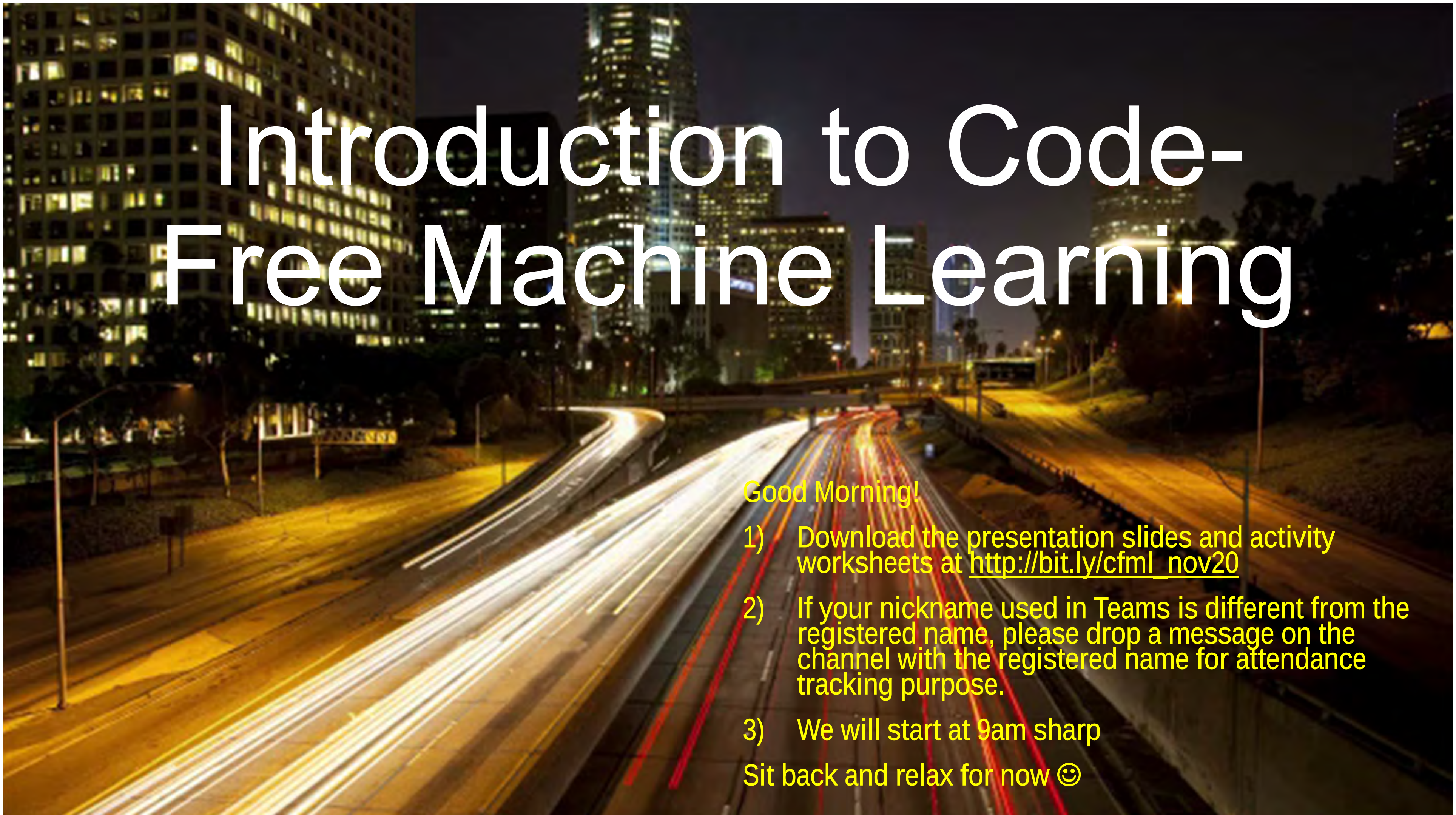
REPUBLIC POLYTECHNIC
DISCOVER. TRANSFORM. ACHIEVE



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 ☺

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

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Seow Khee Wei

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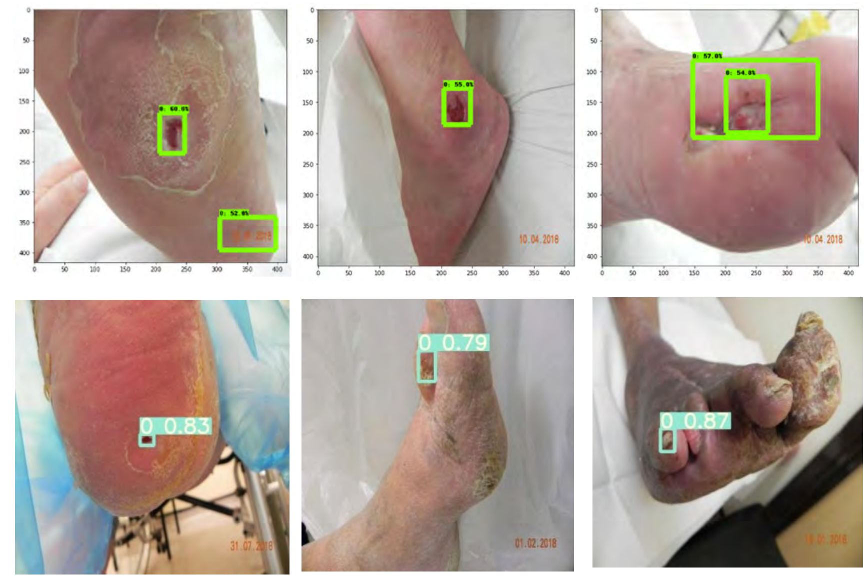
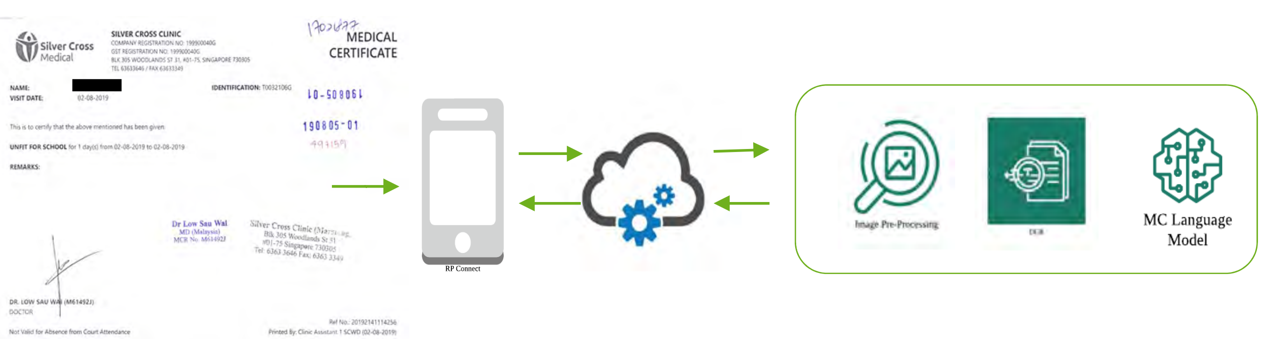
Projects

Screen Understanding

Diabetic Foot At Risk Reconstruction

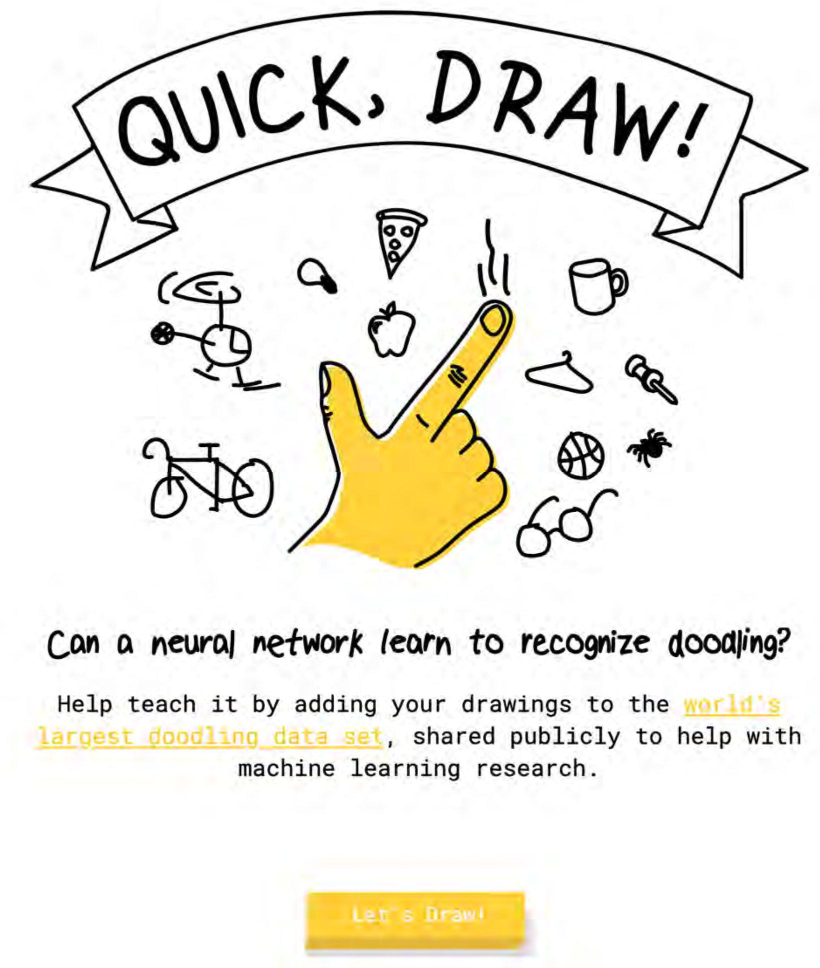


Language model for Medical Certificates



Quickdraw Game

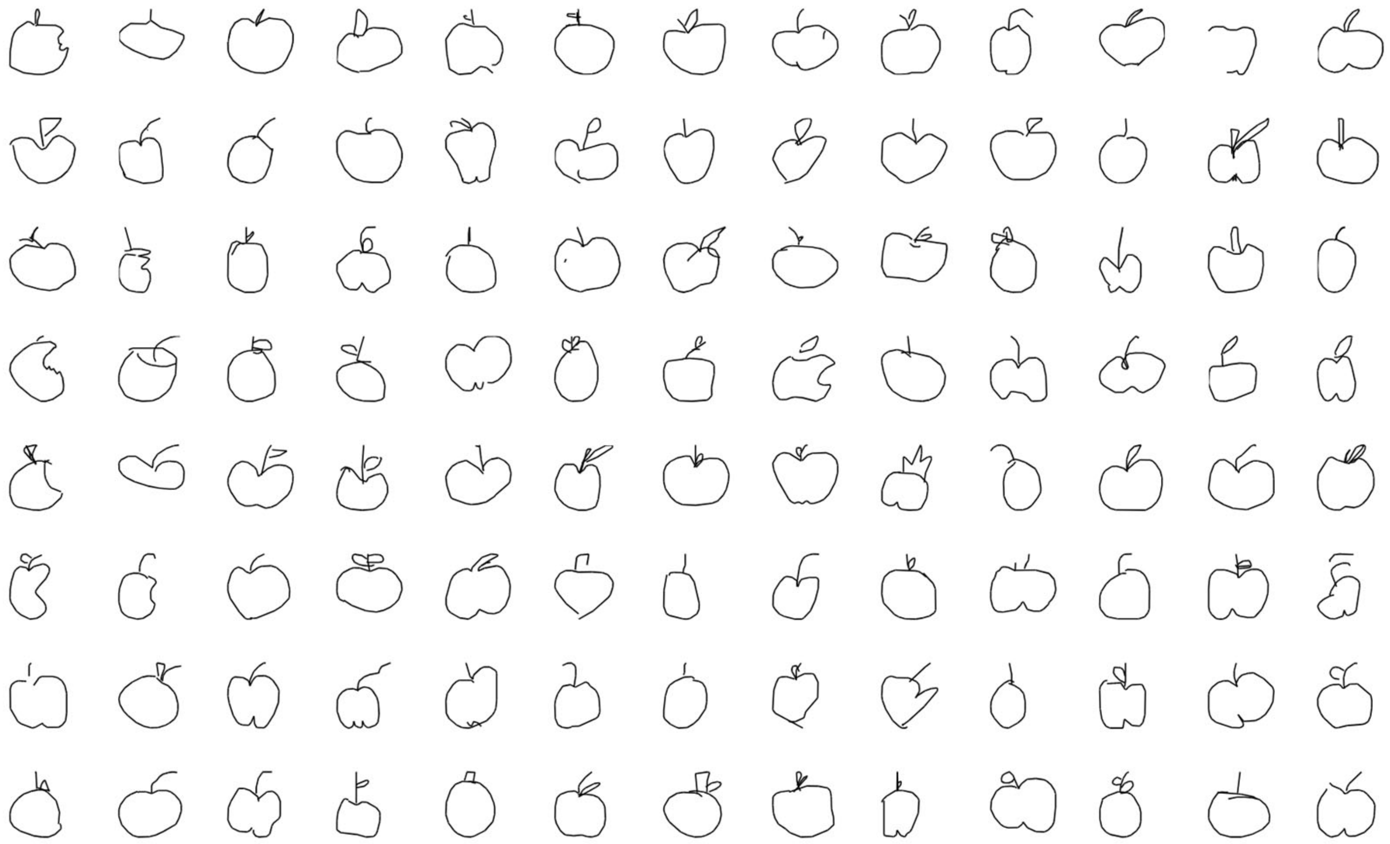
https://quickdraw.withgoogle.com



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

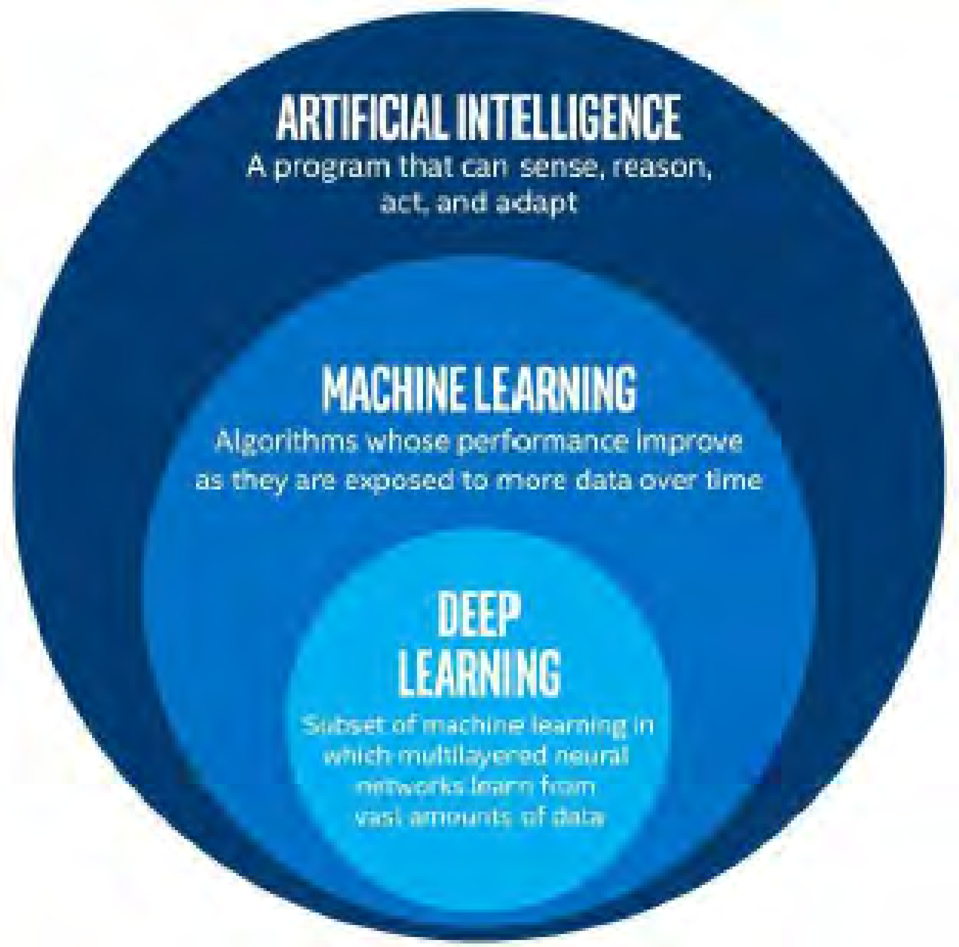
Google promised a fix after its photo-categorization software labeled black people as gorillas in 2015. More than two years later, it hasn't found one.

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/

Machine Learning

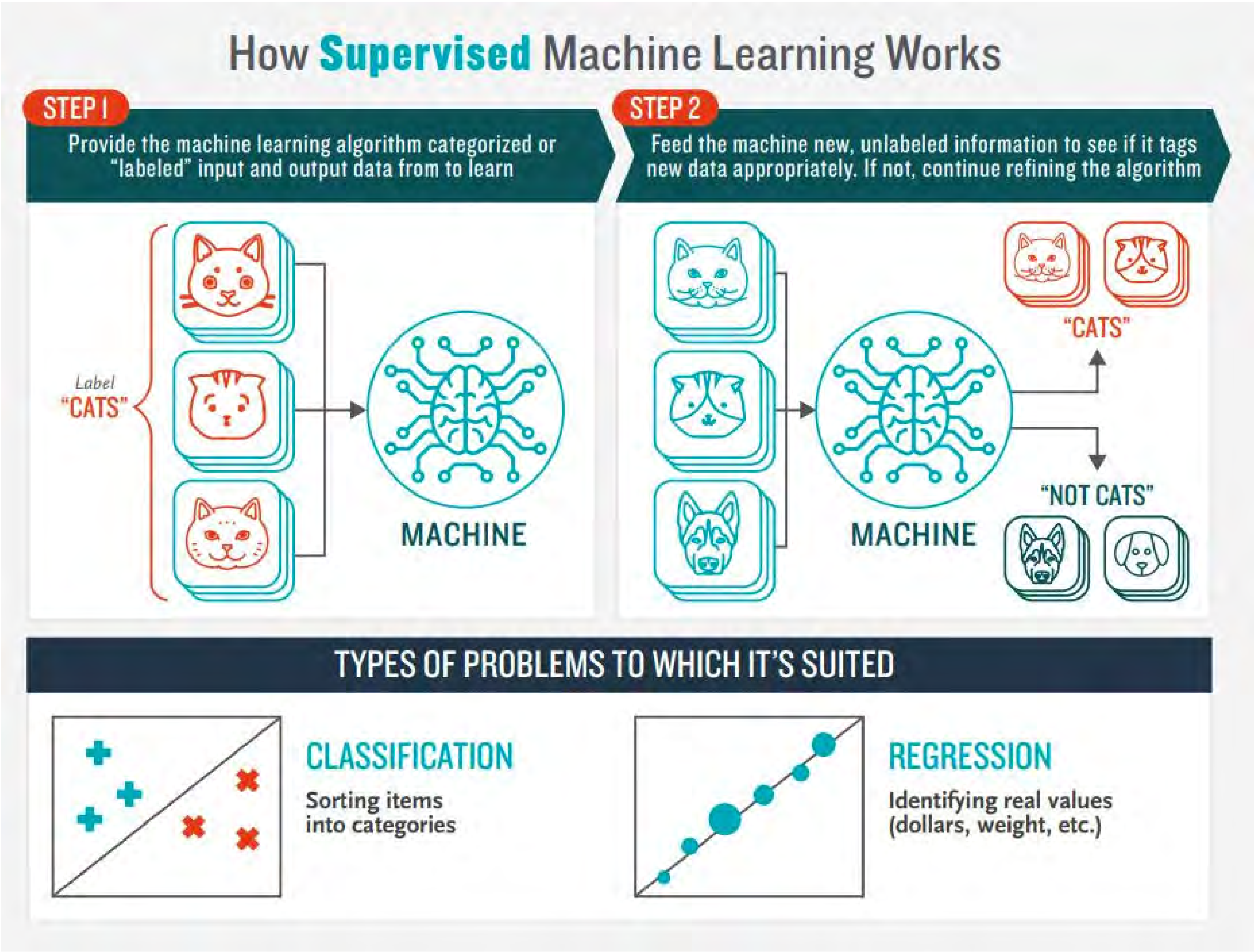
- These programs learn from repeatedly seeing data, rather than being explicitly programmed by humans



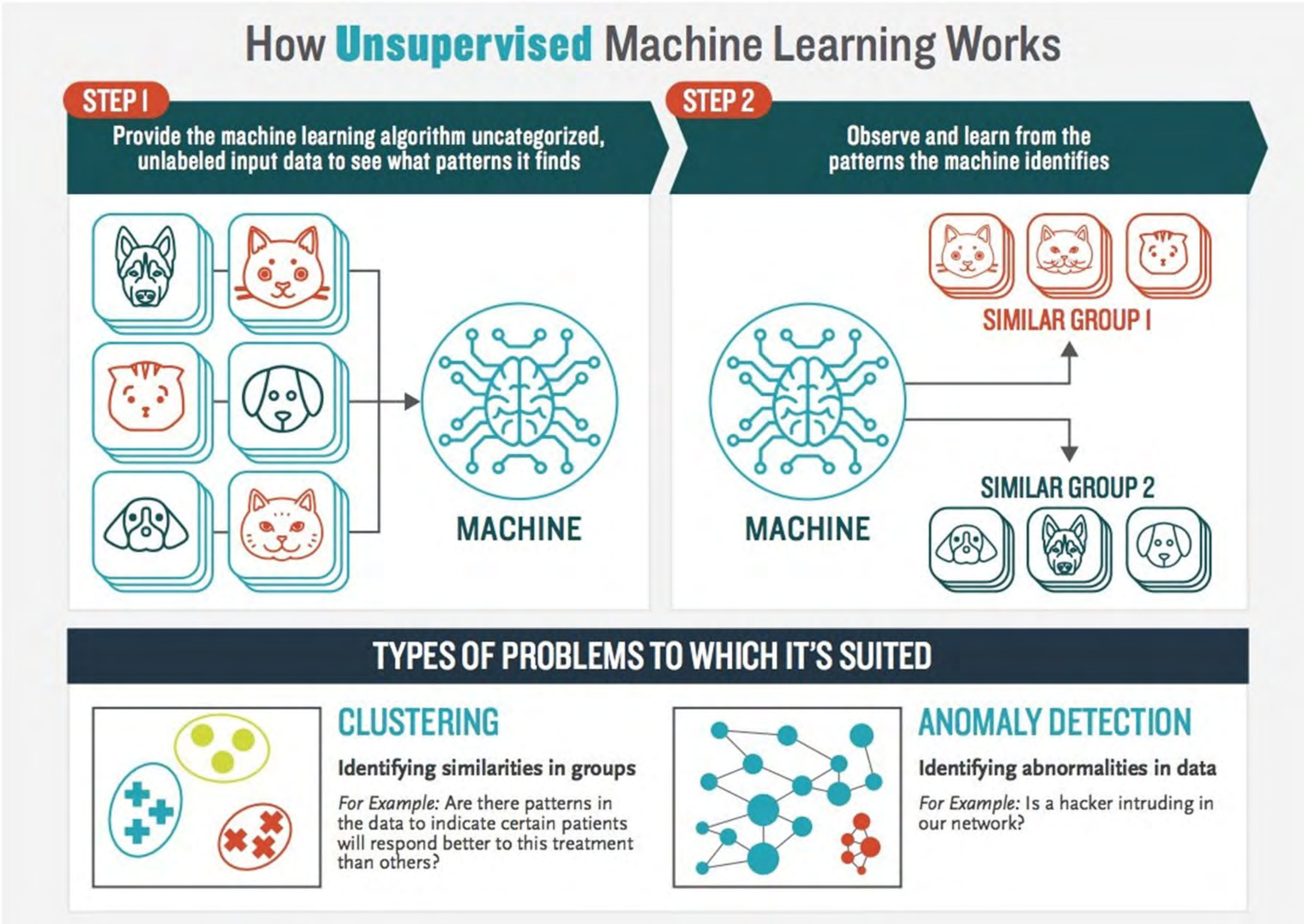
Machine Learning

- **Two main types of learning**
  - Supervised Learning
    - Data points have known outcome
    - Goal is to make predictions - Classify 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

Supervised Learning



Unsupervised Learning



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)

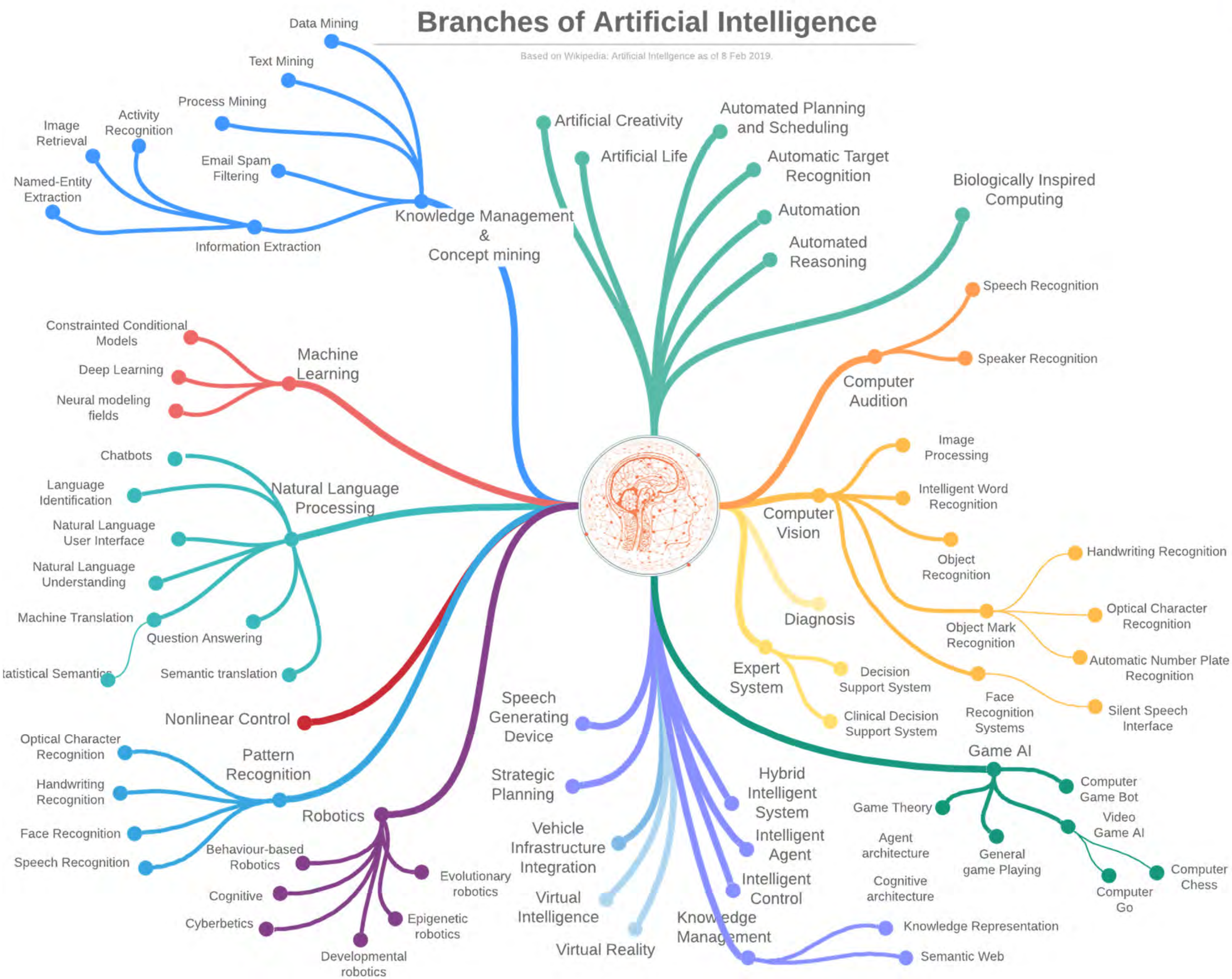
What will the temperature be next Tuesday?
What will my fourth quarter sales be?

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.
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
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
tatistical Semantics
Semantic translation
Computer Vision
Image Processing
Intelligent Word Recognition
Object Recognition
Handwriting Recognition
Object Mark Recognition
Optical Character Recognition
Automatic Number Plate Recognition
Face Recognition Systems
Silent Speech Interface
Diagnosis
Expert System
Decision Support System
Clinical Decision Support System
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
Game AI
Computer Game Bot
Game Theory
Agent architecture
Cognitive architecture
General game Playing
Video Game AI
Computer Go
Computer Chess

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.

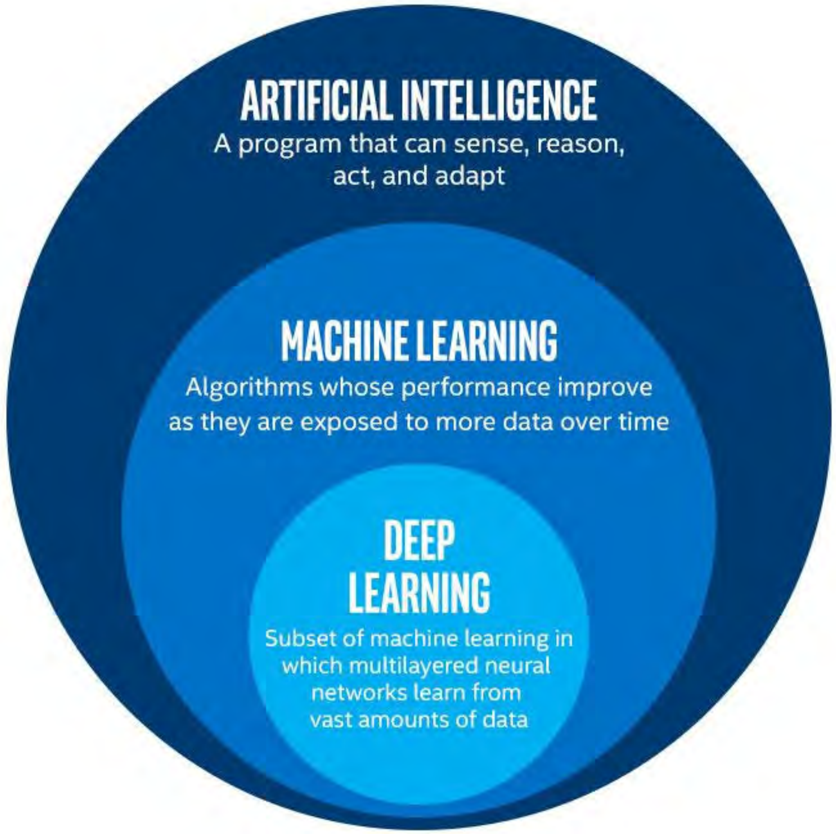
Dog and cat recognition

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

- Deep learning is a class of machine learning algorithms that:
  - use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.
  - learn in supervised (e.g., classification) and/or unsupervised (e.g., pattern analysis) manners.
  - learn multiple levels of representations that correspond to different levels of abstraction; the levels form a hierarchy of concepts.

Ref: https://en.wikipedia.org/wiki/Deep_learning#Deep_learning_revolution

Deep Learning Example

Classic Machine Learning

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

Feature Detection

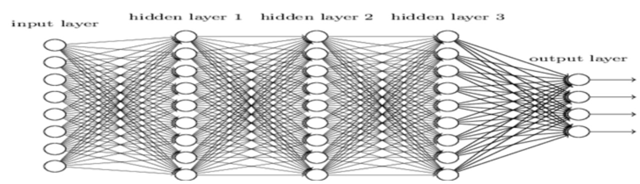
Machine Learning Classifier Algorithm

“Arjun"

Deep Learning

Steps 1 and 2 are combined into 1 step.

Neural Network



“Arjun"

Deep Learning in Action

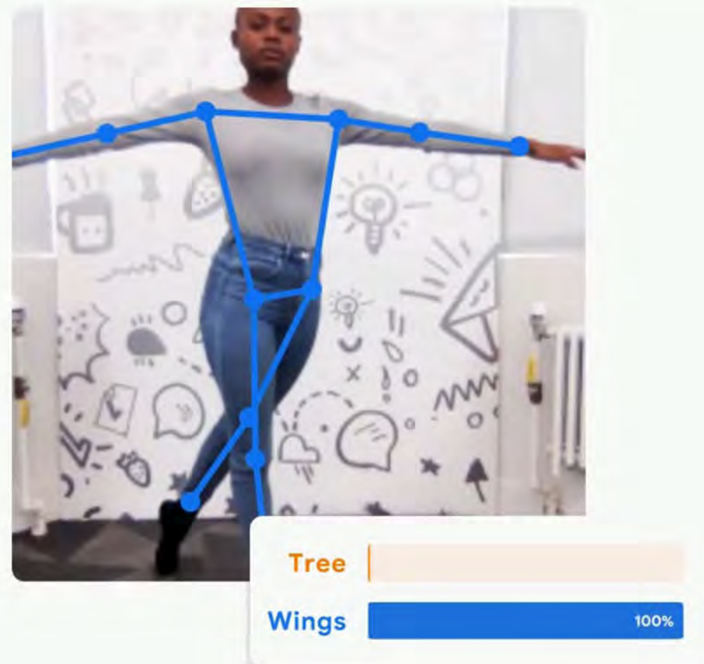
10 mins

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.

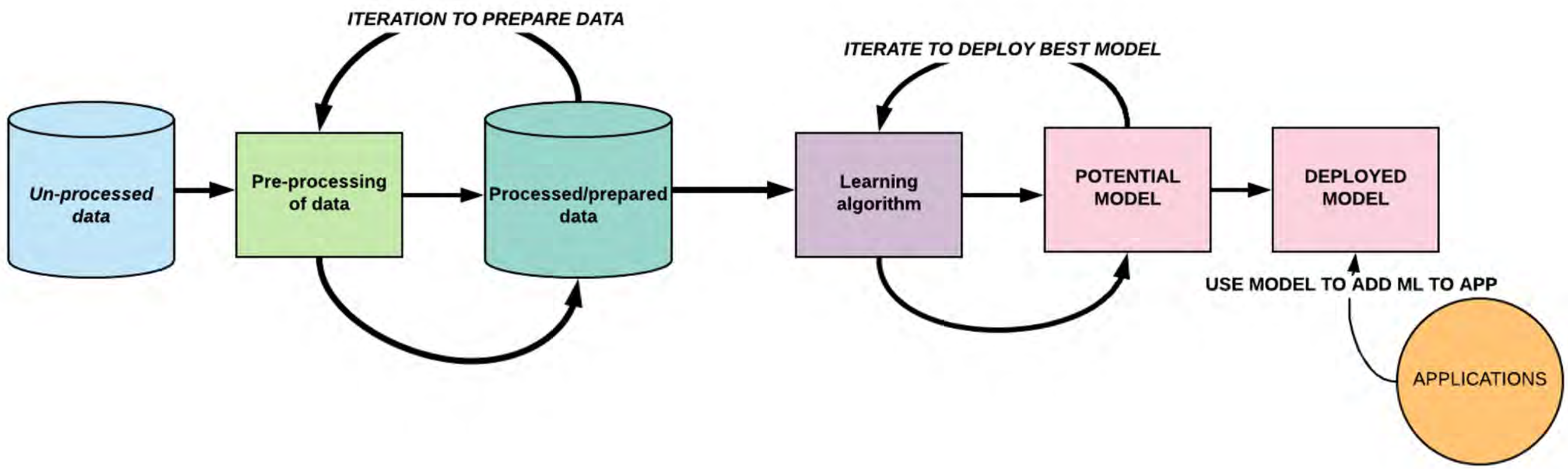


Get Started

p5.js Coral

Optional Activity

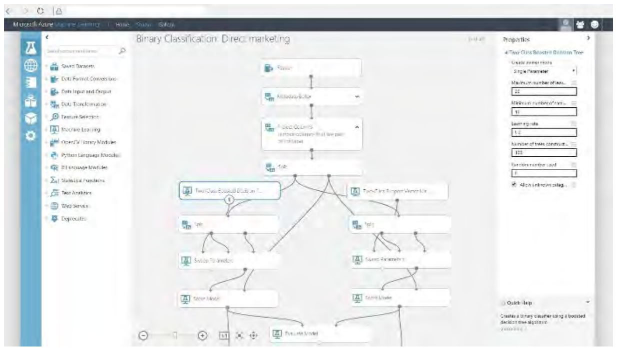
Machine Learning workflow



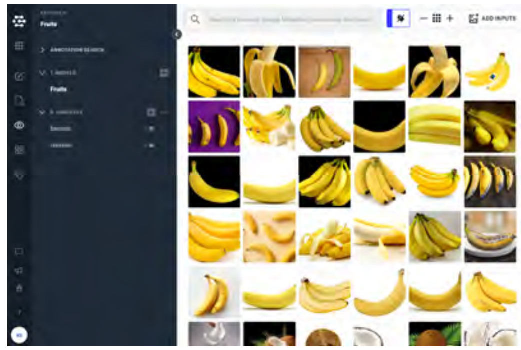
Ref: https://cloudacademy.com/blog/what-is-azure-machine-learning/

Code-Free Machine Learning tools

Microsoft Azure
Machine Learning Studio
(Classic)



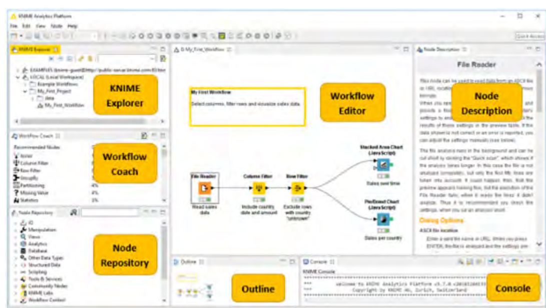
Clarifai



Peltarion

bigml

KNIME



Rapidminer

Activity 1 – First Machine Learning with Azure

- **Automobile Price Prediction**

symboling	normalized	make	fuel-type	aspiration	num-of-dc	body-style	drive-whe	engine-loc	wheel-bas	length	width	height	curb-weigl	engine-typ	num-of-cy	engine-size	fuel-systen	bore	stroke
3	?	alfa-romei	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-romei	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-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
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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
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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

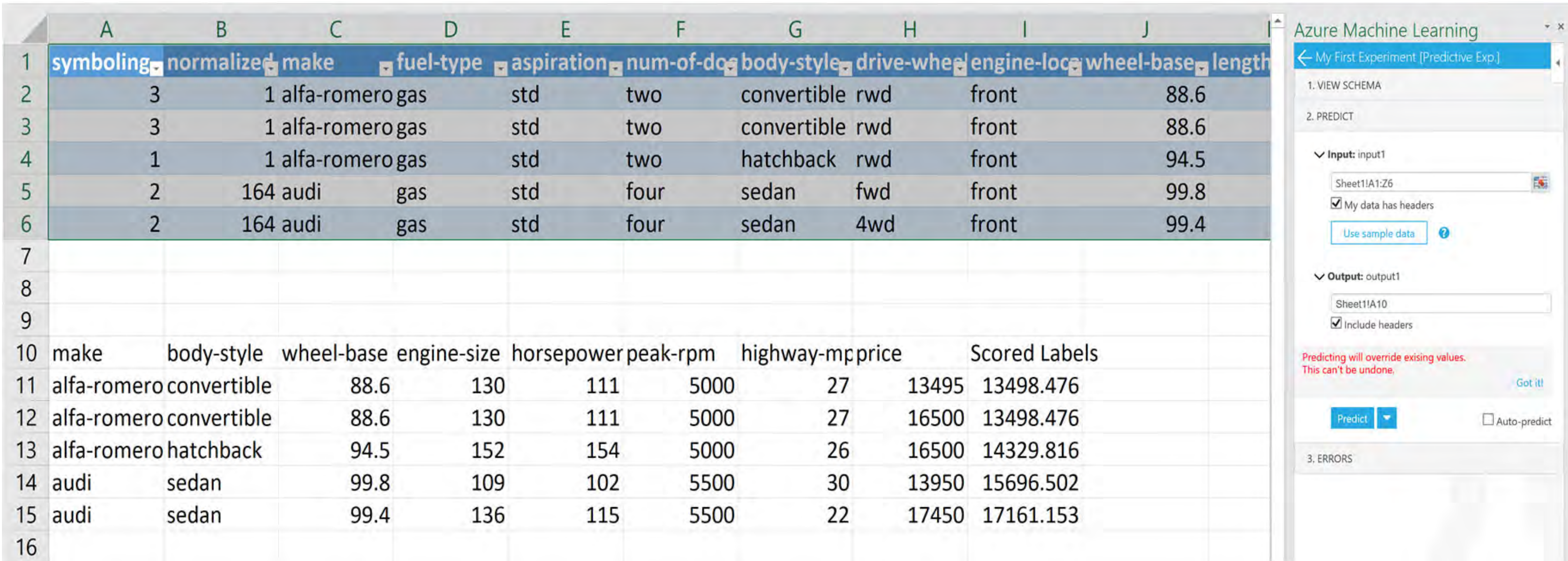
45 mins

15 Mins Break

bit.ly/top10_2020

Activity 2

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



symboling	normalized	make	fuel-type	aspiration	num-of-do	body-style	drive-whee	engine-loc	wheel-base	length
3	1	alfa-romero	gas	std	two	convertible	rwd	front	88.6	
3	1	alfa-romero	gas	std	two	convertible	rwd	front	88.6	
1	1	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	
2	164	audi	gas	std	four	sedan	fwd	front	99.8	
2	164	audi	gas	std	four	sedan	4wd	front	99.4	

make	body-style	wheel-base	engine-size	horsepower	peak-rpm	highway-mp	price	Scored Labels
alfa-romero	convertible	88.6	130	111	5000	27	13495	13498.476
alfa-romero	convertible	88.6	130	111	5000	27	16500	13498.476
alfa-romero	hatchback	94.5	152	154	5000	26	16500	14329.816
audi	sedan	99.8	109	102	5500	30	13950	15696.502
audi	sedan	99.4	136	115	5500	22	17450	17161.153

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

15 mins

Step 2:
Work through the activities

Individual Activity

45 mins

Activity 2

- Activity 2 - Deploying your experiment as a Web Service
- Activity 3 - Importing data
- Activity 4 - Cleaning and Structuring Data
- Activity 5 - Using Binary Classification Algorithm
- Activity 6 – Evaluating a Regression Model with Cross Validation
- Activity 7 – Optimising your model (Hyperparameter Tuning)

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

10 mins

Step 2:
Work through the activities

Individual Activity

80 mins

60 mins Lunch Break

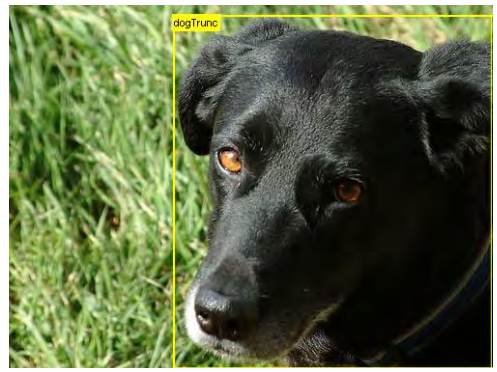
Some interesting videos

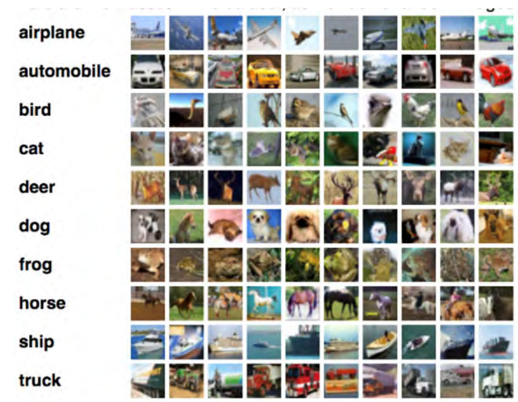
https://www.youtube.com/watch?v=bmNaLtC6vkU

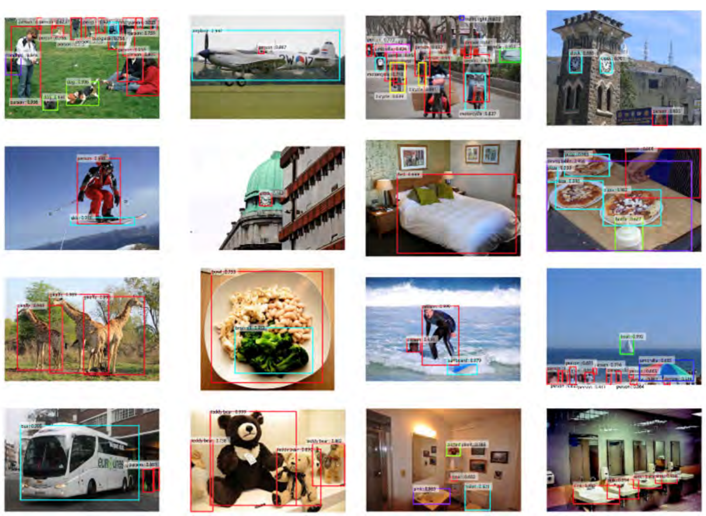
https://www.youtube.com/watch?v=Nnf8P5A_saE

Applications of Computer Vision

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



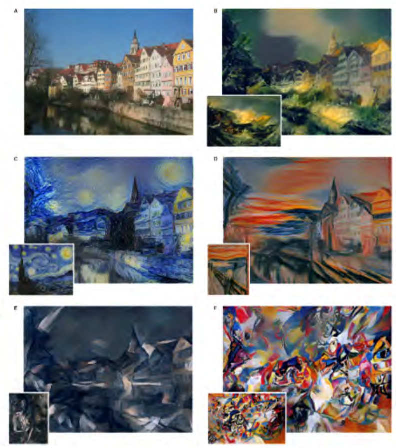


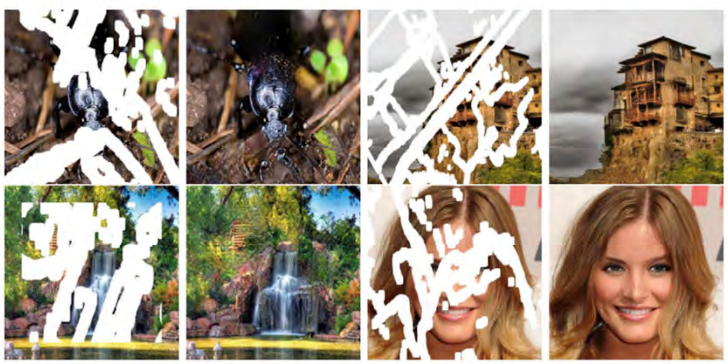


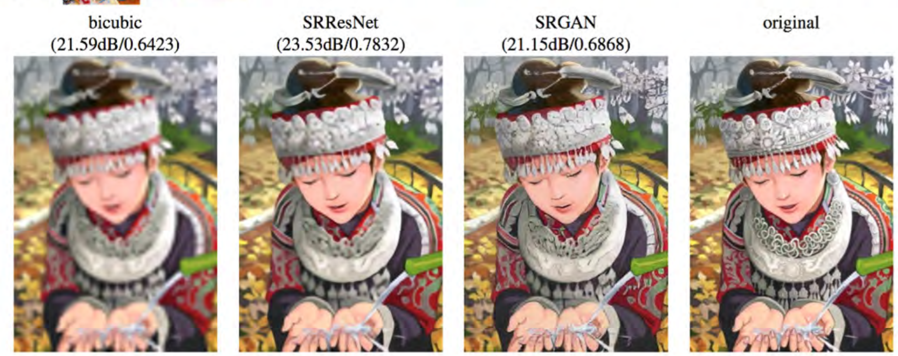
https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/

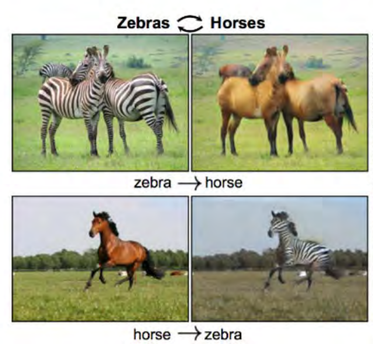
Applications of Computer Vision

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

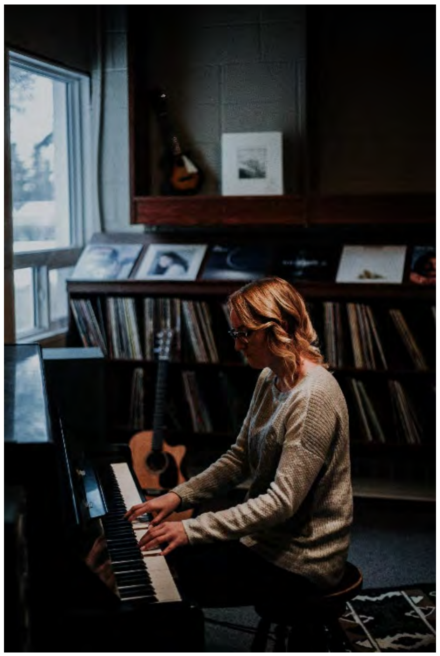








Transfer Learning



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.

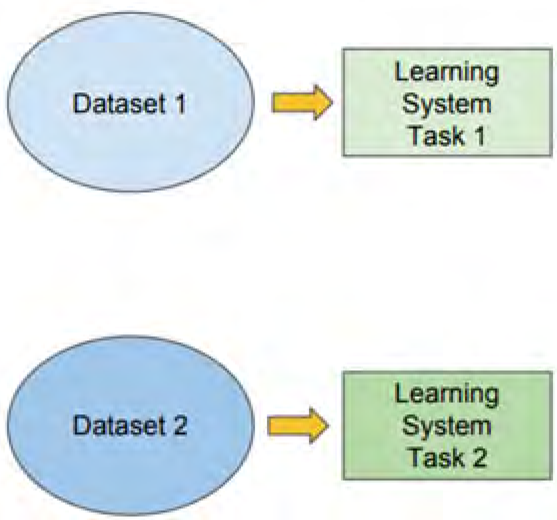
Some simple examples would be,
* Know how to ride a motorbike ➦ Learn how to ride a car
* Know how to play classic piano ➦ Learn how to play jazz piano

- 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

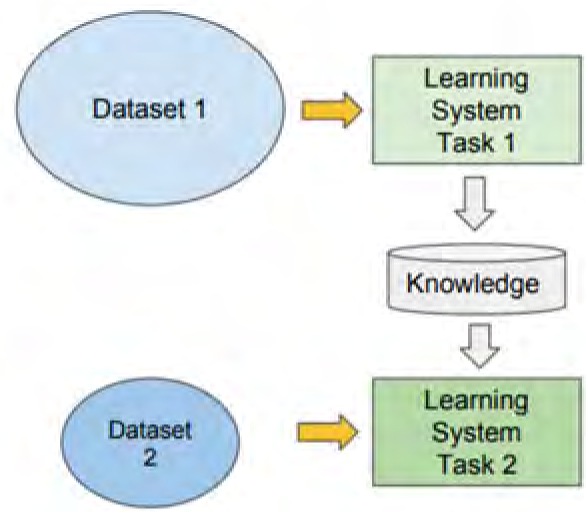
Transfer Learning

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



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

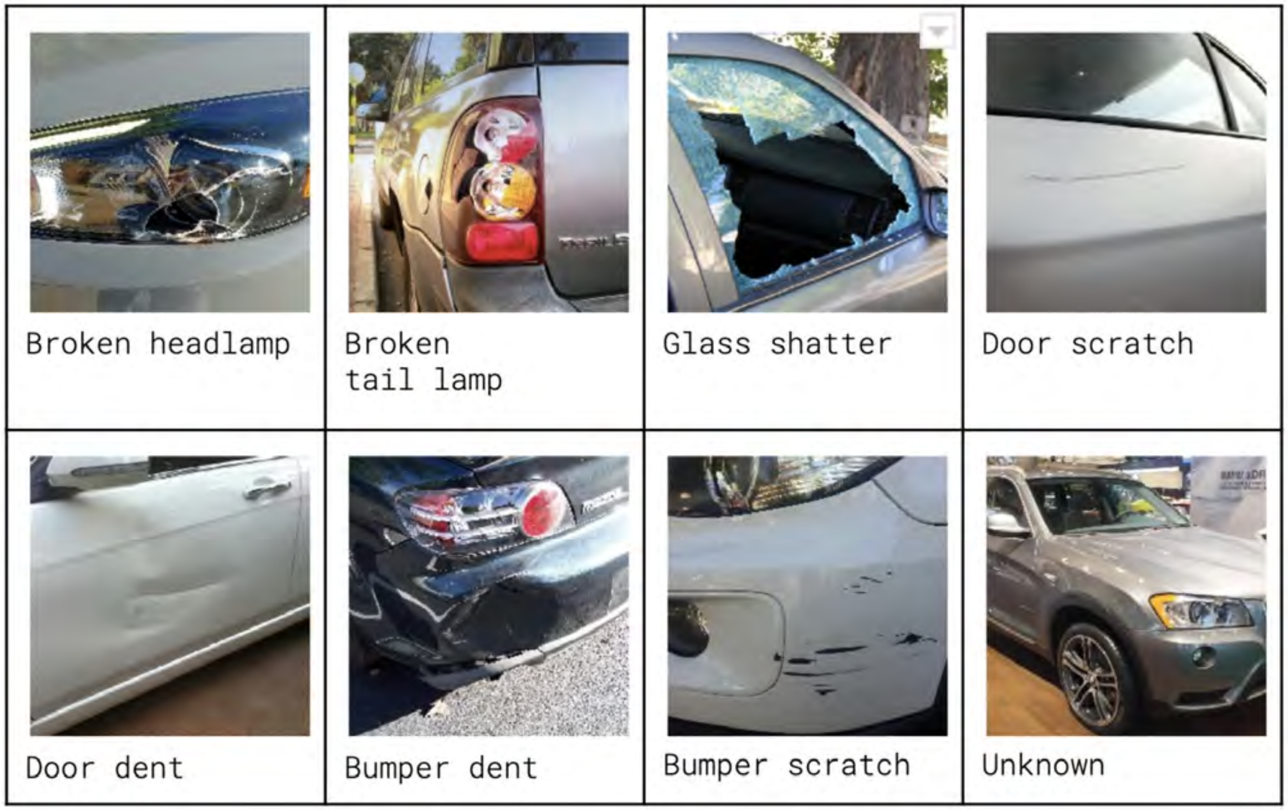
- **Create csv file**
  - **Create a text file with all image names**
  - **Create a file with all labels**
  - **Combine image names and labels in one file - index.csv**

Step 4

- **Create the zip-file**

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

Activity 3 – Car Damage Classifier



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

20 mins

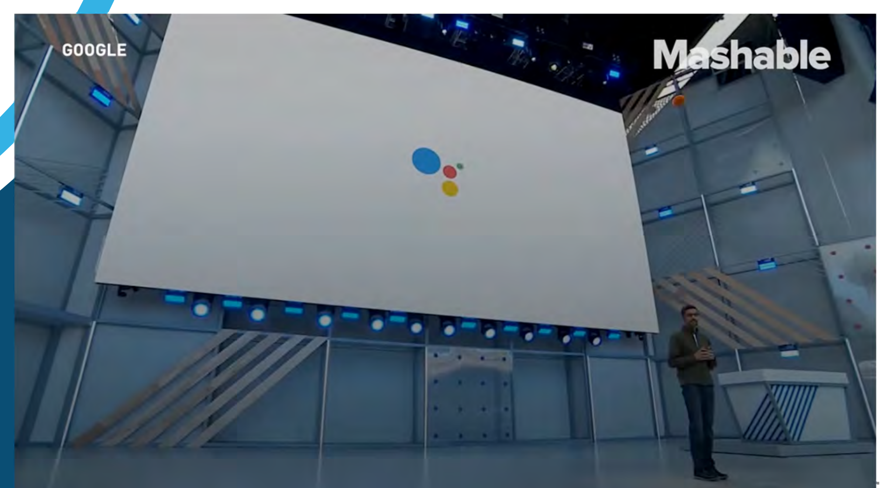
Step 2:
- Do on your own

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/

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

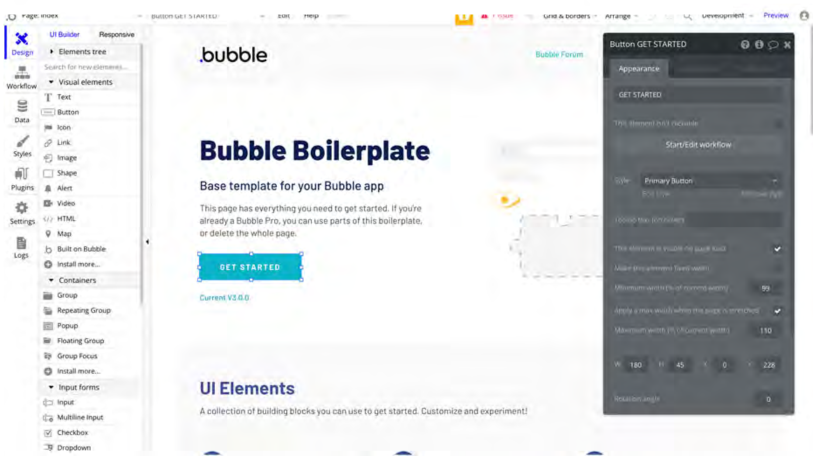
Linking Them Together

App Development

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

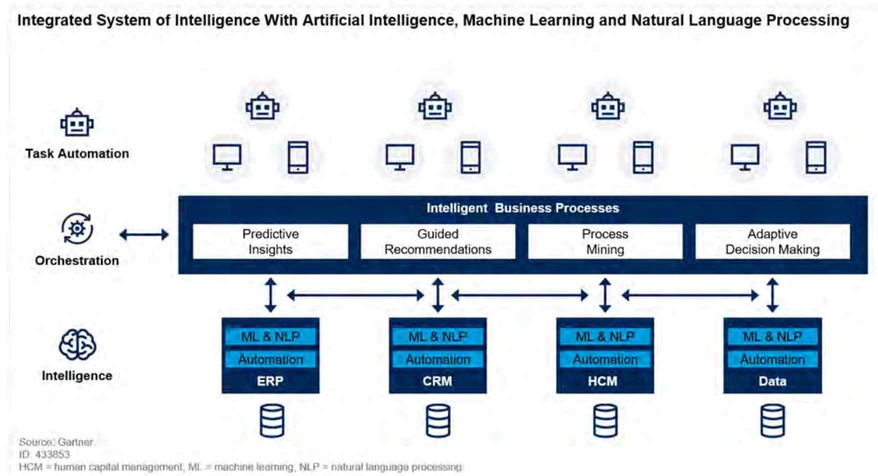
We're here to prove that **"building the best product"** is possible not only with Bubble.

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

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

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.**

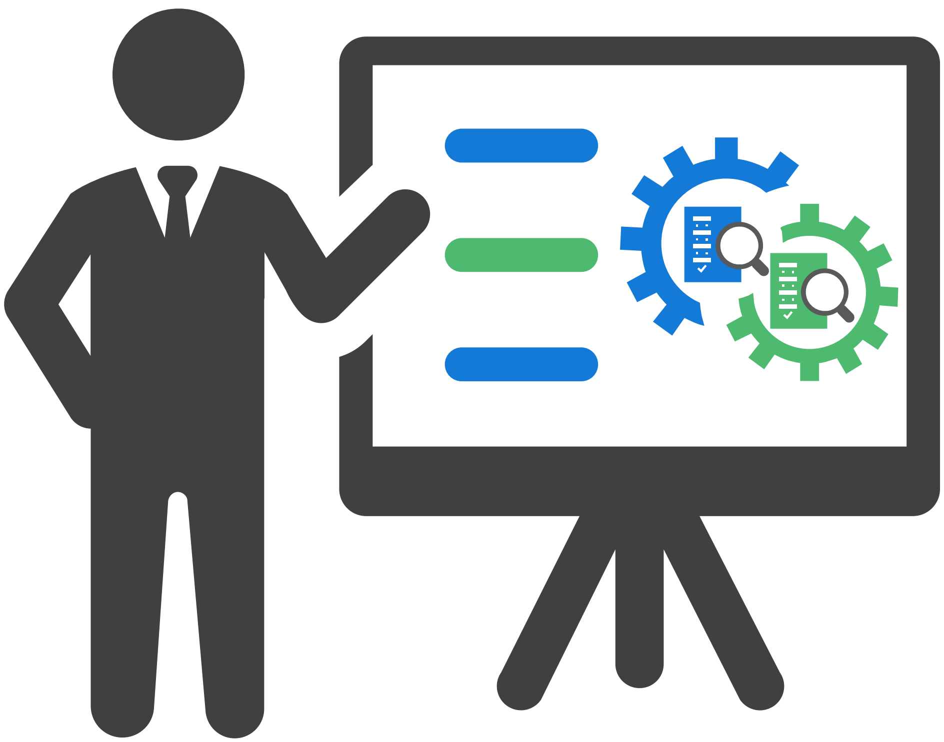
3 mins

Quiz

https://bit.ly/kw_poll

SCAN ME

Summary



Email
seow_khee_wei@rp.edu.sg

Telegram
@kwseow

Source code:

Thank you