```
from google.colab import files
import requests
from bs4 import BeautifulSoup
from urllib.request import urlopen
import pandas as pd
import numpy as np
import re
import time
import random
import io
import datetime
import matplotlib.pyplot as plt
import seaborn as sns

import scipy.stats
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
```

```
#Import All Matchups with Scores.csv, and NFL Historical Data.csv
data = files.upload()
```

Choose Files 2 files

- **All Matchups with Scores.csv**(text/csv) - 576176 bytes, last modified: 4/13/2024 - 100% done
- **NFL Historical Data.csv**(text/csv) - 911016 bytes, last modified: 4/13/2024 - 100% done

```
Saving All Matchups with Scores.csv to All Matchups with Scores (1).csv
Saving NFL Historical Data.csv to NFL Historical Data (1).csv
```

Data Gathering: Scraping the Web for Matchups

This shows how we gathered the information used in the following models. The main function calls for these have been commented out to avoid scraping the data again. Feel free to run on a small scale, to see how they work!

If "All Matchup Score.csv" and "NFL Historical Data.csv" have not all been imported, then these cells may be used to create the datasets used for the rest of the code.

```
# NFL Historical Data Scraper Functions
def single_season(season):
  dflist = []
  modes = ["offense","defense","special-teams"]
  #List of all possible options
  alloptions = [["passing","rushing","receiving","scoring","downs"],["passing","rushing","receiving","scoring","tackles","downs","intercept
           ,["field-goals","scoring","kickoffs","kickoff-returns","punts","punt-returns"]]

  for i in range(len(modes)):
    mode = modes[i]
    options = alloptions[i]
    for j in range(len(options)):
      option = options[j]
      print(f"Gathering {mode} {option} data for {season}...")
      url = f"https://www.nfl.com/stats/team-stats/offense/{option}/{season}/reg/all"
      page = requests.get(url)
      contents = page.content
      soup = BeautifulSoup(contents,"html.parser")
      tables = soup.find_all("table")
      if len(str(tables)) == 0:
          print("This is gonna be a problem")
      df = pd.read_html(io.StringIO(str(tables)))[0]
      year = np.ones(len(df)) * season
      df.insert(loc = 0, column = "Year", value = year)
      df["Year"] = df["Year"].astype(int)

      teams = df["Team"]
      correctedteams = []
      for team in teams:
        correctedteams.append(team.split(" ")[0])
      df["Team"] = correctedteams

      dfheadings = list(df)[2:]
      newheadings = []
      headingdict = {}
      for heading in dfheadings:
        newheading = mode+" "+option+" "+heading
        newheadings.append(newheading)
      for j in range(len(newheadings)):
        headingdict[dfheadings[j]] = newheadings[j]
      df.rename(columns = headingdict,inplace=True)

      dflist.append(df)
  return dflist

class NFLData:
  def __init__(self,start,end):
    self.start = start
    self.end = end
    self.dflist = []
    self.df = pd.DataFrame()
  def pull_all(self):
    log = self.start
    if self.dflist != []:
      print("Data already collected.")
      return
    #Pulls the next years data and adds it onto each pulled table
    while (log <= self.end):
      dfs = single_season(log)
      if dfs == 1:
          print("Data not present")
          return None
          break
      if not self.dflist or len(self.dflist) == 0:
        newdflist = dfs
      else:
        newdflist = []
        for i in range(len(self.dflist)):
          if dfs:
            onedf = dfs[i]
            twodf = self.dflist[i]
            newdf = pd.concat([onedf,twodf])
            newdflist.append(newdf)
      self.dflist = newdflist
      log+=1
  def to_one_df(self):
    print("Merging to one DataFrame...")
```

```
    df1 = self.dflist[0]
    df2 = self.dflist[1]
    common_columns = ['Team', 'Year']  # Specify common columns
    # Merge the first two dataframes
    combined_df = pd.merge(df1, df2, on=common_columns, how='inner')
    for df in self.dflist[2:]:
      combined_df = pd.merge(combined_df,df,on=common_columns,how="inner")
    self.__df = combined_df
    print("Merge Complete!")
  def append(self,df):
      print("Appending analysis to DataFrame...")
      self.__df = pd.concat((self.__df,df))
  def display(self):
    if len(self.__df) > 0:
      return self.__df
    else:
      raise ValueError("No DataFrame to Display")
      return
  def save(self,name):
    if len(self.__df) == 0:
      raise ValueError("No DataFrame to Save")
      return
    self.df.to_csv(name)

#Function that will automatically update the player_data df if it sees the df isn't fully updated
def update_player_data(df):
    #See what years are in the highest table
    highest_current_year = df["Year"].max()

    desired_years = datetime.date.today().year - 1
    #If the dataset is not as updated as possible...
    if desired_years > highest_current_year:
        #Starts a datascraping object to grab all needed years
        NewData = NFLData(highest_current_year + 1,desired_years)
        #scrapes relevant years
        NewData.pull_all()
        #Combines dflist in Newdata to one dataframe
        NewData.to_one_df()
        #Adds existing data to NewData object
        NewData.append(df)
        NewData.save("DataSets/NFL Historical Data.csv")
        print("player_data DataFrame up to date!")
        return NewData.display()
    else:
        print("player_data DataFrame up to date!")
        return df

#player_data = pd.read_csv("NFL Historical Data.csv")
#Commented to prevent accidentally running
#update_player_data(player_data)

#Example Function Calls for 2023
#test_df = NFLData(2023,2023)
#test_df.pull_all()
#test_df.to_one_df()
#test_df.display()
```

```
# Matchup Scraper functions
def get_team_name(s):
  if type(s) != str:
    raise ValueError("Team must be string")
    return
  if " " not in s:
    raise ValueError("Team must contain a space")
    return

  arr = s.split(" ")
  return arr[len(arr)-1]
def grab_one_season(year):
  url = f"https://www.pro-football-reference.com/years/{year}/games.htm"
  page = requests.get(url)
  contents = page.content
  soup = BeautifulSoup(contents,"html.parser")
  tables = soup.find_all("table")
  #Don't know if this line is necessary in GitHub
  time.sleep(5)

  df = line_score = pd.read_html(io.StringIO(str(tables[0])))[0]
  years = [year] * len(df)
  df["Year"] = years
  df.set_index("Week",inplace=True)
  df = df[(df["Day"] != "Day") & (df["Date"] != "Playoffs")]
  for col in ["Winner/tie","Loser/tie"]:
   df.loc[:, col] = df[col].apply(get_team_name)

  team1list = []
  team2list = []
  for index,row in df.iterrows():
    #Create a shuffled state to randomly assing team 1 and team 2
    state = random.randint(1,2)
    if state == 1:
      team1 = row["Winner/tie"]
      team2 = row["Loser/tie"]
    else:
      team1 = row["Loser/tie"]
      team2 = row["Winner/tie"]
    team1list.append(team1)
    team2list.append(team2)
  df.insert(loc=2,column="Team 1",value = team1list)
  df.insert(loc=3,column="Team 2",value = team2list)
  columns = ["Year","Team 1","Team 2","Winner/tie","Loser/tie","Pts","Pts.1"]
  df = df[columns]
  return df
def grab_all_seasons(start,end):
  """
  period: tuple. (startyear,endyear). Determines which years are pulled"""

  print(f"Gathering {start} season matchup data...")
  df = grab_one_season(start)
  #Termination case
  if start+1 <= end:
    #Recursion!
    df = pd.concat([df,grab_all_seasons(start+1,end)])
  if start == end:
    print("Done!")
  return df

##Commented to prevent accidentally running
#all_dfs = grab_all_seasons(1970,2023)
#all_dfs.to_csv("All Matchups with Scores.csv")
```

Data Modifications: How did we modify the scraped data?

Dataset 1: Individual Game Prediction

To make an ML model for individual game prediction, we did a "merge" of sorts on the Historical and Matchup Data dfs. Historical df was turned into a dictionary to allow lookups by team and year to result in a large df with 300+ features corresponding to "Team 1" and "Team 2" stats for each game.

```
player_data = pd.read_csv("NFL Historical Data.csv")
matchup_data = pd.read_csv("All Matchups with Scores.csv")

#Add Score Diff column
matchup_data["Score Diff"] = matchup_data["Pts"]-matchup_data["Pts.1"]

#Remove all non-numeric columns from NFL Historical data to allow ML model computation
for col in list(player_data):
  if col != "Team" and player_data[col].dtype == object:
    player_data.drop(col,axis=1,inplace=True)


#Complex df manipulation functions
def pull_all_matchups(data):
  """Takes an input matchup_data df and return 2 items:
  bothlist: a 2D array of each game's team 1 and team 2 (randomly shuffled in creation -- see grab_one_season function for details)
  winnerslist: a list of each game's winner (team 1 or team 2, not specific team name specific) """
  bothlist = []
  winnerslist = []
  scoreslist = []

  for index, row in data.iterrows():
    bothlist.append([str(row["Year"])+ " " +str(row["Team 1"]),str(row["Year"])+ " " +str(row["Team 2"])])
    scoreslist.append(row["Score Diff"])
  inputlist = (data["Team 1"] == data["Winner/tie"])
  for row in inputlist:
    if row == True:
      winnerslist.append("Team 1")
    if row == False:
      winnerslist.append("Team 2")
  return bothlist,winnerslist, scoreslist
def pull_data_by_year(data):
  data_dict = {}
  for index, row in data.iterrows():
    data_dict[str(row["Year"])+ " " +str(row["Team"])] = row[2:]
  return data_dict
def get_team_name(s):
  if type(s) != str:
    raise ValueError("Team must be string")
    return
  if " " not in s:
    raise ValueError("Team must contain a space")
    return

  arr = s.split(" ")
  return arr[len(arr)-1]
def create_headings(player_data_df):
    """Input: player_data_df

    Output: list of relevant headings for regression that helps in final_df creation"""
    headingnames = list(player_data_df)[2:]
    team1headings = []
    team2headings = []
    #Create headings for final df
    for heading in headingnames:
      team1headings.append("Team 1 "+heading)
      team2headings.append("Team 2 "+heading)
    expandedheadings = ["Team 1","Team 2"] + team1headings + team2headings
    return expandedheadings

#Turn the player_data df into a dictionary
team_data_dict = pull_data_by_year(player_data)
#Turn the matchups df into two lists, game_data has team 1 and team 2, winners has which team won, scores has the diference in scores betwe
game_data , winners, scores = pull_all_matchups(matchup_data)
#Create an expanded list of headings for the final_df
expandedheadings = create_headings(player_data)
```

```
all_games_data = []
all_game_winners = []
all_game_scores = []
#Put the winners and stats of each game into lists (faster iteration)
for i in range(len(game_data)):
  game = game_data[i]

  team1 = game[0]
  team2 = game[1]
  winner = winners[i]
  score = scores[i]
  if ((team1 in team_data_dict) and (team2 in team_data_dict)):
    #Search each team in the team_data_dict dictionary, and append their data to the all_game_winners list.
    team1data = list(team_data_dict[team1])
    team2data = list(team_data_dict[team2])
    combineddata = [team1,team2]+team1data+team2data
    all_games_data.append(combineddata)
    all_game_winners.append(winner)
    all_game_scores.append(score)

#Turn all_games_data into a big df for ML computation
final_df = pd.DataFrame(all_games_data,columns = expandedheadings)

#Drop unnessecary doubled label columns
final_df.drop(["Team 1 Team","Team 2 Team"],inplace = True,axis=1)

final_df
```

	Team 1	Team 2	Team 1 offense passing Att	Team 1 offense passing Cmp	Team 1 offense passing Cmp %	Team 1 offense passing Yds/Att	Team 1 offense passing Pass Yds	Team 1 offense passing TD	Team offens passir IN
0	1970 Rams	1970 Cardinals	426	218	51.2	6.2	2658	17	1
1	1970 Bears	1970 Giants	422	210	49.8	5.8	2431	21	2
2	1970 Bills	1970 Broncos	402	213	53.0	7.2	2916	13	2
3	1970 Raiders	1970 Bengals	418	210	50.2	7.2	3029	28	2
4	1970 Cowboys	1970 Eagles	297	149	50.2	8.2	2445	18	1
...	...	...	...	...	...	...	...	...	
12924	2023 Lions	2023 Buccaneers	606	408	67.3	7.6	4606	30	1
12925	2023 Bills	2023 Chiefs	579	385	66.5	7.4	4306	29	1
12926	2023 Ravens	2023 Chiefs	494	328	66.4	7.9	3881	27	
12927	2023 49ers	2023 Lions	491	336	68.4	9.3	4577	33	1
12928	2023 49ers	2023 Chiefs	491	336	68.4	9.3	4577	33	1

12929 rows × 302 columns

```
all_games_data = []
all_game_winners = []
all_game_scores = []
#Put the winners and stats of each game into lists (faster iteration)
for i in range(len(game_data)):
  game = game_data[i]

  team1 = game[0]
  team2 = game[1]
  winner = winners[i]
  score = scores[i]
  if ((team1 in team_data_dict) and (team2 in team_data_dict)):
    #Search each team in the team_data_dict dictionary, and append their data to the all_game_winners list.
    team1data = list(team_data_dict[team1])
    team2data = list(team_data_dict[team2])
    combineddata = [team1,team2] + team1data + team2data
    all_games_data.append(combineddata)
    all_game_winners.append(winner)
    all_game_scores.append(score)

#Turn all_games_data into a big df for ML computation
final_df = pd.DataFrame(all_games_data,columns = expandedheadings)

#Drop unnessecary doubled label columns
final_df.drop(["Team 1 Team","Team 2 Team"],inplace = True,axis=1)

final_df
```

	Team 1	Team 2	Team 1 offense passing Att	Team 1 offense passing Cmp	Team 1 offense passing Cmp %	Team 1 offense passing Yds/Att	Team 1 offense passing Pass Yds	Team 1 offense passing TD	Team offens passir IN
0	1970 Rams	1970 Cardinals	426	218	51.2	6.2	2658	17	1
1	1970 Bears	1970 Giants	422	210	49.8	5.8	2431	21	2
2	1970 Bills	1970 Broncos	402	213	53.0	7.2	2916	13	2
3	1970 Raiders	1970 Bengals	418	210	50.2	7.2	3029	28	2
4	1970 Cowboys	1970 Eagles	297	149	50.2	8.2	2445	18	1
...	...	...	...	...	...	...	...	...	
12924	2023 Lions	2023 Buccaneers	606	408	67.3	7.6	4606	30	1
12925	2023 Bills	2023 Chiefs	579	385	66.5	7.4	4306	29	1
12926	2023 Ravens	2023 Chiefs	494	328	66.4	7.9	3881	27	
12927	2023 49ers	2023 Lions	491	336	68.4	9.3	4577	33	1
12928	2023 49ers	2023 Chiefs	491	336	68.4	9.3	4577	33	1

12929 rows × 302 columns

ML Models

ML Model 1: Random Forest Classifier to predict which team will win

This was done for both end of year statistics and end of previous year statistics, with the latter chosen to make a model that can be used to predict games that have not already happened

```
#NOTE: This cell will take a while to run, as it checks for the most effective setting combo using nested iteration over a pretty hefty cre
#Only grabs numerical data

inputdata = final_df.iloc[:,2:]

data_train,data_test,label_train,label_test = train_test_split(inputdata,all_game_winners,random_state = 110)

def try_different_settings(data_train,label_train):
  #Attempt different input settings for a RandomForest Classifier, print the best settings and their cross_val_score
  best_crossval = 0
  bestsettings = []
  estimators = [50,100,200]
  features = ["sqrt","log2"]
  max_depths = [10,20,None]
  best_model = None
  for estimator in estimators:
    for feature in features:
      for depth in max_depths:
        forest = RandomForestClassifier(n_estimators=estimator, max_features=feature, max_depth=depth,random_state=110)
        forest.fit(data_train,label_train)
        score = np.mean(cross_val_score(forest,data_train,label_train))
        if score > best_crossval:
          best_crossval = score
          bestsettings = [estimator,feature,depth]
          best_model = forest
  print(f"The best settings were: \n-{bestsettings[0]} estimators\n-{bestsettings[1]} max_features\n-{bestsettings[2]} max depth\n \
  These settings achieved a cross_val score of {score:.4f} on the cross-val set.")
  return best_model

#WILL TAKE A WHILE, BUT YOU CAN RUN THIS TO SEE WHERE OUR SETTINGS CAME FROM
#try_different_settings(data_train,label_train)


all_games_forest = RandomForestClassifier(n_estimators = 100, max_depth = 10, max_features = "sqrt",random_state = 110)
all_games_forest.fit(data_train,label_train)
effectiveness = all_games_forest.score(data_test,label_test)
print(f"The effectiveness of the ML model when given the current year's data is about {round(effectiveness,4)}")
```

```
The effectiveness of the ML model when given the current year's data is about 0.6576
```

```
#Manipulations to pair each game with the previous years' data if possible. Less effective for prediction, but actually feasible for future

def change_to_last_year(team_name):
    """Changes the given team_name:string to the previous year
    Output: team1:string

    >>>change_to_last_year("2022 Rams") == "2021 Rams"
    """

    splitteam1 = team_name.split(" ")
    year1 = splitteam1[0]
    steam1 = splitteam1[1:]
    modteam1 = ""
    for word in steam1:
        modteam1 += (word + " ")
    year1 = int(year1) - 1
    team1 = str(year1) + " " + modteam1.strip()
    return team1

#Pairing last years stats to next year winners
all_games_data_ly = []
all_game_winners_ly = []
all_game_scores_ly = []
for i in range(len(game_data)):
  game = game_data[i]

  origteam1 = game[0]
  team1 = change_to_last_year(origteam1)

  origteam2= game[1]
  team2 = change_to_last_year(origteam2)

  winner = winners[i]
  score = scores[i]
  #If the last year's team_data is in the dataset we'll add these result to the dataframe
  if ((team1 in team_data_dict) and (team2 in team_data_dict)):
    team1data = list(team_data_dict[team1])
    team2data = list(team_data_dict[team2])
    combineddata = [origteam1,origteam2]+team1data+team2data
    all_games_data_ly.append(combineddata)
    all_game_winners_ly.append(winner)
    all_game_scores_ly.append(score)


final_df_ly = pd.DataFrame(all_games_data_ly,columns = expandedheadings)

final_df_ly.drop("Team 1 Team",inplace = True,axis=1)
final_df_ly.drop("Team 2 Team",inplace=True,axis=1)

final_df_ly["Team 1"] = final_df_ly["Team 1"].apply(get_team_name)
final_df_ly["Team 2"] = final_df_ly["Team 2"].apply(get_team_name)

final_df_ly
```

	Team 1	Team 2	Team 1 offense passing Att	Team 1 offense passing Cmp	Team 1 offense passing Cmp %	Team 1 offense passing Yds/Att	Team 1 offense passing Pass Yds	Team 1 offense passing TD	Team 1 offense passing INT
0	49ers	Falcons	383	226	59.0	7.8	2990	25	10
1	Bills	Cowboys	402	213	53.0	7.2	2916	13	26
2	Eagles	Bengals	410	218	53.2	6.5	2651	16	23
3	Oilers	Browns	470	238	50.6	5.9	2768	12	23
4	Patriots	Raiders	392	176	44.9	5.0	1975	7	28
...	...	...	...	...	...	...	...	...	...
12593	Lions	Buccaneers	588	383	65.1	7.6	4444	29	7
12594	Bills	Chiefs	574	361	62.9	7.5	4291	35	14
12595	Ravens	Chiefs	488	300	61.5	6.6	3202	19	13
12596	49ers	Lions	512	338	66.0	7.9	4049	30	9
12597	49ers	Chiefs	512	338	66.0	7.9	4049	30	9

12598 rows × 302 columns

```
inputdata_ly = final_df_ly.iloc[:,2:]
data_train_ly,data_test_ly,label_train_ly,label_test_ly = train_test_split(inputdata_ly,all_game_winners_ly,random_state = 110)

#COMMENTED OUT TO AVOID LONG RUN TIME, ONCE AGAIN WILL DIAGNOSE BEST CROSSVAL SETTINGS IF RAN
#try_different_settings(data_train_ly,label_train_ly)


all_games_forest = RandomForestClassifier(n_estimators = 200,max_depth = 20, random_state = 110)
all_games_forest.fit(data_train_ly,label_train_ly)
effectiveness_ly = all_games_forest.score(data_test_ly,label_test_ly)

#Shows that this model can still be used on last year's scores
print(f"Even when given the last years' player data, the accuracy of the model is ~{effectiveness_ly:.4f}, substantially more accurate than
```

```
Even when given the last years' player data, the accuracy of the model is ~0.5956, substantially more accurate than random chance!
```

ML Model 2: MutliRegression to Predict Game Score (unsuccessful)

```
lm_data_train,lm_data_test,lm_label_train,lm_label_test = train_test_split(inputdata,all_game_scores,random_state = 110)
linear_model = LinearRegression()
linear_model.fit(lm_data_train,lm_label_train)
CofDetermination = linear_model.score(lm_data_train,lm_label_train)
print(f"Even in the trainin set, the coefficient of determination for this dataset is {CofDetermination:.4f}, linear regression not strong.
```

```
Even in the trainin set, the coefficient of determination for this dataset is 0.0336, linear regression not strong.
```

```
#Note: This cell will take a long time to run
score_predictor = RandomForestRegressor(random_state = 110,max_features = "sqrt")
score_predictor.fit(lm_data_train,lm_label_train)

train_cod = score_predictor.score(lm_data_train,lm_label_train)
test_cod = score_predictor.score(lm_data_test,lm_label_test)
predicted_scores = score_predictor.predict(lm_data_test)
print(f"Though for Random Forest Regression the predictor appears to be more accurate in the training set with a CoD of {train_cod:.4f},\nt
and test set CoD is still {test_cod:.4f}.")
```

```
Though for Random Forest Regression the predictor appears to be more accurate in the training set with a CoD of 0.8023,
the model severly overfits the data and test set CoD is still -0.0625.
```

ML Model 3: Super Bowl Data

This model was done just for fun, and to get more intricate data for visualization and statistical modeling.

Note: There is some web scraping in the following cell, this will only access one website and will not take a long time to run; therefore, it is left in the finalized code instead of a file upload

```
#Dictionary to help the superbowl data and NFL Historical.csv data talk to each other
superbowl_dict ={
 'Pittsburgh': 'Steelers',
 'Dallas': 'Cowboys',
 'Atlanta': 'Falcons',
 'Washington': 'Commanders',
 'Tampa Bay': 'Buccaneers',
 'Green Bay': 'Packers',
 'Seattle': 'Seahawks',
 'New England': 'Patriots',
 'New Orleans': 'Saints',
 'Kansas City': 'Chiefs',
 'Buffalo': 'Bills',
 'Tennessee': 'Titans',
 'Arizona': 'Cardinals',
 'Philadelphia': 'Eagles',
 'Denver': 'Broncos',
 'Miami': 'Dolphins',
 'Carolina': 'Panthers',
 'San Francisco': '49ers',
 'Minnesota': 'Vikings',
 'Cincinnati': 'Bengals',
 'Baltimore': 'Ravens',
 'Chicago': 'Bears',
 'Los Angeles Rams': "Rams",
 "Los Angeles Raiders":"Raiders",
 "New York Giants": "Giants",
 "Oakland":"Raiders",
 "San Diego": "Chargers",
 "St. Louis":"Rams",
 "New York Jets":"Jets",
 "Indianapolis":"Colts"
}

def pull_superbowl_data(start,end):
  """
  start,end Desired start and end year of superbowl histories.

  2 Outputs:
    Pandas dataframe of the superbowl winner history by year
    Set of winners in the form of "Year Team" """

  url = "https://www.espn.com/nfl/superbowl/history/winners"
  html = urlopen(url)
  soup = BeautifulSoup(html, "html.parser")

  # Find all tables in the HTML
  tables = soup.find_all("table")

  #Initialize pd dataframe from the dataset
  df = pd.read_html(io.StringIO(str(tables[0])))[0]
  colnames = {0:"Superbowl",1:"Year",2:"Location",3:"Result"}
  df.rename(columns = colnames,inplace=True)
  df.set_index(["Superbowl"],inplace=True)

  #Remove unnecessary top rows.
  df = df.iloc[2:,:]
  #Break down full date format into just the provided year
  years = []
  for year in df["Year"]:
    years.append(int(year.split(", ")[1]))
  df["Year"] = years
  bowl_stats = df["Result"]

  #Breakdown results column into four column with winning team, winning score, losing team, losing score
  winning_teams = []
  winning_scores = []
  losing_teams = []
  losing_scores = []

  for stat in bowl_stats:
    winning_team,losing_team = stat.split(",")

    winning_team_split = winning_team.split(" ")
    winning_team_city = winning_team_split[0:len(winning_team_split)-1]
    output = ""
    for item in winning_team_city:
```

```
        output+= (item+ " ")
      winning_team_city = output.strip()
      winning_score = winning_team_split[len(winning_team_split)-1]
      winning_teams.append(superbowl_dict[winning_team_city])
      winning_scores.append(winning_score)

      losing_team_split = losing_team.split(" ")
      losing_team_city = losing_team_split[0:len(losing_team_split)-1]
      losing_score = losing_team_split[len(losing_team_split)-1]
      output = ""
      for item in losing_team_city:
        output+= (item+ " ")
      losing_team_city = output.strip()
      losing_teams.append(losing_team_city)
      losing_scores.append(losing_score)

    df["Winning Team"] = winning_teams
    df["Winning Score"] = winning_scores
    df["Losing Team"] = losing_teams
    df["Losing Score"] = losing_scores
    df.drop(["Result"],axis=1,inplace=True)
    df = df[(df["Year"] >= start) & (df["Year"] <= end)]
    #Filter df by years
    winners = set()
    for index, row in df.iterrows():
      winner = str(row["Year"]) + " " + row["Winning Team"]
      winners.add(winner)
    return df,winners
```

```
#Keeps code dynamic, will grab you most recent year
most_recent = datetime.date.today().year
superbowl_data,superbowl_winners = pull_superbowl_data(1970,most_recent - 1)
print("superbowl_data DataFrame up to date!")
```

```
superbowl_data DataFrame up to date!
```

```
#Creates a list of whether each row in the dataset won the superbowl or not
superbowl_win_status = []
for index, row in player_data.iterrows():
  teamname = str(row["Year"])+" "+row["Team"]
  if teamname in superbowl_winners:
    superbowl_win_status.append(True)
  else:
    superbowl_win_status.append(False)

#Creates training and test data with team names and years removed/moved to index
no_team = player_data.drop(["Team","Unnamed: 0"],axis=1,inplace=False)
no_team.set_index("Year",inplace=True)

#Assignment here before inserting labels to avoid confusion
sb_data_train,sb_data_test,sb_label_train,sb_label_test = train_test_split(no_team,superbowl_win_status,random_state=110)

#Establshes a winners dataframe to separate the teams that won
no_team.insert(loc=0,column="Superbowl Status",value = superbowl_win_status)
winners = no_team[no_team["Superbowl Status"] == True]
newdf = winners.drop("Superbowl Status",axis=1,inplace=False)
winners = newdf
print("Super Bowl Winners up to date!")
```

```
Super Bowl Winners up to date!
```

```
superbowl_forest = RandomForestClassifier(n_estimators=100,random_state=110)
superbowl_forest.fit(sb_data_train,sb_label_train)
#Test on all of the data set. How well does it predict all teams win ability
print(f"The classifier is generally correct ~{round(superbowl_forest.score(sb_data_test,sb_label_test)*100,2)}% of the time\nThe classifier
```

```
The classifier is generally correct ~96.02% of the time
The classifier guessed that the superbowl winning team would win ~68.0% of the time.
```

```
#What are the most important features for the model? Data used in later visualization
features = list(sb_data_train)
feature_importances = superbowl_forest.feature_importances_
values = []
for i in range(len(features)):
    values.append([features[i],feature_importances[i]])
features_df = pd.DataFrame(values,columns =  ["Features","Importances"])
features_df.set_index("Features",inplace= True)
features_df.sort_values("Importances",ascending=False)
```

	Importances
Features	
offense rushing Att	0.020561
defense rushing Att	0.019279
special-teams punt-returns Ret	0.015674
special-teams punts OOB	0.015316
special-teams punts TB	0.014186
...	...
defense rushing 40+	0.000899
special-teams kickoff-returns KRet TD	0.000826
special-teams punts TD	0.000812
special-teams punt-returns PRet T	0.000620
special-teams kickoff-returns FUM	0.000444

150 rows × 1 columns

Statistical Tests

Test 1: Chi^2 Test

Our Distrubtion vs Standard "Pro Gambler" Performance:

```
#Chi^2 test code here

#Recall this variable is the measure of the effectiveness of our ML model using last year player statistics
effectiveness_ly

n = len(data_test_ly)

#Comparing the effectiveness of our model to the standard for pro-betters of 0.54, is the sucess of our model statistically better?
M = [[effectiveness_ly * n,(1-effectiveness_ly) *  n],[0.54*n,0.46*n]]

_,p,_,_ = scipy.stats.chi2_contingency(M)
print(f"p value is ~{round(p,10)}, the result is HIGHLY statistically significant.")
```

```
p value is ~9.6338e-06, the result is HIGHLY statistically significant.
```

Test 2: T-test

Are the means of Superbowl Winning Teams' stats different than losing teams in a stastiscally significant way?

```
#Add the markers for whether they won the superbowl as a column to a new df.
with_win_status = player_data.copy()
with_win_status.set_index("Unnamed: 0",inplace = True)
with_win_status["Won?"] = superbowl_win_status

#Split by winners and losers of the superbowl, the delete the superbowl boolean column
winners = with_win_status[with_win_status["Won?"] == True]
losers = with_win_status[with_win_status["Won?"] == False]
winners = winners.drop("Won?",axis=1)
losers  = losers.drop("Won?",axis=1)

winning_teams_data = winners.iloc[:,2:]
losing_teams_data = losers.iloc[:,2:]

winning_teams_data = winning_teams_data.dropna(axis=1, how='all')
losing_teams_data = losing_teams_data.dropna(axis=1, how='all')

results = {}

for column in winning_teams_data.columns:
  t_stat,p_val = scipy.stats.ttest_ind(winning_teams_data[column],losing_teams_data[column])
  results[column] = (t_stat,p_val)

significant_stats = {k: v for k, v in results.items() if v[1] < 0.05}
print("Superbowl winning teams showed statistically significant differences in the following stats:")
for k in significant_stats:
  print(f"{k} (p-value={significant_stats[k][1]:.3f})")
```

```
Superbowl winning teams showed statistically significant differences in the following stats:
offense passing Cmp % (p-value=0.002)
offense passing Yds/Att (p-value=0.000)
offense passing Pass Yds (p-value=0.008)
offense passing TD (p-value=0.000)
offense passing Rate (p-value=0.000)
offense passing 1st (p-value=0.012)
offense passing 1st% (p-value=0.007)
offense passing Sck (p-value=0.031)
offense passing SckY (p-value=0.008)
offense rushing TD (p-value=0.001)
offense rushing Rush 1st (p-value=0.032)
offense receiving Yds (p-value=0.008)
offense receiving TD (p-value=0.000)
offense receiving Rec 1st (p-value=0.012)
offense scoring Rsh TD (p-value=0.001)
offense scoring Rec TD (p-value=0.000)
offense scoring Tot TD (p-value=0.000)
offense downs Rec 1st (p-value=0.012)
offense downs Rush 1st (p-value=0.032)
defense passing Cmp % (p-value=0.002)
defense passing Yds/Att (p-value=0.000)
defense passing Pass Yds (p-value=0.008)
defense passing TD (p-value=0.000)
defense passing Rate (p-value=0.000)
defense passing 1st (p-value=0.012)
defense passing 1st% (p-value=0.007)
defense passing Sck (p-value=0.031)
defense passing SckY (p-value=0.008)
defense rushing TD (p-value=0.001)
defense rushing Rush 1st (p-value=0.032)
defense receiving Yds (p-value=0.008)
defense receiving TD (p-value=0.000)
defense receiving Rec 1st (p-value=0.012)
defense scoring Rsh TD (p-value=0.001)
defense scoring Rec TD (p-value=0.000)
defense scoring Tot TD (p-value=0.000)
defense tackles Sck (p-value=0.030)
defense downs Rec 1st (p-value=0.012)
defense downs Rush 1st (p-value=0.032)
special-teams field-goals FGM (p-value=0.022)
special-teams field-goals Att (p-value=0.039)
special-teams scoring Rsh TD (p-value=0.001)
special-teams scoring Rec TD (p-value=0.000)
special-teams scoring Tot TD (p-value=0.000)
special-teams kickoffs KO (p-value=0.000)
special-teams kickoff-returns Ret (p-value=0.021)
special-teams punts Net Yds (p-value=0.001)
special-teams punts Punts (p-value=0.000)
special-teams punts Yds (p-value=0.001)
special-teams punts Dn (p-value=0.015)
special-teams punts FC (p-value=0.039)
special-teams punts Ret (p-value=0.001)
special-teams punts RetY (p-value=0.024)
```

```
special-teams punt-returns Ret (p-value=0.004)
special-teams punt-returns Yds (p-value=0.024)
```

Visualizations

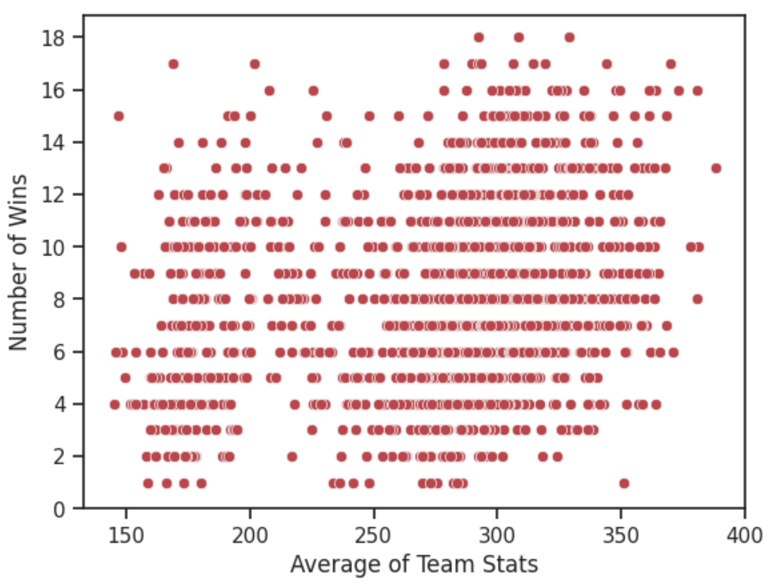
Visualization 1: Number of Season wins vs Average player stats

After our Machine Learning and statistical analysis we wondered if there was any correlation between the number of wins a team had and their end of year offense statistics.

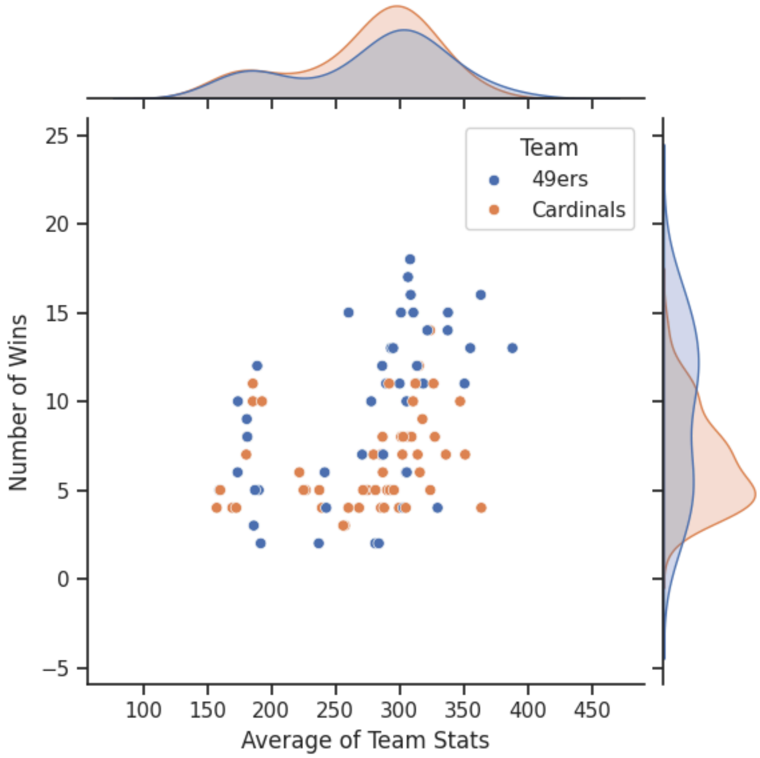
On a large scale this visualization initially does not seem useful;however there is a general upward trends seen when examining some teams individually such as the 49ers.

Interestly, teams that historically have done well: such as the 49ers and Patriots show a vague positive relationship, but the teams that are not historically poor performing (Ex: Cardinals and Browns) show no correlative increase between team statistics and number of games won

```
##Code here
pd.pivot_table(matchup_data,values="Team 1",index=["Year","Winner/tie"],aggfunc="count")

table = matchup_data[["Year","Winner/tie","Team 1"]].groupby(["Year","Winner/tie"]).count()

stat_means = []
for (year, team), row in table.iterrows():
  if str(year) + " "+team in team_data_dict:
    numwins = row["Team 1"]
    teamstats = team_data_dict[str(year) + " "+team][1:] #Gets measure of team's stats from dictionary
    stat_means.append([numwins,teamstats.mean(),team])

wins_vs_stats_df = pd.DataFrame(stat_means,columns=["Number of Wins","Average of Team Stats","Team"])

def scatter(df):
  sns.set_theme(style="ticks")
  scatter = sns.scatterplot(data = df,x="Average of Team Stats",y="Number of Wins",color="#b9484e")
  scatter.set(yticks=np.arange(0,19,2))
  plt.show()
scatter(wins_vs_stats_df)
```



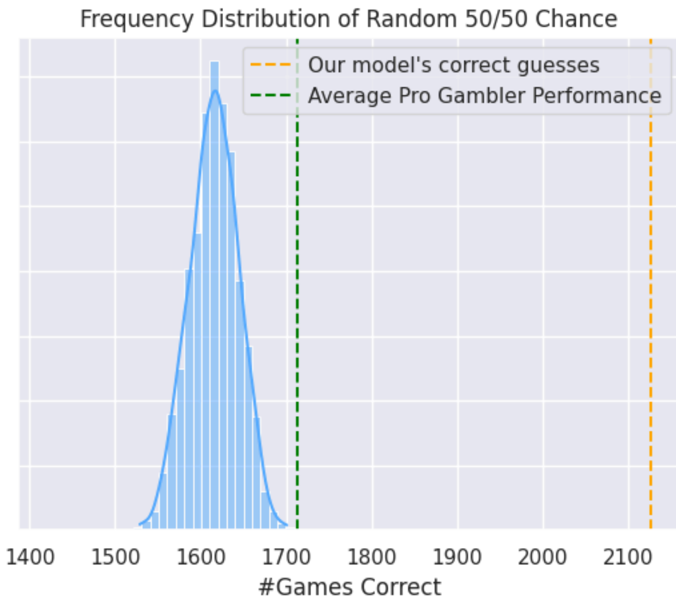

```
sns.set_theme(style='ticks') # Remove grid to make it look cleaner
scatter_stats = wins_vs_stats_df[(wins_vs_stats_df["Team"] == "49ers")| (wins_vs_stats_df["Team"]=="Cardinals")]
sns.jointplot(data=scatter_stats, x="Average of Team Stats", y="Number of Wins", hue="Team")
plt.savefig("TeamComparison.png")
plt.show()
```



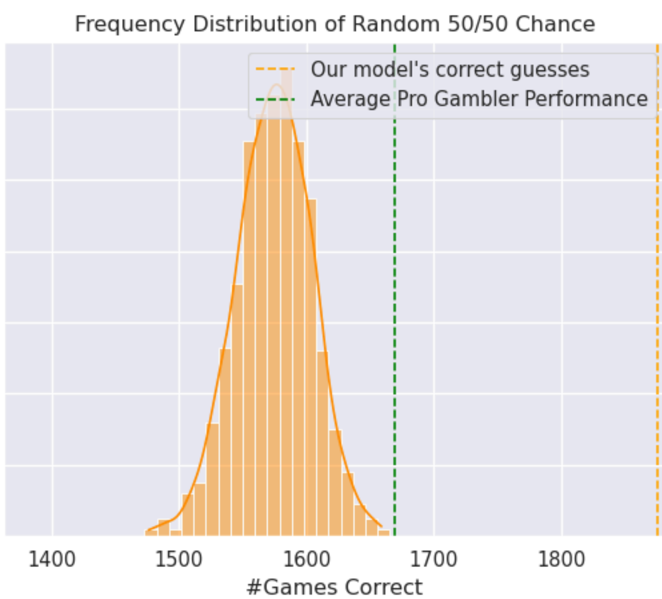
Visualization 2: Distribution of 50/50 random chance model vs our model in prediction of Game Winners

Displayed for both current-year-based and previous-year-based model

```
def show_likelihood(effectiveness,ntrials,name,experiments = 1000,filename="img.csv"):
    if name == "Current Year Model":
        bar_color = "#55AAFF"
    else:
        bar_color = "darkorange"
    probabilities = []
    for experiment in range(experiments):
      repetitions = ntrials
      #list comprehension generate ntrials random numbers
      random_integers = [random.randint(0, 1) for _ in range(repetitions)]
      probabilities.append(sum(random_integers))
    sns.set_style("darkgrid")
    hist = sns.histplot(data=probabilities,kde=True,bins=np.linspace(0.44*ntrials,0.59*ntrials,50),color=bar_color)
    plt.axvline(x=effectiveness*ntrials, color="orange", linestyle='--',label="Our model's correct guesses")
    plt.axvline(x=0.53*ntrials,color="green",linestyle="--",label="Average Pro Gambler Performance")
    hist.set(xlabel="#Games Correct",ylabel = "",title="Frequency Distribution of Random 50/50 Chance",yticklabels=[])
    plt.legend(loc="upper right")
    sns.set_context("paper",font_scale = 1.2)
    plt.savefig(filename)
    plt.show()

show_likelihood(effectiveness,len(data_test),"Current Year Model",filename="CurrentYear.png")
```




```
show_likelihood(effectiveness_ly,len(data_test_ly),"Last Year Model",filename="LastYear.png")
```

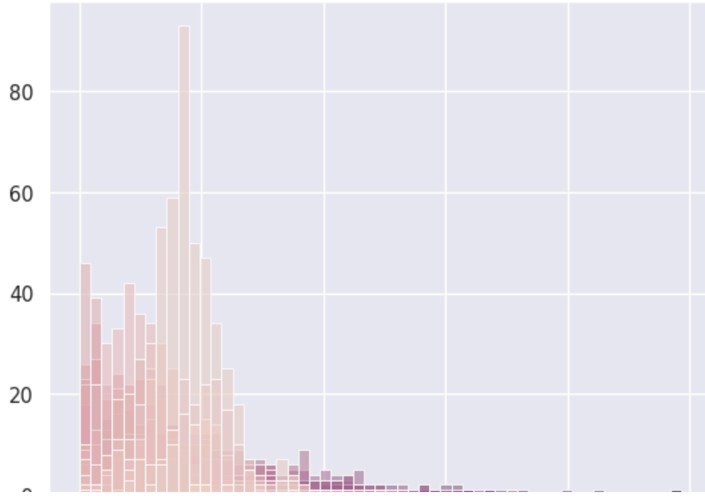


Visualization 3: Distribution of Residuals from Score Predictor

The color of the bars is a gardient on a scale of the actual difference in score: larger actual score differences are darker, and vice versa.

Meaningfully this graph shows that the model got worse (residuals increased) as actualized scores increased -- higher actualized scores lead to high residuals in score difference estimation.

```
df_showcase = pd.DataFrame(data={"Actual Score Diff":lm_label_test,"Predicted Score Diff":predicted_scores})
df_showcase["Abs Residuals"] = abs(df_showcase["Predicted Score Diff"] - df_showcase["Actual Score Diff"])


res_hist = sns.histplot(data=df_showcase,x="Abs Residuals",hue="Actual Score Diff")
res_hist.set(ylabel = "")
#Line from stackoverflow to remove the visually overwhelming legend that autopopulates from the hues
plt.legend([],[], frameon=False)
plt.savefig("ResDistribution.png")
plt.show()
```



Visualization 4: Top and Bottom 5 Feature Importances to Predict Super Bowl Winners

Could be interpreted as what stats matter most?

```
def create_bar_chart(n,df,report_mode = "top and bottom",dark_mode = False):
    sns.set_context("paper")
    top_n = df.nlargest(n,"Importances")
    bottom_n = df.nsmallest(n,"Importances")
    top_and_bottom_n = pd.concat((top_n,bottom_n))


    sns.set_theme()
    if report_mode == "top and bottom":
        report = top_and_bottom_n
    elif report_mode == "top":
        report = top_n
    else:
        report = bottom_n

    report.sort_values("Importances",ascending = False,inplace= True)
    hst = sns.barplot(report,y="Features",hue="Features",x="Importances")
    hst.set(xlabel="Feature Importance",xticks=np.arange(0,0.02,0.005))

    if dark_mode == True:
        hst.tick_params(axis='x', colors='white')
        hst.tick_params(axis='y', colors='white')
        hst.set_xlabel("Feature Importances",color="white")
        # hst.set_ylabel(None)
    plt.title("Features Importance of SuperBowl ML Model",fontdict={"fontweight":"bold"},loc="right",pad=15)
    plt.tight_layout()
    plt.savefig("FeatureImportances.png")
    plt.show()

create_bar_chart(n = 5,df=features_df,report_mode="top and bottom",dark_mode = False)
```