Big Data Event Analytics in Football for Tactical Decision Support

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"Not everything that can be counted counts and not everything that counts can be counted".

Attributed to Albert Einstein

Acknowledgements

When I was growing up in the small country of Macedonia, I used to watch football with my dad and two sisters. Sometimes, I found it fascinating, other times I just watched it because my dad was so much into it. He was something of a local star and everyone knew him as a very good player showing quite the talent in the local football games. Who knew that twenty something years later I would be graduating in a doctoral program in Germany with a topic focused on football analytics?!

My doctoral studies were nice and challenging at times. But I can see the end. Therefore, I would like to thank the people who supported me in this process.

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Pavlina Kröckel

Abstract

The thesis shows how tactical information in football can be obtained by applying analytics techniques from the fields of network science, machine learning and process mining. It uses professional event tracking data from the European Championship in 2016.

The main motivation behind this research is, on the one hand, the lack of studies that use professional tracking data in football, and on the other, the lack of studies investigating real-time decision support in football based on data analytics. Therefore, the thesis aims at demonstrating how event tracking data can support football coaches and their staff to make decisions pre- and post-match, as well as during live games.

As a theoretical basis for the analytics concept followed in this thesis, the dynamic system theory is used. According to this theory football teams are dynamic systems, composed of elements (the players) who interact constantly with each other and their environment and who, by their dynamic interactions, form behavioral patterns over time. These patterns are due to the self-organization ability of the players, and thanks to this, they are able to reorganize themselves and regain a state of balance following a perturbation occurrence (e.g., a counter attack). By following the principles of this theory, analytics techniques such as social network analysis, self-organizing maps, and process mining are applied on football event data.

Social network analysis answers questions related to the relevance of a player, the structure of a team, as well as sudden changes occurring in the team related to different metrics of interest. Self-organizing maps help to transform highly dimensional data about what happened in the game into more understandable two dimensional maps. Process mining analyzes sequence data of a football team and can be used to gain a quick idea about the team's behavior, as well as identifying key players.

The final chapter demonstrates how some of the results discussed in the thesis can be used for real time decision support. A mockup displays examples of a dashboard and the type of results that a coach can use in order to decide which players should be substituted.

The main contributions of the thesis are related to the use of a real world dataset, the methods used for the analysis as well as the discussion of how the results can be used for real-time decision support in football, which has previously not been sufficiently investigated in literature.

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List of Abbreviations

CD	Community Discovery
DCD	Dynamic Community Discovery
DNA	Dynamic Network Analysis
DST	Dynamic System Theory
DSS	Decision Support System
EPL	English Premier League
IVM	Inductive Visual Miner
N/A	Not applicable
PA	Performance Analysis
PI	Performance Indicator
SLR	Systematic Literature Review
SNA	Social Network Analysis
SOM	Self-organizing Map

Part I – Theoretical and Conceptual Foundations

1 Introduction

The overall motivation, research questions and research design of the thesis described in the first chapter, have been published in Kröckel (2017). In this chapter, they are modified and extended.

1.1 Motivation and research problem

Analytics in sports has become increasingly popular in the last decade. Major factors contributing to this are the rapid development of tracking technologies, cheaper and more powerful data storage and processing hardware and software. While some sports, as baseball, have been more prone to using statistics to explain wins and losses, football or soccer, is one of the sports where the traditional view on the game keeps dominating. Decision makers in football have been long rejecting the idea of being told that they have been missing something, that there is something they do not know (Anderson and Sally, 2014). Even though major clubs like Liverpool and Chelsea are more open in admitting and discussing how they use analytics, there are still managers who claim analytics cannot explain the game or prescribe their decisions i.e. gut feeling is everything (Anderson and Sally, 2014; Lewis, 2014). And yet, analytics becomes more of a rule rather than an exception in football.

There have been major developments in sports science and sports analytics in both academia and practice in the last two decades. In ***academia***, the volume of published articles in the last decade has significantly increased, compared to the 1980s or 1990s (see section 2.1). There are clearly defined performance indicators (PIs) relevant for performance assessment in football (see section 2.3). It is nowadays relatively easy to calculate such indicators not only pre- and post-match, but during live matches as well. Not only coaches and their staff, but also football fans have access to basic statistics about their favorite team and player as the game develops. However, the field of performance analysis (PA) in football keeps developing, and latest research has called for more in-depth analysis of the game that goes beyond simple statistics and indicators like shots on goal, tackles, distance run etc. New methods have been suggested in the literature that look not only at the team's and player's actions but also their *interactions* that are bounded by environment factors like the pitch dimensions, location (home or away), opponent's strength, position on the field, and current score. These interactions change and adapt constantly depending on the mentioned factors. The theoretical basis for this new direction in performance analysis research is inspired by the dynamic system theory (see chapter 3).

In ***practice***, various tracking technologies are now available and used in live games (see section 2.2). Moreover, sensors and wearable technology are being used in training sessions to collect biometric data from the players. The tendency is that in the near future, some of these technologies will be allowed during live games as well. In fact, the first steps towards this have been already undertaken. In 2015, the International Football Association Board (IFAB) decided to allow wearables in football (FIFA, 2016b). Following this decision, FIFA invited wearable producing companies to their quarters to learn more about how the technology works (FIFA, 2016b). Before they can be allowed in live matches, wearables need to satisfy the IMS standard as set by the FIFA Quality Program for Wearable Electronic Performance and Tracking Systems (FIFA, 2017a). In addition, during the FIFA Confederations Cup, Germany and Chile participated in a technology tests in which their analysts and medical staff were given tablets via which they can access statistics and match footage in real-time. This shows that FIFA has serious intentions in allowing technology for decision making in real-time but it needs to test its benefits and challenges first (FIFA, 2017c).

Consequently, the opportunities for further decision support for coaches and their teams via analytic methods, are endless. Currently, we see many examples where analytics are applied in football decision making. Some of the most popular areas are scouting (Forouhar et al., 2015), training (Carling et al., 2005), player recruitment (Smith, 2017), pre- and post-match strategy preparation and debriefs (Lewis, 2014; Macrae, 2017). Even college football in the US increasingly relies on analytics (Joslyn et al., 2017).

Most importantly, though, analytics in sports, and football in particular, will keep developing further in the upcoming years. We will witness increasingly sophisticated technology, especially in ***real-time*** applications. This appears to be the area where the next frontier of innovative analytics will happen. The subject was recently discussed in a panel session at the MIT Sports Analytics conference in February 2017 (Zebra Technologies, 2017). Finally, the global sports analytics market is expected to grow at a CAGR of 40.1% between 2016-2022, and is expected to reach $3.97 billion by 2022 (GlobeNewswire, 2017). The rise is due to the increased use of wearable technologies and sensors (GlobeNewswire, 2017). A more recent report by the company WellPlayedSports, predicts that the global market for technologies aiming at boosting the performance of professional football clubs will reach $1 billion until 2022 (PrNewsWire.com, 2017). The same source mentions that clubs will focus primarily on artificial intelligence and virtual reality technologies.

In football, the most important decision a coach needs to make during the match, is to ***adjust the team's tactics***. One example is *player substitution*. It is an important decision as we have seen many times how a substitute player can change the course of the game. Considering that a coach can substitute at most three times during the 90 minute timeframe, it is even more relevant to make these decisions wisely. Potential injuries or red cards must also be considered and anticipated. The literature on tactical decision support and substitution in football is rather scarce (see section 4.2). An in-depth literature review revealed several problems with existing research on the topic, but also uncovered interesting directions for future research. On the one hand, more research is needed to understand how coaches make substitution, and which factors they consider. On the other hand, there are no studies that discuss opportunities to support the coach in real-time decision making by means of advanced analytics on player tracking data.

Finally, research has shown that coaches can remember only part of what actually happened during a match. In their study, Franks and Miller (1991) found that international coaches in football recall 45 percent of key events correctly; according to Carling et al. (2005) coaches can remember less than 50 percent of key match events, while Laird and Waters (2008) found this to be 59 percent of critical events in only 45 minutes of play.

Considering the recent advancements in performance analysis and tracking technology and the under researched but promising area of real-time decision support in football, a ***research gap*** is identified. There is a lack of studies regarding decision support of coaches during live matches. Making a decision during a live game is different compared to pre- and post-match decision making. This is primarily due to the stressful situation in which the coach needs to make an informative decision quickly and on which the outcome of the game depends on. One of the main ways to influence the game is deciding on which player should be substituted. Player substitution has been researched in the literature, but not in relation to data analysis and how analytics can support the coach in deciding which player should leave the game. Thus, it is of relevance to explore further real-time tactical decision support in football based on data analytics, and more specifically, supporting the coach and their staff in the substitution decision during live matches. Finally, very few studies use realistic datasets from tracking companies. Researchers typically generate datasets themselves by processing video data. This requires a considerable manual effort but it is also prone to mistakes and the amount of attributes that can be collected in this way is limited. Thus, the resulting datasets are usually limited in their ability to describe the behavior of the teams and their players.

1.2 Research questions

To address the research gap identified above, the thesis aims at answering the following main research question:

How can the tactical decisions of coaches be supported by using event-based player tracking data?

To answer the main research question the following sub-questions need to be addressed as well:

RQ1: Which ***factors*** drive the tactical decision making of coaches, especially during live games?

RQ2: Which ***analytical methods*** can be applied on event data to give the required insights?

RQ3: How can the research results be applied to the tactical decision of ***player substitution***?

1.3 Research design

The current study follows a ***mixed methods research*** design. As a guideline for the thesis, the in-depth book on mixed methods research by Creswell and Plano Clark (2011) and the seminal paper by Venkatesh et al. (2013, p.8) on using mixed methods research in information systems, are used.

Mixed methods as a research design is used when quantitative and qualitative methods are combined to answer the same research question (Venkatesh et al., 2013). This is contrary to a *multi-method design* in which the researcher employs two or more methods but may or may not restrict the research to the same worldview (either qualitative or quantitative) to answer the research question (Venkatesh et al., 2013). In a mixed methods study, both qualitative and quantitative data are collected, either sequentially, concurrently or embedding one within the other (Creswell and Plano Clark, 2011). For the most part, choosing this type of design depends on the research question, as well as the skills and time of the researcher (Creswell and Plano Clark, 2011). Not all research questions can and should be answered by a mixed methods research. Some of the research problems suitable for this type of design are "*those in which one data source may be insufficient, results need to be explained, exploratory findings need to be generalized, a second method is needed to enhance a primary method, a theoretical stance needs to be employed, and an overall research objective can be best addressed with multiple phases, or projects*" (Creswell and Plano Clark, 2011, p. 8).

The reason for employing a mixed methods research design in the current thesis is that the main research question cannot be answered by conducting either qualitative or quantitative studies alone. First, the literature on tactical decision support during the game (substitution factors) was insufficient and inconclusive. This made the qualitative study in the form of interviews, mandatory. Therefore, the qualitative study was conducted before the quantitative studies. The findings from the interviews and the literature were consolidated in a list of substitution factors relevant for coaches, which then informed the quantitative studies by means of advanced analytics methods applied to live player tracking data. This means that the first study informs the subsequent studies, which is in line with the guidelines mentioned by Creswell and Plano Clark (2011). And second, the framework for decision support cannot be developed without the quantitative studies which should provide the necessary information to the decision makers in a suitable format.

The study follows an ***exploratory sequential design***, based on the guidelines by Creswell and Plano Clark (2011). This type of mixed methods design is employed when, for instance, a guiding framework or theory is not available, or when the variables for the quantitative study are not known. For the research objective of the thesis, a definite list of factors for substitution could not be readily used, and the nature of the substitution decision has not been studies in sufficient depth. Furthermore, this type of design is best suitable for exploring a phenomenon or when the researcher needs to develop and test an instrument when such is not available (Creswell and Plano Clark, 2011). In the last part of the thesis, a decision support framework is developed for supporting the coaches and their teams in their analytics strategy during live games. No such framework, guideline or prototype have been identified in the existing literature that could be used in real-time decision making in football. Creswell and Plano Clark also provide instructions on how to create procedural diagrams to represent the design properly. Uppercase or lowercase letters are used to demonstrate which method takes priority. For instance, QUAL -> quan means that the quantitative study is conducted first and has a higher priority. In the current design, the scheme employed is QUAN -> QUAL since both studies take equal priority in reaching the research objective.

Figure 1 gives an overview of the research design comprising five major steps.

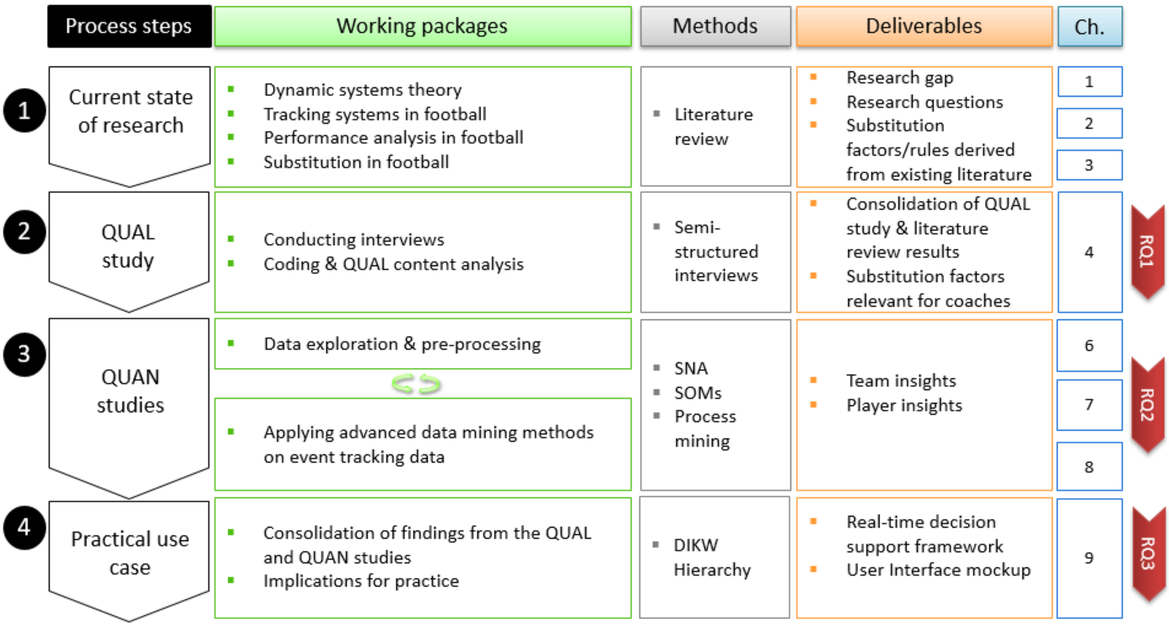


Figure 1. Mixed methods research design

Below, an explanation of each step is given in more detail for a better overview of the thesis structure.

The ***current state of research*** is discussed in chapters 1 to 3. This part gives the conceptual and theoretical background, which introduces the reader to the topic and main concepts in football analytics that need to be understood in order to follow the rest of the thesis. These are mainly, performance analysis and performance indicators in football, tracking systems currently available on the market, tactical decision making and dynamic system theory. The method employed at this stage is literature review. At the end of this chapter, the reader will be familiar with the latest developments in football performance analysis research and the theory followed in this study.

A systematic literature review and a ***qualitative study*** are conducted and presented in chapter 4. The aim of this part is to derive factors relevant for tactical decision making from previous research and directly from football experts. These factors are then consolidated from both the literature and practice. The derived factors will serve to choose appropriate advanced analytical methods, which in turn should produce relevant team and player insights, some of which can be used for substitution. The choice of methods will also follow the requirements of dynamic system theory. For more information on the theory, refer to chapter 3.

The methodology used for the advanced analytics methods is discussed in chapter 5. The ***quantitative studies*** are presented in chapters 6, 7 and 8. This is the main part of the thesis, in which three methods applied on the acquired dataset (provided by OPTA Sports) are presented, the analytical models are built, and derived team and player insights are discussed. Furthermore, the applicability of these insights are discussed for various purposes in football practice.

Having identified factors for real-time decision making (specifically substitution), and applied data analysis on real-world tracking data, chapter 9 discusses a real-time decision support use case – a decision support framework for player substitution in football is developed based on the results from the previous chapters. The main goal is to discuss requirements of a real-time player substitution system and to demonstrate how coaches can be supported in this tactical decision by using some of the insights derived from the advanced analytics methods used in the thesis.

Contribution

The contribution of the current research is twofold. From an ***academic perspective***, the thesis examines issues that have not been investigated sufficiently in previous literature. On the one hand, it presents the first qualitative study with coaches and co-coaches on how they make substitution decisions and which technologies they use in live games, if any. On the other hand, it is the first study to investigate the opportunity for real-time analytics and decision support enhancement regarding the most important in-game decision – player substitution. Substitution factors from both literature and practice are consolidated and influence the quantitative studies, as well as the framework developed in chapter 9. The analytics methods in the current thesis have also not been previously applied to event data and for the proposed research objective. Moreover, process mining has not been previously applied for performance analysis in any sport.

From ***practical perspective***, the study will give a starting point to discuss the feasibility of using a decision support system during live games. The developed decision support framework aims to give an overview of how a substitution system could look like and be implemented in practice. In light of the fact that wearable technology is starting to be allowed during live games as well, there is definitely need for more research on real-time decision support in football.

2 Current State of Research

This current chapter gives an overview of key terms and concepts related to the topic and contributing to its understanding.

2.1 Development of analytics in football

Trends in academia and practice

The idea of using science as a way of supporting the decision making process in sports is not novel at all. Back in 1954, in his letter to the Journal of the Operations Research Society of America, a military man Mottley made the following suggestion: "if coaches were to use scientific method to help them make decisions regarding the future course of the "operations" under their control, they might be able to make significant improvements in team performance" (Wright, 2009, p. 161). Two decades later, not much was changed as, for instance, a sports scientist in British football in the late 1970s would be completely disregarded or frostily welcomed (Reilly, 1998). Interestingly though, the application of science to football happened before the actual formal recognition of sports science as a study area in universities (Reilly, 1998). Already in the 1980s it became clear that football can and should take advantage of, at that time, management science for clubs' organization or establishing systematic training programs (Reilly, 1998). Those clubs that recognized this opportunity early and took advantage of it, were more successful than the others who ignored it (Reilly, 1998). A similar situation developed in the last few years, when analytic and tracking technologies became available. For a while, clubs resisted relying on data for decision making until it became clear that those who do, have a competitive advantage. Considering the money involved in the football business, this was reason enough to change even the most traditional mindset.

In *academia*, the beginning of the new century marked a more prolific development of sports science in general, and football science in particular. Main reason for this was also the rapid development of tracking systems, enabling data collection and advanced analytics technologies. In the end of the 1980s only 20 to 30 articles were published in the field of sports science (Kuper and Szymanski, 2014). Over the next two decades more data became available to scientists than ever before. Coleman (2012) searched for articles on sports analytics in 140 sports and non-sports journals and identified 1146 articles. His results are presented in Figure 2. There is a clear increase in sports analytics articles after 1990 but especially in the beginning of the new century.

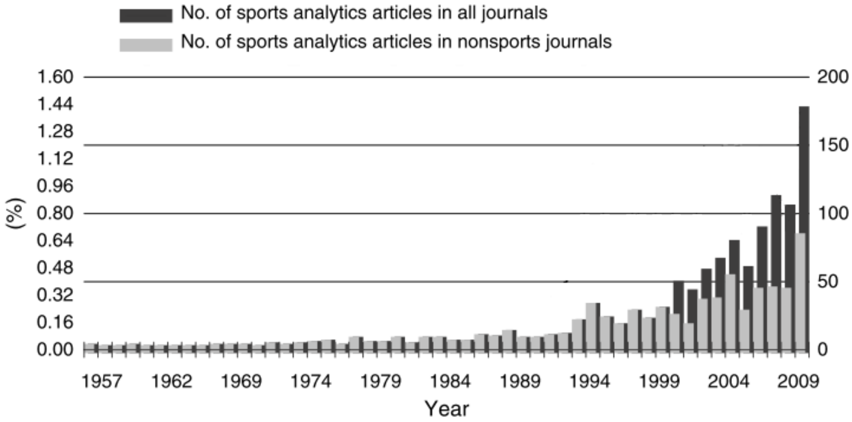


Figure 2. Proportion of journal articles on sports analytics
Source: Coleman, 2012, p.112 – partly modified

In *practice*, a quick search on Google Trends reveals the overall public interest in the topic since 2004. This is presented in Figure 3. Three terms are compared: "sports analytics", "soccer analytics" and "football analytics". "Soccer" is the American term but nevertheless it is used here for general overview, while "football" can also refer to "American football". The German term did not render enough search results to enable comparison.

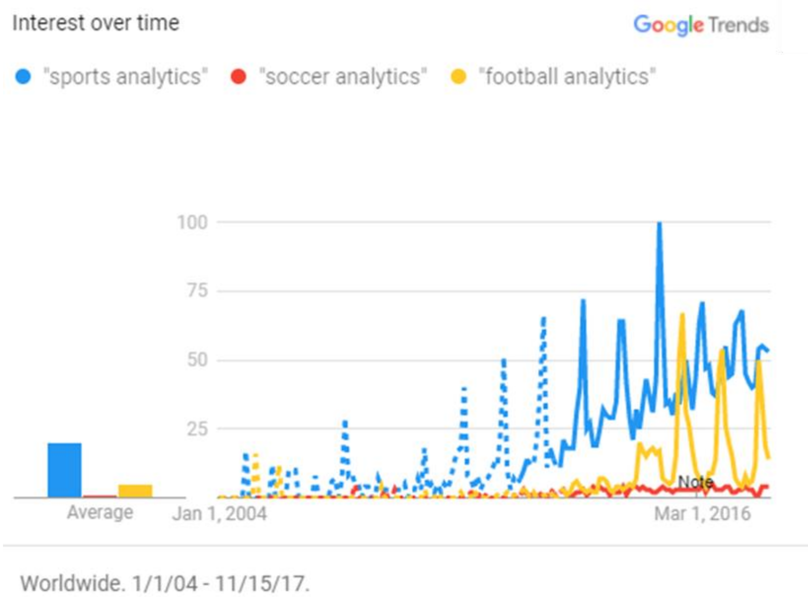


Figure 3. Interest in sports analytics on Google.com
Source: extracted from Google Trends on November 15, 2017

Figure 3 shows that the interest increases in 2012, with most search queries related to sports analytics in general. The year is not unexpected as this is the time analytics in practice became more prominent.

The development of football match analysis can be split in four different stages, each characterized by different focus in the evaluation of the game. This is presented in Figure 4.

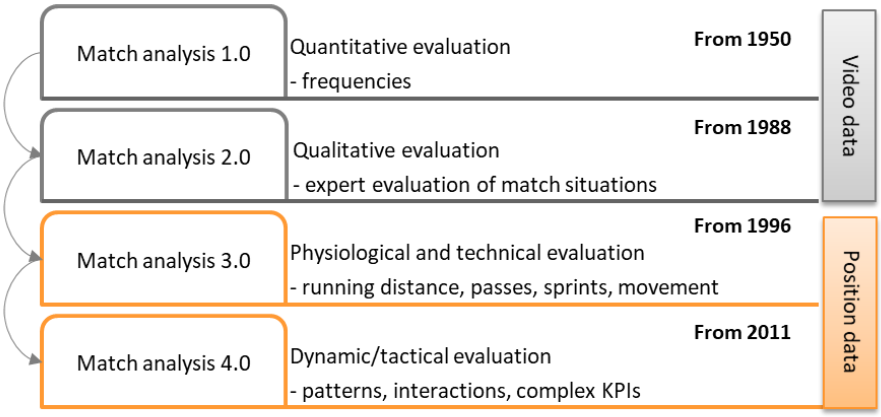


Figure 4. The four stages of match analysis development
Source: Memmert and Raabe, 2017, p. 8 – partly modified

Match analysis in football has developed from (1) simple counting i.e. how many times certain action occurred; (2) qualitative assessment of the game by experts, which also tends to be rather subjective; (3) slightly more sophisticated quantitative evaluation of number of passes, movement and running distances; to, finally, (4) dynamic tactical analysis where advanced analytics are used on large datasets to reveal patterns, interactions and calculate more complex KPIs than frequencies of actions. Even though the figure might give an impression that the standard performance indicators like passes, tackles etc., have been around since the 1950s, it should be kept in mind that any observations at that time were done mostly by pen and paper. The real revolution in football match analysis occurred in the late 2000s with the fast technological development. When Carling et al. (2005) wrote their book on soccer analysis, guidelines for paper based notational analysis were still included. At that time, one would talk about video based statistical and tracking systems, electronic tracking systems especially for supporting the referees in their decisions (Carling et al., 2005). Since then, however, the hardware and software developed rapidly allowing for more portable systems with small environmental footprint, as well as fast and accurate real-time data processing.

Acceptance of data analytics by decision makers

Analytics as part of the decision making process, however, was not immediately welcomed by practitioners. From a traditional perspective, watching football players displaying their individual skills and creativity, was considered an aesthetic experience and compared to an artistic performance in the theatre or music hall (Carling et al., 2005). Coaches and other football professionals were of the opinion that numbers cannot assess the performance as they themselves could, based on years of experience, and that not being able to foresee the future is part of the game's appeal (Carling et al., 2005). For a long time football escaped Enlightenment because clubs were run by people who were doing things in a way because that was the way they have always done it (Kuper and Szymanski, 2014). Big data, however, reached football as well and nowadays, coaches who refuse to apply analytics for performance evaluation, or any other decision for that matter, are considered negligent (Carling et al., 2005; Kuper and Szymanski, 2014).

2.2 Tracking systems

The revolution that currently takes place in football and other sports, would not be available without advanced tracking technologies. FIFA defines these as Electronic Performance and Tracking Systems (EPTS) which are used to monitor and improve player performance by tracking the player and ball positions, and can be used in combination with other devices like heart rate monitors, accelerometers, gyroscopes or other devices for measuring physiological parameters (FIFA, 2017b). FIFA also defines three major types of devices: (1) Optical-based camera systems; (2) Local positioning systems (LPS), and (3) GPS/GNSS satellite systems (FIFA, 2017b). Taking into account the available systems on the market today which are also used by professional football clubs, the categorization was slightly modified to portray a full picture of what is currently available and used. This is presented in Table 1 together with an example of a company that offers the respective type of tracking system.

Table 1. Types of tracking systems currently available on the market

Type		System	Company
Camera based		Performance Data Feed	OPTA Sports, UK
		TRACAB Optical tracking	ChyronHego, USA
Wearables	GPS based	SportVU	STATS, USA
		OptimEye S5	Catapult, Australia
	Radio based	ZXY Wearable Tracking	ChyronHego, USA
Radio-based non-wearable		RedFIR	Fraunhofer IIS, Germany

Source: Self-compiled

Each of the systems in the table above has its own advantages and disadvantages. Most clubs, therefore, rely on at least one of the above systems, often two or more. A comparison of their features is included in Table 2.

The ***camera based systems*** usually rely on several cameras installed around the football field which provide information on the events that happen as well as timestamps and positional data. OPTA Sports is a leading provider of event data in several sports including football. The most detailed data feed available via OPTA is the *Performance Feed* which includes detailed information on all events, the timestamps, and player positions (OPTA Sports, 2017c). The basic feed is the *Core Data Feed* which consists of mainly schedules, squads and line-ups, team and player profiles, and scores, while the mid-tier *Classic Feed* gives information on the events without position and timestamps included (OPTA Sports, 2017a, 2017b). OPTA has its own proprietary software with which trained analysts work to record all the events as they occur during live games. Two analysts work on a single match, each of them responsible for one of the teams involved. The process of how data is collected by the company, has been compared by some to video games, as one hand is on the keyboard choosing the actions, while the other is on the mouse, choosing the location, and the systems adds the timestamps (IETFaraday, 2008). As soon as an event is collected it is sent to a central database system, and it is pushed out to media broadcasters, clubs, and sports websites (IETFaraday, 2008).

Table 2. Tracking systems comparison

System	OPTA Sports	TRACAB optical tracking	OptimEye S5	ZXY	RedFIR	SportVU
Physiological data						
Distance	–	x	x	x	x	x
Speed	–	x	x	x	x	x
Acceleration	–	x	x	x	x	x
Deceleration	–	x	x	x	x	x
Body Load	–	–	x	–	–	
Heart Rate	–	–	x	x	–	
Fatigue	–	–	–	–	–	
Tactical data						
Ball Position	–	x	–	–	x	x
Player position	x	x	x	x	x	
Player movement	–	x	x	x	x	
Events	x	Selected	–	–	Selected	
Team formation	x	x	–	–	–	x
Timestamps	x	x	–	–	x	
Context	x	–	–	–	–	
Other						
Live information	x	x	x	x	x	
Used by clubs for:	▪ Player recruitment ▪ Opposition analysis ▪ Performance analysis	▪ Training ▪ Pre- and post-match analysis ▪ Opposition analysis ▪ Scouting	▪ Training ▪ Injury prevention ▪ Rehabilitation	▪ Training	▪ Player performance evaluation ▪ Scouting ▪ Simulate tactics	
Other users	▪ Broadcasters ▪ Betting companies ▪ Brands & Sponsors	▪ Broadcasters ▪ Betting companies ▪ Brands & Sponsors	–	–	▪ Broadcasters	

Source: Self-compiled based on publicly available information on the companies' websites as of November, 2017

TRACAB is another camera based system which captures x, y and z coordinates of the players, referee and the ball at up to 25 times per second (ChyronHego, 2017). Both Tracab and Opta have similar customers (clubs, broadcasters, bookmakers, sponsors) and it is also possible for a club to integrate data from both types of systems as the companies have an established partnership (OPTA Sports, 2017e).

The second category are ***wearable based systems*** which can be either GPS or radio-based. This depends on how the position data is captured. Examples of this category are the SportVU and the OptimEye S5 devices which extract the position data via GPS or satellite, and the ZXY device which uses radio technology for positioning. The mutual aspect is that they come in the form of a small device that is usually attached to the players with the help of a bra-like vest. Furthermore, aside from the position coordinates, they provide mostly physiological and fitness data like distance run, speed, acceleration and deceleration, heart rate, intensity level among others (McGann, 2014; Premier League, 2017). With these devices one can also infer the level of fatigue and it is hard for the players to hide how hard they work during training (McGann, 2014; Ogden, 2011). One of the first elite football clubs to adopt GPS technology was Manchester United back in 2010 (Ogden, 2011). Currently, wearables are mostly used in training sessions, with clubs being the primary customers of these companies. As mentioned in chapter 1, however, it is highly likely that wearables will be soon allowed in live games as well.

Finally, a third type of system relying on radio frequencies is the ***RedFIR*** system developed by the Fraunhofer Institute in Nuremberg, Germany. Although the system works with sensors being attached to the jerseys and shoes of the players, and the ball, it is not a wearable in the full sense of the term's meaning. It is a more complex system than those described above as it works with more than one sensor/transmitter attached to the objects of interest whose signals are picked up by several antennas installed around the sports field or any other area of observation (Fraunhofer IIS, 2017b). It provides physiological data (sprints and high intensity running, speed, distances) as well as some tactical and technical data like position, player movement, selected events (possession, passes, and shots on goal) (Fraunhofer IIS, 2017a). RedFIR does not seem to be widely used by clubs at the moment, but it is a system that provides both fitness and tactical data unlike the systems from the previous categories which seem to focus on one or the other type of information they provide.

In summary, the camera based systems like OPTA and TRACAB provide detailed tactical information, while the wearable systems have a stronger focus on fitness data. The above solutions are primarily used by clubs in their pre- and post-match analysis in assessing the player performance, informing them of what went wrong and where they can improve, as well as injury prevention and better training programs. The camera systems have a wider range of customer base spanning from clubs, to broadcasters, betting companies, and other content providers, while the wearable companies have mostly clubs as customers. Another difference is that camera systems cannot provide the position of the players and the ball at any point of time throughout the game as GPS and radio systems do. Due to the advantages and disadvantages of each system, clubs rely on at least two of them as mentioned earlier. A limitation for researchers is that the data from these systems can be prohibitively expensive, especially when data for more than once season or competition are required.

In the current thesis, data provided by OPTA Sports is used. More on this in chapter 5.

2.3 Performance analysis in football

Performance analysis (PA) is concerned with investigating actual sports performance in competitions or in training, and not in a laboratory setting (O'Donoghue, 2010). Before the technological advancements of recent years, coaches and their staff have done PA of some sort but mainly via observation, which is very subjective, or by using manual notational systems (Carling et al., 2005; O'Donoghue, 2010). The rationale behind PA is to increase the understanding of performance via objective measures, but an established theoretical basis which can explain results, is still missing (O'Donoghue, 2010). Recently, the dynamic system theory has been suggested as a novel way to explain team performance as a complex system beyond simple action frequencies (more on this in chapter 3).

In general, performance analysis involves notational and motion analysis. ***Notational analysis*** refers to the recording of all actions or events in a “what”, “where” and “when” manner (Carling et al., 2005). It allows for key elements of the performance to be quantified in a valid and consistent way (Nevill et al., 2008) to ensure an accurate and objective representation of the game (Carling et al., 2005). There are four major *purposes* of notational analysis: (1) analysis of movement; (2) tactical evaluation; (3) technical evaluation; (4) database developing, and (5) evaluation and immediate feedback by coaches (Hughes and Franks, 2004). Notational analysis has contributed significantly to the coaching process over the years, something that is in no small part due to the computerized tracking systems. However, in the last decade, it has undergone some criticism mainly due to focusing on what happens and not how and why it happens i.e. focus has been on frequencies of actions and considering them in isolation (Travassos et al., 2013). It has been suggested that more advanced analytical methods such as artificial neural networks (ANNs) may allow to overcome the limitations of notational analysis (Lees, 2002). ***Motion analysis*** (biomechanics) is concerned with the raw aspects of player movement and mainly examines the work-rate and fitness levels of players (Carling et al., 2005). As these factors are excluded from the thesis, the definition is kept short.

An effective PA will depend on focusing on what information is important and why (Carling et al., 2005). In general, there are a few aspects of team and player behavior that are well established in PA research over the years. These are technical, biomechanical, tactical and physical aspects (Carling et al., 2005; Hughes and Bartlett, 2002; Nevill et al., 2008). To measure skills in each category, performance indicators are used. A ***performance indicator*** (PI) is not just a variable, but it is a term for variables that have been established as valid measures of important aspects of performance and can be interpreted (O'Donoghue, 2010). PIs differ between sports. An overview of the PIs in football per category is presented in Table 3.

Table 3. Overview of football performance indicators per category

Match classification	Biomechanical	Technical	Tactical	Physical
Scores No. of shots on target No. of shots off target Corners Crosses	Kicking Ball projection velocity and spin Kinematics and kinetics of kicking leg Throw-in Ball release velocity Kinematics of arms, including sequence of peak segment speeds	Passes to opposition Tackles won and lost Shots off target Dribbles Lost control On-target crosses Off-target crosses	Passes/possession Pace of attack Shots Tackles won and lost Passing distribution Length of passes Dribbles Etc.	Heart rate Total distance High-intensity running distance Work rate Blood lactate Sprint Body fat Oxygen level

Source: Hughes and Bartlett, 2002, p. 747; Rampinini et al., 2007; Sporis et al., 2009

a) ***Match classification*** indicators, as the name suggests, are used to classify the performance of each team in a match, to determine more objectively the team that showed better performance.

b) ***Biomechanical*** indicators are related to studying the fine details of movement. The biomechanics discipline is well established in sports and is related to mechanics and anatomy. (Bartlett, 2001).

c) ***Technical*** indicators refer to winning and errors, like for instance, accuracy in passing or loss of possession (Hughes and Bartlett, 2002). Actions such as passing, shooting and heading are also part of technical PA (Carling et al., 2005).

d) ***Tactical*** indicators reflect the relative importance of teamwork, pace, fitness and movement, and target the technical strengths and weaknesses of the players (Hughes and Bartlett, 2002). They are interrelated with and influenced by the technical indicators (see 2.4).

e) ***Physical*** indicators are generally related to the overall fitness of the player, and also refer to variables such as heart rate, total distance or high-intensity running distance. (Carling et al., 2005).

An overview of the PIs per player position and category is included in Appenix A. The table above should serve as a brief and general overview of the standard PIs in each category. It should be noted, however, that for answering the research question set by the current thesis, the technical and tactical aspects are of relevance. The physical PIs especially, distance, work-rate and high-intensity running, are also important as they are an indication of fatigue, but they are not present in the dataset used in this research project. Data for these PIs are typically collected via wearables which at the moment are allowed only in training. The full overview of factors that can be considered in answering the research question set in the current thesis is displayed in section 4.5 and it is based on consolidation of PA literature, systematic literature review and empirical study.

The above mentioned PIs are used for analysis in three ***stages***: (1) *pre-match* – to counteract the opponent's strength and exploit their weaknesses, decide on team's strategy; (2) *in-game* – to improve tactical decisions; and (3) *post-game* – detailed analysis of the past game performance by qualitative and quantitative methods to reinforce good performance and identify areas for improvement (Carling et al., 2005; Travassos et al., 2013).

2.4 Decisions in football: strategy versus tactics

In preparation for the upcoming game, coaches need to make several important decisions, primarily decide on the roster and the strategy. This depends on several factors like the current status in the competition, level of the opponent and the overall fitness of the players, or perhaps even the weather (Rein and Memmert, 2016).

In sports science, there is an ongoing debate on whether tactic and strategy carry the same meaning. Below is a table with definitions for both terms from the Collins and Merriam Webster dictionaries.

Table 4. Definitions of tactics and strategy

Term	Dictionary	Definition
Tactic	Collins	The methods that you choose to use in order to achieve what you want in a particular situation
	Merriam Webster	A device for accomplishing an end
Strategy	Collins	A strategy is a general plan or set of plans intended to achieve something, especially over a long period
	Merriam Webster	A careful plan or method

Source: Self-compiled based on Merriam Webster and Collins online editions as of November 2017

At first glance, it seems that the definitions are quite similar. However, one can also recognize subtle differences. For instance, Collins defines tactic as a method to achieve a goal in a *particular situation*, while it defines strategy in a similar way but adding the *long-term* aspect. Merriam Webster, on the other hand, defines both terms in a similar way. As the thesis is concerned with the question of supporting the coach mainly with the real-time decision making, it is of relevance to examine whether these terms refer to the same aspects or not.

Some sports scientists consider both terms as different. For instance, Gréhaigne et al. (1999) write that strategy and tactic have a different relationship with time. ***Strategy*** are the decisions made *before the game* when there is no time restriction, while ***tactics*** operate under strong time constraint (Gréhaigne et al., 1999). Furthermore, strategy concerns aspects such as team composition and *assigned position* – the one that each player is instructed to cover during training, while tactics refer to *effective position* – position based on the place of the opponent during the game, and flexibility – adapting to the conditions of play (Gréhaigne and Godbout, 1995). Carling et al. (2005) also consider both terms to be different. According to the authors, strategy is the overall plan to achieve a specific goal, while tactics are applied to achieve that strategy. Rein and Memmert (2016) however, write that they do not understand the delineation between these terms as the real-time interactions between the players will depend on the strategy that was pre-determined before the game. According to the authors, tactics includes decisions taken *both* before and during the game. The thesis follows the argumentation by Rein and Memmert (2016) and considers the terms tactics and strategy in the case of football as synonyms. Throughout the rest of the thesis, tactics is used over strategy. When used, strategy will refer exclusively to decisions made before the game. Below a more detailed overview of tactics in football is presented and discussed.

Tactical behavior has not been investigated in the literature as often as technical behavior, primarily perhaps due to lack of appropriate data (Garganta, 2009; Rein and Memmert, 2016). An overview of tactics definition from different points of view is presented in Figure 5.

Figure 5. Definitions of tactics
Source: Self-compiled based on Rein & Memmert, 2016

According to the number of players whose behavior is analyzed, tactics can be a) *individual* – when the actions of single players are considered; b) *group* tactics – when sub-groups of players and their actions are analyzed; c) *team* tactics – mostly refers to the chosen formation for a specific game and shows whether the team plans to play more aggressively or to focus more on the defense (e.g., the 4-4-2 is more offensive formation while 5-2-2-1 is more defensive formation), and finally, d) *game* tactics refer mostly to the overall team philosophy and whether the team prefers to take advantage of counter attacks, or they try to keep the ball longer in possession, etc.

The tactical behavior of a football team is related to the state of ball possession i.e. the *defensive phase* - without ball possession, and *offensive phase* - with ball possession (Clemente, Couceiro, Martins, Mendes et al., 2013). The thesis, thus, analyzes mostly the offensive phase, as the analyses are done on event data which is mostly the ball related actions. The tactical performance of a team depends on the quality of actions of players and teams in space and time (Memmert et al., 2017). *Space* refers to location on the pitch where an action takes place, or the area which the team wants to occupy during attack or defense; *time* refers to frequency of events or how quick actions are initiated, while *individual actions* are the various types of actions or events that happen on the field (Rein and Memmert, 2016). How teams and players manage spice and time, however, and thus, the quality of their tactics is influenced by a wide variety of factors. Some of these are contextual factors like the location of the match (whether the team plays home or away), type of competition, current standing in the league, referee decisions, the skills (technical and physiological) of the opponent's team, or even the weather (Rein and Memmert, 2016).

Essentially, all performance indicators mentioned in section 2.3, in addition to contextual factors and historical data, influence the tactical performance of teams and players. The extent of this influence, though, has not been researched enough in literature (Garganta, 2009; Rein and Memmert, 2016). Some authors have suggested a few metrics that could give coaches an objective view of their team's tactics. Such ***metrics*** are, for instance, the *team's centroid* (the mean position of all outfield players from one team), *stretch index* (dispersion of the team in relation to the team's centroid) and the team's *effective area of play* (the number of triangles of each team over time and the effective space to play) (Clemente, Couceiro, Martins, Mendes, 2013; Memmert et al., 2017). Indicators suggested by Garganta (2009) are: related to *space* – effective play-space, player movement paths, paths of ball circulation, and players' action zone; related to *time* – frequency of events, individual and team pace, and time of ball possession; *game task* – types of actions like interceptions, turnovers, passes, shots on target. However, there are no standard variables established for measuring the tactical performance (Rein and Memmert, 2016). Since a team game is composed of several related micro-events "*the main subject of tactical analysis should not be the player's actions, taken disjointedly, but the game play sequences resulting from the actions that occur during the different phases of the match*" (Garganta, 2009, p. 85).

A ***tactical change*** during a live game can be done by changing the formation or player substitution (Hirotsu and Wright, 2002). *Formations* are different combinations of players in various positions. Selecting a formation is one way to know whether the team plans on playing defensively or offensively (Hirotsu and Wright, 2006). During the game, this can change by either making a defensive or offensive *substitution* or instructing a player to temporarily assume another position (see 4.2). The primary goal of a coach during a match is to use limited resources to support his team in adapting to the current situation, to either maintain advantage or to save a losing situation (Del Corral et al., 2008). There are no timeouts, the only stoppage is half-time, and therefore, the substitutions can be a determining factor that can make or break the game. This is why substitutions are scarce resources which coaches should use wisely (Myers, 2012). They should be ready to face any circumstances during the course of the game, and change the tactics accordingly (Janković and Leontijević, 2006). In this regard, the most effective measure is to replace a player, who has characteristics that fit better to what is happening at that moment in the game (Janković and Leontijević, 2006).

3 Theory and Concept for Analytics

3.1 A theory for performance analysis in football

The discussed performance indicators have been well studied in the literature on performance analysis in football. However, mostly statistical methods have been applied in the effort to demonstrate the usability of such indicators for accurately describing the performance. Several authors have questioned the reliability of the above indicators in explaining sports performance for several reasons mentioned in detail in a recent critical review of the literature on performance analysis in football by Mackenzie and Cushion (2013). The authors observe that there has been little evolution in this research area and little to no evidence that the results of the existing research are applied in practice by coaches and other sports professionals. Therefore, this has produced a ***theory-practice gap***. By reviewing 60 articles spanning over 24 years, Mackenzie and Cushion have identified three main issues in performance analysis research as presented in Figure 6.

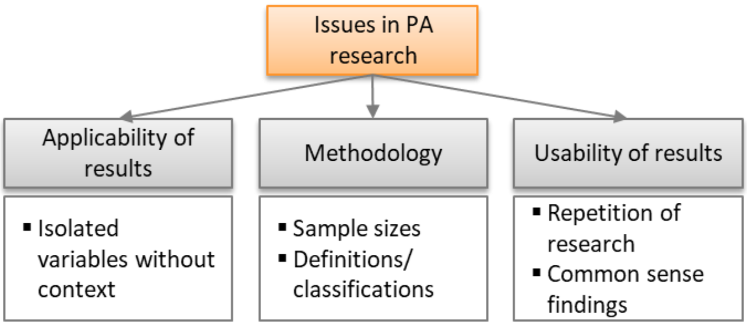


Figure 6. Issues in PA research in football
Source: Self-complied based on Mackenzie and Cushion, 2013

The first issue of ***results' applicability*** is related to the fact that despite suggestions, research in performance analysis has continued to investigate aspects of the game in isolation, using similar methodologies repetitively. This is one of the most often mentioned concerns in the literature especially in the last couple of years. Several authors (Lames and McGarry, 2007; O'Donoghue, 2009; Reed and Hughes, 2006) point out that considering isolated variables like ball possession and linking them to the successful/unsuccessful outcomes of the game are meaningless. The reasons are mainly the fact that football is an unpredictable sport in which "chance dominates the game" as Reep and Benjamin concluded back in 1968 (Reep and Benjamin, 1968). A widely proposed solution to the above concern has been the suggestion to include contextual factors like the type of the opposition, match location, period of the season. Most importantly, a theoretical basis for improving the performance analysis research has been continuously mentioned in the literature since 2002. This is based on the ecological dynamics theory explained below.

The second issue that Mackenzie and Cushion identified relates to two main ***methodological aspects***. One is sample size used for generalizations and the other transparent definitions from which results have been derived in some studies. Concerning *sample sizes*, there is little to no consensus in the literature of what is a representative sample size (James, 2006). Mackenzie and Cushion make the observation that out of 44 technical articles included in their review, only 10 used a sample size of 100 or more games, which does not seem sufficient if we consider that a season can consist of 380 games. Furthermore, Castellano et al. (2014) reviewed the quality of 38 studies that used semi-automated tracking systems like Prozone to quantify the physical profiles of players in football. The authors observed that 50% of the studies only analyzed one team and the remainder studied more than on team or did not specify the exact number analyzed. The problem with *definitions and classifications* as pointed out by Mackenzie and Cushion (2013) is that 79% of the technical papers in their review did not fully define the variables used in the analysis. This becomes an issue due to the impossibility to directly compare and replicate the results of previous studies. If authors continue to use their own variables without clearly defining them, this in turn also contributes to the third issue – usability of results.

The ***usability*** of performance analysis research results relates to the fact that most studies end with the same predictable findings, which are often common sense for coaches. Therefore, Mackenzie and Cushion question whether and to which extent performance analysis research furthers the understanding of performance.

To address these issues, the ***ecological dynamic theory*** has been promoted as a theoretical basis for performance analysis research in team sports such as football.

Nine papers in total on dynamic system theory have been reviewed in detail. These papers have been often cited and can therefore be considered as a very good representation of the literature suggesting the shift in performance analysis research towards this theory. These are the studies by: Dutt-Mazumder et al., 2011; Lames and McGarry, 2007; McGarry et al., 2002; McGarry, 2009; O'Donoghue, 2009, 2009; Reed and Hughes, 2006; Travassos et al., 2010; Travassos et al., 2013; Vilar et al., 2012. What comes to the attention is that very few authors appear regularly in the literature on ecological dynamics, which coincides with the view of Coleman (2012) that the field of sports analytics is still fragmented and very few prolific authors comprise the entire sports analytics research group at a given school.

The above publications demonstrates that the idea of using dynamic system theory for performance analysis has been around for over a decade. However, not much progress has been achieved meanwhile on the subject. One reason for this is that the computer systems for notational analysis only started to improve since 2005 and have been implemented by clubs in the last couple of years. Another reason is the confidentiality of the research results on the part of the clubs – they prefer not to share their results since any success in analytics gives them a competitive advantage. However, performance analysis research in football continues with the efforts of establishing a new theoretical basis for interpretation that would aid coaches to better understand the "how" and the "why" of the occurring events.

Back in 2002, McGarry et al., realized that unlike previous conclusions, players exhibit different behavior against different opponents in a study of squash games. Therefore, they propose an alternative approach for sports performance analysis, one that views the team as a complex system. A ***complex system*** consists of many degrees of freedom in constant flux, but in which some regularity emerges (McGarry et al., 2002). It consists of many components which interact among themselves and, as a whole, interact with the environment (Hristovski et al., 2014). Complex systems can be homogenous or heterogeneous. The differences and mutual characteristics of the two categories are presented in Table 5.

Table 5. Types of complex systems and their characteristics

Complex Systems	
Homogenous	**Heterogeneous**
Example: piece of ice	• Living (biological) systems • Social systems
One kind of interaction between its components	Different kinds of interactions (informational and/or mechanical)
A component of the system can be studied in isolation – the behavior of the system will stay the same.	• Isolating one part of the system is not possible • Adaptive and goal oriented • Evolve, develop and learn to negotiate with their environment by changing and fitting their behavior to emerging constraints.
• Mutual interaction and interdependence between constituent components • Exhibit nonlinear dynamical properties • Under some constraints new forms of behavior emerge spontaneously without being previously designed • May exhibit complex or simple behavior i.e. complexity of behavior should not be confused with complexity of the system.	

Source: Self-complied based on Hristovski et al., 2014

Football is a heterogeneous complex system in which two teams pursue the same objective simultaneously, a feature that is typical of game sports (Lames and McGarry, 2007). Both teams have aims that are mutually exclusive but are pursued at the same time, and therefore, tight ***interactions*** between them arise. Since these interactions change over time, they are dynamic (Lames and McGarry, 2007). The behavior that results as a consequence is therefore not an expression of stable properties of individual players (e.g., technical skills). Therefore, game sports like football, should be considered as ***unique action chains*** which are context and time dependent and not repeatable (Lames and McGarry, 2007).

Similarly, Travassos et al. (2010) write that team sports are characterized by the formation of spontaneous patterns through self-organization processes and that team behavior can be regarded as an emergent process that results from the interaction between the individual (player), environment and task constraints (e.g., distance to goal). This is presented in Figure 7.

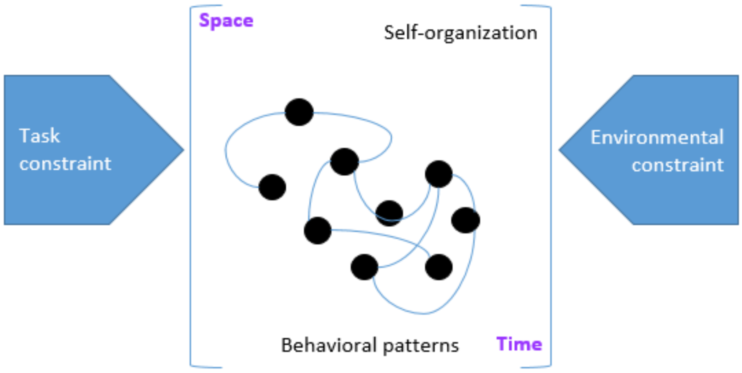


Figure 7. The eco-dynamics account of performance
Source: Self-complied based on Vilar et al., 2012

Self-organization is a key aspect of complex systems which explains how order emerges among different components (Vilar et al., 2012). The spatio-temporal trajectories of each player can be thought of as a product of self-organization (Duarte et al., 2012). Dynamical system theory can be considered as a reliable approach for accurate description and measurement of the space-time patterns that emerge in the game (Travassos et al., 2010). Such approach can describe, explain and predict the coordination patterns that emerge, adapt, persist and dissolve in complex systems (Button et al., 2014). By using nonlinear equations to model behavior, it becomes clear how seemingly complex systems follow simple, elegant principles (Button et al., 2014). In general, most scientist know about nonlinearity and usually try to avoid it (Hughes, 2008). However, it is important to study a system not only in its linear range of operation where a change is smooth, but also to exploit its qualitative change to identify variables that are essential to the system – the idea being that because these variables change abruptly, they are key variables when the system operates in the linear range (Hughes, 2008). This is explored in the thesis by using the CUSUM metric calculation (see section 6.5).

Simply put, a dynamic system is a system in which a change occurs. The challenge is to model the behavior of the football team or players in a way that it will allow the analyst to detect when such change occurs and to find ways to avoid it or tackle it when it does happen. So far, performance indicators are used to describe the behavior of the players and teams. However, these are static measures that poorly represent any change to the system as a whole and also its separate elements – the players. This is why the dynamic system theory aims at finding new metrics, or indicators that would better describe the state of the players and will better reflect changes that occur in the system (team). Aside from the change that occurs in the system, the dynamic system theory suggests that dynamic complex systems are also capable of adapting following a change and that stable relationships are then formed at different levels of the system (e.g., different sub-groups of its components) (Dutt-Mazumder et al., 2011).

3.2 A concept for analysis based on the dynamic system theory

The literature does not offer a concrete list of dynamics that are relevant to measure in football. But the theory is used as an inspiration and starting point for the analysis employed in the thesis. This is discussed below.

The literature on nonlinear dynamics of team sports mentions two analytics methods that can be used for analyzing the team and its players as a dynamic, complex system. The first method is a type of artificial neural network architecture, known as Kohonen maps or ***self-organizing maps*** (SOMs). This method is suggested as the best nonlinear method for pattern analysis. As self-organization refers to the development of regularities of behavior of the system without the control of an external agent, a method like SOM seems to be appropriate for studying behavior patterns of sports teams as dynamic systems (Dutt-Mazumder et al., 2011). The SOM algorithm is capable of preserving the nonlinear topological relationships in the data sets and, thus, retains the relevant information while discarding the irrelevant information in high dimensional data sets, which is typical of dynamic systems (Dutt-Mazumder et al., 2011).

Social network analysis is the second method that is mentioned in the literature in relation to analysis based on the dynamic system theory. This type of analysis helps to discover patterns of interactions between the players. It can reveal the collective behavior of team sports by quantifying the frequency of internodal pairing (Dutt-Mazumder et al., 2011). Team sports are composed of multiple and dynamic couplings among dyads of players, which function under similar principles of coordination dynamics (Dutt-Mazumder et al., 2011). By plotting the interactions between the players as a network it is possible to calculate network measures at team, player and sub-group level, observe how these change over time and link them to successful or unsuccessful outcomes.

Based on what is discussed so far, the main goal of analysis based on the dynamic system theory is to discover new metrics that can properly describe the behavior and state of players and teams, as well as measures to detect changes in the system, and using valid metrics to show how the system change over time. The thesis works with event tracking data which is suitable for this type of analysis as it contains all events that happen during the game, the players involved as well as the position and the timestamps. As the position data is only related to the event that occurs, i.e. there is no information on the position of all players and the ball at any point in time, spatio-temporal pattern detection is not part of the analysis in the thesis. For this type of analysis, detailed GPS data is necessary in order to measure the influence of the rest of the players and the ball on the event or player of interest. For example, when the player with the ball is in the 10 meter section, about to shoot towards the goal, what is the influence of the position of the other players from his team and the opposition on the way he behaves? There are various options for analysis, but as mentioned, detailed positional data is necessary for this.

Therefore, the analysis in this thesis are mainly focused on the events that happen during the game, the players involved and the timestamps. Both the self-organizing maps and the social network analysis methods can be applied on such data. In addition, considering the events and the timestamps together, it is possible to analyze event sequences, as it was previously said, football can be considered as consisting of unique action chains. A new method is used for this type of analysis. It is based on ***process mining*** techniques and algorithms. It is a novel approach to analyze sequence data in team sports and there is no study that has applied the same techniques for analyzing team sports data. However, considering the structure of the dataset, which is in fact an event log data, it seems that process mining can be a suitable collection of methods to gain deeper insights into player and team behavior based on event data. From the discussion in section 2.4., it is clear that individual actions as well as team actions are an important part of the team and player tactics in football. Considering that in the last few years, the static performance indicators derived from those actions/events are prone to critique, new methods that allow the analysis of events and event sequences can be useful in football performance analysis especially because event data is one of the main data type available during live matches.

Part II – Qualitative Study on Tactical Decision Making in Football

4 Tactical decision making in football

4.1 Overview and study design

The main research goal of the thesis is to investigate how coaches can be supported in their tactical decision making, especially during live matches. The most important decision during live games is player substitution. Therefore, in this chapter the substitution decision making will be analyzed in more detail in order to identify relevant factors for substitution important to coaches. Carling et al. (2005) mention that it is very important to identify what exactly coaches are looking for to get as insight from a match analysis system, and that such systems must meet the individual needs of the coach and not vice versa.

An overview of the steps undertaken in this chapter is given in Figure 8.

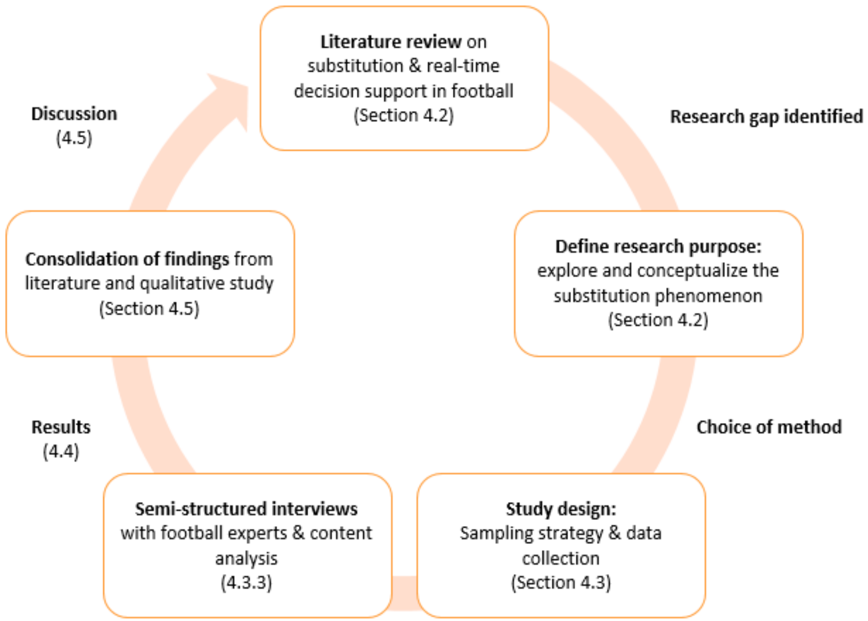


Figure 8. Qualitative study steps

The first step in any research enquiry is the analysis of the current state of research of the topic of interest for the researcher and/or related work. Therefore, the current study starts with a detailed literature review on (real-time) decision making in football to understand better how coaches make decisions. Following this step, a research gap is identified which requires the conducting of qualitative analysis to extend the literature findings and explore the phenomenon in more detail to generalize the findings. Semi-structured expert interviews were conducted and processed via content analysis. Findings from both the literature and empirical study were consolidated in the form of a list with relevant substitution factors.

4.2 Related work

In this section, the process of literature search regarding decision support during live games in football is explained and results are presented and discussed. Several types of reviews exist depending on the purpose of inquiry. The current thesis, follows the guidelines for systematic literature review (SLR) as provided by Kitchenham (2004), and partly the PRISMA guidelines specifically for the structure and reporting of the review (Moher et al., 2009). This type of review is used for identifying, analyzing and interpreting all available research relevant to a topic of interest in an unbiased and reproducible way (Kitchenham and Charters, 2007). Some of the reasons for conducting a SLR are a) identify existing gaps in literature, or b) establishing a framework to appropriately position upcoming research activities (Kitchenham, 2004; Kitchenham and Charters, 2007). This is especially relevant in the current inquiry because, on the one hand, no existing review of substitution or real-time decision support in football could be identified, and on the other, the primary reason to conduct it is to understand how far existing literature is on the topic, identify gaps and decide how to proceed concerning the quantitative analysis. Furthermore, the SLR follows a rigorous methodology for collecting and analyzing the literature, and therefore ensures lower bias than traditional reviews (Mariano et al., 2017).

Following the clarification of the literature review purpose, the next step is to specify the ***search strategy***. This includes primarily the search terms and databases used. Table 6 presents all search terms used to extract relevant papers on the topic.

Table 6. Search terms used

Search terms
substitution
substitution AND sport
soccer AND substitution
football AND substitution
association football AND substitution
Auswechslung AND Fußball

The terms in the table above were chosen after a quick preliminary literature search to get a first impression of the amount of existing research as well as the keywords used by the retrieved papers. To ensure that all relevant papers are retrieved, Boolean queries were constructed by adding the different terms for football in the US, Europe and in German language. In total, nine databases were searched for the paper collection, and all search terms were used in all nine databases with search in all fields, with no restriction. Table 7 includes the databases together with the number of potentially interesting articles collected in the first phase.

Table 7. Databases searched and number of papers collected

Database	Results
PubMed	2
Sport Discus	14
Scopus	2
Science Direct	0
Web of Science	0
Google Scholar	79
Sports Medicine	8
Exercise and Sport Sciences Reviews	0
Springer	5
Total	**110**

An initial search was conducted in March 2015, with final search conducted in June 2017. Since it was clear from the preliminary search that the existing literature was rather scarce, all papers that seemed potentially relevant (addressing any aspect of substitution or real-time decision support) based on the title were included for further examination, regardless of the publication date.

The next step in a SLR is to define the ***selection strategy*** i.e. the criteria for filtering out the retrieved papers. The selection is a three-stage process, where the first stage is selection based on title, the second – based on abstract, and third stage – after reading the full paper (Heckman and Williams, 2011). The selection process is presented in Figure 9.

Initially 110 publications in total were identified as potentially relevant for the research goal. Snowball sampling strategy was used to identify additional studies, but no such studies were found. After all duplicates were removed, 103 publications were screened further by reading the abstract. At this stage, most of the publications were excluded form a more detailed review. These were publications a) studying substitutions in children's, college or women's football teams, as the current thesis focuses specifically on professional football; b) analyzing various aspects of performance in football, such as movement, goals, fitness aspects, GPS tracking, among others; and c) 10 publications in total were not available as full-text. One is a PhD thesis which was later incorporated in two papers included in the final review stage (Hirotsu et al., 2009; Hirotsu and Wright, 2006), and the rest were not available including via inter-library loan. Therefore, they had to be excluded. In total, 26 publications were included for final eligibility assessment which required full-text reading.

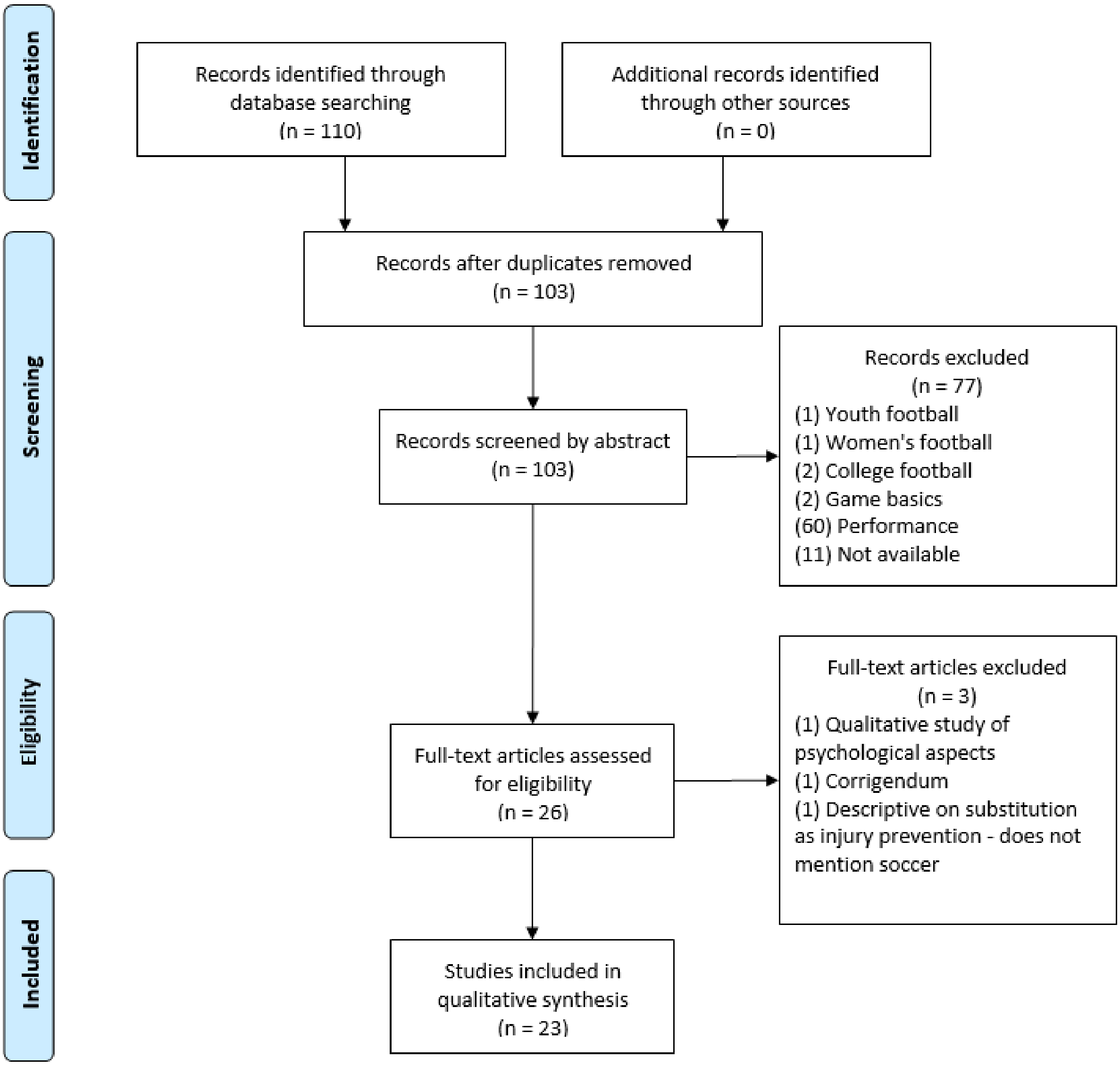


Figure 9. Flow Diagram of the methodology for article search and selection (based on PRISMA)

Following this stage, three publications were excluded: (1) a qualitative study on the psychological effects of being a substitute player by Woods and Thatcher (2009) - this study did not fit the research objective of the literature review which focuses on factors relevant for substituting players and how these can be used to support the coach in live games; (2) Corrigendum of the paper by Hirotsu and Wright (2002) referring to formulas they used; and (3) an opinion piece on substitution as a way of injury prevention in teams sports by Orchard, 2012) with no mention of football, however. Finally, 23 papers were chosen for detailed analysis and included for further review. These are presented in Table 8.

Table 8. Overview of papers included in the literature review[1]

Author	Title	Year	Published in
Hirotsu & Wright	Using a Markov Process Model of an Association Football Match to Determine the Optimal Timing of Substitution and Tactical Decisions	2002	The Journal of the Operational Research Society
Lenahan & Solari	The right players, right system: choosing lineups, changing systems, making substitutions in Real Madrid's title run	2002	Soccer Journal
Hirotsu & Wright	Determining the Best Strategy for Changing the Configuration of a Football Team	2003	The Journal of the Operational Research Society
Hirotsu & Wright	Modeling Tactical Changes of Formation in Association Football as a Zero-Sum Game	2006	Journal of Quantitative Analysis in Sports
Janković & Leontijević	Substitution of players in function of efficiency increase of tactic play plan in football	2006	Fizička kultura
Ledru	A Formalisation of the Soccer Substitution Rules	2006	International Workshop on Regulations Modelling and their Validation and Verification
del Corral, Barros & Prieto-Rodríguez	The Determinants of Soccer Player Substitutions: A Survival Analysis of the Spanish Soccer League	2008	Journal of Sports Economics
Geyer	Auswechselverhalten im Fußball − eine empirische Analyse	2009	Sport und Gesellschaft – Sport and Society
Hirotsu, Ito, Miyaji, Hamano, & Taguchi	Modeling Tactical Changes of Formation in Association Football as a Non-Zero-Sum Game	2009	Journal of Quantitative Analysis in Sports
Mengel	Never change a winning team: The effect of substitutions on success in football tournaments	2009	Maastricht Research School of Economics of Technology and Organization (METEOR)
Carling et al.	Work-rate of substitutes in elite soccer: A preliminary study	2010	Journal of Science and Medicine in Sport
Coelho et al.	Effect of player substitutions on the intensity of second-half soccer match play	2012	Revista Brasileira de Cineantr. & Desem. Humano
Myers	A Proposed Decision Rule for the Timing of Soccer Substitutions	2012	Journal of Quantitative Analysis in Sports
Siegle & Lames	Game interruptions in elite soccer	2012	Journal of Sports Sciences
Bradley & Noakes	Match running performance fluctuations in elite soccer: Indicative of fatigue, pacing or situational influences?	2013	Journal of Sports Sciences
Bradley et al.	Evaluation of the Match Performances of Substitution Players in Elite Soccer	2014	International journal of sports physiology and performance
Bartling, Brandes & Schunk	Expectations as Reference Points: Field Evidence from Professional Soccer	2015	Gutenberg School of Management and Economics Discussion Paper Series
Purnomo et al.	Soccer game optimization with substitute players	2015	Journal of Computational and Applied Mathematics
Rey et al.	Timing and tactical analysis of player substitutions in the UEFA Champions League	2015	International Journal of Performance Analysis in Sport
Gomez et al.	The influence of substitutions on elite soccer teams' performance	2016	International Journal of Performance Analysis in Sport
Harper et al.	Practitioners' Perceptions of the Soccer Extra-Time Period: Implications for Future Research	2016	PLoS ONE
Silva & Swartz	Analysis of substitution times in soccer	2016	Journal of Quantitative Analysis in Sports
Varela-Quintana et al.	The effect of an additional substitution in association football. Evidence from the Italian Serie A	2016	Revista de Psicologia del Deporte

[1] Initial version of the table is published in Kröckel (2017).

From the table above two things can be observed. On the one hand, studies are published by different authors, except for the papers by Hirotsu and Wright and two papers by Bradley. On the other hand, there is also a noticeable diversity in the publication outlets. This issue has been previously reported by Coleman (2012) who noted that most papers in sports science research are written by authors who do not write more papers, and that at times, scientists are not sure about the right outlet to publish their papers. Over the years, this has improved with some sports journals establishing themselves as high quality outlets in sports science research (e.g., SportsMed, especially for review articles, the International Journal of Performance Analysis in Sport, the Journal of Quantitative Analysis in Sports, to name a few). It can also be seen in Table 8 that in the last few years, the above publication outlets are becoming a preferred choice by researchers. An overview of the distribution of publications on substitution over the years is presented in Figure 10. It shows an interesting observation with three papers published in 2006, 2009 and 2012, with a visible increase from 2014 onwards. This also shows that the topic is becoming more relevant.

Table 9 presents an overview of the number of publications per outlet. The Journal of Quantitative Analysis in Sport is represented with the highest number of papers (4), while International Journal of Performance Analysis in Sport, Journal of Sport Sciences, and The Journal of the Operational Research Society have two publications each. 21 papers are in English language, one paper in Serbian and one in German.

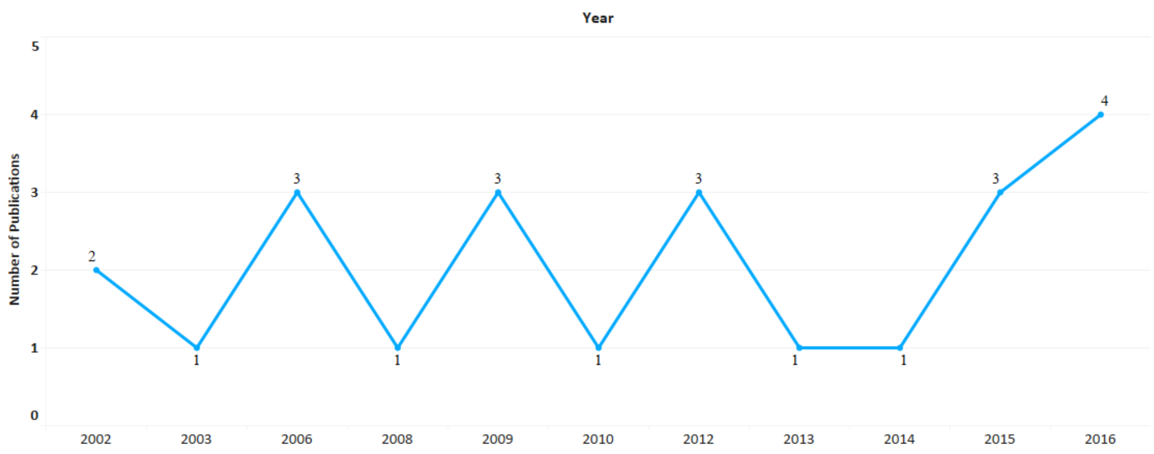


Figure 10. Substitution-related publications per year

Table 9. Number of publications per outlet

Published in	Number of publications
Fizicka kultura	1
Gutenberg School of Management and Economics Discussion Paper Series	1
International Journal of Performance Analysis in Sport	2
International Journal of Sports Physiology and Performance	1
International Workshop on Regulations Modelling and their Validation and Verification	1
Journal of Computational and Applied Mathematics	1
Journal of Quantitative Analysis in Sports	4
Journal of Science and Medicine in Sport	1
Journal of Sports Economics	1
Journal of Sports Sciences	2
Maastricht Research School of Economics of Technology and Organization (METEOR)	1
PLoS ONE	1
Revista Brasiliera de Cineantr. & Desem. Humano	1
Revista de Psicologia del Deporte	1
Soccer Journal	1
Sport und Gesellschaft – Sport and Society	1
The Journal of Operational Research Society	2

Even though previous research on player substitution and tactical decisions, in general, during live matches, has not been extensive, a review of the selected papers shows a development and growing interest. One reason is most likely the availability of more tracking data than before, and the realization that analytics, when done right, can significantly contribute to a team’s success. A coach has limited chance to influence a football match as, with the exception of the half-time break, there are no timeouts as in other sports (e.g., basketball) (Geyer, 2009; Myers, 2012). Some of the options a coach has are change in formation or replacing a player (Hirotsu and Wright, 2002). Formations are different combinations of players in various positions which show whether the team plans on playing defensively or offensively (Hirotsu and Wright, 2006). A formation change occurs when the team switches a defender for a forward player, for instance. Hirotsu and Wright (2002) and Hirotsu and Wright (2006) mention something called *reversible tactics* – another strategy in addition to substitution for game influence. For instance, a midfielder can be instructed to play as an attacker and once the desired outcome is achieved, the midfielder can revert to his normal position (Hirotsu and Wright, 2006). According to the authors, the effects are similar as to making a substitution. They investigate this briefly but use hypothetical games and no other mention of this strategy has been found in the rest of the reviewed literature. It can be concluded that previous research has investigated substitution as a primary way for a coach to influence the game. Therefore, this is discussed in more detail below.

Substitution can make or break a team’s performance (Myers, 2012). Historically, FIFA regulated the application of substitution in football, allowing for two replacements, back in 1970 for the World Cup that same year (Varela-Quintana et al., 2016). The rule was slightly modified in 1994 when an extra substitution was allowed for an injured goalkeeper (Janković and Leontijević, 2006). This restriction for the third substitution was later removed and the flexible system as we know it today (with three substitutions allowed) has not been changed (Varela-Quintana et al., 2016). Recently, however, FIFA has allowed an experimental fourth substitution in specific games, and it is likely that an extra substitution will be allowed in the World Cup in 2018. This would offer a wide range of possibilities for coaches to influence the match (Varela-Quintana et al., 2016). It is therefore even more interesting to analyze this decision in more detail and suggest strategies to make it more effective.

Table 10 presents the methods, sample data and tools used in the reviewed publications.

Table 10. Methods, samples and tools used in previous research

Author	Method	Sample	Sample from	Tool
Hirotsu & Wright, 2002	Dynamic programming; Markov process model	Single match data of game in EPL, season 1998/99 5 hypothetical games	Not mentioned	Not mentioned
Lenahan & Solari, 2002	Narrative/qualitative expert analysis	5 games	Not applicable	Not applicable
Hirotsu & Wright, 2003	Dynamic programming	Match statistics from the EPL from season 1999/2000. Few games from the same team were analyzed.	OPTA Sports	GLIM statistical software
Hirotsu & Wright, 2006	Poisson regression; Game theory; Quantitative Analysis	Team data of two teams of the Japanese J. League from the 2002 season	Not mentioned	Not mentioned
Janković & Leontijević, 2006	Counting	The first 4 teams at World Cups 1998, 2002 and 2006.	Not mentioned	Not mentioned
Ledru, 2006	Modelling language	One game	Not mentioned	VDM specification language KIDS and VDM Tools
del Corral, Barros & Prieto-Rodríguez, 2008	Inverse Gaussian hazard model	380 matches from the Spanish Primera División from season 2004/05	PC Futbol Game	Not mentioned
Geyer, 2009	Empirical data Analysis	German Bundesliga matches from seasons 1985/86 – 2004/05.	DFB Fußballdaten vmLOGIC	Not mentioned
Hirotsu et al., 2009	Poisson regression; Game theory	Team data of two teams of the Japanese J.League from the 2002 season	Not mentioned	Not mentioned
Mengel, 2009	Spearman test for correlation Logictis regression	WC 1986-2006, U20 WC 1997-2008, Olympic football tournament 1980-2008.	FIFA.com	NA
Carling et al., 2010	Quantitative analysis Bonferroni t-tests	Elite soccer team from the French 1st division in the 07/08 season. 18 matches, 11 M and 14 CF 2nd half subs.	AMISCO Pro	AMISCO Pro SPSS
Coelho et al., 2012	ANOVA Post hoc Tukey's test.	45 male professional soccer players from Brazilian 1st division over 29 official games	Not mentioned	Not mentioned

Table 10. Methods, samples and tools used in previous research (Continued)

Author	Method	Sample	Sample from	Tool
Myers, 2012	Summary measures Hypothesis testing via one way ANOVA, t-tests. Decision tree	Game data of 155, 172, and 158 respective matches from the English Premier League, Italian Serie A and Spanish La Liga.	ESPN Soccernet	SAS Enterprise Miner
Siegle & Lames, 2012	ANOVA MANOVA Scheffe post hoc tests	16 matches of German 1st league 09/10 season.	Videos	SPSS
Bradley & Noakes, 2013	Descriptive statistics ANOVA	Match data from 169 players from the English FA PL seasons 2006/07 - 2008/09.	Prozone	Prozone proprietary software SPSS
Bradley et al., 2014	Independent-measures analysis ANOVA Tukey post-hoc tests	EPL matches 810 players competing the entire match and 286 substitute players	Prozone	Prozone proprietary software SPSS
Bartling, Brandes & Schunk, 2015	Descriptive statistics Regression	Match data of 8200 matches from the German Bundesliga (19998/99 – 2009/10) and the EPL (2000/01 – 2011/12).	Free from the internet Impire Press Association Sport ODDSET & Interwetten	Not mentioned
Purnomo et al., 2015	Metaheuristic method, called SGO.	Not mentioned	Not mentioned	Not mentioned
Rey et al., 2015	ANOVA, Student's t-test, Chi-square analysis. Decision tree	677 substitutions over 124 matches played in 2013-14 UEFA Champions League.	UEFA.com	WEKA SPSS
Gomez et al., 2016	Descriptive statistics Linear regression, multiple linear regression, Pearson Chi-square & Fisher exact test.	292 subs from 50 elite soccer games randomly chosen from the Spanish LaLiga 2014/15 season	whoscored.com	SPSS
Harper et al., 2016	Online survey Inductive content analysis.	46 respondents	Not applicable	Not mentioned
Silva & Swartz, 2016	Bayesian logistic regression	Myers' sample plus 3 more seasons from the EPL seasons 10/11, 11/12, 12/13	Not mentioned	WinBUGS programming language
Varela-Quintana et al., 2016	Exploratory analysis Hypothesis testing	Substitution data from Italian Serie A matches from seasons 1994/95 & 95/96.	footballdatabase.ue worldfootball.com pointafter.com	Not mentioned

The following observations can be made from the table above:

(1) ***Methods***: most publications rely on statistical methods for their analysis with ANOVA, regression, and chi-square being among the most used; only Myers (2012) and Rey et al. (2015) used machine learning in the form of decision tree method for their analysis.

(2) ***Sample***: most of the publications, with the exception of Purnomo and Wee (2015), mention the sample data used for analysis. However, a serious lack of reported dataset source can be observed. Nine papers in total did not report how they obtained their sample data and many did not explain the exact attributes their data consists of.

(3) ***Tool***: a similar issue is observed when it comes to the analytics tools. Eleven papers do not report the tools. As to the rest, SPSS is mostly used, which is understandable as most of the methods employed were statistical. In all of their papers, Hirotsu and Wright most likely use a statistical software GLIM, which is no longer developed. They reported it in only one of their papers from 2003, but as the analysis are similar, this is inferred here. Professional tracking software was used in the papers by Carling et al. (2010), Bradley and Noakes (2013), and Bradley et al. (2014).

In a next step, all papers were analyzed qualitatively in order to retrieve ***factors*** discussed as relevant for replacing a player. An overview of all factors that have been analyzed or mentioned additionally by the authors is presented in Table 11.

The most mentioned factor is ***tactical reasons***, with 16 papers out of the 23 reviewed, mentioning it. That is not surprising considering that by replacing a player, the coach directly influences and changes the tactical plan for his team (Janković and Leontijević, 2006). Tactics are influenced by and related to everything from substitution type and timing, to current score, location, and team formation, all of which are explained below.

The ***game score*** is the most important factor for the timing of substitution – when the team is tied or losing, substitutions are made earlier and vice versa (Del Corral et al., 2008; Geyer, 2009; Myers, 2012; Rey et al., 2015). This is also confirmed by Bartling et al. (2015), who in addition observe that, on average, there is no strategy adjustment before a goal is scored. According to the authors, the behavior of players and coaches depends in large part on whether or not the team is losing. When the team is winning, the coach should preferably encourage the same playing style that lead to this win, and consider defensive strategy as not optimal in this case (Silva and Swartz, 2016).

Timing refers to attempts by authors to find the right time for making the first, second and third substitution, depending on factors like the current score, opponent’s strength, location (home/away), among others. The other research focus is mostly retrospective analysis on determining the timeframes or minutes when coaches substitute the most. Studies are uniform in that there are very few substitutions done in the first half, and mostly due to reasons that cannot be influenced, like injury or red card (Bartling et al., 2015; Del Corral et al., 2008; Myers, 2012; Rey et al., 2015). Large number of substitutes are made at the half time break (Del Corral et al., 2008; Rey et al., 2015). Most substitutions are done between 60 to 75 minute (Janković and Leontijević, 2006); 46 to 70 minute (Del Corral et al., 2008); on average, first substitution at 57 min, second at 71 min, and third at 81 or 82 min (Myers, 2012); 57 to 78 minute (Rey et al., 2015), first substitution 46 to 75 min, second between 61-90, and third between 76-90 (Gomez et al., 2016). Finally, in the last 20 minutes of the match according to Del Corral et al. (2008), there are less substitutes, while Rey et al. (2015) set this time to last 10 minutes of the match.

Table 11. Substitution factors retrieved from reviewed literature

	Substitution factor														
Reference	Tactics	Opponent's tactics	Opponent strength	Timing	Type	Score	Performance	Player availability/ protection	Fatigue	Injury	Yellow Card	Location	Weather	Substitution rule	**# of factors**
Hirotsu & Wright, 2002	x			x		x	x	x							5
Lenahan & Solari, 2002			x							x		x	x		4
Hirotsu & Wright, 2003	x						x		x	x		x			5
Hirotsu & Wright, 2006	x														1
Janković & Leontijević, 2006	x			x	x	x									4
Ledru, 2006														x	1
del Corral et al., 2008	x			x	x	x				x	x	x			7
Geyer, 2009	x	x			x	x		x	x	x					7
Hirotsu et al., 2009	x	x													2
Mengel, 2009				x											1
Carling et al., 2010	x				x		x		x						4

Table 11. Substitution factors retrieved from reviewed literature (Continued)

	Substitution factor														
Reference	Tactics	Opponent's tactics	Opponent strength	Timing	Type	Score	Performance	Player availability/ protection	Fatigue	Injury	Yellow Card	Location	Weather	Substitution rule	**# of factors**
Coelho et al., 2012	x								x						2
Myers, 2012				x		x			x			x			4
Siegle & Lames, 2012	x														1
Bradley & Noakes, 2013					x	x	x		x						4
Bradley et al., 2014	x			x	x	x	x		x						6
Bartling et al., 2015	x			x	x	x	x			x					6
Purnomo et al., 2015							x								1
Rey et al., 2015	x	x	x	x	x	x		x	x	x	x				10
Gomez et al., 2016	x		x	x	x	x			x	x	x	x			9
Harper et al., 2016	x								x	x				x	4
Silva & Swartz, 2016		x		x		x	x					x			5
Varela-Quintana et al., 2016	x		x	x	x	x						x		x	7
Total	**16**	**4**	**4**	**11**	**10**	**12**	**8**	**3**	**10**	**8**	**3**	**7**	**1**	**3**	

Myers (2012) went as far as suggesting a concrete rule to guide coaches on the right substitution timings depending on the current game score. Rule is presented in Table 12.

Table 12. Proposed decision rule by Myers 2012

If down:
Make 1st substitution prior to 58th minute
Make 2nd substitution prior to 73rd minute
Make 3rd substitution prior to 79th minute
If tied or ahead:
Make substitution at will

The suggested rule seems very attractive due to its simplicity, clarity and seemingly easy implementation in practice (Silva and Swartz, 2016). Following its publication, it gathered a lot of attention from mainstream media, and was even recognized by Anderson and Sally in their popular book "The Numbers Game" (Silva and Swartz, 2016). The authors Silva and Schwartz review the proposed rule by Myers and offer an alternative method of analysis. Their results do not identify times in the second half in which it is beneficial to substitute, but as the authors mention themselves, they are using different method (Bayesian logistic regression) and different variables. Silva and Swartz then go on to say that coaches make good decisions and they start the game with the best team possible, which in turn makes a substitution basically a replacement of a good quality with a slightly lower or at least equal quality. The authors' conclusions are rather general and superficial, and a coach does not always start with the best team for various reasons (e.g., to protect a player who has a recent injury or is more important for another game, or the opponent is not at the same strength level). Furthermore, they do mention that considering their contradicting results to Myers, the question arises of what the managers are supposed to do in practice. This question, however, remains unanswered. The author of this thesis does accept their recommendation that substitutions should be made, especially when a player's performance drops, but that these replacements should not be tied to specific timings as done by Myers.

Substitution type refers to the position of the players that leave and enter the game. An offensive substitution is done when, for instance, an attacker enters, and a midfielder leaves; defensive, when e.g., a defender enters, and an attacker leaves; neutral, when e.g., a midfielder is exchanged for a midfielder (Rey et al., 2015). Defensive substitutions are made later in the match than offensive substitutions; especially when losing, more offensive substitutions are made and vice versa (Bartling et al., 2015; Del Corral et al., 2008; Geyer, 2009). Overall, offensive substitutions are more frequent than defensive ones (Del Corral et al., 2008; Rey et al., 2015), and substitutions become more offensive in general, as the second half progresses (Bartling et al., 2015; Bradley et al., 2014). If team is winning, there will be a tendency towards more defensive strategy (Bartling et al., 2015). More specifically, considering the player positions separately, most often chosen positions for leaving the game are midfielders, followed by forward players or strikers, and defenders, while for entering the game, most preferred are strikers, then midfielders and defenders (Janković and Leontijević, 2006). In contrast, Del Corral et al. (2008) and Rey et al. (2015) observe that most substitutes are midfielders, and the most often used combination is midfielder for midfielder. This, however, also contradicts to another statement by Del Corral et al., that offensive substitutions were the most frequent ones. Another contradiction can be found in the results by Gomez et al. (2016) who found that central midfielders were mostly used as substitutes, followed by forwards, and wide midfielders, while neutral substitutions were the most common. Finally, when analyzing the effect of an additional substitution on coaches decisions, Varela-Quintana et al. (2016) found that a change in the rule resulted in more neutral substitutions done by coaches. Overall, it seems that one thing which is common in these studies is that defenders are replaced and used as substitutes the least, compared to other positions.

Fatigue as a substitution factor was investigated in more detail in four publications (Bradley et al., 2014; Bradley and Noakes, 2013; Carling et al., 2010; Coelho et al., 2012), and mentioned in seven others. The four papers mentioned analyzed the effect of substitute players on the high intensity activities, distance ran, and work-rate performances of substitute players compared to the players they replaced, or their own performances when playing from the beginning. Bradley and Noakes, (2013) and Bradley et al. (2014) found that substitute players cover greater distance and had more high intensity running compared to the equivalent time when playing the full match, as well as compared to the rest of the players in the game, and the players they replaced. The tendency of players to decrease their effort intensity during the second half, suggests that fatigue develops during the game (Coelho et al., 2012). Thus, substitute players are likely to be able to perform higher intensity actions than athletes who played the entire game, and as a result, increase the chances of winning (Coelho et al., 2012). Furthermore, with regard to player positions of in- and out players, it was determined that midfielders cover greater overall distance including in high intensity activity compared to midfielders who remained in the game (Bradley et al., 2014; Carling et al., 2010). However, there is a contradictory finding regarding the attackers' performance. Carling et al. (2010) found that attackers cover less distance as a substitute compared to their profile when playing from the beginning, while Bradley et al. (2014) found the opposite – attackers covered more high-intensity running than peers or their own performances during an entire match. Bradley and Noakes (2013), however, got a similar result as Carling et al. (2010). The reasons for the different results are hard to estimate. One possibility could be the different datasets used and the fact that Carling et al., distinguished between midfielders and attackers only, while Bradley et al., considered five different playing positions. Overall, regarding this substitution factor, it can be concluded that from a work-rate perspective, a substitution seems to be effective, but it is still not clear whether substitution is also effective from a technical and outcome perspective (Bradley et al., 2014). Having this information would help the coach in optimizing the performances of his players during the game, as it will become more clear the contribution of each player position to the overall team performance (Bradley et al., 2014). This understanding is very important for gaining tactical advantage (Coelho et al., 2012).

There are a few factors retrieved from the reviewed literature which seem to be less important or at least have been discussed only by few studies. ***Weather*** was only mentioned once by Lenahan and Solari (2002) and does not seem to be an important factor, especially compared to the rest. ***Opponent's strength*** and ***tactics*** (especially opponent's substitutions) have been mentioned in a few papers as possibilities for future research (Geyer, 2009; Hirotsu and Wright, 2003; Rey et al., 2015). ***Yellow card*** is mentioned but not studied in detail, as a way to protect the player who received warning and to avoid his potential dismissal by e.g., red card (Gomez et al., 2016; Rey et al., 2015). ***Location*** refers to whether the team plays home or away. Additionally, it does not seem that existing research has focused enough on the technical aspects of players' ***performance*** in relation to substitution and how this affects the game outcome and the team's performance overall. Myers (2012) and Rey et al. (2015) specifically call for the integration of more factors when studying substitution in the future.

Existing research on player substitution in football has advanced and in recent years the papers build upon previous research results. Professional tracking data contributes the most for better quality of the studies, as early research relies mostly on hypothetical data (e.g., the papers by Hirotsu), or data freely available on the web with which very limited information about the game is available, and it tends to be aggregated. A major drawback of previous research is the lack of rigorous dataset description which makes the reproducibility impossible. Small sample sizes make generalization of the results meaningless. In addition, as seen previously, there have been contradictory findings in previous research results. Most importantly, though, almost none of the papers included in the review process discuss the implications for practice. There are no guidelines on how and why coaches should implement the results in practice, or the potential outcome by following some of the rules and recommendations found. However, with the differences reported between studies, this would also make not much sense. Most of the authors are not sports scientists, so even though this makes the statistical analysis rigorous, the interpretation of the results is superficial or non-existing. Another important outcome of the review is that existing research has focused on analyzing aspects of the substitution decision, but none have referred directly to decision makers to investigate how they make their decisions, and which factors they consider. If research outcomes are to have practical implications, then it would be mandatory to first understand the decision-making process of coaches and find out what would be important for them to have as information.

Considering the critical review of previous research results, in a next step, a qualitative study is conducted with coaches and football experts from the world of professional football in Germany.

4.3 Qualitative study

In this section, a qualitative study is conducted via semi-structured interviews with football experts from the professional football league in Germany. The study's main ***objective*** is to understand in more detail how experts decide on which player should leave the game and when. To achieve the research goal, it is of relevance to (1) confirm, revoke and extend the derived substitution factors from literature and, thus, make generalization possible, and (2) to investigate whether coaches and their teams rely on tracking systems when making this decision – the goal here is to get an understanding of how coaches perceive the use of analytical support systems in such situation.

Following the definition of the research objective, the next step in a qualitative study is deciding on the ***method*** which would give the best results in reaching this objective. Some of the methods used in this type of study design are interviews, observations or focus groups (Anderson, 2010). In this case, interviews were chosen to be most appropriate, and specifically, *semi-structured interviews*. This type of interviews has the advantage that on the one hand, the researcher can ask all the predetermined questions, but on the other, they can leave space to the interviewees to offer new meanings to the studied phenomenon, and thus allows for considerable reciprocity between the participant and researcher (Galletta, 2013). This offers both structure and flexibility in the research inquiry.

In a next step, the ***interview questions*** need to be defined. These should relate to the objective which in turn is derived from the literature review. Stemming from the review findings, the interview questions were developed. Each question is related to one or more of the derived substitution factors. An overview is given in Figure 11.

Mostly factors that were often mentioned and analyzed were chosen when formulating the interview questions. As it was anticipated that experts will tend to give short and clear answers and will have a limited time at their disposal, the number of questions was kept as short as possible. Opportunity to gain additional information was taken spontaneously, depending on the answers of the interviewees.

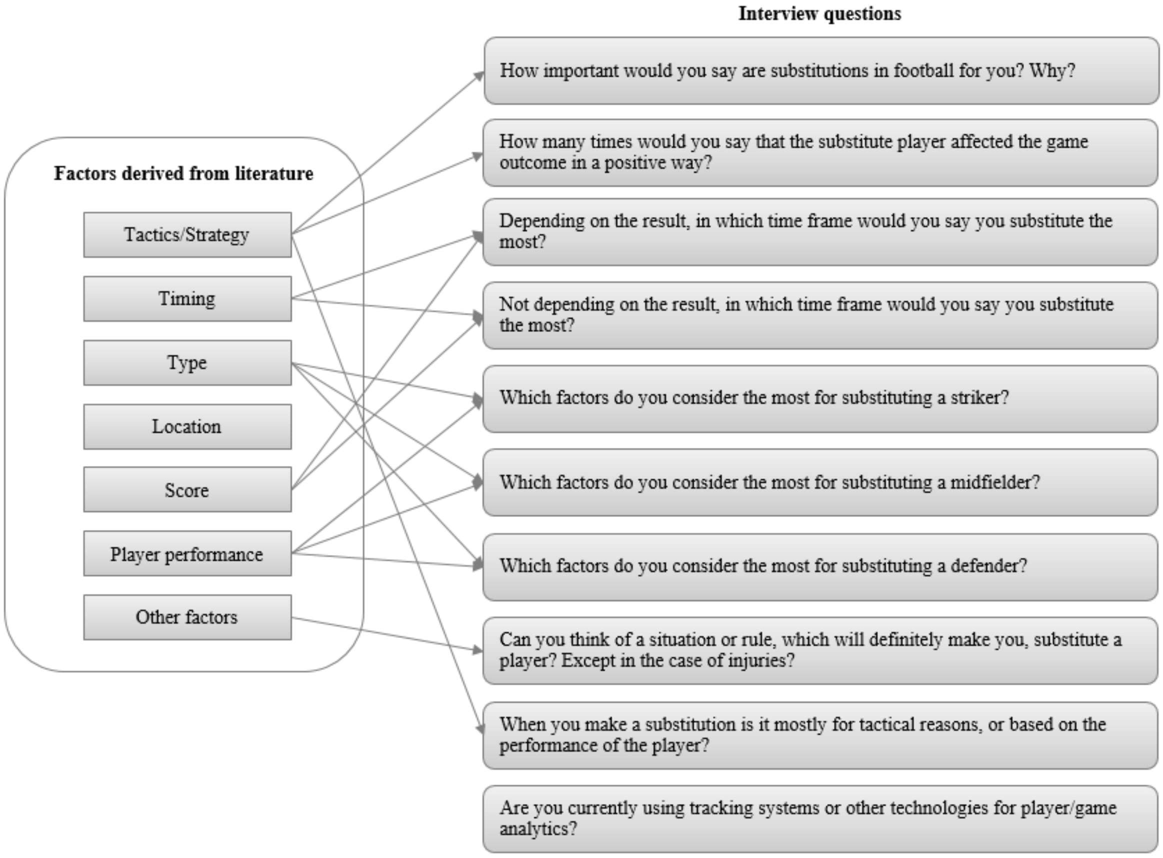


Figure 11. Interview questions based on the literature review findings

4.3.1 Participants

Potential participants were chosen by using the *purposive sampling* method. This means, only participants who have characteristics relevant to the study and can be most informative were contacted (Anderson, 2010). Data was collected as part of a bachelor thesis (Tümer, 2016), under the supervision of the author of the current thesis. The student was part of a professional tracking system company and had direct access to football experts. Therefore, the contact was established relatively easy and what could have been a major obstacle, was avoided in this case. The major criteria for sampling, was the expertise level of the participants. An *expert coach* is someone who (a) has extensive knowledge obtained via a number of formal (e.g., certification programs) or non-formal (e.g., coaching workshops) learning environments, (b) who’s knowledge and experience allows them to make intuitive decisions, and (c) who achieves consistent and superior performance (O'Connor, 2013). In this case, as football expert we considered someone who works/has worked in the professional Bundesliga either as football player turned coach or a coach who has demonstrated expertise and success over the years. Experts were divided into three categories, according to their level of expertise. *Category A* is the highest level and consists of former national players turned professional coaches. These are well-known experts whom we have watched over the years in either capacity, and professionals about whom we read in magazines and TV shows. *Category B* are coaches and experts who work currently at professional level but have not yet achieved the stardom level of category A. Finally, *category C* are former players or coaches with professional coaching license that work as support staff or are at the beginning of their coaching career.

4.3.2 Data collection

Football experts were contacted between November 2015 and March 2016. An interview guideline consisting of ten main and four additional questions, was prepared in advance in both German and English. In total, ten interviews were conducted. The number of interviews was not pre-determined as it was decided to conduct interviews until data saturation was reached. Data saturation is a concept related to sampling in qualitative research studies, and helps researchers decide when to stop with data collection. Saturation is reached “when no additional data are found” (Saunders et al., 2017), or when those “data do not lead to any new emergent themes” (Given, 2015). Following the ten interviews, clear patterns in the answers of the experts were observed and it was decided that further interviews would not influence significantly the results. Table 13 gives an overview of all the interviewees, the language and duration of the interviews.

Interviewees 7 and 8 work at the same club and both participated in the interview. Another point of observation is that interviews were rather short with average duration of 12 minutes. This confirmed the initial expectation that questions should be short and precise. Most interviews took place either in person (5 in total) or via phone (4 in total). Only one expert, number 6, preferred to answer via email. As it is an expert of category A, his answers were considered extremely relevant, so this was allowed. Finally, a larger portion of the interviewees is from category A (6 participants), with one from category B and three from category C.

Table 13. Overview of participants and interview durations

#	Interviewee	Position	Expert level	Language	Via	Min.
1	Marco Pezzaiuoli	▪ Former coach of the German youth team ▪ Former head coach at TSG Hoffenheim ▪ Currently, coach in China	A	DE	Person	7
2	Fredi Bobic	▪ Former sports director at VFB Stuttgart & German national player	A	DE	Person	6
3	Krasimir Balakov	▪ Former Bulgarian national player ▪ Former player in the Bundesliga ▪ Assistant and head coach in clubs in Germany, Switzerland and Bulgaria	A	DE	Phone	15
4	Cihan Yilmaz	▪ Professional football player ▪ DFB licensed coach	C	DE	Phone	17
5	Taner Koc	▪ Former professional football player ▪ UEFA A license	C	DE	Person	10
6	Christoph Daum	▪ One of the most famous football coaches in the German professional football league	A	ENG	Email	/
7	Tobias Gitschier	▪ Former youth coach in the 2nd Bundesliga ▪ Video analyst of a 1st Bundesliga team	B	DE	Person	14
8	Steffen Conrad	▪ Supports assistant manager and coaching staff in a 1st Bundesliga team	C	DE	Person	
9	Falko Götz	▪ Former German football player ▪ Professional football coach	A	DE	Phone	13
10	Stefan Effenberg	▪ Former German national football player ▪ Professional coach in the Bundesliga	A	DE	Phone	15
					Total	97
					Average	12

4.3.3 Analysis

All interviews were recorded and transcribed by using the *smooth verbatim* transcription system, as described by (Mayring, 2014). This system was chosen because transcription is done word by word but utterances like *uhms* or *ahs*, or decorating words like, *right*, *you know*, *yeah* are left out (Mayring, 2014, p. 45). The coding procedure was done twice by two coders, and in two cycles. In the first cycle, codes were predefined based on the interview questions. During the first coding cycle, additional emerging themes were assigned new codes. When the first round was finalized, codes were reviewed and restructured or modified as needed. The final list of codes contained four categories, and under each category, several codes were added. These are presented and described in Table 14.

Table 14. Coding categories and codes overview

Category	Code	Description
General	Sub-Importance	Is substitution important for the interviewee?
	Sub-Positive influence	How often the substitute player had a positive influence?
	Sub-definite rule	A rule/situation which will definitely provoke substitution.
Factors	Tactics	Anything referring to tactical aspects.
	Score	The role of current game score as a factor.
	Timing-Score dependent	Timing of substitution depending on the current score.
	Timing-General	Timing in general.
	Performance	Technical performance
	Weather and pitch conditions	Are these factors relevant for player substitution?
	Injury	Injury as a sub factor.
	Cards	Cards, including yellow and red cards.
	Other	Other factors mentioned by participant.
Position	Forward	Factors for sub forward players.
	Midfielder	Factors for sub midfield players.
	Defender	Factors for sub defenders.
	Position-General	General comments on sub positions.
Tracking systems	Reasons	Reasons and experience for using tracking systems (TS)
	Timing	When are these TS used the most? Pre- post or during the game?
	Results presentation	How are results presented and communicated to the team?

QDA Miner[2] was chosen as tool for the coding and content analysis (Version 5.0.17, Provalis Research).

4.4 Results

Following the coding system presented in the previous section, this step of the content analysis resulted in 169 coded segments. An overview is presented in Figure 12. The highest number of coded segments belongs to the categories relevance of the substitution decision, positive influence of substitute players, definite rule that will provoke substitution, timing in general, factors for replacing strikers, midfielders and defenders, and finally reasons for using tracking systems. Below, results will be summarized based on each of the four categories.

[2] https://provalisresearch.com/

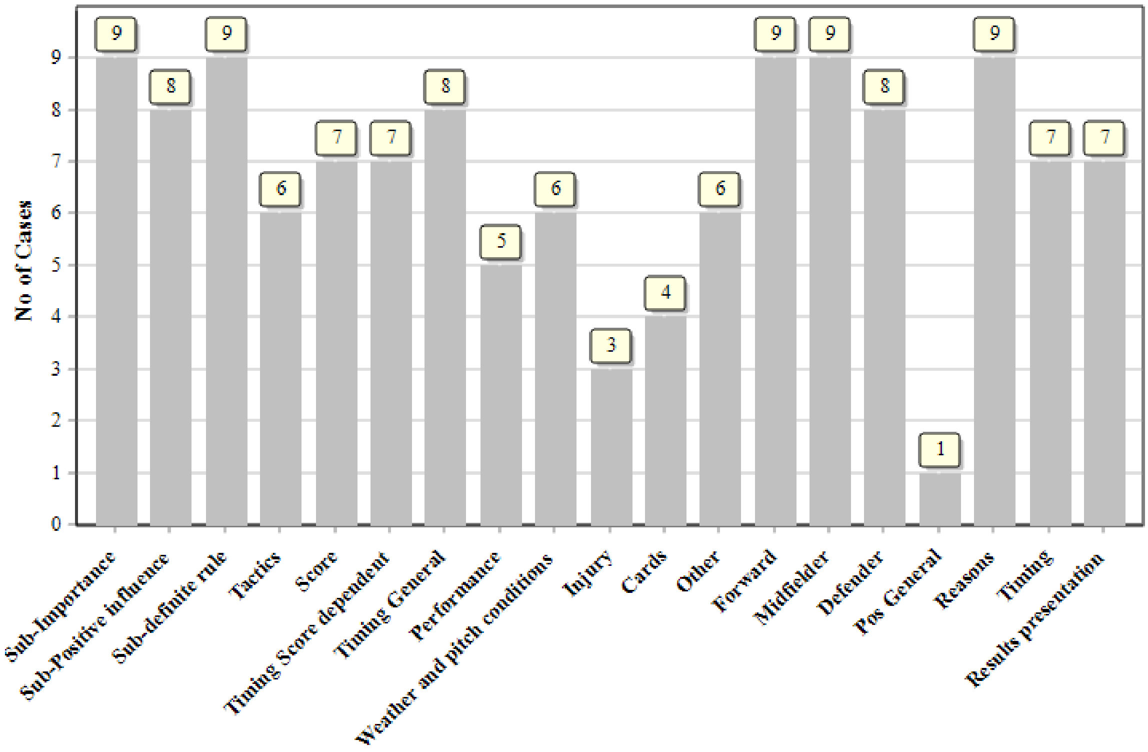


Figure 12. Distribution of codes (N_o of cases per code)

Category 1: General perspectives

All participants, apart from Effenberg, agreed that substitution is a very *important decision* in football. Reasons mentioned here are mainly to give a new impulse to the game, to have the chance to influence and make a difference when the match develops not as expected, tactical reasons or injuries. Effenberg was the only expert who had a stricter view on the relevance of substitution, stating that it can be important only in the case of injury. Otherwise, the coach would have no reason to replace players if the game runs as expected. He does state, however, that there are a lot of factors for substitution, but stresses his earlier point that it should not take place if unnecessary.

Regarding the *positive influence* of a substitute player on the game, the opinion is divided. Balakov, Bobic and Goetz have positive experiences with substitutive players, and state that it often happens that a player who enters the game at a later stage positively affects the game via e.g., scoring a goal. Balakov even estimates this at 60 percent. Koc is mostly neutral and gives an estimation of 50 percent positive influence. Gitschier, Konrad, Effenberg and Daum have a more negative opinion on the matter. However, only Daum states what is already discussed in the literature – that there is no evidence of the effect of substitute players on the game. "*If a substituted player scores or prepares a goal or make an unbelievable save or interception, we say this substitution made the difference*" (Daum). Otherwise, the only way to estimate the influence of a substitute is by measuring, what Daum calls "objective parameters" such as "*winning duels, pass accuracy, preparing or scoring goals or even physical parameters*". This line of reasoning is in relation to review findings and, in general, any percentage can be considered as purely a rule of thumb estimation, as there is no scientific proof, yet.

Three main *situations* would make coaches *definitely replace a player*: (1) tactical reasons, (2) unsatisfactory physical (i.e. fatigue) and technical performance, and (3) current score or the way in which the game develops in general.

Category 2: Factors for substitution

Factors discussed often overlapped with each other and at times tactics was not coded separately to avoid too much overlap. However, overall, all participants discussed mostly ***tactics*** and ***performance*** as factors that they consider for replacing a player. When asked to choose between these two factors, some slightly different answers were received. Daum, Effenberg, and Balakov chose tactical reasons, while Gitschier said that both factors are relevant, and one cannot choose one over the other. Gitschier's colleague, though, from the same club, had a different opinion. According to Konrad, performance is the more relevant factor: „*Ich würde es schon auf die Leistung des Spielers zurückführen, weil wenn ich merke mein Stürmer oder meine Außenspieler sind unglücklich und bringen am heutigen Tage wenig zustande, dann wechsle ich aus Leistungsgründen, aber würde am System dann wenig ändern*". In his view, when a player underperforms, coach can make a neutral substitution (e.g., midfielder for midfielder) and not change his tactical plan at all. Bobic also considers the performance as more relevant, while tactics are important towards the end depending on the score.

Timing was often mentioned in relation to the current ***score*** or the course of the game. Coaches substitute rarely in the first half (Daum, Balakov), while in the second half, they substitute the most between 60 and 70 minutes (Effenberg, Koc, Yilmaz), from the 60th minute on (Daum, Pezzaiuoli), or in the 70 to 75 minutes (Gitschier & Konrad). Replacements in the first half are due to tactical requirements not being followed (Balakov), injury or bad performance (Gitschier & Konrad). The score and the ways the game develops has a high relevance for coaches when deciding on substitution. The 60th minute or any other timing does not matter to Goetz, as he says that it all depends on the situation at hand „*Also ich mach das in keinster Weise abhängig von Minuten, sondern da verlasse ich mich auf mein Gefühl und auf meine Beobachtungsgabe*". A similar viewpoint was expressed by Effenberg – he does not start the game with a plan by the minute but observes how things develop and decided based on whether his team is in the lead or not and with how much goal difference.

Weather does not have an influence on player substitution, at least not in Germany. This is normally cleared out beforehand (Effenberg) and everyone plays on the same pitch (Bobic). ***Injury*** as a factor is considered when a player is injured unexpectedly, or a player who has recently recovered (to give him practice time), or to protect a player from a possible injury (Daum). Cards are also something to keep in mind, especially yellow cards, as a second yellow card will mean player needs to skip next game (Bobic), or red cards including for goalkeepers (Gitschier, Yilmaz). These are unforeseeable, but a coach must always be prepared for them and be able to react accordingly.

At times, coaches gave a longer answer on substitution factors, and in this case, segments were coded under "other" as it was difficult to extract full sentences regarding one single factor. In addition to referring to the previously mentioned factors, some coaches also mentioned aspects like replacing a player who performed very well (e.g., scored 3 goals) to give a chance to the audience to award him with applause (Daum, Götz, Koc), interpersonal skills (Daum), whether it is important to win the game, or perhaps a tie is enough (Effenberg), is the team palying home or away (Effenberg), and finally, regarding the opponent – to disturb their rhythm (Daum), to prepare in advance for a specific opponent, considering theor strengths and weaknesses (Effenberg), or to respond to the tactical moves of the opponent (Gitschier & Konrad, Goetz).

Category 3: Substituting per player position

One reason for substitution a ***forward*** player is tactical reasons (Balakov, Koc). Most of all, though, "not fulfilling his tasks" was pointed out as a factor (Bobic, Gitschier & Konrad, Goetz, Koc, Pezzaiuoli). A forward's task is not only to score goals, but in modern football he is also a provider – "*Wenn wir schnell in die Tiefe spielen wollen, ist er unser erster Anspielpartner, wenn er die gut macht und der Außenstürmer dann das Tor macht oder der Mittelfeldspieler dann reinstoßt, dann erfüllt er seine Aufgabe*" (Pezzaiuoli). Yilmaz refers to something that was also found in the literature, that when the team is in the lead, he would use a defensive substitution, and when losing, an offensive player will enter the game. There are also different types of forward players who have different strengths, for instance, winning air duels, if player is taller, or more aggressive in the attacking third. This should also be kept in mind when replacing forward players.

Tactical reasons are also relevant for substituting a ***midfielder*** (Balakov, Effenberg, Pezzaiuoli, Yilmaz). A midfielder is very important as he is the engine of the team (Yilmaz), he is someone who needs to assist and push the team (Daum) and runs more kilometers than the rest of the players (Gitschier & Konrad). Therefore, when midfielders have high passing, tackles and other error quotes, they need to be considered for replacement (Pezzaiuoli, Yilmaz, Gitschier & Konrad, Bobic).

Defenders are generally not substitution targets (Balakov, Gitschier & Konrad, Koc, Yilmaz). Some reasons for their replacement are tactics (Balakov, Goetz, Pezzaiuoli), performance is really underwhelming, e.g., high error quote, fatigue, not able to deal with the offensive play of the opponent (Pezzaiuoli, Yilmaz, Koc, Gitschier & Konrad, Balakov), and of course, injury (Goetz, Gitschier & Konrad).

Category 4: Tracking systems

All coaches stated that they are using tracking systems. Some of the systmes mentioned are: Opta, POLAR, MiCoach, Mastercoach, Scouting feed, Sportscode, and allowed GPS systems. ***Reasons*** for using are: showing the players where their errors were (Balakov, Effenberg), coaches' own errors (Yilmaz), speed and heart rate (Pezzaiuoli), preparation for the next game (Goetz, Yilmaz), analysis of the opponent (Effenberg, Yilmaz, Gitschier & Konrad), training program. Most of the coaches have very positive experiences with analytics systems: "*Ich bin schon ein großer Fan*" (Balakov), "*…dass es sehr hilfreich ist für die Spieler*" (Yilmaz). Effenberg, is still more reserved: „*aber unter dem Strich steht dann das Fußballspiel*".

All respondents said they are using tracking systems before and after the game. Bobic uses them also in real-time mostly during the half-time break, when analysts show directly with the most important information in a shortened form. Gitschier and Konrad even show short video snippets during the half-break to their team, while Goetz is using them reluctantly as, according to him, there is not enough time to act on the results.

Coaches discuss the videos and analysis results either with the whole team, or in separate groups, especially groups comprised of the separate positions. Individual talks are not conducted very often, only when necessary (Balakov).

4.5 Discussion and consolidation of findings

A constant theme throughout all interviewees' answers was that there is no single factor that can be acknowledged as the most relevant when it comes to deciding which player should leave the game. All factors are tightly related with each other. Some influence or depend on others, some are more, or less important. Therefore, it is not wise to define if-then rules as it was the case in the paper by Myers (2012). All coaches mention that everything depends on the current situation and the way the game develops, as well as their own goals for that particular match – is a win necessary or is tie also acceptable? Additionally, it can be observed that there are some differences between coaches' views regarding certain factors. This means that when a solution for real-time decision support is offered, it must be flexible and adjusted to each coach wishes. It needs to display the information that a coach specifically requires. All interviewees are currently using such system, but as expected primarily pre- and post-match. Only the three mentioned coaches use them during live games. However, at the moment the opportunities for this are also limited as so far, the focus has been primarily on analysis during training or before/after the game.

Regarding performance, all coaches state that when a player is not fulfilling the delegated tasks, regardless of position, they will be considered for replacement. However, some coaches also point out that players must not be immediately punished for their mistakes and some margin of error is allowed. For instance, Balakov stated that he is patient with his players, especially when he trusts a player, and knows that he will eventually not disappoint.

The empirical study confirms some of the literature findings and extends the knowledge base further. An overview of which findings from the literature were confirmed by the QUAL study is presented in Table 15.

Table 15. Comparison of literature and empirical study findings

Literature finding	Confirmed in QUAL study?	Elaboration
Tactics is one of the most relevant factors	Yes	
Current game score is important factor and strongly related to timing of substitution	Yes	
Attempts to find specific time slots for substitution	No	Interviewees point out minutes in which most substitutes are made but mention that this depends on the current situation.
If the team is winning, there will be a tendency towards more defensive strategy	Yes	
Most often chosen positions for leaving the game are midfielders, followed by forward players or strikers, and defenders	Partly	Midfielders and strikers are mentioned as substituted most often, while defenders are confirmed to be replaced the least.
Fatigue as relevant factor	Yes	But mostly based on simple observation, and not analytics.
Weather does not seem to be relevant factor	Yes	At least not in Germany.
Opponent's strength and tactics as future research	Yes	Coaches consider this as a relevant factor which they consider for player substitution.
Yellow card as way to protect players from being completely dismissed and red cards should be anticipated	Yes	
Location	Partly	Only mentioned by one coach.
Additional substitution and its effect on the types of substitutions	No	This was omitted from QUAL study.

The major difference between research and practice was found in the timing of substitution. Large body of previous research has focused on finding the best time for replacing a player depending mostly on the current score. In practice, this is not relevant, and it depends on the interaction of a wider variety of factors in addition to the current game score. Coaches are not interested in finding the perfect timing and it is questionable if such can be determined, or more importantly, if this makes sense. The effect or relevance of additional substitution was not investigated in the empirical study and therefore comparison is not possible. However, according to latest developments, as mentioned earlier, such substitution is most likely going to be permanently introduced and allowed in professional football. Future studies could make perhaps a comparison between the effect of the third and fourth additional substitution rule changes.

Based on the results from previous research and the empirical study, it is possible to derive a more detail overview of factors that could be considered for substitution in football. These are presented in Figure 13.

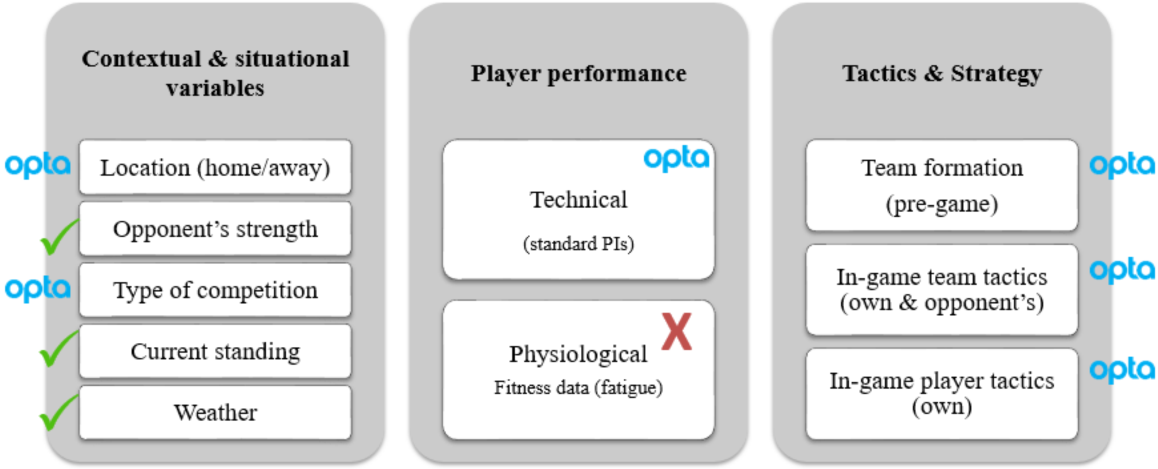


Figure 13. Derived substitution factors

Derived factors are categorized in three different categories. First category consists of the ***contextual and situational variables***: match location, opponent's strength, competition type (national, international, cup league), current standing in the table, weather (included for full representation). Second, the ***player performance*** factors: technical and physiological performance which refers to typical PIs as described in section 2.3. And third category, related to ***tactics and strategy***: team formation – the team structure determined pre-game, in-game team tactics from own team and the opponent, and in-game player tactics (own and opponent's players). Additionally, in the figure above, the availability of capturing data related to each factor is displayed, including which data are available via Opta Sports, as this will be the dataset used in the current thesis. The only factor that cannot be investigated in the current study is the physiological performance which is related to fatigue. These data are currently not being collected in live games, and are therefore, not readily available for analysis.

4.6 Limitations and future research

The empirical study does have some limitations. First, participants were football experts primarily from Germany, although few are of foreign background like Balakov or Yilmaz. Others have international careers and experience outside of Germany, for instance, Daum. However, a more extensive study with coaches spanning several professional leagues across Europe or other continents, can be conducted. In this way, perspectives on real-time decision making and support from various leagues around the world can be gained which will contribute to the existing knowledge base. Cultural aspects may also be considered in such case. Second, the questionnaire can be modified in two ways: (1) questions which refer to aspects that confirm previous research findings, can be removed, and (2) additional questions perhaps focusing on future possibilities or new research findings meanwhile, could be considered. Some aspects form literature in the current study had to be omitted as the questionnaire had to be kept as short and concise as possible. Only the factors from literature that were identified as most relevant to answer the thesis' research question, were chosen when formulating the interview questions. Finally, focus groups with several coaches could be considered as a method of data collection, if this would be feasible.

Part III - Advanced Analytics Methods for Team and Player Insights

5 Study Design

5.1 Data analysis process

Three different methods for data analysis are applied on football tracking data to derive player and team insights. The practical implications of the results are discussed in general, while the applicability for real-time tactical decision support is further discussed in Part IV. The ***analytics methods*** used in this chapter are inspired by and chosen based on the dynamic system theory, the findings in chapter 4, and the acquired dataset. These are: a) *dynamic network analysis* – for analyzing the team and player interactions (chapter 6); b) *self-organizing maps* – a type of neural network architecture (chapter 7), and c) *process mining* – for analyzing action sequences (chapter 8). The structure of each chapter is based on the Knowledge Discovery in Databases (KDD) process. It is one of the well-established processes for data mining projects. An overview of the process steps followed in this part is presented in Figure 14.

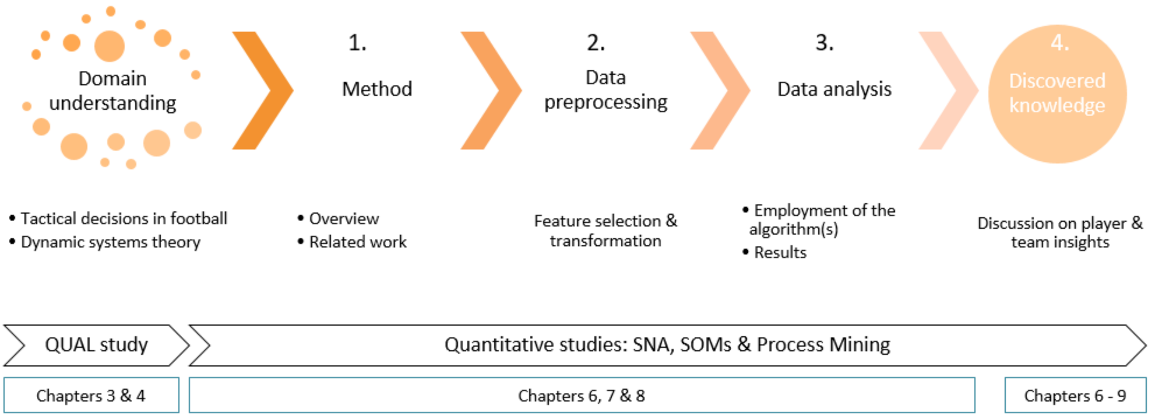


Figure 14. Steps followed in Part III

A first step in any data analytics project is understanding the domain, goals that need to be reached, and the questions that should be answered by means of advanced analytics methods. Chapters 3 and 4 discussed the dynamic system theory as an alternative way of analyzing football performance data, and explained the tactical aspects of football, with special focus on tactical decisions during live games – mainly the substitution decision. By conducting a literature review and a qualitative study a better understanding of the *domain area*, in this case, tactical decision making in football, could be gained.

Following the domain understanding, three different analytics methods, or collection of methods of different types (social network analysis, artificial neural networks and process mining), are applied on professional tracking data. Each method is described in a separate chapter that follows a similar structure:

1. The *method* itself is described and related work in the area of football performance analysis is presented and discussed.
2. A brief explanation of the *data preprocessing* is given, describing which attributes from the dataset are relevant for the specific method and how data was transformed so that it is possible to apply the method. This step is the most time consuming but also one of the crucial steps in any data mining process, as any mistakes at this point will affect the quality of the final results.
3. *Data analysis* by applying analytics techniques from the three methods.
4. *Discovered knowledge* - discussing the derived player and team insights and their practical implications. In chapter 9, it is further discussed which of these insights could be used by coaches during real-time decision making.

5.2 Dataset description

For the analysis employed in the current thesis, a professional tracking data was acquired by the company OPTA Sports[3]. It was provided by the Institute for Football Management in Ismaning, as part of a cooperation with the Chair of Information Systems, Services, Processes, Intelligence headed by Prof. Dr. Freimut Bodendorf in the area of football analytics.

OPTA was founded in 1996 and since then it has established itself as the leading provider of event data in several sports and countries around the world. It has more than 800 clients in approximately 40 countries (OPTA Sports, 2017d). OPTA collects event data and records every action that occurs during a game in a *"who-what-where-when"* manner. On average, 2600 events are collected per game. An event in football is not as simple to record as it may seem initially. To describe a single event e.g., shot on goal, OPTA uses so called *qualifiers*. They span over several rows and contain additional information about the action that took place. A snapshot of how an event is represented in an .xml file, can be seen in Figure 15.

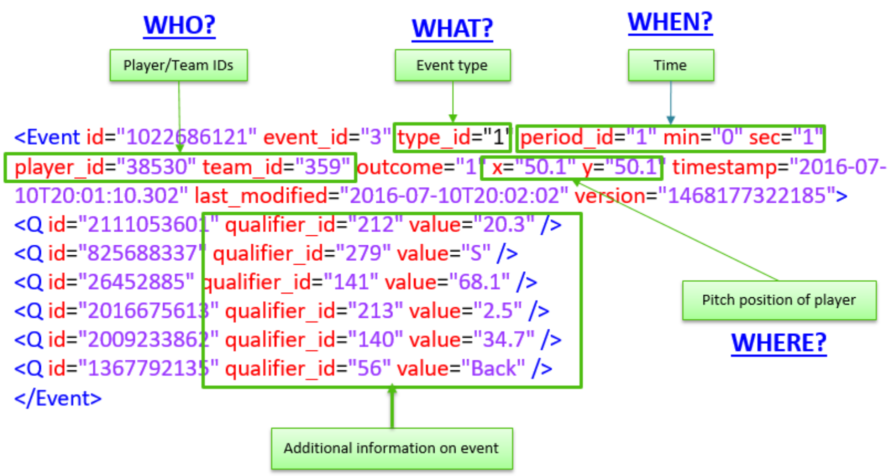


Figure 15. Example of a passing event as recorded by OPTA

[3] http://www.optasports.com/

OPTA uses numbers to describe what happened and each number has a specific meaning. For example, in the figure above the event in question is a "pass" marked with the number 1 ("*what*"). OPTA distinguishes between approximately 67 different events and each event then has several qualifiers which contain additional information about the event. There are in total 280 qualifiers. In this example here, there are six qualifiers which give additional information on the pass (e.g., 140 – Pass end x, 141 – Pass end y, showing the coordinates of the pass). Basically, there is a very detailed description of "what" happened, and in addition there is information on "*who*" did that or who was involved in this action/event, plus the timestamp. The min and the sec are also available ("*when*"), plus there is an additional timestamp with date and time which denotes the time of the event during the game. Information is also available on the "*where*", by using the x and y pitch coordinates. Furthermore, every action/event has a specific definition and these actions are also grouped in categories e.g., attacking or defensive events, goalkeeper events among others. As mentioned in section 2.2, data is retrieved from cameras installed on the football pitch and two operators use a proprietary software to record each action, the time and position of it. Operators go through rigorous training and familiarize themselves with the system and OPTA's event definitions but also the characteristics of football in each country.

The dataset contains all the games from the European Championship in 2016 (Euro 2016) which was won by Portugal. There are 51 games in total available for the analysis. Not all games are used for each method. A selection is made depending on the purpose of the analysis and the required amount of data. Below is an overview of the games which were used in each chapter in Part III. In Appendix B a list of all 51 games from the Championship and the final result is included.

Table 16. Overview of matches included in the data analysis

Method	**Chapter**	**Matches included in the analysis**	**Matches total**
Social Network Analysis	5	England vs. Russia England vs. Iceland Portugal vs. Iceland	3
Self-organizing Maps (SOMs)	6	Winning matches of favorite teams Winning matches of underdog teams	35
Process Mining	7	England vs. Iceland	1

Self-organizing Maps or SOMs are a type of neural network, a method which is used in chapter 7. In total, 35 games are selected for the analysis. All winning matches of the favorite (20) and all winning matches of the underdog teams (15) are part of this analysis. Process Mining techniques are used in chapter 8. This is an exploratory study, and therefore, one game was sufficient in order to evaluate whether a certain algorithm or analytics technique from the area of process mining is suitable for football performance analysis. In addition, some of the algorithms (for instance, Markov chain clustering) take longer if more data is used.

The questions which are investigated in each chapter are chosen based on characteristics of the Euro 2016 championship, what was considered interesting, controversial or unique for the competition. This makes the analysis more interesting but it also gives a chance to (dis)prove the popular opinions with concrete data analytics results.

5.3 Data reliability and preparation

Research based on computerized tracking systems for performance analysis in sports has been evaluated by Castellano et al. (2014). The authors conclude that such systems are a valuable data collection tool and they provide adequate detail on the players' physical and technical performances. The reliability of the OPTA system to collect football event data has been investigated by Liu et al. (2013). They identify potential issues concerning the definitions of events as, at times, different operators may make a different choice as to which event exactly occurred. Nevertheless, the conclusion is positive and according to their test results, the OPTA method for collecting data which partly relies on human operators, is a reliable method and that the data can be subsequently used for statistical and other analytics methods.

Despite the previous findings, as a standard step in any data analytics project, ***preparation*** and ***cleaning*** of the data is performed. The Euro 2016 dataset is checked for errors and missing values. For this purpose, a database is constructed comprising all 51 games. During this step it became obvious that the data and OPTA's own documentation were not without errors. The primary issues concerning the acquired dataset are: a) different number of attributes in some of the game files; b) attributes misplaced i.e. not always in the same column; c) data format differs in some instances; d) some team formations (e.g., 21 and 23) are not included in the documentation; e) qualifier IDs with different meanings (e.g., id 235 can mean both "away team possession" or "goal line").

The identified issues are solved prior to the data analysis to the best of the author's knowledge.

6 Dynamic and social network analysis

In this chapter, player and team interactions are analyzed by means of (dynamic) social network methods. First, a general *method* overview of social and dynamic network analysis is given followed by related work which discusses how these methods have been used in previous research in football. Second, the *data preprocessing* steps are briefly described to give an overview of which data attributes are relevant for this type of analysis and how they need to be transformed so that the methods can be applied properly. Third, the *data analysis* and results are presented, and finally, the derived insights are discussed together with their *practical implications*.

Part of the results presented in section 6.5 have been presented at the EUSN 2017 conference (Kröckel and Piazza, 2017). The results in this chapter are modified and extended.

6.1 Method

Social network analysis (SNA) is used to analyze relationship between entities. There are networks in many parts of life and the sciences. For example, transportation networks, biological networks, corporate networks, to name a few. Entities are represented by vertices or *nodes*, while the relationship between them is represented by *edges* in a visualization that is called a *network graph*. SNA methods date back to the 1700s but became popular in the 1990s mainly due to the work done in statistical physics and computer science (Kolaczyk and Csárdi, 2014). Statistical physics has encouraged the use of network science for analyzing complex systems, and especially the idea that by understanding how the separate parts of one system interact with each other, one can better understand what drives the collective behavior of the system as a whole (Kolaczyk and Csárdi, 2014). This is rooted in the dynamic system theory, as seen in chapter 3. A complex system, as discussed, is not static in nature but dynamic. It evolves and changes over time as it adapts to its environment. The logical consequence is that a network, corresponding to a complex system, is also dynamic, and should be represented as such (Kolaczyk and Csárdi, 2014). However, up to now, networks have been mostly analyzed and presented as static, as the people in the networks were not considered as adaptive agents capable of taking action, learning, and altering their networks (Carley, 2003; Kolaczyk and Csárdi, 2014).

Dynamic networks are networks which undergo structural changes over time - nodes and edges appear and disappear or their attributes change over a certain time period (Shi et al., 2015; Zaidi et al., 2014). Thus, such networks can be used to display time-varying relationships (Shi et al., 2015). In general, one can consider the a) dynamics *of* a network (edges and nodes change over time); b) dynamics *on* a network (attributes of edges or nodes change in time), or c) both simultaneously, if applicable (Kolaczyk and Csárdi, 2014). In mathematic terms, a dynamic graph is represented in the following way:

Equation 1. Mathematical formulation for dynamic networks

An agglomerated graph $G = (V, E)$
and an ordered sequence of subgraphs:
$S = \{G_1 = (V_1, E_1), G_2 = (V_2, E_2), ..., G_k = (V_k, E_k)\}$
where each G_t is the subgraph of G at time t where t can be a specific time or it can be a time period. $V, V_1, V_2, ..., V_k$ are finite and non-disjoint sets of nodes,
$E, E_1, E_2, ..., E_k$ are finite and non-disjoint sets of edges such that
$V = V_1 \cup V_2 \cup ... \cup V_k$ and
$E = E_1 \cup E_2 \cup ... \cup E_k$.

Source: Zaidi et al., 2014, p.8

Dynamic network analysis (DNA) is concerned more with the actors' activity and their relationships and to a lesser extent with the structural changes of the network, part of traditional SNA (Trier, 2008). Efficiency and stability of the network are in the focus of the analysis (Zaidi et al., 2014). The reasons why DNA gained popularity in research only recently are mainly related to the lack of network data with timestamps available, and consequently the relative immaturity of the field itself as it was challenging to test theories without available data (Kolaczyk and Csárdi, 2014; Rossetti and Cazabet, 2017; Zaidi et al., 2014). Another challenge is that the field of study is done in various disciplines without much connection between them, which results in different terminologies being used for the same concepts (Holme and Saramäki, 2012). For instance, except "dynamic networks", one can also use terms as "temporal networks", "dynamic graphs" or "longitudinal networks" to extract potentially valuable research discussing similar ideas. On the other hand, while real-world networks are rarely static, it does not necessarily mean that networks with time data should not be represented as static graphs or with some level of aggregation. According to Holme and Saramäki (2012, p.99), a temporal network is suitable for modelling and analysis when "the system under study should consist of agents that interact pairwise, so that the interactions have both some degree of randomness and some regularity (i.e., there is some structure)". This statement relates to the dynamic system theory which considers a system as dynamic when its separate elements interact in a state of constant change but with a certain degree of regularity.

A detailed review of the literature on temporal or dynamic networks is out of the scope of this thesis. However, a brief overview of the main research areas of the field is presented in the following.

Research in the area of DNA can be roughly split up in two (overlapping) areas. One area is ***analytics*** which, up to now, has focused mainly on developing relevant metrics, detecting change or discovering communities in a dynamic network. However, previous studies are mostly isolated works which focus on specific problems, and therefore, not many have dealt with developing a general methodology for DNA (Sloot et al., 2013). The three research directions are explained briefly below.

Concerning the ***dynamic metrics***, their number, type, complexity and value changes as traditional SNA metrics cannot be directly mapped to dynamic networks due to the temporal factor (Carley, 2003; Zaidi et al., 2014). Research in this area is ongoing, and so far there are no well-established dynamic metrics as there are such for traditional network analysis (e.g., betweenness or closeness centrality, degree centralization). Furthermore, some metrics are more suitable for networks aggregated in several time windows, while other metrics are dependent on the order of link activations (Holme and Saramäki, 2012). Metrics that have been suggested in the context of DNA are: paths, as they are known in SNA, or *time preserving paths* in DNA, connectivity and *transitive connectivity*, latency and distance in temporal networks, diameter or *network efficiency* (the harmonic average of the latency), *closeness* and *betweenness centrality* adjusted to dynamic networks, *motifs* and *entropies*[4].

The second focus of DNA is the ***detection of change*** in dynamic networks. Changes in interaction patterns could be linked to team's effectiveness or the emergence of informal leaders, and being able to detect changes early before they impacts the whole group can be of great significance as it would enable faster response to change and prevent unwanted consequences (McCulloh and Carley, 2008a). According to McCulloh (2009), in dynamic or longitudinal networks, there are four potential ***network states***: *stability* – when the relationship between group members stays the same over time; *evolution* – interactions between members lead to a change in the relationships over time; *shock* – change that is exogenous to the social group, and *mutation* – when an exogenous change initiates evolutionary behavior. Most of the existing research is focused on network evolution and there is not much research on the states of shock and mutation (McCulloh, 2009). These are not the only possible changes, however, as some authors discuss changes in dynamic events over networks (Li, S. et al., 2017). The change that occurs can be *local*, which can mean, for instance, change in node attributes, or *global*, for example, change in network topology (Li, W. et al., 2017). Although they are interdependent and change in the nodes can lead to a global change in the network, research has mostly investigated them independently (Li, W. et al., 2017). In principle, change detection can be applied to network measures of any level – node, graph, or edge level (McCulloh and Carley, 2011). The challenge is to develop metrics that can detect meaningful change in a state of normal variability (McCulloh and Carley, 2011). Existing research on methods for change detection in dynamic networks is limited. McCulloh and Carley (2008) discuss three such *methods*: the cumulative sum (CUSUM), the exponentially weighted moving average (EWMA), and a scan statistic (SS). In their study, they conclude that the CUSUM works best for detecting a sudden and unexpected network change. They demonstrate that the CUSUM statistic shows a clear network change compared to a graph that only shows how a metric changes over time. Such result is due to CUSUM considering previous changes of the network. This method has

[4] For more detail overview of the metrics, the reader is referred to Holme and Saramäki (2012), Holme (2015) and Lerman et al. (2010) for a centrality metric in dynamic networks.

also been implemented in a tool for DNA developed by the authors' research group at Carnegie Mellon University, called ORA. The tool is also used for the analysis in section 5.5. The results are confirmed in a later study by the authors in which they stress on the fact that the CUSUM statistic not only informs that a change has occurred (change detection), but also when this change happened (known as change point detection) (McCulloh and Carley, 2011). Other studies have used the SS method (Marchette, 2012; Neil et al., 2013). However, in their recent paper, Zou and Li (2017) point out that studies like the mentioned above treat network data from different time-steps as independent observations instead of as time series, and thus, exclude the natural evolution of the dynamic networks from the change detection methods. The authors suggest their own method, called Network State Space Model (NSSM) which addresses the problem with previous research, and is based on the classical SSM approach for modelling multivariate time series data.

The third area of research is focused on community discovery (CD) or graph clustering, an area known as ***Dynamic Community Discovery*** (DCD). Community discovery has been widely researched in the area of static social networks, however, there is no formal definition of community, yet (Cazabet, 2017). Even though intuitively, the notion of community is clear, the problem arises with its formulation, as any given network can have different partitions each capturing valuable network information (Rossetti and Cazabet, 2017). A community has been defined in the literature as sets of nodes densely connected together and weakly connected to the rest of the network (Cazabet, 2017); simply as dense network subgraphs (Rossetti and Cazabet, 2017); or entities that share a set of actions with the other community members (Coscia et al., 2011). As there is no widely accepted definition of community in the literature, there is no perfect algorithm for extracting a community. Each algorithm, focuses on one or few network properties and, thus, it implies its own definition of community (Coscia et al., 2011). The goal of DCD is to detect time-varying clusters of densely connected communities that evolve over time (Zaidi et al., 2014). An overview of algorithms used in the literature for DCD is given by Coscia et al. (2011) and Bedi and Sharma (2016). It should be noted, however, that most of the codes are not available publicly and not all of the suggested algorithms would be applicable for CD in football. Finally, it is important to note that the nature of the DCD does not depend on the manner in which the network evolution is represented - e.g., whether the chosen time-steps are sequential or overlapping (Cazabet and Amblard, 2014).

The second research area is ***visualization*** of dynamic networks, in which the main question is how to appropriately incorporate the notion of time in the network graph (Kolaczyk and Csárdi, 2014). In an ideal case, one would like to maintain as much of the available temporal information (Kolaczyk and Csárdi, 2014). There are a few aspects that should be considered when deciding on the visualization type. These are summarized in Table 17.

Table 17. Dynamic network analysis terms

<table>
<tr><th></th><th>Term</th><th>Explanation</th></tr>
<tr><td rowspan="4">Theoretical considerations</td><td>Relational pace</td><td>Rate of change in relations, with focus on irregularities. It can be described by:
a) Levels: fast, slow
b) Change: accelerating, decelerating
c) Stability: cascades, jumps and starts</td></tr>
<tr><td>Sequence</td><td>The order in which relations occur</td></tr>
<tr><td>Concurrency</td><td>The intersection of pace and sequence: two relations are concurrent if they overlap in time and share at least one person</td></tr>
<tr><td>Transitivity</td><td>When three or more nodes are all connected to each other</td></tr>
<tr><td rowspan="5">Time considerations</td><td>Discrete</td><td>Snapshots of the network in specific time-frames</td></tr>
<tr><td>Continuous</td><td>Interactions being recorded with exact starting and ending time</td></tr>
<tr><td>Time-step</td><td>Individual subgraphs according to time periods samples from G</td></tr>
<tr><td rowspan="2">Time window</td><td>The time period for each subgraph</td></tr>
<tr><td>Non-overlapping
Overlapping</td></tr>
</table>

Source: Self compiled based on Moody et al., 2005; Zaidi et al., 2014

When analyzing dynamic networks, there are some ***theoretical*** aspects for the researcher to consider: a) the *pace of change* in the relations between entities – the exact meaning will depend on the context (Moody et al., 2005). In football, there is not enough research in the area of dynamic networks for football match analysis (see 6.2). Therefore, the assumption is that analysis can be focused on all three types of irregularities mentioned in Table 17. One can think of change in seconds, minutes, weeks, months etc. (Moody et al., 2005). In a single football match, the change can be investigated over seconds and minutes; b) the *sequence* in which relations occur – helps to explain the prevalence of a given network structure (Moody et al., 2005). Sequence is important in football as well and we can consider sequences of actions, or in the case of network analysis, sequences of interactions between the players; c) *concurrency* – the case of overlapping relations in time which share at least one person (Moody et al., 2005); and d) *transitivity* – the proportion of node triples that form triangles i.e. all three node pairs are connected by edges (Kolaczyk and Csárdi, 2014). It is not yet clear whether and to what extent concurrency and transitivity, or any other measurement in DNA are relevant in the case of football PA, as the field of research is only recently taking off. However, this is investigated in more detail in 6.5.

Temporal aspects, also relevant for visualization are: a) *discrete* time –networks are represented as snapshots in discrete time windows, within which nodes and interactions appear or disappear (Zaidi et al., 2014); b) *continuous* streaming – continuous time scales are used to represent nodes and edges, for instance, data packets moving over a LAN or the Internet (Zaidi et al., 2014). Continuous time representations help researchers to identify how overall network changes emerge through ordered dyadic events (Moody et al., 2005); c) *time-step* is the term used for indication of the subgraph of a network and d) *time window* is the amount of time which is represented in each subgraph (Zaidi et al., 2014). For example, if one splits the first half of a football match in three snapshots or subgraphs, the time-step can be noted as a, b, c, or 1, 2, 3, or 0-15 min, 15 to 30 min etc., while the time window for each would be, in this case, 15 minutes.

To sum up, the research in the area of dynamic networks is still relatively young. The fact that the field is interdisciplinary, and contributions come from various scientific fields is a blessing and a curse at the same time. On the one hand, quite a few algorithms are developed for similar issues e.g., community discovery. On the other, they are not available or are not based on existing research. It can also be the case that an algorithm developed for a specific biology problem, for example, cannot be readily adopted in another area of study. The differences in terminology and definitions also makes it harder to find and consolidate relevant research. Therefore, as a next step, the application of network analysis, including DNA, in football specifically will be discussed by reviewing existing publications in the literature. The findings serve as a starting point for the network analysis included in this thesis.

6.2 Related work

Social network analysis techniques have been also applied in football as an alternative way of performance analysis. By following the same procedure for retrieval of relevant literature, as the one followed in section 4.2, 22 papers were extracted for in-depth analysis, published between 2010 and 2017 (see Table 18). Below is a summary and overview of the related work.

One of the major triggers for SNA research in football have been the available statistics released by the UEFA following the Euro Cup in 2008 (Duch et al., 2010). Since then, performance data are available for all major leagues and cups, which gives the opportunity for some interesting, albeit basic statistical analysis. Nevertheless, this opened the door for researchers around the world to tap into the various methods and measurements offered by the field of SNA and display alternative analysis and views of team and player performance. Analyzing the interactions between players can give important insights into the team's playing style but can also be used for player's performance assessment and, thus, reveal the key players in a team (Gudmundsson and Horton, 2017). Combined with spatial information, SNA is an interesting approach for tactical analysis, which can be complimentary to the traditional notational analysis (Rein and Memmert, 2016).

In team sports research, there have been mainly two type of networks considered for analysis – passing and transition networks (Gudmundsson and Horton, 2017). *Passing networks* are generated by only considering the successful passes between players, where the nodes are the players and the edges between them are weighted based on the successful number of passes. The reason why only successful passes are taken into consideration, is because there is simply no way of knowing what was the original destination of the failed pass (Grund, 2012). *Transition networks*, on the other hand, usually have additional nodes added which can represent, shots on goal, goal or any other event or outcome of interest (Gudmundsson and Horton, 2017). The football research literature has considered passing networks mostly. Of the 22 papers on SNA in football that were retrieved and considered in a detail review, only two added an additional node(s) – Cintia et al. (2015) added a node for "goal attempts", while Duch et al. (2010) added two nodes for "shots on goal" and "shots wide".

Table 18. Overview of data and tools in SNA research in football

Paper	Level of analysis	Sample data	Tool(s)
Lusher et al., 2010	N/A	N/A	N/A
Duch et al., 2010	Team & Player	EuroCup 2008 UEFA stats. All matches.	Not mentioned
Yamamoto and Yokoyama, 2011	Team	1 Kirin Cup match & the WC 06 final	Mathematica
Peña and Touchette, 2012	Team & Player	WC 2010 Round of 16	Sage, Net-workX & Mathematica
Grund, 2012	Team	OPTA data with 760 EPL matches	Not mentioned
Cotta et al., 2013	Team	3 matches from Spain in the WC 2010 – data manually extracted	Not mentioned
Clemente, Martins et al., 2014	Team	One match from the professional Portu-guese league.	wgPlot script & Matlab
Clemente, Mendes et al., 2014	Player	3 matches of Spain in FIFA 2014	SocNetV
Gama et al., 2014	Team & Player	6 matches of a single team from the Portuguese league	Amisco
Clemente, Couceiro et al., 2014	Player	5 matches of a single team from the Portuguese league	Matlab
Cintia et al., 2015	Team	Event data from all games from FIFA WC 2014 and Italian Serie A 2013/14.	Not mentioned
Clemente, Martins, Kalama-ras, Wong et al., 2015	Team	64 matches from FIFA WC 2014 – manually collected	SocNetV & SPSS
Trequattrini et al., 2015	Team & Player	One UEFA 12/13 Championship match between AC Milan and Barcelona.	UCINET
Mendes et al., 2015	Player	3 matches of Portugal in WC 2014	Not mentioned
Clemente, Martins, Kalama-ras, Oliveira et al., 2015	Team & Player	4 matches from Switzerland's team in FIFA WC 2014	SocNetV
Clemente, Couceiro et al., 2015	Team & Player	5 matches of a single team from the Portuguese league	Matlab
Clemente, José et al., 2016	Player	20 matches from La Liga and EPL	SocNetV
Grund, 2016	Team & Player	Career histories of 800 players from soccerbase.com, & 760 EPL matches from OPTA.	Not mentioned
Clemente and Martins, 2017	Team	109 matches of best 16 teams in UEFA 15/16	SocNetV & SPSS
McLean et al., 2017	Team & Player	Quarter final teams from Euro 16 & COPA 16	Agna & SPSS
Wäsche et al., 2017	N/A	N/A	N/A
Ribeiro et al., 2017	N/A	N/A	N/A

Furthermore, most publications consider the attacking and ignore the defensive performances. Attacking performance is, in general, easier to analyze and quantify than defense. Additionally, when networks are created, they are based on the *attacking sequences* – a sequence starts from the moment the team gains possession of the ball, and ends when it loses the ball to an opposition player. Whenever the team has the ball, one considers that they are in attack. Therefore, most analysis have been focusing on this part of the players' and teams' performance.

From the overview in Table 18, several observations can be made. First, SNA in football has only become popular since 2010. Nine papers are published by the same set of authors, mainly Clemente, Martins, Couceiro and Mendes. Although all of the papers have a valuable contribution to SNA research in football, as the field is still quite young, the structure and methodology used by Clemente and colleagues is rather repetitive in most of their papers. The papers by Lusher et al. (2010), Wäsche et al. (2017) and Ribeiro et al. (2017) are review papers discussing the potential and recent advancements of network methods for sports team performance analysis, not exclusively focused on football.

Next, the papers retrieved use different *data sets* in their analysis, with only few publications using professional tracking systems data - Grund (2012) and Grund (2016) used OPTA data, while Gama et al. (2014) used the Amisco system. The rest of the authors either extracted the data from UEFA or other online channels or have retrieved the passes manually from recorded matches. The variety in number and type of matches analyzed also makes it difficult to generalize findings. Additionally, authors have been mostly using team *level of network analysis*, while the combination of both team and player network metrics, has been employed in eight of the reviewed papers. Third, various *tools*, not necessarily network analysis tools, have been used so far. SPSS seems to be preferred when statistical analysis were employed, while a few of the papers relied on Matlab and Mathematica for their calculations. It is interesting that some well-established SNA tools have not been broadly adopted by researchers in this area. In a few papers, there is no mention at all of the tools or programming languages used (Cintia et al., 2015; Cotta et al., 2013; Duch et al., 2010; Grund, 2012, 2016; Mendes et al., 2015).

Network metrics

Previous research has used well established network metrics when analyzing the interaction between football players. An overview of the metrics that have been used so far is given in Table 19. A definition of the metrics and their meaning in football is given in Appendix C.

Table 19. Social network metrics used in football performance analysis

Metric	Used/Discussed in	Level
Betweenness centrality	• Pena and Touchette, 2012 • Trequattrini, Lombardi & Battista, 2015 • Ribeiro et al., 2017	Player
Centralization	• Grund, 2012 • Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014 • Clemente, Couceiro, Martins & Mendes, 2015 • Grund, 2016 • Ribeiro et al., 2017	Team
Centroid	• Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014 • Clemente, Couceiro & Mendes, 2014	Player
Clique	• Pena and Touchette, 2012 • Trequattrini, Lombardi & Battista, 2015	Team
Closeness centrality	• Pena and Touchette, 2012 • Clemente, Mendes & Martins, 2014 • Ribeiro et al., 2017	Player
Clustering	• Pena and Touchette, 2012 • Cotta et al., 2013 • Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014 • Clemente, Couceiro & Mendes, 2014 • Clemente, Martins, Kalamaras, Wong & Mendes, 2015 • Clemente, Couceiro, Martins & Mendes, 2015 • Clemente & Martins, 2017 • Ribeiro et al., 2017	Team
Cohesion	• McLean et al., 2017 • Wäsche et al., 2017	Team
Degree centrality	• Lusher & Robins, 2010 • Cotta et al., 2013 • Clemente, Mendes & Martins, 2014 • Trequattrini, Lombardi & Battista, 2015 • Clemente, Martins, Kalamaras, Oliveira, Oliveira & Mendes, 2015 • Clemente et al., 2016 • Ribeiro et al., 2017	Player
Density	• Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014 • Clemente, Martins, Kalamaras, Wong & Mendes, 2015 • Trequattrini, Lombardi & Battista, 2015 • Clemente, Martins, Kalamaras, Oliveira, Oliveira & Mendes, 2015 • Clemente, Couceiro, Martins & Mendes, 2015 • Clemente & Martins, 2017 • McLean et al., 2017 • Ribeiro et al., 2017	Team
Diameter	• Clemente, Martins, Kalamaras, Wong & Mendes, 2015	Team
Distance	• Pena and Touchette, 2012 • Trequattrini, Lombardi & Battista, 2015	Team
Eigenvector centrality	• Cotta et al., 2013 • Ribeiro et al., 2017	Player
Flow centrality	• Duch et al., 2010	Player

Table 19. Social network metrics used in football performance analysis (continued)

Metric	Used/Discussed in	Level
Heterogeneity	• Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014 • Cintia et al., 2015 • Clemente, Couceiro, Martins & Mendes, 2015	Team
Hub	• Yamamoto & Yokoyama, 2011	Player
Network intensity	• Grund, 2016	Team
PageRank	• Pena and Touchette, 2012 • Clemente et al., 2016	Player
Path length	• Ribeiro et al., 2017	Team
Prestige	• Clemente, Mendes & Martins, 2014 • Clemente, Martins, Kalamaras, Oliveira, Oliveira & Mendes, 2015 • Clemente et al., 2016	Player
Reciprocity	• Lusher & Robins, 2010	Team
Transitivity	• Lusher & Robins, 2010	Team

The above table shows that eight network metrics at player level have been used by researchers while there are 12 metrics at team level used to explain performance in football. Some of the more popular metrics are betweenness centrality, closeness centrality, degree centrality and prestige at player level, while centralization, clustering, density, and heterogeneity are mostly used at team level analysis. Additionally, Clemente, Martins et al. (2016) discuss several metrics at player (micro), team (macro) and sub-group (meso) level which the authors suggest can be used in network performance analysis in football. An overview is presented in Figure 16.

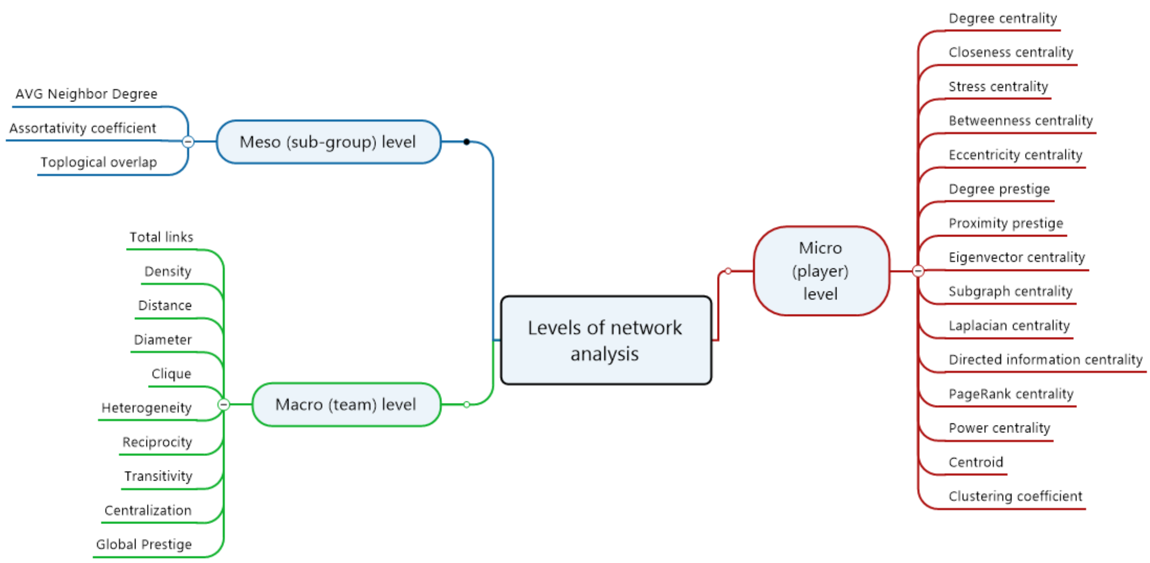


Figure 16. Network metrics for football performance analysis
Source: Self-compiled based on Clemente, Martins et al., 2016

As seen, there is not a lack of metrics to use in football PA. The issue is rather with choosing the right metrics to answer a specific question. Moreover, there are several mathematical definitions of the same metric. It is not clear whether this would have an effect on the results when different definitions are used. In theory, the equations should reflect the same idea behind a metric, but with various SNA tools and equations available it is worth pointing out that this could be a possibility. However, when researchers use tools for SNA, like for instance Gephi, Pajek or ORA, not all metrics are available, and the definitions are sometimes lacking. This also has to be considered when one conducts SNA. Finally, previous research has not thoroughly discussed if a metric should have a higher or lower value in order for the player or team to show a better performance. This is hard to achieve, however, as to make such conclusions, there need to be quite a few studies, conducted on the same type of data and following the same methodology. Otherwise, it would be hard to generalize the findings and say e.g., a team needs to have a higher degree of centralization in order to be successful, or a striker needs to have higher betweenness centrality in order to have more shots on goal.

The thesis uses most of the mentioned metrics in Figure 16. All metrics that are available in the ORA tool are used in the analysis. At sub-group level, the network assortativity metric is used. At the team level, total links, density, diameter, clique, transitivity, reciprocity, and degree centralization are calculated. And finally, at the player level, betweenness, closeness, eigenvector, and PageRank centralities are used. The list in Figure 16 should not be considered as an exhaustive list, however, and thus, the metrics in the analysis part of the thesis are based on the metrics that have been used in the literature (as seen in Table 19), the suggestions in Figure 16, as well as the metrics available in the ORA tool. Also, some metrics provide similar information about the relevance of a player and, thus, not all metrics need to be included in the analysis. Most importantly, metrics are chosen in a way that they help to best answer the question of interest (e.g., “was substituting Rooney a good decision?”).

Dynamic analysis

Previous research in the area of SNA has struggled to determine whether the network topology or structure drives the performance of a team, or the different performance levels would promote a certain type of network structures – known as the *issue of causality* (Grund, 2012). In the previous section, it is mentioned that one can consider the dynamic of a network (i.e. global dynamics) and dynamics on a network (local dynamics). In adaptive networks, such as the network of football players, both types of dynamics interchange and the feedback gives rise to the complex player interactions i.e. the cooperation patterns of a team (the network topology) influence the local dynamics of the players, which in turn affect the global dynamics or topology itself (Yamamoto and Yokoyama, 2011).

Small-world vs. scale-free networks

Current SNA research in football discusses a football team network as potentially displaying the properties of small-world and a scale-free network. In a ***small-world network***, any two nodes can be connected by a path of only a few links (Passos et al., 2011). As networks in football consist of 11 players per single team, one can reasonably assume that the small-world effect can be observed in such networks. Specifically, a point of interest would be to examine the interactions in an attacker or defender subunits consisting of more than two players, for instance, 2 vs. 1 or 3 vs. 2 situations (Passos et al., 2011). So far, very few papers have focused on sub-group analysis in football. Grund (2016) suggests own measure for what he calls “network experience” which is based on the dyadic experience between team mates, while Yamamoto and Yokoyama (2011) looked into the connection between the number of triangles and the frequency of successful attacks. They concluded that the game momentum may be represented by the number of triangles in each attacking sequence (Ribeiro et al, 2017). *Triangles* as a measurement, has been mentioned briefly in Ribeiro et al. (2017), Lusher et al. (2010), Peña and Touchette (2012) and Wäsche et al. (2017) but has not been subject of analysis in any of the reviewed papers, with the exception of the paper by Yamamoto and Yokoyama (2011) who found that the more triangles existed in the five minute intervals, the more attacks the team had. This metric is closely related to *transitivity*, a mechanism that leads to cohesion or clustering in a network, and gives indication of how the network as a whole is held together (Lusher et al., 2010).

A ***scale-free network***, has two main properties: *growth*, as new nodes are being added to the network over a period of time, and *preferential attachment*, the case when the new nodes tend to connect mostly to nodes that already have many connections themselves (Wang and Chen, 2003). Such nodes in a scale-free network are also known as *hubs*. In a football team, players that are preferred by their teammates, i.e. who get the ball passed to them more often, are the preferential attachments nodes or hubs in that network (Passos et al., 2011). Identifying such players will give insight into who are the key decision makers in the specific match, and one could also investigate how the team will re-organize itself if a hub is removed from the network (Passos et al., 2011). This aspect is related to the Achilles Heel of complex networks, the “robust, yet fragile feature” – these networks are robust against random attacks but vulnerable to targeted attacks (Wang and Chen, 2003). The only paper which investigated this aspect in football is also one of the very few papers on DNA in football – the paper by Yamamoto and Yokoyama (2011). The authors assume that a football team network must have simultaneously low vulnerability to intentional attacks, and a power law for self-organization of the network. This would in turn mean that when a hub is attacked, the network topology will change to follow the power law, when the function of the hub switches to another node (Yamamoto and Yokoyama, 2011).

Previous research has several ***limitations***. Most papers have considered team or player metrics in isolation. It is not yet clear which metrics should be chosen for team and player performance evaluations, and metrics at the sub-group level are under-researched overall. With a few exceptions, specifically Grund (2012; 2016), most of the other papers have a problematic methodology and at times superficial or narrow interpretation and discussion of the results. There has not been a sufficient reflection on the connection between specific metric values and the different player positions nor the correlation between a) standard performance indicators and network metrics, b) different team level metrics and the course of the game development, c) the network insights and the game outcome, or d) the network and PIs of the opponent. Finally, there is a high diversity of the publication outlets, which not only suggests the immaturity of the field, as pointed out by Wäsche et al. (2017), but it also raises concerns regarding the quality of the peer review process – not just regarding the quality of the publication outlet but also the qualifications of the reviewers and their knowledge in this area. Not all outlets are sports or network related.

There have been a few ***contradictory findings*** in existing research. For instance, contradictory to Grund (2012) who found that high density was associated with better performance, Clemente, Martins, Kalamaras, Oliveira et al. (2015) found different density values in two matches and in both Switzerland won. This perhaps serves to show that one cannot consider network metrics in isolation, as every match is different, as are the opponents as well. There are a lot of factors that influence simultaneously the performance and self-organization capability of the team, and researchers should be careful when making general conclusions regarding any of the network metrics.

As seen, research of SNA and especially DNA in football is still an emerging research area. Thus, there are many possible avenues that can be explored in ***future research***. For instance, most papers have investigated similar and rather few social network metrics, mainly, density, degree centrality, betweenness centrality, clustering and centralization. Moreover, the temporal aspect was not included as the authors have mostly used non-temporal and aggregated passing data from UEFA or manually collected the passes from video footage. One paper investigated the scale-free properties of a football network in five minute intervals on two matches from different competitions, not mentioning how data was collected (Yamamoto and Yokoyama, 2011), and a second paper conducted spatio-temporal analysis on a manually collected game data split in 15 minute intervals (Cotta et al., 2013). Recently, the paper by Kröckel et al. (2017) presented preliminary results from DNA of the final game from the EU Championship in 2016. The paper demonstrates how by tracking certain network metrics and their change over the course of the match, as well as the change in network topology can be a valuable method to support coaches in their decision making during live matches. Another potential research direction is the linkage between metric values and good or bad performances at player and team level, as well as linking certain network metrics to the different player positions. This has not been investigated enough but it would be worthwhile to explore it in more detail as, for instance, not every player position should have a high degree of betweenness centrality. Such findings will be of high relevance for assessing team and player performance based on network metrics. For these type of analyses, however, much larger datasets are necessary.

Finally, recent papers call for more dynamic network analysis in football (Ribeiro et al., 2017; Wäsche et al., 2017). However, there are no specific directions for future research mentioned in this regard, except employing spatio-temporal aspects. Thus, one could focus specifically on investigating how sub-group interactions affect performance, detecting sudden network changes, integrating the opponent analysis via network metrics, or perhaps also using simulation methods to assess the effect of removing a specific player from the team/network.

6.3 Analytics goal

Based on the findings in the related work section, there are several questions that are worth answering when it comes to using network techniques in football performance analysis. These are briefly presented below:

1) ***Player performance analysis*** – SNA can reveal key players within the team. Different metrics reveal different aspects or strengths of the players, and are thus, applicable for various tactical decisions, both pre and post-match. For instance, there are a few metrics which based on their definition are suitable for supporting the coach in deciding which player should be substituted. Other metrics can be used in order to prepare better against a specific opponent by e.g., choosing the right players for a match.
    - ➢ This level of analysis is used in the current thesis to investigate a **controversial substitution decision** in the match between England and Russia.
2) ***Team performance*** – there are several options for data analysis when evaluating the performance of football teams with network metrics. In the thesis, the following aspects are examined: a) examine how the network topology and player interactions change during the course of a game; b) investigate change detection and its influence on team performance.
3) ***Sub-group level of analysis*** – this has been an under-researched but promising area of interest in SNA football performance analysis. It refers to the interaction between smaller groups of players from the same team (e.g., dyad or triad relationships). Triad formation as well as community detection algorithms are used at this level of analysis.
    - ➢ The team and subgroup level of analysis is applied to two games of Iceland in order to explain the surprisingly **good performance** of Iceland and the **bad performances** of their opponents.

All of the three levels of analysis are conducted by using various network metrics and results are presented and discussed in section 6.5.

Match data used in the analysis:

In this chapter, three games are used to demonstrate how network metrics can help in evaluating player and team performances. These are the games between:

- England vs. Russia (player level)
- England vs. Iceland, and Iceland vs. Portugal (team and subgroup level).

The ***tools*** used for SNA analysis are the following:

- **ORA Lite**[5] - this is a dynamic network analysis tool developed by Carnegie Mellon University. It is chosen over other tools with user interface because it offers a wide variety of metrics, has a good documentation and offers the possibility for dynamic network analysis and change detection, which is important for the analysis.
- **UCINET**[6] – is a software package for the analysis of social network data, developed by Lin Freeman, Martin Everett and Steve Borgatti. The tool was used for calculation of team level network metrics.

6.4 Data preparation

The original data is transformed to be suitable for the network analysis algorithms. Specifically, all the successful passes between players of each team must be extracted. Almost any network analysis tool requires that the data is imported either as an *adjacency matrix* or containing two columns representing a *source* (player from who the pass originates) and a *target* (player who receives the pass). Most of the reviewed papers on SNA in football, used adjacency matrices to calculate network metrics, as this is an aggregated version of all passes between players. The OPTA data allows for passes to be extracted at a more granular level, as additional information is also available. Thus, in addition to a source and target nodes, the timestamp is also extracted.

The above requirements for the data format are done by using a Python code, which prepared the data in the format presented in Table 20.

Table 20. Data attributes used for (dynamic) social network analysis

Source	Target	Timestamp
Player who starts a pass	Player who receives the pass	Time when pass is made

The “source” attribute includes the initiator of the pass, while the “target” attribute refers to the player that receives the pass. The attribute “timestamp” includes the time when the source passed the ball towards the target. For the analysis conducted in the current thesis, the location data of the passes is not considered as this is not part of the network metrics calculations i.e. the metrics con-

[5] http://www.casos.cs.cmu.edu/projects/ora/

[6] https://sites.google.com/site/ucinetsoftware/home

sider the interactions (passes) between the players and it does not matter for these analyses where the pass originates and towards which part of the pitch it is directed.

6.5 Data analysis and results

The analysis is conducted in several steps and at different levels, to give a detailed picture of the complex interactions between the teams and players analyzed.

Player level

As the current thesis has a special focus on real-time decision support, in this part of the social network analysis at player level, a controversial substitution decision during the Euro 2016 is investigated in more detail. This is the decision of England's coach Roy Hodgson to substitute Wayne Rooney (a midfielder) in the 78th minute in the match against Russia with Jack Wilshere (midfielder). Hodgson defended his decision by telling reporters: "*I thought he [Rooney] had a good game, but was tiring*" (Paul, 2016). He also made a second substitution, when he replaced Raheem Sterling, "*who had worked very hard*", with James Milner in minute 87 (Paul, 2016). The decision to substitute Rooney is perhaps even more controversial considering that the leading goal for England was scored in minute 73 by Dier. Thus, it is indeed surprising that England's coach would decide only 5 minutes later, to replace what was most likely one of his key players. Nine minutes later the second substitution followed, and 5 minutes after that – Russia managed to score a goal and the game ended in a draw. A timeline of the events in this crucial part of the game is presented in Figure 17.

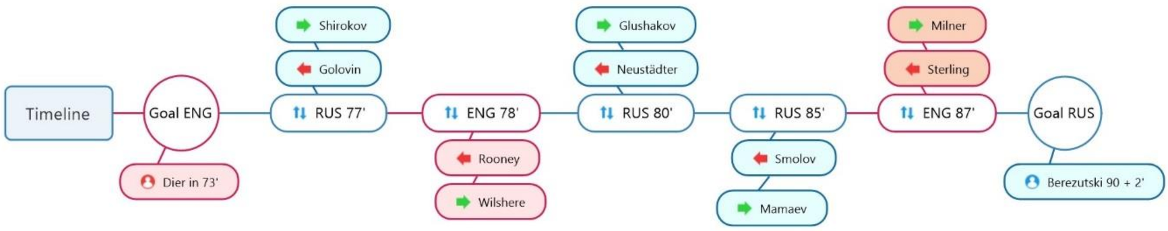


Figure 17. Timeline of crucial events during 2nd half of the ENG vs. Russia match

The above figure presents an interesting situation with a team managing to even the score following three substitutions 13 minutes before the official time ends, and another team losing the lead by making perhaps a fatal substitution only 5 minutes following this lead goal. The standard performance indicators do not give a clear picture of which team was better. A summary of the main PIs of this match for both teams is presented in Figure 18. From the figure, one can conclude that both teams were very close in their performance with England's team showing stronger offense as they have more total attempts on goal and total on-target shots. This, however, does not give a clear picture on the team's performances, and is thus, not helpful for evaluating a substitution decision.

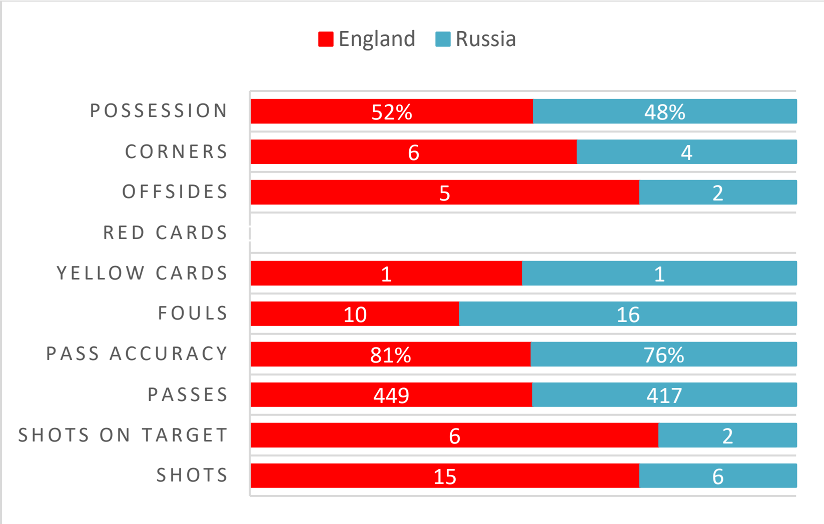


Figure 18. Match statistics for England and Russia
Source: UEFA, 2016a

In a next step, network metrics on player level are calculated to find key players in England's team, in order to investigate the substitution decision more closely. The related work section showed that at player level metrics such as betweenness, degree, PageRank or eigenvector centrality are recommended. All of these metrics are used in the current analysis in addition to metrics that have not been used in previous research but that have the potential to be useful when determining valuable players in a football team. These are the Authority and Contribution Centralities. A definition of the new metrics is given below.

Authority Centrality

A **node is authority-central** to the extent that its in-links are from nodes that have many out-links. Individuals or organizations that act as authorities are receiving information from a wide range of others each of whom sends information to a large number of others. *(ORA, Documentation File, 2018)*

Contribution Centrality

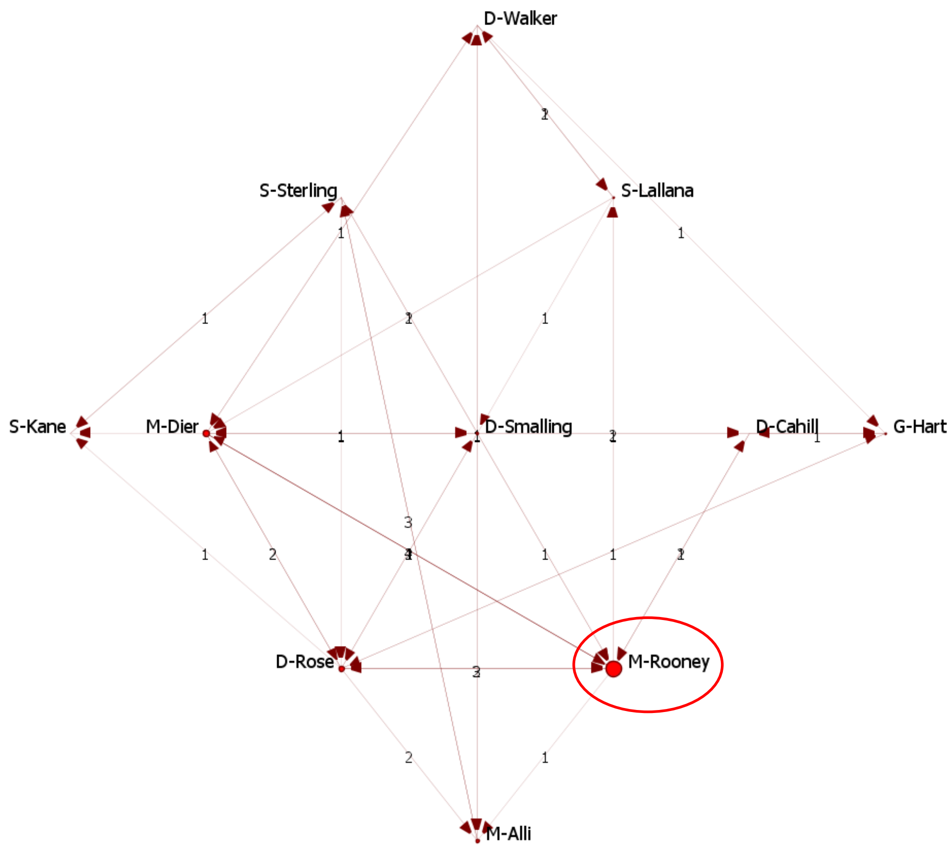
This computes Eigenvector Centrality on a transformation of the input network. Link values are transformed to be proportional to the dissimilarity of the nodes they connect. The intuition is that a link between two nodes with the same neighbors is not an important link since neither node gains new neighbors by the connection. Specifically, each link is weighted by the inverse of the Jaccard similarity of its nodes.

In a given organization, this measure can tell us who is connected to the most powerful (e.g., other highly connected agents) people. *(ORA, Documentation File, 2018)*

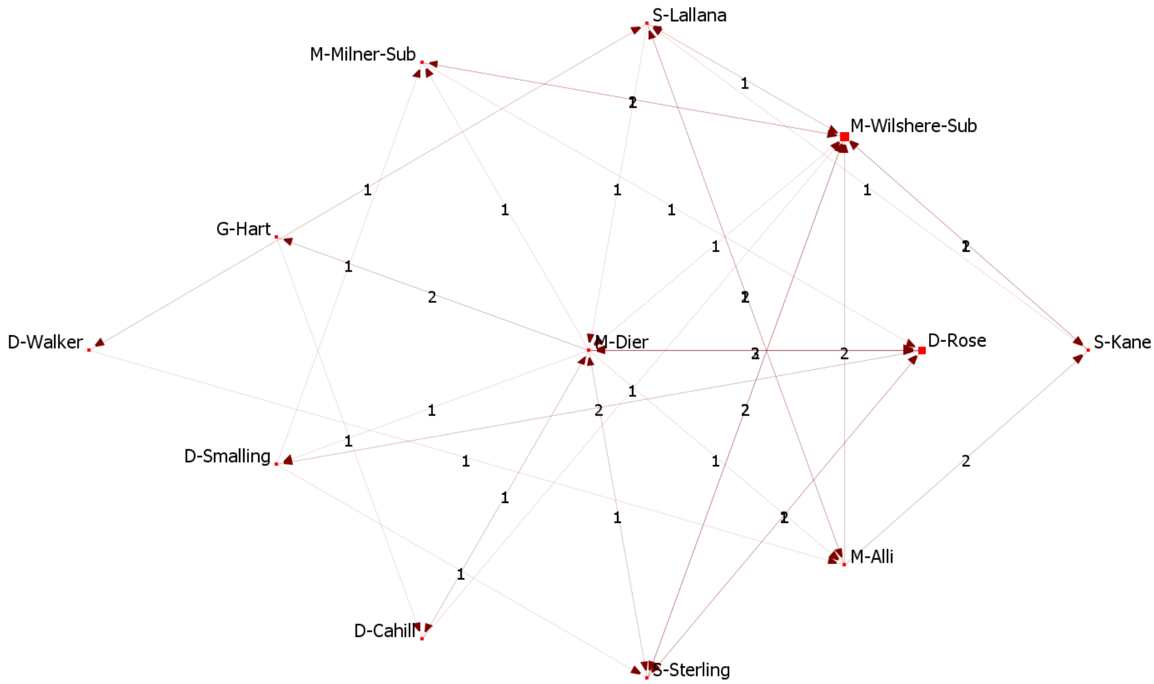
Based on the definitions above, both metrics show which nodes in the network have incoming links from other well connected nodes, but the contribution centrality additionally considers the (dis)similarity between two nodes and gives more weight to links that open more connection options to the nodes in question.

To gain an initial impression on the team structure before and after Rooney's substitution, the network of England's team is visualized in two different periods – a) 15 minutes before Rooney was replaced, and b) 15 minutes after his replacement (which is until the end of the match). Both networks are included in Figure 19. The timeframe was set at 15 minutes as this is what was used in the literature so far, as presented in the related work section in the study by Cotta et al. (2013). Besides, a shorter time frame would not be sufficient for meaningful analysis as the number of passes in a few minutes time is rather small.

Figure 19 (a) shows that Rooney is a player who receives many passes from his teammates, which suggests high popularity. Also, there is a visible triangle between Rooney, Rose and Dier which leads to the assumption that these three players may be part of a core subgroup in England's team, the removal of which can bring significant changes to the network as a whole. This is investigated further by calculating several centrality metrics for England's players.



a) England's network for the 15 min before Rooney's substitution



b) England's network for the 15 min after Rooney's substitution

Figure 19. England's team networks before and after Rooney's substitution

Note: The link widths are scaled to their values between a pair of nodes. The player in the middle is the one with the highest betweenness centrality. Nodes are scaled based on the Authority metric.

Based on the figures above and the centrality metrics presented in Table 21, Rooney is one of the key players in the 15 minutes before he was replaced. He has the highest value for Authority (1.0) in this timeframe, which means that he receives a lot of passes from players that themselves have many outgoing passes (i.e., they pass to many other players). He also has the highest values for contribution and eigenvector centralities. Thus, in the timeframe before his replacement Rooney is the player to whom other teammates preferred to pass the ball to, which in turn means that he was crucial for his team's offensive actions (high authority); he is the player who has the most options to pass the ball to other important players that themselves can reach other players (high contribution), and finally, he is the player with a central regulatory role, and the player who is crucial for organization of the offensive actions in his team (high eigenvector centrality).

Table 21. Selected metrics for England's players 15 minutes before Rooney is replaced

Player	authority	betweenness	closeness	contribution	eigenvector	hub	pageRank	totalDegree
D-Smalling	0.271	0.198	0.625	0.328	0.337	0.337	0.054	0.095
D-Cahill	0.127	0.031	0.357	0.275	0.223	0.341	0.056	0.071
M-Rooney	1	0.178	0.455	0.744	0.754	0.443	0.179	0.226
D-Rose	0.46	0.163	0.5	0.599	0.582	0.825	0.138	0.202
S-Lallana	0.228	0.006	0.526	0.374	0.457	0.262	0.071	0.107
M-Dier	0.514	0.076	0.5	0.594	0.64	0.83	0.124	0.19
D-Walker	0.163	0.149	0.526	0.251	0.23	0.232	0.056	0.095
G-Hart	0.198	0.144	0.4	0.177	0.13	0.117	0.051	0.071
M-Alli	0.329	0.054	0.37	0.413	0.352	0.06	0.066	0.095
S-Sterling	0.075	0.125	0.5	0.356	0.322	0.253	0.13	0.095
S-Kane	0.169	0.044	0.345	0.142	0.117	0.012	0.077	0.048

Compared to the rest of his teammates, Rooney also is often situated between his teammates (high betweeness centrality), and it is highly likely to have the ball after a reasonable amount of passes has been made (high PageRank centrality). Rooney is not the player with the highest hub centrality. These are Rose and Dier – players that have more connections than the average player in England's team does, and are thus the dominant players in their team. Rooney's hub value is half of the value of these players but higher than 8 of his teammates.

Based on the initial analysis, the substitution decision of coach Hodgson seems to be unreasonable. To further confirm these results, additional analyses are performed. One option is to measure the ***immediate impact*** a removal of a node has on a network. In this case, England's network for the 15 minutes timeframe before his substitution took place is considered again. Rooney is removed from the network and a comparison between both networks is conducted by calculating several metrics at team level. This shows what the immediate impact of removing Rooney is on the team network. Results are presented in Table 22.

Table 22. Immediate impact of removing Rooney on the team network

Network metric	Before	After	Percent change	Change type
Overall Complexity	0.322	0.290	-10.03%	⬇
Diffusion	0.919	0.884	-3.82%	⬇
Clustering Coefficient	0.266	0.210	**-21.35%**	⬇
Characteristic Path Length	2.227	2.467	+10.75%	⬆
Social Density	0.322	0.290	-10.03%	⬇
Average Communication Speed	0.449	0.405	-9.71%	⬇

The table above shows that all the team level network metrics change for the worse when Rooney is removed. The network *complexity* is a measure that in the case of football gives an impression about the overall cohesion between teammates. This metric decreases by 10.03% when Rooney is removed. The *clustering coefficient* is the metric that decreases the most (21.35%). It measures the level of cooperation between teammates. Greater values suggest the capacity of players to involve the teammates in the cooperation processes (Clemente and Martins, 2017). The fact that it decreases by 20% means that the ability of some players to involve their teammates in the offensive play would decrease following Rooney's replacement. Changes in both the *diffusion* and the *characteristic path length* metrics suggest that Rooney's removal makes passing of the ball between teammates more difficult. The decrease of *social density* means that overall the affection between teammates would decrease by 10.03%, while the lower *average communication speed* means that passing of the ball between any two reachable players is slower than before. Thus, England's offensive actions would become less effective with Rooney's removal from the network.

As a next step, the ***core network*** i.e. the largest sub-graph in the network of 15 minutes before Rooney's substitution is calculated. This shows which group of players are most densely connected between each other and to other smaller, and less significant groups of players. The resulting graph is presented in Figure 20.

The core network, comprised of the most connected and influential players in England's team for the 15 minute time period, is comprised of Rooney, Rose, Smalling and Dier, and partly includes Cahill. Player nodes belonging to the same sub-graph are colored the same and nodes are sized based on their values for betweenness and degree centralities. Removing players belonging to the core network will most likely cause significant changes to the team network. Thus, such analysis can also be helpful for coaches to decide which players should perhaps *not be substituted*. Once again, the decision to replace Rooney makes less sense as proved by the additional analysis conducted so far. Thus, a logical next question is, if Rooney is a bad substitution decision, is there a player in England's team who was a better candidate for replacement?

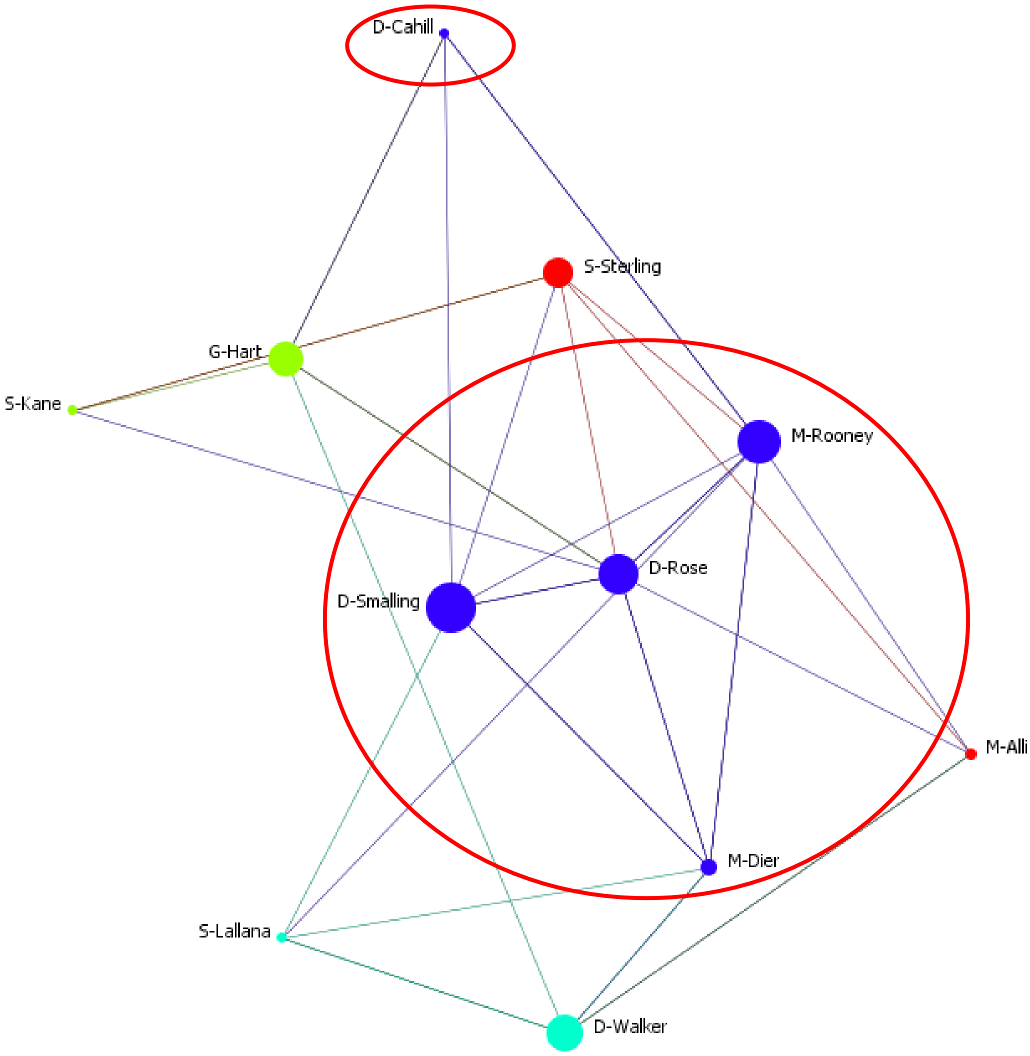
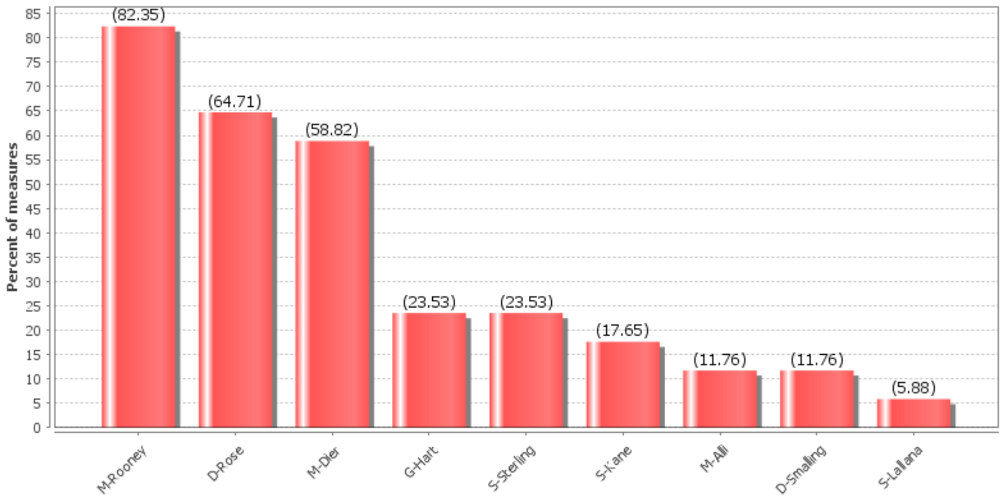


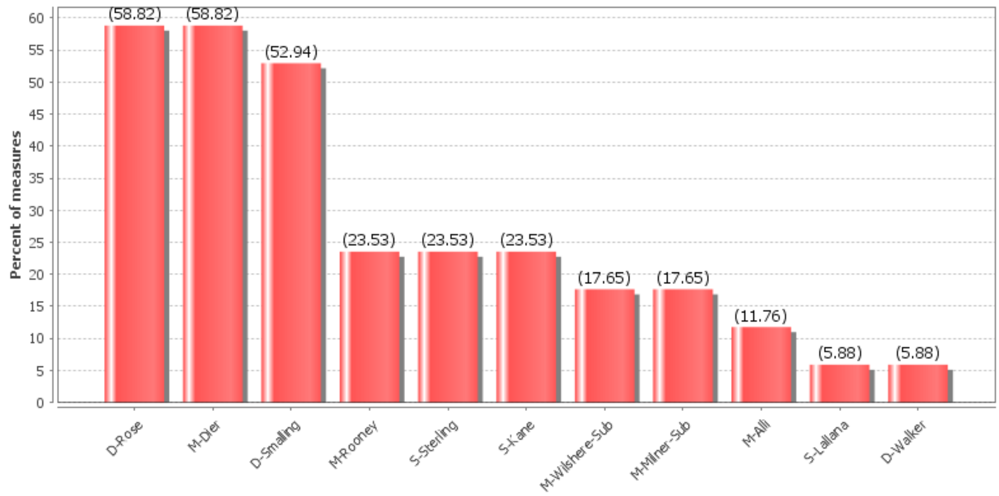
Figure 20. Core network in England's team 15 min before Rooney's substitution

In order to answer this question, the player network metrics that have been used so far are calculated for all players from the start of the match. The goal is to see if there is a player who has consistently performed worse than the rest throughout the game, or alternatively a player that shows low values from the beginning of the 2nd half compared to his performance during the 1st half. Figure 21 shows the players that are top ranked based on the mentioned metrics for the first and second half of the match.

All players were included in the analysis. Substitutes were not excluded in order to compare their overall performance with the rest of the players during the 2nd half. Substitute players would normally have lower network metrics values than their teammates, and are, therefore, usually ranked lower when the network is calculated for all teammates together. That should be considered when discussing the performance of the players in general, and it is necessary to consider whether substitutes should be excluded from the analysis. But in this case, it is interesting to see if there are some players who have lower values than the substitute players.



a) Top ranked players for England, 1st half



b) Top ranked players for England, 2nd half

Figure 21. Top ranked players for England's team throughout the match

From Figure 21 few interesting observations can be made: Lallana, Walker and Alli have lower values in general for all measured metrics throughout the whole game; in the 2nd half, the metric values for these players are even lower than both of the substitutes (Milner and Wilshere); Smalling, however, has visibly improved ranking during the 2nd half, when he is ranked as the third key player compared to rank 8 during the 1st half. Therefore, these three players are investigated further.

The question is: Should one of Alli, Lallana and Walker be substituted instead of Rooney and Sterling? Unfortunately, a straightforward answer is not possible in this case. There is no way to know what would happen when either of these players leaves the game instead of Rooney. However, one can make reasonable assumptions based on analysis such as: "immediate impact" conducted earlier on replacing Rooney from the network of 15 minutes before his actual substitution; the dynamic change of a few key metrics over a period of time can be observed for these players and in combination with additional data, e.g., negative event they participated in (loss of ball possession, foul etc.), a more detailed player evaluation during the live game can be conducted. Tables 23, 24, and 25 present the immediate impact a removal of players Alli, Lallana and Walker has on the team network of 15 minutes before Rooney is replaced.

Table 23. Immediate impact 15 min before Rooney - Alli

	Before	After	Percent Change
Overall Complexity	0.322	0.340	+5.49%
Diffusion	0.919	0.910	-1.00%
Clustering Coefficient	0.266	0.291	+9.35%
Characteristic Path Length	2.227	2.233	+0.27%
Social Density	0.322	0.340	+5.49%
Average Communication Speed	0.449	0.448	-0.27%

Table 24. Immediate impact 15 min before Rooney - Lallana

	Before	After	Percent Change
Overall Complexity	0.322	0.330	+2.38%
Diffusion	0.919	0.912	-0.73%
Clustering Coefficient	0.266	0.234	-12.19%
Characteristic Path Length	2.227	2.144	-3.72%
Social Density	0.322	0.330	+2.38%
Average Communication Speed	0.449	0.466	+3.86%

Table 25. Immediate impact 15 min before Rooney - Walker

	Before	After	Percent Change
Overall Complexity	0.322	0.320	-0.72%
Diffusion	0.919	0.906	-1.41%
Clustering Coefficient	0.266	0.327	+22.61%
Characteristic Path Length	2.227	2.467	+10.75%
Social Density	0.322	0.320	-0.72%
Average Communication Speed	0.449	0.405	-9.71%

The results from the tables above are summarized in Figure 22.

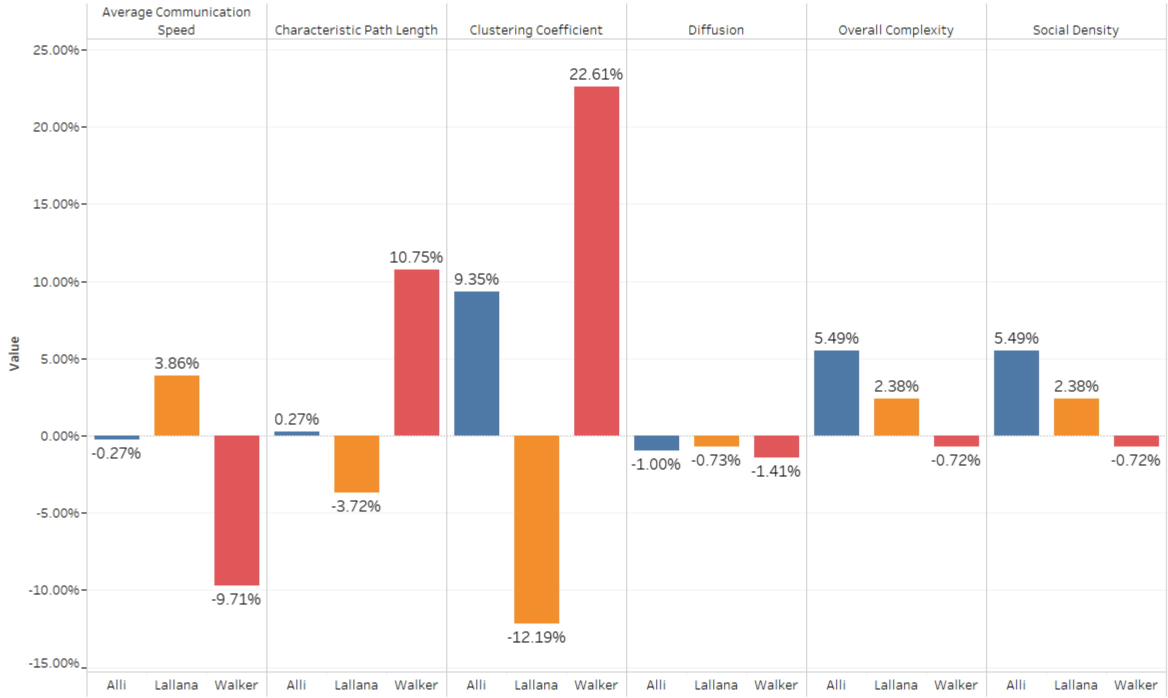


Figure 22. Immediate impact of removing Alli, Lallana or Walker on the team network

Note: The percentage change that occurs in the network metrics after removing each node is displayed. Network is the team network of England, 15 minutes before Rooney is replaced.

The biggest change in the network occurs when Walker is removed. Specifically, the clustering coefficient increases by 22.61%. This means that the cooperation level between his teammates improves when he is removed from the network. The path length also increases by 10.75 % while the communication speed decreases by 9.71%. The removal of the other two players brings less significant changes to the team network. Walker played as a defender in this game. Previous research has found that defenders are the players with highest centrality values (specifically central defenders) and highest prestige values (external defenders) as their tactical position means that they are the ones who mostly initiate the offensive sequences. The fact that Walker keeps having the lowest values from the beginning of the game, combined with the results of the immediate impact on the network following his removal, suggests that Walker should have been substituted instead of Rooney or even Sterling. Opinions form football analysts on Walker's performance in this game differ (which is not unusual in football). The Telegraph writes: "Final ball could be more consistent though and still not totally convincing defensively", while the BBC correspondent remarks: "Vibrant attacking performance in the first half justified his selection. May be put under more pressure against Wales but did well here". These are two rather contrasting opinions on the performance of the same player. The network analysis presented so far, support the first point of view. Finally, this proves that an opinion without data to support it, is only a subjective view of a situation. Data analysis can give a more clear idea of a player's performance.

Team level analysis

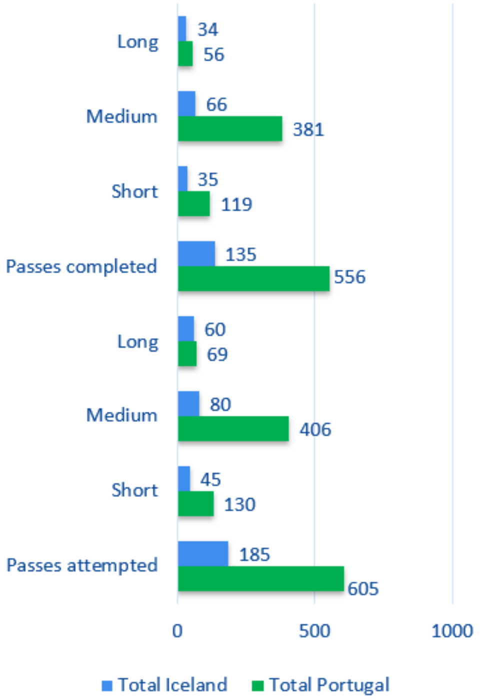
In the second part of the social network analysis, the focus is primarily on the team network analysis. The goal is to demonstrate how metrics at the team level can help explain good or bad performances of a football team. This is driven mostly by the fact that traditional team performance indicators cannot always demonstrate meaningful differences between the teams.

Two games of Iceland's team are chosen for the analysis at network level because this was one of the underdog teams that marked the Euro2016 with their unexpectedly good performance. There are a couple of aspects that make this team interesting to analyze. First, this was the first appearance of Iceland in the 60 years of history of the European Championship. Second, Iceland does not have professional football clubs and its national team players are not playing at high professional level as the players of other more popular teams. Third, Iceland demonstrated that a tactic considered outdated by most modern managers, the 4-4-2, should not be overlooked. Iceland was eliminated at the quarter finals stage by France which is a strong competitor. Nevertheless, the team managed a draw against Portugal and a win against England. A brief overview of both games is presented in Table 26.

Table 26. Brief overview of Iceland's matches

Date	Teams	Outcome	Substitutes	Goals
14 June 2016	Portugal - Iceland	1 - 1	3 / 2	31' Nani – 50' Bjarnason
27 June 2016	England - Iceland	1 - 2	3 / 2	4' Rooney – 6'R.Sigurdsson 18' Sigthorsson

In both matches, Iceland used two out of three substitutions. In the match against England, all three goals were scored in the first 18 minutes. Therefore, this timeframe is generally more interesting for the analysis. The game against Portugal ended in a draw with one goal on each side and per match half. Iceland scored in the 2nd half in minute 50 with a goal by Bjarnason. The overall team statistics for both matches are presented in Figures 23 and 24.



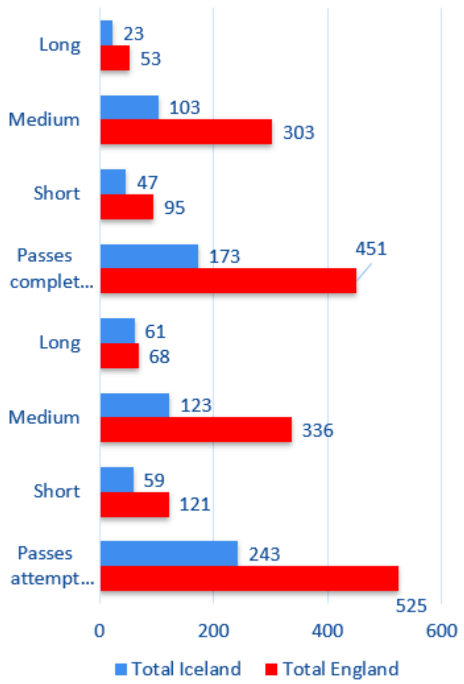
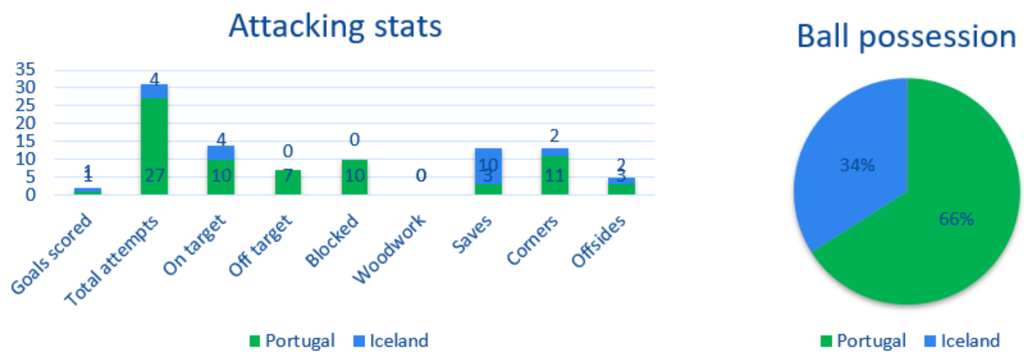
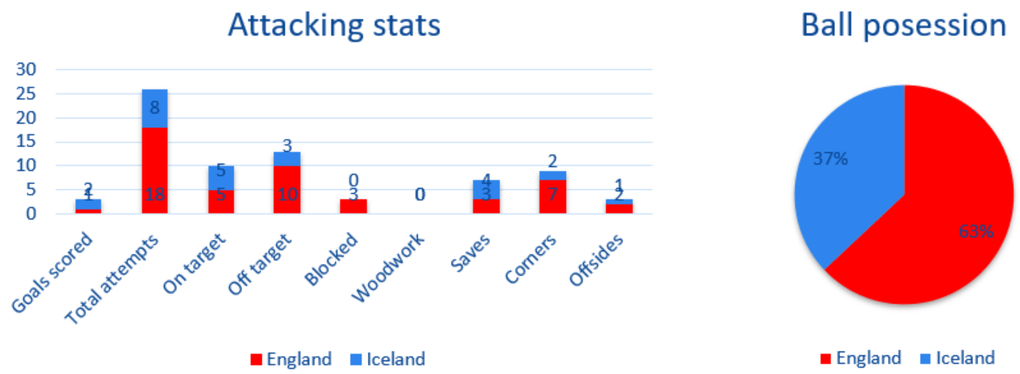


Figure 23. Total passes from both games



a) Iceland vs. Portugal

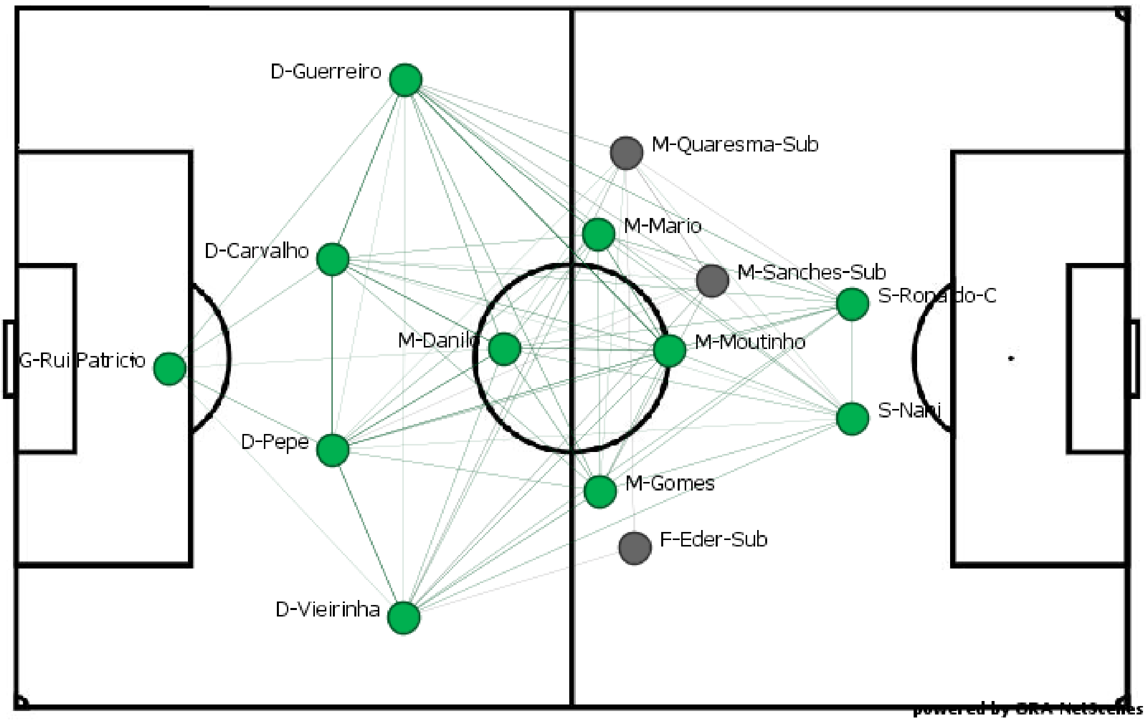


b) England vs. Iceland

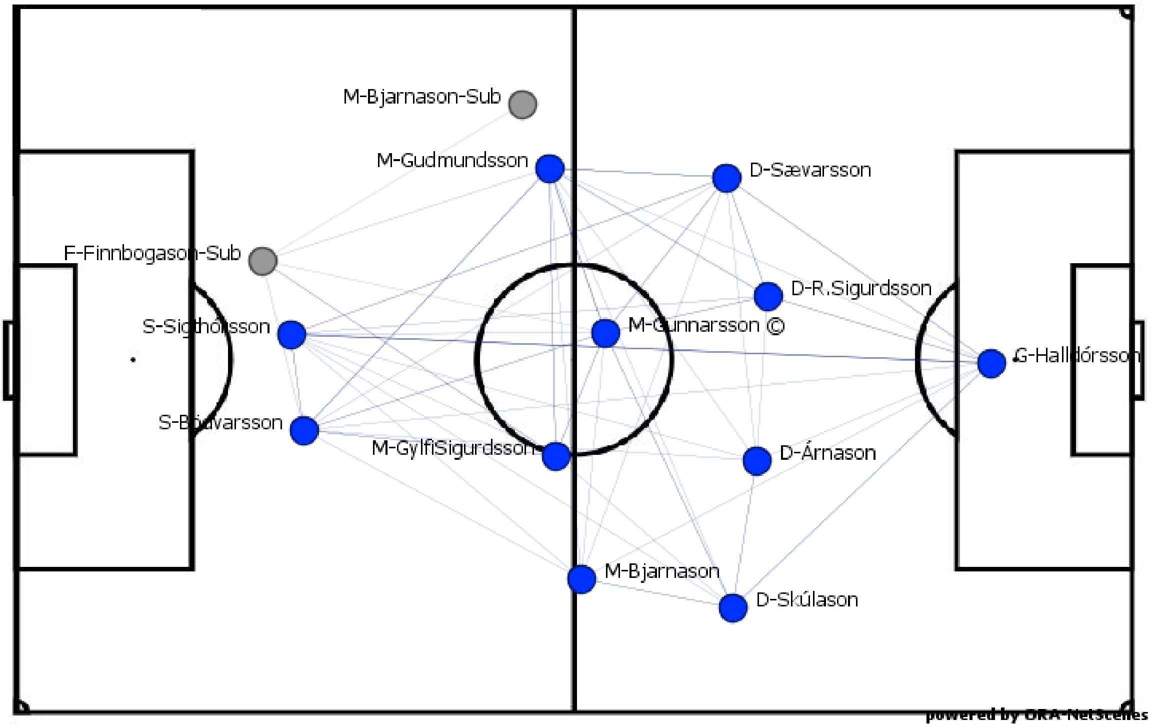
Figure 24. Ball possession and attacking indicators for Iceland vs. Portugal

Considering the attacking performance indicators in Figure 24, an initial conclusion would be that Iceland showed worse performance than Portugal or England. England and Portugal have both more attempts for shot-on-goal, more corners and higher ball possession. Additionally, Iceland has considerably less passes in both matches, although the long passes are similar to both England and Iceland. All three teams preferred to avoid long passes, which means that they did not take advantage of quick attacking sequences, and preferred to be more conservative during attack. Considering the above charts, the goal of the analysis in this part is to investigate if there are some interesting patterns or observations to be found in Iceland's games by means of social network analysis that could explain the good performance of Iceland in the games against Portugal and England.

In a first step, the team networks over the course of the game as well as the main network level metrics are calculated. The goal is to gain an initial impression about the differences between the teams in each match. The team network are presented in Figures 25 and 26 for the matches against Portugal and England respectively.



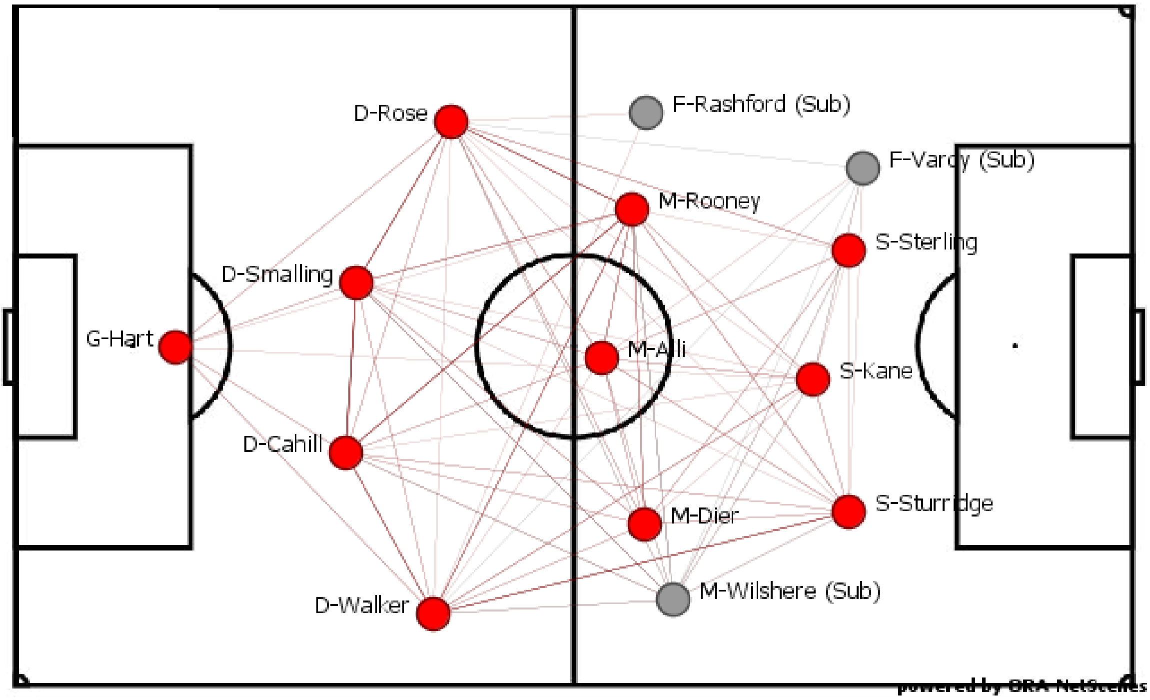
a) Portugal's team network – Strategy 4-1-2-1-2



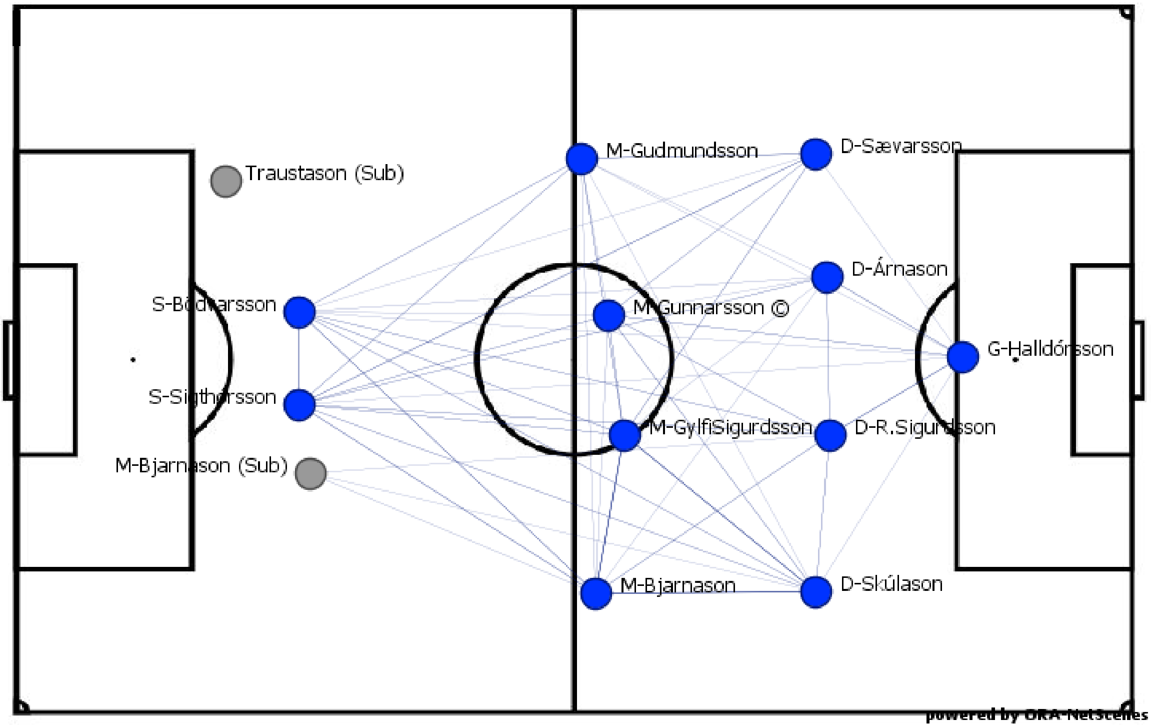
b) Iceland’s team network – Strategy 4-4-2

Figure 25. Team networks of Portugal and Iceland

Note: Nodes are arranged on the field based on the team’s strategy in that match. Grey nodes are substitute players.



a) England’s team network – Strategy 4-3-3



b) Iceland's team network – Strategy 4-4-2

Figure 26. Team networks of England and Iceland

Note: Nodes are arranged on the field based on the team's strategy in that match. Grey nodes are substitute players.

The team networks show that Iceland's players were well connected in spite of having less passes than their opponents. The networks of both Portugal and England show a strong connection (thicker edges) between their defense players. This is not visible in Iceland's case. In the match against Portugal, Iceland seems to have stronger connections between midfield players, visibly more passes between the midfielder Gudmundsson and the striker Bjarvasson. There is also a strong connection between the goalkeeper and the striker Sigthorsson, which suggests that there were a few attempts for a counter attack against Portugal, involving these two players. In the match against England, the results are similar. There is a strong midfield and a visible triad involving two defenders – Sigurdsson and Bjarnason, and a defender – Skulason.

Table 27 shows the results for the teams' network metrics.

Table 27. Team network metrics for both matches[7]

Network-Level Measure	Portugal	Iceland	England	Iceland
Clique Count	4	20	7	11
Density	0.633	0.423	0.617	0.494
Diameter	6	182	238	104
Diffusion	0.972	0.87	0.907	0.885
Hierarchy	0	0.154	0.143	0.154
Interdependence	0.014	0.022	0.015	0.02
Network Centralization-Betweenness	0.155	0.121	0.137	0.111
Network Centralization-Closeness	0.285	0.392	0.303	0.022
Network Centralization-Eigenvector	0.292	0.383	0.356	0.312
Network Centralization-Total Degree	0.177	0.068	0.161	0.139
Reciprocity	0.063	0.138	0.112	0.149
Transitivity	0.778	0.531	0.804	0.618

Iceland has the highest values for *clique count* in both matches. The difference is especially high in the match with Portugal. The network *density* is in both matches lower than the opponents. This contradicts to the findings of (Clemente, Martins, Kalamaras, Wong et al., 2015) who found that teams who are successful tend to have higher density values than their opponents. *Diffusion* values are also lower for Iceland but the gap is not significant. Both values are close to 1 which means that nodes are closer together and not farther apart. In this case this means ball can travel well between teammates in all teams.

What is rather surprising is that Iceland has low *betweenness* and *degree centralizations* in both matches, compared to their opponents. Iceland's *closeness* and *eigenvector centralizations* are higher than Portugal's, while in the match against England, which the team won, the values for these metrics are lower. Iceland is also visibly different than its opponents in the *interdependence* and *hierarchy* metrics, which are higher in both matches. The interdependence measures the extent to which passes go in both directions (from player A to B and vice versa). For this reason, Iceland has higher values for *reciprocity*. In general, when a network has higher reciprocity, it tends to be a more stable network, where players tend to form dyadic relationships (Clemente, Martins et al., 2016). In this case, what is interesting is that Iceland has lower values for *transitivity*, which means players form less triadic relationships (there is a link between A and B, and B and C, but not between A and C), and prefer to pass the ball to the same players (hence the higher reciprocity). The higher hierarchy value is thus also related to this, and means that in Iceland's team there are a few players more popular than the others, i.e. there is a hierarchical structure of relations and more asymmetric connections.

[7] The network metrics on team level are explained in Appendix D.

The analysis on team level reveal some differences between Iceland and their opponents. However, to gain a more clear picture of the differences which led to the goals scored in each match, a ***dynamic analysis*** at the network level is conducted in a next step. Specifically, the change in a few selected metrics over the course of the game is investigated, as well as the change in the team network topology.

Figure 27 and Figure 28 present the change in reciprocity and transitivity of Portugal and Iceland respectively throughout the course of the match. The change in crucial time periods (goals scored in minutes 30 and 50 are highlighted).

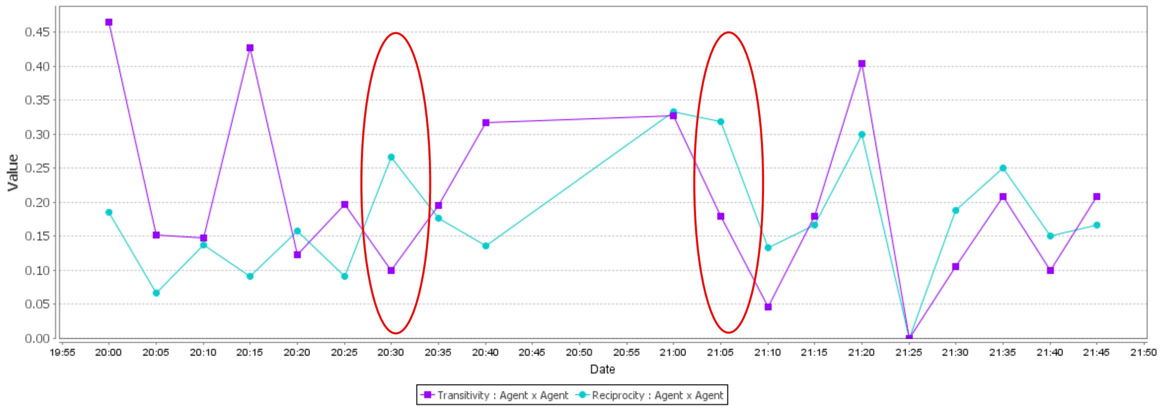


Figure 27. Transitivity and Reciprocity of Portugal's network throughout the match

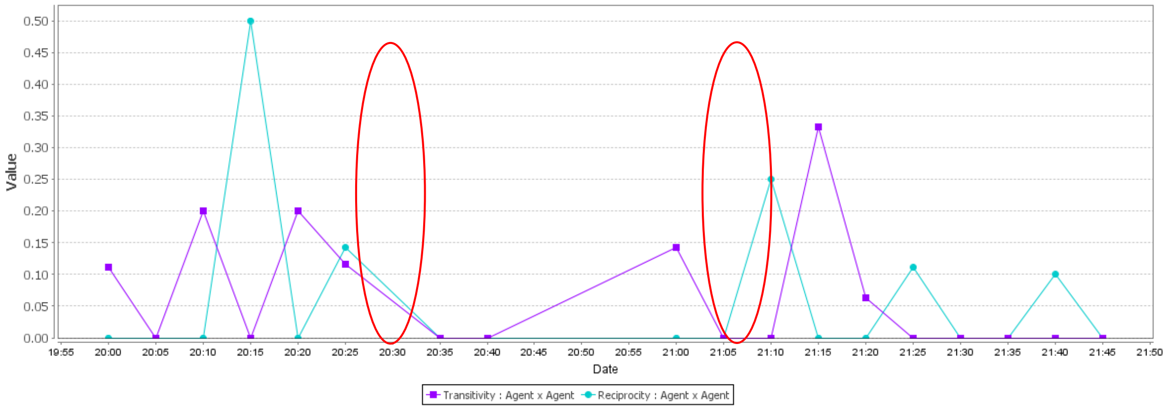


Figure 28. Transitivity and Reciprocity of Iceland's network throughout the match

The figures above show that in the minutes before each team scored a goal, there is an increase in reciprocity and decrease in transitivity for their own team, while the opposition has a decrease in both reciprocity and transitivity. These results suggest that both teams took advantage of successful dyadic relationships between their players, while triads were not preferred in both cases. One can replicate the study over more data and see whether this is true for all successful teams. Triads give an information on how the network as a whole is being held together and it leads to cohesion of the network (Lusher et al., 2010), which is considered as a positive aspect in network level analysis. However, in football, it may be that dyadic relationships are more important than triadic ones. The ability to form triads is one of the metrics that is also part of subgroup level of network analysis, and it is thus discussed later with the network assortativity metric.

Subgroup level analysis

This level of analysis has been under researched in the SNA literature in football performance analysis. It is, however, an important one and future studies should investigate this in more detail. One of the reasons is that players cooperate with a certain interdependency between them (e.g., forward players depending on the midfielders or defenders to receive the ball) (Clemente, Martins et al., 2016). Thus, it is important to understand how players cluster together and depend on each other. There are a few metrics that can be used at this level of analysis. These are the network assortativity metric, community detection by using various algorithms that group the players together, triad computation and types of triads, ego networks of individual players, to name a few. In the literature, a few authors have discussed transitivity and triads (Cotta et al., 2013; Lusher et al., 2010; Wäsche et al., 2017), while Clemente, Martins et al. (2016) suggest that the assortativity metric can be used for subgroup analysis, but there are no other studies investigating this in more detail. Therefore, these metrics are discussed below and results are presented for Iceland's matches against Portugal and England.

Network assortativity measures the extent to which nodes of similar degree are inter-connected (ORA Documentation File, 2018). High values (+1) mean that the nodes with high degree are clustered together and nodes of low degree are clustered together; low values (-1) mean that high degree nodes connect to low degree nodes (ORA Documentation File, 2018). The network assortativity is calculated as presented in Equation 2.

Equation 2. Network Assortativity

Formula
let A be the unimodal input network with N nodes
let d be the out-degree of each node
let CoVariance = $\sum(A_{i,j} - d_i d_j/2m)*(d_i d_j)$
let Variance = $\sum(d_{i,j}*kron_{i,j} - d_i d_j/2m)*(d_i d_j)$
where $kron_{i,j} = 1$ if i == j, else 0
Then Network Assortativity = CoVariance / Variance

Source: ORA Documentation File, 2018

The results for the assortativity metric for all three teams in the two matches analyzed, are presented in Table 28.

Table 28. Network assortativity for all teams in the analyzed matches

	Match 1		Match 2	
Subgroup metric	**Portugal**	**Iceland**	**England**	**Iceland**
Network Assortativity	-0.053	-0.212	-0.004	0.164

The positive value of the network assortativity for Iceland in the match against England, means that in this game, players who are similar to each other in terms of connectivity, tend to be clustered together, i.e. they pass more to each other than to players with lower degree of connections. This metric has not been investigated in previous research on SNA in football PA and there is, unfortunately, no basis for comparison. Iceland's positive value in a game they won, suggests that it may be better that a team has positive values for this metric. To examine this further, the assortativity metric for both England and Iceland throughout the game is presented in Figure 29 and Figure 30 respectively.

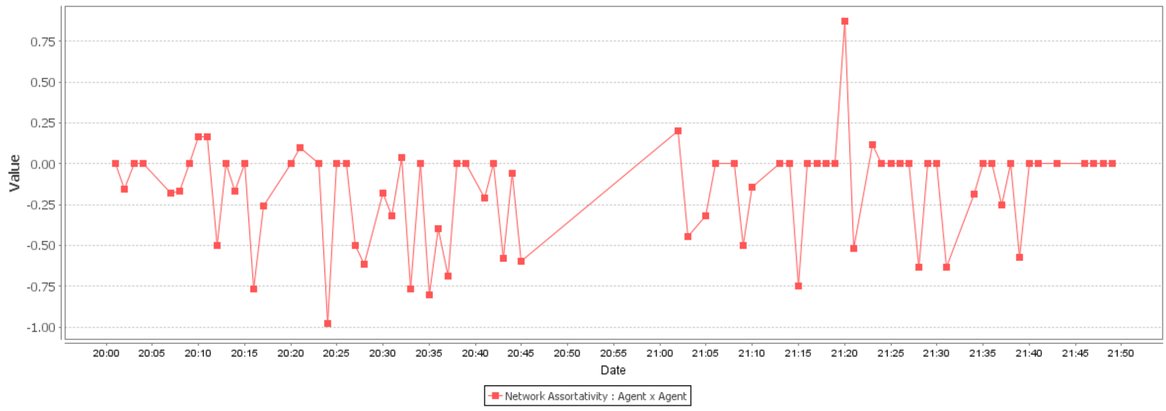


Figure 29. Network assortativity for England throughout the whole match

Figure 30. Network assortativity for Iceland throughout the whole match

The dynamic analysis for this metric give a more clear picture regarding the metric and its values in a game. Not only does England has mostly negative values throughput the whole match but most of the values are close to (-1). The only period of the match when their assortativity index was visibly positive i.e. nearing (+1) value is during the 2^{nd} half of the match around minute 65' (21:20 hrs). Iceland also has negative values, but during the 1^{st} half of the game when both goals were scored there are two periods with a high positive value for assortativity. The first period is a few minutes before the 2nd goal was scored, and the 2nd period is between minutes 30' and 35'. Iceland and England both have negative assortativity values when the opposition manages to score a goal. These results suggest that a positive and higher values for assortativity contribute for a better team performance in football i.e. players with high connectivity should connect to other players well connected themselves.

Change detection

Part of the dynamic analysis of a network is the topic of change detection. Change detection is the process of monitoring networks to determine when significant changes to their organizational structure occur and what caused them (McCulloh and Carley, 2008b). Different network level measures over a period of time can be monitored and a control chart can be used to signal when significant changes occur in the network (McCulloh and Carley, 2008b). Using a control chart is inspired by the Statistical Process Control (SPC) technique. This is used in manufacturing processes for quality control and monitoring the process stability. A process is said to be "in statistical control" if the probability distribution representing a quality characteristic is constant over time; if there is some change over time in this distribution, the process is said to be "out of control" (Woodall, 2000).

As mentioned in section 6.1, several studies have shown that the Cumulative Sum (CUSUM) as a control chart is a reliable technique for change detection in network metrics over time. The calculation of CUSUM is presented in Equation 3.

Equation 3. Calculation of CUSUM

The decision rule of the CUSUM chart runs off the cumulative statistic

$$C_t = \sum_{j=1}^{t} (Z_i - k)$$

where Z_i is the standardized normal of each observation,

$$Z_i = \frac{(\bar{x}_i - \mu_0)}{\sigma_{\bar{x}}}$$

and the common choice for k is 0.5, which corresponds to a standardized magnitude of change of 1. The CUSUM control chart sequentially compares the statistic C_t against a control limit A' until $C_t > A'$. Since we are not interested in concluding that the network is unchanged, the cumulative statistic is

$$C_t^+ = \max\{0, Z_t - k + C_{t-1}^+\}$$

Equation 3. Calculation of CUSUM (Continued)

The statistic C_t^+ is compared to the constant control limit, h^+. If $C_t^+ > h^+$, then the control chart signals that an increase in a network measure has occurred. Since this rule only detects increases in the mean, a second cumulative statistic rule must be used to detect decreases in the mean.

$$C_t^- = \max\{0, -Z_t - k + C_{t-1}^-\}$$

which signals a decrease in a network measure's mean when $C_t^- > h^-$.

Source: (McCulloh and Carley, 2008b, p. 4)

One advantage of CUSUM is that it is able to detect small changes in the network. An argument against it could be that sometimes changes develop quickly in football, and thus, detecting small changes is not relevant. However, when things develop quickly, there is not much of an opportunity for a quick counter action to it. If small changes are detected, they can be perhaps signals of more drastic changes ahead (McCulloh and Carley, 2008b). This can be still of relevance in football performance analysis. So far, the literature has not considered this. Thus, change detection is examined further by the example of Iceland's match against Portugal.

There are different metrics that can be considered when detecting a change in the network. Usually, network level measures work better as metrics at node level need to be translated into a network picture of the entire graph (McCulloh and Carley, 2008b). Furthermore, the metrics values are normalized in order to be able to compare them across different time periods (McCulloh and Carley, 2008b). In the current analysis, three metrics at the network level were chosen as they give an idea on how the team works together as a whole, its structure and connectedness. These metrics are: density, assortativity and efficiency. Density is a metric that is often used in football PA to analyze the team performances. Earlier, the assortativity metric and its meaning was explained. The *efficiency* metric shows the degree to which each component in a network contains the minimum links necessary to keep it connected (ORA Documentation File, 2018). The resulting CUSUM calculation for Iceland's team (in the match against Portugal) is presented in Figures 31 and 32.

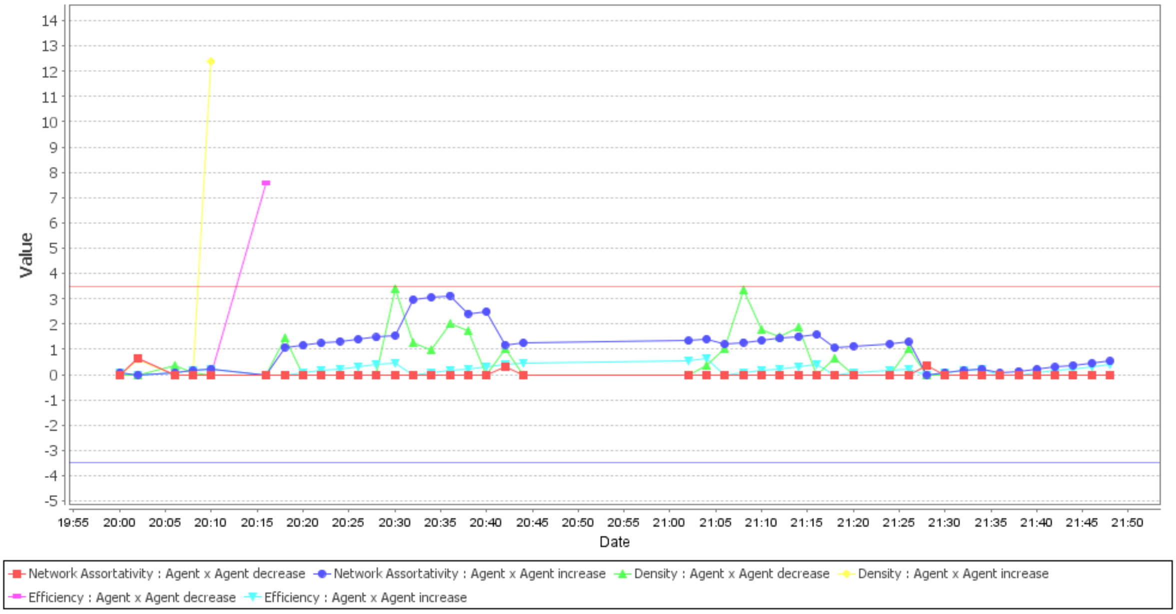


Figure 31. CUSUM for Iceland‘s team

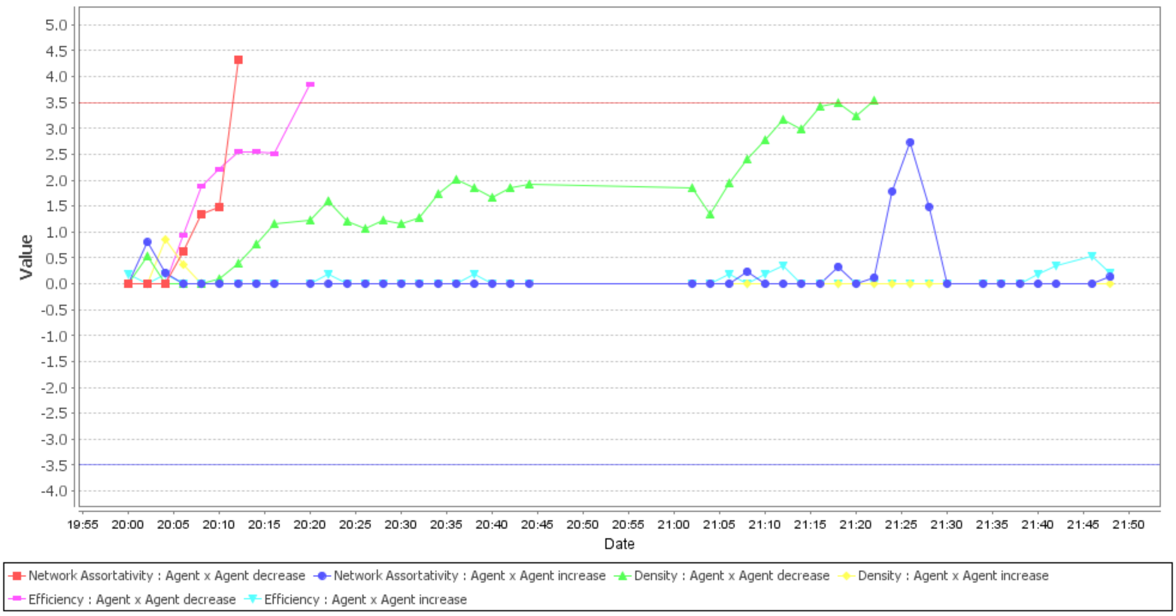
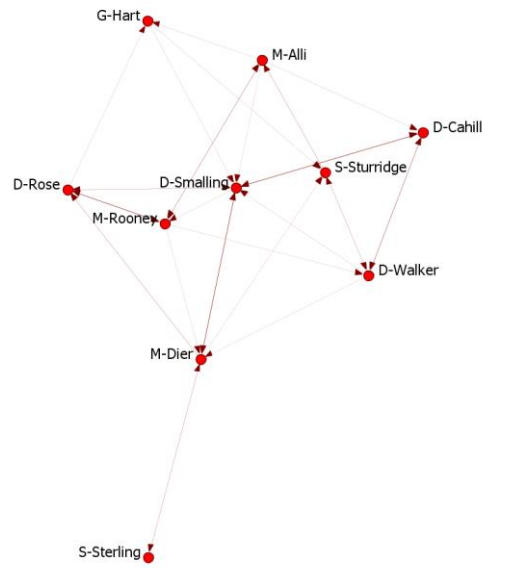
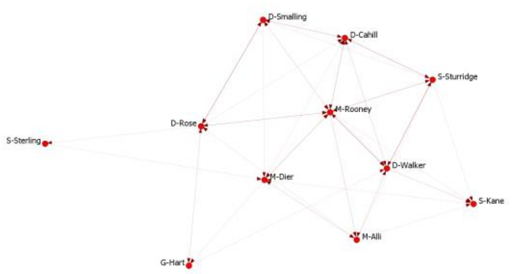


Figure 32. CUSUM for England’s team

It is of relevance to mention that change detection is not about predicting a change but determining that a change has occurred quickly and being able to make some inference about the actual time of change (ORA Documentation File, 2018). The figures above demonstrate that a change in the networks of both teams occurs between minutes 10 and minutes 25 (England) and minutes 5 and 20 (Iceland).

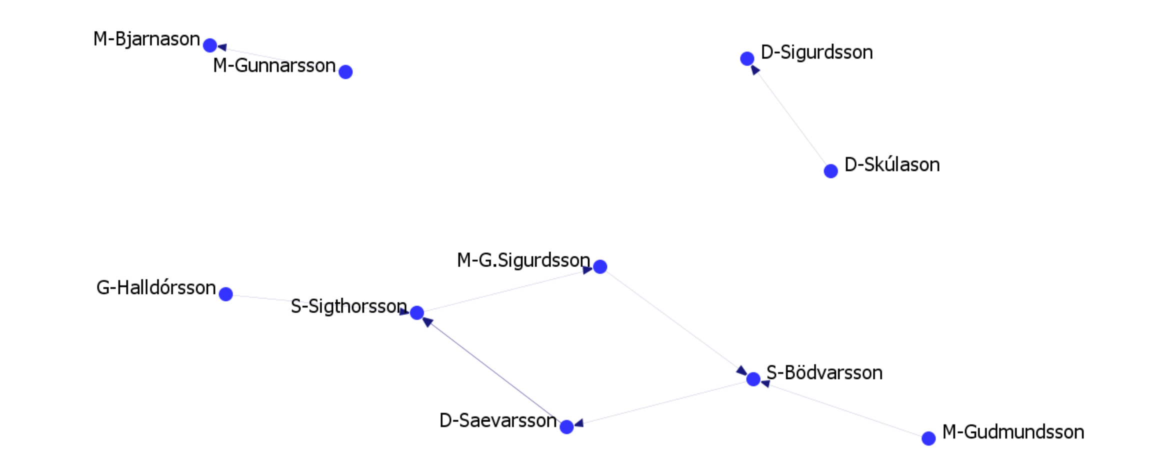
Network analysis allows for more in-depth studying of the networks in the suspected time period of network change. By analyzing the networks further, as well as the opponent’s network, it is possible to gain a more detailed understanding of the changes that occur in players’ interactions especially when there are important events happening in those same time periods. For this reason, two networks are created for both teams and the timeframe is based on the CUSUSM charts for both teams. The investigated time of the match is between minutes 0' and 30' for Englad and 0' and 15' for Iceland. The network topologies in each time frame and the network level metrics for each topology are presented in Tables 29 and 30 for England and Iceland respectively. .

Table 29. Dynamic network topologies and network level metrics – England 0' – 20'

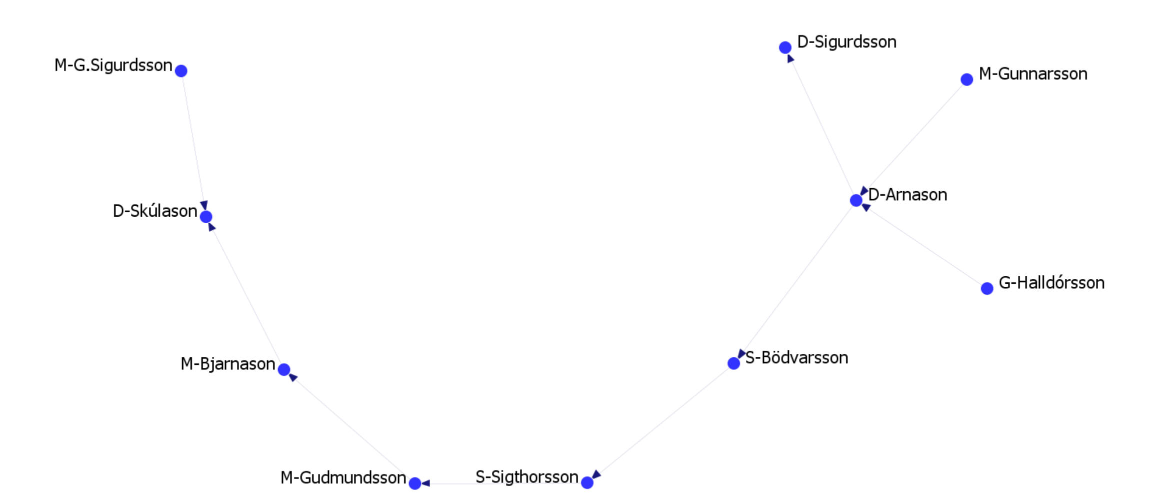
 	**England** • minutes 0 – 10 • 10 nodes, 30 links	• Deg Centralization 0.139 • Out-Central 0.123 • In-Central 0.370 • Density 0.333 • Connectedness 1 • Fragmentation 0 • Closure 0.244 • Avg Distance 1.822 • SD Distance 0.676 • Diameter 3 • Breadth 0.359 • Compactness 0.641 • Small Worldness **0.947** • Mutuals 0.178 • Asymmetrics 0.311 • Nulls 0.511 • Arc Reciprocity 0.533 • Dyad Reciprocity 0.364 • Transitivity 0.244 • Reciprocity: 0.3636
 	**England** • minutes 10 – 20 • 11 nodes, 44 links	• Deg Centralization **0.489** • Out-Central **0.440** • In-Central 0.220 • Density 0.400 • Connectedness 1 • Fragmentation 0 • Closure **0.462** • Avg Distance 1.773 • SD Distance: 0.734 • Diameter: 4 • Breadth: 0.328 • Compactness: 0.672 • Small Worldness: **0.146** • Mutuals: 0.255 • Asymmetrics: 0.291 • Nulls: 0.455 • Arc Reciprocity: 0.636 • Dyad Reciprocity: 0.467 • Transitivity: **0.462** • Reciprocity: **0.4667**

Note: A brief description of the metrics used in this table is included in Appendix F.

Table 30. Dynamic network topologies and network level metrics – Iceland 0‘ – 15‘



Iceland • minutes 0 – 5 • 10 nodes, 8 links	Avg Degree 0.800 Deg Centralization 0.028 Out-Central 0.025 In-Central 0.148 Density 0.089 Connectedness 0.244 Fragmentation 0.756 Closure 0 Avg Distance 2.091 SD Distance 0.996	Diameter 4 Breadth 0.850 Compactness 0.150 Small Worldness 0 Mutuals 0 Asymmetrics 0.178 Nulls 0.822 Arc Reciprocity 0 Dyad Reciprocity 0 Transitivity 0



Iceland • minutes 6 – 15 • 10 nodes, 9 links	Avg Degree 0.900 Deg Centralization **0.153** Out-Central **0.136** In-Central 0.136 Density 0.100 Connectedness 0.344 Fragmentation 0.656 Closure 0 Avg Distance 2.677 SD Distance **1.553**	Diameter **6** Breadth 0.816 Compactness 0.184 Small Worldness 0 Mutuals 0 Asymmetrics 0.200 Nulls 0.800 Arc Reciprocity 0 Dyad Reciprocity 0 Transitivity 0

Note: A brief description of the metrics used in this table is included in Appendix F.

By conducting the dynamic network analysis in addition to the change detection, it is possible to see how exactly the network of both teams have changed in the analyzed timeframes. The CUSUM charts for both teams show an alert when there is a visible decrease in the efficiency value of the network. The efficiency is the degree to which each node in a network contains the minimum links necessary to keep it connected. For Iceland's team it decreases drastically following their first goal, while for England it decreases before the 2nd goal of Iceland. This suggests that after Iceland equalized the score to 1:1, England's some of England's players are significantly disconnected from the rest of their teammates. A closer look at the network level metrics from the time period before and after the change detection for England, reveals that there is significant change in a few metrics. Most significantly, the *small worldness* of the team decreases drastically in the second timeframe of 10 to 20 minutes in the game. Thus, it can be concluded that England's players are more dispersed and there is longer distance between the players i.e. if A is connected to B and C, there is not necessarily a link between B and C as well (Gama et al., 2014). Therefore, it is understandable that the efficiency of the network as a whole decreases as well as not all players are close to each other.

In Iceland's team the main change is increase in the degree centralization and specifically, the out-degree centralization. This signifies that some of its players have become more prominent by passing more to other players. Consequently, this signals Iceland's has significantly intensified its attacking play. An information like this might be useful for the coach to try and react before another goal is scored (as it happened in this case). This type of analysis shows that network metrics should never be considered in isolation but only in combination with additional analysis, to avid misleading conclusions.

***Community detection* -** As mentioned in section 6.1, community detection in social networks is a problematic area of research simply because of various definitions of community as well as algorithms that detect such communities. In football, a community can be defined as a smaller group of three to five players that are more closely connected with each other than to the rest of their teammates. The literature on football performance analysis and SNA, has mostly relied on cliques and clustering metrics to determine the cohesion of the team as a whole. There is little research on community detection in football teams. Therefore, below several algorithms are used to calculate such communities in the teams of Iceland and England.

Table 31. Community detection in the teams of Iceland and England

Algorithm	Team	Group	Size	Members
Girvan-Newman Clustering Algorithm	England	1	14	M-Alli, M-Rooney, D-Walker, S-Sturridge, D-Cahill, D-Smalling, M-Dier, S-Sterling, D-Rose, G-Hart, S-Kane, M-Wilshere-Sub, F-Vardy-Sub, F-Rashford-Sub
	Iceland	1	12	M-Gunnarsson, M-Bjarnason, D-Skúlason, D-Sigurdsson, M-G.Sigurdsson, S-Bödvarsson, G-Halldórsson, S-Sigthorsson, D-Saevarsson, M-Gudmundsson, D-Arnason, Bjarnason-Sub
Newman Clustering Algorithm	England	1	8	M-Rooney, D-Cahill, D-Smalling, M-Dier, S-Sterling, D-Rose, M-Wilshere-Sub, F-Rashford-Sub
		2	6	M-Alli, D-Walker, S-Sturridge, G-Hart, S-Kane, F-Vardy-Sub
	Iceland	1	5	M-Bjarnason, D-Skúlason, M-G.Sigurdsson, S-Bödvarsson, Bjarnason-Sub
		2	4	M-Gunnarsson, S-Sigthorsson, D-Saevarsson, M-Gudmundsson
		3	3	D-Sigurdsson, G-Halldórsson, D-Arnason
CONCOR Structural Equivalence Algorithm	England	1	7	M-Alli, M-Rooney, D-Smalling, S-Sterling, G-Hart, F-Vardy-Sub, F-Rashford-Sub
		2	7	D-Walker, S-Sturridge, D-Cahill, M-Dier, D-Rose, S-Kane, M-Wilshere-Sub
	Iceland	1	7	M-Gunnarsson, M-Bjarnason, M-G.Sigurdsson, S-Bödvarsson, G-Halldórsson, D-Saevarsson, Bjarnason-Sub
		2	5	D-Skúlason, D-Sigurdsson, S-Sigthorsson, M-Gudmundsson, D-Arnason
Johnson's Hierarchical Clustering Algorithm	England	1	12	M-Alli, M-Rooney, D-Walker, S-Sturridge, D-Cahill, D-Smalling, M-Dier, S-Sterling, D-Rose, G-Hart, S-Kane, M-Wilshere-Sub
	Iceland	1	7	M-Gunnarsson, M-Bjarnason, D-Skúlason, M-G.Sigurdsson, S-Sigthorsson, D-Saevarsson, M-Gudmundsson
		2	4	D-Sigurdsson, S-Bödvarsson, G-Halldórsson, D-Arnason
Dense Subgraph Extraction	England	1	13	M-Alli, M-Rooney, D-Walker, S-Sturridge, D-Cahill, D-Smalling, M-Dier, S-Sterling, D-Rose, G-Hart, S-Kane, M-Wilshere-Sub, F-Rashford-Sub
	Iceland	1	11	M-Gunnarsson, M-Bjarnason, D-Skúlason, D-Sigurdsson, M-G.Sigurdsson, S-Bödvarsson, G-Halldórsson, S-Sigthorsson, M-Gudmundsson, D-Arnason, Bjarnason-Sub
k-Means	England	1	9	M-Alli, D-Walker, D-Cahill, D-Smalling, M-Dier, D-Rose, G-Hart, S-Kane, M-Wilshere-Sub
		2	3	S-Sturridge, S-Sterling, F-Rashford-Sub
	Iceland	1	6	M-Gunnarsson, D-Sigurdsson, G-Halldórsson, S-Sigthorsson, M-Gudmundsson, D-Arnason
		2	4	M-Bjarnason, D-Skúlason, M-G.Sigurdsson, S-Bödvarsson

Note: The algorithms are briefly described in Appendix E.

Six different algorithms are used for community detection and detecting smaller and cohesive groups in England and Iceland's teams. The results from these analyses demonstrate that England's team does not tend to form clusters as much as Iceland's team. Most of the algorithms clustered all team members of England's team together, except for the k-Means, CONCOR and Newman clustering algorithms. The Dense Subgraph Extraction and the Girvan-Newman algorithms does not seem to be suitable for community extraction in football teams as they tend to cluster the whole team together. Results were similar for the match between Iceland and Portugal as well. In general, with only 11 players, a football team tends to have high clustering tendency, and in most cases, connections exist between all players. Thus, community detection algorithms seem to not be helpful for detecting closely connected subgroups of players. Techniques such as the core network presented earlier, clique counts or triads seem to be more useful.

In a next step, ***triads*** are calculated for the teams of England and Iceland. In simple terms, a triad is three actors and the relations between them (Lusher et al., 2010). It is an important approach to study social structures as it goes beyond the dyad level and may indicate how the network as whole is held together (Lusher et al., 2010). The formula for this calculation is presented in Equation 4.

Equation 4. Triad count formula

Formula
let A be the binary, unimodal input network
We create a new network called TriadCount such that:
TriadCount(i,j) = number of triads using link (i,j) =
= cardinality{ k | A(i,j)*A(j,k)*A(i,k) = 1 ∀i,j,k distinct}
The Triad Count for node i = sum(TriadCount(i,:))

Source: ORA Documentation File, 2018

The results for both teams are displayed in Table 32. The types of triads and the triad count is calculated for both teams, as well as the percentage of each triad type.

Table 32. Triad types and count for England and Iceland

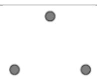
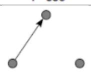
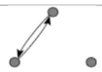
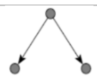
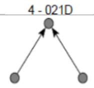
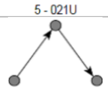
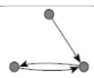
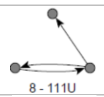
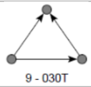
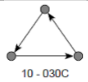
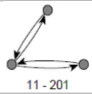
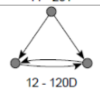
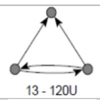
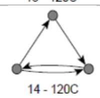
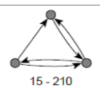
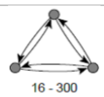
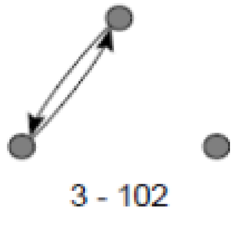
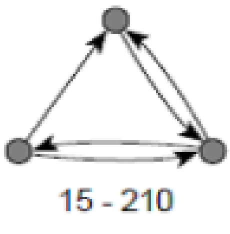
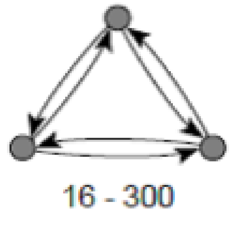
	Iceland		**England**	
Triad	**Count**	**Percent of all triads**	**Count**	**Percent of all triads**
 1 - 003	3	1.36%	11	3.30%
 2 - 012	18	8.18%	21	5.77%
 3 - 102	21	9.55%	**56**	**15.38%**
 4 - 021D	6	2.73%	4	1.10%
 5 - 021U	2	0.91%	1	0.27%
 6 - 021C	6	2.73%	4	1.10%
 7 - 111D	19	8.64%	19	5.22%

Table 32. Triad types and count for England and Iceland (continued)

	Iceland		England	
Triad	**Count**	**Percent of all triads**	**Count**	**Percent of all triads**
	26	11.82%	29	7.97%
	6	2.73%	1	0.27%
	1	0.45%	1	0.27%
	24	10.91%	29	7.97%
	9	4.09%	3	0.82%
	7	3.18%	8	2.20%
	14	6.36%	14	3.85%
	**38**	**17.27%**	61	16.76%
	20	9.09%	**101**	**27.75%**

There are significant differences between both teams. England has the highest amount of type 16 triad, while Iceland's players participate mostly in type 15 triad. Both teams have a lot of connections from type 3 triad, which is practically a dyad.

Table 33. Popular triads in Iceland and England's teams

		
Triad type 3	Triad type 15	Triad type 16

By studying the triadic relationships between players it is possible to gain additional information on the exact way players interact with each other. Obviously, dyadic relationships are crucial for the success of a team, however, players display more complex interactions than the dyadic level which is mostly studies in existing literature.

6.6 Discussion

The results demonstrate how network analytics techniques can be used for performance evaluation in football as well as to make tactical adjustments during the game or prepare for an upcoming match.

At player level, the analyses in the current thesis use the centrality metrics most often mentioned in the literature, but also extend them by adding two new metrics (authority and contribution). The results are used to demonstrate how such analysis at player level can support decision makers in football during live matches in deciding which player should leave the game. According to the findings based on network metrics, Rooney leaving the game against Russia was not a wise decision as the impact on the network was significant. Furthermore, additional calculations based on network metrics, such as immediate impact and core network, as well as dynamic analysis of the metrics over a period of time, can show not only who are the key players but this can also be used to decide which players should not be considered for substitution. These type of analyses have not been applied in previous research.

Team level analysis can be used to explain good or bad performances of teams. The results show that by calculating change detection, network metrics in key timeframes of the game, as well as triadic relationships, it is possible to understand better how players connect with each other. This can be used for decisions both pre- and during the match. In this case, Iceland is the team with less ball possession, and thus lower number of passes overall. However, their performance is better than or at least as good as their opponents'. Iceland takes advantage of successful dyadic relationship between its players and thus, it is the team with higher reciprocity. On the other hand, the team has lower transitivity as players participated in less triadic relationships than their opponents. If decision makers know that Iceland's players are successful due to these dyadic relationships, such analysis can support real-time tactical adjustments based on this information as well as which players are involved in the dyads. Therefore, relying on dyads could also increase Iceland's vulnerability if such information is to be used by their opponents.

Similarly, by knowing the interaction patterns between players of a team, coaches can prepare better against the opposition by having more insights on the opposition's tactical strengths and weaknesses. They can make more informative decisions on the roster for the next match. By knowing who the key players are and with whom they interact mostly, specific strategies can be devised on how to intercept those interactions during the match.

Finally, in a football scenario, change detection techniques can be used for a real-time system signaling that a change has occurred in the team. With various network metrics available, different aspects of interest regarding the team's interactions can be implemented in such system. It can be used to alert the coach and their team on sudden changes in their team as well as their opponent. The implementation of such techniques in real-time would not be straightforward, however. There is an overall difficulty in using network metrics for explaining team and player performances related to the wide range of metrics available and the lack of methodology and guidelines for their application in practice.

The dynamics in the interactions between the players are analyzed with the help of metrics and algorithms from the area of network science. Static network analysis only focuses on calculation of the various network metrics which give a summarized view of the player interactions in a match. The thesis shows how in depth analysis of the metrics change can answer important questions during the live match – such as, “which player should be replaced?”, “who are the key players in the team?”, “what impact would a replacement of a player have on the team?”, “in which way do the players interact the most?” (the amount and direction of passes analyzed between the players through the use of triads), “what is the team network like before and after a player replacement/or before and after a goal or another key event?”, “when does a change occur in the team?”. These are all questions that can be answered by means of network analysis focused on the dynamic interactions between the players in different time periods throughout the game.

7 Self-organizing maps (SOMs)

According to the dynamic system theory, a football team is a complex system, displaying non-linear properties. Thus, its behavior cannot be accurately described, explained and predicted by standard statistical and non-linear methods, at least not entirely. The typical performance indicators give only a partial idea of who was the better team, but cannot explain the complex patterns which are not visible to the naked eye. As Dutt-Mazumder et al. (2011, p.1007) write: “Complexity is something “hidden” within the time-series of movement sequence or strategy as it emerges over time”. One set of methods suitable for detecting complex (movement) patterns according to the dynamic system theory is the machine learning model of Artificial Neural Networks (ANNs). ANNs can be used either for a) prediction or classification in which case a labeled training data is required i.e. observations with known outcomes (e.g., win or loss), or b) learning patterns from unlabeled data i.e. when there is no known outcome. The former is a case of supervised learning, while the latter is a case of unsupervised learning. For the purpose of studying dynamic systems, the supervised learning is not suitable as a target output needs to be specified for the model to work, while a dynamic system is undergoing constant change in space and time, and therefore, it is not possible to predefine an outcome (Dutt-Mazumder et al., 2011).

Considering the above, only unsupervised neural network models are suitable for detecting patterns based on the dynamic system theory. The unsupervised learning is favored by researchers in the area of pattern recognition because the absence of any target output vector ensures that the outcome of learning is not predetermined and the network will find its own solution (Dutt-Mazumder et al., 2011).

7.1 Method

An unsupervised neural network model that is applicable for performance analysis of football as a complex dynamic system is the Self-Organizing Map or SOM. SOMs have been proposed in the 1970s by Willshaw and Von Der Malsburg, who used the method to model neurobiological phenomena in animals (Bonaccorso, 2018). However, SOMs were made popular by the Finnish scientist Teuvo Kohonen in the late 1980s, and his particular SOM model is also known as Kohonen feature maps (KFM) or simply Kohonen network(s)[8]. This method is used for converting complex multi-dimensional data into a simpler (and usually) two dimensional map. It is a powerful technique for clustering records based on hidden patterns in the data.

[8] Whenever a SOM is mentioned it is meant a Kohonen SOM.

A SOM has an input and an output layer with no hidden layers in between. It operates on the "winner-takes-all" principle as during the training phase, all units in the output layer are equally excited by an input signal, but only one unit will produce the highest response (Bonaccorso, 2018). That "winner" unit then becomes a candidate to be the recipient of that specific pattern (Bonaccorso, 2018). Thus, a SOM structures the output nodes into clusters where similar nodes are in close proximity, while nodes that are different (i.e. recognize different patterns) are farther apart from each other on the two dimensional map (Larose and Larose, 2015). A typical SOM architecture is presented in Figure 33.

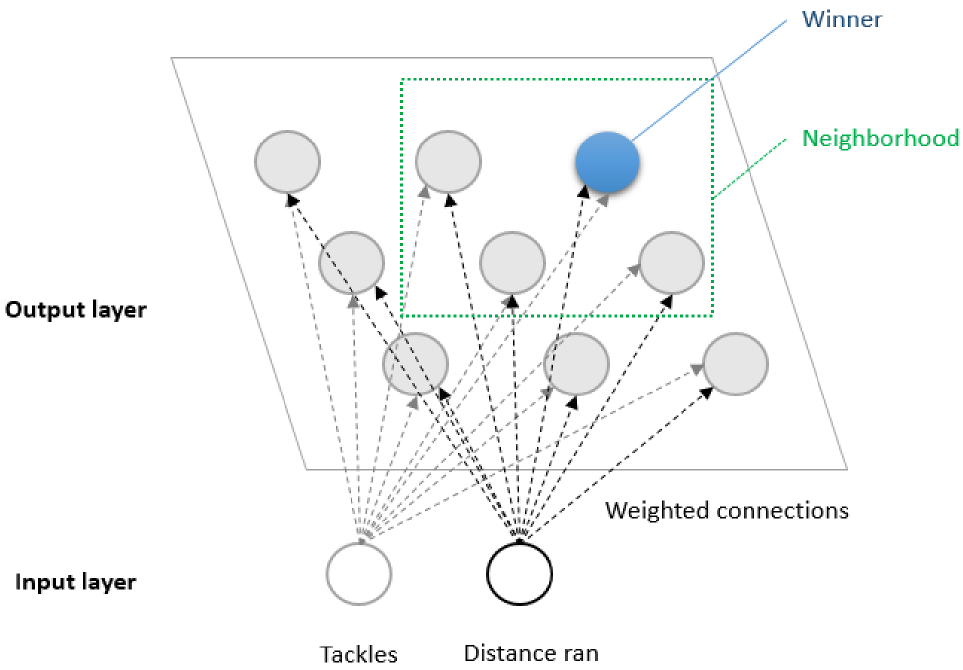


Figure 33. SOM architecture
Source: Self-compiled based on Bigus, 1996; Larose and Larose, 2015

As seen in Figure 33, a SOM is a feedforward network, which means that every node in the output layer is connected to all input nodes. However, output nodes are not connected to each other. Input signals are passed from an input node to all of the output nodes and each output node competes to be the "winner". This is determined based on a *scoring function*, such as Euclidean distance (Larose and Larose, 2015). The value of an input node together with the assigned weights of the connection will determine the values of the scoring function for a particular output node. The output node with the highest value of the scoring function will be the *winning node* (Larose and Larose, 2015). This node will then have its connection weight adjusted by a factor determined by the learning rate parameter (Bigus, 1996). In addition, the weights of the neighborhood nodes of the "winner" are also readjusted and so the whole neighborhood moves closer to the input pattern (Bigus, 1996). In the beginning, the weight values of the connections between the nodes in both layers are randomized. This is similar to the backpropagation algorithm. As training progresses, the size of the wining node neighborhood decreases – smaller number of output nodes is being updated, and in the end of the training process, only the winning node is adjusted (Bigus, 1996). Once the training is completed, a new instance (observation) will activate only one neuron on the map – the neuron whose weight vector is closest to the input vector (Géron, 2017). Thus, this method is especially suitable for clustering or dimensionality reduction. When used for pattern recognition, the types of patterns recognized by the SOM will depend on the data used for training (Perl et al., 2013). For example, if the training data consist of interactions, consisting of movement data from two teams and the ball, the patterns will show typical interactions (Perl et al., 2013).

Based on the above, a SOM is characterized by three processes:

1. *Competition* – due to the output nodes competing with each other to produce the best value for a particular scoring function.
2. *Cooperation* – the adjacent nodes of the winning node also are "rewarded" and share the "excitement" earned by the winning node.
3. *Adaptation* – refers to the adjusted weights of the neighboring nodes of the winning node. This is part of the learning process.

The Kohonen SOM algorithm consists of the steps described in Equation 5.

A Kohonen feature map has some ***limitations***. First, it usually requires a lot of training data, and second, continuous training is not possible – once the training process is finished, it cannot be restarted (Perl and Dauscher, 2006). This is due to the learning process being controlled by an external algorithm with parameters that have final values, which means that eventually the learning process will end (Perl and Dauscher, 2006). Once the learning process is closed, the network can only be used for testing and is not able to learn any new patterns (Perl, 2002). To deal with these limitations, an alternative type of Kohonen Feature Map was developed by the Institute of Computer Science at the University of Mainz in Germany. This type of KFM is known as ***Dynamically Controlled Network*** or ***DyCoN***. A DyCoN consists of a conventional KFM combined with a time-independent neuron-driven control (Perl, 2001). Each neuron in a DyCoN contains an internal memory and a self-controlling algorithm. Thus, a DyCoN has no final state and can always adapt its internal memory to new input – it can learn continuously over time; can continue learning processes after interruptions, and it can learn in separate phases (Perl, 2002, 2004). A DyCoN needs only some hundred data to recognize a pattern, compared to a conventional KFM which needs 10 000 to 20 000 (Perl, 2001). However, as the DyCoN model is used commercially, technical information is not publicly available, and it is only used in publications by the members of the Computer Science department at the University of Mainz – mainly Prof. Juergen Perl. Other scholars, however, use the conventional KFM algorithm for studying sports behaviors. An overview of the studies in football behavior based on the dynamic system theory and SOM is given in the next section.

Equation 5. Kohonen feature map algorithm

Step 1: Initialization — Initialize the weights by random numbers,
$W_i(0) = (w_{i1}(0), w_{i2}(0), \ldots, w_{in}(0)) \in R^n$, $i = 1, 2, \ldots, L$.

Step 2: Sampling — Draw a sample X from the input distribution.

Step 3: Matching — Find the winner W_c (best-matching node) using the minimum Euclidean distance criterion:

$$c(X) = \arg\min_i \|X(k) - Wi\|, \qquad i = 1, 2, \ldots, L.$$

Step 4: Updating — Update the winner and its neighbors by
$W_i(k+1) = W_i(k) + \alpha(k) \wedge (i, c)\, [X(k) - W_i(k)]$,

where k = 0,1, … denotes the discrete time steps, α(k) is the learning rate, and ∧(i, c) is the neighborhood function of the winner.

Step 5: Continuation — Compute $E_k = \sum_I \|Wi(k+1) - Wi(k)\|$, if $E_k \leq \in$ stop; else repeat from step 1.

- **Neighborhood function:**

In the steps described above, the neighborhood function, ∧(i, c), equals 1 for *i* = *c*, and falls off with the distance $\| r_c - r_i \|$ between node *i* and the winner *c* in the output layer, where r_c and r_i denote the coordinate positions of the winner *c* and node *i* in the output layer, respectively.

Thus, nodes close to the winner, as well as the winner *c* itself, will have their weights change appreciably, whereas those further away, where ∧*(i, c)* is small, will experience little effect.

The original neighborhood function, as defined by Kohonen (1988) was the *squared neighborhood function*, defined as

$$\Lambda(i, c) = \begin{cases} 1 & \text{for } \|r_i - r_c\| \leq N_c(k) \\ 0 & \text{otherwise} \end{cases}$$

where $N_c(k)$ is a decreasing function of time. Its value is usually large at the beginning of the learning and shrinks as training progresses. Frequently used in practice has also been the *bell-shaped neighborhood function* by Kohonen (1990):

$$\wedge(i, c) = \exp(-\| r_c - r_i \|^2 / 2\sigma^2(k))$$

Where *σ(k)* is the width parameter that affects the topology order in the output map and is gradually decreasing during training.

- **Learning rate:**

The learning rate is denoted with *α(k)* in the above description of the SOM algorithm. It is essential for convergence and it should be largen enough so that the network could adapt quickly to the new training patterns. It should, however, be small enough so that the network does not forget experience from past training patterns. It varies from 0 to 1. If *α(k) = 0,* there is no update*;* if *α(k) = 1*, W_c becomes *X*.

Source: Si et al., 2003, p.58

7.2 Related work

In sports science, ANNs, and specifically, SOMs, are usually applied in the area of movement pattern analysis. What is common in those studies is that they are characterized by time-dependent behavioral processes, which can be classified by an ANN (Perl and Dauscher, 2006). Each neuron in the Kohonen map will then represent a type of process, and each cluster will represent a class of similar process types (Perl and Dauscher, 2006). A ***process analysis*** in sport is the analysis of time series of positions, constellations, or tactical patterns in games or of positions, angles, or speed of articulations and limbs in motions (Grunz et al., 2009). Such analyses are characterized by the complexity and the dynamics of the data, which make it difficult to use conventional statistical approaches to detect patterns (Grunz et al., 2009).

In sports science, SOMs have been usually applied for movement pattern analysis.

Other than movement analysis, SOM has also been applied for tactical PA in various sports. For instance in rugby, Croft et al (2015) applied a SOM neural network on OPTA data in order to find out which performance indicators discriminate best between successful and unsuccessful outcomes. As input data the authors used the frequencies of common performance indicators in rugby. In handball, Pfeiffer and Perl (2006) trained a DyCoN network with offensive attempts (processes) from all teams in order to coin offensive attempt patterns. The authors showed that a neural network can be used to identify typical tactics of handball teams. In a study of basketball, two different types of SOMs, a hierarchical model (DyCoN) and recursive model in the form of merge self-organising map (MSOM), were applied on player tracking data to test whether an automatic recognition of tactical behaviors (fastbreak, high-pick and horns) is possible (Kempe et al., 2015). The authors concluded that both SOM architectures achieve high accuracy, although, not surprisingly, the DyCoN resulted in higher accuracy (97%).

In football, there has not been a wide use of SOM for performance analysis. One reason for this is most likely the inability, until recently, to collect detailed datasets from a football game. As this is no longer the case, one could reasonably expect that in the future, there will be more studies taking advantage of the SOM method for football PA. Another reason could be that ANNs are known as a black box method. They produce an output without explanation, which makes the interpretation harder. Thus, a considerable effort and experience is required from the researcher to explain the "reasoning" of the network (Dutt-Mazumder et al., 2011). Very few performance analysts have the required skills to achieve this (Dutt-Mazumder et al., 2011). Therefore, it is not unusual to come across studies in football PA done by scientists from various disciplines, mainly sports and computer scientists. Studies that have applied SOM in football are briefly mentioned below.

Grunz et al. (2009) use constellations (collections of the player positions of offensive and defensive groups) from the world championship final in 2006 as input data for training a neural network. This results in a neural network with neurons representing the different constellations. Then, those constellations or specific sequences of them can be matched to categories of situations or tactical units from a soccer category system (Grunz et al., 2009). The authors discuss the difficulty of this type of analysis in football, as compared to basketball, for example. Specifically, they briefly touch the problem that a SOM has a fixed dimension and cannot work with vectors of different length, which happens when the data consists of constellations in which different numbers of players are involved – which is very usual in football. Therefore, they choose a solution in which they work with a fixed number of players, representing offense or defense players. This type of analysis, although valid, does not seem to be very practical. In a more recent publication, Grunz et al. (2012) use positional player data to automatically classify long and short game initiations in football. The authors define a long game initiation if the first pass after winning the ball is longer than 30 meters. Otherwise, it is considered a short game initiation. A DyCoN network is trained and the results show that it is possible to use a hierarchical SOM network for automatic detection of tactical patterns in football. Their approach detected 84% of all game initiations. They use the sliding window technique though, which makes the analysis rather cumbersome. Bartlett et al. (2012) though not using SOM in their study on coordination dynamics between opposing teams in open play attacks, suggest that SOMs can be used to analyze multidimensional coordination of groups of more than two players. As input data, the authors suggest the use of player trajectories along and across the pitch or the various types of attack; or alternatively, some inter-player measure, such as the stretch index (calculating this measure with the OPTA data is not possible, however)[9]. Finally, Perl and Memmert (2016) use the DyCoN network to analyze the formations of tactical groups where the positions of the players are condensed to those of tactical groups, and the formations of the tactical groups are mapped to a small number of characteristic patterns. The idea is to reduce the team's activities to a smaller number of tactical patterns, which in turn would make it easier to detect regular or striking/unusual tactical features.

Based on the above, the few studies that used SOM for tactical analysis in football, are largely published by the same group of authors, who have access to DyCoN and other proprietary tools used in some of their papers (like, for instance the SOCCER tool also created by the group of Prof. Juergen Perl). Obviously, the results of these studies are interesting to read, however, the contribution, especially to their practical application is questionable. Evidently, SOM have a high potential and can be a useful tool for performance analysis in football. A SOM could potentially allow researchers to objectively quantify the skill level of teams or players in a game; it could also reduce time and effort to convert recorded data into useful tactical information, so that such analyses could be done even during the half time break during a football match (Dutt-Mazumder et al., 2011; Grunz et al., 2012). SOMs are a valuable technique to reduce high-dimensional datasets in low-dimensional relevant information (Dutt-Mazumder et al., 2011). The method can be very useful in an initial

[9] Stretch index is defined as the average radial distance of the players' positions to the team centroid Benito Santos et al. (2018).

exploratory analysis of the data and gaining some insights via their map visualizations. Therefore, it is interesting to explore this method further especially having the opportunity to train a SOM network on a real player tracking data by OPTA.

7.3 Analytics goal

Based on the related work, a SOM network is to be applied for team performance analysis, and it does not seem to be useful for analyzing the behavior of football players. As explained in chapter 3, the SOM as a method for performance analysis in football is inspired by the dynamic system theory. If one is to follow the theory in its entirety, a very detailed dataset from a football game is necessary. Specifically, the positions of all players and the ball at any point during the entire game. In addition, tactical information of the events and actions that occurred is useful as well. The OPTA data does not offer all of this information. However, it can still be used in a study that follows the dynamic system theory and it is suitable for analysis using the SOM neural network. The data does have positional x and y coordinates of the players and contains a very rich and detailed event information. Both data types are useful to gain tactical insights from the game. Thus, next question would be what would be interesting to analyze from a team perspective. The Euro 2016 was characterized by an unexpected success of teams that can be classified as "underdogs" because they were not expected to achieve the success they did, especially because some of them, like Iceland, participated in the tournament for the first time. Therefore, it is interesting to investigate the differences between two types of participants: the favorite teams and the underdogs.

The term ***underdog*** originates from dog fighting in the 19th century, where "the losing dog was declared the ''under dog'' because it would usually submit, rolling over on its back, allowing the stronger dog to tower over it" (Goldschmied and Vandello, 2012). In sports, an underdog has been defined as a team with worse record in a competition, while a favorite team, as the one with the best record (Ben-Naim et al., 2007). In the Euro 16, due to the structural changes introduced, many low-ranked teams qualified for the competition, five of which for the first time in history: Albania, Iceland, Northern Ireland, Slovakia and Wales (UEFA, 2016c).

For the purpose of this analysis, teams were classified in favorite and underdogs based on their appearances and track record in the European championship since the 1960s. Additionally, only the teams that reached the Round of 16 stage were included because the focus is comparing successful underdog teams to favorite teams. Obviously, teams like Belgium, England, Germany, France, Spain and Italy are automatically classified as favorite teams due to their rich history in the tournament. Iceland, N. Ireland, Slovakia and Wales were classified as underdogs as these are teams that participated for the first time in the tournament. Hungary was also allocated to this group as they have been absent from major tournaments prior to the Euro2016 and only participated because UEFA expanded the tournament (Malyon, 2016). Poland, R. of Ireland and Switzerland were also added to this group as based on their track record, no one expected these teams to achieve success in the competition. Portugal, although perhaps not a typical favorite team, was classified as such as according to the FIFA rankings before the championship took place, the national team was ranked 8th in the UEFA teams list (FIFA, 2016a). And the team does have talented players who compete in the biggest European clubs, as well as the World's best player, Ronaldo. Similarly, Croatia was ranked 23rd right before Wales in the FIFA ranking list, therefore their team was also classified as an underdog. The final list is presented in Table 34.

Table 34. List of underdog and favorite teams and their market values (prior to Euro 2016)

Favorite teams	**Market value [mil. €]**	**Underdog teams**	**Market value [mil. €]**
Belgium	468 €	Croatia	288 €
England	477 €	Hungary	27 €
France	487 €	Iceland	42 €
Germany	580 €	N. Ireland	38 €
Spain	592 €	Poland	193 €
Italy	264 €	R. of Ireland	87 €
Portugal	322 €	Slovakia	84 €
		Switzerland	175 €
		Wales	170 €
Averages	**456 mil. €**		**123 mil. €**

The table above also shows the market values[10] of each team. There is a clear difference between the teams in both groups. The average market value of the favorite teams is 456 (in million EUR) while the average value of the underdogs is 123 million euros.

7.4 Data preparation

For the SOM clustering to work, the OPTA data has to be separately pre-processed and only relevant variables need to be extracted as well as arranged in a specific way. Extracting, transforming, and formatting the data from OPTA for the purposes of the SOM analysis was conducted with Python, and the SOM itself was implemented in R by using the *kohonen* and *gsom* packages. These are briefly described below:

- Kohonen R package – offers various functions for self-organizing maps with focus on visualization. It has a function for the standard SOM, supervised SOM, and supersom – a SOM with multiple parallel maps (Wehrens and Buydens, 2007).
- Gsom package - A growing self-organizing map (GrowingSOM, GSOM) is a growing variant of the popular self-organizing map. It was developed to address the issue with finding

[10] Market values were extracted from Transfermarkt.de.

a suitable map size. It starts with a minimal number of nodes and grows new nodes on the boundary based on a heuristic. (Hunziker, 2017)

The final dataset consists of all performance indicators listed under the variable *type_id* in OPTA which includes all events that happened during the game, including direct-play performance indicators such as pass, goal, tackle, corner, keeper punch, etc. The table below gives an overview of the final dataset.

Table 35. Extract from the dataset used for training the SOM

Match data			**Event types**						
Match ID	**Team ID**	**Result**	**Pass**	**Offside Pass**	**Take On**	**Foul**	**Out**	**Corner Awarded**	…
838508	497	2	3187	25	36	160	78	28	
838508	534	0	2656	10	21	160	78	27	
838509	507	0	3066	14	60	198	122	16	
838509	508	2	2342	0	39	198	122	15	

Note: The variable “Result” shows whether the team lost (0) or won (2).

As seen, each row of the dataset represents the aggregated OPTA statistics per match and per team (thus, for each match included, there are two rows). In total, there are 47 different event types analyzed for each team.

7.5 Data analysis and results

Two experiments are conducted using the SOM algorithm. First, in order to examine the performance of favorite teams when they win, 20 matches that include one of these teams as winners are examined. Furthermore, to compare how underdog team performance differs, a separate experiment is conducted that includes only matches where an underdog team wins (against any other team in the tournament).

Before selecting a final configuration for the analysis, several different combinations of learning parameters are tested, before arriving at the final setup as described below:

- learning rate: 0.8
- neighborhood width: 0.1
- sigma: 4
- cluster sensitivity: 0.000005

Several experiments are conducted with manual and automatic sizing of the SOM grid, as well as with a super SOM and growing SOM. The best results are generated when using an auto-sizing growing SOM. An ideal size for SOM nodes is such that not too many or too few samples (rows from the dataset) are in each SOM node/neuron. Both experiments have a 2x3 SOM grid.

The training progress of the SOM clustering is presented in Figure 34.

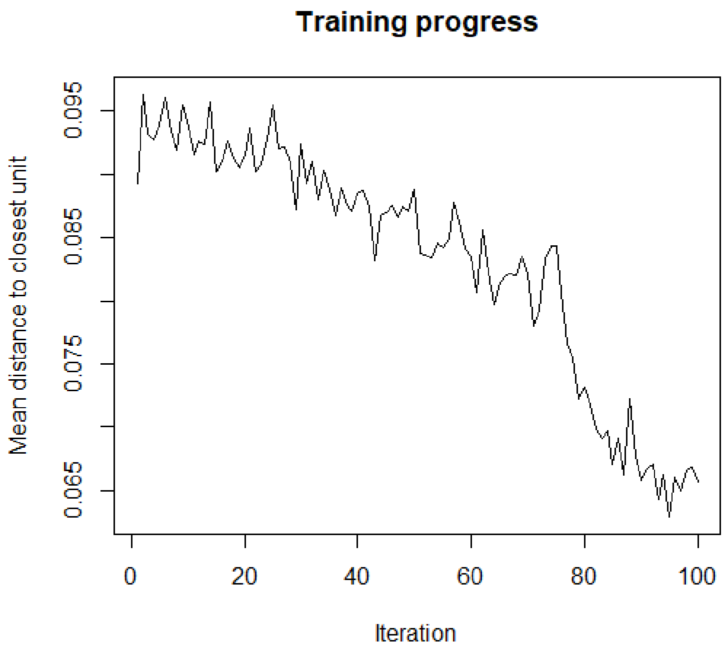


Figure 34. SOM training progress in Experiment 1

The chart above represents the training progress of a SOM network. The measure of how well a SOM network has been trained is the distance between node weights and the respective data points included in a specific node. In other words, with the training process, the aim is to minimize this distance. Once this distance has reached a kind of minimum plateau (i.e. the distance does not decrease further), the training process has been completed. The visualization shows the training process for the Underdogs Win experiment. As the training iterations go on, the distance decreases, meaning the model is learning. It shows that after 100 iterations, the mean distance has fallen to about 0.065 and is not decreasing further.

Experiment 1: Underdogs' wins

For this experiment, all the matches in which an underdog team wins are considered. These are presented in Table 36.

Table 36. Matches considered in Experiment 1

	Match	Result	Date
1	Albania - **Switzerland**	0 - 1	6/11/2016
2	**Wales** - Slovakia	2 - 1	6/11/2016
3	Turkey - **Croatia**	0 - 1	6/12/2016
4	**Poland** - N. Ireland	1 - 0	6/11/2016
5	Austria - **Hungary**	0 - 2	6/14/2016
6	Russia - **Slovakia**	1 - 2	6/15/2016
7	Ukraine - **N. Ireland**	0 - 2	6/16/2016
8	Russia - **Wales**	0 - 3	6/20/2016
9	Ukraine - **Poland**	0 - 1	6/21/2016
10	**Croatia** - Spain	2 - 1	6/21/2016
11	**Iceland** - Austria	2 - 1	6/22/2016
12	Italy - **R. Ireland**	0 - 1	6/22/2016
13	**Wales** - N. Ireland	1 - 0	6/25/2016
14	England - **Iceland**	1 - 2	6/27/2016
15	**Wales** - Belgium	3 - 1	7/1/2016

Note: The winning underdog is highlighted.

The below visualizations represent regular (i.e. not normalized) results from the SOM analysis of matches where the underdog team wins. For example, the visualization for the variable “Result” represents the ordering/clustering of win, loss, or draw per team per match. The red color nodes represent teams that have noted more favorable results, while the blue color represents teams that tended to accumulate more losses.

This type of visualization allows for a quick and intuitive inspection of the SOM analysis. For example, only by comparing the *Result* and *Pass* grids, one can see that those underdog teams that had less passes also tended to end the game with a favorable result. The red colored nodes on the cluster grid for “result” are colored blue in the “pass” grid. Red means higher values while blue denotes lower values for the given attribute. In case of the connection between passes and final outcome, the result is not surprising as underdogs usually have lower ball possession rate than favorite teams.

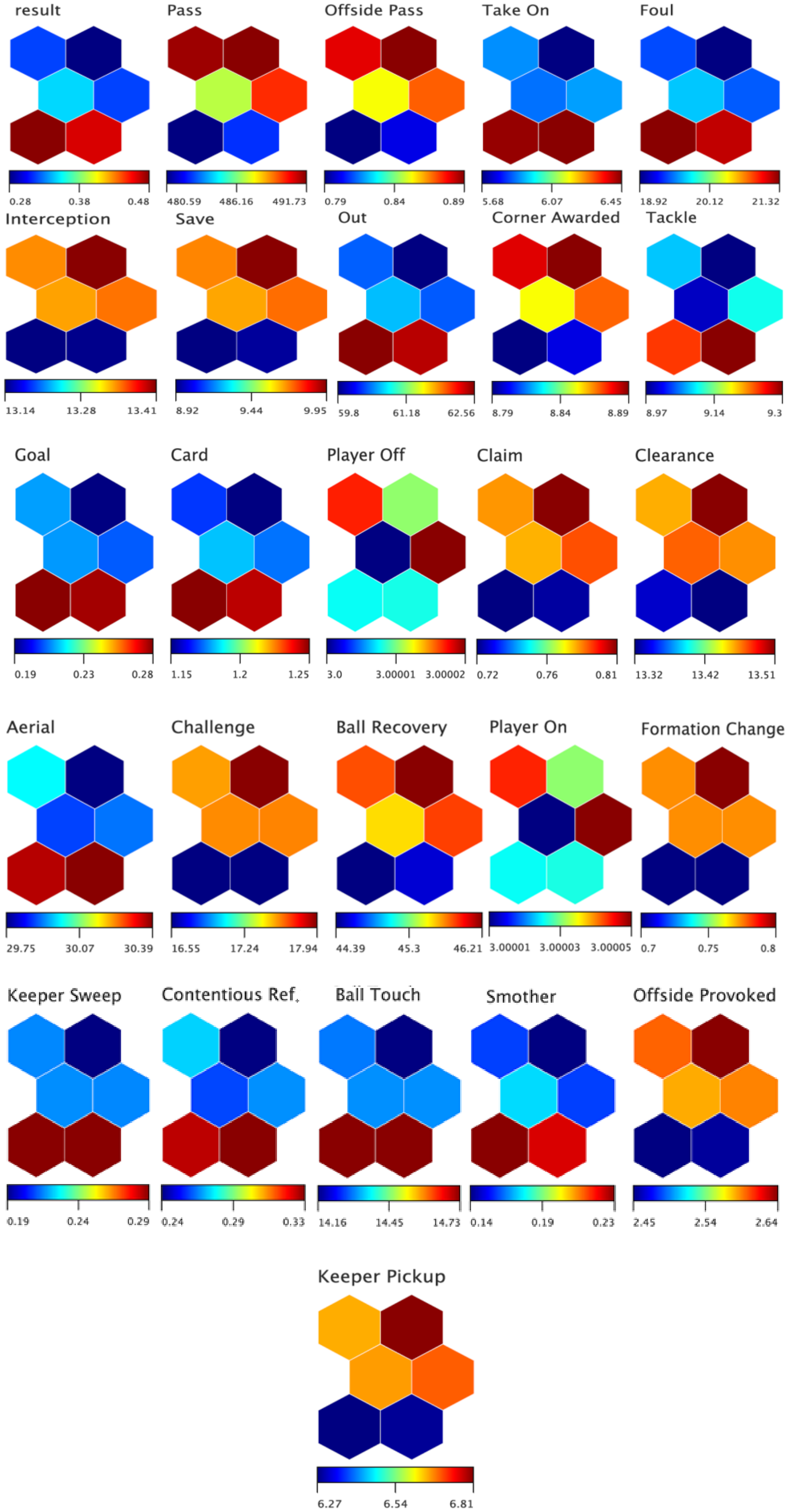


Figure 35. SOM clusters for underdogs‘ winning matches

The table below contains a summary of the clustering results and shows which events exactly have a positive or negative influence on the final outcome of the underdog games in which they win.

Table 37. Influence of event type on match outcome for underdogs

Positive	Negative
Take On	Pass
Foul	Offside Pass
Out	Interception
Tackle	Save
Goal	Corner Award
Card	Player Off
Aerial	Claim
Keeper Sweep	Clearance
Contentious Referee Decision	Challenge
Ball Touch	Ball Recovery
Smother	Player On
	Formation Change
	Offside Provoked
	Keeper Pickup

Experiment 2: Favorite teams' wins

For this experiment, all the matches in which a favorite team won are included in the analysis. These are presented in Table 38.

Table 38. Matches considered in Experiment 2

	Match	Result	Date
1	**France** - Romania	2 - 1	6/10/2016
2	**Germany** - Ukraine	2 - 0	6/12/2016
3	**Spain** – Czech R.	1 - 0	6/13/2016
4	Belgium - **Italy**	0 - 2	6/13/2016
5	**France** - Albania	2 - 0	6/15/2016
6	**England** - Wales	2 - 1	6/16/2016
7	**Italy** - Sweden	1 - 0	6/17/2016
8	**Spain** - Turkey	3 - 0	6/17/2016
9	**Belgium** – R. Ireland	3 - 0	6/18/2016
10	N. Ireland - **Germany**	0 - 1	6/21/2016
11	Sweden - **Belgium**	0 - 1	6/22/2016

Table 38. Matches considered in Experiment 2 (continued)

	Match	Result	Date
12	Croatia - **Portugal**	0 - 1	6/25/2016
13	**France** – R. of Ireland	2 - 1	6/26/2016
14	**Germany** - Slovakia	3 - 0	6/26/2016
15	Hungary - **Belgium**	0 - 4	6/26/2016
16	**Italy** - Spain	2 - 0	6/27/2016
17	**France** - Iceland	5 - 2	7/3/2016
18	**Portugal** - Wales	2 - 0	7/6/2016
19	Germany **- France**	0 -2	7/7/2016
20	**Portugal** - France	1 - 0	7/10/2016

The results from the SOM clustering analysis involving the winning matches of the favorite teams are presented in Figure 36.

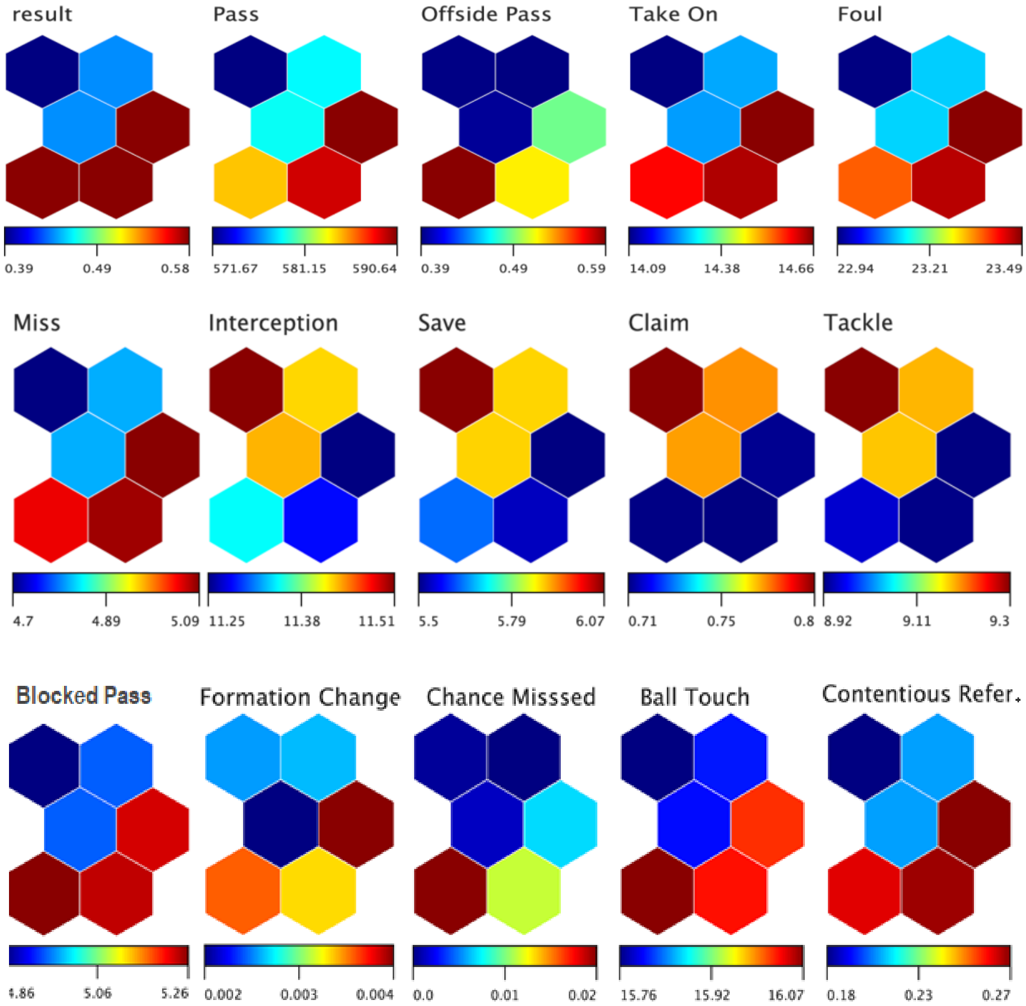


Figure 36. SOM clusters for favorite teams‘ winning matches

The table below summarizes the events that have a positive and negative influence for the winning matches of the favorite teams.

Table 39. Influence of event type on match outcome for favorite teams

Positive	Negative
Pass	Interception
Take On	Save
Foul	Claim
Miss	Tackle
Blocked Pass	Keeper Pickup
Formation Change	Card
Chance Missed	
Ball Touch	
Contentious Referee Decision	
Keeper Sweep	
Offside Provoked	
Attempt Saved	
Goal	

7.6 Discussion

From the analyses presented in the previous section, it is possible to determine which types of events have a positive or negative influence for the outcome of the matches for favorite and underdog teams. Events that are positive for the match outcome only for underdog teams are: **Out, Aerial, Smother**. This means that winning aerial fights is crucial for underdog team performance. *Smother* is the event when a keeper comes out and gains possession of the ball in the box. This usually happens during corners or high balls in the box meant to be played by head. Therefore, an active keeper who can win these aerial balls is of benefit to an underdog.

Events with a positive influence on the match outcome of favorite teams are: **miss, blocked pass, chance missed, attempt saved**. It is interesting to note that both favorites and underdogs tend to commit more fouls when winning, but only the underdogs get more yellow or red cards. The event *miss* may be positive only for favorite teams because they create more chances than the underdogs. The events *blocked pass* and *attempt saved* suggest that an active defense, i.e. a defense style that challenges the attackers, is required for victory.

What is positive for both types of teams are the following events: **take on, foul, goal, keeper sweep, contentious referee decision, ball touch**. *Keeper sweep* is an event where the goalkeeper leaves the 11-meter box, which suggests that in this case the winning team is also the one attacking. Other variables also suggest that the team that takes the initiative and plays more aggressively (take on/dribble, foul, ball touch-that’s a touch with an arm) secures a favorable outcome.

Events that have a negative influence for the outcome of the matches for both favorite and underdog teams are: **interception, save, claim, keeper pickup.** *Keeper pickup* is an event where the goalkeeper picks up the ball with a hand. This event happens frequently when a team plays defensive football, and defense players interact with the keeper in order to prolong ball possession. Looking at keeper events such as sweep and pickup clearly suggests that a defensive tactic is a bad decision for underdog teams. This is further confirmed by the fact that more saves suggests a loss (more saves implies again a defensive tactic).

More *Tackle* and *Card* are positive for underdogs, and negative for favorites. Clearly, a game where individual underdog team players challenge the opponent players more through tackling, as well as more physical play which would result in more cards, pays off for underdog teams. On the other hand, registering more *passes*, *offsides provoked*, as well as trying out *formation changes*, are positive for favorites, and negative for underdogs. The different influence of the number of passes on favorite and underdogs' success simply relates to the fact that underdogs have lower possession rates in their winning matches. Similarly, the *offsides provoked* having a positive influence for favorites and negative for underdogs, is due to the more chances created/missed by the favorite teams, while *formation changes* shows that underdog teams tend to stay with a tactic and not experiment too much throughout a game. This has brought them success especially if one considers Iceland's decision to stick to the traditional, and what some consider an outdated strategy, the 4-4-2.

Based on the results presented so far, it can be concluded that an analytics method like SOM can be used to gain a quick understanding of the tactical aspects of a team and the dependencies between the attributes in a dataset. The frequencies of events are important but there are many other factors that are challenging to be analyzed quickly, which is important especially in a real-time scenario. SOM could be used for tactical analysis of the opponent team and readjustment of the strategy and tactics in the break before the 2nd half. It can also be a valuable tool to study an opponent before the game itself. By analyzing the match data of the opponent, it is possible to find patterns in their behavior otherwise not visible to the naked eye. Furthermore, the results from these analyses show that SOM as a method has advantages over linear methods because various different types of behaviors expressed through the occurring events and their frequencies can lead to different outcomes. The decision to classify similar pattern is not either – or and thus, linear methods are not suitable for this purpose.

Future research could focus on analyzing specific games versus specific opponents, or with a larger dataset it is possible to analyze in more detail successful versus unsuccessful teams or alternatively analyzing player behavior is worth mentioning as well. However, larger dataset is required for this purpose to reveal meaningful patterns and make generalizations. Furthermore, pattern classification by SOM can cluster similar game processes in a match that are hidden in the large number of complex variables (Dutt-Mazumder et al., 2011).

The *limitation* of SOM as an analytics tool is the level of intuitive interpretation i.e. the ease of use of the self-organizing maps. As neural network methods are famously known as black box methods because of the inability to understand their reasoning behind the results, one could assume that for coaches and their team it is not the most intuitive way to conduct performance analysis. However, considering that almost all teams from the premier leagues and even the second leagues have in-house analysts, the interpretation should not be a problem.

8 Process Mining

Analyzing the tactical behavior in team sports is of paramount importance in sports performance analysis. As discussed in section 2.4., the individual actions performed are of interest when analyzing the team's tactics. For quite some time, the action frequencies by teams and players has been the only way to gain insight into this performance aspect. However, this is not enough to gain a complete picture of the performance, and especially the tactical behavior. Therefore, action/event sequences have been suggested for deeper insight into the game. One reason mentioned by Carling et al. (2008) is that "on-the-ball" activity, physical contact and the sequence in which these actions occur contribute to physiological energy expenditure. This means that in addition to tactics, sequential analysis could give insight into the player fatigue. ***Action sequences*** are chains of sequential single actions during a game (Schrapf et al., 2017). As the OPTA data is based entirely on event or action data, with timestamps and positional coordinates available, it is especially suitable for this type of analysis.

In this chapter, a novel technique for sequence analysis of event data is suggested and its advantages and disadvantages for decision making in football are presented and discussed.

8.1 Method

Process mining aims at discovering, monitoring and improving real processes by extracting knowledge from event logs (van der Aalst, 2011). As a discipline, process mining sits between, on the one hand, machine learning and data mining, and on the other hand, process modelling and analysis (van der Aalst, 2011). Some of the answers which process mining can deliver are: (a) what really happened, (b) why did it happen, (c) what is likely to happen in the future, (d) when and why do organizations and people deviate, to name a few (van der Aalst, 2011). The pioneer of this technique is Prof. van der Aalst from the TU Eindhoven in The Netherlands. When he started with process mining in the early 2000s, most people were saying that there is no data for automated process discovery (Rozinat, 2011). This has changed over the course of a decade, and currently in the Big Data era, companies can be at times overwhelmed with the amount of data they collect from all of their business operations.

There are different algorithms used in process mining, depending on the data available and the questions that need to be answered – heuristic, genetic. Irrespective of this, process mining requires structured data, and specifically, event logs of business (or other) processes. The goal is to analyze event data from a process oriented perspective (van der Aalst, 2011). An example of a typical event log necessary for process mining is presented in Figure 37.

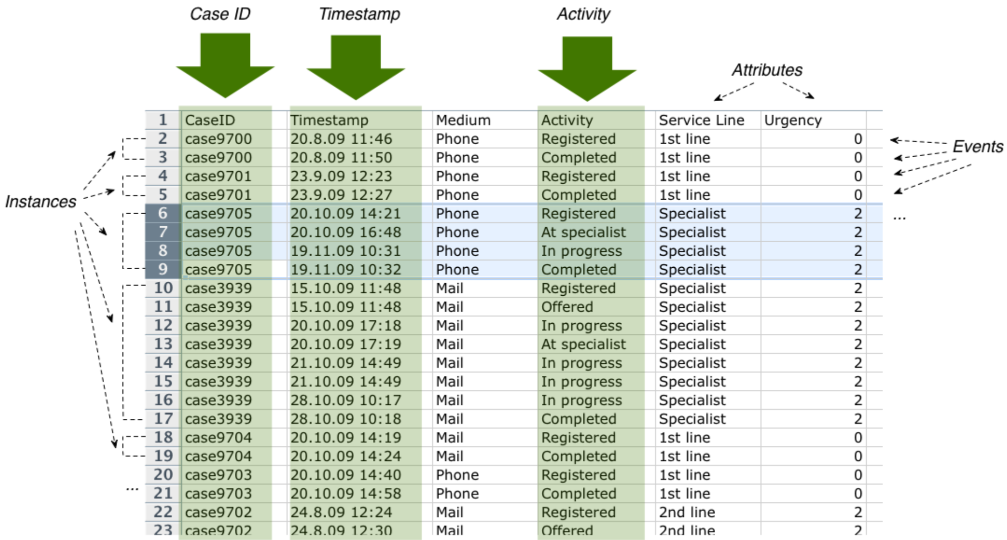


Figure 37. An example of event log for process mining
Source: Rozinat, 2012

The event log in the figure above contains information from a call center. Each row represents an ***event***, and each event corresponds to an ***activity*** executed in the process (names for different process steps or status changes that were performed in the process); multiple events are linked together in a process ***instance*** or ***case*** (necessary to distinguish different executions of the same process); each case forms a sequence of events which are ordered by their ***timestamp*** (Rozinat, 2012). Usually, an event log will have additional information about the activities in the process, as for instance, above the columns "service line" and "urgency". These columns are called ***attributes***. They are not mandatory, but if available give more detailed information on the processes. As a process is a sequence of steps, in order to successfully apply process mining, the event log must fulfill the three minimum requirements – it must have case IDs (e.g., customer number, order number, patient ID), timestamps, and activity columns (Rozinat and Gunther, 2015), as highlighted in Figure 37.

Event logs can be used to conduct three ***types of process mining***: discovery, conformance checking and enhancement (van der Aalst et al., 2012). These are presented in Figure 38.

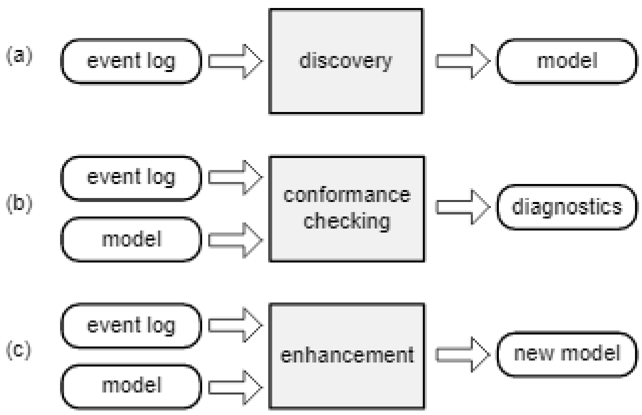


Figure 38. Types of process mining
Source: van der Aalst et al., 2012

The most often used type of process mining is ***discovery*** (van der Aalst et al., 2012). As the name suggests, this techniques converts an event log into a process model, without any a-priori information (van der Aalst, 2011). The discovered model can be in the form of a Petri net, BPMN, EPC, or UML activity diagram, but it can also be a social network model, depending on the perspective needed (van der Aalst et al., 2012). ***Conformance checking*** uses an event log and a model as inputs. It is used for finding discrepancies between the reality (event log) conforms to the model and vice versa (van der Aalst, 2011; van der Aalst et al., 2012). The third type, ***enhancement***, also uses an event log and a model as an input, but the information form the event log is used to improve the existing process model (van der Aalst et al., 2012).

Finally, process mining may refer to different ***perspectives*** of the analyzed processes. These are explained below:

Control-flow perspective – ordering of activities. Its goal is to find a good characterization of all possible paths by deriving a process model that provides the best summary of the flow followed by most or all of the cases in the event log (ProM, 2017a). It can answer questions such as:

- Which tasks precede which other ones?
- Are there concurrent tasks?
- Are there loops?

There are several options for analyzing the case-flow. Some of the algorithms that can be used are the Alpha algorithm, the Heuristic Miner, Fuzzy Miner, Inductive Visual Miner, among others. A short comparison of these algorithms is presented in Table 40.

Table 40. Comparison of mining algorithms

Algorithm	Input	Output	When to use
Alpha Miner	Event log	Petri Net	Not recommended for real-life data.
Heuristic Miner	Event log	Heuristic net	For real-life data with not too many different events.
Fuzzy Miner	Event log	Fuzzy Model	For complex and unstructured log data or for simplification of the model.
Inductive Visual Miner	Event log	Petri Net or Process Tree	For discovering process delays, deviations, and animation of the model.

Source: Self-compiled based on Rozinat, 2010; Leemans et al., 2014

The answer of which algorithm should be used in a specific case is not a straightforward one. The above table provides a starting guideline, but there are other options in ProM, and best is to test various algorithms and inspect the results. As seen from Table 40, the *Alpha algorithm*, which was the first process mining algorithm developed, is not recommended for analysis of a real-world event log data. The *Heuristic Miner* was developed following the Alpha Miner to address its deficiencies and is therefore also able to simplify the process model abstracting exceptional behavior and noise - by leaving out edges (Rozinat, 2010). This algorithm is able to detect short loops and skipping of activities. However, it still shows rather complex process models (Buijs, 2017a). The

Fuzzy Miner interactively simplifies the process model by hiding some activities and paths, if desired (Rozinat, 2010). The Disco tool relies on this algorithm for deriving process models.

Organizational perspective – focuses on information about the resources, which can be people, departments, roles etc., and how they are related with each other. This relationship can be also represented as a social network based on the activities of the resources and can be used to find interaction patterns or evaluate the role of individuals (RapidProM, 2017). There are three options which can give answers regarding these questions in the ProM tool. These are the *Social Network Miner*, which creates a social network model of the event log by using various metrics, the *Dotted Chart*, which gives an overview of working patterns, or time and date patterns, and the *Inductive Miner*, which shows how cases are handed over between activities (Buijs, 2017b).

Social network mining is the most useful in the case of the organizational perspective, since network science is an area that studies interactions and relations between individuals. To discover sociograms from event logs, there are a few categories of metrics that have been developed (see Table 41).

Table 41. Types of social network metrics used for analyzing relationships from event logs

Metric category	Definition	Examples of metrics
Metrics based on (possible) causality	Analyze how work moves among performers.	Handover of work (HoW)
		Subcontracting
Metrics based on joint cases	Count how frequently two individuals are performing activities for the same case.	Working Together
Metrics based on joint activities	Focus on the activities performed by individuals -> people are more similar if they perform the same activities.	Similar task metric
Metrics based on special event types	Consider the type of event.	Reassignment

Source: Self compiled based on van der Aalst et al., 2005

The *metrics based on (possible) causality* consider how work moves among performers (van der Aalst et al., 2005). In a football game, it will consider the flow of events between the players. For instance, there will be a *Handover of Work*, or HoW, between two players, if there are two subsequent activities/events where the first is completed by player A and the second by player B. In addition to a direct succession, it is also possible to analyze "*indirect succession using a "causality fall factor" β, i.e., if there are 3 activities in-between an activity completed by i and an activity completed by j, the causality fall factor is* β^3" (van der Aalst et al., 2005, p. 9). The *subcontracting* metric counts the number of times when player B executed an activity in between two activities done by player A. For instance, Player A -> Player B-> Player A. This could indicate that work was subcontracted from Player A to Player B.

Metrics based on joint cases, as the name suggests, ignore the causality and simply count how often individuals are performing activities within the same case i.e., sequence of activities (van der Aalst and Song, 2004). Thus, the metric *Working Together*, will show which players most often participate or "work together" in the same ball possession sequence. If two individuals often work together on cases, they are considered to have a stronger relation than individuals rarely working together (van der Aalst et al., 2005; van der Aalst and Song, 2004).

Metrics based on joint activities consider the activities performed by the individuals in general, regardless of whether they work on the same case or not (van der Aalst et al., 2005). If two players are engaged in the same activities, they are considered to be more similar to each other than if they would execute different activities. One such metric is the *Similar Task* metric. The way this metric is calculated is in two steps. First, a matrix of the activities by each individual is created, and second, the distances between the individuals are calculated. Various distance metrics are available in ProM – Euclidian or Hamming distance, correlation or similarity coefficient.

Metrics based on special event types consider the type of event, as sometimes, there can be events such as reassigning an activity to someone else (van der Aalst and Song, 2004). A *reassignment* occurs when i frequently delegates work to j but not vice versa, and thus, it is likely that i is in a hierarchical relation with j (van der Aalst et al., 2005; van der Aalst and Song, 2004). However, the information needed for this type of metric is rarely available in an event log (Buijs, 2017b). The OPTA logs also are not suitable for calculating the reassignment between players. However, it is possible to calculate the first three categories of metrics. In the current thesis, two metrics are used in the analysis: the Handover of Work and the Working Together metrics.

Case perspective – focuses on the properties of the cases. It can answers questions, such as (ProM, 2017a):

- What are the most frequent paths in the process?
- Are there any loop patterns in the process?
- What is the distribution of all cases over the different paths through the process?
- Can you select a subset of traces where particular paths were executed?
- Can you simplify the log by abstracting the most frequent paths?

Some options to answer the above questions in the ProM tool are the *Pattern Abstractions*, *Trace Variants*, *Dotted Chart* visualizations, and the *trace and sequence clustering* plugins among others.

To gain further details in the case analysis perspective, it is possible to use the trace/sequence clustering algorithms in ProM. This solution was inspired by a real-world scenarios and issues associated with it. Specifically, in some domains, the behavior of the agents (i.e. participants in a process) can be very flexible. This means that the sequences in which they are involved can be quite diverse. When the log information is analyzed, usually a very uninformative process model is derived, known as spaghetti-like process model. These models are so complex and the visualizations are very overwhelming and hard to comprehend (Bose and van der Aalst, 2009). A solution to this problem is found in trace and sequence clustering.

The basic idea of ***trace clustering*** is to split the event log into homogeneous subsets and for each subset to create a process model (Song et al., 2009). What this technique does is basically identification and clustering of similar sequences. A high level of the process is depicted in Figure 39. The similarity is calculated based on a distance metric – usually the Euclidean or Hamming distance, while the clustering can be performed by using different algorithms, like k-Means or SOM (Veiga, 2009). A list of the algorithms available for clustering in ProM is presented in Table 42.

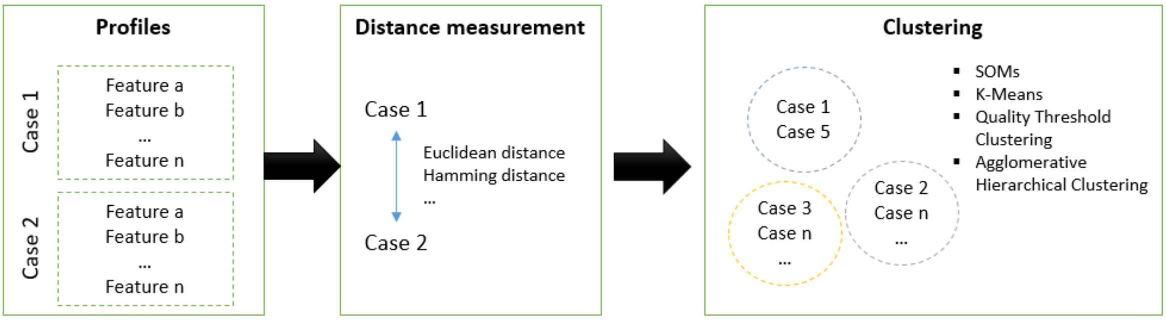


Figure 39. Trace clustering process
Source: Self-compiled based on Song et al., 2009

As seen from Figure 39, trace clustering works by creating a set of profiles, each measuring a number of features for each case from a specific perspective (Song et al., 2009). In a second step, the distance between each case is measured by a distance metric; in this case, the Euclidean distance is used as it is found to be the most reliable. This measure is defined as

$$\text{Euclidean distance } (c_j\, , c_k) = \sqrt{\sum_{l=1}^{n}(i_{jl} - i_{kl})^2}$$

Equation 6. Euclidean distance
Source: Song et al., 2009

Finally in a third step, similar cases are put together by using a clustering algorithm. Clusters can be analyzed independently from one another which improves the quality of the results for flexible environments (Song et al., 2009). Considering that football consists of 11 players which do not act according to a specific pre-defined process but rather based on quite a few distinct factors from their surrounding environment, one could reasonably assume that football can be considered a flexible environment within the process mining analytics area. Therefore, it would be interesting to see if and how trace/sequence clustering could be helpful for football performance analysis.

Sequence clustering is based on a similar idea as trace clustering. However, this type of clustering is performed directly on the input data, i.e. no features are extracted from the sequences (Veiga, 2009). The plugin in ProM 5.7 has been implemented by Veiga (2009) whose algorithm is based on first-order Markov chains in which case the current state depends only on the previous state (Ferreira et al., 2007). The probability that an observed sequence is assigned to a given cluster is the probability that the observed sequence was produced by the Markov chain associated with that cluster or simply the assignment of sequences to clusters is based on the probability of each cluster producing the given sequence (Ferreira et al., 2007; Veiga, 2009). Thus, a given sequence will be assigned to the cluster that is able to produce it with higher probability (Veiga, 2009). In his implementation of the algorithm in the ProM plugin, Veiga also adds two additional dummy states in the Markov chain – an input and output states. This is necessary in order to represent the probability of a given event being the first or the last event in a sequence, which could be useful to distinguish between some types of sequences (Veiga, 2009). The algorithm as implemented by Veiga is included in Appendix G.

In the analysis section, the SOM clustering algorithm and Markov chain clustering are used. SOM is used because it is one of the main analytics methods in the current thesis, and it is interesting to use the same method applied on football game sequences. Additionally, SOM is very efficient with respect to computation time and is also quite robust concerning the results, especially for situations, where the characteristics of the process underlying an event log are largely unknown (Günther, 2009). The Markov chain clustering is preferred because it also discovers clusters without the analyst having to predefine the number of clusters.

Table 42. Clustering algorithms in ProM

Algorithm	Description
K-Means	The most commonly used in practice among partitioning methods, which constructs k clusters by dividing the data into k groups.
Quality Threshold Clustering	It is predictable (i.e., guaranteed to return the same set of clusters over multiple runs).
Agglomerative Hierarchical Clustering	Gradually generate clusters by merging nearest traces, i.e., smaller clusters are merged into large ones.
Self-Organizing Map	The aim of SOM is grouping similar cases close together in certain areas of the value range.
Markov clustering	Allows for identification of normal or exceptional behavior based on the input sequences. It discovers the clusters rather than requiring to set them beforehand.

Source: Self-compiled based on Song et al., 2009;Hompes et al., 2015

Time perspective – timing and frequency of events. If timestamps are available, it is possible to detect bottlenecks, monitor the utilization of resources, or predict the remaining processing time of running cases. On its own, this perspective will most likely not be too interesting in the football scenario. However, combined with the other perspectives, it can give interesting insights.

Each of these perspectives gives a different view of the process analyzed. The control-flow perspective relates to the “How” question, the organizational perspective to the “Who” question, while the case perspective answers the “What” question (ProM, 2017b). For a proper business understanding users typically have to extract several models that describe different perspectives in the process analyses (Ingvaldsen and Gulla, 2008).

As seen, process mining is not a reporting, but an analysis tool, which is able to model and analyze complex processes (Rozinat and Gunther, 2015). Even though it works with historical data, it does not mean that it is limited to offline analysis, as the results can be applied to running cases (van der

Aalst et al., 2012). Not all of the process mining types and perspectives can be applied in a football game scenario. From the three types of process mining mentioned, only the discovery type is applicable in this case, as conformance checking and enhancement require a model to which the discovered model from the OPTA log can be compared to. In football, there is no “perfect” or pre-defined model of the game process. Therefore, process mining can help with modelling the real-world process of what actually happened during the game. As to the perspectives, it is possible to view the event logs of the matches from all four perspectives discussed above.

8.2 Related work

To the author’s knowledge, no previous study has examined process mining as a method to analyze performance in team sports, including football. However, based on the method description in the previous section and the type of data it requires for the various algorithms, an assumption is made that process mining could potentially be a valuable analytical method to detect relevant patterns of behavior of football teams. It could reveal tactical patterns leading to important events as, for instance, shot on goal or goal, among other possibilities, which will be explored in the current thesis. In the following, a brief overview of similar technique applied in football performance analysis is given. It shows the idea behind applying process mining as well as an explanation of why it is interesting and necessary to explore this topic further.

A significant portion of the existing literature in this area focuses on event detection in videos and on modelling techniques for sequence analysis in team sports. Those techniques, however, do not exclusively look into the sequences of events to detect unique event patterns over specific time periods, but focus on examining movement patterns (which require GPS data), spheres of influence and coordination patterns, as described in Schrapf et al. (2017). One of the methods closer to the main idea behind event sequence analysis in football is the *time-pattern*, also known as ***T-pattern*** method. A T-pattern is a “combination of events in which the events occur in the same order with the real-time differences between consecutive pattern components remaining relatively invariant (i.e. the time difference between A and B will be x ± y) with respect to an expectation assuming, as a null hypothesis, that each component is independently and randomly distributed over time” (Borrie et al., 2002, p. 846). Another way to describe this, is given by the developer of the first T-pattern algorithm and one of the scientists behind the most used tool for T-pattern detection, called Theme, Magnus Magnusson. He writes that “if A is an earlier and B a later component of the same recurring T-pattern then after an occurrence of A at t, there is an interval [t + d1, t + d2] (d2 ≥ d1 ≥ 0) that tends to contain at least one occurrence of B more often than would be expected by chance” (Magnusson, 2000, p. 94). The temporal relationship between the components A and B is called *critical interval*, and it is a concept that lies in the center of the T-pattern algorithms (Casarrubea et al., 2015). A T-pattern is depicted in Figure 40.

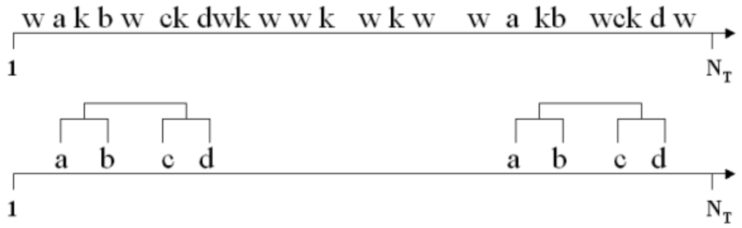


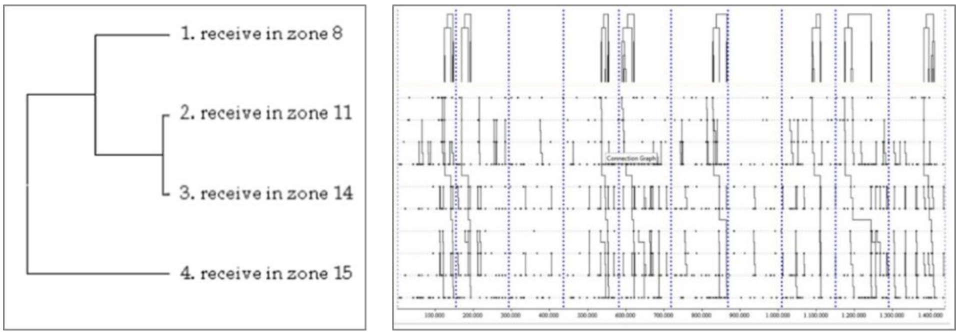
Figure 40. Schematic representation of a T-pattern
Source: Jonsson et al., 2010, p. 96

Assuming that the letters above line 1 depict events (e.g., pass, tackle or shot) which appear in proportion to their occurrence during the game, then line 1 is a visual representation of the temporal structure of football performance (Borrie et al., 2002; Jonsson et al., 2010). Four events, a, b, c and d, represent a temporal pattern that appears regularly. However, in the first representation this is not visible to the eye, as other more randomly occurring events w and k, prevent the observation of the pattern (Jonsson et al., 2010). This is one of the strengths of the T-pattern detection algorithms. They allow the separation of random events from temporal patterns (Jonsson et al., 2010). Another thing that Figure 40 shows is that there is a larger pattern ((a, b) (c, d)) consisting of two simpler patterns (a, b) and (c, d) (Borrie et al., 2002). Consequently, even in smaller datasets, the amount of patterns detected can be quite high – if there are 100 event types the potential event patterns, if all time windows are considered, is greater than 100^{10} (Borrie et al., 2002). Furthermore, T-patterns can be cyclical or acyclical, which means that they can occur in regular time intervals but not necessarily. A pattern of play may occur a few times in the first half of the match and not reoccur till the last 5 minutes of the same match (Jonsson et al., 2010). Another issue is causality – just because a pattern exists it should not be assumed that the elements in the pattern are causally related (Borrie et al., 2002; Jonsson et al., 2010). Finally, detected patterns could be used for prediction by estimating the probability that when A occurs at time t, B will occur within a critical interval defined as [t + d1, t + d2] (Jonsson et al., 2010).

The idea of studying temporal patterns and recurrence of events did not originate in sports performance analysis. The inspiration came from studying animal and human behavior in various other disciplines, based on the premise that repeated patterns of events exist in the behaviors of humans and animals (Casarrubea et al., 2015). Studies on temporal patterns observed in human behavior have been done in the area of healthcare and medicine (autism, schizophrenia, dementia), in communication and conversation, stress factors and routine tasks, and in language practice, to name a few (Casarrubea et al., 2015).

Certainly, this relates to the question of whether football, and thus the behavior of the football players, is predictable or not. It is a popular debate in sports science with practitioners having some extreme points of view. Offering a solution to this debate is not a goal of the thesis. However, it should be pointed out that considering the success of analytics in various sports nowadays, it is becoming clear that the game is not that unpredictable as it was thought previously. In an interview, the Head of Opposition Analysis of Liverpool FC, Chris Davies, answers a question of the interviewer on whether football players are more predictable than they would like to think. In his opinion, players are predictable, especially under pressure when they revert to habits that are ingrained in them, possibly since childhood, like for instance, “what foot you take the ball with, and what movements you make, and what actions you make”. He also states that the best players tend to be less predictable and offer more variability in their game, but that overall, if one watches a player 20, 30 or more games, it is possible to detect some of their habits. The full interview is available in Pearce and Vladimirov (2014).

T-pattern analysis has been applied in a few studies in football. Some examples of how a T-pattern on football data looks like can be seen in Figure 41. Back in 2002, Borrie et al., published one of the first studies on the topic specifically focusing on football. By coding 13 matches they demonstrated that many temporal patterns exist in football, and thus, the behavior of a football team is more synchronized than the human eyes can detect. Their study showed that new kinds of team and player profiles can be discovered based on the detected patterns of behavior. Almost a decade later, Jonsson et al. (2010) presented preliminary results of how T-patterns can be used in soccer, basketball, boxing and swimming, for detecting temporal event patterns with a focus on the motor skill performances. Recently, Castañer et al. (2017) analyzed the playing styles of Ronaldo and Messi, especially the way they use their motor skills in attacking sequences that result in a goal. They detected patterns characterizing both players in terms of body parts they used the most, foot contact zone, body orientation and action. Diana et al. (2017) use T-patterns to detect the effect of game location (home/away) on the structure of play. Their focus is on attacking actions and comparing T-patterns between home and away matches.



(a) (b)

Figure 41. Representations of T-patterns on football event data
(a) Temporal and hierarchical representation of a T-pattern (Jonsson et al., 2010); (b) Complex T-pattern with a length of 10 events and 5 levels

Source: Diana et al., 2017

Overall, in football, there is a lack of studies on the temporal structure and interrelationship between different events. This is especially the case concerning professional tracking data. The reviewed papers on T-pattern analysis in football are using an observation method and different event coding techniques, basing their analysis on semi-manual extraction of video recorded football matches. The results, although valuable, cannot be compared with event data provided by a company like OPTA, mainly due to the detail with which events are recorded. Another limitation of previous studies employing the T-pattern method in football, is that their structure, results and discussion sections are rather repetitive, as they tend to be published by the same group of authors – a similar case as with the SNA studies in section 6.2. In summary, there does not seem to be significant development between the paper published by Borrie et al. (2002) and the newer papers by Diana et al. (2017) and Castañer et al. (2017). A major limitation of previous studies is that they do not go further to investigate if and how this method can be used by practitioners. Considering the large amount of potential patterns that can be detected, it is questionable if the method is helpful for practitioners as some of the visualizations tend to be overwhelming and not very intuitive, at least for real-time decision support. Finally, all previous studies use a selection of matches and it is not clear how and if the findings can be generalized and applied in practice. Further investigation to establish the relevance is imperative.

Beyond T-patterns, another interesting technique used for visualization of temporal event sequences, called *Outflow*, is studied by (Wongsuphasawat and Gotz, 2012). They show how Outflow can be used to give a summarized overview of the way in which specific event pathways are linked to positive and negative outcomes – in football, for example, a win or a loss. A study with 12 participants also demonstrates that the users can learn how to use the technique after a 15 minute of training. However, no other papers have been found that discuss this type of visualization and its relevance for decision making in football.

Taking into consideration the findings so far, it is of interest to explore alternative methods for pattern detection which will give deeper insights into the tactics of players and teams in football. A reason for using T-patterns, as mentioned by Camerino et al. (2012), is that tactical patterns cannot be detected directly or through visual inference. However, process mining can offer a visual and quick approach to this. Finally, more studies are needed to explore the technical and tactical strategies during different times of the match (Cavalera et al., 2015).

8.3 Analytics approach

An exploratory study is presented to investigate which process mining analytics techniques are useful for performance analysis in football. All of the process mining analytic perspectives explained previously (case-flow, case and organizational – see section 8.1) are used in the analysis. The analytics steps are presented in Figure 42.

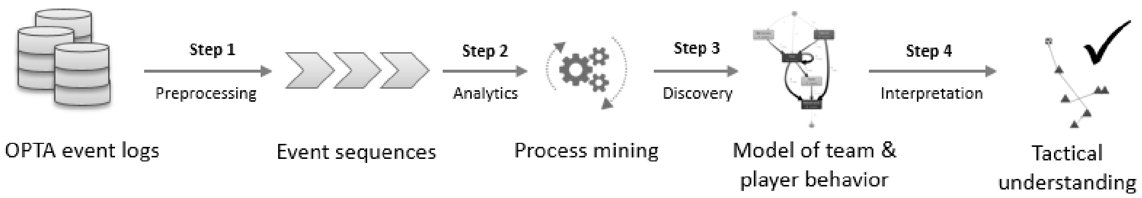


Figure 42. Process mining steps for analysis of the OPTA event data

In a first step, the original OPTA data needs to be preprocessed and converted in a specific way required by the process mining algorithms, i.e. the original data need to be converted into an event log data (see section 8.4). This is followed by analysis of the resulting event logs, discovery of the process models and interpretation (see section 8.5). The potential of the applied analytics techniques to gain a tactical understanding in football is presented in the discussion section (8.6).

One exemplary game is analyzed as the goal is to demonstrate the techniques. The game between England and Iceland is chosen, because Iceland won, while the England team showed one of its worst performances in a tournament. Therefore, it is interesting to explore what process mining will reveal about the player and team behaviors. A summary of the game is presented in Table 43.

Table 43. Match statistics of England vs. Iceland's game

Date: June 27, 2016		
England	**Performance indicators**	**Iceland**
1	Goals scored	2
63	Possession (%)	37
18	Total attempts	8
5	on target	5
10	off target	3
3	blocked	0
0	against woodwork	0
7	Corners	2
2	Offsides	1
1	Yellow cards	2
0	Red Cards	0
6	Fouls committed	15
14	Fouls suffered	6
525	Passes	243
451	completed	173

Source: (UEFA, 2016b)

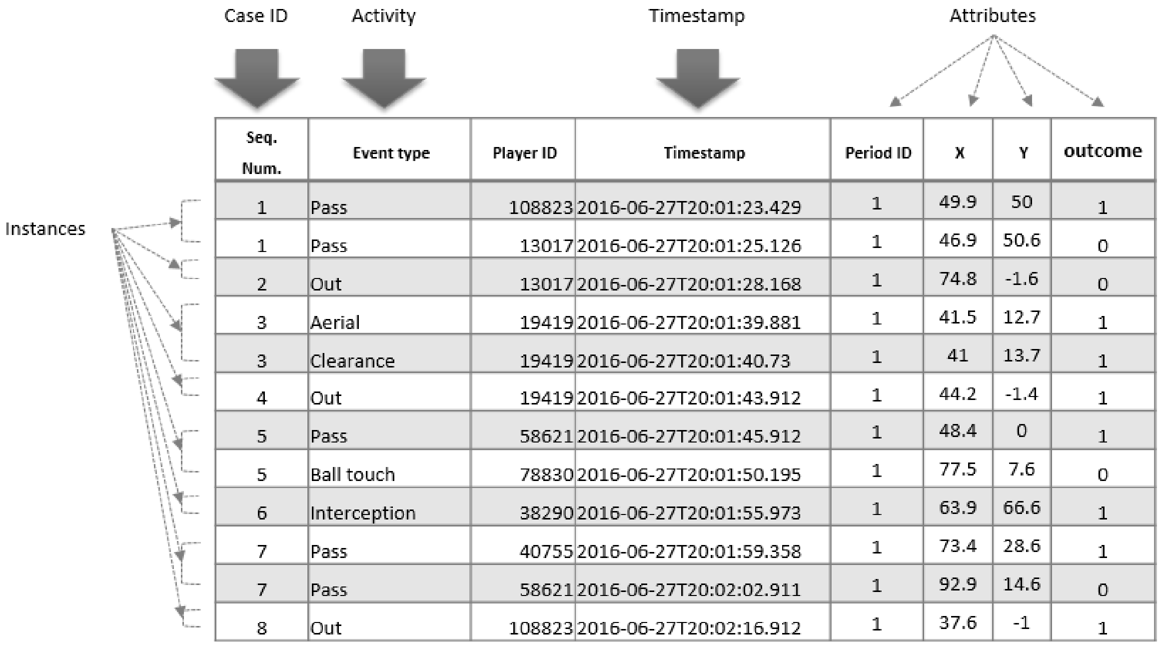
8.4 Data preparation

The first step of process mining is to pre-process the event log data from OPTA for the analyzed teams. Depending on the amount of additional information needed on each event, i.e., the attributes, as described previously, the task can vary in complexity. The main issue, converting the log data into a format required by the process mining algorithms, is that each event in the OPTA log is described over several rows. Each row has different types and amount of qualifiers which describe the event further. For instance, if a pass is analyzed, it can have qualifiers referring to the length of the pass, the angle, the x and y coordinates, etc. There are 36 qualifiers in total that can be used to describe the pass in more detail. Not all of them are used for each pass. The situation is similar with the rest of the 73 event types. Thus, it is a challenge to extract the relevant information in a way that the attributes of each event are added on a single row. A Python script tackles this challenge. Below a few key steps executed by the code are introduced:

1. Eliminate unnecessary event types (formation change; deleted event, namely all events not related to ball possession or loss thereof).
2. Re-sort the data according to the scheme provided by OPTA, so that an accurate sequence of events can be obtained.
3. Pivot the qualifiers (each tuple of qualifier ID and value is transposed to one column per qualifier)
4. Summarize data by event IDs (one row per event including all values for qualifiers)
5. Assign case IDs

The output of the pre-processing step is a sequence of all events referring to the game with the ball. This means that a sequence for team A starts when the team gains ball possession and ends when the team losses the ball. This is a similar procedure followed in the SNA part. The difference is that here all events are included and not just the passes. An overview of the final data format is presented in Figure 43.

The minimum requirements for process mining are available via the columns “Seq. Num.”, “Event type”, and “Timestamp”. Additionally, the Period ID column (1 - first half of the game), the x and y coordinates of the event in question, and its outcome (1 – successful, 0 – not successful) are available as attributes.



Seq. Num.	Event type	Player ID	Timestamp	Period ID	X	Y	outcome
1	Pass	108823	2016-06-27T20:01:23.429	1	49.9	50	1
1	Pass	13017	2016-06-27T20:01:25.126	1	46.9	50.6	0
2	Out	13017	2016-06-27T20:01:28.168	1	74.8	-1.6	0
3	Aerial	19419	2016-06-27T20:01:39.881	1	41.5	12.7	1
3	Clearance	19419	2016-06-27T20:01:40.73	1	41	13.7	1
4	Out	19419	2016-06-27T20:01:43.912	1	44.2	-1.4	1
5	Pass	58621	2016-06-27T20:01:45.912	1	48.4	0	1
5	Ball touch	78830	2016-06-27T20:01:50.195	1	77.5	7.6	0
6	Interception	38290	2016-06-27T20:01:55.973	1	63.9	66.6	1
7	Pass	40755	2016-06-27T20:01:59.358	1	73.4	28.6	1
7	Pass	58621	2016-06-27T20:02:02.911	1	92.9	14.6	0
8	Out	108823	2016-06-27T20:02:16.912	1	37.6	-1	1

Figure 43. Pre-processed OPTA event log suitable for process mining tasks

Tools used for the analyses are:

ProM – this is an open source process mining software which offers a wide range of algorithms and techniques to process and analyze event logs. There are also various plugins available to extend the analytics options further. In the current thesis two versions of the software were used: ProM 5.2 and 6.7[11]. Some useful techniques, like for instance, the SOM trace clustering are missing in the later version, and this is why both of these versions were used in the analysis.

Disco – this is a proprietary process mining software developed by Fluxicon[12]. It is far more user friendly than ProM and it is easier to read-in the event logs and get quick results. Although having a better learning curve and results that are easy to interpret, it does offer far less analytical options than ProM. However, some of the techniques are easier for analysis, and therefore it is used in combination with ProM.

8.5 Data analysis and results

The game analyzed is the England vs Iceland game. This is a game of a favorite team (England) versus an underdog team (Iceland) in which England did not show a stellar performance. Therefore, it is interesting to see what insights process mining will bring regarding Iceland's victory.

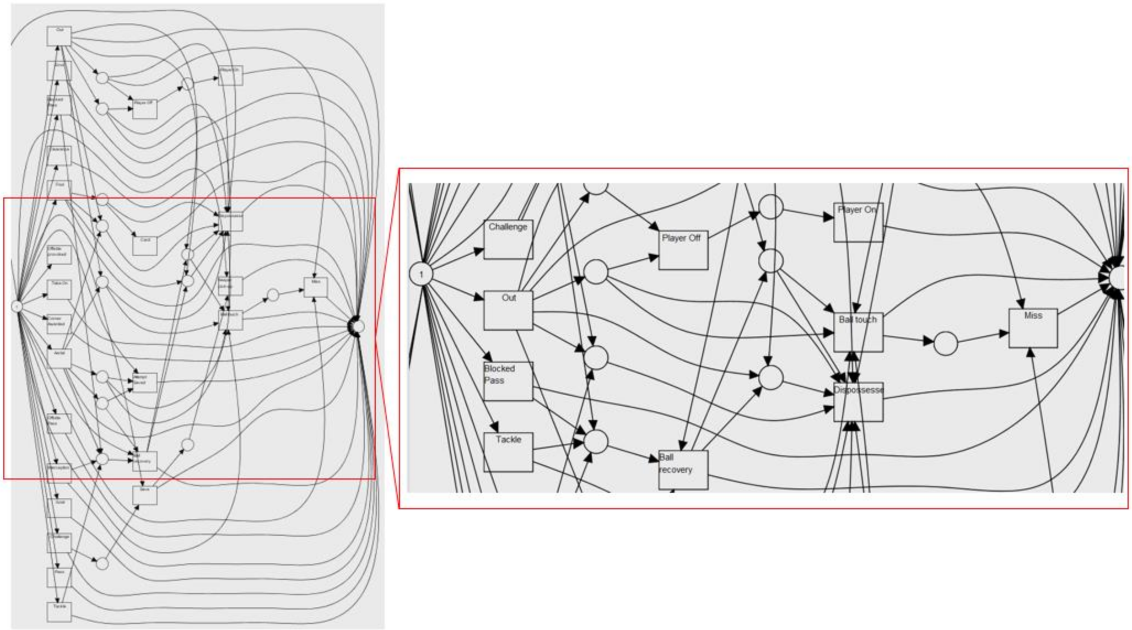
Mining the case-flow perspective

In a first step, the games are analyzed from a broader viewpoint, particularly the case-flow perspective. It gives a "helicopter" view of the sequences that happened for both teams and a summary of

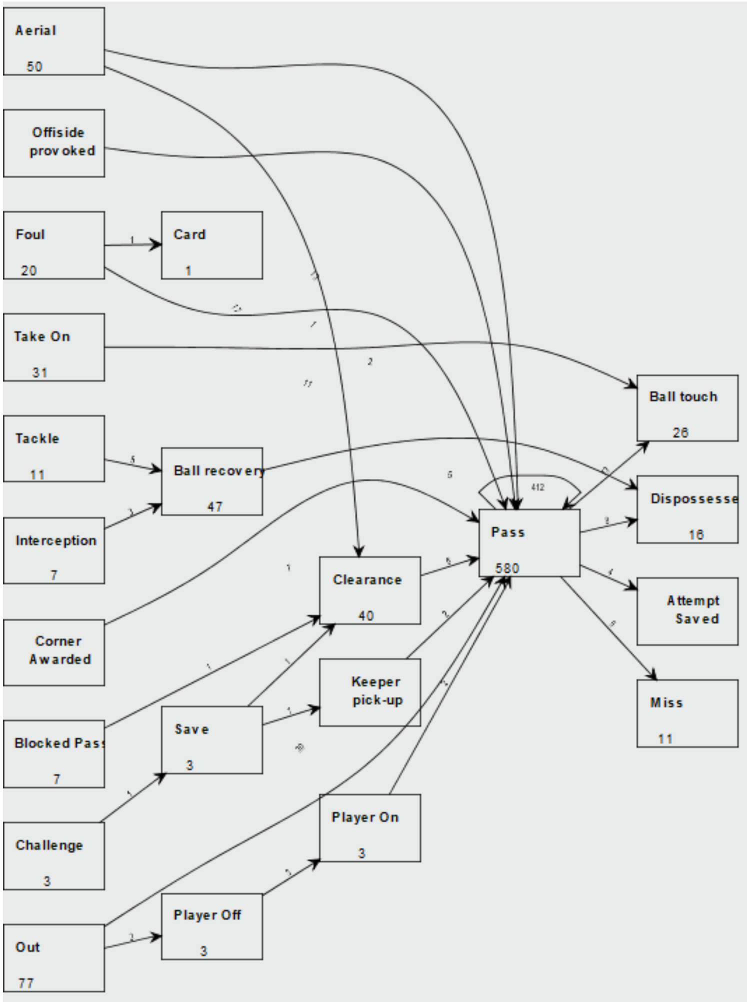
[11] http://www.promtools.org/doku.php

[12] http://fluxicon.com/disco/

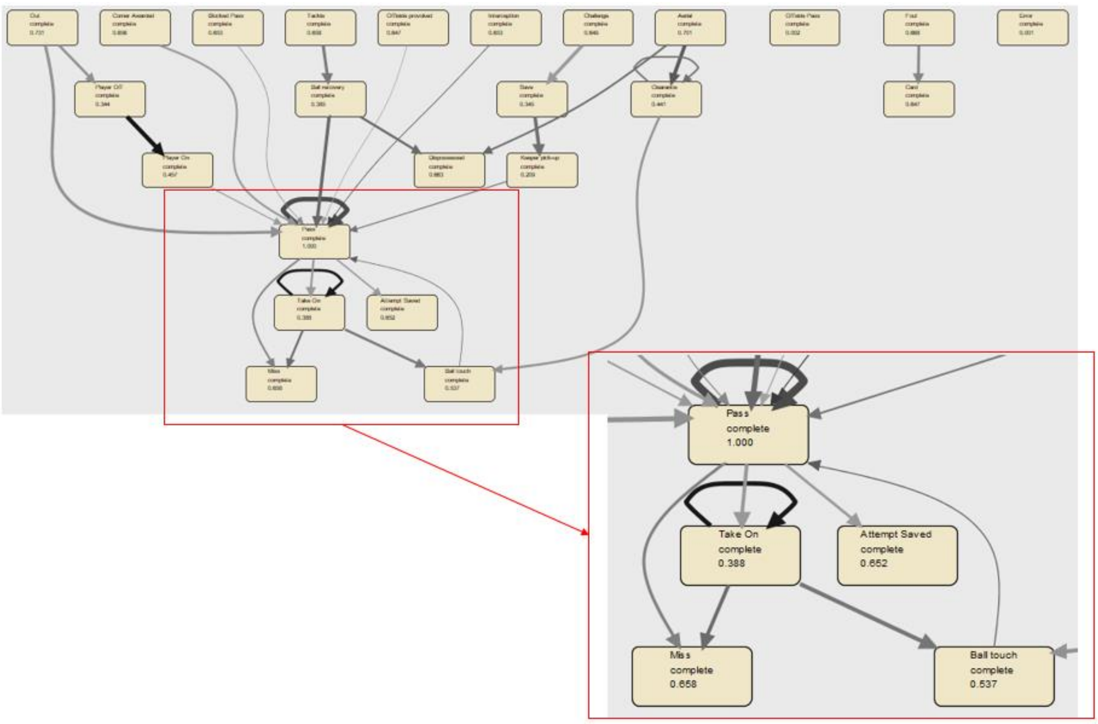
actions that characterize both the team and its players. As discussed in 8.1., there are various algorithms that can be used to derive a process model from event log data. The algorithms are initially run with default settings, as this works well in most cases, at least in giving an initial idea of the usefulness of the algorithm in each individual case. In Figure 44 the results from the four algorithms, Alpha, Fuzzy, Heuristic and Inductive Visual Miner are presented for the team of England.



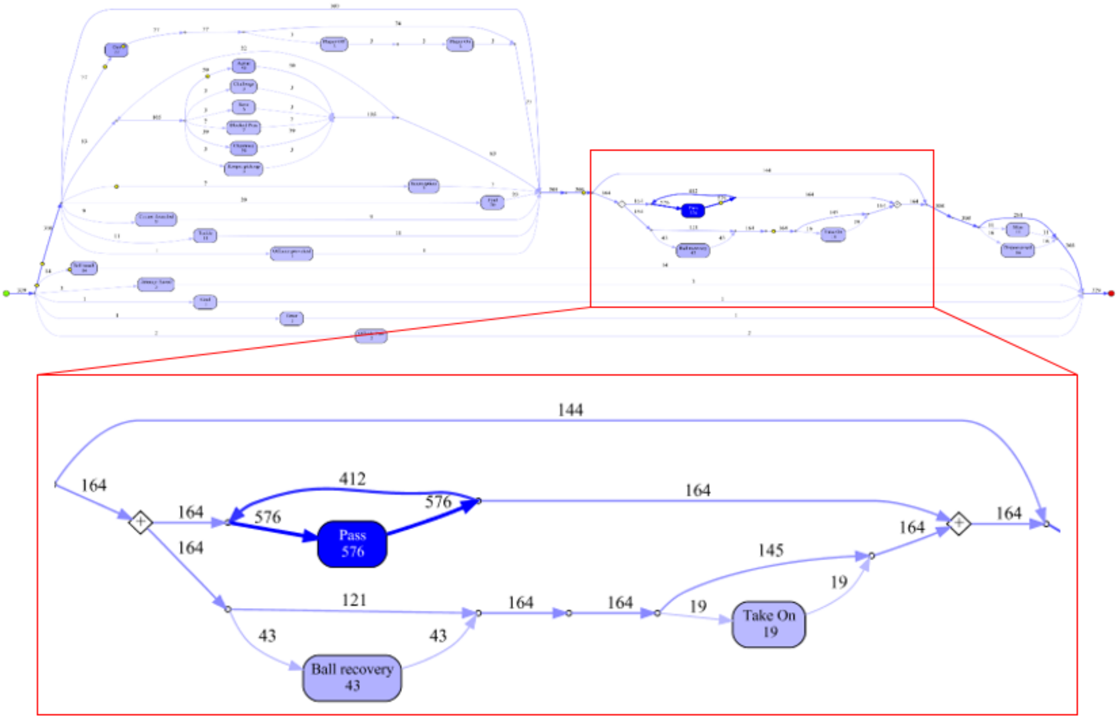
a) Alpha Miner



b) Heuristic Miner



c) Fuzzy Miner



d) Inductive Visual Miner

Figure 44. Process models of England's team by using different algorithms

From the figure above, the Alpha Miner is the algorithm that derives the least helpful model. This can be seen in Figure 44 – a), as there are a lot of events connected to the initial starting point as well as to the end point. While the Heuristic Miner derives a more process-like model, it lacks the ability to integrate three of the events (see Figure 44 – b). The model derived from the Fuzzy Miner shows a more detailed view of the process by adjusting the thickness of the connectors to the likelihood that a sub-sequence of two events occurs. Similar to the Heuristic Miner, the Fuzzy Miner is also not capable to create one holistic process out of all the events. Therefore, these algorithms not be considered in the analysis. The Inductive Visual Miner (IDV) is able to find sound process model (Figure 44 – d). Furthermore, it is able to give a detailed overview on the most likely paths in the process model. Therefore, it is chosen as the best algorithm to generate the process models of both teams.

Figure 45 and Figure 46 present the process models for England and Iceland respectively.

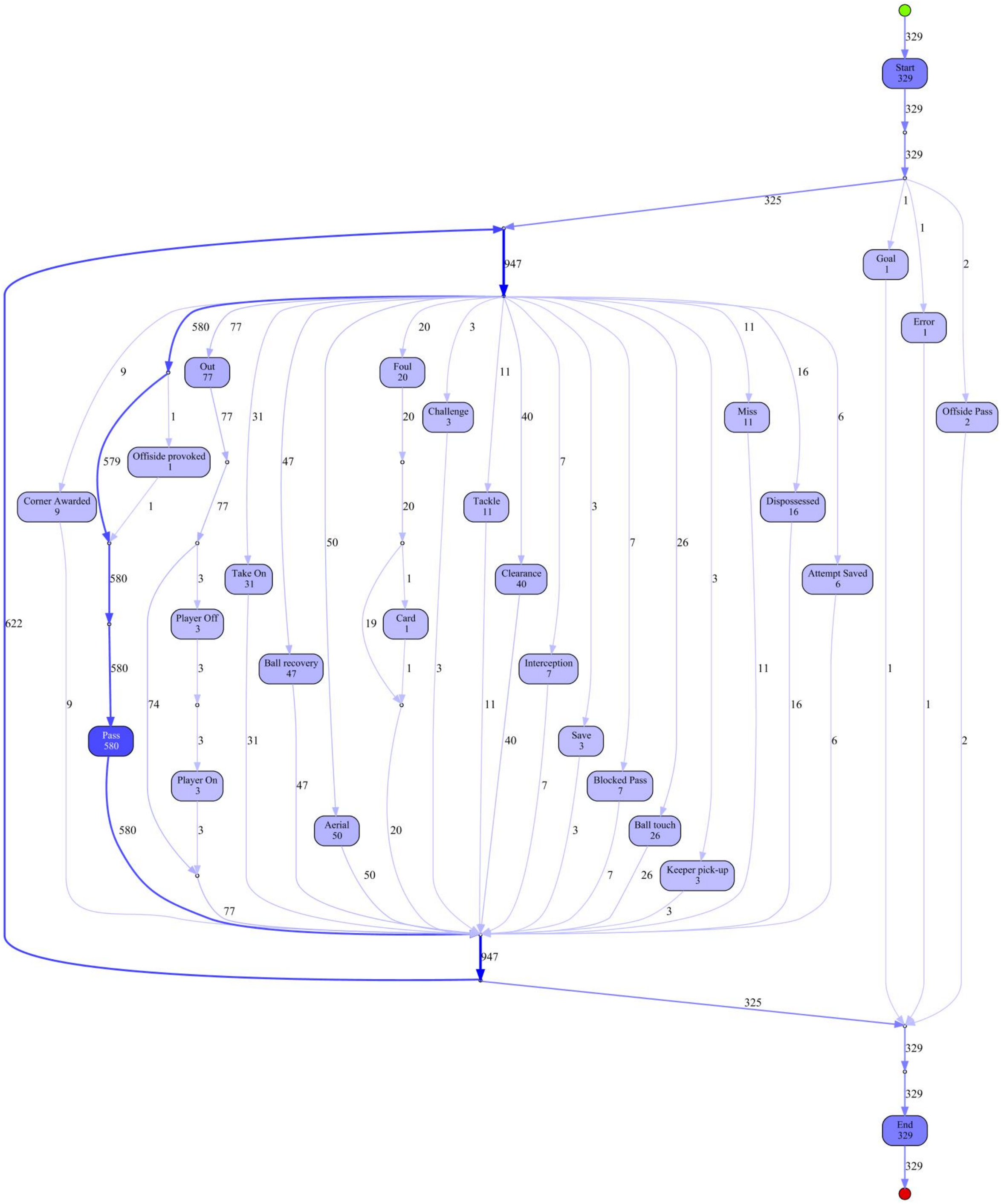


Figure 45. Process model of England (vs. Iceland) mined with the IVM

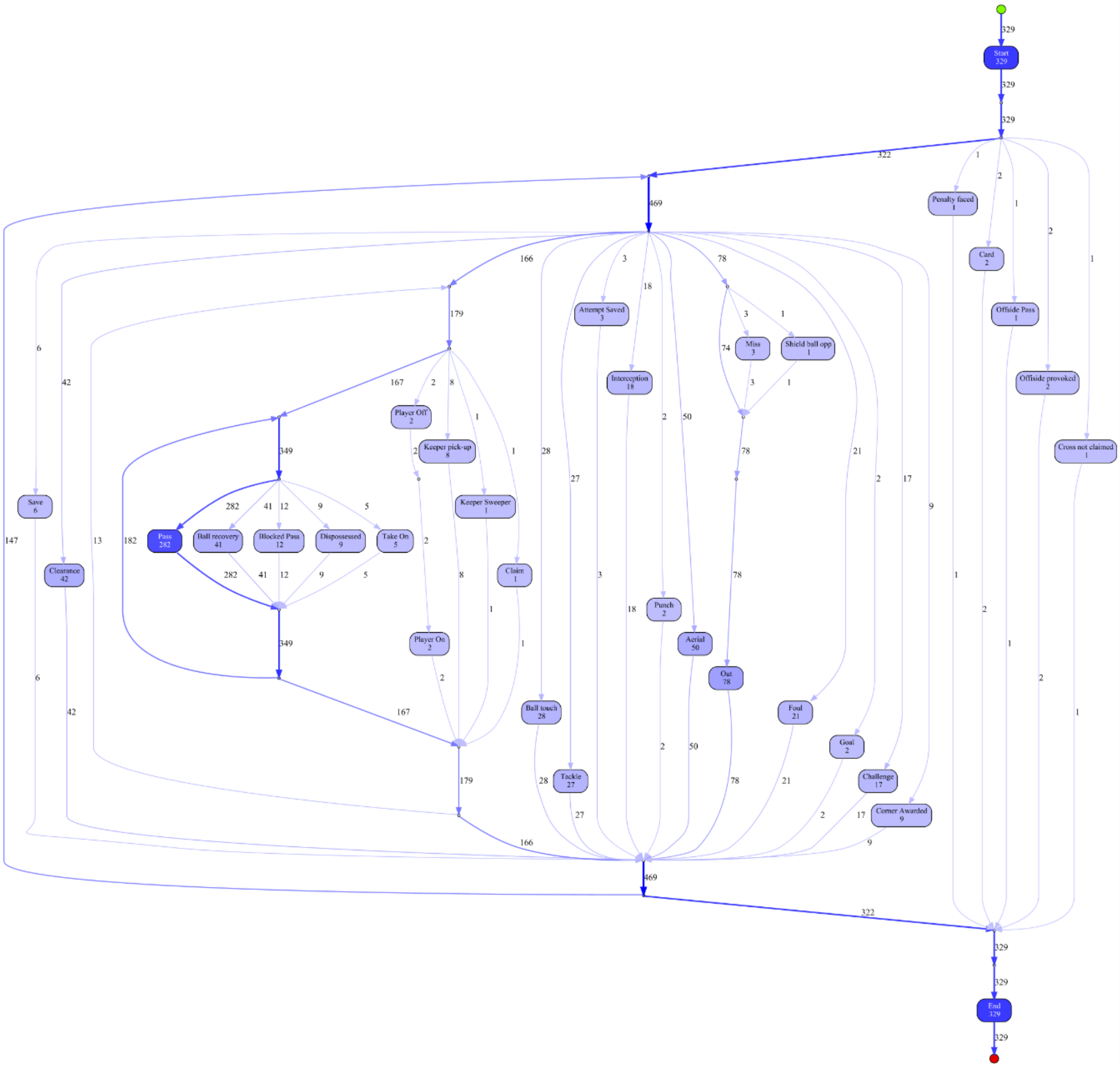


Figure 46. Process model of Iceland (vs. England) mined with the IVM

Both models display all activities and paths for each team during the game. The darker blue color indicates that those activities (events) occur more often during the game. Not surprisingly, the event "pass" is usually highlighted in this way. From an initial inspection of the models, it is possible to gain first impression about the *event frequency*, e.g., for England it is immediately visible that the team had 580 passes or 9 corners awarded. But more interestingly, it is possible to visualize the *dependency* between events i.e., how often an event was followed by another. For instance, in England's team, once, a "foul" (out of 20), was followed by a "card" event. Unfortunately, the model does not distinguish whether the foul was caused or suffered by England. Therefore, the process model for Iceland also shows that there are 20 fouls in the match.

Mining the case perspective

The case flow perspective does not seem to be very useful in a football case scenario as the frequencies of events are not interesting enough and are part of the traditional notational analysis.

Therefore, in a next step, various techniques and visualizations from the case perspective are applied. These are explained below.

One option is to examine closely sequences that are of interest to the coach or his team. For instance, it is possible to inspect the sequences that contain the event ”*miss*” (any shot on goal which goes wide or over the goal). With a single click on it the paths that have this event at least once, are highlighted. In this way, it is possible to inspect each sequence separately by using the highlighting filters in the IVM ProM window. The sequences containing the event “miss” for England are presented in Figure 47.

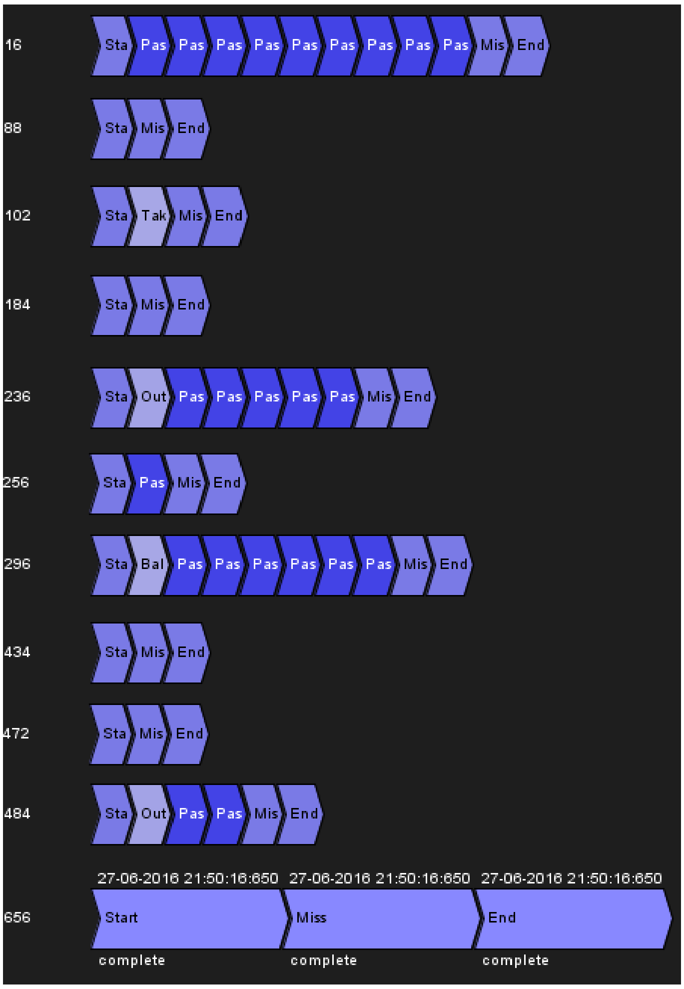


Figure 47. Instances ending in a „miss“ event for England

On the left, the sequence number is visible, and on the right, each block is an activity ordered by the timestamp. Sequences have a start and an end point. Each sequence is clickable, which extends the view and it is possible to see the timestamps as well as an information on whether the event was completed or not (see last sequence). Clearly, in 3 out of 11 instances, England missed a scoring chance after a longer passing sequence. In addition to the possibility to inspect a specific sequence separately, it is also possible to directly see what the input and output activities are for an event of interest. For instance, it is possible for the coach to see which events occur before his team is dispossessed, or which events follow a dispossessed event. This is done by using the sequence patterns options in process mining. One option is presented in Figure 48.

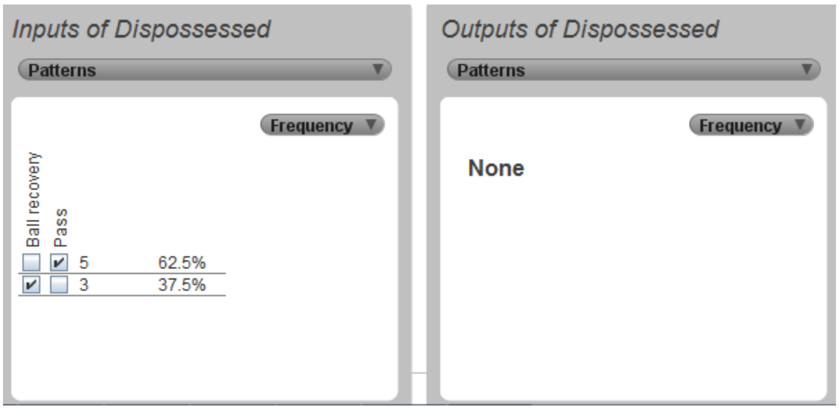


Figure 48. Input and Output patterns for the event „dispossessed“ for Iceland’s team

Figure 48 shows the input patterns for the event “dispossessed” (player is successfully tackled and loses possession of the ball) for Iceland’s team. In 62.5 percent of the sequences ending in dispossession, a pass occurred, while in 37.5 percent a “ball recovery” was also part of the sequence. As with England’s team, by using the IVM, it is possible to check the exact sequences that end in dispossession. This is presented in Figure 49.

Figure 49. Instances ending in a „dispossessed“ event for Iceland

On the left side in the figure above, a sequence number is visible. In this way, it is possible to refer directly to that sequence and gain additional information about it. For instance, if the coach or analyst decides he/she would like to have more information on sequence 453, the Log Visualizer can give quite a few details about it (see Figure 50). Some of the information available is: this sequence occurred in the second half of the game (62’10”) and consists of three events in total, in which two players were involved – the midfielder Gudmundsson recovered the ball, then made a pass to the striker Sigthorsson, who in turn lost the ball. This happened at coordinates x: 28.3, y:15, which falls in the center zone, that is, the defense zone for Iceland. Clearly, this represents a dangerous situation as England regains possession in their offense zone.

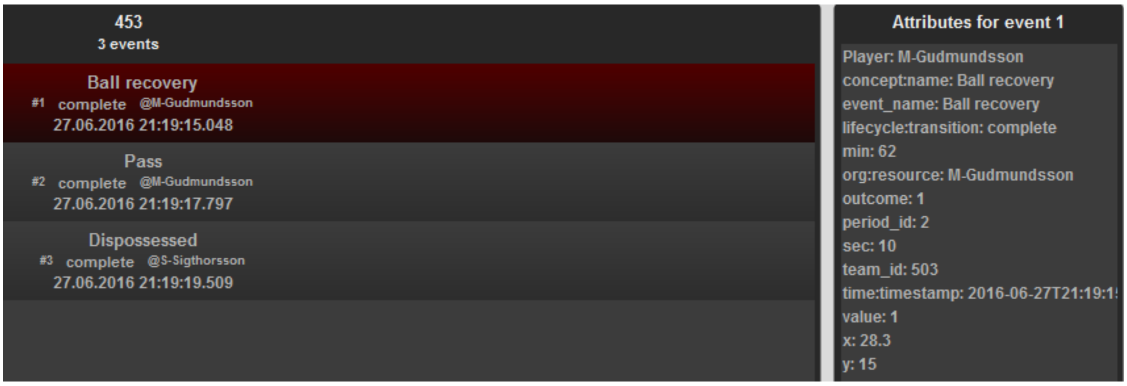


Figure 50. Sequence details from the Log Visualizer in ProM

From the sequences it is also possible to gain more insights about the ***value of a player***. When assigning credit to a player, standard statistics do not give enough credit to players who managed to keep the ball in possession by successfully getting out of tight situations (Gregory, 2017). One should not only look at players who shot towards the goal or made the key assist, as sometimes it can be much more difficult to enable that assist in the first place (Gregory, 2017). Process mining can be used to gain additional insights into a player’s involvement in such situations. One option is to filter out all sequences that end in the following events: miss, post, attempt saved and goal. These are the four events that OPTA records and which mean a shot on goal has been made.

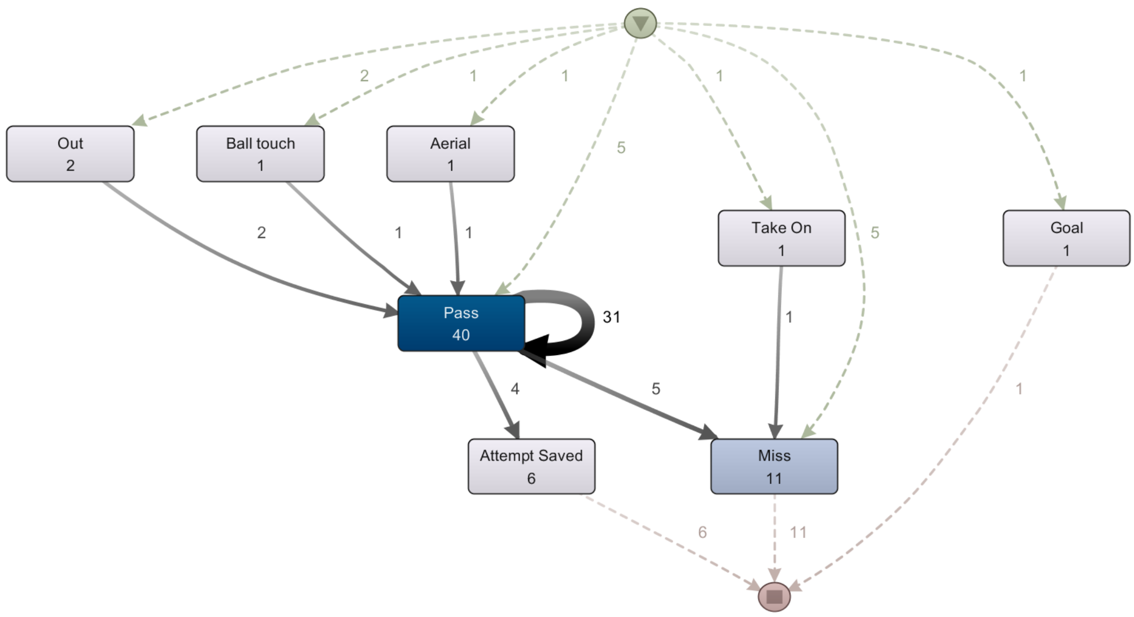


Figure 51. England's offensive sequences ending in a shooting attempt

All sequences of England's team that end in one of the mentioned events are filtered out. The resulting process model is presented in Figure 51. Obviously, 11 sequences ended in "miss" and 6 in "attempt saved", while one sequence ended in "goal". The question is, which players mostly started and ended those sequences. This information is also available from the filtered sequences and it is presented in Table 44. Based on Table 44 – b and c, it becomes clear that Kane and Alli are both frequently initiators and end-ers of offensive sequences in England's team. This makes these two players very valuable.

Table 44. Overview of players involved in the offensive sequences

Resource	Frequency
S-Kane	11
M-Alli	10
D-Walker	6
S-Sturridge	5
M-Rooney	5
M-Wilshere-Sub	5
S-Sterling	4
D-Rose	4
F-Vardy-Sub	4
D-Cahill	3
D-Smalling	3
M-Dier	3

a) List of all players involved in the offensive sequences

Resource	Frequency
S-Kane	11
M-Alli	10
D-Walker	6
M-Rooney	5
M-Wilshere-Sub	5
S-Sterling	4
D-Rose	4
F-Vardy-Sub	4

b) Sequence initiators

Resource	Frequency
S-Kane	11
M-Alli	10
S-Sturridge	5
M-Rooney	5
M-Wilshere-Sub	5
S-Sterling	4
F-Vardy-Sub	4
D-Smalling	3

c) Sequence end-ers

The *Dotted Chart* is another visual analytics technique available in process mining. It is simple, yet extremely useful for having a quick look at various aspects of the game and the players. It can be tweaked to present different dependencies between time, events and players. Some options are presented in the figures below, but more are possible.

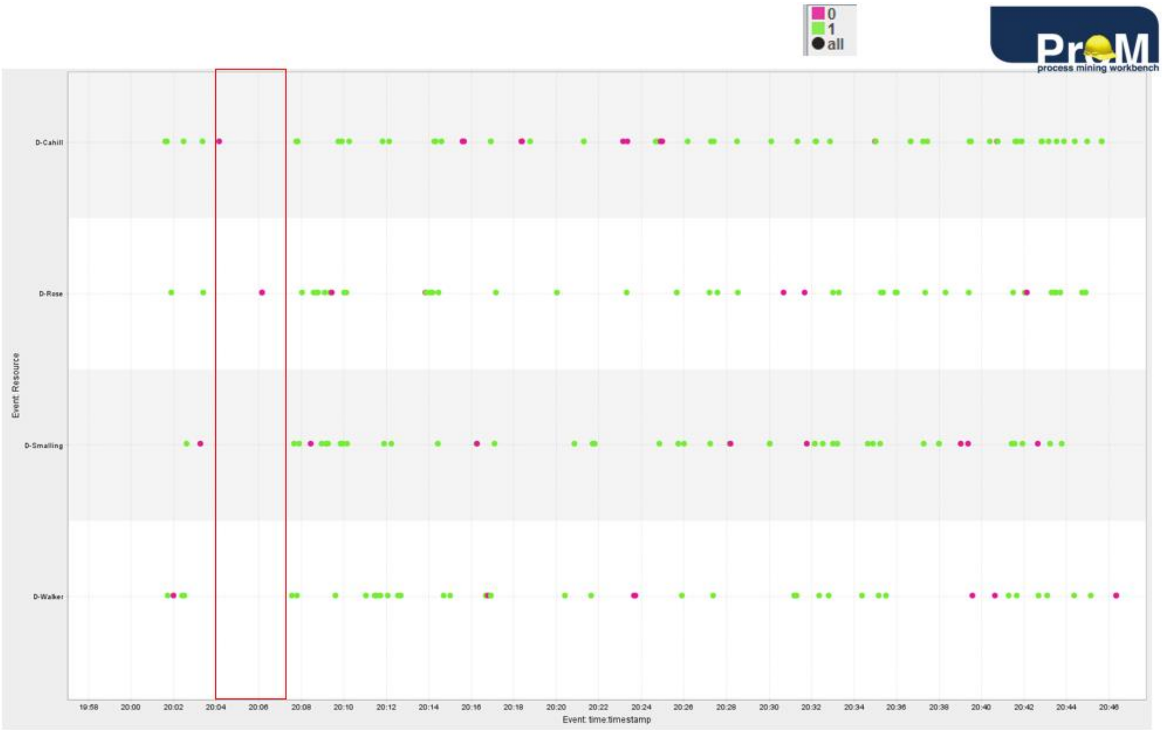


Figure 52. Outcome of activities of England's defenders in first-half

Figure 52 visualizes the outcome of events in which England's defenders were involved in the first half of the game. Red is unsuccessful outcome (for instance, ball lost) while green is successful outcome (for instance, successful pass). It is possible also to clearly see how often and when the defenders are engaged in the game. If one is to observe the timeframe between the first two goals, England's defenders show little action and the two visible actions in the highlighted part above have a negative outcome. It is also possible to immediately see which defenders were involved in an unsuccessful activity, in this case Cahill and Rose.

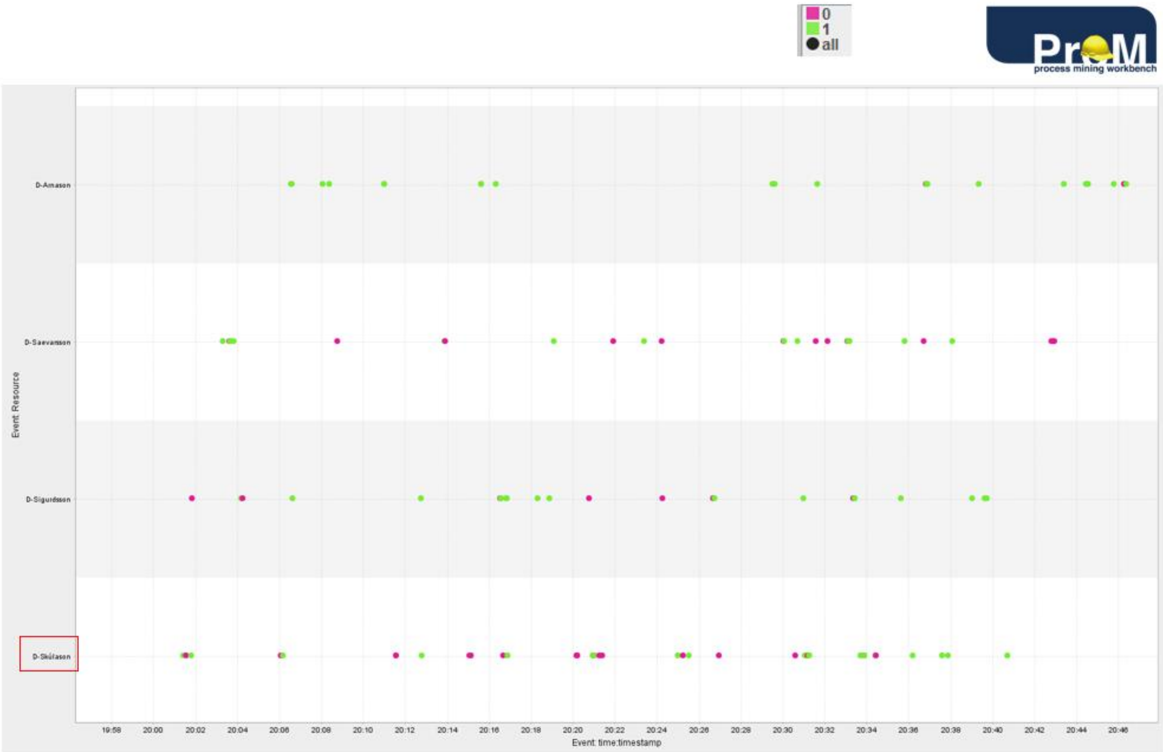


Figure 53. Outcome of activities of Iceland‘s defenders in first-half

Figure 53 similarly presents the outcome of the activities in which Iceland's players were involved during the first half. In this case, it can be seen that Iceland's defender Skulason (last one in the Figure above) makes more mistakes on average compared to the rest of the defenders.

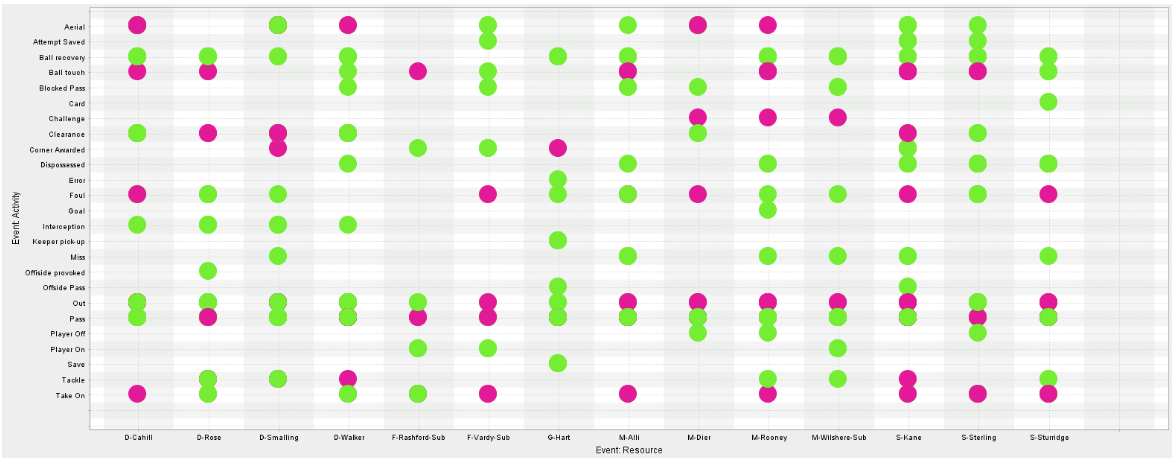


Figure 54. Event types and outcomes per player from England's team

Finally, it is also possible to visualize the exact types of events and their outcomes per player. This is presented in Figure 54. This type of visualization makes it very easy to immediately know which player made mistake in which type of event.

Another useful visualization is the *Meter Chart* under the Basic Performance Analysis option in ProM 5.2. It displays the events and the players involved in them, by using frequency measure (other measures are also possible, like average, minimum, maximum, among others). This is presented in Figure 55.

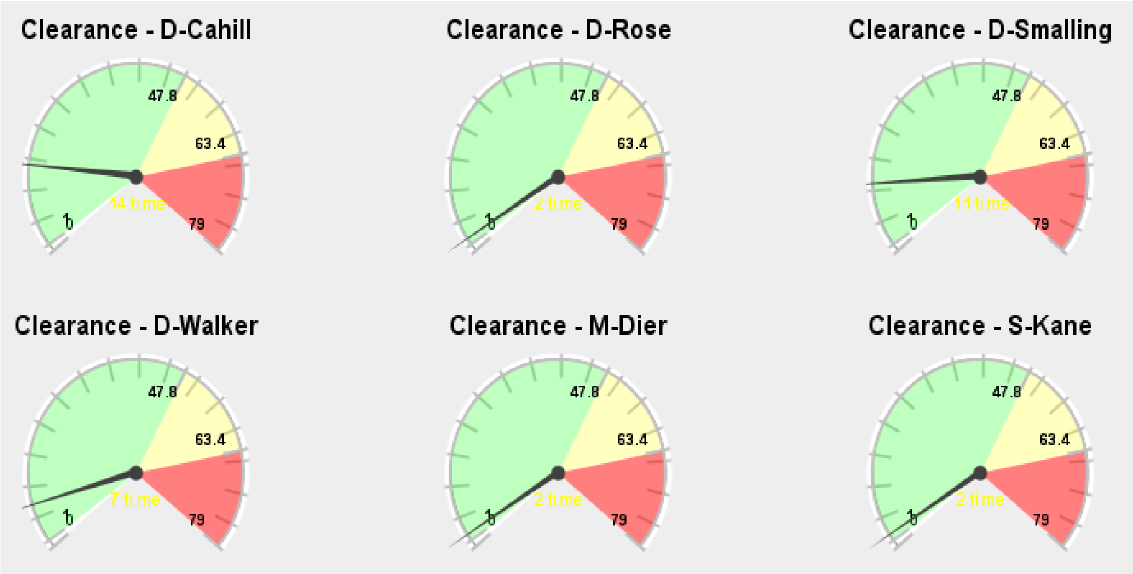


Figure 55. Meter chart displaying event „Clearance” and player involvement from England’s team

From the figure above it can be seen that defenders are mostly involved in the event “clearance”[13], which is understandable. However, one can also quickly see that the defender Cahill is the one who has done most clearances, followed by Smalling and Walker.

As a final step in the case perspective analysis, trace and sequence clustering is performed by using two clustering algorithms, SOM, and Markov Chain clustering.

In order to use a SOM to perform ***trace clustering***, as described in the previous chapter, profiles of the traces are built based on some features. There are several options that can be chosen in ProM, and to do this right, one needs to ask what makes two sequences in football similar to each other. That would be the number and type of events in each sequence, the sequence duration, as well as the participants in each sequence, i.e. the players. These were all selected in ProM as features based on which the profiles of the sequences should be built, before the SOM clustering algorithm is used. There are several parameters for the SOM network which can be fine-tuned in the training process. These are briefly explained below:

- Width and Height: this refers to the number of cells that should be used for the resulting rectangular grid. Each cell corresponds to one neuron.
- Radius: usually set to 2
- Random seed
- Training epochs

[13] OPTA defines „clearance“ as: Player under pressure hits the ball clear of the defensive zone or/and out of play.

In a few publications that have used SOM for trace clustering (Buddhika, 2016; Günther, 2009; Song et al., 2009), parameter tuning was not discussed in detail. Usually, the Euclidean distance is used in combination with SOM and this combination is applied in the thesis as well. As to the width and height, there should not be more cells than there are traces (Günther, 2009). This is chosen usually intuitively after trial and error. The radius value which is used in step 5 of the SOM algorithm (as described in 7.1) as well as the random seed parameters are usually kept at their default values of 2 and 999 respectively. This is the choice also for the analysis employed below. Additionally, the colors in the resulting map, indicate the relationship between the neurons, i.e. neurons with a similar weight vector will be painted in a similar color (Günther, 2009). Clusters with many similarities, exhibiting normal behavior are located in "high land" colored in green, while the clusters with exceptional cases are located at "sea" colored in blue (Buddhika, 2016). The final results of the SOM clustering are presented in Figures 56 and 57 for England and Iceland respectively.

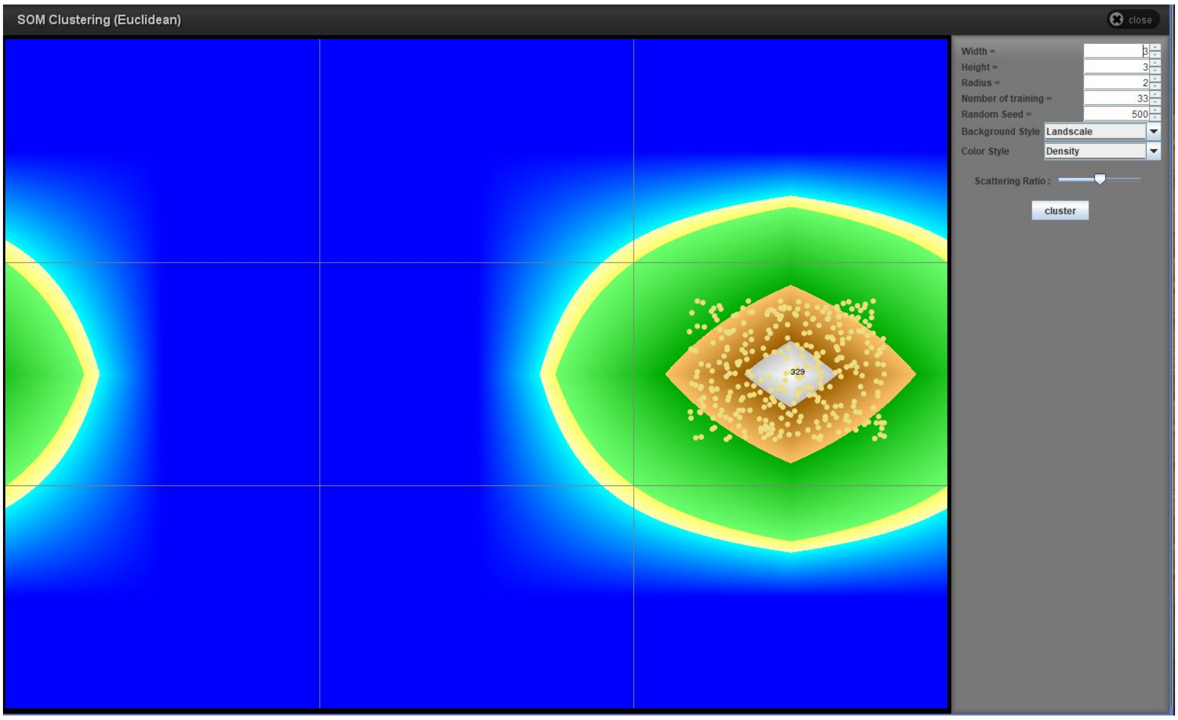


Figure 56. SOM trace clustering – England

The parameters are modified in a trial and error, however, the trace clustering for England's team results in a similar looking graphic as depicted in Figure 56. There is no significant change in the final outcome. On the other hand, for Iceland's team, the trial and error results in more diverse clusters by changing the parameters' values. In the end, the result depicted in Figure 57 is chosen because it is the most sensible combination considering the rest of the results.

The trace clustering results for these two teams lead to the conclusion that England's players demonstrated a more homogenous behavior, while Iceland's players seem to be more creative. This can be confirmed by popular opinion following the game.

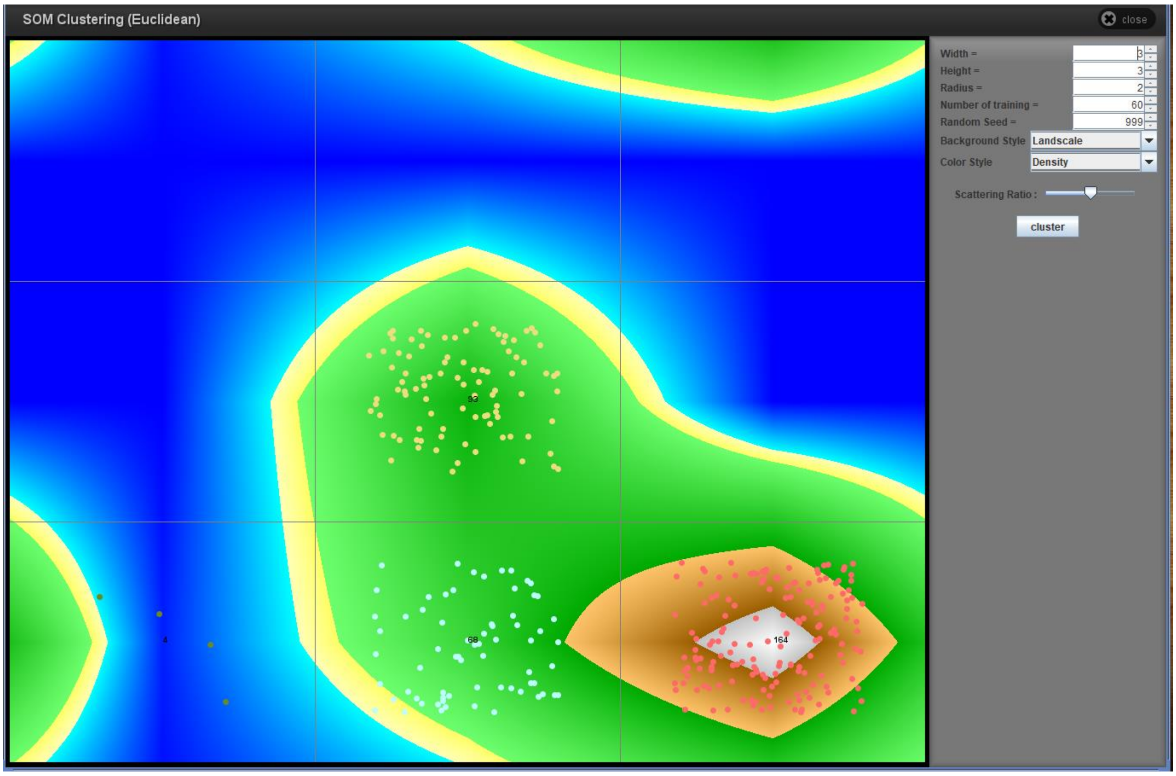


Figure 57. SOM trace clustering – Iceland

The SOM results are confirmed by the ***sequence clustering*** and the generated Markov chains for recognized clusters. As one must first pre-define the number of clusters that need to be recognized, a trial and error for England’s team reveals that when choosing a smaller number of pre-defined clusters (e.g., 2 to 4 clusters) the resulting clusters are of similar size and the Markov chains look relatively similar to each other. This again confirms the impression from the SOM clustering that England’s team plays in a rather predictable manner and not much about their behavior is exceptional or unique. The Markov chains though show more precisely a summarized overview of the main behavior of the team. In addition, one can also see the probabilities that one event is follow by another. Finally, there are a few pre-processing steps that can be used to have better clustering results, especially because without such preprocessing, the analysis can take more than 24 hours. The options that ProM offers are:

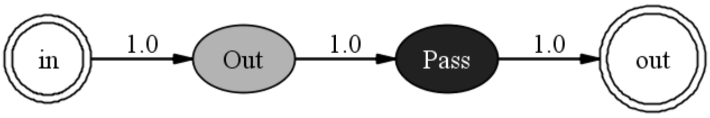
- Min event occurrence
- Max event occurrence
- Min number of events in a sequence
- Max number of events in a sequence
- Min sequence occurrence
- Max sequence occurrence

For the football case scenario, the preprocessing parameters are set as presented in Table 45.

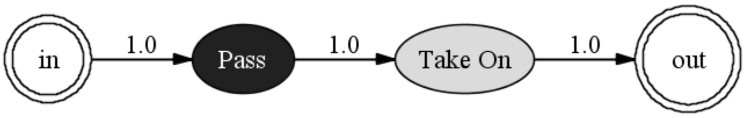
Table 45. Preprocessing parameters for Markov chain sequence clustering for England's team

Parameter	Value
Min event occurrence (%)	3
Max event occurrence (%)	100
Min number of events in a sequence	2
Max number of events in a sequence	18
Min sequence occurrence	3
Max sequence occurrence	329

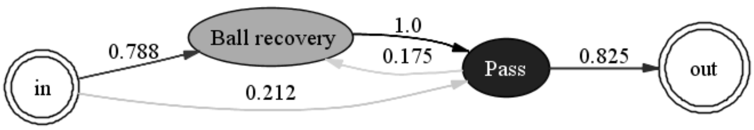
It is chosen that an event should occur minimum 30 percent and that there should be a minimum of 2 events in a sequence, to avoid rare and not interesting sequences of only one event. A sequence should also occur at least 3 times, while the maximum parameters are left at default. The number of clusters with these preprocessing steps applied is set to 4. The resulting Markov chains can be seen in Figure 58 (a, b, c, and d).



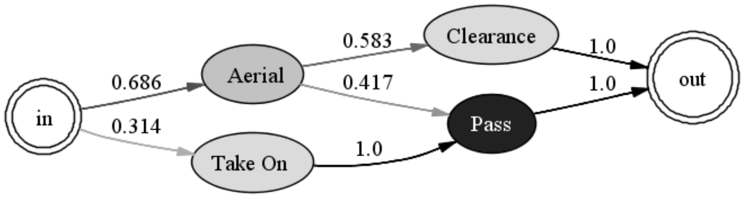
a) Cluster 0: 30 instances



b) Cluster 1: 3 instances



c) Cluster 2: 33 instances



d) Cluster 3: 35 instances

Figure 58. Markov chains for England's team

This method gives an opportunity to easily drill down and get a quick overview of not only in which events the players are mostly involved and how often, but also the exact sequences that occurr the most often. One can also choose a higher percentage and find out if there are some sequences that occur 50 or even 80 percent of the time. In England's case, when the minimum sequence occurrence is increased to 10 and the minimum event occurrence is increased to 40 percent, two clusters are generated with Markov chains in Figure 58, a) and d).

From England's Markov chains its can be concluded that in roughly 30 percent of their game play, the ball is lost following just one pass after the ball was out of play. This means that they recover the ball and then lose it with just one pass (cluster 0). Furthermore, in 3 instances, England's team makes an unsuccessful dribble attempt past an opponent (cluster 1); there is a probability of 0.825 that they will lose the ball following a pass after a ball recovery (cluster 2), and finally, following an aerial duel, the probability for a clearance is 0.583 (cluster 3). This all speaks against England's team and shows at least some of the reasons behind their loss.

For Iceland's team it is more difficult to generate Markov chains that can summarize the behavior well. One reason is that they are more resourceful than England's team. Thus, understandably, it is less likely that their play can be clustered in a meaningful way. As it is the case with England, the minimum number parameters are modified while the maximum number parameters are kept at default. Using the same parameter setting for England, only 6 instances are left after the preprocessing steps. The situation is similar when the parameter "min event occurrence" is increased. Therefore, after a trial and error it is decided not to use the preprocessing parameters in Iceland's case and to proceed with the clustering directly. Cluster results by pre-defining a different number of clusters are presented in Table 46.

Table 46. Clusters and number of sequences for Iceland's team

Number of clusters	Cluster	Number of sequences
4	0	120
	1	58
	2	102
	3	49
5	0	120
	1	79
	2	21
	3	**34**
	4	75
6	0	127
	1	45
	2	26
	3	60
	4	58
	5	13

The Markov chains and the instances are inspected for all the clusters in Table 46. It is decided that the 5 clusters summarize the behavior in the best way. For instance, cluster 3 is presented in Figure 59.

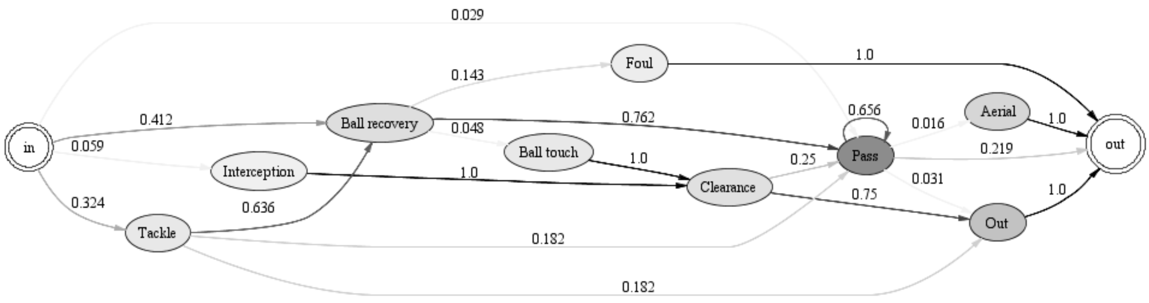


Figure 59. Markov chain for Iceland's team: cluster 3 with 34 instances

From the Figure above one can conclude that Iceland's team often is engaged in passing events (which is not that informative, as passes are the most frequent events for every team), but also events such as "ball recovery", "interception", "clearance" and "out". Furthermore, every time there is an interception, it is most likely followed by clearance, which is then followed by "out" with a probability of 0.75. This means that Iceland's team is quite successful in defending their half and intercepting the ball from the opponent's team.

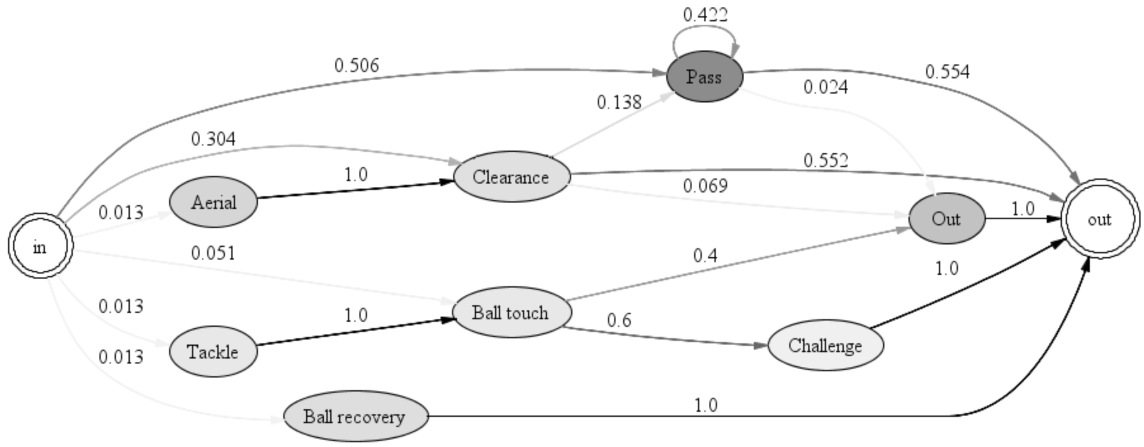


Figure 60. Markov chain for Iceland's team: cluster 1 with 79 instances

Figure 60 shows that a "tackle" is most likely followed by a "ball touch" which in turn is followed by "out" (with a probability of 0.4) or "challenge" (with a probability of 0.6). This means that following a tackle, for Iceland's players the ball goes out of play for a throw-in or goal kick (out), or a player fails to win the ball as an opponent successfully dribbles past them (challenge). By using further analyses which are offered by process mining, for instance, the dotted chart, one can also check which players are involved in these unsuccessful events.

Mining social and organizational perspective of a process

As mentioned in section 8.1., a process can be analyzed by looking at the organizational or social perspective. In the case of a football game, this mainly refers to viewing the process from the resource i.e., player perspective. The social network and dynamic network analyses consider one type of event (pass) to calculate various interaction metrics, which give diverse insights about the teams' structure and relationship between the players. In this part, all of the events available in the OPTA log will be considered to gain a deeper understanding of the relationships from the process perspective.

The first metric used in this analysis, is the ***Handover-of-Work*** (HoW) metric. Figures 61 and 62 show which players from both England and Iceland's teams hand over work to other players in all action sequences. Only direct succession is considered. The HoW can be displayed by using different SNA metrics, like degree, in and out degree, betweenness and closeness centrality. In this case, the degree centrality is chosen as it expresses the relation between the *in* and *out* degree of the connections between the nodes (ProM, 2017a). The graphs do not change significantly by using the other metrics.

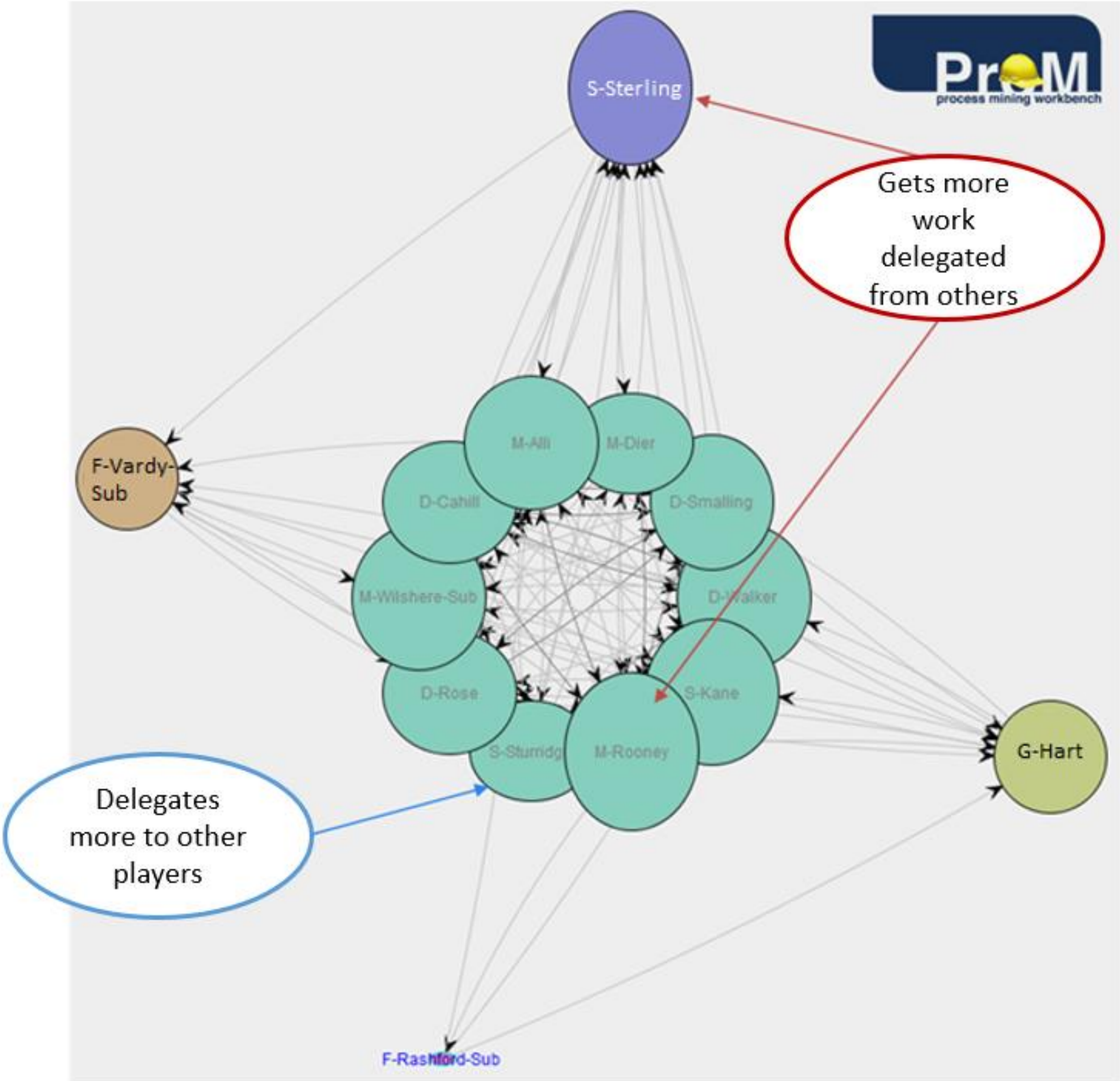


Figure 61. England - Handover of Work

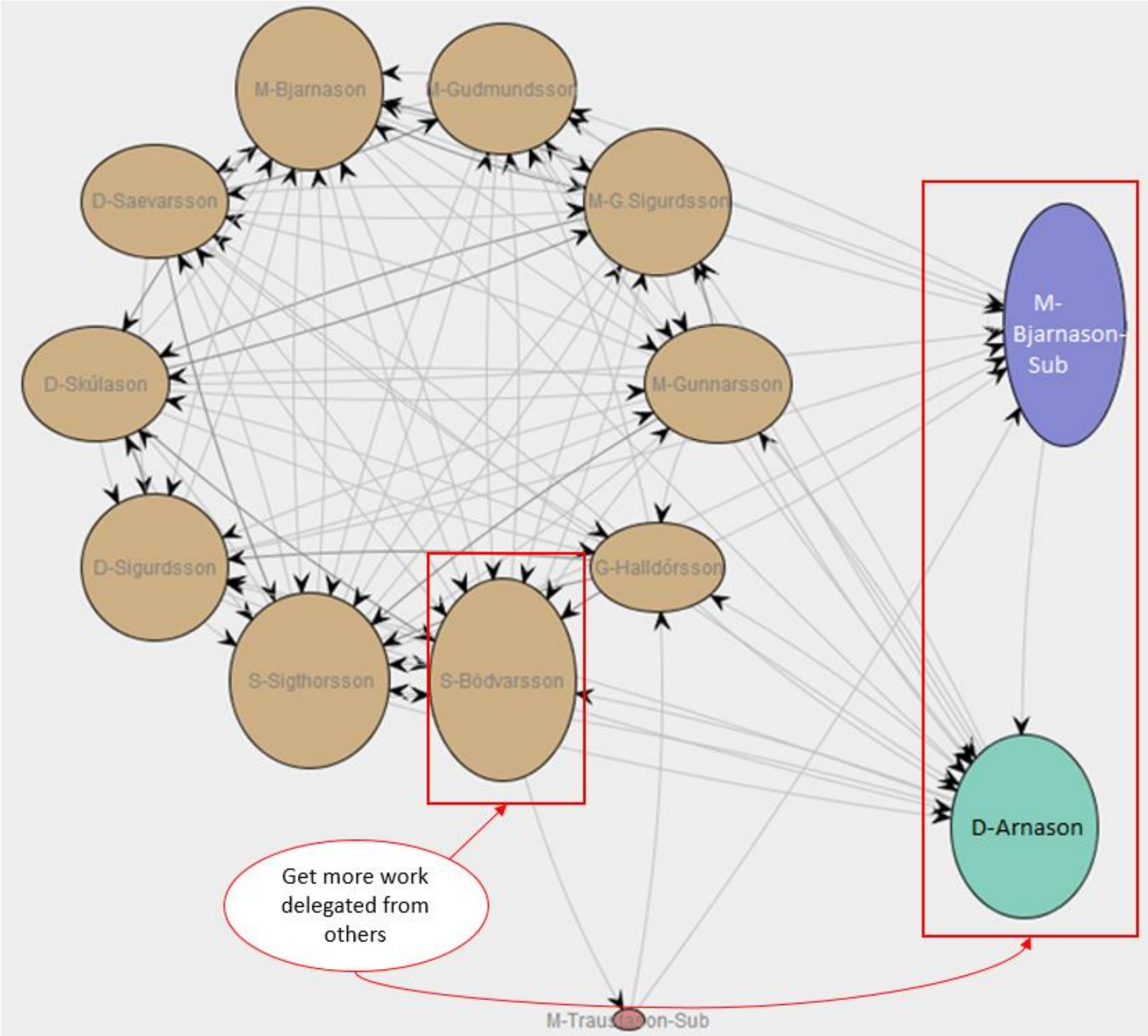


Figure 62. Iceland - Handover of Work

In Figures 61 and 62 the colors add a cluster point of view to get a better visual perspective. The oval shape also has a meaning. The more vertical shaped nodes have a higher proportion of ingoing arcs, while the more horizontal shaped nodes have more outgoing arcs (ProM, 2017a). In this case, the clusters do not change significantly by removing more edges, which means that players from both teams have, on average, good participation over the course of the game, and display balanced participation. There are a few players that distinguish themselves from the others, however. In Iceland's team, Bjarnason, a midfield substitute player has a distinctly vertical shape which means he gets more work delegated from the other players. Arnason, a defender and Bodvarsson, a striker, also gets more work delegated than they themselves did for other players. In general, strikers would perhaps be players who are expected to have more incoming than outgoing arcs due to the nature of their position and, thus, the tasks that are required from them. Defenders, on the other hand, would ideally have more outgoing than incoming arcs. In England's team, Sterling and Rooney display slightly more vertical shapes, but overall, all players have a more balanced handover compared to Iceland's team.

The second metric investigated is the ***Working Together*** metric. This gives an insight into which two players often participate together in the same attacking sequence – for example, they pass the ball to each other in the same sequence.

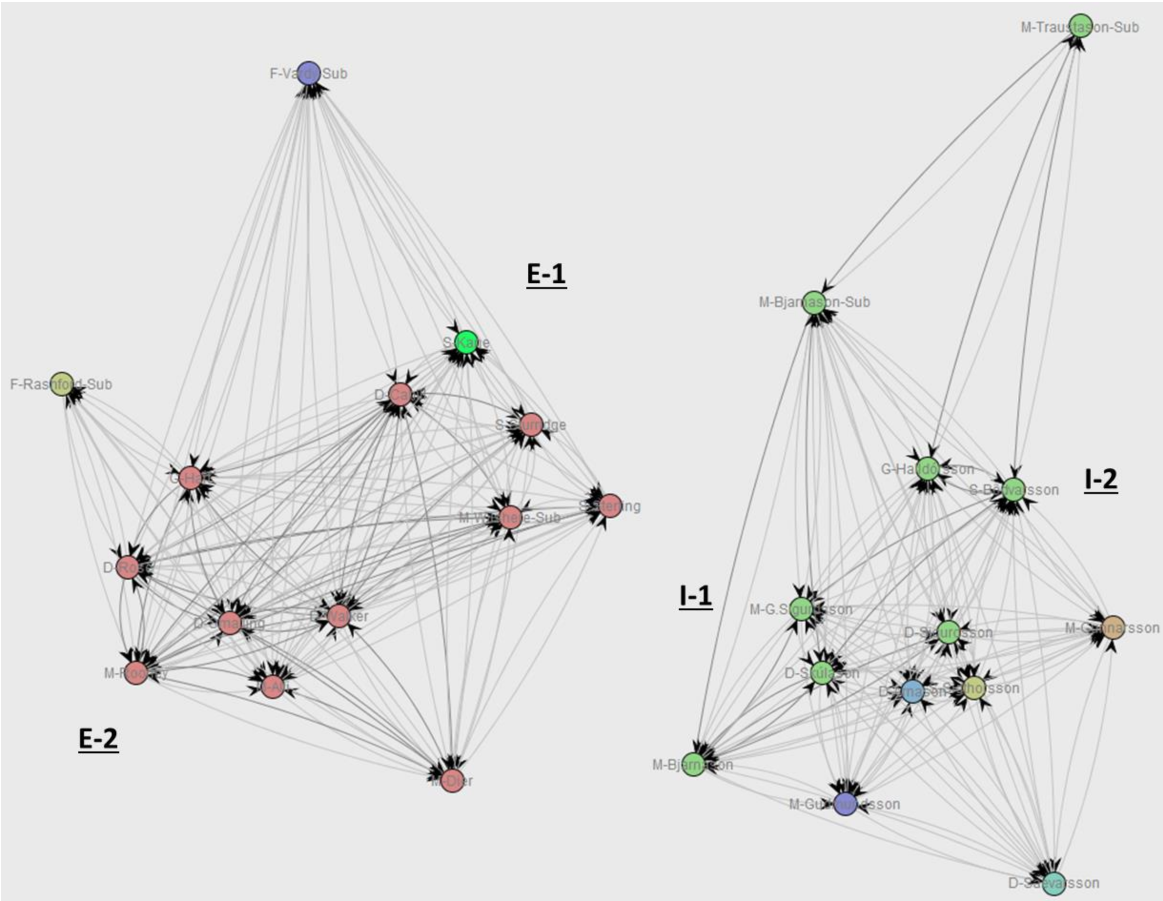


Figure 63. Working Together comparison between England (left) and Iceland (right)

The network graphs are generated by using the ISOM Layout and degree centrality. As it is the case with the HoW, the graphs are not too different if other network metrics are used. This layout algorithm shows that in the team of England there are two more distinctive clusters of players that work together during attack and which consist of most of the players in the team – cluster E-1 consists of five players (S-Sterling, S-Kane, S-Sturridge, D-Cahill, M-Wilshere-Sub); cluster E-2 consists of six players (M-Rooney, M-Alli, D-Walker, D-Smalling, D-Rose, G-Hart). Three players from this team are isolated from the clusters – F-Vardy-Sub, F-Rashford-Sub, and M-Dier. The two substitute players come in minutes 60 and 86 respectively, so it is not surprising that they are outside of a cluster. Dier, on the other hand, plays as a central midfielder, and therefore, has connections to both the E-1 and E-2 clusters. However, he is substituted at half-time by Wilshere, who did not perform well in an earlier match against Slovakia (Glendenning, 2016). From this SNA metric, Wilshere does appear to have stronger relationship with the players from the E-2 cluster as well. In Iceland's team, players are closely clustered together, with Traustason connected with the other substitute player, Bjarnason, the goalkeeper and Bodvarsson. The midfielder, Bjarnasson, appears to have the closest connection to Skulasson and Sigurdsson. The defender Saevarsson works together occasionally with the rest of his teammates but does not seem to have a stronger relationship with a particular player. In the case of defenders, this behavior could mean also that the defender, by the nature of his task, more often interrupts a sequence of the opposite team. Skulasson works together with Bodvarsson quite often.

8.6 Discussion

This chapter presents an exploratory study with the aim to evaluate the potential and suitability of process mining for football performance analysis. As seen, process mining is a collection of algorithms and analytics techniques which are widely used in other domains for analyzing all kinds of business processes. It has never been applied to sports, however. Not all algorithms and visualization techniques are demonstrated in this thesis and not all types of process mining can be used for performance analysis in football. As seen, the discovery type of process mining algorithms makes the most sense, as they can demonstrate the exact behavior of teams and players. The conformance checking type of process mining cannot be useful in this scenario because one does not have the perfect process model according to which players need to behave during the game. Enhancement of the process model does not seem to be useful in this case either. However, the discovery algorithms and techniques proved to be very useful for analyzing a football game from a process perspective. Table 47 presents a summary of the techniques and algorithms used and whether they give information about the team or the players.

Table 47. Process mining techniques and their insights in football

Perspective	Algorithm/ Analytics Technique	Type of insights
Case-flow perspective	Inductive Visual Miner	Team
Case perspective	Filtering of specific sequences (e.g., offensive)	Team and player
	Instances inspector	Team and player
	Dotted Chart	Team and player
	Meter chart	Player
	SOM trace clustering	Team
	Markov chain sequence clustering	Team
Social / Organizational perspective	Handover of Work	Player
	Working Together	Player

The *case-flow perspective* with the various types of algorithms for discovering the process model does not seem to be very useful in a football scenario. On the one hand, one can immediately see which event types occur the most often and how events are connected, but for some event types, this perspective is not useful. For instance, the event “foul” will appear in both teams, and it is not clear from the mined process model which team has made or suffered how many fouls. This is due to the way in which the sequences are extracted from the original dataset. As each event has different qualifiers, if all those are considered when creating the process model, there would be too many variants. As the idea of the model is to give a quick overview of what actually happened as well as some dependencies between the activities, such level of detail is omitted in the thesis. It is unfortunately not possible to avoid this issue. However, this is the case only for a limited number of events. This type of visualization, as the Inductive Visual Miner, can be normally used also to analyze the process from a time perspective i.e. to check which activities last too long and discover bottlenecks. However, due to the nature of football, analyzing this process model from the time perspective would make no sense. The other two perspectives, however, (case and social perspectives) are more useful for performance analysis.

The *case perspective* offers various useful visual analytic techniques and clustering algorithms which can give valuable insights into the team and player behavior. For instance, once the process model has been generated with the Inductive Visual Miner, it is possible to drill down and filter out specific sequences which are of interest for the analyst. In this case, the offensive sequences are filtered out, and this gives answers to questions like:

- How many times did a team’s action ended up in events leading to shot-on-goal?
- Which events are those exactly? E.g., miss, post, attempt saved or goal.
- Which players were involved`?
- When did these events occur and how long did the sequences last?

By using this option, it is possible to not only visualize the sequences leading to shot on goal for England’s team but also to find out which players mostly started or ended a sequence. These analyses can be very useful in assessing the value of a player in a game.

Furthermore, by using clustering algorithms like SOM and first order Markov chains, it is possible to gain a quick insight into the behavior of a team. Such analyses can be useful for example during the half-time break in order to make tactical readjustments for the second half. Finally, social network analysis is used in this case to gain more player insights. In this case, all event types occurring between the players are used in order to analyze their cooperation patterns. The two metrics that are applied, Handover of Work, and Working Together, prove to be valuable in revealing important information about separate players. For instance the Working Together metric can reveal which two players often cooperate in a sequence of ball possession, which in turn helps to plan tactical adjustments accordingly, especially concerning the defense of one own team. The Handover of Work metric can show which player is overwhelmed by having more work delegated from the other players. This could indicate fatigue or for the opponent can mean that that player should be the focus of their own defense.

To sum up, process mining does seem to offer valuable techniques and algorithms which give quick insights into players' and team's behavior. The results are usually quick and understandable, i.e. it is not too challenging to understand the results and visualizations, except perhaps for the SOM trace clustering. This type of analysis can be used for analyzing successful and unsuccessful sequence outcomes, establishing defensive strategies against specific players, and overall gaining insights from team and player behaviors. It is more user friendly compared to the T-pattern analysis. The sequences of events are clearer. There are also various options for additional analyses of the sequences as well as filtering out and focusing on specific types of sequences, e.g., offensive or defensive, sequences ending in a specific event, or sequences in which a particular player is involved, sequences that last longest, etc.

Process mining offers even more possibilities for analyses of the action sequences. Therefore, *future research* could explore whether the conformance checking type of process mining would be helpful in a football scenario. For instance, it may be possible to use conformance checking techniques to simulate and test the outcomes of sequences by enhancing the event log with other events.

Interim conclusion of Part III

Chapters 6, 7 and 8 demonstrate how network analytics methods, unsupervised artificial neural networks, and process mining techniques can reveal valuable information about the players' and teams' behaviors. The results in these chapters show concretely how such methods can be applied to answer specific questions about performance in football. In the literature, these methods have always been discussed as tools for pre- and post-match analysis. Here, however, many examples of applying these methods in real-time scenarios are given.

The *social network analysis* chapter demonstrates that a) network metrics at the team, player and sub-group level can support the coach and their teams with decisions regarding which player should be substituted; b) who the core team members are, and thus players that most likely should not be considered for replacement; c) the effect that a removal of a player has on the team behavior; d) change detection and its implications in practice, and e) ways to study team behaviors via various sub-group network metrics such as community detection and triad formations.

The chapter on self-organizing maps demonstrates how a neural network can convert a high-dimensional dataset consisting of 47 different event types in 35 matches into an understandable two dimensional cluster grid that reveals the dependencies between teams, match outcome and events they are involved in.

Finally, *process mining* techniques are used for the first time on sports event data. Although not every part of process mining is useful or suitable for performance analysis in football, quite a few of the available algorithms and visualization analytics options prove to be useful. Process mining allows for a quick inspection of specific sequences of interest for the coach and their team. It is possible to analyze specific plays that end in an event in which the coach is interested in, e.g., miss, shot on goal, dispossessed to name a few. One can filter out and inspect sequences in which a player is part of. Furthermore, it is possible to analyze the cooperation among teammates by using metrics from SNA with the difference being that in process mining, all events and not just the passes are included in the analysis. Sequences of play can be clustered together which allows for the behavior of a team to be summarized, by revealing the most likely way of play. One can use such information to prepare against an opponent. A summary of the techniques and metrics applied in each chapter as well as their purpose is included in Table 48.

Table 48. Methods and techniques used in Part III

Method	Metric/Technique	Useful for
(Dynamic) social network analysis	Player centrality metrics	• Evaluating the relevance of a player in a match • Useful for player substitution
	Immediate impact	• Examine the impact a removal of a player would have on a team's network • Useful for player substitution
	Core network	• Discover the largest subgroup in the team • Removal of those players is not advisable as it will most likely have negative consequences for the network structure • Can also be useful for player substitution decisions
	Team level network metrics	• Information on the interaction patterns of a team • Prepare against an opponent
	Dynamic network topology and network metrics change	
	Change detection	• Detecting a change in the network. • Useful for real-time tactical adjustment and study of opponent's team
	Community detection	• Detecting tightly connected subgroups of players • Useful for preparation against an opponent and real-time tactical adjustments
	Triads	• Understanding better how players from own and opponent's team are interconnected • Useful for real-time tactical adjustments and pre-match strategy
Self-organizing maps	Unsupervised neural network architecture	• Tactical understanding of team behavior • Visualization of high dimensional data

Table 48. Summary of methods and techniques used in Part III (continued)

Method	Metric/Technique	Useful for
Process Mining	Attacking play sequence inspection	• Examining specific sequences of interest which end in a specific event or involve a specific player • Determining the value of a player by considering sequence starters and sequence end-ers
	Dotted chart Meter chart	• Visual inspection of team and player behavior • Positive or negative events players are involved in • Good for quick analysis beyond event frequencies
	Sequence of play clustering with Self-organizing Maps and Markov chains	• Summary of the team behavior • Good for revealing typical (normal) and unusual behavior of a team • Suitable for pre- and post-match analysis mostly
	Social Network Analysis on event data	• Shows the interaction patterns between players involving all events and considering different perspectives e.g., who “hands over” the most to whom; or players that work together most of the time • Suitable for pre- and post-match analysis as well as real-time

Part IV discusses further the application of the results in a real-time decision support use case for player substitution. It establishes a link between the findings in Part II and Part III.

Part IV – Decision Support Application

9 Use Case

The objectives of this chapter are twofold. First, an analytics framework for real-time decision support is created which aims to give a concise overview of the data and methods available, factors relevant for the coaches, and establish a link between them. Such a framework should aid coaches and their team in practice when deciding on an analytics strategy. Second, a mock-up is created which demonstrates how a decision support solution based on the data analyses could look like in practice.

Parts of the results outlined in this chapter have been published in Davcheva et al. (2016). This chapter extends and discusses the research.

9.1 Requirements for real-time decision support in football

9.1.1 Real-time decision making in football and the necessity of data-driven decision support

As discussed previously, most of the analytics results in football performance analysis have been used for various decisions pre- and post-match. The use of analytics for decision making in a real-time scenarios, i.e. during a live game, has not been thoroughly discussed. However, this is becoming an increasingly relevant topic that needs to be addressed by the research community considering the recent developments and usage of various technologies during live matches. Additionally, there are studies in the performance analysis literature discussing the design and usefulness of a notational analysis system, and the usefulness of feedback by computerized systems in football. The findings from these studies are used as a basis for the conclusions and recommendations in this chapter. Moreover, previous chapters present several analytical techniques on event tracking data and discuss the results and their usefulness for tactical decision support. A few of these methods and techniques can be useful for real-time decision making during live matches. There are two main factors that drive the development of real-time decision support in football based on data analytics.

The first factor is related to the decision making process of football coaches and humans in general. During live matches, coaches need to make decisions quick and under pressure. Even though coaches are normally experts who have long experience, making a decision in such circumstances is not straightforward. Furthermore, several studies in the literature show that the observations of coaches and their recollection of events are subjective and often in error (Franks and Miller, 1986; McDonald, 1984); in two additional studies, coaches could recall only around 30 percent of factors that lead to successful performance in football and were less than 45 per cent correct in their post-game assessment of the events happening during the game (Franks and Miller, 1986; Franks and

Miller, 1991b). Another study also found that experienced coaches were more likely to report a difference in performance when none existed and were very confident in their decisions, even when incorrect (Franks, 1993). This memory issue is compared to the testimony of witnesses of crime scenes as these can often be inaccurate or incomplete, depending on the degree of violence, the number of perpetrators, or focus of attention during the crime (Franks, 2004). Similarly, in a sports scenario, coaches can have a different excitement levels throughout the game. What is considered important differs from game to game, and coaches tend to direct their attention to more central features of performance, ignoring the non-critical events or their sequence (Franks, 2004). Lastly, personal biases are also a factor that affects the ability of coaches to give an accurate and objective account on the events that happened (McDonald, 1984). Thus, it is important that coaches base their decisions on objective information, as an error in the observation and evaluation of match performances can have “knock-on” effects on the match outcome and the entire coaching process (Carling et al., 2005).

To tackle the issues associated with proper recollection of events, back in 1986, Franks and Goodman suggested that one solution is to record the occurrence of behavioral events in some coded form. This refers to what is now known as notational analysis. At that time, however, the problem was to conduct comprehensive, sequential analysis completed in real-time (Franks and Goodman, 1986). This is no longer the case as nowadays there are various tracking companies collecting event and fitness data.

The second driver behind a real-time data-driven decision support in football is the rapid development and adoption of technology in football, especially pre- and post-match. Nowadays, technology is being used in live matches to support the referees (still controversial), and the opportunity to use it for medical purposes and injury prevention are being worked on. There have been a few instances when the use of data-driven decision support during live matches has been discussed, e.g., at the MIT Sports Analytics Conference. Recently, the tracking company ChyronHego published an article on its blog in which it is mentioned that “*to have the capability to access player performance data from the team bench during the game is the next crucial step…*” (Gederman, 2018). This is one of the rare cases a professional tracking company discusses this publicly, but they do mention that this has not been done previously and that they are testing the concept with several European clubs.

9.1.2 Requirements for a decision support solution

One of the first challenges for a data-driven solution in football is the large amount of potentially interacting variables in any one game (Franks and Goodman, 1986). This leads to the question of finding the right way to model a football game. It is a huge research area, and a model that is able to describe the behavior of football players in mathematical terms is not yet available. Thus, it is up to choosing the right performance indicators and other measures that will provide coaches with the most relevant information for making crucial decisions during live matches. The challenge in this case is that there are a lot of performance indicators which vary per player position and which in the past decade have proven to be not entirely useful for determining success in football. Most notable example is the ball possession as an indicator. A team that has higher possession is not necessarily a more successful one.

Thus, an important first requirement is that the solution displays only the *most relevant information*. A wealth of data means that coaches and their staff will have to dedicate more time in evaluating the information and discussing possible actions (Maslovat and Franks, 2008). Therefore, one of the first steps in developing a solution is to determine what exactly is relevant for decision makers, in this case, the coaches. This is a challenging task as coaches can have different perceptions on what is relevant and what is not. However, chapter 4 consolidates findings from the literature and a qualitative study with football experts. As a result, several categories of factors which are important for coaches for real-time decision making can be identified. Another issue is that coaches sometimes consider different aspects of the player performance as relevant. This is a common knowledge and not surprising but it is confirmed in the qualitative study (see chapter 4). Therefore, another important requirement for a solution is that it is *flexible and adaptable* to coaches' wishes. This means that it should be possible to add and remove functionalities and relevant metrics and performance indicators depending on what the coach would like to work with. Similar conclusion is reached by Davcheva et al. (2016) following a survey with football analysts and coaches working with various technology solutions to analyze team and player performances.

The decision support solution would be delivered most likely via a graphical user interface by, for instance, using dashboards. Below are a few requirements for the UI:

- *Ease of use* – it should be straightforward and clear to coaches how to navigate through the dashboard in order to get the information they want without too much effort.
- The charts and graphs should convey a *single message* and needs to be accompanied by a descriptive title, annotation and labels (Power, 2013).
- More *historical data* should be available to allow users to compare metrics of interest to previous matches (Malik, 2005).
- There should be *no delay* in retrieving information from the dashboard (Malik, 2005).
- The solution needs to be *scalable* and allow for more users to simultaneously be logged in without causing it to crash or delay (Malik, 2005).

A data-driven solution should also include information on the behavior of the players when they are not in touch with the ball, as for a significant portion of the game players do not have a ball contact (Maslovat and Franks, 2008). This is not possible to achieve with the Opta data as these focus on event tracking, which records all events during the game, and thus, mostly reflects the ball related actions. It is an important aspect of the performance by all means, but certainly not the only one.

In this thesis, analytics techniques from three different methods are used in order to transform event data into a useful information for coaches. They require different preprocessing efforts:

- Social network analysis – Compared to the other analytics methods, the SNA metrics require relatively less data processing. Specifically, successful passes between the players need to be extracted in order for most calculations to be possible. As soon as that is done, however, the calculations are extremely fast and reliable. In return, it is a powerful tool that gives information regarding the communication patterns, and the sources and sinks of influence in the team, allowing identification of those players that can most effectively influence the team (Bennet and Bennet, 2008).
- Self-organizing maps – This method requires the most data preprocessing effort and is thus recommended only for decision support during the half-time break. Additionally, it is the most sophisticated method used in the thesis, at least considering the preprocessing effort together with the parameters tuning required. Therefore, a specialist in this area is required to build and test the model before it is implemented in the solution. Some of the questions that need to be answered in advance are: a) what is the right size of the lattice; b) which are the input variables and how can they be normalized; c) what should be the setting for each parameter, especially learning rate and momentum; d) what is the desired error level; e) how long to train (Delen and Sharda, 2008). It is thus important to hide the complexity of the model from the end user (Delen and Sharda, 2008). This is equally valid for any other complex method that can be used for decision support solution during a live match.
- Process mining – Preprocessing steps are not too simple and not too complex. However, once the data is processed, most of the calculations run fast. It is the least useful of the methods for real-time decision support, with a few exceptions.

Finally, a solution based on data will require a trial and error period, even more so than other decision support systems and solutions. Besides, the technology will keep developing further and more sophisticated solutions will make the whole process of data collection, integration and processing easier.

9.2 Analytics framework

The framework presented below aims at giving a starting point to coaches and their staff when developing a real-time decision support solution (see Figure 64). It is based on the widely used DIKW Hierarchy (Data, Information, Knowledge, Wisdom) used in knowledge management and unifies the results from the qualitative and quantitative studies in the thesis. The structure of the framework is presented in Figure 64.

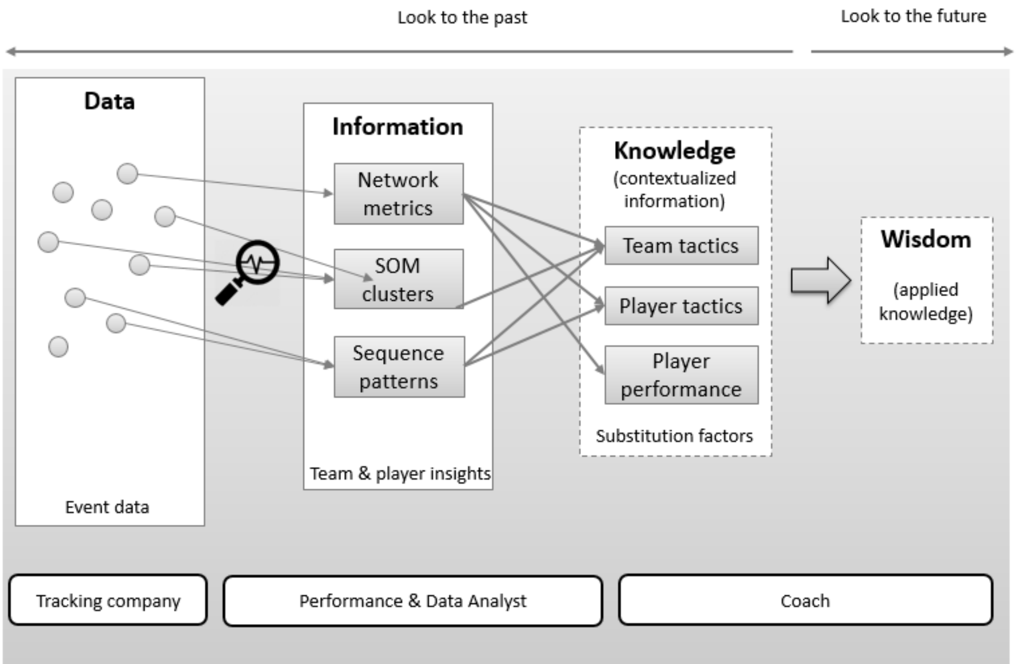


Figure 64. Analytics framework for real-time decision support

The original framework was developed by Russell Lincoln Ackoff in 1989 and represented as a pyramid. Data is at the bottom of the pyramid, while wisdom at the top – to show that there is a lot of data, and little wisdom (Bernstein, 2009).

Data refers to symbolic representations of some observable properties of items or entities (Frické, 2009). Data are the unprocessed raw representations of reality (Anand and Singh, 2011). An overview of the data available in football nowadays, together with the most important applications of these data, is given in Figure 65.

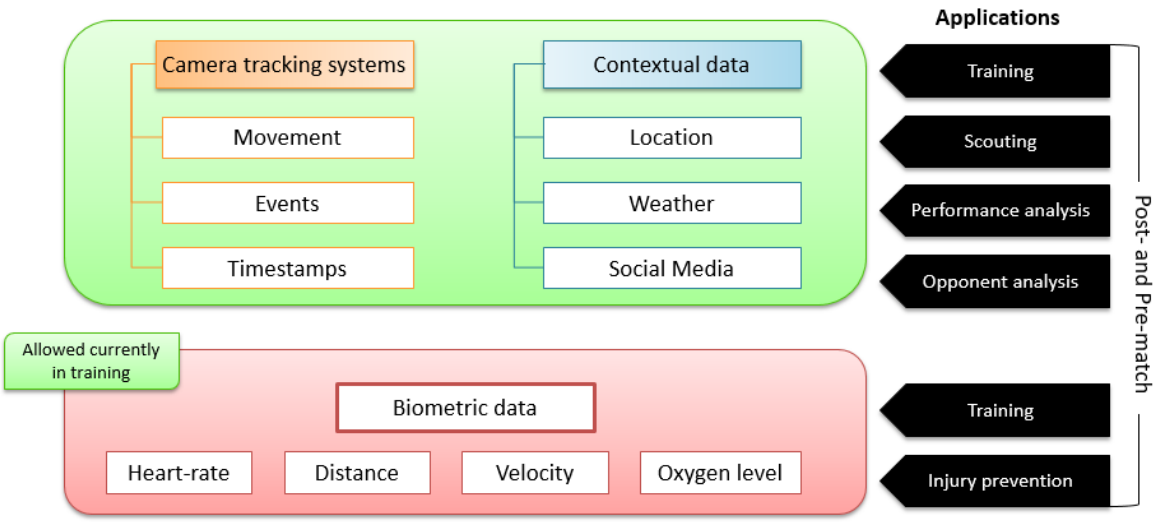


Figure 65. Data available for football performance analysis
Source: Self-compiled based in part on Stein et al., 2017

While the thesis works with event data and timestamps, positional data via GPS devices is also being collected in real-time. It allows to have a detailed information on the position of each player and the ball during any moment of the game. Additionally, wearable devices specifically designed for football, give important biometric information like heart-rate, distance, velocity speed, or oxygen level. Unfortunately, at the moment, biometric data is only available during training. However, these data can be a valuable source in calculating the fatigue rates of players during the game. It is also related to injury prevention – for instance, one might notice that over a period of time a player is getting increasingly tired in the 2nd half of a game, or more than their usual. A coach might decide to spare him to prevent an injury for a future more important match. The contextual data are not the most relevant category but are included for completion. Location refers to whether the team plays home or away, but for a real-time decision scenario this does not necessarily affect the analytics processes. Weather is information the coaches would require before a match while during the match it has perhaps minimal influence on the decision making process. Finally, social media is an interesting source of data that is normally used for fan entertainment rather than decision making, yet alone in real-time. Arsene Wenger, however, the former manager of Arsenal FC, predicted last year that social media opinions of fans especially via Twitter, would end up deciding which player should be substituted (O'Brien, 2018). Such prediction probably is far-fetched at the moment, but there is a strong tendency towards using data when it comes to deciding on who should leave the game.

Information is data which have been processed in a meaningful way and make decision making possible (Anand and Singh, 2011). It is data related to each other through a context and providing a story, as for instance, the linking of who, what, when, and where data to describe a specific person at a specific time (Jennex, 2009). In this case, the information results from the three methods and techniques from network science, SOM neural network clustering and process mining.

As to the information that a decision support solution should give as output, a guiding base are the factors relevant for substitution identified in chapter 4. Most relevant factors are the performance of a player, tactics and fatigue. Analyses of the opponent team are also considered important. An overview of how these factors are derived from an event tracking data as well as the data analysis methods are outlined in Table 49.

Knowledge further refines information by transforming it into instructions, which makes control of a system possible and enables it to work efficiently (Bernstein, 2009). Knowledge is construed usually as a know-how or skill and not as know-that of propositional knowledge (Frické, 2009). In more simple terms, knowledge explains the why and how of something or provides insight and understanding of something (Jennex, 2009). In this case, if the CUSUM metric, for example, informs the coach that a change in the betweenness centrality has occurred, and via continuous analysis and observation it is established that every time a certain degree of change in this metric leads to decrease in performance – this would be the knowledge obtained.

Wisdom allows the knowledge to be applied in different and not necessarily intuitive situations (Jennex, 2009). It is achieved by applying the knowledge into practice. It is the highest level of abstraction, with vision, foresight and the ability to see beyond the horizon (Anand and Singh, 2011). Using the same example with the CUSUM metric, wisdom is achieved when the coach and his staff know which actions to undertake in order to tackle decreased performance due to the change in the betweenness centrality metric. Wisdom is not discussed here in detail because it is reached after the information and knowledge obtained by a decision support solution are actually implemented in practice by coaches and consequences are observed. It would be only possible to discuss this category after a data-driven solution has been successfully implemented and used in practice for a prolonged period of time.

In the thesis, the major focus is on data and information parts of the framework. This is elaborated more in Table 49.

Not all analysis conducted in the thesis are useful for a real-time decision support scenario and not all are helpful for player substitution. From Table 49, it is clear that there are various player level network metrics that are useful in order to assess the importance of a player in a team network. Additionally, the core network and immediate impact are very useful calculations which give straightforward information to coaches about the relevance of a player. By using these metrics, the coach can gain a quick and reliable information during the game, that can help him decide whether a player should be substituted or not. Change detection is another useful metric that shows when something in one’s own team has changed and it can help to make some timely adjustments of the strategy. The positive aspect of this metric is that it can be based on any of the network metrics of interest (e.g., betweenness centrality, efficiency, etc.). The triads give information on the interaction patterns of the team including the direction of communication. This can be used especially for opponent analysis during the game. For instance, when the coach knows what the strongest communication triad in the opponent’s team is, he can instruct his players accordingly to be more attentive of those players in the triad and perhaps interrupt the ball flow between them.

Self-organizing maps are a great analytic method which can convert a highly dimensional data into visualization that is easier to understand. Although not the most intuitive or the quickest method, it can be used in the half-time break to gain a quick understanding of the opponent’s team tactics.

The process mining techniques are not as useful for real-time decision support. Two visualization techniques – the dotted and the meter chart can be used for a quick look into the activity profiles of players. The social network analysis on the process data is the most useful technique in this case, because it can give additional insight into the way players interact with each other. It can reveal valuable information about players from the opposite team and help the coach make tactical adjustments during the game.

Table 49. Data and information useful for real-time decision support

Data	Method/ Technique Used	Information	Elaboration
Passes Timestamps	• Authority • Betweenness • Closeness • Contribution • Eigenvector • Hub • PageRank • Degree centrality	Player centrality metrics	Who is the most important player in terms of connection to other players, ability to keep the team together? Who is a leader and has the potential to organize his teammates? Which player is the weakest link in terms of interconnectedness?
	Team level metrics: • Overall Complexity • Diffusion • Clustering Coefficient • Characteristic Path Length • Social Density • Average Communication Speed	Immediate Impact	What is the immediate impact on a team when a specific player is removed? How will it affect the team structure and efficiency?
	• Degree Centrality • Betweenness Centrality	Core Network	Which of the players form the largest and most connected subgroup in the team?
	CUSUM	Change Detection	Detect that a change has occurred in the team. This change can refer and be based on different metric of interest.
	Triad Count Formula	Triads	Understand better the interaction patterns of own and opponent's team.
All Events in a Match	Self-organizing Map	Clusters	Gain a quick understanding of the opponent team's tactics during the break.
All Events Timestamps	Dotted Chart	Activity Profiles of Players	Discover which player was less active, or was involved in negative events and when.
	Meter Chart	Player Comparison	Quickly compare the efficiency of e.g., defenders.
	Social Network Analysis	Working Together Handover of Work	Understand better the interaction patterns of own and opponent's team. Find out which players delegate the most work and which players cooperate the most.

9.3 Decision support solution mockup

A mockup of a decision support solution is developed. It is used to demonstrate how the mentioned techniques for real-time decision support can be implemented in practice, and how coaches can benefit from that information. Not all possible analyses for real-time decision support are integrated in this mockup as the focus is primarily on decision making regarding player substitution. However, the mockup gives an idea on how a solution for real-time decision support should look like in practice. The mockup is presented in Figure 66 (player analysis dashboard), Figure 67 (own team analysis dashboard), and Figure 68 (opponent analysis dashboard).

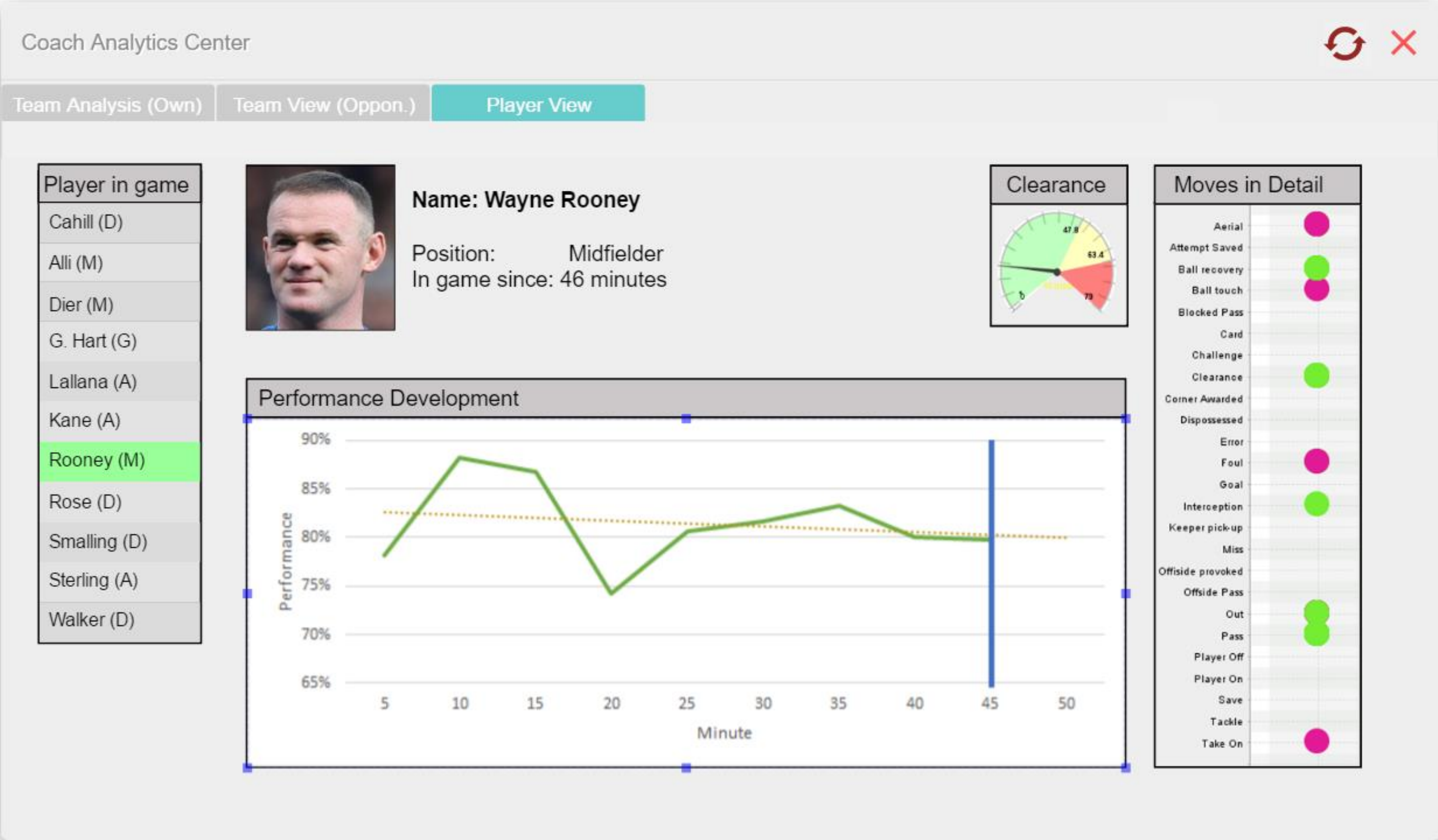


Figure 66. Player analysis dashboard

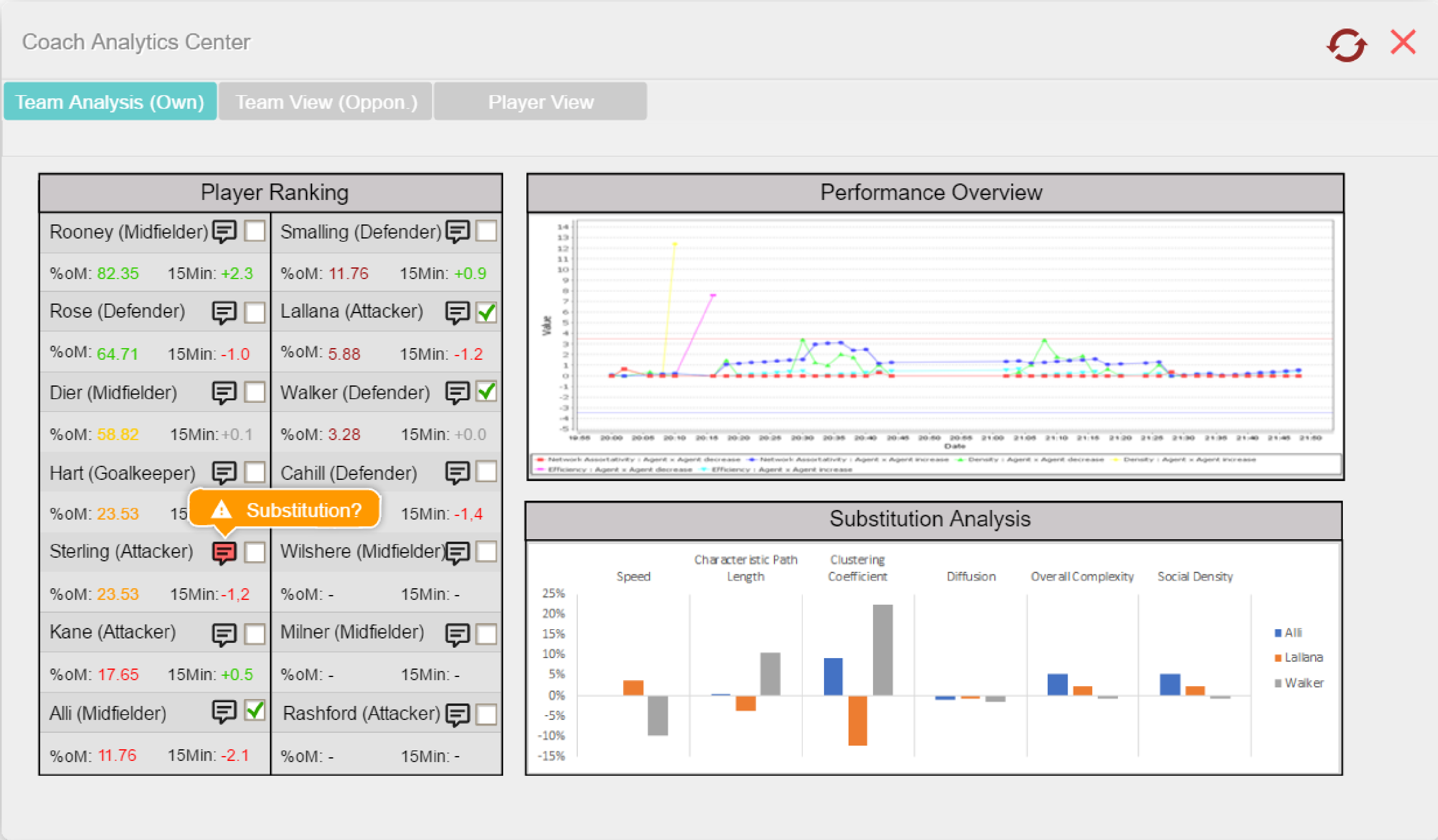


Figure 67. Own team analysis dashboard

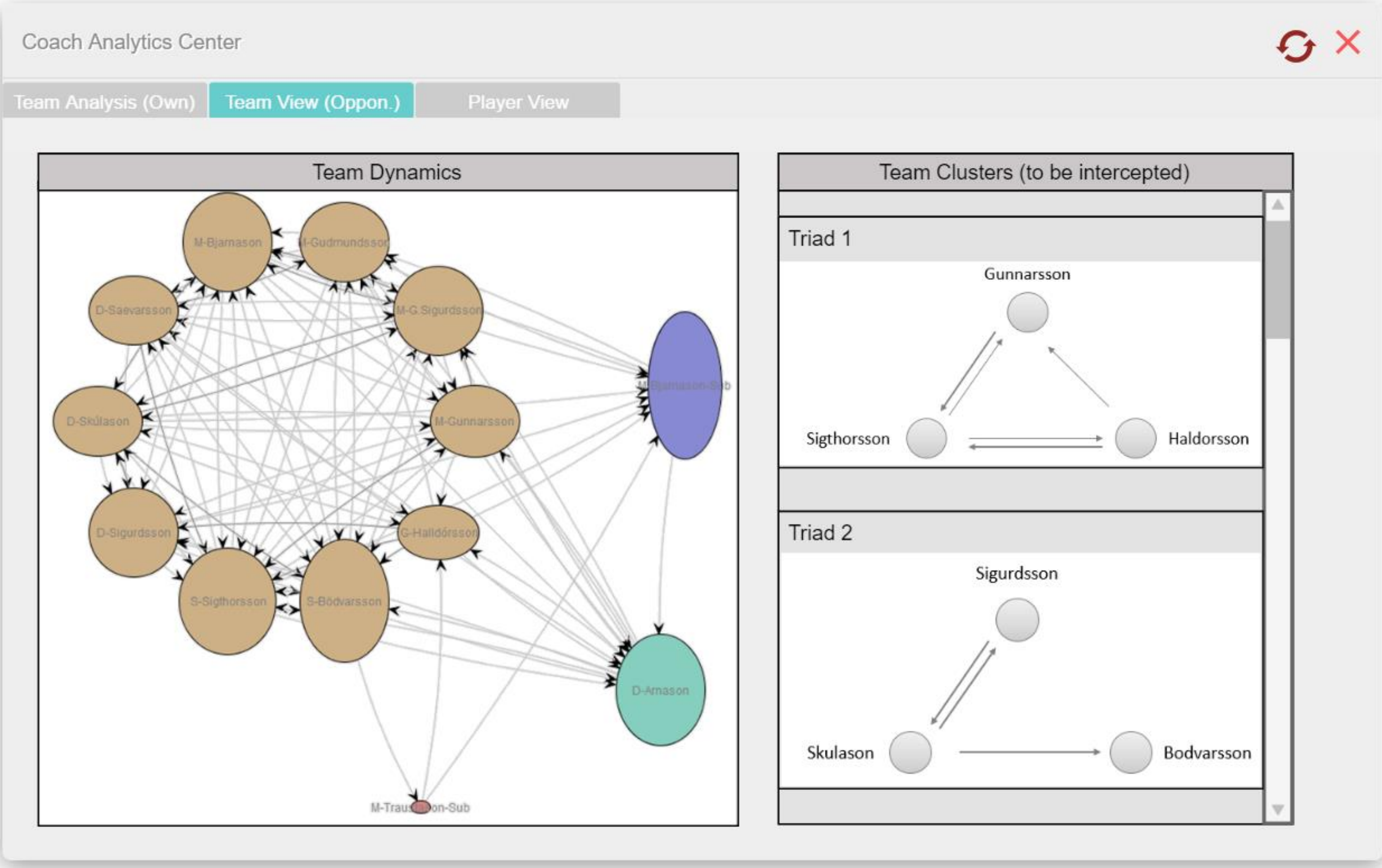


Figure 68. Opponent team analysis dashboard

The mockup dashboards contain information about the performances of players (own team) as well as performance and tactical information at the team level (own and opposition teams).

Figure 66 presents the ***player view dashboard***. This view shows a list of all the players currently in the game (left side of the dashboard). The coach can click on a player's name in the list and he can view information on a) the performance development of that player during the current game (in the mockup dashboard the performance development is visible for the first 45 minutes of the game); b) an information on an event that is relevant for that player's position – in this case clearance as Rooney is a midfielder (this event can be changed based on what is important for a specific player position); and c) an overview of the events in which the player has been involved in the current game as well as the outcome in each of these events (red for negative outcome, and green for positive). The meter chart and the dotted charts from process mining are used in this dashboard as well as player level network metrics are used for the performance developemtn chart which shows the overall performance of the player in the 1st half of the match.

The ***own team analysis dashboard*** presented in Figure 67 shows ranking of the players as well as a tendency of performance improvement or performance drop in the last 15 minutes of play (left side of the dashboard). The ranking is based on calculation of several network metrics as discussed in section 6.5 (see Table 21). When the performance of a player is quite low compared to the rest of his teammates, the coach gets a warning message which suggests that this player should perhaps be considered for substitution. On the right side of the screen, additional information is displayed. First, a change detection chart based on the CUSUM metric (see section 6.5) monitors a few network metrics on team level and displays alert messages when a significant change in one of these metrics occurs. The choice of monitored metrics depends on the coaches and this can be easily modified. The second chart is focused on substitution analysis by using the "immediate impact" calculation as discussed in section 6.5. It shows the impact of removing the three worst performing players currently in the game. It gives coaches an idea of what could happen when one of these players is removed from the game and is supposed to help them decide, especially when they are having doubts or considering more than one player for replacement.

The ***opponent team analysis dashboard*** in Figure 68, gives information on the dynamic interactions of the players from the opponent's team. On the left side of the screen an overview of the opponents' interactions is given by using the Handover-of-Work metric as discussed in section 8.5. It shows which players from the opposing team are most overwhelmed by, for instance, receiving a lot of passes from their teammates. In this context, such information can be very valuable during a live match because it gives a clear picture of the way the players from that team cooperate with each other. When the coach knows which player receives more work delegated from his teammates, he can instruct his team to pay more attention to that player, and be closer to him. To make this easier on the coach to interpret, additionally on the right side of the screen the most relevant variants of interactions between the players are displayed by calculating the triads as seen in section 6.5. These analyses give an even more concise idea of how the players from the opposing team interact with each other. For instance, based on the information from triad 1 in Figure 68, it is clear that Gunnarsson and Sigthorsson interact often with each other, and moreover, the direction of this communication link is primarily from Gunnarsson towards Sigthorsson. Knowing this, the coach can instruct his players to pay attention to these two players and try to intercept the passes between them.

The dashboards presented here are all based on part of the results presented in chapters 6, 7 and 8. Those analyses are done based on the factors relevant for decision making in live matches identified in chapter 4. When a solution is developed for a club, one of the first requirements is to decide which information exactly needs to be displayed, i.e. what does the coach need to know to make tactical adjustments during the game. As soon as this is clear, analytics options can be discussed in order to be able to derive the needed information. As mentioned in section 9.1.2, it is important to keep in mind the amount of pre-processing steps the chosen methods would require, as well as the type and amount of data needed and finally the amount of time needed for the actual analysis. Most importantly, every data solution needs to be adjusted to the individual wishes of the coach who is supposed to use the results, and not vice versa (Carling et al., 2005).

In any case, as Carling et al. (2005) mention, errors can occur most likely due to:

- Disagreements on match criteria or definitions of game actions. For instance, if the coach wants to see successful attacks, it has to be clearly defined what this means exactly – and it can mean different things to the performance analyst or the coach.
- Difficulty or misinterpretations in understanding the results. This happens mostly by using statistics that poorly represent the actual performance of the players.
- Inadequate, too many, irrelevant, inaccurate or poorly presented results. When in doubt, it is best to keep it simple and concise, and not create too overwhelming dashboards.

Finally, all the results in the dashboards need to present the state of the team and player performance in specific time intervals. These can be determined by the coaches themselves. For instance, the player ranking in Figure 67 is based on continuous calculation of several network metrics at the player level in an interval of 5 minutes. If the coach would like to have the latest status, however, he can click on the refresh button in the upper right corner. In this way, he can always see the latest calculations regarding the information he is interested in.

10 Conclusion

10.1 Summary and contributions

This thesis addresses the question of supporting coaches and their team regarding tactical decision making in football, with special focus on real-time decision support. In football, there are various data available that can give a detailed picture of player and team performance. Based on event data, for instance, one can analyze the technical and tactical aspects of performance, while data extracted from wearables can give an idea about the physical performance. Although at the moment not every kind of data gathering is allowed during live matches, this will soon change. Tracking companies like Tracab are already working on solutions for real-time data monitoring and decision support. However, research in this area has been scarce, and analytics has been mostly researched for pre- and post-match analysis decisions. Thus, there is a noticeable research gap in the performance analysis literature on decision support during live matches. The types of analysis that are used for pre- and post-match decision making are different than those needed during live matches. On the one hand, making a decision during the match means that the decision is done in a stressful situation, taken short-term and should have an immediate impact on the game. On the other hand, decisions during live matches address other issues than what is important pre- and post-match. One of the biggest issues during a live game is which player should be substituted. Coaches have currently the right to substitute three players. Considering risks of injuries, unexpected events like red cards, this is a decision that can have a real impact on the match outcome.

The substitution decision is one of the most important tactical decisions during a match. It is the main way in which a coach can influence the game outcome. In literature, substitution has been researched mostly from the perspective of finding the perfect timing or the perfect rule which is supposed to help coaches decide when to substitute (see section 4.2). A qualitative study with coaches and football experts, reveals that this is not what coaches are interested in. In fact, they do not believe that there is the perfect timing or rule for substitution. What matters to them is the player performance during the match and how they can change their tactics (including by choosing the right player to substitute) during the game (see sections 4.4 and 4.5). A number of factors are relevant to coaches for decision making during live matches. These are identified and discussed in chapter 4.

The thesis uses professional event tracking data to demonstrate how coaches and their staff can make tactical adjustments during (or also after) the game based on data analytics. Methods and techniques from three different areas are used: network science, self-organizing maps, and process mining. Each of these analytics methods has advantages and disadvantages and takes a different perspective of the team or player performances.

S*ocial network analysis* focuses on the interactions between the players during the game. Specifically, the passes between the players as the main form of interaction that occurs during a football match. Network science is a huge field of research and there are quite a few concepts and metrics that can be tested in a football scenario. The literature on football performance analysis and network science has so far focused on a limited number of network metrics and their usefulness in football (see section 6.2). The thesis demonstrates concretely the usefulness of new metrics such as the authority and network assortativity metrics, the CUSUM change detection metric, the concepts of core network and immediate impact, especially for the decision of player substitution. Additionally, the triadic relationships are discussed as well as the potential of community detection algorithms and their (non)usefulness in a football scenario (see section 6.5). All of these network metrics and concepts are used for the first time for football performance analysis and demonstrate concretely how they can be applied for decision making by coaches.

Self-organizing maps (SOMs) are a special type of unsupervised neural network architecture that has been recommended by several authors in the performance analysis literature in football, but not widely applied on actual data. One of the reasons is the lack of data availability, as the method usually requires a lot of data. In this thesis, the method is used on real event tracking data to demonstrate how tactical differences between favorite and underdog teams can be quickly revealed by SOM cluster analysis. It is a useful method for converting high dimensional data into understandable, two dimensional maps. It is not the most convenient method for real-time decision support but it could be useful, for instance, for quick tactical insights of the opposition team during the half-time break (see chapter 7).

Various techniques and algorithms from the area of *process mining* are applied on event data in chapter 8. These techniques consider the action/event sequences in order to describe the behavior of the players and teams. Process mining offers useful visual analytics techniques such as the dotted chart, the meter chart as well as filtering out specific sequences that are of interest to coaches. The thesis demonstrates how by filtering all offensive sequences it is possible to find out immediately which players are mostly initiating or ending an attack. This is an important information that reveals the value of a player (see section 8.5). Additionally, self-organizing maps are used for clustering event sequences to reveal the behavior of teams. It gives an impression on whether the team exhibits a more creative or more similar behavior (i.e. sequences are more similar to each other). Process mining has not been used previously for analysis of event tracking data in any sport. Thus, this chapter also has a methodological contribution to the field. It demonstrates a new type of method for analysis of player and team behavior in football.

Finally, the last chapter puts the results from the qualitative and quantitative studies into perspective and discusses their usefulness for real-time decision support. Not all of the results are useful for real-time tactical decision support and especially player substitution. Those methods and techniques that are useful, are integrated in a mockup to illustrate a real-time decision support solution. It demonstrates how results from analytics methods used in the thesis can be integrated into a decision support system. These kind of solutions have not been thoroughly discussed in the literature. There are quite a few options for future research in this regard.

10.2 Limitations

One limitation is that only event data is used in the analysis. Even though this is a detailed account of the game, it does not give a full picture of the performance and behavior of the players and teams. Combined with biometric data, it can offer a very detailed overview of all facets of the player and team performances. As biometric data is currently not available during live games, there is, unfortunately, no possibility to demonstrate how all these data can be used for decision support during the game. Furthermore, the thesis uses methods from network science, neural networks and process mining to gain insights from event data. There are certainly more analytics methods and techniques that can be applied on event data in football to gain further insights (see section 10.3).

Finally, the mockup in chapter 9 focuses on player substitution and integrates only parts of the techniques used in the thesis. Most importantly, it is not tested or evaluated in practice. However, the mockup in itself is not the main focus of the research project, and is thus not discussed in more detail. It needs to be addressed in a separate study which will focus entirely on the design and implementation of a decision support solution for real-time analysis.

10.3 Future research

The thesis is one of the first studies that uses event tracking data and demonstrates how these data can be used for real-time decision support in football. Thus, there are several directions for future research.

Social network analysis – as mentioned, network science is a vast field of research and there are still many options for further research in this area. For instance, agent based modelling is something that has recently become popular. There are many network metrics at team and player level. Future studies should make a thorough analysis and attempt to link metric and their values to player positions. For instance, an attacker probably should not be evaluated negatively if he has a lower betweenness centrality. Every player position has specific requirements. Those should be linked to various network metrics that reflect that. Another question that can be further explored is whether a football team is a scale-free network. Some authors have suggested that as there are players within the team that act as hubs, a football team can be considered to have the properties of a scale-free network. However, there is not enough evidence to support this view, yet.

Self-organizing maps – this method has been applied to movement analysis in football, while the thesis demonstrates how it can be used to gain a quick overview of the tactical patterns of a favorite versus underdog teams. In addition, SOMs were used to cluster action sequences in the process mining chapter. Future studies could cluster teams and players based on variables from social network analysis. One option is to cluster players based on their network metrics values in a game and try to find out whether there is a connection between the values of some network metrics and winning or losing the game.

Process mining – the thesis shows that the discovery part of process mining offers useful techniques and algorithms to find behavior patterns of players and teams based on action sequences. The other perspective of process mining is conformance checking. This type of process mining is not feasible for football performance analysis at it requires a comparison between an event log and the required process model. In football, however processes are different than in a business organization. They are more stochastic and cannot be pre-determined. The third type of process mining, however, called enhancement, can be investigated in more detail in future studies. Enhancement requires an event log as well as a model and as a result gives a new “enhanced” model. In football, an event log can be enhanced with a process model that, for instance, has more passes. This can be used as a simulation analysis to test how different types of models would affect the existing one.

Nonlinear time series analysis – this type of analytics methods is suggested in the literature as potentially valuable for assessing and explaining performance in football. The dynamic system theory considers a football team as a nonlinear system – the whole can differ from the sum of its parts. Thus, nonlinear time series methods are potentially suitable methods for football performance analysis based on this theory. Up to now, a limited number of studies have applied these methods. Kuznetsov et al. (2014) discuss Sample Entropy as a potentially useful method, but the authors only give a simple example of the calculation and discuss the potential benefits of the method in a restrictive manner. Silva et al. (2016) describe how Shannon entropy, approximate entropy and sample entropy can be useful in sports performance analysis. For the most part, the mentioned entropy measures are used to estimate the variability in players’ movements over space and time which can provide tactical information about the team (Silva et al., 2016). The limitation of the existing studies is that they mostly use approximate and sample entropy, while there are other nonlinear time series methods that can be explored. Recently, the Long Short-Term Memory (LSTM) networks (a type of neural network architecture) are gaining popularity in the analysis of sequence data.

Design and evaluation of a decision support solution in practice – the thesis demonstrates a first attempt at how a decision support solution can look like in practice. A few requirements for a solution are also discussed. However, future studies can provide more detailed requirements by conducting more qualitative studies with football experts. It should be kept in mind, however, that a one-size-fits-all solution is not feasible as every coach has his own need for a specific type of information he would like to obtain from the analytics solution. Professional tracking systems do not offer a detailed view of their dashboards due to confidentiality. Some insights for designing an analytics solution for a decision support dashboard can be found in the studies by Perin et al. (2013), Beetz et al. (2005), Rodrigues et al. (2013), and Janetzko et al. (2014). One important observation from these studies is that while developing a decision support solution it is important to define exactly what is meant by each performance indicator of interest, as well as to limit the amount of variables that are measured and especially displayed on the screen. Complexity will likely lead to a failure of the solution as the coaches would not be interested in using it, or eventually will feel overwhelmed by the complex visualizations.

Furthermore, the solution should be developed and tested to work with different data, for example, biometric in addition to event data. Finally, the developed solution or system needs to be continuously tested in practice over a longer period of time – for instance, throughout a season. The evaluation should focus not only on whether the solution works, but also on the usefulness of the displayed results/suggestions.

Appendix A: Performance indicators per player position

Performance indicators	GK	Full Backs	Centre Backs	HM	AM	WM	Strikers
Physiological	Height Strength Power Agility Coordination Reaction Time	Speed Power Stamina	Height Strength Speed Power Stamina	Stamina Speed Power Strength	Stamina Speed Power Strength	Speed Stamina Power Strength	Speed Agility Power Strength Stamina
Tactical	Vision Organisation Communication Distribution	Support play When to cross Passing Running off the ball Forcing offside	Vision Organisation Communication Passing	Vision Organisation Communication	Vision Organisation Communication	Vision Organisation Communication	Vision – awareness of space Anticipation Organisation Communication
Technical – Def	Shot stopping Coordination Recovery speed Save Punch	Tackle Pressing opposition Interception – anticipation Clearance Defensive header	Tackle Defensive header Pressing opposition Interception – anticipation Clearance	Tackle Pressing opposition Interception – anticipation Heading	Tackle Pressing opposition Interception – anticipation Heading	Tackle Pressing opposition Cover full back Interception – anticipation Heading	Tackle Pressing opposition Interception – anticipation Heading
Technical – Att	Passing Throw Ball control with feet Kick Tackle	Tackle Interception – anticipation Dribbling Running with the ball Clearance Defensive header	Passing Heading Running with the ball Support play Dribbling Crossing Shooting	Passing Running with the ball Dribbling Support play Crossing Shooting Heading	Passing Running with the ball Dribbling Support play Crossing Shooting Heading	Passing Running with the ball Dribbling Support play Crossing Shooting Heading	Shooting Heading Reception Dribbling Passing Running with the ball Support play Crossing
Psychological	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language	Concentration Motivation Attitude Body language
GK – Goal Keepers; HM – Holding Midfield; AM – Attacking Midfield; WM – Wide Midfield							

Source: Hughes et al., 2012, p. 407

Appendix B: List of all games in the Euro 2016

Date	Home	Away	Home Score	Away Score	Phase
6/10/2016	France	Romania	2	1	Stage 1
6/11/2016	Albania	Switzerland	0	1	Stage 1
6/11/2016	Wales	Slovakia	2	1	Stage 1
6/11/2016	England	Russia	1	1	Stage 1
6/12/2016	Turkey	Croatia	0	1	Stage 1
6/12/2016	Poland	N. Ireland	1	0	Stage 1
6/12/2016	Germany	Ukraine	2	0	Stage 1
6/13/2016	Spain	Czech R.	1	0	Stage 1
6/13/2016	R. of Ireland	Sweden	1	1	Stage 1
6/13/2016	Belgium	Italy	0	2	Stage 1
6/14/2016	Austria	Hungary	0	2	Stage 1
6/14/2016	Portugal	Iceland	1	1	Stage 1
6/15/2016	Russia	Slovakia	1	2	Stage 2
6/15/2016	Romania	Switzerland	1	1	Stage 2
6/15/2016	France	Albania	2	0	Stage 2
6/16/2016	England	Wales	2	1	Stage 2
6/16/2016	Ukraine	N. Ireland	0	2	Stage 2
6/16/2016	Germany	Poland	0	0	Stage 2
6/17/2016	Italy	Sweden	1	0	Stage 2
6/17/2016	Czech R.	Croatia	2	2	Stage 2
6/17/2016	Spain	Turkey	3	0	Stage 2
6/18/2016	Belgium	R. of Ireland	3	0	Stage 2
6/18/2016	Iceland	Hungary	1	1	Stage 2
6/18/2016	Portugal	Austria	0	0	Stage 2
6/19/2016	Switzerland	France	0	0	Stage 3
6/19/2016	Romania	Albania	0	1	Stage 3
6/20/2016	Slovakia	England	0	0	Stage 3
6/20/2016	Russia	Wales	0	3	Stage 3
6/21/2016	Ukraine	Poland	0	1	Stage 3
6/21/2016	N. Ireland	Germany	0	1	Stage 3
6/21/2016	Czech R.	Turkey	0	2	Stage 3
6/21/2016	Croatia	Spain	2	1	Stage 3
6/22/2016	Iceland	Austria	2	1	Stage 3
6/22/2016	Hungary	Portugal	3	3	Stage 3
6/22/2016	Italy	R. of Ireland	0	1	Stage 3
6/22/2016	Sweden	Belgium	0	1	Stage 3

Date	Home	Away	Home Score	Away Score	Phase
6/25/2016	Switzerland	Poland	1	1	Round of 16
6/25/2016	Wales	N. Ireland	1	0	Round of 16
6/25/2016	Croatia	Portugal	0	1	Round of 16
6/26/2016	France	R. of Ireland	2	1	Round of 16
6/26/2016	Germany	Slovakia	3	0	Round of 16
6/26/2016	Hungary	Belgium	0	4	Round of 16
6/27/2016	Italy	Spain	2	0	Round of 16
6/27/2016	England	Iceland	1	2	Round of 16
6/30/2016	Poland	Portugal	1	1	Quarter Finals
7/1/2016	Wales	Belgium	3	1	Quarter Finals
7/2/2016	Germany	Italy	1	1	Quarter Finals
7/3/2016	France	Iceland	5	2	Quarter Finals
7/6/2016	Portugal	Wales	2	0	Semi Finals
7/7/2016	Germany	France	0	2	Semi Finals
7/10/2016	Portugal	France	1	0	Final

Appendix C: Network metrics used in football performance analysis

Metric	Meaning	Interpretation
Betweenness centrality	Measures the extent to which a node lies on paths between other nodes. (*Pena and Touchette, 2012, p.3).*	Betweenness does not measure how well-connected a player is, but rather how the ball-flow between other players depends on that particular player i. It thus provides a measure of the impact of removing that player from the game, either by getting a red card or by being isolated by the rival's defense. A betweenness score of 0 means, in particular, that a player is not getting involved in the game, and so can be removed without much effect. (*Pena and Touchette, 2012, p.3).*
Centralization	A network is considered highly centralized when one actor is clearly more central than all other actors in the network. A network is decentralized when all actors have the same node centrality. *(Grund, 2016, p.1266).*	Network centralization refers to how unequally distributed passes are over dyads of players and single individuals. (*Grund, 2016, P.1265).* The closer the centralization is to 1, the more likely is the network to have a star-like topology, thus a tendency to play for the same player. The closer to 0, the more likely it is that the nodes of the network have on average the same connectivity, thus representing a more homogenous type of interaction. . *(Clemente, Martins and Mendes, 2016, p.82).*
Centroid	The centroid can be defined as one of the most highly connected node(s) in the network. (*Clemente, Couceiro & Mendes, 2014, p.266).*	A player with high centroid value compared to the average centroid value of the network, will be possibly involved in coordinating the activity of other highly connected players, altogether devoted to the regulation of team play. *(Clemente, Martins and Mendes, 2016, p.62).*
Clique	A clique is a sub-network in which all the nodes are linked by an arrow. The analysis of cliques is the basis for finding communities within networks. *(Pena and Touchette, 2012, p.4)*	A clique in a team represents a subset of players that are all pairwise-connected by direct passes. A well connected team will present a very large maximal clique, meaning that almost everybody gets to pass the ball to everybody else, whereas the size will be smaller for more fragmented teams. *(Pena and Touchette, 2012, p.4)*
Closeness centrality	Closeness centrality of a vertex is defined as the sum of distances from all other vertices presented in a graph, with this distance defined as the length of the shortest paths from one vertex to another. *(Ribeiro et al., 2017, p.6).*	It shows how close, in terms of passes, a player has been to all other teammates during the development of the team's attack. *(Clemente, Mendes & Martins, 2014, p.584).* This network metric provides information on adjacency of one player to others, where players with low closeness scores are adjacent to others, providing conditions for receiving flows (e.g. receive a pass or rotate with the nearest player) more rapidly. *(Ribeiro et al., 2017, p.6).*
Clustering	Measures the degree of clustering in a network by averaging the clustering coefficient of each node, which is defined as the density of the node's ego network. *(ORA Documentation File, 2018)*	Clustering coefficients provide coaches and performance analysts with knowledge about subgroups of players who coordinate their actions more frequently. Globally, high values of a clustering coefficient might indicate a team disposition to form functional clusters, with players tending to create tightly knit groups comprising high-density ties. (*Ribeiro et al., 2017, p.6).*

Metric	Meaning	Interpretation
Cohesion	Cohesion is defined as the number of reciprocal connections in the network divided by the maximum number of possible connections. (*McLean et al., 2017, p.376).*	It gives an indication of how often a player was involved within a network. For example, a reciprocal pass occurs when player A passes to player B who then passes back to player A. (*McLean et al., 2017, p.376).*
Degree centrality	Degree centrality consists of the number of ties incident upon a node. (*Ribeiro et al., 2017, p.6).* Since in team sports players pass the ball in a specific direction from one player to another, the degree of a vertex can be defined according to two types of centrality: 'indegree' (number of passes directed to the player) and 'outdegree' (number of passes that the player directs to others). (*Ribeiro et al., 2017, p.6).*	Players with larger centrality scores are those who contributed more to their team's offensive attempts through their passes to the other players of their team. *(Clemente, Martins and Mendes, 2016, p.49).*
Density	In graph theory, the density of a (directed) graph is the proportion of the maximum possible links present between nodes. *(Clemente, Martins and Mendes, 2016, p.73).*	Describes the overall level of cooperation/coordination between teammates. (*Ribeiro et al., 2017)* It measures the overall affection between teammates. *(Clemente, Martins and Mendes, 2016, p.73).*
Diameter	In graph theory, two players are connected if a sequence of players exists and their connections are adjacent. The diameter of a graph is the maximum distance (the length of the largest geodesic) between any two connected players. *(Clemente, Martins and Mendes, 2016, p.75).*	Quantifies the distance between the farthest two players in the graph. A small diameter reflects a low maximum distance between teammates, which may reveal that the team's passing game was diffused among most of its players (rather than a few acting as central ones). (*Clemente, Martins, Kalamaras, Wong & Mendes, 2015, p.86).*
Distance	Computes the shortest path lengths between all node pairs. If no path exists between two nodes, then a distance of zero is given. The distance from a node to itself is also zero. *(ORA Documentation File, 2018)*	If distances are great, it may suggest that the ball take a long time to move for the teammates. The players who are closer to others may be able to exert more power than those who are more distant. *(Clemente, Martins and Mendes, 2016, p.74).*
Eigenvector centrality	Eigenvector centrality measures the influence of a vertex in a graph. (*Ribeiro et al., 2017).*	A player with a very high Eigenvector is a player interacting with several important teammates, thus suggesting a central regulatory role. A player with low Eigenvector, can be considered a peripheral teammate, interacting with few and not central players. *(Clemente, Martins and Mendes, 2016, p.57).*
Flow centrality	Captures the fraction of times that a player intervenes in those paths that result in a shot. *(Duch et al., 2010, p.2).*	
Heterogeneity	Heterogeneity of the network estimates the variation of connectivity between teammates. *(Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014, p. 143).*	Highest values reveals a high level of sub communities and a low cooperation between all teammates during the attacking units. Smallest values suggest a higher participation in the same time, thus a more homogeneity participation. (*Clemente, Martins, Couceiro, Mendes & Figueiredo, 2014, p. 143).*
Hub	Hubs are nodes that have many more connections than the average node does. *(Yamamoto & Yokoyama, 2011).*	

Metric	Meaning	Interpretation
Network intensity	Network intensity refers to the total number of passes made by a team in a particular match (per minute ball possession). *(Grund, 2016, p.1265).*	
PageRank	Pagerank centrality is a recursive notion of 'popularity' or importance which follows the principle that 'a player is popular if he gets passes from other popular players'. *(Clemente, Martins and Mendes, 2016, p.60).*	Page Rank is the probability that each player will have the ball after a reasonable number of passes have been made *(Peña & Touchette, 2012).*
Path length	Measures the separation between two vertices (e.g. players in team games) in a graph (global property). (*Ribeiro et al., 2017).*	It can reveal how many passes are needed for the ball to traverse from one particular player to another. (*Ribeiro et al., 2017).*
Prestige	The degree prestige considers only inbound links, it is often used as indication of the "prestige" of each node among its peers. Nodes with high degree prestige are those that receive many inbound links from other nodes. *(Clemente et al., 2016, p.380)*	In the case of football the players with higher degree prestige are those to whom their teammates preferred to pass the ball more often. *(Clemente et al., 2016, p.380).* These players might possibly be the ones crucial for their team's offensive development because they receive the ball more often than other players during their team's attempt to attack. *(Clemente, Martins and Mendes, 2016, p.56).*
Reciprocity	Reciprocity is the tendency for mutuality in relations between people in a network. This is a key social process, indicated by the acceptance of a handshake, or the philosophy "you scratch my back, I scratch yours". *(Lusher & Robins, 2010, p. 218).*	Reciprocity measures the tendency of players' pairs to form mutual connections between each other. *(Clemente, Martins and Mendes, 2016, p.80).*
Transitivity	Transitivity is the tendency to form triadic relations with others. It gives some indication of how the network as a whole may be held together and is the social mechanism that leads to cohesion or clustering in a network. *(Lusher & Robins, 2010, p. 219).*	This measure allows to identify balanced triads and to identify the "equilibrium" or natural state toward which triadic relationships tend. Transitivity allows identifying the capacity to the triad of players act in a balance way and not with tendencies such as pass for the same player. *(Clemente, Martins and Mendes, 2016, p.80).*

Appendix D: Network metrics for team level analysis

Metric	Description
Clique Count	The number of distinct cliques to which each node belongs. A clique is defined as a group of three or more nodes that are all connected together and that cannot be made larger by adding another node.
Density	The ratio of the number of links versus the maximum possible links for a network.
Diameter	The maximum shortest path length between any two nodes in a unimodal network. If there exists a node that is not reachable from another node, then the diameter is technically infinite. In this case, the Diameter returned is V*N where V is the maximum link value in the network.
Diffusion	Computes the degree to which something could be easily diffused (spread) throughout the network. This is based on the shortest path length between nodes. A large diffusion value means that nodes are close to each other, and a smaller diffusion value means that nodes are farther apart.
Hierarchy	The degree to which a unimodal network exhibits a pure hierarchical structure, meaning, if there is a path from nodes A to C, there is not also a path from C to A.
Interdependence	The fraction of links in a unimodal network that are Pooled or Reciprocal.
Network Centralization-Betweenness	Network centralization based on the betweenness score for each node in a square network.
Network Centralization-Closeness	Network centralization based on the closeness centrality of each node in a square network.
Network Centralization-Eigenvector	Network centralization based on the eigenvector centrality of each node in a square network.
Network Centralization-Total Degree	Network centralization based on the total-degree centrality of each node in a square network.
Reciprocity	The fraction of links in the network that go in both directions.
Transitivity	The fraction of link pairs {(i,j), (j,k)} in the network such that (i,k) is also an link in the network.

Source: ORA Documentation File, 2018

Appendix E: Clustering algorithms for community detection

Girvan-Newman Clustering Algorithm
This is a hierarchical clustering method where all nodes start off in the same group and are split off into new groups based on maximum betweenness scores.
Newman Clustering Algorithm
Newman's Algorithm starts with each node as its own group, and then combines groups in a hierarchical manner until only one group remains (e.g. it is agglomerative hierarchical clustering). At each step, which two groups to merge is based on what will maximize the modularity value - or group community structure value.
CONCOR Structural Equivalence Algorithm
Concor recursively splits partitions and the user selects n splits. (n splits -> 2n groups). At each split it divides the nodes based on maximum correlation in outgoing connections. Helps find groups with similar roles in networks, even if dispersed.
Johnson's Hierarchical Clustering Algorithm
This is a hierarchical clustering technique based on a Similarity Standard hierarchical approach that builds groups based on similarity scores.
Dense Subgraph Extraction
No documentation available.
k-Means
This clustering aims to partition n observations into k sets (k ? n) S = {S1, S2, ., Sk} so as to minimize the within-cluster sum of squares.

Source: ORA Documentation File, 2018

Appendix F: Network metrics used for dynamic topology comparison

Metric	Description
Avg Degree:	The average degree in the underlying graph (=average in/out degree).
Deg Centralization	Value for symmetric data only.
Out-Central	Out-degree centralization for directed data.
In-Central	In-degree centralization for directed data.
Density	Number of edges divided by the maximum number possible, note the diagonal is ignored.
Connectedness	1 minus the fragmentation (see below).
Fragmentation	Proportion of pairs of vertices that are unreachable.
Closure	The number of non-vacuous transitive triples divided by number of paths of length 2.
Avg Distance	Average geodesic distance amongst reachable pairs.
SD Distance	Standard deviation of the geodesic distances amongst reachable pairs.
Diameter	Length of the longest geodesic.
Breadth	1 minus the compactness (see below).
Compactness	The mean of all the reciprocal distances.
Mutuals	Proportion of dyads that have reciprocated links.
Asymmetrics	Proportion of dyads that have an unreciprocated links.
Nulls	Proportion of dyads that have no links.
Arc Reciprocity	Number of reciprocated arcs divided by total number of arcs.
Dyad Reciprocity	Number of reciprocated dyads divided by total number of dyads.

Source: UCINET Help File, 2018

Appendix G: Sequence clustering algorithm as implemented in the ProM 5.2 plugin

Let (◦) and (•) denote the input and output states, respectively. To calculate the probability of a sequence $x = \{\circ, x_1, x_2, \cdots, x_L, \bullet\}$ being produced by cluster *Ck* the following formula is used:

$$p(\overline{x} \mid c_k) = p(x_1 \mid \circ; c_k) \cdot \left[\prod_{i=2}^{L} p(x_i \mid x_{i-1}; c_k)\right] \cdot p(\bullet \mid x_L; c_k)$$

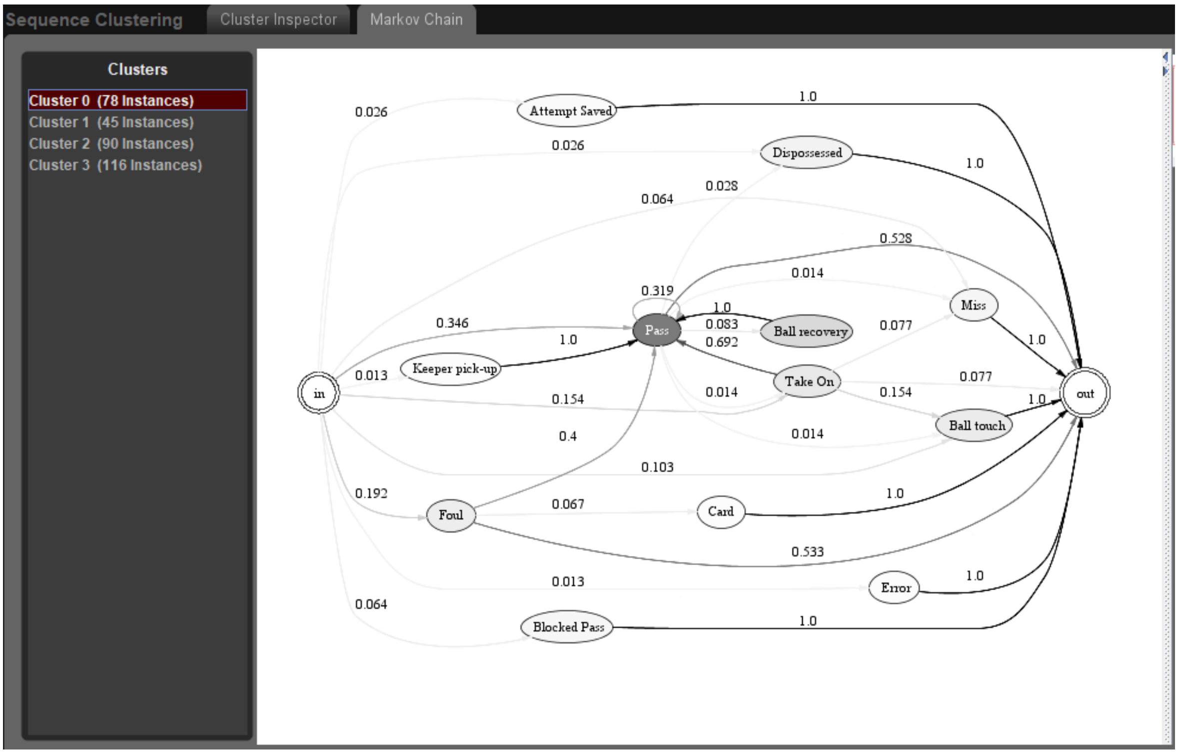
where $p(x_i \mid x_i-1; C_k)$ is the transition probability from x_{i-1} to x_i in the Markov chain associated with cluster C_k.

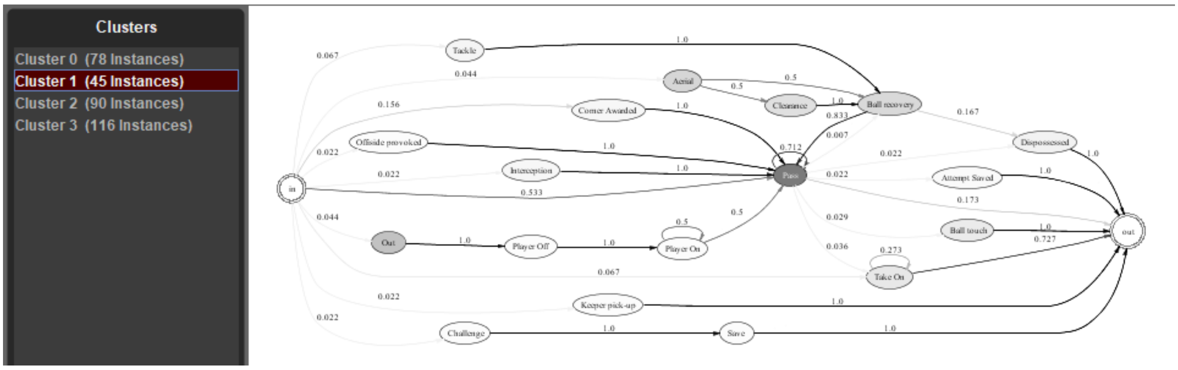
The goal of sequence clustering is to estimate these parameters for all clusters C_k (with $k = 1, 2, . . . , K$) based on a set of input sequences. For that purpose, the algorithm relies on an Expectation–Maximization procedure [11] to improve the model parameters iteratively. For a given number of clusters K the algorithm proceeds as follows:

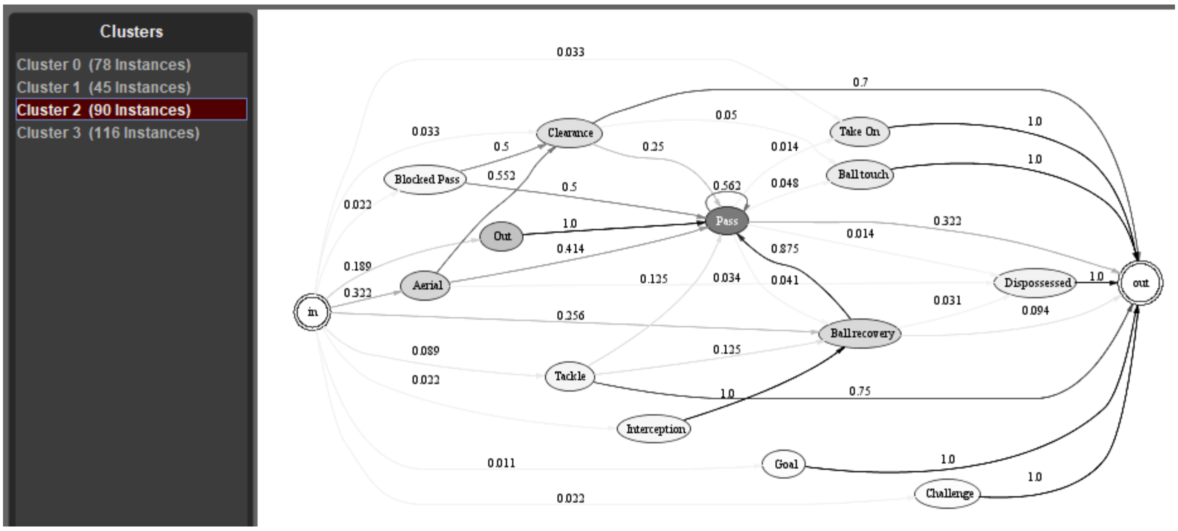
1. Initialize randomly the state transition probabilities of the Markov chains associated with each cluster.
2. For all input sequences, assign each sequence to the cluster that can produce it with higher probability according to equation (1).
3. Compute the state transition probabilities of the Markov chain of each cluster, considering the sequences that were assigned to that cluster in step 2.
4. Repeat steps 2 and 3 until the assignment of sequences to clusters does not change, and hence the cluster models do not change either.

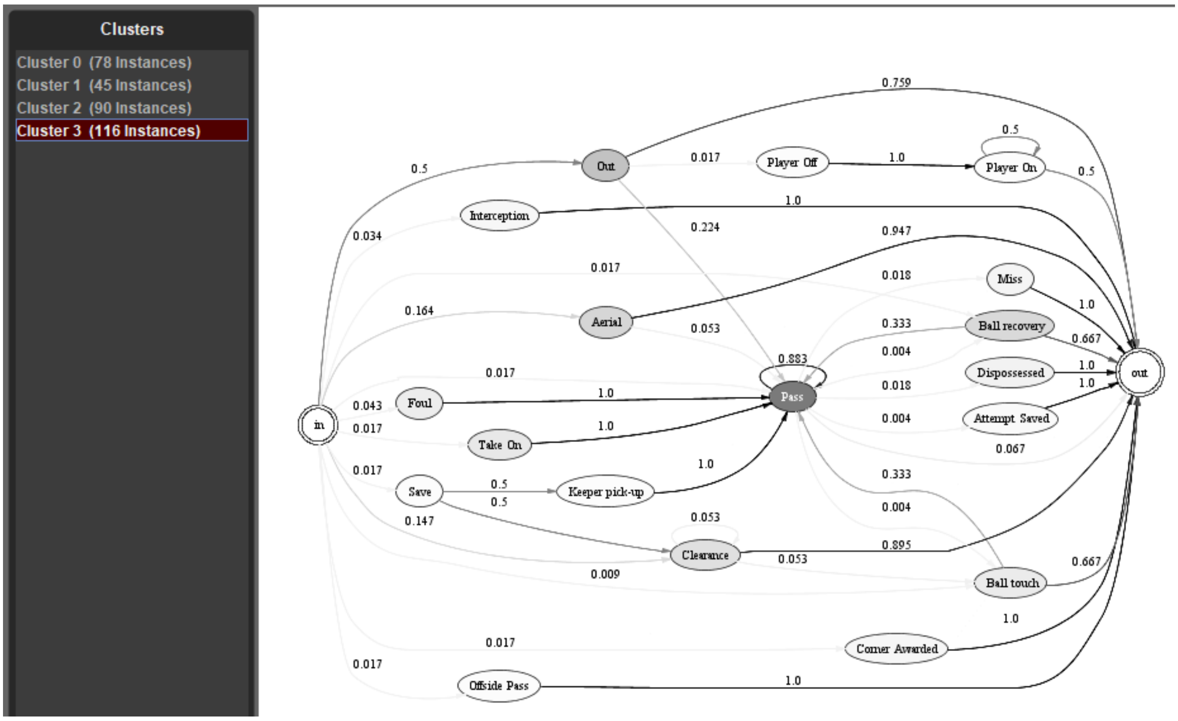
Source: Veiga, 2009, p. 17

Appendix H: Markov chains for England's team






Clusters
Cluster 0 (78 Instances)
Cluster 1 (45 Instances)
Cluster 2 (90 Instances)
Cluster 3 (116 Instances)
in
out
Pass
Clearance
Blocked Pass
Out
Aerial
Take On
Ball touch
Dispossessed
Ball recovery
Tackle
Interception
Goal
Challenge


Clusters
Cluster 0 (78 Instances)
Cluster 1 (45 Instances)
Cluster 2 (90 Instances)
Cluster 3 (116 Instances)
in
out
Out
Player Off
Player On
Interception
Miss
Aerial
Ball recovery
Dispossessed
Pass
Foul
Take On
Attempt Saved
Save
Keeper pick-up
Clearance
Ball touch
Corner Awarded
Offside Pass

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