INTRODUCTION

2110573 Pattern Recognition

Sections

- 21 : Undergrad
- 1 : Masters

- Switch sections if wrong, if full please tell me to increase.

Mycourseville and discord

https://discord.gg/nJvBSTW8

TA office hours: 8-9 pm Tuesdays, Fridays

MyCourseVille
https://www.mycourseville.com?q=courseville/course/28315

Password: nya

For homework submission

Github

https://github.com/ekapolc/pattern_2022

For slides and homework instructions

Playlist

https://youtube.com/playlist?list=PLcBOyD1N1T-MnWcKQZqE8FXrgoiiVdXvI

Syllabus

คาบเรียนที่	เนื้อหา	การบ้านและควิซ
1 - 13/1	Introduction	
2 - 20/1	K-mean, Regression	เริ่มHW1
3 - 27/1	MLE, MAP, and Naive Bayes	ส่งHW1, Quiz 1, เริ่มHW2
4 - 3/2	GMM and EM	
5 - 10/2	Dimensionality reduction (PCA, LDA, RP) and visualization techniques (t-sne, UMAP, PHATE)	ส่งHW2, Quiz 2, เริ่มHW3
6 - 17/2	SVM	
7 - 24/2	Neural network basics	ส่งHW3, Quiz 3, เริ่มHW4
8 - 3/3	CNNs & Pytorch demo	เริ่ม HW5
9 - 10/3	Midterm week - No midterm for this class	
10 - 17/3	Recurrent, attention, and transformers	ส่งHW4, Quiz 4
11 - 24/3	Deep generative models (VAE, GAN, Diffusion)	ส่งHW5, Quiz 5, ส่ง course project proposal, เริ่ม HW6
11 - 31/3	Unsupervised methods	
12 - 7/4	Semi-supervised, self-supervised, and contrastive learning	ส่งHW6, Quiz 6, เริ่ม HW7
13 - 14/4	Songkran Holiday	
14 - 21/4	Reinforcement Learning	ส่งHW7, Quiz 7
15 - 28/4	No regular class - meeting/progress presentation with project mentors	Course project progress
16 - 5/5	Tricks of the trade: machine learning in the real world + Guest	
Some time during final exam	Project presentation No final exam for this class	ส่งcourse project

Plagiarism Policy

- You shall not show other people your code or solution
- Copying will result in a score of zero for both parties on the assignment
- Many of these algorithms have code available on the internet, do not copy paste the codes

Plagiarism vs. Cheating

What is the difference?

Grades

<u>การส่งการบ้านสาย</u>

สายไม่เกิน 6 ชม. -0.5 คะแนน

สายไม่เกิน 24 ชม. -2 คะแนน

ถ้าส่งสายเกิน 24 ชม.จะไม่ได้รับการตรวจ

<u>เกณฑ์การวัดผล</u>

Attendance and in-class activities 10%

Quizzes 20%

Homework 40%

Project 30%

<u>การตัดเกรด</u>

> 85% A

> 80% B+

> 75% B

> 70% C+

> 65% C

> 60% D+

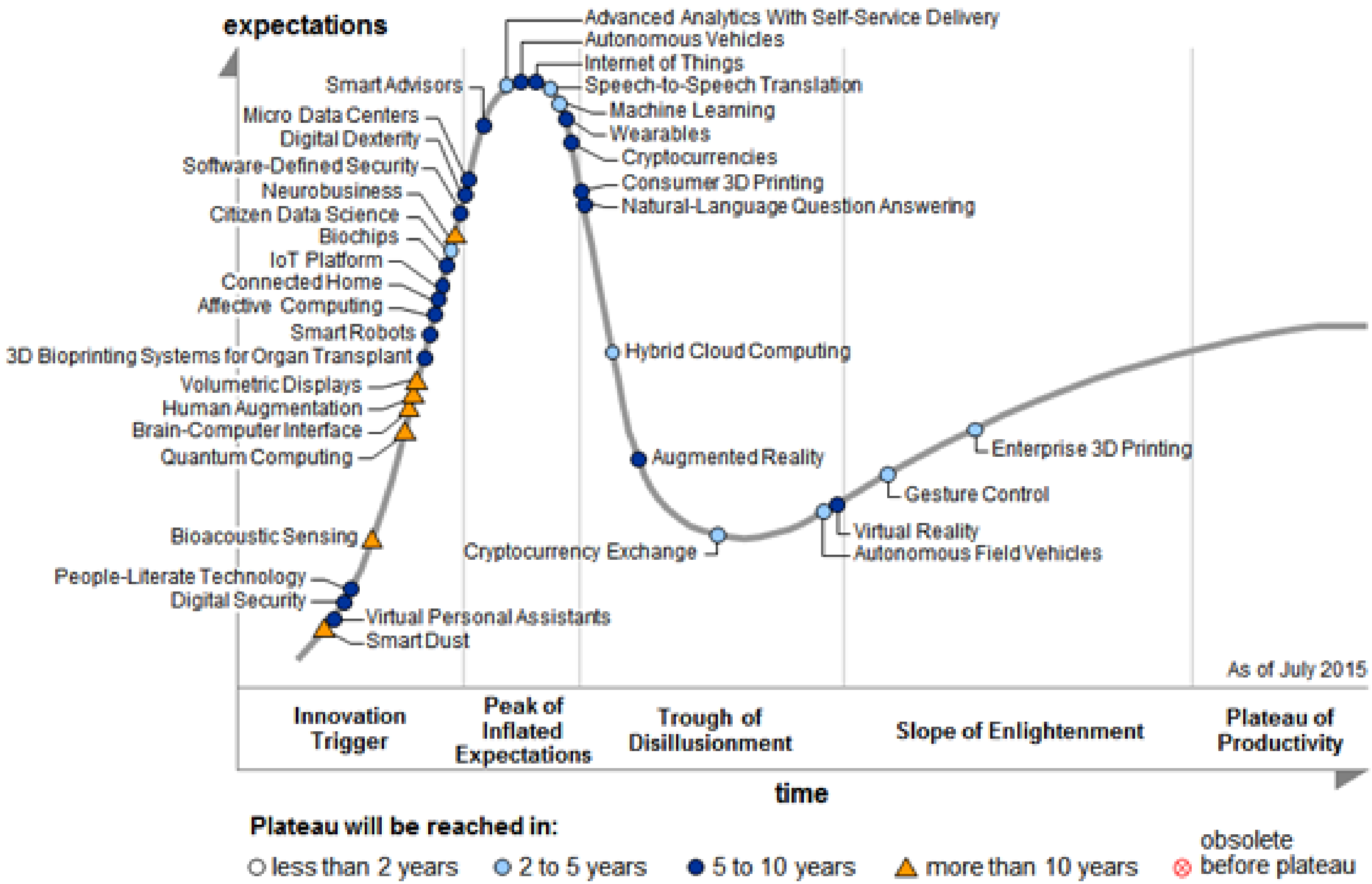
> 55% D

< 55% F

Course project

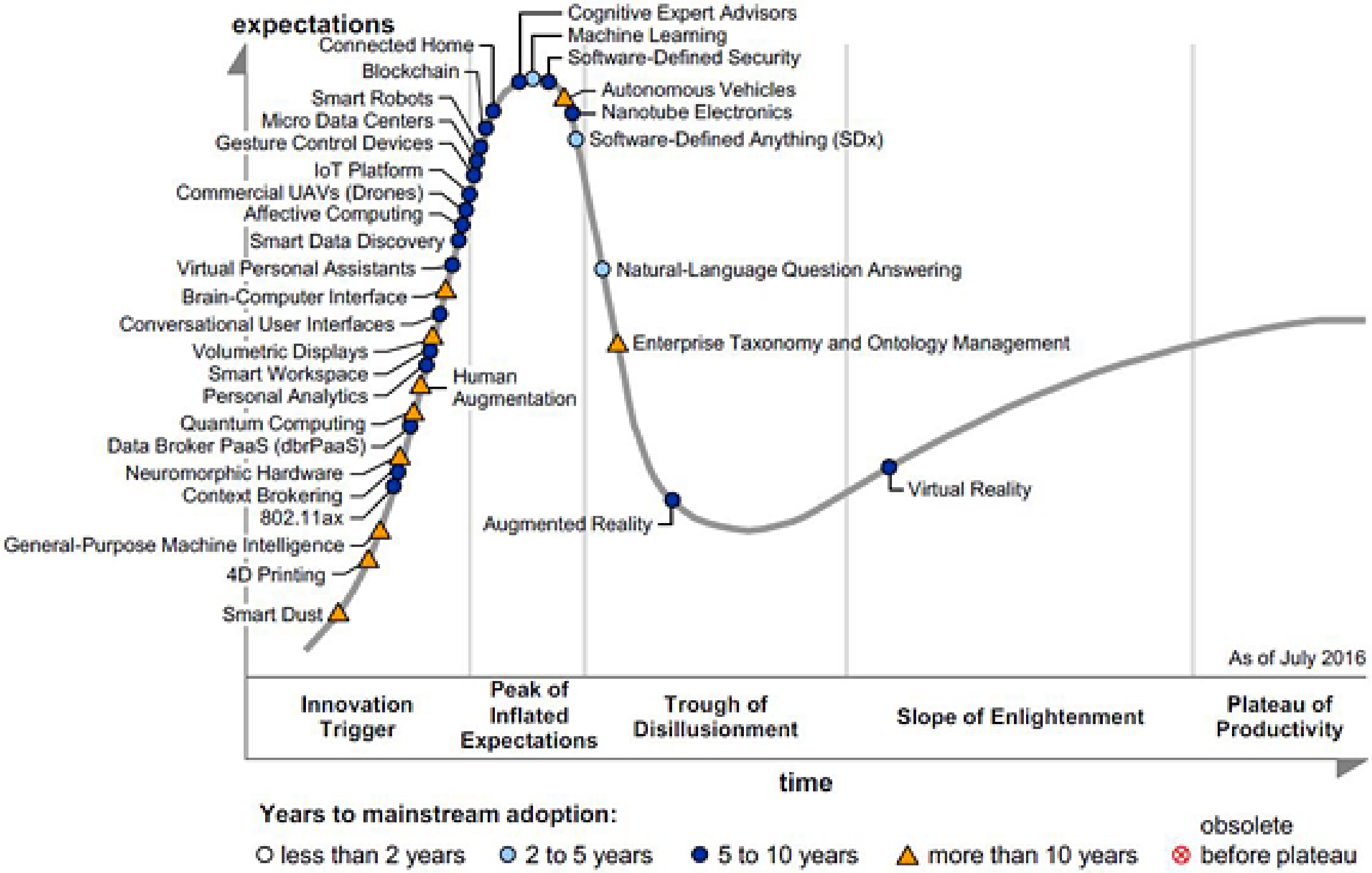
- <= 5 people
- Topic of your choice
  - Can be implementing a paper
  - Extension of a homework
  - Project for other courses with an additional machine learning component
  - Your current research (with additional scope)
  - Or work on a new application
  - Must already have existing data! No data collection!
- Topics need to be pre-approved
  - Details about the procedure TBA

The machine learning trend 2015



http://www.gartner.com/newsroom/id/3114217

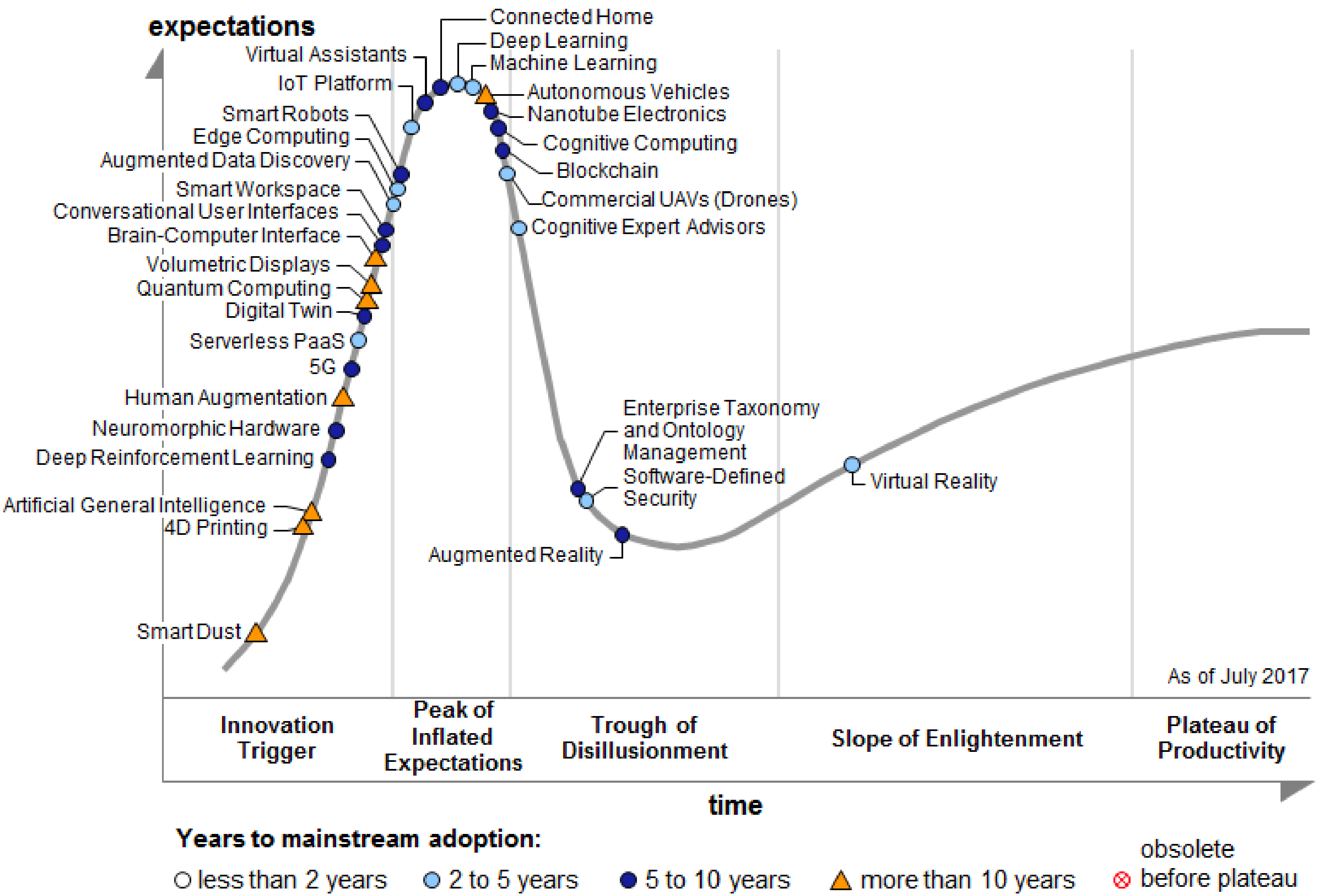
The machine learning trend 2016



Source: Gartner (July 2016)

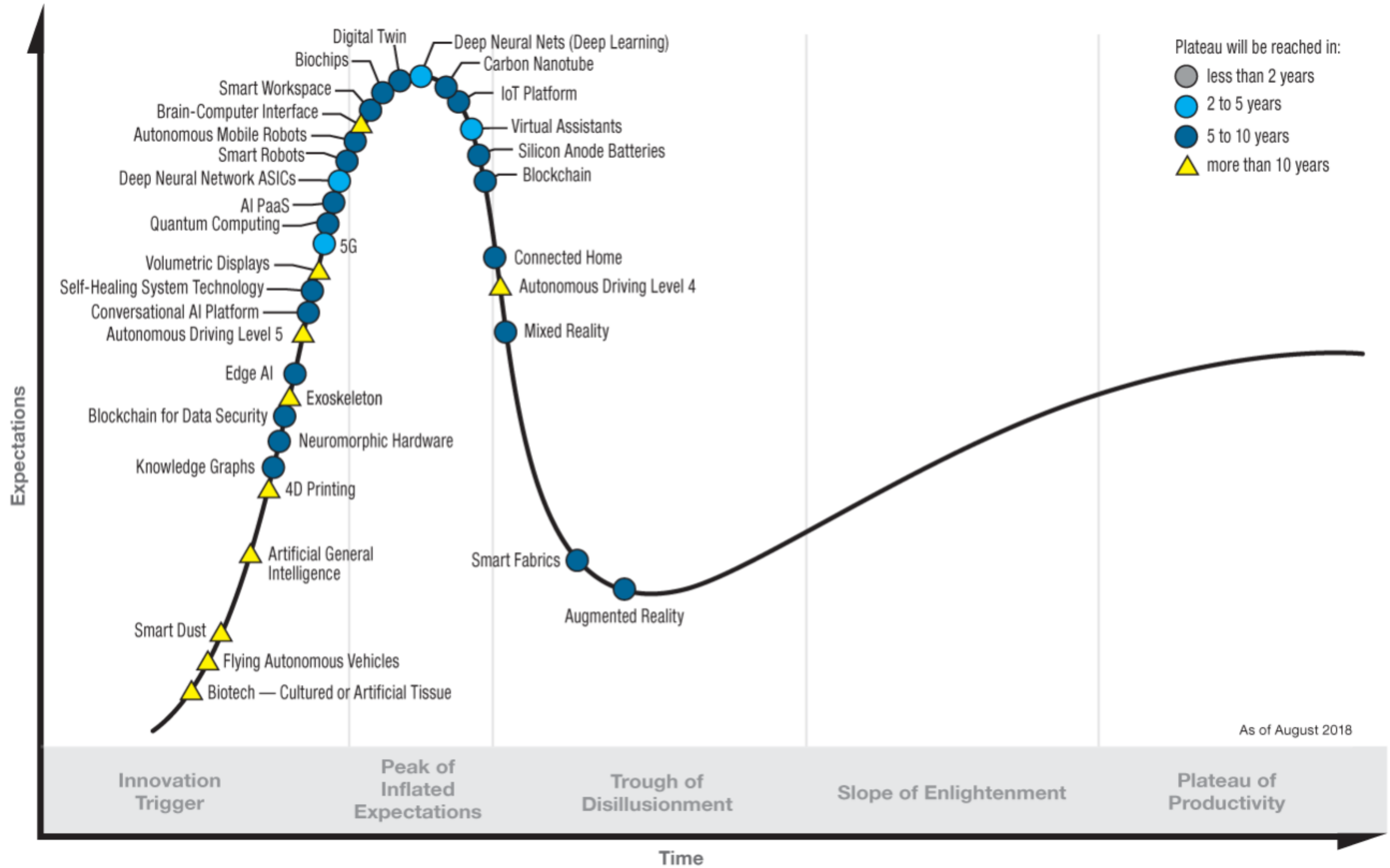
http://www.gartner.com/newsroom/id/3412017

The machine learning trend 2017



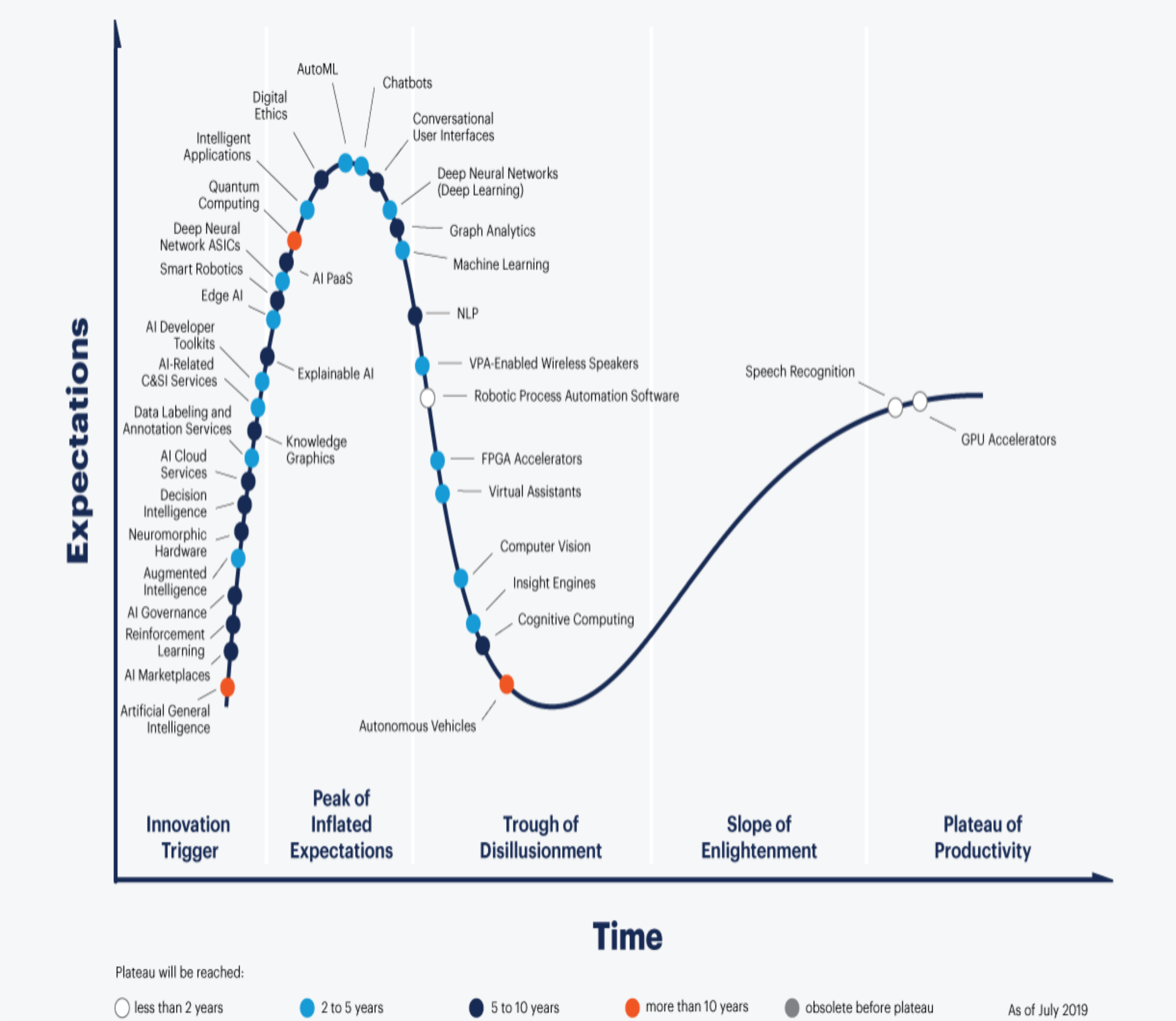
http://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017/

The machine learning trend 2018



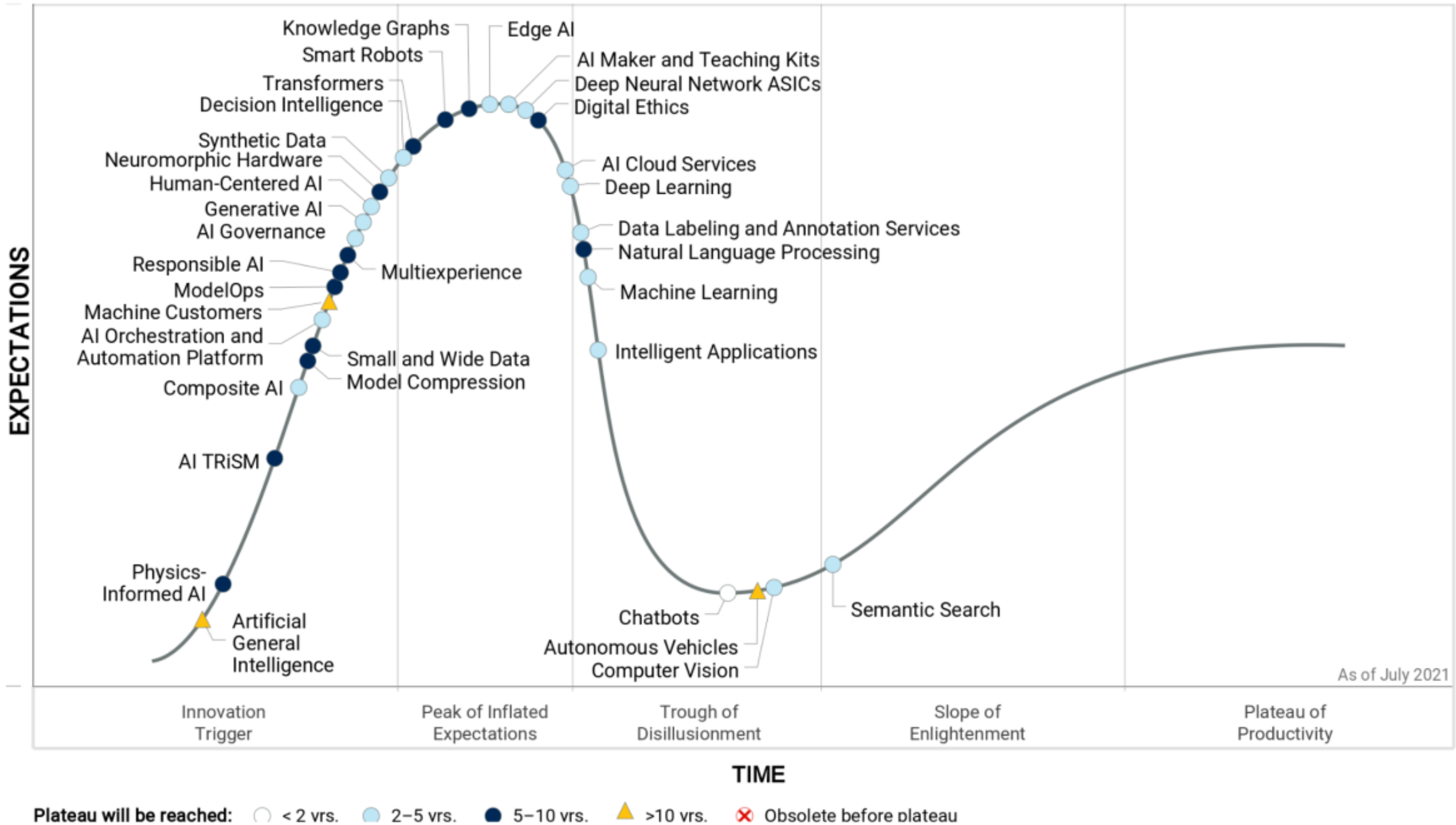
https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018/

The machine learning trend 2019



https://www.gartner.com/smarterwithgartner/top-trends-on-the-gartner-hype-cycle-for-artificial-intelligence-2019/

The machine learning trend 2021



Gartner

2022

Source: Gartner

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The metaverse hype

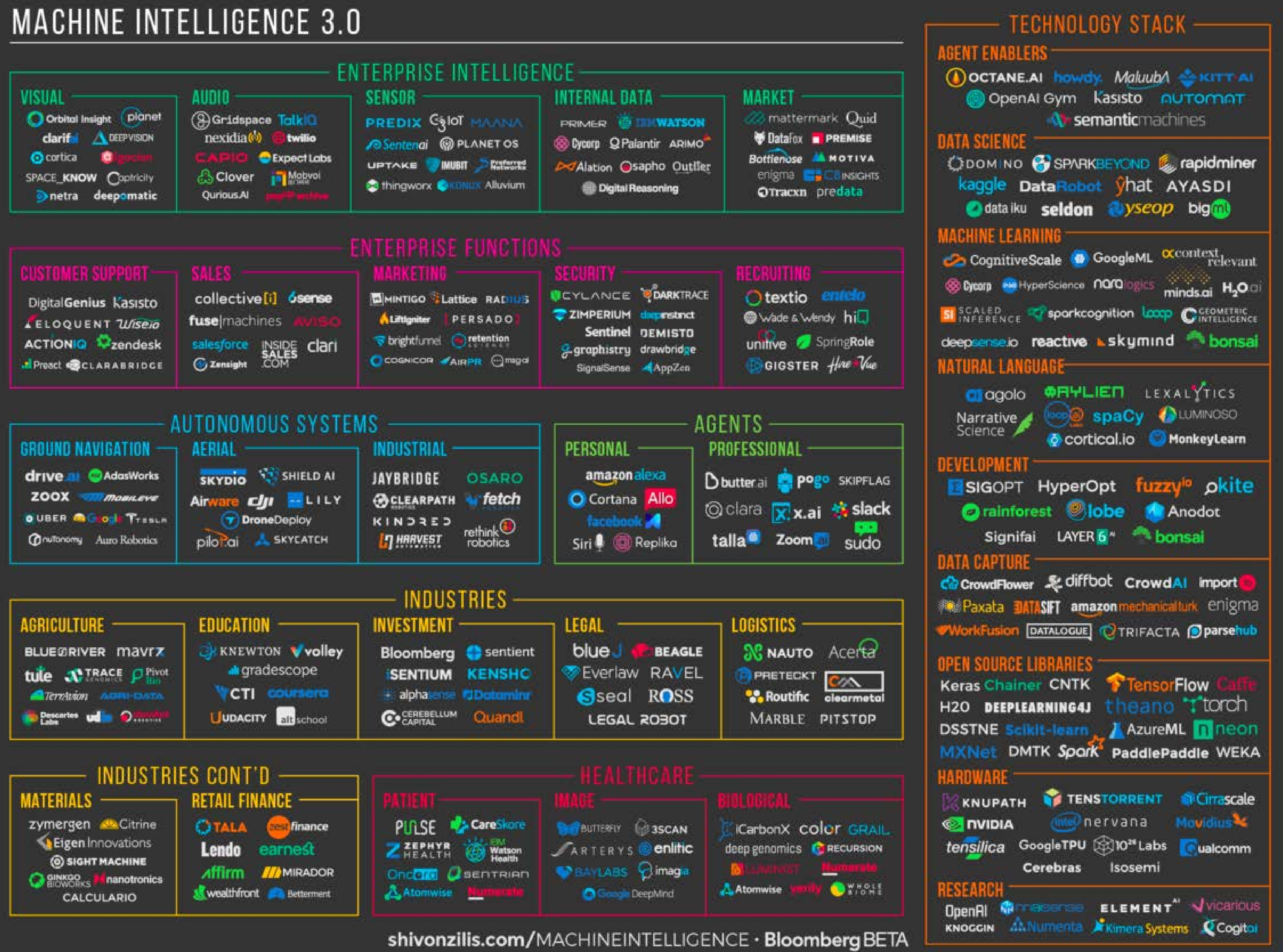
Facebook's metaverse may usher in impressive hyperrealistic tech but your privacy could be at risk

https://www.euronews.com/next/2022/01/12/facebook-s-metaverse-may-see-impressive-hyperrealistic-tech-but-your-privacy-could-be-at-r

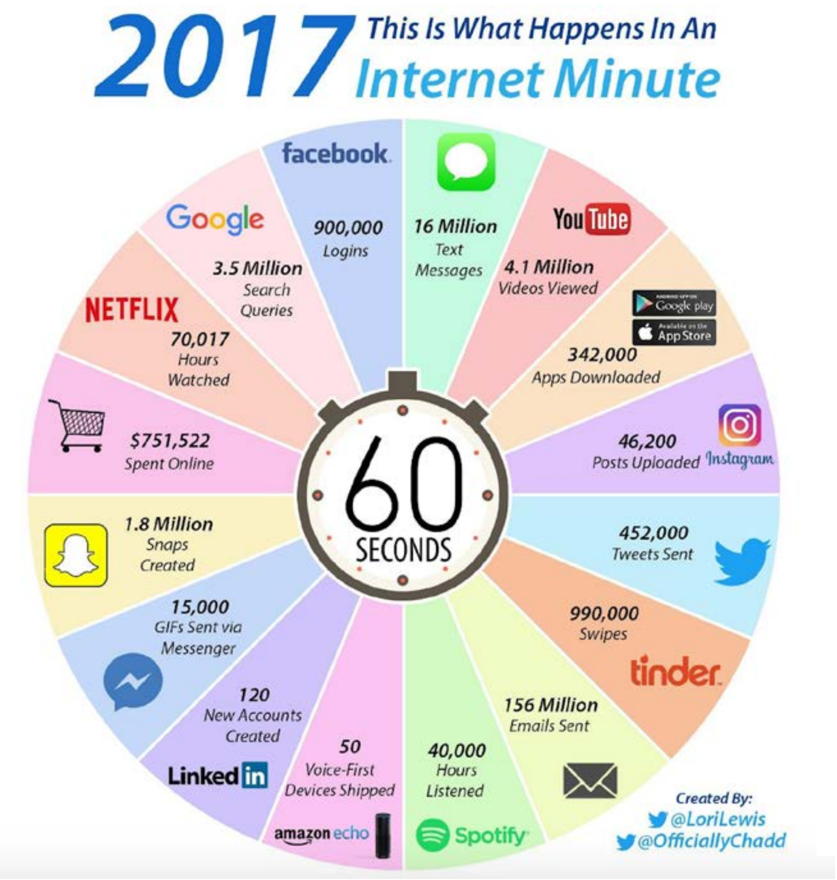
Full-time positions around Metaverse @ Meta Inbox ×

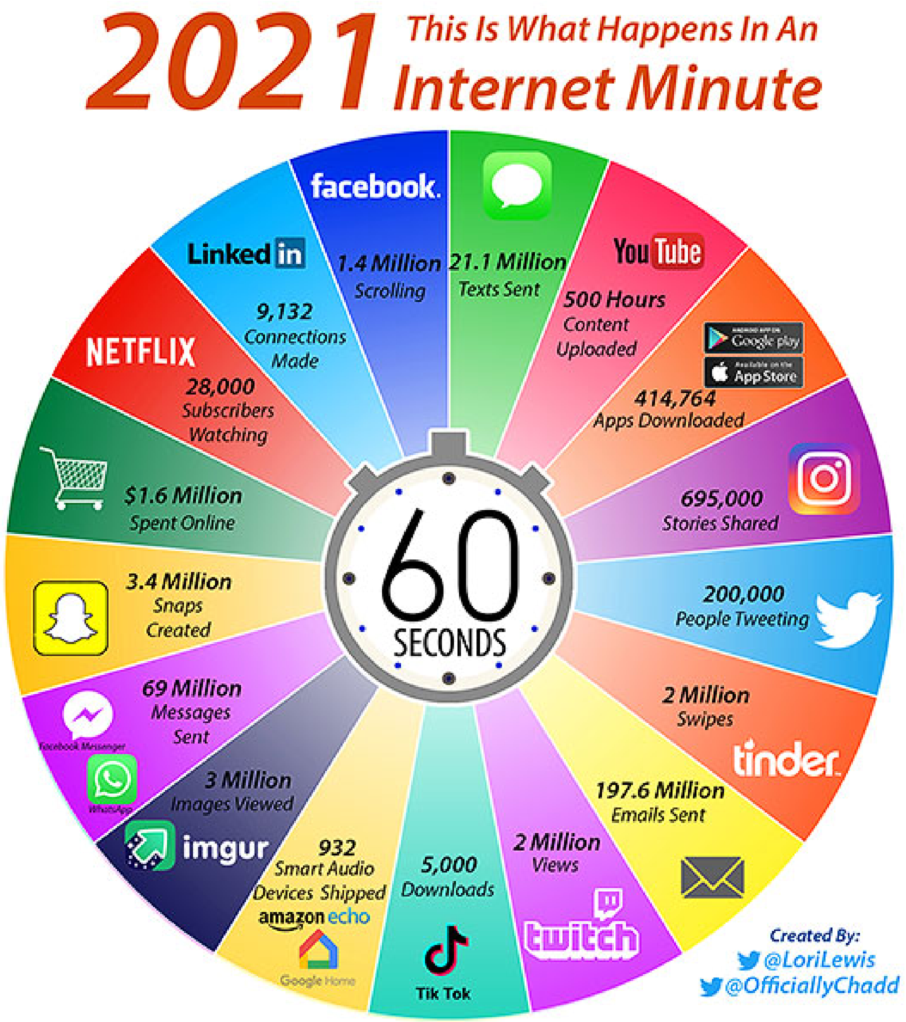
8:57 PM (1 hour ago)

Meta is now expanding its efforts around Metaverse and I am on the look for bright minds in areas of conversational AI, reinforcement learning, multi-modal interaction, and multi-agent systems applied to augmented reality. For Research Scientist positions a PhD degree is required. For Software eng. positions you can apply with BSc. and up.


MACHINE INTELLIGENCE 3.0
ENTERPRISE INTELLIGENCE
VISUAL
Orbital Insight
planet
clarifai
DEEPVISION
cortica
SPACE_KNOW
Captricity
netra
deepomatic
AUDIO
Gridspace
TalkIQ
nexidia
twilio
CAPIO
Expect Labs
Clover
Mobvoi
Qurious.AI
SENSOR
PREDIX
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
ACTIONIQ
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
mogul
SECURITY
CYLANCE
DARKTRACE
ZIMPERIUM
deepinstinct
Sentinel
DEMISTO
graphistry
drawbridge
SignalSense
AppZen
RECRUITING
textio
entelo
Wade & Wendy
hiQ
unitive
SpringRole
GIGSTER
HireVue
AUTONOMOUS SYSTEMS
GROUND NAVIGATION
drive.ai
AdasWorks
ZOOX
MOBILEYE
UBER
Google
TESLA
nuTonomy
Auro Robotics
AERIAL
SKYDIO
SHIELD AI
Airware
dji
LILY
DroneDeploy
pilot.ai
SKYCATCH
INDUSTRIAL
JAYBRIDGE
OSARO
CLEARPATH
fetch
KINDRED
rethink robotics
HARVEST
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
iSENTIUM
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
dataiku
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
H2O
DEEPLEARNING4J
theano
torch
DSSTNE
Scikit-learn
AzureML
neon
MXNet
DMTK
Spark
PaddlePaddle
WEKA
HARDWARE
KNUPATH
TENSTORRENT
Cirrascale
NVIDIA
intel nervana
Movidius
tensilica
GoogleTPU
10^{26} Labs
Qualcomm
Cerebras
Isosemi
RESEARCH
OpenAI
maluuba
ELEMENT AI
vicarious
KNOGGIN
Numenta
Kimera Systems
Cogitai
shivonzilis.com/MACHINEINTELLIGENCE · Bloomberg BETA

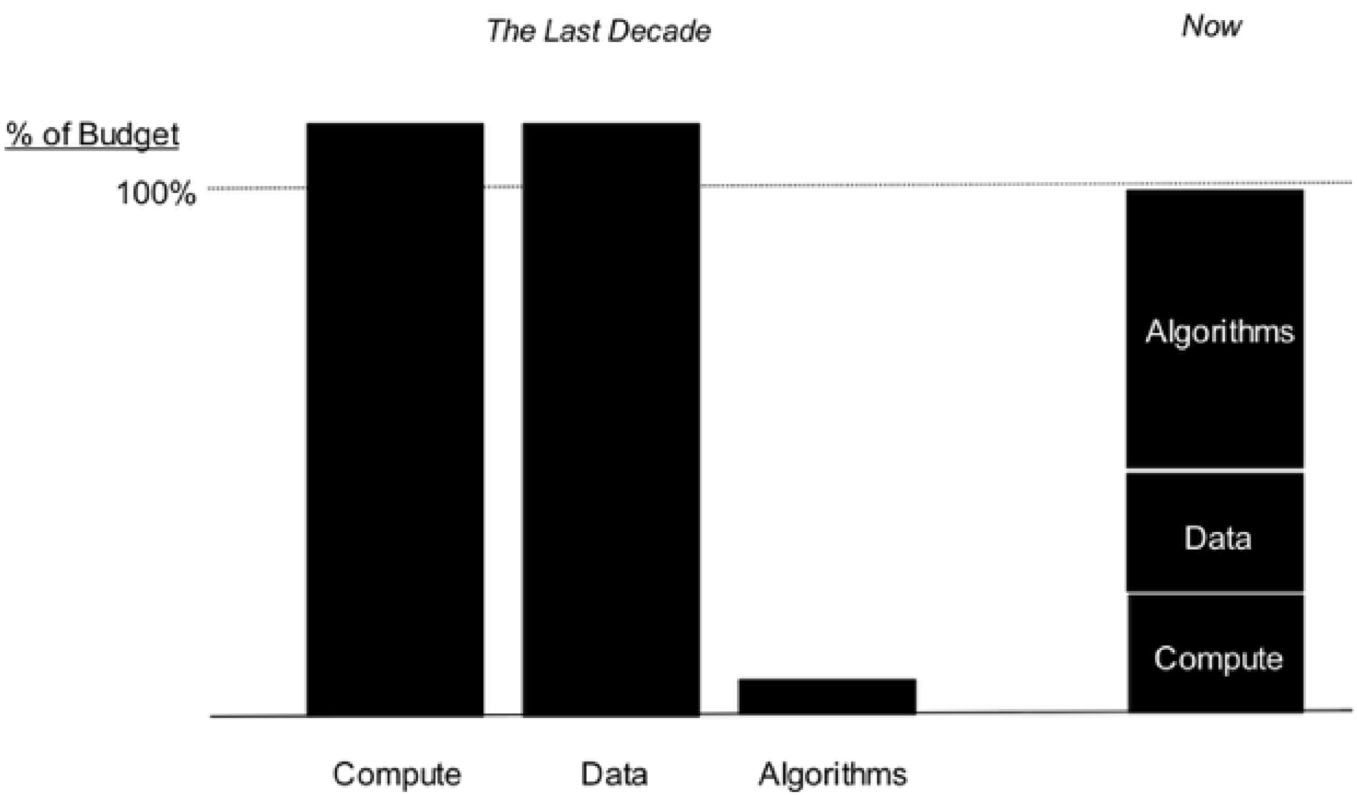
The data era


2017 This Is What Happens In An Internet Minute
facebook
900,000 Logins
16 Million Text Messages
You Tube
4.1 Million Videos Viewed
Google
3.5 Million Search Queries
NETFLIX
70,017 Hours Watched
342,000 Apps Downloaded
$751,522 Spent Online
46,200 Posts Uploaded Instagram
60 SECONDS
1.8 Million Snaps Created
452,000 Tweets Sent
15,000 GIFs Sent via Messenger
990,000 Swipes
tinder
120 New Accounts Created
Linked in
50 Voice-First Devices Shipped
amazon echo
40,000 Hours Listened
Spotify
156 Million Emails Sent
Created By: @LoriLewis @OfficiallyChadd


2021 This Is What Happens In An Internet Minute
facebook
1.4 Million Scrolling
21.1 Million Texts Sent
Linked in
9,132 Connections Made
You Tube
500 Hours Content Uploaded
NETFLIX
28,000 Subscribers Watching
414,764 Apps Downloaded
$1.6 Million Spent Online
695,000 Stories Shared
60 SECONDS
3.4 Million Snaps Created
200,000 People Tweeting
69 Million Messages Sent
2 Million Swipes
tinder
3 Million Images Viewed
imgur
197.6 Million Emails Sent
932 Smart Audio Devices Shipped
amazon echo
5,000 Downloads
Tik Tok
2 Million Views
twitch
Created By: @LoriLewis @OfficiallyChadd

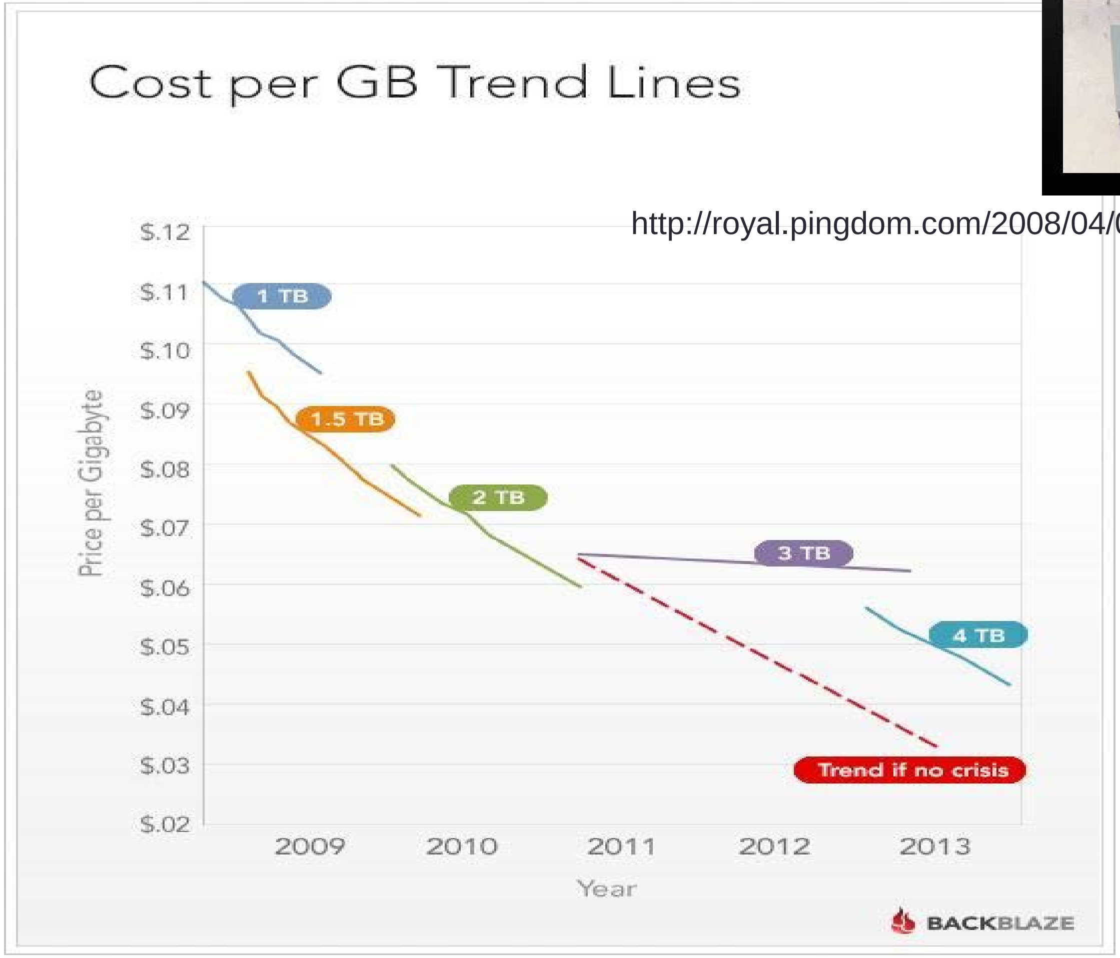
Factors for ML

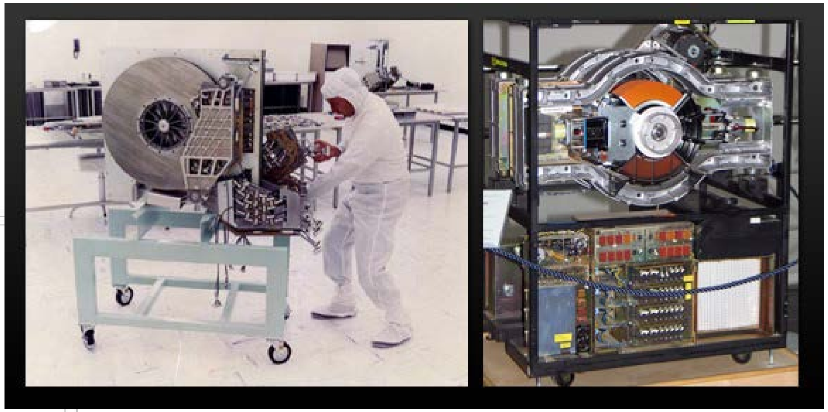
- Data
- Compute
- Algo



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

The cost of storage



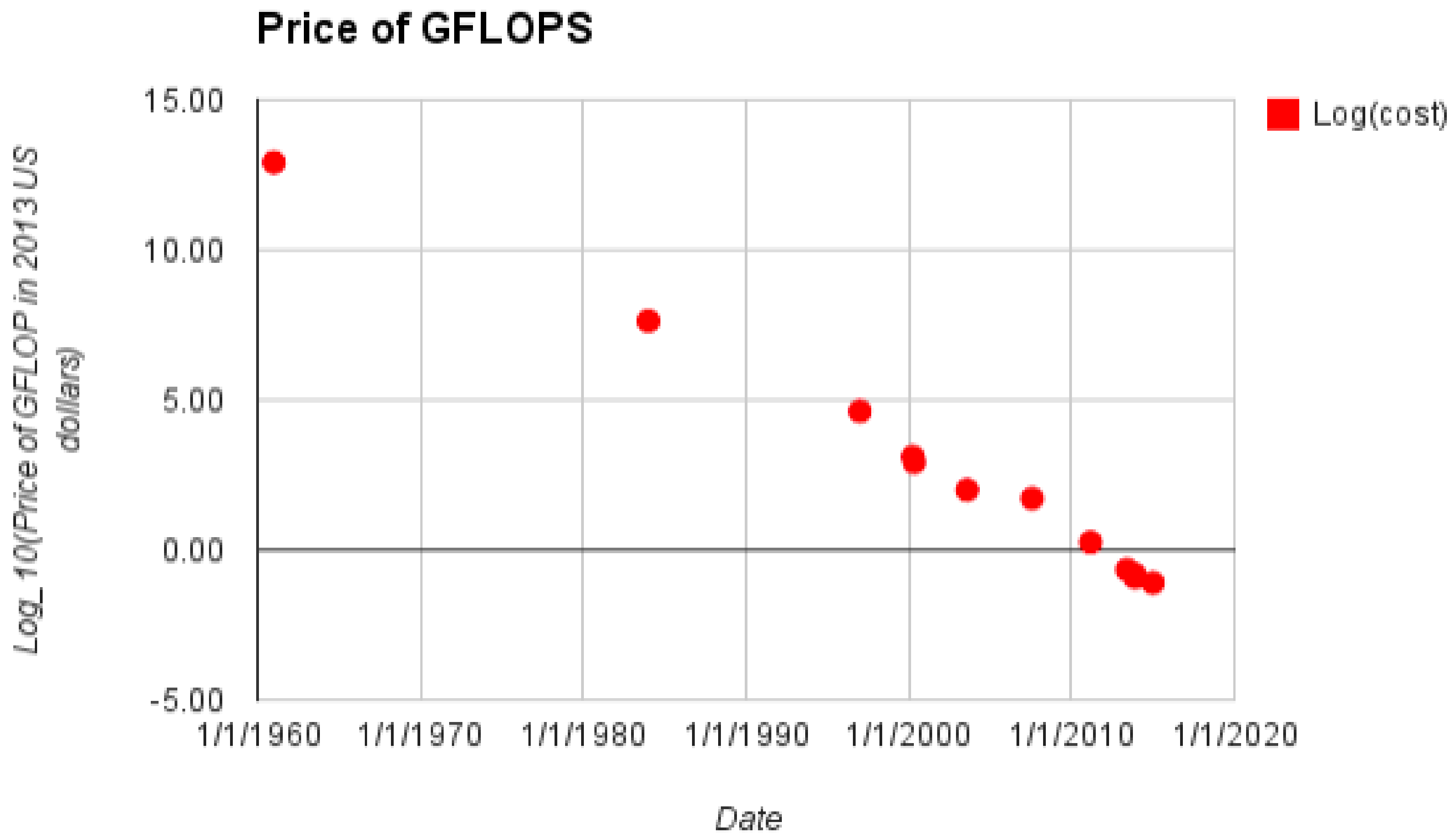


http://royal.pingdom.com/2008/04/08/the-history-of-computer-data-storage-in-pictures/

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

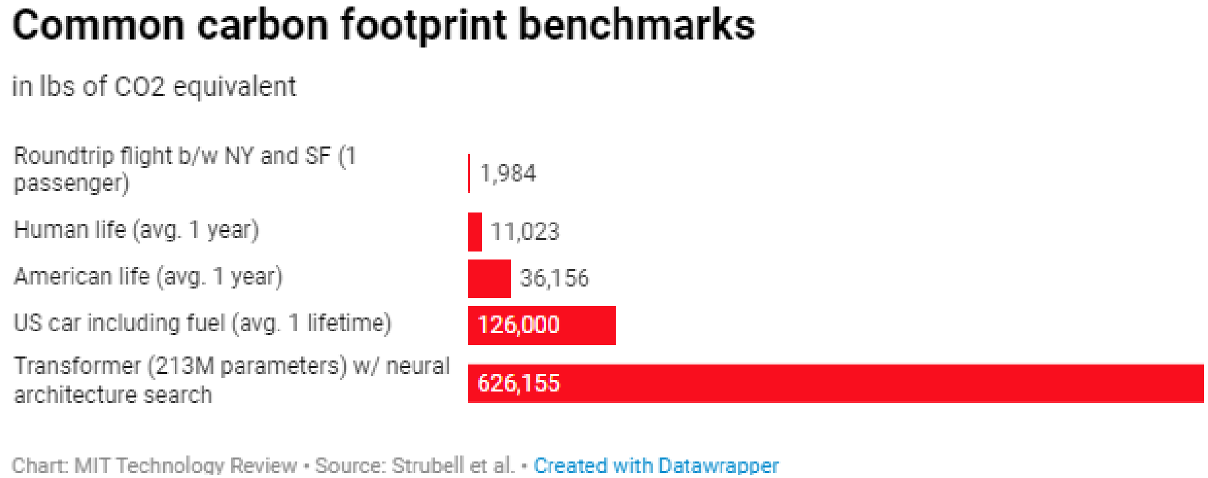
https://www.backblaze.com/blog/farming-hard-drives-2-years-and-1m-later/

The cost of compute

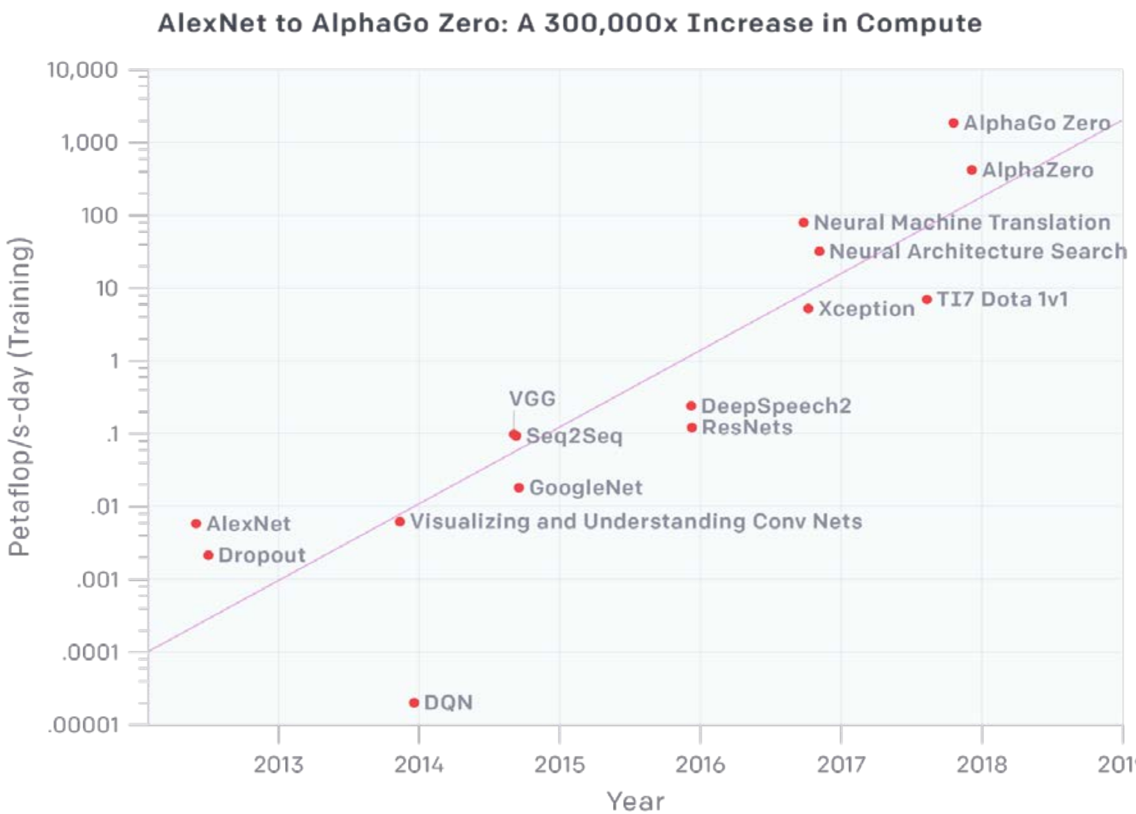


http://aiimpacts.org/trends-in-the-cost-of-computing/

Deep learning and compute

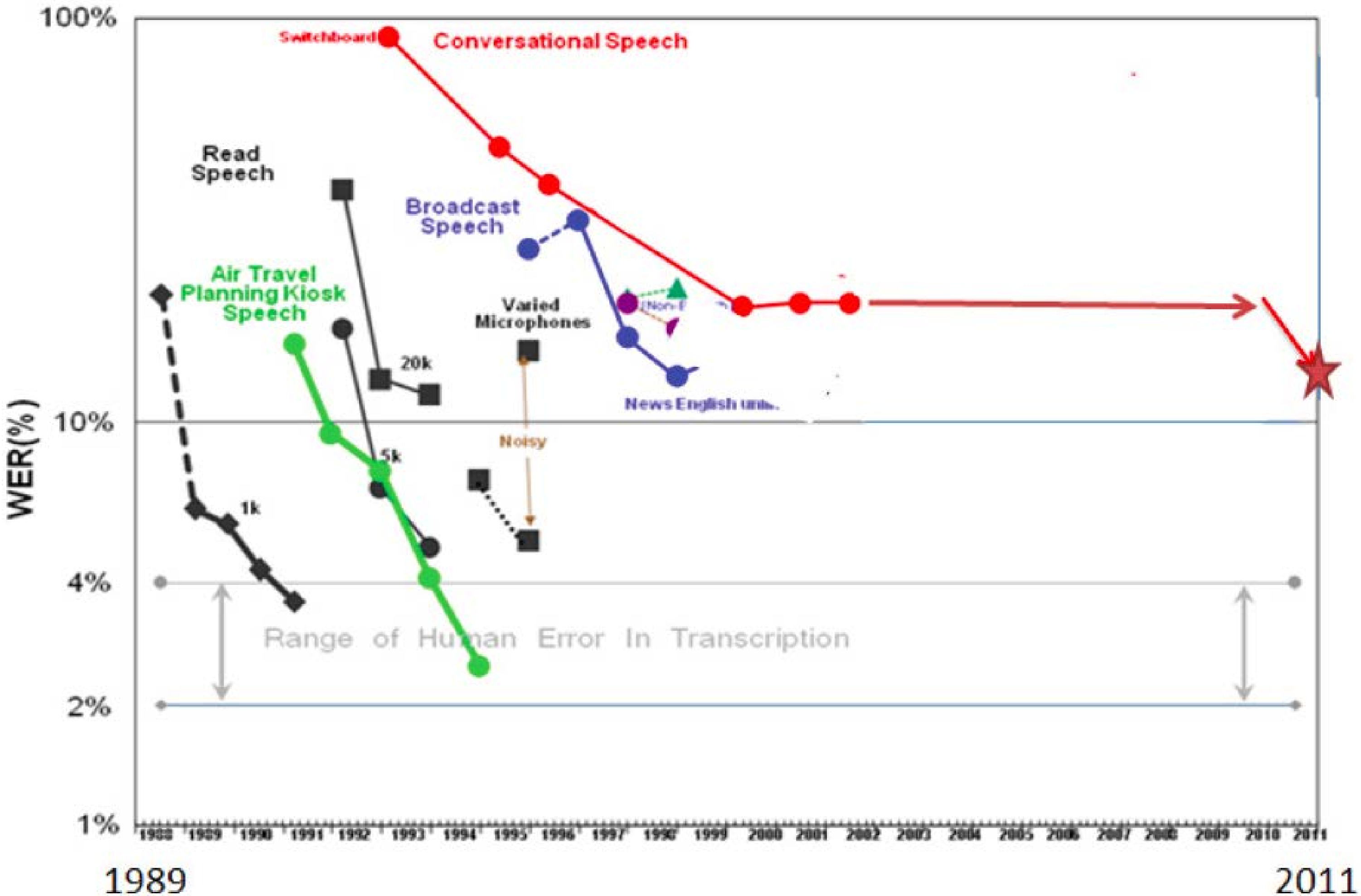


https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/



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

- “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.”

- "I think people who are naysayers and try to drum up these doomsday scenarios — I just, I don't understand it. It's really negative and in some ways I actually think it is pretty irresponsible"

Darren Cunningham @dcunni · 6h

Zuckerberg blasts @elonmusk warnings against artificial intelligence as 'pretty irresponsible' bizjournals.com/sanjose/news/2... @svbizjournal #ai

Facebook CEO Mark Zuckerberg blasts Tesla CEO Elon Musk's warn...

"People who are naysayers and try to drum up these doomsday scenarios — I just, I don't understand it," the Facebook CEO said. "It's really negative

bizjournals.com

30 296 566

Elon Musk

@elonmusk

Following

Replying to @dcunni @SVbizjournal

I've talked to Mark about this. His understanding of the subject is limited.

8:07 AM - 25 Jul 2017

© Twitter

Poll

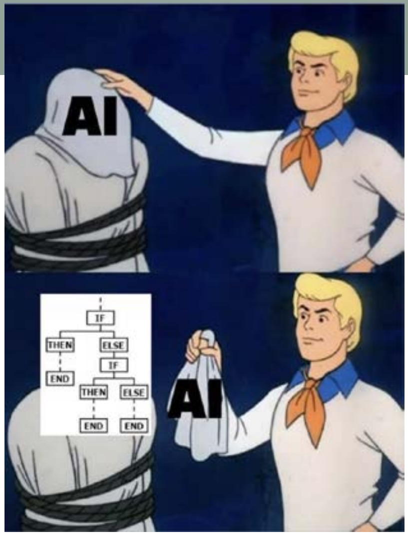
What is Pattern Recognition?

- "Pattern recognition is a branch of machine learning that focuses on the recognition of patterns and regularities in data, <u>although it is in some cases considered to be nearly synonymous with machine learning</u>."

  wikipedia

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

What is AI?



- Classical definition
  - A system that <u>appears</u> intelligent
- Populace definition

- Probably what the field means right now
  - ML
    - narrow AI
      - Specialized

ทปอ. เปิดตัว "AI ช่วยเลือกสาขาเรียน" เผยระบบพร้อมรับผู้สมัครใช้งานราว 500,000 คน

พฤศจิกายน 26, 2018 | By Techsauce Team

ที่ประชุมอธิการบดีแห่งประเทศไทย (ทปอ.) ประกาศความพร้อมการคัดเลือกบุคคลเข้าศึกษาต่อระดับอุดมศึกษาของระบบ TCAS ประจำปีการศึกษา 2562 เปิดตัวระบบไอทีสุดล้ำอีก 3 ระบบ พร้อม AI ช่วยผู้สมัครเลือกสาขาและ Cloud Computing รองรับผู้สมัคร 500,000 คน

https://techsauce.co/pr-news/tcas-use-cloud-computing-and-ai-for-admission

Artificial General Intelligence (AGI)

- "hypothetical ability of an intelligent agent to understand or learn any intellectual task that a human being can."

Wikipedia

Can continue to learn new skills on its own.

Probably not of much interest besides philosophical debates

Works done in baby steps

ML vs PR 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

History

- Pattern Recognition started from the engineering community (mainly Electrical Engineering and Computer Vision)
- Machine learning comes out of AI and mostly considered a Computer Science subject
- Data mining starts from the database community

Different community viewpoints

- A screw looking for a screw driver
- A screw driver looking for a screw

Different applications

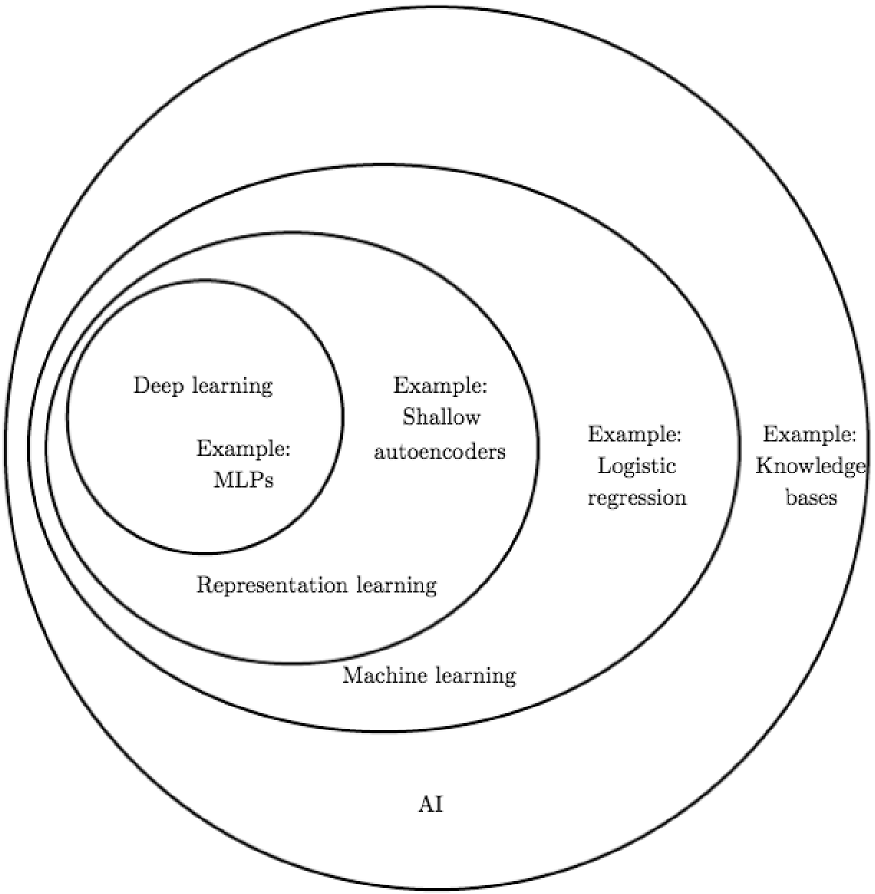
Different tools

The Screwdriver and the Screw

DM PR ML AI

Distinguishing things

- DM – Data warehouse, ETL
- AI – search, swarm intelligence
- PR – Signal processing (feature engineering)



http://www.deeplearningbook.org/

Different terminologies

http://statweb.stanford.edu/~tibs/stat315a/glossary.pdf

Machine learning	Statistics
network, graphs	model
weights	parameters
learning	fitting
generalization	test set performance
supervised learning	regression/classification
unsupervised learning	density estimation, clustering
large grant $= \$1{,}000{,}000$	large grant$= \$50{,}000$

Merging communities and fields

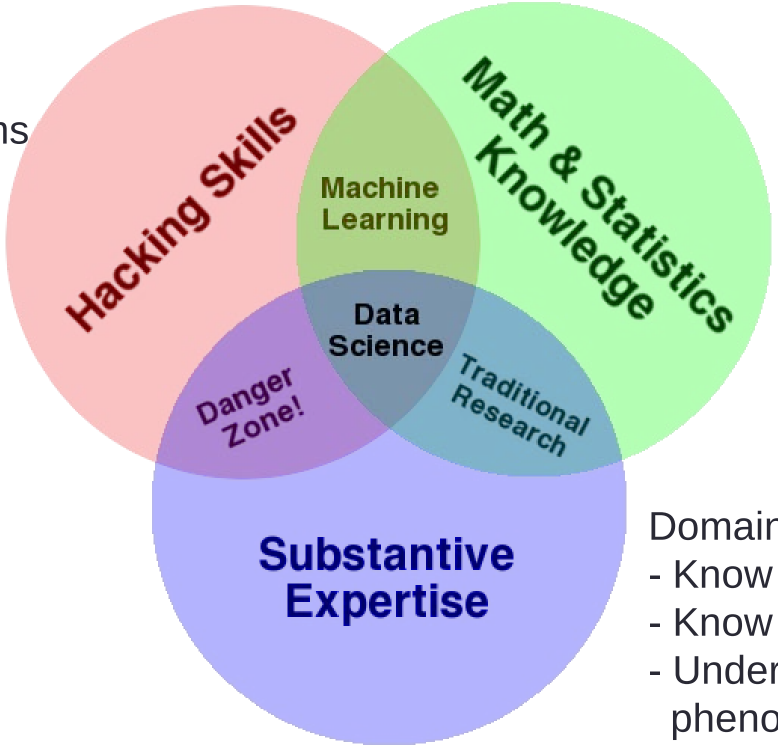
- With the advent of Deep learning the fields are merging and the differences are becoming unclear

Data science & Data analytics

- How to get value from data
  - Data-driven decision making

Programming
- Algorithms
- Distributed systems
- Database
- Hardware

Math knowledge
- Statistics
- Probability
- Optimization
- Linear algebra

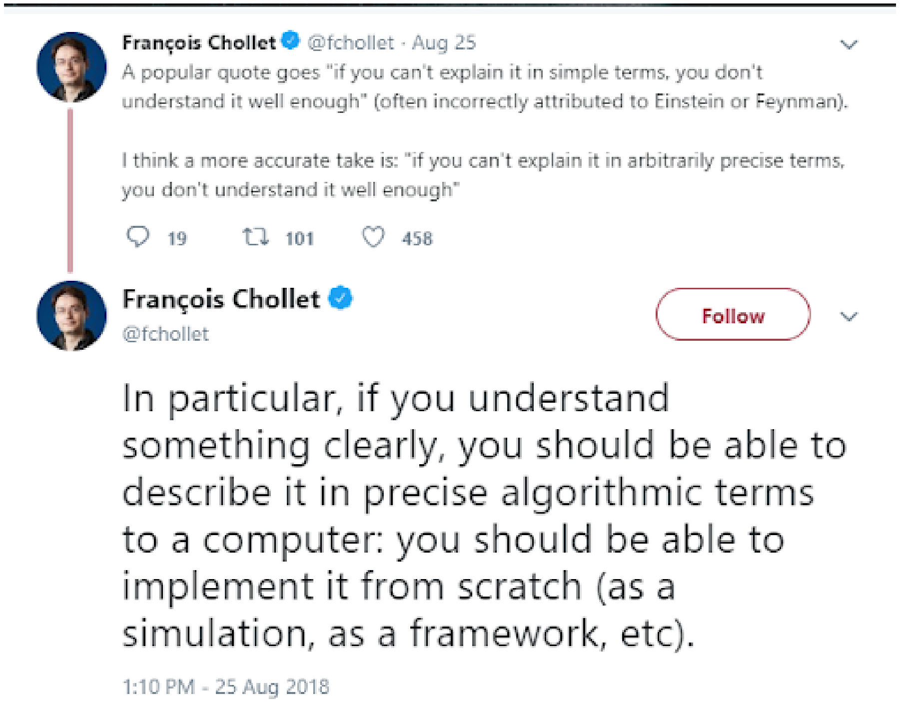


Domain knowledge
- Know the right questions to ask
- Know the relevant information
- Understand the underlying phenomena

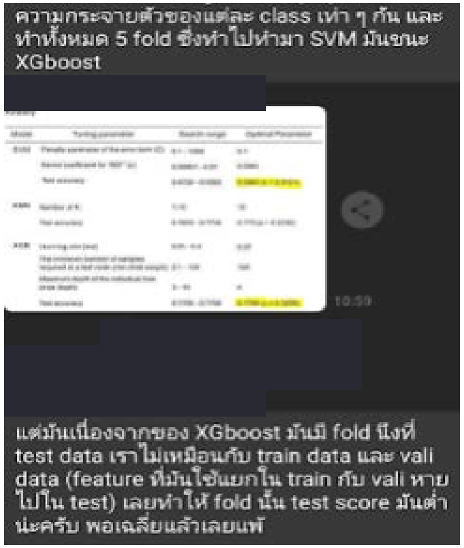
http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

Course philosophy

- Going beyond the black box
- In this course you will
  - Understand models on a deeper level
  - Implement stuff from scratch



The danger zone



อาจารย์ครับ ผมมีประโยคตัดเป็นคำ ใส่เป็น word bag ที่มีขนาดเท่ากับ vocab
ใส่เป็นความถี่ของคำในประโยค
แล้วผ่าน TF-IDF แล้วเข้า Multinomial NB มันพังกว่าไม่ผ่าน TF-IDF ครับ ผมสงสัยว่าเป็นเพราะอะไร ผมรู้แค่ว่าค่า prob มันเปลี่ยนจริงๆ มันน่าจะดี เพราะผมทำ TF-IDF บน SVM แล้วผลมันดีครับ

ผมใช้ laplace ด้วยครับ แต่ผลไม่น่าพังขนาดนั้น alpha=1 ครับ

อาจารย์ครับ ควรแบ่ง data ไงดีครับตอนทำ neural net
ผมมี data อยู่ของช่วงวันที่ 9-16 ครับ
คือ ตอนที่ทำ linear กับ pca ผมใช้ train เป็นช่วงวันที่ 9 - 13 ครับ ส่วน test ผมใช้ช่วง 14-15
ตอนทำ neural net ถ้าผมใช้เป็นวันที่ 16 วันเดียวพอไหมครับ หรือควรแบ่ง data ใหม่ครับ
ตอนนี้ training set ผมมีประมาณ 360000 ครับ ส่วน test set มีประมาณ 150000 ครับ

แล้วจึงนำภาพ3D 11440 ไป Train เข้า CNN แล้ว Classify ว่า เป็น 1(Depression Group) หรือ 0(Control Group)

ซึ่งผมก็พยายามปรับพารามิเตอร์ต่าง ๆ ก็ได้ Acc สูงสุดที่ 65%

ผมเลยมามองว่าจะใช้ GRU ด้วย

ปล.การ Train ครั้งก่อน ทำการ shuffle ดาต้าเรียบร้อยแล้วนะครับ

คราวนี้ GRU จะต้องรับ input ยังไงเหรอครับ คือ รับเปน 11440 โดยไม่ shuffle แล้วตั้ง batch=143 เพื่อให้มันมองเป็น คน ๆ ไปเหรอครับ ?

หรือผมต้องมี 1 timesteps มาคั่นระหว่าง sample เพื่อให้มันแยกได้

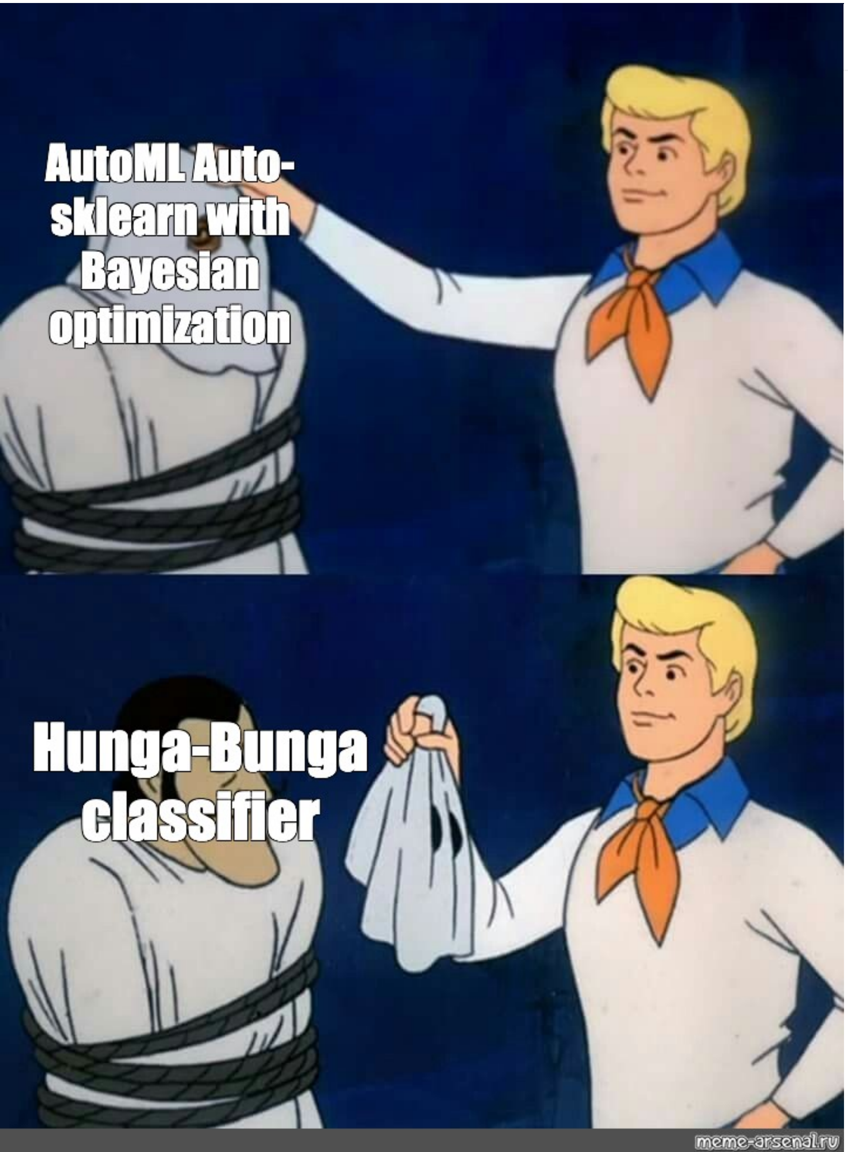
อย่างถ้าเป็นใน HW1 ของ NLP มันจะให้เราทำ model ที่บอกว่าขึ้นประโยคใหม่หรือยัง แต่ของผมจะเป็นแบบนอกจากบอกว่าขึ้นประโยคใหม่แล้ว ยังต้องบอกด้วยว่าเป็น Noun, Verb, หรือ Adj. ประมาณนั้นอ่ะครับ เพราะของผมคือต้องบอกว่าเป็น control หรือ depression โดยใช้ทั้งหมด 143 timesteps

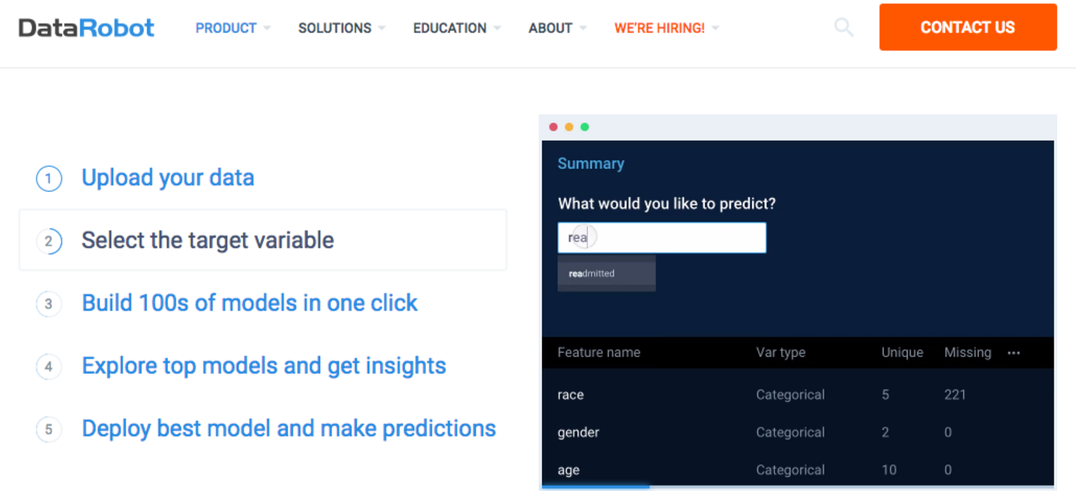
อีกอย่างที่สงสัยคือตอน test น่ะครับ อย่างงี้หมายความว่าถ้าผม test แต่ละ sample ด้วย 143 timestep input ผมก็จะได้ 143 outputs ใช่มั้ยครับ แต่ที่ผมต้องการคือ output ตัวเดวที่บอกว่าเป็น Depression หรือ Control เพียงค่าเดียว

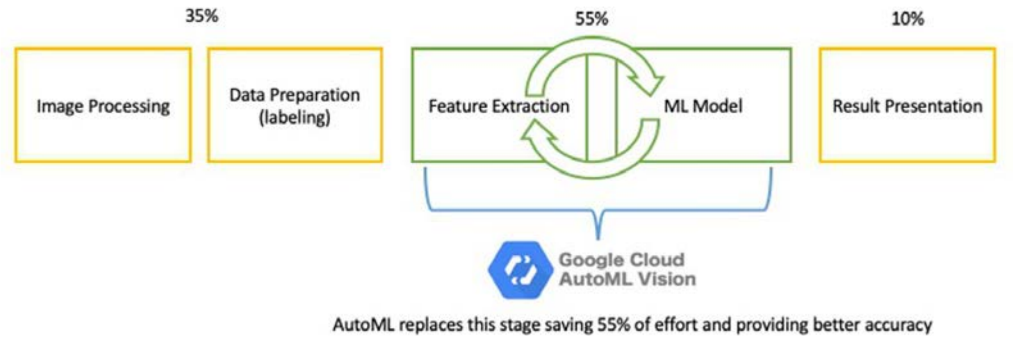
Driving a car analogy

- Just drive without knowing where you are going
- Getting there vs getting there effectively
- Putting the wrong fuel into the car

Be better than autoML







https://towardsdatascience.com/ocr-for-scanned-numbers-using-googles-automl-vision-29d193070c64

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 display
- 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

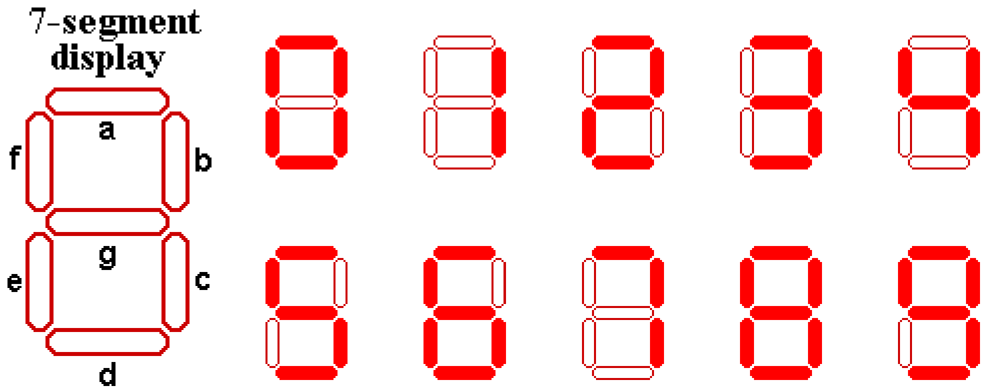
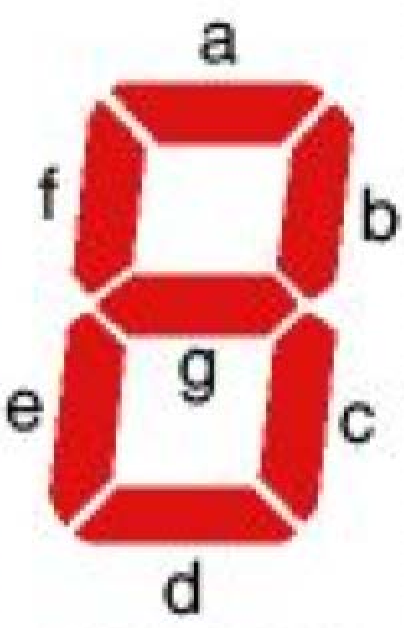


Image from http://www.physics.udel.edu/~watson/scen103/colloq2000/7-seg.html

Mapping function

Y ← X →

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

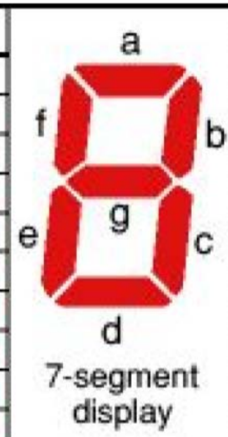


7-segment display

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)

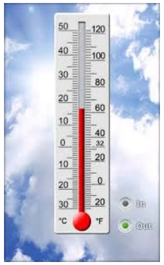
The 3D model

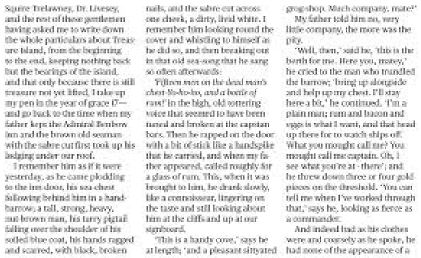

HANA_Tool_Reader
SkinnedMeshRenderer
None (Skinned Mesh R
Update Files
VRoid_v11_2_Female_Add.txt
VRoid_v11_2_Male_Add.txt
VRoid_v11_3_Female_Add.txt
VRoid_v11_3_Male_Add.txt
VRoid_v12_Female_Add.txt
VRoid_v12_Male_Add.txt
FirstPersonOffset

Learning from data

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

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:

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'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

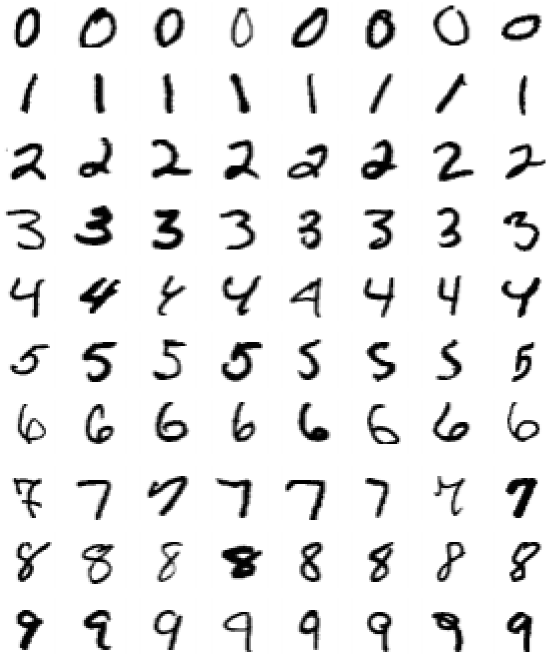
This is the hardest part of data science and the last part to be replaced by machines.

https://cloud.google.com/blog/products/gcp/how-a-japanese-cucumber-farmer-is-using-deep-learning-and-tensorflow

An example

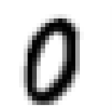
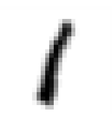
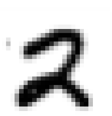
- Handwritten digit recognition
- Input: **x** = 28 x 28 pixel image
- Output: y = digit 0 to 9
- Task: find F(**x**) such that y ≈ F(**x**)

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

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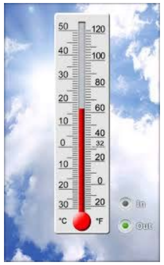

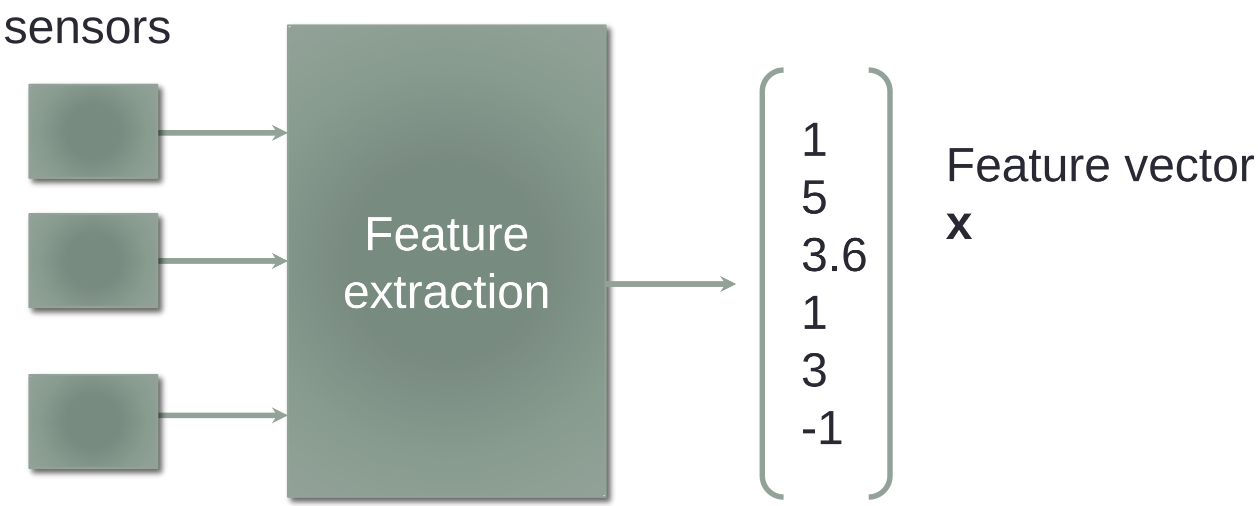

Hotdog classifier

https://www.youtube.com/watch?v=pqTntG1RXSY

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?

New input **X**

$$\begin{bmatrix} 1 \\ 5 \\ 3.6 \\ 1 \\ 3 \\ -1 \end{bmatrix} \longrightarrow \boxed{h} \longrightarrow \text{Predicted output } \mathbf{y}$$

Testing phase

Feature extraction

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

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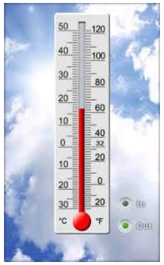


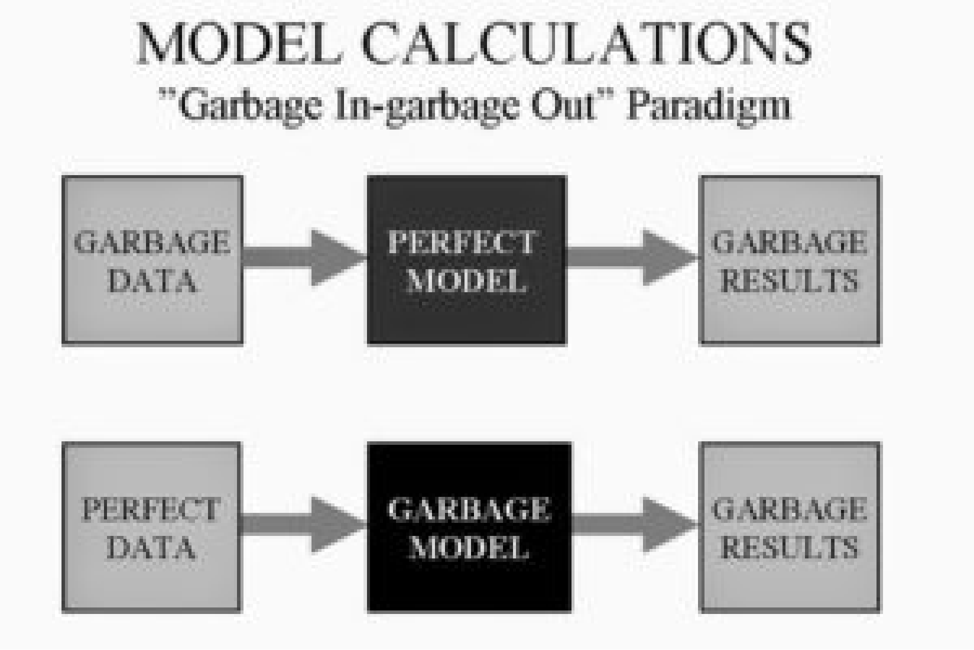
data1 →

data2 →

data3 →

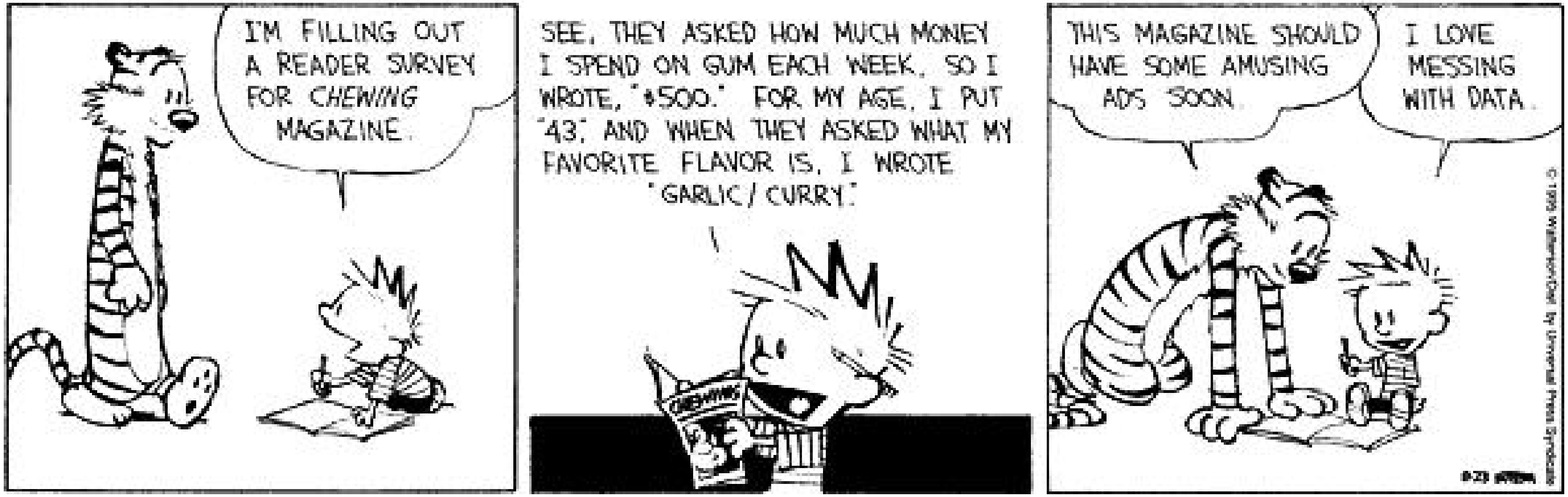
Garbage in Garbage out

- 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/

The need for data cleaning

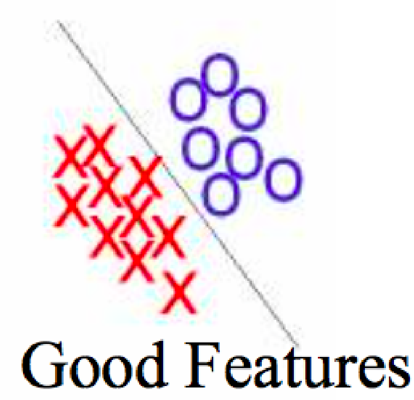


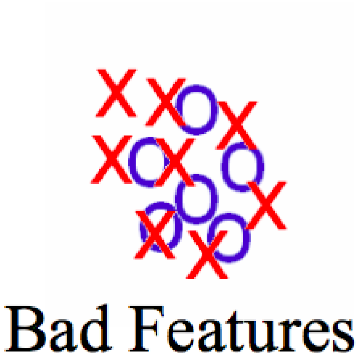
However, good models should be able to handle some dirtiness!

https://www.linkedin.com/pulse/big-data-conundrum-garbage-out-other-challenges-business-platform

Feature properties

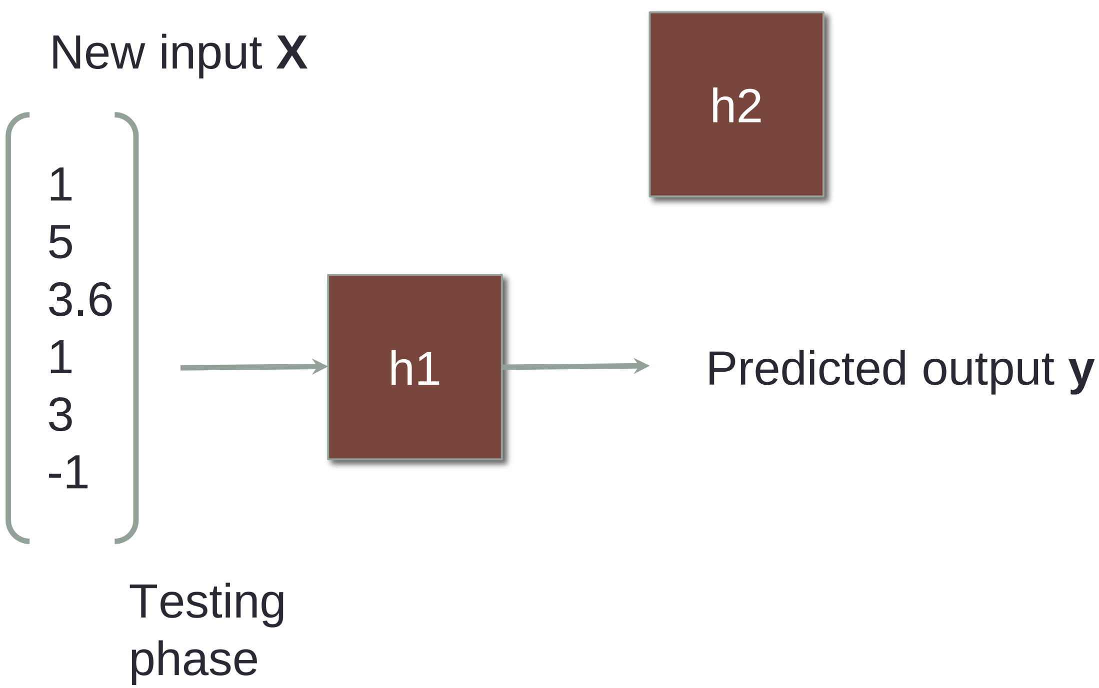
- The quality of the feature vector is related to its ability to discriminate samples from different classes





Model evaluation

How to compare h1 and h2?



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?

ไปไหน

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

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

Ground truths can be hard

Slides from https://github.com/goldmermaid/mlrs

Credit to Andrej Karpathy

Labelling

"Label lane lines"

Credit to Andrej Karpathy

Labelling issues

How do you annotate lane lines when they do this?

abel lane lines”

Credit to Andrej Karpathy

Credit to Andrej Karpathy

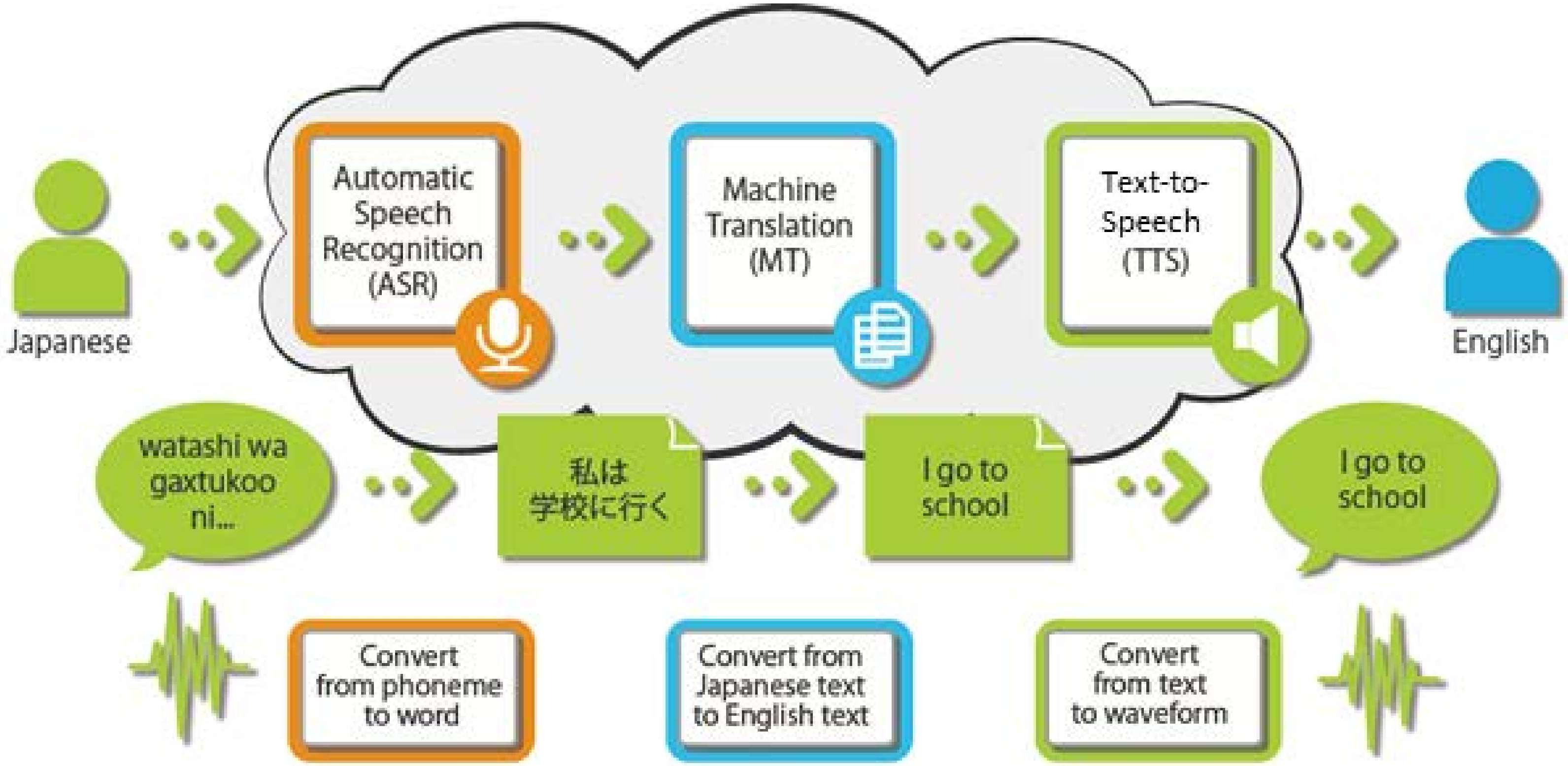
Metrics consideration 1

- Are there several metrics?

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

Metrics consideration 2

- Are there sub-metrics?

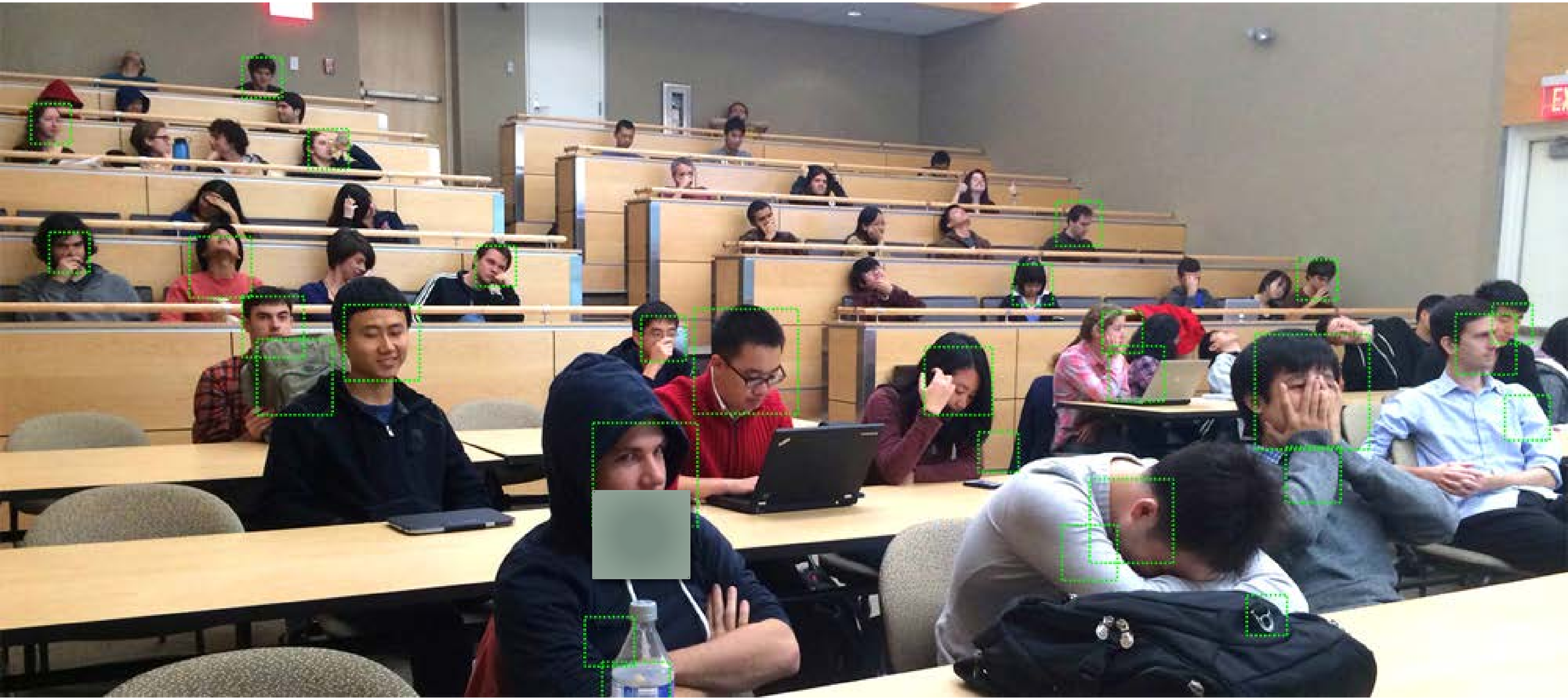


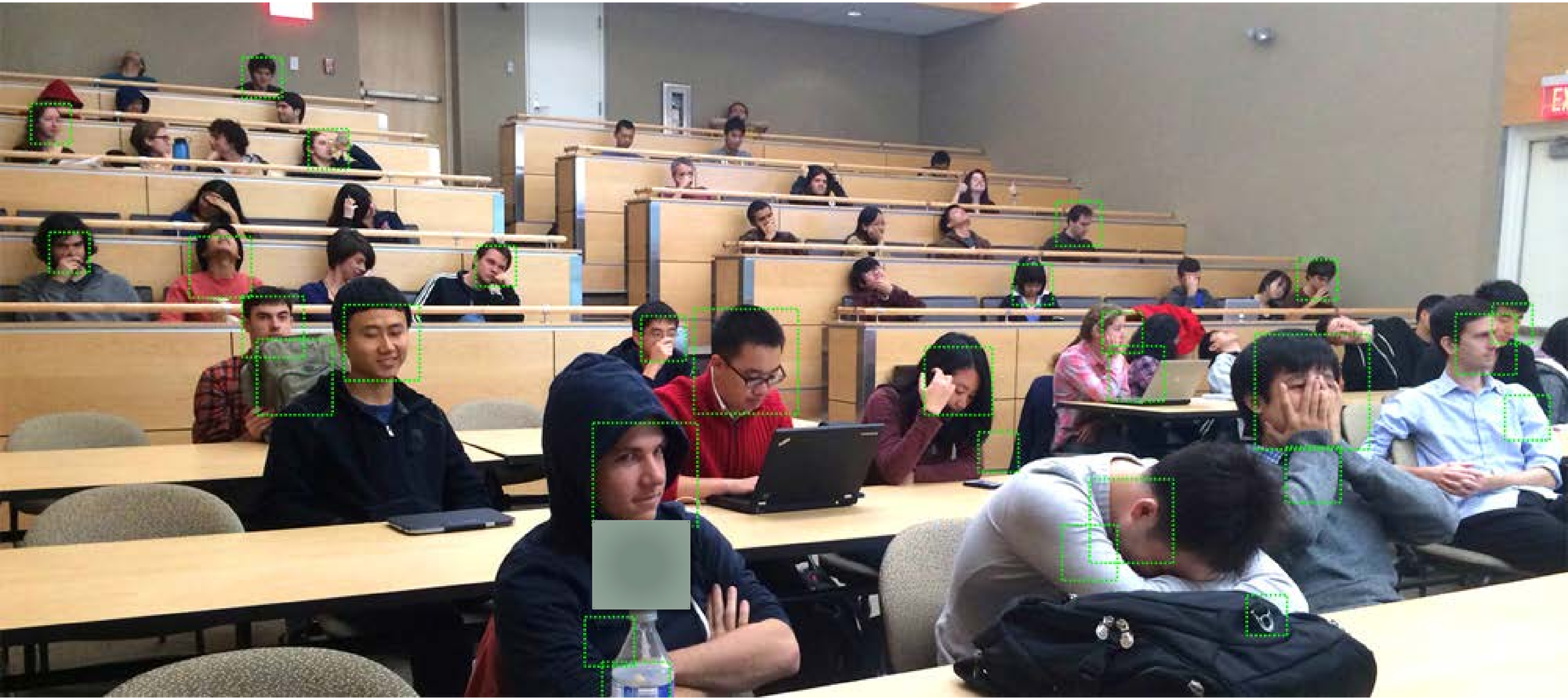
http://www.ustar-consortium.com/qws/slot/u50227/research.html

Metrics definition

- Defining a metric can be tricky when the answer is flexible

https://www.cc.gatech.edu/~hays/compvision/proj5/

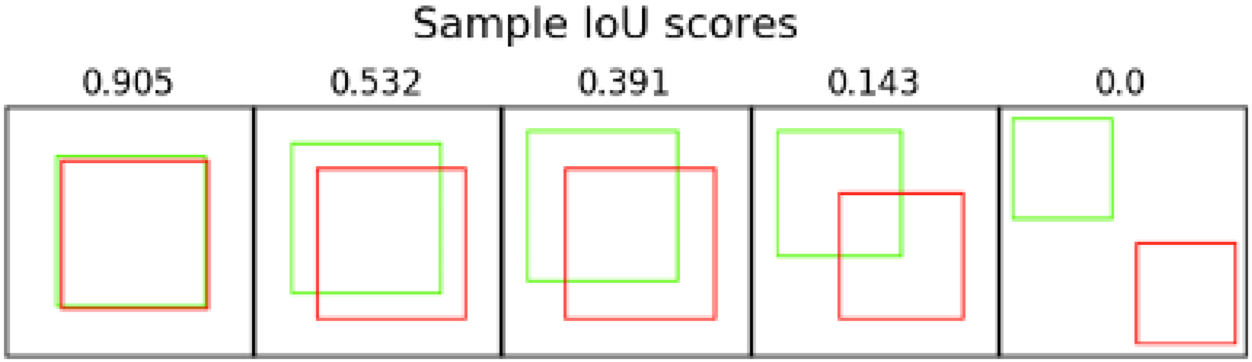




Be clear about your definition of an error before hand!
Make sure that it can be easily calculated!
This will save you a lot of time.

IoU (Intersection over Union)

What IoU score should be considered a detection?



http://ronny.rest/tutorials/module/localization_001/iou/

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

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

- True positive rate (Recall, sensitivity)

  = # true positive / # of actual yes
- False positive rate (False alarm rate)

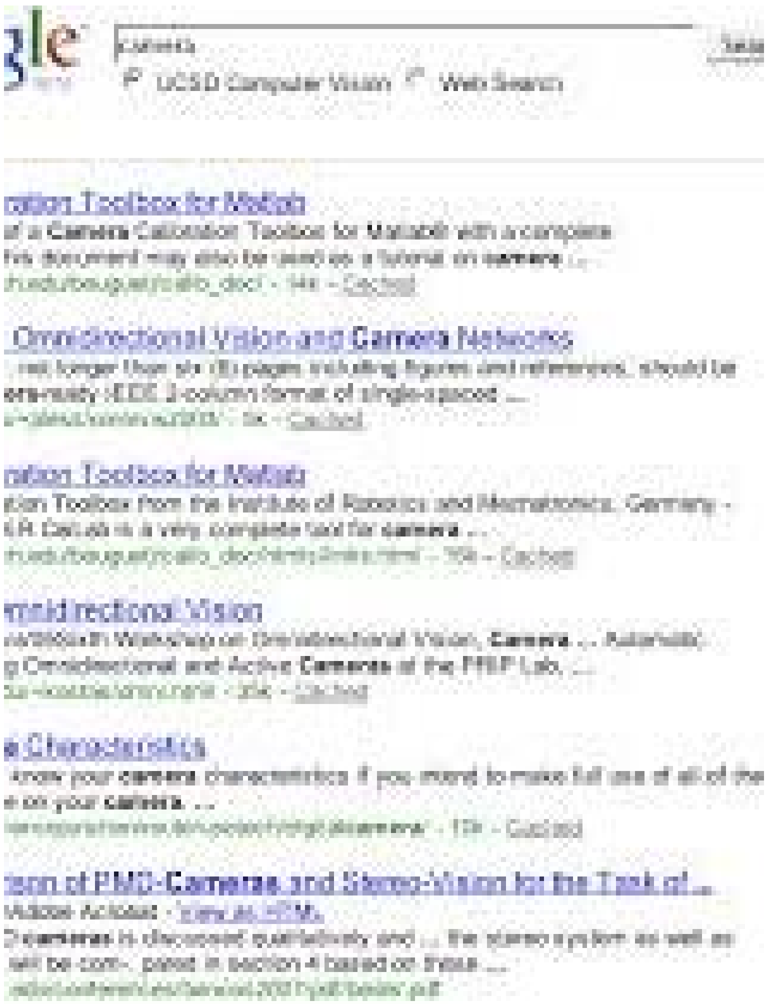
  = # false positive / # of actual no
- False negative rate (Miss rate)

  = # 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?

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
- COVID screening: ATK vs PCR

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

Let’s consider a case

- A: COVID screening kit 100% recall 10% precision
- B: COVID screening kit 10% accuracy

Let’s consider a case

- A: COVID screening kit 100% recall 10% precision
- B: COVID screening kit 10% accuracy
  - Always answer positive

		Detector	
		Yes	No
Actual	Yes	100	0
	No	900	0

- This population has 10% COVID cases
- What if the population has 20% COVID cases?
  - Prevalence of the data effects the metric values.

		Detector	
		Yes	No
Actual	Yes	30	22
	No	10	35

Let’s consider another case

- A: no rain predictor has 97% accuracy

Let's consider another case

- A: no rain predictor has 97% accuracy
  - Always say no rain.
- Accuracy is not a good metric for biased data
- A good model should be better than stupid baselines

		Detector	
		Yes	No
Actual	Yes	0	1
	No	0	30

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

Harmonic mean vs Arithmetic mean

- You travel for half an hour for 60 km/hr, then half an hour for 40 km/hr. What is your average speed?
  - Arithmetic mean = 50 km/hr
  - Harmonic mean

$$\frac{n}{\frac{1}{x_1}+\ldots+\frac{1}{x_n}} = \frac{2}{\frac{1}{40}+\frac{1}{60}} = \text{48 km/hr}$$

  - Total distance covered in 1 hour = 30+20 = 50

30 mins | 30 mins
60 km/hr | 40 km/hr

Harmonic mean vs Arithmetic mean

- You travel for distance X for 60 km/hr, then another X for 40 km/hr. What is your average speed?
  - Arithmetic mean = 50 km/hr
  - Harmonic mean

$$\frac{n}{\frac{1}{x_1}+\ldots+\frac{1}{x_n}} = \frac{2}{\frac{1}{40}+\frac{1}{60}} = \text{48 km/hr}$$

  - Total distance covered 2X

X km X km

60 km/hr 40 km/hr

Harmonic mean vs Arithmetic mean

- For the arithmetic mean to be valid you need to compared over the same number of hours (denominator)
  - Mean accuracy uses arithmetic mean

- For precision and recall, you have different denominators, but the same numerator, which fits the harmonic mean.

True positive rate (Recall, sensitivity) = # true positive / # of actual yes

Precision = # true positive / # of predicted positive

Evaluating models

- We talked about the training set used to learn the model
- We use a different data set to test the accuracy/error of models – “test set”
- We can still compute the error and accuracy on the training set
- Training error vs Testing error
- We will discuss how we can use these to help guide us later

Other considerations when evaluating models

- Training time
- Testing time
- Memory requirement
- Parallelizability
- Latency

Course walkthrough

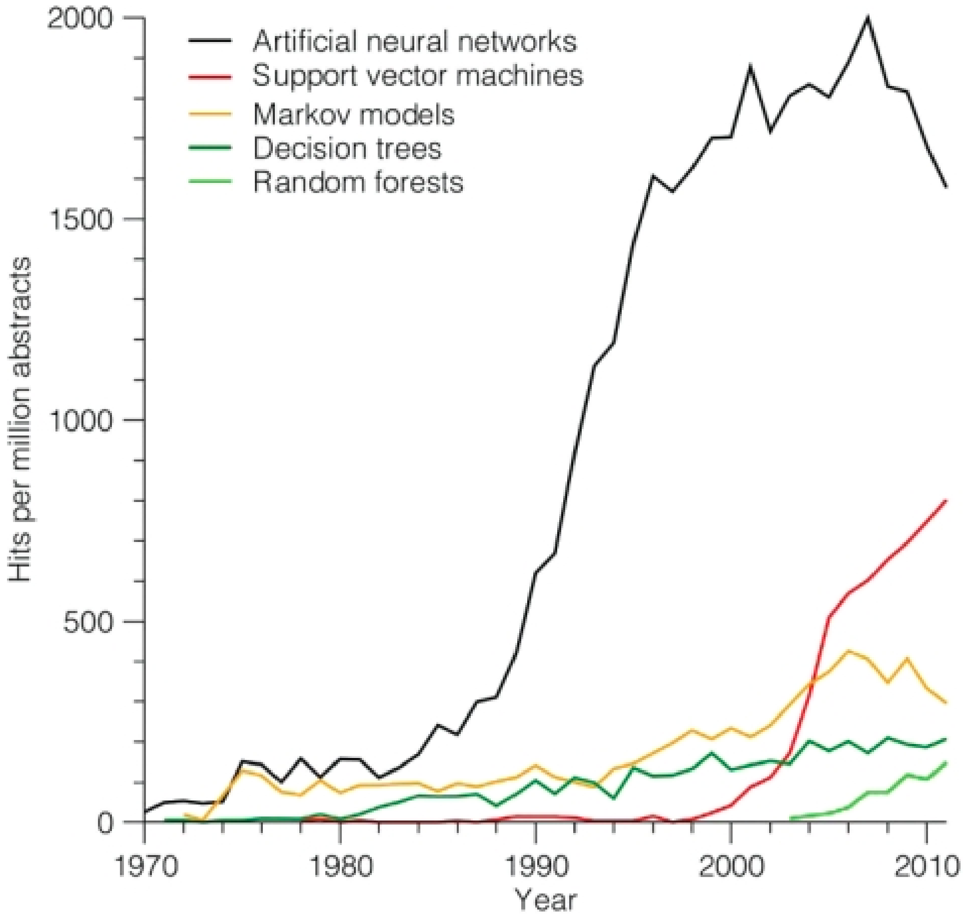
Traditional Machine learning

Deep learning

คาบเรียนที่	เนื้อหา	การบ้านและควิซ
1 - 13/1	Introduction	
2 - 20/1	K-mean, Regression	เริ่มHW1
3 - 27/1	MLE, MAP, and Naive Bayes	ส่งHW1, Quiz 1, เริ่มHW2
4 - 3/2	GMM and EM	
5 - 10/2	Dimensionality reduction (PCA, LDA, RP) and visualization techniques (t-sne, UMAP, PHATE)	ส่งHW2, Quiz 2, เริ่มHW3
6 - 17/2	SVM	
7 - 24/2	Neural network basics	ส่งHW3, Quiz 3, เริ่มHW4
8 - 3/3	CNNs & Pytorch demo	เริ่ม HW5
9 - 10/3	Midterm week - No midterm for this class	
10 - 17/3	Recurrent, attention, and transformers	ส่งHW4, Quiz 4
11 - 24/3	Deep generative models (VAE, GAN, Diffusion)	ส่งHW5, Quiz 5, ส่ง course project proposal, เริ่ม HW6
11 - 31/3	Unsupervised methods	
12 - 7/4	Semi-supervised, self-supervised, and contrastive learning	ส่งHW6, Quiz 6, เริ่ม HW7
13 - 14/4	Songkran Holiday	
14 - 21/4	Reinforcement Learning	ส่งHW7, Quiz 7
15 - 28/4	No regular class - meeting/progress presentation with project mentors	Course project progress
16 - 5/5	Tricks of the trade: machine learning in the real world + Guest	
Some time during final exam	Project presentation No final exam for this class	ส่งcourse project

Why anything else besides deep learning

- The rise and fall of machine learning algorithms

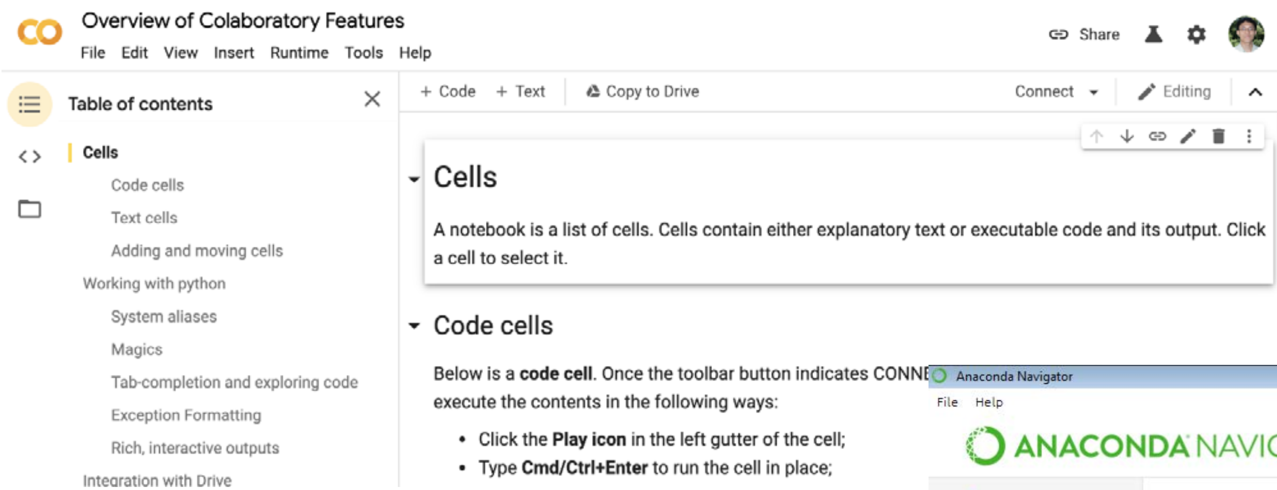


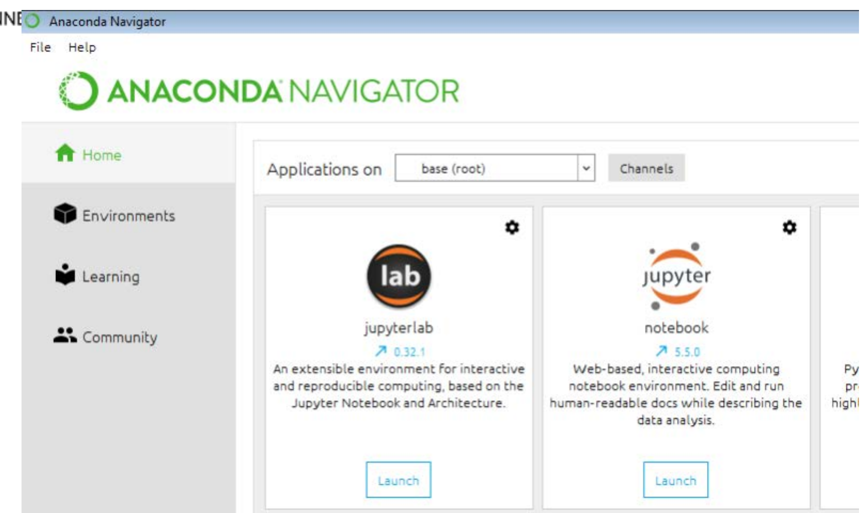
Methods used in bioinformatics papers

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

Jupyter lab and Colaboratory

- We will use Jupyter lab and/or Colaboratory for this course





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