# DraftKings NFL Optimizer: Using a Genetic Algorithm to Generate Optimal Fantasy Football Lineups

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## Background

First, a discussion about DraftKings daily fantasy football. Fantasy sports are a way to compete with other football fans by choosing players for your fantasy team. The performance of the fantasy team is determined by the real results from the games being played on the field. Different formats of fantasy football have different rules for point scoring. For instance, PPR formats (point per reception) reward a player one point for catching a pass, regardless of how many yards are gained on the catch. Other formats include bonuses for certain bench marks achieved by a player. For example, DraftKings rewards quarterbacks with 3 extra points for throwing for more than 300 yards. The rules/scoring used by DraftKings fantasy football is available at DraftKings' official website.

Daily fantasy football is much different from typical fantasy football. A typical fantasy football format would be a season-long league consisting of 8 or more teams where the teams draft players at the beginning of the season. In this format, no two teams can own the same player. This is significantly different from daily fantasy football. Daily fantasy sports is centered around the idea that money can be won just by playing for a single day (or weekend when it comes to football) of games. Football fans can enter a contest for as little as 10 cents. Some entry fees exceed 100 dollars for one day which is extremely aggressive given the volatility of football, and subsequently, daily fantasy football. There are two main types of contests that can be entered: multiplies and tournaments. For example, a double up is a type of multiplier contest where the return is either nothing or double the entry fee. This would mean that the top half of entries would get paid out. In tournament contests, the payout structure varies heavily. An example of this would be a 5000 entry tournament with a fee of 5 dollars. Hypothetically, the top entry in the contest would be paid out $2000 while the second entry would receive $1000, and so on. This is a much more risky, but lucrative, strategy while playing daily fantasy. According to a study done in 2021, new daily fantasy players can get hooked easily after a big time win. However, new players often do not have the necessary football knowledge to keep up with the competition (Edson 2021). Newcomers to fantasy football need tools to help them with lineup decisions, like a lineup optimizer.

DraftKings fantasy was legalized years before sports gambling and was the closest thing to it for many fans for a long time. A lot of DraftKings users come around during the latter half of the season. This is because most fantasy football players are in a normal league format, but not all teams can make the playoffs. Injuries and other factors can lead to a promising team falling apart down the stretch. When this happens, fantasy football players will turn to daily fantasy formats to add excitement back to their Sunday afternoon.

## Motivation

DraftKings is the most prominent daily fantasy sports platform as of 2019, with Fanduel being a close second (Losak 2022). Back in 2015, DraftKings raked in around $4 billion in entries throughout the calendar year (Leishman 2016). Since then, DraftKings and the rest of the daily fantasy market have exploded. The overarching goal of this project was to generate optimal DraftKings fantasy football lineups using a genetic algorithm. The top weekly prize in DraftKings NFL fantasy is $1 million (Chung 2022). While the ultimate goal of playing fantasy sports is to make money, there is more at stake than this. Playing fantasy football is supposed to be fun, but losing can put a damper on any NFL Sunday. A study conducted this year found that fans have predominantly positive or negative experiences while playing fantasy football (Wilkins 2023). Therefore, the secondary goal of this project is to maximize the joy that comes from playing DraftKings NFL fantasy.

Hence, the research question is: Can genetic algorithms generate optimal DraftKings daily fantasy football lineups? This project idea was inspired while playing DraftKings Fantasy UFC (Ultimate Fighting Championship). Football is the focus sport of this project due to the author's (Kenneth Woodard's) prolonged interest in football as well as fantasy football. Having been a hardcore football fan since age 7, Kenneth first played fantasy football in 2010 and has not missed a season since. Surprisingly, the author has more emotional investment in his fantasy team than his favorite real team, the Tennessee Titans. This phenomenon is explored in a study that found that only 61% of fantasy players chose to watch their favorite real NFL team over the games that involved their fantasy players. 17% of fans would try to watch both their NFL team and their fantasy players equally, while the rest preferred to focus their attention on their fantasy team's performance (Dwyer 2011). It is safe to say that the accumulated experience of the author contributed to the success of this optimizer.

Since most daily fantasy players rely on their knowledge and instincts while selecting players for their lineup, using an algorithm based on real data, in theory, should only help increase the performance while choosing a lineup. A few different bio-inspired computing methods were considered. Eventually, a genetic algorithm was selected due to its ability to maintain diversity in the population and converge on potential solutions (Katoch 2020). There are over a trillion different lineups to choose from each week, and it is impossible to search through them all. But genetic algorithms excel at solving optimization problems that also have a large exploration space. Genetic algorithms also employ mutation (and crossover, which was not implemented) which helps with exploring new lineup combinations and finding the best-projected lineup. The fitness functions used in genetic algorithms are also extremely customizable which allows certain rules to be put in place to maximize the potential of the lineup. These rules can either reward or penalize a particular lineup based on the players chosen. Many different strategies can and were used in the fitness function for our genetic algorithm optimizer. One example was adjusting the rating of a lineup based on how many players in the lineup were playing at home versus away. This gave the algorithm the ability to mutate the correct lineups and search for even more optimized lineups.

## Related Work

This project was inspired by the *We Want Picks* YouTube channel and website, which offers a DraftKings UFC optimizer exclusively for its premium members. This particular tool served as a source of inspiration for the present project. Despite its influence, the specifics regarding the algorithm and dataset employed by their optimizer remain undisclosed. It should be noted that the focus of their optimizer lies within an entirely distinct sport, namely mixed martial arts, thereby rendering direct comparisons and extrapolations challenging.

In seeking to delve deeper into the realm of fantasy and betting strategies embraced by fans, this study drew upon the research article titled "Behavioral Biases in Daily Fantasy Baseball: The Case of the Hot Hand" published in the Journal of Sports Economics. The intention was to investigate the impact of adopting the widely employed strategy of "riding the hot hand" in the context of fantasy sports and betting (Losak 2022). Notably, our model did not take into account recent performance as a contributing factor due to the lack of publicly available data.

Moreover, the project acknowledged the existence of other related works in the field, such as "DFL-Opt: A Daily Fantasy Lineup Optimizer" implemented by another student. This particular study incorporated Linear Programming as a key technique and primarily centered around optimizing lineups for the DraftKings Showdown Captain Mode Format, albeit within the realm of NBA (Aurori 2020).

In addition to the aforementioned contributions, the project considered the work titled "A Dynamic Modeling and Optimization Approach to Daily Fantasy Basketball" by South (2016) as a reference. South's research delved into the intricacies of daily fantasy basketball and employed a wide range of diverse optimization techniques. However, using genetic algorithms was not one of them. The study sought to provide valuable insights within the context of NBA-related fantasy sports in relation to different optimization techniques (South 2016).

Carefully, considering these varied sources of inspiration, the present project embarked on an endeavor to explore the realm of fantasy sports optimization, drawing on a diverse set of methodologies and focusing on unique sports contexts. This study aimed to contribute to the growing body of research in the field of daily fantasy sports optimization.

## Methodology

The process for the goal of this project can be separated into a few different sections. The first step is to determine the setup. This requires determining several factors such as the salary cap and floor, which positions are needed, and obtaining all of the player data. The team decided to focus solely on the offensive lineup, leading to the establishment of a salary cap of $47,000. This cap was chosen based on the average salary of a defensive lineup, which is $3,000 on DraftKings. However, the maximum salary total for a defense is typically $5,000. Therefore, the team decided to set the salary floor at $45,000, as there is no incentive to not spend the entire salary budget.

Only weeks 7 through 10 of the NFL 2021 season were used for this project. The reason for this is that there is only one free resource that has DraftKings fantasy data, and they stopped operating their site at the end of the 2021 NFL season. To avoid paying for data, the team decided to just focus on that season. The reason weeks 7 through 10 were chosen is because the players were scored based on their average fantasy production. This means that the optimizer is dependent on having multiple data points for each player.

Furthermore, too many daily fantasy players attempt to maximize their used salary for the sake of being efficient. This strategy is flawed for two reasons. First, in tournament formats, decreasing average ownership is key to increasing the value of your lineup. This is because in tournaments there are thousands of entries. Having a player that scores 20 points in your lineup that is only owned by 5 percent of the pool is more valuable than having another 20-point performance player that is owned by half the pool. The other reason that it is usually not a great strategy to maximize the amount of salary used is that players with potential are overlooked. This basically says, "If a player is cheaper than another in terms of salary, then they must be better." This is flawed logic. Sometimes a top 5 running back only has 5 fantasy points. Meanwhile, a third-string running back can get thrown into a game due to injury and score two touchdowns.

The next step in the project involved gathering all the necessary data on players and teams. This data was crucial in determining the fitness of a lineup and projecting their performance. Many databases charged a fee to access individual player information, making it challenging to obtain the required data. After extensive online searches, two websites: lineups.com and http://rotoguru.net/, were identified as having the necessary data. However, these two sources had different formatting styles for players' names, such as using "Jr." and "II." This inconsistency created several issues down the line. To standardize all discrepancies and put the information into one CSV file with proper formatting, the team used Python scripts. Additionally, lineups.com was missing approximately 5% of the players who had recorded fantasy points during the season. To address this, a customized column was created to contain a rating based on each player's previous average fantasy production. This rating ranged from 65 to 99, with 65 being the lowest and 99 being the highest. The rating was also based on each position's average points, as different positions had varying averages. This was necessary to prevent the algorithm from giving too much emphasis to quarterbacks, who generally score higher than other positions. To fill in the rating for each missing player, each position's average rating in each salary bracket was calculated and used to fill in the missing value. For example, if all running backs in the $6,000 to $6,500 range had an average rating of 83.67, then a missing running back in that salary range would be assigned a rating of 83. Each average value was rounded down to the nearest integer.

The first step in any genetic algorithm optimization is to generate an initial population. In the context of this project, the genomes represent the players and each chromosome represents whether a player is included in the lineup (1) or not (0). To generate the initial population, certain constraints needed to be followed, such as the salary cap/floor, the focus on offense only, and filling each position. The offensive lineup required one quarterback (QB), two running backs (RB), three wide receivers (WR), a tight end (TE), and a FLEX position that can hold any position except for a quarterback. The initial population generation function was created with a parameter to set the size and had to follow specific constraints, such as not selecting the same player for multiple spots in the lineup and adhering to the salary floor and cap of $45,000 and $47,000, respectively. Additionally, minimum requirements were set for each position, such as a minimum salary for quarterbacks of $5,100 and a minimum rating for tight ends. This allowed for selecting boom-or-bust players with at least a little bit of production history.

After generating the initial population, the team needed to evaluate the fitness of each lineup to determine which were better than others. To do this, they focused on five aspects of a lineup: Individual Player Rating, Opposing Defense Rating, Home vs. Away Game, Stacking, and Position Rules. The Individual Player Rating was determined by generating an overall rating for each player based on their stats and performance each week. The Opposing Defense Rating was more complex, as the team scaled all of the defenses to a scale from 5 to negative 5, with the best being negative 5 and the worst being positive 5. They looked at each player and inspected the defense they were playing against for that game, and based on the scale they made and the defense they were playing, the lineup score would go up or down within the bounds of that scale. This was done by adding half of the opponent's defensive rating to the corresponding offensive player. The choice to only add 50 percent of the defensive rating to the player's rating was based on rigorous testing. Values of 0%, 25%, 50%, 100%, and 200% were all tested, and it was determined that 50% provided the best results.

Home versus away is a small adjustment to fitness, where the team decided to add 1 point to the lineup's total fitness score if it was a home game. Otherwise, an away game would take a point from it. Another strategy that was implemented to increase the maximum potential points is called stacking (Haugh 2021). Stacking is an exciting aspect of fantasy football, where if a quarterback and a wide receiver from the same team were chosen, there is a chance that a lot of the passes (and subsequent yardage and touchdowns) would go to the selected wide receiver. This meant that the team was essentially getting double points, since both the quarterback and wide receiver on the lineup were getting points from the same play. However, the opposite could occur too. If the quarterback was performing terribly, then the selected wide receiver would perform badly as well. Although stacking could lead to a poor-performing lineup, the team rewarded lineups that used stacking since it could result in the best performance possible. To prevent too many players on the same team from being stacked together, another penalty was implemented. If there was a same team QB-WR-WR stack, then no points were added or removed. However, for each additional player on the same team added to the lineup beyond this, a penalty of 5 points was assigned. This is because there are only so many yards and touchdowns to go around each week. Stacking too many players from the same team is a bad strategy in daily fantasy because it lowers the potential for fantasy points.

Another type of stacking called “inverted stacking” was also implemented to increase the optimization. This involved rewarding the model if a quarterback and a wide receiver or tight end were on teams playing against each other. In football, some games become “shootouts,” which means that it is a high-scoring game. One team's offensive success can put pressure on the opposing team’s offense which leads to more points. Stacking lineups in this way is beneficial to increasing the ability to generate a very high-scoring lineup. No penalty for additional players was implemented like the previous stacking method.

The final technique used to evaluate lineup fitness, involves using position rules that dialed in on the FLEX position and how it was filled. As mentioned before, a tight end should never be put as the FLEX, so the team severely punished a lineup if it had one in the flex position. Tight ends are typically much slower than receivers and backs. This limits that position group’s ability to accumulate yards and get into the endzone. Therefore, having two tight ends in a lineup means that it is a non-optimal lineup. The other rule was designed to favor wide receivers slightly. This is because the point-per-reception format favors wide receivers, but some running backs catch a decent amount of passes as well. Therefore, we do not want to exclude them. Choosing wide receivers over running backs increases the volatility of a lineup because wide receivers generally have a lower production floor than running backs as well. This means that the position rules could cost a potential lineup some points because starting running backs (and even some backups) can expect to have at least 10 touches per game. The best wide receivers can have only one reception on a given week, and then follow up the next game with 9 receptions.

Using this evaluation method, the algorithm had a way to evaluate the fitness of each lineup from the random population and each generation to come after it. These choices were made based on the ability to select lineups that were more optimal than the initial choices, but also the ability to select lineups with higher potential. The defensive ratings and home/away parts of the fitness calculation helped maximize the average selected lineups. Conversely, the stacking and position rules allowed the optimizer to select higher-scoring lineups to help in DraftKings tournament formats. The balance struck between increasing the average lineup score and increasing the maximum potential for a lineup yielded positive results. The next step was to develop a way to select lineups to create multiple generations of optimal lineups that converged on the best possible solution. Keep in mind that it is nearly impossible to find the “one-in-a-trillion” or perfect lineup.

The chosen method for the selection process is tournament selection. The algorithm selects a predetermined number of the fittest lineups from the population to be used for further breeding. Each lineup, or parent, is selected for mutation. This step is crucial in starting the convergence process on a selection of lineups that are deemed the most optimal. This is because tournament selection emphasizes the fitter individuals within the population.

To produce the next generation of lineups, the team needed to take the selected lineups and breed them. There were two methods available, one being crossover and the other being mutation. However, because of the requirements for the lineups, implementing crossover could lead to lineups going over or significantly under the salary cap, resulting in their elimination from the population pool. If one half of the lineup is expensive in terms of salary and the other half is cheap, then it would take a lot of attempts to create a legitimate crossover. This would require lots of computational time that is unavailable.

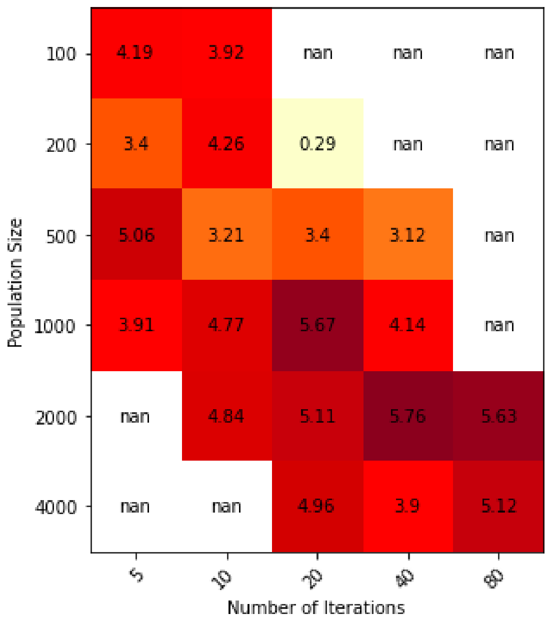
Therefore, the team opted to use mutation as the sole breeding method. This involved going through each position and applying a predetermined probability of mutation. If the mutation was successful, the position would randomly mutate to a new player. After mutation, the team ensured that the lineup still fit within the parameters of salary and filled positions. Making sure the mutated lineup fit within the same constraints of the initial population’s lineups was an extensive process filled with many conditional statements. Instead of just giving a lineup a fitness score of zero if it fell outside of the constraints, the mutation would reset the lineup to the original parent and mutate again. For around every 40 mutation attempts, only one would work within the constraints on average. This also contributed to the longer average computational time. This overview describes the process of mutation in the fantasy football optimizer.

The last step of this process is to replace the population and start again. The newly mutated population is used to replace the previous population so that their fitness can be evaluated. This cycle is repeated for a predetermined number of iterations. The performance of the optimizer could be improved by maximizing the number of iterations but this also costs a significant amount of computation resources.

The entire process of the genetic algorithm involves generating a population, evaluating the population's fitness, selecting the fittest lineups, mutating them, and replacing the previous population with the newly mutated one. After running a predetermined number of iterations, the fittest lineups are provided, and the average fitness of the initial population is compared to the final population to evaluate the optimization.

Multiple runs of the algorithm were performed with a population size of 1000, 10 iterations, a tournament size of 5 lineups, and a mutation rate of 10%. A total of 500 runs were conducted during hyperparameter testing. This number was chosen due to the massive variance in fantasy football (and there being more than a trillion lineup combinations), which took approximately 4.5 hours to complete. The next step is to optimize the parameters and the weighting of the fitness coefficients to improve the performance of the algorithm in generating higher-performing lineups.

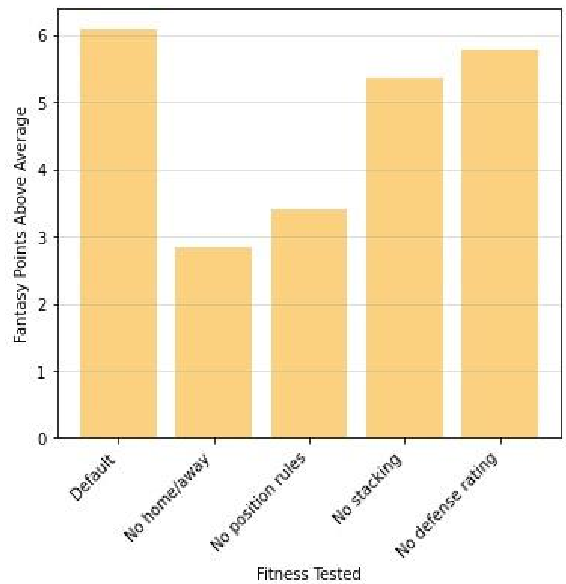
To improve the performance of the algorithm, the parameters used for the program need to be fine-tuned. Different values were used for population size and iteration amount, and the results were analyzed. Other parameter combinations were tested, but they were even less conclusive and insightful than the population versus the number of iterations. Therefore they were not included. The following heatmap shows parameter testing the population size against the number of iterations. Each score is the average selected lineup score minus the average score of the initial lineup population across 250 tests:




This data reveals that beyond a population size of 1000 and 20 iterations, there was a very slight increase in performance. It is probable that increasing both parameters in a proportional manner would yield better results, but this would require more computing power. Because the performance of 20 iterations and 1000 initial lineups performed well, this combination was chosen to save computing time.

As mentioned above, other parameters such as tournament size and mutation were also extensively tested to try to find the most optimal choices. However, adjusting these parameters did not correspond to much improvement in the performance of the optimization. This led to the choice of 5 for the tournament selection number and the choice of 0.1 for the mutation rate. These values were chosen simply because the amount of computational time required for testing was more optimal than other options; and on top of that, the performance was solid.

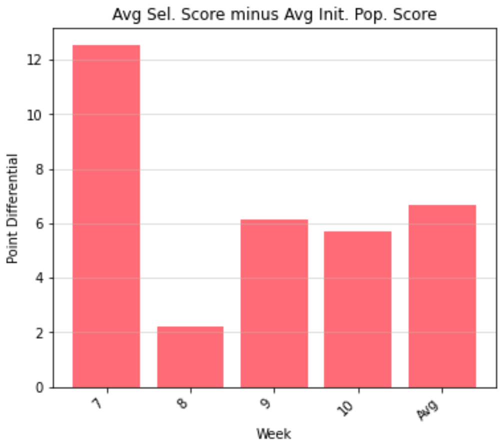
To get a little bit more out of the algorithm, it is necessary to optimize the weights of each fitness coefficient. By removing each coefficient one at a time, it became clear which ones had a higher impact on the final selected lineups. This information proved useful to determine the weights for each coefficient. Below is a bar graph showing the performance of the model when each element of the final fitness function was removed. “Fantasy points above average” was calculated by taking the average selected lineup score and subtracting the average score of the initial lineup population across 500 tests. Hence, each configuration for fitness evaluation below was tested for 500 runs:



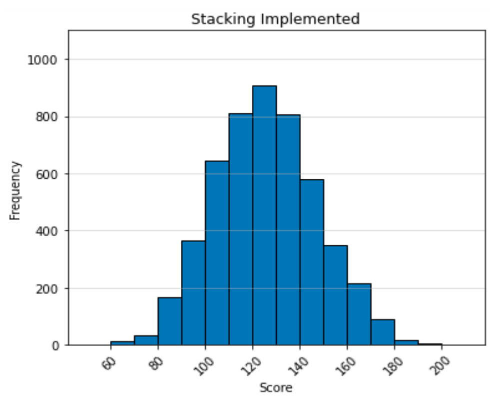

Using this information, certain weights were chosen for the fitness function to perform its best. The defensive rating of the opponent for each player was multiplied by 0.5 and added to each corresponding player. If the player was playing at home 1 point was added, if the player was on the road a point was taken away. The position rules were as follows. If a tight end was selected in the flex position, 20 points were taken from the lineup. If a wide receiver was chosen for the flex spot, then 2 points were added. No points were added or taken away based on whether or not a third running back was selected for the spot. Finally, if a typical quarterback-wide receiver stack was present in the lineup, then the lineup was awarded 5 points. To prevent too many pass catchers in the lineup from being on the same team, a penalty of 5 points was assigned to the lineup if more than two wide receivers from the same team were selected. The other stacking method awarded 3 points to a lineup if an inverted stack was present in the lineup. Each of these factors was tested, tweaked, and retested to find the best possible configuration. There is certainly more that can be done with more available player-in-game statistics and other factors.

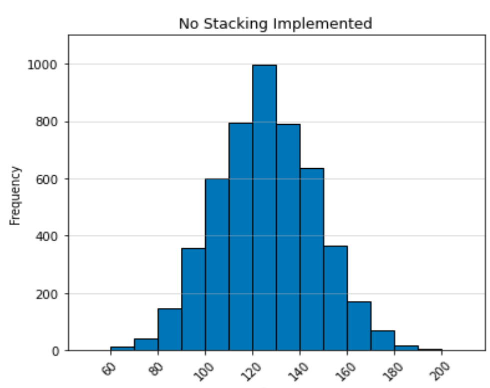
## Results

The performance of the optimizer from weeks 7 to 10 during the 2021 NFL season has been extremely encouraging. It demonstrated great success, particularly during week 7 when it had an average of 12.54 points above the average for that week. The average performance across those 4 weeks of the season was between a touchdown and a touchdown plus an extra point. A touchdown in DraftKings Daily fantasy can be the difference between winning and losing money on NFL sunday. The following figure is a bar graph that depicts the optimizer's performance from weeks 7 to 10 (in terms of the average point differential) during the 2021 NFL season:




As mentioned previously, stacking can increase the performance and volatility for a fantasy football lineup. Stacking players forces the optimizer to produce better lineups for tournament formats specifically. The following histograms depict these findings (5000 optimized lineups generated):




## Conclusion and Future Work

To conclude, optimal DraftKings NFL fantasy lineups can be generated randomly using a genetic algorithm. Achieving positive results during each week that was tested proves this. These results and findings provide valuable insight for the community of daily fantasy sports as well as the application of genetic algorithms in this domain. Having access to more datasets would allow the fitness function to be improved vastly. Specific matchup data like yards per game allowed to the "slot" receiver would allow the optimizer to select players that have better matchup specific opportunities would improve the optimizer's performance significantly. Further research and refinement of the algorithm could enhance lineup performance and provide valuable tools for fantasy football enthusiasts seeking to improve their chances of success on platforms like DraftKings.

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