

Analysis of NFL Player Valuation

Isaiah Bryant, Edan Eingal, Kevin Li, Steven Liao

OVERVIEW

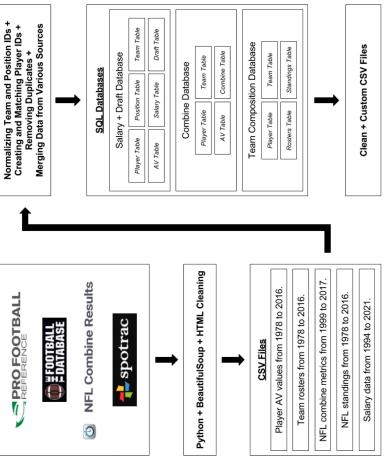
The central objective of our project is to create a means by which to evaluate the ‘true value’ of a player in the NFL. Our objectives surrounding the determination of true value include:

- Approximating an appropriate salary for a player given their performance.
- Determining which players are over or underpaid.
- Predicting a draft prospect’s performance based on combine metrics.
- Elucidating a draft pick’s fair dollar value.
- Predicting a player’s contribution to a team’s playoff performance in a trade.

A key statistic in all of our models is the **Approximate Value (AV)** of a player. AV is a metric developed by Pro Football Reference that can be used as a proxy to describe the performance of a player at a given position over a period of one or more seasons.



DATA COLLECTION



CHALLENGES

- Merging roster data and combining data from various sources and removing duplicates.
- Finding salary data from before 2011.
- Assigning the correct player IDs to players from different data sets.
- Deciding on a standard set of position and team IDs.
- Tuning the team composition model and attempting to avoid overfitting.

SALARY ANALYSIS

Our goal with salary analysis was to value players and draft picks in relation to how much they are paid. In other words, given the NFL's salary cap restraint, the value of a player is determined not just by performance, but also by how much money must be spent to acquire that player.

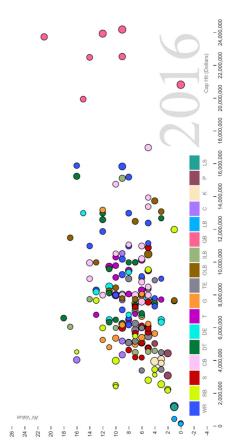
- A decreasing average AV value as draft rounds increase.
- A higher contribution to AV from certain positions such as quarterbacks (QB).
- A relatively steady average AV value for kickers (K) indicating that teams may wish to draft these positions in later rounds.

Our analysis of the draft begins with the **1980** class, and groups all players in a given position and round together (with the exception of Round 8 and undrafted players). The results clearly show:

- A decreasing average AV value as draft rounds increase.
- A higher contribution to AV from certain positions such as quarterbacks (QB).
- A relatively steady average AV value for kickers (K) indicating that teams may wish to draft these positions in later rounds.

DRAFT ANALYSIS

AV vs. Salary (top 10% in each position based on AV value)

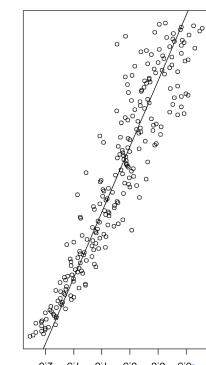


We began by creating a ‘fair salary’ metric which measures the salary a player deserves to earn based on their performance for a given year. The formula for the fair salary of a player is:

$$fair_salary(player_av) = \frac{player_av}{total_av} * salary_cap * number_of_teams$$

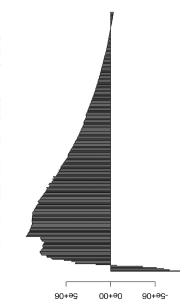
Next, we wanted to value draft picks. Since NFL rookie contracts are standardised and four years long, we looked at historical data for the performance over the first four years of a player’s career.

PICK NUMBER vs. Average AV per Season over Rookie Contract (log)



Fitting an **exponential regression** to these data, we can approximate a player’s AV contributions over their rookie contract given their draft pick number. From here, we approximate the fair contract for each rookie using our fair salary metric. The true value of a draftpick can be construed as the difference between the actual and fair salaries of a draft pick.

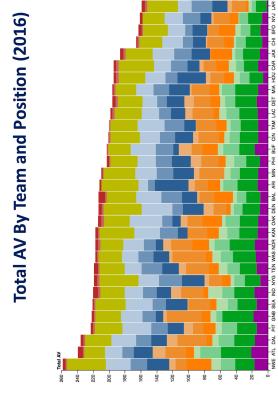
Pick Number vs. Pick Value in Dollars



TEAM COMPOSITION

Our team composition analysis was done with rosters since 1978 (the year the NFL switched to a 16-game regular season). The visualization below displays the sum of the AVs of each position for every team in the 2016 season.

- The total AV of each team is **highly correlated** with its success in the 2016 season and playoffs.
- Balance in team composition is important; the best-performing teams receive significant contributions from all positions.



COMPOSITION ENGINE

Model Selection - We wanted to select a model that would perform well for our classification task and allow transparency about which components of a team contributed to play-off success. We decided on using Sklearn’s Random Forest Classifier with 2500 trees, balanced class weights and use of out-of-bag error set to ‘True’.

Feature Engineering - We trained our model on summary statistics with respect to each position. These included the mean, sum, and max AV by position as well as the number of players for a given position.

Validation - We validated our models for each playoff milestone using stratified 10-fold cross validation.

Results - For all playoff milestones the maximum AV and sum of AVs for DBs and QBs were found to be the most important components of a successful team. Among Super Bowl champions, the sum of DB AVs was the most important feature by a margin of 160% over a team’s total QB AV. It is trained in importance by the max DB AV and the sum of LB AVs, suggesting that defense does indeed win championships.

Trading Tony Romo to the Houston Texans:

- Wildcard Team Prediction: True (P=0.5524)
- Divisional Team Prediction: False (P=0.5636)
- Conference Team Prediction: False (P=0.8892)
- Super Bowl Team Prediction: False (P=0.9712)
- Championship Team Prediction: False (P=0.982)