Final Presentation

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Introduction

Can we predict top fantasy point performers in the NFL using publicly available advanced metrics?

- Training set: 2018-2020 seasons; Testing set: 2021 season
- Data scraped from pro-football-reference.com
- Tried range of models to predict point-worthy statistics:

Stat	Pts
PassYds	0.04
PassTD	4.00
PassInt	-1.00
RushYds	0.10
RushTD	6.00
Rec	1.00
RecYds	0.10
RecTD	6.00
FL	-2.00

Passing Analysis pt. 1

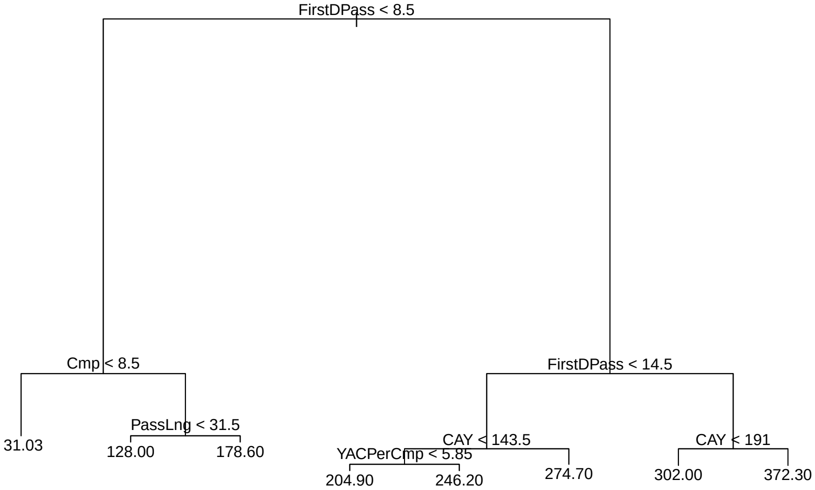
Models that were used:

- Multiple Linear Regression (MLR)
- LASSO
- Principal Component Analysis/Regression
- Tree
- Bagging

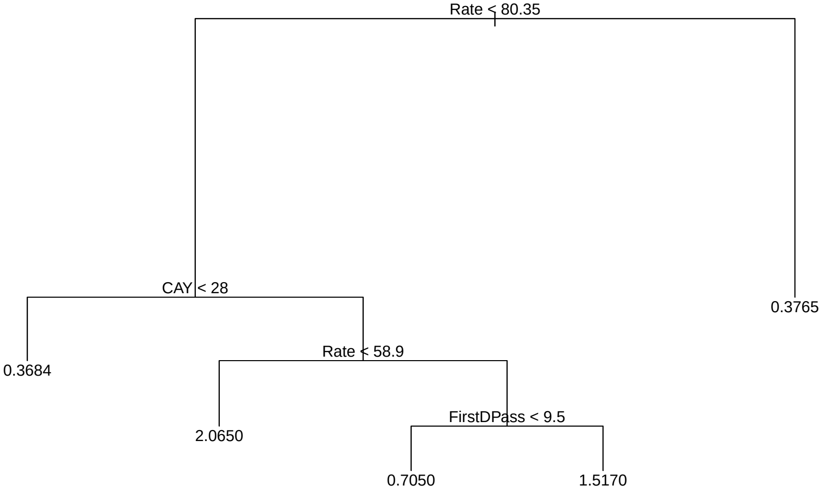
Predictors: `Cmp`, `PassAtt`, `Sk`, `YdsLost`, `PassLng`, `Rate`, `FirstDPass`, `FirstDPassPer`, `CAY`, `YACPerCmp`, `PassDrops`, `BadThrow`, `BadPer`

Dropped `PassYAC` (multicollinearity)

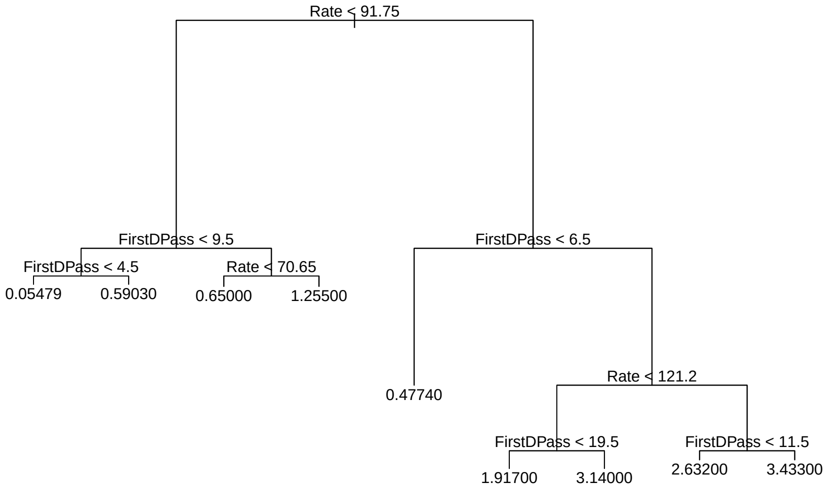
Tree (Passing Yards)



Tree (Interceptions)



Tree (Passing Touchdowns)



Passing Analysis MSE Matrix

```
## # A tibble: 4 x 6
##   Model        MLR   LASSO     PCR     Tree Bagging
##   <chr>      <dbl>   <dbl>   <dbl>    <dbl>   <dbl>
## 1 PassYds 420.    429.    691.    1641.    168.
## 2 PassInt   0.513   0.515   0.656    0.51    0.305
## 3 PassTD    0.374   0.647   0.788    0.609   0.468
## 4 FL        0.191   0.211   0.193    0.201   0.21
```

Receiving Analysis

Predictors: Tgt, RecLng, Fmb, FirstDRec, RecYBC, YBCPerR, RecYAC, YACPerR, ADOT, RecBrkTkl, RecPerBr, RecDrop, DropPerRec, RecInt, Rat

- Goal of simplicity and predictive accuracy
- Correlation matrix and VIF scores to identify multicollinearity (`FirstDRec`, `RecYBC`, `YBCPerR`, `YACPerR`, `DropPerRec`)
- `RecYAC` dropped

Dimension Reduction

- Dimension reduction techniques:
  - Best Subset -> 3-5 predictors
  - LASSO -> 5-10 predictors
  - PC regression -> 7-8 principal components
  - Pruned trees -> 2 terminal nodes for `RecTD` and 6-7 otherwise
  - Bagging and Random Forest -> 1 important variable for `RecTD` and 4-5 otherwise
  - `Tgt` and `Rat` predictors appear often

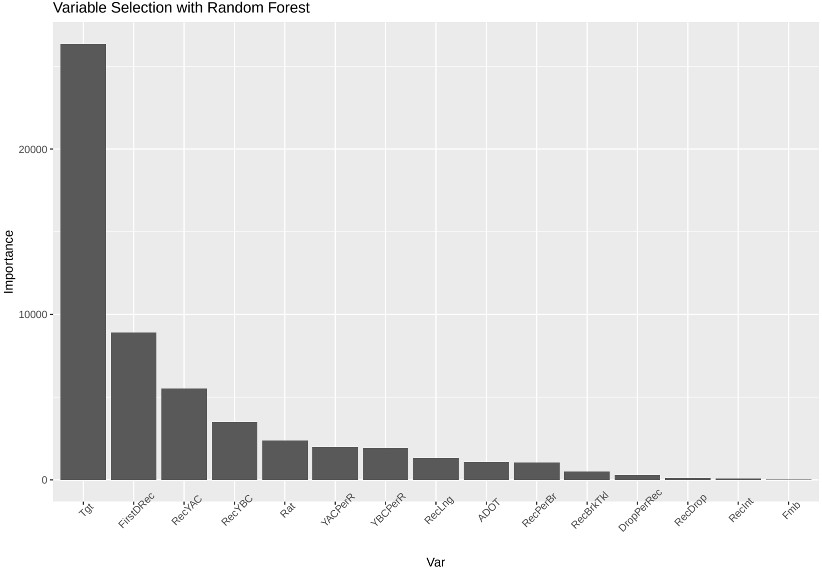
Receiving Results

Model	MLR	Subset	LASSO	PCR	Tree
Rec	0.513	0.532	0.587	0.607	1.178
RecYds	64.832	71.766	84.867	47.466	191.374
RecTD	0.094	0.107	0.077	0.153	0.104

Model	Boost	Bag	RF
Rec	0.398	0.154	0.135
RecYds	50.249	17.797	22.757
RecTD	0.086	0.048	0.057

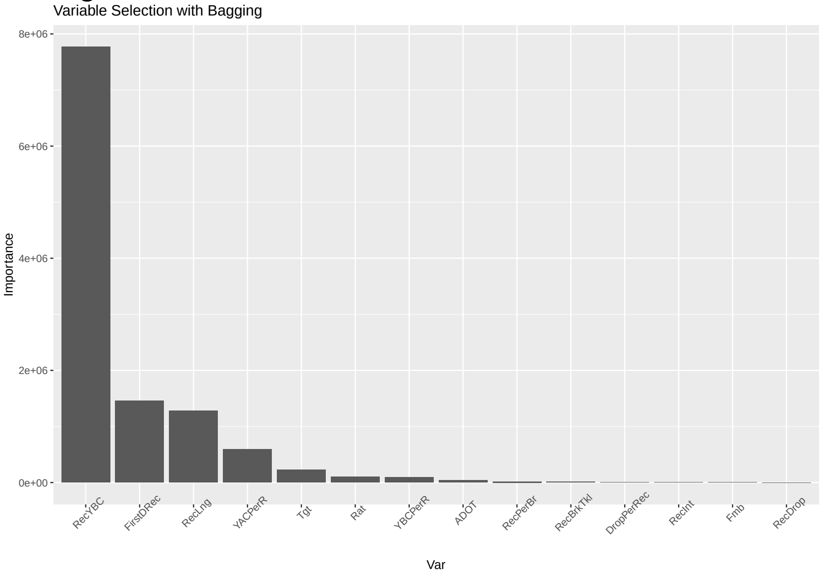
Receptions Model

Rec: Random forest model chosen with `Tgt`, `FirstDRec`, `RecYAC`, `RecYBC`, `Rat`



Receiving Yards Model

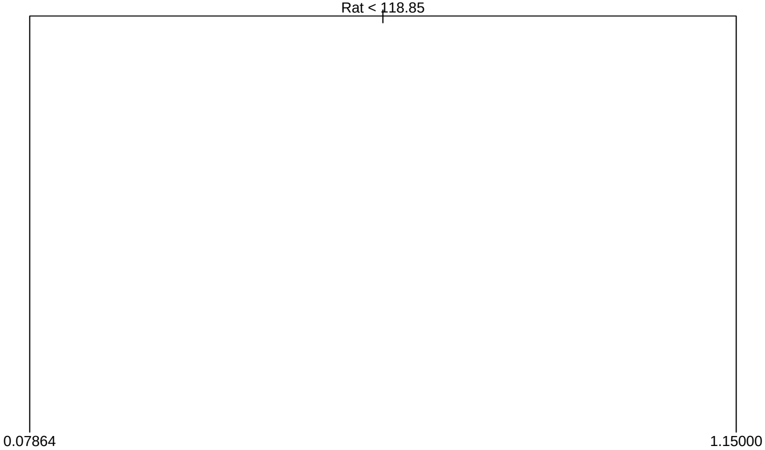
RecYds: Bagged tree model chosen with `RecYBC`, `FirstDRec`, `RecLng`, `YACPerR`



Receiving TDs Model

RecTD: Tree model chosen with only `Rat` as a predictor

- QBR uses frequencies of completions, yards, touchdowns, and interceptions



Rushing Analysis pt. 1

Rushing Predictors: RushYds, RushTD, FL

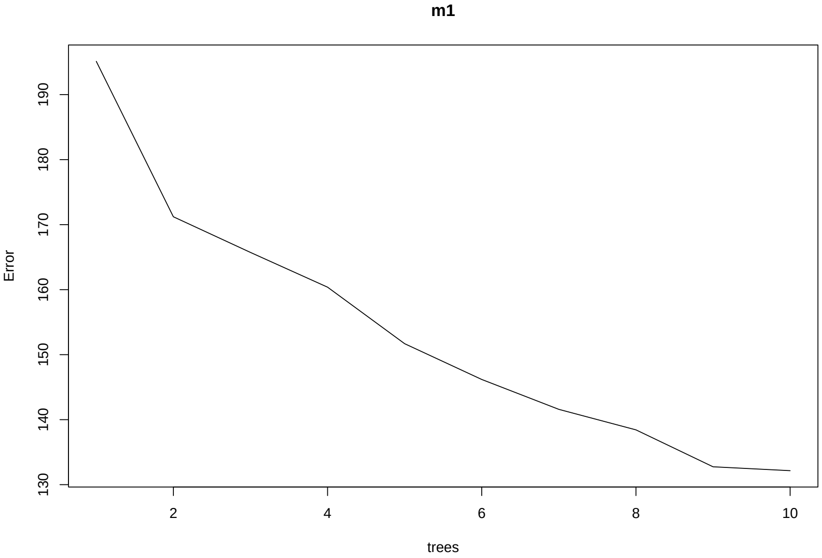
- Started out with a number of predictors but determined that these 3 were the most important in this case.
- When analyzing rushing data, we found that there are a lot of variables that are colinear.
- One example of a predictor that I did not end up needing is 'FirstDRush'. This variable does not lead to fantasy points and relates closely with 'RushYds'.

Rushing Analysis pt. 2

- Machine Learning Models:
  - The models I ended up using were Muliple Linear Regression, Lasso, PCR, Bagging, and Boosting
  - PCR ended up giving values that were not as useful for our rushing experimentation.
  - MLR provided the best MSE values for RushTD and FL (Fumbles lost)
  - Bagging gave the best value for RushYds
  - Thus these models were selected for final testing.

Rushing Analysis pt. 3

Models:



Fumbles Analysis

- Fumbles lost is the count of fumbles a player has that result in a turnover.
- Analyzing fumbles lost was cool because we were all building models for the same variable but using different predictors.
- The best FL model for Receptions predictors was a Tree model with an MSE of .028
- The best FL model for Passing predictors was a MLR model with an MSE of .191
- The best FL model for Rushing predictors was a MLR model with an MSE of .084
- As you can see overall the best was to predict fumbles lost in our data is to use the tree model for Rec data.

Validation

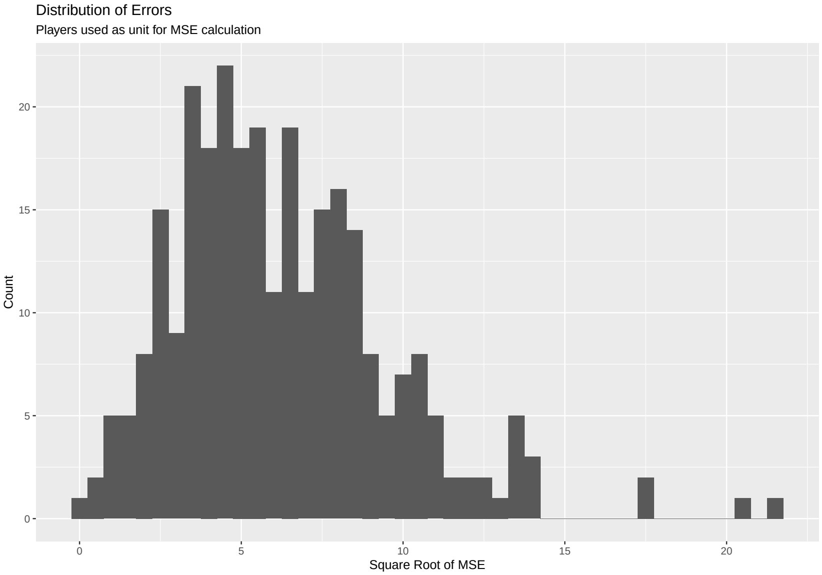
- Prediction performed on averaged data set of each player's last 17 games
- Resulted in an expected 'typical performance' for MSE calculations

Stat	MSE
PassYds	1647.63
PassTD	0.18
PassInt	0.98
RushYds	259.96
RushTD	0.12
Rec	3.84
RecYds	640.48
RecTD	0.20
FL	0.05
fanPts	50.29

Results

	Player	Pos	fanPts	MSE
223	Lamar Jackson	QB	30.00	103.62164
65	Christian McCaffrey	RB	26.10	90.37000
222	Kyler Murray	QB	25.56	72.31625
282	Patrick Mahomes	QB	24.22	97.51247
307	Russell Wilson	QB	23.68	105.13337
192	Josh Allen	QB	22.50	70.22672
77	Dak Prescott	QB	22.46	71.10427
134	Gardner Minshew II	QB	21.84	457.96000
4	Aaron Rodgers	QB	21.42	66.35480
107	Derek Carr	QB	21.42	45.94648
308	Ryan Fitzpatrick	QB	21.28	422.71360

MSE



Distribution of Errors
Players used as unit for MSE calculation
Count
Square Root of MSE
0
5
10
15
20

Future Efforts

- Use bootstrap or MC methods to generate large sample size
- Assume a discrete (Poisson?) distribution for `Rec`, `TD`, `Int`, `FL`
- Other factors to consider:
  - Expectation of injury
  - Strength of opponent