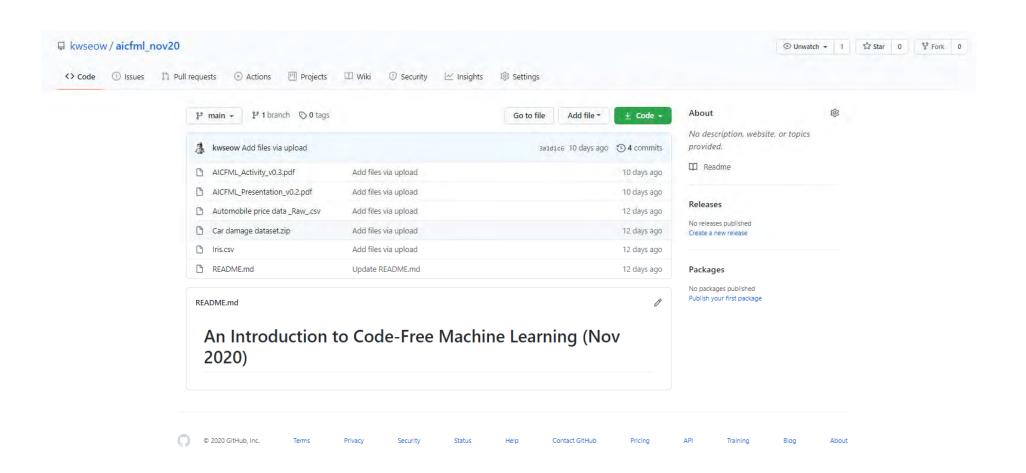




Download from Github

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.





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

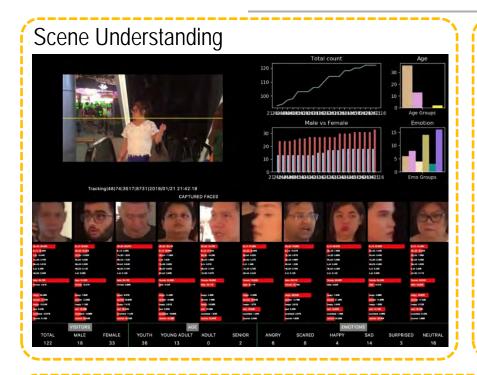


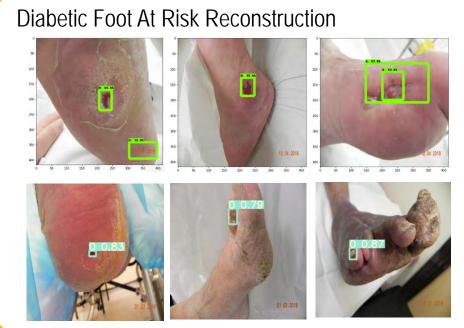
Name Seow Khee Wei Telegram @kwseow

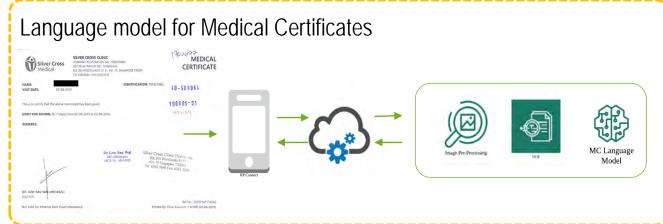
Email seow_khee_wei@rp.edu.sg

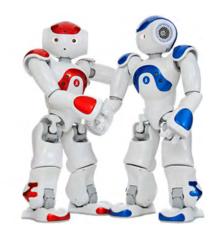


Projects





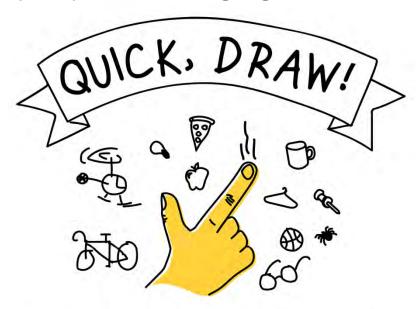




7

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!

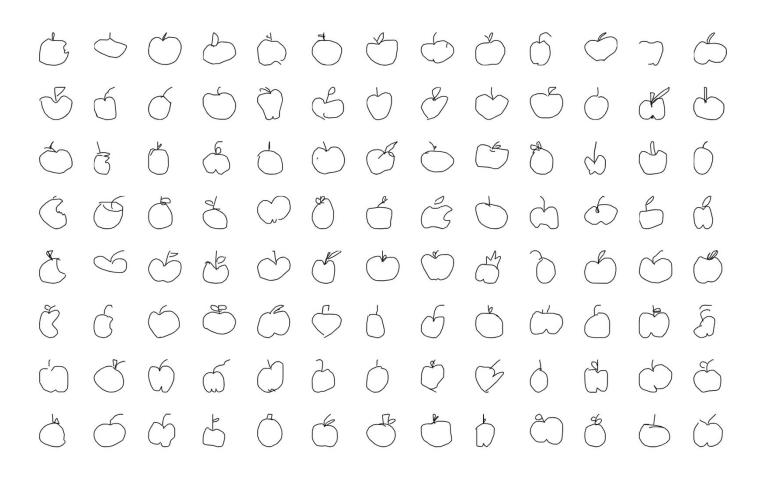
Optional Activity





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.

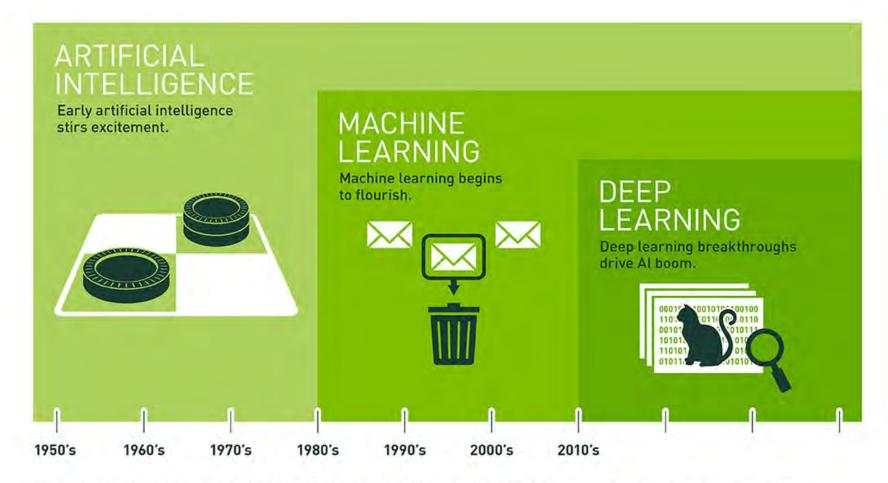


In WIRED's tests, Google Photos did identify some primates, but no gorillas like this one were to be found. RICK MADDNIK/TORONTO STAR/GETTY IMAGES

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



Al Time line



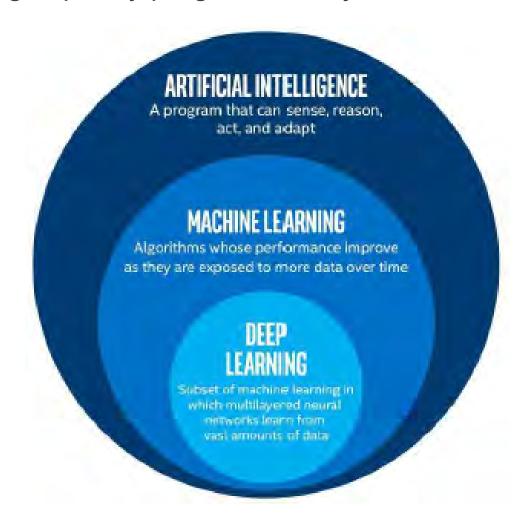
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: Nvidia



Machine Learning

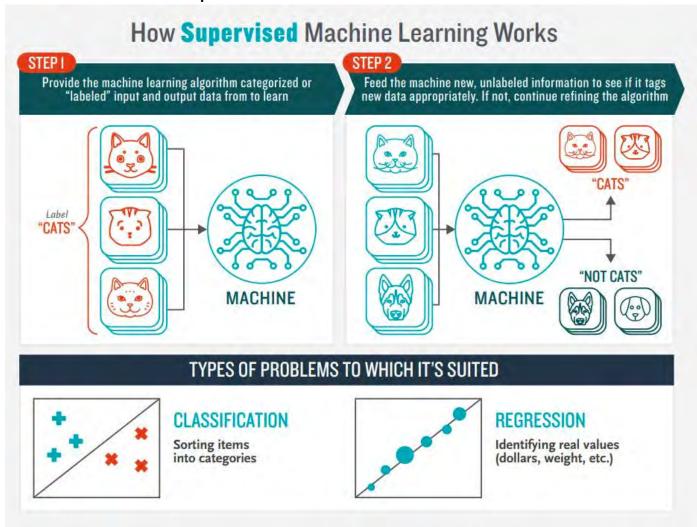
 These programs learn from repeatedly seeing data, rather than being explicitly programmed by humans





Supervised Learning

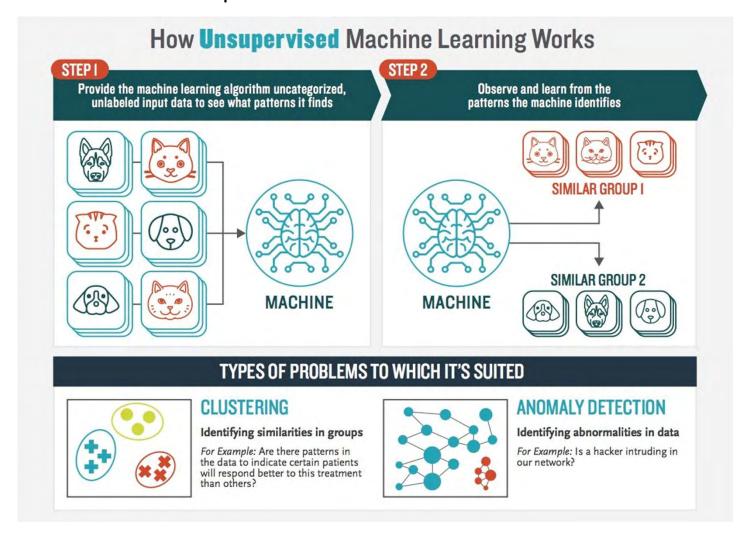
Data points have **known** outcome





Unsupervised Learning

Data points have **unknown** outcome





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)

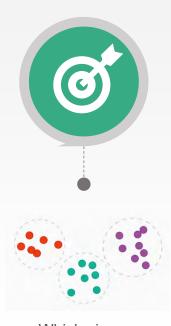


Monday 72°

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

Tuesday

How is this organized? (Clustering)



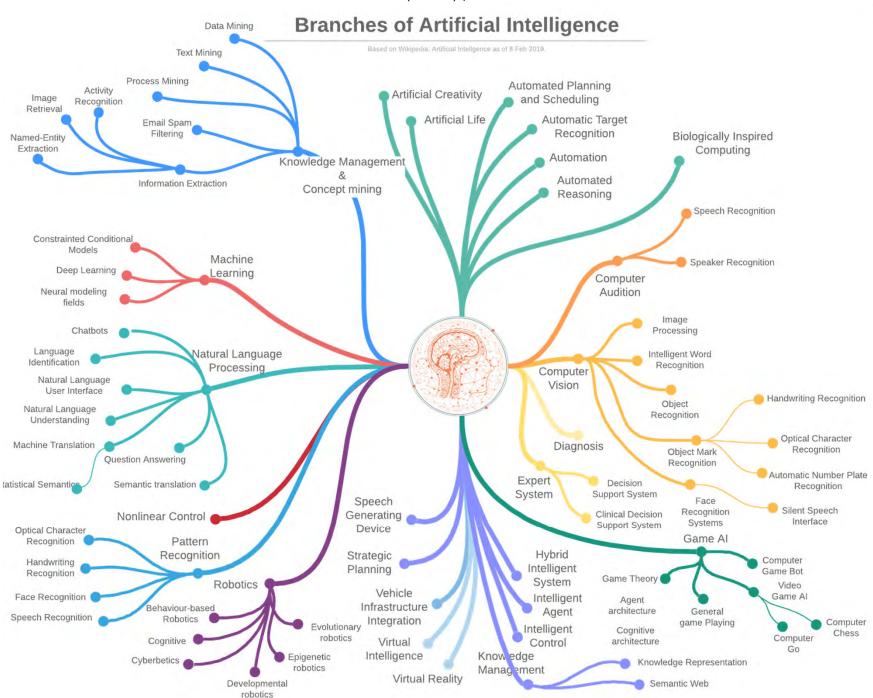
Which viewers like the same types of movies? Which printer models fail the same way?

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.

A program that can sense, reason, act, and adapt Algorithms whose performance improve as they are exposed to more data over time DEEP Subset of machine learning in which multilayered neural networks learn from vast amounts of data



Deep Learning Example

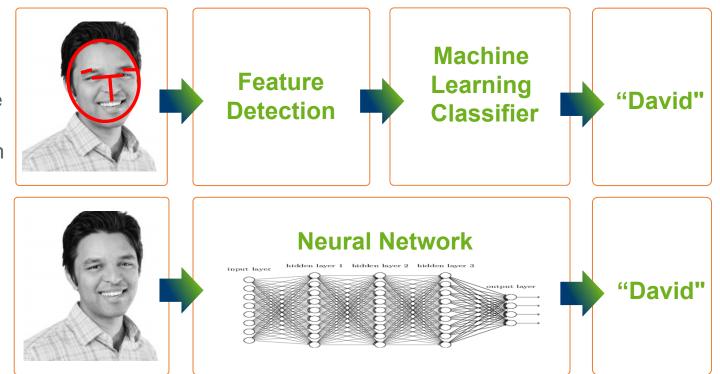
Classic Machine Learning

Step 1: Determine features.

Step 2: Feed them through model.

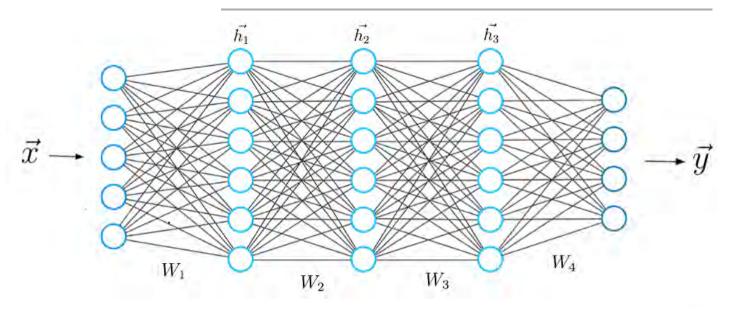
Deep Learning Steps 1 and 2

are combined into 1 step.

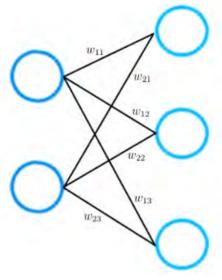




Neural Networks

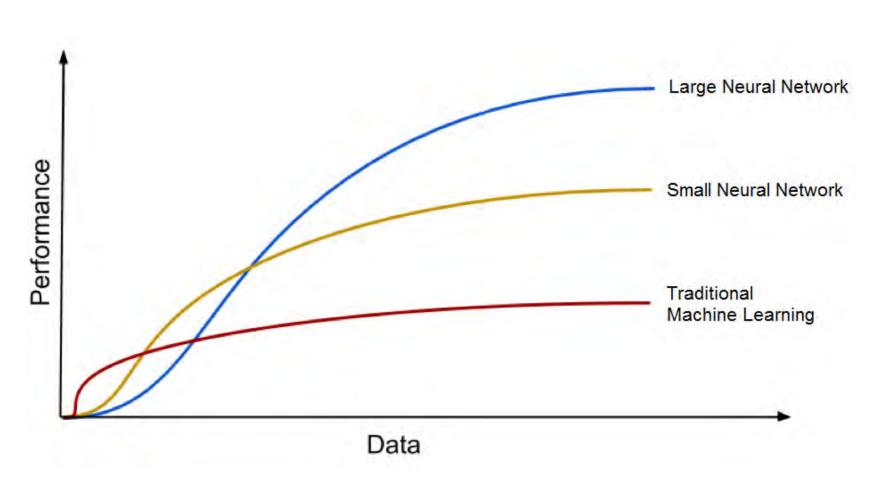


The challenge in training a neural networks is finding a set of weights the give the most accurate output.





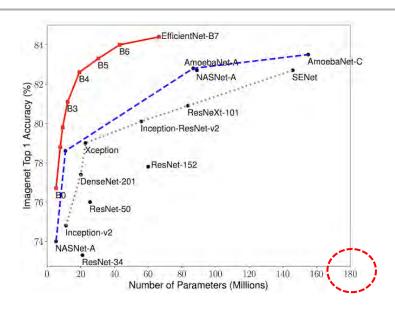
Performance



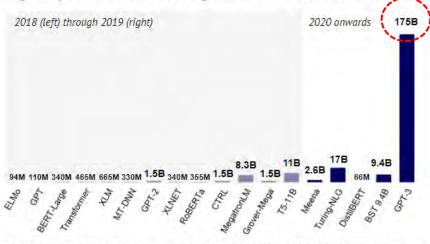
Deep Learning Algorithms get better with the increasing amount of data.



Size



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



23

Deep Learning in Action



10 mins

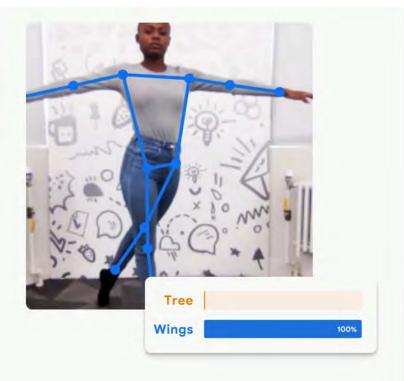
bit.ly/google_teachable

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





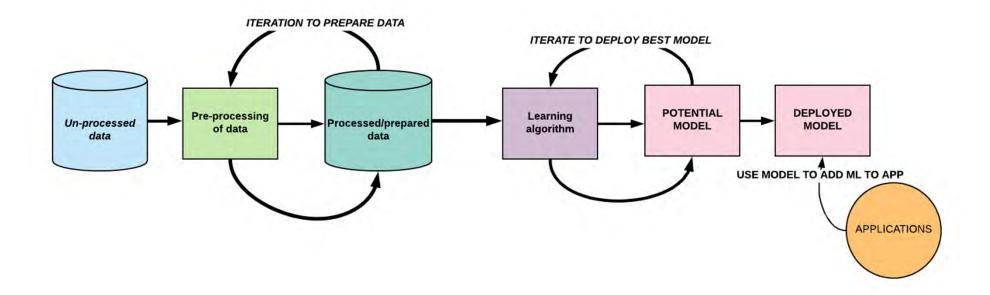
15 Mins Break

bit.ly/top10_2020





Machine Learning workflow



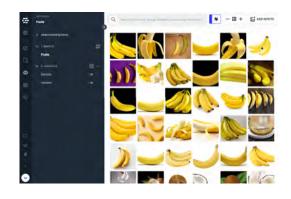
Code-Free Machine Learning tools

Microsoft Azure Machine Learning Studio (Classic)



Clarifai

Peltarion

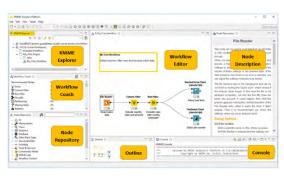




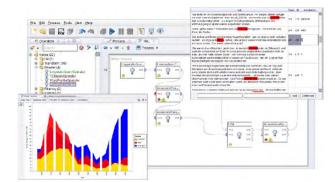
bigml



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



	normalize							engine-loc			width						fuel-syster		stroke
3		alfa-rome		std	two	convertible		front	88.6	168.8	64.1	48.8	2548		four	130		3.47	2.
3		alfa-rome		std	two	convertible		front	88.6	168.8	64.1	48.8	2548		four	130		3.47	2.
1		alfa-rome	gas	std	two	hatchback		front	94.5	171.2	65.5	52.4	2823		six	152		2.68	3.
2		audi	gas	std	four	sedan	fwd	front	99.8	176.6	66.2	54.3	2337		four	109		3.19	
2		audi	gas	std	four	sedan		front	99.4	176.6	66.4	54.3	2824		five	136		3.19	- 3
2			gas	std	two	sedan	fwd	front	99.8	177.3	66.3	53.1	2507		five	136		3.19	
1			gas	std	four		fwd	front	105.8	192.7	71.4	55.7	2844		five	136		3.19	- 3
1			gas	std	four		fwd	front	105.8	192.7	71.4	55.7	2954		five	136		3.19	
1			gas	turbo	four	sedan	fwd	front	105.8	192.7	71.4	55.9	3086		five	131		3.13	
0			gas	turbo	two	hatchback		front	99.5	178.2	67.9	52	3053		five	131		3.13	- :
2			gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2395		four	108		3.5	
0			gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2395		four	108		3.5	
0			gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2710		six	164		3.31	3.
0		bmw	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2765		six	164		3.31	3.
1		bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3055		six	164		3.31	3.
0			gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3230		six	209		3.62	3.
0			gas	std	two	sedan	rwd	front	103.5	193.8	67.9	53.7	3380		six	209		3.62	3.
0		bmw	gas	std	four	sedan	rwd	front	110	197	70.9	56.3	3505		six	209		3.62	3.
2			gas	std	two	hatchback		front	88.4	141.1	60.3	53.2	1488		three		2bbl	2.91	3.
1			gas	std	two	hatchback		front	94.5	155.9	63.6	52	1874		four		2bbl	3.03	3.
0			gas	std	four		fwd	front	94.5	158.8	63.6	52	1909		four		2bbl	3.03	3.
1			gas	std	two	hatchback		front	93.7	157.3	63.8	50.8	1876		four		2bbl	2.97	3.
1			gas	std	two	hatchback		front	93.7	157.3	63.8	50.8	1876		four		2bbl	2.97	3.
1			gas	turbo	two	hatchback		front	93.7	157.3	63.8	50.8	2128		four		mpfi	3.03	3.
1			gas	std	four	hatchback		front	93.7	157.3	63.8	50.6	1967		four		2bbl	2.97	3.
1			gas	std	four		fwd	front	93.7	157.3	63.8	50.6	1989		four		2bbl	2.97	3.
1			gas	std	four	sedan	fwd	front	93.7	157.3	63.8	50.6	1989		four		2bbl	2.97	3.
1			gas	turbo	?		fwd	front	93.7	157.3	63.8	50.6	2191		four		mpfi	3.03	3.
-1			gas	std	four		fwd	front	103.3	174.6	64.6	59.8	2535		four	122		3.34	3.
3			gas	turbo	two	hatchback		front	95.9	173.2	66.3	50.2	2811		four	156		3.6	- :
2			gas	std	two	hatchback		front	86.6	144.6	63.9	50.8	1713		four	92		2.91	3.
2			gas	std	two	hatchback		front	86.6	144.6	63.9	50.8	1819		four		1bbl	2.91	3.
1			gas	std	two	hatchback		front	93.7	150	64	52.6	1837		four		1bbl	2.91	3.
1			gas	std	two	hatchback		front	93.7	150	64	52.6	1940		four		1bbl	2.91	3.
1			gas	std	two	hatchback		front	93.7	150	64	52.6	1956		four		1bbl	2.91	3.
0			gas	std	four		fwd	front	96.5	163.4	64	54.5	2010		four	92		2.91	3.
0			gas	std	four		fwd	front	96.5	157.1	63.9	58.3	2024		four		1bbl	2.92	3.
0			gas	std	two	hatchback		front	96.5	167.5	65.2	53.3	2236		four	110		3.15	3.
0			gas	std	two	hatchback		front	96.5	167.5	65.2	53.3	2289		four	110		3.15	3.
0		honda	gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2304		four	110		3.15	3.
0		honda	gas	std	four		fwd	front	96.5	175.4	62.5	54.1	2372		four	110		3.15	3.
0			gas	std	four	sedan	fwd	front	96.5	175.4	65.2	54.1	2465		four	110		3.15	3.
1			gas	std	two	sedan	fwd	front	96.5	169.1	66	51	2293		four	110		3.15	3.
0			gas	std	four	sedan	rwd	front	94.3	170.7	61.8	53.5	2337		four	111		3.31	3.
1		isuzu	gas	std	two	sedan	fwd	front	94.5	155.9	63.6	52	1874		four		2bbl	3.03	3.
0			gas	std	four	sedan	fwd	front	94.5	155.9	63.6	52	1909		four		2bbl	3.03	3.
2		isuzu	gas	std	two .	hatchback		front	96	172.6	65.2	51.4	2734		four	119		3.43	3.
0			gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066		six	258		3.63	4.
0		jaguar	gas	std	four	sedan	rwd	front	113	199.6	69.6	52.8	4066		six	258		3.63	4.
0		jaguar	gas	std	two	sedan	rwd	front	102	191.7	70.6	47.8	3950		twelve	326		3.54	2
1			gas	std	two	hatchback		front	93.1	159.1	64.2	54.1	1890		four		2bbl	3.03	3
1		mazda	gas	std	two	hatchback		front	93.1	159.1	64.2	54.1	1900		four		2bbl	3.03	3
1			gas	std	two	hatchback		front	93.1	159.1	64.2	54.1	1905		four		2bbl	3.03	3
1			gas	std	four		fwd	front	93.1	166.8	64.2	54.1	1945		four		2bbl	3.03	3
1			gas	std	four		fwd	front	93.1	166.8	64.2	54.1	1950		four		2bbl	3.08	3
3			gas	std	two	hatchback		front	95.3	169	65.7	49.6	2380		two				?
3		mazda	gas	std	two	hatchback		front	95.3	169	65.7	49.6	2380		two				?
3			gas	std	two	hatchback		front	95.3	169	65.7	49.6	2385		two				?
3			gas	std	two	hatchback		front	95.3	169	65.7	49.6	2500		two				?
1		mazda	gas	std	two	hatchback		front	98.8	177.8	66.5	53.7	2385		four	122		3.39	3
0		mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410		four	122		3.39	3
1		mazda	gas	std	two	hatchback		front	98.8	177.8	66.5	53.7	2385		four	122		3.39	3
0		mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410		four	122		3.39	3.
0	>	mazda	diesel	std	?	sedan	fwd	front	98.8	177.8	66.5	55.5	2443	ohc	four	122	idi	3.39	3

Step 1:

Watch and listen to the instructor's demonstration

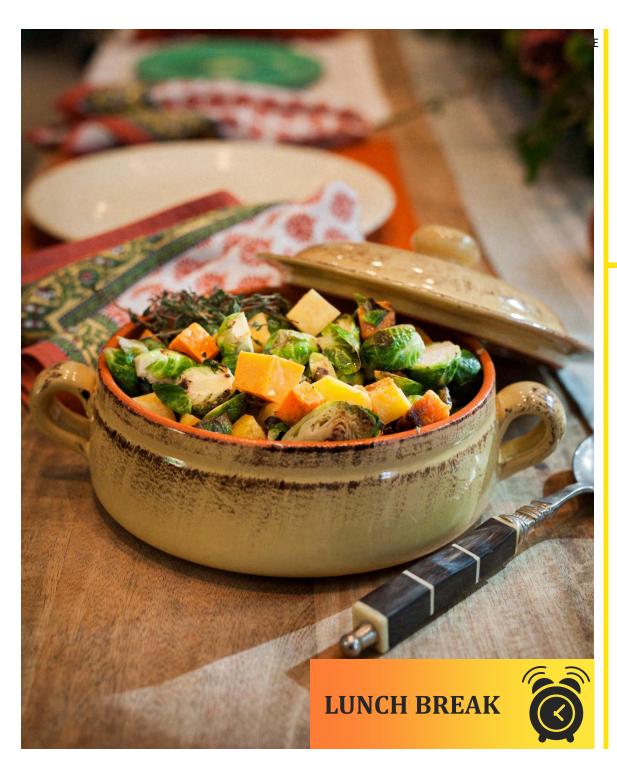


Step 2:

- Do on your own



Individual Activity



60 mins Lunch Break

Some interesting videos

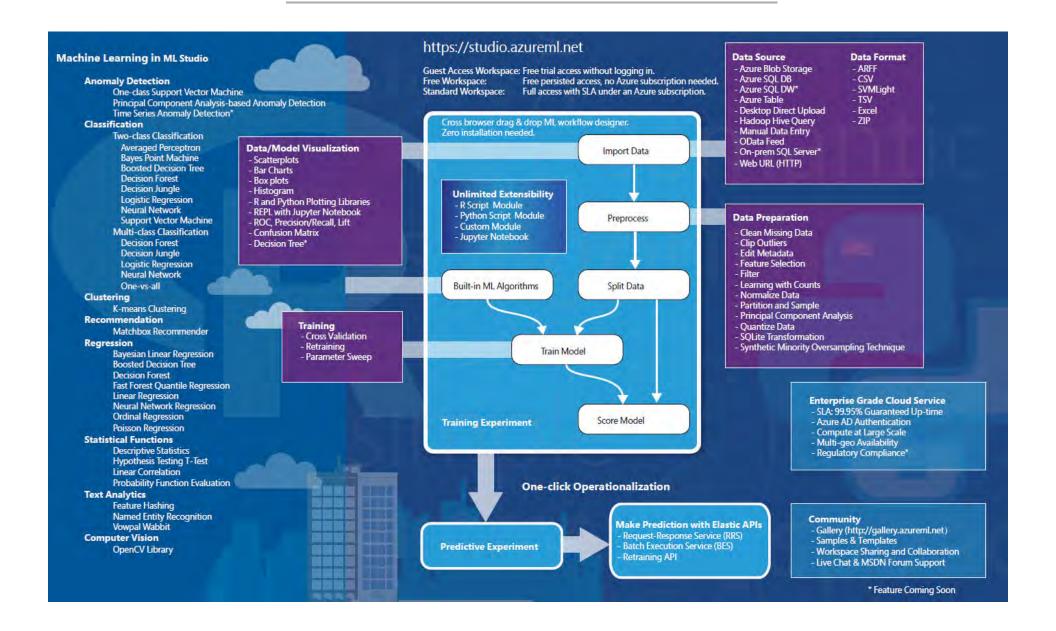
https://www.youtube.com/watch?v=bmNaLt
C6vkU

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

Lunch break 12:20-13:20



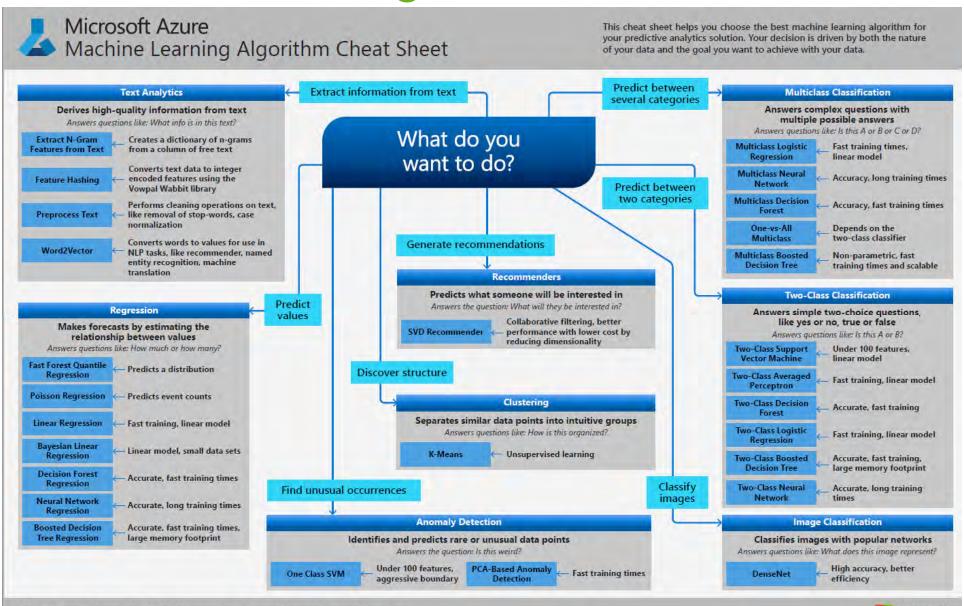
Recap





Microsoft

Azure ML Algorithm Cheat Cheet

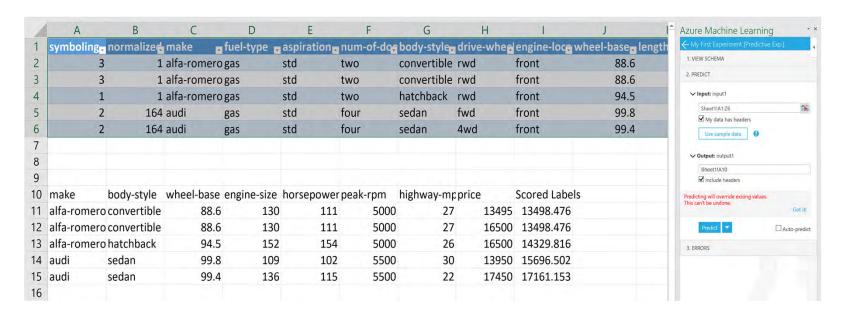


© 2019 Microsoft Corporation. All rights reserved. Share this poster: aka,ms/mlcheatsheet



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

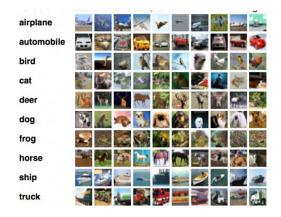
- Activity 6 Importing data
- Activity 7 Cleaning and Structuring Data
- Activity 8 Using Binary Classification Algorithm



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

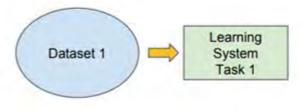


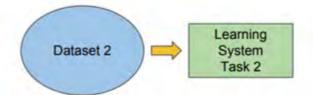
Transfer Learning

Traditional ML

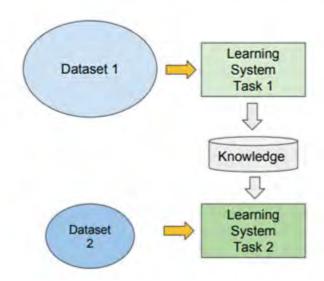
vs Transfer Learning

- 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

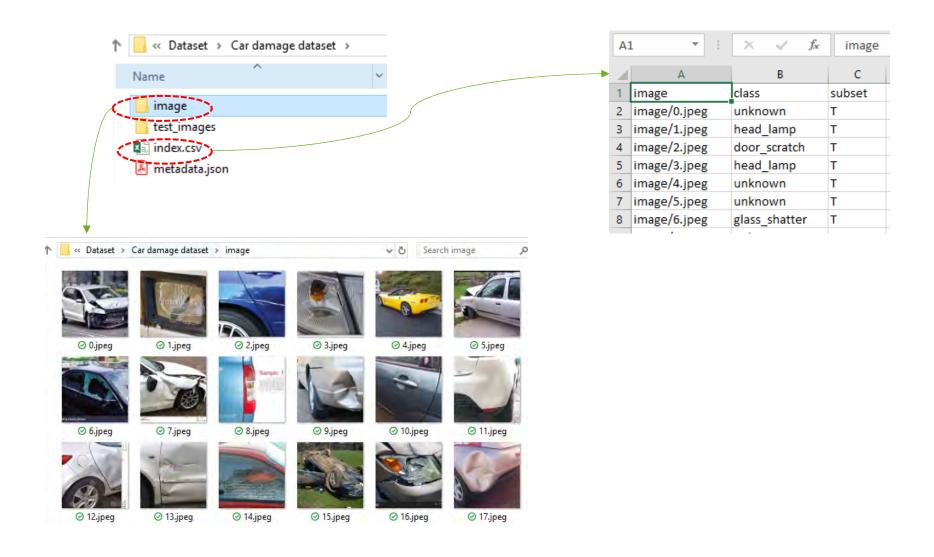
- ·Create csv file
- ·Create a text file with all image names
- Create a file with all labels
- •Combine image names and labels in one file index.csv

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







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. Style / 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. Sbr />Sbr />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



Step 2:

- Do on your own

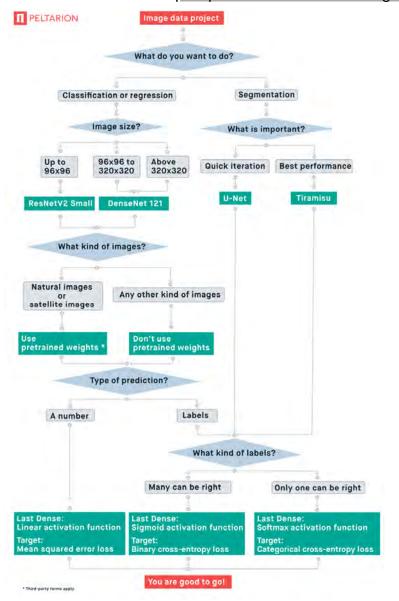


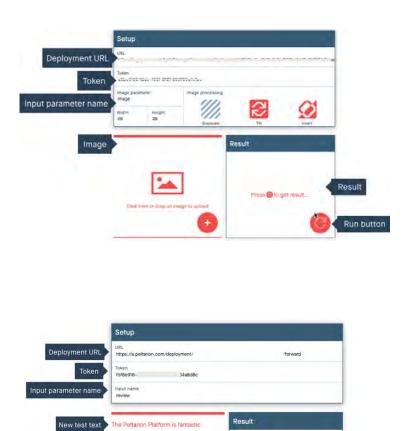
Individual Activity



Cheatsheets

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







Linking Them Together

App Development

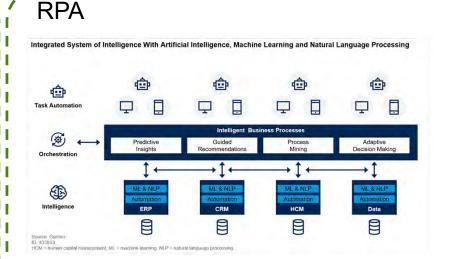
Top 9 No-Code Web App Development Tools that May Compete with Bubble

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





https://uibakery.io/bubble-alternatives







blueprism





https://www.youtube.com/watch?v=FV8IM9SIFQ8 46

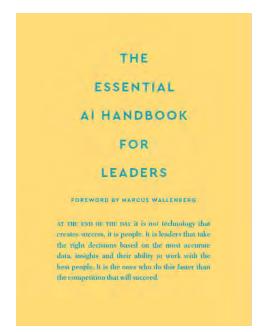


When to use Machine Learning

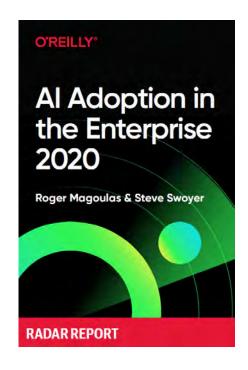
- What are our most pressing problems right now?
 - Just like any other tool in business, Al should be viewed as a tool that can help make your organization more effective, profitable or streamlined
- What parts of our business generate revenue but currently have low profit margins?
 - These revenue streams could provide fertile ground for automation and acceleration via Al.
- 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 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 Al.



Some easy readings









Datasets and Data Prep



https://kwseow.github.io/



https://datasetsearch.research.google.com/



https://www.kaggle.com/datasets



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











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





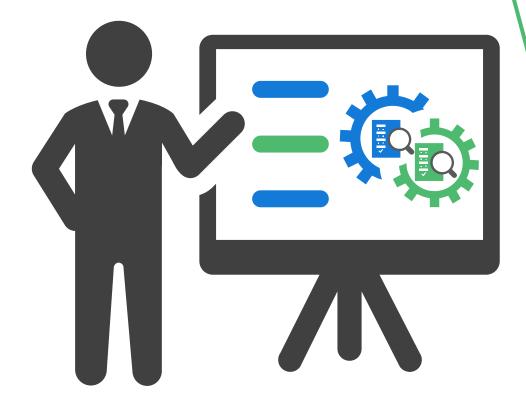
Survey



https://bit.ly/2UvFXfK



Summary



Email seow_khee_wei@rp.edu.sg

Telegram @kwseow

Source code:



Thank you