

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
- 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
- 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
- Solving the regression analytically
- Gradient descent principles
- 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
 - Solving the regression analytically
 - Gradient descent principles
 - 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
 - Solving the regression analytically
 - Gradient descent principles
 - Gradient descent principles
 - Other algorithms : LDA, Polynomial expansion

1 Linear Models

Starting point :

- Outcome measurement Y (also called dependent variable, response, target, label) ;
- Vector of p predictor measurements X_i (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, sales, categories, blood pressure) ;
- We have training data $(x_1, y_1), \dots, (x_N, y_N)$. These are observations (examples, instances) of these measurements.

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
- Solving the regression analytically
- Gradient descent principles
- Gradient descent principles
- Other algorithms : LDA, Polynomial expansion
- Summary

Linear Regression model with one variable

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

$$Price_{house30} = \beta_0 + \beta_1 Surface_{House30} + \epsilon$$

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

$$Price_{house30} =$$

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

In general :

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

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
- Solving the regression analytically
- Gradient descent principles
- 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

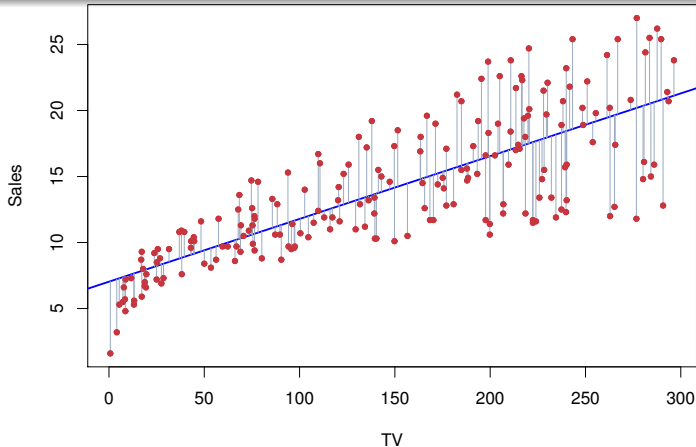
Solving the regression analytically

Gradient descent principles

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
- Solving the regression analytically
- Gradient descent principles
- 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 : β_0 is the intercept (i.e. the average value for Y if all the X s are zero), β_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
- Solving the regression analytically
- Gradient descent principles
- 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 :

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

Recall naming and indices are not universal, you will find sometimes n instead of N or p , or m instead of N , etc.

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**
- Solving the regression analytically
- Gradient descent principles
- Gradient descent principles
- Other algorithms : LDA, Polynomial expansion
- Summary

- We want to minimize the quantity $\sum_{i=1}^N (h(X^i) - Y_i)^2$ called MSE Mean Square Error
- Solution in one dimension : write partial derivatives in β_0 and β_1 of the cost function. To be done
- Solution in p dimension : Matrix

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
- **Solving the regression analytically**
- Gradient descent principles
- Gradient descent principles
- Other algorithms : LDA, Polynomial expansion
- Summary

- In one dimension you will derive a 2x2 linear system :

$$\begin{cases} \beta_0 \sum_{i=1}^N x_i + \beta_1 \sum_{i=1}^N x_i^2 = \sum_{i=1}^N x_i y_i, \\ N\beta_0 + \beta_1 \sum_{i=1}^N x_i = \sum_{i=1}^N y_i. \end{cases}$$
- To recall : you can shift the variables (x_i, y_i) to be centred on the mean, new variables (\bar{x}_i, \bar{y}_i) , verifies $\sum_i \bar{x}_i = 0$, $\sum_i \bar{y}_i = 0$ it gives directly the well-known slope coefficient $\beta_1 = \frac{\sum_{i=1}^N \bar{x}_i \bar{y}_i}{\sum_{i=1}^N \bar{x}_i^2}$
- Solution in p dimensions : Matrix X including a column vector of 1, verify $(X^T X)\beta = X^T Y$ gives $\beta = (X^T X)^{-1}(X^T Y)$ assuming that the square matrix $X^T X$ is invertible. This is the **Normal Equation**.

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
- Solving the regression analytically
- **Gradient descent principles**
- 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

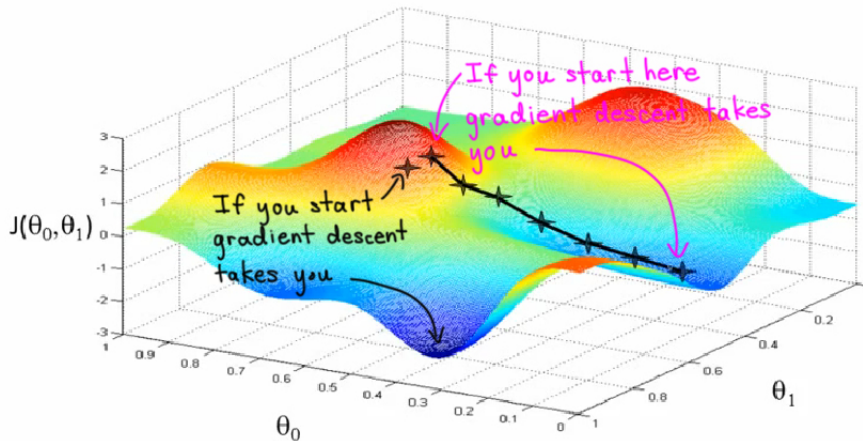
Solving the regression analytically

Gradient descent principles

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
- Solving the regression analytically
- Gradient descent principles
- **Gradient descent principles**
- Other algorithms : LDA, Polynomial expansion
- Summary

- Levels on a curve or surface, directions of steepest descent
- Stochastic approach steps :
 - Initialize $\beta_0, \beta_1, \dots, \beta_p$
 - Compute the new direction : $\beta_j := \beta_j - \alpha_j \frac{\partial J(\beta)}{\partial \beta_j}$, for $j = 0, \dots, p$
 - Evaluate $J(\beta)$ and iterate
- Compare the complexity of the 2 methods

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
- Solving the regression analytically
- Gradient descent principles
- Gradient descent principles
- **Other algorithms : LDA, Polynomial expansion**
- Summary

- LDA
- Polynomial expansion : beyond the linearity (another chapter)

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
- Solving the regression analytically
- Gradient descent principles
- 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

Solving the regression analytically

Gradient descent principles

Gradient descent principles

Other algorithms : LDA, Polynomial expansion

Summary

- Linearity is a limitation but solving principles are more general ;
- Introducing complexity/flexibility of a model vs interpretability

