Machine Learning: What is?

A First Step to Practical Machine Learning

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Student, Kasetsart U.

October 30, 2018

Acknowledgements

Resources on this slides are mainly adapted and rearranged from

- W. Jitkrittum: Machine Learning Fundamentals I
- K. Muandet: Machine Learning Fundamentals II
- Google's Machine Learning Crash Course

Make sure these are installed on your computer.

- Python 3.6
- NumPy, Scipy, Matplotlib, Scikit-learn, MLxtend:
  Run `pip install numpy scipy matplotlib sklearn mlxtend`
- MNIST loader
  `pip install git+https://github.com/datapythonista/mnist.git`

Outline

Introduction to Machine Learning

What is Machine Learning?

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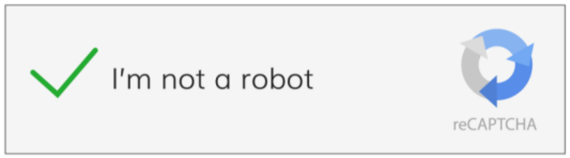

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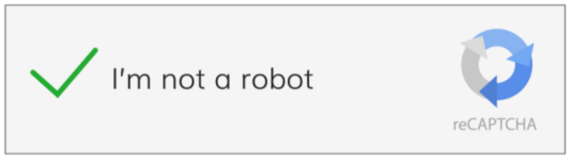

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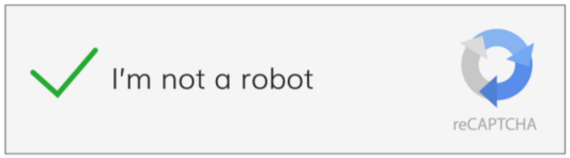

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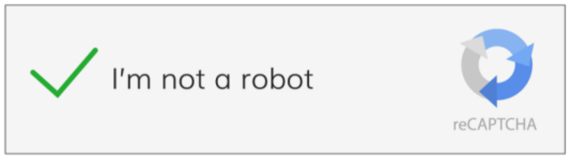

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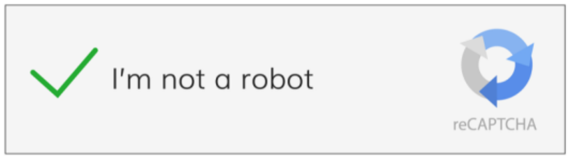

- This is Recaptcha.
  - Recaptcha helps stop millions of spam a day.
  - In some old days, we have to type Captcha texts to distinguish ourself from bots.
  - How is it possible that with a single click, an automated system can distinguish bots from humans?

Machine **Learning**

Machine **Learning**

= Improves performance on a specific task.

Machine Learning Problems

Types of Machine Learning problems

1. Supervised learning

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2. Unsupervised learning

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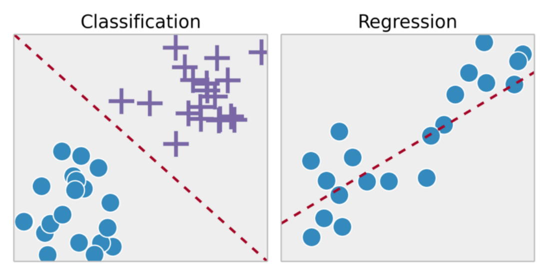
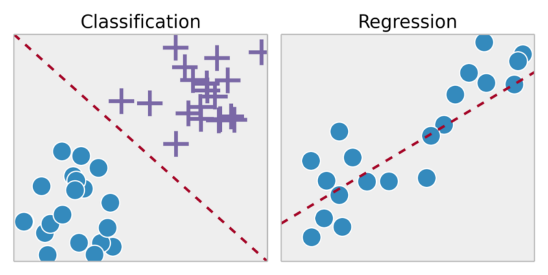
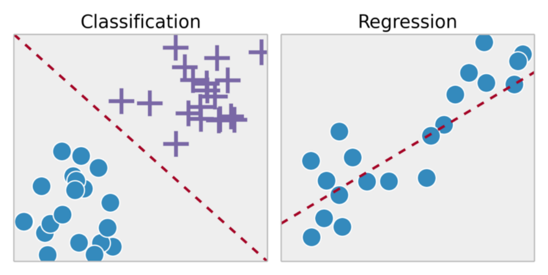
1. Supervised learning
2. Unsupervised learning
3. Reinforcement learning

Supervised learning





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



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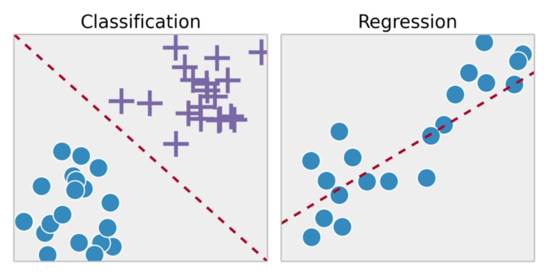

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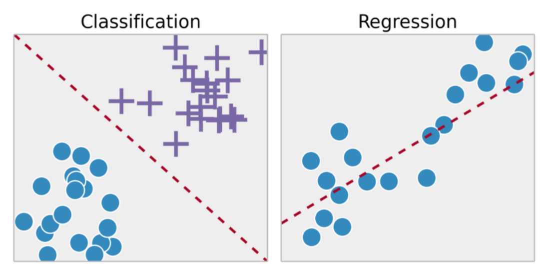

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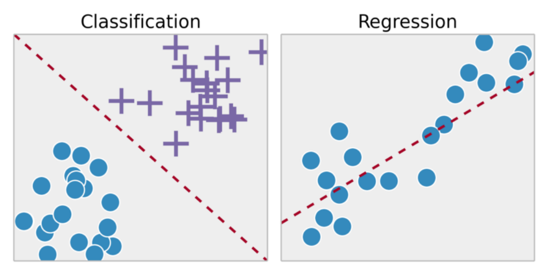

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  - Classification: On the discrete data
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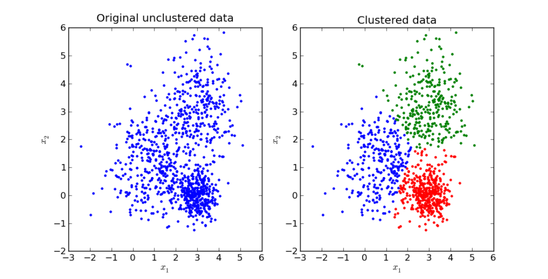
- Example problems: Spam E-mail detection, Facial recognition


Original unclustered data
Clustered data
x_1
x_2
−3 −2 −1 0 1 2 3 4 5 6
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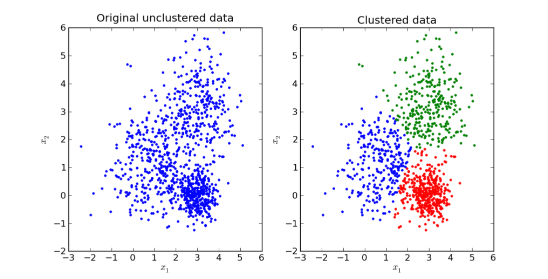
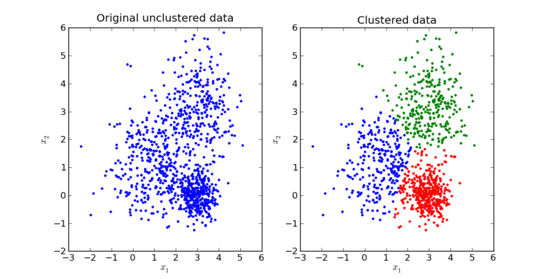


- Discover **hidden** structure in **non-labelled** data.



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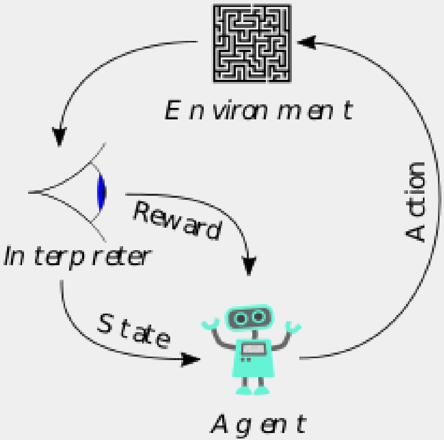
- Example: Clustering, Generative models


Environment
Interpreter
Reward
State
Action
Agent

Model

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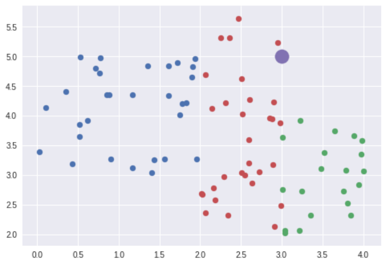

Data

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  - a **method** to recognise the data, and
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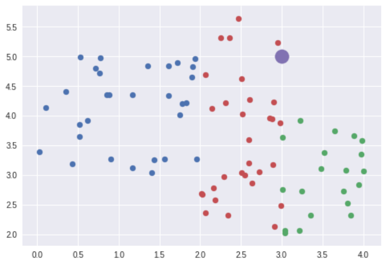

Determine which group should the purple dot be in (red/green/blue) by **checking the colour of its nearest dot.**

Data

Method

The Goal of Machine Learning

Generalise

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- Our model should not "adhere" to one set of data, but instead knows the pattern of all the data.
- Therefore, we want our model to **generalise** over any set of data, given the small portion of data that we used to teach the model.

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  - 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.

Machine Learning Process

Choosing the parameter for k-NN algorithm

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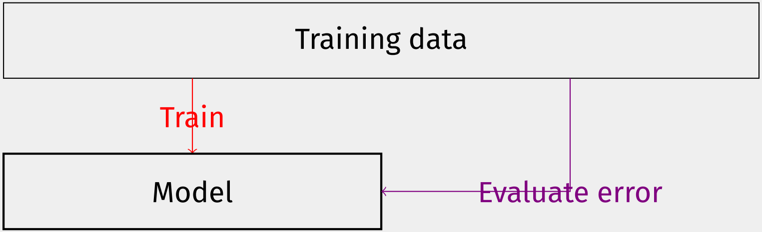
- What if we choose $k = 1$?
  - Let's try!

Training Error



Loss function

$$L(y, \hat{y}) = \begin{cases} 0 & y = \hat{y} \\ 1 & y \neq \hat{y} \end{cases}$$

Error

$$\sigma = \frac{1}{N} \sum_{i=0}^{N} L(y_i, \hat{y}_i)$$

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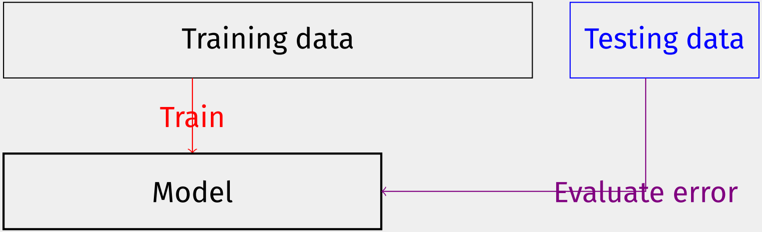
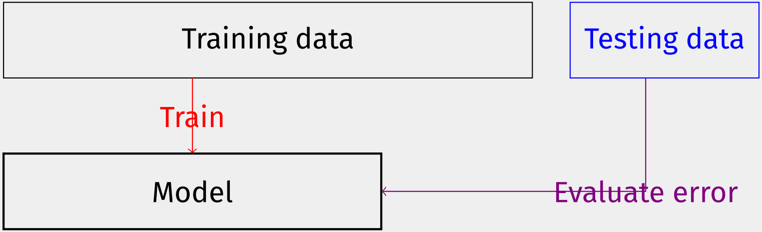
- Why? Because our model already knows the answer to that data point! It could just simply answer by looking at the "answer key"
- So how should we evaluate our model?

Training and Testing set





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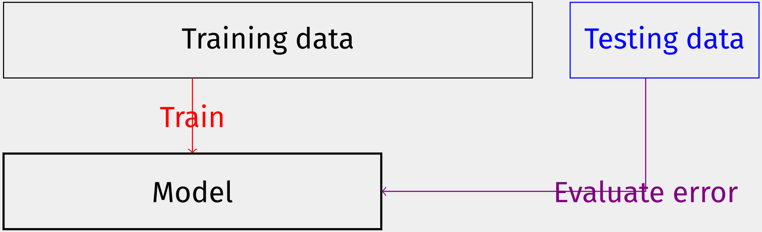

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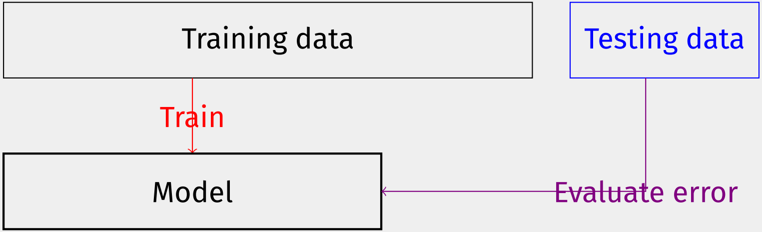

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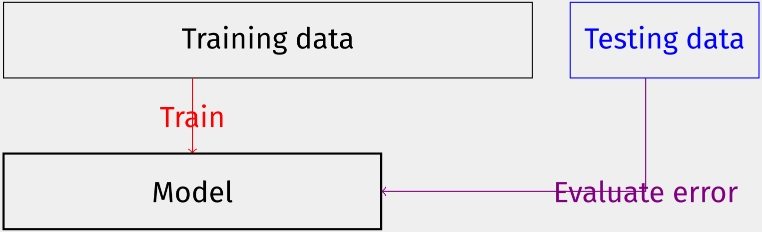


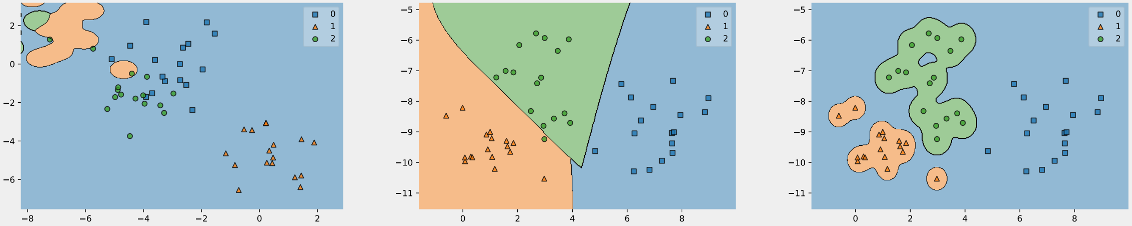
- We separate our dataset into 2 parts: the **training set** and **testing set**
  - Our model sees the correct label of the training set, but not the testing set.
  - We all know the correct label of both the training and testing set.
  - Teach our model with the training set, see how it performs with the testing set.

Choosing the best k

What will happen if...

- our k is too small?
- our k is too large?

Which decision region is good?



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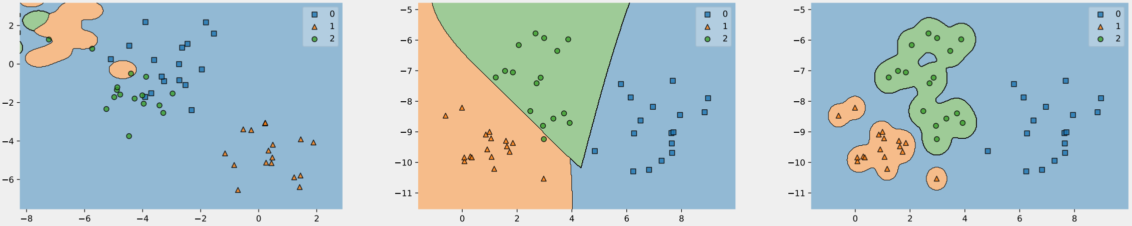

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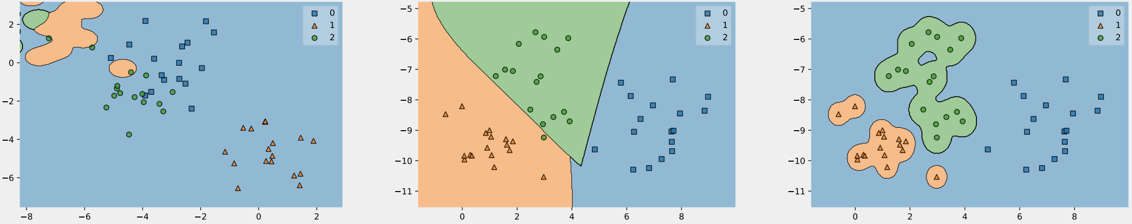

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Overfit: The model **remembers** data pattern instead of generalising.

Overfitting and underfitting

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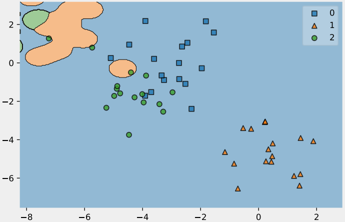

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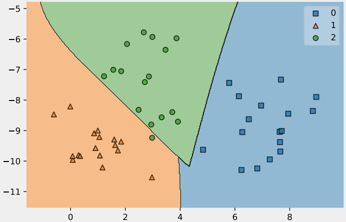
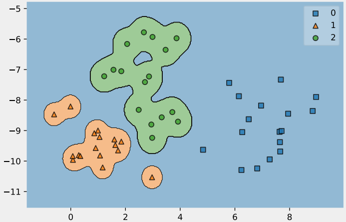


Good fit: The model recognises data pattern **generally**



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

Good model must **generalise**

Parameter Optimisation

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

Norm for k-NN algorithm

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- l_p Norm: $|x|_p = \left(\sum_{i=1}^{n} |x_i|^p\right)^{1/p}$ (Minkowski)

Algorithms for Machine Learning Classification Problem

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- Decision Tree
- Logistic Regression

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

Can we *guess* the gender from hair's length?

	Gender	Hair
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Can we *guess* the gender from hair's length?

Bayes Theorem

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

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Naïve Bayes

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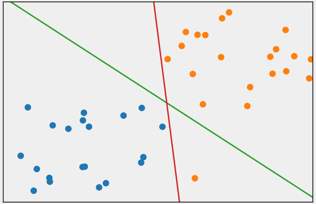
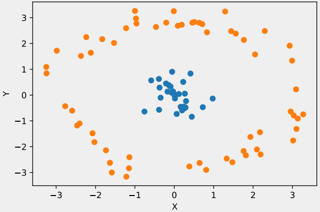
Can we *guess* the gender from hair's length?

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

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




Y
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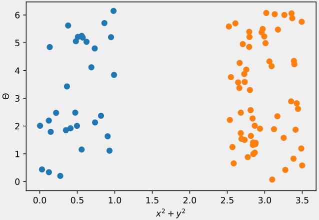
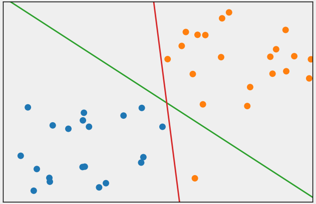
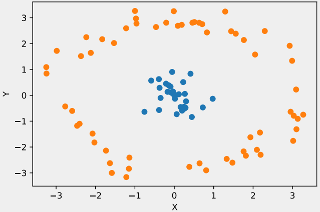
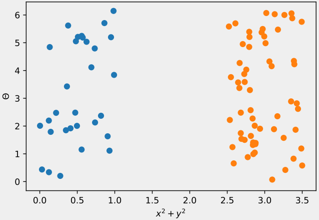
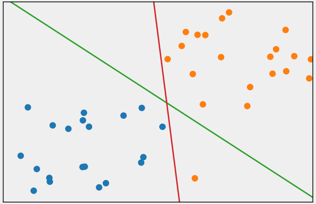

θ
$x^2 + y^2$

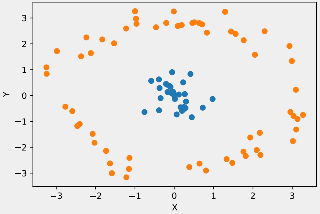


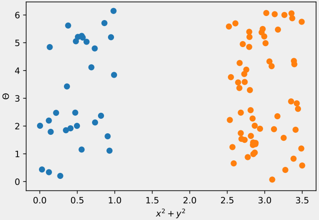




- Goal: to draw a line to separate groups of data







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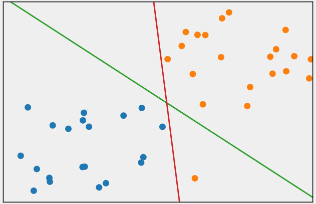
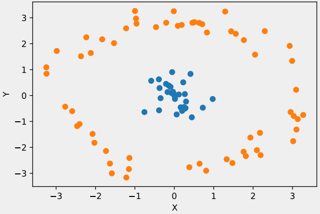
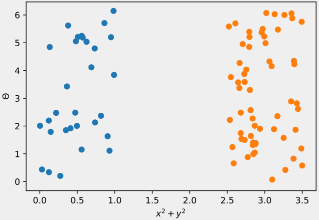
- Ideal good line: maximising the distant between the line and classes of data points

Support Vector Machines (SVM)

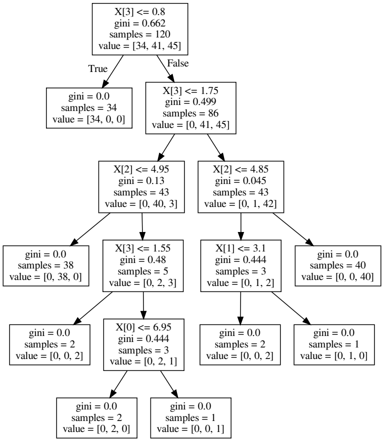






- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distant between the line and classes of data points
- What if the data is not linearly separable? **Kernel tricks**

Decision Tree



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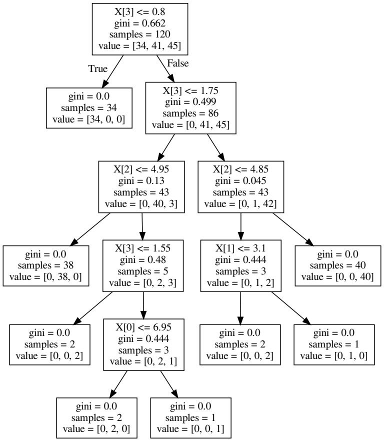

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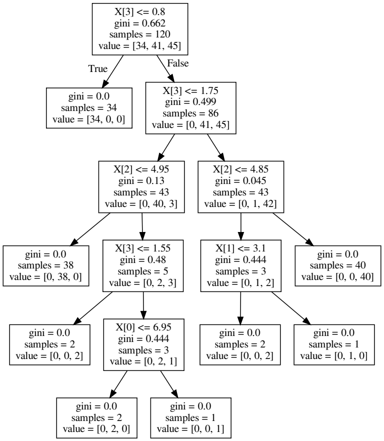


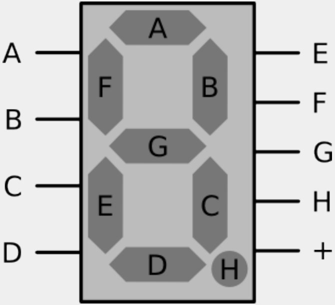
- Creating an if-else conditions automatically
- Nested conditions with a parameter to determine how does the separating of the "tree" performs.

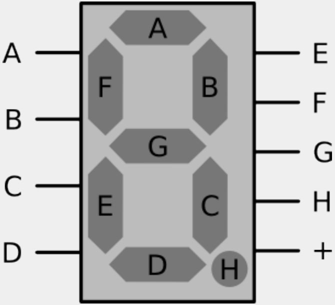
Figure: xkcd - Compiling

Figure: xkcd - Compiling (shamelessly modified)

Problems for Machine Learning

7-Segment display





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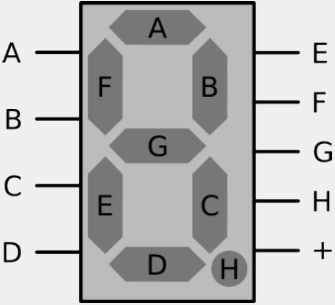
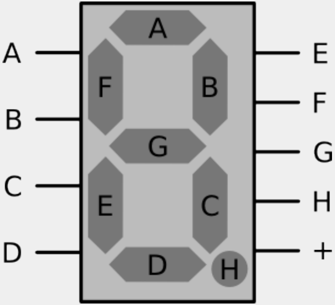


- This is a 7-segment display.
- It consists of a bulb labelled from A-G that could form a number.



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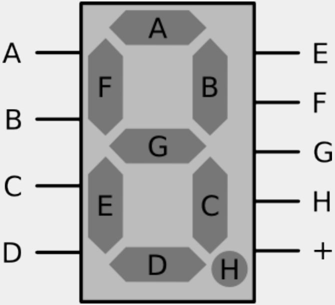
When the list of the bulb that went on were given, can we determine the number?



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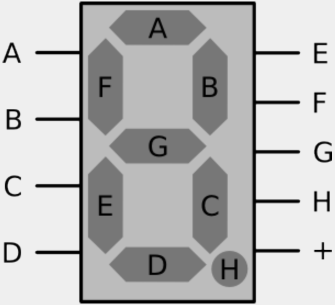
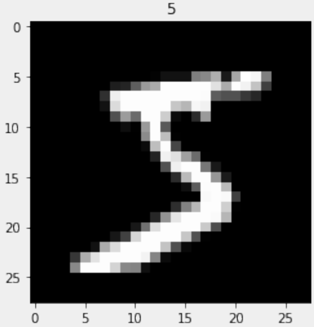


Problem

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

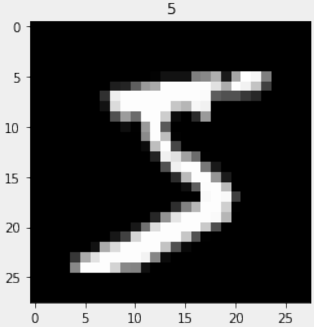
Not only yes, but *easily* yes!

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



Problem

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



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!

MNIST Dataset

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

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  - Later to be viewed as a vector of 784 dimensions

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- 60,000 training images

MNIST Dataset

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  - Later to be viewed as a vector of 784 dimensions
- 60,000 training images
- 10,000 testing images

k-NN WITH MNIST

- Training: Pretty fast, no calculations on training phase

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      (this excludes sorting, of which is a $\mathcal{O}(n)$ process)

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  - = 600,000,000 calculations to be made
    (this excludes sorting, of which is a $\mathcal{O}(n)$ process)
  - = **(relatively) slow**
- Good results with *k*-NN were achieved.
  (*k*-NN w/ non-linear deformation (P2DHMDM), preprocessed with shiftable edges, results into 0.52% error rate.)

SVM with MNIST

- Training: Slow as hell.

  Trust me, I've tried.

SVM with MNIST

- Training: Slow as hell.

  Trust me, I've tried.
- Good results with SVM were achieved.
  (Virtual SVM, deg-9 poly, 2-pixel jittered with deskewing preprocessing results into 0.56% error rate.)

Neural Networks

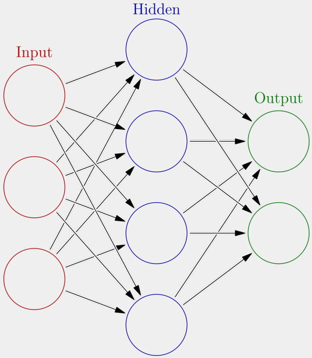


Figure: Neural network (Courtesy: Glosser.ca from Wikimedia Commons)

This seems complex, right? We'll get start a little by little...

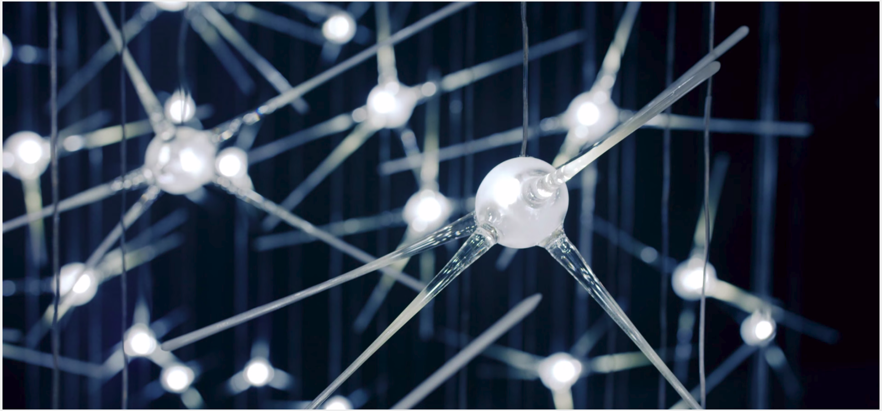


Figure: "Neurons" chandelier installed at Princh Mahidol Hall, Nakhon Pathom, Thailand (Courtesy: LASVIT’s promotion video)

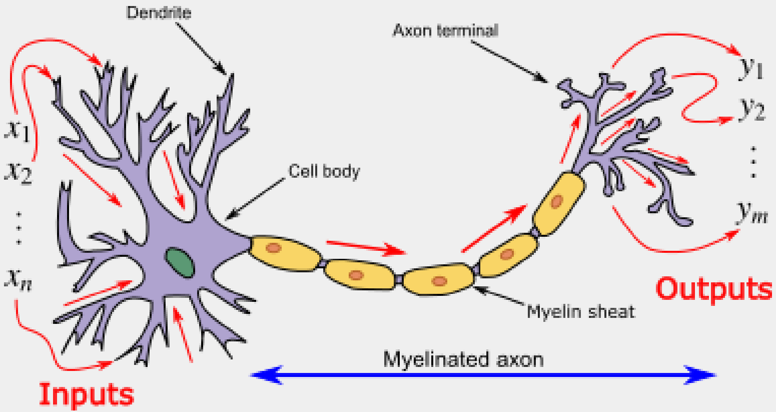
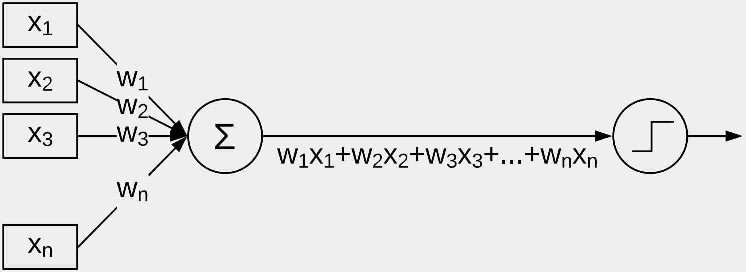


Figure: Neuron (Courtesy: Egm4313.s12 from Wikimedia Commons)

Perceptron



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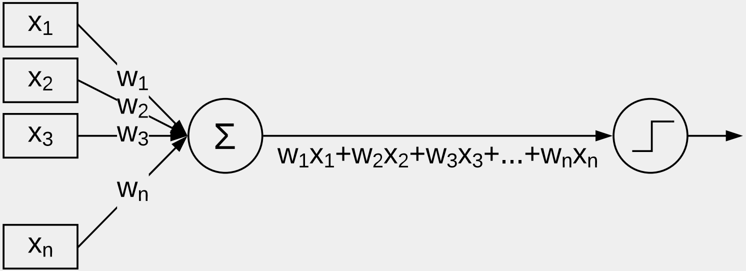
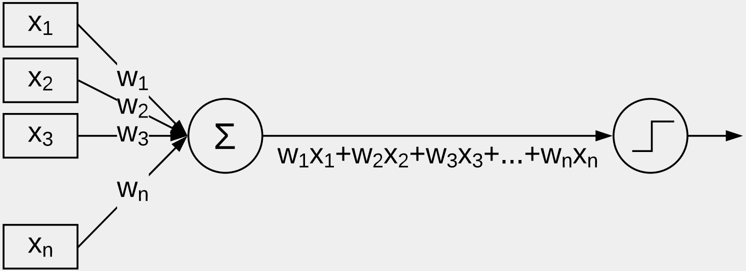


- **Inputs** consisting of n inputs from x_1, x_2 ... to x_n.



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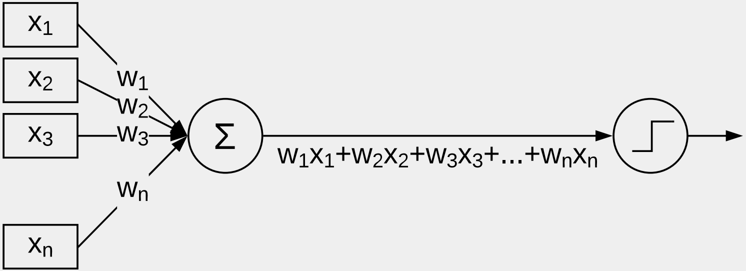

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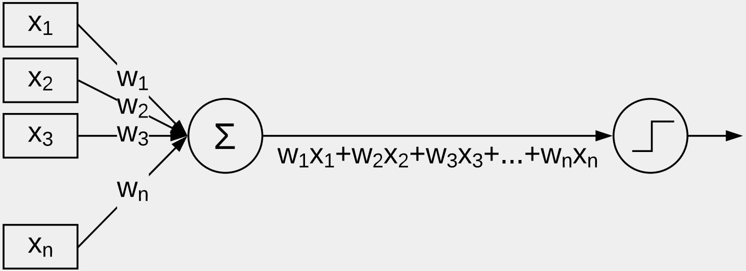

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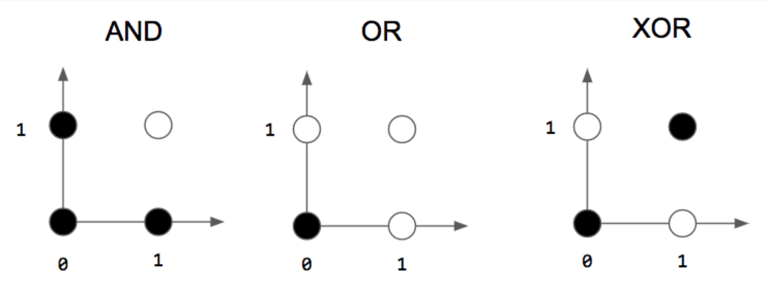
- **Activation function** in either the form of $\Sigma > k$ or $\Sigma < k(nonlinear)$


AND
OR
XOR
1
0
1
1
0
1
1
0
1

Logic gates with Perceptron

AND gate

OR gate

XOR gate

AND gate

- $w_1 = 1$
- $w_2 = 1$
- $\Sigma = 1x_1 + 1x_2$
- $f : \Sigma \geq 2$

OR gate

XOR gate

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XOR gate

Why can't XOR gate be created using a perceptron?

Linearly Separable Problem

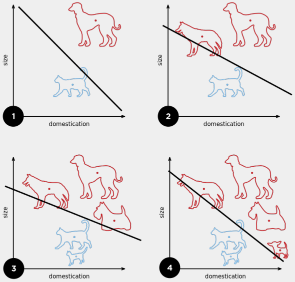

Figure: Linearly Separable Problem (Courtesy: Elizabeth Goodspeed from Wikimedia Commons)

- Now our problem is that the perceptron is a **linear classifier**, that means it could only separate datas that is linearly separable.
- Real-world problems are not that easy to separate
- How can we solve this problem?

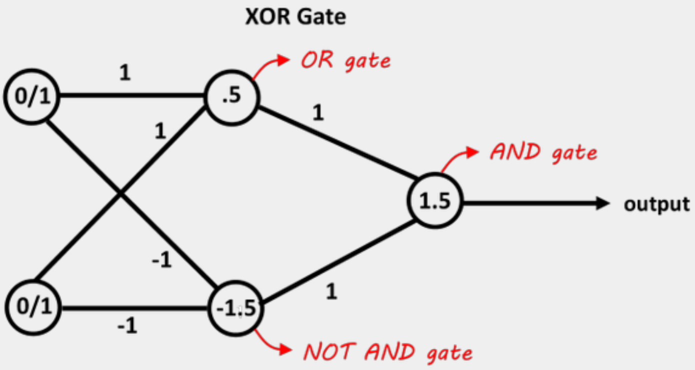

Figure: XOR gate with Perceptrons connected together (Courtesy: Parth Udawant)

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    (Seriously, one day it will converge. There exists a mathematical proof)

Demo

https://playground.tensorflow.org/

Challenges in Machine Learning Problems

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- Can we do better? How?
- Error rate of 0.35% were achieved by neural networks for the MNIST problem.

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Problem's complexity

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Problem's complexity

- Although looked similar, some problems are much more complex than it looks
- **CIFAR-10**, a 32*32 pixel RGB images of 10 classes
- Straightforward neural networks (like what we've did) yields only 56% accuracy.

Your next step into Machine Learning

There are more things to learn so

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- Train-Validate-Test procedure

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- Dimension reduction

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- Train-Validate-Test procedure
- Dimension reduction
- Dealing with outliers
- Ensemble learning
- Etc...

Courses in KU-CPE to be taken

- Engineering Mathematics I
- Discrete Mathematics and Linear Algebra
- Probability and Statistics
- Statistics for Computer Engineers
- Aritificial Intelligence/Machine Learning

MOOCs

For practical use, go ahead with...

- Google's Machine Learning Crash Course
- Udemy's Machine Learning (UD120)

What are the applications of Machine Learning?

How should we cope with news like "Danger! Experts claims AI to be dangerous, creates its own language"? (Source: Thairath)

Other questions?

Thanks!

https://twitter.com/public_srakrn
https://www.facebook.com/srakrn
sirakorn.l@ku.th

(2-shots with me after this course are totally welcomed)

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