利用AI科技
跨界共創醫療新未來

陽明大學 醫務管理所

助理教授
陳翎

1.自我介紹
2. AI的趨勢與機會
3. 從那裡開始

先簡單地自我介紹


THE UNIVERSITY
OF QUEENSLAND
AUSTRALIA


tm
TrademarkVision

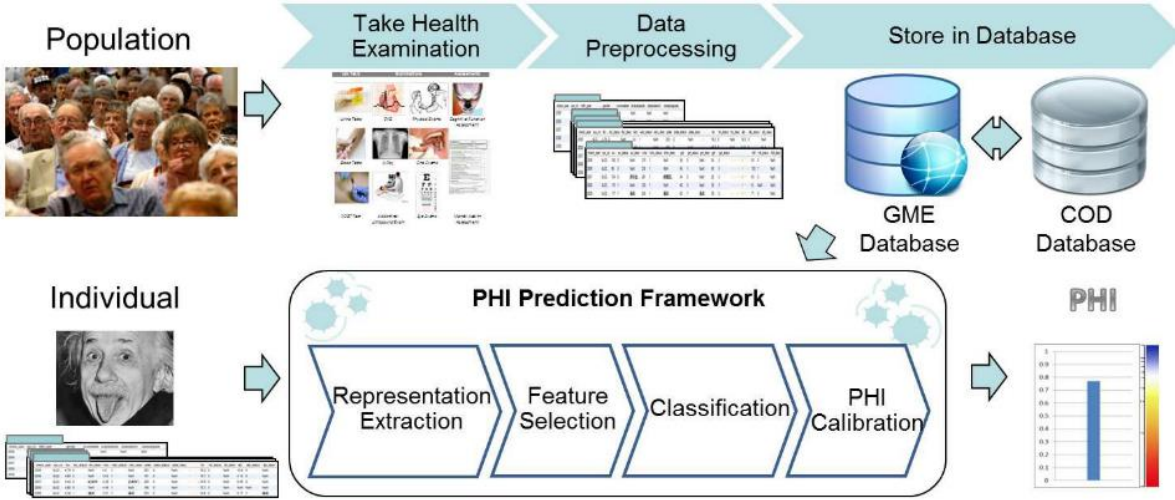

Clarivate
Analytics

博士研究: 健康指標探勘

- Annual Geriatric Health Examination, Taipei
  - 102,258 participants (65+) with 262,424 records (2005 - 2010)
  - 7.4% has Cause of Death code (ICD 9/ ICD 10)
  - 136 (89) features extracted

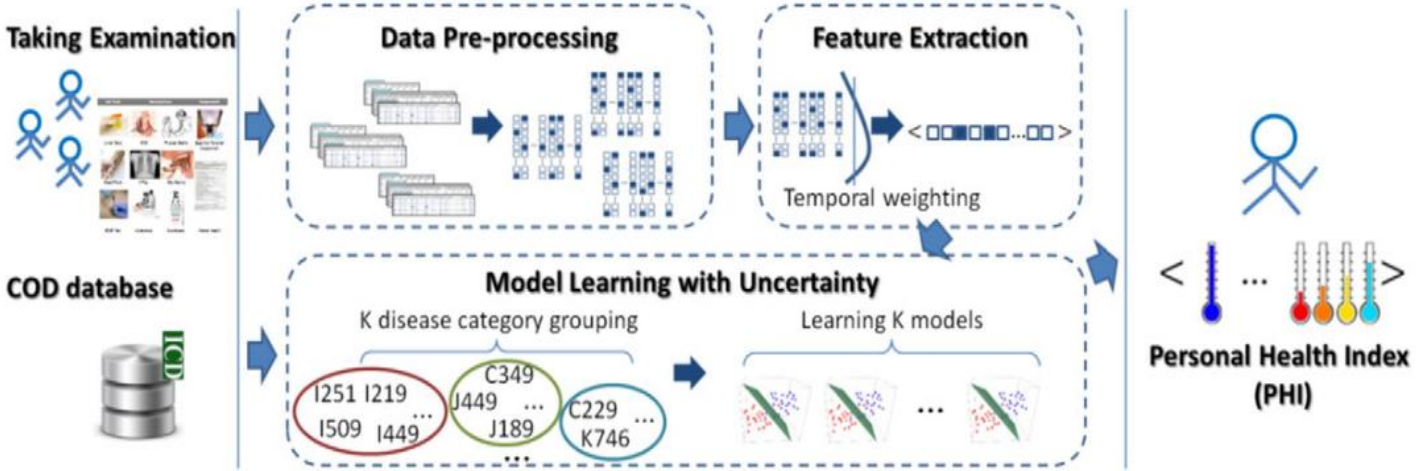
Type	Category	Attribute (example)
Patient Profile	Demographics	age, marital status, gender, education level, residential suburb
	Habits	reasons-for-taking-medicine, smoking, drinking, exercise, drink-milk, eat-vegetable, clean-teeth
Lab Tests	Biochemical	glu-ac, total cholesterol (tcho), thyroglobulin (tg), got, gpt, albumin (alb), thyroid stimulating hormone (tsh)
	Blood	red blood cell, white blood cell, plate, hematocrit (hct), mean corpuscular volume (mcv), mean corpuscular hemoglobin (mch), alpha-fetoprotein (afp), hemoglobin (hb)
	Urine	outlook, ph, protein, sugar, blood, red blood cell, white blood cell, pus cell, epithelium cell, casts
	Other	faecal occult blood test (fobt)
Examinations	Physical	weight, height, waist, systolic blood pressure, diastolic blood pressure, pulse rate
	External	neck, chest, heart, breast, abdomen, back, rectum, limbs, prostate
	Other	X-ray, EKG, cervical smear, abdominal ultrasound
Mental Health	BSRS	5 questions regarding nervousness, anger, depression, comparison with others, and sleep
Cognitive Function	SPMSQ	10 questions, e.g., current date, day of the week, where the person is situated, home address, age, year of birth, etc.

博士研究: 健康指標探勘



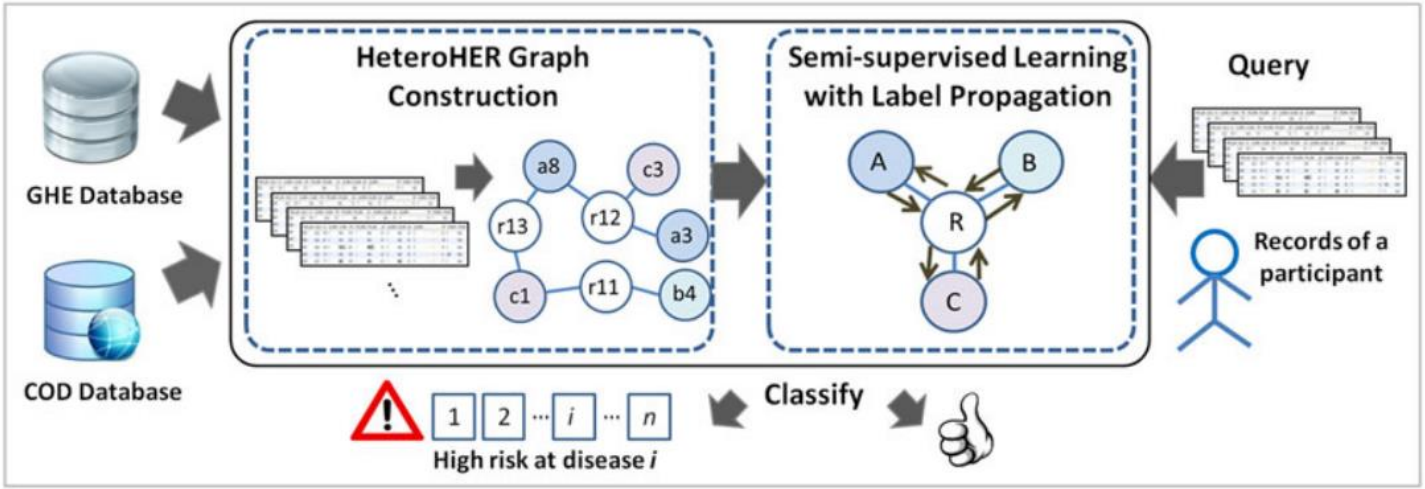
Chen, L., Li, X., Wang, S., Hu, H. Y., Huang, N., Sheng, Q. Z., & Sharaf, M. (2014). Mining Personal Health Index from Annual Geriatric Medical Examinations. *Proceedings - IEEE International Conference on Data Mining, ICDM*, 761–766.

博士研究: 健康指標探勘



Chen, L., Li, X., Yang, Y., Kurniawati, H., Sheng, Q. Z., Hu, H. Y., & Huang, N. (2016). Personal health indexing based on medical examinations: A data mining approach. *Decision Support Systems*, *81*, 54–65. IF:5.420

博士研究: 健康指標探勘



Chen, L., Li, X., Sheng, Q. Z., Peng, W. C., Bennett, J., Hu, H. Y., & Huang, N. (2016). Mining Health Examination Records - A Graph-Based Approach. *IEEE Transactions on Knowledge and Data Engineering*, *28*(9), 2423–2437. IF: 4.561

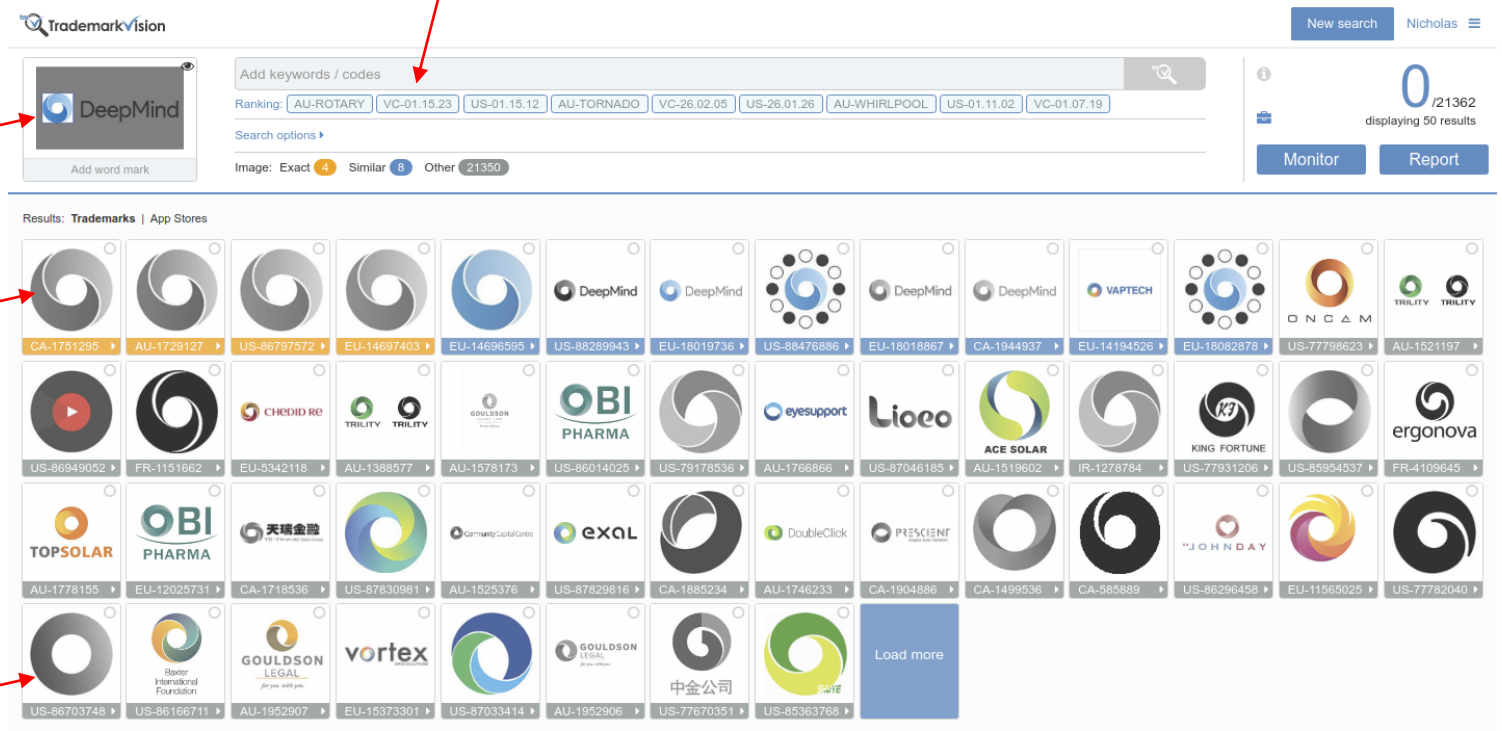
四年業界經驗: 圖像識別

Classification

Object detection & segmentation

Deep feature learning

Image Denoising



我們正面對
一個嶄新的時代

強大的運算能力

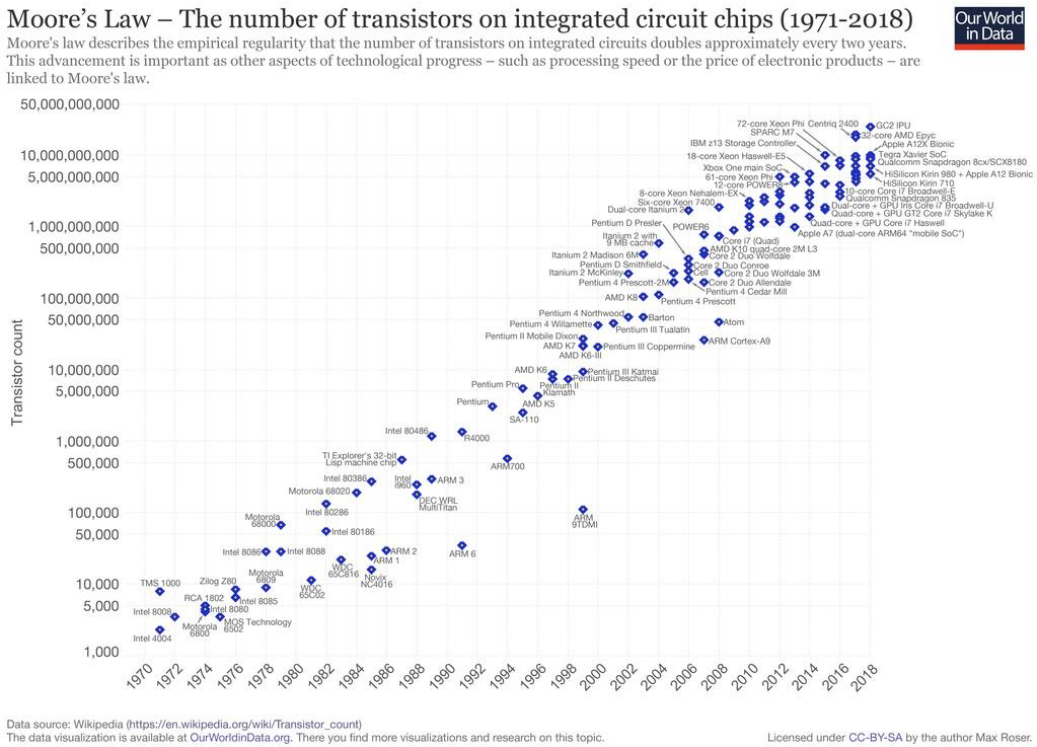


Image: https://en.wikipedia.org/wiki/Moore%27s_law#/media/File:Moore's_Law_Transistor_Count_1971-2018.png

強大的儲存能力

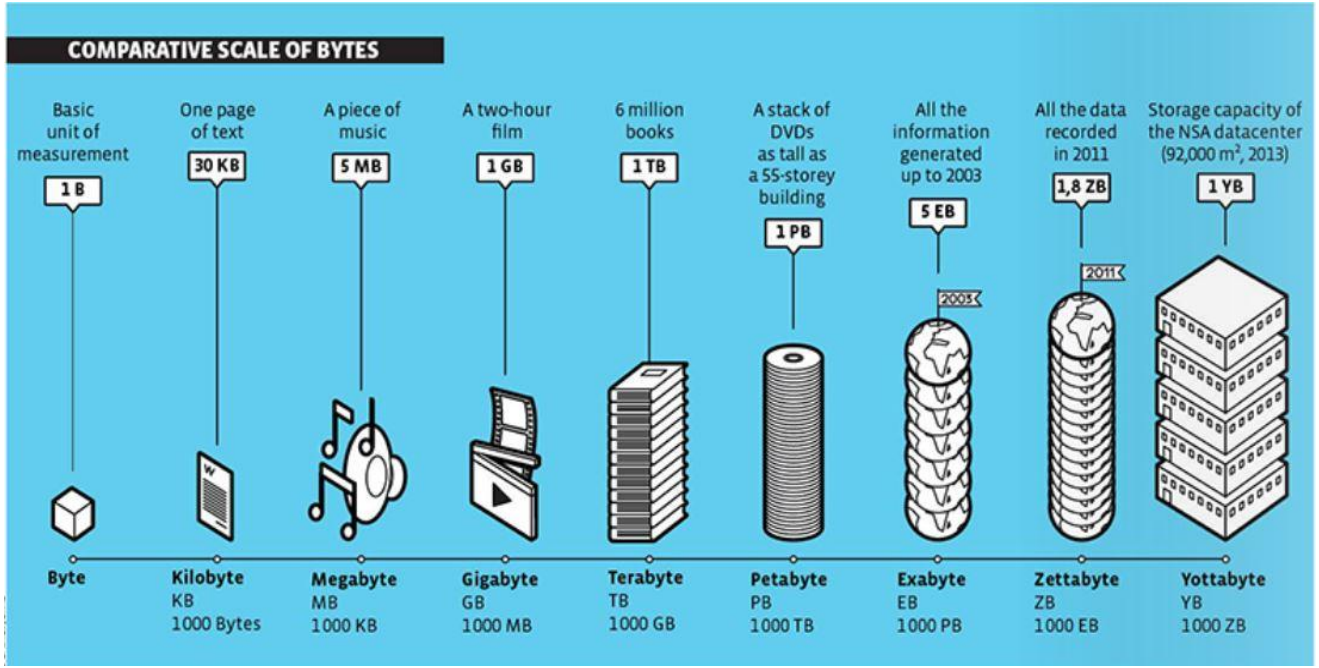


Image: https://waterfordtechnologies.com/just-big-big-data/

大數據

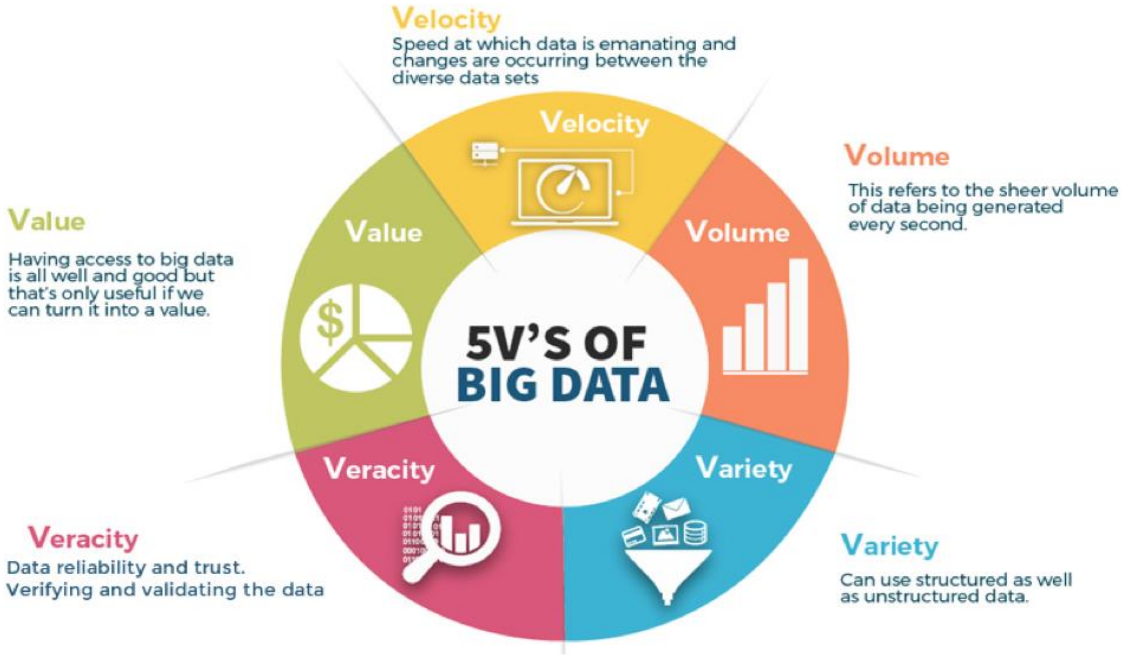


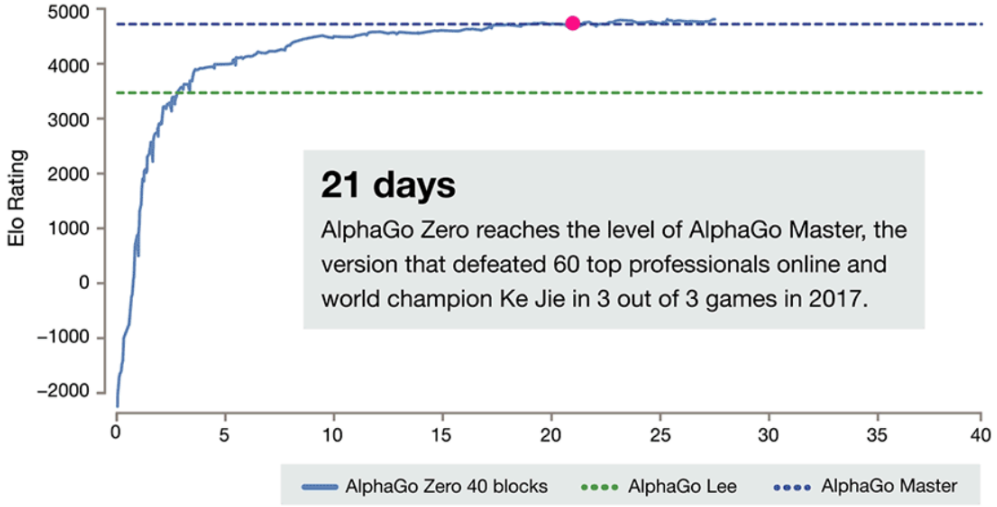
Image: https://www.techentice.com/the-data-veracity-big-data/

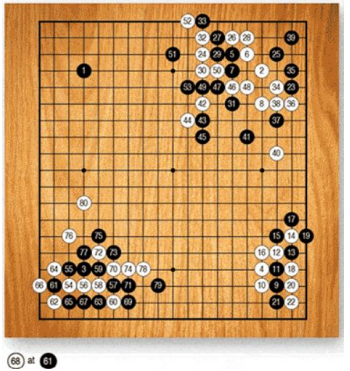
醫療大數據

Siddique, Musfira, et al. "A survey of big data security solutions in healthcare." *International Conference on Security and Privacy in Communication Systems*. Springer, Cham, 2018.

AI 正在不同領域
接近甚至超越人類

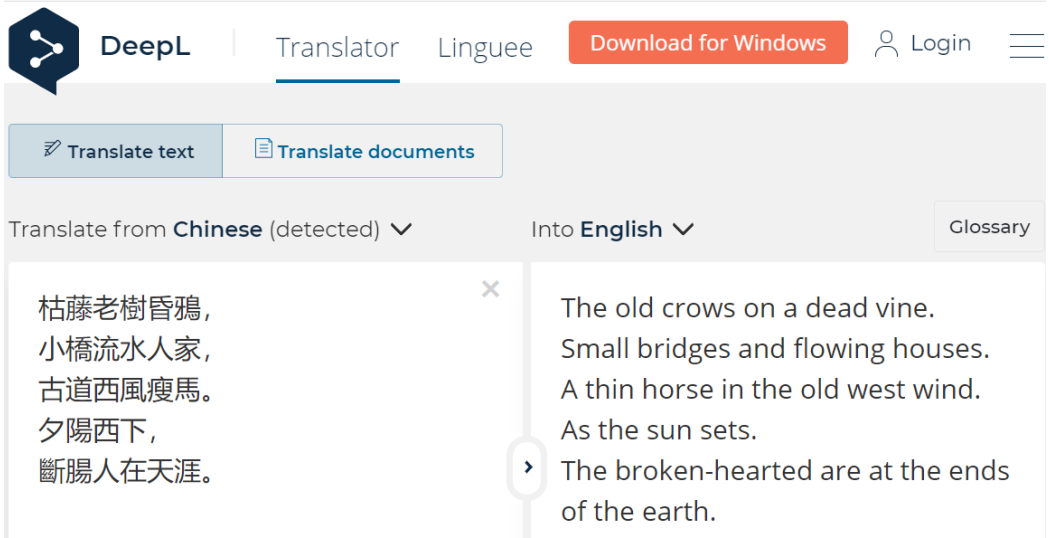
AlphaGoZero





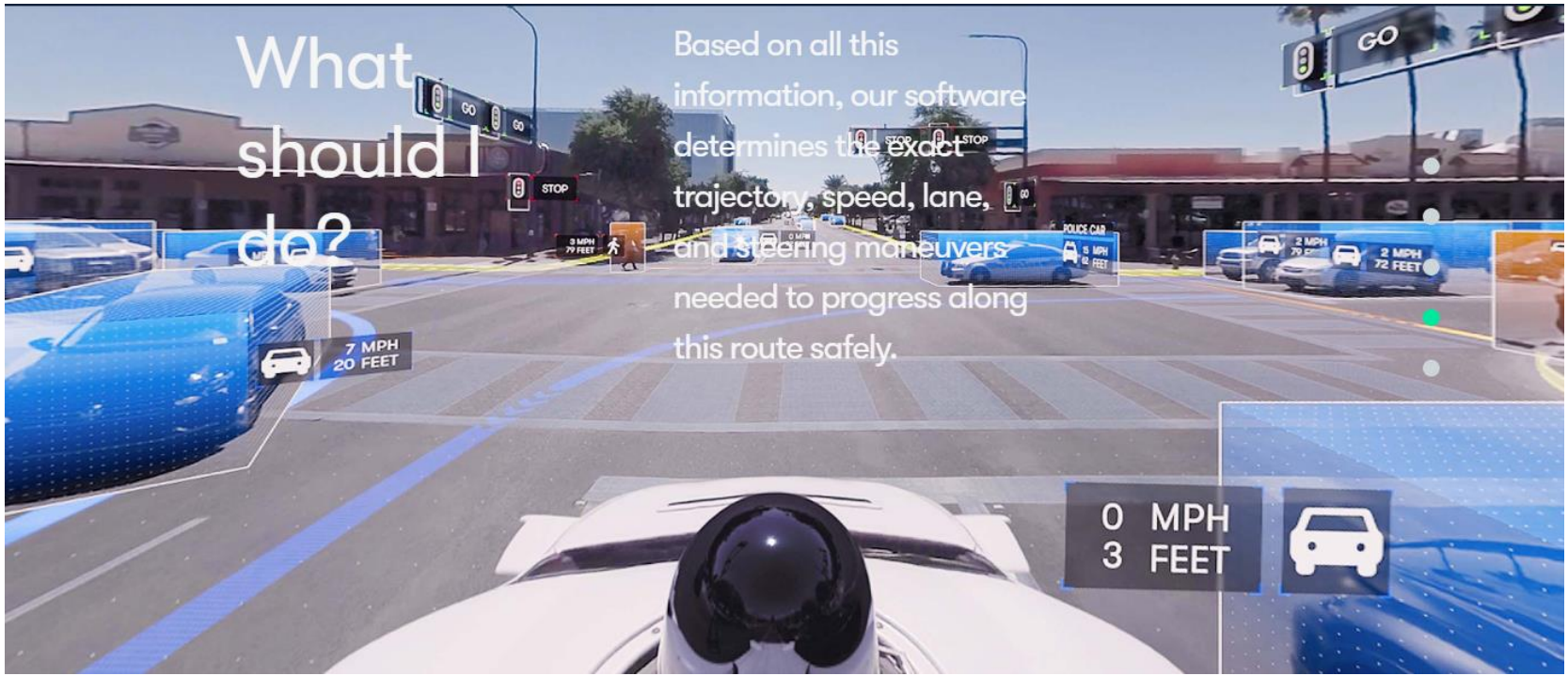
https://deepmind.com/blog/article/alphago-zero-starting-scratch

DeepL



https://www.deepl.com/home

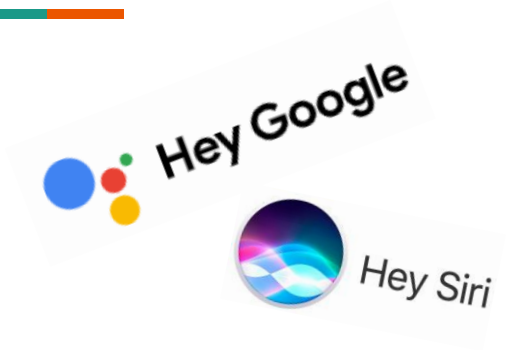
Self-driving cars

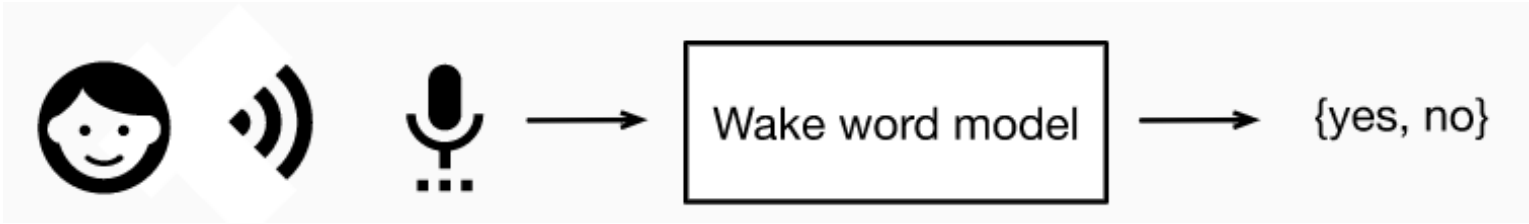


https://waymo.com/tech/

AI 也在
你我身邊

Hey Siri!





https://d2l.ai/chapter_introduction/index.html

AI口罩與紅外線溫度檢測

https://news.microsoft.com/zh-tw/cth-ms-ai-mask-temparture-detector/

不同型式的醫療數據

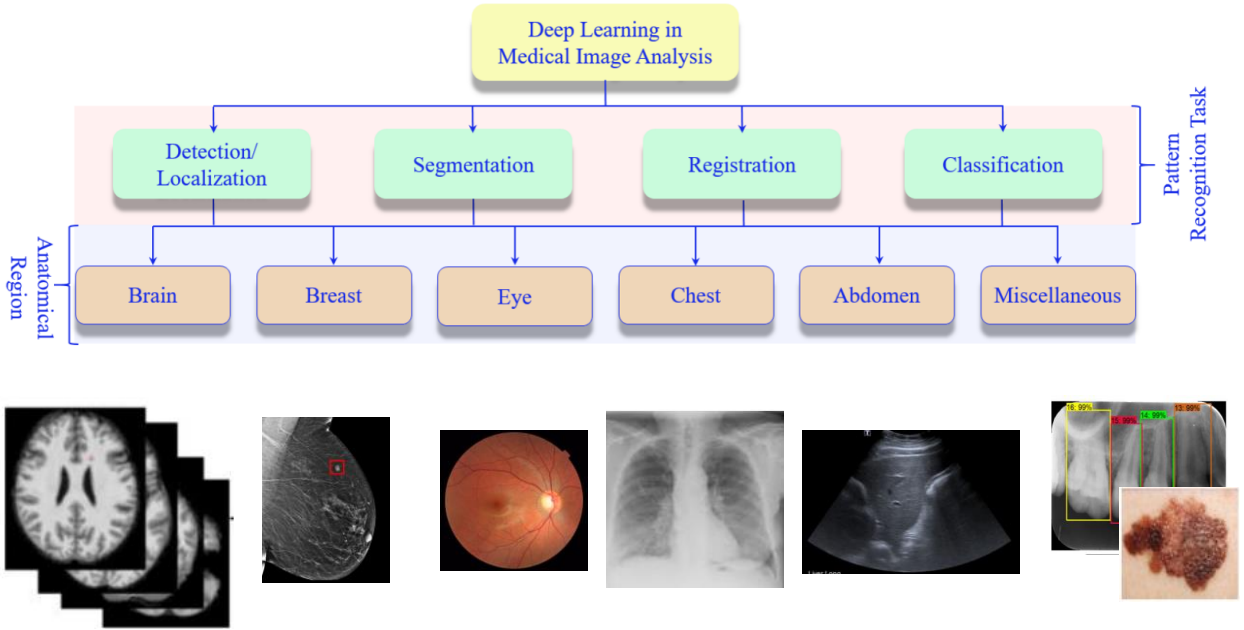
EHRs

SUMMARY OF EHR DEEP LEARNING TASKS.

Task	Subtasks	Input Data	Models	References
Information Extraction	(1) Single Concept Extraction	Clinical Notes	LSTM, Bi-LSTM, GRU, CNN	[15], [16], [34]
	(2) Temporal Event Extraction		RNN + Word Embedding	[35]
	(3) Relation Extraction		AE	[36]
	(4) Abbreviation Expansion		Custom Word Embedding	[37]
Representation Learning	(1) Concept Representation	Medical Codes	RBM, Skip-gram, AE, LSTM	[23], [36]
	(2) Patient Representation		RBM, Skip-gram, GRU, CNN, AE	[14], [18]–[23], [36], [38]–[40]
Outcome Prediction	(1) Static Prediction	Mixed	AE, LSTM, RBM, DBN	[14], [18], [23], [41]–[43]
	(2) Temporal Prediction		LSTM	[19]–[21], [38], [44]–[48]
Phenotyping	(1) New Phenotype Discovery	Mixed	AE, LSTM, RBM, DBN	[14], [40], [44], [49], [50]
	(2) Improving Existing Definitions		LSTM	[45], [51]
De-identification	Clinical text de-identification	Clinical Notes	Bi-LSTM, RNN + Word Embedding	[52], [53]

Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis. *IEEE Journal of Biomedical and Health Informatics*, *22*(5), 1589–1604.

Medical Imaging

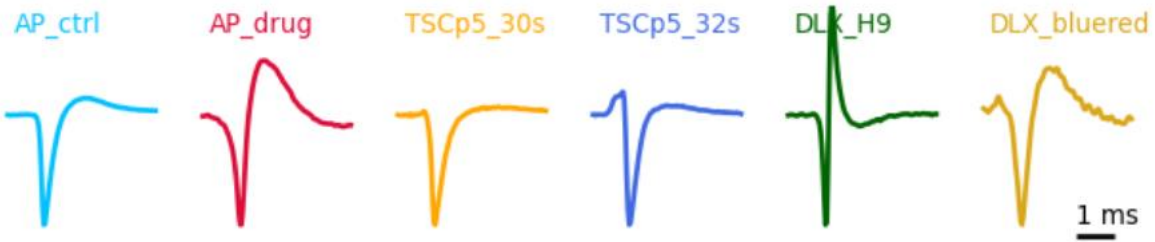


Altaf, F., Islam, S. M. S., Akhtar, N., & Janjua, N. K. (2019). Going Deep in Medical Image Analysis: Concepts, Methods, Challenges, and Future Directions. *IEEE Access*, *7*(3), 99540–99572.

Clinical Notes

Respiratory support
O2 Delivery Device: Endotracheal tube
Ventilator mode: CPAP/PSV
Vt (Set): 500 (500 - 500) mL
Vt (Spontaneous): 657 (424 - 657) mL
PS : 5 cmH2O
RR (Set): 14
RR (Spontaneous): 24
PEEP: 5 cmH2O
FiO2: 50%
PIP: 11 cmH2O
Plateau: 13 cmH2O
Compliance: 62.5 cmH2O/mL
SPO2: 100%
ABG: 7.39/36/130/24/-2
Ve: 12.8 L/min
PaO2 / FiO2: 260
Physical Examination
General Appearance: No acute distress
HEENT: PERRL
Cardiovascular: (Rhythm: Regular) occasional PAC
Respiratory / Chest: (Expansion: Symmetric), (Breath Sounds: CTA bilateral :), (Sternum: Stable)
Abdominal: Soft, Non-distended, Non-tender, Bowel sounds present, hypoactive
Left Extremities: (Edema: Trace), (Temperature: Warm), (Pulse - Dorsalis pedis: diminshed)
Right Extremities: (Edema: Trace), (Temperature: Warm), (Pulse - Dorsalis pedis: diminished)
Skin: (Incision: Clean / Dry / Intact), Left leg EVH ACE wrap
Neurologic: Follows simple commands, Moves all extremities
Labs / Radiology

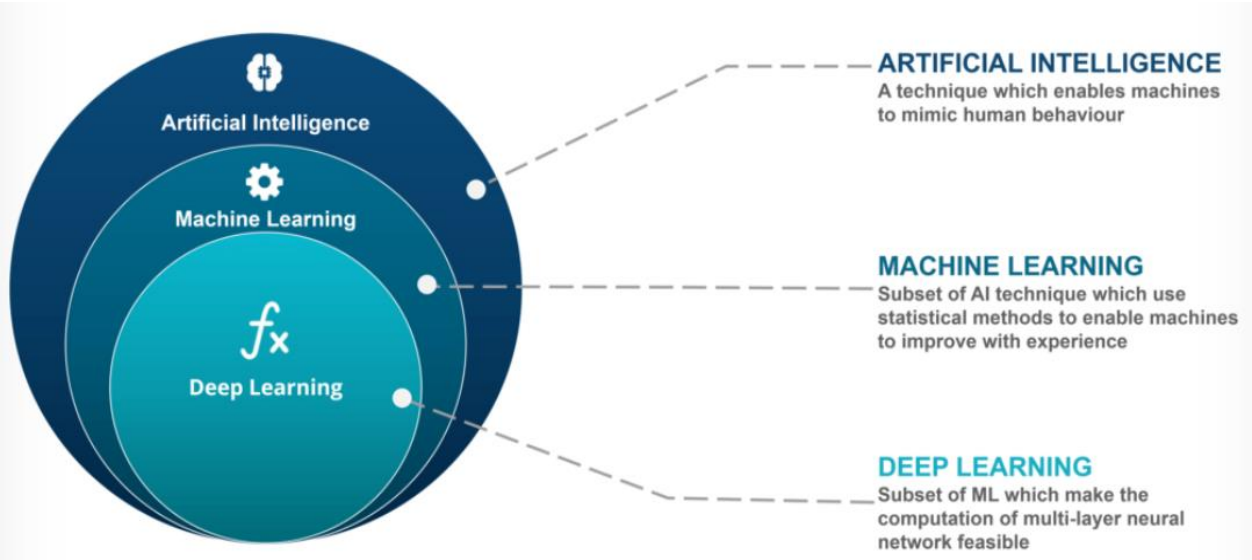
Waveforms



https://www.kaggle.com/joseguzman/unsupervised-waveform-classification

AI背後的
深度學習模型

Concept Relationship



Images: https://mc.ai/ai-vs-machine-learning-vs-deep-learning-vs-data-science/

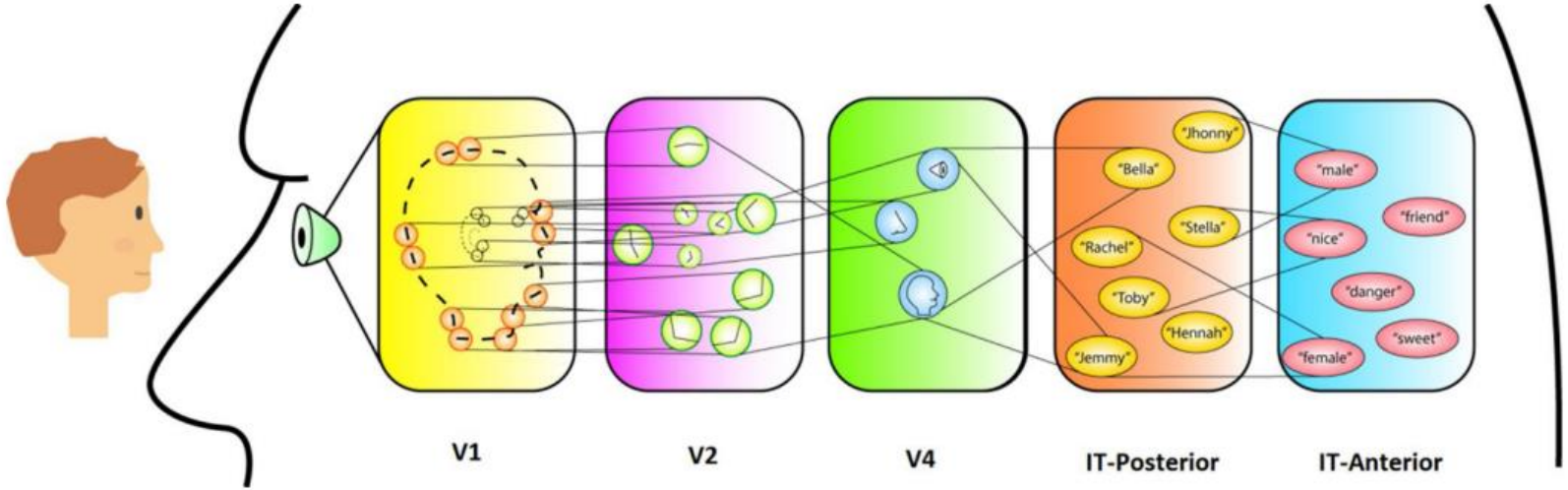
What does a machine learn?

$$argmin_w E(||Goal - F(x, w)||)$$

➔ Example

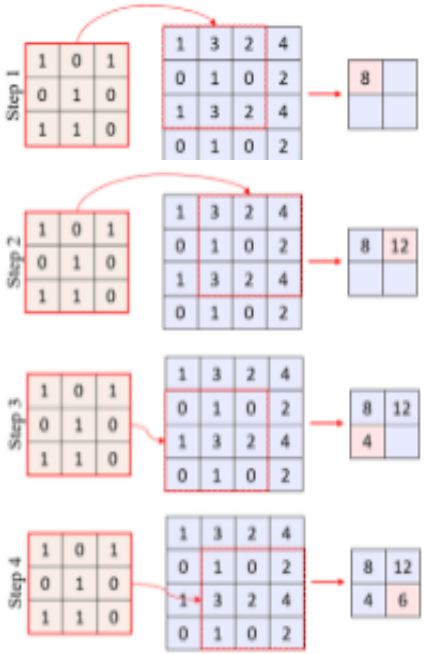
$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - f(x_i))^2$$

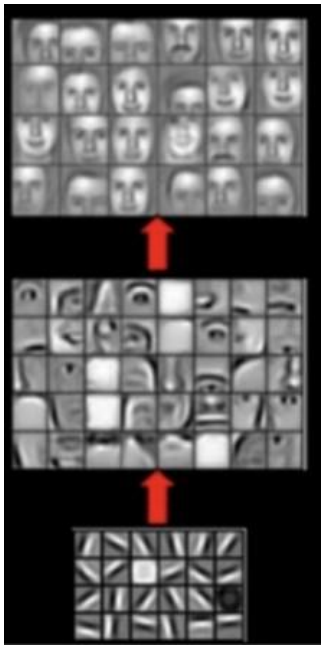
Layers of Abstraction



Saba, L., Biswas, M., Kuppili, V., Cuadrado Godia, E., Suri, H. S., Edla, D. R., Omerzu, T., Laird, J. R., Khanna, N. N., Mavrogeni, S., Protogerou, A., Sfikakis, P. P., Viswanathan, V., Kitas, G. D., Nicolaides, A., Gupta, A., & Suri, J. S. (2019). The present and future of deep learning in radiology. *European Journal of Radiology*, *114*(February), 14–24.

Convolution Layer

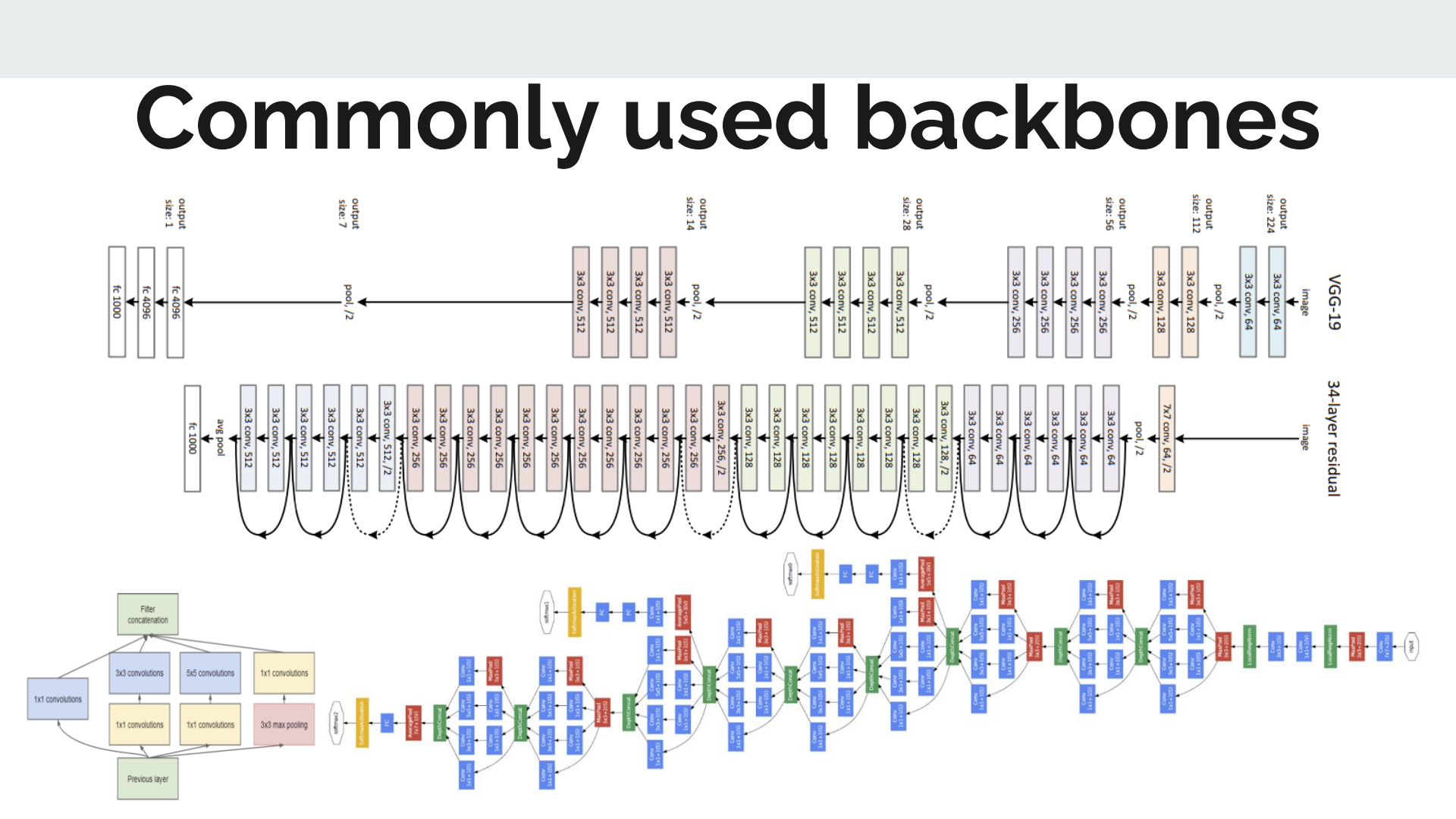




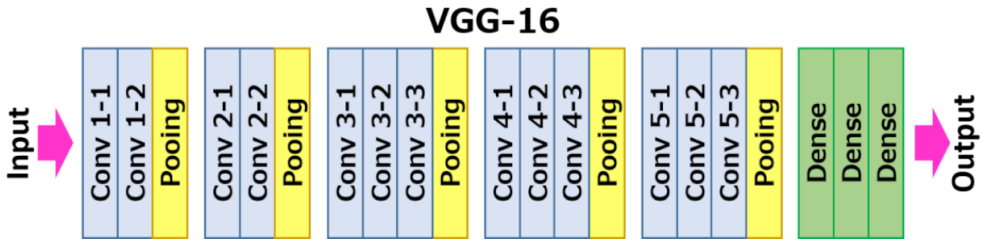
https://www.topbots.com/advanced-topics-deep-convolutional-neural-networks/

站在巨人的肩膀上
pre-trained models

Commonly used backbones



A simple line of code…



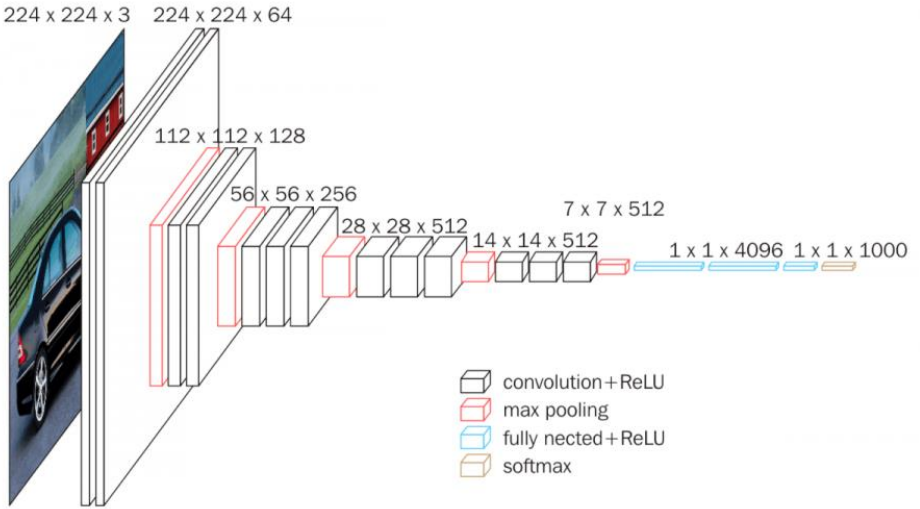
Keras TensorFlow

```
tf.keras.applications.VGG16(
    include_top=True, weights='imagenet', input_tensor=None, input_shape=None,
    pooling=None, classes=1000, classifier_activation='softmax'
)
```

https://www.tensorflow.org/api_docs/python/tf/keras/applications/VGG16

Behind the code…

```
188     with tf.variable_scope(
189         scope, 'vgg_16', [inputs], reuse=reuse) as sc:
190       end_points_collection = sc.original_name_scope + '_end_points'
191       # Collect outputs for conv2d, fully_connected and max_pool2d.
192       with slim.arg_scope([slim.conv2d, slim.fully_connected, slim.max_pool2d],
193                           outputs_collections=end_points_collection):
194         net = slim.repeat(inputs, 2, slim.conv2d, 64, [3, 3], scope='conv1')
195         net = slim.max_pool2d(net, [2, 2], scope='pool1')
196         net = slim.repeat(net, 2, slim.conv2d, 128, [3, 3], scope='conv2')
197         net = slim.max_pool2d(net, [2, 2], scope='pool2')
198         net = slim.repeat(net, 3, slim.conv2d, 256, [3, 3], scope='conv3')
199         net = slim.max_pool2d(net, [2, 2], scope='pool3')
200         net = slim.repeat(net, 3, slim.conv2d, 512, [3, 3], scope='conv4')
201         net = slim.max_pool2d(net, [2, 2], scope='pool4')
202         net = slim.repeat(net, 3, slim.conv2d, 512, [3, 3], scope='conv5')
203         net = slim.max_pool2d(net, [2, 2], scope='pool5')
204
205         # Use conv2d instead of fully_connected layers.
206         net = slim.conv2d(net, 4096, [7, 7], padding=fc_conv_padding, scope='fc6')
207         net = slim.dropout(net, dropout_keep_prob, is_training=is_training,
208                            scope='dropout6')
209         net = slim.conv2d(net, 4096, [1, 1], scope='fc7')
```



https://github.com/tensorflow/models/blob/master/research/slim/nets/vgg.py#L147; https://neurohive.io/en/popular-networks/vgg16/

該從那裡開始?

該從那裡開始?
學習篇

Python

learnpython.org

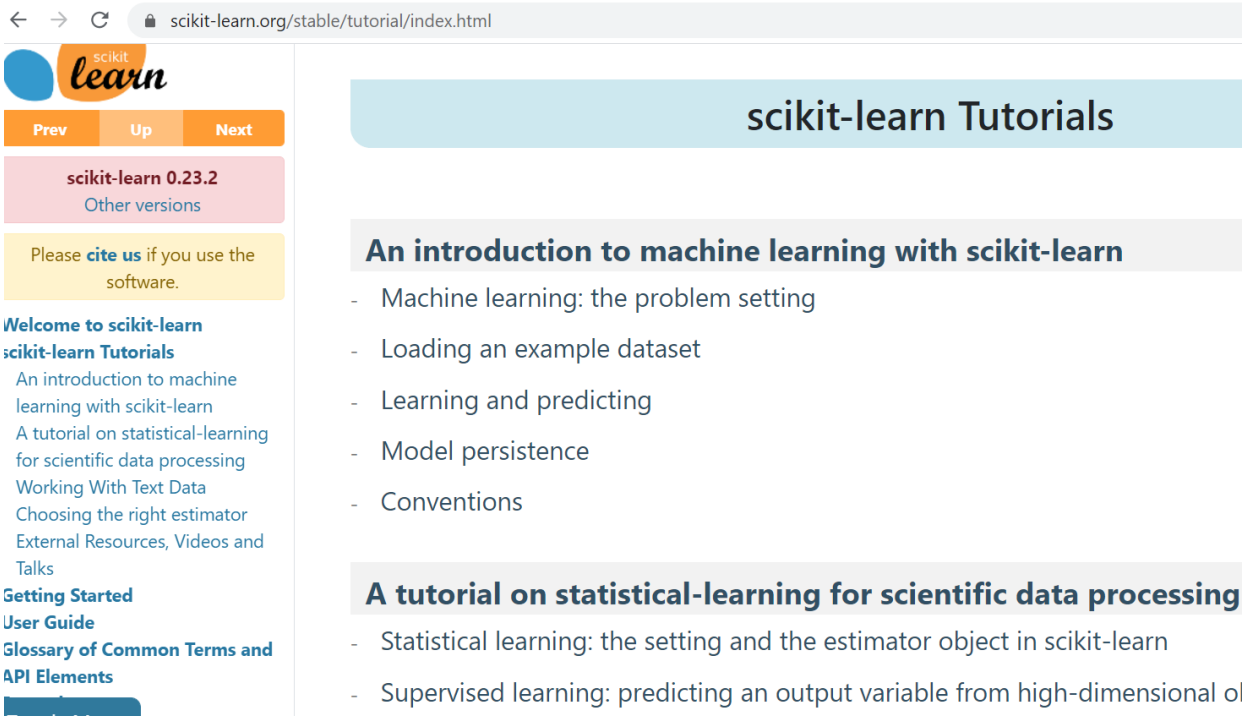
Learn the Basics

- Hello, World!
- Variables and Types
- Lists
- Basic Operators
- String Formatting
- Basic String Operations
- Conditions
- Loops
- Functions
- Classes and Objects
- Dictionaries
- Modules and Packages

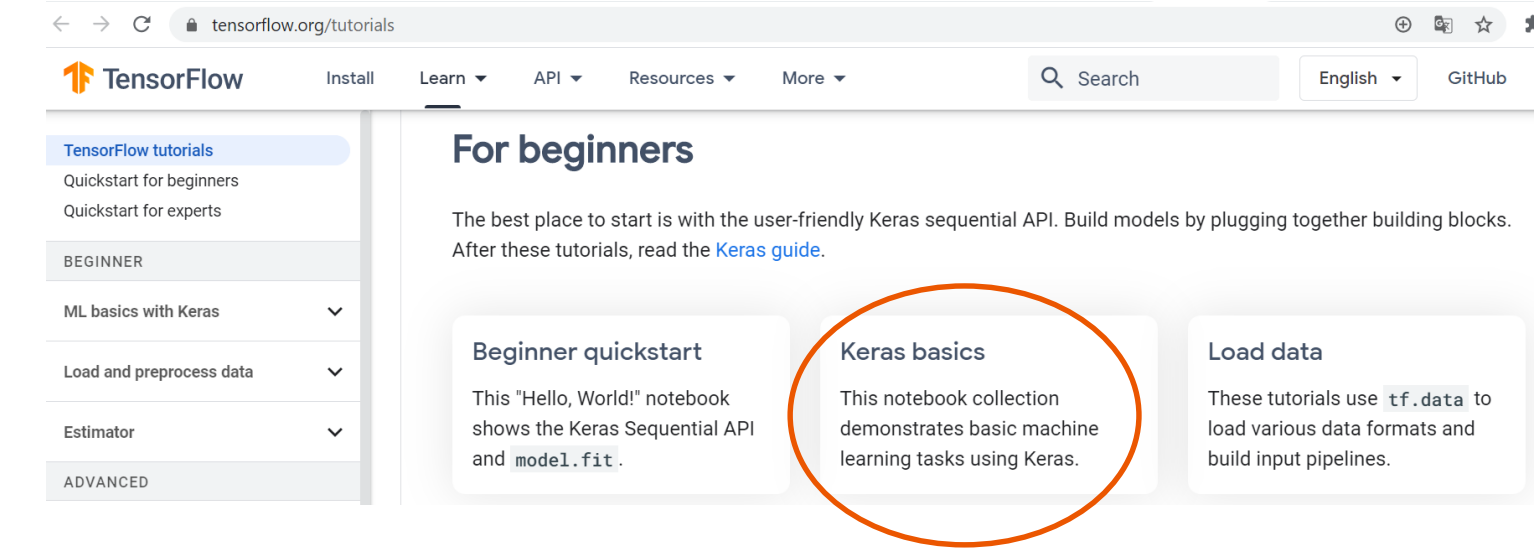
Data Science Tutorials

- Numpy Arrays

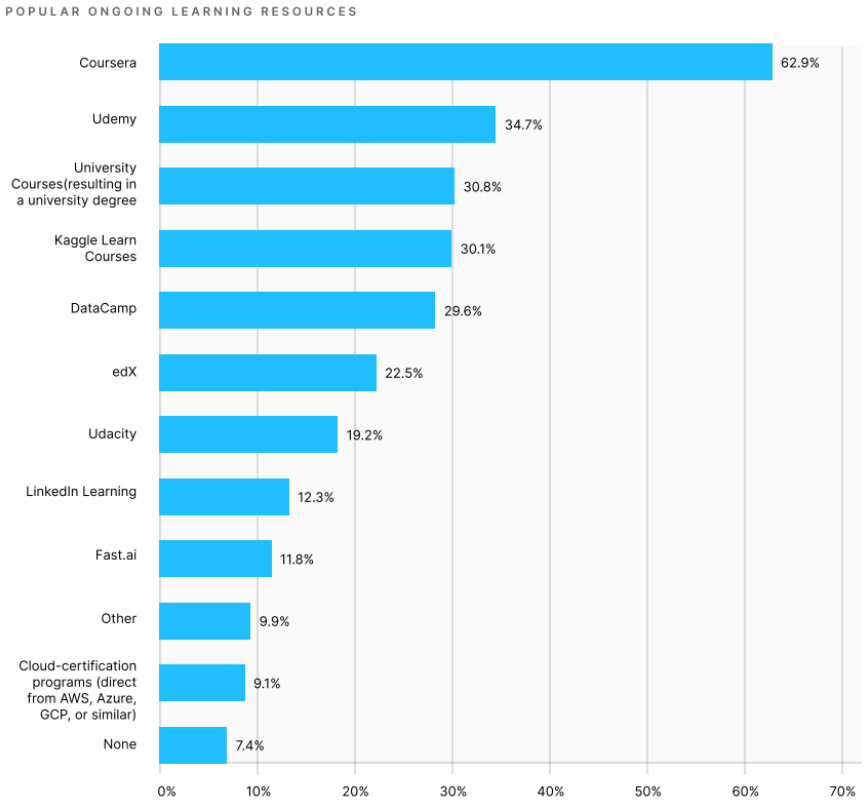
Scikit-learn



Tensorflow


tensorflow.org/tutorials
TensorFlow
Install
Learn
API
Resources
More
Search
English
GitHub
TensorFlow tutorials
Quickstart for beginners
Quickstart for experts
BEGINNER
ML basics with Keras
Load and preprocess data
Estimator
ADVANCED
For beginners
The best place to start is with the user-friendly Keras sequential API. Build models by plugging together building blocks. After these tutorials, read the Keras guide.
Beginner quickstart
This "Hello, World!" notebook shows the Keras Sequential API and model.fit.
Keras basics
This notebook collection demonstrates basic machine learning tasks using Keras.
Load data
These tutorials use tf.data to load various data formats and build input pipelines.

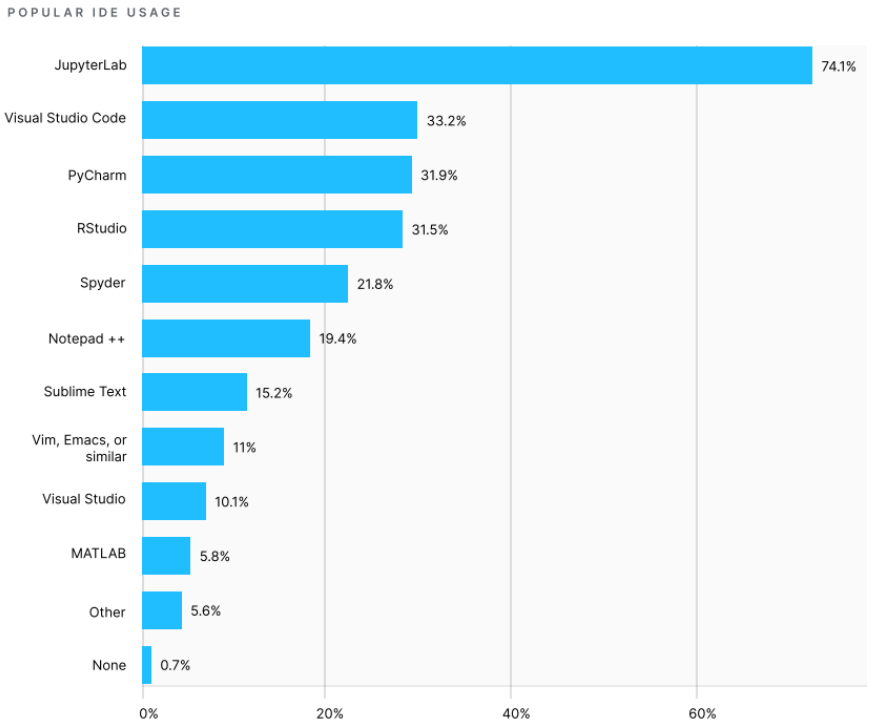
Self-Learning Resources



https://www.kaggle.com/kaggle-survey-2020

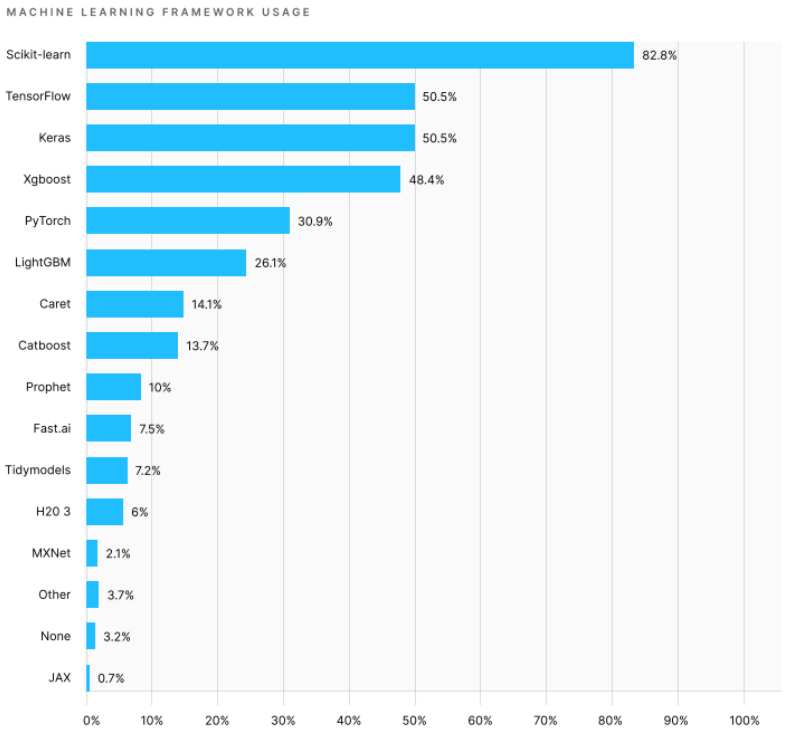
該從那裡開始?
工具篇

Popular IDEs



https://www.kaggle.com/kaggle-survey-2020

Popular ML Frameworks



https://www.kaggle.com/kaggle-survey-2020

該從那裡開始?
數據預處理篇

Data Preprocessing

➔ DICOM images

```python
import pydicom

file_path = "ID_000039fa0.dcm"
output_path = "./"
medical_image = pydicom.read_file(file_path)
image = medical_image.pixel_array
```

```python
def transform_to_hu(medical_image, image):
    intercept = medical_image.RescaleIntercept
    slope = medical_image.RescaleSlope
    hu_image = image * slope + intercept

    return hu_image
```

➔ Texts

Natural Language Toolkit

jieba

https://vincentblog.xyz/posts/medical-images-in-python-computed-tomography

該從那裡開始?
模型篇

Pipeline

Input / Output?
- What is the problem to solve?
- What are the available data?
- How to define Input/ Output?

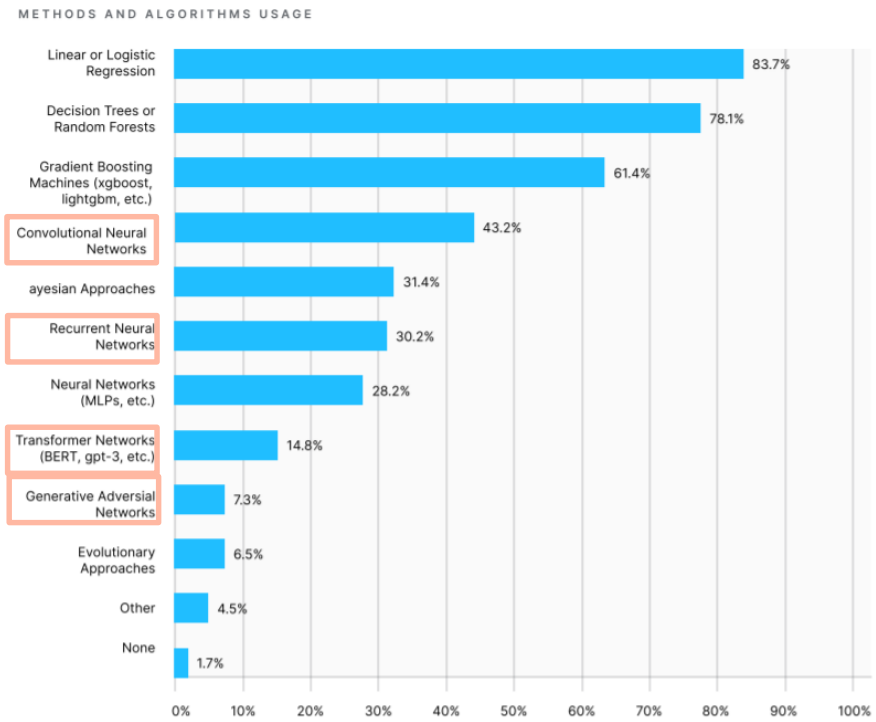
Any label?
- Where are the labels?
- What data types are they?

Size enough?
- Total data size?
- Labeled data size?
- Distribution balanced?

Choice of Model

gif: https://www.pinterest.com/pin/613404411726165689/

Popular Models



https://www.kaggle.com/kaggle-survey-2020

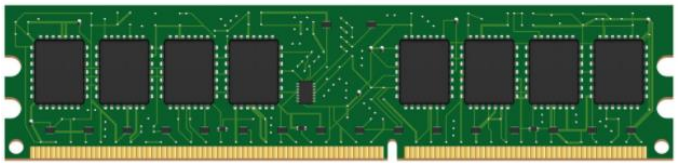
該從那裡開始?
硬體篇

To hire or to buy?

- To hire cloud services:
  - AWS, Azure, Google Cloud
- To buy:
  - Server
  - PC

Memory Calculation

- ➔ a 16-bit grayscale pixel = 2 bytes
- ➔ a DICOM slice image: 512*512*2 = 0.5 GB
- ➔ a common choice of batch size = 8 or 16 (4 or 8 GB)
- ➔ also have to consider model size



Now
Let's Get Started!

Thank You ☺

請多多指教!