# INTRODUCTION

IST 515 Computational Machine Intelligence and Applications

# Course Materials

Google classroom

- Code: 8ni43h0

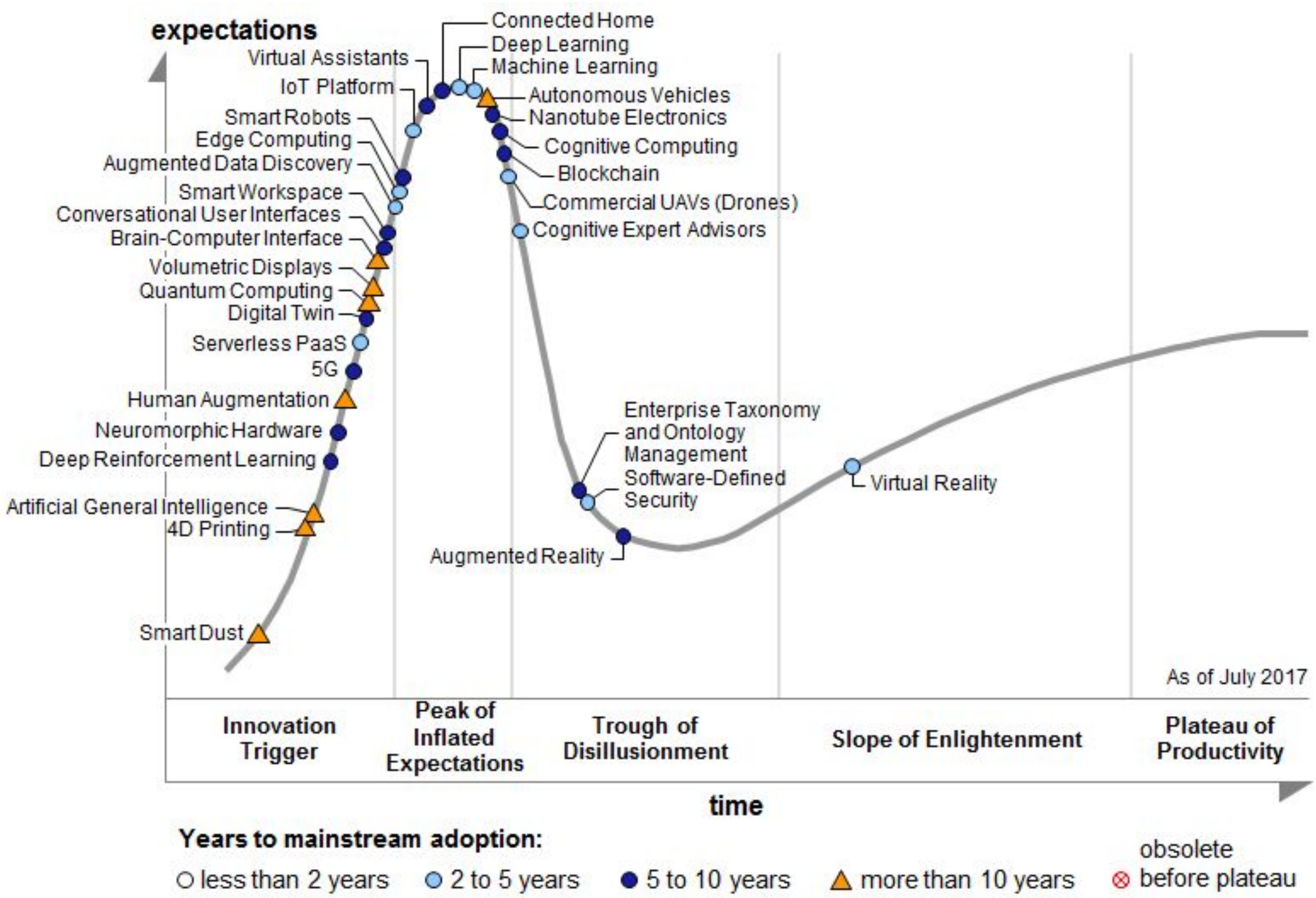
Github

- https://github.com/Pataweepr/applyML_vistec_2019/

Videos

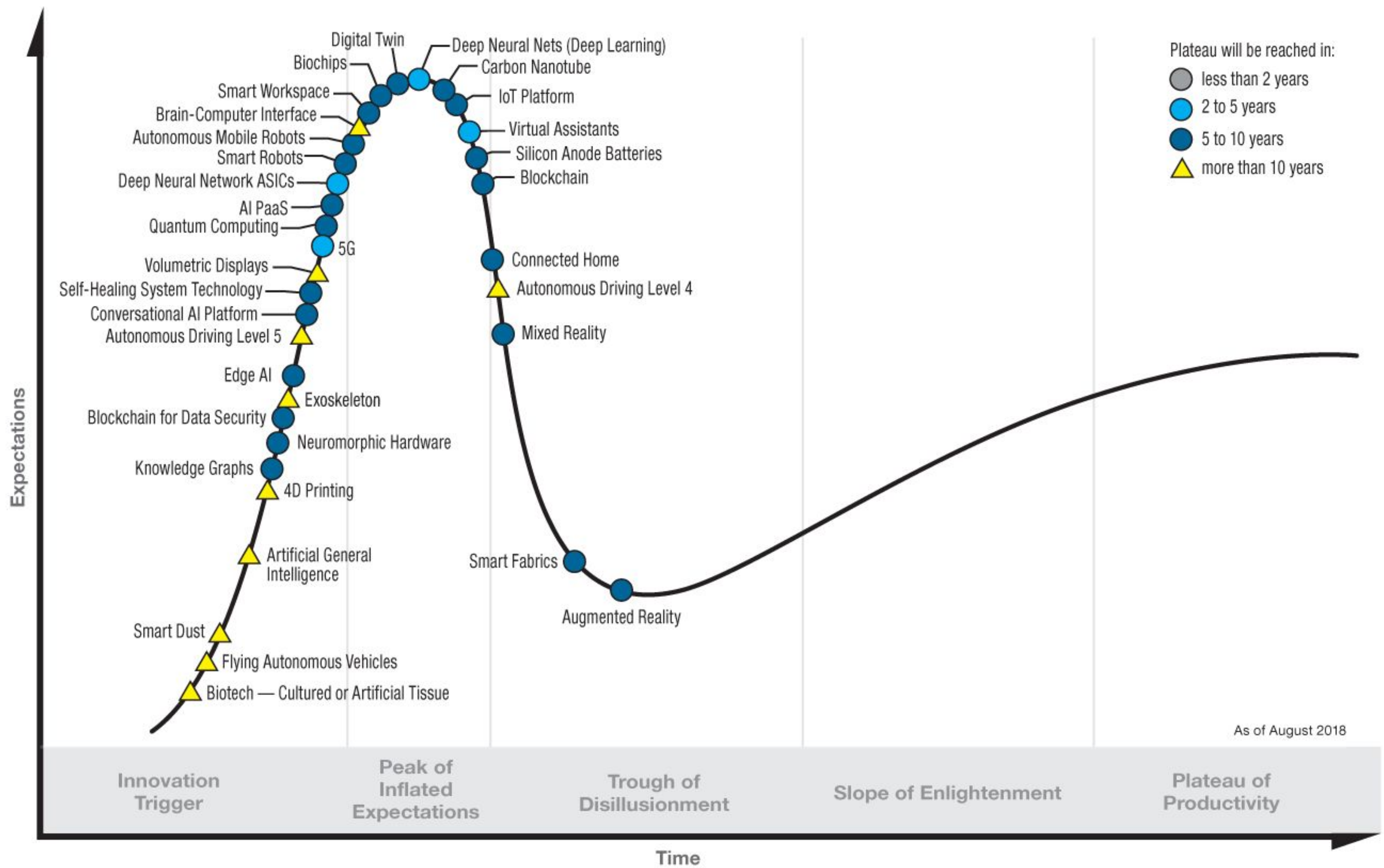
- https://www.coursera.org/learn/python-machine-learning/
- Sign-up as audit

# The machine learning trend 2017




http://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/

# The machine learning trend 2018

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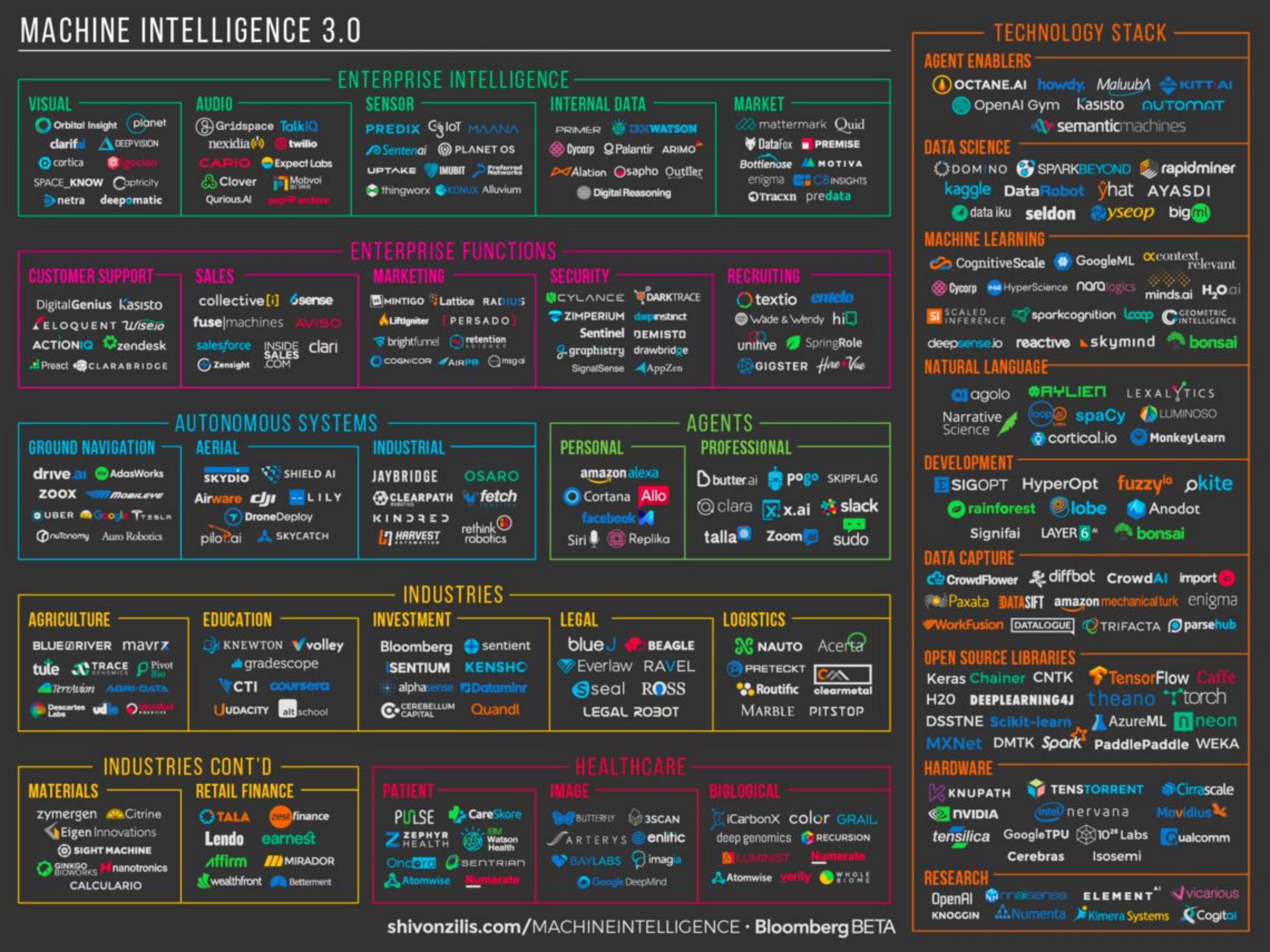

MACHINE INTELLIGENCE 3.0
ENTERPRISE INTELLIGENCE
VISUAL
Orbital Insight
planet
clarifai
DEEPVISION
cortica
gigocion
SPACE_KNOW
Captricity
netra
deepomatic
AUDIO
Gridspace
TalkIQ
nexidia
twilio
CAPIO
Expect Labs
Clover
Mobvoi
Qurious.AI
pop up archive
SENSOR
PREDIX
C3 IoT
MAANA
Sentenai
PLANET OS
UPTAKE
IMUBIT
Preferred Networks
thingworx
KONUX
Alluvium
INTERNAL DATA
PRIMER
IBM WATSON
Cycorp
Palantir
ARIMO
Alation
sapho
Outlier
Digital Reasoning
MARKET
mattermark
Quid
DataFox
PREMISE
Bottlenose
MOTIVA
enigma
CB INSIGHTS
Tracxn
predata
ENTERPRISE FUNCTIONS
CUSTOMER SUPPORT
DigitalGenius
Kasisto
ELOQUENT
Wiseio
ACTION IQ
zendesk
Preact
CLARABRIDGE
SALES
collective[i]
6sense
fuse machines
AVISO
salesforce
INSIDE SALES .COM
clari
Zensight
MARKETING
MINTIGO
Lattice
RADIUS
Liftigniter
PERSADO
brightfunnel
retention science
COGNICOR
AIRPR
msg.ai
SECURITY
CYLANCE
DARKTRACE
ZIMPERIUM
deepinstinct
Sentinel
DEMISTO
graphistry
drawbridge
SignalSense
AppZen
RECRUITING
textio
entelo
Wade & Wendy
hiQ
unitive
SpringRole
GIGSTER
Hire Vue
AUTONOMOUS SYSTEMS
GROUND NAVIGATION
drive.ai
AdasWorks
ZOOX
MOBILEYE
UBER
Google
TESLA
nuTonomy
Auro Robotics
AERIAL
SKYDIO
SHIELD AI
Airware
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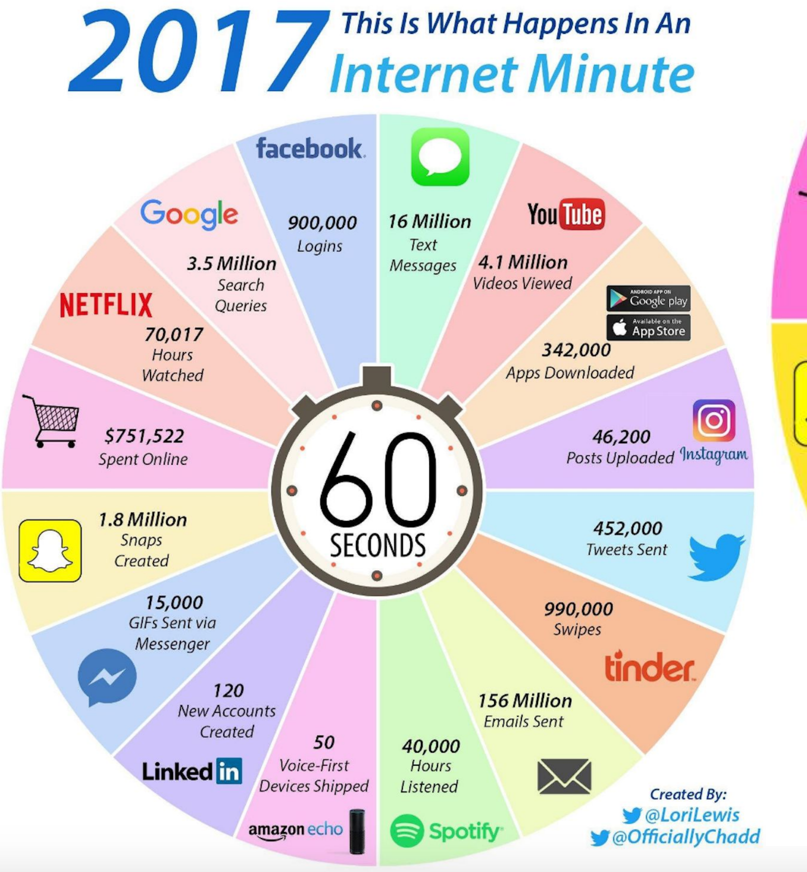
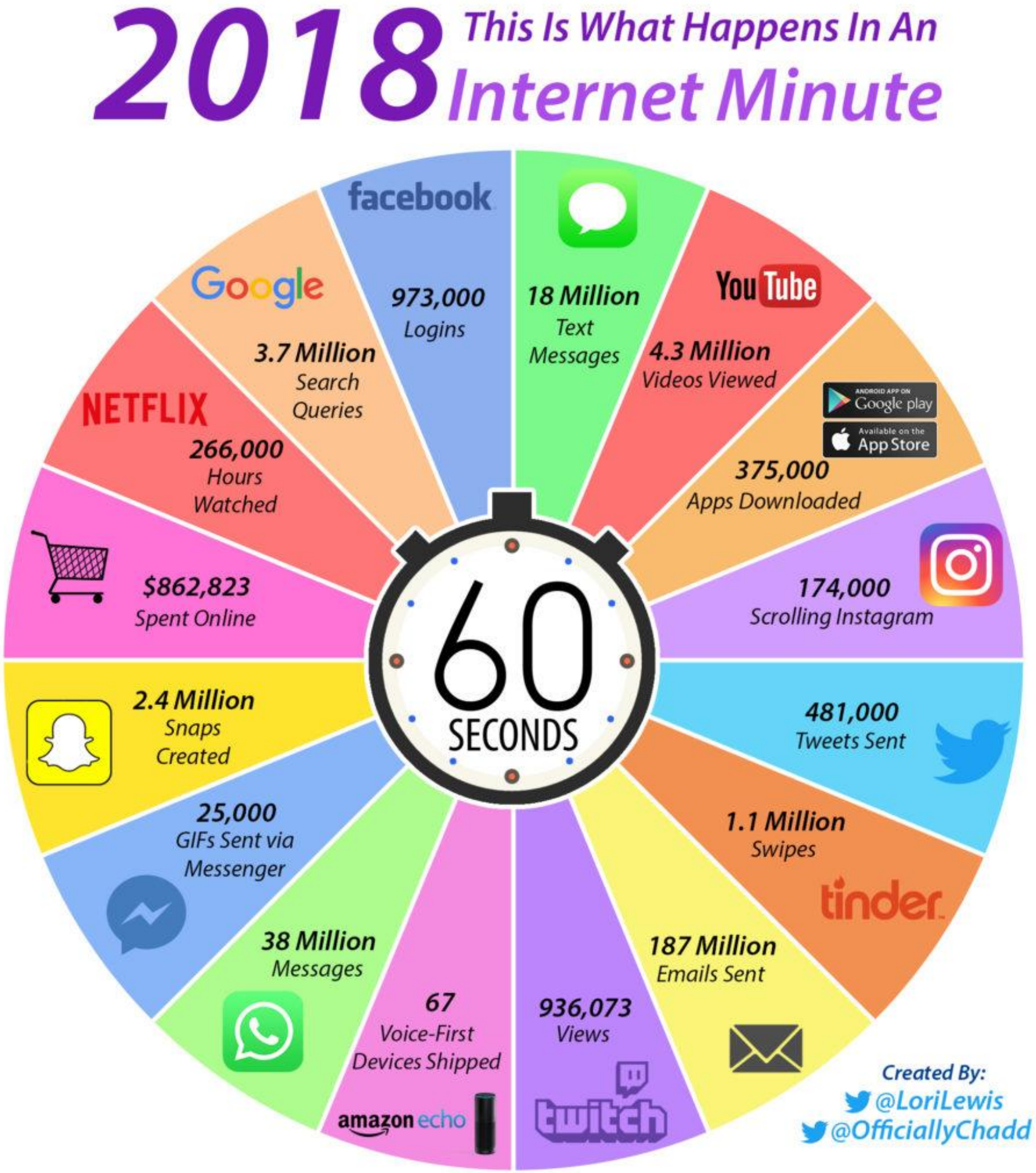
LILY
DroneDeploy
pilot.ai
SKYCATCH
INDUSTRIAL
JAYBRIDGE
OSARO
CLEARPATH
fetch robotics
KINDRED
HARVEST AUTOMATION
rethink robotics
AGENTS
PERSONAL
amazon alexa
Cortana
Allo
facebook M
Siri
Replika
PROFESSIONAL
butter.ai
pogo
SKIPFLAG
clara
x.ai
slack
talla
Zoom.ai
sudo
INDUSTRIES
AGRICULTURE
BLUE RIVER
mavrx
tule
TRACE GENOMICS
Pivot Bio
TerrAvion
AGRI-DATA
Descartes Labs
udio
abundant robotics
EDUCATION
KNEWTON
volley
gradescope
CTI
coursera
UDACITY
altschool
INVESTMENT
Bloomberg
sentient
SENTIUM
KENSHO
alphasense
Dataminr
CEREBELLUM CAPITAL
Quandl
LEGAL
blue J
BEAGLE
Everlaw
RAVEL
seal
ROSS
LEGAL ROBOT
LOGISTICS
NAUTO
Acerta
PRETECKT
Routific
clearmetal
MARBLE
PITSTOP
INDUSTRIES CONT'D
MATERIALS
zymergen
Citrine
Eigen Innovations
SIGHT MACHINE
GINKGO BIOWORKS
nanotronics
CALCULARIO
RETAIL FINANCE
TALA
zestfinance
Lendo
earnest
affirm
MIRADOR
wealthfront
Betterment
HEALTHCARE
PATIENT
PULSE
CareSkore
ZEPHYR HEALTH
IBM Watson Health
Oncora
SENTRIAN
Atomwise
Numerate
IMAGE
BUTTERFLY
3SCAN
ARTERYS
enlitic
BAYLABS
imagia
Google DeepMind
BIOLOGICAL
iCarbonX
color
GRAIL
deep genomics
RECURSION
LUMINIST
Numerate
Atomwise
verily
WHOLE BIOME
TECHNOLOGY STACK
AGENT ENABLERS
OCTANE.AI
howdy.
Maluuba
KITT.AI
OpenAI Gym
Kasisto
AUTOMAT
semanticmachines
DATA SCIENCE
DOMINO
SPARKBEYOND
rapidminer
kaggle
DataRobot
yhat
AYASDI
data iku
seldon
yseop
bigml
MACHINE LEARNING
CognitiveScale
GoogleML
context relevant
Cycorp
HyperScience
naralogics
minds.ai
H2O.ai
SCALED INFERENCE
sparkcognition
loop
GEOMETRIC INTELLIGENCE
deepsense.io
reactive
skymind
bonsai
NATURAL LANGUAGE
agolo
AYLIEN
LEXALYTICS
Narrative Science
loop ai labs
spaCy
LUMINOSO
cortical.io
MonkeyLearn
DEVELOPMENT
SIGOPT
HyperOpt
fuzzy.io
kite
rainforest
lobe
Anodot
Signifai
LAYER 6
bonsai
DATA CAPTURE
CrowdFlower
diffbot
CrowdAI
import.io
Paxata
DATASIFT
amazon mechanical turk
enigma
WorkFusion
DATALOGUE
TRIFACTA
parsehub
OPEN SOURCE LIBRARIES
Keras
Chainer
CNTK
TensorFlow
Caffe
H20
DEEPLEARNING4J
theano
torch
DSSTNE
Scikit-learn
AzureML
neon
MXNet
DMTK
Spark
PaddlePaddle
WEKA
HARDWARE
KNUPATH
TENSTORRENT
Cirrascale
NVIDIA
intel nervana
Movidius
tensilica
GoogleTPU
10²⁶ Labs
Qualcomm
Cerebras
Isosemi
RESEARCH
OpenAI
maluuba
ELEMENT AI
vicarious
KNOGGIN
Numenta
Kimera Systems
Cogitai
shivonzilis.com/MACHINEINTELLIGENCE · Bloomberg BETA

# The data era

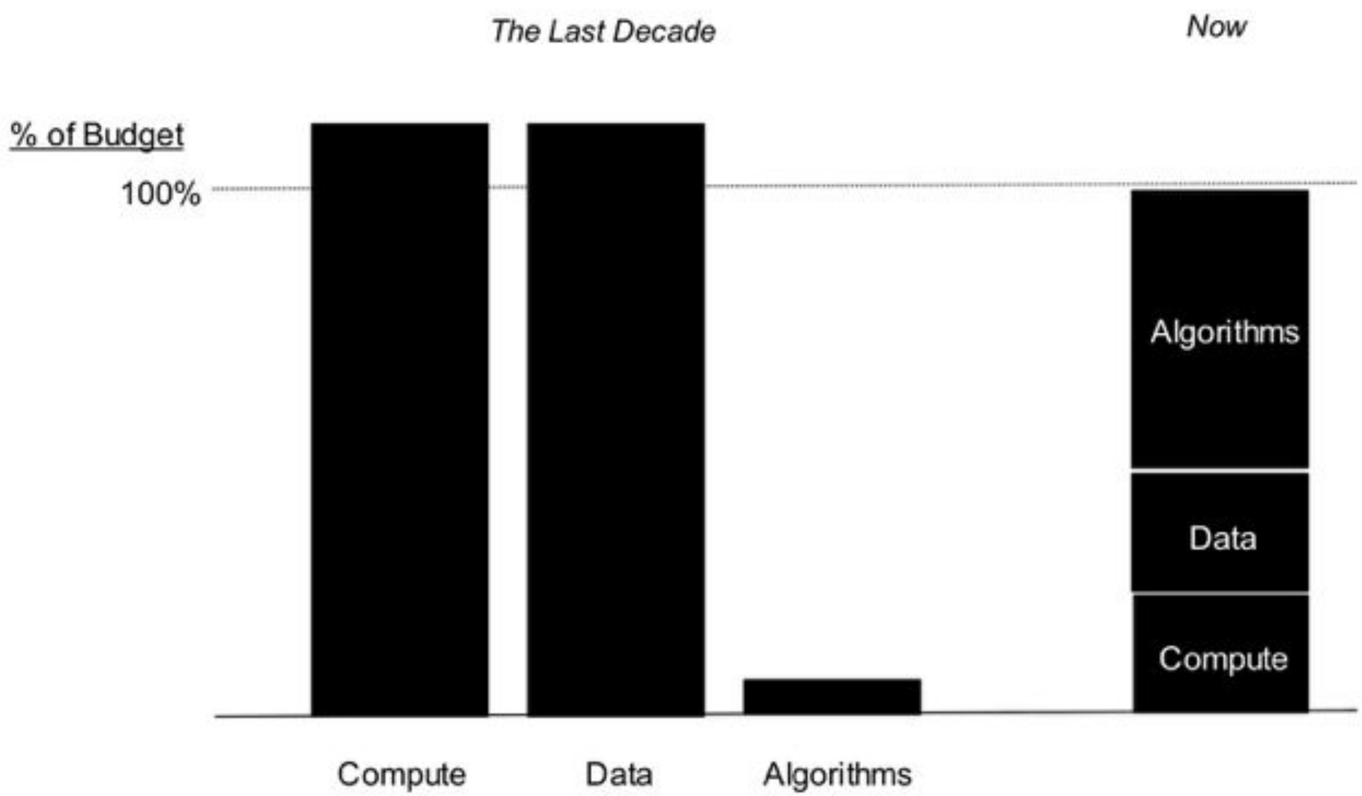



http://www.visualcapitalist.com/internet-minute-2018/

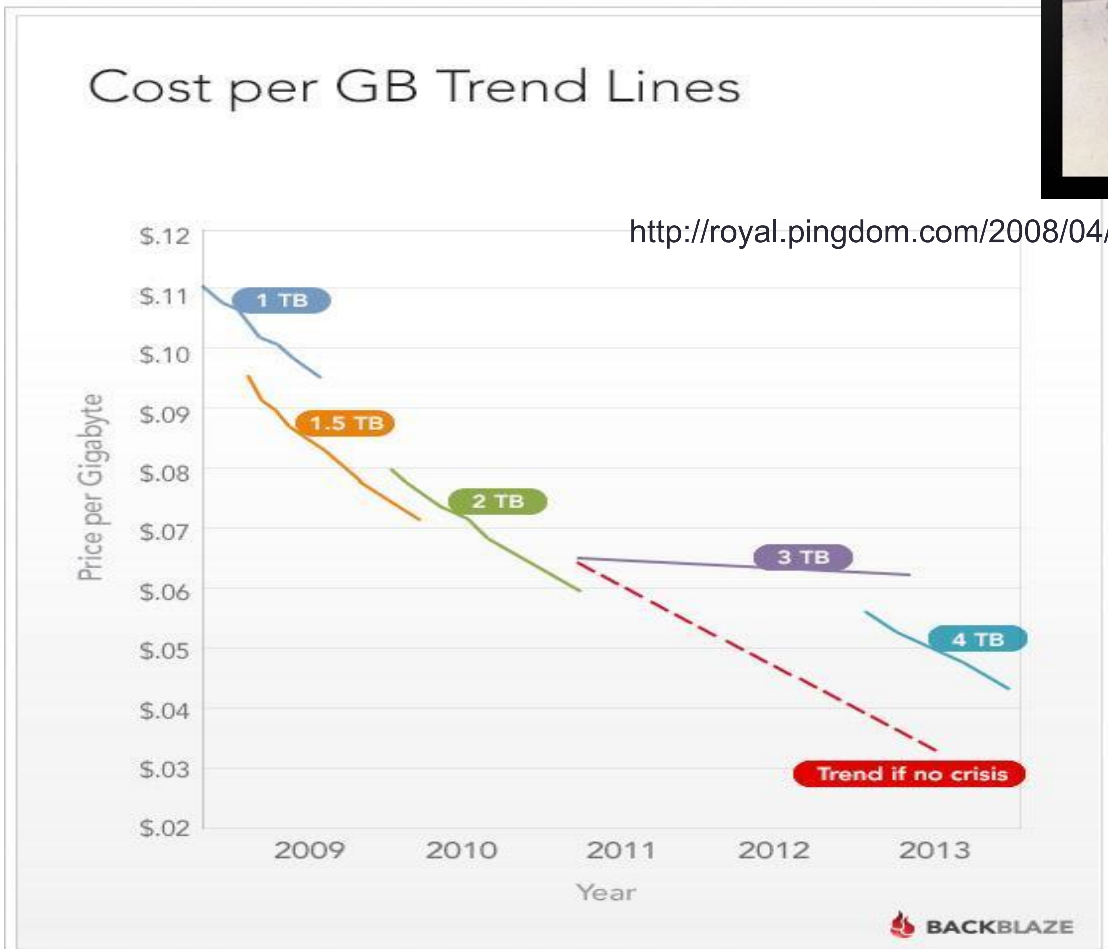
# Factors for ML

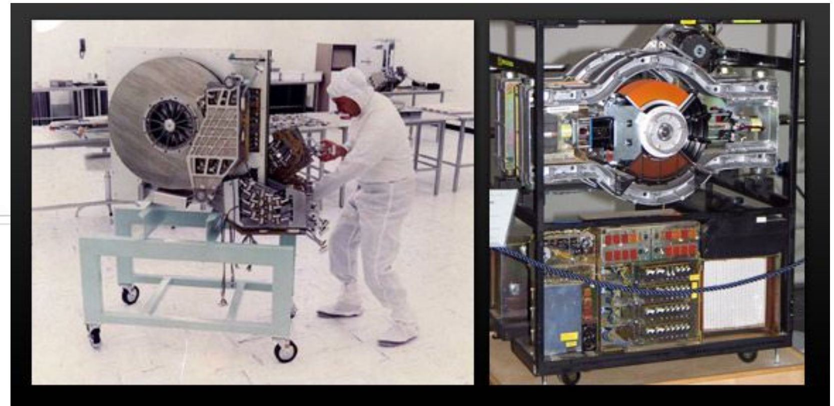
- Data
- Compute
- Algo




http://www.kdnuggets.com/2017/06/practical-guide-machine-learning-understand-differentiate-apply.html

# The cost of storage



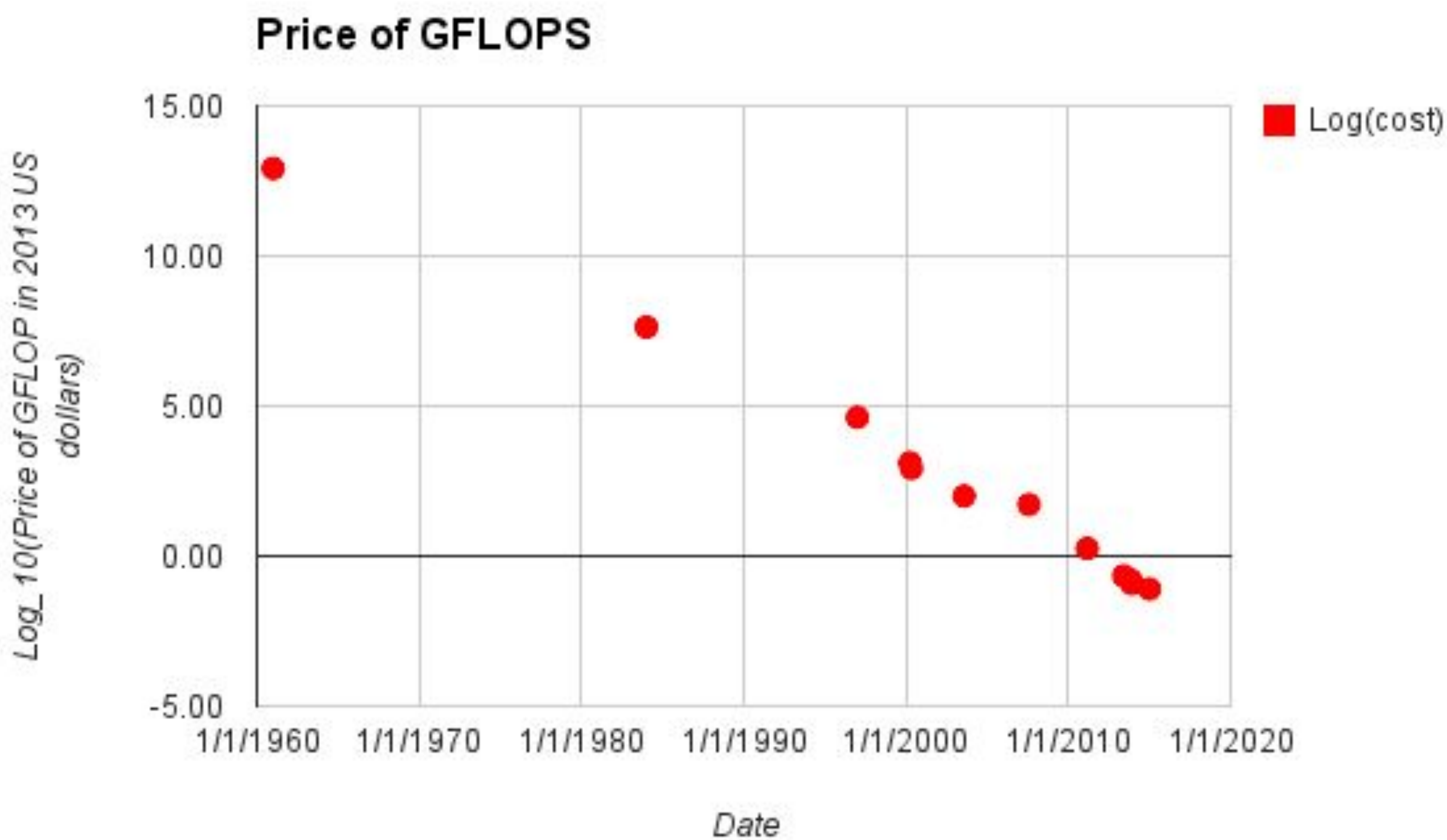



http://royal.pingdom.com/2008/04/08/the-history-of-computer-data-storage-in-pictures/

1980 250MB hard disk drive 250 kg 100k USD (300k USD in today's dollar)

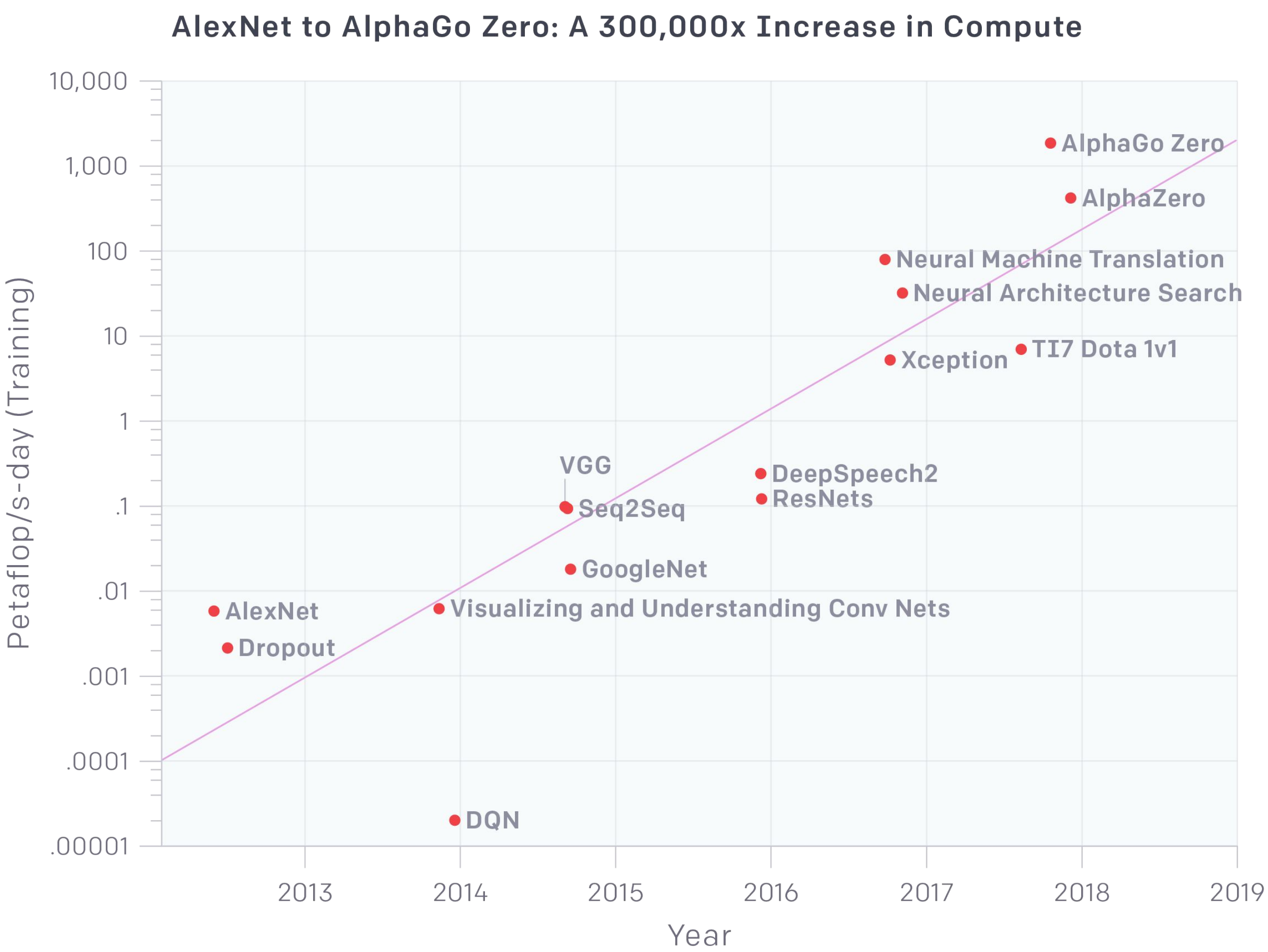
https://www.backblaze.com/blog/farming-hard-drives-2-years-and-1m-later/

# The cost of compute



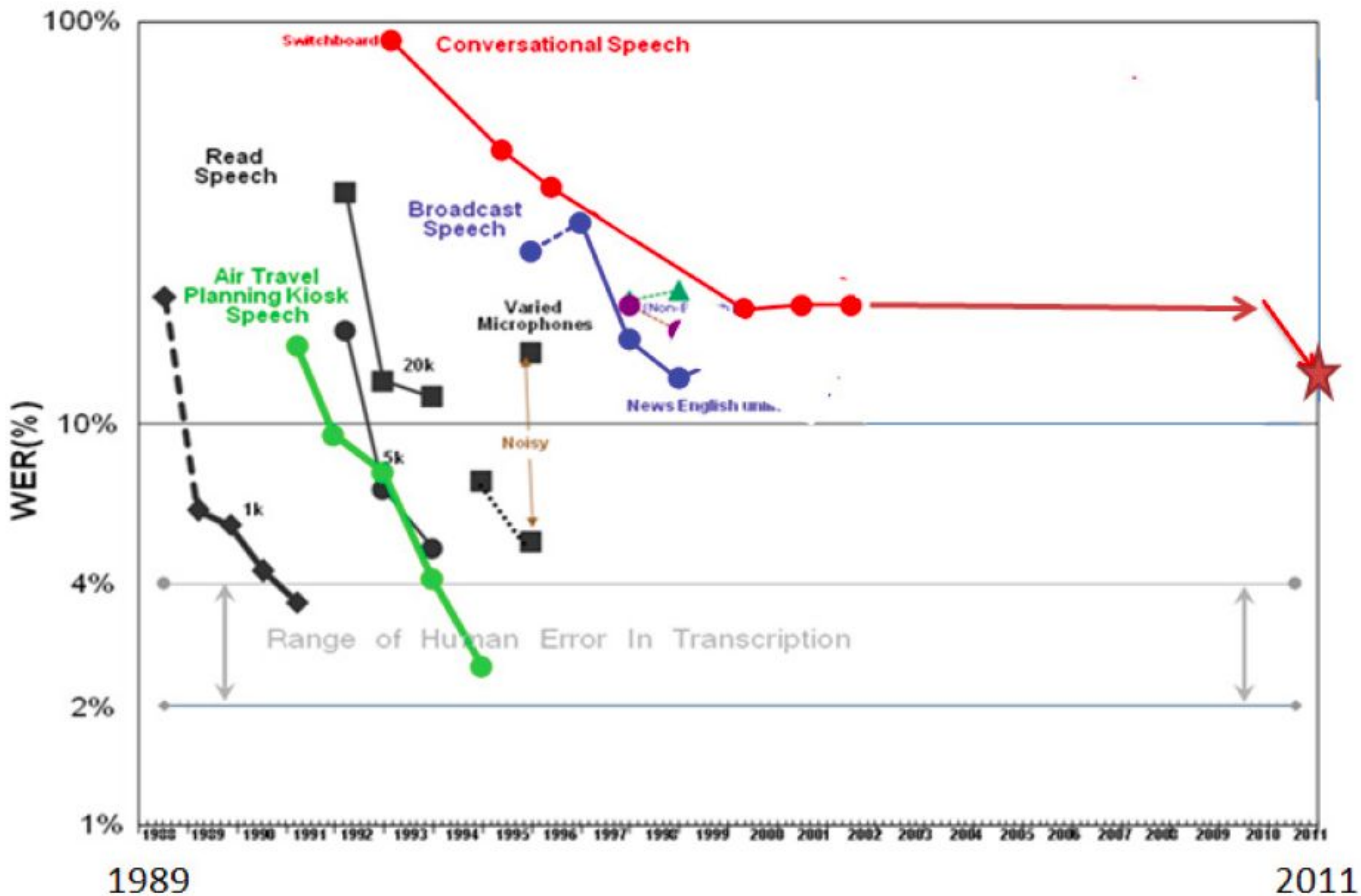

http://aiimpacts.org/trends-in-the-cost-of-computing/

# Deep learning and compute




https://blog.openai.com/ai-and-compute/

# Hitting the sweet spot on performance




http://recognize-speech.com/acoustic-model/knn/benchmarks-comparison-of-different-architectures

# Hitting the sweet spot in performance

PRESS RELEASE
OCTOBER 4, 2011

## Apple Launches iPhone 4S, iOS 5 & iCloud

iPhone 4S Features Dual-Core A5 Chip, All New Camera, Full 1080p HD Video Recording & Introduces Siri

CUPERTINO, California—October 4, 2011—Apple® today announced iPhone® 4S, the most amazing iPhone yet, packed with incredible new features including Apple's dual-core A5 chip for blazing fast performance and stunning graphics; an all new camera with advanced optics; full 1080p HD resolution video recording; and Siri™, an intelligent assistant that helps you get things done just by asking. With the launch of iPhone 4S

# Now time for videos


https://www.youtube.com/watch?v=wiOopO9jTZw 2017

# Now time for videos


https://blog.openai.com/openai-five/
https://youtu.be/eHipy_j29Xw

2018

# Now time for videos

- “If I were to guess like what our biggest existential threat is, it’s probably that. So we need to be very careful with the artificial intelligence. There should be some regulatory oversight maybe at the national and international level, just to make sure that we don’t do something very foolish.”

# What is Machine Learning?

- "Machine learning (ML) is the scientific study of algorithms and statistical models that computer systems use to effectively perform a specific task without using explicit instructions, relying on models and inference instead. It is seen as a subset of artificial intelligence."

  wikipedia

- What about
  - Data mining
  - Knowledge Discovery in Databases (KDD)
  - Statistics
  - Data science

# ML vs DM vs KDD

- “The short answer is: None. They are … concerned with the same question: how do we learn from data?”

  Larry Wasserman – CMU Professor

- Nearly identical tools and subject matter

# Types of machine learning

1. Supervised learning
2. Unsupervised learning
3. Reinforcement learning

0. Pre-machine learning: rule-base

# Pre-machine learning: 7-segment display

- **Input:** 7 binary values (0,1) forming a dispaly
- Given **x** = (A, B, C, D, E, F, G)
- **Output:** y, either 0, 1, …, 9 or not a number
- **Task:** write a program (a function F) that maps
  **x** to y;  F(**x**) = y

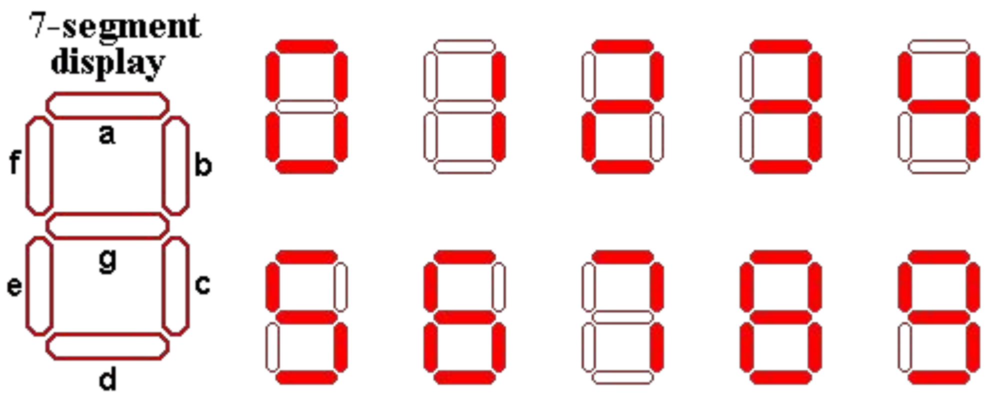
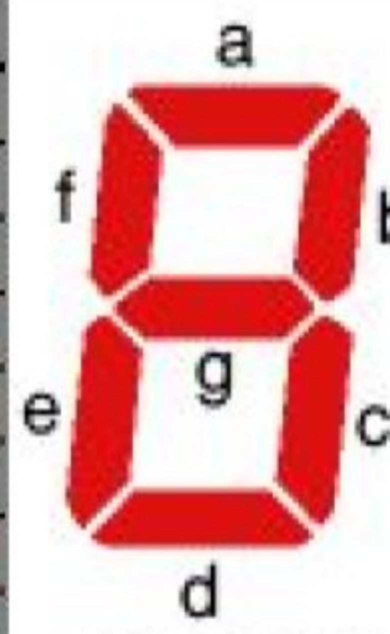



Image from
http://www.physics.udel.edu/~watson/scen103/colloq2000/7-seg.html

# Mapping function

Y X

| Count | a | b | c | d | e | f | g |
|---|---|---|---|---|---|---|---|
| 0 | ● | ● | ● | ● | ● | ● | |
| 1 | | ● | ● | | | | |
| 2 | ● | ● | | ● | ● | | ● |
| 3 | ● | ● | ● | ● | | | ● |
| 4 | | ● | ● | | | ● | ● |
| 5 | ● | | ● | ● | | ● | ● |
| 6 | ● | | ● | ● | ● | ● | ● |
| 7 | ● | ● | ● | | | | |
| 8 | ● | ● | ● | ● | ● | ● | ● |
| 9 | ● | ● | ● | ● | | ● | ● |

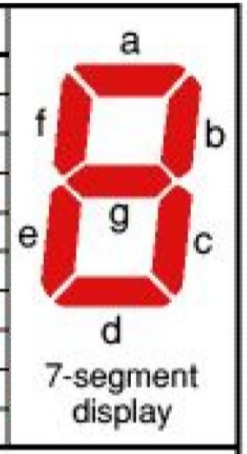



7-segment display

Image from: http://www.instructables.com/id/DIY-7-Segment-Display/

# Mapping function

| Count | a | b | c | d | e | f | g |
|---|---|---|---|---|---|---|---|
| 0 | ● | ● | ● | ● | ● | ● | |
| 1 | | ● | ● | | | | |
| 2 | ● | ● | | ● | ● | | ● |
| 3 | ● | ● | ● | ● | | | ● |
| 4 | | ● | ● | | | ● | ● |
| 5 | ● | | ● | ● | | ● | ● |
| 6 | ● | | ● | ● | ● | ● | ● |
| 7 | ● | ● | ● | | | | |
| 8 | ● | ● | ● | ● | ● | ● | ● |
| 9 | ● | ● | ● | ● | | ● | ● |




- IF A==1 && B==1 && C==1 && D==1 && E==1 && F==1 && G==0, THEN output(0).
- IF B==1 && C==1, THEN output(1)
- …..
- OTHERWISE, output("not number")

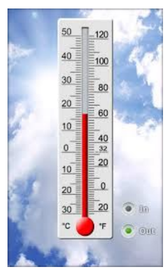
F(x)

# Learning from data

- Machine learning requires identifying the same ingredients
  - Input, Output, Task



Real world observations





This is the hardest part of data science and the last part to be replaced by machines.

# An example

- Handwritten digit recognition
- Input: **x** = 28 x 28 pixel image
- Output: y = digit 0 to 9
- Task: find F(**x**) such that y ≈ F(**x**)

Goal of machine learning is to find the <u>best</u> F(**x**) automatically from data

# Supervised learning

- Learn a classifier F from a training set (input-output pairs)
  - $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), (\mathbf{x}_3, y_3), \ldots, (\mathbf{x}_n, y_n)\}$

| **x** | y |
|---|---|
|  | 0 |
|  | 1 |
|  | 2 |

Need a training set for training.
Training = finding (optimizing) a good function f

Labeling (i.e., assigning y for each **x** in the training set) is typically done manually.

# Types of machine learning

1. Supervised learning

   Learn a model F from pairs of (**x**,y)

2. Unsupervised learning

   Discover the hidden structure in unlabeled data **x** (no y)

3. Reinforcement learning

   Train an agent to take appropriate actions in an environment by maximizing rewards

# Typical workflow of machine learning

1. Feature extraction (getting the **x**)
2. Modeling
   - Training (getting the function F)
3. Evaluation
   - Metrics (defining what's the best function F)
   - Testing (getting the y for unseen inputs)

# Typical workflow of machine learning

- The typical workflow

Real world observations

Squire Trelawney, Dr. Livesey, and the rest of these gentlemen having asked me to write down the whole particulars about Treasure Island, from the beginning to the end, keeping nothing back but the bearings of the island, and that only because there is still treasure not yet lifted, I take up my pen in the year of grace 17— and go back to the time when my father kept the Admiral Benbow inn and the brown old seaman with the sabre cut first took up his lodging under our roof.

I remember him as if it were yesterday, as he came plodding to the inn door, his sea-chest following behind him in a hand-barrow; a tall, strong, heavy, nut brown man, his tarry pigtail falling over the shoulder of his soiled blue coat, his hands ragged and scarred, with black, broken nails, and the sabre cut across one cheek, a dirty, livid white. I remember him looking round the cover and whistling to himself as he did so, and then breaking out in that old sea-song that he sang so often afterwards:

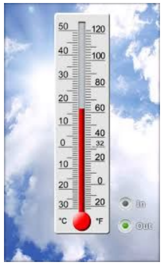
*'Fifteen men on the dead man's chest-Yo-ho-ho, and a bottle of rum!'* In the high, old tottering voice that seemed to have been tuned and broken at the capstan bars. Then he rapped on the door with a bit of stick like a handspike that he carried, and when my father appeared, called roughly for a glass of rum. This, when it was brought to him, he drank slowly, like a connoisseur, lingering on the taste and still looking about him at the cliffs and up at our signboard.

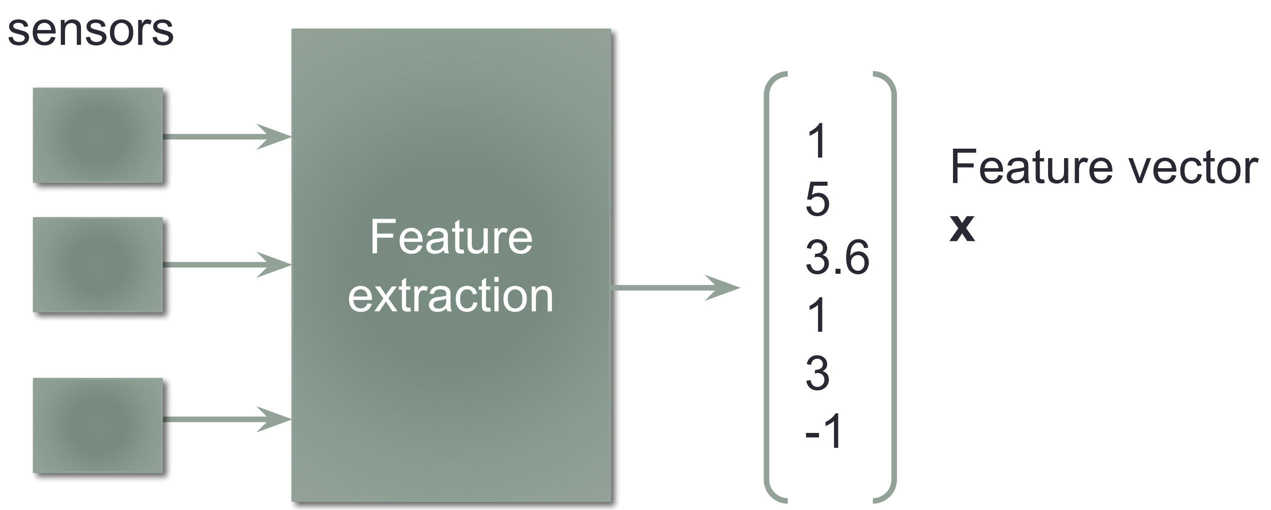
'This is a handy cove,' says he at length; 'and a pleasant sittyated grog-shop. Much company, mate?'

My father told him no, very little company, the more was the pity.

'Well, then,' said he, 'this is the berth for me. Here you, matey,' he cried to the man who trundled the barrow; 'bring up alongside and help up my chest. I'll stay here a bit,' he continued. 'I'm a plain man; rum and bacon and eggs is what I want, and that head up there for to watch ships off. What you mought call me? You mought call me captain. Oh, I see what you're at - there'; and he threw down three or four gold pieces on the threshold. 'You can tell me when I've worked through that,' says he, looking as fierce as a commander.

And indeed bad as his clothes were and coarsely as he spoke, he had none of the appearance of a





# How do we learn from data?

1
5
3.6
1
3
-1

Training set

Learning algorithm

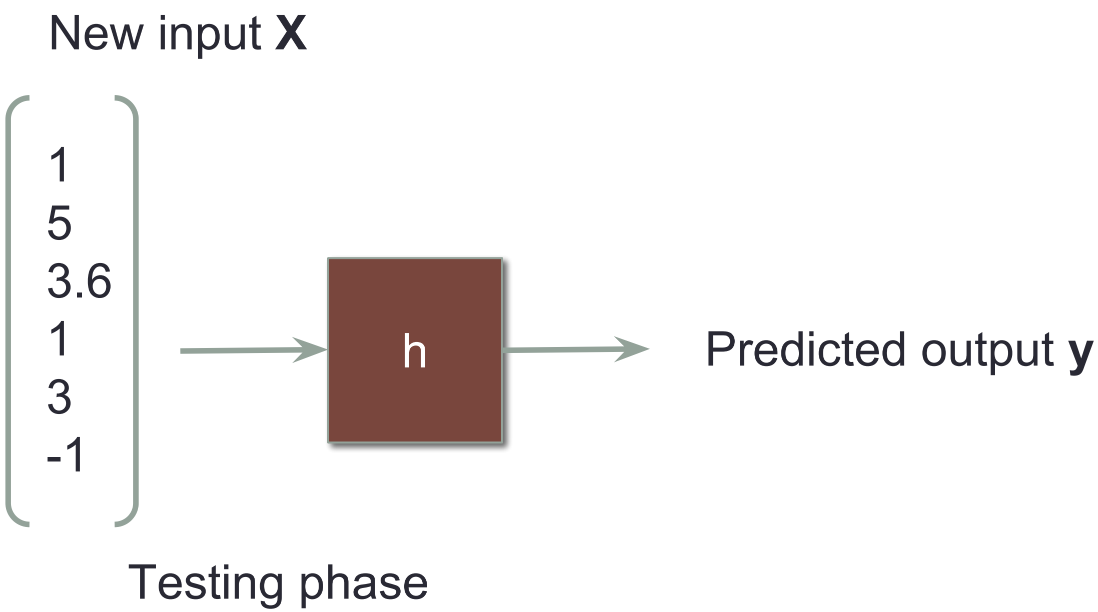
Model

h

Desired output **y**

Training phase


# How do we learn from data?



# Feature extraction

- The process of extracting meaningful information related to the goal
- A distinctive characteristic or quality
- Example features

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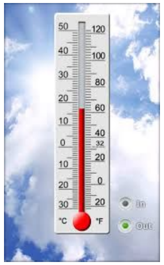
data1 →

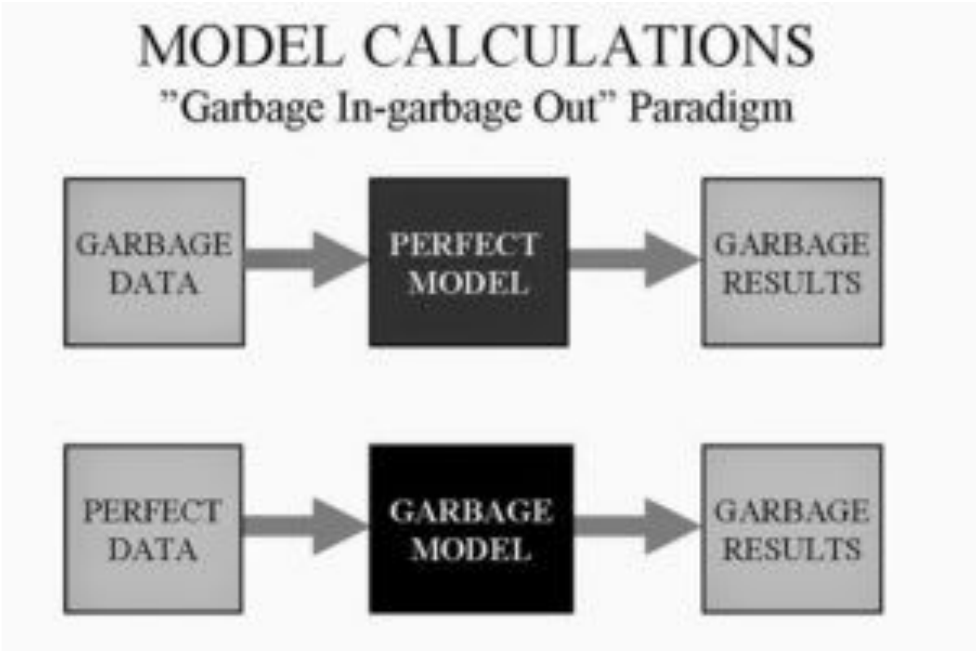
data2 →




data3 →

# Garbage in Garbage out

- The machine is as intelligent as the data/features we put in
- “Garbage in, Garbage out”
- Data cleaning is often done to reduce unwanted things

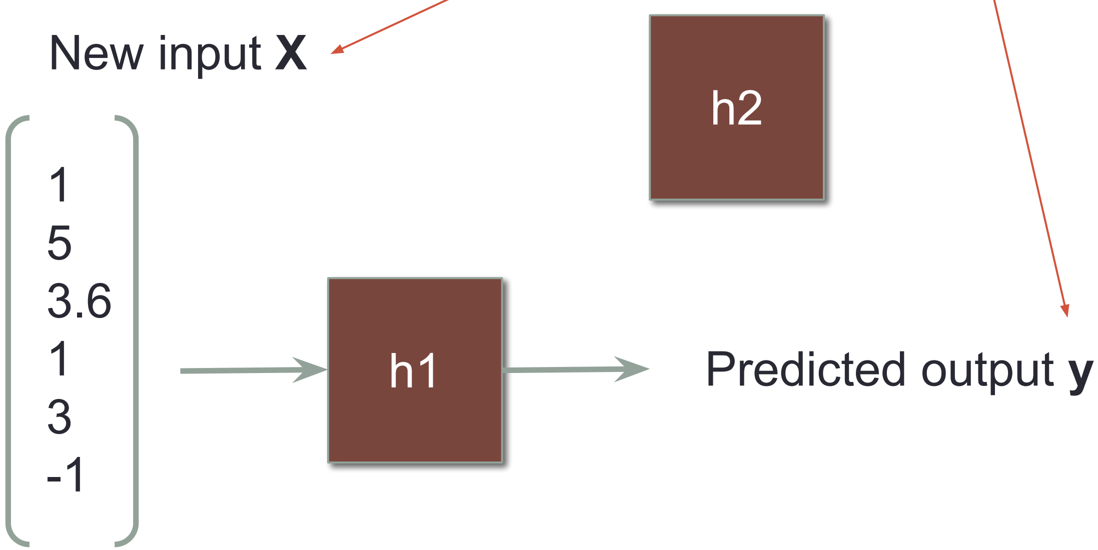



https://precisionchiroco.com/garbage-in-garbage-out/

# Model evaluation

Another set of labelled data, not seen in training. Then, we can know how the model generalizes to unseen data

How to compare h1 and h2?




Testing phase

# Metrics

- Compare the output of the models
  - Errors/failures, accuracy/success
- We want to quantify the error/accuracy of the models
- How would you measure the error/accuracy of the following



# Ground truths

- We usually compare the model predicted answer with the correct answer.
- What if there is no real answer?
  - How would you rate machine translation?

ไป
ไหน
Model A: Where are you going?
Model B: Where to?

Designing a metric can be tricky, especially when it's subjective

# Metrics consideration

- Are there several metrics?


- Use the metric closest to your goal but never disregard other metrics.
    - May help identify possible improvements

# Commonly used metrics

- Error rate
- Accuracy rate

- Precision
- True positive
- Recall
- False alarm
- F score

# A detection problem

- Identify whether an event occur
- A yes/no question
- A binary classifier

Smoke detector


Hotdog detector

# Evaluating a detection problem

- 4 possible scenarios

| | | Detector | |
|---|---|---|---|
| | | Yes | No |
| Actual | Yes | True positive | False negative (Type II error) |
| | No | False Alarm (Type I error) | True negative |

True positive + False negative = # of actual yes
False alarm + True negative = # of actual no

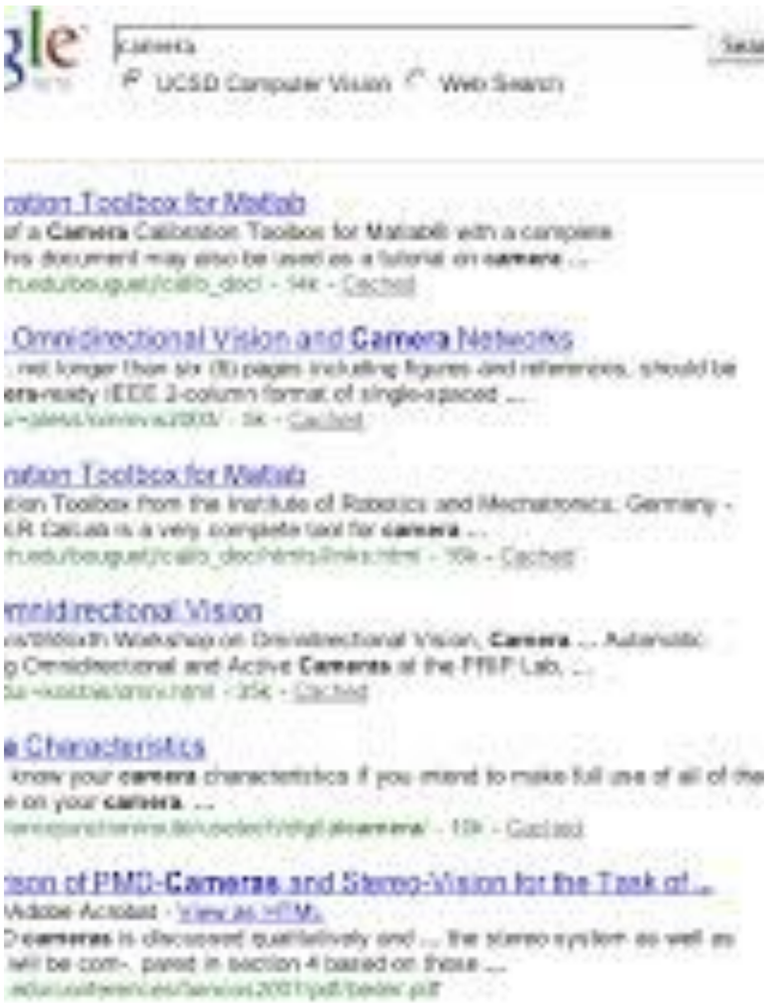
- False alarm and True positive carries all the information of the performance.

# Definitions

- True positive rate (Recall, sensitivity)
  = # true positive / # of actual yes
- False positive rate (False alarm rate)
  = # false positive / # of actual no
- False negative rate (Miss rate)
  = # false negative / # of actual yes
- True negative rate (Specificity)
  = # true negative / # of actual no

- Precision = # true positive / # of predicted positive

# Search engine example




A recall of 50% means?

A precision of 50% means?

When do you want high recall?
When do you want high precision?

# Recall/precision

- When do you want high recall?
- When do you want high precision?

- Initial screening for cancer
- Face recognition system for authentication
- Detecting possible suicidal postings on social media

Usually there's a trade off between precision and recall. We will revisit this later

# Definitions 2

- F score (F1 score, f-measure)

$$F_1 = 2 \cdot \frac{1}{\frac{1}{\mathrm{recall}} + \frac{1}{\mathrm{precision}}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}.$$

  - A single measure that combines both aspects
  - A harmonic mean between precision and recall (an average of rates)

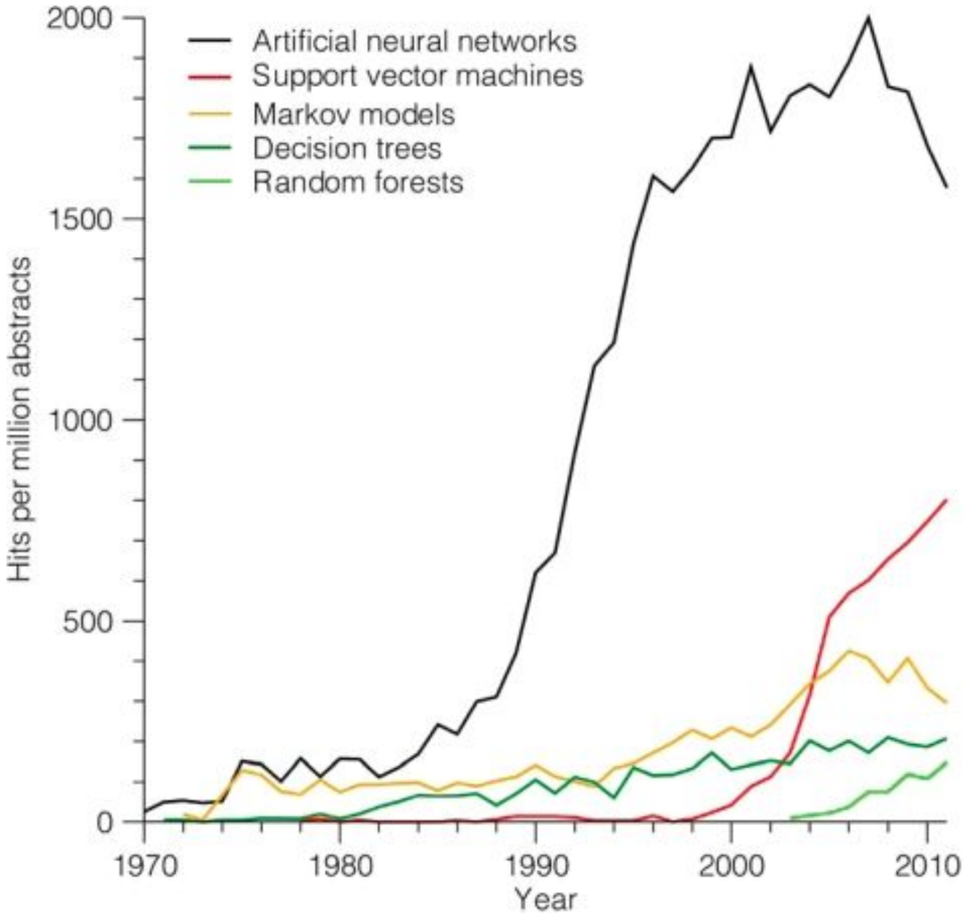
Note that precision and recall says nothing about the true negative

# Course walkthrough

| Lecture | Topic | Assignments and Quizzes |
|---|---|---|
| 1-5 Feb | Introduction to ML and introduction to Python, SciPy, Pandas, matplotlib, and scikit-learn | HW1 |
| 2-12 Feb | Nearest neighbor and K-Means | HW2 |
| 3-26 Feb | Regression | HW3 |
| 4-5 Feb | Support Vector Machines | HW4 |
| 6-12 Mar | Probability and estimation | HW5, Quiz 1 |
| 7-19 Mar | Naives Bayes Classifier | HW6 |
| 8-26 Mar | Dimensionality reduction and Visualization | Course project starts |
| 9-2 Apr | Random Forests | HW7 |
| 10-9 Apr | Neural Networks 1 | HW8 |
| 11-16 Apr | Neural Networks 2 | Quiz 2 |
| 12-23 Apr | Tricks of the trade: machine learning in the real world | |
| 13-30 Apr | Project presentation | Course project due |

# Why anything else besides deep learning

- The rise and fall of machine learning algorithms

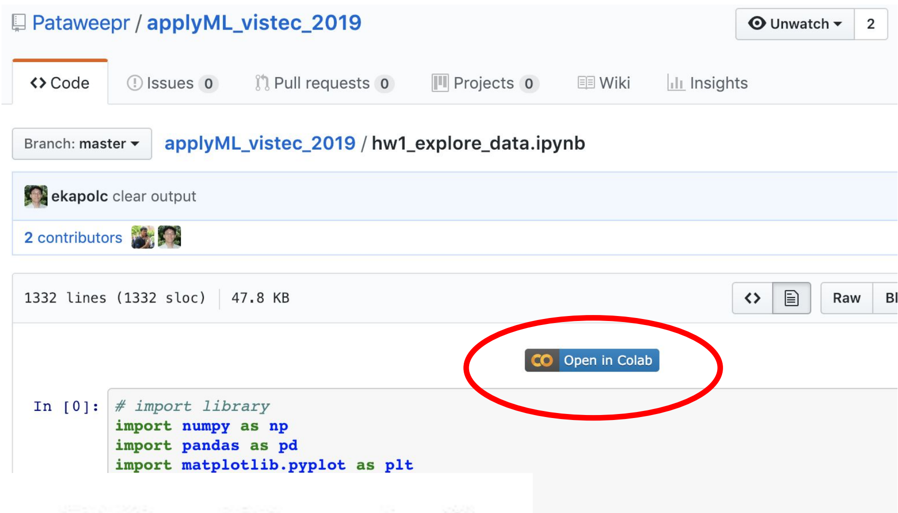



Methods used in bioinformatics papers

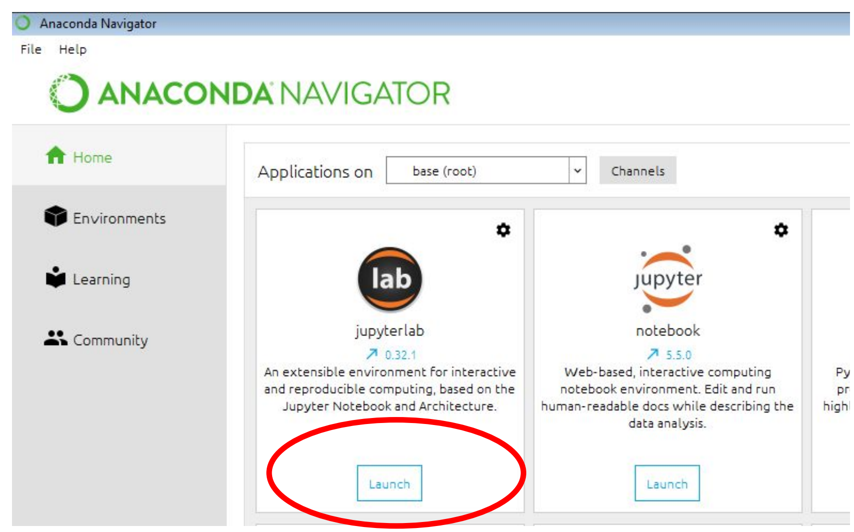
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3232371/figure/F1/

# Jupyter lab and Colaboratory

- We will use Jupyter lab and Colaboratory for this course








https://www.anaconda.com/download/

# Homework

- Upload the finished collab files on Google Classroom
- Finish week 1 of the coursera videos