A Convolutional Neural Network for Image Classification of Cats and Dogs

Status update

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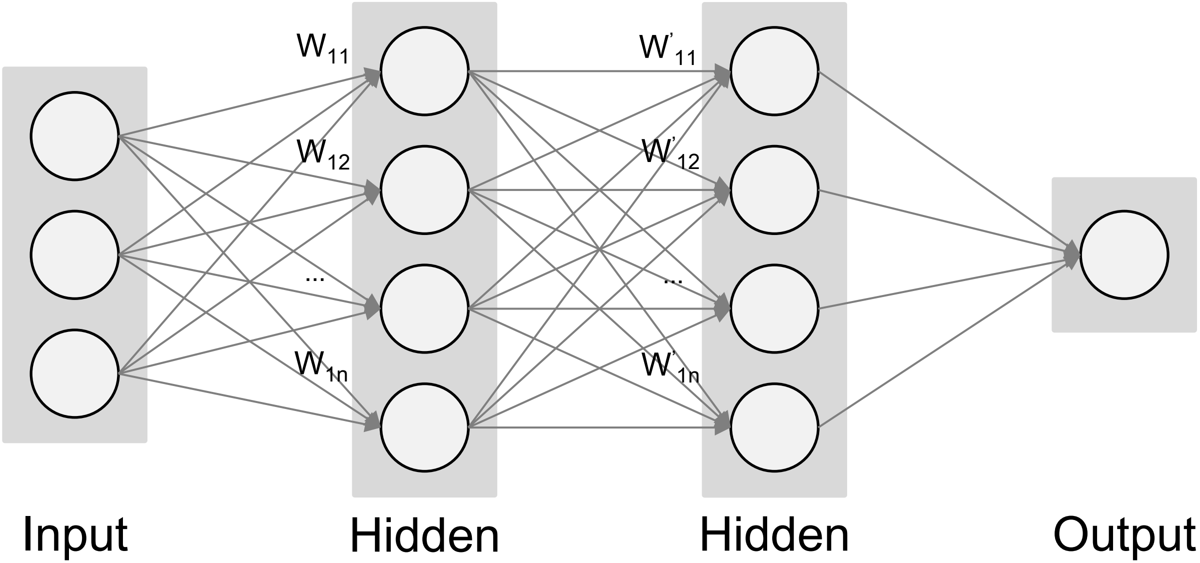
Structure

- Neural Nets (NN)
- Convolution NN (CNN)
- Problem
- Evaluation
- Aims

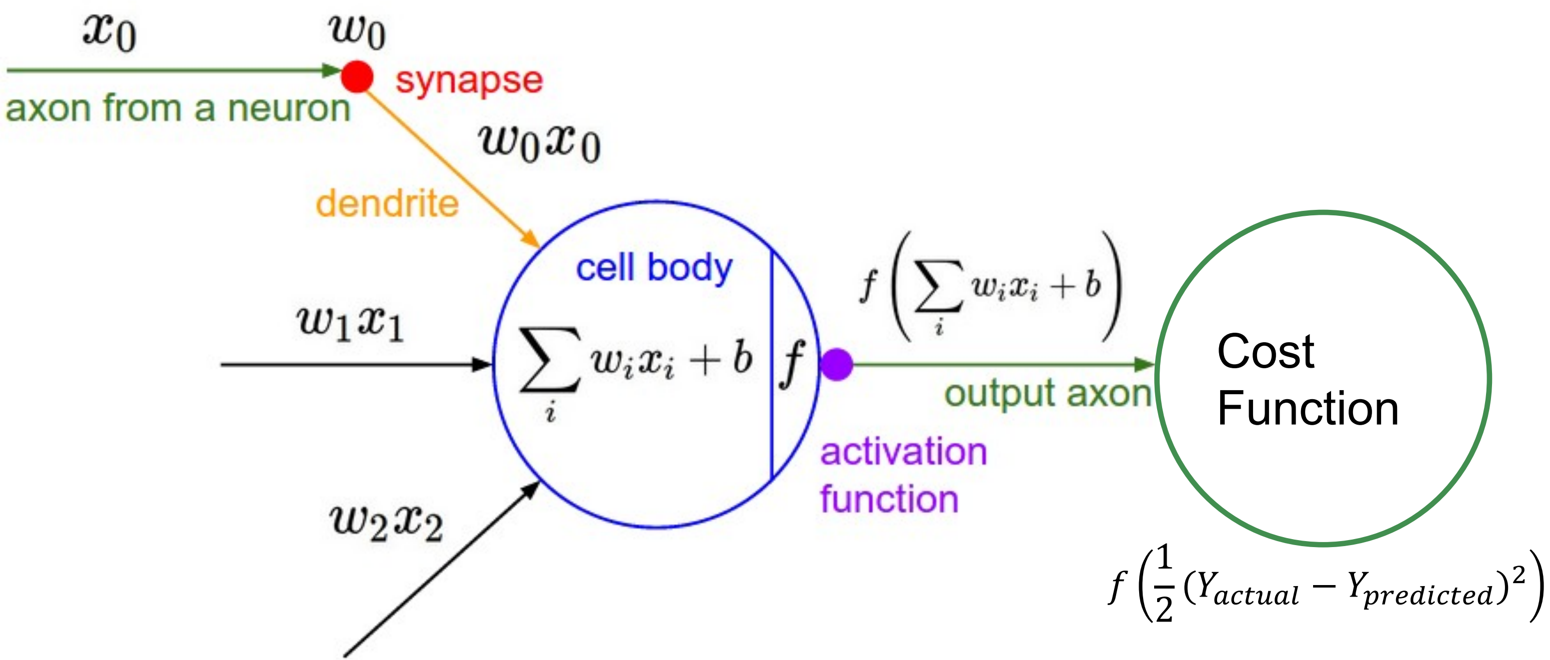
NEURAL NETS

Introduction – Neural Nets



Quelle: http://cs231n.github.io/convolutional-networks/

Neuron Model



Mathematical view

- Input, Weights
- Compute Sigmoid (Activation Function)
- Measure how much we missed (Cost Function)
- Multiply Err by the Sigmoid slope
- Update Weights

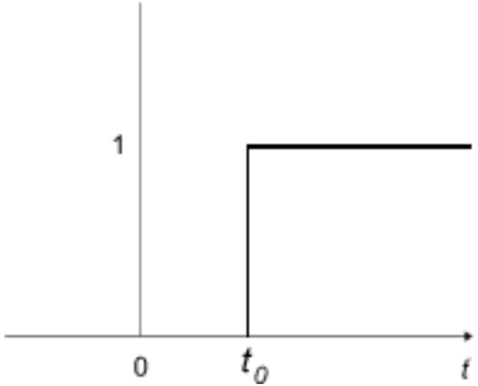
- $l_0 = X_i$, W = rand()
- $l_1 = Sig(X_i . W)$
- Err = $l_0 - l_1$
- Δl_1 = Err*$\Delta\left(Sig(Err)\right)$
- W = W+$(l_0 . \Delta l_1)$

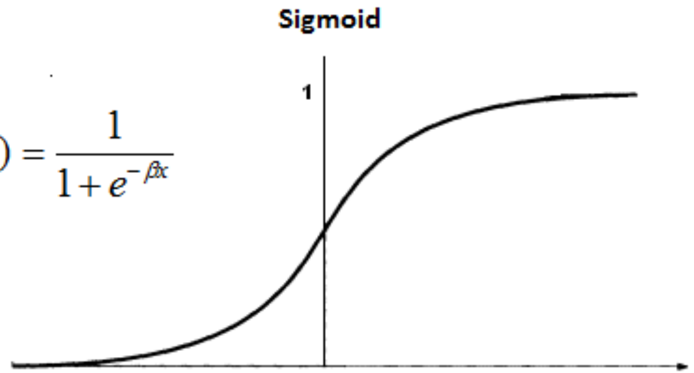
Activation Functions

- Non-Linear
  - sigmoid, tanh, elu, softplus, and softsign
- continuous but not everywhere differentiable functions
  - relu, relu6, crelu and relu_x

Activation functions

- Why Sigmoid?
  - Not telling in which direction should we move in.
  - Non-differentiability at certain points

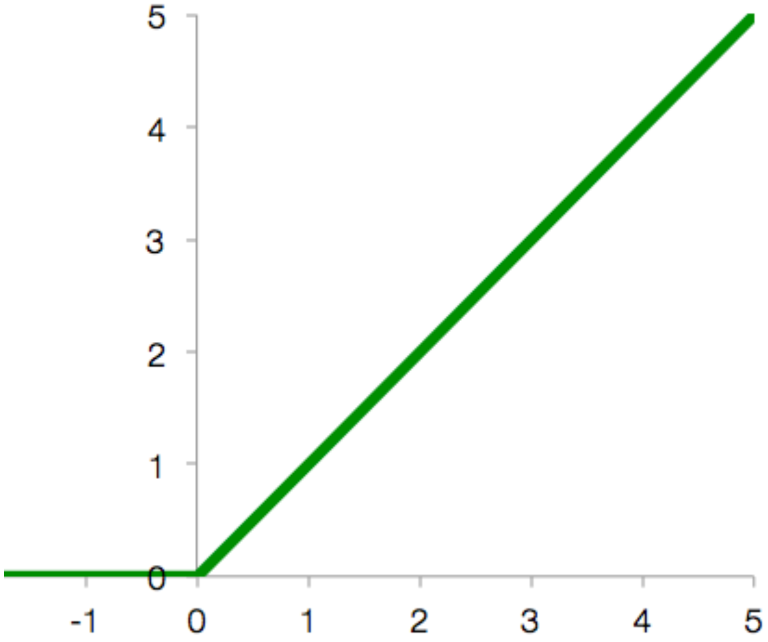




$$f(x) = \frac{1}{1+e^{-\beta x}}$$

Activation functions

- Why Relu?
  - Accelerates the convergence rate
  - Simply implementation



Cost Functions

- Squared Error Measure

- Softmax Cross-entropy Function

Squared Error Measure Function

- $Error = \frac{1}{2}(Y_{actual} - Y_{predicted})^2$
- Drawbacks
  - No gradient to get from 0.000…1 to 1.
    - To do so it will take quite longer.
  - Deprives NN of probability information.

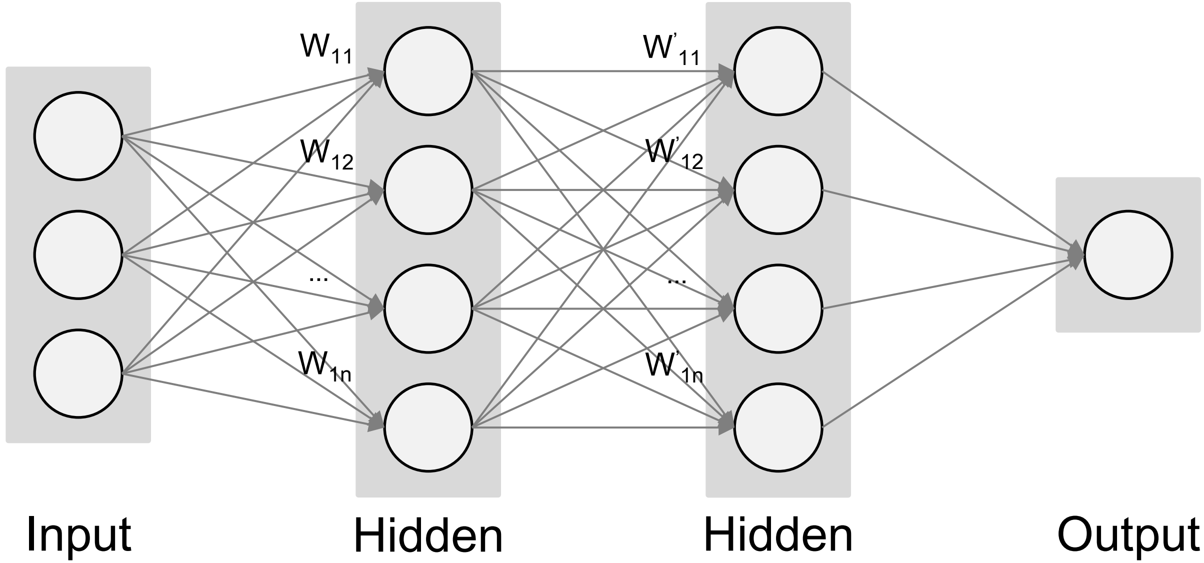
Advantages to Squared Error Measure

- $C = -\sum_j t_j \log\, Y_j$
- Very big gradient when:
  - Target value is 1.
  - Actual output is 0.
- Balance between
  - Steepness of $\frac{dC}{dy}$ and
  - Flatness of $\frac{dy}{dZ}$

$$\frac{\partial C}{\partial Z_j} = \sum_j \frac{\partial C}{\partial y_j}\frac{\partial y_j}{\partial Z_j}$$

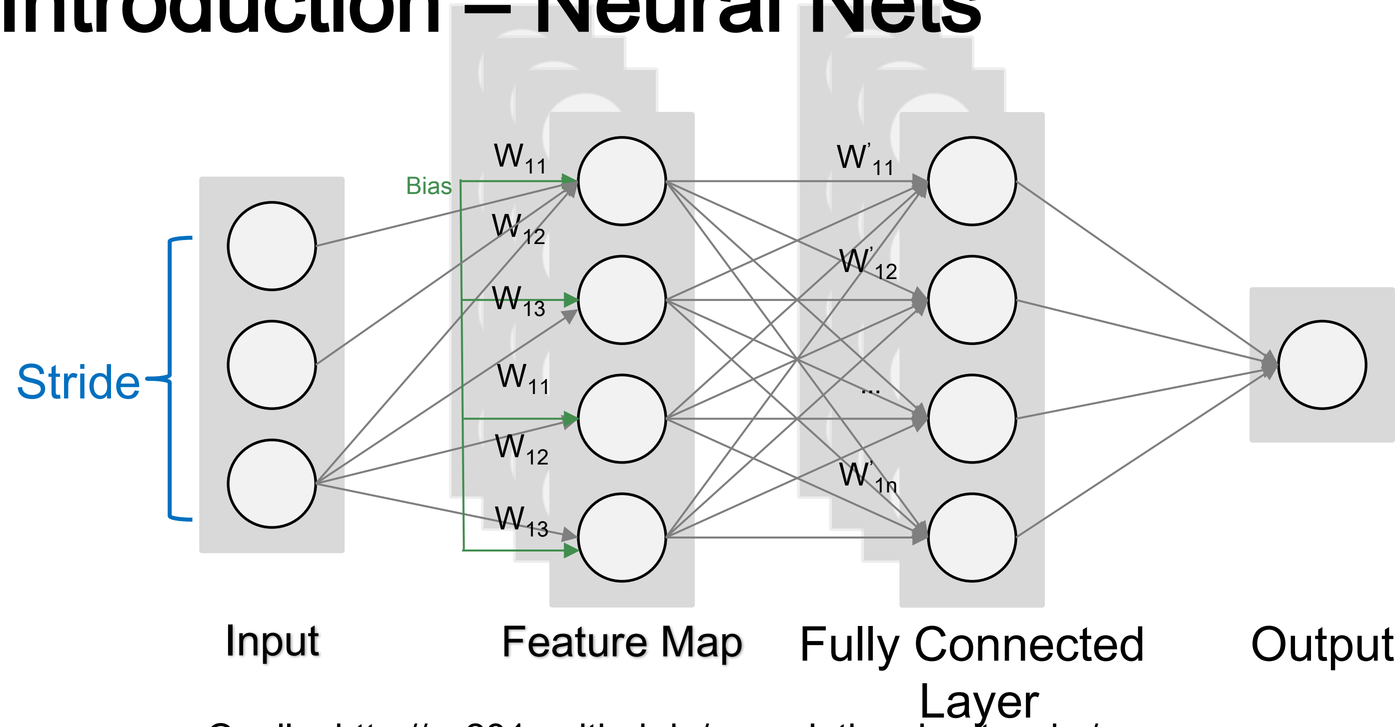
CONVOLUTIONAL NN

Neural Nets to CNN



Quelle: http://cs231n.github.io/convolutional-networks/

Introduction – Neural Nets



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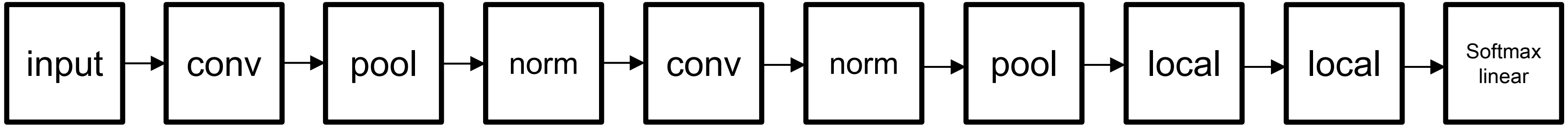
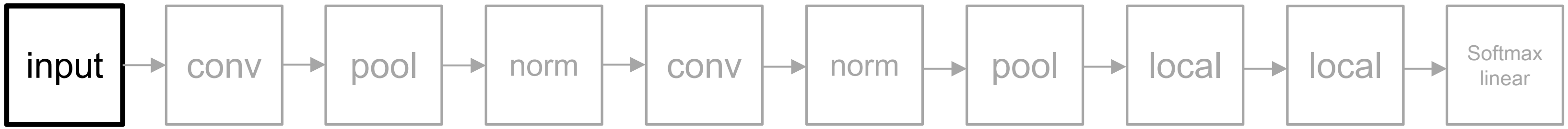
TensorFlow

- Developed by Google Brain Team
- Use cases
  - Handwritten patterns, image recognition, Word2Vec
- Input data
  - Audio, image, text
- Used techniques
  - Linear classifiers, NN

Structure of the CNN we used



Input layer


input
conv
pool
norm
conv
norm
pool
local
local
Softmax
linear

Convolutional layer - Filter

Input

0	0	0	0	0	0	0
0	2	1	0	0	2	0
0	2	2	2	0	2	0
0	1	2	0	2	0	0
0	2	1	2	**1**	**2**	**0**
0	1	2	1	**0**	**0**	**0**
0	0	0	0	**0**	**0**	**0**

Filter

0	0	0
0	2	1
0	2	2

Bias

1

Output

1

$$1*0 + 2*0 + 0*0 + 0*0 + 0*2 + 0*1 + 0*0 + 0*2 + 0*2 + 1 = \mathbf{1}$$

http://cs231n.github.io/convolutional-networks/

input → **conv** → pool → norm → **conv** → norm → pool → local → local → Softmax linear

Convolutional layer - Parameters

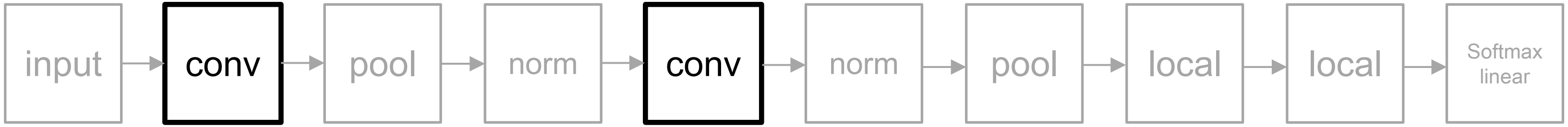
- Input volume size
- Number of filters
- Filter size
- Zero padding

Input

0	0	0	0	0	0	0
0	2	1	0	0	2	0
0	2	2	2	0	2	0
0	1	2	0	2	0	0
0	2	1	2	**1**	**2**	**0**
0	1	2	1	**0**	**0**	**0**
0	0	0	0	**0**	**0**	**0**

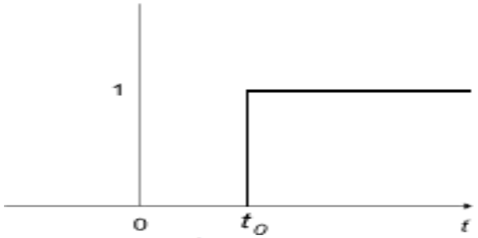
Filter

0	0	0
0	2	1
0	2	2



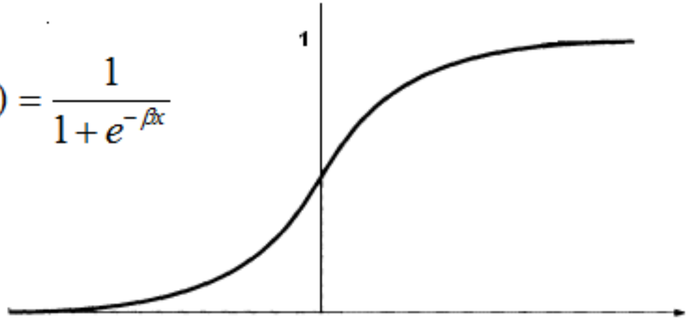
Convolutional layer – Activation function

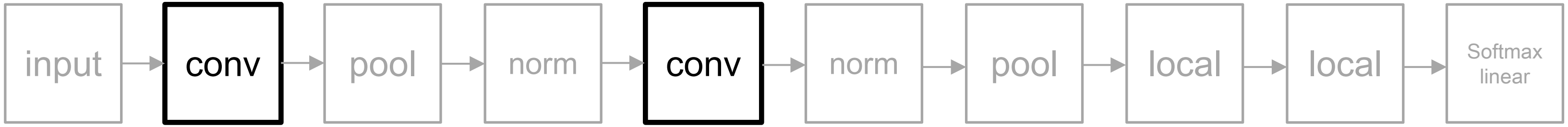
- Sigmoid
  - Not telling in which direction should we move in.
  - Non-differentiability at certain points



Sigmoid

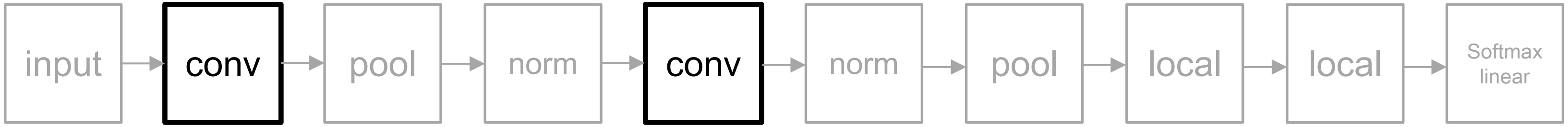
$$f(x) = \frac{1}{1+e^{-\beta x}}$$



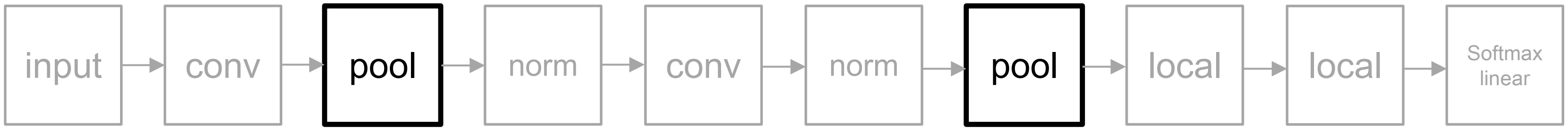


Convolutional layer – Activation function

- Rectified linear
  - $Element\ Wise: \max(0, x)$
  - Leaky ReLU
  - If x < 0, Output = 0.01x.
  - Non-zero gradient when the input is negative



Pool layer


input
conv
pool
norm
conv
norm
pool
local
local
Softmax
linear

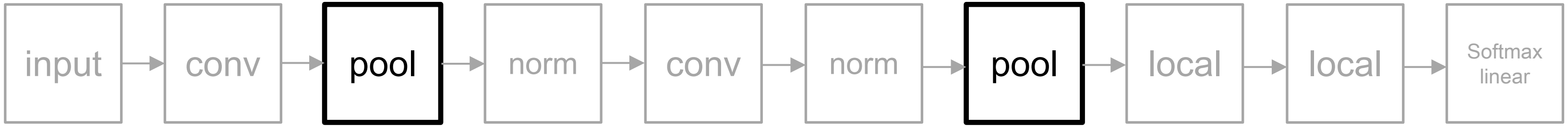
Pool layer – Max pooling

- Reduce the spatial dimension of an image

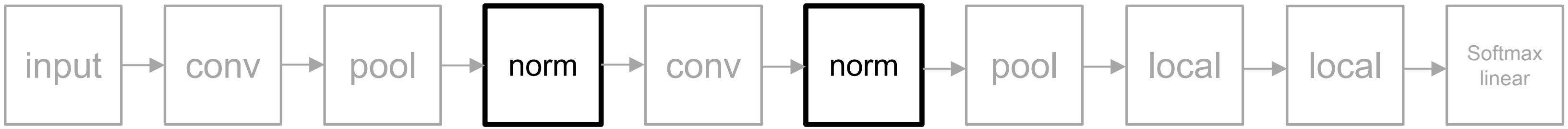
1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

6	8
3	4

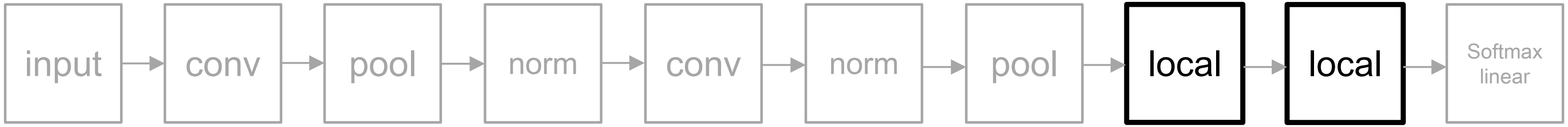
http://cs231n.github.io/convolutional-networks/



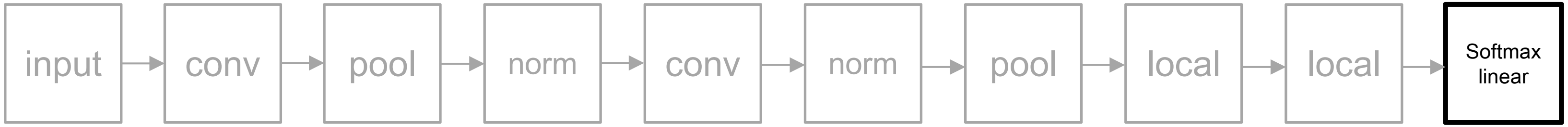
Norm layer


input
conv
pool
norm
conv
norm
pool
local
local
Softmax linear

Local layer

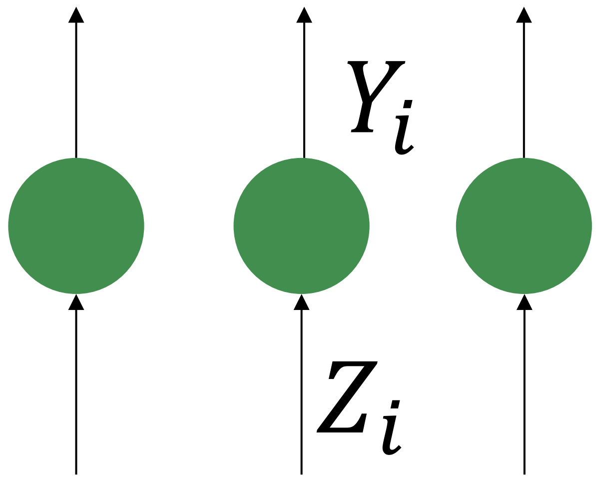

input
conv
pool
norm
conv
norm
pool
local
local
Softmax
linear

Softmax-linear layer



Softmax Output Function

- Soft continuous version of Max Function
- Forces $\sum(Output\ of\ NN) = 1.$



$$Y_i = \frac{e^{Z_i}}{\sum_{j \in group} e^{Z_j}}$$

Derivative Softmax

- $\frac{\delta Y_i}{\delta Z_i} = Y_i \, (1 - Y_i)$
- Nice Simple derivative
- Even though Y_i depends of Z_i ,
  - Derivative
    - for an individual neuron
    - of an I/P in respect to O/P is just $Y_i \, (1 - Y_i)$

Cost Measure for Softmax Output Function

- $C = -\sum_j t_j \log Y_j$
  - Negative log probability of correct answer
- Maximise the log probability of getting answer right

HYPERPARAMETERS

Learning Rate

- how fast the network trains
- High learning rate
  - Convergence or global minimum finding is problem
- Low learning rate
  - High training times

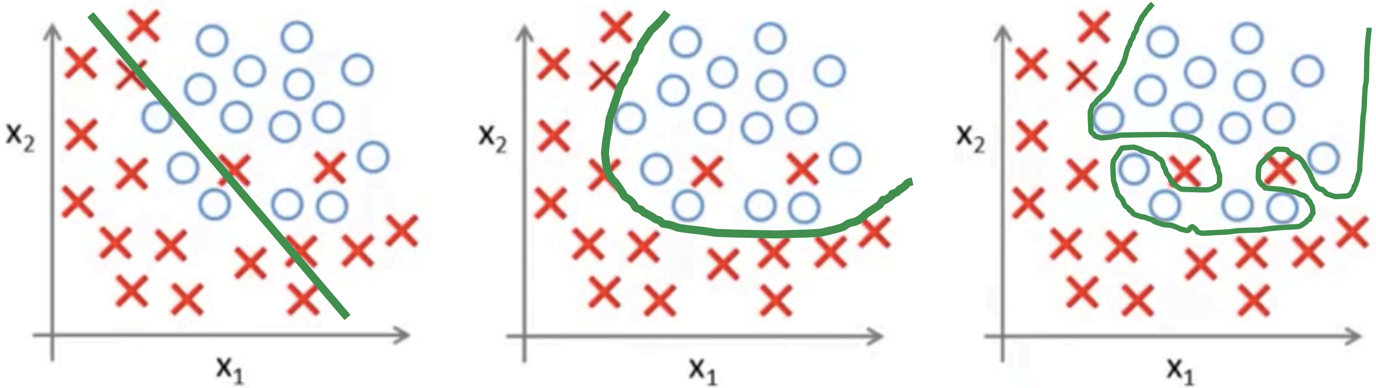
Learning Rate decay

- Learning rate decay means the learning rate decreases over time
  - higher learning rate is well suited to get close to the global minimum
  - small learning rate is better at fine tuning the global minimum

- Several ways to do it:
  - Exponential decay, reduction by factor of n
  - GoogLeNet: function to decrease the learning rate by 4%

Overfitting or Underfitting

Example: Logistic regression



- $h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$

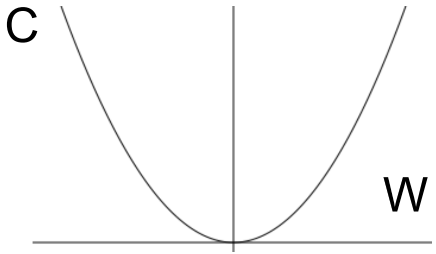
  (g = sigmoid function)

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2$
$+\theta_3 x_1^2 + \theta_4 x_2^2$
$+\theta_5 x_1 x_2)$

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2$
$+\theta_3 x_1^2 x_2 + \theta_4 x_1^2 x_2^2$
$+\theta_5 x_1^2 x_2^3 + \theta_6 x_1^3 x_2 + \ldots)$

Weight Penalty

- Adding λ to penalise
  - Keeps weight small
  - Big error derivatives

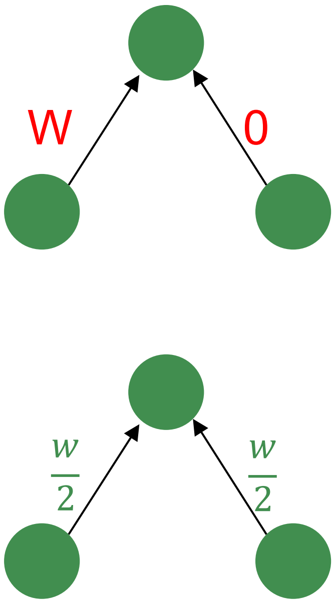


- $C = E + \frac{\lambda}{2}\sum_{i=1} w_i^2$
- $\frac{\partial C}{\partial w_i} = \frac{\partial E}{\partial w_i} + \lambda w_i$
- When $\frac{\partial C}{\partial w_i}$ =0;
  - $w_i = -\frac{1}{\lambda}\frac{\partial E}{\partial w_i}$
  - So, at minimum of Cost function if $\frac{\partial E}{\partial w_i}$ is big, the weights are big

TU Clausthal

Weight Penalty - Advantages

- Preventing network from the weights it does not need
  - Don't have a lot of weights not doing anything
  - So output changes more slowly as input changes.
- Putting half the weight on each and not on one



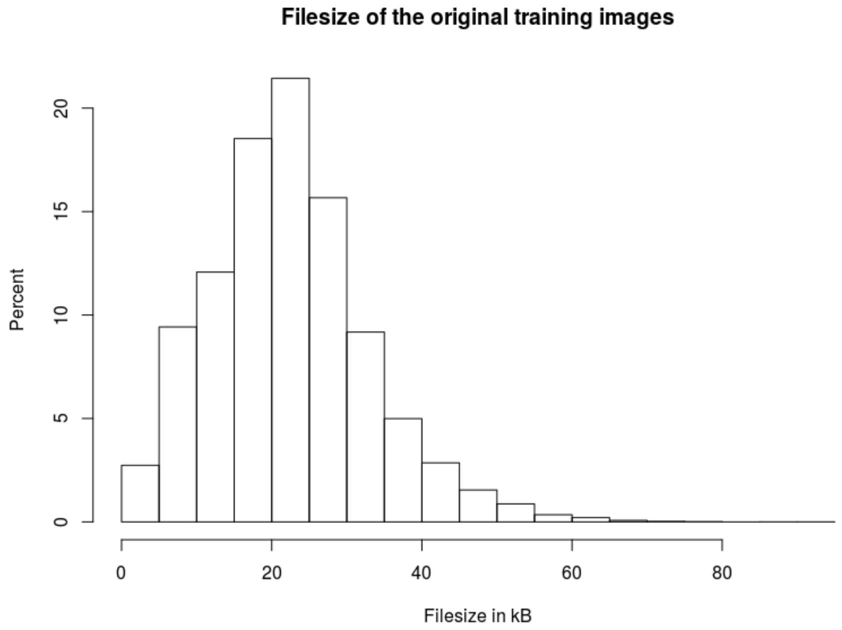
PROBLEM

The data

- Images of cats and dogs
- File format is *.jpg
- Color space is RGB

Training data

- 25,000 images
  - 12,500 of dogs
  - 12,500 of cats
- Avg. file size
  - 22.34 kB



Test data

- 12,500 images
  - x of dogs
  - y of cats
  - x + y = 12,500

Process images

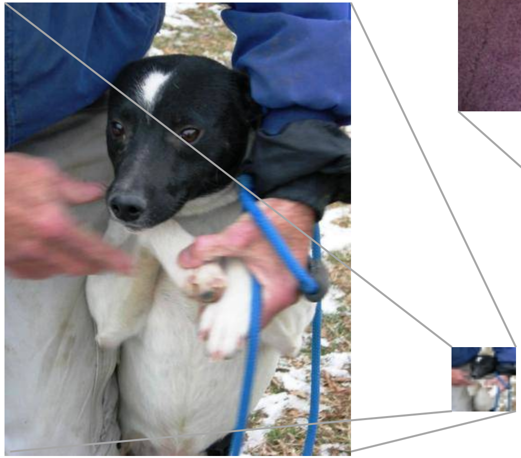
- Resize to 32 * 32 * 3
- Convert to array
  - 25,000 * 3,073

dog1.jpg

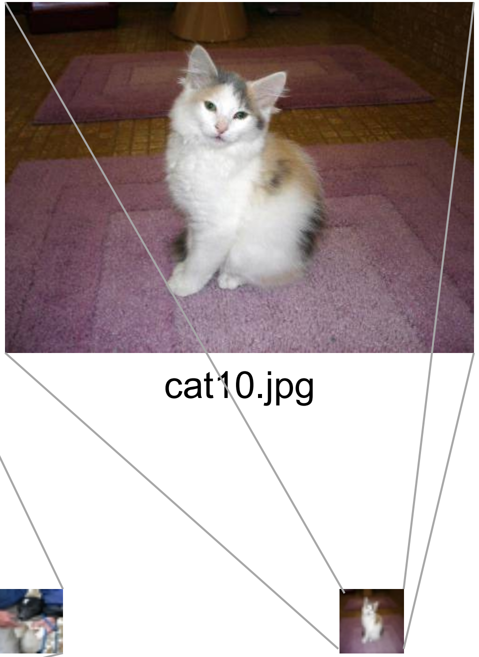
cat10.jpg

Process images

- Resize to 32 * 32 * 3
- Convert to array
  - 25,000 * 3,073



dog1.jpg



cat10.jpg

EVALUATION

AIMS

Aims

- Removing normalization layer

QUESTIONS

Quellen

- http://cs231n.github.io/convolutional-networks/
- https://www.tensorflow.org/tutorials/deep_cnn/
- Maas, Andrew L., Awni Y. Hannun, and Andrew Y. Ng. "Rectifier nonlinearities improve neural network acoustic models." *Proc. ICML*. Vol. 30. No. 1. 2013.