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ESCOLA TÈCNICA SUPERIOR D'ENGINYERIA

A Complex Network Analysis of the 2011 UCL Final

Master in Health Data Science — MHEDAS

Subject: Complex Networks
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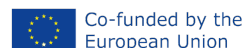


Table of Contents

1. Introduction	1
1.1 Objectives	1
1.2 Scope	2
2. Methodology	2
2.1 Network Construction	2
2.1.1 Data Acquisition and Preprocessing	2
2.1.2 Node and Edge Definitions	3
2.1.3 Temporal Segmentation	3
2.2 Macro and Micro-Level Metrics	8
2.3 Community Detection	8
2.4 Percolation Analysis	8
2.5 Diffusion Analysis	9
3. Results	9
3.1 Macro-Micro Level Comparison	9
3.2 Whatever Community Detection	9
3.3 Player Removal Impact	9
3.4 Efficiency Analysis via Random Walks	9
4. Conclusions	9
References	9

1. Introduction

The UEFA Champions League Final held on May 28, 2011, at Wembley Stadium is frequently cited as one of the most significant matches in modern football history. The game saw Pep Guardiola's FC Barcelona defeat Sir Alex Ferguson's Manchester United 3-1, but the scoreline only partially captures the nature of the event. It represented the culmination of the *Juego de Posición* a.k.a. *Tiki-Taka* philosophy, characterized by high passing frequency, fluid movement, and the tactical innovation of the *False 9*.

In my time as a manager, I would say they're the best team we've faced. Everyone acknowledges that and I accept that. It's not easy when you've been well beaten like that to think another way. No one has given us a hiding like that.

— **Sir Alex Ferguson**, Post-match press conference [1]

Traditionally, football analysis has relied on aggregate statistics such as possession percentage, shots on target, or total passes. However, these metrics often fail to capture the structural complexity and the relational dynamics of a team. Football is inherently a system of interactions; a team can be modeled as a complex network where players are nodes and passes represent the edges linking them. This project applies Network Science to deconstruct the 2011 Final. By visualizing and analyzing the passing networks of both teams, we aim to uncover the underlying topology that allowed Barcelona to dismantle Manchester United's defensive structure.

1.1 Objectives

The main goal of this project is to perform a comparative network analysis of FC Barcelona and Manchester United during the 2011 Champions League Final. To achieve this, we have established the following specific objectives:

- **Network metrics comparison:** Calculate and compare key network metrics (e.g., degree centrality, betweenness centrality, clustering coefficient) for both teams to identify structural differences in their passing networks. We aim to quantify the robustness of Barcelona's connectivity compared to the rigidity of United's structure.
- **Community structure analysis:** Analyze the community structures within each team's passing network to identify clusters of players who frequently interact. We expect Barcelona's network to exhibit more cohesive subgroups, reflecting their fluid positional play.
- **Role analysis:** Investigate the importance of individual players within the network by removing them and observing the impact on overall network connectivity and performance. Key players such as Messi, Pedro, and Busquets for Barcelona, and Rooney and Giggs for Manchester United will be the focus of this analysis.
- **Game build-up analysis:** Examine how effectively each team built up play from defense to attack through their passing networks using Random Walks.

1.2 Scope

The scope of this analysis is defined by the following boundaries and constraints:

- **Temporal scope:** The analysis is strictly limited to the passing events that occurred during the regulation 90 minutes of the 2011 UEFA Champions League Final. Stoppage time is included, but historical season averages or post-match data are excluded.
- **Data representation:** The network is constructed solely from successful passing data. Off-the-ball movements, defensive actions (tackles, interceptions), and dribbles are not explicitly modeled as network edges.
- **Dynamic limitations:** While player positions may be visualized using average spatial coordinates to provide context, the core analysis focuses on topological metrics (graph properties) rather than spatial metrics.

2. Methodology

In this section, we detail the process followed to construct and analyze the passing networks of FC Barcelona and Manchester United during the 2011 UEFA Champions League Final.

2.1 Network Construction

Next, we will describe the steps taken to generate the passing networks.

2.1.1 Data Acquisition and Preprocessing

To construct the passing networks, we utilized event data obtained via the statsbombpy Python library [2], which interfaces with the StatsBomb Open Data API. We filtered the competition dataset for the 2010/2011 UEFA Champions League season to isolate the final match between FC Barcelona and Manchester United. The complete data acquisition and cleaning pipeline is illustrated in **Figure 2.1**.

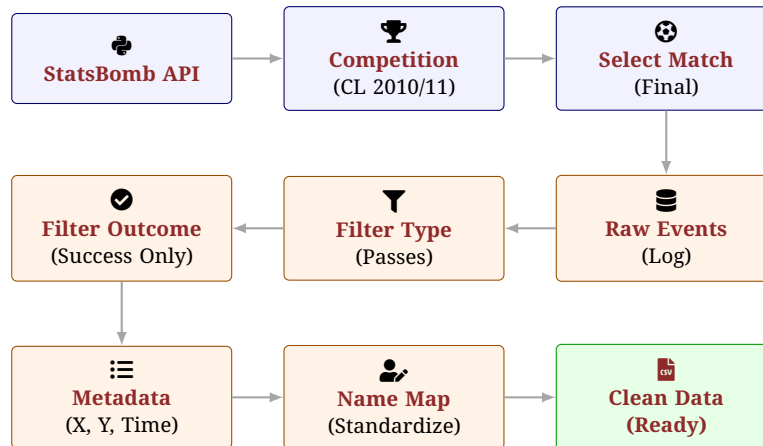


Figure 2.1: Data acquisition and preprocessing pipeline.

The extracted event log provides details for every ball action. For our analysis, we specifically filtered for events categorized as *Pass* where the `pass_outcome` attribute was null,

indicating a successful completion. Each pass event includes crucial metadata used in the network generation: the identity of the passer and receiver, the timestamp (minute), and the (x, y) coordinates of the pass origin.

Prior to network generation, player names were standardized using a mapping dictionary (e.g., converting Lionel Andrés Messi Cuccittini to Messi) to ensure consistency and readability in the final visualizations.

2.1.2 Node and Edge Definitions

The generated network is a directed, weighted graph $G = (V, E)$ where V represents the set of players and E the set of directed edges weighted by pass frequency. Specifically:

- **Node Positioning:** The spatial position of each node was determined by calculating the centroid (mean x, y coordinates) of all successful passes initiated by that player during the observed time window.
- **Node Size:** Node markers were scaled proportionally to the player's total pass volume.
- **Edge Attributes:** Edges were weighted by frequency. To enhance visual clarity, edge width and opacity were dynamically scaled based on the number of passes exchanged, ensuring that primary passing channels are distinct from occasional interactions.
- **Edge Coloring:** We implemented a categorical color scheme to highlight specific pass types extracted from the API metadata: red for crosses, cyan for switches of play, light green for through balls, and yellow for standard passes.

The formula used in Edge Attributes can be expressed as:

$$\text{Edge Width} = 0.5 + \frac{\text{Number of Passes}}{6} \quad (2.1)$$

So, basically, what it means is that for every 6 passes between two players, the edge width increases by 1 unit, starting from a minimum width of 0.5 units.

2.1.3 Temporal Segmentation

To capture the evolving tactical dynamics of the match, we initially segmented the game into distinct temporal windows based on substitution events. Substitutions can significantly alter team structure, and analyzing these segments individually allows us to observe how each team's passing patterns evolved throughout the match.

For FC Barcelona (**Figure 2.2**), we generated four temporal networks: the first half (0'–45'), the second half before substitutions (45'–86'), the period after the first two substitutions introducing Keita and Puyol (86'–92'), and the final segment after Afellay's introduction (92'–94'). Note that Keita and Puyol's substitutions were combined into a single segment because the game was paused for an extended period due to a tackle on Busquets requiring medical attention. Since minimal active play occurred between these substitutions, analyzing them separately would not provide meaningful tactical insights.

FC Barcelona Passing Networks

Data provided by StatsBomb (<https://statsbomb.com>)

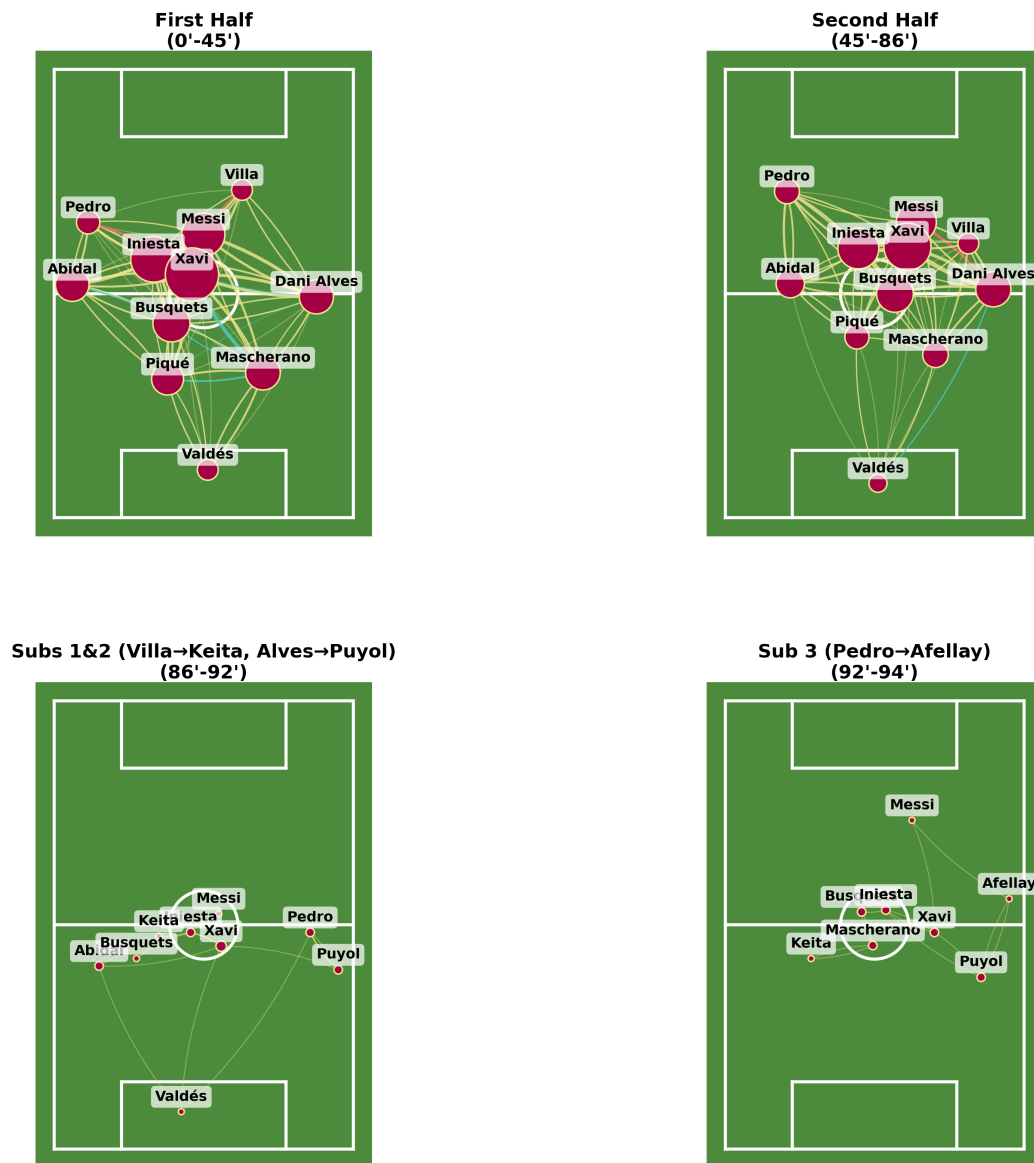


Figure 2.2: FC Barcelona passing networks across different match segments.

For Manchester United (**Figure 2.3**), we also created four temporal networks: the first half (0'–45'), the second half before substitutions (45'–69'), the period after Nani's introduction (69'–77'), and the final segment after Scholes' introduction (77'–94').

While temporal segmentation reveals the evolution of passing patterns, it also presents analytical challenges. For FC Barcelona, the late substitution windows contain sparse data due to defensive tactics in the final minutes. For Manchester United, the shorter temporal segments result in insufficient edge density to reliably identify structural patterns—each individual window captures too few passing interactions to reveal meaningful tactical tendencies.

Manchester United Passing Networks

Data provided by StatsBomb (<https://statsbomb.com>)

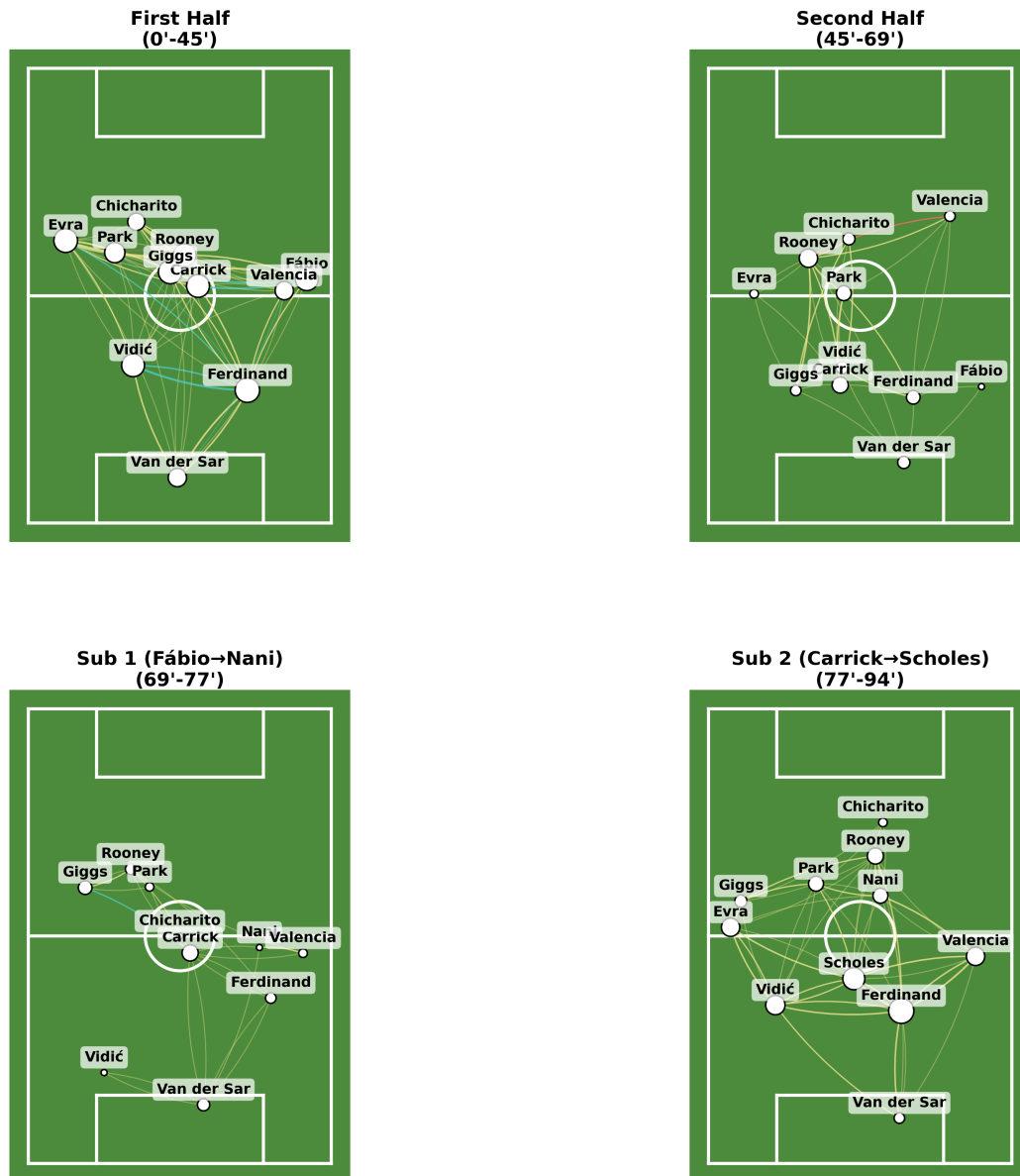


Figure 2.3: Manchester United passing networks across different match segments.

To address these limitations and obtain a more comprehensive view of each team's passing behavior, we constructed full match networks (0'-94') that aggregate all passing interactions across the entire game. Importantly, these networks include all players who participated, with substitutes appearing as separate nodes rather than merging their contributions with the players they replaced. This approach provides several advantages: it maintains the complete picture of each team's squad utilization, preserves the individual contributions of substitute players, and generates sufficient data density for robust network analysis.

Figure 2.4 and **Figure 2.5** display the final networks that will be used for our analyses in the subsequent sections.

FC Barcelona Passing Network

Data provided by StatsBomb (<https://statsbomb.com>)

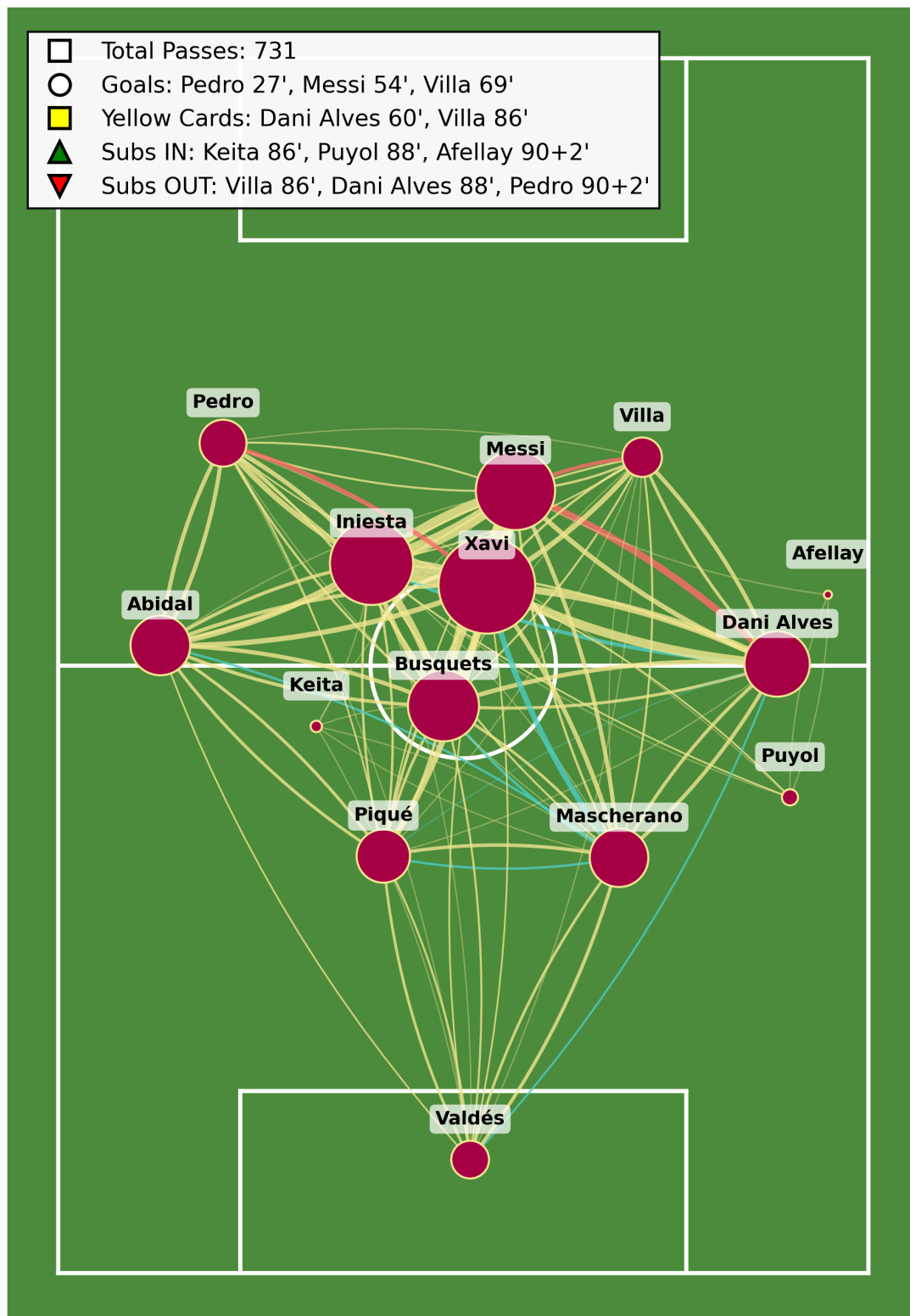


Figure 2.4: FC Barcelona full match passing network with all players.

Manchester United Passing Network

Data provided by StatsBomb (<https://statsbomb.com>)

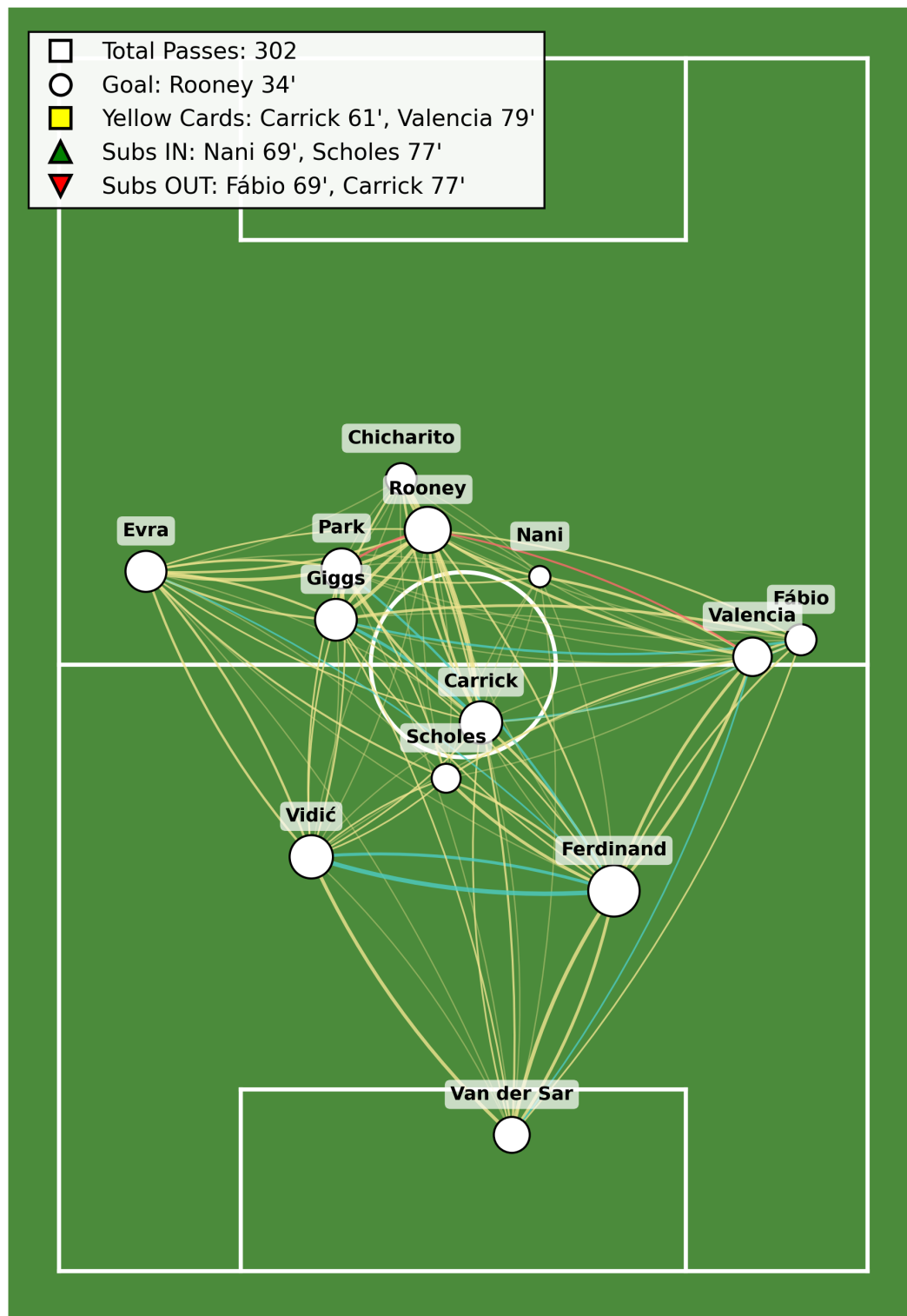


Figure 2.5: Manchester United full match passing network with all players.

2.2 Macro and Micro-Level Metrics

For the network analysis, we computed a suite of macro-level (global) and micro-level (node-specific) metrics to quantitatively characterize the passing networks of both teams. In this section, we will shortly describe the metrics calculated and their relation to football tactics.

At the macro-level, we calculated the following metrics:

- **Average Degree:** Measures the average number of connections (passes) per player. A higher average degree indicates a more interconnected team.
- **Maximum and Minimum Degree:** Identifies the most and least connected players, highlighting key playmakers and isolated individuals within the team structure.
- **Average Clustering Coefficient:** Quantifies the tendency of players to form tightly-knit groups. A higher clustering coefficient suggests effective short-passing combinations and local support networks.
- **Assortativity:** Assesses the preference of players to connect with others of similar connectivity. Positive assortativity indicates that well-connected players tend to pass among themselves, while negative assortativity suggests a more hierarchical structure.
- **Average Shortest Path Length:** Reflects the efficiency of ball movement across the team. A shorter average path length indicates that players can reach each other through fewer passes, facilitating quick transitions.
- **Network Diameter:** Represents the longest shortest path between any two players. A smaller diameter indicates a compact team structure, enhancing overall cohesion.

At the micro-level, we focused on the following node-specific metrics:

- **Degree Centrality:** Measures the number of direct connections (passes) a player has. High degree centrality indicates a player who is heavily involved in the team's passing network.
- **Betweenness Centrality:** Quantifies the extent to which a player lies on the shortest paths between other players. Players with high betweenness centrality often act as crucial intermediaries in ball distribution.
- **Eigenvector Centrality:** Evaluates a player's influence based on the connectivity of their neighbors. Players connected to other well-connected players will have higher eigenvector centrality, indicating their strategic importance.

2.3 Community Detection

Sofia

2.4 Percolation Analysis

Teferi

2.5 Diffusion Analysis

Rahul

3. Results

3.1 Macro-Micro Level Comparison

Rahul

3.2 Whatever Community Detection

Sofia

3.3 Player Removal Impact

Teferi

3.4 Efficiency Analysis via Random Walks

Rahul

4. Conclusions

Everyone

References

- [1] D. Fifield, “Sir Alex Ferguson: No one has given United a hiding like Barcelona did,” *The Guardian*, May 2011. Accessed: 2025-12-23.
- [2] StatsBomb, “statsbombpy: A Python package to easily stream StatsBomb data.” <https://github.com/statsbomb/statsbombpy>, 2025. Maintained by Hudl. Accessed: 2025-12-23.