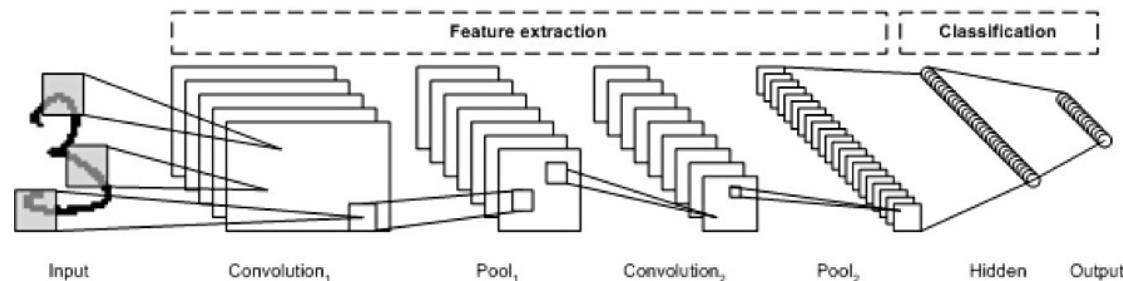




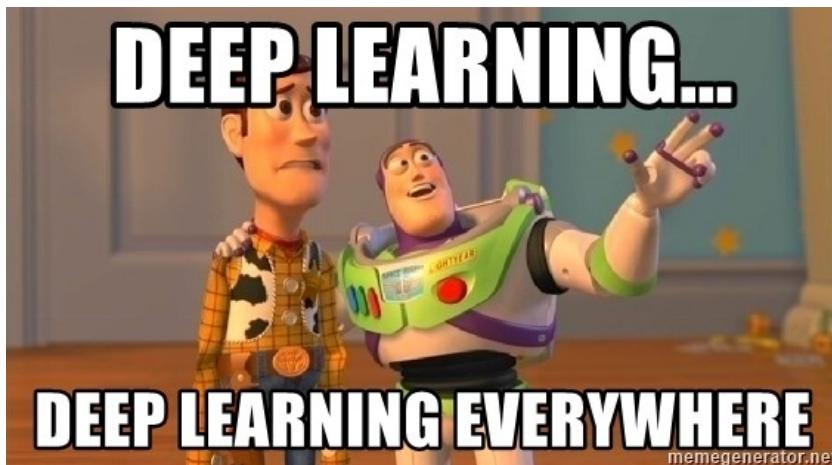
Computational vision: Convolutional Neural Networks

Class 10: Visión Artificial

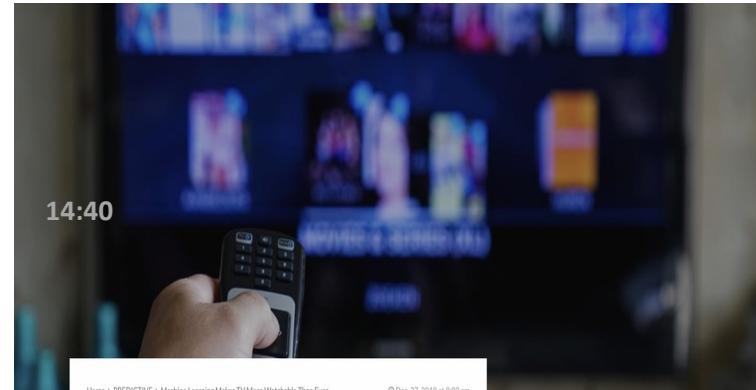


- AI, Machine learning & Deep learning
- What is a Convolutional Neural Network?
 - Layers
 - Optimization
- Applications

Deep learning everywhere



Artificial Intelligence in Cars
Powers an AI Revolution in
the Auto Industry



Home > PREDICTIVE > Machine Learning Makes TV More Watchable Than Ever

© Dec. 27, 2018 at 9:09 am

PREDICTIVE

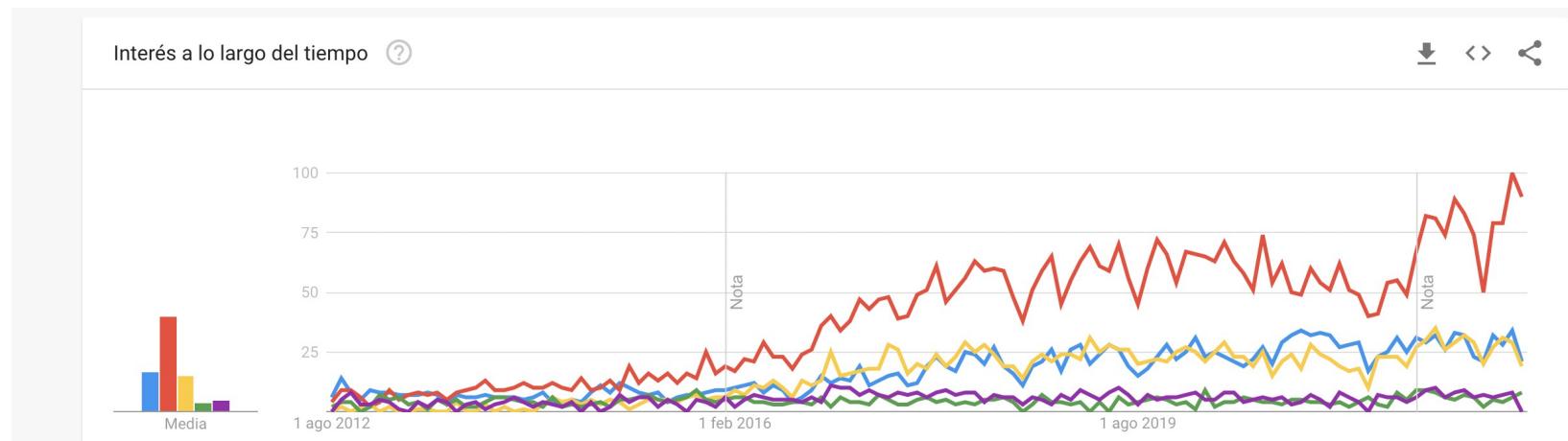
Machine Learning Makes TV More Watchable Than Ever

NEWSLETTER

Get news and stories from Data Makes Possible delivered to your inbox.

Artificial Intelligence

- ↗ Machine Learning
- ↗ Artificial Intelligence
- ↗ Deep learning
- ↗ Neural networks
- ↗ Computer Vision

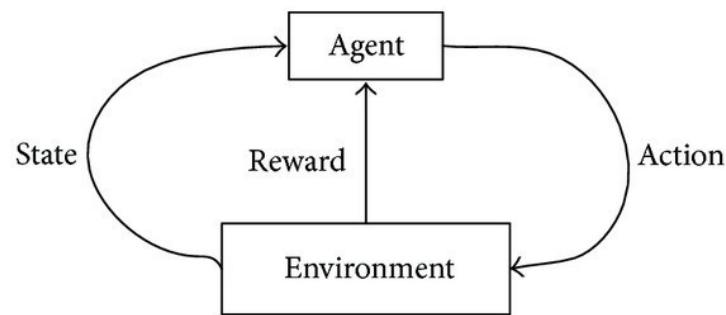
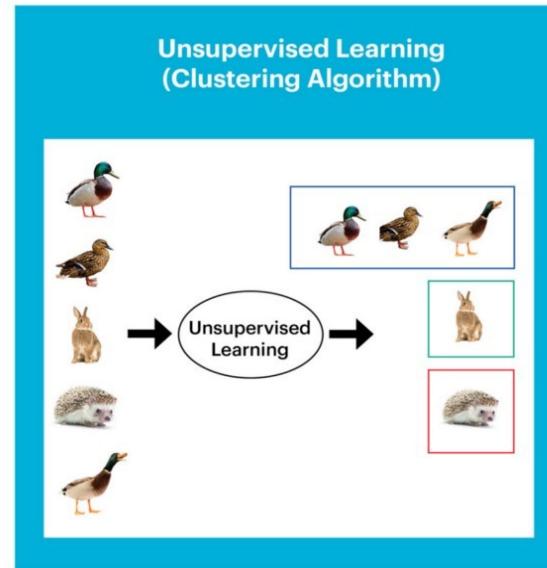
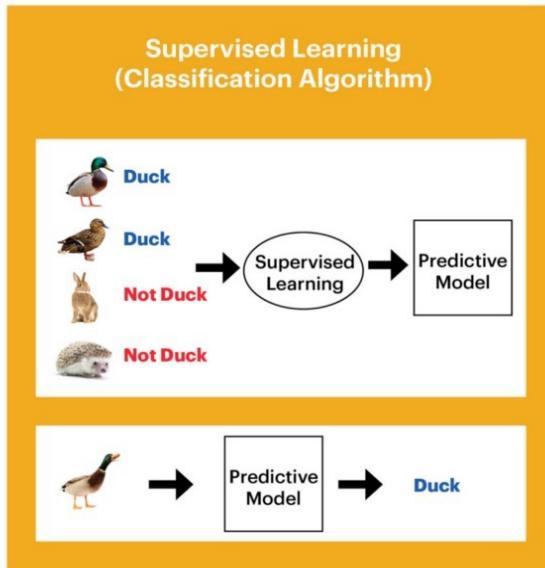


Google Scholar reveals its most influential papers



1. **"Deep Residual Learning for Image Recognition"** (2016) *Proceedings of the IEEE/CVPR Computer Vision and Pattern Recognition* 25,256 citations
Deep learning
Yann LeCun, Yoshua Bengio & Geoffrey Hinton
Affiliations | Corresponding author
Nature 521, 436-444 (28 May 2016) | doi:10.1038/nature14539
Received: 25 February 2015 | Accepted: 01 May 2015 | Published online: 27 May 2015
2. **"Deep learning"** (2015) *Nature* 16,750 citations
3. **"Going Deeper with Convolutions"** (2015) *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* 14,424 citations
4. **"Fully Convolutional Networks for Semantic Segmentation"** (2015) *Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition* 10,153 citations
5. **"Prevalence of Childhood and Adult Obesity in the United States, 2011-2012"** (2014) *JAMA* 8,057 citations
6. **"Global, regional, and national prevalence of overweight and obesity in children and adults during 1980–2013: a systematic analysis for the Global Burden of Disease Study 2013"** (2014) *Lancet* 7,371 citations
7. **"Observation of Gravitational Waves from a Binary Black Hole Merger"** (2016) *Physical Review Letters* 6,009 citations

Supervised vs. Unsupervised vs Reinforcement Learning



Ai, ML and DL evolution

1950

Alan Turing created a test to check if a machine could fool a human being into believing it was talking to a machine.

1957

First neural network for computers (the perceptron) was invented by Frank Rosenblatt, which simulated the thought processes of the human brain.

1979

Students of Stanford University, California, invented the Stanford Cart which could navigate and avoid obstacles on its own.

2002

A software library for Machine Learning, named Torch is first released.

1952

The first computer learning program, a game of checkers, was written by Arthur Samuel.

1967

The Nearest Neighbor Algorithm was written.

1997

IBM's Deep Blue beats the world champion at Chess.

2016

AlphaGo algorithm developed by Google DeepMind managed to win five games out of five in the Chinese Board Game Go competition.

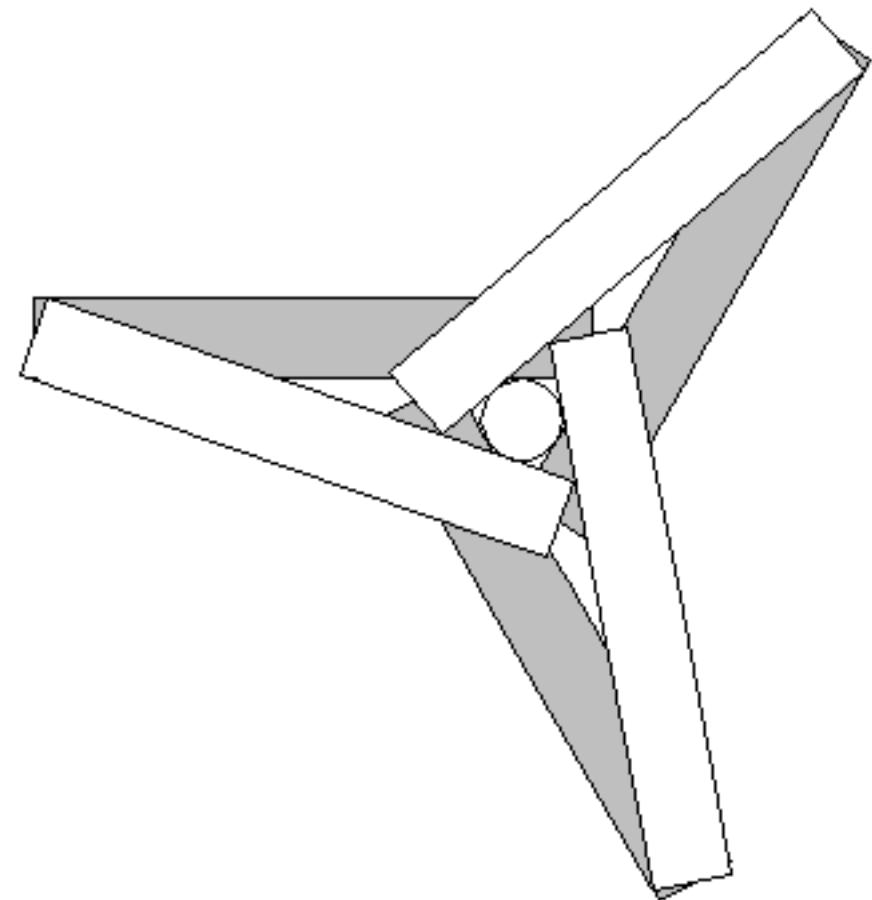
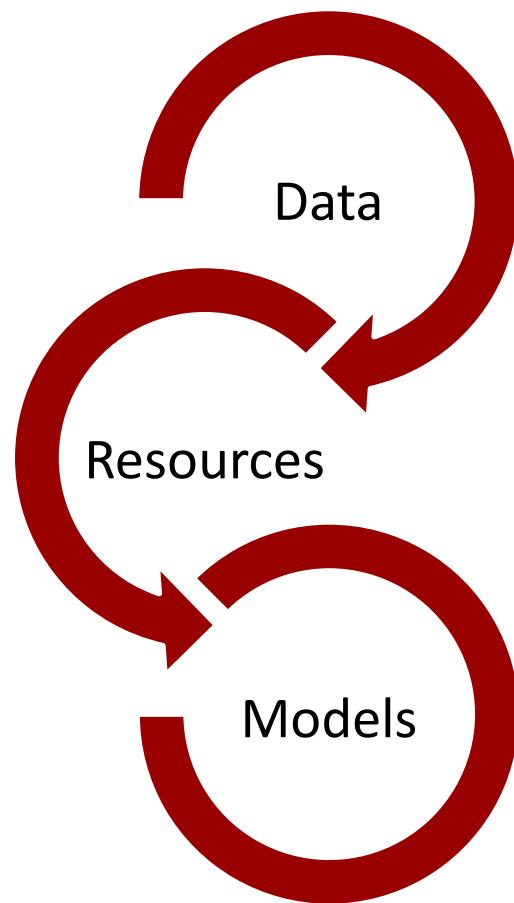


Deep learning – where does it come from?

- ↗ **1943:** neurophysiologist Warren McCulloch and mathematician Walter Pitts – a **neuronal model** using an electrical circuit
- ↗ **1950:** Alan Turing created the world-famous **Turing Test:** a computer to pass, has to be able to convince a human that it is a human and not a computer.
- ↗ **1952:** Arthur Samuel created the first computer **program which could learn** as it ran. It was a game which played checkers.
- ↗ **1958:** Frank Rosenblatt designed the first artificial neural network, called **Perceptron**. The main goal of this was pattern and shape recognition.
- ↗ **1959,** Bernard Widrow and Marcian Hoff created
 - ↗ ADELINe to detect binary patterns (in a stream of bits, to predict the next one).
 - ↗ MADELINE to eliminate echo on phone lines, still in use today.
- ↗ **1986:** Neural networks use **back propagation** allowing multiple layers to be used in a neural network, creating what are known as 'slow learners'.
- ↗ Late **1980s** and **1990s** did not bring much to the field.
- ↗ **1997,** the IBM computer Deep Blue (a chess-playing computer) beat the world chess champion.
- ↗ **1998** AT&T Bell Laboratories on digit recognition resulted in good accuracy in detecting handwritten postcodes from the US Postal Service.

What changed today?

The magic triangle

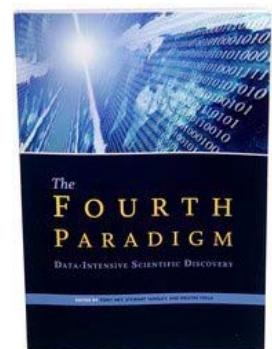
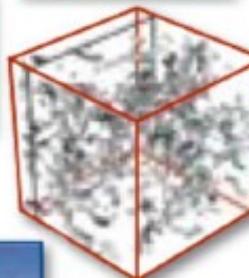


The Jim Cray's paradigms

Science Paradigms

- Thousand years ago:
science was **empirical**
describing natural phenomena
- Last few hundred years:
theoretical branch
using models, generalizations
- Last few decades:
a computational branch
simulating complex phenomena
- Today: **data exploration** (eScience)
unify theory, experiment, and simulation
 - Data captured by instruments or generated by simulator
 - Processed by software
 - Information/knowledge stored in computer
 - Scientist analyzes database/files using data management and statistics

$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G p}{3} - K \frac{c^2}{a^2}$$



Toni Hey, 2009

Data

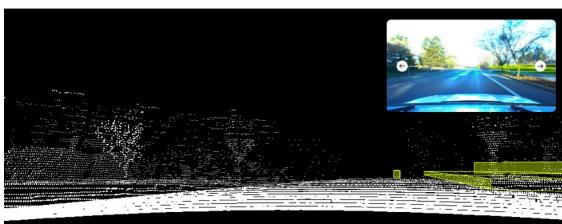
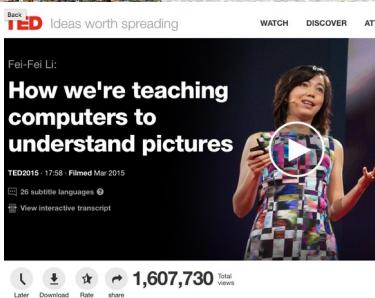
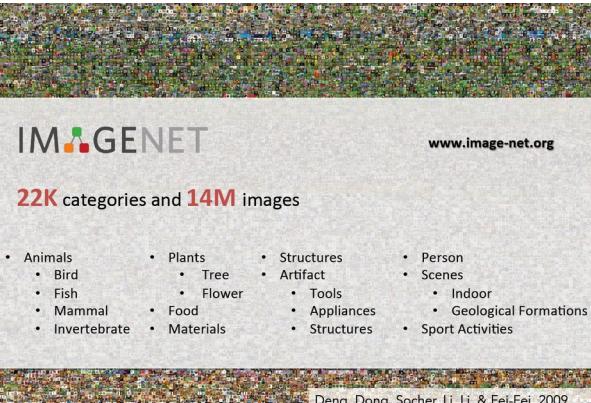
90% of all digital data were generated last 2 years.

Every minute of the day:

- ↗ 4M YouTube videos watched
 - ↗ 456K tweets on Twitter
 - ↗ 46K photos posted in Instagram
 - ↗ 16M text messages sent
 - ↗ 103M spam emails sent



DL Datasets



Lyft Level 5

<https://www.datasetlist.com>



LVIS Challenge:
2.2M masks, 16K images

00:29 → 00:37 Steven went, got the keys and we are gonna have them back. That easy.

(serious face)

I couldn't... (serious face)

(Interrupts) But this was Friday! This was Friday... (serious face)

(shocked)

You said you were going to do it and you are not doing it!

Q1: How is the man who is not being blamed responding to the situation? *advanced*
A1: He thinks the other man is slackin even if he is not saying it. *intermediate*
A2: He is showing support for the woman by taking her side. *intermediate*
A3: He thinks he is better than both of the people arguing. *easy*
A4: He is trying to ignore the situation. *intermediate*

Q2: How is the woman who is being blamed responding to the situation? *advanced*
A1: Because a small problem became a huge problem. *intermediate*
A2: She has too much on her plate, and this new problem overwhelms her. *advanced*
A3: The man is being a jerk. *intermediate*
A4: Because both of them seem to be ignoring her. *intermediate*

SocialIQ



FastMRI



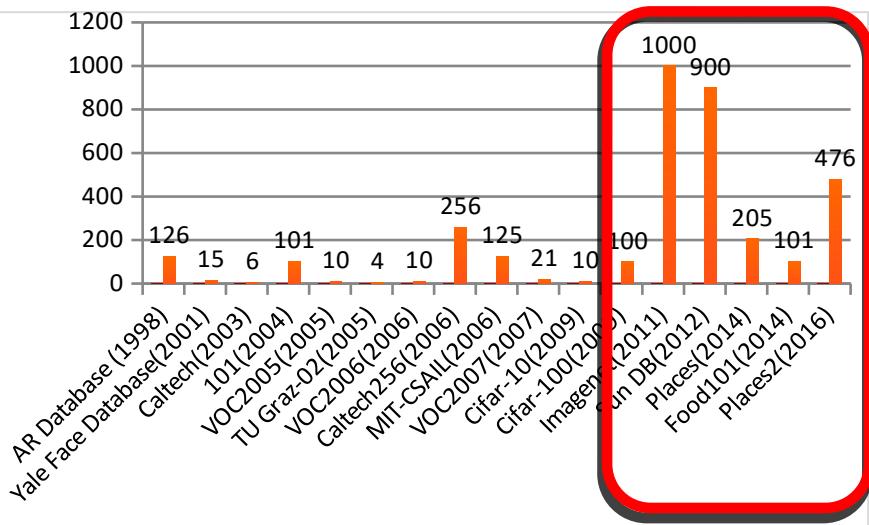
Places2: 10M images



TACO: Waste
in the wild

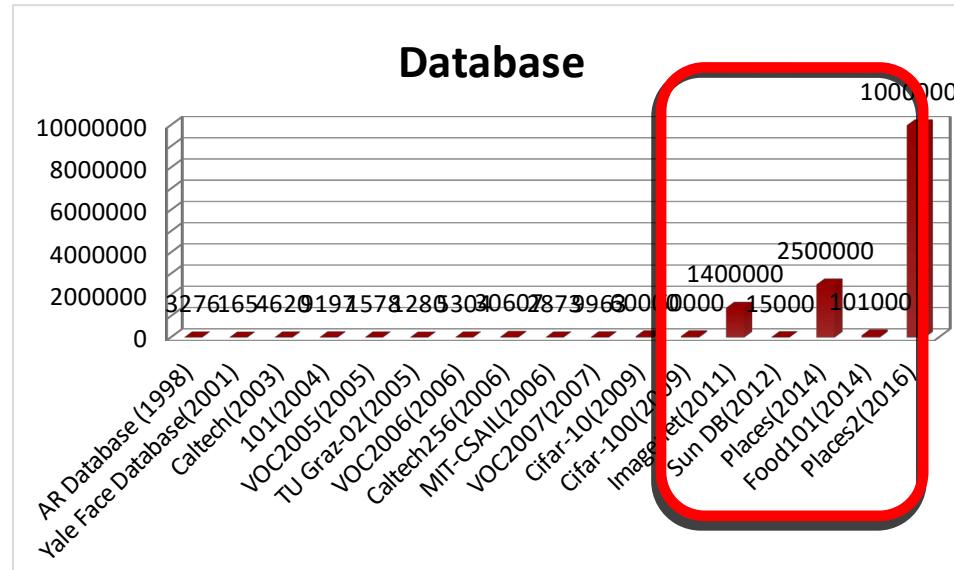
Image databases evolution

Number of objects/Database



ImageNet & Deep learning

Number of images/Database



Imagenet



IMAGENET

www.image-net.org

22K categories and **14M** images

- Animals
 - Bird
 - Fish
 - Mammal
 - Invertebrate
- Plants
 - Tree
 - Flower
 - Food
 - Materials
- Structures
 - Artifact
 - Tools
 - Appliances
 - Structures
- Person
- Scenes
 - Indoor
 - Geological Formations
 - Sport Activities



Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

Back TED Ideas worth spreading

WATCH DISCOVER ATT

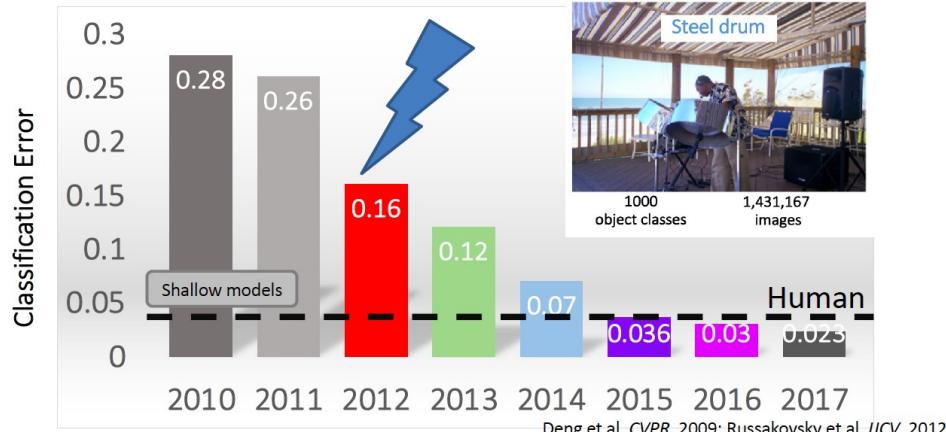
Fei-Fei Li:
How we're teaching computers to understand pictures

TED2015 · 17:58 · Filmed Mar 2015

26 subtitle languages ⓘ
View interactive transcript

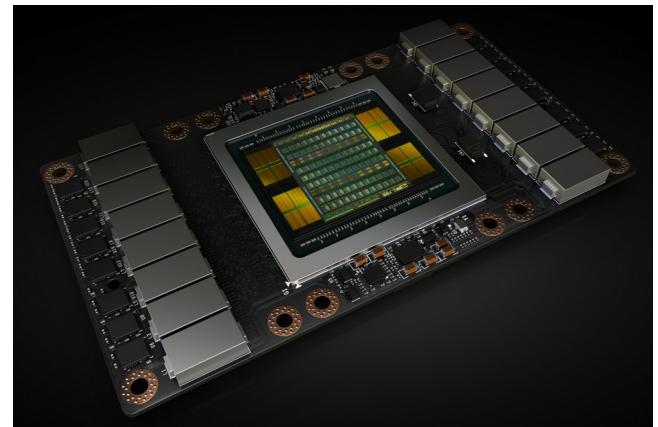
A screenshot of a TED talk by Fei-Fei Li. She is standing on stage, wearing a colorful patterned dress, holding a remote, and gesturing with her hands. The title of the talk is "How we're teaching computers to understand pictures". The video was filmed at TED2015 on March 2015. There are 26 subtitle languages available. The video has 1,607,730 total views.

IMAGENET Classification Task



The Importance of GPUs

- ↗ Nvidia Tensor Cores - 2017
- ↗ Google Tensor Processing Unit (TPU) - 2016
- ↗ Intel - Nervana Neural Processor - 2017
- ↗ GPUs in Cloud Computing (Google, 2017)



$$D = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix}_{\text{FP16 or FP32}} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix}_{\text{FP16}} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}_{\text{FP16 or FP32}}$$

GPU cores is based on matrix multiplication

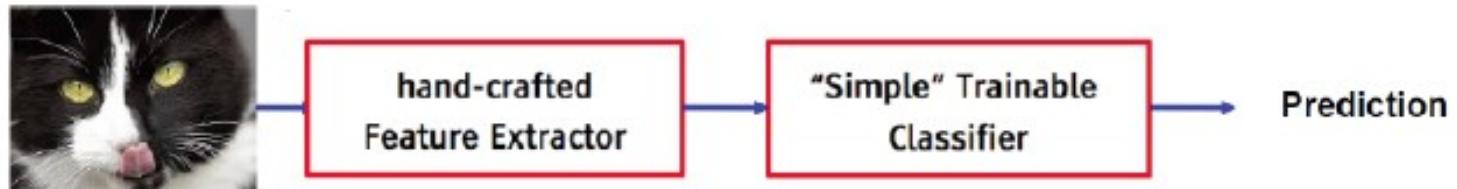


What is a Neural Network?

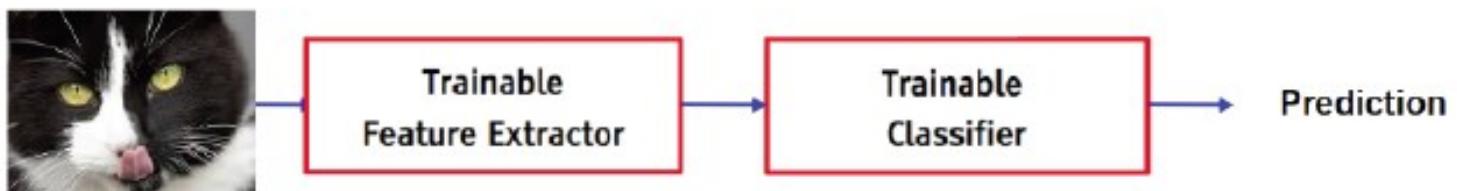
- ↗ AI, Machine learning & Deep learning
- ↗ What is a Convolutional Neural Network?
 - ↗ Layers
 - ↗ Optimization
- ↗ Applications

Why Deep learning?

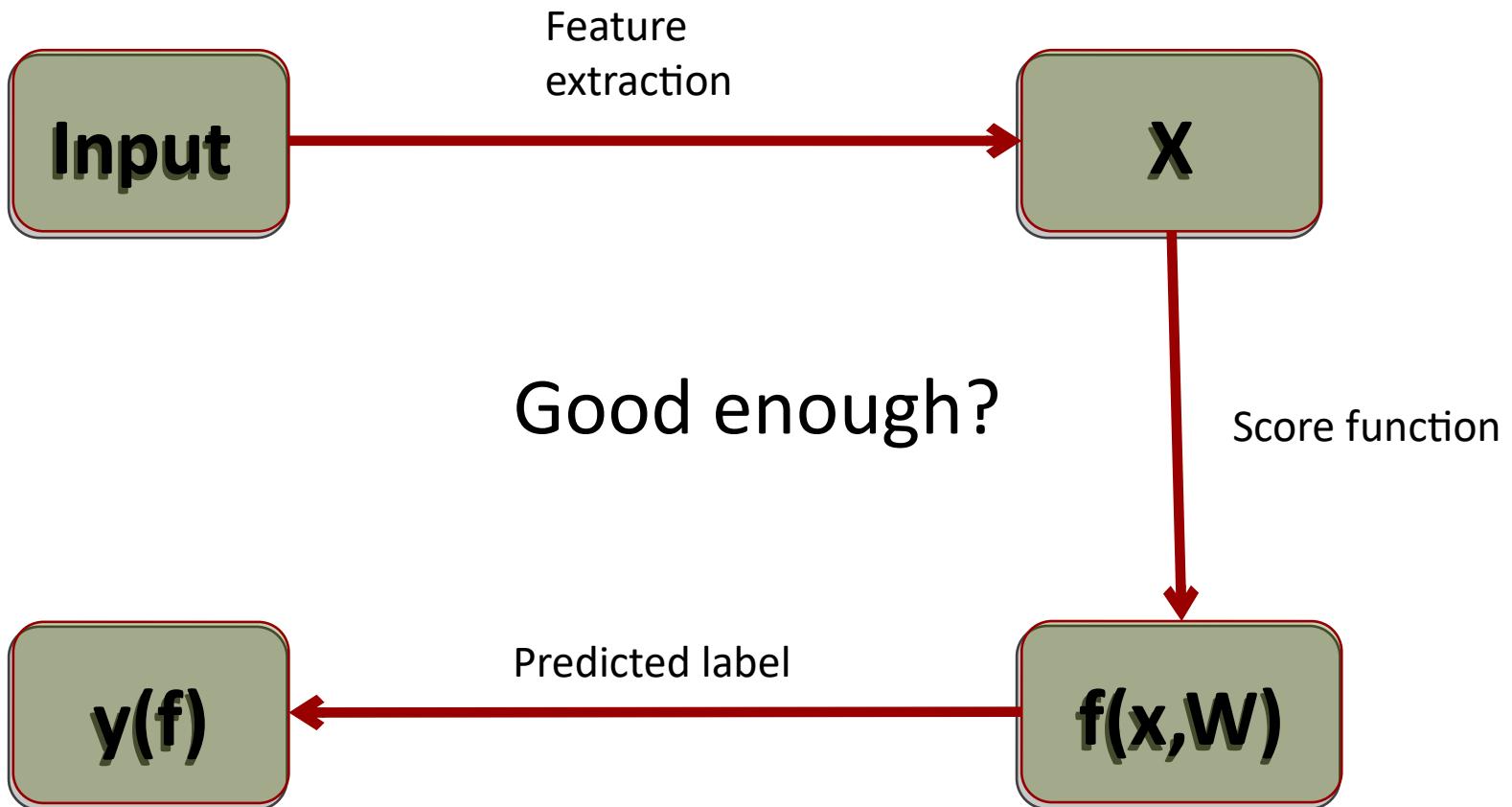
Classical way of solving Computer Vision problems



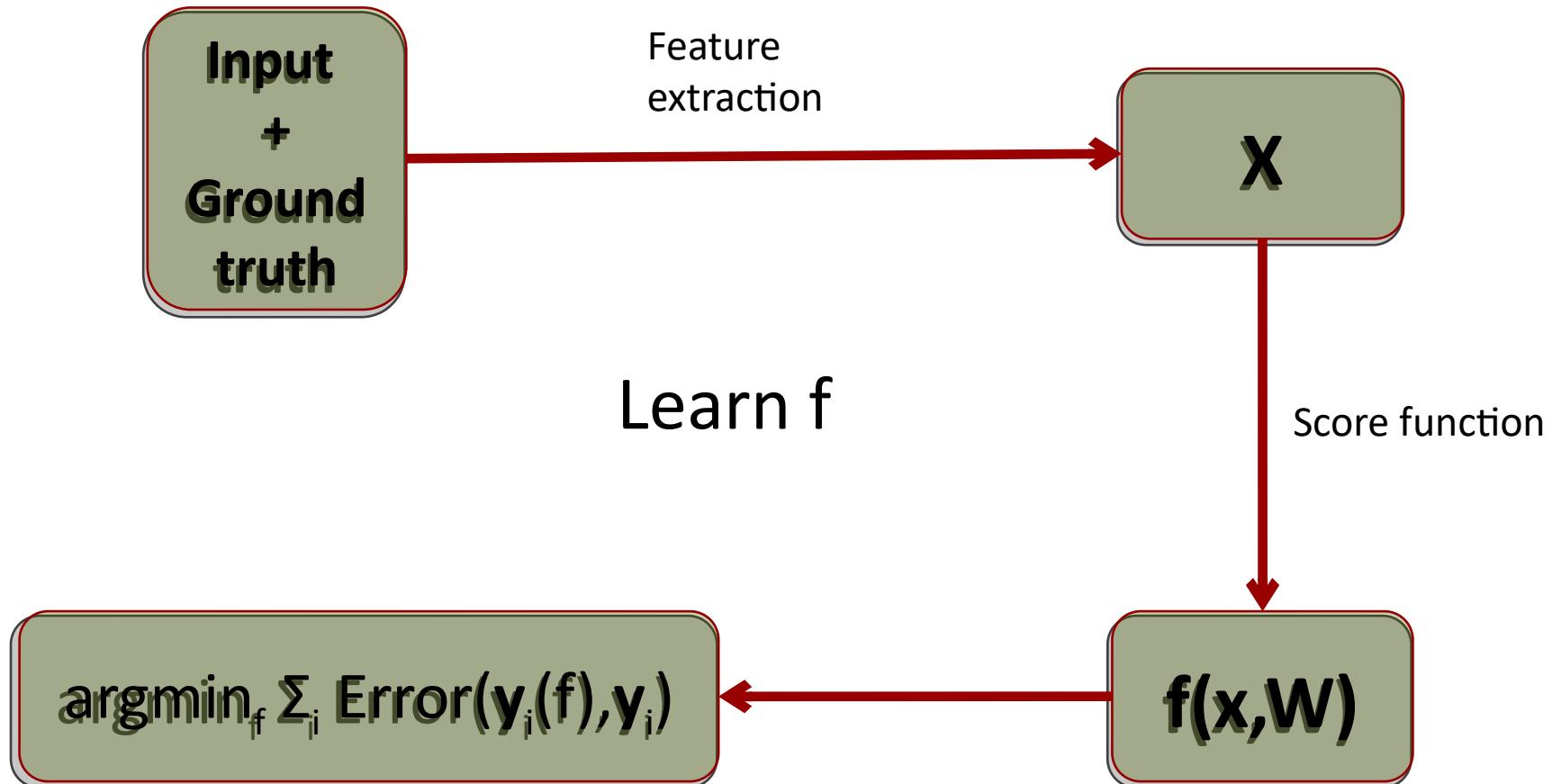
How Computer Vision problems are solved by Deep Learning



The learning pipeline



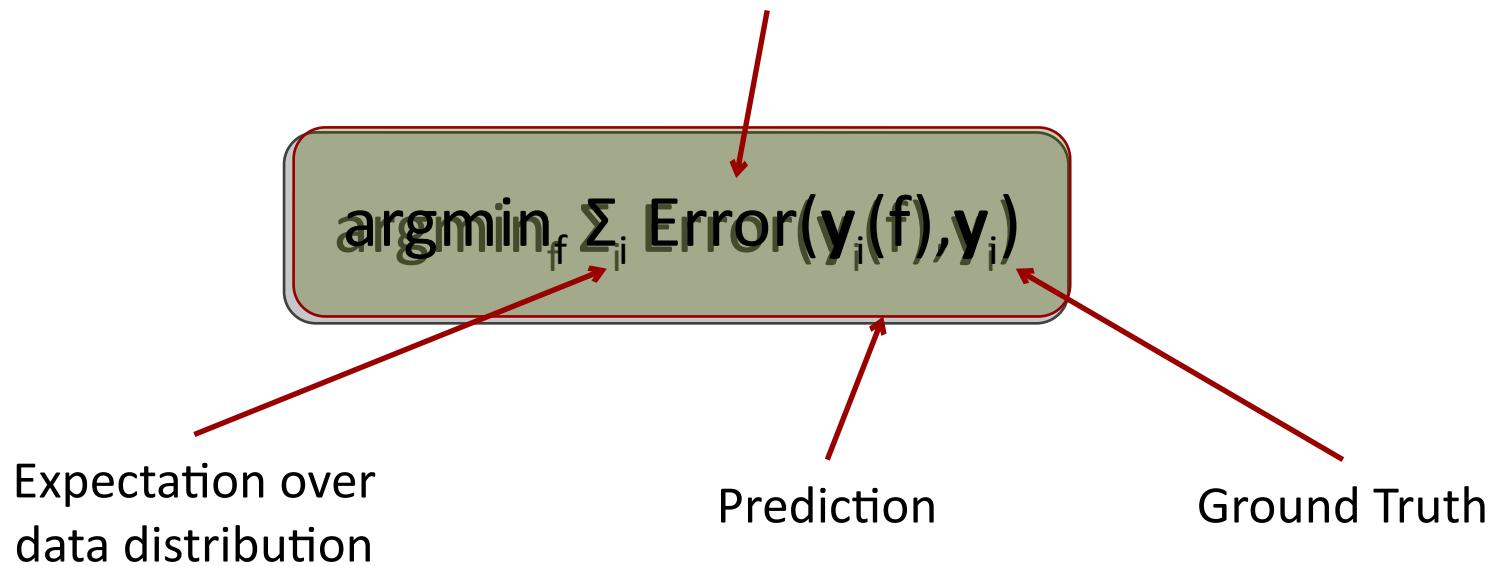
The traning process



The learning process

Training data $\{(x_i, y_i), i = 1, 2, \dots, n\}$

Measure of prediction quality (error, loss)

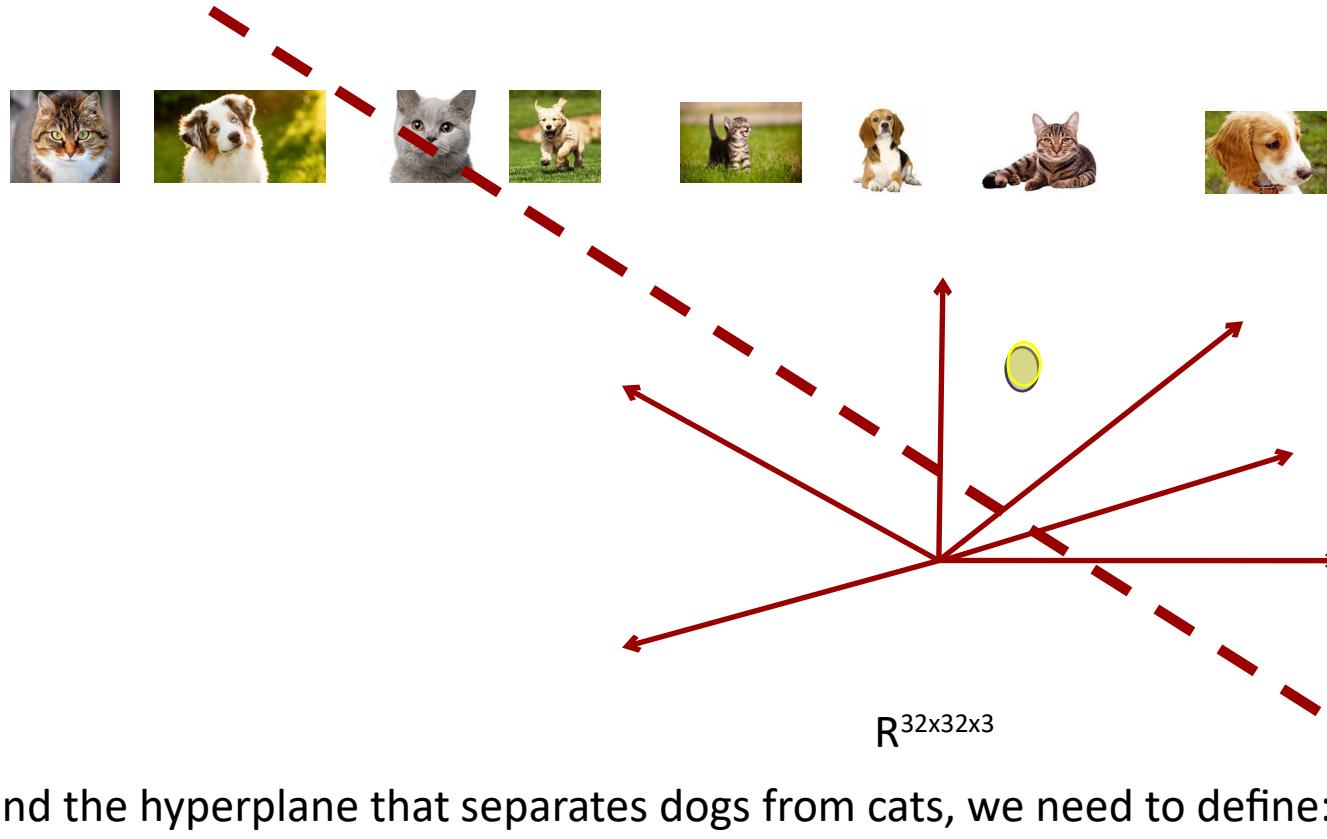


Loss function the negative conditional log-likelihood, with the interpretation that $f_i(X)$ estimates $P(Y=i | X)$:

$$L(f(x), y) = -\log f_i(x), \text{ where } f_i(x) \geq 0, \sum_i f_i(x) = 1.$$

Linear classification

Given two classes how to learn a hyperplane to separate them?



To find the hyperplane that separates dogs from cats, we need to define:

- The score function
- The loss function
- And the optimization process.

How to project data in the feature space:

3x1

3072x1

$$f(x) = W x + b$$

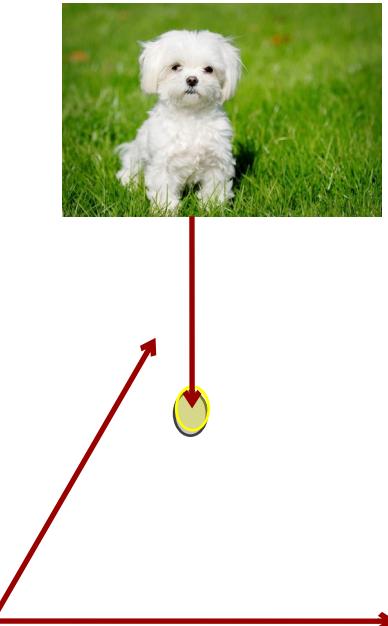
3x3072

3x1

If x is an image of $(32 \times 32 \times 3)$, $\rightarrow x$ in R^{3072} ,

The matrix W is (3×3072) .

The bias vector b is 3-dimensional.



How to project data in the feature space:

3x1

3072x1

$$f(x) = W x + b$$

3x3072

3x1

If we have 3 classes, $f(x)$ will give 3 scores.

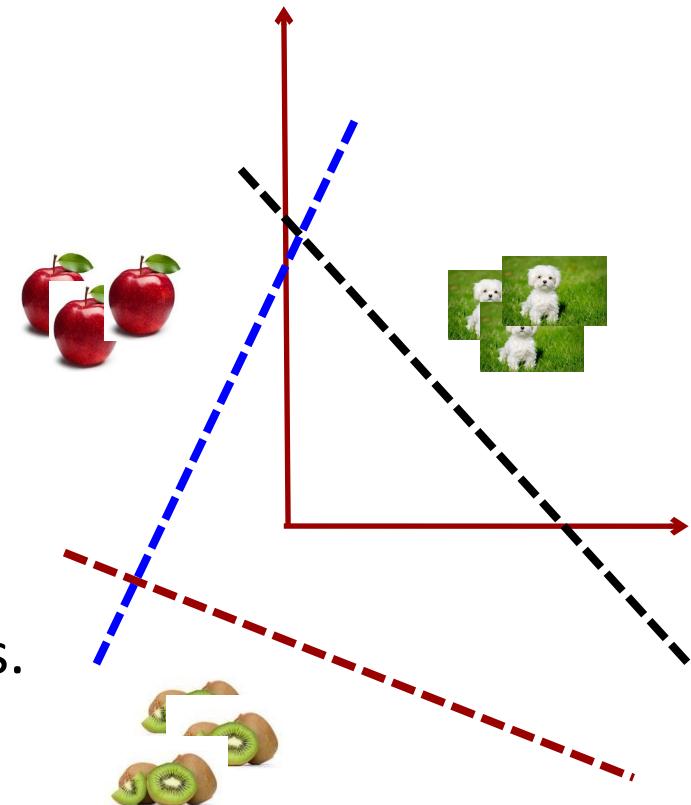
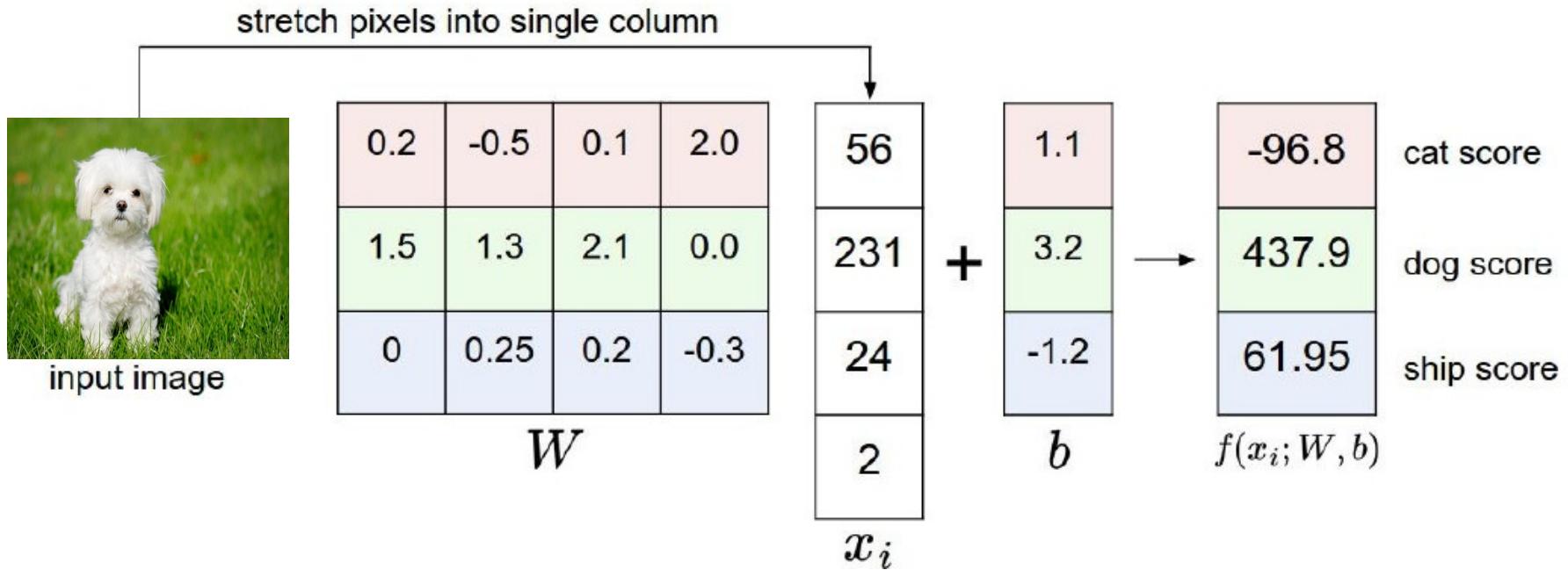


Image classification

Example with an image with 4 pixels, and 3 classes (**cat/dog/ship**)

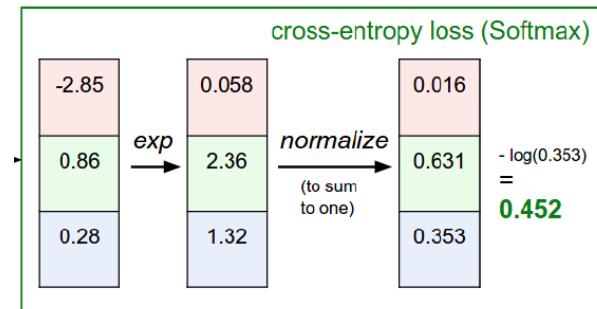


Loss function and optimisation

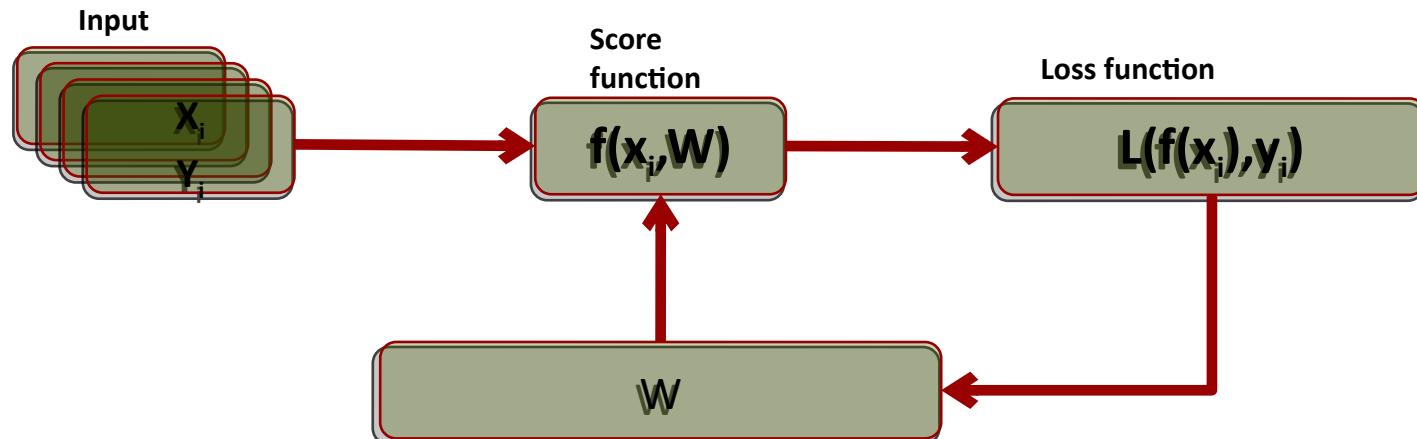
↗ **Question:** if you were to assign a single number to how unhappy you are with these scores, what would you do?

$$L_i = -\log \left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}} \right)$$

softmax function

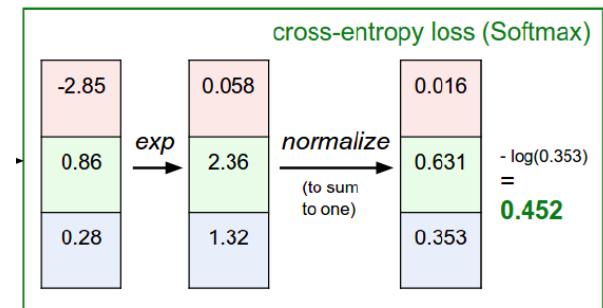


Question : Given the score and the loss function, how to find the parameters W?

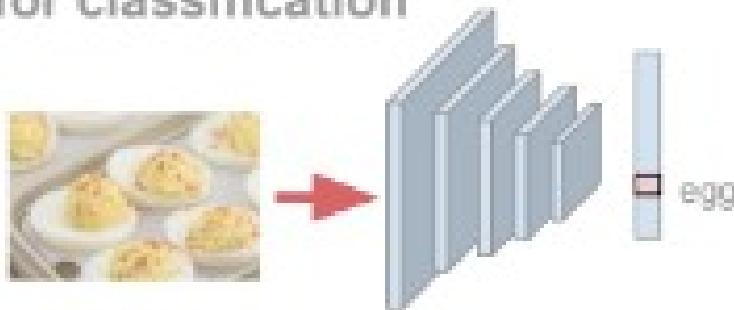


Single-label classification

- Change the lost function to the Binary cross-entropy function L_b :



Conventional approach:
CNN for classification



Softmax

$$P(y_i|x) = \frac{\exp^{f(x)_i}}{\sum_i \exp^{f(x)_j}}$$

loss

Categorical cross-entropy

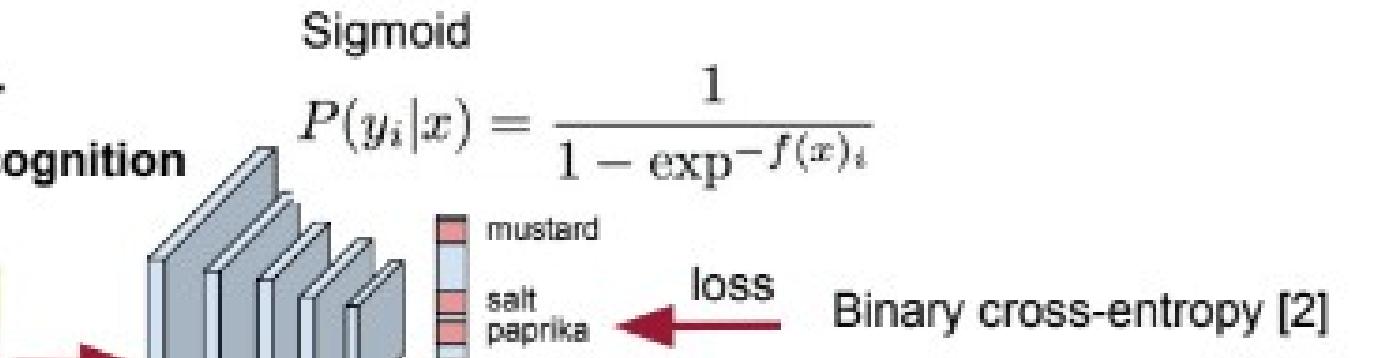
$$L_c = - \sum_x \log(P(\hat{y}_x|x))$$

Multi-label classification

- Change the loss function to the Binary cross-entropy function L_b :

Our proposal:

**Adaptation for
multi-label recognition**



$$L_b = - \sum_x \sum_i^N (\hat{y}_x^i \cdot \log(P(y_i|x)) + (1 - \hat{y}_x^i) \cdot \log(1 - P(y_i|x)))$$

- ↗ AI, Machine learning & Deep learning
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How is a CNN doing deep learning?

$$y = Wx$$



$$\begin{matrix} 0.2 & -0.5 & 0.1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0 & 0.25 & 0.2 & -0.3 \end{matrix}$$

W

$$y_1 = \sum_i W_{1i} x_i$$

$$\begin{matrix} 56 \\ 231 \\ 24 \\ 2 \end{matrix} + \begin{matrix} 1.1 \\ 3.2 \\ -1.2 \end{matrix} \rightarrow \begin{matrix} \dots \\ -96.8 \\ 437.9 \\ 61.95 \end{matrix}$$

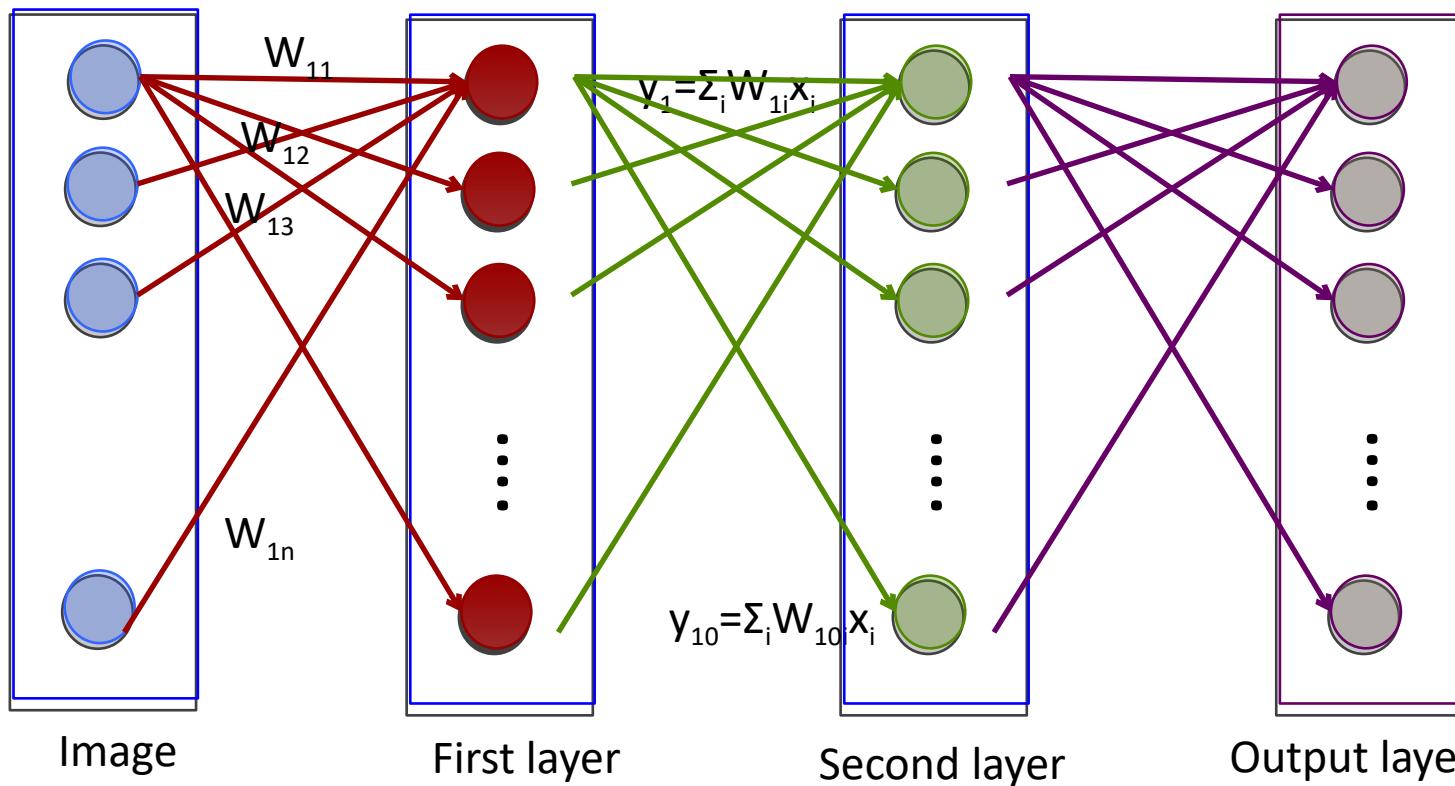
cat score
dog score
ship score

$f(x_i; W, b)$

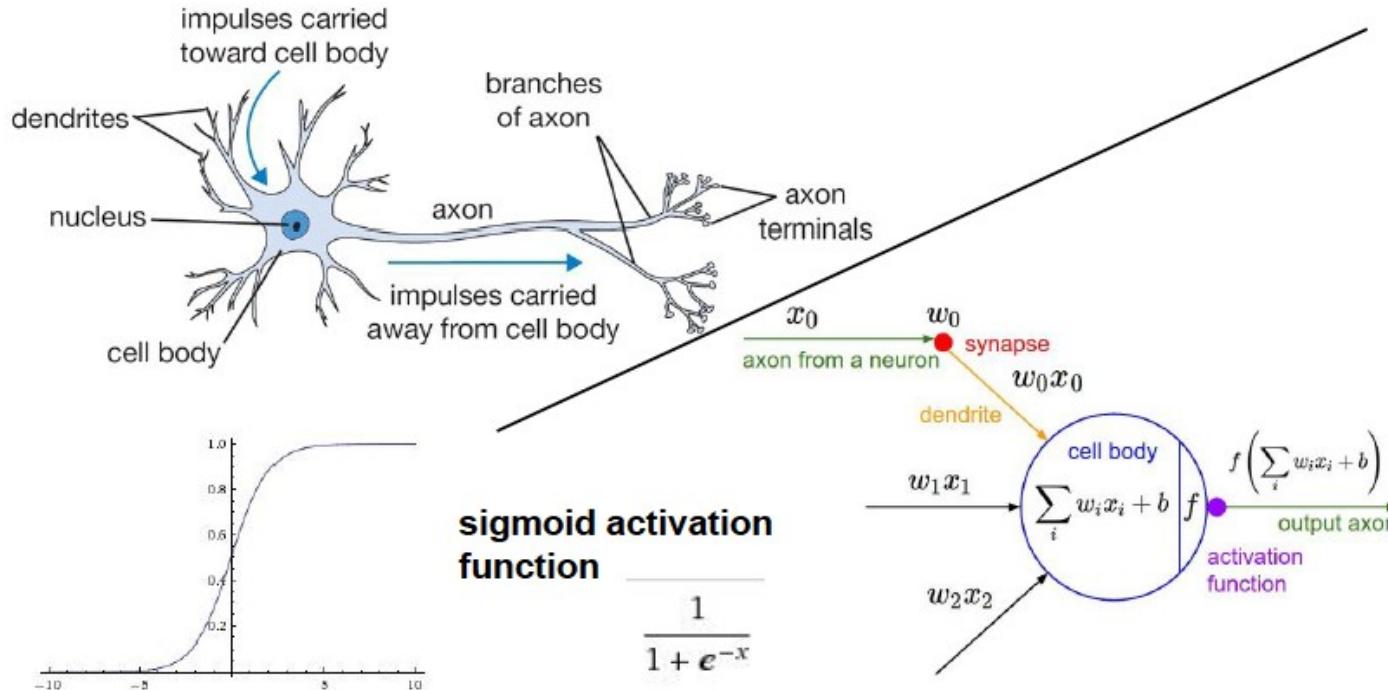
$$y = W(Wx)$$

$$y = W(W(Wx))$$

Fully connected layers



Why a CNN is a neural network?

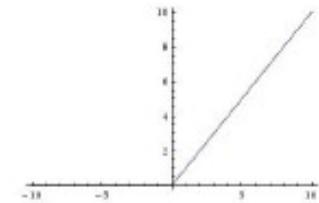


Modern CNNs – 10M neurons

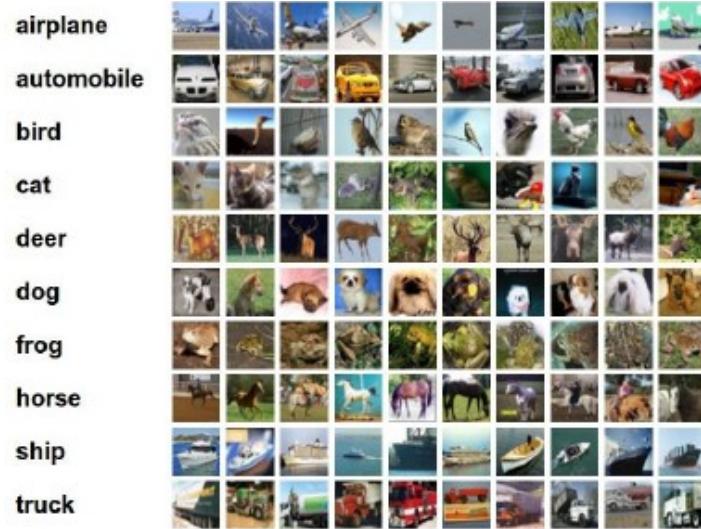
Human CNNs – 5B of neurons.

From: Fei-Fei Li & Andrej Karpathy & Justin Johnson

ReLU $\max(0, x)$



Why is it convolutional?



$$f(x_i, W, b) = Wx_i + b$$

Diagram illustrating the computation of a feature map element:

The input image x_i is represented by a 4x4 grid of blurred pixels. The weight matrix W is a 4x4 matrix of weights. The bias vector b is a vertical vector of four values. The computation involves multiplying the input image by the weight matrix and then adding the bias vector to produce the final output value.

0.2	-0.5	0.1	2.0
1.5	1.3	2.1	0.0
0	0.25	0.2	-0.3
W			

x_i

W

b

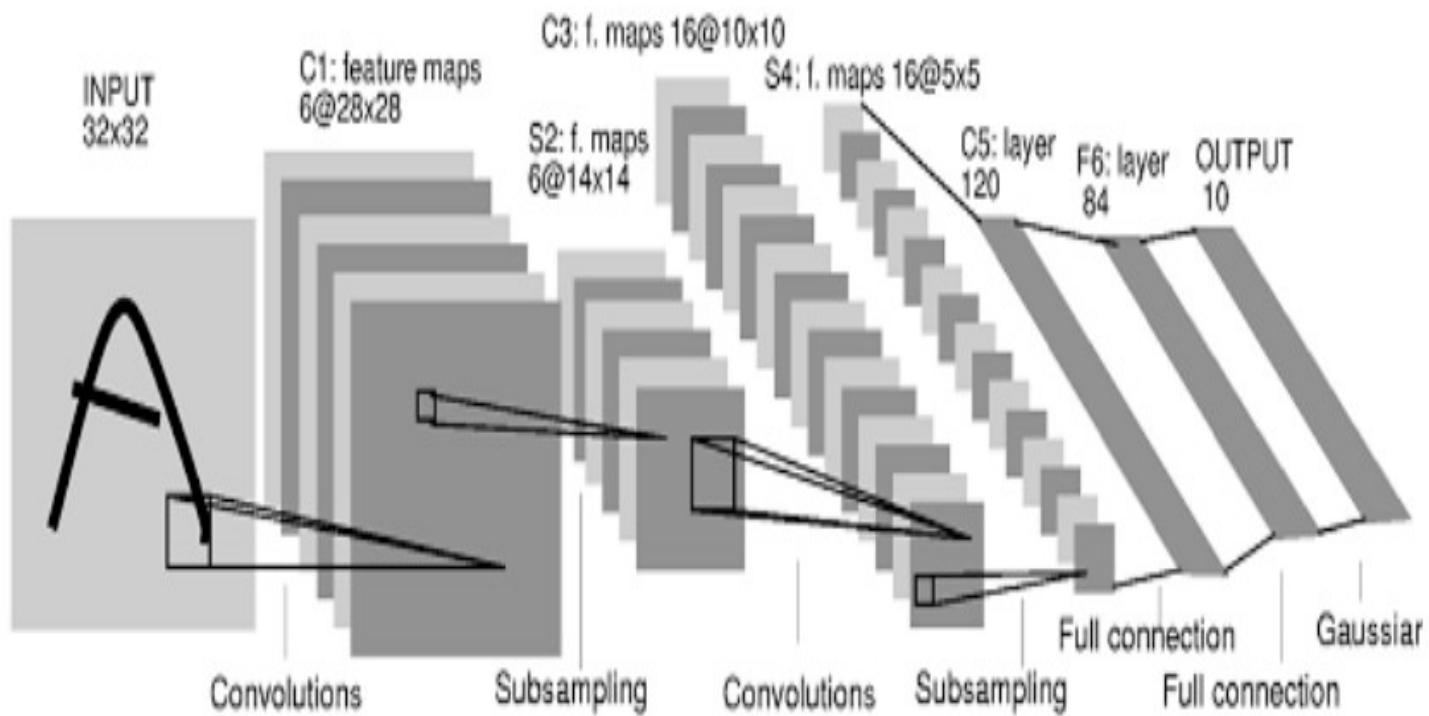
$f(x_i; W, b)$

Adapted from: Fei-Fei Li & Andrej Karpathy & Justin Johnson

What is new in the Convolutional Neural Network?

1998

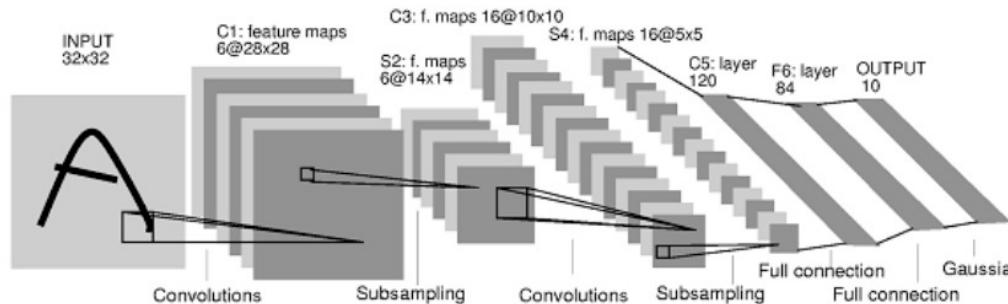
LeCun et al.



CNN evolution

1998

LeCun et al.



of transistors



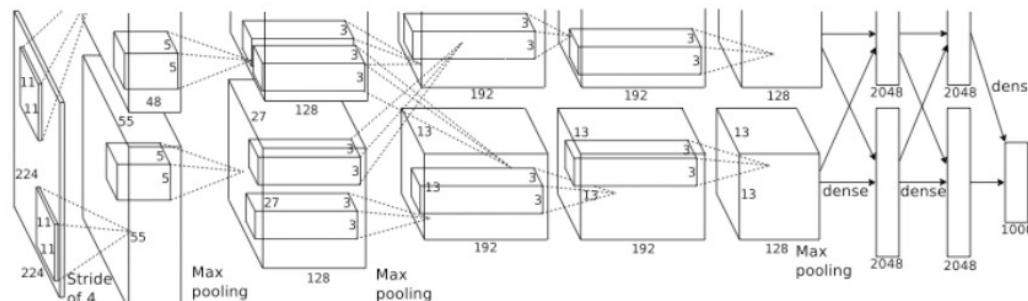
10^6

of pixels used in training

10^7

2012

Krizhevsky
et al.



of transistors



10^9

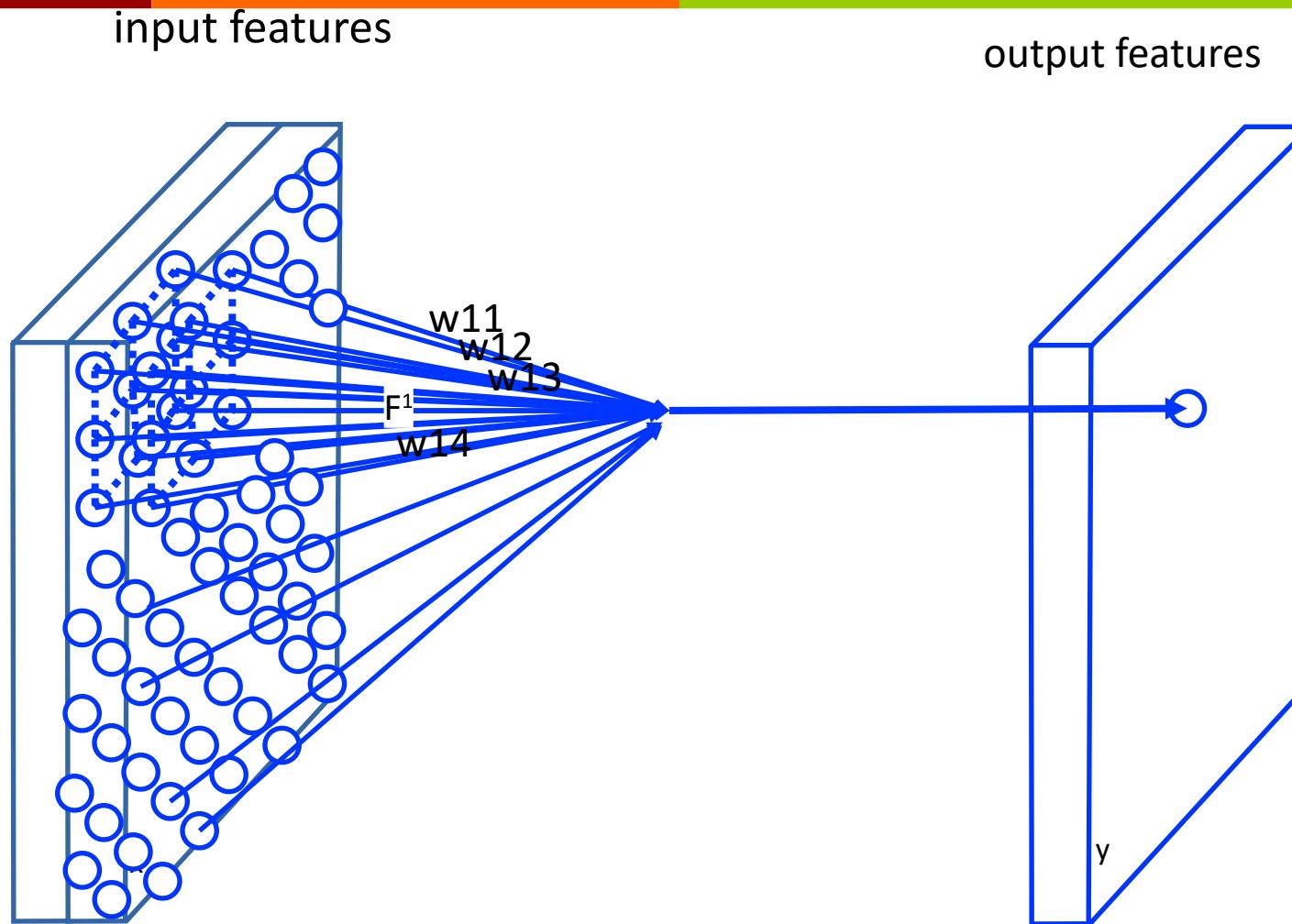
GPUs



of pixels used in training

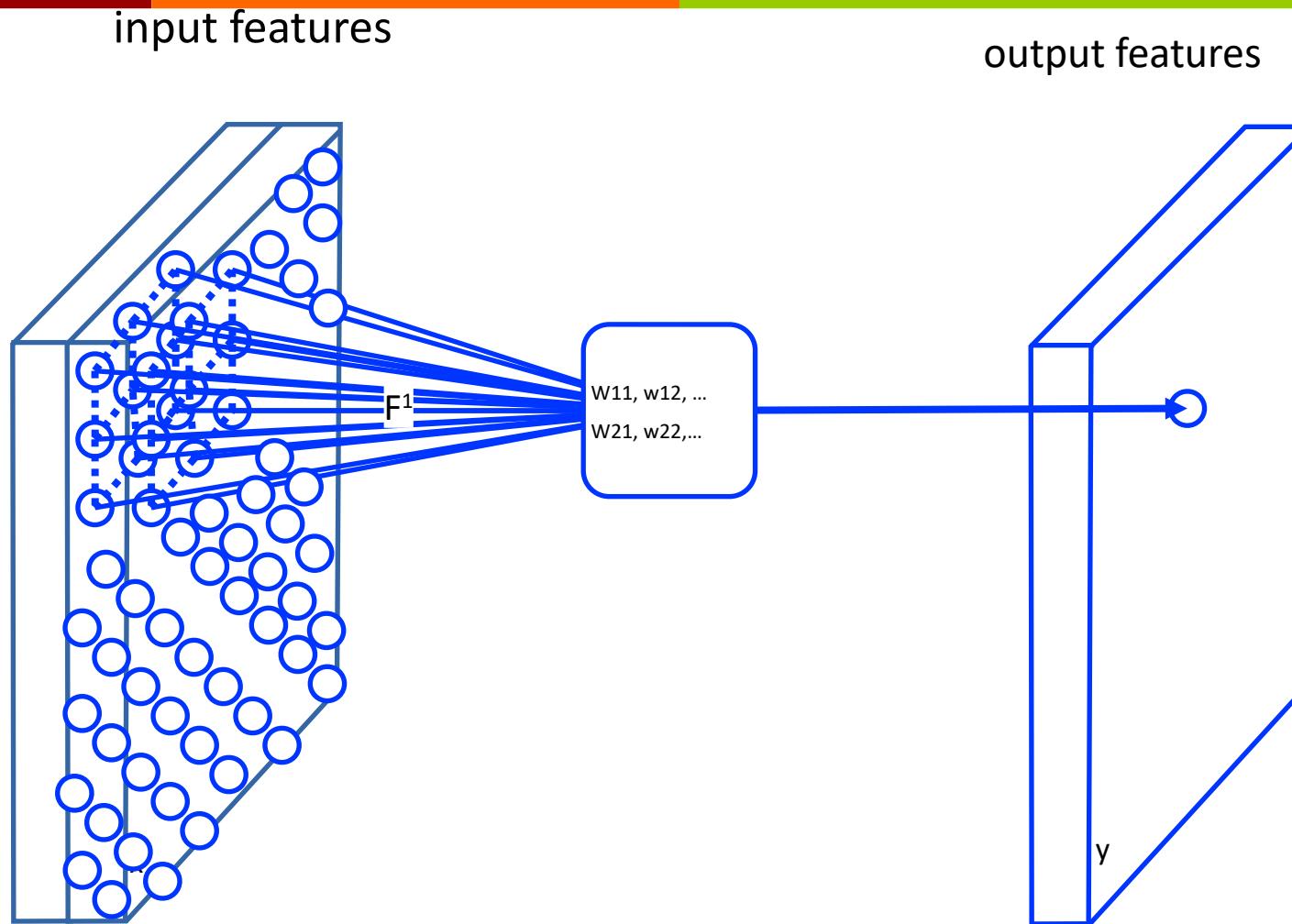
10^{14}

Why is it convolutional?



Let's consider a fully connected layer

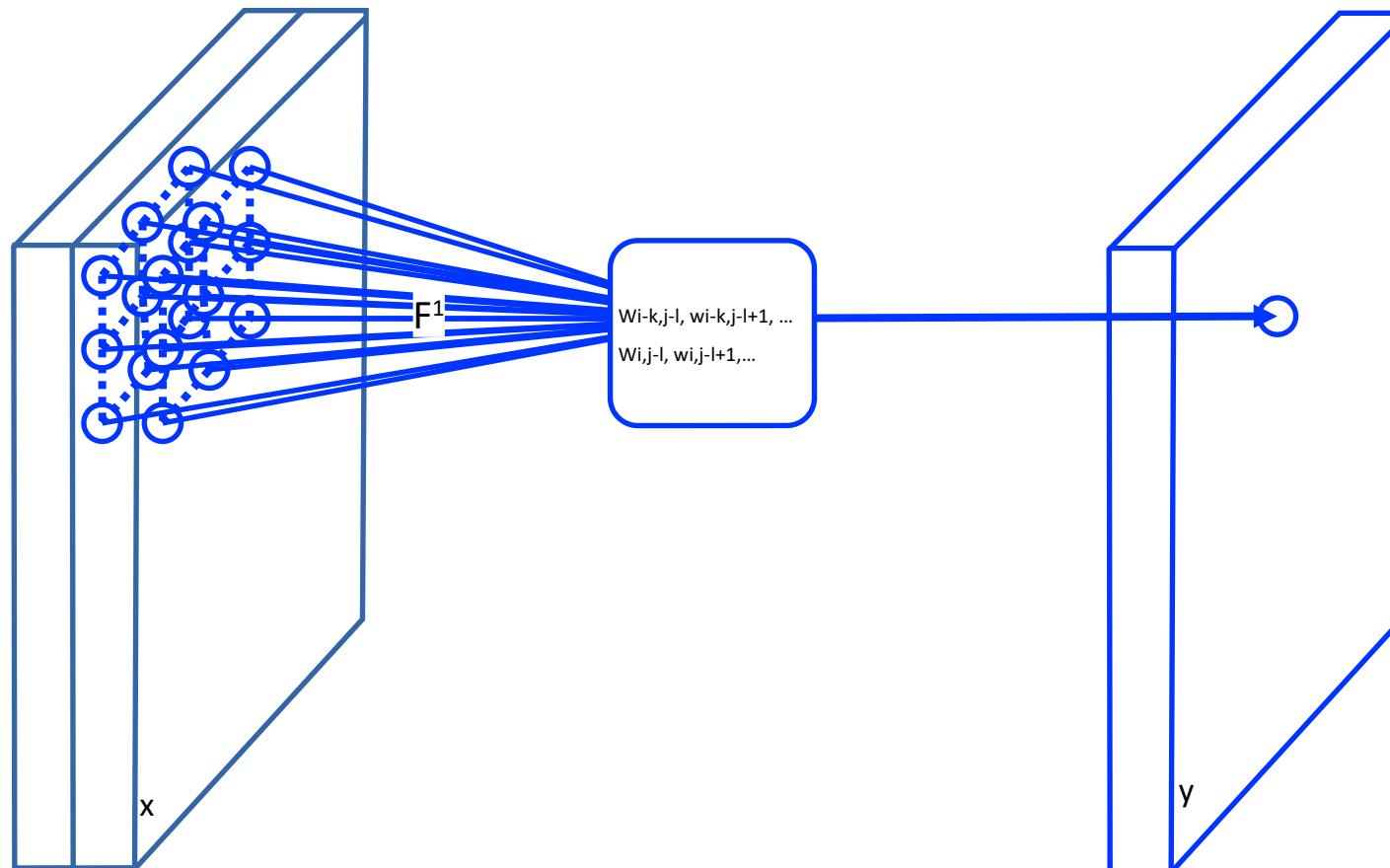
Why is it convolutional?



Let's consider a fully connected layer

Why is it convolutional?

input features a mask output features



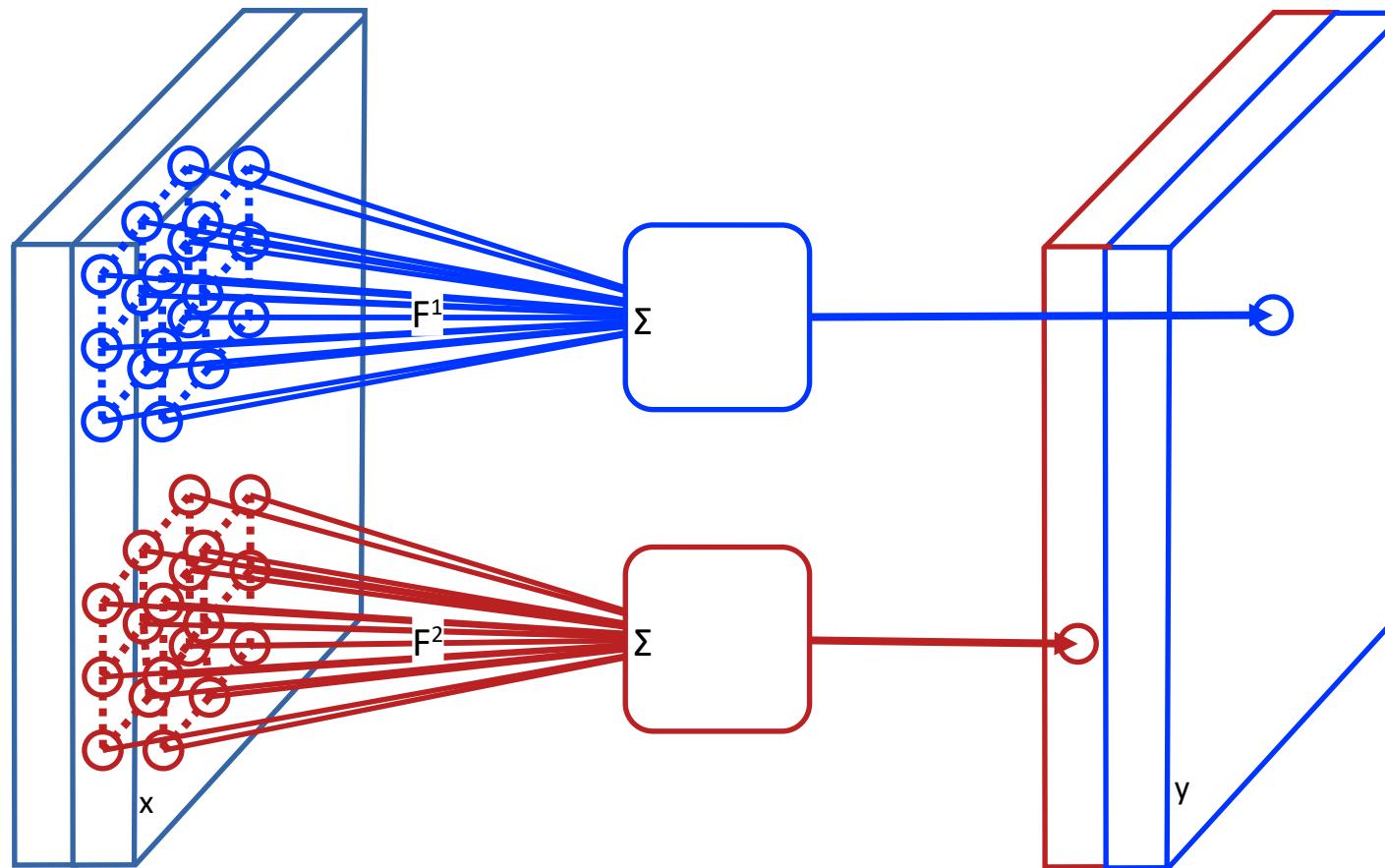
Convolution

Why is it convolutional?

input features

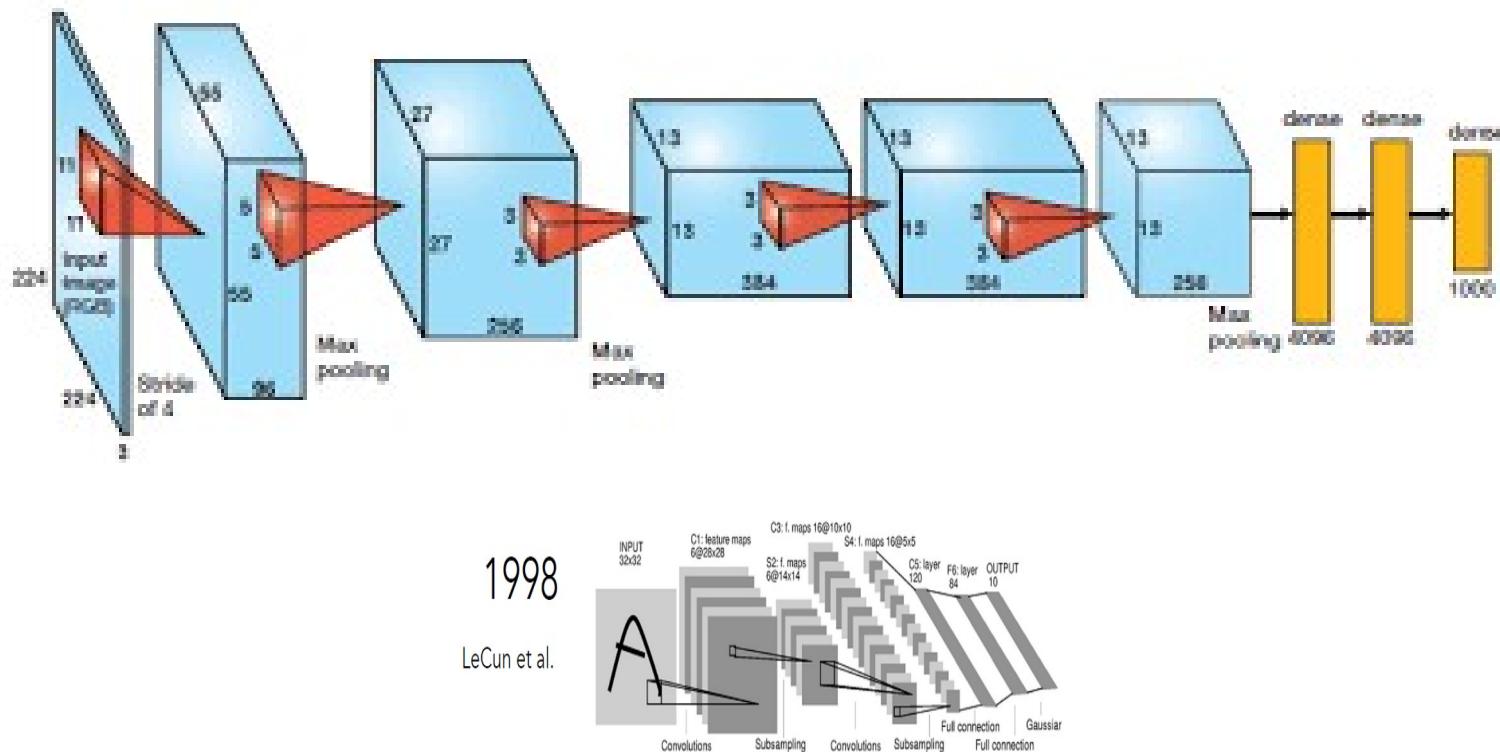
a bank of 2 filters

2-dimensional
output features



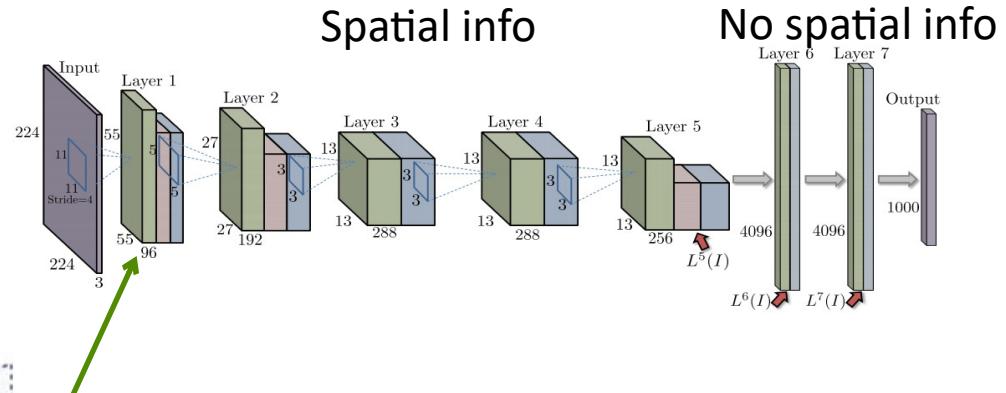
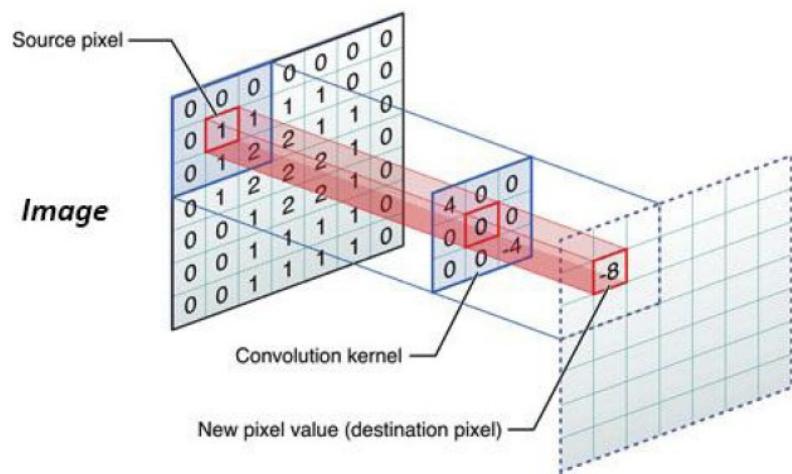
Convolution

Why is it convolutional?



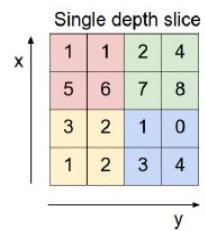
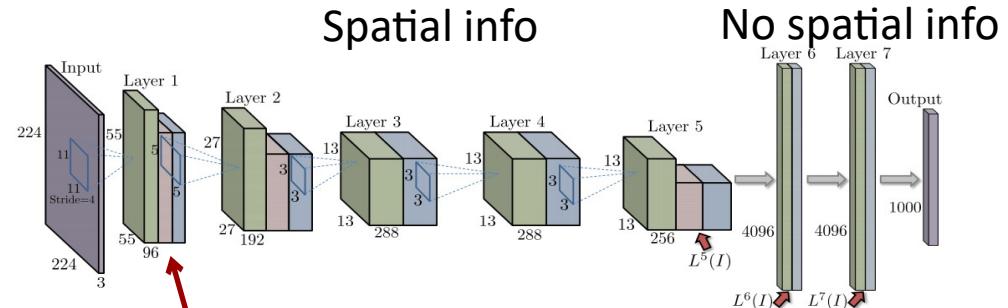
LeCun, Chief AI Scientist for Facebook AI Research (FAIR), and a Silver Professor at New York University

Convolutional layer



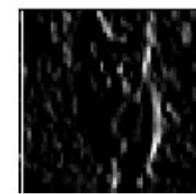
Convolutional layer

Max-pooling layer



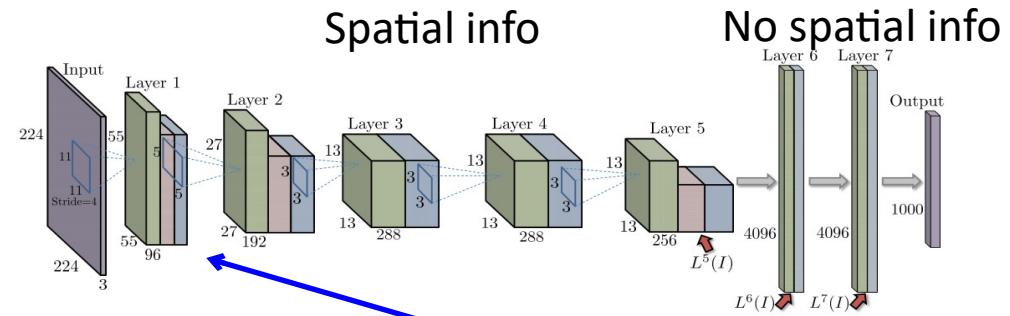
max pool with 2x2 filters and stride 2

6	8
3	4



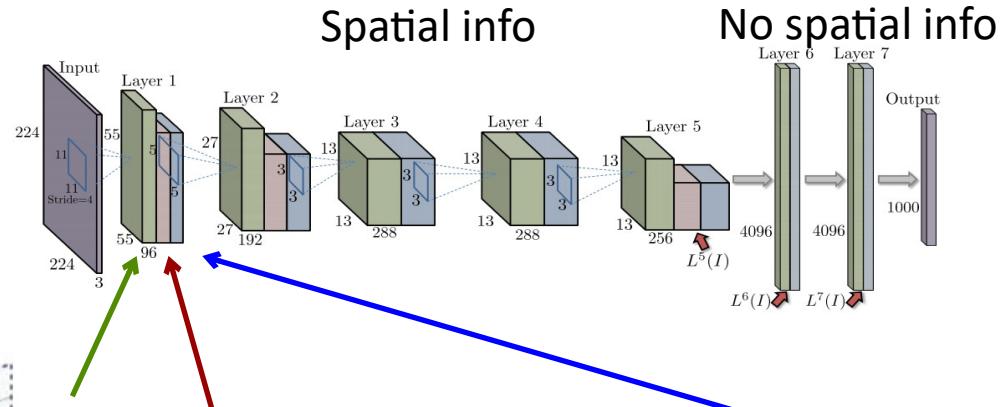
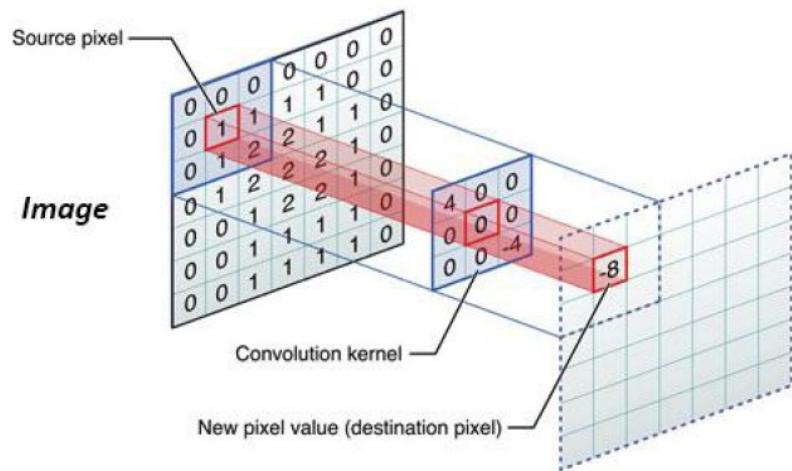
Max-pool layer

ReLU layer



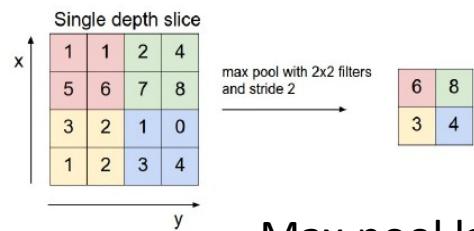
ReLU $\max(0, x)$

All layers



ReLU $\max(0, x)$

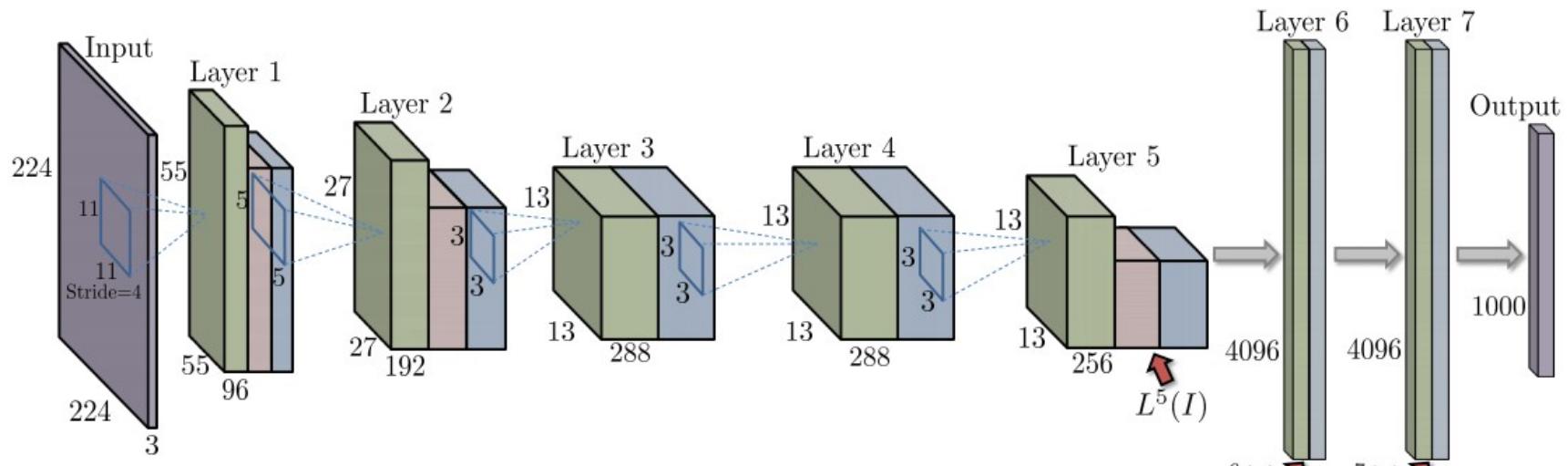
Convolutional layer



Max-pool layer



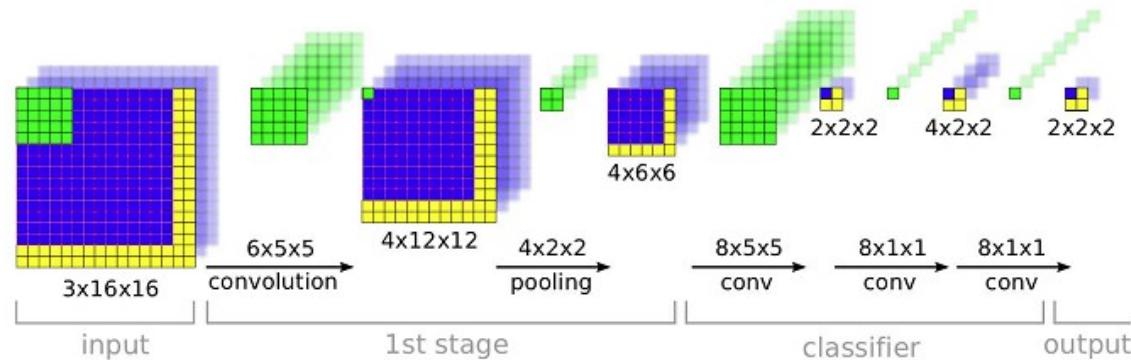
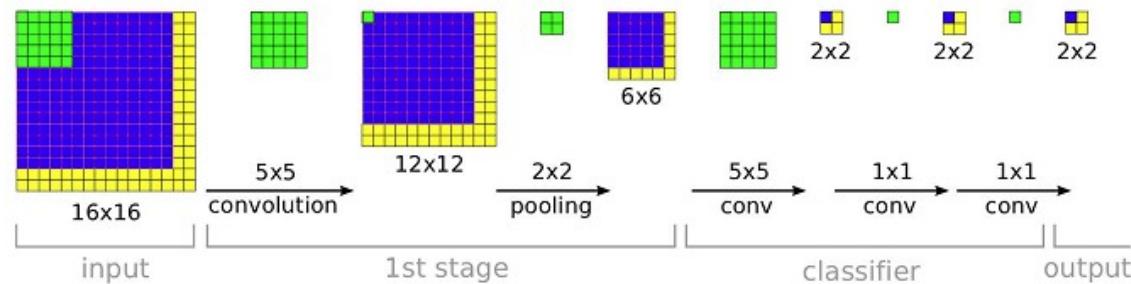
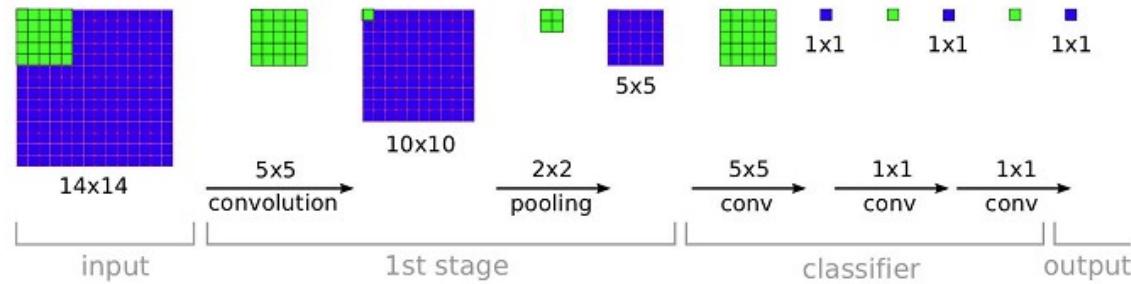
Training a CNN



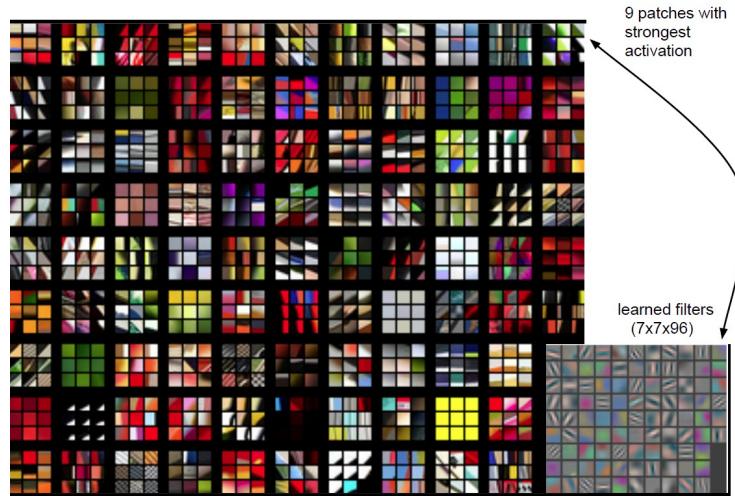
The process of training a CNN consists of training all hyperparameters: convolutional matrices and weights of the fully connected layers.

- **Several millions of parameters!!!**

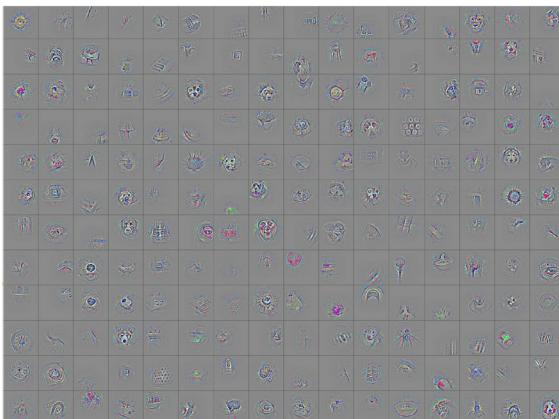
How does the CNN work?



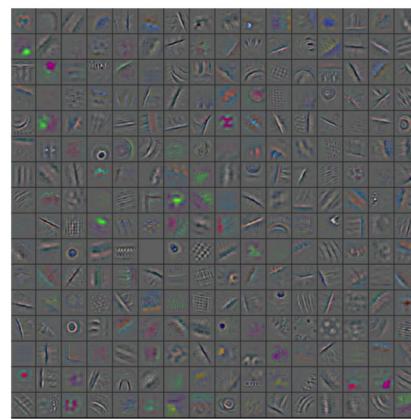
Learned convolutional filters



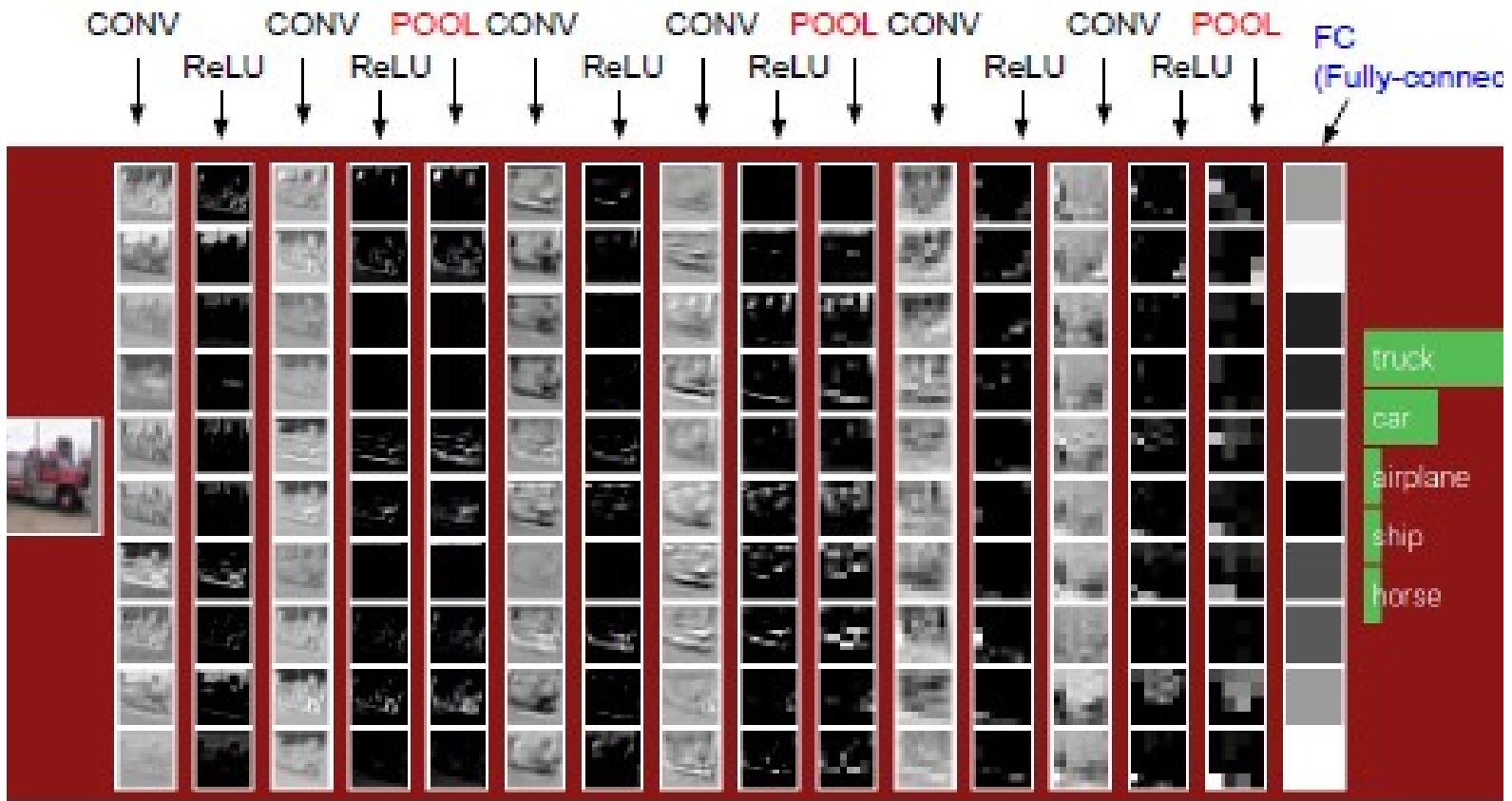
Strongest activations: Stage 5



Strongest activations: Stage 2



Example architecture



The trick is to train the weights such that when the network sees a picture of a truck, the last layer will say “truck”.

1001 benefits of CNN



Transfer learning: Fine tuning for object recognition

Replace and retrain the classifier on top of the ConvNet

Fine-tune the weights of the pre-trained network by continuing the backpropagation

Feature extraction by CNN

Object detection

Object segmentation

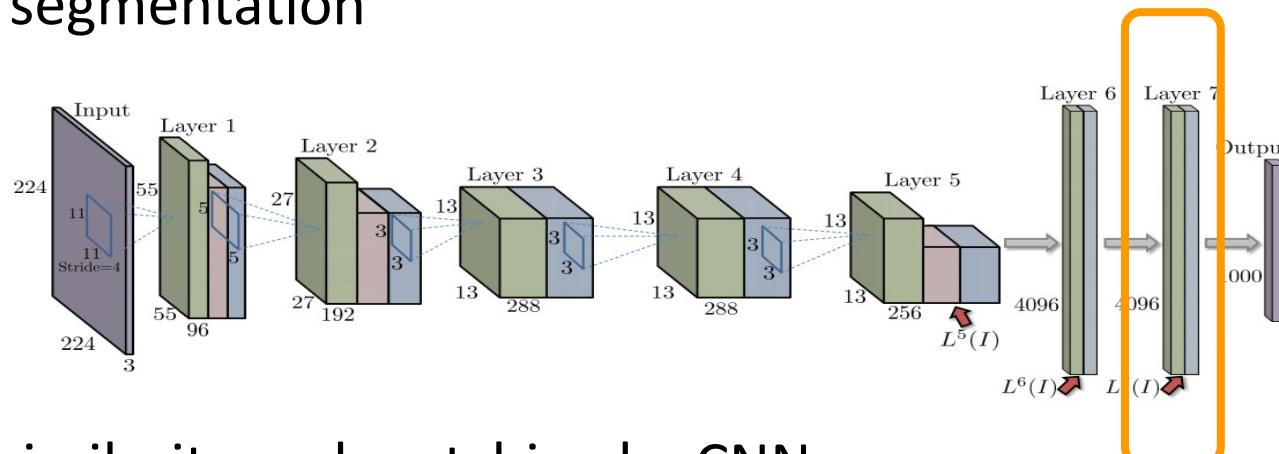


Image similarity and matching by CNN

IMAGENET Large Scale Visual Recognition Challenge

Year 2010

NEC-UIUC



Dense descriptor grid:
HOG, LBP

Coding: local coordinate,
super-vector

Pooling, SPM

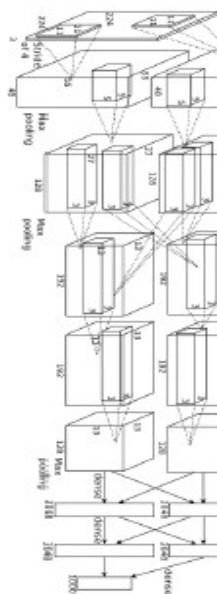
Linear SVM

[Lin CVPR 2011]

Lion image by Swissfrog
is
licensed under CC BY 3.0

Year 2012

SuperVision



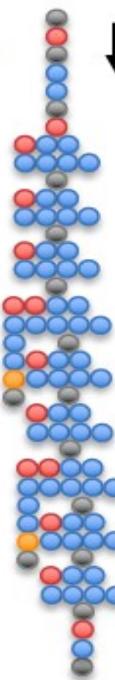
[Krizhevsky NIPS 2012]

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012.
Reproduced with permission.

Year 2014

GoogLeNet

- Pooling
- Convolution
- Softmax
- Other



[Szegedy arxiv 2014]

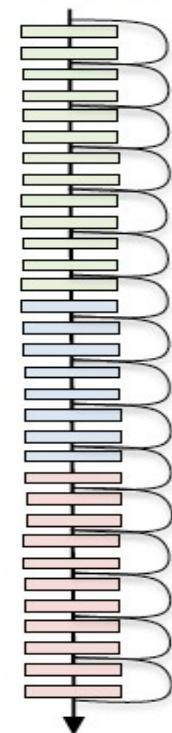
VGG



[Simonyan arxiv 2014]

Year 2015

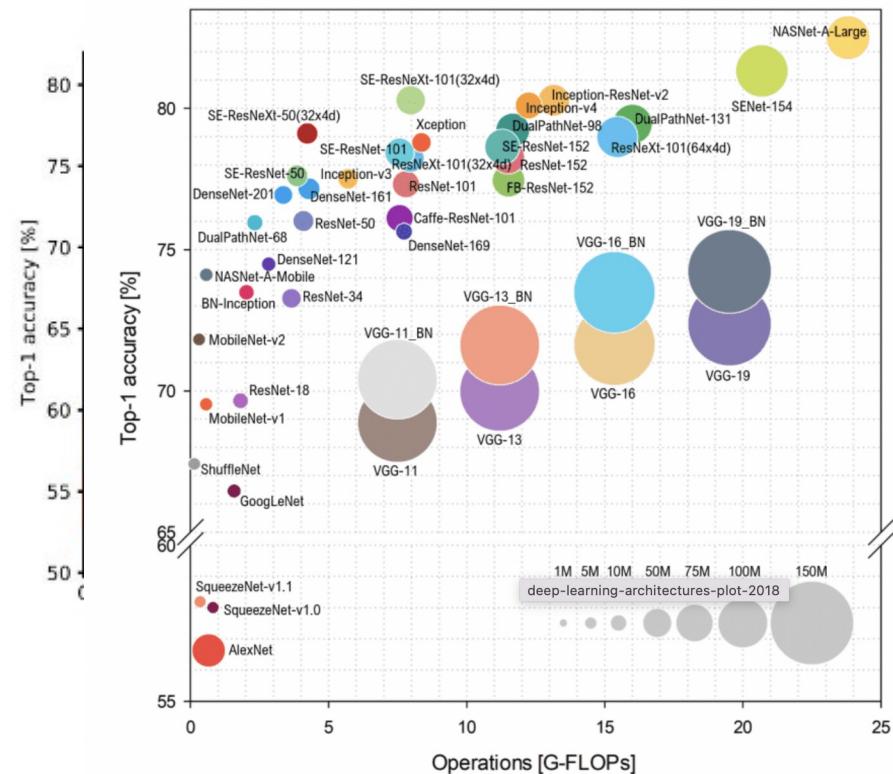
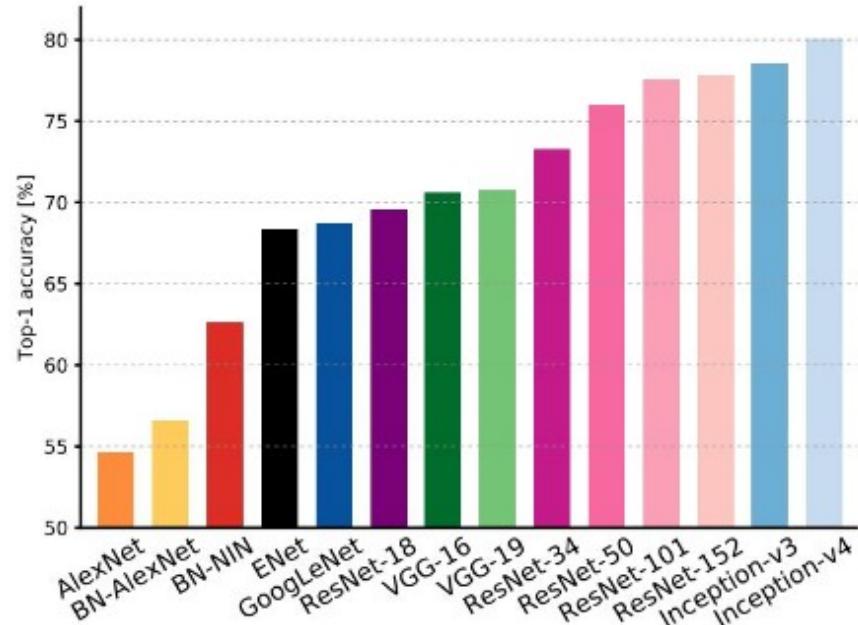
MSRA



[He ICCV 2015]

))))

Analysis of CNNs



- Millions of parameters!!!

The process of training a CNN consists of training all hyperparameters: convolutional matrices and weights of the fully connected layers.

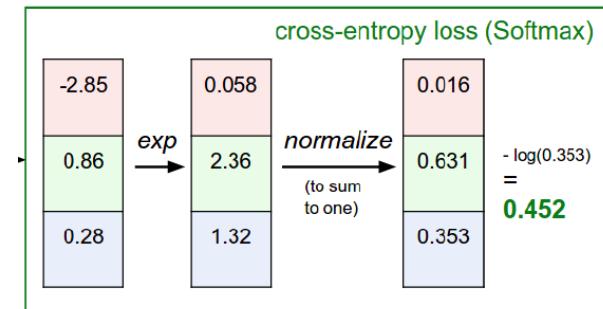
- ↗ AI, Machine learning & Deep learning
- ↗ What is a Convolutional Neural Network?
 - ↗ Layers
 - ↗ Loss function and CNN Optimization
- ↗ Applications

Loss function and optimisation

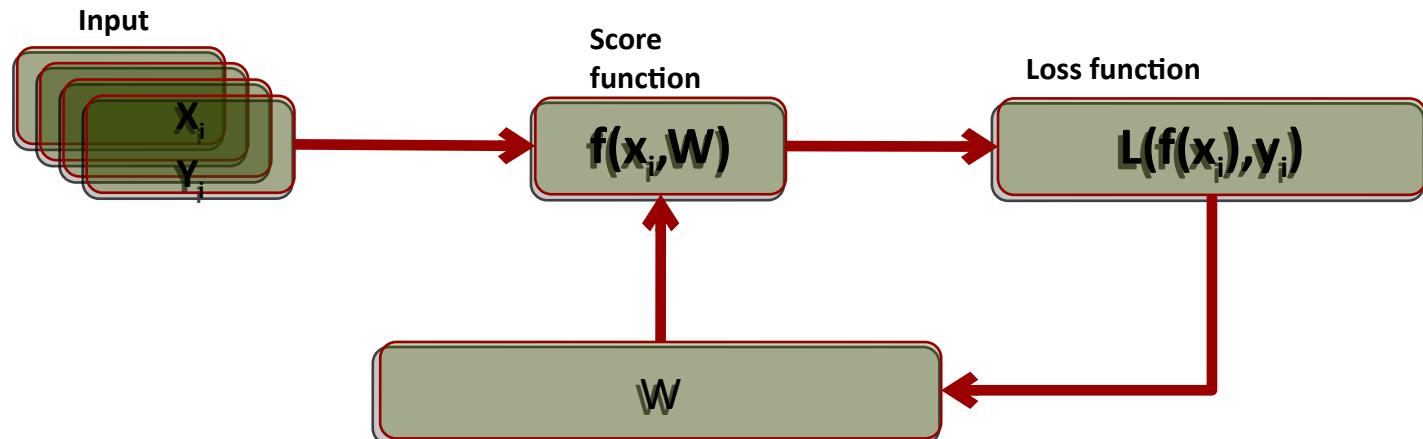
↗ **Question:** if you were to assign a single number to how unhappy you are with these scores, what would you do?

$$L_i = -\log \left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}} \right)$$

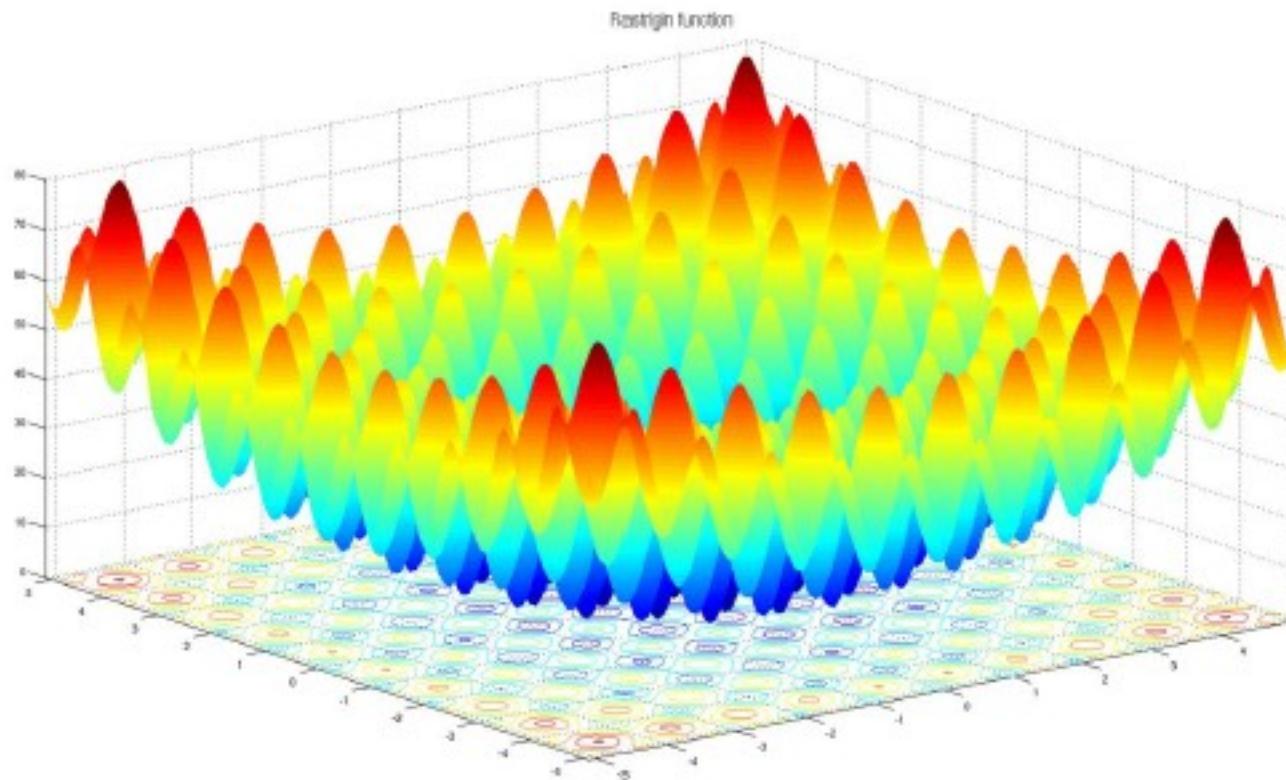
softmax function



Question : Given the score and the loss function, how to find the parameters W?



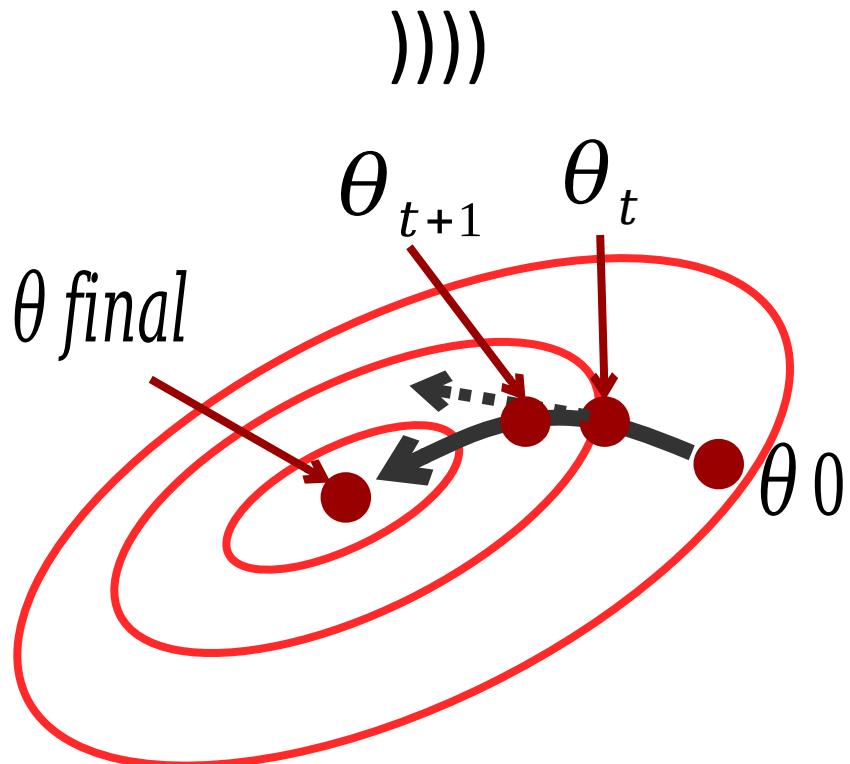
Optimization



The process of training a CNN consists of training all hyperparameters: convolutional matrices and weights of the fully connected layers.

- Millions of parameters!!!

Gradient descent



- ↗ Initialize randomly
 - ↗ For t in $0, \dots, T_{\text{maxiter}}$
- Gradient of the objective
- Learning rate (step size)

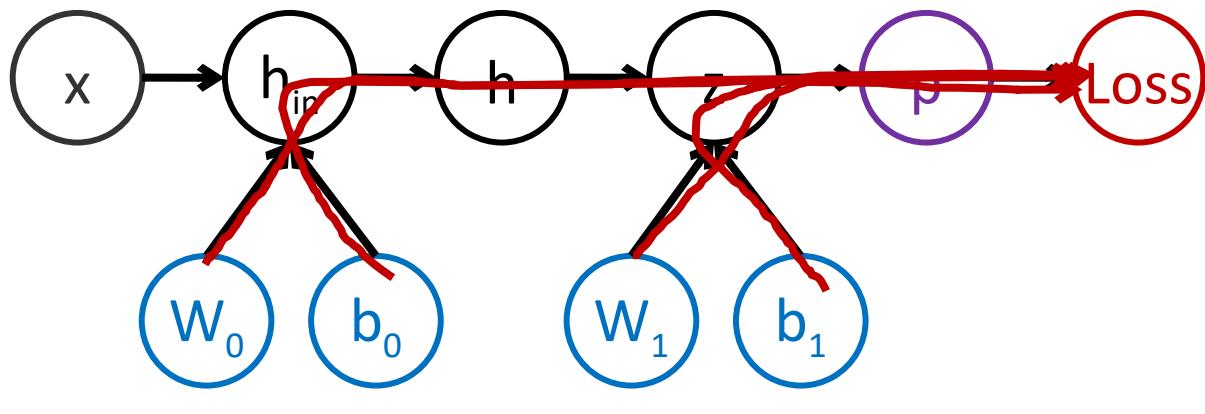
- Computation of $J(\theta)$ requires a full sweep over the training data
- Per-iteration comp. cost = $O(n)$

Chain rule

- Identify how each variable influence the loss

$$\frac{\partial \text{Loss}}{\partial W_1} = \frac{\partial \text{Loss}}{\partial p} \cdot \dots \cdot \frac{\partial z}{\partial W_1}$$

$$\frac{\partial \text{Loss}}{\partial b_1} = \frac{\partial \text{Loss}}{\partial p} \cdot \dots \cdot \frac{\partial z}{\partial b_1}$$

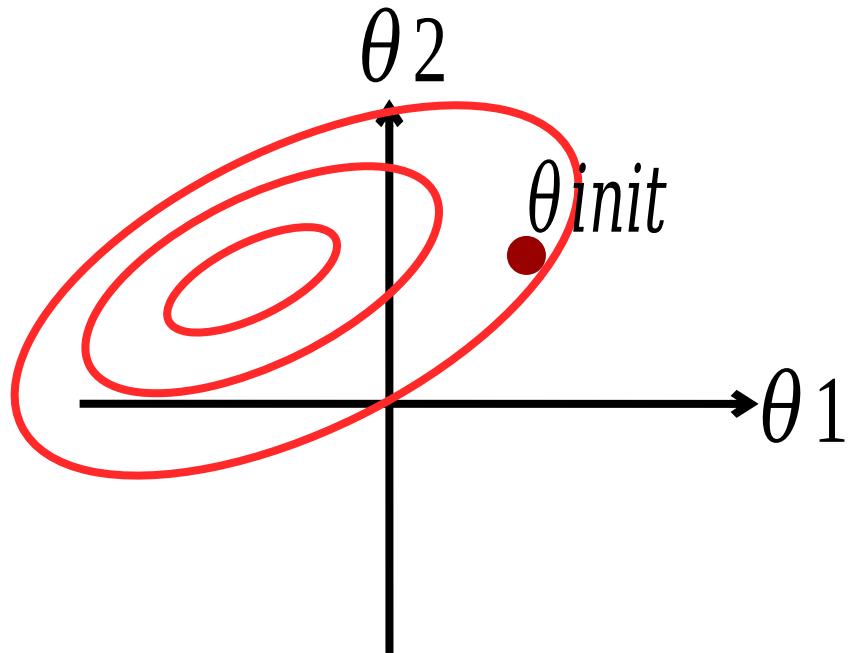


$$\frac{\partial \text{Loss}}{\partial W_0} = \frac{\partial \text{Loss}}{\partial p} \cdot \dots \cdot \frac{\partial h_{in}}{\partial W_0}$$

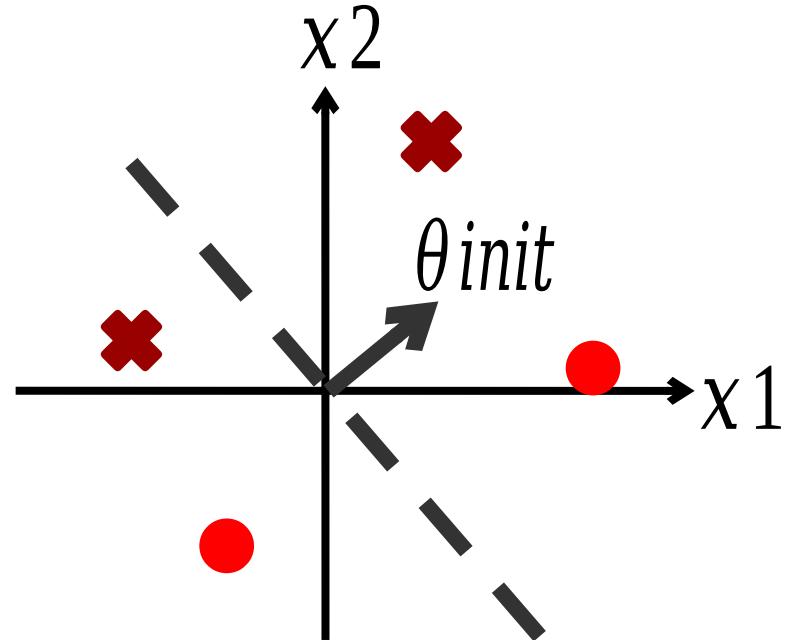
$$\frac{\partial \text{Loss}}{\partial b_0} = \frac{\partial \text{Loss}}{\partial p} \cdot \dots \cdot \frac{\partial h_{in}}{\partial b_0}$$

Landscape of training objective

Parameter space

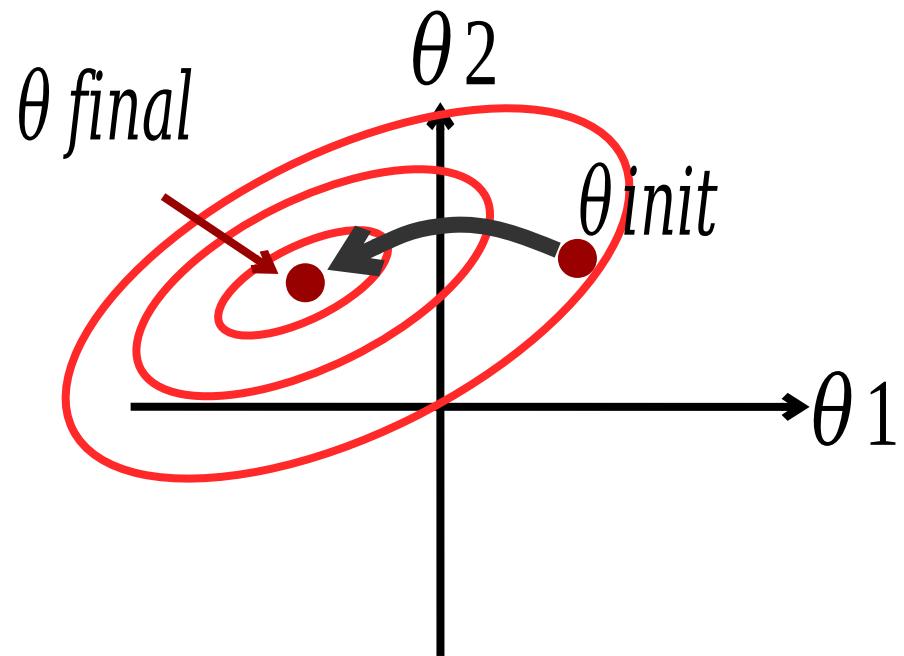


Example space

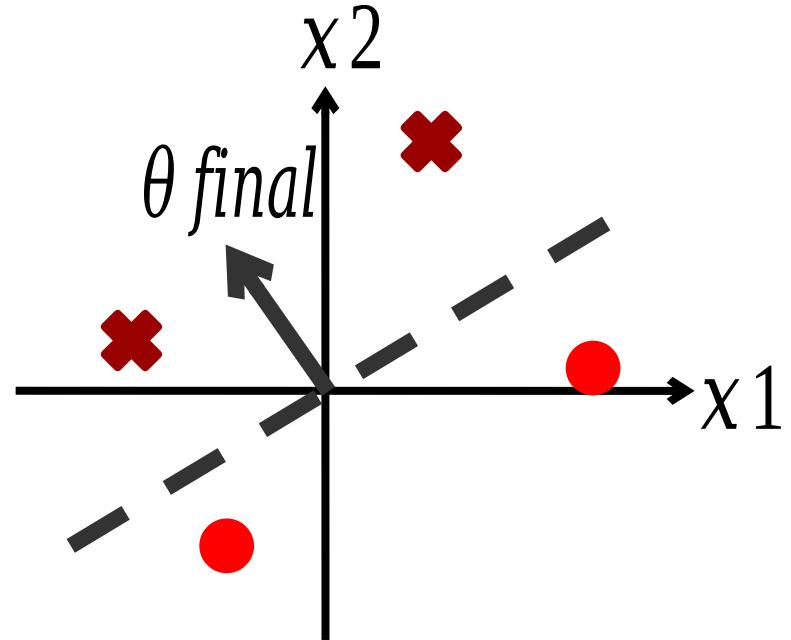


Landscape of training objective

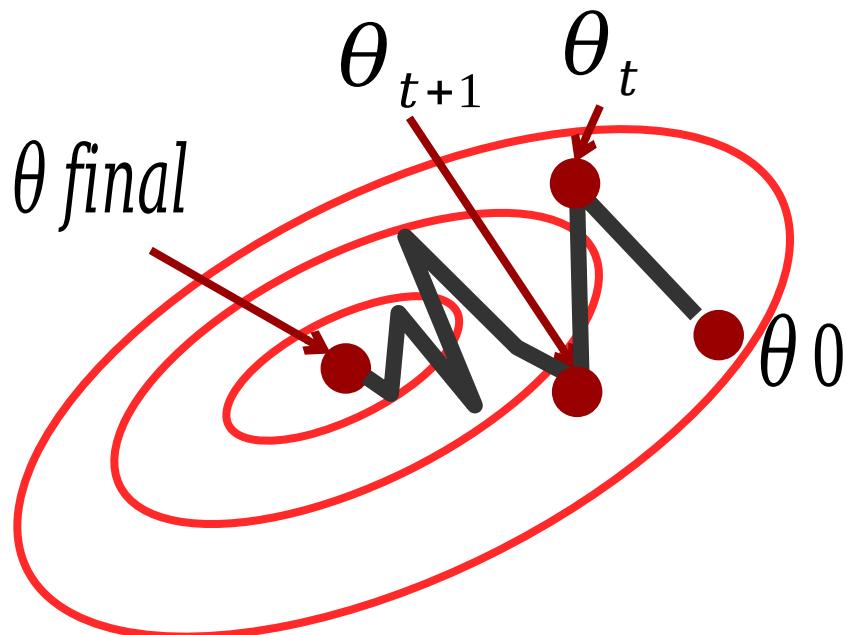
Parameter space



Example space



Stochastic gradient descent (SGD)



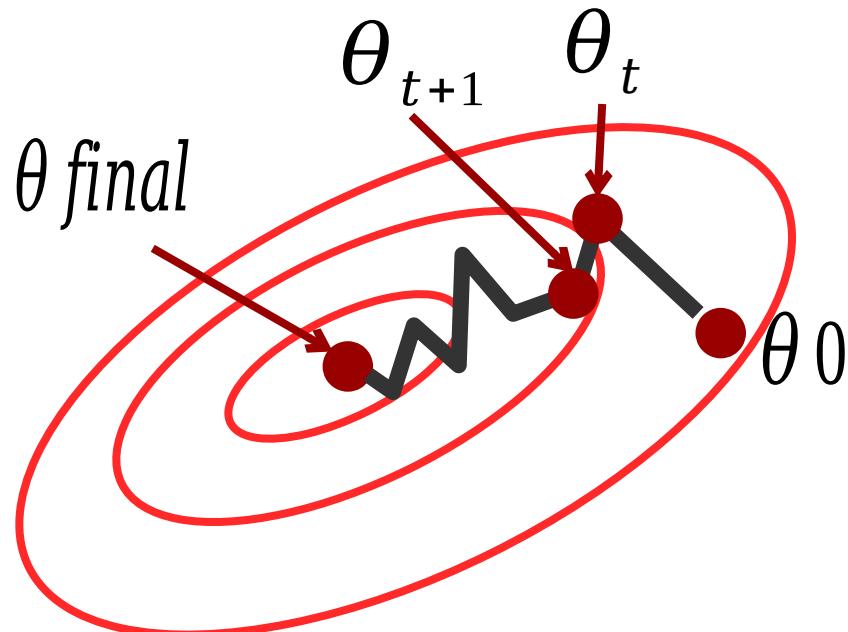
- ↗ Initialize randomly
- ↗ For t in $0, \dots, T_{\text{maxiter}}$

Stochastic gradient

where index i is chosen randomly

- computation of θ_i requires only one training example
- Per-iteration comp. cost = $O(1)$

Mini-batch stochastic gradient descent



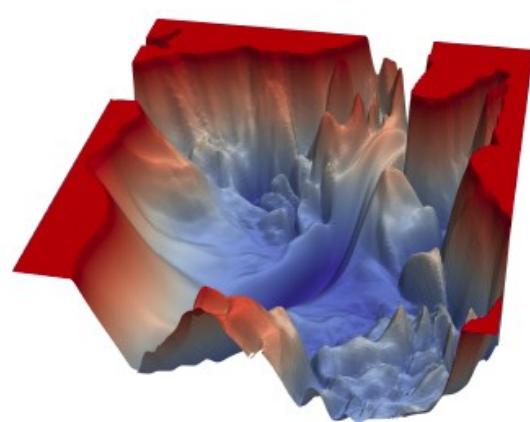
- ↗ Initialize randomly
- ↗ For t in $0, \dots, T_{\text{maxiter}}$

minibatch gradient

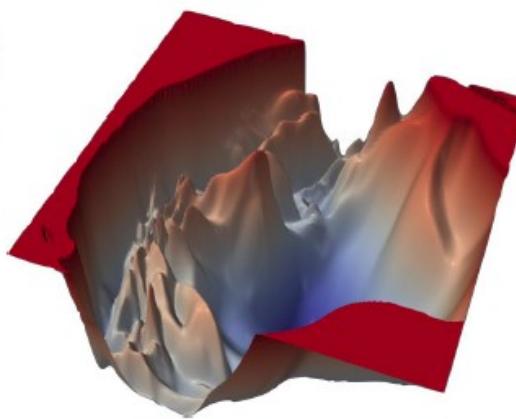
where minibatch B is chosen randomly

- is average gradient over random subset of data of size B
- Per-iteration comp. cost = $O(B)$

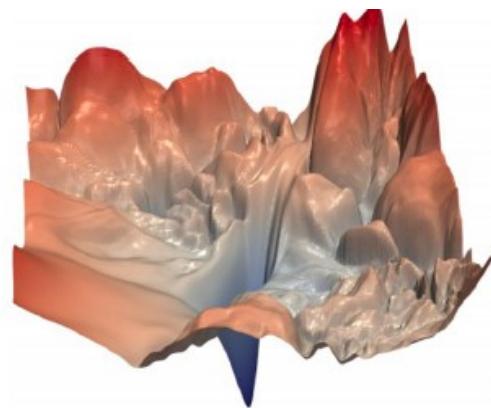
Stochastic Gradient Descent



VGG-56



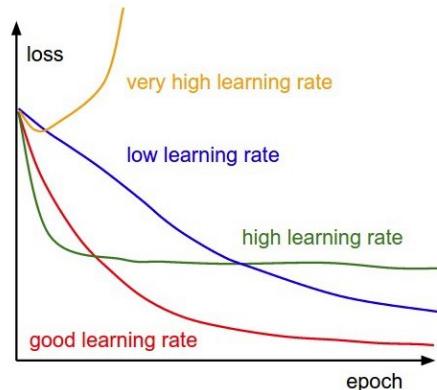
VGG-110



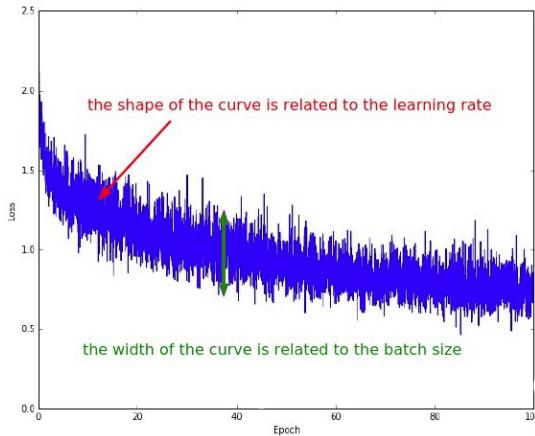
ResNet-56

Hao Li et al., NIPS, 2017

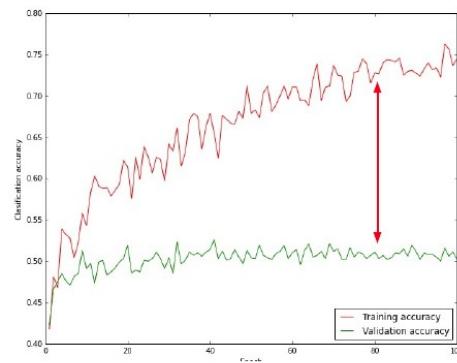
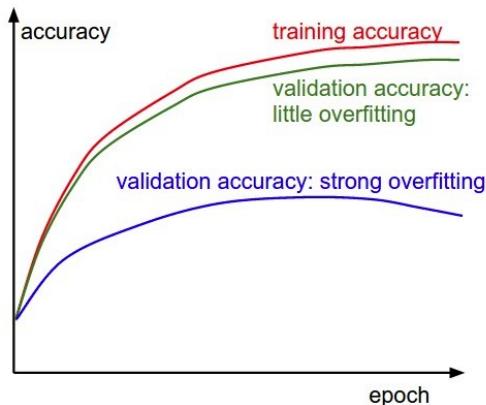
Monitoring loss and accuracy



Adapted from Fei Fei slides



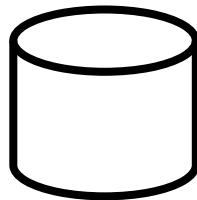
Looks linear?
Learning rate too low!
Decreases too slowly?
Learning rate too high.
Looks too noisy?
Increases the batch size.



Big gap?
- you're overfitting,
increase
regularization!

Overfitting – what is signal vs noise?

- Imagine:



Training
data



cat



dog

Validation data



- Powerful models are more likely to overfit
- We need validation data: leave out some portion of the training data to validate the generalizability of the model

Overfitting



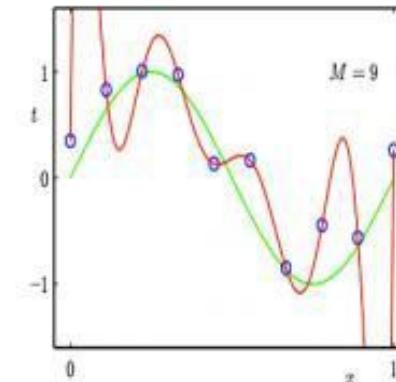
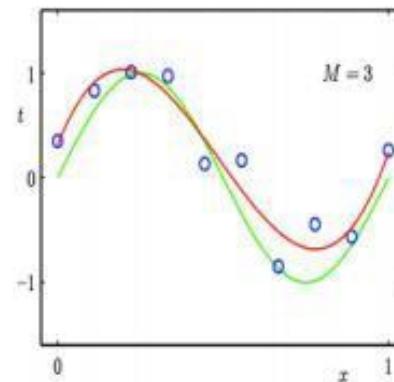
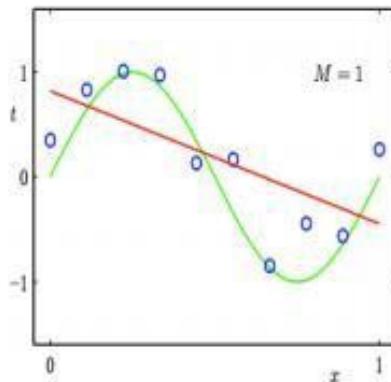
With four parameters I can fit an elephant, and with five I can make him wiggle his trunk.

— *John von Neumann* —

AZ QUOTES

Under- and Over-fitting

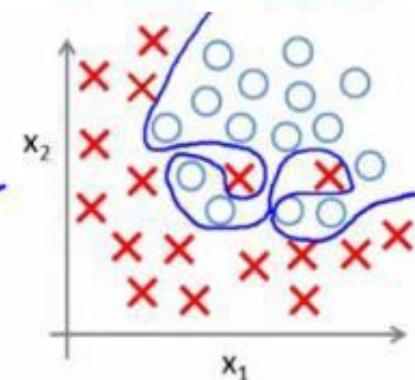
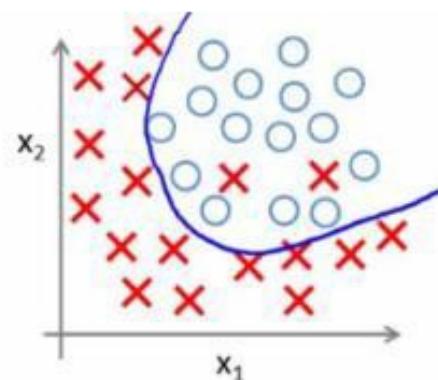
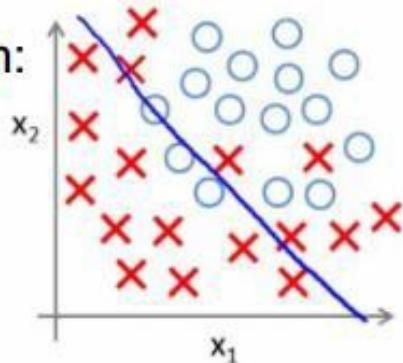
Regression:



predictor too inflexible:
cannot capture pattern

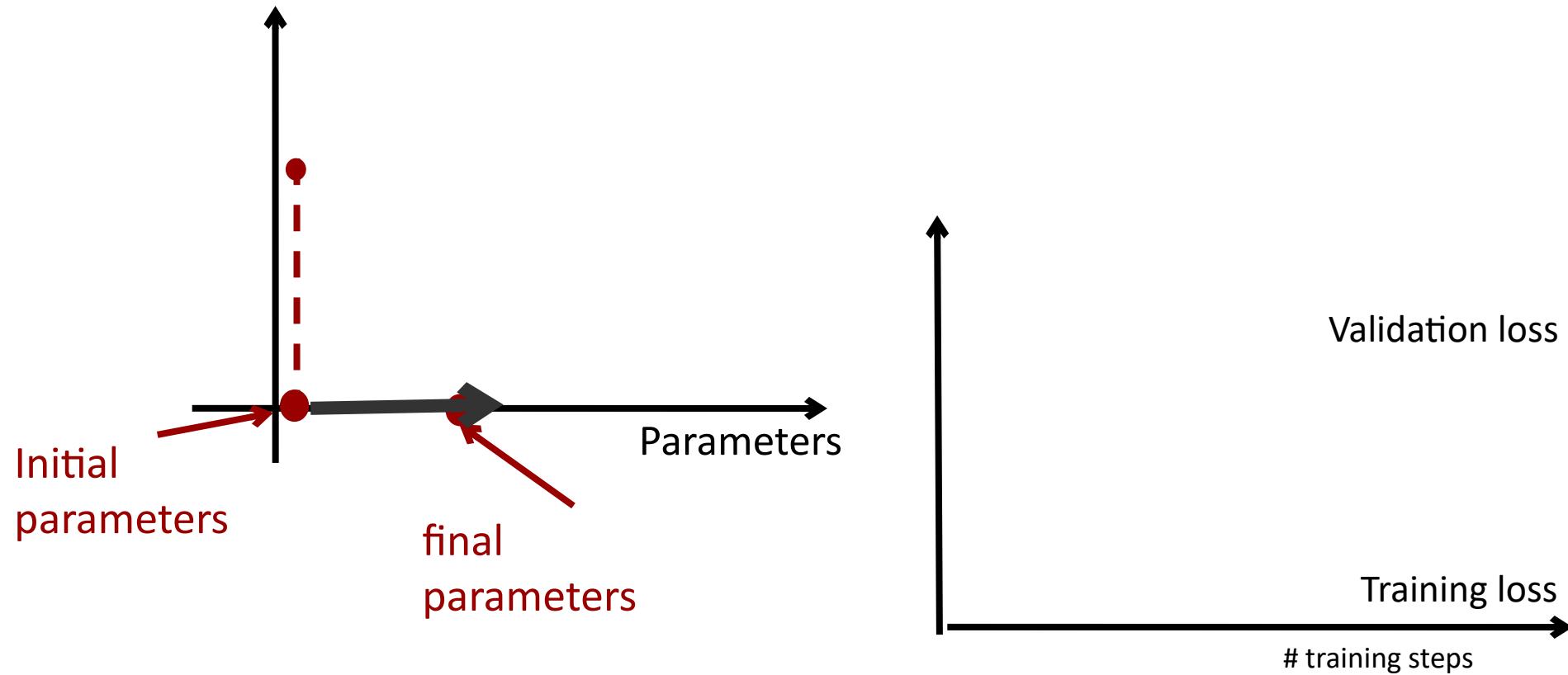
predictor too flexible:
fits noise in the data

Classification:



Landscape of training objective

Objective function:



Techniques to reduce overfitting

- ↗ Reduce the number of parameters
 - ↗ Parameter sharing (convnets, recurrent neural nets)
- ↗ Early stopping
 - ↗ Indirectly controls the magnitude of the parameters
- ↗ Weight decay (aka L2 regularization)
 - ↗ Penalizes the magnitude of the parameters
- ↗ There are several other alternatives
 - ↗ Dropout, batch normalization

Against overfitting: data augmentation

- Resizing images keeping the aspect ratio.
- Enhancing images using random distortions (color, contrast, brightness and sharpness).
- Applying random crops using the same dimension for the width and height.
- Applying random horizontal flips.



- ↗ AI, Machine learning & Deep learning
- ↗ What is a Convolutional Neural Network?
 - ↗ Layers
 - ↗ Optimization
- ↗ Applications

Everybody dances now

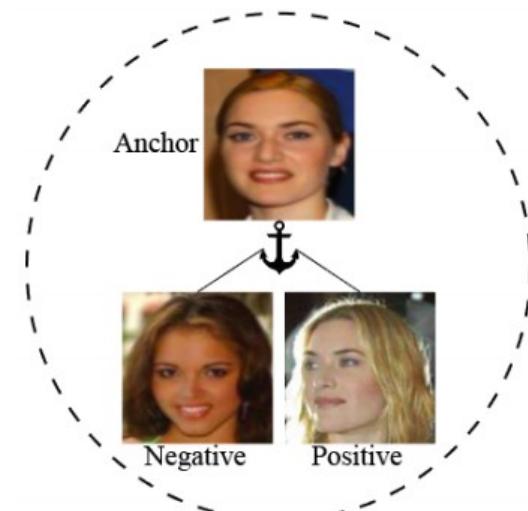
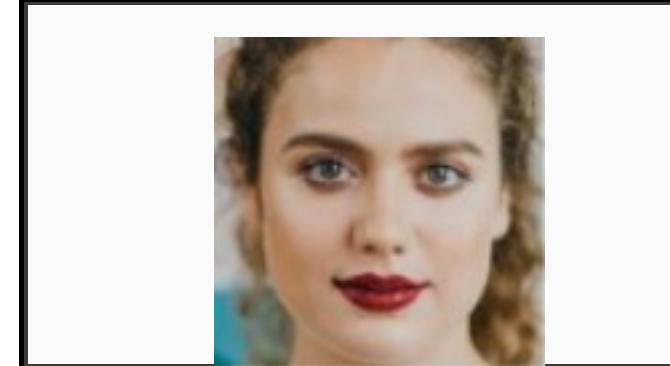


[More links](#)

Convolutional NN

CNN beat humans in many tasks as:

- ↗ object recognition,
- ↗ lip reading,
- ↗ high-end surveillance,
- ↗ facial recognition,
- ↗ object-based searches,
- ↗ license plate readers,
- ↗ traffic violations detection,
- ↗ breast tomosynthesis diagnosis,
- ↗ etc., etc.



Computer Vision & Deep Learning ↗



Social media



Autodriving (Tesla)

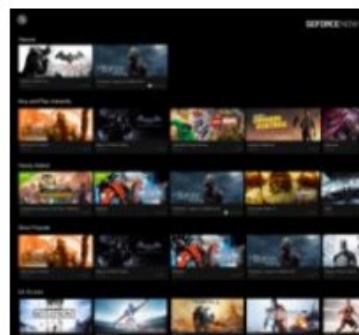
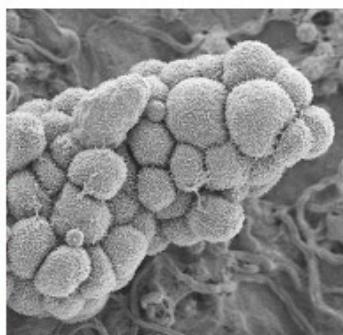


Security (Airports)



Shopping (Mango, Amazon)

Deep learning everywhere



INTERNET & CLOUD

Image Classification
Speech Recognition
Language Translation
Language Processing
Sentiment Analysis
Recommendation

MEDICINE & BIOLOGY

Cancer Cell Detection
Diabetic Grading
Drug Discovery

MEDIA & ENTERTAINMENT

Video Captioning
Video Search
Real Time Translation

SECURITY & DEFENSE

Face Detection
Video Surveillance
Satellite Imagery

AUTONOMOUS MACHINES

Pedestrian Detection
Lane Tracking
Recognize Traffic Sign

Deep learning - one of the 10 breakthrough technologies



10 BREAKTHROUGH TECHNOLOGIES 2013

[Introduction](#)[The 10 Technologies](#)[Past Years](#)

Deep Learning

With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

Temporary Social Media

Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.

Prenatal DNA Sequencing

Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?

Additive Manufacturing

Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.

Baxter: The Blue-Collar Robot

Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.

Memory Implants

A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next: testing a prosthetic implant for people suffering from long-term memory loss.

Smart Watches

The designers of the Pebble watch realized that a mobile phone is more useful if you don't have to take it out of your pocket.

Ultra-Efficient Solar Power

Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it possible.

Big Data from Cheap Phones

Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave – and even help us understand the spread of diseases.

Supergrids

A new high-power circuit breaker could finally make highly efficient DC power grids practical.

Deep learning everywhere

[“Preparing for the Future of Artificial Intelligence.” ★₁](#)



This 58-page report outlines a number of important topics related to artificial intelligence.

AI & ML: from R+D lab to hospital



TOPICS ▾ MAIN MENU ▾

APAC EMEA Global Edition

FDA permits marketing of AI software that autonomously detects diabetic retinopathy

By Dave Muoio | April 12, 2018 | 11:10 am

The FDA has granted diagnostics company IDx's De Novo request to market its AI-based software system for the autonomous detection of diabetic retinopathy in adults who have diabetes, called IDx-DR.

This decision represents the first AI-based diagnostic system authorized by the FDA for commercialization in the US that can provide a screening decision without the need for clinician interpretation, according to the agency. The news comes just months after the [FDA's De Novo approval of Viz.ai](#), another AI software tool that analyzes stroke indicators and highlights CT images that could require additional clinical attention.

"Early detection of retinopathy is an important part of managing care for the millions of people with diabetes, yet many patients with diabetes are not adequately screened for diabetic retinopathy since about 50 percent of them do not see their eye doctor on a yearly basis," Dr. Malvina Eydelman, director of the Division of Ophthalmic and Ear, Nose, and Throat Devices at the FDA's Center for Devices and Radiological Health, said in a statement. "Today's decision permits the marketing of a novel artificial



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HIMSS TV

(China Daily) 14:15, July 02, 2018

Follow on Apple News



Radiologist Zhang Junhai from Shanghai Huashan Hospital reads a medical image display during a competition with BioMind, an artificial intelligence system, in Beijing

MARKETS BUSINESS INVESTING TECH POLITICS CNBC TV WATCHLIST PRO ▾

Google's DeepMind A.I. beats doctors in breast cancer screening trial

PUBLISHED THU, JAN 2 2020 8:13 AM EST | UPDATED THU, JAN 2 2020 8:13 AM EST

David Reid
#DAVREID73

SHARE f t in em

KEY POINTS

- Anonymous scans of 29,000 women were used in the trial.
- The biggest improvements over human scanning was found in the U.S. portion of the study.
- Google-owned DeepMind has already used AI to read eye scans and spot neck cancer.



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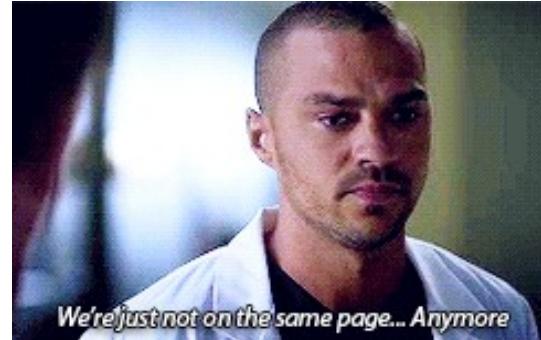
TRENDING NOW



14:42

Concerns about DL

- Different development approach.



- No clear view on how insight is generated.



- A system is only as good as the data it learns from.

Conclusions



Deep learning – a technology that came to stay

A new technological trend that is affecting directly our environment

4 kind of layers (convolutional, RELU, maxpooling and fully connected) form any neural network.

The loss function controls the performance, small loss function means high performing score function

Overfitting is one of the main problems due to the millions of parameters.

Stochastic gradient descent and similar approaches are used to optimize the loss function.

Different CNN models can be found. No optimal one exists.

What are the next challenges?

1. Uncertainty modeling

- ↗ Why are CNNs so efficient? Optimal?
- ↗ Inference: In many serious applications, we need error bar

2. Interpretability and explainability: causality models

3. Unsupervised and Few-shot learning

4. Dataset models

1. Data are not free,
2. GDPR doesn't help always

5. GPUs-hungry research

1. Energy-overconsuming

6. Technology is still very young

7. Talent deficit

