Overview

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
data = pd.read_csv('drive/MyDrive/DS_Intern_Assessment/data/starcraft_player_data.csv')
data.head()
```

	GameID	LeagueIndex	Age	HoursPerWeek	TotalHours	APM	SelectByHotkeys	Ass
0	52	5	27	10	3000	143.7180	0.003515	
1	55	5	23	10	5000	129.2322	0.003304	
2	56	4	30	10	200	69.9612	0.001101	
3	57	3	19	20	400	107.6016	0.001034	
4	58	3	32	10	500	122.8908	0.001136	

```
data.shape
```

```
(3395, 20)
```

There are 3395 rows and 20 columns

Our aim is to predict the league that the player is in (player's rank)

We set `LeagueIndex` as response variable and other 18 variables including `Age`, `HoursPerWeek`, `TotalHours`, `APM`, `SelectByHotKeys`,`AssignToHotkeys`, `UniqueHotkeys`, `MinimapAttacks`, `MinimapRightClicks`, `NumberOfPACs`, `GapBetweenPACs`, `ActionLatency`,`ActionsInPAC`, `TotalMapExplored`, `WorkersMade`, `UniqueUnitsMade`,`ComplexUnitsMade`, `ComplexAbilitiesUsed`.

`GameID` is Unique ID number for each game rather than an attribute of players, so we will not consider it in further analysis.

```
df = data.drop('GameID', axis = 1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3395 entries, 0 to 3394
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   LeagueIndex           3395 non-null   int64
 1   Age                   3395 non-null   object
 2   HoursPerWeek          3395 non-null   object
 3   TotalHours            3395 non-null   object
 4   APM                   3395 non-null   float64
 5   SelectByHotkeys       3395 non-null   float64
 6   AssignToHotkeys       3395 non-null   float64
 7   UniqueHotkeys         3395 non-null   int64
 8   MinimapAttacks        3395 non-null   float64
 9   MinimapRightClicks    3395 non-null   float64
 10  NumberOfPACs          3395 non-null   float64
 11  GapBetweenPACs        3395 non-null   float64
 12  ActionLatency         3395 non-null   float64
 13  ActionsInPAC          3395 non-null   float64
 14  TotalMapExplored      3395 non-null   int64
 15  WorkersMade           3395 non-null   float64
 16  UniqueUnitsMade       3395 non-null   int64
 17  ComplexUnitsMade      3395 non-null   float64
 18  ComplexAbilitiesUsed  3395 non-null   float64
dtypes: float64(12), int64(4), object(3)
memory usage: 504.1+ KB
```

```
print(sum(df['Age'] == '?'))
print(sum(df['HoursPerWeek'] == '?'))
print(sum(df['TotalHours'] == '?'))
```

```
55
56
57
```

```
# drop NA value

df = df[df['Age'] != '?']
df = df[df['HoursPerWeek'] != '?']
df = df[df['TotalHours'] != '?']

df.shape
```

```
(3338, 19)
```

```
# convert string to integer

df['Age'] = df['Age'].astype(int)
df['HoursPerWeek'] = df['HoursPerWeek'].astype(int)
df['TotalHours'] = df['TotalHours'].astype(int)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3338 entries, 0 to 3339
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   LeagueIndex           3338 non-null   int64  
 1   Age                   3338 non-null   int64  
 2   HoursPerWeek          3338 non-null   int64  
 3   TotalHours            3338 non-null   int64  
 4   APM                   3338 non-null   float64
 5   SelectByHotkeys       3338 non-null   float64
 6   AssignToHotkeys       3338 non-null   float64
 7   UniqueHotkeys         3338 non-null   int64  
 8   MinimapAttacks        3338 non-null   float64
 9   MinimapRightClicks    3338 non-null   float64
 10  NumberOfPACs          3338 non-null   float64
 11  GapBetweenPACs        3338 non-null   float64
 12  ActionLatency         3338 non-null   float64
 13  ActionsInPAC          3338 non-null   float64
 14  TotalMapExplored      3338 non-null   int64  
 15  WorkersMade           3338 non-null   float64
 16  UniqueUnitsMade       3338 non-null   int64  
 17  ComplexUnitsMade      3338 non-null   float64
 18  ComplexAbilitiesUsed  3338 non-null   float64
dtypes: float64(12), int64(7)
memory usage: 521.6 KB
```

```
df.describe()
```

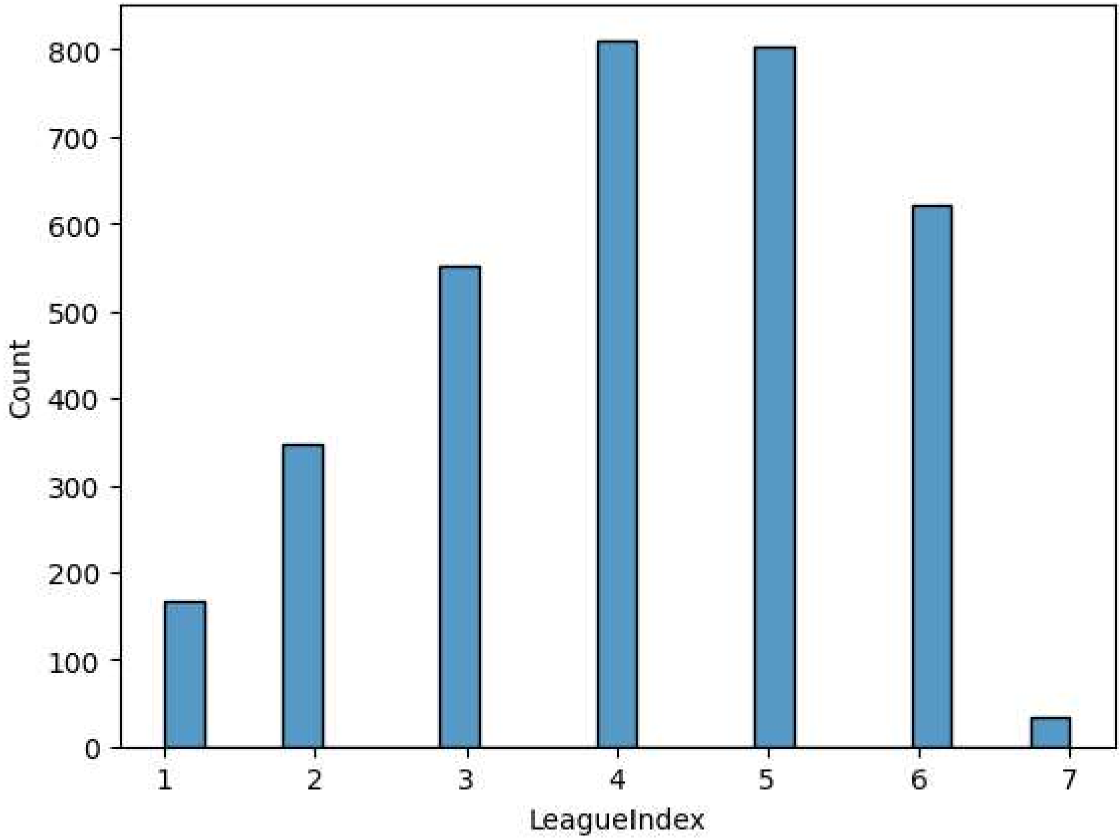
	LeagueIndex	Age	HoursPerWeek	TotalHours	APM	SelectByH
count	3338.000000	3338.000000	3338.000000	3338.000000	3338.000000	3338.(
mean	4.120731	21.650389	15.909527	960.421809	114.575763	0.(
std	1.448170	4.206357	11.964495	17318.133922	48.111912	0.(
min	1.000000	16.000000	0.000000	3.000000	22.059600	0.(
25%	3.000000	19.000000	8.000000	300.000000	79.231500	0.(
50%	4.000000	21.000000	12.000000	500.000000	107.070300	0.(
75%	5.000000	24.000000	20.000000	800.000000	140.156100	0.(
max	7.000000	44.000000	168.000000	1000000.000000	389.831400	0.(

Exploratory Data Analysis (EDA)

As our aim is to predict player's rank, I will visualize the data and see the relationship between

```
# Histogram of LeagueIndex
sns.histplot(df['LeagueIndex'])
```

```
<Axes: xlabel='LeagueIndex', ylabel='Count'>
```



Most players (approximately 800) are in 4 and 5. Less than 100 players are in 7.

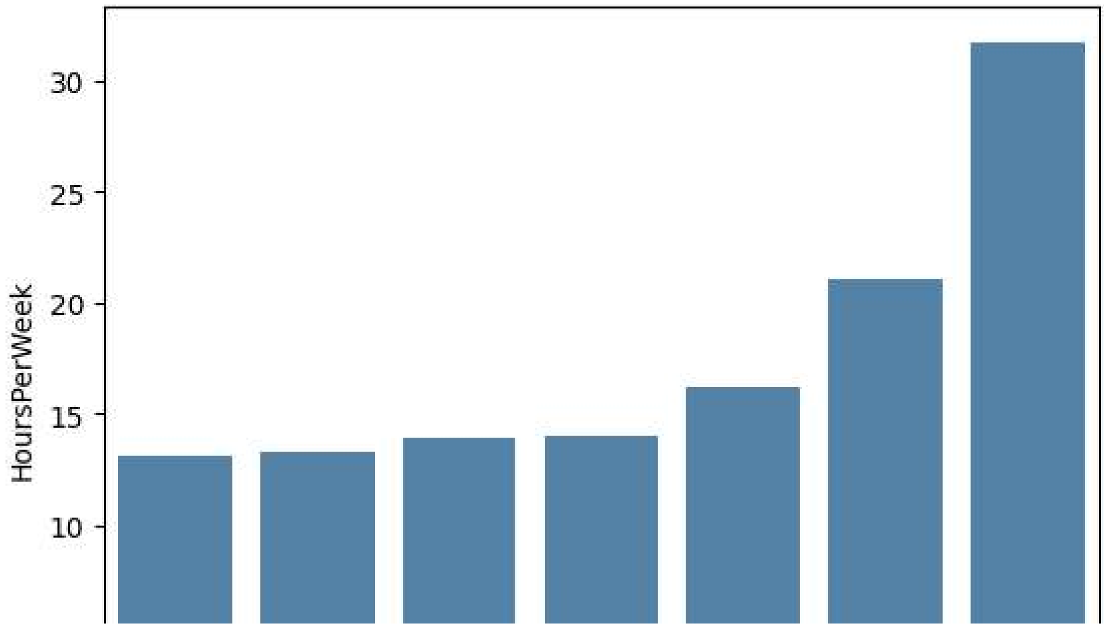
Following are several variables that are most related to the rank. Let's see how these varaibles are related to the rank.

1. Hours Per Week (Reported hours spent playing per week)
2. APM (Action per minute)
3. GapBetweenPACs (Mean duration in milliseconds between PACs)

```
# HoursPerWeek vs LeagueIndex

subdf_hours = df.groupby('LeagueIndex')['HoursPerWeek'].mean().reset_index()
sns.barplot(data=subdf_hours, x="LeagueIndex", y="HoursPerWeek", color='steelblue')
```

```
<Axes: xlabel='LeagueIndex', ylabel='HoursPerWeek'>
```



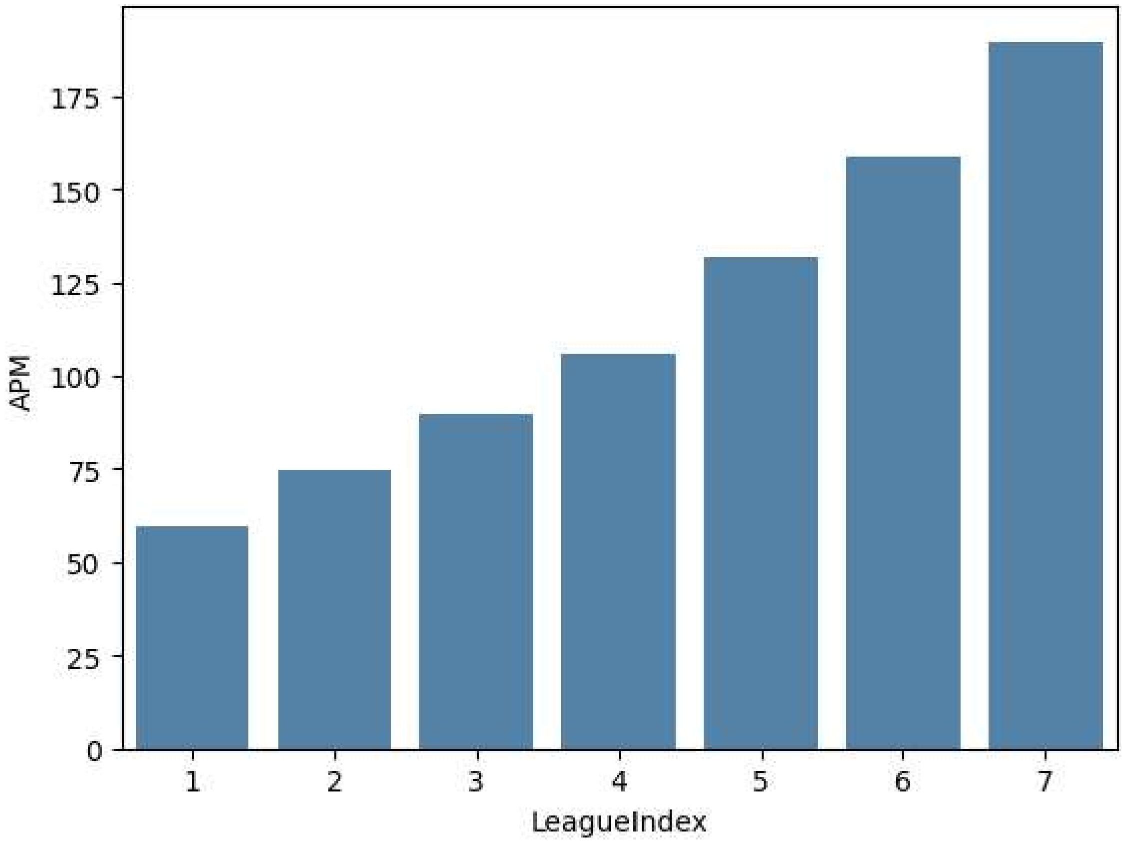
On average, players who are in rank 7 (high rank) spend approximately 30 hours per week. Players in other rank spend less than 20 hours per week. We can conclude that if a player spend more than 20 hours per week can get a high rank.

LeagueIndex

```
# APM vs LeagueIndex

subdf_apm = df.groupby('LeagueIndex')['APM'].mean().reset_index()
sns.barplot(data=subdf_apm, x="LeagueIndex", y="APM", color='steelblue')
```

```
<Axes: xlabel='LeagueIndex', ylabel='APM'>
```

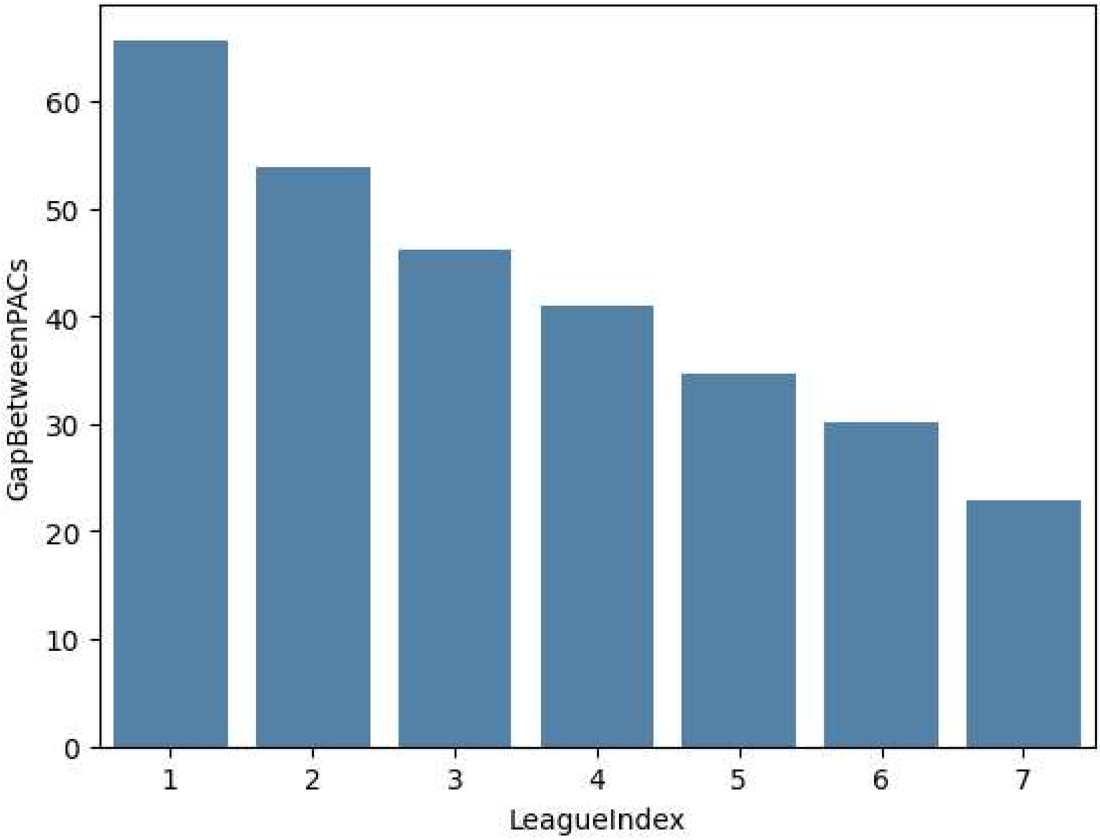


As the APM increases, rank is increasing. If a player made more APM, he/she can get a higher rank.

```
# GapBetweenPACs vs LeagueIndex

subdf_pac = df.groupby('LeagueIndex')['GapBetweenPACs'].mean().reset_index()
sns.barplot(data=subdf_pac, x="LeagueIndex", y="GapBetweenPACs", color='steelblue')
```

```
<Axes: xlabel='LeagueIndex', ylabel='GapBetweenPACs'>
```

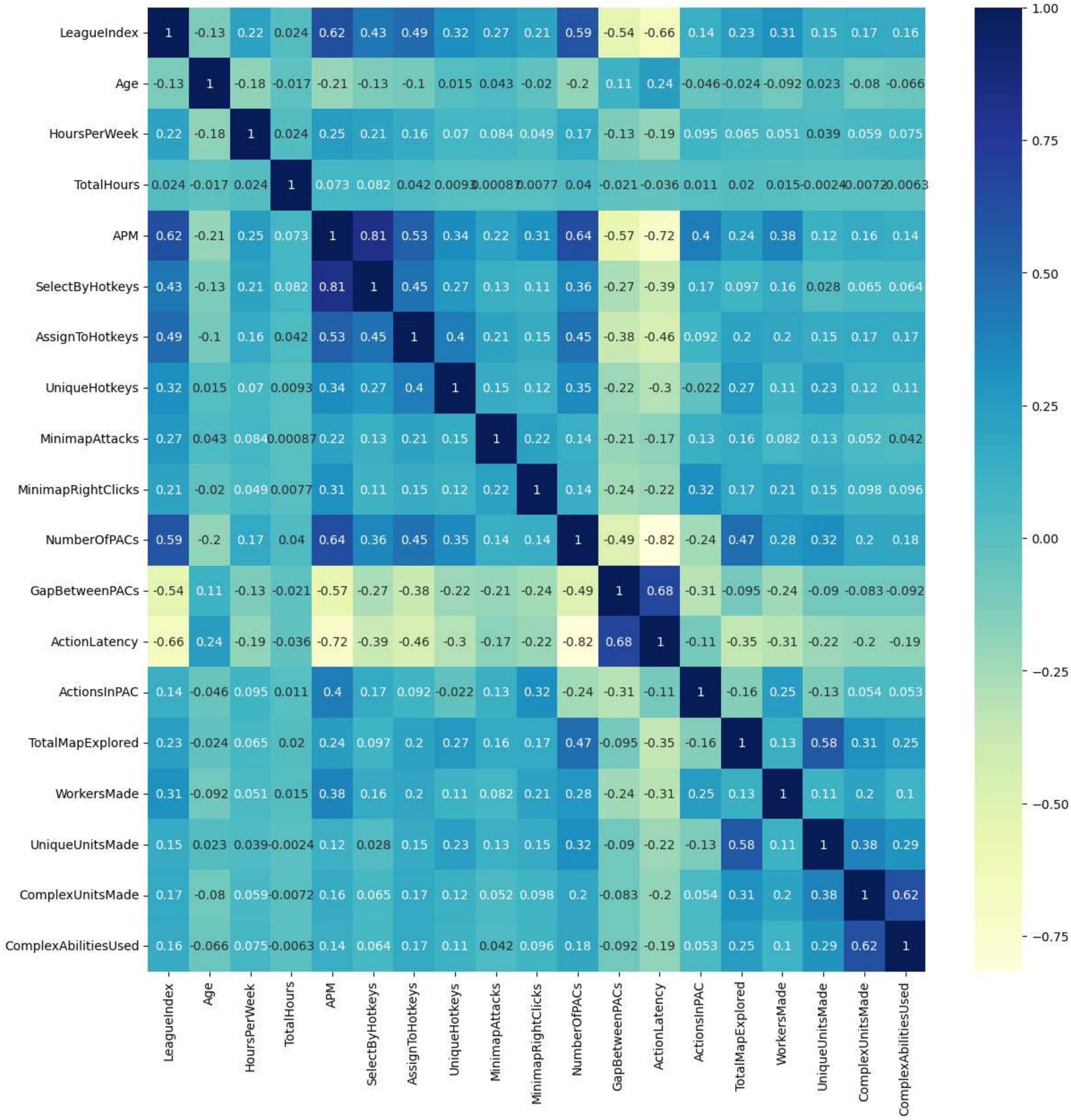


PAC is a perception action cycle which means how fast the player shifts to the next part of the map/actions. GapBetweenPACs means mean duration in milliseconds between PACs.

We can conclude that if mean duration between PACs is less, players can get higher ranks. That makes sense because players shifts fast to the next part of the map/actions, they can make more actions and explore more on the map and get better ranks.

```
corr = df.corr()
plt.subplots(figsize=(14,14))
sns.heatmap(corr,annot=True,vmax=1,cmap='YlGnBu')
```

<Axes: >



LeagueIndex
Age
HoursPerWeek
TotalHours
APM
SelectByHotkeys
AssignToHotkeys
UniqueHotkeys
MinimapAttacks
MinimapRightClicks
NumberOfPACs
GapBetweenPACs
ActionLatency
ActionsInPAC
TotalMapExplored
WorkersMade
UniqueUnitsMade
ComplexUnitsMade
ComplexAbilitiesUsed
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

The graph shows the correlation matrix between 19 variables. It shows the correlation between LeagueIndex and other 18 variables and also the correlation of 18 independent variables so we can see if there is Multicollinearity.

Model

Ordinal Logistic Regression

As our aim is to predict player's rank, we consider it as a classification problem and rank is an ordinal variable. Therefore, I'll construct Ordinal Logistic Regression model to solve this problem.

```
from sklearn.model_selection import train_test_split
from statsmodels.miscmodels.ordinal_model import OrderedModel


# split train and test set

X = df.drop('LeagueIndex', axis = 1)
y = df['LeagueIndex']

train_X, test_X, train_y, test_y = train_test_split(X, y, test_size=0.3, random_state=1234


mod_log = OrderedModel(train_y, train_X, distr='logit')
res_log = mod_log.fit(method='bfgs')
res_log.summary()
```

```
Optimization terminated successfully.
         Current function value: 1.344783
         Iterations: 205
         Function evaluations: 214
         Gradient evaluations: 214
```

OrderedModel Results

Dep. Variable:	LeagueIndex	**Log-Likelihood:**	-3141.4
Model:	OrderedModel	**AIC:**	6331.
Method:	Maximum Likelihood	**BIC:**	6469.
Date:	Sun, 28 May 2023		
Time:	20:08:29		
No. Observations:	2336		
Df Residuals:	2312		
Df Model:	24		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Age	0.0123	0.010	1.268	0.205	-0.007	0.031
HoursPerWeek	0.0097	0.004	2.559	0.011	0.002	0.017
TotalHours	0.0004	8.71e-05	4.189	0.000	0.000	0.001
APM	-0.0050	0.005	-1.035	0.301	-0.015	0.005
SelectByHotkeys	100.9454	28.791	3.506	0.000	44.516	157.375
AssignToHotkeys	1474.0168	242.258	6.084	0.000	999.200	1948.834
UniqueHotkeys	0.0851	0.019	4.503	0.000	0.048	0.122
MinimapAttacks	2061.2883	295.841	6.968	0.000	1481.450	2641.127
MinimapRightClicks	45.1679	121.339	0.372	0.710	-192.651	282.987

```
predicted = res_log.model.predict(res_log.params, exog=test_X)
predicted[0:5]
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/miscmodels/ordinal_model.py:419:
  xb = xb[:, None]
array([[6.49925286e-01, 2.70606169e-01, 6.08341736e-02, 1.51275857e-02,
        2.94610115e-03, 5.52666313e-04, 8.01832026e-06],
       [1.32438105e-03, 6.88197791e-03, 2.80483306e-02, 1.32475545e-01,
        3.91376564e-01, 4.28792431e-01, 1.11007699e-02],
       [8.90151512e-04, 4.63804976e-03, 1.91222229e-02, 9.53531106e-02,
        3.41038586e-01, 5.22523913e-01, 1.64339666e-02],
       [6.86089873e-03, 3.44613782e-02, 1.22534689e-01, 3.50089251e-01,
        3.55042651e-01, 1.28860908e-01, 2.15022451e-03],
       [2.78938212e-03, 1.43639140e-02, 5.63612262e-02, 2.26272917e-01,
        4.28893090e-01, 2.66025722e-01, 5.29374844e-03]])
```

```
pred_choice = predicted.argmax(1) + 1
pred_choice[0:5]
```

```
array([1, 6, 6, 5, 5])
```

```
print('Accuracy:', (np.asarray(test_y) == pred_choice).mean())
```

```
Accuracy: 0.4281437125748503
```

Precision of the model is only 42.8% which is not good. I considered if there is Multicollinearity so I used PCA for dimension reduction. However, the result is worse. So other powerful models should be considered such as random forest

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_scor
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from scipy.stats import randint
```

```
rf = RandomForestClassifier(max_depth=10, random_state=12345)
rf.fit(train_X, train_y)
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=10, random_state=12345)
```

```
pred = rf.predict(test_X)
```

```
accuracy = accuracy_score(test_y, pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.4111776447105788
```

The accuracy of random forest is not as good as Ordinal Logistic Regression. Therefore, we will then go back to Ordinal Logistic Regression model.

Result

```
res_log.summary()
```

OrderedModel Results

Dep. Variable:	LeagueIndex	**Log-Likelihood:**	-3141.4
Model:	OrderedModel	**AIC:**	6331.
Method:	Maximum Likelihood	**BIC:**	6469.
Date:	Sun, 28 May 2023		
Time:	20:22:28		
No. Observations:	2336		
Df Residuals:	2312		
Df Model:	24		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Age	0.0123	0.010	1.268	0.205	-0.007	0.031
HoursPerWeek	0.0097	0.004	2.559	0.011	0.002	0.017
TotalHours	0.0004	8.71e-05	4.189	0.000	0.000	0.001
APM	-0.0050	0.005	-1.035	0.301	-0.015	0.005
SelectByHotkeys	100.9454	28.791	3.506	0.000	44.516	157.375
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UniqueHotkeys	0.0851	0.019	4.503	0.000	0.048	0.122
MinimapAttacks	2061.2883	295.841	6.968	0.000	1481.450	2641.127
MinimapRightClicks	45.1679	121.339	0.372	0.710	-192.651	282.987
NumberOfPACs	595.3058	151.439	3.931	0.000	298.492	892.120
GapBetweenPACs	-0.0230	0.004	-6.334	0.000	-0.030	-0.016
ActionLatency	-0.0390	0.005	-7.611	0.000	-0.049	-0.029

As the result shown above, player's rank is affected by `HoursPerWeek`, `TotalHours`, `SelectByHotKeys`,`AssignToHotkeys`, `UniqueHotkeys`, `MinimapAttacks`, `NumberOfPACs`, `GapBetweenPACs`, `ActionLatency`, `WorkersMade`, `UniqueUnitsMade` with significance level $\alpha = 0.05$.

1/2	4.1206	0.796	5.177	0.000	5.681	2.560

Suggestions about collecting data: collect data with more information about Hotkeys and PACs and actions.

5/6	0.6077	0.038	15.852	0.000	0.533	0.683
6/7	1.4464	0.055	26.262	0.000	1.338	1.554