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Machine learning in men's professional football: Current applications and future directions for improving attacking play

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Abstract

It is common practice amongst coaches and analysts to search for key performance indicators related to attacking play in football. Match analysis in professional football has predominately utilised notational analysis, a statistical summary of events based on video footage, to study the sport and prepare teams for competition. Recent increases in technology have facilitated the dynamic analysis of more complex process variables, giving practitioners the potential to quickly evaluate a match with consideration to contextual parameters. One field of research, known as machine learning, is a form of artificial intelligence that uses algorithms to detect meaningful patterns based on positional data. Machine learning is a relatively new concept in football, and little is known about its usefulness in identifying performance metrics that determine match outcome. Few studies and no reviews have focused on the use of machine learning to improve tactical knowledge and performance, instead focusing on the models used, or as a prediction method. Accordingly, this article provides a critical appraisal of the application of machine learning in football related to attacking play, discussing current challenges and future directions that may provide deeper insight to practitioners.

Keywords

Artificial intelligence, association football, performance analysis, sport analytics, tactical knowledge

Introduction

The search for key performance indicators related to goal-scoring in elite association football is of great interest to researchers, coaches, and analysts. Historically, researchers and practitioners have predominately utilised observational analysis to optimise the training process and game preparation of their players and teams.[1] Studies have shown successful football teams create more goal-scoring opportunities than the opposition[2] by penetrating the defence[3] and achieving greater entries into the penalty box (defined as 'an event that took place either when the team in possession of the ball passed it into the opponent's penalty area, regardless of whether the pass was received by a teammate, or when a player in possession of the ball went into that area of the pitch').[4–6] These findings are valuable for identifying key game events, however, such time-consuming approaches give little or no consideration to the interaction process between teams, including rapidly changing contextual circumstances. Thus, the demand for more automated approaches to analyse tactical behaviour in men's professional football is increasing.[7]

In the last decade, the ability to find key individual and team performance indicators has been greatly increased due to technological developments in (but not limited to) automatic tracking systems, video-based motion analysis, and Global Positioning System[8] units.[9] As well as their widespread use in

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training sessions, FIFA have permitted the use of wireless sensors to track player positions and physiological parameters during competitions.[10] Accounting for complex interactions occurring within a match, network analysis[11] and spatio-temporal metrics[12,13] have been employed for dynamic analysis and data simulation in sports.[14–17] Such information can be helpful to guide analysts, coaches, and players in making crucial tactical decisions at the highest levels of elite football.[18]

Aside from current approaches, the application of machine learning in football is an emerging field of research used to reveal trends and distinguish between successful and less successful teams.[19,20] Machine learning is the practice of utilising statistical and computational methods for classification, pattern recognition (similar to data mining), prediction[21] and to draw inferences from datasets consisting of input data without labelled responses.[22] Machine learning is typically divided into two areas: supervised and unsupervised learning. In supervised learning, one aims to optimise a model on a set of labelled training data to fit to a given response. Case in point, the team tactic of penetrating passes can be learned by feeding the machine with examples of penetrating passes. Ultimately, supervised learning is aimed at satisfying the following equation

$$y = f(x)$$

where y is a given response which is binary, multi-class, or continuous; X is the data comprising features and f is a function that machine learning attempts to optimise in order to approximate the equation. An example of supervised learning research in football is the work of Wei et al.,[23] who used a decision tree to map player movement to the response of different phases of the game (shots, corners, free kicks, etc.).

In unsupervised approaches, a model aims to uncover structures and patterns in unlabelled data. For complex problems with an unknown desired response, unsupervised machine learning approaches have been used to measure inter-player coordination, team–team interaction including the time preceding key game events such as shots on goal, and compactness.[23–27] Serving as an example of an unsupervised learning approach, Bialkowski et al.,[24] used tracking data to define a specific 'role' within the formation of the team for individual players at various intervals of the game. More specifically, they utilised minimum entropy data partitioning which does not rely on a fundamental pre-determined model.

As illustrated by those examples, machine learning algorithms hold the potential to provide coaches and analysts with additional information to evaluate the game. By identifying specific patterns in large datasets, machine learning models can perform tasks such as automatically identifying team formations,[28] or predicting how players move on offense and defence.[29] Further, due to the subjective perspectives of the coach or scout observing a game and rating the tactics, the data often lack objectivity and reliability.[30] In this regard, machine learning may allow a more profound analysis of complex process variables, potentially offering more scientifically backed, evidence-based information to coaches and analysts.[11,31–33]

As new possibilities arise with the use of new data sources and new approaches to analyse these data, there is a demand to further understand the advantages and limitations of applying machine learning methods to football.[34–36] Tracking data contrasts with the traditional event data approach as the volume, variety and precision provide detailed datasets to sports visualization researchers.[37] Professional players nowadays are tracked during every training session and match by different systems, but the quality of data remains in question.[38] Further, it is plausible that mounts of data without solid theory will not accurately inform decisions and thus, these methods must be meticulously validated. Accordingly, a multi-disciplinary approach, including the collaboration of big data technologies with football research may facilitate a comprehensive theoretical model and understanding of tactical performance. The aim of this review is to provide a critical appraisal of the literature related to machine learning in football, and in turn, inspire the future application of these complex approaches in a more relevant manner.

This review consists of two sections: (a) a review of existing research on machine learning in football related to attacking play, outlining findings and limitations and (b) emphasising the practical application of machine learning, identify challenges and suggest avenues of future research to improve upon the features and practices associated with football performance.

Methods

A descriptive review of the available literature on match analysis in elite professional male football was conducted. Data were collected from the following computerized databases for the period 1996–2018: PubMed, Web of Science, MEDLINE, SPORTDiscus, Research gate, Elsevier, and ProQuest. Multiple searches were conducted. The search terms included football, soccer, machine learning, match analysis, performance analysis, game analysis, notational analysis, dynamic analysis, performance indicators.

The inclusion criteria for these articles were[39] relevant data concerning technical and tactical evaluation,[39] participants included professional adult male footballers[39] and written in the English language.

Studies were excluded if they[39] included children or adolescents (under 18 years),[39] included females,[39] focused on set plays, small-sided games or futsal.

The focus on professional male football was determined by several factors:

1. There is greater relevance and a larger number of studies have been conducted with machine learning approaches using match data versus training data. This enables the comparison of different studies.
2. There are behavioural differences between match play and training.[40]
3. Studies using small-sided games have shown important physiological and tactical differences to 11 versus 11 football.[41,42]
4. There are differences in tactical behaviour between youth football and the elite.[43]

To evaluate the included studies, we looked for several characteristics. The general machine learning approach (supervised vs unsupervised), the specific machine learning approach (e.g. neuronal networks, *k*-nearest neighbour), the input data used (event vs tracking data) and if the authors provided sufficient information to redo the analysis (see Table 1).

Machine learning in football

The purpose of this section will be to review the existing research on machine learning in football related to attacking play, outlining findings and limitations. This section is split into two sections: studies using event data and studies using tracking data.

Machine learning models in football using event data

Event data is the standard source to quantify and evaluate individual and team performance in the last decades.[20,44] Event data consists of outcome measures such as frequencies, proportions and other accumulated performance indicators of events happening throughout a match.[44] In general, those studies were interested in identifying tactical patterns in a game using unsupervised machine learning approaches or predicting individual or team success using supervised approaches.

To derive tactical patterns from match data, Hirano and Tsumoto[45] created a multi-scale matching and rough clustering method based on temporal event data consisting of 168 time-series sequences from 64 games of the 2002 FIFA World Cup. Pass patterns such as side-attacks and zig-zag pass transactions leading to a goal could be automatically clustered. In another implementing a pattern recognition approach, Montoliu et al.[46] formulated a Bag-of-Words-based method to analyse the most common movements in a dataset of two regular Spanish La Liga matches played by four professional teams. Among other possible uses, common team activities such as ball possession, quick attacks and set-piece plays could be recognized to identify and evaluate one's own team, and the opponent team's strengths and weaknesses before, during and after a match. Although the results of those studies were promising, the quality of their models should be questioned due to the relatively low number of data points. In addition, they did not include test sets of data not used to build their models and to validate them.

A recent study involving a much larger dataset including 6396 games and 10 million events from the 2013–2014, 2014–2015 and 2015–2016 seasons of the Premier League, Serie A, La Liga, Bundesliga, Dutch Eredivisie, Ligue 1 used machine learning to quantify the relation between performance (passes, crosses, shots, tackles, dribbles, clearances, goalkeeping actions, fouls, intercepts, aerial duels, goals scored and goals conceded) and success based on goal difference.[47] The logistical regression and classification model could predict simulated team rankings close to the actual rankings. The discriminatory features between top teams and bottom teams included producing more passes and shots than the opponent, and committing less fouls, tackles and goalkeeping actions. Although the events extracted from the match appear like traditional notational analysis, a team's playing quality including pass precision and a team's spatial and temporal dominance including average team position, speed and accelerations could be measured as well. However, there was some observed divergence due to the erratic nature of football, such as psychological factors and contextual factors either not captured by soccer logs or not measurable by existing technologies. It was concluded that combining their data logs with player tracking data and mathematical models could better describe the spatio-temporal trajectories of players during a match. Reproducing game patterns between two teams would more accurately characterise the relationship between technical performance and success.

In addition to pass quality and variability, the location of passes is also a determinant of successful offense. Providing context related to playing in critical pitch zones, Brooks et al.[48] used a *k*-nearest neighbour approach to qualitatively assess the effect of passes travelling into and out of Zone 14, the zone located in the middle of the pitch immediately outside the opposing penalty area (see Figure 1). Based on all passes from the 2012–2013 Spanish La Liga season, possession in Zone 14 often correlates to shooting opportunities. This is in support of previous studies using notational analysis, where Zone 14 was correlated with assists by making forward passes into the penalty area.[49,50] However, one limitation of using pitch zones is that achieving

Table 1. Data extraction table (machine learning in men's professional football).

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Hirano and Tsumoto[45]	Unsupervised (clustering)	Multi-scale matching/ induced dissimilarity matrix and rough clustering method	Yes	Presented a method for grouping pass patterns such as side-attacks after complex pass transactions, and zig-zag pass transactions in soccer game records.	Set stage for future work to help coaches identify and execute passing patterns to increase goal-scoring.	64 games of the FIFA world cup 2002	Event
Joseph et al.[81]	Supervised (classification)	Several techniques were used: MC4, a decision tree learner; Naive Bayesian learner; Data Driven Bayesian and a K-nearest neighbour learner	Yes	With a MC4 learner, identified attributes which have the largest effect on the outcome of the game. The Bayesian network looked for correlations between the values of the attributes including the result.	Can help analyse and identify important factors from past games.	Matches played by Tottenham Hotspur (1995–1997)	Event
Hucaljuk and Rakipović[80]	Supervised (prediction)	Naïve Bayesian Network, KNN, ANN, Random Forests	Yes	Based on number of injuries, goals, team formation and other factors training a supervised ML model to predict scores. ML model had 60% accuracy in predicting the score.	Model can be improved and then can be used to predict score and prioritise tactics accordingly.	The group stage of Champions League (96 matches)	Event
Lucey et al.[61]	Supervised (classification)	*k*-nearest neighbours	Yes	Proposed a method to characterise team behaviour for soccer by representing team behaviour via play segments, which are spatio-temporal descriptions of ball movement over fixed windows of time. Using these representations, it characterized team behaviour from entropy maps, which gives a measure of predictability of team behaviours across the field.	Can be used to predict tactics using spatio-temporal data.	2010–2011 English Premier League soccer data	Tracking
Chassy[64]	Unsupervised (clustering)	PCA for clustering. Correlation to judge efficacy of passing and compare it with possession	Yes	Explored the idea that a football team can be formalised as a self-organising system. By applying the definition of self-organisation to football, the study concluded that team play constitutes the core of performance.	Coaches can use this information to improve passing behaviour.	Data from the 2013 European Champions League	Event

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Wei et al.[23]	Supervised (classification) and Unsupervised (clustering)	*k*-means, PCA, Decision Trees	Yes	Presented a method for large-scale analysis of team behaviour across large volumes of player and ball tracking data. Clustered plays of a team to describe their most likely motion patterns associated with an event (such as shots, corners, free-kicks). Proposed a two-layer hierarchical approach to automatically segment a match. Using a decision-tree formulation, can accurately retrieve events or detect highlights.	A useful method to improve the understanding about decision-making and identify patters related to goal-scoring.	Tracking data across nine complete matches from a top-tier European soccer league	Tracking
Bialkowski et al.[28]	Unsupervised (clustering)	Expectation Maximization (like *k*-means)	Yes	Could automatically detect and visualize formations from soccer player tracking data. Utilizing an entire season's data from Prozone from a top-tier professional league, they used an automatic approach to see whether the formation they played had anything to do with explaining why teams are more successful at home rather than away. Could automatically detect and visualise formations using tracking data. Could determine if formation had anything to do with playing home versus away, discovering teams at home play higher up the pitch.	Can help analysts discover and implement new tactical behaviours.	20 teams who played every team home and away and the data consisted of the location of every player at 10 frames-per-second as well as the ball events. 20 teams who played every team home and away and the data consisted of the location of every player at 10 frames-per-second as well as the ball events. 20 teams who played every team home and away and the data consisted of the location of every player at 10 frames-per-second as well as the ball events. Top tier professional league consisting of 20 teams who played every team home and away	Tracking

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Bialkowski et al.[24]	Unsupervised (clustering)	Expectation Maximization, *k*-means clustering, Minimum Entropy data partitioning	Yes	Presented a role-based representation to represent player tracking data, which was found by minimizing the entropy of a set of player role distributions. Showed how this could be efficiently solved using an EM approach which simultaneously assigns players to roles throughout a match and discovers the team's overall role distributions.	Can help perform individual player and team analysis, including large-scale team analysis over a full season.	One season of ball tracking data from a professional soccer league ($\approx$40,00,00,000 data points)	Tracking
Lucey et al.[73]	Supervised (prediction) Unsupervised (clustering)	Logistic Regression and Conditional Random Field	Yes	Found that not only is the game phase important (i.e. corner, free-kick, open-play, counter-attack etc.), the strategic features such as defender proximity, interaction of surrounding players, speed of play, coupled with the shot location play an impact on determining the likelihood of a team scoring a goal.	Can help coach know important factors leading to a goal.	One season ball tracking data taken from a professional league ($\approx$40,00,00,000 data points)	Both
Eggels and Pechenizkiy[54]	Supervised (prediction)	Logistic Regression, Decision Trees, Random Forests	Yes	Proposed a method to determine the expected winner of a match by estimating the probability of scoring for the individual goal-scoring opportunities. The outcome of a match is then obtained by integrating these probabilities.	Can pre-strategise according to predicted results obtained using the proposed model.	Event data tracked by ORTEC. Data about the quality of players extracted from the web. Spatio-temporal data from seven different leagues over three seasons	Both, but only classified with event data due to accuracy issues with ORTEC
Fernando et al.[25]	Unsupervised (clustering)	*k*-means	Yes	Presented a method which can be used to compare the scoring methods of teams in soccer using fine-grained player tracking and ball-event data.	Help compare goal-scoring style of teams.	One season of tracking data from Prozone consisting of 20 teams	Tracking

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Horton et al.[57]	Supervised (classification)	Multinomial Logistic Regression	Yes	Presented a motion model that calculates regions such as 'passable regions' for every pass that can learn a classifier to rate the quality of passes made during a football match with an accuracy of up to 85.8%. Evaluated passes according to difficulty or decision quality.	Help use quality of pass to train players on improving their passing behaviour.	Four Home Games of Arsenal Football Club	Both
Montoliu et al.[46]	Supervised (classification)	Bag of Words, *k*-Nearest Neighbour, the Support Vector Machine and the Random Forest	Yes	Proposed a new method based on using local motion features and a Bag-of-Words strategy to characterise short Football video clips. Approach can correctly distinguish between actions related to Ball Possession, Quick Attack and Set-Piece plays. The proposed Bag-of-Word feature vector appropriately captures the behaviour of players. The proposed method is useful to analyse the most common movements of a team when playing a match. The Random Forest classifier obtains the best classification.	Can be used to predict opponent activity and prepare for it more quickly. Identify the opponent team's strengths and weaknesses before the match, obtain the opponent's main tactics during a match, observe his/her team's performance during a match and evaluate the players as a whole or individually immediately after the match, among other possible applications.	A private dataset of football videos of four games	Event
Ruiz et al.[53]	Supervised (prediction)	Multilayer Perceptron (algorithm for supervised learning of binary classifiers)	Yes	Model can predict shot expectancy accurately and can be used to strategise for an advantage.	Modelling the expected goal value of shots gives an additional level of detail to the analysis of offensive and defensive performance in football.	10,318 shots taken during the 2013–2014 English Premier League, extracted from Prozone Matchviewer event data	Event
Tax and Joustra[82]	Supervised (prediction)	PCA, Naïve Bayesian, Multilayer Perceptron	Yes	Model can predict result of a match using relevant input up to a high accuracy.	Can be used to determine areas where a team needs to improve on and/ or plan strategy to combat the expected result.	A public data based match prediction system for the Dutch Eredivisie	Event

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Bialkowski et al. [22]	Unsupervised (clustering)	Expectation Maximization, *k*-means clustering, Minimum Entropy data partitioning	Yes	Could identify team structure or 'formation' which served as a strong descriptor for identifying a team's style.	Can be useful for strategic planning, evaluation and tactical adjustments.	20 teams who played home and away. 38 matches for each team or 380 matches overall. Six of these matches were omitted due to missing data	Tracking
Brooks et al.[48]	Supervised (classification and prediction)	*k*-Nearest Neighbours	Yes	Using heatmaps and KNN, ranked offensive players and identified team patterns using passing data.	Can help improve passing behaviour.	2012–2013 La Liga season. Dataset provided by Opta Sports.	Event
Feuerhake[26]	Supervised (classification) and Unsupervised (clustering)	*k*-means, Apriori, Levenstein distances, DBSCAN, Euclidean movement space	Yes	Used distances, clustering and classification to analyse sequence of movements (pattern recognition) in a soccer game.	Needs more research, but being able to predict the trajectories of players can potentially help coaches devise tactical plans and for player selection that favours different playing styles.	Three datasets with different characteristics. The first two datasets contain movement information of players during football matches and the third contains car trajectories and thus is from a completely different context	Tracking
Knauf et al.[67]	Unsupervised (clustering)	Clustering tasks and *k*-medoids. Temporal kernels were Gaussian kernel combined with three different spatial kernels	Yes	Presented spatio-temporal convolution kernels for multi-object scenarios.	Clusters can help coaches identify how teams behave in attack. That is, teams preferring many short moves that involve multiple players versus teams utilising long moves with more linear actions and less ball contacts.	10 soccer games of the German Bundesliga from the 2011–2012 seasons	Tracking
Szczepański and McHale[60]	Supervised (classification and prediction)	Additive Mixed Modelling	Yes	Presented a method which can be used to evaluate passing skill of footballers controlling for the difficulty of their attempts. Combined proxies for various factors influencing the probability that a pass is successful in a statistical model and evaluate the inherent player skill in this context.	Coaches can use it to improve passing for players.	2006–2007 season of the English Premier League provided by Opta	Event

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Chawla et al.[59]	Supervised (classification)	Multinomial Logistic Regression	Yes	Present a model that can teach a classifier to rate the quality of passes made during a football match with an accuracy of up to 85.8%. Furthermore, a rating of the quality of each of the passes made in the four matches was made by two human observers.	Help use quality of pass to train players on improving their passes.	Four home matches played by Arsenal Football Club (2007–2008)	Both
Le et al.[29]	Supervised (prediction)	LSTM Neural Networks	Yes	Generated the defensive motion pattern of the 'league average' team, resulting in a similar expected goal value (69.1% for Swansea and 71.8% for the 'league average' ghosts).	Further research can help build automated strategies against specific opponents.	100 games of player tracking and event data from a professional soccer league	Tracking
Memmert et al.[27]	Supervised (classification) and Unsupervised (clustering)	Neural Networks	Yes	Demonstrated different kinds of computer science approaches to obtain and analyse new parameters such as inter-player coordination, inter-team coordination before critical events and team–team interaction and compactness coefficients.	Potentially help coaches modify their training methods (e.g. focusing on recent trends in game philosophy and tactics) according to their needs and to improve the tactical behaviour of their players. Can be an important step towards objectification of tactical performance components in team sports.	A single set of position data from an 11 versus 11 match (Bayern Munich against FC Barcelona)	Event
Pappalardo and Cintia[47]	Supervised (classification and prediction)	Logistic Regression	Yes	A team's position in a competition final ranking is significantly related to its typical performance, as described by a set of technical features extracted from the soccer data. Victory and defeats can be explained by the team's performance during a game, but it is difficult to detect draws.	Helps coaches prioritise objectives and predict success based on performance features correlated to success.	More than 6000 games and 10 million events in six European leagues	Event

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Power et al.[75]	Supervised (classification) Unsupervised (clustering)	Logistic Regression and *k*-means clustering	Yes	Presented an objective method of estimating the risk and reward of all passes using a supervised learning approach.	Can be used to coach and choose players according to opposition in terms of pass risk and reward.	English Premier League games between 2014–2015 and 2015–2016 seasons totalling 726 matches	Both
Rathke[52]	Supervised (prediction)	Logistic Regression	Yes	Demonstrated the value and reliability that xG has within professional football. The variables of distance and angle together were seen to have a major impact of calculating xG rather than distance as a variable alone.	No direct practical application; however, it could be incorporated into training and as a teaching tool on both offense (how attacking players should strike certain shots) and defence (optimise positioning to defend dangerous shots).	Shots from the Premier League and Bundesliga games (380 and 306) from the 2012–2013 season	Event
Ruiz et al.[53]	Supervised (prediction)	Multilayer Perceptron	Yes	Model can predict shot expectancy accurately and can be used to strategise.	Modelling the expected goal value of shots gives an additional level of detail to the analysis of offensive and defensive performance in football.	10,318 shots taken during the 2013–2014 English Premier League, extracted from Prozone Matchviewer event data	Event
Barron et al.[51]	Supervised (classification and prediction)	Multilayer Artificial Neural Network	Yes	Using match and player data and artificial neural network, the model learns which player can be helpful or conducive to team by predicting his career trajectory using quantifiable features.	Possibly useful for player recruitment.	Performance data from 966 outfield players90-min performances in the English Football League	Event
Goes et al.[62]	Supervised (prediction) Unsupervised (clustering)	Multiple Linear Regression, PCA	Yes	Presented approach is the first quantitative model to measure pass effectiveness based on tracking data that are not linked directly to goal-scoring opportunities.	Help coaches train their players to increase the efficacy of passes.	18 competitive professional soccer matches of 1 team against 13 different teams during the 2017–2018 Dutch premier league (Eredivisie)	Tracking

(continued)

Table 1. Continued

Study	ML approach	Used ML algorithms	Reproducible details reported	Study synopsis	Transfer to practice	Data	Tracking versus event data
Hobbs et al.[77]	Unsupervised (clustering)	Spatio-temporal Trajectory Clustering	Yes	Could objectively and automatically identify counter-attacks and counter-pressing without requiring unreliable human annotations.	Knowledge about the types of plays a team runs immediately after regaining the ball has use for tactical planning and game adjustment.	Counter-attack data both for and against each team during the 2016–2017 English Premier League	Tracking
Spearman[76]	Supervised (classification)	Logistic regression and Bayesian approach	Yes	Presented a new approach to using this tracking data to quantify off-ball scoring opportunity. This metric can be used as a leading indicator of future player scoring, and there are many possible applications for the opportunity model.	Can be used to improve player's off-ball movement and improve passing decisions. Use as a scouting tool to identify players who are making good movements off the ball but are not being rewarded with passes.	58 matches played between teams from a 14-team professional soccer league during the 2017–2018 season	Both

ML: machine learning; PCA: principle component analysis; KNN: k-nearest neighbors; ANN: artificial neural network; DBSCAN: density based clustering algorithm; LSTM: long short term memory; EM: expectation maximization.

possession in a specific zone does not guarantee or provide information about whether a team is penetrating the opponent's defence. As an illustration, a team with possession in Zone 14 can still face an opposition with 11 players behind the ball such as a rebound after a set play, or against a team that tactically emphasises a defensive structure. Moreover, long completed passes showed a negative relationship with shots taken, suggesting teams should consider how the ball arrives to Zone 14.[48]

In a study demonstrating the potential for machine learning to be used in the scouting and recruitment process in a professional football, technical performance data were collected from 966 outfield players in the English Football League Championship during the 2008–2009 and 2009–2010 seasons.[51] Key performance indicators that influence players' league status and accurately predict their future success in football were identified using quantifiable features, circumventing the subjective process and bias using traditional notational observation. Players most likely to end up in the English Premier League averaged the fewest unsuccessful first-time passes, had a higher mean number of possessions and averaged more passes to teammates in the penalty area. The authors stated that future work assessing players should account for positional differences as well as pass accuracy over varying distances and directions in specific areas of the pitch.

In recent years, an expected goal value (xG) model has been developed to evaluate the offensive performance of players and teams. The xG model assigns a value between 0 and 1 (with 1 being the maximum and representing a certain goal) to every attempt based on the quantity and quality (i.e. assist type, shot angle and distance from goal, whether it was a headed shot etc.) of shots taken. While a variety of these models have proven valuable in predicting shooting outcomes and scouting for players with high conversion rates, they either did not acknowledge[52,53] or capture[54] opponent positioning and thus, failed to provide context that coaches and analysts can apply to the match. In general, studies conducted to predict individual or team success used larger samples to build their model. However, they mostly used rather simple regression models to build classification or prediction models.

Machine learning models using tracking data

In the second part of the review, we present studies using tracking data to build their machine learning models. One of the advantages of tracking data is that it allows analysts to make quantitative comparisons between two teams, different groups of players or among different individual players.[55] Therefore, newer

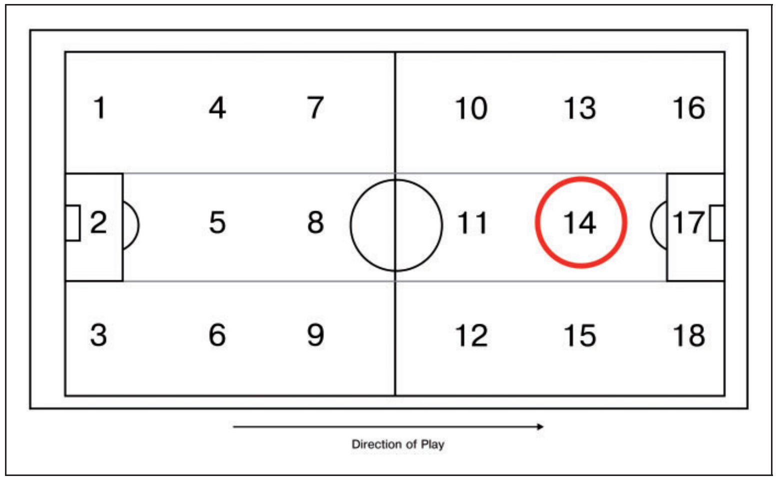

Figure 1. Zone 14: By dividing the field into a six-by-three grid, there are 18 zones on the pitch. Zone 14 is the zone located in the middle of the pitch immediately outside the penalty area.

studies using machine learning approaches tend to use the richer input data. In general, the use of machine learning approaches in this section can be split into four thematic sections. The first includes studies that try to find patterns of pass sequences or evaluate passes of individual players, while the second looks at the same characteristics on a team level. The third line of research investigated the use of time and space to create goals and goal scoring opportunities. The last section is concerned with defending or regaining the ball (in this case the concept of pressing).

Pass pattern recognition and classification. Advanced analysis on offensive tactics has mostly included the study of movement patterns and passing behaviour. For instance, using simulation data, Gudmundsson and Wolle[56] created a 2D model based on Frechet distance and the average Euclidean distances between trajectory paths to cluster sequences of passes between distinct players. After inputting 23 trajectories representing the movement of the ball and 22 players on the pitch, the model automatically output a description of every possible pass. They could then evaluate players' ability to execute a pass, become available for a pass and receive a pass, as well as measure a player's perception and decision-making ability based on all passes a player made, and every time the player did not make a pass. The authors concluded that the incorporation of a classification scheme (including examples of 'good' and 'bad' passes determined by expert football analysts) would be necessary before the tool could be used by coaches and analysts on a practical level.

Implementing such a classification scheme, Horton et al.[57] added to Gudmundsson and Wolle's[56] motion models by incorporating a multinomial logistic regression model (supervised learning). Given input data from four home matches played by Arsenal football club consisting of 2932 observations, the input features included location of players, player trajectories, strategic positioning of a team based on dominant regions[58] and physiological attributes using a motion model to determine how quickly a player can reach a given point. As a heuristic to evaluate and validate the use of a machine learning classifier to the inter-rater agreement between the two observers, Cohen's kappa coefficient was calculated. Yielding a score of 0.393, the authors concluded the experts were in moderate agreement. From this, the model could predict the quality of a pass of Good, Ok and Bad with an accuracy of 85.6%. Due to a limited number of observations, the labels were then condensed from a 6-class problem to a 3-class problem. Although accuracy was high, precision and recall were relatively low, stating that false negatives and false positives were high. In other words, passes classified as good were indeed 'Bad' or 'Ok,' and vice versa. The greatest limitations of this paper are the absence of data and the use of only two observers, which is not enough to reach a consensus. Despite these limitations, the methodology set the stage for future work, including the design of improved predictor variables.

Further expanding on the earlier work exploring pass classification, a supervised machine learning model was developed by Chawla et al.[59] to automatically classify the quality of all passes on the field. Passes were labelled as 'Good', 'OK' or 'Bad', with an accuracy level of 90.2% between the classifier ratings and the ratings made by a human observer. Whilst the accuracy was high, the subjective rankings are limited in that they did not give quantitative measurements of pass effectiveness or information about ball velocity, ball trajectory and what direction players were facing during each pass (common issue with tracking data). Despite challenges, the technological progress enabling analysts to classify passes can be used as a scouting tool. By applying spatio-temporal metrics to player trajectories, Feuerhake[26] could recognise and predict individual and group movement patterns, including differences between playing positions. For example, the wing players use mainly straight runs fixed along the sideline compared to the central midfielder displaying more freedom and significantly more turns. Due to computational complexities, real-time information about why a player might have changed their behaviour could not be provided. Another study focused on creating an individual evaluation tool for player recruitment that evaluated the passing ability of individual players by controlling for the difficulty of their attempts based on the probability of completion.[60] Contextual factors such as the skill of the player and the conditions of the player passing the ball were unable to be considered, and only the distance between the passer and the receiver could be derived directly from the model. Thus, comparing players performing similar types of passes, in similar circumstances, was most useful. The authors suggested that future work should account for different playing positions, defensive pressure, and rather than their difficulty, passes should be evaluated by their value for the team.

To sum up this section, authors used more complex machine learning approaches to cluster (unsupervised) or classify (supervised) passes. Compared to the event data studies, a higher degree of data variety could be observed as authors tried to enrich their models. In addition, the methodology used in those studies was solid, as they validated their models with a test set that was not part of the training data.

Team passing behaviour. In a first attempt to utilise artificial intelligence to provide process-oriented tactical insight in a football match, the validity of an unpredictable passing strategy was investigated by tracing *play-segments* defined as spatio-temporal descriptions of ball movement (where the ball started and ended) over fixed windows of time.[52] Measuring ball trajectories in 380 games from the English Premier League showed a high level of entropy, a measure of predictability for team behaviour, and was an attribute of the top 5 ranked teams. This was the case, especially around the penalty area where more defensive players are trying to protect their goal.[61] The authors then attempted to show how discriminative their entropy map approach was by identifying the home versus away team based by classification of playing style using a *k*-nearest neighbour approach. Combining their entropy map approach with 23 match statistics currently used in analysis (e.g. passes, shots, tackles, fouls, aerials, possession and time in-play), they reached 47% classification accuracy. Coaches and analysts can apply this information to measure their team's entropy levels and that of their opponents. However, knowledge about what types of off-ball movements encouraged the greater variety of passing, and how specific passing sequences lead to goal-scoring were unable to be identified.

Earlier work using notational analysis provided evidence that direct counter-attacking tactics effective against imbalanced defences (defined 'as only without second defender within 5 m estimated distance from first defender') are not necessarily effective against balanced ones.[4] For that reason, evaluating the quality of a pass should be considered by the effect a pass has on the opposition. Accounting for the interactive dynamics of both teams to determine the effects of passing behaviour, Goes et al.[62] considered previous research on team centroid, spread and surface[63] in the evaluation of defensive organisation. Goes et al.[62] calculated the defensive disruptiveness (D-Def) score as an index that represents the change in defensive organisation resulting from a pass. Based on the line formations and starting formations (substitutions accounted for) of teams provided by coaches before the match, D-Def was calculated based on the displacement of the average X and Y positions (or centroids) for the full team, as well as the defensive, midfield and attacking lines between the moment a pass was given ($t0$) and 3 s later ($t0+3$). The authors discovered that greater amounts of individual movement (I-Mov) occurring after a pass result in a disruption of the D-Def. Moreover, they could distinguish top, average and low performance passes, and determine which players are more effective passers using a one-way analysis of variance comparing the I-Mov, D-Def, pass length, pass angle and pass velocity in the top 10%, average 80% and bottom 10% passes ranked on D-Def score. Consistent with the findings of Chassy,[64] the speed and precision of passes are predictors of success, causing greater D-Def scores. Although passes in a slightly more forward direction produced the best D-Def scores, passing angle was not a determining factor for the effectiveness of passes. This was the first model that did not favour passes in the forward direction, demonstrating the value of backwards and sideways passes in the overall attacking process. Still, previous studies have shown that the teams with increased space control in the attacking third have a greater chance of winning,[65] with scoring probability increasing as the distance from the goal decreases and centrality increases.[66] Therefore, Goes et al.[62] suggested that to rate the actual effectiveness of a pass, future work should incorporate pitch values to measure space creation and investigate the relationship between D-Def and game outcome (goals). Furthermore, by only including successful passes, the authors were unable to measure decision-making or determine whether a certain player was a good passer overall.

In a related work analysing both player trajectories and passing behaviour for two different teams in the Bundesliga 2011–2012 season, Knauf et al.[67] used spatio-temporal convolution kernels to extract strategies used during the build-up phase of attack and during scoring opportunities. The authors could identify the difference between teams utilising rehearsed methods consisting of shorter passes amongst several players compared with more chaotic approaches characterised by long, straight passes.

The studies presented in this section show a lot of potential for practical applications. A main weakness of most of the presented studies is that their data sample is on the edge of being big enough to conduct their used methods.

Team behaviour related to time, space and goal-scoring. Studies using a multiple regression model[68] and comparative analysis[69] have reported that successful teams create a higher number of shots and shots on target. Other studies using notational analysis suggest that rather than the total number of shots, shot effectiveness best discriminated between successful and unsuccessful performance.[44,70] Machine learning methods based on tracking data have also been used to evaluate offensive tactics related to the management of space and time.[71,72] Applying a machine learning approach to gain insight into the process behind creating more effective scoring chances, Lucey et al.[73] used the spatio-temporal patterns of the 10-s window before a shooting attempt to determine that expected goals depend on several factors. These include the interaction of surrounding players, speed of play, and in support of the observational analysis by Schulze et al.,[74] shot location and defender proximity to the shooter. Compared to statistics such as shots, and shots on goal that do not provide information on the quality of the shooting attempt, their xG model could provide a better approximation about whether a team was 'dominant', with a higher number of quality (high xG value) chances, or 'lucky', with significantly less quality chances but still won the match. However, isolated plays such as their finding that 'a play which has the left-winger controlling down the left uncontested and then slotting the ball between the back four to a player in the six-yard box results in a chance of 70.59%' (p.7)[73] does not explain the origins of that scenario, nor how the probabilities may change depending on specific players being utilised against various opponents.

In another study involving the concept of a 10-s window before a shot, Power et al.[75] used tracking data to evaluate passes based on risk, the likelihood of executing a pass in each situation and reward, the likelihood of a pass creating a chance. They defined a Dangerous Pass (DP) as an attempted pass that has a >6% chance of leading to a shot in the next 10 s. It was discovered that the passes with the highest reward (DP) occurred around the edge of the penalty area, and these passes also have the highest risk. The ability of a team to play high reward passes that lead to scoring chances also depends on the function of players not in possession of the ball. In a similar manner to calculating expected goals based on instantaneous game state, Spearman[76] created opportunity maps based on spatio-temporal tracking data to measure 'off-ball scoring opportunity' (OBSO), the probability that a player currently not in possession of the ball will score. This study also measured individual finishing ability, team attacking trends and team decision-making within and around the penalty area by comparing OBSO to actual goals scored. The model suggested that certain players get into dangerous positions but are not always rewarded with a pass, and some players have distinct zones of the pitch where they are more dangerous. This information is valuable to coaches and analysts as a tool to scout for prospective players, prepare for specific opponents, evaluate offensive movement and decision-making, and answers questions about how some players' off-ball movement gives them seemingly greater 'instinctive' qualities. This model, however, fails to assess how different types of defensive pressure and player speed influence the ability to successfully deliver a pass to a teammate. Furthermore, this method of measuring OBSO does not include information about how individual skill and awareness determine conversion rates, and why some players and teams have lower conversion rates than others.

Defence and pressing tactics related to attacking play. In a continuous, interactive sport like football, there are frequent turnovers of the ball from one team to the other. Attacking sequences occurring quickly after recovering the ball facilitate space exploitation in the defence. Due to the inherent imbalance of a team transitioning from offence to defence, counter-attacks generated a greater number of high-quality shots, and top teams were effective at both utilising and stopping counter-attacks.[77] Hobbs et al.[77] implemented machine learning to automatically identify the precise time-stamp of counter-attacks and come up with a metric known as 'offensive threat', the likelihood of a shot being taken in the next 10 s. The authors were also able to identify the types of plays a team runs immediately after regaining the ball. The challenge remains to identify how parameters such as the direction and total number of passes, time taken and distance covered correspond to a counter-attack's success. Nevertheless, machine learning-based studies could exceed the capabilities of notational analyses[78] and provide a method for evaluating team tactical behaviour as well as understanding that of their opponents.

Using advanced machine learning methodologies called 'deep imitation learning' (a subfield of machine learning that can learn and make intelligent decisions on its own), researchers compared fine-grain movement patterns from a season's worth of tracking data from the English Premier League.[29] Although it has only been presented at a rather commercially oriented conference and some critical distance should be exercised, their ghosting method could access the location, velocity and acceleration of every player at the frame level to visualize the defensive movement patterns of a league average team. By fine-tuning the model, they could also identify how a specific team would have responded to an attacking situation. For example, if the opponent produces a shot on goal, perhaps the hypothetical ghosting player would have more proactively closed the player's passing lane that could have prevented the shot. The capacity to estimate how a team could have responded to an offensive situation enables coaches and analysts to measure the effectiveness of defensive positioning. Moreover, a broader understanding of defensive tactics and team trends facilitates the scouting process and the development of superior attacking strategies.

Current challenges and future directions of machine learning in football

Current challenges of machine learning in football

The latest advances in technology have the potential to add novelty and speed to exploring contextual variables related to football. The automatic, quantitative analysis that machine learning offers is beyond the scope of observational analysis, as supervised classifying models are able to produce the same and richer observational data.[59] We differentiated between two types of input data: event data and tracking data. The main findings from event data include the recognition of team patterns and characteristics, and the identification of key performance indicators as predictors of success. The main findings from tracking data were more process oriented, such as the determinants of effective passes and the scoring probabilities of players not in possession of the ball, or after quick regains. In general, studies used classification/clustering to model decisions experts normally do, and to predict goals, game outcome and league success (see Figure 2).

Despite the advantages of tracking data, scenarios involving quick, unpredictable movements including frequent occlusions between players provide challenges to practitioners in regards to the accuracy of the information provided compared to what is occurring on the pitch.[38] Future projects should be aimed at diminishing these inherent errors,[38] and it is recommended that practitioners use caution when comparing results between different tracking systems. Nonetheless, player tracking data are being used more and more frequently by teams to turn raw data into useful information.

Most studies using machine learning are performed by computer scientists as they use more complex approaches. However, the downside of using those complex models is that they result in a 'black box' where a result (model) is obtained (especially using neuronal networks), but determining what the important factors are is not always possible. For instance, you can have a passing model that does a good job quantifying passes, but it does not tell if pass length, velocity, position etc.

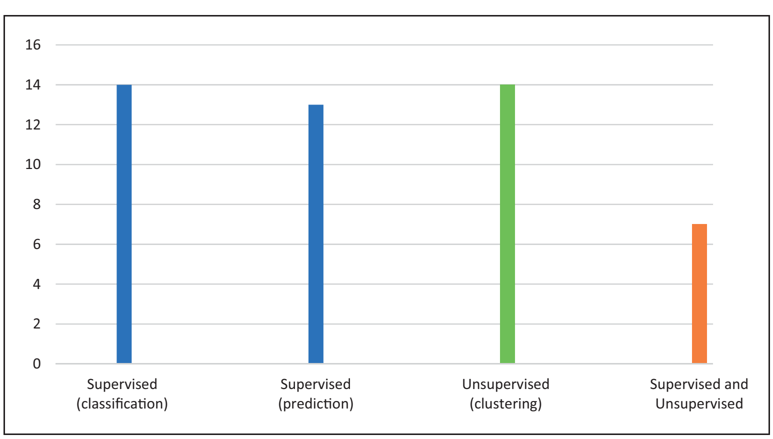

Figure 2. A frequency distribution of studies using supervised learning, unsupervised learning and both. Within supervised learning, prediction (continuous y variable) versus classification (categorical y variable), are shown.

makes it a good pass. Thus, it is hard to provide feedback to coaches and practitioners who favour straightforward analyses that provide a quick 'snapshot' of the team's performance.[7] Performance analysis research including substantial and complex statistics and mathematical equations are not priorities for coaches, nor have they been successfully integrated into coaching.[33] As such, the majority of machine learning analyst's work has been done by computer science research groups with little involvement of sports scientists, match analysts or coaches.[79] Additionally, many studies have aimed at match prediction which offers little in terms of how conclusions are drawn outside of which team is more likely to outscore their opponent.[25,80–82] Due to the lack of interaction between practice and computer science, the outcomes seldom transfer into practice, leaving considerable room to improve upon applying knowledge gained by the data to knowledge that can be applied to the actual game. Therefore, it is suggested that machine learning analysts/computer scientists, sports scientists and football coaches/analysts combine to obtain more accurate information with respect to individual and collective performance that may influence the outcome of football matches (Figure 3).

Another issue of applying machine learning to football is the lack of a learning curve. Unlike other domains that build on previous findings, there has been a greater emphasis on trying to develop new, fancy approaches. This means that research in this field is more concerned with creating new machine learning approaches rather than incorporating existing approaches to build a better model for practice. One example is the study by Goes et al.[62] that evaluated passing performance. They mention in their discussion section that their model would benefit from including the actual playing formation rather than the starting formations of a team, which could have been implemented using the findings of Bialkowski et al.[22] From a methods standpoint, early research studies rarely validated their results with a test sample, and several studies had relatively small samples (some with just one to two games). With some exceptions (like expected goals), more recent studies have improved upon this and provide descriptions of their methods that allow for rebuilding their model and redoing their analysis. In doing so, practitioners can be sure that those approaches can be applied to new data sets and hold some predictive value, rather than overfitting the training data to show promising results within a publication.

One of the challenges for machine learning is to provide information about football beyond the capabilities of the human observer. When spatio-temporal data based on methods from computational geometry were used to create an approximation algorithm to identify pitch dominant regions and rate the quality of passes in a football match, results indicated accuracy levels of 85.8%[57] and 90.2%,[59] an agreement between the machine classifier and a football expert observer similar in magnitude to the level of agreement between two observers. Despite the accuracy between machine learning and human observers, analysts are still using observational notation analysis to study aspects of the game that machine learning has not yet been able to satisfy. For example, in studying the subtle behaviours that separate the top players from the rest, observational notation analysis was used to study English Premier League players' visual exploration (moving their bodies and heads to enable perception of the full, 360°, external environment) in the 10 s prior to receiving the ball.[83] Results showed that players

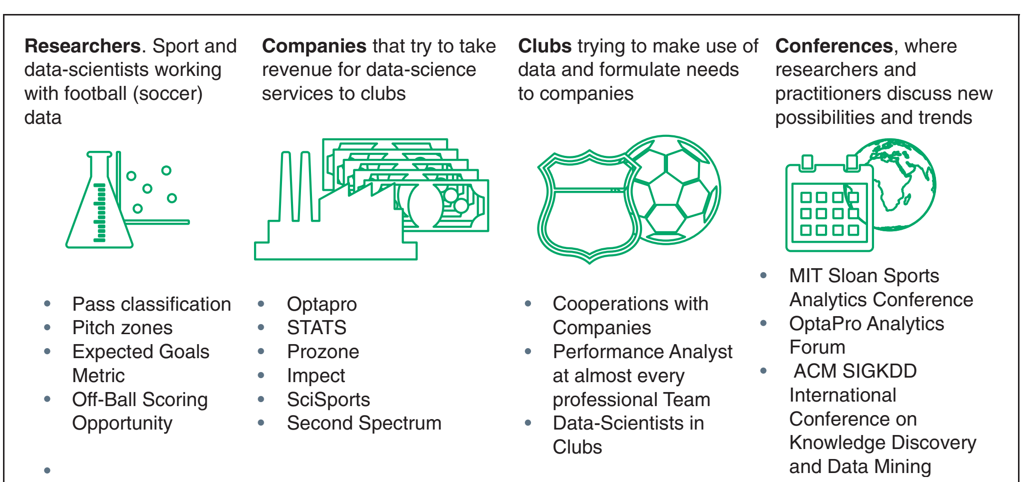

Figure 3. A collaborative effort between sport scientists, computer scientists and football clubs will optimise the application of machine learning in a more relevant manner.

exhibiting higher frequency of visual explorations are more consistent in completing passes to their teammates, especially midfielders making forward passes. If machine learning can measure these visual explorations combined with positioning data, it would save analysts' time, amplify the amount of data that can be collected and help teams find better playing solutions in specific match contexts.

Whilst positional data have improved, the machine learning algorithms need further refining and the gap in analysing event data in unison with football theory needs narrowing.[84] To improve transferability to practice, mathematical-based measures that are not the highest priority for coaches need to be simplified, and the research should incorporate important aspects of football match performance that are not yet fully understood. Some of these areas include team adaptability, communication, penetrating defensive lines, how possession is regained and the effects of playing at varying tempos during different phases of the match.[33]

Future directions of machine learning in football

As technology enhances analysts' ability to compare and value performance, more data continue to drive a revolution in football analytics. At present, machine learning is a new concept in football, and more research is necessary to realise its potential to inform coaches and analysts on a practical level. Further studies should aim to use larger samples and include both training and testing data sets to allow for feedback and model validation. Providing clear descriptions of the steps of their approach and the methods section (or sharing via GitHub) will improve subsequent models and improve applicability.

If machine learning can decipher situations quickly and reliably, it would demonstrate a practical impact not yet apparent in the literature. There are also other pertinent questions related to football that machine learning can address in future research. Some of these questions include understanding more about how off-ball movement characteristics impact the decision-making and passing ability of a team. Furthermore, information about how different defensive schemes influence ways of penetrating the defence is needed, including the constellations of players and off-ball movements that are most effective.

Conclusion

To date, most of the match analysis work has predominantly used simple description and associations between variables. Moreover, advanced analyses have been driven by computer scientists and research-based approaches that lack practicality and adoptability by coaches and teams. It is possible that the integration of machine learning with coaches and analysts in applied settings can account for a larger number of interacting variables, providing teams with practical information at faster speeds. However, relying on increasingly complex data analysis techniques will also present new challenges for future sports scientists. It is not only a matter of improving the machine learning techniques, but the challenge of representing the knowledge in a way that can be understood and utilised in practice. This implies the use of multi-disciplinary approaches including computer science research groups and sports scientists competent in football to interpret the relevant value of the information and patterns produced by the machine.

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