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Addressing the Complexity of MOBA Games through Simple Geometric Clues (extended version)

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Abstract. Recently, the analysis of e-sport data has particularly attracted the attention of machine learning researchers. We contribute here by proposing, on the MOBA (Multiplayer Online Battle Arena) game *DotA2* (Defense of the Ancients 2), an analysis of the relevance of geometric clues relating to the behavior of the players. The geometric clues we have chosen concern the trajectories of the players and the characteristics of the polygon described by the players of a team. More precisely, for the polygon clues, we computed, for each second of the game: the convex area, the diameter, the grouping capacity (average of the distances to the barycenter), the inertia (second order moment of the distances to the barycenter) and finally the distance to the opponent's fortress. During a regression on the number of alive heroes, the learning performance of an RNN (precisely a LSTM) fed by our simple clues allowed us to evaluate their relevance in describing this complex game.

Keywords: trajectory analysis, MOBA games, important moments highlighting, RNN

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1 Introduction

Context Electronic sport or e-sport consists of the competitive playing of video games. This activity provides numerous traces that data science researchers like to study. Indeed, these researchers are often gamer themselves so they are familiar with the subject of their study. Moreover, e-sport has emerged as a serious discipline, operating in a similar way to sport, with the arrival of classic clubs such as Paris SG, AS Monaco, AS Roma and FC Grenoble. This craze is reflected in the particularly attractive financial amounts (up to millions of dollars) offered to the teams participating in the tournaments. For example, in 2018, The International 2018 tournament allowed the first 18 teams to share more than 25 millions Dollars (40 millions this year).

E-sport is a boon for data science research because activity traces are easily and massively available. Unlike traditional sports where it is difficult to obtain accurate data, each e-sport game is archived on servers in a very precisely exploitable format. The interest of e-sport also lies in the expression of human and collective organizations, for example the tactics and strategy of a team of players, which are comparable to those implemented in real sport.

Motivations Our main motivation is to analyze MOBA games (Multiplayer Online Battle Arena games) in order to better understand the performance of the best teams. This understanding would allow us to explain the reasons for the failure or success of a team and would provide means of analysis for the games. These means could then be used to automatically produce game summaries by characterizing highlights.

However, MOBA games are particularly complex to analyze: each player can choose his avatar from among a hundred, each avatar can cast four exclusive spells and improve his skills (movement speed, attack frequency, armor, mana regeneration, etc.) thanks to six items of equipment to be chosen from among a hundred. It is therefore desirable to reduce this complexity.

We believe that the spatial organization of the players is crucial for analyzing performance in these games and that it is not necessary to examine all the minute details of a game to characterize its important moments. Moreover, MOBA games are team games and the study of spatial organization allows us to focus attention on the collective aspects of this practice rather than on individual details.

Position Compared to other works in the field, our proposal presents two originalities. Firstly, we focused our study on the *collective* character of the practice of a MOBA, because it is fundamentally a team game emphasizing group actions to the detriment of individual ones [10]. To do so, we compared the relevance of clues related to the individual position of the players on the field and the geometry of the collective organization. We are looking for simple clues to calculate and exploit and we do not wish to focus our attention on individual behaviors and characteristics (equipment, skill tree).

We therefore compared the contribution to a learning method of the individual trajectories of the heroes *versus* the geometric measurements on the polygon described by the players (area, diameter, distance to the objective, etc.). This approach is qualified as *wrapper* in [11]: the relevance of a descriptor is measured by its contribution to the classification or regression model, it is a method of feature selection. The target of our model was the number of living heroes in each team.

Secondly, we have decided to work only on data from games played by e-sport professionals, grouped in renowned teams. We wanted to study games performed by players who are used to play together and producing a high level of performance. This position is original in the literature [16, 10]. In order to privilege quality over quantity, we did not wish to study millions or even billions of games [6]. Indeed, the matchmaking of occasional players is based on

their expectation of winning, which leads to the constitution of balanced teams. However, it is very frequent that these matches oppose two extremely efficient players, accompanied by *extras*. In this case, the collective performance is lousy.

This article is organized as follows: Section 2 presents the material and the method of our study, Section 3 delivers our results and their comments, we end with a quick review of the literature in Section 4 and conclude in Section 5.

2 Related work

The popularity of video games in general and e-sports in particular has led to a number of articles studying the mechanics of these games, using a data science approach. MOBA games are very relevant for comparative studies because they offer a complex but relatively formatted game, both in terms of the playground and the way the games are played. Themes range from studies of individual behaviour to game summaries, outcome prediction, the use of geometric clues and RNN [16].

In order to make this review understandable, we start by explaining the main characteristics of a MOBA game.

2.1 MOBA games

We analyzed data from a video game, DotA2 (Defense of the Ancients 2), which is emblematic of the MOBA type: Multiplayer Online Battle Arena. These games feature two teams of five players embodying avatars called *heroes*. Each player develops his hero during the game by collecting gold and experience. Thanks to these resources, the hero can get new equipment items and new abilities to help him in the battle against the heroes of the opposing team.

The goal in DotA2 is to gain ground on the opponent and ultimately destroy the opposing team's fortress as a condition of victory. Each of the two fortresses (the yellow stars at the bottom-left and top-right corners in Figure 1, a.k.a *Ancient*) is accessible by three lanes (top, middle, bottom). These routes are defended by three towers, symbolized by a yellow circle on Figure 1. In order to destroy the towers and the opponent's fortress, each team escorts the progression of waves of minions. These minions are creatures generated in groups of four every 30 seconds, and they travel across the map from the allied fortress towards the enemy fortress. When two waves of opposite minions are facing, they fight for about twenty seconds and neutralize each other, which defines a front line. The objective of the game is thus, with the help of the heroes embodied by the players, to favor the progression of its minions in the direction of the opponent. A MOBA could be seen as a simulation of rugby with five players teams on a very large field (60s are needed to go from one fortress to the opposite) with three balls in three different lanes. A game of DotA2 lasts between 35min and 50min.



Fig. 1. DotA2 map from <http://dota2.fandom.com/wiki/Map>

2.2 Individual actions and regulation

In spite of the strong collective character of the practice of a MOBA, individualities are studied a lot. It is indeed important to categorize players according to their behavior during the game, which provides useful information on the game's progress but also on their behavior outside the game [20]. Behavioral telemetry can be used for this task, producing usable patterns of behavior. Analysis of in-game behavior then leads to elements of data-driven co-design: exceptional behavior is detected relative to established standards in professional games [2]. A visual analysis system to help game designers find key events and game parameters that lead to a *snowball* effect (one team overpowering the other) is proposed in [15].

As gaming activity sometimes involves millions of players and competitive events with large prizes, its regulation is an essential task. For example, the phase of choosing avatars can be studied, one can formulate recommendations for winning and set out rules for choosing one character over another [24, 23]. The audience's adherence to the show generated also arouses interest. In particular, an analysis of the data shows a correlation between the snowball effect and the loss of audience [14].

2.3 Game summary

Performed manually, automatic generation of game summaries and their indexing are tedious tasks, as shown in [1], which presents action labelling for the supervision of a graph system, all over only two matches. The ultimate goal

is to understand the underlying tactics, complex dynamics and strategic decisions made in specific contexts. Automatic summary generation is also desirable: during a MOBA game, there are many events and fights, which ones are particularly interesting? These questions are also of interest to researchers in traditional sports (see for example [28, 8, 22] for football) and more recently for e-sports [18].

As there are many games, their exhaustive analysis is tedious and one wishes to obtain a summary of the important moments or, during a live transmission, to anticipate the essential actions, for example to determine the axis of broadcast. Companions applications are available, fed with elements of analysis [12]. In [4],[5] the authors design and extract game-specific features taking into account visual content, event semantics and viewer reaction. Then, they integrate clues from these three domains based on a psychological and data-driven approach to characterize the game’s highlights.

2.4 Geometric clues

The analysis of a collective practice on a given field naturally lends itself to studies of the trajectories and geometry of player organizations. Thus, for football, a work similar to the one presented in this article is proposed in [9], with the aim of predicting the outcome of the match. For DotA2, the geometric clues allow to correctly predict the outcome of a match and this relevance is confirmed on 6 billion matches of League Of Legends (MOBA competitor of DotA2) via a RandomForest system with an F-measure of 92%. Regularities in the trajectories, discriminating for the winning of the match, could also be extracted [3]. Behavior on a MOBA court is indeed crucial and differences between levels of play are revealed by positional clues: change of zone, distance between players, which allows a grouping of matches according to the similarity of movements [7].

2.5 Use of an RNN

The chronological nature of a video game match and the popularity of neural network methods are leading to a significant use of recurrent neural network techniques, for example to predict the outcome of the match [17, 21, 13]. This type of network can help to understand the strategic preparation phases of the game (pick/ban of heroes) [27]. As the game progresses, an important task is the recommendation of equipment items, supported by an LSTM in [26] that models player interest from historical match sequences. An RNN can also predict a player’s performance based on previous performances [25].

2.6 Outcome

This quick overview of the contributions around DotA2 shows two things. On the one hand, the tools used in this article (geometric clues, trajectories, RNN) are part of the classic toolbox for this domain. On the other hand, the relevance of the clues is rarely discussed as we did here, and the predictions mostly address the outcome of the match or the recommendation of behavior, whereas our predictions were linked to a measure of performance.

3 Addressing the complexity through geometric clues

DotA2 is a team game where coordinated and synchronized movements are paramount, independently of individual behavior. We believe (as [6]) and show here that geometric clues from player trajectories are sufficient to reveal the complexity of this game. Considering these geometric clues alone rather than examining individual player behaviors in terms of inventory and skill tree allowed us to propose a generic approach for the MOBA genre and to work on the basis of simple hypotheses.

We therefore compared the relevance of three types of geometric or positional clues: (i) player trajectories, (ii) trajectories *enriched* by the coordinates of the hero's orientation vector (this data is simply provided by the game engine) and (iii) the characteristics of the polygon described by all the players of a team. We normalized the data provided by the game engine so as to obtain one measurement per second of game time.

More precisely, for the polygon representing each team, we calculated:

- the area of the convex envelope;
- the diameter (the maximum distance between two points on the polygon);
- the clustering capacity (average of distances to the barycentre);
- the inertia (second-order moment of the distances to the barycentre);
- the distance from the barycentre to the opposing fortress.

We considered that a game is divided into three major phases of play:

- the early-game:** the first 15 minutes during which the heroes are weak and seek to obtain gold and experience to gain power. It is during this phase that ambushes are attempted to gain an advantage and ruin the opponent's progress;
- the mid-game:** (from 16 to 35mn) some heroes are powerful enough to make team fights possible;
- the late-game:** (36mn and beyond), the heroes have their maximum power and no longer seek to collect gold or experience: towers and the enemy fortress becomes the only objective.

DotA2 provides traces of game activities in the form of a *replay* file that can be retrieved after each game. For each hero played by a human, the following information is available at each second: its coordinates, its orientation, its life points, its progress in the skill tree, the items in its inventory, *etc.*

The 258 games we analyzed were those of a major tournament of the game, The International 2018¹. Our goal was to determine clues, characteristic of the spatial organization of the players. Highlights occur approximately every three minutes and correspond to the confrontations of the players giving rise to the disappearance of some (virtual *death* followed by a resurrection after a variable time). In order to obtain results that are sufficiently general and do not depend on the intrinsic complexity of the game, we focused our attention on geometric clues linked to the positions of the heroes.

¹ see <https://www.dota2.com/esports/ti10> for this year's edition

3.1 Wrapper Approach with RNN

We used a *wrapper* approach [11] which assumes that the relevance of a feature is related to its capacity to improve the quality of learning. Unlike the *filter* approach, more common in statistics, which attempts to evaluate the credit of features from the data alone, the wrapper approach attempts to identify the best subset of features to use with a learning algorithm. We used this approach to compare the suitability of trajectories with that of polygon features by examining the performance obtained by models computed on these clues.

The learning algorithm we used was a Long Short Term Memory (LSTM), a particular recurrent neural network (RNN) [19] architecture. RNNs are designed to handle temporally evolving data: if a cell computes an output signal from the inputs, it additionally transmits a hidden state to the next cell, that influences it. The cells of an LSTM additionally include a memory/forget mechanism that solves the problem of vanishing gradient.

The LSTM was here well adapted to our goal which was the study of a long game (35 to 50mn x 60 measures/mn). The target was the number of players alive 5 seconds into the future (as recommended by [4]), because the position of a dead hero was conventionally frozen at the place of its death, and then it was reborn at the fortress position. If this time lag was not introduced, the LSTM could use this information and introduce a bias in the results. The performance of the LSTM was evaluated by the MSE (*Mean Square Error*), whether it is fed by the trajectories, the enriched trajectories or the polygon features.

The results we report in the next section were obtained on a single-layer LSTM with 128 cells, which allowed us to best assess the difference in relevance between our choices of clues. However, adding additional layers allowed the network to acquire a universal approximator behavior and thus, fed by the trajectories, to potentially capture the expressive power of the geometric clues of the polygon. The experiments we have carried out in this sense show that the more layers we added, the less noticeable the differences between the types of clues (see Figure 4).

Finally, we performed a Student's t test to check whether there was a significant difference in relevance between the use of trajectories, enriched trajectories or polygon clues. The Student test calculates a value between two distributions called p -value. If the score is less than 0.05, then the hypothesis that the means are equal can be rejected and therefore one descriptor can be valued over the other.

3.2 Experimental conditions

In the experiments whose results are presented in the next section, we fed an LSTM with either player coordinates or polygon geometric clues and evaluated the relative relevance of these attributes by examining the MSE. The objective function was the number of living heroes in each team (from 0 to 5). We considered that the LSTM worked in *regression* because it had to predict two

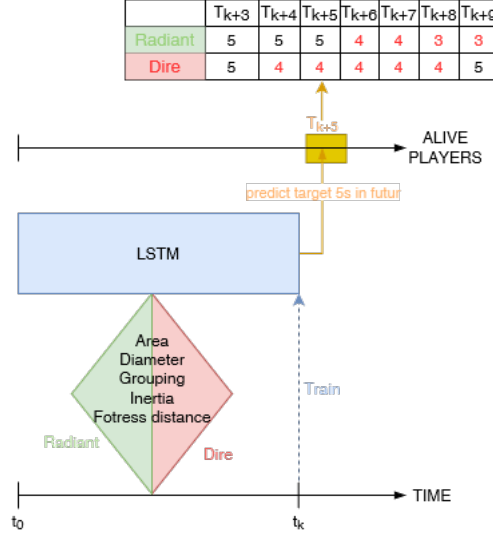


Fig. 2. LSTM training scheme on the continuity of the game.

continuous quantities on the interval $[0, 5]$. Figure 2 shows a schematic of our training process.

During our experiments, we also considered two types of chronology for the LSTM inputs:

learning since the beginning of the game phase: the LSTM was fed *continuously* by a single sequence, with data between instants 0 and t and predicted a value at $t + 5$;

sliding window learning: the LSTM was fed with multiple sequences from $t - w$ to t and predicted at $t + 5$, for w a window width that we let vary between 5 and 120s.

The following section presents the results obtained in regression, in continuous and sliding window mode.

4 Results

4.1 Learning since the beginning

Figure 3 represents the MSE boxplots, for each phase of the game. It can be observed that, independently of the phase, the polygon clues allowed a better prediction: the median of the MSE is the lowest and the dispersion is less important. Table 1 provides the values of the corresponding Student's tests: when the cell has a green background, the means are not equal.

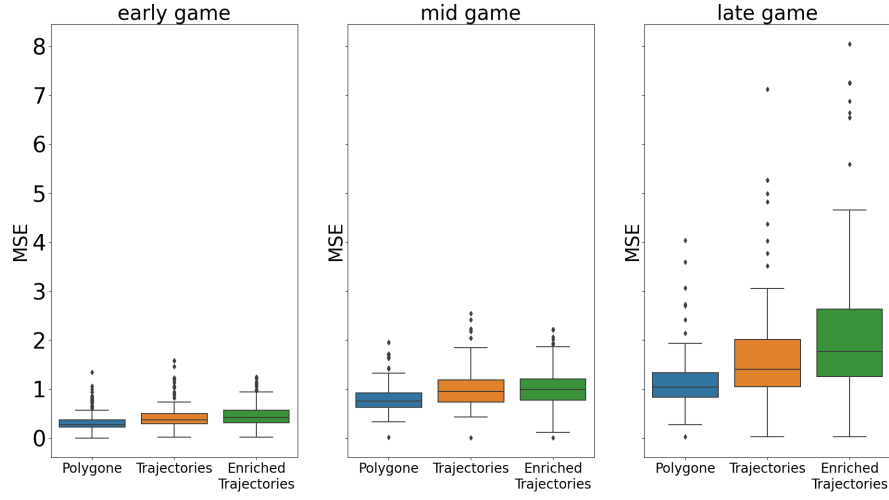


Fig. 3. Distribution of the MSE over the continuity of the game in regression.

Phase	Poly vs traj	Poly vs enriched traj	Enriched traj vs traj
Early	$2.989.10^{-6}$	$1.104.10^{-10}$	0.113
Mid	$1.121.10^{-11}$	$4.633.10^{-13}$	0.782
Late	$4.366.10^{-9}$	$1.761.10^{-16}$	$4.043.10^{-5}$

Table 1. P-values of Student test for regression.

During the early and middle of the game, the trajectories induced a slightly lower median error than the enriched trajectories, but the dispersion for the enriched trajectories is lower. For the end of the game, the results were more marked, the dispersion increased for the three types of clues and there were many more outliers. This could be explained by the fact that at the end of the game the virtual deaths are much more punitive (their duration depends linearly on the level of the player, maximum at this period). When a collective behavior led to an important moment, the model detected it, however the players were more cautious because of the stake and canceled their action at the last moment.

Figure 4 shows the evolution of the relevance when increasing the number of layers of the LSTM (each one has 128 cells). Although the polygon clues were still the most relevant, there was a convergence of the three types of clues when the number of layers increased. However, the addition of layers had a significant algorithmic cost, particularly in terms of the number of epochs.

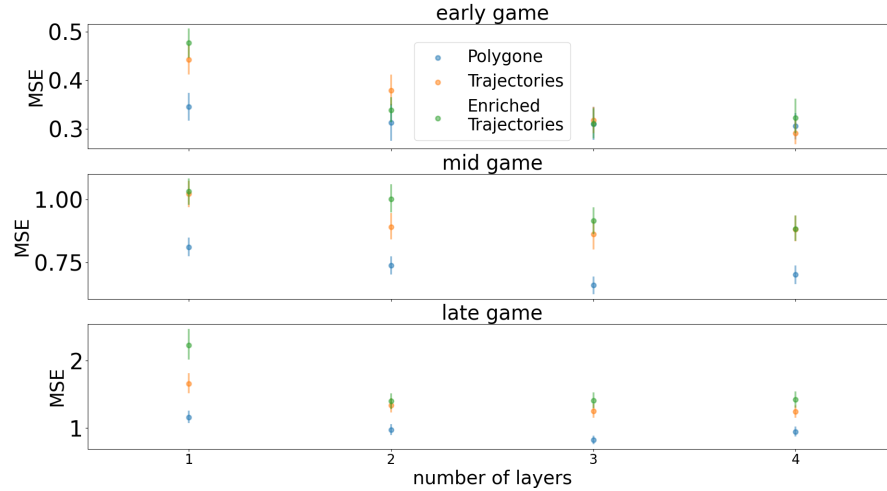


Fig. 4. Evolution of the MSE according to the number of layers for the regression.

Finally, the polygons were the most relevant geometric clues for the regression problem, regardless of the game phase, both from an evaluation and computational time perspective. We also found that the LSTM converged faster when fed by the polygon clues rather than the trajectories.

4.2 Sliding window learning

Regression learning When using sliding windows, Figure 5 shows the performance of the different types of clues, depending on the width of the window. Switching to sliding windows greatly improved the results obtained with the

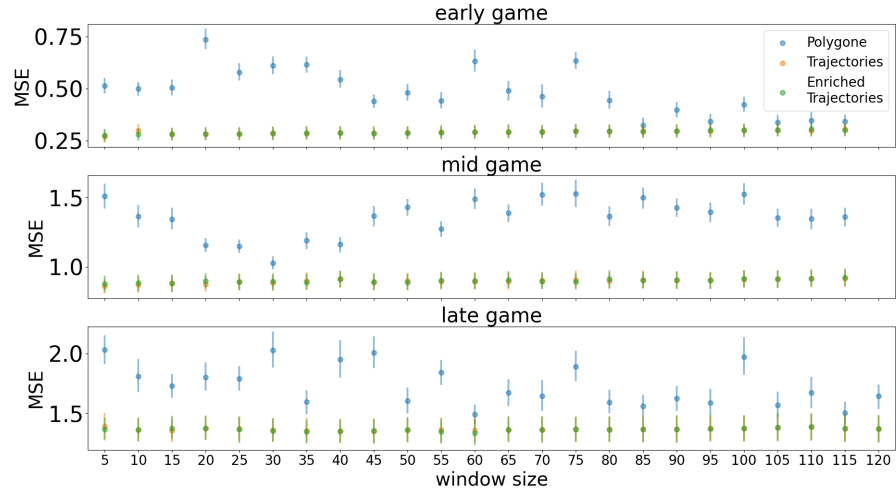


Fig. 5. Distribution of MSE by sliding window in regression.

clues on the trajectories, equally for the trajectories and the enriched trajectories. The performance of the clues on the polygon was much poorer, and using sliding windows did not allow them to be sufficiently highlighted. These clues need to be taken into account for the entire period to reveal their potential relevance.

However, in the middle and at the end of the game, the best results obtained on sliding windows by trajectories did not improve the results obtained by polygons on the continuity of the game. This is potentially due to the low frequency of events at the beginning of the game.

5 Conclusion

Using an LSTM that predicted the number of living heroes, we have shown that it was possible, by valuing geometric clues about the players' positions, to draw attention to important moments in a *DotA2* game. Although *DotA2* is a complex game, there is a strong relationship between simple positional clues and the occurrence of important moments. It is therefore not necessary to scrutinize the precise behavior of heroes in terms of attack or skill development, nor their equipment.

Among the examined clues (geometry of the polygon described by the heroes, trajectories and trajectories enriched by orientations), those on the polygon proved to be more relevant for all phases, but it was necessary to learn on the continuity of the game. When using windows of variable size, the trajectories relatively gave better results but did not reach the performance of the polygon on the continuity of the game.

We have also found that increasing the number of layers in the LSTM allowed it to behave as a universal approximator: the more layers, the less sensitive the differences in performance between the feature types, although trajectories still required more learning epochs. The polygon clues, with the development of a small amount of preliminary computation, thus allowed for a reduction in the computation required for learning.

References

1. Ahmad, S., Bryant, A., Kleinman, E., Teng, Z., Nguyen, T.H.D., Seif El-Nasr, M.: Modeling individual and team behavior through spatio-temporal analysis. In: *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. pp. 601–612 (2019)
2. Block, F., Hodge, V., Hobson, S., Sephton, N., Devlin, S., Ursu, M.F., Drachen, A., Cowling, P.I.: Narrative bytes: Data-driven content production in esports. In: *Proceedings of the 2018 ACM International Conference on Interactive Experiences for TV and Online Video*. pp. 29–41 (2018)
3. Cavadenti, O., Codocedo, V., Boulicaut, J.F., Kaytoue, M.: What did I do Wrong in my MOBA Game?: Mining Patterns Discriminating Deviant Behaviours. In: *International Conference on Data Science and Advanced Analytics*. Montréal, Canada (Oct 2016), <https://hal.archives-ouvertes.fr/hal-01388321>
4. Chu, W.T., Chou, Y.C.: Event detection and highlight detection of broadcasted game videos. In: *Computational Models of Social Interactions*. pp. 1–8 (2015)
5. Chu, W.T., Chou, Y.C.: On broadcasted game video analysis: event detection, highlight detection, and highlight forecast. *Multimedia Tools and Applications* **76**(7), 9735–9758 (2017)
6. Deja, D., Myślak, M.: Topological clues for predicting outcomes of multiplayer online battle arena games. In: *IADIS* (07 2015)
7. Drachen, A., Yancey, M., Maguire, J., Chu, D., Wang, I.Y., Mahlmann, T., Schubert, M., Klabajan, D.: Skill-based differences in spatio-temporal team behaviour in defence of the ancients 2 (dota 2). In: *2014 IEEE Games Media Entertainment*. pp. 1–8. IEEE (2014)
8. Ekin, A., Tekalp, A.M., Mehrotra, R.: Automatic soccer video analysis and summarization. *IEEE Transactions on Image processing* **12**(7), 796–807 (2003)
9. Frencken, W., Lemmink, K., Delleman, N., Visscher, C.: Oscillations of centroid position and surface area of soccer teams in small-sided games. *European Journal of Sport Science* **11**(4), 215–223 (2011)
10. Katona, A., Spick, R., Hodge, V.J., Demediuk, S., Block, F., Drachen, A., Walker, J.A.: Time to die: Death prediction in dota 2 using deep learning. In: *2019 IEEE Conference on Games (CoG)*. pp. 1–8. IEEE (2019)
11. Kohavi, R., John, G.H.: The wrapper approach. In: *Feature extraction, construction and selection*, pp. 33–50. Springer (1998)
12. Kokkinakis, A., Demediuk, S.P., Nölle, I., Olarewaju, O., Patra, S., Robertson, J., York, P., Pedrassoli Chitayat, A., Coates, A., Slawson, D., et al.: Dax: Data-driven audience experiences in esports. In: *Proceedings of ACM International Conference on Interactive Media Experience (IMX) 2020*. pp. 1–12. Association for Computing Machinery (ACM) (2020)
13. Lan, X., Duan, L., Chen, W., Qin, R., Nummenmaa, T., Nummenmaa, J.: A player behavior model for predicting win-loss outcome in MOBA games. In: *International*

- Conference on Advanced Data Mining and Applications. pp. 474–488. Springer (2018)
14. Li, Q., Wu, Z., Xu, P., Qu, H., Ma, X.: A multi-phased co-design of an interactive analytics system for MOBA game occurrences. In: Proceedings of the 2018 Designing Interactive Systems Conference. pp. 1321–1332 (2018)
 15. Li, Q., Xu, P., Chan, Y.Y., Wang, Y., Wang, Z., Qu, H., Ma, X.: A visual analytics approach for understanding reasons behind snowballing and comeback in MOBA games. *IEEE transactions on visualization and computer graphics* **23**(1), 211–220 (2016)
 16. Mora-Cantalops, M., Sicilia, M.Á.: MOBA games: A literature review. *Entertainment computing* **26**, 128–138 (2018)
 17. Qi, Z., Shu, X., Tang, J.: Dotanet: Two-stream match-recurrent neural networks for predicting social game result. In: 2018 IEEE Fourth International Conference on Multimedia Big Data (BigMM). pp. 1–5 (Sep 2018). <https://doi.org/10.1109/BigMM.2018.8499076>
 18. Ringer, C., Nicolaou, M.A.: Deep unsupervised multi-view detection of video game stream highlights. In: Proceedings of the 13th International Conference on the Foundations of Digital Games. pp. 1–6 (2018)
 19. Sherstinsky, A.: Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network. *Physica D: Nonlinear Phenomena* **404**, 132306 (2020)
 20. Sifa, R., Drachen, A., Bauckhage, C.: Profiling in games: Understanding behavior from telemetry. *Social Interactions in Virtual Worlds: An Interdisciplinary Perspective* (2018)
 21. Silva, A.L.C., Pappa, G.L., Chaimowicz, L.: Continuous outcome prediction of league of legends competitive matches using recurrent neural networks. In: SBC- Proceedings of SBCGames. pp. 2179–2259 (2018)
 22. Stensland, H.K., Gaddam, V.R., Tennøe, M., Helgedagsrud, E., Næss, M., Alstad, H.K., Mortensen, A., Langseth, R., Ljødal, S., Landsverk, Ø., et al.: Bagadus: An integrated real-time system for soccer analytics. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* **10**(1s), 1–21 (2014)
 23. Summerville, A., Cook, M., Steenhuisen, B.: Draft-analysis of the ancients: predicting draft picks in dota 2 using machine learning. In: Twelfth Artificial Intelligence and Interactive Digital Entertainment Conference (2016)
 24. Wang, W.: Predicting Multiplayer Online Battle Arena (MOBA) Game Outcome Based on Hero Draft Data. Master’s thesis, Dublin, National College of Ireland (December 2016), <http://trap.ncirl.ie/2523/>
 25. White, A., Romano, D.: Scalable psychological momentum estimation in esports. In: Workshop SUM ’20: State-based User Modelling, The Thirteenth ACM International Conference on Web Search and Data Mining (WSDM ’20). ACM (2020)
 26. Yao, Q., Liao, X., Jin, H.: Hierarchical attention based recurrent neural network framework for mobile MOBA game recommender systems. In: 2018 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Ubiquitous Computing & Communications, Big Data & Cloud Computing, Social Computing & Networking, Sustainable Computing & Communications (ISPA/IUCC/BDCloud/SocialCom/SustainCom). pp. 338–345. IEEE (2018)
 27. Yu, C., Zhu, W.n., Sun, Y.m.: E-sports ban/pick prediction based on bi-lstm meta learning network. In: International Conference on Artificial Intelligence and Security. pp. 97–105. Springer (2019)

28. Zawbaa, H.M., El-Bendary, N., Hassanien, A.E., Kim, T.h.: Event detection based approach for soccer video summarization using machine learning. *International Journal of Multimedia and Ubiquitous Engineering* **7**(2), 63–80 (2012)