Deep Convolutional Networks

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Machine Learning 10-315
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Slides Courtesy: Barnabas Poczos, Ruslan Salakhutdinov, Joshua Bengio, Geoffrey Hinton, Yann LeCun, Pat Virtue

Convolutional Neural Networks

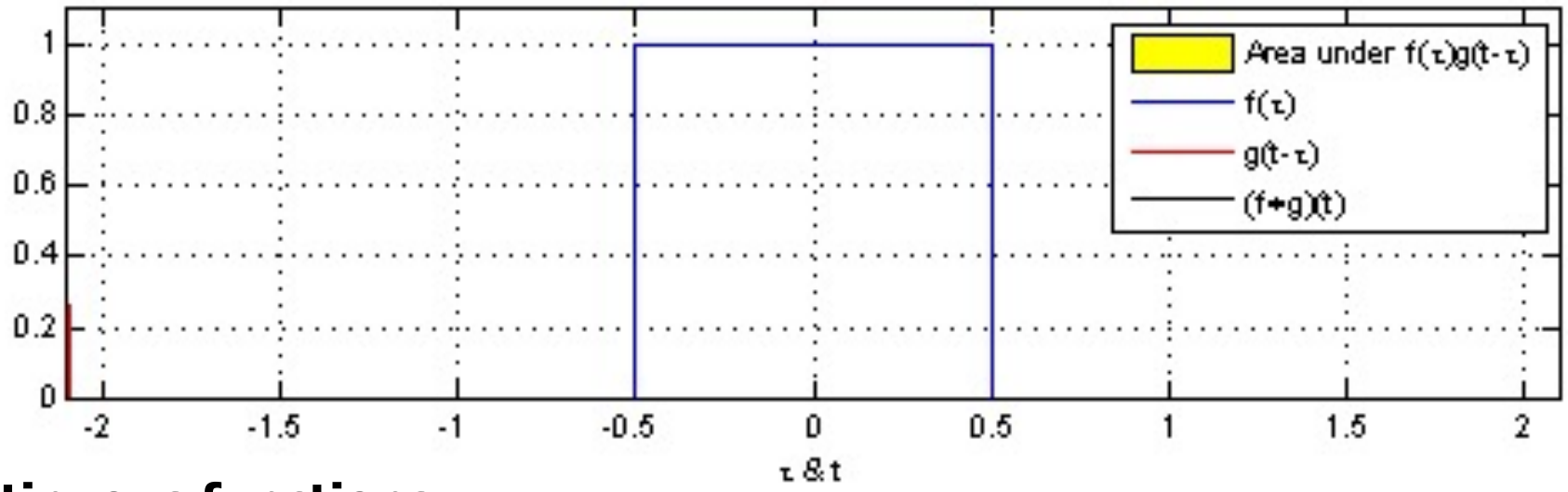
Compared to standard feedforward neural networks with similarly-sized layers,

- CNNs have much fewer connections and shared 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 operator



Continuous functions:

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

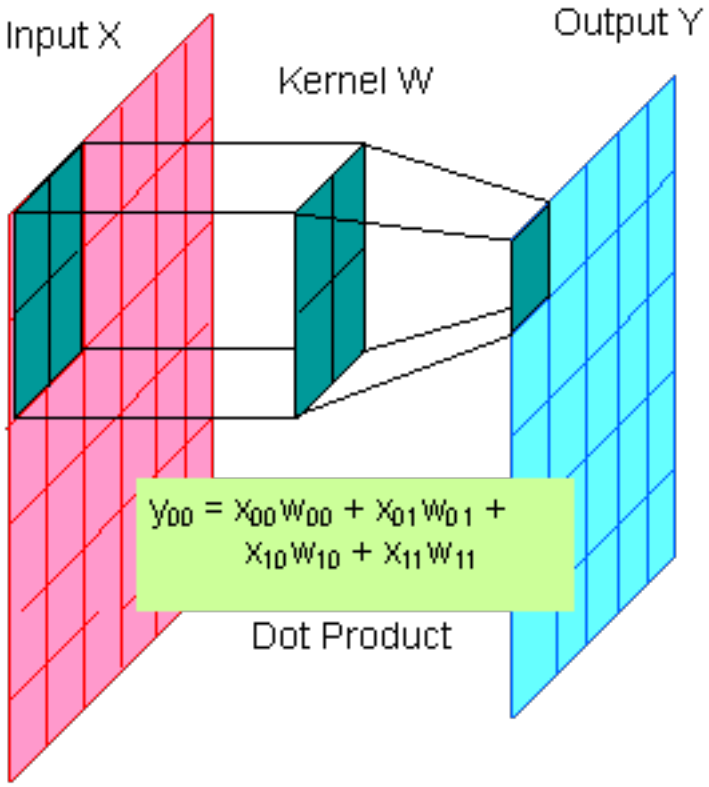
Discrete functions:

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

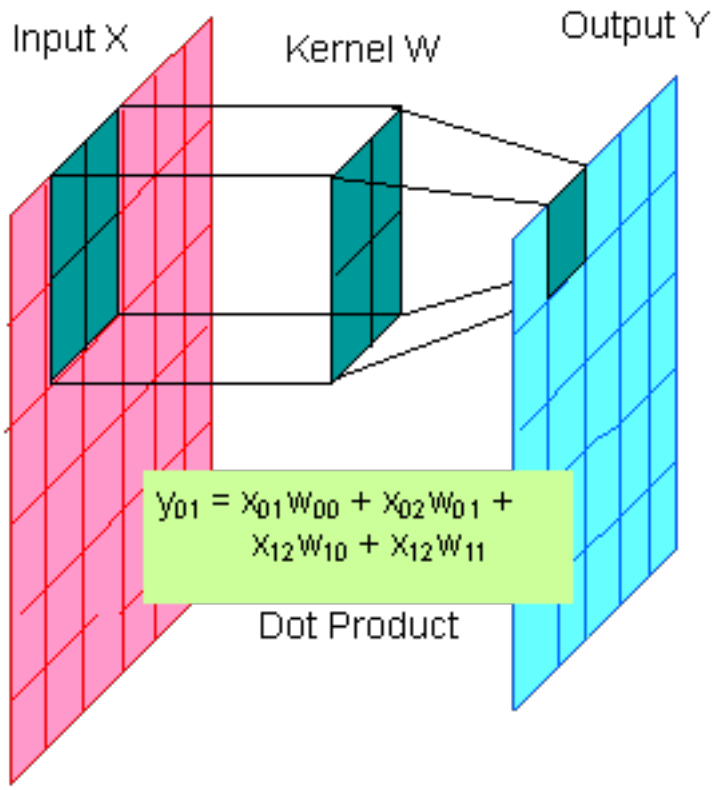
If discrete g has support on {-M,...,M} :

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

2-Dimensional Convolution filter



2-Dimensional Convolution filter



2-Dimensional Convolution filter

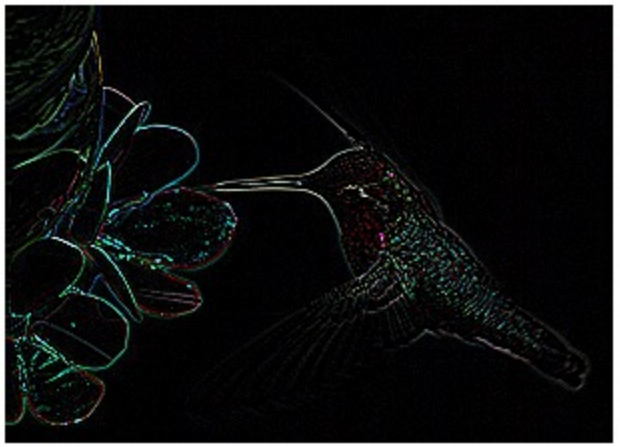
$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

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

Original

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



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

Poll: Which filter 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 filter 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

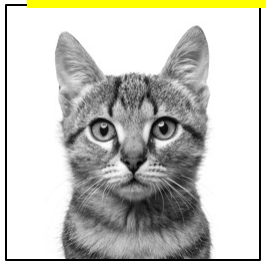
Im2

Im3

Convolutional Neural Networks

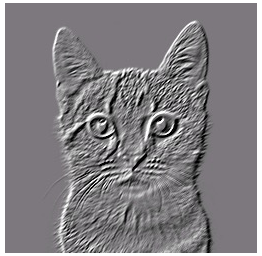
[Convolution filter + Nonlinear activation] + Pooling

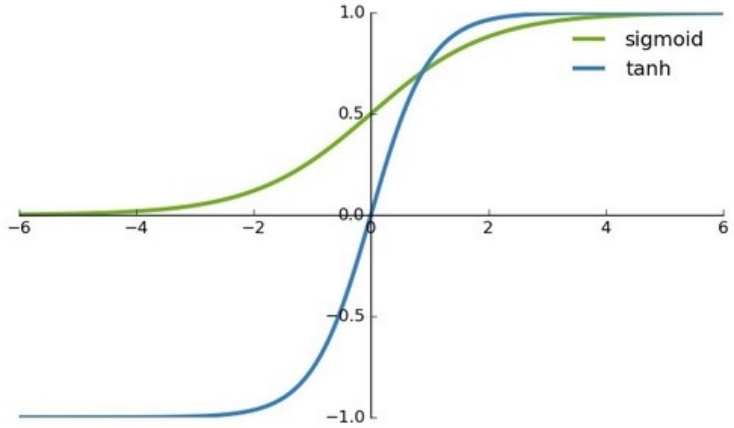
Without zero padding?



-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



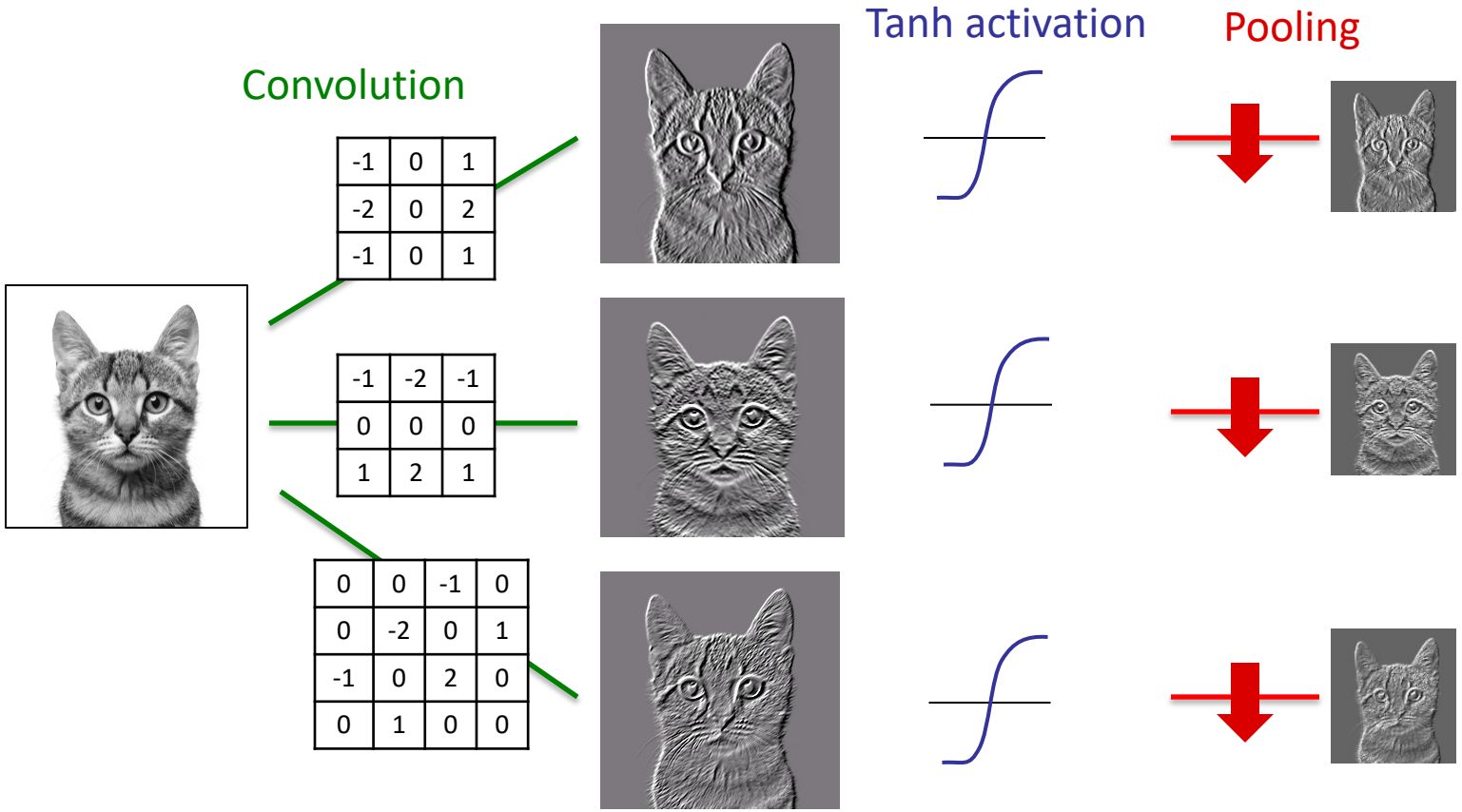


LeNet – tanh activation

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

Convolutional Neural Networks

[Convolution filter + Nonlinear activation] + Pooling



Pooling = Down-sampling

Reduce size to reduce number of parameters

Average pooling: convolution with stride = filter size

.25	.25
.25	.25

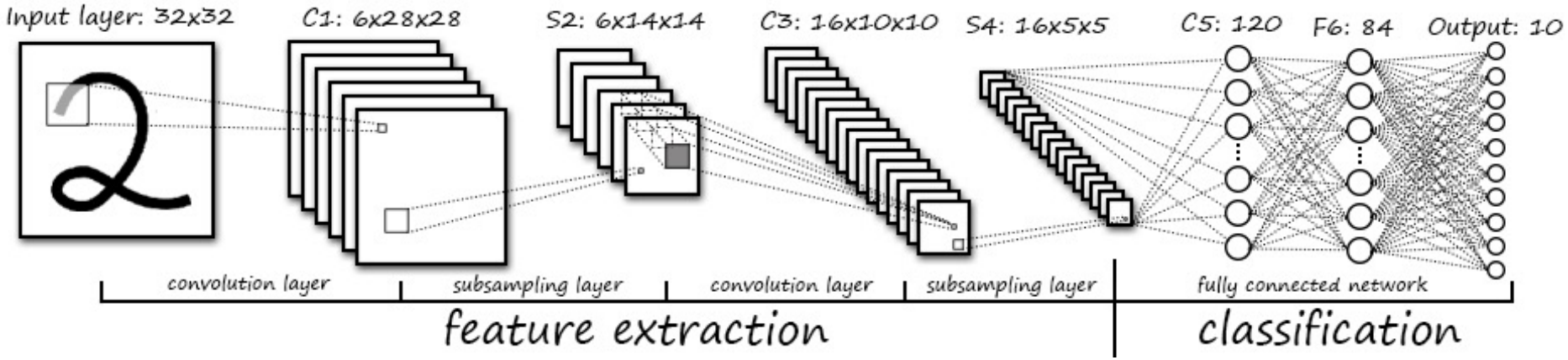
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0

Convolutional Neural Networks

Lenet5 – Lecun, et al, 1998

- Convnets for digit recognition

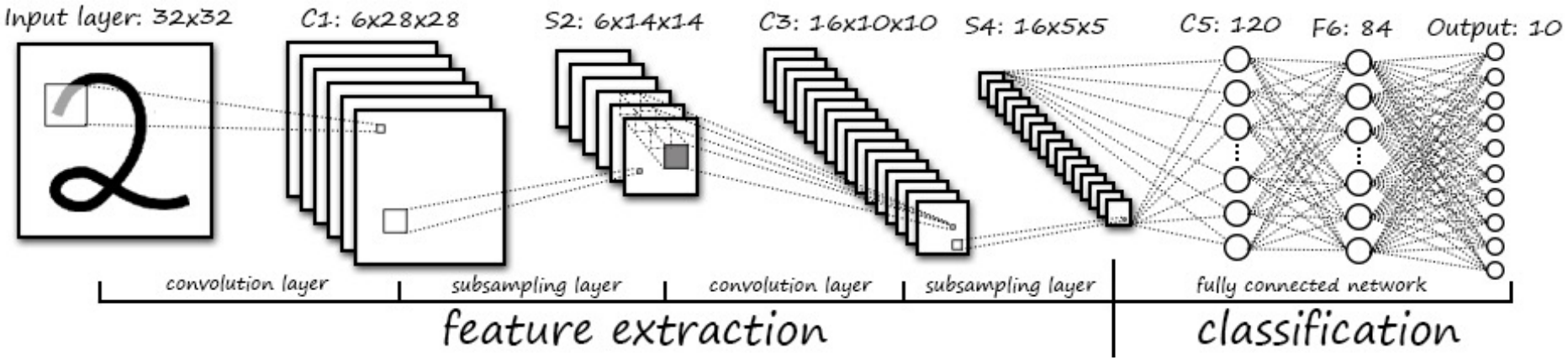
C5 convolution or FC?



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

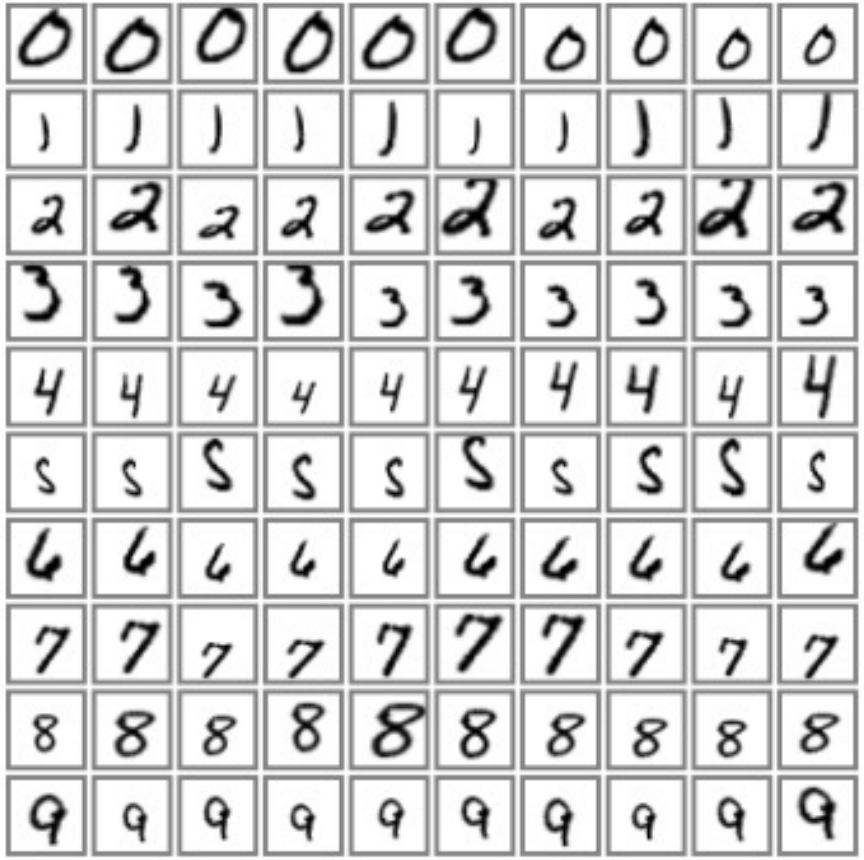


- **Input:** 32x32 pixel image. Largest character is 20x20
  (All important info should be in the center of the receptive fields of the highest level feature detectors)
- **Cx:** Convolutional layer (C1, C3, C5) tanh nonlinear units
- **Sx:** Subsample layer (S2, S4) average pooling
- **Fx:** Fully connected 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

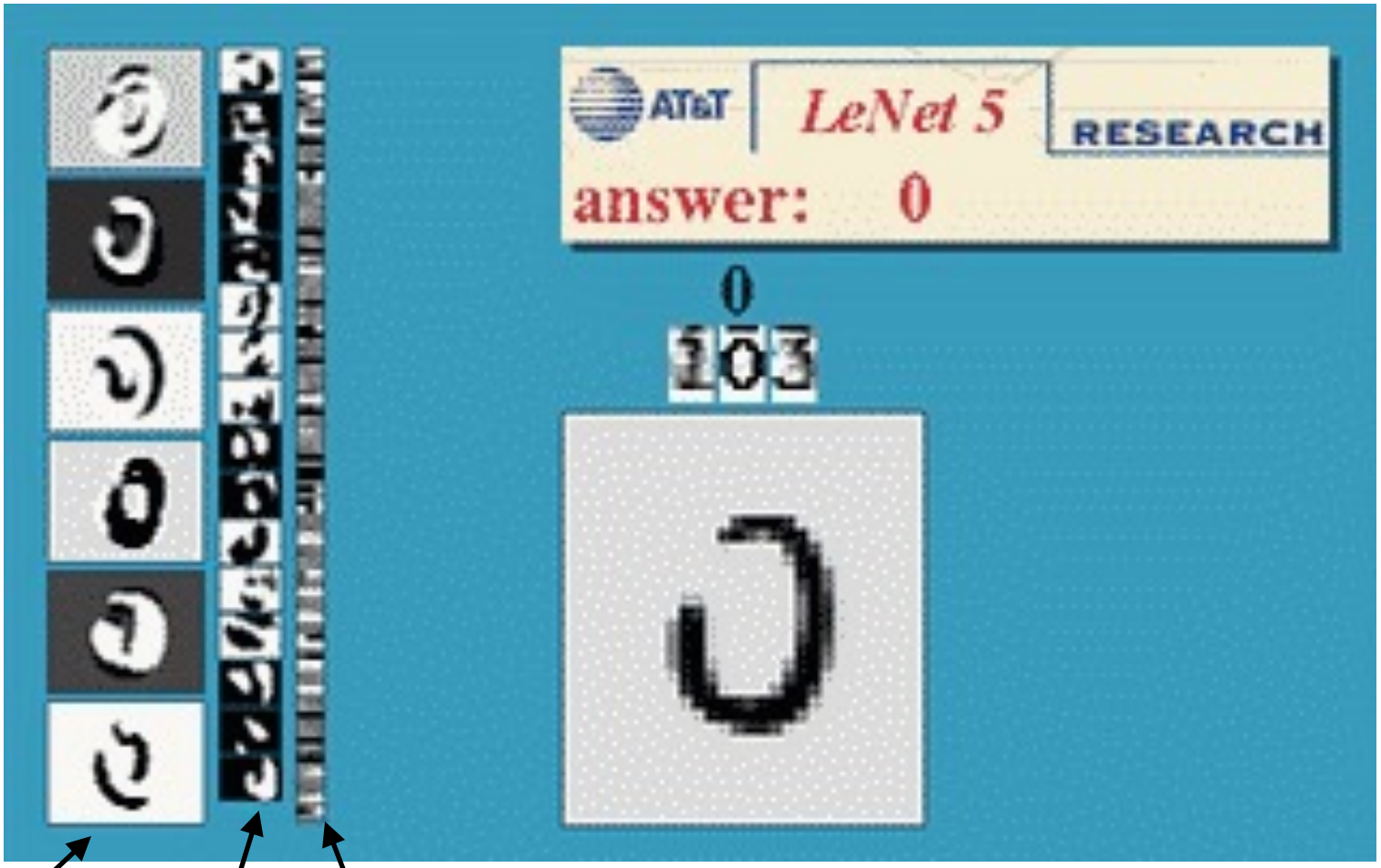
+ 60,000 original

Test error: 0.8%

Misclassified examples

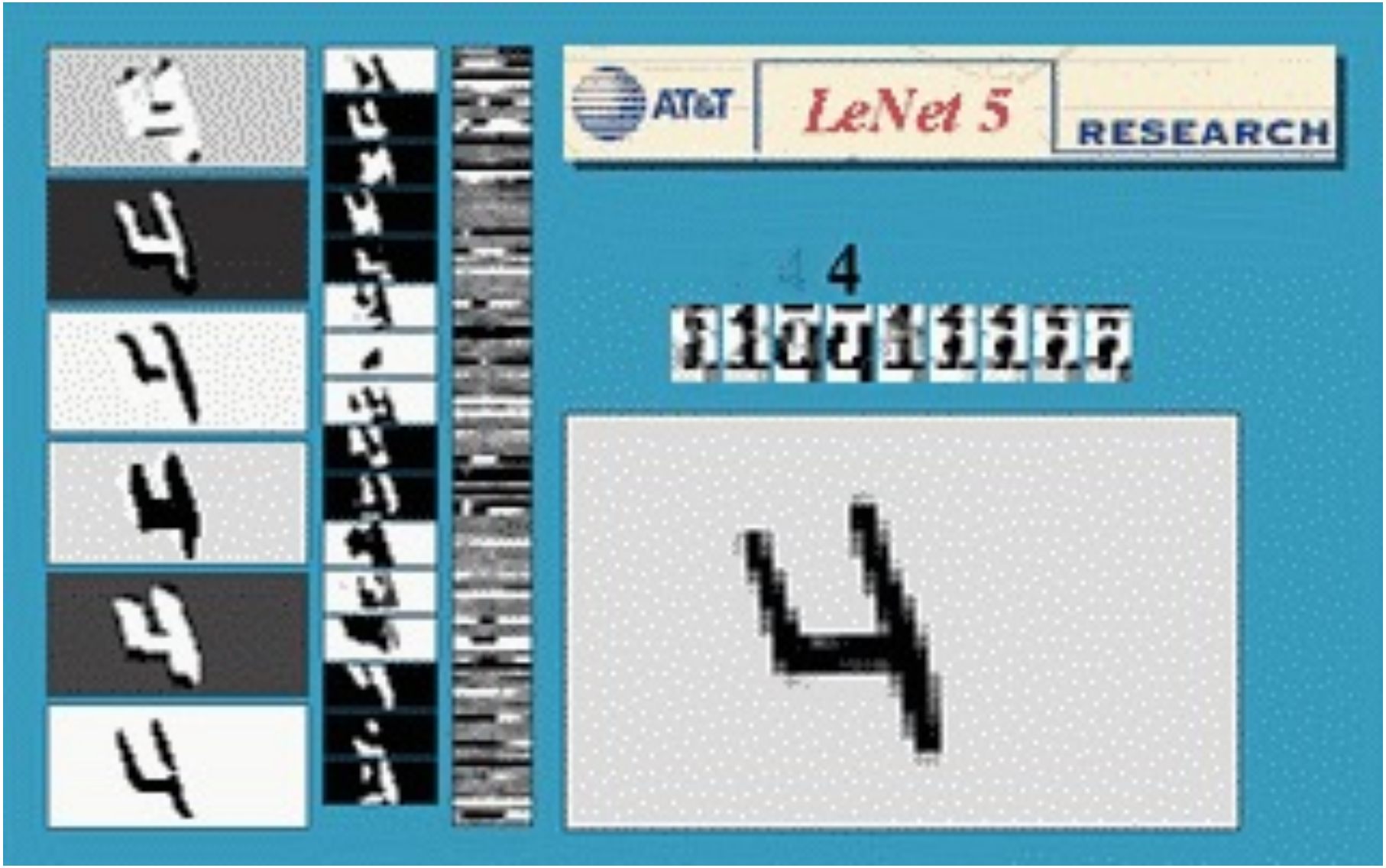
True label -> Predicted label

LeNet 5 in Action

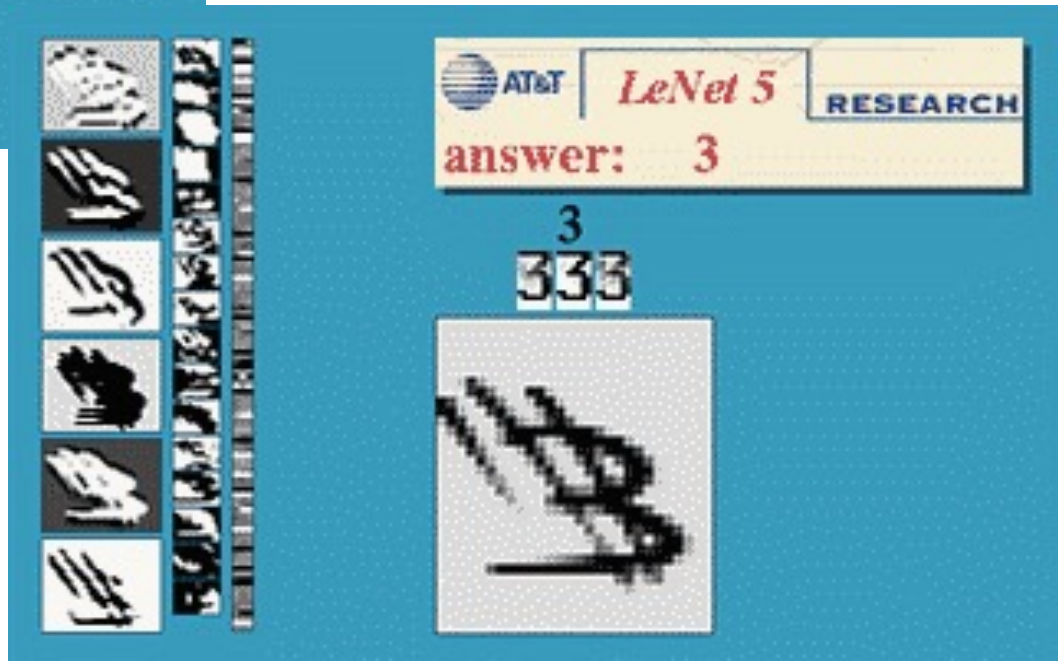


LeNet 5, Shift invariance

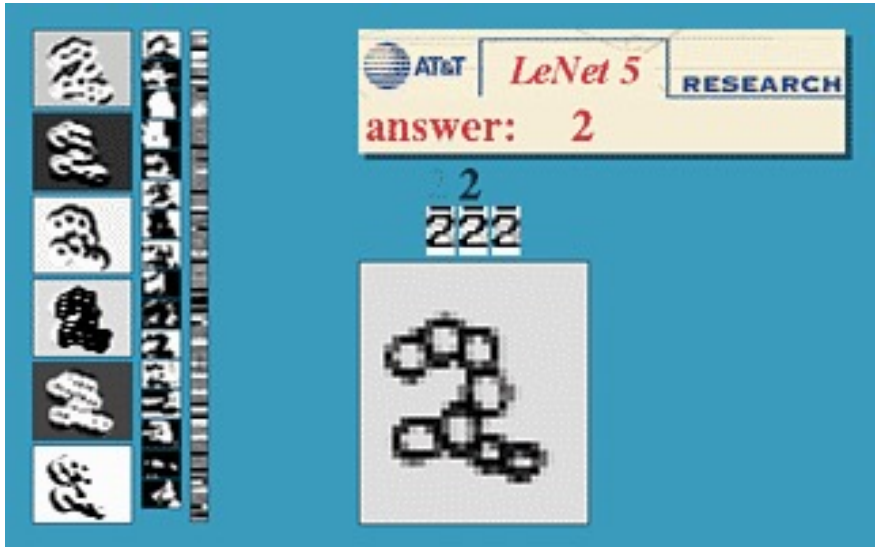
LeNet 5, Rotation invariance

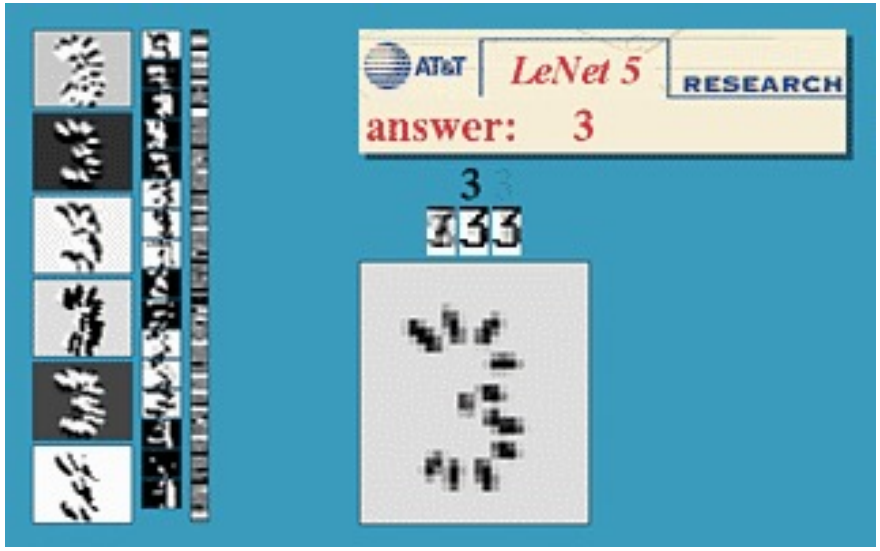


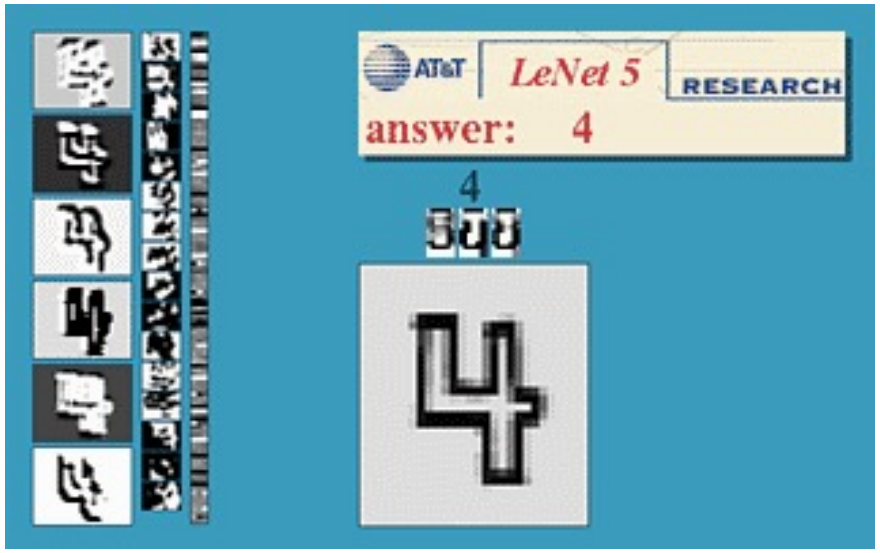
LeNet 5, Noise resistance

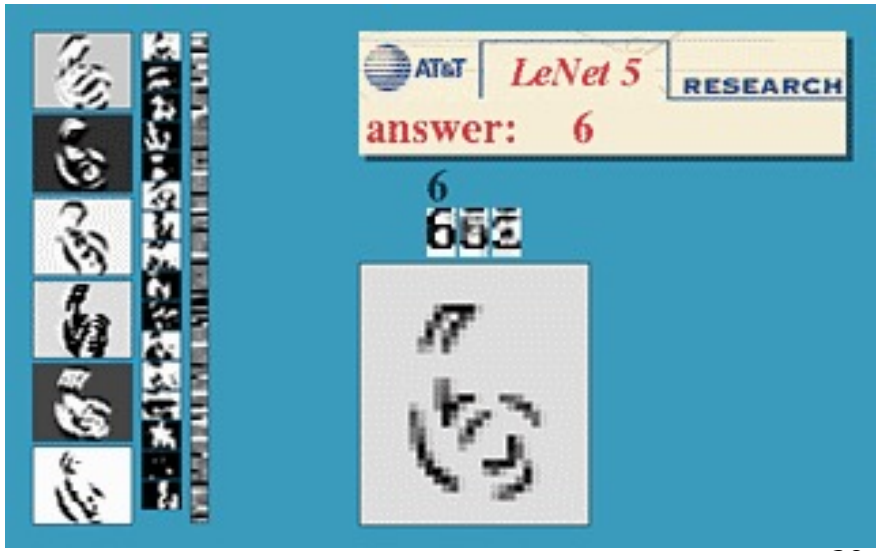


LeNet 5, Unusual Patterns









ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton,

Advances in Neural Information Processing Systems 2012

Alex Net

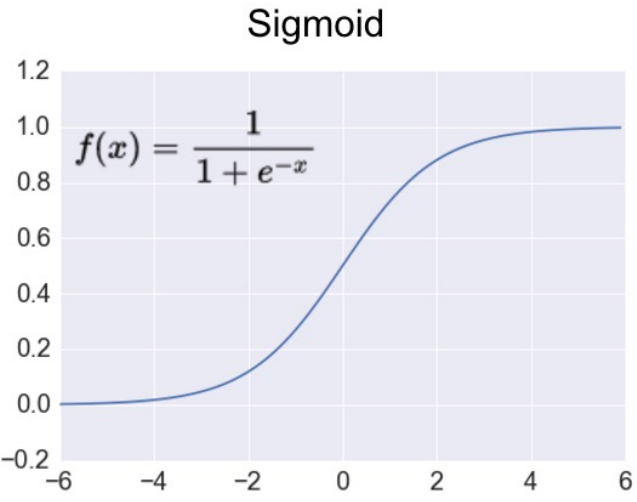
The Architecture

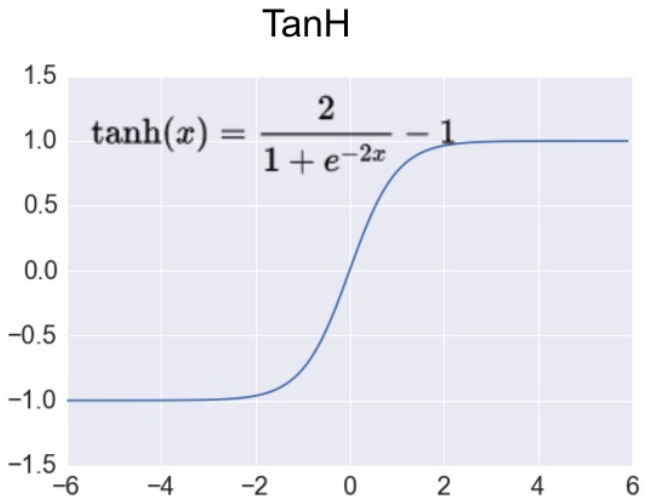
Typical nonlinearities: $f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

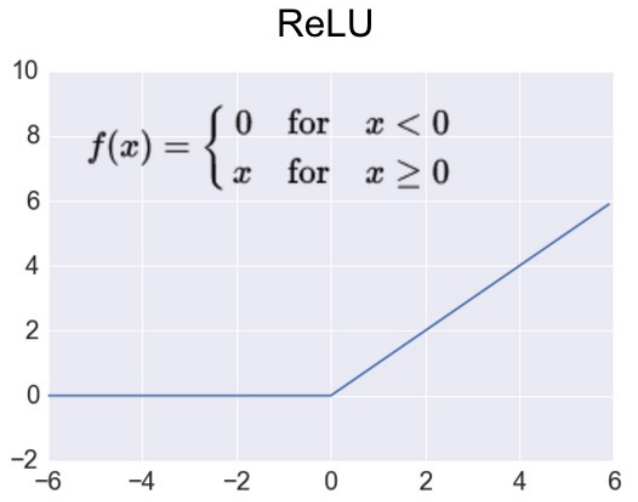
$f(x) = (1 + e^{-x})^{-1}$ (logistic function)

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

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







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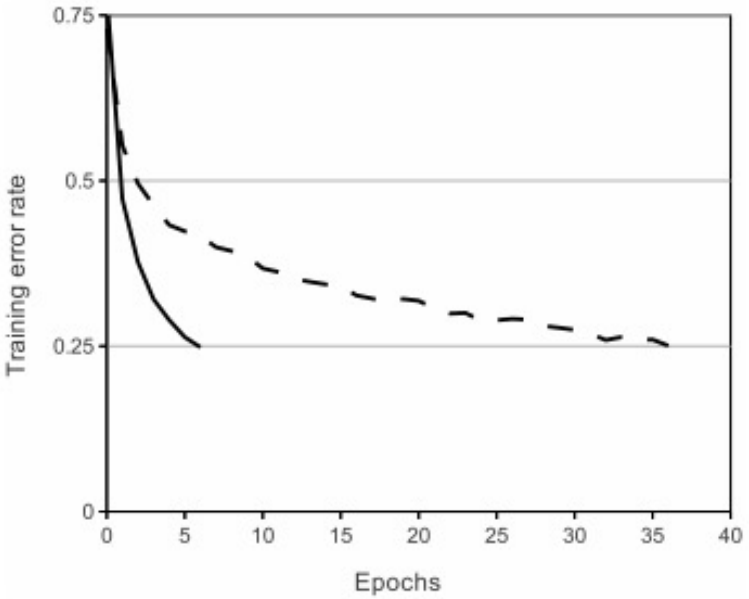
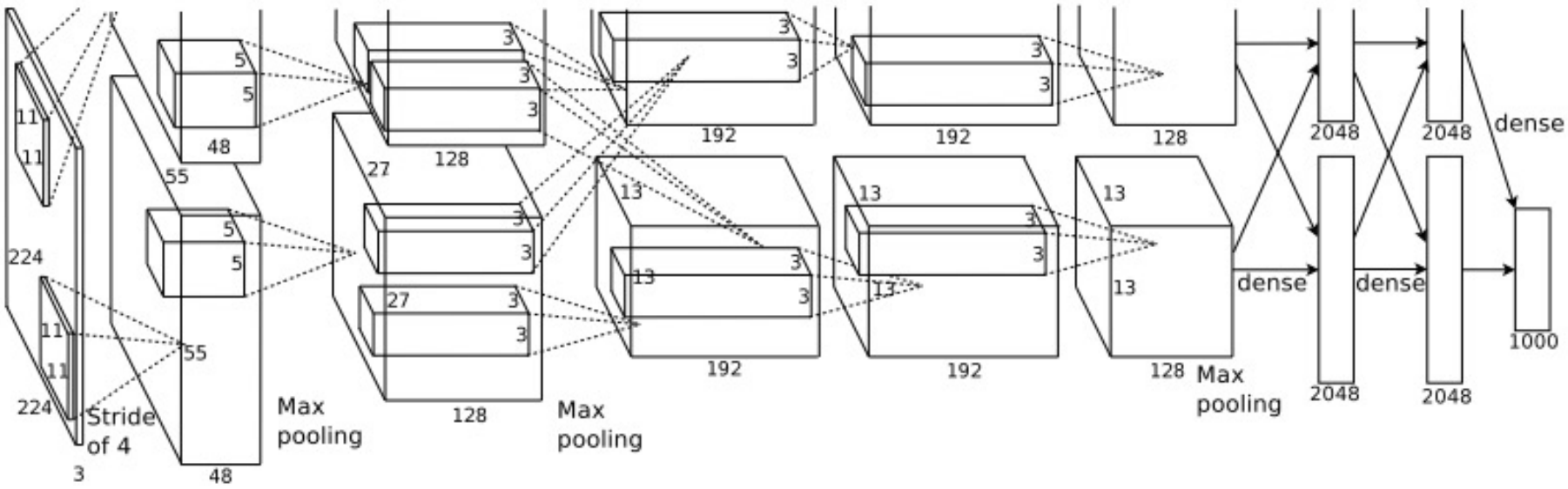


A four-layer convolutional neural network with ReLUs (solid line) reaches a 25% training error rate on CIFAR-10 six times faster than an equivalent network with tanh neurons

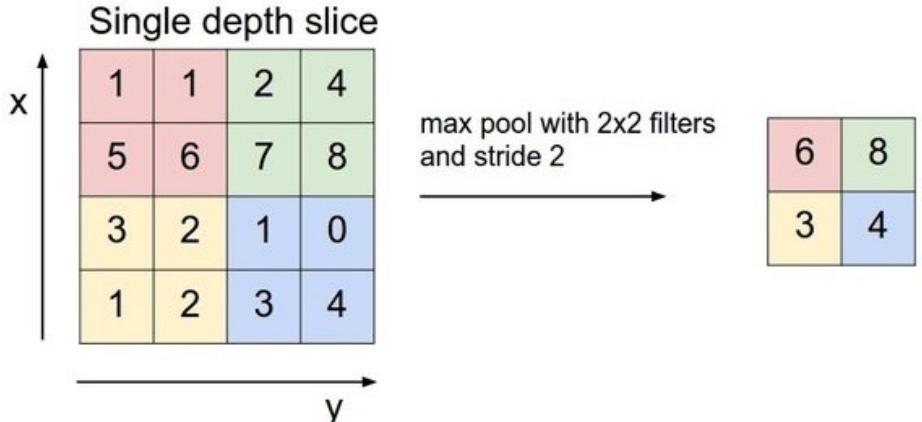
(dashed line)

The Architecture

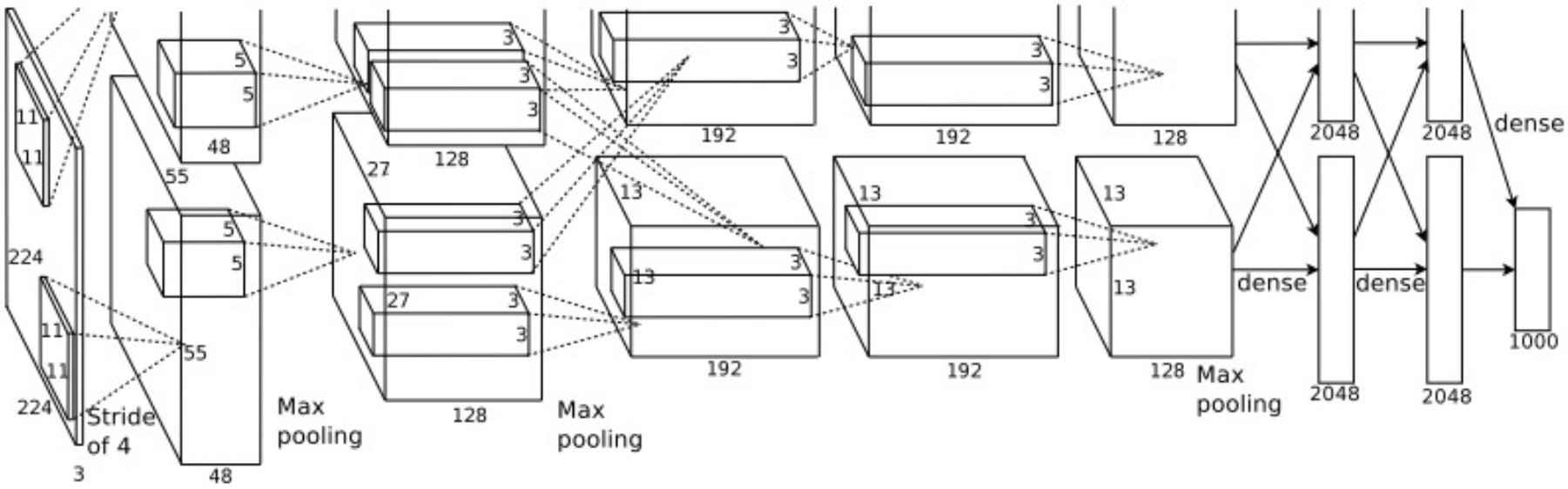


5 convolution layers (ReLU)

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.

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

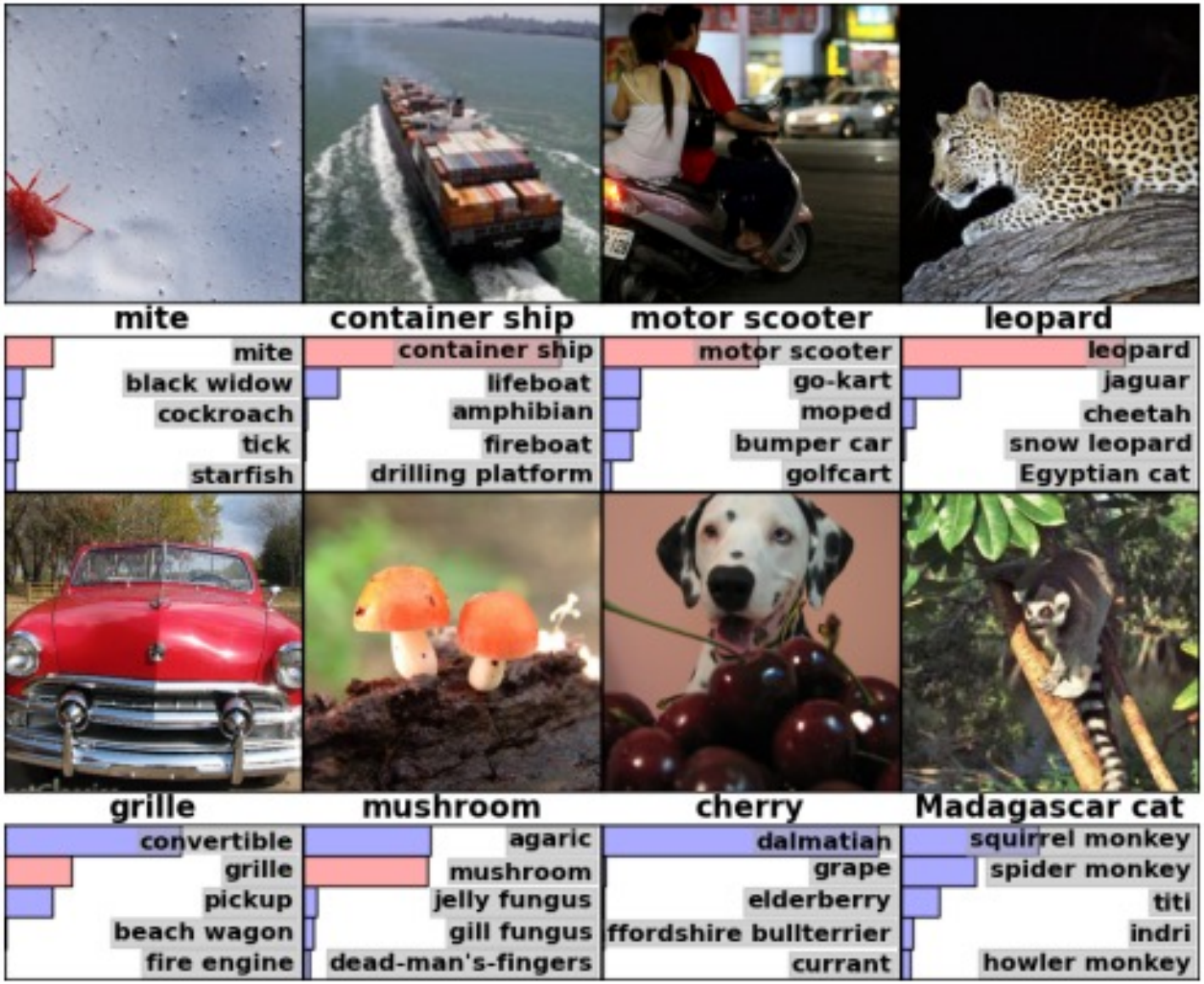
- RGB images
- Variable-resolution, but this architecture scales them to 256x256 size

ImageNet

Classification goals:

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

Results

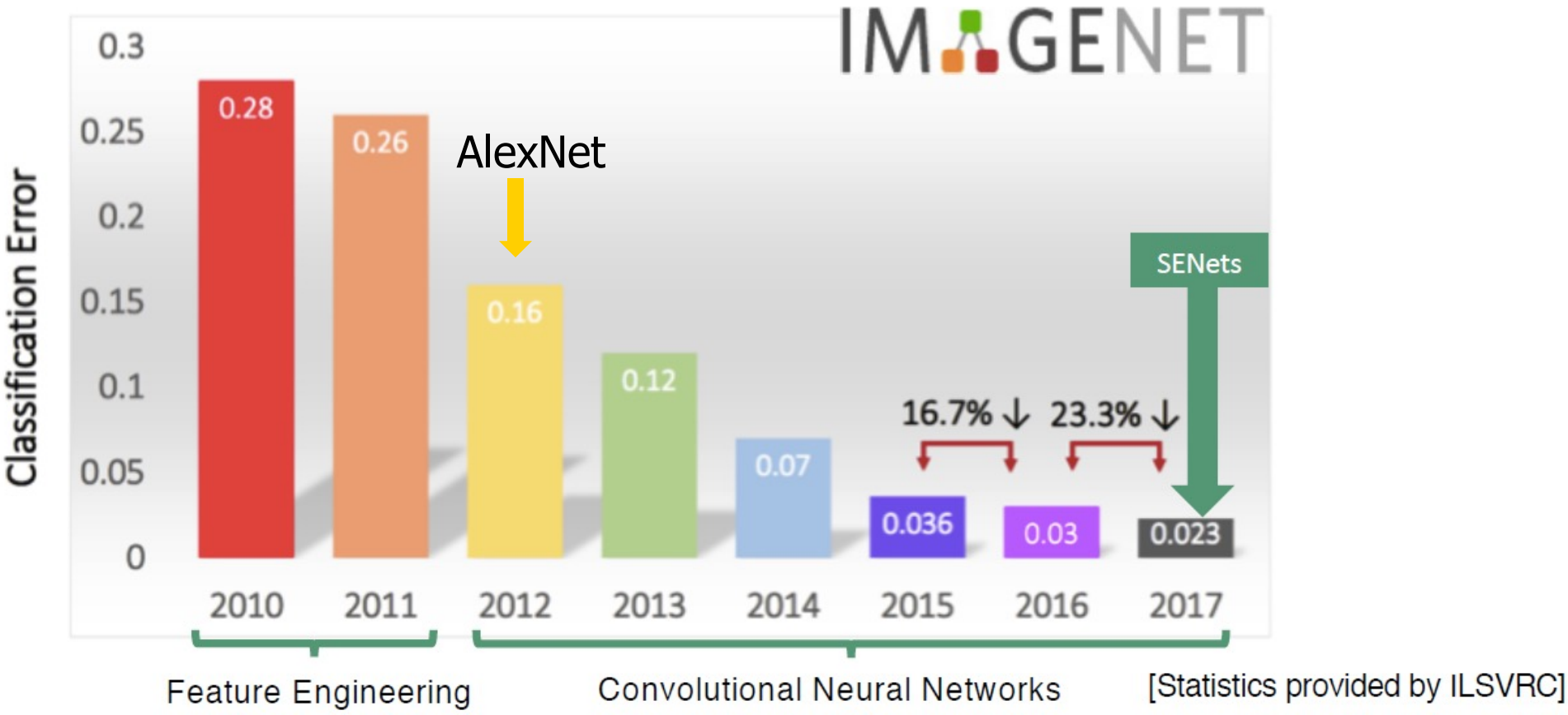

mite
mite
black widow
cockroach
tick
starfish
container ship
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
motor scooter
go-kart
moped
bumper car
golfcart
leopard
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
convertible
grille
pickup
beach wagon
fire engine
mushroom
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

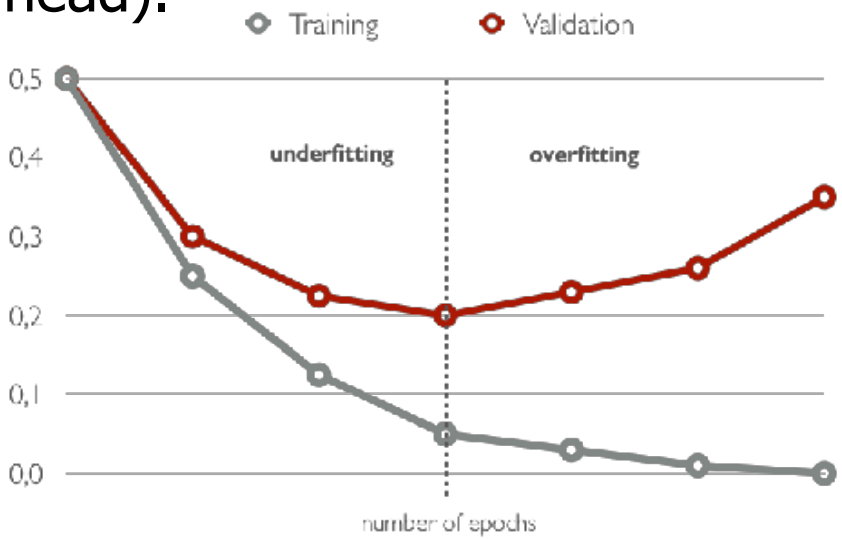
six training images that produce feature vectors in the last hidden layer with the smallest Euclidean distance from the feature vector for the test image.

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
16.7% ↓
23.3% ↓
SENets
2010
2011
2012
2013
2014
2015
2016
2017
Feature Engineering
Convolutional Neural Networks
[Statistics provided by ILSVRC]

Tips and tricks for preventing overfitting

- **Dropout**
- **Data augmentation**
- **Early stopping:** stop training when validation set error increases (with some look ahead).



- **Neural Architecture search:** tune number of layers and neurons per layer using grid search or clever optimization

Other optimization tips and tricks

- **Initialization:** cannot initialize to same value, all units in a hidden layer will behave same; randomly initialize to small value

- **Momentum:** use exponentially weighted sum of previous gradients

$$\overline{\nabla}_{\boldsymbol{\theta}}^{(t)} = \nabla_{\boldsymbol{\theta}} l(\mathbf{f}(\mathbf{x}^{(t)}), y^{(t)}) + \beta \overline{\nabla}_{\boldsymbol{\theta}}^{(t-1)}$$

$\boldsymbol{\theta}$ - Weights of Network

can get pass plateaus more quickly, by "gaining momentum"

- **Adaptive learning rates:** one learning rate per weight

e.g. RMSProp uses exponentially weighted average of squared gradients

$$\gamma^{(t)} = \beta \gamma^{(t-1)} + (1-\beta) \left(\nabla_{\theta} l(\mathbf{f}(\mathbf{x}^{(t)}), y^{(t)}) \right)^2 \qquad \overline{\nabla}_{\theta}^{(t)} = \frac{\nabla_{\theta} l(\mathbf{f}(\mathbf{x}^{(t)}), y^{(t)})}{\sqrt{\gamma^{(t)} + \epsilon}}$$

Adam combines RMSProp with momentum

Tips and Tricks for training deep NNs

- First hypothesis (underfitting): better optimize

➢ Increase the capacity of the neural network

➢ Check initialization

➢ Check gradients (saturating units and vanishing gradients)

➢ Tune learning rate

- Second hypothesis (overfitting): use better regularization

➢ Dropout

➢ Data augmentation

➢ Early stopping

➢ Architecture search

- For many large-scale practical problems, you will need to use both: better optimization and better regularization!