Dummy variables (categorical predictors)

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('3.01.Dummies.csv')
```

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

Out[5]:

	SAT	GPA	Attendance
0	1714	2.40	No
1	1664	2.52	No
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

In [6]:
```
# Map all 'No' entries with 0, and all 'Yes' entries with 1
data = raw_data.copy()
data['Attendance'] = data['Attendance'].map({'Yes':1, 'No':0})

# What's inside
data
```

Out[6]:

	SAT	GPA	Attendance
0	1714	2.40	0
1	1664	2.52	0
2	1760	2.54	0
3	1685	2.74	0
4	1693	2.83	0
...	...	...	...
79	1936	3.71	1
80	1810	3.71	1
81	1987	3.73	0
82	1962	3.76	1
83	2050	3.81	1

84 rows × 3 columns

In [7]:
```
# descriptive statistics
data.describe()
```

Out[7]:

	SAT	GPA	Attendance
count	84.000000	84.000000	84.000000
mean	1845.273810	3.330238	0.464286
std	104.530661	0.271617	0.501718
min	1634.000000	2.400000	0.000000
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]:
```
# 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']]

# Add a constant. Essentially, we are adding a new column (equal in lenght to x), which consists only of 1s
x = sm.add_constant(x1)
# Fit the model, according to the OLS (ordinary least squares) method with a dependent variable y and an indepen
results = sm.OLS(y,x).fit()
# Print a nice summary of the regression.
results.summary()
```

Out[8]:

OLS Regression Results

Dep. Variable:	GPA	**R-squared:**	0.565
Model:	OLS	**Adj. R-squared:**	0.555
Method:	Least Squares	**F-statistic:**	52.70
Date:	Tue, 04 Oct 2022	**Prob (F-statistic):**	2.19e-15
Time:	14:47:28	**Log-Likelihood:**	25.798
No. Observations:	84	**AIC:**	-45.60
Df Residuals:	81	**BIC:**	-38.30
Df Model:	2		
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	0.000	7.141	0.000	0.001	0.002
Attendance	0.2226	0.041	5.451	0.000	0.141	0.304

Omnibus:	19.560	**Durbin-Watson:**	1.009
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	27.189
Skew:	-1.028	**Prob(JB):**	1.25e-06
Kurtosis:	4.881	**Cond. No.**	3.35e+04

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.

Plot the regression line(s) on the scatter plot

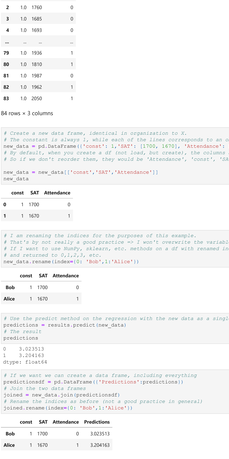
In [10]:
```
# Create a scatter plot of SAT and GPA
plt.scatter(data['SAT'],y)
# Define the two regression equations, depending on whether they attended (yes), or didn't (no)
yhat_no = 0.6439 + 0.0014*data['SAT']
yhat_yes = 0.8665 + 0.0014*data['SAT']
# Plot the two regression lines
fig = plt.plot(data['SAT'],yhat_no, lw=2, c='#006837')
fig = plt.plot(data['SAT'],yhat_yes, lw=2, c='#a50026')
# Name your axes :)
plt.xlabel('SAT', fontsize = 20)
plt.ylabel('GPA', fontsize = 20)
plt.show()
```

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

In [11]:
```
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']

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



Add the original regression line

In [12]:
```
# 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')
fig = plt.plot(data['SAT'],yhat, lw=3, c='#4C7BB7', label ='regression line')

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


Predictions based on the regressions

In [13]:
```
# Let's see what's inside the independent variable.
# The first column comes from the 'add_constant' method
x
```

Out[13]:

	const	SAT	Attendance
0	1.0	1714	0
1	1.0	1664	0
2	1.0	1760	0
3	1.0	1685	0
4	1.0	1693	0
...	...	...	...
79	1.0	1936	1
80	1.0	1810	1
81	1.0	1987	0
82	1.0	1962	1
83	1.0	2050	1

84 rows × 3 columns

In [14]:
```
# Create a new data frame, identical in organisation to X.
# The constant is always 1, while each of the rows corresponds to an observation (student)
new_data = pd.DataFrame({'const': 1,'SAT': [1700, 1670], 'Attendance': [0, 1]})
# By default, when you create a df (not used, but create), the columns are sorted alphabetically
# So if we don't reorder them, they would be 'Attendance', 'const', 'SAT'
new_data
```

In [15]:
```
new_data = new_data[['const','SAT','Attendance']]
new_data
```

Out[14]:

	const	SAT	Attendance
0	1	1700	0
1	1	1670	1

In [15]:
```
# I am renaming the indices for the purposes of this example.
# That's by not really a good practice -> I won't overwrite the variable.
# If I want to see Rudy, aleksey, etc. methods on a df with renamed indices, they will simply be lost
# and returned to 0,1,2,3, etc.
new_data.rename(index={0: 'Bob',1:'Alice'})
```

Out[15]:

	const	SAT	Attendance
Bob	1	1700	0
Alice	1	1670	1

In [16]:
```
# Use the predict method on the regression with the new data as a single argument
predictions = results.predict(new_data)
# The result
predictions
```

Out[16]:
```
0    3.023533
1    3.204163
dtype: float64
```

In [17]:
```
# If we want we can create a data frame, including everything
predictionsdf = pd.DataFrame({'Predictions':predictions})
# Join the two data frames
joined = new_data.join(predictionsdf)
# Rename the indices as before (not a good practice in general)
joined.rename(index={0: 'Bob',1:'Alice'})
```

Out[17]:

	const	SAT	Attendance	Predictions
Bob	1	1700	0	3.023533
Alice	1	1670	1	3.204163