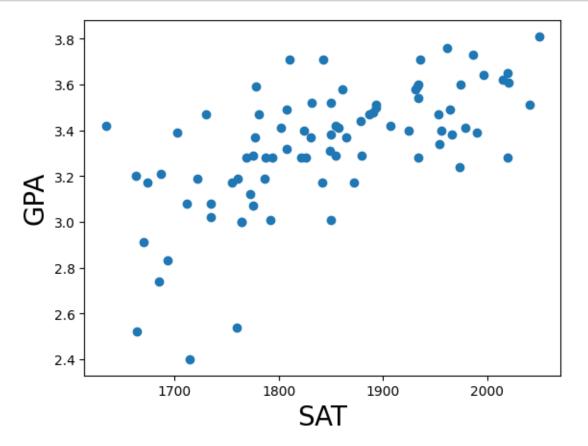
Ejemplo1

July 16, 2025

```
[3]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import statsmodels.api as sm
[4]: data = pd.read_csv('1.01.+Simple+linear+regression.csv')
[5]:
    data
[5]:
          SAT
                GPA
     0
         1714
              2.40
     1
         1664 2.52
     2
         1760 2.54
     3
         1685 2.74
     4
         1693 2.83
          •••
     79
         1936 3.71
     80
         1810 3.71
     81
         1987
               3.73
     82
         1962 3.76
         2050
     83
              3.81
     [84 rows x 2 columns]
[6]: data.describe()
[6]:
                    SAT
                                GPA
              84.000000
                         84.000000
     count
            1845.273810
     mean
                           3.330238
     std
             104.530661
                           0.271617
            1634.000000
    min
                           2.400000
     25%
            1772.000000
                           3.190000
     50%
            1846.000000
                           3.380000
     75%
            1934.000000
                           3.502500
            2050.000000
                           3.810000
     max
[7]: y = data['GPA']
     x1 = data['SAT']
```

```
[8]: plt.scatter(x1,y)
  plt.xlabel('SAT',fontsize=20)
  plt.ylabel('GPA',fontsize=20)
  plt.show()
```



```
[9]: x = sm.add_constant(x1)
result = sm.OLS(y,x).fit()
result.summary()
```

[9]:

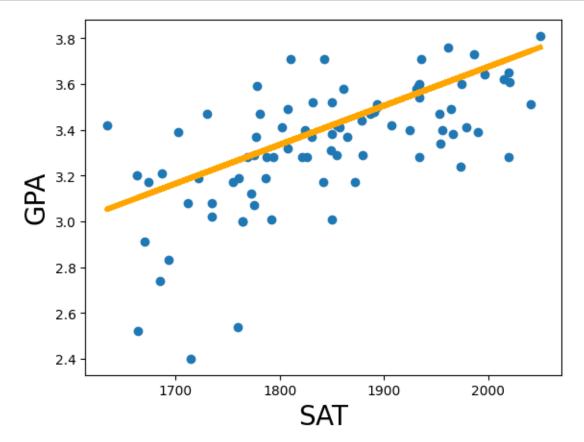
| Dep. Variable: | GPA | R-squared: | 0.406 |
|-------------------|------------------|---------------------|----------|
| Model: | OLS | Adj. R-squared: | 0.399 |
| Method: | Least Squares | F-statistic: | 56.05 |
| Date: | Tue, 08 Jul 2025 | Prob (F-statistic): | 7.20e-11 |
| Time: | 16:03:54 | Log-Likelihood: | 12.672 |
| No. Observations: | 84 | AIC: | -21.34 |
| Df Residuals: | 82 | BIC: | -16.48 |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |

| | | \mathbf{coef} | std err | \mathbf{t} | $\mathbf{P} \gt \mathbf{t} $ | [0.025 | 0.975] |
|----------------|----------------|-----------------|--------------------------|-----------------|-------------------------------|--------|----------|
| | onst AT | 0.2750 0.0017 | 0.409 | 0.673 7.487 | 0.503 | -0.538 | 1.088 |
| | | 0.0011 | 0.000 | 11101 | 0.000 | 0.001 | 0.002 |
| Omnibus: | | 12.839 | Durbin-Watson: | | | 0.950 | |
| Prob(Omnibus): | | 0.002 | Jarque-Bera (JB): | | | 16.155 | |
| Ske | \mathbf{w} : | | -0.722 | \mathbf{Prob} | o(JB): | | 0.000310 |
| Kurtosis: | | 4.590 | Cond. No. | | 3.29e+04 | | |

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 3.29e+04. This might indicate that there are strong multicollinearity or other numerical problems.

```
[12]: plt.scatter(x1,y)
  yhat = 0.0017*x1 + 0.275
  fig = plt.plot(x1,yhat, lw=4, c='orange', label ='regression line')
  plt.xlabel('SAT', fontsize = 20)
  plt.ylabel('GPA', fontsize = 20)
  plt.show()
```



[]:[