

Exploring Relationships Between Athletic Tests and Football Performance

Introduction

The goal of Notre Dame Sports Performance is to optimize athletic development through data-driven decision making. In this project, I analyze physical and psychological testing metrics and detect which, if any, bear influence on Pro Football Focus (PFF) Grades, a measure of on-field football performance.

Exploratory Data Analysis

The data utilized included 1121 rows of athletic testing metrics and 195 rows of PFF Grades, across 15 student-athletes throughout 2024. Each row of testing metric data displayed the results of tests taken that day for the student-athlete. Each row of PFF Grade data includes a PFF grade recorded in a game setting, for the respective student-athlete. Because the dates between the two datasets did not necessarily align, and different tests are conducted at different points throughout the year, creating a centralized dataset with both testing and PFF data involved two steps. First, copying testing data forward so that each row includes the results from tests conducted on that day, or the most recent available result. Second, joining testing data to PFF data on the closest date in common, to most resemble the physical and psychological conditions a player inhabited in their game performance. The result was a singular dataset of 195 rows with the most recent test metrics a player received in relation to their PFF grade.

Because significant differences existed between testing metrics of different positions (Linebacker, Defensive Lineman, and Defensive Back) via ANOVA, outliers were dealt in comparison to other data points within the same position. To detect extreme outliers, if less than 20 data points existed within a position, a Modified Z-score was applied, with IQR-based outlier detection used otherwise. Outliers were set missing.

Looking at the figure below, no trends, linear or otherwise, immediately stand out between test metrics and PFF grades. However, for test metrics such as Bodyweight, Eccentric Duration, Muscle Mass, Peak Power, and Field Time, data points with similar positions tend to cluster, signaling likely interactions between these test metrics and player position. This is corroborated by high correlation coefficients between these interacting variables, and extremely low coefficients between all variables and PFF grades.

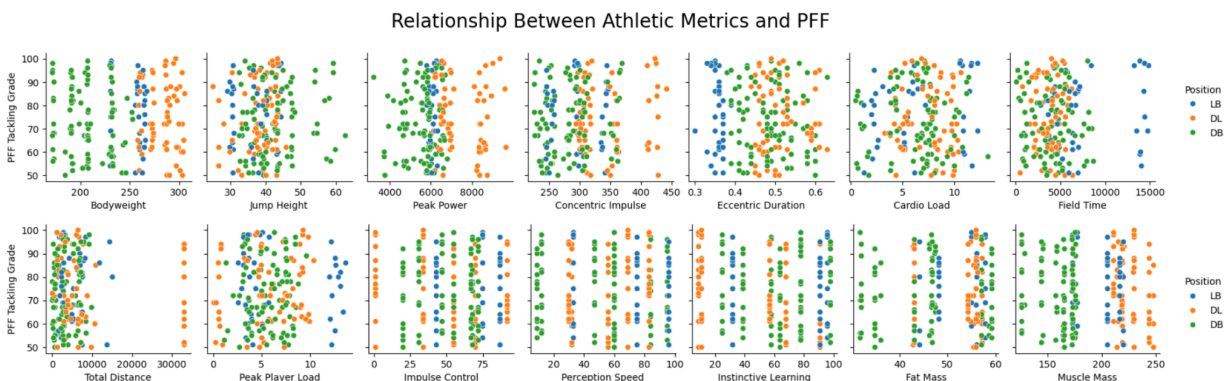


Figure 1: Displays each athletic test metric plotted against PFF grades, separated in color by position.

Analysis of data stratifying PFF into high (greater than 75th percentile), medium (25th to 75th percentile) and low (below 25th percentile) scores showed lower Body Weight (excluding defensive linemen) and higher Jump Height,

Concentric Impulse, and Peak Power as characteristic of high-scoring PFFs for all positions. However, differences in test metrics between PFF score strata were all statistically insignificant, across and within player position groups.

Statistical Framework

Knowledge of the game of football tells us that the strengths of Defensive Linemen lie in strength, power, quickness and endurance, Linebackers in instinctive learning and strength, and Defensive Backs in speed, agility, and quick perception. Performing ANOVA for each athletic test metric revealed significant differences in virtually all metrics between positions. Although PFF grades did not show significant differences, I decided separate models dedicated to each position would be beneficial to highlight varying demands. Before modeling, testing metrics were standardized to prevent disproportionate scaling influences. After poor performances with Linear and Ridge Regression models, XGBoost was settled upon, given its ability to handle non-linear data. The following figures display the most influential testing metrics on PFF grades and their magnitude for Defensive Linemen.

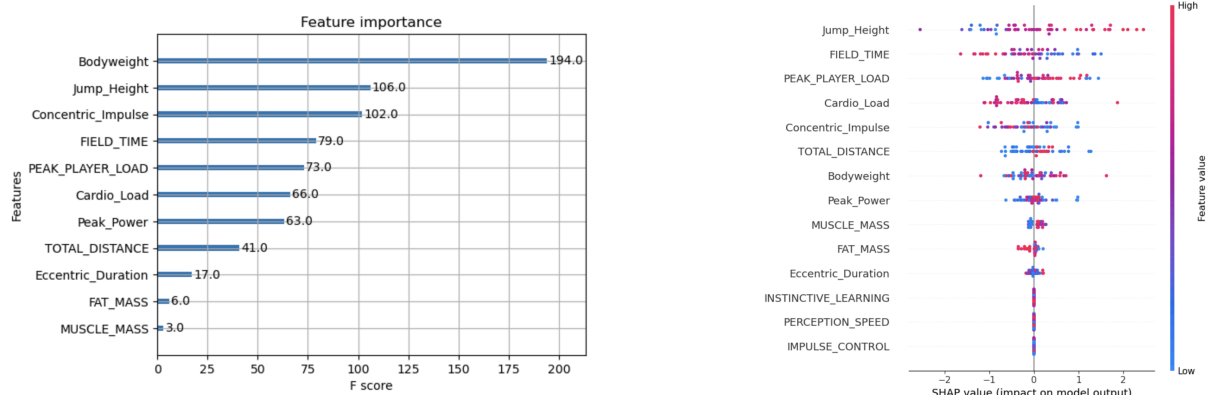


Figure 2: For Defensive Linemen, most influential variables in descending order (left). SHAP Values (right) quantify influence; greater magnitude (ex: 2 or -2) indicates greater effect, with positive (ex: +2) indicating increase in prediction value, and vice versa. Red or blue colors of data points indicate higher or lower values of the test metric.

The leftmost graph shows test metrics, in descending order, like Body Weight, Jump Height, and Concentric Impulse, influencing PFF grades the most for Defensive Linemen. The rightmost graph includes SHAP values, which quantify this influence. Plots displaying potential interactions were generated as well, although not pictured, showing interaction between Concentric Impulse and Jump Height. Graphs generated for Linebackers showed Peak Player Load, Peak Power, Concentric Impulse and Bodyweight as the most important features, and negligible interactions present. For Defensive Backs, Concentric Impulse, Bodyweight and Jump Height were most influential, with negligible interactions present. It should be noted that these models did not perform very well predictively when tested across different folds of the data, but can still be helpful in identifying potential relationships.

Recommendations

To increase on-field football performance, Defensive Linemen should focus on skills related to increasing metrics in Jump Height, Peak Player Load, Total Distance, Muscle Mass, and Body Weight, and decreasing Cardio Load, Field Time, Concentric Impulse, and Fat Mass. Higher Concentric Impulse appears to diminish the effect of Jump Height on PFF, which makes sense given Defensive Linemen in this dataset are significantly heavier than other positions. Linebackers should increase Field Time and Jump Height, and decrease Body Weight and Cardio Load. Defensive Backs should improve Peak Player Load and Cardio Load.

To improve this analysis in the future, more data collection across the board is crucial, especially in collecting PFF grades from a more frequent number of games.