

Machine Learning



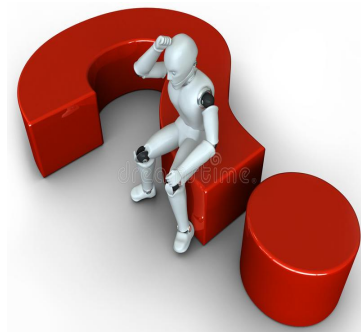


Apple



Human

Learn from experience



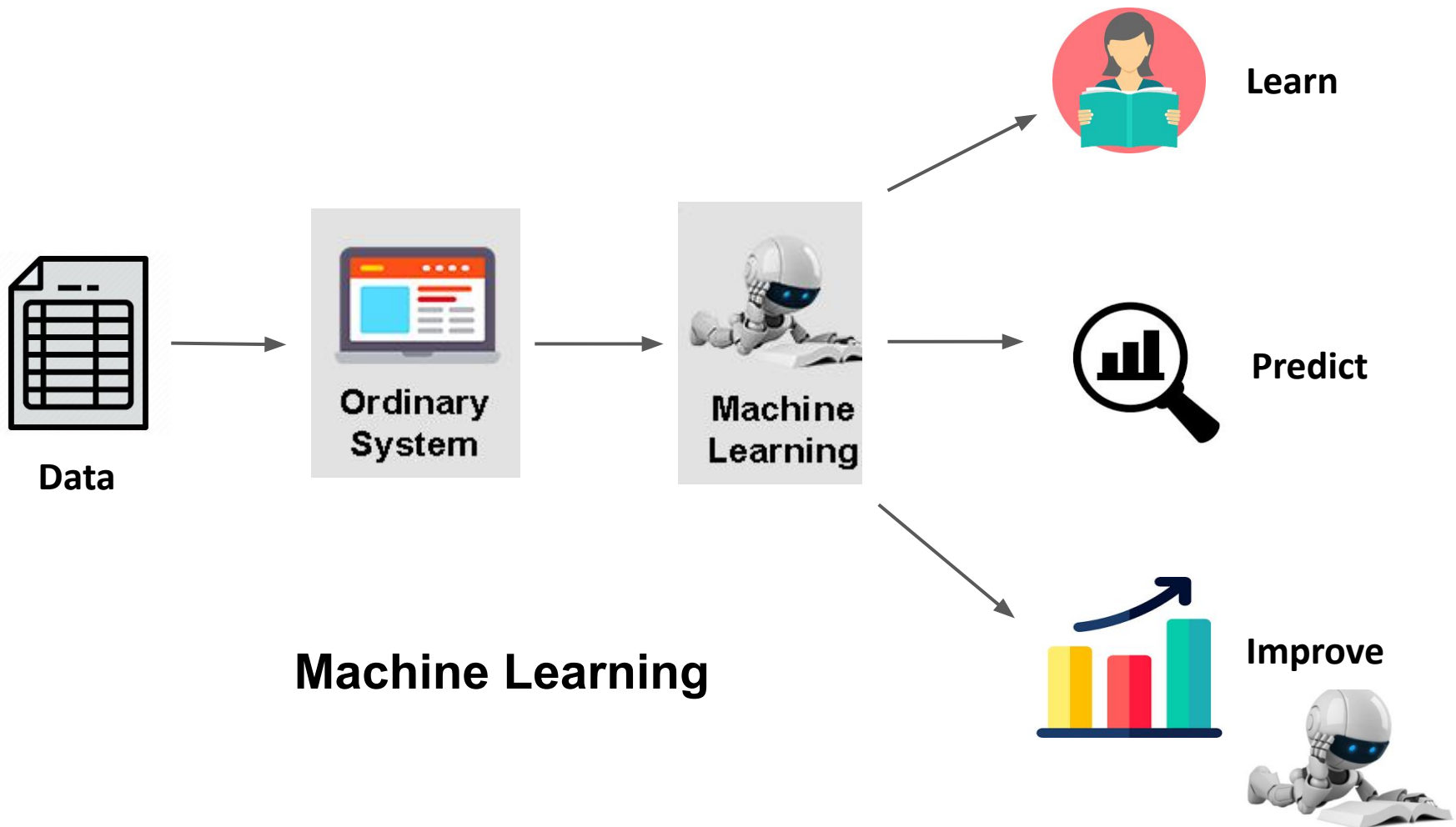
Machine

Learn from past data

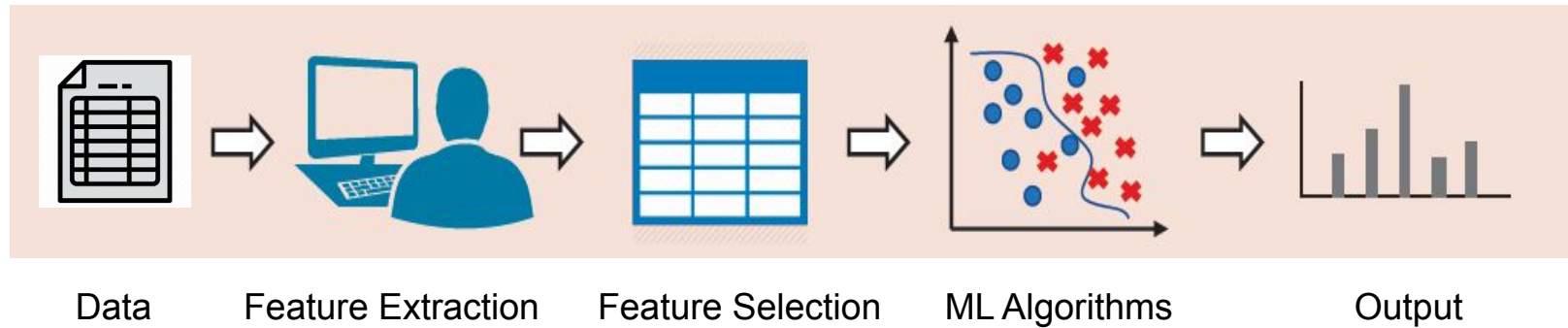


Machine Learning





How Machine Learning ?



Why Machine Learning?

- Rapid increment in the production of data
- Solving complex problems, which are difficult for a human
- Decision making in various sector including finance
- Finding hidden patterns and extracting useful information from data



Definition:

Field of Study that gives computers the ability to learn without being explicitly programmed.

Formal Defn:

A computer Program is said to learn from experience E w.r.t some task T and some performance measures P , if its performance on T as measured by P improves with experience E



Machine Learning Algorithms:

- Supervised Learning
- Unsupervised learning

Others: Reinforcement Learning, Recommender Systems



Supervised Learning



Supervised Learning

pear apple



Labelled Data

?



?

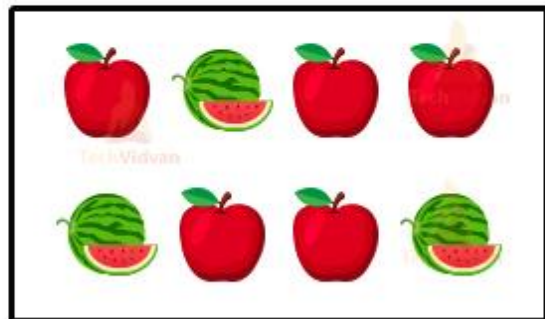


New Data



Unsupervised Learning in ML

Input Data



Tech Vidvan



Model

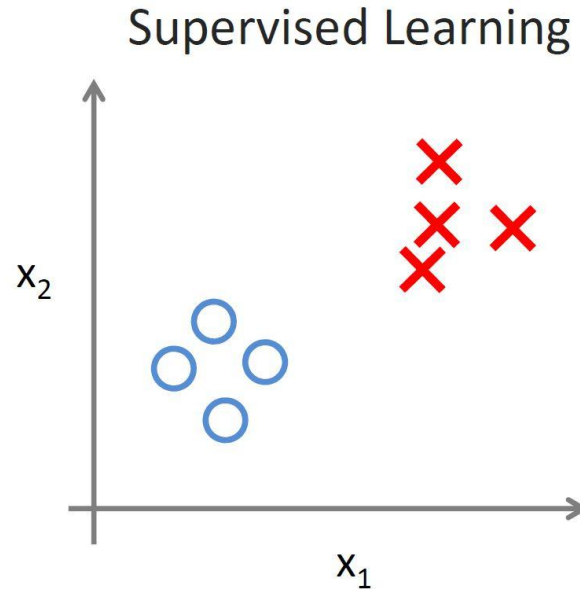


Output



Supervised Learning:

- Learns an Input and O/P map.
 - Classification: categorical O/P
 - Regression: Continuous O/P



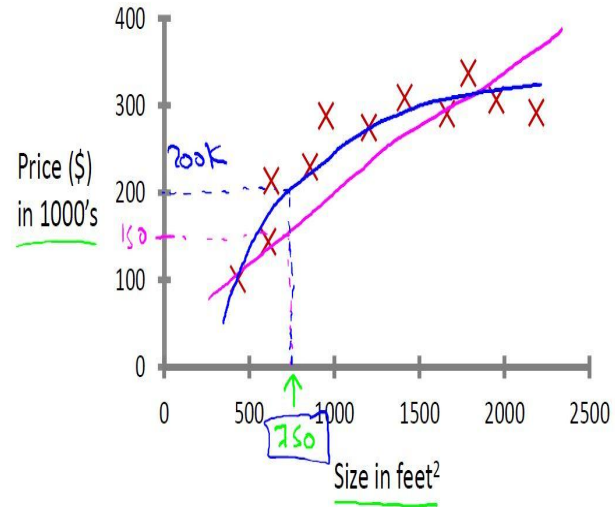
Regression:

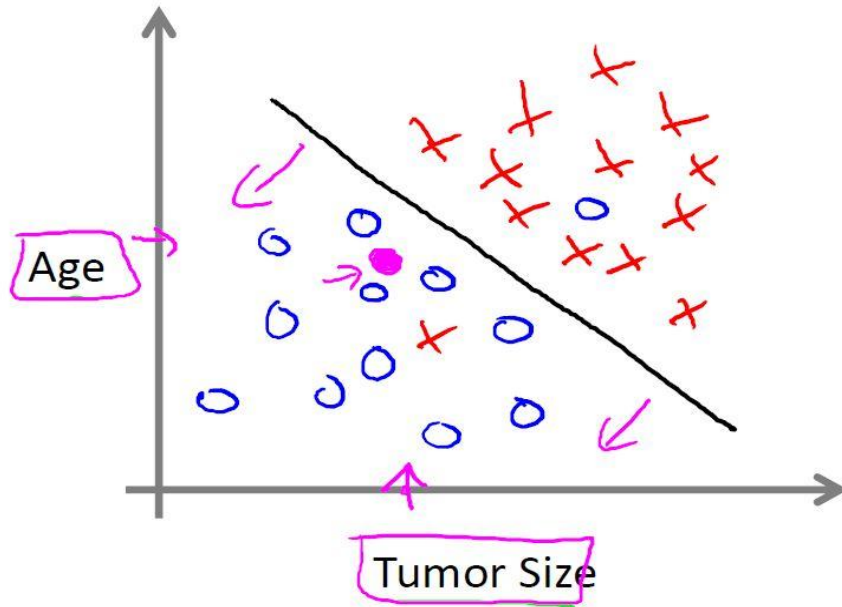
Given huge dataset, when the machine is given several inputs it finds the right answer accordingly.

This terminology is also known as Regression

Regression: Predict Continuous valued output (price)

Housing price prediction.



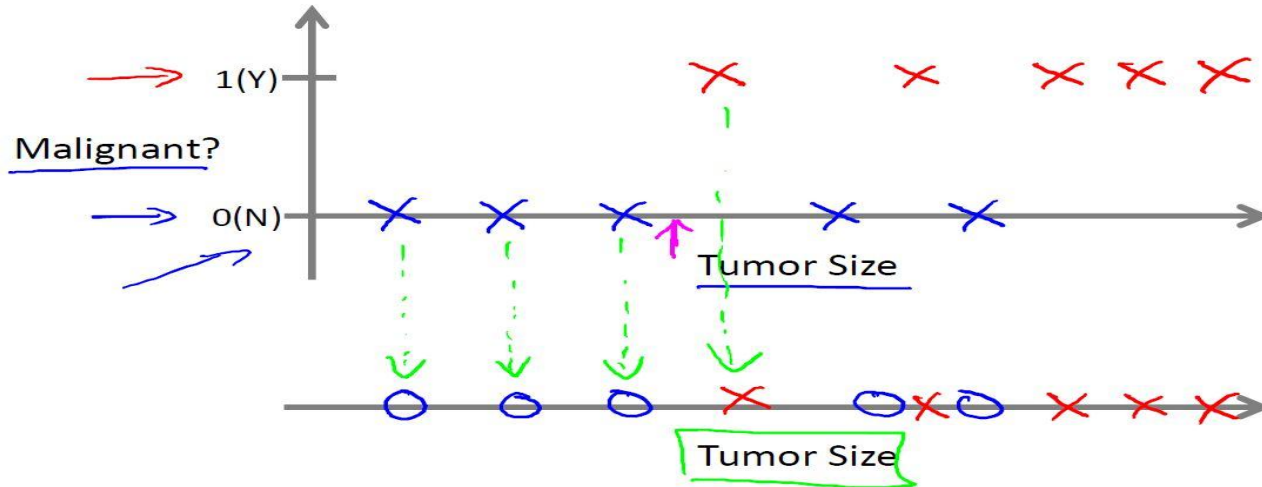


- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape
- ...



Classification:

Breast cancer (malignant, benign)



Classification

Discrete valued
output (0 or 1)

0, 1, 2, 3
↓ ↓ ↓ ↓
benign type 1
cancer



Identify:

For infinite feature vectors we need some mathematical tool for access.(e.g in vector machine)

#identical - Regression problem

#unique - Classification



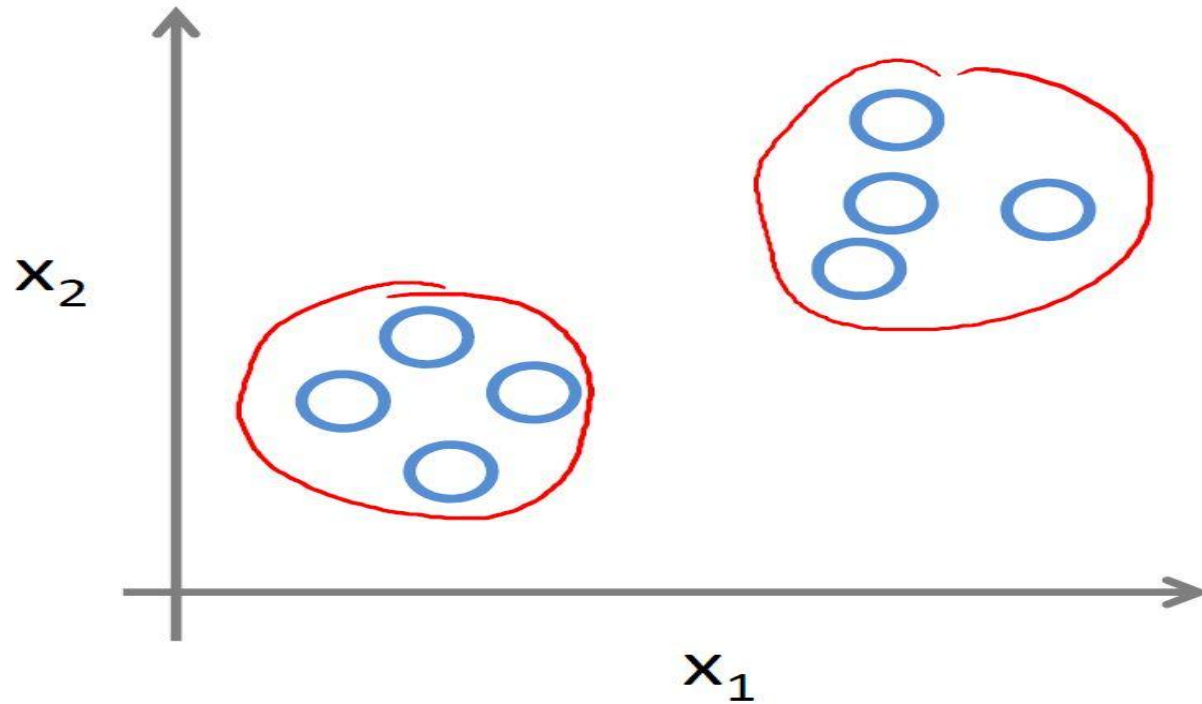
Unsupervised Learning:

The goal is not really to discover some O/P but here the goal is to discover some patterns in data.

- Discover patterns in the data.
 - **Clustering: Cohesive Grouping** - Categories of customers in a shop
 - College student
 - IT professionals etc.
 - **Association: Frequent Co-occurrence** [finding frequent co-occurrence of items in the dataset given to me. If I see 'A' then it is very likely to see B in my shop.]



Unsupervised Learning



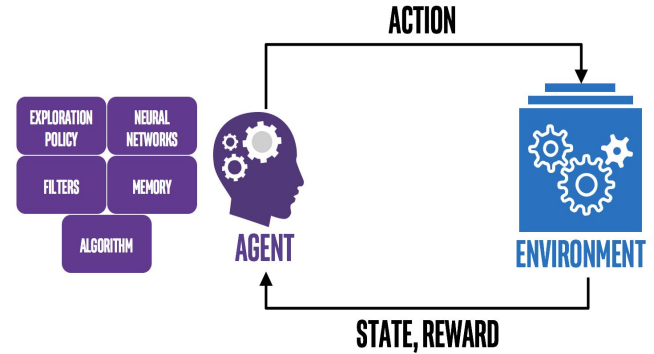
Reinforcement Learning:

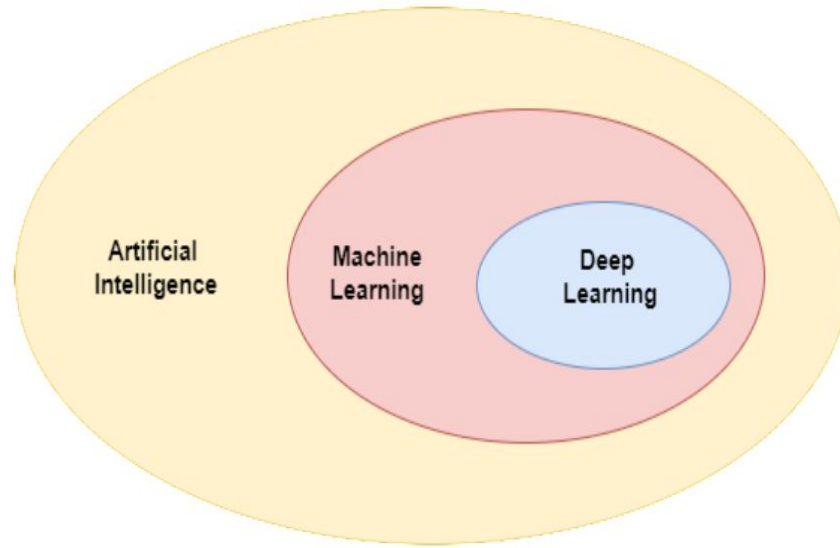
Learning to control behaviour of a system.

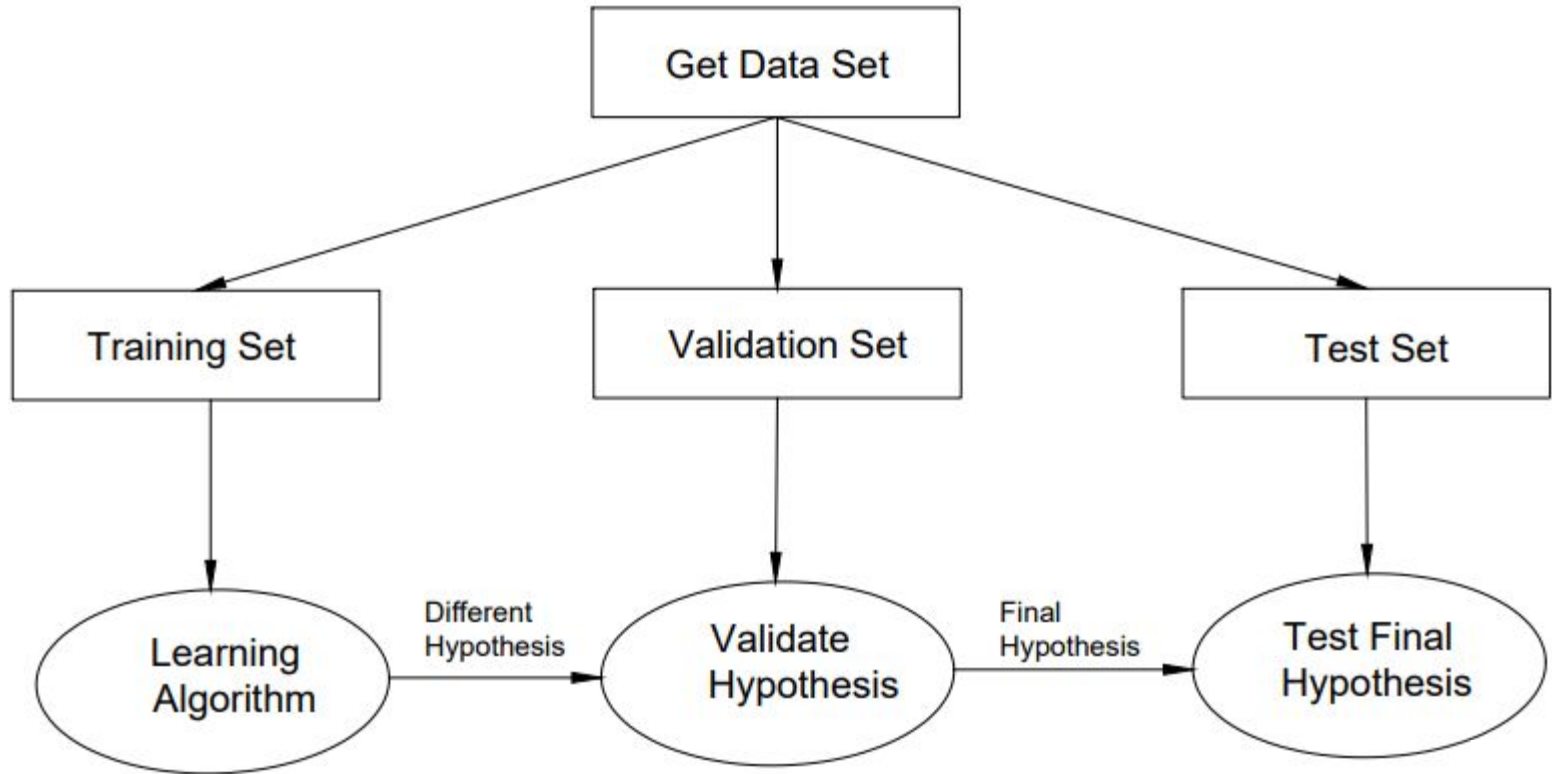
How did you learn to cycle?

- Neither of SV nor USV.
- Some trial or error.
- Falling down Hurts.

This type of learning is a method to learn to control the system through the trial and error and minimal feedback is essential.







Dimensionality Reduction

- PCA
- Encoders



Regression -

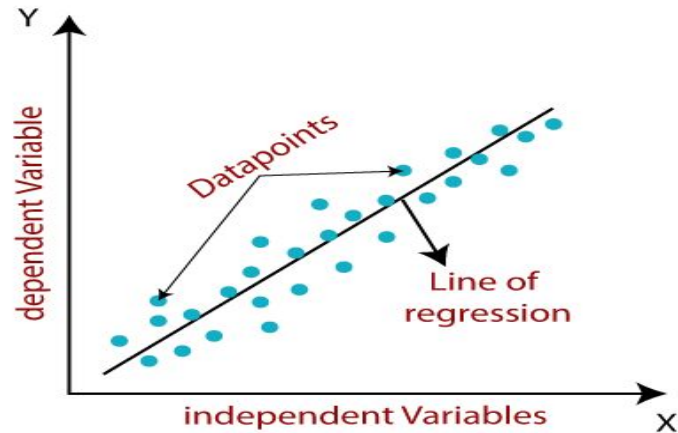
- Linear Regression
- Multiple Regression
- Polynomial Regression
- Support Vector Regression
- Decision Tree Regression
- Random Forest Regression



Linear regression -

Algorithm shows a linear relationship between a dependent (y) and one or more independent (x) variables.

Linear regression makes predictions for continuous/real or numeric variables



House Pricing Prediction -

Training set

Size in feet ² (x)	Price (\$) in 1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

$m = 47$

- Notation:

- m = Number of training examples
- x = Input variable / features
- y = Output variable / target variable
- (x, y) = One training example
- $(x^{(i)}, y^{(i)}) = i^{th}$ training example

Examples:

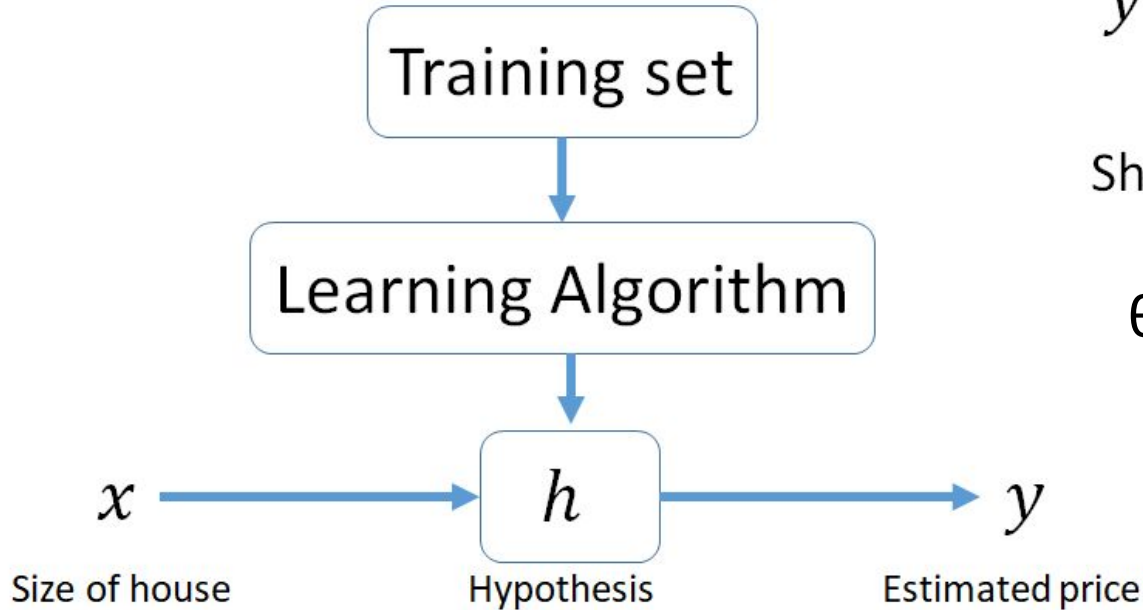
$$x^{(1)} = 2104$$

$$x^{(2)} = 1416$$

$$y^{(1)} = 460$$



Model representation



$$y = h_{\theta}(x) = \theta_0 + \theta_1 x$$

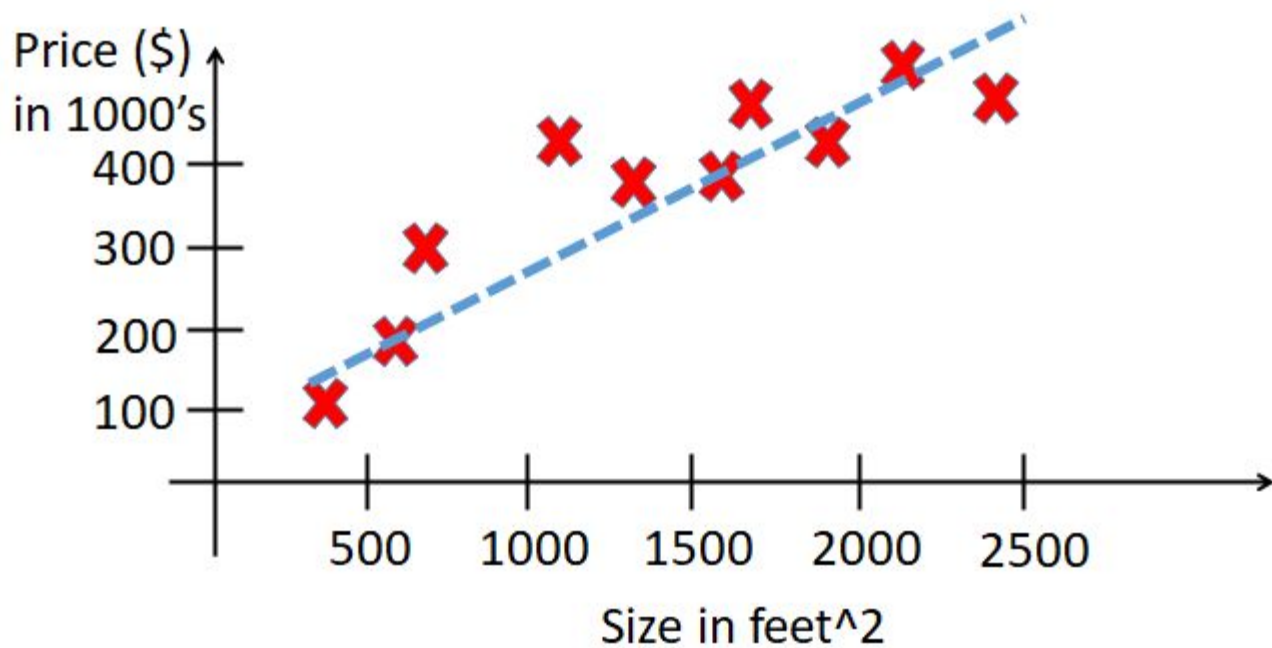
Shorthand $h(x)$

θ_0, θ_1 : parameters/weights

How to choose θ_i 's?



House pricing prediction



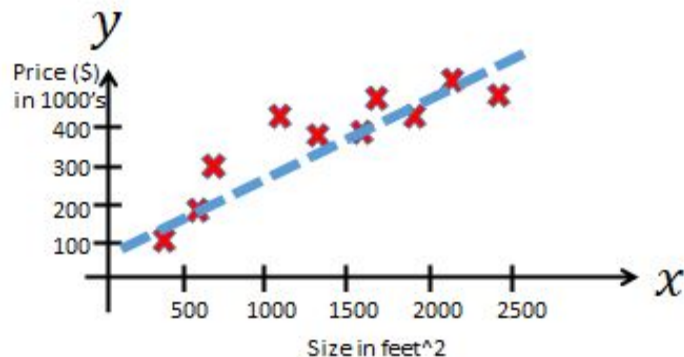
Cost function (Root Mean Squared Error (RMSE))

- Idea:

Choose θ_0, θ_1 so that $h_{\theta}(x)$ is close to y for our training example (x, y)

$$\underset{\theta_0, \theta_1}{\text{minimize}} \quad \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$h_{\theta}(x^{(i)}) = \theta_0 + \theta_1 x^{(i)}$$



$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$\underset{\theta_0, \theta_1}{\text{minimize}} \quad \boxed{J(\theta_0, \theta_1)} \quad \text{Cost function}$$



Simplified

- **Hypothesis:**

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$



- **Hypothesis:**

$$h_{\theta}(x) = \theta_1 x$$

$$\theta_0 = 0$$

- **Parameters:**

$$\theta_0, \theta_1$$



- **Parameters:**

$$\theta_1$$

- **Cost function:**

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

- **Cost function:**

$$J(\theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

- **Goal:**

$$\underset{\theta_0, \theta_1}{\text{minimize}} \quad J(\theta_0, \theta_1)$$

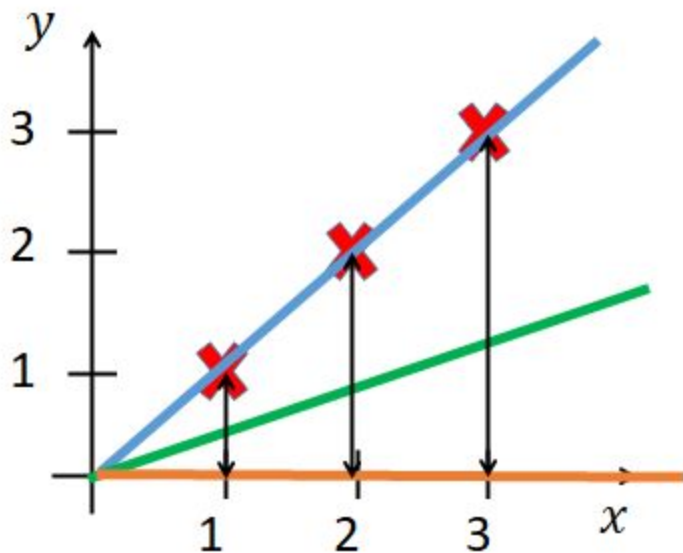


- **Goal:**

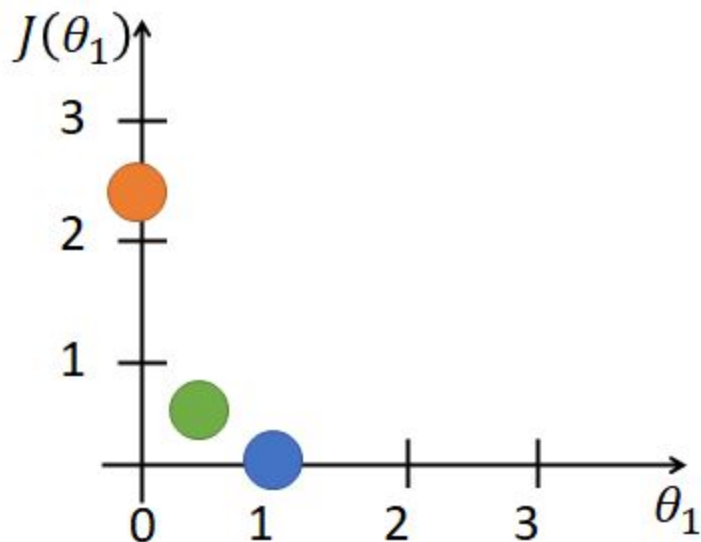
$$\underset{\theta_0, \theta_1}{\text{minimize}} \quad J(\theta_1)$$



$h_{\theta}(x)$, function of x



$J(\theta_1)$, function of θ_1



• **Hypothesis:** $h_{\theta}(x) = \theta_0 + \theta_1 x$

• **Parameters:** θ_0, θ_1

• **Cost function:** $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$

• **Goal:** minimize $J(\theta_0, \theta_1)$ θ_0, θ_1 ?



Gradient descent

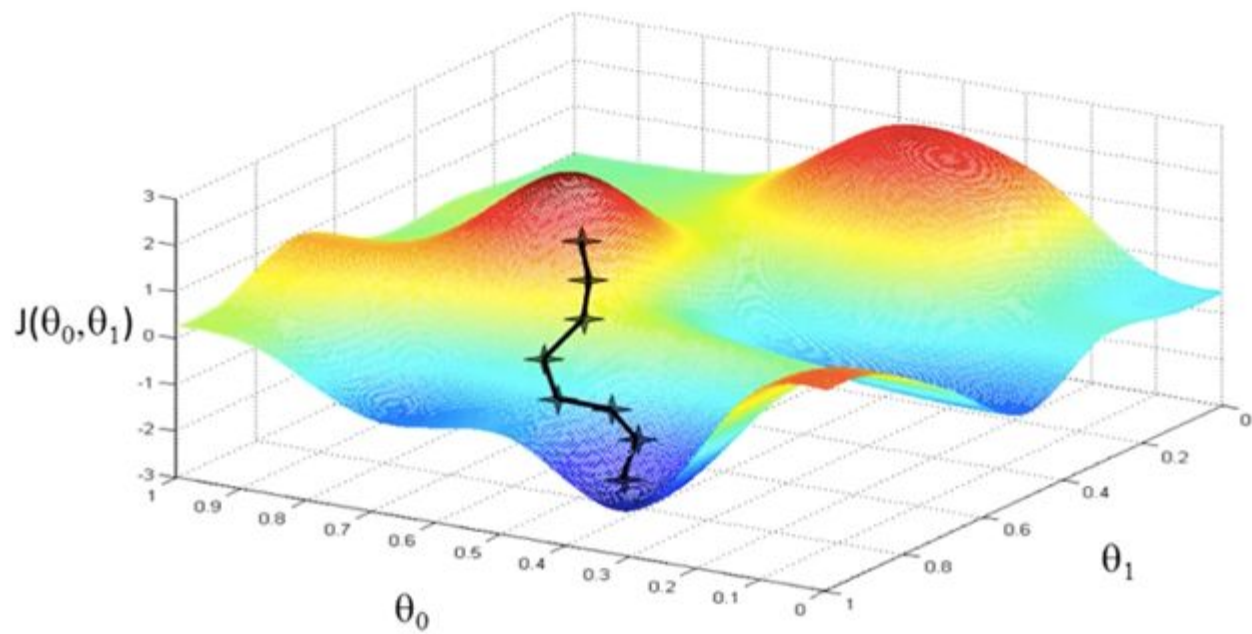
Have some function $J(\theta_0, \theta_1)$

Want $\operatorname{argmin}_{\theta_0, \theta_1} J(\theta_0, \theta_1)$

Outline:

- Start with some θ_0, θ_1
- Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$
until we hopefully end up at minimum





Data Preprocessing -

- **Getting the dataset**
- **Importing libraries**
- **Importing datasets**
- **Finding Missing Data**
- **Encoding Categorical Data**
- **Splitting dataset into training and test set**
- **Feature scaling**



Multiple Linear Regression -

Regression algorithms which models the linear relationship between a single dependent continuous variable and more than one independent variable.

Hypothesis

Previously:

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

Now:

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$



Multiple features (input variables)

Size in feet ² (x_1)	Number of bedrooms (x_2)	Number of floors (x_3)	Age of home (years) (x_4)	Price (\$) in 1000's (y)
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178
...				...

Notation:

n = Number of features

$x^{(i)}$ = Input features of i^{th} training example

$x_j^{(i)}$ = Value of feature j in i^{th} training example

$$x_3^{(2)} = ?$$

$$x_3^{(4)} = ?$$



$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$$

- For convenience of notation, define $x_0 = 1$
($x_0^{(i)} = 1$ for all examples)

$$\bullet \mathbf{x} = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in R^{n+1} \qquad \boldsymbol{\theta} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix} \in R^{n+1}$$

$$\begin{aligned} \bullet h_{\theta}(x) &= \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n \\ &= \boldsymbol{\theta}^T \mathbf{x} \end{aligned}$$



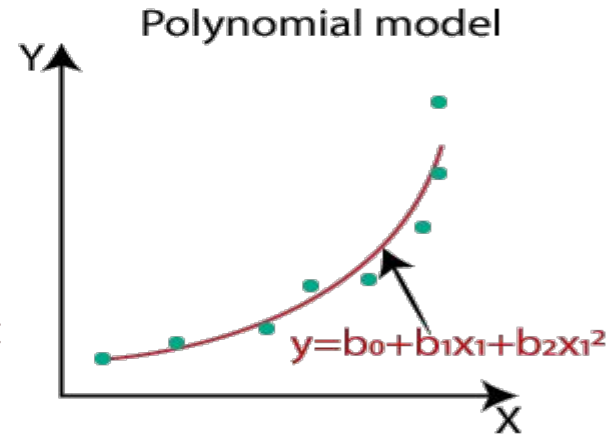
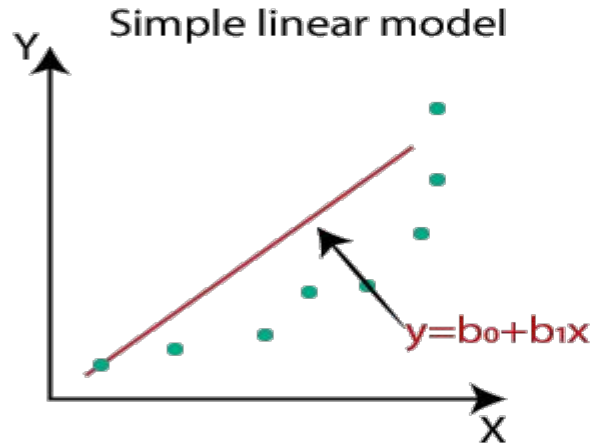
House prices prediction

- $h_{\theta}(x) = \theta_0 + \theta_1 \times \text{frontage} + \theta_2 \times \text{depth}$
- Area $x = \text{frontage} \times \text{depth}$
- $h_{\theta}(x) = \theta_0 + \theta_1 x$



Polynomial Regression -

Regression algorithm that models the relationship between a dependent(y) and independent variable(x) as nth degree polynomial



Coding content:

1. Linear Regression with two datasets
2. Linear Regression with data preprocessing.

