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Passing Network Analysis of the 2011 UCL Final

Master in Health Data Science — MHEDAS

Subject: Complex Networks

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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. Pep Guardiola's FC Barcelona defeated 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]*

1.1 Goals

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 FC Barcelona to dominate Manchester United's defensive structure.

1.2 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 establish 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 FC Barcelona's connectivity compared to Manchester 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 FC Barcelona's network to exhibit more cohesive subgroups.
- **Role analysis:** Investigate the importance of individual players within the network by removing them and observing the impact on overall network connectivity and performance. Specifically, we aim to quantify the loss in the passing network when different players are removed.
- **Game build-up analysis:** Examine how effectively each team builds up play from defense to attack through their passing networks.

1.3 Scope

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

- **Data limitation:** The analysis is limited to this match only, no external data is considered which could provide additional context or comparative data.
- **Data representation:** The main 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 or attributes.
- **Dynamic limitations:** While player positions may be visualized using average spatial coordinates to provide context, the core analysis focuses only on topological metrics (graph properties).

2. Methodology

In this section, we outline the methodology employed to construct and analyze the passing networks of FC Barcelona and Manchester United.

2.1 Network Construction

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**.

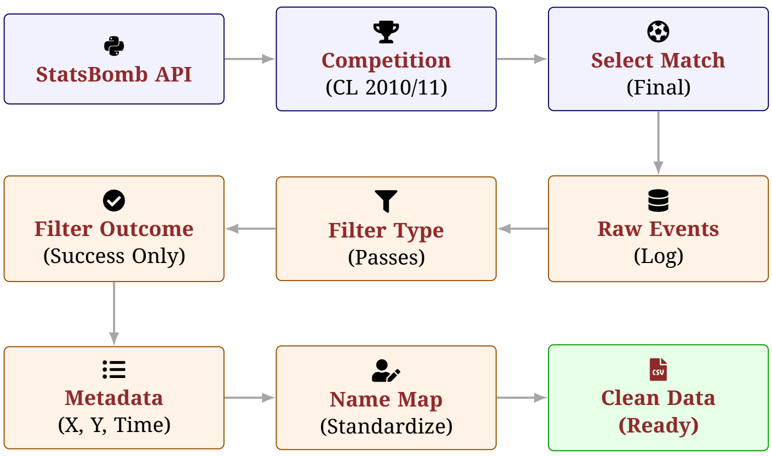

Figure 2.1: Data acquisition and preprocessing pipeline.

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.

2.1.2 Node and Edge Definitions

The generated network is a directed, weighted graph $G = (V, E)$ where V represents the set of the top 11 players by completed pass count for each team, and E the set of edges weighted by pass frequency. Specifically:

- **Node Selection:** For each team, the 11 players with the highest number of completed passes were selected to ensure a fair comparison between teams and to focus on the primary contributors to each team's passing network.
- **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, with the zoom factor calculated as:

$$\text{Zoom} = 0.18 + \frac{\text{Pass Count}}{200} \tag{2.1}$$

- **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, with the edge width calculated as:

$$\text{Edge Width} = 0.5 + \frac{\text{Number of Passes}}{6} \tag{2.2}$$

  This means that for every 6 passes between two players, the edge width increases by 1 unit, starting from a minimum width of 0.5 units. Edge opacity was set to 0.4 for connections with fewer than 2 passes and 0.8 otherwise.

In the beginning we considered temporal segmentation to capture the evolution of passing patterns, but it also presented analytical challenges. On the one hand, for FC Barcelona, the late substitution windows contained sparse data due to a more defensive mindset to conserve the lead in the final minutes. On the other hand, for Manchester United, the shorter temporal segments resulted in insufficient edge density to identify structural patterns.

To address these limitations and obtain a more comprehensive view of each team's passing behavior, we constructed full match networks (0'–94') that aggregated all passing interactions across the entire game. These networks included all players who participated, with substitutes appearing as separate nodes rather than merging their contributions with the players they replaced. This approach provided several advantages: it maintained the complete picture of each team's squad, preserved the individual contributions of substitute players, and generated sufficient data density for network analysis.

Figure 2.2 and **Figure 2.3** display the final networks that were used for our analyses. Note that depending on the specific analysis, we added or removed attributes from the edges, but the baseline network structure remained as shown. To enhance visualizations, we utilized player headshots from Transfermarkt [3] as node icons.

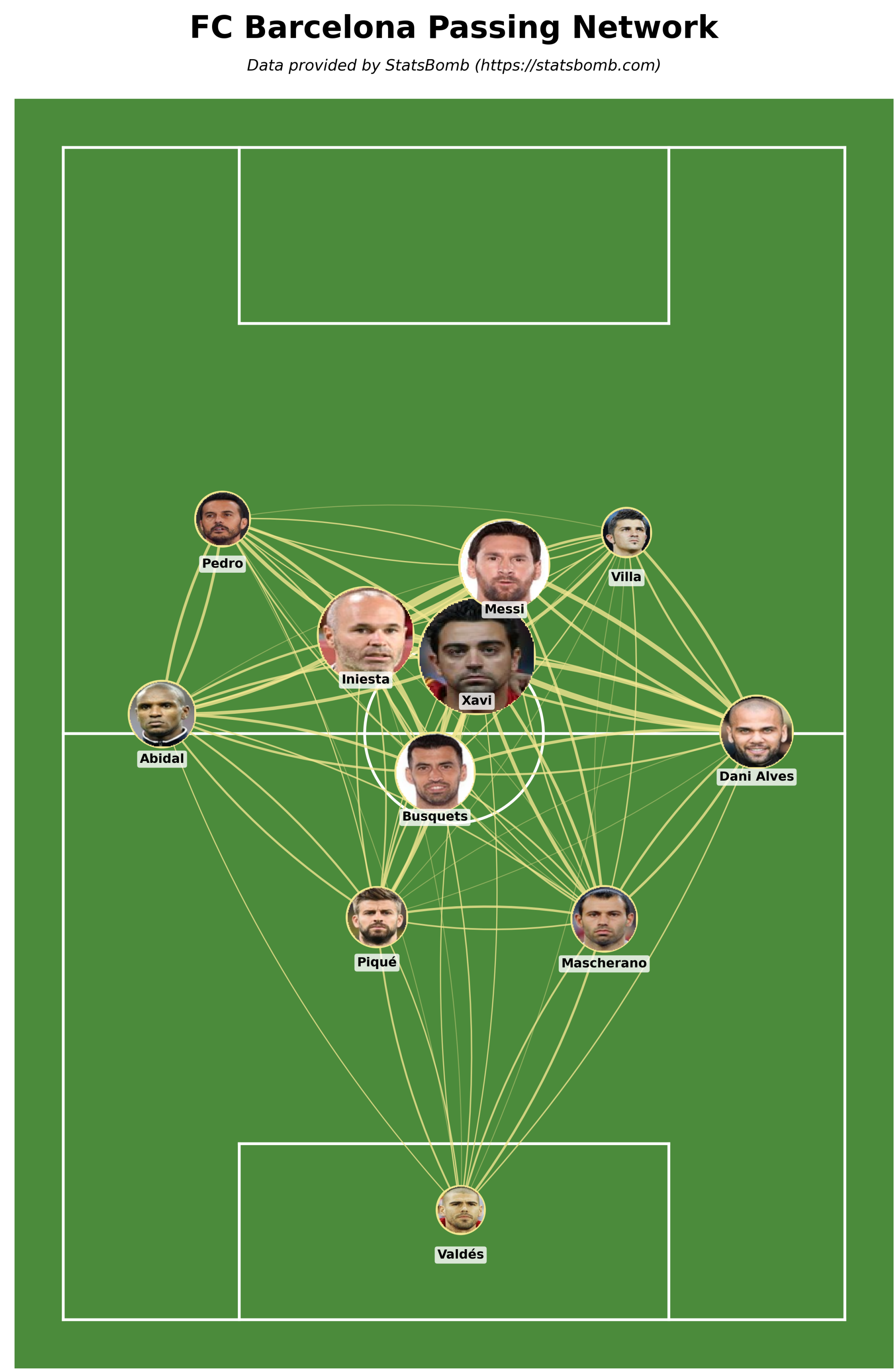

Figure 2.2: FC Barcelona full match passing network.

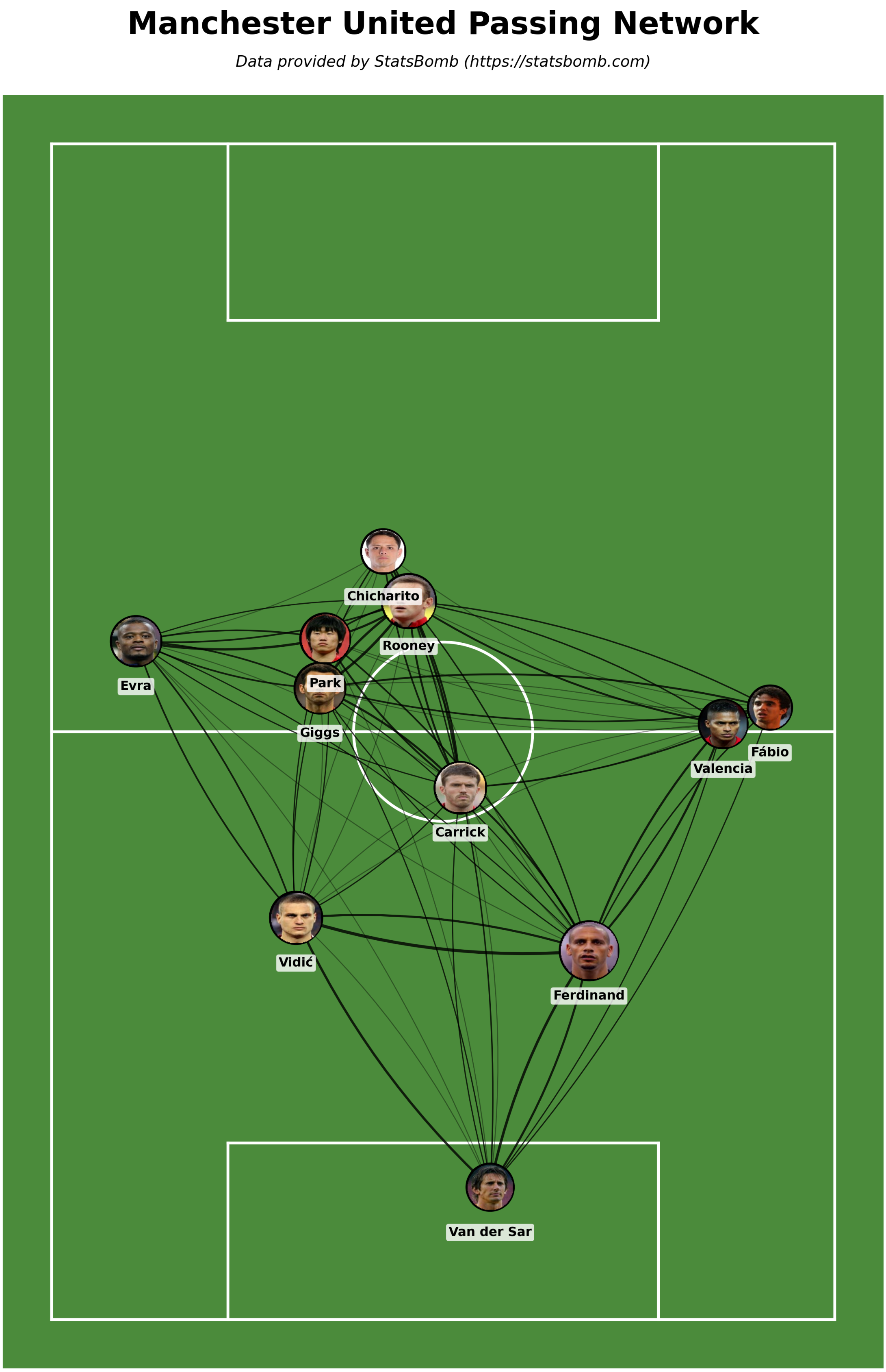

Figure 2.3: Manchester United full match passing network.

2.2 Macro and Micro-Level Metrics

We computed macro-level (global) and micro-level (node-specific) metrics to quantitatively characterize the passing networks of both teams. The network was constructed as a directed weighted graph, where edges represented passes from sender to receiver and weights (w_{ij}) indicated pass frequency. To accurately model the efficiency of ball circulation for path-based metrics (Shortest Path and Betweenness), we defined the distance or cost of an edge as the inverse of its frequency, $d_{ij} = 1/w_{ij}$.

At the macro-level, we calculated:

- **Average Degree:** Measures the average level of player involvement in the game. A higher value indicates a team that dominates possession through a high volume of passes, rather than relying on individual runs or direct play.
- **Average Clustering Coefficient:** Quantifies the tendency of players to form passing triangles. A higher value indicates a style relying on tight, short combinations and triangular structures, whereas lower values suggest a more linear or direct playstyle.
- **Assortativity:** Assesses whether high-volume passers tend to connect with other high-volume passers. A positive value implies that key players pass primarily among themselves, while a negative value indicates a hierarchical structure where playmakers distribute the ball to less central players.
- **Average Shortest Path Length:** Reflects the efficiency and speed of ball circulation across the team. A lower value indicates less resistance in the network, implying that the ball can move between any two players rapidly through frequently used passing lanes.

At the micro-level, we computed:

- **Degree Centrality:** Measures the number of unique teammates a player connects with relative to the team size. High values highlight players who act as broad distributors, linking with a wide variety of teammates across the pitch rather than focusing on a single partner.
- **Betweenness Centrality:** Identifies players who act as bridges along the most efficient passing routes. High values indicate players who are critical for transition, connecting otherwise disconnected areas of the field (e.g., linking defense to attack).
- **Eigenvector Centrality:** Measures a player's influence based on the importance of the teammates they connect with. High values identify players who are key in the overall network structure, frequently exchanging the ball with other influential playmakers.

2.3 Community Detection

Community detection in network analysis aims to identify groups of nodes that are more densely connected to each other than to the rest of the network. In the context of football passing networks, communities represented groups of players who frequently exchanged passes among themselves, forming tactical units within the team's overall structure.

These communities often correspond to positional groups (defenders, midfielders, forwards) or functional units that execute specific tactical roles during the match. Note that we were interested in the general flow of passing connections rather than the specific directionality of in-flow and out-flow between players. Therefore, we converted the original directed network into an undirected network $G_u = (V, E_u)$ by summing the weights of bidirectional edges. Specifically, for any pair of players u and v, if there existed edges (u, v) with weight w_{uv} and (v, u) with weight w_{vu} in the directed graph, we created a single undirected edge $\{u, v\}$ with combined weight.

In our analysis, we applied four distinct community detection algorithms. Each algorithm employs a different optimization strategy to partition the network:

- **Louvain Method**: This algorithm maximizes modularity, a measure that quantifies the density of connections within communities compared to connections between communities. The algorithm works hierarchically, first optimizing local modularity by moving individual players between communities, then aggregating communities and repeating the process until no further improvement is possible.
- **Greedy Modularity**: Similar to Louvain, this method also maximizes modularity but follows a different optimization path. This method builds tactical units by identifying pairs and groups of players with the strongest passing connections first, gradually expanding into broader positional clusters.
- **Stochastic Block Model (SBM)**: Rather than maximizing modularity, SBM takes a probabilistic approach by fitting a generative model to the network structure. The algorithm assumes that communities exist and that the probability of a pass between two players depends primarily on which communities they belong to. SBM seeks a model by balancing fit to the observed data against model complexity, identifying communities based on statistical equivalence—players in the same community exhibit similar passing patterns with players in other communities.
- **Infomap**: This algorithm takes an information-theoretic approach, minimizing the description length of random walks on the network. It identifies communities by finding groups where a random walker (representing ball flow) tends to get trapped for extended periods.

Finally, to evaluate and compare the tactical effectiveness of the detected communities, we quantified their performance across multiple dimensions. For each community, we computed passing metrics (total passes, pass success rate, average pass length), offensive contributions (total shots, expected goals, dribble success rate), and defensive actions (duels won, interceptions, clearances).

2.4 Percolation Analysis

Percolation theory has been widely applied in network science for understanding system resilience and robustness. In the context of football, percolation analysis allows us to quantify how a team's passing efficiency degrades as key players are removed.

In this study, we implemented an individual player impact analysis to measure how each player's removal affected the team's overall pass completion rate, a fundamental indicator of possession quality and tactical effectiveness. We began by representing the team's passing structure as a network $G = (V, E)$ where players are nodes (V) and passes are connections between them (E). To establish our baseline, we calculated the team's overall pass completion rate across all attempted passes P during the match:

$$\rho_{\text{baseline}} = \frac{\text{Number of completed passes}}{\text{Total passes attempted}} \tag{2.3}$$

The core of our analysis involved a simple thought experiment: what happens to the team's passing accuracy if we remove a specific player v from the network? To answer this, we recalculated the pass completion rate using only the subset of passes P_{-v} where that player was neither giving nor receiving the ball:

$$\rho_{-v} = \frac{\text{Completed passes not involving player } v}{\text{Total passes not involving player } v} \tag{2.4}$$

The difference between these two rates revealed the player's impact. We expressed this as a percentage change:

$$\Delta\rho_v = \frac{\rho_{-v} - \rho_{\text{baseline}}}{\rho_{\text{baseline}}} \times 100\% \tag{2.5}$$

When $\Delta\rho_v$ was negative, it told us the player was crucial, meaning removing them hurt the team's passing efficiency. Positive values, on the other hand, suggested the player was involved in lower-quality passing sequences that brought down the team's average.

To add depth to our understanding of each player's role, we also examined what types of passes they typically made. For every player v, we looked at all the passes they attempted and calculated the proportion of each pass height type:

$$\pi_v^h = \frac{\text{Number of passes by player } v \text{ of height } h}{\text{Total passes by player } v} \tag{2.6}$$

where h represents ground passes, low passes, or high passes. This breakdown helped us understand whether a player's impact came from their involvement in short, ground-level combinations, aerial battles, or long-range distribution across the pitch.

2.5 Diffusion Analysis

Diffusion analysis in complex networks studies how information, influence, or resources propagate through a networked system over time. In the context of football passing networks, diffusion models can be adapted to simulate how possession flows from one player to another, mimicking the ball movement during match play. This is valuable for understanding team dynamics, as it allows us to identify critical players who facilitate ball progression, detect potential bottlenecks in passing sequences, and quantify the probability of successful attacking transitions from defensive to offensive positions.

For our analysis, we employed diffusion simulation to model the ball's journey from the goalkeeper to the striker. This could give us an idea of each team's ability to build attacks through passing sequences. By simulating multiple passing sequences, we evaluated the likelihood of successfully reaching the striker from the goalkeeper, thereby quantifying each team's attacking effectiveness.

Let $G = (V, E)$ represent the directed passing network for a team, where V is the set of players (nodes) and E is the set of directed edges representing passing connections. Each edge $(u, v) \in E$ had the following attributes:

- w_{uv}: the weight representing the number of completed passes from player u to player v
- f_{uv}: the failure rate of passes from u to v, computed as:

$$f_{uv} = 1 - \frac{\text{completed passes from } u \text{ to } v}{\text{total passes from } u \text{ to } v} \tag{2.7}$$

For each simulation run, we initialized the ball at a source player s (goalkeeper) with the objective of reaching a target player t (striker). The simulation proceeded iteratively, tracking the ball's current position at each step i. At each iteration, the next player was selected probabilistically from the current player's available passing options. To avoid cycles and encourage forward progression, we applied a visit penalty that reduced the probability of passing to previously visited players:

$$\tilde{w}_{uv} = w_{uv} \cdot \gamma^{c_v} \tag{2.8}$$

where w_{uv} is the original pass weight, c_v counts how many times player v has already been visited in the current sequence, and $\gamma = 0.3$ is the penalty decay factor. The target player was exempt from this penalty to allow the sequence to terminate successfully.

Thus, the probability of selecting player v as the next recipient was then computed as:

$$P(v) = \frac{\tilde{w}_{uv}}{\sum_{\text{all neighbors}} \tilde{w}_{uk}} \tag{2.9}$$

Once a player was selected, the pass success was determined based on the failure rate f_{uv}. The pass succeeded if $f_{uv} < 0.5$, otherwise the simulation terminated.

If the pass succeeded, the ball moved to player v, and the iteration continued. The simulation terminated under one of the following conditions:

- **Success**: The ball reaches the target player t.
- **Pass failed**: A pass from p_i to p_{i+1} fails based on the failure rate threshold.
- **Dead end**: The current player has no available successors in the network.
- **Max passes reached**: The number of passes exceeds a predefined limit (25).

3. Results

In the following sections, we report the findings from our analysis of the passing networks of FC Barcelona and Manchester United.

3.1 Macro-Level Network Comparison

FC Barcelona completed 716 passes among their top 11 players, forming 91 unique passing connections, while Manchester United completed 256 passes with 80 unique connections. This represented almost three times as many passes for FC Barcelona compared to Manchester United. This first observation highlighted a significant difference in play-styles between the two teams. FC Barcelona relied heavily on maintaining possession through frequent passing, while Manchester United's lower passing volume suggested a more direct approach to advancing the ball. **Table 3.1** presents key macro-level network metrics for both teams.

Table 3.1: Key macro-level network metrics for FC Barcelona and Manchester United.

Metric	FC Barcelona	Manchester United
Avg. Degree	130.18	46.55
Max. Degree	280	71
Player with Max. Degree	Xavi	Rooney
Min. Degree	35	27
Player with Min. Degree	Valdés	Chicharito
Average Clustering Coefficient	0.170	0.216
Assortativity	-0.151	-0.185
Average Shortest Path Length	0.163	0.367

Barcelona exhibited a significantly higher average degree (130.18) compared to Manchester United (46.55), indicating that Barcelona players had substantially more passing interactions on average. The maximum degree was observed for Xavi (280) in Barcelona's network, while Rooney had the highest degree (71) for Manchester United (less than a third of Xavi's passing volume). Barcelona's most connected player was a central midfielder, which aligned with their tactical philosophy of building play through the middle of the pitch, whereas Manchester United's top passer being a forward rather than a midfielder suggested potential struggles in midfield control. However, over the years Rooney had often been deployed in a deeper playmaking role, especially when the team was under pressure. The minimum degree players were Valdés (35) for Barcelona and Chicharito (27) for Manchester United, which was expected given their respective positions as goalkeeper and striker.

Manchester United exhibited a slightly higher clustering coefficient (0.216) compared to Barcelona (0.170). The fact that United had a higher clustering coefficient could have two readings: either it indicated superior tactical organization through coordinated passing triangles, or it revealed the constraints of playing under pressure. Given the context of the match, and under Barcelona's intense pressing, United were forced into localized passing triangles with nearby teammates within confined areas of the pitch. In contrast, Barcelona's lower clustering indicated a more distributed passing network where the ball circulated freely across the entire team, consistent with their approach of stretching the opposition and utilizing the full width and depth of the pitch through constant movement and rotation.

Both networks exhibited negative assortativity, with Barcelona at -0.151 and Manchester United at -0.185, indicating that highly connected players (hubs) tended to pass to less connected players in both teams. This pattern was typical of hierarchical structures in football networks, where central playmakers distributed the ball to various teammates across different positions. The average shortest path length revealed a big contrast between the two teams: Barcelona (0.163) versus Manchester United (0.367). Barcelona's lower value meant the ball could reach any player through fewer intermediate passes, while Manchester United's higher value indicated that connecting any two players required more passing steps on average, pointing to potential bottlenecks in their transitions.

To better understand the tactical differences, we examined micro-level metrics that analyzed individual player roles and their influence within the passing networks. **Figure 3.1** presents scatter plots comparing individual player centrality metrics for both teams. The left plot shows the relationship between degree centrality and eigenvector centrality, while the plot on the right compares degree centrality versus betweenness centrality.

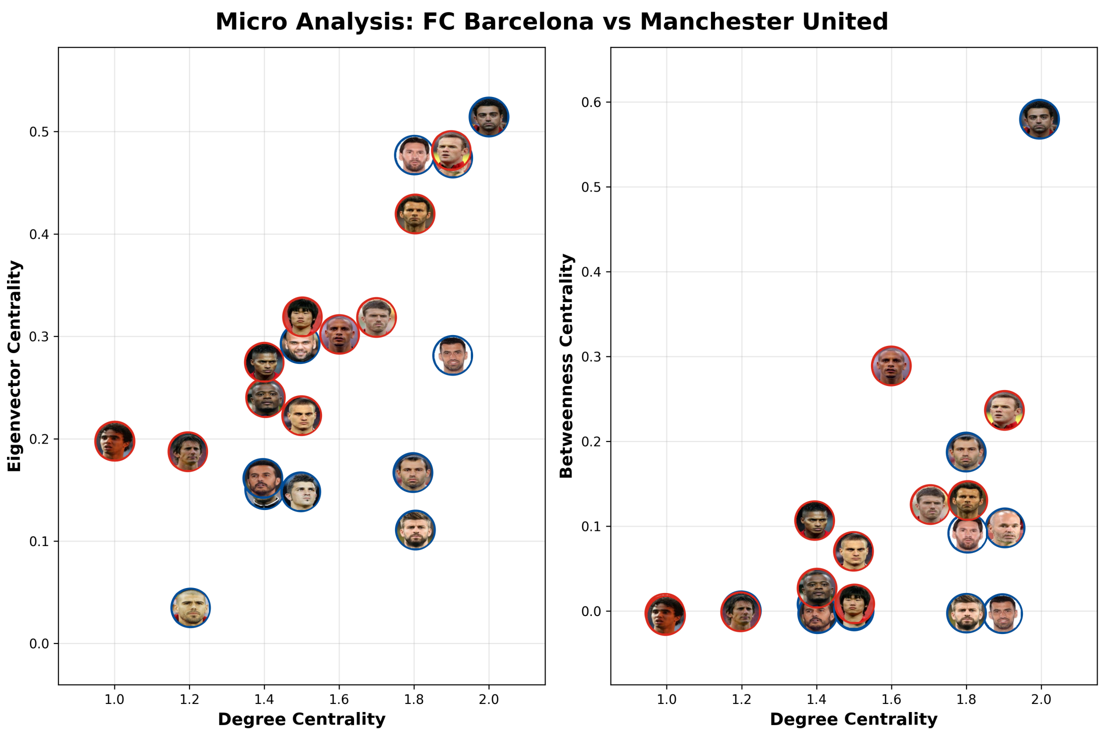

Figure 3.1: Player centrality analysis comparing FC Barcelona and Manchester United. Blue borders indicate FC Barcelona players, red borders indicate Manchester United players.

The plot on the left revealed FC Barcelona players (blue borders) clustered in the upper-right region, particularly Xavi (degree: 2.0, eigenvector: 0.51), Iniesta (1.9, 0.48), and

Messi (1.8, 0.48), who exhibited both high degree centrality and high eigenvector centrality. These players not only made numerous passes but were also connected to other highly active players, forming the core of Barcelona's passing engine. Busquets (1.9, 0.28), often underappreciated in traditional analyses, showed high degree centrality but moderate eigenvector centrality, suggesting he was highly active but connected to a more diverse set of players rather than exclusively to the team's most central figures. This allowed Barcelona to build up play from deeper positions, linking defense to attack effectively. Manchester United players (red borders) were more dispersed and generally occupied lower positions on both axes, with Rooney (1.9, 0.48) and Giggs (1.8, 0.42) being the notable exceptions.

The plot on the right revealed Xavi's dominance in the midfield with the highest betweenness centrality (0.58) among all players, significantly outpacing any Manchester United player. More revealing was Ferdinand's betweenness centrality (0.29), the highest among Manchester United players despite being a center-back. This indicated Ferdinand was crucial in linking play from defense to midfield, essentially acting as United's main distribution point. On the other hand, Giggs, who as a midfielder would be expected to link different areas of the pitch, showed relatively low betweenness (0.13), suggesting he operated more as an endpoint in passing sequences rather than as a transitional hub. The fact that a center-back had the highest betweenness centrality meant that United's midfielders were being bypassed in the build-up rather than serving as the central connectors. Likely, with long balls as we will see later.

3.2 Louvain Community Detection

After applying the various community detection algorithms described in the Methodology section, we ultimately selected the Louvain method for our primary analysis. The reason for this choice stemmed from the interpretability and tactical relevance of the communities it identified within both teams' passing networks. The visualization for the other methods can be found in the Annexes.

In **Figure 3.2** and **Figure 3.3**, we present the Louvain community structures for FC Barcelona and Manchester United, respectively. For FC Barcelona, three communities were identified: Community 1 included the right flank duo of Pedro and Abidal; Community 2 made up the central core with Xavi, Iniesta, Busquets, Messi, Villa, and Dani Alves; and Community 3 was the defensive unit of Piqué, Mascherano, and Valdés. Manchester United also showed three communities: Community 1 consisted of the central defensive unit including Van der Sar, Ferdinand, and Vidić; Community 2 comprised the wide defensive pairing of Park and Evra; while Community 3 included the remaining block of Valencia, Fábio, Giggs, Carrick, Rooney, and Chicharito.

From a qualitative tactical interpretation, Barcelona's communities represented a well-organized possession setup built around control of the central areas while maintaining defensive balance. The main central group (Xavi, Iniesta, Busquets, Messi, Villa, and Dani Alves) showed how the team functioned more as a connected unit than as a fixed 4-3-3. Alves

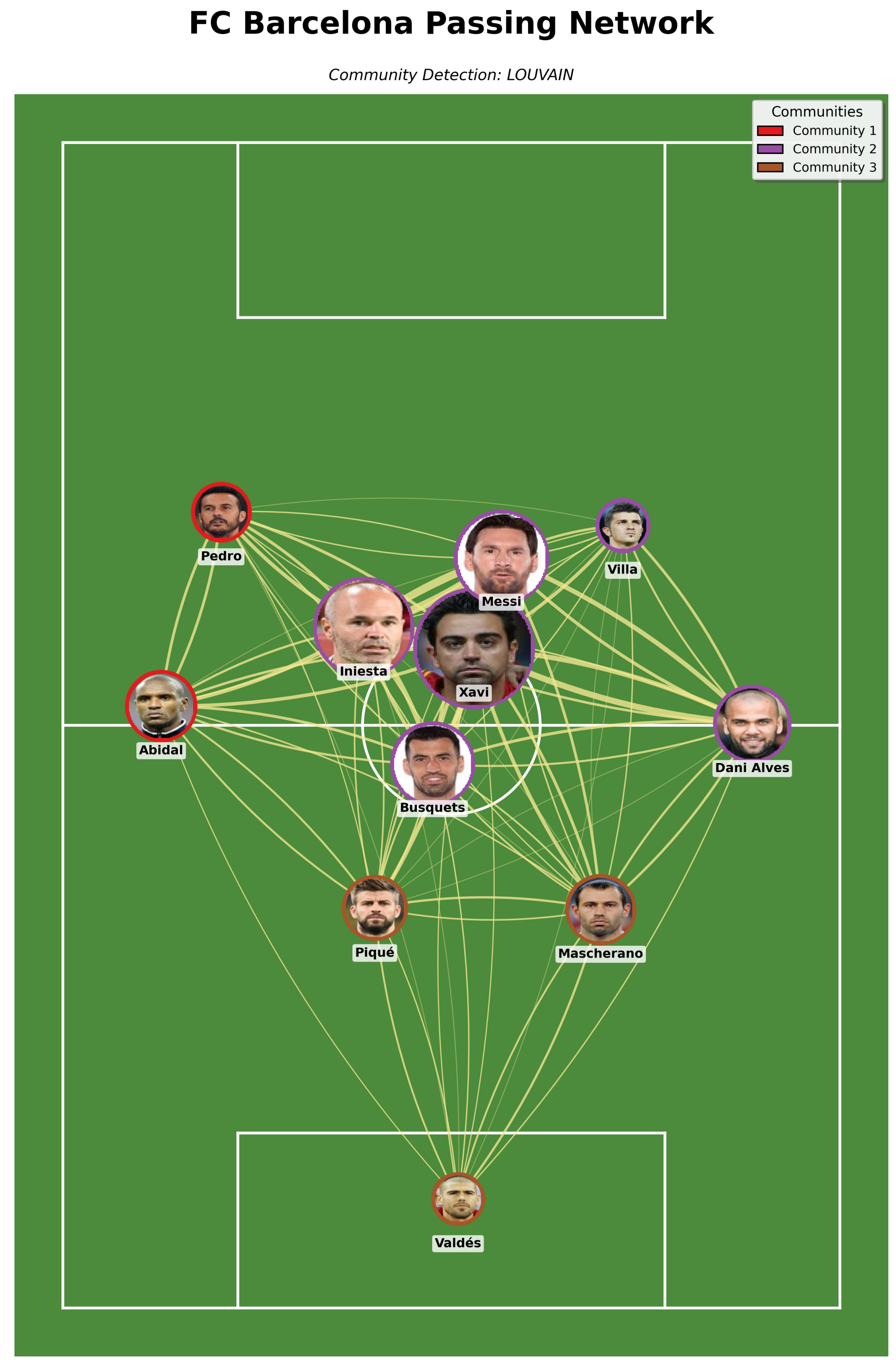

Figure 3.2: Louvain community detection for FC Barcelona's passing network.

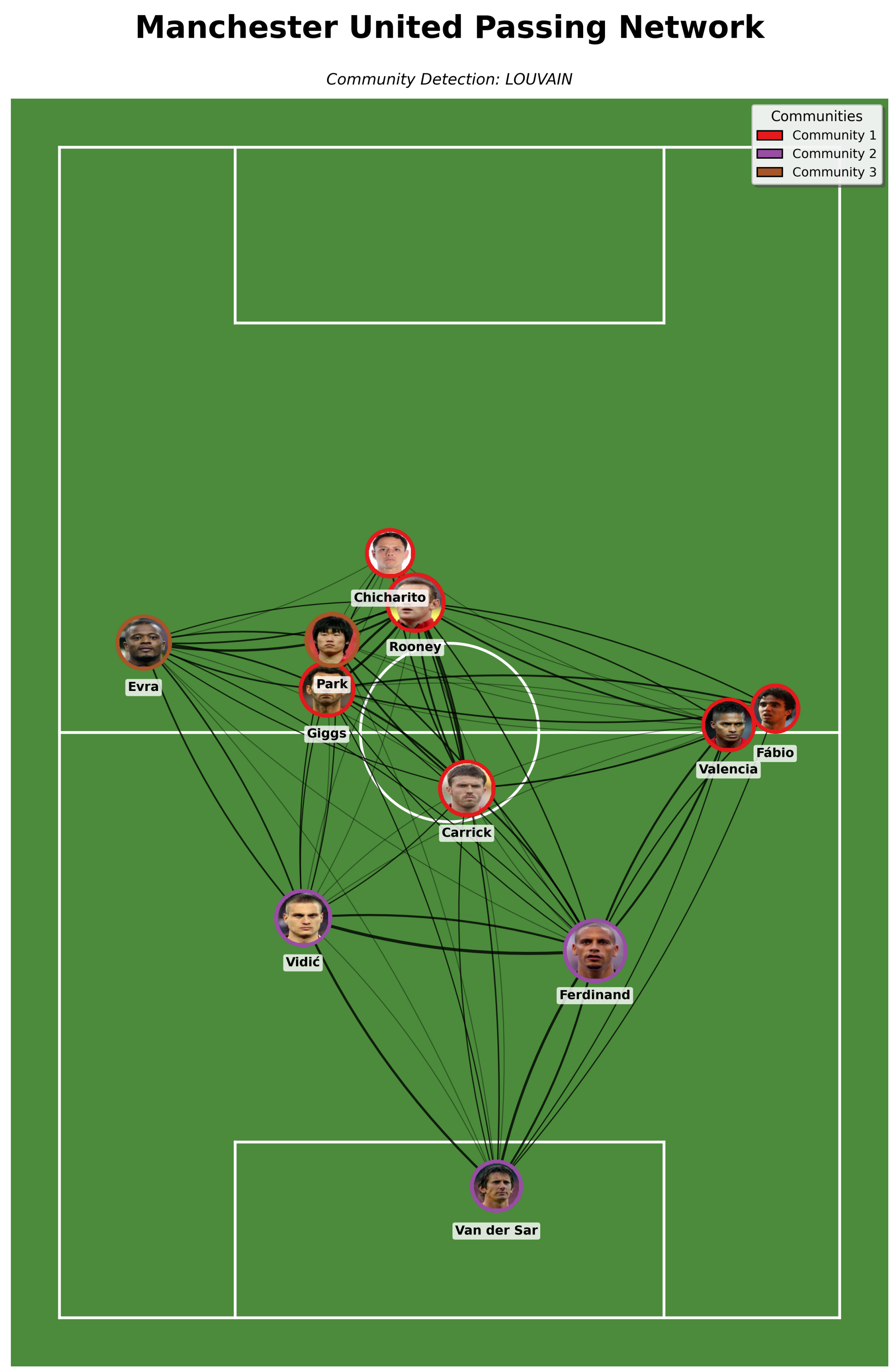

Figure 3.3: Louvain community detection for Manchester United's passing network.

constantly pushed higher, often working almost as an extra midfielder on the right side, while Abidal stayed deeper on the left, forming a back three with Piqué and Mascherano whenever Barcelona had the ball. Messi, as a false nine, frequently dropped into midfield to receive, combine, and pull United's centre-backs out of position, opening spaces for teammates to attack. Also, note how Pedro and Abidal formed their own small community on the left flank. This showed one aspect that was always valued from Pedro which was his defensive work rate to support Abidal, while also making constant forward runs to stretch play. In contrast, Villa acted more like a true striker, keeping a central position and staying near the defenders to fix their line and maintain depth.

Conversely, Manchester United's three-community division reflected a fragmented setup. The defensive responsibility was split between a central block and a specific left-sided unit. The central defensive unit (Van der Sar, Ferdinand, Vidić) focused on protecting the goal and clearing lines, operating somewhat independently. The wide defensive pairing (Park and Evra) formed a distinct community on the left, highlighting their intensive workload in containing Barcelona's right-sided attacks. The third community, comprising Valencia, Fábio, Giggs, Carrick, Rooney, and Chicharito, functioned as a mixed unit covering the right flank and the central channels. This larger group suggested that while the left side (Park/Evra) was isolated to deal with pressure, the right side (Valencia/Fábio) remained more connected to the midfield and forward lines (Rooney/Chicharito) for counter-attacking transitions.

From a quantitative perspective, **Table 3.2** presents detailed statistics for each of the identified communities.

			Passing			Attack				Defense				
Team	**Com**	**N**	**Tot**	**%**	**Len**	**Sh**	**xG**	**Dr**	**%**	**Dl**	**%**	**Int**	**Clr**	**Aer**
FC Barcelona	1	2	102	87.3	15.6	2	0.40	2	0.0	6	16.7	0	0	0
	2	6	569	90.7	15.8	19	1.53	27	81.5	9	11.1	3	1	0
	3	3	146	81.5	25.2	0	0.00	0	0.0	10	10.0	3	4	0
Man. Utd.	1	3	119	75.6	33.9	0	0.00	0	0.0	3	33.3	3	6	1
	2	2	66	77.3	14.6	0	0.00	2	50.0	10	20.0	6	3	0
	3	6	185	76.2	21.5	3	0.26	10	50.0	16	0.0	13	2	1

Table 3.2: Community efficiency stats. **Legend:** **N**: No. of Players, **Tot**: Total Passes, **%**: Success Rate, **Len**: Avg Length (m), **Sh**: Shots, **xG**: Expected Goals (computed by StatsBomb), **Dr**: Dribbles, **Dl**: Duels, **Int**: Interceptions, **Clr**: Clearances, **Aer**: Aerial Clearances. **Community Definitions: FC Barcelona**: (1) Pedro, Abidal; (2) Xavi, Iniesta, Busquets, Messi, Villa, Dani Alves; (3) Piqué, Mascherano, Valdés. **Man. Utd.**: (1) Van der Sar, Ferdinand, Vidić; (2) Park, Evra; (3) Valencia, Fábio, Giggs, Carrick, Rooney, Chicharito.

From a passing perspective, Barcelona's central community (Community 2) had the highest passing success rate (90.7%) and the greatest total passes (569), highlighting their dominance in ball circulation. In contrast, Manchester United's main group (Community 3) had a significantly lower passing success rate (76.2%) and far fewer total passes (185). The average pass length revealed a stark contrast within United's defensive setup: the central defensive unit (Community 1) averaged 33.9 meters per pass, indicating a clearance-heavy direct style, while the wide defensive pairing of Park and Evra (Community 2) averaged only 14.6 meters. This incredibly short average length suggests that Park and Evra were often pinned back, exchanging short passes to escape pressure on the flank.

Moving on to the attacking metrics, Barcelona's central community generated 19 shots with an expected goals (xG) value of 1.53, far higher than United's main mixed unit (Community 3) which only managed 3 shots and an xG of 0.26. Also, note how Barcelona's first community (Pedro and Abidal) was also higher in xG (0.40) than United's main attacking group. The separation of Park and Evra into their own community (Community 2) is telling; they recorded zero shots, focusing entirely on defensive duties and ball progression (2 dribbles).

Finally, from a defensive perspective, Barcelona's defensive unit made 10 duels with a 10% success rate. Manchester United's defensive workload was notable in the small Park/Evra community (Community 2), which engaged in 10 duels and made 6 interceptions despite having only 2 players. This confirms the heavy traffic down their side. The central defensive unit (Community 1) recorded the most clearances (6), acting as the last line of defense, while the larger mixed group (Community 3) had high volume in duels (16) and interceptions (13) but zero success rate in duels, suggesting a struggle to win clean possession in midfield areas.

3.3 Player Removal Impact

In **Figure 3.4**, we present the impact of removing each player from their respective team's passing network. The y-axis represents the percentage point change in pass completion rate when a player was removed compared to the baseline of the full network (88.4% for FC Barcelona and 76.5% for Manchester United). Positive values indicate that removing the player increases pass completion, suggesting their passes had lower success rates, while negative values indicate that removing the player decreases pass completion.

On one hand, for FC Barcelona, Xavi's removal caused the most negative impact (−4.88%), primarily through the loss of highly successful ground passes, confirming his role as the team's most reliable passer. Iniesta's removal also showed substantial negative impact (−2.67%). Conversely, Villa's removal had the largest positive impact (+1.23%), which could be attributed to his tendency to work in a zone where passing options were limited. On the other hand, Manchester United displayed a markedly different pattern, with Ferdinand's removal causing the most severe negative impact (−5.07%), followed by Vidić (−2.10%) and Carrick (−2.30%), which reflects their crucial roles in initiating play from the back with reliable, safe distribution. Conversely, Chicharito's removal caused the largest positive impact (+4.10%), followed by Rooney (+3.72%) and Van der Sar (+1.35%). Suggesting riskier attacking transitions with Rooney attempting through balls to Chicharito's runs and Van der Sar launching long passes under Barcelona's high press. Also, note how United players are more keen to long passes compared to Barcelona.

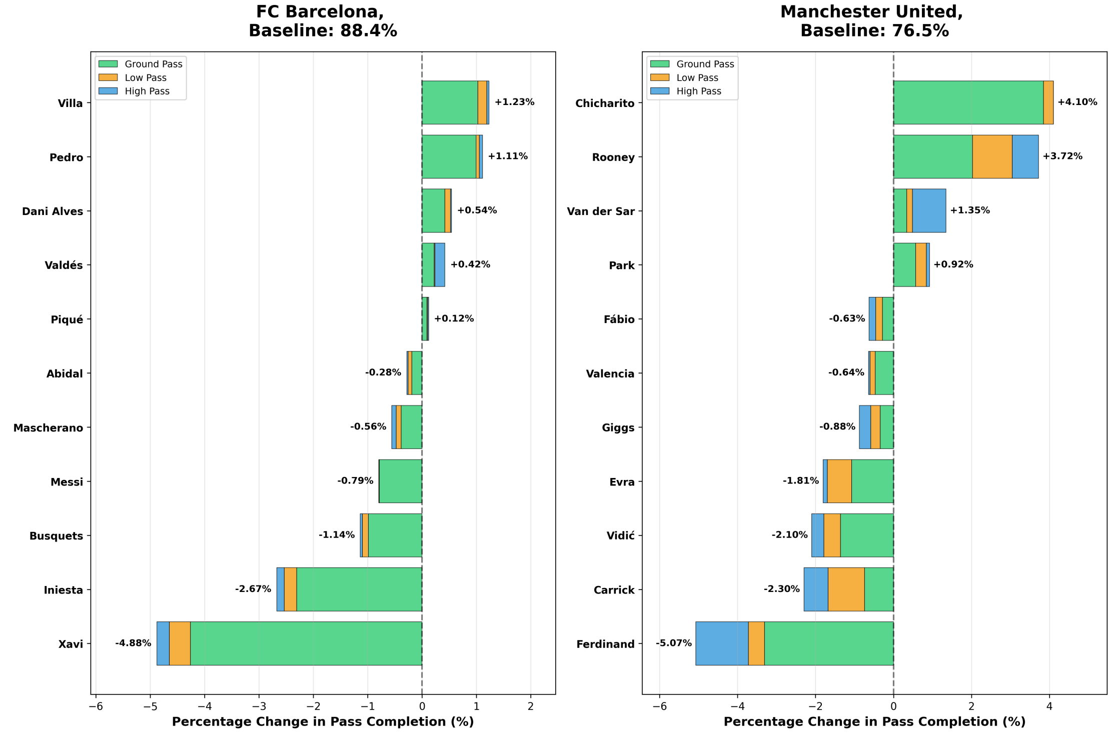

Figure 3.4: Impact of individual player removal on team pass completion rate, decomposed by pass type (ground, low, high).

3.4 Ball Diffusion Simulation

For the diffusion simulation, we ran 100 iterations in which FC Barcelona succeeded 80/100 times, compared to a success rate of only 45/100 for Manchester United. The frequency of player involvement during these sequences is visualized in **Figure 3.5**. In Annexes, we have also provided a full map of passing sequences for both teams, highlighting the successful and failed paths.

For FC Barcelona, since the ball display was characterized by high-volume, low-risk circulation, it was unsurprising that almost all the players had positive contributions to successful sequences. And as happened in the previous analyses, Xavi stood out as the most involved player in successful sequences, whose involvement exceeded 100 total appearances across the 100 iterations. This means that in many successful sequences, the ball circulated through him multiple times before reaching the target. This was particularly striking as in the simulation we accounted for a penalty when revisiting the same player; however, the edge weights connecting him to teammates (likely Iniesta or Messi) were so massive that even when the algorithm artificially penalized the pass-back option to 30% of its original value, Xavi remained the statistically optimal destination. The most common sequence patterns revealed Barcelona's typical build-up structure: Valdés → Mascherano → Xavi occurred 9 times, while Valdés → Mascherano → Messi (7 times) and Valdés → Mascherano → Busquets (6 times) further demonstrated the central role of Mascherano in initiating possession from the back. Valdés appeared to be the player with the most failures, which made us think that some simulations might have ended right at the start because Valdés

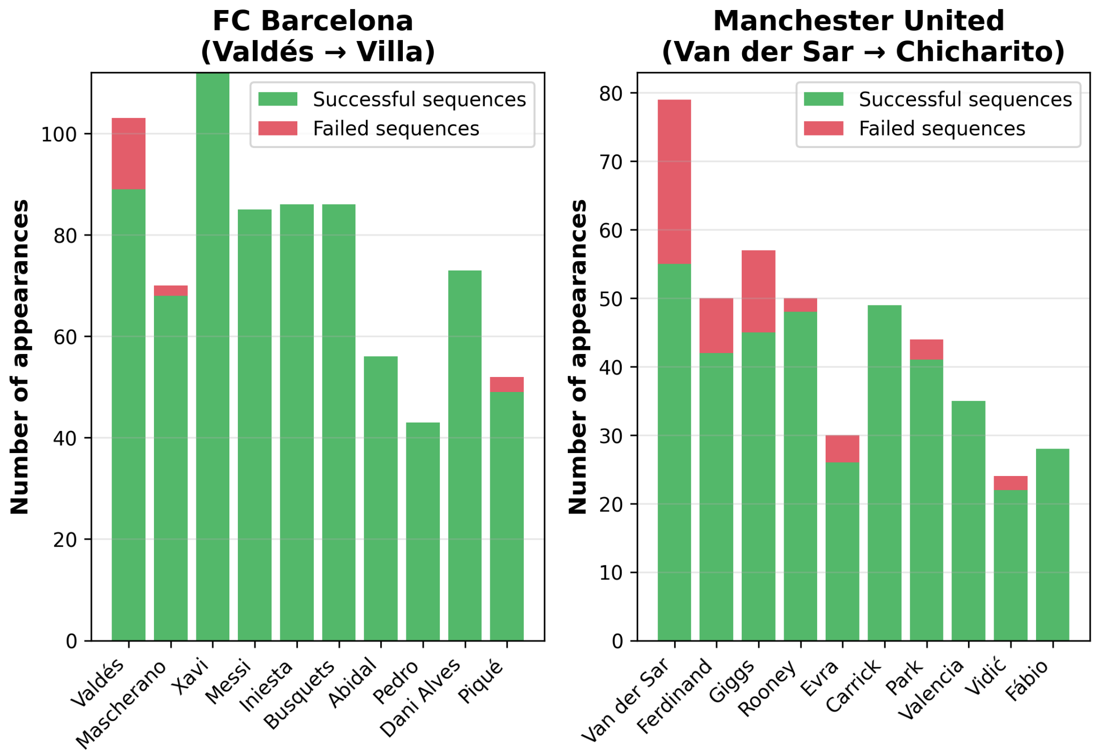

Figure 3.5: Player involvement in 100 simulated passing sequences. Green bars indicate involvement in sequences that successfully reached the target (Villa/Chicharito), while red bars indicate involvement in failed sequences.

took a long risky pass that got intercepted, as only 9 long pass sequences (defense to attack) were attempted throughout all iterations.

In contrast, Manchester United showed a markedly different pattern, favoring more direct passing. Van der Sar dominated involvement with nearly 80 total appearances, with approximately 25 of these in failed sequences, suggesting many simulations ended immediately after his distribution. The posterior quantitative analysis revealed that Manchester United attempted 22 long passes from defense to attack compared to only 9 for Barcelona, and 29 failed sequences were direct attempts of 3 passes or fewer (only 4 succeeded). Among outfield players, Giggs was most involved (57 appearances) but also had high failures (around 12), while Ferdinand, Rooney, and Carrick hovered around 49–50 appearances each. The most common pattern, Van der Sar ⟶ Ferdinand ⟶ Valencia (10 times), illustrates their reliance on wide distribution after goalkeeper clearances, contrasting with Barcelona's more central build-up through Mascherano and Xavi. When looking at successful sequences, United averaged 8.69 passes compared to Barcelona's 9.34, indicating that when United did succeed, they required nearly as many passes but with much lower success rates overall (45% vs 80%).

4. Conclusions

By modeling the 2011 UEFA Champions League Final as a passing network, we achieved a detailed comparative analysis of FC Barcelona and Manchester United beyond traditional match statistics. Through macro-level metrics, player-centric roles, community structures, resilience analysis, and simulated ball diffusion, we quantified the structural foundations underlying Barcelona's tactical dominance.

The results reveal Barcelona's highly efficient, well-connected, and resilient network structure. Short average path lengths, high degree centrality in midfield playmakers, and tight integration across positions created a system optimized for rapid ball circulation and positional flexibility. In contrast, Manchester United's network showed greater fragmentation, longer passing paths, and a clear structural separation between defensive and attacking units. This separation limited their ability to sustain possession and build coherent attacks under Barcelona's relentless pressure.

The community detection, percolation, and diffusion analyses collectively reinforced the tactical interpretation of the match. Barcelona's central community remained stable under risk, redistributing possession efficiently even when key players attempted higher-variance actions. Player removal experiments confirmed Xavi's irreplaceable structural role as the network's central hub, while diffusion simulations showed Barcelona's ability to progress the ball reliably from defense to attack with an 80% success rate. Manchester United, meanwhile, relied heavily on direct, lower-probability passing sequences from defensive areas, resulting in higher failure rates (45% success) and reduced attacking effectiveness. One finding that stood out was that while Messi is widely considered the defining player of this era, our passing network perspective reveals Xavi as the true architect of Barcelona's dominance in this match. Xavi dominated every metric we examined, from degree and betweenness centrality to his role in percolation analysis and his appearance in over 100% of diffusion sequences. This does not diminish Messi's brilliance, but rather highlights the limitations of our scope. A more comprehensive analysis incorporating other metrics such as off-ball movement, spatial influence or goal-creation actions would likely restore Messi to prominence. However, when viewed exclusively through the lens of passing network topology, Xavi emerges as the man of the match.

This project successfully met its objectives by quantitatively validating well-known qualitative narratives about the match. More importantly, it demonstrates the power of network science as a rigorous analytical framework for understanding collective performance in team sports.

References

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[2] StatsBomb, "statsbombpy: A Python package to easily stream StatsBomb data." `https://github.com/statsbomb/statsbombpy`, 2025. Maintained by Hudl. Accessed: 2025-12-23.

[3] Transfermarkt, "Football transfers, rumours, market values and news," 2026. Accessed: January 5, 2026.

Annexes

A. Community Detection Additional Figures

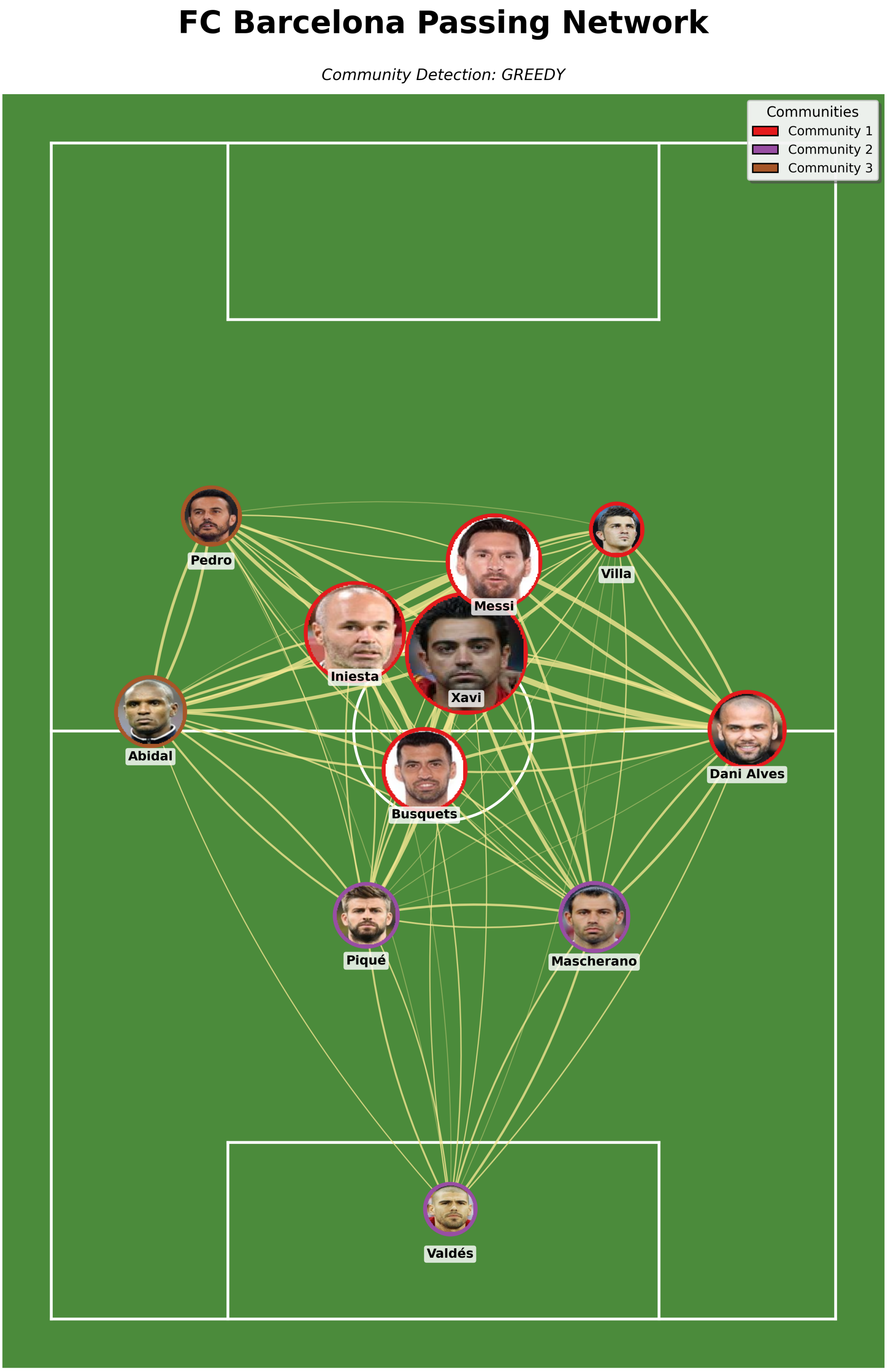

Figure A.1: Greedy community detection on FC Barcelona passing network.

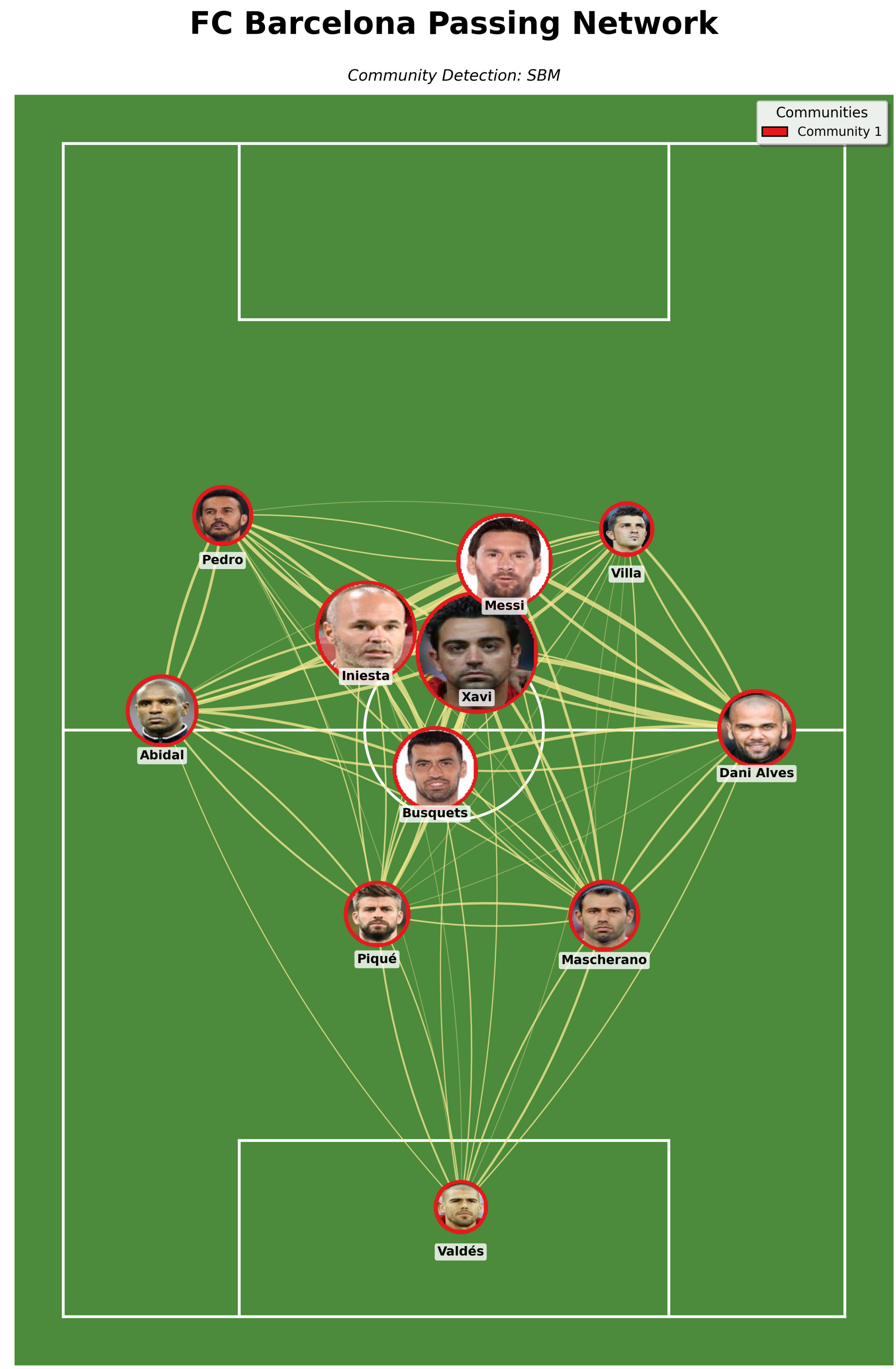

Figure A.2: Stochastic Block Model (SBM) community detection on FC Barcelona passing network.

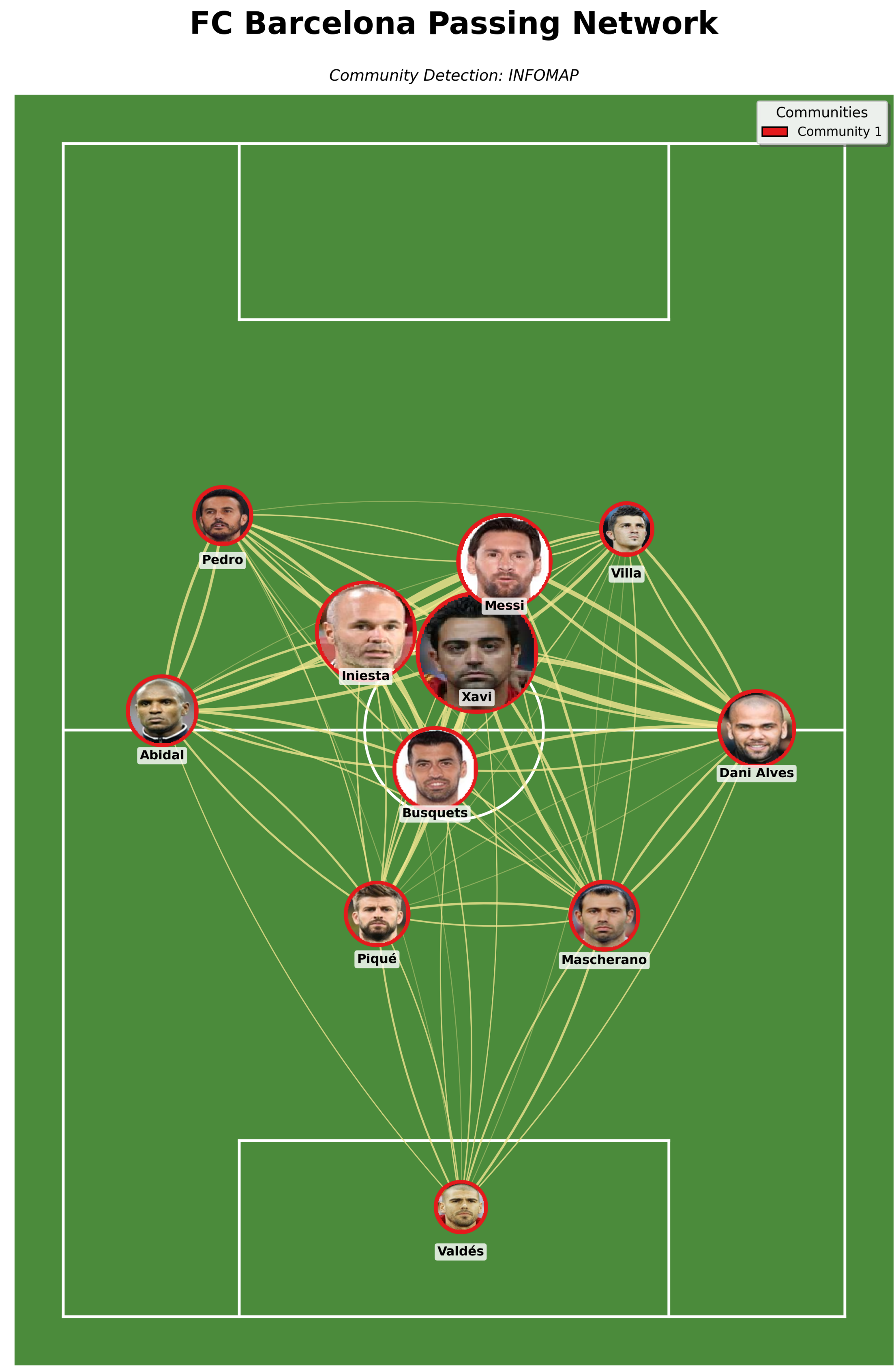

Figure A.3: Infomap community detection on FC Barcelona passing network.

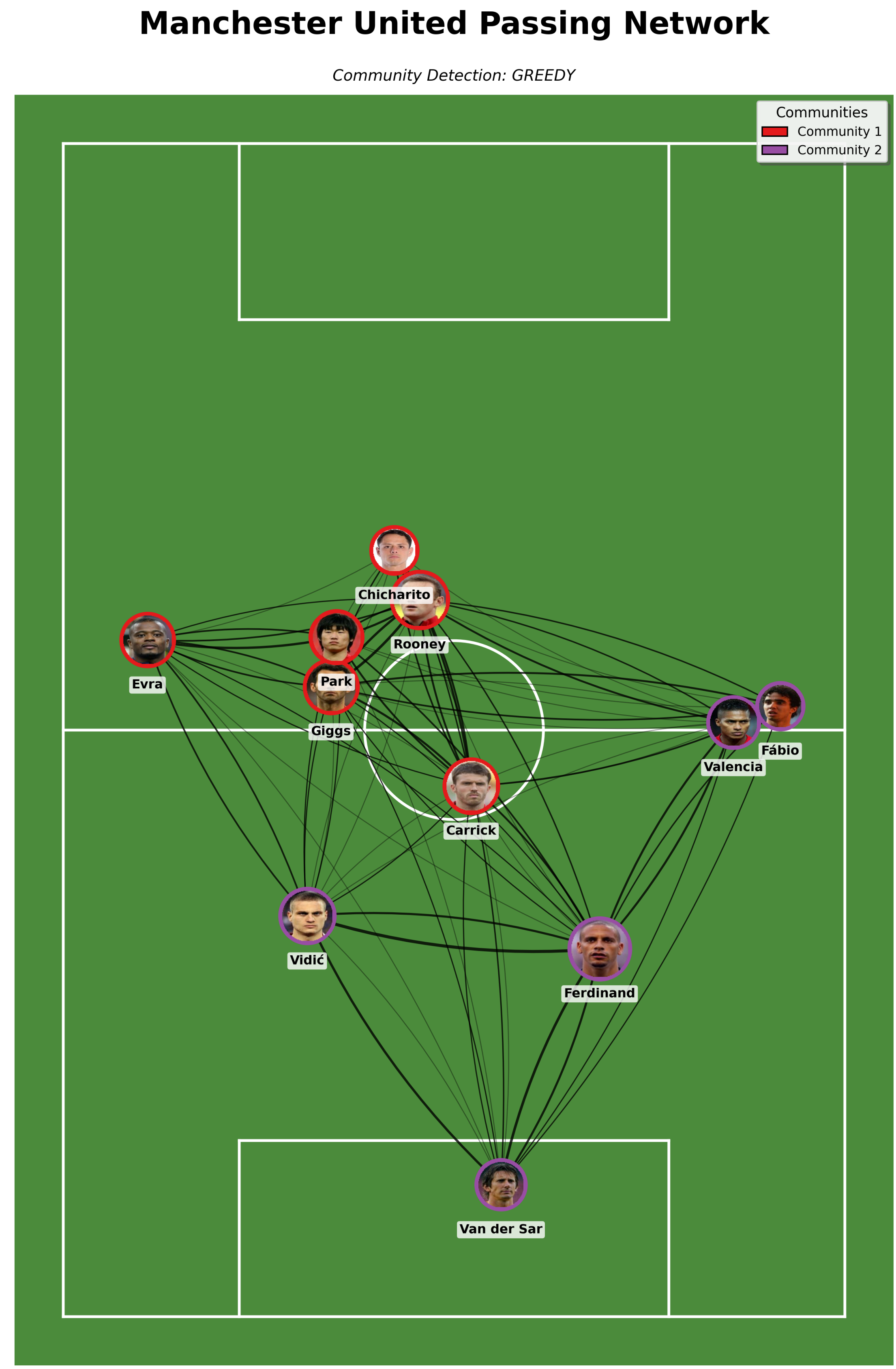

Figure A.4: Greedy community detection on Manchester United passing network.

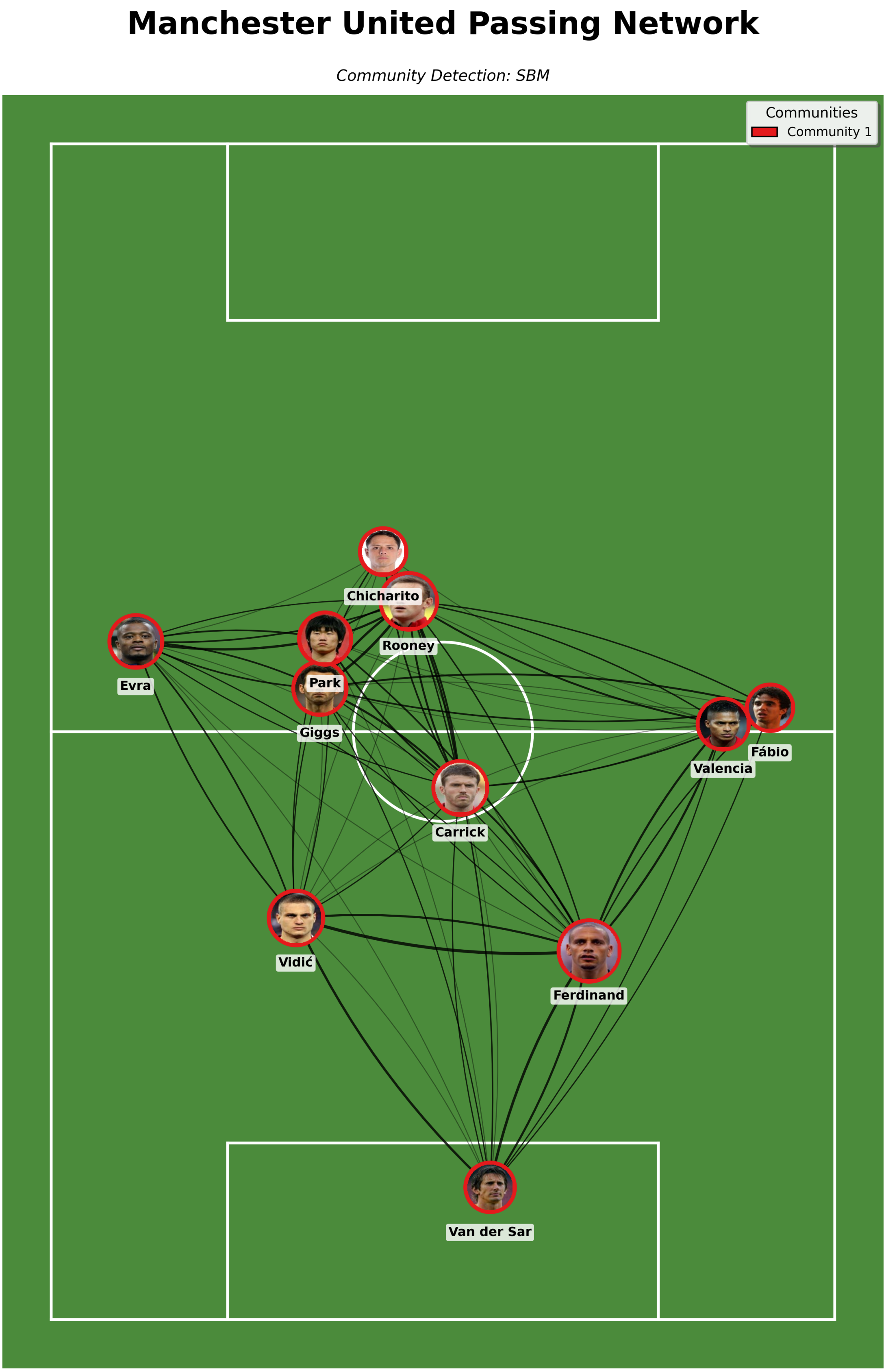

Figure A.5: Stochastic Block Model (SBM) community detection on Manchester United passing network.

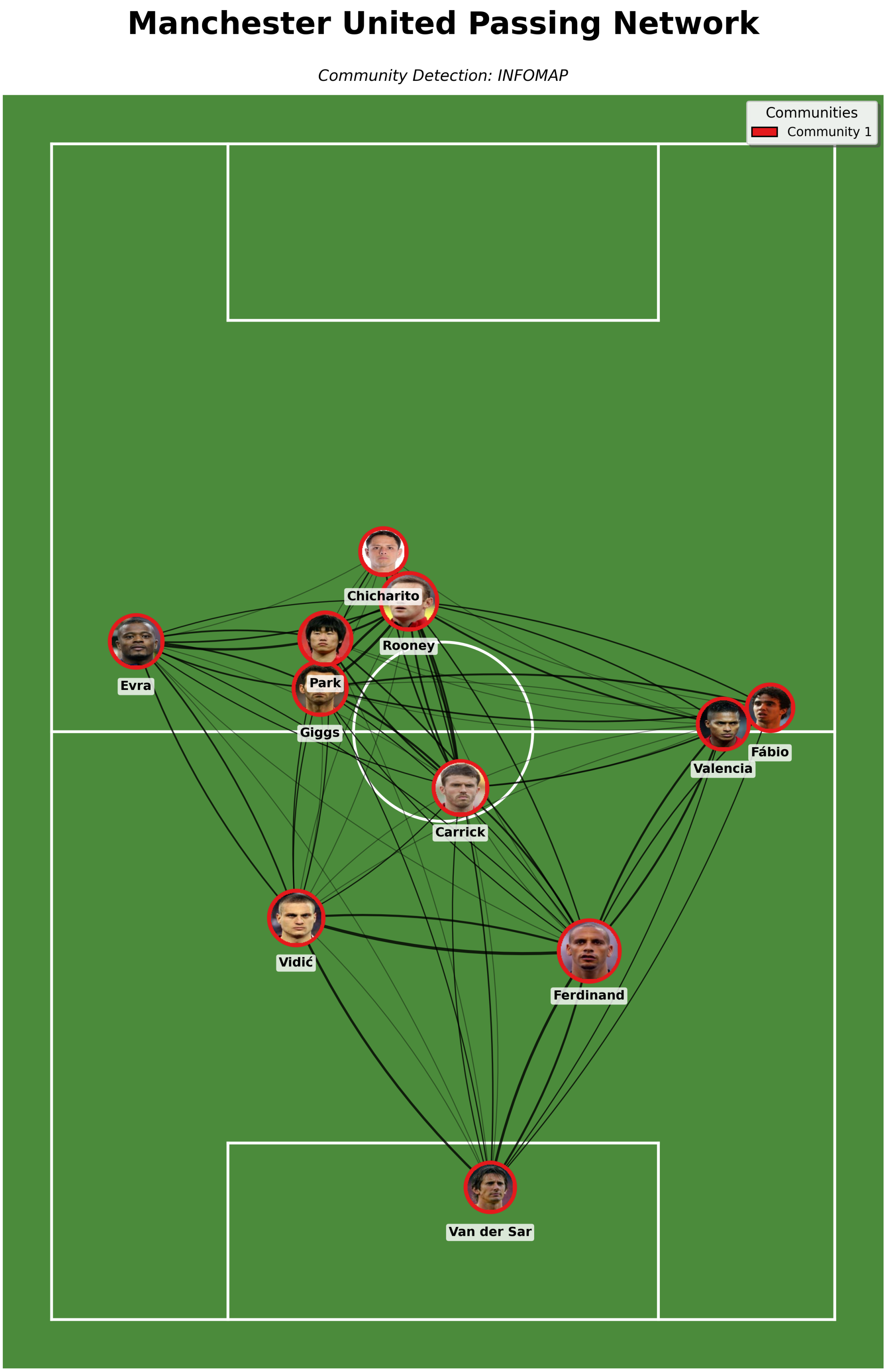

Figure A.6: Infomap community detection on Manchester United passing network.

B. Effective Passing Pathways

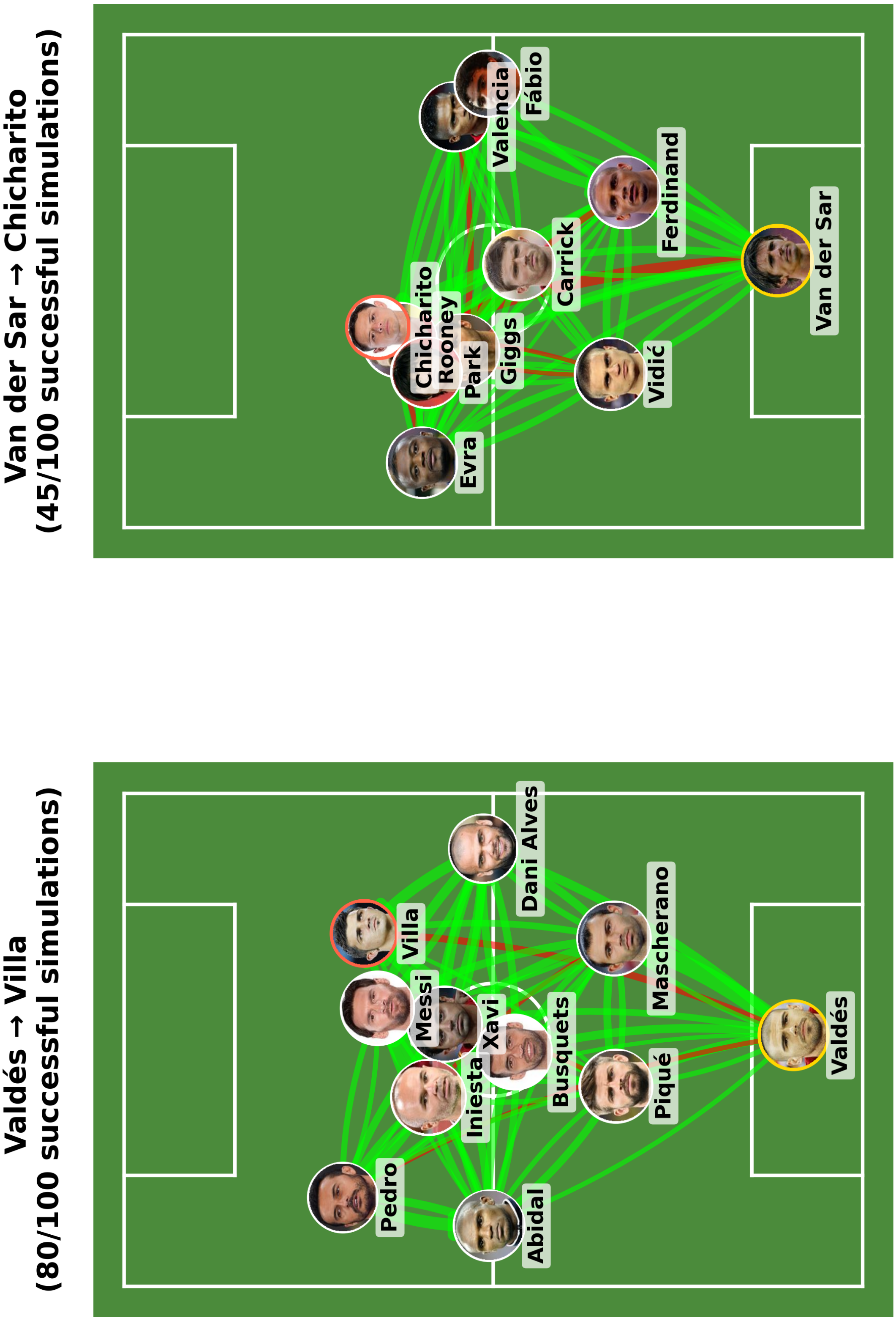

Figure B.1: Ball passing simulation for FC Barcelona vs Manchester United match. Each arrow represents a pass between players, with the thickness of the arrow indicating the frequency of passes. Red indicates failed passes, while green indicates successful passes.