

# Contents

- 1 Linear Models
  - Framework and notations

# Contents

- 1 Linear Models
  - Framework and notations
  - Toy example : Housing price prediction

# Contents

- 1 Linear Models
  - Framework and notations
  - Toy example : Housing price prediction
  - Toy example (from the book) : Sales prediction

# Contents

- 1 Linear Models
  - Framework and notations
  - Toy example : Housing price prediction
  - Toy example (from the book) : Sales prediction
  - Linear model properties

# Contents

- 1 Linear Models
  - Framework and notations
  - Toy example : Housing price prediction
  - Toy example (from the book) : Sales prediction
  - Linear model properties
  - Fitting the regression

# Contents

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically

# Contents

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles

# Contents

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion



# Contents

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

Starting point :

- Outcome measurement  $Y$  (also called dependent variable, response, target) ;
- Vector of  $p$  predictor measurements  $X$  (also called inputs, regressors, covariates, features, independent variables).  $X$  is a matrix of dimension  $(N,p)$ , where  $n$  is the number of measurements ;
- In the **regression problem**,  $Y$  is quantitative (e.g price, blood pressure) ;
- We have training data  $(x_1, y_1), \dots, (x_N, y_N)$ . These are observations (examples, instances) of these measurements.

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

Linear Regression model with one variable

$$Y_i = \beta_0 + \beta_1 X_1$$

$$Price_{house30} = K + \beta_1 Surface_{House30}$$

Figure (TBD) In fact, we could imagine the price depends from several factors, so we come with Linear Regression with several variables :

$$Price_{house30} =$$

$$K + \beta_1 Surface_{House30} + \beta_2 NbOfRooms_{House30} + \beta_3 Location_{House30}$$

In general :

$$Y_i = h(X^i) = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \dots + \beta_p X_{i,p}$$

Traditionally  $p$  is called the number of features. We will use matrix notation, so there will be double indices.

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- **Toy example (from the book) : Sales prediction**
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

## Linear Models

Framework and notations

Toy example : Housing price prediction

Toy example (from the book) : Sales prediction

Linear model properties

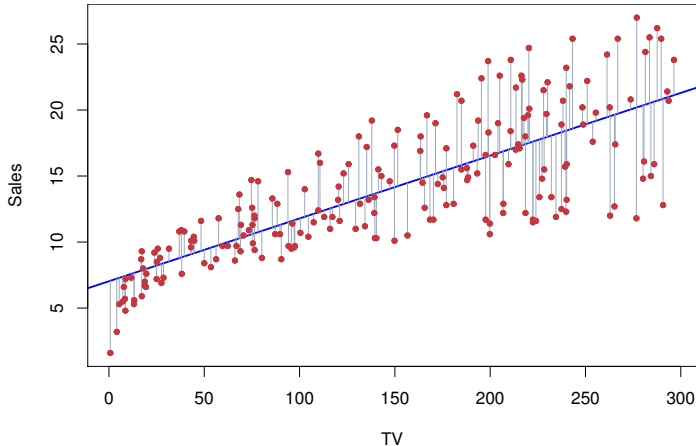
Fitting the regression

Solving the regression analytically

Gradient descent principles

Other algorithms LDA, Polynomial expansion

Summary



$$\text{Sales} \approx \beta_0 + \beta_1 \text{TV}$$

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- **Linear model properties**
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary



- The parameters in the linear regression model are very easy to interpret.
- $\beta_j, 1 \leq j \leq p$  is the average increase in  $Y$  when  $X_j$  is increased by one and all other  $X_i$  are held constant.
- Vocabulary :  $\beta_0$  is the intercept (i.e. the average value for  $Y$  if all the  $X$ 's are zero),  $\beta_j$  is the slope for the  $j$ th variable  $X_j$

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- **Fitting the regression**
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

- Historical method : least square regression ;
- Modern method : numerical iterative process : gradient descent and a huge family of similar algorithms (Maths : (Numerical)(Convex or not) Optimization.

Cost function, traditionally noted  $J(\beta)$  is given by :

$$J(\beta) = \frac{1}{2n} \sum_{i=1}^n (h(X^i) - Y_i)^2$$

n is N explained before.

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- **Solving the regression analytically**
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- Summary

Explanation,  
Solution in One dim  
Solution in  $p$  dim



# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- **Gradient descent principles**
- Other algorithms LDA, Polynomial expansion
- Summary

- Level on a curve or surface, direction of steepest descent
- Stochastic approach (SGD)

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- **Other algorithms** LDA, Polynomial expansion
- Summary



- The goal of Unsupervised Learning is to discover interesting things about the measurements : is there an informative way to visualize the data ? Can we discover subgroups among the variables or among the observations ?
- We discuss two methods :
  - **principal components analysis (PCA)**, a tool used for data visualization or data pre-processing before supervised techniques are applied, and
  - **clustering**, a broad class of methods for discovering unknown subgroups in data.

# Outline

## 1 Linear Models

- Framework and notations
- Toy example : Housing price prediction
- Toy example (from the book) : Sales prediction
- Linear model properties
- Fitting the regression
- Solving the regression analytically
- Gradient descent principles
- Other algorithms LDA, Polynomial expansion
- **Summary**

## Linear Models

Framework and notations

Toy example : Housing price prediction

Toy example (from the book) : Sales prediction

Linear model properties

Fitting the regression

Solving the regression analytically

Gradient descent principles

Other algorithms LDA, Polynomial expansion

Summary

Linearity is a limitation but solving principles are more general