

MACHINE LEARNING: WHAT IS?

A FIRST STEP TO PRACTICAL MACHINE LEARNING

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STUDENT, KASETSART U.

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

1 Introduction to Machine Learning

- What is Machine Learning?

2 Machine Learning Problems

- Supervised learning
- Unsupervised learning
- Reinforcement learning

3 Model

- The Goal of Machine Learning

4 Machine Learning Process

- Evaluating Machine Learning Performance

5 Algorithms for Machine Learning Classification Problem

6 Problems for Machine Learning

- Handwriting recognition

7 Neural Networks

8 Challenges in Machine Learning Problems

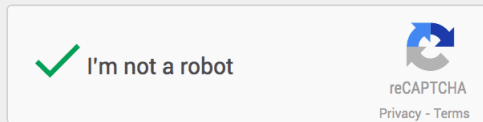
9 Your next step into Machine Learning

10 Questions and Answers

INTRODUCTION TO MACHINE LEARNING

WHAT IS MACHINE LEARNING?

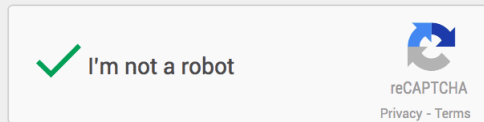
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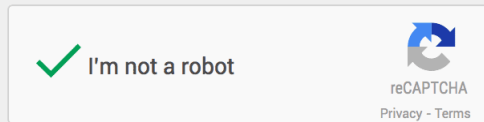
WHAT IS MACHINE LEARNING?



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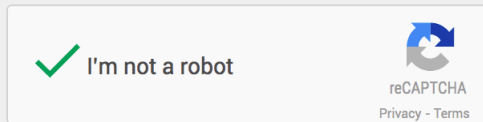


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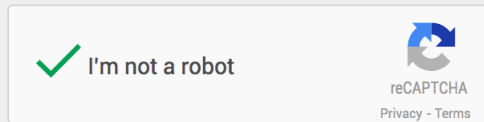
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WHAT IS MACHINE LEARNING?



■ 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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SUPERVISED LEARNING

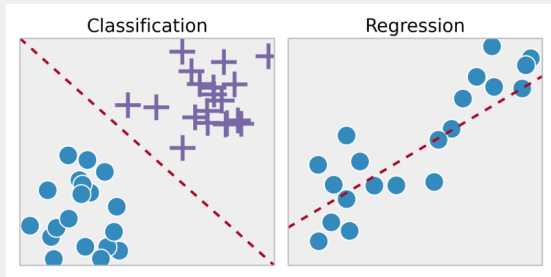


Figure: Supervised learning (Courtesy: Towards Data Science)

SUPERVISED LEARNING

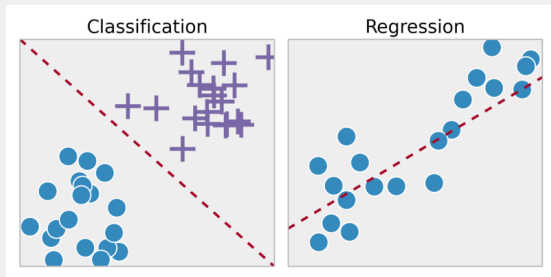


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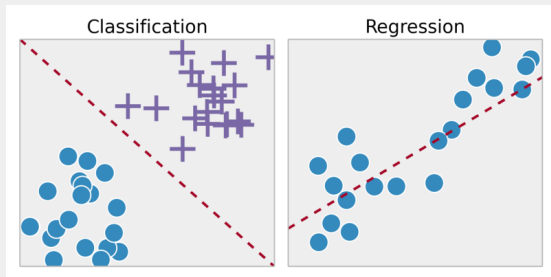


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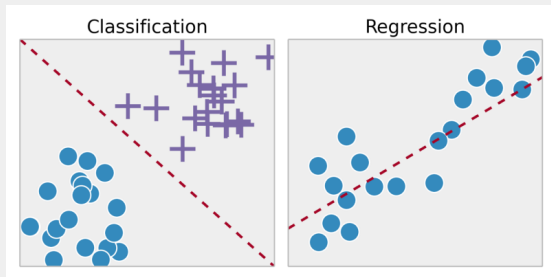


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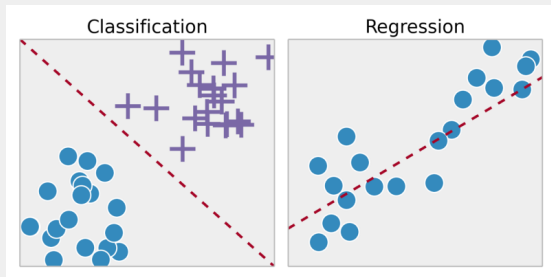


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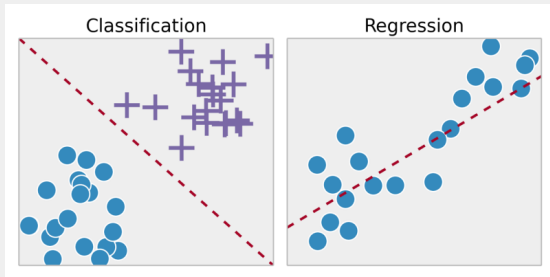


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- Two main supervised learning problems
 - ▶ Classification: On the discrete data
 - ▶ Regression: On the continuous data
- Example problems: Spam E-mail detection, Facial recognition

UNSUPERVISED LEARNING

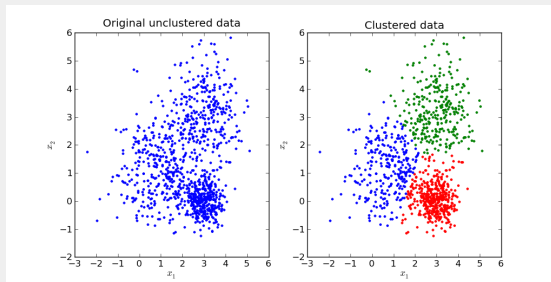


Figure: k -Means (Courtesy: Mubaris NK)

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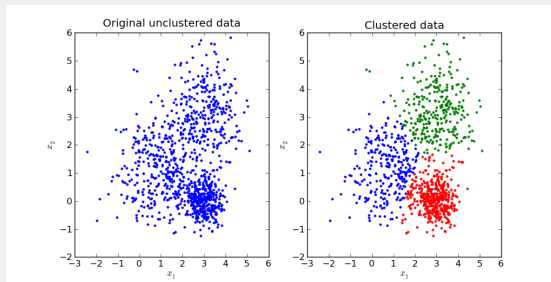


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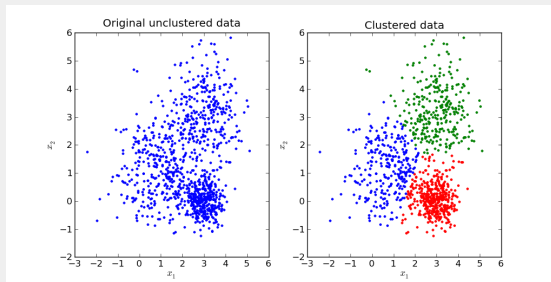


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- Discover **hidden** structure in **non-labelled** data.
- Example: Clustering, Generative models

REINFORCEMENT LEARNING

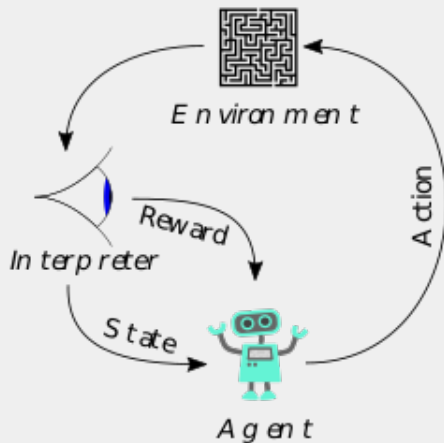


Figure: Reinforcement Learning (Courtesy: Megajuce from Wikimedia Commons)

MODEL

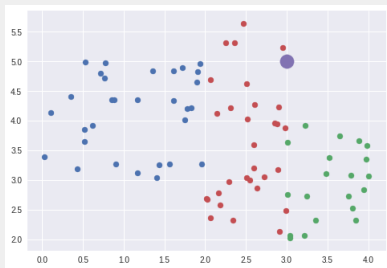
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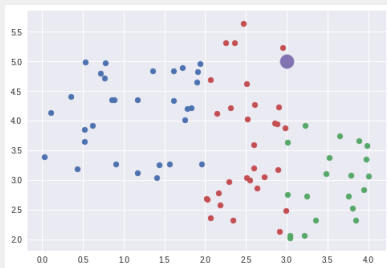
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Data

MODEL

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Data

Method

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

THE GOAL OF MACHINE LEARNING

Generalise

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- We want our model to know how 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

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

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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

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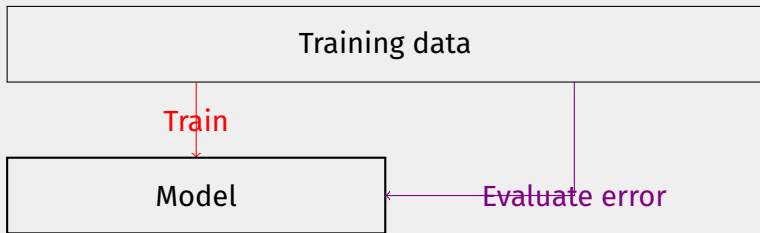
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 - ▶ Answer: Our model will always answer the labels with the highest data point count.
- What if we choose $k = 1$?
 - ▶ Let's try!

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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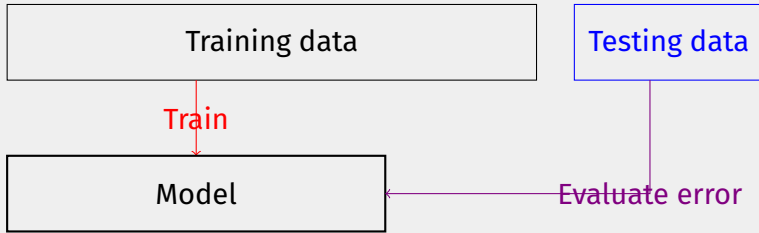
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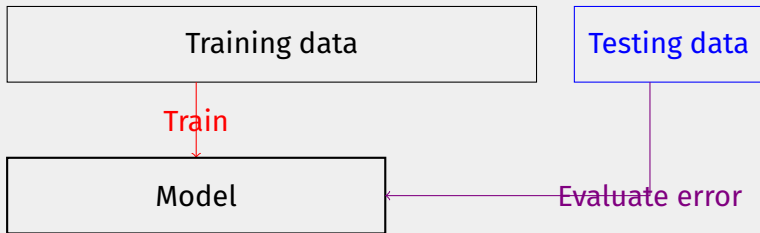
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- So how should we evaluate our model?

TRAINING AND TESTING SET

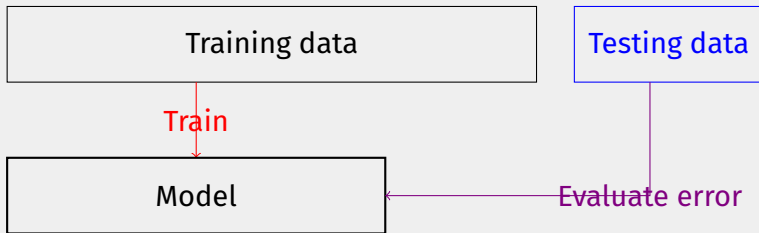


TRAINING AND TESTING SET



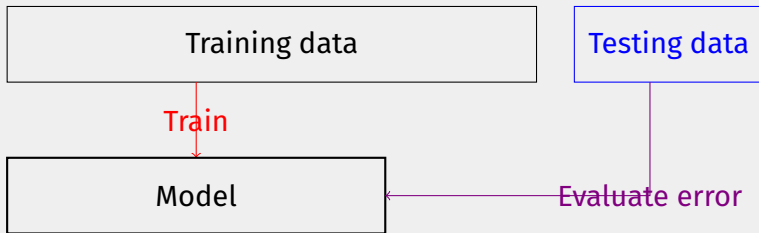
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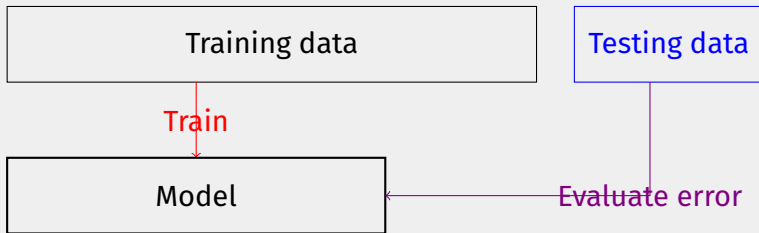
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 - ▶ Our model sees the correct label of the training set, but not the testing set.
 - ▶ We all know the correct label of both the training and testing set.
 - ▶ Teach our model with the training set, see how it performs with the testing set.

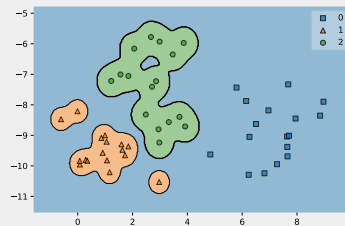
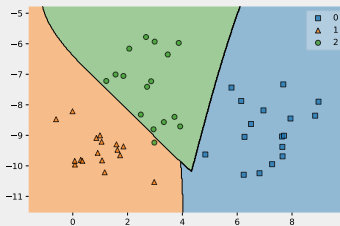
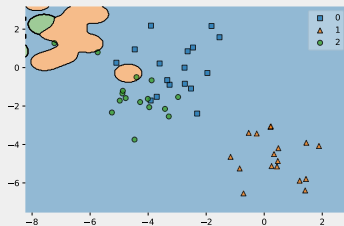
CHOOSING THE BEST k

What will happen if...

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

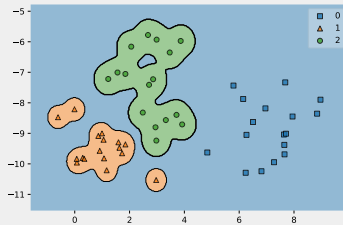
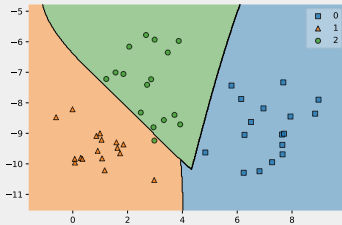
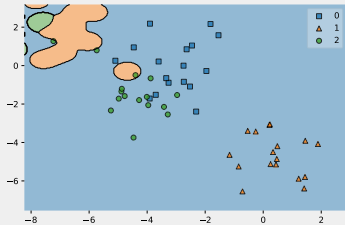
OVERFITTING AND UNDERFITTING

Which decision region is good?



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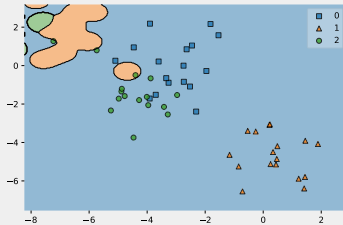
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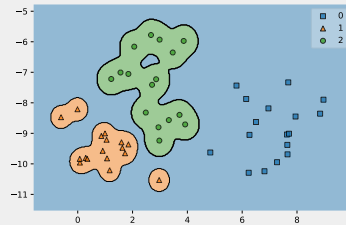
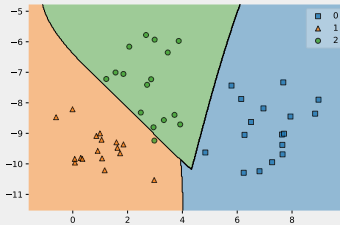
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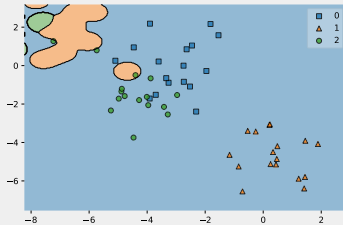
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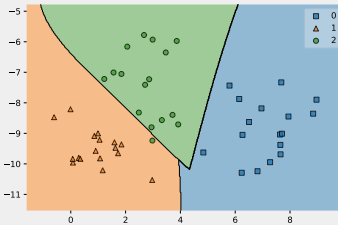
Overfit: The model **remembers** data pattern instead of generalising.

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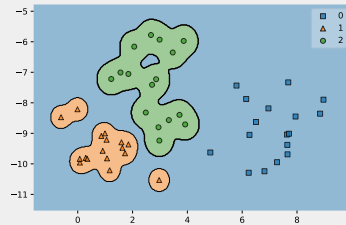
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Underfit: The model fails to recognise data pattern



Good fit: The model recognises data pattern generally



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

Good model must **generalise**

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

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

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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_1 Norm: $|x|_1 = \sum_{i=0}^N |x_i|$ (Manhattan)
- l_2 Norm: $|x|_2 = \sqrt{\sum_{i=0}^N x_i^2}$ (Euclidian)
- l_p Norm: $|x|_p = (\sum_{i=1}^n |x_i|^p)^{1/p}$ (Minkowski)
- l_∞ Norm: $|x|_\infty = \max(x_1, x_2, \dots, x_n)$ (Maximum norm)

ALGORITHMS FOR MACHINE LEARNING CLASSIFI- CATION PROBLEM

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NAÏVE BAYES

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

NAÏVE BAYES

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

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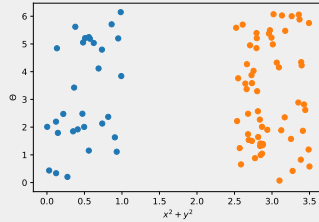
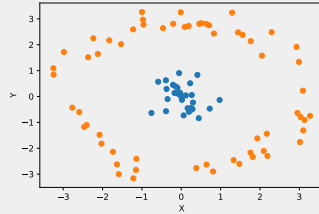
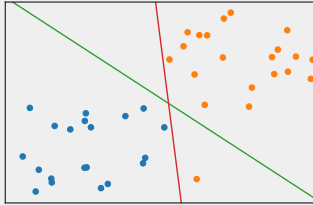
- $P(\text{Female}|\text{Long hair}) = \frac{2}{3}$

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

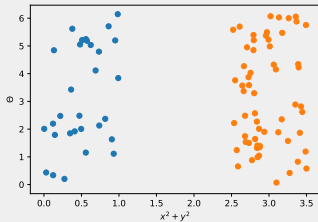
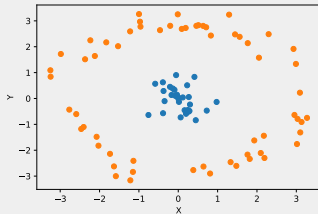
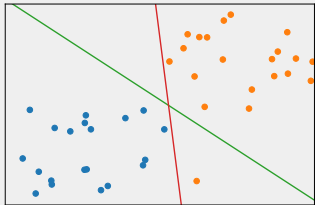
Bayes Theorem

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

SUPPORT VECTOR MACHINES (SVM)

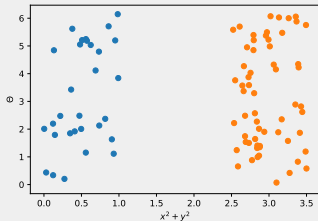
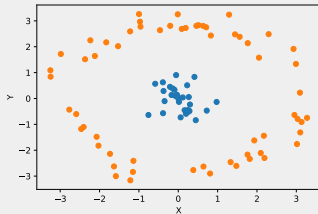
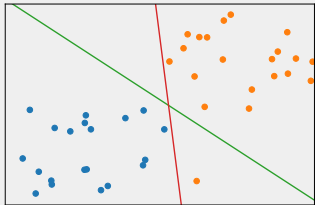


SUPPORT VECTOR MACHINES (SVM)



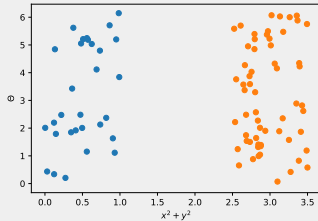
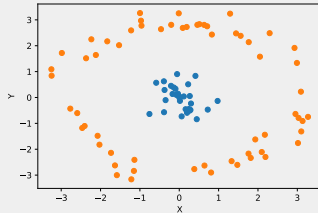
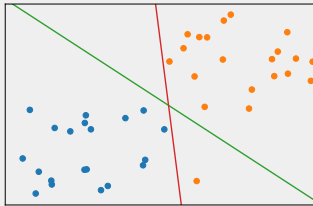
- Goal: to draw a line to separate groups of data

SUPPORT VECTOR MACHINES (SVM)



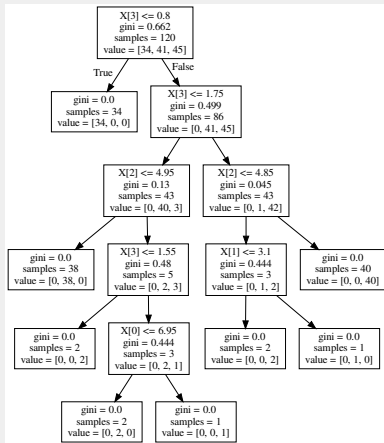
- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distance between the line and classes of data points

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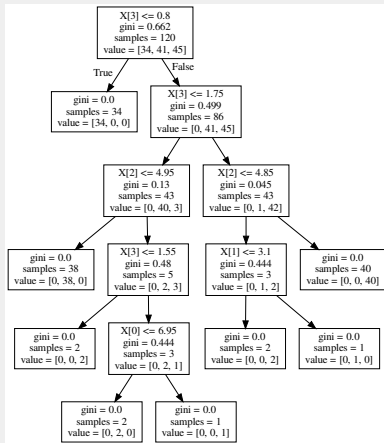


- Goal: to draw a line to separate groups of data
- Ideal good line: maximising the distance between the line and classes of data points
- What if the data is not linearly separable? **Kernel tricks**

DECISION TREE

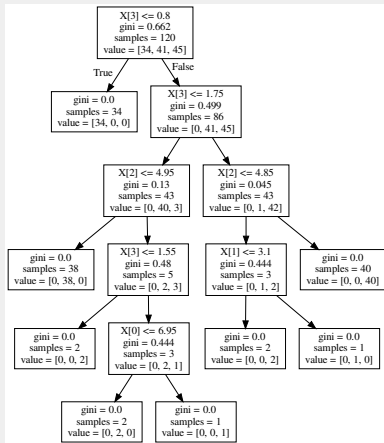


DECISION TREE



■ Creating an if-else conditions automatically

DECISION TREE



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



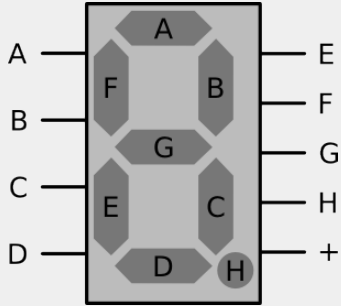
Figure: xkcd - Compiling



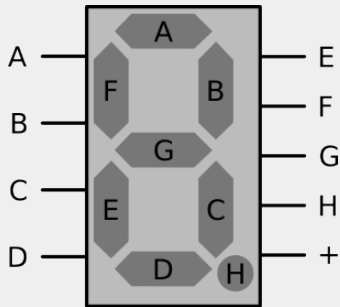
Figure: xkcd - Compiling (shamelessly modified)

PROBLEMS FOR MACHINE LEARNING

7-SEGMENT DISPLAY

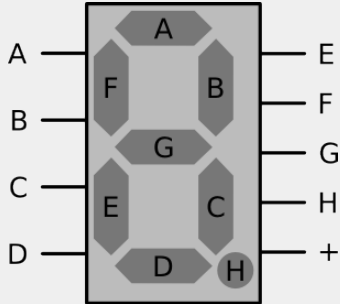


7-SEGMENT DISPLAY



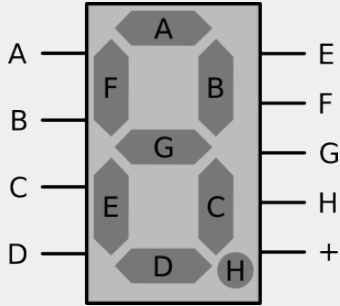
■ This is a 7-segment display.

7-SEGMENT DISPLAY



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

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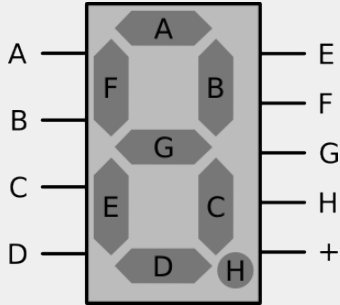


- This is a 7-segment display.
- It consists of a bulb labelled from A-G that could form a number.

Problem

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

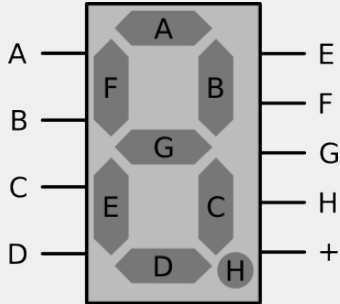
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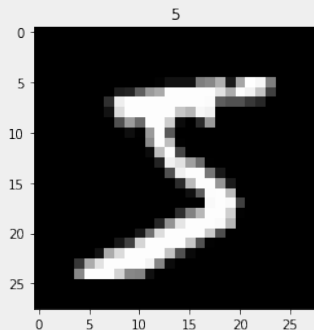


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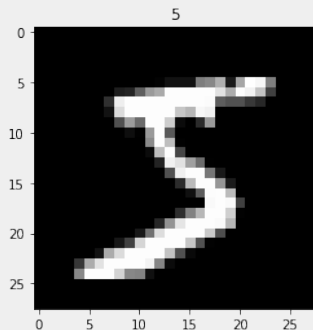
Not only yes, but *easily* yes!

```
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



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

MNIST DATASET



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

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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

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- 60,000 training images

MNIST DATASET



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

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

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

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(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.

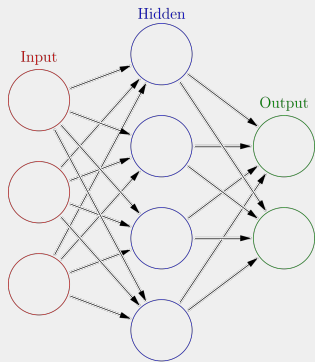
- Training: Slow as hell.

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)



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

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

NEURONS

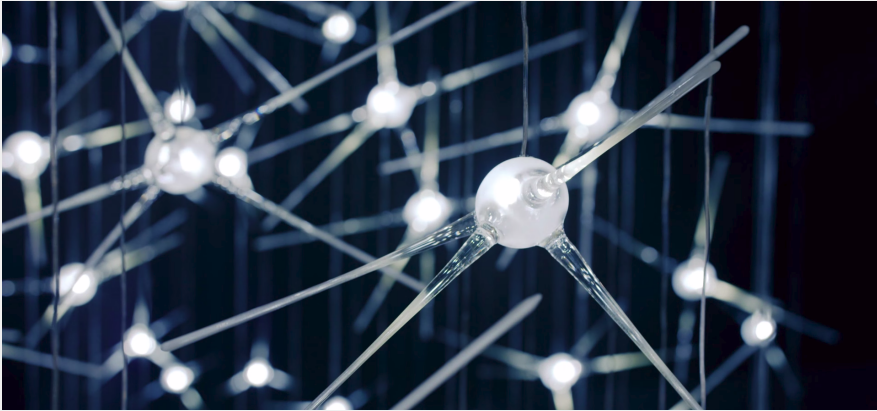


Figure: "Neurons" chandelier installed at Prince Mahidol Hall, Nakhon Pathom, Thailand
(Courtesy: LASVIT's promotion video)

NEURON

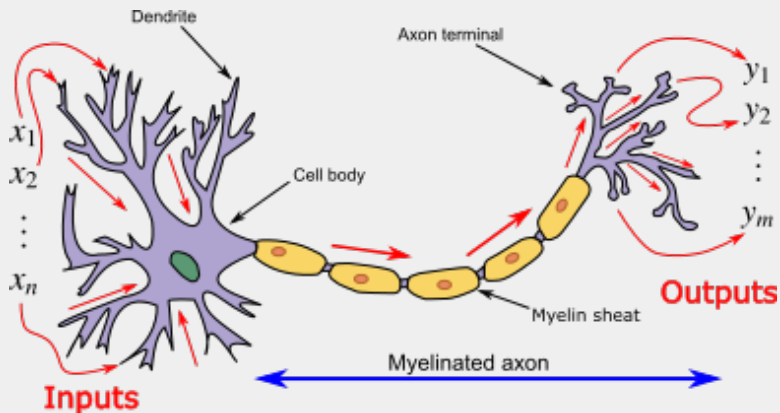
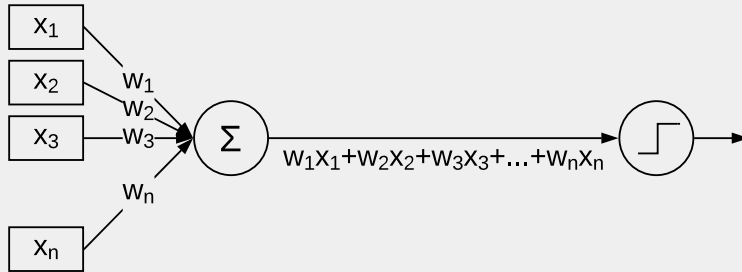
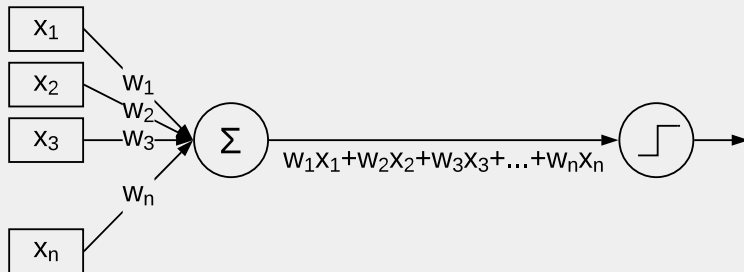


Figure: Neuron (Courtesy: Egm4313.s12 from Wikimedia Commons)

PERCEPTRON

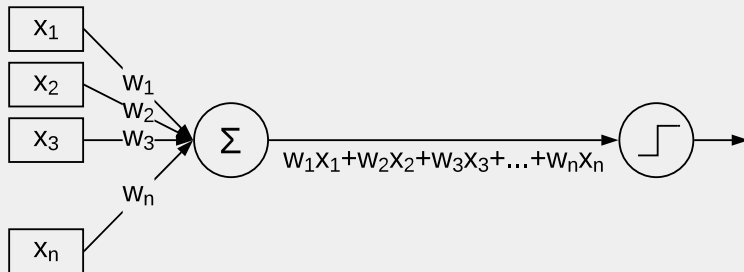


PERCEPTRON



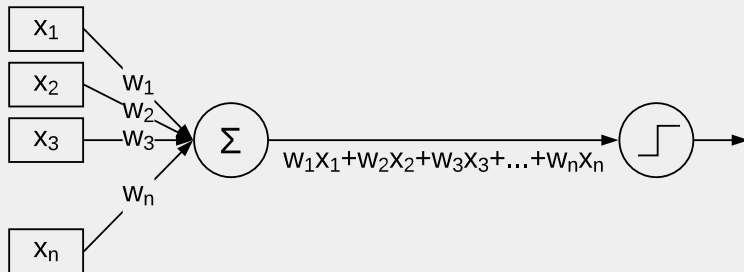
- **Inputs** consisting of n inputs from $x_1, x_2 \dots$ to x_n .

PERCEPTRON



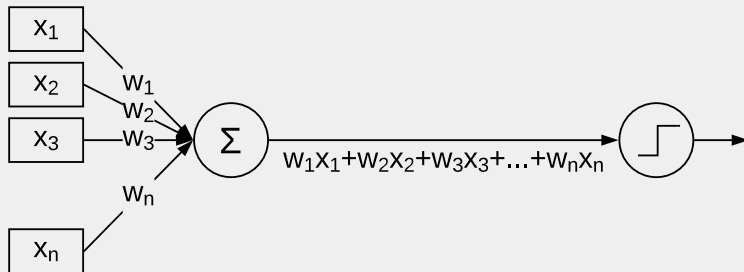
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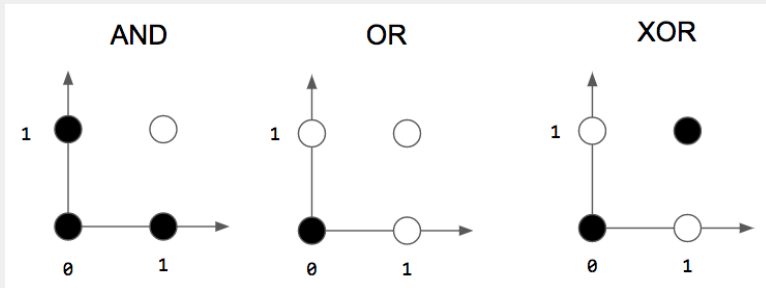
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PERCEPTRON



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

LOGIC GATES WITH PERCEPTRON



LOGIC GATES WITH PERCEPTRON

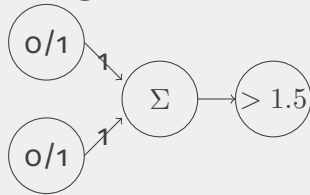
AND gate

OR gate

XOR gate

LOGIC GATES WITH PERCEPTRON

AND gate

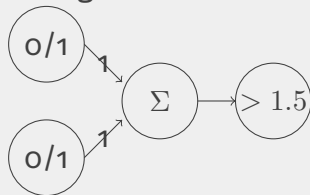


OR gate

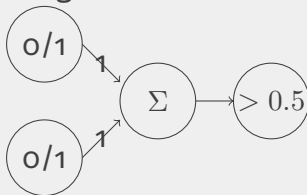
XOR gate

LOGIC GATES WITH PERCEPTRON

AND gate



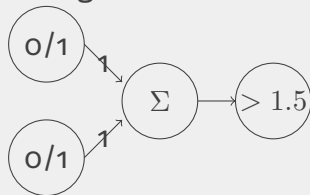
OR gate



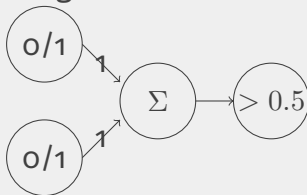
XOR gate

LOGIC GATES WITH PERCEPTRON

AND gate



OR gate



XOR gate

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

LINEARLY SEPARABLE PROBLEM

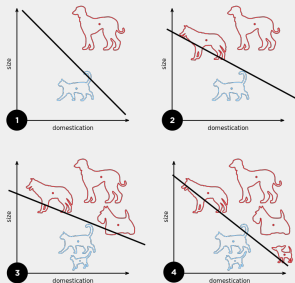


Figure: Linearly Separable Problem
(Courtesy: Elizabeth Goodspeed
from Wikimedia Commons)

- 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?

LINEARLY SEPERABLE?

AND gate

OR gate

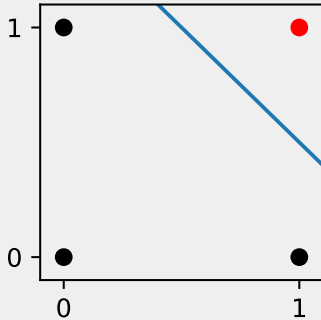
XOR gate

LINEARLY SEPERABLE?

AND gate

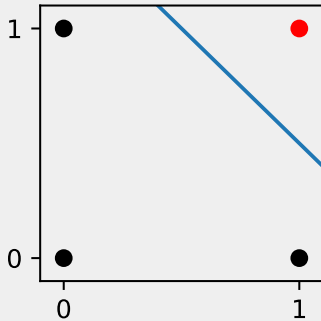
OR gate

XOR gate

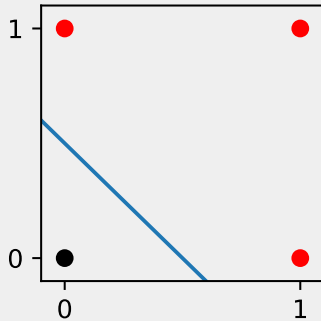


LINEARLY SEPERABLE?

AND gate



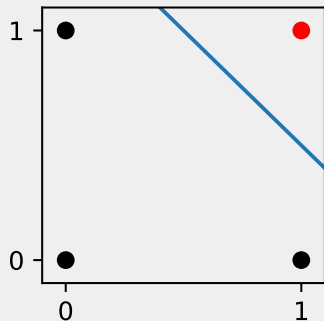
OR gate



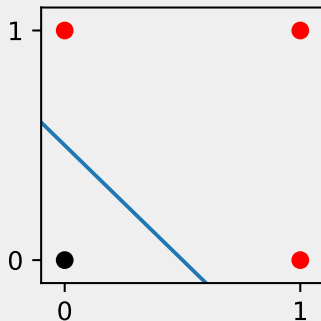
XOR gate

LINEARLY SEPERABLE?

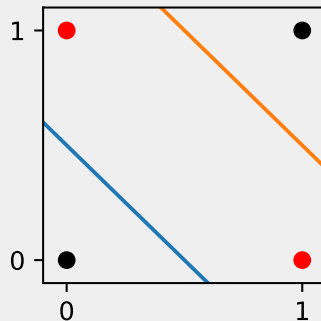
AND gate



OR gate



XOR gate



SOLUTION FOR XOR GATE

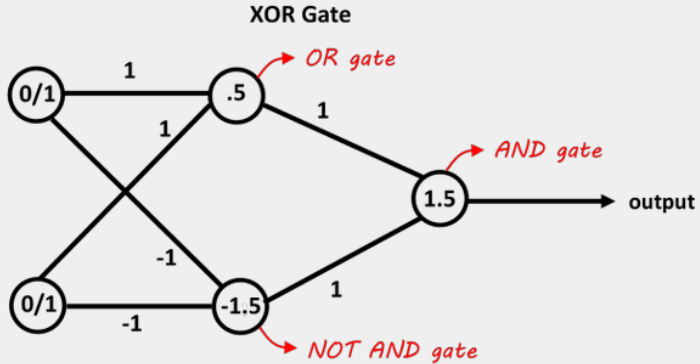


Figure: XOR gate with Perceptrons connected together (Courtesy: Parth Udawant)

How are the weights of each dendrites (inputs) are automatically adjusted?

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■ Through a **backpropagation** Process

- ▶ Initiate weights randomly
- ▶ Calculate the error over the training set
- ▶ Attempts to adjust weights little by little to minimise loss

(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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$$0.87^5 = 0.4984$$

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- **More than half of the letter/parcel's postal code will be wrongly labelled!**
- Can we do better? How?
- Error rate of 0.35% were achieved by neural networks for the MNIST problem.

CHALLENGES IN MACHINE LEARNING PROBLEMS



Figure: xkcd - Tasks



Problem's complexity

Figure: xkcd - Tasks



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Problem's complexity

- Although looked similar, some problems are much more complex than it looks



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- **CIFAR-10**, a 32*32 pixel RGB images of 10 classes



Figure: xkcd - Tasks

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

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THERE ARE MORE THINGS TO LEARN SO

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

COURSES IN KU-CPE TO BE TAKEN

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

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://www.facebook.com/srakrn_sirakorn.l@ku.th

(2-shots or 10-seconds handshake with me after this course are totally welcomed)

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