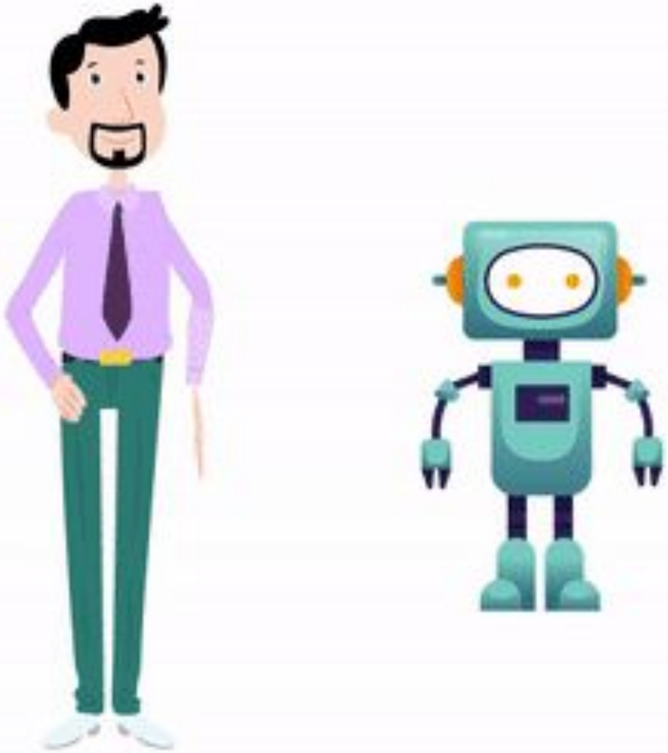
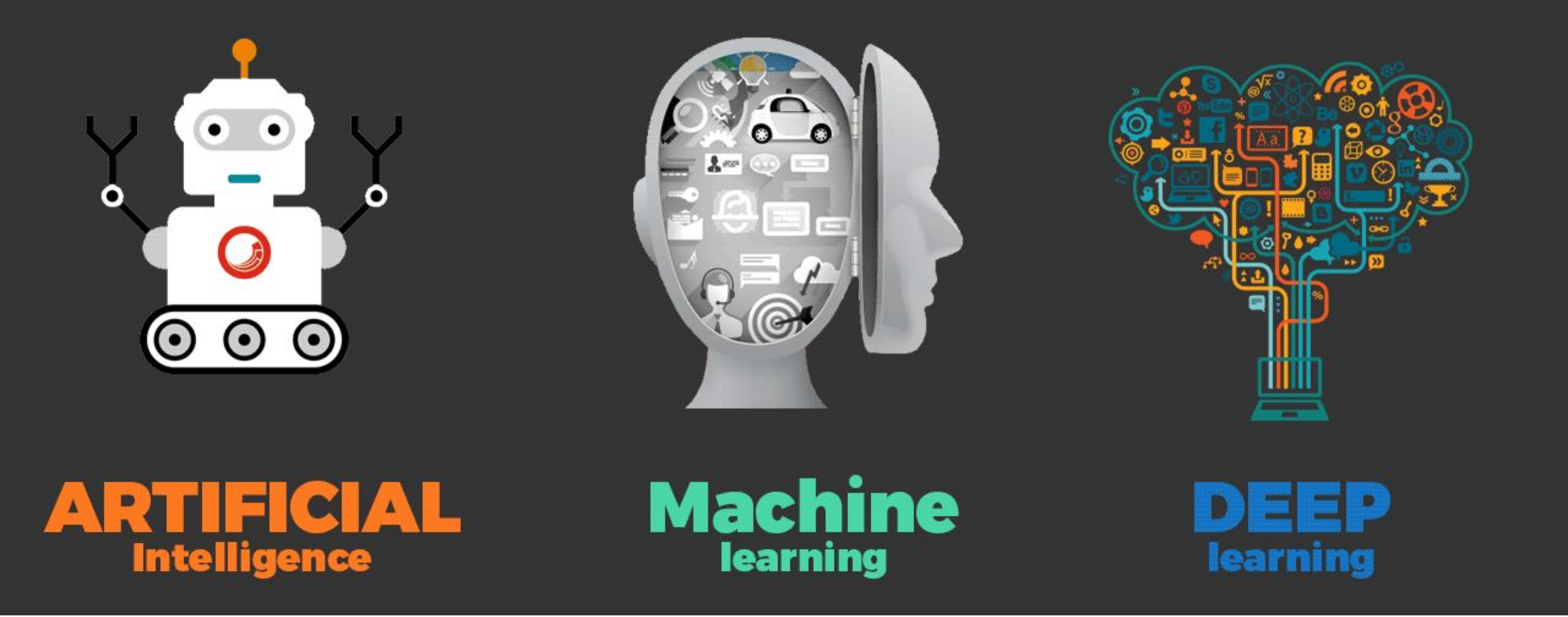
Support Vector Machine



How to train your machine



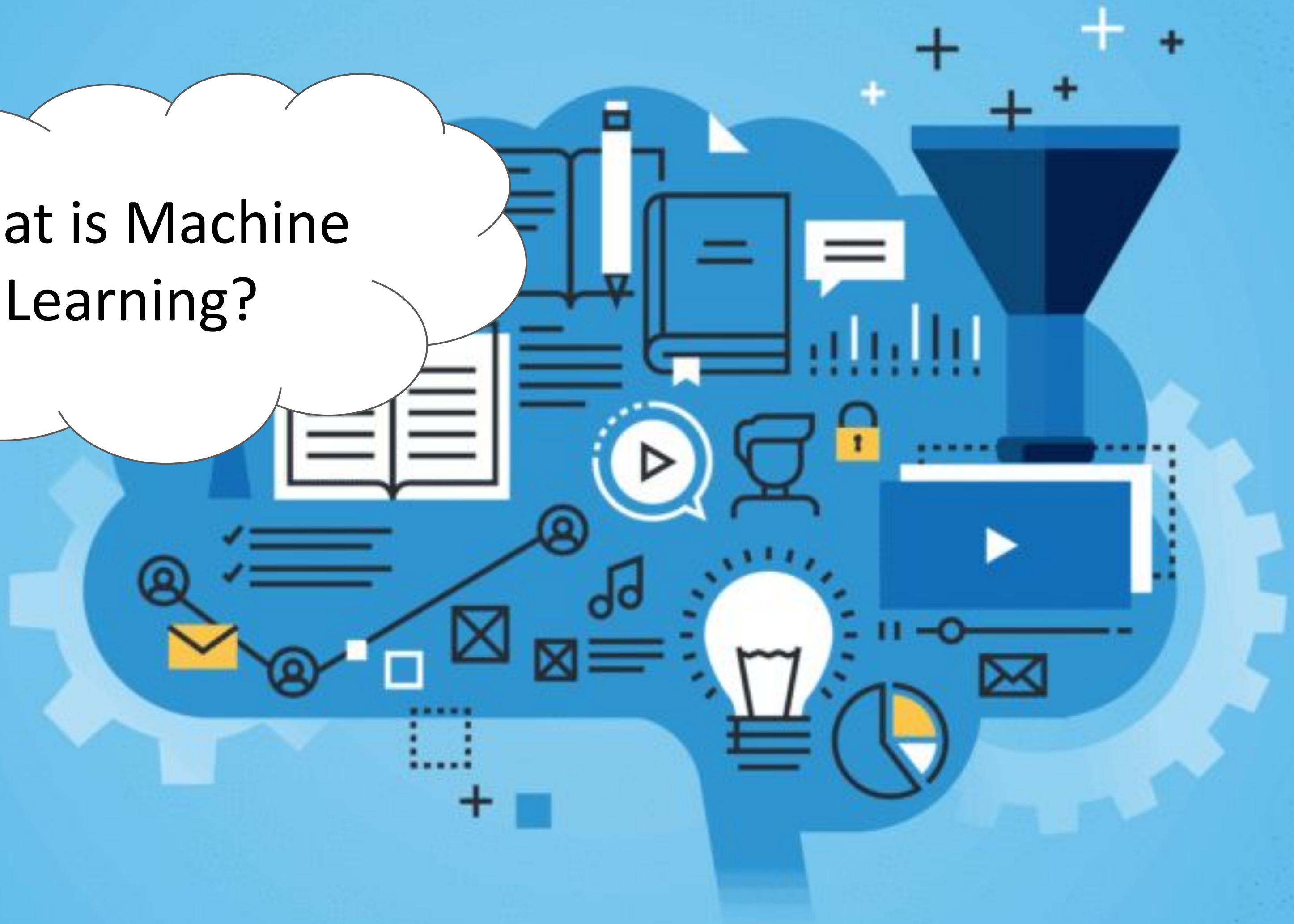
HOW TO TRAIN YOUR MACHINE

AI enables the machine to think and take its own decision

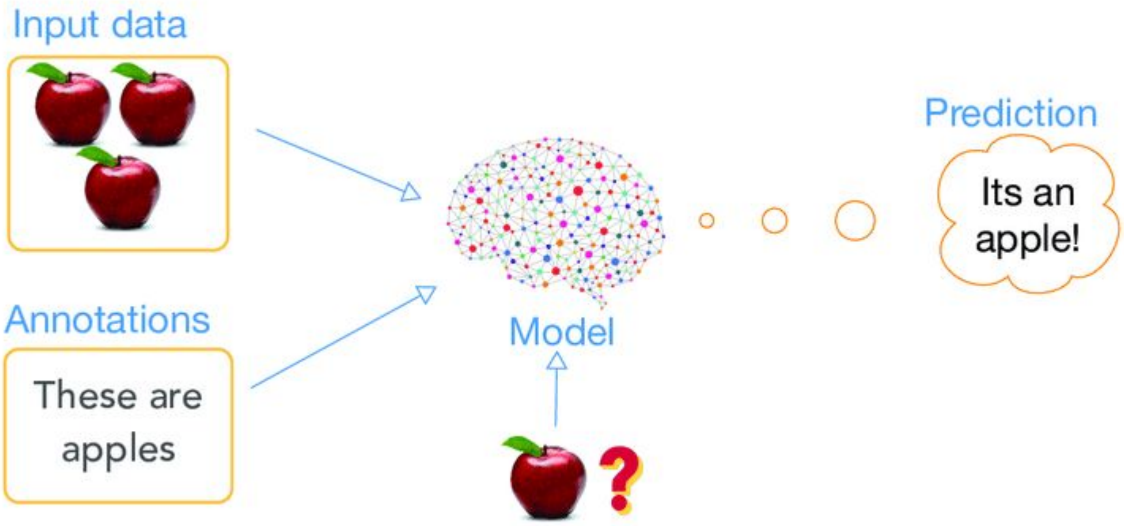
Deep Learning is basically mimicking the human brain

uses statistical learning algorithms to build systems that can automatically learn and improve from experiences

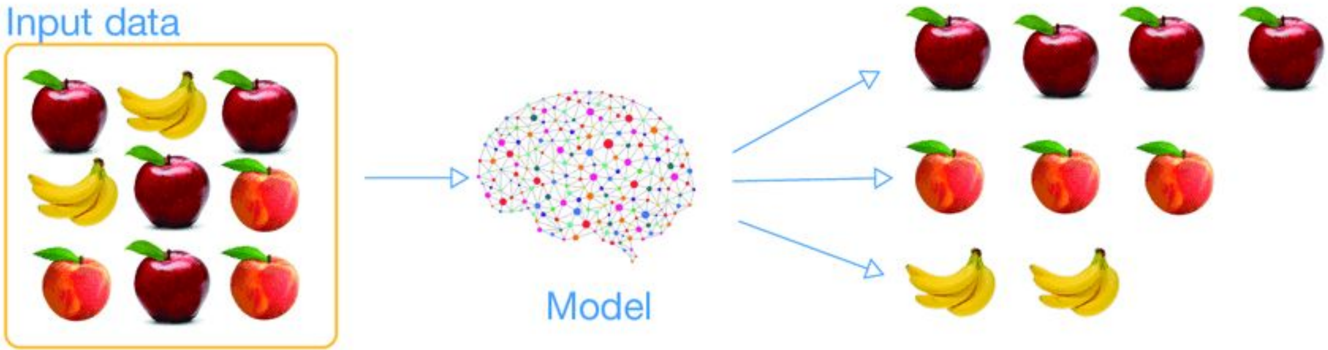
What is Machine Learning?



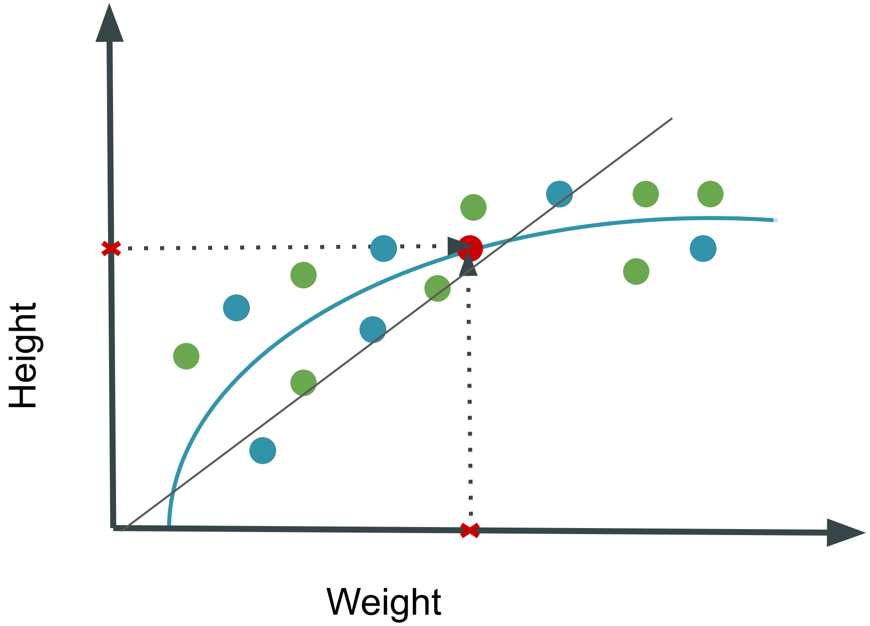
supervised learning



unsupervised learning

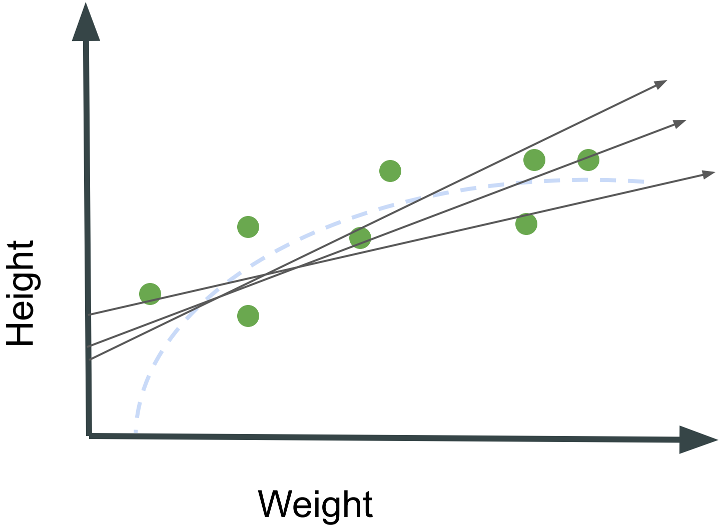


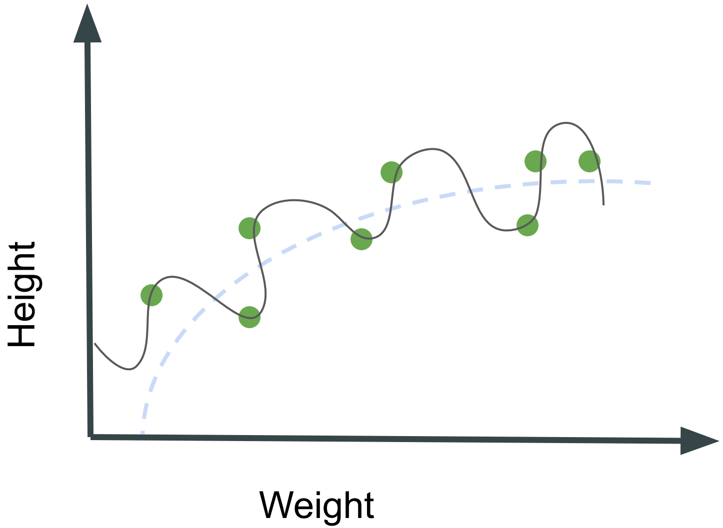
Training Data and Test Data



Bias

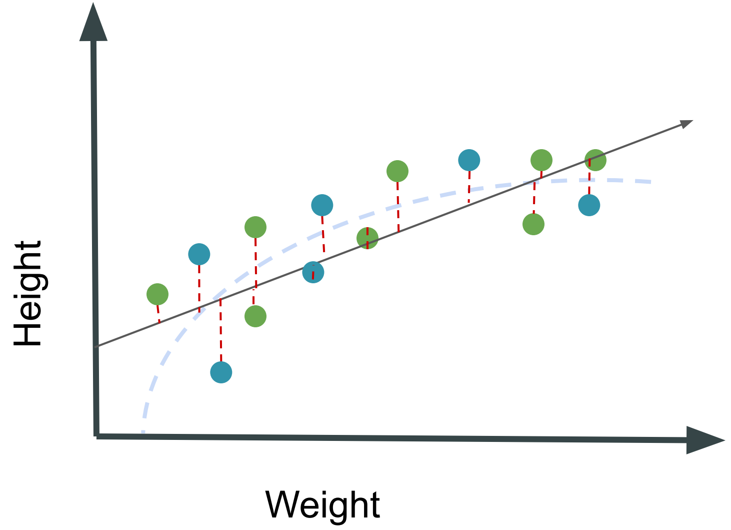
The inability for a machine learning method to capture the true relationship is called **bias**

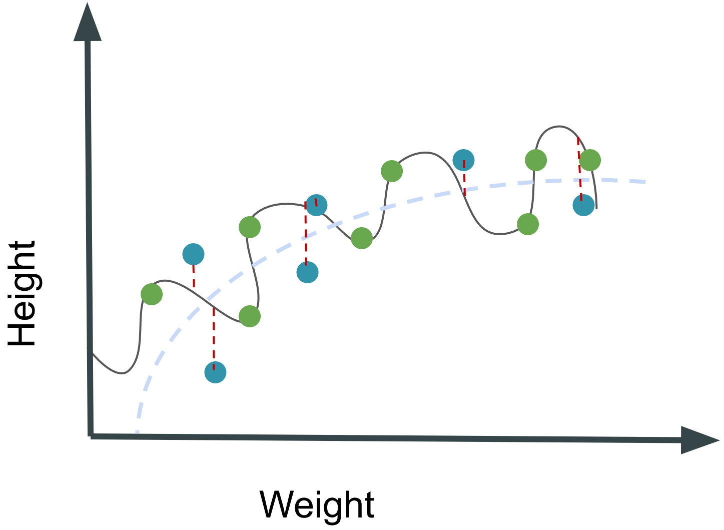




Variance

The **difference in fits between data sets** is called **variance**





CROSS VALIDATION

Test Data

Training Data

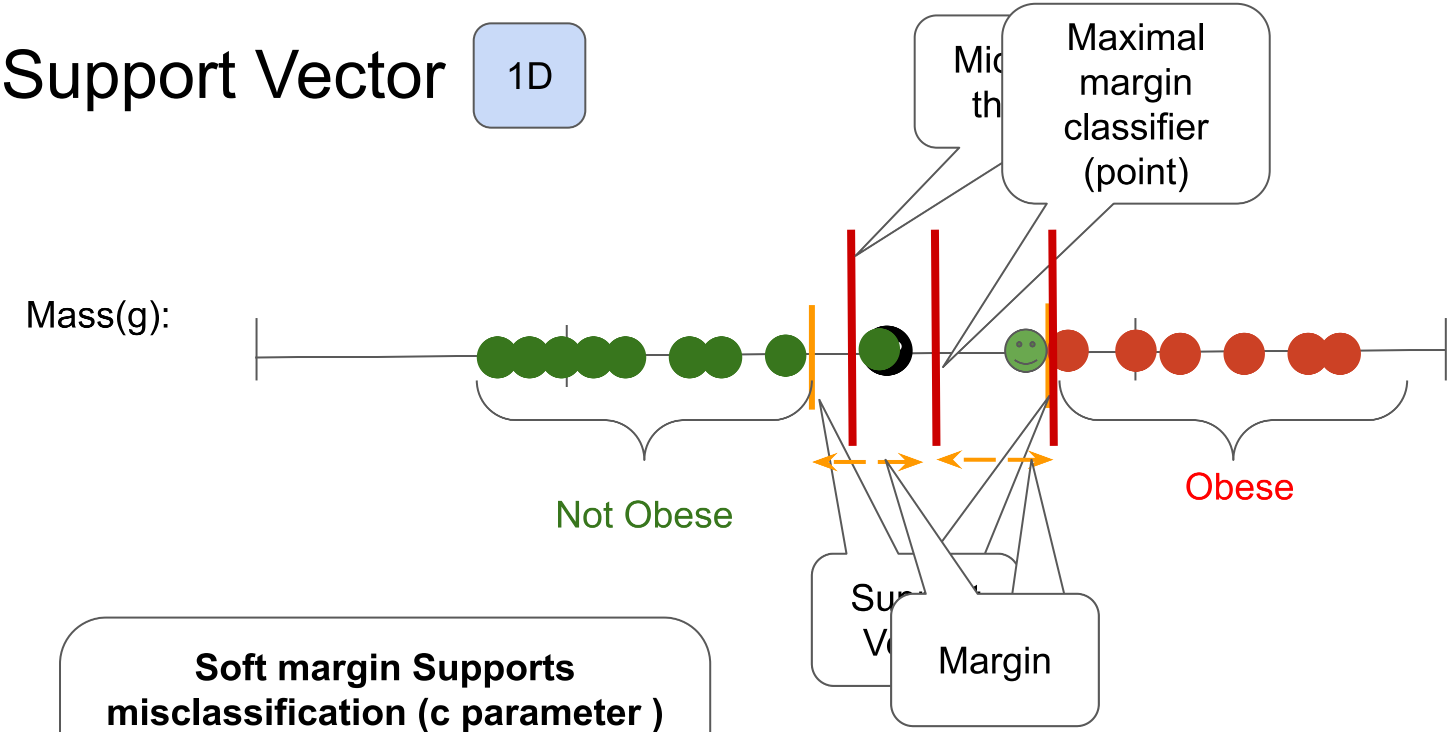
How do you decide which portion of your dataset is test data and which portion is training data??

Divide whole dataset in k portions

Make one portion test data each time and use rest to train the model

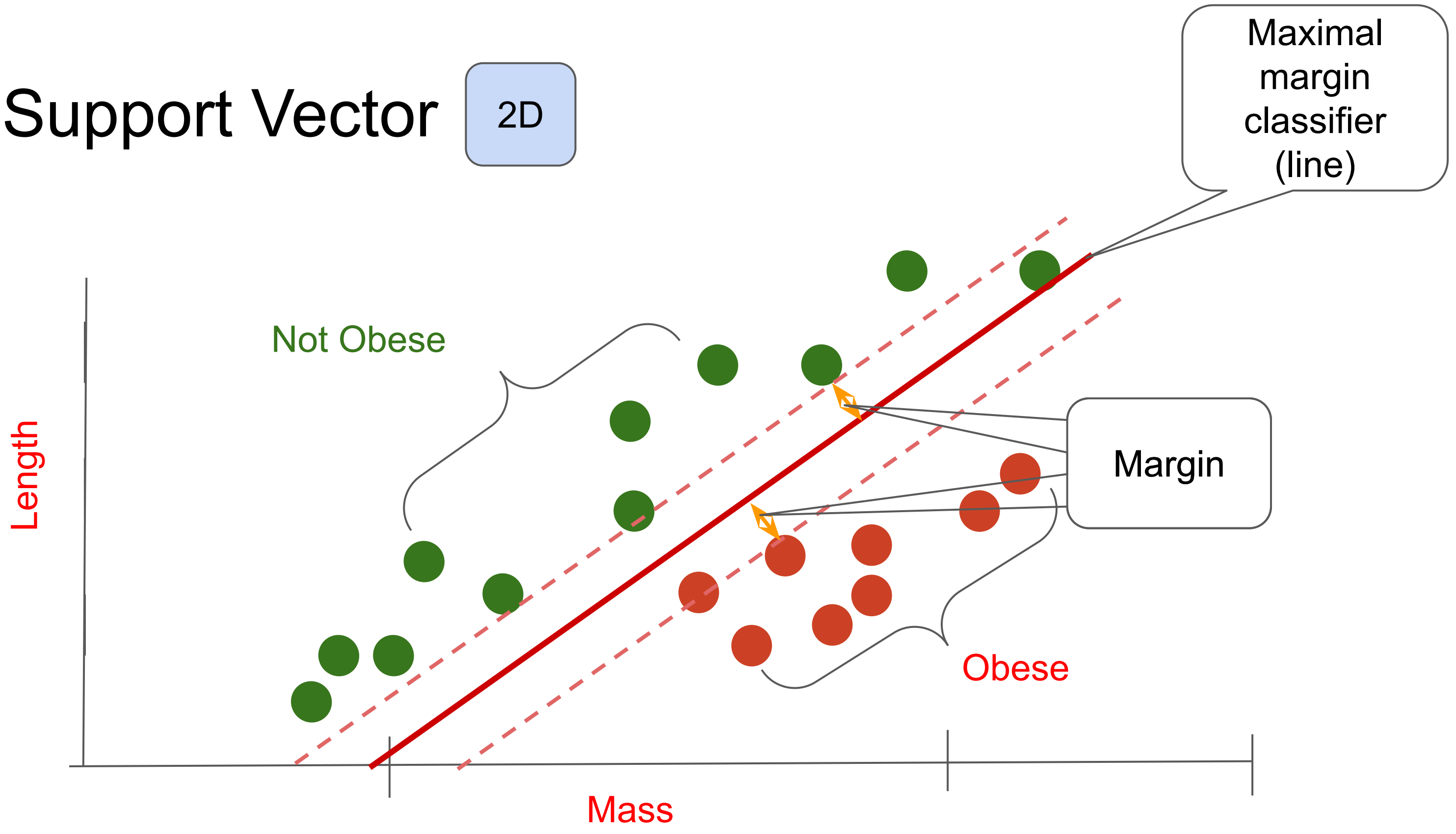
Summarize the results at end

Support Vector



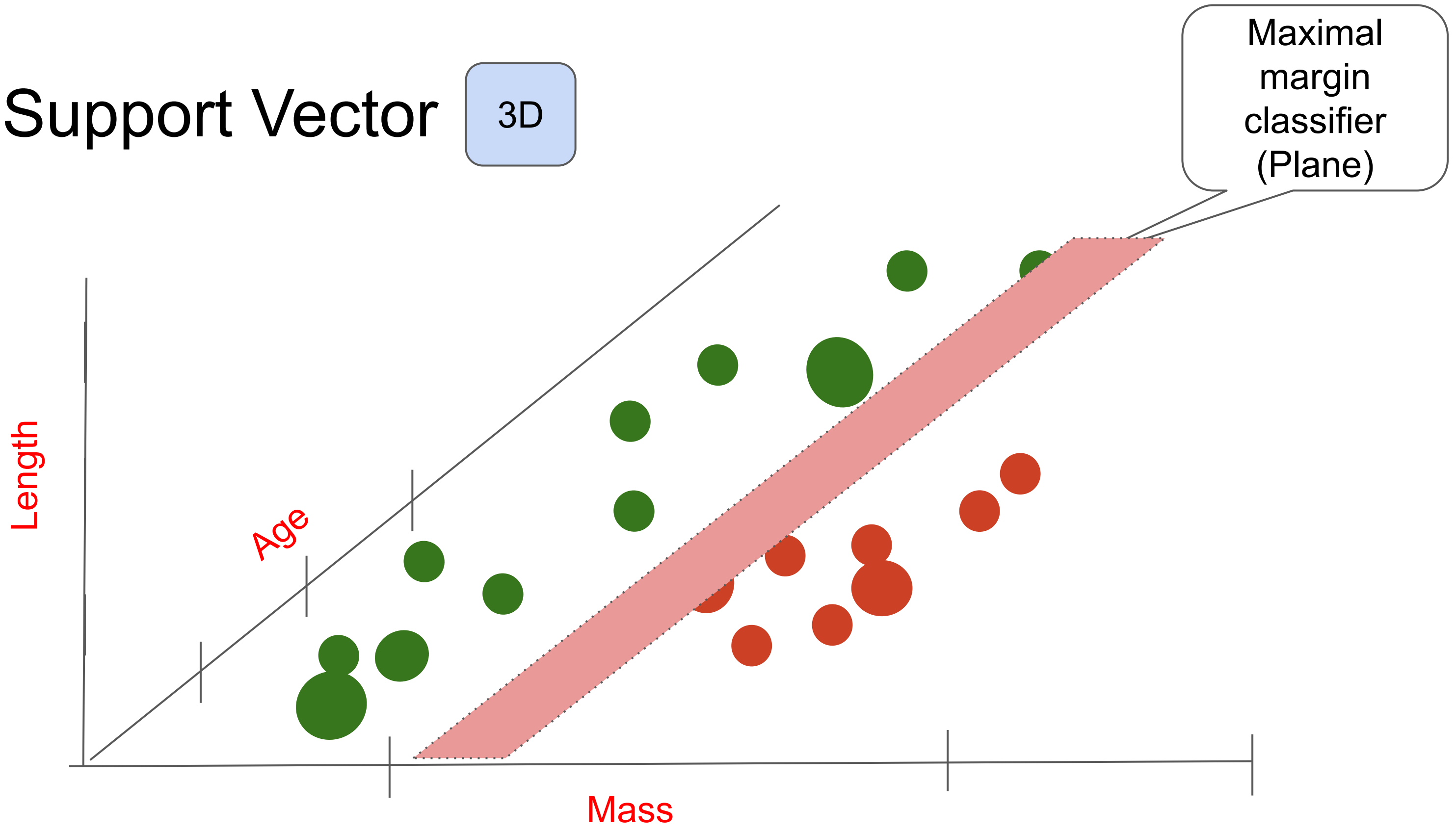
Soft margin Supports misclassification (c parameter)
Higher bias
Lower variance
Low c

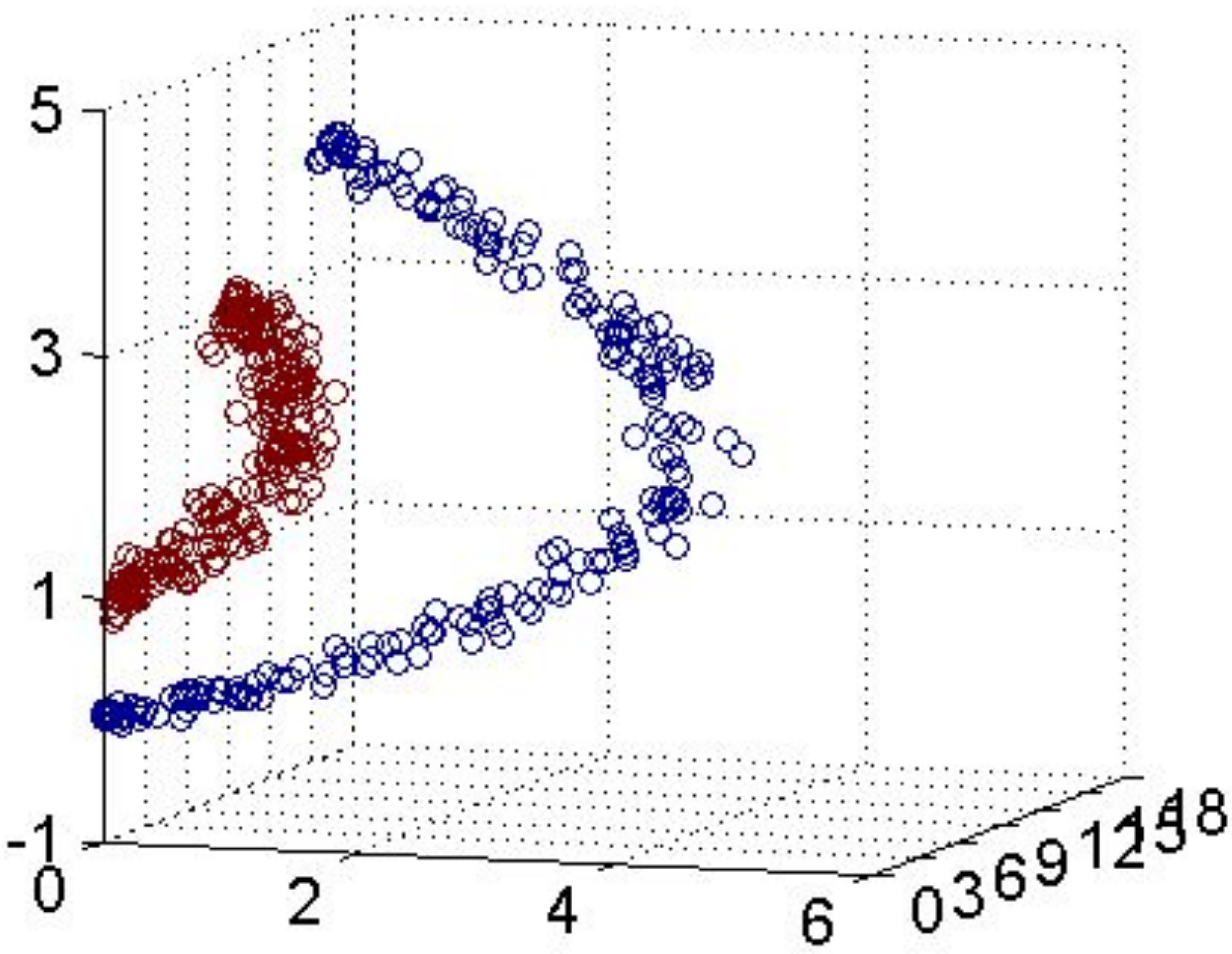
Support Vector 2D



Support Vector

3D




5
3
1
-1
0
2
4
6
0 3 6 9 12 15 18

Support vector Classifier in a 1D line is a single point

Did you notice something weird?

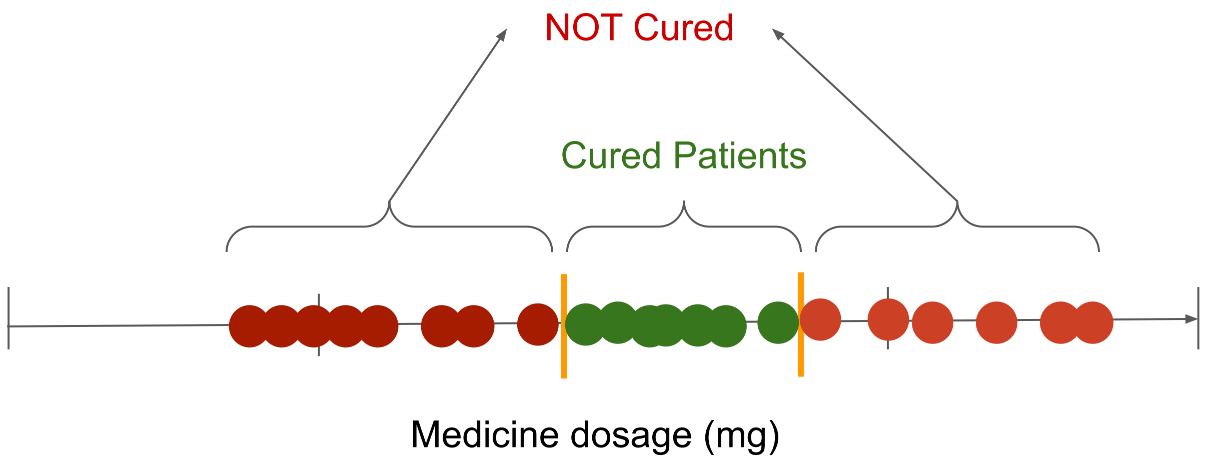
Support vector Classifier in a 3D space is a 2D plane

Support vector Classifier in a 2D space is a 1D line

Support vector Classifier in a 4 or more dimensional data space is a **HYPERPLANE**

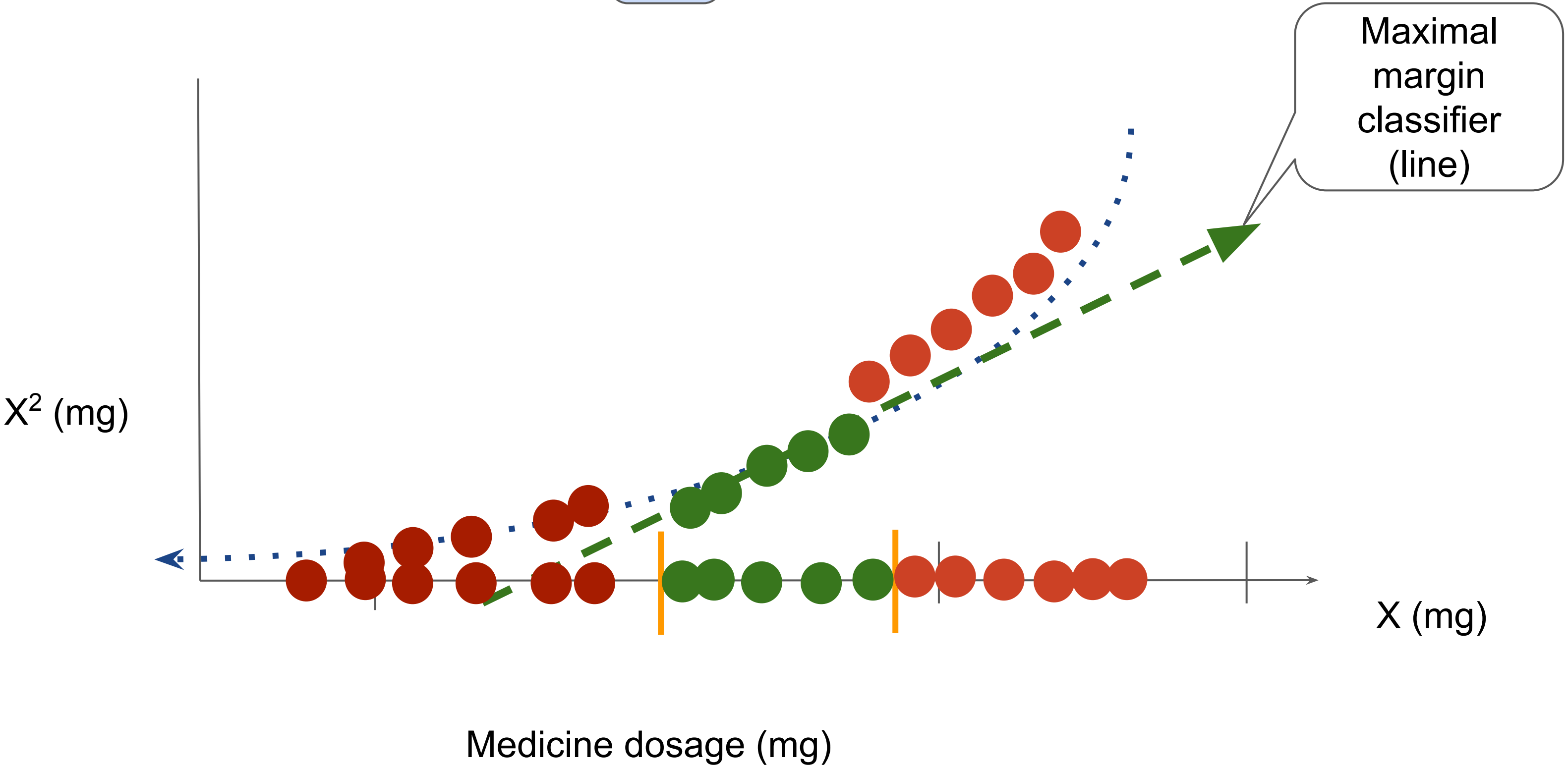
Support Vector Machine

1D



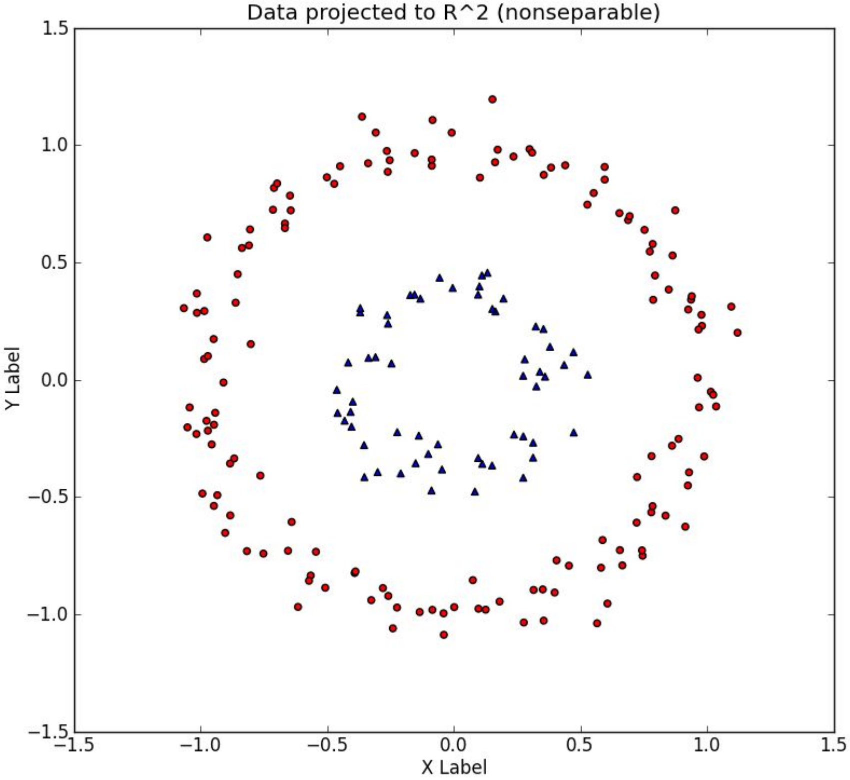
Support Vector Machine(cont)

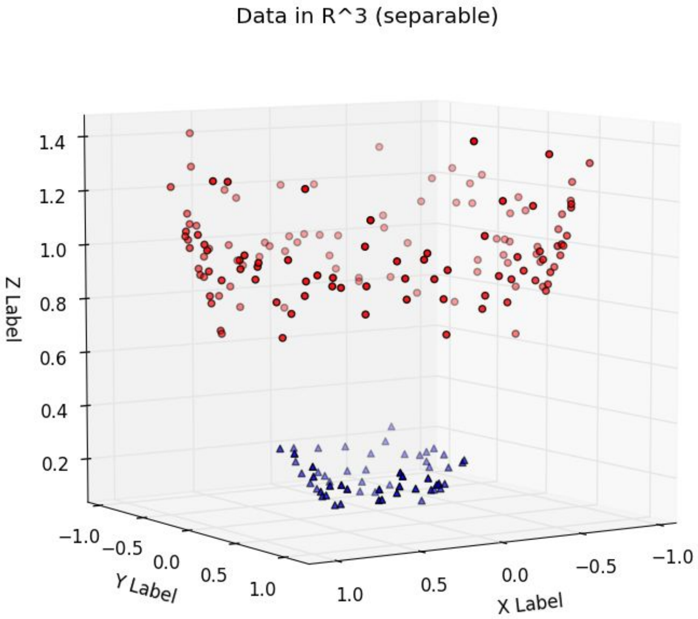
1D



Support Vector Machine(cont)

2D





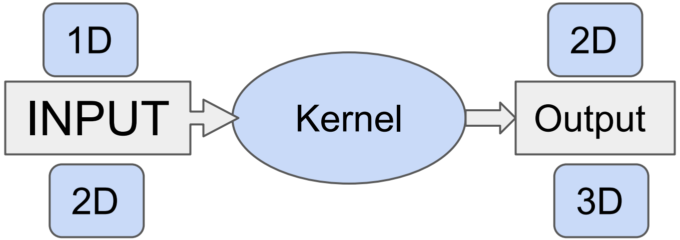
THE **KERNEL** FUNCTION

Systematically **increases dimension to find support vector classifiers in higher dimensions**

Why x^2?!

How do we decide how to **transform** the data?

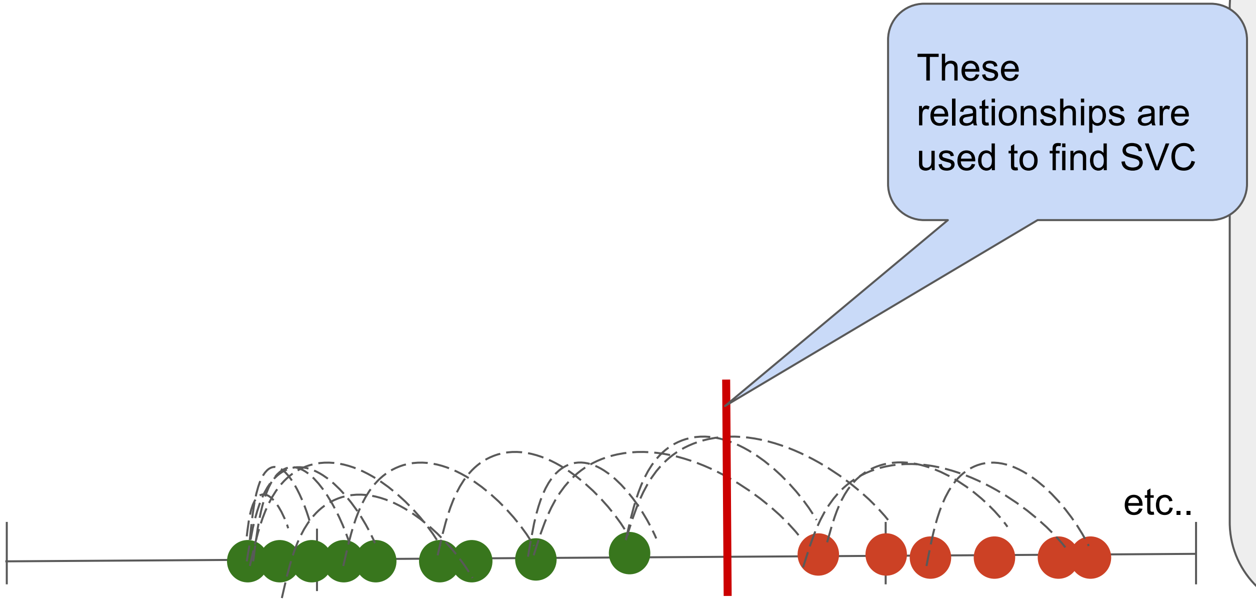
KERNEL Function



Different types of Kernel functions:

- Linear
- Nonlinear
- Polynomial
- Radial basis function (RBF)
- Sigmoid

Polynomial Kernel

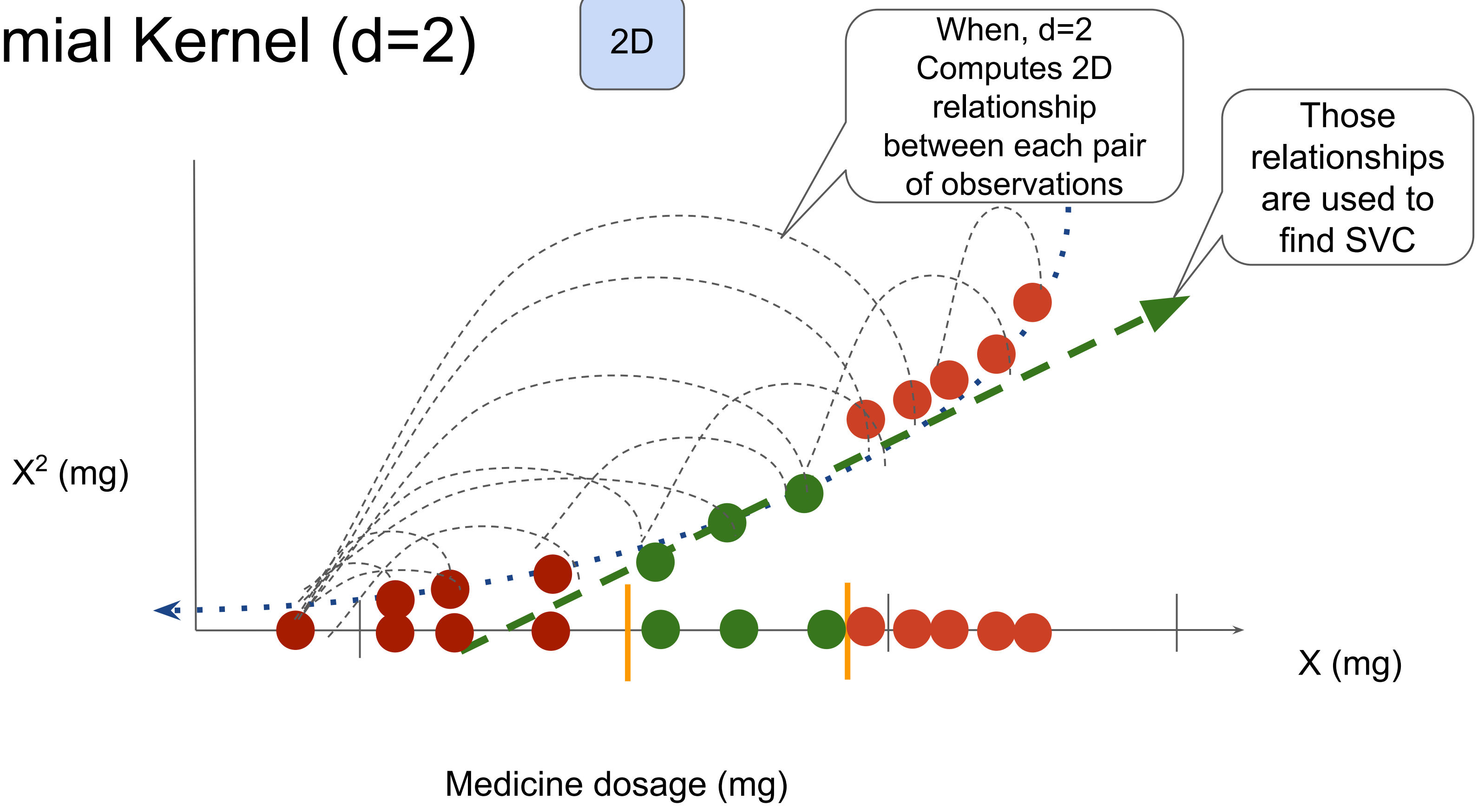


Polynomial Kernel has a parameter d, which stands for the degree of the polynomial.

When d=1, the polynomial kernel computes the relationship between each pair of the observations in 1D

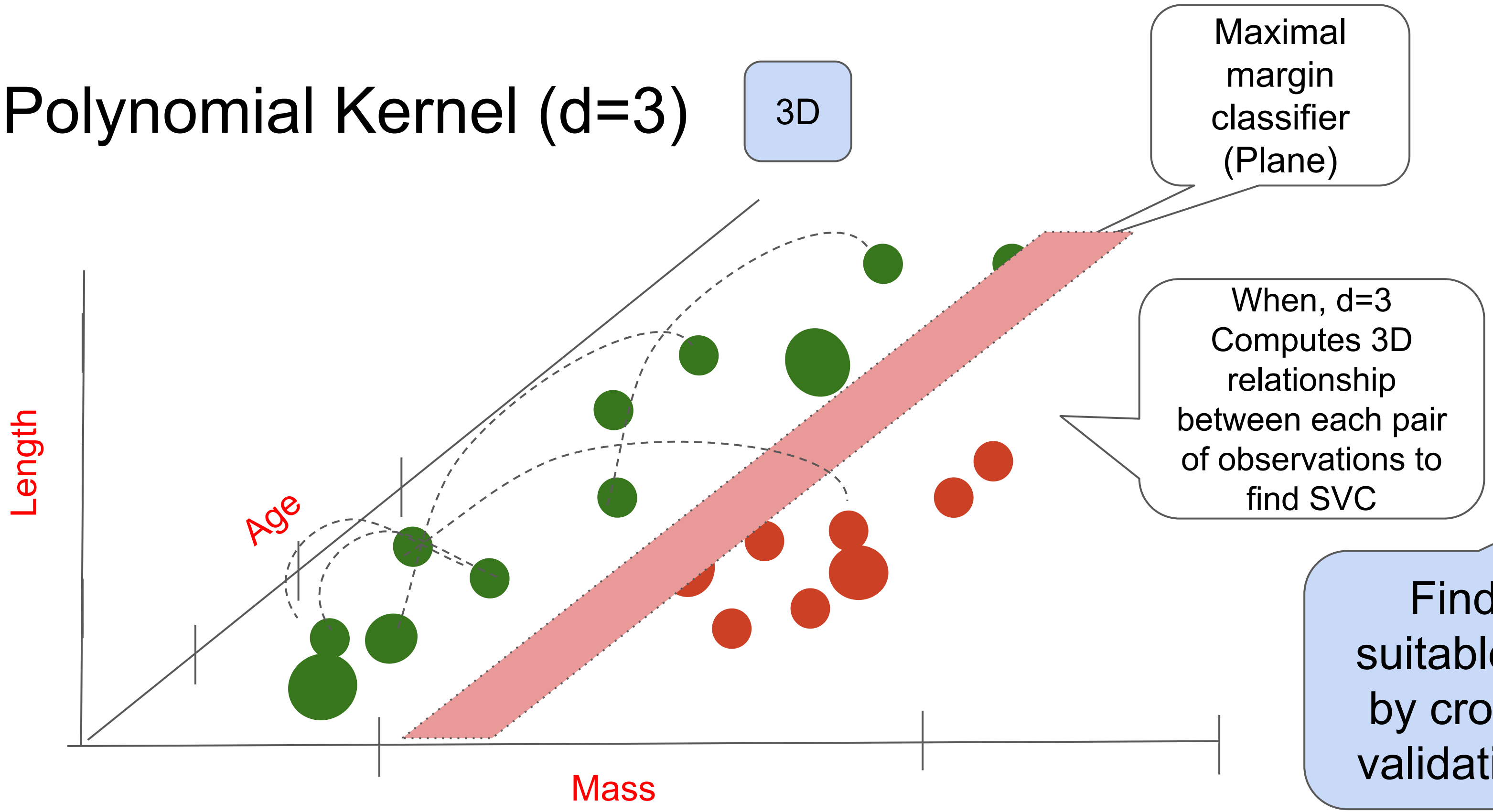
Polynomial Kernel (d=2)

2D



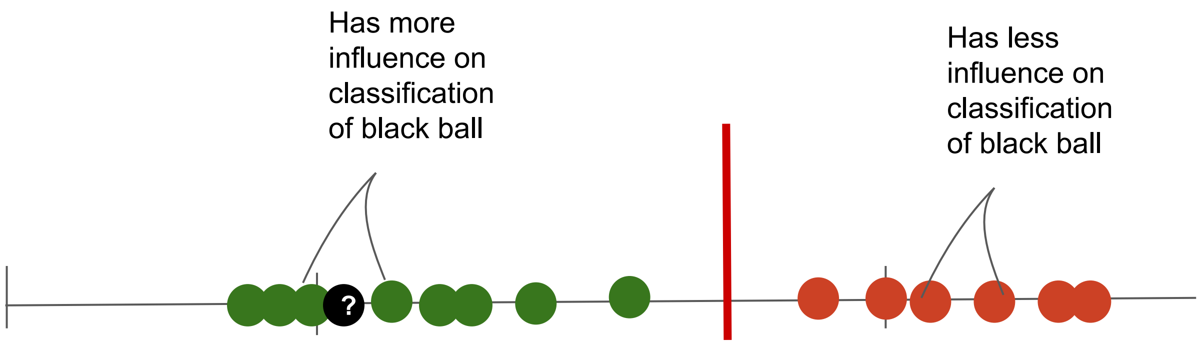
Polynomial Kernel (d=3)

3D



Find suitable d by cross validation

Radial Basis Function



Finds SVC in infinite dimensions

Behaves like weighted nearest neighbor model

The Kernel trick

Although previous examples show the data being transformed from relatively low dimension to higher dimension, **kernel functions only calculate the relationships between each pair of points as if they are in the higher dimension**; they don't actually do the transformation.This trick is called "The kernel trick". This reduces the amount of computation

The "Kernel Trick"

- The linear classifier relies on an inner product between vectors $K(\mathbf{x_i},\mathbf{x_j})=\mathbf{x_i}^\mathbf{T}\mathbf{x_j}$
- If every datapoint is mapped into high-dimensional space via some transformation Φ: $\mathbf{x} \rightarrow \varphi(\mathbf{x})$, the inner product becomes:

$$K(\mathbf{x_i},\mathbf{x_j})= \varphi(\mathbf{x_i})^\mathbf{T}\varphi(\mathbf{x_j})$$

- A *kernel function* is some function that corresponds to an inner product in some expanded feature space.
- Example:

  2-dimensional vectors $\mathbf{x}=[x_1 \;\; x_2]$; let $K(\mathbf{x_i},\mathbf{x_j})=(1 + \mathbf{x_i}^\mathbf{T}\mathbf{x_j})^2$,

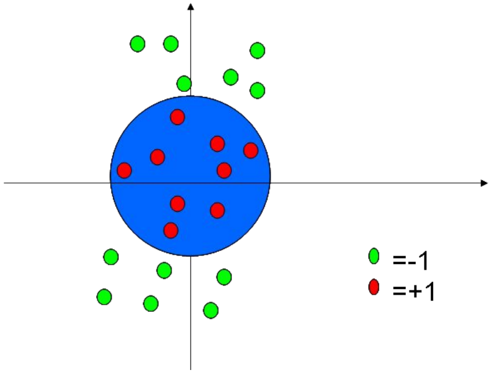
  Need to show that $K(\mathbf{x_i},\mathbf{x_j})= \varphi(\mathbf{x_i})^\mathbf{T}\varphi(\mathbf{x_j})$:

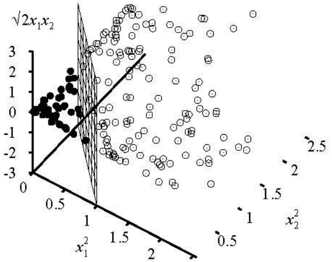
  $K(\mathbf{x_i},\mathbf{x_j})=(1 + \mathbf{x_i}^\mathbf{T}\mathbf{x_j})^2{}_{,}= 1+ x_{i1}^2x_{j1}^2 + 2\, x_{i1}x_{j1}\, x_{i2}x_{j2}+ x_{i2}^2x_{j2}^2 + 2x_{i1}x_{j1} + 2x_{i2}x_{j2}=$

  $= [1 \;\; x_{i1}^2 \;\; \sqrt{2}\, x_{i1}x_{i2} \;\; x_{i2}^2 \;\; \sqrt{2}x_{i1} \;\; \sqrt{2}x_{i2}]^\mathbf{T} [1 \;\; x_{j1}^2 \;\; \sqrt{2}\, x_{j1}x_{j2} \;\; x_{j2}^2 \;\; \sqrt{2}x_{j1} \;\; \sqrt{2}x_{j2}]$

  $= \varphi(\mathbf{x_i})^\mathbf{T}\varphi(\mathbf{x_j})$ where $\varphi(\mathbf{x}) = [1 \;\; x_1^2 \;\; \sqrt{2}\, x_1x_2 \;\; x_2^2 \;\; \sqrt{2}x_1 \;\; \sqrt{2}x_2]$

Kernel Trick





Data points are linearly separable in the space $(x_1^2, x_2^2, \sqrt{2}x_1x_2)$

We want to maximize $\sum_i \alpha_i - \frac{1}{2}\sum_{i,j} y_i y_j \alpha_i \alpha_j \langle F(\mathbf{x}_i) \cdot F(\mathbf{x}_j) \rangle$

Define $K(\mathbf{x}_i, \mathbf{x}_j) = \langle F(\mathbf{x}_i) \cdot F(\mathbf{x}_j) \rangle$

Cool thing : K is often easy to compute directly! Here,

$K(\mathbf{x}_i, \mathbf{x}_j) = \langle \mathbf{x}_i \cdot \mathbf{x}_j \rangle^2$

Questions?

Contents

Reference

https://www.youtube.com/watch?v=efR1C6CvhmE