

# Hello and Welcome to AI Camp



# Linear Regression

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# Workshop Structure

1. Introduction
2. Understanding Linear Regression
3. Types of Linear Regression
4. Methods for Training a Linear Regression Model
5. Evaluation Metrics
6. Conclusion

# 1- Introduction

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**Supervised**

# Supervised Machine Learning



# Supervised Machine Learning

## 1-Regression

# Supervised Machine Learning

1-Regression

2-Classification

# Regression

This is when we want to predict a continuous output ( aka a number ) :

ie: house price prediction in a certain area, medical cost prediction, ....etc

# Classification

This is when we want to predict a discrete and finite output ( aka 0/1 ):

ie : prediction if a photo is a dog or no , spam detection model ( detect if a mail is a spam or no ), ....etc

## 2- Understanding Linear Regression

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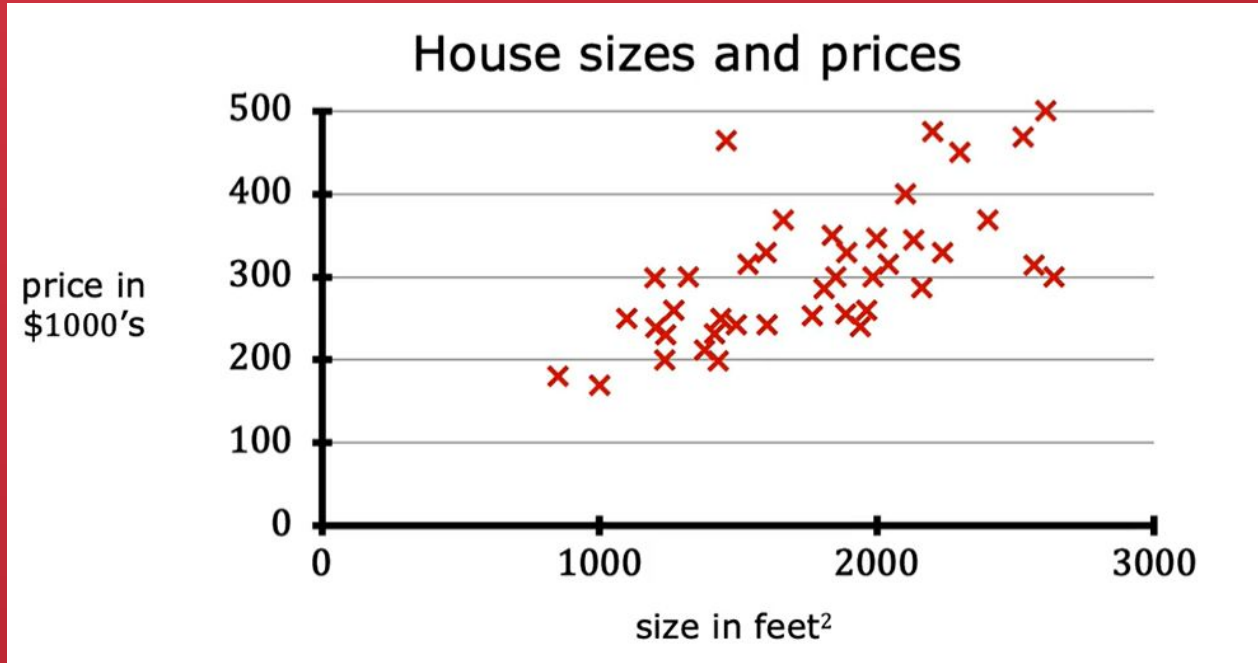
### House price prediction problem

## 2- Understanding Linear Regression

Suppose a client came to you and asked you to predict his house price .and you are provided with the following informations. first we will plot the data to have a better glance of how it looks

Data table	
size in feet <sup>2</sup>	price in \$1000's
2104	400
1416	232
1534	315
852	178
...	...
3210	870

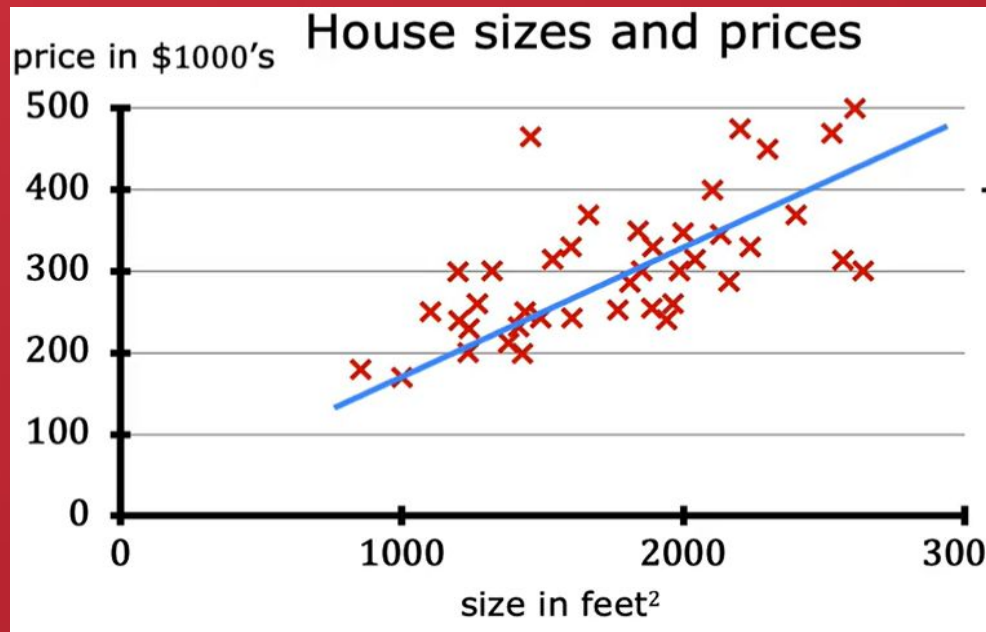
## 2- Understanding Linear Regression





## 2- Understanding Linear Regression

we create a line that  
fits our data and that's  
all About  
**Linear Regression**



# Thank you for attending

any questions ?



# Just Joking LOL



## 2- Understanding Linear Regression

So here the function  
in blue has the  
following equation

$$\hat{y} = \theta_0 + \theta_1 x_1$$



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## 2- Understanding Linear Regression

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**BUT HOW ?**



# Notation

- $\hat{y}$  is the predicted value.
- $n$  is the number of features.
- $x_1$  is the feature value.
- $\theta_0$  is the bias and the feature weight is  $\theta_1$
- we define our  $h_{\theta}$  function as follows

$$\hat{y} = h_{\theta}(x) = \theta \cdot x$$

## 2- Understanding Linear Regression

We Should Define then Root Mean Squared Error Cost Function

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

For every row in our dataset we sum :

- we take  $y_i$  ( in our case it is the house price ) and we subtract from it the value that we predict for the same house  $\hat{y}_i$  using our linear function
- we square the result .

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## 2- Understanding Linear Regression

Now we should minimize the error of our cost function By finding the right parameters  $\theta_0$  and  $\theta_1$  that minimize it .

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

## 2- Understanding Linear Regression

In practice, it is simpler to minimize the mean squared error (MSE) than the RMSE, and it leads to the same result (because the value that minimizes a positive function also minimizes its square root).

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

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### 3- Types Of Linear Regression

Let's continue from our previous example of house price prediction , we had only 1 feature ( size in feet<sup>2</sup> ) .

This is called simple Linear regression or univariate linear regression

## 3- Types Of Linear Regression

Suppose now we don't only have size as feature but also the year it was built in , and the ocean proximity

This is called Multiple Linear regression or  
Multivariate linear regression

### 3- Types Of Linear Regression

Most of the linear regression problems are multivariate linear regression , since using multiple features will give you more information about your dataset so the performance of the model will be better

### 3- Types Of Linear Regression

So now the equation of  $\hat{y}$  will become like that

$$\hat{y} = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n$$

With  $\hat{y} = h\theta(x) = \theta \cdot x$



## 4- Methods For Training a Linear Regression Model

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**The Normal  
Equation**

**Gradient Decent**

## 4- Methods For Training a Linear Regression Model

**The normal Equation method** is an analytical approach used to find the exact parameters ( $\theta$ ) that minimize the cost function

It has the following formula

$$\hat{\theta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

# The Normal Equation method

## Benefits

- It provides a closed-form solution, meaning it solves the problem in one calculation.
- The Normal Equation is computationally efficient when the number of features ( $n$ ) is small

## Inconvenients

- However, if the number of features is large, the computational complexity increases, as it involves matrix inversion.

$$\hat{\boldsymbol{\theta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

# What's the Alternative then ?

# Gradient descent

Let's go back to our first example :

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

Parameters:  $\theta_0, \theta_1$

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

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



# Gradient descent

We will use the following for each parameter  $\theta_j$  until we reach the value that minimize the previous cost function

Repeat until convergence {

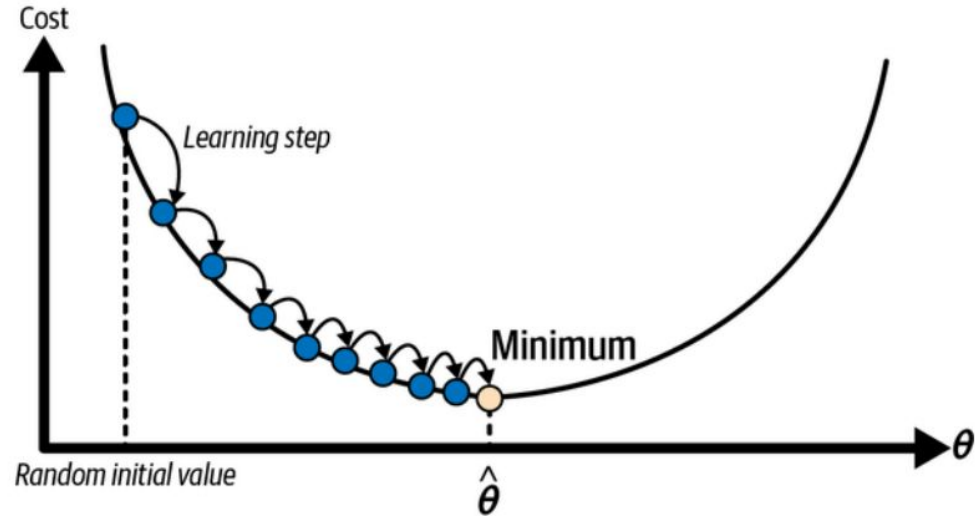
$$\theta_j \leftarrow \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

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

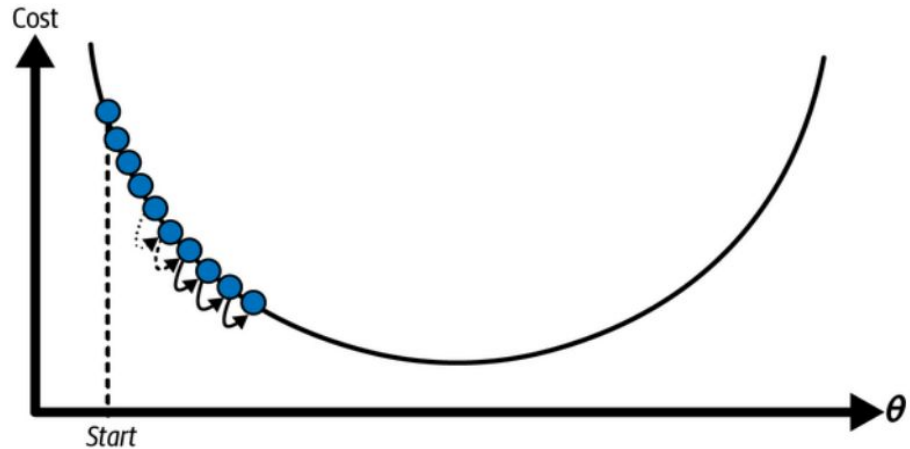
# Gradient descent

With the right value of the Learning Rate ( Learning Step ) we will have a learning curve that looks just like that



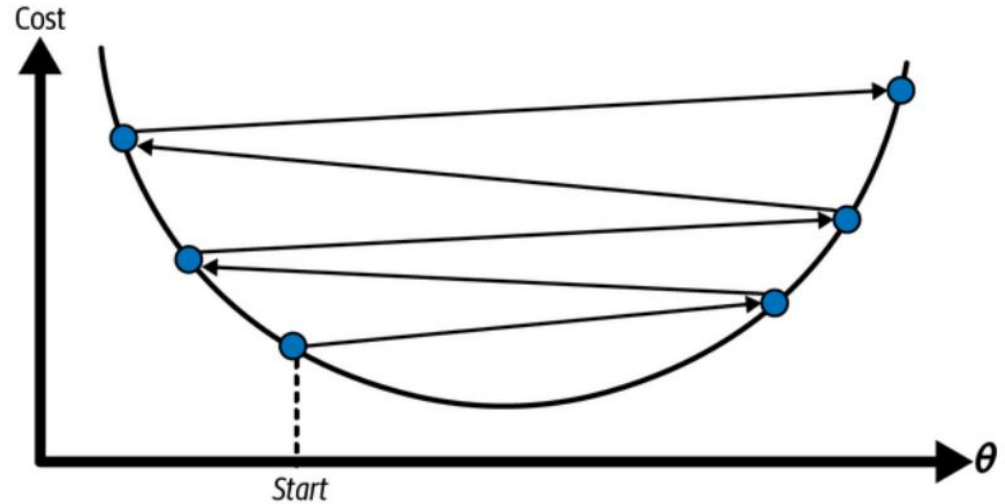
# Gradient descent

If the learning rate is too small, then the algorithm will have to go through many iterations to converge, which will take a long time



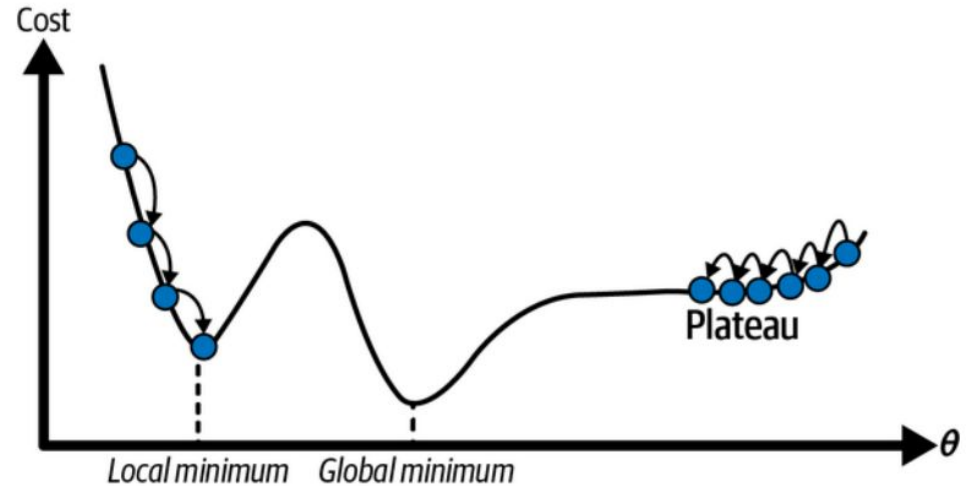
# Gradient descent

On the other hand, if the learning rate is too high, you might jump across the valley and end up on the other side, possibly even higher up than you were before



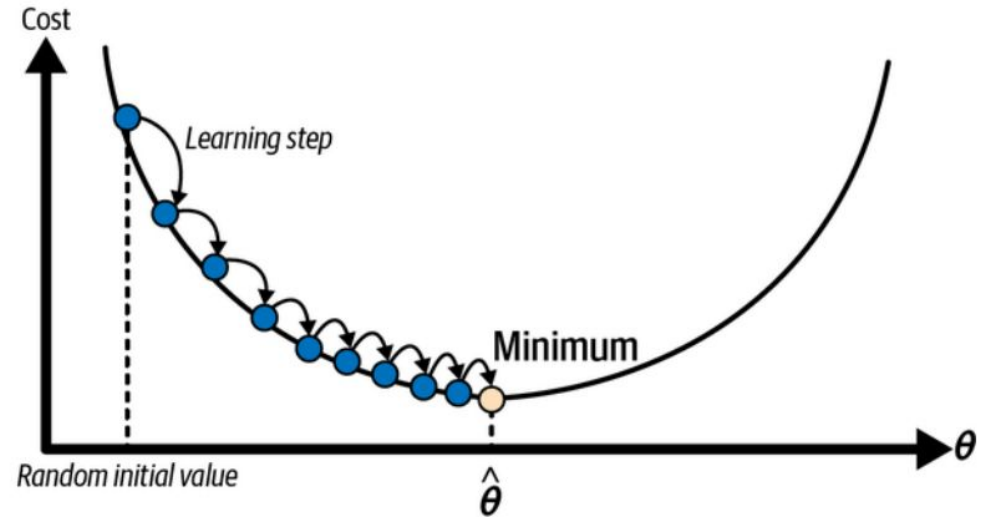
# Gradient descent

Additionally, not all cost functions look like nice, regular bowls. There may be holes, ridges, plateaus, and all sorts of irregular terrain, making convergence to the minimum difficult.



# Gradient descent

Fortunately, the MSE cost function for a linear regression model happens to be a convex function. so we will always have a learning curve that looks similar to this



## 4- Methods For Training a Linear Regression Model

### 1) Data Preprocessing:

Imagine you're preparing ingredients for a recipe. Data preprocessing is like washing, chopping, and organizing those ingredients before you cook.

### 2) Handling Missing Values:

Some ingredients might be missing (data missing). Decide if you can still cook with what you have or if you need to replace missing ingredients.

### 3) Handling Outliers:

Outliers are like unexpected ingredients – they can throw off your recipe. Decide if you keep them or replace them with something more common.

### 4) Feature Scaling:

Feature scaling is like making sure all ingredients are in the same units. If one ingredient is in grams and another in kilograms, the recipe might not turn out well

## 5- Evaluation Metrics

We always hear people bragging about their model's **accuracy**.

So, how do we calculate our **Linear Regression** model's **accuracy**?

Long story short : we **can't** !

**Accuracy** is an **evaluation metric** for **classification** tasks.

How do we **evaluate** our model then ?



## 5- Evaluation Metrics

- Mean Squared Error (MSE).

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

- R-squared Score (R<sup>2</sup>).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

- Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

# Time To practice !

let's head to our notebooks

# Thank you for attending

any questions ?



Thanks for iness that contributed to the workshop  
preparation