REPUBLIC POLYTECHNIC
DISCOVER. TRANSFORM. ACHIEVE

Introduction to Code-Free Machine Learning

Good Morning!

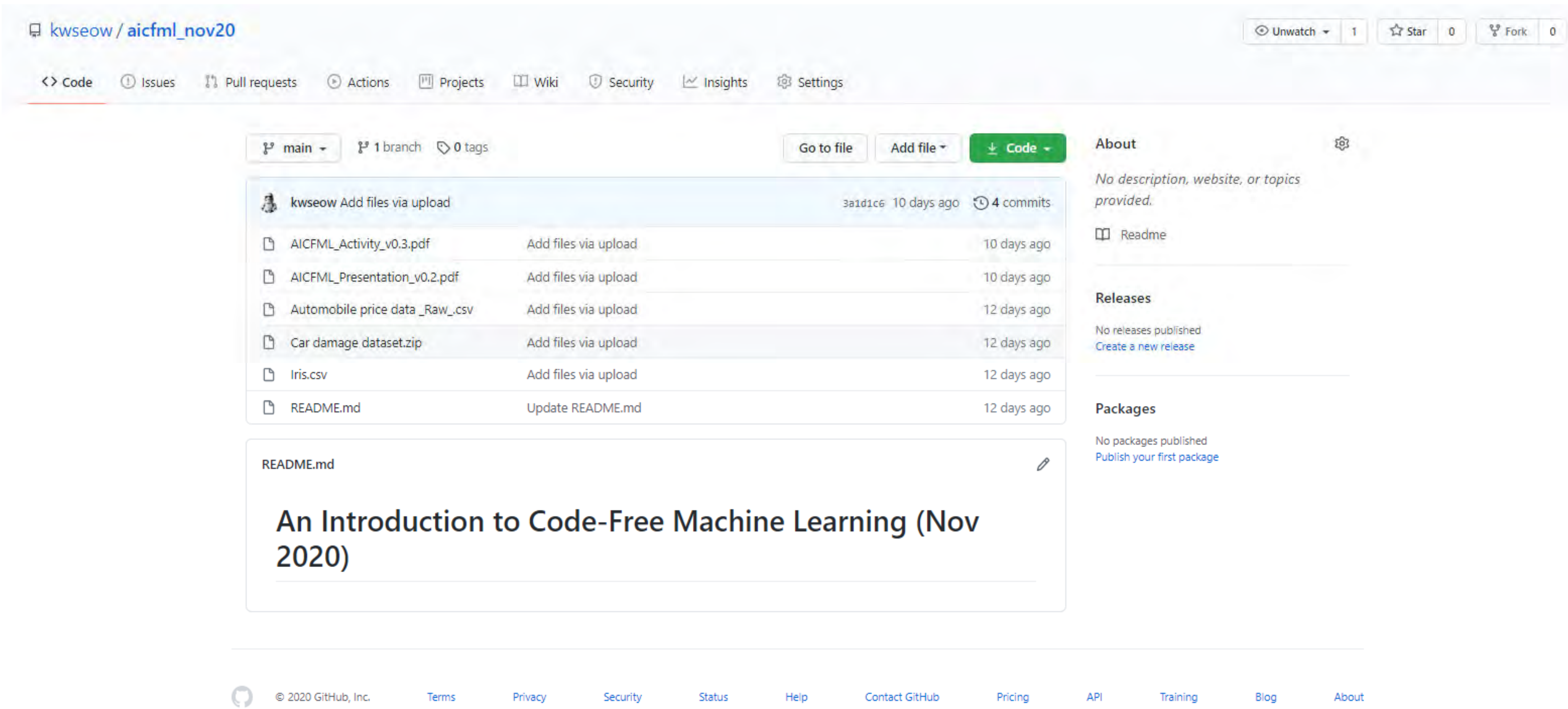
1) Download the presentation slides and activity worksheets at http://bit.ly/cfml_nov20
2) If your nickname used in Teams is different from the registered name, please drop a message on the channel with the registered name for attendance tracking purpose.
3) We will start at 9am sharp

Sit back and relax for now ☺

Version 1.0

Download from Github

http://bit.ly/cfml_nov20



Warm up!

Step 1: Go to the following url

http://bit.ly/cfml_warmup

Step 2: facilitator will walk you through the following 2 questions

1) Write down what you know about code-free and machine learning

2) What do you hope to gain from this workshop.

3 mins

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 – Book Genre Classifier
Section 6:	Linking them together
Section 7:	Debrief

Introduction of trainer

Name
Seow Khee Wei

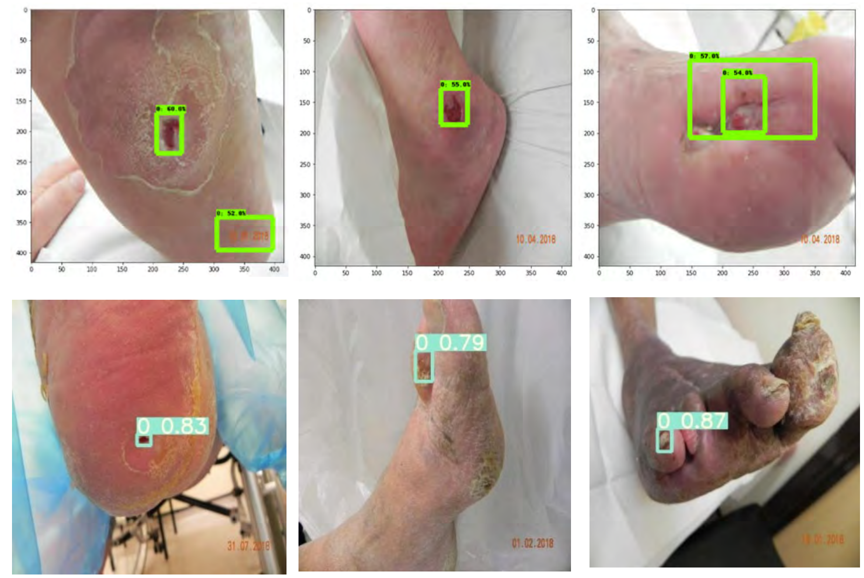
Telegram
@kwseow

Email
seow_khee_wei@rp.edu.sg

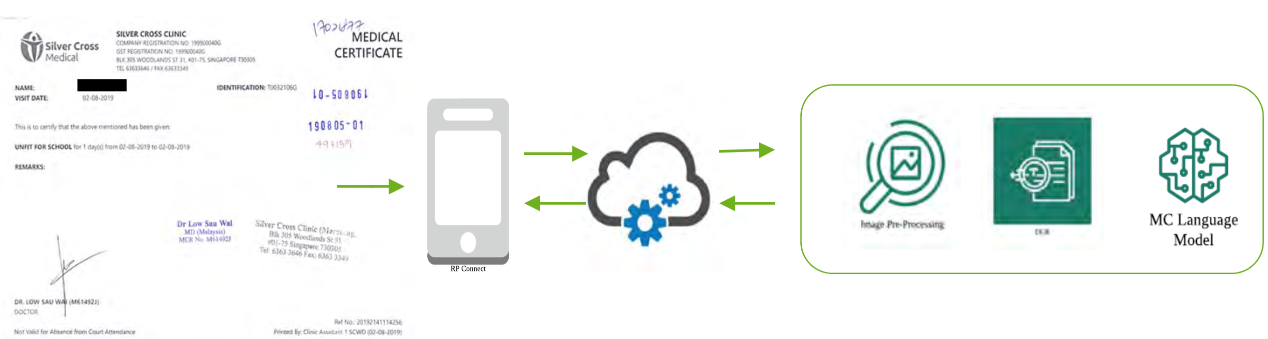
Projects

Scene Understanding

Diabetic Foot At Risk Reconstruction

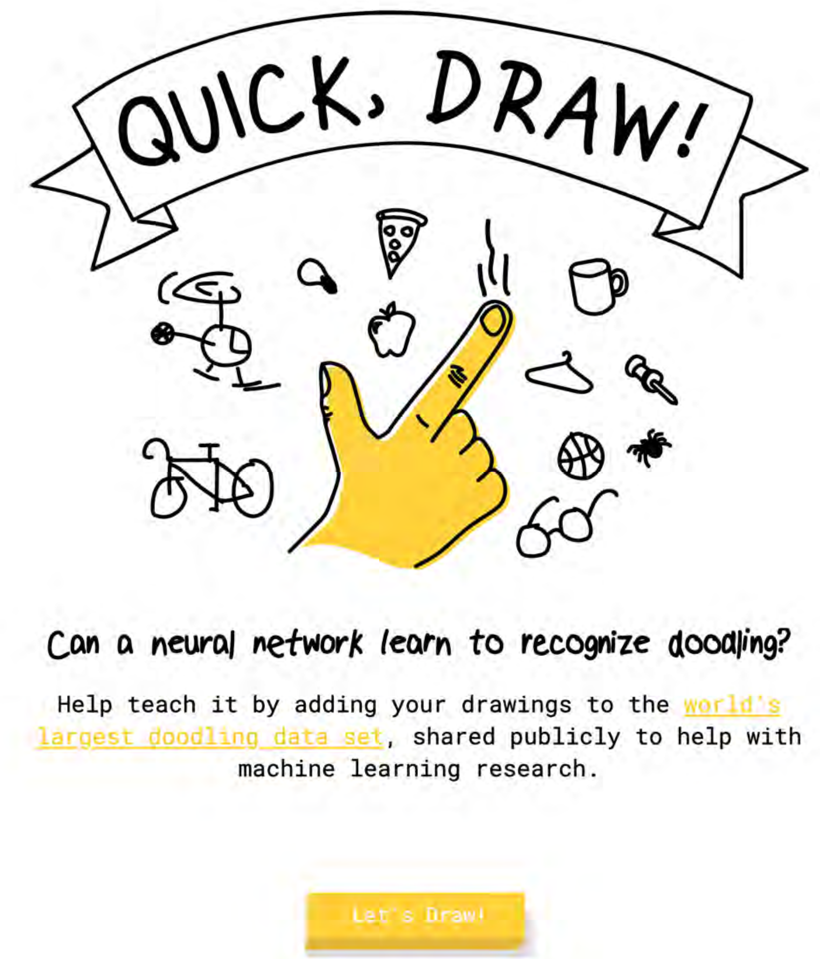


Language model for Medical Certificates



Quickdraw Game

https://quickdraw.withgoogle.com

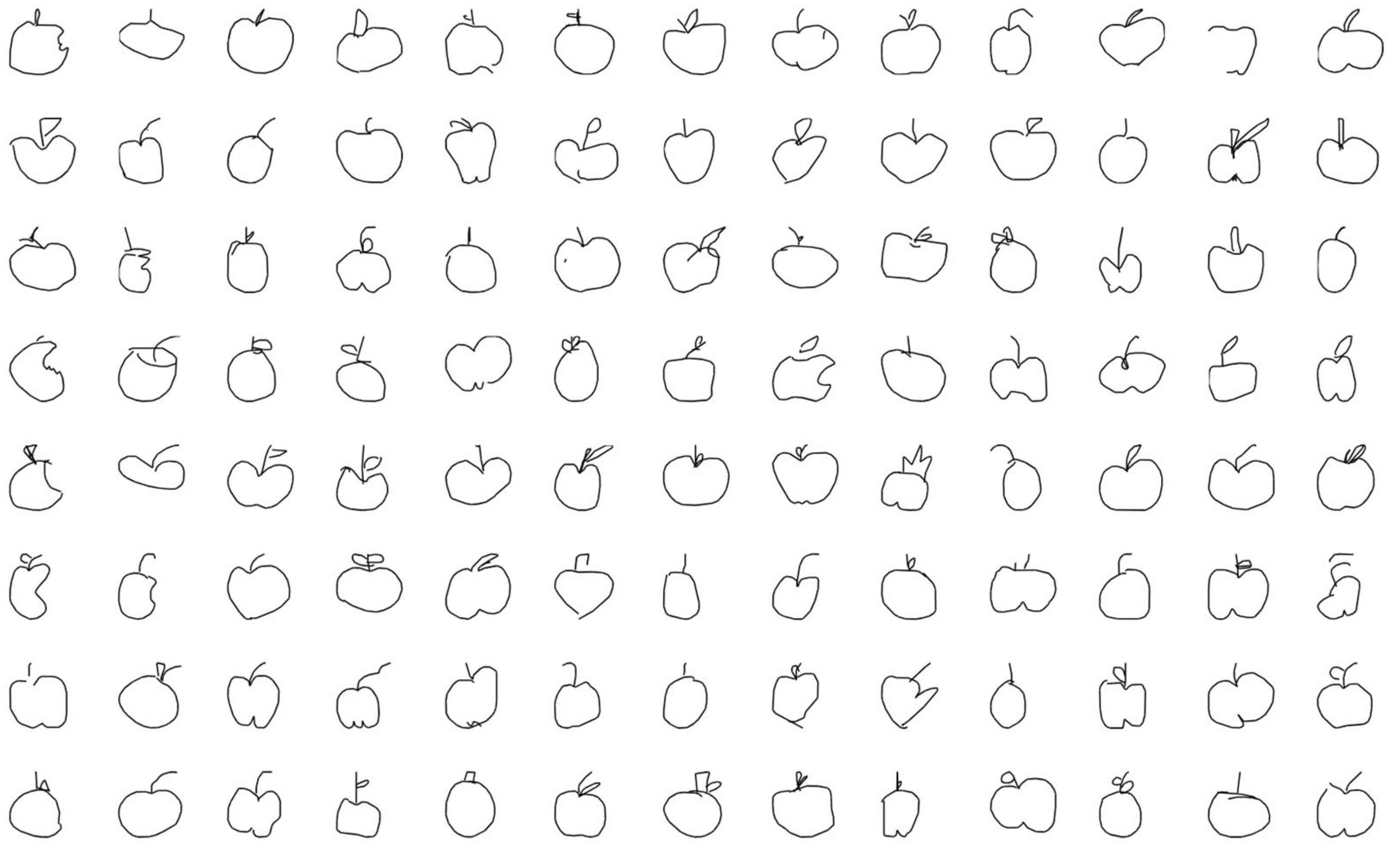


Optional Activity

5 mins

How does ML work in QuickDraw?

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



Bias Bias Bias

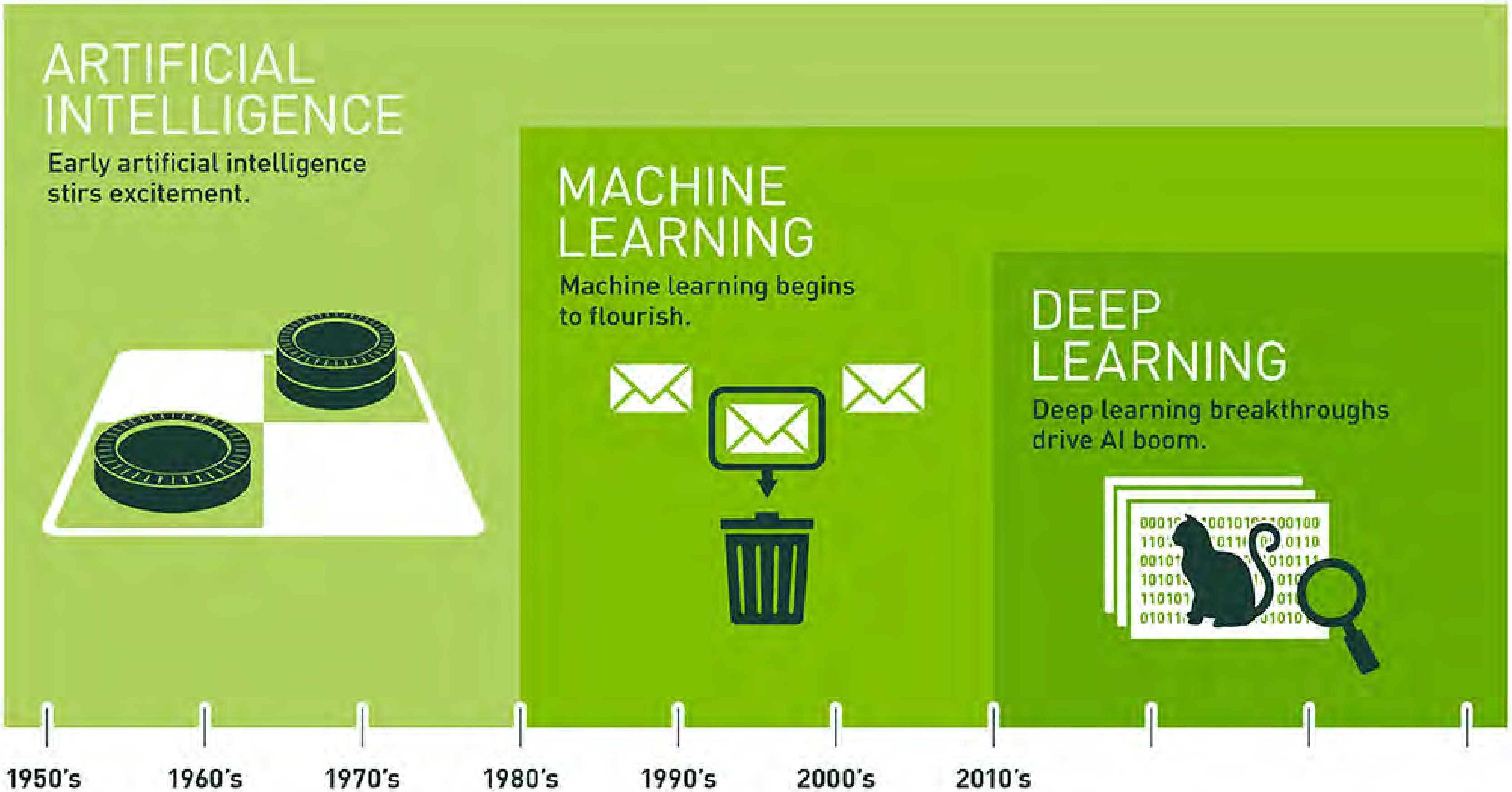
When It Comes to Gorillas, Google Photos Remains Blind

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/

AI Time line

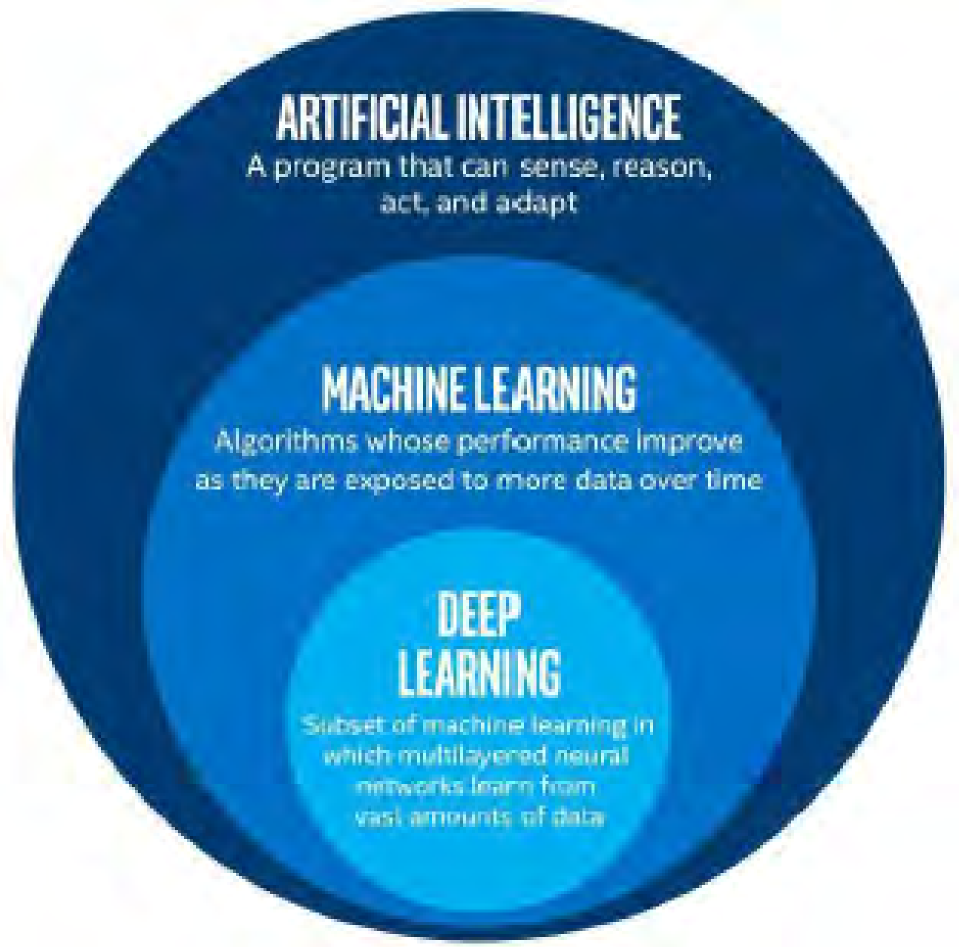


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: Nvidia

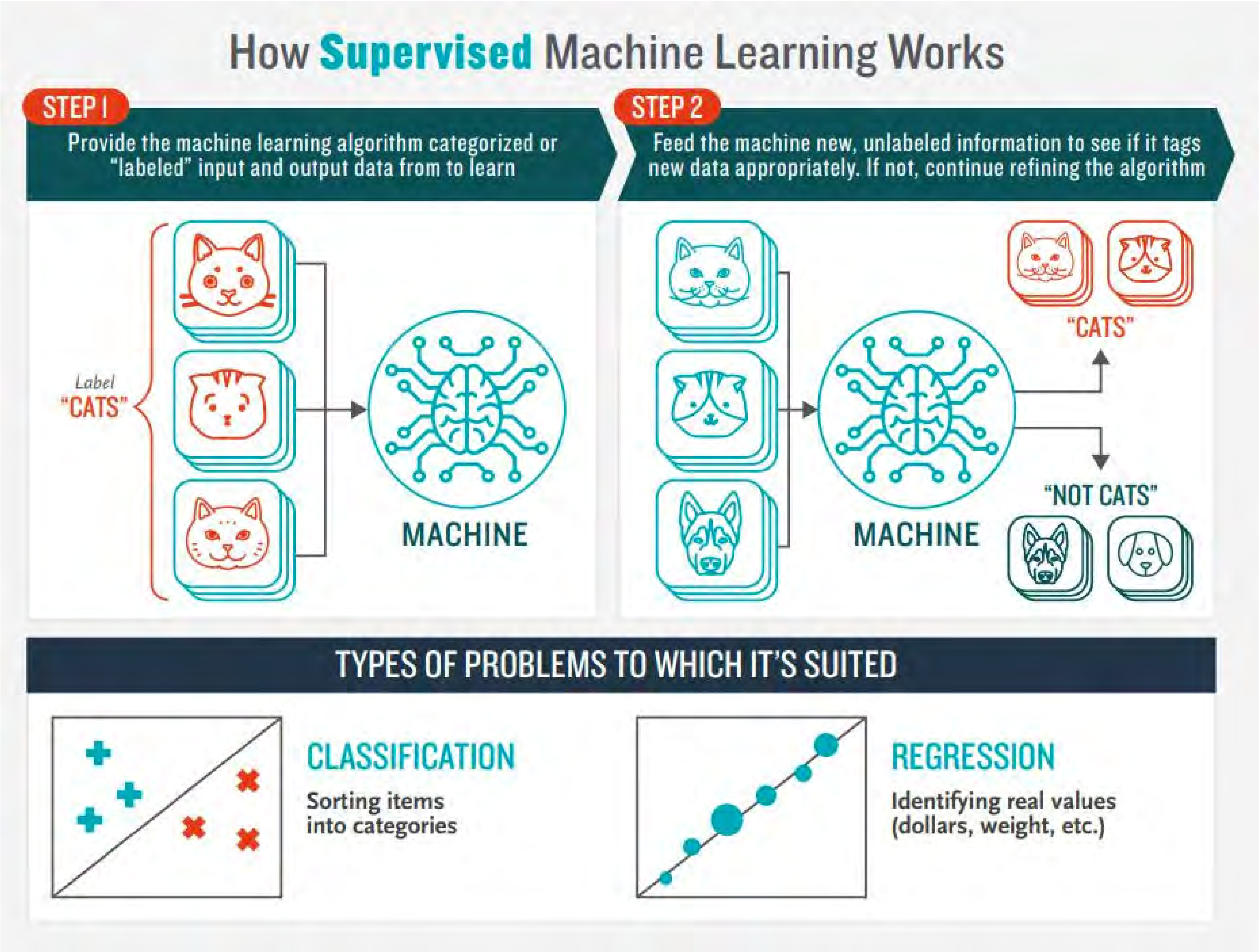
Machine Learning

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



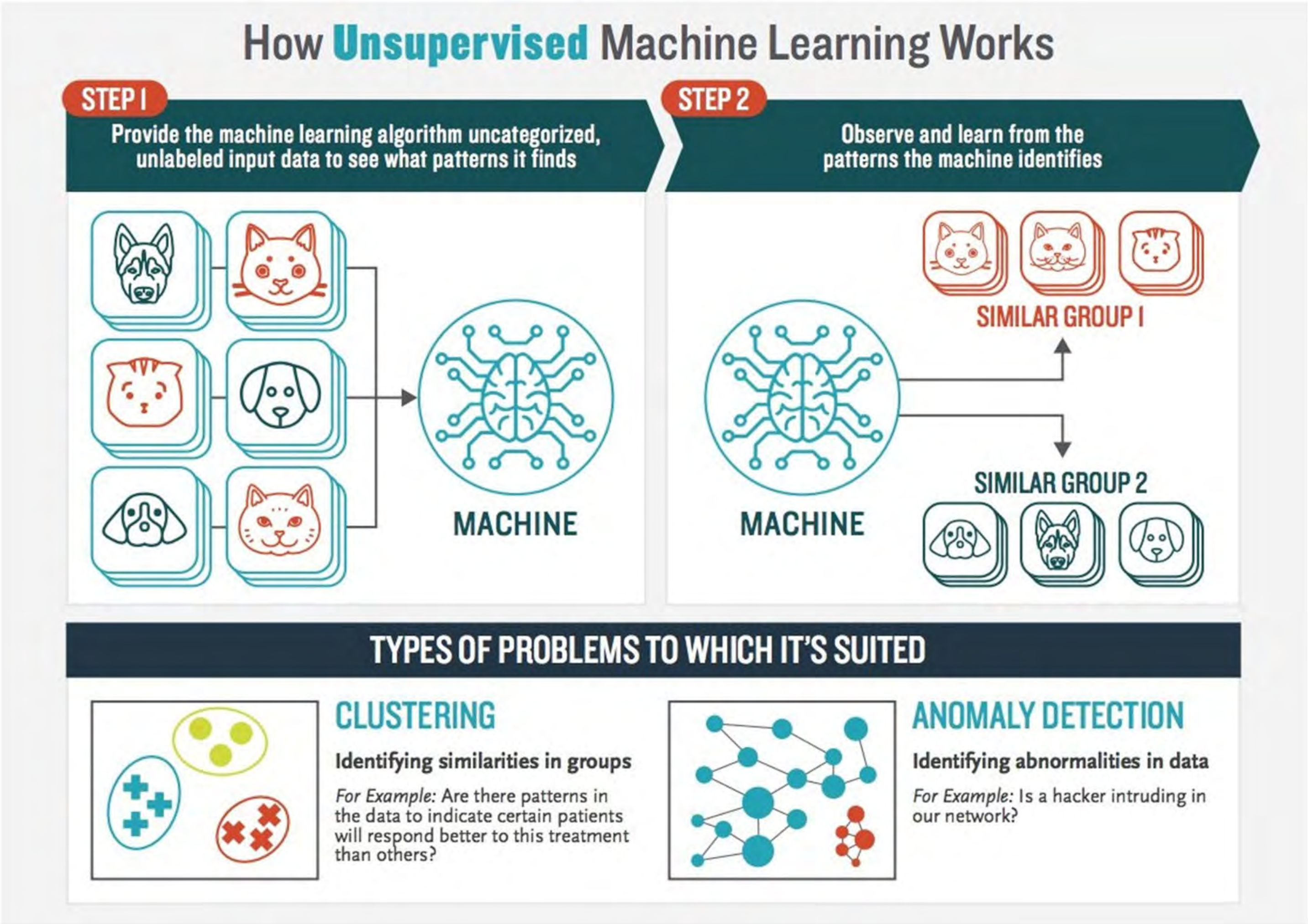
Supervised Learning

Data points have **known** outcome



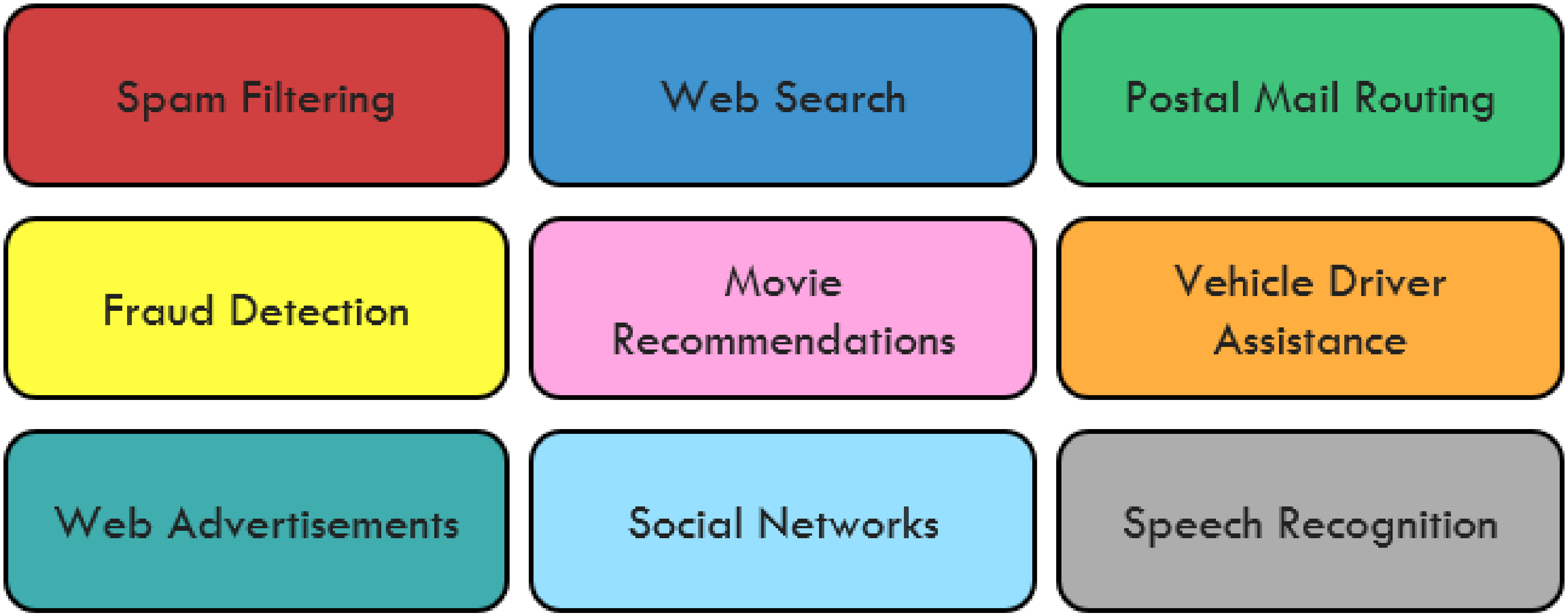
Unsupervised Learning

Data points have **unknown** outcome



Machine Learning

- Applications in our daily lives



5 fundamental questions

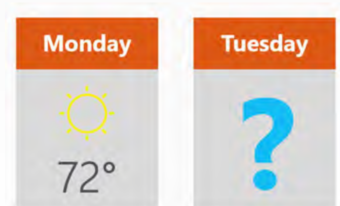
Is this weird? (Anomaly detection)

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)



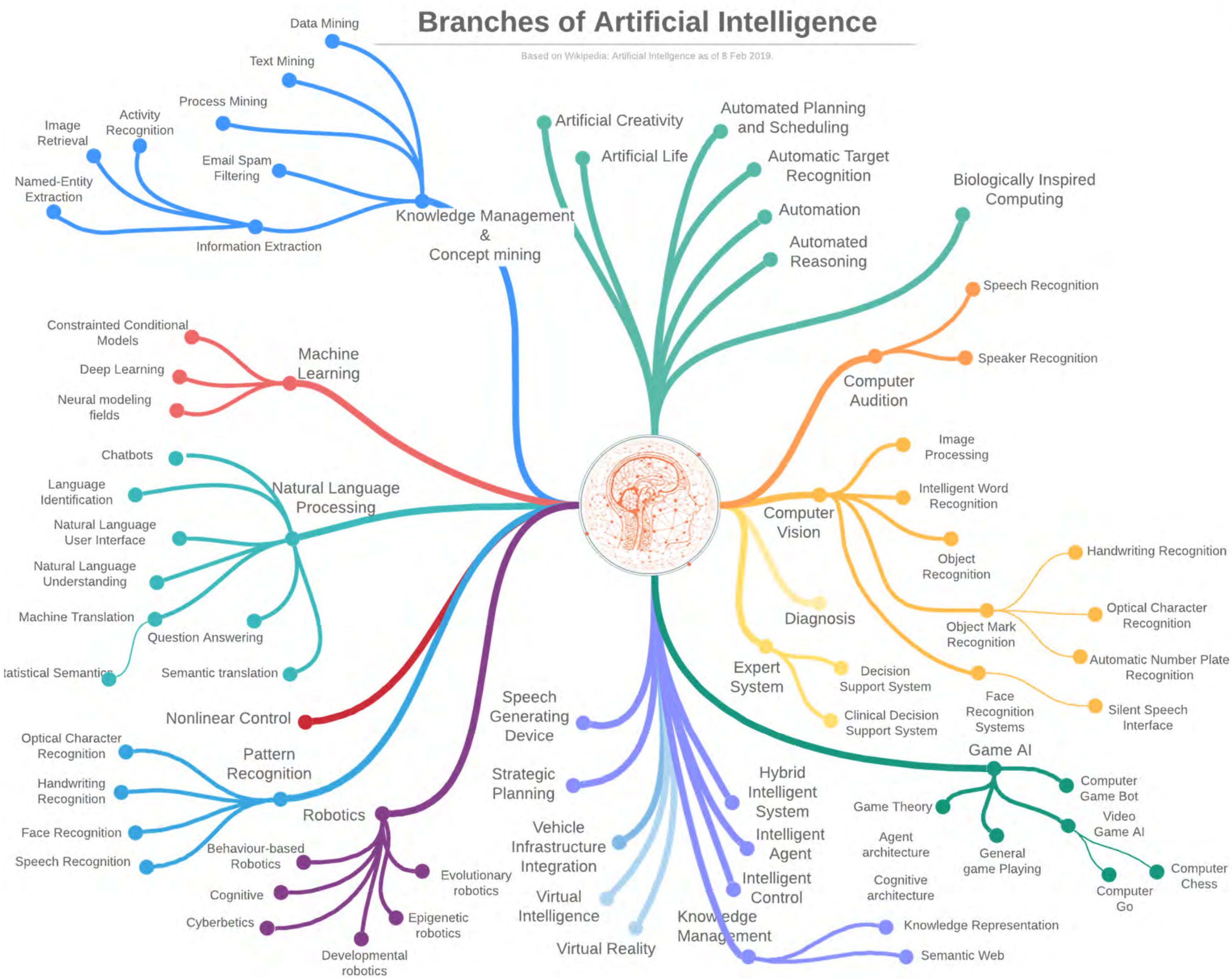
What will the temperature be next Tuesday?
What will my fourth quarter sales be?

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.
Knowledge Management & Concept mining
Data Mining
Text Mining
Process Mining
Email Spam Filtering
Activity Recognition
Image Retrieval
Named-Entity Extraction
Information Extraction
Artificial Creativity
Artificial Life
Automated Planning and Scheduling
Automatic Target Recognition
Automation
Automated Reasoning
Biologically Inspired Computing
Computer Audition
Speech Recognition
Speaker Recognition
Computer Vision
Image Processing
Intelligent Word Recognition
Object Recognition
Object Mark Recognition
Handwriting Recognition
Optical Character Recognition
Automatic Number Plate Recognition
Face Recognition Systems
Silent Speech Interface
Diagnosis
Expert System
Decision Support System
Clinical Decision Support System
Game AI
Computer Game Bot
Game Theory
Video Game AI
General game Playing
Computer Go
Computer Chess
Agent architecture
Cognitive architecture
Machine Learning
Constrainted Conditional Models
Deep Learning
Neural modeling fields
Natural Language Processing
Chatbots
Language Identification
Natural Language User Interface
Natural Language Understanding
Machine Translation
Question Answering
Statistical Semantics
Semantic translation
Nonlinear Control
Pattern Recognition
Optical Character Recognition
Handwriting Recognition
Face Recognition
Speech Recognition
Robotics
Behaviour-based Robotics
Cognitive
Cyberbetics
Developmental robotics
Epigenetic robotics
Evolutionary robotics
Speech Generating Device
Strategic Planning
Vehicle Infrastructure Integration
Virtual Intelligence
Virtual Reality
Hybrid Intelligent System
Intelligent Agent
Intelligent Control
Knowledge Management
Knowledge Representation
Semantic Web

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.

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.

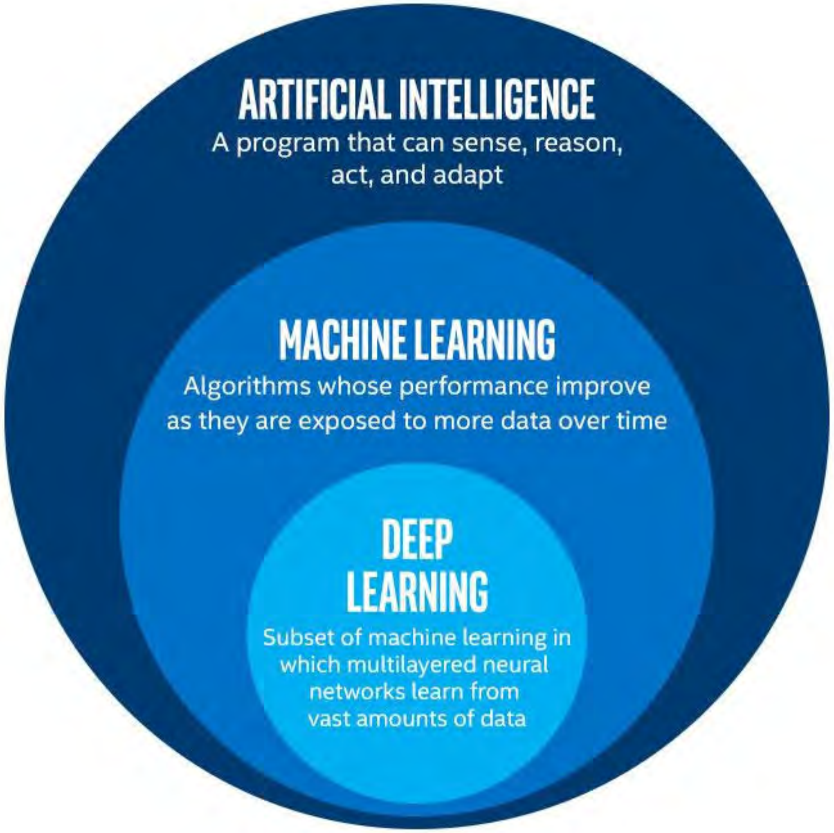
Dog and cat recognition

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

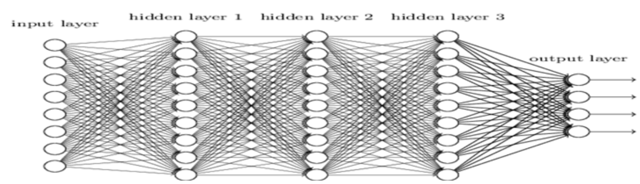
Machine Learning Classifier

“David"

Deep Learning

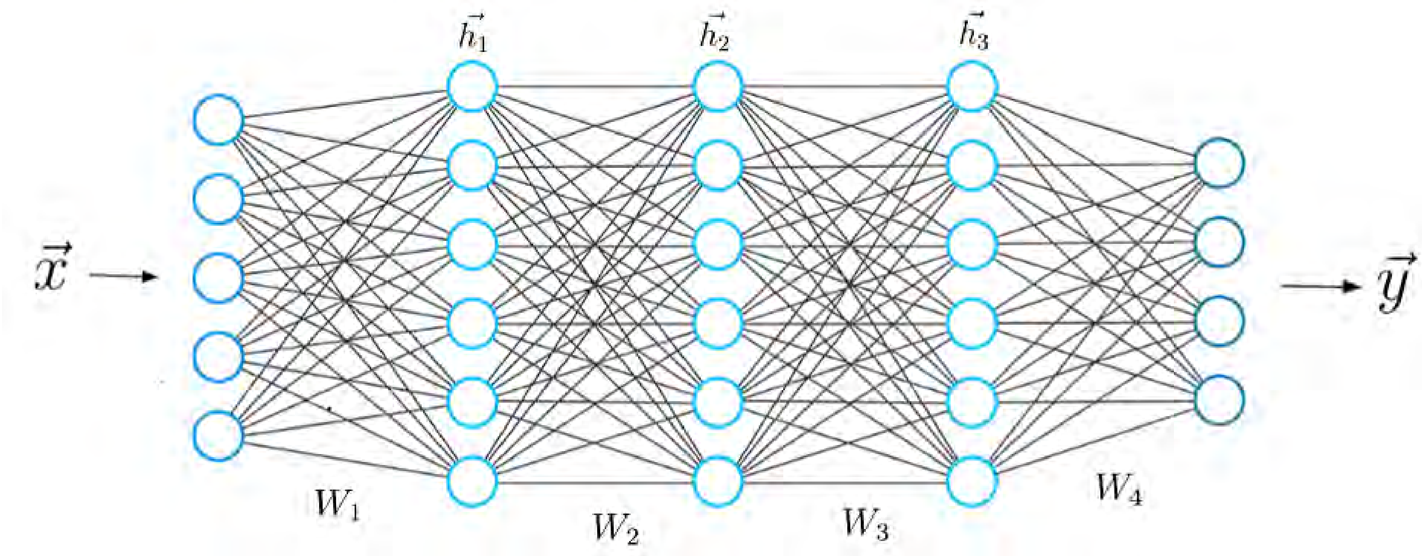
Steps 1 and 2 are combined into 1 step.

Neural Network

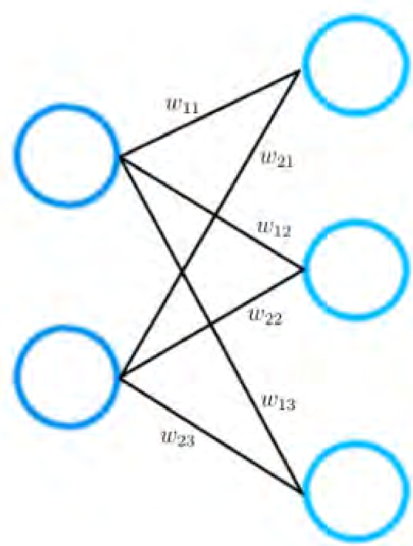


“David"

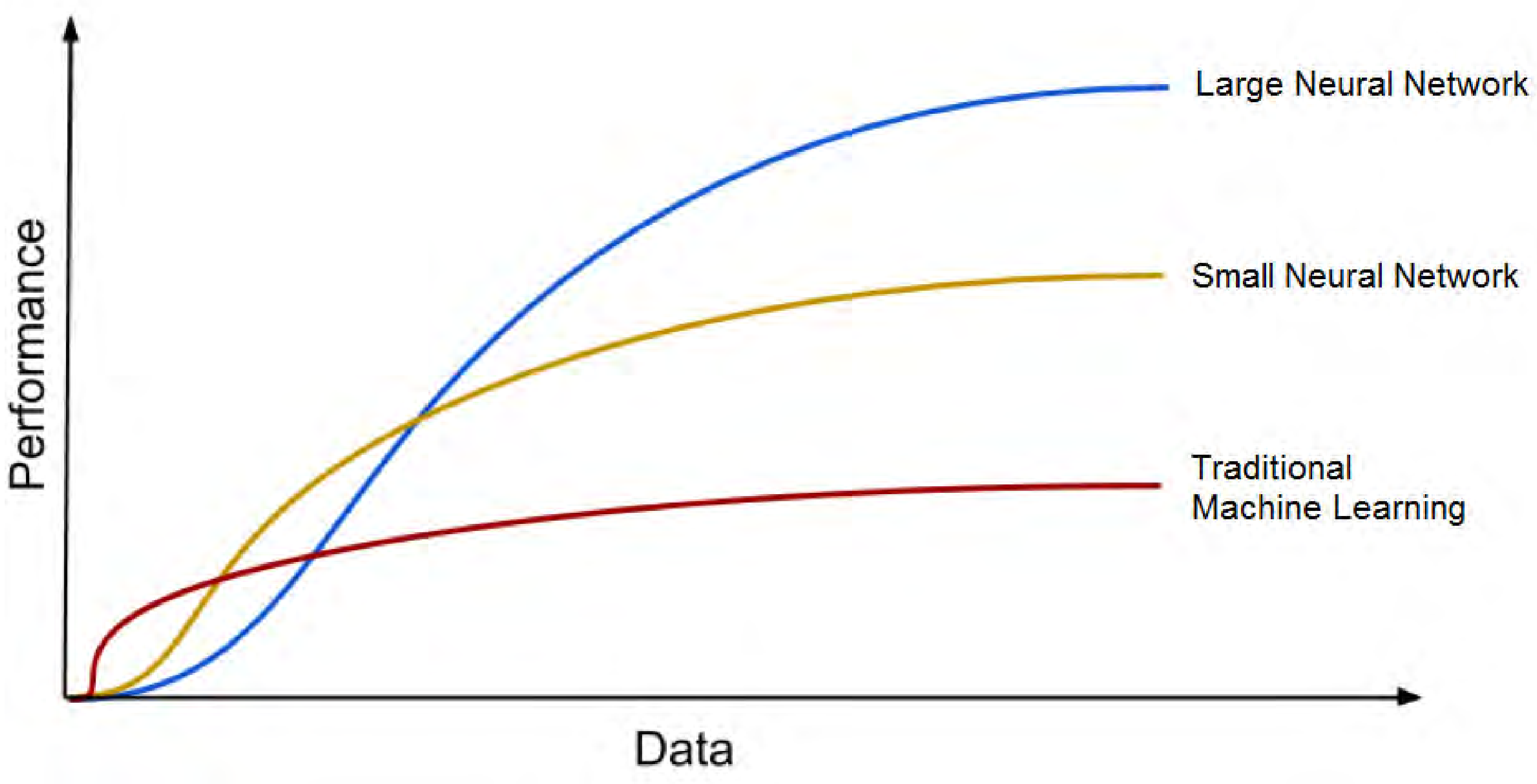
Neural Networks



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

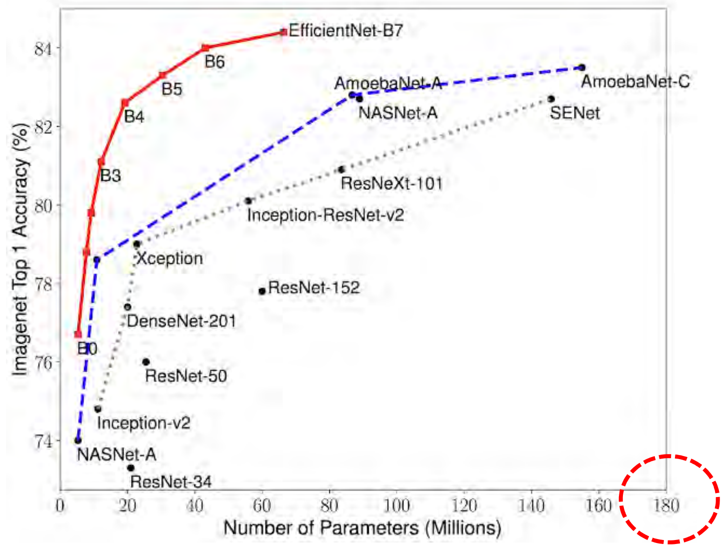


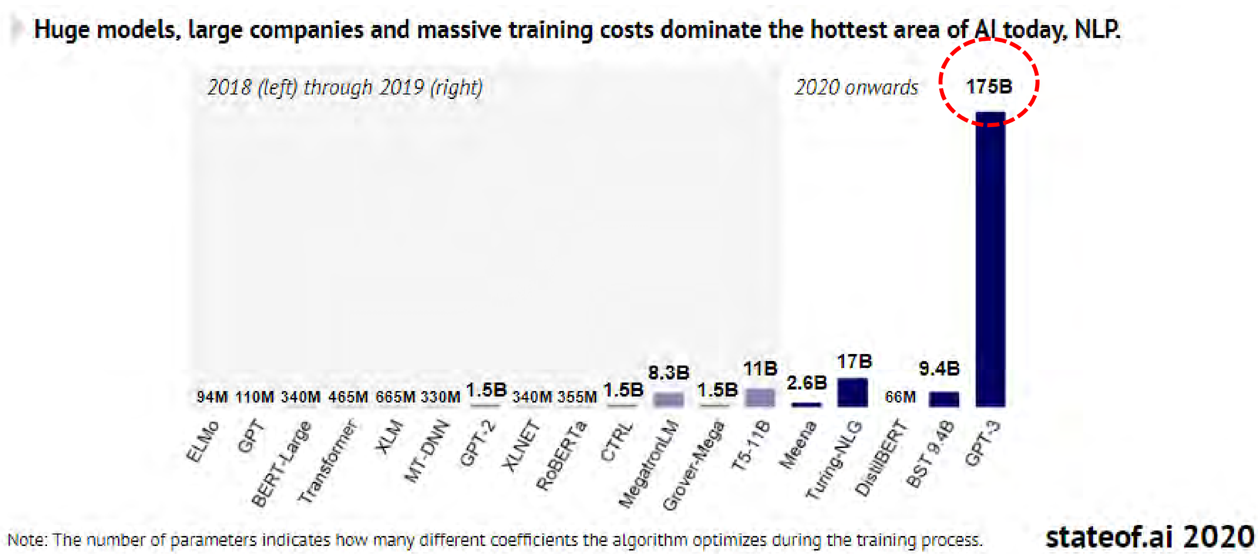
Performance



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

Size


EfficientNet-B7
B6
B5
B4
B3
B0
AmoebaNet-A
AmoebaNet-C
NASNet-A
SENet
ResNeXt-101
Inception-ResNet-v2
Xception
ResNet-152
DenseNet-201
ResNet-50
Inception-v2
NASNet-A
ResNet-34
Imagenet Top 1 Accuracy (%)
Number of Parameters (Millions)


Huge models, large companies and massive training costs dominate the hottest area of AI today, NLP.
2018 (left) through 2019 (right)
2020 onwards
175B
94M 110M 340M 465M 665M 330M 1.5B 340M 355M 1.5B 8.3B 1.5B 11B 2.6B 17B 66M 9.4B
ELMo
GPT
BERT-Large
Transformer
XLM
MT-DNN
GPT-2
XLNET
RoBERTa
CTRL
MegatronLM
Grover-Mega
T5-11B
Meena
Turing-NLG
DistilBERT
BST 9.4B
GPT-3
Note: The number of parameters indicates how many different coefficients the algorithm optimizes during the training process.
stateof.ai 2020

Deep Learning in Action

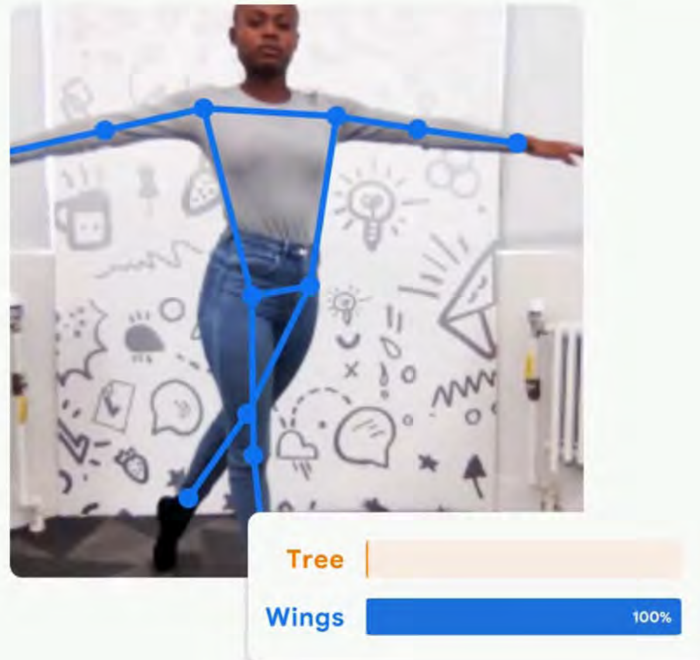
bit.ly/google_teachable

10 mins

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

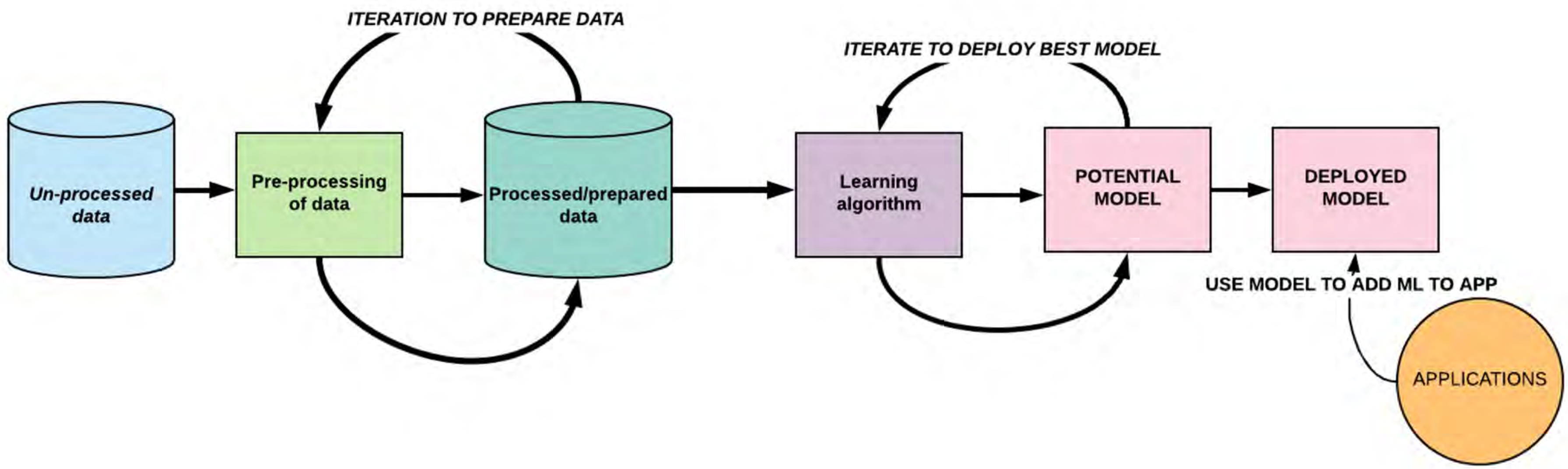
p5.js Coral node

Optional Activity

15 Mins Break

bit.ly/top10_2020

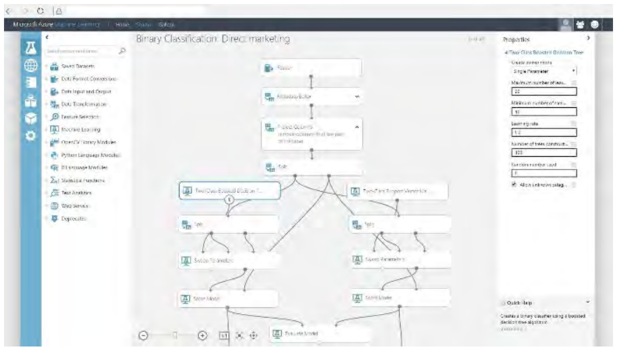
Machine Learning workflow



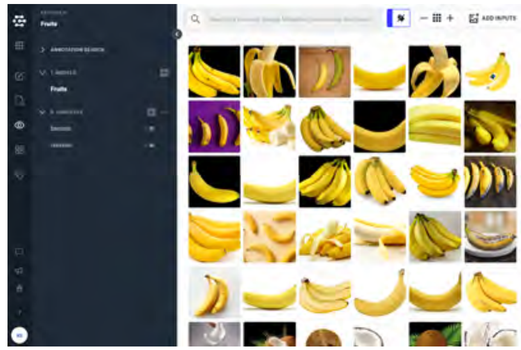
Ref: https://cloudacademy.com/blog/what-is-azure-machine-learning/

Code-Free Machine Learning tools

Microsoft Azure Machine Learning Studio (Classic)



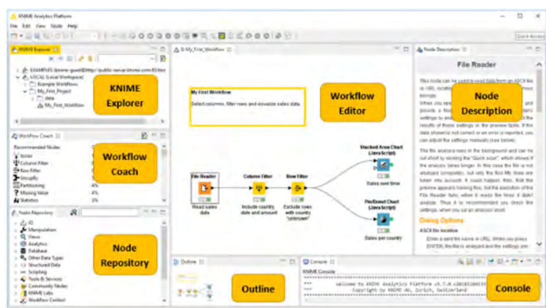
Clarifai



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	normalized	make	fuel-type	aspiration	num-of-dc	body-style	drive-whee	engine-loc	wheel-bas	length	width	height	curb-weigl	engine-typ	num-of-cy	engine-size	fuel-syster	bore	stroke
3	?	alfa-romei	gas	std	two	convertibl	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
3	?	alfa-romei	gas	std	two	convertibl	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
1	?	alfa-romei	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

30 mins

60 mins Lunch Break

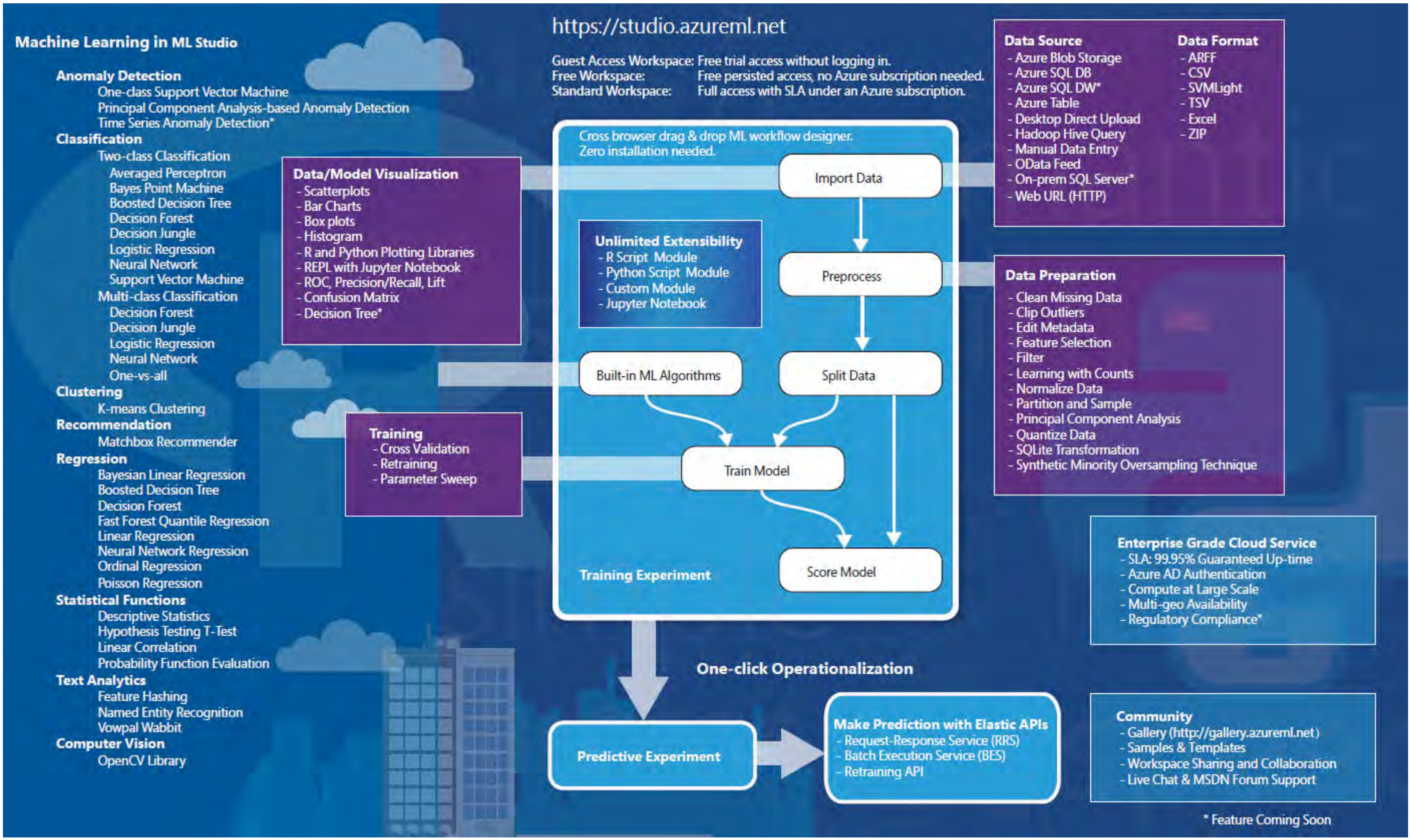
Some interesting videos

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

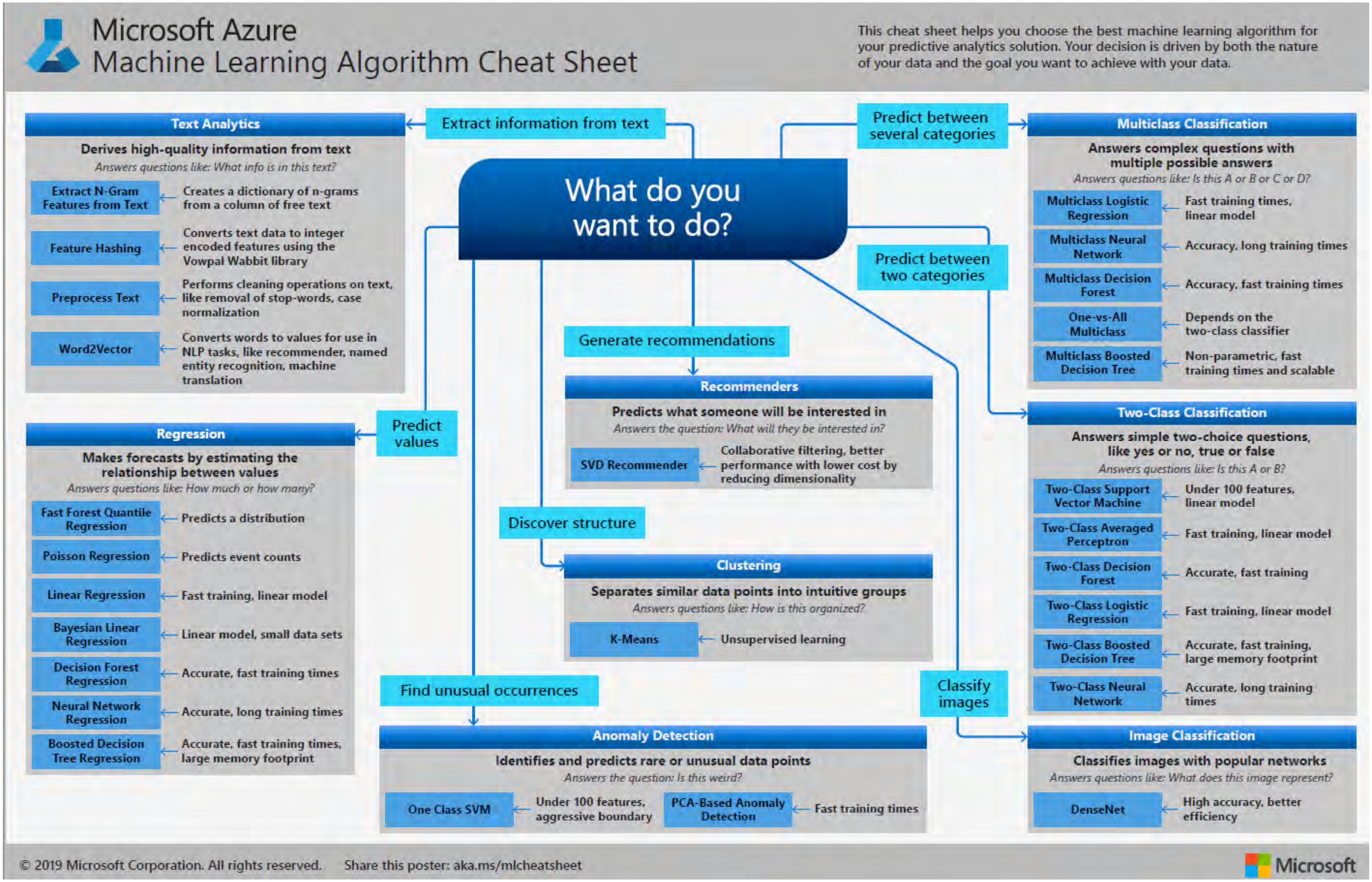
https://www.youtube.com/watch?v=Nnf8P5A_saE

Lunch break 12:20-13:20

Recap

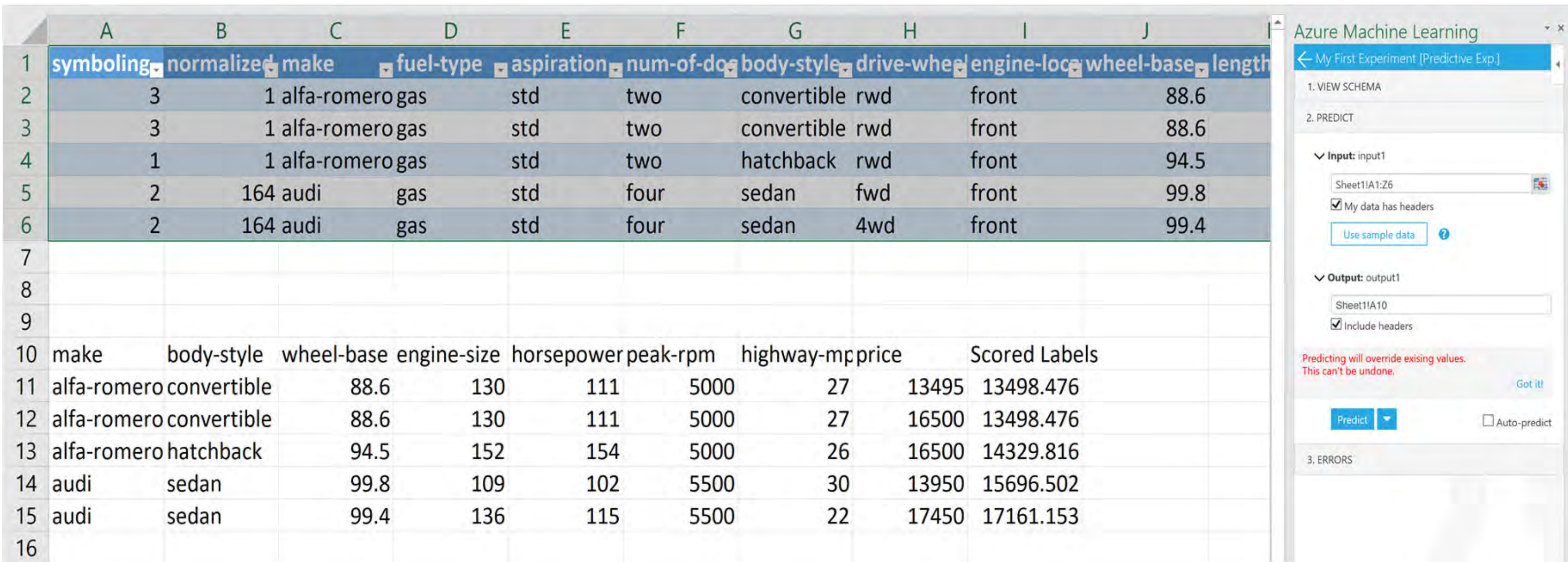

Machine Learning in ML Studio
Anomaly Detection
One-class Support Vector Machine
Principal Component Analysis-based Anomaly Detection
Time Series Anomaly Detection*
Classification
Two-class Classification
Averaged Perceptron
Bayes Point Machine
Boosted Decision Tree
Decision Forest
Decision Jungle
Logistic 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 Cheet



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

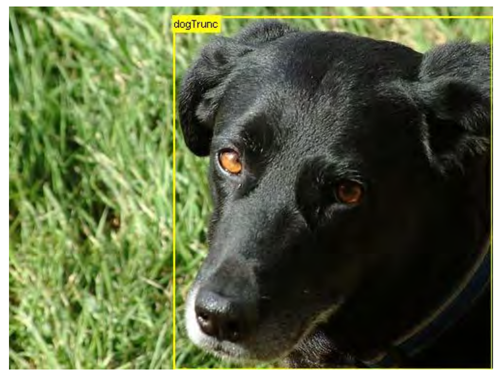
30 mins

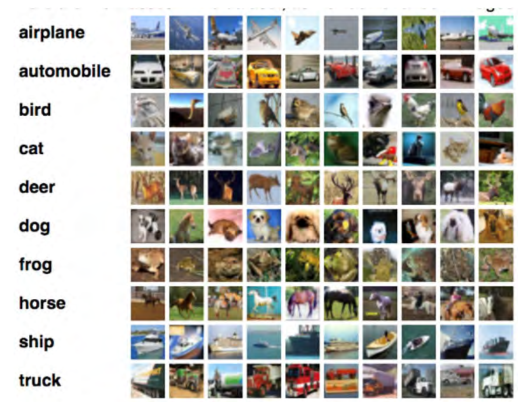
Optional Activities

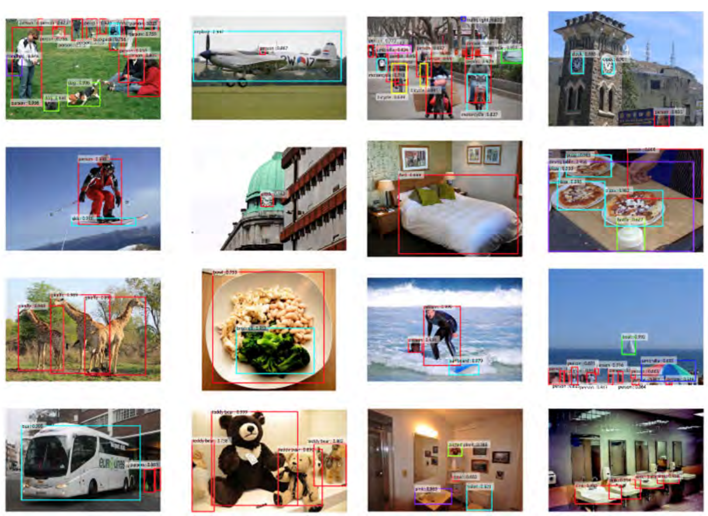
- Activity 6 - Importing data
- Activity 7 - Cleaning and Structuring Data
- Activity 8 - Using Binary Classification Algorithm

Applications of Computer Vision

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



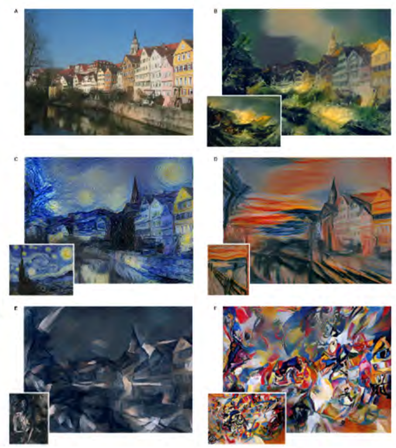


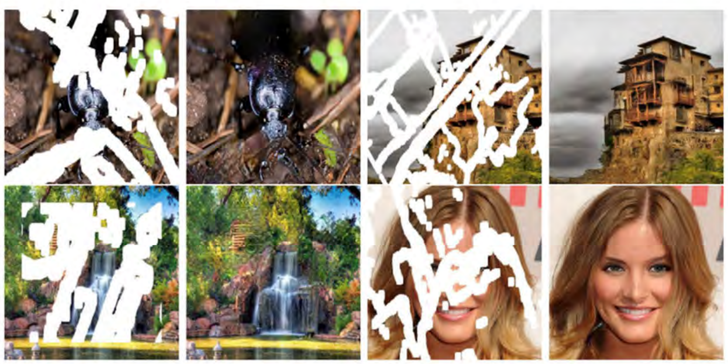


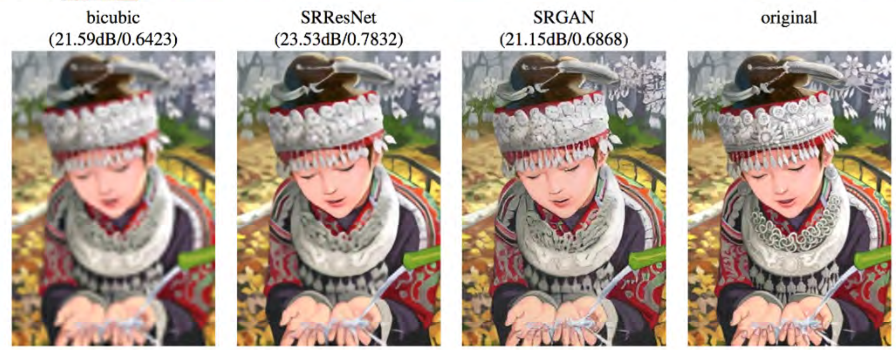
https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/

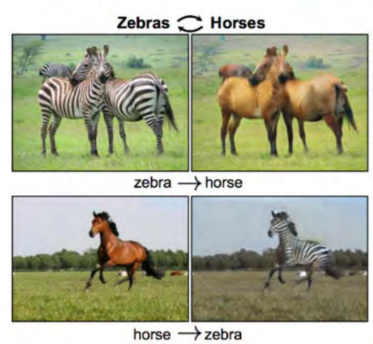
Applications of Computer Vision

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

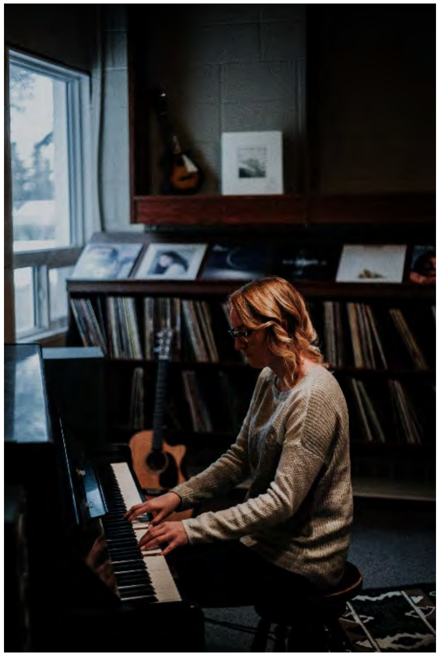








Transfer Learning



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

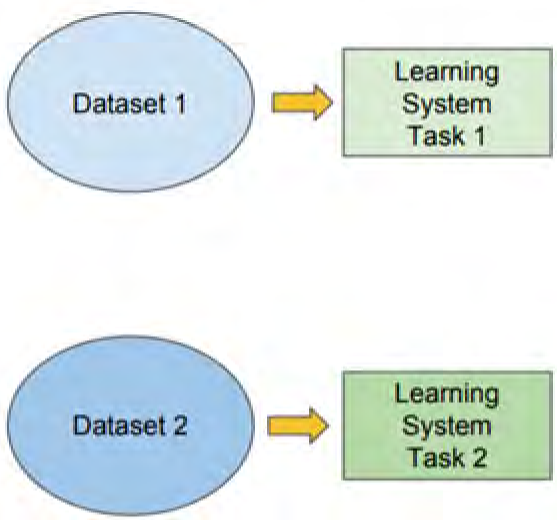
- Models are difficult to train from scratch
  - Huge datasets (like ImageNet)
  - Long number of training iterations
  - Very heavy computing machinery
  - Time experimenting to get hyper-parameters just right

Transfer Learning

Traditional ML vs Transfer Learning

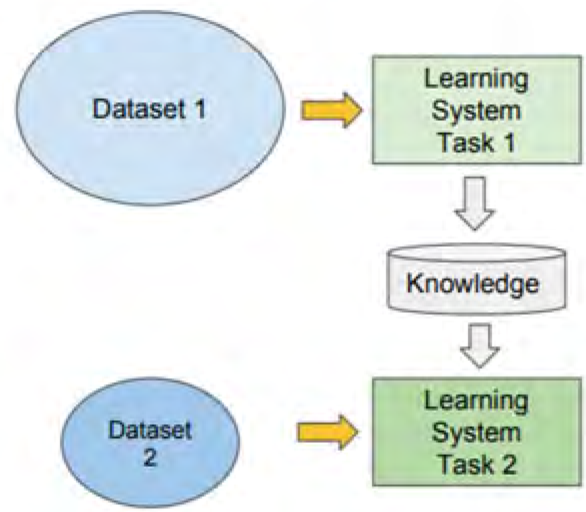
Traditional ML

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



Transfer Learning

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



https://towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer-learning-with-real-world-applications-in-deep-learning-212bf3b2f27a

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

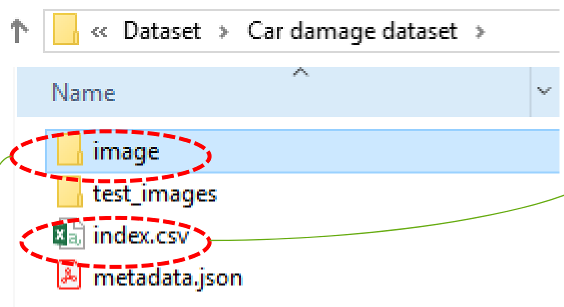
- **Create csv file**
  - **Create a text file with all image names**
  - **Create a file with all labels**
  - **Combine image names and labels in one file - index.csv**

Step 4

- **Create the zip-file**

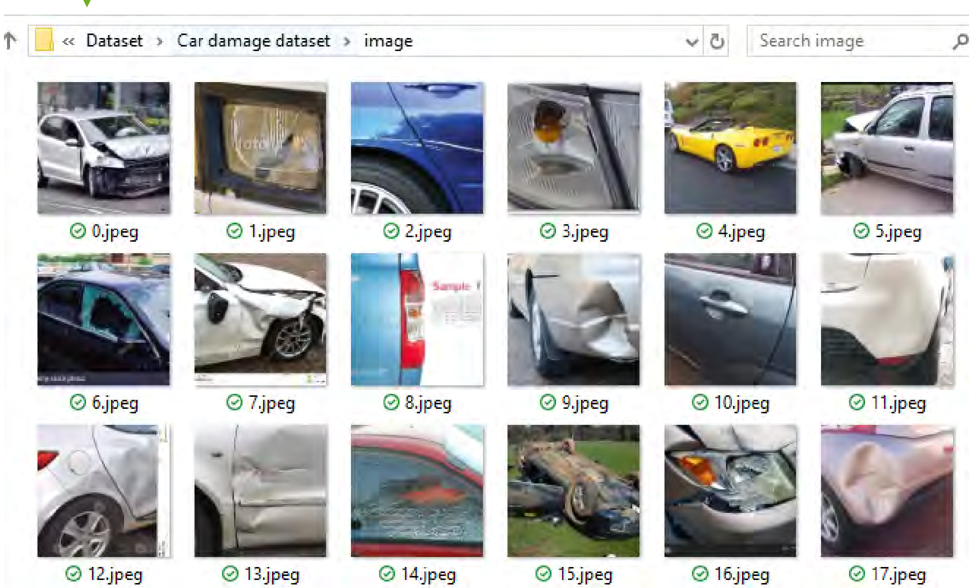
https://peltarion.com/knowledge-center/documentation/datasets-view/example-workflows---datasets-view/create-new-dataset-/-example-workflow

Example

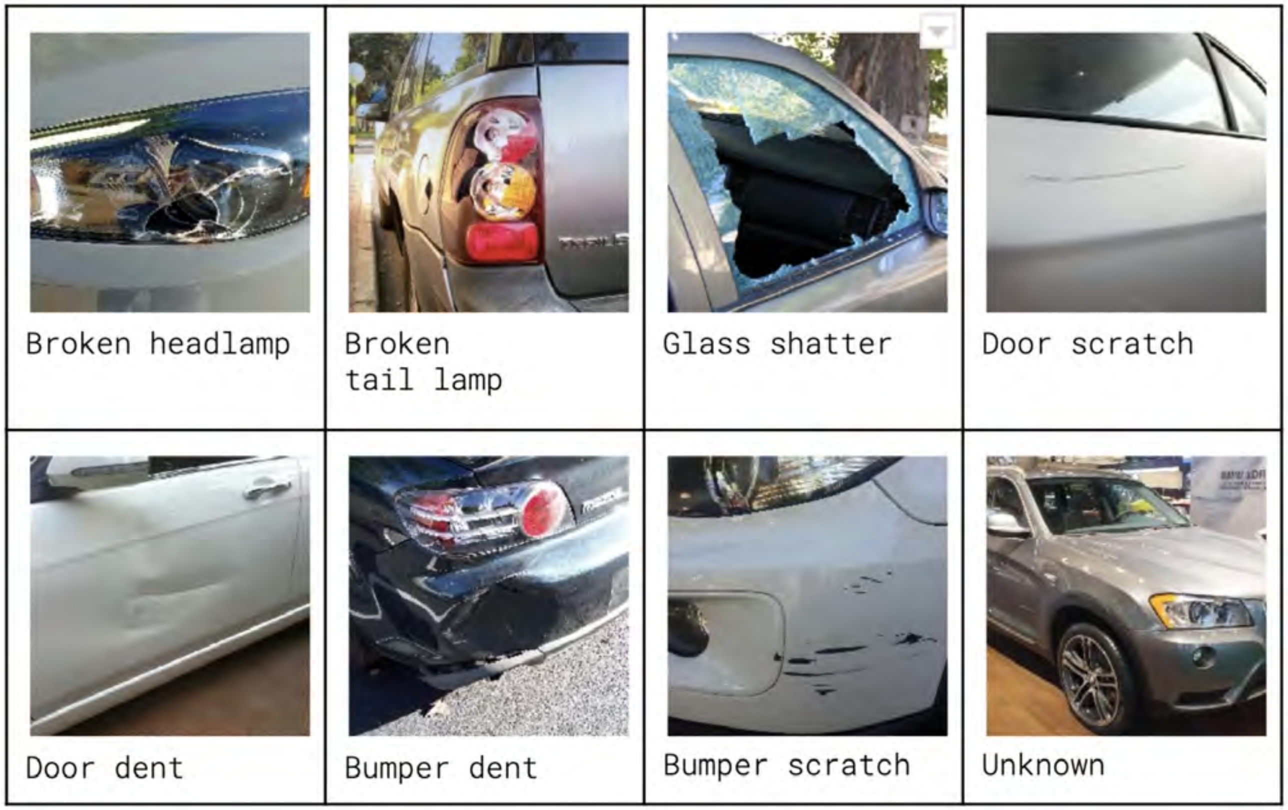


A1 | image

	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

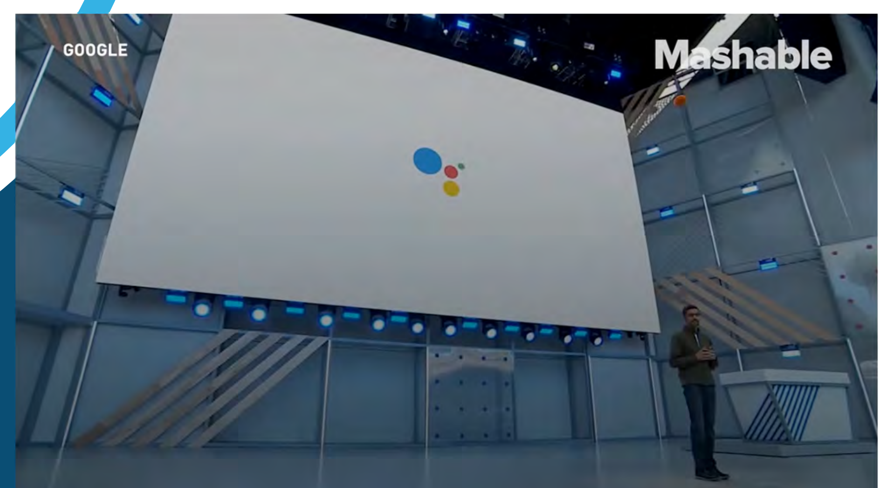
Step 2:
- Do on your own

Individual Activity

30 mins

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

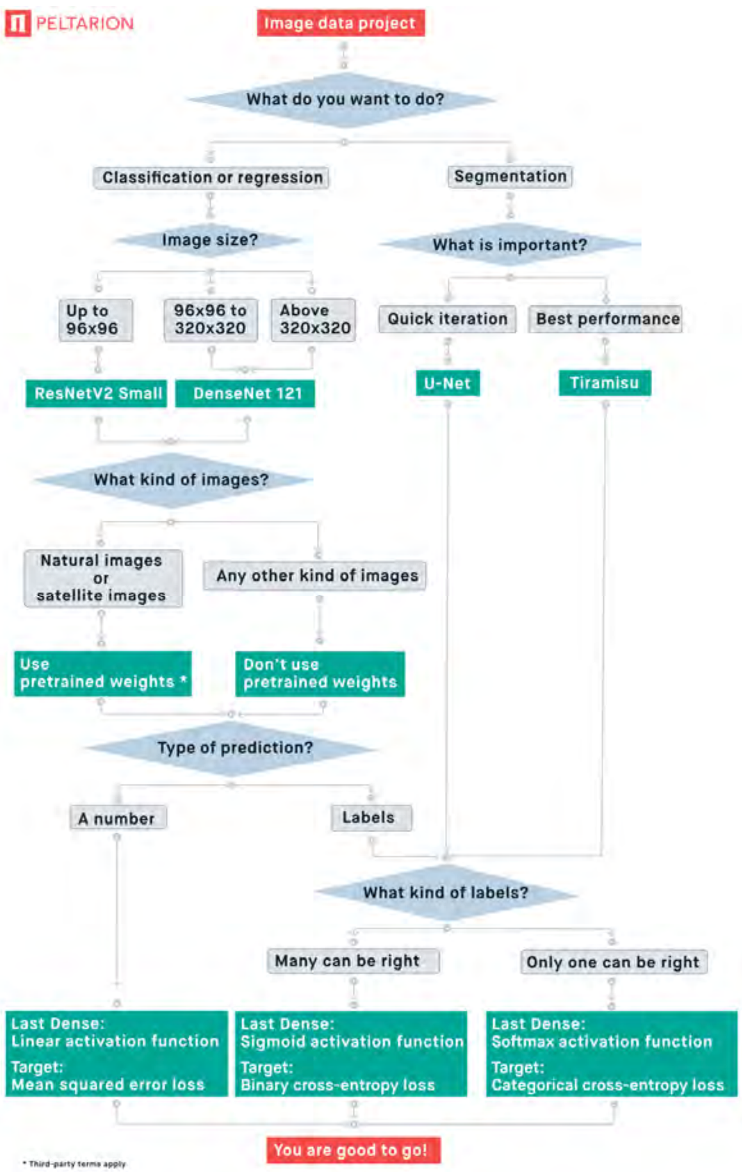
Step 2:
- Do on your own

40 mins

Individual Activity

Cheatsheets

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



Linking Them Together

App Development

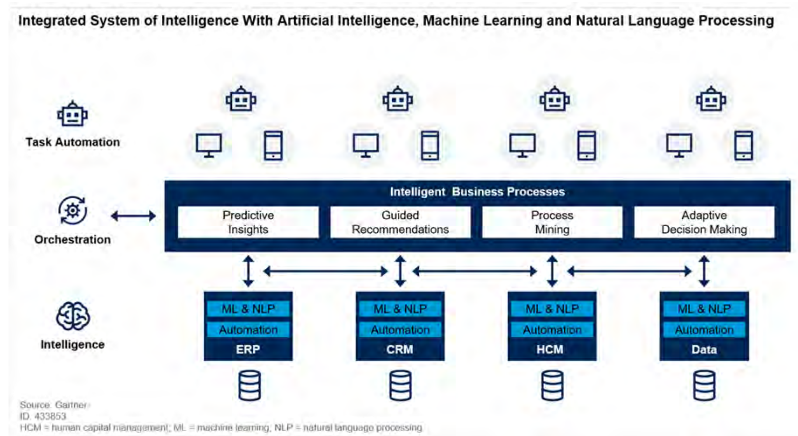
Top 9 No-Code Web App Development Tools that May Compete with Bubble

We're here to prove that **"building the best product"** is possible not only with Bubble.

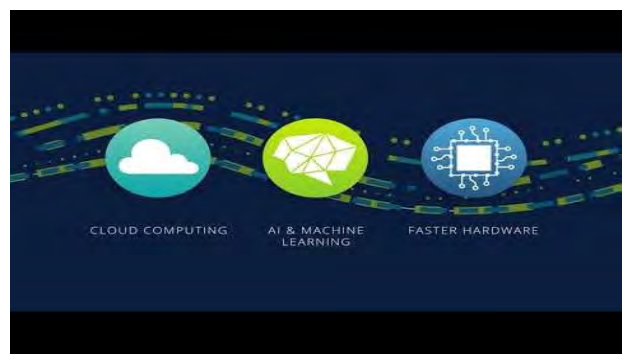
Airtable bubble webflow

https://uibakery.io/bubble-alternatives

RPA



UiPath WorkFusion blueprism



Adobe Acrobat Document

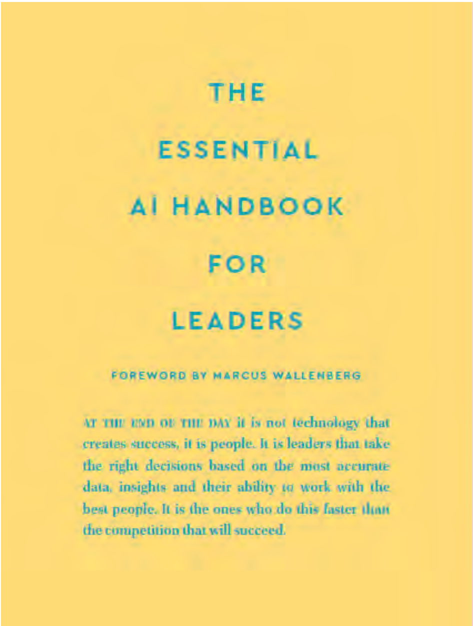
https://www.youtube.com/watch?v=FV8lM9SIFQ8

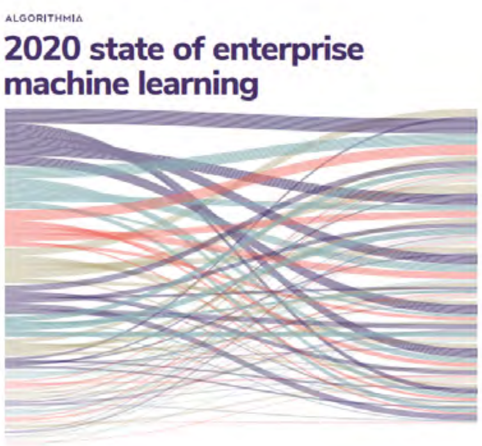
When to use Machine Learning

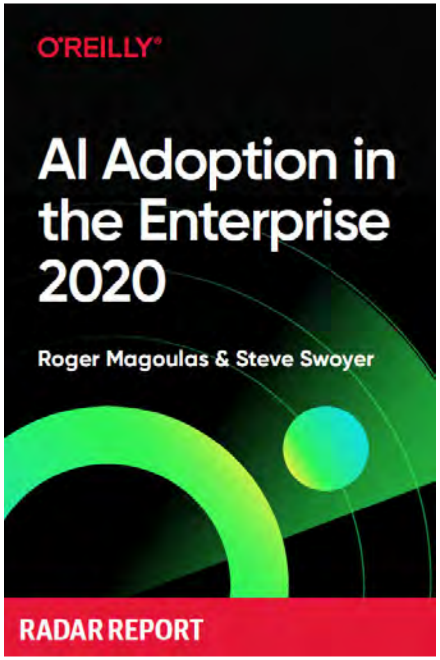
- **What are our most pressing problems right now?**
  - Just like any other tool in business, AI should be viewed as a tool that can help make your organization more effective, profitable or streamlined
- **What parts of our business generate revenue but currently have low profit margins?**
  - These 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.

Ref: The essential AI Handbook for leaders

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

Debrief

Step 1: Go to the following url

http://bit.ly/cfml_debrief

Step 2: facilitator will walk you through the following

1) **Share 1 insight that you gained from this workshop.**

2) **Share 1 project that you may want to work on.**

3 mins

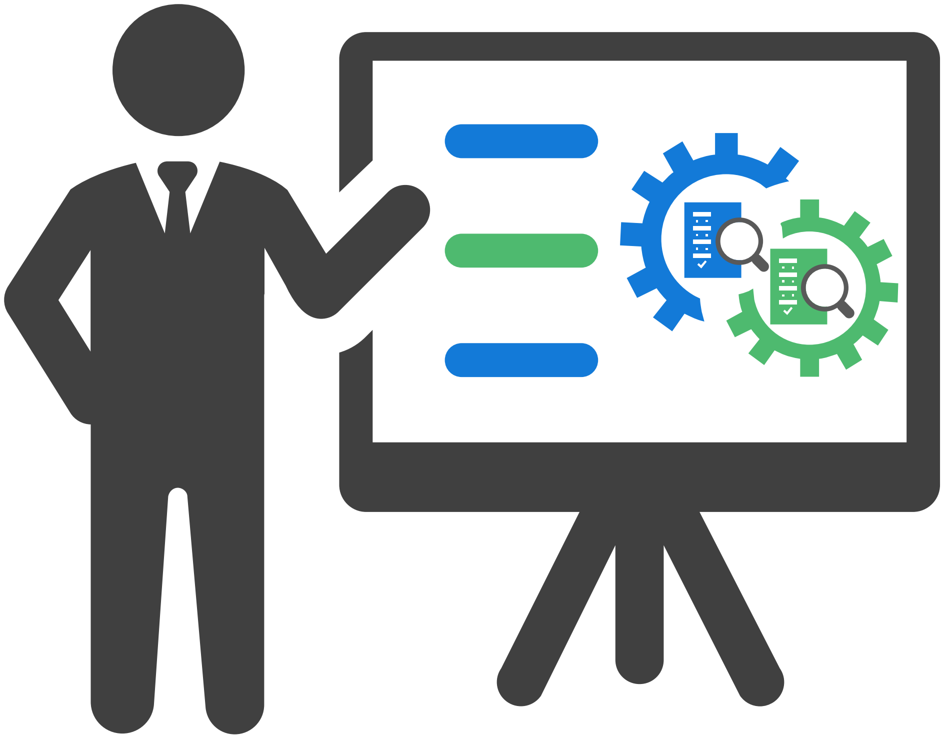
Quiz

https://bit.ly/kw_poll

SCAN ME

Survey

Summary



Email
seow_khee_wei@rp.edu.sg

Telegram
@kwseow

Source code:

Thank you