

NFL Big Data Tackle Analysis

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EDA

We use visualizations to understand the structure and distribution of the data



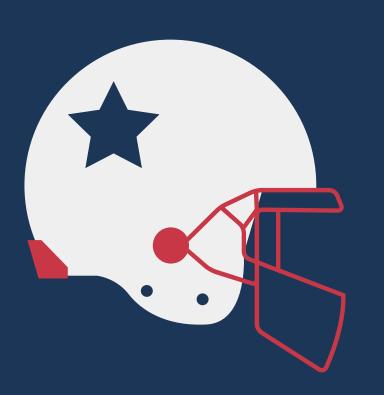
Metric: Yards Saved

We use data manipulation and modeling to design new metric for play evaluation



Results

Comparison of traditional tackling efficiency with the new yards saved metric.



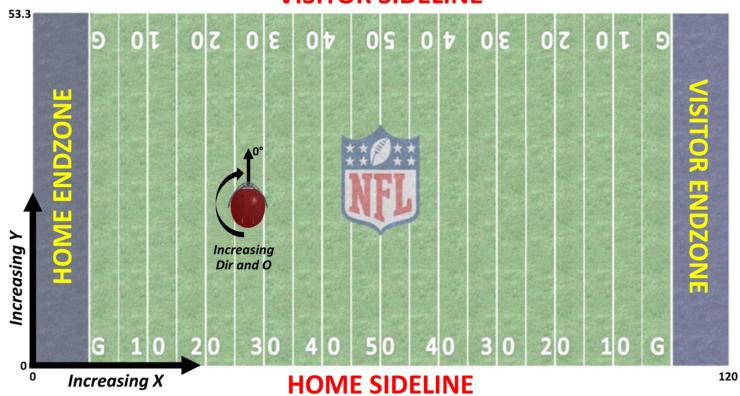
Part OI

Exploratory Data Analysis

Data Source: Provided by the NFL Next Gen Stats team on Kaggle

- Game Data: Basic structure of the season, listed out week of the game and teams involved
- Play Data: Dives into each game's specifics, like play description and quarter of the game
- Player Data: Understand the key players, their background information, and physical attributes
- Tackles Data: Insights into defensive plays and player performance
 - Key Fields: gameld, playId, nflId, tackle, assist, forcedFumble, pff_missedTackle
- Tracking Data: The Game in motion records Detailed player movements and in-game dynamics
 - Key Fields: gameId, playId, nfIId, x, y, s, a, dir, event (specific play types of a frame)

VISITOR SIDELINE



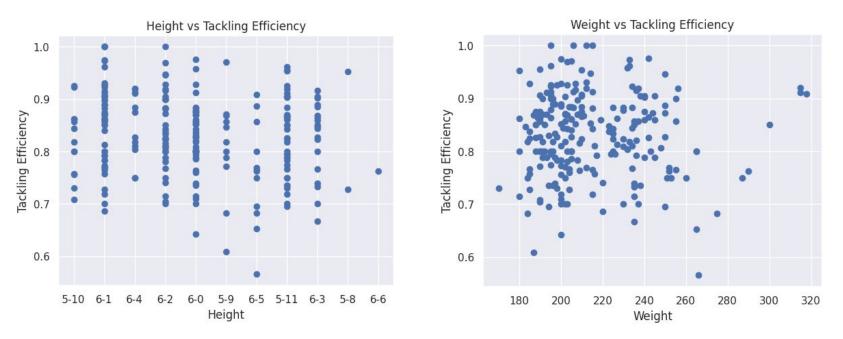
Objective

- Identify what makes a tackler not just good, but great?
- Understand each player's strength, ultimately enhancing the team's defensive tactics on the field

The Traditional Measure: Tackle Efficiency

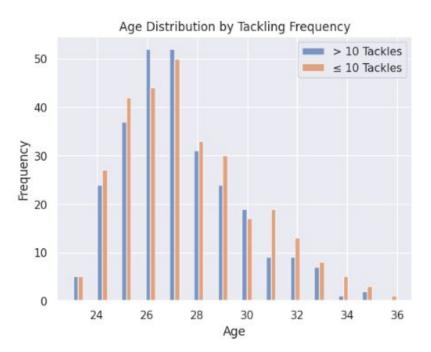
- Tackle Efficiency := Total Tackles / (Total Tackles + Total Missed Tackles)
 - The ratio of successful tackles to total tackle attempts, reflecting a player's reliability in halting the opposition

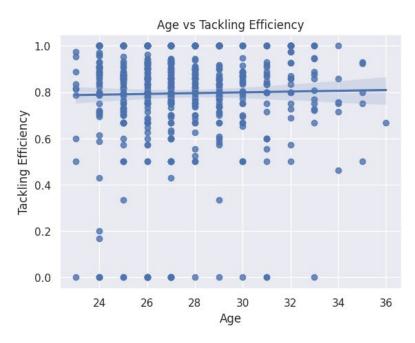
Does Height and Weight affect Tackling Efficiency? (After filtering out total tackles < 20)



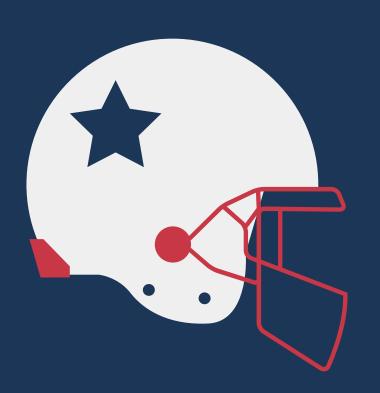
Not really, since players are usually matched to defend players with similar physical attributes

Does Age matter for Tackling Efficiency





• No linear correlation, we will now use 10 tackles as a threshold for ranking consideration



Part 02

Metric:

Yards Saved

Introduction

- What is nflBigData class? What is it for?
 - Purpose: NFL Big Data Bowl datasets manipulations
 - A database with methods and pipelines
 - Inspired by

https://www.kaggle.com/code/carrot1500/evaluating-tackle-difficulty

Class Attributes

- PLAYIDS: Key indices for dataset merging
- Datasets Used:
 - Tackles: Data on player tackles
 - Plays: Information on game plays
 - Players: Player profiles and statistics
 - Weekly Tracking: Player tracking data for weeks 1-9

Initialization

- Instance variables are initialized with class-level data
- Creation of empty lists for carrier and defender views

```
lass nflBigData:
  A class for analyzing NFL Big Data Bowl datasets.
  This class includes methods for calculating various metrics related to player movements and interactions
  during NFL plays, using data from multiple sources, including tracking data, play information, and player
  attributes.
  Attributes:
      PLAYIDS (list): A list of strings used as primary keys to index the datasets.
      tackles (DataFrame): DataFrame containing tackle data.
      plays (DataFrame): DataFrame containing play data.
     players (DataFrame): DataFrame containing player data.
      weekly tracking (list): A list of DataFrames containing weekly tracking data.
      carrier list (list): A list to store DataFrames merged with ball carrier information.
      defender_list (list): A list to store DataFrames merged with defender information.
  PLAYIDS = ["gameId", "playId"] # Combination of indices used for merging datasets.
  # Reading CSV files containing tackles, plays, and player data.
  tackles = pd.read_csv("/content/drive/MyDrive/DSGA1007/data/tackles.csv")
  plays = pd.read_csv("/content/drive/MyDrive/DSGA1007/data/plays.csv")
  players = pd.read csv("/content/drive/MyDrive/DSGA1007/data/players.csv")
  # Reading weekly tracking data for weeks 1 to 9.
  weekly tracking = [pd.read csv(f"/content/drive/MyDrive/DSGA1007/data/tracking week {i}.csv") for i in range(1, 10)]
  def init (self):
      # Initialize instance variables with class variables.
      self.PLAYIDS = nflBigData.PLAYIDS
      self.plays = nflBigData.plays
      self.players = nflBigData.players
      self.tackles = nflBigData.tackles
      self.trackings = nflBigData.weekly_tracking
      self.carrier_list = [] # Initialize empty list for merged DataFrames (ball carriers).
      self.defender list = [] # Initialize empty list for merged DataFrames (defenders).
```

Data manipulation Methods

- Ball Carrier View Construction:
 - Merges tracking data with play and ball carrier information
 - Appends processed data to carrier list
- Defender View Construction:
 - Combines latest ball carrier view with tracking data
 - Identifies nearby defenders and blockers
- Physical Characteristics Construction:
 - Adds height and weight information to player data
 - Merges physical characteristics with defender data
- Labeling
 - Merges tackling data to label defenders' actions

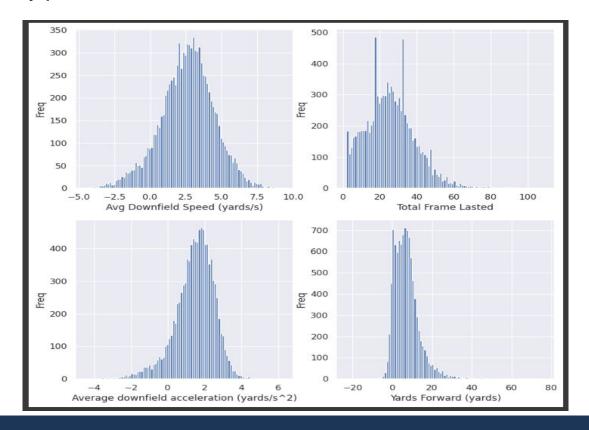
Calculation methods

- Downfield Speed calculation method
- Downfield Acceleration calculation method
- Distance to Carrier calculation method
- Yards Forward calculation method

Additional (outside-of-class) calculation and Data manipulation methods

- Average Downfield Speed calculation method
- Average Downfield Acceleration calculation method
- Total frames lasted calculation method
- Total yards gained calculation method

The distribution of the key quantities needed for metric calculation:



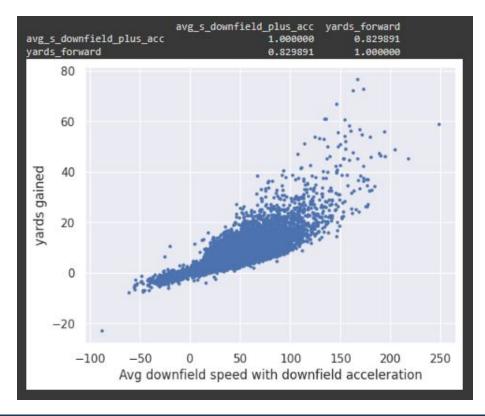
Now that we have...

- the average ball carrier downfield speed in a play
- the average ball carrier downfield acceleration in a play
- the total number of frames lasted in a play

We can fit a linear regression model to...

- predict potential yards that a ball carrier can gain at any given frame in a play!
- Our assumption: yards ~ speed + time * acceleration

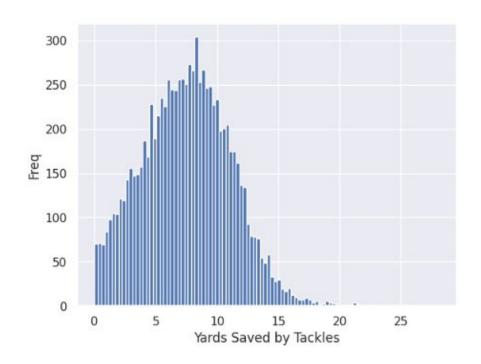
The correlation of the yards gained and downfield speed with acceleration:

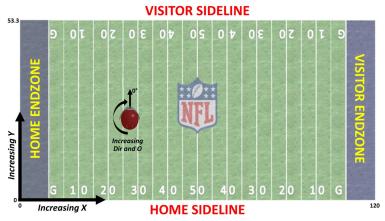


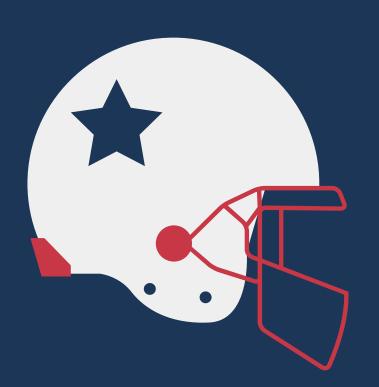
Our Metric to evaluate a tackle: Yards Saved

- Our LR can predict the potential yards will be gained at any given frame in a play
- We can then plug in the downfield speed of a ball carrier at the frame when he is successfully tackled by a defender
 - The output of the LR model can then be interpreted as:
 - the yards the ball carrier could have gained if the defender had missed the tackle.
 - Or # of yards saved by a successful tackle

The distribution of the Metric:



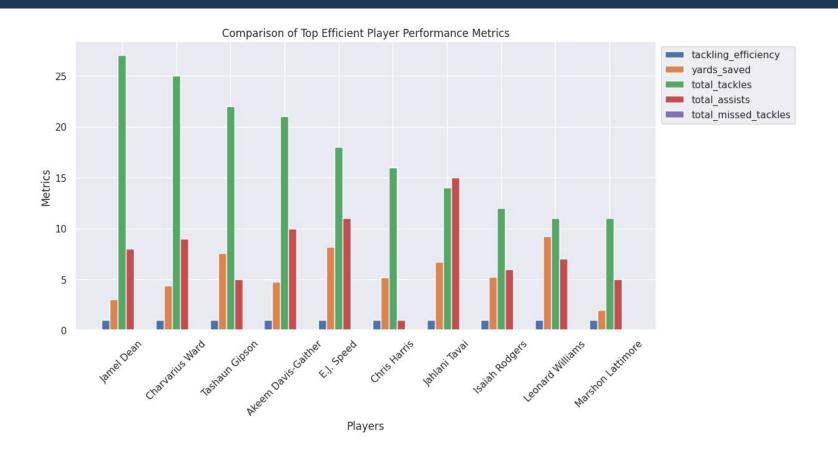


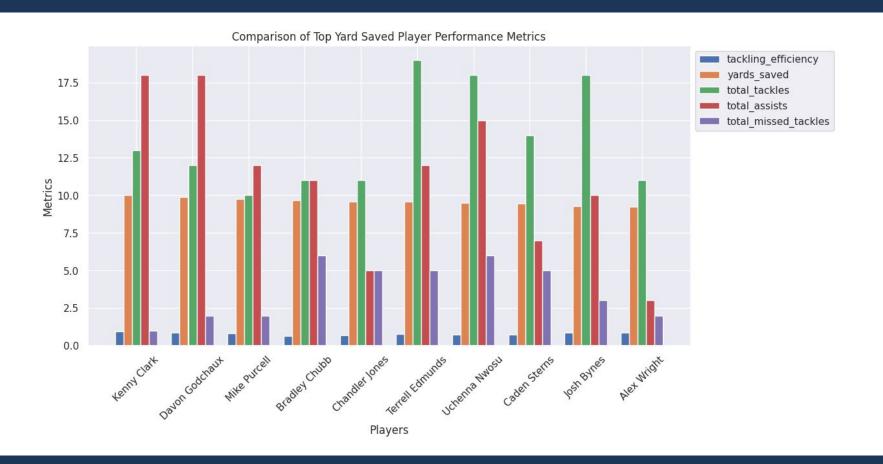


Part 03

Results



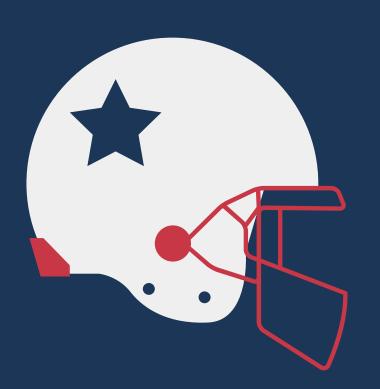




Future work

- More Advanced Metrics: Evaluating the difficulty of one's tackle (based on their starting distance from the ball carrier, speed, angle, weight difference etc.)
- Prediction Models: Based on a given formation/play setup, how likely a certain defensive player can stop the offense from making plays
- **Visualization**: Visualize the detailed play based on the tracking data using heatmap etc.
- Miscellaneous: Further explore the ideas we encountered during the data exploration (see appendix)

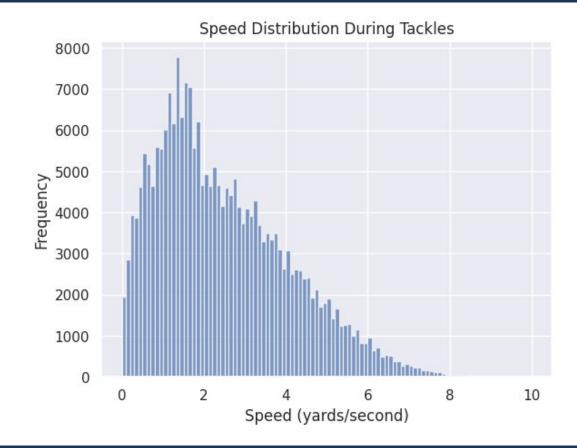
Thank You!



Part 04

Appendix

Appendix A



Appendix B.1

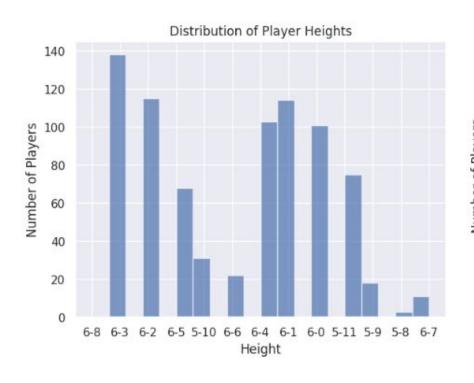


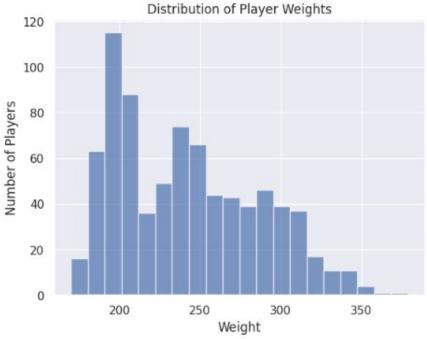
Appendix B.2

Group by 'playType' and calculate tackling efficiency

	playType	total_attempts	successful_tackles	tackling_efficiency
0	After Pass	7035	4798	0.682018
1	Other	10391	5121	0.492830

Appendix C





Appendix D.1

```
games.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 136 entries, 0 to 135
Data columns (total 9 columns):
     Column
                        Non-Null Count
                                         Dtype
     gameId
                        136 non-null
                                         int64
                        136 non-null
                                         int64
     season
                        136 non-null
                                         int64
     week
     gameDate
                        136 non-null
                                         object
     gameTimeEastern
                        136 non-null
                                         object
     homeTeamAbbr
                        136 non-null
                                         object
     visitorTeamAbbr
                        136 non-null
                                         object
                        136 non-null
     homeFinalScore
                                         int64
     visitorFinalScore 136 non-null
                                         int64
dtypes: int64(5), object(4)
memory usage: 9.7+ KB
```

plays.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 12486 entries, 0 to 12485 Data columns (total 35 columns): Column Non-Null Count Dtype gameId 12486 non-null playId 12486 non-null ballCarrierId 12486 non-null int64 ballCarrierDisplayName 12486 non-null object playDescription 12486 non-null obiect quarter 12486 non-null down 12486 non-null int64 yardsToGo 12486 non-null int64 possessionTeam 12486 non-null defensiveTeam 12486 non-null yardlineSide 12319 non-null yardlineNumber 12486 non-null int64 gameClock 12486 non-null object preSnapHomeScore 12486 non-null preSnapVisitorScore 12486 non-null passResult 6105 non-null object float64 passLength 5634 non-null float64 penaltyYards 615 non-null prePenaltyPlayResult 12486 non-null int64 playResult 12486 non-null int64 plavNullifiedBvPenaltv 12486 non-null obiect absoluteYardlineNumber 12486 non-null offenseFormation 12482 non-null defendersInTheBox 12481 non-null float64 passProbability 12149 non-null float64 preSnapHomeTeamWinProbability 12486 non-null float64 preSnapVisitorTeamWinProbability 12486 non-null homeTeamWinProbabilityAdded 12486 non-null float64 visitorTeamWinProbilityAdded 12486 non-null float64 expectedPoints 12486 non-null float64 expectedPointsAdded 12485 non-null float64 foulName1 592 non-null object foulName2 25 non-null object foulNFLId1 592 non-null float64 34 foulNFLTd2 25 non-null float64 dtypes: float64(12), int64(12), object(11)

Appendix D.2

<pre>players.info()</pre>	<pre>tackles.info()</pre>			
<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 1683 entries, 0 to 1682 Data columns (total 7 columns): # Column</class></pre>	<pre><class 'pandas.core.frame.dataframe'=""> RangeIndex: 17426 entries, 0 to 17425 Data columns (total 7 columns): # Column</class></pre>			
memory usage: 92.2+ KB	mamama:			

weekly_tracking[0].info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1407439 entries, 0 to 1407438
Data columns (total 17 columns):

Data	cotamins (totat	I/ Cocumiis/.					
#	Column	Non-Null Count	Dtype				
0	gameId	1407439 non-null	int64				
1	playId	1407439 non-null	int64				
2	nflId	1346246 non-null	float64				
3	displayName	1407439 non-null	object				
4	frameId	1407439 non-null	int64				
5	time	1407439 non-null	object				
6	jerseyNumber	1346246 non-null	float64				
7	club	1407439 non-null	object				
8	playDirection	1407439 non-null	object				
9	X	1407439 non-null	float64				
10	у	1407439 non-null	float64				
11	S	1407439 non-null	float64				
12	a	1407439 non-null	float64				
13	dis	1407439 non-null	float64				
14	0	1346397 non-null	float64				
15	dir	1346397 non-null	float64				
16 event		130268 non-null	object				
dtype	es: float64(9),	int64(3), object(5)					
memory usage: 182 5+ MR							

memory usage: 182.5+ MB