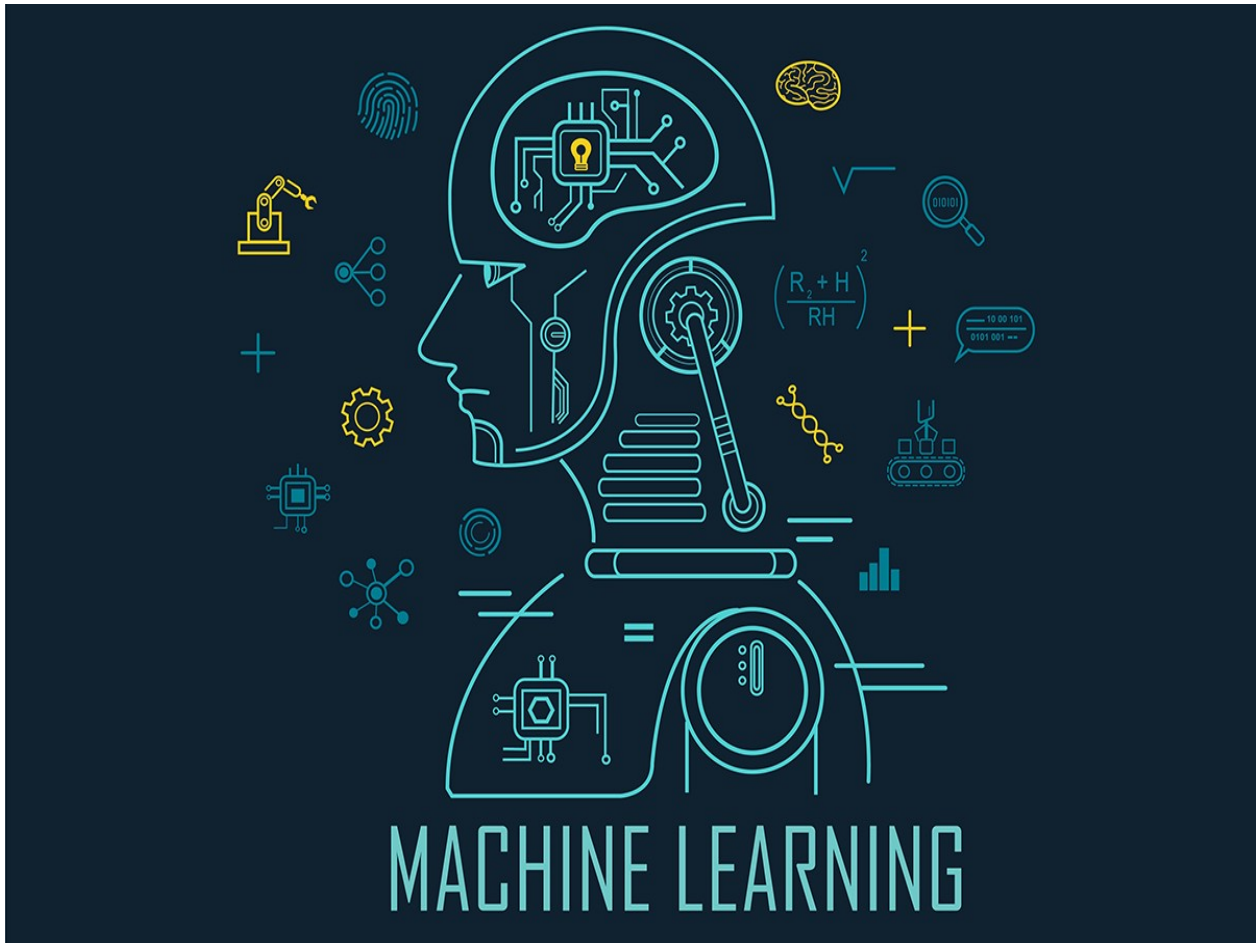
Machine Learning 1
Introduction



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"A program learns from experience E of performing task T with a performance measure P"

- Tom Mitchell 1998

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• The task is generally quite narrow in scope, largely because of issues in well defining a general performance measure.

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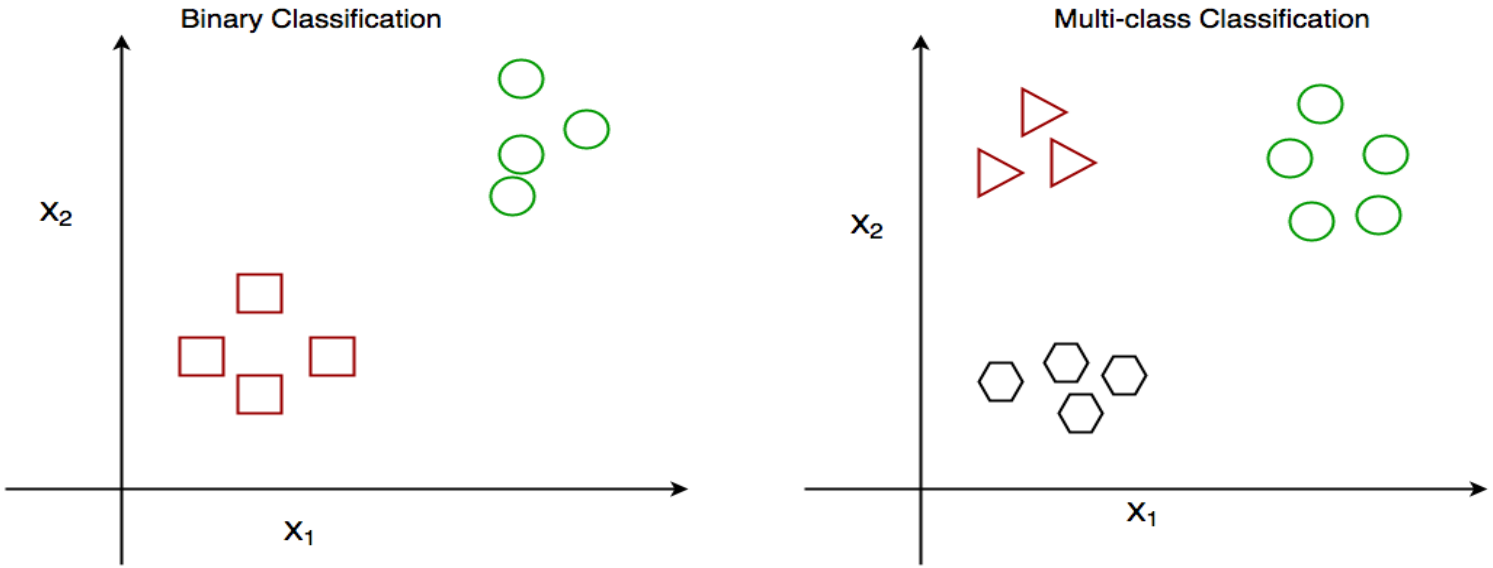

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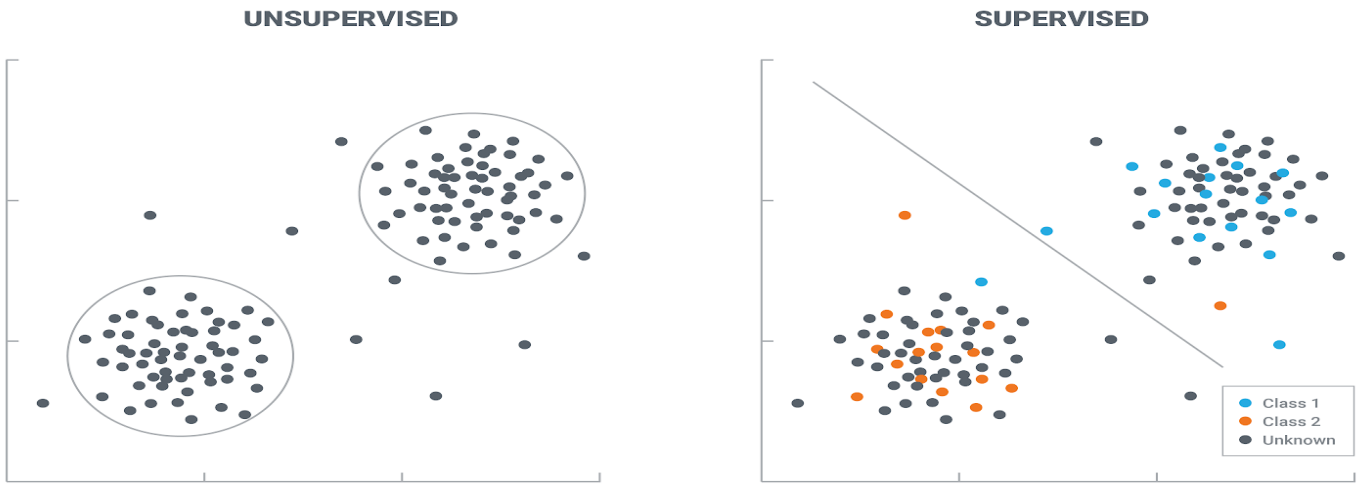

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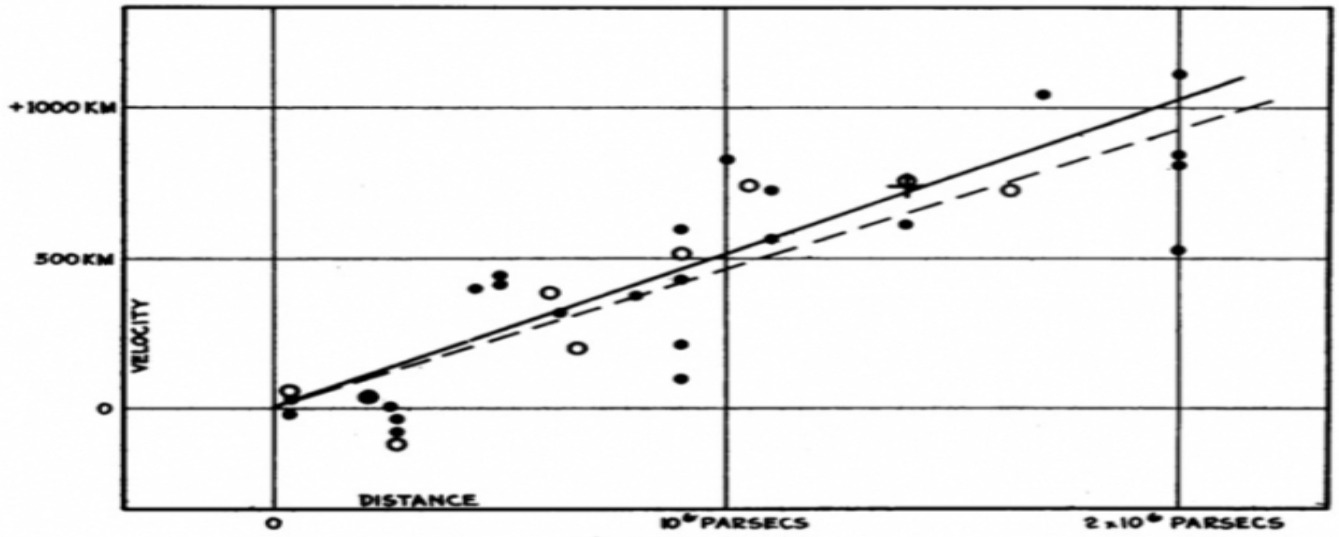
$\vec{\theta}$ **:** will denote a vector of (fitted) coefficients that transform the feature vector into a prediction.

Let's take a basic example...



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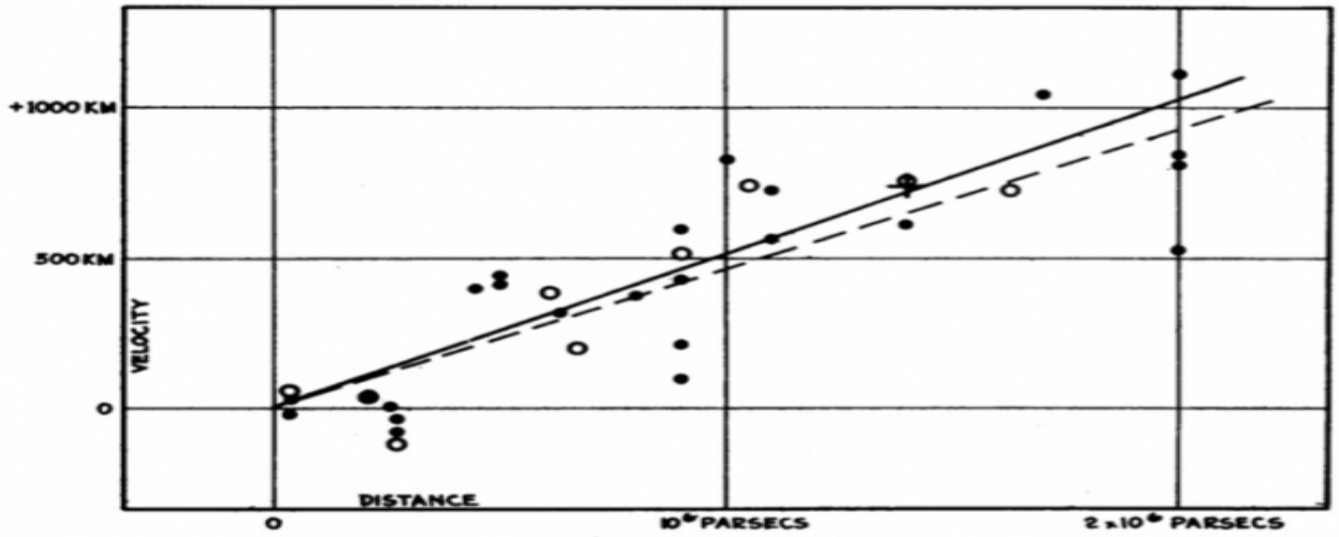

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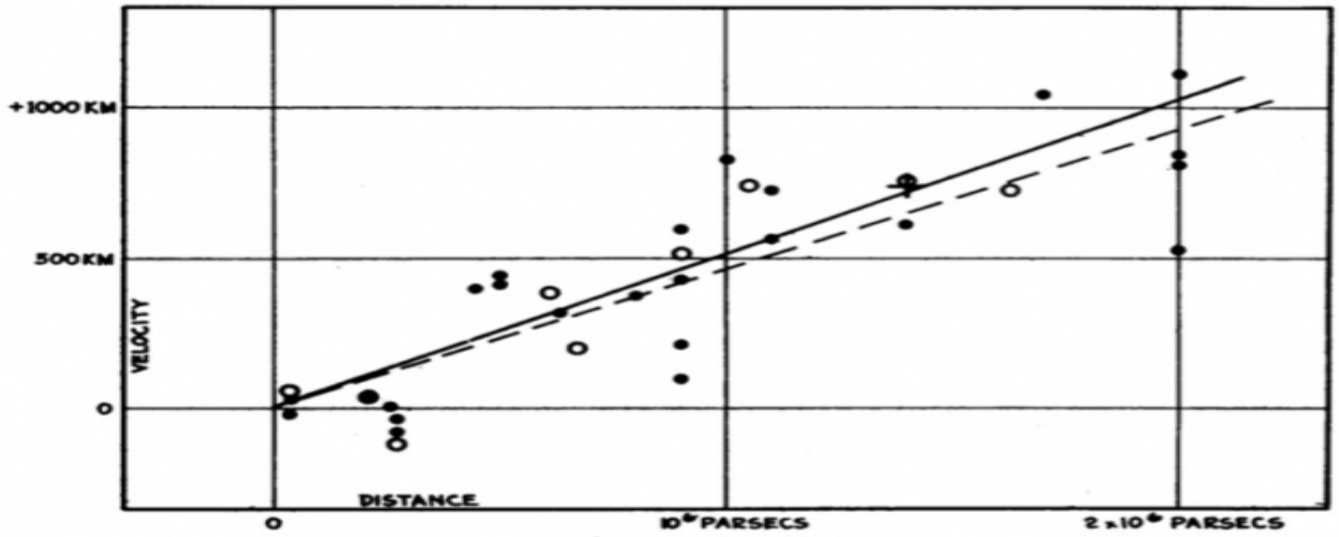

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$$\min_\theta J(\theta) = \min_\theta \frac{1}{2m} \sum_{i=1}^{m} \frac{(\theta^T \vec{x}^{(i)} - \vec{y}^{(i)})^2}{(\sigma^i)^2} \tag{1}$$

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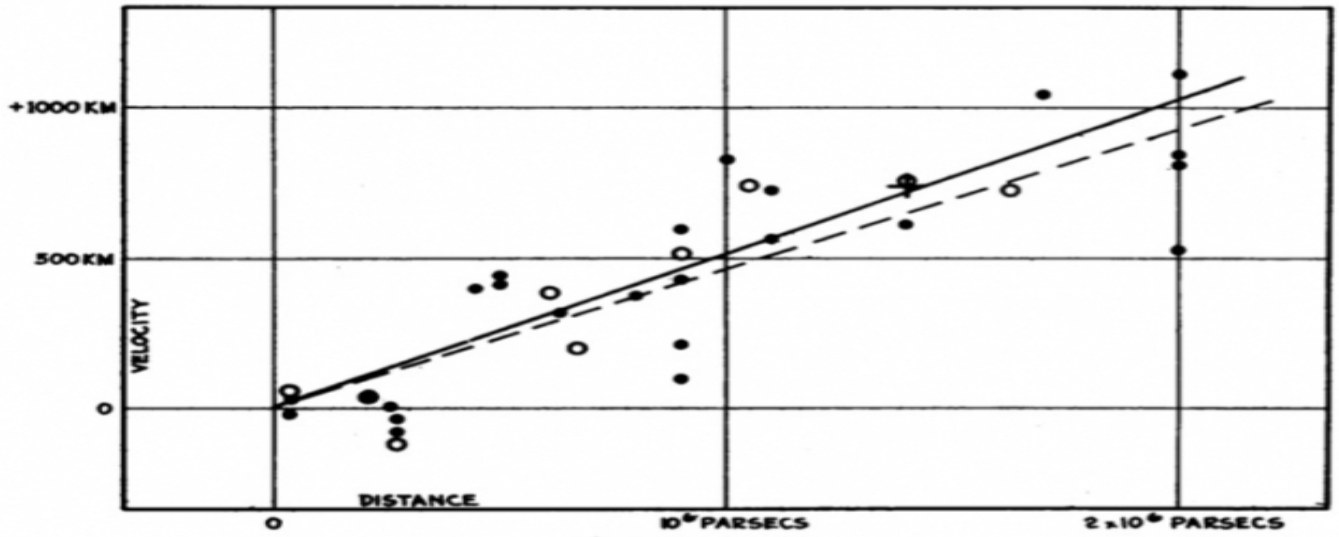

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where in the end Edwin Hubble found $\theta = \{0, H_0\}$.

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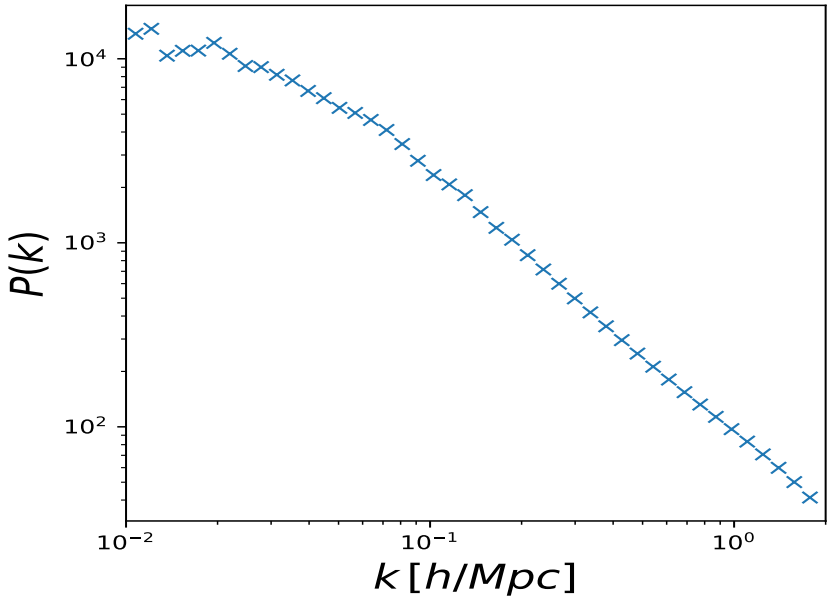

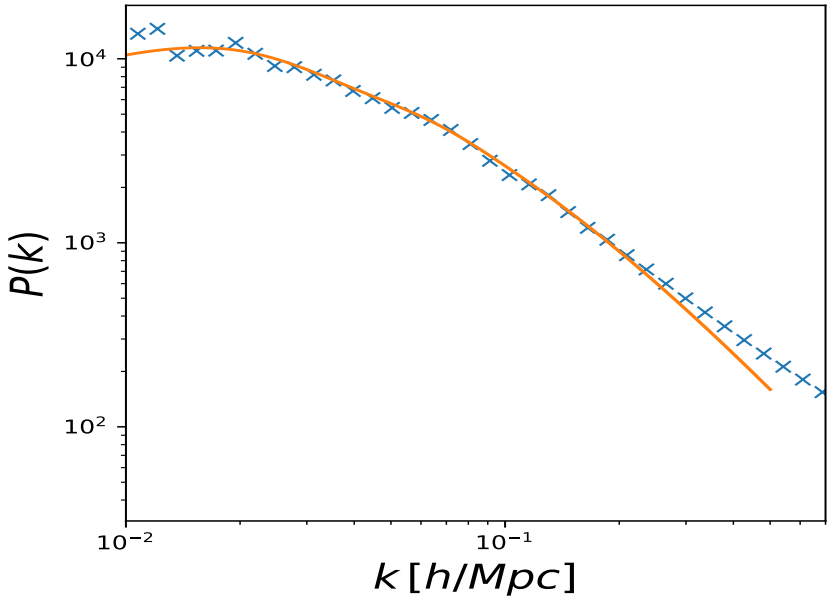

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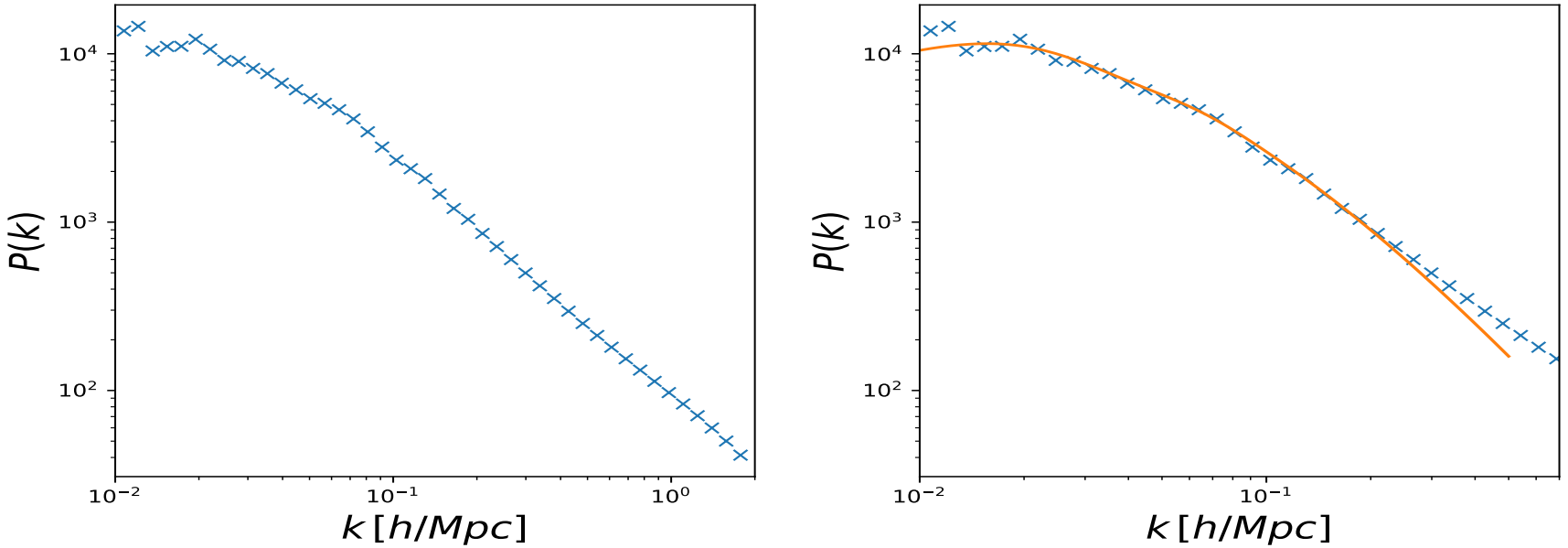


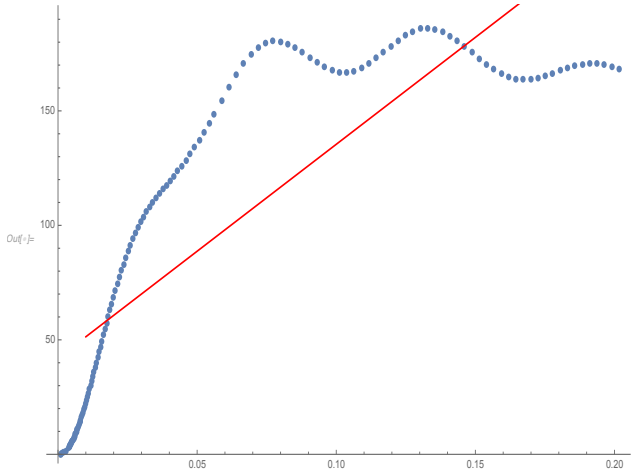
In this case, **m** is the number of k-bins, **n** is the number of features.
Let us then take features $\{1, k, k^2, k^3 ... k^n\}$

$$J(\theta) = \chi^2 = \sum_{k_{\text{bins}}} \frac{[\theta^T \vec{x}^{(i)} - P^{\text{measured}}(k_i)]^2}{\sigma_i^2}. \tag{2}$$

`See python example 1`

A note on variance and bias

High bias:



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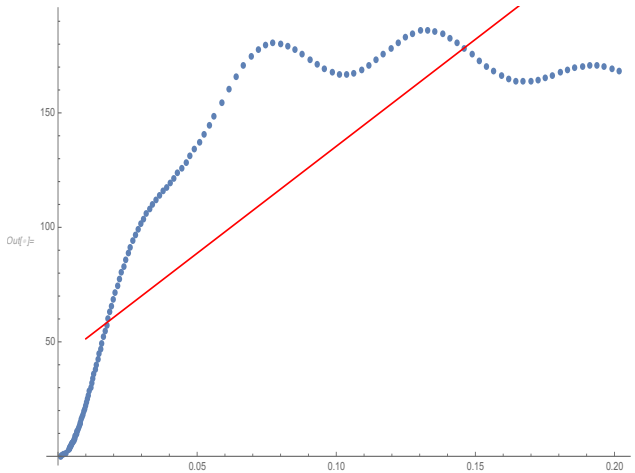

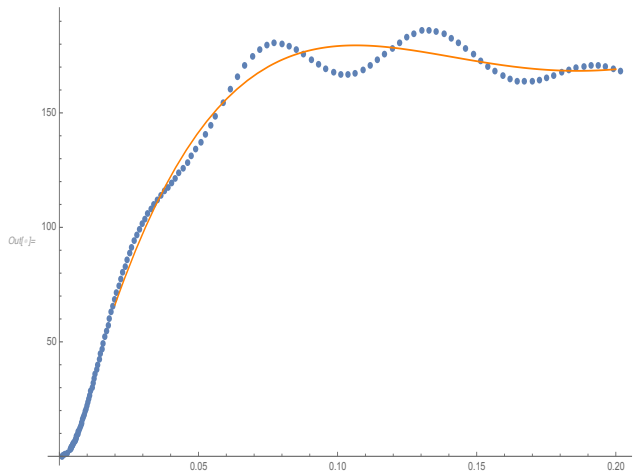

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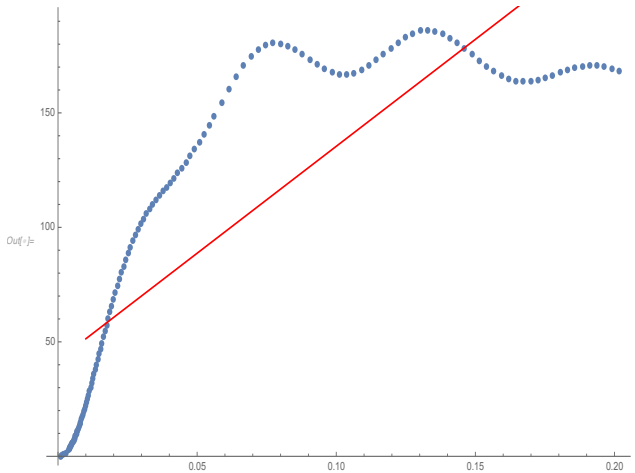

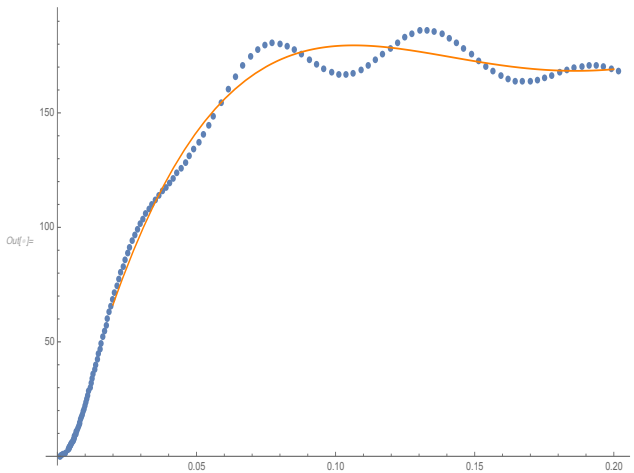

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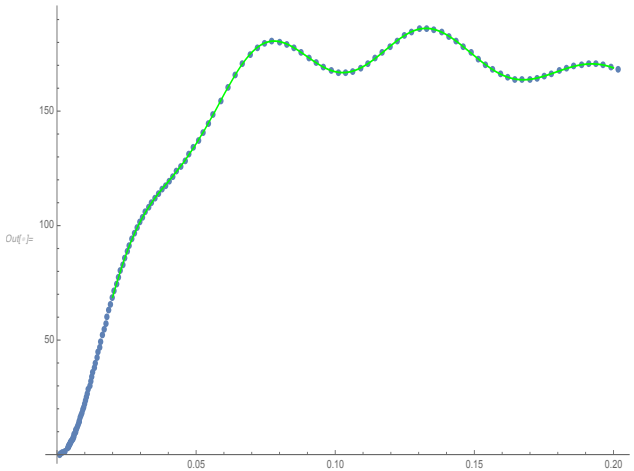

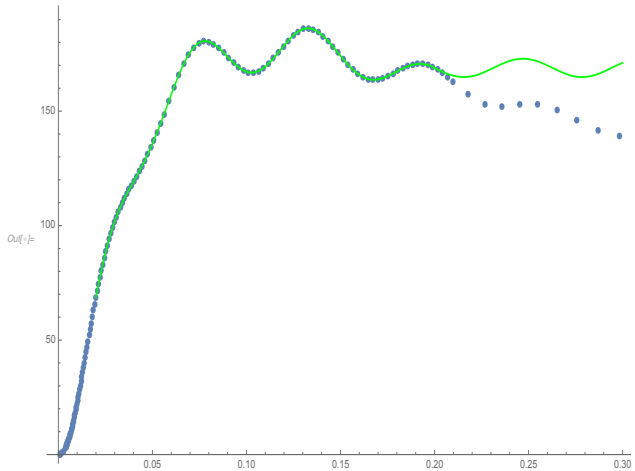

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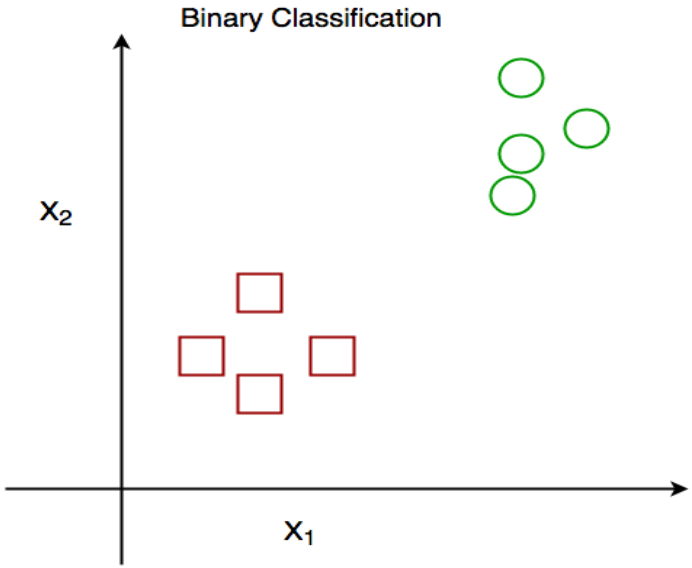
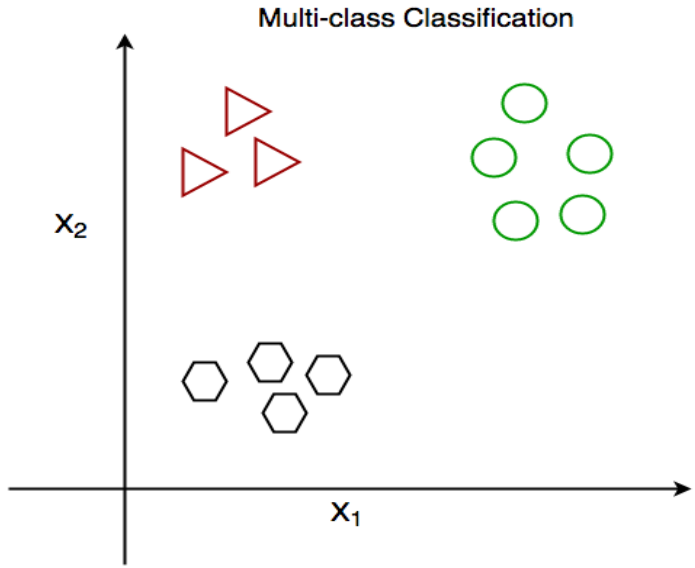
- For polynomial regression, **feature scaling** is very important - renormalise features to be of the same order + mean normalisation ($\mu_x = 0$).

What about classification?





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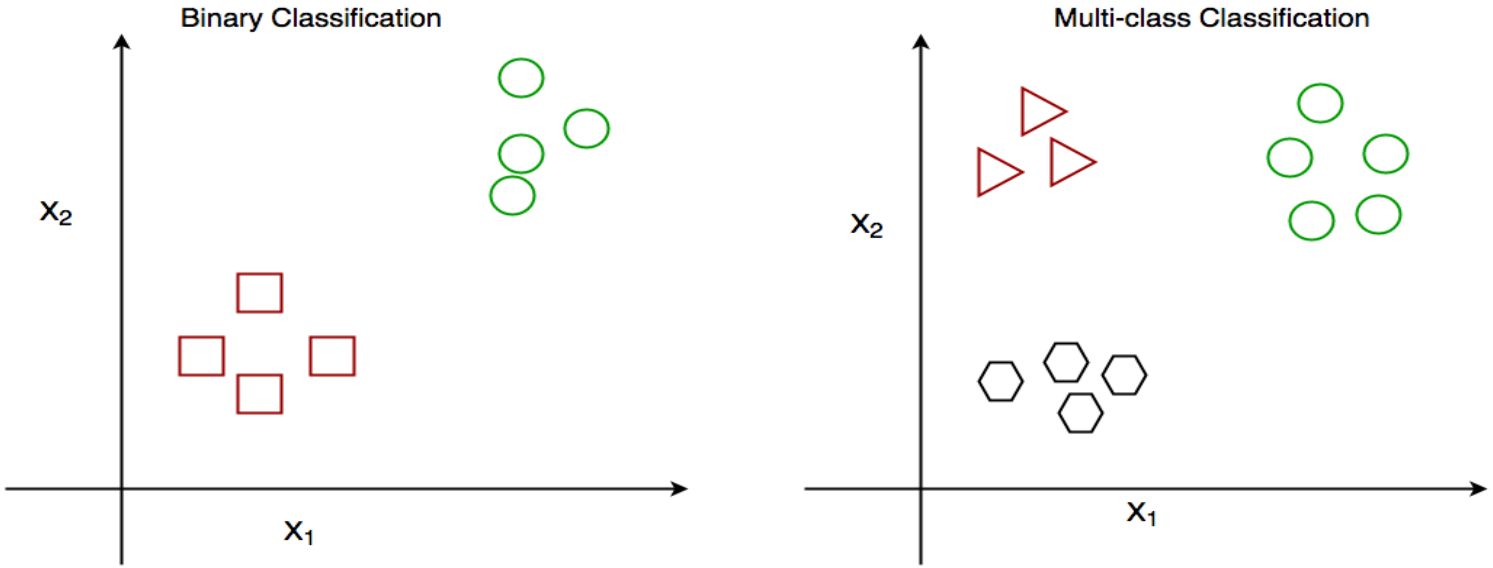
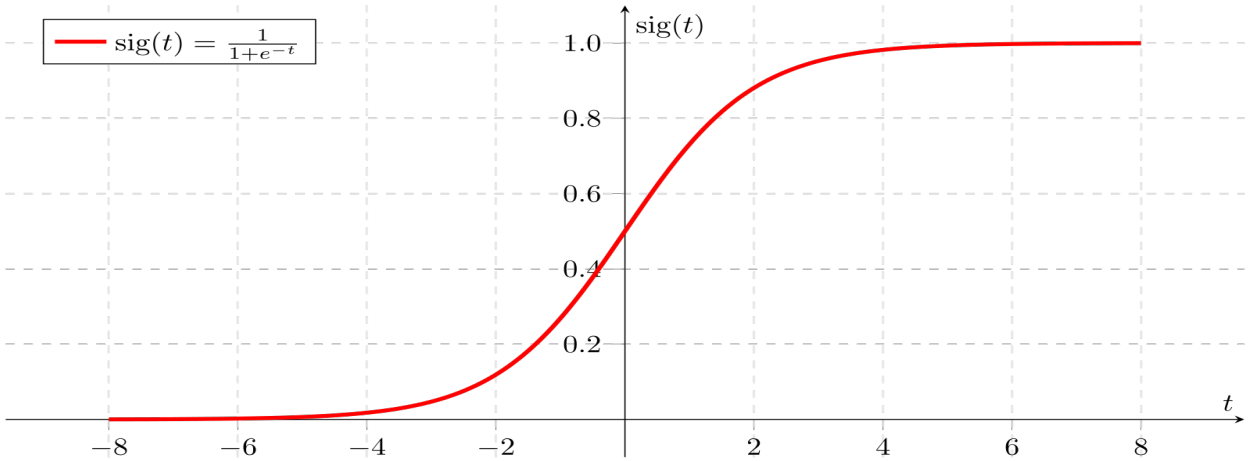


We can use **logistic regression** and the **sigmoid function** to handle this.



Consider binary classification (2 classes)

1. Let $y = 1$ (class 1) and $y = 0$ (class 2) denote the the two classes.
2. Now set our prediction to be given by

$$h(\theta^T x) = \begin{cases} 1 & \text{if } sig(\theta^T x) \geq 0.5 \\ 0 & \text{if } sig(\theta^T x) < 0.5 \end{cases}, y = \begin{cases} 1 & \text{if } \theta^T x \geq 0.5 \\ 0 & \text{if } \theta^T x < 0.5 \end{cases}$$

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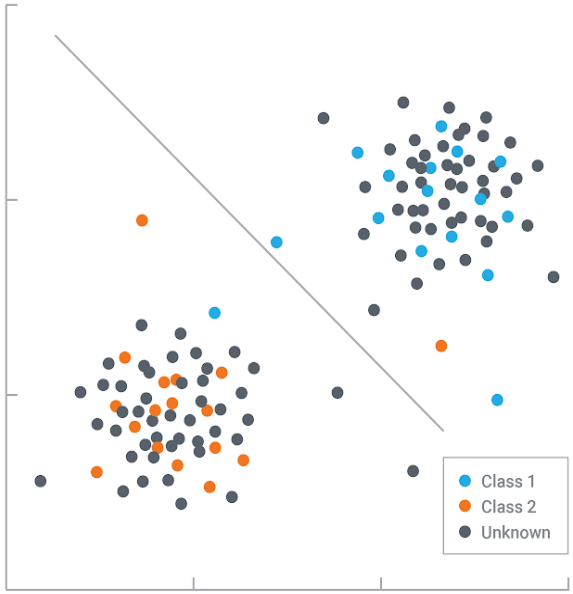
$\theta^T x$ then draws out what is called the **decision boundary**.



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- For multi-class classification, we can use the **one vs all** method:
  1. Delimit classes numerically as $\{0, 1, 2, 3, ...k\}$.
  2. Train for k-sets of optimised θ, one for each class.
  3. For a new example $\bar{x}$, choose the class j that gives the maximum value of $sig(\theta_j^T \bar{x})$.

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If we want to include frequency, then we might set $x_j = n_j$ where n_j is the number of times the j^{th} word appears.

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- In supervised learning we have the answers in the form of a training set. The correct answer could be a predicted value or a classification.
- We can form a hypothesis for the prediction or classification using linear/polynomial regression OR logistic regression + one vs all.
- Feature selection is very important!

Example 2: Puzzle classifier

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Features are shades of blue:

- $x_j = 1, 0$ if average of pixels on a piece are in some blue category j.
- $x_j = \bar{B}$ in RGB context. We should rescale/normalise this feature.