Algorithmic Clustering of Kickoffs in Rocket League

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Abstract

In this research paper, we use clustering techniques to analyze kickoffs in the vehicular soccer video game Rocket League. Rocket League is a popular game with an exciting and emerging esports scene. Professional competitions, most notably the Rocket League Championship Series (RLCS), have grown in prize pool, popularity, and entertainment value year after year. Kickoffs, which occur at the start of a game and after each goal, are a crucial but often neglected part of the game that can greatly impact the outcome of a match, as demonstrated by the many iconic kickoff goals in the RLCS.

To conduct our research, we utilized tracking data from the 3v3(3's) Super Sonic Legend (SSL) ranked playlist, the highest rank in the game. The original dataset of around 500 games, consists of just over 1800 kickoffs. This was the maximum amount of data we could store, as the precise timing of a kickoff required using data with a high frequency, 30 hertz.

We applied three different clustering algorithms - affinity propagation, K-means clustering, and Density-Based spatial clustering of applications with noise (DBSCAN) - to our dataset, and evaluated the data using internal evaluation methods and data visualizations.

Our study attempted to identify distinct kickoff strategies using clustering algorithms, analyze the effectiveness of these algorithms, and use these algorithms to provide insight on how a professional Rocket League team can improve their kickoff performance. Our study found that the K-means algorithm was the most effective at clustering kickoffs into unique strategies, and provided insight on the effectiveness of a "soft" cheat as opposed to a more aggressive "hard" cheat that, if developed further, could lead towards optimized kickoff strategies. This research has shown the potential of clustering algorithms in regards to identifying and optimizing kickoff strategies in Rocket League.

Introduction

Rocket League is a team-based, vehicular soccer video game created in 2015. In the game, players control boost-powered cars that can accelerate, turn, boost, jump, and rotate in three dimensions on a field. Teams of one, two, or three cars compete to outscore their opponents.

For our research, we focused on 3v3 gameplay. This is the primary game mode used in professional competitions such as the RLCS, and there is more strategy involved in a 3's kickoff than in other game modes.

In Rocket League, a kickoff occurs at the beginning of the game and after every goal. There are 3 unique team spawn permutations at when a kickoff occurs.

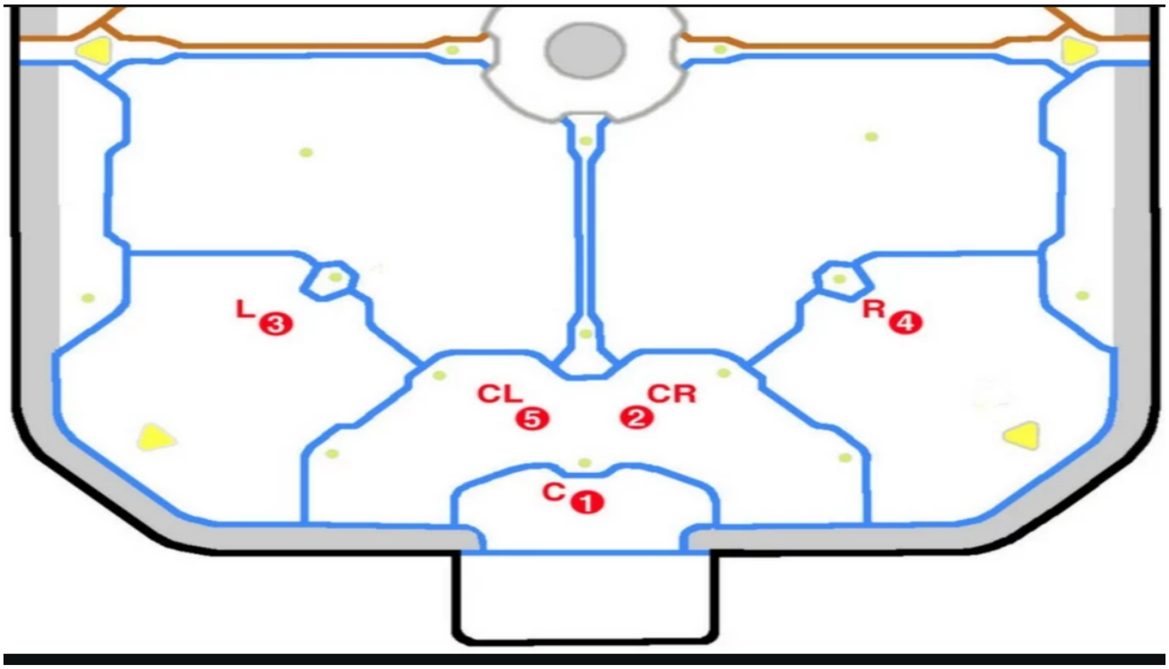


Fig 1

As per Fig 1, the possible pre-kickoff permutations are: Permutation one ={Team 1=(3,4,2), Team 2=(3,4,5)}, Permutation two ={Team 1 =(3,2,1), Team 2 = (4,5,1)}, Permutation 3 = {Team 1 and Team 2 =(5,2,1)}. Team positions are symmetrical about the ball, but kickoffs are not symmetrical. It is accepted practice for the player on the left to go for the ball when two players on a team are spawned into positions that are an even distance from the ball. Therefore, if the blue team is in the pre-kickoff configuration (3,4,2) the player in position 3 is much more likely to go for the ball than the number 4 player.

At the start of the kickoff all cars are frozen at their spawn point, the ball is placed in the middle of the pitch and a timer counts down from three, once the timer hits 0, the cars are able to move and the game is on! Due to the fast-paced gameplay, Rocket League kickoffs have a higher conversion rate compared to a kickoff in soccer. In fact Rocket League kickoffs have a higher conversion rate than a corner kick, a common set piece in soccer.The kickoff goal seen in this clip, https://www.youtube.com/watch?v=LmHfBgY7HO8 is a recent example of a kickoff that directly changed the outcome of a 7 game series, in a large RLCS event.

Recent occurrences of kickoff goals have highlighted both the inefficiencies of kickoff strategy, and the importance of kickoffs in Rocket League. Therefore an RLCS team that employs statistical analysis on their kickoff strategies would have a great advantage over teams that employ current strategies used.

A typical Rocket League kickoff strategy involves the closest player to the ball going for the ball as fast as they can. The second closest player to the ball usually “cheats” behind the first player ready to pounce wherever the ball is headed, and the third player will usually collect a large boost pad located in the corner of their half which gives them 100 boost, boost is the only resource in Rocket League, and “boosts” you with extra speed when you use it.

The most strategic decision of the kickoff is made by the “cheating” player. The player who is “cheating” can either “hard cheat” by following the first player very closely, the more aggressive “high risk, high reward” choice, or “soft cheat” by following the first player from a further distance, decreasing the risk of the ball flying over them and into the net, but also decreasing the amount of pressure being applied to the other team.

Data

Our dataset[1] consisted of one week's worth of 3v3 SSL games that uploaded to the Ball Chasing API. Our data corresponds to the 1st week of August 2022. Our dataset is approximately 500 games of gameplay with

$\# \, rows\, of\, data/game \;=\; 30\, Hertz/second * 60\, seconds/minute * 5\, minutes/game$

$\# \, rows\, of\, data\, /game \;=\;$ 9000 rows of data per game.

$\# \, rows\, of\, data \;=\; 9000 * 500 \;=\; 4,500,000\; Starting\; Data\; Points$

We then restricted our dataset to the x and y positions of all blue team players during the first frame after a kickoff which was a sample of size and that was split with a ratio such that 80% of the data went into the training set and the rest the test set.

Literature Review/Methodology

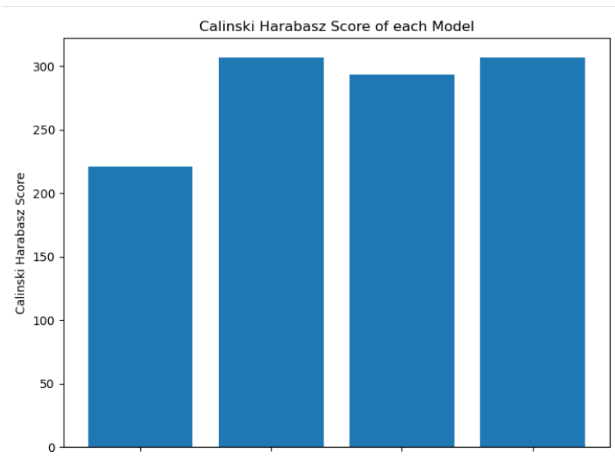
The first statistical model we fit our data to was the affinity propagation algorithm. This technique resulted in 25 different clusters, too many to obtain any statistical insight from, and decided to look at other models.

Our data was unlabeled, therefore we had to rely on visualization tools and internal evaluation methods to evaluate the fit of our models. To determine the optimal K in our K-means clustering model we first used the Elbow method[2] by plotting the corresponding SSE for each cluster. We determined that $K = \{6, 7, 8\}$ were the clusters were worth further investigation, with $K = 6$ as the “elbow”. We then evaluated these models using the Silhouette Coefficient[3]and the Calinski Harabasz Score[4]

Finally we fit our data to a DBSCAN model, We used the Silhouette Coefficient and Calinski Harabasz Score to determine the optimal value for our EPS parameter to be 1988.

Figures

Fig4



[1] Special thanks to James Kieren
[2] See Fig 2
[3] See Fig 3
[4] See Fig 4

Fig2

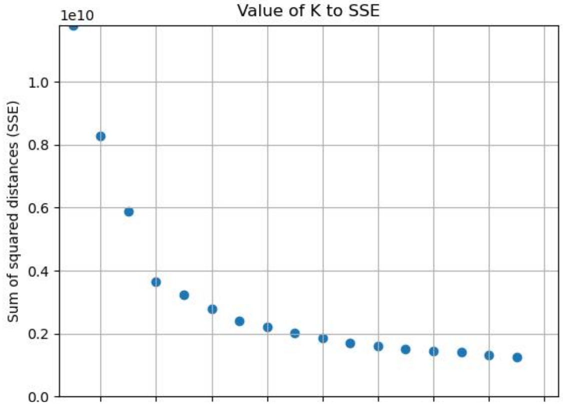
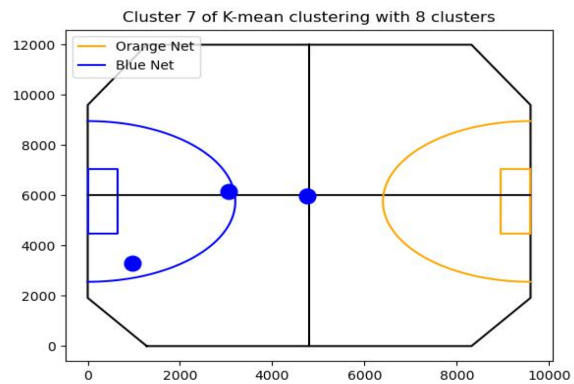


Fig5



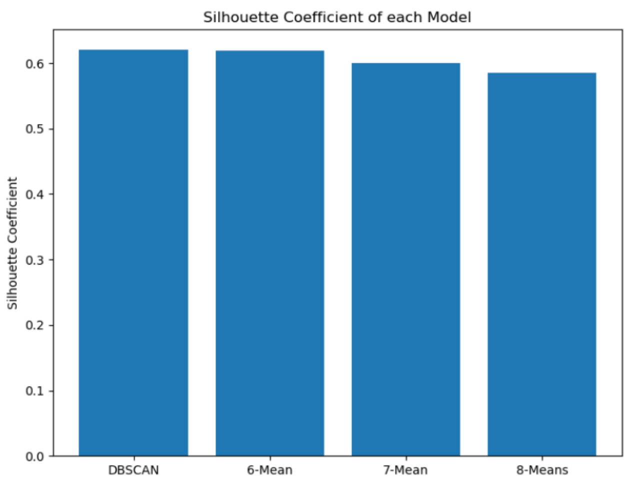
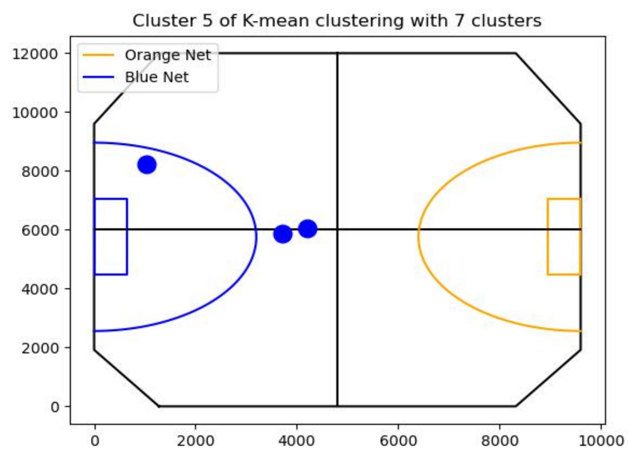


Fig3 Fig6



Results

As seen in Fig 3 The Silhouette Coefficient corresponding to the models are very similar with the differences being marginal and insignificant, even though the DBSCAN did have the largest Silhouette coefficient it can be seen in the Calinski Harabasz Score that the DBSCAN model is inferior to the K-means models that we have been analyzing. More evidence that the DBSCAN model is inferior to the K-means models is the plot of the cluster centers of the model especially Cluster Five[5]. Cluster Five is very far removed from all other clusters of all the other models, it is possible that Cluster Five could be a cluster of “Fake” kickoff where the player closest to the ball does not go for the ball after kickoff, however it is more likely that this is a degenerative cluster.

The 7-means model has a significantly smaller Calinski Harabasz score than both the 6-mean and 8-mean model. This indicates that the 7-means model has a worse fit and less

[5] Plots of all clusters can be found on github

compact cluster structure than the other two models. ‘The smaller Calinski Harabasz score suggests that there is more variability within the clusters of the 7-means model.

The metrics we used to measure against the 6-mean and 8-mean cluster’s slightly favor the 6-mean but not by a significant enough amount indicate that the 6-mean model is better. The clusters in the 8-mean model are less homogeneous, especially in terms of the x position of the 2nd closest player to the ball. These players' decisions have the most impact on a kickoffs strategy therefore we conclude that the 8-mean model is the best model.

To determine whether "soft cheating” is more effective than "hard cheating” we examined the clusters where the “cheating” player was positioned the closest to their goal(soft cheating) . These clusters along with their respective sample size of the testing data and probability of scoring the next goal are 6-means - Cluster 4(n=35,0.6%), 7-means - Cluster 3(n=38,51.315%) and Cluster 6(n=46,55.4%), 8-means - Cluster 1(n=50,51%) and Cluster 6(n=46,55.54%). It is interesting to note that all probabilities are over 50%. We conducted a T-test to see if any of these results were statistically significant indications that the clusters mean goals scored were above 50. Cluster 4 of the 6-mean model had a resulting P-value of 0.11, and Cluster 6 of the 8-mean model had a P-val of .022. The percentage goals of each cluster are not independent of each other, therefore we can not do a T test on the amalgamation of our clusters.

Conclusion

Our research has shown that clustering algorithms can be an effective tool to analyze and optimize kickoffs in Rocket League. We fit three different clustering algorithms to our tracking data, affinity propagation, K-means clustering, and DBSCAN. We evaluated our models using the Silhouette coefficient, and the Calinski Harabasz Score as metrics and combined that with data visualization techniques. From this we found that the K-means algorithm was the most effective algorithm for our data. We then calculated the percent likelihood of certain “soft-cheating” clusters to score the next goal and used this to conduct T-tests. Our results seem to indicate that “soft-cheating” may be superior to “hard-cheating” ; however, our dataset was too small to provide us with a statistically significant result if $a < 0.1$. We believe that continued research in this field will show that the K-means algorithm is an effective tool to analyze Rocket League kickoffs, and that if continued upon could help develop our understanding of the intricacies of Rocket League kickoff strategy!

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