In [14]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns
sns.set()
```

In [15]:
```
raw_data = pd.read_csv('1.03. Dummies.csv')
```

In [3]:
```
raw_data
```

Out[3]:

	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

In [4]:
```
data = raw_data.copy()
```

In [5]:
```
data['Attendance'] = data['Attendance'].map({'Yes':1, 'No':0})
```

In [6]:
```
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]:
```
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

In [8]:
```
## Regression
```

In [9]:
```
y = data['GPA']
x1 = data[['SAT','Attendance']]
```

In [10]:
```
x = sm.add_constant(x1)
results = sm.OLS(y,x).fit()
results.summary()
```

Out[10]:

OLS Regression Results

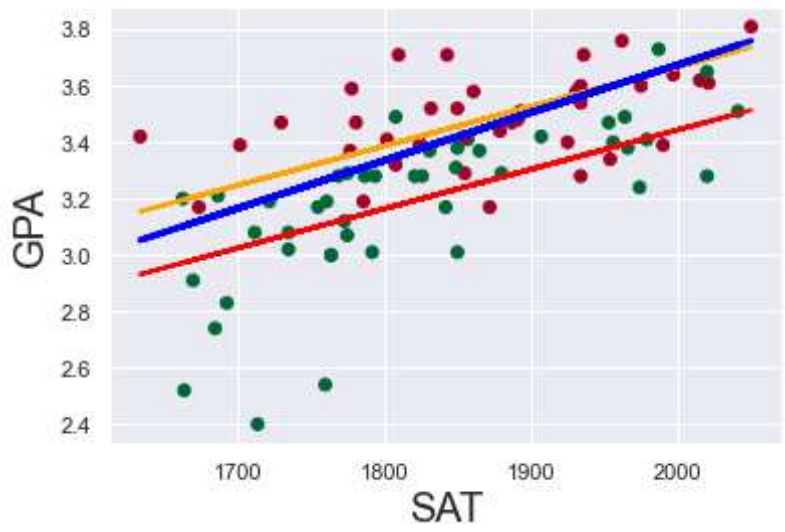
Dep. Variable:	GPA	**R-squared:**	0.565
Model:	OLS	**Adj. R-squared:**	0.555
Method:	Least Squares	**F-statistic:**	52.70
Date:	Thu, 26 Aug 2021	**Prob (F-statistic):**	2.19e-15
Time:	14:52:22	**Log-Likelihood:**	25.798
No. Observations:	84	**AIC:**	-45.60
Df Residuals:	81	**BIC:**	-38.30
Df Model:	2		
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

Warnings:
[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.

In [11]:
```
plt.scatter(data['SAT'],y, c=data['Attendance'], cmap='RdYlGn_r')
yhat_no = 0.6439 + 0.0014 * data['SAT']
yhat_yes = 0.6439 + 0.2226 + 0.0014 * data['SAT']
yhat = 0.0017 * data['SAT'] + 0.275
fig = plt.plot(data['SAT'], yhat_no, lw=2, c='red', label='regression line 1')
fig = plt.plot(data['SAT'], yhat_yes, lw=2, c='orange', label ='regression line 2
fig = plt.plot(data['SAT'], yhat, lw=3, c='blue', label ='regressionline')
plt.xlabel('SAT', fontsize=20)
plt.ylabel('GPA', fontsize=20)
plt.show()
```



In [17]:
```
x
```

Out[17]:

	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 [20]:
```
new_data = pd.DataFrame({'const':1, 'SAT':[1700,1670], 'Attendance':[0,1]})
new_data = new_data[['const', 'SAT', 'Attendance']]
new_data
```

Out[20]:

	const	SAT	Attendance
0	1	1700	0
1	1	1670	1

In [22]:
```
new_data.rename(index={0:'Bob', 1:'Alice'})
```

Out[22]:

	const	SAT	Attendance
Bob	1	1700	0
Alice	1	1670	1

In [24]:
```
predictions = results.predict(new_data)
predictions
```

Out[24]:
```
0    3.023513
1    3.204163
dtype: float64
```

In [25]:
```
predictionsdf =  pd.DataFrame({'Predictions':predictions})
joined = new_data.join(predictionsdf)
joined.rename(index={0:'Bob', 1:'Alice'})
```

Out[25]:

	const	SAT	Attendance	Predictions
Bob	1	1700	0	3.023513
Alice	1	1670	1	3.204163

In [ ]:
```

```