General Information:

- Python 3.9 was used in this project
- Necessary Python libraries were used (numpy,pandas,seaborn..)
- The project was coded on Jupyter Notebook
- We made Regression, Heatmap, Predict.

```python
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv("CollegeBasketballPlayers2009-2021.csv", sep=",")

df = df.head(762)

x1 = df.GP
x2 = df.Min_per
x3 = df.Ortg
x4 = df.usg
x5 = df.eFG
x6 = df.TS_per
x7 = df.ORB_per
x8 = df.stops
y =  df.pts

d = pd.DataFrame({'GP': x1, 'Min_per' : x2, 'Ortg' : x3,'Usage': x4,
                  'eFG' : x5, 'TS_per' : x6,'ORB_per' : x7,'Stops' : x8, 'pts' : y })
d = d.head(762)
```

From our data, we used 9 data. We used the pts data as a reference. We assigned the remaining 8 data as x. Since there are 760 data in the Drafted Players dataset, we limited our data to 760.

```python
d.describe()
```

	GP	Min_per	Ortg	Usage	eFG	TS_per	ORB_per	Stops	pts
count	762.000000	762.000000	762.000000	762.000000	762.000000	762.000000	762.000000	762.000000	762.000000
mean	25.906824	45.761155	95.229265	18.725984	46.552231	49.895551	5.944751	102.421394	6.938586
std	8.721293	27.214129	22.400932	5.718022	14.586158	13.870970	4.741042	65.884007	5.276197
min	1.000000	0.100000	0.000000	0.000000	0.000000	0.000000	0.000000	0.084114	0.000000
25%	23.000000	22.625000	89.200000	15.200000	43.325000	46.600000	2.300000	47.254675	2.414125
50%	29.000000	49.100000	98.800000	18.300000	48.500000	51.665000	5.200000	104.951500	6.038700
75%	31.000000	68.675000	107.000000	22.400000	52.700000	56.040000	8.900000	151.247000	10.536300
max	38.000000	93.700000	264.600000	45.800000	150.000000	150.000000	51.000000	275.974000	27.733300

We found the Measures of Central Tendency our data with the Describe method.

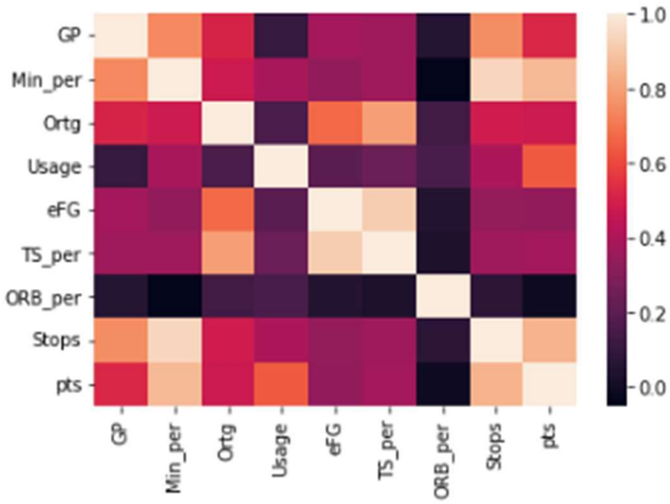
```
d.corr()
```

	GP	Min_per	Ortg	Usage	eFG	TS_per	ORB_per	Stops	pts
GP	1.000000	0.744803	0.507896	0.098494	0.374844	0.365548	0.055876	0.751970	0.520776
Min_per	0.744803	1.000000	0.478515	0.385775	0.331900	0.359948	-0.050438	0.942149	0.860943
Ortg	0.507896	0.478515	1.000000	0.157482	0.667722	0.792459	0.126306	0.485682	0.476490
Usage	0.098494	0.385775	0.157482	1.000000	0.199973	0.240782	0.152848	0.398141	0.638628
eFG	0.374844	0.331900	0.667722	0.199973	1.000000	0.916080	0.048791	0.339746	0.332000
TS_per	0.365548	0.359948	0.792459	0.240782	0.916080	1.000000	0.029724	0.364372	0.373276
ORB_per	0.055876	-0.050438	0.126306	0.152848	0.048791	0.029724	1.000000	0.069013	-0.011119
Stops	0.751970	0.942149	0.485682	0.398141	0.339746	0.364372	0.069013	1.000000	0.844674
pts	0.520776	0.860943	0.476490	0.638628	0.332000	0.373276	-0.011119	0.844674	1.000000

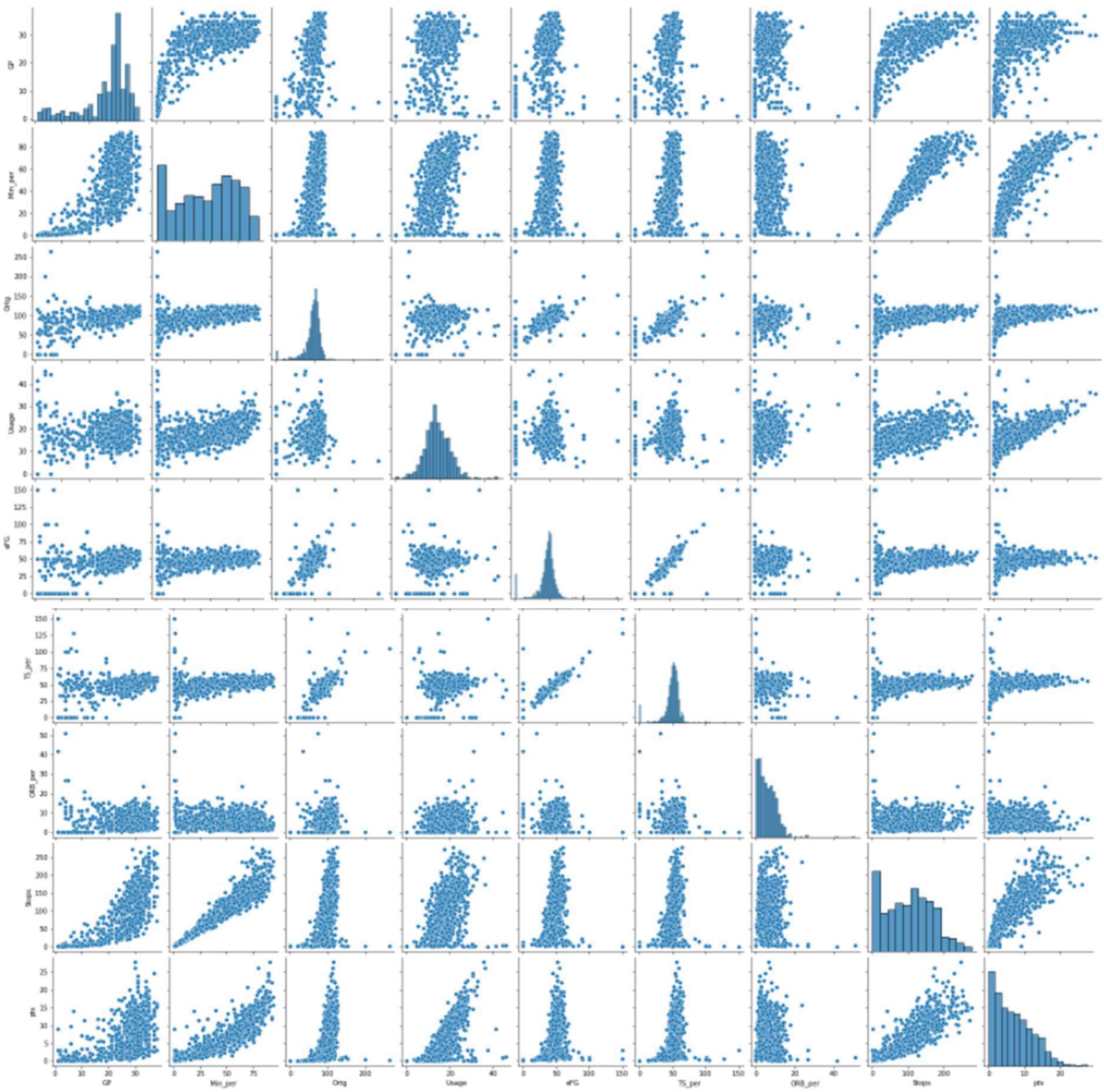
We found the correlation coefficient values between our data with the corr() method.

```
sns.heatmap(d.corr())
```

<AxesSubplot:>



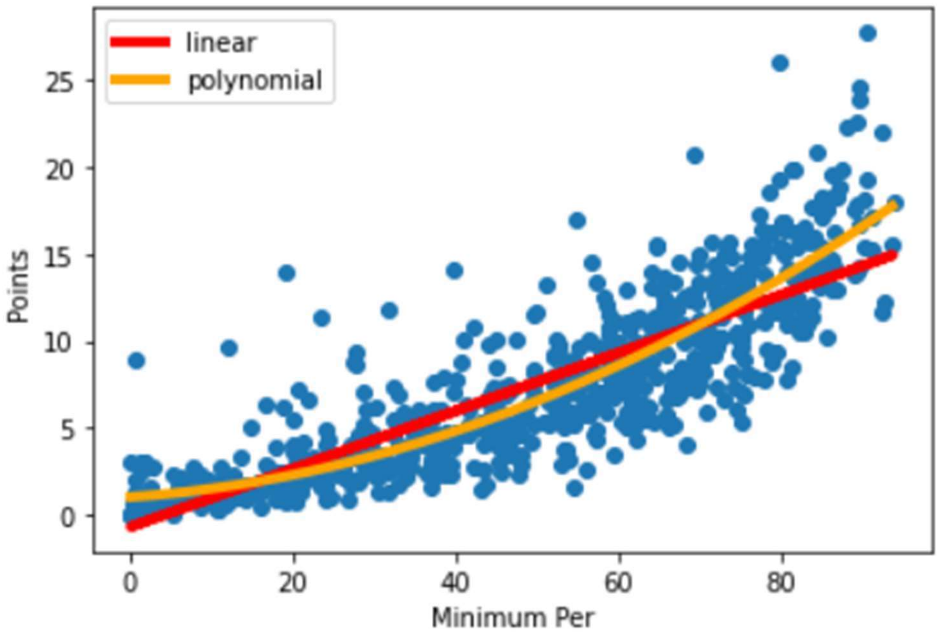
We printed the heatmap of our correlation coefficient values.



We created graphs of our correlation coefficient values with **sns.pairplot()** method.

```
plt.scatter(x2,y)

x2 = x2.values.reshape(-1,1)
y = y.values.reshape(-1,1)

from sklearn.linear_model import LinearRegression

lr = LinearRegression()

lr.fit(x2,y)

#predict
y_head = lr.predict(x2)

plt.plot(x2,y_head,color="red",linewidth=4, label="linear")

# Linear regression
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

polynomial_regression = PolynomialFeatures(degree = 2)
x_polynomial = polynomial_regression.fit_transform(x2)
polynomial_regression.fit(x_polynomial,y)

linear_regression2 = LinearRegression()
linear_regression2.fit(x_polynomial, y)

x_grid = np.arange(min(x2), max(x2), 0.1)
x_grid = x_grid.reshape((len(x_grid), 1))

y_head2 = linear_regression2.predict(polynomial_regression.fit_transform(x_grid))

plt.plot(x_grid,y_head2,color="orange",linewidth=4, label="polynomial")
plt.xlabel("Minimum Per")
plt.ylabel("Points")
plt.legend()
plt.show()
```

We chose two examples. Our first example; We got our data whose correlation coefficient is closest to 1 relative to the reference value. We created linear regression with the codes we wrote above. To determine which linear regression model to use, we constructed both linear and polynomial regressions. And we decided that polynomial regression was a better fit for this dataset.



The regression equation is
pts = 1.025 + 0.03261 Min_per + 0.001560 Min_per^2

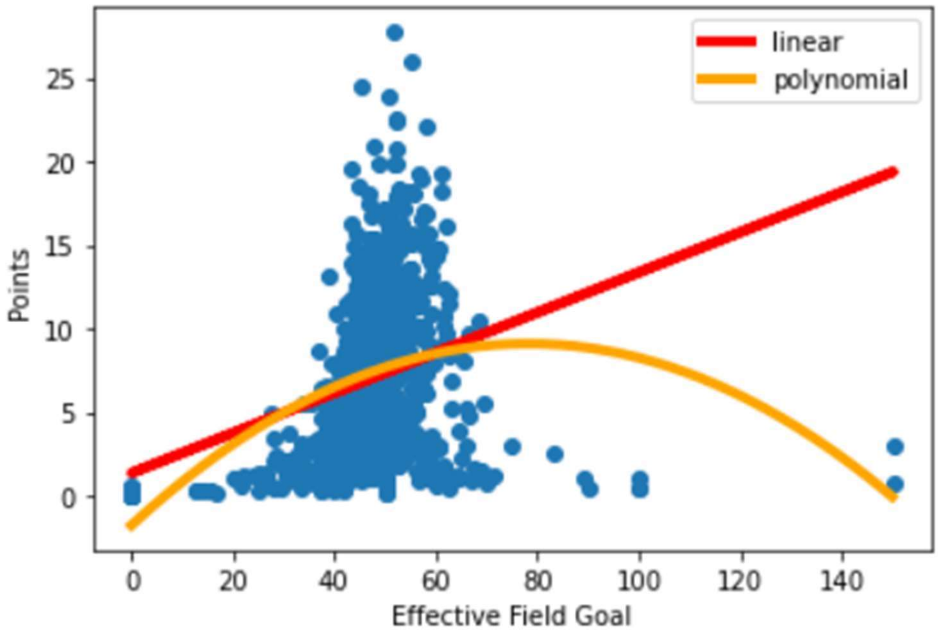
```
print("intercept : ",linear_regression2.intercept_)
print("coef(eğim) : ",linear_regression2.coef_)
print("predict : ", lr.predict([[72]]))
print("r^2 : ",lr.score(x2,y))
```

```
intercept :  [1.0263237]
coef(eğim) :  [[0.         0.03253405 0.00156101]]
predict :  [[11.3183005]]
r^2 :  0.7412233033479845
```

We found the intercept and slope values with the code we wrote above. We wrote the line equation with the values we found. We found our r^2 value with the lr.score(x2, y) method. Finally, we can do the estimation with the lr.predict([[value]]) method. For example, an NBA player who plays for 72 minutes will score an average of 11 points.

```
plt.scatter(x5,y)

x5 = x5.values.reshape(-1,1)

from sklearn.linear_model import LinearRegression

lr = LinearRegression()

lr.fit(x5,y)

#predict
y_head = lr.predict(x5)

plt.plot(x5,y_head,color="red",linewidth=4, label="linear")

# linear regression
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

polynomial_regression = PolynomialFeatures(degree = 2)
x_polynomial = polynomial_regression.fit_transform(x5)
polynomial_regression.fit(x_polynomial,y)

linear_regression2 = LinearRegression()
linear_regression2.fit(x_polynomial, y)

x_grid = np.arange(min(x5), max(x5), 0.1)
x_grid = x_grid.reshape((len(x_grid), 1))

y_head2 = linear_regression2.predict(polynomial_regression.fit_transform(x_grid))

plt.plot(x_grid,y_head2,color="orange",linewidth=4, label="polynomial")
plt.legend()
plt.xlabel("Effective Field Goal")
plt.ylabel("Points")
plt.show()
```

Our second example; We got our data whose correlation coefficient is closest to 0 relative to the reference value. We created linear regression with the codes we wrote above. To determine which linear regression model to use, we constructed both linear and polynomial regressions. And we decided that, since the correlation of these 2 data is closer to 0, a line equation suitable for our data did not come out.




```
print("intercept",linear_regression2.intercept_)
print("coef(eğim)",linear_regression2.coef_)
print("r^2 : ",lr.score(x2,y))
```

```
intercept [-1.77319707]
coef(eğim) [[ 0.          0.27808849 -0.00177924]]
r^2 :  0.6825699040987444
```

We found the intercept and slope values with the code we wrote above. We found our r^2 value with the lr.score(x2, y) method.

Thanks for reading this far

GLHF 😉😊