

# ImageNet (AlexNet) Classification with Deep Convolutional Neural Networks

Presenter: Shuoze Li

08/30/2022

# ImageNet Large Scale Visual Recognition Challenge (ILSVRC 2012)

❖ What do we do with AlexNet?



<b>Images</b>	Color images with nature objects
<b>Size</b>	469 x 387
<b># examples</b>	1.2 M
<b># classes</b>	1,000

# Experimental Results

## ❖ ILSVRC-2010 Test Set Error Rate

Model	Top-1	Top-5
<i>Sparse coding [2]</i>	47.1%	28.2%
<i>SIFT + FVs [24]</i>	45.7%	25.7%
CNN	<b>37.5%</b>	<b>17.0%</b>

## ❖ Results on 2012 Validation and Testing Set

Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
<i>SIFT + FVs [7]</i>	—	—	26.2%
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	<b>16.4%</b>
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	<b>15.3%</b>

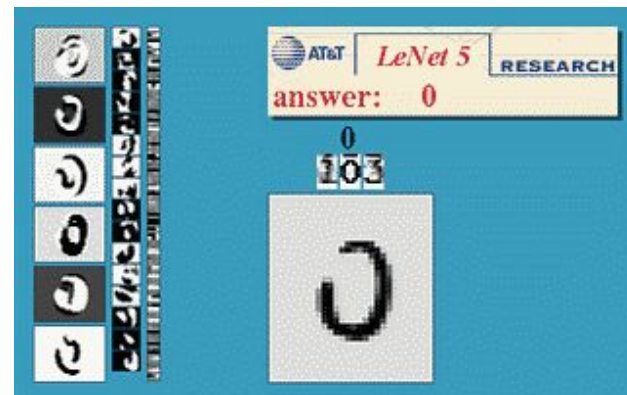
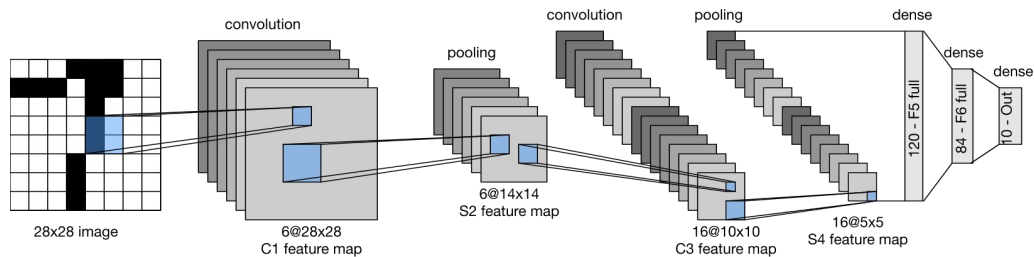
- 5 CNNs: averaging 5 similar CNNs trained with ILSVRC-2010
- 1 CNN: six convolutional layers trained with ILSVRC-2011 and fine-tuning it on ILSVRC-2012
- 7 CNNs: averaging two 1 CNN trained with ILSVRC-2011 and 5 CNNs trained with ILSVRC-2010



# Historical Background

## ◆ LeNet (for image classification, LeCun et al. in 1989)

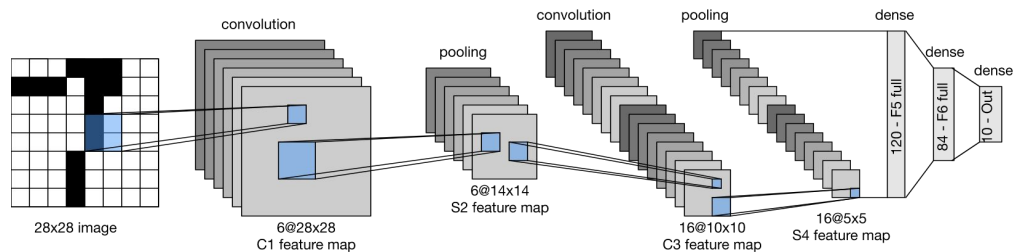
- Trained on MNIST (60,000, 28×28 handwritten number digit)
- One of earliest largely deployed CNN in Post Service and Banks



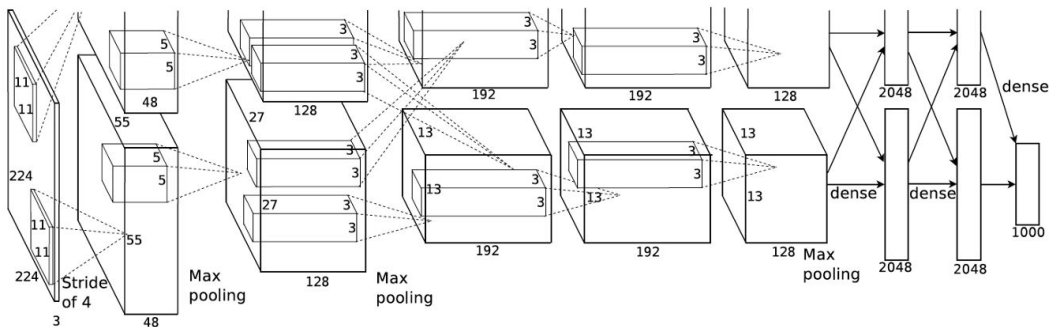
# Historical Background

## Why does it take so long for AlexNet to come?

LeCun et al. in 1989



Krizhevsky et al. in 2012



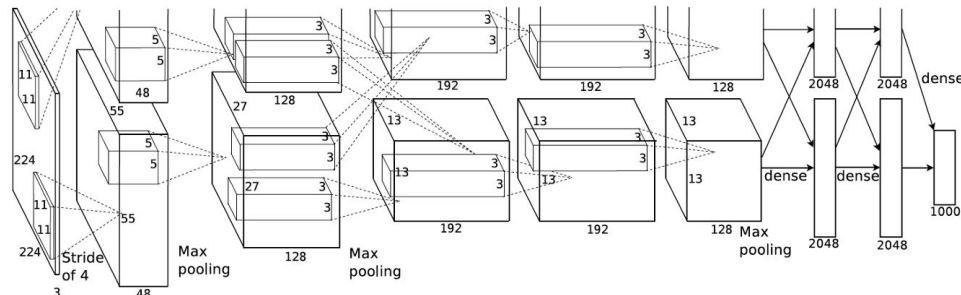
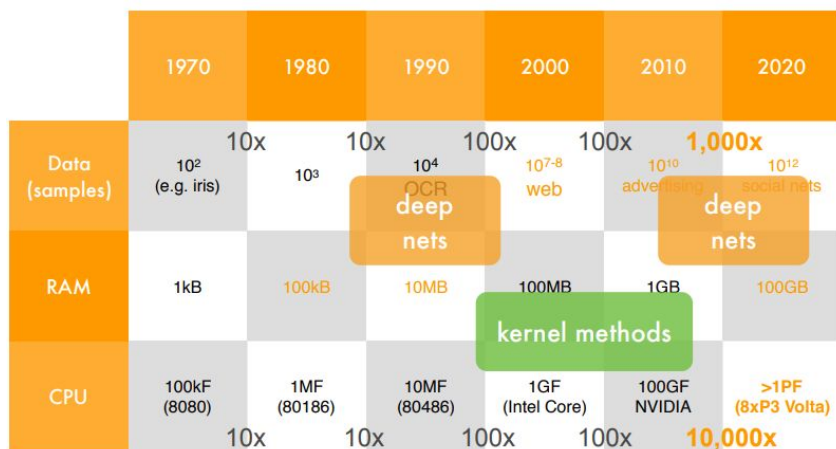
# Historical Background



2 2 2 2 2 2 2 2 2 2 2  
 3 3 3 3 3 3 3 3 3 3 3  
 4 4 4 4 4 4 4 4 4 4 4  
 5 5 5 5 5 5 5 5 5 5 5  
 6 6 6 6 6 6 6 6 6 6 6

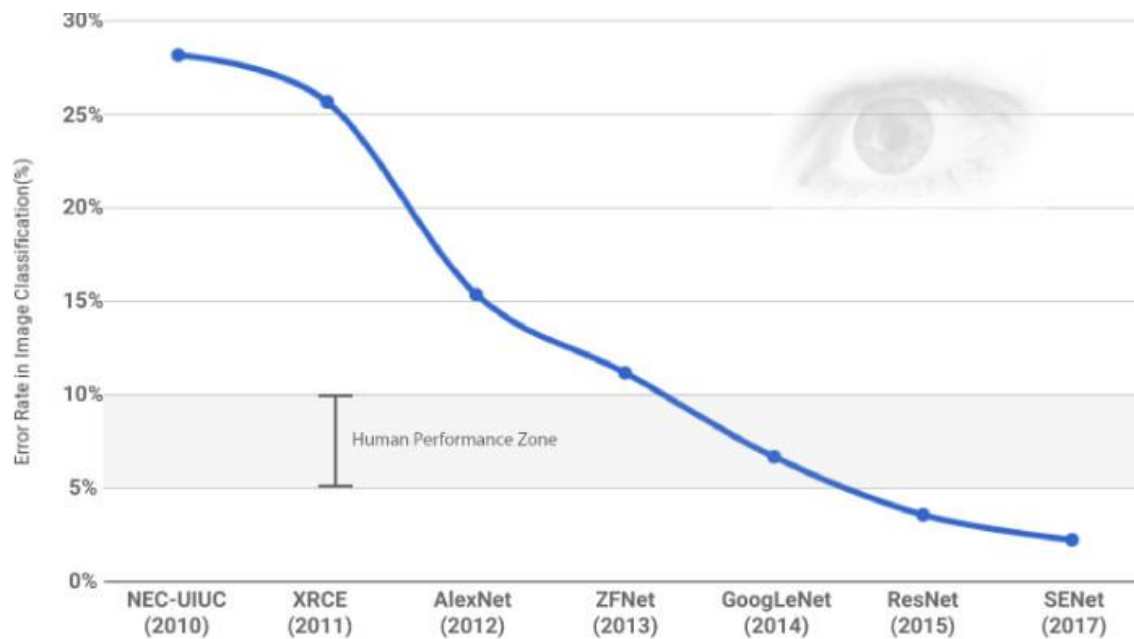
<b>Images</b>	Color images with nature objects	Gray image for hand-written digits
<b>Size</b>	469 x 387	28 x 28
<b># examples</b>	1.2 M	60 K
<b># classes</b>	1,000	10

◆ Why does it take so long for AlexNet to come?



# Historical Background

## ◆ AlexNet, the Game Changer



# Implementation Details

◆ **Pre-Process:** Rescaled to 256x256

◆ **Data Augmentation:**

**During Training:**

1. Random cropping to 224x224 with Horizontal Reflections (enlarged by a scale factor of 2048)
2. Random changing to the intensity and color of the illumination

$$I_{xy} = [I_{xy}^R, I_{xy}^G, I_{xy}^B]^T + [\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3][\alpha_1 \lambda_1, \alpha_2 \lambda_2, \alpha_3 \lambda_3]^T$$

$I_{xy}$  :RGB image pixel

$\mathbf{p}_i, \lambda_i$  :ith eigenvector and eigenvalue by PCA

$\alpha_i$  :Drawn from  $N(\text{avg}=0, \sigma=0.1)$

**During Testing:**

Apply Horizontal Reflection and 4 corner and 1 center

Cropping, averaging the predictions of ten patches from softmax





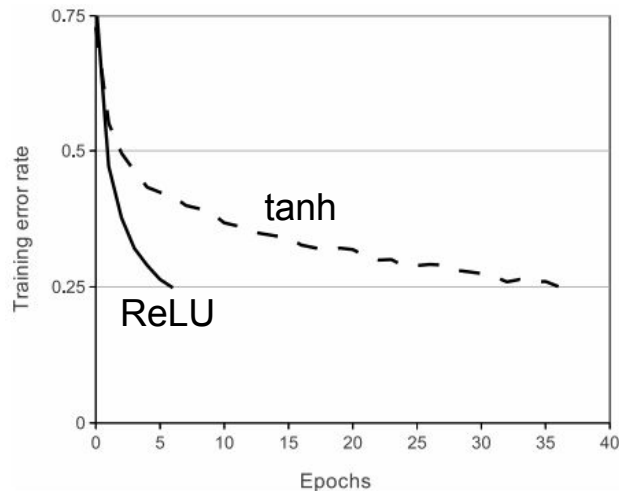
# Network Architecture

## ◆ ReLU Nonlinearity:

- shorter training time with gradient descent than tanh() or sigmoid

## ◆ Local Response Normalization:

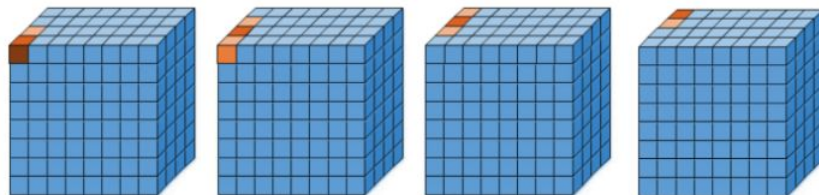
- constrain ReLU output within a bounded range
- lateral inhibition: carry out local contrast enhancement for the next layers



$$b_{x,y}^i = a_{x,y}^i / \left( k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a_{x,y}^j)^2 \right)^\beta$$

$a_{x,y}^i$ : activity of a neuron  
 $N$ : number of channel  
 $n$ : neighborhood length

$i$ : index of center neuron  
 $k$ : avoid division by zero  
 $\alpha$ : normalization constant  
 $\beta$ : contrasting constant



a) Inter-Channel LRN (n=2)

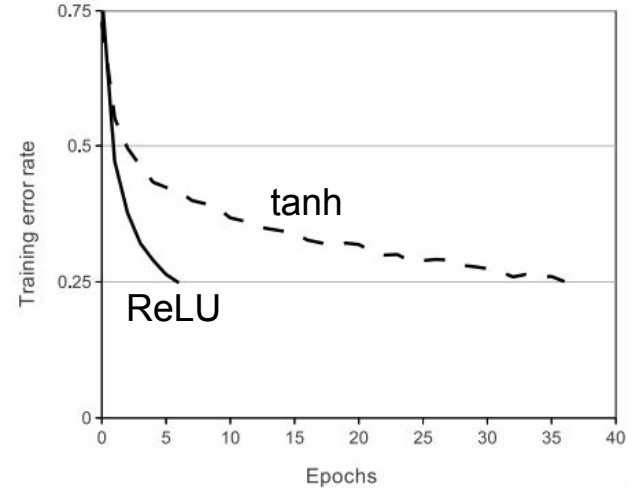
# Network Architecture

## ◆ ReLU Nonlinearity:

- shorter training time with gradient descent than tanh() or sigmoid

## ◆ Local Response Normalization:

- constrain ReLU output within a bounded range
- lateral inhibition: carry out local contrast enhancement for the next layers

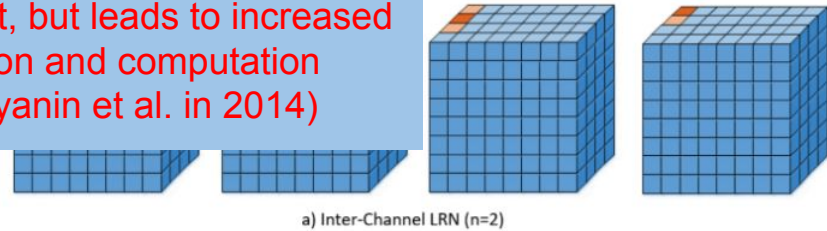


$$b_{x,y}^i = a_{x,y}^i / \left( k + \alpha \sum_{j=\max(0, i-\beta)}^{\min(N-1, i+\beta)} a_{x,y}^j \right)$$

$a_{x,y}^i$ : activity of a neuron  
 $N$ : number of channel  
 $\beta$ : neighborhood length

$i$ : index  
 $k$ : avoid division by zero  
 $\alpha$ : normalization constant  
 $\beta$ : contrasting constant

LRN "does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time" (VGG, Simonyan et al. in 2014)



a) Inter-Channel LRN (n=2)

# Network Architecture

## ❖ Overlapping MaxPooling (LeNet: non-overlapping average pooling):

- introducing overlap maxpooling to prevent overfitting

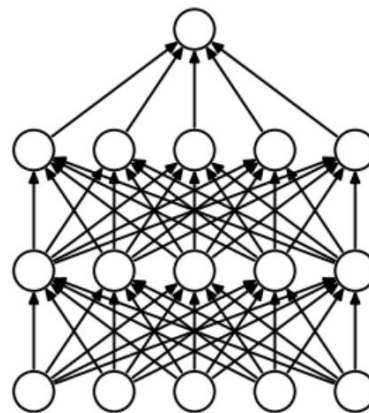
## ❖ Dropout:

- combining the predictions of many different models

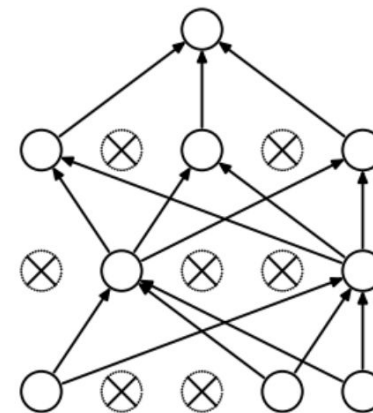
$$x = \begin{cases} 0 & \text{with probability } 0.5 \\ 0.5x & \text{otherwise} \end{cases}$$



$$x = \begin{cases} 0 & \text{with probability } p \\ \frac{x}{1-p} & \text{otherwise} \end{cases}$$



(a) Standard Neural Net



(b) After applying dropout.

# Network Architecture

## ❖ Overlapping Pooling:

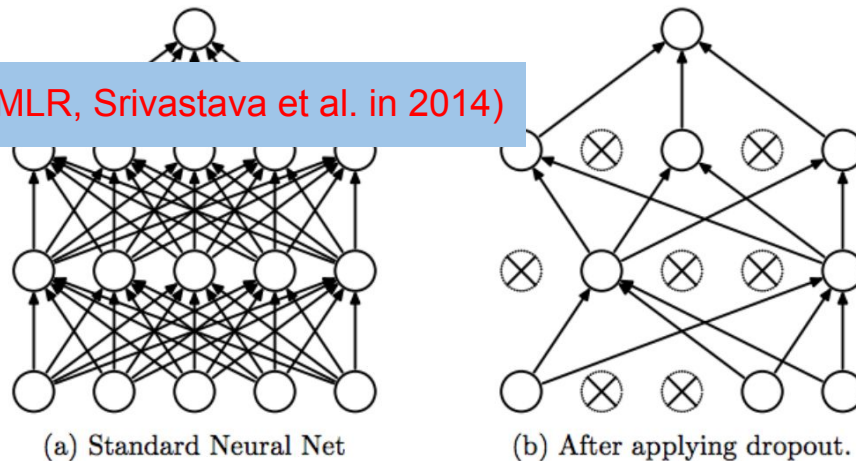
- introducing overlap maxpooling to prevent overfit

## ❖ Dropout:

- ~~combining the predictions of many different models~~

Dropout "is a modified form of L2 regularization" (JMLR, Srivastava et al. in 2014)

$$x = \begin{cases} 0 & \text{with probability } p \\ \frac{x}{1-p} & \text{otherwise} \end{cases}$$



# Details of Training

- ❖ Stochastic Gradient Descent with batch size of 128, Momentum of 0.9, Weight Decay of 0.0005

$$v_{i+1} := 0.9 \cdot v_i - 0.0005 \cdot \epsilon \cdot w_i - \epsilon \cdot \left\langle \frac{\partial L}{\partial w} \Big|_{w_i} \right\rangle_{D_i}$$

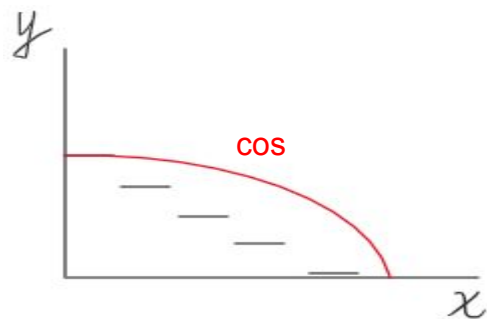
$$w_{i+1} := w_i + v_{i+1}$$

- ❖ Learning Rate initialized at 0.01 and divide by 10 when the validation error rate stopped improving

- more techniques on adjusting learning rate  
Ex. Cosine or more specific Learning Rate Scheduler

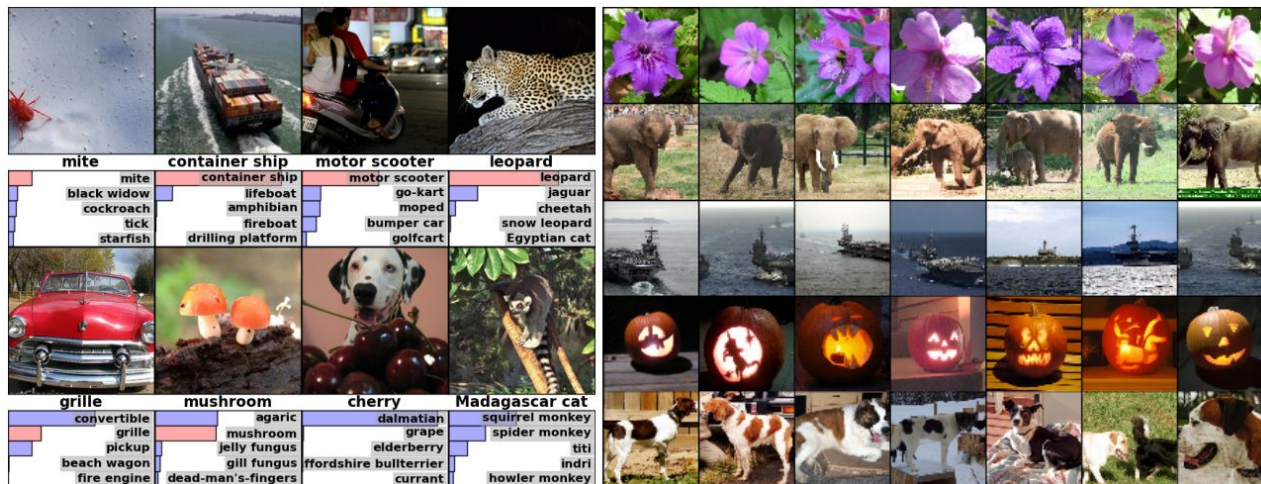
- ❖ Weights Initialization: set bias to 1 accelerates the early stage of learning (ReLU)

- nowadays, does not really matter



# Discussion of Results

## ◆ Test Images from ILSVRC-2010



Some test images and the five labels considered most probable by AlexNet

when comparing the output from the last fully connected layer, from right to the left, these are the six images that have small Euclidean separation to the first image

# Summary

- ❖ **A variant from LeNet with techniques:** Dropout, ReLU, MaxPooling, Local Response Normalization
- ❖ **AlexNet won ImageNet classification challenge in 2012**
- ❖ **Changes the game of Computer Vision**

## What Will Come After?

- ❖ **Can we build even deeper and wider CNNs to perform better? YES!**  
VGG: K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *CoRR*, vol. abs/1409.1556, 2014.
- ❖ **Can we use a similar network architecture on object localization and detection in image? YES!**  
(OverFeat) P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun, "OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks." 24-2014.

Thank You!

Shuoze Li



# ImageNet Large Scale Visual Recognition Challenge (ILSVRC 2012)

❖ What do we do with AlexNet?



MNIST



<b>Images</b>	Color images with nature objects	Gray image for hand-written digits
<b>Size</b>	469 x 387	28 x 28
<b># examples</b>	1.2 M	60 K
<b># classes</b>	1,000	10