## FIRST STEP TO PRACTICAL MACHINE LEARNING

KNOWLEDGE SHARING FOR CPE/SKE STUDENTS

SIRAKORN LAMYAI

STUDENT, KASETSART U.

OCTOBER 30, 2018

#### BEFORE WE START...

Make sure these are installed on your computer.

This page is a guide for installing on Windows

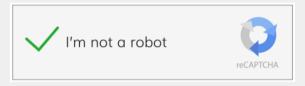
- Python 3.6: Download and install at https://www.python.org
- NumPy, Scipy, Matplotlib, Scikit-learn, MLxtend: Run pip install numpy scipy matplotlib sklearn mlxtend

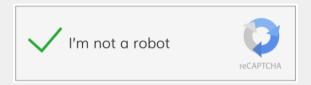
#### **OUTLINE**

- 1 Introduction to Machine Learning
  - What is Machine Learning? Traditional programming approach Machine learning approach
- 2 Machine Learning Problems
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
- 3 Model
- 4 Machine Learning Process
- 5 Algorithms for Machine Learning Classification Problem
- 6 Problems for Machine Learning
  - Handwriting recognition
- 7 Neural Networks



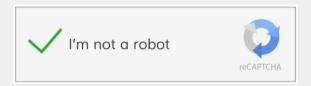
# INTRODUCTION TO MACHINE LEARNING



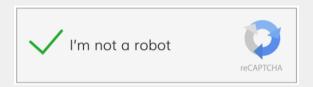


■ This is Recaptcha.

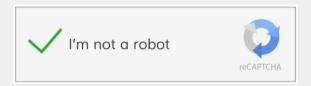
3 | 34



- This is Recaptcha.
  - ► Recaptcha helps stop millions of spam a day.

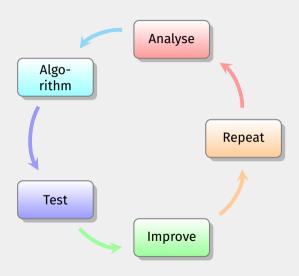


- This is Recaptcha.
  - Recaptcha helps stop millions of spam a day.
  - ▶ In some old days, we have to type Captcha texts to distinguish ourself from bots.

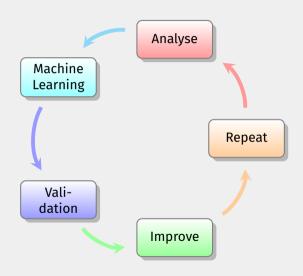


- This is Recaptcha.
  - ► Recaptcha helps stop millions of spam a day.
  - ▶ In some old days, we have to type Captcha texts to distinguish ourself from bots.
  - ► How is it possible that with a single click, an automated system can distinguish bots from humans?

## TRADITIONAL PROGRAMMING APPROACH



#### MACHINE LEARNING APPROACH



## IN OTHER WORDS...

Machine Learning

#### **Machine Learning**

= Data + Data analysis algorithm

#### Machine Learning

Data + Data analysis algorithmAdapt to change



# MACHINE LEARNING PROBLEMS

## Types of Machine Learning Problems

#### Types of Machine Learning problems

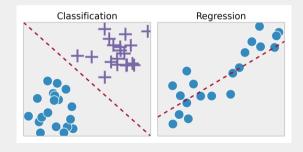
1. Supervised learning

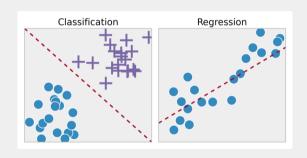
## Types of Machine Learning Problems

- 1. Supervised learning
- 2. Unsupervised learning

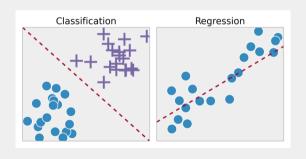
#### Types of Machine Learning problems

- 1. Supervised learning
- 2. Unsupervised learning
- 3. Reinforcement learning

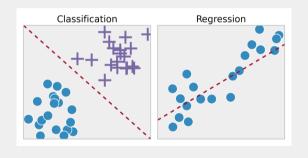




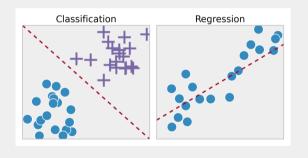
■ Given a **training set** for the data, find a **model** to **generalise** well to **unseen** data.



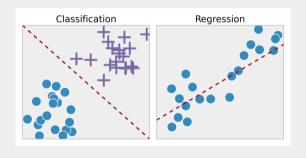
- Given a training set for the data, find a model to generalise well to unseen data.
- Two main supervised learning problems



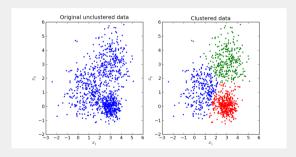
- Given a training set for the data, find a model to generalise well to unseen data.
- Two main supervised learning problems
  - ► Classification: On the discrete data



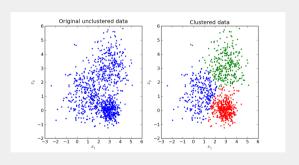
- Given a training set for the data, find a model to generalise well to unseen data.
- Two main supervised learning problems
  - ► Classification: On the discrete data
  - ► Regression: On the continuous data



- Given a **training set** for the data, find a **model** to **generalise** well to **unseen** data.
- Two main supervised learning problems
  - ► Classification: On the discrete data
  - ► Regression: On the continuous data
- Example problems: Spam E-mail detection, Facial recognition

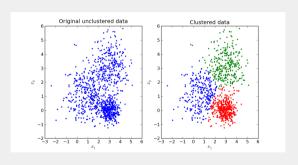


#### Unsupervised Learning



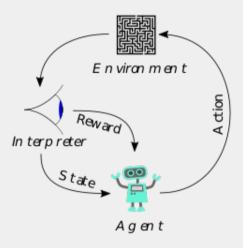
■ Discover hidden structure in non-labelled data.

#### Unsupervised Learning



- Discover **hidden** structure in **non-labelled** data.
- Example: Clustering, Generative models

## REINFORCEMENT LEARNING



## MODEL

## MODEL

## Model

■ A result of the combination between...

#### Model

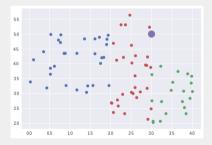
- A result of the combination between...
  - ► a **method** to recognise the data, and

#### MODEL

- A result of the combination between...
  - ► a **method** to recognise the data, and
  - ► sample datas for such the method

#### Model

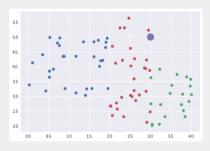
- A result of the combination between...
  - ▶ a **method** to recognise the data, and
  - ► sample datas for such the method



**Data** 

#### MODEL

- A result of the combination between...
  - a method to recognise the data, and
  - sample datas for such the method



Determine which group should the purple dot be in (red/green/blue) by checking the colour of its nearest dot.

**Data** 

Method

■ We're going to write our **first own** machine learning algorithm called **k-Nearest Neighbour** (k-NN)

- We're going to write our **first own** machine learning algorithm called **k-Nearest Neighbour** (k-NN)
  - ► k-NN is known to be very simple, with its concept as

- We're going to write our **first own** machine learning algorithm called **k-Nearest Neighbour** (k-NN)
  - $\blacktriangleright$  k-NN is known to be very simple, with its concept as

#### k-NN algorithm

To classify label of a data point, get *k* nearest data points to the data point, and select the major label among those data points.

# Coding time!

■ Train

- Train
- Test

- Train
- Test

(There'll be more of this, trust me.)

What is the bad way to choose k?

What is the bad way to choose *k*?

■ What if we choose k = # of all points?

#### What is the bad way to choose *k*?

- What if we choose k = # of all points?
  - ► What will happen if our dataset's got 3 labels of A, B, C with 10, 20, and 30 data points of each?

#### What is the bad way to choose *k*?

- What if we choose k = # of all points?
  - ► What will happen if our dataset's got 3 labels of A, B, C with 10, 20, and 30 data points of each?
  - Answer: Our model will always answer the labels with the highest data point count.

#### What is the bad way to choose *k*?

- What if we choose k = # of all points?
  - ► What will happen if our dataset's got 3 labels of A, B, C with 10, 20, and 30 data points of each?
  - Answer: Our model will always answer the labels with the highest data point count.
- What if we choose k = 1?

#### What is the bad way to choose *k*?

- What if we choose k = # of all points?
  - ► What will happen if our dataset's got 3 labels of A, B, C with 10, 20, and 30 data points of each?
  - Answer: Our model will always answer the labels with the highest data point count.
- What if we choose k = 1?
  - ► Let's try!

## Coding time!

■ We separate our dataset into 2 parts: the **training set** and **testing set** 

- We separate our dataset into 2 parts: the training set and testing set
  - ▶ Most of the time, the testing set will be around 10-25% of the entire dataset

- We separate our dataset into 2 parts: the training set and testing set
  - ▶ Most of the time, the testing set will be around 10-25% of the entire dataset
  - ► What will happen if we train on the testing set?

- We separate our dataset into 2 parts: the training set and testing set
  - ▶ Most of the time, the testing set will be around 10-25% of the entire dataset
  - ► What will happen if we train on the testing set?
  - What will happen if we test on the training set?

- We separate our dataset into 2 parts: the **training set** and **testing set** 
  - ▶ Most of the time, the testing set will be around 10-25% of the entire dataset
  - ► What will happen if we train on the testing set?
  - What will happen if we test on the training set?
    - Cheating! Like letting the model remembers the answer instead of generalising the data pattern.

- We separate our dataset into 2 parts: the **training set** and **testing set** 
  - ▶ Most of the time, the testing set will be around 10-25% of the entire dataset
  - ► What will happen if we train on the testing set?
  - ► What will happen if we test on the training set?
    - Cheating! Like letting the model remembers the answer instead of generalising the data pattern.
  - ► In other words, don't test and train model on the same set of data.

#### CHOOSING THE BEST k

#### CHOOSING THE BEST k

■ Train with the training set, to let our model know how will the data looks like.

#### Choosing the best k

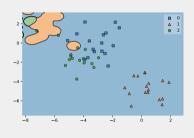
- Train with the training set, to let our model know how will the data looks like.
- **Test** with the testing set, to see on how our model performs.

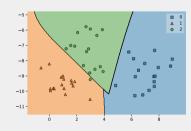
#### Choosing the best k

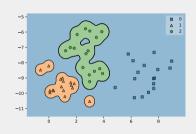
- Train with the training set, to let our model know how will the data looks like.
- **Test** with the testing set, to see on how our model performs.

Warning! This is a simplified Machine Learning model training process, there are more to concerns!

#### Which decision region is good?

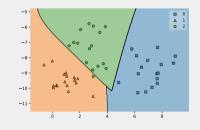


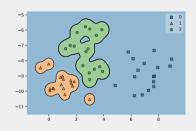




#### Which decision region is good?





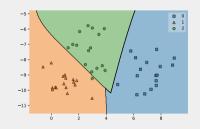


**Underfit:** The model fails to recognise data pattern

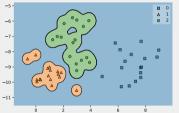
#### Which decision region is good?



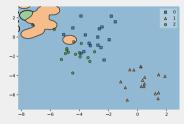
**Underfit:** The model fails to recognise data pattern



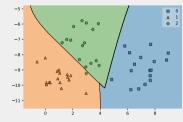
Overfit: The model remembers data pattern instead of generalising.



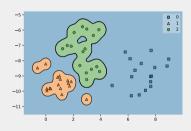
#### Which decision region is good?



**Underfit:** The model fails to recognise data pattern



**Good fit:** The model recognises data pattern **generally** 



**Overfit:** The model **remembers** data pattern instead of generalising.

### Good model must generalise

#### PARAMETER OPTIMISATION

- Actually, the key point in *k*-NN algorithm is choosing *k* points with the least **distant**.
- What is **distant**?

## NORM FOR k-NN ALGORITHM

#### Norm

In linear algebra, a **norm** is a function that assigns a strictly positive length or size to each vector in a vector space - except for the zero vector, which is assigned a length of zero.

Given  $\vec{x}$  as an N-dimension vector of  $\begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix}$ 

- $\blacksquare$   $l_1$  Norm:  $|x|_1 = \sum_{i=0}^N |x_i|$  (Manhattan)
- $l_2$  Norm:  $|\mathbf{x}|_2 = \sqrt{\sum_{i=0}^N x_i^2}$  (Euclidian)
- $l_p$  Norm:  $|x|_p = \left(\sum_{i=1}^n |x_i|^p\right)^{1/p}$  (Minkowski)

# **ALGORITHMS FOR MACHINE LEARNING CLASSIFI-**

**CATION PROBLEM** 

## ALGORITHMS FOR MACHINE LEARNING CLASSIFICATION PROBLEM

*k*-NN is a very simple intuition for machine learning algorithms. However, there exists more algorithm that performs well to other problems. Example algorithms:

- Naïve Bayes
- SVM
- Decision Tree
- Logistic Regression

# Naïve Bayes

	Gender	Hair
1	М	Long
2	M	Short
3	F	Long
4	F	Long
5	F	Short

# **Bayes Theorem**

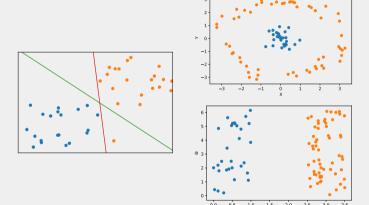
$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A) \times P(A)}{P(B)}$$

Can we guess the gender from hair's length?

- $P(\text{Male}|\text{Long hair}) = \frac{1}{3}$
- $P(\text{Female}|\text{Long hair}) = \frac{2}{3}$

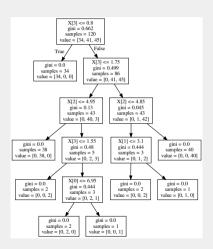
Therefore, we guess that the long-haired person is more likely to be a female.

# SUPPORT VECTOR MACHINES (SVM)



- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distant between the line and classes of data points
- What if the data is not linearly separable? Kernel tricks

#### **DECISION TREE**



- Creating an if-else conditions automatically
- Nested conditions with a parameter to determine how does the separating of the "tree" performs.

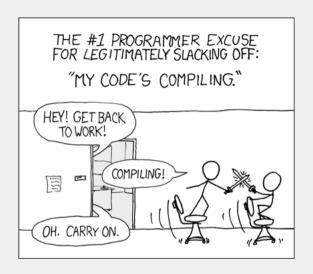


Figure: xkcd - Compiling

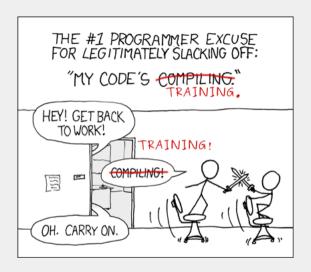
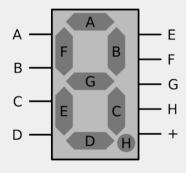
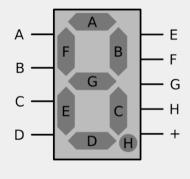


Figure: xkcd - Compiling

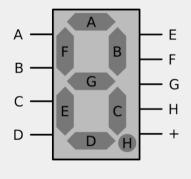


# PROBLEMS FOR MACHINE LEARNING

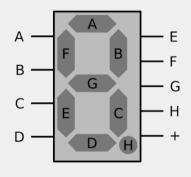




■ This is a 7-segment display.



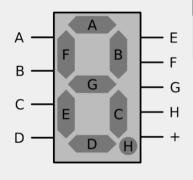
- This is a 7-segment display.
- It consists of a bulb labelled from A-G that could form a number.



- This is a 7-segment display.
- It consists of a bulb labelled from A-G that could form a number.

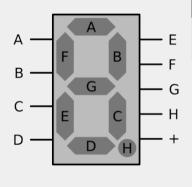
#### Problem

When the list of the bulb that went on were given, can we determine the number?



## Problem

When the list of the bulb that went on were given, can we determine the number?



#### Problem

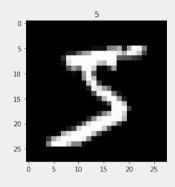
When the list of the bulb that went on were given, can we determine the number?

Not only yes, but easily yes!

```
if led_on == (b, c):
    return 1
elif led_on == (a, b, g, e, d):
    return 2
```

. . .

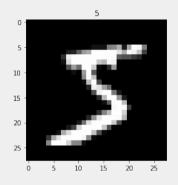
# **HANDWRITING**



# Problem

When the image of the handwriting were given, can we determine the number?

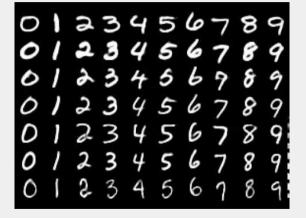
#### **HANDWRITING**

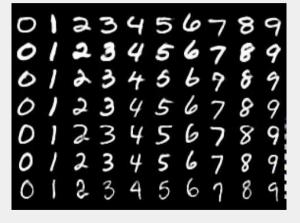


#### Problem

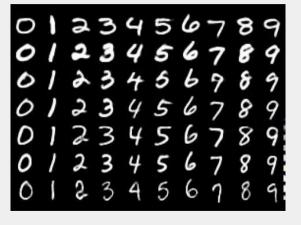
When the image of the handwriting were given, can we determine the number?

With an **explicit algorithm**? Obviously no! There are too many ways of drawing the number!

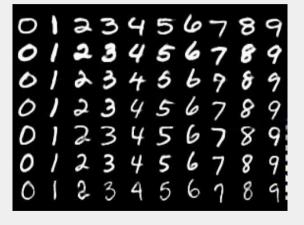




■ 28\*28 pixel images of handwritten numbers (0-9)



- 28\*28 pixel images of handwritten numbers (0-9)
- 60,000 training images



- 28\*28 pixel images of handwritten numbers (0-9)
- 60,000 training images
- 10,000 testing images

#### k-NN WITH MNIST

- Training: Pretty fast, no calculations on training phase
- Testing: \*thinking\*
  - ▶ 60,000 data points to calculate the distant + 10,000 data points to test
  - ► = 600.000,000 calculations to be made (this excludes sorting, of which is a  $\mathcal{O}(n)$  process)
  - ► = (relatively) slow