NFL Prospect Evaluation with Combine Data Executive Summary

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Github: https://github.com/dnguyen25/NFLStatsproject

Overview:

The National Football League (NFL) is one of the largest professional sports organizations in the United States; generating nearly $12 billion dollars in revenue in 2022 (NBC). Currently, there are 32 NFL teams and each year, the teams share the same goal--winning the Super Bowl.

A major part of achieving this goal is having an excellent team-building process in which high quality players are brought in while navigating the NFL's salary cap. Teams can sign free agents from other teams, but they are often very expensive and make dealing with the salary cap difficult. Because of this, the annual NFL draft is highly anticipated as it allows teams to select players eligible to leave college football in the hopes of adding talented, young individuals on team-friendly (cheap) contracts.

Owing to the complicated nature of playing football, evaluating players eligible for the draft (called prospects) is notoriously difficult. There are 22 players on the field for every play; each player is typically assigned different tasks depending on their position. Teams use a combination of scouting reports, player measurements, and watching player tape to give themselves a better chance of selecting players that will do well in the NFL. Scouts, coaches, and team executives stake their jobs on accurately measuring a player's performance. Sponsorship decisions are frequently made based on a player's projected play.

Here, we attempt to predict a prospect's contribution to their respective team over several years based on their workout statistics at the annual NFL combine (simply a workout session for many prospects) and the value of the draft slot they are taken at.

Goals and Measurements:

We evaluated players by the following metrics:

- PFR's (ProFootballReference) SRS metric, which measures team performance in the years after the player was drafted, adjusted for strength of schedule, and scoring randomness.
- PFR's DrAV metric, which measures a player's approximate value to the drafting team.
- A player's draft position.

Our feature metrics were the measurements taken at the NFL combine for height, weight, forty-yard dash time, vertical jump distance, bench reps, broad jump distance, cone drill time and shuttle drill time.

Data Pre-Processing:

We used data provided by the NFL combine and PFR. We grouped players into nine positions and removed UDFAs. After preprocessing, we had 2885 players.

Preliminary Models

We started by doing exploratory analysis on the relationship between a player's draft position and their DrAV. We found that this relationship was linear in (x+180)^(-0.5). We used this function to transform our draft pick variable, giving stronger predictive power in our later models. As expected, the players' contribution is much higher in the first round and trails off to near zero in the later rounds. We also observed that the distribution was left skewed; no matter the draft position, most players contributed very little. Thus, we chose to use a Poisson regression for the other models. When broken down by position, we found slight differences in player value.

Main Models

We built a Poisson regression for DrAV broken down by position. We used cross validation to remove correlation with irrelevant statistics. Success was measured by comparing the mean Poisson deviation (MPD) of the model to a dummy model that predicted the mean DrAV.

We built a KNN model for draft position, linearized as above, and broken down by position. We scaled the data because the feature variables have different units and scales. Success was measured by comparing the mean squared error of the model to a dummy model that predicted the mean DrAV.

Conclusion:

The model for player performance had small to negligible improvements in predicting DrAV from the base model on testing data. This suggests that there is some contribution to player performance based on combine data, but it is so small that teams should place low emphasis on combine statistics when making draft decisions.

The model for draft position confirms that, currently, combine statistics do influence teams' decisions, however it only accounts for a small portion (<10%) of variation in draft position as measured by mean squared error. Players and analysts should keep this in mind when adjusting expectations based on combine data.

The preliminary models showed that there is variation in draft value based on player position. Namely, we found that first round quarterbacks provided more value than other picks. Offensive linemen were slightly underdrafted and defensive backs and tight ends were overdrafted based on their DrAV.

We tried to create a model for the SRS of the drafting team, but no correlation was found with the combine statistics during cross validation.

These models confirmed the difficulty of player evaluation in the NFL. To construct a better machine learning model, more data is necessary including college stats or play by play analysis. Alternatively, a more precise measure of player performance may show a correlation with combine statistics. We also recognize that player performance will never be fully predictable due to the dependence on coaching, effort, scheme fit, etc.