EXPLORING PLAYER PERFORMANCE & POSITIONING

FIFA 22 DATASET

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Abstract

This project covers data exploration, dimensionality reduction (PCA), multivariate hypothesis testing (MANOVA), and attribute interrelationships to unveil insights into the complex dynamics of football player statistics in FIFA 22 (CCA). Through rigorous statistical analyses, I aim to shed light on the factors that define player positions, their statistical distinctions, and how these attributes culminate in a player's overall performance rating.

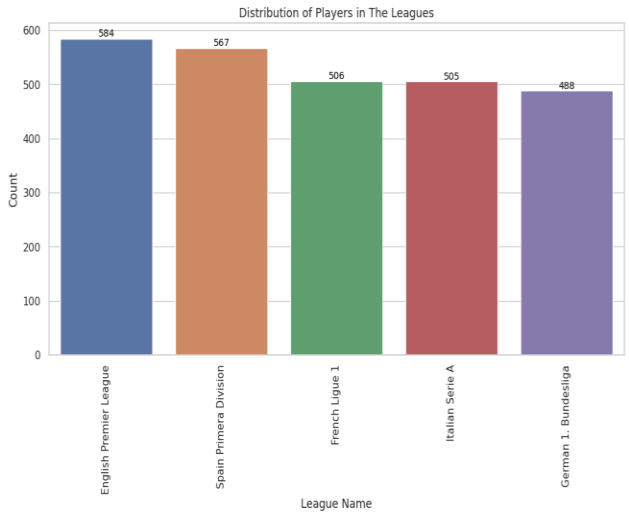
1. Introduction & Dataset Description:

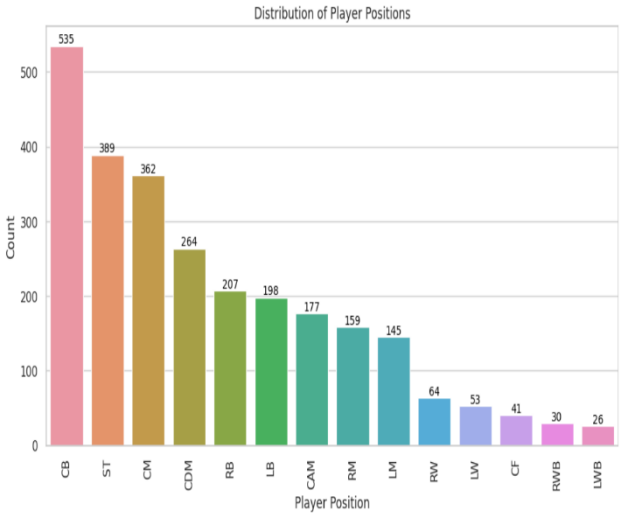
The dataset is obtained from Kaggle, and it contains the football players data from FIFA 22, originally the dataset contained 110 columns, however only the columns that are relevant to this analysis have been selected. It's also worth noting that goalkeepers have been filtered out and only players playing in the top 5 European leagues have been selected. Players' data can be described into two categories, general information, and football attributes. The purpose of utilizing this dataset is to provide a straightforward and relatable dataset suitable for conducting multivariate statistical analyses. The types of analysis that are going to be conducted are the following:

- Exploratory data analysis
- Principal Component Analysis
- Multivariate Analysis of Variance
- Canonical Correlation Analysis

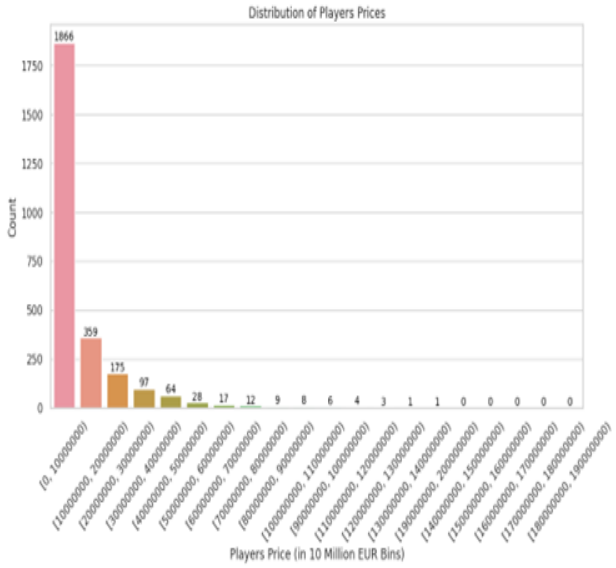
2. Exploratory Data Analysis:

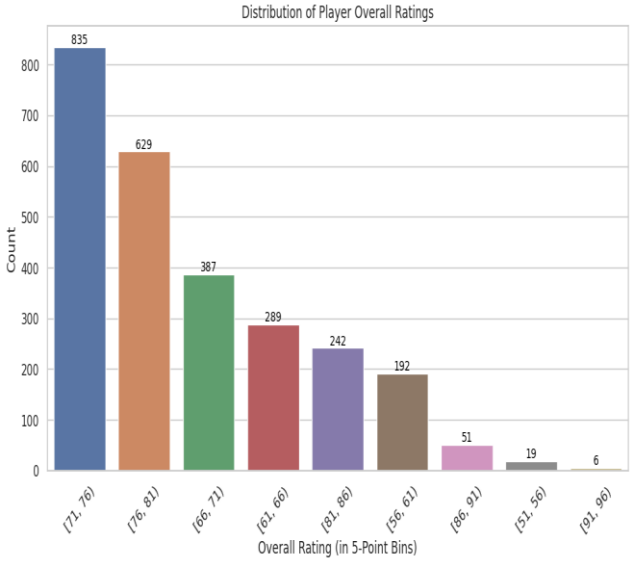
This analysis was divided into three main parts, In the first part I analyze player distribution by league, player position, overall rating, player value, and overall rating within each league. First observation one can make is that there is a somewhat distribution of players across the 5 leagues, which is what we should be expecting.



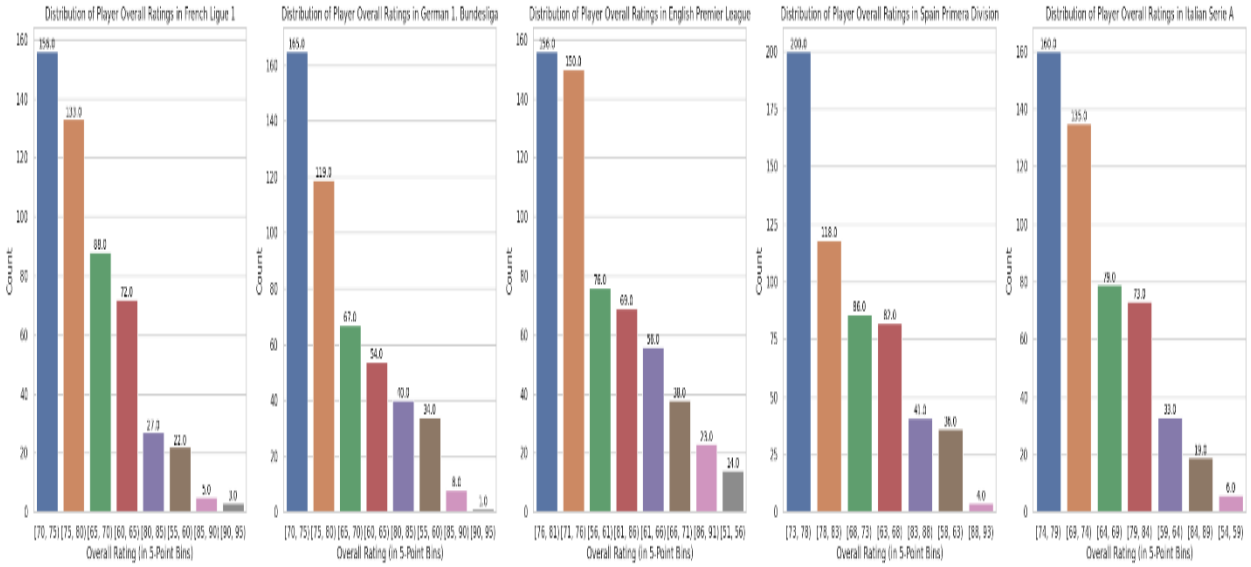


Another observation is that most of the players in this dataset have their values less than or equal to 10 million.

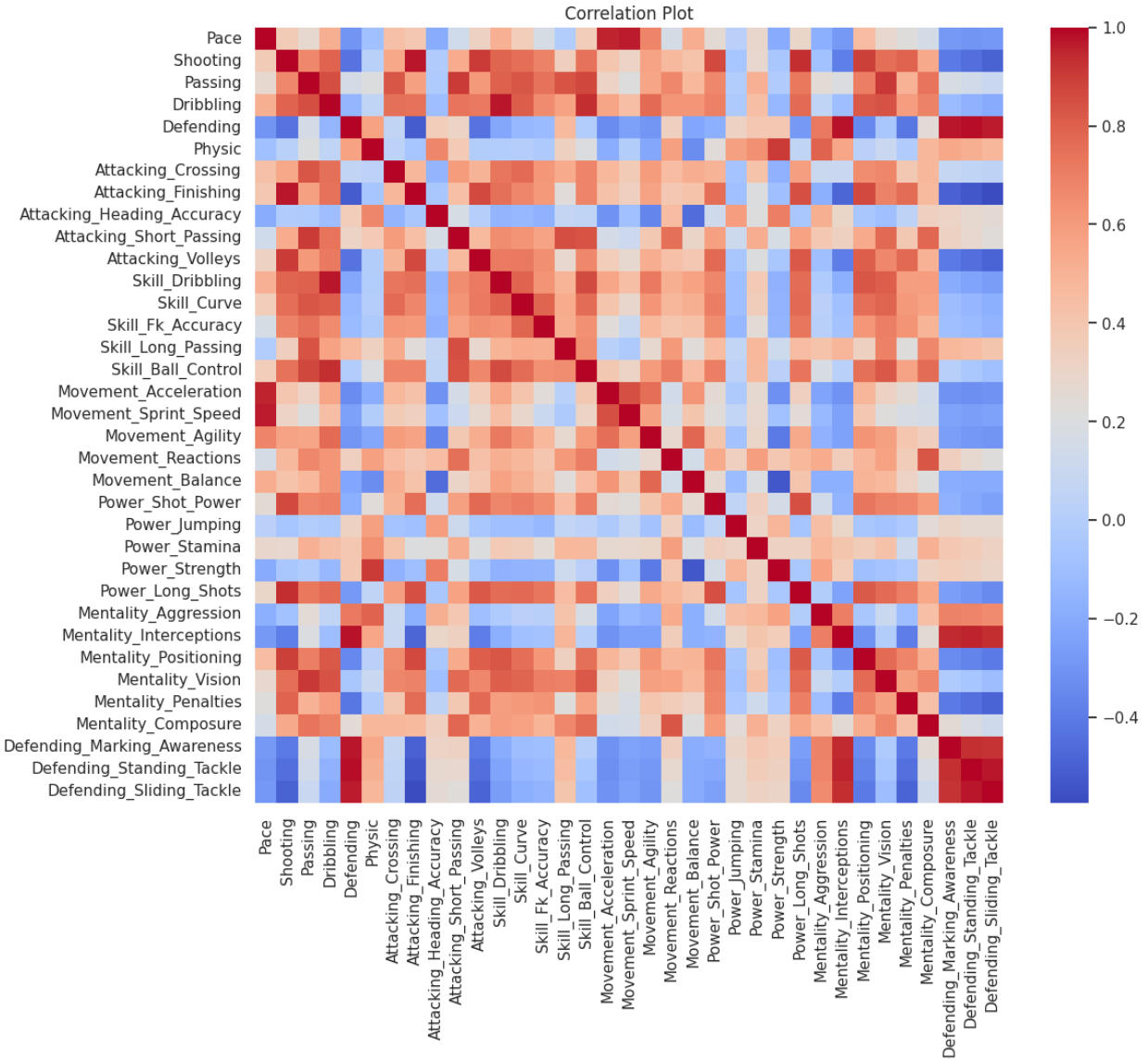




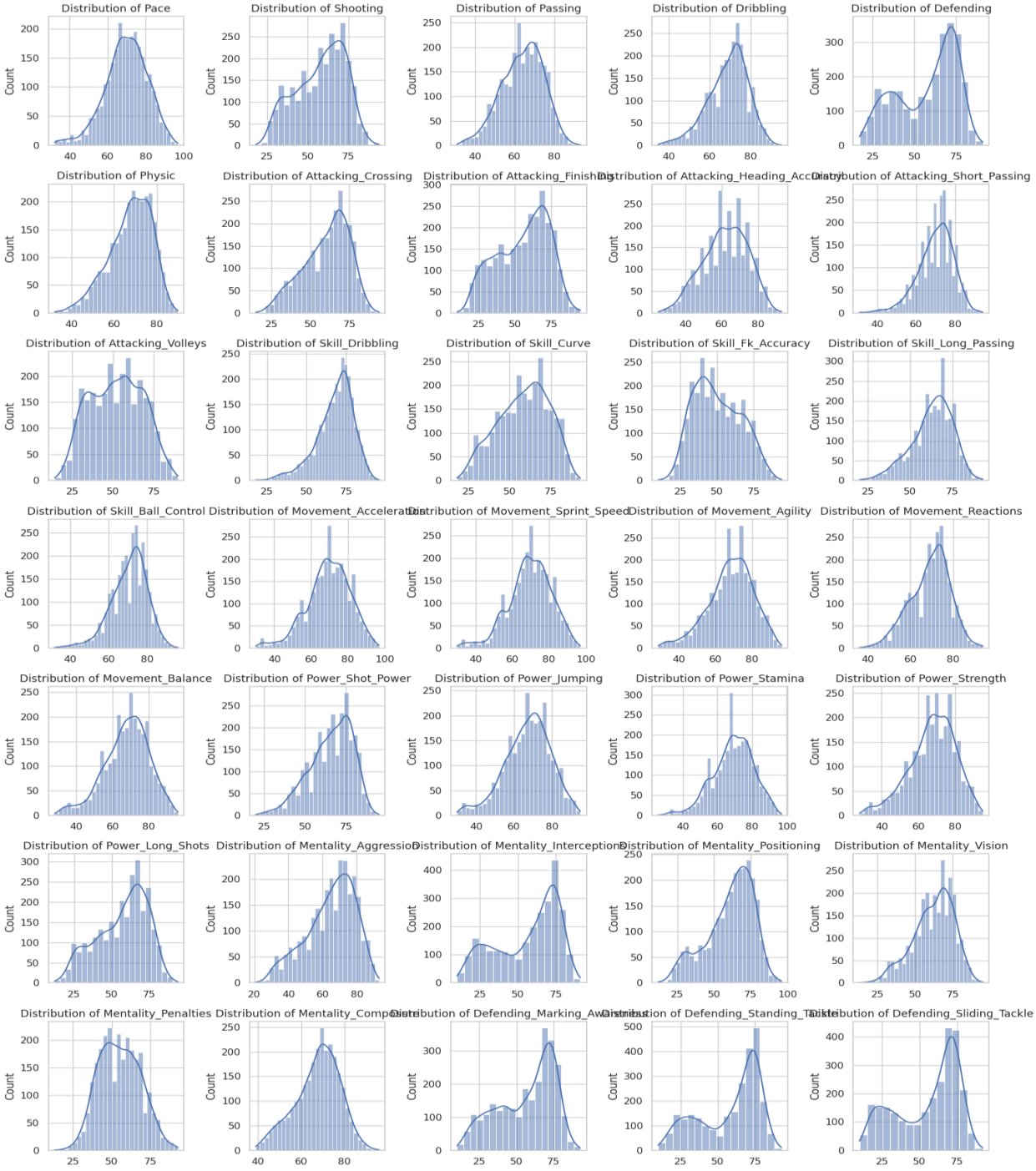
Final observation in this section is that the English Premier League appears to have players with higher overall ratings when compared to other leagues.



In the second part, I analyze the correlation between the players' football attributes, for instance we can observe positive correlation between dribbling and passing or dribbling and shooting, which is understandable as these are usually common attributes for an offensive type of player, while for example we can see a positive correlation between defense and physic, this is also expected as defenders are required to be strong. We can also observe the negative correlation between defensive and attacking attributes, this is because an offensive player would have weaker defensive stats than a defensive player and vice versa.

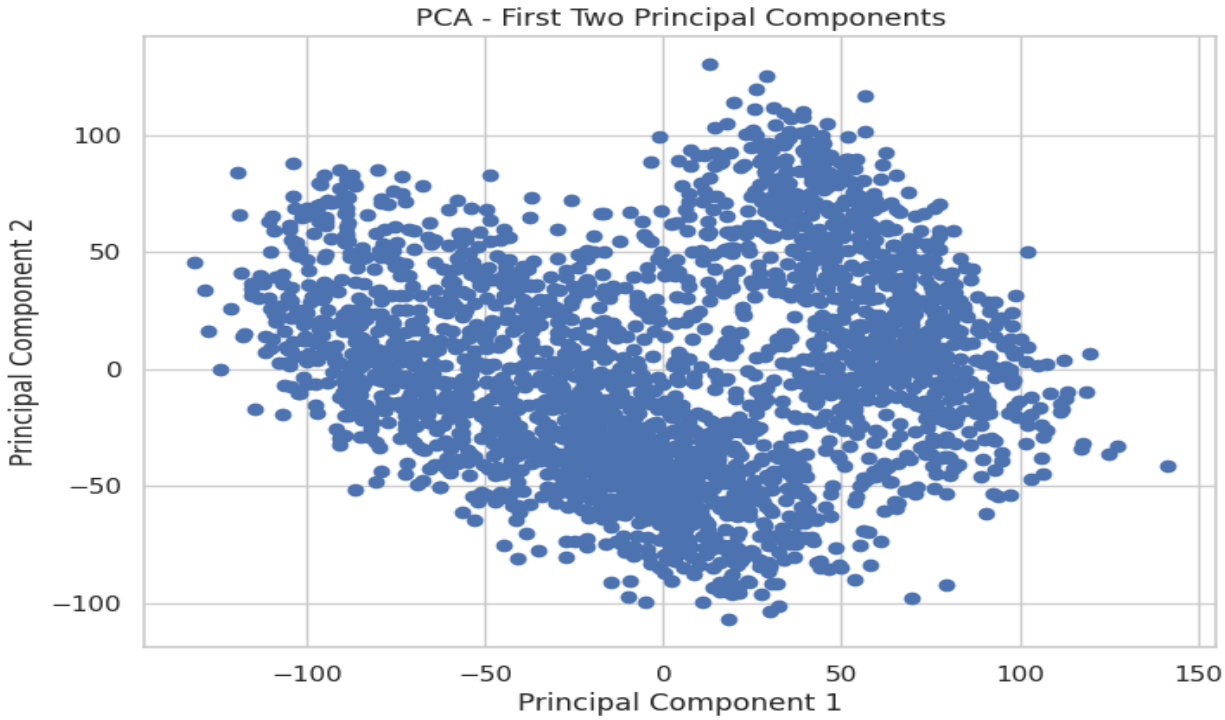


The third and final part I analyze in this section is the distribution of players attributes. From looking at the plot below, we can observe that most of the attributes are somewhat following a bell-shaped distribution.



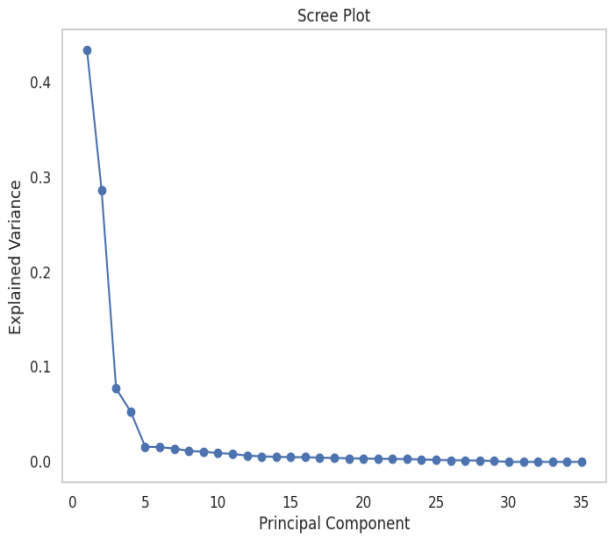
3. Principal Component Analysis (PCA):

For this type of analysis, I am only interested in the player's football attributes, so I create a new dataframe containing such attributes. PCA was used in order to have a better visualization with the aim of producing a low dimensional representation of a dataset. Its goal is to find a sequence of linear combinations of the variables that have maximal variance and are mutually uncorrelated. PCA finds the best fitting line by maximizing the sum of squared distances from the projected points to the origin, once found that line is considered as a principal component.



An initial plot was created with the aim of visualizing the data in a reduced two-dimensional space. An assumption that can be reasonably made is that offensive and defensive players may exhibit some degree of separation or clustering in the PCA plot.

Creating a scree plot is a common method to determine the number of components that can explain as much of the original data's variation as possible. Analyzing the scree plot reveals that the first two components account for 72.02% of the variance in the original data.

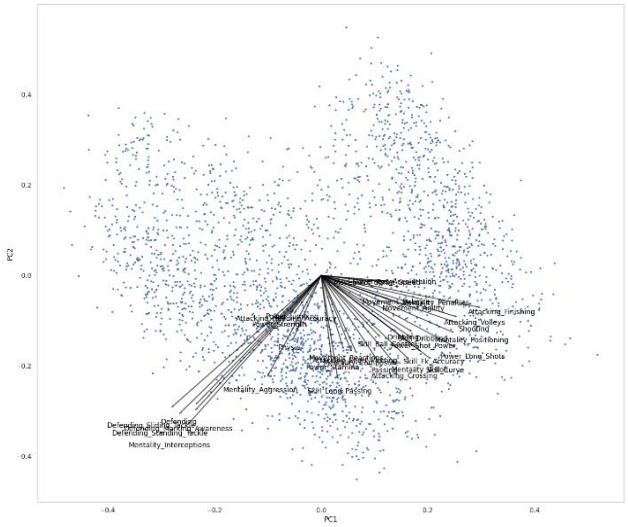


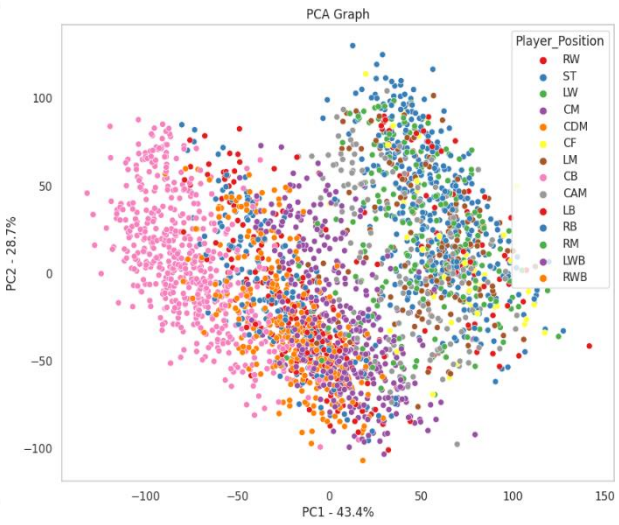

```
Principal Component 1 explains 43.35% of the variance.
Principal Component 2 explains 28.67% of the variance.
Principal Component 3 explains 7.72% of the variance.
Principal Component 4 explains 5.30% of the variance.
Principal Component 5 explains 1.60% of the variance.
Principal Component 6 explains 1.56% of the variance.
Principal Component 7 explains 1.41% of the variance.
Principal Component 8 explains 1.16% of the variance.
Principal Component 9 explains 1.08% of the variance.
Principal Component 10 explains 0.94% of the variance.
Principal Component 11 explains 0.85% of the variance.
Principal Component 12 explains 0.66% of the variance.
Principal Component 13 explains 0.59% of the variance.
Principal Component 14 explains 0.54% of the variance.
Principal Component 15 explains 0.50% of the variance.
Principal Component 16 explains 0.49% of the variance.
Principal Component 17 explains 0.45% of the variance.
Principal Component 18 explains 0.41% of the variance.
Principal Component 19 explains 0.38% of the variance.
Principal Component 20 explains 0.36% of the variance.
Principal Component 21 explains 0.33% of the variance.
Principal Component 22 explains 0.32% of the variance.
Principal Component 23 explains 0.29% of the variance.
Principal Component 24 explains 0.27% of the variance.
Principal Component 25 explains 0.21% of the variance.
Principal Component 26 explains 0.18% of the variance.
Principal Component 27 explains 0.17% of the variance.
Principal Component 28 explains 0.15% of the variance.
Principal Component 29 explains 0.08% of the variance.
Principal Component 30 explains 0.00% of the variance.
Principal Component 31 explains 0.00% of the variance.
Principal Component 32 explains 0.00% of the variance.
Principal Component 33 explains 0.00% of the variance.
Principal Component 34 explains 0.00% of the variance.
Principal Component 35 explains 0.00% of the variance.
```

I then confirm that the first two components are not correlated with each other, in other words they are independent, and I also visualize the loading scores of the top 10 attributes of each component.

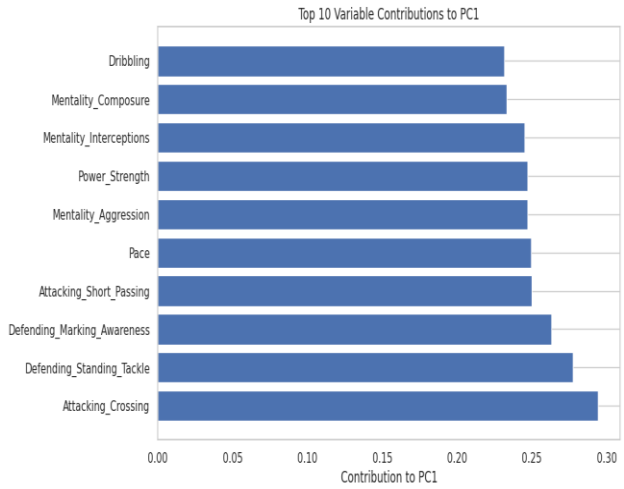
```
DataFrame with the X and Y coordinates:

            X          Y
0  141.558524 -41.621812
1  106.530757 -44.931528
2  127.396346 -32.984515
3  124.825584 -36.186879
4   79.351439 -92.259110

Correlation Coefficient: 1.4741584203520414e-16

First Component:

Attribute 1: Loading Score 0.1036 - Attacking_Finishing
Attribute 2: Loading Score 0.2494 - Defending_Sliding_Tackle
Attribute 3: Loading Score 0.1026 - Defending_Standing_Tackle
Attribute 4: Loading Score 0.1332 - Attacking_Volleys
Attribute 5: Loading Score -0.2318 - Shooting
Attribute 6: Loading Score -0.0516 - Mentality_Interceptions
Attribute 7: Loading Score 0.1364 - Power_Long_Shots
Attribute 8: Loading Score 0.2943 - Mentality_Positioning
Attribute 9: Loading Score -0.0564 - Defending_Marking_Awareness
Attribute 10: Loading Score 0.0554 - Defending

Second Component:

Attribute 1: Loading Score -0.0128 - Mentality_Interceptions
Attribute 2: Loading Score -0.1029 - Defending_Standing_Tackle
Attribute 3: Loading Score -0.1828 - Defending_Marking_Awareness
Attribute 4: Loading Score -0.1196 - Defending_Sliding_Tackle
Attribute 5: Loading Score -0.2818 - Defending
Attribute 6: Loading Score -0.1390 - Skill_Long_Passing
Attribute 7: Loading Score -0.1929 - Mentality_Aggression
Attribute 8: Loading Score -0.0699 - Attacking_Crossing
Attribute 9: Loading Score -0.0825 - Passing
Attribute 10: Loading Score -0.1634 - Skill_Curve
```

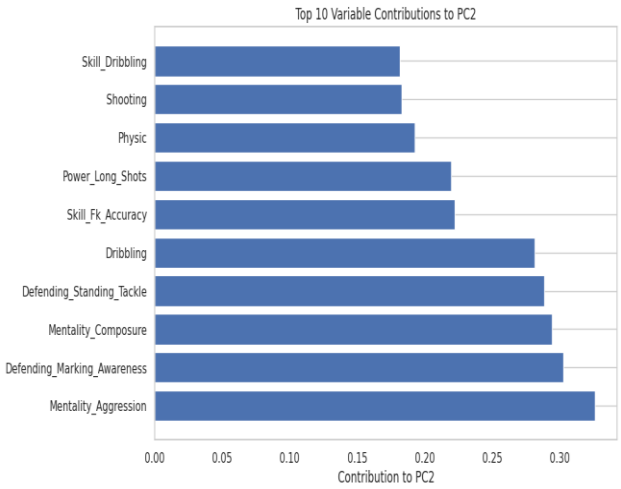
The next visualization is the biplot, which is used to view the relationships between datapoints and variables in a reduced-dimensional space. The arrows in the plot serve as a visual representation of the eigenvectors and their relationship to the original variables, they show how the original variables are aligned with the principal components. In our case we can see that there are two main directions of these arrows, lower left, and lower right. We can see that the arrows are separated into two categories, defensive attributes (lower left) and offensive attributes (lower right).





To confirm this, another visualization was created, a scatterplot showing the distribution of players in the reduced two-dimensional space. We can clearly see that the offensive players are on the right side while the defensive players are on the left side. Next, I try to visualize the contribution of the top 10 variables in each dimensional space, or rather in each component.





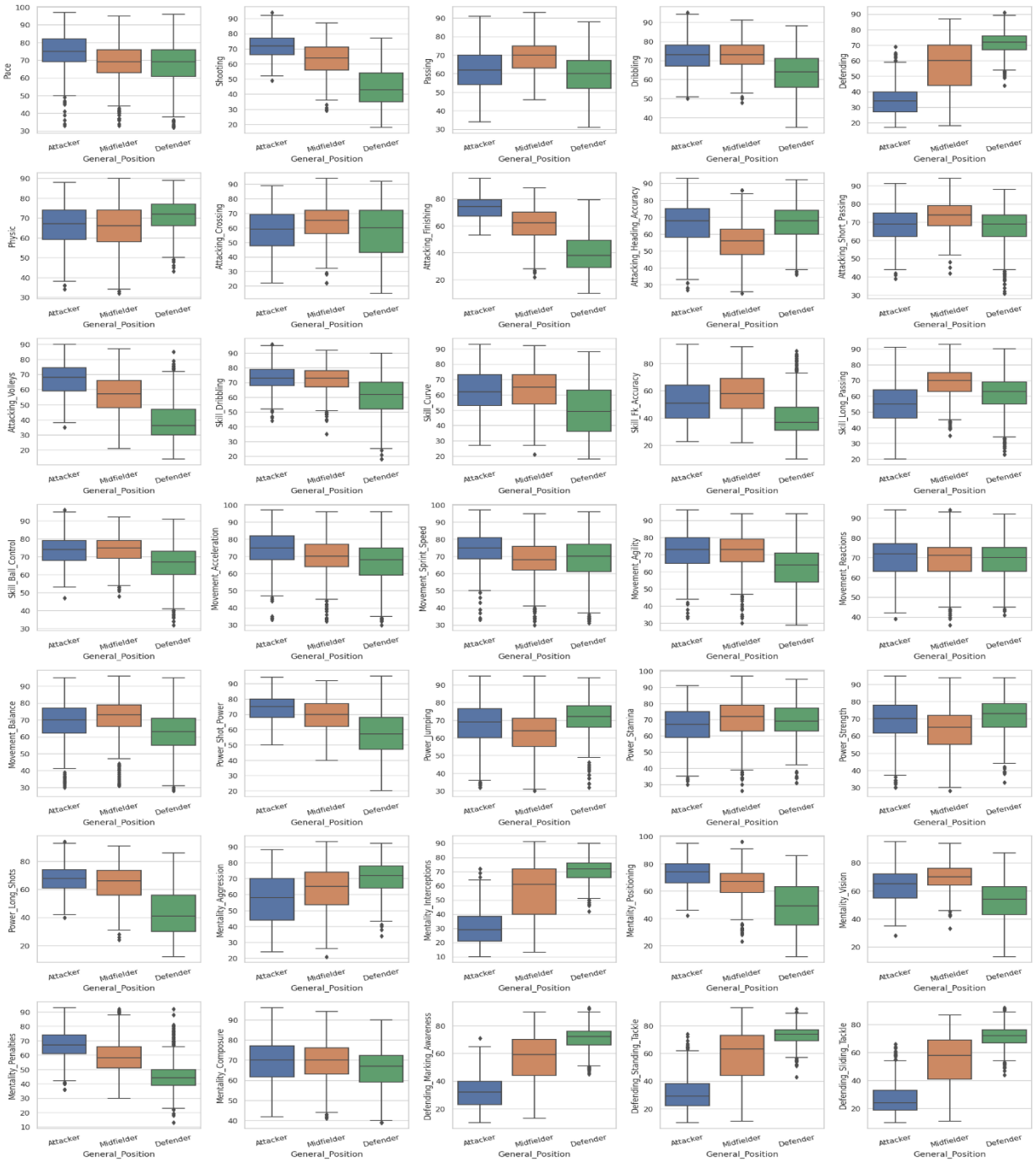
Finally, I perform OLS regression with the aim of understanding how the principal components, as independent variables, relate to the dependent variable, overall rating. This provides insights into which combination of attributes influence player overall ratings.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                Overall   R-squared:                       0.678
Model:                            OLS   Adj. R-squared:                  0.678
Method:                 Least Squares   F-statistic:                     2789.
Date:                Sat, 21 Oct 2023   Prob (F-statistic):               0.00
Time:                        02:39:33   Log-Likelihood:                -7475.2
No. Observations:                2650   AIC:                         1.496e+04
Df Residuals:                    2647   BIC:                         1.497e+04
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         72.3958      0.079    916.771      0.000      72.241      72.551
PC1            0.0334      0.001     23.243      0.000       0.031       0.036
PC2           -0.1254      0.002    -70.974      0.000      -0.129      -0.122
==============================================================================
Omnibus:                       19.436   Durbin-Watson:                   1.329
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               19.366
Skew:                           0.194   Prob(JB):                     6.23e-05
Kurtosis:                       2.841   Cond. No.                         55.0
==============================================================================
```

It appears that the two principal components (PC1 and PC2) are significant for determining the overall rating. The R-squared value of 0.678 indicates that approximately 67.8% of the variance in the overall rating can be explained by the two principal components in the model. This suggests that PC1 and PC2 collectively have a substantial influence on the overall rating.

4. Multivariate Analysis of Variance (MANOVA):

In this analysis, I aim to test whether player attributes vary significantly among players from different positions, but first in order to get a clear analysis, I decided to generalize the players' positions into three categories: Attacker, Midfielder and Defender. I then decided to create a set of boxplots that visualize the distribution of players' attributes based on their general positions.



The MANOVA assumptions are the following:

- Groups that are compared should be independent
- Having multivariate normality
- Homogeneity of the covariance matrices
- No multicollinearity, meaning there should not be a too strong correlation between the dependent variables.
- Existence of linear relationship between the dependent variables for each group.

In order to apply MANOVA, the assumptions should not be strictly or severely violated. For instance, one way to assess one of the mentioned assumptions is to conduct Shapiro-Wilk's test, in order to check if the dependent variables are multivariate normally distributed within each group. The Shapiro-Wilk test is a statistical test used to determine whether a dataset follows a normal distribution. We can see in the output below that all p-values are very close to 0 (p-value=0.00000), indicating that the data in these players' football attributes significantly deviates from a normal distribution.

```
Shapiro-Wilk Test for "Pace": Statistic=0.9853806495666504, p-value=0.00000
Shapiro-Wilk Test for "Shooting": Statistic=0.9670935273170471, p-value=0.00000
Shapiro-Wilk Test for "Passing": Statistic=0.9895201325416565, p-value=0.00000
Shapiro-Wilk Test for "Dribbling": Statistic=0.9781668782234192, p-value=0.00000
Shapiro-Wilk Test for "Defending": Statistic=0.9231054782867432, p-value=0.00000
Shapiro-Wilk Test for "Physic": Statistic=0.9718323945999146, p-value=0.00000
Shapiro-Wilk Test for "Attacking_Crossing": Statistic=0.9686995148658752, p-value=0.00000
Shapiro-Wilk Test for "Attacking_Finishing": Statistic=0.9643842577934265, p-value=0.00000
Shapiro-Wilk Test for "Attacking_Heading_Accuracy": Statistic=0.9895935654640198, p-value=0.00000
Shapiro-Wilk Test for "Attacking_Short_Passing": Statistic=0.9734395742416382, p-value=0.00000
Shapiro-Wilk Test for "Attacking_Volleys": Statistic=0.9802194833755493, p-value=0.00000
Shapiro-Wilk Test for "Skill_Dribbling": Statistic=0.9550522565841675, p-value=0.00000
Shapiro-Wilk Test for "Skill_Curve": Statistic=0.9803358912467957, p-value=0.00000
Shapiro-Wilk Test for "Skill_Fk_Accuracy": Statistic=0.9756494164466858, p-value=0.00000
Shapiro-Wilk Test for "Skill_Long_Passing": Statistic=0.976019024848938, p-value=0.00000
Shapiro-Wilk Test for "Skill_Ball_Control": Statistic=0.9758882522583008, p-value=0.00000
Shapiro-Wilk Test for "Movement_Acceleration": Statistic=0.9836359024047852, p-value=0.00000
Shapiro-Wilk Test for "Movement_Sprint_Speed": Statistic=0.982881486415863, p-value=0.00000
Shapiro-Wilk Test for "Movement_Agility": Statistic=0.9807958602905273, p-value=0.00000
Shapiro-Wilk Test for "Movement_Reactions": Statistic=0.986078679561615, p-value=0.00000
Shapiro-Wilk Test for "Movement_Balance": Statistic=0.9817516803741455, p-value=0.00000
Shapiro-Wilk Test for "Power_Shot_Power": Statistic=0.9679257273674011, p-value=0.00000
Shapiro-Wilk Test for "Power_Jumping": Statistic=0.9840214252471924, p-value=0.00000
Shapiro-Wilk Test for "Power_Stamina": Statistic=0.9868588447570801, p-value=0.00000
Shapiro-Wilk Test for "Power_Strength": Statistic=0.9786337614059448, p-value=0.00000
Shapiro-Wilk Test for "Power_Long_Shots": Statistic=0.9604361057281494, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Aggression": Statistic=0.9631208181381226, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Interceptions": Statistic=0.9114976525306702, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Positioning": Statistic=0.9533140659332275, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Vision": Statistic=0.9763776659965515, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Penalties": Statistic=0.9927334785461426, p-value=0.00000
Shapiro-Wilk Test for "Mentality_Composure": Statistic=0.9818636775016785, p-value=0.00000
Shapiro-Wilk Test for "Defending_Marking_Awareness": Statistic=0.9320263862609863, p-value=0.00000
Shapiro-Wilk Test for "Defending_Standing_Tackle": Statistic=0.8950558304786682, p-value=0.00000
Shapiro-Wilk Test for "Defending_Sliding_Tackle": Statistic=0.8984090685844421, p-value=0.00000
```

A more robust assessment of the normality of the data by taking into account the variability is introduced by bootstrapping. Bootstrapping resamples our data with replacement, creating many resampled datasets. In the output below we get information about the normality of each attribute, considering the uncertainty introduced by bootstrapping. The output is divided into two parts:

- Shapiro-Wilk Statistic
- Shapiro-Wilk p-value

If the confidence intervals for the Shapiro-Wilk statistics contain values close to 1 (above 0.95), and the p-values are close to 0, it suggests that the data is approximately normally distributed. If the intervals are far from 1, it indicates deviations from normality. From observing the partial output below we can see that most of the attributes are normally distributed. Hence, the multivariate normality assumption is not severely violated.

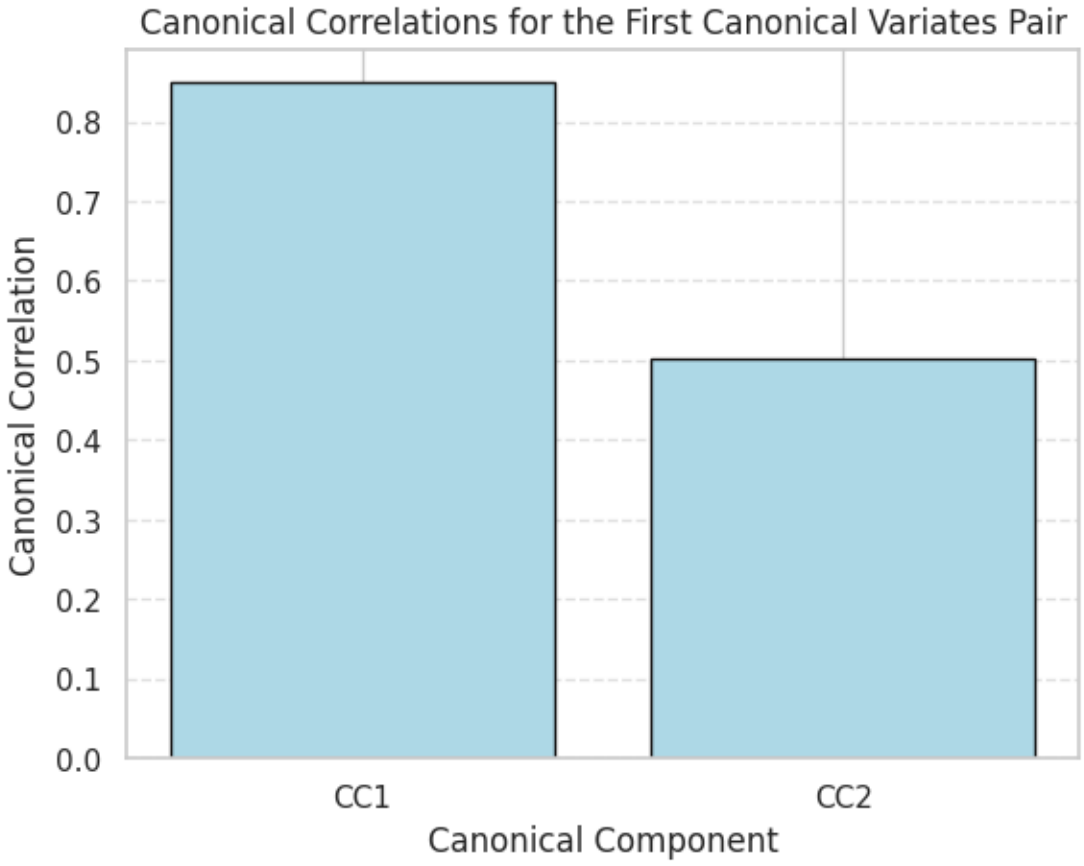
```
Confidence Intervals for "Pace":
Shapiro-Wilk Statistic: [0.98016834 0.98917739]
Shapiro-Wilk p-value: [8.89220120e-19 2.71053919e-13]

Confidence Intervals for "Shooting":
Shapiro-Wilk Statistic: [0.96090549 0.97153243]
Shapiro-Wilk p-value: [3.70597449e-26 1.51703879e-22]

Confidence Intervals for "Passing":
Shapiro-Wilk Statistic: [0.98528828 0.99208504]
Shapiro-Wilk p-value: [6.06302766e-16 7.25784086e-11]

Confidence Intervals for "Dribbling":
Shapiro-Wilk Statistic: [0.97146724 0.98292797]
Shapiro-Wilk p-value: [1.43213772e-22 2.52538330e-17]

Confidence Intervals for "Defending":
Shapiro-Wilk Statistic: [0.91545664 0.92939284]
Shapiro-Wilk p-value: [3.91286796e-36 1.18596873e-33]

Confidence Intervals for "Physic":
Shapiro-Wilk Statistic: [0.96581077 0.97687762]
Shapiro-Wilk p-value: [1.35028098e-24 2.47753196e-20]

Confidence Intervals for "Attacking_Crossing":
Shapiro-Wilk Statistic: [0.96240541 0.97353844]
Shapiro-Wilk p-value: [1.07109130e-25 9.38814447e-22]

Confidence Intervals for "Attacking_Finishing":
Shapiro-Wilk Statistic: [0.95851108 0.96927528]
Shapiro-Wilk p-value: [7.24757465e-27 2.17906323e-23]

Confidence Intervals for "Attacking_Heading_Accuracy":
Shapiro-Wilk Statistic: [0.98567376 0.99191158]
Shapiro-Wilk p-value: [1.05291602e-15 5.02897049e-11]
```

One of the tests that can be implemented that is considered to be the most robust against violations of the assumptions behind MANOVA is Pillai's Trace test. Pillai's trace is used as one of the test statistics to determine the overall significance of the differences among groups in a MANOVA. It tests the null hypothesis that there are no group differences in the multivariate outcome variable(s). In other words, it helps answer the question of whether there is any significant variation in the combination of dependent variables across groups. In the output below, the Pillai's trace value is 0.978, i.e., close to 1, which means a close relationship between the grouping variable and the dependent variables. The very low p-value (Pr > F = 0.0000) indicates that there is a highly significant relationship between the "General Position" variable and the set of dependent variables. In this case, we reject the null hypothesis.

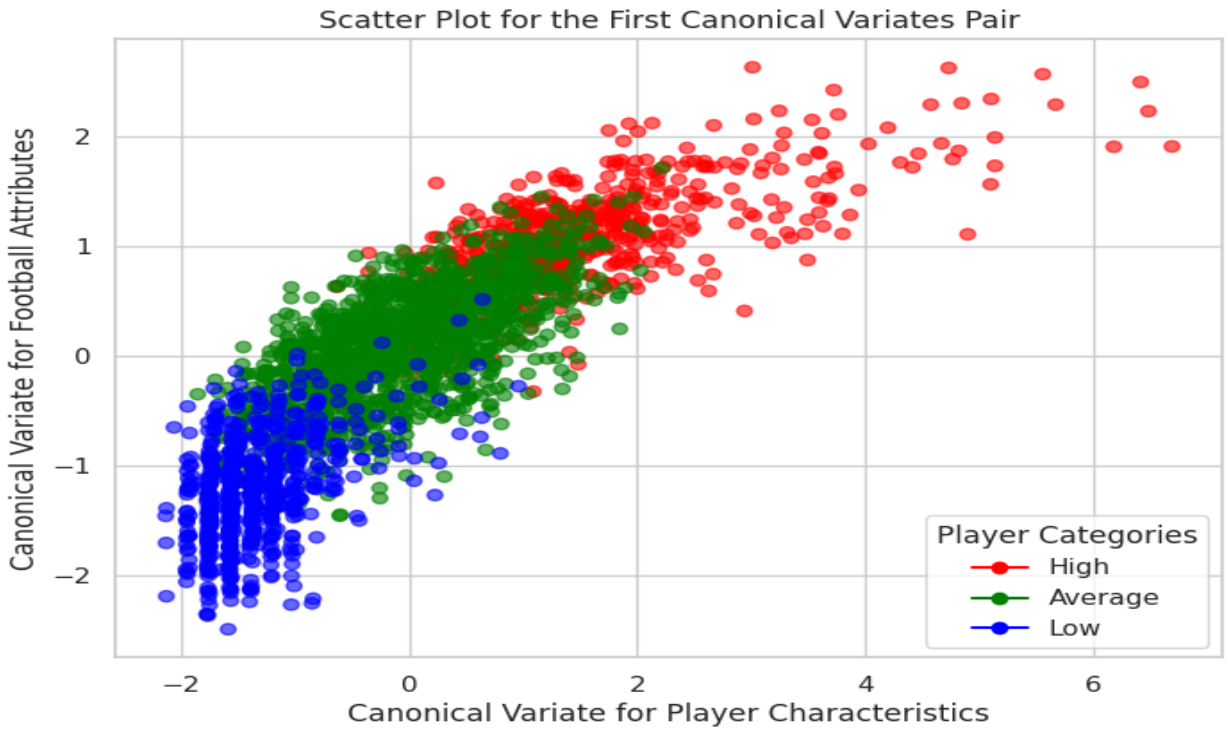
```
                  Multivariate linear model
================================================================

----------------------------------------------------------------
      Intercept         Value   Num DF   Den DF   F Value  Pr > F
----------------------------------------------------------------
         Wilks' lambda  0.0218 35.0000 2613.0000 3343.7755 0.0000
        Pillai's trace  0.9782 35.0000 2613.0000 3343.7755 0.0000
Hotelling-Lawley trace 44.7884 35.0000 2613.0000 3343.7755 0.0000
   Roy's greatest root 44.7884 35.0000 2613.0000 3343.7755 0.0000
----------------------------------------------------------------

----------------------------------------------------------------
     General_Position    Value   Num DF   Den DF  F Value  Pr > F
----------------------------------------------------------------
           Wilks' lambda 0.1008 70.0000 5226.0000 160.5418 0.0000
          Pillai's trace 1.2909 70.0000 5228.0000 135.9770 0.0000
  Hotelling-Lawley trace 5.0373 70.0000 4945.6757 187.9685 0.0000
     Roy's greatest root 4.0858 35.0000 2614.0000 305.1545 0.0000
================================================================
```

5. Canonical Correlation Analysis (CCA):

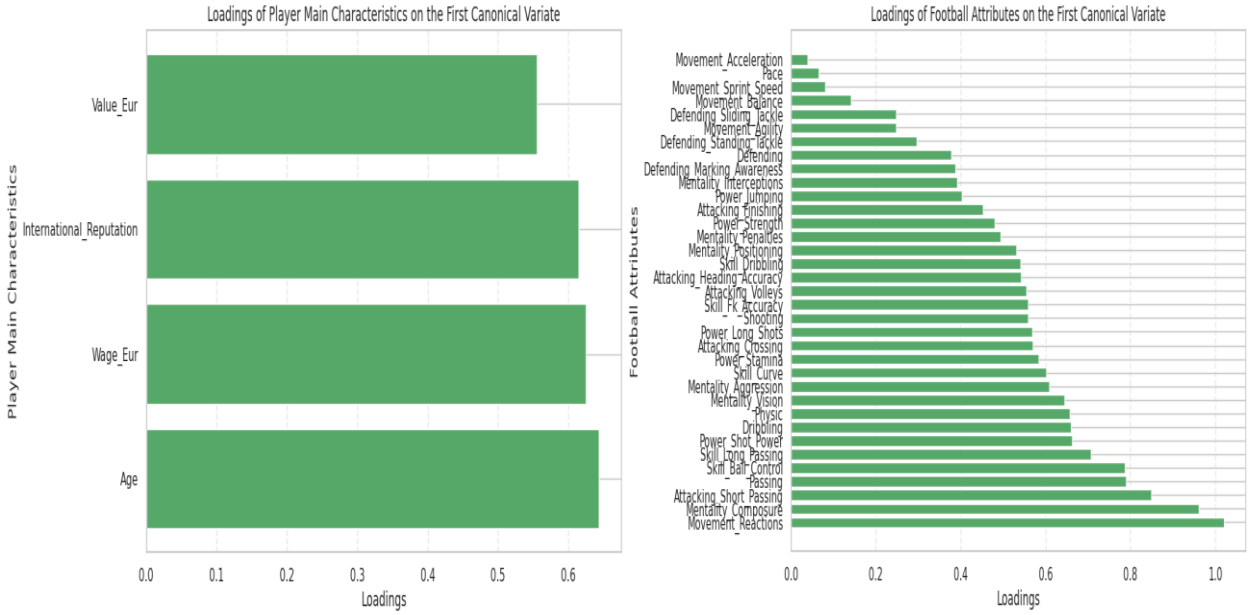
The aim of this analysis is to observe the correlation between two separate categories of data: player general information and player football attributes, and to investigate how they collectively impact a player's overall rating. Before diving into this analysis, I decided to generalize the players' overall rating into three categories: High, Average, Low. To implement this analysis, firstly I try to visualize the correlation for the first two canonical variates (CC1 and CC2), a canonical variate is a linear combination of variables from one set of data that is maximally correlated with a linear combination of variables from another set of data. From the bar plot created, we can see that the first canonical variate indicates a strong association (0.85) between the player's general information and football attributes, while the second canonical variate captures somewhat weaker (0.5) but still significant relationship. In my analysis, I decided to focus only on the first canonical variate.



By plotting a scatterplot, we can indeed see a linear relationship between the two sets of variables, where an increase in both leads to a higher player overall level.



Then to get a more detailed understanding of the relationship between the two sets of variables, I decided to visualize the loadings of variables on the first canonical variate. Loadings represent the strength and direction of the relationship between variables and the component. They are used to interpret the significance of each variable in the context of the component they load onto, the first canonical variate in our case.



In the bar plots above, we can note two things, first we do not have negative loadings, meaning an increase of a given variable won't lead to a decrease in the player's overall general level. Second, the left side shows the magnitude of the loadings for the player's general information, while the right side displays the magnitude of the loadings for the player's football attributes. These loadings indicate the strength of the positive relationship of each variable with the player's overall level.

6. Conclusion:

In conclusion, this project provided valuable insights into FIFA 22 player statistics. It identified the key attributes influencing overall player ratings, examined variations in attributes across different positions, and revealed the correlation between general player information and football attributes in determining a player's overall rating.