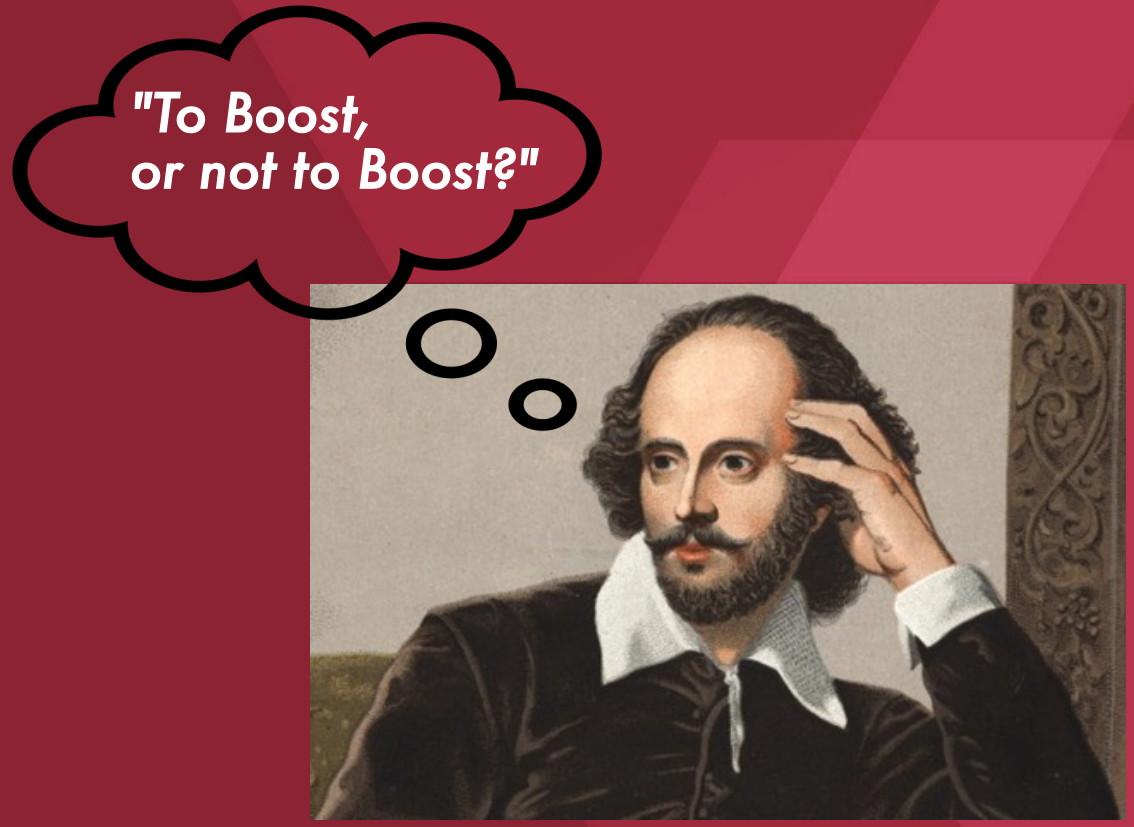

An Analysis of Gradient-Boosting Methods

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Research Question:

Does an increase in sophistication of tree-based boosting algorithms impact the accuracy & efficiency of NFL play predictions?

Methodology:

- Split multiple, consecutive years of processed **play-by-play** data into *training* & *test* sets
- Run a basic **decision-tree** model for baseline classification performance
- Implement a standard **gradient-boosting** algorithm & an **extreme-gradient boosting** algorithm (XG-Boost)
- Evaluate performance based on:
  - **Accuracy** rate of predicting a multiclass categorical output (RUN vs. PASS vs. FIELD-GOAL vs. PUNT)
  - Relative **time** to run models

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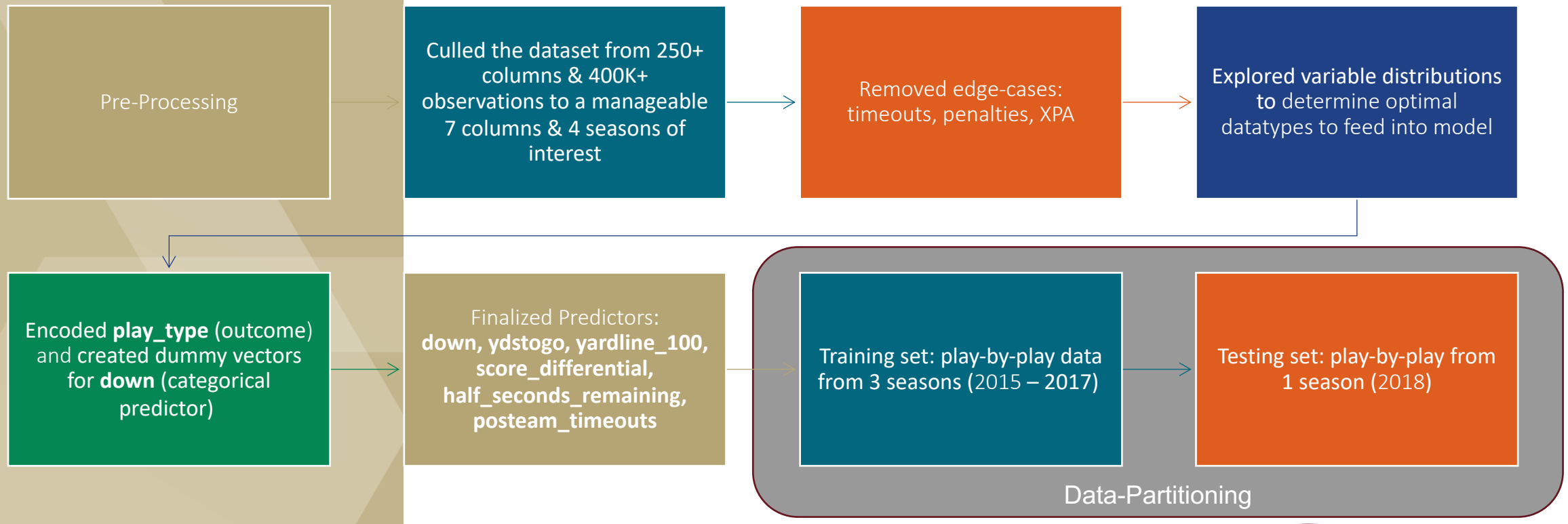
Data Source and Definitions

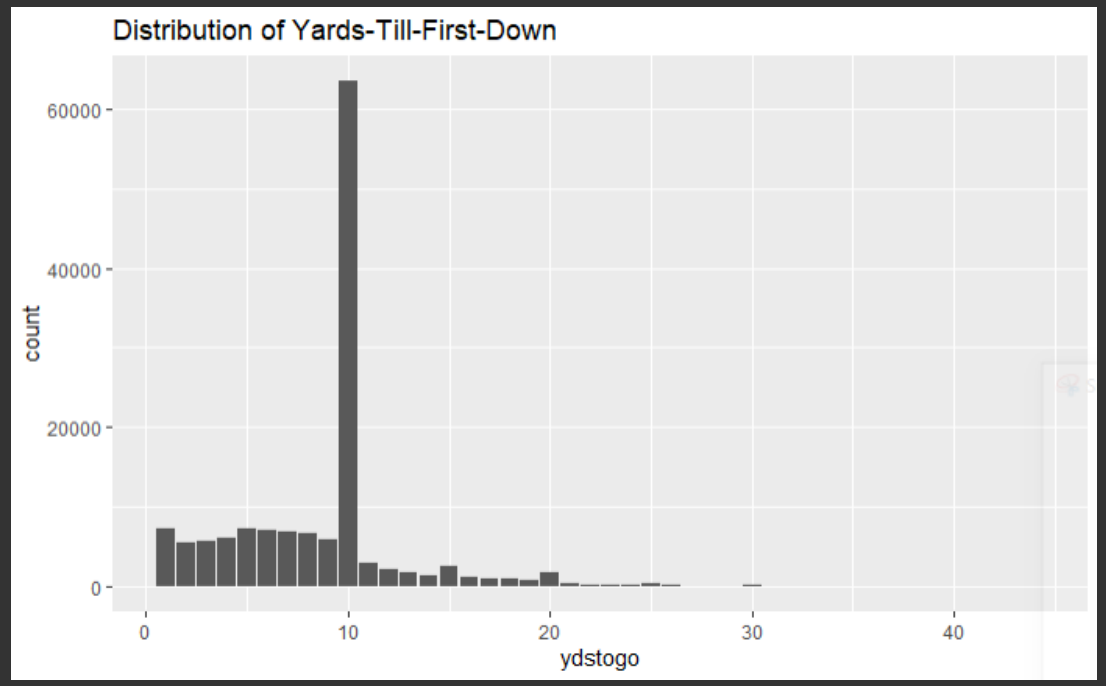
Variable	Description	Data Type	Type
yardline_100	Yards until the goal line	Integer from [0, 100]	Independent
half_seconds_remaining	Seconds remaining in the half	Integer from [0, 1800]	Independent
down	The current play down	Integer from [1, 4]	Independent
ydstogo	Yards until first down	Integer from [0, 100]	Independent
posteam_timeouts	Offensive team timeouts remaining	Integer from [0, 3]	Independent
score_differential	The difference in score between teams	Integer from (-∞, ∞)	Independent
play_type	The resulting type of play	Categorical: run, pass, field_goal, punt	Dependent

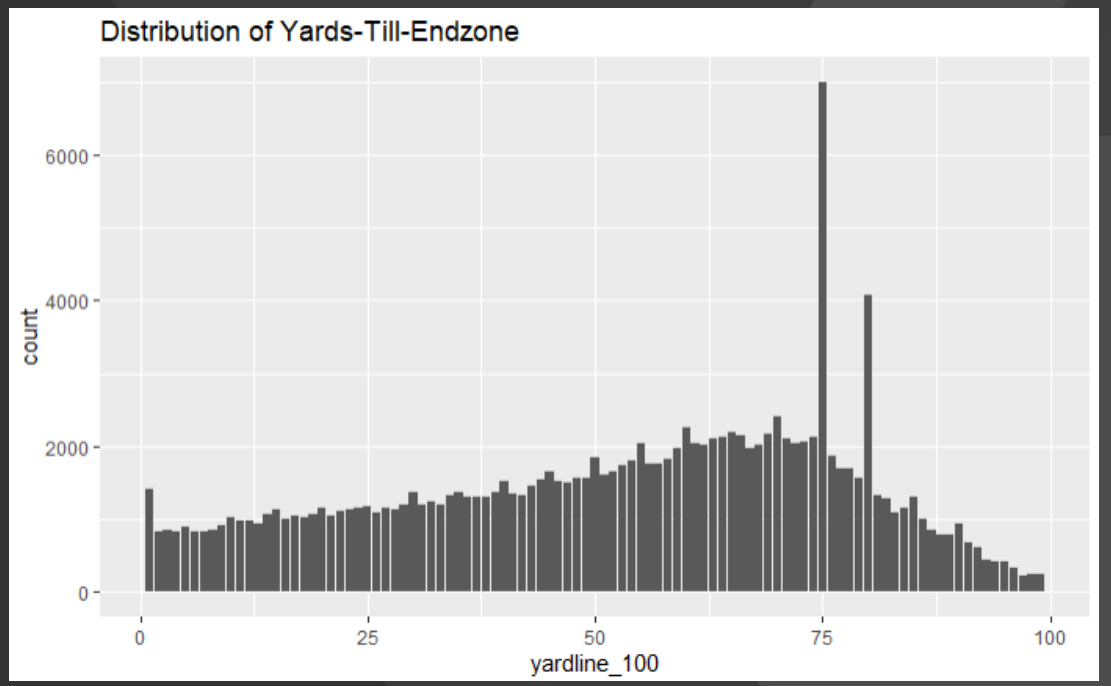
Source: *https://www.kaggle.com/maxhorowitz/nflplaybyplay2009to2016*

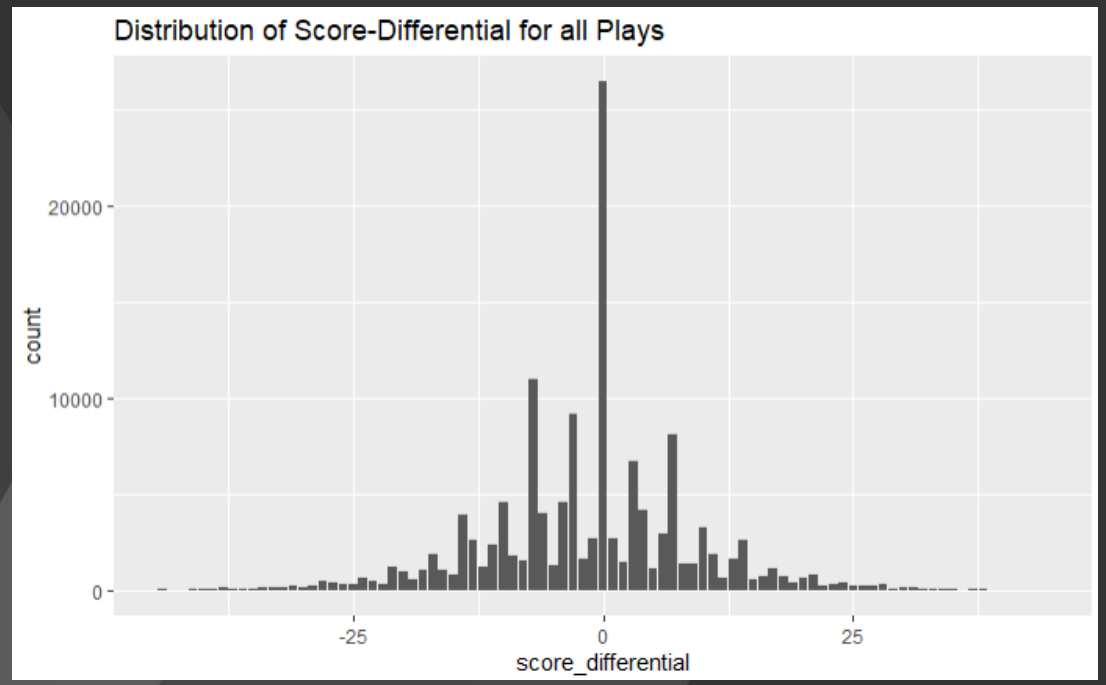
Data was scraped and uploaded onto **Kaggle** by the Carnegie Mellon Sports Analytics Club

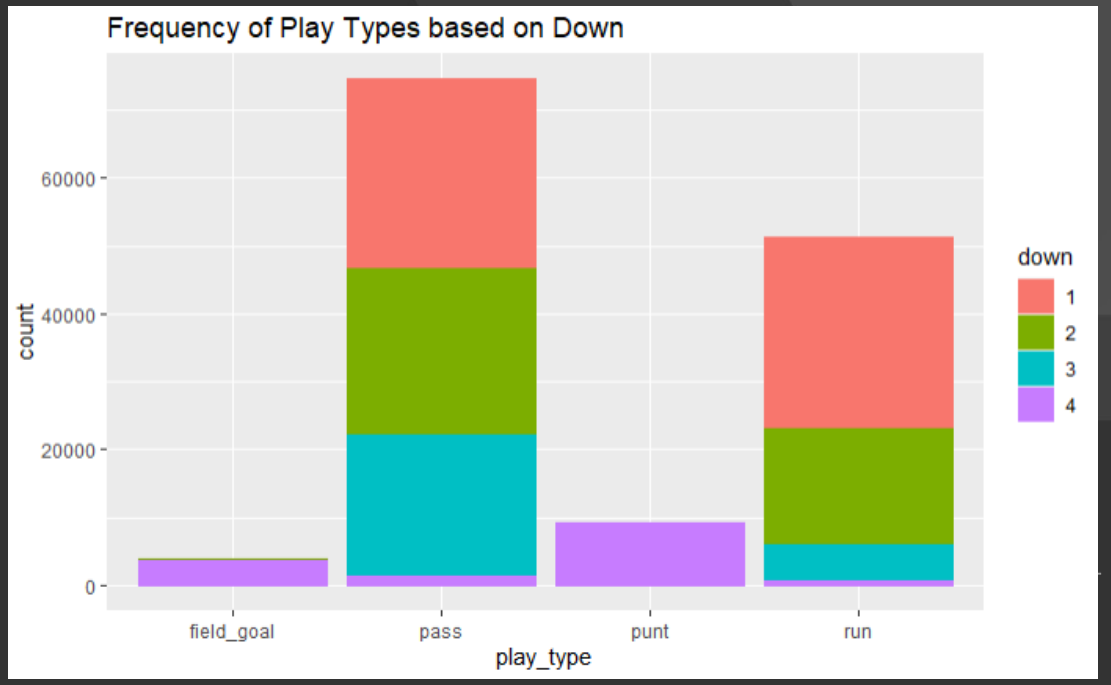
EDA and Data Preparation

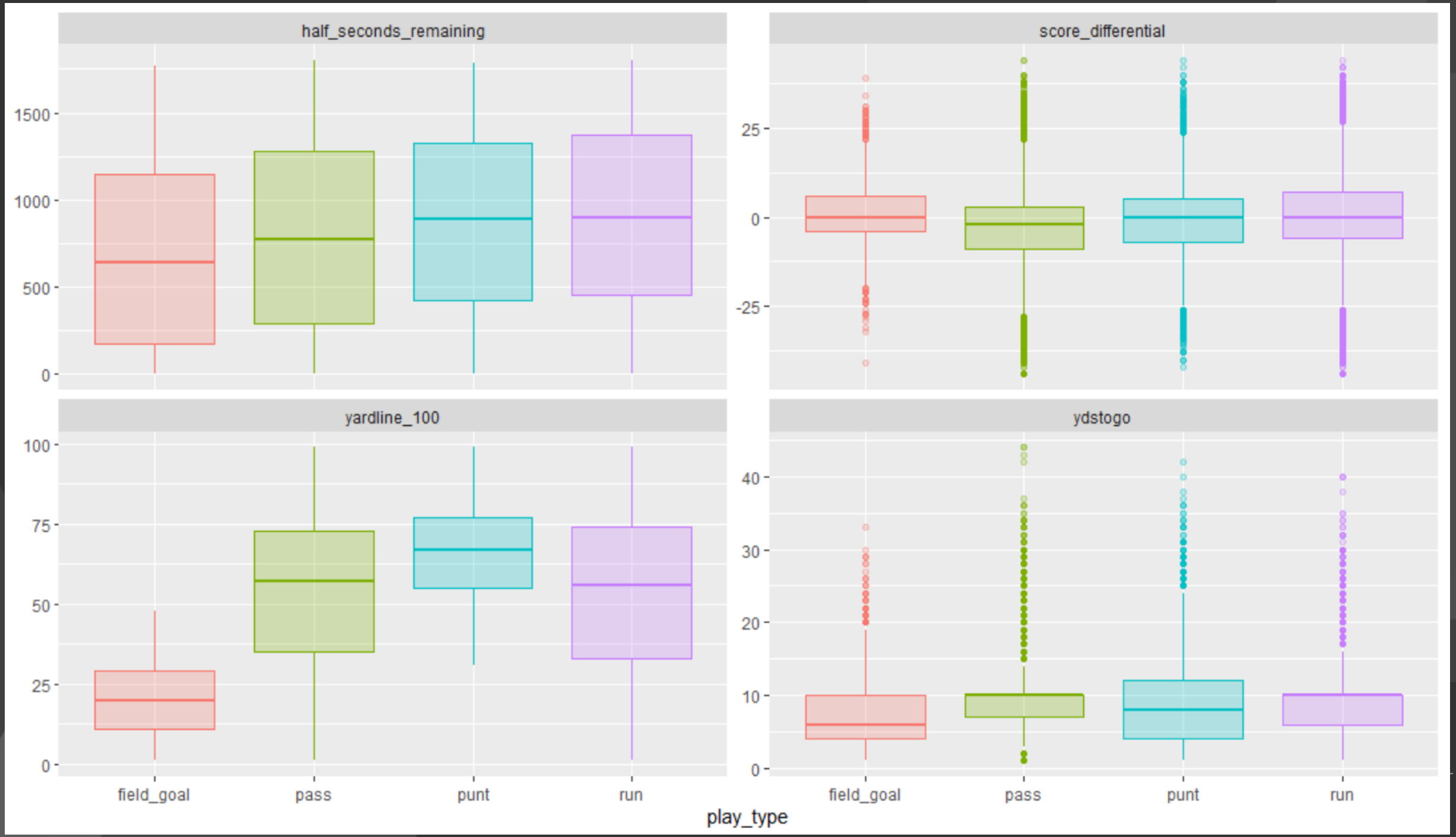



Distribution of Yards-Till-First-Down
60000
40000
20000
0
count
0
10
20
30
40
ydstogo


Distribution of Yards-Till-Endzone
6000
4000
2000
0
count
0
25
50
75
100
yardline_100


Distribution of Score-Differential for all Plays
20000
10000
0
count
-25
0
25
score_differential


Frequency of Play Types based on Down
60000
40000
20000
0
count
field_goal
pass
punt
run
play_type
down
1
2
3
4


half_seconds_remaining
score_differential
yardline_100
ydstogo
1500
1000
500
0
25
0
-25
100
75
50
25
0
40
30
20
10
0
field_goal
pass
punt
run
play_type

How do tree-based boosting algorithms address our research question?

Decision Tree

- A single model of decision-making branches to reach a predicted classification
- Serves as a "baseline" model for our study

Gradient-Boosting

- Combine multiple models that sequentially learns from past decision trees
- Leads to higher accuracy but can be time-intensive

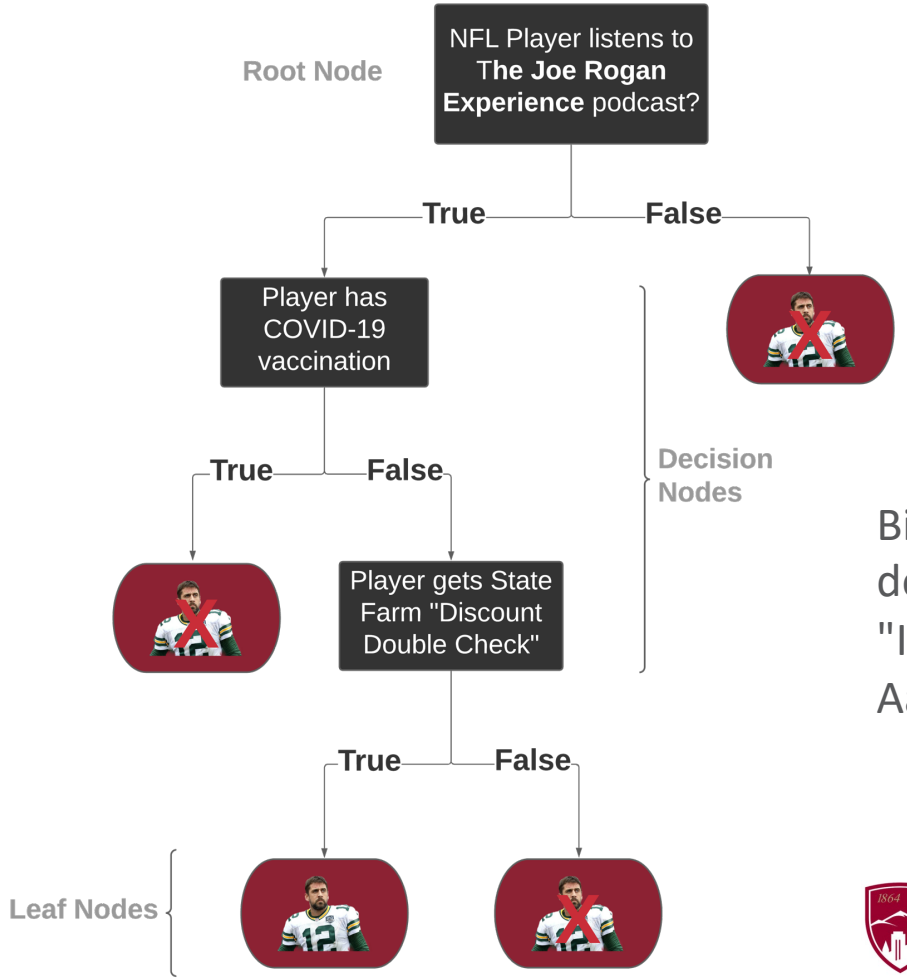
Extreme Gradient-Boosting (XG-Boost)

- Optimizes for speed, while retaining predictive power of standard gradient-boosting
- Allows for more control in fine-tuning parameters

Background — Decision Trees

Principles of Decision Trees (for Classification)

Begin	Begin with a root node
Find Attributes	Find the best attributes in the dataset from all unused attributes
Select Attribute	Select the attribute with the most purity (least uncertainty) and generate a new decision node
Make Split	Split the data by the selected attribute to create a new subset of the data
Continue Splitting	Continue to recur on each subset until no more splits can be made
Predict	Make predictions



Binary classification decision tree for "Is an NFL player Aaron Rodgers?"

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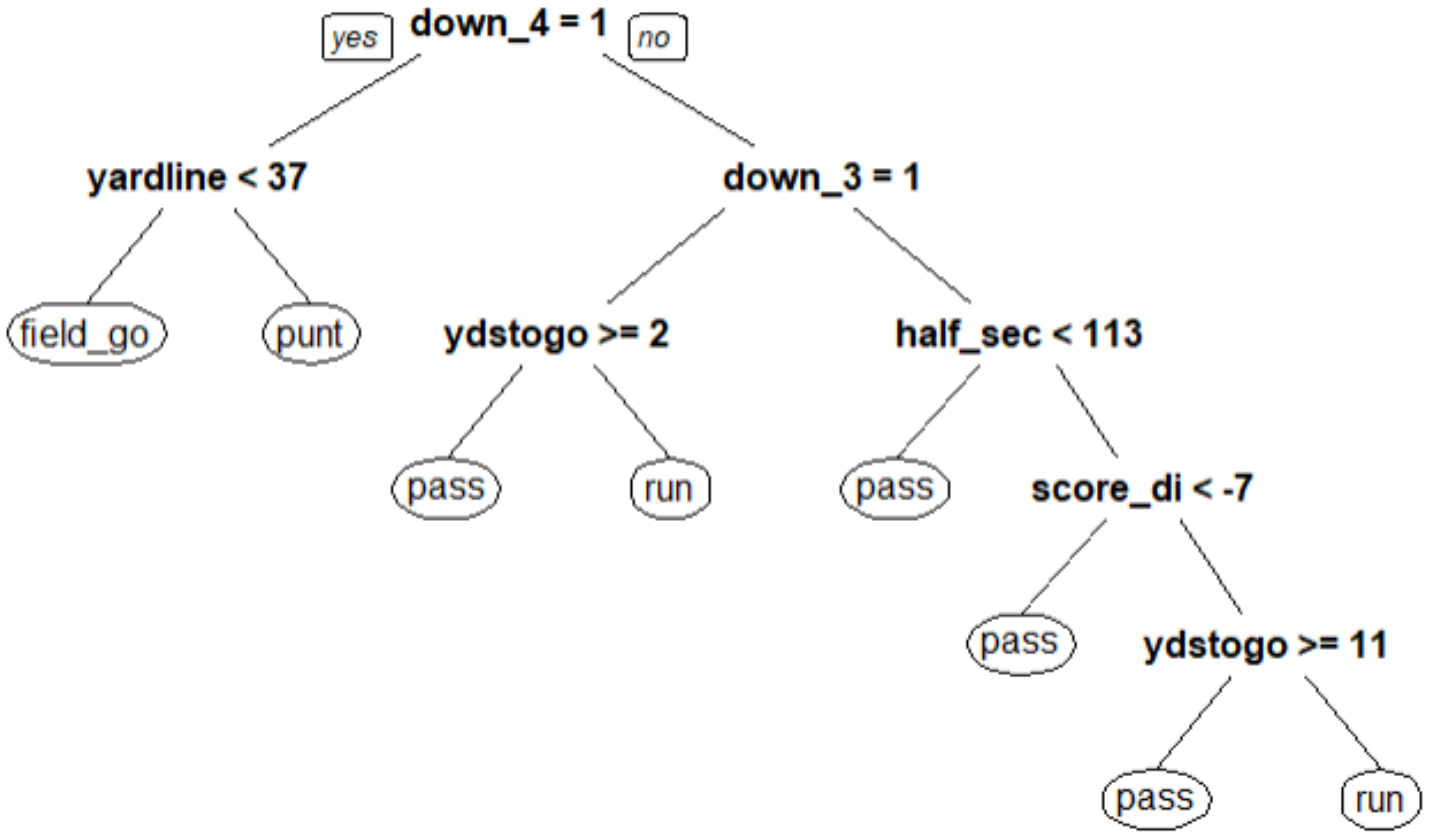
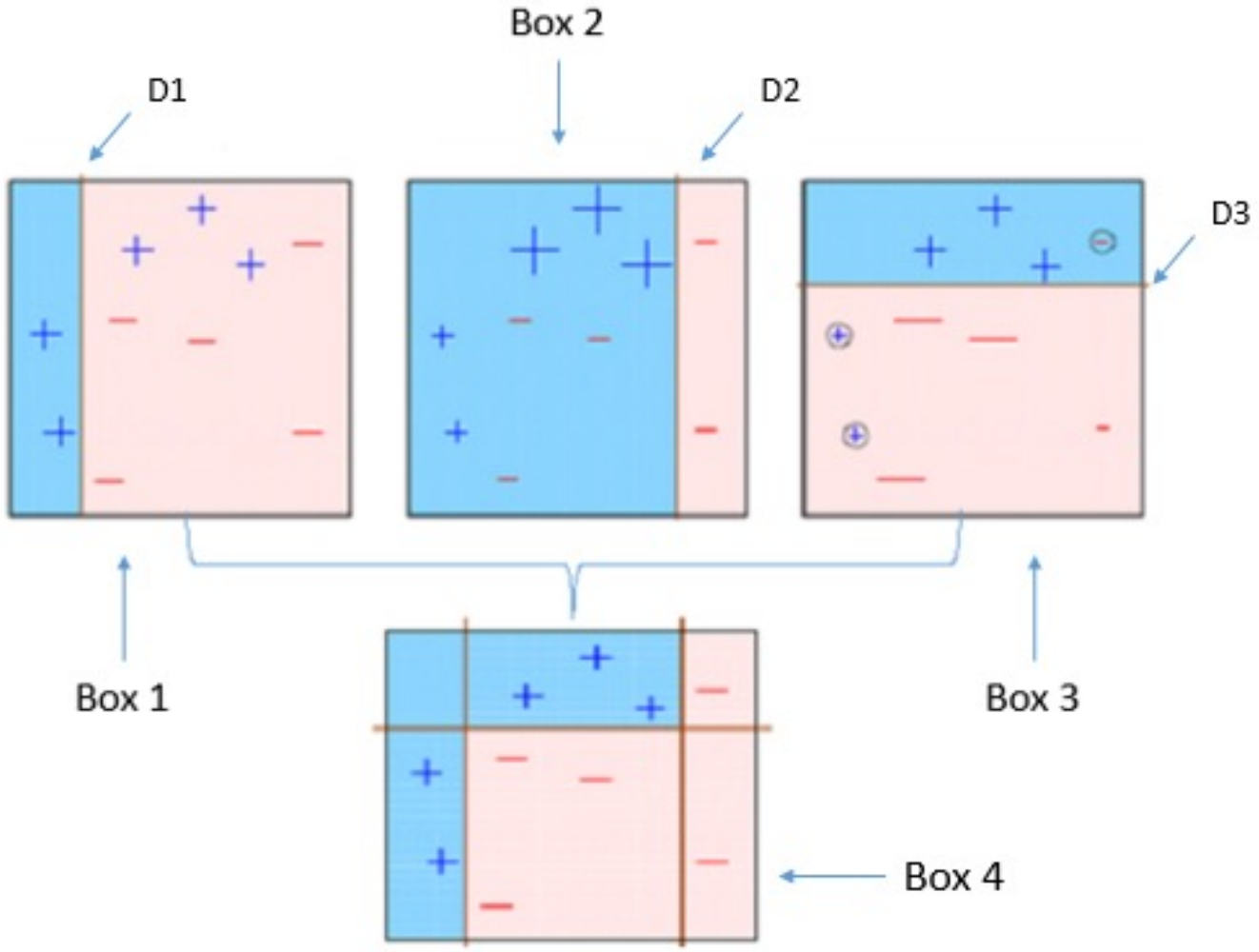
Decision Tree

Baseline Decision Tree



Primary Method: Boosting

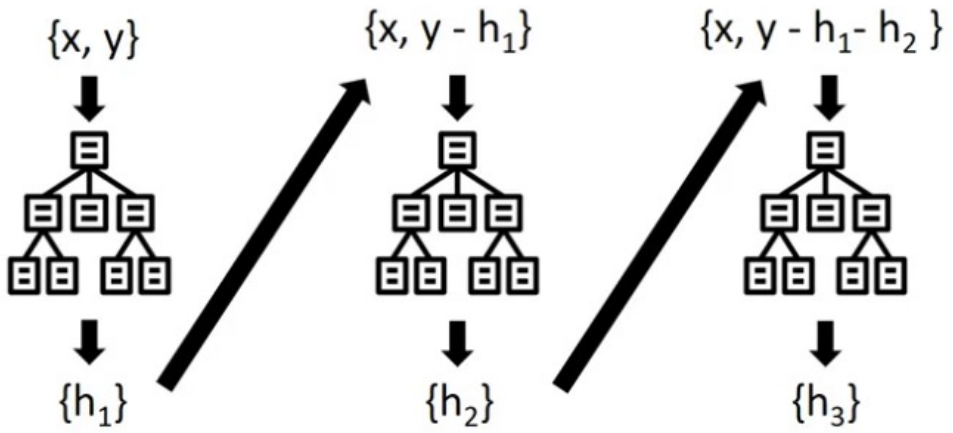
Boosting – An ensemble method using multiple Decision Trees



Source: https://www.hackerearth.com/practice/machine-learning/machine-learning-algorithms/beginners-tutorial-on-xgboost-parameter-tuning-r/tutorial/

Primary Method: Boosting

Gradient-Boosting



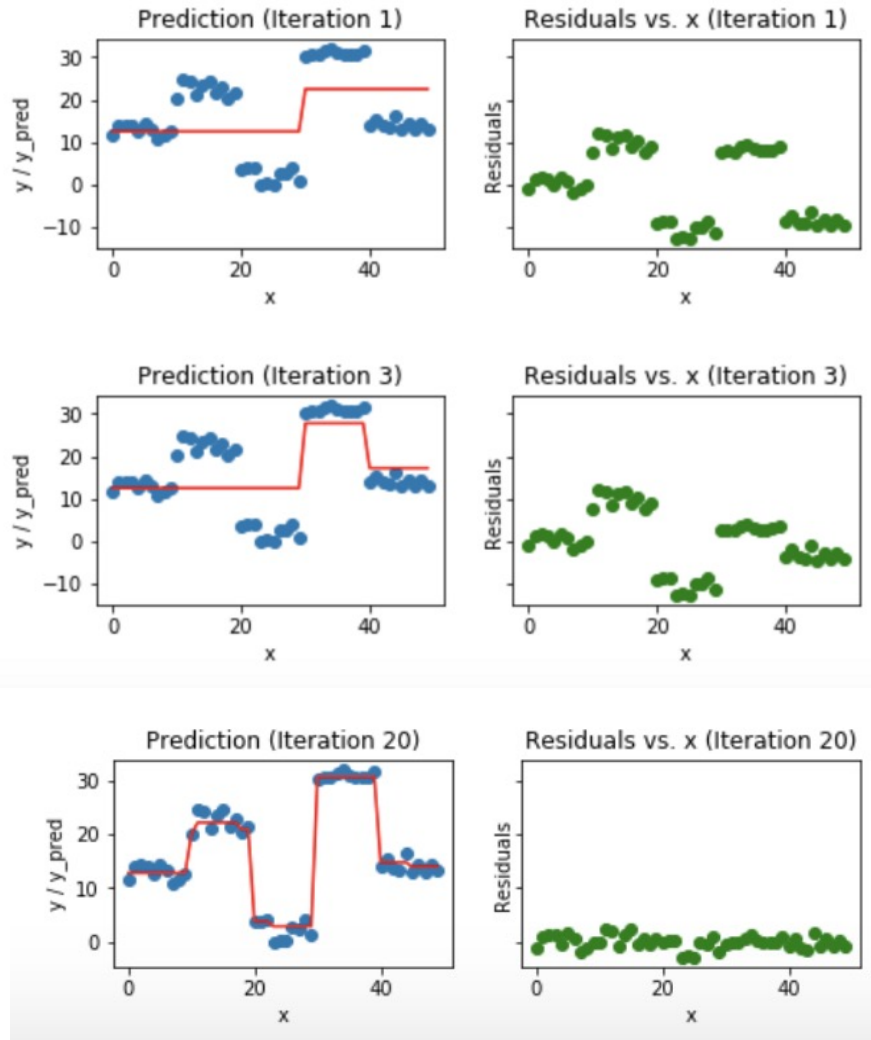
Source: https://sefiks.com

- Base model
- Compute residual errors
  - Differentiable loss function (classification: **logloss**)
  - Gradient-Descent
- Parameters to avoid overfitting and output a final model with low variance and low bias

#1

#3

#20

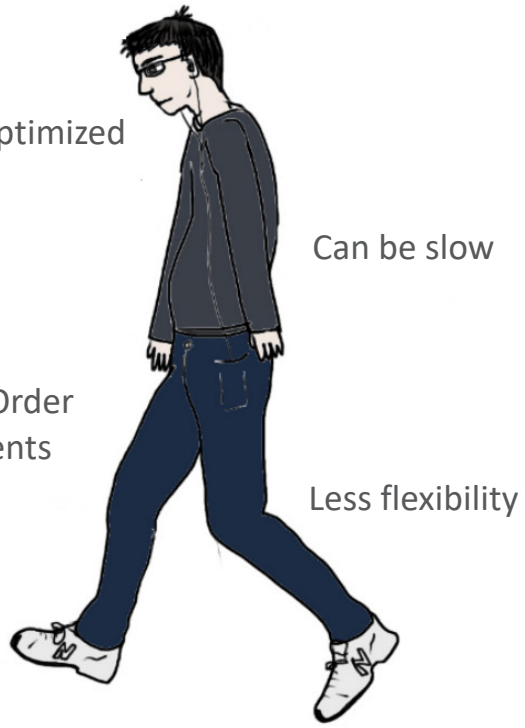


Source: https://blog.mlreview.com/gradient-boosting-from-scratch-1e317ae4587d

Primary Method: Boosting

XG-Boost (Extreme Gradient-Boosting)

GRADIENT-BOOSTING



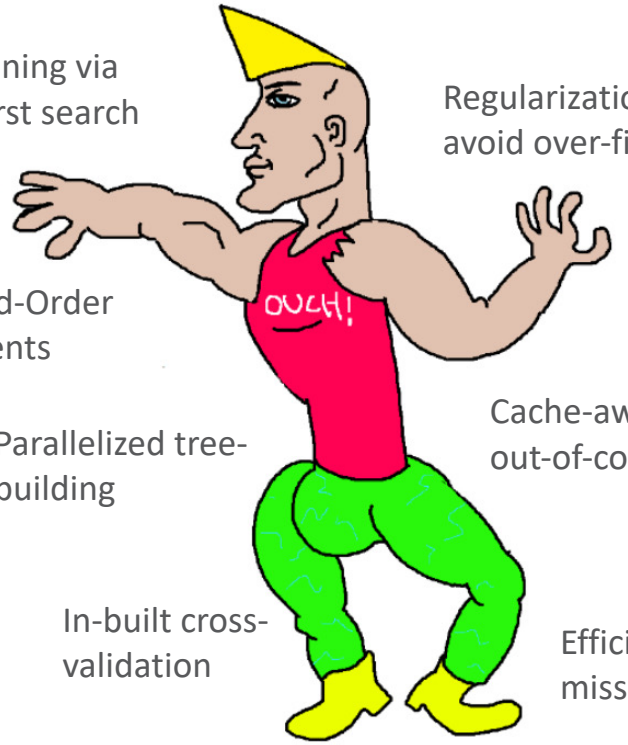
Not optimized

Can be slow

First-Order gradients

Less flexibility

THE "CHAD" XG-BOOST



Tree-pruning via depth-first search

Regularization to avoid over-fitting

Second-Order Gradients

Cache-awareness & out-of-core computing

Parallelized tree-building

In-built cross-validation

Efficiently handles missing data

Primary Method: Boosting

XG-Boost Implementation

Data Requirement	Approach to Satisfy Requirement
Factor variable for classification problems	- Predictor Factors: dummy-vectorized down - Remaining variables kept in numeric form
Only numeric vectors (must include 0 for converted factors)	Model matrix form of predictors and outcome converted to specialized matrix in xgb package (xgb.DMatrix)
Input data structure for model: sparse matrix (cells containing 0 not stored, so enforcing memory-efficiency)	Encoded Outcome Variable: fg → 0 | pass → 1 | punt → 2 | run → 3

XG-Boost handles the following data characteristics: **correlated features** and **null values**

Primary Method: Boosting

XG-Boost Implementation

Parameter	Option Used	Description
objective	multi:softprob	Outputs predicted probability of observations belonging to each class
eval_metric	mlogloss	Type of metric for validation for each tree; negative log-likelihood for classifications
eta	0.1	Learning rate [0, 1]; lower eta avoids overfitting
max_depth	5	Maximum depth of each tree; lower max_depth avoids overfitting
lambda	1	Regularization term; higher lambda leads to reduce overfitting
gamma	1	Minimum loss reduction to make partition in tree; larger gamma avoids overfitting
nrounds	50	Number of iterations

- Other notable parameters: **min_child_weight, colsample_bytree, subsample**
- **Grid Search** for hyper-parameter tuning

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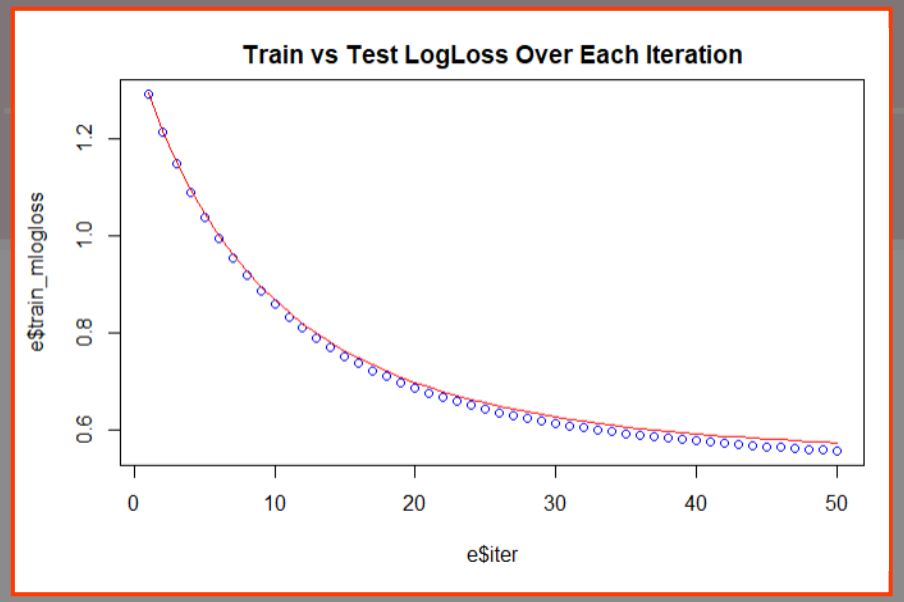
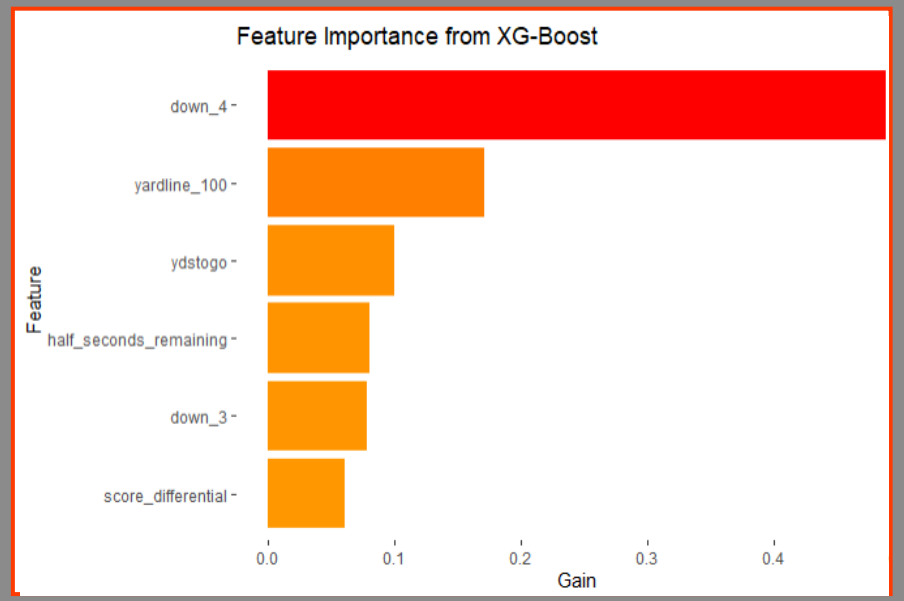
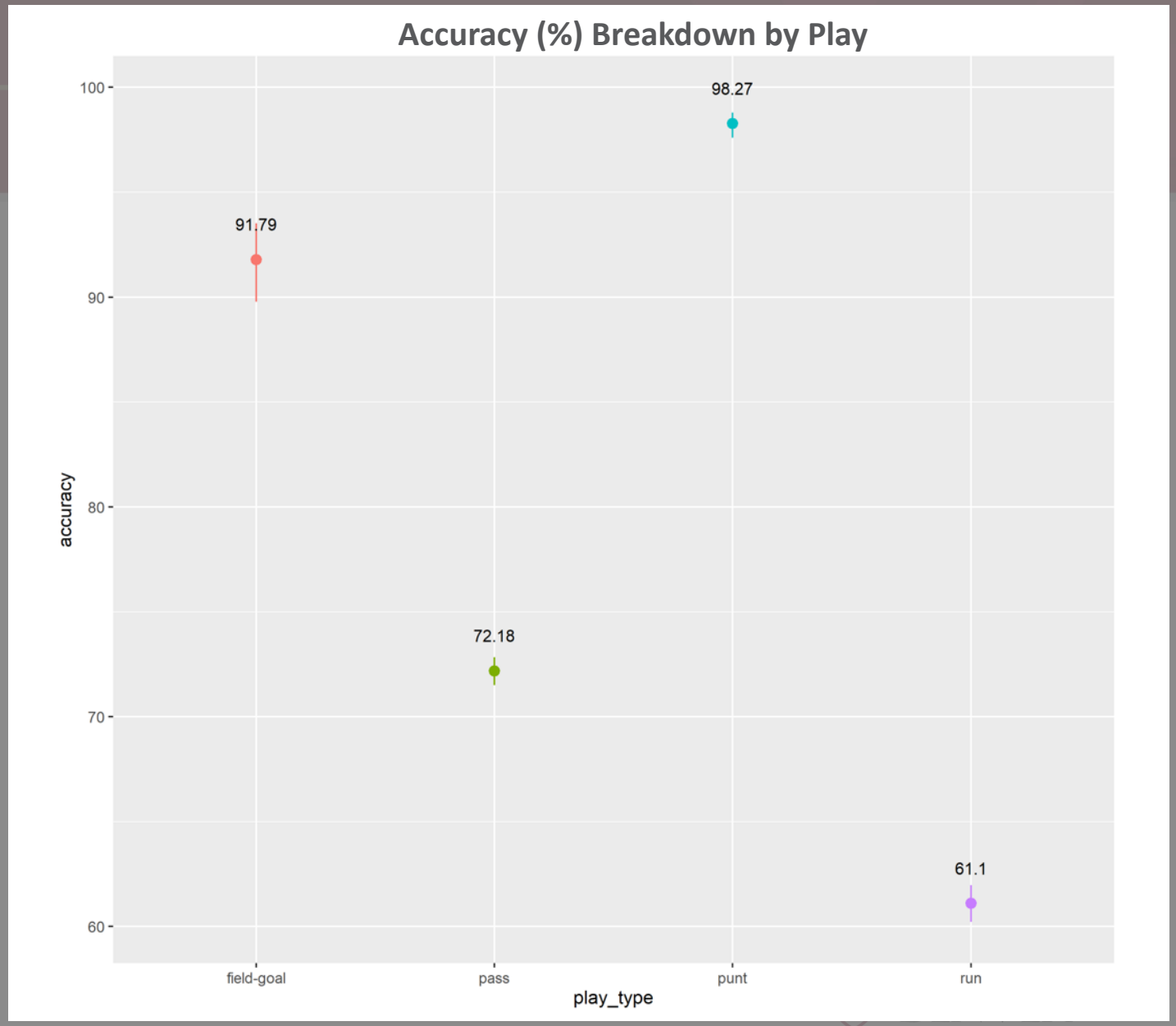
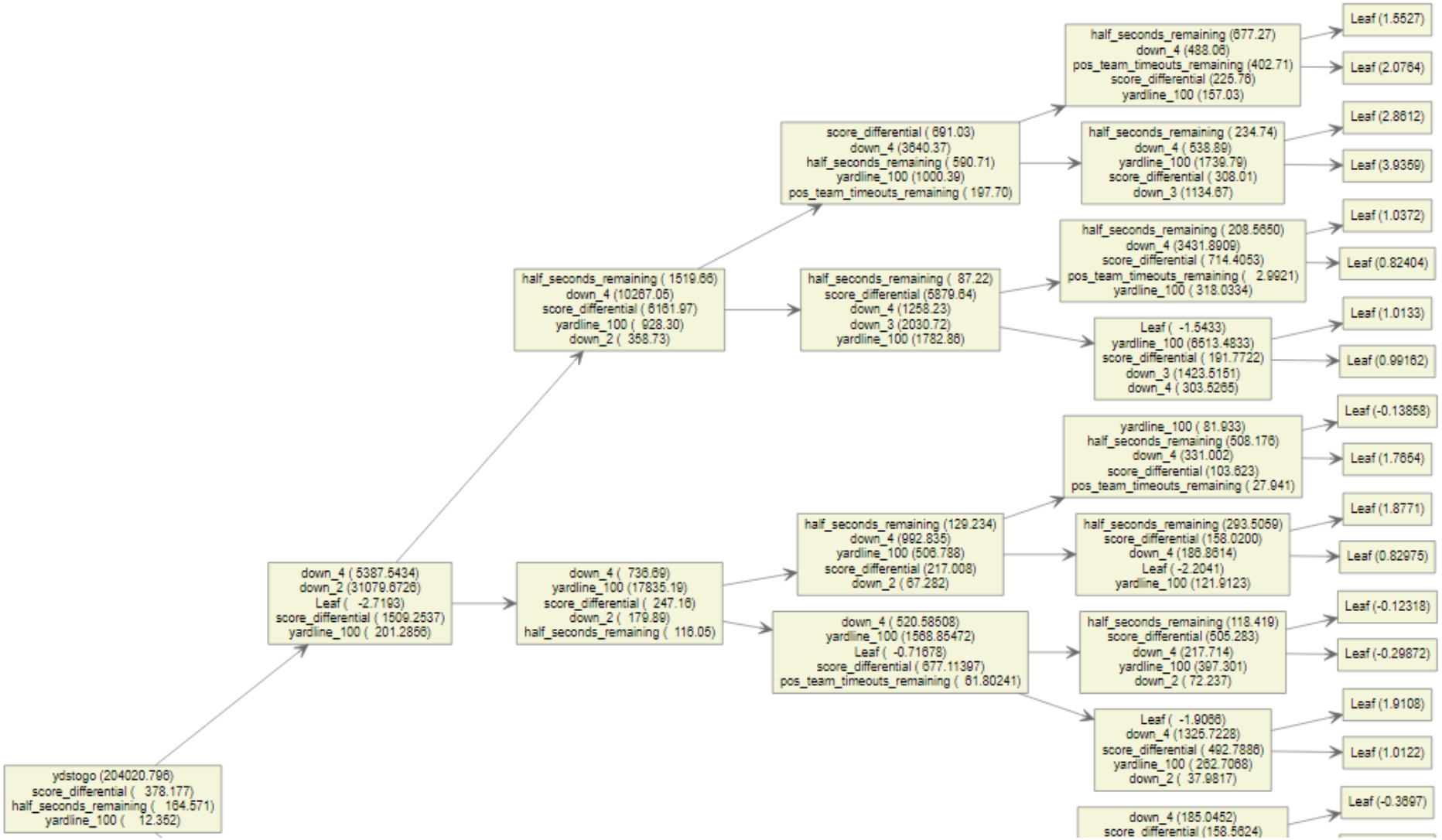

Train vs Test LogLoss Over Each Iteration
e$train_mlogloss
0.6
0.8
1.0
1.2
0
10
20
30
40
50
e$iter


Feature Importance from XG-Boost
down_4
yardline_100
ydstogo
half_seconds_remaining
down_3
score_differential
Feature
0.0
0.1
0.2
0.3
0.4
Gain


Accuracy (%) Breakdown by Play
100
90
80
70
60
accuracy
91.79
98.27
72.18
61.1
field-goal
pass
punt
run
play_type


ydstogo (204020.796)
score_differential (378.177)
half_seconds_remaining (164.571)
yardline_100 (12.352)
down_4 (5387.5434)
down_2 (31079.6726)
Leaf (-2.7193)
score_differential (1509.2537)
yardline_100 (201.2856)
half_seconds_remaining (1519.66)
down_4 (10267.05)
score_differential (6161.97)
yardline_100 (928.30)
down_2 (358.73)
down_4 (736.69)
yardline_100 (17835.19)
score_differential (247.16)
down_2 (179.89)
half_seconds_remaining (116.05)
score_differential (691.03)
down_4 (3640.37)
half_seconds_remaining (590.71)
yardline_100 (1000.39)
pos_team_timeouts_remaining (197.70)
half_seconds_remaining (87.22)
score_differential (5879.64)
down_4 (1258.23)
down_3 (2030.72)
yardline_100 (1782.86)
half_seconds_remaining (129.234)
down_4 (992.835)
yardline_100 (506.788)
score_differential (217.008)
down_2 (67.282)
down_4 (520.58508)
yardline_100 (1568.85472)
Leaf (-0.71678)
score_differential (677.11397)
pos_team_timeouts_remaining (61.80241)
half_seconds_remaining (877.27)
down_4 (488.06)
pos_team_timeouts_remaining (402.71)
score_differential (225.76)
yardline_100 (157.03)
half_seconds_remaining (234.74)
down_4 (538.89)
yardline_100 (1739.79)
score_differential (308.01)
down_3 (1134.67)
half_seconds_remaining (208.5650)
down_4 (3431.8909)
score_differential (714.4053)
pos_team_timeouts_remaining (2.9921)
yardline_100 (318.0334)
Leaf (-1.5433)
yardline_100 (6513.4833)
score_differential (191.7722)
down_3 (1423.5151)
down_4 (303.5265)
yardline_100 (81.933)
half_seconds_remaining (508.176)
down_4 (331.002)
score_differential (103.623)
pos_team_timeouts_remaining (27.941)
half_seconds_remaining (293.5059)
score_differential (158.0200)
down_4 (186.8614)
Leaf (-2.2041)
yardline_100 (121.9123)
half_seconds_remaining (118.419)
score_differential (505.283)
down_4 (217.714)
yardline_100 (397.301)
down_2 (72.237)
Leaf (-1.9066)
down_4 (1325.7228)
score_differential (492.7886)
yardline_100 (262.7068)
down_2 (37.9817)
down_4 (185.0452)
score_differential (158.5624)
Leaf (1.5527)
Leaf (2.0764)
Leaf (2.8612)
Leaf (3.9359)
Leaf (1.0372)
Leaf (0.82404)
Leaf (1.0133)
Leaf (0.99162)
Leaf (-0.13858)
Leaf (1.7654)
Leaf (1.8771)
Leaf (0.82975)
Leaf (-0.12318)
Leaf (-0.29872)
Leaf (1.9108)
Leaf (1.0122)
Leaf (-0.3697)

Does an increase in sophistication of tree-based boosting algorithms impact the accuracy & efficiency of NFL play predictions?

Method	Classification Accuracy	Runtime
Decision Tree (Baseline)	62.64 %	1.1 sec
Gradient-Boosting	69.01 %	36.8 sec (50 iterations)
XGBoost	70.25 %	2.9 sec (50 iterations)

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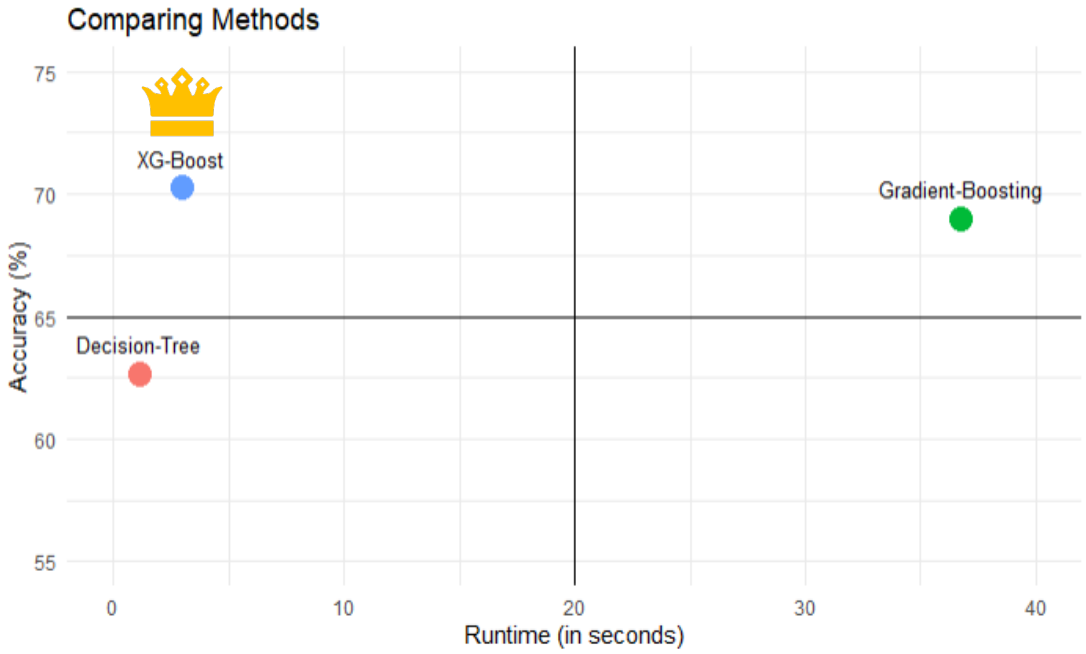
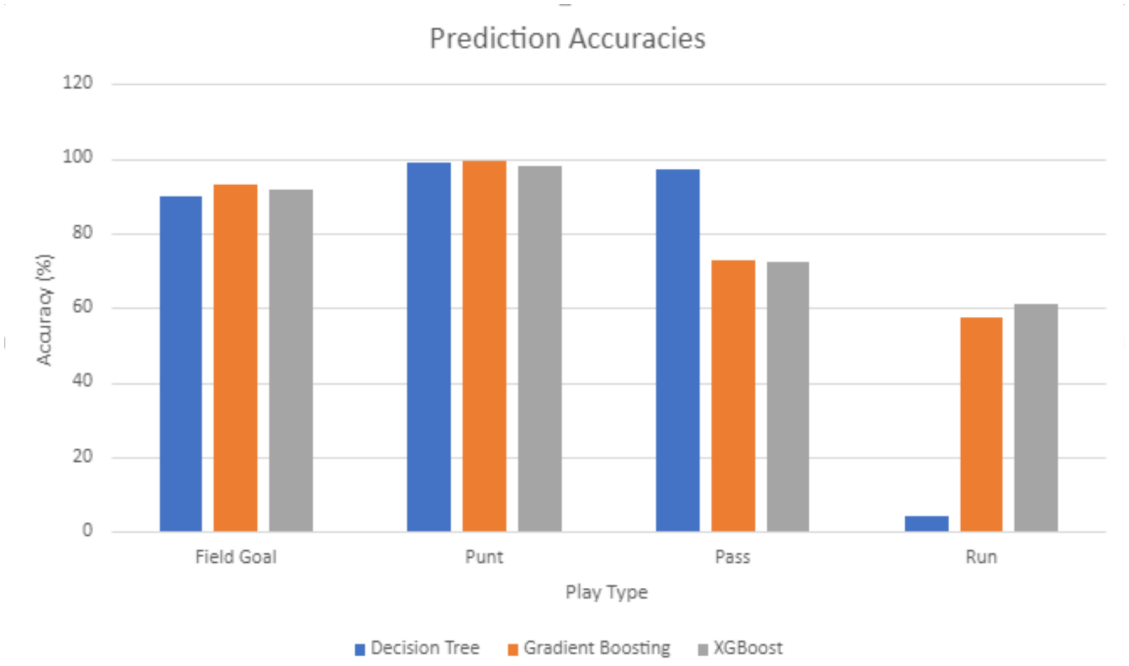
Conclusions

Summary of Model Analysis





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"Questions?"


John Edwards
@John_B_Edwards
was inspired by this to share my own, personal cheat sheet i rely on for my projects in case it's helpful
JOHN EDWARDS' PATENTED MACHINE LEARNING ALGORITHM CHEAT SHEET
START
USE XGBOOST