Ashhad Alam
Mohammed Isuf Ahmed

Optimizing Football Lineups

Abstract

With such a significant amount of the world population that watch and play football, naturally it is not just one of the most loved sports in the world, but one of the most debated too. In all corners of the globe, one could find disputes about football, whether it be decisions made during a loss, or hypotheses about an upcoming game. In this paper, we attempt to enrich these discussions, by using optimization methods to determine what formation and lineup a team should play, for each individual game in a season. Specifically, we decided to look at Liverpool FC 21/22, and determine the optimal lineup for each game in the Premier League season. Depending on the number of constraints and the severity of specific penalties, we found that our model could suggest how many changes per lineup to make over the whole season to potentially win the Premier League. Additionally, we can look at games that Liverpool drew or lost, and suggest changes that could have been made to potentially alter the result.

The code and dataset used can be found in this GitHub repo.

Introduction

Football is the most watched sport in the world, with 1.12 billion people who viewed the 2018 World Cup Final live, and a total of 3.572 billion people who viewed the 2018 World Cup [1]. Naturally, with such a vast percentage of the World population that watches this sport, it has become ingrained in many cultures around the globe, and it can become the topic of heated debates that can encapsulate these footballing communities, cultures, and even countries. In the past, most of these discussions on who should have won a game, or why a team lost a game, were mainly based on what a viewer saw and felt. Even the top commentators, analysts and managers of the late 90s were wary of the use of data analysis [2]. However, with the beginning of the 21st Century and mainstream collection of football data, managers have begun to place more importance in the use of analysis, and the top teams of the modern day have highly technical data analysis teams that are truly embraced by the managers of these modern clubs. To give a specific example, Mo Salah was signed by Liverpool in 2017 for a record fee. Seen by many as a gamble, including the manager of Liverpool at the time, the data analysis team of Liverpool pushed for the transfer, and as they say, the rest is history.

In this research, we will use the data available to us to determine the optimal lineup and formation for Liverpool for each game in the 21/22 Premier League season, under certain constraints. The purpose of the research is to analyse the players picked for certain games, and decide whether decisions based on pure data could have perhaps been better than the lineup that was used in real life. To give further context, there is one specific game in this particular season that was arguably the reason Liverpool did not win the league, as they drew to Tottenham on matchweek 36, and the 2 points lost in the game would have been the points needed to win the league over Manchester City. We want to see if our model can suggest different lineups for this game, and then develop a conversation on how Liverpool could have done something different to win this game in hindsight.

Ashhad Alam
Mohammed Isuf Ahmed

Data and Preprocessing

We obtained player ratings, positions, teams, and so on from a Kaggle dataset [3], which was extracted from FIFA 22. A point to note is that this information does not reflect any changes made during the Winter transfer window (so, a player like Luis Diaz, who featured in many games for Liverpool in the second half of the 21/22 season is not a part of this data). This is what we want, since we are trying to optimise for information based on the squad at the start of the season.

The data is in the form of a spreadsheet, and we extracted the Liverpool players, and all their attributes from it. We then narrowed it down to the 25 players who actually played for Liverpool in this season. In addition, we wanted players to not be played out of position, so we set the player rating for all positions except their natural position to be -100 in some iterations of our model.

In addition, we scraped team ratings from the FIFA Index [4] for all teams in the Premier League. No changes were made to this data. Lastly, we manually created the fixture list, and manually extracted the actual lineups that Liverpool played in those games.

Formulation

For the initial formulation, we had 2 decision variables. We had one binary decision variable, x_{ijk}, to determine whether player i played game j in position k. We also had one more binary decision variable, z_j, which would indicate whether our model will try to win a certain game or not (this will be explained clearer).

We also had a number of constraints. The initial constraints ensured that there were 11 players in a game, and that each player at most played once every game (this ensured that a player didn't play Striker (ST) and Left Winger (LW) at the same time in the same game). We then added constraints to ensure that whatever lineup was suggested by the model, it would either be in 4-3-3 or 4-2-3-1, or anything reasonable inbetween (for example, this constraint allowed us to play 4-2-3-1, but with a Left Midfielder (LM) and Right Midfielder (RM) variation). More constraints were added in this manner to ensure Center Backs (CB) were playing at CB if they were to play in a game, and so on and so forth.

The final constraint made sure that the average rating of our team was at least better than the rating of the opposing team for that game. Each player had a rating in every possible position, with their natural position having the highest rating. To determine the lineup for a game, the model selects a player and their position, and adds it to the current teams' rating. The average rating of the team selected should then be at least the opposition teams' rating. However, we multiply that opposition rating by z_j. This is because if z_j is 1, then the constraint to better the opposing team for that game is activated. However, if we cannot beat the opposition rating, z_j will be 0, so the model remains feasible (this can also be interpreted as Liverpool not focusing on winning this game). Finally, the objective function was simply to maximise z_j.

We also implemented a penalty function, which counted how many games a player played contiguously up to the current game, and would decrease the rating by this amount in a percentage. For example, if a player had played games 1, 3 and 4. Then for game 5, we see that they played 2 games contiguously up to that point (games 3 and 4). So their rating for game 5 will be the original*(penatly_factor)**(2), which will influence whether they play that game or not.

Results

We found that tweaking things slightly could have huge effects on the optimal lineups created by the model. We found that if the constraint for the team average was to at least be better than the opposing team, then you could get a maximised objective, however each lineup was very weak compared to what Liverpool might reasonably play. However, if you were to add a constraint that the average squad rating should at least be greater than some minimum (a minimum we used was 75), the lineups looked more realistic and reasonable. We also experimented with limiting how many games the squad players normally play, and giving the starting players a minimum number of games they can play.
The penalty needed many adjustments before it stopped making the model infeasible. We found that a penalty below 0.99 was infeasible, regardless of constraints (it was feasible if you removed almost all constraints that would suggest reasonable lineups). However, after implementing such a simple penalty, the rotations we observed in lineup from game to game were reasonable and realistic.

We did try to make a model that would be 'perfect', where the optimal lineup was close to identical for every game and was Liverpool's strongest team on paper for that season. However, although it performed well in our evaluation and was actually closest to the lineups Liverpool played in real life, it was our intention to look at other optimal lineups to create discussion.

Evaluation

Without some ML algorithm or analysis from experts on the optimal lineups we created, we had no real way to test how well our model performed, other than seeing how many changes per game our lineups suggest, and running a simulation on FIFA 22.

Our first set of optimal lineups had no penalty implemented, and the average rating of our team per game had to be at least as good as the rating of the opposing team (with the z_j binary variable, so if the condition could not be met, the model would still be feasible). Compared to the lineups that were actually played for the season, this set of lineups suggested 5.6 changes per game. However, this is simply too many, and if we were to look at a specific game, such as matchweek 3 (lineup presented on the next page), our lineup suggested that Liverpool may have won playing Jota over Mané at LW and not playing Mané at all, which is not a realistic suggestion to make.

Another, more optimal set of lineups we created suggested 3.63 changes per game. This time, we used our penalty function, removed all players that did not play for Liverpool in the Premier League for this season, and encouraged players to play in their more natural positions by reducing their

Liverpool actual lineup matchweek 3

Our model's lineup for matchweek 3

rating in others. We also forced the Liverpool starting 11 to play at least 25 games, and if the average team rating was not able to beat the opposition, it had to at least be better than the minimum that we chose. We observed significantly more consistent lineups per game with this iteration of our model, which was realistic as in real life a team would do its best to keep the starting 11 highly consistent. The changes suggested were all extremely reasonable, and looking at the games Liverpool drew or lost, the changes suggested could have been game altering. For example, on matchweek 3, Liverpool drew to Chelsea, and our model suggested playing Thiago and Jota over Elliot and Firmino. It is up to us to determine if making this change would have won Liverpool the game.

The last lineup we created was highly optimised; there was a penalty and the average rating of the lineup our model selected had to beat the opposition, had to beat a maximum, and if it couldn't do either, had to at least beat the minimum. We found that this iteration suggested just 2.63 changes per game. If we look at matchweek 3 again (the model's predicted lineup is presented above), it suggested the same changes as the previous for this game. Therefore, if one was to evaluate why Liverpool didn't win this game, one may want to look into why these changes were not made. We also found that with more constraints attempting to recreate real life, our lineups got significantly closer to real life, suggesting around 2 changes to make per game. Additionally, many models suggested making the same changes per game. If multiple optimal lineups were suggesting the same changes for specific games, we interpret this as a very good change in lineup that Liverpool should have made.

Running our first set of optimal lineups through FIFA made us lose a string of matches right at the start of the season, and got us fired less than halfway through the season due to poor performances. Since we were just trying to be better than the opposing team's average rating, we were unnecessarily making games riskier, and hence, lost many games that Liverpool should have won.

On the other hand, for our highly optimised lineups, we made it all the way through to matchday 31 before we got fired for not focusing on the Champions League, and the League Cup. In the Premier League, however, we had 70 points (which barely falls short of the 92 points that Liverpool actually had at the end of the 38 game season). One significant observation we made was that most of the matches that we lost or drew were when Thiago was injured, which shows his importance to the team in the simulation. A very interesting thing to note is that the game Liverpool drew to Chelsea on matchweek 3, our optimal lineup won that game 1-0. The optimal lineup suggested making two changes to the one used in real life (as discussed earlier).

Something to note is that sometimes our model will suggest playing a certain player that was injured in real life for a certain game. We interpret this as suggesting that if Liverpool did not win this game, then it was simply out of their hands, as they couldn't make the change that our model suggested would win Liverpool the game.

Criticisms

There are some problems with the model we created, which we recognise. If we were to use the full Liverpool squad, our model would suggest for some games to use certain players that never played that season. Although one could argue that this suggests these players should actually have played, we decided that it was too unrealistic to suggest players that have never played a Premier League match for Liverpool to be in a lineup, as the information we obtained for these players was not ever influenced by playing in the Premier League.

Another problem that we could not entirely work out, was that for some specific constraints, our model would suggest playing certain players for an unrealistic amount of games. For example, one iteration of our model suggested playing Tsimikas over Roberston for the majority of the season, and while a valid choice to make based on the data perhaps, it is not what would ever happen in real life.

Additionally, although we had a potential rating for every player in every position, when we did use all possible ratings, some of the lineups would be nonsensical; playing a Goalkeeper at Right back (RB), playing Virgil van Dijk at Right-sided Attacking Midfielder (RAM). Although we overcame this problem by reducing the rating of unrealistic positions for players by a significant amount, one could argue we would have created a more realistic model by adding in significantly more constraints that would influence players to play in their more natural positions.

Lastly, another valid criticism of our model is that it did not take substitutions into account, and substitutions are sometimes what defines the end result of a game. However, substitutions are usually very game-dependent; based on the game's scoreline, how the different players have been performing, etc, and we are looking at optimising lineups based on the information we have at the start of the season. As a result, we decided not to include them as part of our model.

Next Steps

There are some clear next steps that could be taken to make our model more realistic. While potentially extremely computationally expensive to gather and analyse the data, we could have implemented a Winter transfer window. Even though the penalty function should encourage lineup rotation throughout the season, we did not take into account the time between games into our penalty (if a player has played 2 games consecutively, but then there is a week break till the next game, our penalty does not take into account that the player may have recovered to full fitness). So, a more sophisticated penalty function could be implemented.

We wanted to take our model the next step further, and implement some sort of Machine Learning algorithm to determine if we could then win games based on a lineup, which could then influence the lineup for future games. However, it was not possible to complete this in time.

Finally, it would have been intriguing to test this on a team that is not so data focused. Liverpool is known to be very technical and successful in their use of data driven decisions for the game, but a team like Manchester United is known to not be so open minded. United are criticised by many for being archaic in their ways, and for having a good squad but not being able to get the best out of the squad, so to optimise over a team like that could have led to lineups we never saw in real life for Manchester United.

Conclusion

Although we were happy with the results we found, and were intrigued by the suggestions that our model created, we understand that it was not as complex as we would have liked. As mentioned earlier, having some sort of implementation where we could not only suggest the optimal lineup, but then determine if Liverpool would win the game, would have been ideal, and other things such as a January transfer window and a chemistry factor would have been interesting to implement. All in all, we believe that our results show that Liverpool do use data analysis to make serious decisions about the game, but we also believe that decisions based purely on data could have led to a better season for Liverpool. Even if that is not the case, our research still enriches the discussion of who should have played what game, which is exactly the purpose of our research.

Citations

https://www.fifa.com/tournaments/mens/worldcup/2018russia/media-releases/more-than-half-the-world-watched-record-breaking-2018-world-cup [1]

https://analyisport.com/insights/how-is-data-used-in-the-premier-league/ [2]

https://www.kaggle.com/datasets/stefanoleone992/fifa-22-complete-player-dataset [3]

https://www.fifaindex.com/teams/fifa22/?league=13 [4]

https://www.buildlineup.com/ [5]