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Simulation and Optimization Project Report
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7 December 2023

Problem Statement

The National Football League (NFL) is one of the most popular sports leagues in the US. With 17.5 million average viewers per game, it is a huge source of entertainment for people across the country. It is also a widely debated topic amongst fans of the sport who believe they could manage their favorite team better than the current owners do. They get a chance to do this somewhat through the popular game of fantasy football, where people compete in a league with their friends to draft skill position players and score points based on how the players actually perform on the field each week. With this in mind, we are aiming to put together the optimal NFL roster, similar to how fantasy football works. We are looking at offensive positions including quarterback, running back, wide receiver, tight end, and kicker.

This is an interesting problem to us because we are all avid football fans and participate in fantasy football each year, and it is exciting to see what a model chooses as the optimal lineup compared to the teams we see on the field each week.

Analysis

The dataset we are using to conduct our analysis is the Madden 24 Ratings file, which has each player on every team, along with their madden rating (a rating of their overall skill level, derived using several metrics), position, years they have been pro, team, salary, and several other individual level ratings such as speed, acceleration, agility, and others. We filtered down to the top 100 players, since we want to only focus on choosing the top players in the league.

We ran two optimization models using integer programming, with our objective function being to maximize the team's average player rating given our set of constraints. The difference in the two models lies in one of our constraints, which we will explain below.

Assumptions

There were several assumptions we had to make in order to conduct this analysis. First, we had to assume that we had free reign to choose all of these players. In fantasy football, each player chooses one player each round, and doesn't get to pick another player until after everyone in the league has also chosen a player. In the actual NFL, it is more complicated, with players getting drafted from College, getting signed to contracts, trades taking place, and players getting cut and picked up off of waivers. We also had to assume that every player would be able to mesh together and that their Madden rating would translate to on field production. In reality, some players may have a lower Madden rating than others but fulfill their duty as a role player exceptionally well, which translates to a higher team success. Finally, because our data set did not include salary per year, we could not include that as a constraint. Some players have one year deals while others have multi-year deals with a huge salary. When broken down each year, the salary is more reasonable. However, we could not include a salary budget constraint for this reason. We are assuming that the team could feasibly afford the players the model chooses.

Constraints

In order for our model to not simply choose the players with the top overall rating, we had to set some constraints. First, we set a position constraint, similarly to how there is in fantasy football. Our team must have at least a certain number of players per position. There must be at least one quarterback, two running backs, two wide receivers, one tight end, one kicker, and one flex position player, which can either be a running back, wide receiver, or a tight end. This ensures that we have a mixture of positions and that the model doesn't only select quarterbacks. Another constraint we used was a total player constraint to put a cap on the number of players selected. Just like there is in fantasy football and the NFL, teams have a maximum number of players they are allowed to roster. We set our maximum number of players to 10 players. The third constraint we chose to put in is the same team constraint. We want our model to choose players from different teams around the league, and we don't want it to select multiple players from the same team. With that in mind, we set the maximum number of players from the same team to one, so that there are no repeated teams. The final constraint is the one we switched between the models. Here, we focused on average years-as-a-pro constraint. For the first model, we want our team to be full of players that are young, so that they can stick together and play for multiple seasons in order to give themselves the best chance for success. We don't want players that are older and more likely to retire soon (even if they are still playing at a high level). We also didn't want rookie players or those with little experience. We set the average years pro for our team to be between three and five years. For the second model, we wanted to focus more on seasoned players that have played a while, and are accustomed to the league. They have either already experienced success and know what it takes to win, or they have spent most of their career on losing teams and are anxious to win before their career is over. We set the cutoff for these veteran players to be 7 or more years as a pro and added a constraint using this value so the model could only select from veterans. This meant we no longer needed the average years-as-a-pro constraint because the model could only select veterans, so we knew the average would have to be 7 or greater.

<u>Results</u>

After running our first optimization model, with the average years pro being between three to five years, our selected team is listed below:

Patrick Mahomes, QB *(Kansas City Chiefs)*

Josh Allen, QB (*Buffalo Bills)*

Nick Chubb, RB (*Cleveland Browns)*

Christian McCaffery, RB (*San Francisco 49ers)*

Justin Jefferson, WR (*Minnesota Vikings)*

Tyreek Hill, WR *(Miami Dolphins)*

Cooper Kupp, WR (*Los Angeles Rams)*

Ja'Marr Chase, WR (*Cincinnati Bengals)*

Mark Andrews, TE (*Baltimore Ravens)*

Daniel Carlson, K *(Las Vegas Raiders)*

Our average player rating is 95.1. This is exceptional as it is hard for a player to be rated over 90 in Madden. There is a slight bias towards the AFC with seven players coming from the AFC and three players coming from the NFC. This lineup features many pro bowlers and what could be eventual Hall of Famers if these players stay at the current pace they are on. Because of our constraint setting the average years pro to be between three to five years, these players are all just hitting their prime and have several years left to play. Overall, this is a team anyone would be ecstatic to have on their fantasy football team, and it is bound to win them many championships.

After running our second optimization model, with each player having to have played for seven or more years, our selected team is listed below:

Dak Prescott, QB *(Dallas Cowboys)*
Derrick Henry, RB (*Tennessee Titans)*
Kyle Juszcyk, RB *(San Francisco 49ers)*
Tyreek Hill, WR *(Miami Dolphins)*
Davante Adams, WR *(Las Vegas Raiders)*
Stefon Diggs, WR *(Buffalo Bills)*
Amari Cooper, WR *(Cleveland Browns)*
Mike Evans, WR *(Tamba Bay Buccaneers)*
Travis Kelce, TE *(Kansas City Chiefs)*
Justin Tucker, K *(Baltimore Ravens)*

Our average player rating is 93.0. While it is slightly lower than the first model, it is still full of very talented players that could help a team win many games. Interestingly, the breakdown between conferences is again seven to three in favor of the AFC, though the teams are different.

Analysis and Conclusion

After looking at our results, both of our teams appear to be set up for success. However, it is important to note that it is not realistic for either of these teams to be put together for a few reasons. First, as noted above, in fantasy football, players are drafted one by one, with other teams having the opportunity to pick players. Because of the skill level of these players, it is likely that some of them would be taken by other teams before one could select them all. For the NFL, these players all have high salaries because of how good they are, so most teams can only afford a few players of this caliber. Due to time and availability constraints, we were not able to factor this in.

If we were to conduct further analysis on this topic, we would look into salary per year and set a team salary cap or budget, so that the model would be forced to look for more niche players that have a lower salary but also provide good value to a team.