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 scikit-learn mlxtend`
- MNIST loader
  `pip install git+https://github.com/datapythonista/mnist.git`

Introduction to Machine Learning

What is Machine Learning?

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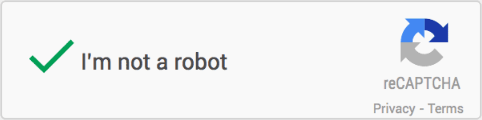

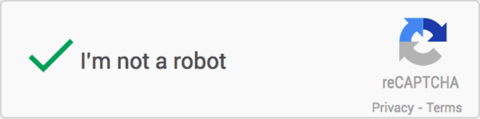

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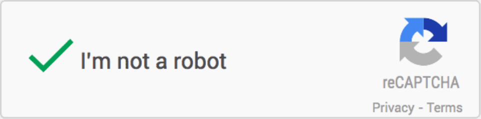

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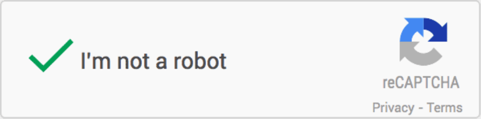

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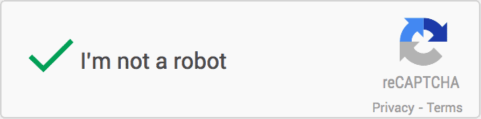

- This is Recaptcha.
  - Recaptcha helps stop millions of spam a day.
  - In some old days, we have to type Captcha texts to distinguish ourself from bots.
  - How is it possible that with a single click, an automated system can distinguish bots from humans?

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

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

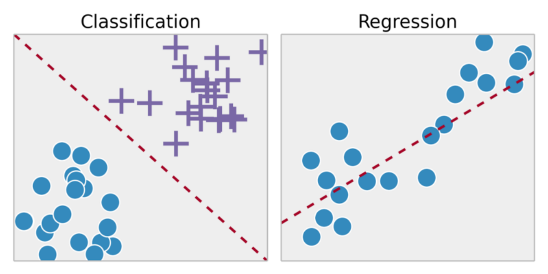
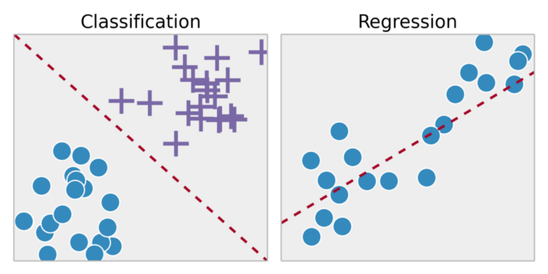


Figure: Supervised learning (Courtesy: Towards Data Science)



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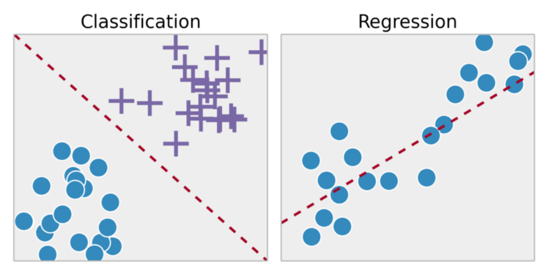

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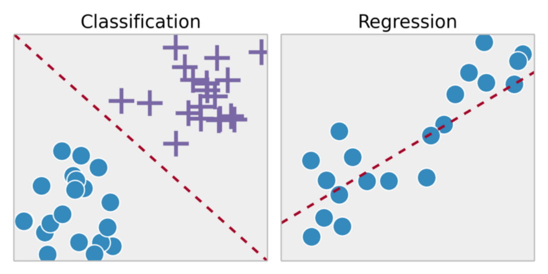
SUPERVISED LEARNING



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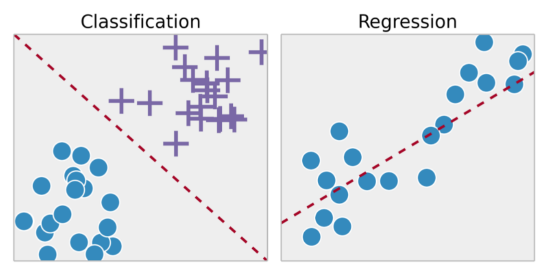

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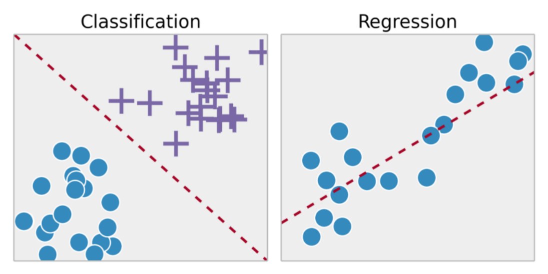

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- Two main supervised learning problems
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- Example problems: Spam E-mail detection, Facial recognition

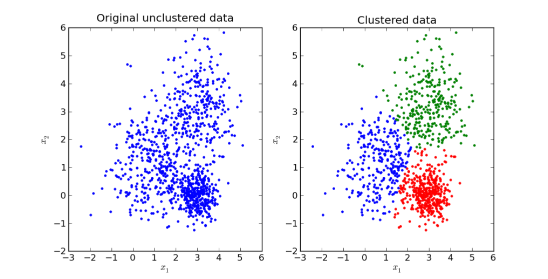
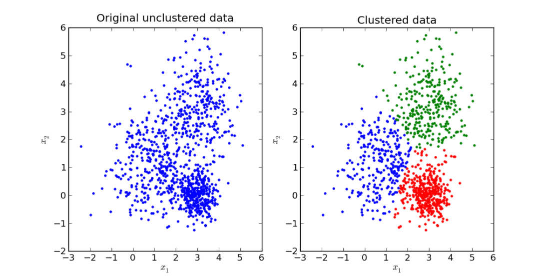


Figure: *k*-Means (Courtesy: Mubaris NK)



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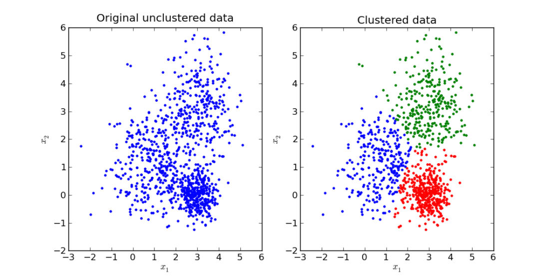

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- Discover **hidden** structure in **non-labelled** data.
- Example: Clustering, Generative models

Reinforcement learning

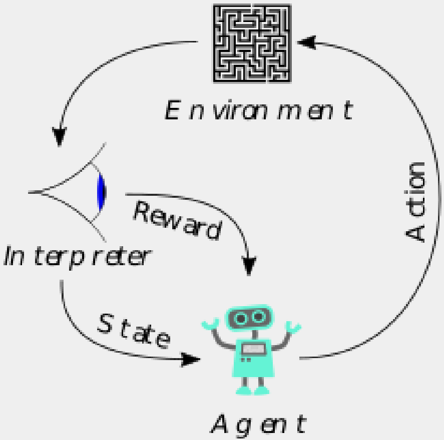

Figure: Reinforcement Learning (Courtesy: Megajuice from Wikimedia Commons)

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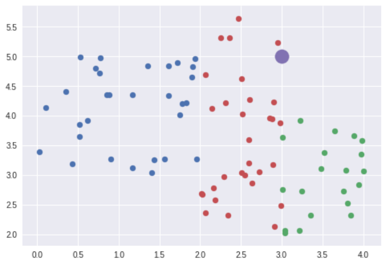

Data

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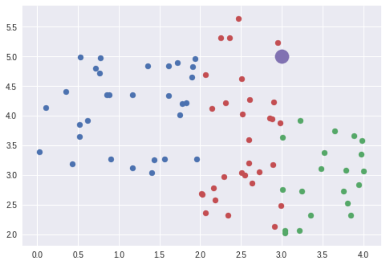

Determine which group should the purple dot be in (red/green/blue) by **checking the colour of its nearest dot.**

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 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

CHOOSING THE PARAMETER FOR k-NN ALGORITHM

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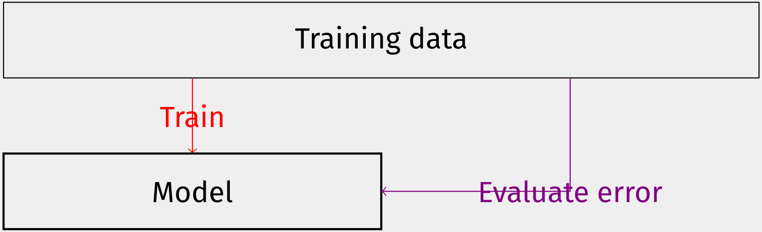
- What if we choose $k = 1$?
  - Let's try!

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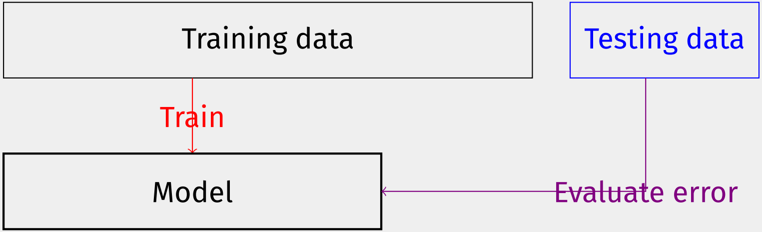
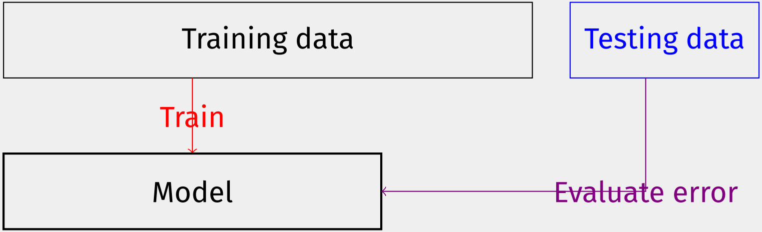
- Why? Because our model already knows the answer to that data point! It could just simply answer by looking at the "answer key"
- So how should we evaluate our model?


Training data
Testing data
Train
Model
Evaluate error



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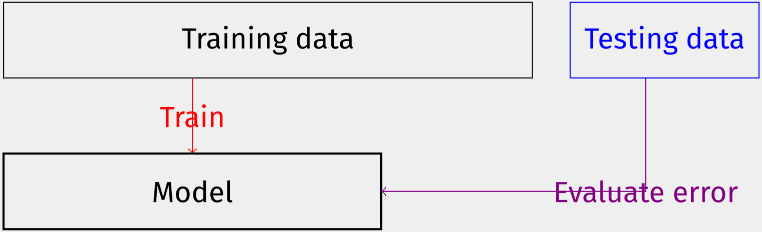
Training and Testing set



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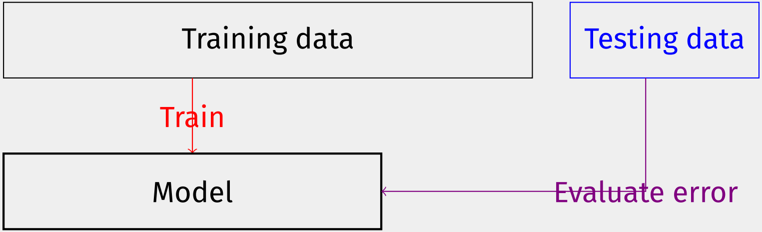

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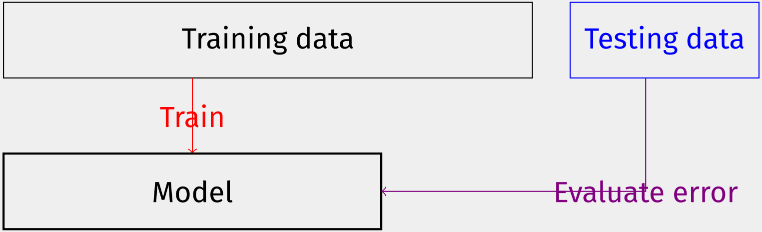
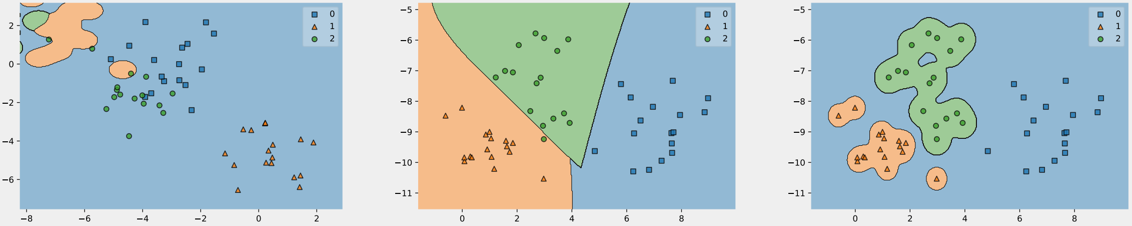


- We separate our dataset into 2 parts: the **training set** and **testing set**
  - Our model sees the correct label of the training set, but not the testing set.
  - We all know the correct label of both the training and testing set.
  - Teach our model with the training set, see how it performs with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

What will happen if...

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

Which decision region is good?



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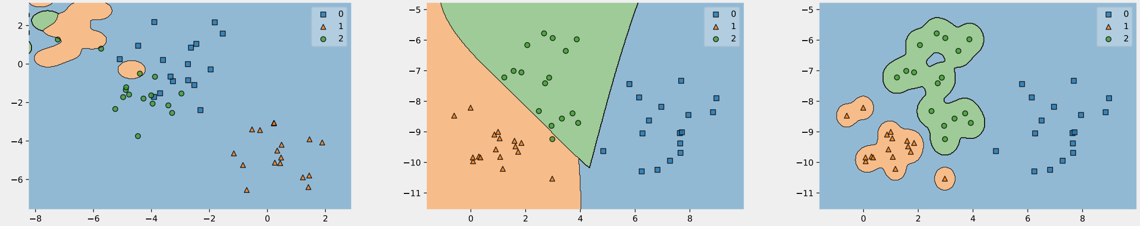

Underfit: The model fails to recognise data pattern

Overfitting and underfitting

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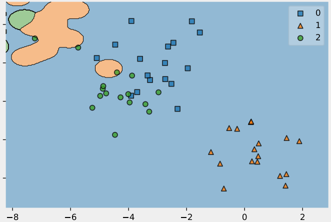

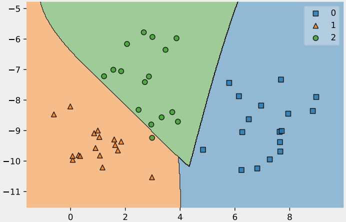

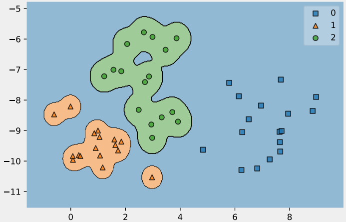

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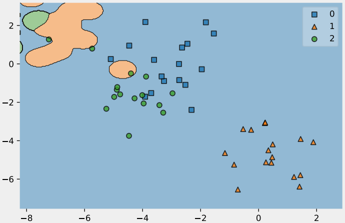

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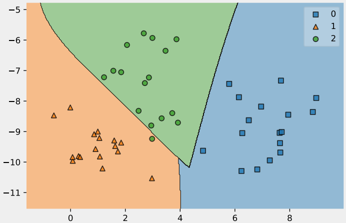
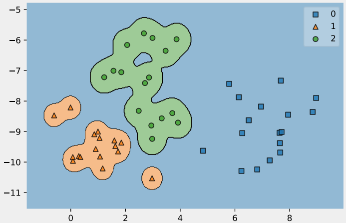


Good fit: The model recognises data pattern **generally**



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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**.

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

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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Norm for k-NN algorithm

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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)
- l_∞ Norm: $|x|_\infty = \max(x_1, x_2, ..., x_n)$ (Maximum norm)

Algorithms for Machine Learning Classification Problem

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- Logistic Regression

Naïve Bayes

	Gender	Hair
1	M	Long
2	M	Short
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Can we *guess* the gender from hair's length?

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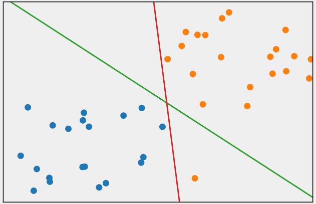
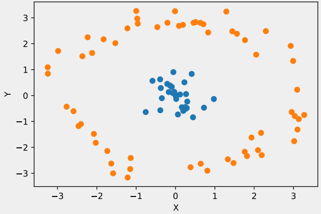
Can we *guess* the gender from hair's length?

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

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




Y
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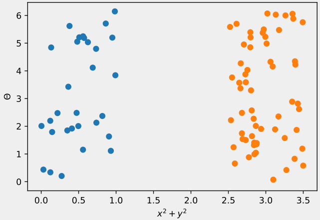
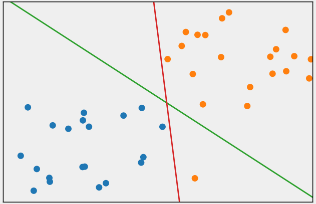
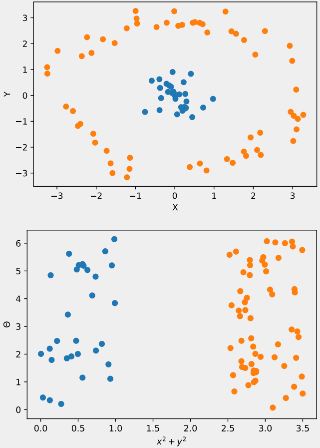

Θ
$x^2 + y^2$

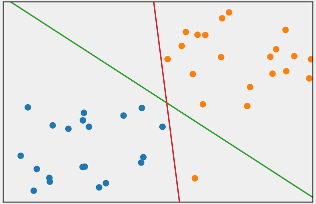
Support Vector Machines (SVM)

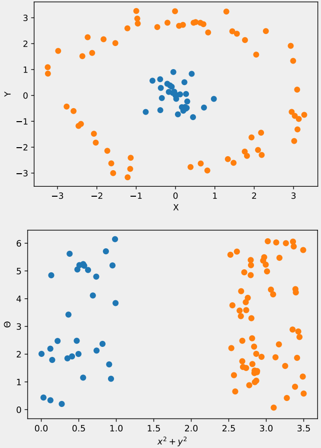




- Goal: to draw a line to separate groups of data

Support Vector Machines (SVM)





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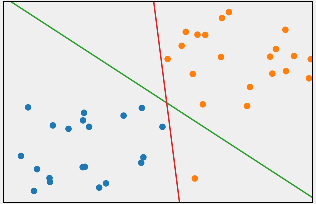
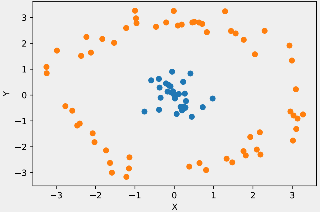
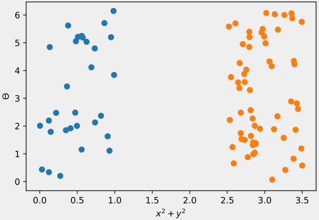
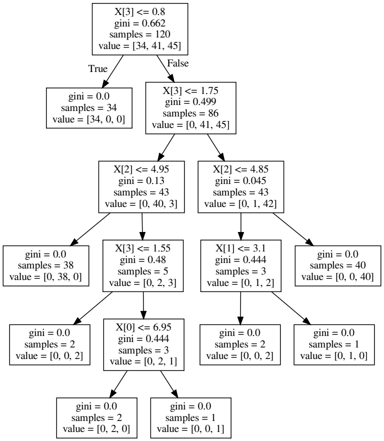


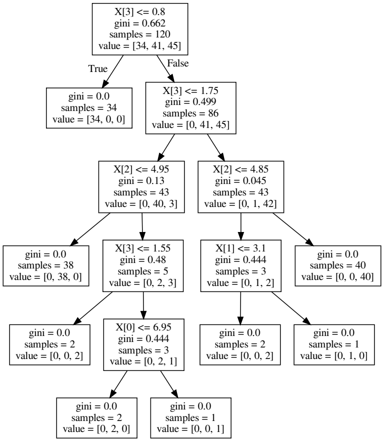




- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distant between the line and classes of data points
- What if the data is not linearly separable? **Kernel tricks**

Decision Tree





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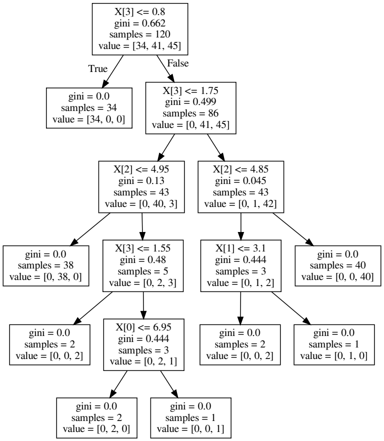


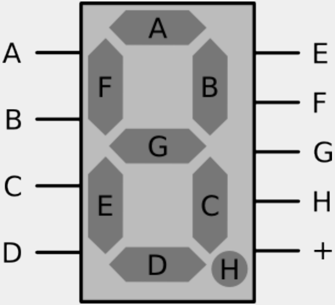
- Creating an if-else conditions automatically
- Nested conditions with a parameter to determine how does the separating of the "tree" performs.

Figure: xkcd - Compiling

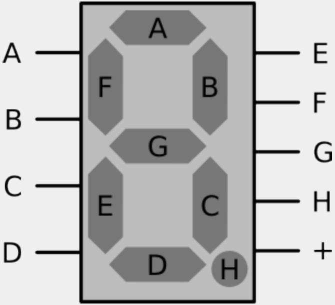
Figure: xkcd - Compiling (shamelessly modified)

Problems for Machine Learning

7-Segment display



7-Segment display



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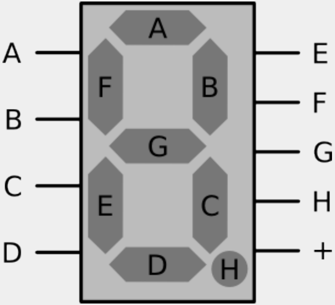
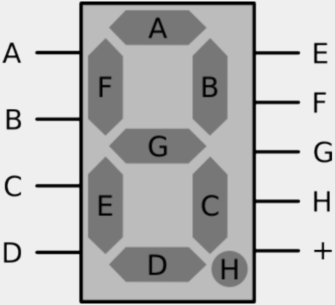


- This is a 7-segment display.
- It consists of a bulb labelled from A-G that could form a number.



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

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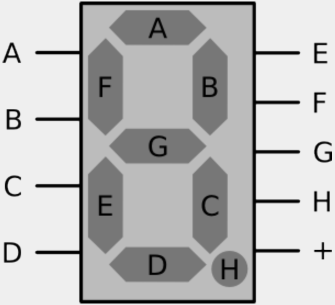

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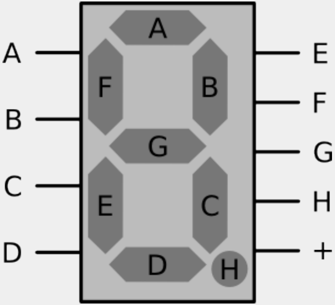
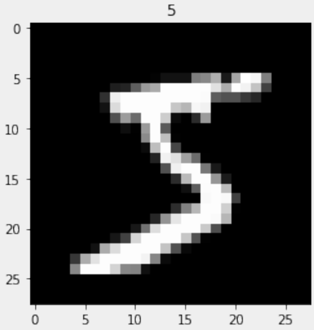


Problem

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

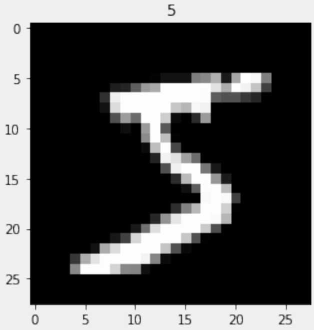
Not only yes, but *easily* yes!

```
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!

Figure: MNIST Dataset (Courtesy: LeCun, Towards Data Science)

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

MNIST Dataset

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MNIST Dataset

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  - 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

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k-NN WITH MNIST

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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

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- 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

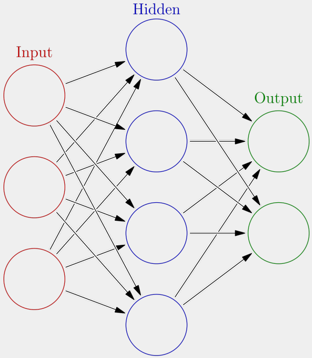


Figure: Neural network (Courtesy: Glosser.ca from Wikimedia Commons)

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

Neurons

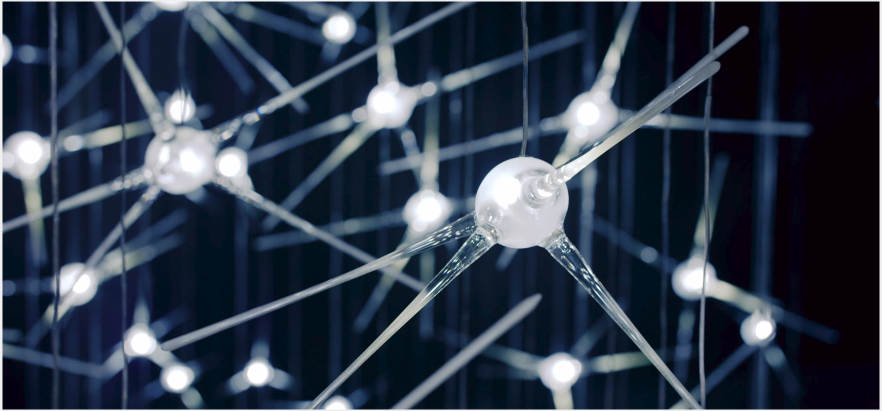


Figure: "Neurons" chandelier installed at Prince Mahidol Hall, Nakhon Pathom, Thailand (Courtesy: LASVIT's promotion video)

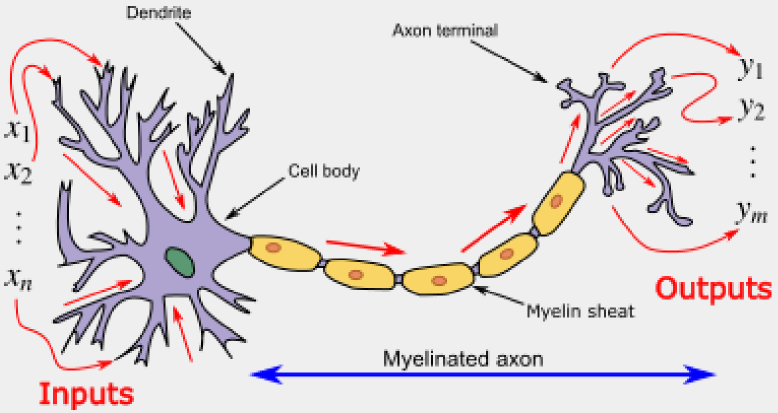
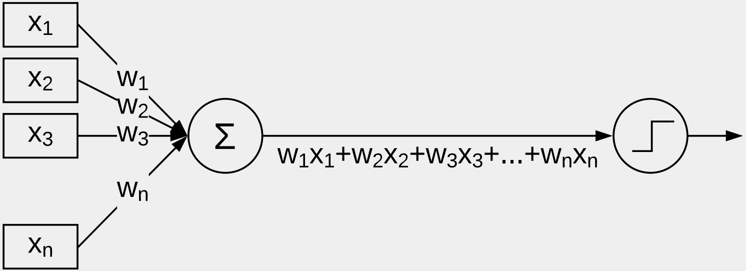
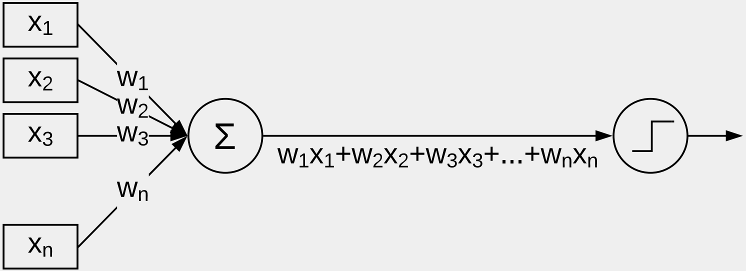


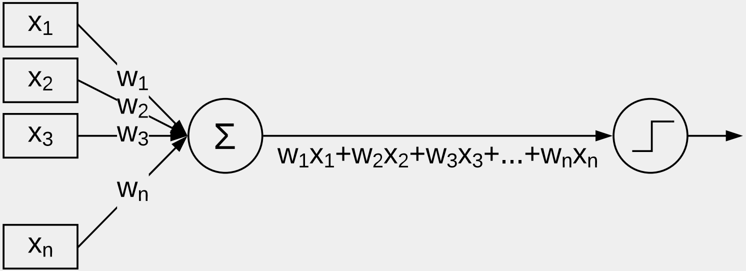
Figure: Neuron (Courtesy: Egm4313.s12 from Wikimedia Commons)

Perceptron





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



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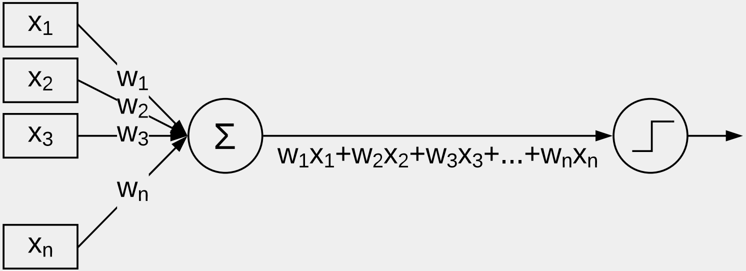

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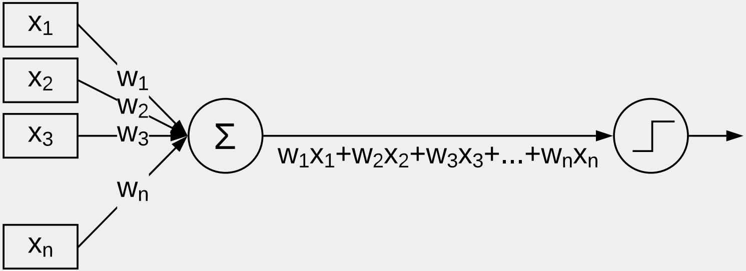

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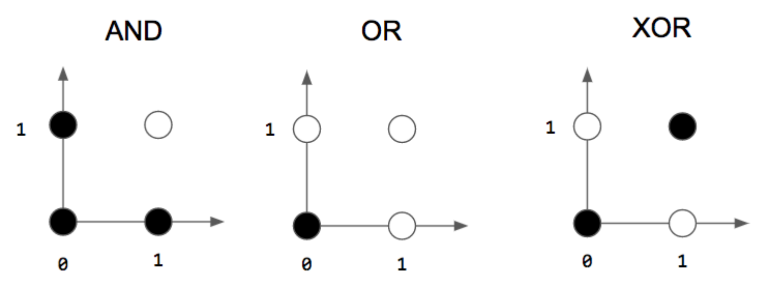
- **Summation** of all the weighted inputs $\Sigma = w_1x_1 + w_2x_2 + \ldots + w_nx_n$
- **Activation function** in either the form of $\Sigma > k$ or $\Sigma < k(nonlinear)$

Logic gates with Perceptron



Logic gates with Perceptron

AND gate

OR gate

XOR gate

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

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XOR gate

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

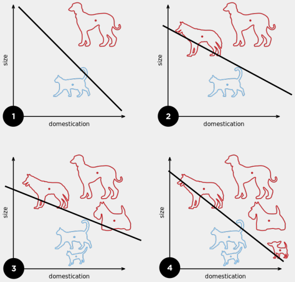

Figure: Linearly Separable Problem (Courtesy: Elizabeth Goodspeed from Wikimedia Commons)

- 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?

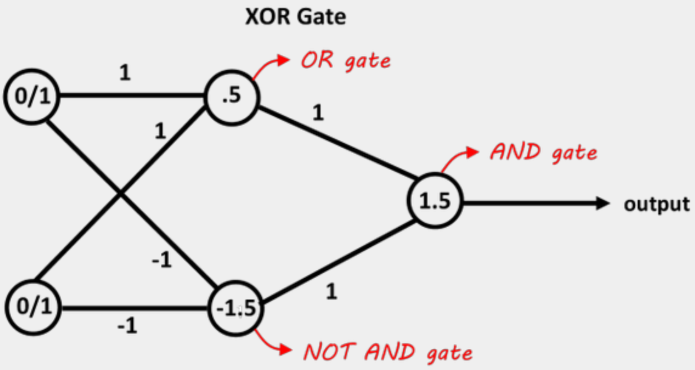

Figure: XOR gate with Perceptrons connected together (Courtesy: Parth Udawant)

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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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- 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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- 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)

Questions and Answers

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)

CU Cancer Immunotherapy Fund

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