THE BEST REPLACEMENT FOR VIRGIL VAN DIJK IN THE SEASON 2022-2023 (Player Recommender System using Python)

I. Motivation:

- Season 2022-2023 has been a horrific drop in form of arguably the best Centre defender: Virgil van Dijk, which lead to a decline in the strength of Liverpool F.C.'s defensive system. The cause may mainly lead back to Virgi van DijkI's hamstring problem. Liverpool F.C.'s solution to the problem is using young academy players to replace Virgil van Dijk, but they are all underqualified to compete in an intense league like EPL. This project will use a python recommender system to find Virgil Van Dijk replacements.

Let's define the KPIs of a Central defender:

- Defensive actions:
  Van Dijk has done a remarkable job at stopping opponents' attacks by tackles, interceptions, clearances, and stopping shots. These metrics can score these actions:
  + Number of dribblers tackled per 90: Tkl/90
  + Win percentage in tackles: TklWon%
  + Percentage of getting dribbled through: TklDriPast
  + Number of times blocking a shot by standing in its path per90: BlkSh/90
  + Number of interceptions per 90: Int/90
  + Clearances per 90: Clr/90
- Ariael action:
  With a height of 1m94 and sensible position choice, Van Dijk has proven to be a great aerial warrior both on defense and offense. These actions can be scored by these metrics:
  + Total of aerial duels per 90: AerDuels/90
  + Percentage of aerial duels won: AerWon%
- Passing action:
  Van Dijk is a great deep-lying playmaker, his passes and crosses play a vital role in Liverpool F.C.'s success. These actions can be scored by these metrics:

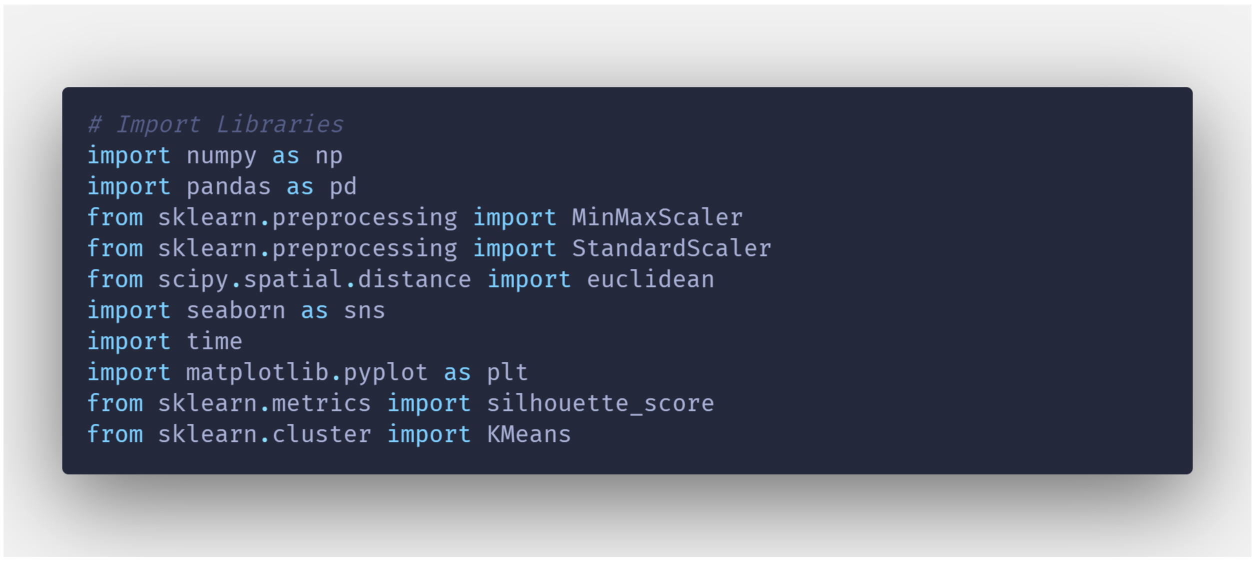
+ Passes attempted per 90: PasTotAtt/90
+ Pass completion percentage: PasTotCmp%
+ Long passes attempted (>30 yards) per 90: PasLonAtt/90
+ Long pass completion (>30 yards) percentage: PasLonCmp%

Some notes when processing the data:

- The dataset is taken from Kaggle: 2022-2023 Football Player Stats | Kaggle, This dataset contains 2022-2023 football player stats per 90 minutes. Only players from the Premier League, Ligue 1, Bundesliga, Serie A, and La Liga are listed.
- The dataset has 2689 players, including players who are not central defenders.
- All the variables are scaled to minimize the deviation.
    + To avoid differences in ratio, we scale the data using the MinMaxScaler function, where the data is transformed into values from 0 to 1.
- The similarities between players can be found by using a "ruler" to find who is the player closest to Virgil van Dijk on the KPIs performance scale.
    + We choose to use the Euclidean distance formula because of its "ruler" property.

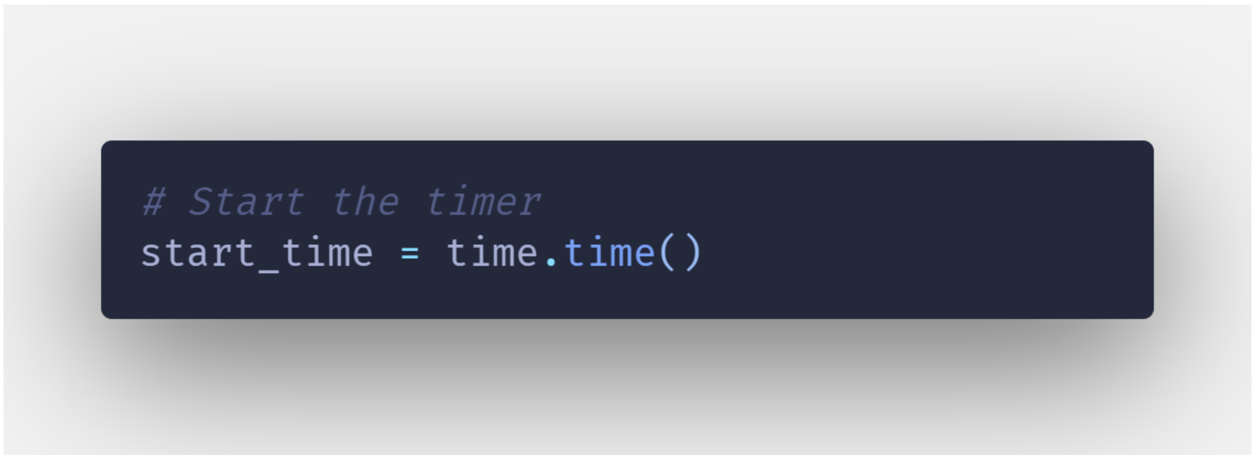
II. Project Processing step by step:

- Importing Libraries: First, the necessary libraries are imported.



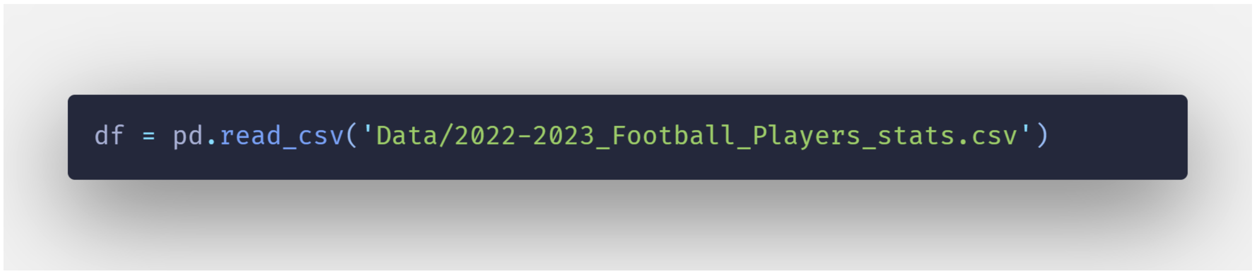
```
# Import Libraries
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from scipy.spatial.distance import euclidean
import seaborn as sns
import time
import matplotlib.pyplot as plt
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
```

- Start the timer: We use function time() to calculate the project's running time.



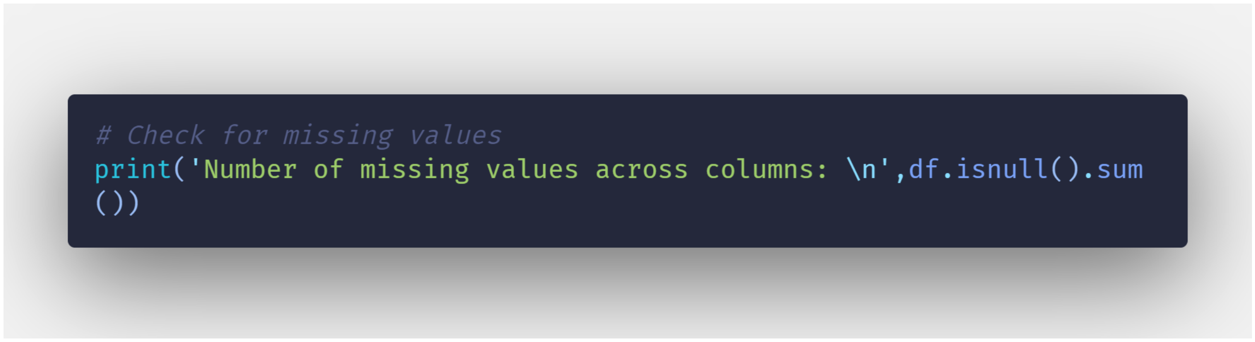
```
# Start the timer
start_time = time.time()
```

- Loading Data: The football player stats data is loaded using the read_csv function from the pandas library. The file is in a CSV format and the file path is specified as an argument.



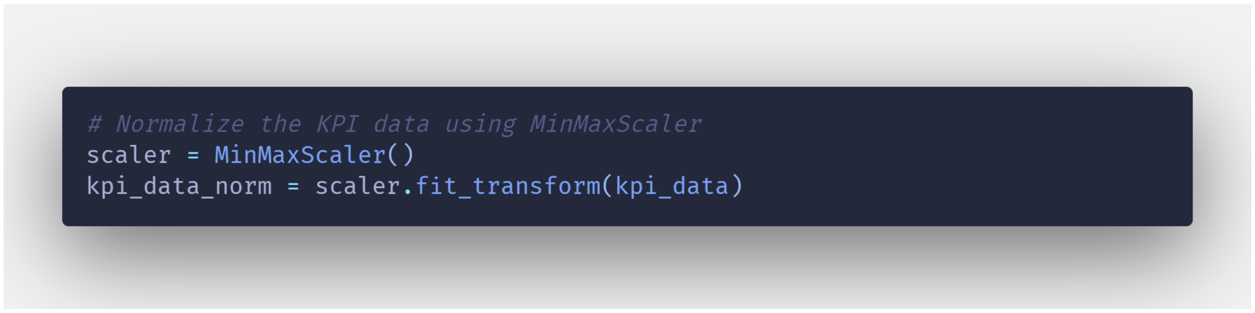
```
df = pd.read_csv('Data/2022-2023_Football_Players_stats.csv')
```

- Data Checking: Data checking is performed to find nad remove any missing values and convert the KPI columns to a numeric data type.



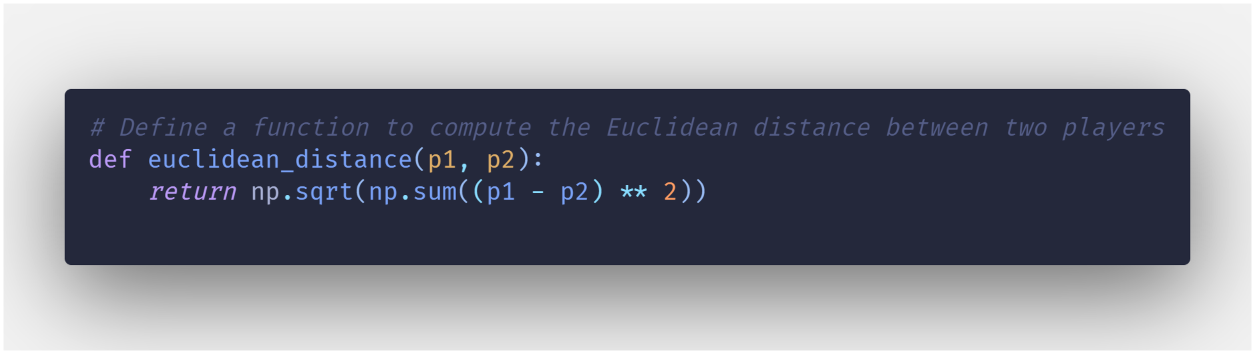
```
# Check for missing values
print('Number of missing values across columns: \n',df.isnull().sum
())
```

- Normalizing Data: The KPI data is normalized using the MinMaxScaler function from scikit-learn. This is done to ensure that all KPIs are on the same scale, where the data is transformed into values from 0 to 1 and can be compared fairly.



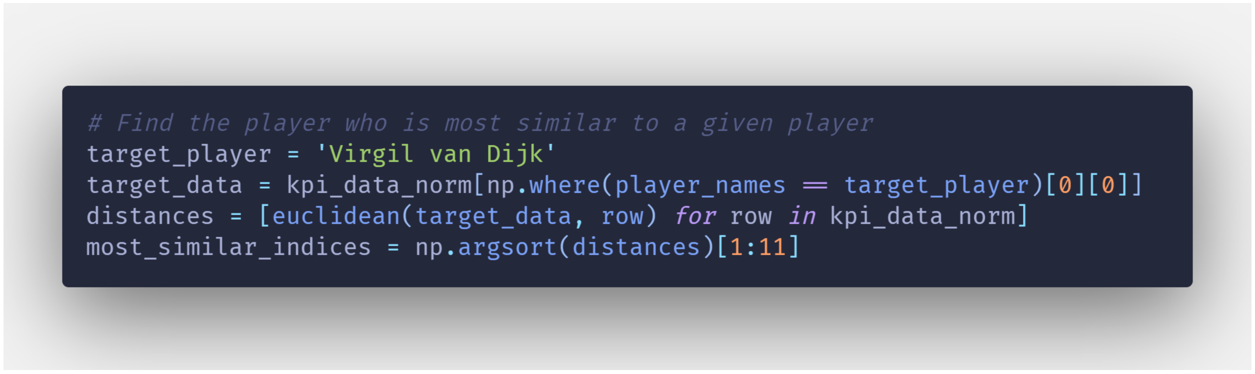
```
# Normalize the KPI data using MinMaxScaler
scaler = MinMaxScaler()
kpi_data_norm = scaler.fit_transform(kpi_data)
```

- Computing Distance Metrics: A function to compute the Euclidean distance between two players is defined using the euclidean function from scipy. This is the distance metric that is used to determine the similarity between two players.



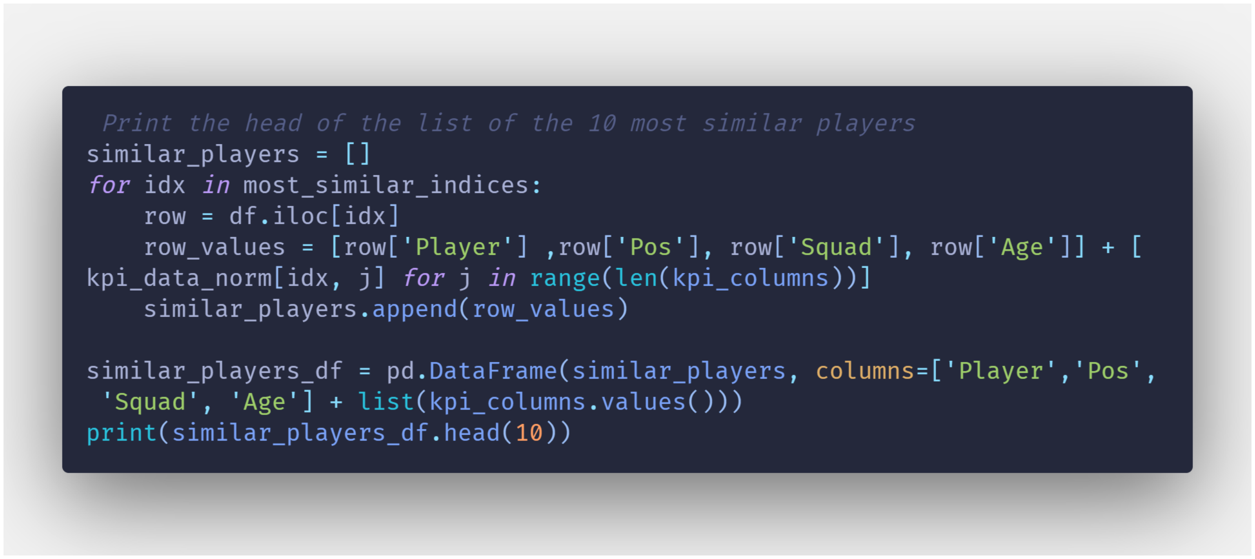
```
# Define a function to compute the Euclidean distance between two players
def euclidean_distance(p1, p2):
    return np.sqrt(np.sum((p1 - p2) ** 2))
```

- Finding Similar Players: The player who is most similar to Virgil van Dijk is determined by computing the Euclidean distance between the target player's KPI data and the KPI data of all other players. The 10 players with the smallest distances are selected as the most similar players. This is done using the argsort function from numpy.



```
# Find the player who is most similar to a given player
target_player = 'Virgil van Dijk'
target_data = kpi_data_norm[np.where(player_names == target_player)[0][0]]
distances = [euclidean(target_data, row) for row in kpi_data_norm]
most_similar_indices = np.argsort(distances)[1:11]
```

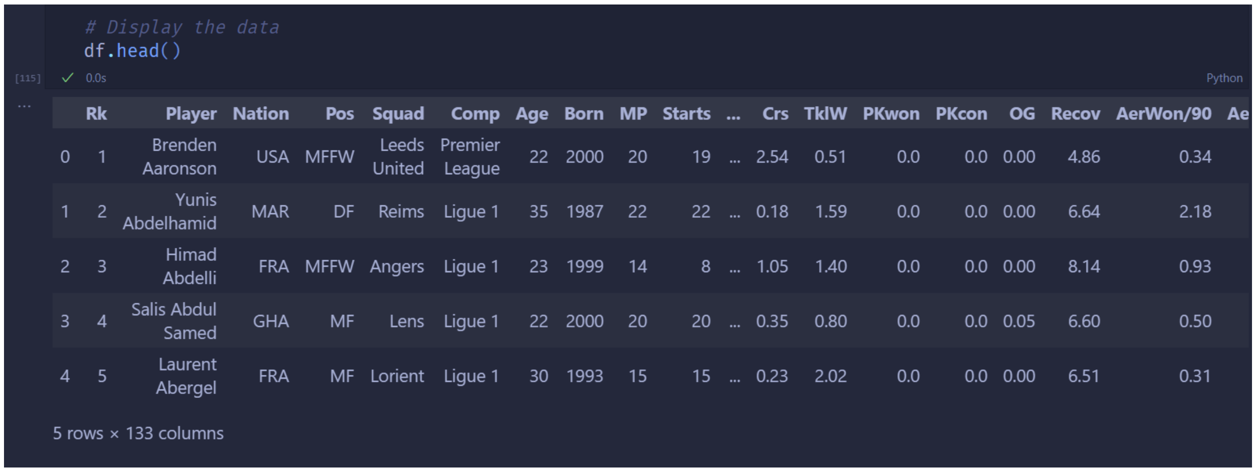
- Creating a DataFrame of Similar Players (Similar Players under 25): A DataFrame is created to display the most similar players, along with their positions, squad, age, and KPI values. The DataFrame is created using the iloc function from pandas to select the rows for the most similar players.



```python
 Print the head of the list of the 10 most similar players
similar_players = []
for idx in most_similar_indices:
    row = df.iloc[idx]
    row_values = [row['Player'] ,row['Pos'], row['Squad'], row['Age']] + [
kpi_data_norm[idx, j] for j in range(len(kpi_columns))]
    similar_players.append(row_values)

similar_players_df = pd.DataFrame(similar_players, columns=['Player','Pos',
 'Squad', 'Age'] + list(kpi_columns.values()))
print(similar_players_df.head(10))
```

III. Data Analysis:

- Simple dataset descriptions:

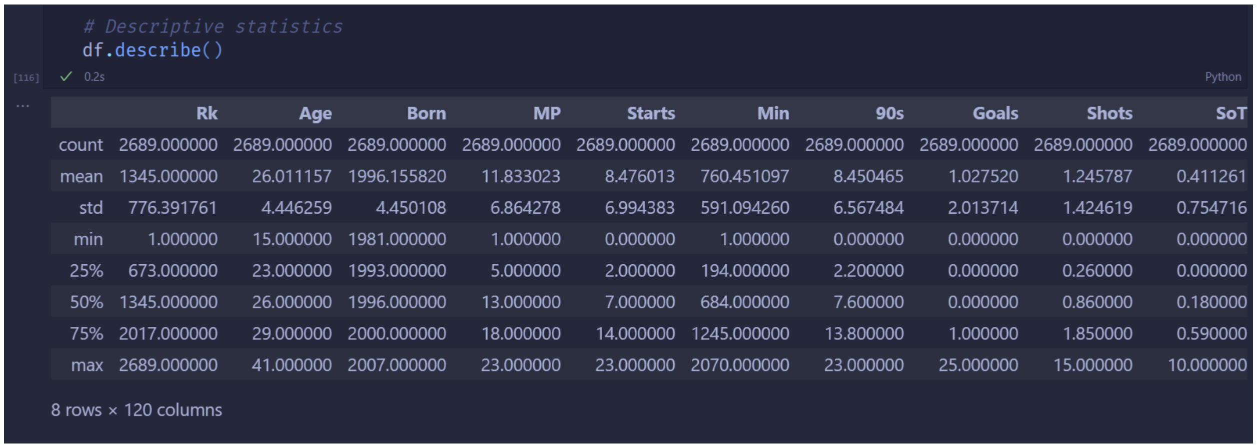


```python
# Display the data
df.head()
```

[115] ✓ 0.0s Python

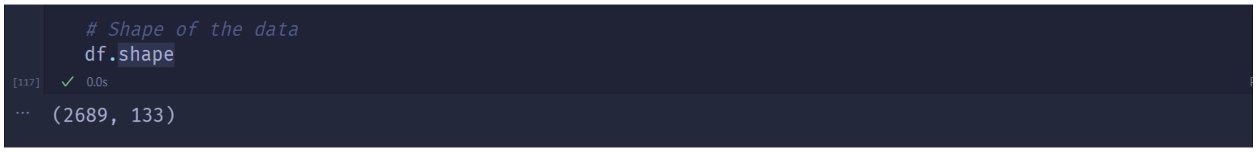
	Rk	Player	Nation	Pos	Squad	Comp	Age	Born	MP	Starts	...	Crs	TklW	PKwon	PKcon	OG	Recov	AerWon/90	Ae
0	1	Brenden Aaronson	USA	MFFW	Leeds United	Premier League	22	2000	20	19	...	2.54	0.51	0.0	0.0	0.00	4.86	0.34	
1	2	Yunis Abdelhamid	MAR	DF	Reims	Ligue 1	35	1987	22	22	...	0.18	1.59	0.0	0.0	0.00	6.64	2.18	
2	3	Himad Abdelli	FRA	MFFW	Angers	Ligue 1	23	1999	14	8	...	1.05	1.40	0.0	0.0	0.00	8.14	0.93	
3	4	Salis Abdul Samed	GHA	MF	Lens	Ligue 1	22	2000	20	20	...	0.35	0.80	0.0	0.0	0.05	6.60	0.50	
4	5	Laurent Abergel	FRA	MF	Lorient	Ligue 1	30	1993	15	15	...	0.23	2.02	0.0	0.0	0.00	6.51	0.31	

5 rows × 133 columns



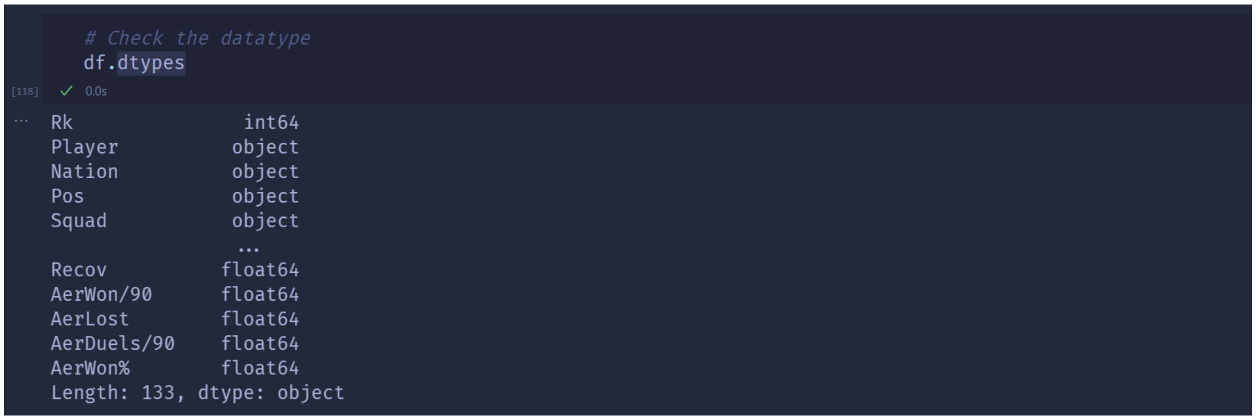
```python
# Descriptive statistics
df.describe()
```

```
           Rk          Age          Born         MP           Starts       Min          90s          Goals        Shots        SoT
count  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000  2689.000000
mean   1345.000000    26.011157  1996.155820    11.833023     8.476013   760.451097     8.450465     1.027520     1.245787     0.411261
std     776.391761     4.446259     4.450108     6.864278     6.994383   591.094260     6.567484     2.013714     1.424619     0.754716
min       1.000000    15.000000  1981.000000     1.000000     0.000000     1.000000     0.000000     0.000000     0.000000     0.000000
25%     673.000000    23.000000  1993.000000     5.000000     2.000000   194.000000     2.200000     0.000000     0.260000     0.000000
50%    1345.000000    26.000000  1996.000000    13.000000     7.000000   684.000000     7.600000     0.000000     0.860000     0.180000
75%    2017.000000    29.000000  2000.000000    18.000000    14.000000  1245.000000    13.800000     1.000000     1.850000     0.590000
max    2689.000000    41.000000  2007.000000    23.000000    23.000000  2070.000000    23.000000    25.000000    15.000000    10.000000

8 rows × 120 columns
```



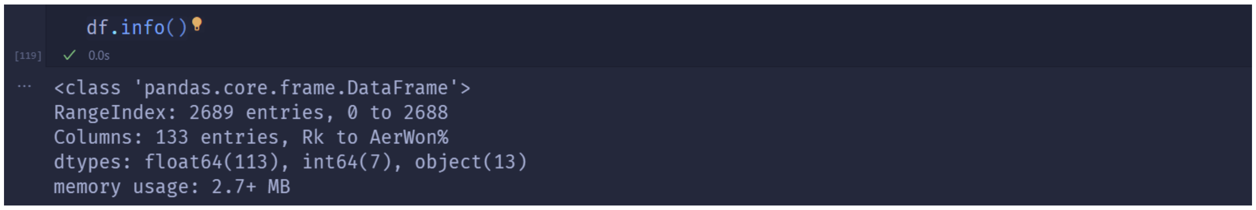
```python
# Shape of the data
df.shape
```

```
(2689, 133)
```



```python
# Check the datatype
df.dtypes
```

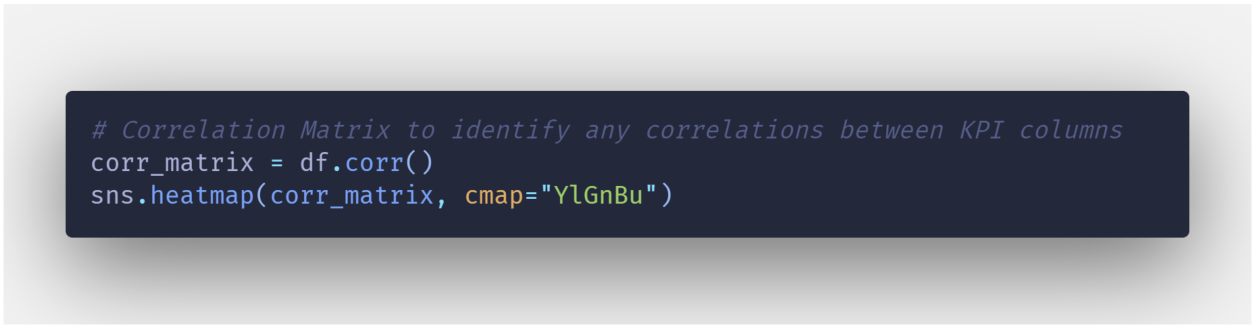
```
Rk                int64
Player           object
Nation           object
Pos              object
Squad            object
                  ...
Recov           float64
AerWon/90       float64
AerLost         float64
AerDuels/90     float64
AerWon%         float64
Length: 133, dtype: object
```



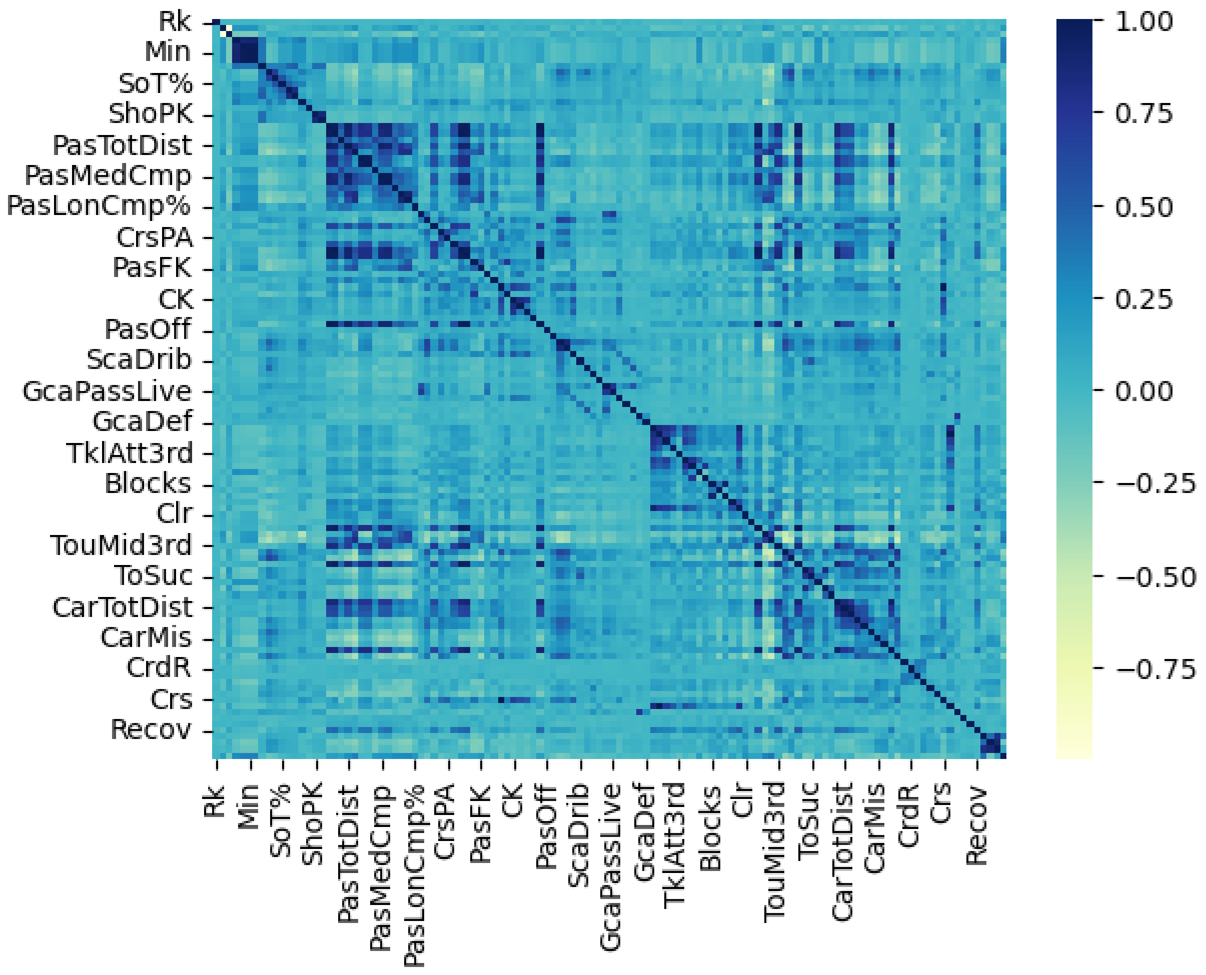
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2689 entries, 0 to 2688
Columns: 133 entries, Rk to AerWon%
dtypes: float64(113), int64(7), object(13)
memory usage: 2.7+ MB
```

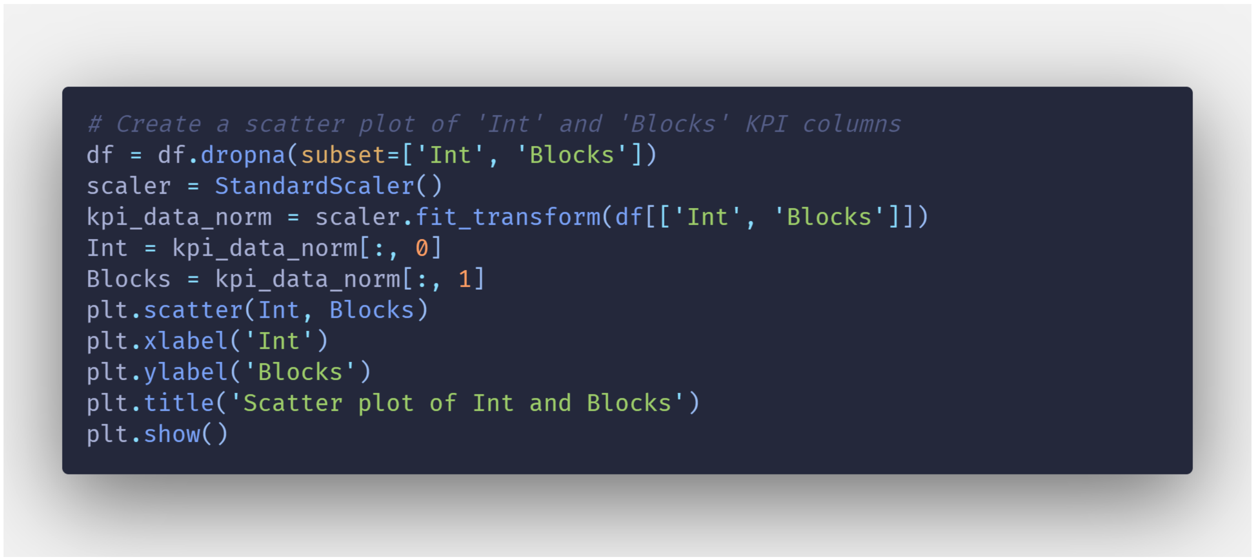
- Correlation Matrix:



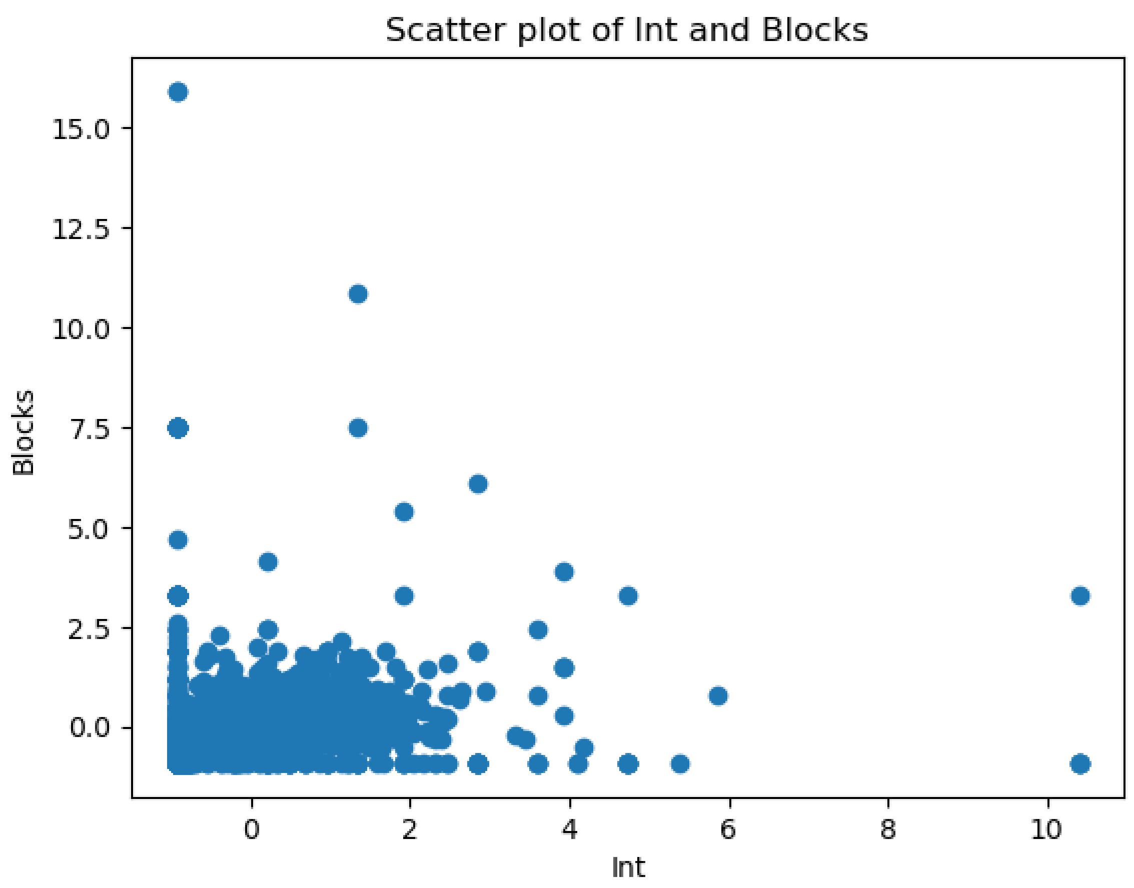
```python
# Correlation Matrix to identify any correlations between KPI columns
corr_matrix = df.corr()
sns.heatmap(corr_matrix, cmap="YlGnBu")
```



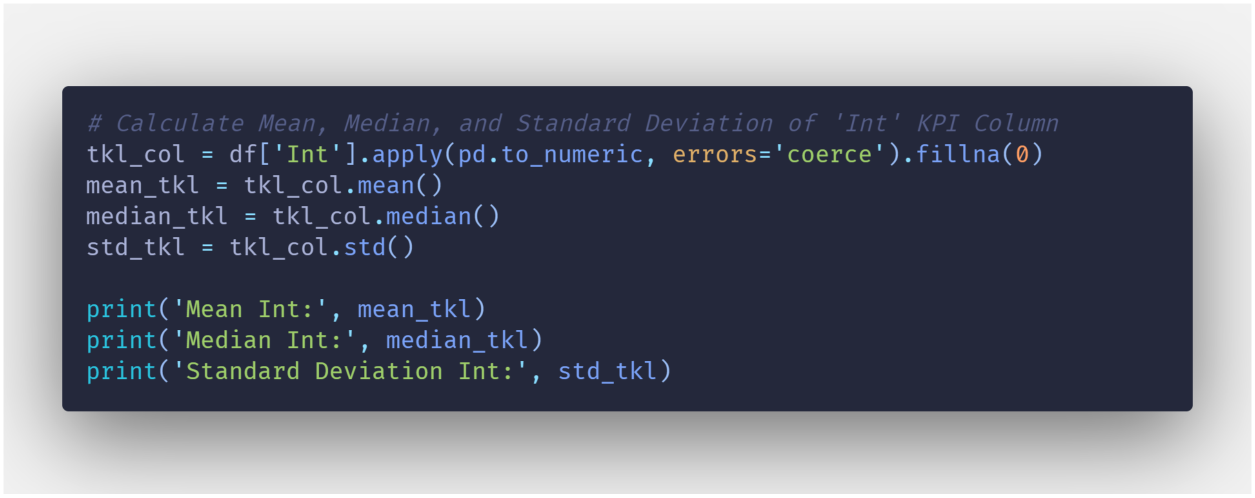
- Scatter plot between of 'Int' and 'Blocks' KPI columns:



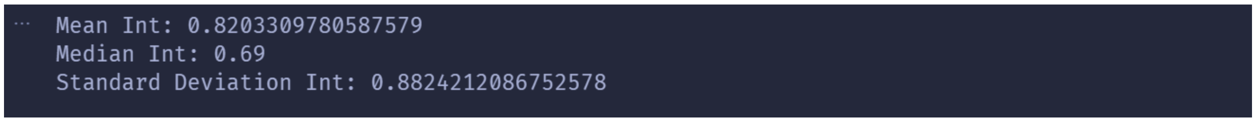
```
# Create a scatter plot of 'Int' and 'Blocks' KPI columns
df = df.dropna(subset=['Int', 'Blocks'])
scaler = StandardScaler()
kpi_data_norm = scaler.fit_transform(df[['Int', 'Blocks']])
Int = kpi_data_norm[:, 0]
Blocks = kpi_data_norm[:, 1]
plt.scatter(Int, Blocks)
plt.xlabel('Int')
plt.ylabel('Blocks')
plt.title('Scatter plot of Int and Blocks')
plt.show()
```



- Calculate Mean, Median, and Standard Deviation of “Int” column:

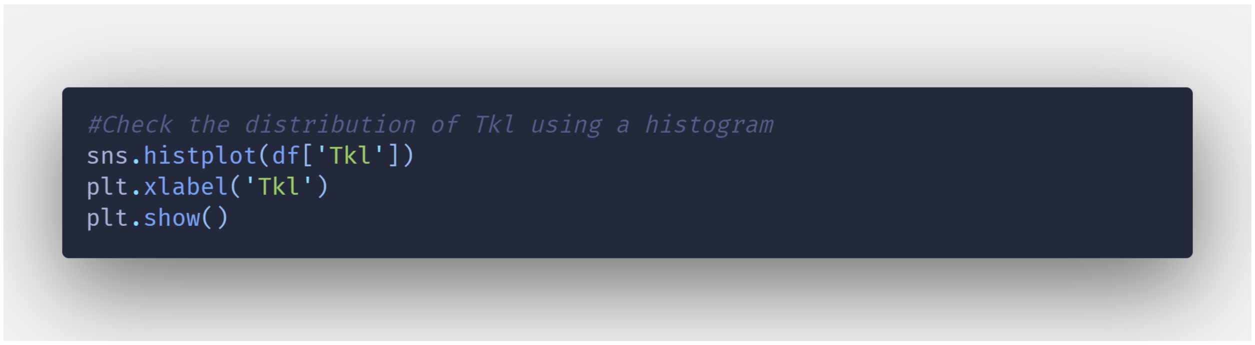


```
# Calculate Mean, Median, and Standard Deviation of 'Int' KPI Column
tkl_col = df['Int'].apply(pd.to_numeric, errors='coerce').fillna(0)
mean_tkl = tkl_col.mean()
median_tkl = tkl_col.median()
std_tkl = tkl_col.std()

print('Mean Int:', mean_tkl)
print('Median Int:', median_tkl)
print('Standard Deviation Int:', std_tkl)
```

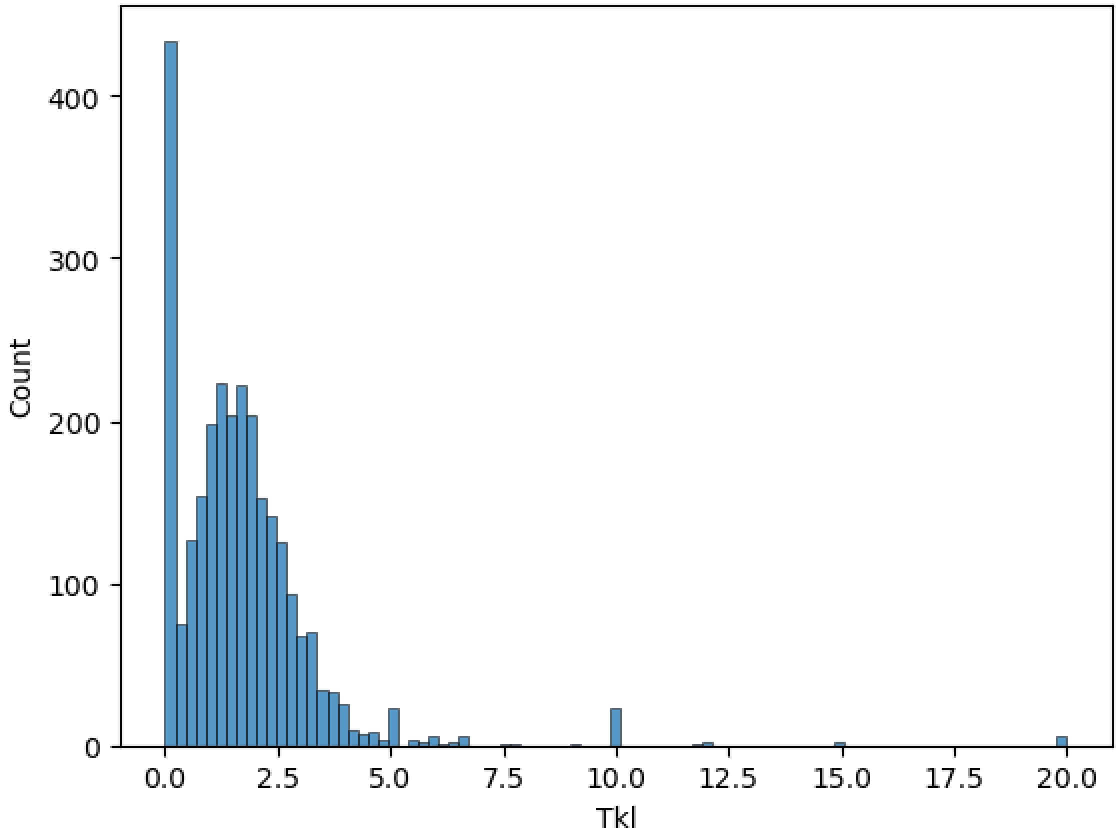


```
Mean Int: 0.8203309780587579
Median Int: 0.69
Standard Deviation Int: 0.8824212086752578
```

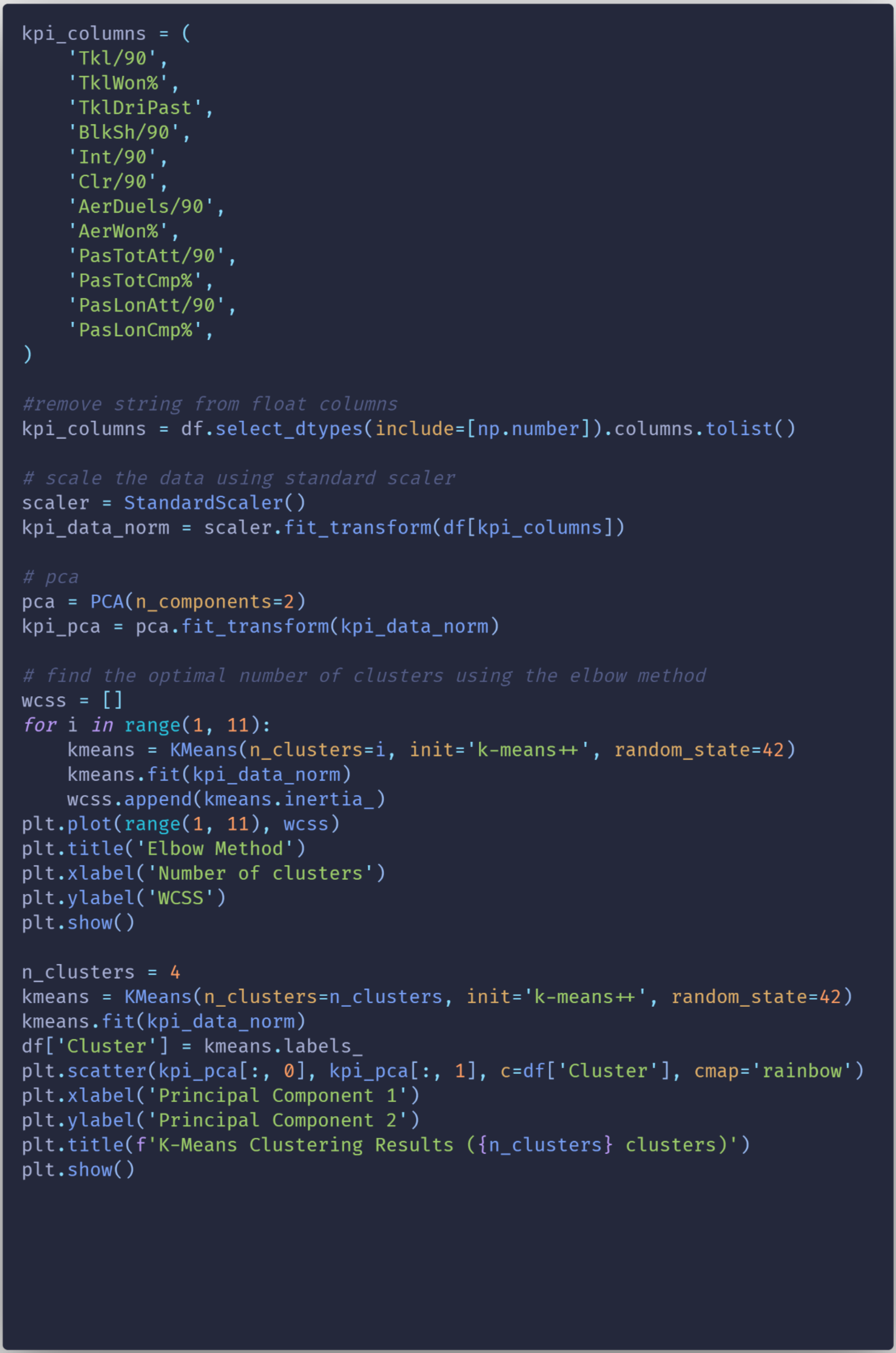
- Check the distribution of Tkl using a histogram:



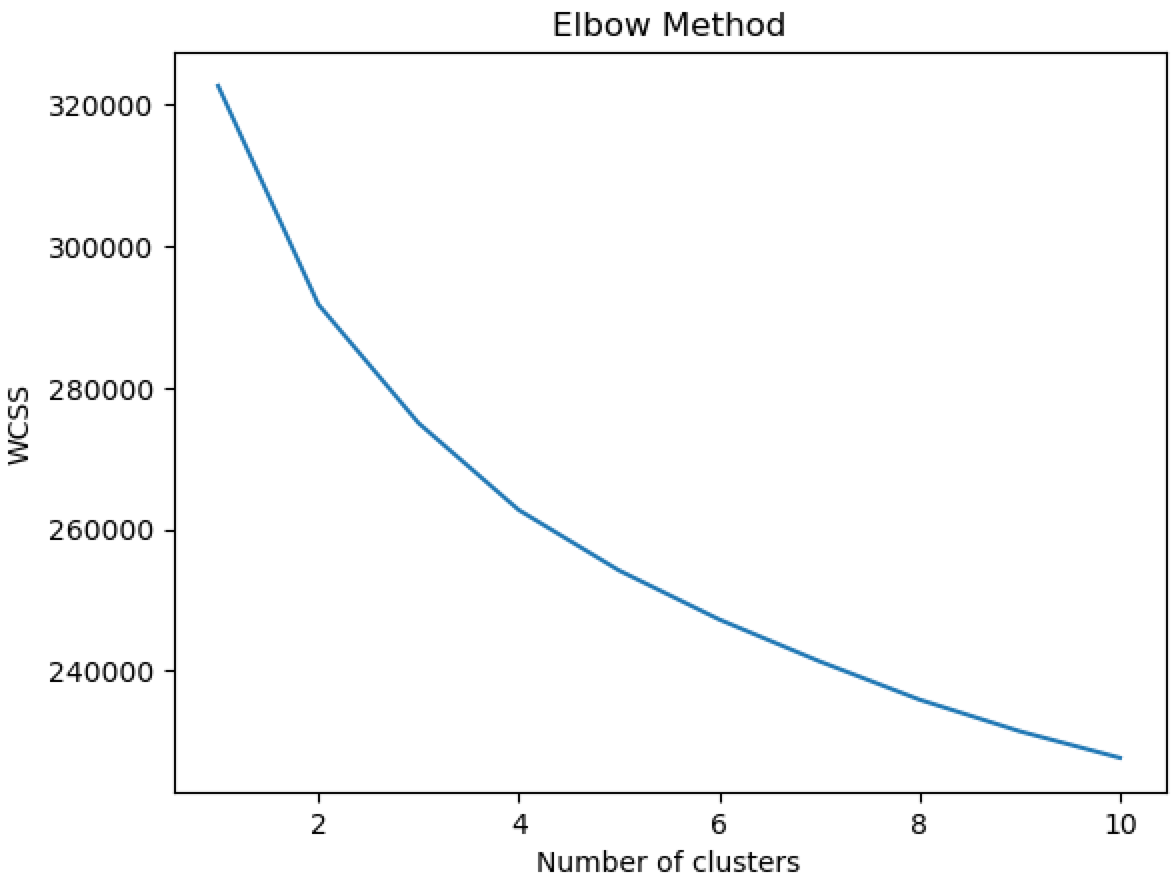
```
#Check the distribution of Tkl using a histogram
sns.histplot(df['Tkl'])
plt.xlabel('Tkl')
plt.show()
```

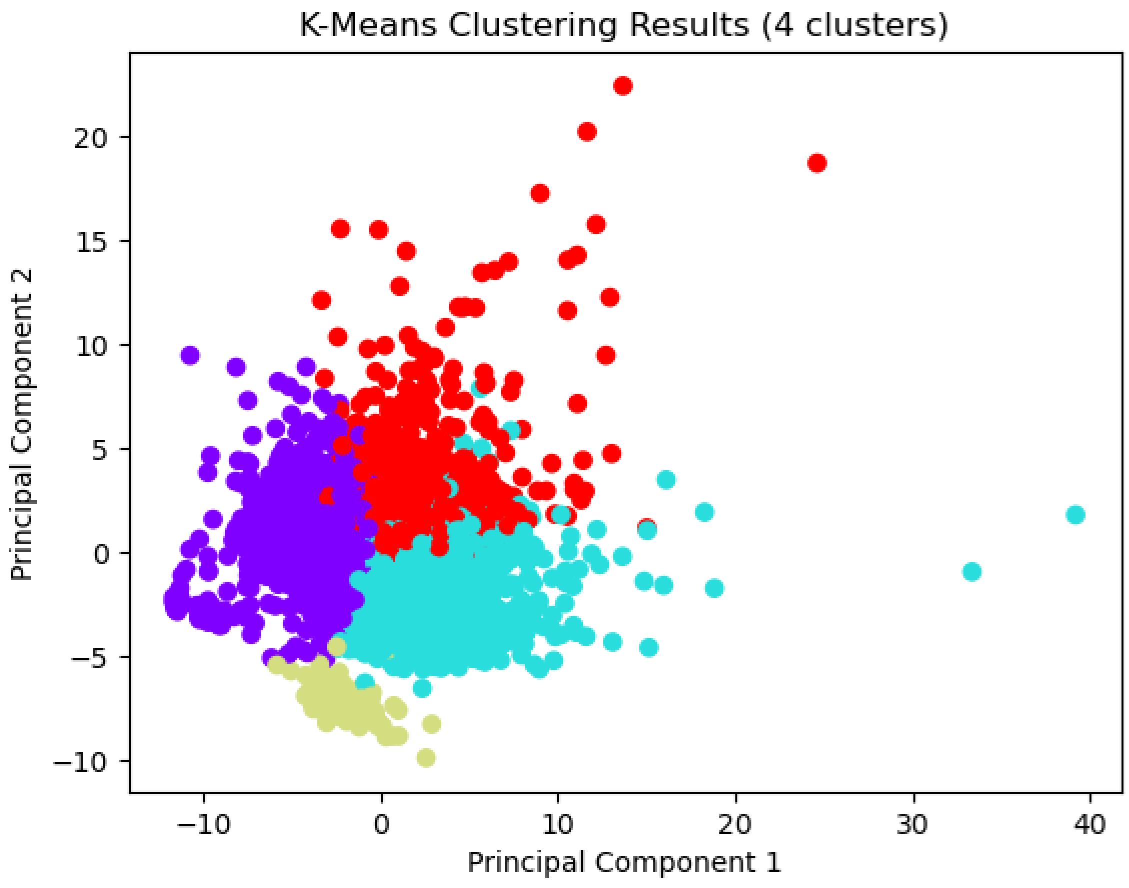


- Use K-means to group players:



```python
kpi_columns = (
    'Tkl/90',
    'TklWon%',
    'TklDriPast',
    'BlkSh/90',
    'Int/90',
    'Clr/90',
    'AerDuels/90',
    'AerWon%',
    'PasTotAtt/90',
    'PasTotCmp%',
    'PasLonAtt/90',
    'PasLonCmp%',
)

#remove string from float columns
kpi_columns = df.select_dtypes(include=[np.number]).columns.tolist()

# scale the data using standard scaler
scaler = StandardScaler()
kpi_data_norm = scaler.fit_transform(df[kpi_columns])

# pca
pca = PCA(n_components=2)
kpi_pca = pca.fit_transform(kpi_data_norm)

# find the optimal number of clusters using the elbow method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(kpi_data_norm)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

n_clusters = 4
kmeans = KMeans(n_clusters=n_clusters, init='k-means++', random_state=42)
kmeans.fit(kpi_data_norm)
df['Cluster'] = kmeans.labels_
plt.scatter(kpi_pca[:, 0], kpi_pca[:, 1], c=df['Cluster'], cmap='rainbow')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title(f'K-Means Clustering Results ({n_clusters} clusters)')
plt.show()
```

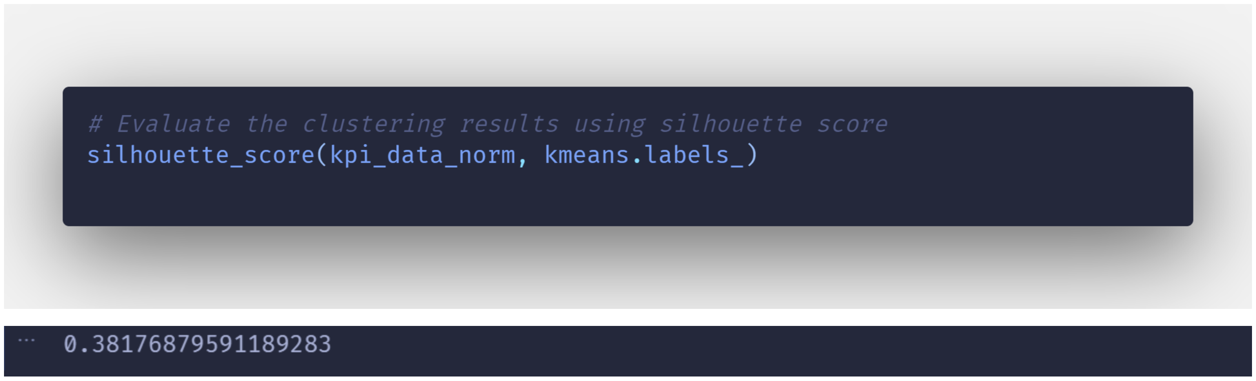

Elbow Method
WCSS
Number of clusters
320000
300000
280000
260000
240000
2
4
6
8
10



```
print(df['Cluster'])
```

```
... 0       0
    1       1
    2       1
    3       1
    4       1
           ..
    2684    3
    2685    3
    2686    3
    2687    0
    2688    0
    Name: Cluster, Length: 2689, dtype: int32
```

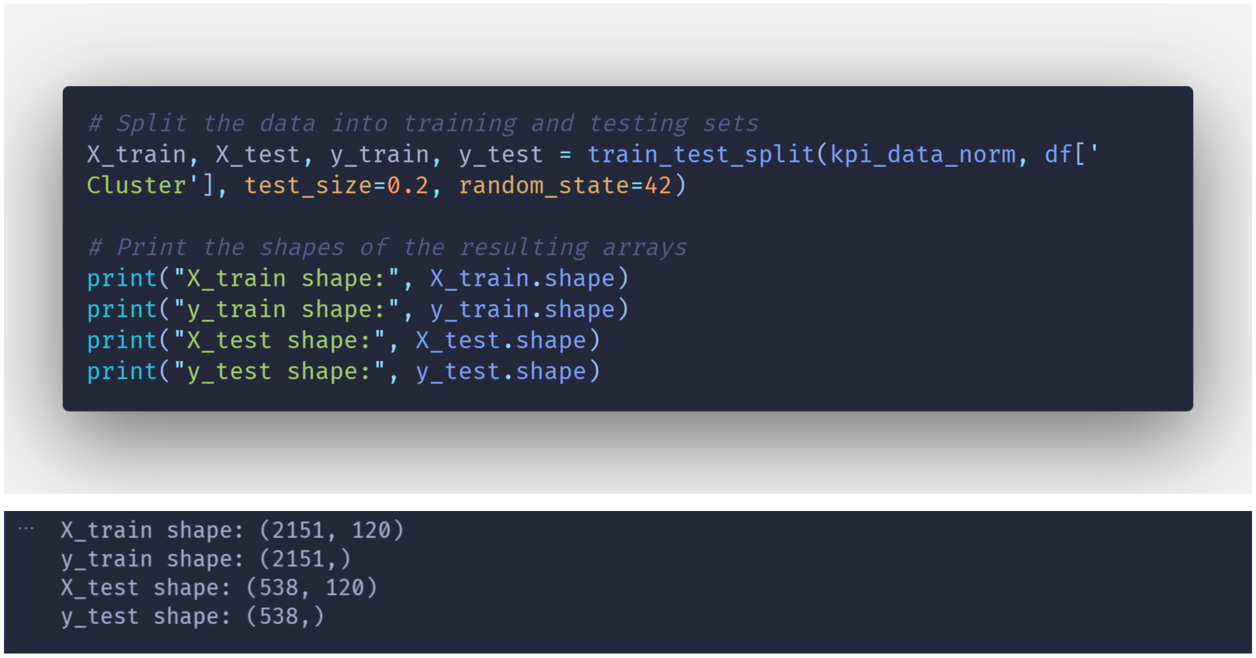
- Evaluate the clustering results:



```python
# Evaluate the clustering results using silhouette score
silhouette_score(kpi_data_norm, kmeans.labels_)
```

```
··· 0.38176879591189283
```

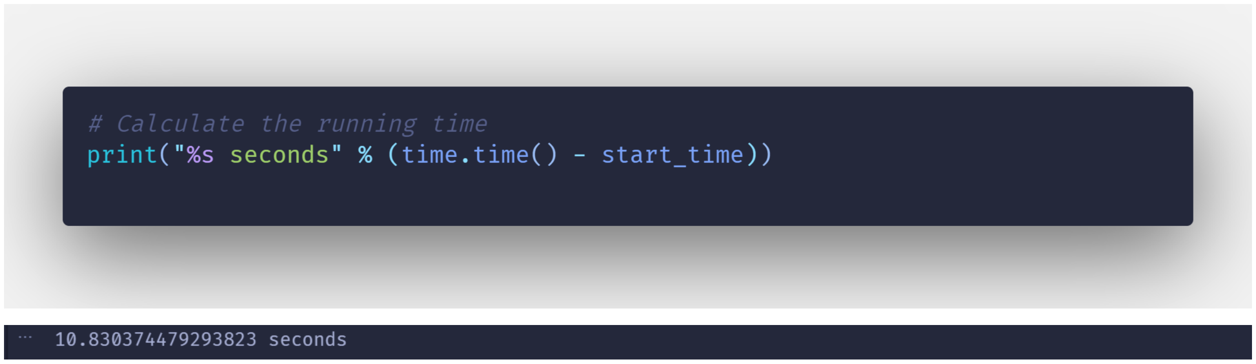
- Split the data to train



```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(kpi_data_norm, df['
Cluster'], test_size=0.2, random_state=42)

# Print the shapes of the resulting arrays
print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
```

```
··· X_train shape: (2151, 120)
    y_train shape: (2151,)
    X_test shape: (538, 120)
    y_test shape: (538,)
```

IV. Calculate the running time using `import time`:



```python
# Calculate the running time
print("%s seconds" % (time.time() - start_time))
```

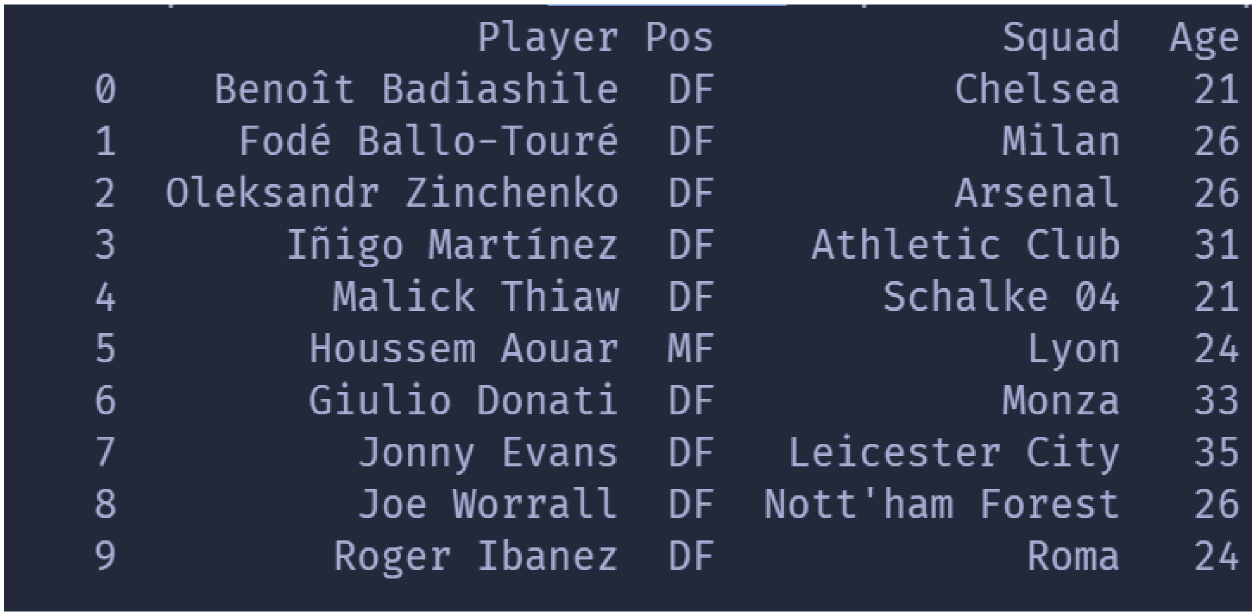
```
··· 10.830374479293823 seconds
```

V. Calculate the complexity of the program:

- Because we use the Euclidean distance algorithm, due to the nested loop, the time complexity is O(n^2) where n is the number of players in the dataset.

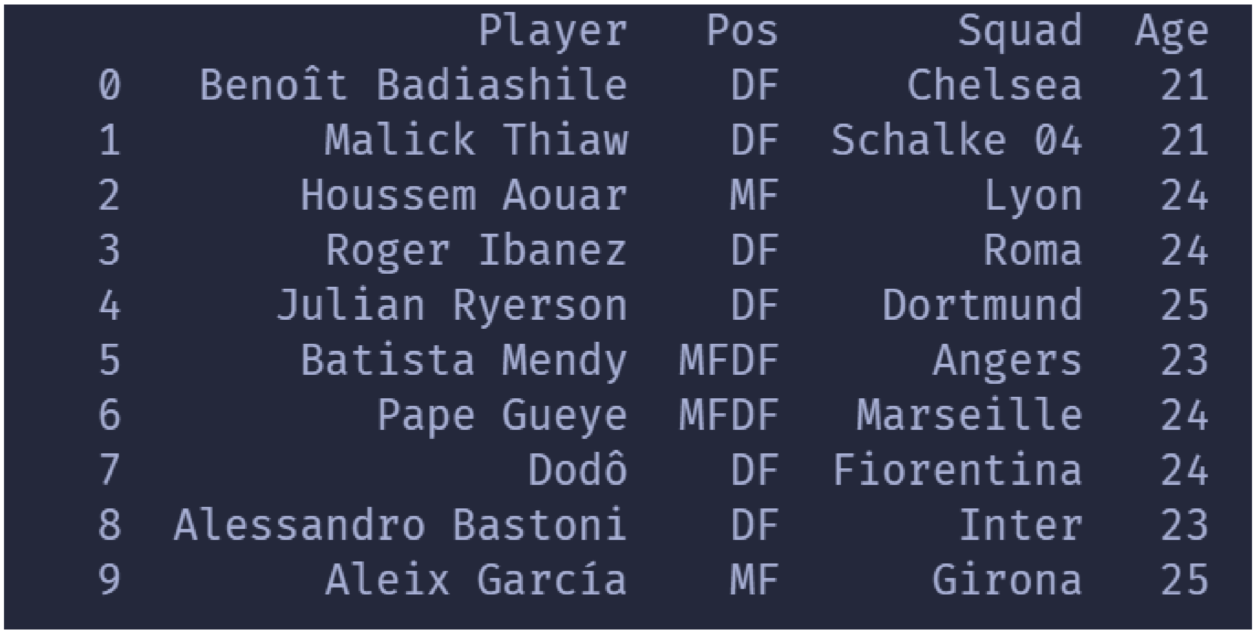
VI. Conclusion:

- After running the program, here are the top 10 most similar players to Virgil van Dijk, using 2022-2023 Van Dijk's stats as Model-based collaborative filtering:



```
                 Player Pos             Squad  Age
0    Benoît Badiashile  DF           Chelsea   21
1     Fodé Ballo-Touré  DF             Milan   26
2  Oleksandr Zinchenko  DF           Arsenal   26
3       Iñigo Martínez  DF     Athletic Club   31
4         Malick Thiaw  DF       Schalke 04   21
5        Houssem Aouar  MF              Lyon   24
6        Giulio Donati  DF             Monza   33
7          Jonny Evans  DF    Leicester City   35
8          Joe Worrall  DF  Nott'ham Forest   26
9         Roger Ibanez  DF              Roma   24
```

- Also, here is the top 10 most similar players under 25:



```
                   Player   Pos        Squad  Age
0     Benoît Badiashile    DF      Chelsea   21
1          Malick Thiaw    DF   Schalke 04   21
2         Houssem Aouar    MF         Lyon   24
3          Roger Ibanez    DF         Roma   24
4        Julian Ryerson    DF     Dortmund   25
5         Batista Mendy  MFDF       Angers   23
6            Pape Gueye  MFDF    Marseille   24
7                  Dodô    DF   Fiorentina   24
8   Alessandro Bastoni    DF        Inter   23
9          Aleix García    MF       Girona   25
```

- We understand that using data is just one part of finding the perfect replacement for Virgil van Dijk, as the centre-back position requires many uncollectable data. But these players above do have the potential to fill Virgil van Dijk's shoe.

And that is the end of our report!
Thanks you for your attention ❣️

Collaborators on this project:

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