TU WIEN Informatics

Recommending Similar Players using Technical Performance Indicators

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1. Motivation

- Modern football has become increasingly **data-driven**, particularly in **game analysis**, **physica health monitoring**, and **player scouting**
- Yet, clubs still face the **sudden loss of key players** due to transfers or long-term injuries, which weakens team performance and **demands replacements** who match not only the position but also the playing style of the missing player
- However, **finding ad-hoc replacements** among thousands of candidates remains **highly challenging**, as **scouts** rely on statistics, visualizations, and video clips but are **constrained by human capacity** to a limited pool of players
- Meanwhile, **transfer fees** and player salaries represent some of the **largest cost factors** for professional clubs, and **misjudgments** in recruitment can **lead to significant financial losses**

2. Objective

The goal is to develop a data-driven recommendation method that instantly identifies top-k player replacements based on advanced statistics that captures player characteristics.

3. Data

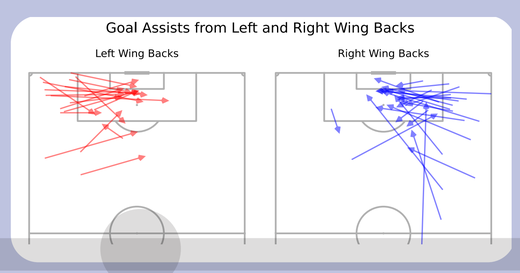
- The StatsBomb Python API serves as the data source source
- It provides **detailed game-event data** for the 2015/16 season across the Premier League, Bundesliga, La Liga, Serie A, Ligue 1, and the UEFA Champions League
- The raw dataset contains of **6,391,338 rows and 122 columns** where each row records an event with its type, outcome, and location

4. Feature Engineering

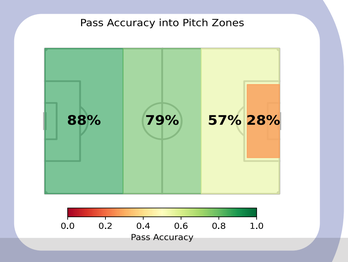
Aggregated Feature Vector
- Raw event-level data transformed into aggregated player vectors to derive general statistics
- Contextual variables added that refine generic statisitcs by accounting for pitch location, under pressure situation, and its outcome
- 1000+ features generated, grouped into dimension goalkeeping, defending, possession, passing, and shooting

Heatmap
- evaluated for each feature dimension
- Reduced to a fixed set of principal components

5. Exploratory Data Analysis



- Extracted features set compromises **3,069 players and 1,032 features**
- **Distinct movement patterns** across positions show varying involvement during matches
- **Role-based** action **patterns** emerge
- Performance **metrics**, such as pass accuracy, **vary with pitch location**

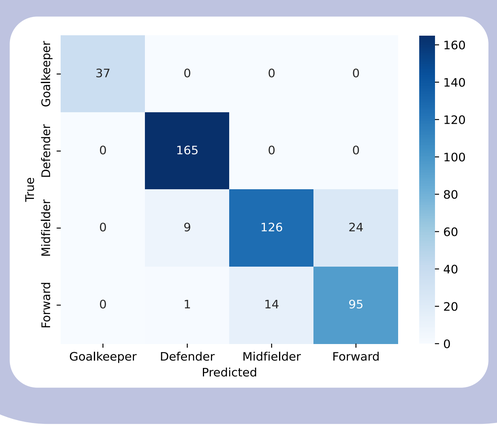


6. Feature Selection

- Reducing features is necessary to **address multicollinearity** and prevent **overfitting**
- Two feature sets were created and evaluated
- **Feature Set 1**: Logistic Regression with L1 regularization
- **Feature Set 2**: Prefiltering correlated features, followed by manual selection using domain knowledge

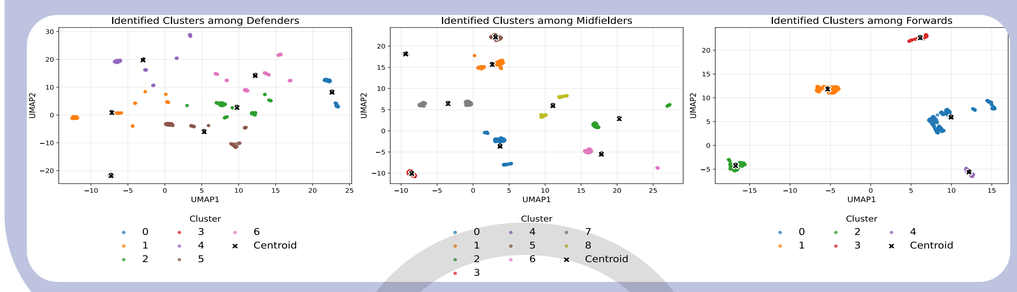
7. Modeling

- **Set of experiments** configurations with selected models evaluated predictive power using 5-fold cross-validation to **predict player positions**
- **Best model** chosen based on **stability** (lowest accuracy std) and **performance** (highest mean accuracy)
- LightGBM **achieved 90% accuracy**, with **perfect** prediction **for goalkeepers** and **defenders**



8. Clustering

- Unsupervised **K-Means applied** on SHAP-transformed features, reprojected **to 2D** with UMAP
- **At positions level**, clusters achieved **perfect homogeneity** and **completeness score** (goalkeeper, defender, midfielder, and forward)
- **Within positions**, clusters were more **heterogeneous**, grouping diverse role labels



9. Recommendation

- Split feature set into **test collection** and **player database**, stratified by position
- **Generated recommendation lists** (k=10, k=30) using cosine similarity; relevance defined by matching position labels
- Results show **accurate recommendations**, with **relevant players ranking high**

	AP@10	MAP@10	MRR@10	AP@30	MAP@30	MRR@30
$Goalkeeper$	1	1	1	1	1	1
$Defender$	0.7	0.93	0.95	0.66	0.93	0.95
$Midfielder$	0.9	0.80	0.85	0.93	0.80	0.85
$Forward$	0.8	0.84	0.88	0.6	0.84	0.88

10. Conclusion

- **Contextual** and **spatially-aware** aggregated **player vectors** provide a **strong representation of** positions by encoding **on-field behavior**
- **Player** vectors **reveal heterogeneous clusters** within positions, **indicating** that **players with different** official **role labels** may **share overlapping on-field** performance **patterns**
- **Engineered features** combined with cosine similarity **enable fast, good-quality scouting shortlists**