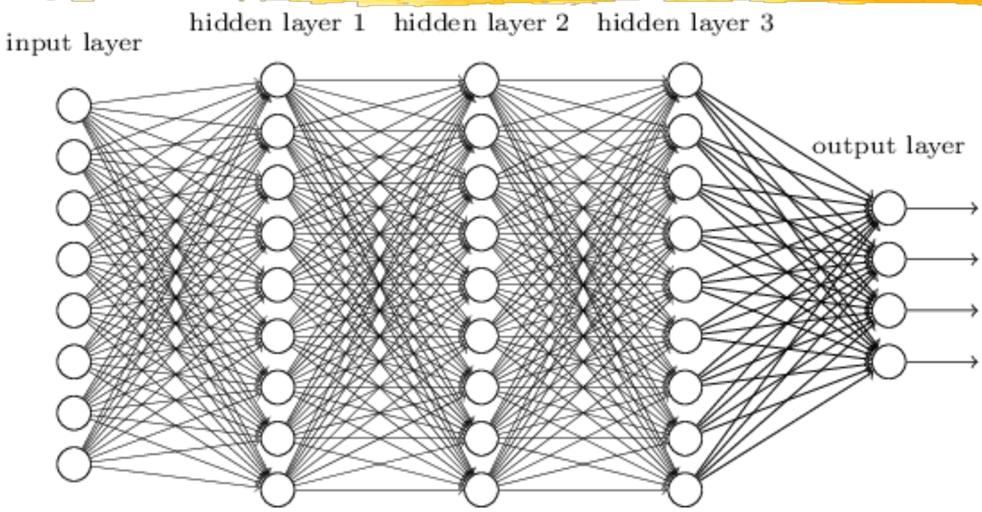


• The network takes as input 28x28 images represented as 784D vectors.

• The output is a 10D vector giving the probability of the image representing any of the 10 digits.

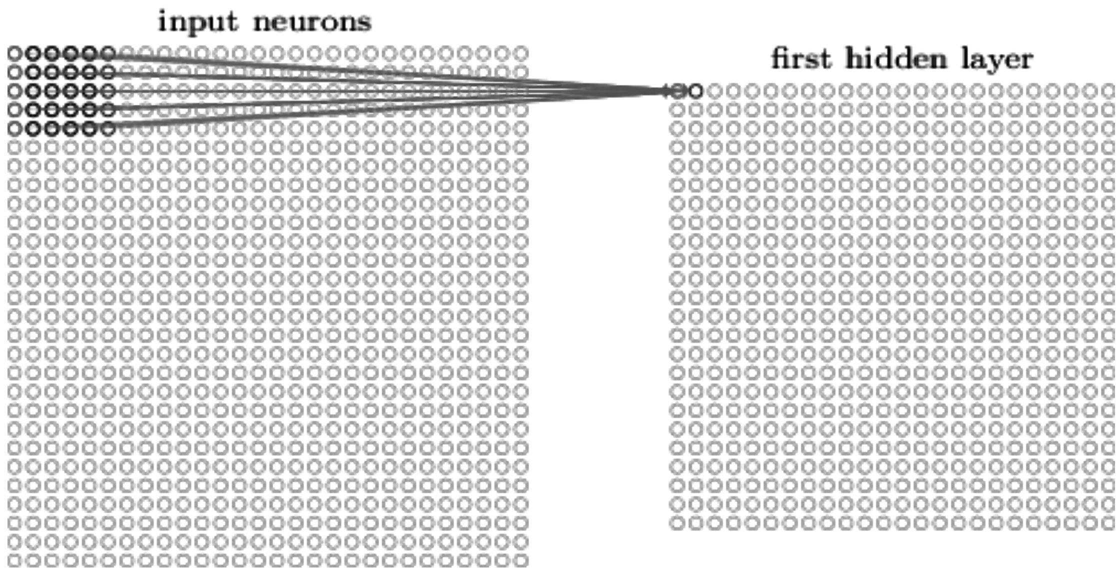
• There are 50’000 training pairs of images and the corresponding label, 10’000 validation pairs, and 5’000 testing pairs.

DEEP LEARNING



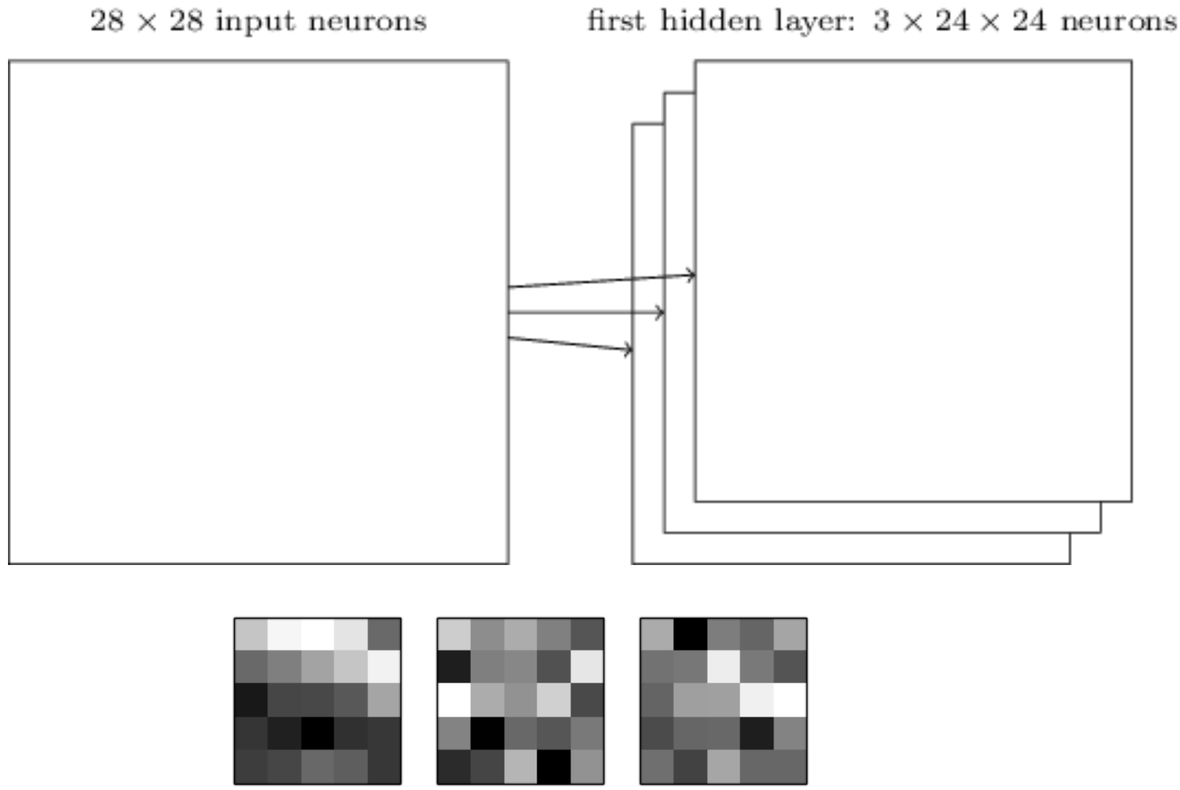
- The descriptive power of the net increases with the number of layers.
- Since every neuron is connected to every other in adjacent layers, the number of parameters to be learned increases quickly.
- Does not take into account the specific topology of images.

CONVOLUTIONAL LAYER

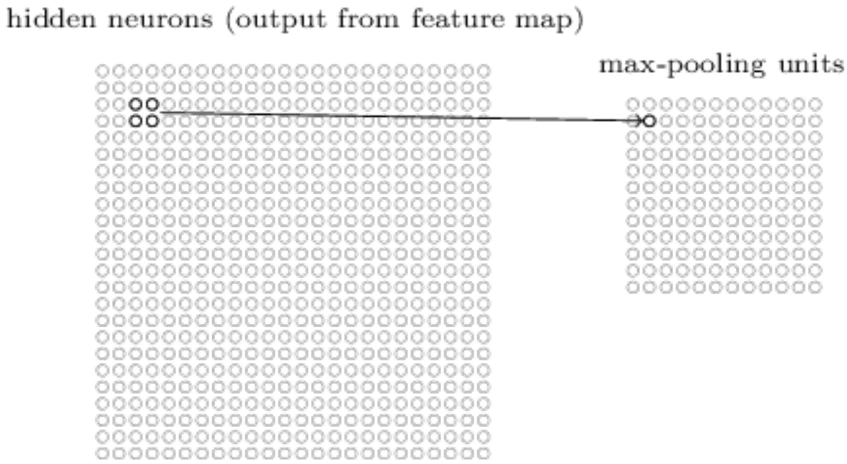


$$\sigma\left(b+\sum_{x=0}^{n_x}\sum_{y=0}^{n_y} w_{i,j}a_{i+x,j+y}\right)$$

FEATURE MAPS

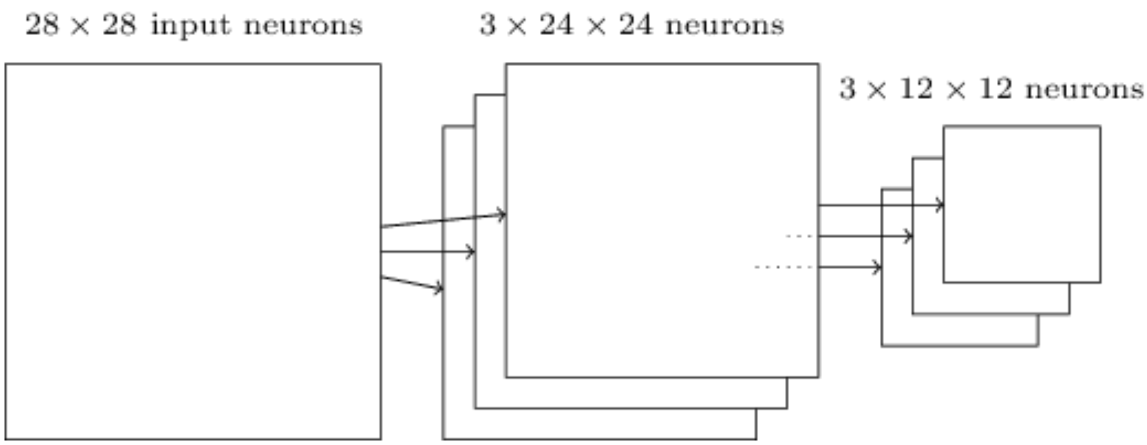


POOLING LAYER



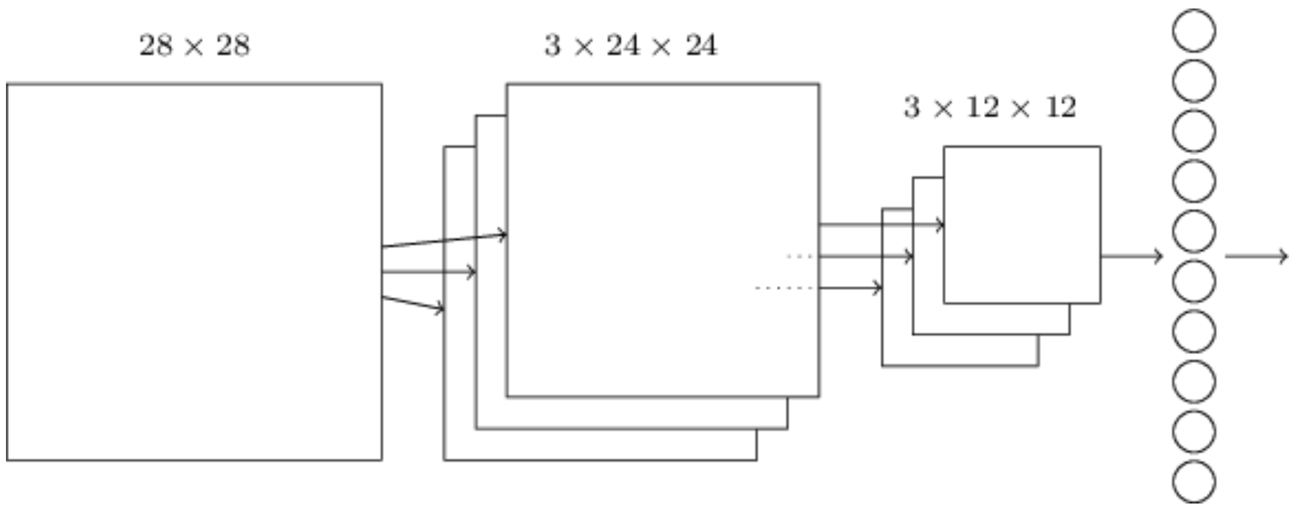
- Reduce the number of inputs by replacing all activations in a neighbourhood by a single one.
- Can be thought as asking if a particular feature is present in that neighbourhood while ignoring the exact location.

ADDING THE POOLING LAYERS



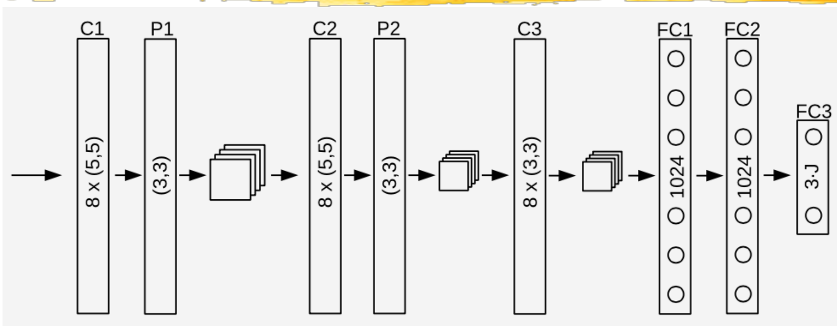
The output size is reduced by the pooling layers.

ADDING A FULLY CONNECTED LAYER



- Each neutron in the final fully connected layer is connected to all neurons in the preceding one.
- Deep architecture with many parameters to learn but still far fewer than an equivalent multilayer perceptron.

HAND POSE ESTIMATION

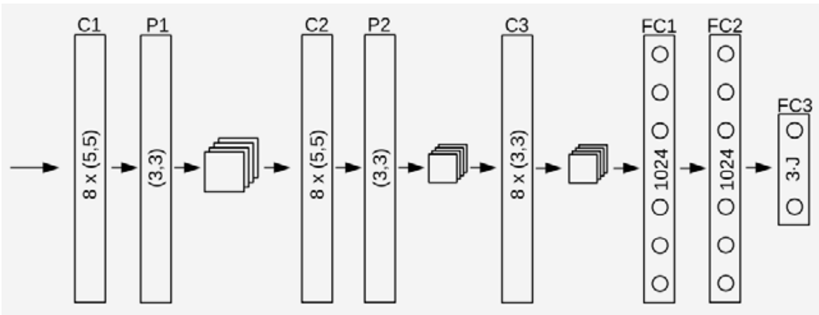


Input: Depth image.

Output: 3D pose vector.

Oberweger et al. , ICCV'15

OPTIMIZATION

Input  Output

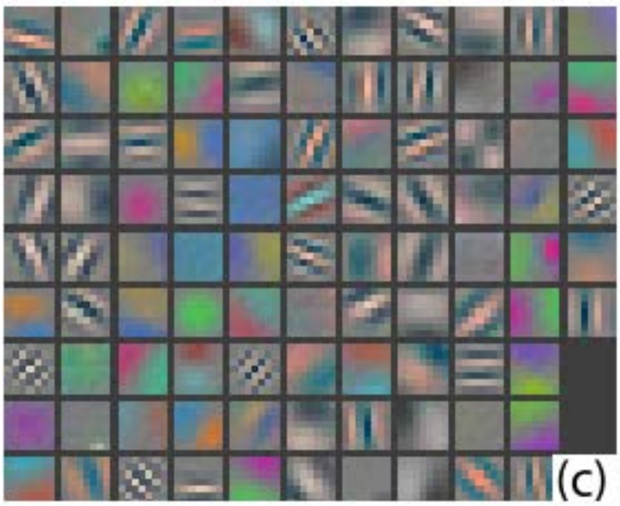
Network parameters are found by minimizing and objective function of the form

$$\min_{\mathbf{W}_l,\mathbf{B}_l} \sum_i ||\mathbf{F}(\mathbf{x}_i, \mathbf{W}_1, \ldots, \mathbf{W}_L, \mathbf{b}_1, \ldots, \mathbf{b}_L) - \mathbf{y}_i||^2$$

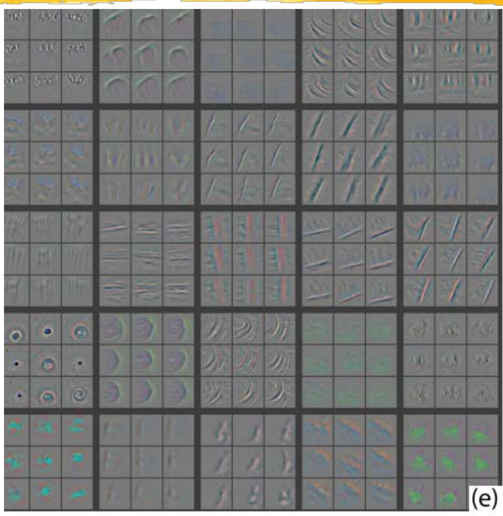
using

- stochastic gradient descent on mini-batches,
- dropout,
- hard example mining,
- ………..

FEATURE MAPS LEARNED FOR IMAGE CLASSIFICATION



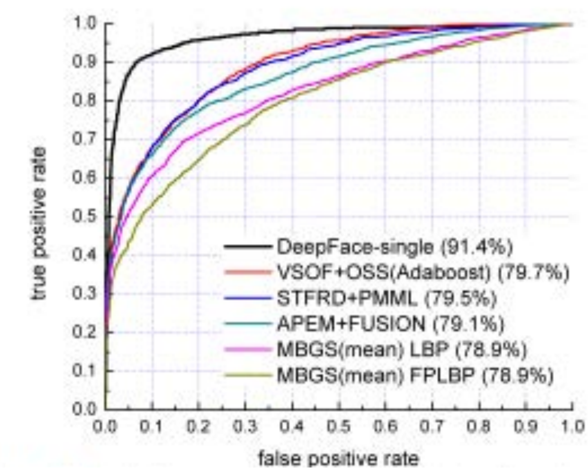
First convolutional layer



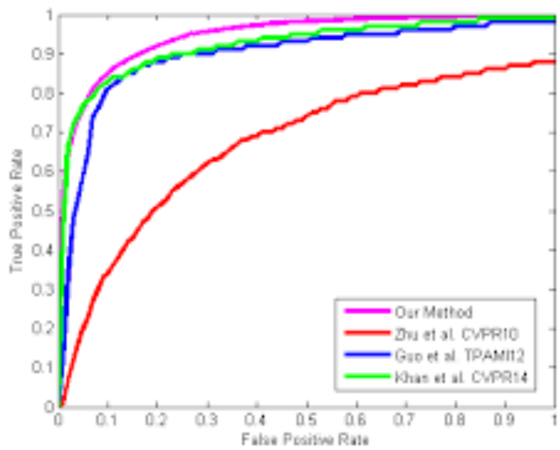
Second convolutional layer

- Some of the convolutional masks seem very similar to oriented Gaussian or Gabor filters!
- Much ongoing work to better understand this.

ROC HUNTING

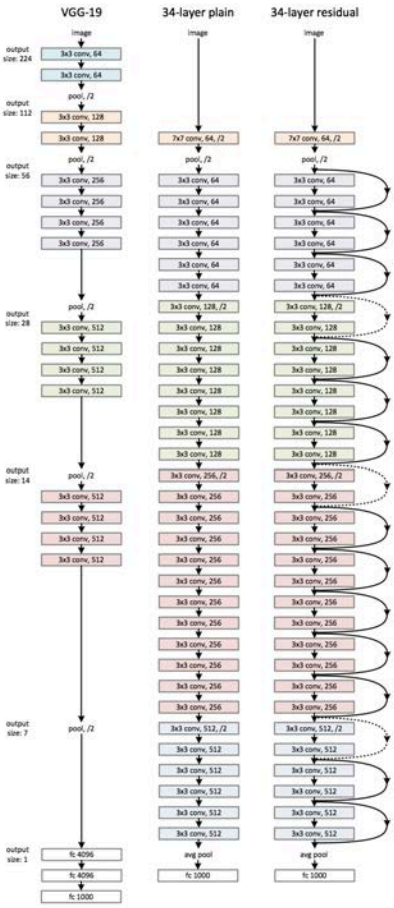


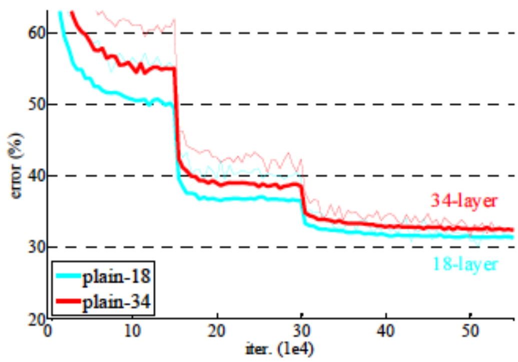
DeepFace
Taigman et al. 2014

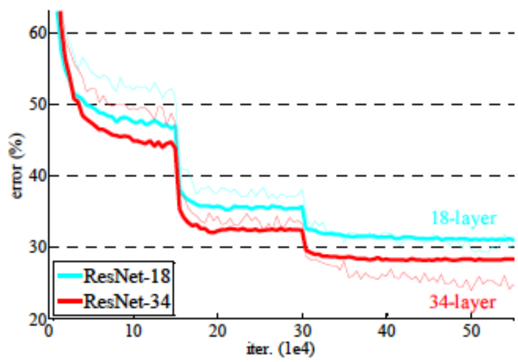


Deep Edge Detection
Shen et al. 2015

DEEPER AND DEEPER

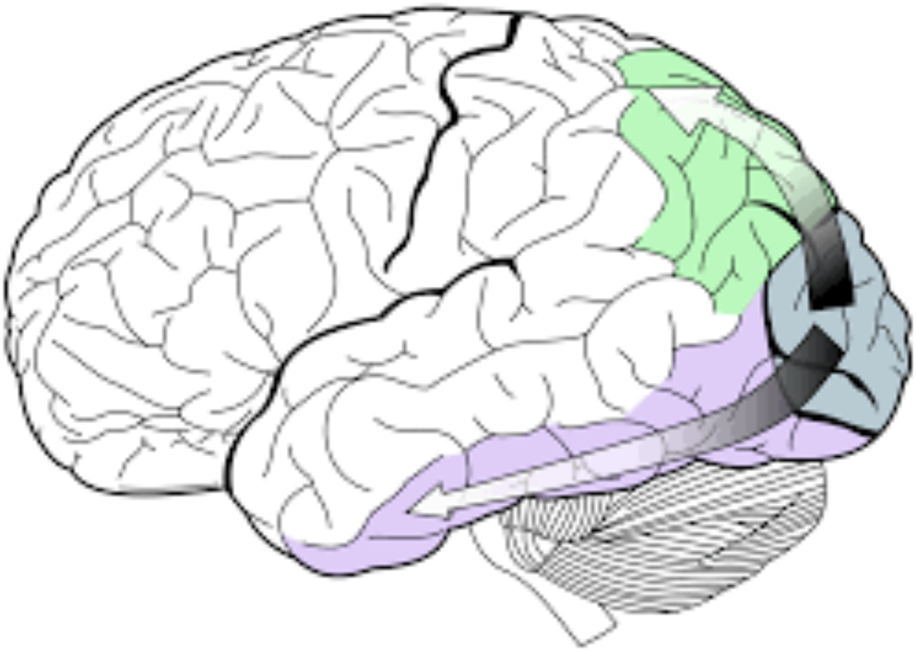


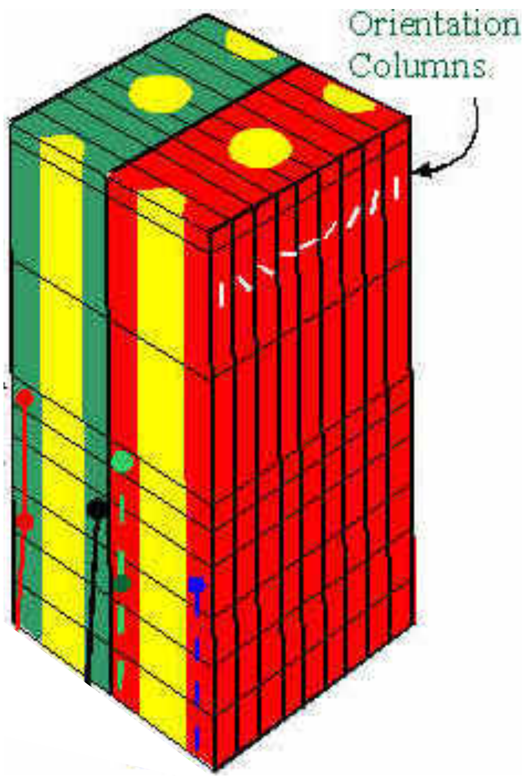




He et al. , CVPR’16

VISUAL CORTEX

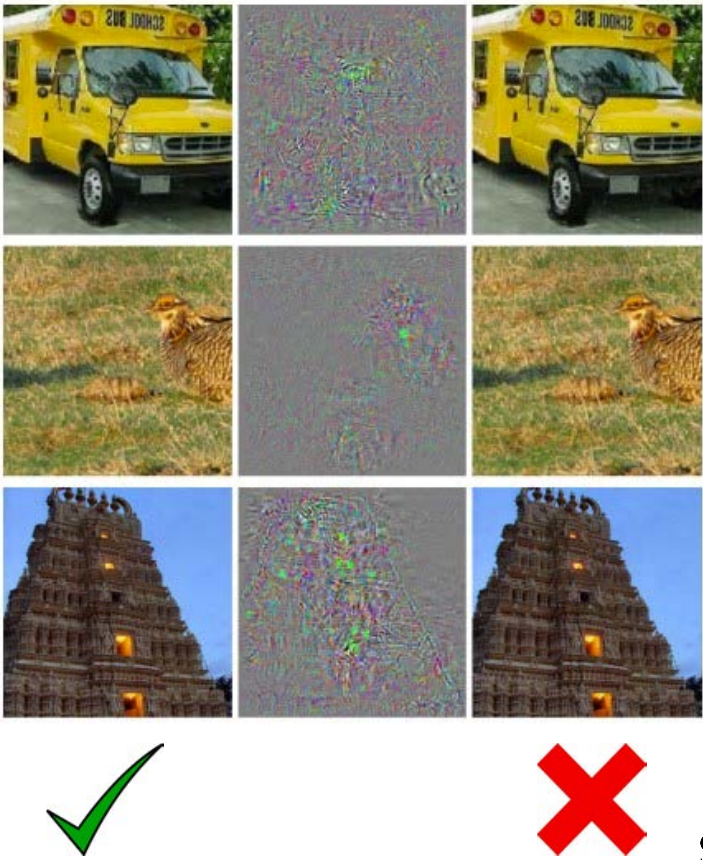




AlphaGo

- Uses Deep Nets to find the most promising locations to focus on.
- Performs Tree based search when possible.
- Relies on reinforcement learning and other ML techniques to train.

ADVERSARIAL IMAGES



Szegedy et al. 2013

IN SHORT

- Deep Belief Networks in general and Convolutional Neural Nets in particular outperform conventional Computer Vision algorithms on many benchmarks.
- It is not fully understood why and unexpected failure cases have been demonstrated.
- They require a lot of manual tuning to perform well and performance is hard to predict.

—> Many questions are still open and there is much work left to do.