

# Introduction to Data Science



# Chapter 4

# Predictive Analysis

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# Outline

## Predictive Analysis

### 1. Predictive Analysis

- Preparing Datasets

### 2. Classification Analysis

- K-Nearest Neighbor
- Decision Tree
- Naïve Bayes
- Artificial Neural Network
- Classification Assessment

### 3. Regression Analysis

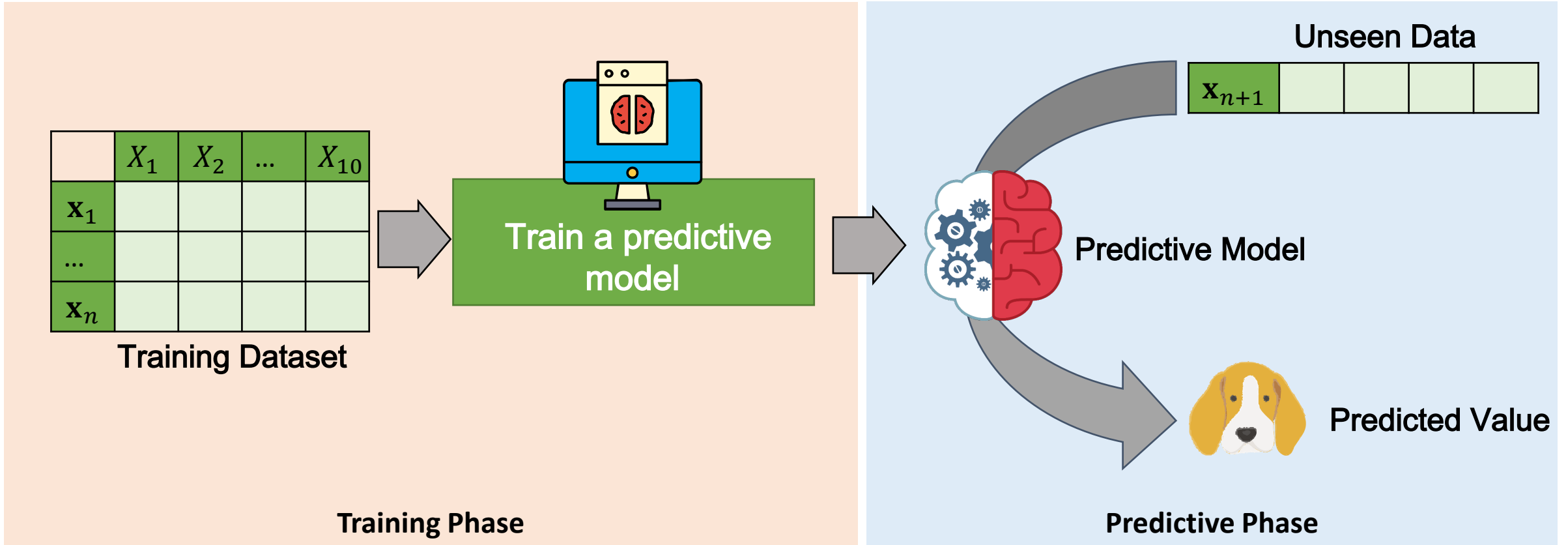
- Linear Regression
- Polynomial Regression
- Artificial Neural Network
- Regression Assessment

### 4. Time Series Analysis

- Autoregressive Model
- Moving Average Model
- Autoregressive Integrated Moving Average
- Moving Average Smoothing

# Predictive Analysis

Analyze current and historical data to make predictions about future or otherwise unknown events.



# Preparing Dataset

## Predictive Analysis

	Features				Target values
D	$X_1$	$X_2$	...	$X_{10}$	Y
$x_1$					
$x_2$					
$x_3$					
...					
$x_l$					
$x_{l+1}$					
$x_{l+2}$					
...					
$x_n$					

### To perform a predictive analysis:

- We should have two datasets: training and test datasets.
- The target value of each datapoint must be available.

#### Training dataset

- Will be used to train a predictive model.
- Target value of each data point must be available.

#### Test dataset

- Will be used to evaluate the predictive model
- Assume that target value of each data point is not known, but it should be available.

# Classification Analysis

	Features				Target class
D	$X_1$	$X_2$	...	$X_{10}$	Y
$x_1$					
$x_2$					
$x_3$					
...					
$x_l$					
$x_{l+1}$					
$x_{l+2}$					
...					
$x_n$					

## For classification analysis

- The value we want to predict is **categorical data**.
- Known as **class**

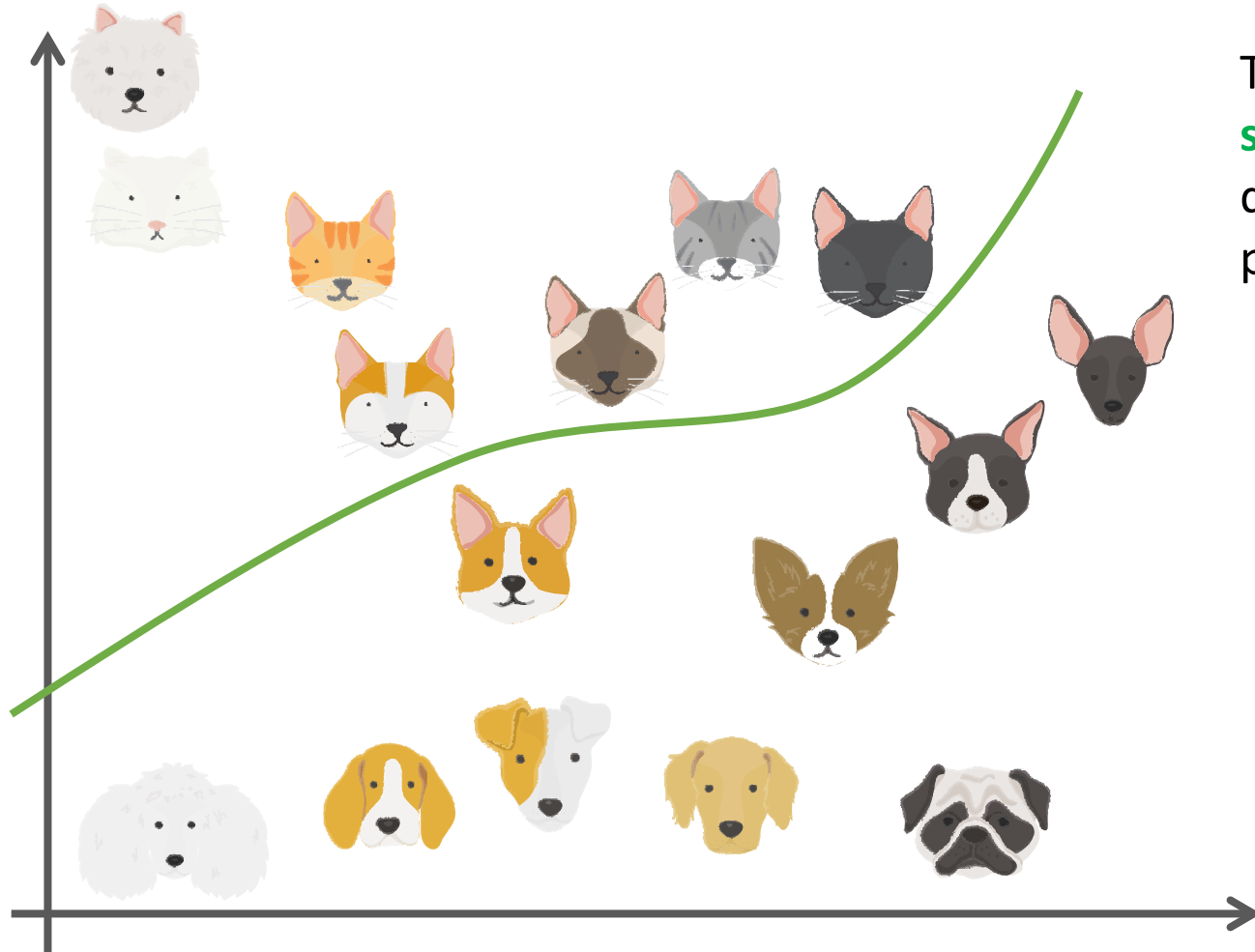
## Example

We know some characteristics of an animal, and we want to predict it is a cat or a dog.



**cat or dog?**

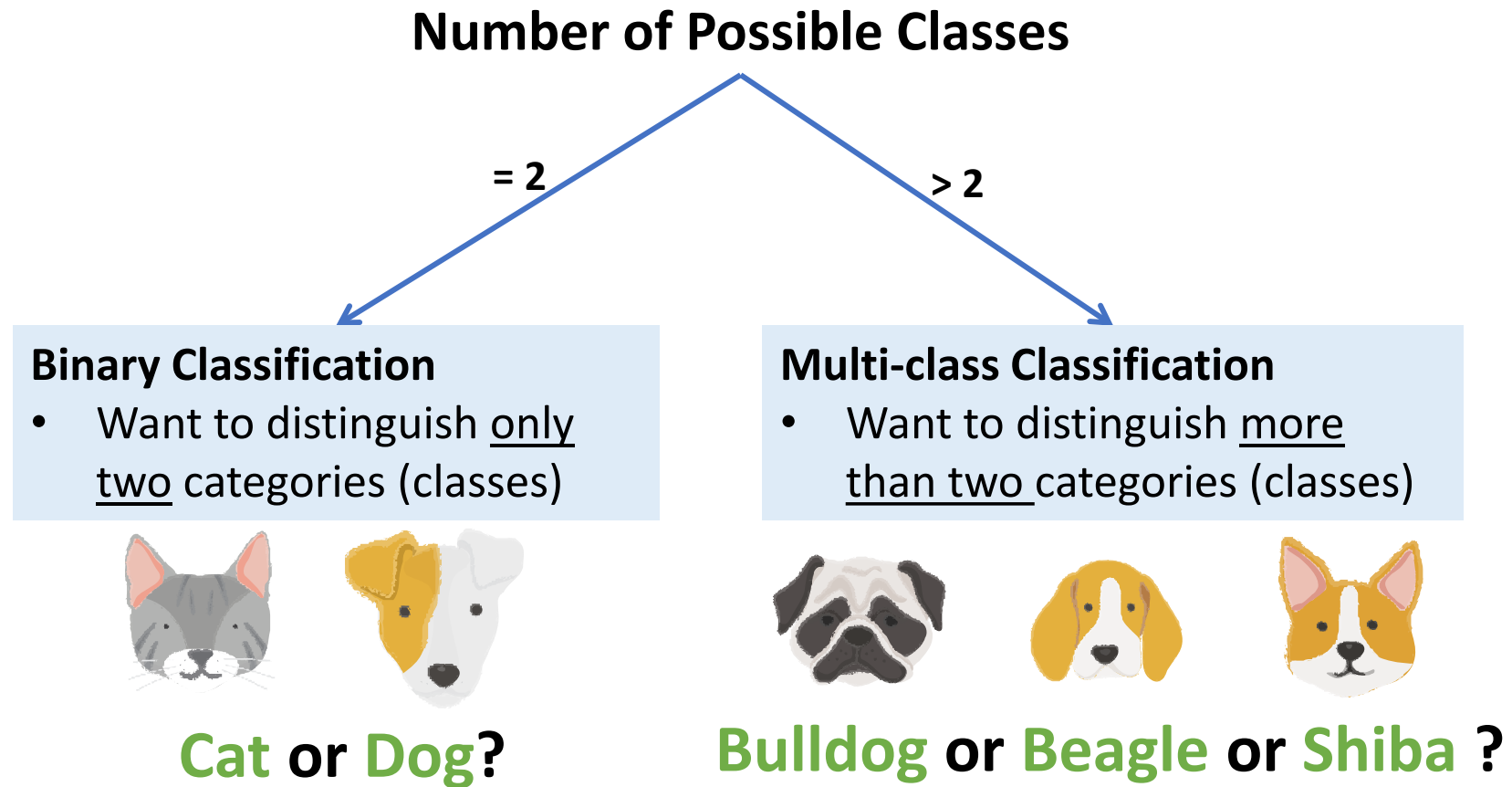
# Classification Analysis



The task of classification is one of finding **separating lines** that separate classes of data from a training dataset as best as possible.

# Classification Analysis

## Types of Classification Problems





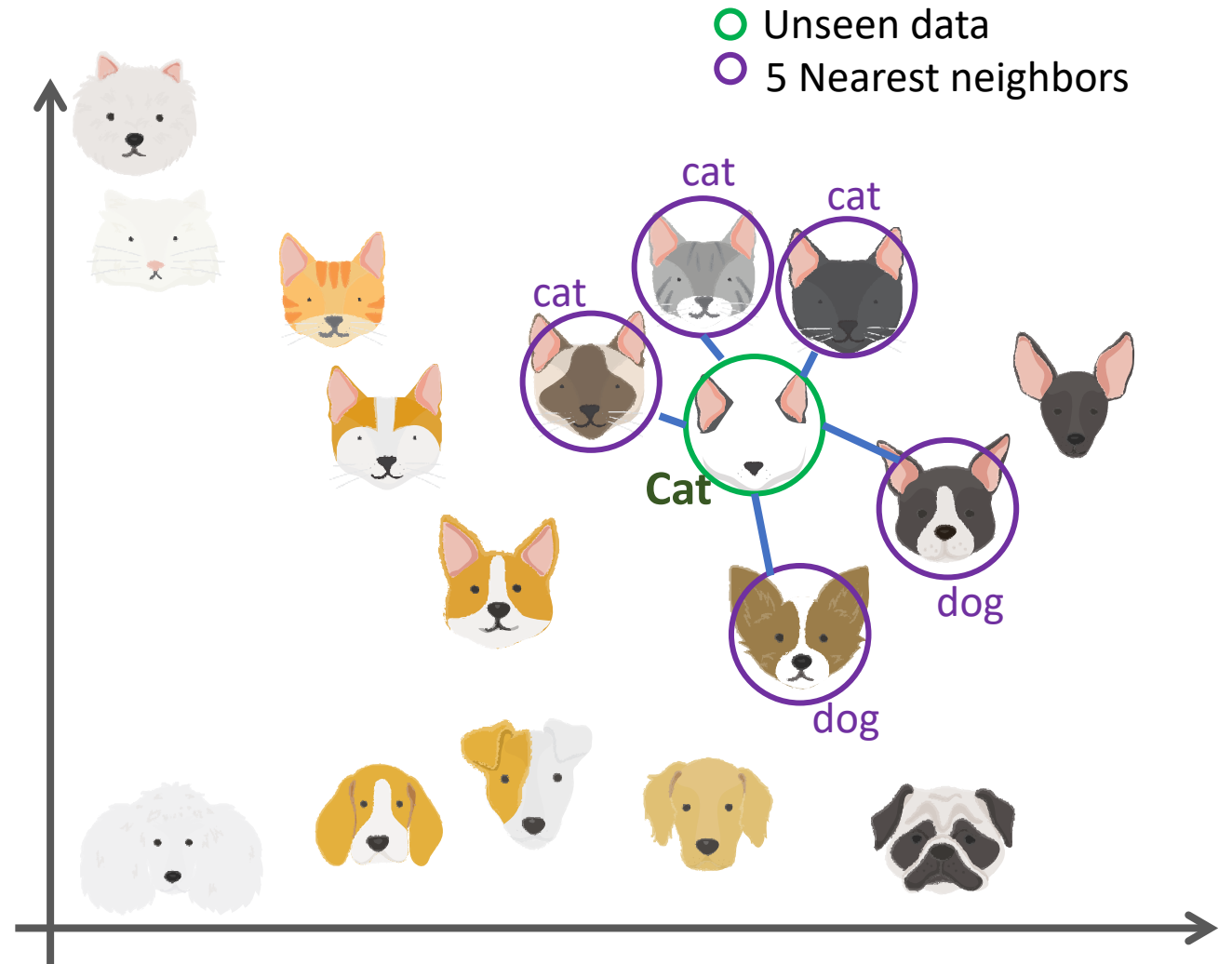
# K-Nearest Neighbor

## Classification Analysis

K-Nearest Neighbor classifier assigns the class label of an unseen data with the majority class labels of k neighbor data (in the training dataset)

### How the k-nearest neighbor works

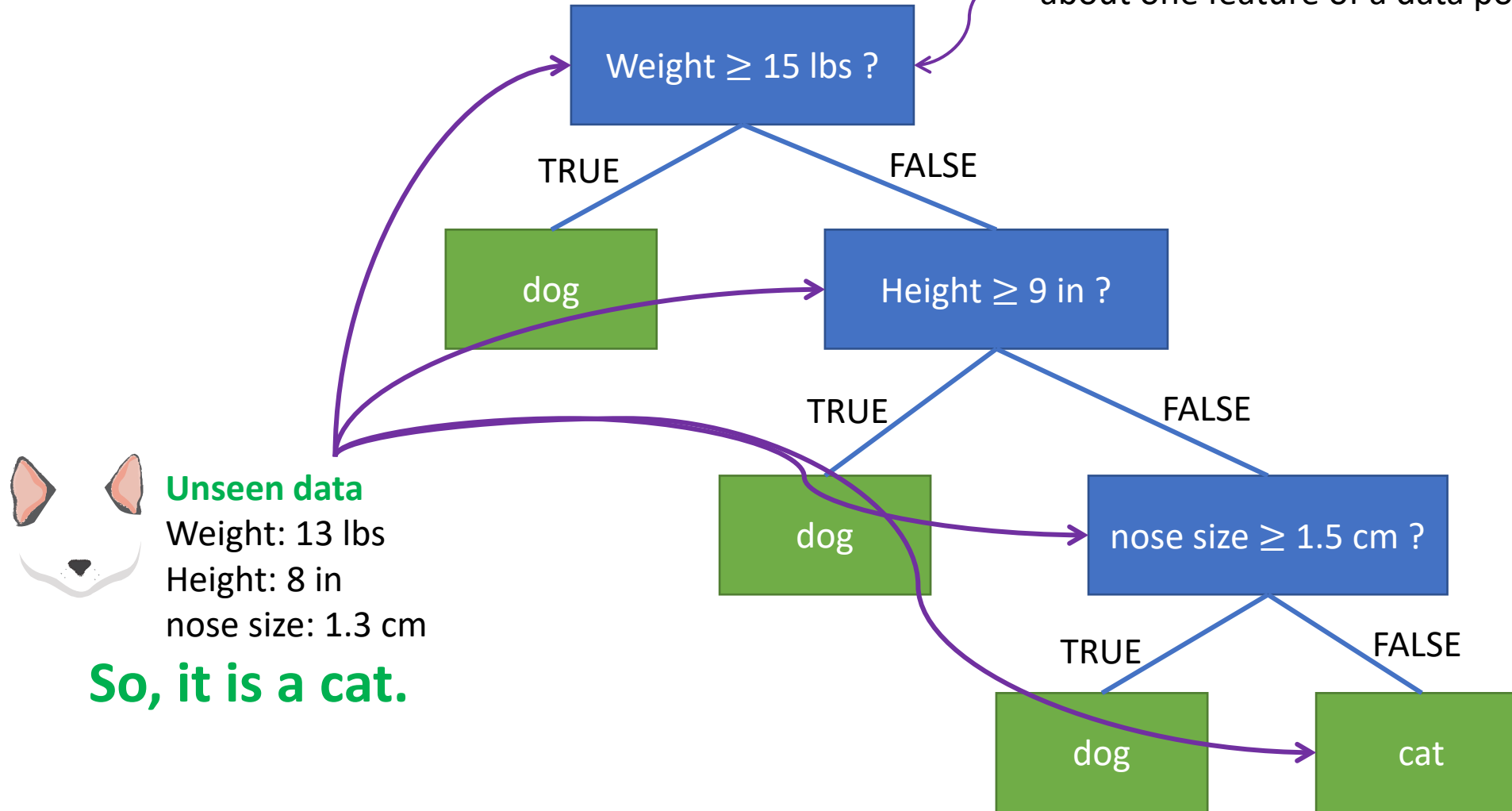
- STEP 1: Calculate distances between an unseen data and training data
- STEP 2: Find  $k$  nearest neighbor
- STEP 3: Find majority class label
- STEP 4: Assign the majority class label to the class label of the unseen data



# Decision Tree

## Classification Analysis

Every node in the tree asks a question about one feature of a data point.



# Decision Tree

## Classification Analysis

### Construct a decision tree

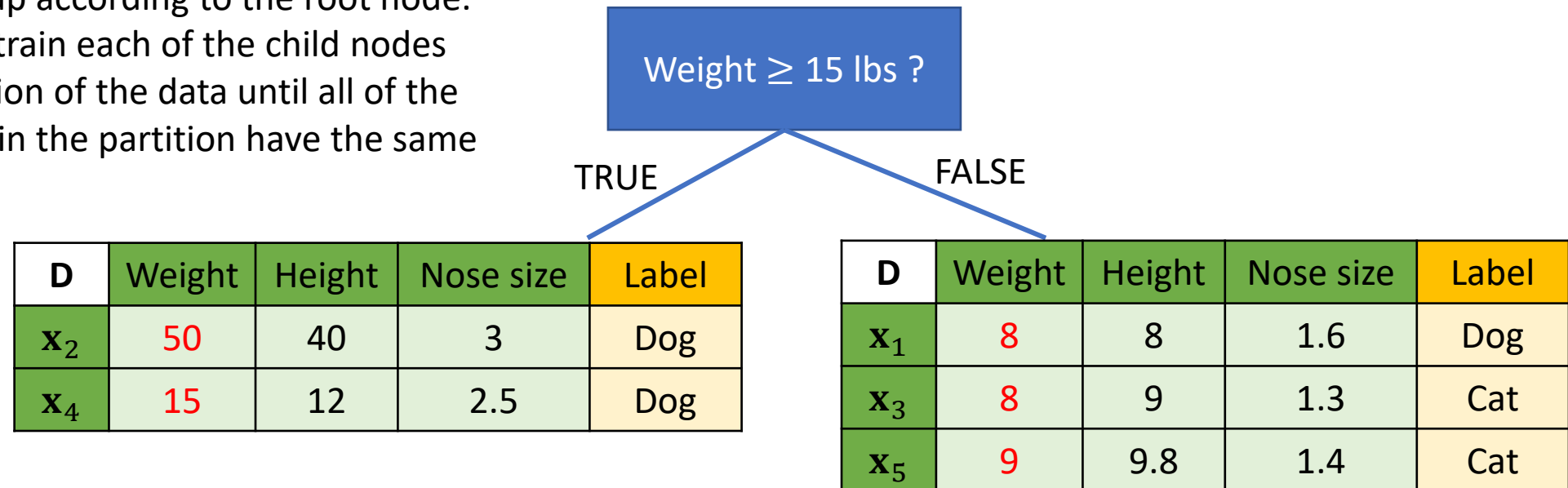
STEP 1: Given a training data  $D$ , find the single feature (and cutoff for that feature, if it's numerical) that best partitions your data into classes.

STEP 2: This single best feature/cutoff becomes the root of your decision tree.

STEP 3: Partition  $D$  up according to the root node.

STEP 4: Recursively train each of the child nodes on its partition of the data until all of the data points in the partition have the same label.

D	Weight	Height	Nose size	Label
$x_1$	8	8	1.6	Dog
$x_2$	50	40	3	Dog
$x_3$	8	9	1.3	Cat
$x_4$	15	12	2.5	Dog
$x_5$	9	9.8	1.4	Cat



# Decision Tree

## Classification Analysis

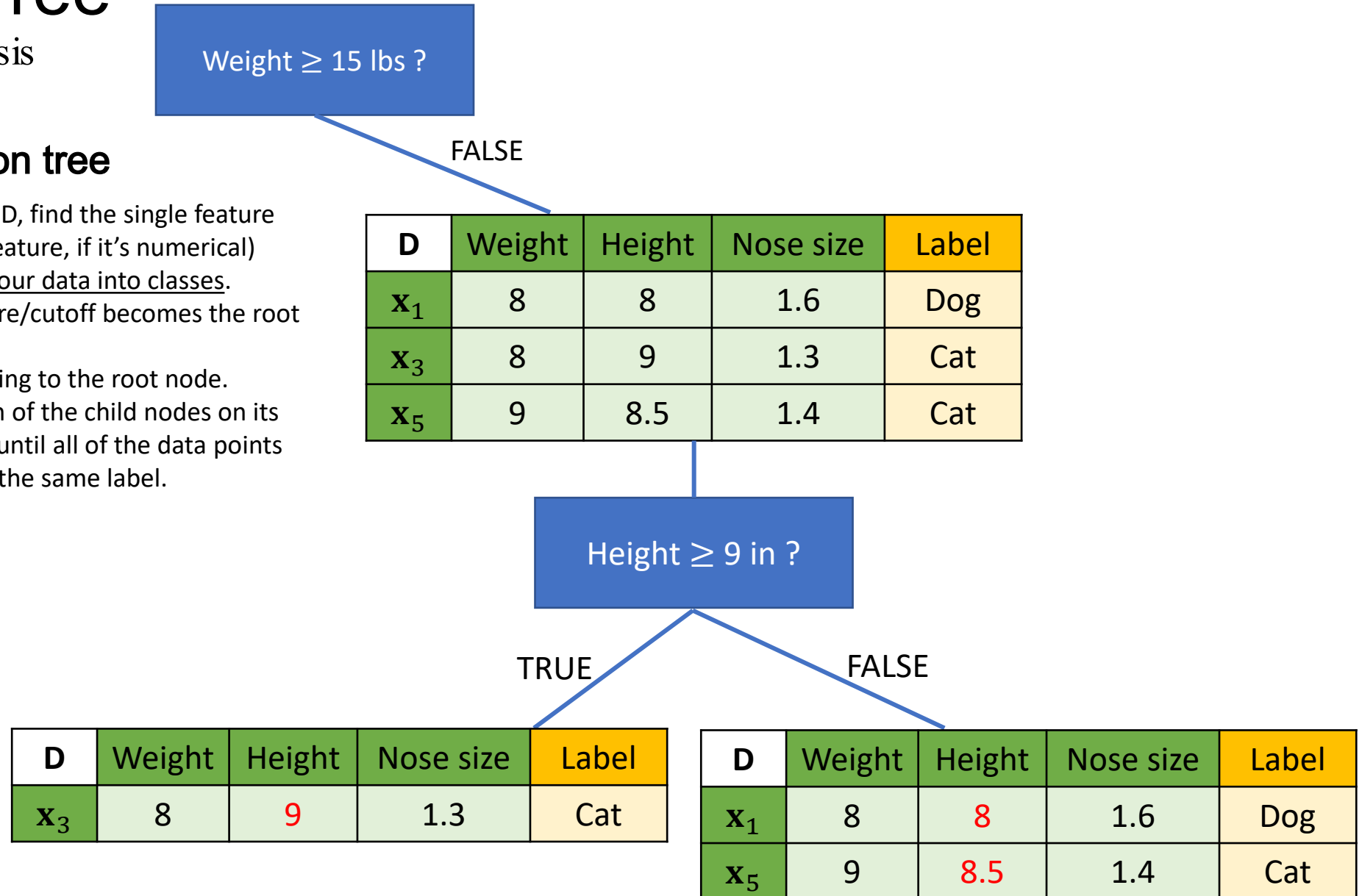
### Construct a decision tree

STEP 1: Given a training data  $D$ , find the single feature (and cutoff for that feature, if it's numerical) that best partitions your data into classes.

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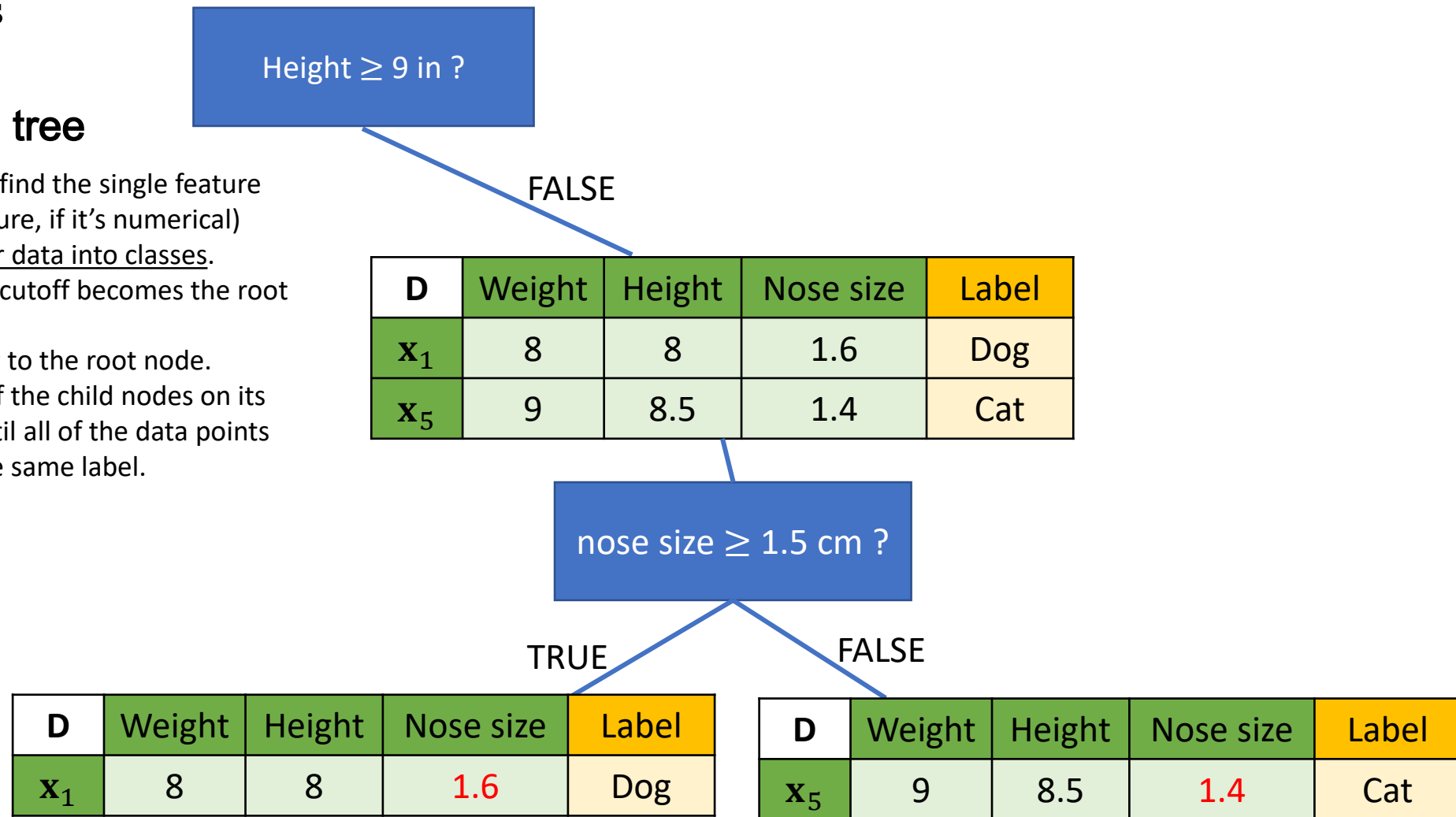


# Decision Tree

## Classification Analysis

### Construct a decision tree

- STEP 1: Given a training data  $D$ , find the single feature (and cutoff for that feature, if it's numerical) that best partitions your data into classes.
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# Decision Tree

## Classification Analysis

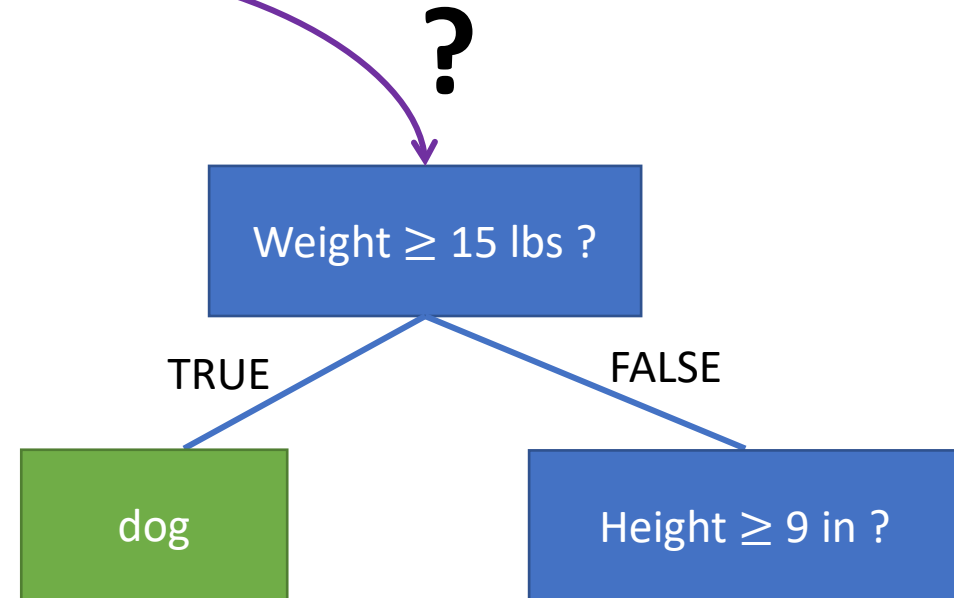
### How to determine the best feature and cutoff

The most common ones are:

- Information gain
- Gini impurity.

You can find more details in:

- Zaki, M., & Meira, W. (2014). Data mining and analysis : Fundamental concepts and algorithms. New York: Cambridge University Press.
- [https://en.wikipedia.org/wiki/Decision\\_tree\\_learning](https://en.wikipedia.org/wiki/Decision_tree_learning)



# Naïve Bayes

## Classification Analysis

Bayes Theorem:

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

Probability of **A** happening,  
given that **B** has occurred

The *prior*, the initial  
degree of belief in **A**.

The likelihood of event **B**  
occurring given that **A** is  
true.



**Thomas Bayes**

**1701-1761**

Source:

[https://en.wikipedia.org/wiki/Thomas\\_Bayes#/media/File:Thomas\\_Bayes.gif](https://en.wikipedia.org/wiki/Thomas_Bayes#/media/File:Thomas_Bayes.gif)

# Naïve Bayes

## Classification Analysis

Classify whether the day is suitable for playing golf, given the features of the day.

Bayes theorem can be rewritten as:

$$P(y|\mathbf{x}) = \frac{P(y)P(\mathbf{x}|y)}{P(\mathbf{x})}$$

**We want to classify**

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
$\mathbf{x}_1$	Rainy	Hot	High	False	No
$\mathbf{x}_2$	Rainy	Hot	High	True	No
$\mathbf{x}_3$	Overcast	Hot	High	False	Yes
$\mathbf{x}_4$	Sunny	Mild	High	False	Yes
$\mathbf{x}_5$	Sunny	Cool	Normal	False	Yes
$\mathbf{x}_6$	Sunny	Cool	Normal	True	No
$\mathbf{x}_7$	Overcast	Cool	Normal	True	Yes
$\mathbf{x}_8$	Rainy	Mild	High	False	No
$\mathbf{x}_9$	Rainy	Cool	Normal	False	Yes
$\mathbf{x}_{10}$	Sunny	Mild	Normal	False	Yes
$\mathbf{x}_{11}$	Rainy	Mild	Normal	True	Yes
$\mathbf{x}_{12}$	Overcast	Mild	High	Ture	Yes
$\mathbf{x}_{13}$	Overcast	Hot	Normal	False	Yes
$\mathbf{x}_{14}$	Sunny	Mild	High	True	No



# Naïve Bayes

## Classification Analysis

### How the Naïve Bayes works

STEP 1: Calculate  $P(y)$  for all possible value of  $y$  from the training dataset.

STEP 2: Calculate  $P(\mathbf{x}|y) = \prod_{i=1}^p P(x_i|y)$  for all possible value of  $y$  from the training dataset.

STEP 3: Calculate  $P(y|\mathbf{x}) = P(y) \prod_{i=1}^p P(x_i|y)$

STEP 4: Assign  $y$  that reach the highest  $P(y|\mathbf{x})$  to the class label of  $\mathbf{x}$

**We want to classify**

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
$\mathbf{x}_1$	Rainy	Hot	High	False	No
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STEP 4: Assign  $y$  that reach the highest  $P(y|\mathbf{x})$  to the class label of  $\mathbf{x}$

$$P(\text{Play golf} = \text{No}) = \frac{5}{14}$$
$$P(\text{Play golf} = \text{Yes}) = \frac{9}{14}$$

We want to classify

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
$\mathbf{x}_1$	Rainy	Hot	High	False	No
$\mathbf{x}_2$	Rainy	Hot	High	True	No
$\mathbf{x}_3$	Overcast	Hot	High	False	Yes
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$$P(\text{Outlook} = \text{Sunny} | \text{Play golf} = \text{No}) = \frac{2}{15}$$

$$P(\text{Outlook} = \text{Sunny} | \text{Play golf} = \text{Yes}) = \frac{3}{9}$$

We want to classify

$\mathbf{x} = (\text{Sunny}, \text{Hot}, \text{Normal}, \text{True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
$\mathbf{x}_1$	Rainy	Hot	High	False	No
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$$P(\text{Temperature} = \text{Hot} | \text{Play golf} = \text{No}) = \frac{2}{5}$$

$$P(\text{Temperature} = \text{Hot} | \text{Play golf} = \text{Yes}) = \frac{2}{9}$$

We want to classify

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

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# Naïve Bayes

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$$P(\text{Humidity} = \text{Normal} | \text{Play golf} = \text{No}) = \frac{1}{5}$$

$$P(\text{Humidity} = \text{Normal} | \text{Play golf} = \text{Yes}) = \frac{6}{9}$$

We want to classify

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
$\mathbf{x}_1$	Rainy	Hot	High	False	No
$\mathbf{x}_2$	Rainy	Hot	High	True	No
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# Naïve Bayes

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$$P(\text{Windy} = \text{True} | \text{Play golf} = \text{No}) = \frac{3}{15}$$

$$P(\text{Windy} = \text{True} | \text{Play golf} = \text{Yes}) = \frac{3}{9}$$

We want to classify

$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$

D	Outlook	Temperature	Humidity	Windy	Play golf
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$\mathbf{x}_2$	Rainy	Hot	High	True	No
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$\mathbf{x}_7$	Overcast	Cool	Normal	True	Yes
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$\mathbf{x}_9$	Rainy	Cool	Normal	False	Yes
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# Naïve Bayes

## Classification Analysis

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$$P(\text{Play golf} = \text{No} | \text{Sunny, Hot, Normal, True}) \\ = \frac{5}{14} \times \frac{2}{5} \times \frac{2}{5} \times \frac{1}{5} \times \frac{3}{5} = 0.0069$$

$$P(\text{Play golf} = \text{Yes} | \text{Sunny, Hot, Normal, True}) \\ = \frac{9}{14} \times \frac{3}{9} \times \frac{2}{9} \times \frac{6}{9} \times \frac{3}{9} = \mathbf{0.0106}$$

So, it is suitable to **play golf** given the conditions (Outlook = Sunny, Temperature = Hot, Humidity = Normal and Windy = True).

### We want to classify

$$\mathbf{x} = (\text{Sunny, Hot, Normal, True})$$

$$P(\text{Play golf} = \text{No}) = \frac{5}{14}$$

$$P(\text{Play golf} = \text{Yes}) = \frac{9}{14}$$

$$P(\text{Outlook} = \text{Sunny} | \text{Play golf} = \text{No}) = \frac{2}{5}$$

$$P(\text{Outlook} = \text{Sunny} | \text{Play golf} = \text{Yes}) = \frac{3}{9}$$

$$P(\text{Temperature} = \text{Hot} | \text{Play golf} = \text{No}) = \frac{2}{5}$$

$$P(\text{Temperature} = \text{Hot} | \text{Play golf} = \text{Yes}) = \frac{2}{9}$$

$$P(\text{Humidity} = \text{Normal} | \text{Play golf} = \text{No}) = \frac{1}{5}$$

$$P(\text{Humidity} = \text{Normal} | \text{Play golf} = \text{Yes}) = \frac{6}{9}$$

$$P(\text{Windy} = \text{True} | \text{Play golf} = \text{No}) = \frac{3}{5}$$

$$P(\text{Windy} = \text{True} | \text{Play golf} = \text{Yes}) = \frac{3}{9}$$

# Naïve Bayes

## Classification Analysis

### Quiz:

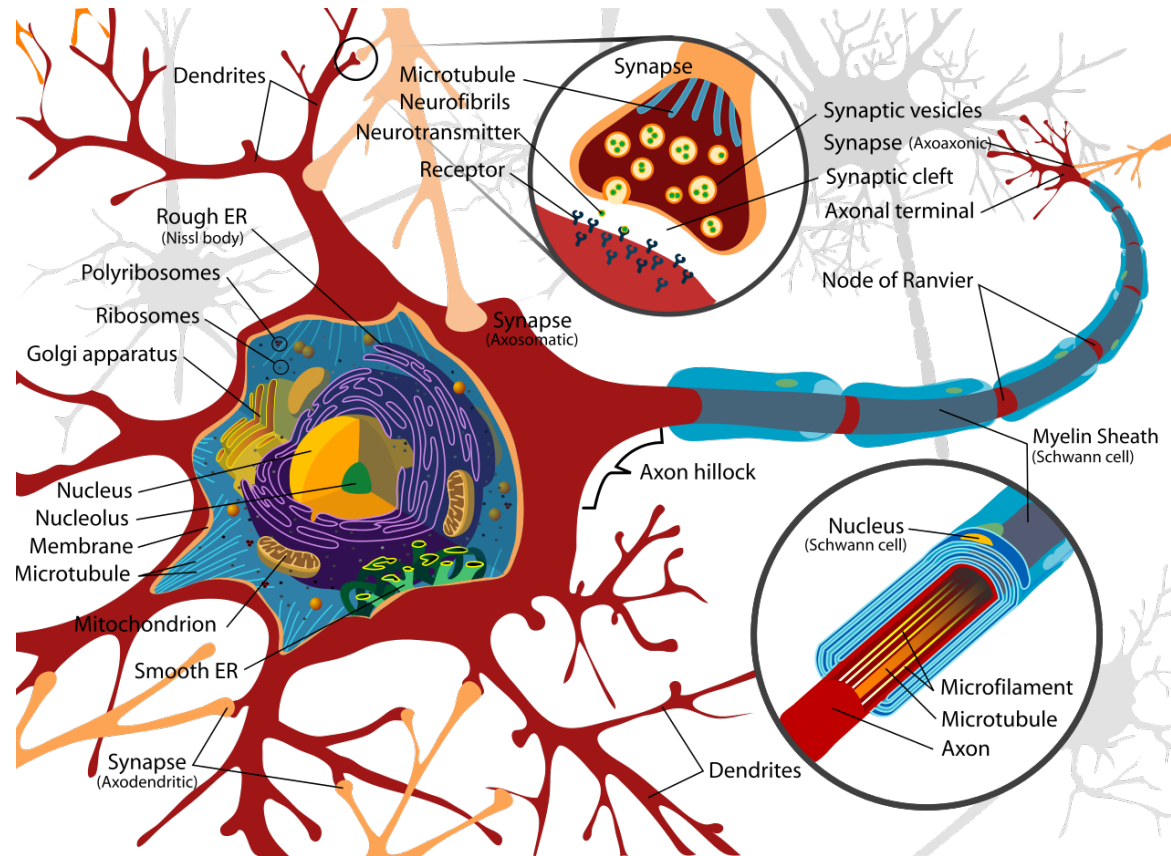
It is suitable to play golf or not given the conditions (Outlook = Rainy, Temperature = Mild, Humidity = Normal and Windy = False).

D	Outlook	Temperature	Humidity	Windy	Play golf
$x_1$	Rainy	Hot	High	False	No
$x_2$	Rainy	Hot	High	True	No
$x_3$	Overcast	Hot	High	False	Yes
$x_4$	Sunny	Mild	High	False	Yes
$x_5$	Sunny	Cool	Normal	False	Yes
$x_6$	Sunny	Cool	Normal	True	No
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$x_{12}$	Overcast	Mild	High	Ture	Yes
$x_{13}$	Overcast	Hot	Normal	False	Yes
$x_{14}$	Sunny	Mild	High	True	No



# Artificial Neural Network

## Classification Analysis



Source:

[https://en.wikipedia.org/wiki/Neuron#/media/File:Complete\\_neuron\\_cell\\_diagram\\_en.svg](https://en.wikipedia.org/wiki/Neuron#/media/File:Complete_neuron_cell_diagram_en.svg)

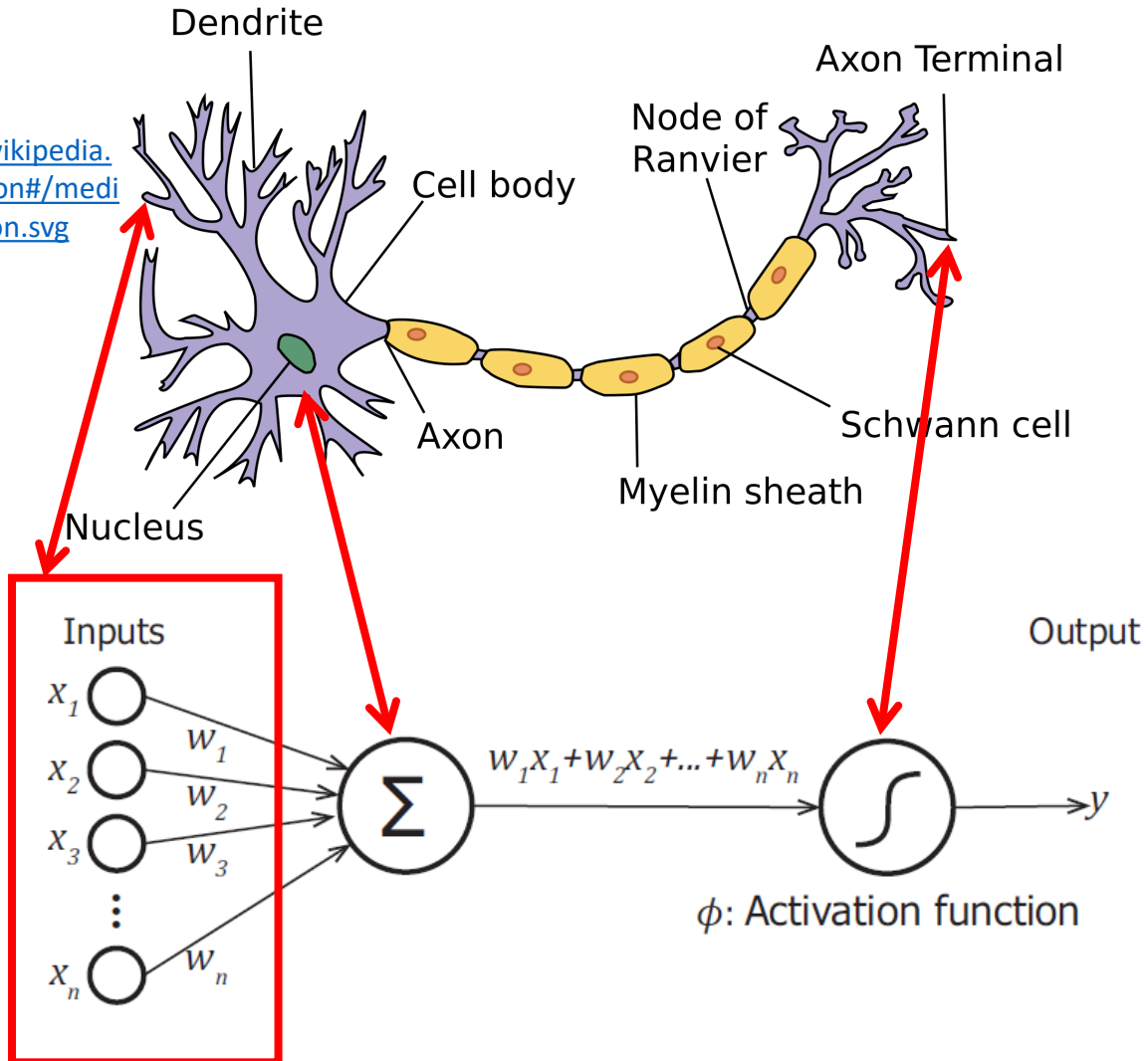
- **Artificial Neural Network (ANN)** is a computational model inspired structurally and functionally in biological neural networks.
- **ANN** is a web of neuron nodes.

# Artificial Neural Network

## Classification Analysis

Source:

<https://en.wikipedia.org/wiki/Axon#/media/File:Neuron.svg>

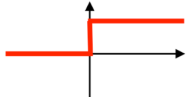
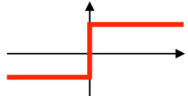
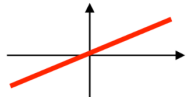


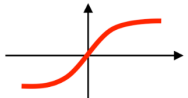
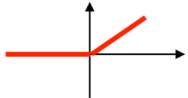



For a neuron, the output  $y$  is produced by:

$$y = \phi \left( \sum_{i=1}^n w_i x_i + b \right)$$

# Artificial Neural Network

## Classification Analysis

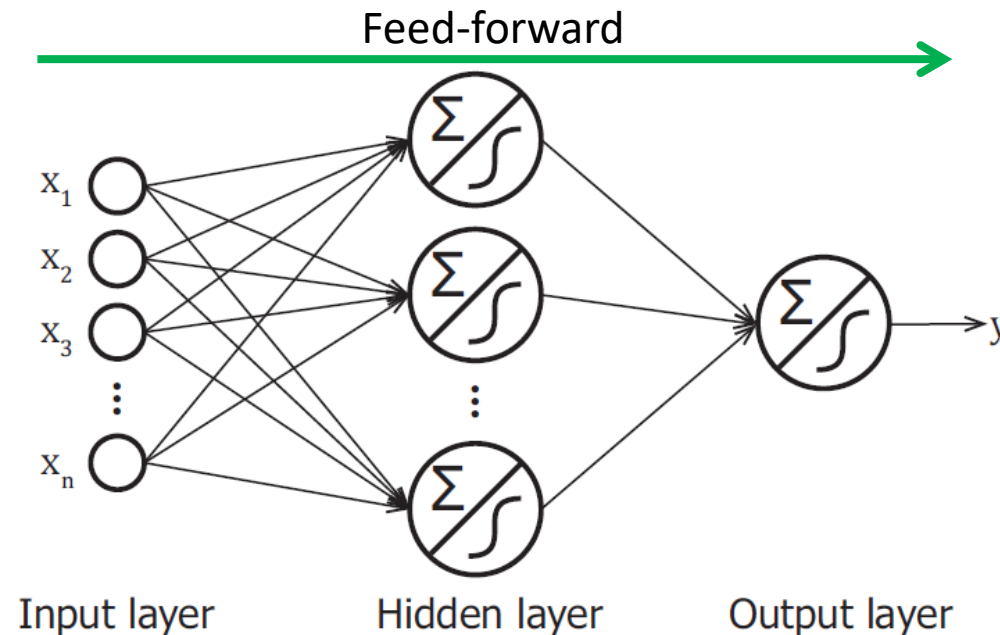
Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

# Artificial Neural Network

## Classification Analysis

A well-known structure of ANN is the multilayer perceptron:

- Neurons are arranged in a layer
- Output of one layer serving as the input to the next layer and possibly other layers.

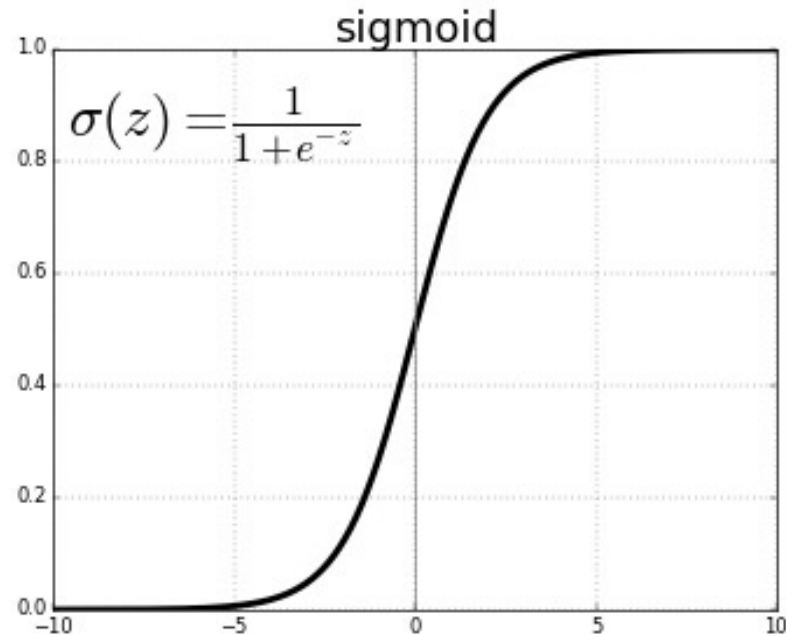


# Artificial Neural Network

## Classification Analysis

### For Classification,

Neurons in output layer applies *sigmoid* function as the *activation function*.



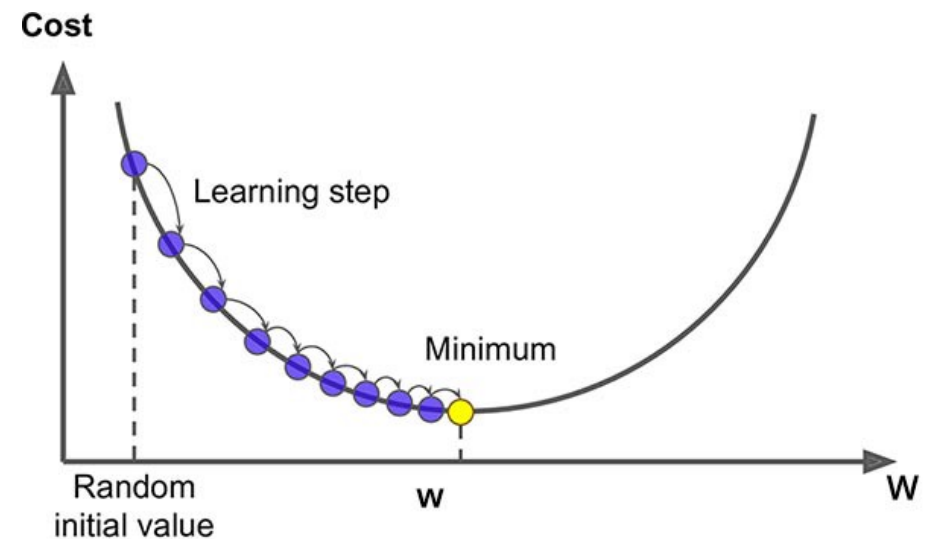
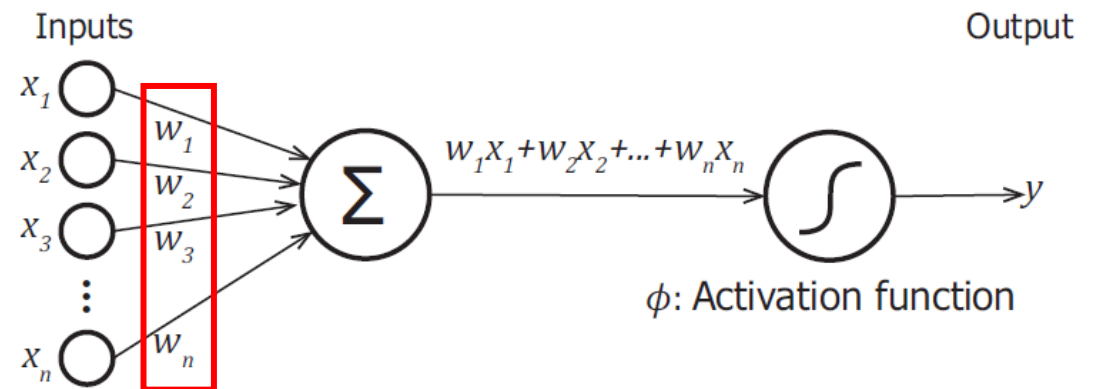
# Artificial Neural Network

## Classification Analysis

### Using an ANN

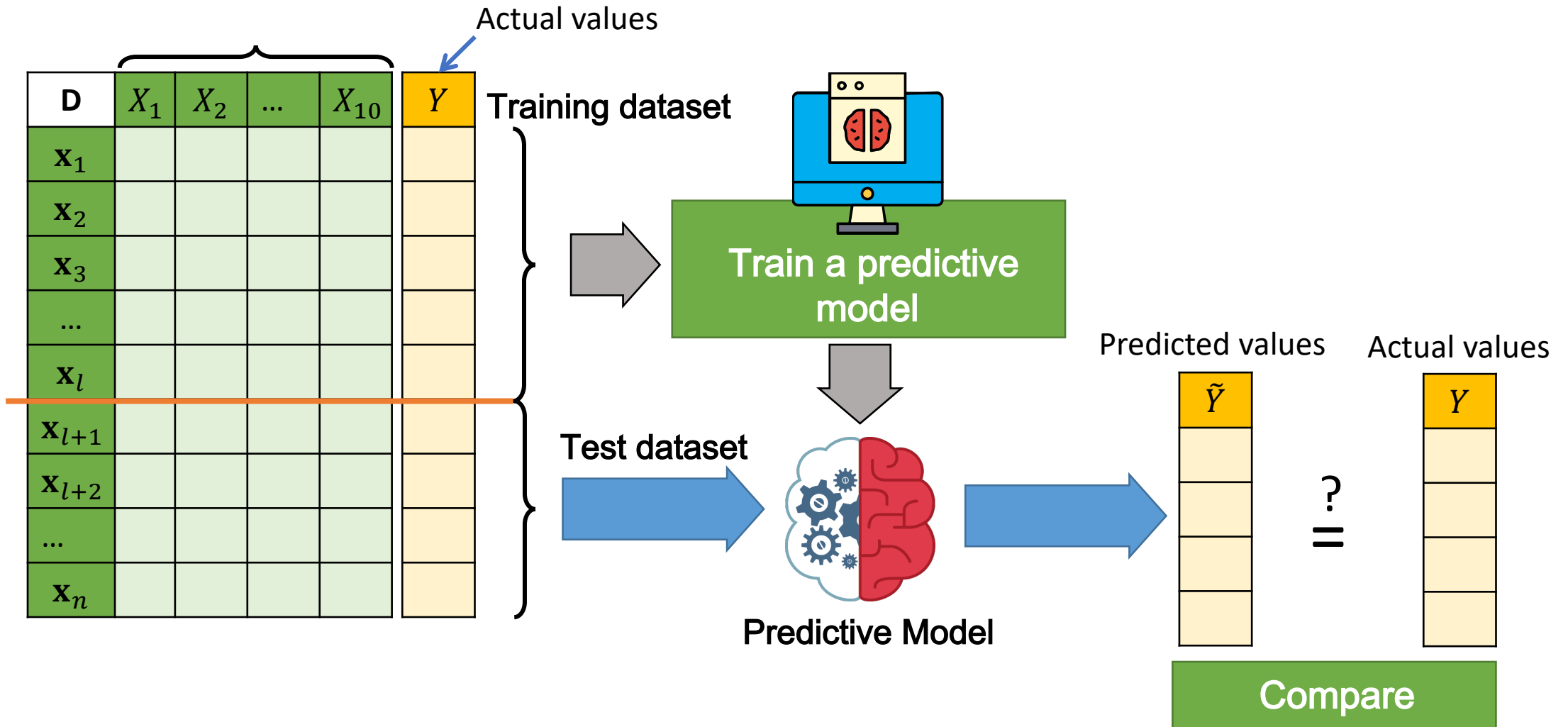
- Design the structure of ANN
- Train the ANN using a **training dataset**
  - Find optimal values of weight  $w_i$  that minimize an **objection function** e.g. square error
- A well-known approach to training an ANN is **gradient descent**

Source:  
<https://mc.ai/an-introduction-to-gradient-descent-2/>



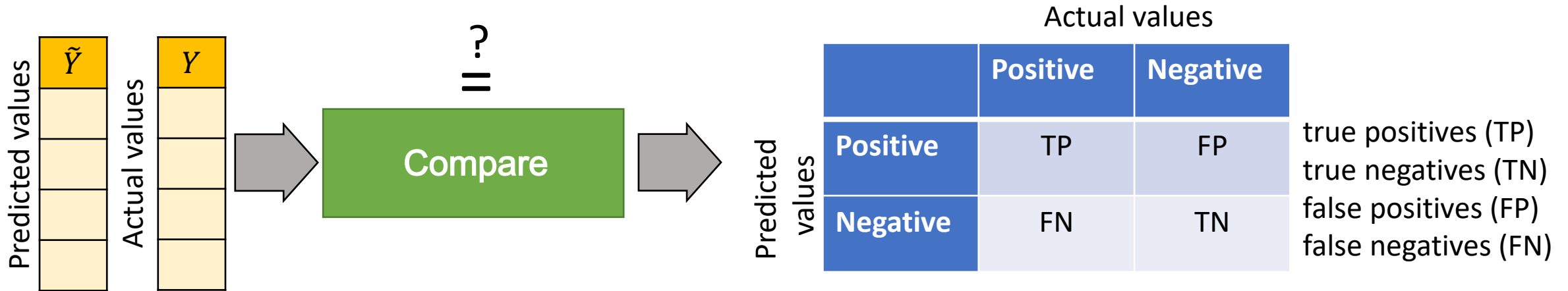
# Classification Assessment

## Classification Analysis



# Classification Assessment

## Classification Analysis



$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{\text{Total}}$$

$$\begin{aligned} \text{Misclassification Rate} &= \frac{(\text{FP} + \text{FN})}{\text{Total}} \\ &= 1 - \text{Accuracy} \end{aligned}$$

### Confusion matrix

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

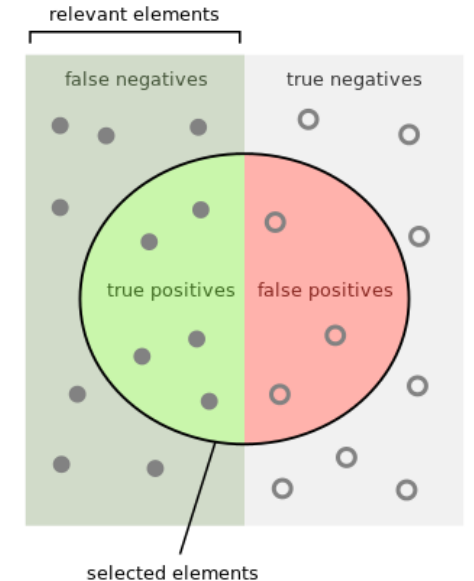
How many selected items are relevant?

$$\text{Precision} = \frac{\text{green}}{\text{green} + \text{red}}$$



How many relevant items are selected?

$$\text{Recall} = \frac{\text{green}}{\text{green} + \text{grey}}$$



Source:

[https://en.wikipedia.org/wiki/Precision\\_and\\_recall](https://en.wikipedia.org/wiki/Precision_and_recall)

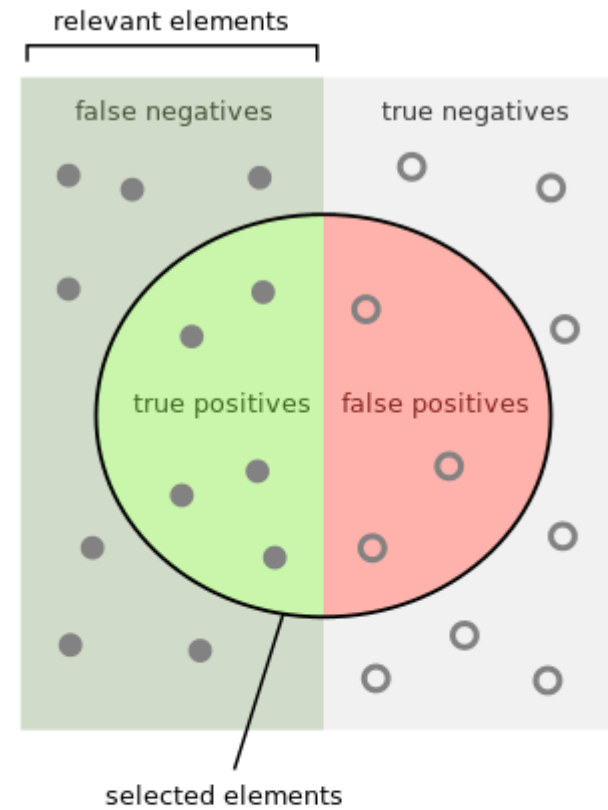


# Classification Assessment

## Classification Analysis

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$



How many selected items are relevant?

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

# Classification Assessment

## Classification Analysis

### Example

		Actual values		
		setosa	versicolor	virginica
Predicted values	setosa	<b>10</b>	2	4
	versicolor	1	<b>16</b>	1
	virginica	0	2	<b>9</b>

$$\text{Recall}_{\text{virginica}} = ?$$

$$\text{Precision}_{\text{virginica}} = ?$$

$$\text{Accuracy} = \frac{(10 + 16 + 9)}{45} = \frac{35}{45} = 0.78$$

$$\text{Misclassification Rate} = 1 - 0.78 = 0.22$$

$$\text{Recall}_{\text{setosa}} = \frac{10}{10 + 1 + 0} = \frac{10}{11} = 0.91$$

$$\text{Precision}_{\text{setosa}} = \frac{10}{10 + 2 + 4} = \frac{10}{16} = 0.625$$

$$\text{Recall}_{\text{versicolor}} = \frac{16}{2 + 16 + 2} = \frac{16}{20} = 0.8$$

$$\text{Precision}_{\text{versicolor}} = \frac{16}{1 + 16 + 1} = \frac{16}{18} = 0.89$$

# Classification Assessment

## Classification Analysis

### Example

		Actual values	
		Cat	Dog
Predicted values	Cat	5	2
	Dog	3	3

$$\text{Accuracy} = \frac{(5 + 3)}{13} = \frac{8}{13} = 0.62$$

$$\text{Misclassification Rate} = \frac{(2 + 3)}{13} = \frac{5}{13} = 0.38$$

$$\text{Recall} = \frac{5}{5 + 3} = \frac{5}{8} = 0.625$$

$$\text{Precision} = \frac{5}{5 + 2} = \frac{5}{7} = 0.714$$

# Regression Analysis

Independent variable

Dependent variable

D	$X_1$	$X_2$	...	$X_{10}$	Y
$x_1$					
$x_2$					
$x_3$					
...					
$x_l$					
$x_{l+1}$					
$x_{l+2}$					
...					
$x_n$					

## For regression analysis

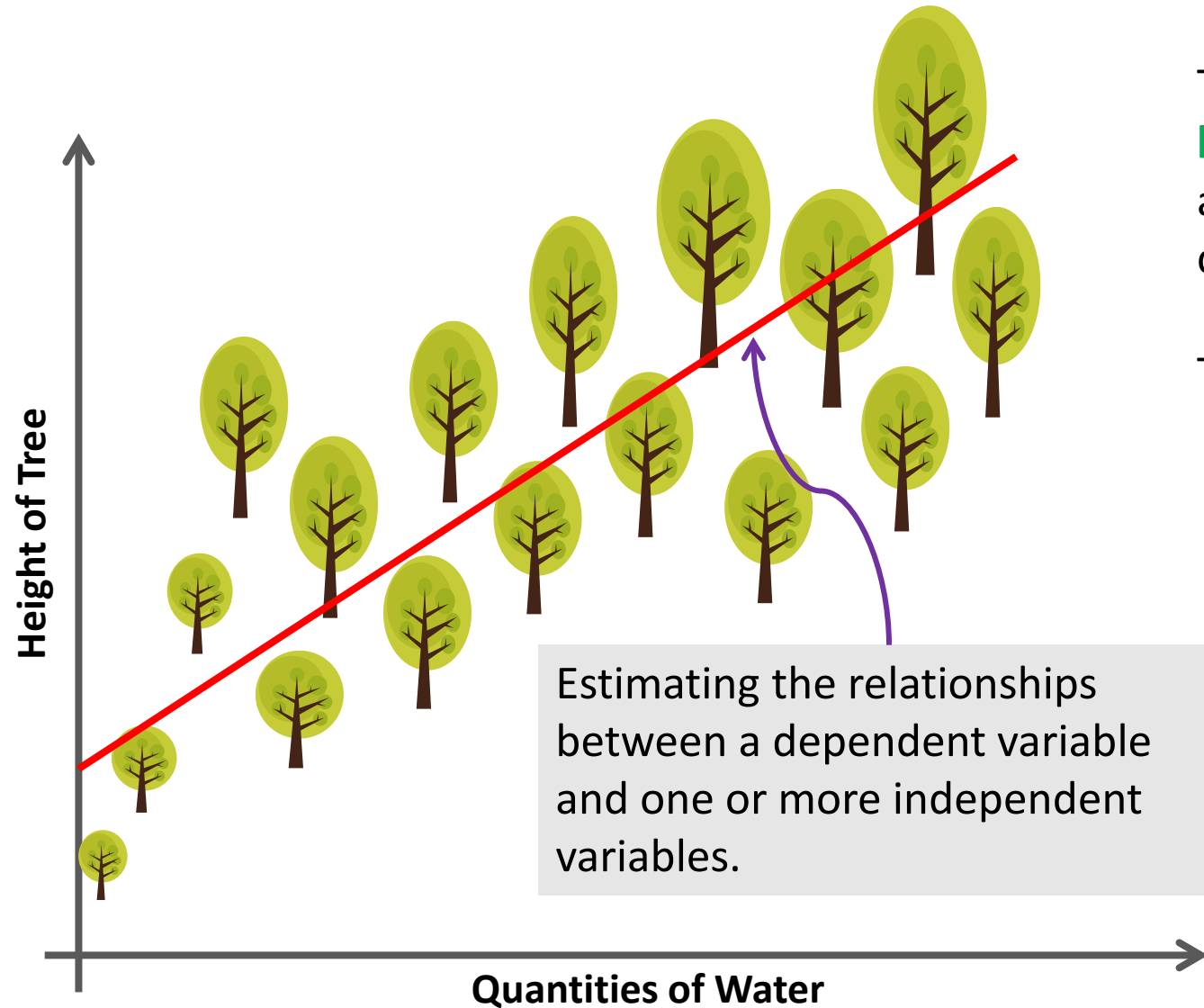
- The value we want to predict is **numeric data**.
- Known as **Dependent variable**

## Example

- We know quantities of water and fertilizer providing to a tree for a month
- We want to predict the growth rate (height) of the tree.



# Regression analysis

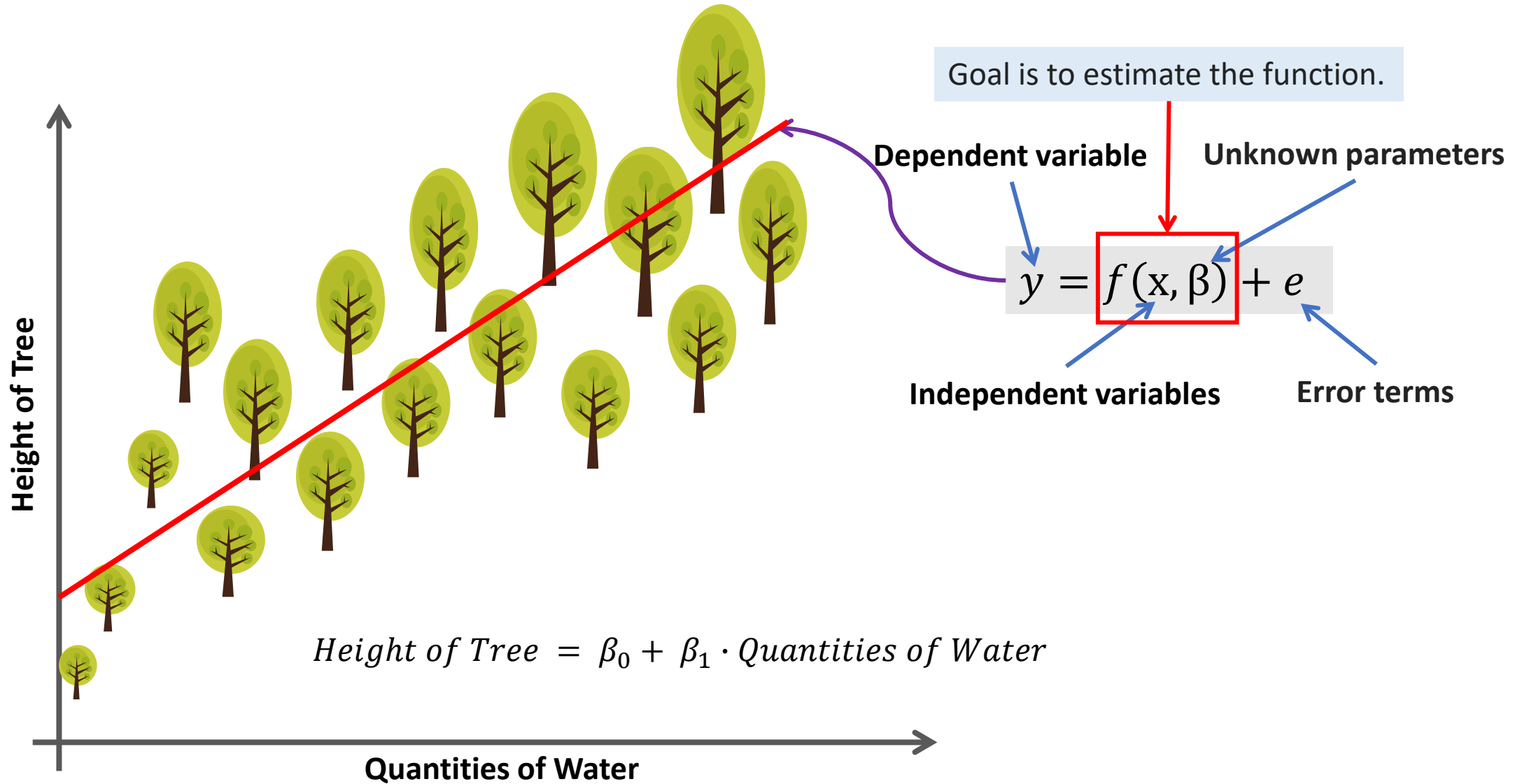


The task of regression is one of finding a **line** that most closely fits the data according to a specific mathematical criterion.

The line can be used for

- prediction and forecasting
- describing relationships between the independent and dependent variables.

# Regression analysis



# Regression Analysis

## Types of Regression Problems

### Number of Independent Variable

```
graph TD; A[Number of Independent Variable] -- "= 1" --> B[Simple Regression]; A -- "> 1" --> C[Multiple Regression];
```

= 1

> 1

#### Simple Regression

Concerns two-dimensional sample points:

- one independent variable
- one dependent variable

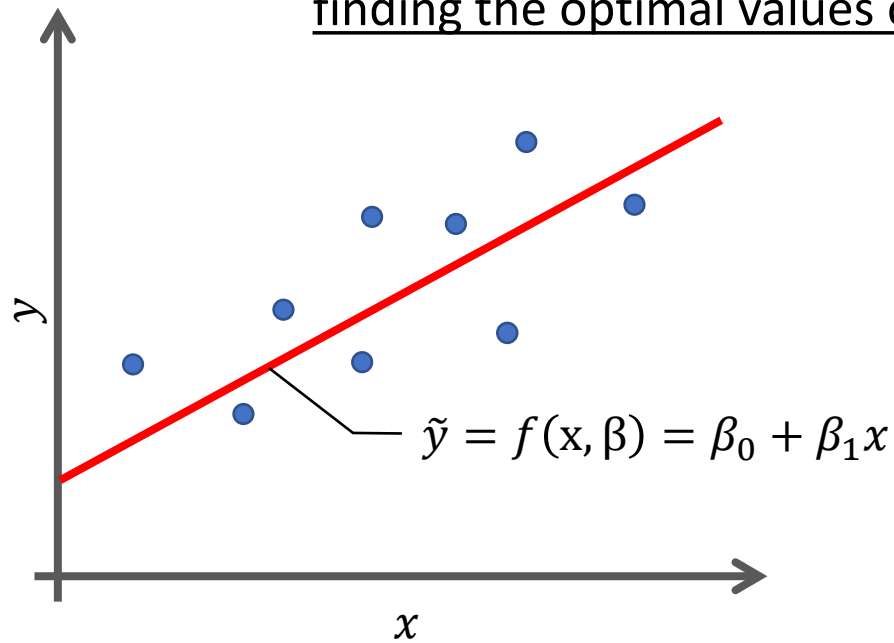
#### Multiple Regression

Uses several independent variables to predict the outcome of a dependent variable.

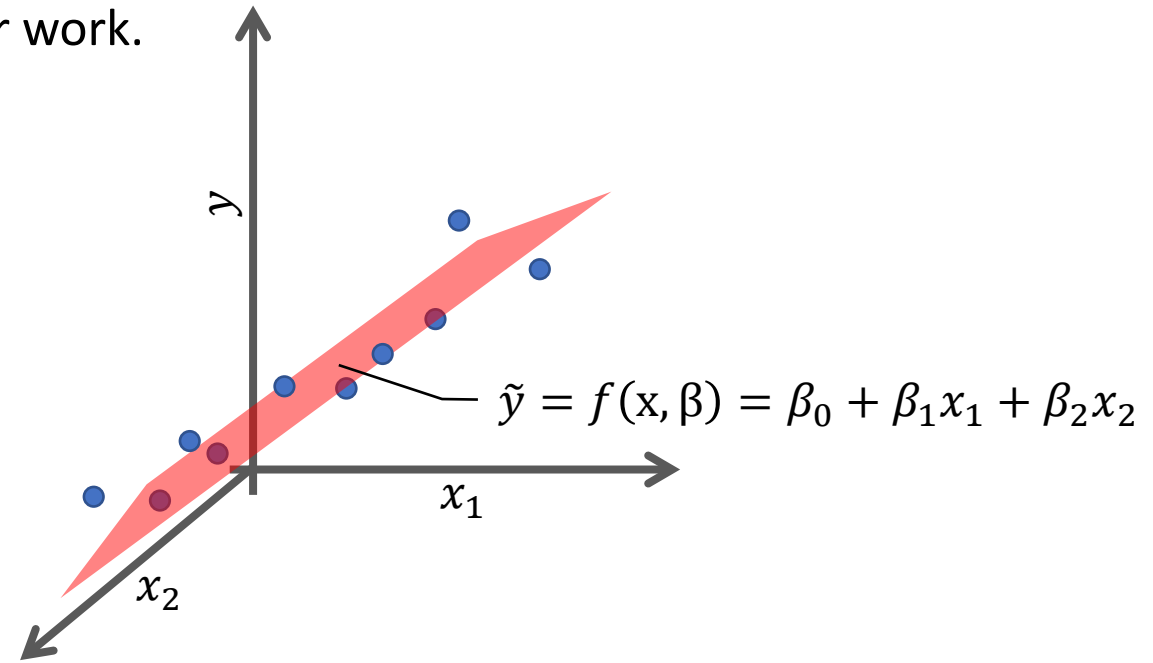
# Linear Regression

## Regression Analysis

We aim to fit **a line** or **hyperplane** to a scattering of data.  
As the line or hyperplane is described by the parameters  $\beta$ ,  
finding the optimal values of  $\beta$  is our work.



**Simple Linear Regression**



**Multiple Linear Regression**

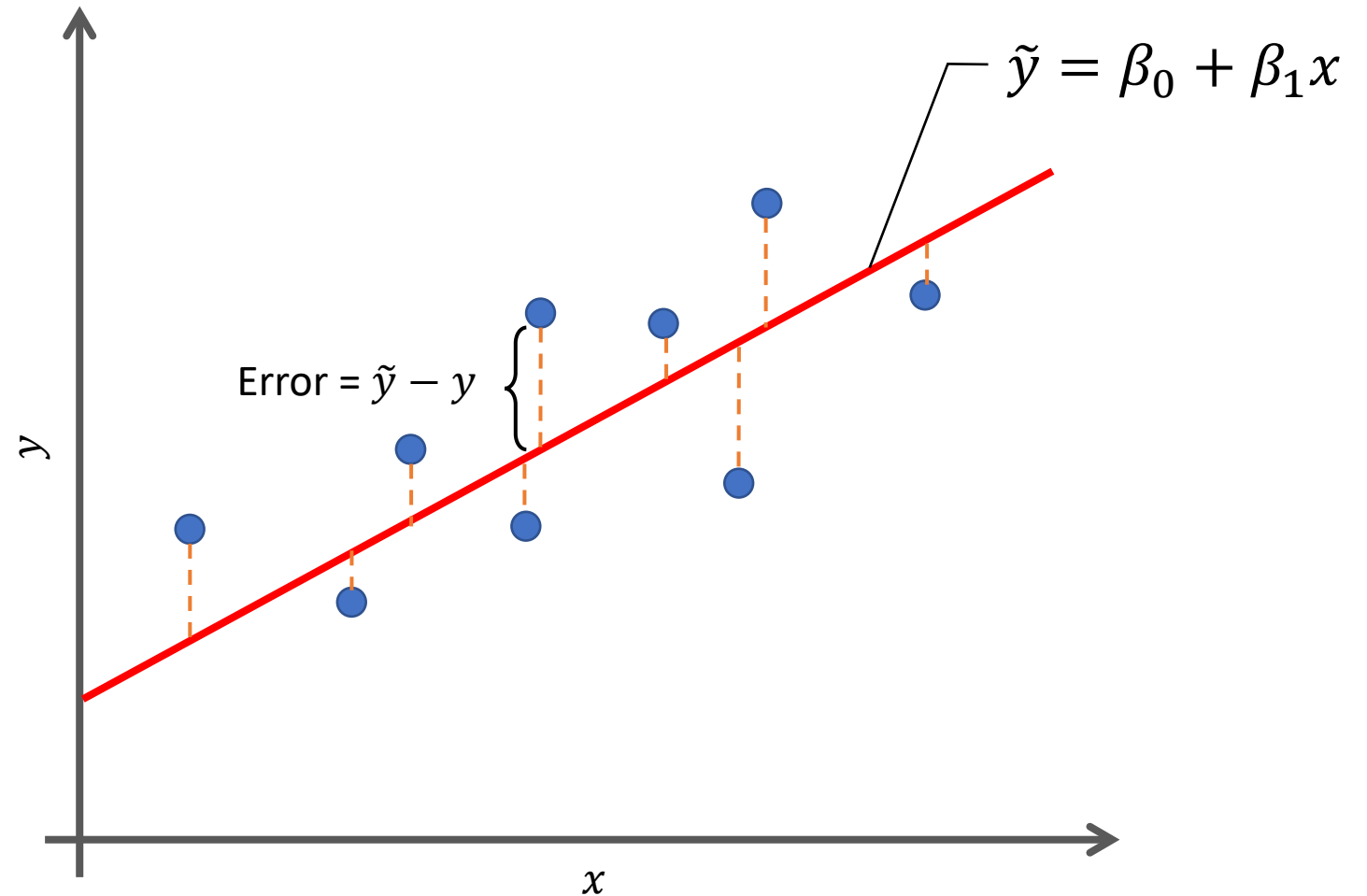


# Linear Regression

## Regression Analysis

The value of parameters will be determined by fitting the line to training data.

**Done by:** minimize an *error function*.



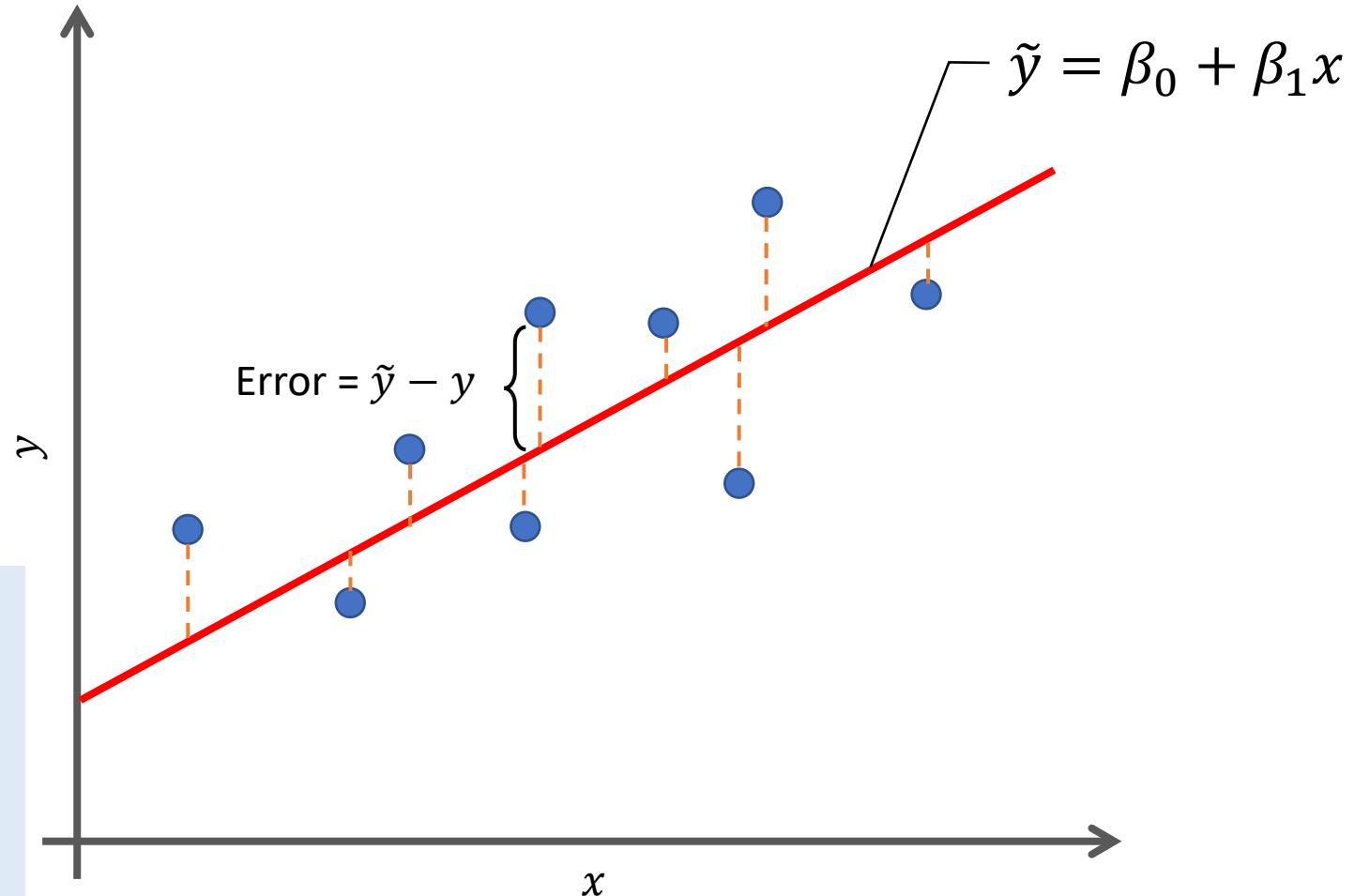
# Linear Regression

## Regression Analysis

### Sum of squared errors

$$\begin{aligned} E(\beta) &= \sum_{i=1}^n (\tilde{y}_i - y_i)^2 \\ &= \sum_{i=1}^n (\beta_0 + \beta_1 x_i - y_i)^2 \end{aligned}$$

**So**, we find the parameter  $\beta = [\beta_0, \beta_1]$  that provide a small value for  $E(\beta)$ .  
**This problem can be solved by optimization tools.**



# Linear Regression

## Regression Analysis

### Extend to multiple linear regression

$$\tilde{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

$$\tilde{y} = \beta_0 + \sum_{j=1}^p \beta_j x_j$$

- The sum of squared error function can be defined by

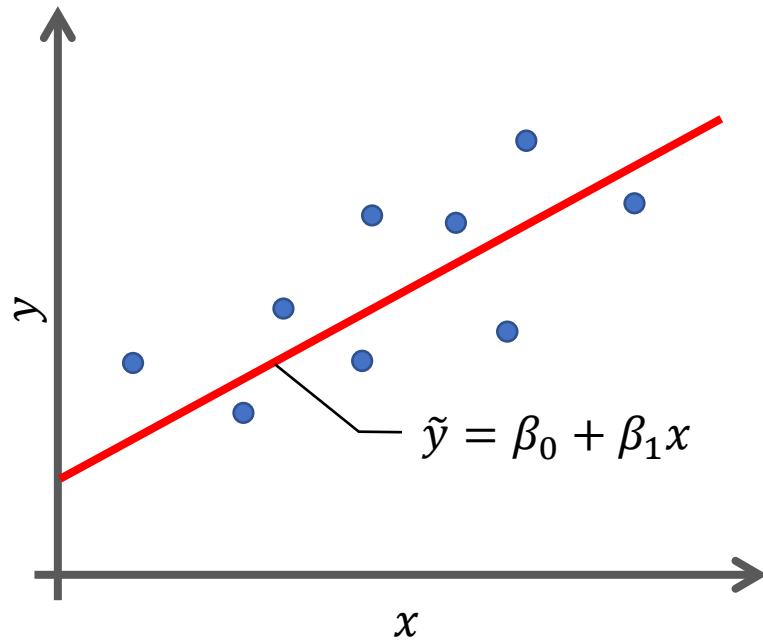
$$E(\beta) = \sum_{i=1}^n (\tilde{y}_i - y_i)^2$$

$$E(\beta) = \sum_{i=1}^n \left( \beta_0 + \sum_{j=1}^p \beta_j x_j - y_i \right)^2$$

# Polynomial Regression

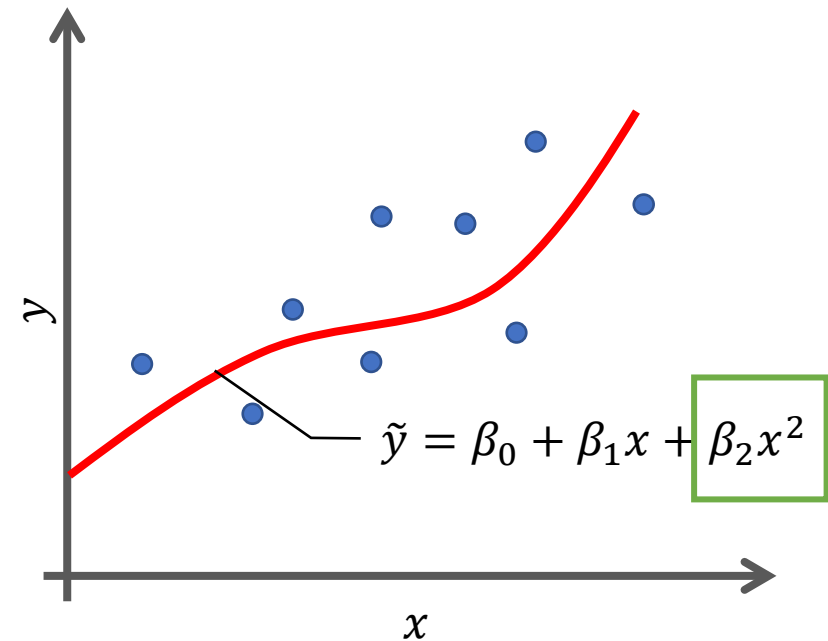
## Regression Analysis

### Linear Regression



Relationship between the independent variable  $x$  and the dependent variable  $y$  is a linear model.

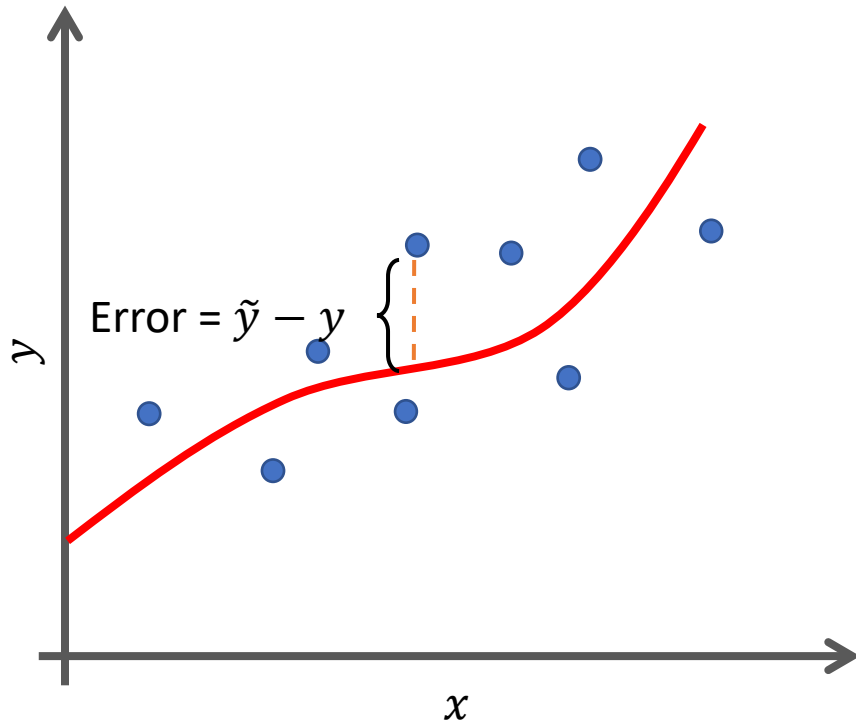
### Polynomial Regression



Relationship between the independent variable  $x$  and the dependent variable  $y$  is modelled as an  $n^{\text{th}}$  degree polynomial in  $x$ . (i.e.  $n=2$ )

# Polynomial Regression

## Regression Analysis



The general form of polynomial regression model:

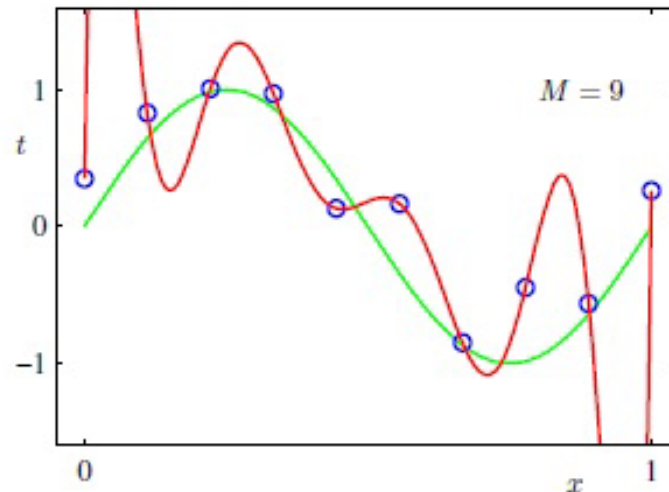
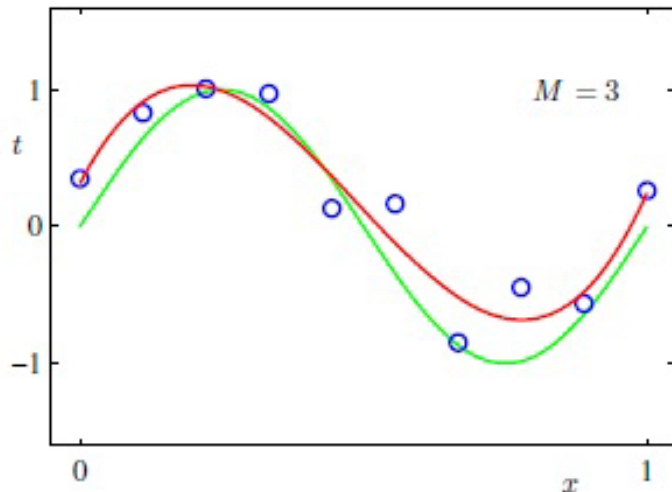
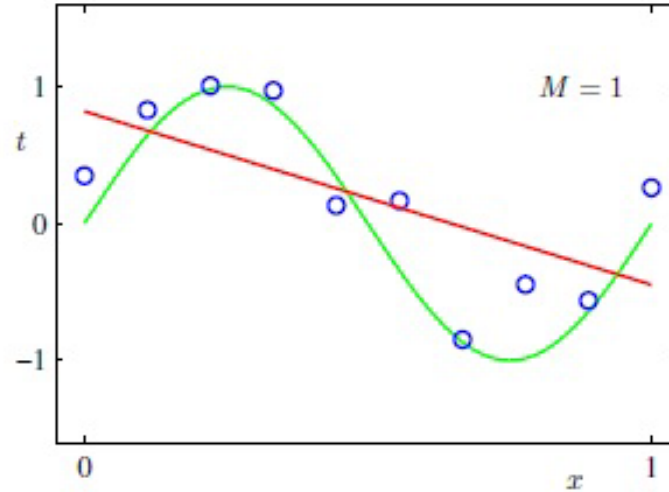
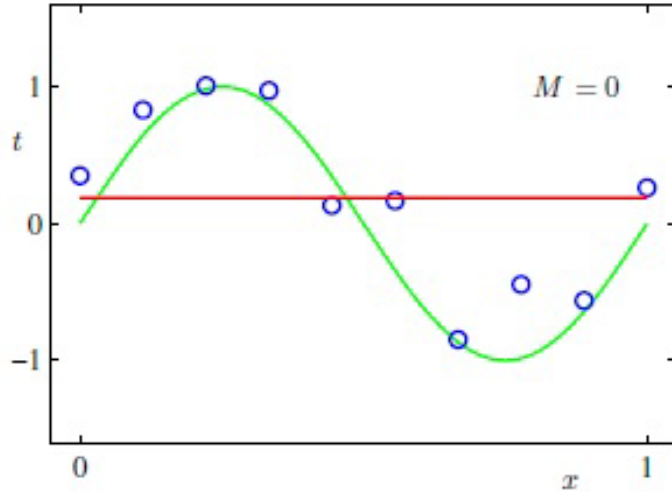
$$\tilde{y} = \beta_0 + \sum_{d=1}^M \beta_d x^d$$

The best values of parameter  $\beta = [\beta_0, \beta_1, \dots, \beta_M]$  can be determined by minimizing the sum of squared errors:

$$E(\beta) = \sum_{i=1}^n (\tilde{y}_i - y_i)^2$$
$$E(\beta) = \sum_{i=1}^n \left( \beta_0 + \sum_{d=1}^M \beta_d x^d - y_i \right)^2$$

# Polynomial Regression

## Regression Analysis



Plot of polynomials having various orders  $M$ , shown as red curves.

*Source:* Christopher M. Bishop (2006).  
Pattern Recognition and Machine Learning.  
New York: Springer-Verlag.

**What happens when we go to a much higher order polynomial?**

**Over-fitting!**

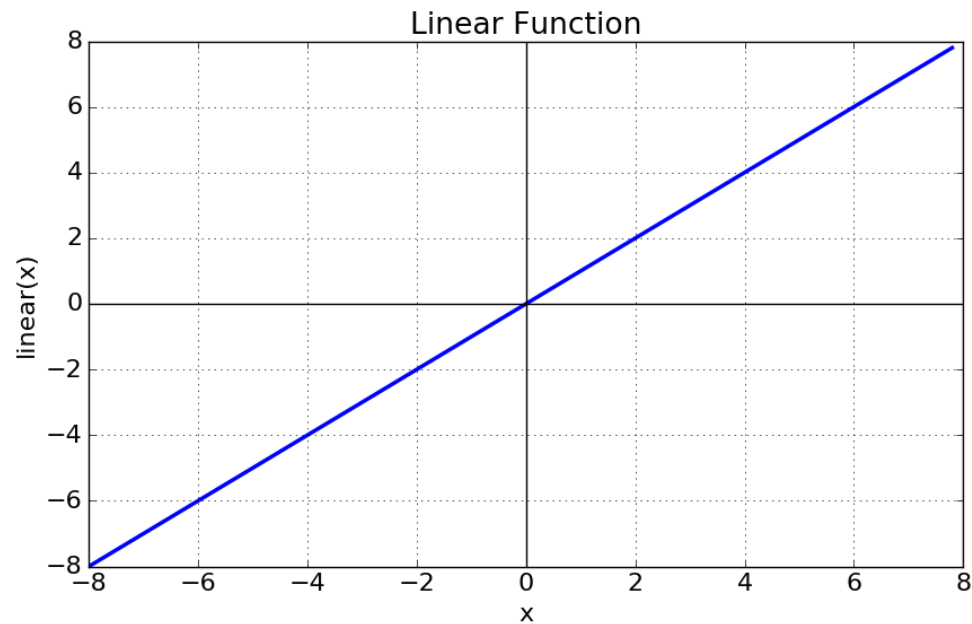
# Artificial Neural Network

## Regression Analysis

**Artificial Neural Network can be also applied to regression analysis**

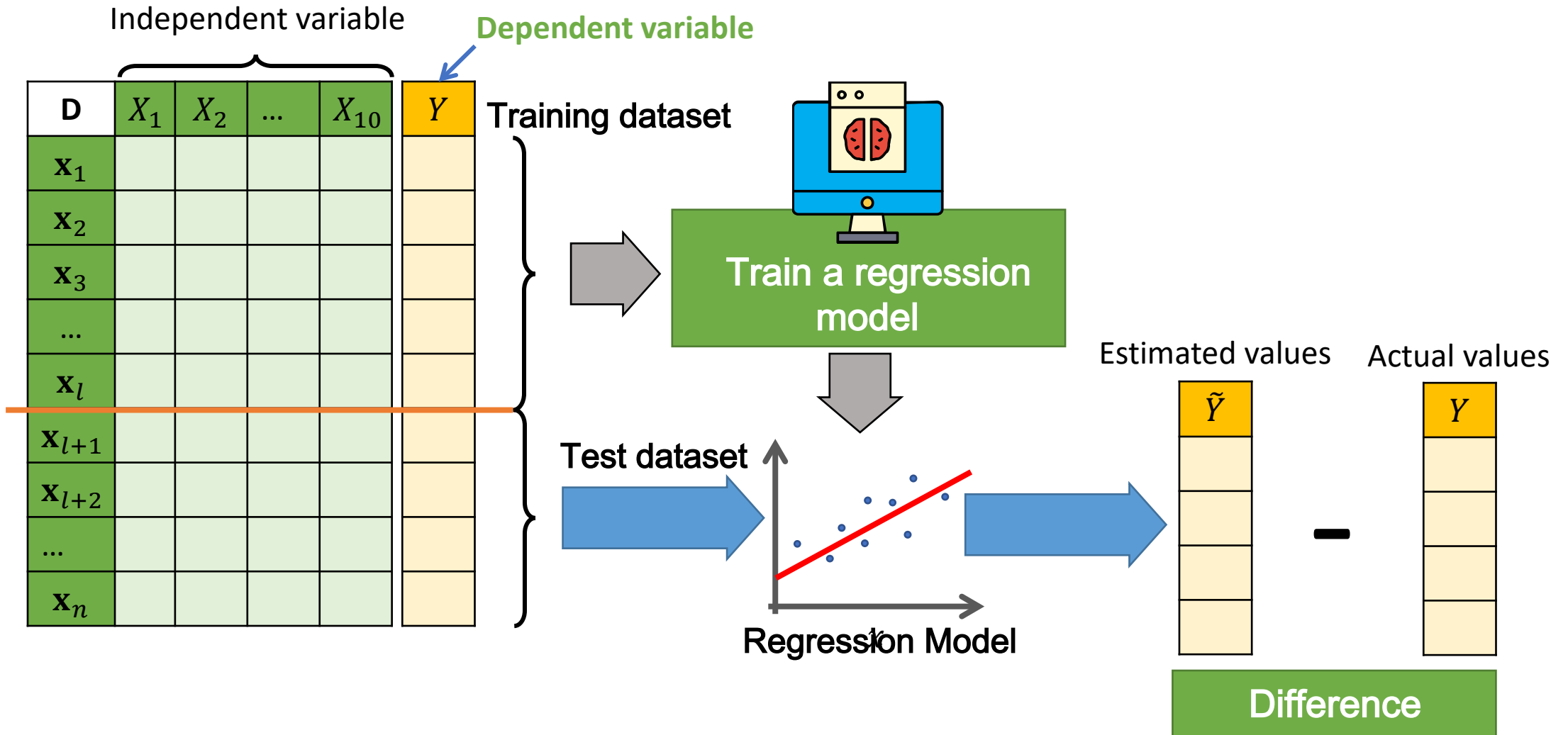
**For regression,**

Neurons in output layer applies *linear* function as the *activation function*.



# Regression Assessment

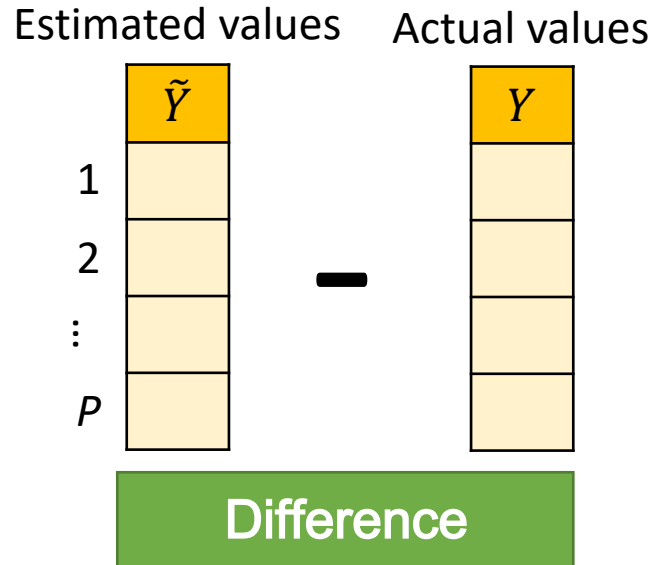
## Regression Analysis





# Regression Assessment

## Regression Analysis



### Mean Squared Error (MSE)

$$MSE = \frac{1}{P} \sum_{i=1}^P (\tilde{y}_i - y_i)^2$$

### Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{P} \sum_{i=1}^P (\tilde{y}_i - y_i)^2}$$

### Mean Absolute Error (MAE)

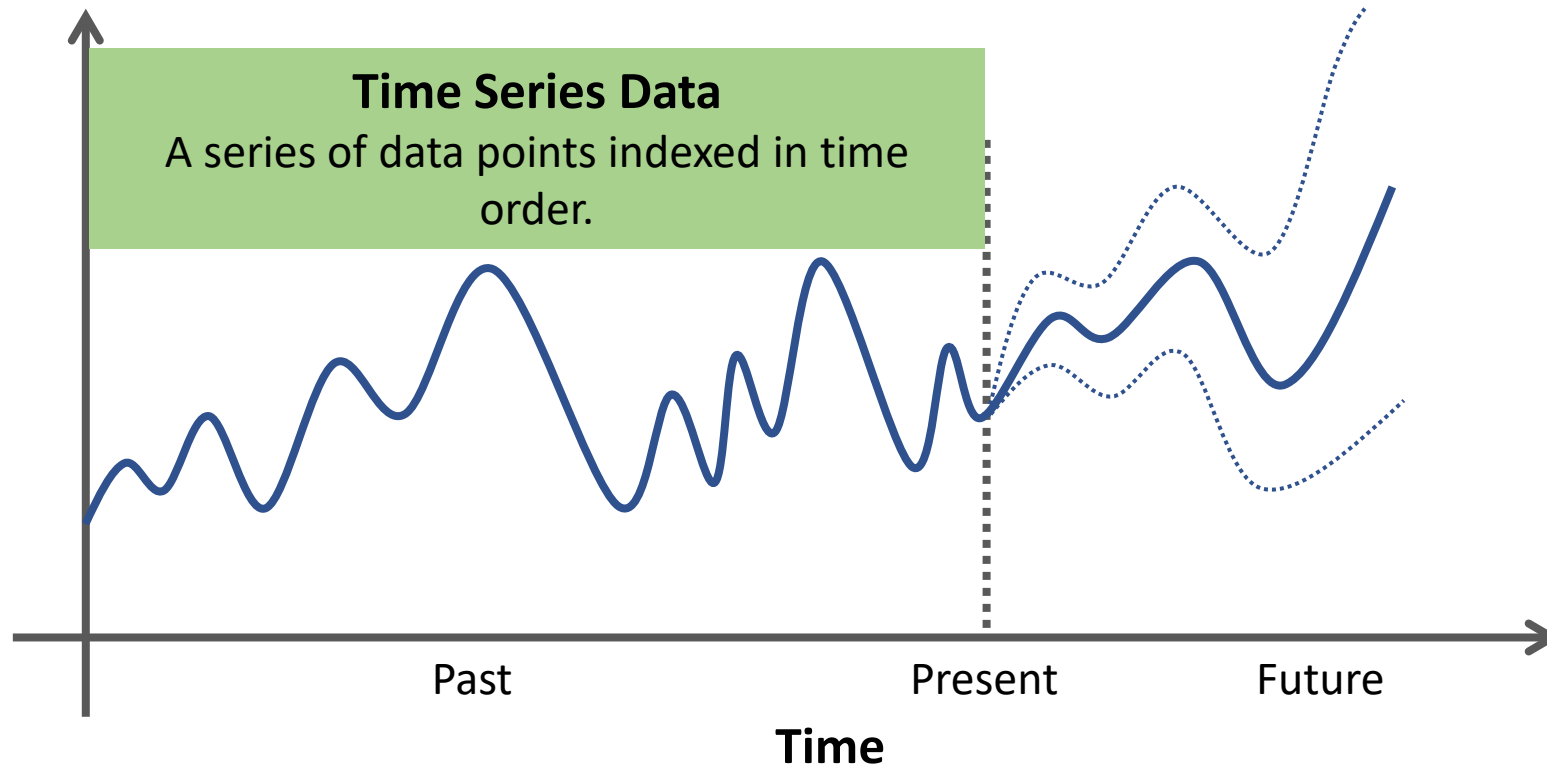
$$MAE = \frac{1}{P} \sum_{i=1}^P |\tilde{y}_i - y_i|$$

MSE, RMSE and MAE  $\geq 0$

**A lower value and is better than a higher one.**

# Time Series Analysis

## Time Series Data



Time series data can be found in **signal processing, econometrics, mathematical finance, weather forecasting, control engineering, astronomy, communications engineering, etc.**

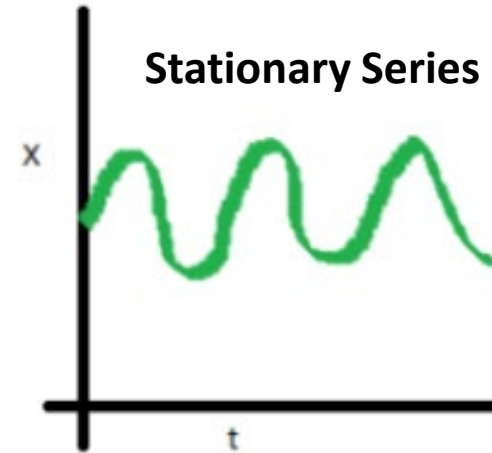
# Time Series Analysis

## Characteristics of Time Series Data

### Stationary

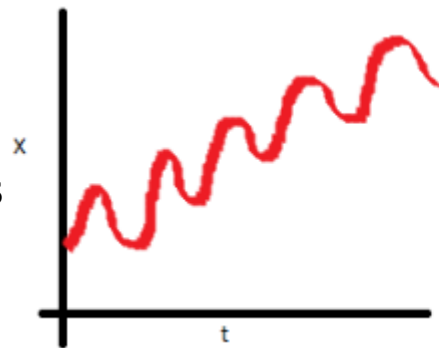
Statistical properties do not change over time.

- Mean
- Variance
- Covariance

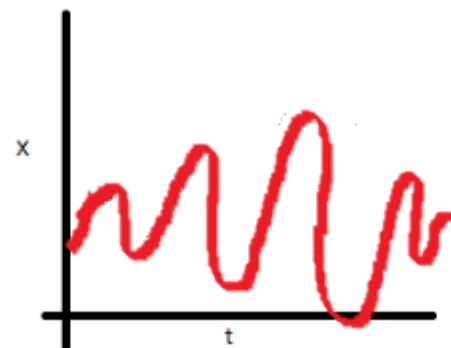


Source: <https://medium.com/greyatom/time-series-b6ef79c27d31>

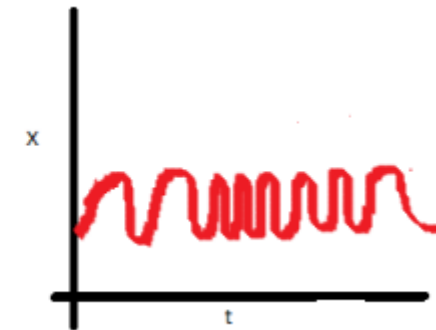
### Non-stationary Series



Mean increases with time.



Variance of the series is a function of time.



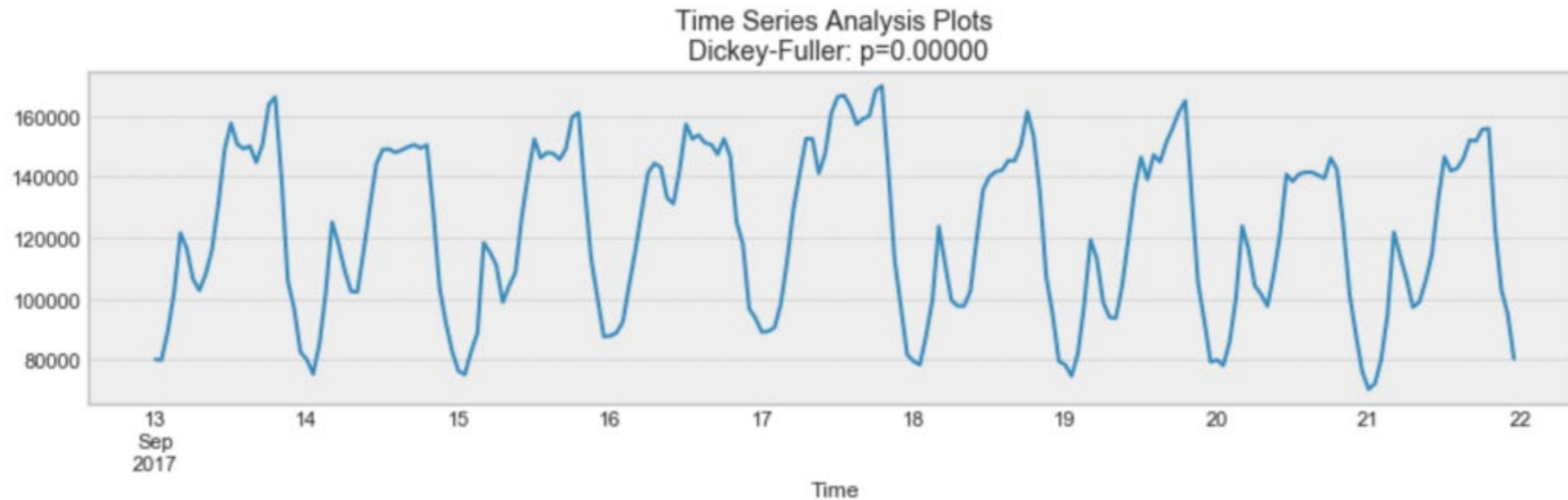
The spread becomes closer as the time increases.

# Time Series Analysis

## Characteristics of Time Series Data

### Seasonality

Periodic fluctuations - pattern that recurs or repeats over regular intervals.



### Example of seasonality

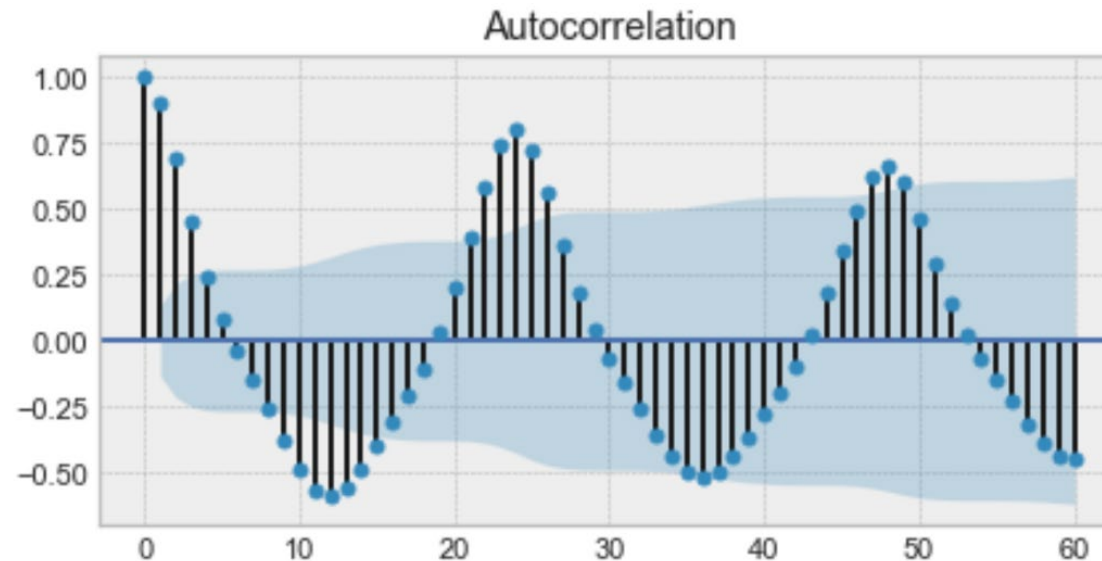
Source: <https://towardsdatascience.com/the-complete-guide-to-time-series-analysis-and-forecasting-70d476bfe775>

# Time Series Analysis

## Characteristics of Time Series Data

### Autocorrelation

- Internal correlation in a time series.
- The similarity between observations as a function of the time lag between them.



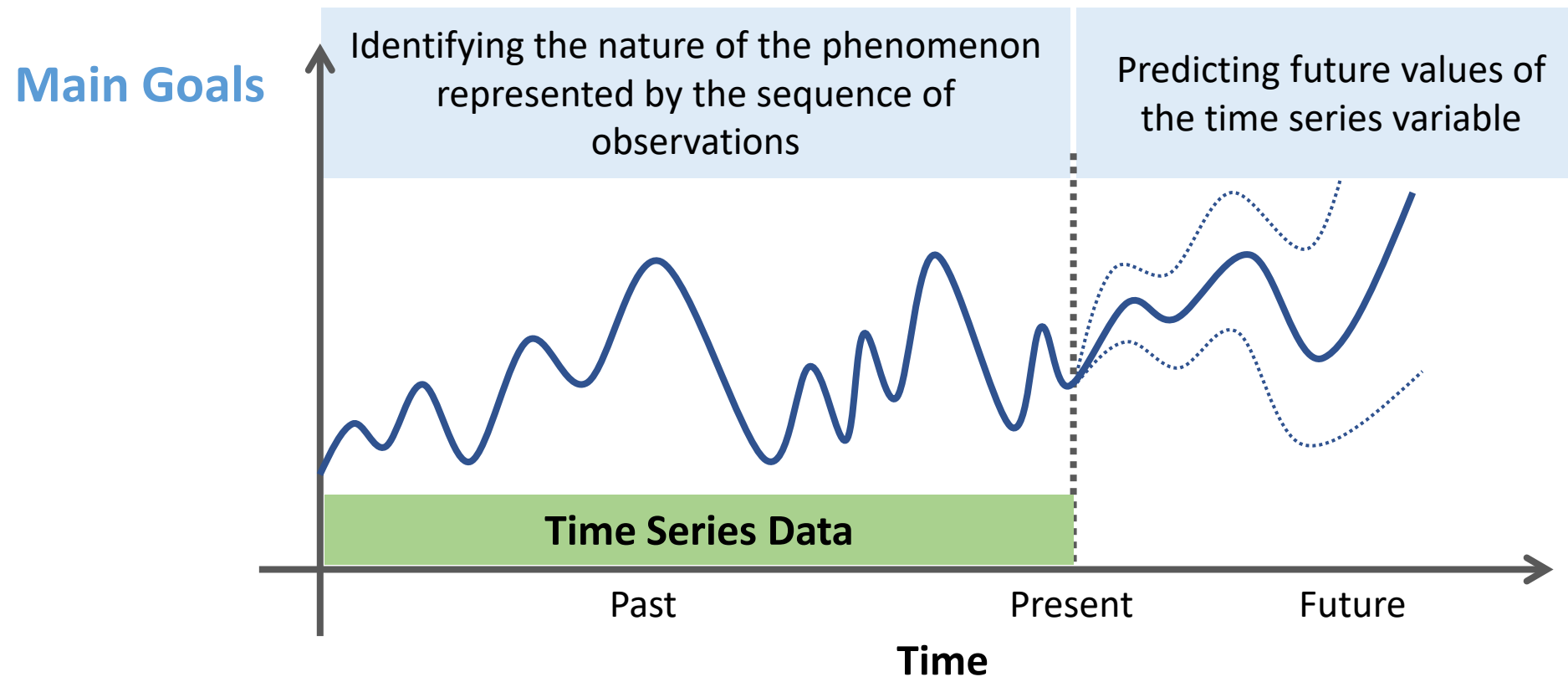
Example of an autocorrelation plot - we will find a very similar value at every 24 unit of time.

Source: <https://towardsdatascience.com/the-complete-guide-to-time-series-analysis-and-forecasting-70d476bfe775>

# Time Series Analysis

## Time Series Analysis

Analysis techniques that deal with time series data.

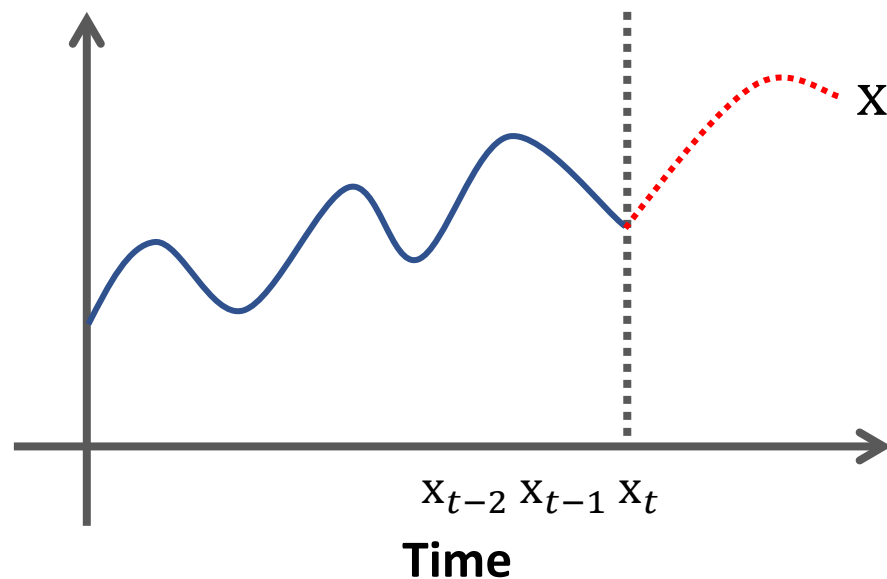


# Autoregressive Model

## Time Series Analysis

The output variable depends linearly on:

- Its own previous values
- A stochastic term (an imperfectly predictable term)



Linear combination of  $p$  previous observations

$$x_t = c + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \dots + \varphi_p x_{t-p} + \varepsilon_t$$

stochastic term

where  $c$  is a constant

$\varphi_1, \varphi_2, \dots, \varphi_p$  are the autoregressive model parameters

$\varepsilon_t$  is white noise

**Finding the optimal values of  $\varphi_1, \varphi_2, \dots, \varphi_p$  is the work for fitting the model.**

There are many ways to estimate the parameters, such as

- The ordinary least squares procedure
- Method of moments (through Yule–Walker equations).

# Autoregressive Model

Time Series Analysis

$$\mathbf{AR}(p) \text{ model : } x_t = c + \sum_{i=1}^p \varphi_i x_{t-i} + \varepsilon_t$$

**How can we determine the maximum lag  $p$ ?**

**Decide based on:**

- **Autocorrelation *function***
- **Partial autocorrelation *function***



# Autoregressive Model

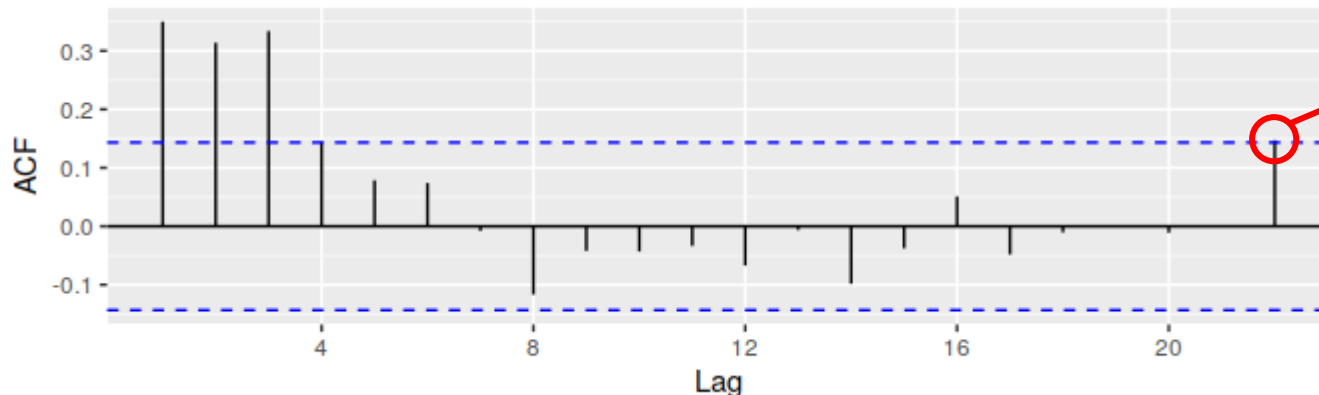
## Time Series Analysis

### Autocorrelation Function

- Autocorrelation refers to how correlated a time series is with its past values.
- It measures the linear relationship between *lagged values* of a time series.

$$ACF(k) = \frac{\sum_{t=k+1}^T (x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^k (x_t - \bar{x})^2}$$

where  $T$  is the length of the time series.



Always measured between +1 and -1.

- +1 : a strong positive association
- -1 : a strong negative association
- 0 : no association.

ACF of quarterly percentage change in US consumption.

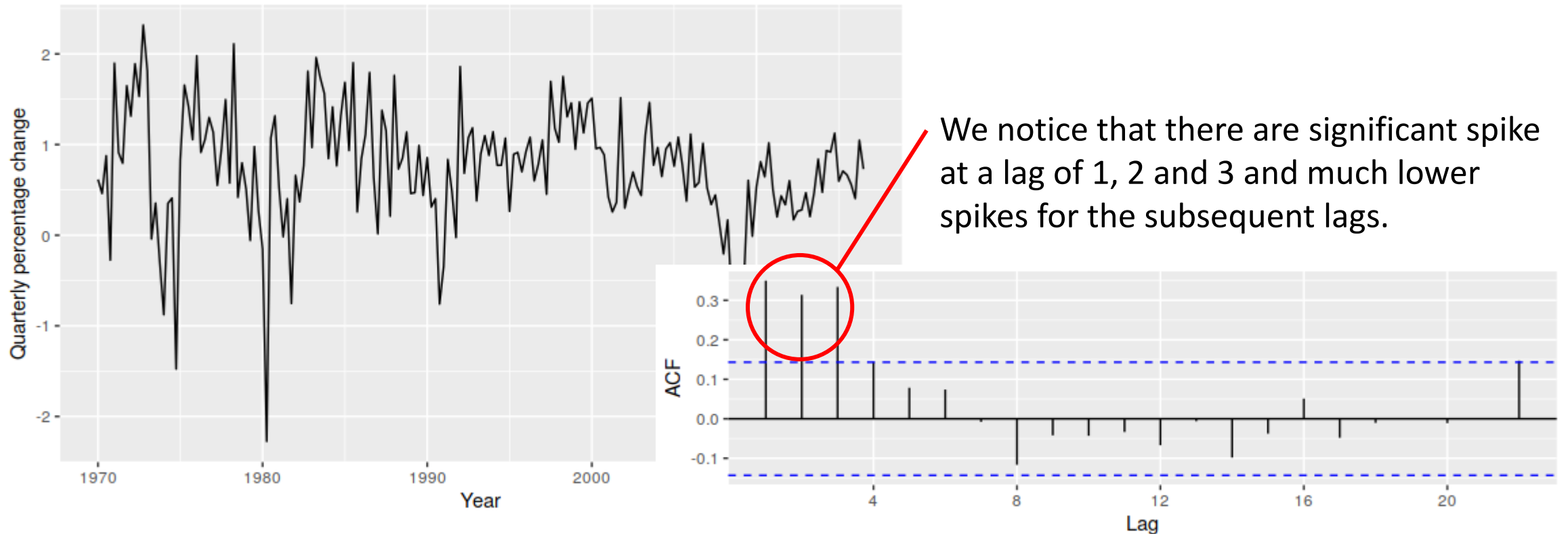
Source: <https://otexts.com/fpp2/non-seasonal-arima.html>

# Autoregressive Model

## Time Series Analysis

Quarterly percentage change in US consumption expenditure.

Source: <https://otexts.com/fpp2/non-seasonal-arima.html>



ACF of quarterly percentage change in US consumption

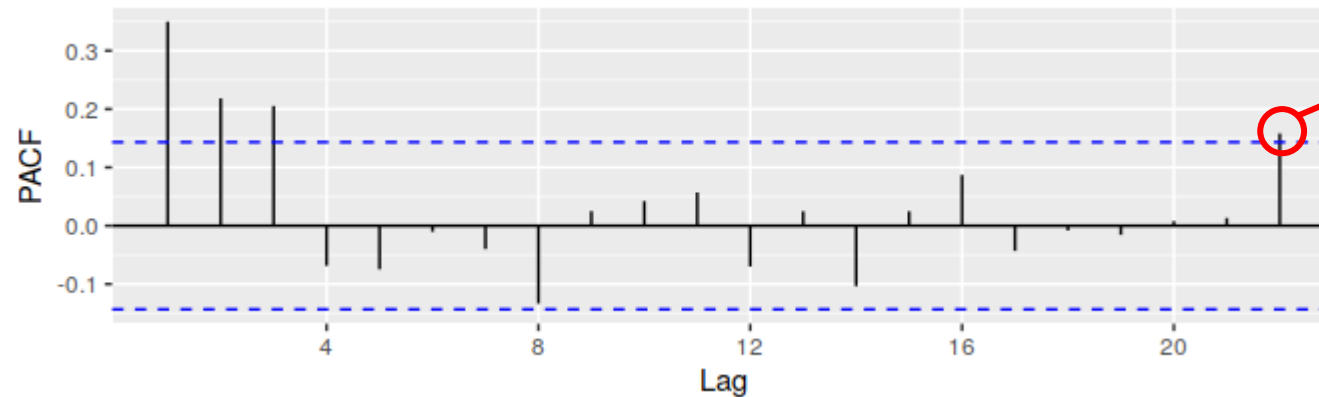
So, our AR model becomes  $x_t = c + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varphi_3 x_{t-3} + \varepsilon_t$  **AR(3)**

# Autoregressive Model

## Time Series Analysis

### Partial Autocorrelation Function

- It measures the relationship between  $x_t$  and  $x_{t-k}$  after removing the effects of lags  $1, 2, 3, \dots, k - 1$ .



Always measured between +1 and -1.

- +1 : a strong positive association
- -1 : a strong negative association
- 0 : no association.

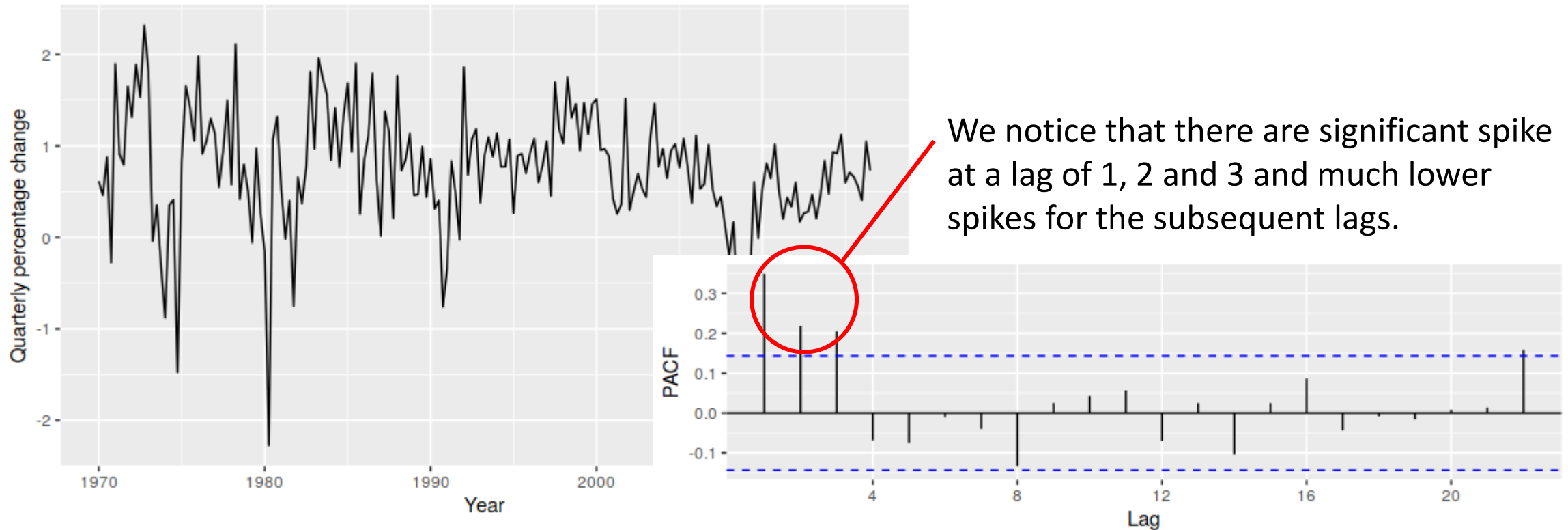
PACF of quarterly percentage change in US consumption.

Source: <https://otexts.com/fpp2/non-seasonal-arima.html>

# Autoregressive Model

## Time Series Analysis

Quarterly percentage change in US consumption expenditure. Source: <https://otexts.com/fpp2/non-seasonal-arima.html>



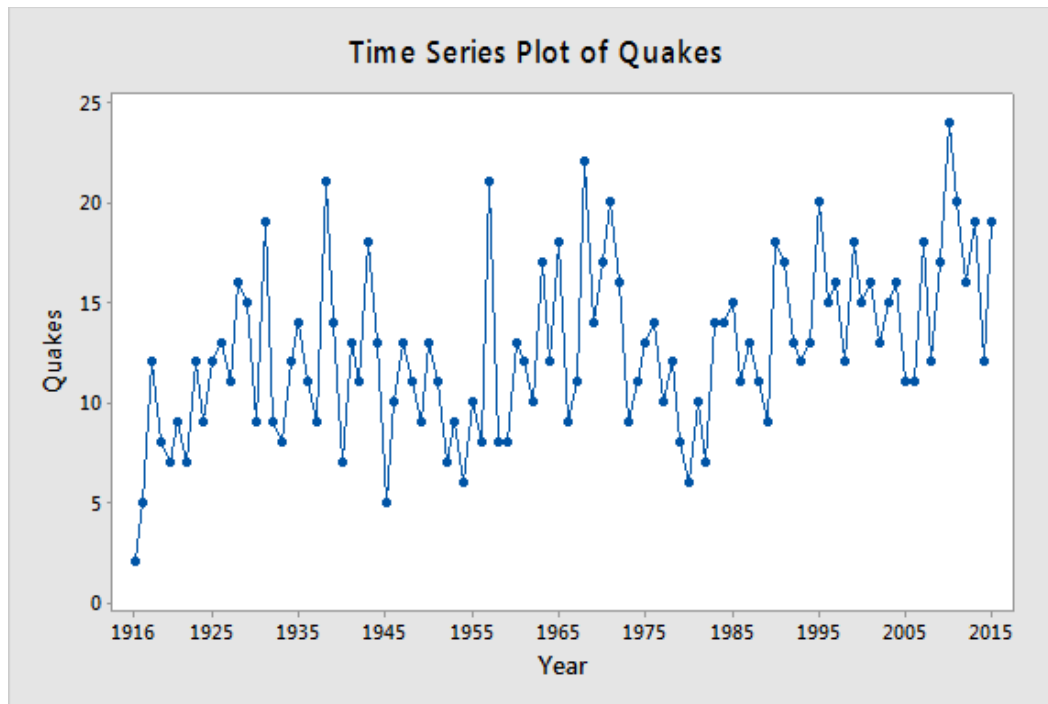
PACF of quarterly percentage change in US consumption

So, our AR model becomes  $x_t = c + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varphi_3 x_{t-3} + \varepsilon_t$  **AR(3)**

# Autoregressive Model

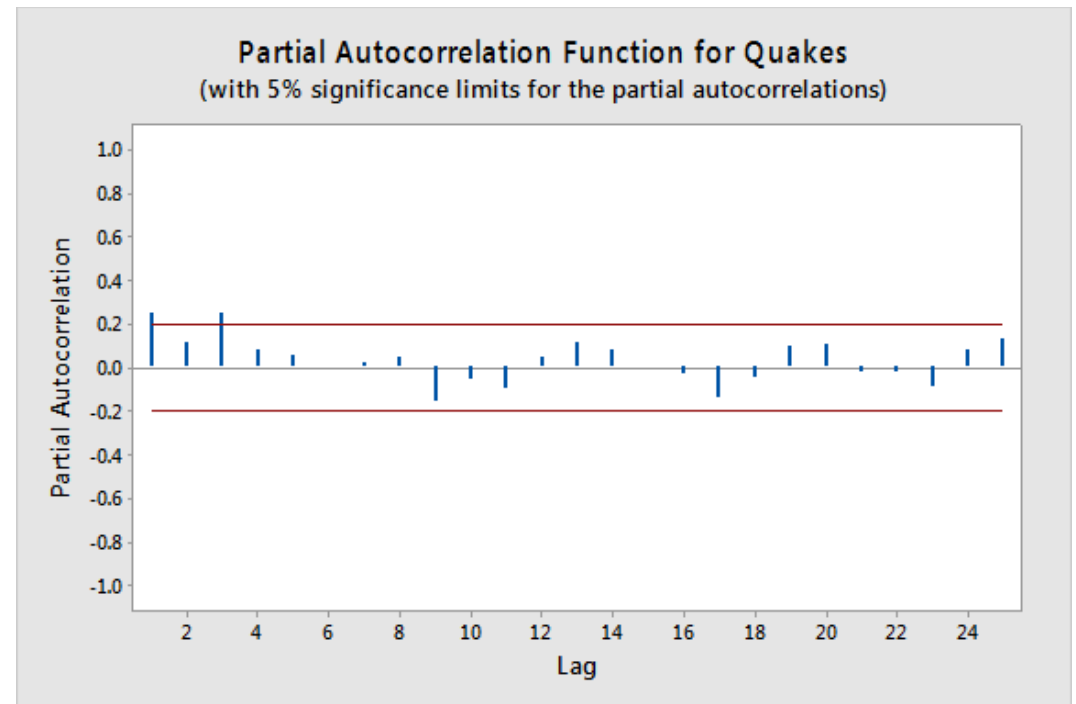
## Time Series Analysis

The annual number of worldwide earthquakes with magnitude greater than 7 on the Richter scale for  $n = 100$  years



## Quiz:

What is an appropriate AR model of quake?

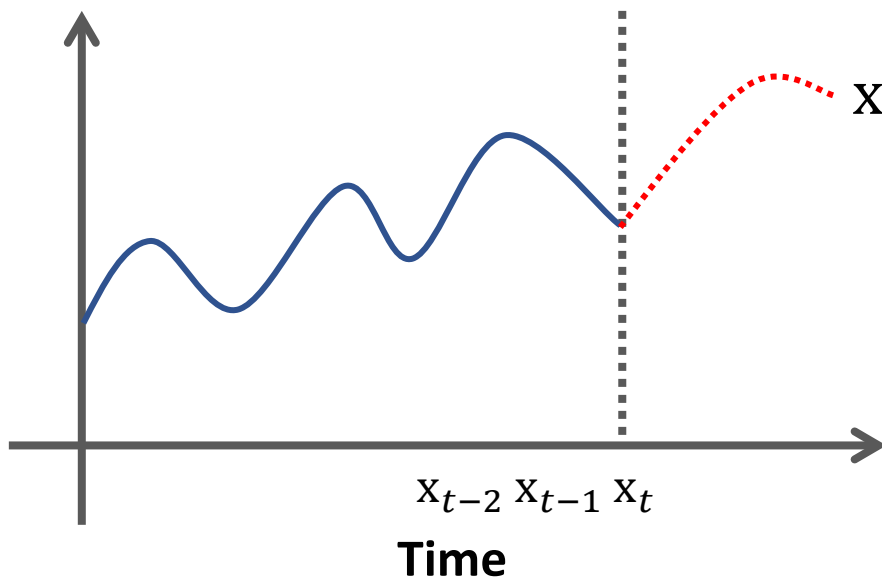


# Moving Average Model

## Time Series Analysis

The output variable depends linearly on:

- Past forecast errors
- A stochastic term (an imperfectly predictable term)



Linear combination of  $q$  previous forecast errors

$$x_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_p \varepsilon_{t-q}$$

where  $\mu$  is the mean of the series

$\theta_1, \theta_2, \dots, \theta_q$  are the moving average model parameters

$\varepsilon_t$  is white noise

**Finding the optimal values of  $\theta_1, \theta_2, \dots, \theta_q$  is the work for fitting the model.**

- Fitting the MA estimates is more complicated than it is in autoregressive models, because the lagged error terms are not observable.
- Iterative non-linear fitting procedures need to be used.

# Moving Average Model

Time Series Analysis

$$\text{MA}(q) \text{ model : } x_t = \mu + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t$$

**How can we determine the maximum lag  $q$ ?**

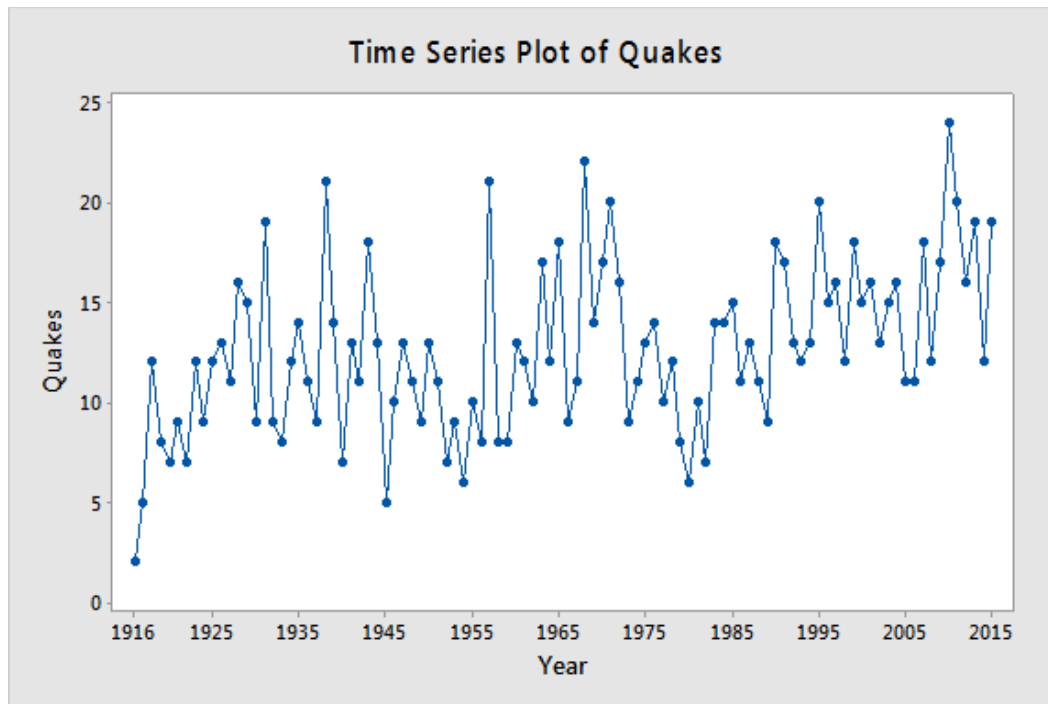
**Decide based on:**

- **Autocorrelation *function***
- **Partial autocorrelation *function***

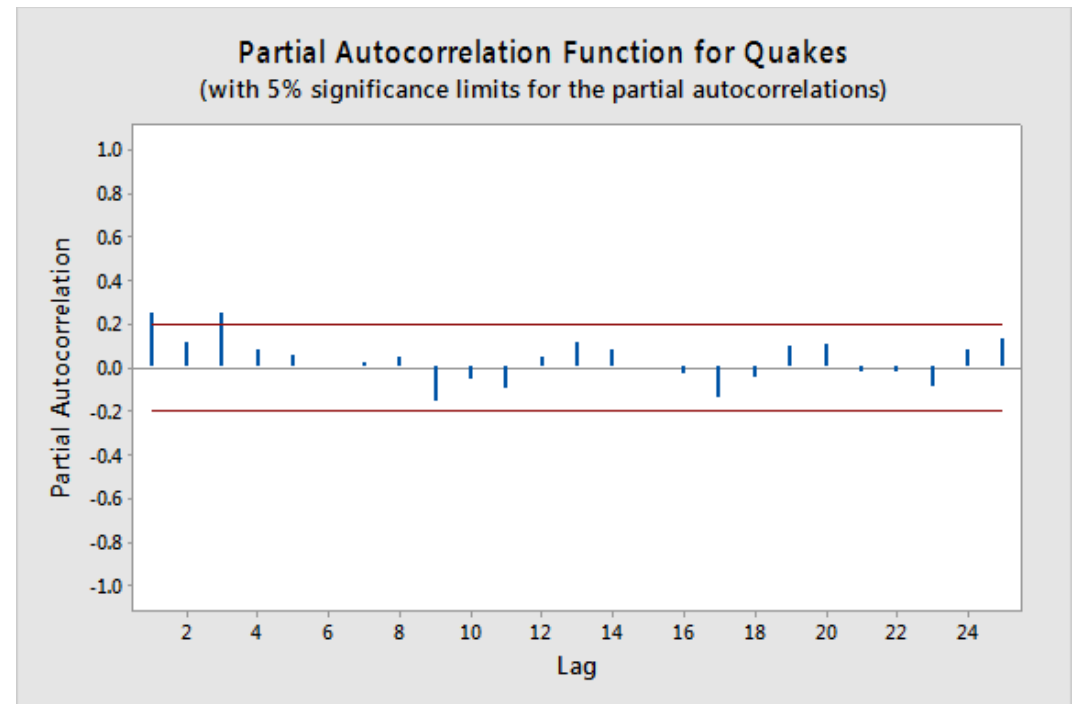
# Moving Average Model

## Time Series Analysis

The annual number of worldwide earthquakes with magnitude greater than 7 on the Richter scale for  $n = 100$  years



**Quiz:**  
What is an appropriate MA model of quake?



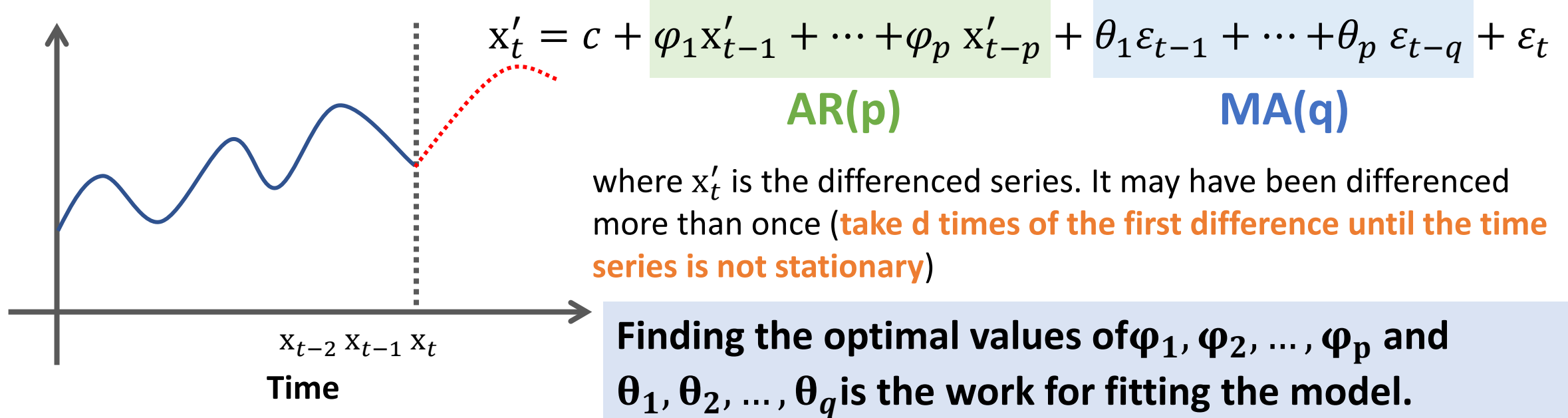


# Autoregressive Integrated Moving Average (ARIMA)

## Time Series Analysis

Combination of autoregressive and moving average models.

- **Autoregression** - AR(p):  $x_t = c + \sum_{i=1}^p \varphi_i x_{t-i} + \varepsilon_t$
- **Moving Average** - MA(q):  $x_t = \mu + \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t$
- **Integration** - the reverse of differencing (transform non-stationarity to stationarity)

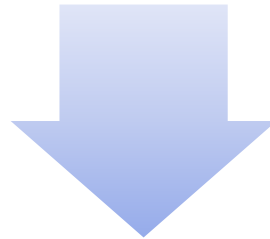


# Autoregressive Integrated Moving Average (ARIMA)

## Time Series Analysis

$$x'_t = c + \underbrace{\varphi_1 x'_{t-1} + \dots + \varphi_p x'_{t-p}}_{\text{AR}(p)} + \underbrace{\theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}}_{\text{MA}(q)} + \varepsilon_t$$

where  $x'_t$  is the differenced series. It may have been differenced more than once (**take  $d$  times of the first difference until the time series is not stationary**)



**ARIMA(p,d,q)**

**p, d and q are hyper-parameters that we need to determine.**

# Autoregressive Integrated Moving Average (ARIMA)

## Time Series Analysis

### Perform ARIMA

<b>Step 1</b> Check stationarity	If a time series has a trend or seasonality component, it must be made stationary before we can use ARIMA to forecast.	
<b>Step 2</b> Difference	If the time series is not stationary, it needs to be stationarized through differencing.	Parameter <b><i>d</i></b> is determined here.
<b>Step 3</b> Filter out a validation sample	This will be used to validate how accurate our model is. Use train test validation split to achieve this	
<b>Step 4</b> Select AR and MA terms	Use the ACF and PACF to decide whether to include an AR term(s), MA term(s), or both.	
<b>Step 5</b> Build the model	Build the model and set the number of periods to forecast to N (depends on your needs).	
<b>Step 6</b> Validate model	Compare the predicted values to the actuals in the validation sample.	

# Autoregressive Integrated Moving Average (ARIMA)

## Time Series Analysis

**Determine suitable values of  $p$  and  $q$  using either AIC, AICc or BIC value.**

### Akaike information criterion (AIC)

$$\text{AIC} = -2 \log(L) + 2(p + q + k + 1)$$

where  $L$  is the likelihood of the data,  
 $k = 1$  if  $c \neq 0$  and  $k = 0$  if  $c = 0$ .

### Corrected AIC (AICc)

$$\text{AICc} = \text{AIC} + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}$$

### Bayesian Information Criterion (BIC)

$$\text{BIC} = \text{AIC} + [\log(T) - 2](p + q + k + 1)$$

**Good models are obtained by minimizing the AIC, AICc or BIC.**

# Autoregressive Integrated Moving Average (ARIMA)

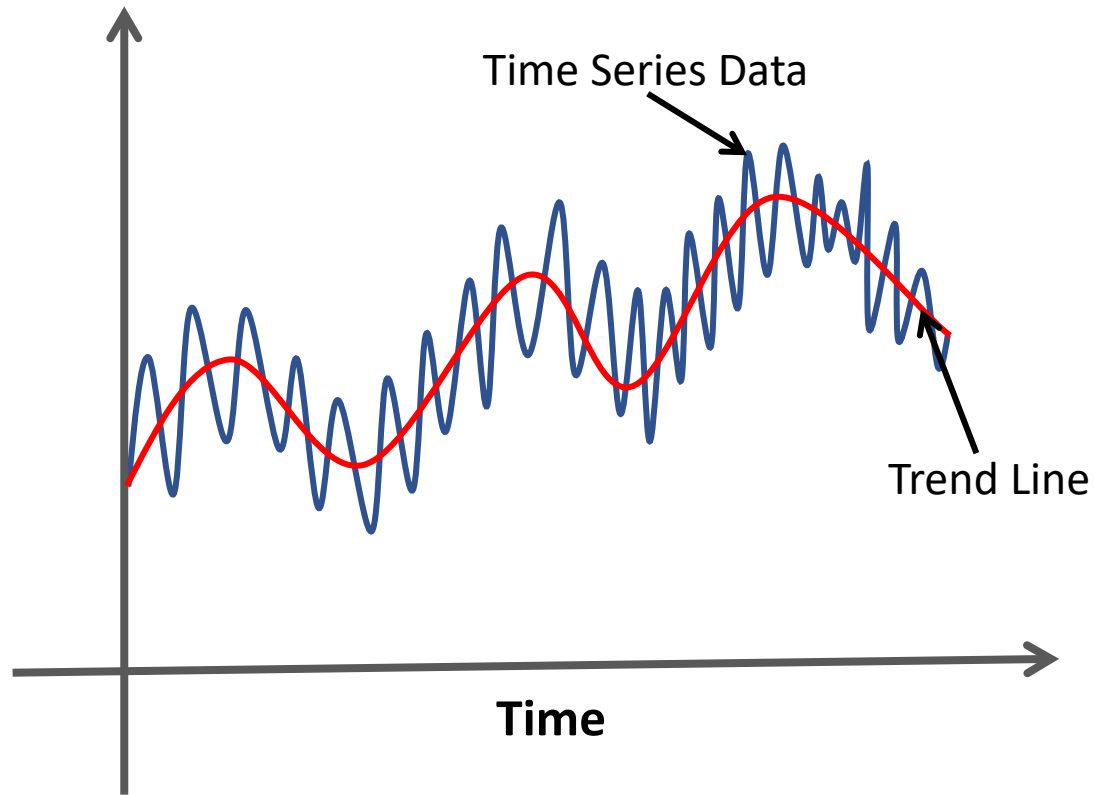
## Time Series Analysis

**Determine suitable values of  $p$  and  $q$  using either AIC, AICc or BIC value.**

		p in AR(p)					
		0	1	2	3	4	5
q in MA(q)	0	4588.666	4588.472	4589.884	4591.619	4592.181	4593.312
	1	4588.618	4584.675	4586.262	4588.261	4590.172	4592.002
	2	4590.031	4586.263	4588.317	4590.25	4590.726	4594.104
	3	4591.883	4589.089	4583.762	4593.013	4589.644	4590.99
	4	4592.883	4590.161	4592.254	4594.099	4583.88	4586.875
	5	4594.055	4590.793	4594.07	4596.018	4586.779	4587.788

# Moving Average Smoothing

## Time Series Analysis



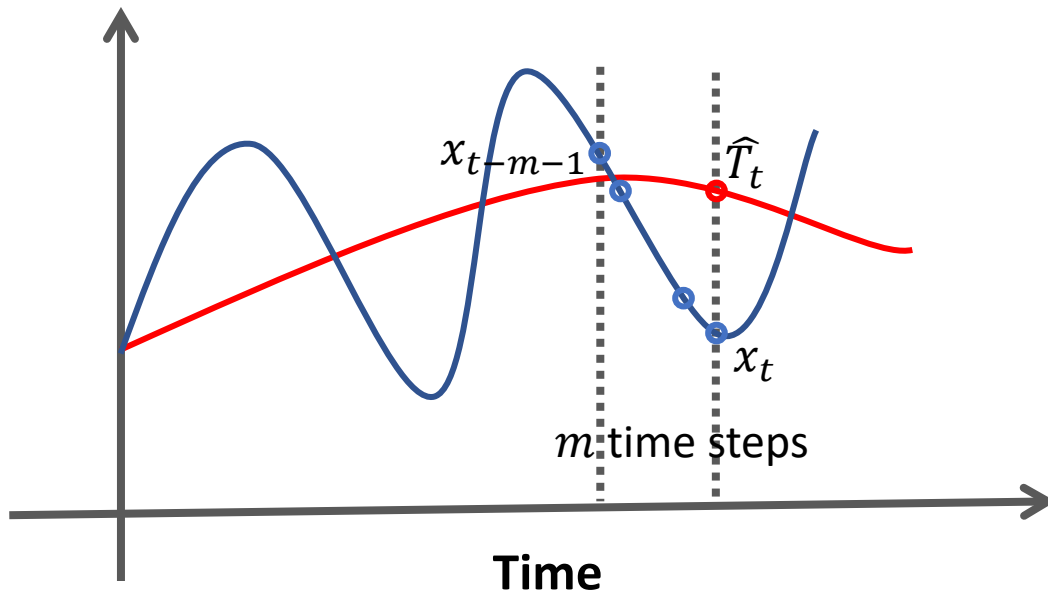
- Smooth out short-term fluctuations
- Highlight longer-term trends or cycles.

**Purpose:** to help improve understanding of the time series

# Moving Average Smoothing

Time Series Analysis

## Simple Moving Average



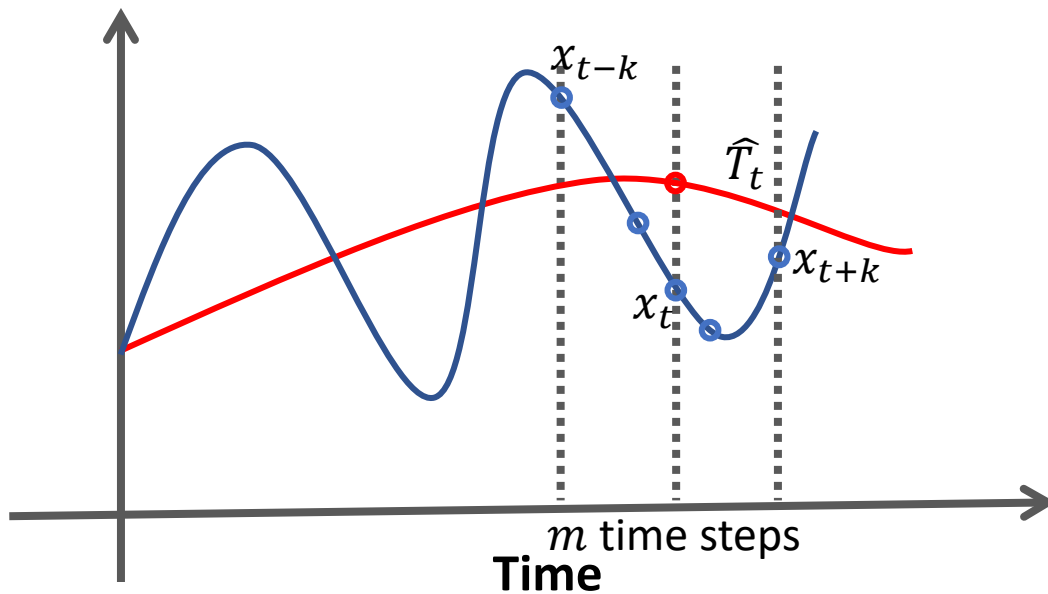
**Financial Applications:** the unweighted mean of the previous n data.

$$\hat{T}_t = \frac{1}{m} \sum_{i=0}^{m-1} x_{t-i}$$

# Moving Average Smoothing

Time Series Analysis

## Simple Moving Average



**Science and Engineering:** the mean is taken from an equal number of data on either side of a central value.

$$\hat{T}_t = \frac{1}{m} \sum_{i=-k}^k x_{t+i}$$

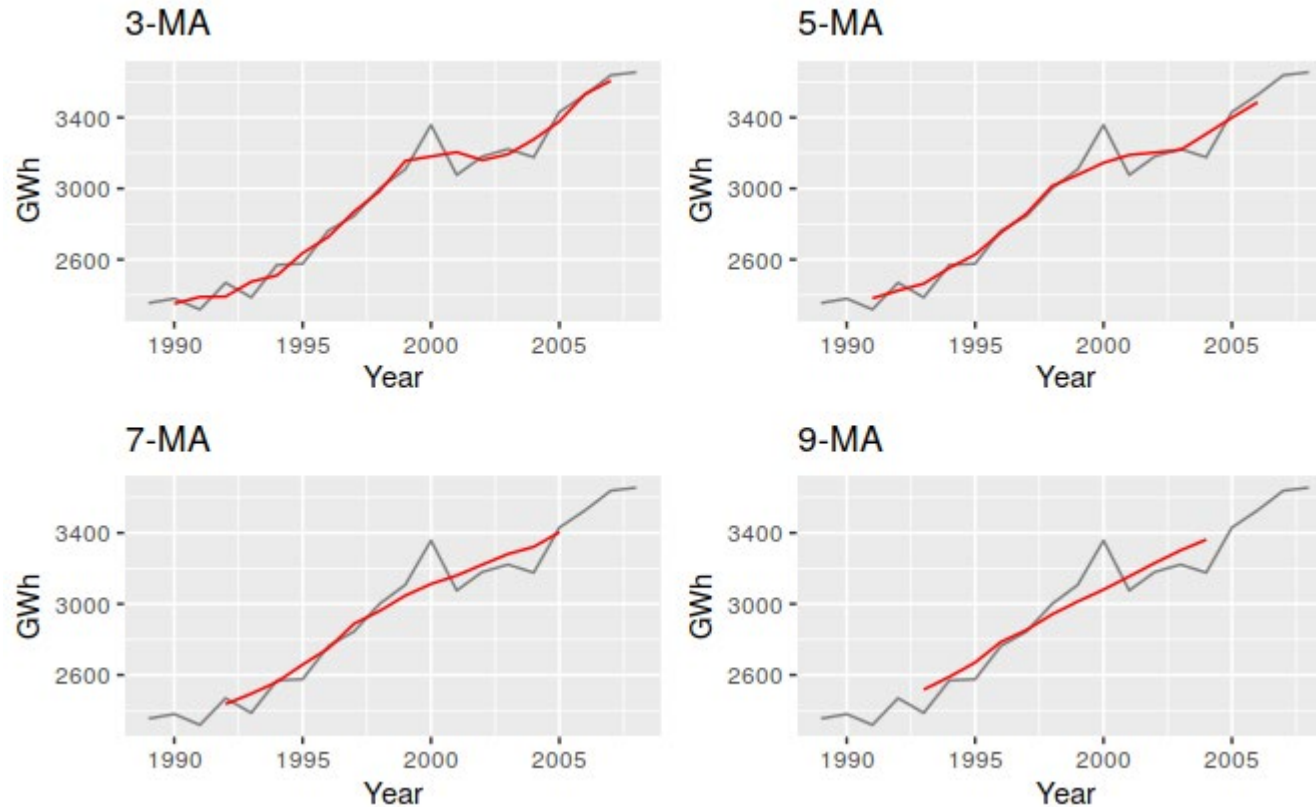
where  $m = 2k + 1$



# Moving Average Smoothing

## Time Series Analysis

### Simple Moving Average



**Example:** Different moving averages applied to the residential electricity sales data.

Source: <https://otexts.com/fpp2/moving-averages.html>

# Further Study

- **Book:**

- Zaki, M., & Meira, W. (2014). Data mining and analysis : Fundamental concepts and algorithms. New York: Cambridge University Press.
- Christopher M. Bishop (2006). Pattern Recognition and Machine Learning. New York: Springer-Verlag.
- Jeremy Watt, Reza Borhani & Aggelos K. Katsaggelos (2016). Machine Learning Refined: Foundations, Algorithm, and Application. New York: Cambridge University Press.

- **Website**

- <https://medium.com/swlh/an-introduction-to-time-series-analysis-ef1a9200717a>
- <https://towardsdatascience.com/the-complete-guide-to-time-series-analysis-and-forecasting-70d476bfe775>
- [https://en.wikipedia.org/wiki/Autoregressive\\_model](https://en.wikipedia.org/wiki/Autoregressive_model)
- <https://otexts.com/fpp2/>
- <https://online.stat.psu.edu/stat510/lesson/5/5.2>