


FACULTY OF MATHEMATICS,
PHYSICS AND INFORMATICS
Comenius University
Bratislava

Neural Networks for Computer Vision

Lecture 1: Introduction

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26.9.2022

Acknowledgment

The majority of slides are directly adopted from slides for CS231n[1] course at Stanford University!

[1] *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

Contents

Course Information

The course information and resources can be found on Github:
`https://github.com/kocurvik/edu`.

Grading

You can get 100 points total - standard A-Fx grading.

- Labs - max 60 pts towards final grade - min 30 pts to pass the course
  - Labs homework - 3 assignments - 30 pts total
  - Final project - 40 pts total based on difficulty
- Exam - 40 pts - min 20 pts to pass the course
  - Written questions - 10 pts
  - 3 topics - 10 pts each - oral exam

There will be multiple dates for final project presentations. At least one will be at the end of the exam period. You will be allowed to do the exam even before you get the required 30 pts from the lab. In such case the final grade will be assigned after your project presentation.

Final Project

The project points will be awarded based on difficulty and the correctness of the project implemenatation. Below are some approximate ranges:

- Demo of some existing work on custom data (less than 10 pts)
- Evaluating existing networks on some new data without training (10-20 pts) or with training (10-30 pts)
- Implementing an existing neural network within a larger system such as a mobile app or robotic system (5-30 pts)
- Performing experiments with training of multiple variants of neural network pipelines with extensive evaluation (up to 40 pts).

Project proposal: To be eligible for the oral exam you need to submit a short project proposal in which you will describe your project and have it approved by me. You must send me the project proposal **by the end of the semester**.

Syllabus I

- Introduction
- Learning, training and optimization
  - training, testing and validation sets
  - gradient optimization, loss functions
- Intro to neural nets
  - fully-connected neural nets
  - backpropagation
  - SGD
- Convolutional neural nets
  - convolution, pooling
  - activation functions

Syllabus II

- CNN Training I
  - vanishing/exploding gradients
  - batchnorm, dropout, normalization
  - hyperparameter tuning
- CNN Training II
  - Ada, Adam, Adagrad
  - augmentation
  - transfer learning
- Architectures
  - AlexNet, VGG, GoogLeNet
  - ResNets, DenseNets
  - MobileNets, EfficientNets
  - Visual transformers

Syllabus III

- Recurrent neural nets and NLP
  - LSTM, GRU
  - transformers
  - CLIP
- Object detection and instance segmentation
  - RetinaNet, YOLO, CenterNet, ATSS
  - Faster RCNN, Mask RCNN
- Generative models
  - VAE, GAN
  - Stable Diffusion

Syllabus IV

- Visualizing DL nets
  - filters, activation patches, saliency maps
  - DeepDream, adversarial attacks
  - textures, style transfer
- Ethics and science of deep learning
  - algorithmic bias
  - mass data collection
  - model robustness, ablation experiments

Computer Vision

CV is an interdisciplinary scientific field that deals with how computers can gain high-level understanding from digital images or videos.

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Understanding

Understanding in this context means the transformation of visual images into descriptions of the world that make sense to thought processes and can elicit appropriate action.

Two approaches

Engineering

From the perspective of engineering, it seeks to understand and automate tasks that the human visual system can do.

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Science

The scientific discipline of computer vision is concerned with the theory behind artificial systems that extract information from images.

CV is interdisciplinary

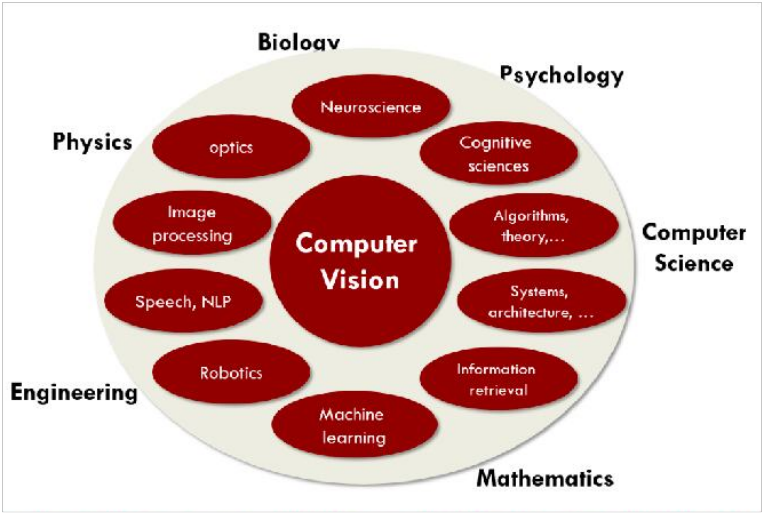


Image adopted from: *Stanford CS131 class notes*. `http://vision.stanford.edu/teaching/cs131_fall1718/files/cs131-class-notes.pdf`

Computer Vision and Computer Graphics

CV: Visual Information $\rightarrow$ Abstract Representation

CG: Abstract Representation $\rightarrow$ Visual Output

Visual data

- There is an abundance of visual data
- Variety of sensors
- 80 % of internet traffic is video
- YT - 5 hours of video get uploaded every second

Fundamental CV Task - Object Recognition

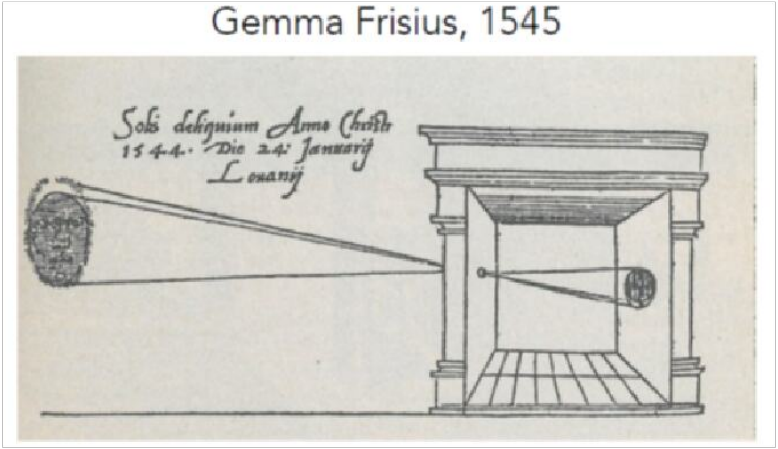
Fundamental CV Task - Object Recognition

$\rightarrow$ dog

Biological Visual Systems

- Over millions of years vision has evolved to be the greatest sensory system in most animals.
- 50 % of human neurons are related to visual processing.
- Our visual system helps us survive, work, move, use tools, communicate, entertain ourselves and much more...

History - Camera Obscura



Camera obscura - Ibn al-Haytham (11th century)

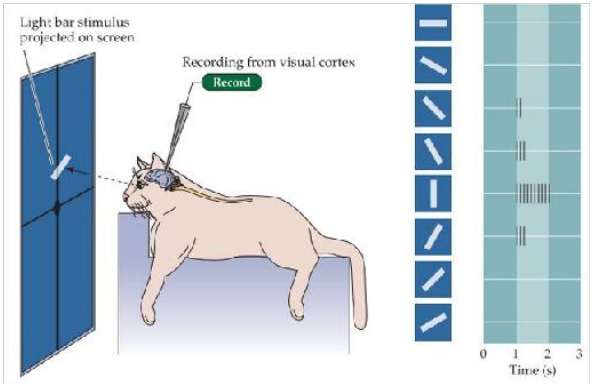
History - Image Capture

Joseph Nicéphore Niépce (1825)

History - Digital Imaging

- Metal-oxide-semiconductor (MOS)
  - Mohamed M. Atalla and Dawon Kahng at Bell Labs
  - 1959
- Charged-coupled device (CCD)
  - Willard S. Boyle and George E. Smith at Bell Labs
  - 1969
  - Nobel prize in 2009
- Complementary MOS (CMOS)
  - Eric Fossum's team at the NASA Jet Propulsion Lab
  - 1993

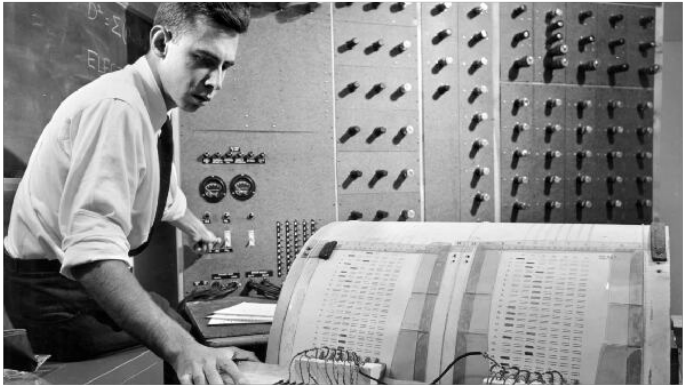
Early experiments



Hubel and Wiesel (1959)

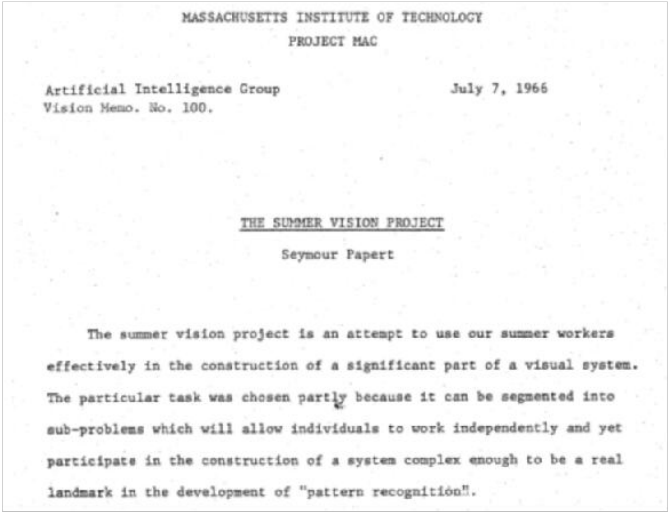
Image adopted from: Dale Purves. *Brains: how they seem to work*. Ft Press, 2010

Perceptron



Frank Rosenblatt - Perceptron (1960)

Computer Vision a Summer Project - 1966



MASSACHUSETTS INSTITUTE OF TECHNOLOGY
PROJECT MAC

Artificial Intelligence Group
Vision Memo. No. 100.

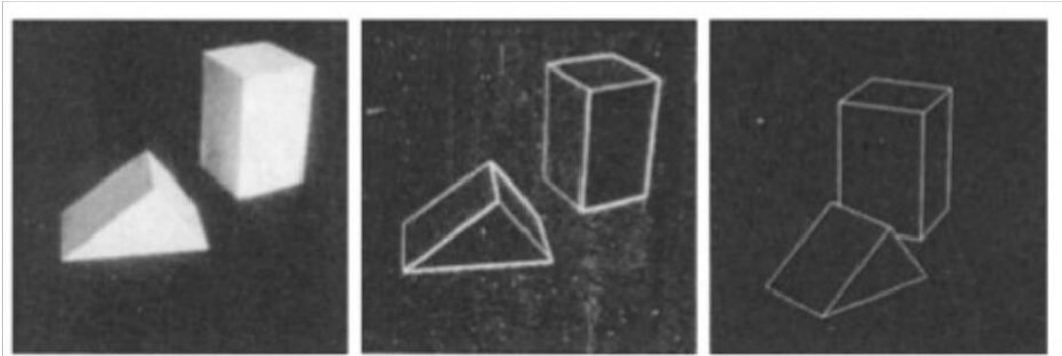
July 7, 1966

THE SUMMER VISION PROJECT

Seymour Papert

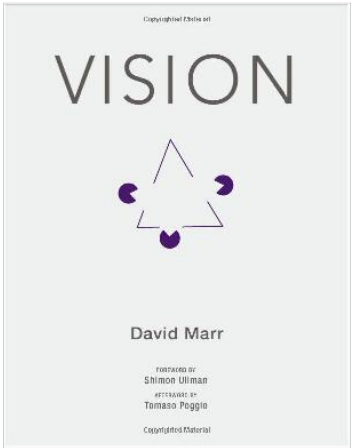
The summer vision project is an attempt to use our summer workers effectively in the construction of a significant part of a visual system. The particular task was chosen partly because it can be segmented into sub-problems which will allow individuals to work independently and yet participate in the construction of a system complex enough to be a real landmark in the development of "pattern recognition".

First CV PhD Thesis



Lawrence Roberts (1963)

Human Vision from Computational Perspective



David Marr (1970s)

Human Vision from Computational Perspective

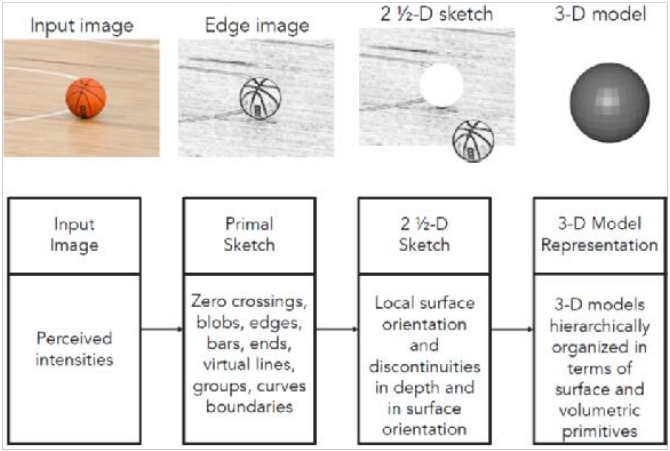


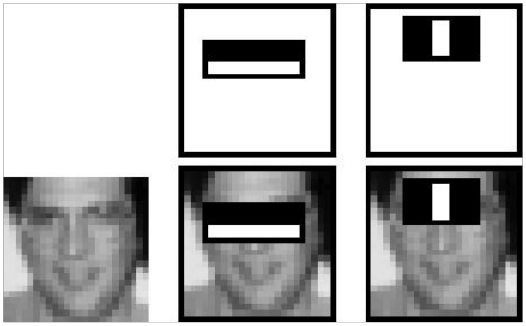
Image adopted from: *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

Local Features SIFT

David G. Lowe (1999)

Image adopted from: David G Lowe. "Object recognition from local scale-invariant features." In: *Proceedings of the seventh IEEE international conference on computer vision*. Vol. 2. Ieee. 1999, pp. 1150–1157

Face Detection - Machine Learning



Viola and Jones (2001)

Image adopted from: Paul Viola and Michael Jones. "Rapid object detection using a boosted cascade of simple features." In: *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001*. Vol. 1. Ieee. 2001, pp. I–I

HOG

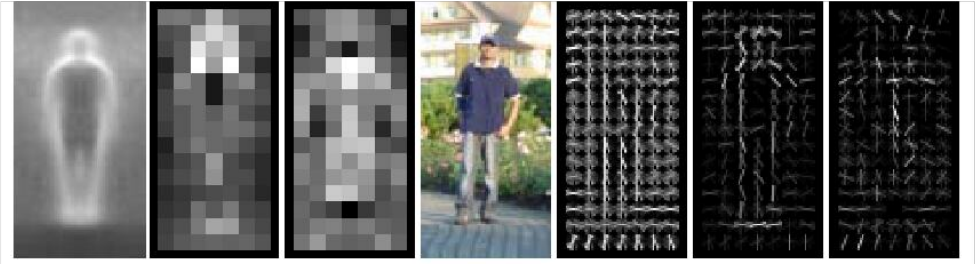
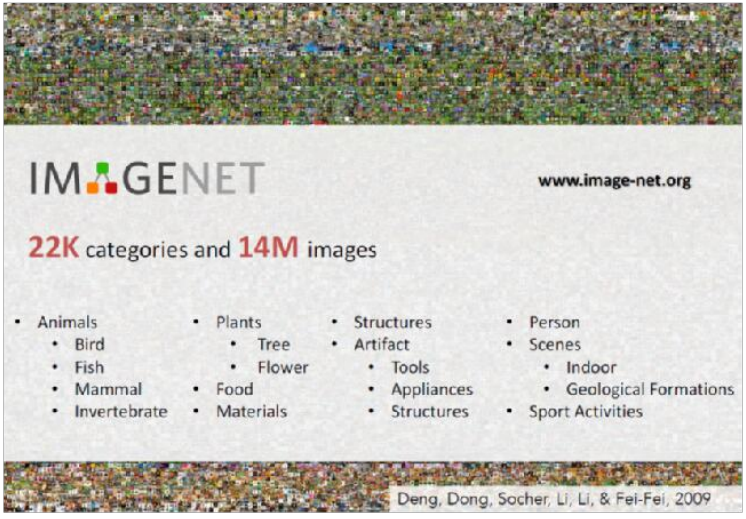


Figure 6. Our HOG detectors cue mainly on silhouette contours (especially the head, shoulders and feet). The most active blocks are centred on the image background just *outside* the contour. (a) The average gradient image over the training examples. (b) Each "pixel" shows the maximum positive SVM weight in the block centred on the pixel. (c) Likewise for the negative SVM weights. (d) A test image. (e) It's computed R-HOG descriptor. (f,g) The R-HOG descriptor weighted by respectively the positive and the negative SVM weights.

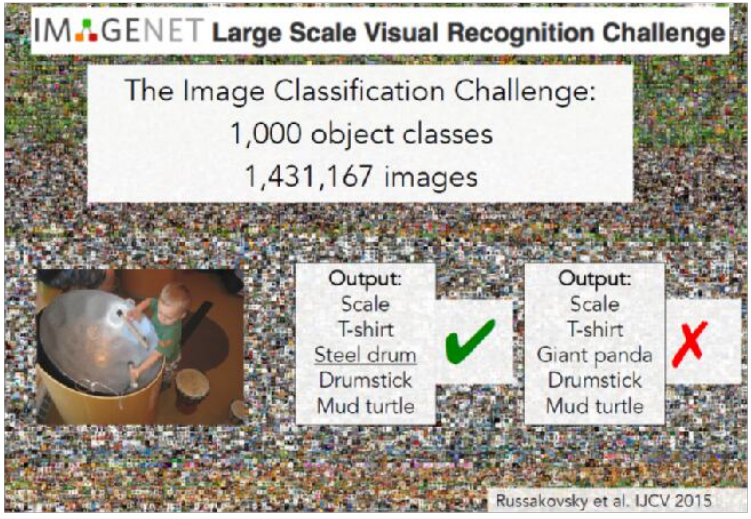
Dalal and Triggs (2005)

Image adopted from: Navneet Dalal and Bill Triggs. "Histograms of oriented gradients for human detection." In: *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*. Vol. 1. Ieee. 2005, pp. 886–893

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

ILSVRC


IMAGENET Large Scale Visual Recognition Challenge
The Image Classification Challenge:
1,000 object classes
1,431,167 images
Output:
Scale
T-shirt
Steel drum
Drumstick
Mud turtle
Output:
Scale
T-shirt
Giant panda
Drumstick
Mud turtle
Russakovsky et al. IJCV 2015

ILSVRC

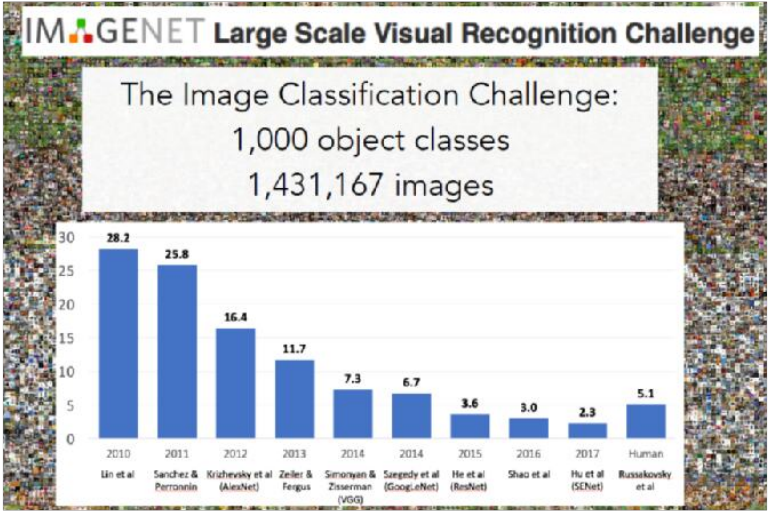
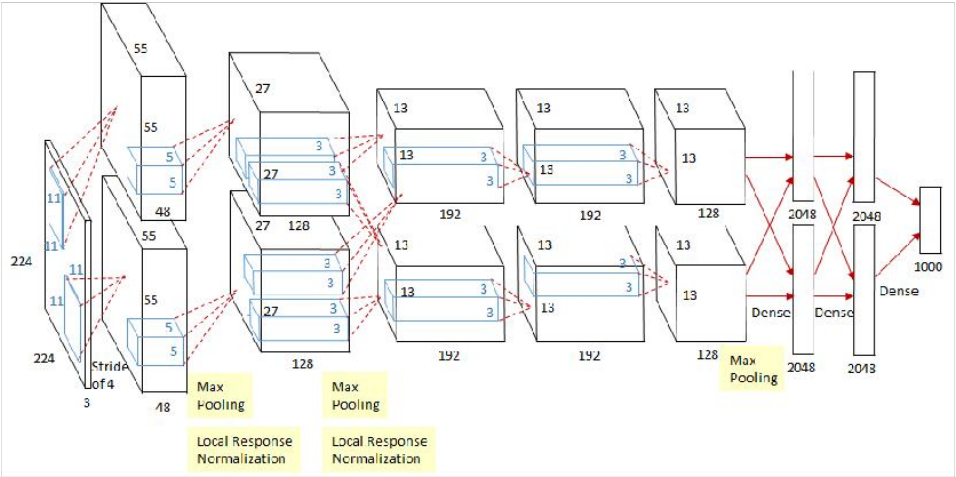


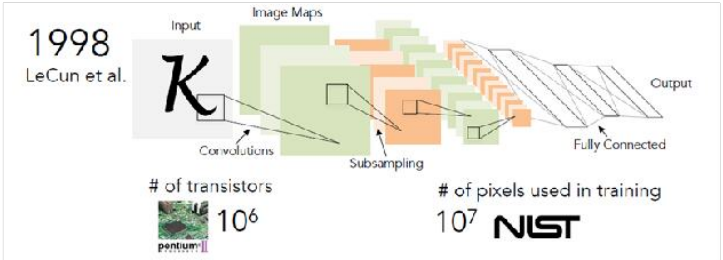
Image adopted from: *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

AlexNet



Krizhevsky, Sutskever and Hinton (2012)

AlexNet


1998
LeCun et al.
Input
Image Maps
Output
Convolutions
Subsampling
Fully Connected
# of transistors
10^6
# of pixels used in training
10^7
NIST
2012
Krizhevsky et al.
Max pooling
Max pooling
Max pooling
Stride of 4
dense
dense
dense
# of transistors
GPUs
# of pixels used in training
10^9
10^{14}
IMAGENET

Convolutional Neural Networks

- Replace human-engineered features (SIFT, HOG, etc.) with learned low level features
- Possible to use on different task with only the training data replaced
- Higher-level features emerge in later layers of the network due to training
- Convolution enables parameter-sharing and results in translational equivariance

Why CNNs became viable

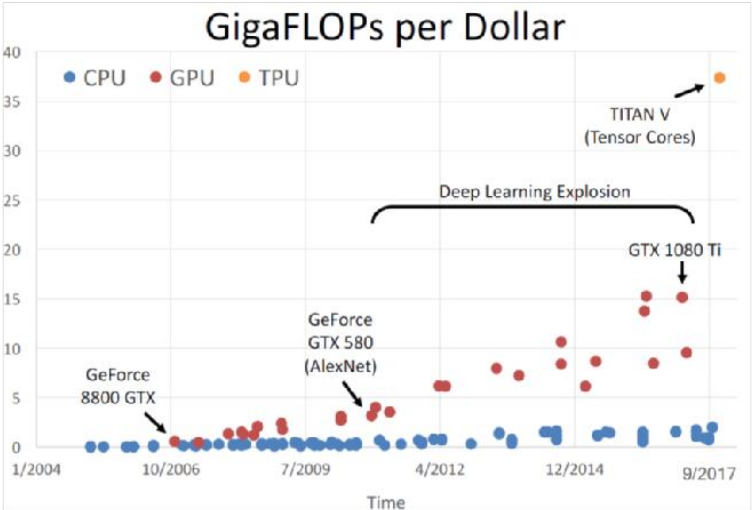
Necessary conditions:

- More quality images available $\rightarrow$ large datasets
- GPU computing power

To win Imagenet AlexNet also employed:

- Custom CUDA implementation
- Splitting computation to two branches on separate GPUs
- Augmentation and preprocessing tricks

Evolution of Computational Efficiency



CV Tasks - Object Detection

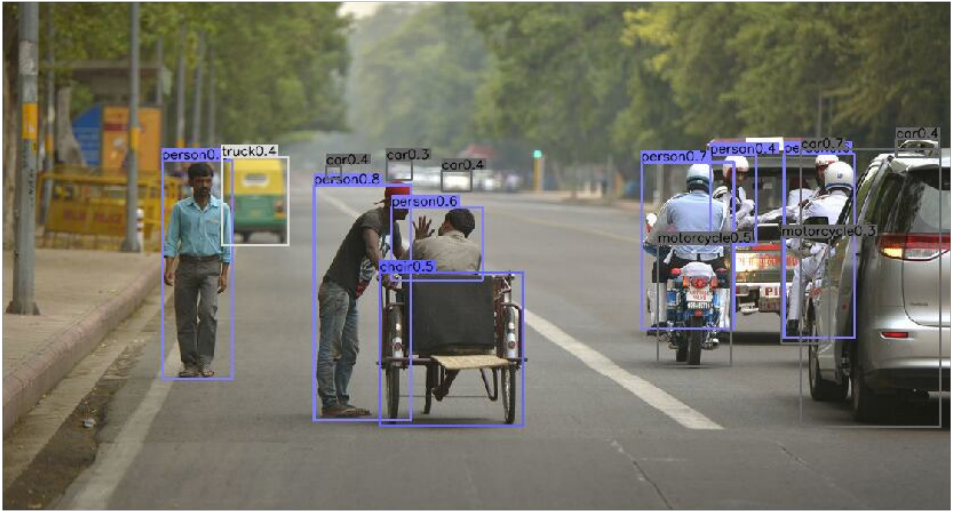


Image adopted from: Xingyi Zhou. *CenterNet Github repo*. `https://github.com/xingyizhou/CenterTrack`

CV Tasks - Object Detection

Image adopted from: Viktor Kocur and Milan Ftáčnik. "Detection of 3D bounding boxes of vehicles using perspective transformation for accurate speed measurement." In: *Machine Vision and Applications* 31.7 (4), pp. 1–15

CV Tasks - Object Detection

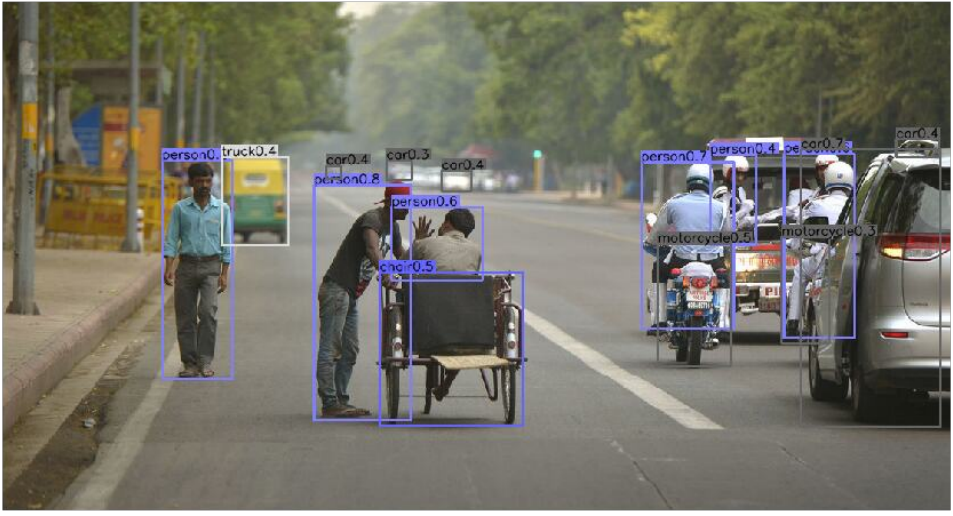


Image adopted from: Xingyi Zhou. *CenterNet Github repo*. `https://github.com/xingyizhou/CenterTrack`

CV Tasks - Pose Estimation

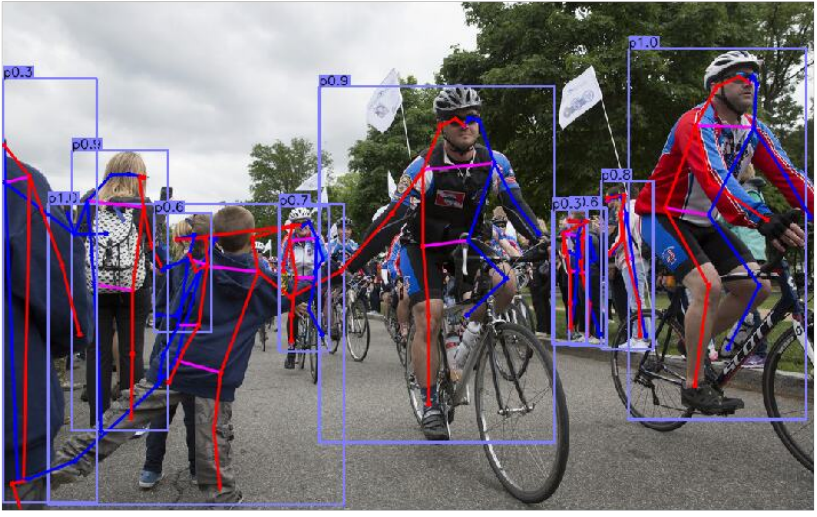


Image adopted from: Xingyi Zhou. *CenterNet Github repo*. `https://github.com/xingyizhou/CenterTrack`

CV Tasks - Pose Estimation

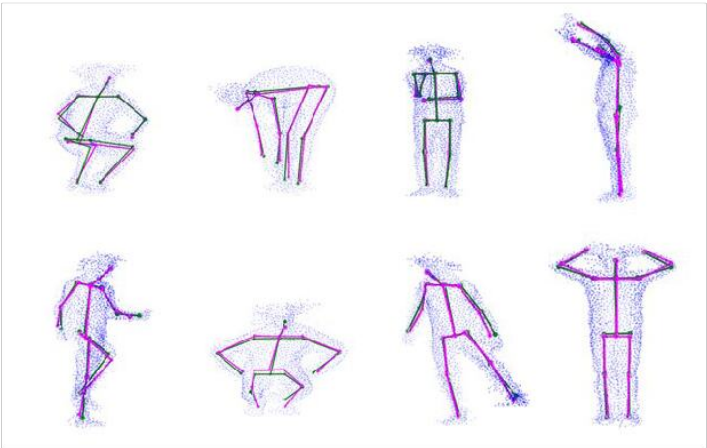


Image adopted from: Dana Skorvankova and Martin Madaras. “Human Pose Estimation using Per-Point Body Region Assignment.” In: *Computing and Informatics* 32 (July 2021), pp. 1001–1020

CV Tasks - Instance Segmentation

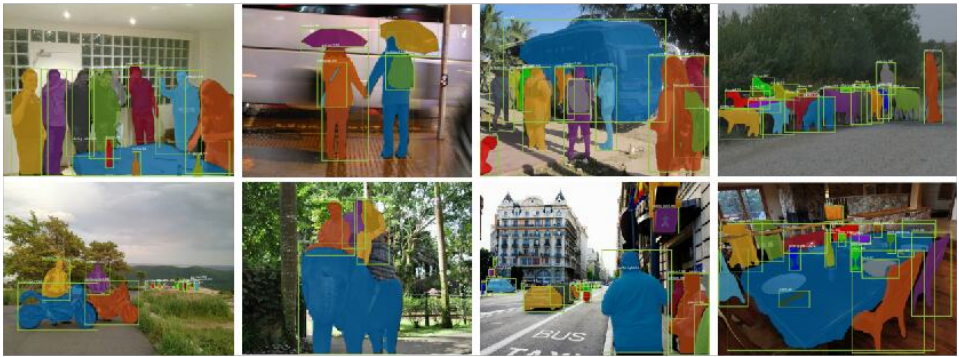


Image adopted from: Kaiming He et al. "Mask r-cnn." In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2961–2969

CV Tasks - Depth Estimation

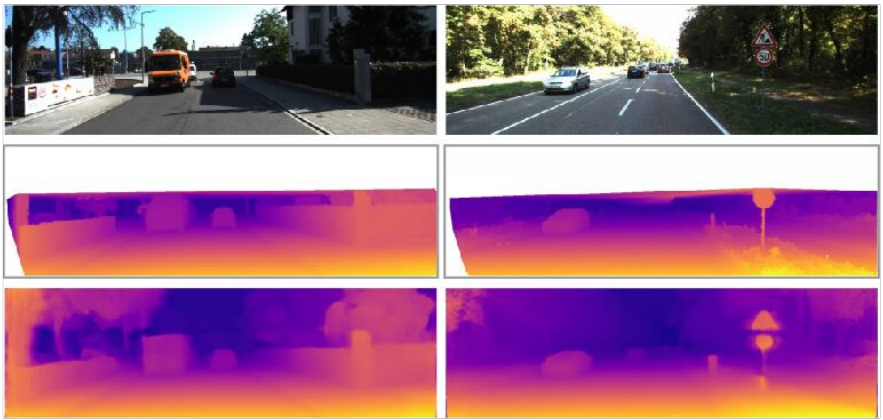


Image adopted from: Clément Godard, Oisin Mac Aodha, and Gabriel J Brostow. "Unsupervised monocular depth estimation with left-right consistency." In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 270–279

CV Tasks - Sentence Generation

{aeroplane,fly,airport,at}
the aeroplane is flying at the airport.

{person,motorbike,ride,field,in}
the person is riding the motorbike in the field.

{person,bicycle,ride,street,on}
the person is riding the bicycle on the street.

{person,table,sit,room,in}
three people are sitting at the table in the room.

Image adopted from: Yezhou Yang et al. "Corpus-guided sentence generation of natural images." In: *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*. 2011, pp. 444–454

Style Transfer

Image adopted from: Leon A Gatys, Alexander S Ecker, and Matthias Bethge. “A neural algorithm of artistic style.” In: *arXiv preprint arXiv:1508.06576* (2015)

Image Generation

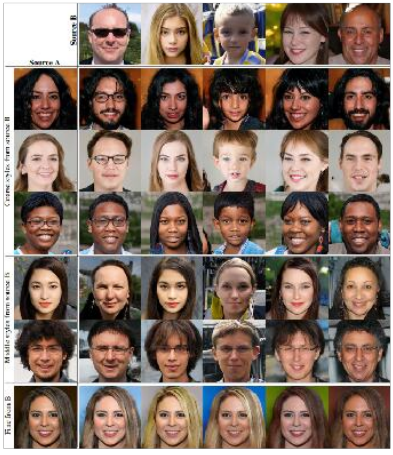


Image adopted from: Tero Karras, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019, pp. 4401–4410

Image Generation

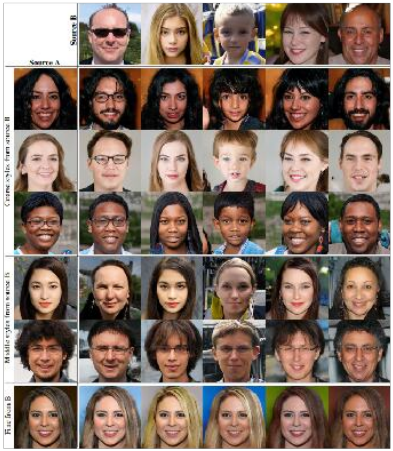


Image adopted from: Tero Karras, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019, pp. 4401–4410

Deep Learning Revolution

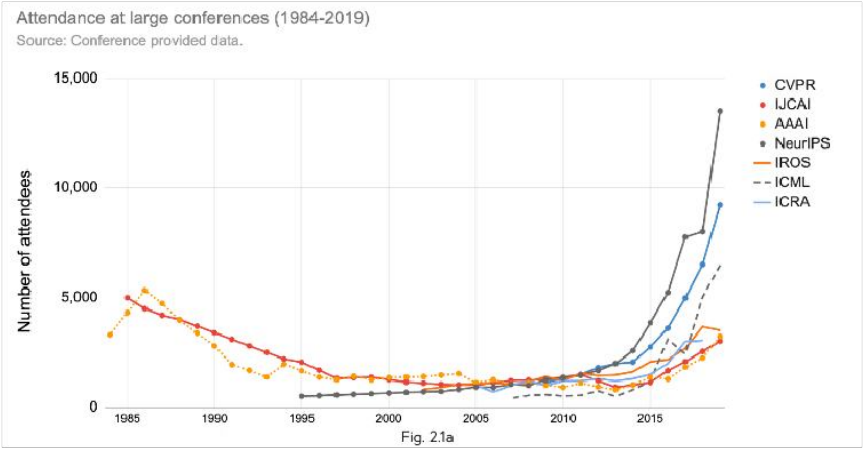


Image adopted from: *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

AI Startups

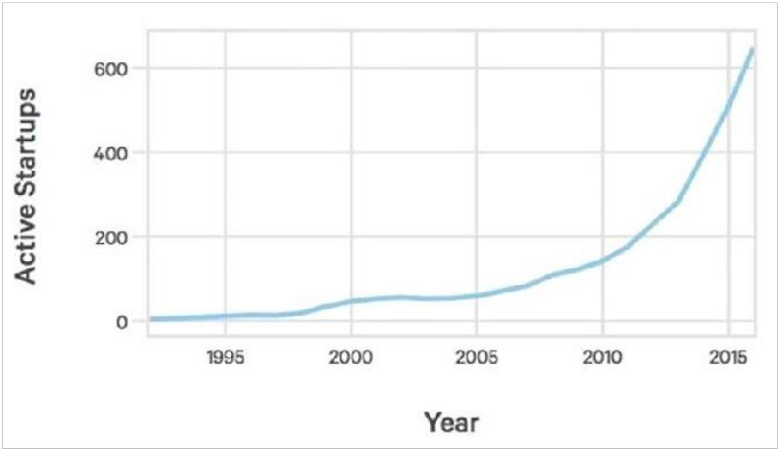


Image adopted from: *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

AI Enterprise Revenue

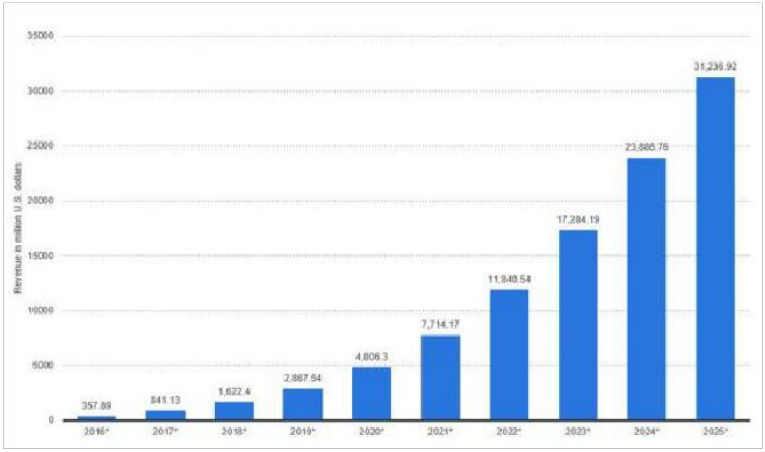


Image adopted from: *Stanford CS231n lecture slides.* `http://cs231n.stanford.edu/slides/`

Are we close to true image understanding?

Image adopted from: Andrej Karpathy. *The state of Computer Vision and AI: we are really, really far away.*
`https://karpathy.github.io/2012/10/22/state-of-computer-vision/`

What about classical CV

Classical CV methods are still usable!

- Insufficient/expensive data
- 3D Vision
- Image preprocessing
- Vision in enterprise solutions
- Domain specific problems
- Combination with DL

Recommended literature

- Ian Goodfellow et al. - Deep Learning, MIT Press
  `http://deeplearningbook.com`
- Michael Nielsen - Neural Networks and Deep Learning
  `http://neuralnetworksanddeeplearning.com`
- CS231n Stanford Course `http://cs231n.stanford.edu`
- Adrian Rosebrock - Computer vision and deep learning, Resource guide
- Charu C. Aggarwal - Neural Networks and Deep Learning: A Textbook

Related courses

- 2-AIN-147/19 - Computer Vision
- 2-AIN-233/00 - Computer Vision Applications
- 2-AIN-112/15 - Advanced Image Processing
- 2-AIN-148/22 - 3D Vision
- 2-AIN-204/10 - Pattern Recognition
- 2-AIN-223/15 - Virtual and Extended Reality
- 2-AIN-132/15 - Neural Networks
- 2-INF-150/15 - Machine Learning
- 2-INF-188/17 - Current Approaches in Machine Learning