Deep Networks

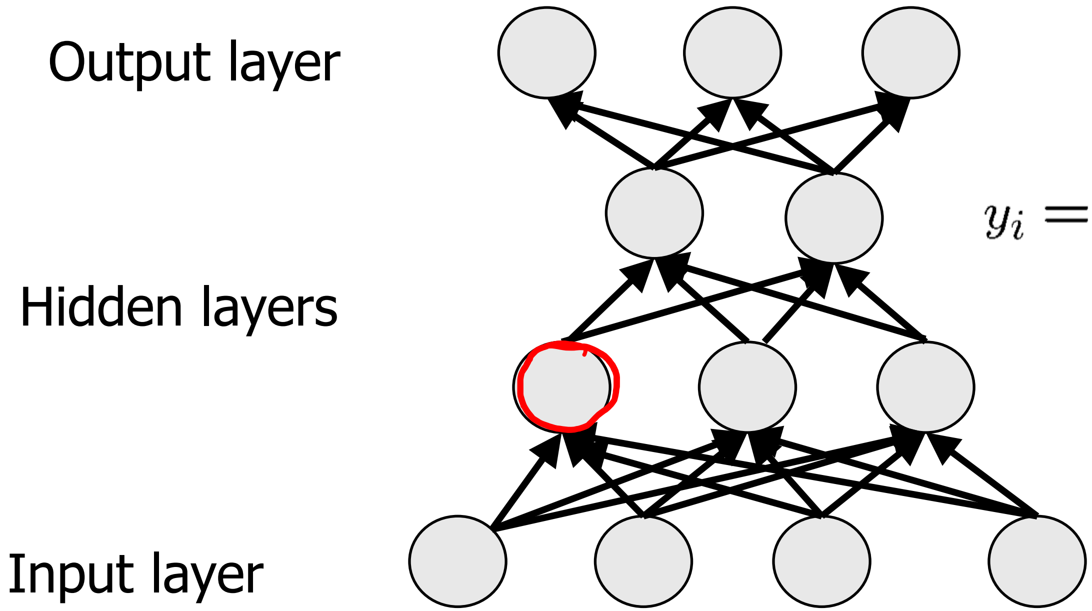
Aarti Singh

Machine Learning 10-315
Oct 7, 2020

Slides Courtesy: Barnabas Poczos, Ruslan Salakhutdinov, Joshua Bengio, Geoffrey Hinton, Yann LeCun, Pat Virtue

Deep architectures

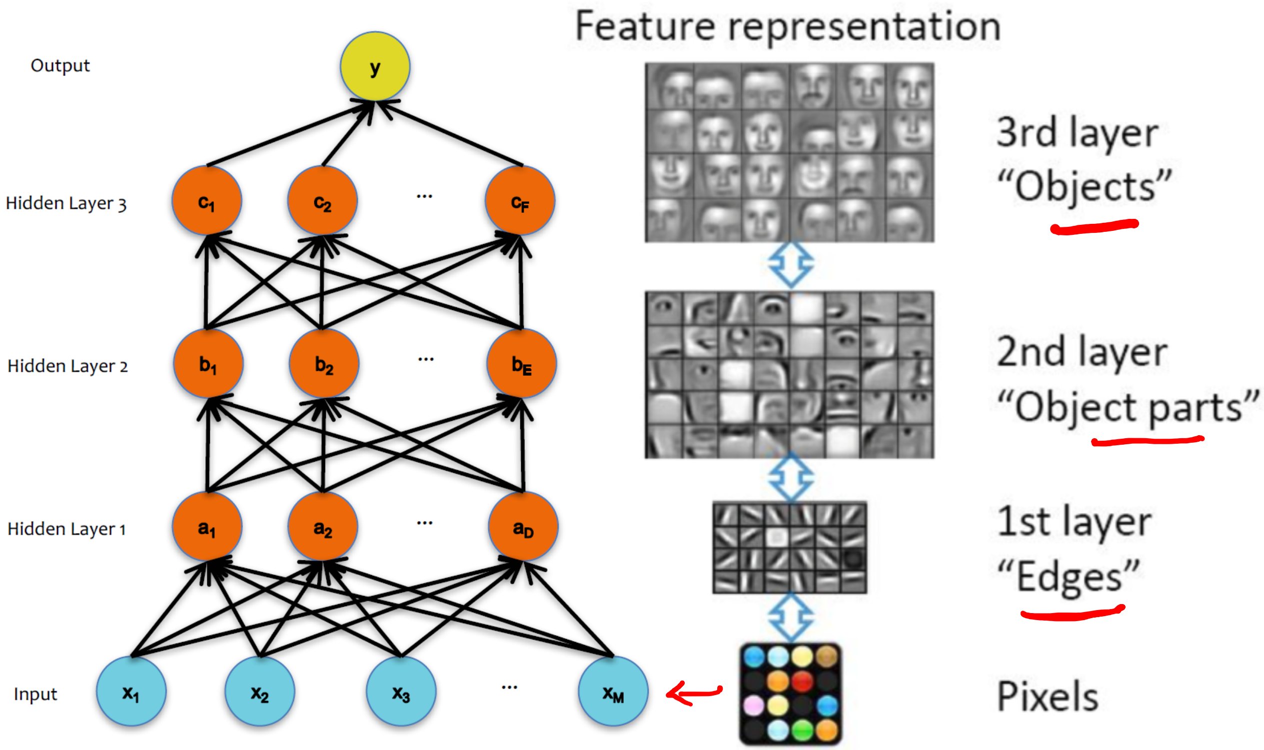
Defintion: Deep architectures are composed of *multiple levels* of non-linear operations, such as neural nets with many hidden layers.



$$y_i = \sigma\left(\sum_j W_{ij} x_j + W_{i0}\right)$$

Goal of Deep architectures

Goal: Deep learning methods aim at learning *feature hierarchies*



where features from higher levels of the hierarchy are formed by lower level features.

Example from Honglak Lee (NIPS 2010)

- ❑ Neurobiological motivation: The mammal brain is organized in a deep architecture (Serre, Kreiman, Kouh, Cadieu, Knoblich, & Poggio, 2007) (E.g. visual system has 5 to 10 levels)

Deep Learning History

- **Inspired** by the architectural depth of the brain, researchers wanted for decades to train deep multi-layer neural networks.
- **No** very **success**ful attempts were reported before 2006 …

  Researchers reported positive experimental results with typically two or three levels (i.e. one or two hidden layers), but training deeper networks consistently yielded poorer results.

- **SVM**: Vapnik and his co-workers developed the Support Vector Machine (1993). It is a shallow architecture.
- **Digression**: In the 1990's, many researchers abandoned neural networks with multiple adaptive hidden layers because SVMs worked better, and there was no successful attempts to train deep networks.
- **GPUs + Large datasets -> Breakthrough in 2006**

Breakthrough

Deep Belief Networks (DBN)

Hinton, G. E, Osindero, S., and Teh, Y. W. (2006).
A fast learning algorithm for deep belief nets.
Neural Computation, 18:1527-1554.

Autoencoders

Bengio, Y., Lamblin, P., Popovici, P., Larochelle, H. (2007).
Greedy Layer-Wise Training of Deep Networks,
Advances in Neural Information Processing Systems 19

Convolutional neural networks running on GPUs (2012)
Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton, Advances in Neural Information Processing Systems 2012

Deep Convolutional Networks

Convolutional Neural Networks

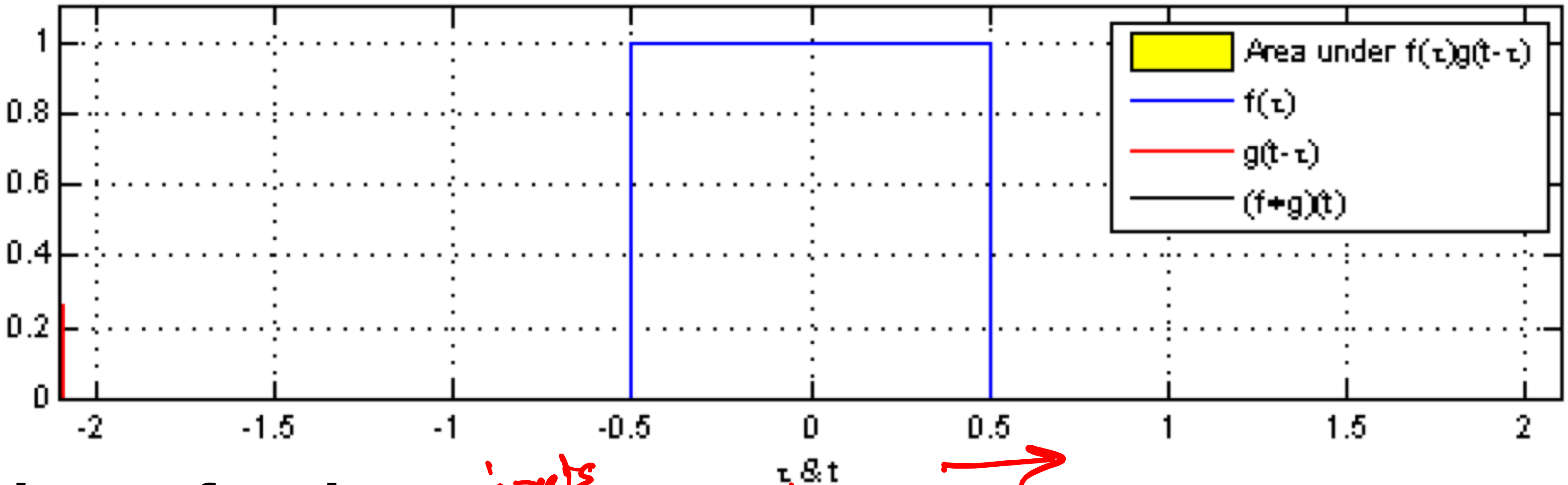
Compared to standard feedforward neural networks with similarly-sized layers,

- CNNs have much fewer connections and parameters
- and so they are easier to train,
- while their performance is likely to be only slightly worse, particularly for images as inputs.

LeNet 5

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: **Gradient-Based Learning Applied to Document Recognition**, *Proceedings of the IEEE, 86(11):2278-2324, November* ***1998***

Convolution



Continuous functions:

inputs weights

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)\, g(t - \tau)\, d\tau - = \int_{-\infty}^{\infty} f(t - \tau)\, g(\tau)\, d\tau.$$

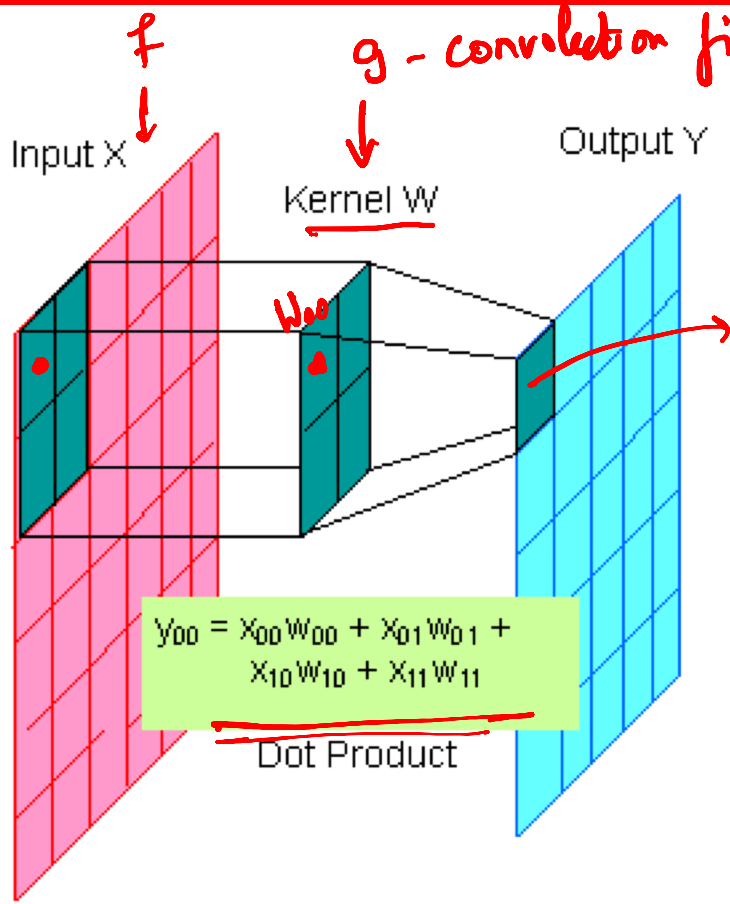
Discrete functions:

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m]\, \underbrace{g[n - m]}_{w[m]} = \sum_{m=-\infty}^{\infty} f[n - m]\, g[m]$$

If discrete g has support on {-M,...,M} :

$$(f * g)[n] = \sum_{m=-M}^{M} f[n - m] g[m]$$

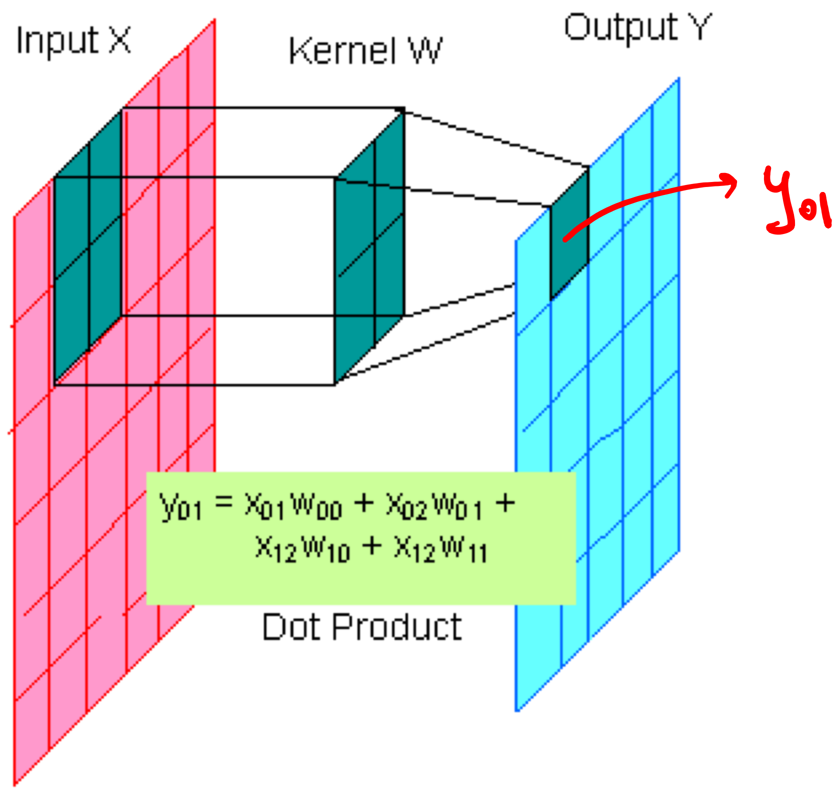
2-Dimensional Convolution



$$y_{00} = \sum_{ij} x_{ij} w_{ij}$$

$$= \vec{x} \cdot \vec{w}$$

2-Dimensional Convolution



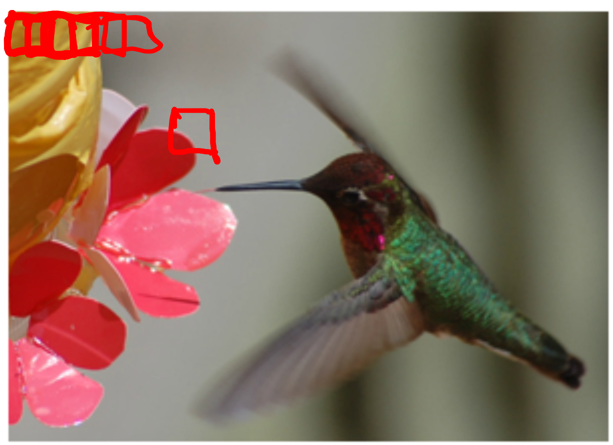
feed-forward
ll
fully connected
NN

2-Dimensional Convolution

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

https://graphics.stanford.edu/courses/cs178/applets/convolution.html

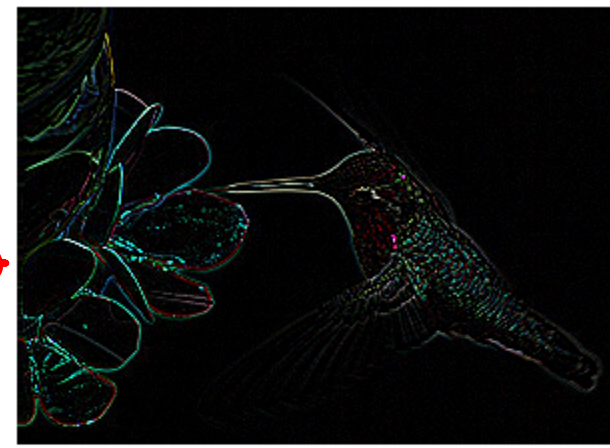
Original



Input

Filter (=kernel)

0.00	0.00	0.00	0.00	0.00
0.00	0.00	-2.00	0.00	0.00
0.00	-2.00	+8.00	-2.00	0.00
0.00	0.00	-2.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00



5 pixels

5 pixels

0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04
0.04	0.04	0.04	0.04	0.04

Convolution

Input image

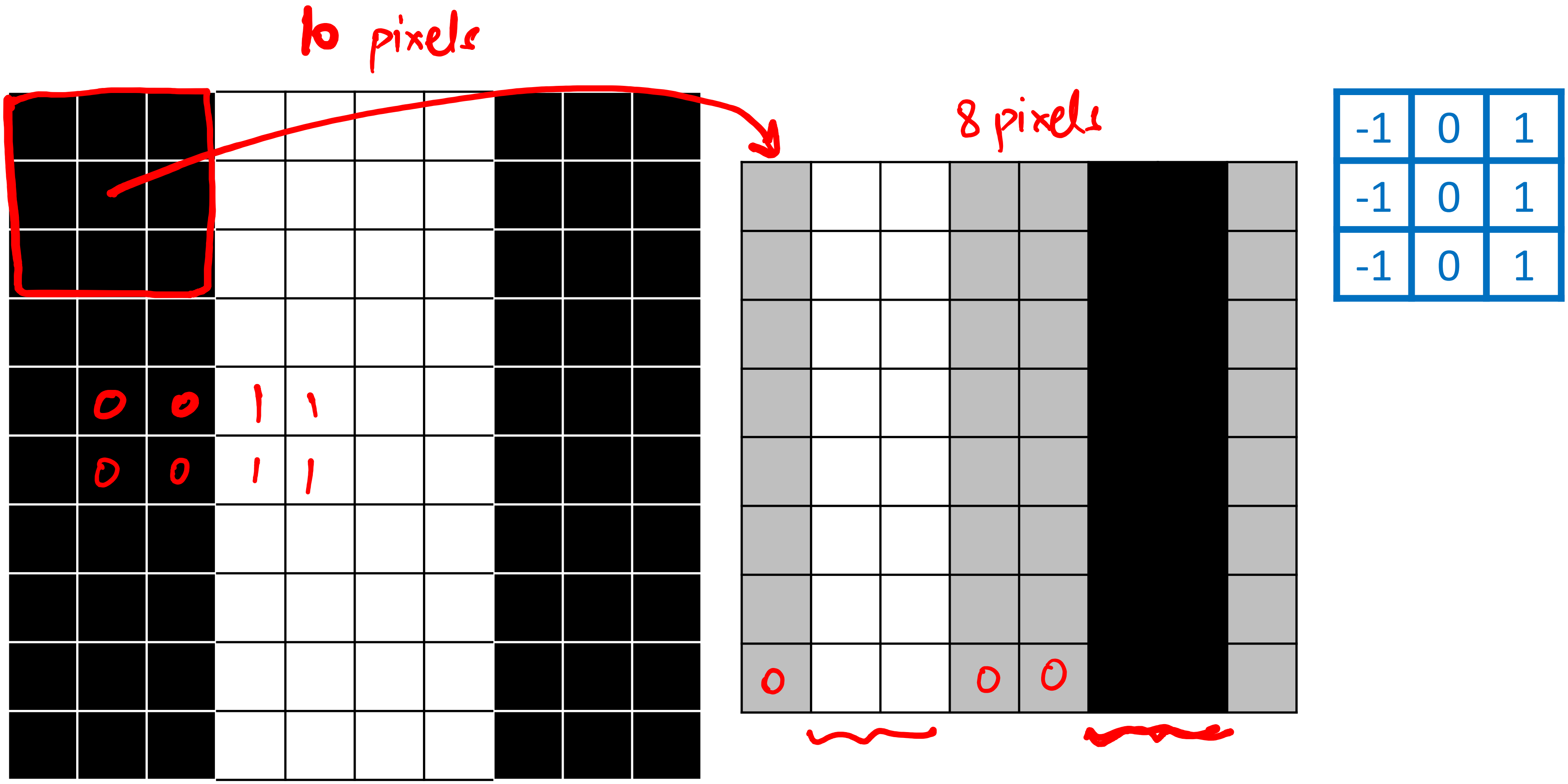
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0

0 3 3 0 0 -3 -3 0

Convolution filter

-1	0	1
-1	0	1
-1	0	1

Convolution



Convolution: Padding

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

0	2	2	0	0	-2	-2	0
0	3	3	0	0	-3	-3	0
0	3	3	0	0	-3	-3	0
0	3	3	0	0	-3	-3	0
0	3	3	0	0	-3	-3	0
0	3	3	0	0	-3	-3	0
0	3	3	0	0	-3	-3	0
0	2	2	0	0	-2	-2	0

Poll: Which kernel goes with which output image?

Input

K1

-1	0	1
-2	0	2
-1	0	1

K2

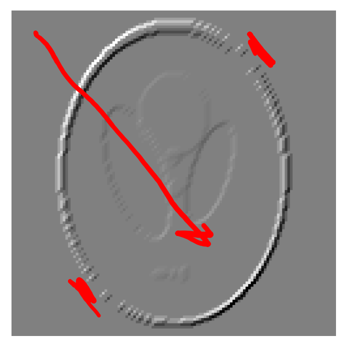
-1	-2	-1
0	0	0
1	2	1

K3

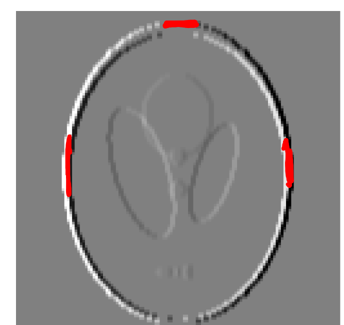
0	0	-1	0
0	-2	0	1
-1	0	2	0
0	1	0	0

Im1

Im2



Im3



Poll: Which kernel goes with which output image?

Input

K1

-1	0	1
-2	0	2
-1	0	1

K2

-1	-2	-1
0	0	0
1	2	1

K3

0	0	-1	0
0	-2	0	1
-1	0	2	0
0	1	0	0

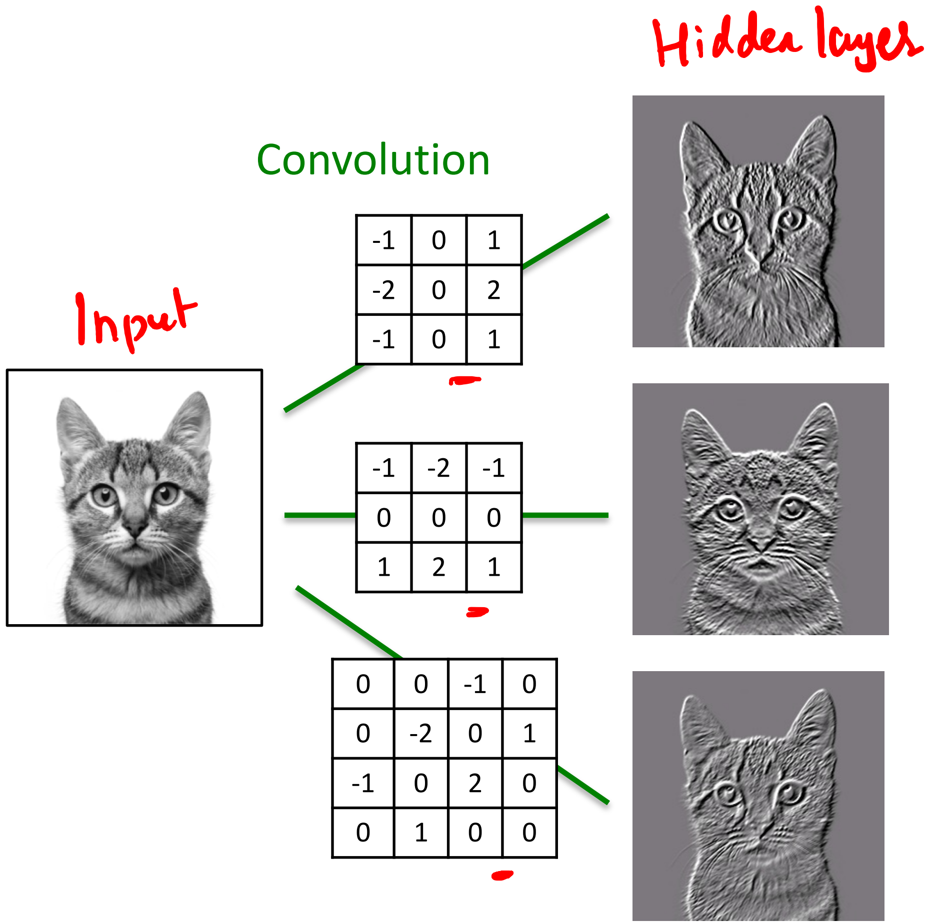
Im1

Im2

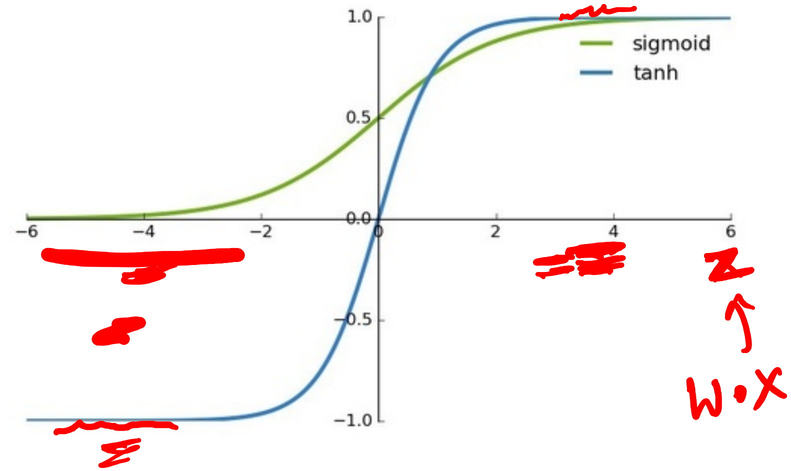
Im3

Convolutional Neural Networks

[Convolution + Nonlinear activation] + Pooling



saturating units



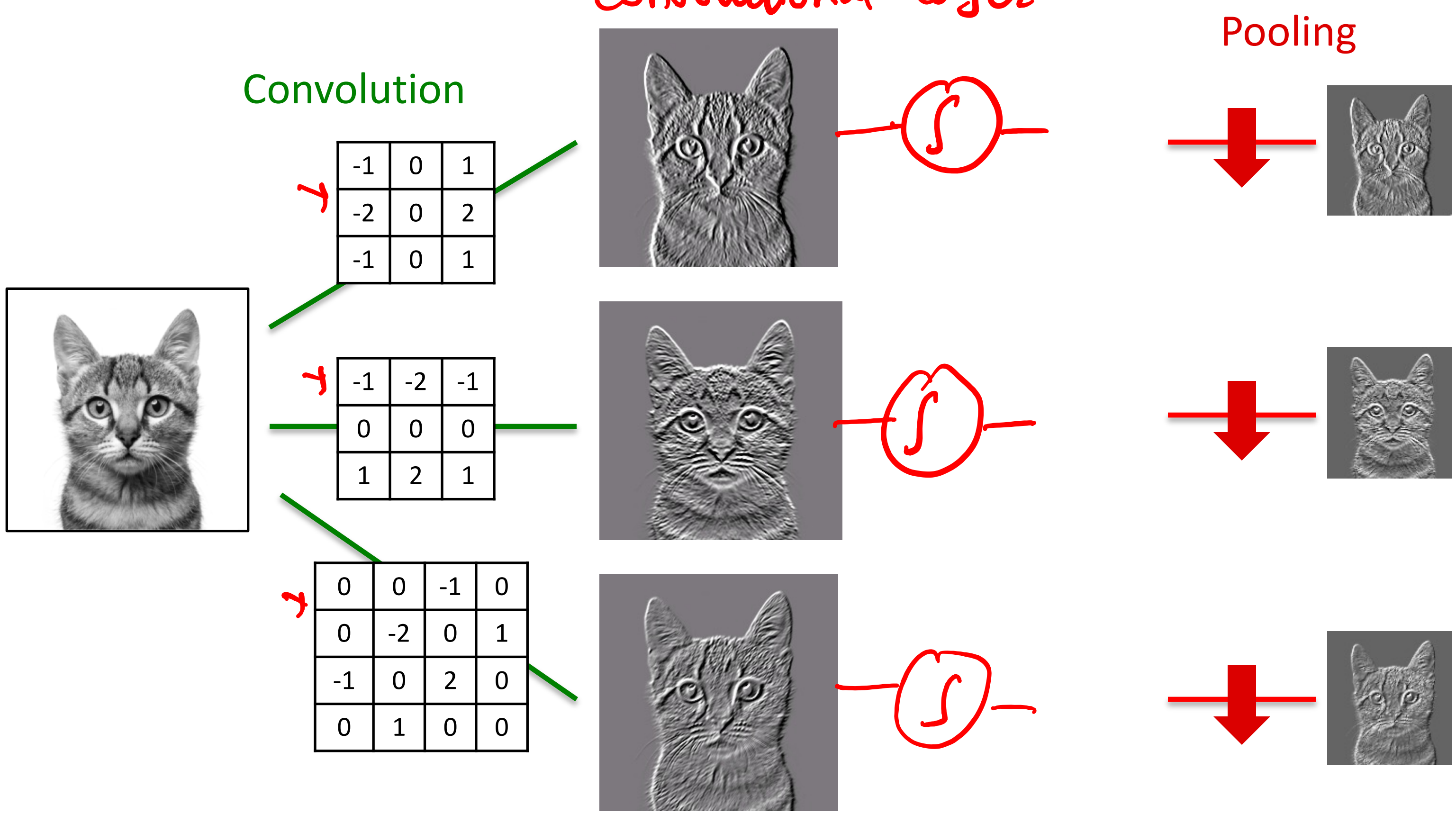
LeNet – tanh activation

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

vanishing gradients

Convolutional Neural Networks

[$\underbrace{\text{Convolution + Nonlinear activation}}_{\text{convolutional layer}}$] + Pooling



-1	0	1
-2	0	2
-1	0	1

-1	-2	-1
0	0	0
1	2	1

0	0	-1	0
0	-2	0	1
-1	0	2	0
0	1	0	0

Pooling = Down-sampling

Reduce size to reduce number of parameters

Average pooling: convolution with stride = filter size

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

Image

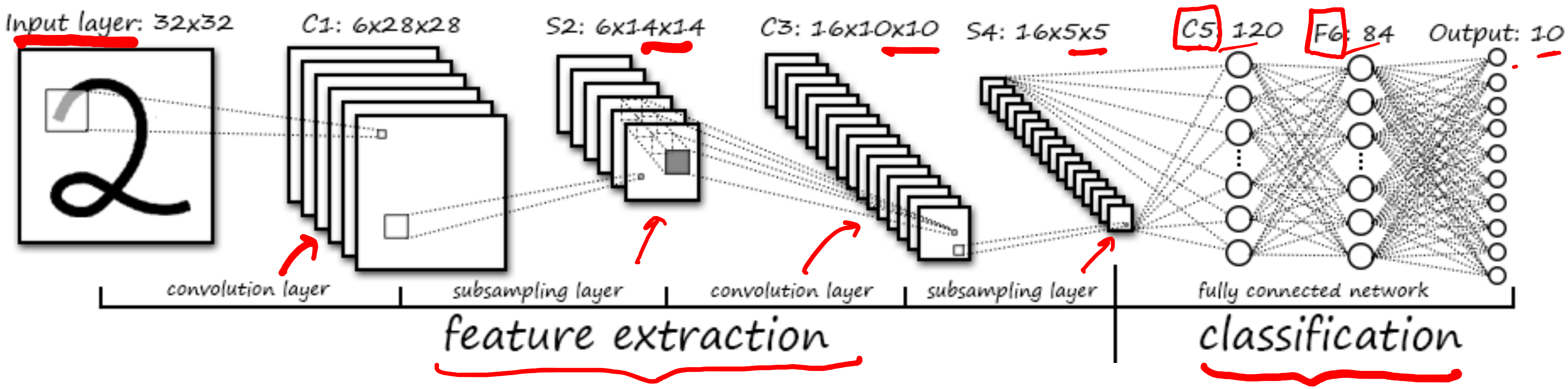
.25	.25
.25	.25

Average pool

Convolutional Neural Networks

Lenet5 – Lecun, et al, 1998

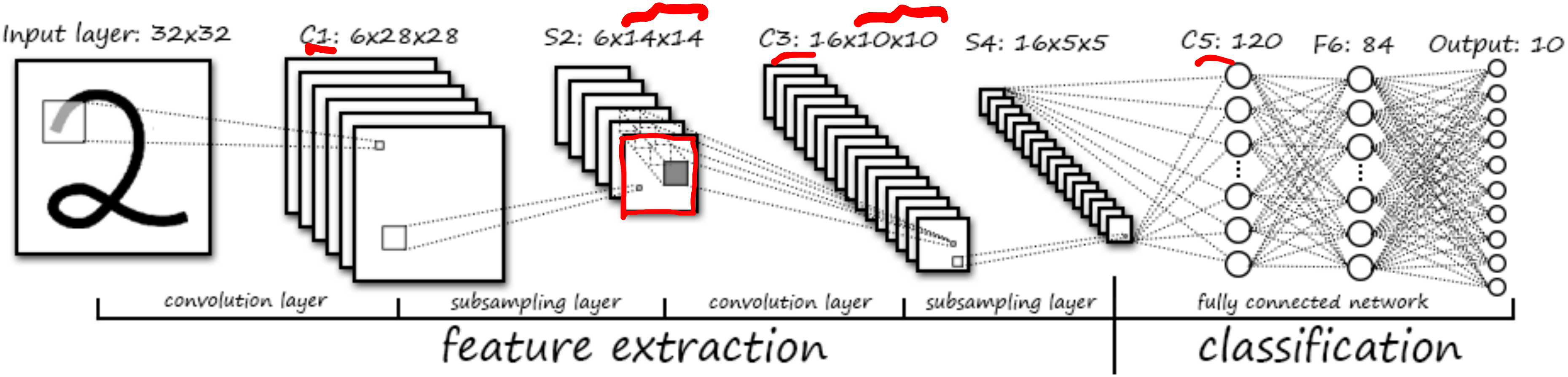
- Convnets for digit recognition



LeNet 5

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: **Gradient-Based Learning Applied to Document Recognition**, *Proceedings of the IEEE, 86(11):2278-2324, November* ***1998***

LeNet 5, LeCun 1998

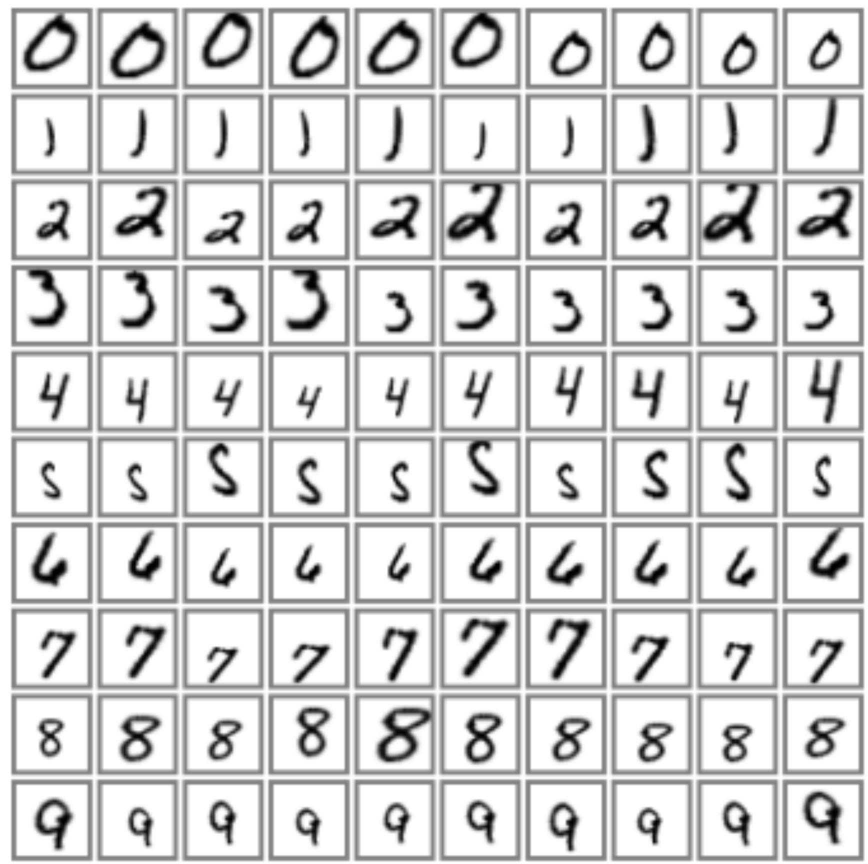


- **Input:** 32x32 pixel image. Largest character is 20x20
(All important info should be in the center of the receptive fields of the highest level feature detectors)
- **Cx:** Convolutional layer (C1, C3, C5) tanh nonlinear units
- **Sx:** Subsample layer (S2, S4) average pooling
- **Fx:** Fully connected layer (F6) logistic/sigmoid units
- Black and White pixel values are normalized:
E.g. White = -0.1, Black =1.175 (Mean of pixels = 0, Std of pixels =1)

MINIST Dataset

60,000 original dataset

Test error: 0.95%



540,000 artificial distortions

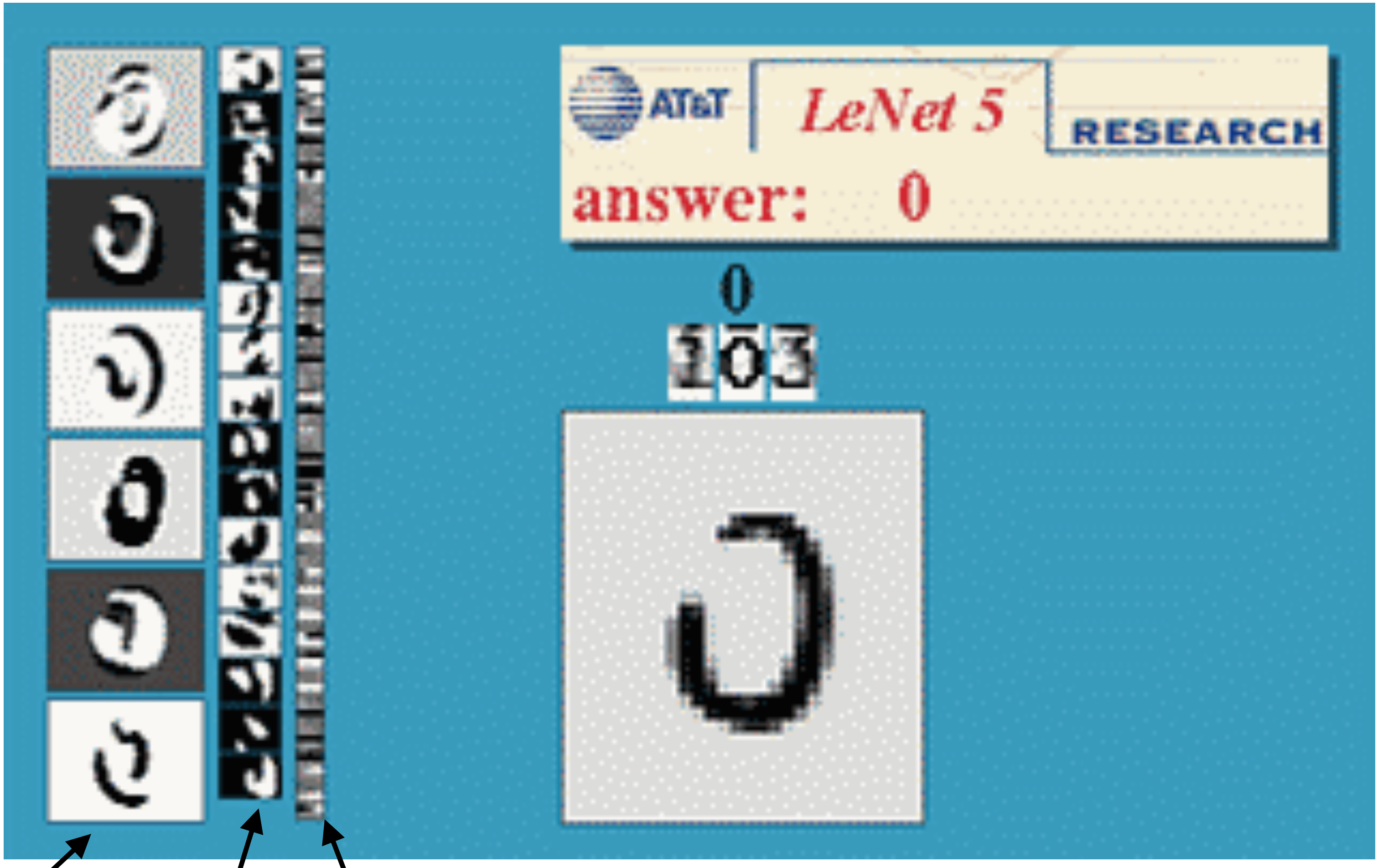
+ 60,000 original

Test error: 0.8%

Misclassified examples

True label -> Predicted label

LeNet 5 in Action

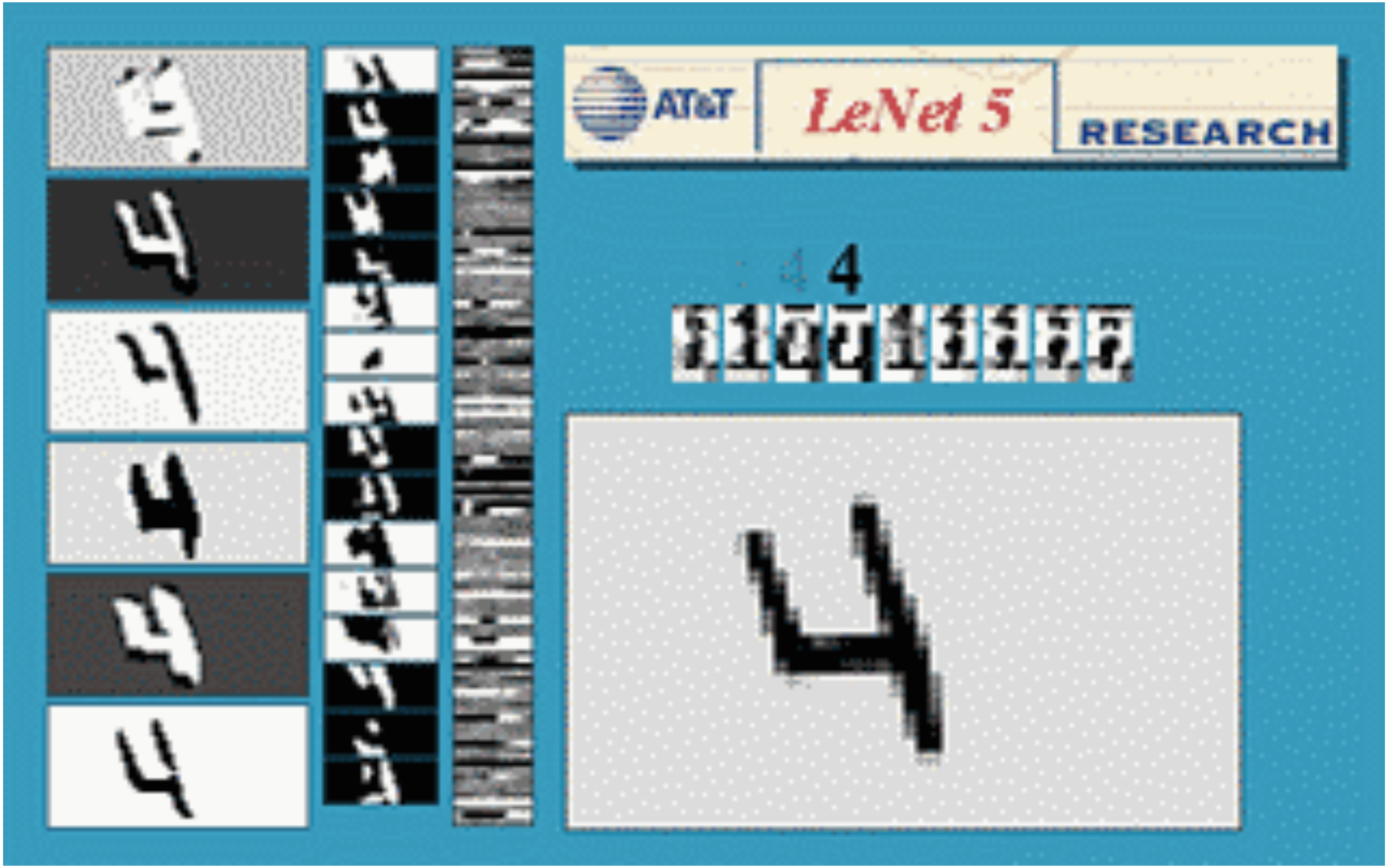


C1 C3 S4

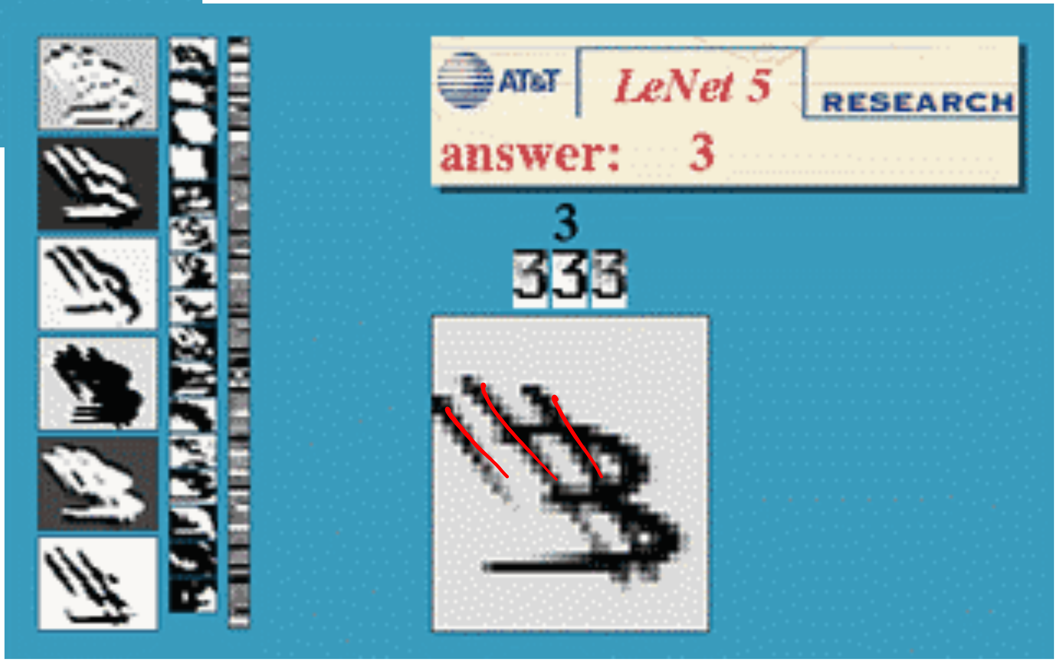
Input

LeNet 5, Shift invariance

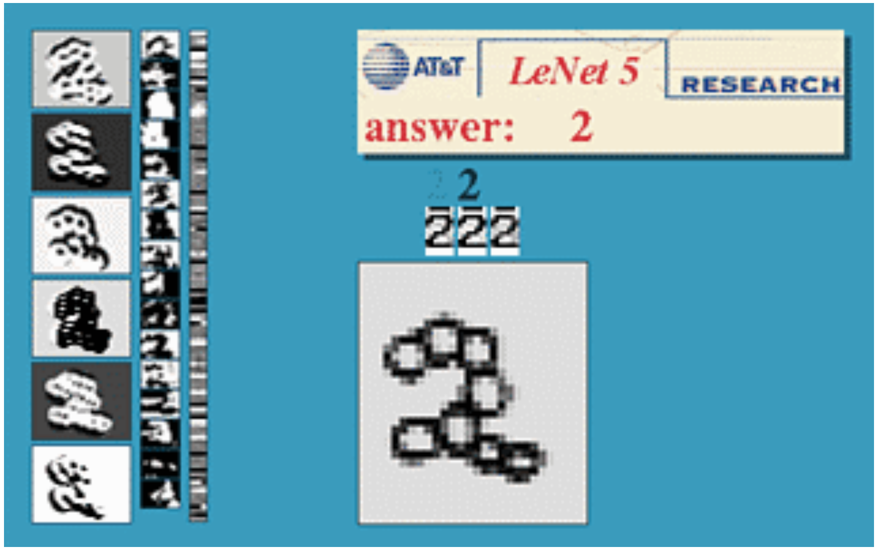
LeNet 5, Rotation invariance

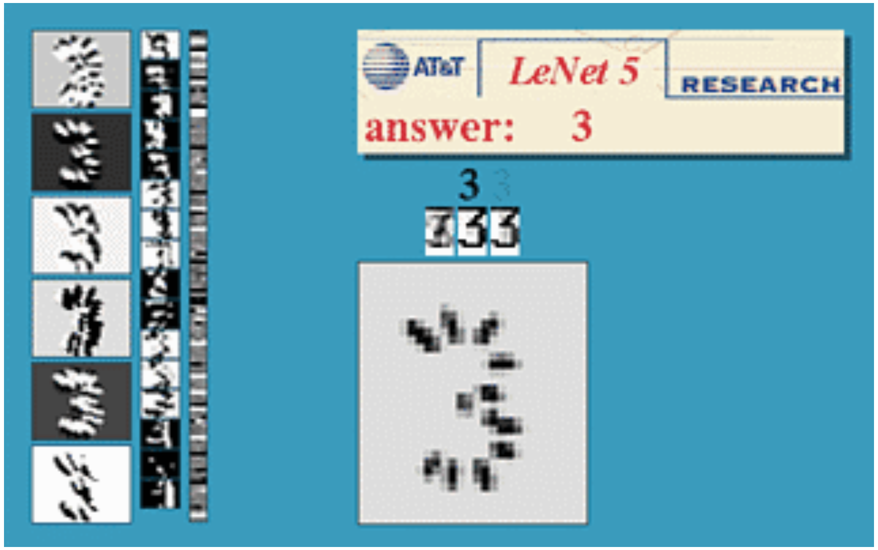


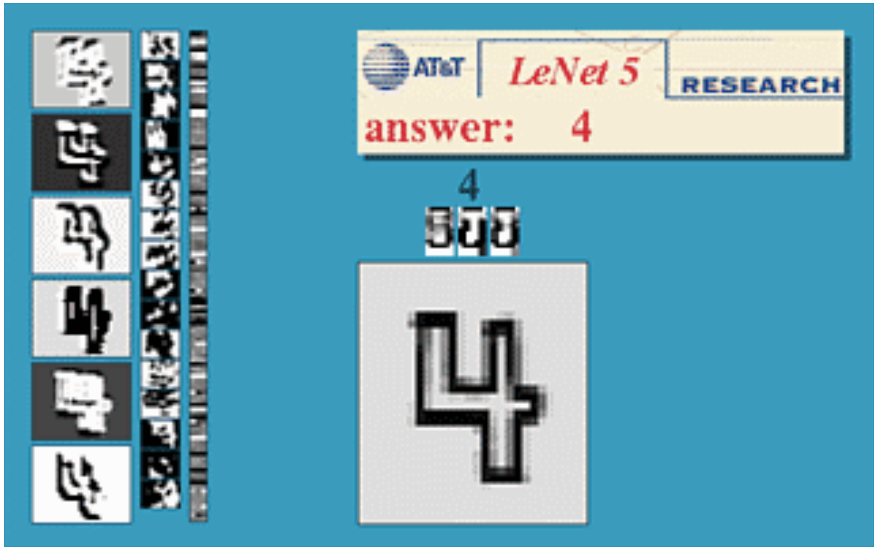
LeNet 5, Noise resistance

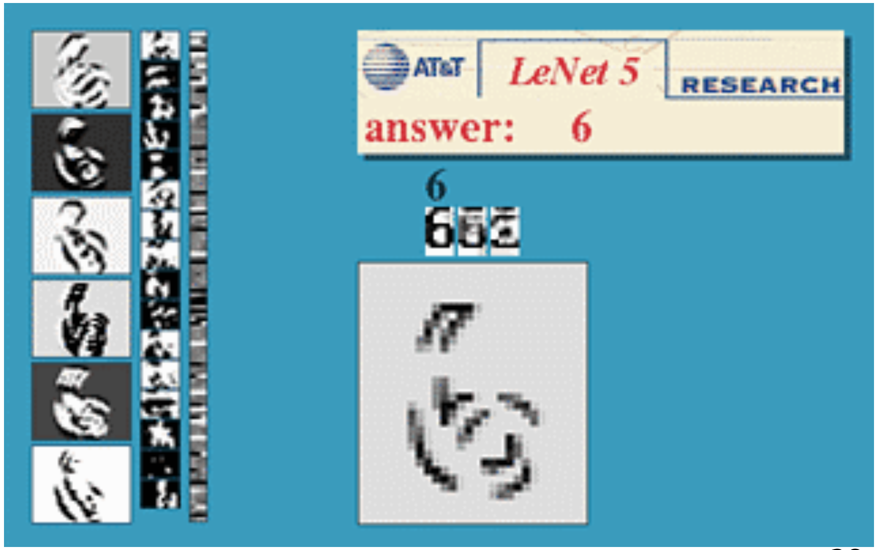


LeNet 5, Unusual Patterns









ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton,

Advances in Neural Information Processing Systems 2012

Alex Net

The Architecture

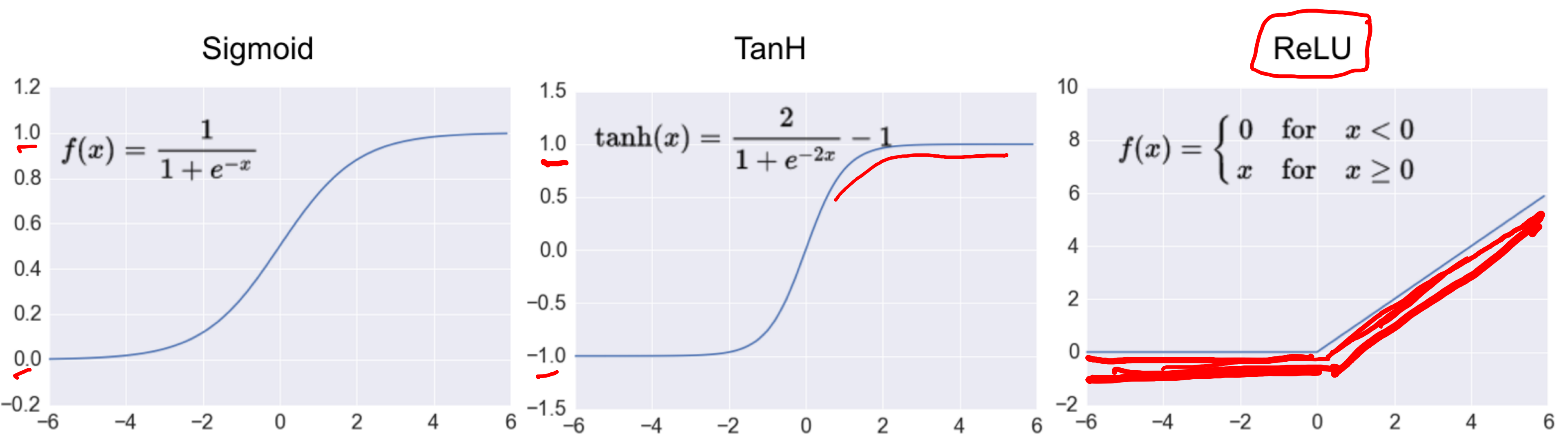
Typical nonlinearities:

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

$$f(x) = (1 + e^{-x})^{-1} \quad \text{(logistic function)}$$

Here, **Rectified Linear Units (ReLU)** are used: $f(x) = \max(0, x)$

Non-saturating/Gradients don't vanish – faster training



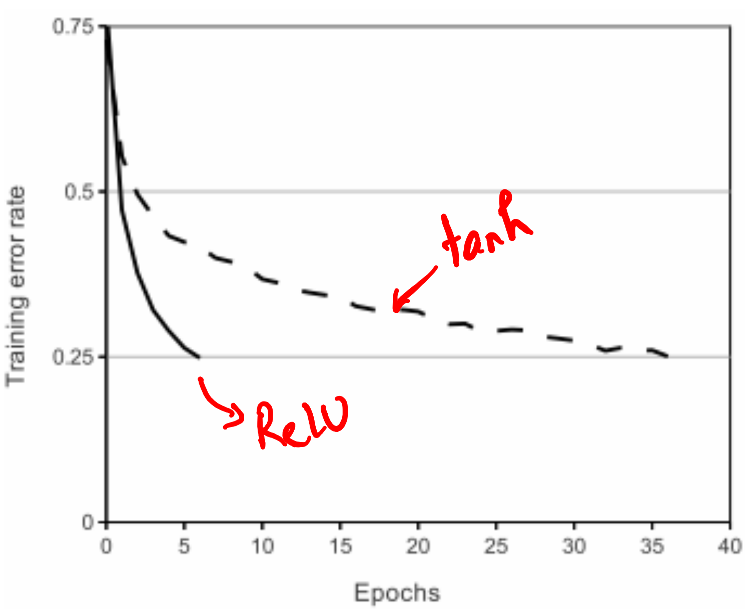
The Architecture

Typical nonlinearities: $f(x) = \tanh(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$

$f(x) = (1 + e^{-x})^{-1}$ (logistic function)

Here, **Rectified Linear Units (ReLU)** are used: $f(x) = \max(0, x)$

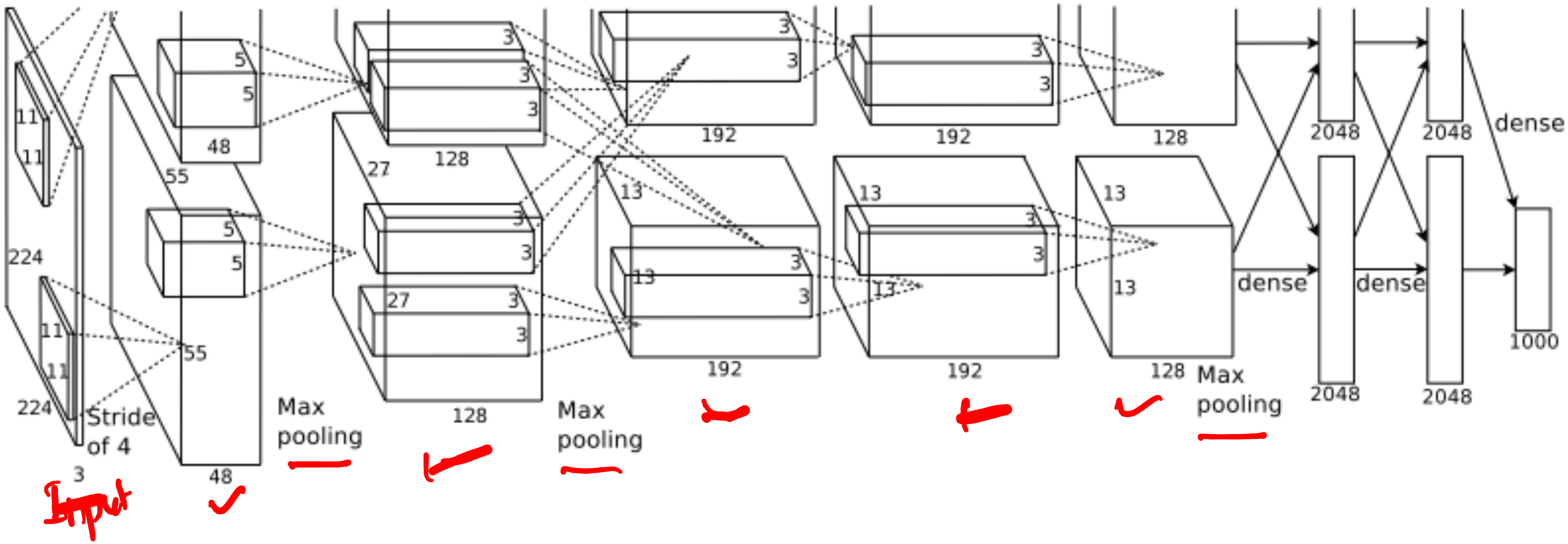
Non-saturating/Gradients don't vanish – faster training



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

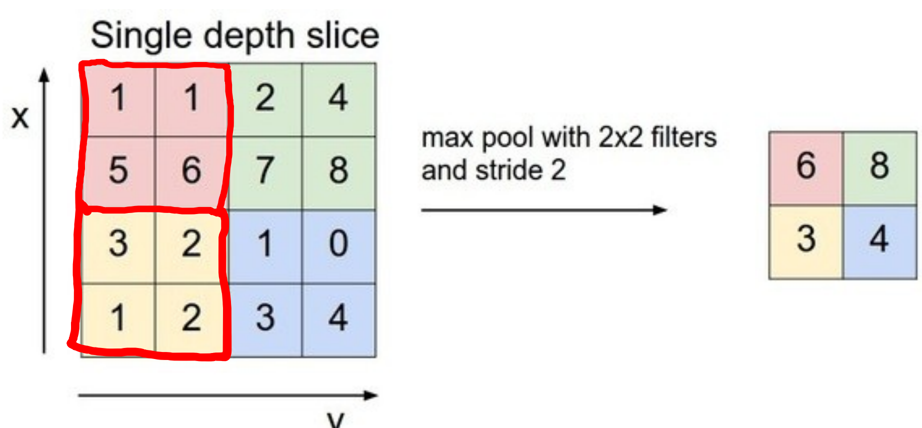
(dashed line)

The Architecture

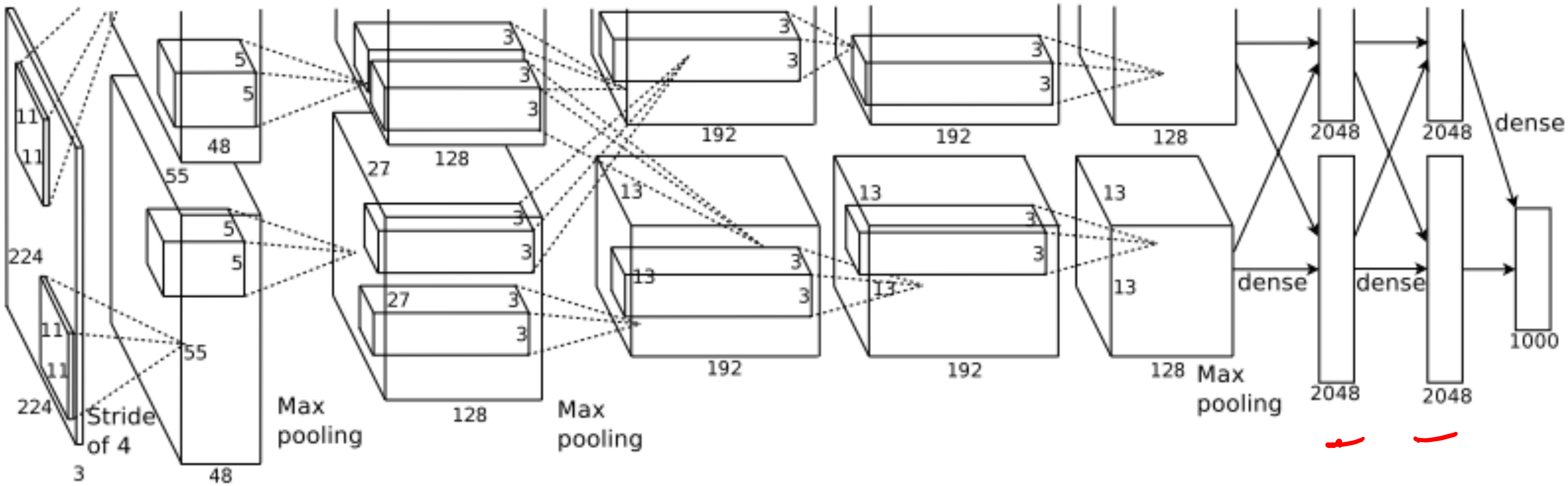


5 convolution layers (ReLU)

3 overlapping max pooling – nonlinear downsampling (max value of regions)



The Architecture



5 convolution layers (ReLU)

3 overlapping max pooling – nonlinear downsampling (max value of regions)

2 fully connected layers

output softmax

Training

- Trained with stochastic gradient descent
- on two NVIDIA GTX 580 3GB GPUs
- for about a week

- 650,000 neurons
- 60,000,000 parameters
- 630,000,000 connections
- 5 convolutional layer with Rectified Linear Units (ReLUs), 3 overlapping max pooling, 2 fully connected layer
- Final feature layer: 4096-dimensional

- Prevent overfitting – data augmentation, dropout trick
- Randomly extracted 224x224 patches for more data

Preventing overfitting

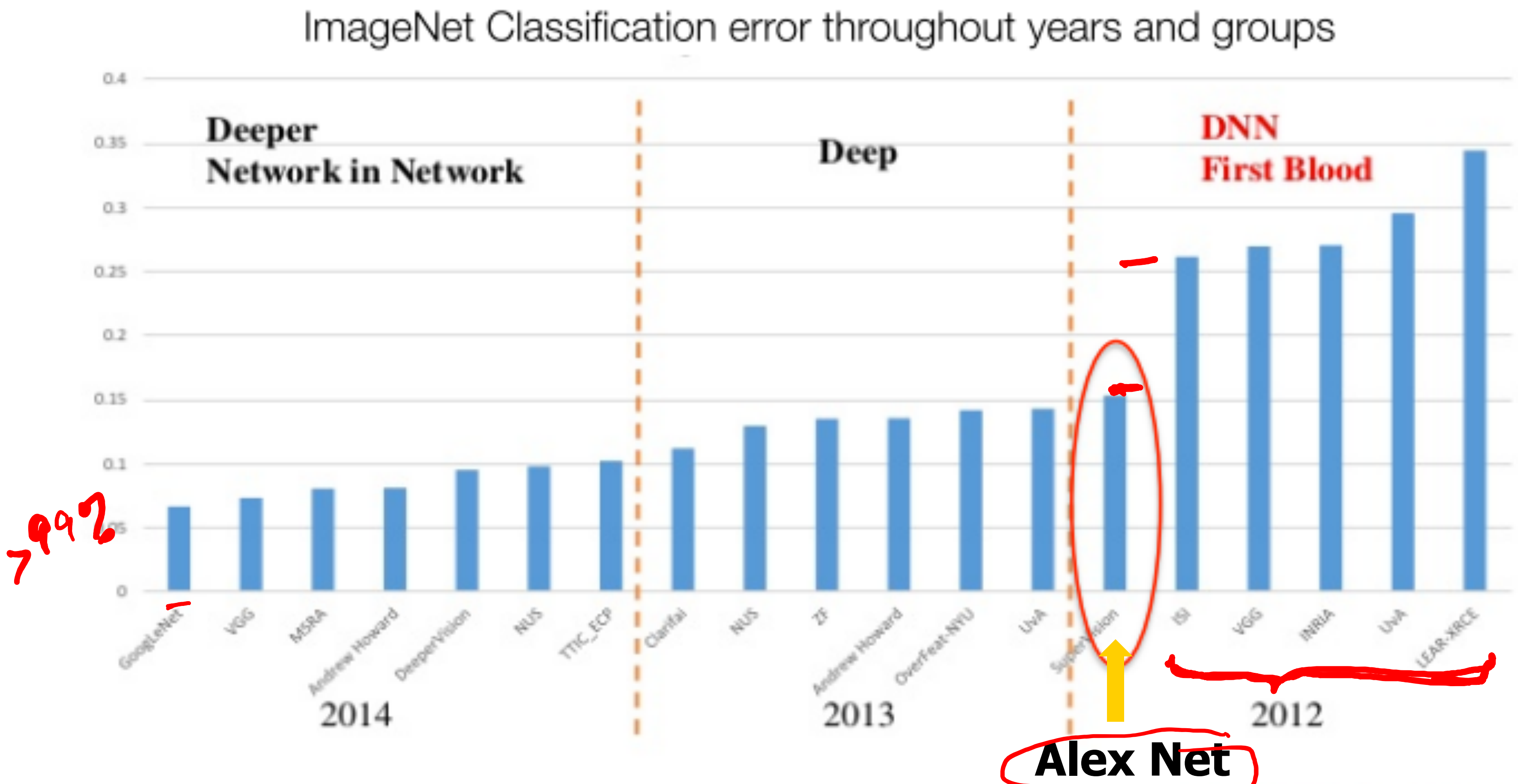
1) **Data augmentation**: The easiest and most common method to reduce overfitting on image data is to artificially enlarge the dataset using label-preserving transformations:

- image translation
- horizontal reflections
- changing RGB intensities

2) **Dropout**: set the output of each hidden neuron to zero w.p. 0.5.

- So every time an input is presented, the neural network samples a different architecture, but all these architectures share weights.
- This technique reduces complex co-adaptations of neurons, since a neuron cannot rely on the presence of particular other neurons.
- forced to learn more robust features that are useful in conjunction with many different random subsets of the other neurons.

Large part of the recent success of NNs, particularly for spatial image data, is due to Convolution Neural Network (CNN) architectures (LeNet, AlexNet, VGG, GoogLeNet, ResNet, …)



Li Fei-Fei: ImageNet Large Scale Visual Recognition Challenge, 2014 http://image-net.org/

ImageNet

- 15M images
- 22K categories
- Images collected from Web
- Human labelers (Amazon's Mechanical Turk crowd-sourcing)
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC-2010)
  - 1K categories
  - 1.2M training images (~1000 per category)
  - 50,000 validation images
  - 150,000 testing images
- RGB images
- Variable-resolution, but this architecture scales them to 256x256 size

ImageNet

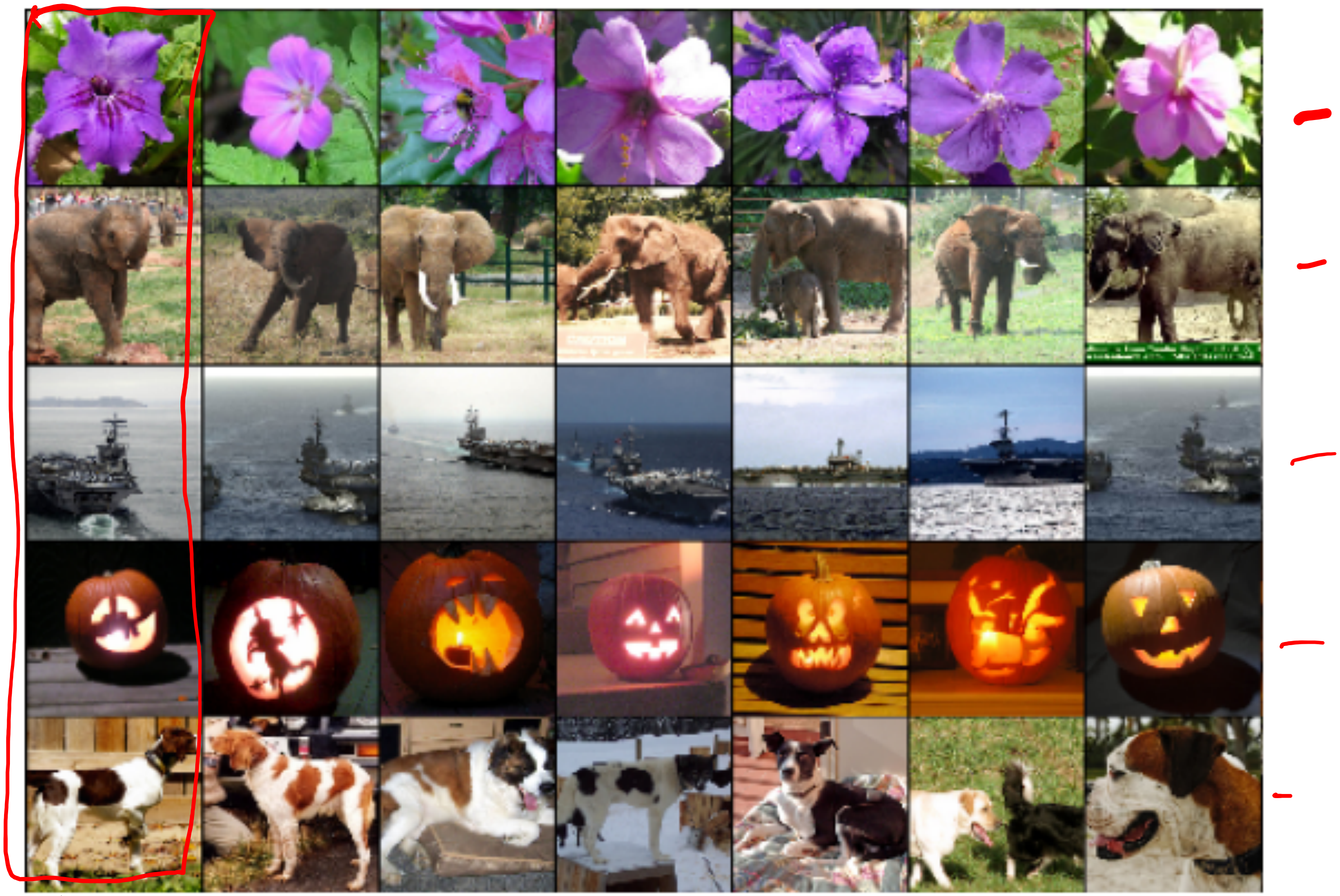
Classification goals:

- Make 1 guess about the label (Top-1 error)
- make 5 guesses about the label (Top-5 error)

Results


mite
mite
black widow
cockroach
tick
starfish
container ship
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
motor scooter
go-kart
moped
bumper car
golfcart
leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
convertible
grille
pickup
beach wagon
fire engine
mushroom
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
cherry
dalmatian
grape
elderberry
ffordshire bullterrier
currant
Madagascar cat
squirrel monkey
spider monkey
titi
indri
howler monkey

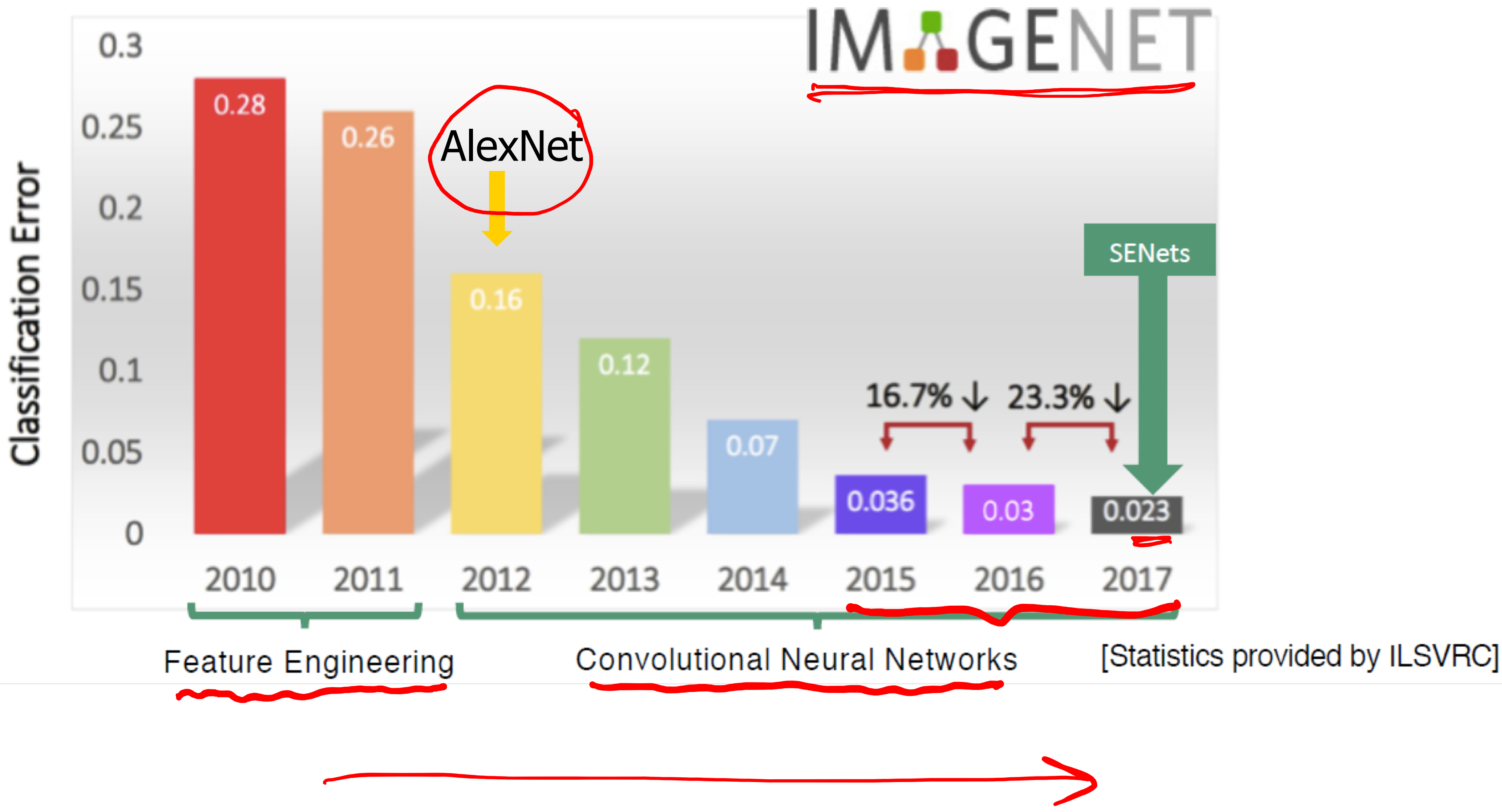
Results: Image similarity



Test column

six training images that produce feature vectors in the last hidden layer with the smallest Euclidean distance from the feature vector for the test image.

Results


IMAGENET
Classification Error
0.3
0.25
0.2
0.15
0.1
0.05
0
0.28
0.26
AlexNet
0.16
0.12
0.07
0.036
0.03
0.023
SENets
16.7% ↓
23.3% ↓
2010
2011
2012
2013
2014
2015
2016
2017
Feature Engineering
Convolutional Neural Networks
[Statistics provided by ILSVRC]