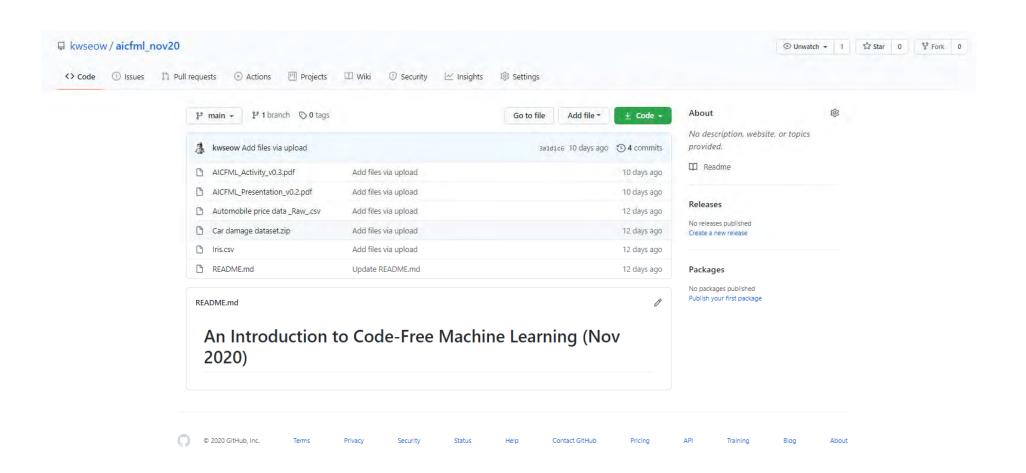




### Download from Github

### 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<br>Activity 4 – Book Genre Classifier                     |  |  |  |  |  |  |  |
| Section 6: | Linking them together   |  |  |  |  |  |  |  |
| Section 7: | Debrief   |  |  |  |  |  |  |  |



### Introduction of trainer

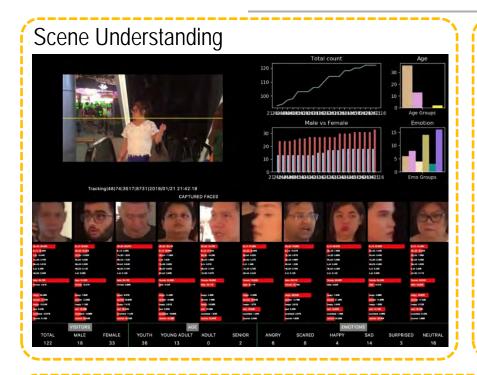


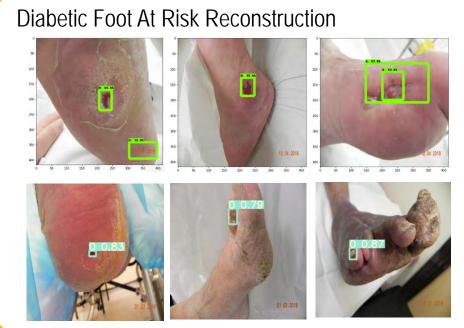
Name Seow Khee Wei Telegram @kwseow

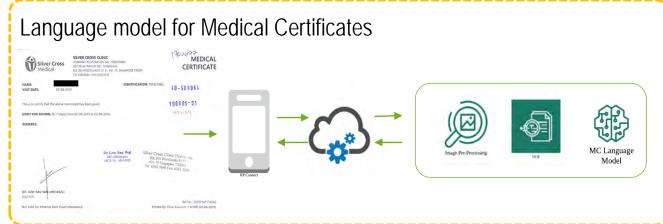
Email seow\_khee\_wei@rp.edu.sg

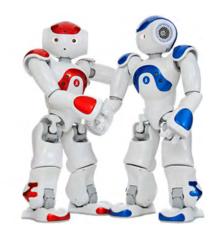


# **Projects**





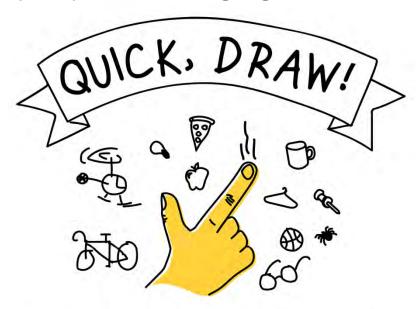




### $\overline{\mathbf{C}}$

### 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!

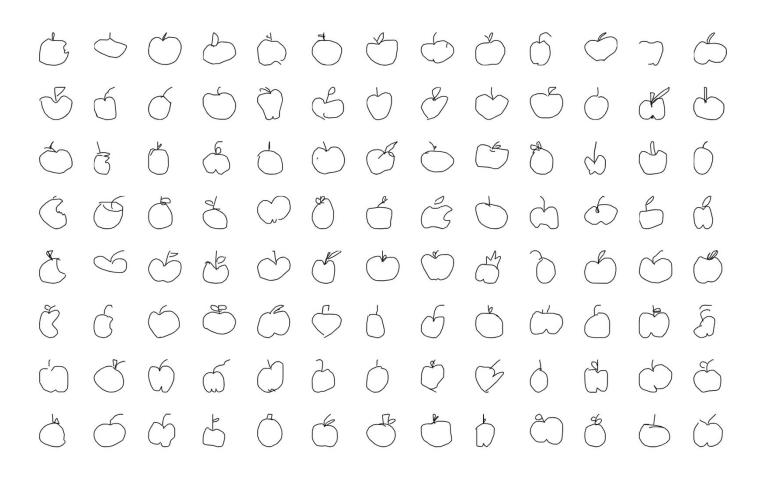
Optional Activity





### 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.

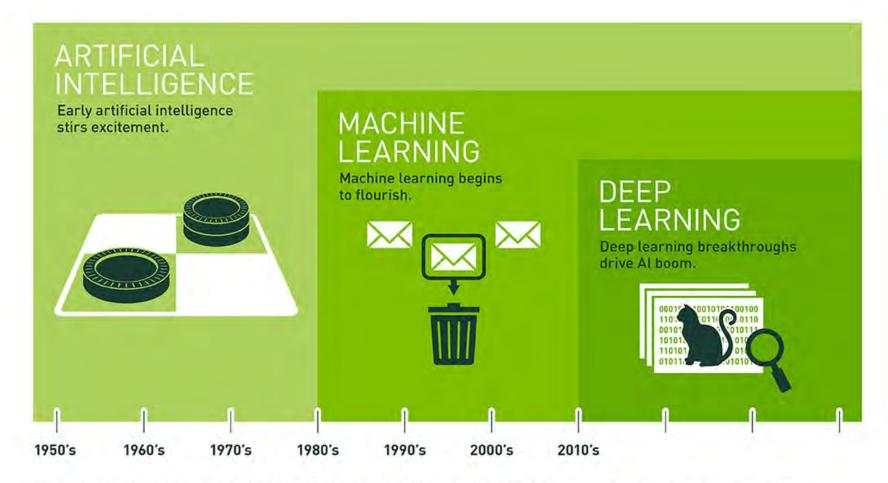


In WIRED's tests, Google Photos did identify some primates, but no gorillas like this one were to be found. RICK MADDNIK/TORONTO STAR/GETTY IMAGES

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



### Al Time line



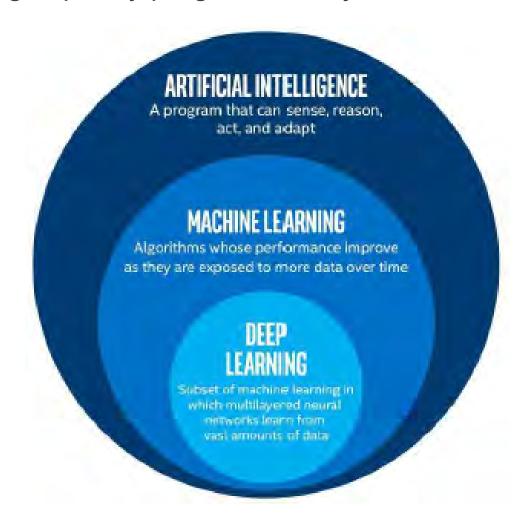
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: Nvidia



### Machine Learning

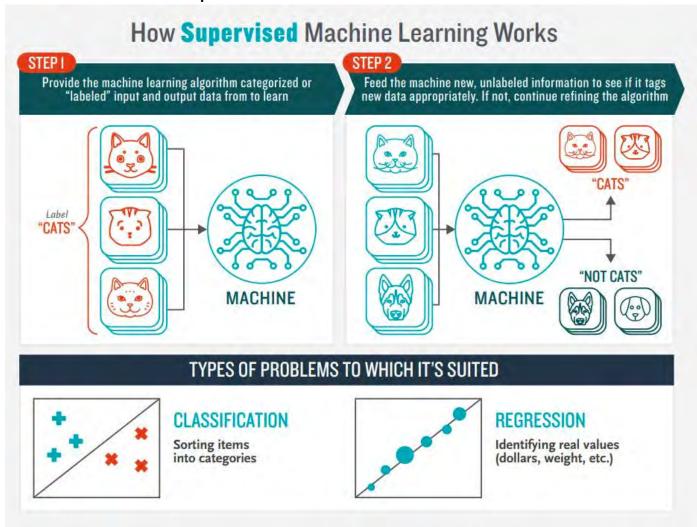
 These programs learn from repeatedly seeing data, rather than being explicitly programmed by humans





## Supervised Learning

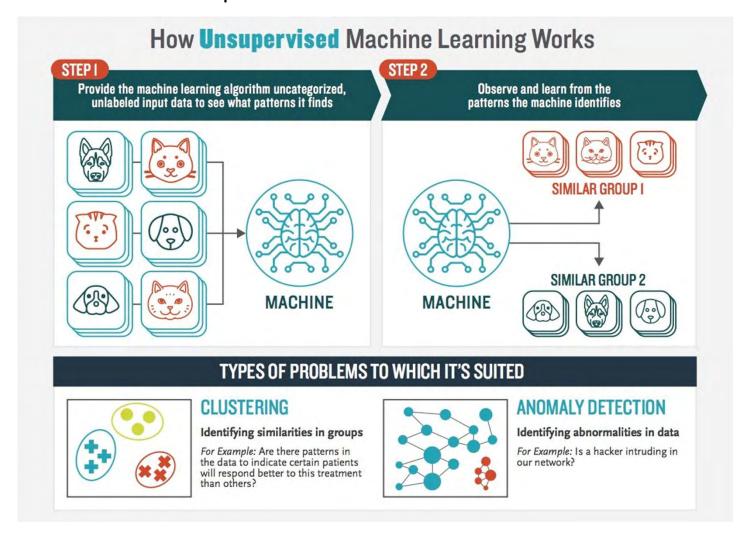
#### Data points have known outcome





### **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)

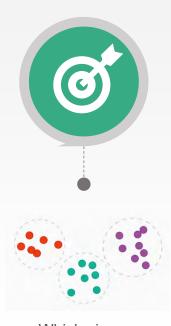


Monday 72°

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

Tuesday

# How is this organized? (Clustering)



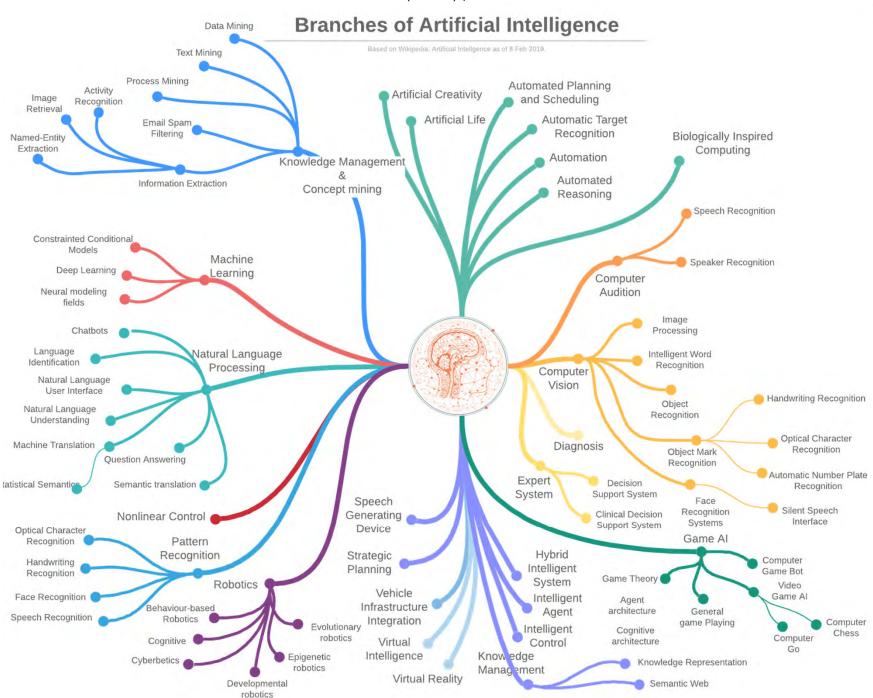
Which viewers like the same types of movies? Which printer models fail the same way?

#### 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

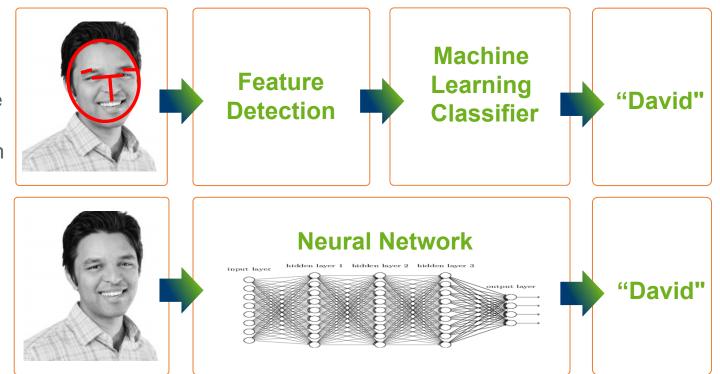
#### Classic Machine Learning

Step 1: Determine features.

Step 2: Feed them through model.

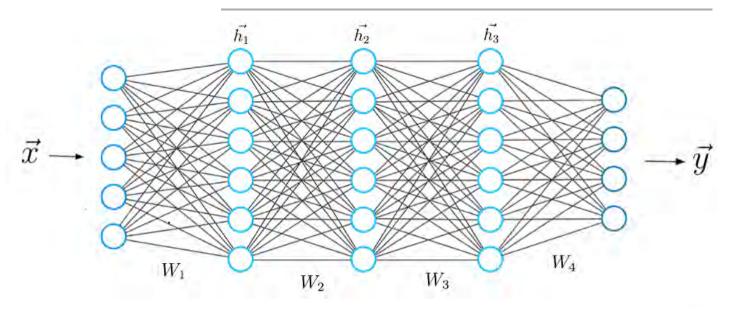
#### Deep Learning Steps 1 and 2

are combined into 1 step.

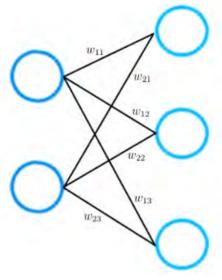




### **Neural Networks**

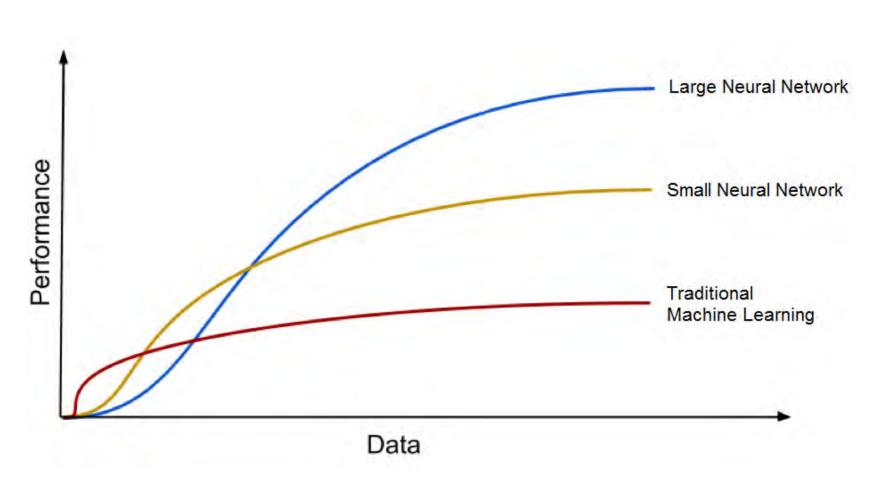


The challenge in training a neural networks is finding a set of weights the give the most accurate output.





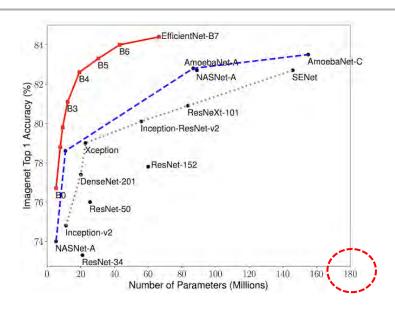
### Performance



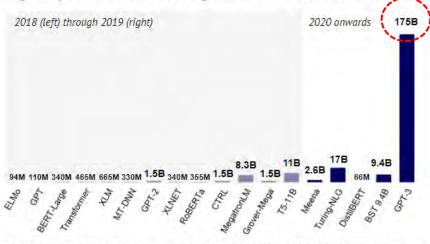
Deep Learning Algorithms get better with the increasing amount of data.



### Size



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



23

# Deep Learning in Action



10 mins

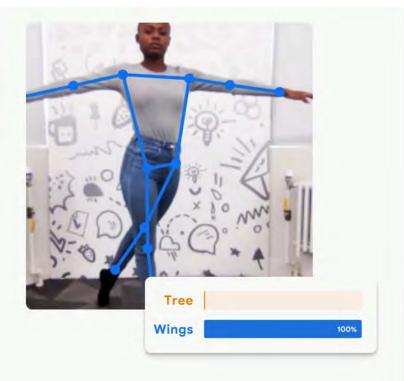
bit.ly/google\_teachable

# 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** 





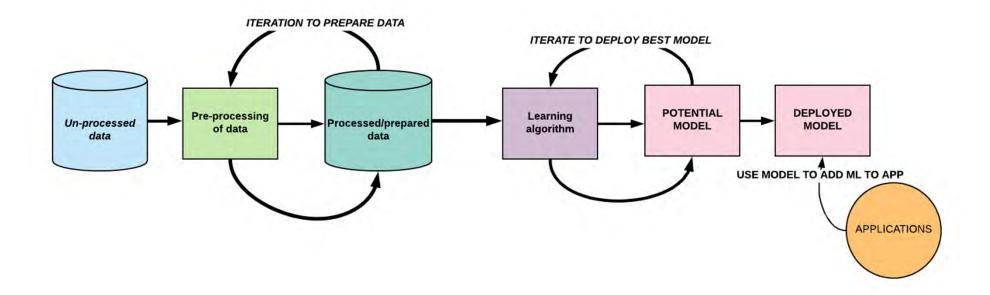
# 15 Mins Break

bit.ly/top10\_2020





# Machine Learning workflow



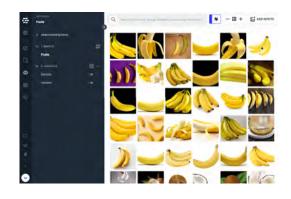
# Code-Free Machine Learning tools

Microsoft Azure Machine Learning Studio (Classic)



#### Clarifai

#### Peltarion

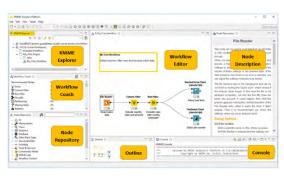




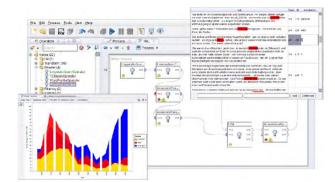
#### bigml



#### **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

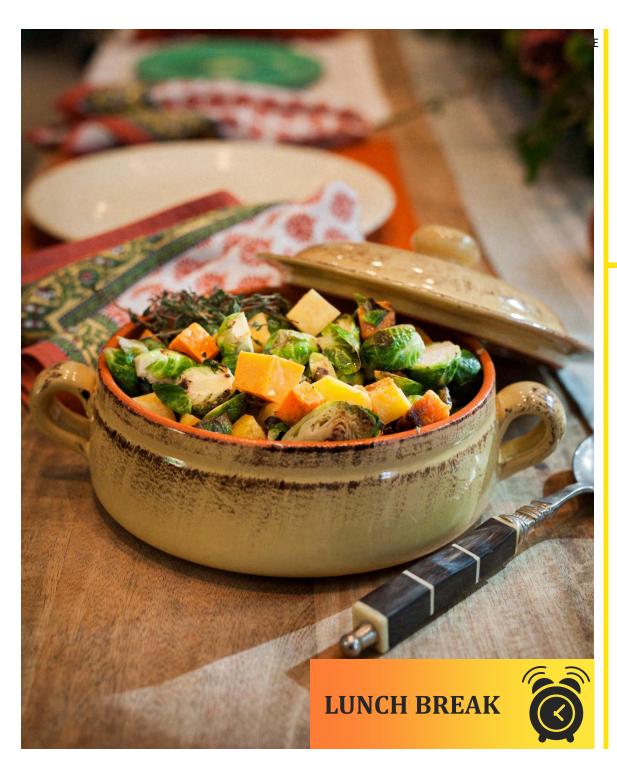


#### Step 2:

- Do on your own



**Individual Activity** 



# 60 mins Lunch Break

#### Some interesting videos

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

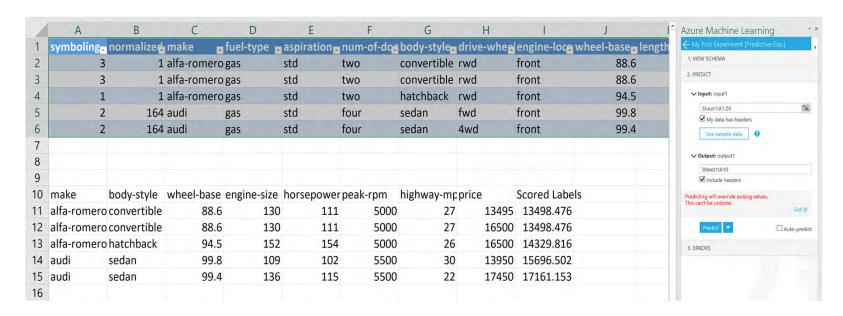
https://www.youtube.com/watch?v=Nnf8P5
A saE

Lunch break 12:20-13:20



# 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





### **Optional Activities**

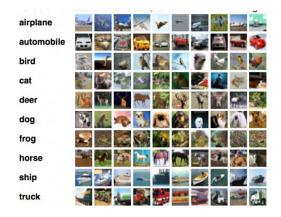
- Activity 6 Importing data
- Activity 7 Cleaning and Structuring Data
- Activity 8 Using Binary Classification Algorithm



# **Applications of Computer Vision**

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

















































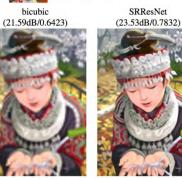


# **Applications of Computer Vision**

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







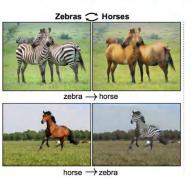














### **Transfer Learning**



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

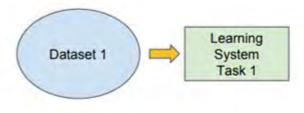


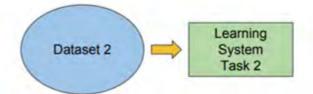
### **Transfer Learning**

### Traditional ML

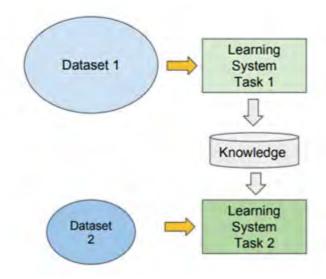
### vs Transfer Learning

- 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

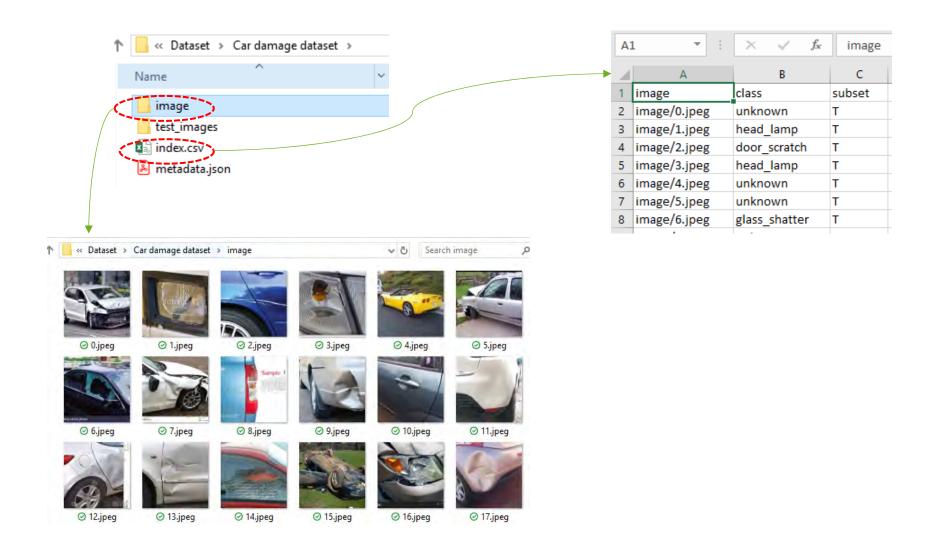
- ·Create csv file
- ·Create a text file with all image names
- ·Create a file with all labels
- Combine image names and labels in one file index.csv

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**

|   | review Encoding Text   | sentiment Encoding Binary Positive class positive | B |
|---|--|---|---|
| 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.<br>Aronofsky did.<br>/>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.<br>'> 'br />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 |  |  |



## Linking Them Together

App Development

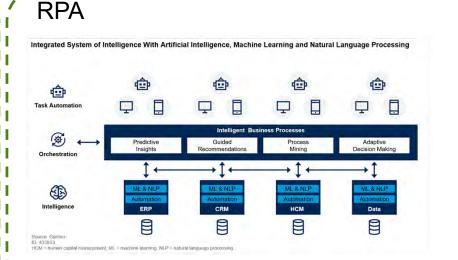
#### Top 9 No-Code Web App Development Tools that May Compete with Bubble

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





https://uibakery.io/bubble-alternatives







**blue**prism





https://www.youtube.com/watch?v=FV8IM9SIFQ8 43



## When to use Machine Learning

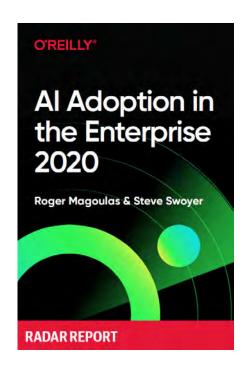
- What are our most pressing problems right now?
  - Just like any other tool in business, Al should be viewed as a tool that can help make your organization more effective, profitable or streamlined
- What parts of our business generate revenue but currently have low profit margins?
  - These revenue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

# THE ESSENTIAL AI HANDBOOK FOR LEADERS FOREWORD BY MARCUS WALLENDERS AT THE EXEL OF THE DAY It is not (echnology 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 that the competition that will succeed.







#### Datasets and Data Prep



https://kwseow.github.io/



https://www.kaggle.com/datasets



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



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

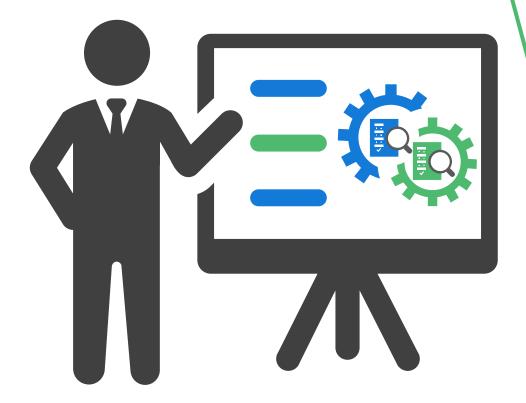




# Survey



### Summary



Email seow\_khee\_wei@rp.edu.sg

Telegram @kwseow

Source code:



# Thank you