## Dummy variables

## Import the relevant libraries

```
In [3]: import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

```
Load the data

In [4]: # Load the data from a .csv in the same folder.
raw_data = pd.read_csv('Dummies.csv')

In [5]: # what's inside this data frame
```

2 1760 2.54 No
3 1685 2.74 No
4 1693 2.83 No
... ... ... ...
79 1936 3.71 Yes
80 1810 3.71 Yes
81 1987 3.73 No
82 1962 3.76 Yes
83 2050 3.81 Yes
84 rows × 3 columns

Map the data

**0** 1714 2.40

```
In [6]: # Map all 'No' entries with 0, and all 'Yes' entries with 1. Put that in a new variable called 'data'

data = raw_data.copy()
data['Attendance'] = data['Attendance'].map({'Yes': 1, 'No': 0})

# what's inside
data
Out[6]: SAT GPA Attendance
```

**SAT count** 84.000000

mean

std

data.describe()

In [7]:

Out[7]:

min 1634.000000 2.400000
25% 1772.000000 3.190000

results.summary()

Time:

**Omnibus:** 19.560

Skew:

0.000

-1.028

In [10]: # Create a scatter plot of SAT and GPA
plt.scatter(data['SAT'],y)

yhat\_no = 0.6439 + 0.0014\*data['SAT']

Prob(Omnibus):

1845.273810

104.530661

# descriptive statistics

**GPA** Attendance

84.000000

0.464286

0.501718

0.000000

84.000000

3.330238

0.271617

	25%	1772.000000	3.190000	0.000000							
	50%	1846.000000	3.380000	0.000000							
	75%	1934.000000	3.502500	1.000000							
	max	2050.000000	3.810000	1.000000							
	Regression										
In [8]:	y = d # Sim	# Following the regression equation, our dependent variable (y) is the GPA y = data ['GPA'] # Similarly, our independent variable (x) is the SAT score									

```
x1 = data [['SAT', 'Attendance']]
In [9]: # Add a constant
x = sm.add_constant(x1)
# Fit the model, according to the OLS method with a dependent variable y and an idependent x
results = sm.OLS(y,x).fit()
# Print a nice summary of the regression.
```

Out[9]:

Dep. Variable:

GPA

R-squared:

0.565

Model:

OLS

Adj. R-squared:

52.70

25.798

**Prob (F-statistic):** 2.19e-15

1.009

27.189

**Prob(JB):** 1.25e-06

Log-Likelihood:

No. Observations: AIC: -45.60 84 **Df Residuals:** 81 BIC: -38.30 2 Df Model: **Covariance Type:** nonrobust coef std err t P>|t| [0.025 0.975] **const** 0.6439 0.358 1.797 0.076 -0.069 1.357 **SAT** 0.0014 0.001 0.002 0.000 0.000 Attendance 0.2226 0.041 5.451 0.000 0.141 0.304

**Durbin-Watson:** 

Jarque-Bera (JB):

14:40:25

**Date:** Tue, 04 Oct 2022

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.35e+04. This might indicate that there are

strong multicollinearity or other numerical problems.

## yhat\_yes = 0.8665 + 0.0014\*data['SAT'] # Plot the two regression lines fig = plt.plot(data['SAT'], yhat\_no, lw=2, c='#006837') fig = plt.plot(data['SAT'], yhat\_yes, lw=2, c='#a50026'

plt.show()

3.8

2.4

2.8

1700

yhat\_no = 0.6439 + 0.0014\*data['SAT']
yhat yes = 0.8665 + 0.0014\*data['SAT']

# Plot the two regression lines

plt.xlabel('SAT', fontsize = 20)
plt.ylabel('GPA', fontsize = 20)

1800

In [11]: plt.scatter(data['SAT'], data['GPA'], c=data['Attendance'], cmap='RdYlGn r')

fig = plt.plot(data['SAT'], yhat\_no, lw=2, c='#006837')
fig = plt.plot(data['SAT'], yhat\_yes, lw=2, c='#a50026')

SAT

# Define the two regression equations (one with a dummy = 1, the other with dummy = 0)

fig = plt.plot(data['SAT'], yhat\_yes, lw=2, c='#a50026')
# Name axes
plt.xlabel('SAT', fontsize = 20)
plt.ylabel('GPA', fontsize = 20)

Plot the regression line(s) on the scatter plot

```
3.6

3.4

3.2

3.0

2.8

2.6
```

1900

Plot the regression line(s) on the scatter plot and color the data points

2000

# Define the two regression equations, depending on whether they attended (yes), or didn't (no)

```
3.8
3.6
3.4
4
3.2
0
3.0
```

## 2.4 1700 1800 SAT Add the original regression line

In [12]: # Same as above, this time we are including the regression line WITHOUT the dummies.

plt.scatter(data['SAT'], data['GPA'], c=data['Attendance'], cmap='RdYlGn\_r')

# Define the two regression equations (one with a dummy = 1, the other with dummy = 0)

# We have those above already, but for the sake of consistency, we will also include them here

```
yhat_no = 0.6439 + 0.0014*data['SAT']
yhat_yes = 0.8665 + 0.0014*data['SAT']
# Original regression line
yhat = 0.0017*data['SAT'] + 0.275

# Plot the two regression lines
fig = plt.plot(data['SAT'],yhat_no, lw=2, c='#006837', label ='regression line1')
fig = plt.plot(data['SAT'],yhat_yes, lw=2, c='#a50026', label ='regression line2')
# Plot the original regression line
fig = plt.plot(data['SAT'],yhat, lw=3, c='#4C72B0', label ='regression line')

plt.xlabel('SAT', fontsize = 20)
plt.ylabel('GPA', fontsize = 20)
plt.ylabel('GPA', fontsize = 20)
plt.show()
3.8
```

```
3.6
3.4
3.2
3.0
2.8
2.6
2.4
1700
1800
SAT
1900
2000
```