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MSDE621: Final Project

Regis University

Calcuating Base Runs

Assignment Objective

For this assignment a calculation from sabermetrics called **Base Runs** will be used to evaluate team batting performance. Base runs uses several of the "on base" statistics for players or entire teams to estimate an offensive potential. The base runs calculation is below.

BaseRunners x ScoreRate + HR

```
BaseRunners = A
ScoreRate = (B/(B+C))
HR = D
```

The the calculations can be represented by

```
A*(B/(B + C)) + D

where,
A = H + BB - HR
B = (1.4*TB - .6*H - 3*HR + .1*BB)*1.02
C = AB - H
D = HR
```

Part 1. Pulling the Japanese Statistics

Part 1 will focus on (A) pulling the tables for the Japanese Teams. (B) compiling the tables into 1 data frame for all the Japanese Teams. (C) calculating the Base Runs for the Japanese Teams.

The first step of the project will focus on using the gazpacho library to scrap the required data for analysis.

In [1]:
```
# Loading all the Libraries taht will be used in this notebook
from gazpacho import get, Soup
import numpy
import pandas
import requests, bs4
import re, os
import time
```

First step is going to be collecting all the urls off of the Japan Central League

Part 1 (A) Pulling the Japanese Teams

To start a list of all the url's, one for each year, will be collected. This can then be iterated over to collect the correct tables from each page.

In [2]:
```
# The url for the Japanses Baseball Site
japan_url = f'https://www.baseball-reference.com/register/league.cgi?code=JPCL&clas
html = get(japan_url)
soup = Soup(html)
```

After inspecting the site using Chrome the individual urls are stored under "th and data-stat / year_ID"

In [3]:
```
urls = Soup(get(japan_url)).find('th', {'data-stat':'year_ID'})
```

In [4]:
```
# Checking how long the list is
print(len(urls))
```

```
75
```

Now that I have a giant list of all the information I need to pull out just the parts of the url that are needed. After some trial and error I can split each list from 63:94 to get what I need, I will do that and add them to a new list.

In [5]:
```
# Collecting each unique part of the url into a list
tiny_urls = []
for i in urls:
    i = str(i)
    t = i[63:94]
    tiny_urls.append(t)
    #print(t) was used to test what is being stored
```

In [6]:
```
# Triming the first return out of the list, which is not an url, and checkign the l
tiny_urls = tiny_urls[1:]
print(tiny_urls)
```

```
['register/league.cgi?id=e62e602d', 'register/league.cgi?id=6ffa4c10', 'register/le
ague.cgi?id=0549ac26', 'register/league.cgi?id=4b244907', 'register/league.cgi?id=7
f5a1dca', 'register/league.cgi?id=8449fb1b', 'register/league.cgi?id=5ed71981', 're
gister/league.cgi?id=fa996fac', 'register/league.cgi?id=ef7a4bc6', 'register/leagu
e.cgi?id=cbf62e9e', 'register/league.cgi?id=00cea8f5', 'register/league.cgi?id=d458
83da', 'register/league.cgi?id=c512db3e', 'register/league.cgi?id=0e8aae4b', 'regis
ter/league.cgi?id=98417e4d', 'register/league.cgi?id=d2b06889', 'register/league.cg
i?id=102ee2ae', 'register/league.cgi?id=bd17499f', 'register/league.cgi?id=4ce6298f
', 'register/league.cgi?id=2a13bfad', 'register/league.cgi?id=5f92acab', 'register/
league.cgi?id=b9ec01cb', 'register/league.cgi?id=f0f9b0a0', 'register/league.cgi?id
=bbaa3356', 'register/league.cgi?id=3231e024', 'register/league.cgi?id=1b91c1f4', '
register/league.cgi?id=ed2dcf6e', 'register/league.cgi?id=6428c92c', 'register/leag
ue.cgi?id=6a1368cc', 'register/league.cgi?id=77c2bf4f', 'register/league.cgi?id=425
993a2', 'register/league.cgi?id=54673f36', 'register/league.cgi?id=50153bfe', 'regi
ster/league.cgi?id=714c6526', 'register/league.cgi?id=645570eb', 'register/league.c
gi?id=2a35d196', 'register/league.cgi?id=184fee04', 'register/league.cgi?id=2b381bf
1', 'register/league.cgi?id=bc6a038a', 'register/league.cgi?id=a36600ac', 'register
/league.cgi?id=551f8d6b', 'register/league.cgi?id=d9928d45', 'register/league.cgi?i
d=f760c756', 'register/league.cgi?id=9a2c7147', 'register/league.cgi?id=70974d67',
'register/league.cgi?id=4a8c866b', 'register/league.cgi?id=0f522bd9', 'register/lea
gue.cgi?id=c7087a9c', 'register/league.cgi?id=b03b10db', 'register/league.cgi?id=17
09a01b', 'register/league.cgi?id=e4658f58', 'register/league.cgi?id=358472d5', 'reg
ister/league.cgi?id=ec42b1b3', 'register/league.cgi?id=85108179', 'register/league.
cgi?id=e5f882c3', 'register/league.cgi?id=e3fa4aed', 'register/league.cgi?id=77b8ec
e0', 'register/league.cgi?id=9a6d98a7', 'register/league.cgi?id=090fb106', 'registe
r/league.cgi?id=84679774', 'register/league.cgi?id=6ec6c3e8', 'register/league.cgi?
id=5b1ae5b9', 'register/league.cgi?id=d6bb1846', 'register/league.cgi?id=1b94f89d',
'register/league.cgi?id=75bfd8cd', 'register/league.cgi?id=41783612', 'register/lea
gue.cgi?id=20eaf68e', 'register/league.cgi?id=72483eb5', 'register/league.cgi?id=eb
da0083', 'register/league.cgi?id=11e72055', 'register/league.cgi?id=349646e1', 'reg
ister/league.cgi?id=f4370daa', 'register/league.cgi?id=fefaea36', 'register/league.
cgi?id=ea185063']
```

Part 1 (B) Pulling the Japanese Teams Tables

The next step will be pulling the table out of each years specific url. This was the most challenging part of the assignment, as the tables are nested very deep. I used the code provided by Ben Kite to find what tables were on each page and how to correctly pull them.

In [7]:
```
# This was taken from the suggested github profile
# https://github.com/BenKite/baseball_data/blob/master/baseballReferenceScrape.py
def findTables(url):
    res = requests.get(url)
    ## The next two lines get around the issue with comments breaking the parsing.
    comm = re.compile("<!--|-->")
    soup = bs4.BeautifulSoup(comm.sub("", res.text), 'lxml')
    divs = soup.findAll('div', id = "content")
    divs = divs[0].findAll("div", id=re.compile("^all"))
    ids = []
    for div in divs:
        searchme = str(div.findAll("table"))
        x = searchme[searchme.find("id=") + 3: searchme.find(">")]
        x = x.replace("\"", "")
        if len(x) > 0:
            ids.append(x)
    return(ids)
## For example:
## findTables("http://www.baseball-reference.com/teams/KCR/2016.shtml")
```

In [8]:
```
findTables('https://www.baseball-reference.com/register/league.cgi?id=e62e602d')
```

Out[8]:
```
['regular_season', 'league_batting', 'league_pitching', 'league_fielding']
```

In [9]:
```
# This was also taken from the suggested github
# https://github.com/BenKite/baseball_data/blob/master/baseballReferenceScrape.py
def pullTable(url, tableID):
    res = requests.get(url)
    ## Work around comments
    comm = re.compile("<!--|-->")
    soup = bs4.BeautifulSoup(comm.sub("", res.text), 'lxml')
    tables = soup.findAll('table', id = tableID)
    data_rows = tables[0].findAll('tr')
    data_header = tables[0].findAll('thead')
    data_header = data_header[0].findAll("tr")
    data_header = data_header[0].findAll("th")
    game_data = [[td.getText() for td in data_rows[i].findAll(['th','td'])]
        for i in range(len(data_rows))
        ]
    data = pandas.DataFrame(game_data)
    header = []
    for i in range(len(data.columns)):
        header.append(data_header[i].getText())
    data.columns = header
    data = data.loc[data[header[0]] != header[0]]
    data = data.reset_index(drop = True)
    return(data)
```

In [10]:
```
# pulling the first table
table_2023 = pullTable('https://www.baseball-reference.com/register/league.cgi?id=e
```

In [11]:
```
# Adding in the year for the table
table_2023['Year'] = 2023
table_2023
```

Out[11]:

	Tm	Aff	BatAge	R/G	G	PA	AB	R	H	2B	...	OBP	SLG	OPS	TB
0	Hanshin Tigers		27.2	3.88	105	4029	3512	407	863	137	...	.321	.346	.667	1214
1	Yomiuri Giants		28.5	3.87	103	3868	3510	399	896	149	...	.309	.413	.721	1448
2	Yokohama Bay Stars		29.3	3.64	104	3860	3463	379	859	161	...	.306	.367	.674	1272
3	Yakult Swallows		27.4	3.63	104	3875	3418	378	813	147	...	.308	.361	.669	1235
4	Hiroshima Carp		29.8	3.44	106	3867	3489	365	851	145	...	.301	.352	.654	1229
5	Chunichi Dragons		26.8	2.93	104	3821	3487	305	844	146	...	.291	.334	.625	1164
6	League Totals		28.2	3.57	626	23320	20879	2233	5126	885	...	.306	.362	.668	7562

7 rows × 28 columns

Now that everyting is working the code can be compiled into a loop to pull each table from the yearly stats page and build it into one larger table. A time pause was added, otherwise the pull request was rejected from the website.

In [12]:

```
# Code for pulling each table and building the data frame
import pandas as pd
year = 2022

japanese_frame = table_2023

for i in tiny_urls:
    url = 'https://www.baseball-reference.com/' + i
    print(url)
    table = pullTable(url, 'league_batting')
    table['Year'] = year
    japanese_frame = pd.concat([japanese_frame, table])
    year = year - 1
    print(year)
    time.sleep(5) # pull timing
```

```
https://www.baseball-reference.com/register/league.cgi?id=e62e602d
2021
https://www.baseball-reference.com/register/league.cgi?id=6ffa4c10
2020
https://www.baseball-reference.com/register/league.cgi?id=0549ac26
2019
https://www.baseball-reference.com/register/league.cgi?id=4b244907
2018
https://www.baseball-reference.com/register/league.cgi?id=7f5a1dca
2017
https://www.baseball-reference.com/register/league.cgi?id=8449fb1b
2016
https://www.baseball-reference.com/register/league.cgi?id=5ed71981
2015
https://www.baseball-reference.com/register/league.cgi?id=fa996fac
2014
https://www.baseball-reference.com/register/league.cgi?id=ef7a4bc6
2013
https://www.baseball-reference.com/register/league.cgi?id=cbf62e9e
2012
https://www.baseball-reference.com/register/league.cgi?id=00cea8f5
2011
https://www.baseball-reference.com/register/league.cgi?id=d45883da
2010
https://www.baseball-reference.com/register/league.cgi?id=c512db3e
2009
https://www.baseball-reference.com/register/league.cgi?id=0e8aae4b
2008
https://www.baseball-reference.com/register/league.cgi?id=98417e4d
2007
https://www.baseball-reference.com/register/league.cgi?id=d2b06889
2006
https://www.baseball-reference.com/register/league.cgi?id=102ee2ae
2005
https://www.baseball-reference.com/register/league.cgi?id=bd17499f
2004
https://www.baseball-reference.com/register/league.cgi?id=4ce6298f
2003
https://www.baseball-reference.com/register/league.cgi?id=2a13bfad
2002
https://www.baseball-reference.com/register/league.cgi?id=5f92acab
2001
https://www.baseball-reference.com/register/league.cgi?id=b9ec01cb
2000
https://www.baseball-reference.com/register/league.cgi?id=f0f9b0a0
1999
https://www.baseball-reference.com/register/league.cgi?id=bbaa3356
1998
https://www.baseball-reference.com/register/league.cgi?id=3231e024
1997
https://www.baseball-reference.com/register/league.cgi?id=1b91c1f4
1996
https://www.baseball-reference.com/register/league.cgi?id=ed2dcf6e
1995
https://www.baseball-reference.com/register/league.cgi?id=6428c92c
1994
https://www.baseball-reference.com/register/league.cgi?id=6a1368cc
1993
https://www.baseball-reference.com/register/league.cgi?id=77c2bf4f
```

```
1992
https://www.baseball-reference.com/register/league.cgi?id=425993a2
1991
https://www.baseball-reference.com/register/league.cgi?id=54673f36
1990
https://www.baseball-reference.com/register/league.cgi?id=50153bfe
1989
https://www.baseball-reference.com/register/league.cgi?id=714c6526
1988
https://www.baseball-reference.com/register/league.cgi?id=645570eb
1987
https://www.baseball-reference.com/register/league.cgi?id=2a35d196
1986
https://www.baseball-reference.com/register/league.cgi?id=184fee04
1985
https://www.baseball-reference.com/register/league.cgi?id=2b381bf1
1984
https://www.baseball-reference.com/register/league.cgi?id=bc6a038a
1983
https://www.baseball-reference.com/register/league.cgi?id=a36600ac
1982
https://www.baseball-reference.com/register/league.cgi?id=551f8d6b
1981
https://www.baseball-reference.com/register/league.cgi?id=d9928d45
1980
https://www.baseball-reference.com/register/league.cgi?id=f760c756
1979
https://www.baseball-reference.com/register/league.cgi?id=9a2c7147
1978
https://www.baseball-reference.com/register/league.cgi?id=70974d67
1977
https://www.baseball-reference.com/register/league.cgi?id=4a8c866b
1976
https://www.baseball-reference.com/register/league.cgi?id=0f522bd9
1975
https://www.baseball-reference.com/register/league.cgi?id=c7087a9c
1974
https://www.baseball-reference.com/register/league.cgi?id=b03b10db
1973
https://www.baseball-reference.com/register/league.cgi?id=1709a01b
1972
https://www.baseball-reference.com/register/league.cgi?id=e4658f58
1971
https://www.baseball-reference.com/register/league.cgi?id=358472d5
1970
https://www.baseball-reference.com/register/league.cgi?id=ec42b1b3
1969
https://www.baseball-reference.com/register/league.cgi?id=85108179
1968
https://www.baseball-reference.com/register/league.cgi?id=e5f882c3
1967
https://www.baseball-reference.com/register/league.cgi?id=e3fa4aed
1966
https://www.baseball-reference.com/register/league.cgi?id=77b8ece0
1965
https://www.baseball-reference.com/register/league.cgi?id=9a6d98a7
1964
https://www.baseball-reference.com/register/league.cgi?id=090fb106
1963
```

```
https://www.baseball-reference.com/register/league.cgi?id=84679774
1962
https://www.baseball-reference.com/register/league.cgi?id=6ec6c3e8
1961
https://www.baseball-reference.com/register/league.cgi?id=5b1ae5b9
1960
https://www.baseball-reference.com/register/league.cgi?id=d6bb1846
1959
https://www.baseball-reference.com/register/league.cgi?id=1b94f89d
1958
https://www.baseball-reference.com/register/league.cgi?id=75bfd8cd
1957
https://www.baseball-reference.com/register/league.cgi?id=41783612
1956
https://www.baseball-reference.com/register/league.cgi?id=20eaf68e
1955
https://www.baseball-reference.com/register/league.cgi?id=72483eb5
1954
https://www.baseball-reference.com/register/league.cgi?id=ebda0083
1953
https://www.baseball-reference.com/register/league.cgi?id=11e72055
1952
https://www.baseball-reference.com/register/league.cgi?id=349646e1
1951
https://www.baseball-reference.com/register/league.cgi?id=f4370daa
1950
https://www.baseball-reference.com/register/league.cgi?id=fefaea36
1949
https://www.baseball-reference.com/register/league.cgi?id=ea185063
1948
```

In [13]:

```
# Checking the pulled data
japanese_frame
```

Out[13]:

	Tm	Aff	BatAge	R/G	G	PA	AB	R	H	2B	...	SLG	OPS	TB
0	Hanshin Tigers		27.2	3.88	105	4029	3512	407	863	137	...	.346	.667	1214
1	Yomiuri Giants		28.5	3.87	103	3868	3510	399	896	149	...	.413	.721	1448
2	Yokohama Bay Stars		29.3	3.64	104	3860	3463	379	859	161	...	.367	.674	1272
3	Yakult Swallows		27.4	3.63	104	3875	3418	378	813	147	...	.361	.669	1235
4	Hiroshima Carp		29.8	3.44	106	3867	3489	365	851	145	...	.352	.654	1229
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4	Yomiuri Giants		27.1	5.17	140	5461	4831	724	1297	208	...	.401	.747	1937
5	Nishinippon Pirates		29.2	4.65	136	5197	4731	633	1233	175	...	.383	.706	1810
6	Hiroshima Carp		28.3	3.70	138	5173	4703	511	1145	162	...	.345	.651	1624
7	Kokutetsu Swallows		28.2	3.48	138	5070	4626	480	1131	142	...	.334	.638	1545
8	League Totals		28.8	5.00	1106	42666	38549	5526	10227	1587	...	.396	.727	15267

529 rows × 29 columns

In [14]:

```
# creating clean copy
j_df = japanese_frame
```

In [15]:

```
j_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 529 entries, 0 to 8
Data columns (total 29 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Tm      487 non-null    object
 1   Aff     529 non-null    object
 2   BatAge  529 non-null    object
 3   R/G     529 non-null    object
 4   G       529 non-null    object
 5   PA      529 non-null    object
 6   AB      529 non-null    object
 7   R       529 non-null    object
 8   H       529 non-null    object
 9   2B      529 non-null    object
 10  3B      529 non-null    object
 11  HR      529 non-null    object
 12  RBI     529 non-null    object
 13  SB      529 non-null    object
 14  CS      529 non-null    object
 15  BB      529 non-null    object
 16  SO      529 non-null    object
 17  BA      529 non-null    object
 18  OBP     529 non-null    object
 19  SLG     529 non-null    object
 20  OPS     529 non-null    object
 21  TB      529 non-null    object
 22  GDP     529 non-null    object
 23  HBP     529 non-null    object
 24  SH      529 non-null    object
 25  SF      529 non-null    object
 26  IBB     529 non-null    object
 27  Year    529 non-null    int64 
 28  Finals  42 non-null     object
dtypes: int64(1), object(28)
memory usage: 124.0+ KB
```

The data is stored as objects, and will need to be numeric to use in calculations, so that will need to be fixed. It also needs the index reset

In [16]:

```
# Reset Index
j_df = j_df.reset_index()
j_df = j_df.apply(pd.to_numeric, errors='ignore')
j_df.info(5)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 529 entries, 0 to 528
Data columns (total 30 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   index   529 non-null    int64  
 1   Tm      487 non-null    object 
 2   Aff     0 non-null      float64
 3   BatAge  529 non-null    float64
 4   R/G     529 non-null    float64
 5   G       529 non-null    int64  
 6   PA      529 non-null    int64  
 7   AB      529 non-null    int64  
 8   R       529 non-null    int64  
 9   H       529 non-null    int64  
 10  2B      529 non-null    int64  
 11  3B      529 non-null    int64  
 12  HR      529 non-null    int64  
 13  RBI     528 non-null    float64
 14  SB      529 non-null    int64  
 15  CS      529 non-null    int64  
 16  BB      529 non-null    int64  
 17  SO      529 non-null    int64  
 18  BA      529 non-null    float64
 19  OBP     529 non-null    float64
 20  SLG     529 non-null    float64
 21  OPS     529 non-null    float64
 22  TB      529 non-null    int64  
 23  GDP     529 non-null    int64  
 24  HBP     455 non-null    float64
 25  SH      529 non-null    int64  
 26  SF      497 non-null    float64
 27  IBB     529 non-null    int64  
 28  Year    529 non-null    int64  
 29  Finals  42 non-null     object 
dtypes: float64(10), int64(18), object(2)
memory usage: 124.1+ KB
```

Part 1 (C) Calculating Base Runs for the Japanese Teams

Calcuating Base Runs

After you have collected all the data for all the teams and all the years, it is time to create the base runs column. According to https://en.wikipedia.org/wiki/Base_runs, the formula to calculate base runs is:

BaseRunners x ScoreRate + HR

BaseRunners = A ScoreRate = (B/(B+C)) HR = D

The the calculations can be represented by

A*(B/(B + C)) + D

where, A = H + BB - HR B = (1.4*TB* - .6H - 3*HR* + .1BB)*1.02 C = AB - H D = HR

In [17]:

```
# Building out the calculation
H = j_df.iloc[1]['H']
BB = j_df.iloc[1]['BB']
HR = j_df.iloc[1]['HR']
B2 = j_df.iloc[1]['2B']
B3 = j_df.iloc[1]['3B']
AB = j_df.iloc[1]['AB']
TB = j_df.iloc[1]['TB']

A = H + BB - HR
print("A is" , A)
B1 = (1.4*TB)
print("B1  ", B1)
B2 = (0.6*H)
print("B2  ", B2)
B3 = (3*HR)
print("B3  ", B3)
B4 = (.1*BB)
B = (B1-B2-B3+B4)
B = B*1.02

print("B is   ", B)
C = AB - H
print("C is    ", C)
D = HR
print("D is    ", D)

BaseRuns = A*(B/(B+C))+D

print(BaseRuns)
```

```
A is 1018
B1   2027.1999999999998
B2   537.6
B3   381
B is    1156.17
C is     2614
D is     127
439.18249044472793
```

In [18]:
```
# Calculating the base runs
i = 0
base_runs = []
while i < 529:
    H = j_df.iloc[i]['H']
    BB = j_df.iloc[i]['BB']
    HR = j_df.iloc[i]['HR']
    B2 = j_df.iloc[i]['2B']
    B3 = j_df.iloc[i]['3B']
    AB = j_df.iloc[i]['AB']
    TB = j_df.iloc[i]['TB']
    A = H + BB - HR
    B1 = (1.4*TB)
    B2 = (0.6*H)
    B3 = (3*HR)
    B4 = (.1*BB)
    B = (B1-B2-B3+B4)
    B = B*1.02
    C = AB - H
    D = HR
    x = A*(B/(B+C))+D
    base_runs.append(x)
    #print(i)
    #print(x)
    i = i+1
```

In [19]:
```
# There should be 529 values, checking to make sure that is true
print(len(base_runs))
```

```
529
```

In [20]:
```
# converting to a dataframe
base_run_df = pd.DataFrame(base_runs, columns=['BaseRuns'])
```

In [21]:
```
# Joining the dataframe with base runs to the japanese frame
j_new_df = j_df.join(base_run_df)
j_new_df.drop(['index'], axis=1, inplace=True)
```

In [22]:
```
# Checking to make sure that the frames were joined
j_new_df.head(5)
```

Out[22]:

	Tm	Aff	BatAge	R/G	G	PA	AB	R	H	2B	...	OPS	TB	GDP	HBP	SI
0	Hanshin Tigers	NaN	27.2	3.88	105	4029	3512	407	863	137	...	0.667	1214	62	39.0	7
1	Yomiuri Giants	NaN	28.5	3.87	103	3868	3510	399	896	149	...	0.721	1448	65	31.0	5
2	Yokohama Bay Stars	NaN	29.3	3.64	104	3860	3463	379	859	161	...	0.674	1272	81	40.0	7
3	Yakult Swallows	NaN	27.4	3.63	104	3875	3418	378	813	147	...	0.669	1235	78	27.0	7
4	Hiroshima Carp	NaN	29.8	3.44	106	3867	3489	365	851	145	...	0.654	1229	84	36.0	6

5 rows × 30 columns

Part 2. Pulling the American Statistics

The same process will be repeated as with the Japenese Statistics

Taking a look at the American Team Links

Arizona Link

https://www.baseball-reference.com/teams/ARI/

Colorado Link

https://www.baseball-reference.com/teams/COL/

Part 2 (A) Creating a List of the American URLs

First, the links for each team are going to need to be pulled. The base link for each team is https://www.baseball-reference.com/team + ARI, COL, SFG, LAD, and SDP. Using that infomation the sub links can all be pulled using a similar method to the one above.

In [23]:
```
# creating a list of all the team names
team_names = ['ARI', 'COL', 'SFG', 'LAD', 'SDP', 'ATL', 'BAL', 'BOS', 'CHC', 'WSN',
              'PHI', 'OAK', 'NYY', 'NYM', 'MIN', 'MIL', 'FLA', 'ANA', 'KCR', 'HOU',
```

In [24]:
```
# The url for the American Leagues
def get_urls(team):
    amer_tiny_urls = []
    base_url = f'https://www.baseball-reference.com/teams/'
    for i in team:
        print(i)                    # Print Command Used to Check i
        team_url = base_url + i + '/batteam.shtml'
        print(team_url)             # Print Command Used to check final url
        amer_tiny_urls.append(team_url)
    return(amer_tiny_urls)
```

In [25]:
```
# Creating a list of all the American Teams url's
amer_tiny_urls = get_urls(team_names)
```

```
ARI
https://www.baseball-reference.com/teams/ARI/batteam.shtml
COL
https://www.baseball-reference.com/teams/COL/batteam.shtml
SFG
https://www.baseball-reference.com/teams/SFG/batteam.shtml
LAD
https://www.baseball-reference.com/teams/LAD/batteam.shtml
SDP
https://www.baseball-reference.com/teams/SDP/batteam.shtml
ATL
https://www.baseball-reference.com/teams/ATL/batteam.shtml
BAL
https://www.baseball-reference.com/teams/BAL/batteam.shtml
BOS
https://www.baseball-reference.com/teams/BOS/batteam.shtml
CHC
https://www.baseball-reference.com/teams/CHC/batteam.shtml
WSN
https://www.baseball-reference.com/teams/WSN/batteam.shtml
TOR
https://www.baseball-reference.com/teams/TOR/batteam.shtml
TEX
https://www.baseball-reference.com/teams/TEX/batteam.shtml
TBD
https://www.baseball-reference.com/teams/TBD/batteam.shtml
STL
https://www.baseball-reference.com/teams/STL/batteam.shtml
SEA
https://www.baseball-reference.com/teams/SEA/batteam.shtml
PIT
https://www.baseball-reference.com/teams/PIT/batteam.shtml
PHI
https://www.baseball-reference.com/teams/PHI/batteam.shtml
OAK
https://www.baseball-reference.com/teams/OAK/batteam.shtml
NYY
https://www.baseball-reference.com/teams/NYY/batteam.shtml
NYM
https://www.baseball-reference.com/teams/NYM/batteam.shtml
MIN
https://www.baseball-reference.com/teams/MIN/batteam.shtml
MIL
https://www.baseball-reference.com/teams/MIL/batteam.shtml
FLA
https://www.baseball-reference.com/teams/FLA/batteam.shtml
ANA
https://www.baseball-reference.com/teams/ANA/batteam.shtml
KCR
https://www.baseball-reference.com/teams/KCR/batteam.shtml
HOU
https://www.baseball-reference.com/teams/HOU/batteam.shtml
DET
https://www.baseball-reference.com/teams/DET/batteam.shtml
CLE
https://www.baseball-reference.com/teams/CLE/batteam.shtml
CIN
https://www.baseball-reference.com/teams/CIN/batteam.shtml
CHW
```

```
https://www.baseball-reference.com/teams/CHW/batteam.shtml
```

In [26]:
```
# Checkign the length of the list
print(len(amer_tiny_urls))
```

```
30
```

Part 2 (B) Pulling all the Tables

In [27]:
```
def table_pull(url):
    html = get(url)
    soup = Soup(html)
    # parse the outter level 'div'
    div = soup.find('div',{'id':'content'},mode='all')
    # Reconstruct the html string to represent what we want it to look like
    table = str(div[0].find('table', {'id':'yby_team_bat'})) + str(div[0].find('tbo
    # read into a pd dataframe
    df = pd.read_html(table)[0]
    return(df)
```

In [28]:
```
fullframe = table_pull(amer_tiny_urls[0])
fullframe['Team'] = 'ARI'

j = 0


while j<30:
    for i in amer_tiny_urls:
        z = (team_names[j])
        df = table_pull(amer_tiny_urls[j])
        df['Team'] = z
        df.head(5)
        fullframe = pd.concat([fullframe, df])
        j = j+1
        time.sleep(5)
        print(z)
        #z = table_pull(amer_tiny_urls[j])
        #z['Team'] = z
```

```
ARI
COL
SFG
LAD
SDP
ATL
BAL
BOS
CHC
WSN
TOR
TEX
TBD
STL
SEA
PIT
PHI
OAK
NYY
NYM
MIN
MIL
FLA
ANA
KCR
HOU
DET
CLE
CIN
CHW
```

In [29]:
```
# Checking that the full data set was pulled
fullframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2830 entries, 0 to 122
Data columns (total 28 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Year
2830 non-null   int64
 1   Lg
2830 non-null   object
 2   W
2830 non-null   int64
 3   L
2830 non-null   int64
 4   Finish
2830 non-null   int64
 5   R/G
2830 non-null   float64
 6   G
2830 non-null   int64
 7   PA
2830 non-null   int64
 8   AB
2830 non-null   int64
 9   R
2830 non-null   int64
 10  H
2830 non-null   int64
 11  2B
2830 non-null   int64
 12  3B
2830 non-null   int64
 13  HR
2830 non-null   int64
 14  RBI
2828 non-null   float64
 15  SB
2790 non-null   float64
 16  CS
2408 non-null   float64
 17  BB
2830 non-null   int64
 18  SO
2830 non-null   int64
 19  Gold means awarded title at end of year." data-filter="1" data-name="Batting A
verage">BA  2830 non-null   float64
 20  OBP
2830 non-null   float64
 21  SLG
2830 non-null   float64
 22  OPS
2830 non-null   float64
 23  E
2830 non-null   int64
 24  DP
2830 non-null   int64
 25  Fld%
2830 non-null   float64
```

```
 26  BatAge
2830 non-null   float64
 27  Team
2830 non-null   object
dtypes: float64(10), int64(16), object(2)
memory usage: 641.2+ KB
```

In [30]:
```
# making a clean copy of the data frame
a_df = fullframe
```

In [31]:
```
# dropping the one odd column
a_df.drop(['Gold means awarded title at end of year." data-filter="1" data-name="Ba
```

In [32]:
```
a_df.head(5)
```

Out[32]:

	Year	Lg	W	L	Finish	R/G	G	PA	AB	R	...	BB	SO	OBP	SLG	OPS	
0	2023	NL West	60	60	3	4.68	120	4536	4052	561	...	390	926	0.323	0.420	0.742	4
1	2022	NL West	74	88	4	4.33	162	6027	5351	702	...	531	1341	0.304	0.385	0.689	8
2	2021	NL West	52	110	5	4.19	162	6144	5489	679	...	537	1465	0.309	0.382	0.692	10
3	2020	NL West	25	35	5	4.48	60	2238	1997	269	...	181	461	0.312	0.391	0.704	3
4	2019	NL West	85	77	2	5.02	162	6315	5633	813	...	540	1360	0.323	0.434	0.757	8

5 rows × 27 columns

Part 2 (C) Calculating the American Stats

The TB column does not exist, so the calculation will need to be changed to account for this

In [33]:
```
# Building out the calculation
H = a_df.iloc[1]['H']
BB = a_df.iloc[1]['BB']
HR = a_df.iloc[1]['HR']
B2 = a_df.iloc[1]['2B']
B3 = a_df.iloc[1]['3B']
AB = a_df.iloc[1]['AB']
TB1 = (H + (B2*2) + (B3*3) + (HR*4))
#print(TB1)
TB2 = (B2+B3+HR)
#print(TB2)
TB = TB1 - TB2
#print("TB IS    ", TB)
print("HR is    ", HR)
print("BB is    ", BB)

A = H + BB - HR
print("A is" , A)
B1 = (1.4*TB)
print("B1  ", B1)
B2 = (0.6*H)
print("B2  ", B2)
B3 = (3*HR)
print("B3  ", B3)
B4 = (.1*BB)
B = (B1-B2-B3+B4)
B = B*1.02

print("B is   ", B)
C = AB - H
print("C is    ", C)
D = HR
print("D is    ", D)

BaseRuns = A*(B/(B+C))+D

print(BaseRuns)
```

```
HR is    173
BB is    531
A is 1590
B1   2885.3999999999996
B2   739.1999999999999
B3   519
B is    1713.9059999999997
C is     4119
D is     173
640.1960323036235
```

In [34]:
```
# Calculating the base runs
i = 0
base_runs = []
while i < 2202:
    H = a_df.iloc[i]['H']
    BB = a_df.iloc[i]['BB']
    HR = a_df.iloc[i]['HR']
    B2 = a_df.iloc[i]['2B']
    B3 = a_df.iloc[i]['3B']
    AB = a_df.iloc[i]['AB']
    TB1 = (H + (B2*2) + (B3*3) + (HR*4))
    TB2 = (B2+B3+HR)
    TB = TB1 - TB2
    A = H + BB - HR
    B1 = (1.4*TB)
    B2 = (0.6*H)
    B3 = (3*HR)
    B4 = (.1*BB)
    B = (B1-B2-B3+B4)
    B = B*1.02
    C = AB - H
    D = HR
    x = A*(B/(B+C))+D
    base_runs.append(x)
    #print(i)
    #print(x)
    i = i+1
```

In [35]:
```
print(len(base_runs))
```

```
2202
```

In [36]:
```
# Reseting the Index
a_df = a_df.reset_index()
```

In [37]:
```
base_run_df = pd.DataFrame(base_runs, columns=['BaseRuns'])
```

In [38]:
```
a_new_df = a_df.join(base_run_df)
a_new_df.drop(['index'], axis=1, inplace=True)
```

In [39]:
```
a_new_df.head(5)
```

Out[39]:

	Year	Lg	W	L	Finish	R/G	G	PA	AB	R	...	SO	OBP	SLG	OPS	E	D
0	2023	NL West	60	60	3	4.68	120	4536	4052	561	...	926	0.323	0.420	0.742	40	9
1	2022	NL West	74	88	4	4.33	162	6027	5351	702	...	1341	0.304	0.385	0.689	86	13
2	2021	NL West	52	110	5	4.19	162	6144	5489	679	...	1465	0.309	0.382	0.692	100	11
3	2020	NL West	25	35	5	4.48	60	2238	1997	269	...	461	0.312	0.391	0.704	35	5
4	2019	NL West	85	77	2	5.02	162	6315	5633	813	...	1360	0.323	0.434	0.757	86	13

5 rows × 28 columns

Part 3 Combining the Data Frames

In [40]:

```
# Checking the Japanese Frame
j_new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 529 entries, 0 to 528
Data columns (total 30 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Tm        487 non-null    object 
 1   Aff       0 non-null      float64
 2   BatAge    529 non-null    float64
 3   R/G       529 non-null    float64
 4   G         529 non-null    int64  
 5   PA        529 non-null    int64  
 6   AB        529 non-null    int64  
 7   R         529 non-null    int64  
 8   H         529 non-null    int64  
 9   2B        529 non-null    int64  
 10  3B        529 non-null    int64  
 11  HR        529 non-null    int64  
 12  RBI       528 non-null    float64
 13  SB        529 non-null    int64  
 14  CS        529 non-null    int64  
 15  BB        529 non-null    int64  
 16  SO        529 non-null    int64  
 17  BA        529 non-null    float64
 18  OBP       529 non-null    float64
 19  SLG       529 non-null    float64
 20  OPS       529 non-null    float64
 21  TB        529 non-null    int64  
 22  GDP       529 non-null    int64  
 23  HBP       455 non-null    float64
 24  SH        529 non-null    int64  
 25  SF        497 non-null    float64
 26  IBB       529 non-null    int64  
 27  Year      529 non-null    int64  
 28  Finals    42 non-null     object 
 29  BaseRuns  529 non-null    float64
dtypes: float64(11), int64(17), object(2)
memory usage: 124.1+ KB
```

In [41]:
```
# Checking the American Frame
a_new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830 entries, 0 to 2829
Data columns (total 28 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Year      2830 non-null   int64
 1   Lg        2830 non-null   object
 2   W         2830 non-null   int64
 3   L         2830 non-null   int64
 4   Finish    2830 non-null   int64
 5   R/G       2830 non-null   float64
 6   G         2830 non-null   int64
 7   PA        2830 non-null   int64
 8   AB        2830 non-null   int64
 9   R         2830 non-null   int64
 10  H         2830 non-null   int64
 11  2B        2830 non-null   int64
 12  3B        2830 non-null   int64
 13  HR        2830 non-null   int64
 14  RBI       2828 non-null   float64
 15  SB        2790 non-null   float64
 16  CS        2408 non-null   float64
 17  BB        2830 non-null   int64
 18  SO        2830 non-null   int64
 19  OBP       2830 non-null   float64
 20  SLG       2830 non-null   float64
 21  OPS       2830 non-null   float64
 22  E         2830 non-null   int64
 23  DP        2830 non-null   int64
 24  Fld%      2830 non-null   float64
 25  BatAge    2830 non-null   float64
 26  Team      2830 non-null   object
 27  BaseRuns  2202 non-null   float64
dtypes: float64(10), int64(16), object(2)
memory usage: 619.2+ KB
```

The Japanese frame has 30 columns, the American only 27. The American Frame includes Lg (league) which could be removed as it does not apply to the Japanese frame, as well as 'E', 'DP', and "Fld%). The Japanese Frame also includes Finals and and Aff, which can be dropped, as wells at 'TB', 'GDP', 'HBP', 'SH', 'SF', and 'IBB'. That will be the next step.

In [42]:

```
a_new_df.drop(['Lg', 'E', 'DP', 'Fld%', 'Finish', 'W', 'L'], axis=1, inplace = True
a_new_df.head(5)
```

Out[42]:

	Year	R/G	G	PA	AB	R	H	2B	3B	HR	...	SB	CS	BB	SO	OBP	SLG
0	2023	4.68	120	4536	4052	561	1028	217	28	133	...	123.0	18.0	390	926	0.323	0.420
1	2022	4.33	162	6027	5351	702	1232	262	24	173	...	104.0	29.0	531	1341	0.304	0.385
2	2021	4.19	162	6144	5489	679	1297	308	31	144	...	43.0	16.0	537	1465	0.309	0.382
3	2020	4.48	60	2238	1997	269	482	101	12	58	...	23.0	7.0	181	461	0.312	0.391
4	2019	5.02	162	6315	5633	813	1419	288	40	220	...	88.0	14.0	540	1360	0.323	0.434

5 rows × 21 columns

In [43]:
```
a_new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2830 entries, 0 to 2829
Data columns (total 21 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Year      2830 non-null   int64  
 1   R/G       2830 non-null   float64
 2   G         2830 non-null   int64  
 3   PA        2830 non-null   int64  
 4   AB        2830 non-null   int64  
 5   R         2830 non-null   int64  
 6   H         2830 non-null   int64  
 7   2B        2830 non-null   int64  
 8   3B        2830 non-null   int64  
 9   HR        2830 non-null   int64  
 10  RBI       2828 non-null   float64
 11  SB        2790 non-null   float64
 12  CS        2408 non-null   float64
 13  BB        2830 non-null   int64  
 14  SO        2830 non-null   int64  
 15  OBP       2830 non-null   float64
 16  SLG       2830 non-null   float64
 17  OPS       2830 non-null   float64
 18  BatAge    2830 non-null   float64
 19  Team      2830 non-null   object 
 20  BaseRuns  2202 non-null   float64
dtypes: float64(9), int64(11), object(1)
memory usage: 464.4+ KB
```

In [44]:
```
j_new_df.drop(['Finals', 'Aff', 'TB', 'GDP', 'HBP', 'SH', 'SF', "IBB", 'BA'],axis=1
j_new_df.head(5)
```

Out[44]:

	Tm	BatAge	R/G	G	PA	AB	R	H	2B	3B	...	RBI	SB	CS	BB	SO	O
0	Hanshin Tigers	27.2	3.88	105	4029	3512	407	863	137	26	...	391.0	55	21	367	881	0.3
1	Yomiuri Giants	28.5	3.87	103	3868	3510	399	896	149	11	...	390.0	37	19	249	800	0.3
2	Yokohama Bay Stars	29.3	3.64	104	3860	3463	379	859	161	15	...	367.0	21	22	261	610	0.3
3	Yakult Swallows	27.4	3.63	104	3875	3418	378	813	147	7	...	362.0	54	15	328	808	0.3
4	Hiroshima Carp	29.8	3.44	106	3867	3489	365	851	145	13	...	355.0	62	36	258	763	0.3

5 rows × 21 columns

In [45]:
```
# Replacing tm with Team
j_new_df.rename(columns = {'Tm' : 'Team'}, inplace=True)
j_new_df.head(5)
```

Out[45]:

	Team	BatAge	R/G	G	PA	AB	R	H	2B	3B	...	RBI	SB	CS	BB	SO	O
0	Hanshin Tigers	27.2	3.88	105	4029	3512	407	863	137	26	...	391.0	55	21	367	881	0.3
1	Yomiuri Giants	28.5	3.87	103	3868	3510	399	896	149	11	...	390.0	37	19	249	800	0.3
2	Yokohama Bay Stars	29.3	3.64	104	3860	3463	379	859	161	15	...	367.0	21	22	261	610	0.3
3	Yakult Swallows	27.4	3.63	104	3875	3418	378	813	147	7	...	362.0	54	15	328	808	0.3
4	Hiroshima Carp	29.8	3.44	106	3867	3489	365	851	145	13	...	355.0	62	36	258	763	0.3

5 rows × 21 columns

In [46]:

```
j_new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 529 entries, 0 to 528
Data columns (total 21 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Team      487 non-null    object 
 1   BatAge    529 non-null    float64
 2   R/G       529 non-null    float64
 3   G         529 non-null    int64  
 4   PA        529 non-null    int64  
 5   AB        529 non-null    int64  
 6   R         529 non-null    int64  
 7   H         529 non-null    int64  
 8   2B        529 non-null    int64  
 9   3B        529 non-null    int64  
 10  HR        529 non-null    int64  
 11  RBI       528 non-null    float64
 12  SB        529 non-null    int64  
 13  CS        529 non-null    int64  
 14  BB        529 non-null    int64  
 15  SO        529 non-null    int64  
 16  OBP       529 non-null    float64
 17  SLG       529 non-null    float64
 18  OPS       529 non-null    float64
 19  Year      529 non-null    int64  
 20  BaseRuns  529 non-null    float64
dtypes: float64(7), int64(13), object(1)
memory usage: 86.9+ KB
```

In [47]:

```
# Adding a country tag to the data tables
a_new_df['Country'] = 'US'
j_new_df['Country'] = 'Japan'
```

In [61]:
```
# Combining the two frames
frames = [a_new_df, j_new_df]
complete_df =pd.concat(frames)

complete_df.head(5)
```

Out[61]:

	Year	R/G	G	PA	AB	R	H	2B	3B	HR	...	CS	BB	SO	OBP	SLG	OPS
0	2023	4.68	120	4536	4052	561	1028	217	28	133	...	18.0	390	926	0.323	0.420	0.742
1	2022	4.33	162	6027	5351	702	1232	262	24	173	...	29.0	531	1341	0.304	0.385	0.689
2	2021	4.19	162	6144	5489	679	1297	308	31	144	...	16.0	537	1465	0.309	0.382	0.692
3	2020	4.48	60	2238	1997	269	482	101	12	58	...	7.0	181	461	0.312	0.391	0.704
4	2019	5.02	162	6315	5633	813	1419	288	40	220	...	14.0	540	1360	0.323	0.434	0.757

5 rows × 22 columns

Part 4 Visualization

First, the list will be aggregated and sorted to determine which team has the highest Base Runs value and which team has the lowest base runs average.

In [72]:
```
df_avg = complete_df.groupby(['Team'])['BaseRuns'].agg(['mean'])
df_avg = df_avg.reset_index()
df_avg = df_avg.sort_values('mean')
df_avg
```

Out[72]:

	Team	mean
36	Sankei Swallows	389.663634
18	Kokutetsu Swallows	404.548803
42	Taiyo-Shochiku Robins	405.719119
44	Yakult Atoms	426.189752
41	Taiyo Whales	464.710150
35	Sankei Atoms	471.267354
28	Osaka Tigers	484.723793
25	Nagoya Dragons	511.242116
15	Hiroshima Carp	515.998322
14	Hanshin Tigers	527.363503
10	Chunichi Dragons	533.412200
47	Yokohama Taiyo Whales	551.481223
37	Shochiku Robins	556.713186
16	Hiroshima Toyo Carp	559.685965
45	Yakult Swallows	570.616492
46	Yokohama Bay Stars	576.415185
48	Yomiuri Giants	580.279528
26	Nishinippon Pirates	586.951802
2	ATL	615.514539
5	CHC	633.867484
30	PIT	634.363049
31	SDP	638.411811
29	PHI	639.920838
19	LAD	643.296913
23	NYM	648.644644
34	STL	652.400889
33	SFG	656.781660
3	BAL	658.984095
27	OAK	659.772870
22	MIN	660.868005
12	FLA	665.708312
43	WSN	665.870730
0	ANA	675.059984

	Team	mean
21	MIL	693.841327
32	SEA	698.688447
38	TBD	700.817259
39	TEX	703.854961
4	BOS	712.290793
1	ARI	714.394705
40	TOR	726.441414
24	NYY	728.829909
9	COL	772.025649
20	League Totals	3240.546856
6	CHW	NaN
7	CIN	NaN
8	CLE	NaN
11	DET	NaN
13	HOU	NaN
17	KCR	NaN

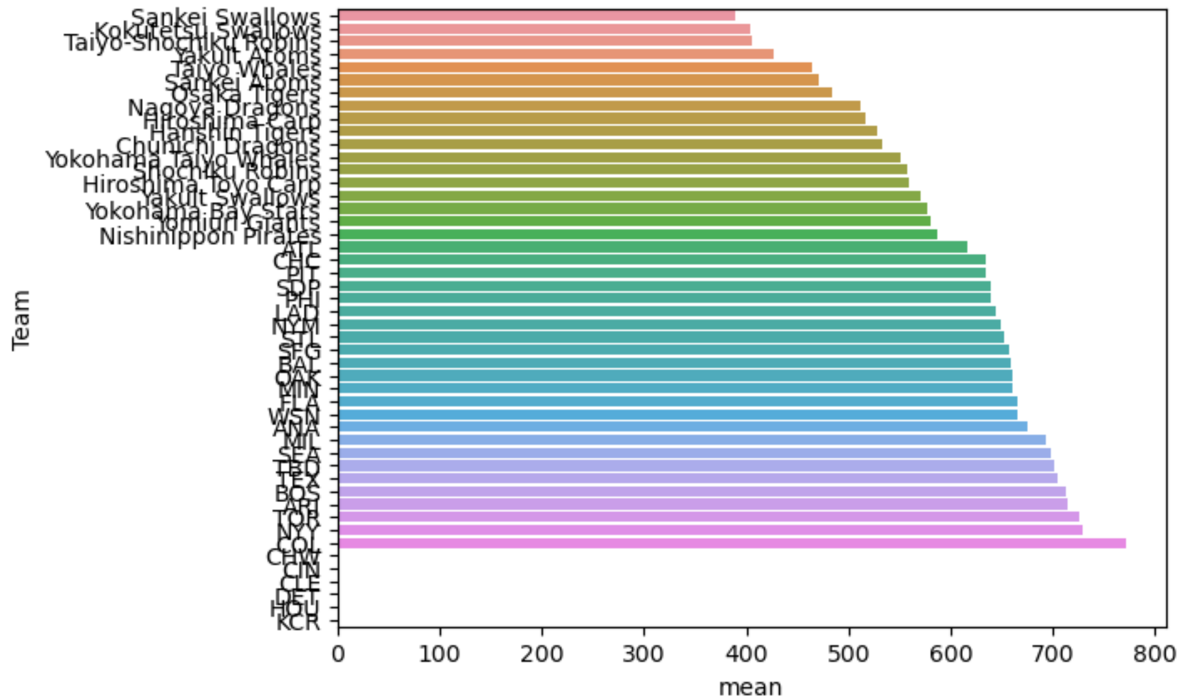
It would appear that Colorado has the best Base Runs value and Sankei Swallows has the lowest.

Next, using the seaborn library, graphs will be constructed to view the data.

In [73]:
```
import seaborn as sns
```

In [74]:
```
df_avg = df_avg.drop([20]) # Dropping League Totals
sns.barplot(data=df_avg, y="Team", x="mean")
```

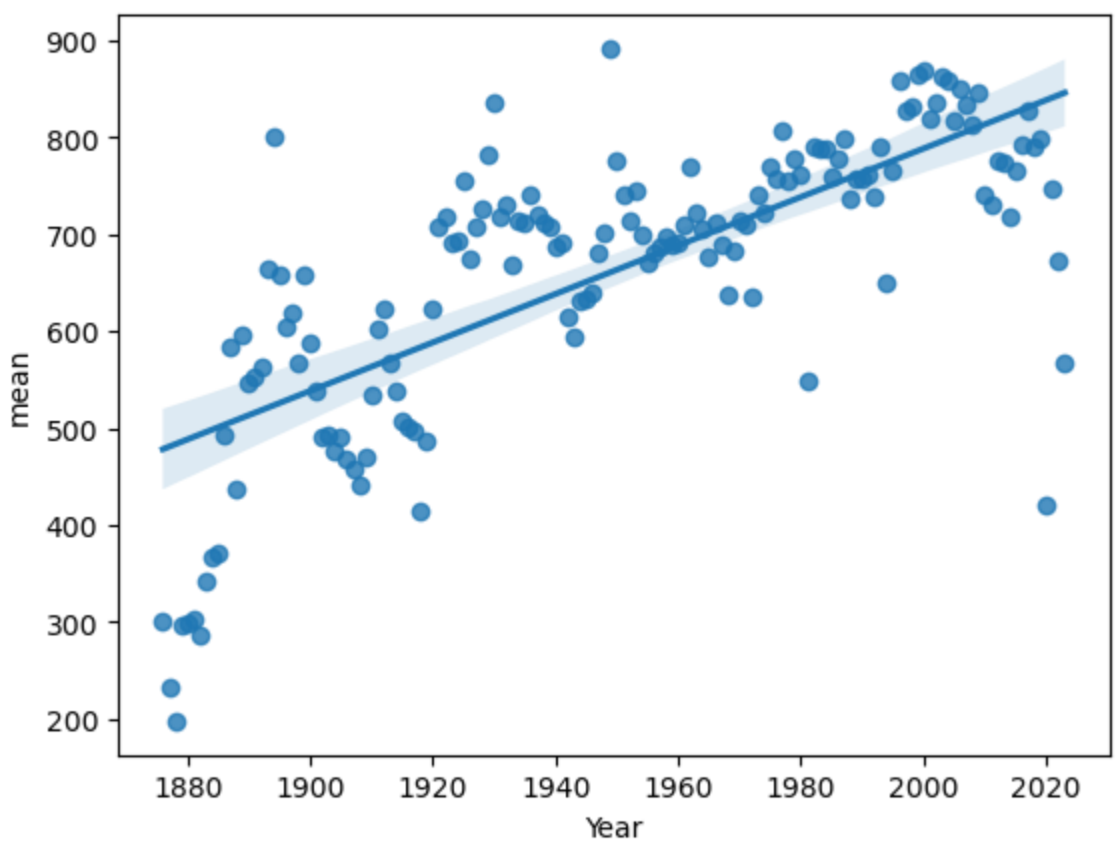
Out[74]:
```
<Axes: xlabel='mean', ylabel='Team'>
```



Taking a look to see how the metrics have changed over the years

In [55]:
```
df_avg_year = complete_df.groupby(['Year'])['BaseRuns'].agg(['mean'])
df_avg_year = df_avg_year.reset_index()
sns.regplot(data=df_avg_year, x="Year", y="mean")
```

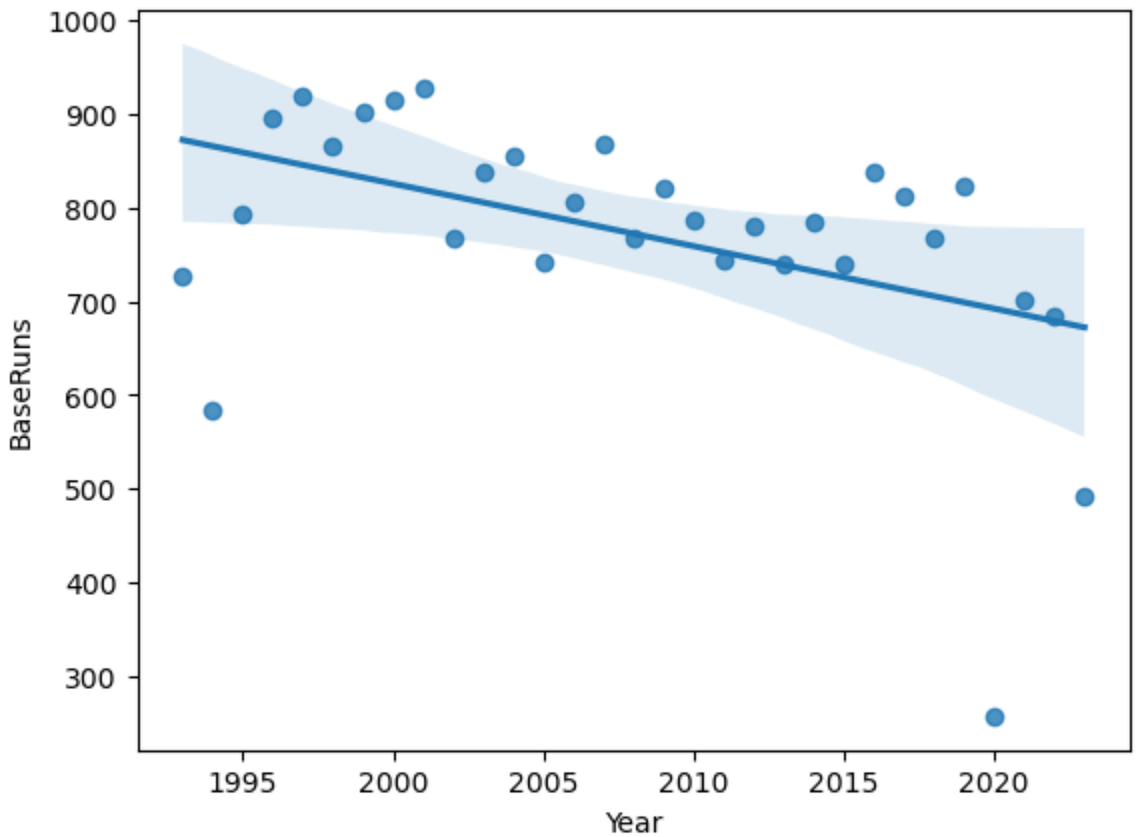
Out[55]: <Axes: xlabel='Year', ylabel='mean'>



Taking a look at just the Colorado Rockies over the years

In [80]:
```
df_col = complete_df[complete_df['Team'] == 'COL']
sns.regplot(data=df_col, x="Year", y = "BaseRuns")
```

Out[80]: <Axes: xlabel='Year', ylabel='BaseRuns'>



According to the regression plot, the Colorado Rockies have declined in performance over the year.

In [56]:
```
country_frame = complete_df.drop(columns = ['Team'])
#country_frame
country_runs = country_frame.groupby(['Country']).agg(['mean', 'count'])
country_runs
```

Out[56]:

	Year		R/G		G		PA		
	mean	count	mean	count	mean	count	mean	count	mean
Country									
Japan	1985.725898	529	3.923894	529	229.047259	529	8579.931947	529	7649.538752
US	1966.909894	2830	4.499311	2830	154.185866	2830	5901.122615	2830	5257.596820

2 rows × 40 columns

T-Test of Japans vs US Data to see if one has a better Base Runs value than another

In [75]:
```
from scipy.stats import ttest_ind

group1 = complete_df[complete_df['Country'] == "Japan"]
group2 = complete_df[complete_df['Country'] == "US"]
group2 = group2.dropna()



ttest_ind(group1['BaseRuns'], group2['BaseRuns'])

#print(group1['BaseRuns'])
#print(group2['BaseRuns'])


#data_japan.head()
```

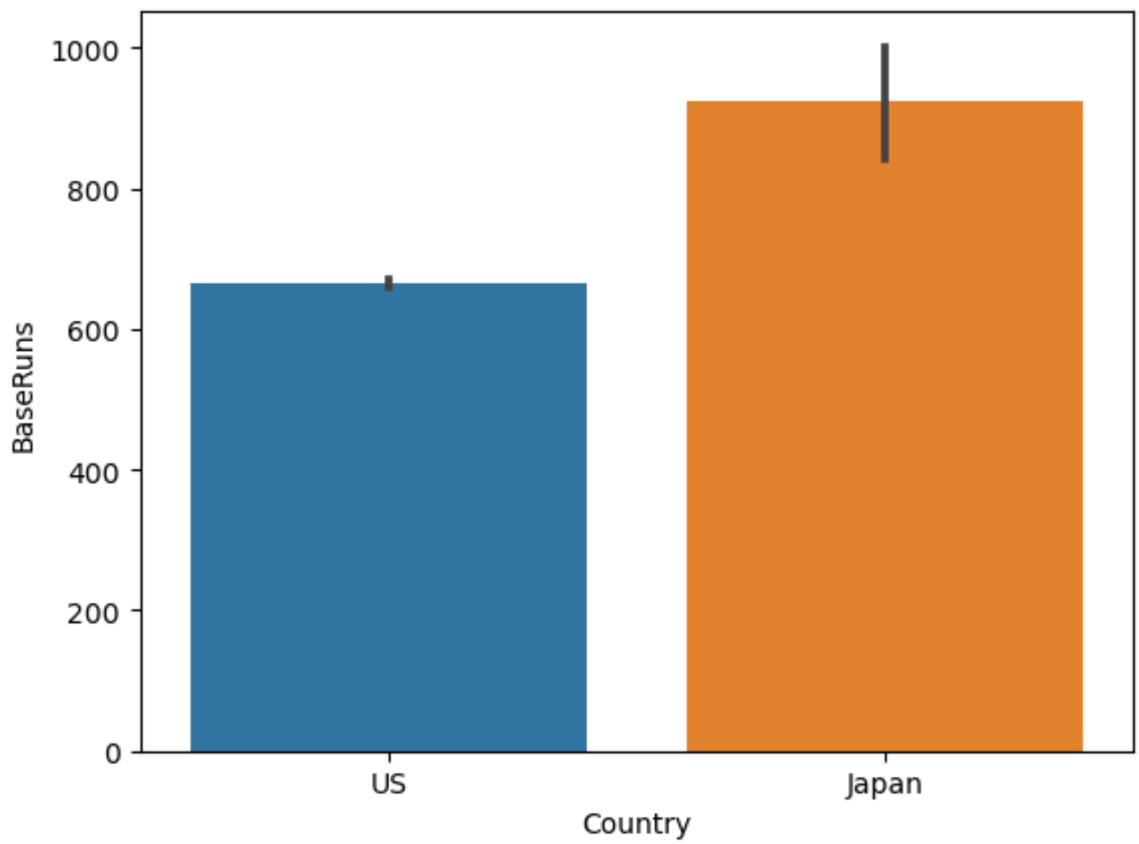
Out[75]:
```
Ttest_indResult(statistic=10.034009703146108, pvalue=3.092189321227097e-23)
```

Based on the P value there is a statistical difference.

A visualization of the Base Runs between the two contries.

In [77]:
```
sns.barplot(data=complete_df, x='Country', y='BaseRuns')
```

Out[77]:
```
<Axes: xlabel='Country', ylabel='BaseRuns'>
```



Summary

A scraper was used to collect baseball data off of a statistics website. That data was then used to calculate the metric "base runs", which can be used to compare base ball teams performance. Using those metrics it was determined that the Colorado Rockies have one of the best Base Run means in the country. The statisitic was also used to compare the Japanese League to the American teams. It was determined with statistical significance that the Japanese Teams outperform American Teams when looking at Base Run.