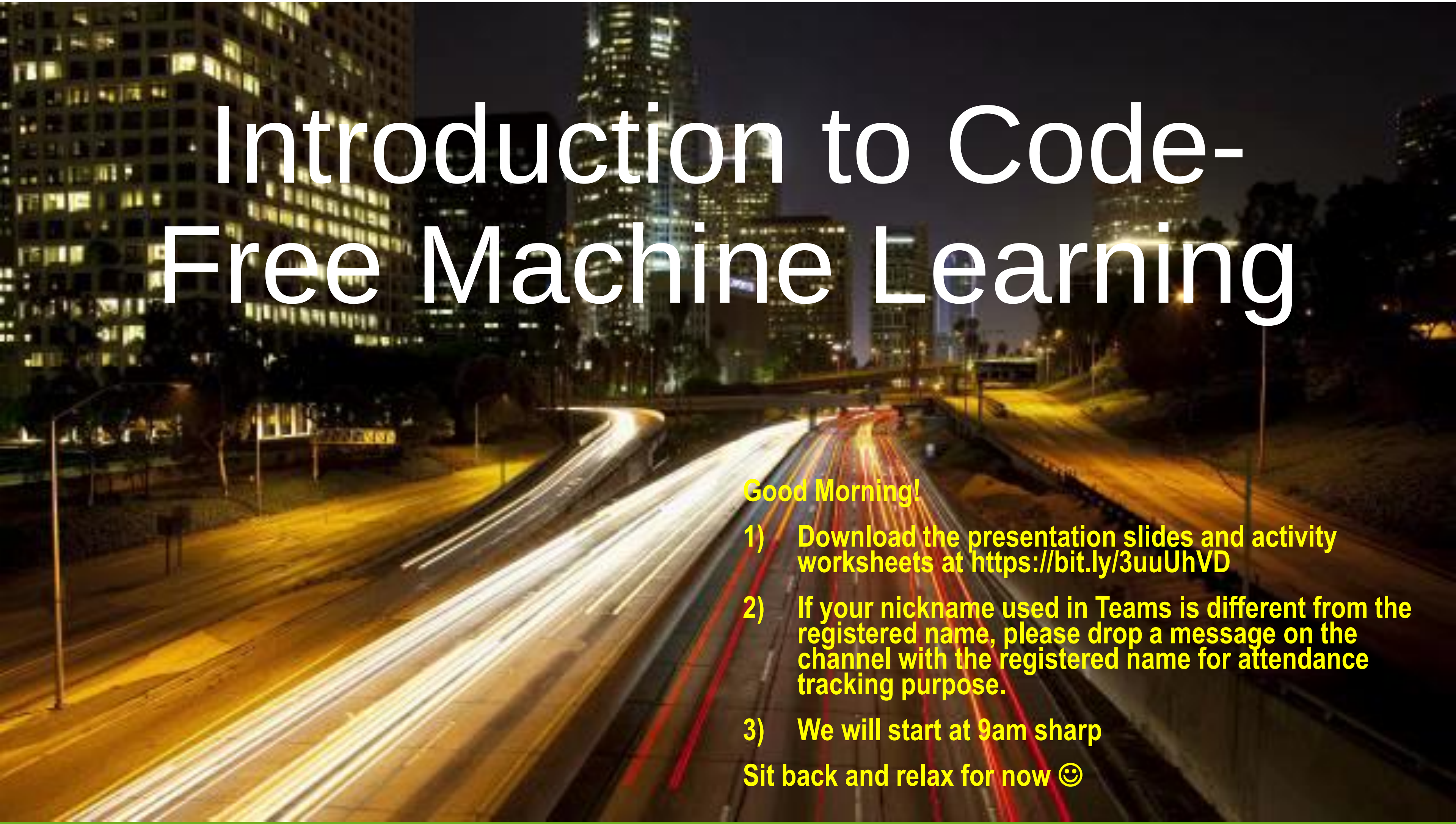
REPUBLIC POLYTECHNIC
DISCOVER. TRANSFORM. ACHIEVE



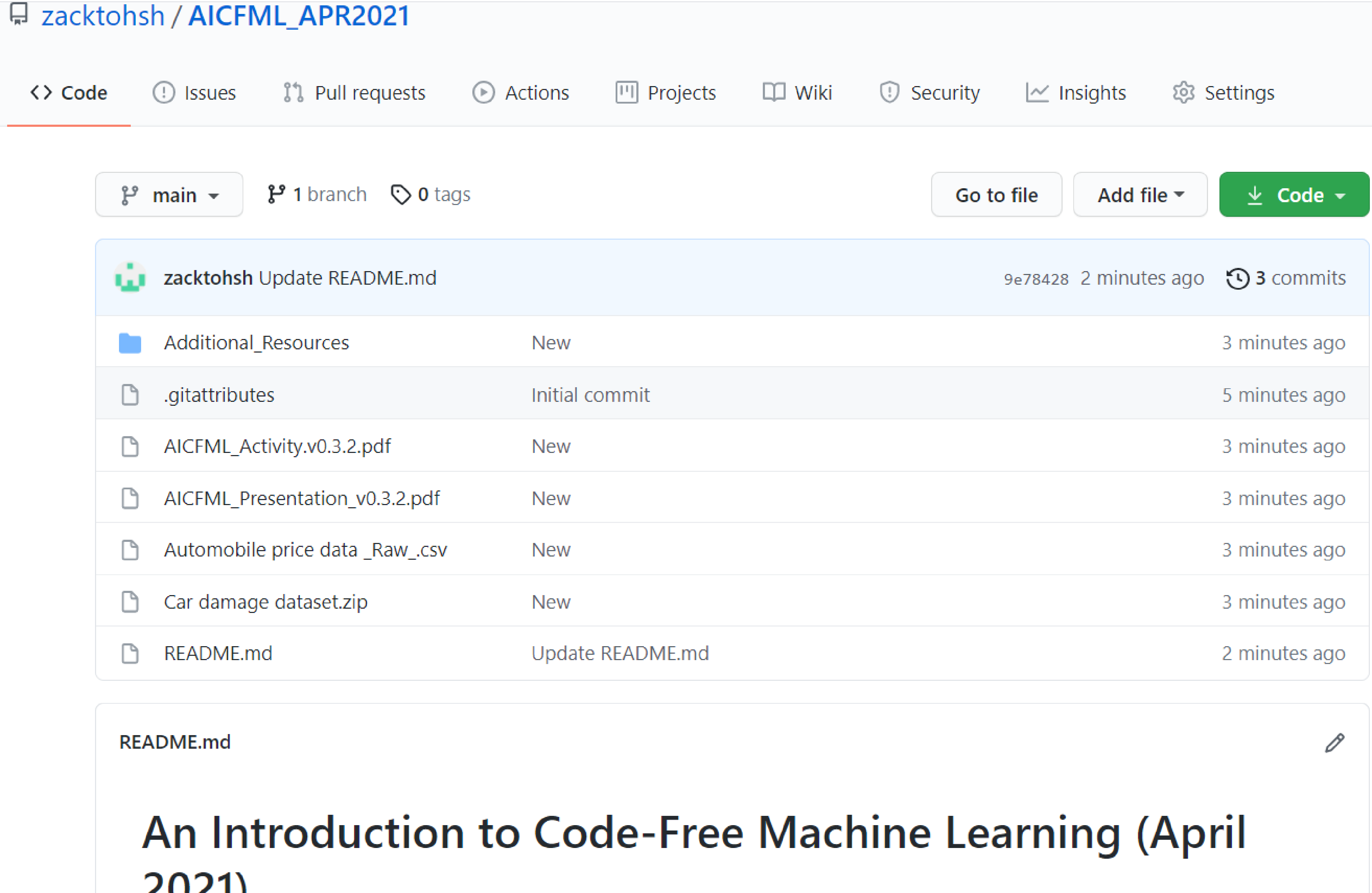
Introduction to Code-Free Machine Learning

Good Morning!

1) Download the presentation slides and activity worksheets at https://bit.ly/3uuUhVD
2) If your nickname used in Teams is different from the registered name, please drop a message on the channel with the registered name for attendance tracking purpose.
3) We will start at 9am sharp

Sit back and relax for now ☺

Download from Github



Programme

Section 1:	What is Machine Learning Machine Learning Workflow
Section 2:	Activity 1 – First Machine Learning with Azure
Section 3:	Activity 2 - Deploying your experiment as a Web Service & Make Prediction using Excel
	Lunch Break
Section 4:	Transfer Learning Computer Vision: Activity 3 – Car Damage Assessment Classification
Section 5:	Natural Language Processing Activity 4 – Creating a Sentiment Analyser
Section 6:	Linking them together
Section 7:	Debrief

Introduction of trainer

Name
Zack Toh

Telegram
@zacktohsh

Email
Zack_toh@rp.edu.sg

Past Projects (Crowd Detection) (18RIGO09)

SSDv1

SSDv2

Yolo

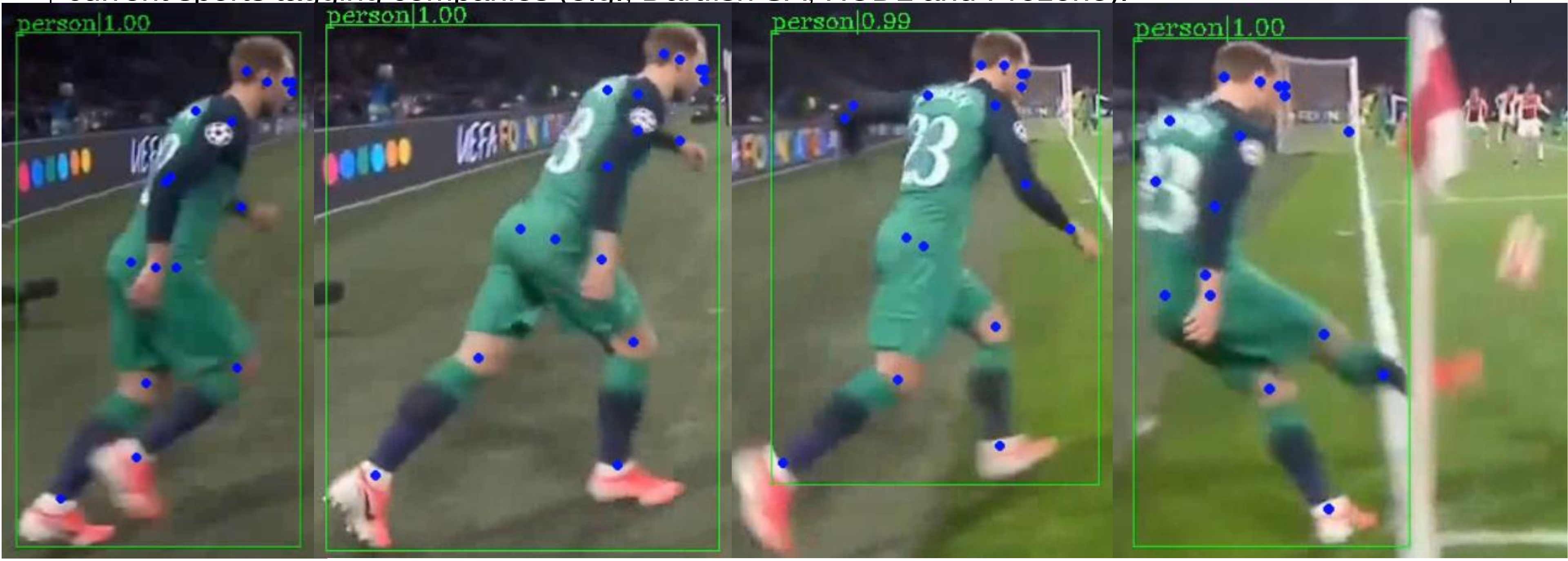
Pose Recognition

Video obtained from: https://www.pexels.com/

Pose generated with Posenet

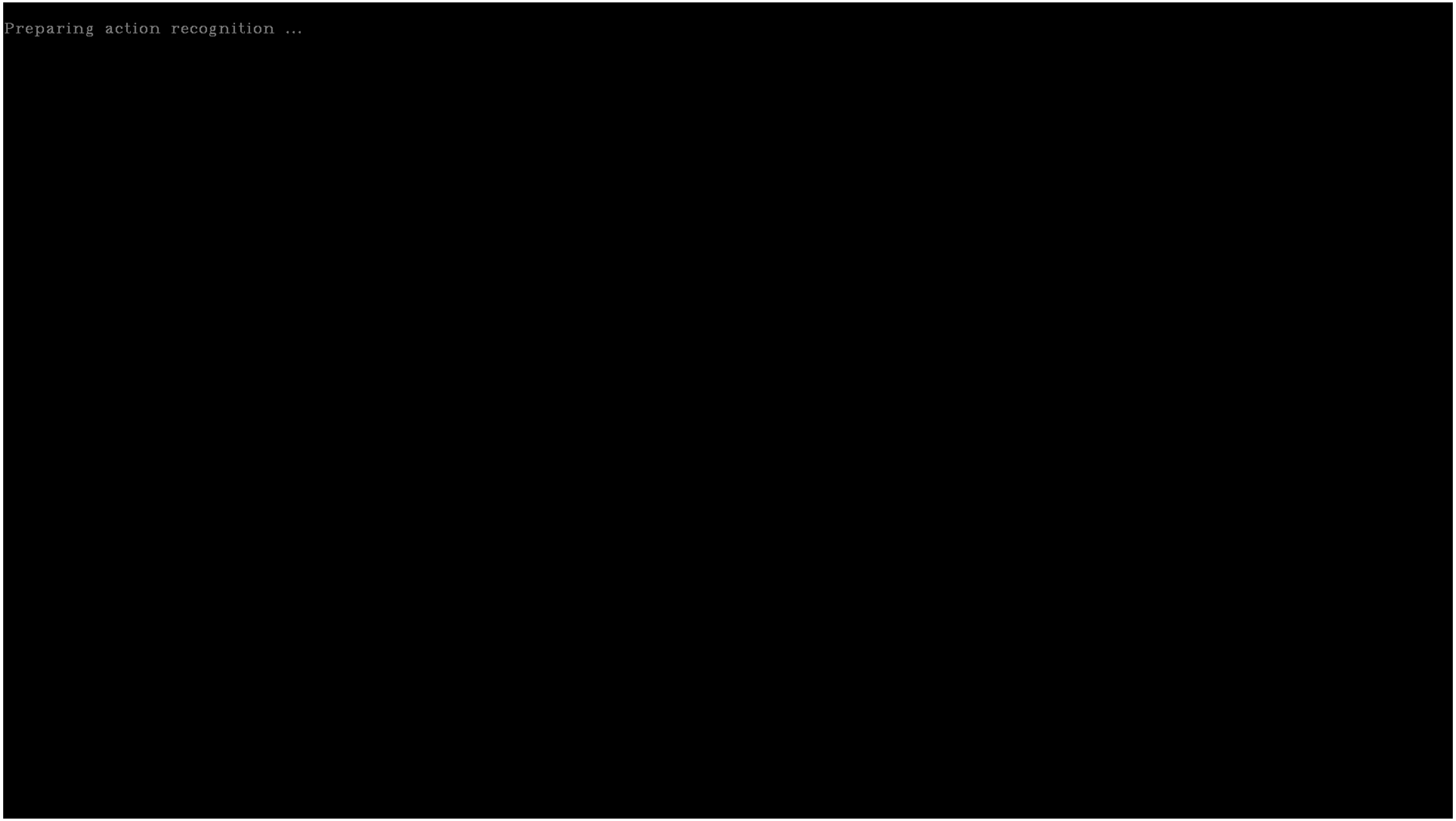
Deep Learning for Sports Tagging (19RBRF07)

Contextual awareness is the holy grail of computer vision. It aims at equipping a machine with the ability of deciphering what is happening in any given image. The automated tagging in sports is a new emerging area in sports industry. This project would contribute tremendously to the productivity and efficiency of sports tagging and dramatically reduce the labor needed in curating the sports statistic. The proposed prototype has high commercialization potential as shared by current sports tagging companies (e.g., Dartfish SA, HUDL and Prozone).



Processed Throw-in

Outcome of Project



Innovative Approach and Value (PA13)

Testing of Model Created

[redacted]

Talk to flower

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

Plants can 'communicate' with humans, move, and exhibit distress through electrical signals

SINGAPORE - Imagine a day when crops are able to tell you they are thirsty or when you can instruct a plant to delicately pick up an item.

Far-fetched? Scientists in Singapore have actually created a way for humans and plants to communicate with each other - via a smartphone, no less.

The team at Nanyang Technological University (NTU) did this by developing a small conductive material that allows electrical signals to enter and leave the plant.

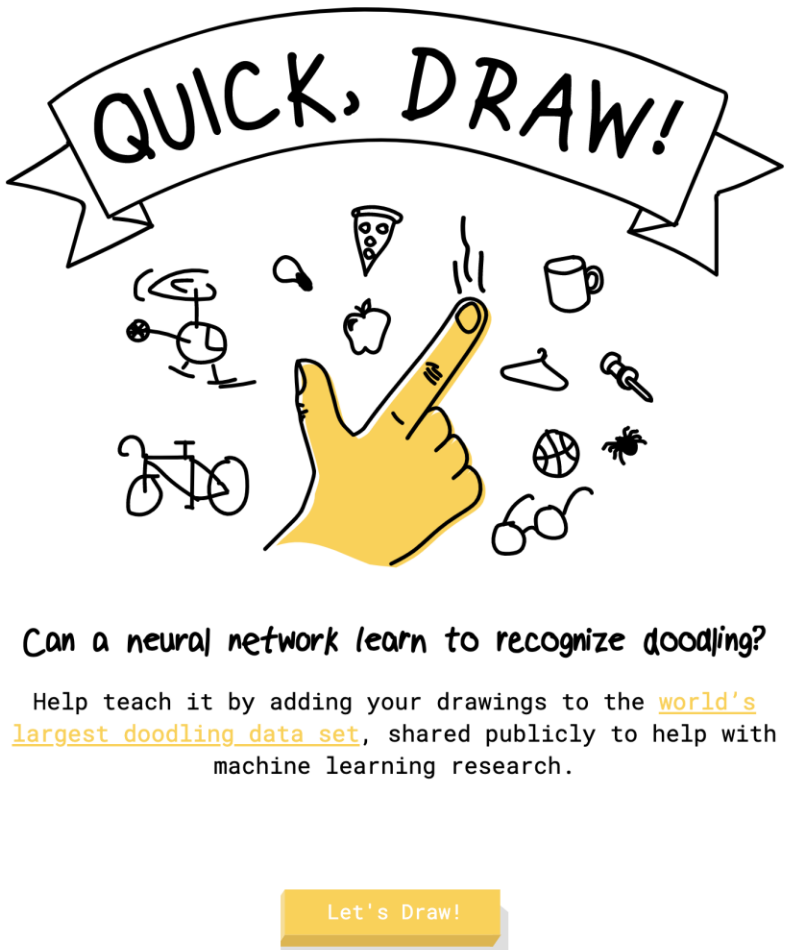
THE STRAITS TIMES

PUBLISHED MAR 16, 2021, 2:37 PM SGT

As part of an experiment, electrical signals were transmitted to the plant using a smartphone, causing the Venus flytrap to close its leaves on demand. PHOTO: NTU SINGAPORE

Quickdraw Game

https://quickdraw.withgoogle.com

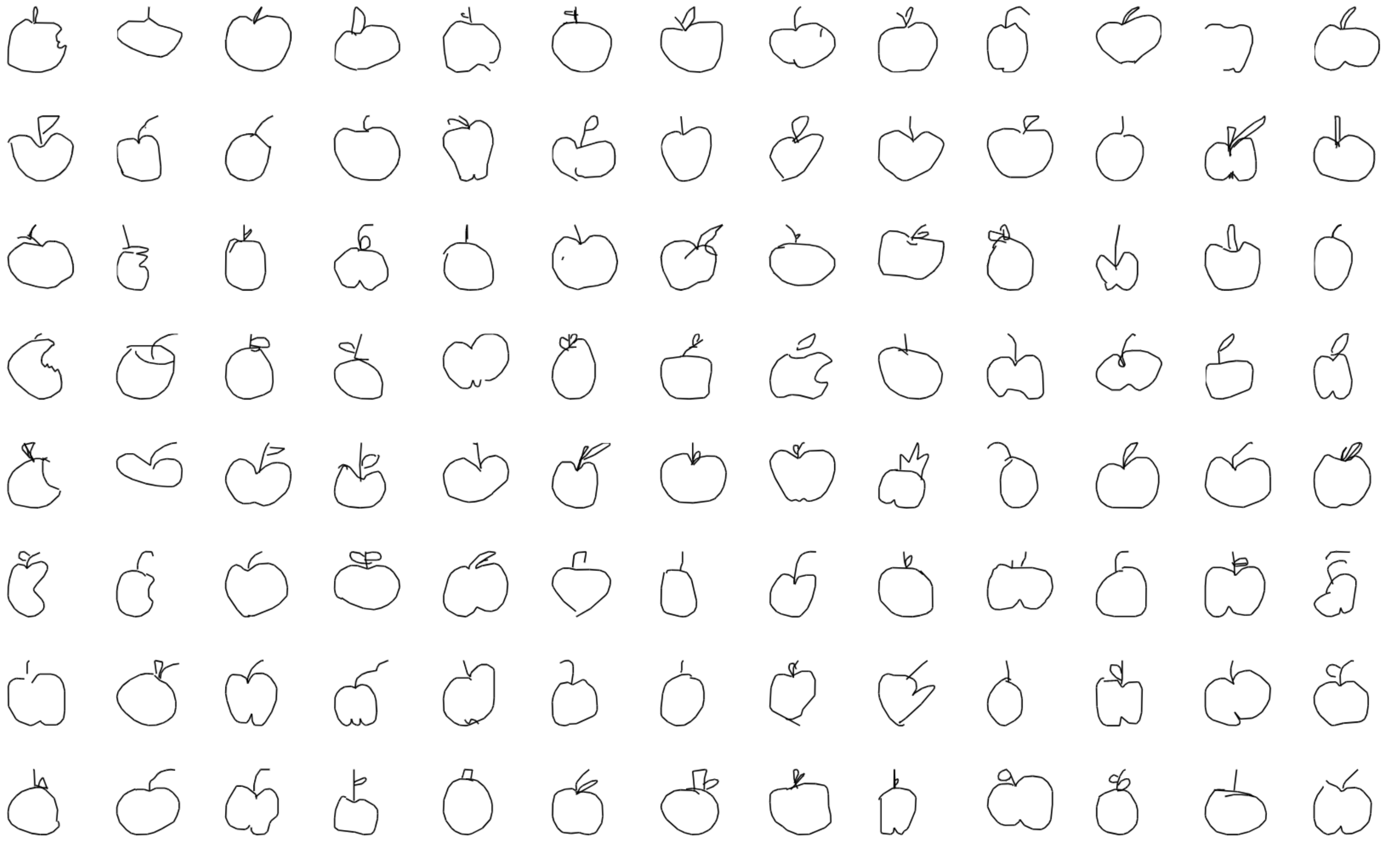


Optional Activity

5 mins

How does ML work in QuickDraw?

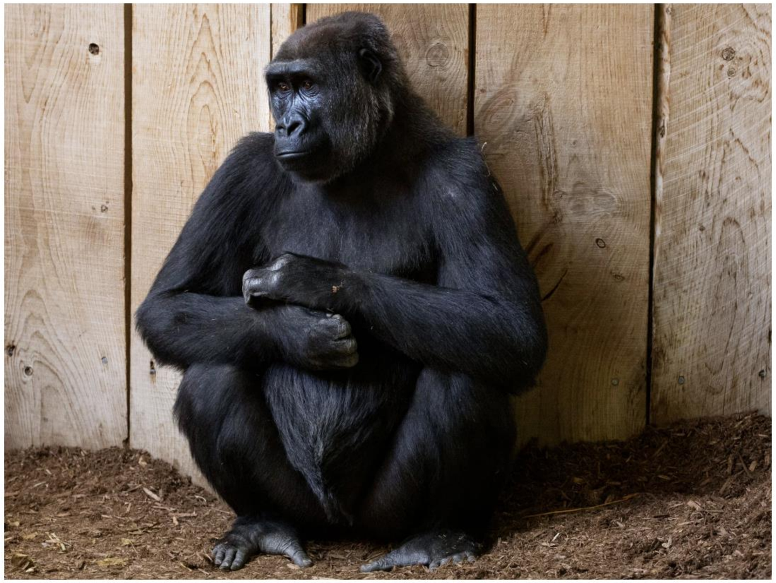
- https://quickdraw.withgoogle.com/data/apple



Bias Bias Bias

When It Comes to Gorillas, Google Photos Remains Blind

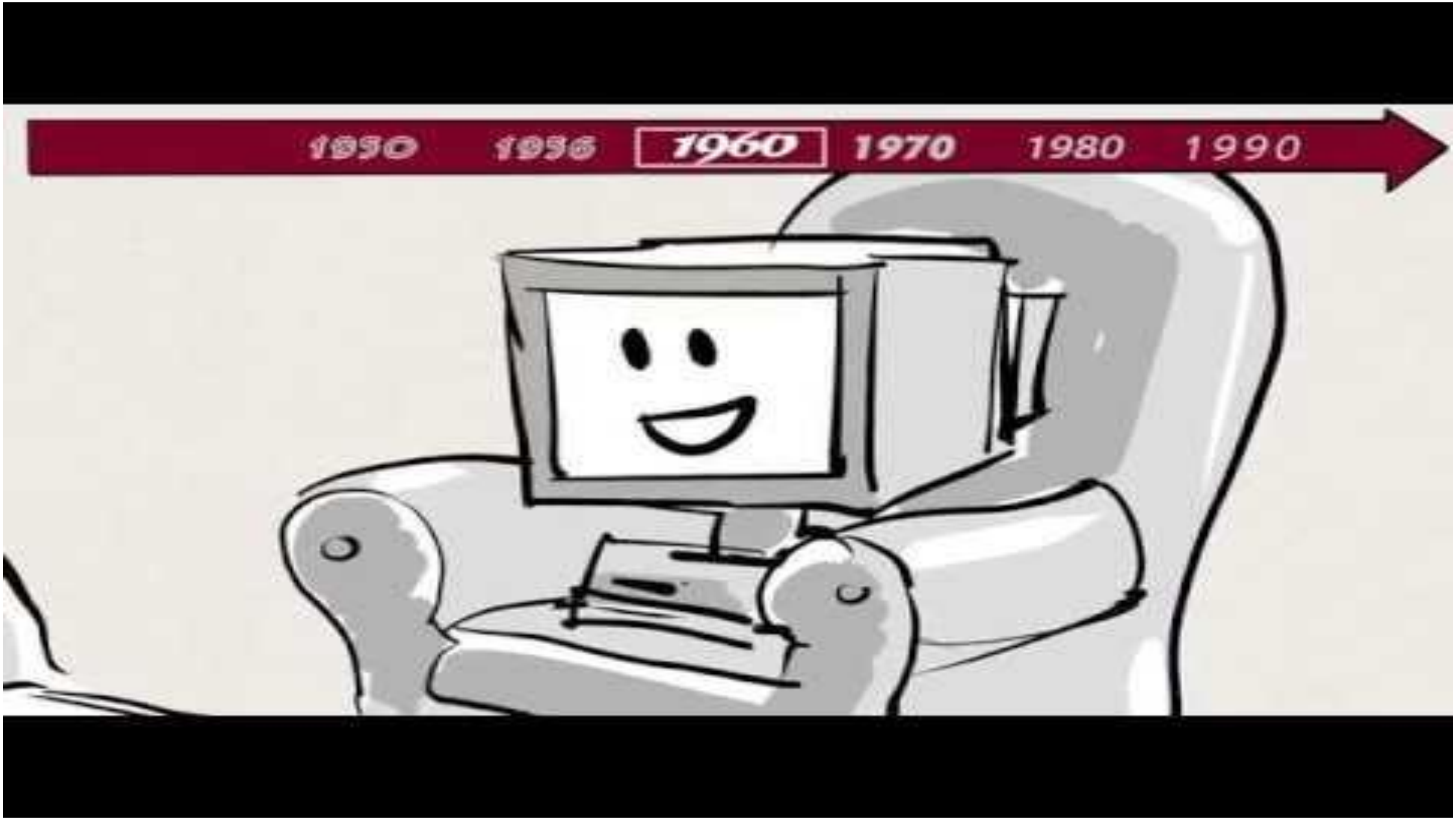
Google promised a fix after its photo-categorization software labeled black people as gorillas in 2015. More than two years later, it hasn't found one.



In WIRED's tests, Google Photos did identify some primates, but no gorillas like this one were to be found. RICK MADONIK/TORONTO STAR/GETTY IMAGES

https://www.wired.com/story/when-it-comes-to-gorillas-google-photos-remains-blind/

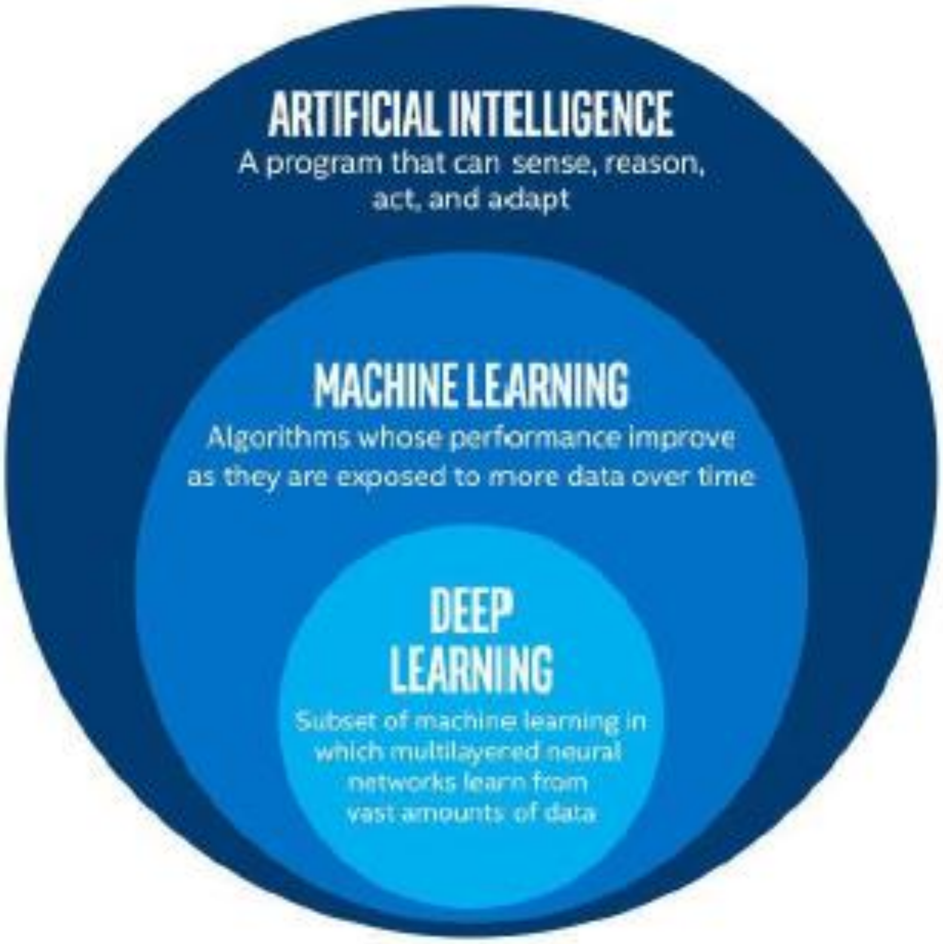
A brief history of AI



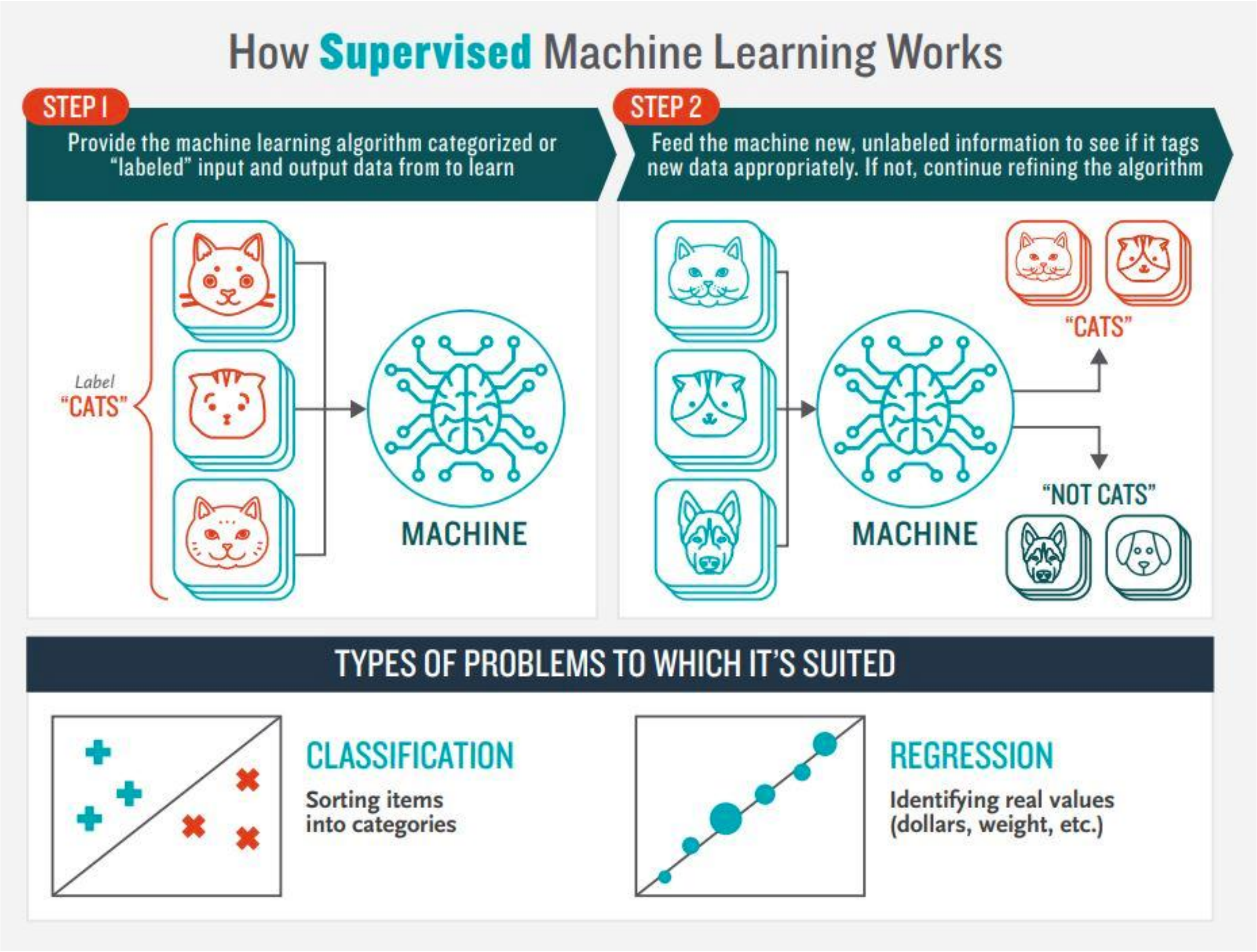
https://www.youtube.com/watch?v=yaL5ZMvRRqE

Machine Learning

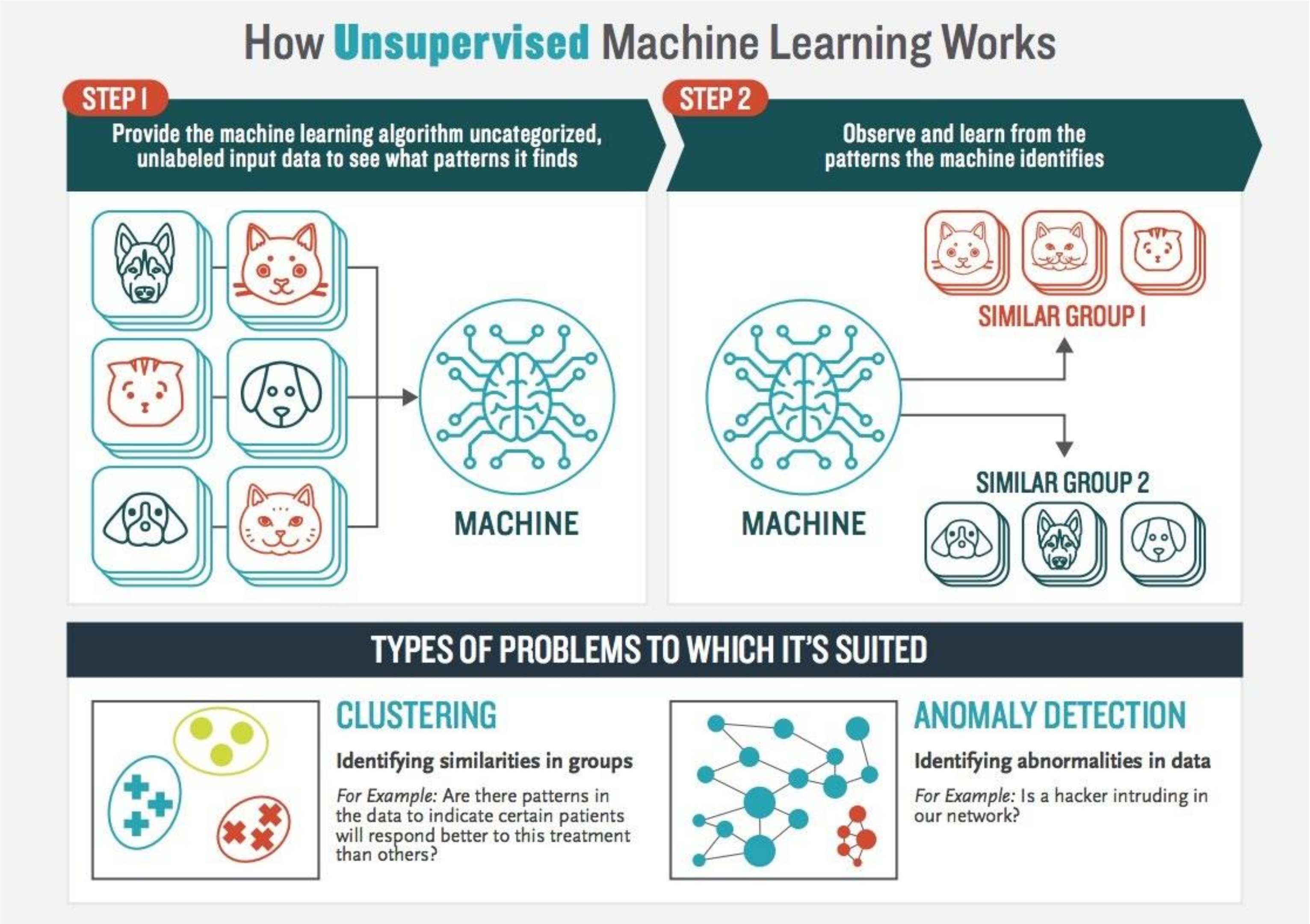
- These programs learn from repeatedly seeing data, rather than being explicitly programmed by humans



Supervised Learning



Unsupervised Learning



Machine Learning

- **Two main types of learning**
  - Supervised Learning
    - Data points have known outcome
    - Goal is to make predictions - Classification and Regression
  - Unsupervised Learning
    - Data points have unknown outcome
    - Goal is to find structure within the data – Clustering
- **Other types of learning**
  - Reinforcement Learning
  - Genetic Algorithm

Machine Learning

- Applications in our daily lives

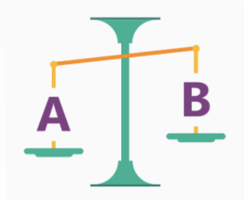
Spam Filtering	Web Search	Postal Mail Routing
Fraud Detection	Movie Recommendations	Vehicle Driver Assistance
Web Advertisements	Social Networks	Speech Recognition

5 fundamental questions

Is this weird? (Anomaly detection)

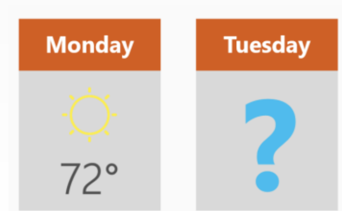
Is this pressure gauge reading normal?
Is this message from the internet typical?

Is this A or B? (Classification) (discrete values)



Will this tire fail in the next 1,000 miles: Yes or no?
Which brings in more customers: a $5 coupon or a 25% discount?

How many? How Much? (Regression) (Continuous)



What will the temperature be next Tuesday?
What will my fourth quarter sales be?

How is this organized? (Clustering)

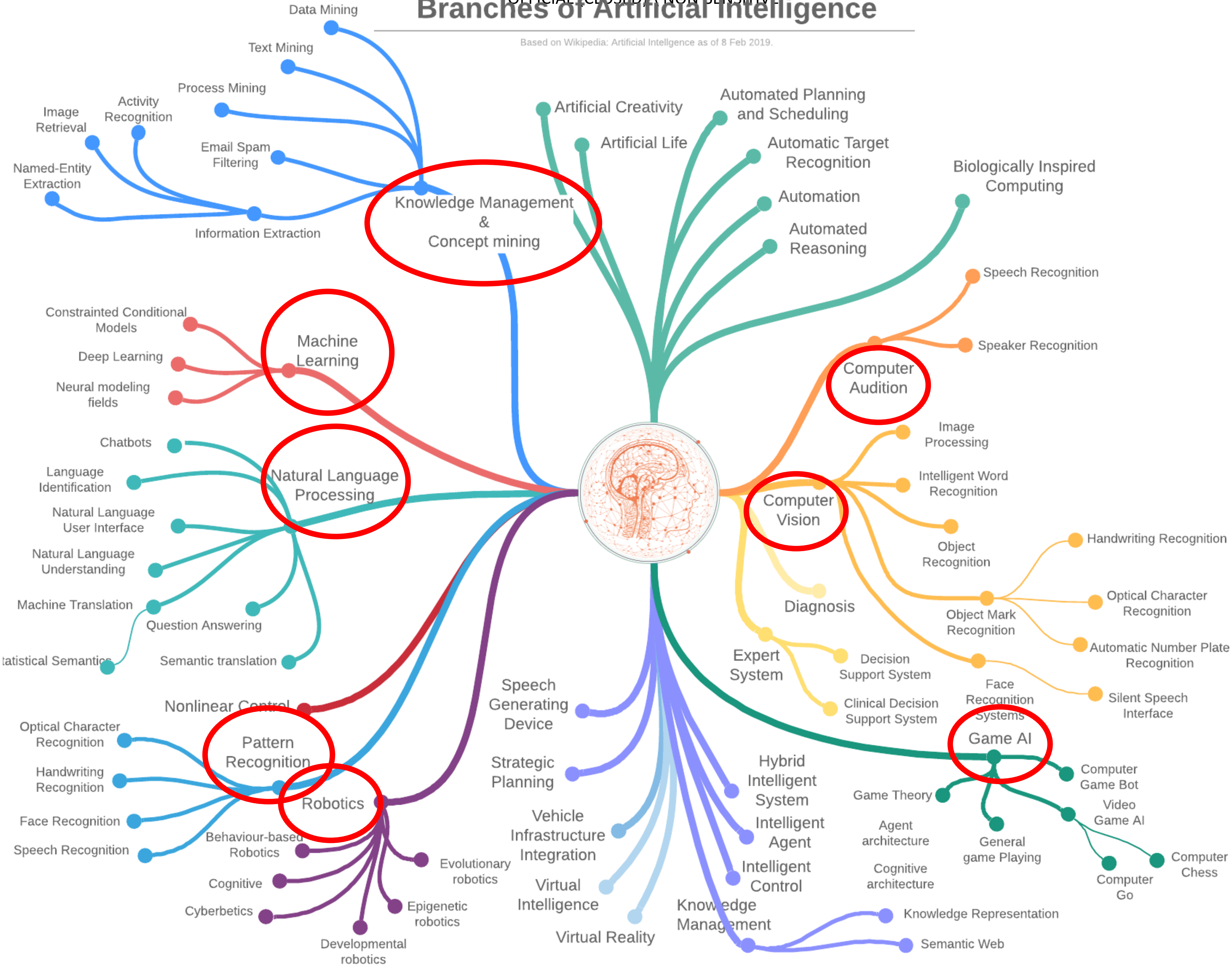
Which viewers like the same types of movies?
Which printer models fail the same way?

What should I do? (Reinforce Learning)

If I'm a self-driving car: At a yellow light, brake or accelerate?
For a robot vacuum: Keep vacuuming, or go back to the charging station?

Branches of Artificial Intelligence

Based on Wikipedia: Artificial Intelligence as of 8 Feb 2019.



Machine Learning Example

- Suppose you wanted to identify fraudulent credit card transactions.

- You could define features to be:
  - Transaction time
  - Transaction amount
  - Transaction location
  - Category of purchase
- The algorithm could learn what feature combinations suggest unusual activity.

THE STRAITS TIMES

Tuesday, April 06, 2021

AI tapped to predict cheaters' next move

David Sun

Bank fraud experts are using artificial intelligence (AI) to outsmart scammers who think they can fool financial institutions into believing they are customers and gain access to funds in accounts.

They are harnessing the technology to monitor scammers' behav- ... d predict their next move.

... the assistance of machine ... g and data analytics, banks ... d the police have built sys- ... hat monitor transactions on ... recedented scale.

... Singapore Police Force's ... cam Centre (ASC) said it has ... ted robotic process automa- ... o its operations.

... ates a standardised format ... sharing of information on ... ious accounts ... enabling them to ... t steps taken by ba... oyston Soon, vice-... d risk management ... aid its systems are ... y identify transacti... cams.

"Using a machine- ... model, we are able to the... probability of the next tra... being fraudulent," he add...

"If the system detects ... haviour on a new device ... will be triggered, and w... this to identify money mules. We ... hen able to take action on such ... unts even before the funds get ... ferred out."

... Soon said OCBC launched its ... l surveillance system in 2016.

... e system monitors online ... actions and gives each a risk ... . High-risk ones trigger an ... , which is then reviewed by a ... analyst.

FRAUD DETECTION

Even if you are using spoof technology, this system is able to identify your true IP and location. Fraudsters typically use one or a few devices to access multiple money mule accounts, which will then be flagged to our fraud analysts.

MR ROYSTON SOON, vice-president of fraud risk management at OCBC Bank.

He said that a machine-learning ...

... analysts."

The system also captures behavioural biometrics, noting a user's typical finger movements and clicks on a device.

Mr Soon said the system would be able to capture one's mouse movements, typing speed and how a user navigates, backspaces and uses autofill components.

"We are able to then differentiate whether or not the one interacting on our platform is really our client," he noted.

Fraud analysts can the... account takeover scenario... termine if it is a case of a... being used by a money mu...

He said the system is c... learning as new data p... added.

Together with the inf... from the ASC, the bank ... able to create what is ess... scam-hunting sentinel o... form.

DBS Bank also has its o... detection system that ... chine learning and AI.

Mr Elvin Lim, head of group investigation at the bank, said: "We rely on machine learning and AI to basically identify transaction patterns of usage of customers' accounts, and using all the data points to tell us the story about whether this is a real customer or a potential scammer."

He pointed out that this network link analysis is like a spider web.

When one account gets hit, they analyse the kind of transactions that happen through that account.

The data is then proce... in a pictorial for... nk other fraud... ogether and pr... ensive picture ... rations.

... e learning is als... tentially fraudul... t UOB, said Mr ... of investigatio... tegrated Fraud ... artment.

... hese systems h... well, they need ... as scammers ch... , he added.

"This is why we ... strengthen our collaboration with the other banks through the ASC," he said. "A combined approach with the whole banking community is needed so that we can all harness and build on technology together to complement our efforts to stop crime."

davidsun@sph.com.sg

Mr Elvin Lim, head of group investigation at the bank, said: "We rely on machine learning and AI to basically identify transaction patterns of usage of customers' accounts, and using all the data points to tell us the story about whether this is a real customer or a potential scammer."

"Using a machine-learning model, we are able to then rate the probability of the next transaction being fraudulent," he added.

"If the system detects a new behaviour on a new device, an alert will be triggered, and we can use this to identify money mules. We are then able to take action on such accounts even before the funds get transferred out."

The system also captures behavioural biometrics, noting a user's typical finger movements and clicks on a device.

Mr Soon said the system would be able to capture one's mouse movements, typing speed and how a user navigates, backspaces and uses autofill components.

"This is why we hope to strengthen our collaboration with the other banks through the ASC," he said. "A combined approach with the whole banking community is needed so that we can all harness and build on technology together to complement our efforts to stop crime."

The system monitors online transactions and gives each a risk score. High-risk ones trigger an alert, which is then reviewed by a fraud analyst.

Machine Learning Limitations

- Suppose you wanted to determine if an image is of a cat or a dog.
- What features would you use?
- This is where **Deep Learning** can come in.

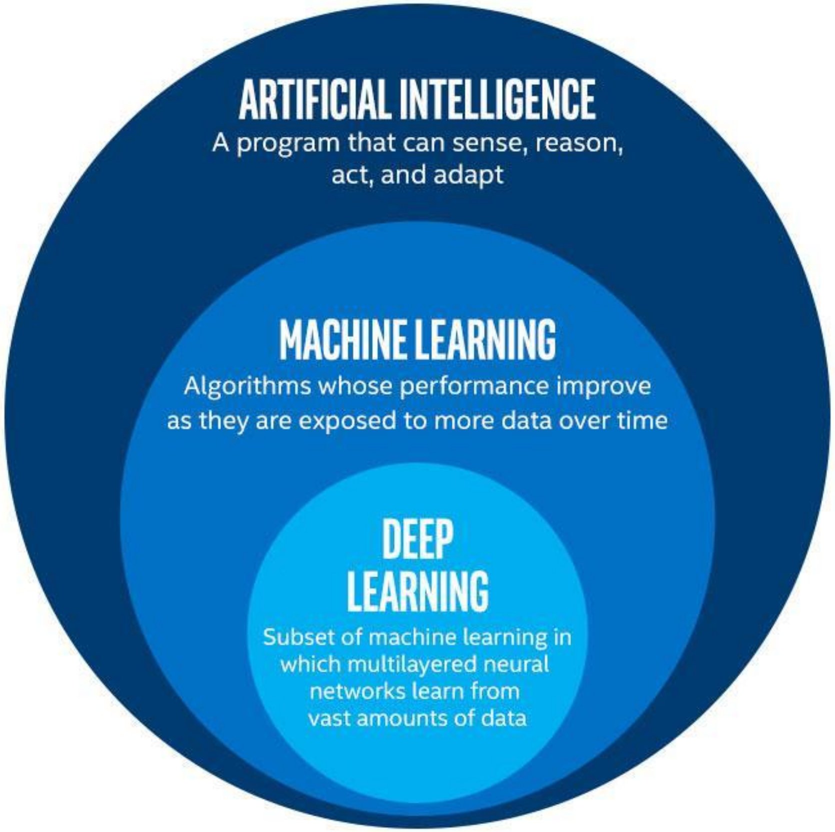
Dog and cat recognition

What is deep learning?

Deep Learning

“Machine learning that involves using very complicated models called “deep neural networks”." (Intel)

Models determine best representation of original data; in classic machine learning, humans must do this.



Deep Learning Example

Classic Machine Learning

Step 1: Determine features.
Step 2: Feed them through model.

Feature Detection

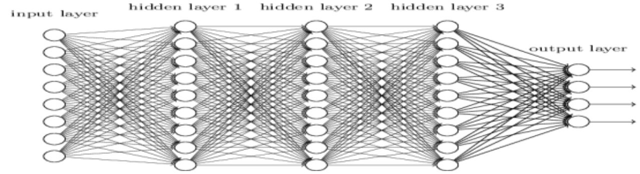
Machine Learning Classifier

"David"

Deep Learning

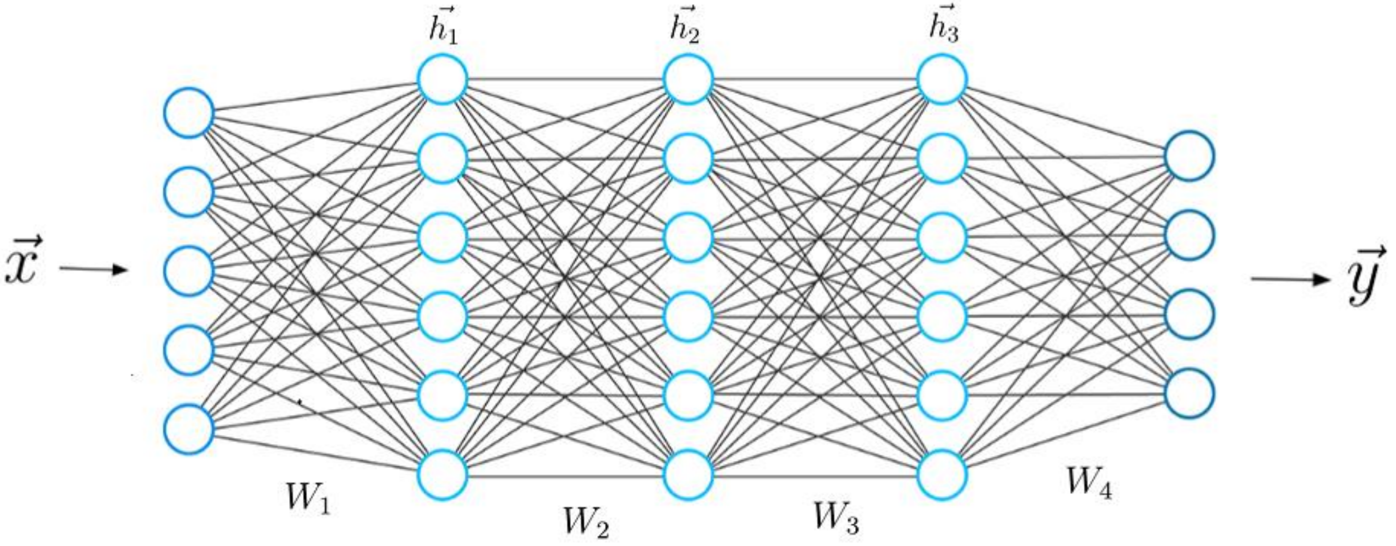
Steps 1 and 2 are combined into 1 step.

Neural Network

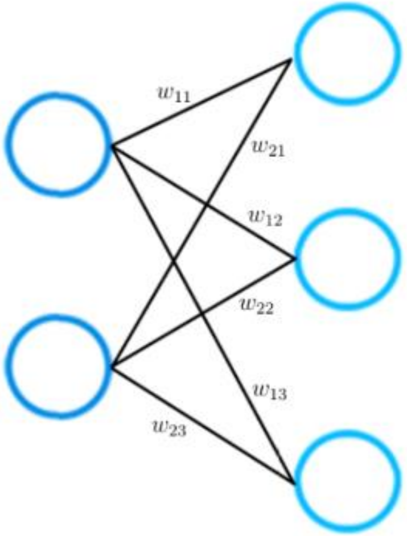


"David"

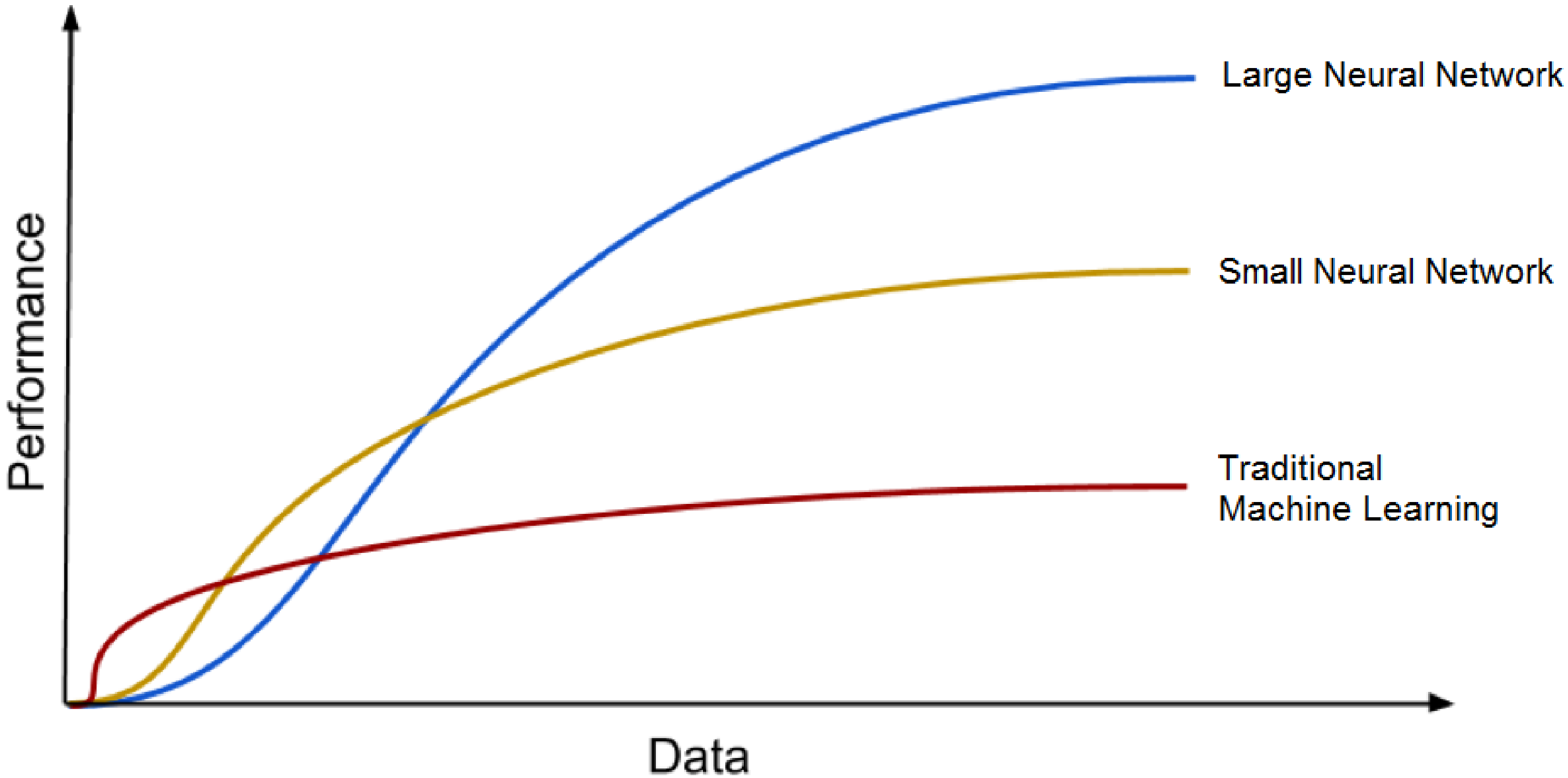
Neural Networks



The challenge in training a neural networks is finding a set of weights the give the most accurate output.

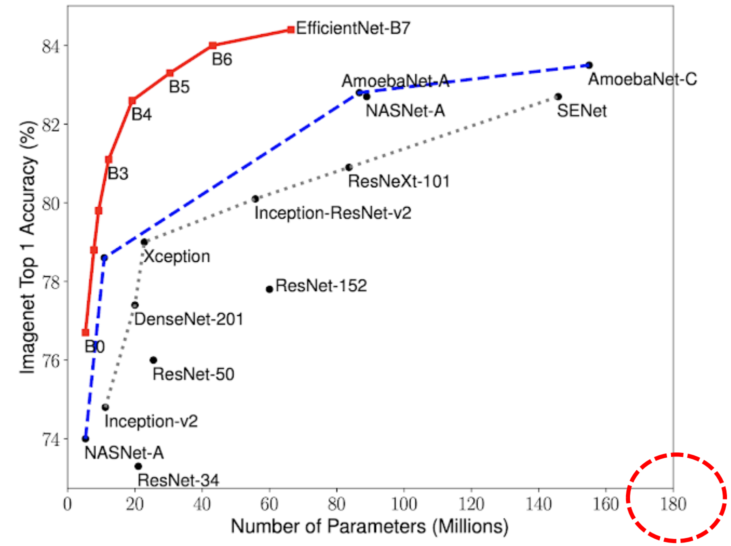


Performance

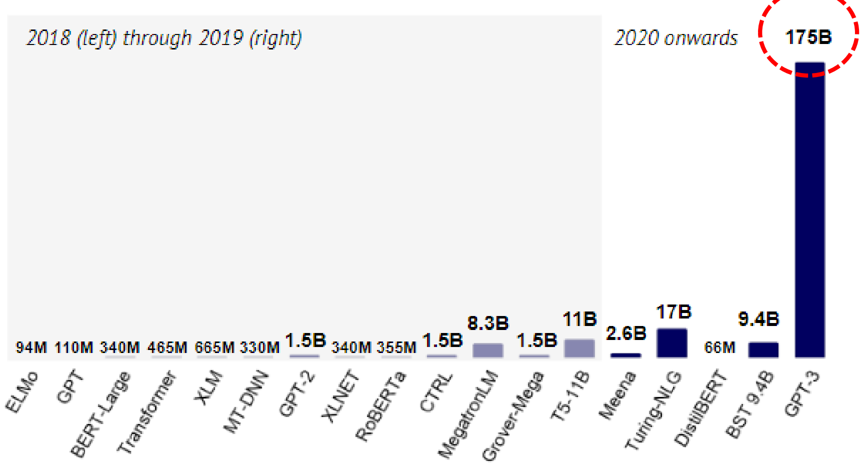


Deep Learning Algorithms get better with the increasing amount of data.

Size



Huge models, large companies and massive training costs dominate the hottest area of AI today, NLP.



Note: The number of parameters indicates how many different coefficients the algorithm optimizes during the training process.

stateof.ai 2020

Deep Learning in Action

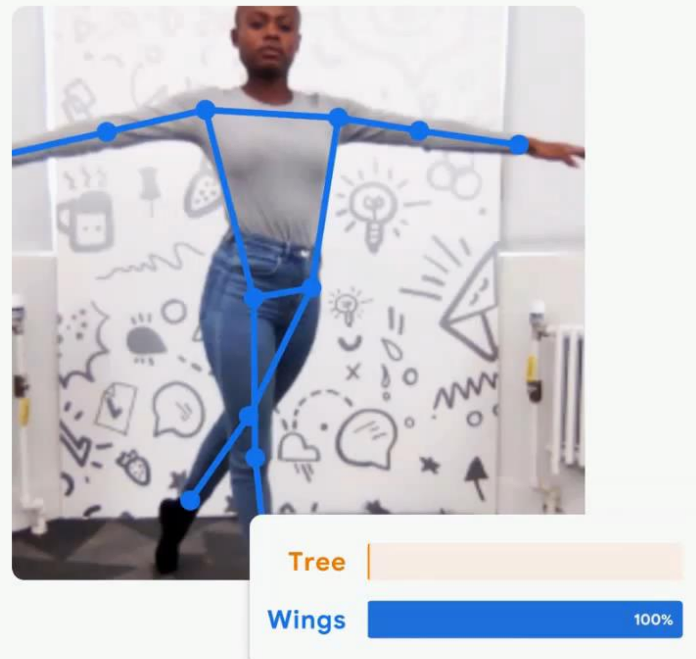
10 mins

bit.ly/google_teachable

Teachable Machine

Train a computer to recognize your own images, sounds, & poses.

A fast, easy way to create machine learning models for your sites, apps, and more – no expertise or coding required.



Get Started

Optional Activity

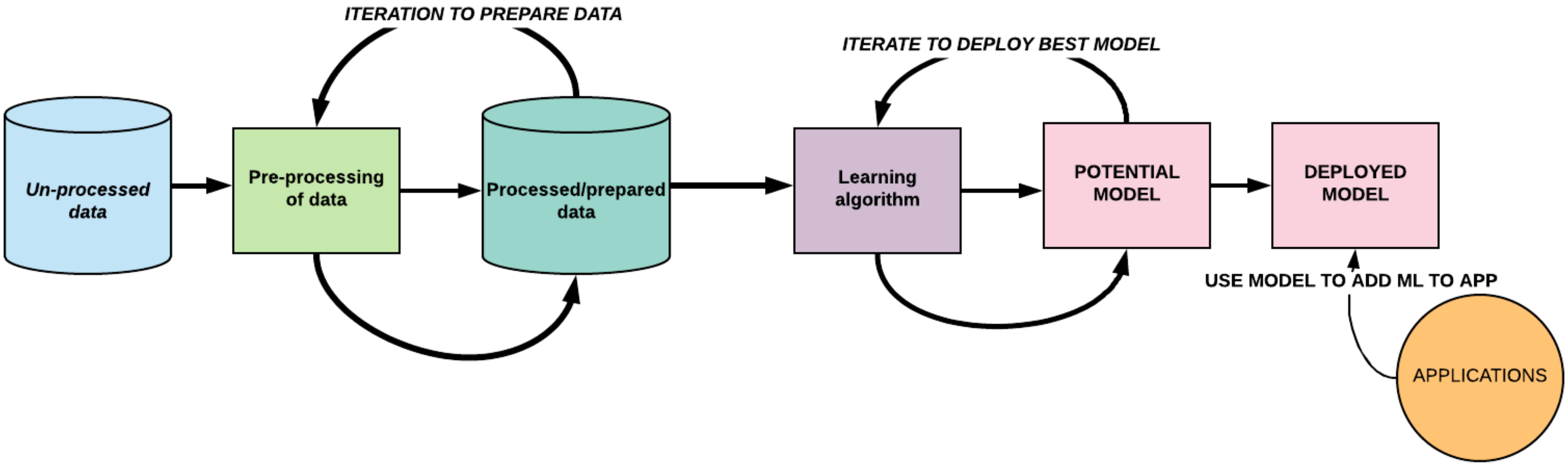
Teachable Machine

https://teachablemachine.withgoogle.com/

15 Mins Break

bit.ly/top10_2020

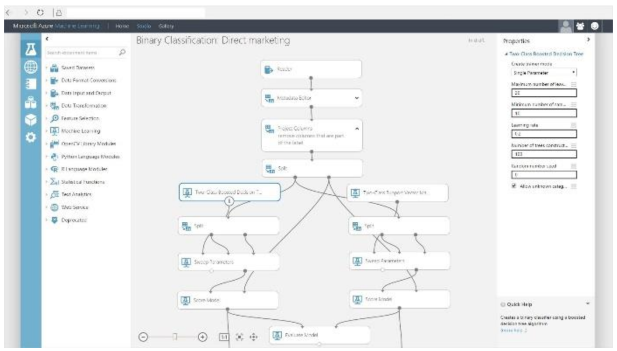
Machine Learning workflow



Ref: https://cloudacademy.com/blog/what-is-azure-machine-learning/

Code-Free Machine Learning tools

Microsoft Azure
Machine Learning Studio
(Classic)



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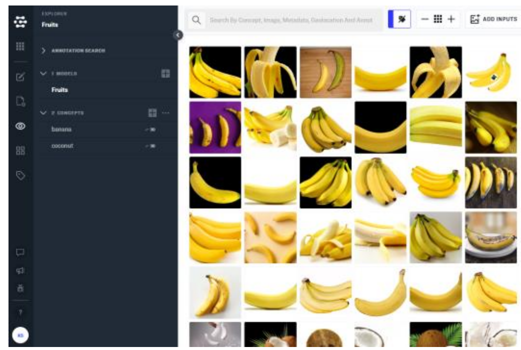
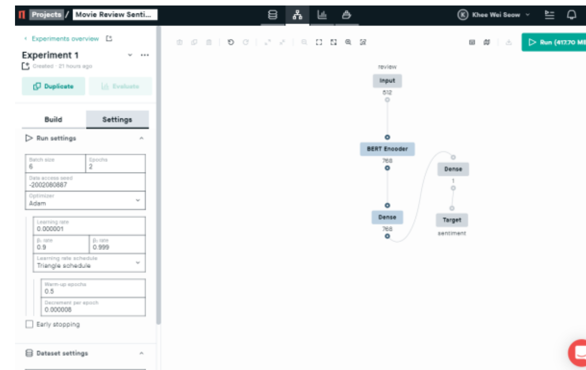
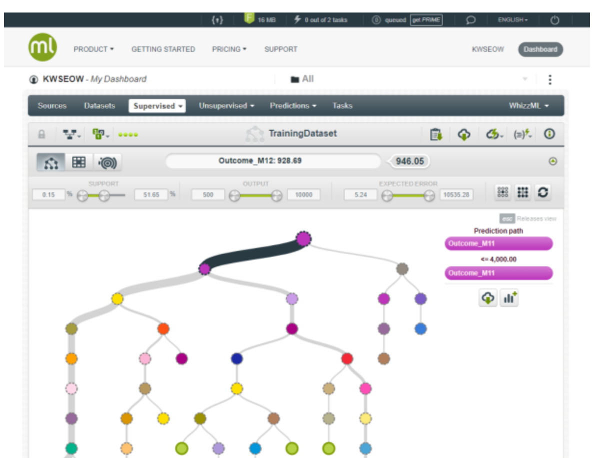


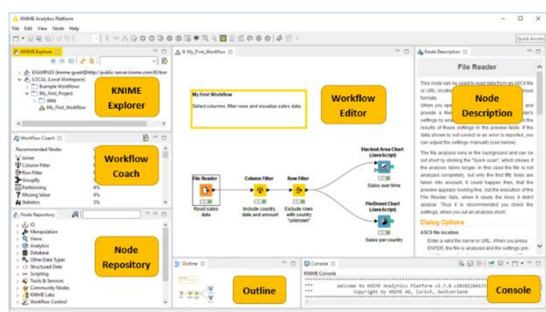
Peltarion



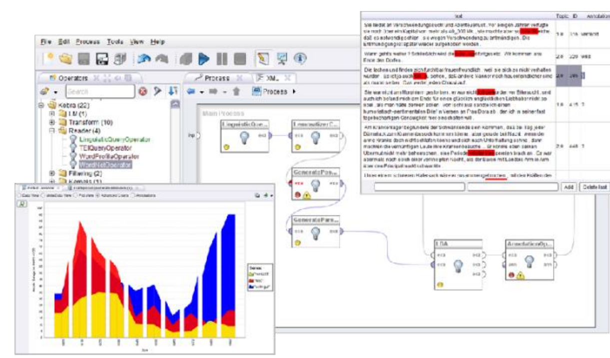
bigml



KNIME



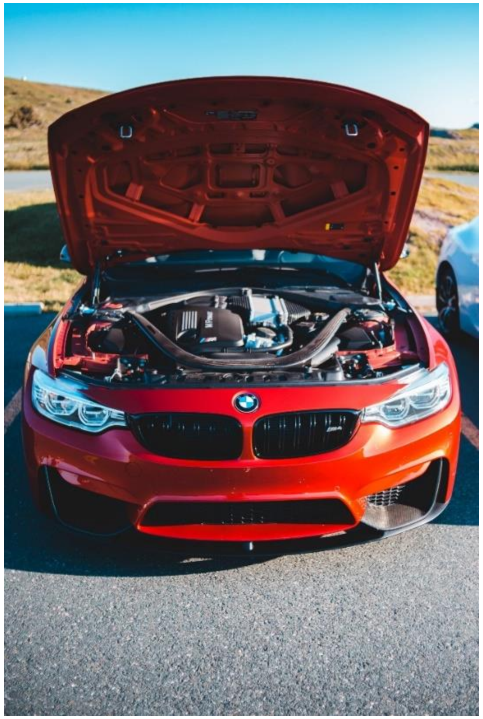
Rapidminer



Activity 1 – First Machine Learning with Azure

- **Automobile Price Prediction**

Given some features of a car, e.g. engine capacity, no of doors, horsepower, predict the selling price



symboling	normalizec	make	fuel-type	aspiration	num-of-dc	body-style	drive-whee	engine-loc	wheel-bas	length	width	height	curb-weigh	engine-typ	num-of-cy	engine-size	fuel-syster	bore	stroke
3	?	alfa-romer	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
3	?	alfa-romer	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
1	?	alfa-romer	gas	std	two	hatchback	rwd	front	94.5	171.2	65.5	52.4	2823	ohcv	six	152	mpfi	2.68	3.47
2	164	audi	gas	std	four	sedan	fwd	front	99.8	176.6	66.2	54.3	2337	ohc	four	109	mpfi	3.19	3.4
2	164	audi	gas	std	four	sedan	4wd	front	99.4	176.6	66.4	54.3	2824	ohc	five	136	mpfi	3.19	3.4
2	?	audi	gas	std	two	sedan	fwd	front	99.8	177.3	66.3	53.1	2507	ohc	five	136	mpfi	3.19	3.4
1	158	audi	gas	std	four	sedan	fwd	front	105.8	192.7	71.4	55.7	2844	ohc	five	136	mpfi	3.19	3.4
1	?	audi	gas	std	four	wagon	fwd	front	105.8	192.7	71.4	55.7	2954	ohc	five	136	mpfi	3.19	3.4
1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	192.7	71.4	55.9	3086	ohc	five	131	mpfi	3.13	3.4
0	?	audi	gas	turbo	two	hatchback	4wd	front	99.5	178.2	67.9	52	3053	ohc	five	131	mpfi	3.13	3.4
2	192	bmw	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8
0	192	bmw	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8
0	188	bmw	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2710	ohc	six	164	mpfi	3.31	3.19
0	188	bmw	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2765	ohc	six	164	mpfi	3.31	3.19
1	?	bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3055	ohc	six	164	mpfi	3.31	3.19
0	?	bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3230	ohc	six	209	mpfi	3.62	3.39
0	?	bmw	gas	std	two	sedan	rwd	front	103.5	193.8	67.9	53.7	3380	ohc	six	209	mpfi	3.62	3.39
0	?	bmw	gas	std	four	sedan	rwd	front	110	197	70.9	56.3	3505	ohc	six	209	mpfi	3.62	3.39
2	121	chevrolet	gas	std	two	hatchback	fwd	front	88.4	141.1	60.3	53.2	1488	l	three	61	2bbl	2.91	3.03
1	98	chevrolet	gas	std	two	hatchback	fwd	front	94.5	155.9	63.6	52	1874	ohc	four	90	2bbl	3.03	3.11
0	81	chevrolet	gas	std	four	sedan	fwd	front	94.5	158.8	63.6	52	1909	ohc	four	90	2bbl	3.03	3.11
1	118	dodge	gas	std	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	1876	ohc	four	90	2bbl	2.97	3.23
1	118	dodge	gas	std	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	1876	ohc	four	90	2bbl	2.97	3.23
1	118	dodge	gas	turbo	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	2128	ohc	four	98	mpfi	3.03	3.39
1	148	dodge	gas	std	four	hatchback	fwd	front	93.7	157.3	63.8	50.6	1967	ohc	four	90	2bbl	2.97	3.23
1	148	dodge	gas	std	four	sedan	fwd	front	93.7	157.3	63.8	50.6	1989	ohc	four	90	2bbl	2.97	3.23
1	148	dodge	gas	std	four	sedan	fwd	front	93.7	157.3	63.8	50.6	1989	ohc	four	90	2bbl	2.97	3.23
1	148	dodge	gas	turbo	?	sedan	fwd	front	93.7	157.3	63.8	50.6	2191	ohc	four	98	mpfi	3.03	3.39
-1	110	dodge	gas	std	four	wagon	fwd	front	103.3	174.6	64.6	59.8	2535	ohc	four	122	2bbl	3.34	3.46
3	145	dodge	gas	turbo	two	hatchback	fwd	front	95.9	173.2	66.3	50.2	2811	ohc	four	156	mfi	3.6	3.9
2	137	honda	gas	std	two	hatchback	fwd	front	86.6	144.6	63.9	50.8	1713	ohc	four	92	1bbl	2.91	3.41
2	137	honda	gas	std	two	hatchback	fwd	front	86.6	144.6	63.9	50.8	1819	ohc	four	92	1bbl	2.91	3.41
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1837	ohc	four	79	1bbl	2.91	3.07
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1940	ohc	four	92	1bbl	2.91	3.41
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1956	ohc	four	92	1bbl	2.91	3.41
0	110	honda	gas	std	four	sedan	fwd	front	96.5	163.4	64	54.5	2010	ohc	four	92	1bbl	2.91	3.41
0	78	honda	gas	std	four	wagon	fwd	front	96.5	157.1	63.9	58.3	2024	ohc	four	92	1bbl	2.92	3.41
0	106	honda	gas	std	two	hatchback	fwd	front	96.5	167.5	65.2	53.3	2236	ohc	four	110	1bbl	3.15	3.58
0	106	honda	gas	std	two	hatchback	fwd	front	96.5	167.5	65.2	53.3	2289	ohc	four	110	1bbl	3.15	3.58
0	85	honda	gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2304	ohc	four	110	1bbl	3.15	3.58
0	85	honda	gas	std	four	sedan	fwd	front	96.5	175.4	62.5	54.1	2372	ohc	four	110	1bbl	3.15	3.58
0	85	honda	gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2465	ohc	four	110	mpfi	3.15	3.58
1	107	honda	gas	std	two	sedan	fwd	front	96.5	169.1	66	51	2293	ohc	four	110	2bbl	3.15	3.58
0	?	isuzu	gas	std	four	sedan	rwd	front	94.3	170.7	61.8	53.5	2337	ohc	four	111	2bbl	3.31	3.23
1	?	isuzu	gas	std	two	sedan	fwd	front	94.5	155.9	63.6	52	1874	ohc	four	90	2bbl	3.03	3.11
0	?	isuzu	gas	std	four	sedan	fwd	front	94.5	155.9	63.6	52	1909	ohc	four	90	2bbl	3.03	3.11
2	?	isuzu	gas	std	two	hatchback	rwd	front	96	172.6	65.2	51.4	2734	ohc	four	119	spfi	3.43	3.23
0	145	jaguar	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066	dohc	six	258	mpfi	3.63	4.17
0	?	jaguar	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066	dohc	six	258	mpfi	3.63	4.17
0	?	jaguar	gas	std	two	sedan	rwd	front	102	191.7	70.6	47.8	3950	ohcv	twelve	326	mpfi	3.54	2.76
1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1890	ohc	four	91	2bbl	3.03	3.15
1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1900	ohc	four	91	2bbl	3.03	3.15
1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1905	ohc	four	91	2bbl	3.03	3.15
1	113	mazda	gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1945	ohc	four	91	2bbl	3.03	3.15
1	113	mazda	gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1950	ohc	four	91	2bbl	3.08	3.15
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2380	rotor	two	70	4bbl	?	?
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2380	rotor	two	70	4bbl	?	?
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2385	rotor	two	70	4bbl	?	?
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2500	rotor	two	80	mpfi	?	?
1	129	mazda	gas	std	two	hatchback	fwd	front	98.8	177.8	66.5	53.7	2385	ohc	four	122	2bbl	3.39	3.39
0	115	mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410	ohc	four	122	2bbl	3.39	3.39
1	129	mazda	gas	std	two	hatchback	fwd	front	98.8	177.8	66.5	53.7	2385	ohc	four	122	2bbl	3.39	3.39
0	115	mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410	ohc	four	122	2bbl	3.39	3.39
0	?	mazda	diesel	std	?	sedan	fwd	front	98.8	177.8	66.5	55.5	2443	ohc	four	122	idi	3.39	3.39

Step 1:
Watch and listen to the instructor's demonstration

30 mins

Step 2:
- Do on your own

Individual Activity

45 mins

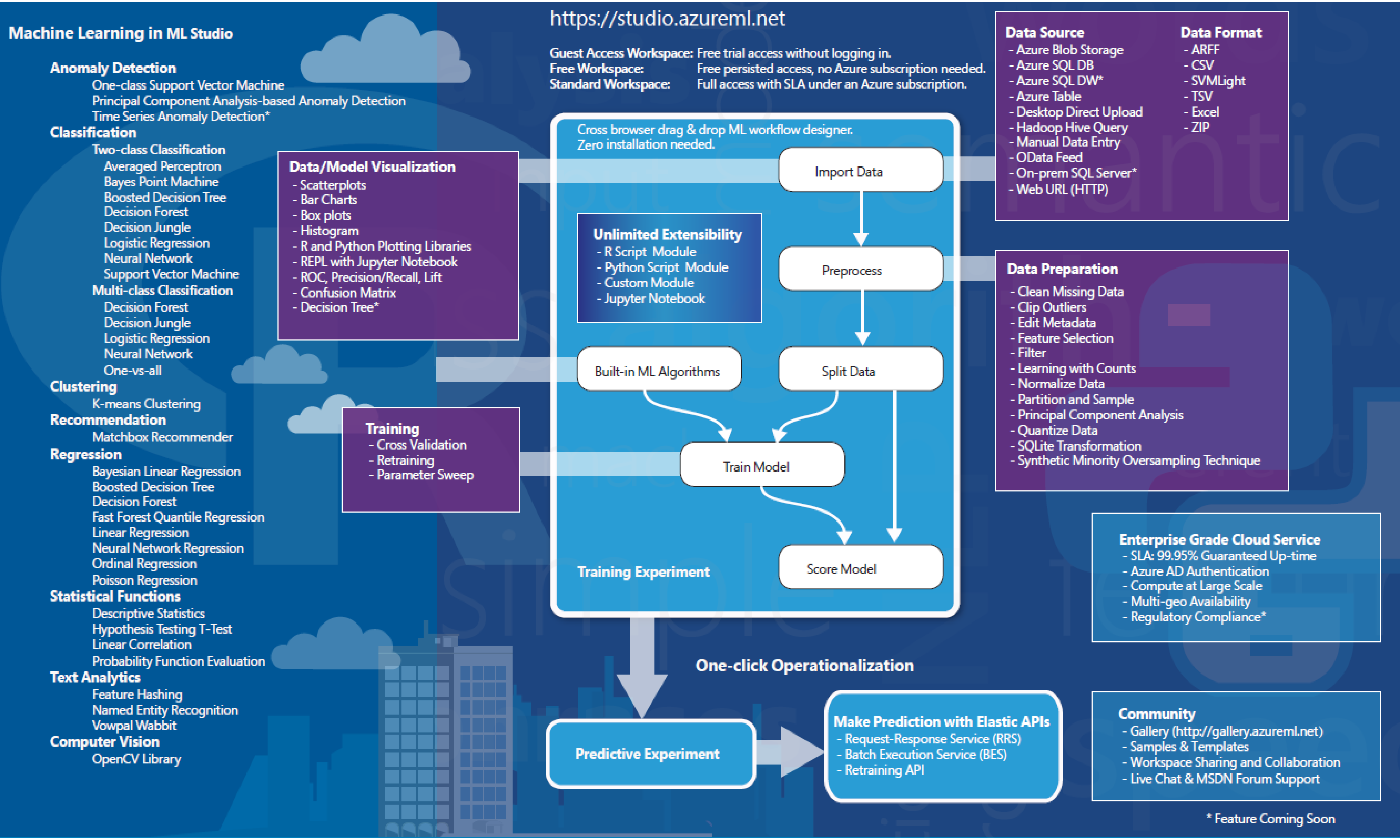
60 mins Lunch Break

Some interesting videos

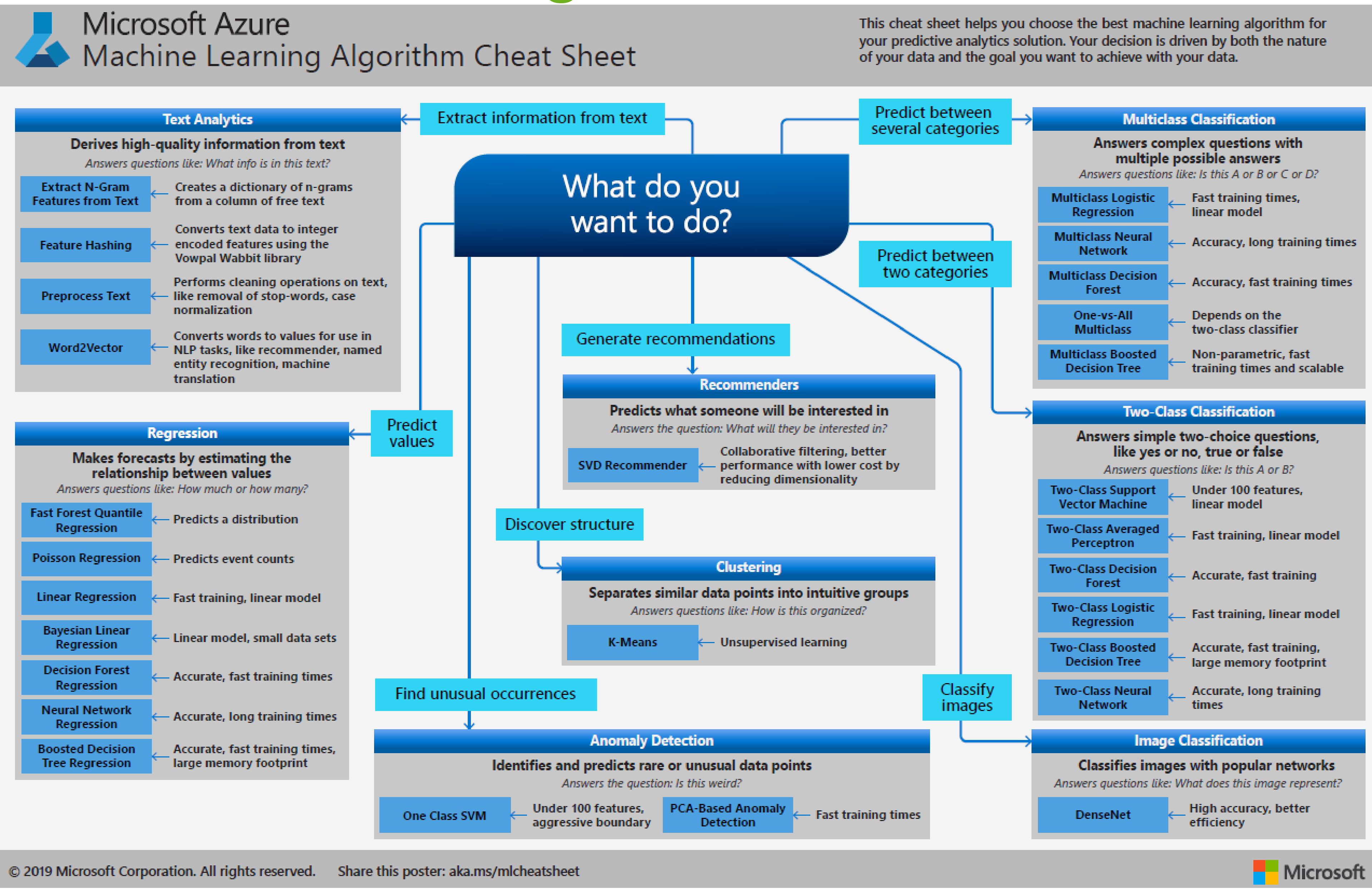
https://www.youtube.com/watch?v=bmNaLtC6vkU

https://www.youtube.com/watch?v=Nnf8P5A_saE

Recap

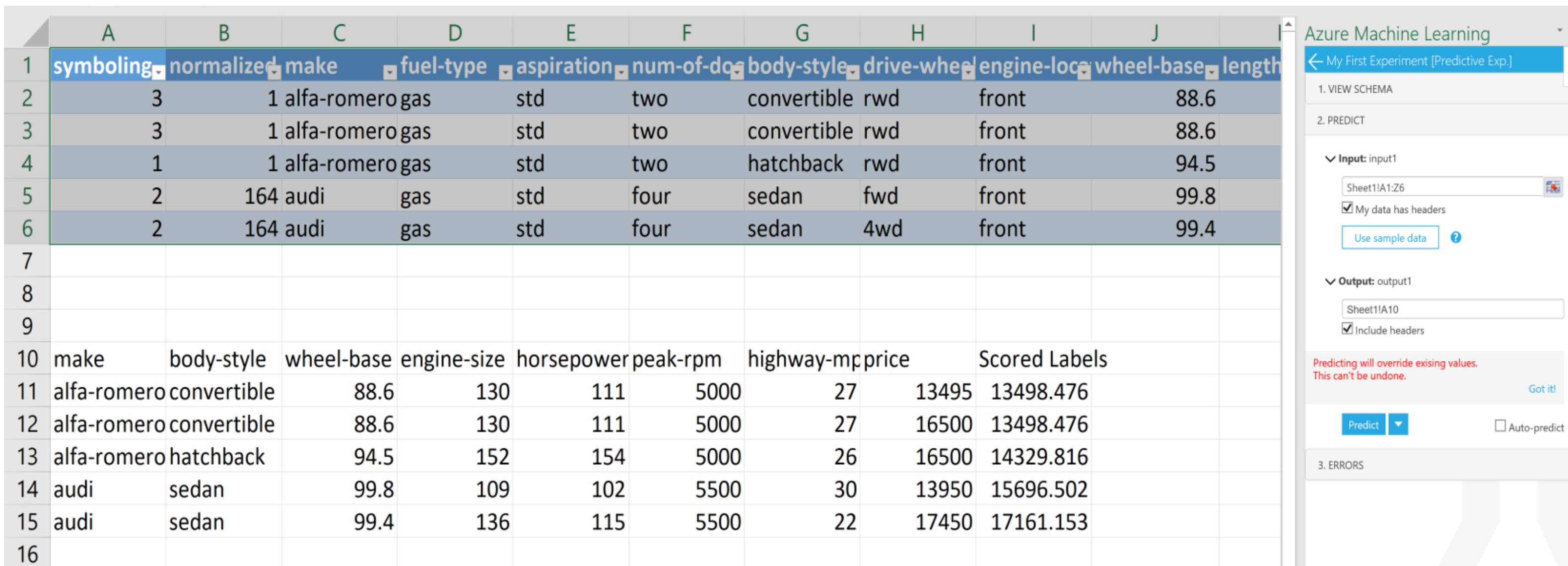

Machine Learning in ML Studio
Anomaly Detection
One-class Support Vector Machine
Principal Component Analysis-based Anomaly Detection
Time Series Anomaly Detection*
Classification
Two-class Classification
Averaged Perceptron
Bayes Point Machine
Boosted Decision Tree
Decision Forest
Decision Jungle
Logistic Regression
Neural Network
Support Vector Machine
Multi-class Classification
Decision Forest
Decision Jungle
Logistic Regression
Neural Network
One-vs-all
Clustering
K-means Clustering
Recommendation
Matchbox Recommender
Regression
Bayesian Linear Regression
Boosted Decision Tree
Decision Forest
Fast Forest Quantile Regression
Linear Regression
Neural Network Regression
Ordinal Regression
Poisson Regression
Statistical Functions
Descriptive Statistics
Hypothesis Testing T-Test
Linear Correlation
Probability Function Evaluation
Text Analytics
Feature Hashing
Named Entity Recognition
Vowpal Wabbit
Computer Vision
OpenCV Library
https://studio.azureml.net
Guest Access Workspace: Free trial access without logging in.
Free Workspace: Free persisted access, no Azure subscription needed.
Standard Workspace: Full access with SLA under an Azure subscription.
Data/Model Visualization
- Scatterplots
- Bar Charts
- Box plots
- Histogram
- R and Python Plotting Libraries
- REPL with Jupyter Notebook
- ROC, Precision/Recall, Lift
- Confusion Matrix
- Decision Tree*
Cross browser drag & drop ML workflow designer.
Zero installation needed.
Import Data
Unlimited Extensibility
- R Script Module
- Python Script Module
- Custom Module
- Jupyter Notebook
Preprocess
Built-in ML Algorithms
Split Data
Training
- Cross Validation
- Retraining
- Parameter Sweep
Train Model
Score Model
Training Experiment
Data Source
- Azure Blob Storage
- Azure SQL DB
- Azure SQL DW*
- Azure Table
- Desktop Direct Upload
- Hadoop Hive Query
- Manual Data Entry
- OData Feed
- On-prem SQL Server*
- Web URL (HTTP)
Data Format
- ARFF
- CSV
- SVMLight
- TSV
- Excel
- ZIP
Data Preparation
- Clean Missing Data
- Clip Outliers
- Edit Metadata
- Feature Selection
- Filter
- Learning with Counts
- Normalize Data
- Partition and Sample
- Principal Component Analysis
- Quantize Data
- SQLite Transformation
- Synthetic Minority Oversampling Technique
Enterprise Grade Cloud Service
- SLA: 99.95% Guaranteed Up-time
- Azure AD Authentication
- Compute at Large Scale
- Multi-geo Availability
- Regulatory Compliance*
One-click Operationalization
Predictive Experiment
Make Prediction with Elastic APIs
- Request-Response Service (RRS)
- Batch Execution Service (BES)
- Retraining API
Community
- Gallery (http://gallery.azureml.net)
- Samples & Templates
- Workspace Sharing and Collaboration
- Live Chat & MSDN Forum Support
* Feature Coming Soon

Azure ML Algorithm Cheat Sheet



Activity 2

- Deploying your experiment as a Web Service & Make Prediction using Excel



Step 1:
Watch and listen to the instructor's demonstration

15 mins

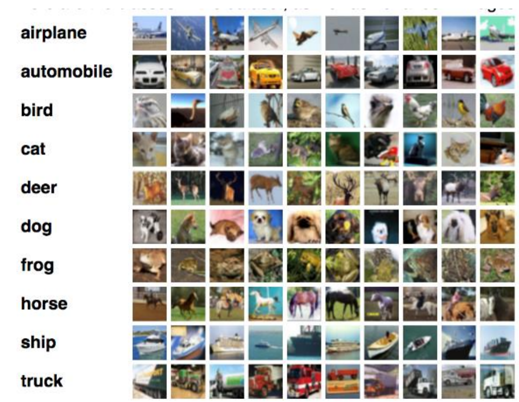
Step 2:
Work through the activities

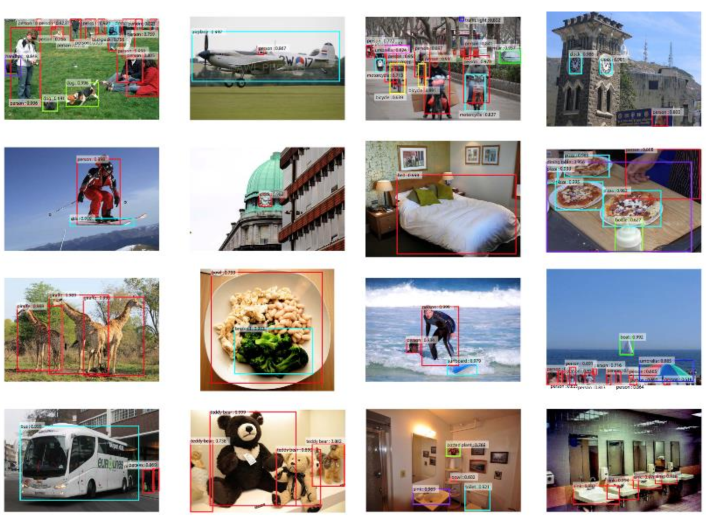
Individual Activity

45 mins

Applications of Computer Vision

- Image Classification
- Image Classification With Localization
- Object Detection
- Object Segmentation

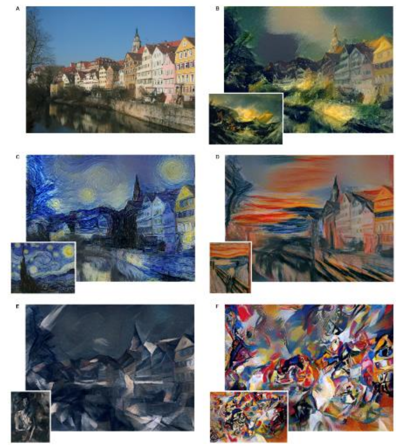


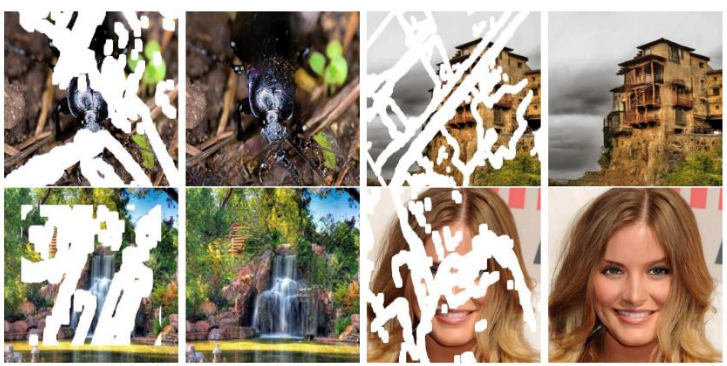


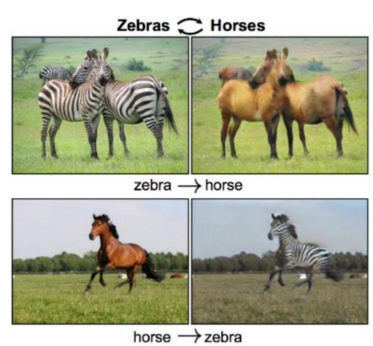
https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/

Applications of Computer Vision

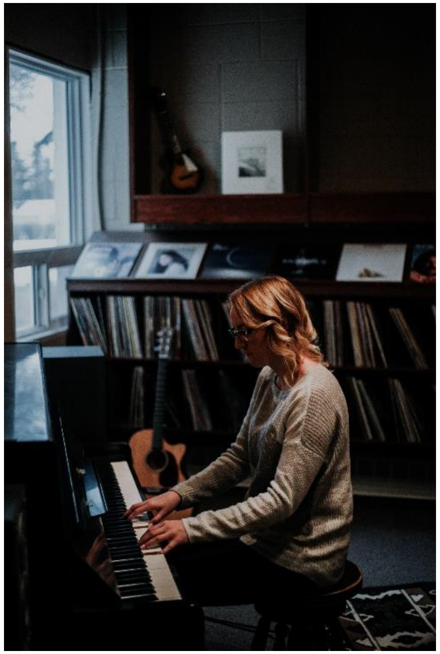
- Image Style Transfer
- Image Colorization
- Image Reconstruction
- Image Super-Resolution
- Image Synthesis
- Other Problems







Transfer Learning



Humans have an inherent ability to transfer knowledge across tasks.

What we acquire as knowledge while learning about one task, we utilize in the same way to solve related tasks.

The more related the tasks, the easier it is for us to transfer, or cross-utilize our knowledge.

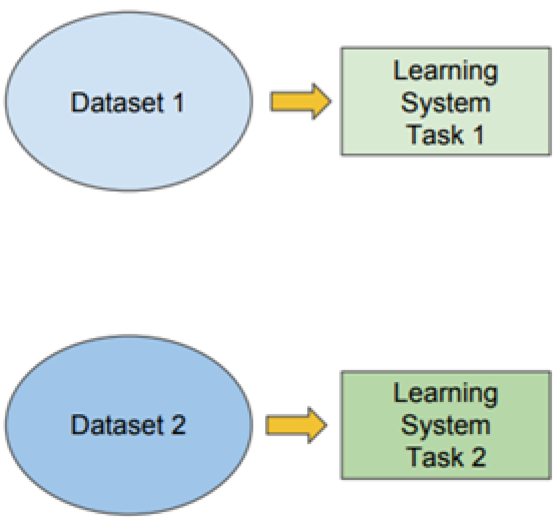
Some simple examples would be,
* Know how to ride a motorbike ➦ Learn how to ride a car
* Know how to play classic piano ➦ Learn how to play jazz piano

- Models are difficult to train from scratch
  - Huge datasets (like ImageNet)
  - Long number of training iterations
  - Very heavy computing machinery
  - Time experimenting to get hyper-parameters just right

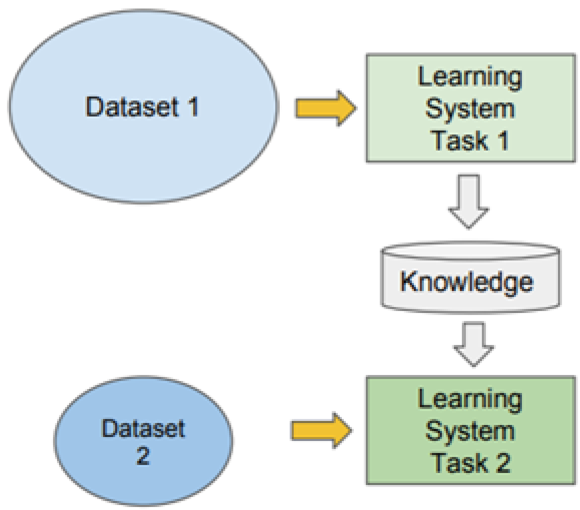
Transfer Learning

Traditional ML vs Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



Creating a new dataset

Step 1

- **Data acquisition**
  - Take pictures of the subject. Try to position subject in the middle of the image.
  - Import all images to your computer in a folder named MyImages.

Step 2

- **Data preprocessing**
  - **Resize images to 224x224 pixels**
  - **Label all images**

Step 3

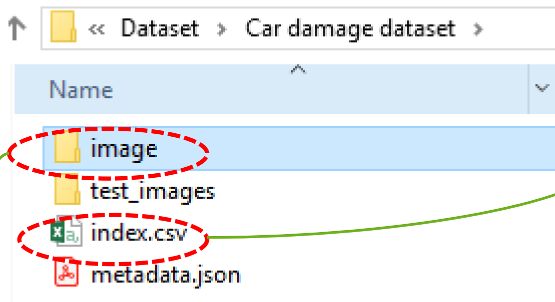
- **Create csv file**
  - **Create a text file with all image names**
  - **Create a file with all labels**
  - **Combine image names and labels in one file - index.csv**

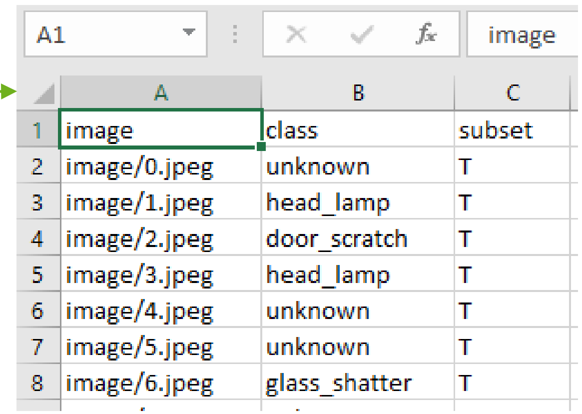
Step 4

- **Create the zip-file**

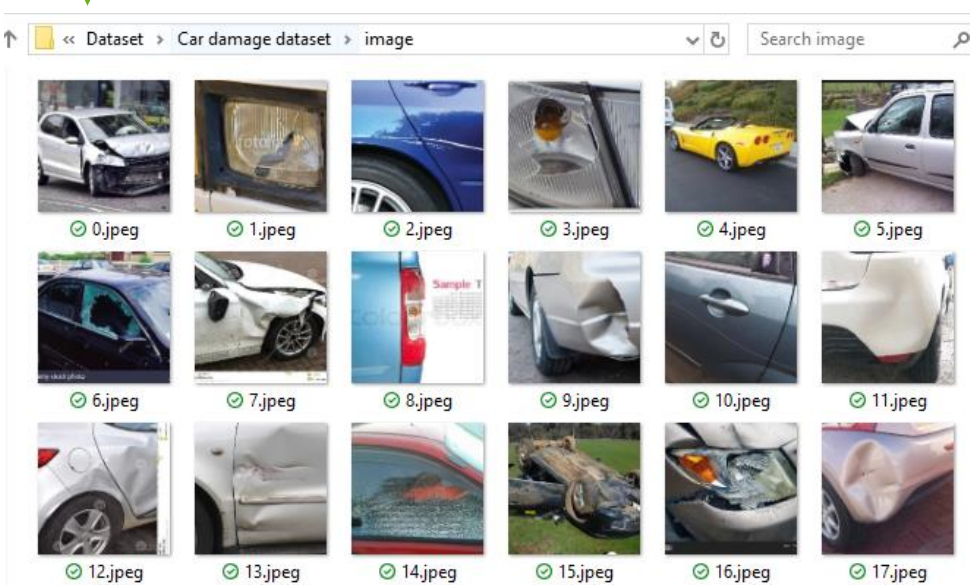
https://peltarion.com/knowledge-center/documentation/datasets-view/example-workflows---datasets-view/create-new-dataset-/-example-workflow

Example

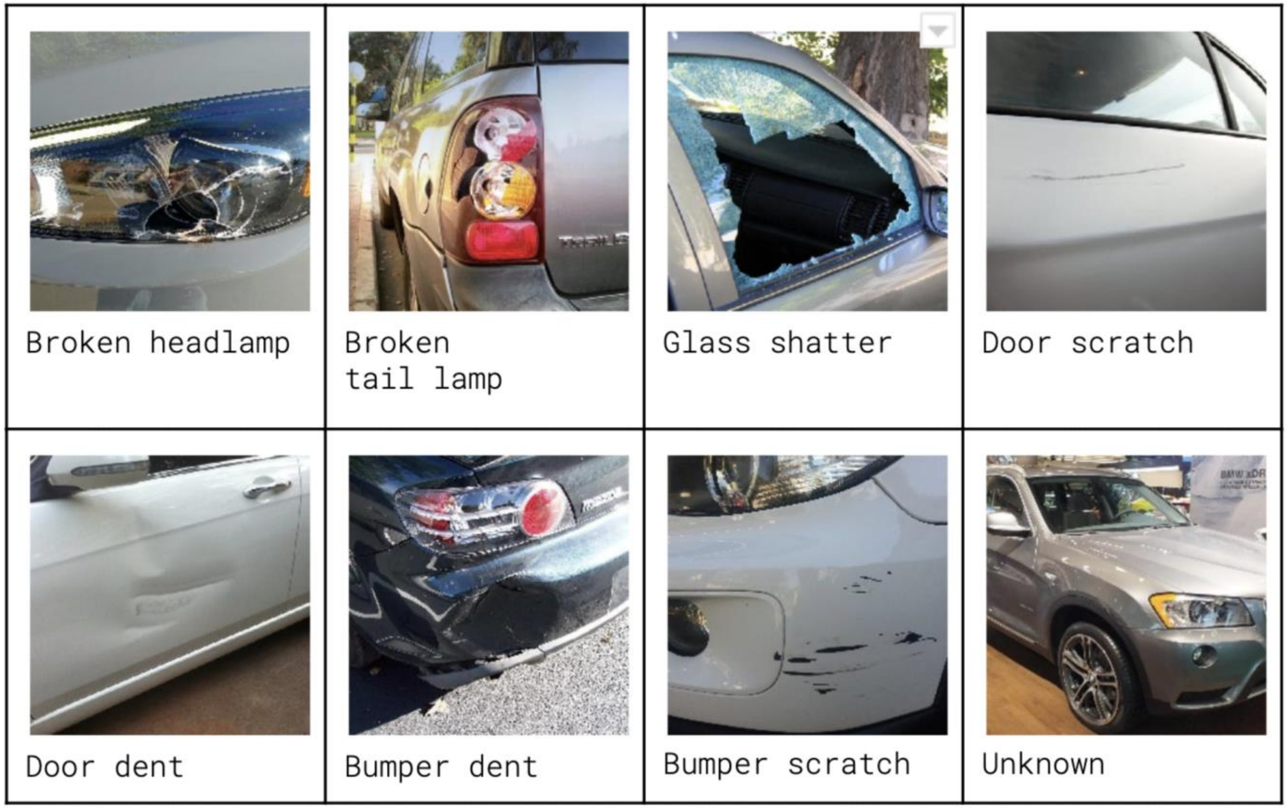




	A	B	C
1	image	class	subset
2	image/0.jpeg	unknown	T
3	image/1.jpeg	head_lamp	T
4	image/2.jpeg	door_scratch	T
5	image/3.jpeg	head_lamp	T
6	image/4.jpeg	unknown	T
7	image/5.jpeg	unknown	T
8	image/6.jpeg	glass_shatter	T



Activity 3 – Car Damage Classifier



Step 1:
Watch and listen to the instructor's demonstration

20 mins

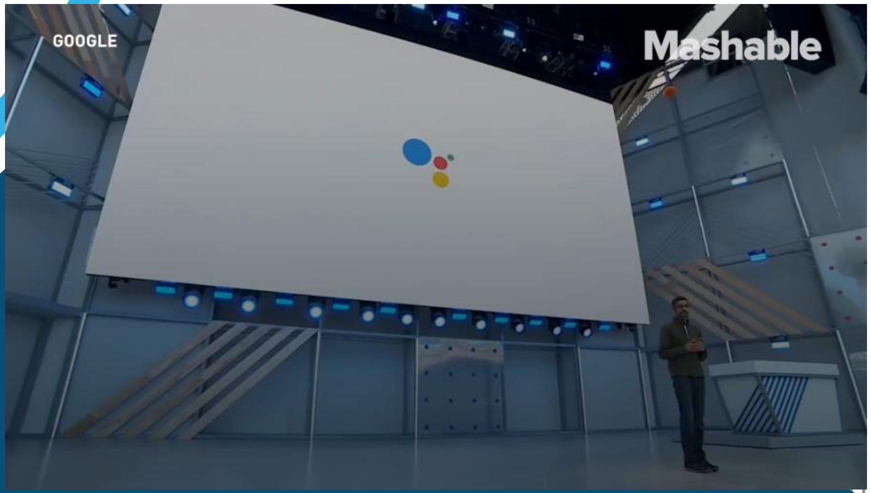
Step 2:
- Do on your own

40 mins

Individual Activity

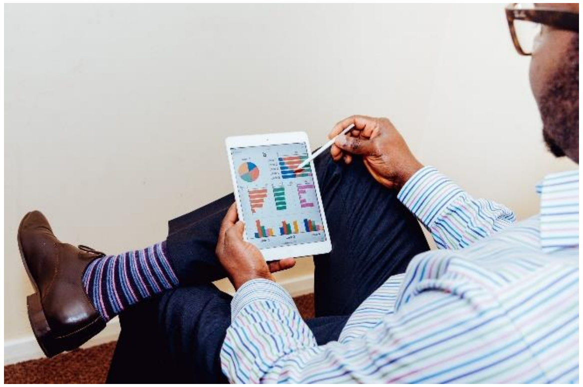
15 Mins Break

bit.ly/google_duplex2019



Natural Language Processing

- Search Autocorrect and Autocomplete
- Language Translator
- **Social Media Monitoring**
- Chatbots
- **Survey Analysis**
- Targeted Advertising
- Hiring and Recruitment
- Voice Assistants
- Grammar Checkers
- Email Filtering



https://www.analyticsvidhya.com/blog/2020/07/top-10-applications-of-natural-language-processing-nlp/

Dataset

	review Encoding Text	sentiment Encoding Binary Positive class positive
1	Hubert Selby Jr. gave us the book "Requiem For A Dream" and co-wrote the screenplay to Aronofsky's movie of it. That movie succeeded on every level by delivering an intimate, and unbiased portrait of the horrors of the characters lives and the vices that destroyed them. "Last Exit To Brooklyn" still has the vice and the multiple characters living sad lives, but it hardly does them the same justice Aronofsky did. The film seems laughably anti-gay at times. Especially when in the film homosexuality equals death. One gay character gets stoned, is launched skyward by a speeding car, and lands dead on the pavement. Another is crucified and still more are simply beat up. Another exaggerated piece of shock value, that might actually hav...	negative
2	There are very few performers today who can keep me captivated throughout an entire film just by their presence. One of those few is Judy Davis, who has built a successful career out of creating characters that are headstrong in attitude but very vulnerable at heart. She takes roles that most other performers would treat melodramatically and adds a fiery, deeply emotional intensity that pulls attention away from everything else on the screen. Her skills are well displayed in "High Tide," a film that matches her up a second time with director Gillian Armstrong, who gave Davis her first major success with "My Brilliant Career." In that film, Davis played a young woman who was determined to make it in the world, despite the suffocat...	positive
3	C'mon guys some previous reviewers have nearly written a novel commenting on this episode. It's just an old 60's TV show ! This episode of Star Trek is notable	negative

Information

Creator	-
Features	Review, Sentiment
Rows	25 000
Size	13 MB
Categories	Text, Classification

Activity 4 - Creating a Sentiment Analyser

About this dataset

This dataset contains textual movie reviews from IMDB users, together with the rating (simplified as positive or negative) that the user gave to the movie.

Inspiration

Use this dataset to predict a simple positive or negative category from paragraph-sized text data.

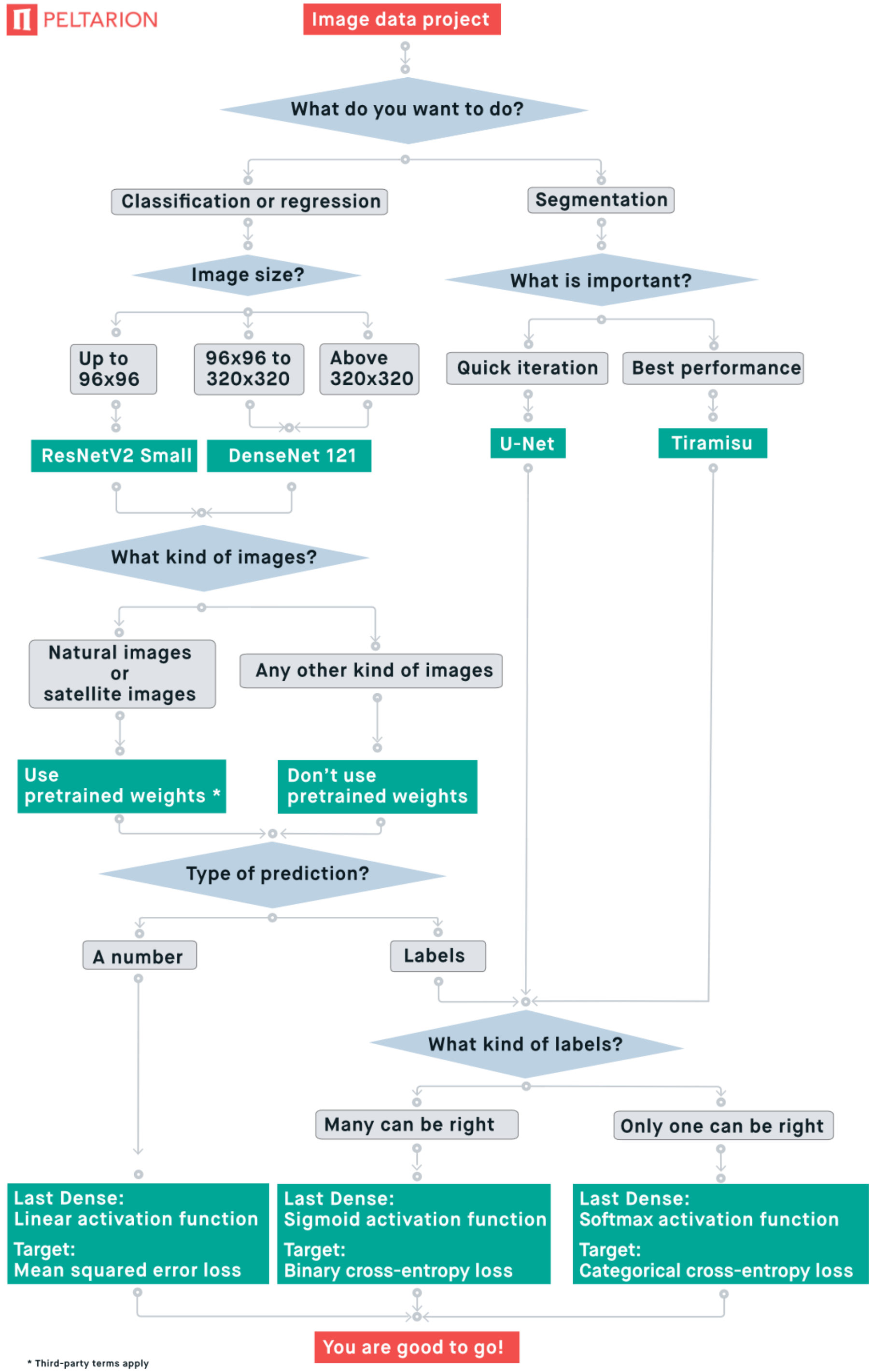
Step 1:
Watch and listen to the instructor's demonstration

20 mins

Step 2:
- Do on your own

40 mins

Individual Activity



Cheatsheet

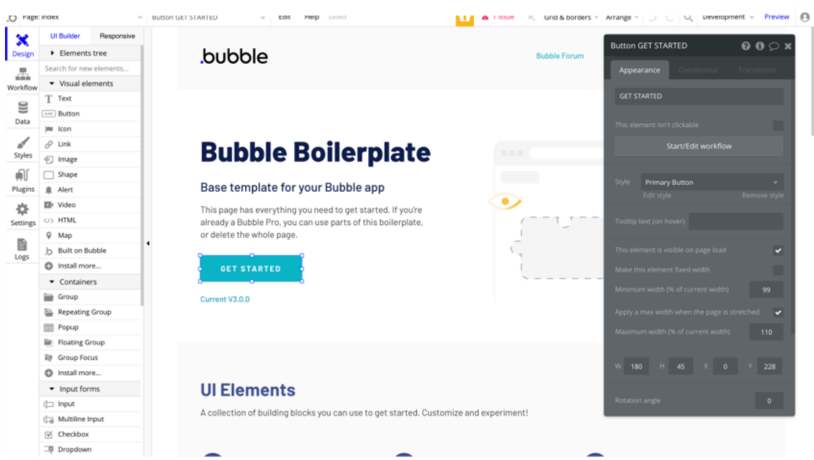
https://peltarion.com/knowledge-center/documentation/cheat-sheets

Linking Them Together

App Development

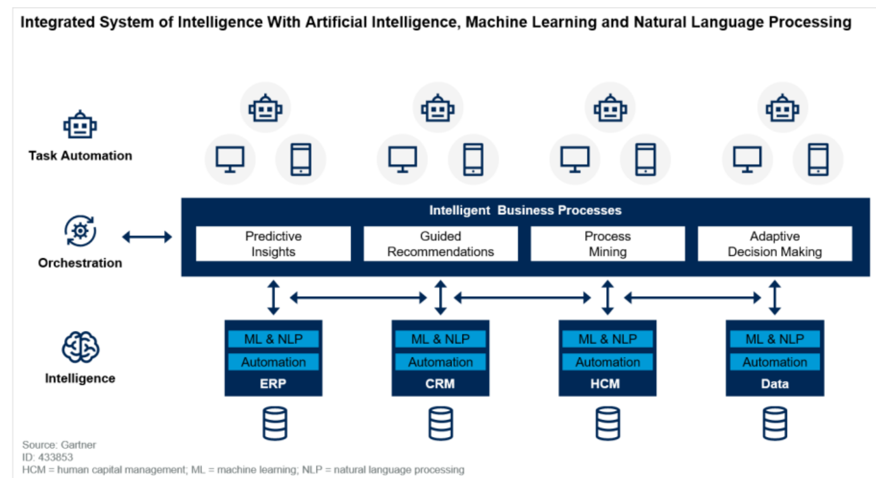
Top 9 No-Code Web App Development Tools that May Compete with Bubble

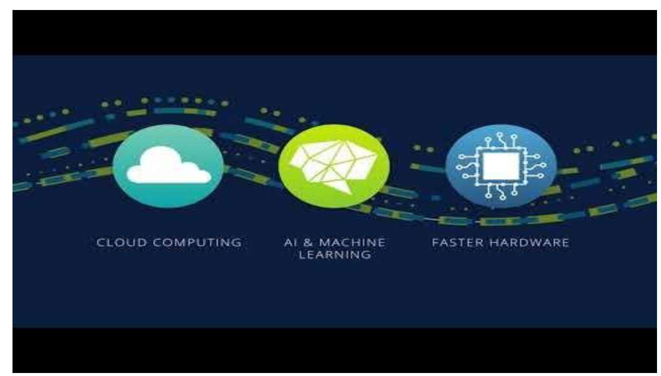
We're here to prove that **"building the best product"** is possible not only with Bubble.
Discover the *5 most powerful Bubble alternatives* in the comparison table below to decide which one fits you best. Find more detailed information about the other Bubble.io alternatives after the table.



https://uibakery.io/bubble-alternatives

RPA





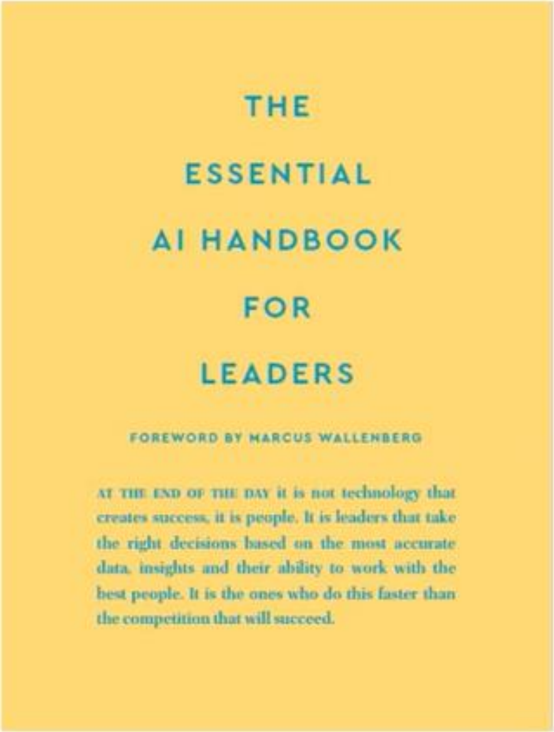
Adobe Acrobat Document

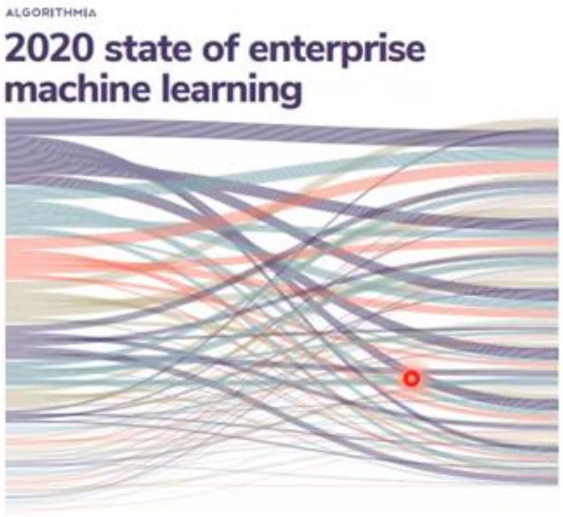
https://www.youtube.com/watch?v=FV8lM9SIFQ8

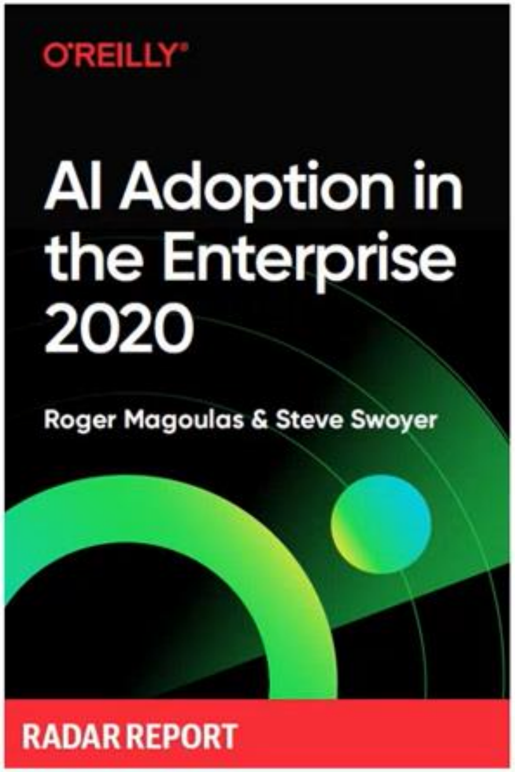
When to use Machine Learning

- **What are our most pressing problems right now?**
  - Just like any other tool in business, AI should be viewed as a tool that can help make your organization more effective, profitable or streamlined
- **What parts of our business generate revenue but currently have low profit margins?**
  - These revenue streams could provide fertile ground for automation and acceleration via AI.
- **Where would we like to cut costs?**
  - Review your costs and pinpoint the ones you'd like to reduce. AI can help you better understand what generates costs and identify areas that could be optimized or changed to reduce them.
- **Where do we make a high percentage of errors in our work?**
  - A well-trained AI model has the capacity to perform with far less margin of error than humans
- **What work do our employees do that they don't particularly like?**
  - If it's repetitive or annoying for a human to do, there might be a component of the task better done by AI.

Some easy readings







Datasets and Data Prep

GitHub
https://kwseow.github.io/

Google Dataset Search Beta
https://datasetsearch.research.google.com/

kaggle
https://www.kaggle.com/datasets

KDnuggets™
https://www.kdnuggets.com/datasets/index.html

Excel

tableau

Microsoft Power BI

roboflow

Dataset and Data Prep

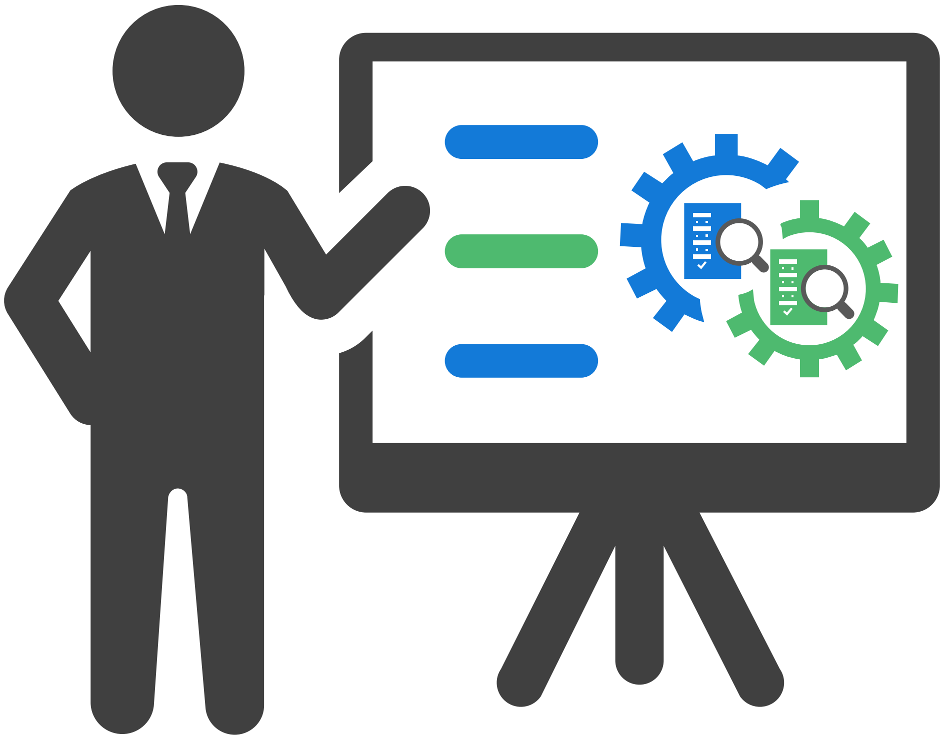
- Datasets
  - http://kwseow.github.io
  - https://datasetsearch.research.google.com/
  - https://www.kaggle.com/

- Data prep
  - Excel
  - Tableau Prep
  - Power BI

Survey

https://bit.ly/3dsqFkE

Summary



Email
zack_toh@rp.edu.sg

Telegram
@zacktohsh

Source code:

Thank you