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**KHOA CÔNG NGHỆ THÔNG TIN 1**

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**MÔN HỌC: LẬP TRÌNH PYTHON**

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# REPORT

## Statistical Analysis of Premier League Players 2024-2025 using Python

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#### 1. Introduction

##### 1.1 Rationale

As a student pursuing data science and analytics, I was drawn to this topic because football is both a personal interest and a compelling domain to apply real-world data skills. Football statistics offer a rich, high-dimensional dataset where insights can have actual implications in sports strategy and economics. Through this project, I aim to

simulate a mini data analytics pipeline involving data collection, cleaning, analysis, clustering, and value estimation.

## 1.2 Objectives and Requirements

The main goals of this project are:

- To build a complete pipeline for web-scraping and integrating multiple statistical tables from fbref.com.
- To clean and normalize the resulting dataset for consistency and usability.
- To explore descriptive statistics across players and teams.
- To identify standout players via top/bottom comparisons.
- To cluster players based on performance data and interpret the characteristics of each group.
- To collect external market value data and propose a framework for estimation.

## 1.3 Tools and Libraries

- Python 3.10 as the programming language
- Selenium for automated browsing and scraping dynamic content
- BeautifulSoup for parsing HTML and handling nested table comments
- Pandas and NumPy for data manipulation
- Matplotlib for plotting histograms and scatter plots
- Scikit-learn for normalization, clustering (KMeans), and dimensionality reduction (PCA)

## 2. Data Collection (BTL1.py)

The first step was to retrieve player statistics from fbref.com. This site organizes data by category: standard, shooting, passing, possession, defense, and more. These tables are often hidden inside HTML comments, so I built a function to parse both visible and commented-out tables.

After cleaning duplicate entries and ensuring that each row corresponds to an individual player, I merged the data using 'Player' as the key. I then filtered out players with fewer than 90 minutes of playtime to maintain statistical relevance. The final dataset contained 78 standardized metrics for 397 players, which was saved as results.csv.

### 3. Descriptive Statistical Analysis (BTL2.py)

To begin analyzing, I first converted all string-based statistics to numeric types where applicable. This included removing percent signs, commas, and dealing with 'N/a' values.

#### 3.1 Top/Bottom Performer Analysis

Using Pandas, I extracted the top 3 and bottom 3 players for each metric. For instance:

Top Goalscorer: Mohamed Salah (28 goals)

Top Pass Accuracy: William Saliba (94.2%)

Least Minutes Played (above 90 threshold): Billy Gilmour (98 mins)

These rankings were saved to a file called top\_3.txt.

#### 3.2 Team and League Summary Statistics

I calculated mean, median, and standard deviation both across the league and for each team. These insights were exported to results2.csv, which is useful for team comparisons.

#### 3.3 Visualization

For each metric, I plotted histograms showing the distribution of player performance—both for the entire league and split by team. These were saved to the histograms/ folder.

### 4. Clustering with KMeans and PCA (BTL3.py)

After identifying the numeric columns, I applied StandardScaler to normalize the data. Then I tested k-values from 2 to 10 to evaluate clustering performance.

#### 4.1 Choosing Optimal k

- Elbow Method: The inertia graph showed an inflection at k=3.
- Silhouette Score: Peaked at k=3, indicating strong cohesion and separation.

I finalized k=3 and fit the KMeans model accordingly.

#### 4.2 Dimensionality Reduction with PCA

Using PCA, I reduced the dataset to two principal components. This allowed me to

visualize the clusters on a scatter plot (pca\_clusters.png) with color-coded labels.

### 4.3 Cluster Interpretation

Based on cluster centroids (see cluster\_comments.txt):

- Cluster 0: Midfielders with balanced contributions across metrics.
- Cluster 1: Attackers with high xG, shots, and touches in the final third.
- Cluster 2: Goalkeepers and defenders with high save percentages and clearances.

## 5. Transfer Value and Estimation (BTL4.py)

To evaluate economic value, I scraped market values from footballtransfers.com, filtering for the Premier League.

### 5.1 Value Parsing and Merging

Values were stored as text (e.g., €12.5m), so I converted them to numeric values in euros. I then merged these values with the results.csv dataset, restricting to players with >900 minutes. The merged file is saved as transfer\_values.csv.

### 5.2 Toward a Predictive Model

Although a regression model was not implemented in this iteration, future steps could include using metrics like xG, assists, age, and minutes played as features to train a model that predicts market value. Linear Regression or Random Forests would be suitable starting points.

## 6. Evaluation and Conclusion

### 6.1 Key Findings

- Data from multiple fbref tables was successfully merged and filtered into a usable dataset.
- KMeans clustering revealed three meaningful player archetypes based on roles.
- PCA visualization helped confirm cluster separability.
- Top players like Mohamed Salah and Joško Gvardiol appeared in several metrics' top 3.

## 6.2 Limitations

- Several players lacked available transfer value data.
- No predictive model was trained to estimate market value.
- Positional encoding, injury history, and salary were not considered due to data availability.

## 7. Appendix

Below are key visualizations included in the analysis:

- PCA Clusters
- Elbow Method
- Silhouette Score
- results.csv: Consolidated player statistics
- top\_3.txt: Metric-wise performance rankings
- results2.csv: Team-based summary stats
- pca\_clusters.png, elbow.png, silhouette.png: Diagnostic visualizations
- transfer\_values.csv: Combined performance and market data

## 8. References

<https://fbref.com>

<https://www.footballtransfers.com>

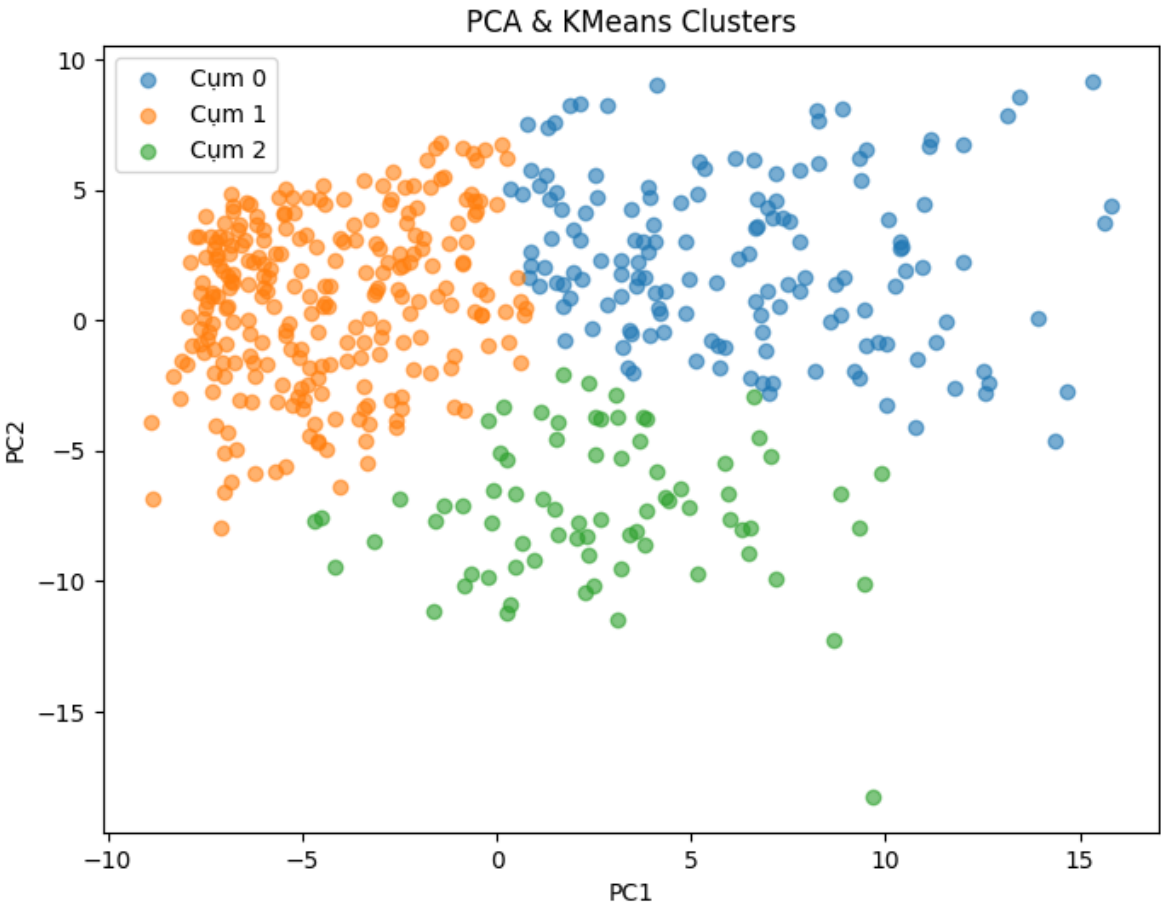
<https://scikit-learn.org>

<https://pandas.pydata.org>

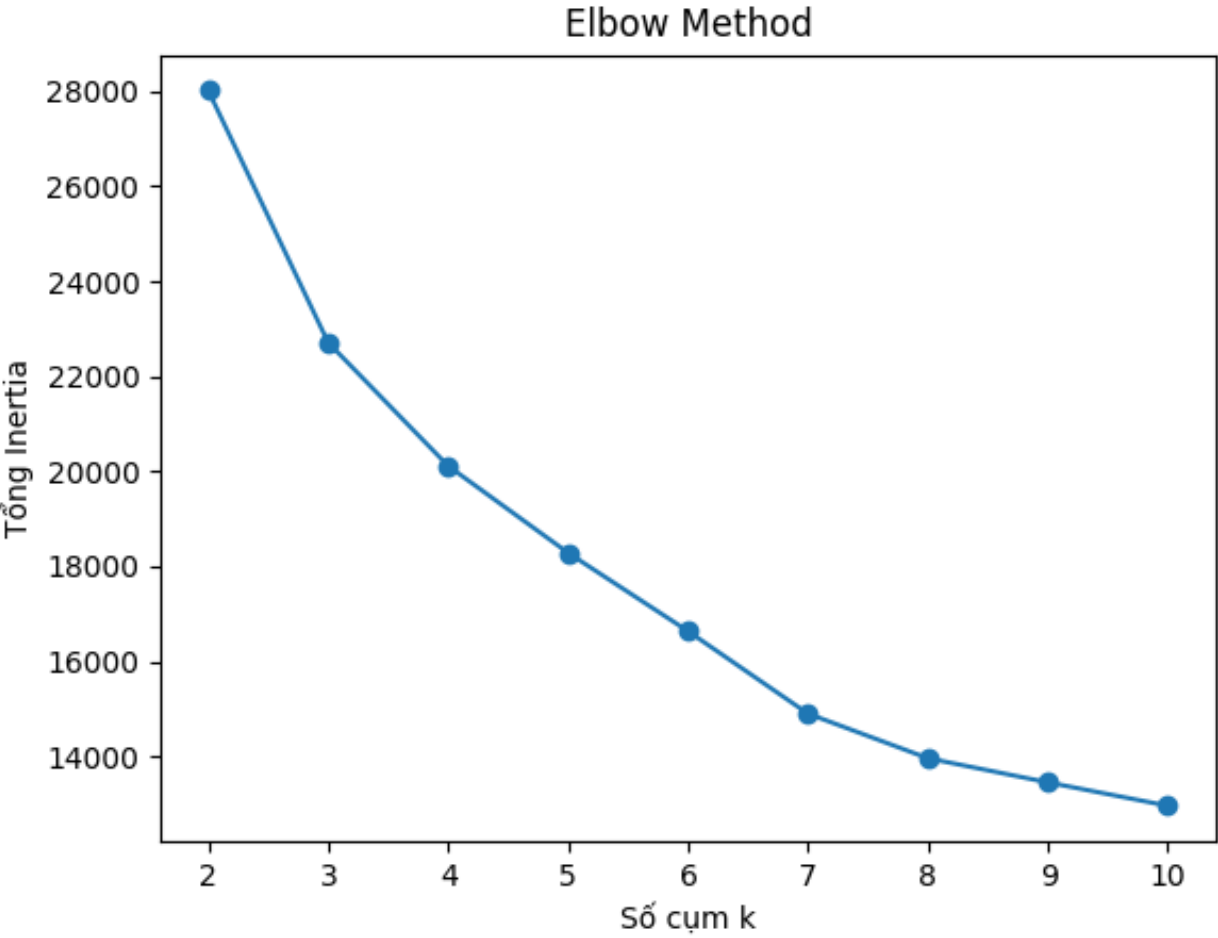
<https://matplotlib.org>

<https://selenium.dev>

# PCA Clusters



# Elbow Method





## Silhouette Score

