index

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Data Analytics on Player Performance in Major League Baseball

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[1]:
```
import sqlite3
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import matplotlib.ticker as mticker
import requests
from bs4 import BeautifulSoup
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from scipy.stats import pearsonr
import seaborn

pd.set_option('display.max_columns', None)
```

0.0.1 Introduction

Baseball is a game of scoring runs. There's a reason that the team with the most runs at the end of a game wins. Major Leage Baseball (MLB), especially in the past 20 years has seen an uptick of scoring, as the game has become more and more about offensive firepower rather than pitchers completely dominating the hitters. A team's front office and everyone that is included into the decision making behind roster formations need to be able to analyze player performance and determine which players will score them the most runs, and in effect, help them win the most games. In this project, we will analyze which offensive metrics are most closely related to scoring runs, using team data between 2011-2021. Then, based on our findings, we will then create a predictive model that will extrapolate which players are most likely to perform well with regards to the metrics we deem to important in driving in runs.

0.0.2 Part I: Scraping Team Data for 2000-2021 Seasons

The first thing we are going to do is analyze a variety of offensive metrics and their relation to producing runs on offense. In order to do this, we will need to scrape team data from FanGraphs (https://www.fangraphs.com/). We will gather basic, advanced, and batted ball data that each team accumulated over each season for the last decade. Below are two functions that scrape the data from the website.

The following function scrapes the table that is located at the specified url, and creates a dataframe using pandas from the table that is scraped. The additional year and team arguments allow us to add respective columns based on which team each row is for.

[109]:
```
def scraping_FanGraphs(url, year, team):
    # Extracting text from webpage
    html = requests.get(url).text

    # Parsing the text into html code
    soup = BeautifulSoup(html,"html.parser")

    # Finding the table in the html code - we are searching by the id of the␣
 ↪table
    table = soup.find("table", attrs={"class": "rgMasterTable"})


    table_data = table.tbody.find_all("tr")

    dataset = []
    for tr in table_data:
        temp = ()
        for td in tr.find_all("td"):
            if '\xa0' in td.text:
                temp += ('0.0',)
            else:
                temp += (td.text,)
        dataset.append(temp)

    stats = pd.DataFrame(data = dataset)
    stats = stats.replace(to_replace=" NULL",value=0)

    table_header = table.thead.find_all("tr")
    columns = []
    count = 0
    for tr in table_header:
        if count == 1:
            th = tr.find_all("th")
            for a in th:
                columns.append(a.text)
        count = 1
    stats.columns = columns
    stats = stats.assign(Year = year)
    if team != 'None':
        stats = stats.assign(Team = team)

    return stats
```

The function below simply compiles a list of urls based on which FanGraphs page we want to visit.

Since the basic, advanced, and batted ball statistics are on separate urls, we have an argument, stat, which determines which url we are looking to scrape from. This function will be used to create urls for all 30 MLB teams for the years that are specified (2011-2021). The page argument is used because some teams have too many players to fit on one page, so the remaining are placed on separate pages. As you can see, we wil use this function for both team and player scraping.

[127]:
```python
def get_urls(team, year, page, stat):

#####################################################################
#                        Player Stats Urls                          #
#####################################################################

    if stat == 'player_standard':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=0&season=' + str(year[1]) +␣
 ↪'&month=0&season1=' + str(year[0]) + '&ind=1' \
            '&team='+ str(team)␣
 ↪+'&rost=0&age=0&filter=&players=0&startdate=&enddate=&page=' + str(page) +␣
 ↪'_50'

    if stat == 'player_advanced':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=1&season=' + str(year[1]) +␣
 ↪'&month=0&season1=' + str(year[0]) + '&ind=1' \
            '&team='+ str(team)␣
 ↪+'&rost=0&age=0&filter=&players=0&startdate=&enddate=&page=' + str(page) +␣
 ↪'_50'

    if stat == 'player_batted':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=2&season=' + str(year[1]) +␣
 ↪'&month=0&season1=' + str(year[0]) + '&ind=1' \
            '&team='+ str(team)␣
 ↪+'&rost=0&age=0&filter=&players=0&startdate=&enddate=&page=' + str(page) +␣
 ↪'_50'

    if stat == 'player_statcast':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=24&season=' + str(year[1]) +␣
 ↪'&month=0&season1=' + str(year[0]) + '&ind=1' \
            '&team='+ str(team)␣
 ↪+'&rost=0&age=0&filter=&players=0&startdate=&enddate=&page=' + str(page) +␣
 ↪'_50'

    if stat == 'player_plate_discipline':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
```

```
            '&lg=all&qual=0&type=5&season=' + str(year[1]) +␣
↪'&month=0&season1=' + str(year[0]) + '&ind=1' \
            '&team='+ str(team)␣
↪+'&rost=0&age=0&filter=&players=0&startdate=&enddate=&page=' + str(page) +␣
↪'_50'

######################################################################
#                        Team Stats Urls                             #
######################################################################

    if stat == 'team':
        url = 'https://www.fangraphs.com/leaders.aspx?
↪pos=all&stats=bat&lg=all&qual=0&type=0&season=' + str(year) +  \
            '&month=0&season1=' + str(year) +␣
↪'&ind=0&team=0,ts&rost=0&age=0&filter=&players=0&startdate=' + str(year) +␣
↪'-01-01&enddate=' + str(year) + '-12-31'

    if stat == 'team_advanced':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=1&season=' + str(year) + '&month=0&season1=' +␣
↪str(year) + '&ind=0&team=0,'\
            'ts&rost=0&age=0&filter=&players=0&startdate=' + str(year) +␣
↪'-01-01&enddate=' + str(year) + '-12-31'

    if stat == 'team_batted':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=2&season=' + str(year) + '&month=0&season1=' +␣
↪str(year) + '&ind=0&'\
            'team=0,ts&rost=0&age=0&filter=&players=0&startdate=' + str(year) +␣
↪'-01-01&enddate=' + str(year) + '-12-31'

    if stat == 'team_statcast':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=24&season=' + str(year) + '&month=0&season1='␣
↪+ str(year) + '&ind=0' \
            '&team=0,ts&rost=0&age=0&filter=&players=0&startdate=' + str(year)␣
↪+ '-01-01&enddate=' + str(year) + '-12-31'

    if stat == 'team_plate_discipline':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats=bat' \
            '&lg=all&qual=0&type=5&season=' + str(year) + '&month=0&season1=' +␣
↪str(year) + '&ind=0' \
            '&team=0,ts&rost=0&age=0&filter=&players=0&startdate=' + str(year)␣
↪+ '-01-01&enddate=' + str(year) + '-12-31'
    return url
```

Scraping Team Data From Fangraphs Here we are actually compiling the web scrape results and merging all resulting dataframes into one overall dataframe called team_batting.

[13]:
```
years = [i for i in range(2000,2022)]

######################################################################
#               Creating a Dataframe for Team Stats                  #
######################################################################

count = 0
for year in years:
    # Since we are scraping for team, we don't need to specify a team or page␣
 ↪(those are arguments for player scraping)
    url = get_urls('None', year, 'None', 'team')
    if count == 0:
        team_batting = scraping_FanGraphs(url, year, 'None')
        # In 2011, Miami Marlins were the Florida Marlins (they changed to␣
 ↪Miami in 2012)
        team_batting['Team'] = team_batting['Team'].replace({'FLA':'MIA'},␣
 ↪regex = True)
        count = 1
    else:
        team_batting = pd.concat([team_batting, scraping_FanGraphs(url, year,␣
 ↪'None')])


team_batting = team_batting.drop_duplicates()
team_batting = team_batting.reset_index(drop=True)
team_batting = team_batting[['Year', 'Team', 'AB', 'PA', 'AVG', 'H', '1B',␣
 ↪'2B', \
                             '3B', 'HR', 'R', 'RBI', 'BB', 'IBB', 'SO', 'HBP', \
                             'SF', 'SH', 'GDP', 'SB', 'CS']]

######################################################################
#            Adding Advanced Batting Stats to Dataframe              #
######################################################################

count = 0
for year in years:
    # Since we are scraping for team, we don't need to specify a team or page␣
 ↪(those are arguments for player scraping)
    url = get_urls('None', year, 'None', 'team_advanced')
    if count == 0:
        team_advanced_batting = scraping_FanGraphs(url, year, 'None')
        # In 2011, Miami Marlins were the Florida Marlins (they changed to␣
 ↪Miami in 2012)
```

```
        team_batting['Team'] = team_batting['Team'].replace({'FLA':'MIA'},␣
↪regex = True)
        count = 1
    else:
        team_advanced_batting = pd.concat([team_advanced_batting,␣
↪scraping_FanGraphs(url, year, 'None')])


team_advanced_batting = team_advanced_batting.drop_duplicates()
team_advanced_batting = team_advanced_batting.reset_index(drop=True)
team_advanced_batting = team_advanced_batting[['Year', 'Team', 'PA', 'BB%',␣
↪'K%', \
                                               'BB/K', 'AVG', 'OBP', 'SLG',␣
↪'OPS', 'ISO', \
                                               'Spd', 'BABIP', 'UBR', 'wGDP',␣
↪'wSB', 'wRC', \
                                               'wRAA', 'wOBA', 'wRC+']]

# Merge data into team batting dataframe
team_batting = pd.merge(team_batting, team_advanced_batting, on = ['Year',␣
↪'Team', 'PA', 'AVG'])

######################################################################
#             Adding Batted Ball Stats to Dataframe                  #
######################################################################

count = 0
for year in years:
    # Since we are scraping for team, we don't need to specify a team or page␣
↪(those are arguments for player scraping)
    url = get_urls('None', year, 'None', 'team_batted')
    if count == 0:
        team_advanced_batting = scraping_FanGraphs(url, year, 'None')
        # In 2011, Miami Marlins were the Florida Marlins (they changed to␣
↪Miami in 2012)
        team_batting['Team'] = team_batting['Team'].replace({'FLA':'MIA'},␣
↪regex = True)
        count = 1
    else:
        team_advanced_batting = pd.concat([team_advanced_batting,␣
↪scraping_FanGraphs(url, year, 'None')])


team_advanced_batting = team_advanced_batting.drop_duplicates()
team_advanced_batting = team_advanced_batting.reset_index(drop=True)
```

```
team_advanced_batting = team_advanced_batting[['Year', 'Team', 'BABIP', 'GB/
↪FB', \
                                              'LD%', 'GB%', 'FB%', 'IFFB%',␣
↪'HR/FB', \
                                              'IFH', 'IFH%', 'BUH', 'BUH%',␣
↪'Pull%', \
                                              'Cent%', 'Oppo%', 'Soft%',␣
↪'Med%', 'Hard%']]

# Merge data into team batting dataframe
team_batting = pd.merge(team_batting, team_advanced_batting, on = ['Year',␣
↪'Team', 'BABIP'])

######################################################################
#               Adding Statcast Data to Dataframe                    #
######################################################################

count = 0
for year in years:
    # Since we are scraping for team, we don't need to specify a team or page␣
↪(those are arguments for player scraping)
    url = get_urls('None', year, 'None', 'team_statcast')
    if count == 0:
        team_advanced_batting = scraping_FanGraphs(url, year, 'None')
        # In 2011, Miami Marlins were the Florida Marlins (they changed to␣
↪Miami in 2012)
        team_batting['Team'] = team_batting['Team'].replace({'FLA':'MIA'},␣
↪regex = True)
        count = 1
    else:
        team_advanced_batting = pd.concat([team_advanced_batting,␣
↪scraping_FanGraphs(url, year, 'None')])


team_advanced_batting = team_advanced_batting.drop_duplicates()
team_advanced_batting = team_advanced_batting.reset_index(drop=True)
team_advanced_batting = team_advanced_batting[['Year', 'Team', 'EV', 'LA',␣
↪'Barrel%', 'HardHit%']]

# Merge data into team batting dataframe
team_batting = pd.merge(team_batting, team_advanced_batting, on = ['Year',␣
↪'Team'])

######################################################################
#           Adding Plate Discipline Data to Dataframe                #
######################################################################
```

```
count = 0
for year in years:
    # Since we are scraping for team, we don't need to specify a team or page␣
 ↪(those are arguments for player scraping)
    url = get_urls('None', year, 'None', 'team_plate_discipline')
    if count == 0:
        team_advanced_batting = scraping_FanGraphs(url, year, 'None')
        # In 2011, Miami Marlins were the Florida Marlins (they changed to␣
 ↪Miami in 2012)
        team_batting['Team'] = team_batting['Team'].replace({'FLA':'MIA'},␣
 ↪regex = True)
        count = 1
    else:
        team_advanced_batting = pd.concat([team_advanced_batting,␣
 ↪scraping_FanGraphs(url, year, 'None')])


team_advanced_batting = team_advanced_batting.drop_duplicates()
team_advanced_batting = team_advanced_batting.reset_index(drop=True)
team_advanced_batting = team_advanced_batting[['Year', 'Team', 'O-Swing%',␣
 ↪'Z-Swing%', 'Swing%', \
                                               'O-Contact%', 'Z-Contact%',␣
 ↪'Contact%', 'Zone%', \
                                               'F-Strike%', 'SwStr%', 'CStr%',␣
 ↪'CSW%']]

# Merge data into team batting dataframe
team_batting = pd.merge(team_batting, team_advanced_batting, on = ['Year',␣
 ↪'Team'])

######################################################################
#               Adding Wins and Losses to Dataframe                  #
######################################################################

teams_table = pd.read_csv('tables/Teams.csv')
teams_table = teams_table[teams_table.yearID > 1999]

teams_table = teams_table.rename(columns = {'yearID':'Year','franchID':'Team'})

# Taking only the necessary columns
teams_table = teams_table[['Year', 'Team', 'W', 'L']]

data = []
for team_index, team_row in teams_table.iterrows():
    for my_team_index, my_team_row in team_batting.iterrows():
```

```
        if my_team_row['Team'] == team_row['Team'] and my_team_row['Year'] ==␣
↪team_row['Year']:
            team = list(my_team_row)
            team.append(team_row['W'])
            team.append(team_row['L'])
            team = tuple(team)
            data.append(team)

# Creating a dataframe from the list of tuples above
team_batting = pd.DataFrame(data, columns=['Year', 'Team', 'AB', 'PA', 'AVG', \
                                           'H', '1B', '2B', '3B', 'HR', 'R',␣
↪'RBI',\
                                           'BB', 'IBB', 'SO', 'HBP', 'SF',␣
↪'SH', 'GDP',\
                                           'SB', 'CS', 'BB%', 'K%', 'BB/K',␣
↪'OBP', 'SLG',\
                                           'OPS', 'ISO', 'Spd', 'BABIP', 'UBR',␣
↪'wGDP', \
                                           'wSB', 'wRC', 'wRAA', 'wOBA',␣
↪'wRC+', 'GB/FB',\
                                           'LD%', 'GB%', 'FB%', 'IFFB%', 'HR/
↪FB', 'IFH', \
                                           'IFH%', 'BUH', 'BUH%', 'Pull%',␣
↪'Cent%', 'Oppo%',\
                                           'Soft%', 'Med%', 'Hard%', 'EV',␣
↪'LA', 'Barrel%', 'HardHit%', \
                                           'O-Swing%', 'Z-Swing%', 'Swing%',␣
↪'O-Contact%', 'Z-Contact%', \
                                           'Contact%', 'Zone%', 'F-Strike%',␣
↪'SwStr%', 'CStr%', 'CSW%', 'W', 'L'])

# Removing the % in the values so that they can be used as numbers
team_batting['BB%'] = team_batting['BB%'].replace({'\%':''}, regex = True)
team_batting['K%'] = team_batting['K%'].replace({'\%':''}, regex = True)
team_batting['LD%'] = team_batting['BB%'].replace({'\%':''}, regex = True)
team_batting['GB%'] = team_batting['GB%'].replace({'\%':''}, regex = True)
team_batting['FB%'] = team_batting['FB%'].replace({'\%':''}, regex = True)
team_batting['HR/FB'] = team_batting['HR/FB'].replace({'\%':''}, regex = True)
team_batting['Pull%'] = team_batting['Pull%'].replace({'\%':''}, regex = True)
team_batting['Cent%'] = team_batting['Cent%'].replace({'\%':''}, regex = True)
team_batting['Oppo%'] = team_batting['Oppo%'].replace({'\%':''}, regex = True)
team_batting['Soft%'] = team_batting['Soft%'].replace({'\%':''}, regex = True)
team_batting['Med%'] = team_batting['Med%'].replace({'\%':''}, regex = True)
team_batting['Hard%'] = team_batting['Hard%'].replace({'\%':''}, regex = True)
team_batting['Barrel%'] = team_batting['Barrel%'].replace({'\%':''}, regex =␣
↪True)
```

```
team_batting['HardHit%'] = team_batting['HardHit%'].replace({'\%':''}, regex =␣
    ↪True)
team_batting['O-Swing%'] = team_batting['O-Swing%'].replace({'\%':''}, regex =␣
    ↪True)
team_batting['Z-Swing%'] = team_batting['Z-Swing%'].replace({'\%':''}, regex =␣
    ↪True)
team_batting['Swing%'] = team_batting['Swing%'].replace({'\%':''}, regex = True)
team_batting['O-Contact%'] = team_batting['O-Contact%'].replace({'\%':''},␣
    ↪regex = True)
team_batting['Z-Contact%'] = team_batting['Z-Contact%'].replace({'\%':''},␣
    ↪regex = True)
team_batting['Contact%'] = team_batting['Contact%'].replace({'\%':''}, regex =␣
    ↪True)
team_batting['Zone%'] = team_batting['Zone%'].replace({'\%':''}, regex = True)
team_batting['F-Strike%'] = team_batting['F-Strike%'].replace({'\%':''}, regex␣
    ↪= True)
team_batting['SwStr%'] = team_batting['SwStr%'].replace({'\%':''}, regex = True)
team_batting['CStr%'] = team_batting['CStr%'].replace({'\%':''}, regex = True)
team_batting['CSW%'] = team_batting['CSW%'].replace({'\%':''}, regex = True)



# Making all values numeric if they have only numbers
team_batting = team_batting.apply(pd.to_numeric, errors='ignore')

# Replace zero values with NaN (because some years don't have data for certain␣
    ↪newer stats
team_batting['EV'] = team_batting['EV'].replace(0.0, np.nan)
team_batting['LA'] = team_batting['LA'].replace(0.0, np.nan)
team_batting['Barrel%'] = team_batting['Barrel%'].replace(0.0, np.nan)
team_batting['HardHit%'] = team_batting['HardHit%'].replace(0.0, np.nan)

# Reordering columns
team_batting = team_batting[['Year', 'Team', 'W', 'L', 'AB', 'PA', 'AVG', \
                             'H', '1B', '2B', '3B', 'HR', 'R', 'RBI', \
                             'BB', 'IBB', 'SO', 'HBP', 'SF', 'SH', 'GDP', \
                             'SB', 'CS', 'BB%', 'K%', 'BB/K', 'OBP', 'SLG', \
                             'OPS', 'ISO', 'BABIP', 'wOBA', 'wRC+', 'GB/FB', \
                             'LD%', 'GB%', 'FB%', 'HR/FB', 'EV', 'LA',␣
    ↪'Barrel%', \
                             'HardHit%', 'O-Swing%', 'Z-Swing%', 'Swing%',␣
    ↪'O-Contact%', 'Z-Contact%', 'Contact%']]
team_batting
```

[13]:

```
     Year Team   W   L    AB    PA    AVG     H    1B   2B  3B   HR    R  \
0    2002  ANA  99  63  5678  6327  0.282  1603  1086  333  32  152  851
```

1	2002	ARI	98	64	5508	6318	0.267	1471	982	283	41	165	819
2	2002	ATL	101	59	5495	6224	0.260	1428	959	280	25	164	708
3	2002	BAL	67	95	5491	6096	0.246	1353	850	311	27	165	667
4	2002	BOS	93	69	5640	6332	0.277	1560	1002	348	33	177	859
..	…	…	…	…	…	…	…	…	…	…	..	…	…
541	2021	SFG	107	55	5462	6196	0.249	1360	823	271	25	241	804
542	2021	STL	90	72	5351	6001	0.244	1303	822	261	22	198	706
543	2021	TEX	60	102	5405	5943	0.232	1254	838	225	24	167	625
544	2021	TOR	91	71	5476	6070	0.266	1455	895	285	13	262	846
545	2021	WSN	65	97	5385	6113	0.258	1388	914	272	20	182	724

	RBI	BB	IBB	SO	HBP	SF	SH	GDP	SB	CS	BB%	K%	BB/K	OBP	\
0	811	462	42	805	74	64	49	105	117	51	7.3	12.7	0.57	0.341	
1	783	643	58	1016	50	53	62	130	92	46	10.2	16.1	0.63	0.346	
2	669	558	68	1028	54	49	67	147	76	39	9.0	16.5	0.54	0.331	
3	636	452	25	993	64	49	40	128	110	48	7.4	16.3	0.46	0.309	
4	810	545	39	944	72	53	22	139	80	28	8.6	14.9	0.58	0.345	
..	…	…	…	…	…	..	..	…	…	..	…	…	…	…	
541	768	602	45	1461	64	30	36	117	66	14	9.7	23.6	0.41	0.329	
542	678	478	32	1341	86	44	40	99	89	22	8.0	22.3	0.36	0.313	
543	598	433	10	1381	58	31	16	113	106	29	7.3	23.2	0.31	0.294	
544	816	496	14	1218	51	35	10	112	81	20	8.2	20.1	0.41	0.330	
545	686	573	43	1303	84	31	38	158	56	26	9.4	21.3	0.44	0.337	

	SLG	OPS	ISO	BABIP	wOBA	wRC+	GB/FB	LD%	GB%	FB%	HR/FB	\
0	0.433	0.773	0.150	0.303	0.336	105	1.04	7.3	39.4	38.1	8.2	
1	0.423	0.769	0.156	0.298	0.335	97	1.36	10.2	45.2	33.2	11.1	
2	0.409	0.741	0.150	0.290	0.322	94	1.39	9.0	46.3	33.2	11.1	
3	0.403	0.712	0.157	0.271	0.311	90	1.05	7.4	41.0	39.2	9.4	
4	0.444	0.789	0.168	0.302	0.343	107	1.22	8.6	43.1	35.4	10.6	
..	…	…	…	…	…	…	…	…	…	…	…	
541	0.440	0.769	0.191	0.295	0.329	108	1.03	9.7	39.7	38.5	15.6	
542	0.412	0.725	0.168	0.287	0.312	97	1.04	8.0	40.5	38.9	12.6	
543	0.375	0.670	0.143	0.280	0.291	84	1.34	7.3	46.4	34.6	12.0	
544	0.466	0.797	0.200	0.296	0.340	112	1.04	8.2	40.4	38.8	15.8	
545	0.417	0.754	0.159	0.307	0.326	101	1.54	9.4	47.4	30.8	14.5	

	EV	LA	Barrel%	HardHit%	O-Swing%	Z-Swing%	Swing%	O-Contact%	\
0	NaN	NaN	NaN	NaN	18.1	69.9	47.1	55.1	
1	NaN	NaN	NaN	NaN	15.6	67.6	43.7	46.6	
2	NaN	NaN	NaN	NaN	17.1	72.4	47.4	47.7	
3	NaN	NaN	NaN	NaN	18.9	70.8	47.3	52.5	
4	NaN	NaN	NaN	NaN	17.8	70.7	46.4	49.0	
..	…	…	…	…	…	…	…	…	
541	88.7	14.8	9.3	38.7	28.2	68.8	45.6	62.5	
542	88.7	14.0	7.9	37.2	31.5	68.2	47.0	64.2	
543	87.9	10.9	6.6	35.6	32.6	68.8	47.9	64.1	

```
544  90.3  13.6       9.7       42.2       31.9       72.5     48.8          63.3
545  88.6   9.5       6.9       39.2       29.2       68.0     45.7          62.7

     Z-Contact%  Contact%
0          88.3      82.7
1          86.3      79.8
2          84.6      78.6
3          87.1      80.8
4          87.6      80.8
..          …        …
541        84.6      76.7
542        84.4      76.6
543        83.9      76.1
544        86.7      77.8
545        86.0      77.4

[546 rows x 48 columns]
```

Correlation Between Scoring Runs and Various Batting Metrics Since the team that has more runs wins the game, run are directly correlated to winning games. Obviously, that is a generic statement that can have some nuance; of course, a team that scores a lot of runs but gives up even more runs, will lose games, so really a team's Run%, Runs Scored / (Runs Scored + Runs Scored), is more directly related to winning, but we aren't worried about defense for this exercise. Below, we are going to try to find the offensive metric(s) that best correlate with scoring runs, because scoring runs wins games, to an extent. We will plot the important metrics, described below, against a team's run total and find the correlation between the datapoints. This will show which stat is most correlated to scoring runs, and thus the stat that is likely important in terms of helping a team win games. Below are the metrics that we will be analyzing:

AVG: Batting Average > The percentage of times the batter gets a hit of out of all of his at-bats. (H/AB) **Formula:** H / AB

OBP: On-Base Percentage > The ratio of the sum of the batter's hits, walks, hit by pitches to their number of plate appearances. **Formula:** (H + BB + IBB + HBP) / PA

SLG: Slugging Percentage > The total number of bases a player records per at-bat **Formula:** (1B + 2(2B) + 3(3B) + HR)/AB

OPS: On-Base Plus Slugging Percentage > Measures the ability of a player both to get on base and to hit for power **Formula:** OBP + SLG

wOBA: Weighted On-Base Average > Designed to measure a player's overall offensive contributions per plate appearance **Formula:** (0.69 * NIBB) + (0.719 * HBP) + (0.87 * 1B) + (1.217 * 2B) + (1.529 * 3B) + (1.94 * HR) / (AB + BB - IBB + SF + HBP)

SLOB: Slugging Times On-Base > **Formula:** SLG * OBP

[356]:
```
# 2020 was shortened due to COVID, so only 60 regular season games were played␣
↪meaning less runs were scored,
# so we will ignore that for this exercise
```

```
team = team_batting[team_batting.Year != 2020]

fig, ax = plt.subplots(3, 3)
fig.subplots_adjust(wspace=.25)
fig.set_figheight(25)
fig.set_figwidth(35)
fig.suptitle("Correlation Between Runs Scored and Various Batting Metrics",␣
 ↪fontsize=40)


######################################################################
#       Plotting Correlation Batting Average vs. Runs Scored         #
######################################################################

plt.sca(ax[0,0])
plt.gca().set_title('Batting Average vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Batting Average (AVG)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['AVG'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['AVG'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['AVG'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#          Plotting Correlation Home Runs vs. Runs Scored            #
######################################################################

plt.sca(ax[0,1])
plt.gca().set_title('Home Runs vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Home Runs (HR)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
```

```
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['HR'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['HR'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['HR'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#           Plotting Correlation OBP vs. Runs Scored                 #
######################################################################

plt.sca(ax[0,2])
plt.gca().set_title('On-Base Percentage vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('On-Base Percentage (OBP)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['OBP'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['OBP'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['OBP'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#           Plotting Correlation SLG vs. Runs Scored                 #
######################################################################
```

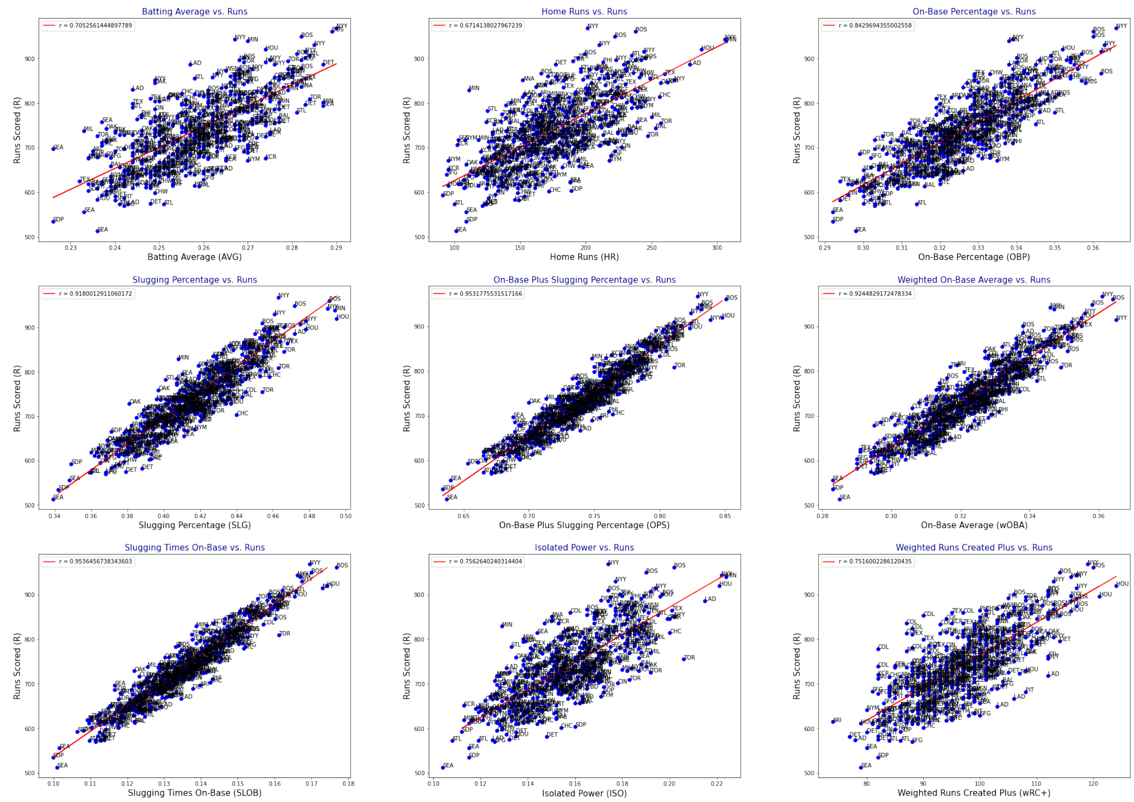
```
plt.sca(ax[1,0])
plt.gca().set_title('Slugging Percentage vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Slugging Percentage (SLG)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['SLG'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['SLG'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0, train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}', color='red')
plt.scatter(team['SLG'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#            Plotting Correlation OPS vs. Runs Scored                #
######################################################################

plt.sca(ax[1,1])
plt.gca().set_title('On-Base Plus Slugging Percentage vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('On-Base Plus Slugging Percentage (OPS)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['OPS'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['OPS'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0, train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
```

```
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['OPS'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#            Plotting Correlation wOBA vs. Runs Scored               #
######################################################################

plt.sca(ax[1,2])
plt.gca().set_title('Weighted On-Base Average vs. Runs', fontsize=15, c =␣
 ↪'DarkBlue')
plt.gca().set_xlabel('On-Base Average (wOBA)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['wOBA'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['wOBA'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['wOBA'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#             Plotting Correlation SLOB vs. Runs Scored              #
######################################################################

plt.sca(ax[2,0])
plt.gca().set_title('Slugging Times On-Base vs. Runs', fontsize=15, c =␣
 ↪'DarkBlue')
plt.gca().set_xlabel('Slugging Times On-Base (SLOB)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['SLOB'], row['R']))
```

```
# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['SLOB'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['SLOB'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#             Plotting Correlation SLOB vs. Runs Scored              #
######################################################################

plt.sca(ax[2,1])
plt.gca().set_title('Isolated Power vs. Runs', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Isolated Power (ISO)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['ISO'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['ISO'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['ISO'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#             Plotting Correlation wRC+ vs. Runs Scored              #
######################################################################
```

```python
plt.sca(ax[2,2])
plt.gca().set_title('Weighted Runs Created Plus vs. Runs', fontsize=15, c =␣
↪'DarkBlue')
plt.gca().set_xlabel('Weighted Runs Created Plus (wRC+)', fontsize=15)
plt.gca().set_ylabel('Runs Scored (R)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['wRC+'], row['R']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['wRC+'].values.reshape(-1,1), team['R'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['wRC+'], team['R'], color = 'blue')
plt.legend(loc = 'upper left')
plt.show()
```

Correlation Between Runs Scored and Various Batting Metrics



A baseball fan with basic knowledge might be under the assumption that a batting average can determine whether or not a player is good at hitting. As the plots have shown, this is not exactly the case. At the end of the day, teams want to score runs, regardless of how they do so. The plots, however, show that out of the five metrics we studied, batting average was the least correlated to scoring runs, with a correlation coefficient of just .705. The metric that had the greatest correlation to scoring runs was Slugging Times On-Base (SLOB), with a marginally close second in On-Base Plus Slugging (OPS), both with a correlaton coefficient of .953.

What we can gather from this is that teams should value a player with a high SLOB and high OPS rather than just a looking at AVG and HR like we used to. A player who has a batting average of .330 but only hits singles and hardly ever walks is going to be less valueable than a player who hits .330 but all of his hits are extra base hits on top of working walks.

Correlation Between Plate Discipline and Scoring Runs Now, with SLOB, we have an offensive metric that we determined to be highly correlated to scoring runs. Next, we want to determine what metrics are going to correlate to having a high SLOB rating. One of the most important skills a player can have, that diligent teams stress on, is plate discipline. In an era where strikeouts are happening at historic rates, having a player with a keen batting eye can be the difference between starting a rally and ending one. The metrics we will look at are below:

BB/K: Walk to Strikeout Rate Rate > The rate at which a batter walks compared to stirking out. A value over 1 means that the batter walks more than he strikes out and a value under 1 means that he strikes out more than he walks.

O-Swing%: Swing Rate on Pitches Outside the Strike Zone > The percentage of pitches that are outside of the strike zone that the batter swings at.

Z-Swing%: Swing Rate on Pitches Inside the Strike Zone > The percentage of pitches that are inside of the strike zone that the batter swings at.

Swing%: Swing Rate > The percentage of pitches that the batter swings at.

[489]:
```
team = team_batting[team_batting.Year != 2020]

fig, ax = plt.subplots(2, 3)
fig.subplots_adjust(wspace=.25)
fig.set_figheight(25)
fig.set_figwidth(35)
fig.suptitle("Effect of Plate Discipline on a Player's Ability to Produce at␣
↪the Plate", fontsize=40)


######################################################################
#             Plotting Correlation Walks vs. SLOB                    #
######################################################################

plt.sca(ax[0,0])
plt.gca().set_title('Walks vs. Slugging Times On-Base', fontsize=15, c =␣
↪'DarkBlue')
plt.gca().set_xlabel('Walks (BB)', fontsize=15)
plt.gca().set_ylabel('Slugging Times On-Base (SLOB)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['BB'], row['SLOB']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['BB'].values.reshape(-1,1), team['SLOB'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['BB'], team['SLOB'], color = 'blue')
plt.legend(loc = 'upper left')
```

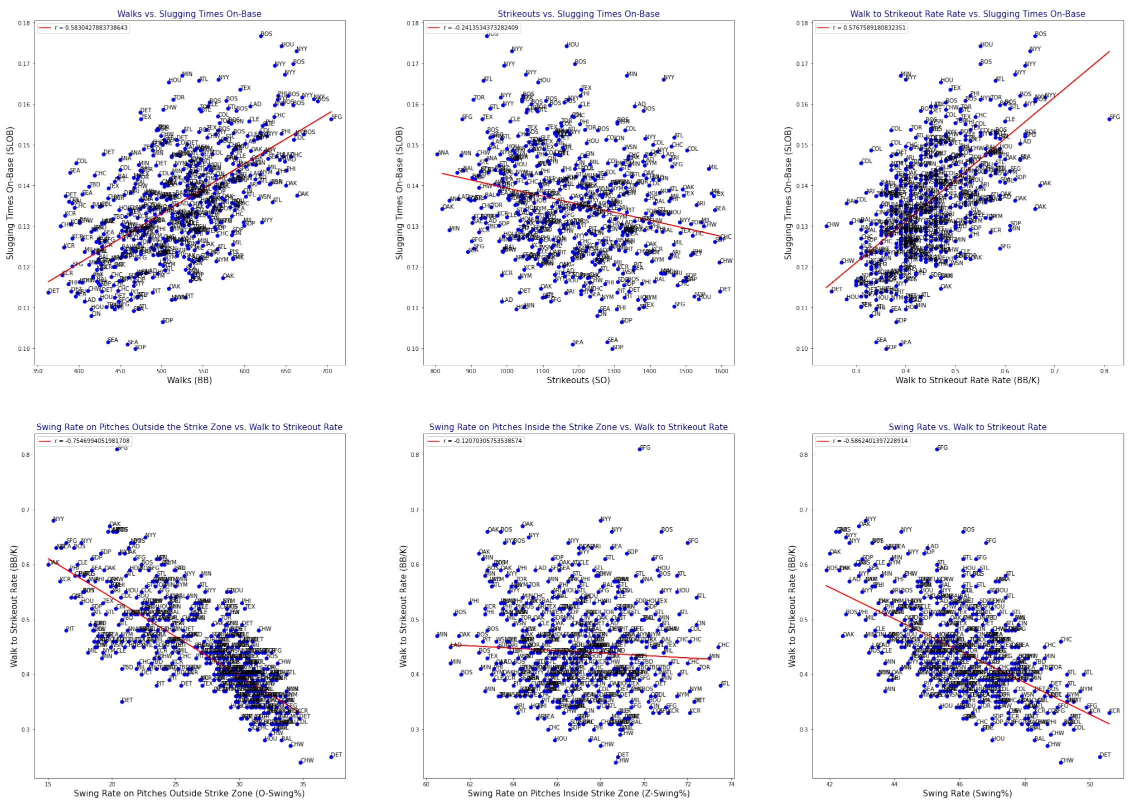
```
#####################################################################
#           Plotting Correlation Strikeouts vs. SLOB                #
#####################################################################

plt.sca(ax[0,1])
plt.gca().set_title('Strikeouts vs. Slugging Times On-Base', fontsize=15, c =␣
 ↪'DarkBlue')
plt.gca().set_xlabel('Strikeouts (SO)', fontsize=15)
plt.gca().set_ylabel('Slugging Times On-Base (SLOB)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['SO'], row['SLOB']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['SO'].values.reshape(-1,1), team['SLOB'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
 ↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
 ↪color='red')
plt.scatter(team['SO'], team['SLOB'], color = 'blue')
plt.legend(loc = 'upper left')

#####################################################################
#               Plotting Correlation BB/K vs. SLOB.                 #
#####################################################################

plt.sca(ax[0,2])
plt.gca().set_title('Walk to Strikeout Rate Rate vs. Slugging Times On-Base',␣
 ↪fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Walk to Strikeout Rate Rate (BB/K)', fontsize=15)
plt.gca().set_ylabel('Slugging Times On-Base (SLOB)', fontsize=15)

team = team.assign(SLOB = team.SLG * team.OBP)
# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['BB/K'], row['SLOB']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
```

```
x, y = team['BB/K'].values.reshape(-1,1), team['SLOB'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['BB/K'], team['SLOB'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#                Plotting Correlation BB/K vs. SLOB.                 #
######################################################################

plt.sca(ax[1,0])
plt.gca().set_title('Swing Rate on Pitches Outside the Strike Zone vs. Walk to␣
↪Strikeout Rate', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Swing Rate on Pitches Outside Strike Zone (O-Swing%)',␣
↪fontsize=15)
plt.gca().set_ylabel('Walk to Strikeout Rate (BB/K)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['O-Swing%'], row['BB/K']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['O-Swing%'].values.reshape(-1,1), team['BB/K'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['O-Swing%'], team['BB/K'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#                Plotting Correlation BB/K vs. SLOB.                 #
######################################################################

plt.sca(ax[1,1])
```

```
plt.gca().set_title('Swing Rate on Pitches Inside the Strike Zone vs. Walk to␣
↪Strikeout Rate', fontsize=15, c = 'DarkBlue')
plt.gca().set_xlabel('Swing Rate on Pitches Inside Strike Zone (Z-Swing%)',␣
↪fontsize=15)
plt.gca().set_ylabel('Walk to Strikeout Rate (BB/K)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['Z-Swing%'], row['BB/K']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['Z-Swing%'].values.reshape(-1,1), team['BB/K'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)

# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['Z-Swing%'], team['BB/K'], color = 'blue')
plt.legend(loc = 'upper left')

######################################################################
#              Plotting Correlation BB/K vs. SLOB.                   #
######################################################################

plt.sca(ax[1,2])
plt.gca().set_title('Swing Rate vs. Walk to Strikeout Rate', fontsize=15, c =␣
↪'DarkBlue')
plt.gca().set_xlabel('Swing Rate (Swing%)', fontsize=15)
plt.gca().set_ylabel('Walk to Strikeout Rate (BB/K)', fontsize=15)

# Add labels for each point
for idx, row in team.iterrows():
    plt.annotate(row['Team'], (row['Swing%'], row['BB/K']))

# Calculate regression line and plot it in the same graph
model = LinearRegression()
x, y = team['Swing%'].values.reshape(-1,1), team['BB/K'].values
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=0,␣
↪train_size=0.3)
model = model.fit(x_train, y_train)
prediction = model.predict(x_test)
```

```
# Plot regression line and scatter the data points on the same axis
plt.plot(x_test, prediction, label = f'r = {pearsonr(x.flatten(), y)[0]}',␣
↪color='red')
plt.scatter(team['Swing%'], team['BB/K'], color = 'blue')
plt.legend(loc = 'upper left')

plt.show()
```

Effect of Plate Discipline on a Player's Ability to Produce at the Plate



As the plots show, a batter's strikeout to walk rate is moderately correlated to a player's ability to produce at the plate, as it has a .577 correlation coefficient. Furthermore, after looking at how plate disicpline effects a batter's strikeout to walk rate, we determined that the correlation between a batter having a low BB/K and a batter swinging at pitches outside of the strike zone is strong. In addition, we also found that the more pitches that a batter swings overall will lead to a decrease in BB/K. Through this, we can conclude that in order for a batter to be productive at the plate, it's important for them to make smart swing decisions, meaning that they should be selective of what pitches to swing at; minimizing the number of pitches that are outside of the strike zone that a batter swings at will be veryu beneficial to improving their BB/K and consequently improving their overall production with the bat in their hands.

0.0.3 Part II: Scraping Player Data for 2011-2021 Seasons

Scraping Standard Player Data From Fangraphs

[111]:
```
pages = [i for i in range(1, 14)]
team_idx = [i for i in range(1, 31)]
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']
urls = []

for team in team_idx:
    for page in pages:
        urls.append((get_urls(team, (2010, 2021), page, 'player_standard'),␣
 ↪teams[team-1]))

count = 0
for url in urls:
    if count == 0:
        player_standard = scraping_FanGraphs(url[0], None, url[1])
        count = 1
    else:
        player_standard = pd.concat([player_standard,␣
 ↪scraping_FanGraphs(url[0], None, url[1])])
player_standard
```

[111]:
```
      #  Season             Name   G  AB  PA  H  1B  2B  3B  HR  R  RBI  BB  IBB  SO  HBP  \
0     1    2018    Juan Graterol   1   1   1  1   1   0   0   0  0    0   0    0   0    0
1     2    2011   Tyler Chatwood  27   3   5  2   2   0   0   0  1    0   0    0   0    0
2     3    2011    Gil Velazquez   4   6   7  3   3   0   0   0  0    1   0    0   0    0
3     4    2011    Ervin Santana  33   2   2  1   1   0   0   0  0    0   0    0   1    0
4     5    2012     Jered Weaver  30   2   3  1   1   0   0   0  1    0   1    0   1    0
..  ...     ...              ...  ..  ..  .. ..  ..  ..  ..  .. ..  ...  ..  ...  ..
19  570    2021     Conner Menez   8   0   0  0   0   0   0   0  0    0   0    0   0    0
20  571    2021    Caleb Baragar  25   2   2  0   0   0   0   0  0    0   0    0   2    0
21  572    2021    Kervin Castro  10   0   0  0   0   0   0   0  0    0   0    0   0    0
22  573    2021  Gregory Santos   3   0   0  0   0   0   0   0  0    0   0    0   0    0
23  574    2021     Camilo Doval  29   0   0  0   0   0   0   0  0    0   0    0   0    0

   SF  SH  GDP  SB  CS    AVG  Year Team
0   0   0    0   0   0  1.000  None  LAA
1   0   2    0   0   0   .667  None  LAA
2   1   0    0   0   0   .500  None  LAA
3   0   0    0   0   0   .500  None  LAA
4   0   0    0   0   0   .500  None  LAA
..  ..  ..  ..  ..  ..    ...   ...  ...
19  0   0    0   0   0   .000  None  SFG
20  0   0    0   0   0   .000  None  SFG
```

```
21  0  0   0  0  0   .000  None  SFG
22  0  0   0  0  0   .000  None  SFG
23  0  0   0  0  0   .000  None  SFG

[18060 rows x 25 columns]
```

Scraping Advanced Player Data From Fangraphs

[125]:
```python
pages = [i for i in range(1, 14)]
team_idx = [i for i in range(1, 31)]
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']
urls = []

for team in team_idx:
    for page in pages:
        urls.append((get_urls(team, (2010, 2021), page, 'player_advanced'),␣
 ↪teams[team-1]))

count = 0
for url in urls:
    if count == 0:
        player_advanced = scraping_FanGraphs(url[0], None, url[1])
        count = 1
    else:
        player_advanced = pd.concat([player_advanced,␣
 ↪scraping_FanGraphs(url[0], None, url[1])])
player_advanced
```

[125]:
```
      #  Season            Name  PA     BB%      K%  BB/K    AVG    OBP    SLG  \
0     1    2015      Jett Bandy   2    0.0%    0.0%  0.00   .500   .500  2.000
1     2    2018   Juan Graterol   1    0.0%    0.0%  0.00  1.000  1.000  1.000
2     3    2013     John Hester   1  100.0%    0.0%  1.00   .000  1.000   .000
3     4    2011  Tyler Chatwood   5    0.0%    0.0%  0.00   .667   .667   .667
4     5    2010     Ryan Budde  11    9.1%   45.5%  0.20   .400   .455   .800
..  …     …             … ..    …     …   …    …    …     …
19  570    2021    Conner Menez   0    0.0%    0.0%  0.00   .000   .000   .000
20  571    2021   Caleb Baragar   2    0.0%  100.0%  0.00   .000   .000   .000
21  572    2021   Kervin Castro   0    0.0%    0.0%  0.00   .000   .000   .000
22  573    2021  Gregory Santos   0    0.0%    0.0%  0.00   .000   .000   .000
23  574    2021    Camilo Doval   0    0.0%    0.0%  0.00   .000   .000   .000

      OPS    ISO  Spd  BABIP   UBR  wGDP   wSB  wRC  wRAA   wOBA  wRC+  Year  Team
0   2.500  1.500  0.1   .000   0.0   0.0   0.0    1   1.1  1.033   597  None   LAA
1   2.000   .000  0.1  1.000   0.0   0.0   0.0    1   0.5   .880   484  None   LAA
2   1.000   .000  2.6   .000   0.0   0.0   0.0    0   0.3   .690   361  None   LAA
```

```
3   1.333   .000  2.6   .667   0.0  0.0  0.0   2   1.1   .594   289  None  LAA
4   1.255   .400  1.1   .750  -0.1  0.0  0.0   3   1.8   .530   244  None  LAA
..    …     …    …     …     …    …    …    ..    …     …    …     …    …
19   .000   .000  0.1   .000   0.0  0.0  0.0   0   0.0   .000   0.0  None  SFG
20   .000   .000  0.1   .000   0.0  0.0  0.0   0  -0.5   .000  -100  None  SFG
21   .000   .000  0.1   .000   0.0  0.0  0.0   0   0.0   .000   0.0  None  SFG
22   .000   .000  0.1   .000   0.0  0.0  0.0   0   0.0   .000   0.0  None  SFG
23   .000   .000  0.1   .000   0.0  0.0  0.0   0   0.0   .000   0.0  None  SFG

[18060 rows x 23 columns]
```

Scraping Batted Ball Player Data From Fangraphs

[128]:
```
pages = [i for i in range(1, 14)]
team_idx = [i for i in range(1, 31)]
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']
urls = []

for team in team_idx:
    for page in pages:
        urls.append((get_urls(team, (2010, 2021), page, 'player_batted'),␣
 ↪teams[team-1]))

count = 0
for url in urls:
    if count == 0:
        player_batted = scraping_FanGraphs(url[0], None, url[1])
        count = 1
    else:
        player_batted = pd.concat([player_batted, scraping_FanGraphs(url[0],␣
 ↪None, url[1])])
player_batted
```

[128]:
```
      # Season            Name BABIP GB/FB    LD%    GB%     FB% IFFB%  \
0     1   2018    Ryan Schimpf  .000  1.00   0.0%  50.0%   50.0%  0.0%
1     2   2019   Cesar Puello  .433  4.40  18.2%  66.7%   15.2%  0.0%
2     3   2010     Ryan Budde  .750  0.00  60.0%   0.0%   40.0%  0.0%
3     4   2015     Jett Bandy  .000  0.00   0.0%   0.0%  100.0%  0.0%
4     5   2018  Nolan Fontana  .000  0.33  20.0%  20.0%   60.0%  0.0%
..   …     …              …    …     …      …      …       …     …
19  570   2021      Joey Bart  .500  1.00  50.0%  25.0%   25.0%  0.0%
20  571   2021  Kervin Castro  .000  0.00   0.0%   0.0%    0.0%  0.0%
21  572   2021 Gregory Santos  .000  0.00   0.0%   0.0%    0.0%  0.0%
22  573   2021   Camilo Doval  .000  0.00   0.0%   0.0%    0.0%  0.0%
23  574   2021     Sammy Long  .167  4.00  33.3%  66.7%    0.0%  0.0%
```

```
     HR/FB  IFH    IFH% BUH   BUH%  Pull%  Cent%  Oppo%  Soft%   Med%  Hard%  \
0   100.0%    0    0.0%   0   0.0%   0.0%  50.0%  50.0%  50.0%   0.0%  50.0%
1    60.0%    3   13.6%   0   0.0%  48.5%  33.3%  18.2%  24.2%  36.4%  39.4%
2    50.0%    0    0.0%   0   0.0%  40.0%  40.0%  20.0%   0.0%  80.0%  20.0%
3    50.0%    0    0.0%   0   0.0%  50.0%   0.0%  50.0%   0.0%  50.0%  50.0%
4    33.3%    0    0.0%   0   0.0%  60.0%  20.0%  20.0%   0.0%  60.0%  40.0%
..     …   ..     …  ..    …      …      …      …      …      …
19    0.0%    1  100.0%   0   0.0%   0.0%  75.0%  25.0%  50.0%  50.0%   0.0%
20    0.0%    0    0.0%   0   0.0%    0.0    0.0    0.0    0.0    0.0    0.0
21    0.0%    0    0.0%   0   0.0%    0.0    0.0    0.0    0.0    0.0    0.0
22    0.0%    0    0.0%   0   0.0%    0.0    0.0    0.0    0.0    0.0    0.0
23    0.0%    0    0.0%   0   0.0%  14.3%  42.9%  42.9%  42.9%  42.9%  14.3%

    Year Team
0   None  LAA
1   None  LAA
2   None  LAA
3   None  LAA
4   None  LAA
..   …   …
19  None  SFG
20  None  SFG
21  None  SFG
22  None  SFG
23  None  SFG

[18060 rows x 22 columns]
```

Scraping Statcast Player Data From Fangraphs

[129]:
```
pages = [i for i in range(1, 14)]
team_idx = [i for i in range(1, 31)]
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']
urls = []

for team in team_idx:
    for page in pages:
        urls.append((get_urls(team, (2010, 2021), page, 'player_statcast'),
 ↪teams[team-1]))

count = 0
for url in urls:
    if count == 0:
        player_statcast = scraping_FanGraphs(url[0], None, url[1])
```

```
        count = 1
    else:
        player_statcast = pd.concat([player_statcast,␣
↪scraping_FanGraphs(url[0], None, url[1])])
player_statcast
```

[129]:

```
        # Season              Name  PA Events    EV  maxEV     LA Barrels  \
0      1   2020  Franklin Barreto  18      9  95.6  109.2   10.4       0
1      2   2019      Tyler Skaggs   3      1  95.6   95.6  -36.0       0
2      3   2018      Jabari Blash  45     16  94.6  116.2   17.9       2
3      4   2021    Andrew Heaney   3      1  94.1   94.1   10.2       0
4      5   2018        Joe Hudson  12     12  94.0  103.9   12.8       0
..   …    …               … ..   …    …    …     …      …
19   570   2021      Conner Menez   0      0   0.0    0.0    0.0     0.0
20   571   2021     Caleb Baragar   2      0   0.0    0.0    0.0       0
21   572   2021     Kervin Castro   0      0   0.0    0.0    0.0     0.0
22   573   2021    Gregory Santos   0      0   0.0    0.0    0.0     0.0
23   574   2021      Camilo Doval   0      0   0.0    0.0    0.0     0.0

   Barrel% HardHit HardHit%   AVG  xBA   SLG xSLG  wOBA xwOBA  Year Team
0     0.0%       5    55.6%  .118  0.0  .118  0.0  .139   0.0  None  LAA
1     0.0%       1   100.0%  .000  0.0  .000  0.0  .230   0.0  None  LAA
2    12.5%       8    50.0%  .103  0.0  .128  0.0  .163   0.0  None  LAA
3     0.0%       0     0.0%  .500  0.0  .500  0.0  .524   0.0  None  LAA
4     0.0%       7    58.3%  .167  0.0  .250  0.0  .177   0.0  None  LAA
..      …      …        …    …  …    …    …    …     …    …  …
19     0.0     0.0      0.0  .000  0.0  .000  0.0  .000   0.0  None  SFG
20     0.0       0      0.0  .000  0.0  .000  0.0  .000   0.0  None  SFG
21     0.0     0.0      0.0  .000  0.0  .000  0.0  .000   0.0  None  SFG
22     0.0     0.0      0.0  .000  0.0  .000  0.0  .000   0.0  None  SFG
23     0.0     0.0      0.0  .000  0.0  .000  0.0  .000   0.0  None  SFG

[18060 rows x 20 columns]
```

Scraping Plate Discipline Player Data From Fangraphs

[130]:

```
pages = [i for i in range(1, 14)]
team_idx = [i for i in range(1, 31)]
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']
urls = []

for team in team_idx:
    for page in pages:
        urls.append((get_urls(team, (2010, 2021), page,␣
↪'player_plate_discipline'), teams[team-1]))
```

```
count = 0
for url in urls:
    if count == 0:
        player_plate_discipline = scraping_FanGraphs(url[0], None, url[1])
        count = 1
    else:
        player_plate_discipline = pd.concat([player_plate_discipline,␣
↪scraping_FanGraphs(url[0], None, url[1])])
player_plate_discipline
```

[130]:

```
      #  Season            Name O-Swing% Z-Swing%  Swing% O-Contact%  \
0     1    2010    Scot Shields      0.0     0.0%    0.0%        0.0
1     2    2010   Brian Fuentes      0.0      0.0     0.0        0.0
2     3    2010  Fernando Rodney     0.0      0.0     0.0        0.0
3     4    2010       Dan Haren      0.0      0.0     0.0        0.0
4     5    2010   Ervin Santana      0.0      0.0     0.0        0.0
..   …     …               …       …        …       …
19  570    2012    Clay Hensley   100.0%    50.0%   66.7%     100.0%
20  571    2013      Jean Machi   100.0%   100.0%  100.0%       0.0%
21  572    2014      Jean Machi   100.0%   100.0%  100.0%     100.0%
22  573    2018   Roberto Gomez   100.0%    42.9%   50.0%     100.0%
23  574    2021     Jay Jackson   100.0%     0.0%   50.0%     100.0%

   Z-Contact% Contact%   Zone% F-Strike% SwStr%   CStr%    CSW%  Year Team
0         0.0      0.0  100.0%    100.0%   0.0%  100.0%  100.0%  None  LAA
1         0.0      0.0     0.0       0.0    0.0     0.0     0.0  None  LAA
2         0.0      0.0     0.0       0.0    0.0     0.0     0.0  None  LAA
3         0.0      0.0     0.0       0.0    0.0     0.0     0.0  None  LAA
4         0.0      0.0     0.0       0.0    0.0     0.0     0.0  None  LAA
..        …        …       …         …      …       …       …   …    …
19     100.0%   100.0%   66.7%    100.0%   0.0%   33.3%   33.3%  None  SFG
20      50.0%    33.3%   66.7%    100.0%  66.7%    0.0%   66.7%  None  SFG
21     100.0%   100.0%   50.0%    100.0%   0.0%    0.0%    0.0%  None  SFG
22      33.3%    50.0%   87.5%    100.0%  25.0%   50.0%   75.0%  None  SFG
23        0.0   100.0%   50.0%    100.0%   0.0%   50.0%   50.0%  None  SFG

[18060 rows x 16 columns]
```

Merging Dataframes

[502]:

```
# Removing Unnecessary Columns
player_standard = player_standard.drop(columns=['#','Year'], errors='ignore')
player_advanced = player_advanced.drop(columns=['#','Year'], errors='ignore')
player_batted = player_batted.drop(columns=['#','Year'], errors='ignore')
player_statcast = player_statcast.drop(columns=['#','Year'], errors='ignore')
```

```
player_plate_discipline = player_plate_discipline.drop(columns=['#','Year'],␣
 ↪errors='ignore')

player_table = pd.merge(player_standard, player_advanced, on=['Season', 'Name',␣
 ↪'PA', 'AVG', 'Team'])
player_table = pd.merge(player_table, player_batted, on=['Season', 'Name',␣
 ↪'Team', 'BABIP'])
player_table = pd.merge(player_table, player_statcast, on=['Season', 'Name',␣
 ↪'Team', 'AVG', 'PA', 'SLG', 'wOBA'])
player_table = pd.merge(player_table, player_plate_discipline, on=['Season',␣
 ↪'Name', 'Team'])

player_table = player_table.rename(columns={'Season':'Year'})

player_table = player_table.drop_duplicates()

# Removing the % in the values so that they can be used as numbers
player_table['BB%'] = player_table['BB%'].replace({'\%':''}, regex = True)
player_table['K%'] = player_table['K%'].replace({'\%':''}, regex = True)
player_table['LD%'] = player_table['BB%'].replace({'\%':''}, regex = True)
player_table['GB%'] = player_table['GB%'].replace({'\%':''}, regex = True)
player_table['FB%'] = player_table['FB%'].replace({'\%':''}, regex = True)
player_table['HR/FB'] = player_table['HR/FB'].replace({'\%':''}, regex = True)
player_table['Pull%'] = player_table['Pull%'].replace({'\%':''}, regex = True)
player_table['Cent%'] = player_table['Cent%'].replace({'\%':''}, regex = True)
player_table['Oppo%'] = player_table['Oppo%'].replace({'\%':''}, regex = True)
player_table['Soft%'] = player_table['Soft%'].replace({'\%':''}, regex = True)
player_table['Med%'] = player_table['Med%'].replace({'\%':''}, regex = True)
player_table['Hard%'] = player_table['Hard%'].replace({'\%':''}, regex = True)
player_table['Barrel%'] = player_table['Barrel%'].replace({'\%':''}, regex =␣
 ↪True)
player_table['HardHit%'] = player_table['HardHit%'].replace({'\%':''}, regex =␣
 ↪True)
player_table['O-Swing%'] = player_table['O-Swing%'].replace({'\%':''}, regex =␣
 ↪True)
player_table['Z-Swing%'] = player_table['Z-Swing%'].replace({'\%':''}, regex =␣
 ↪True)
player_table['Swing%'] = player_table['Swing%'].replace({'\%':''}, regex = True)
player_table['O-Contact%'] = player_table['O-Contact%'].replace({'\%':''},␣
 ↪regex = True)
player_table['Z-Contact%'] = player_table['Z-Contact%'].replace({'\%':''},␣
 ↪regex = True)
player_table['Contact%'] = player_table['Contact%'].replace({'\%':''}, regex =␣
 ↪True)
player_table['Zone%'] = player_table['Zone%'].replace({'\%':''}, regex = True)
```

```python
player_table['F-Strike%'] = player_table['F-Strike%'].replace({'\%':''}, regex = True)
player_table['SwStr%'] = player_table['SwStr%'].replace({'\%':''}, regex = True)
player_table['CStr%'] = player_table['CStr%'].replace({'\%':''}, regex = True)
player_table['CSW%'] = player_table['CSW%'].replace({'\%':''}, regex = True)

player_table = player_table.apply(pd.to_numeric, errors='ignore')
player_table = player_table.sort_values(by='Year')
player_table
```

[502]:

```
       Year              Name    G   AB   PA   H  1B  2B  3B  HR   R  RBI  BB  \
1230   2010     Clay Buchholz   28    1    1   1   1   0   0   0   0    0   0
19521  2010      Brandon Moss   17   26   27   4   3   1   0   0   2    2   1
4721   2010        Ben Revere   13   28   30   5   5   0   0   0   1    2   2
19528  2010   Jason Jaramillo   33   87   97  13  10   2   0   1   2    6   8
9464   2010        Mike McCoy   46   82   90  16  12   4   0   0   9    3   8
…       …                 …  …  …   …  ..   ..  ..  ..  ..  ..  …  ..
3369   2021      Nomar Mazara   50  165  181  35  25   5   2   3  12   19  15
9424   2021     Cavan Biggio   79  250  294  56  38  10   1   7  27   27  37
3371   2021    Dustin Garneau   20   62   68  13   2   5   0   6   9   11   3
3355   2021      Willi Castro  125  413  450  91  61  15   6   9  56   38  23
25432  2021      Camilo Doval   29    0    0   0   0   0   0   0   0    0   0

       IBB   SO  HBP  SF  SH  GDP  SB  CS    AVG Team   BB%    K%  BB/K  \
1230     0    0    0   0   0    0   0   0  1.000  BOS   0.0   0.0  0.00
19521    0    6    0   0   0    1   0   0  0.154  PIT   3.7  22.2  0.17
4721     0    5    0   0   0    1   0   1  0.179  MIN   6.7  16.7  0.40
19528    1   14    1   1   0    7   0   0  0.149  PIT   8.2  14.4  0.57
9464     0   20    0   0   0    0   5   1  0.195  TOR   8.9  22.2  0.40
…     …  …  …   ..  ..  …  ..  ..  …  …  …   …   …
3369     0   45    0   1   0    4   0   0  0.212  DET   8.3  24.9  0.33
9424     2   78    1   4   1    4   3   1  0.224  TOR  12.6  26.5  0.47
3371     0   18    1   2   0    2   0   0  0.210  DET   4.4  26.5  0.17
3355     1  109    8   3   3    5   9   4  0.220  DET   5.1  24.2  0.21
25432    0    0    0   0   0    0   0   0  0.000  SFG   0.0   0.0  0.00

         OBP    SLG    OPS    ISO  Spd  BABIP   UBR  wGDP   wSB  wRC   wRAA  \
1230   1.000  1.000  2.000  0.000  0.1  1.000   0.0   0.0   0.0    1    0.5
19521  0.185  0.192  0.377  0.038  2.0  0.200  -0.4   0.0   0.0    0   -3.2
4721   0.233  0.179  0.412  0.000  1.6  0.217   0.0  -0.3  -0.4    0   -3.0
19528  0.227  0.207  0.434  0.057  0.1  0.164   0.4  -1.2  -0.1    2   -9.4
9464   0.267  0.244  0.511  0.049  5.5  0.258   0.6   0.3   0.5    4   -6.0
…        …    …      …      …   …     …   …     …    …     …
3369   0.276  0.321  0.597  0.109  2.7  0.271  -0.1   0.3  -0.1   14   -7.6
9424   0.322  0.356  0.678  0.132  3.7  0.290  -1.5   0.3  -0.1   32   -4.0
3371   0.250  0.581  0.831  0.371  1.4  0.175  -0.1  -0.4   0.0    9    1.2
3355   0.273  0.351  0.624  0.131  6.9  0.275   1.6   0.6  -0.2   38  -16.3
```

25432	0.000	0.000	0.000	0.000	0.1	0.000	0.0	0.0	0.0	0	0.0

	wOBA	wRC+	GB/FB	LD%	GB%	FB%	IFFB%	HR/FB	IFH	IFH%	BUH	\
1230	0.895	483.0	1.00	0.0	100.0	0.0	0.0%	0.0	0	0.0%	0	
19521	0.172	0.0	1.83	3.7	55.0	30.0	0.0%	0.0	2	18.2%	0	
4721	0.196	12.0	3.75	6.7	68.2	18.2	0.0%	0.0	1	6.7%	0	
19528	0.200	18.0	1.32	8.2	50.0	37.8	17.9%	3.6	1	2.7%	0	
9464	0.238	40.0	0.93	8.9	42.4	45.8	11.1%	0.0	2	8.0%	0	
…	…	…	…	…	…	…	…	…	…	…	…	
3369	0.264	64.0	1.49	8.3	47.9	32.2	15.4%	7.7	3	5.2%	0	
9424	0.298	84.0	0.94	12.6	37.7	40.0	5.7%	10.0	1	1.5%	1	
3371	0.335	113.0	0.73	4.4	34.8	47.8	22.7%	27.3	0	0.0%	0	
3355	0.271	69.0	1.41	5.1	46.4	32.9	15.0%	9.0	7	5.0%	1	
25432	0.000	0.0	0.00	0.0	0.0	0.0	0.0%	0.0	0	0.0%	0	

	BUH%	Pull%	Cent%	Oppo%	Soft%	Med%	Hard%	Events	EV	maxEV	\
1230	0.0%	100.0	0.0	0.0	0.0	100.0	0.0	0	0.0	0.0	
19521	0.0%	35.0	50.0	15.0	15.0	45.0	40.0	0	0.0	0.0	
4721	0.0%	39.1	34.8	26.1	26.1	47.8	26.1	0	0.0	0.0	
19528	0.0%	33.8	39.2	27.0	24.3	56.8	18.9	0	0.0	0.0	
9464	0.0%	33.9	41.9	24.2	19.4	54.8	25.8	0	0.0	0.0	
…	…	…	…	…	…	…	…	…	…	…	
3369	0.0%	33.9	37.2	28.9	14.0	56.2	29.8	121	90.4	111.5	
9424	50.0%	35.0	35.6	29.4	10.7	58.8	30.5	178	88.9	109.6	
3371	0.0%	56.5	26.1	17.4	26.1	41.3	32.6	46	86.4	106.4	
3355	16.7%	32.3	32.3	35.5	22.3	55.8	21.9	310	85.6	115.4	
25432	0.0%	0.0	0.0	0.0	0.0	0.0	0.0	0	0.0	0.0	

	LA	Barrels	Barrel%	HardHit	HardHit%	xBA	xSLG	xwOBA	O-Swing%	\
1230	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
19521	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	33.3	
4721	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	27.0	
19528	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	27.4	
9464	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	19.5	
…	…	…	…	…	…	…	…	…	…	
3369	11.1	9.0	7.4	48.0	39.7	0.0	0.0	0.0	33.6	
9424	15.4	10.0	5.6	56.0	31.5	0.0	0.0	0.0	22.2	
3371	19.2	5.0	10.9	19.0	41.3	0.0	0.0	0.0	31.6	
3355	11.4	16.0	5.2	91.0	29.4	0.0	0.0	0.0	42.4	
25432	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

	Z-Swing%	Swing%	O-Contact%	Z-Contact%	Contact%	Zone%	F-Strike%	\
1230	100.0	100.0	0.0	100.0	100.0	100.0	100.0	
19521	72.3	52.0	70.6	91.2	84.3	48.0	51.9	
4721	59.5	40.0	76.5	88.0	83.3	40.0	46.7	
19528	61.4	43.3	78.8	92.2	87.7	46.6	68.0	
9464	54.5	37.2	59.4	84.6	78.0	50.5	55.6	

```
…          …       …         …         …         …      …         …
3369        65.4    46.6       62.7      86.1      76.2    41.1       62.4
9424        64.9    41.3       50.7      87.5      76.6    44.8       57.8
3371        74.1    48.6       65.5      77.9      73.0    40.0       52.9
3355        76.4    56.3       56.1      86.2      72.8    40.7       67.6
25432        0.0     0.0        0.0       0.0       0.0     0.0        0.0

       SwStr%  CStr%  CSW%
1230      0.0    0.0   0.0
19521     8.2   12.2  20.4
4721      6.7   21.9  28.6
19528     5.2   19.9  25.1
9464      8.3   21.2  29.5
…         …     …     …
3369     11.1   16.2  27.3
9424      9.7   20.2  29.9
3371     13.1   14.8  27.9
3355     15.3   12.3  27.6
25432     0.0    0.0   0.0

[17611 rows x 77 columns]
```

Removing Suffix From Player Names In order to match the names in the Lahman dataset, which we will take advantage of later, we will remove the suffix from player names. For example, as you will see below, Cedric Mullins is recorded as Cedric Mullins II on Fangraphs, but he is recorded as Cedric Mullins in the Lahman dataset.

[493]:
```
player_table[player_table.Name == 'Cedric Mullins II']
```

[493]:
```
     Year               Name    G   AB   PA    H   1B  2B  3B  HR   R  RBI  \
784  2018  Cedric Mullins II   45  170  191   40   27   9   0   4  23   11
910  2019  Cedric Mullins II   22   64   74    6    4   0   2   0   7    4
700  2020  Cedric Mullins II   48  140  153   38   28   4   3   3  16   12
658  2021  Cedric Mullins II  159  602  675  175  103  37   5  30  91   59

     BB  IBB   SO  HBP  SF  SH  GDP  SB  CS    AVG Team  BB%   K%  BB/K  \
784  17    0   37    2   0   2    1   2   3  0.235  BAL  8.9  19.4  0.46
910   4    0   14    3   1   2    2   1   0  0.094  BAL  5.4  18.9  0.29
700   8    0   37    1   0   4    0   7   2  0.271  BAL  5.2  24.2  0.22
658  59    3  125    8   4   1    2  30   8  0.291  BAL  8.7  18.5  0.47

       OBP    SLG    OPS    ISO  Spd  BABIP  UBR  wGDP   wSB  wRC  wRAA   wOBA  \
784  0.312  0.359  0.671  0.124  2.9  0.279  0.8   0.2  -0.9   20  -2.7  0.298
910  0.181  0.156  0.337  0.063  7.9  0.118  0.5  -0.2   0.2   -1 -10.3  0.159
700  0.315  0.407  0.723  0.136  7.2  0.350  1.8   0.6   0.4   18  -0.9  0.313
658  0.360  0.518  0.878  0.228  6.1  0.322  0.4   2.3   2.1  114  32.0  0.372
```

```
      wRC+  GB/FB  LD%   GB%   FB%  IFFB%  HR/FB  IFH   IFH%  BUH   BUH%  \
784   86.0   1.37  8.9  50.8  37.1  10.9%    8.7    9  14.3%    4  36.4%
910  -12.0   1.35  5.4  52.9  39.2  25.0%    0.0    1   3.7%    0   0.0%
700   95.0   1.25  5.2  43.5  34.8  21.9%    9.4    3   7.5%    9  60.0%
658  136.0   0.95  8.7  39.0  41.1  12.4%   15.5   17   9.2%    5  50.0%

     Pull%  Cent%  Oppo%  Soft%  Med%  Hard%  Events    EV  maxEV    LA  \
784   42.2   33.3   24.4   19.3  54.1   26.7     135  89.3  108.0  10.1
910   43.4   37.7   18.9   34.0  49.1   17.0      53  84.2  110.3  14.9
700   43.0   28.0   29.0   15.9  62.6   21.5     107  88.6  110.2  15.6
658   43.6   32.4   24.1   14.9  51.9   33.2     483  89.4  109.7  14.8

     Barrels  Barrel%  HardHit  HardHit%  xBA  xSLG  xwOBA  O-Swing%  \
784      4.0      3.0     38.0      28.1  0.0   0.0    0.0      22.2
910      1.0      1.9      9.0      17.0  0.0   0.0    0.0      33.9
700      3.0      2.8     34.0      31.8  0.0   0.0    0.0      33.0
658     39.0      8.1    189.0      39.1  0.0   0.0    0.0      30.0

     Z-Swing%  Swing%  O-Contact%  Z-Contact%  Contact%  Zone%  F-Strike%  \
784      64.4    40.6        66.7        90.3      83.1   43.8       58.1
910      62.0    45.4        64.4        85.3      76.1   41.0       66.2
700      68.1    48.0        70.2        85.1      79.2   42.7       59.5
658      64.5    45.1        71.7        87.8      81.7   43.6       59.1

     SwStr%  CStr%  CSW%
784     6.9   19.1  26.0
910    10.8   16.9  27.8
700    10.0   14.6  24.6
658     8.2   17.3  25.5
```

[494]:

```python
names = player_table.Name.str.split(' ', expand=True)[[0, 1]]
names.columns = ['First', 'Last']
names = names.assign(Name = names.First.str.cat(names.Last,sep=' '))
names = names[['Name']]

player_table = player_table.assign(Name = names.Name.to_list())
player_table[player_table.Name == 'Cedric Mullins']
```

[494]:

```
     Year            Name    G   AB   PA    H   1B  2B  3B  HR   R  RBI  BB  \
784  2018  Cedric Mullins   45  170  191   40   27   9   0   4  23   11  17
910  2019  Cedric Mullins   22   64   74    6    4   0   2   0   7    4   4
700  2020  Cedric Mullins   48  140  153   38   28   4   3   3  16   12   8
658  2021  Cedric Mullins  159  602  675  175  103  37   5  30  91   59  59

     IBB   SO  HBP  SF  SH  GDP  SB  CS    AVG Team  BB%   K%  BB/K    OBP  \
784    0   37    2   0   2    1   2   3  0.235  BAL  8.9  19.4  0.46  0.312
910    0   14    3   1   2    2   1   0  0.094  BAL  5.4  18.9  0.29  0.181
```

```
700    0   37    1   0   4    0   7    2  0.271  BAL  5.2  24.2  0.22  0.315
658    3  125    8   4   1    2  30    8  0.291  BAL  8.7  18.5  0.47  0.360

       SLG    OPS    ISO  Spd  BABIP  UBR  wGDP  wSB  wRC  wRAA   wOBA   wRC+  \
784  0.359  0.671  0.124  2.9  0.279  0.8   0.2 -0.9   20  -2.7  0.298   86.0
910  0.156  0.337  0.063  7.9  0.118  0.5  -0.2  0.2   -1 -10.3  0.159  -12.0
700  0.407  0.723  0.136  7.2  0.350  1.8   0.6  0.4   18  -0.9  0.313   95.0
658  0.518  0.878  0.228  6.1  0.322  0.4   2.3  2.1  114  32.0  0.372  136.0

     GB/FB  LD%   GB%   FB%  IFFB%  HR/FB  IFH   IFH%  BUH   BUH%  Pull%  \
784   1.37  8.9  50.8  37.1  10.9%    8.7    9  14.3%    4  36.4%   42.2
910   1.35  5.4  52.9  39.2  25.0%    0.0    1   3.7%    0   0.0%   43.4
700   1.25  5.2  43.5  34.8  21.9%    9.4    3   7.5%    9  60.0%   43.0
658   0.95  8.7  39.0  41.1  12.4%   15.5   17   9.2%    5  50.0%   43.6

     Cent%  Oppo%  Soft%  Med%  Hard%  Events    EV  maxEV    LA  Barrels  \
784   33.3   24.4   19.3  54.1   26.7     135  89.3  108.0  10.1      4.0
910   37.7   18.9   34.0  49.1   17.0      53  84.2  110.3  14.9      1.0
700   28.0   29.0   15.9  62.6   21.5     107  88.6  110.2  15.6      3.0
658   32.4   24.1   14.9  51.9   33.2     483  89.4  109.7  14.8     39.0

     Barrel%  HardHit  HardHit%  xBA  xSLG  xwOBA  O-Swing%  Z-Swing%  Swing%  \
784      3.0     38.0      28.1  0.0   0.0    0.0      22.2      64.4    40.6
910      1.9      9.0      17.0  0.0   0.0    0.0      33.9      62.0    45.4
700      2.8     34.0      31.8  0.0   0.0    0.0      33.0      68.1    48.0
658      8.1    189.0      39.1  0.0   0.0    0.0      30.0      64.5    45.1

     O-Contact%  Z-Contact%  Contact%  Zone%  F-Strike%  SwStr%  CStr%  CSW%
784        66.7        90.3      83.1   43.8       58.1     6.9   19.1  26.0
910        64.4        85.3      76.1   41.0       66.2    10.8   16.9  27.8
700        70.2        85.1      79.2   42.7       59.5    10.0   14.6  24.6
658        71.7        87.8      81.7   43.6       59.1     8.2   17.3  25.5
```

As you can see, the dataset I created from Fangraphs, now has only first and last name in the Name column.

Add Player ID to Player Table from Lahman Dataset

[503]:
```python
player_info = pd.read_csv('tables/People.csv')
player_info = player_info[['playerID', 'nameFirst', 'nameLast']]
player_info = player_info.assign(Name = player_info.nameFirst.str.
 ↪cat(player_info.nameLast,sep=' '))
player_info = player_info[['playerID', 'Name']]

player_table = pd.merge(player_table, player_info, on=['Name'])
```

Add Player's Position to Table

```
[504]: player_pos = pd.read_csv('tables/Appearances.csv')
player_pos = player_pos[['playerID', 'yearID', 'G_p', 'G_c', 'G_1b', 'G_2b',␣
 ↪'G_3b', 'G_ss', 'G_lf', 'G_cf', 'G_rf', 'G_dh']]
player_pos = player_pos[player_pos.yearID > 2010]
player_pos = player_pos.rename(columns = {'yearID':'Year', 'G_p':'P', 'G_c':
 ↪'C', 'G_1b':'1B', 'G_2b':'2B', 'G_3b':'3B', 'G_ss':'SS', 'G_lf':'LF', 'G_cf':
 ↪'CF', 'G_rf':'RF', 'G_dh':'DH'})
player_pos = player_pos.astype({'DH':'int32'})

positions = player_pos[['P', 'C', '1B', '2B', '3B', 'SS', 'LF', 'CF', 'RF',␣
 ↪'DH']]

positions = positions.assign(Pos = positions.idxmax(axis=1))

player_pos = pd.merge(player_pos, positions, on = ['P', 'C', '1B', '2B', '3B',␣
 ↪'SS', 'LF', 'CF', 'RF', 'DH'])
player_pos = player_pos[['playerID', 'Year', 'Pos']]
player_pos = player_pos.drop_duplicates()

player_table = pd.merge(player_table, player_pos, on=['playerID', 'Year'])
```

Reorder Columns of Dataframe

```
[505]: player_table = player_table[['Year', 'Pos', 'Name', 'G', 'AB', 'PA', 'H', '1B',␣
 ↪'2B', \
                              '3B', 'HR', 'R', 'RBI', 'BB', 'IBB', 'SO', 'HBP',␣
 ↪'SF', \
                              'SH', 'GDP', 'SB', 'CS', 'AVG', 'Team', 'BB%',␣
 ↪'K%', \
                              'BB/K', 'OBP', 'SLG', 'OPS', 'ISO', 'Spd',␣
 ↪'BABIP', \
                              'UBR', 'wGDP', 'wSB', 'wRC', 'wRAA', 'wOBA',␣
 ↪'wRC+', \
                              'GB/FB', 'LD%', 'GB%', 'FB%', 'IFFB%', 'HR/FB',␣
 ↪'IFH', \
                              'IFH%', 'BUH', 'BUH%', 'Pull%', 'Cent%', 'Oppo%',␣
 ↪'Soft%', \
                              'Med%', 'Hard%', 'Events', 'EV', 'maxEV', 'LA',␣
 ↪'Barrels', \
                              'Barrel%', 'HardHit', 'HardHit%', 'xBA', 'xSLG', \
                              'xwOBA', 'O-Swing%', 'Z-Swing%', 'Swing%',␣
 ↪'O-Contact%', \
                              'Z-Contact%', 'Contact%', 'Zone%', 'F-Strike%',␣
 ↪'SwStr%', 'CStr%', 'CSW%']]

player_table
```

[505]:

```
        Year Pos           Name   G  AB  PA  H  1B  2B  3B  HR  R  RBI  BB  \
0       2011   P  Clay Buchholz  14   0   0  0   0   0   0   0  0    0   0
1       2012   P  Clay Buchholz  29   2   3  0   0   0   0   0  0    0   0
2       2013   P  Clay Buchholz  16   0   0  0   0   0   0   0  0    0   0
3       2014   P  Clay Buchholz  28   2   2  1   1   0   0   0  0    0   0
4       2015   P  Clay Buchholz  18   6   6  0   0   0   0   0  0    0   0
…        …  ..             …  ..  ..  .. ..  ..  ..  ..  .. ..   …  ..
16342   2021   P     Joe Barlow  31   0   0  0   0   0   0   0  0    0   0
16343   2021   P     Glenn Otto   6   0   0  0   0   0   0   0  0    0   0
16344   2021  3B    Kevin Smith  18  32  36  3   2   0   0   1  2    1   3
16345   2021  RF  Josh Palacios  13  35  42  7   7   0   0   0  7    4   3
16346   2021   P   Camilo Doval  29   0   0  0   0   0   0   0  0    0   0

        IBB  SO  HBP  SF  SH  GDP  SB  CS    AVG Team  BB%    K%  BB/K    OBP  \
0         0   0    0   0   0    0   0   0  0.000  BOS  0.0   0.0  0.00  0.000
1         0   1    0   0   1    0   0   0  0.000  BOS  0.0  33.3  0.00  0.000
2         0   0    0   0   0    0   0   0  0.000  BOS  0.0   0.0  0.00  0.000
3         0   0    0   0   0    0   0   0  0.500  BOS  0.0   0.0  0.00  0.500
4         0   2    0   0   0    0   0   0  0.000  BOS  0.0  33.3  0.00  0.000
…      …  ..   …  ..  ..    …  ..  ..      …    …    …     …     …      …
16342     0   0    0   0   0    0   0   0  0.000  TEX  0.0   0.0  0.00  0.000
16343     0   0    0   0   0    0   0   0  0.000  TEX  0.0   0.0  0.00  0.000
16344     0  11    1   0   0    0   0   0  0.094  TOR  8.3  30.6  0.27  0.194
16345     0  11    2   1   1    0   0   0  0.200  TOR  7.1  26.2  0.27  0.293
16346     0   0    0   0   0    0   0   0  0.000  SFG  0.0   0.0  0.00  0.000

          SLG    OPS    ISO  Spd  BABIP  UBR  wGDP  wSB  wRC  wRAA   wOBA  \
0       0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0   0.0  0.000
1       0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0  -0.8  0.000
2       0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0   0.0  0.000
3       0.500  1.000  0.000  0.1   0.50  0.0   0.0  0.0    0   0.2  0.446
4       0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0   -1  -1.5  0.000
…           …      …      …    …      …    …     …    …    …     …      …
16342   0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0   0.0  0.000
16343   0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0   0.0  0.000
16344   0.188  0.382  0.094  0.8   0.10  0.3   0.1  0.0    0  -3.9  0.182
16345   0.200  0.493  0.000  2.6   0.28  1.5   0.3  0.0    2  -2.7  0.236
16346   0.000  0.000  0.000  0.1   0.00  0.0   0.0  0.0    0   0.0  0.000

          wRC+  GB/FB  LD%   GB%   FB%  IFFB%  HR/FB  IFH  IFH%  BUH   BUH%  \
0          0.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
1       -100.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
2          0.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
3        187.0   1.00  0.0  50.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
4       -100.0   3.00  0.0  75.0  25.0   0.0%    0.0    0  0.0%    0   0.0%
…            …      …    …     …     …      …      …    …     …    …      …
16342      0.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
```

```
16343    0.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%
16344    6.0   0.24  8.3  19.0  81.0  17.6%    5.9    0  0.0%    0   0.0%
16345   42.0   1.86  7.1  54.2  29.2   0.0%    0.0    0  0.0%    1  50.0%
16346    0.0   0.00  0.0   0.0   0.0   0.0%    0.0    0  0.0%    0   0.0%

       Pull%  Cent%  Oppo%  Soft%   Med%  Hard%  Events    EV  maxEV    LA  \
0        0.0    0.0    0.0    0.0    0.0    0.0       0   0.0    0.0   0.0
1        0.0  100.0    0.0    0.0  100.0    0.0       0   0.0    0.0   0.0
2        0.0    0.0    0.0    0.0    0.0    0.0       0   0.0    0.0   0.0
3        0.0   50.0   50.0    0.0  100.0    0.0       0   0.0    0.0   0.0
4       25.0   25.0   50.0   50.0   25.0   25.0       4  89.4   94.3  14.7
…       …    …      …      …      …      …       …     …      …     …
16342    0.0    0.0    0.0    0.0    0.0    0.0       0   0.0    0.0   0.0
16343    0.0    0.0    0.0    0.0    0.0    0.0       0   0.0    0.0   0.0
16344   33.3   38.1   28.6   28.6   33.3   38.1      21  86.7  102.8  36.5
16345   42.3   38.5   19.2    3.8   65.4   30.8      26  93.5  104.4   8.4
16346    0.0    0.0    0.0    0.0    0.0    0.0       0   0.0    0.0   0.0

       Barrels  Barrel%  HardHit  HardHit%  xBA  xSLG  xwOBA  O-Swing%  \
0          0.0      0.0      0.0       0.0  0.0   0.0    0.0       0.0
1          0.0      0.0      0.0       0.0  0.0   0.0    0.0      42.9
2          0.0      0.0      0.0       0.0  0.0   0.0    0.0       0.0
3          0.0      0.0      0.0       0.0  0.0   0.0    0.0      33.3
4          0.0      0.0      0.0       0.0  0.0   0.0    0.0      14.3
…          …       …        …         …    …    …     …       …
16342      0.0      0.0      0.0       0.0  0.0   0.0    0.0       0.0
16343      0.0      0.0      0.0       0.0  0.0   0.0    0.0       0.0
16344      3.0     14.3      7.0      33.3  0.0   0.0    0.0      35.3
16345      1.0      3.8     11.0      42.3  0.0   0.0    0.0      35.2
16346      0.0      0.0      0.0       0.0  0.0   0.0    0.0       0.0

       Z-Swing%  Swing%  O-Contact%  Z-Contact%  Contact%  Zone%  F-Strike%  \
0           0.0     0.0         0.0         0.0       0.0    0.0        0.0
1          66.7    50.0        33.3       100.0      60.0   30.0       66.7
2           0.0     0.0         0.0         0.0       0.0    0.0        0.0
3          40.0    36.4       100.0        50.0      75.0   45.5      100.0
4          62.5    40.0         0.0        90.0      75.0   53.3       33.3
…           …      …          …          …        …      …        …
16342       0.0     0.0         0.0         0.0       0.0    0.0        0.0
16343       0.0     0.0         0.0         0.0       0.0    0.0        0.0
16344      85.5    57.7        45.8        85.1      71.8   44.7       72.2
16345      65.3    48.5        56.3        78.7      69.6   44.2       45.2
16346       0.0     0.0         0.0         0.0       0.0    0.0        0.0

       SwStr%  CStr%  CSW%
0         0.0    0.0   0.0
1        20.0   10.0  30.0
```

```
2          0.0    0.0   0.0
3          9.1   18.2  27.3
4         10.0   20.0  30.0
…        …    …    …
16342      0.0    0.0   0.0
16343      0.0    0.0   0.0
16344     16.3    9.8  26.0
16345     14.7   16.6  31.3
16346      0.0    0.0   0.0

[16347 rows x 78 columns]
```

Remove Pitchers from Dataset

[506]:
```python
player_table = player_table[player_table.Pos != 'P']
player_table
```

[506]:
```
       Year Pos           Name    G   AB   PA    H  1B  2B  3B  HR   R  RBI  \
9      2011  RF   Brandon Moss    5    6    6    0   0   0   0   0   0    0
10     2012  1B   Brandon Moss   84  265  296   77  38  18   0  21  48   52
11     2013  1B   Brandon Moss  145  446  505  114  58  23   3  30  73   87
12     2014  1B   Brandon Moss  147  500  580  117  67  23   2  25  70   81
13     2015  RF   Brandon Moss   51  132  151   33  21   7   1   4  11    8
…      …  ..              …   …   …   …   …  ..   ..  ..  ..  ..  …
16335  2021  CF    Akil Baddoo  124  413  461  107  67  20   7  13  60   55
16337  2021  SS     Zack Short   61  156  184   22  12   4   0   6  21   20
16340  2021  3B     Ryan Dorow    3    6    7    0   0   0   0   0   0    0
16344  2021  3B    Kevin Smith   18   32   36    3   2   0   0   1   2    1
16345  2021  RF  Josh Palacios   13   35   42    7   7   0   0   0   7    4

       BB  IBB   SO  HBP  SF  SH  GDP  SB  CS    AVG Team   BB%   K%  BB/K  \
9       0    0    2    0   0   0    1   0   0  0.000  PHI   0.0  33.3  0.00
10     26    2   90    3   2   0    5   1   1  0.291  OAK   8.8  30.4  0.29
11     50    3  140    6   3   0    4   4   2  0.256  OAK   9.9  27.7  0.36
12     67    7  153   10   3   0    6   1   0  0.234  OAK  11.6  26.4  0.44
13     17    2   42    2   0   0    3   0   1  0.250  STL  11.3  27.8  0.40
…     ..  …   …   …  ..  ..   …  ..  ..     …   …    …    …    …
16335  45    1  122    0   3   0    5  18   4  0.259  DET   9.8  26.5  0.37
16337  22    1   59    0   6   0    4   2   0  0.141  DET  12.0  32.1  0.37
16340   1    0    3    0   0   0    0   0   0  0.000  TEX  14.3  42.9  0.33
16344   3    0   11    1   0   0    0   0   0  0.094  TOR   8.3  30.6  0.27
16345   3    0   11    2   1   1    0   0   0  0.200  TOR   7.1  26.2  0.27

         OBP    SLG    OPS    ISO  Spd  BABIP   UBR  wGDP  wSB  wRC  wRAA  \
9      0.000  0.000  0.000  0.000  0.1  0.000   0.0  -0.1  0.0   -1  -1.5
10     0.358  0.596  0.954  0.306  2.3  0.359   0.7   0.4 -0.5   54  20.7
11     0.337  0.522  0.859  0.267  4.5  0.301  -3.0   2.3 -0.4   77  21.9
```

12	0.334	0.438	0.772	0.204	3.0	0.283	0.1	2.0	-0.3	75	13.1
13	0.344	0.409	0.753	0.159	2.4	0.337	-0.2	0.4	-0.5	19	1.8
…	…	…	…	…	…	…	…	…	…	…	…
16335	0.330	0.436	0.766	0.177	7.3	0.335	2.0	0.4	1.5	61	5.5
16337	0.239	0.282	0.521	0.141	4.2	0.165	-0.2	0.0	0.3	9	-12.9
16340	0.143	0.000	0.143	0.000	0.1	0.000	0.0	0.1	0.0	0	-1.2
16344	0.194	0.188	0.382	0.094	0.8	0.100	0.3	0.1	0.0	0	-3.9
16345	0.293	0.200	0.493	0.000	2.6	0.280	1.5	0.3	0.0	2	-2.7

	wOBA	wRC+	GB/FB	LD%	GB%	FB%	IFFB%	HR/FB	IFH	IFH%	BUH	\
9	0.000	-100.0	1.00	0.0	50.0	50.0	50.0%	0.0	0	0.0%	0	
10	0.402	160.0	0.72	8.8	32.8	45.8	8.6%	25.9	4	6.9%	0	
11	0.369	137.0	0.58	9.9	30.1	51.8	8.8%	18.8	5	5.4%	0	
12	0.339	122.0	0.62	11.6	30.3	48.7	9.5%	14.8	3	2.9%	2	
13	0.328	109.0	0.82	11.3	36.0	43.8	10.3%	10.3	4	12.5%	1	
…	…	…	…	…	…	…	…	…	…	…	…	
16335	0.329	108.0	1.03	9.8	40.1	39.1	9.6%	11.3	10	8.5%	0	
16337	0.230	41.0	0.48	12.0	27.2	56.3	17.2%	10.3	1	3.6%	0	
16340	0.099	-46.0	0.50	14.3	33.3	66.7	50.0%	0.0	0	0.0%	0	
16344	0.182	6.0	0.24	8.3	19.0	81.0	17.6%	5.9	0	0.0%	0	
16345	0.236	42.0	1.86	7.1	54.2	29.2	0.0%	0.0	0	0.0%	1	

	BUH%	Pull%	Cent%	Oppo%	Soft%	Med%	Hard%	Events	EV	maxEV	\
9	0.0%	25.0	25.0	50.0	50.0	50.0	0.0	0	0.0	0.0	
10	0.0%	42.4	37.3	20.3	14.7	48.6	36.7	0	0.0	0.0	
11	0.0%	43.0	33.7	23.3	11.7	48.5	39.8	0	0.0	0.0	
12	66.7%	45.4	34.0	20.6	16.3	50.6	33.1	0	0.0	0.0	
13	100.0%	52.2	30.0	17.8	18.9	38.9	42.2	90	88.2	113.7	
…	…	…	…	…	…	…	…	…	…	…	
16335	0.0%	37.8	35.0	27.2	17.7	51.0	31.3	294	86.0	111.8	
16337	0.0%	44.7	30.1	25.2	20.4	48.5	31.1	103	87.5	108.2	
16340	0.0%	0.0	33.3	66.7	33.3	66.7	0.0	3	88.5	97.4	
16344	0.0%	33.3	38.1	28.6	28.6	33.3	38.1	21	86.7	102.8	
16345	50.0%	42.3	38.5	19.2	3.8	65.4	30.8	26	93.5	104.4	

	LA	Barrels	Barrel%	HardHit	HardHit%	xBA	xSLG	xwOBA	O-Swing%	\
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	54.5	
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.0	
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.6	
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	32.8	
13	17.9	9.0	10.0	33.0	36.7	0.0	0.0	0.0	31.6	
…	…	…	…	…	…	…	…	…	…	
16335	13.8	26.0	8.8	95.0	32.3	0.0	0.0	0.0	27.7	
16337	24.3	5.0	4.9	34.0	33.0	0.0	0.0	0.0	22.8	
16340	29.6	0.0	0.0	1.0	33.3	0.0	0.0	0.0	40.0	
16344	36.5	3.0	14.3	7.0	33.3	0.0	0.0	0.0	35.3	
16345	8.4	1.0	3.8	11.0	42.3	0.0	0.0	0.0	35.2	

	Z-Swing%	Swing%	O-Contact%	Z-Contact%	Contact%	Zone%	F-Strike%	\
9	85.7	66.7	66.7	50.0	58.3	38.9	66.7	
10	72.0	50.5	48.5	79.4	67.0	41.9	61.1	
11	71.7	49.8	53.3	83.6	70.5	39.4	60.4	
12	67.6	47.0	56.1	85.4	73.3	40.9	57.8	
13	69.4	46.5	50.9	86.2	71.6	39.3	48.3	
…	…	…	…	…	…	…	…	
16335	70.4	45.9	59.4	78.6	72.0	42.7	57.9	
16337	66.0	41.7	58.3	82.3	74.9	43.7	57.6	
16340	66.7	54.5	0.0	87.5	58.3	54.5	85.7	
16344	85.5	57.7	45.8	85.1	71.8	44.7	72.2	
16345	65.3	48.5	56.3	78.7	69.6	44.2	45.2	

	SwStr%	CStr%	CSW%
9	27.8	11.1	38.9
10	16.5	12.7	29.2
11	14.6	12.9	27.6
12	12.4	14.5	26.9
13	13.0	14.7	27.7
…	…	…	…
16335	12.9	14.9	27.8
16337	10.5	20.0	30.5
16340	20.8	16.7	37.5
16344	16.3	9.8	26.0
16345	14.7	16.6	31.3

[7866 rows x 78 columns]

Add Player Salaries to Dataset

[507]:
```
salaries = pd.read_csv('salaries/salaries.csv')

# Split the Name colum into first name and last name (originally stored as␣
↪'Last, First')
# and store it as a separate dataframe
names = salaries.Player.str.split(', ', expand=True)[[0, 1]]

# Create a new column called Name that has the format 'First Last'
names = names.assign(Name = names[1].str.cat(names[0],sep=' '))

# Remove all columns except for the new name column
names = names[['Name']]

# Add the years to the names dataframe
names = names.assign(Year = salaries.Year.to_list())
```

```python
# Add the salaries to the names dataframe
names = names.assign(Salary = salaries.Salary.to_list())

names.Salary = names.Salary.str.replace(',', '')
names.Salary = names.Salary.replace({'\$':''}, regex = True)

# Assign names to the salaries variable
salaries = names

player_table = pd.merge(player_table, salaries, on = ['Name', 'Year'])
player_table
```

[507]:

```
      Year Pos              Name    G   AB   PA    H  1B  2B  3B  HR   R  RBI  \
0     2013  1B      Brandon Moss  145  446  505  114  58  23   3  30  73   87
1     2014  1B      Brandon Moss  147  500  580  117  67  23   2  25  70   81
2     2015  RF      Brandon Moss   51  132  151   33  21   7   1   4  11    8
3     2015  1B      Brandon Moss   51  132  151   33  21   7   1   4  11    8
4     2015  RF      Brandon Moss   94  337  375   73  40  17   1  15  36   50
…      …   ..                …    …    …    …    …  ..  ..  ..  ..  ..   …
5634  2021  SS   Geraldo Perdomo   11   31   37    8   4   3   1   0   5    1
5635  2021  CF  Stuart Fairchild   12   15   17    2   1   1   0   0   3    2
5636  2021  RF        Kyle Isbel   28   76   83   21  13   5   2   1  16    7
5637  2021  SS       Zack Short   61  156  184   22  12   4   0   6  21   20
5638  2021  RF     Josh Palacios   13   35   42    7   7   0   0   0   7    4

      BB  IBB   SO  HBP  SF  SH  GDP  SB  CS    AVG Team   BB%   K%  BB/K  \
0     50    3  140    6   3   0    4   4   2  0.256  OAK   9.9  27.7  0.36
1     67    7  153   10   3   0    6   1   0  0.234  OAK  11.6  26.4  0.44
2     17    2   42    2   0   0    3   0   1  0.250  STL  11.3  27.8  0.40
3     17    2   42    2   0   0    3   0   1  0.250  STL  11.3  27.8  0.40
4     32    2  106    3   3   0    9   0   0  0.217  CLE   8.5  28.3  0.30
…     ..    …    …    …  ..  ..    …  ..  ..      …    …     …     …     …
5634   6    2    6    0   0   0    0   0   0  0.258  ARI  16.2  16.2  1.00
5635   1    0    3    1   0   0    1   0   0  0.133  ARI   5.9  17.6  0.33
5636   7    0   23    0   0   0    0   2   0  0.276  KCR   8.4  27.7  0.30
5637  22    1   59    0   6   0    4   2   0  0.141  DET  12.0  32.1  0.37
5638   3    0   11    2   1   1    0   0   0  0.200  TOR   7.1  26.2  0.27

        OBP    SLG    OPS    ISO  Spd  BABIP  UBR  wGDP  wSB  wRC  wRAA  \
0     0.337  0.522  0.859  0.267  4.5  0.301 -3.0   2.3 -0.4   77  21.9
1     0.334  0.438  0.772  0.204  3.0  0.283  0.1   2.0 -0.3   75  13.1
2     0.344  0.409  0.753  0.159  2.4  0.337 -0.2   0.4 -0.5   19   1.8
3     0.344  0.409  0.753  0.159  2.4  0.337 -0.2   0.4 -0.5   19   1.8
4     0.288  0.407  0.695  0.190  1.7  0.265 -0.7   0.5 -0.1   38  -3.9
…         …      …      …      …    …      …    …     …    …    …     …
5634  0.378  0.419  0.798  0.161  4.3  0.320  0.4   0.2  0.0    5   0.5
5635  0.235  0.200  0.435  0.067  2.6  0.167  0.1  -0.3  0.0    1  -1.5
```

5636	0.337	0.434	0.772	0.158	8.2	0.385	0.4	0.3	0.3	11	1.3
5637	0.239	0.282	0.521	0.141	4.2	0.165	-0.2	0.0	0.3	9	-12.9
5638	0.293	0.200	0.493	0.000	2.6	0.280	1.5	0.3	0.0	2	-2.7

	wOBA	wRC+	GB/FB	LD%	GB%	FB%	IFFB%	HR/FB	IFH	IFH%	BUH	\
0	0.369	137.0	0.58	9.9	30.1	51.8	8.8%	18.8	5	5.4%	0	
1	0.339	122.0	0.62	11.6	30.3	48.7	9.5%	14.8	3	2.9%	2	
2	0.328	109.0	0.82	11.3	36.0	43.8	10.3%	10.3	4	12.5%	1	
3	0.328	109.0	0.82	11.3	36.0	43.8	10.3%	10.3	4	12.5%	1	
4	0.300	86.0	0.65	8.5	31.2	48.3	5.3%	13.3	6	8.2%	0	
…	…	…	…	…	…	…	…	…	…	…	…	
5634	0.331	104.0	0.62	16.2	33.3	54.2	0.0%	0.0	0	0.0%	0	
5635	0.208	24.0	1.25	5.9	41.7	33.3	25.0%	0.0	0	0.0%	0	
5636	0.333	109.0	0.75	8.4	35.3	47.1	16.7%	4.2	3	16.7%	0	
5637	0.230	41.0	0.48	12.0	27.2	56.3	17.2%	10.3	1	3.6%	0	
5638	0.236	42.0	1.86	7.1	54.2	29.2	0.0%	0.0	0	0.0%	1	

	BUH%	Pull%	Cent%	Oppo%	Soft%	Med%	Hard%	Events	EV	maxEV	\
0	0.0%	43.0	33.7	23.3	11.7	48.5	39.8	0	0.0	0.0	
1	66.7%	45.4	34.0	20.6	16.3	50.6	33.1	0	0.0	0.0	
2	100.0%	52.2	30.0	17.8	18.9	38.9	42.2	90	88.2	113.7	
3	100.0%	52.2	30.0	17.8	18.9	38.9	42.2	90	88.2	113.7	
4	0.0%	48.3	30.8	20.9	15.8	46.2	38.0	234	89.4	112.1	
…	…	…	…	…	…	…	…	…	…	…	
5634	0.0%	44.0	32.0	24.0	12.0	72.0	16.0	25	86.5	103.3	
5635	0.0%	58.3	25.0	16.7	16.7	58.3	25.0	12	81.3	106.0	
5636	0.0%	41.5	26.4	32.1	22.6	50.9	26.4	53	87.3	111.0	
5637	0.0%	44.7	30.1	25.2	20.4	48.5	31.1	103	87.5	108.2	
5638	50.0%	42.3	38.5	19.2	3.8	65.4	30.8	26	93.5	104.4	

	LA	Barrels	Barrel%	HardHit	HardHit%	xBA	xSLG	xwOBA	O-Swing%	\
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	35.6	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	32.8	
2	17.9	9.0	10.0	33.0	36.7	0.0	0.0	0.0	31.6	
3	17.9	9.0	10.0	33.0	36.7	0.0	0.0	0.0	31.6	
4	20.5	28.0	12.0	95.0	40.6	0.0	0.0	0.0	33.0	
…	…	…	…	…	…	…	…	…	…	
5634	18.7	1.0	4.0	7.0	28.0	0.0	0.0	0.0	16.9	
5635	12.9	0.0	0.0	2.0	16.7	0.0	0.0	0.0	30.6	
5636	19.0	2.0	3.8	16.0	30.2	0.0	0.0	0.0	39.8	
5637	24.3	5.0	4.9	34.0	33.0	0.0	0.0	0.0	22.8	
5638	8.4	1.0	3.8	11.0	42.3	0.0	0.0	0.0	35.2	

	Z-Swing%	Swing%	O-Contact%	Z-Contact%	Contact%	Zone%	F-Strike%	\
0	71.7	49.8	53.3	83.6	70.5	39.4	60.4	
1	67.6	47.0	56.1	85.4	73.3	40.9	57.8	
2	69.4	46.5	50.9	86.2	71.6	39.3	48.3	

```
3          69.4    46.5        50.9        86.2      71.6    39.3        48.3
4          74.6    50.8        56.7        81.1      72.0    42.8        61.9
…          …       …           …           …         …       …           …
5634       67.2    39.5        50.0        82.1      74.5    45.0        45.9
5635       76.0    49.2        45.5        78.9      66.7    41.0        47.1
5636       60.7    48.6        59.5        93.9      77.6    42.1        56.6
5637       66.0    41.7        58.3        82.3      74.9    43.7        57.6
5638       65.3    48.5        56.3        78.7      69.6    44.2        45.2

      SwStr%  CStr%  CSW%   Salary
0       14.6   12.9  27.6  1600000
1       12.4   14.5  26.9  4100000
2       13.0   14.7  27.7  6500000
3       13.0   14.7  27.7  6500000
4       14.1   13.0  27.1  6500000
…        …      …     …       …
5634    10.1   20.2  30.2   570500
5635    16.4   11.5  27.9   570500
5636    10.9   17.1  28.0   570500
5637    10.5   20.0  30.5   570500
5638    14.7   16.6  31.3   570500

[5639 rows x 79 columns]
```

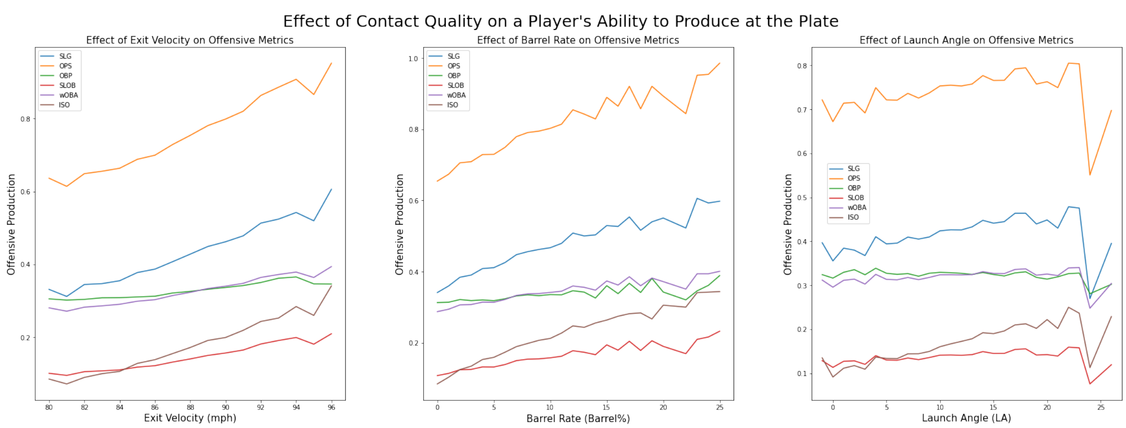
0.0.4 Part III: Analyzing Offensive Metrics Using Player Data

Effect of Contact Quality on Production

[500]:
```
fig, ax = plt.subplots(1, 3)
fig.subplots_adjust(wspace=.25)
fig.set_figheight(10)
fig.set_figwidth(30)
fig.suptitle("Effect of Contact Quality on a Player's Ability to Produce at the␣
  ↪Plate", fontsize=25, y=.95)



players = player_table[player_table.PA > 200]
players = players[players.Year > 2014]
players = players.apply(pd.to_numeric, errors='ignore')

players = players.assign(SLOB = players.SLG * players.OBP)

######################################################################
#                        Plotting Exit Velocity                      #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]
```

```python
players['Velo'] = pd.cut(players.EV, velos, include_lowest=True, labels =␣
 ↪labels)

# Make categorical column (returned by pd.cut) into int -- https://
 ↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
 ↪61761109#61761109
players['Velo'] = players[['Velo']].apply(lambda col:pd.Categorical(col).codes)

players.groupby('Velo')[['SLG', 'OPS', 'OBP', 'SLOB', 'wOBA', 'ISO']].mean().
 ↪plot(legend=True, ax=ax[0])

# Label the title, x-axis, and y-axis
ax[0].set_title('Effect of Exit Velocity on Offensive Metrics', fontsize=15)
ax[0].set_xlabel("Exit Velocity (mph)", fontsize=15)
ax[0].set_ylabel("Offensive Production", fontsize=15)

plt.xlim([80,96])

######################################################################
#                       Plotting Barrel Rate                         #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]

players['Barrel%'] = pd.cut(players['Barrel%'], velos, include_lowest=True,␣
 ↪labels = labels)

# Make categorical column (returned by pd.cut) into int -- https://
 ↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
 ↪61761109#61761109
players['Barrel%'] = players[['Barrel%']].apply(lambda col:pd.Categorical(col).
 ↪codes)

players.groupby('Barrel%')[['SLG', 'OPS', 'OBP', 'SLOB', 'wOBA', 'ISO']].mean().
 ↪plot(legend=True, ax=ax[1])

# Label the title, x-axis, and y-axis
ax[1].set_title('Effect of Barrel Rate on Offensive Metrics', fontsize=15)
ax[1].set_xlabel("Barrel Rate (Barrel%)", fontsize=15)
ax[1].set_ylabel("Offensive Production", fontsize=15)

######################################################################
#                       Plotting Launch Angle                        #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]
```

```python
players['LA'] = pd.cut(players['LA'], velos, include_lowest=True, labels = labels)

# Make categorical column (returned by pd.cut) into int -- https://stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/61761109#61761109
players['LA'] = players[['LA']].apply(lambda col:pd.Categorical(col).codes)

players.groupby('LA')[['SLG', 'OPS', 'OBP', 'SLOB', 'wOBA', 'ISO']].mean().plot(ax=ax[2])

# Label the title, x-axis, and y-axis
ax[2].set_title('Effect of Launch Angle on Offensive Metrics', fontsize=15)
ax[2].set_xlabel("Launch Angle (LA)", fontsize=15)
ax[2].set_ylabel("Offensive Production", fontsize=15)
ax[2].legend(loc=(.05,.5))

plt.xlim([-2,27])

# Display the plot
plt.show()
```



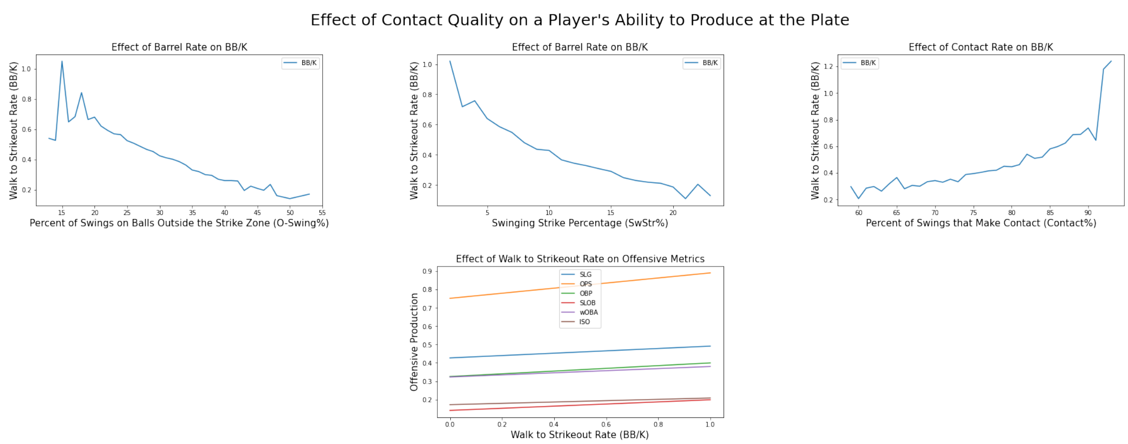
Effect of Plate Discipline on Production

[501]:
```python
fig, ax = plt.subplots(2, 3)
fig.subplots_adjust(wspace=.25)
fig.set_figheight(10)
fig.set_figwidth(30)
fig.delaxes(ax[1,0])
fig.delaxes(ax[1,2])
```

```
fig.suptitle("Effect of Contact Quality on a Player's Ability to Produce at the␣
↪Plate", fontsize=25, y=.99)


players = player_table[player_table.PA > 200]
players = players[players.Year > 2014]
players = players.apply(pd.to_numeric, errors='ignore')

players = players.assign(SLOB = players.SLG * players.OBP)

######################################################################
#                          Plotting O-Swing%                        #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]

players['O-Swing%'] = pd.cut(players['O-Swing%'], velos, include_lowest=True,␣
↪labels = labels)

# Make categorical column (returned by pd.cut) into int -- https://
↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
↪61761109#61761109
players['O-Swing%'] = players[['O-Swing%']].apply(lambda col:pd.
↪Categorical(col).codes)

players.groupby('O-Swing%')[['BB/K']].mean().plot(legend=True, ax=ax[0,0])

# Label the title, x-axis, and y-axis
ax[0,0].set_title('Effect of Barrel Rate on BB/K', fontsize=15)
ax[0,0].set_xlabel("Percent of Swings on Balls Outside the Strike Zone␣
↪(O-Swing%)", fontsize=15)
ax[0,0].set_ylabel("Walk to Strikeout Rate (BB/K)", fontsize=15)

######################################################################
#                  Plotting Swinging Strike Percentage               #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]

players['SwStr%'] = pd.cut(players['SwStr%'], velos, include_lowest=True,␣
↪labels = labels)

# Make categorical column (returned by pd.cut) into int -- https://
↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
↪61761109#61761109
```

```
players['SwStr%'] = players[['SwStr%']].apply(lambda col:pd.Categorical(col).
 ↪codes)

players.groupby('SwStr%')[['BB/K']].mean().plot(legend=True, ax=ax[0,1])

# Label the title, x-axis, and y-axis
ax[0,1].set_title('Effect of Barrel Rate on BB/K', fontsize=15)
ax[0,1].set_xlabel("Swinging Strike Percentage (SwStr%)", fontsize=15)
ax[0,1].set_ylabel("Walk to Strikeout Rate (BB/K)", fontsize=15)

######################################################################
#                         Plotting Contact%                          #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]

players['Contact%'] = pd.cut(players['Contact%'], velos, include_lowest=True,␣
 ↪labels = labels)

# Make categorical column (returned by pd.cut) into int -- https://
 ↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
 ↪61761109#61761109
players['Contact%'] = players[['Contact%']].apply(lambda col:pd.
 ↪Categorical(col).codes)

players.groupby('Contact%')[['BB/K']].mean().plot(legend=True, ax=ax[0,2])

# Label the title, x-axis, and y-axis
ax[0,2].set_title('Effect of Contact Rate on BB/K', fontsize=15)
ax[0,2].set_xlabel("Percent of Swings that Make Contact (Contact%)",␣
 ↪fontsize=15)
ax[0,2].set_ylabel("Walk to Strikeout Rate (BB/K)", fontsize=15)

######################################################################
#                         Plotting BB/K                              #
######################################################################
velos = [i for i in range(0, 100, 1)]
labels = [i for i in range(0, 99, 1)]

players['BB/K'] = pd.cut(players['BB/K'], velos, include_lowest=True, labels =␣
 ↪labels)

# Make categorical column (returned by pd.cut) into int -- https://
 ↪stackoverflow.com/questions/38088652/pandas-convert-categories-to-numbers/
 ↪61761109#61761109
players['BB/K'] = players[['BB/K']].apply(lambda col:pd.Categorical(col).codes)
```

```python
players.groupby('BB/K')[['SLG', 'OPS', 'OBP', 'SLOB', 'wOBA', 'ISO']].mean().plot(legend=True, ax=ax[1,1])

# Label the title, x-axis, and y-axis
ax[1,1].set_title('Effect of Walk to Strikeout Rate on Offensive Metrics', fontsize=15)
ax[1,1].set_xlabel("Walk to Strikeout Rate (BB/K)", fontsize=15)
ax[1,1].set_ylabel("Offensive Production", fontsize=15)

plt.subplots_adjust(left=0.1,bottom=0.1, right=0.9, top=0.9, wspace=0.4, hspace=0.4)

# Display the plot
plt.show()
```



0.0.5 Part IV: Analyzing by Position

In order to successfully analyze a player's value, we need to have more than just the basic metrics like batting average, RBI, and homeruns. We want more advanced data, such as walk rate, strikeout rate, wRC+, etc. Since our original dataset does not include this, I had to scrape data from Fangraphs and Baseball-Reference.

Below, we are scraping WAR and OPS+ from Baseball-Reference (we will discuss these statistics in the coming sections): **WAR: Wins Above Replacement** > Calculates many more wins a baseball team has from a player compared to if the team replaced the player with a replacement-level player in the same position.

[49]:
```python
# Rename Teams ID to match batting dataframe from above
batting_table = batting_table.replace('CHN', 'CHC')
batting_table = batting_table.replace('CHA', 'CHW')
batting_table = batting_table.replace('LAN', 'LAD')
```

```
batting_table = batting_table.replace('KCA', 'KCR')
batting_table = batting_table.replace('NYA', 'NYY')
batting_table = batting_table.replace('NYN', 'NYM')
batting_table = batting_table.replace('SFN', 'SFG')
batting_table = batting_table.replace('SDN', 'SDP')
batting_table = batting_table.replace('SLN', 'STL')
batting_table = batting_table.replace('WAS', 'WSN')
batting_table = batting_table.replace('TBA', 'TBR')
```

[50]:

```
# Scrape data from baseball reference .csv file
baseball_reference_table = pd.read_csv('baseball-reference/batting.csv')
baseball_reference_table = baseball_reference_table[['Name', 'Age', 'Year',␣
 ↪'Team', 'WAR', 'WAR_def', 'WAR_off', 'OPS_plus']]

# Rename OPS_plus to OPS+
baseball_reference_table = baseball_reference_table.rename(columns={'OPS_plus':
 ↪'OPS+'})

# Cast OPS+ column to integer
baseball_reference_table['OPS+'] = baseball_reference_table['OPS+'].fillna(0)
baseball_reference_table['OPS+'] = baseball_reference_table['OPS+'].astype(int)

# Cast Age column to integer
baseball_reference_table.Age = baseball_reference_table.Age.fillna(0)
baseball_reference_table.Age = baseball_reference_table.Age.astype(int)

# Merge dataframe from above with the nex dataframe
batting_table = pd.merge(batting_table, baseball_reference_table, on=['Name',␣
 ↪'Year', 'Team'])

# Reorder the columns
batting_table = batting_table[['Year', 'Name', 'Pos', 'Age', 'Team', 'Lg', 'G',␣
 ↪'AB', 'R', 'H', '2B', '3B', 'HR', 'RBI', 'SB', 'CS', \
                                'BB', 'SO', 'IBB', 'HBP', 'SH', 'SF', 'GIDP',␣
 ↪'OPS+', 'WAR', 'WAR_def', 'WAR_off', 'Salary']]

batting_table
```

[50]:

```
      Year                 Name Pos  Age Team  Lg    G   AB   R    H  2B  \
0     2011        Chone Figgins  3B   33  SEA  AL   81  288  24   54  11
1     2011  Jarrod Saltalamacchia   C   26  BOS  AL  103  358  52   84  23
2     2011       Prince Fielder  1B   27  MIL  NL  162  569  95  170  36
3     2011        Angel Sanchez  SS   27  HOU  NL  110  288  35   69  10
4     2011       Pablo Sandoval  3B   24  SFG  NL  117  426  55  134  26
…     …                      …  ..  …    …   ..   …   …   ..  …   ..
5527  2021        Phillip Evans  1B   28  PIT  NL   76  214  23   44   5
5528  2021         Rhys Hoskins  1B   28  PHI  NL  107  389  64   96  29
```

```
5529  2021           Derek Fisher  RF   27  MIL  NL    4    8   1    2   0
5530  2021          Dustin Fowler  CF   26  PIT  NL   18   41   3    7   1
5531  2021            Kyle Farmer  SS   30  CIN  NL  147  483  60  127  22

      3B  HR  RBI  SB  CS   BB   SO  IBB  HBP  SH  SF  GIDP  OPS+   WAR  \
0      1   1   15  11   6   21   42    1    0   2   2     6    40 -0.92
1      3  16   56   1   0   24  119    1    3   0   1     7    94  0.73
2      1  38  120   1   1  107  106   32   10   0   6    17   164  4.49
3      0   1   28   3   0   27   44    1    1  10   2     3    65 -0.31
4      3  23   70   2   4   32   63    9    0   1   7    12   155  6.00
…     ..  ..  …   ..  ..  …  …  …  …  ..  ..  …   …   …
5527   0   5   16   1   0   28   53    1    5   0   0     3    68 -0.37
5528   0  27   71   3   2   47  108    0    5   0   2     7   129  1.95
5529   1   0    1   0   0    0    1    0    0   0   0     0    94  0.02
5530   0   0    2   1   0    3   20    0    1   0   1     0    20 -0.36
5531   2  16   63   2   3   22   97    1   18   1   5    16    86  1.19

      WAR_def  WAR_off    Salary
0        0.06    -0.78   9500000
1       -0.05     1.51    750000
2       -2.12     5.53  15500000
3        0.12    -0.11    432500
4        1.73     4.40    500000
…         …        …         …
5527    -0.37    -0.24    650000
5528    -1.32     2.70   4800000
5529    -0.01     0.02    582100
5530     0.01    -0.36    575500
5531     0.80     1.03    640000

[5532 rows x 28 columns]
```

Next, we want to include even more metrics that were not easily accessible on Baseball-Reference. For this, we will use data from Fangraphs. Since each Fangraphs webpage only has a single team's players's stats for a given year, I had to create a function that created a dataframe by scraping the table using the given url, which was specific to a team and year. For example, one url would have the datatable for each player on the 2016 Baltimore Orioles. Since one page could only display 50 players, there were 2 pages (an additional url) for each team. Below is the function that creates the dataframe by scraping the data from the inputted url.

[51]:
```python
def scraping_advanced_stats(url, year, team):
    # Extracting text from webpage
    html = requests.get(url).text

    # Parsing the text into html code
    soup = BeautifulSoup(html,"html.parser")
```

```
    # Finding the table in the html code - we are searching by the id of the␣
↪table
    table = soup.find("table", attrs={"class": "rgMasterTable"})


    table_data = table.tbody.find_all("tr")

    dataset = []
    for tr in table_data:
        temp = ()
        for td in tr.find_all("td"):
            if '\xa0' in td.text:
                temp += ('0.0',)
            else:
                temp += (td.text,)
        dataset.append(temp)

    advanced_stats = pd.DataFrame(data = dataset)
    advanced_stats = advanced_stats.replace(to_replace=" NULL",value=0)

    table_header = table.thead.find_all("tr")
    columns = []
    count = 0
    for tr in table_header:
        if count == 1:
            th = tr.find_all("th")
            for a in th:
                columns.append(a.text)
        count = 1
    advanced_stats.columns = columns
    advanced_stats = advanced_stats.assign(Year = year)
    advanced_stats = advanced_stats.assign(Team = team)

    return advanced_stats
```

Since I needed to generate a url for each page for each team for a given year for the years 2011-2021, I needed to create a function that generated a url for each value. See it below:

[52]:
```
def get_urls(team, year, page, stat):
    if stat == 'advanced':
        url = 'https://www.fangraphs.com/leaders.aspx?pos=all&stats' \
          '=bat&lg=all&qual=0&type=1&season=' + str(year) + '&month=0&season1='␣
↪\
           + str(year) + '&ind=0&team='+ str(team)␣
↪+'&rost=0&age=0&filter=&players=0&startdate' \
          '=' + str(year) + '-01-01&enddate=' + str(year) + '-12-31&page=' +␣
↪str(page) + '_50'
```

```
    if stat == 'batted':
        url = 'https://www.fangraphs.com/leaders.aspx?
↪pos=all&stats=bat&lg=all&qual=0&type=2&season' \
            '=' + str(year) + '&month=0&season1=' + str(year) + '&ind=0&team='+␣
↪str(team) +'&rost=0&age=0&filter=&players=0&startdate=' + str(year) +␣
↪'-01-01' \
            '&enddate=' + str(year) + '-12-31&page=' + str(page) + '_50'
    return url
```

Below, I am actually putting the functions made above into use. With the first url, I create an initial dataframe. For the subsequent urls, I just concatenate the created dataframe onto the previous dataframes, to create a single dataframe that holds the data for each player on each team from 2011-2021. Below is the code:

[56]:
```
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']

team_number = [i for i in range(1, 31)]
years = [i for i in range(2011,2022)]
pages = [1,2]

count = 0
for year in years:
    for team in team_number:
        for page in pages:
            url = get_urls(team, year, page, 'player_advanced')
            if count == 0:
                advanced_batting = scraping_FanGraphs(url, year, teams[team-1])
                count = 1
            else:
                advanced_batting = pd.concat([advanced_batting,␣
↪scraping_FanGraphs(url, year, teams[team-1])])

advanced_batting = advanced_batting.drop_duplicates()
advanced_batting = advanced_batting.reset_index(drop=True)
advanced_batting
```

[56]:
```
        #           Name   PA   BB%      K%  BB/K   AVG   OBP   SLG    OPS  \
0       1  Tyler Chatwood    5  0.0%    0.0%  0.00  .667  .667  .667  1.333
1       2   Ervin Santana    2  0.0%   50.0%  0.00  .500  .500  .500  1.000
2       3   Gil Velazquez    7  0.0%    0.0%  0.00  .500  .429  .500   .929
3       4  Howie Kendrick  583  5.7%   20.4%  0.28  .285  .338  .464   .802
4       5    Torii Hunter  649  9.6%   19.3%  0.50  .262  .336  .429   .765
…     ..             …  …    …     …     …    …    …    …     …
16260  50    Conner Menez    0  0.0%    0.0%  0.00  .000  .000  .000   .000
16261  51   Caleb Baragar    2  0.0%  100.0%  0.00  .000  .000  .000   .000
```

```
16262  52   Kervin Castro    0  0.0%    0.0%  0.00  .000  .000  .000   .000
16263  53  Gregory Santos    0  0.0%    0.0%  0.00  .000  .000  .000   .000
16264  54    Camilo Doval    0  0.0%    0.0%  0.00  .000  .000  .000   .000

        ISO  Spd  BABIP  UBR  wGDP   wSB  wRC  wRAA  wOBA  wRC+  Year  Team
0      .000  2.6   .667  0.0   0.0   0.0    2   1.1  .594   289  2011   LAA
1      .000  0.1  1.000  0.0   0.0   0.0    0   0.2  .445   188  2011   LAA
2      .000  0.1   .429  0.0   0.1   0.0    1   0.4  .382   145  2011   LAA
3      .179  6.2   .338  2.3  -2.2  -0.1   81  15.4  .349   123  2011   LAA
4      .167  3.1   .297  1.3  -3.5  -2.4   84  10.7  .337   115  2011   LAA
…      …  …     …  …    …    …  ..    …    …    …    …   …
16260  .000  0.1   .000  0.0   0.0   0.0    0   0.0  .000   0.0  2021   SFG
16261  .000  0.1   .000  0.0   0.0   0.0    0  -0.5  .000  -100  2021   SFG
16262  .000  0.1   .000  0.0   0.0   0.0    0   0.0  .000   0.0  2021   SFG
16263  .000  0.1   .000  0.0   0.0   0.0    0   0.0  .000   0.0  2021   SFG
16264  .000  0.1   .000  0.0   0.0   0.0    0   0.0  .000   0.0  2021   SFG

[16265 rows x 22 columns]
```

[57]:
```python
teams = ['LAA', 'BAL', 'BOS', 'CHW', 'CLE', 'DET', 'KCR', 'MIN', 'NYY', 'OAK', \
         'SEA', 'TBR', 'TEX', 'TOR', 'ARI', 'ATL', 'CHC', 'CIN', 'COL', 'MIA', \
         'HOU', 'LAD', 'MIL', 'WSN', 'NYM', 'PHI', 'PIT', 'STL', 'SDP', 'SFG']

team_number = [i for i in range(1, 31)]
years = [i for i in range(2011,2022)]
pages = [1,2]

count = 0
for year in years:
    for team in team_number:
        for page in pages:
            url = get_urls(team, year, page, 'player_batted')
            if count == 0:
                batted_ball = scraping_advanced_stats(url, year, teams[team-1])
                count = 1
            else:
                batted_ball = pd.concat([batted_ball,␣
 ↪scraping_advanced_stats(url, year, teams[team-1])])

batted_ball = batted_ball.drop_duplicates()
batted_ball = batted_ball.reset_index(drop=True)
```

[58]:
```python
advanced_batting = advanced_batting[['Name', 'Year', 'Team', 'PA', 'AVG',␣
 ↪'BABIP', 'OBP', 'SLG', 'OPS', 'BB%', 'K%', 'BB/K', 'ISO', 'Spd', 'UBR',␣
 ↪'wGDP', 'wSB', 'wRC', 'wRAA', 'wOBA', 'wRC+']]
```

```python
batted_ball = batted_ball[['Name', 'Year', 'Team', 'BABIP', 'GB/FB', 'LD%',
 'GB%', 'FB%', 'IFFB%', 'HR/FB', 'IFH', 'IFH%', 'BUH', 'BUH%', 'Pull%',
 'Cent%', 'Oppo%', 'Soft%', 'Med%', 'Hard%']]

advanced_batting = pd.merge(advanced_batting, batted_ball, on=['Name', 'BABIP',
 'Team', 'Year'])
advanced_batting.head()
```

[58]:

```
              Name  Year Team   PA   AVG  BABIP   OBP   SLG    OPS   BB%  \
0  Tyler Chatwood  2011  LAA    5  .667   .667  .667  .667  1.333  0.0%
1   Ervin Santana  2011  LAA    2  .500  1.000  .500  .500  1.000  0.0%
2   Gil Velazquez  2011  LAA    7  .500   .429  .429  .500   .929  0.0%
3  Howie Kendrick  2011  LAA  583  .285   .338  .338  .464   .802  5.7%
4    Torii Hunter  2011  LAA  649  .262   .297  .336  .429   .765  9.6%

      K%  BB/K   ISO  Spd  UBR  wGDP   wSB wRC  wRAA  wOBA wRC+ GB/FB    LD%  \
0   0.0%  0.00  .000  2.6  0.0   0.0   0.0   2   1.1  .594  289  2.00  33.3%
1  50.0%  0.00  .000  0.1  0.0   0.0   0.0   0   0.2  .445  188  1.00   0.0%
2   0.0%  0.00  .000  0.1  0.0   0.1   0.0   1   0.4  .382  145  0.25  28.6%
3  20.4%  0.28  .179  6.2  2.3  -2.2  -0.1  81  15.4  .349  123  1.94  21.9%
4  19.3%  0.50  .167  3.1  1.3  -3.5  -2.4  84  10.7  .337  115  1.37  21.0%

      GB%    FB%  IFFB%  HR/FB IFH  IFH% BUH   BUH%   Pull%  Cent%  Oppo%  \
0   66.7%   0.0%   0.0%   0.0%   0  0.0%   0   0.0%    0.0%  40.0%  60.0%
1  100.0%   0.0%   0.0%   0.0%   0  0.0%   0   0.0%  100.0%   0.0%   0.0%
2   14.3%  57.1%   0.0%   0.0%   0  0.0%   0   0.0%   14.3%  28.6%  57.1%
3   51.6%  26.5%   0.0%  16.5%  19  9.0%   6  60.0%   32.8%  39.4%  27.8%
4   45.7%  33.3%  13.9%  15.2%  11  5.3%   2  40.0%   40.4%  37.3%  22.3%

   Soft%    Med%  Hard%
0  20.0%   60.0%  20.0%
1   0.0%  100.0%   0.0%
2  42.9%   57.1%   0.0%
3  19.0%   52.5%  28.5%
4  22.9%   44.8%  32.3%
```

Below you will see a naming discrepancy for players with a suffix between my first dataframe (first table displayed) and the newly created dataframe (2nd table displayed). We need to address this to be able to merge our advanced data by name.

[59]:

```python
batting_table[batting_table.Name == 'Cedric Mullins']
```

[59]:

```
      Year            Name Pos  Age Team  Lg    G   AB   R    H  2B  3B  HR  \
3987  2019  Cedric Mullins  CF   24  BAL  AL   22   64   7    6   0   2   0
4644  2020  Cedric Mullins  CF   25  BAL  AL   48  140  16   38   4   3   3
5334  2021  Cedric Mullins  CF   26  BAL  AL  159  602  91  175  37   5  30
```

```
      RBI  SB  CS  BB   SO  IBB  HBP  SH  SF  GIDP  OPS+   WAR  WAR_def  \
3987    4   1   0   4   14    0    3   2   1     2    -8 -0.54     0.17
4644   12   7   2   8   37    0    1   4   0     0    94  0.44     0.05
5334   59  30   8  59  125    3    8   1   4     2   135  5.69     0.35

      WAR_off   Salary
3987    -0.65  557500
4644     0.45  563500
5334     5.75  577000
```

[60]:
```python
advanced_batting[advanced_batting.Name == 'Cedric Mullins II']
```

[60]:
```
                    Name  Year Team   PA   AVG BABIP   OBP   SLG   OPS   BB%  \
10170  Cedric Mullins II  2018  BAL  191  .235  .279  .312  .359  .671  8.9%
11712  Cedric Mullins II  2019  BAL   74  .094  .118  .181  .156  .337  5.4%
13253  Cedric Mullins II  2020  BAL  153  .271  .350  .315  .407  .723  5.2%
14624  Cedric Mullins II  2021  BAL  675  .291  .322  .360  .518  .878  8.7%

          K%  BB/K   ISO  Spd  UBR  wGDP   wSB  wRC   wRAA  wOBA wRC+ GB/FB  \
10170  19.4%  0.46  .124  2.9  0.8   0.2  -0.9   20   -2.7  .298   86  1.37
11712  18.9%  0.29  .063  7.9  0.5  -0.2   0.2   -1  -10.3  .159  -12  1.35
13253  24.2%  0.22  .136  7.2  1.8   0.6   0.4   18   -0.9  .313   95  1.25
14624  18.5%  0.47  .228  6.1  0.4   2.3   2.1  114   32.0  .372  136  0.95

         LD%    GB%    FB%  IFFB%  HR/FB IFH   IFH% BUH   BUH%  Pull%  Cent%  \
10170  12.1%  50.8%  37.1%  10.9%   8.7%   9  14.3%   4  36.4%  42.2%  33.3%
11712   7.8%  52.9%  39.2%  25.0%   0.0%   1   3.7%   0   0.0%  43.4%  37.7%
13253  21.7%  43.5%  34.8%  21.9%   9.4%   3   7.5%   9  60.0%  43.0%  28.0%
14624  19.9%  39.0%  41.1%  12.4%  15.5%  17   9.2%   5  50.0%  43.6%  32.4%

       Oppo%  Soft%   Med%  Hard%
10170  24.4%  19.3%  54.1%  26.7%
11712  18.9%  34.0%  49.1%  17.0%
13253  29.0%  15.9%  62.6%  21.5%
14624  24.1%  14.9%  51.9%  33.2%
```

Below, we will address this issue and fix it so that we can successfully merge by name:

[61]:
```python
names = advanced_batting.Name.str.split(' ', expand=True)[[0, 1]]
names.columns = ['First', 'Last']
names = names.assign(Name = names.First.str.cat(names.Last,sep=' '))
names = names[['Name']]

advanced_batting = advanced_batting.assign(Name = names.Name.to_list())
advanced_batting[advanced_batting.Name == 'Cedric Mullins']
```

[61]:
```
                     Name  Year Team   PA   AVG BABIP   OBP   SLG   OPS   BB%  \
10170  Cedric Mullins  2018  BAL  191  .235  .279  .312  .359  .671  8.9%
11712  Cedric Mullins  2019  BAL   74  .094  .118  .181  .156  .337  5.4%
13253  Cedric Mullins  2020  BAL  153  .271  .350  .315  .407  .723  5.2%
14624  Cedric Mullins  2021  BAL  675  .291  .322  .360  .518  .878  8.7%

          K%  BB/K   ISO  Spd  UBR  wGDP   wSB  wRC   wRAA  wOBA  wRC+  GB/FB  \
10170  19.4%  0.46  .124  2.9  0.8   0.2  -0.9   20   -2.7  .298    86   1.37
11712  18.9%  0.29  .063  7.9  0.5  -0.2   0.2   -1  -10.3  .159   -12   1.35
13253  24.2%  0.22  .136  7.2  1.8   0.6   0.4   18   -0.9  .313    95   1.25
14624  18.5%  0.47  .228  6.1  0.4   2.3   2.1  114   32.0  .372   136   0.95

         LD%    GB%    FB%  IFFB%  HR/FB  IFH   IFH%  BUH   BUH%  Pull%  Cent%  \
10170  12.1%  50.8%  37.1%  10.9%   8.7%    9  14.3%    4  36.4%  42.2%  33.3%
11712   7.8%  52.9%  39.2%  25.0%   0.0%    1   3.7%    0   0.0%  43.4%  37.7%
13253  21.7%  43.5%  34.8%  21.9%   9.4%    3   7.5%    9  60.0%  43.0%  28.0%
14624  19.9%  39.0%  41.1%  12.4%  15.5%   17   9.2%    5  50.0%  43.6%  32.4%

       Oppo%  Soft%   Med%  Hard%
10170  24.4%  19.3%  54.1%  26.7%
11712  18.9%  34.0%  49.1%  17.0%
13253  29.0%  15.9%  62.6%  21.5%
14624  24.1%  14.9%  51.9%  33.2%
```

As you can see, we have successfully removed all suffixes from the advanced_batting dataframe.

Now, we can merge the two dataframes together:

[62]:
```python
# Merging dataframes
batting_table = pd.merge(batting_table, advanced_batting, on = ['Name', 'Year',
 ↪'Team'])

# Reordering columns
batting_table = batting_table[['Year', 'Name', 'Pos', 'Age', 'Team', 'Lg', 'G',
 ↪'PA', 'AB', 'R', 'H', '2B', '3B', \
                              'HR', 'RBI', 'SB', 'CS', 'BB', 'SO', 'AVG',
 ↪'OBP', 'SLG', 'OPS', 'OPS+', 'IBB', \
                              'HBP', 'SH', 'SF', 'GIDP', 'WAR', 'WAR_def',
 ↪'WAR_off', 'BB%', 'K%', 'BB/K', \
                              'ISO', 'Spd', 'BABIP', 'UBR', 'wGDP', 'wSB',
 ↪'wRC', 'wOBA', 'wRC+', 'GB/FB',  \
                              'LD%', 'GB%', 'FB%', 'IFFB%', 'HR/FB','Pull%',
 ↪'Cent%', 'Oppo%', 'Soft%',\
                              'Med%', 'Hard%','Salary']]

batting_table
```

```
[62]:      Year                   Name Pos  Age Team  Lg    G   PA   AB   R    H  \
0     2011          Chone Figgins  3B   33  SEA  AL   81  313  288  24   54
1     2011  Jarrod Saltalamacchia   C   26  BOS  AL  103  386  358  52   84
2     2011         Prince Fielder  1B   27  MIL  NL  162  692  569  95  170
3     2011          Angel Sanchez  SS   27  HOU  NL  110  328  288  35   69
4     2011         Pablo Sandoval  3B   24  SFG  NL  117  466  426  55  134
…      …                      …  ..   …    …  ..    …    …    … ..    …
5503  2021          Phillip Evans  1B   28  PIT  NL   76  247  214  23   44
5504  2021           Rhys Hoskins  1B   28  PHI  NL  107  443  389  64   96
5505  2021           Derek Fisher  RF   27  MIL  NL    4    8    8   1    2
5506  2021          Dustin Fowler  CF   26  PIT  NL   18   46   41   3    7
5507  2021            Kyle Farmer  SS   30  CIN  NL  147  529  483  60  127

      2B 3B  HR  RBI  SB  CS   BB   SO   AVG   OBP   SLG   OPS  OPS+  IBB  \
0     11  1   1   15  11   6   21   42  .188  .241  .243  .484    40    1
1     23  3  16   56   1   0   24  119  .235  .288  .450  .737    94    1
2     36  1  38  120   1   1  107  106  .299  .415  .566  .981   164   32
3     10  0   1   28   3   0   27   44  .240  .305  .285  .590    65    1
4     26  3  23   70   2   4   32   63  .315  .357  .552  .909   155    9
…     .. ..  ..    …  ..  ..    …    …     …     …     …     …     …    …
5503   5  0   5   16   1   0   28   53  .206  .312  .299  .611    68    1
5504  29  0  27   71   3   2   47  108  .247  .334  .530  .864   129    0
5505   0  1   0    1   0   0    0    1  .250  .250  .500  .750    94    0
5506   1  0   0    2   1   0    3   20  .171  .239  .195  .434    20    0
5507  22  2  16   63   2   3   22   97  .263  .316  .416  .732    86    1

      HBP  SH  SF  GIDP   WAR  WAR_def  WAR_off    BB%     K%  BB/K   ISO  \
0       0   2   2     6 -0.92     0.06    -0.78   6.7%  13.4%  0.50  .056
1       3   0   1     7  0.73    -0.05     1.51   6.2%  30.8%  0.20  .215
2      10   0   6    17  4.49    -2.12     5.53  15.5%  15.3%  1.01  .267
3       1  10   2     3 -0.31     0.12    -0.11   8.2%  13.4%  0.61  .045
4       0   1   7    12  6.00     1.73     4.40   6.9%  13.5%  0.51  .237
…       …  ..  ..     …     …        …        …      …      …     …     …
5503    5   0   0     3 -0.37    -0.37    -0.24  11.3%  21.5%  0.53  .093
5504    5   0   2     7  1.95    -1.32     2.70  10.6%  24.4%  0.44  .283
5505    0   0   0     0  0.02    -0.01     0.02   0.0%  12.5%  0.00  .250
5506    1   0   1     0 -0.36     0.01    -0.36   6.5%  43.5%  0.15  .024
5507   18   1   5    16  1.19     0.80     1.03   4.2%  18.3%  0.23  .153

      Spd BABIP   UBR  wGDP   wSB  wRC  wOBA wRC+ GB/FB    LD%    GB%    FB%  \
0     5.0  .215  -2.0   0.5  -0.4   11  .220   37  1.59  18.3%  50.2%  31.5%
1     4.7  .304  -0.6   0.5   0.0   44  .319   95  0.69  21.3%  32.1%  46.7%
2     1.9  .306  -5.9  -0.9  -0.8  129  .410  160  1.16  19.8%  43.1%  37.1%
3     3.7  .278   1.5   1.5   0.3   25  .269   66  1.79  18.1%  52.5%  29.4%
4     2.8  .320  -2.1  -1.2  -1.6   77  .383  149  1.07  19.5%  41.6%  38.9%
…       …     …     …     …     …    …     …    …     …      …      …      …
5503  2.4  .250  -0.1   0.1   0.0   22  .278   73  1.96  15.5%  55.9%  28.6%
```

```
5504  2.8  .270  -1.4   0.5  -0.6   72  .364  127  0.58  19.8%  29.3%  50.9%
5505  5.1  .286   0.0   0.0   0.0    1  .306   89  2.50   0.0%  71.4%  28.6%
5506  4.4  .318  -0.6   0.4   0.2    1  .202   24  1.00  18.2%  40.9%  40.9%
5507  3.0  .296   1.4  -1.6  -1.3   65  .316   91  1.17  23.5%  41.2%  35.3%

      IFFB%  HR/FB  Pull%  Cent%  Oppo%  Soft%   Med%  Hard%     Salary
0     15.8%   1.3%  30.4%  35.6%  34.0%  31.6%  52.8%  15.6%    9500000
1     10.7%  14.3%  41.7%  32.1%  26.3%  18.8%  47.9%  33.3%     750000
2      6.3%  21.8%  37.5%  34.1%  28.4%  18.6%  47.3%  34.1%   15500000
3      4.3%   1.4%  28.1%  37.9%  34.0%  26.6%  61.7%  11.7%     432500
4     11.8%  16.0%  36.4%  33.4%  30.2%  22.1%  47.4%  30.5%     500000
…       …     …      …      …      …      …      …      …        …
5503  15.2%  10.9%  38.5%  38.5%  23.0%  23.0%  45.3%  31.7%     650000
5504  13.2%  18.8%  44.2%  32.2%  23.7%  12.7%  53.0%  34.3%    4800000
5505  50.0%   0.0%  42.9%   0.0%  57.1%  14.3%  57.1%  28.6%     582100
5506  33.3%   0.0%  40.9%  31.8%  27.3%  18.2%  50.0%  31.8%     575500
5507  10.1%  11.6%  39.3%  37.2%  23.5%  15.3%  48.5%  36.2%     640000

[5508 rows x 57 columns]
```

Scraping Basic Position Player Data for 2011-2021 Seasons First, we will need to scrape data from multiple different sources.

Sean Lahman's Batting Dataset: > Contains batting data through the 2021 season.

Sean Lahman's People Dataset: > Contains player information such as birth year, name, etc.

Sean Lahman's Appearances Dataset: > Contains data on how many games a player played at each position throughout the season. We will use this to remove the pitchers from the batting dataset.

Sean Lahman's Salary Dataset: > Contains player salaries for each year up through 2016. For 2016-Present, we will list it as NaN.

[42]:
```python
# Create dataframe of player information like name and age
player_table = pd.read_csv('tables/People.csv')
shortened_player = player_table[['playerID','nameFirst', 'nameLast', 'birthYear']]
shortened_player = shortened_player.assign(Name = shortened_player.nameFirst.str.cat(shortened_player.nameLast,sep=' '))
shortened_player = shortened_player[['playerID', 'Name', 'birthYear']]

# Create dataframe of batting statistics
batting_table = pd.read_csv('tables/Batting.csv')
batting_table = batting_table[batting_table.yearID > 2010]

# Combine the pitching and batting stats
batting_table = pd.merge(batting_table, shortened_player, on='playerID')
```

```
# Rename columns
batting_table = batting_table.rename(columns={'teamID':'Team', 'lgID':'Lg',␣
↪'yearID':'Year'})

# Grabbing only needed columns
batting_table = batting_table[['playerID', 'Name', 'Year','Team', 'Lg', 'G',␣
↪'AB', 'R', 'H', '2B', '3B', 'HR', 'RBI', 'SB', \
                              'CS', 'BB', 'SO', 'IBB', 'HBP', 'SH', 'SF',␣
↪'GIDP']]

# Changing columns to be ints instead of floats
#full_batting.Age = full_batting.Age.astype(int)
batting_table.RBI = batting_table.RBI.astype(int)
batting_table.SB = batting_table.SB.astype(int)
batting_table.CS = batting_table.CS.astype(int)
batting_table.SO = batting_table.SO.astype(int)
batting_table.IBB = batting_table.IBB.astype(int)
batting_table.HBP = batting_table.HBP.astype(int)
batting_table.SH = batting_table.SH.astype(int)
batting_table.SF = batting_table.SF.astype(int)
batting_table.GIDP = batting_table.GIDP.astype(int)

# Sort by year and then reset the index
batting_table = batting_table.sort_values('Year')
batting_table = batting_table.reset_index(drop=True)

batting_table
```

[42]:

```
        playerID             Name  Year Team  Lg    G   AB   R    H  2B  3B  \
0       abadfe01    Fernando Abad  2011  HOU  NL   29    0   0    0   0   0
1      fisheca01   Carlos Fisher  2011  CIN  NL   17    2   0    0   0   0
2      figuene01  Nelson Figueroa  2011  HOU  NL    8    9   0    2   0   0
3      figgich01    Chone Figgins  2011  SEA  AL   81  288  24   54  11   1
4       salech01      Chris Sale  2011  CHA  AL   58    0   0    0   0   0
…            …               …    …   …   ..  …    …  ..   …  ..  ..
16269  flaheja01   Jack Flaherty  2021  SLN  NL   17   17   2    2   0   0
16270  flexech01    Chris Flexen  2021  SEA  AL   31    3   0    0   0   0
16271  fowledu01   Dustin Fowler  2021  PIT  NL   18   41   3    7   1   0
16272  farmeky01     Kyle Farmer  2021  CIN  NL  147  483  60  127  22   2
16273  zerpaan01     Angel Zerpa  2021  KCA  AL    1    0   0    0   0   0

       HR  RBI  SB  CS  BB  SO  IBB  HBP  SH  SF  GIDP
0       0    0   0   0   0   0    0    0   0   0     0
1       0    0   0   0   0   1    0    0   0   0     0
2       0    0   0   0   0   2    0    0   1   0     0
3       1   15  11   6  21  42    1    0   2   2     6
4       0    0   0   0   0   0    0    0   0   0     0
```

```
…     ..  …   ..  ..  ..  ..  …  …   ..  ..   …
16269   1    3   0   0   5   7    0    0   3   1      0
16270   0    0   0   0   0   0    0    0   0   0      0
16271   0    2   1   0   3  20    0    1   0   1      0
16272  16   63   2   3  22  97    1   18   1   5     16
16273   0    0   0   0   0   0    0    0   0   0      0

[16274 rows x 22 columns]
```

Because pitchers can also bat (and they were required to in the National League until 2022), this dataset includes pitchers. For example, Jack Flaherty is a starting pitcher for the St. Louis Cardinals, and he is included in the dataset. However, we want to remove these pitchers and focus only on true position players batting. We will take care of this is the next section.

Removing Pitchers from Batting Table (Except for Shohei Ohtani) Since pitchers are in the dataset too, and most of the time, pitchers are poor hitters, I do not want to include them, as it would skew the dataset. The only exception I am going to make is Shohei Ohtani, who is the only two-way player in MLB. He was so successful that in 2021, he made the All-Star game as both a Designated Hitter, as well as Pitcher, and he also won the AL MVP award. Obviously, we want to include someone as talented as Ohtani in our data. In the below code snippet, I am taking the max number of appearances at each position for each player and whichever position, the max came at, is considered their position. Since Othani will appear in more games at DH than he does as Pitcher, he will remain in the dataset.

[ ]:
```
player_pos = pd.read_csv('tables/Appearances.csv')
player_pos = player_pos[['playerID', 'yearID', 'G_p', 'G_c', 'G_1b', 'G_2b',␣
 ↪'G_3b', 'G_ss', 'G_lf', 'G_cf', 'G_rf', 'G_dh']]
player_pos = player_pos[player_pos.yearID > 2010]
player_pos = player_pos.rename(columns = {'yearID':'Year', 'G_p':'P', 'G_c':
 ↪'C', 'G_1b':'1B', 'G_2b':'2B', 'G_3b':'3B', 'G_ss':'SS', 'G_lf':'LF', 'G_cf':
 ↪'CF', 'G_rf':'RF', 'G_dh':'DH'})
player_pos = player_pos.astype({'DH':'int32'})

positions = player_pos[['P', 'C', '1B', '2B', '3B', 'SS', 'LF', 'CF', 'RF',␣
 ↪'DH']]

positions = positions.assign(Pos = positions.idxmax(axis=1))

player_pos = pd.merge(player_pos, positions, on = ['P', 'C', '1B', '2B', '3B',␣
 ↪'SS', 'LF', 'CF', 'RF', 'DH'])
player_pos = player_pos[['playerID', 'Year', 'Pos']]
player_pos = player_pos.drop_duplicates()
player_pos
```

[ ]:
```
          playerID  Year Pos
0         abadfe01  2011   P
133       baezda01  2011   P
```

```
266      colonba01  2011   P
399      daviswa01  2011   P
532      doteloc01  2011   P
…              …      …   ..
1595012  yastrmi01  2021  RF
1595013  yelicch01  2021  LF
1595014  youngan02  2021  2B
1595015  zimmebr01  2021  CF
1595016  zimmery01  2021  1B

[15124 rows x 3 columns]
```

[ ]:

```python
# Merge
batting_table = pd.merge(batting_table, player_pos, on=['playerID', 'Year'])

batting_table = batting_table[batting_table.Pos != 'P']
batting_table = batting_table[['Name', 'Year', 'Pos', 'Team', 'Lg', 'G', 'AB',␣
 ↪'R', 'H', '2B', '3B', 'HR', 'RBI', 'SB', \
                              'CS', 'BB', 'SO', 'IBB', 'HBP', 'SH', 'SF',␣
 ↪'GIDP']]
batting_table
```

[ ]:

```
                       Name  Year Pos Team  Lg    G   AB   R    H  2B  3B  \
3             Chone Figgins  2011  3B  SEA  AL   81  288  24   54  11   1
5      Jarrod Saltalamacchia  2011   C  BOS  AL  103  358  52   84  23   3
8              Thomas Field  2011  SS  COL  NL   16   48   4   13   0   0
11           Prince Fielder  2011  1B  MIL  NL  162  569  95  170  36   1
12            Angel Sanchez  2011  SS  HOU  NL  110  288  35   69  10   0
…                         …     …  ..   …  ..    …    …  ..    …  ..  ..
16858         Phillip Evans  2021  1B  PIT  NL   76  214  23   44   5   0
16859          Rhys Hoskins  2021  1B  PHI  NL  107  389  64   96  29   0
16863          Derek Fisher  2021  RF  MIL  NL    4    8   1    2   0   1
16866         Dustin Fowler  2021  CF  PIT  NL   18   41   3    7   1   0
16867           Kyle Farmer  2021  SS  CIN  NL  147  483  60  127  22   2

       HR  RBI  SB  CS   BB   SO  IBB  HBP  SH  SF  GIDP
3       1   15  11   6   21   42    1    0   2   2     6
5      16   56   1   0   24  119    1    3   0   1     7
8       0    3   0   0    3   14    0    0   0   0     1
11     38  120   1   1  107  106   32   10   0   6    17
12      1   28   3   0   27   44    1    1  10   2     3
…      ..    …  ..  ..    …    …    …    …  ..  ..     …
16858   5   16   1   0   28   53    1    5   0   0     3
16859  27   71   3   2   47  108    0    5   0   2     7
16863   0    1   0   0    0    1    0    0   0   0     0
16866   0    2   1   0    3   20    0    1   0   1     0
16867  16   63   2   3   22   97    1   18   1   5    16
```

```
[8125 rows x 22 columns]
```

```
[ ]: batting_table[batting_table.Name == 'Jack Flaherty']
```

```
[ ]: Empty DataFrame
Columns: [Name, Year, Pos, Team, Lg, G, AB, R, H, 2B, 3B, HR, RBI, SB, CS, BB,
SO, IBB, HBP, SH, SF, GIDP]
Index: []
```

```
[ ]: batting_table[batting_table.Name == 'Shohei Ohtani']
```

```
[ ]:                Name  Year Pos Team  Lg    G   AB    R    H  2B  3B  HR  RBI  \
11339  Shohei Ohtani  2018  DH  LAA  AL  114  326   59   93  21   2  22   61
12396  Shohei Ohtani  2019  DH  LAA  AL  106  384   51  110  20   5  18   62
14337  Shohei Ohtani  2020  DH  LAA  AL   46  153   23   29   6   0   7   24
16343  Shohei Ohtani  2021  DH  LAA  AL  158  537  103  138  26   8  46  100

       SB  CS  BB   SO  IBB  HBP  SH  SF  GIDP
11339  10   4  37  102    2    2   0   1     2
12396  12   3  33  110    1    2   0   4     6
14337   7   1  22   50    0    0   0   0     3
16343  26  10  96  189   20    4   0   2     7
```

As you can see, Jack Flaherty is no longer in the dataset, all whilebeing able to keep Shohei Ohtani in the dataset, so it appears we have successfully removed all primary pitchers from the dataset.

Scrape Salaries for Players from 2011-2021 Having a discussion about player value would be worthless if we did not include the salaries for each player for every year. Unfortunately, the updated (to the end of the 2021 season) Lahman dataset did not have salaries for any of the players, nor did the baseball reference .csv file. Instead, I had to do some research and found that Cot's Baseball Contracts (https://legacy.baseballprospectus.com/compensation/cots/) had salaries for all players from 2000-2021. There were individual .csv files for each season, so using excel, I just merged them all into one table in one file. I then uploaded that file to my workspace and read it as normal (using the read_csv() function). Below is a little bit of data manipulation; just trying to get the format of the names to be the exact format that my dataframe had, so that it would smoothly merge into my dataframe.

```
[47]: salaries = pd.read_csv('salaries/salaries.csv')

# Split the Name colum into first name and last name (originally stored as␣
 ↪'Last, First')
# and store it as a separate dataframe
names = salaries.Player.str.split(', ', expand=True)[[0, 1]]

# Create a new column called Name that has the format 'First Last'
names = names.assign(Name = names[1].str.cat(names[0],sep=' '))
```

```python
# Remove all columns except for the new name column
names = names[['Name']]

# Add the years to the names dataframe
names = names.assign(Year = salaries.Year.to_list())

# Add the salaries to the names dataframe
names = names.assign(Salary = salaries.Salary.to_list())

names.Salary = names.Salary.str.replace(',', '')
names.Salary = names.Salary.replace({'\$':''}, regex = True)

# Assign names to the salaries variable
salaries = names

salaries
```

[47]:

```
                     Name  Year    Salary
0              Mike Trout  2021  37116667
1             Gerrit Cole  2021  36000000
2            Jacob deGrom  2021  36000000
3       Stephen Strasburg  2021  35000000
4           Nolan Arenado  2021  35000000
…                     …     …       …
11080   Brayan Villarreal  2011    414000
11081       Jordan Walden  2011    414000
11082           Ryan Webb  2011    414000
11083      Tom Wilhelmsen  2011    414000
11084          Matt Young  2011    414000

[11085 rows x 3 columns]
```

Now that we have salaries for every single player in the last decade, we can merge the salary data onto the table that we have that contains the batting statistics for every single player from 2011-2021. Below is the code that achieves this.

[48]:

```python
batting_table = pd.merge(batting_table, salaries, on = ['Name', 'Year'])
batting_table
```

[48]:

```
                         Name  Year Pos Team  Lg    G   AB   R    H  2B  3B  HR  \
0               Chone Figgins  2011  3B  SEA  AL   81  288  24   54  11   1   1
1       Jarrod Saltalamacchia  2011   C  BOS  AL  103  358  52   84  23   3  16
2              Prince Fielder  2011  1B  MIL  NL  162  569  95  170  36   1  38
3               Angel Sanchez  2011  SS  HOU  NL  110  288  35   69  10   0   1
4                Gaby Sanchez  2011  1B  FLO  NL  159  572  72  152  35   0  19
…                         …     …  ..   …   ..    …    …  ..    …  ..  ..  ..
```

```
5650          Phillip Evans  2021  1B  PIT  NL   76  214  23   44   5   0   5
5651           Rhys Hoskins  2021  1B  PHI  NL  107  389  64   96  29   0  27
5652           Derek Fisher  2021  RF  MIL  NL    4    8   1    2   0   1   0
5653          Dustin Fowler  2021  CF  PIT  NL   18   41   3    7   1   0   0
5654            Kyle Farmer  2021  SS  CIN  NL  147  483  60  127  22   2  16

      RBI  SB  CS   BB   SO  IBB  HBP  SH  SF  GIDP    Salary
0      15  11   6   21   42    1    0   2   2     6   9500000
1      56   1   0   24  119    1    3   0   1     7    750000
2     120   1   1  107  106   32   10   0   6    17  15500000
3      28   3   0   27   44    1    1  10   2     3    432500
4      78   3   1   74   97    4    6   2   7    18    431000
…    …  ..  ..  …  …  …  …  ..  ..  …     …
5650   16   1   0   28   53    1    5   0   0     3    650000
5651   71   3   2   47  108    0    5   0   2     7   4800000
5652    1   0   0    0    1    0    0   0   0     0    582100
5653    2   1   0    3   20    0    1   0   1     0    575500
5654   63   2   3   22   97    1   18   1   5    16    640000

[5655 rows x 23 columns]
```

Scrape Advanced Position Player Metrics for 2011-2021 Seasons In order to

[ ]:
```
teams_table = pd.read_csv('tables/Teams.csv')
teams_table = teams_table[teams_table.yearID > 2010]

teams_table = teams_table.rename(columns = {'yearID':'Year','franchID':'Team'})

teams_table = teams_table[['Year', 'Team', 'W', 'L']]

data = []
for team_index, team_row in teams_table.iterrows():
    for player_index, player_row in batting_table.iterrows():
        if player_row['Team'] == team_row['Team'] and player_row['Year'] ==␣
 ↪team_row['Year']:
            player = list(player_row)
            player.append(team_row['W'])
            player.append(team_row['L'])
            player = tuple(player)
            data.append(player)
```

[ ]:
```
batting_table = pd.DataFrame(data, columns = ['Year', 'Name', 'Pos', 'Age',␣
 ↪'Team', 'Lg', 'G', 'PA', 'AB', 'R', 'H', '2B', '3B', \
                                              'HR', 'RBI', 'SB', 'CS', 'BB',␣
 ↪'SO', 'AVG', 'OBP', 'SLG', 'OPS', 'OPS+', 'IBB', \
```

```
                                              'HBP', 'SH', 'SF', 'GIDP', 'WAR',␣
↪'WAR_def', 'WAR_off', 'BB%', 'K%', 'BB/K', \
                                              'ISO', 'Spd', 'BABIP', 'UBR',␣
↪'wGDP', 'wSB', 'wRC', 'wOBA', 'wRC+', 'GB/FB',  \
                                              'LD%', 'GB%', 'FB%', 'IFFB%', 'HR/
↪FB','Pull%', 'Cent%', 'Oppo%', 'Soft%',\
                                              'Med%', 'Hard%','Salary',␣
↪'Team_W', 'Team_L'])

batting_table['BB%'] = batting_table['BB%'].replace({'\%':''}, regex = True)
batting_table['K%'] = batting_table['K%'].replace({'\%':''}, regex = True)
batting_table['LD%'] = batting_table['BB%'].replace({'\%':''}, regex = True)
batting_table['GB%'] = batting_table['GB%'].replace({'\%':''}, regex = True)
batting_table['FB%'] = batting_table['FB%'].replace({'\%':''}, regex = True)
batting_table['IFFB%'] = batting_table['IFFB%'].replace({'\%':''}, regex = True)
batting_table['HR/FB'] = batting_table['HR/FB'].replace({'\%':''}, regex = True)
batting_table['Pull%'] = batting_table['Pull%'].replace({'\%':''}, regex = True)
batting_table['Cent%'] = batting_table['Cent%'].replace({'\%':''}, regex = True)
batting_table['Oppo%'] = batting_table['Oppo%'].replace({'\%':''}, regex = True)
batting_table['Soft%'] = batting_table['Soft%'].replace({'\%':''}, regex = True)
batting_table['Med%'] = batting_table['Med%'].replace({'\%':''}, regex = True)
batting_table['Hard%'] = batting_table['Hard%'].replace({'\%':''}, regex = True)

batting_table['wRC+'] = batting_table['wRC+'].astype('int64')

batting_table = batting_table.apply(pd.to_numeric, errors='ignore')
batting_table
```

Correlation Between Batting Average and Runs Created For many years, people considered batting average (AVG) to be one of the best representations to indicate how skilled a player is. However, in recent decades, it has become clear that there are much more useful statistics that serve this purpose better.

First off, how does a team win games? They score runs! There is a stat called weighted runs created (wRC), that accounts for a player's ability to produce runs. When wRC is standardized to the era and ballpark, it becomes wRC+. This statistic can be used to compare all players' abilities to create runs. Below are the tiers of wRC+ according to Fangraphs: **Excellent:** 160 **Great:** 140 **Above Average:** 115 **Average:** 100 **Below Average:** 80 **Poor:** 75 **Awful:** 60 Now, since we know a stat that represents a person's ability to create runs, we want to know if any stats correlate with wRC+. First, we will start with standard batting average:

[ ]:
```
batting = batting_table[batting_table.PA  > 500].reset_index(drop=True)

fig, ax = plt.subplots()
ax.set_title('Correlation Between Batting Average and Runs Created', pad=10,␣
↪fontsize = 15)
plt.gca().set_xlabel('Batting Average (AVG)', fontsize=15)
```

```
plt.gca().set_ylabel('Weighted Runs Created (wRC+)', fontsize=15)
plt.scatter(batting.AVG, batting['wRC+'])
fig.set_figheight(10)
fig.set_figwidth(10)

# Calculate regression line and plot it in the same graph
reg = np.polyfit(batting.AVG, batting['wRC+'], 1)
reg_fnc = np.poly1d(reg)

m_list = []
p_list = []
for i in range(0, batting.shape[0]):
    wRC_plus = batting.at[i, 'AVG']
    m_list.append(wRC_plus)
    p_list.append(reg_fnc(wRC_plus))

plt.plot(m_list, p_list, color='red')

plt.show()
```

As the graph shows, while there is a positive correlation between AVG and wRC+, we'd like to have the correlation be a little bit stronger. A stronger correlation to wRC+ means that the stats is more directly tied to a player being able to create runs.

Correlation Between OPS+ and Runs Created Text

[ ]:
```
batting = batting_table[batting_table.PA  > 500].reset_index(drop=True)

fig, ax = plt.subplots()
ax.set_title('Correlation Between Standardized On-Base Percentage and Runs␣
 ↪Created', pad=10, fontsize = 15)
plt.gca().set_xlabel('On-Base Plus Slugging (OPS+)', fontsize=15)
plt.gca().set_ylabel('Weighted Runs Created (wRC+)', fontsize=15)

plt.scatter(batting['OPS+'], batting['wRC+'])
fig.set_figheight(10)
fig.set_figwidth(10)

# Calculate regression line and plot it in the same graph
reg = np.polyfit(batting['OPS+'], batting['wRC+'], 1)
reg_fnc = np.poly1d(reg)

m_list = []
p_list = []
for i in range(0, batting.shape[0]):
    wRC_plus = batting.at[i, 'OPS+']
    m_list.append(wRC_plus)
```

```
    p_list.append(reg_fnc(wRC_plus))

plt.plot(m_list, p_list, color='red')

plt.show()
```

As you can see from the graph, OPS+ is a much stronger statsitic in showing a player's ability to create runs for his team. **TALK ABOUT CORRCOEFF** Next, we will want to find out what makes for a high OPS+, and we will discover the players that are best at having a high OPS+. We will do this below.

First, what is OPS+? **OPS+: Normalized on-base plus slugging percentage** > **On-Base Percentage:** The ratio of the sum of the batter's hits, walks, hit by pitches to their number of plate appearances **Slugging Percentage:** The total number of bases a player records per at-bat **(1B + 2Bx2 + 3Bx3 + HRx4)/AB Normalized:** Adjusts the OPS based on park factors by comparing it to league average **(OPS / league OPS) x 100**

Some factors that might impact OPS+ are Hard Hit %, Ground Ball %, Line Drive %, Fly Ball %. We will take a look at these below:

[ ]:
```
batting = batting_table[batting_table.PA  > 500].reset_index(drop=True)



fig, ax = plt.subplots()
ax.set_title('Correlation Between Standardized On-Base Percentage and Runs␣
 ↪Created', pad=10, fontsize = 15)
plt.gca().set_xlabel('On-Base Plus Slugging (OPS+)', fontsize=15)
plt.gca().set_ylabel('Weighted Runs Created (wRC+)', fontsize=15)

plt.scatter(batting['wOBA'], batting['WAR'])
fig.set_figheight(10)
fig.set_figwidth(10)

# Calculate regression line and plot it in the same graph
reg = np.polyfit(batting['wOBA'], batting['WAR'], 1)
reg_fnc = np.poly1d(reg)

m_list = []
p_list = []
for i in range(0, batting.shape[0]):
    wRC_plus = batting.at[i, 'wOBA']
    m_list.append(wRC_plus)
    p_list.append(reg_fnc(wRC_plus))

plt.plot(m_list, p_list, color='red')

plt.show()
```

[ ]:
```
batting_table
```

[ ]:
```
```

[ ]:
```
```