Explainable Game Strategy Rule Learning from Video

Daniel Cyrus*, Ghazal Afroozi Milani and Alireza Tamaddoni-Nezhad*

University of Surrey, GU2 7XH, Guildford, UK

Abstract

The spatial configuration of sports teams, such as soccer matches, indicates their tactic. The specification of team tactics might be either offensive or defensive. We propose a method using Meta Interpretive Learning (MIL) to generate rules that are learned from a video to explain the strategy of a football game. We first track the players to estimate their position and estimate the team's formation. For the purpose of classifying players as defender, midfielder, or attacker, our method combines k-means and OPTIC clustering. We measure the dynamic strategy within the time series by generating background knowledge, then a new rule extracts to explain team strategy regarding the current state. Finally, in order to determine the accuracy using MIL, our experiments compare our approach with a long term short term memory (LSTM) model. In contrast, our research demonstrates the superiority of a MIL system over a deep learning model with a small dataset.

Keywords

Inductive Logic Programming(ILP), Meta Interpretive Learning(MIL), Learning logic programs from video, Machine learning of game strategy, Explainable AI

1. Introduction

Numerous professional sports clubs have recently embraced camera-based monitoring technology that frequently records the whereabouts of both players and the ball. However, they rarely use the crucial information that is concealed in these performance data while making decisions.The computational methods required to fully analyse these data [1]. On the other hand, using deep learning (DL) models to produce match prediction or tactic classification, analysis has generally been done without reasoning and explanation due to DL's characteristic.

Gameplay configuration over a given period is used to predict the match using time series analysis [2]. Although the prediction is highly accurate and is based on the team's past behavior, the outcomes of time series analysis are similar to the pattern of the trained data. The visual analysis [3, 4], which combines several methodologies, assesses the data through visualization and conversation in order to overcome this issue. This type of technique's drawback is that analysis depends on human involvement.

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*Corresponding authors.
d.cyrus@surrey.ac.uk (D. Cyrus); g.afroozimilani@surrey.ac.uk (G. A. Milani); a.tamaddoni-nezhad@surrey.ac.uk (A. Tamaddoni-Nezhad)
https://github.com/danielcyrus/Explanable-Game-Strategy-Rule-Learning-from-Video (D. Cyrus)
0000-0003-3385-8081 (D. Cyrus); 0009-0007-8188-7270 (G. A. Milani); 0000-0003-0460-9545 (A. Tamaddoni-Nezhad)

In this paper, we propose a method to automatically learn the rules from the spatial configuration of players, extracted from a soccer video. We first employ a deep learning model to detect players and statistical method to determine team formation from noisy data. Then we use meta interpretive learning (MIL) techniques with Metagol as the rule learning engine. More precisely, we are interested in identifying and analyzing team behavior that reveals the team's tactics. Our proposed method must take into account player distance and team formation. Additionally, several players may be involved in a single action in team sports like football and basketball. We need to analyze all players in order to correctly recognize the action[5]. To address this issue, we employ ILP approaches that make use of Prolog programming, which can easily handle relational data.

2. Related work

Although there hasn't been much research on game analysis utilizing logic and ILP methods, other techniques like deep learning and statistical methods produce respectable outcomes.

Logic and semantic methods: Vercruysse et al. [6]. proposed a qualitative spatial reasoning approach by investigating the information between players and the dynamic of the game. Their method is to predict if a player passes the ball to the front or to the other players. Automatically discovering the soccer match data to recognize the pattern of offensive by Van Haaren and others[1] using ILP, is another technique to provide the explainability of the data. Semantic analysis on broadcast video[7] is one of the appropriate approaches to express the trajectory of the match into the sort of sentences. However, since the algorithm's foundation was not built on logical expression(e.g. Predicates, Relations or Rules), this method only conveyed occurrences as a form of description.

Statistical and deep learning methods: Most recent research using the LSTM model shows the feasibility of prediction using deep learning. Sports match prediction model [8] proposed a method to combine the LSTM model with the attention mechanism and put forward an AS-LSTM model for predicting match results. [9] examined the playing tactic on goal scoring with assessing opponent interaction. Their approach involved analysing opponent interactions in Norwegian elite men's soccer using a case-control design to analyse the effects of playing strategies, counterattack versus extravagant assault, on the likelihood of goal scoring.
Other approaches with spatial analysis define how a team plays defensively or offensively. [10] proposed a dynamic analysis of team strategy, their method classifies team formation and detects major tactical changes during the course of a match. Their method relies on the spatial shape of teams' players. Collective movement analysis [11] examines the players' motion patterns and the underlying coordination among them, their method provides a comprehension of the collective tactics that contribute to team effectiveness. [11] reviewed the influence of player position to understand their tactical performance. They measured players' distances during a match by tracking their location and measuring the time players were closer than a threshold distance. They also investigated the distance of players depending on their roles. K. Kim et al.

[12] provided a novel approach to predict play evolution by extracting the ground level sparse movement of players. Their data utilize each time step and then generate a dense motion field.

3. Quantitative spacial representation

This section outlines our approach to player tracking as well as our methods for grouping players and estimating their distances. We utilize this data as the raw data. Then we describe the process by which we create relational data from raw data. From the video provided by the [13], we first identify each player using pre-trained single shot detection (SSD) [14] model. Then we fetch players position by the coordinate of bounding box and store them in a data file, frame by frame. Each frame in the data file consist of players position and their team name (e.g

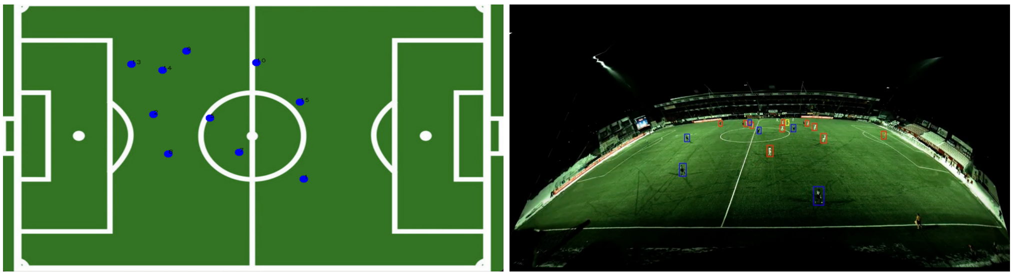

Figure 1: the 2D visualization of a single team(left) and the player detection from real match video(right).

teamA or teamB). By calculating the distance to each player, we keep track of the ball's position to determine which team is in possession. In section 6.1 we explain the usage of the dataset and generating background knowledge.

4. Clustering with noisy data

There is no assurance that to accurately detect objects in videos. There are many factors that can lead to the system misidentifying objects from frame to frame, including an improperly trained convolutional neural network(CNN) model (i.e. A model with insufficient train size), noisy frames, shadows, and brightness variations [15]. Consequently, it is difficult to locate things accurately from videos. To address this issue, we take into account twenty frames of a player's position and utilize K-means to look at the centroid of all positions. As a result, the valid positions of all players can be calculated on the field. This technique enables the system to function without noise or missing data. In order to identify the centre of positions, we use the k-means[16] algorithm described in equation 1 with one cluster for each participant.

$$arg_s min \Sigma_{i=1}^{k} \Sigma \|x - u_i\|^2 \tag{1}$$

Where u denotes the mean of a player's positions collected from a set of 20 frames. As a result, there are 10 positions on the pitch, excluding the goalkeeper, which are divided into three groups: defenders, midfielders, and attackers. For this technique, we use the procedure below 2 to determine the clustering structure from ordering points(OPTICS)[17]:

$$\text{core-dist}_{\epsilon,\text{minPts}}(p) = \begin{cases} \text{undefined}, & \text{if } |N_\epsilon(p)| < \text{minPts} \\ \text{minPts-th smallest distance in } N_\epsilon(p), & \text{otherwise} \end{cases} \tag{2}$$

Where ϵ denotes the distance(radius) of N neighbours with a minimum number of points to form a cluster($minPts$). By linearly arranging the points, the method creates an improved ordering of the data, making the physically closest points to one another neighbours. This cluster-ordering comprises data that is comparable to the clusterings created using density-based methods and covering a wide variety of parameter choices. Figure 2 demonstrates how the noisy data is categorized into soccer roles. Every category counts as one of the set positions in the formation, for example, 4 defenders, 3 midfielders and 3 attackers (4-3-3 formation), which means isolating full-back and supporting attackers. The categorization of the data is repeated over the course of the following 20 frames, allowing the system to recognise dynamic formations during the match.

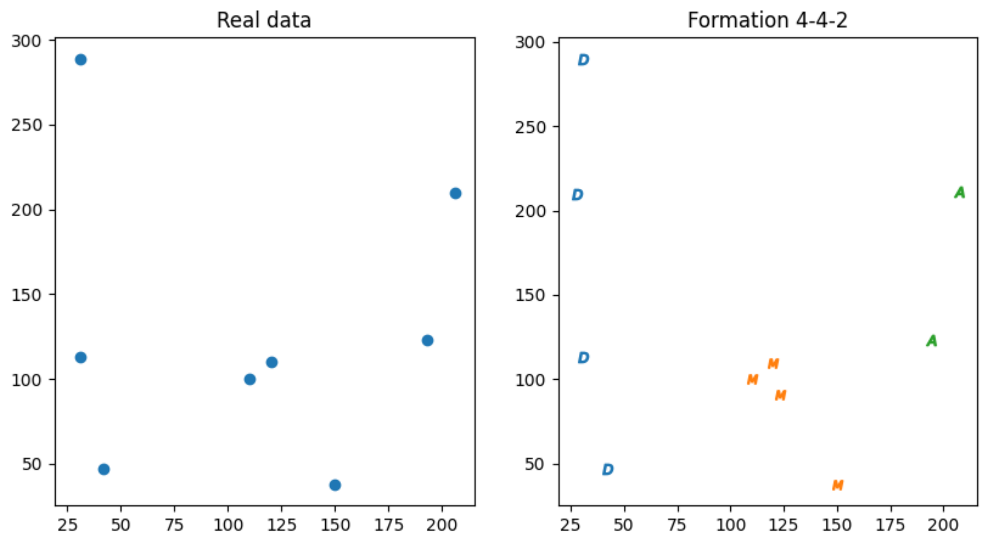

Figure 2: Clustering players' role from the noisy data, the result illustrates 4-3-3 formation. Two players, one in defence and one in midfield, are not apprehended, according to the plot on the left.

5. Long short-term memory (LSTM)

LSTM [18] models have emerged as a pivotal advancement in the field of deep learning and sequential data analysis. LSTMs are characterized by their unique architecture, featuring a network of interconnected memory cells that can store and update information over extended sequences. Unlike conventional RNNs, LSTMs are equipped with gating mechanisms, including input, output, and forget gates, which enable them to selectively retain or discard information

Table 1
The table gives an overview of the records structure and sample data. Each player assigns a number using Joint probabilistic data association algorithm. Position X and Y generated from K-means centroid. Each player is manually given their team name and the ball's possession. The completed clustered data is displayed in Figure 2 on the right side.

field	Attribute	Example
playerID	Number	$0-9$
positionX	Normilized decimal number	0.5785550475120544
positionY	Normilized decimal number	0.31300538778305054
teamName	Atom	teamA/teamB
ballPossession	Boolean	true/false
frame	Number	$0 \sim 10000$

at each time step. This gating mechanism enhances their capacity to maintain relevant context and prevent the loss of crucial information, making them particularly well-suited for tasks that involve capturing patterns and relationships over extended temporal horizons. In our experiment, we incorporate LSTM as a point of comparison with our own method because this model takes into consideration the temporal nature of time series data and serves as an effective model for predicting match outcomes.

6. Meta interpretive learning (MIL)

MIL is a form of ILP [19, 20]. A set of examples E and background knowledge B made up of a set of Prolog definitions B_p and metarules M such that $B = B_p \cup M$ are provided to the learner. To produce a hypothesis H such that $B, H \models E$ is the goal. The Prolog meta-interpreter has been modified for the proof [21]. The ability to learn recursive algorithms and support for predicate invention are two of MIL's core characteristics. The former enable the program to break down the repetition of predicates. The latter makes it possible to decrease the textual complexity of generated rule. A MIL system called Metagol [22], can produce rules from examples, background knowledge, and metarules.

6.1. Dataset and background knowledge

We prepare the initial background knowledge (BK) using Prolog and based on a relational approach. Relational learning is a method of MIL which represents the relation between each rule. For example, the rule

$$tactic(A, B) \leftarrow attackers(A, C), ball(A, D).$$

denotes the tactic of team A is B if attackers of team A are at the position C and have possession of the ball D. The BK includes a list of facts $Q(A, B)$ such as formation types, team's opponent, player roles type (i.e. constant, shrink, expand), ball possession and team position in the field. Each predicate demonstrates fact name Q, relational name A and relational settings B. The system updates BK for a new rule after the data regenerates, over a 20-frame sequence. The names of the formations (e.g. 4-3-3 or 5-2-3), as well as the players' distribution in relational mode(i.e. expand, shrink and constant), can be retrieved from the clustered data. We first calculate the variance percentage of each role within 200 frames using equation 3. Then a Python code relatively generates predicates given from each percentage and it saves predicates into a Prolog BK file. The learner in section 7 repeats learning from new BK and it generates new rules for each sequence. The Table 2 shows how BK file updates with new data. The data is sequentially increased by additional predicates like ball possession and team position, see Section 6.2.

$$Var_{percentage} = (\sigma^2(R_i) - \sigma^2(R_{i-1}))/\sigma^2(R_i) * 100 \tag{3}$$

Where R denotes player distance in each role from the frame i. Therefore, we compute changes in player distance over a period of time. If a value is $constant$, it signifies that the distance between the players hasn't altered significantly; otherwise, it would therefore be $shrink$ or $expand$. The method is motivated from The influence of player position [23] and activity analysis of football players[24]. The method is to take into account the separation between each player in their own role.

Table 2
The initial BK from the first (left) and second(right) sequence.

sequence frame 0-19	**sequence frame 20-39**
oponent(teamA, teamB).	oponent(teamA, teamB).
oponent(teamB, teamA).	oponent(teamB, teamA).
formation(teamA,'4-4-2').	formation(teamA,'4-4-2').
formation(teamB,'4-3-3').	formation(teamB,'4-3-3').
midfielders(teamA, constant).	midfielders(teamA, constant).
defenders(teamA, constant).	defenders(teamA, expand).
attackers(teamA, constant).	attackers(teamA, shrink).
midfielders(teamB, constant).	midfielders(teamB, shrink).
defenders(teamB, constant).	defenders(teamB, shrink).
attackers(teamB, constant).	attackers(teamB, expand).

6.2. Possession and position

Success in soccer has been correlated with the capacity to maintain possession of the ball for extended periods of time [25]. On the other hand, the centroid locations and surface areas of two teams may be used to explain the coordinated flow of offence and defence at the team level [26]. Thus, we take into account the possession of the ball and team positioning as two essential factors for strategy analysis. To accomplish this, we estimate the distance between the ball and each player, then we set the ball possession to the relevant team.

Listing 1: A `Prolog` Sample of defining ball possession

```
ball(teamA, inPossession).
ball(teamB, outOfPossession).
```

Table 3
team position calculation

Term	Condition
centre	abs(PitchCentre - MassCentre) $\leq$ 10
onOpponentSide	PitchCentre - MassCentre $>$ 10
onOwnSide	PitchCentre - MassCentre $<$ -10

Another element that may have an impact on a tactic is the team's position. This section is motivated by Dynamic analysis of team strategy [10], which involves computing the convex hull, determining the mass's centre and its distance from the center of the field. The Table 3 shows the calculation for team position terms and the Figure 3 visualizes them.

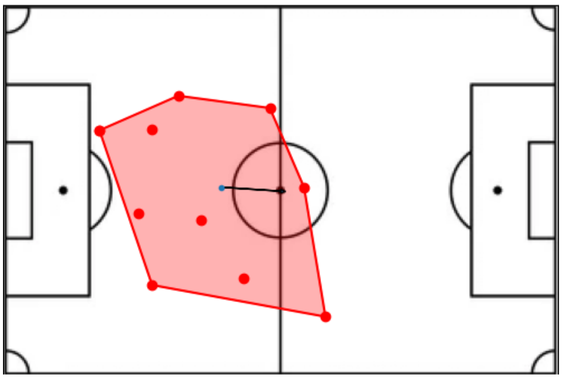

Figure 3: One frame's mass distance from pitch centre using convex hull.

We outline three hypothetical field segments that characterize team position. One of the following predicates can be generated by the system in relation to the calculation in the Table 3:

Listing 2: Placing three sections on the field to define team positions.

```
teamPosition(teamA, onOpponentSide).
teamPosition(teamA, centre).
teamPosition(teamB, onOwnSide).
```

7. Rule learner using $Metagol_{NT}$

In this section, we explain how our method learns rules from generated BK. We first discuss the current strategy in each instant of time in section 7.1 and then we propose the prediction rules in section 7.2. We employ $Metagol_{NT}$ by [27] which is the noise-tolerant version of standard Metagol. $Metagol_{NT}$ looks for hypotheses that are consistent with randomly chosen sections of the training instances, then rates each one on the remaining training set to determine which hypothesis received the greatest score.

7.1. Current strategy state

The BK updates every 200 frames, equivalent to 10 seconds of the video. Thus, the system generates new rules related to the current state. The following rules show an example of one state:

Listing 3: The final rule sample of a 10 second of the game.

```
tactic(A, offensive):- defenders(A, constant), attackers(A, expand).
tactic(A, difensive):- defenders(A, expand), tactic_1(A, constant).
tactic_1(A, constant):- attackers(A, constant), ball(A,
    outOfPossession).
```

The variable A denotes the team's name. The predicate *tactic_1* is a predicate invention, generated by Metagol. By creating more predicates, the Metagol algorithm invents more simple rules than a complex one. The hypothesis defensive or offensive may be accepted for teamA depending on the situation. Our implementation is shown in Algorithm 1. Data from the frames F and initial BK are fed into the $MetagolNT$ alongside the parameters v and n.

Algorithm 1 StrategyRuleLearning(F,iB,E,v,n)

Input : Video frames F; Initial background knowledge iB; Set of examples E; Noise level v and number of iteration n.

Output : Hypothesis H.

$B_f \leftarrow \phi$
while
  $F \leftarrow VideoFrames$ **do**
  $P \leftarrow trackPlayerPosition(F)$
  $D, Po \leftarrow measureDistanceAndPosition(P)$
  $B \leftarrow abductiveFact(D, Po)$
  $B_f \leftarrow iB \cup B$
  $H \leftarrow Metagol_{NT}(B_f, E, v, n)$
end while

7.2. Strategy prediction

In contrast to the current situation, the prediction calls for prior knowledge. As a result, we continue to process the entire set of data sequentially. To determine the most often used strategy, we divide the number of calculated tactics, such as offensive and defensive by the total number of frames. The outcome and the final state of ball possession are favorable to the BK.

Listing 4: The rule to explain next sequence tactic.

```
predict(A, offensive):- tactic(A, offensive), ball(A, inPossession).
predict(A, offensive):- tactic(A, difensive), ball(A, inPossession).
predict(A, difensive):- tactic(A, difensive), ball(A,
    outOfPossession).
```

```
predict(A, difensive):- tactic(A, offensive), ball(A,
    outOfPossession).
```

We evaluate the prediction in the experiment section. The variable A indicates the name of the team, the body predicate *tactic* given from whole prior frames and ball possession on the most recent frame.

8. Experiments

In this section, we evaluate our methodology utilising the MIL technique (Metagol). For comparison with the LSTM model, the evaluation assessed the following hypotheses to determine accuracy:

Null Hypothesis 1: MIL cannot outperform LSTM for prediction soccer match from small train dataset.

Null Hypothesis 2: MIL cannot learn human comprehensible rules of application in Null Hypothesis 1.

Null Hypothesis 3: There is no deference between MIL and ILP in terms of accuracy. We examine an LSTM model in the experiments that have three nodes in the output layer that predict values for defenders, midfielders, and attackers. With a batch size of 64, the mean squared error is employed as the loss function. We divide our dataset's 22961 records into 80% (18300 records) to account for train size.
The train set for Metagol contains 8 examples. The target rule is $predict/2$ with body predicates of $tactic/2$ and $ball/2$.
Results in Table 5 compare the predictive accuracy of deep learning model and MIL approach. The test is fairly selected from 18 samples(9 offensive and 9 defensive), hence the accuracy is set to 50% by default.

Table 4
The Accuracy comparison of MIL and LSTM

Technique	Train type	Train size	Accuracy
LSTM	Array list	18300	62%
$Metagol_{NT}$	Pos/Neg Examples	8 4 Positive,4 Negative	**73%**

8.1. Supplemental materials

The Prolog and Python code and the sample dataset can be found in the following Github repository: https://github.com/danielcyrus/Explanable-Game-Strategy-Rule-Learning-from-Video.git

Table 5
The table compares predictions with actual data. Defensive and offensive are fairly selected from two minutes of the game in the test dataset.

Index	Time of the match	LSTM	$Metagol_{NT}$	Ground Truth
1	18:16:27	offensive	offensive	offensive
2	18:16:37	offensive	offensive	offensive
3	18:16:47	offensive	offensive	offensive
4	18:16:57	offensive	defensive	offensive
5	18:17:06	offensive	defensive	offensive
6	18:17:16	offensive	offensive	offensive
7	18:17:55	offensive	offensive	defensive
8	18:18:05	offensive	offensive	defensive
9	18:18:16	offensive	offensive	defensive
10	18:18:26	offensive	offensive	offensive
11	18:18:36	offensive	offensive	offensive
12	18:18:57	defensive	defensive	defensive
13	18:19:07	offensive	defensive	defensive
14	18:19:17	offensive	offensive	defensive
15	18:19:27	offensive	defensive	offensive
16	18:19:37	offensive	defensive	defensive
17	18:19:47	offensive	defensive	defensive
18	18:19:57	defensive	defensive	defensive

9. Conclusion and future work

This paper studies the learning system using the relational learning and explainability paradigms. We can make use of prior knowledge and visual concept learning tasks by utilising the ILP techniques, including MIL framework.Moreover, Our research demonstrates that MIL methodologies can learn from small sample sizes and outperforms LSTM. Our experiments indicate that our learning system can generate relational rules from background knowledge given from video. This research focuses on tactic analysis in the category of defensive and offensive of a soccer match. However, a limited number of features can be extracted from a single video (i.e. missing tiny objects while detecting players, captured from a single view and using a distorted video), We produce absolute and precise rules by extending and growing additional dataset [5]. We intend to investigate more intricate predicates and predictions in the future to improve accuracy and to examine more relational and semantic data.

References

[1] J. Van Haaren, V. Dzyuba, S. Hannosset, J. Davis, Automatically discovering offensive patterns in soccer match data, in: Advances in Intelligent Data Analysis XIV: 14th International Symposium, IDA 2015, Saint Etienne. France, October 22-24, 2015. Proceedings 14, Springer, 2015, pp. 286–297.

[2] Z. Yue, H. Broich, F. Seifriz, J. Mester, Mathematical analysis of a soccer game. part i: Individual and collective behaviors, Studies in applied mathematics 121 (2008) 223–243.

[3] M. Du, X. Yuan, A survey of competitive sports data visualization and visual analysis, Journal of Visualization 24 (2021) 47–67. doi:http://dx.doi.org/10.1007/s12650-020-00687-2.

[4] M. Stein, H. Janetzko, A. Lamprecht, D. Seebacher, T. Schreck, D. Keim, M. Grossniklaus, From game events to team tactics: Visual analysis of dangerous situations in multi-match data, in: 2016 1st International Conference on Technology and Innovation in Sports, Health and Wellbeing (TISHW), IEEE, 2016, pp. 1–9. doi:http://dx.doi.org/10.1109/TISHW.2016.7847777.

[5] F. Wu, Q. Wang, J. Bian, N. Ding, F. Lu, J. Cheng, D. Dou, H. Xiong, A survey on video action recognition in sports: Datasets, methods and applications, IEEE Transactions on Multimedia (2022). doi:http://dx.doi.org/10.1109/TMM.2022.3232034.

[6] V. Vercruyssen, L. De Raedt, J. Davis, Qualitative spatial reasoning for soccer pass prediction, in: CEUR Workshop Proceedings, volume 1842, CEUR-WS. org, 2016.

[7] G. Zhu, C. Xu, Q. Huang, Y. Rui, S. Jiang, W. Gao, H. Yao, Event tactic analysis based on broadcast sports video, IEEE Transactions on Multimedia 11 (2008) 49–67.

[8] Q. Zhang, X. Zhang, H. Hu, C. Li, Y. Lin, R. Ma, Sports match prediction model for training and exercise using attention-based lstm network, Digital Communications and Networks 8 (2022) 508–515. URL: https://www.sciencedirect.com/science/article/pii/S2352864821000602. doi:https://doi.org/10.1016/j.dcan.2021.08.008.

[9] A. Tenga, I. Holme, L. T. Ronglan, R. Bahr, Effect of playing tactics on goal scoring in norwegian professional soccer, Journal of sports sciences 28 (2010) 237–244. doi:http://dx.doi.org/10.1080/02640410903502774.

[10] L. Shaw, M. Glickman, Dynamic analysis of team strategy in professional football, Barça sports analytics summit 13 (2019).

[11] R. Marcelino, J. Sampaio, G. Amichay, B. Gonçalves, I. D. Couzin, M. Nagy, Collective movement analysis reveals coordination tactics of team players in football matches, Chaos, Solitons & Fractals 138 (2020) 109831. doi:http://dx.doi.org/10.1016/j.chaos.2020.109831.

[12] K. Kim, M. Grundmann, A. Shamir, I. Matthews, J. Hodgins, I. Essa, Motion fields to predict play evolution in dynamic sport scenes, in: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE, 2010, pp. 840–847. doi:http://dx.doi.org/10.1109/CVPR.2010.5540128.

[13] S. A. Pettersen, D. Johansen, H. Johansen, V. Berg-Johansen, V. R. Gaddam, A. Mortensen, R. Langseth, C. Griwodz, H. K. Stensland, P. Halvorsen, Soccer video and player position dataset, in: Proceedings of the 5th ACM Multimedia Systems Conference, MMSys '14, Association for Computing Machinery, New York, NY, USA, 2014, p. 18–23. URL: https://doi.org/10.1145/2557642.2563677. doi:10.1145/2557642.2563677.

[14] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, A. C. Berg, Ssd: Single shot multibox detector, in: Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14, Springer, 2016, pp. 21–37. doi:http://dx.doi.org/10.1007/978-3-319-46448-0_2.

[15] S. Ploeger, L. Dasovic, Issues in object detection in videos using common single-image cnns, arXiv preprint arXiv:2105.12822 (2021).

[16] J. A. Hartigan, M. A. Wong, Algorithm as 136: A k-means clustering algorithm, Journal of

the royal statistical society. series c (applied statistics) 28 (1979) 100–108.

[17] M. Ankerst, M. M. Breunig, H.-P. Kriegel, J. Sander, Optics: Ordering points to identify the clustering structure, ACM Sigmod record 28 (1999) 49–60. doi:http://dx.doi.org/10.1145/304182.304187.

[18] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (1997) 1735–1780.

[19] S. H. Muggleton, D. Lin, N. Pahlavi, A. Tamaddoni-Nezhad, Meta-interpretive learning: application to grammatical inference, Machine learning 94 (2014) 25–49.

[20] A. Cropper, S. Dumančić, R. Evans, S. H. Muggleton, Inductive logic programming at 30, Machine Learning (2022) 1–26. doi:http://dx.doi.org/10.1007/s10994-021-06089-1.

[21] C. Hocquette, S. Muggleton, How much can experimental cost be reduced in active learning of agent strategies?, in: Inductive Logic Programming: 28th International Conference, ILP 2018, Ferrara, Italy, September 2–4, 2018, Proceedings 28, Springer, 2018, pp. 38–53. doi:http://dx.doi.org/10.1007/978-3-319-99960-9_3.

[22] A. Cropper, S. H. Muggleton, Metagol system, https://github.com/metagol/metagol, 2016. URL: https://github.com/metagol/metagol.

[23] D. Garrido, D. R. Antequera, R. L. D. Campo, R. Resta, J. M. Buldú, Distance between players during a soccer match: The influence of player position, Frontiers in Psychology 12 (2021) 723414. doi:http://dx.doi.org/10.3389/fpsyg.2021.723414.

[24] A. R. Amani, Distance covered and activity analysis of football players during world cup 2014, Archivos de medicina del deporte: revista de la Federación Española de Medicina del Deporte y de la Confederación Iberoamericana de Medicina del Deporte 35 (2018) 376–379.

[25] P. Jones, N. James, S. D. Mellalieu, Possession as a performance indicator in soccer., International Journal of Performance Analysis in Sport 4 (2004) 98–102. doi:http://dx.doi.org/10.1080/24748668.2004.11868295.

[26] W. Frencken, K. Lemmink, N. Delleman, C. Visscher, Oscillations of centroid position and surface area of soccer teams in small-sided games, European journal of sport science 11 (2011) 215–223. doi:http://dx.doi.org/10.1080/17461391.2010.499967.

[27] S. Muggleton, W.-Z. Dai, C. Sammut, A. Tamaddoni-Nezhad, J. Wen, Z.-H. Zhou, Meta-interpretive learning from noisy images, Machine Learning 107 (2018) 1097–1118. doi:http://dx.doi.org/10.1007/s10994-013-5358-3.