CENG 4480

Embedded System Development & Applications

Lec 02: Deep Learning Basis

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(Latest update: September 23, 2024)

2024 Fall

Overview

Overview

What happened to Object Detection

Object Detection: PASCAL VOC mean Average Precision (mAP)

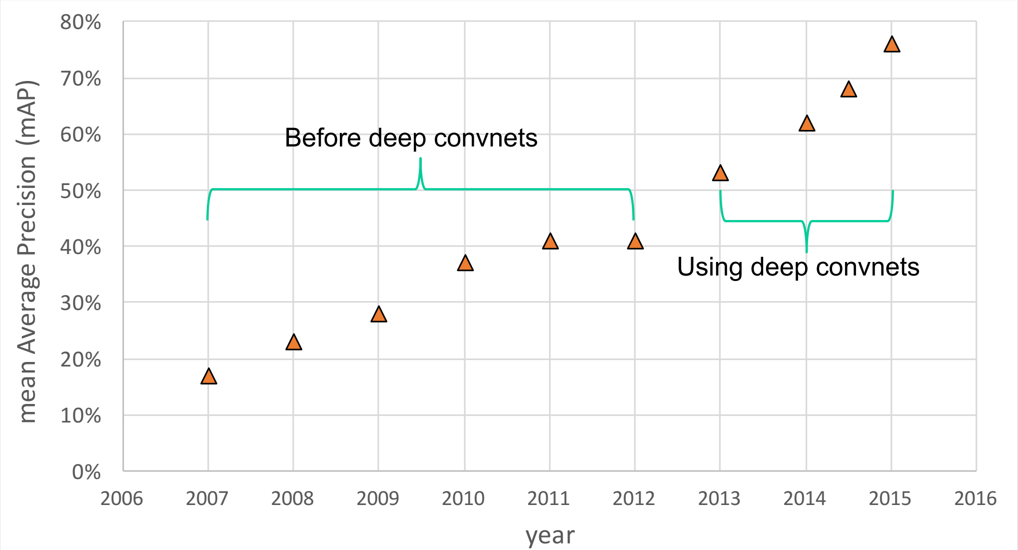
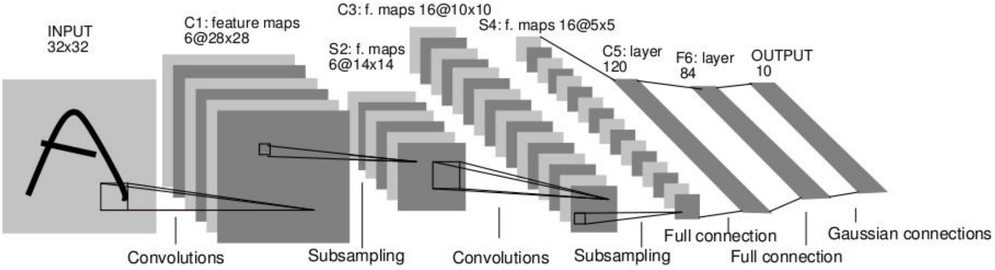


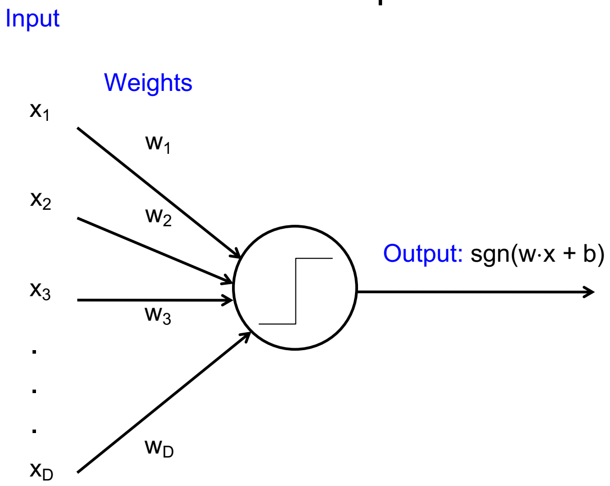
Figure source: Ross Girshick

LeNet 5



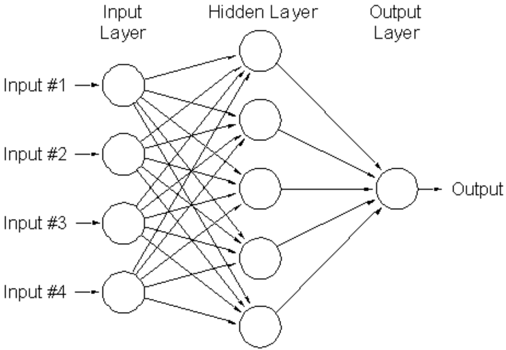
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proc. IEEE 86(11): 2278–2324, 1998.

The Perceptron

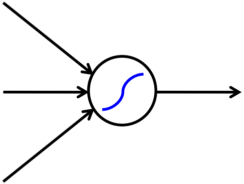


Rosenblatt, Frank (1958), The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Cornell Aeronautical Laboratory, Psychological Review, v65, No. 6, pp. 386–408.

Two-layer neural network



- Can learn nonlinear functions provided each perceptron has a differentiable nonlinearity

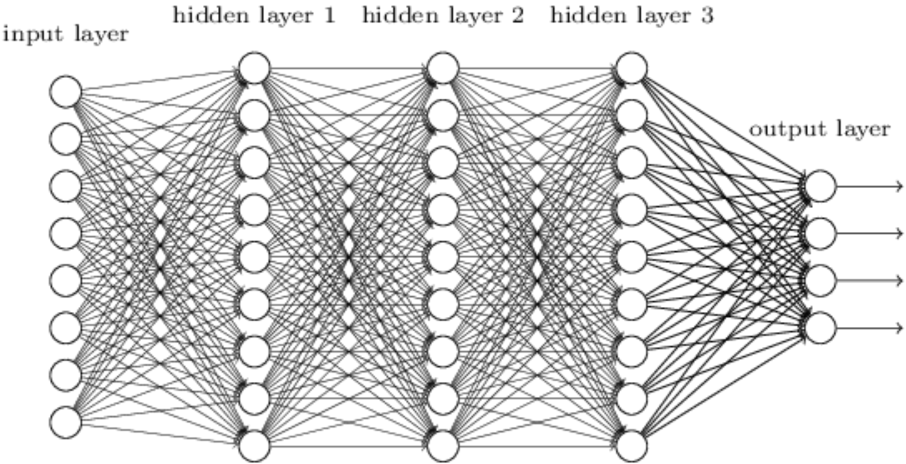


Sigmoid: $g(t) = \dfrac{1}{1+e^{-t}}$

What is the value range of sigmoid activation?

- $[-1, 1]$
- $[-\infty, +\infty]$
- $[0, 1]$
- $[0, +\infty]$

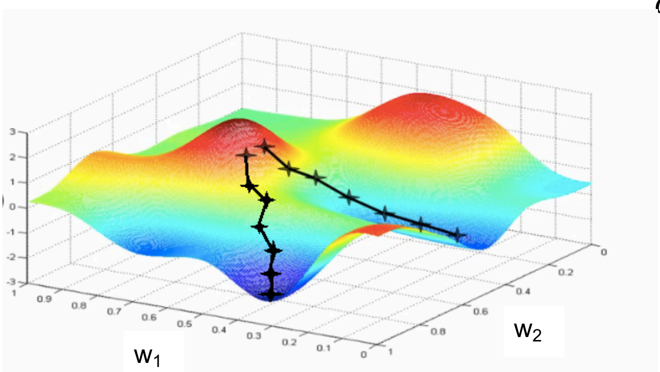
Multi-layer neural network



- Find network weights to minimize the *training error* between true and estimated labels of training examples, e.g.:

$$E(\mathbf{w}) = \sum_{i=1}^{N} \left(y_i - f_{\mathbf{w}}(\mathbf{x}_i)\right)^2$$

- Update weights by **gradient descent:** $\mathbf{w} \leftarrow \mathbf{w} - \alpha \frac{\partial E}{\partial \mathbf{w}}$



Training of multi-layer networks

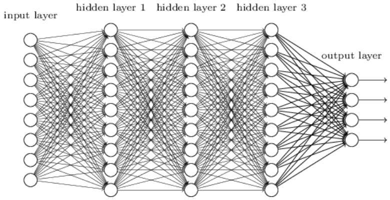
- Find network weights to minimize the *training error* between true and estimated labels of training examples, e.g.:

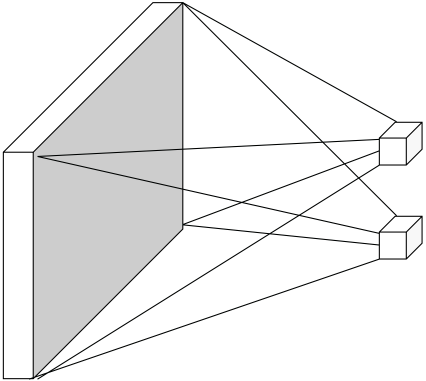
$$E(\mathbf{w}) = \sum_{i=1}^{N} \left(y_i - f_{\mathbf{w}}(\mathbf{x}_i) \right)^2$$

- Update weights by **gradient descent:** $\mathbf{w} \leftarrow \mathbf{w} - \alpha \dfrac{\partial E}{\partial \mathbf{w}}$

- **Back-propagation:** gradients are computed in the direction from output to input layers and combined using chain rule
- **Stochastic gradient descent:** compute the weight update w.r.t. one training example (or a small batch of examples) at a time, cycle through training examples in random order in multiple epochs

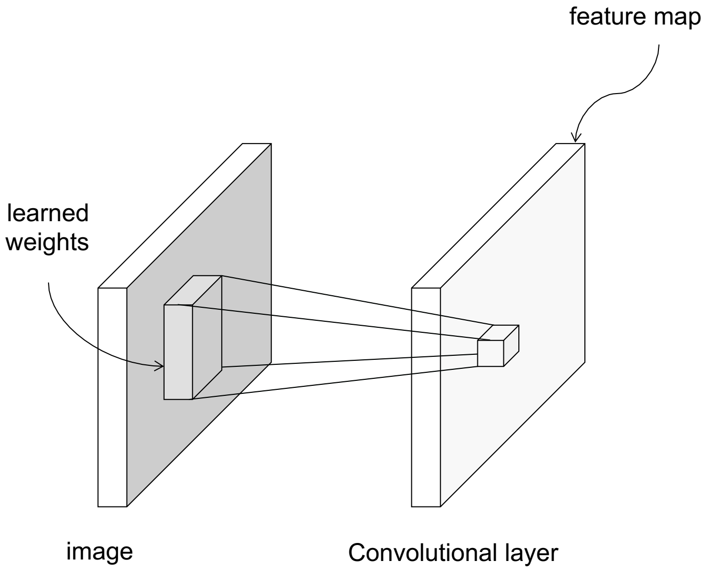
From fully connected to convolutional networks





image

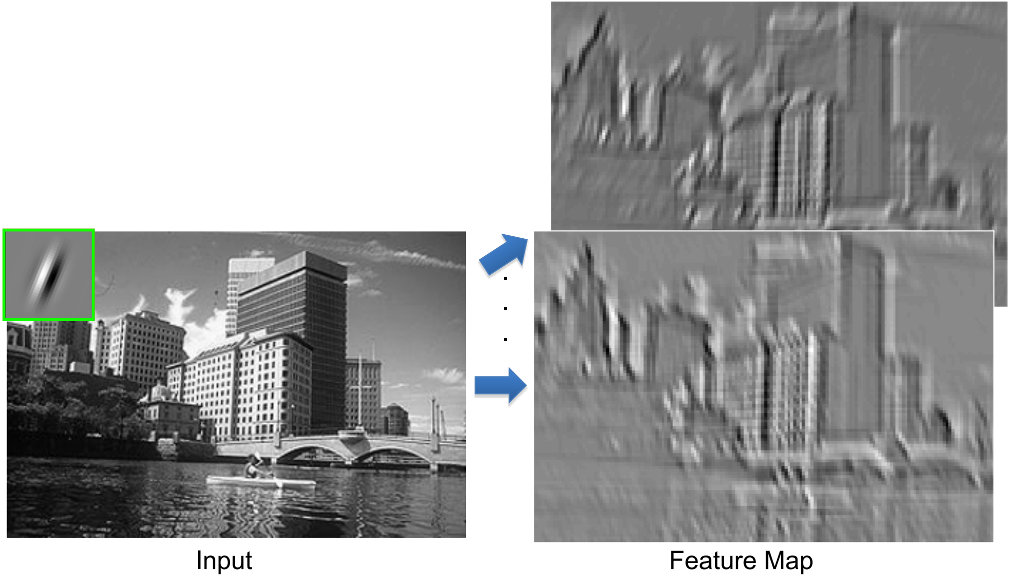
Fully connected layer


feature map
learned
weights
image
Convolutional layer

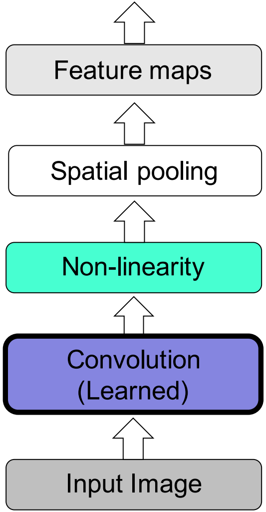
For a convolution kernel with kernel size 3, stride 1, what is the zero padding number to keep the output feature map size unchanged?

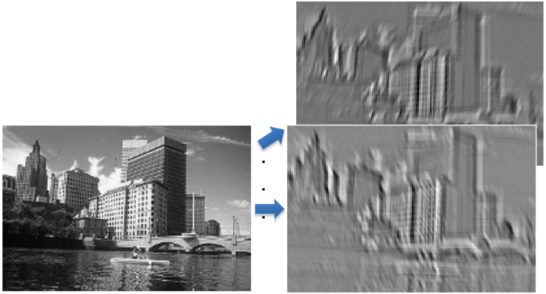
- A: 0
- B: 1
- C: 2
- D: 3

Convolution as feature extraction



Key operations

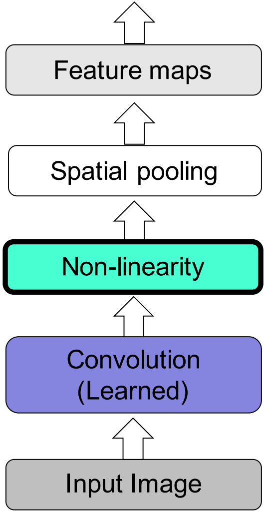


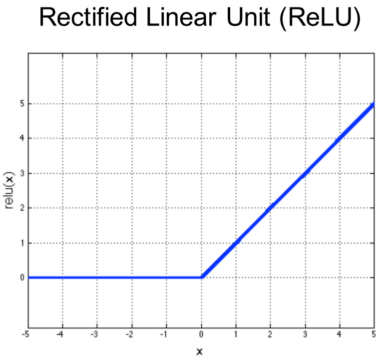


Input

Feature Map

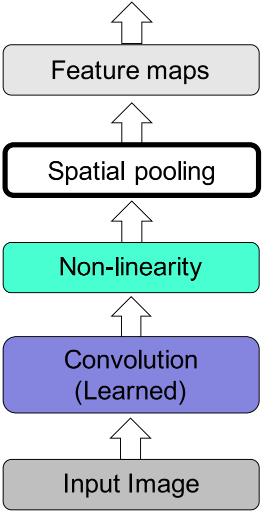
Source: R. Fergus, Y. LeCun

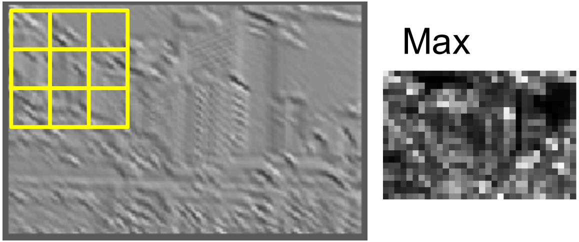




Source: R. Fergus, Y. LeCun

Key operations



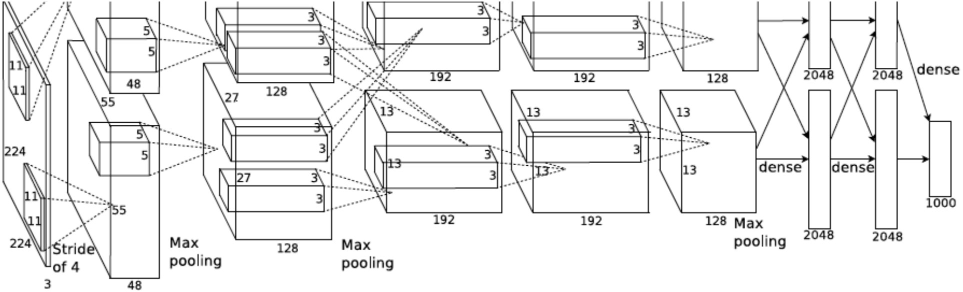


Source: R. Fergus, Y. LeCun

Fast forward to the arrival of big visual data

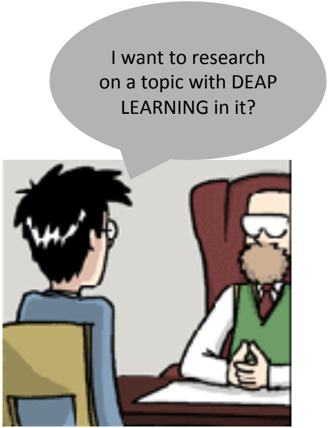
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC): 1.2 million training images, 1000 classes

www.image-net.org/challenges/LSVRC/

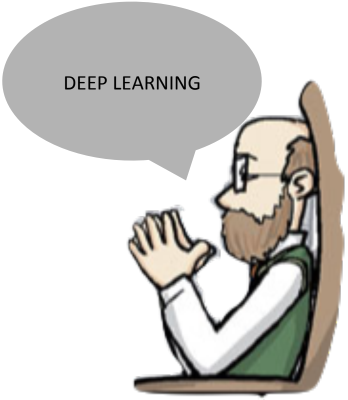


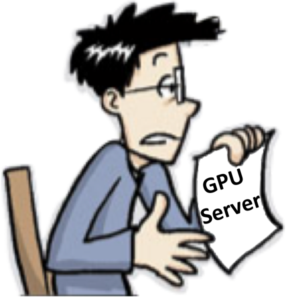
- Similar framework to LeNet but:
  - Max pooling, ReLU nonlinearity
  - More data and bigger model (7 hidden layers, 650K units, 60M params)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Dropout regularization

A. Krizhevsky, I. Sutskever, and G. Hinton, [ImageNet Classification with Deep Convolutional Neural Networks](), NIPS 2012


I want to research on a topic with DEAP LEARNING in it?


What should I learn to do well in computer vision research?

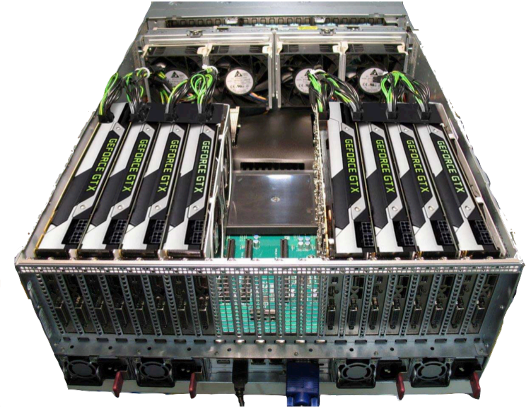

DEEP LEARNING


GPU
Server


Ohhh No!!!

State of the art recognition methods

- Very Expensive
  - Memory
  - Computation
  - Power



HGX A100 4-GPU

Hyperplane 4-A100

- 4 NVIDIA® A100 SXM4 GPUs
- NVLink™ GPU connectivity
- 2 rack unit form factor (2U)
- 2x AMD EPYC processors with up to 64 cores
- Up to 4 TB of system memory

Starting at

$70,376.00

HGX A100 8-GPU

Hyperplane 8-A100

- 8 NVIDIA® A100 SXM4 GPUs
- NVLink™ + NVSwitch™ GPU connectivity
- 4 rack unit form factor (4U)
- 2x AMD EPYC processors with up to 64 cores
- Up to 4 TB of system memory

Starting at

$143,270.00

HGX H100 8-GPU

Hyperplane 8-H100

- 8 NVIDIA® H100 SXM5 GPUs
- NVLink™ + NVSwitch™ GPU connectivity
- 8 rack unit form factor (8U)
- 2x Intel Xeon 8480+ 56-core processors
- Up to 4 TB of system memory

Pre-order

Starting at

$311,221.00

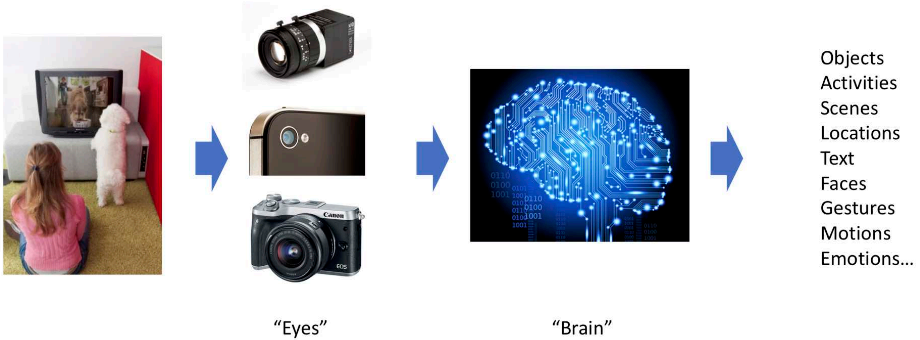
Refer:

https://shop.lambdalabs.com/deep-learning/servers/hyperplane/customize

Overview

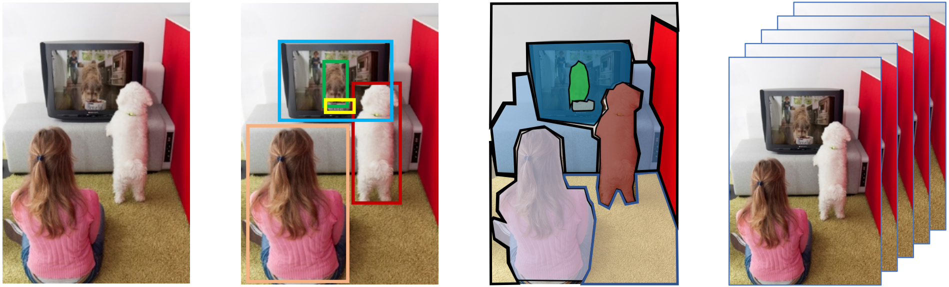
Computer Vision

- Humans use their eyes and their brains to visually sense the world.
- Computers use their cameras and computation to visually sense the world



Jian Sun, "Introduction to Computer Vision and Deep Learning".

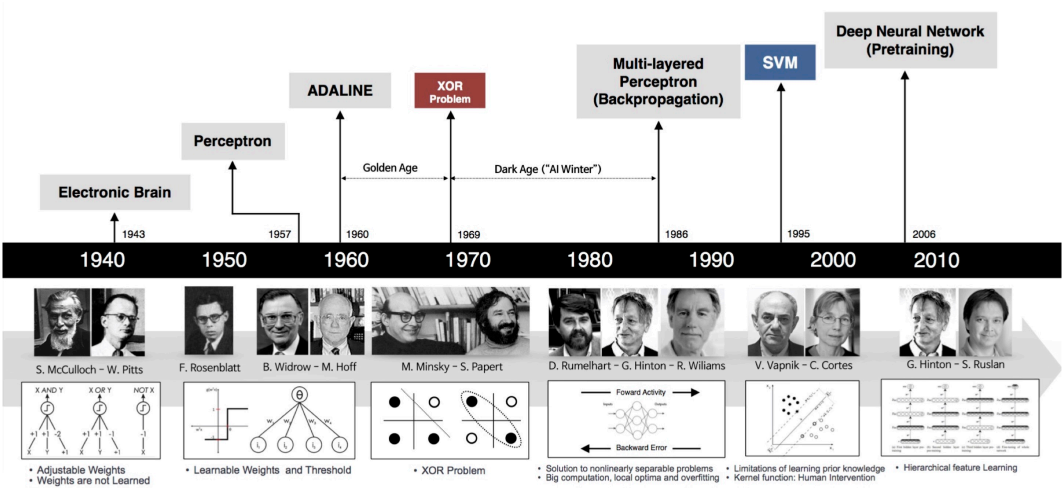
Few More Core Problems



Classification | Detection | Segmentation | Sequence

Image → Region → Pixel | Video

A Bit of History



Winter of Neural Networks (mid 90′ – 2006)

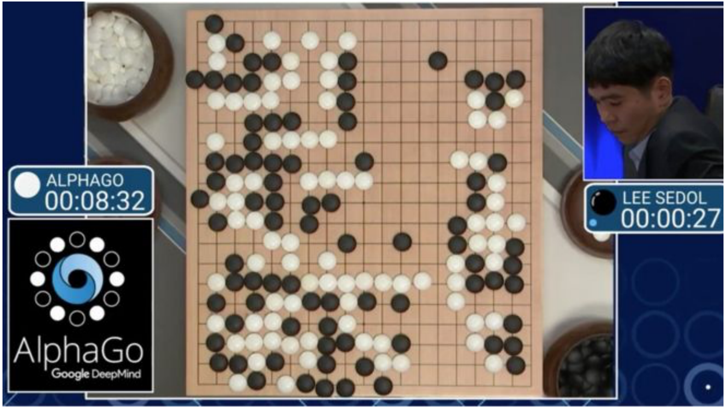
- The rises of SVM, Random forest
- No theory to play
- Lack of training data
- Benchmark is insensitive
- Difficulties in optimization
- Hard to reproduce results

Curse

"Deep neural networks are no good and could never be trained."

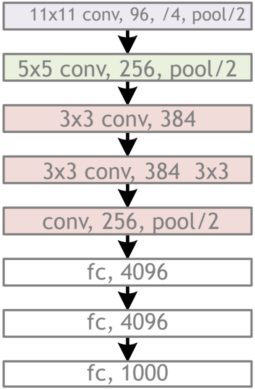
Renaissance of Deep Learning (2006 –)

- A fast learning algorithm for deep belief nets. [Hinton et.al 1996]
- Data + Computing + Industry Competition
- NVidia's GPU, Google Brain (16,000 CPUs)
- Speech: Microsoft [2010], Google [2011], IBM
- Image: AlexNet, 8 layers [Krizhevsky et.al 2012] (26.2% -> 15.3%)



Revolution of Depth

AlexNet, 8 layers (ILSVRC 2012)



Slide Credit: He et al. (MSRA)

Revolution of Depth

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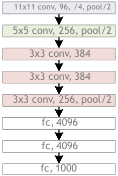
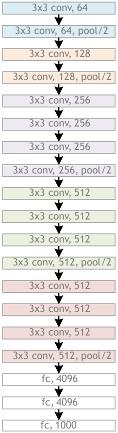
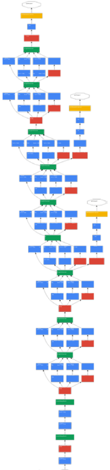


VGG, 19 layers (ILSVRC 2014)



GoogleNet, 22 layers (ILSVRC 2014)



Slide Credit: He et al. (MSRA)

Revolution of Depth

AlexNet, 8 layers (ILSVRC 2012)

VGG, 19 layers (ILSVRC 2014)

ResNet, 152 layers (ILSVRC 2015)

Slide Credit: He et al. (MSRA)

Some Recent Classification Architectures

- AlexNet (Krizhevsky, Sutskever, and E. Hinton 2012) 233MB
- Network in Network (Lin, Chen, and Yan 2013) 29MB
- VGG (Simonyan and Zisserman 2015) 549MB
- GoogleNet (Szegedy, Liu, et al. 2015) 51MB
- ResNet (He et al. 2016) 215MB
- Inception-ResNet (Szegedy, Vanhoucke, et al. 2016)
- DenseNet (Huang et al. 2017)
- Xception (Chollet 2017)
- MobileNetV2 (Sandler et al. 2018)
- ShuffleNet (Zhang et al. 2018)

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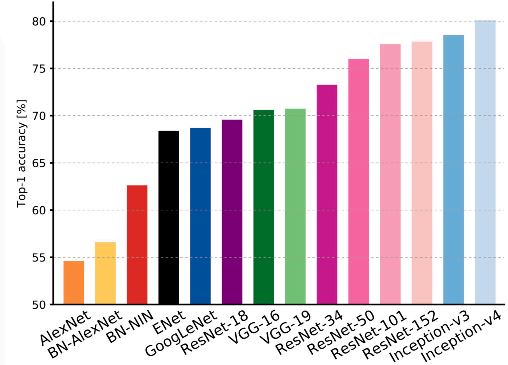
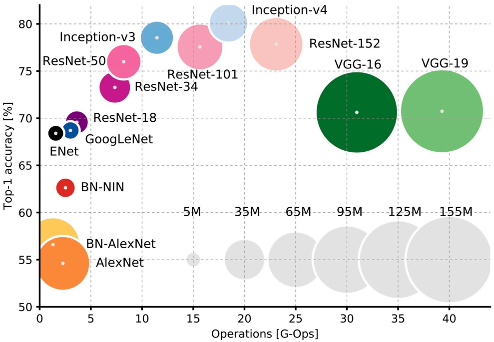
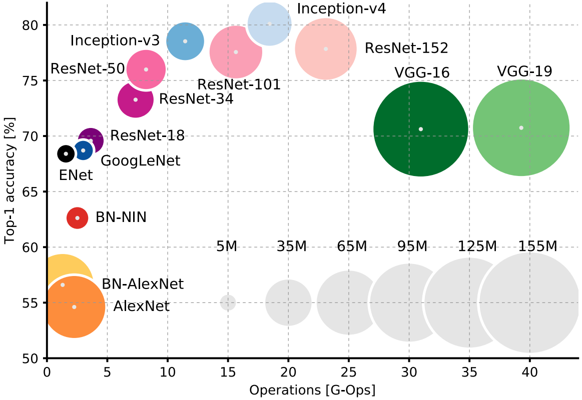
- ResNet (He et al. 2016) 215MB
- Inception-ResNet (Szegedy, Vanhoucke, et al. 2016) 23MB
- DenseNet (Huang et al. 2017) 80MB
- Xception (Chollet 2017) 22MB
- MobileNetV2 (Sandler et al. 2018) 14MB
- ShuffleNet (Zhang et al. 2018) 22MB





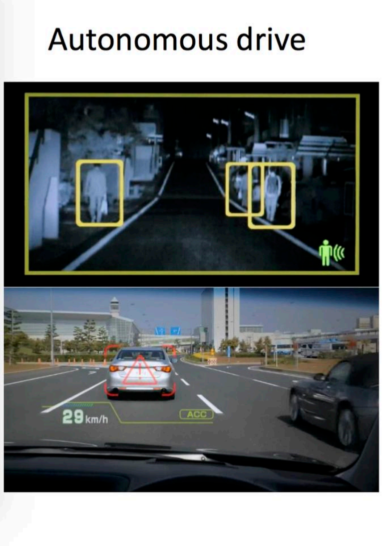
[1]

[1] Alfredo Canziani, Adam Paszke, and Eugenio Culurciello (2017). "An analysis of deep neural network models for practical applications". In: *arXiv preprint*.



Why AlexNet is large in size, but small in operations?

- A: Special FC layers
- B: Special Conv layers
- C: More channels
- D: Some redundant operators


Autonomous drive
29 km/h
ACC

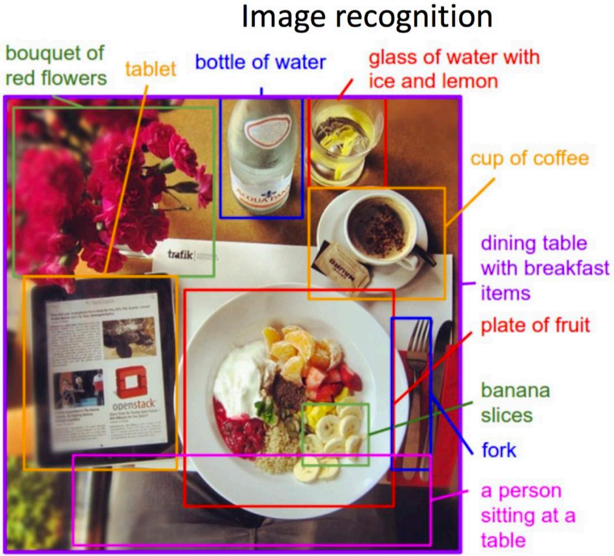
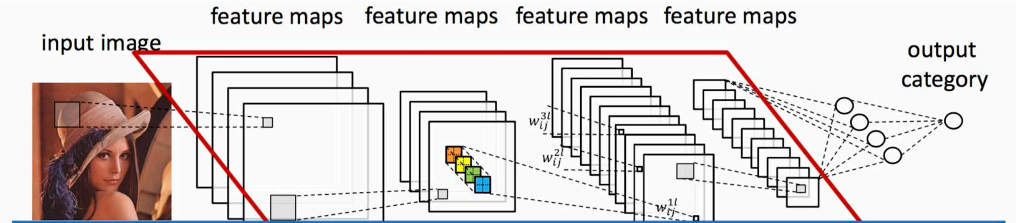


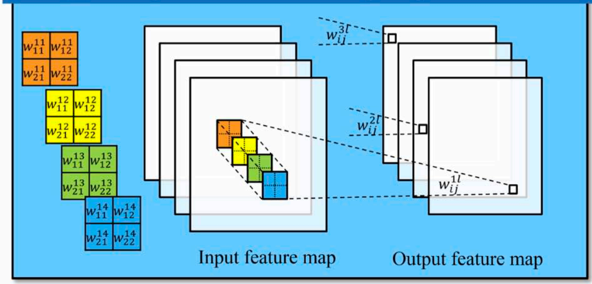
Image recognition
bouquet of red flowers
tablet
bottle of water
glass of water with ice and lemon
cup of coffee
dining table with breakfast items
plate of fruit
banana slices
fork
a person sitting at a table
openstack
trafik

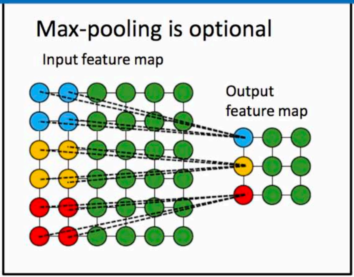
Convolutional Neural Network (CNN)



Convolutional layers account for over 90% computation

[1] A. Krizhevsky, etc. Imagenet classification with deep convolutional neural networks. NIPS 2012.
[2] J. Cong and B. Xiao. Minimizing computation in convolutional neural networks. ICANN 2014






Embedded CV

Example: Hisense ADAS

Start Video