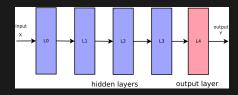
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \lambda \max_{a} Q(s_{t+1}, a) - Q(s_t, a_t)]$$

(The New Action Value = The Old Value) + The Learning Rate x (The New Information - the Old Information)

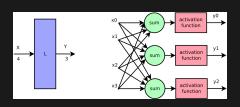


Neural network



- universal function approximator
- learning from examples
- training using parallel architectures NVIDIA GPU, TPU from weeks to months
- inspired by human brain
- thousands of connected neurons

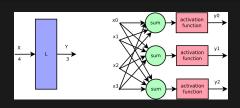
Layer



$$y_j = f(\sum_{i=0}^{N-1} X_i W_{ji} + b_j)$$

where f(x) is activation function X input vector W weights matrix b bias vector Y output vector

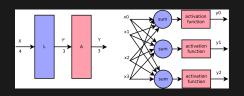
Layer



$$y_0 = f(\sum_{i=0}^3 X_i W_{0i} + b_0)$$

 $y_1 = f(\sum_{i=0}^3 X_i W_{1i} + b_1)$
 $y_2 = f(\sum_{i=0}^3 X_i W_{2i} + b_2)$

Layer - split activation function

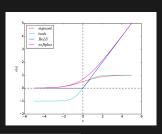


$$y'_0 = \sum_{i=0}^3 X_i W_{0i} + b_0,$$
 $y_0 = f(y'_0)$
 $y'_1 = \sum_{i=0}^3 X_i W_{1i} + b_1,$ $y_1 = f(y'_1)$
 $y'_2 = \sum_{i=0}^3 X_i W_{2i} + b_2,$ $y_2 = f(y'_2)$

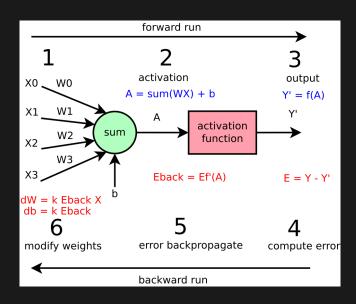
y' is called neuron **Activation**

Activation function

name	function	derivative
Linear	y = x	y'=1
Sigmoid	$y = \frac{1}{1 + e^{-x}}$	$y' = \frac{e^{-x}}{(1+e^{-x})^2}$ $y' = xe^{-x^2}$
RBF	$y = e^{-x^2}$	$y' = xe^{-x^2}$
Relu	$y = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$	$y' = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$
LeakyRelu	$y = \begin{cases} x, & \text{if } x > 0 \\ 0.01x, & \text{otherwise} \end{cases}$	$y' = egin{cases} 1, & ext{if } x > 0 \ 0.01, & ext{otherwise} \end{cases}$



- 1 choose random training dataset sample (X, Y)
- 2 compute neural network output, $\hat{Y} = F(X)$
- 3 obtain error error = target value computed value $E = Y \hat{Y}$
- 4 update weights and biases using error



One neuron weights updating example

- consider Y, \hat{Y}, b are scalar values, and W, X are vectors

$$E = Y - \hat{Y}$$

$$J = \left(Y - f\left(\sum_{i=0}^{N-1} X_i W_i + b\right)\right)^2$$

$$\text{cost function to minimize}$$

$$\frac{\partial J}{\partial W_j} = -2\left(Y - f\left(\sum_{i=0}^{N-1} X_i W_i + b\right)\right) f'\left(\sum_{i=0}^{N-1} X_i W_i + b\right) X_j$$

$$\text{Error E}$$

$$\frac{\partial J}{\partial W_j} = -2Ef'(A)X_j$$

$$\frac{\partial J}{\partial W_j} \approx W_j(n) - W_j(n-1) = \Delta W_j$$

$$\Delta W_j = \eta Ef'(A)X_j$$

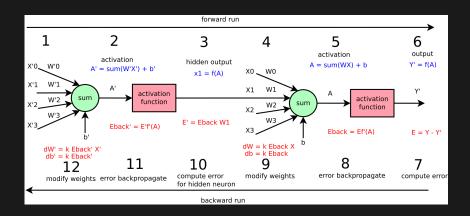
special case for
$$y(x) = x$$

$$\Delta W_j = \eta E X_j$$

special case for y(x) = RELU(x)

$$\Delta W_j = egin{cases} \eta extstyle extstyle X_j ext{ if } \sum_{i=0}^{N-1} X_i W_{ji} + b_0 > 0 \ 0 ext{ otherwise} \end{cases}$$

Error backpropagation



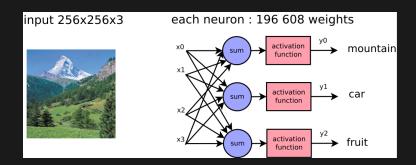
Mnist handwritten numbers classification

- handwritten numbers, 60000 for training, 10000 for testing
- 28x28 pixels, grayscale
 9x9 pixels, mnist tiny
- 10 outputs SCORING

- 0123456789 0123456789 0123456789 0123456789 0123456789 0123456789
- more than 99% A best networks
- more than 98% B average networks
- more than 97% C average networks
- more than 96.5% D pure networks
- more than 96% E pure networks
- otherwise Fx linear classifier

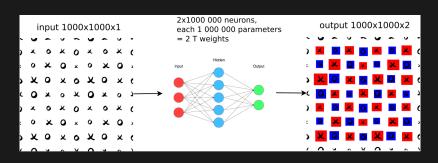
Convolutional neural networks

- goal : recognize image patterns
- input : RGB image, 256x256 pixels
- output : three classes mountain, car, fruit



Convolutional neural networks

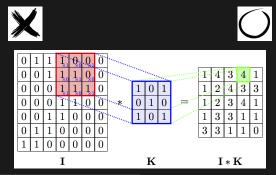
- goal : detect image patterns, X and Os
- input : grayscale image, 1000x1000 pixels
- output : two matrices 1000×1000
 - one for X desctions
 - second for Os detection
- total weights count $2 * (1000^2 * 1000^2) = 2T$



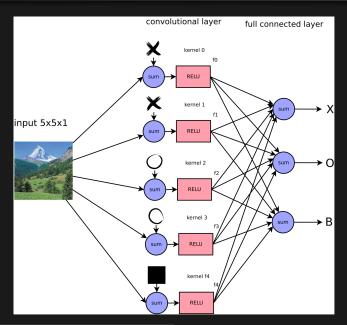
Convolution pattern search

- two neurons
- 25 weights each
- shift 5x5 window over whole 1000x1000 image

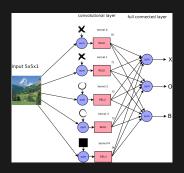
$$\left(\begin{array}{cccccc} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \end{array}\right) \qquad \left(\begin{array}{cccccc} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{array}\right)$$



Minimal toy CNN

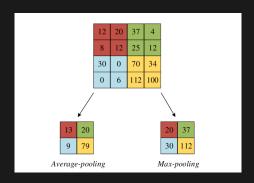


Minimal toy CNN parameters

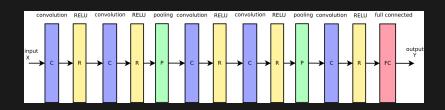


- 5 kernels, 5x5 + 1 parameters each, 130 weights
- 3 full connected, 5 + 1 parameters each, 18 weights
- total parameters to learn 148
- parameters count is INVARIANT to input size
- recognition ability is also SHIFT INVARIANT

Pooling - subsampling



Convolutional network example



layers count : 10 .. 100

kernels size : 1x1, 3x3 or 5x5

pooling size : 2x2

activation : ReLU, LeakyReLU

Advanced Convolutional network architectures

- Old methods (before NN) 2011, 25.8%
- Convolutional, AlexNet 2012, 16.4%
- Google inception 2013, 6.7%
- Microsoft ResNet 2015, 6.1%
- DenseNet 2018, 5.17%
- CNN



ResNET



DenseNet



Usefull links

CHRISTOPHER J.C.H. WATKINS: Q-learning http://www.gatsby.ucl.ac.uk/~dayan/papers/cjch.pdf
Richard S. Sutton: Reinforcement Learning: An Introduction https: //www.amazon.com/Reinforcement-Learning-Introduction-Adaptive-Computation/dp/026219398
Google DeepMind : Playing Atari with Deep Reinforcement Learning https://arxiv.org/pdf/1312.5602.pdf
Google DeepMind: Dueling Network Architectures for Deep Reinforcement Learning https://arxiv.org/pdf/1511.06581.pdf
Google DeepMind: Mastering the Game of Go without Human Knowledge https://deepmind.com/documents/119/agz_unformatted_nature.pdf
Andrej Karpathy : Pong from pixels http://karpathy.github.io/2016/05/31/rl/
Maxim Lapan: Deep reinforcement learning https://www.amazon.com/Practical-Reinforcement-Learning-Maxim-Lapan/dp/1788834240
Mohit Sewak: Practical Convolutional Neural Networks https://www.amazon.com/Practical-Convolutional-Neural-Networks-Implement/dp/1788392303
Densely Connected Convolutional Networks

https://arxiv.org/pdf/1608.06993.pdf



michal chovanec (michal.nand@gmail.com)
www.youtube.com/channel/UCzVvP2ou8v3afNiVrPAHQGg
github.https://github.com/michalnand

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