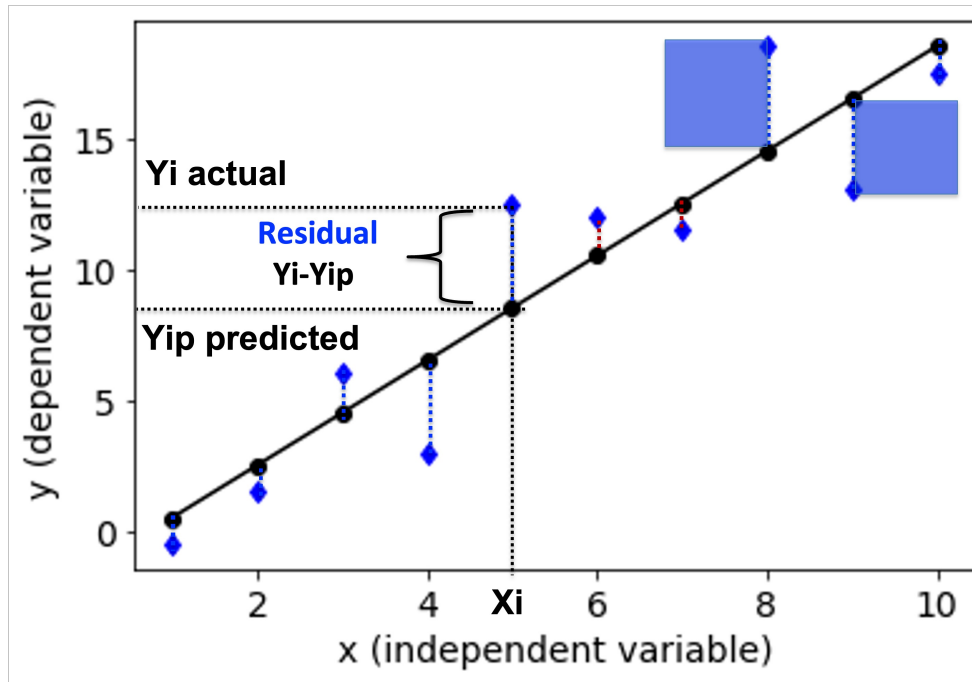


# Least-Squares method

The Least Square method is the process of finding a regression line or best-fitted line for the observed data by minimizing **the sum of the squares of the residuals** between the data the fitting model



**Sum of squared residuals (SSR)** is basically the sum the blue squares in the above figure. Mathematically it is described as:

$$SSR = \sum_i (y_i - y_{ip})^2$$

## Linear models - Coefficient of determination ( $R^2$ )

2

The coefficient of determination  $R^2$  is popularly used to determine the quality of the fit. It is defined as:

$$R^2 = 1 - \frac{\sum_i (y_i - y_{ip})^2}{\sum_i (y_i - \bar{y})^2}$$

Where:

$y_i$  – the  $i^{\text{th}}$  y data

$y_{ip}$  – the  $i^{\text{th}}$  predicted y value from the model

$\bar{y}$  – the average of the y data

**If  $R^2$  close to 1 the model is a good approximation to the data** compared to the mean of the data, but be careful not to overfit data

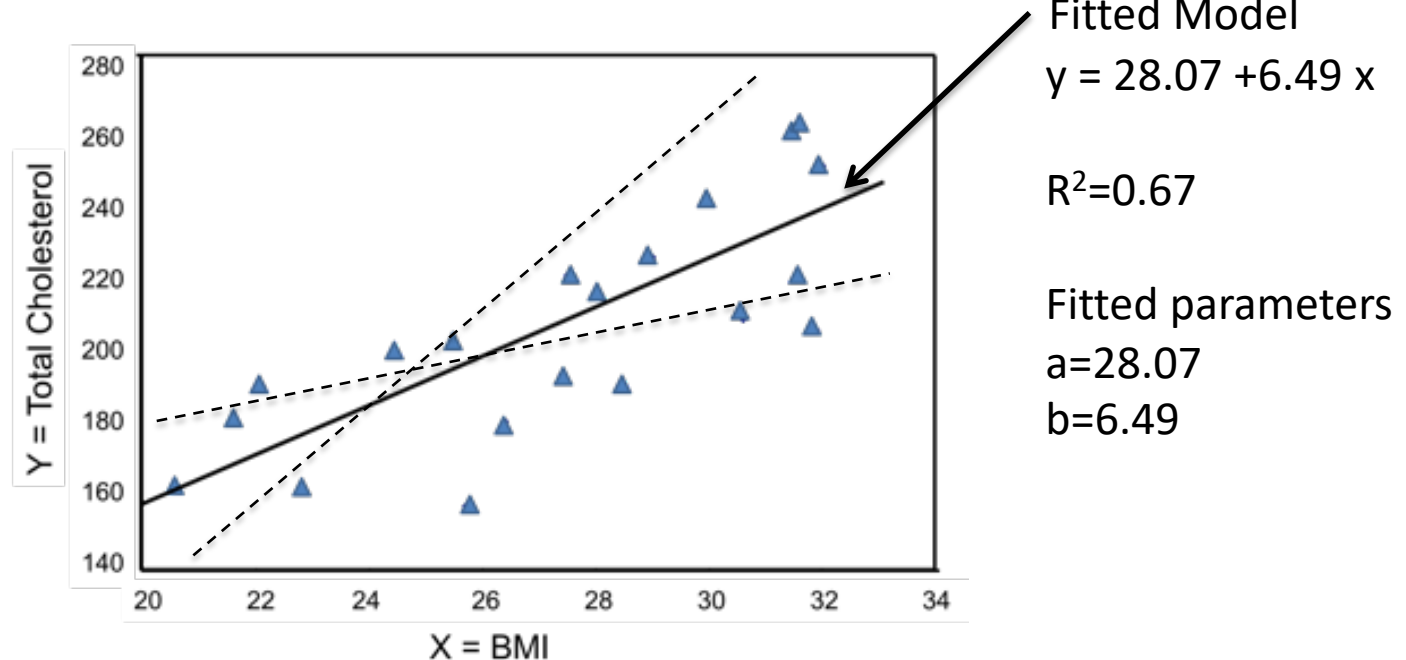
**If  $R^2$  close to 0 the model is poor**, as the two deviations will be comparable

## Example

Below is an example of a linear regression analysis, showing the dependence of the total cholesterol (dependent variable) on the Y-axis vs body mass index (independent variable) on the X-axis:

**Model:** Linear equation:

$y = a + b x$  (a and b are the fitting parameters)



Least Square Regression method finds the line that minimizes the differences between observed and predicted values of the outcome.

**Linear models are linear functions**, i.e., linear in their parameters,  $\beta_0$ ,  $\beta_1$  etc.

## **Polynomials are linear models**

degree 1 – linear function  $y = \beta_0 x + \beta_1$

degree 2 – quadratic function  $y = \beta_0 x^2 + \beta_1 x + \beta_2$

degree 3 – cubic function  $y = \beta_0 x^3 + \beta_1 x^2 + \beta_2 x + \beta_3$   
and so on..

We will use two NumPy functions:

- **np.polyfit** is a function that performs the linear fit based on the **Least-Squares method** and returns the fitted parameters of a polynomial
- **np.poly1d** it constructs a polynomial function from the parameters returned by polyfit. It constructs and returns the fitted model function.

```
coeff_array=np.polyfit(xarray, yarray, deg)
```

**xarray, yarray** - 1D arrays

**deg**: integer number specify the degree of the polynomial

**coeff\_array**: 1D array containing the numerical values of fitted parameters:  $\beta_0$ ,  $\beta_1$ , etc.

```
model_func = np.poly1d(coeff_array) #fitted model function  
yp=model_func(xarray) #returns predicted yp values from the  
model
```

You can use directly both in one line of code:

```
model_func = np.poly1d(np.polyfit(xarray, yarray, deg))
```

## step1 - Look at the raw data and choose the model

```
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt

#create data
x_data = np.arange(1,25)
y_data = x +6 * np.random.random(x.size)**2-1

#plot the raw data
fig, ax= plt.subplots()
ax.plot(x_data,y_data,'Dr',label='data')
ax.set_xlabel('x')
ax.set_ylabel('y')

#choose the model
#the model is  $y = \beta_0 * x + \beta_1$ 
```

## Example – Fit a linear model with NumPy

### step2 - Perform the fit and construct the fitting model function

```
#the model is  $y = \beta_0 * x + \beta_1$   
coeff=np.polyfit(x, y, 1)  
mymodel = np.poly1d(coeff)
```

```
print(mymodel.c) #access the coefficients (fitted parameters)  
[0.95374719 0.97329153] #[ $\beta_0$ ,  $\beta_1$ ]
```

```
print(mymodel.order) #the order of the polynomial, its degree  
1
```

```
#Create 1D array of predicted values yp for each element of x.  
yp = mymodel(x)
```

```
#add the fitting model to the same Axes as the row data plot  
ax.plot(x,yp,'b',label='model')
```

### step3 - Calculating the $R^2$

$$R^2 = 1 - \frac{\sum_i (y_i - y_{ip})^2}{\sum_i (y_i - \bar{y})^2} = 1 - \frac{SSR}{SST}$$

#You can calculate the R2 by applying the formula

```
SSR = ((y_data - yp)**2).sum()
```

```
SST = ((y_data - y_data.mean())**2).sum()
```

```
R2 = 1-(SSR/SST)
```

```
print(R2)
```

```
0.966040933792211
```

#or you can import the r2\_score function from scikit-learn, the Python machine Learning library

```
from sklearn.metrics import r2_score
```

```
print(r2_score(y,yp))
```

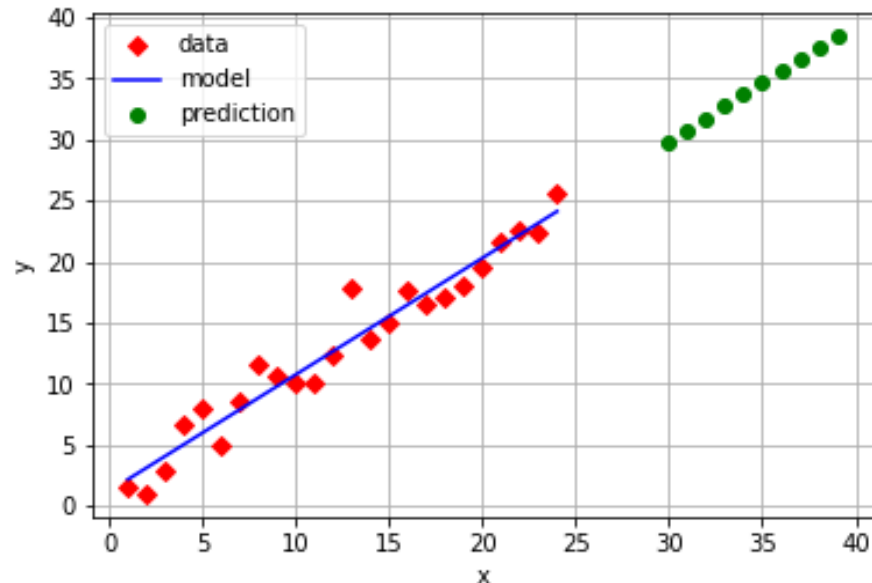
```
0.966040933792211
```



## step4 - Make Predictions

If the model is good, you can use it to make predictions.

```
# predict y values for x values 30-40
xpred=np.arange(30,40)
ypred=mymodel(xpred)
ax.plot(xpred,ypred,'go',label='prediction')
ax.legend()
ax.grid()
plt.show()
```



To install **scikit-learn module** :

if you use Anaconda - type at the IPython Console or bash terminal

```
conda install scikit-learn
```

If you use standard Python3 IDLE:

```
pip3 install scikit-learn
```

To import it use:

```
import sklearn
```

The scikit-learn is a Python machine learning library <https://scikit-learn.org/stable/>

You can also perform linear regression with scikit-learn or with SciPy.