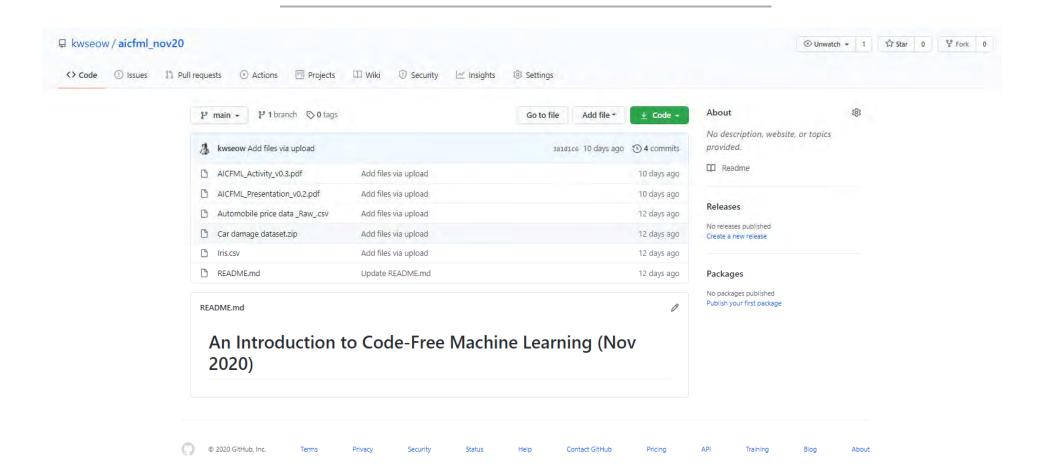
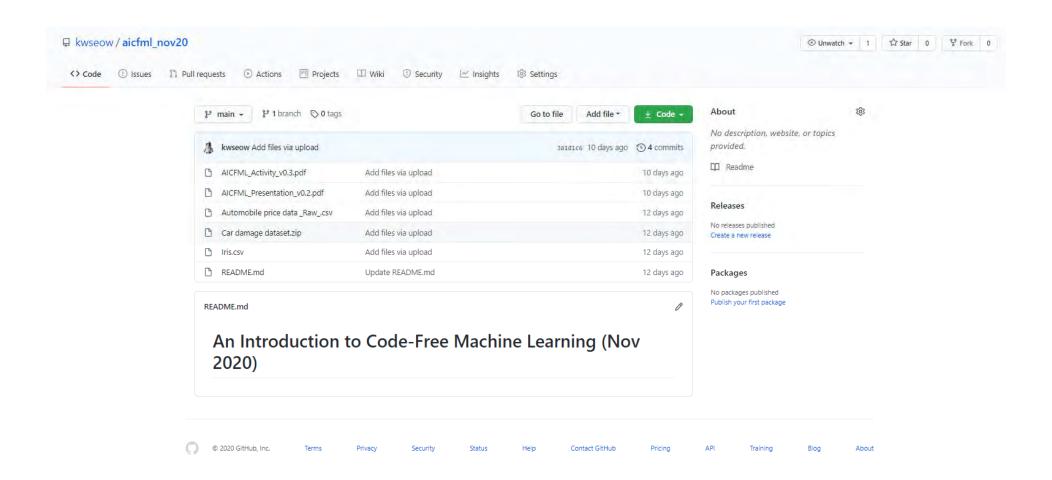




Download from Github









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.





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

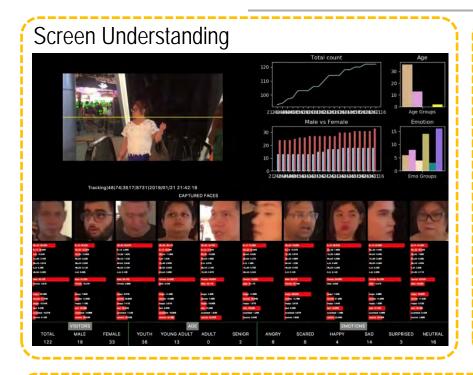


Name Seow Khee Wei Telegram @kwseow

Email seow_khee_wei@rp.edu.sg



Projects











Quickdraw Game

https://quickdraw.withgoogle.com



Can a neural network learn to recognize doodling?

Help teach it by adding your drawings to the world's largest doodling data set, shared publicly to help with machine learning research.



Let's Draw!

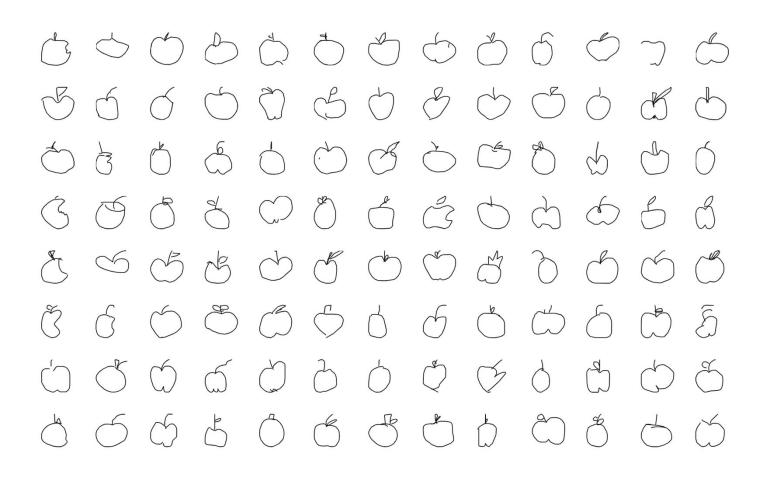
Optional Activity





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.

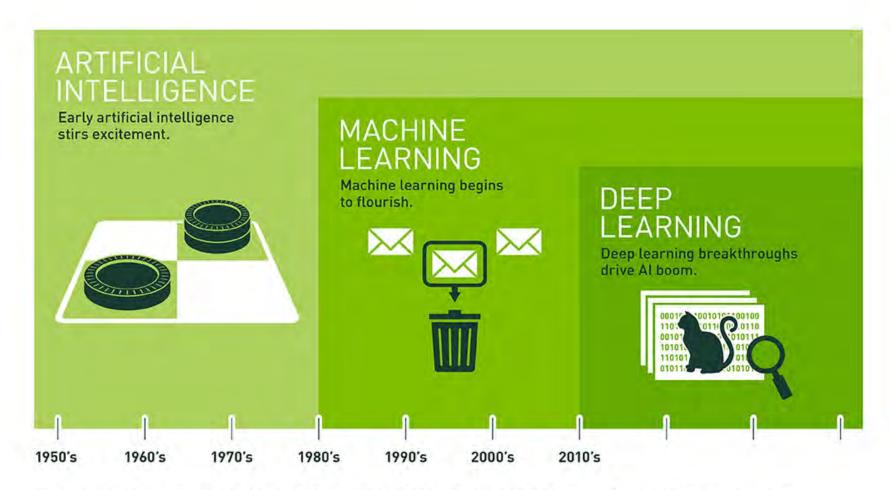


In WIRED's tests, Google Photos did identify some primates, but no gorillas like this one were to be found. RICK MADDNIK/TDRONTO STAR/GETTY IMAGES

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



Al Time line



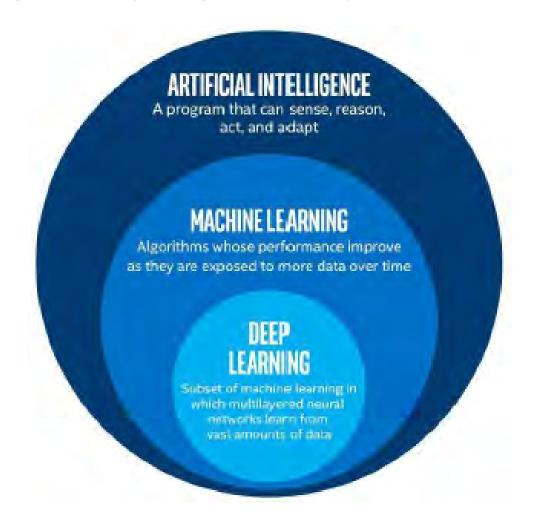
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: Nvidia



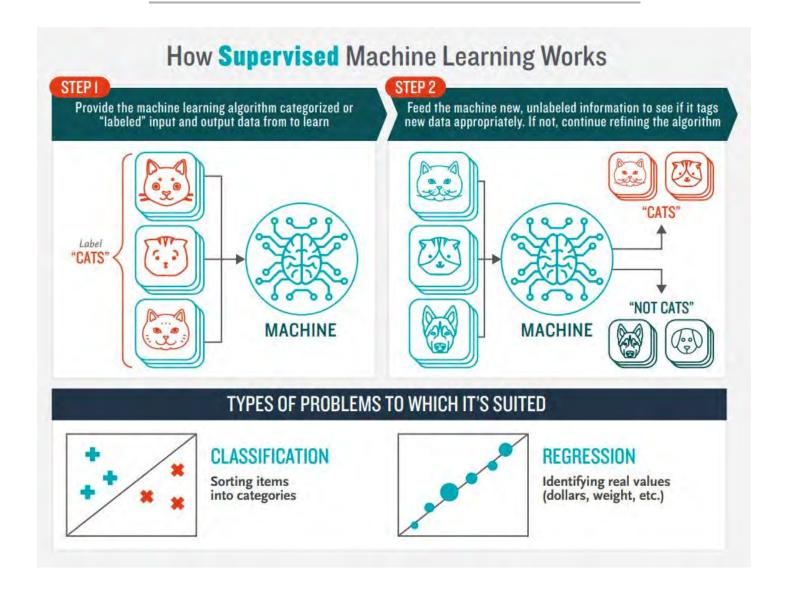
Machine Learning

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



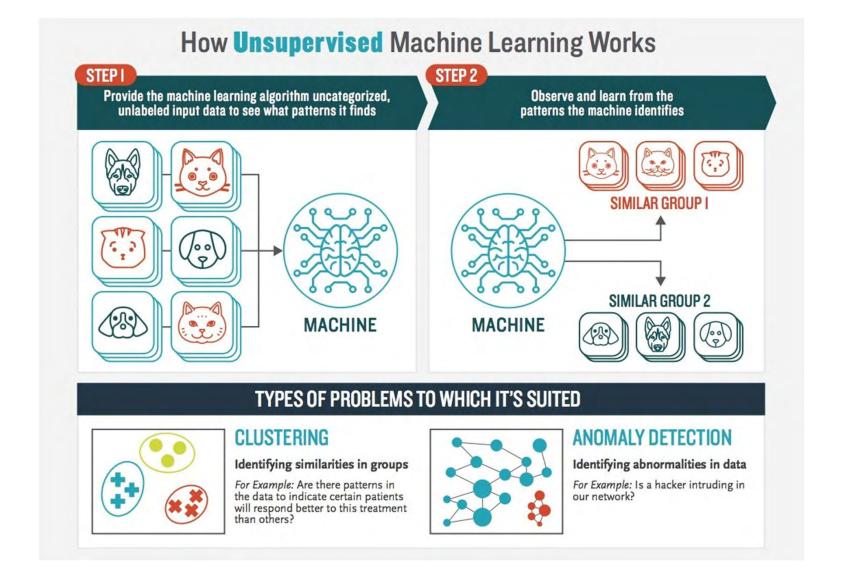


Supervised Learning





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

Movie
Recommendations

Vehicle Driver
Assistance

Web Advertisements

Social Networks

Speech Recognition



5 fundamental questions

(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)

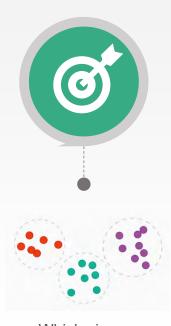


Monday 72°

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

Tuesday

How is this organized? (Clustering)



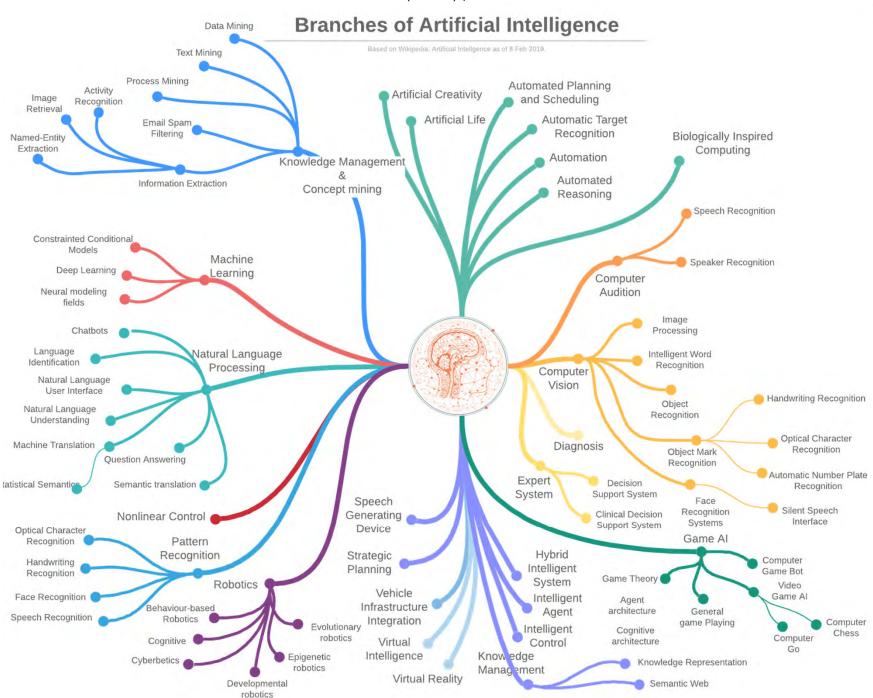
Which viewers like the same types of movies? Which printer models fail the same way?

What should I do? (Reinforce Learning)



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

OFFICIAL (CLOSED) \ NON-SENSITIVE





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

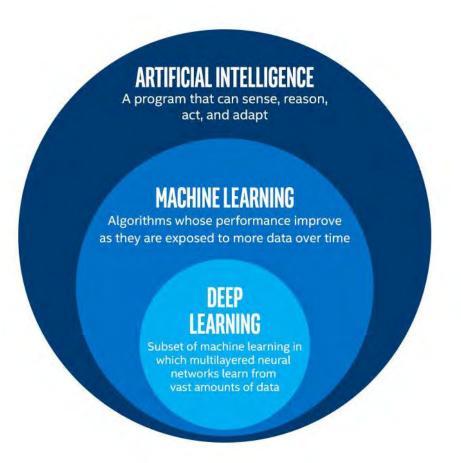


What is deep learning?

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

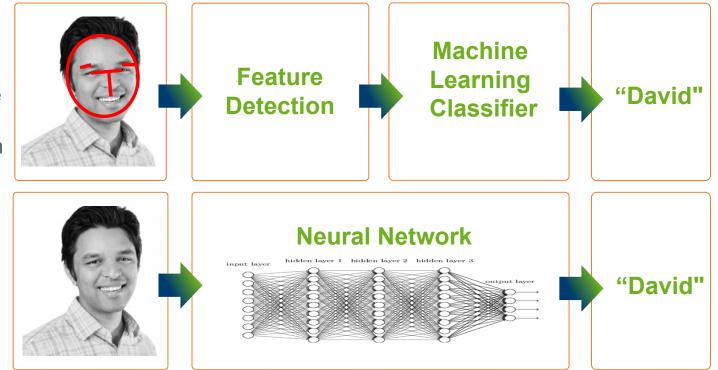
Classic Machine Learning

Step 1: Determine features.

Step 2: Feed them through model.

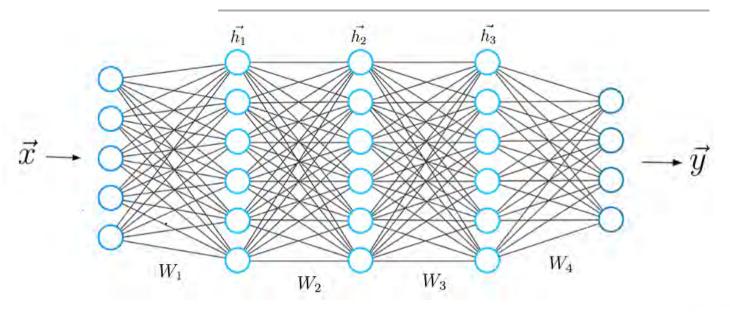
Deep Learning Steps 1 and 2

are combined into 1 step.

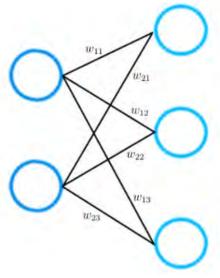




Neural Networks

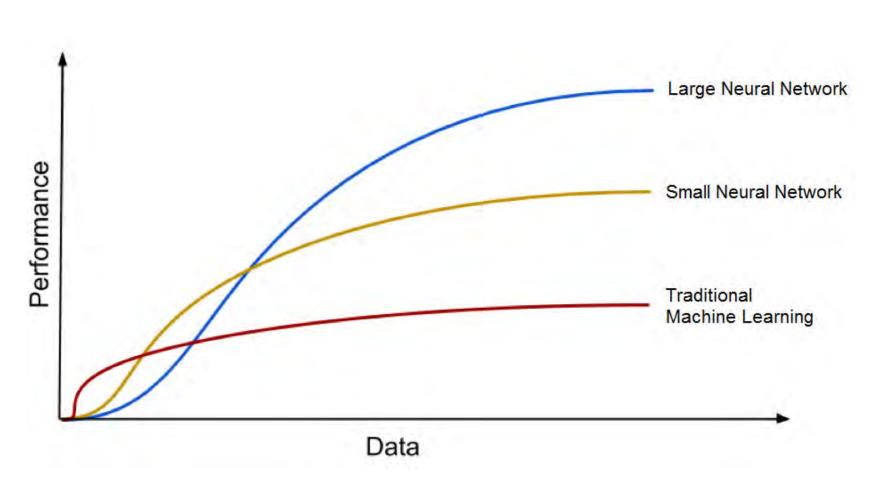


The challenge in training a neural networks is finding a set of weights the give the most accurate output.





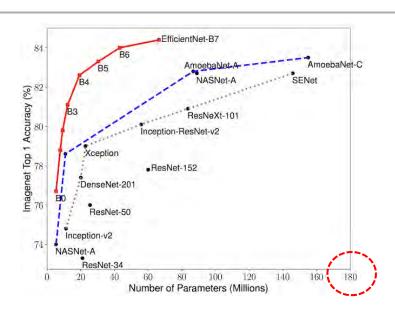
Performance



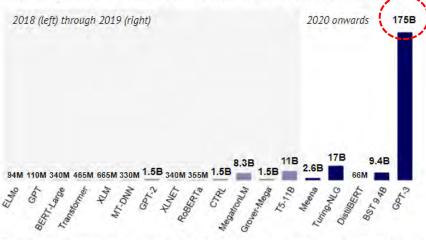
Deep Learning Algorithms get better with the increasing amount of data.



Size



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



Deep Learning in Action



10 mins

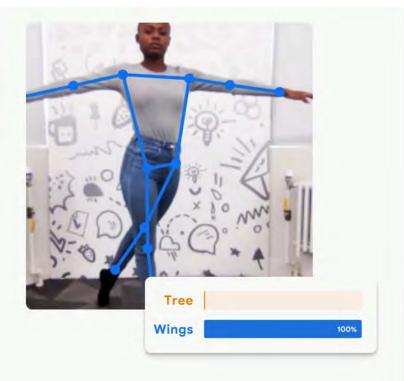
bit.ly/google_teachable

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





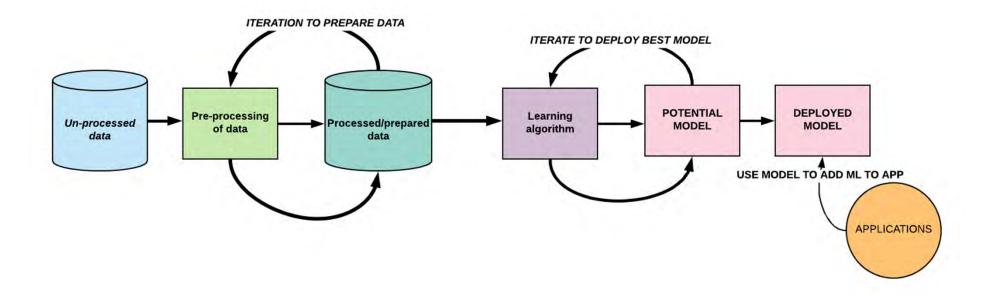
15 Mins Break

bit.ly/top10_2020





Machine Learning workflow



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

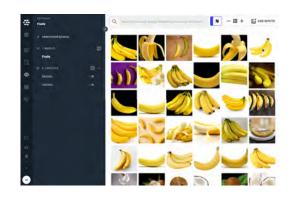
Code-Free Machine Learning tools

Microsoft Azure Machine Learning Studio (Classic)



Clarifai

Peltarion

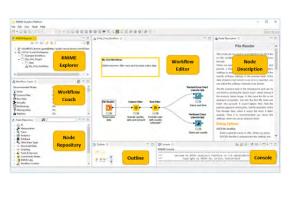




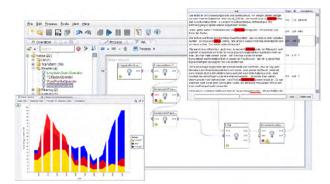
bigml



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



3 ?		alfa-romei		std	two	convertible												
3 ?								front	88.6	168.8	64.1	48.8	2548		four	130 mpfi	3.47	2.6
		alfa-rome		std	two	convertible		front	88.6	168.8	64.1	48.8	2548		four	130 mpfi	3.47	2.6
1 ?		alfa-rome	gas	std	two	hatchback		front	94.5	171.2	65.5	52.4	2823		six	152 mpfi	2.68	3.4
2	164		gas	std	four		fwd	front	99.8	176.6	66.2	54.3	2337		four	109 mpfi	3.19	3.
2	164	audi	gas	std	four	sedan	4wd	front	99.4	176.6	66.4	54.3	2824		five	136 mpfi	3.19	3.
2 ?		audi	gas	std	two	sedan	fwd	front	99.8	177.3	66.3	53.1	2507	ohc	five	136 mpfi	3.19	3.
1	158		gas	std	four	sedan	fwd	front	105.8	192.7	71.4	55.7	2844		five	136 mpfi	3.19	3.
1 ?		audi	gas	std	four	wagon	fwd	front	105.8	192.7	71.4	55.7	2954	ohc	five	136 mpfi	3.19	3.
1	158	audi	gas	turbo	four		fwd	front	105.8	192.7	71.4	55.9	3086		five	131 mpfi	3.13	3.
0 ?			gas	turbo	two	hatchback	4wd	front	99.5	178.2	67.9	52	3053	ohc	five	131 mpfi	3.13	3.
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.
0			gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2395		four	108 mpfi	3.5	2.
0	188	bmw	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2710	ohc	six	164 mpfi	3.31	3.1
0	188	bmw	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2765	ohc	six	164 mpfi	3.31	3.1
1 ?		bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3055	ohc	six	164 mpfi	3.31	3.1
0 ?		bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3230	ohc	six	209 mpfi	3.62	3.3
0 ?		bmw	gas	std	two	sedan	rwd	front	103.5	193.8	67.9	53.7	3380	ohc	six	209 mpfi	3.62	3.3
0 ?		bmw	gas	std	four	sedan	rwd	front	110	197	70.9	56.3	3505	ohc	six	209 mpfi	3.62	3.3
2	121	chevrolet	gas	std	two	hatchback	fwd	front	88.4	141.1	60.3	53.2	1488	1	three	61 2bbl	2.91	3.0
1			gas	std	two	hatchback		front	94.5	155.9	63.6	52	1874		four	90 2bbl	3.03	3.1
0	81	chevrolet	gas	std	four	sedan	fwd	front	94.5	158.8	63.6	52	1909	ohc	four	90 2bbl	3.03	3.1
1			gas	std	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	1876	ohc	four	90 2bbl	2.97	3.2
1	118	dodge	gas	std	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	1876	ohc	four	90 2bbl	2.97	3.2
1			gas	turbo	two	hatchback	fwd	front	93.7	157.3	63.8	50.8	2128	ohc	four	98 mpfi	3.03	3.3
1	148	dodge	gas	std	four	hatchback	fwd	front	93.7	157.3	63.8	50.6	1967	ohc	four	90 2bbl	2.97	3.2
1	148	dodge	gas	std	four	sedan	fwd	front	93.7	157.3	63.8	50.6	1989	ohc	four	90 2bbl	2.97	3.2
1	148	dodge	gas	std	four	sedan	fwd	front	93.7	157.3	63.8	50.6	1989	ohc	four	90 2bbl	2.97	3.2
1	148	dodge	gas	turbo	?	sedan	fwd	front	93.7	157.3	63.8	50.6	2191	ohc	four	98 mpfi	3.03	3.3
-1	110	dodge	gas	std	four	wagon	fwd	front	103.3	174.6	64.6	59.8	2535	ohc	four	122 2bbl	3.34	3.4
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.
2	137	honda	gas	std	two	hatchback	fwd	front	86.6	144.6	63.9	50.8	1713	ohc	four	92 1bbl	2.91	3.4
2	137	honda	gas	std	two	hatchback	fwd	front	86.6	144.6	63.9	50.8	1819	ohc	four	92 1bbl	2.91	3.4
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1837	ohc	four	79 1bbl	2.91	3.0
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1940	ohc	four	92 1bbl	2.91	3.4
1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1956	ohc	four	92 1bbl	2.91	3.4
0	110	honda	gas	std	four	sedan	fwd	front	96.5	163.4	64	54.5	2010	ohc	four	92 1bbl	2.91	3.4
0	78	honda	gas	std	four	wagon	fwd	front	96.5	157.1	63.9	58.3	2024	ohc	four	92 1bbl	2.92	3.4
0	106	honda	gas	std	two	hatchback	fwd	front	96.5	167.5	65.2	53.3	2236	ohc	four	110 1bbl	3.15	3.5
0	106	honda	gas	std	two	hatchback	fwd	front	96.5	167.5	65.2	53.3	2289	ohc	four	110 1bbl	3.15	3.5
0	85	honda	gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2304	ohc	four	110 1bbl	3.15	3.5
0			gas	std	four	sedan	fwd	front	96.5	175.4	62.5	54.1	2372	ohc	four	110 1bbl	3.15	3.5
0	85	honda	gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2465	ohc	four	110 mpfi	3.15	3.5
1	107	honda	gas	std	two	sedan	fwd	front	96.5	169.1	66	51	2293	ohc	four	110 2bbl	3.15	3.5
0 ?			gas	std	four	sedan	rwd	front	94.3	170.7	61.8	53.5	2337	ohc	four	111 2bbl	3.31	3.2
1 ?		isuzu	gas	std	two	sedan	fwd	front	94.5	155.9	63.6	52	1874	ohc	four	90 2bbl	3.03	3.1
0 ?			gas	std	four	sedan	fwd	front	94.5	155.9	63.6	52	1909	ohc	four	90 2bbl	3.03	3.1
2 ?			gas	std	two	hatchback	rwd	front	96	172.6	65.2	51.4	2734	ohc	four	119 spfi	3.43	3.2
0	145	jaguar	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066	dohc	six	258 mpfi	3.63	4.1
0 ?		jaguar	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066	dohc	six	258 mpfi	3.63	4.1
0 ?			gas	std	two	sedan	rwd	front	102	191.7	70.6	47.8	3950	ohcv	twelve	326 mpfi	3.54	2.7
1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1890	ohc	four	91 2bbl	3.03	3.1
1			gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1900	ohc	four	91 2bbl	3.03	3.1
1			gas	std	two	hatchback		front	93.1	159.1	64.2	54.1	1905	ohc	four	91 2bbl	3.03	3.1
1			gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1945		four	91 2bbl	3.03	3.1
1	113	mazda	gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1950	ohc	four	91 2bbl	3.08	3.1
3			gas	std	two	hatchback		front	95.3	169	65.7	49.6	2380		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			gas		two	hatchhack		front	95.3	169	65.7	49.6	2385		two	70 4bbl		?
3			gas	std	two	hatchback		front	95.3	169	65.7	49.6	2500		two	80 mpfi		?
1			gas	std	two	hatchback		front	98.8	177.8	66.5	53.7	2385		four	122 2bbl	3.39	3.3
0			gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410		four	122 2bbl	3.39	3.3
1			gas	std	two	hatchback		front	98.8	177.8	66.5	53.7	2385		four	122 2001	3.39	3.3
0	115	mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410	ohc	four	122 2bbl	3.39	3.3

Step 1:

Watch and listen to the instructor's demonstration

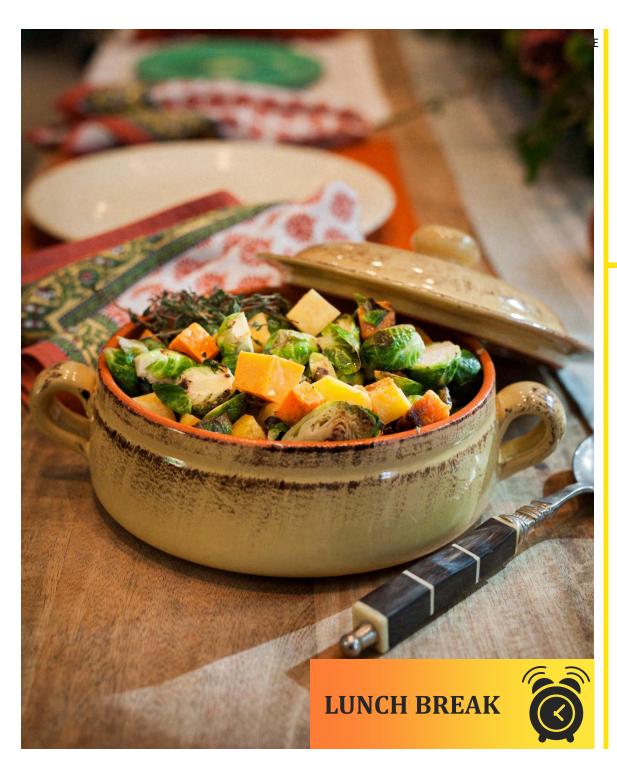


Step 2:

- Do on your own



Individual Activity



60 mins Lunch Break

Some interesting videos

https://www.youtube.com/watch?v=bmNaLt
C6vkU

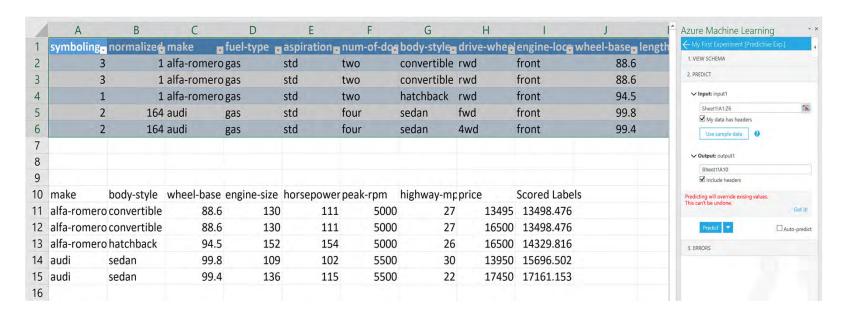
https://www.youtube.com/watch?v=Nnf8P5
A saE

Lunch break 12:20-13:20



Activity 2

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



Step 1:

Watch and listen to the instructor's demonstration



Step 2:

Work through the activities



Individual Activity



Optional Activities

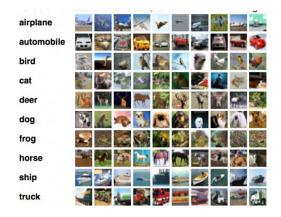
- Activity 6 Importing data
- Activity 7 Cleaning and Structuring Data
- Activity 8 Using Binary Classification Algorithm



Applications of Computer Vision

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



















































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

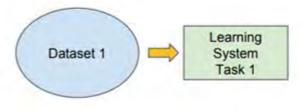


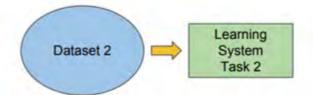
Transfer Learning

Traditional ML

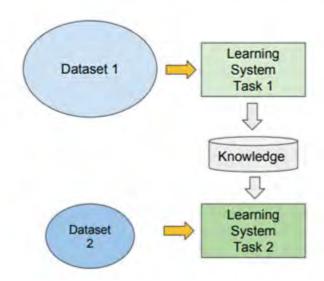
vs Transfer Learning

- 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 Mylmages.

Step 2

- Data preprocessing
- •Resize images to 224x224 pixels
- ·Label all images

Step 3

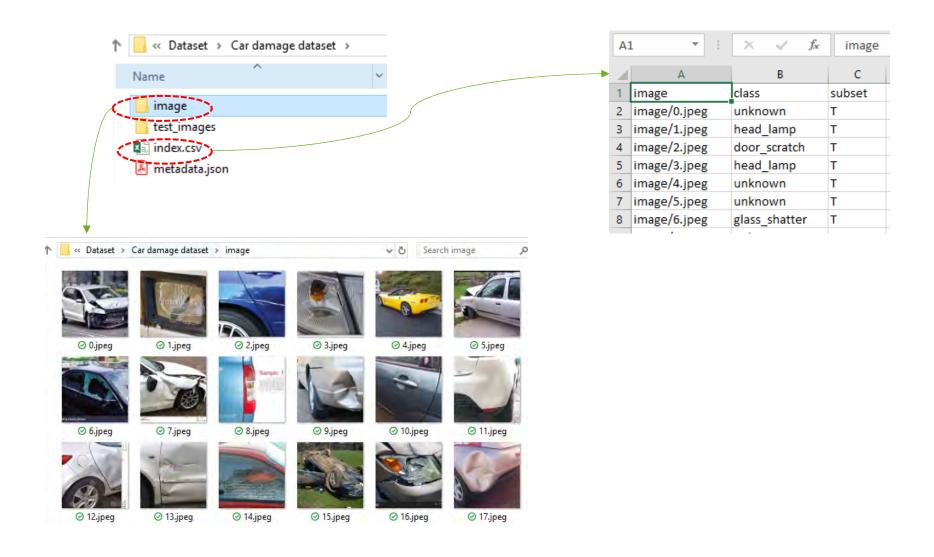
- ·Create csv file
- ·Create a text file with all image names
- Create a file with all labels
- •Combine image names and labels in one file index.csv

Step 4

·Create the zip-file



Example





Activity 3 – Car Damage Classifier



Broken headlamp



Broken tail lamp



Glass shatter



Door scratch



Door dent



Bumper dent



Bumper scratch



Unknown

Step 1:

Watch and listen to the instructor's demonstration



Step 2:

- Do on your own



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





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



Step 2:

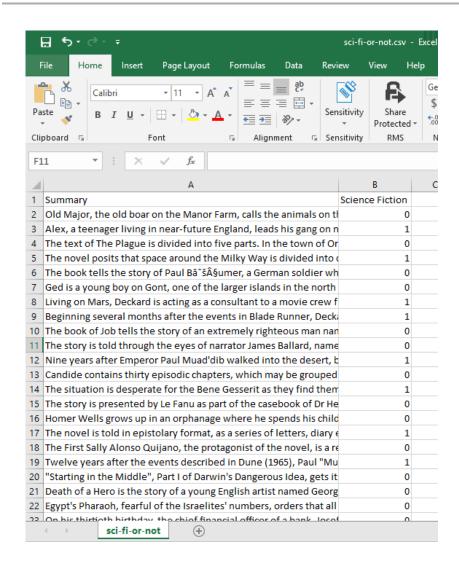
- Do on your own



Individual Activity



Dataset





Linking Them Together

ч

App Development

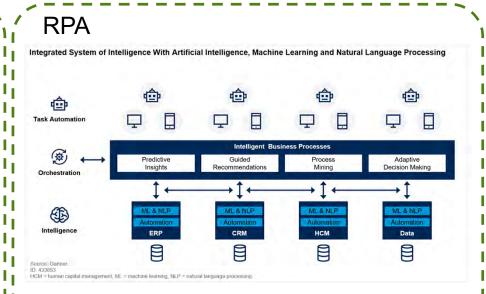
Top 9 No-Code Web **App Development Tools that May** Compete with Bubble

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







Adobe Acrobat Document

https://www.youtube.com/watch?v=FV8IM9SIFQ8 45



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. Al 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 Al 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

THE

ESSENTIAL

AI HANDBOOK

FOR

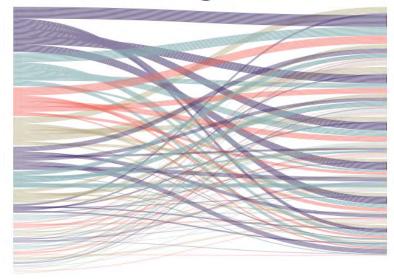
LEADERS

FOREWORD BY MARCUS WALLENBERG

AT THE RND OF THE DAY it is not technology that creates success, it is people. It is leaders that take the right decisions based on the most accurate data, insights and their ability to work with the best people. It is the ones who do this faster than the competition that will succeed.

ALGORITHMIA

2020 state of enterprise machine learning





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.







https://bit.ly/kw_poll





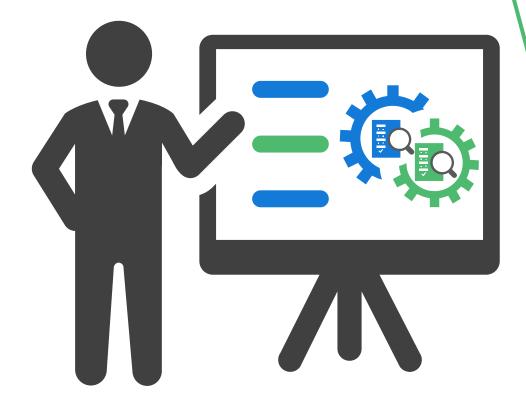
Survey

https://bit.ly/2GRIT2P





Summary



Email seow_khee_wei@rp.edu.sg

Telegram @kwseow

Source code:



Thank you