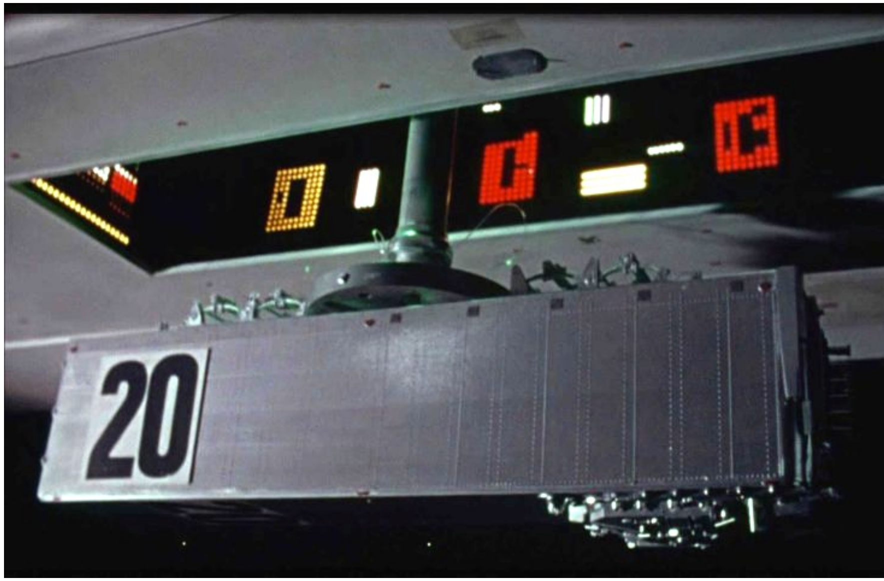
Convolutional Neural Nets II

Hands On



Oliver Dürr

Datalab-Lunch Seminar Series

Winterthur, April 22nd, 2015

Outline

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of Applied Sciences

- Motivation for CNN
  - Focus here on image classification
- Frameworks
  - Caffe / **Lasagne**
- Recap MLP / **Demo MLP**
- Recap CNN / **Demo CNN**
- Some Tricks
  - Dropout
  - Training and Test augmentation (Learning Symmetries)
- Demo **CNN with Augmentation**

Code for demos: https://github.com/oduerr/dl_tutorial

History, milestones of CNN

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- 1980 Kunihiko Fukushima introduction
- 1998 Le Cun (Backpropagation)
- Many Contests won
    - 2011& 2014 MINST Handwritten Dataset
    - 201X Chinese Handwritten Character
    - 2011 German Traffic Signs
- ImageNet Success Story
  - Alex Net (2012) winning solution of ImageNet…

Imagenet 2012,2013,2014

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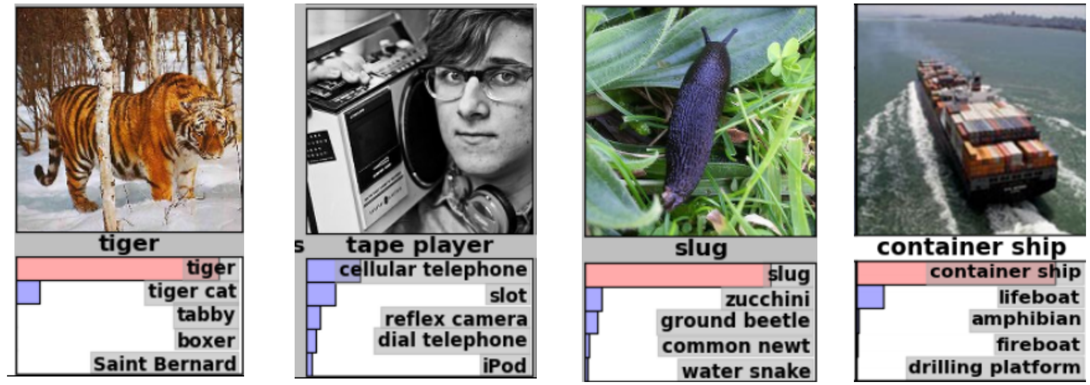
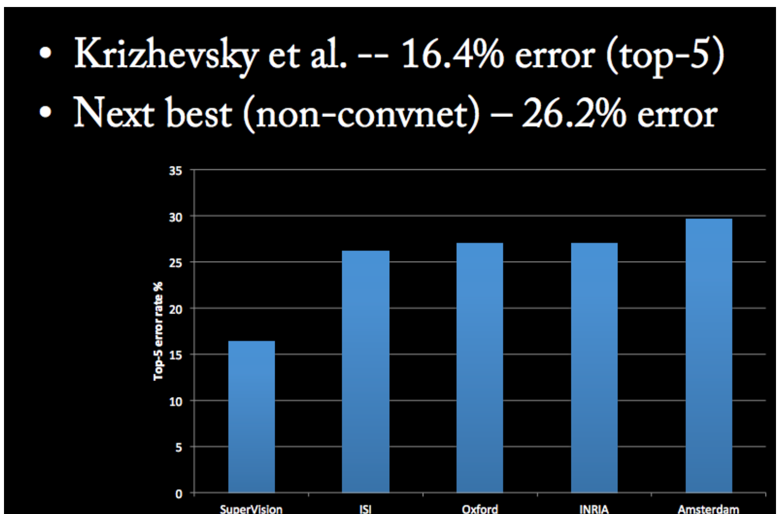
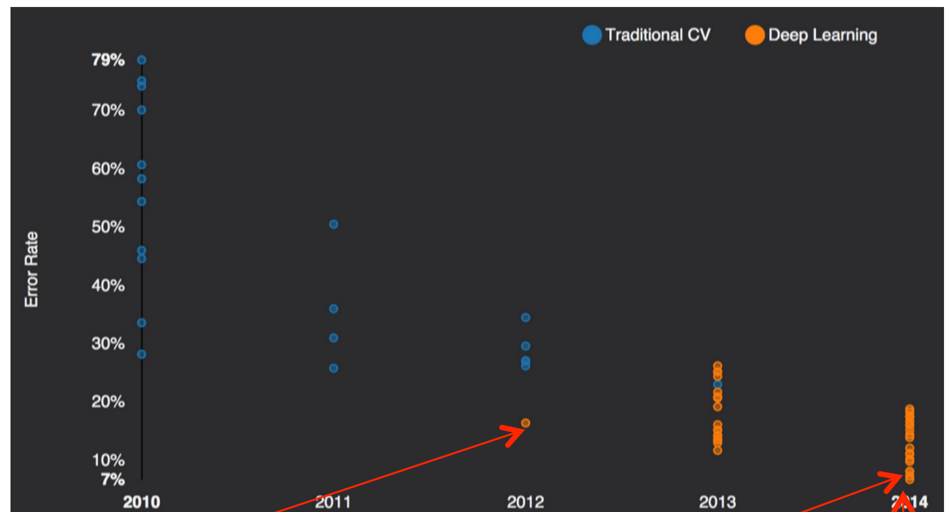
Some Examples
With Alexnet results
1000 Classes



2012



2010-2014



SuperVision
AlexNet 7 layers deep

GoogLeNet 6.7%

Oxfordnet up to 19 layers

http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf
https://medium.com/global-silicon-valley/machine-learning-yesterday-today-tomorrow-3d3023c7b519

A really convincing fact

Kaggle Plankton Competition (2015)

https://www.kaggle.com/c/datasciencebowl/leaderboard/public

Apps PiVi Run Marathonplan unter Wetter: Kreuzlingen WhatsApp Web Keep » Other Bookmarks

249	↓67	plankton_78	0.994107	23	Tue, 03 Mar 2015 21:03:05 (-3.8d)
250	↓67	Evan Cater	0.995265	18	Thu, 29 Jan 2015 20:48:08 (-21.1h)
251	↓66	I do not use CNN	0.997750	38	Sun, 01 Feb 2015 17:50:52 (-0.4h)
252	↓65	Alepf	0.999827	7	Tue, 10 Mar 2015 17:19:22 (-3d)
253	↓65	rm	0.999885	20	Tue, 24 Feb 2015 16:52:59

There is another bold one

634	↓70	NO-CNN	2.988988	4	Thu, 15 Jan 2015 04:25:27

Frameworks

Overview of frameworks

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Disclaimer: „This is a fast changing field. The list is not exclusive“.

Survey from the partcipiants of the Kaggle Challenge (Feb 2015)

Most Mentioned

- **lasagne / nolearn**
  - Python based on Theano, very flexible (winning team „Deep See“ used it)
- **caffe**
  - C++ based library, python bindings, convenience functions, many existing / pretrained models

Also used

- Theano (plain vanilla)
  - Symbolic computation of gradients and construction of numerical C-code
- Torch, lua (used by Facebook)
- Cxxnet
- ...

*https://www.kaggle.com/c/datasciencebowl/forums/t/12839/curiousity-survey-add-upvote-your-toolkit

Caffe

- C++ library with python bindings
- Settings (network layout and others) via files
- Documentation: poor
- Feels like a Blindflug
- Up to data components
  - Alexnet,GoogLeNet
- Input: Images or strange DBs
- Data Augmentation: Not possible from python
- Predefined models available

Lasagne / nolearn

- Lasage: python using theano (library define, optimize, and evaluate mathematical expressions on GPU)
- Nolearn is a wrapper around lasagne to provide a similar interface then scikit-learn
- Documentation: poor, but use the source luke
- Feels like you understand /control bells and whistles
- Custom components possible (provided Theano has functionallity)
- Input: Any numpy arrays
- Data Augmentation: Easy
- No predefined models (yet)

We will focus on lasagne

Links for Caffe

We will focuss on Lasagne but some links to Caffe for reference (thanks to Gabriel)

- https://github.com/oduerr/dl-playground/tree/master/python/FaceCaffe
- http://vision.princeton.edu/courses/COS598/2015sp/slides/Caffe/caffe_tutorial.pdf
- http://vision.stanford.edu/teaching/cs231n/slides/caffe_tutorial.pdf
- https://docs.google.com/presentation/...

Recap Neural Nets

Recap Neural Networks: Basic Unit

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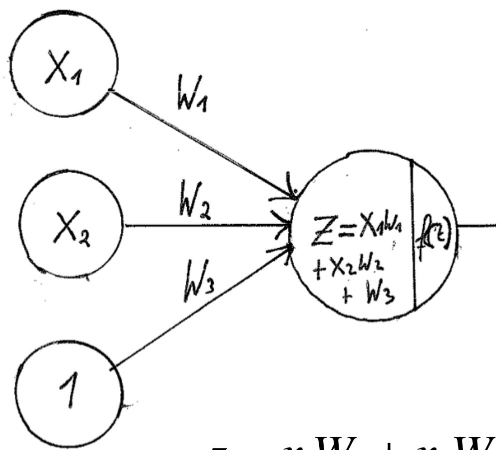
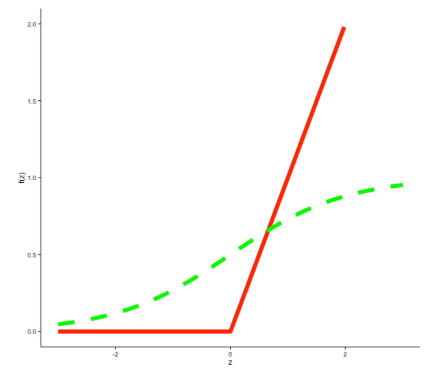
N-D log Regression



$$f(z) = \begin{cases} \dfrac{\exp(z)}{1+\exp(z)} \\ \max(0,z) \end{cases}$$

$$z = x_1 W_1 + x_2 W_2 + W_3 = \theta^T x$$

Activation Function a.k.a. Nonlinearity*f(z)*



Motivation:

Green:
logistic regression.

Red:
ReLU faster
convergence

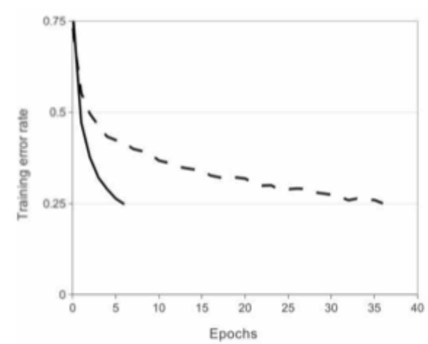


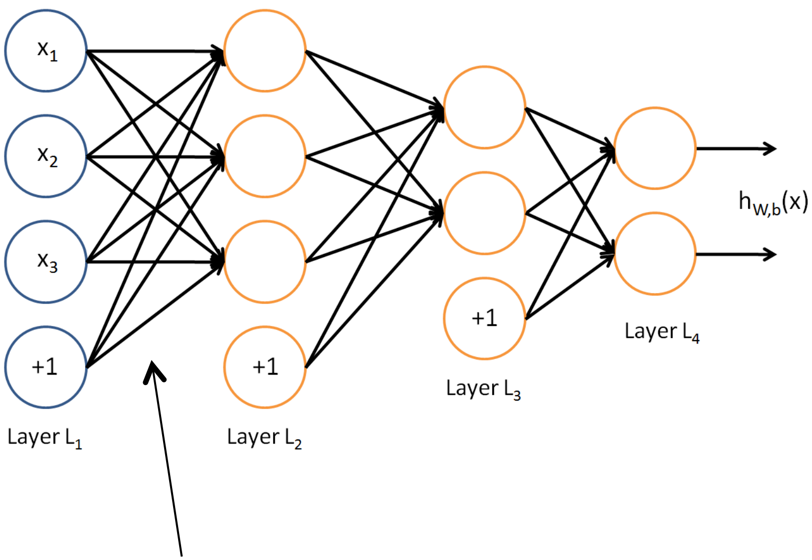
Figure 1: A four-layer convolutional neural network with ReLUs **(solid line)** reaches a 25% training error rate on CIFAR-10 six times faster than an equivalent network with tanh neurons

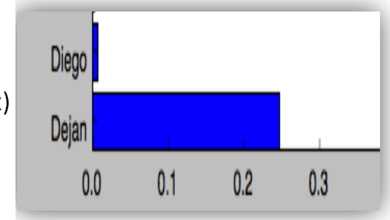
Source:
Alexnet

Krizhevsky et
al 2012

For a more detail explanation see: https://home.zhaw.ch/~dueo/bbs/files/ConvNets_17_Dec_1.pdf

Recap Neural Networks: Stacking things together





Output (Softmax)

$$f(z_i) = \frac{e^{z_i}}{\sum_{i=1}^{N} e^{z_i}}$$

Propability of a class given the input image X

Contains many weights $W^{(l)}_{ij}$

This is just a complex functions of the many weights $\theta = W^{l}_{ij}$ and the input predicting the prob. of a class.

For a more detail explanation see: https://home.zhaw.ch/~dueo/bbs/files/ConvNets_17_Dec_1.pdf
Figure taken from: http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Recap Neural Networks: Training the NN

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- Use the training data j=1,...,N_{train} to optimize a costfunction *J* sensitive to misclassication
  - Usual a subset n (minibatch) of the training data is taken for optimization in one go.

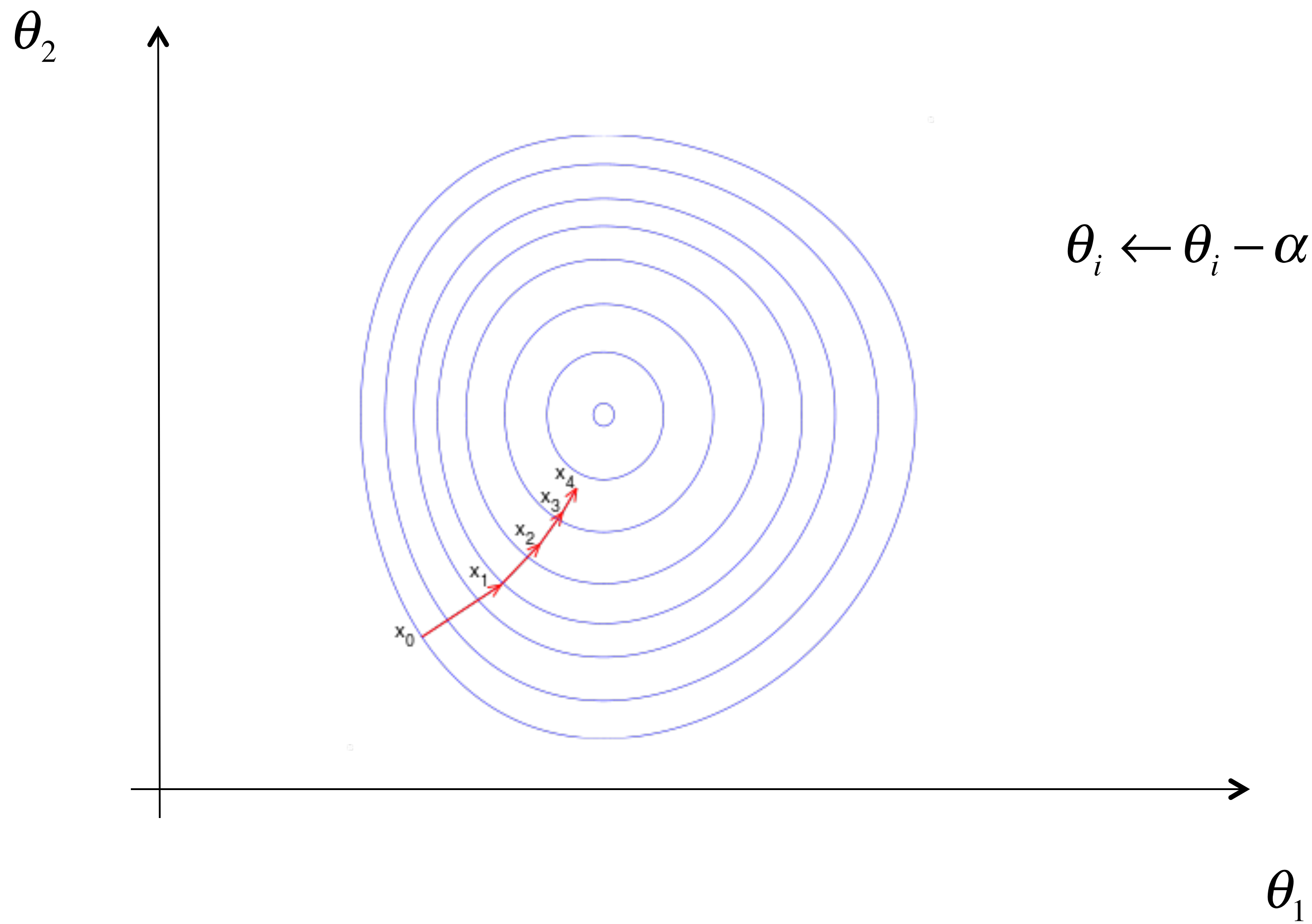
$$-nJ(\theta) = \sum_{i=1}^{n \text{ (Mini Batch Size)}} \text{Cost of Training example } X_i$$

- Motivation of cost function from MaxLikelihhod
- Optimal weights are found in many iterations using gradient descent (α learning rate)

$$\theta_i \leftarrow \theta_i - \alpha \frac{\partial J(\theta)}{\partial \theta_i}$$

- Backpropagation a.k.a chainrule is used to calculate the gradient

Illustration of Gradient Descent



$$\theta_i \leftarrow \theta_i - \alpha \frac{\partial J(\theta)}{\partial \theta_i}$$

θ_1, θ_2 just two from millions

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Demo MLP

Definition Data/Network (MLP)

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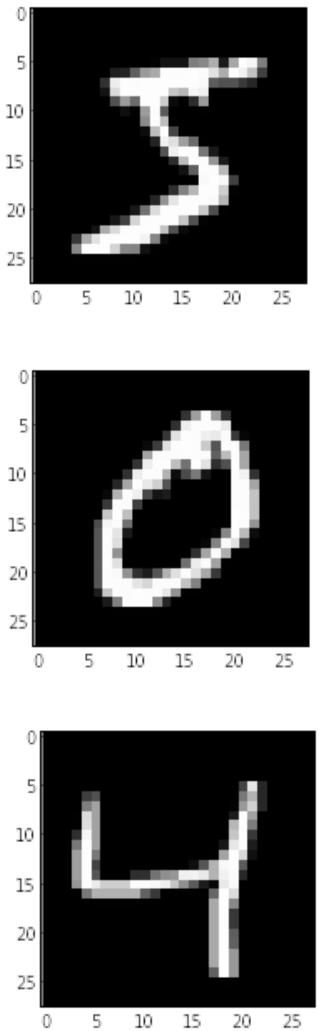
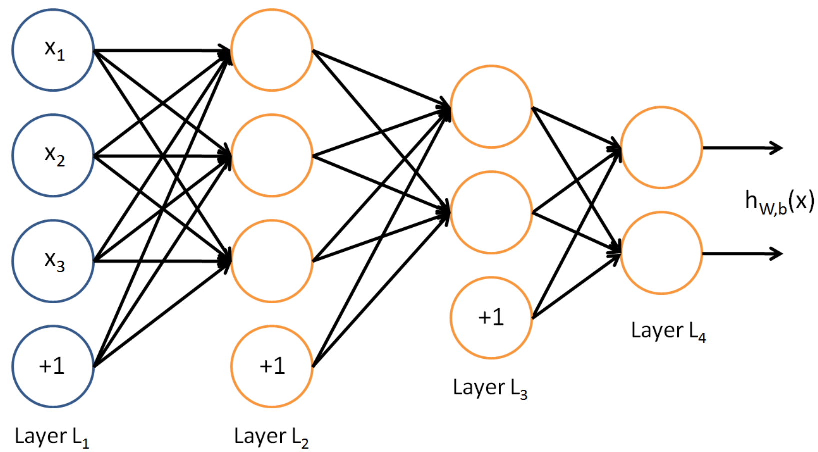


In reality much more nodes



Images 28x28 =784

500

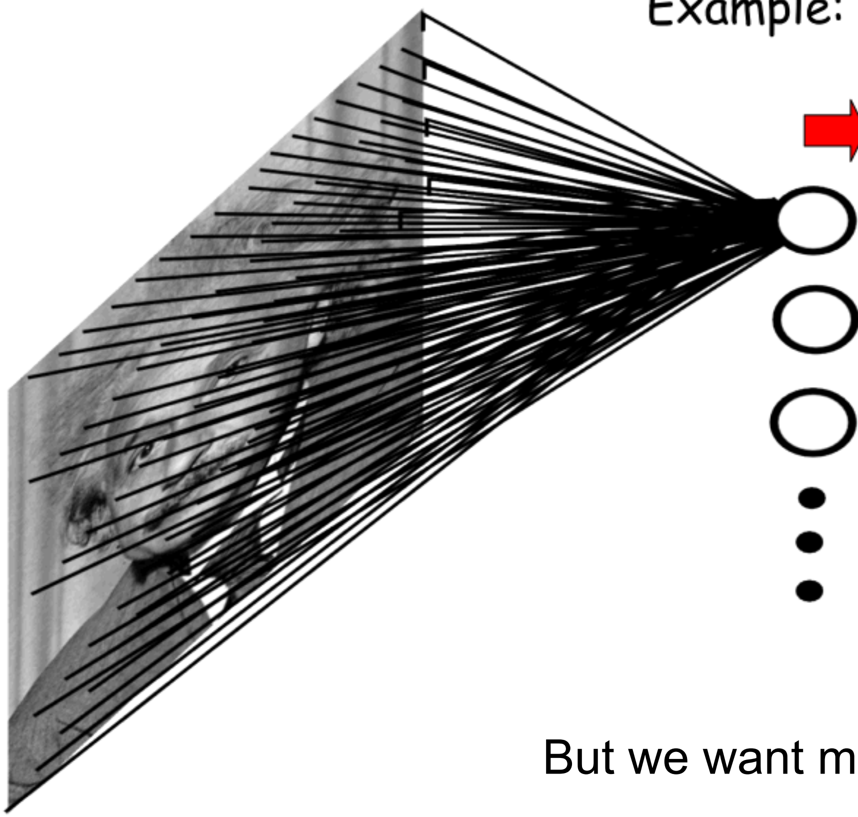
50

10

Now for the Demo…

To many weights

Example: 1000x1000 image
1M hidden units
10^12 parameters!!!



But we want many layers.

Remedy:

- Weight sharing → Convolution
- Sparse connectivity → Pooling

The convolutional layer
Ingredient I: Convolution

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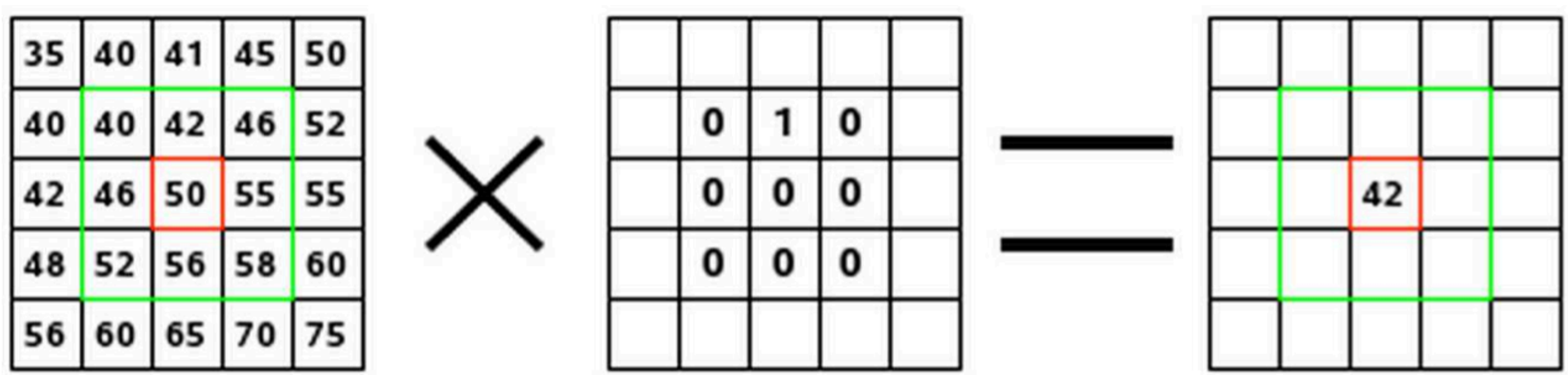
What is convolution?

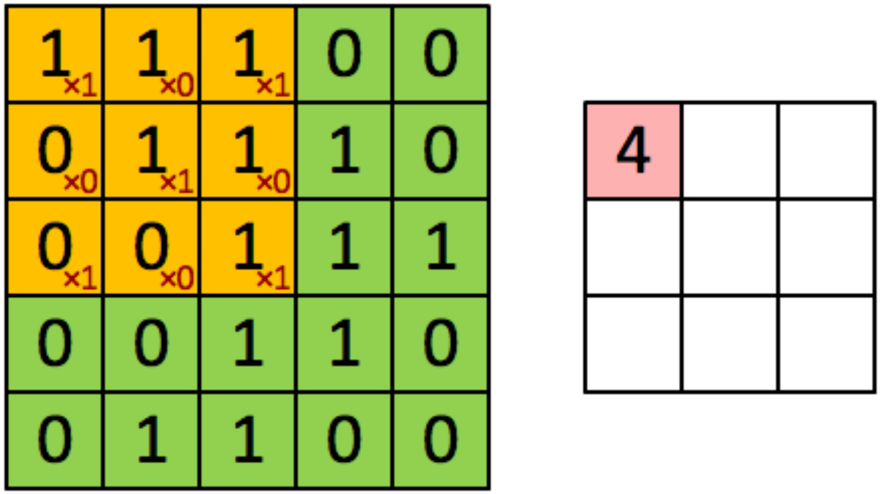


The 9 weights W_{ij} are called Kernel.

The weights are not fixed they are learned!

Gimp documentation: http://docs.gimp.org/en/plug-in-convmatrix.html

The convolutional layer
Ingredient I: Convolution



Image

Convolved Feature

The *same* weights are slid over the image

Illustration: http://deeplearning.stanford.edu/tutorial/

Example of a Kernel

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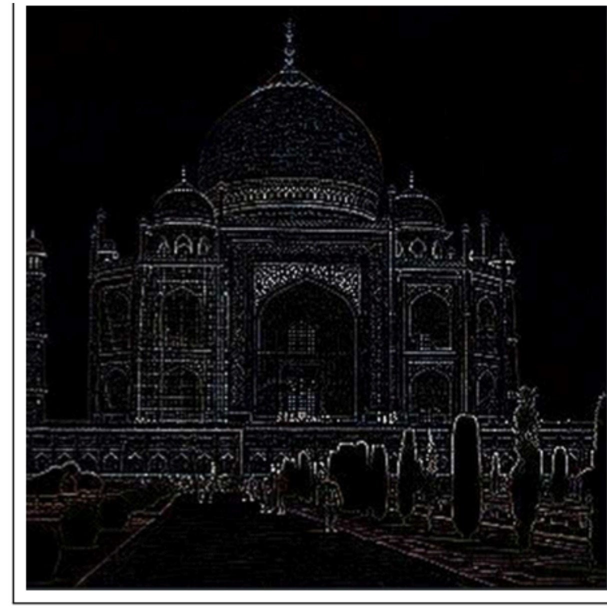
Edge enhance
Filter

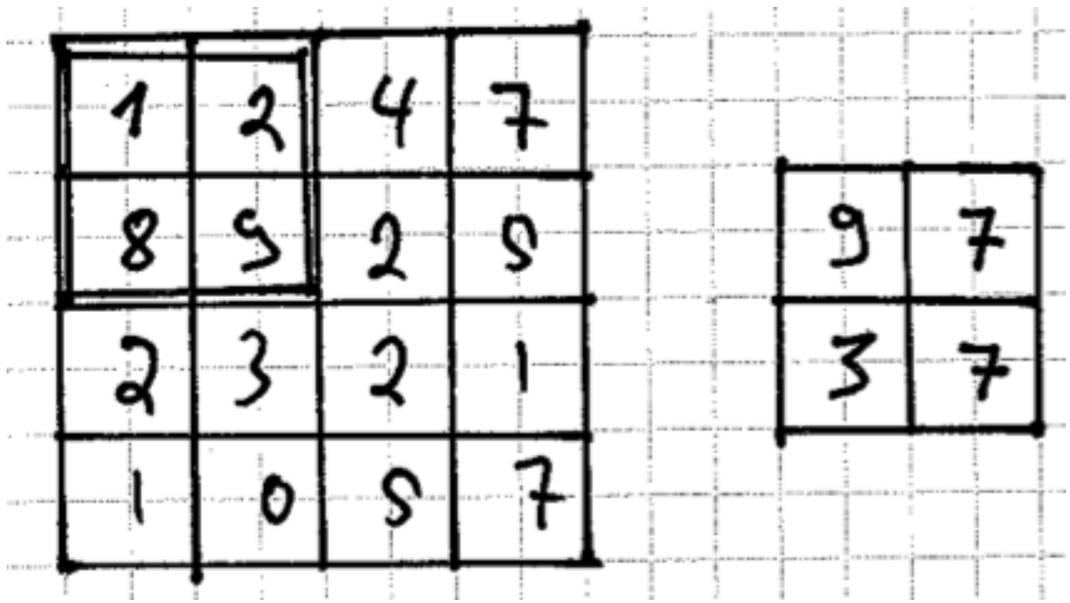
	0	0	0	
	-1	1	0	
	0	0	0	



But again!
The weights are not fixed. They are learned!

Gimp documentation: http://docs.gimp.org/en/plug-in-convmatrix.html

The convolutional layer
Ingredient II: Max-Pooling



Also sliding window versions.

Simply join e.g. 2x2 adjacent pixels in one.

Hinton: „The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster“

A simple version of the CNN (LeNet5 Architecture)

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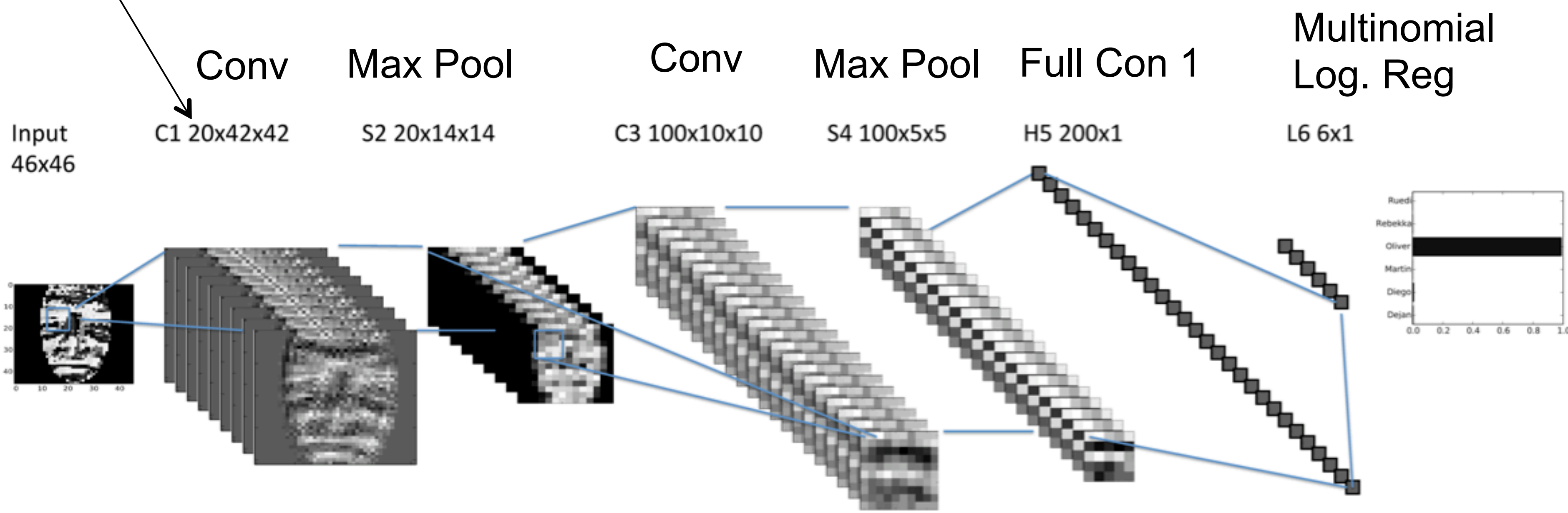
20 Kernels a 5x5 weights to go from one to the next



A typical recent architecture (AlexNet, 2012)

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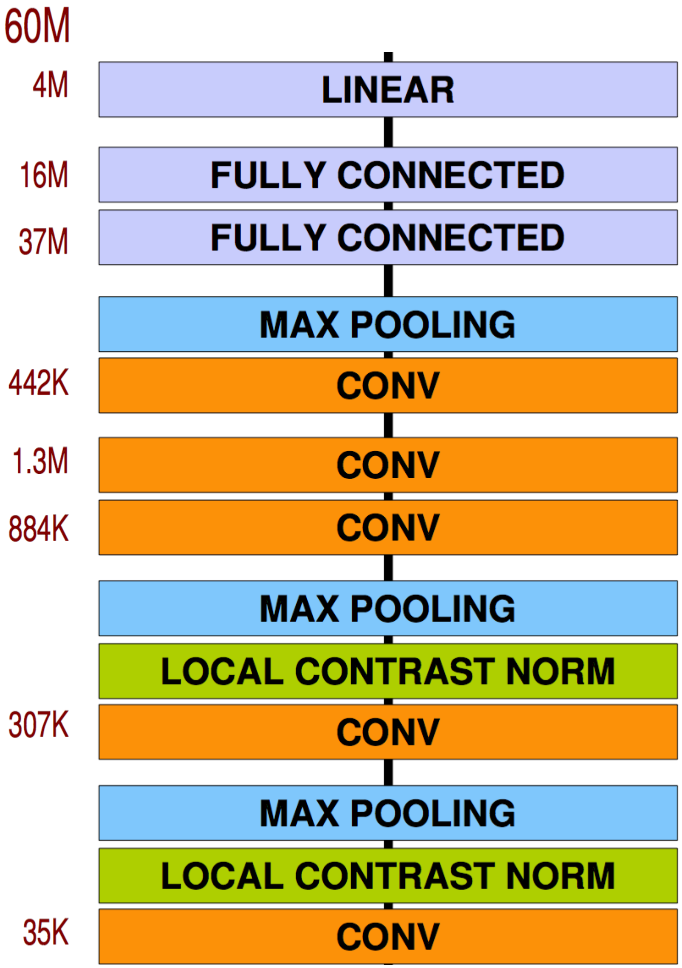
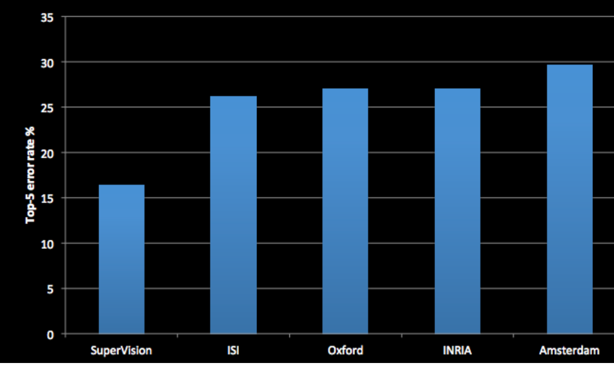


- Krizhevsky et al. -- 16.4% error (top-5)
- Next best (non-convnet) – 26.2% error



Senimal paper. introduced 26.2% error → 16.5%

- Dropout (see below)
- ReLU instead of sigmoid
- Parallelisation on many GPUs
- Local Response Normalization (not used widely nowadays)

A bit of a simplification, since Alex Net is build for 2 GPUs and normalization. Caffe code from here

Winning architecture (GoogLeNet, 2014)

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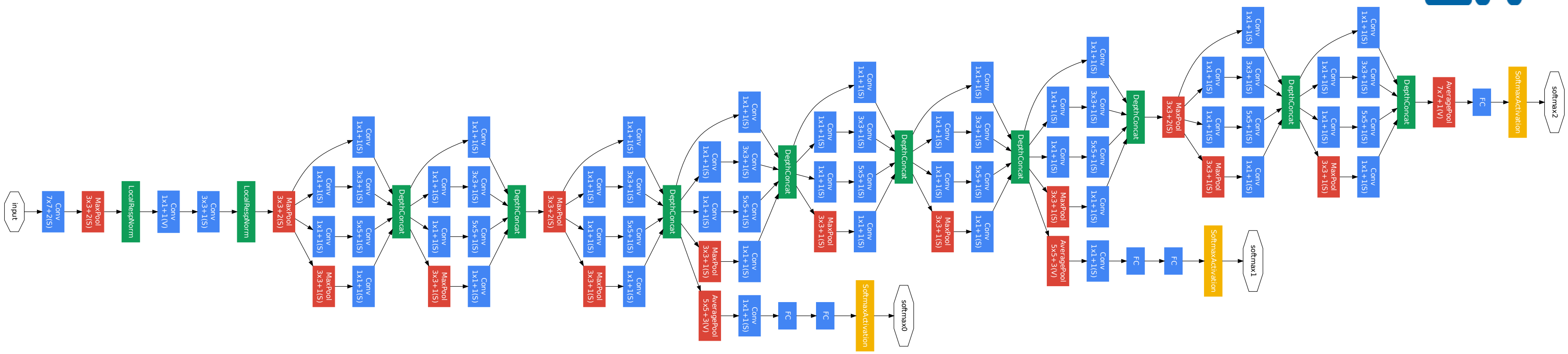
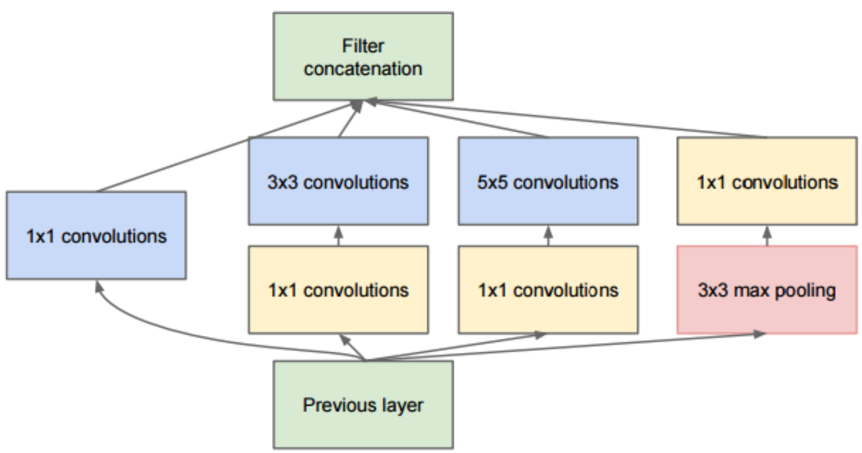


The inception module (convolutions and maxpooling)



Few parameters, quite hard to train.
Comments see [here]

[Going deeper with convolution http://arxiv.org/abs/1409.4842]

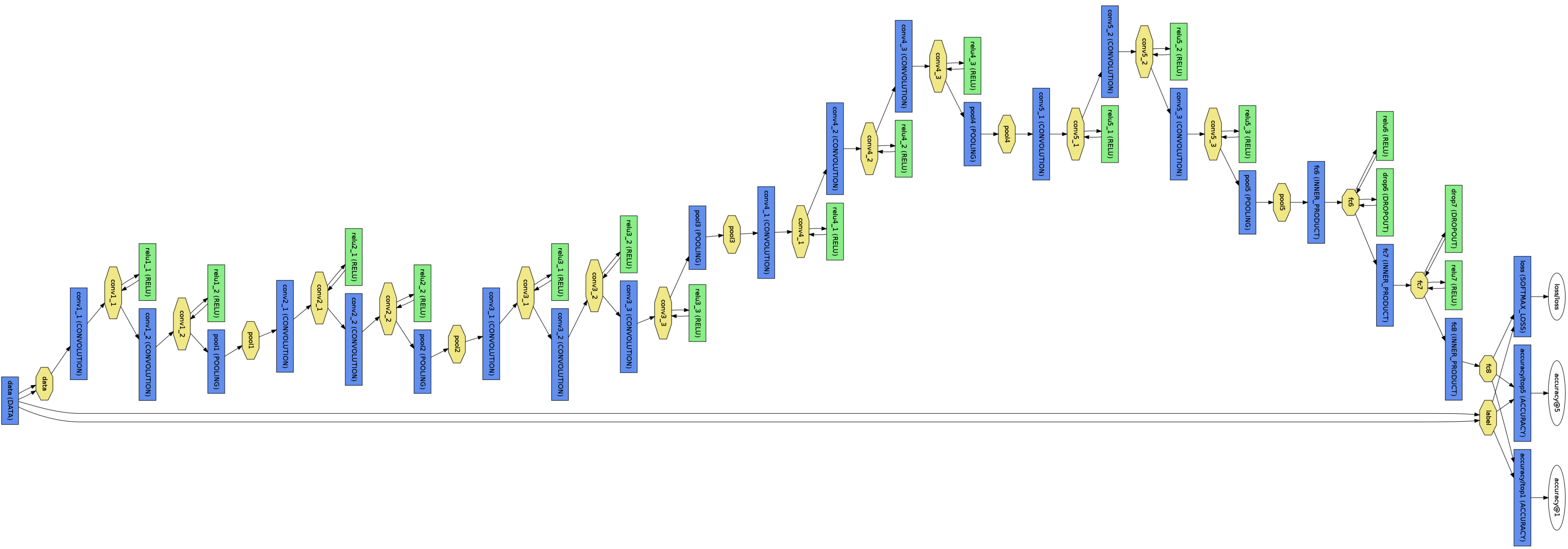
A typical very recent architecture („Oxford Net"(s), 2014)

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

- Small pooling
- More than 1 conv before maxpooling.
- No strides (stride 1)
- ReLU after conv and FC
- More traditional, easier to more weights than GoogLeNet
- Caffe Implementation

http://arxiv.org/abs/1409.1556 ImageNet Challenge 2014, 2nd classification

A typical very recent architecture („Oxford Net"(s), 2014)



Definition (16 Layer) taken from:
https://gist.github.com/ksimonyan/211839e770f7b538e2d8#file-readme-md

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Demo Lasagne II (Convolutional)

Demo: Nolearn/Lasagne (LeNet Architecture)

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```
layers=[
        ('input', layers.InputLayer),
        ('conv1', layers.Conv2DLayer),
        ('pool1', layers.MaxPool2DLayer),
        ('conv2', layers.Conv2DLayer),
        ('pool2', layers.MaxPool2DLayer),
        ('hidden4', layers.DenseLayer),
        ('output', layers.DenseLayer),
        ],
    input_shape=(None, 1, PIXELS, PIXELS),
    conv1_num_filters=32, conv1_filter_size=(3, 3), pool1_ds=(2, 2),
    conv2_num_filters=64, conv2_filter_size=(2, 2), pool2_ds=(2, 2),
    hidden4_num_units=500,
    output_num_units=10, output_nonlinearity=nonlinearities.softmax
```

Have ReLu non-linearity by default

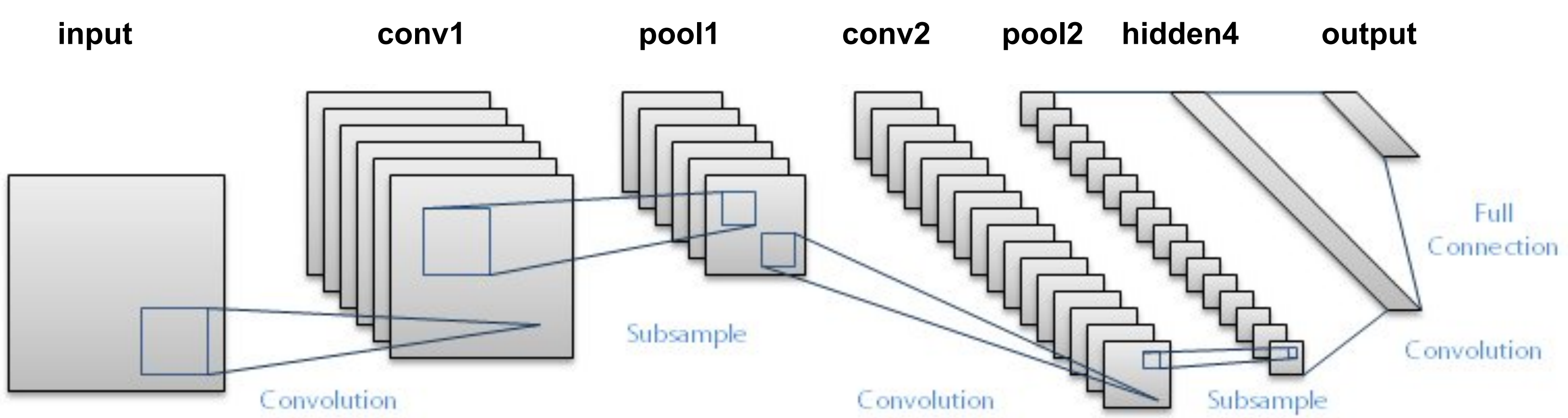
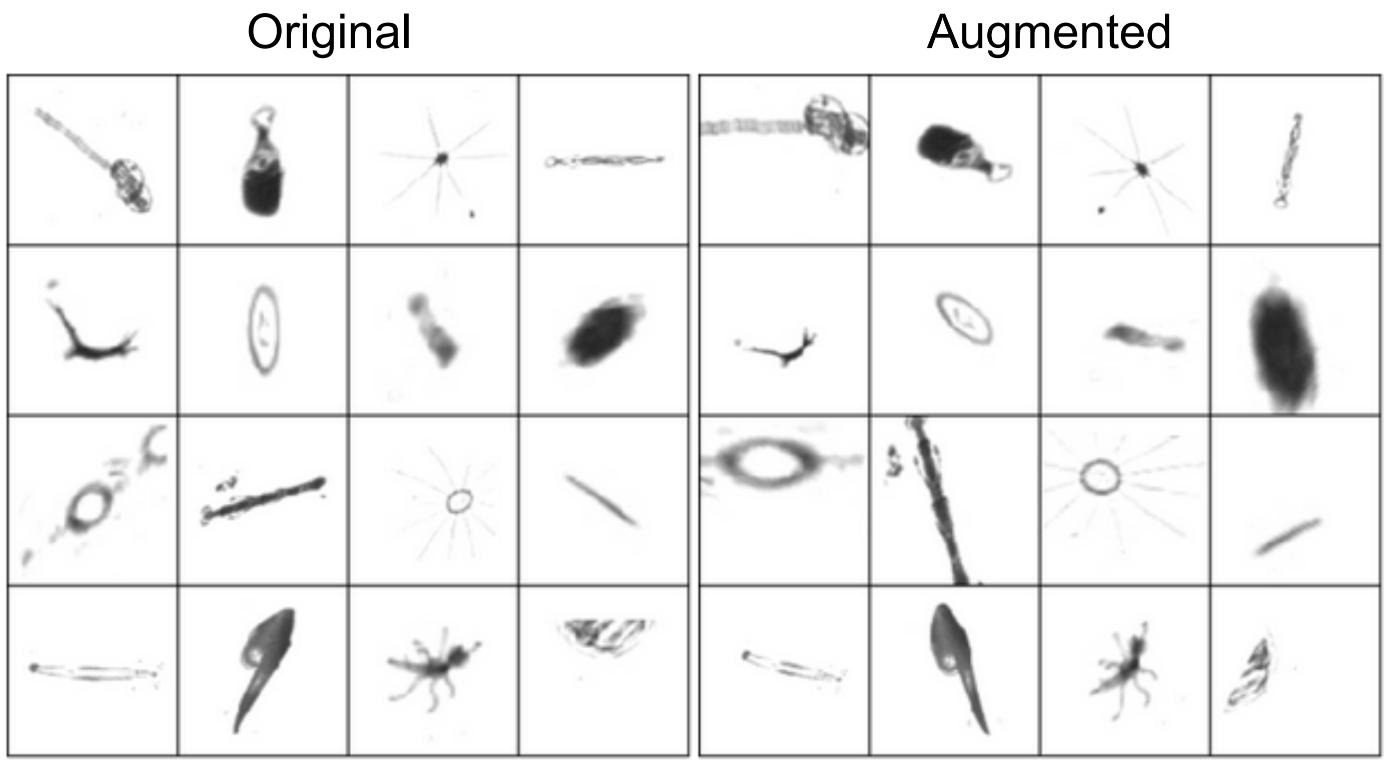


Image taken from: Master Thesis Christopher Mitchell http://www.cemetech.net/projects/ee/scouter/thesis.pdf

(Some) tricks of the trade

Data Augmentation

- Create „new training“ data by „lable preserving transformation“
- Force invariances under translational symetrie (translation, rotation,)



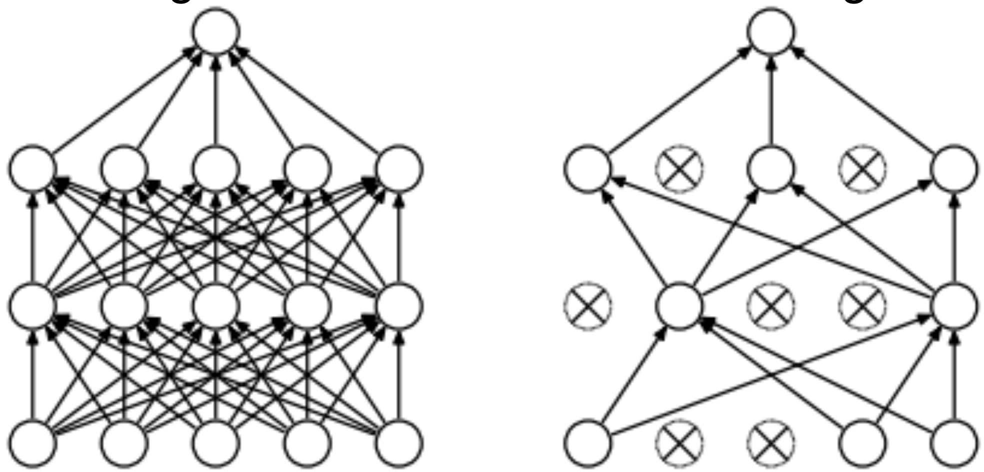
Pre-processed images (left) and augmented versions of the same images (right).

Taken from the winning solution of the plankton challenge. http://benanne.github.io/2015/03/17/plankton.html

Dropout

Original

Training



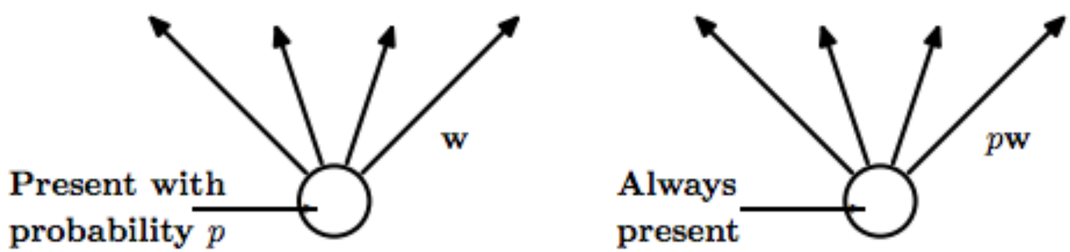
(a) Standard Neural Net

(b) After applying dropout.

At each mini-batch remove random nodes “dropout”

Training time

Test Time



(a) At training time

(b) At test time

Idea: Averaging over many different configuration (exact in case of linear).
Typically 10% performance invcrease

Srivastava et al., Journal of Machine Learning Research 15 (2014) 1929-1958

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Demo Lasagne III (Convolutional with Training-Data Augmentation)

Attic

Taking a closer look: Convolution

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Documentation:

- The convolutional layer is finished with a nonlinearity:
  - Possible:
    - identity (nothing, linear), rectify (default), tanh, softmax (good for last layer), sigmoid

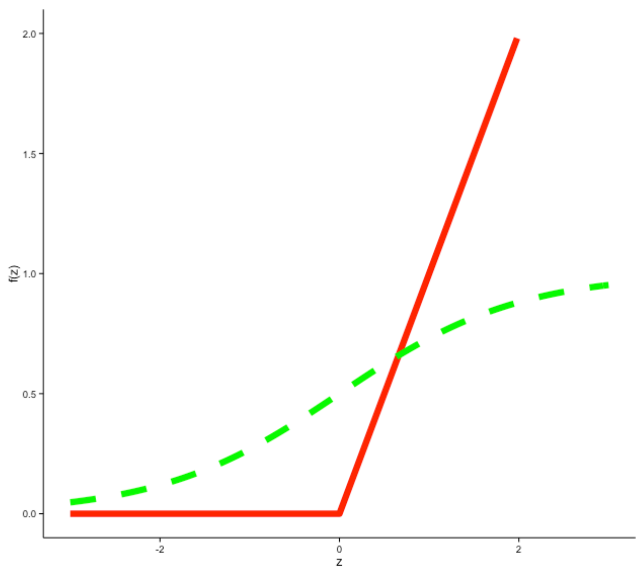
- Different sizes
  - no padding / padding via
    - conv1_border_mode=‘valid‘ #(None, 1, 28, 28) → (None, 32, 26, 26)
    - conv1_border_mode='same‘ #(None, 1, 28, 28) → (None, 32, 28, 28)
    - conv1_border_mode=‘full‘ #(None, 1, 28, 28) → (None, 32, 30, 30) #????

  - stride schrittweite default (1,1)
    - conv1_strides=(2,2) #(None, 1, 28, 28) →(None, 32, 13, 13)

Observation:

Seems to take quite a while for compiling

Cost Functions: ReLU



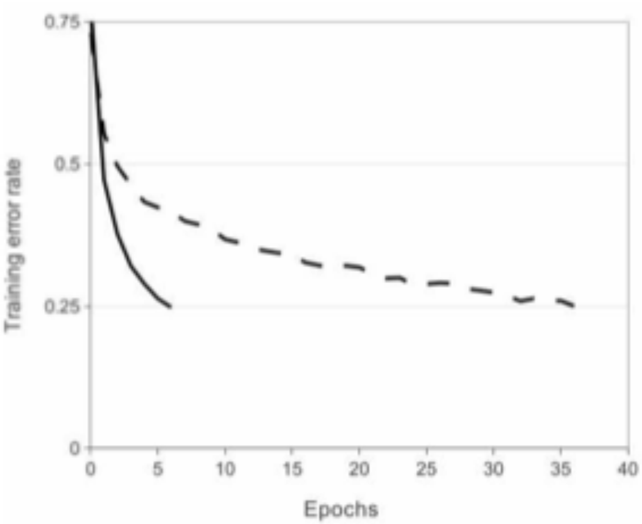


Figure 1: A four-layer convolutional neural network with ReLUs **(solid line)** reaches a 25% training error rate on CIFAR-10 six times faster than an equivalent network with tanh neurons

Source: Krizhevsky et al 2012

Six Times faster Convergence, than traditional approach.

Intuition: Backpropagation

Generell Notes on Optimization

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- Gradient Descent (only first order)
- Newton Taylor Expansion 2nd Order using Hessian
-

Taking a closer look: Learning Rate & Momentum

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- Nice Description [Caffe Tutorial]()
- Nice Visualization:
    - http://danielnouri.org/notes/2014/12/17/using-convolutional-neural-nets-to-detect-facial-keypoints-tutorial/

- Problem with (stochastic) Gradient Descent are Valleys. You bounce up and down the walls and don‘t descent the slope.
    - Solutions Momentum, Nesterov Momentum (NAG)

$$V_{t+1} = \mu V_t - \alpha \nabla L(W_t)$$
$$W_{t+1} = W_t + V_{t+1}$$

$$V_{t+1} = \mu V_t - \alpha \nabla L(W_t + \mu V_t)$$
$$W_{t+1} = W_t + V_{t+1}$$

- Put mu=0 and we have (S)GD

Taking a closer look: Learning Rate & Momentum

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- AdaGrad use all historic information

- Hessian Free Optimizer