Convolutional Neural Networks

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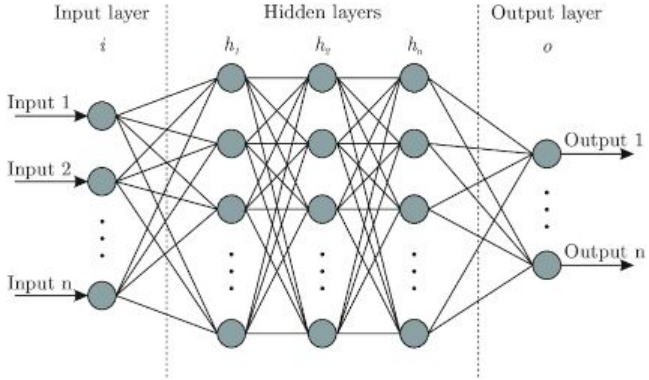
Last time: Multi-layer perceptron



Recap

Data : $(x_1, y_1) \cdots (x_N, y_N)$

Network : $\varphi(x, w)$

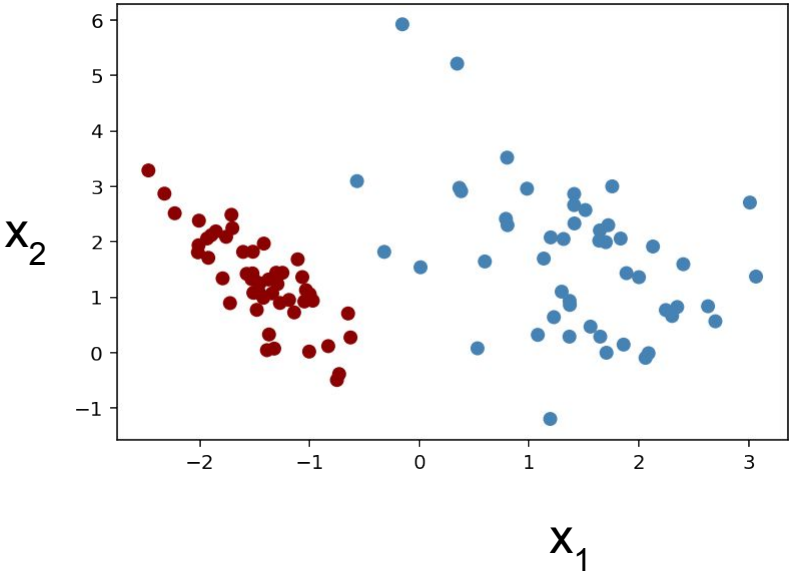
Loss : $\mathcal{L}(\varphi(x_n, w), y_n) = \mathcal{L}_n(w)$

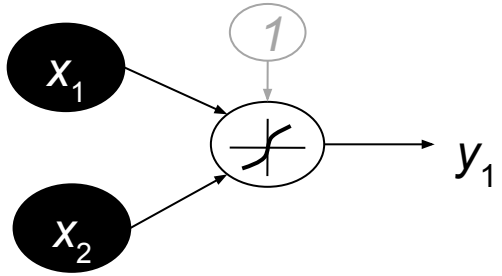
Total objective : $E(w) = \sum_{n=1}^{N} \mathcal{L}_n(w)$

GD : $w' = w - \eta \frac{\partial E}{\partial w}$

Batch Training - Single Layer Linear Classifier Exampl

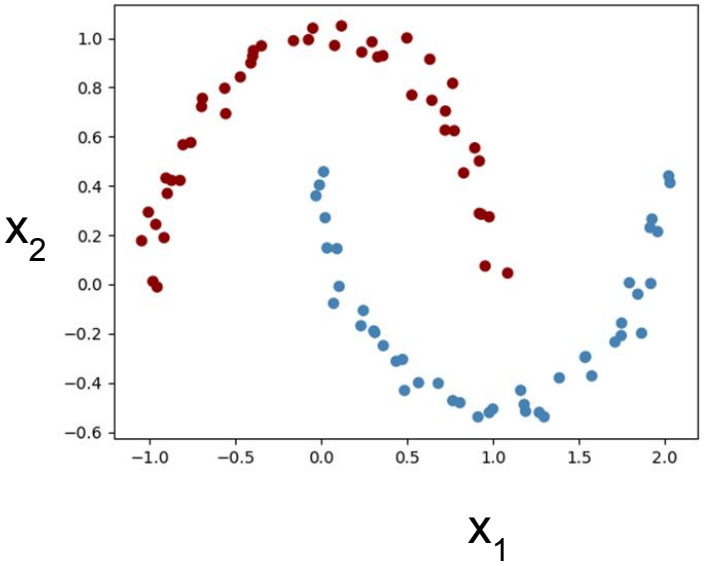
- Linearly separable point clouds

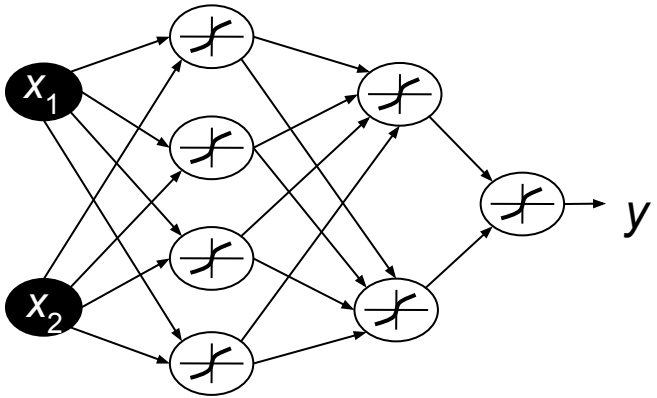




Multilayer Classifier – Example

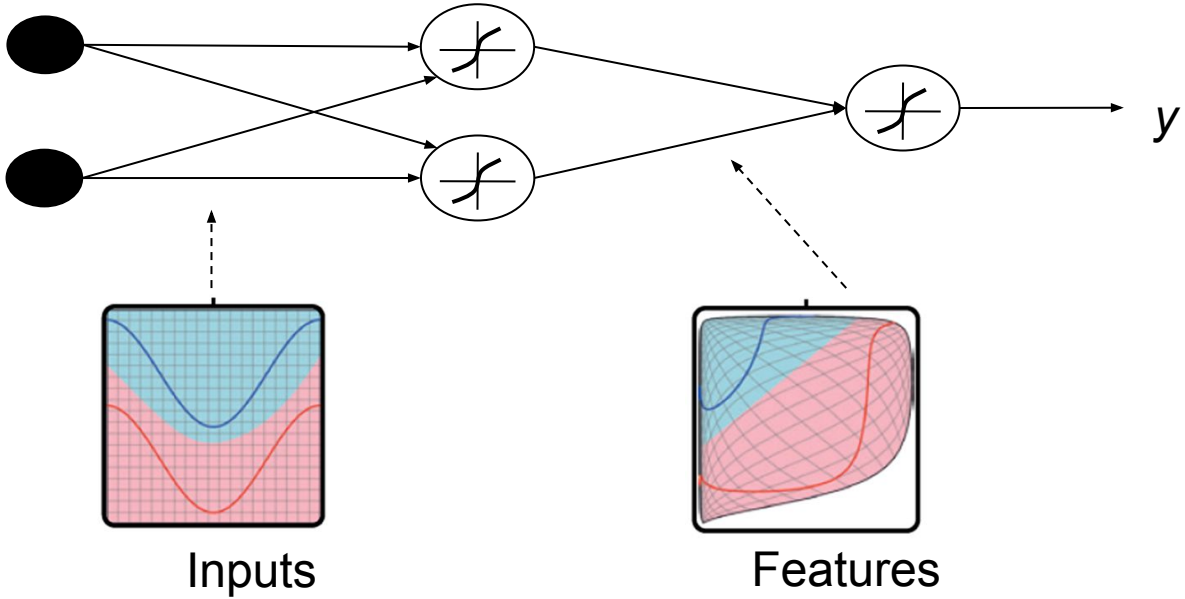
- Non-lineary separable classes





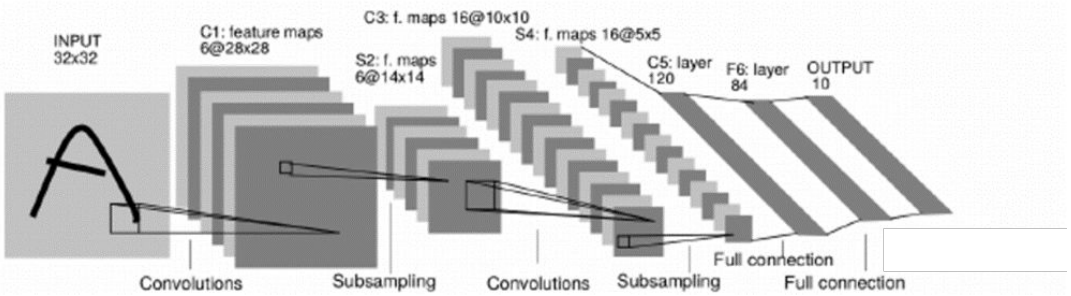
Representation Learning

- The hidden layer(s) produces linearly separable features
- The output layer is a linear classifier

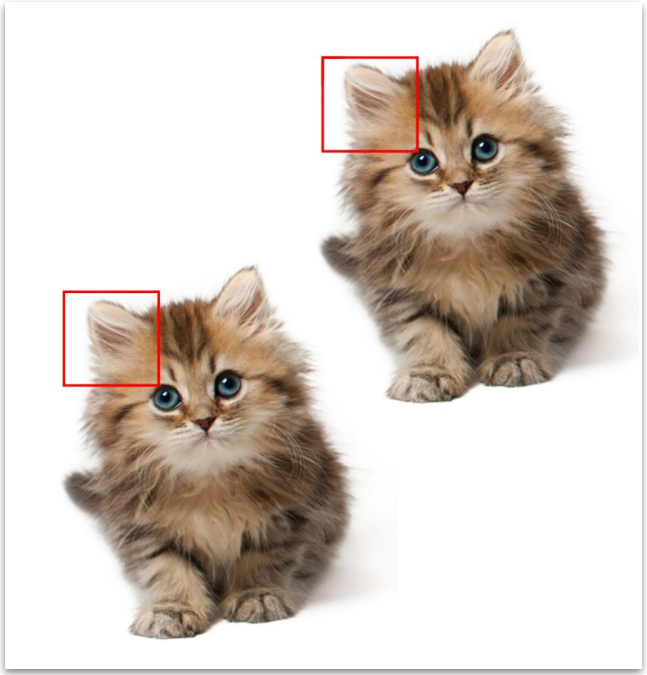


Yann LeCun, Yoshua Bengio, Geoffrey Hinton, “Deep learning”, Nature, Vol 521, 2015

ConvNets

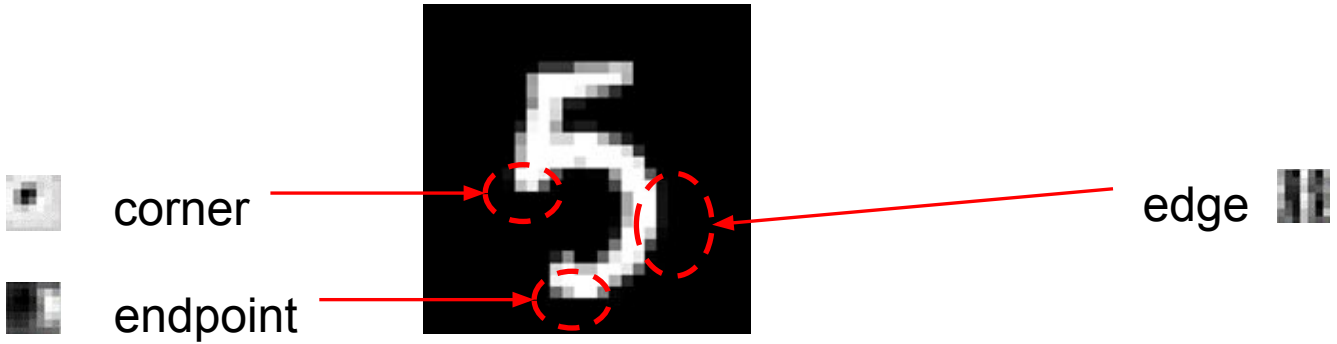

INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection

Equivariance to shift



Feature Learning

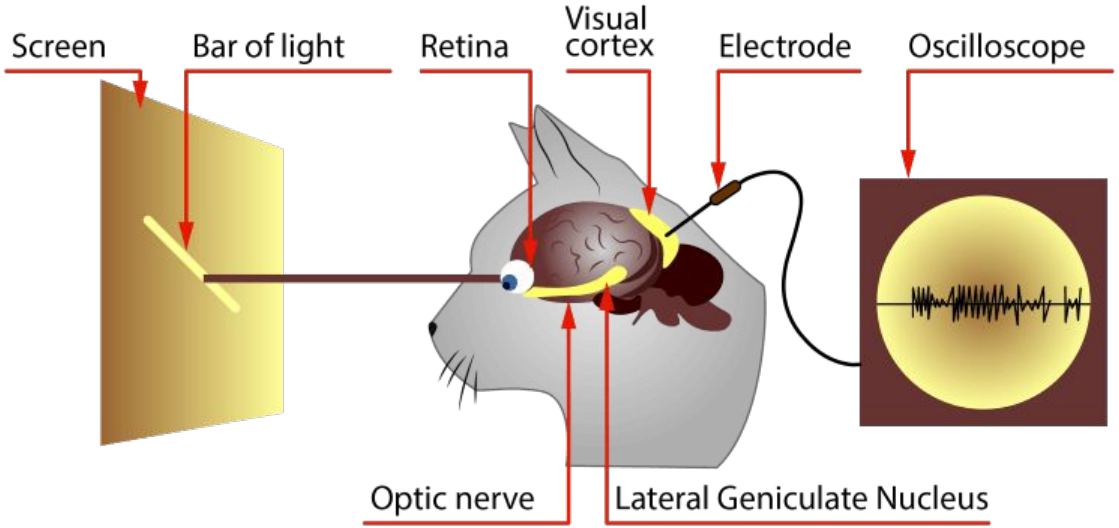
- Images characterized by *features* such as *edges*, *corners*, etc.



We know how to locate keypoints and encode fatures

- Requires ad-hoc feature detector design
- Let the network learn local feature detector(s)
  - Requires new spatial topology-aware neuron structure

The *Hubel* and *Wiesel* experiments ('60s)



Visual cortex neurons acting as specialized **feature** detectors

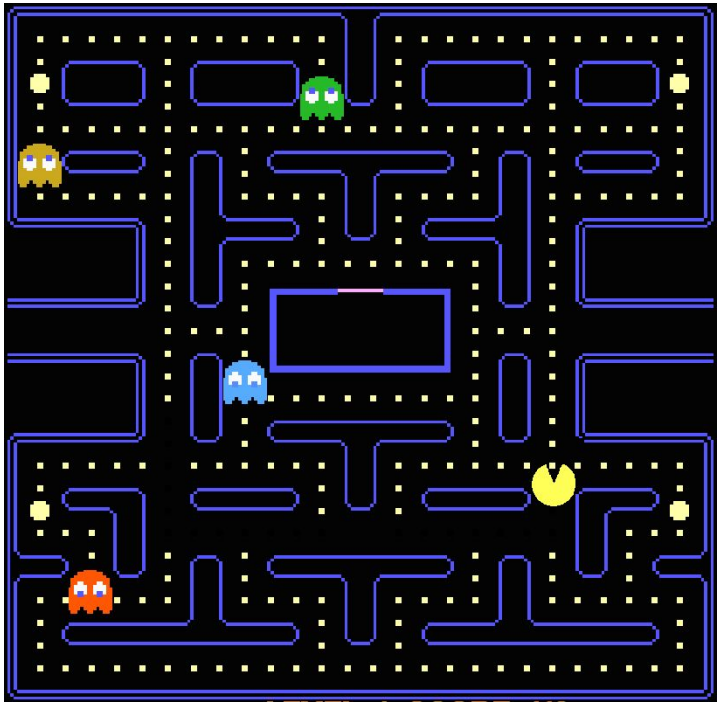
- Some fire upon seeing horizontal lines, others vertical lines
- Some fire upon seeing circles, other squares

The *Hubel* and *Wiesel* experiments ('60s)

Different detectors for different **features** (circles, crosses)

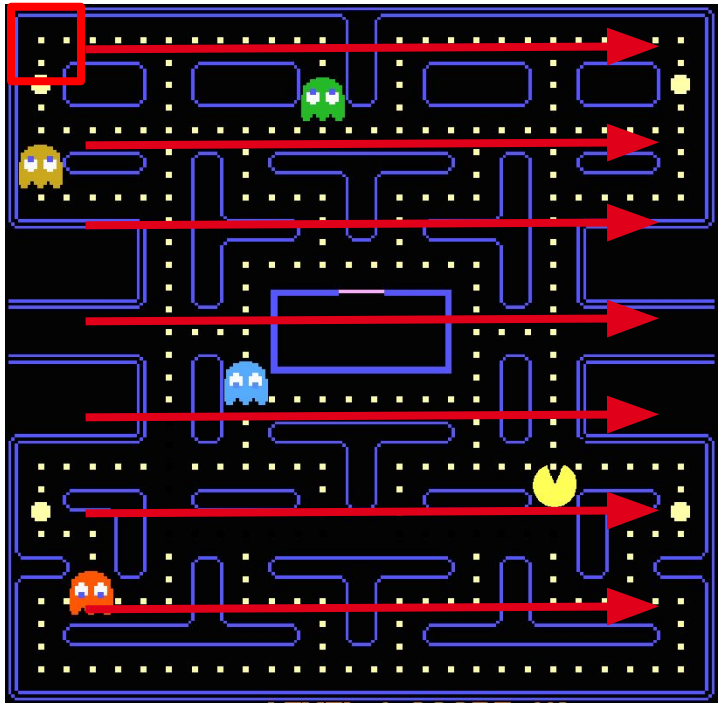
- Watch video with audio (buzz = excited neurons)

Pacman detector



Pacman detector

patches

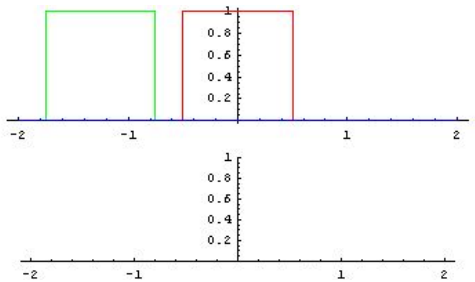


The Convolution Operator

- Usually defined as $k * f$ (k and f continuous functions over x)

$$(k * f)(x) = \int_{t=-+\infty}^{+\infty} k(t) f(x-t) dt$$

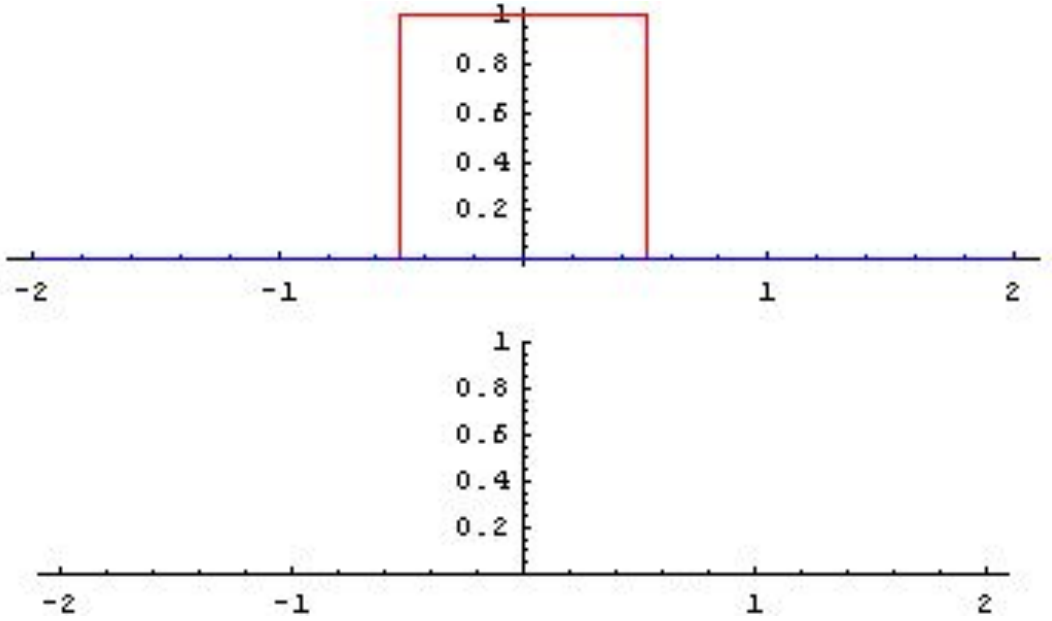
- E.g.: sliding filter (or *kernel*) k applied to signal f



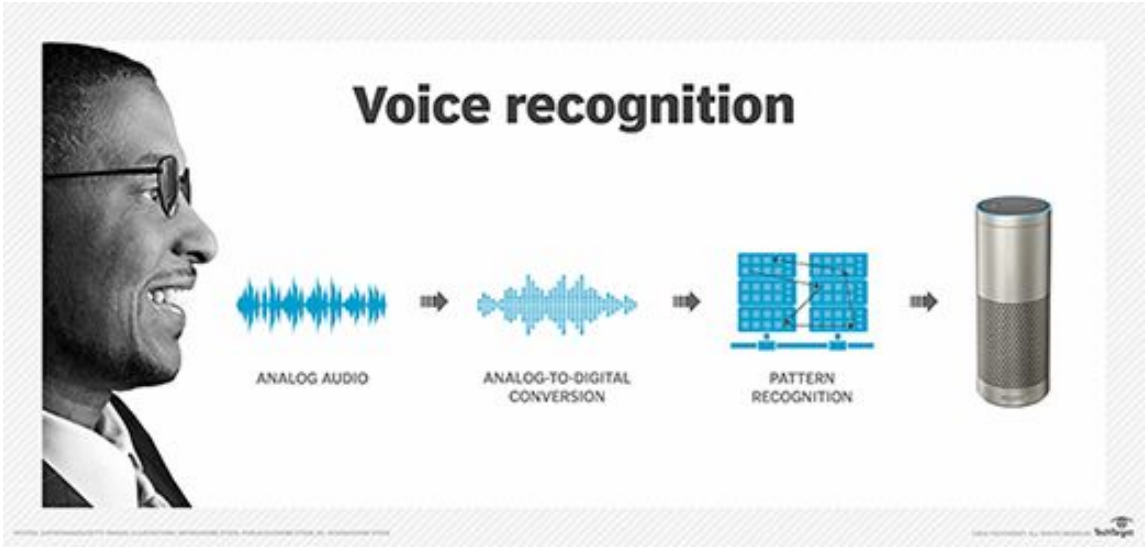
(https://fr.wikipedia.org/wiki/Produit_de_convolution)

The Convolution Operator

$$(k * f)(x) = \int_{t=-\infty}^{+\infty} k(t) f(x-t) dt$$



Example: Speech Recognition



From continuous to discrete

- Continuous: sliding filter (or *kernel*) *k* applied to signal *f*

$$(k * f)(x) = \int_{t=-+\infty}^{+\infty} k(t) f(x-t) dt$$

- Discrete:

$$(k * f)(x) = \sum_{t=-a}^{a} k(t) f(x-t)$$

- 2D:

$$(k * f)(x,y) = \sum_{dx=-a}^{a} \sum_{dy=-b}^{b} k(dx,dy) f(x-dx, y-dy)$$

The 2D Convolution – An Example

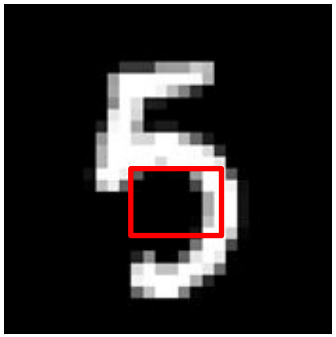
$$(k * f)(x, y) = \sum_{dx=-a}^{a} \sum_{dy=-b}^{b} k(dx, dy) f(x - dx, y - dy)$$

$$\left(\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} * \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \right) [2, 2] = (i \cdot 1) + (h \cdot 2) + (g \cdot 3) + (f \cdot 4) + (e \cdot 5) + (d \cdot 6) + (c \cdot 7) + (b \cdot 8) + (a \cdot 9).$$

The 2D Convolution – An Example

- 5x5 input image crop

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0



- 3x3 filter

1	0	1
0	1	0
1	0	1

$$(k * f)(x, y) = \sum_{dx=-a}^{a} \sum_{dy=-b}^{b} k(dx, dy) f(x - dx, y - dy)$$

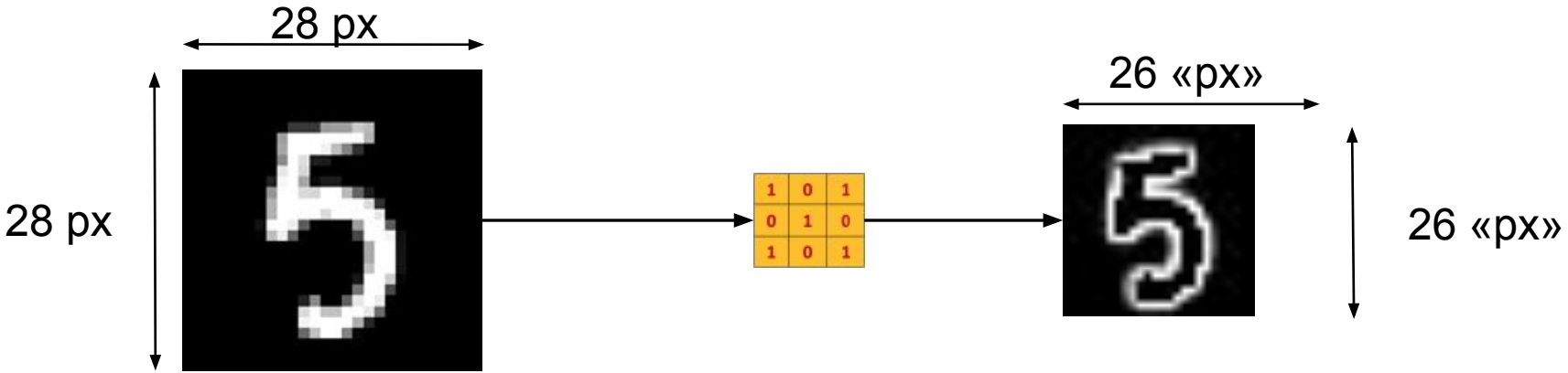
4	3	4
2	4	3
2	3	4

- 3x3 *feature map*

http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

Narrow Convolution

- Feature map smaller than input image

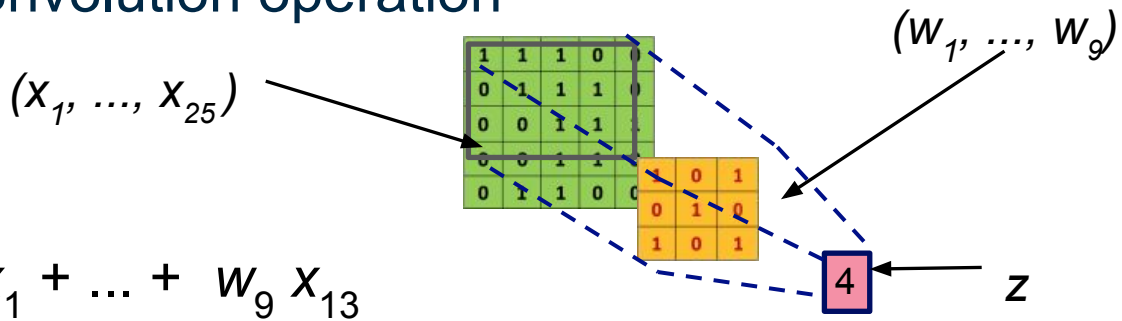


Convolutional Layers – An Example

It’s your turn to play!

The Convolutional Neuron

- 2D convolution operation



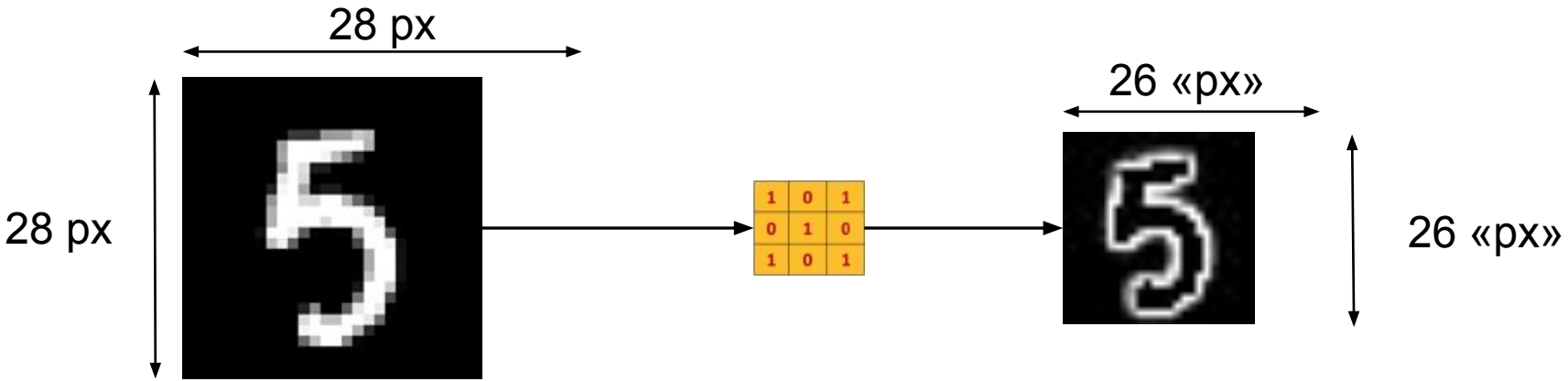
$$z = w_1 x_1 + \ldots + w_9 x_{13}$$

The Convolutional Neuron

- A convolution layer can be seen as a fully connected layer where
  - we impose 0 outside the kernel window
  - the weights are shared over different locations

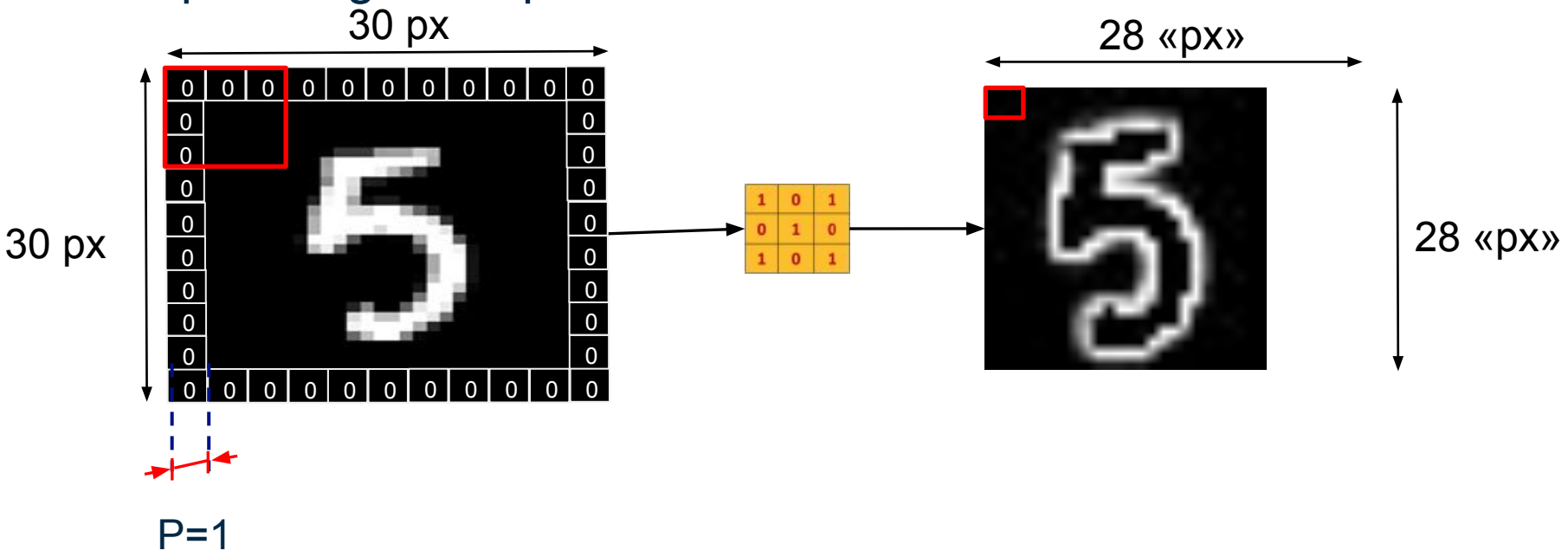
Narrow Convolution

- Feature map smaller than input image



Wide Convolution

- Zero-padding all around image (F=3, S=1, P=1)
  - Input image size preserved



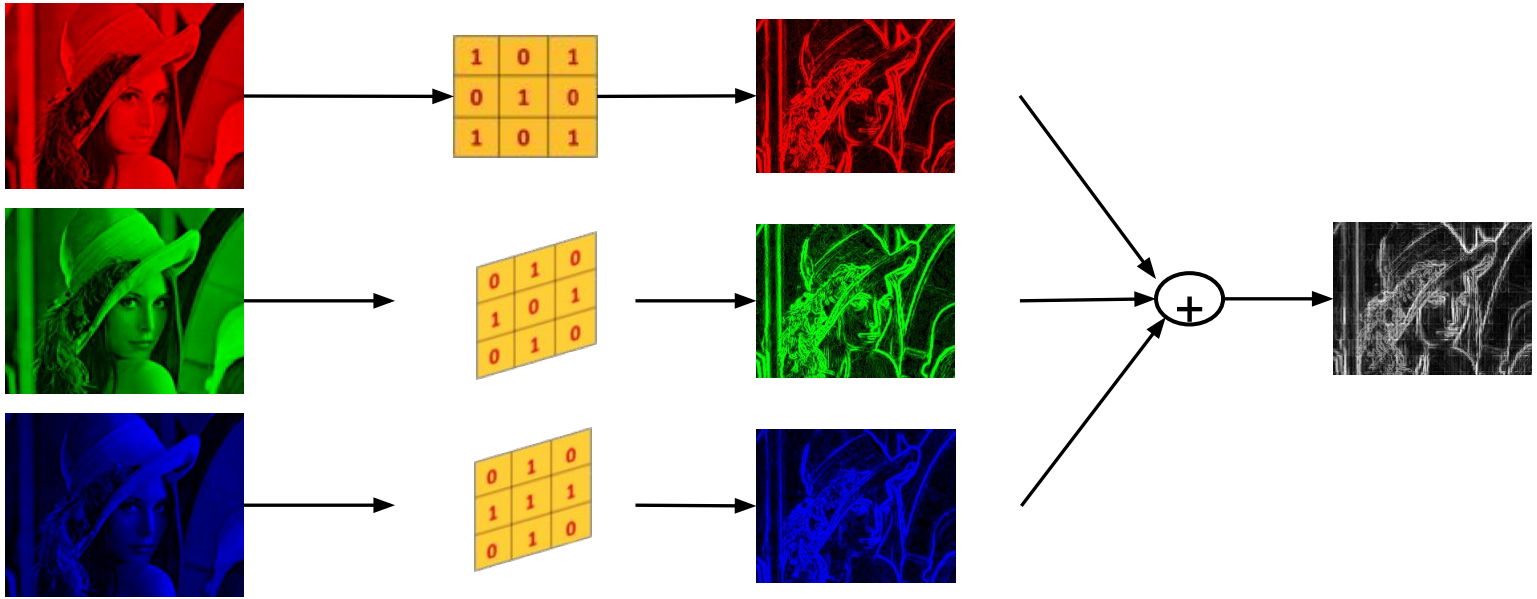
The Convolutional Layer – Multiple Input Channels

- Most images RGB, not grayscale

=

The Convolutional Layer – Multiple Input Channels

- A **different** filter is independently applied to every channel
- Co-located features are summed



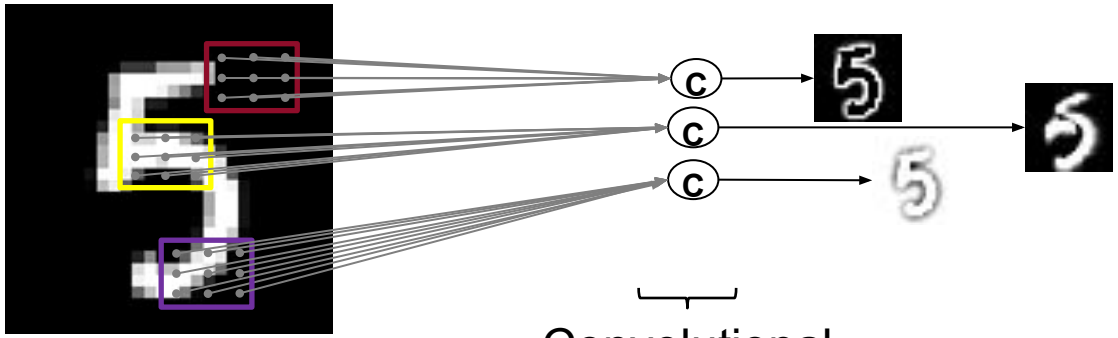
The Convolutional Layer - Complexity

- Number of parameters per FC layer was (e.g., $n_{in} = 28^2$)

  $m * (1+ n)$

- Number of parameters per convolutional layer (e.g., F=3)

  $m * (1+F^2) *$ #channels

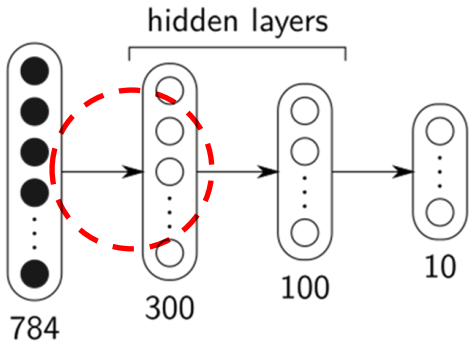


Depends on *number* of input feature maps (*channels*)

Fully Connected *LeNet300*

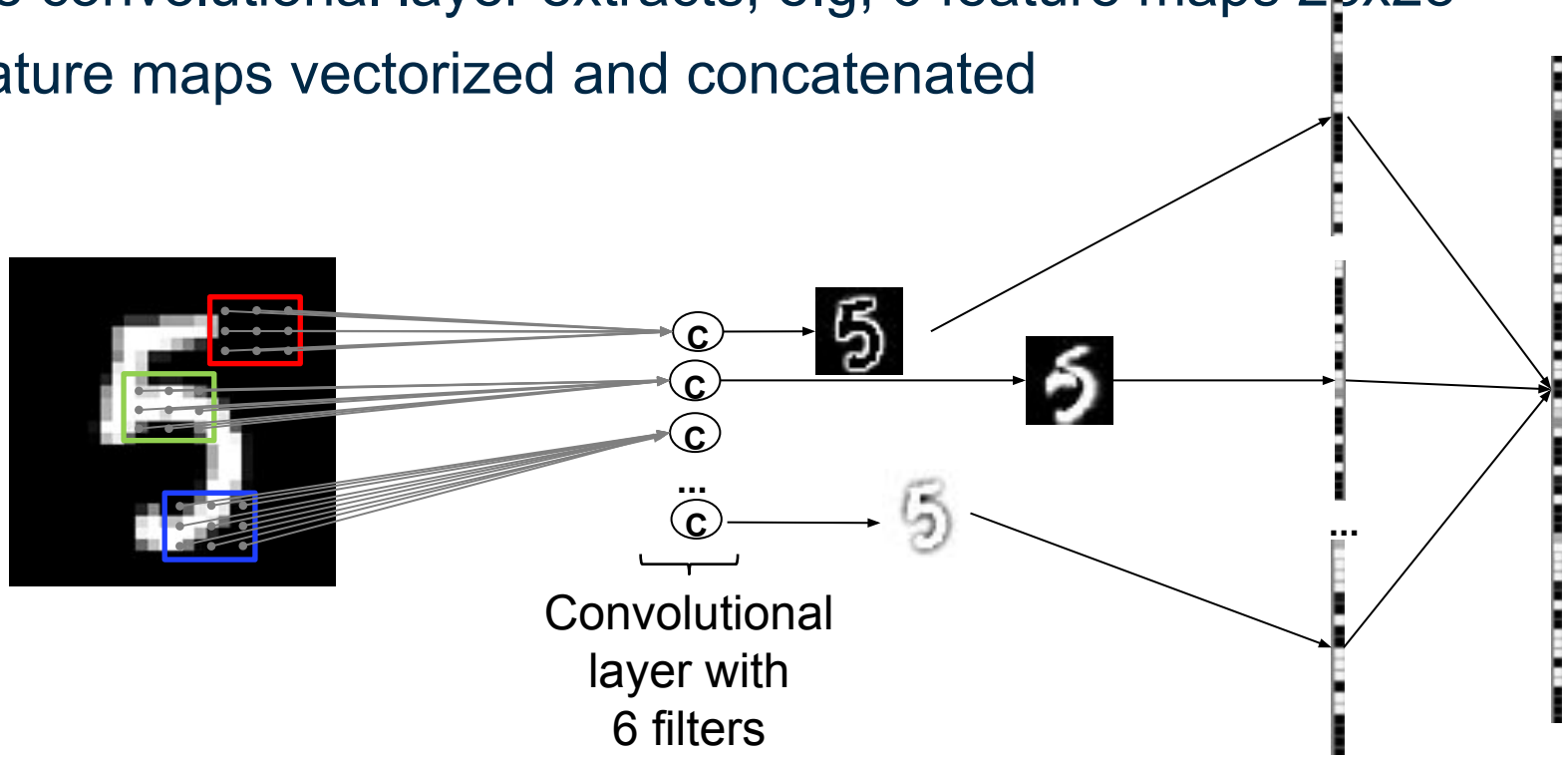
- One of LeNet300 probems was 1st FC layer complexity

	Fully Connected			
Layer	Type	Complexity [prms]		
1	FC-300	300 * (28*28) = 230k		
2	FC-100	100 * 300 = 30k		
3	FC-10	10 * 100 = 1k		



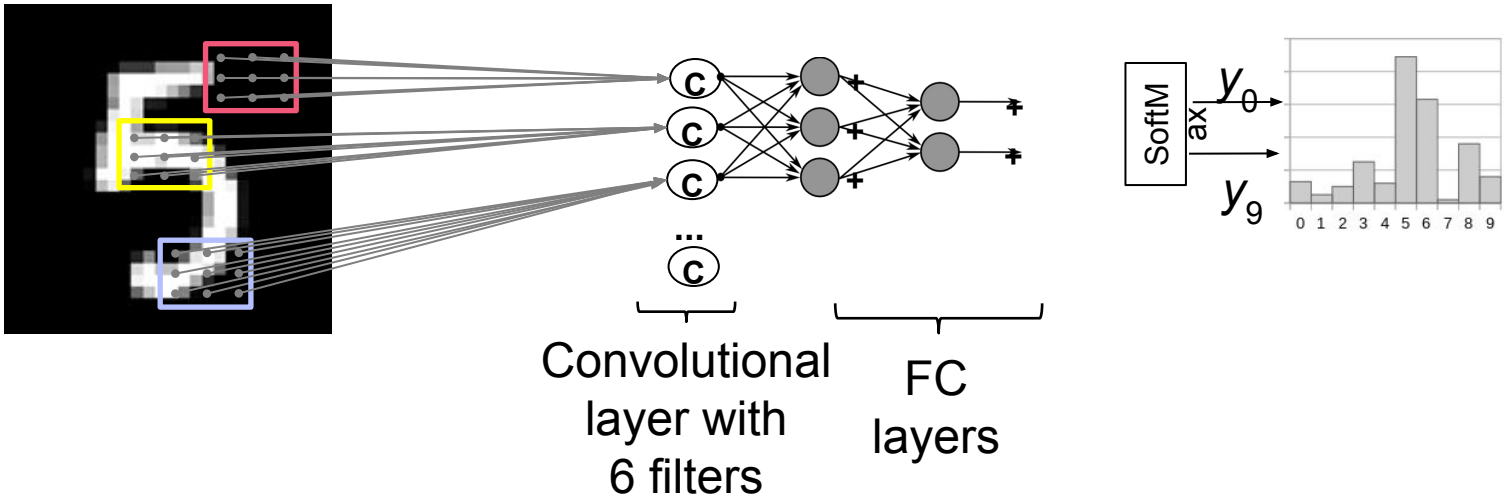
Convolutional *LeNet300*

- One convolutional layer extracts, e.g, 6 feature maps 28x28
- Feature maps vectorized and concatenated



Convolutional *LeNet300*

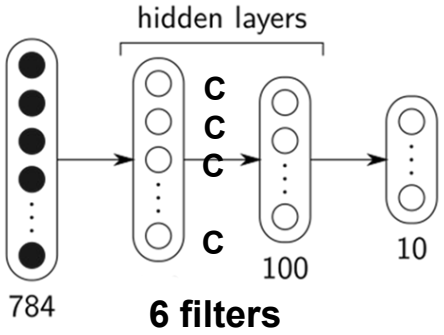
- One convolutional layer extracts, e.g, 6 feature maps 28x28
- Feature maps vectorized and concatenated
- One or more FC layers classify feature maps
- Network output is class probability distribution (C=10)



Convolutional *LeNet300* - Complexity

- 1 st layer complexity drops 230k -> 60 params!

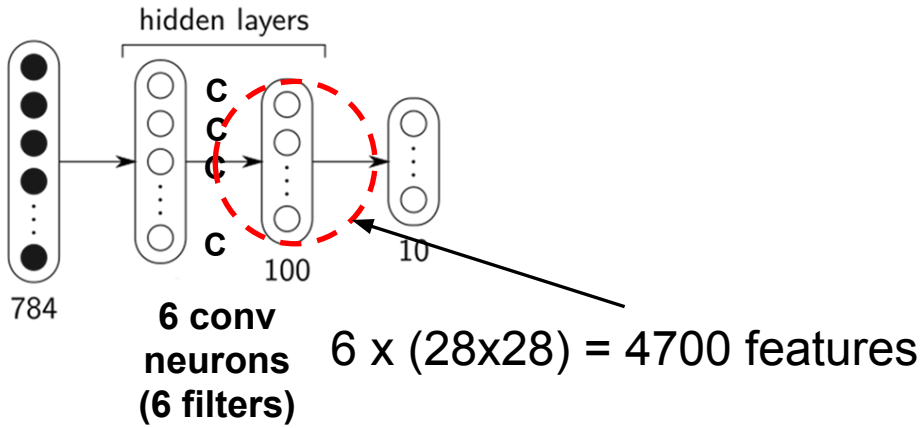
	Fully Connected		Convolutional	
Layer	Type	Complexity [prms]	Type	Complexity [prms]
1	FC-300	300 * (28*28) = 230k	Conv-6	
2	FC-100	100 * 300 = 30k	FC-100	
3	FC-10	10 * 100 = 1k	FC-10	



Convolutional *LeNet300* - Complexity

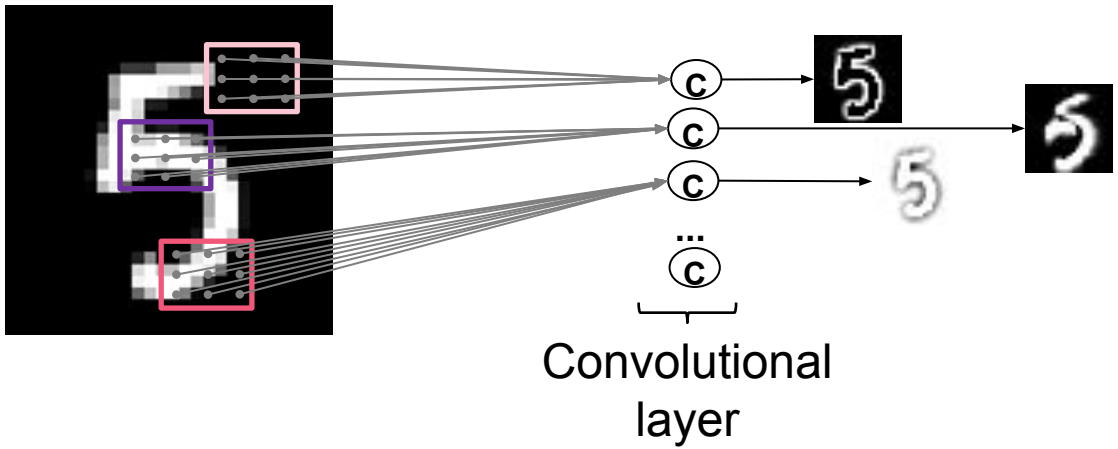
- Total complexity soars 260k -> 400k params!

	Fully Connected		Convolutional	
Layer	Type	Complexity [prms]	Type	Complexity [prms]
1	FC-300	300 * (28*28) = 230k	Conv-6	6 * (5x5 +1) * 1 = 156
2	FC-100	100 * 300 = 30k	FC-100	100 * (6 * (28x28)) = 400k
3	FC-10	10 * 100 = 1k	FC-10	10 * 100 = 1k
	~260k		~400k	



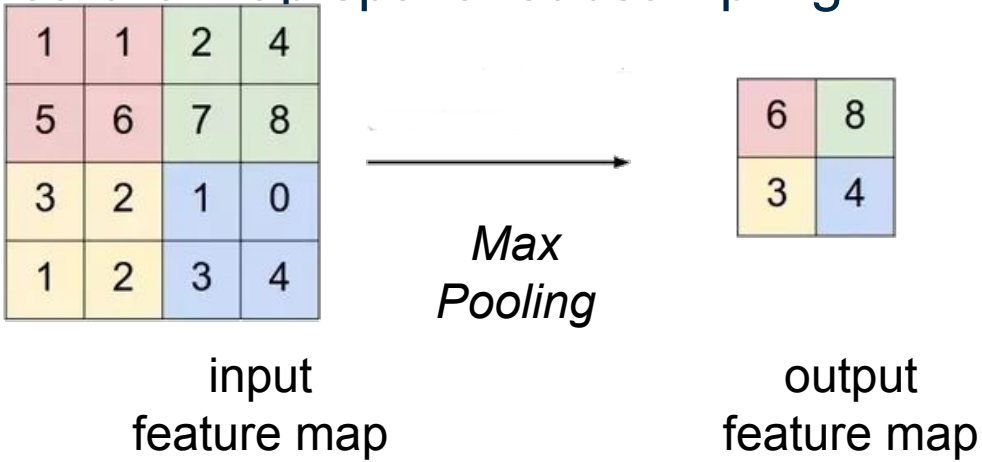
Convolutional *LeNet300*

- Feature maps can be seen as *filtered images*
  - Feature maps can be subsampled as images are



The MaxPooling Layer

- Pick maximum value for each, e.g, 2x2 non-overlapping area
  - Feature map spatial subsampling

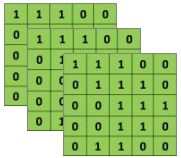


- Why just not averaging ?
  - Maximum response

The Convolve-and-Pool Pattern

- Each Conv layer is followed by MaxPool layer

28x28
image



5x5
filters

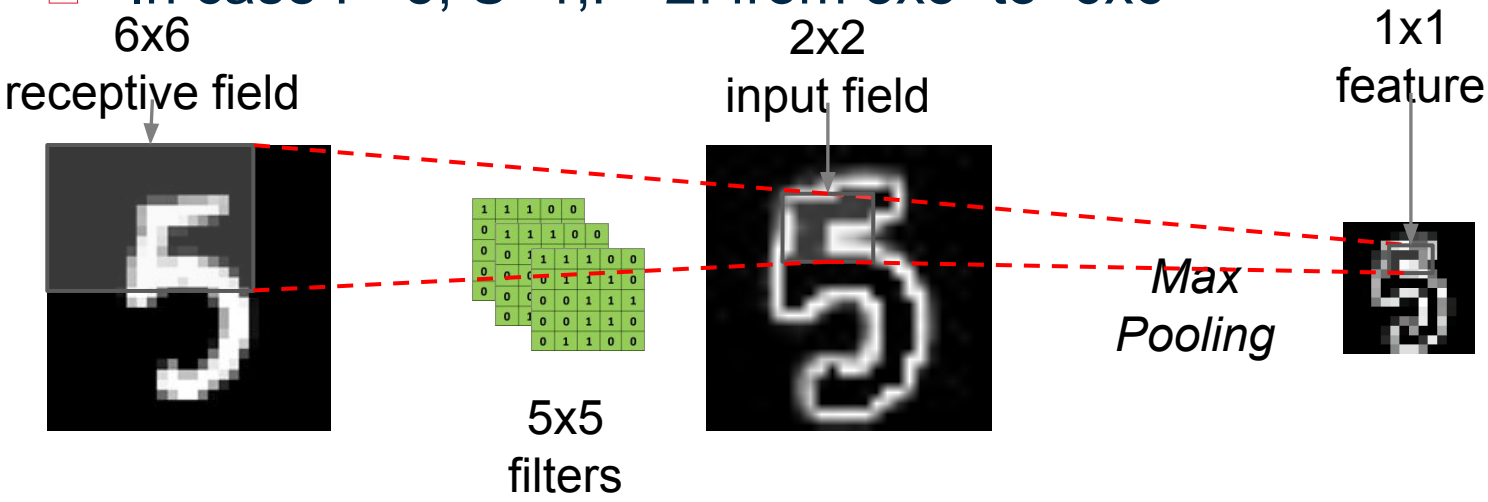
28x28
feature map

Max
Pooling

14x14
feature map

The Convolve-and-Pool Pattern

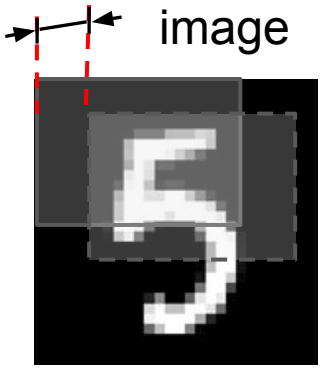
- Each Conv layer is followed by MaxPool layer
- Increases each fature *receptive field*
  - In case F=5, S=1,P=2: from 5x5 to 6x6



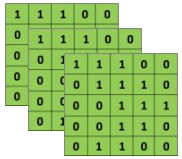
The Convolve-with-Stride Pattern

- Each Conv has stride S=2, no MaxPooling
  - No non-maxima suppression
  - Standard in recent architectures

S=2



28x28
image



5x5
filters

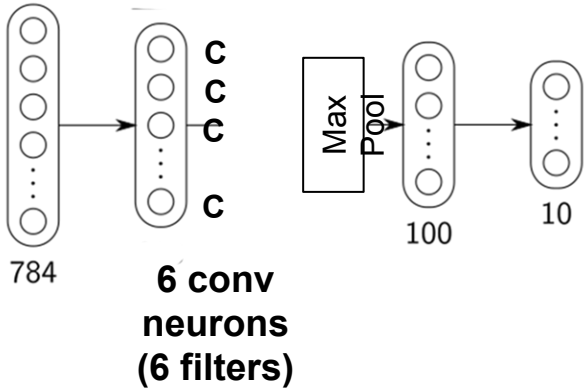
14x14
feature map

Convolutional *LeNet300* - Complexity

- Complexity from ~260k to ~160k params thanks to *Maxpooling*

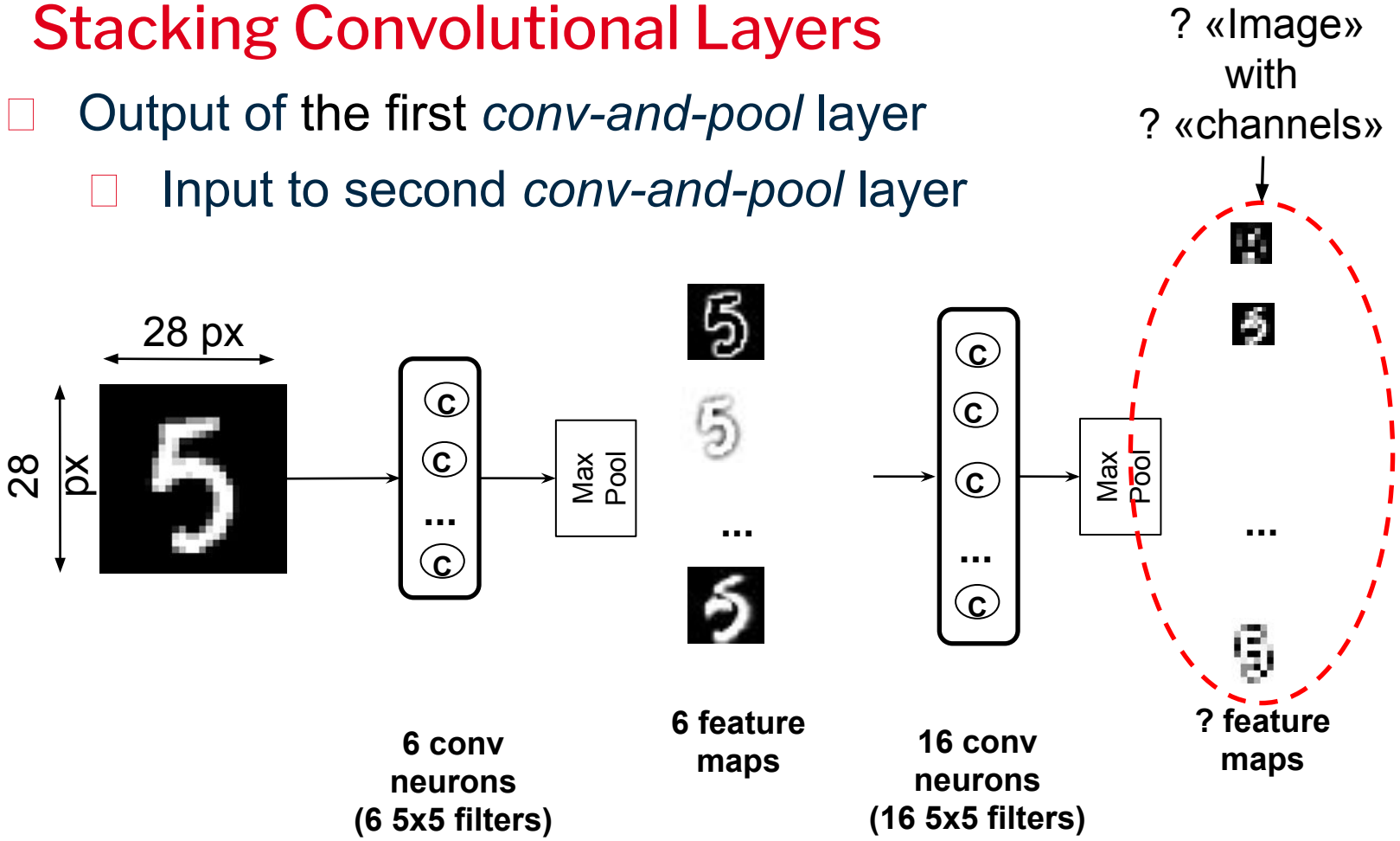
	Fully Connected		Convolutional	
Layer	Type	Complexity [prms]	Type	Complexity [prms]
1	FC-300	300 * (28*28) = 230k	Conv-6	6 * (5x5 +1) * 1 = 156
2	FC-100	100 * 300 = 30k	FC-100	100 * (6 * (14x14)) = ~~400k~~
3	FC-10	10 * 100 = 1k	FC-10	10 * 100 = 1k
Tot	~260k		~118k	

117k



Stacking Convolutional Layers

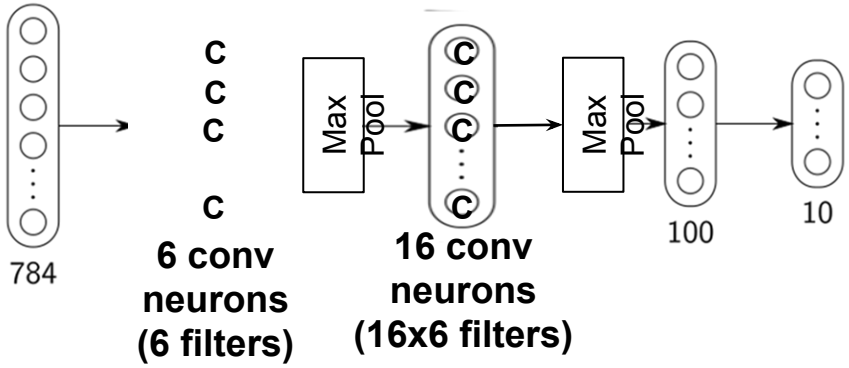
- Output of the first *conv-and-pool* layer
  - Input to second *conv-and-pool* layer



Convolutional *LeNet300* - Complexity

- Total complexity drops from ~260k to ~82k params

	Fully Connected		Convolutional	
Layer	Type	Complexity [prms]	Type	Complexity [prms]
1	FC-300	300 * (28*28) = 230k	Conv-6	6 * (5x5 +1) * 1 = 156
2	FC-100	100 * 300 = 30k	Conv-16	16 * (5x5 +1) * 6 = 2496*
3			FC-100	100 * ((16 * 7x7) +1) = 78k
4	FC-10	10 * 100 = 1k	FC-10	10 * 100 = 1k
Tot	~260k		~82k	



Convolutional *LeNet300* – Performance

- Experiments on MNIST 32x32 dataset

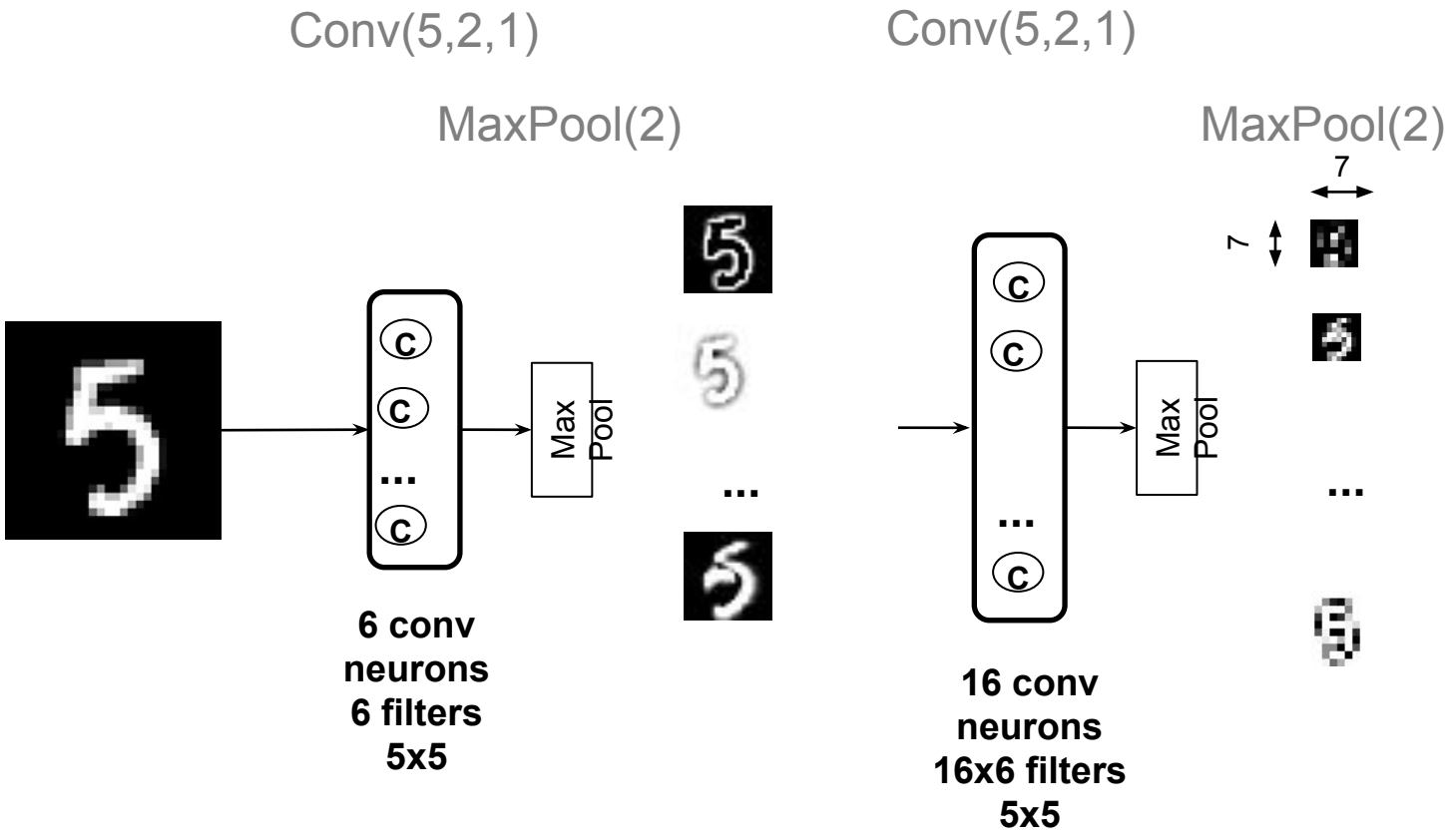
Network	Num. Layers	Error [%]
Fully connected LeNet300	1 FC output layer (10 U)	12.0
	1 hidden FC (300 U), 1 output FC (10 U)	4.7
	2 hidden FCs (300 + 100 U), 1 output FC (10 U)	3.05
Convol. LeNet300	2 Conv (3 F), 1 output FC (*LeNet1)*	1.7
	2 conv (6+16 F), 3 FC layer	0.95

Better performance for lower complexity

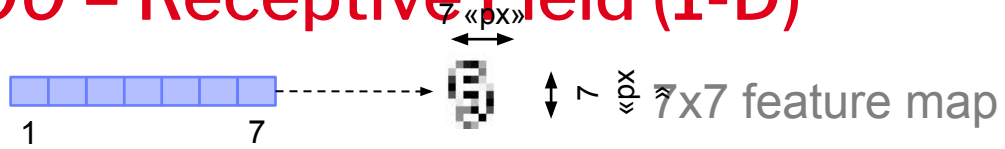
Convolutional *LeNet300* – Reflexions

- The convolutional LeNet300 performs better than its fully connnected counterpart despite:
  - it has fewer parameters due to the convolutional layers
  - the filters are not big enough (5x5) to capture an entire digit (at least 20x20 pixels in a 32x32 image)
- Let us define at the *receptive field*
  - The *receptive field of a feature* is its *back-projection* through the pooling and convolutional layers within the input image

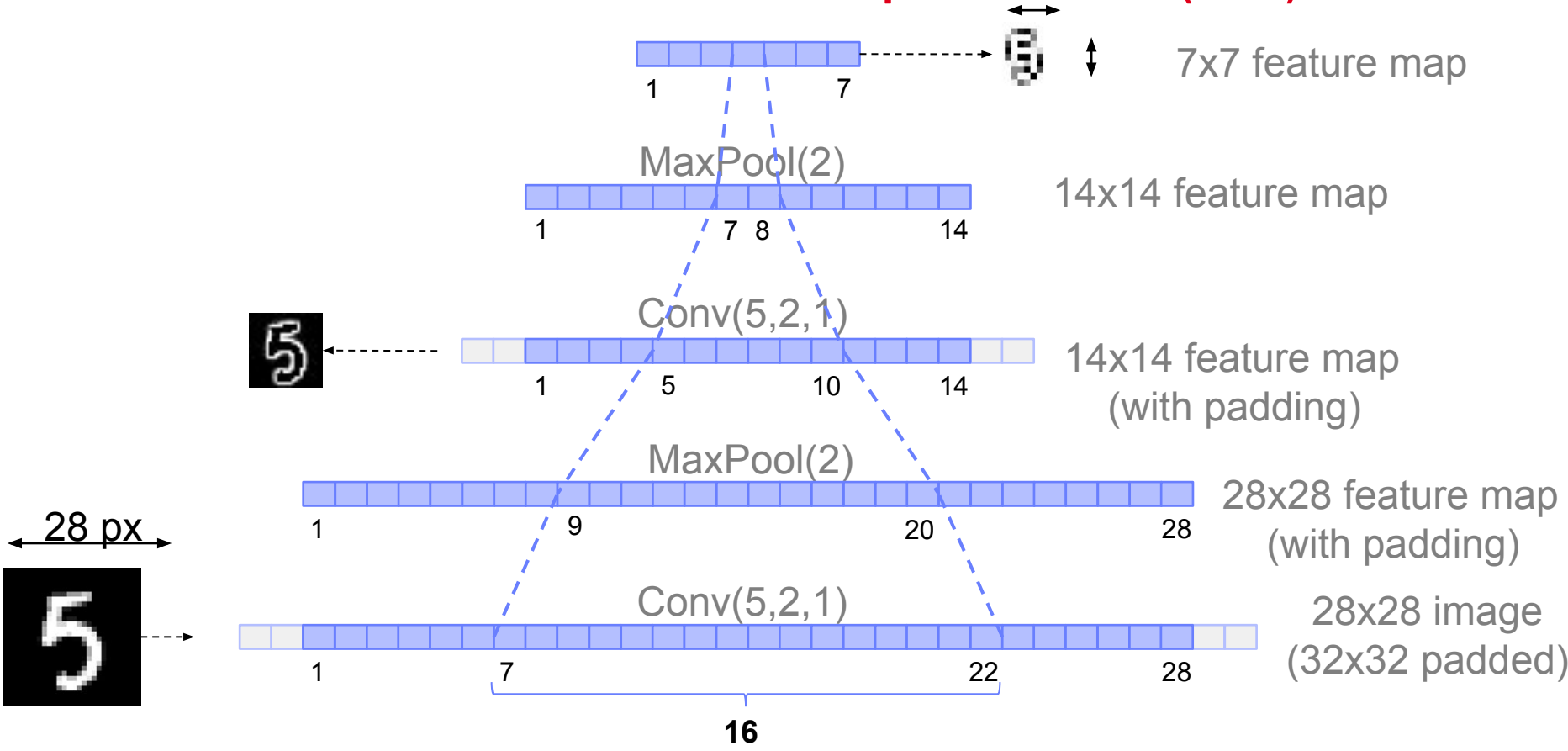
Convolutional *LeNet300* – Receptive Field



Convolutional *LeNet300* – Receptive Field (1-D)

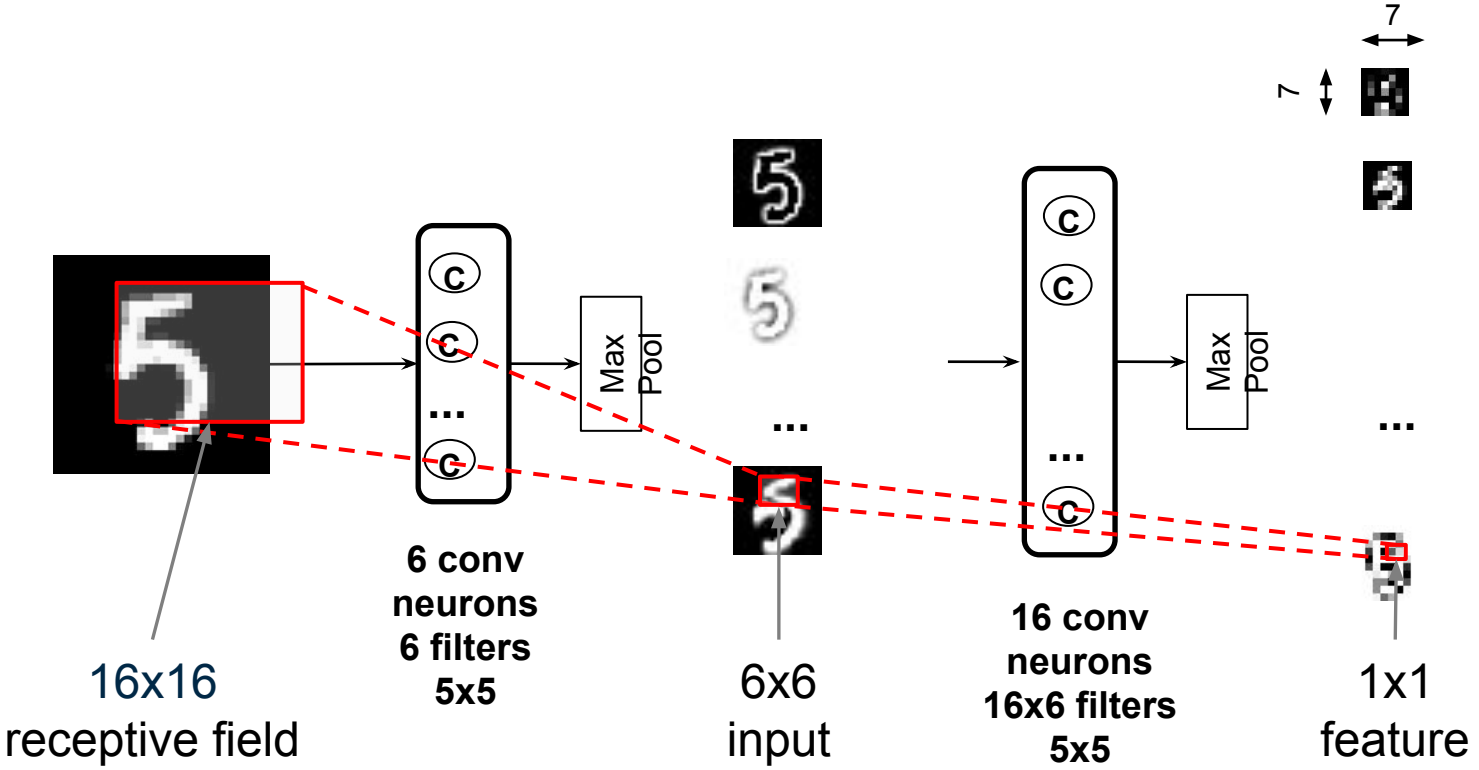


Convolutional *LeNet300* – Receptive Field (1-D)

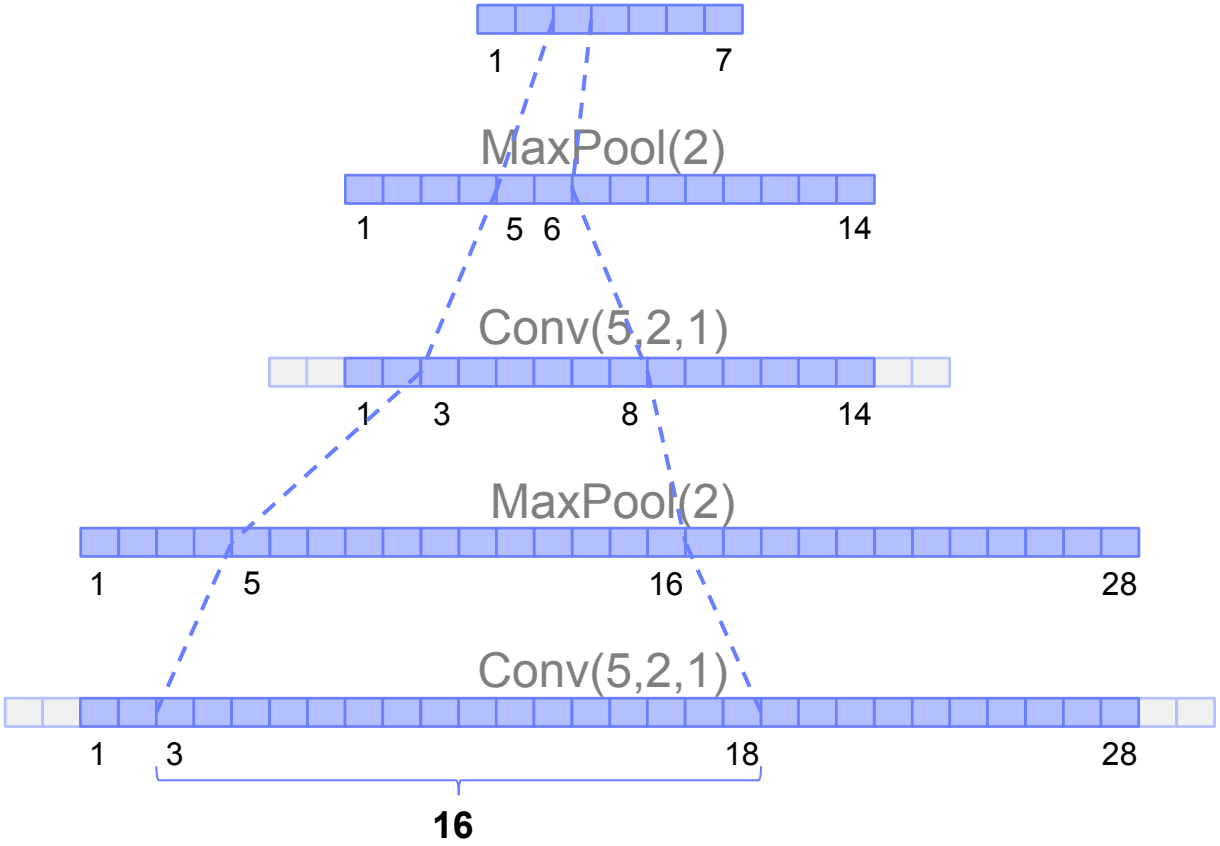


Convolutional *LeNet300* – Receptive Field

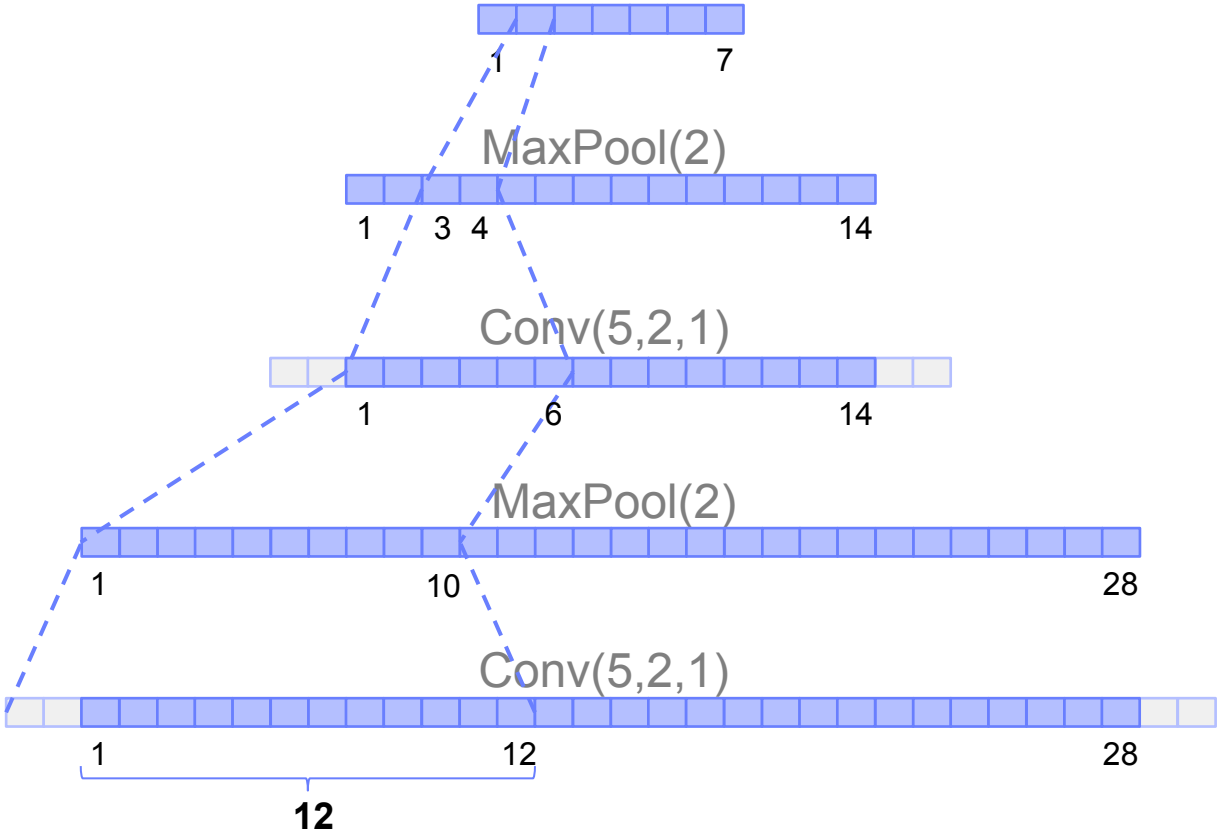
- This holds for *central* features in the last feature map



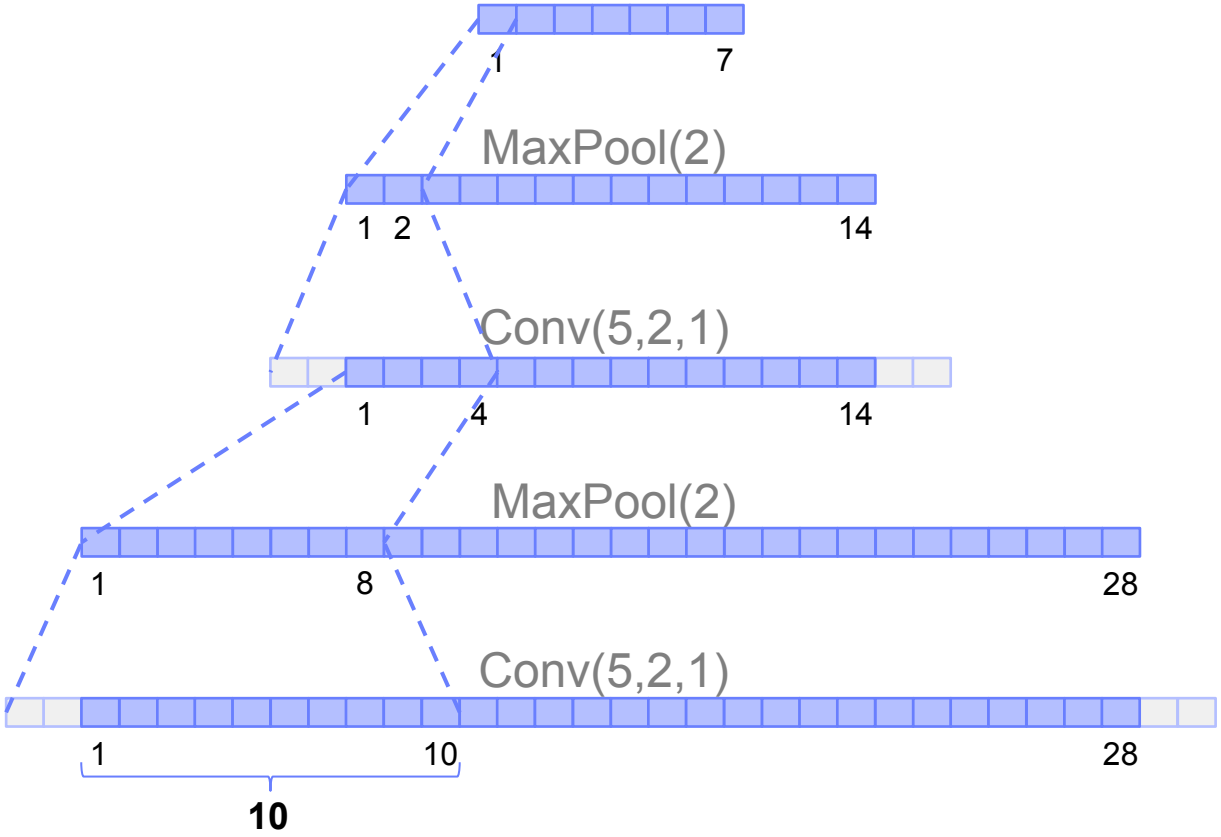
Convolutional *LeNet300* – Receptive Field (1-D)



Convolutional *LeNet300* – Receptive Field (1-D)



Convolutional *LeNet300* – Receptive Field (1-D)



Convolutional *LeNet300* – Receptive Field (1-D)

- Not all pixels contribute to the final FMs equally
  - Pixels on the border contribute less

	Pixel																											
FM#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	1	1	1	1	1	1	1	1	1	1																		
2	1	1	1	1	1	1	1	1	1	1	1	1																
3			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										
4							1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1						
5											1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
6																	1	1	1	1	1	1	1	1	1	1	1	1
7																			1	1	1	1	1	1	1	1	1	1
Tot	2	2	3	3	3	3	4	4	4	4	4	4	3	3	3	3	4	4	4	4	4	4	3	3	3	3	2	2

Receptive field computation for convnets https://distill.pub/2019/computing-receptive-fields/

Convolutional *LeNet300* – Receptive Field (1-D)

- Not all pixels contribute to the final FMs equally
  - Pixels on the border contribute less
- Narrow convolution input stride 2 ^ #maxpools
  - Features only partially overlap

	Pixel																										
FM#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	1	1	1	1	1	1	1	1	1	1																		
2	1	1	1	1	1	1	1	1	1	1	1	1																
3			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										
4							1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1						
5											1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
6																	1	1	1	1	1	1	1	1	1	1	1	1
7																			1	1	1	1	1	1	1	1	1	1
Tot	2	2	3	3	3	3	4	4	4	4	4	4	3	3	3	3	4	4	4	4	4	4	3	3	3	3	2	2

4

4

6

Receptive field computation for convnets https://distill.pub/2019/computing-receptive-fields/

Convolutional *LeNet300* – Receptive Field (1-D)

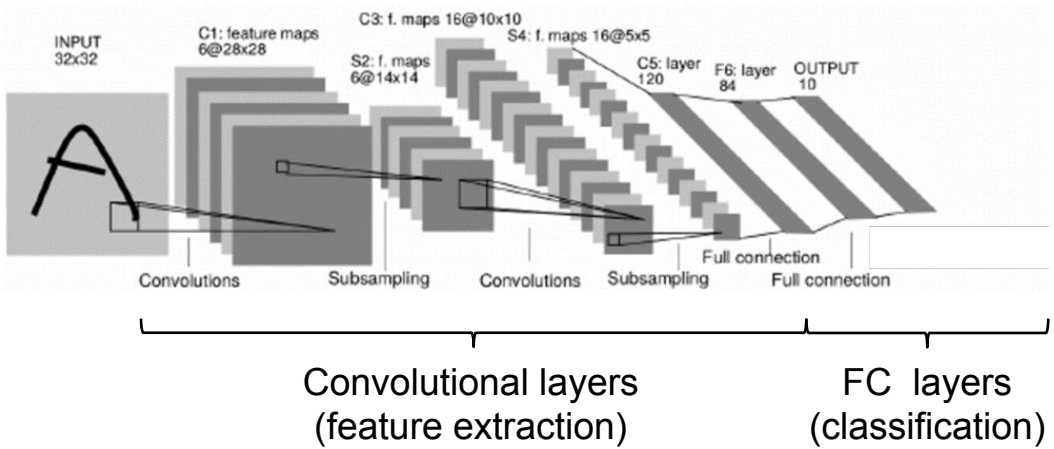
- Not all pixels contribute to the final FMs equally
  - Pixels on the border contribute less
- Narrow convolution input stride 2 ^ #maxpools
  - Features only partially overlap
- Receptive field up to 16x16
- Possible to detect features larger than filters

	Pixel																											
FM#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	1	1	1	1	1	1	1	1	1	1																		
2	1	1	1	1	1	1	1	1	1	1	1	1																
3			1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										
4							1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1						
5											1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
6																	1	1	1	1	1	1	1	1	1	1	1	1
7																			1	1	1	1	1	1	1	1	1	1
Tot	2	2	3	3	3	3	4	4	4	4	4	4	3	3	3	3	4	4	4	4	4	4	3	3	3	3	2	2

Receptive field computation for convnets https://distill.pub/2019/computing-receptive-fields/

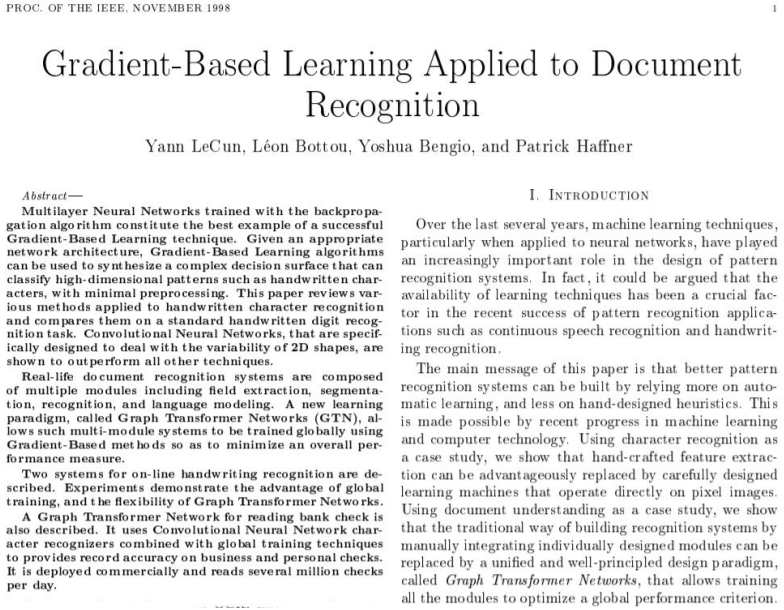
Convolutional Networks – LeNet5

- Stacked sigmoid convolutional layers for feature extraction
- Repeated *convolve-and-pool* pattern
- Multiple FC layer for classification



Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, November 1998 (PDF available online)

Gradient-Based Learning Applied to Document Recognition



Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Abstract—

Multilayer Neural Networks trained with the backpropagation algorithm constitute the best example of a successful Gradient-Based Learning technique. Given an appropriate network architecture, Gradient-Based Learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional Neural Networks, that are specifically designed to deal with the variability of 2D shapes, are shown to outperform all other techniques.

Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition, and language modeling. A new learning paradigm, called Graph Transformer Networks (GTN), allows such multi-module systems to be trained globally using Gradient-Based methods so as to minimize an overall performance measure.

Two systems for on-line handwriting recognition are described. Experiments demonstrate the advantage of global training, and the flexibility of Graph Transformer Networks.

A Graph Transformer Network for reading bank check is also described. It uses Convolutional Neural Network character recognizers combined with global training techniques to provides record accuracy on business and personal checks. It is deployed commercially and reads several million checks per day.

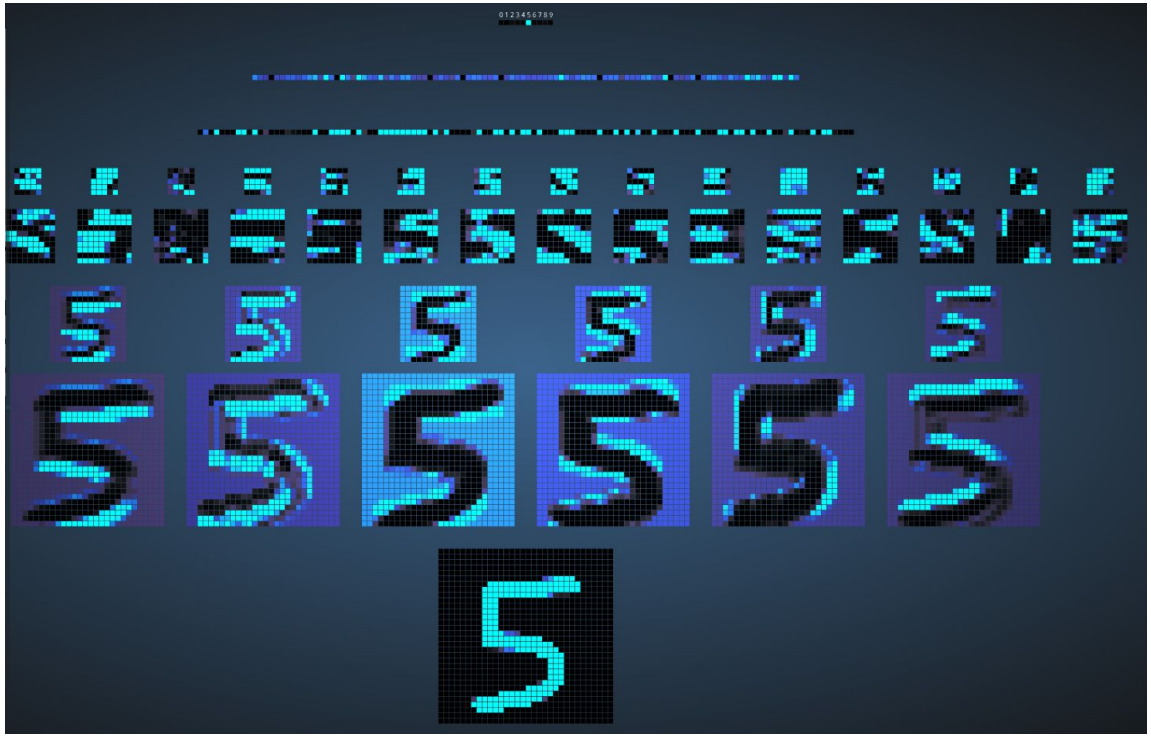
I. Introduction

Over the last several years, machine learning techniques, particularly when applied to neural networks, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability of learning techniques has been a crucial factor in the recent success of pattern recognition applications such as continuous speech recognition and handwriting recognition.

The main message of this paper is that better pattern recognition systems can be built by relying more on automatic learning, and less on hand-designed heuristics. This is made possible by recent progress in machine learning and computer technology. Using character recognition as a case study, we show that hand-crafted feature extraction can be advantageously replaced by carefully designed learning machines that operate directly on pixel images. Using document understanding as a case study, we show that the traditional way of building recognition systems by manually integrating individually designed modules can be replaced by a unified and well-principled design paradigm, called *Graph Transformer Networks*, that allows training all the modules to optimize a global performance criterion.

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, November 1998 (PDF available online)

Convolutional Networks – Visualized



http://scs.ryerson.ca/~aharley/vis/conv/flat.html

Convolutional Network Demo from 1993 – LeNet1

This is a demo of LeNet 1, the first convolutional network that could recognize handwritten digits with good speed and accuracy […] developed between 1988 and 1993 […] at Bell Labs in Holmdel, NJ. This "real time" demo shows ran on a DSP card sitting in a 486 PC with a video camera and frame grabber card. The DSP card had a […] 32-bit floating-point DSP and could reach an amazing 12.5 million multiply-accumulate operations per second. Shortly after […], we started working with a development group and a product group at NCR (then a subsidiary of AT&T). NCR soon deployed ATM machines that could read the numerical amounts on checks, initially in Europe and then in the US. At some point in the late 90's these machines were processing 10 to 20% of all the checks in the US.

Y. LeCun “Convolutional Network Demo from 1993” (https://www.youtube.com/watch?v=FwFduRA_L6Q)

References – Most Relevant

- Y.LeCun, Y.Bengio, G.Hinton, *Deep Learning,* Nature, 2015
  see shared material folder
- Andrej Karpathy's CNN online course
  http://cs231n.github.io/
- Yann LeCun's 1998 paper on CNNs
  Gradient-Based Learning Applied to Document Recognition
  see shared material folder
- I. Goodfellow, Y. Bengio, A. Courville Deep Learnig
  https://www.deeplearningbook.org/

Questions ?

Quiz:

- Mini-bach vs batch
- Momentum
- Kernel size
- Number of channel
- Padding
- Stride

Avoiding Overfit: Regularization

- How to avoid overfit ?
  - Early stop: require a validation set : Split annotated dataset into *train, validation* and *test* samples
    - E.g: 60% train, 20% validation and 20% test
  - Lower capacity/complexity model (fewer parameters)
    - Still suitable for problem ?
  - Introduce regularization factor λ

    $J(\mathbf{w}) = E(\mathbf{w}) + \lambda R(\mathbf{w})$

Regularizer

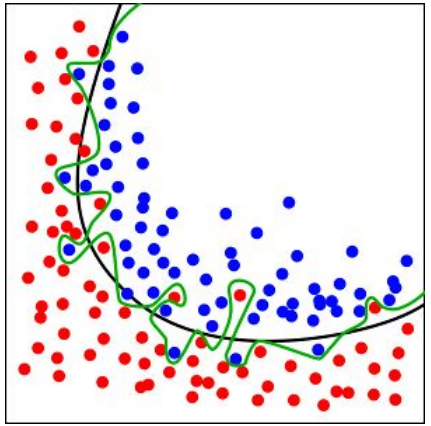
- Introduce a regularization term R(w)

$$R(w) = ||w||_2^{\ 2}$$

- Minimize J = E + *regularization* term R(w)

$$J = E\,(w,x) + \lambda\, R(w)$$

- Effect
  - *Penalizes* solutions with large weights
  - *Promotes* solutions with smaller weights



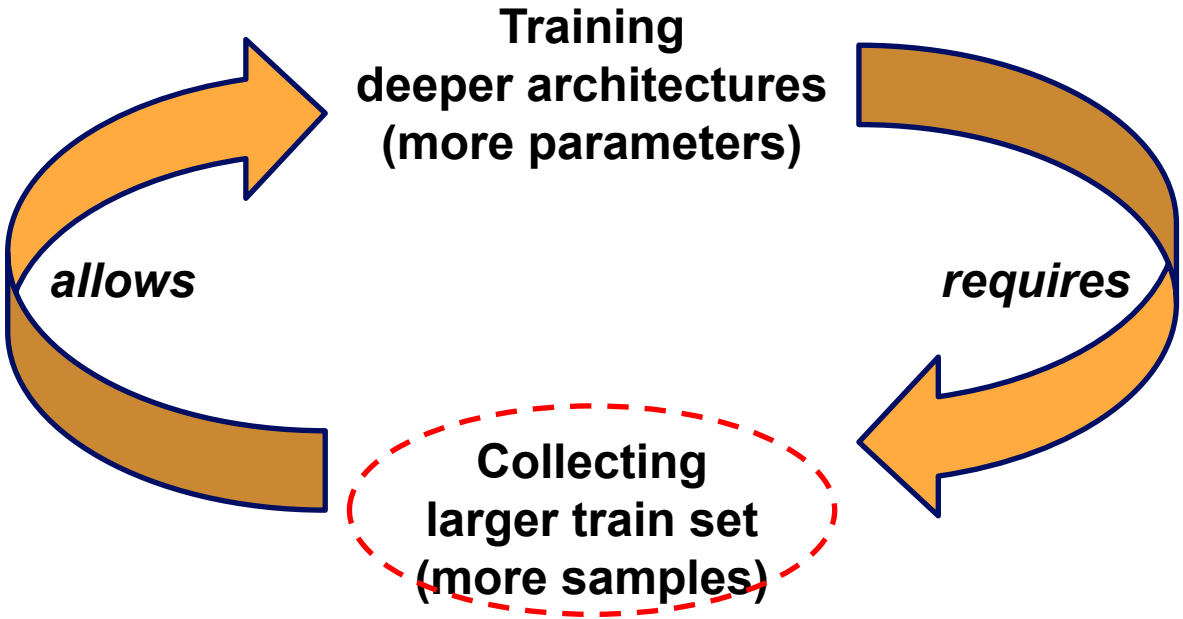
Avoiding Overfit

- How to avoid overfit ?
  - Lower capacity/complexity model (fewer parameters)
    - Still suitable for problem ?
  - Introduce regularization factor λ

    $J(\boldsymbol{w},\boldsymbol{x}) = E(\boldsymbol{w},\boldsymbol{x}) + \lambda R(\boldsymbol{w})$
  - Improve train set
    - Data augmentation

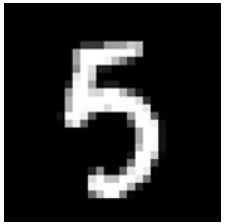
Dataset Augmentation

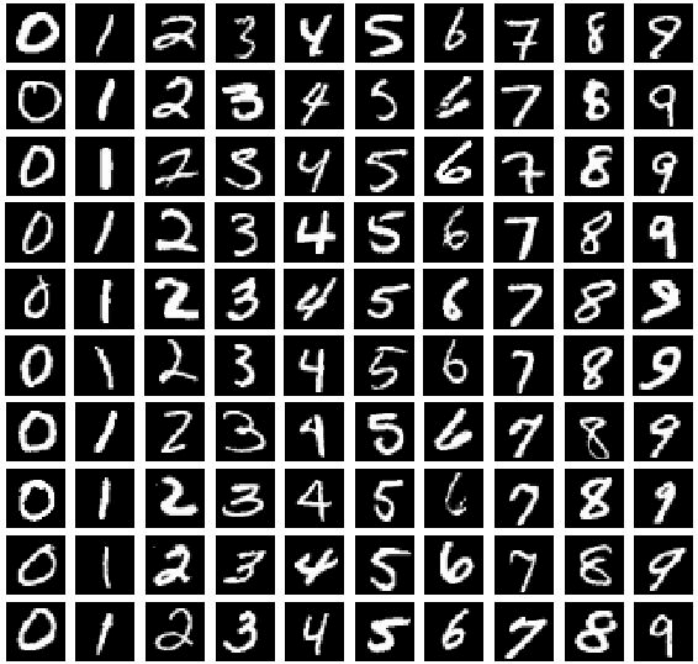
- Deeper supervised architectures improve performance, but..



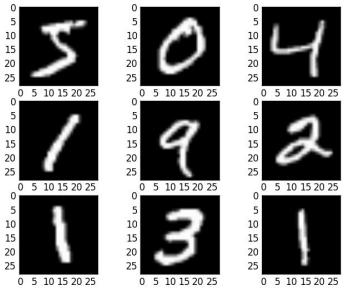
Data Augmentation - MNIST

- Different people may write same digit in different ways
- More intra-class variance





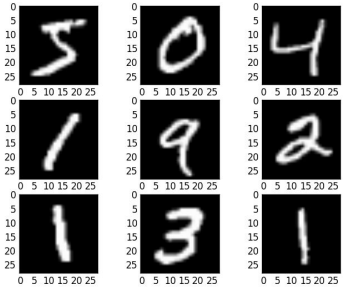
Data Augmentation - MNIST



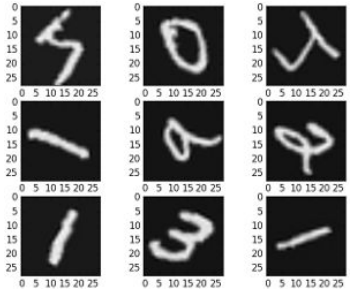
Original samples

https://www.codesofinterest.com/2018/02/using-data-augmentations-in-keras.html

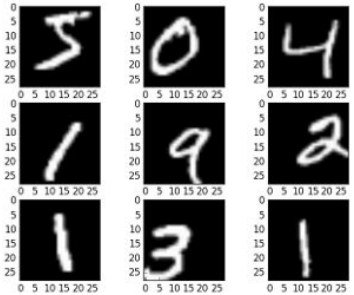
Data Augmentation - MNIST



Original samples



Random rotations

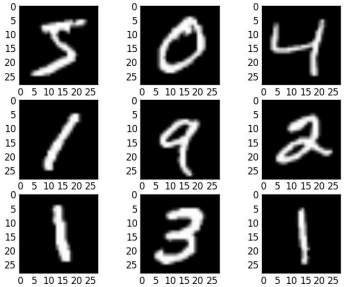


Random shift

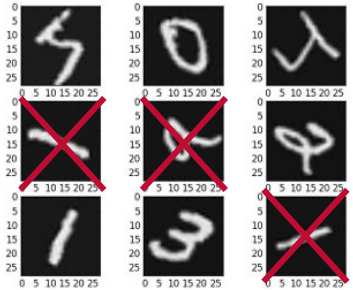
Random flips

https://www.codesofinterest.com/2018/02/using-data-augmentations-in-keras.html

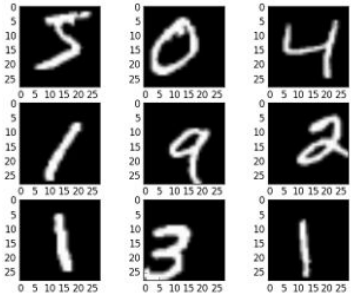
Data Augmentation - MNIST



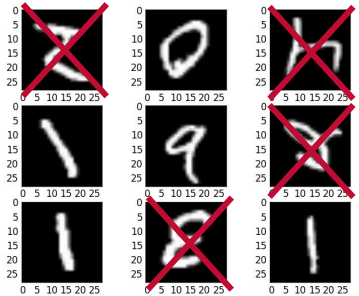
Original samples



Random rotations



Random shift



Random flips

https://www.codesofinterest.com/2018/02/using-data-augmentations-in-keras.html

Data Augmentation – LeNet300 over MNIST

- Train set size does not change (50k images)
- Random augmentation at each epoch

Network Topology	Error [%]
1 hidden (300 U), 1 output (10 U)	4.7
1 hidden (300 U), 1 output (10 U), distorted train set	**3.6 (-0.9)**
2 hidden (300 + 100 U), 1 output (10 U)	3.05
2 hidden (300 + 100 U), distorted train set	**2.45 (-0.6)**

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, November 1998

Data Augmentation – Another Example

Geometric transformations

Color jittering

https://www.codesofinterest.com/2018/02/using-data-augmentations-in-keras.html

https://mxnet.apache.org/versions/1.5.0/tutorials/gluon/data_augmentation.html

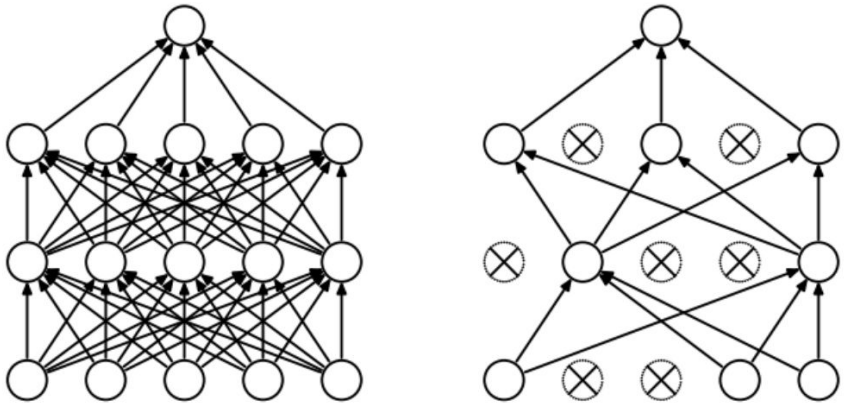
Avoiding Overfit

- How to avoid overfit ?
  - Lower capacity/complexity model (fewer parameters)
    - Still suitable for problem ?
  - Introduce regularization factor λ

    $J(\boldsymbol{w},\boldsymbol{x}) = E(\boldsymbol{w},\boldsymbol{x}) + \lambda R(\boldsymbol{w})$
  - Improve train set
    - Data augmentation
  - Committees of networks
    - *Dropout*

Dropout

- Training: For each ***hidden*** layer, for each sample, for each iteration, ignore each neuron with p_{drop} =0.5



(a) Standard Neural Net (b) After applying dropout.

N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov,
”Dropout: a simple way to prevent neural networks from overfitting”, JMLR 2014

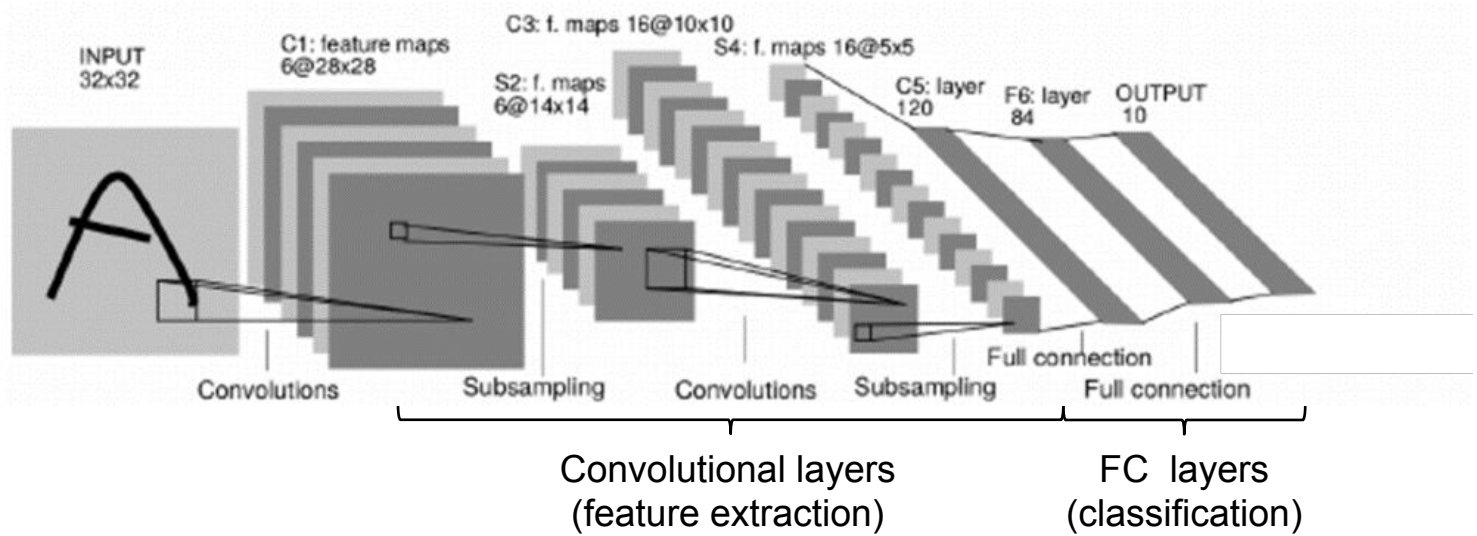
Dropout

N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, R. Salakhutdinov,
”Dropout: a simple way to prevent neural networks from overfitting”, JMLR 2014

From Shallow to Deep Architectures

Recap - LeNet5

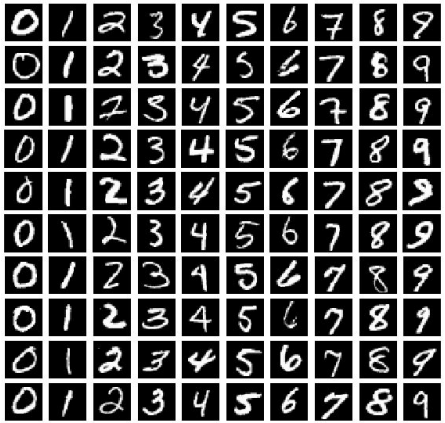
- Repeated *convolve-and-pool* pattern
  - feature extraction
- Multiple FC layers



Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, November 1998 (PDF available online)

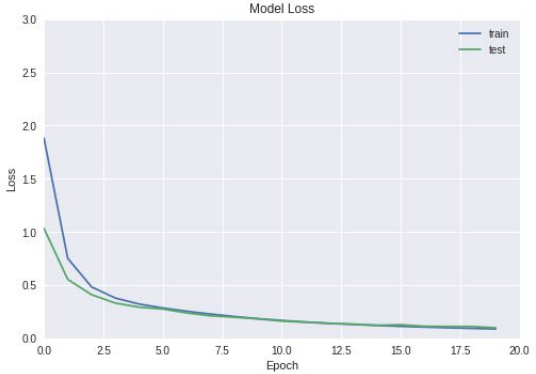
Recap - Convolutional Networks

Network	Architecture	Error [%]
LeNet300	1 FC output layer (10 U)	12.0
	1 hidden FC (300 U), 1 out FC (10 U)	4.7
	2 hidden FCs (300 + 100 U), 1 out FC (10 U)	3.05
LeNet5	2 Conv (3 F), 1 out FC (*LeNet1)*	1.7
	2 conv (6+16 F), 3 FC layer	0.95

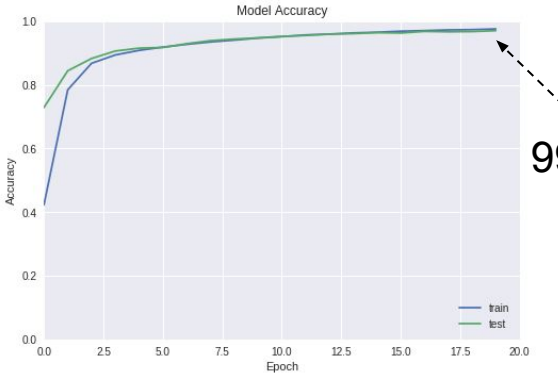


LeNet5: MNIST vs CIFAR10

Loss



Accuracy

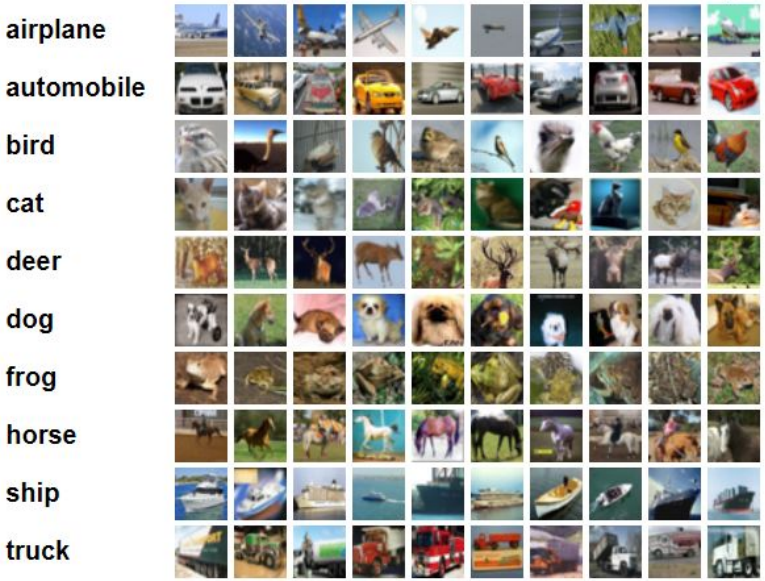


99%

MNIST

The CIFAR10 Datsets

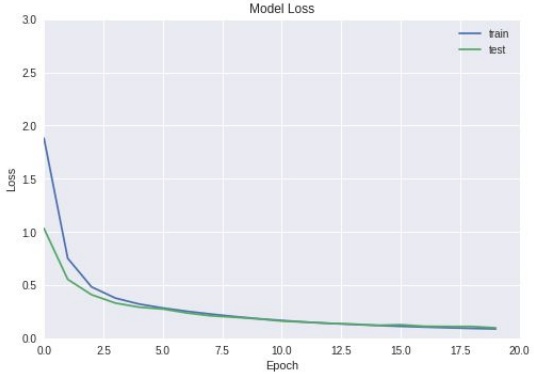
- *CIFAR10* dataset (2009)
  - 50k train images, 10k test images, 10 classes, 32x32

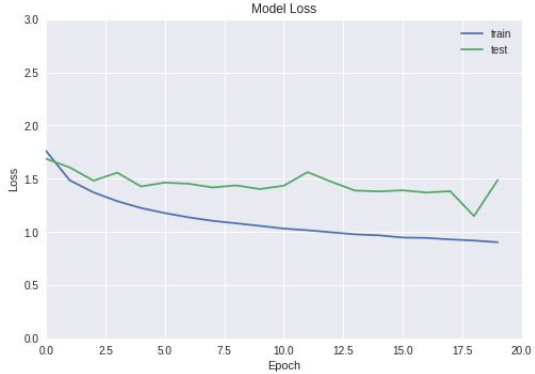


https://www.cs.toronto.edu/~kriz/cifar.html

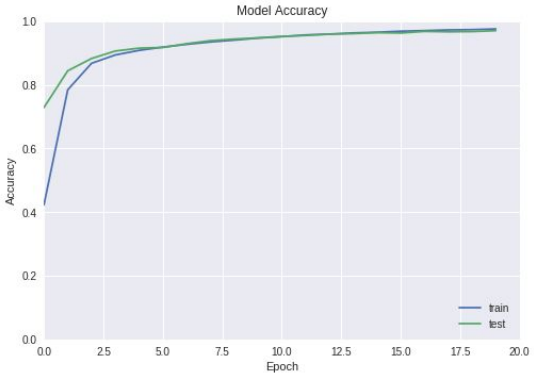
LeNet5: MNIST vs CIFAR10

Loss





Accuracy



MNIST

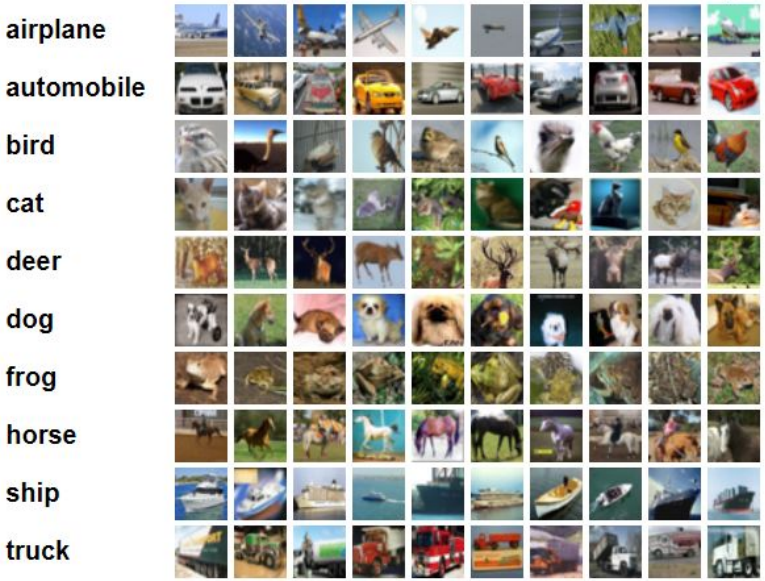
CIFAR-10

From shallow to deep networks

- More parameteres (layers) -> more complex tasks
  - More annotated training samples to avoid *overfitting*

The CIFAR10 Datsets

- *CIFAR10* dataset (2009)
  - 50k train images, 10k test images, 10 classes, 32x32



https://www.cs.toronto.edu/~kriz/cifar.html

«Early» Datsets for Image Classification

- *CalTech101* dataset (2003)
  - ~10k images, 101 classes, variable size

Deng, Jia; Dong, Wei; Socher, Richard; Li, Li-Jia; Li, Kai; Fei-Fei, Li (2009), "ImageNet: A Large-Scale Hierarchical Image Database" (PDF), 2009 conference on Computer Vision and Pattern Recognition

«Early» Datsets for Image Classification

- *CalTech256* dataset (2007)
  - ~30k images, 256 classes, variable size

Fei-Fei, Li, Rob Fergus, and Pietro Perona. "Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories." Computer vision and Image understanding 106, no. 1 (2007): 59-70.

ImageNet Large Scale Virsual Recognition Contest (ILSVRC)

- Originally presented in 2009 (3 M images, 5k classes)
- Since 2010 dataset for ILSVRC (1M images, 1k classes)

Deng, Jia; Dong, Wei; Socher, Richard; Li, Li-Jia; Li, Kai; Fei-Fei, Li (2009), "ImageNet: A Large-Scale Hierarchical Image Database" (PDF), 2009 conference on Computer Vision and Pattern Recognition

From shallow to deep networks

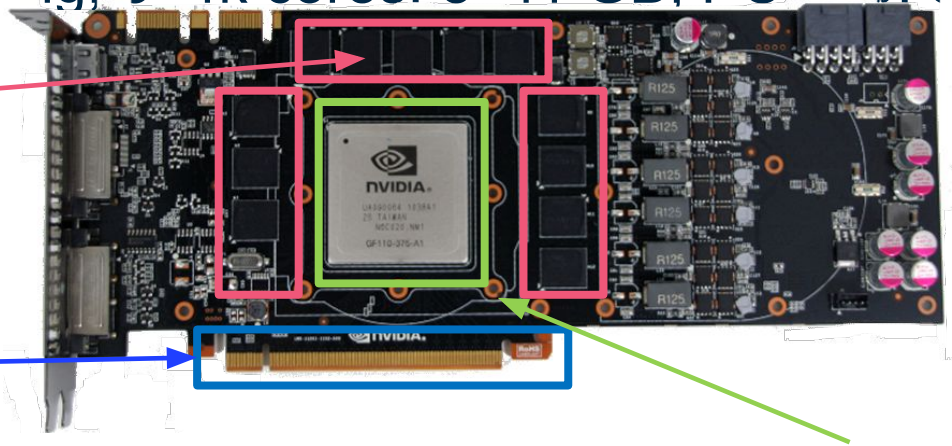
- More parameteres (layers) -> more complex tasks
  - More annotated training samples to avoid *overfitting*
  - Increased (training) complexity

From shallow to deep networks

- CRAY Trinity (End 2010's)
  - X64 architecture, ~1000 CPUs, 174M USD

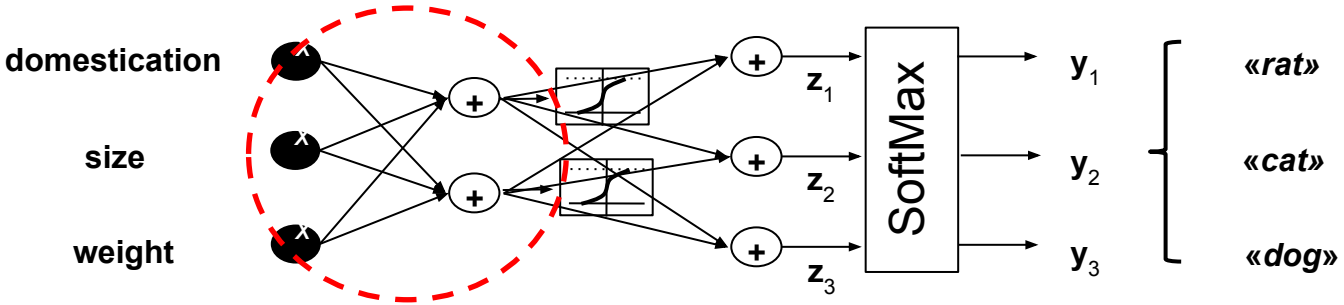
GPUs as Massvely Parallel Computers

- GTX 580 (2010)
  - Fermi, 512 cores, ~2 GB RAM, PCI 2.0, 500 USD
- RTX 2080 (2018)
  - Turing, 3~4k cores. 8~11 GB, PCI 3.0, 800~1200 USD



Matrix-Vector Multilpications in FCNs

- Simple rat/cat/dog classifier
  - Focus on hidden layer



Matrix-Vector Multilpications in FCNs

- Simple rat/cat/dog classifier
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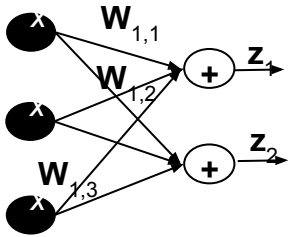
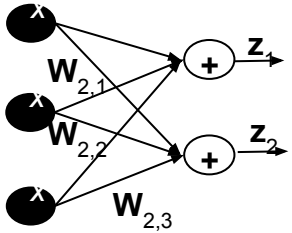


$$z_{1=} x_1 w_{1,1} + x_2 w_{1,2} + x_3 w_{1,3}$$

Matrix-Vector Multilpications in FCNs

- Simple rat/cat/dog classifier
  - Focus on hidden layer

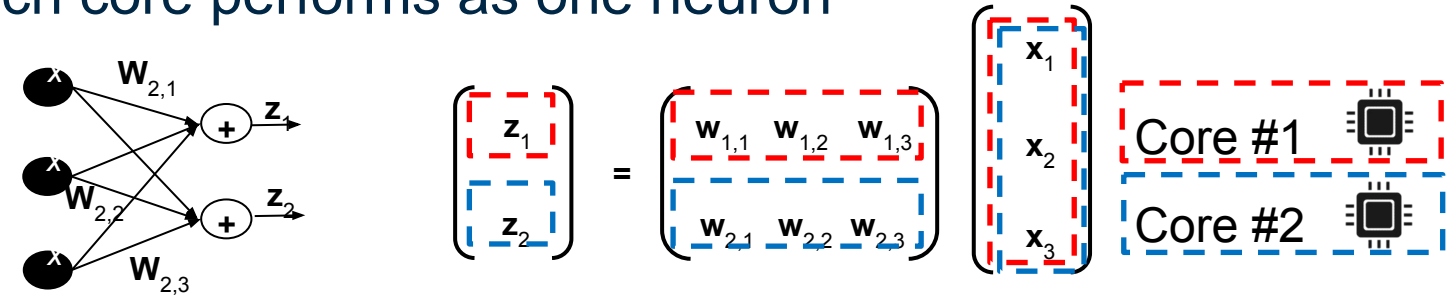


$$z_{1=} x_1 w_{1,1} + x_2 w_{1,2} + x_3 w_{1,3}$$

$$z_{2=} x_1 w_{2,1} + x_2 w_{2,2} + x_3 w_{2,3}$$

Matrix-Vector Multilpications in FCNs

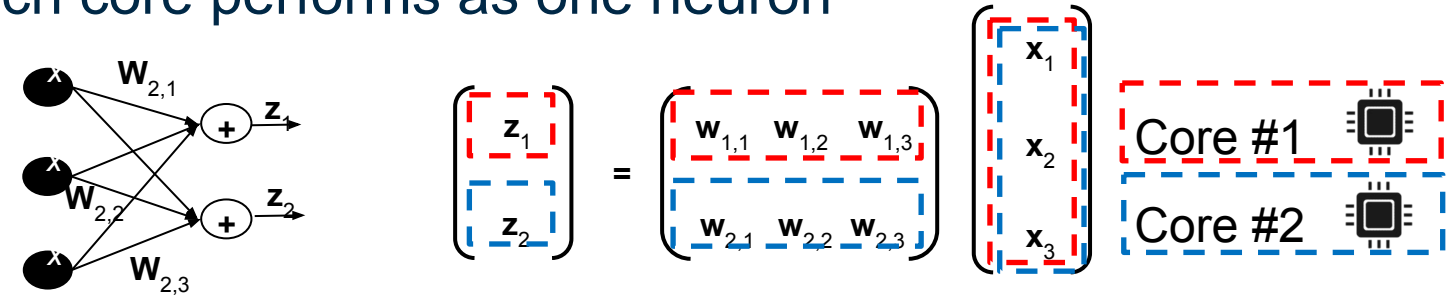
- Simple rat/cat/dog classifier
  - Focus on hidden layer
  - Each core performs as one neuron



The same multiplications (xW) are applied to every input in the mini-batch. GPUs are efficient to perform many times the same matrix multiplications.

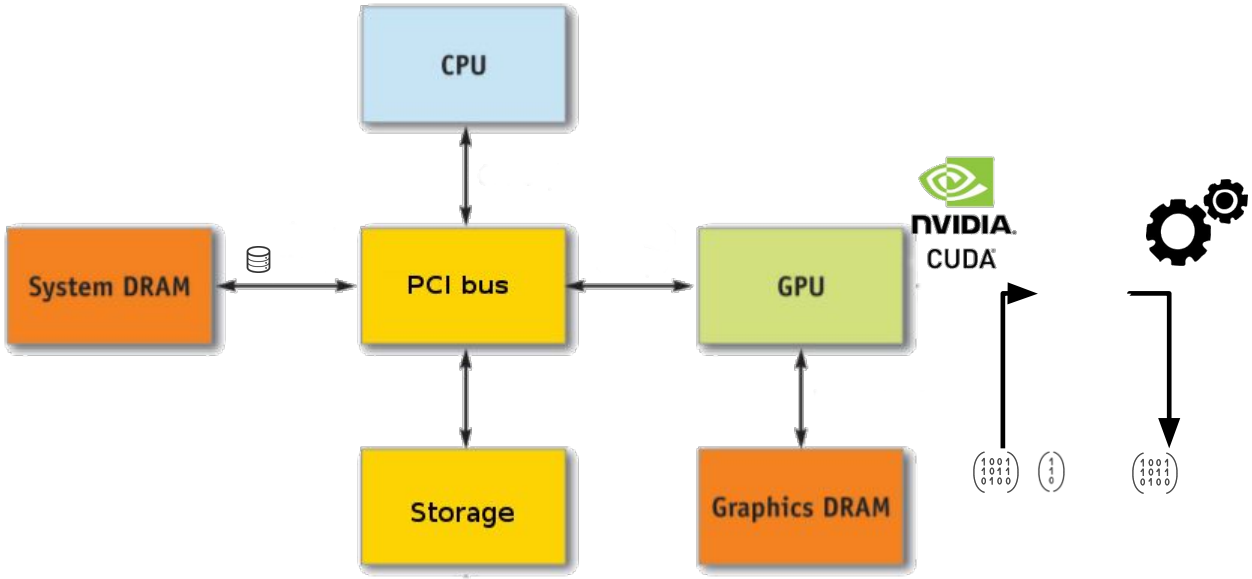
Matrix-Vector Multilpications in FCNs

- Simple rat/cat/dog classifier
  - Focus on hidden layer
  - Each core performs as one neuron

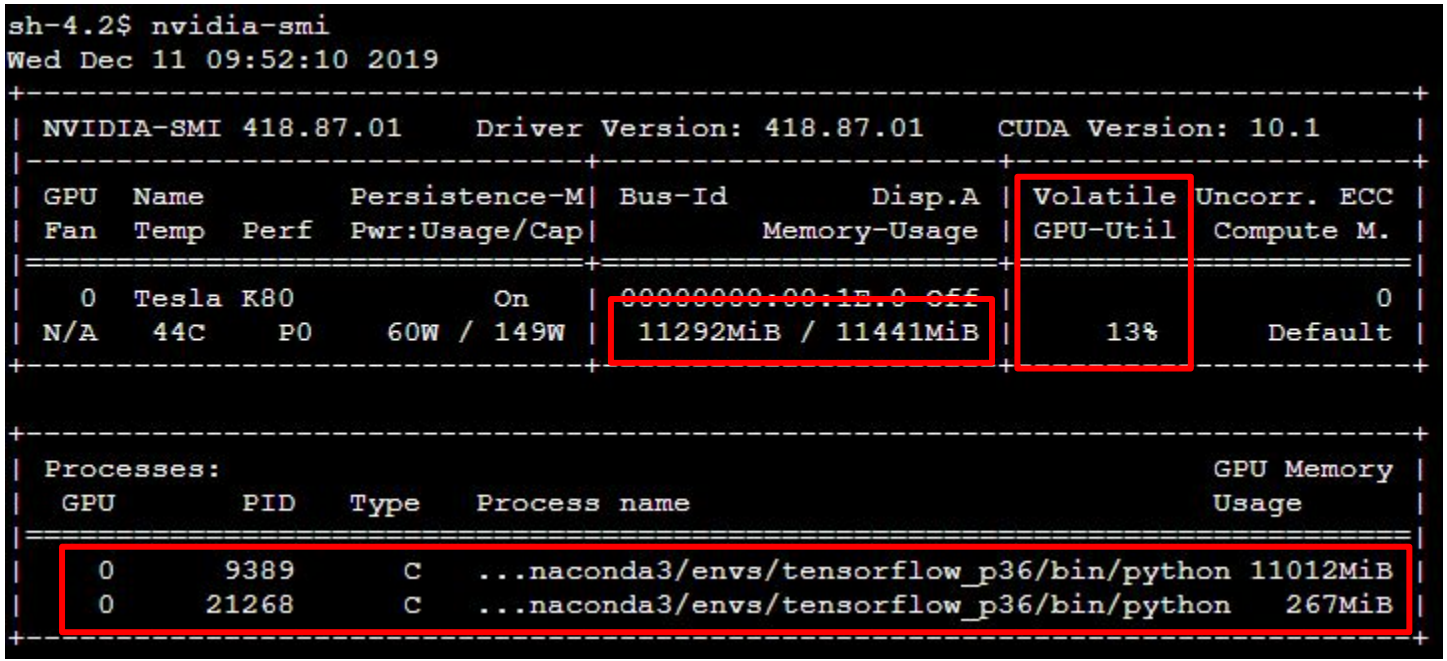


The same multiplications (xx) are applied to filter(w_i). GPUs are efficient to perform many times the same matrix multiplications.

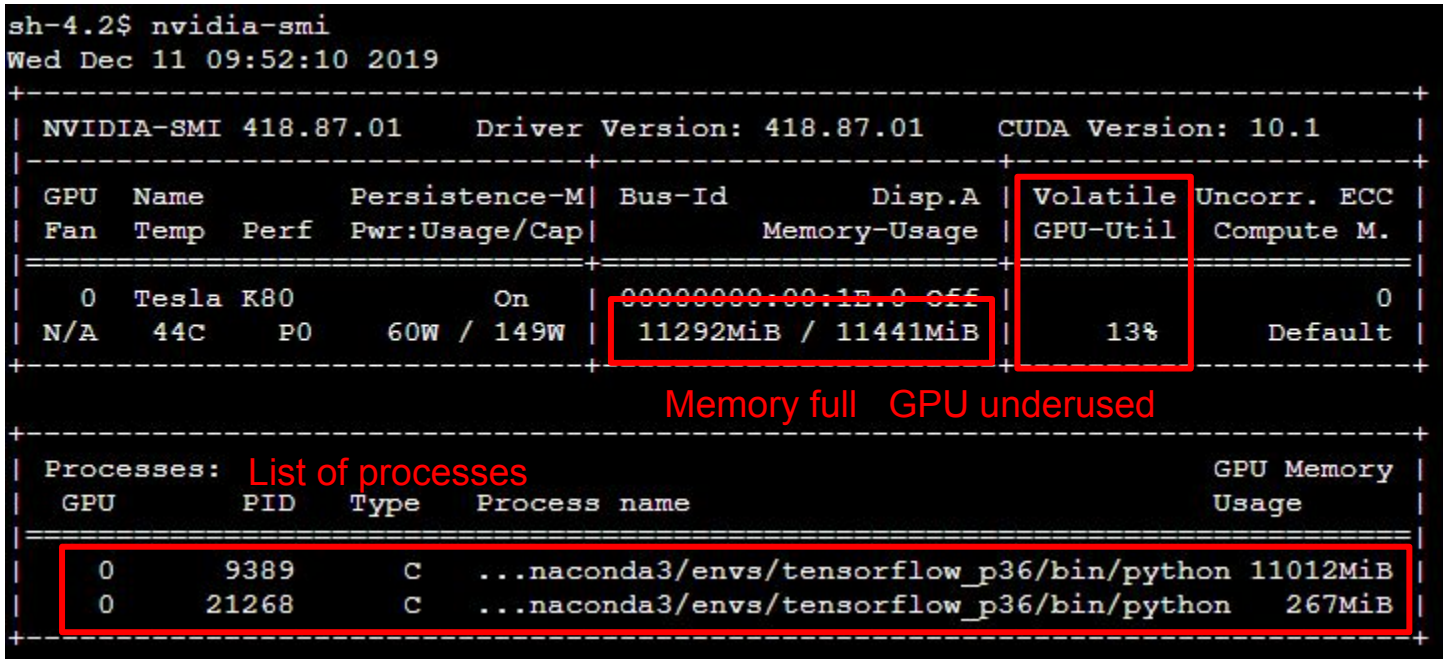
GP-GPUs Typical Workflow



Check your GPUs



Check your GPUs



Check your GPUs: exemple

```
xiongyu@ubuntu:~$ watch nvidia-smi
|    0     47741      C   ./mtcnn_c                                   461MiB |
Every 2.0s: nvidia-smi

Fri Jun 29 11:25:43 2018
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 390.48                 Driver Version: 390.48                    |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla M40           On   | 00000000:03:00.0 Off |                    0 |
|  0%   57C    P0   217W / 250W |  10806MiB / 11448MiB |     99%      Default |
+-------------------------------+----------------------+----------------------+
|   1  Tesla M40           On   | 00000000:04:00.0 Off |                    0 |
|  0%   58C    P0   200W / 250W |   9992MiB / 11448MiB |     99%      Default |
+-------------------------------+----------------------+----------------------+
|   2  Tesla M40           On   | 00000000:84:00.0 Off |                    0 |
|  0%   56C    P0   222W / 250W |   9955MiB / 11448MiB |     99%      Default |
+-------------------------------+----------------------+----------------------+
|   3  Tesla M40           On   | 00000000:85:00.0 Off |                    0 |
|  0%   57C    P0   203W / 250W |   9960MiB / 11448MiB |     98%      Default |
+-------------------------------+----------------------+----------------------+


+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|    0     35346      C   python2                                    110MiB |
|    0     55323      C   python                                   10673MiB |
|    1     55323      C   python                                    9970MiB |
```

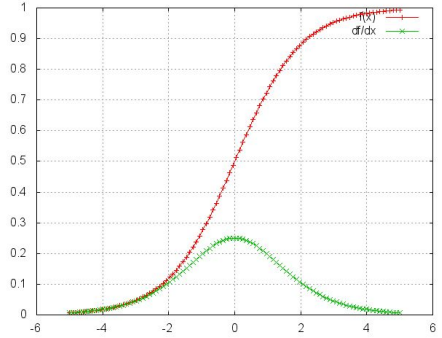
Check your GPUs: exemple

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 418.67       Driver Version: 418.67       CUDA Version: 10.1     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla V100-SXM2...  Off  | 00000000:15:00.0 Off |                    0 |
| N/A   39C    P0    55W / 300W |      0MiB / 32480MiB |      0%      Default |
|-------------------------------+----------------------+----------------------|
|   1  Tesla V100-SXM2...  Off  | 00000000:16:00.0 Off |                    0 |
| N/A   54C    P0   234W / 300W |  31116MiB / 32480MiB |    100%      Default |
|-------------------------------+----------------------+----------------------|
|   2  Tesla V100-SXM2...  Off  | 00000000:3A:00.0 Off |                    0 |
| N/A   42C    P0   140W / 300W |  31048MiB / 32480MiB |     45%      Default |
|-------------------------------+----------------------+----------------------|
|   3  Tesla V100-SXM2...  Off  | 00000000:3B:00.0 Off |                    0 |
| N/A   42C    P0    56W / 300W |      0MiB / 32480MiB |      0%      Default |
|-------------------------------+----------------------+----------------------|
|   4  Tesla V100-SXM2...  Off  | 00000000:89:00.0 Off |                    0 |
| N/A   36C    P0    56W / 300W |      0MiB / 32480MiB |      0%      Default |
|-------------------------------+----------------------+----------------------|
|   5  Tesla V100-SXM2...  Off  | 00000000:8A:00.0 Off |                    0 |
| N/A   38C    P0    56W / 300W |      0MiB / 32480MiB |      0%      Default |
|-------------------------------+----------------------+----------------------|
|   6  Tesla V100-SXM2...  Off  | 00000000:B2:00.0 Off |                    0 |
| N/A   38C    P0    55W / 300W |      0MiB / 32480MiB |      0%      Default |
|-------------------------------+----------------------+----------------------|
|   7  Tesla V100-SXM2...  Off  | 00000000:B3:00.0 Off |                    0 |
| N/A   41C    P0    56W / 300W |      0MiB / 32480MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|    1     22063      C   python                                     31105MiB |
|    2     38649      C   python3                                    31037MiB |
+-----------------------------------------------------------------------------+
```

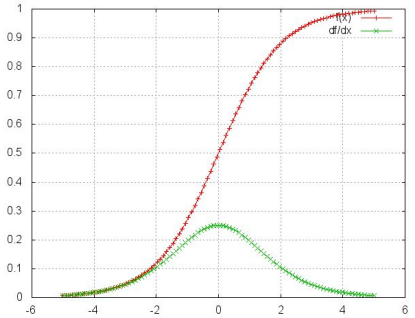
From shallow to deep networks

- More parameteres (layers) -> more complex tasks
  - More annotated training samples to avoid *overfitting*
  - Increased (training) complexity
  - *Vanishing gradient* (with sigmoid activations)



Vanishing Gradient Problem

$$g'(z) = \frac{e^{-z}}{(1+e^{-z})^2}$$

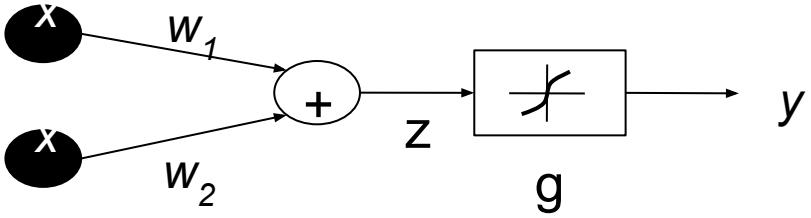


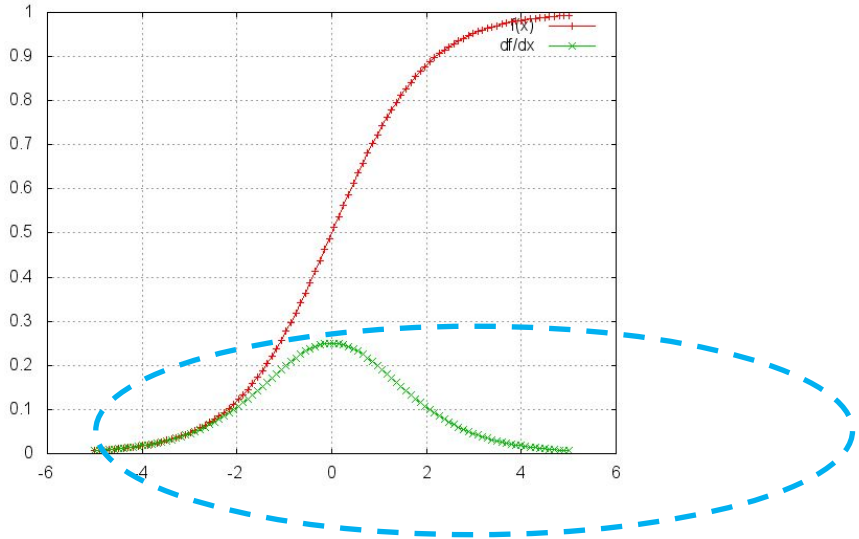
The Sigmoid Activation

- Compute gradient of E w.r.t. to each w_n via *chain rule*, e.g.:

$$\frac{\mathrm{dE}}{\mathrm{d}w_1} = \frac{\mathrm{d}E}{\mathrm{d}y}\frac{\mathrm{d}y}{\mathrm{d}z}\frac{\mathrm{d}z}{\mathrm{d}w_1}$$

$$g(z) = \frac{1}{1+e^{-z}}$$



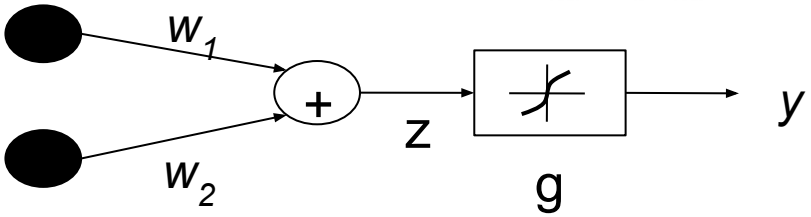


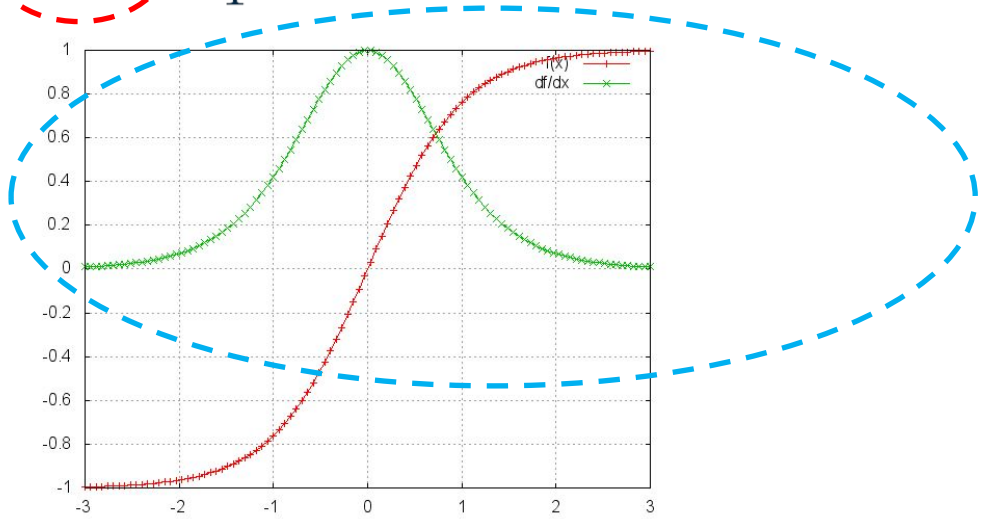
The Hyperbolic Tangent Activation

- Compute gradient of E w.r.t. to each w_n via *chain rule*, e.g.:

$$\frac{\mathrm{d}E}{\mathrm{d}w_1} = \frac{\mathrm{d}E}{\mathrm{d}y}\frac{\mathrm{d}y}{\mathrm{d}z}\frac{\mathrm{d}z}{\mathrm{d}w_1}$$

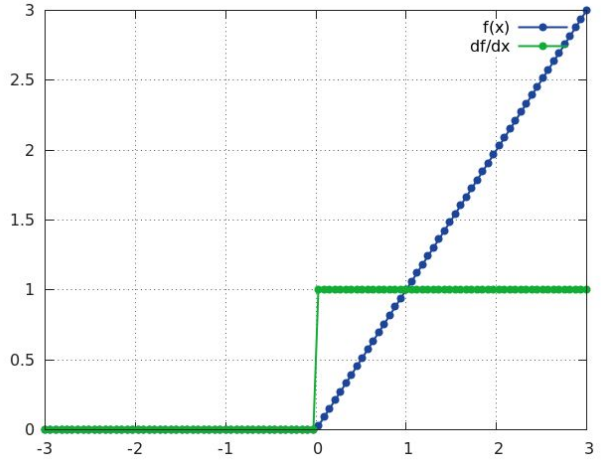
$$g(z) = \tanh(z) = \frac{\mathrm{e}^{z} - \mathrm{e}^{-z}}{\mathrm{e}^{z} + \mathrm{e}^{-z}}$$





The Rectified Liner Unit - ReLU

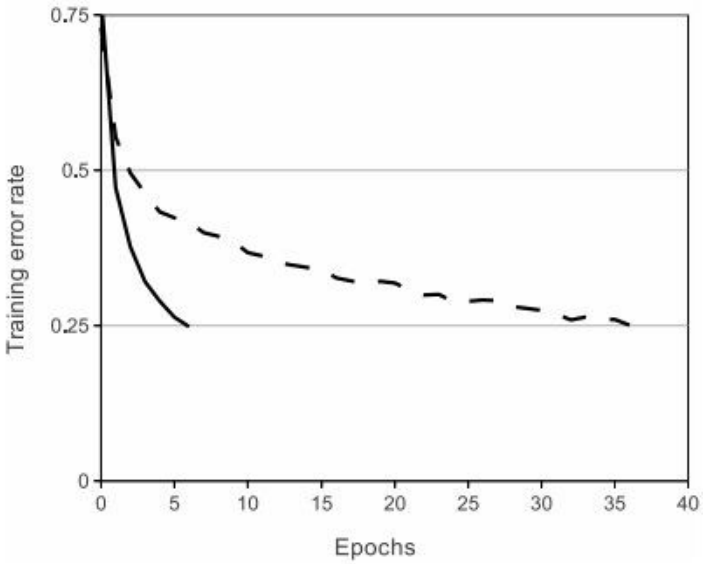
- *Rectified Linear Units* (*halfwave rectifier*) y = max (0,x)
  - Mitigates gradient vanishing problem
  - Easy to compute
  - Sparse activations
  - Biological plausibility (one-sided)



X. Glorot, A. Bordes, Y. Bengio. "Deep Sparse Rectifier Neural Networks." In Aistats, vol. 15, no. 106, p. 275. 2011.

The Rectified Liner Unit - ReLU

- CIFAR-10 training error a 4-layer ConvNet
- 6~7 times faster convergence



A. Krizhevsky, I. Sutskever, G. E. Hinton. "Imagenet classification with deep convolutional neural networks.“
In Advances in neural information processing systems, pp. 1097-1105. 2012.

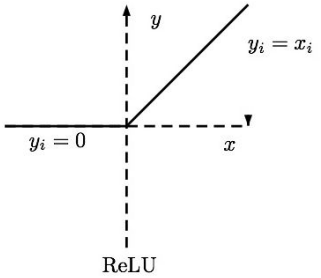
The Leaky/Parametric ReLU

- ReLU may yield *dead neurons*
  - Gradeint propagation problem
- Leaky ReLU

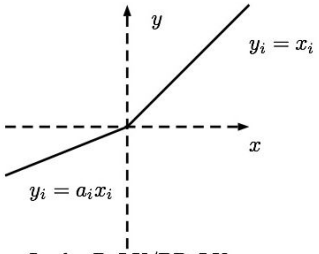
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases}$$

- Parametric ReLU

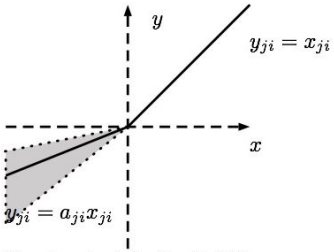
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ ax & \text{otherwise} \end{cases}$$



ReLU



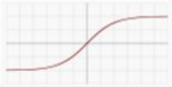
Leaky ReLU/PReLU



Randomized Leaky ReLU

X. Glorot, A. Bordes, Y. Bengio. "Deep Sparse Rectifier Neural Networks." In Aistats, vol. 15, no. 106, p. 275. 2011.

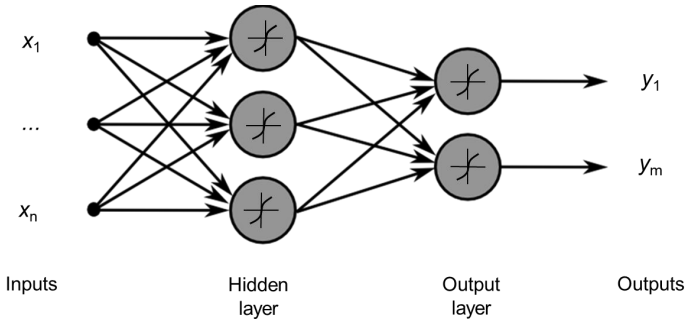
Activation Functions Summary

Name	Plot	Equation	Derivative
Identity		$f(x) = x$	$f'(x) = 1$
Logistic (a.k.a Soft step)		$f(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1-f(x))$
TanH		$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1$	$f'(x) = 1 - f(x)^2$
Rectified Linear Unit (ReLU)		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Parameteric Rectified Linear Unit (PReLU) [2]		$f(x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Exponential Linear Unit (ELU) [3]		$f(x) = \begin{cases} \alpha(e^x - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} f(x) + \alpha & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
SoftPlus		$f(x) = \log_e(1 + e^x)$	$f'(x) = \frac{1}{1+e^{-x}}$

S.Sharma "*Activation Functions Explained*" https://towardsdatascience.com/activation-functions-neural-networks-1cbd9f8d91d6

Which Activation Function ?

- Output layer
  - Classification
    - Sigmoid (binary) or softmax (multiclass)
  - Bounded zero-mean regression
    - Hyperbolic tangent
  - Unbounded regression
    - Linear
- Hidden layer
  - ReLU-like



The Rectified Liner Unit - ReLU

Biol. Cybernetics 36, 193–202 (1980)

Biological Cybernetics

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

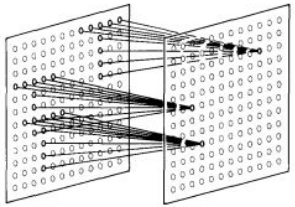


Fig. 3. Illustration showing the input interconnections to the cells within a single cell-plane

All the neural cells employed in this network is of analog type. That is, the inputs and the output of a cell take non-negative analog values proportional to the pulse density (or instantaneous mean frequency) of the firing of the actual biological neurons.

S-cells have shunting-type inhibitory inputs similarly to the cells employed in the conventional cognitron (Fukushima, 1975). The output of an S-cell in the k_l-th S-plane in the l-th module is described below.

$$u_{Sl}(k_l, \mathbf{n}) = r_l \cdot \varphi\left[\frac{1+\sum_{k_{l-1}=1}^{K_{l-1}} \sum_{\mathbf{v}\in S_l} a_l(k_{l-1}, \mathbf{v}, k_l)\cdot u_{Cl-1}(k_{l-1}, \mathbf{n}+\mathbf{v})}{1+\frac{2r_l}{1+r_l}\cdot b_l(k_l)\cdot v_{Cl-1}(\mathbf{n})} - 1\right],$$

where

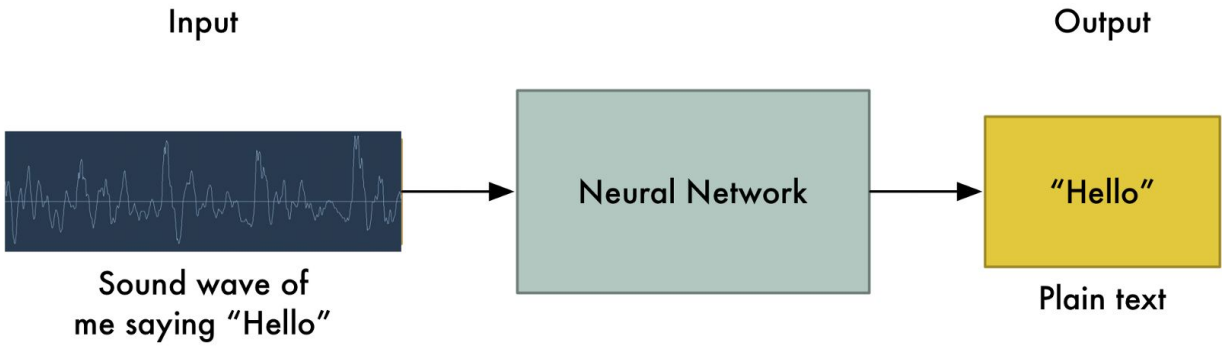
$$\varphi[x] = \begin{cases} x & x \geqq 0 \\ 0 & x < 0. \end{cases} \qquad (2)$$

In case ~~of $l=1$~~ in ~~(1)~~, $u_{Cl-1}(k_{l-1}, \mathbf{n})$ stands for $u_0(\mathbf{n})$, and we have $K_{l-1}=1$.

Fukushima, Kunihiko, Sei Miyake, and Takayuki Ito. "Neocognitron: A neural network model for a mechanism of visual pattern recognition." IEEE transactions on systems, man, and cybernetics 5 (1983): 826-834.

Deep Neural Networks for Speech Recognition

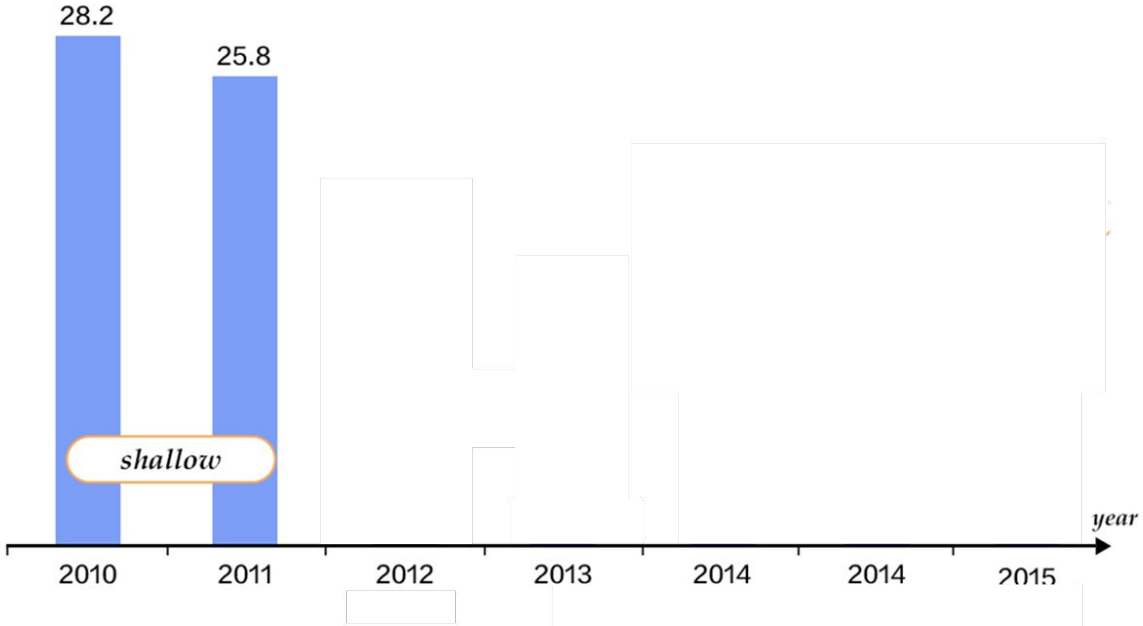
- First successes training *deep* NNs in speech recognition
  - More layers equal better performance
  - “Audio far simpler signals than image/video”



Part 4
Deep Neural Networks for vision

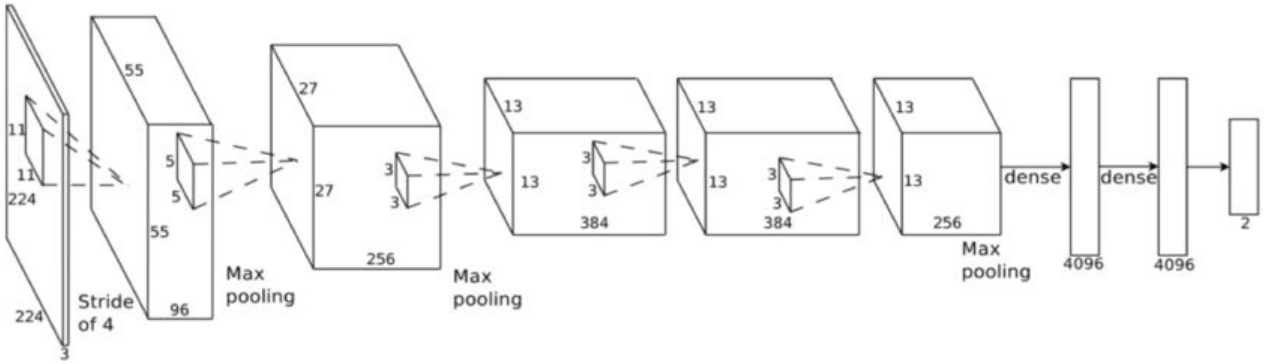
ImageNet Challenge Before the *Deep* Era

- 2010: SIFT descriptors + SVN (NEC)
- 2011: SIFT descriptors, Fisher Vectors, SVM (XRCE)



The *AlexNet* Architecture (2012)

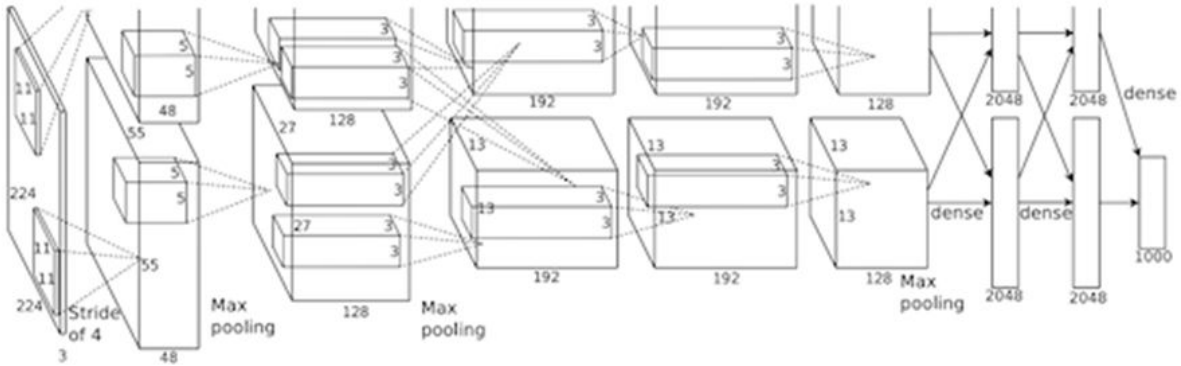
- First «*deep*» convolutional network
  - 5 convolutional layers, 3 fully connected layers
  - 62.3 Mprms (conv layers 6% but take 95% of time)



A. Krizhevsky, I. Sutskever, G. E. Hinton. "Imagenet classification with deep convolutional neural networks."
In Advances in neural information processing systems, pp. 1097-1105. 2012.

The *AlexNet* Architecture (2012)

- Trained over two *GTX580* GPUs (2GB memory each)
  - Split convolutions to different GPUs
  - Distribute the fully connected layers to different GPUs
  - Trained on 2 x GTX 580 for 5~6 days (90 epochs)



A. Krizhevsky, I. Sutskever, G. E. Hinton. "Imagenet classification with deep convolutional neural networks." In Advances in neural information processing systems, pp. 1097-1105. 2012.

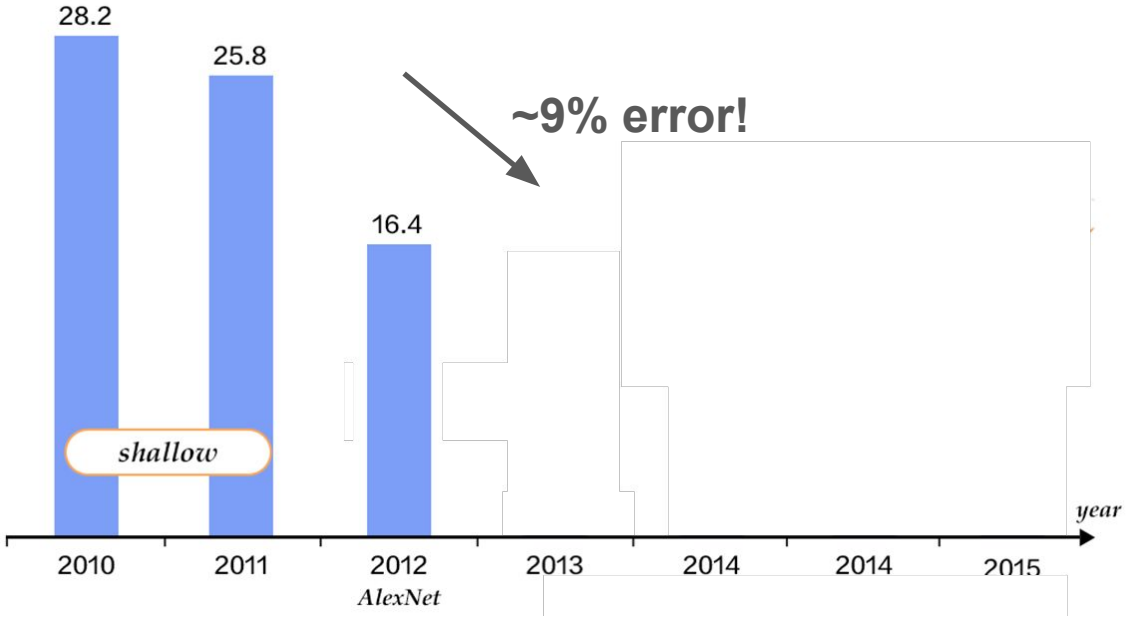
The *AlexNet* Architecture (2012)

- (Main) differences w.r.t. *LeNet5*
  - Deeper than LeNet5 (5 Conv w.r.t. 3)
  - ReLU activations in place of sigmoids
  - Dropout before FC layers (+ L2 regularization)
  - Batch size 128 images
  - Data augmentation
  - LR divide by 10 when valid error settles
- However
  - No batch normalization

A. Krizhevsky, I. Sutskever, G. E. Hinton. "Imagenet classification with deep convolutional neural networks." In Advances in neural information processing systems, pp. 1097-1105. 2012.

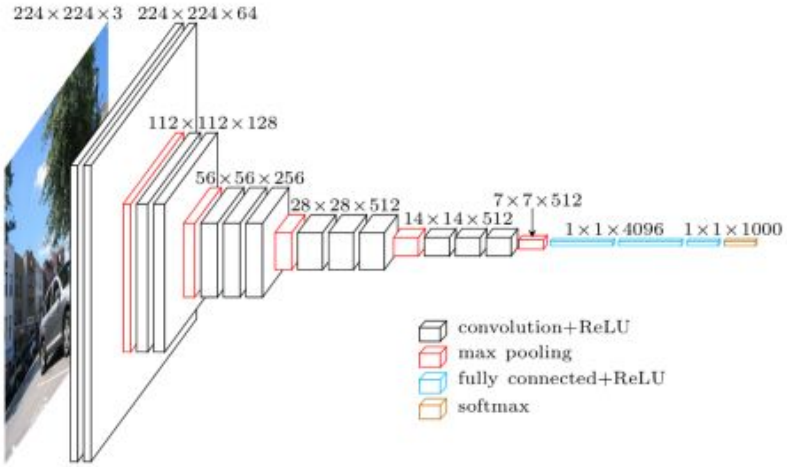
The *AlexNet* Architecture (2012)

- 2012 ILSVRC winner with top-5 error rate 16.4% (vs. 26.2%)
  - Problem: very large 11x11 filters in first conv layer



VGGNet (2014)

- Up to 19 convolutional layers, 3 fully connected layers
- Key idea: 3x3 filters everywhere



K. Simonyan, A. Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

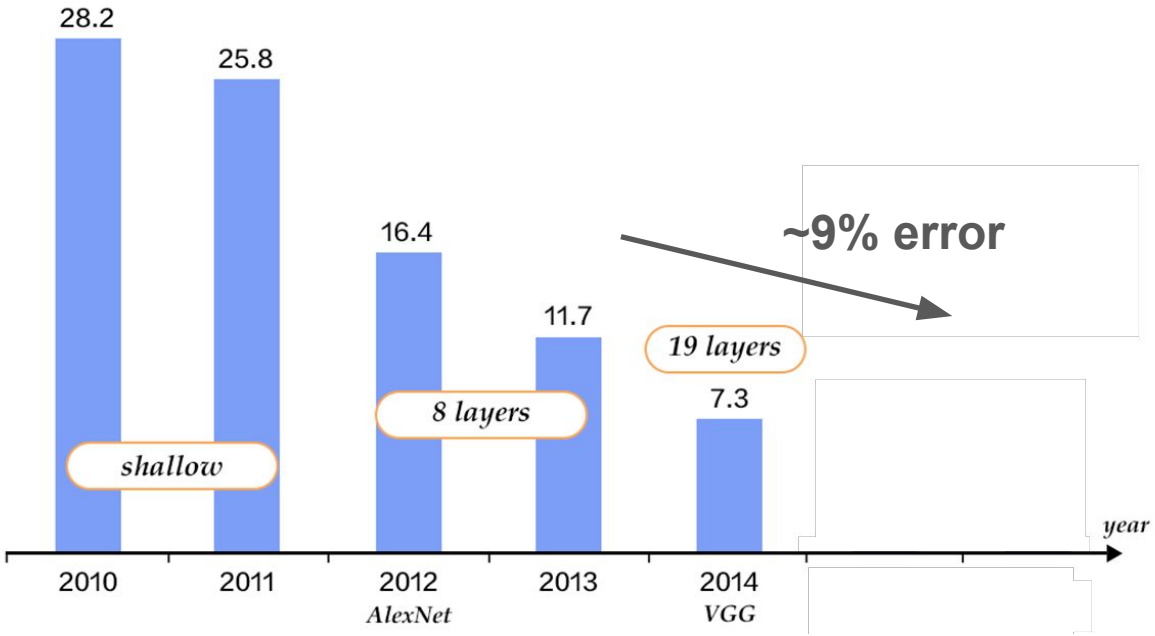
VGGNet (2014)

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 imag)					
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					

K. Simonyan, A. Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).

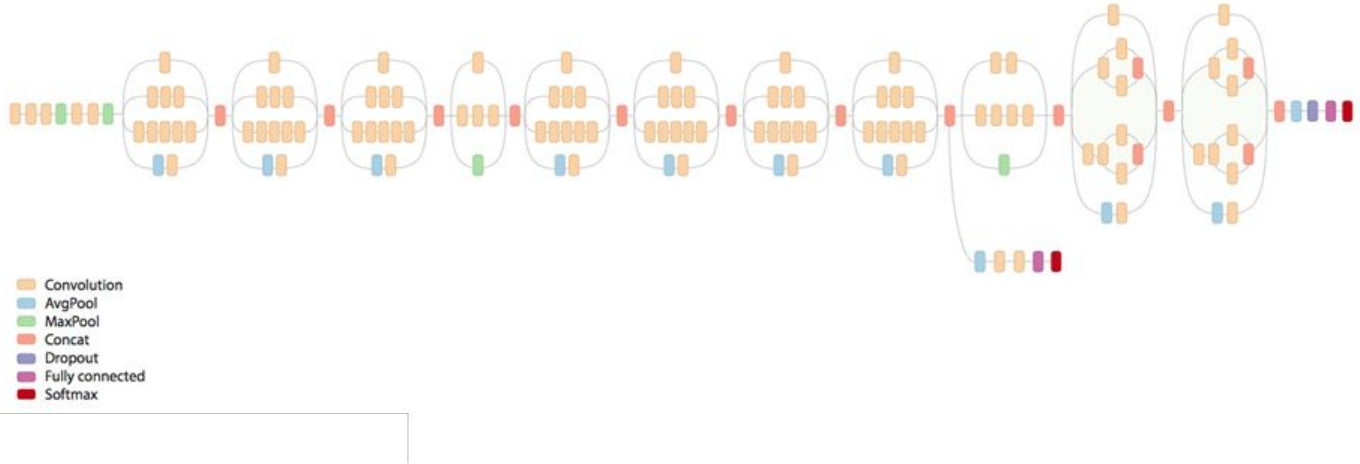
VGGNet (2014)

- 2014 ILSVRC top-5 runner with error rate 7,3%



GoogLeNet (2015)

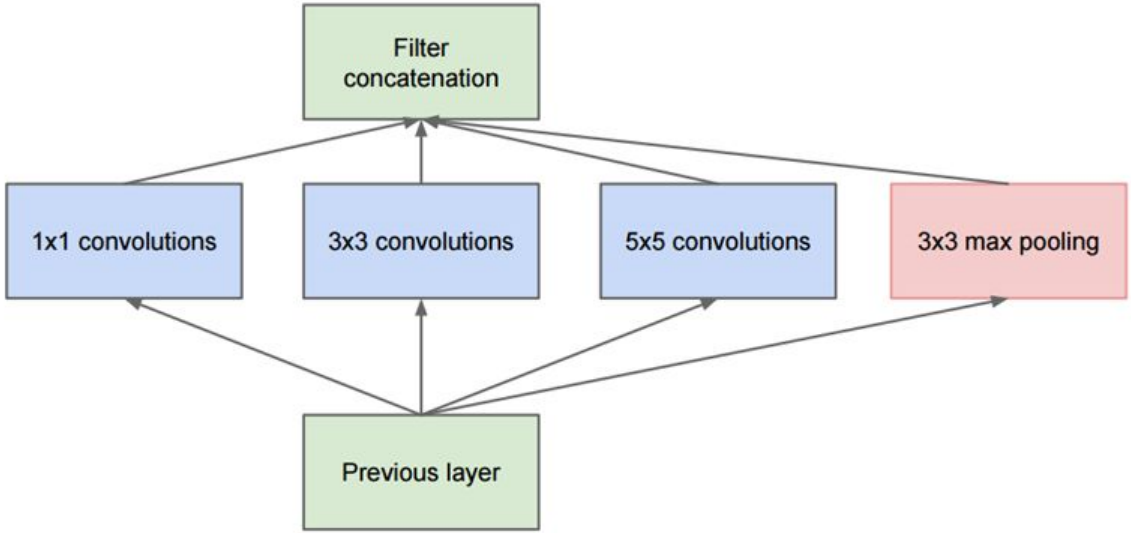
- Big IT firm (Google) wins ILSVRC
- Non-strictly sequential data processing (*Inception* module)



Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1-9. 2015.

GoogLeNet (2015)

- Inception module simplified view
  - Key idea: do convolutions and pooling in parallel



Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1-9. 2015.

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- Inception module simplified view
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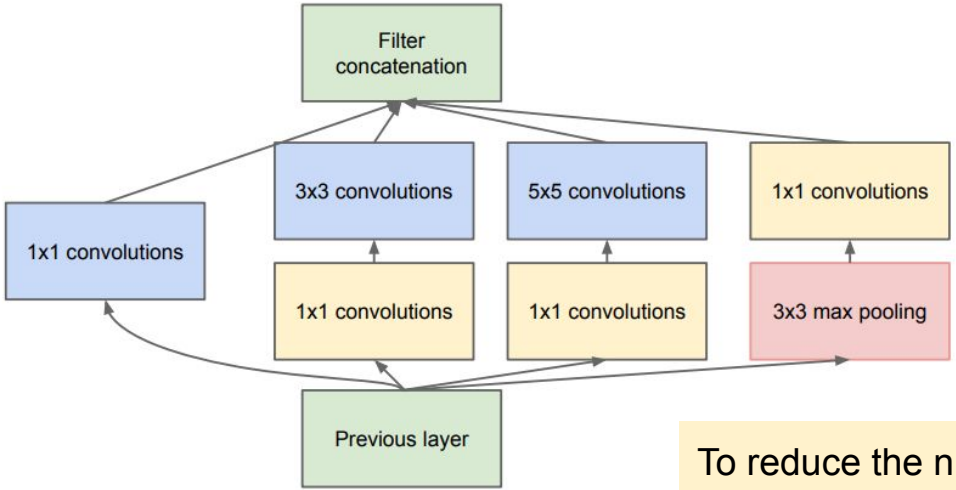


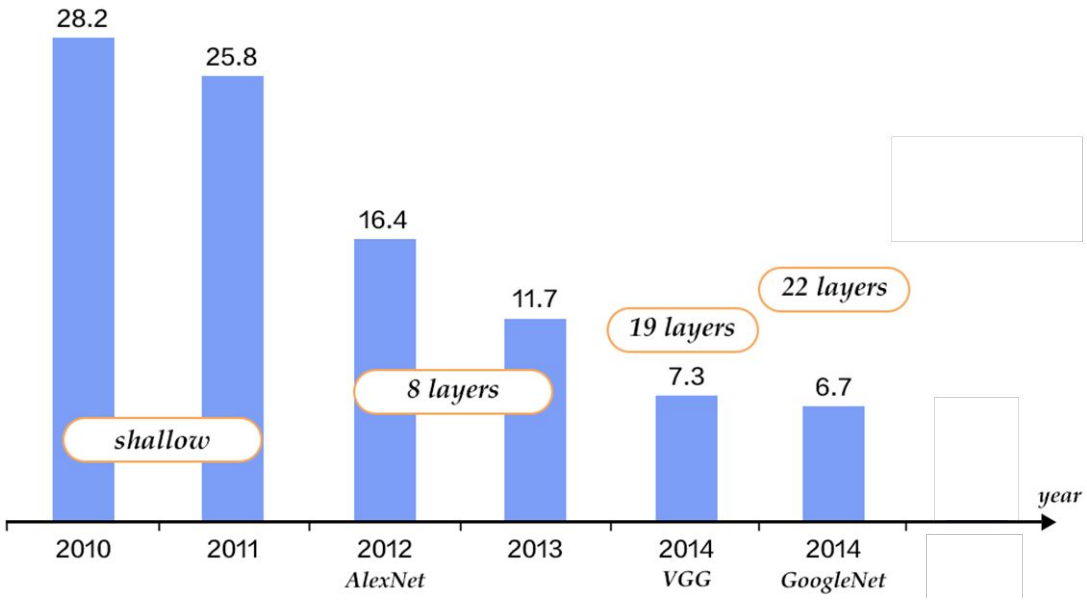
To reduce the number of input channels

(b) Inception module with dimension reductions

Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1-9. 2015.

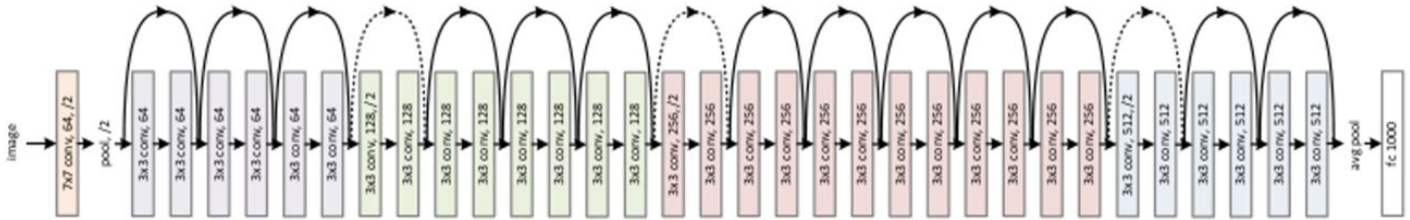
GoogLeNet (2015)

- 2014 ILSVRC winner with top-5 error rate 6.7%



ResNet (2015-present)

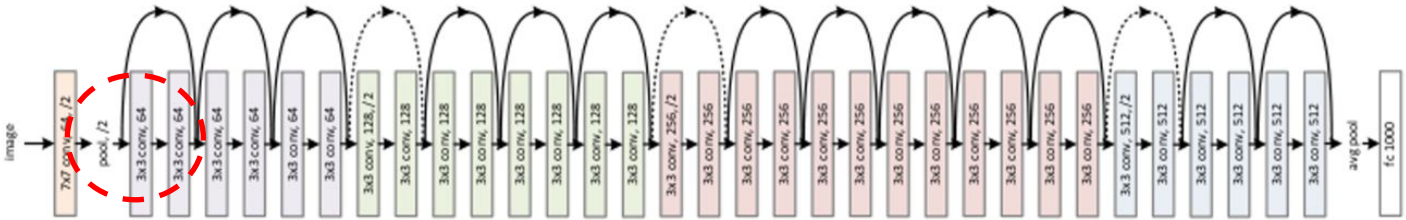
- 2015 ILSVRC winner with top-5 error rate 6.7%
  - 18, **34**, 50, 101,151 layers



He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

ResNet (2015-present)

- 2015 ILSVRC winner with top-5 error rate 6.7%
  - 18, **34**, 50, 101,151 layers
  - (Almost) *pool*-less (2*px* convolution stride)



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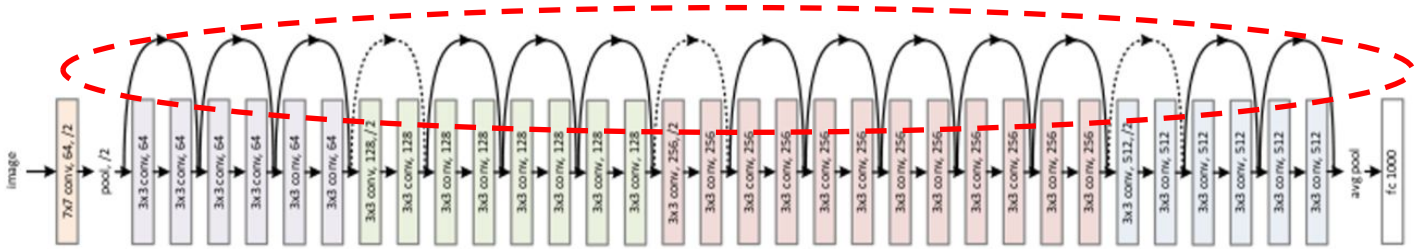
ResNet (2015-present)

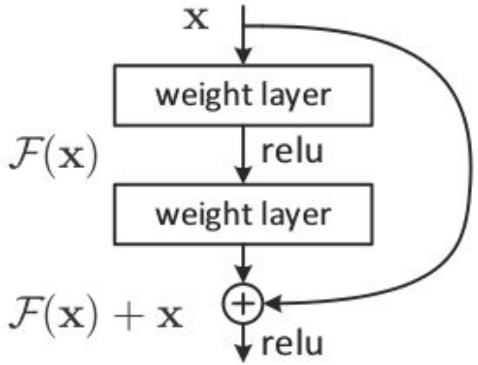
- 2015 ILSVRC winner with top-5 error rate 6.7%
  - 18, **34**, 50, 101,151 layers
  - (Almost) *pool*-less (2*px* convolution stride)
  - Relies on skip connections

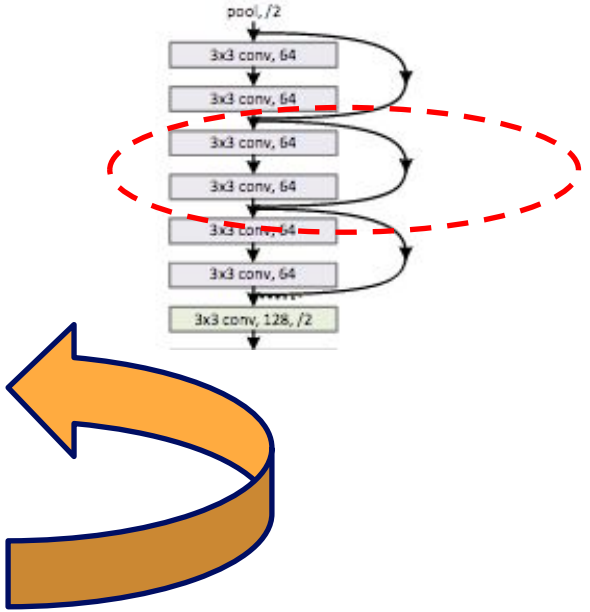


He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

ResNet (2015)

- Relies on skip/shortcut connections
  - Gradient backprop easier





Understanding and Implementing Architectures of ResNet
https://medium.com/@14prakash/understanding-and-implementing-architectures-of-resnet-and-resnext-for-state-of-the-art-image-cf51669e1624

ResNet (2015)

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ResNet (2015)

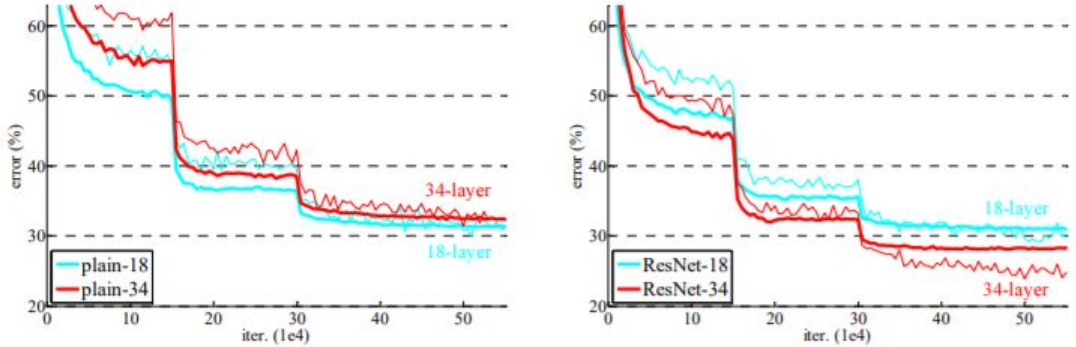
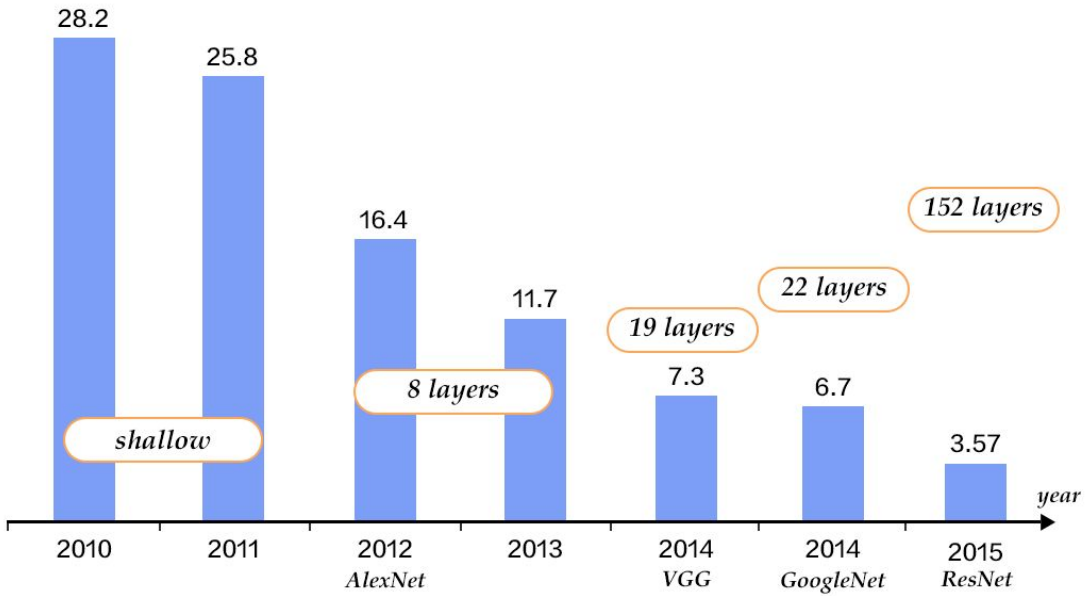


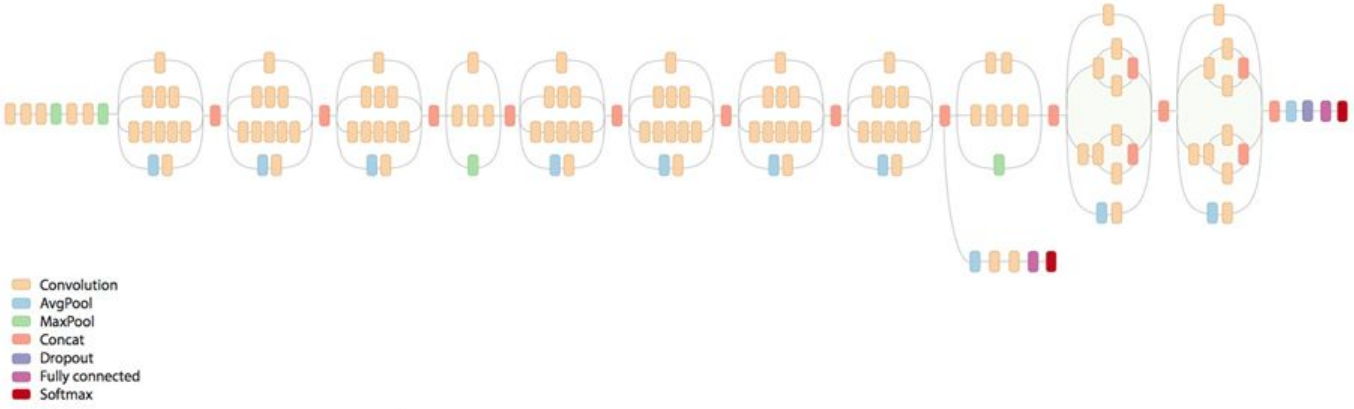
Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

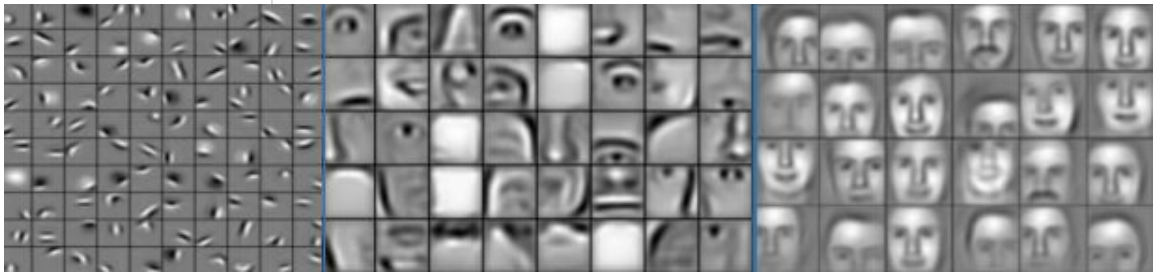
He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.

ILSVRC – Deeper and Better



Why Deeper is Better ?



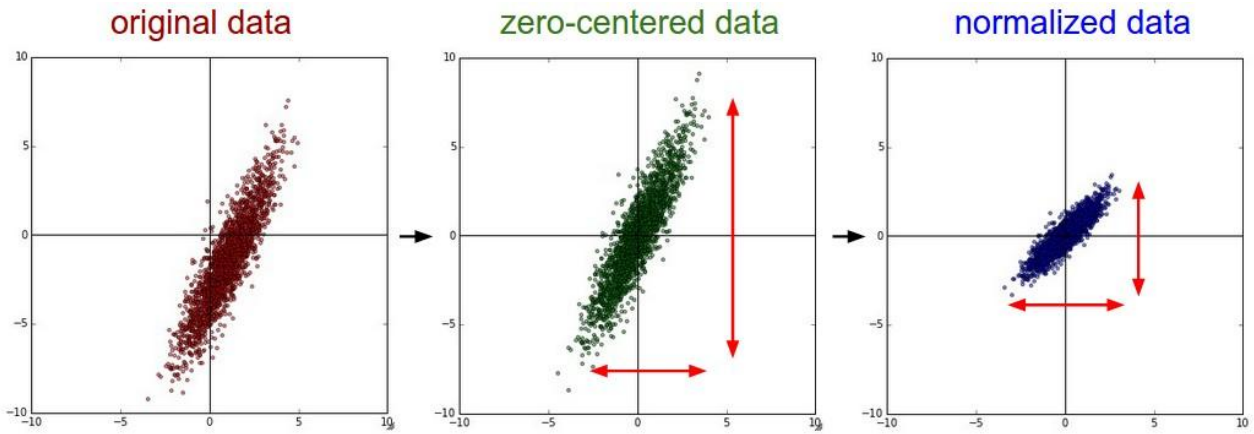


Visualizing and Understanding Deep Neural Networks by Matt Zeiler
https://www.youtube.com/watch?v=ghEmQSxT6tw

Recap: Input Normalization

- Input mean and stdev normalized -> μ=0, σ=1

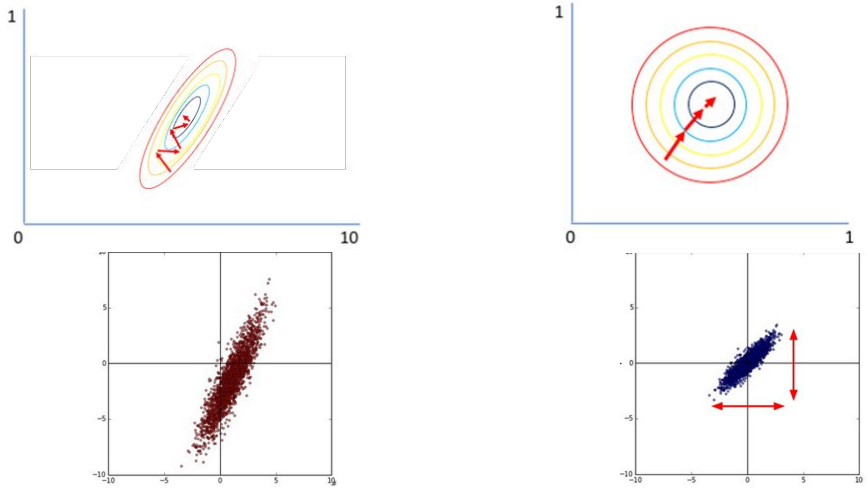
$$x_{i,j} = x_i - \mu(x_{i,j}) / \sigma(x_{i,j})$$



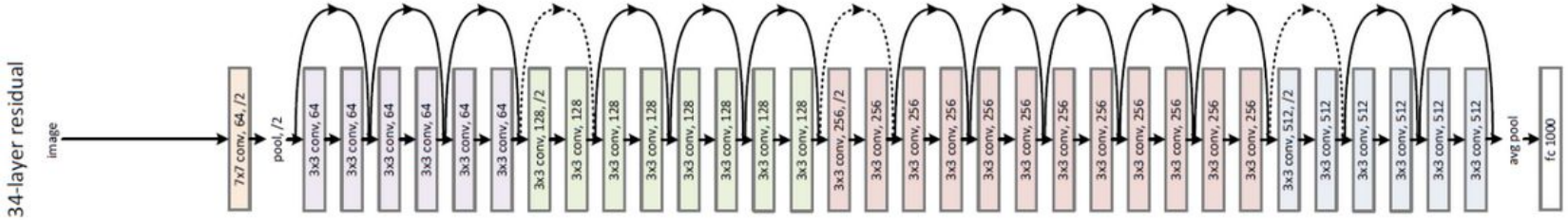
http://cs231n.github.io/neural-networks-2/

Recap: Input Normalization

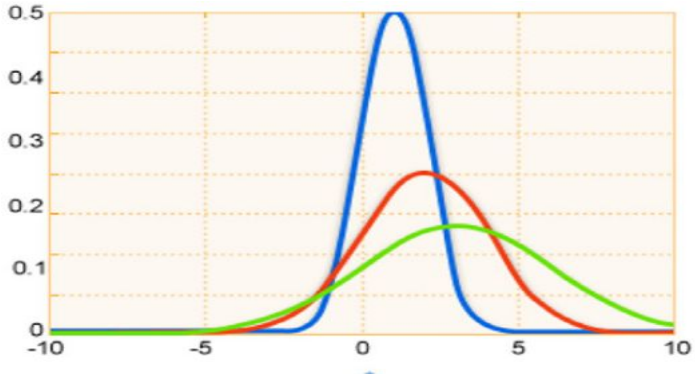
- All w_i updated according to same step-size/LR η
- Assumption: dE/dw_i comparable for all w_i
  - Otherwise, we would need separate η_i (complex problem)



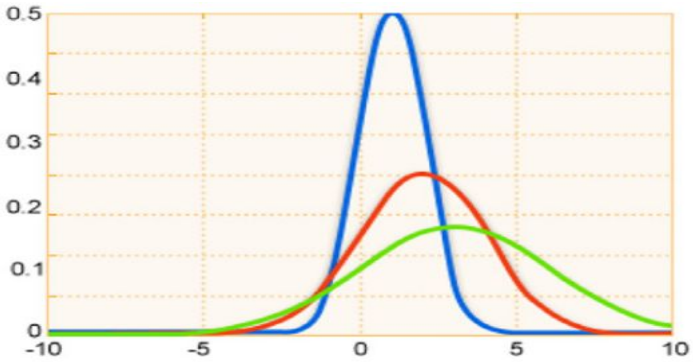
Layers: Batch-normalization

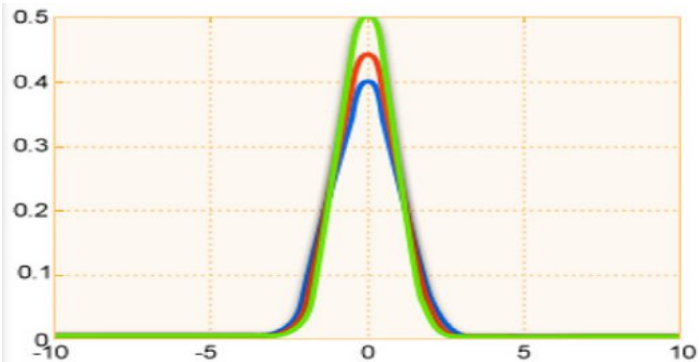


- Problem: how to estimate μ, σ of hidden layers inputs?



Layers: Batch-normalization





Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

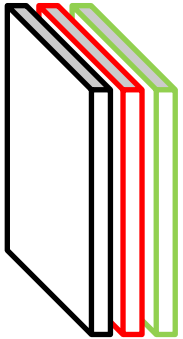
$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

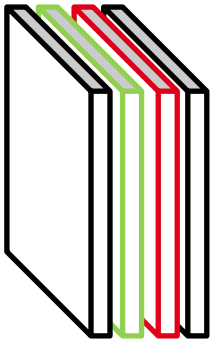
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift
Sergey Ioffe, Christian Szegedy

Convolve-ReLU-Pool-BatchNorm



Conv + ReLU
MaxPooling
BatchNorm

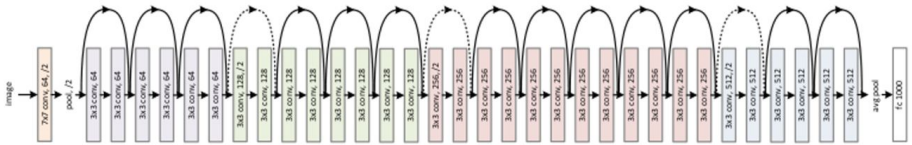


Conv
MaxPooling
BatchNorm
ReLU

S. Ioffe, C. Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." arXiv preprint arXiv:1502.03167 (2015).

Training from Scratch

- Train *ResNet* to recognize K custom objects classes
  - Long training time



The Cost of Training a Deep Network from Scratch

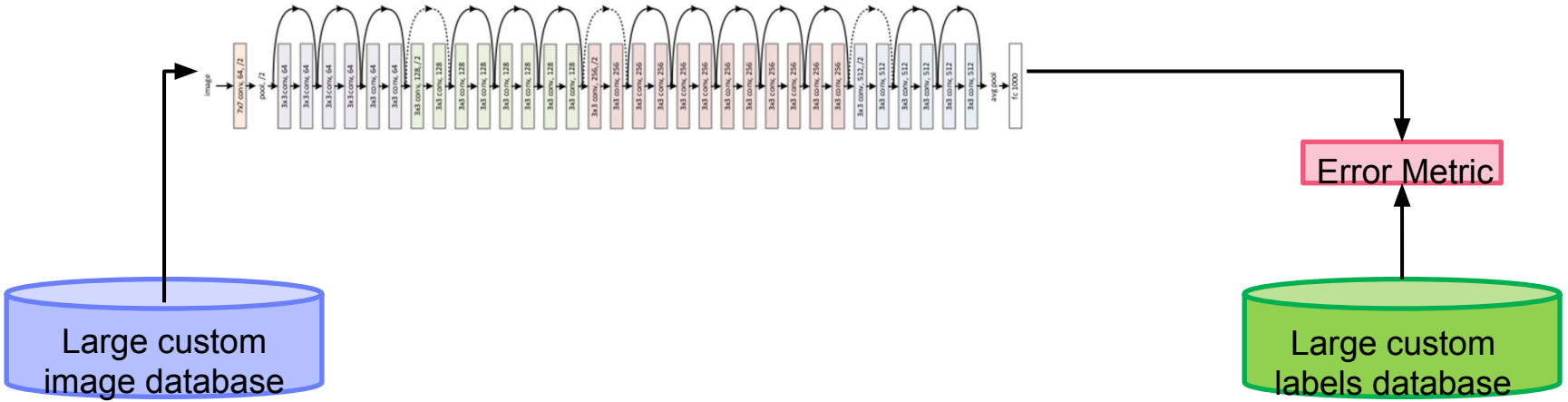
- AlexNet (2012) took 5~6 days over two GTX 580 GPUs
- Nowadays many startups *loan* training time

Select Open-Source Reference Models	Normal training cost (TF 1.8)	Preemptible training cost (TF 1.8)
ResNet-50 (with optimizations from fast.ai): Image classification	~$25	~$7.50
ResNet-50 (original implementation): Image classification	~$59	~$18
AmoebaNet: Image classification (model architecture evolved from scratch on TPUs to maximize accuracy)	~$49	~$15
RetinaNet: Object detection	~$40	~$12
Transformer: Neural machine translation	~$41	~$13
ASR Transformer: Speech recognition (transcribe speech to text)	~$86	~$27

Cost of training from scratch some deep convolutional networks over Google's TPU cloud (2017)
https://www.theregister.co.uk/2018/06/20/google_cloud_tpus/

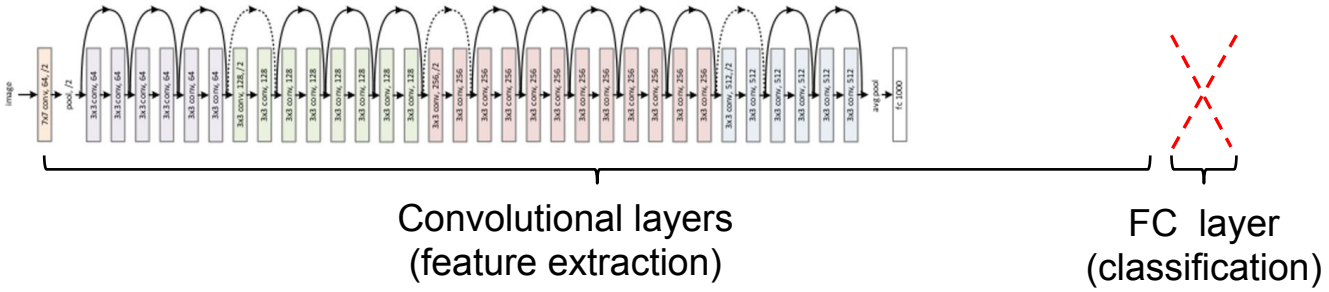
Training from Scratch

- Train *ResNet* to recognize K custom objects classes
  - Long training time
  - Must collect and label **many** train samples



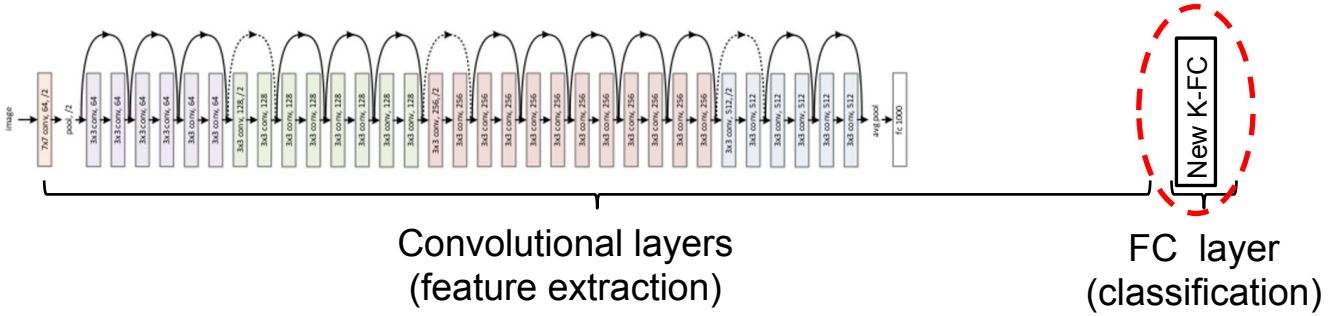
Transfer Learning

- Take ResNet pretrained on *ImageNet*



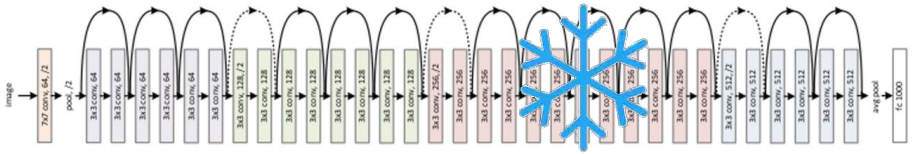
Transfer Learning

- Take ResNet pretrained on *ImageNet*
- Replace FC layer(s) with ad-hoc K-units FC layer



Transfer Learning

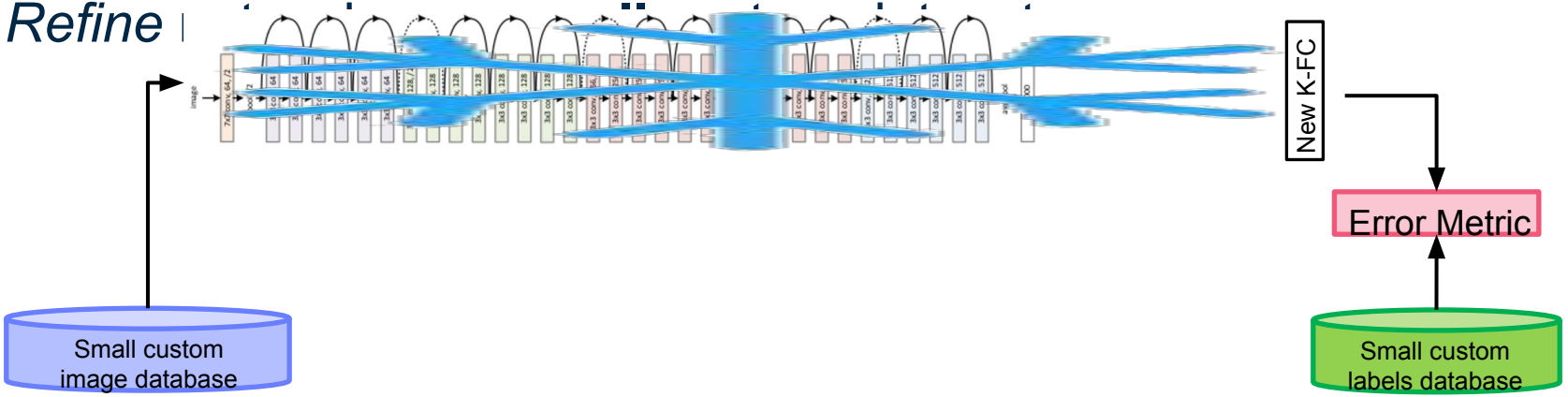
- Take ResNet pretrained on *ImageNet*
- Replace FC layer(s) with ad-hoc K-units FC layer
- *Freeze* (early) convolutional layers (η=0 or close to)



New K-FC

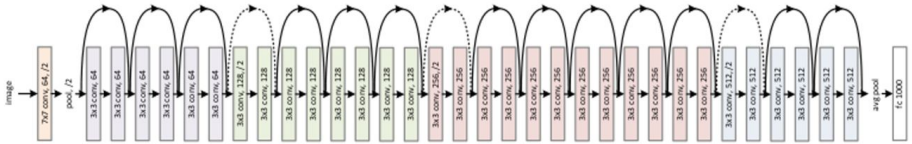
Transfer Learning

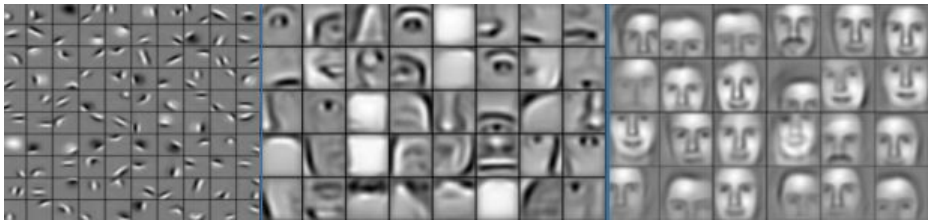
- Take ResNet pretrained on *ImageNet*
- Replace FC layer(s) with ad-hoc K-units FC layer
- *Freeze* (early) convolutional layers (η=0 or close to)
- *Refine* l



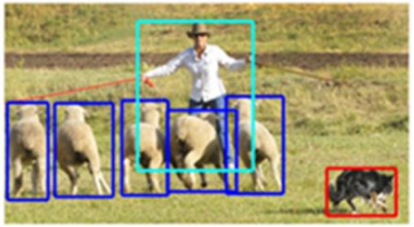
Transfer Learning – Why it Works ?

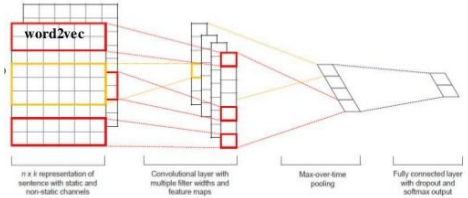
- Early conv. layers more difficult to trend (faint error gradients)
  - Very low level filters (edges, etc.)
    - «Reusing» pre-learned feature detectors

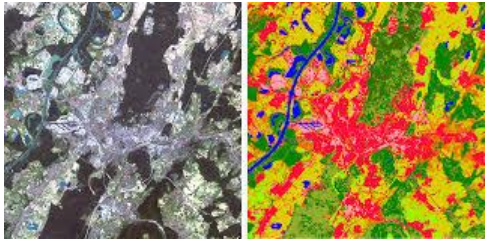




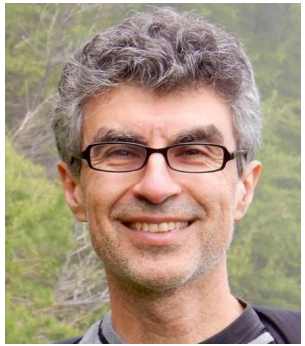
CNNs – Beyond Image Classification







Who's Who



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Jürgen Schmidhuber. “Deep learning in neural networks: An overview”, Neural Networks Volume 61, pp. 85–117 (2015)

Other Resources

Stanford Press *"Feature extraction using convolution"*
http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

Ujjwal Karn, *"An Intuitive Explanation of Convolutional Neural Networks"*
https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

Sebastian Raschka, "*Single-Layer Neural Networks and Gradient Descent*"
https://sebastianraschka.com/Articles/2015_singlelayer_neurons.html

Denny Britz, "*Understanding Convolutional Neural Networks for NLP*"
http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/

Adit Deshpande, "*A Beginner's Guide To Understanding Convolutional Neural Networks*"
https://adeshpande3.github.io/adeshpande3.github.io/Networks/

The University of British Columbia, "CPSC 522 - Artificial Intelligence 2"
http://wiki.ubc.ca/Course:CPSC522

Michael Nielsen, "*Neural Networks and Deep Learning*"
http://neuralnetworksanddeeplearning.com/index.html

I. Goodfellow, Y. Bengio, A. Courville, "*Deep Learning*"
http://www.deeplearningbook.org/

Questions ?