Machine Learning: What is?

A First Step to Practical Machine Learning

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Student, Kasetsart U.

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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

Before we start...

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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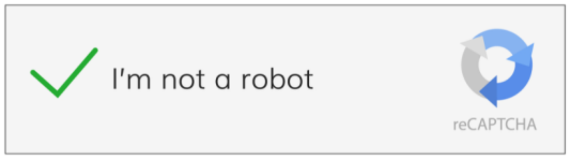

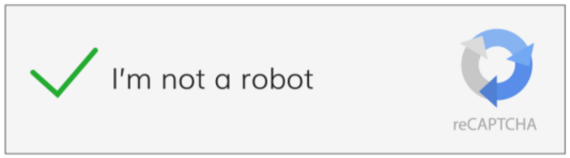

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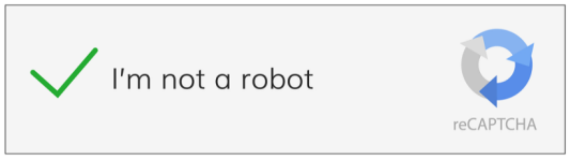

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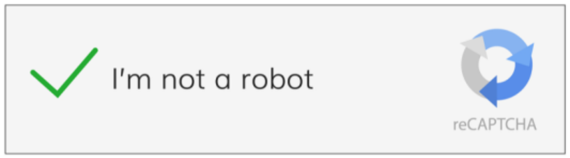

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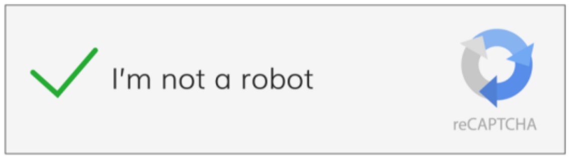

- This is Recaptcha.
  - Recaptcha helps stop millions of spam a day.
  - In some old days, we have to type Captcha texts to distinguish ourself from bots.
  - How is it possible that with a single click, an automated system can distinguish bots from humans?

Machine **Learning**

Machine **Learning**

= Improves performance on a specific task.

Machine Learning Problems

Types of Machine Learning problems

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1. Supervised learning

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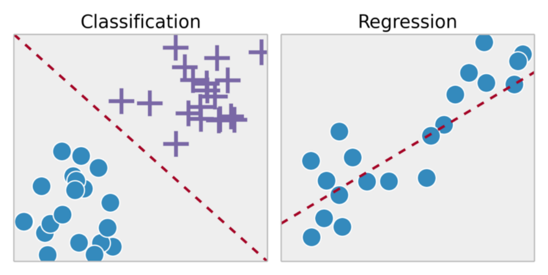
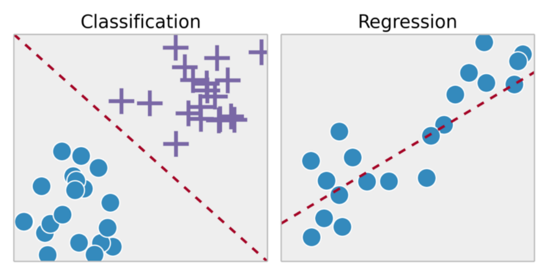
2. Unsupervised learning
3. Reinforcement learning

Supervised learning





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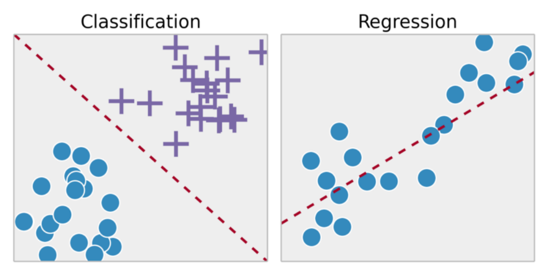

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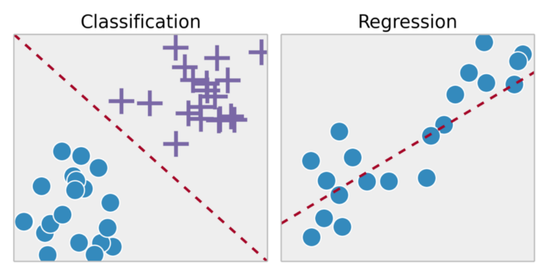

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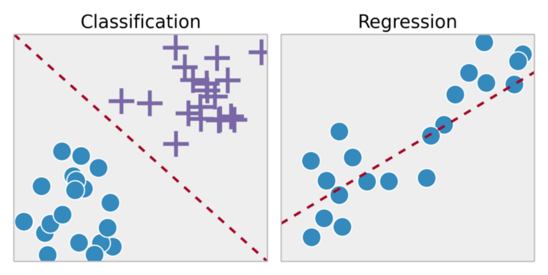

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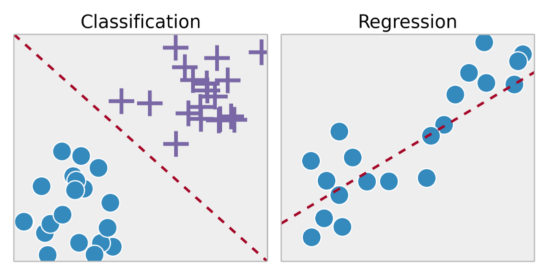

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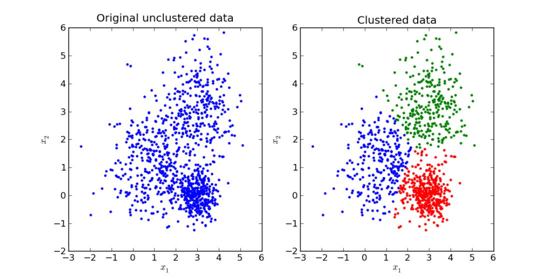
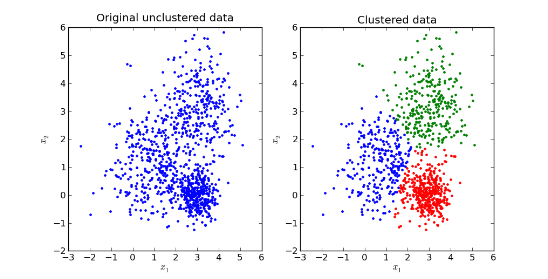
- Example problems: Spam E-mail detection, Facial recognition

Unsupervised learning





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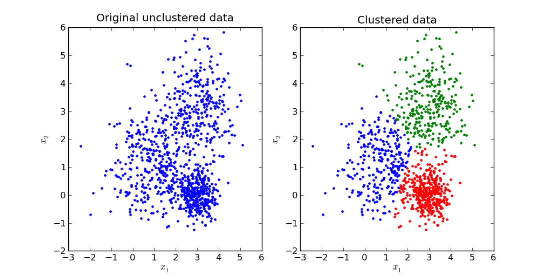

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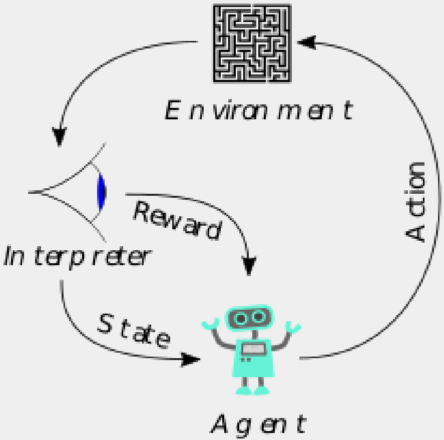
- Example: Clustering, Generative models

Reinforcement learning



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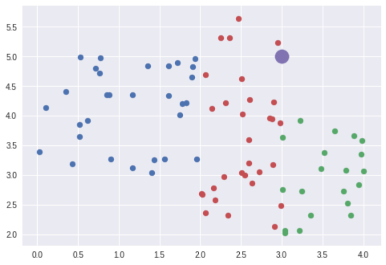

Data

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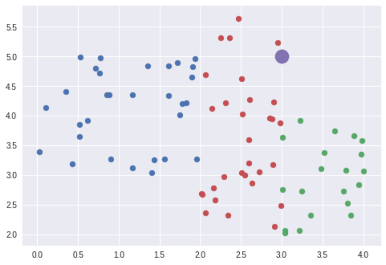

Determine which group should the purple dot be in (red/green/blue) by **checking the colour of its nearest dot.**

Data

Method

The Goal of Machine Learning

Generalise

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- We wants our model to know how does the **data pattern** looks like
- 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.

Beginning with our first model

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_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

What is the bad way to choose k?

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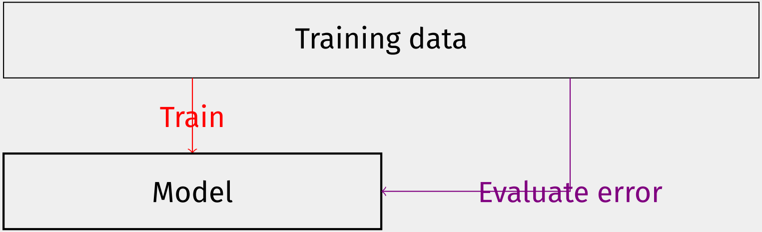
- What if we choose $k = 1$?
  - Let's try!

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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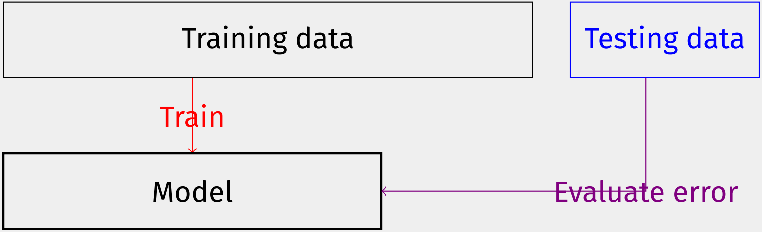
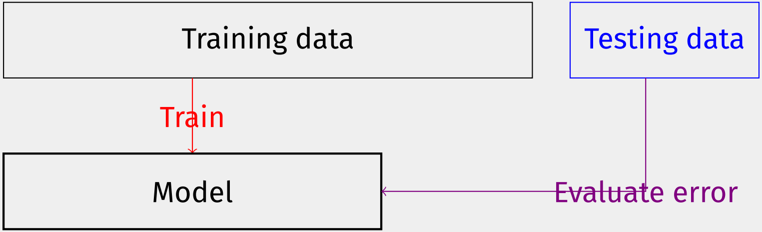
- Evaluating error with a data points that our model had already seen is bad.
- Why? Because our model already knows the answer to that data point! It could just simply answer by looking at the "answer key"
- So how should we evaluate our model?

Training and Testing set





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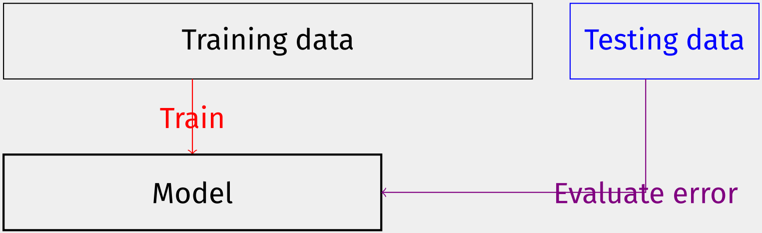

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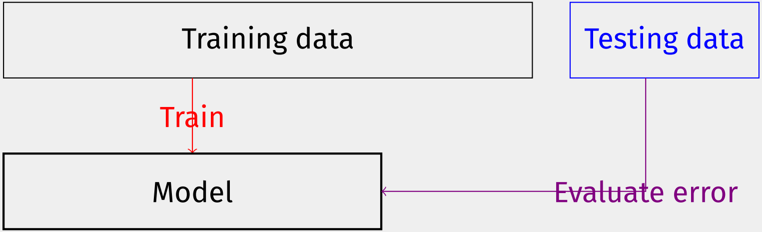

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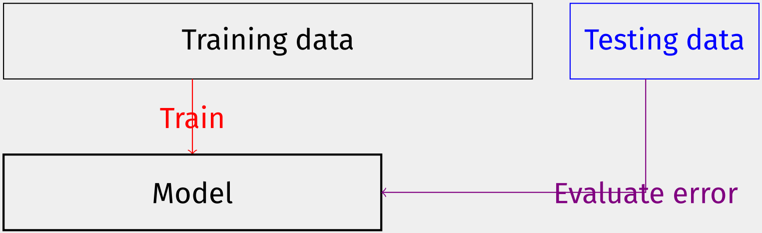
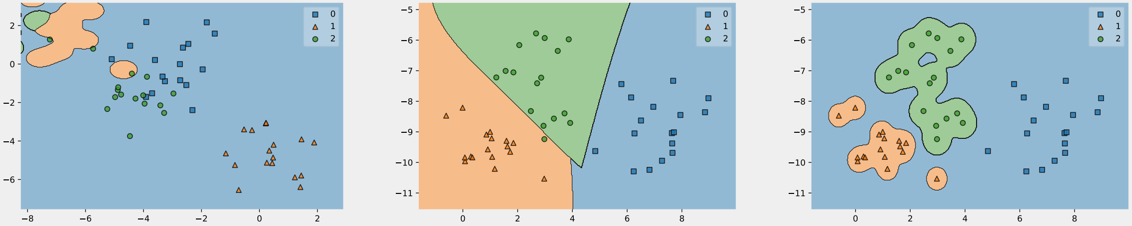


- We separate our dataset into 2 parts: the **training set** and **testing set**
  - Our model sees the correct label of the training set, but not the testing set.
  - We all know the correct label of both the training and testing set.
  - Teach our model with the training set, see how it performs with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

What will happen if...

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

Which decision region is good?



OVERFITTING AND UNDERFITTING

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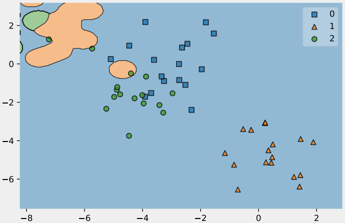

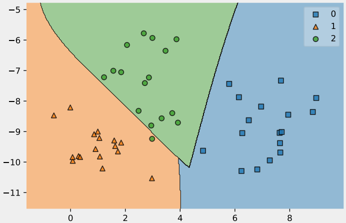

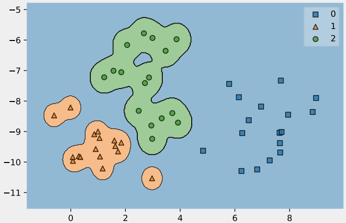

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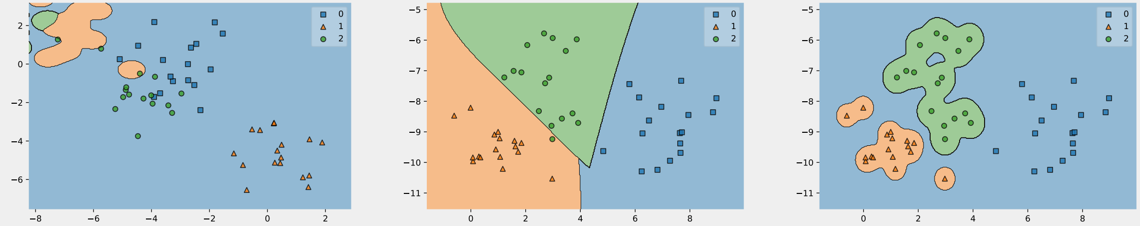

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Overfit: The model **remembers** data pattern instead of generalising.

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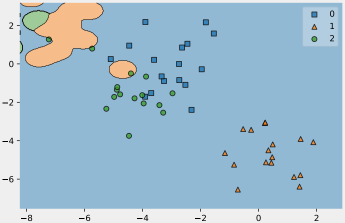

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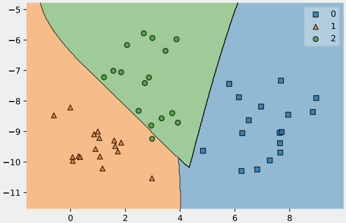
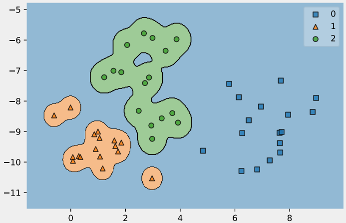


Good fit: The model recognises data pattern **generally**



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

Good model must **generalise**

It's not only k that we can adjust.

It's not only *k* that we can adjust.

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

Parameter Optimisation

It's not only k that we can adjust.

- 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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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.

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

Algorithms for Machine Learning Classification Problem

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Example algorithms:

- Naïve Bayes
- SVM
- Decision Tree
- Logistic Regression

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

Bayes Theorem

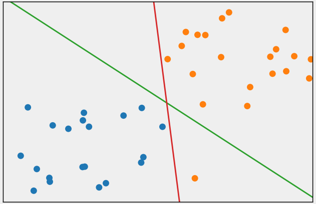
$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A) \times P(A)}{P(B)}$$

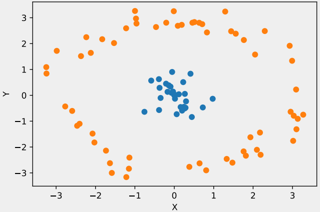
Can we *guess* the gender from hair's length?

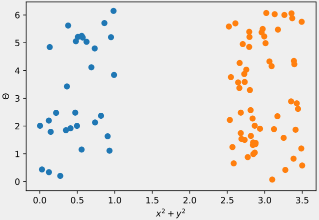
- $P(\text{Male}|\text{Long hair}) = \frac{1}{3}$
- $P(\text{Female}|\text{Long hair}) = \frac{2}{3}$

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

Support Vector Machines (SVM)

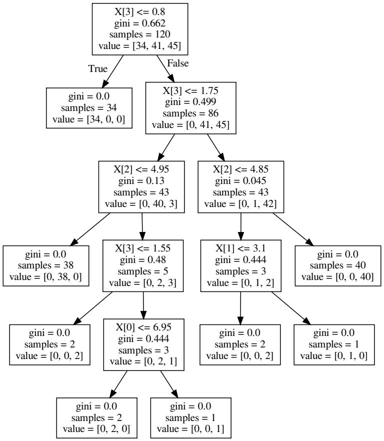






- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distant between the line and classes of data points
- What if the data is not linearly separable? **Kernel tricks**

Decision Tree



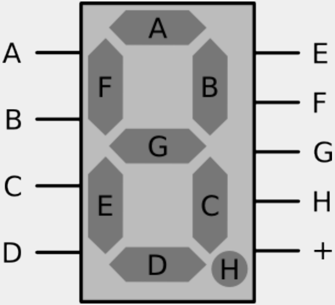
- Creating an if-else conditions automatically
- Nested conditions with a parameter to determine how does the separating of the "tree" performs.

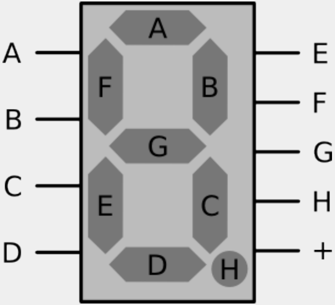
Figure: xkcd - Compiling

Figure: xkcd - Compiling (shamelessly modified)

Problems for Machine Learning

7-Segment display





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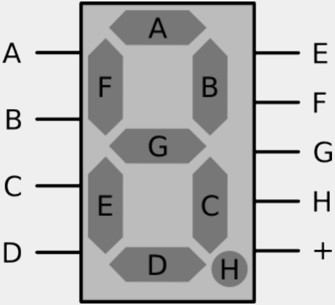

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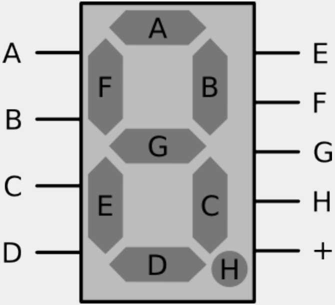
- It consists of a bulb labelled from A-G that could form a number.



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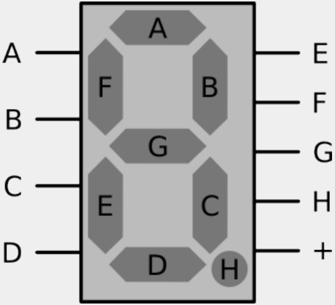

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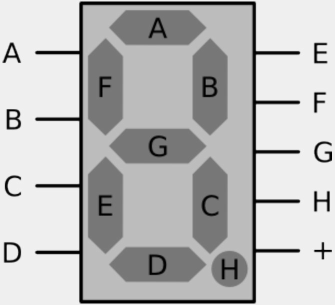
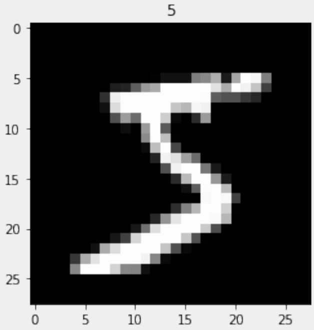


Problem

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

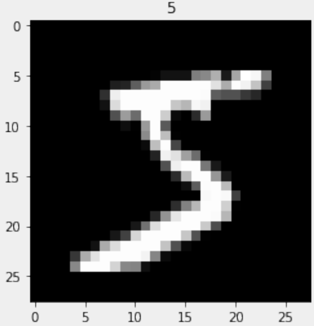
Not only yes, but *easily* yes!

```
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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MNIST Dataset

- 28*28 pixel images of handwritten numbers (0-9)
  - Later to be viewed as a vector of 784 dimensions
- 60,000 training images
- 10,000 testing images

- 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**
- Good results with k-NN were achieved.
  (k-NN w/ non-linear deformation (P2DHMDM), preprocessed with shiftable edges, results into 0.52% error rate.)

- 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

Artificial Neural Networks (ANN)

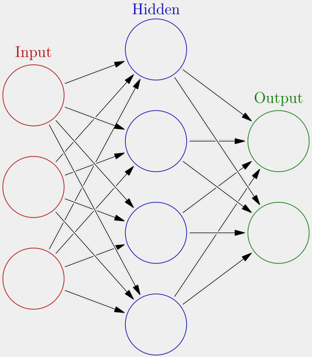


Figure: Neural network (Courtesy: Glosser.ca from Wikimedia Commons)

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

Neurons

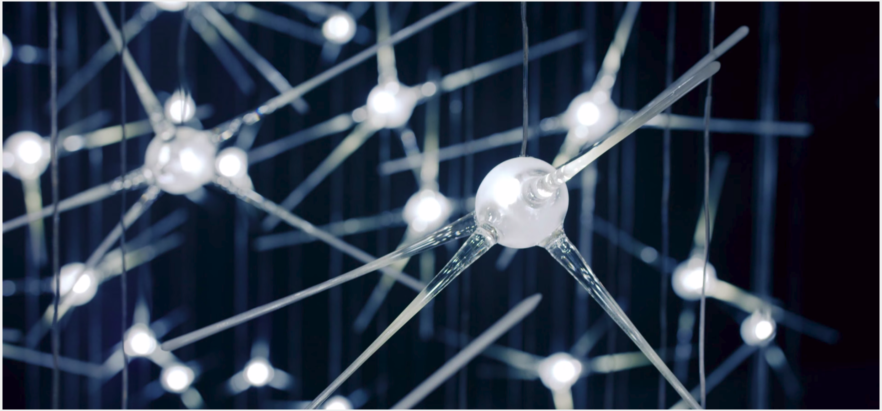


Figure: "Neurons" chandelier installed at Princh Mahidol Hall, Nakhon Pathom, Thailand (Courtesy: LASVIT’s promotion video)

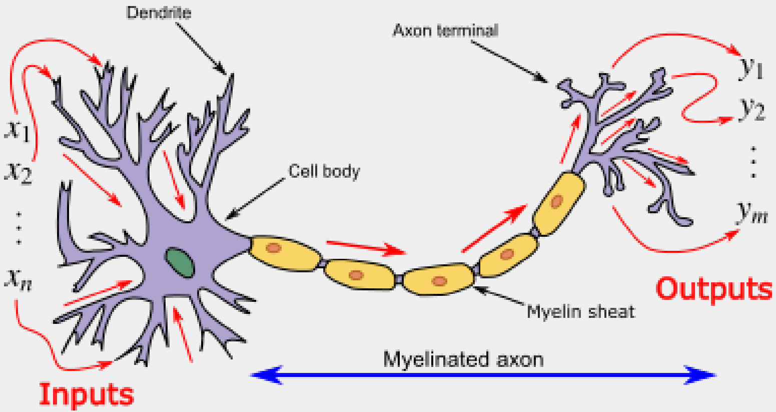
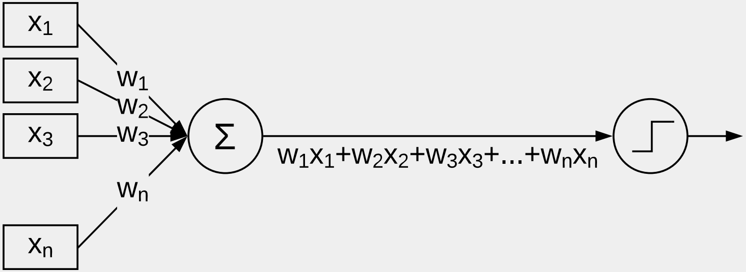
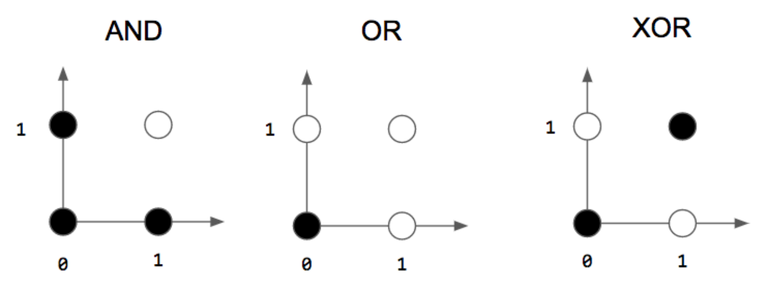


Figure: Neuron (Courtesy: Egm4313.s12 from Wikimedia Commons)



- **Inputs** consisting of *n* inputs from x_1, x_2 ... to x_n.
- **Weights** of each inputs, namely w_1, w_2, ..., w_n
- **Summation** of all the weighted inputs $\Sigma = w_1x_1 + w_2x_2 + \ldots + w_nx_n$
- **Activation function** in either the form of $\Sigma > k$ or $\Sigma < k(nonlinear)$

Logic gates with Perceptron



AND gate

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

OR gate

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

XOR gate

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

Linearly Separable Problem

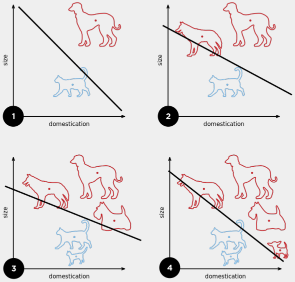


Figure: Linearly Separable Problem (Courtesy: Elizabeth Goodspeed from Wikimedia Commons)

- 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?

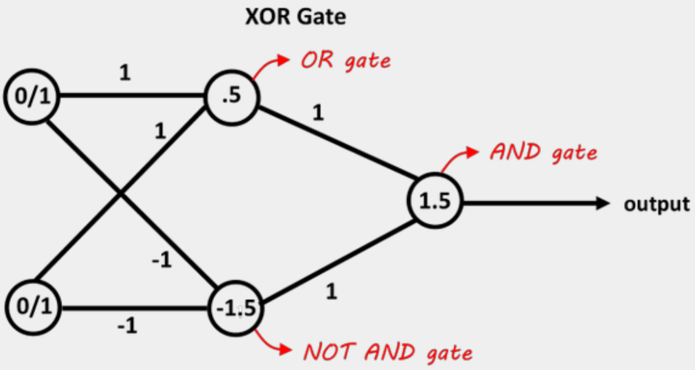


Figure: XOR gate with Perceptrons connected together (Courtesy: Parth Udawant)

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

Your next step into Machine Learning

Courses in KU-CPE to be taken

- Engineering Mathematics I
- Discrete Mathematics and Linear Algebra
- Aritificial Intelligence/Machine Learning

MOOCs

For practical use, go ahead with...

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

Thanks!

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