Can we Predict NFL Success from the Scouting Combine?

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Springboard Capstone Project

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Context

- The NFL Scouting Combine is an annual event where college football players perform physical and mental tests in front of National Football League coaches, general managers, and scouts.
- The purpose of the combine is to provide insight into the medical history, athletic abilities, psychological state, as well as, demonstrations of skill in positional drills of potential prospects.

Problem

- How much stock should coaches/scouts put into the Combine?
- What Combine measurements contribute to NFL success?
- Can we predict individual players NFL performance based solely on Combine measurements?

Who Might Care?

Coaches & Scouts

General Managers

The Data

Data from the 1987 - 2015 NFL Combine & Draft

Number of rows: 10228

Number of columns: 51

Data Merging

Combine Data Specifics

- Source:(https://data.world/sportsvizsunday) and posted on data.world.
- File format: excel sheet 1

Draft Data Specifics

- Source:(https://data.world/sportsvizsunday) and posted on data.world.
- File format: excel sheet 2

Merge sheets together:

- Merged on players who attended both Combine & Draft
- Final data shape: 5643 x 51

Data Wrangling

Steps taken to clean data:

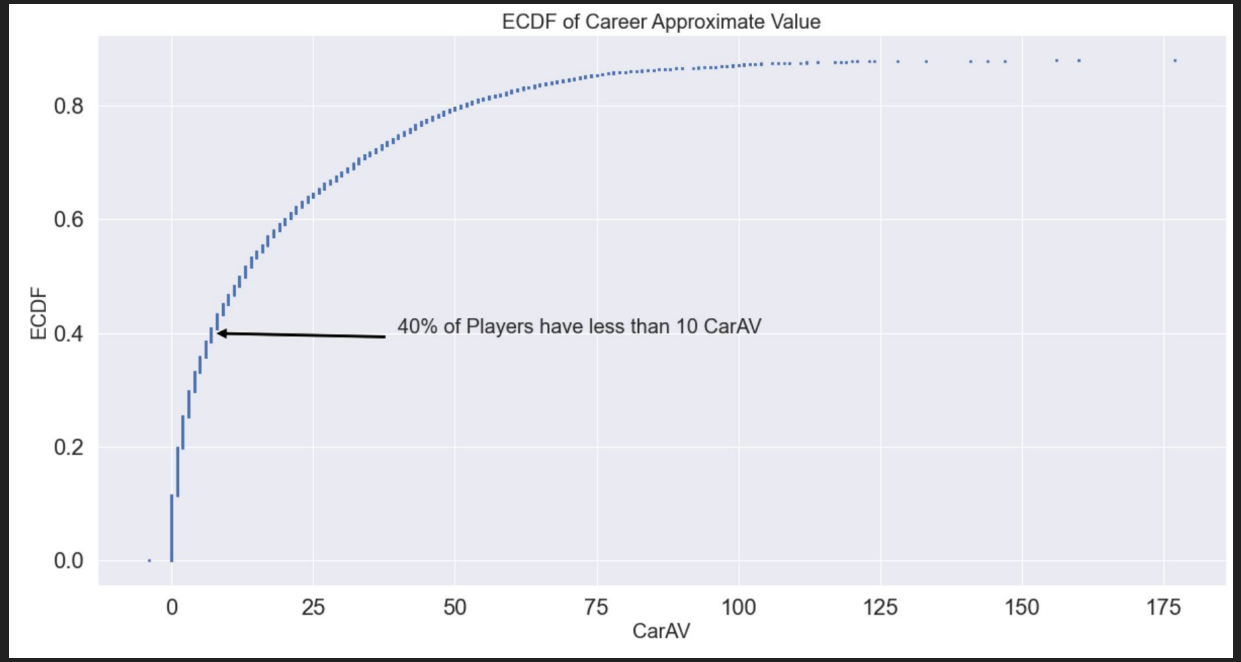
1. Drop ‘HOF since all values were ‘No’
2. Drop ‘To’ column and replace with $ of seasons played.
3. Impute missing values with K-Nearest Neighbors method.
4. Select Target variable approximate value.

Player	HOF	Pos	Position Standard	First4AV	Age	To	AP1	PB	St	CarAV	DrAV	G	Cmp	Pass_Att	Pass_Yds	Pass_TD	Pass_Int	Rush_Att
Jameis Winston	No	QB	QB	13	21.0	2016.0	0	1	2	13.0	13.0	26.0	540.0	913.0	6722.0	42.0	25.0	86.0
Marcus Mariota	No	QB	QB	9	21.0	2016.0	0	0	2	9.0	9.0	23.0	458.0	725.0	5590.0	42.0	18.0	79.0
Dante Fowler	No	OLB	LB	0	21.0	2016.0	0	0	0	0.0	0.0	10.0	NaN	NaN	NaN	NaN	NaN	NaN
Amari Cooper	No	WR	WR	9	21.0	2016.0	0	1	1	9.0	9.0	26.0	NaN	NaN	NaN	NaN	NaN	3.0
Brandon Scherff	No	T	T	7	23.0	2016.0	0	0	2	7.0	7.0	27.0	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Tyrone Sorrells	No	G	G	0	NaN	NaN	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Tony Burse	No	RB	RB	0	22.0	1987.0	0	0	0	0.0	0.0	12.0	NaN	NaN	NaN	NaN	NaN	7.0
Bruce Holmes	No	LB	LB	1	21.0	1993.0	0	0	0	1.0	1.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN
Bill Ransdell	No	QB	QB	0	NaN	NaN	0	0	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
John Holifield	No	RB	RB	0	23.0	1989.0	0	0	0	0.0	0.0	3.0	NaN	NaN	NaN	NaN	NaN	11.0

Exploratory Data Analysis

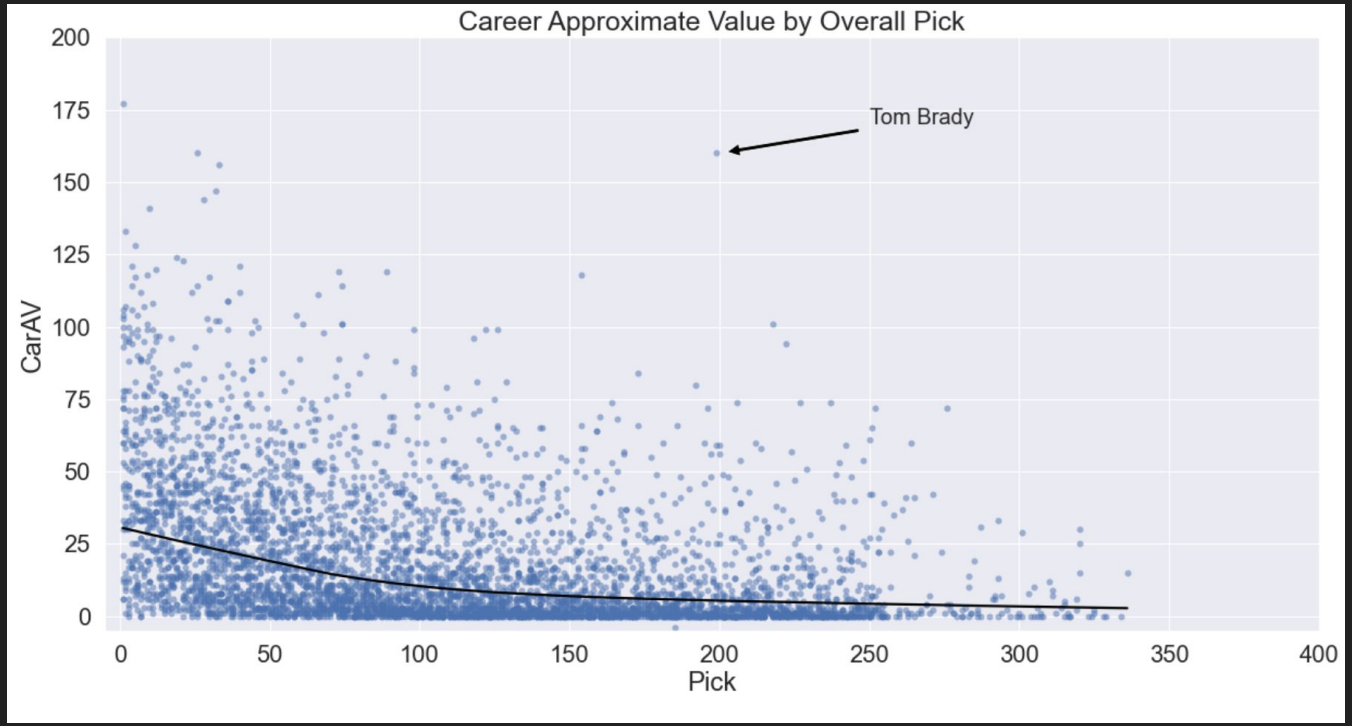
The data follows the pareto distribution

A small portion of players become successful while most players experience very little success.



Do higher draft picks have more success?

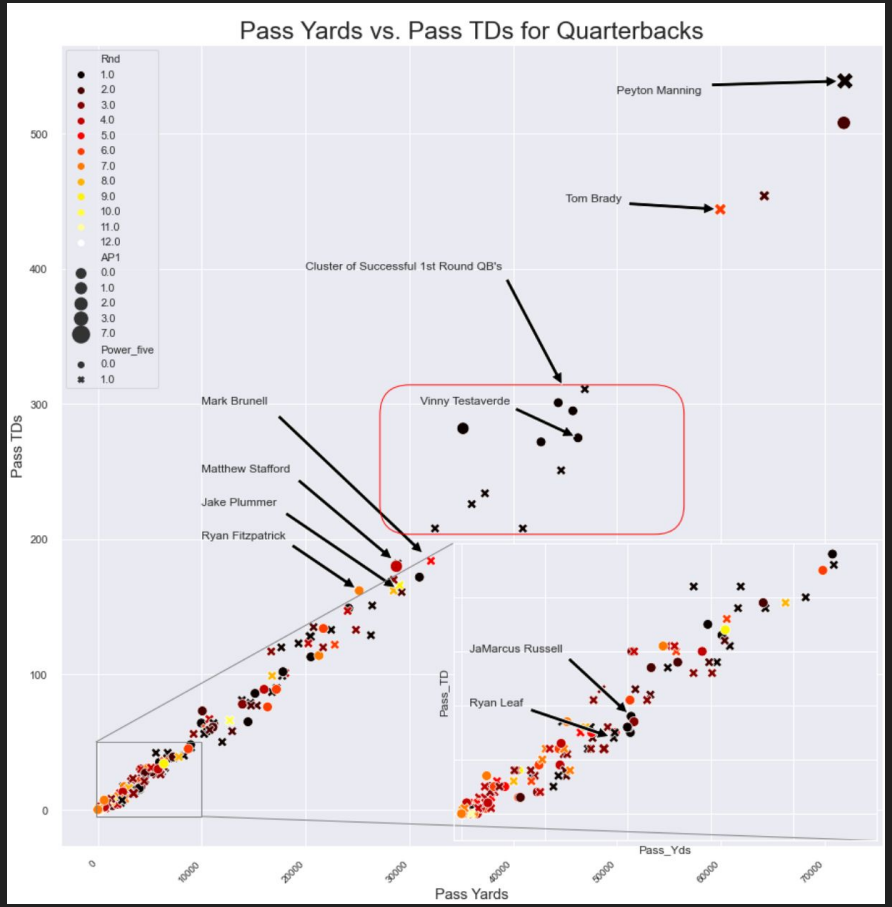
In general, higher draft picks have higher approximate values.



Bust or Steal?

Steal: Tom Brady & Mark Brunell

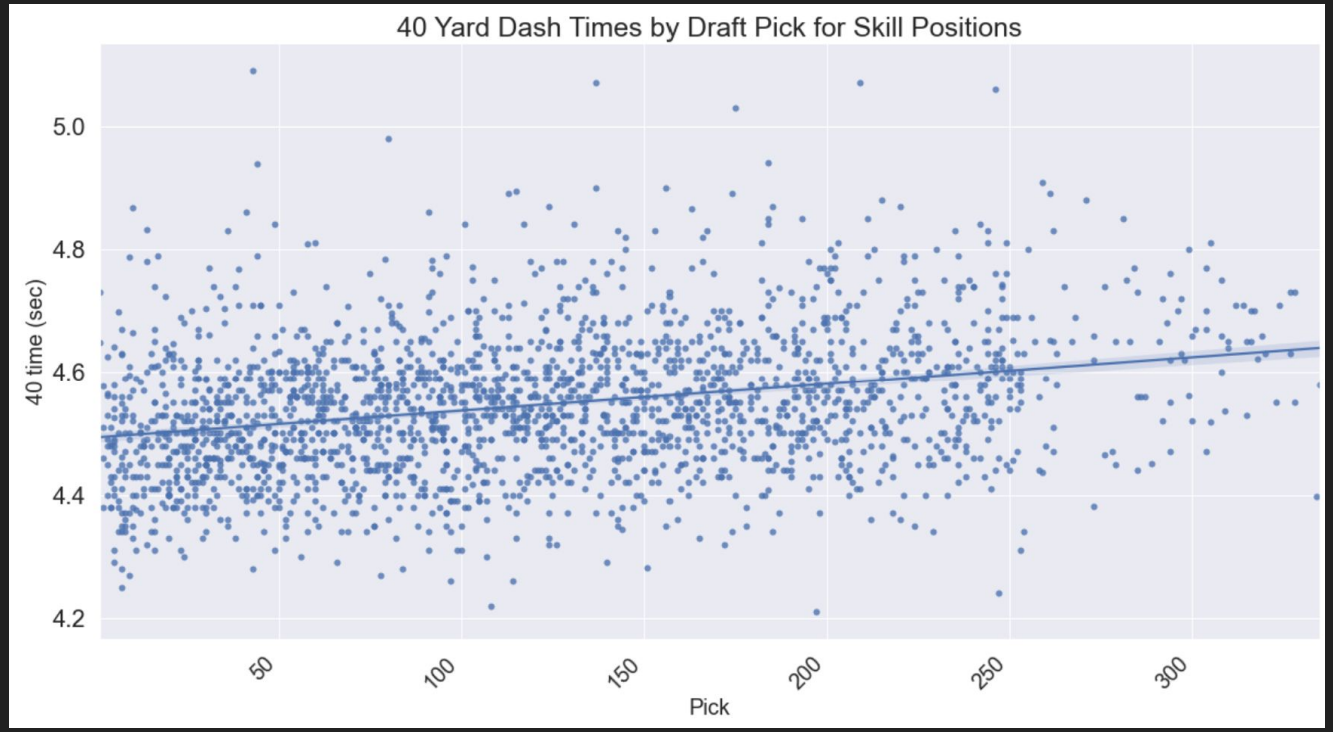
Busts: Jamarcus Russell & Ryan Leaf



Hypothesis Testing: Does a Player's 40 Yard Dash Time Impact Where a Player is Drafted?

After performing permutation test: p-value was close to **zero**.

Result: It is **extremely** unlikely that 40 times don't have an effect on draft position.



Modeling

- Overview:
  - Type: supervised learning regression problem
  - Tools: Scikit-learn's library
  - Modeling evaluation metric: Root mean squared error (RMSE) & R^2.
  - For hyperparameter tuning, I used 5 fold cross validation using scikit-learn's grid search method.
  - Split the train and test data manually to prevent data leakage.
    - Training: data from 1987 - 2010. 80%
    - Test: data from 2011 - 2015. 20%
  - I broke up the modeling into three sections. To determine the best model, I tested 4 models on each section; linear regression, random forest, SVM, and gradient boosting. The modeling sections include:
    - Predict NFL Success from Combine Results
    - Predict Draft Position from Combine Results
    - Separate by Player Position

Modeling Results

Position	Adjusted R2	Root Mean Squared Error	Features Dropped
Quarterbacks	0.059411	73.686792	season stats
Wide Receiver	0.090329	66.619473	season stats
Defensive Backs	0.075714	65.233829	season stats
Running backs	0.097121	58.783971	season stats

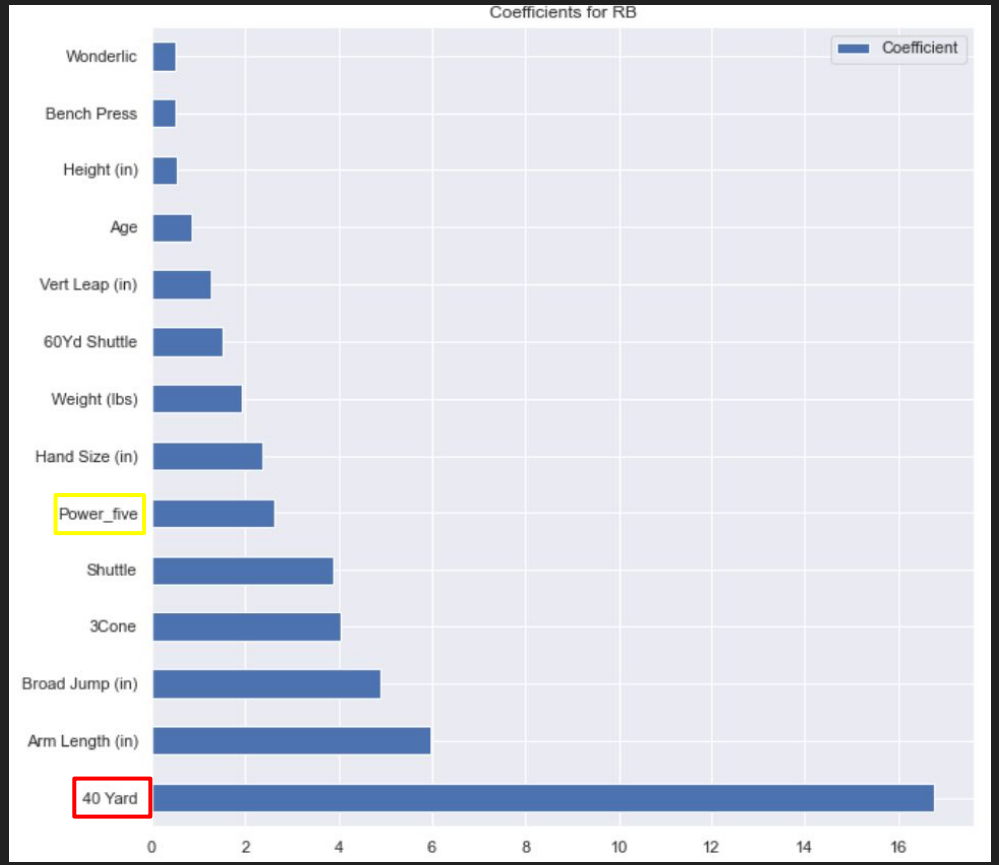
Almost no predictive power in determining draft position for QBs.

Running backs have the most predictive power.

What is the most important Combine measurement determining draft position?

40 yard dash clearly the most important.

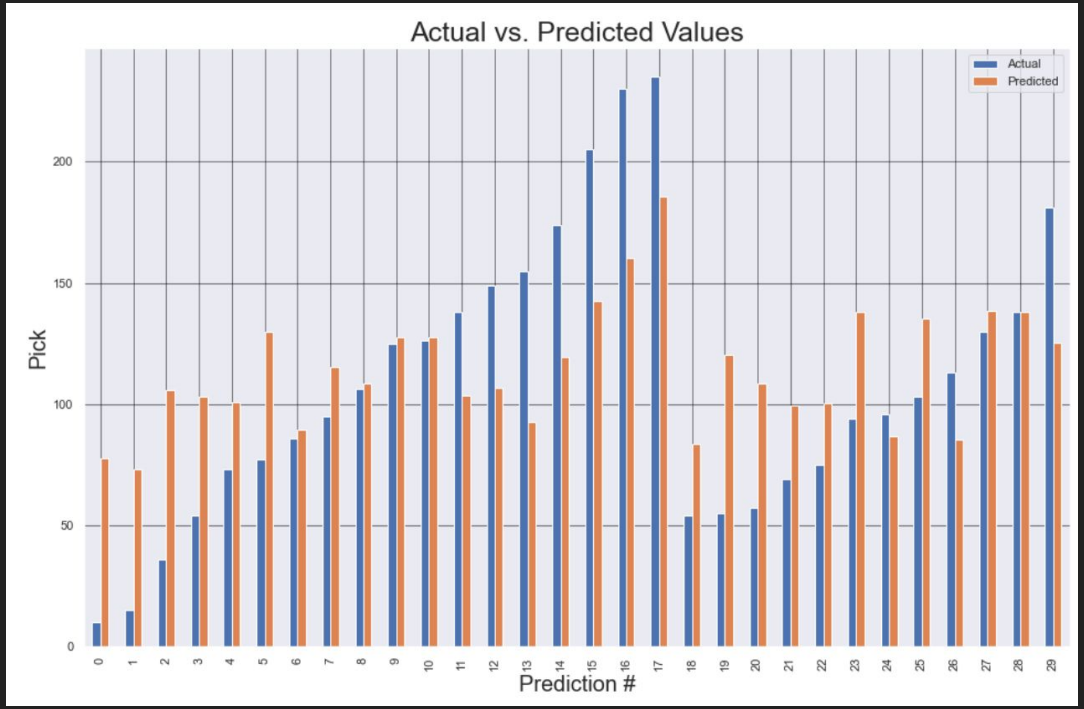
Power 5 conference more important for RBs



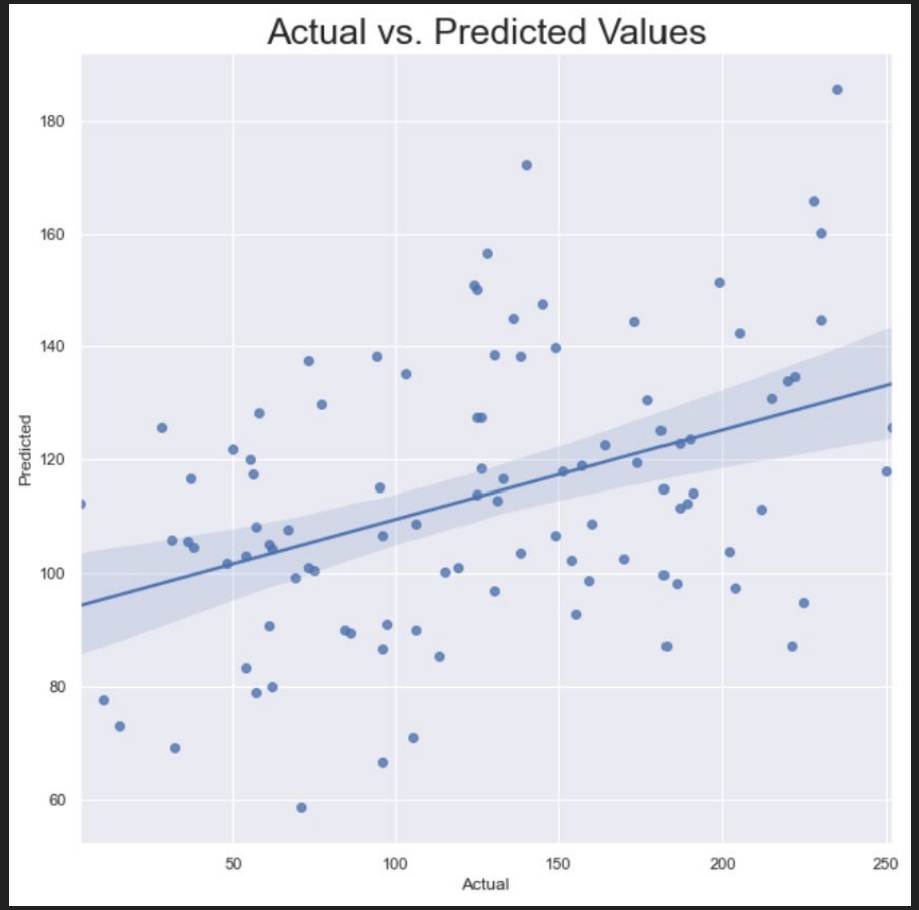
Predictions

Best performing model is off by an average of 59 picks.

Off by almost 2 draft rounds.



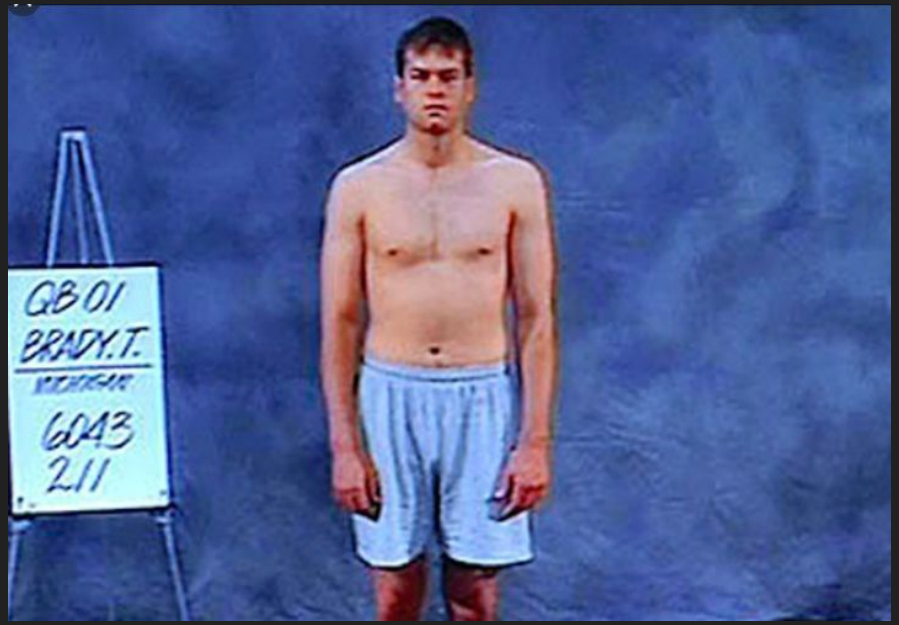
Very little linear relationship.



Conclusions & Key Takeaways

- Raw athleticism may not be as critical as casual NFL fans claim it to be.
- Work ethic, motivation, and attitude combined with athleticism are what it takes to really succeed in the NFL.
- Traditional scouting remains the best way to determine who to pick on draft day.
- Use Combine measurements as supplemental material when selecting a player but don’t put too much stock in them.
    - Vernon Gholston is the perfect example of a workout warrior.
    - Tom Brady is the opposite

Who do you think would be more successful in the NFL?



Future Research

1. Utilizing college statistics could improve prediction models for NFL performance for all positions.
2. It would be interesting to see the difference in NFL performance from players who excel at smaller colleges compared to players who excel at powerhouse programs.
3. It would also be helpful to obtain more data from the most recent draft years and see if that improves the models any.
4. I think it would be interesting to create a “draft grade” feature, assigning a grade to every player going into the draft based on scouting and media sentiment at the time.

Further Reading

- Park, P. (2016, August). Does the NFL Combine Really Matter. https://www.stat.berkeley.edu/~aldous/Research/Ugrad/Paul_Park.pdf

- McGee, K, and Burkett L. The National Football League Combine: A Reliable Predictor of Draft Status? Journal of Strength and Conditioning Research. 17(1): 6-11, 2013.