PredictedOutcomes

October 15, 2024

I was tasked to predict each player's on-base percentage in the 2021 season given only his plate appearance(PA)s and on-base percentage(OBP)s in prior seasons I was given a file that had over 500 players that needed to have their OBP predicted for the 2021 season. This study and analysis will use machine learning techniques to uncover key factors influencing OBP and to develop models with high predictive accuracy. The analysis includes data preprocessing, feature engineering, model training, evaluation, and hyperparameter tuning to identify the most effective approach..

1 Introduction

I was tasked to predict each player's on-base percentage in the 2021 season given only his plate appearances(PA) and on-base percentages(OBP) in prior seasons. I was given a file that had over 500 players that needed to have their OBP predicted for the 2021 season. This study and analysis will use machine learning techniques to uncover key factors influencing OBP and to develop models with high predictive accuracy. This analysis includes data preprocessing, feature engineering, model training, evaluation, and hyperparameter tuning to identify the most effective approach.

1.1 Importing Required Libraries

To show you again so it's easier to follow and understand I have included all the libraries I used to conduct this analysis.

[8]:
```
import pandas as pd
import random
import numpy as np
import matplotlib.pyplot as plt
import xgboost as xgb
from xgboost import XGBRegressor
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,␣
↪AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.feature_selection import RFE
```

2 Loading / Inspecting Data

For this we observed the data and looked at the missing values. As you can see many players did not play in certain seasons, and some never played in a season prior to the 2021 season. There seems to be a lot of missing values and it's best we fix these to get the most accurate predictions

[12]:
```
# Load data into pandas dataframe

df = pd.read_csv('obp.csv')
# Display first few rows to understand dataframe
df.head()
```

[12]:

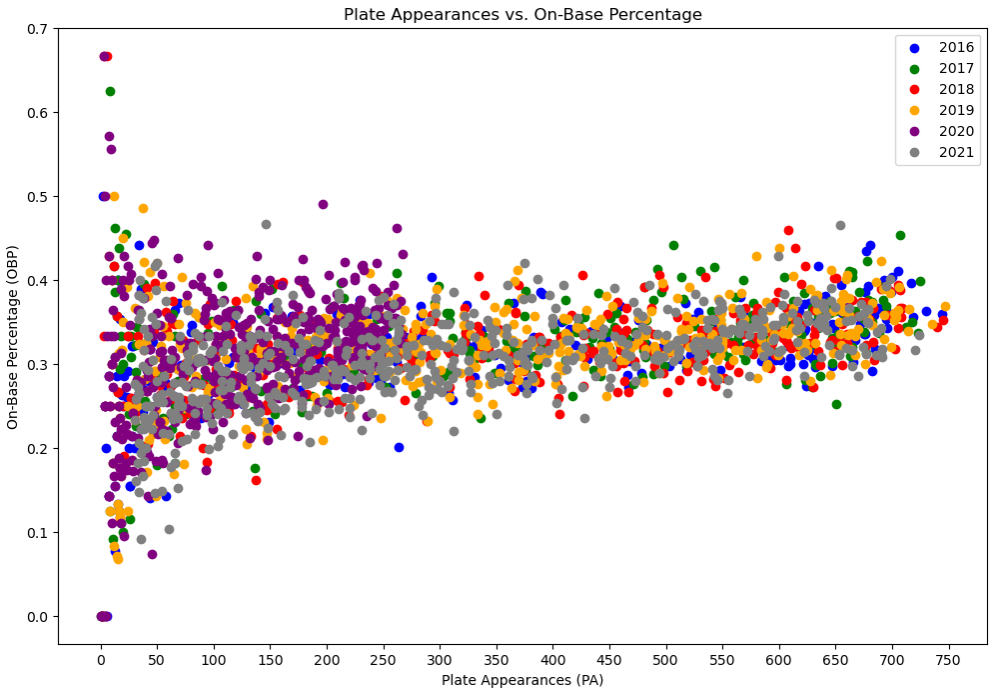
	Name	playerid	birth_date	PA_21	OBP_21	PA_20	OBP_20	PA_19	OBP_19	PA_18	OBP_18	PA_17	OBP_17	PA_16	OBP_16
0	Trayce Thompson	9952	1991-03-15	35	0.400	NaN	NaN	NaN	NaN	137.0	0.162	55.0	0.218	262.0	0.302
1	Mike Trout	10155	1991-08-07	146	0.466	241.0	0.390	600.0	0.438	608.0	0.460	507.0	0.442	681.0	0.441
2	Bryce Harper	11579	1992-10-16	599	0.429	244.0	0.420	682.0	0.372	695.0	0.393	492.0	0.413	627.0	0.373
3	Chris Owings	10030	1991-08-12	50	0.420	44.0	0.318	196.0	0.209	309.0	0.272	386.0	0.299	466.0	0.315
4	Nick Fortes	21538	1996-11-11	34	0.353	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

[13]:
```
# Check columns for null values
df.isnull().sum()
```

[13]:
```
Name            0
playerid        0
birth_date      0
PA_21           0
OBP_21          0
PA_20         106
OBP_20        106
PA_19         135
OBP_19        135
PA_18         213
OBP_18        213
PA_17         274
OBP_17        274
PA_16         325
OBP_16        325
dtype: int64
```

2.1 Visualizing the Relationship between Plate Appearances (PA) and On-Base Percentage (OBP)

Before I handle the missing values I wanted to visually look at the Data and see where the Data tends to look messy. As you can see 0-150 plate appearances on the x-axis seems to look extremely skewed and all over the place. In the next step we will fix this



2.2 Data Cleaning and Preparation modeling.

As you can see here, I created a filter to remove any batter that hasn't had a total of 150 plate appearances (PA_)in total from any year between the years 2016 to 2021. Granted this will remove a fair amount of hitters, but there's no accurate way of predicting hitters who have less at-bats without further data that I dont have access to.

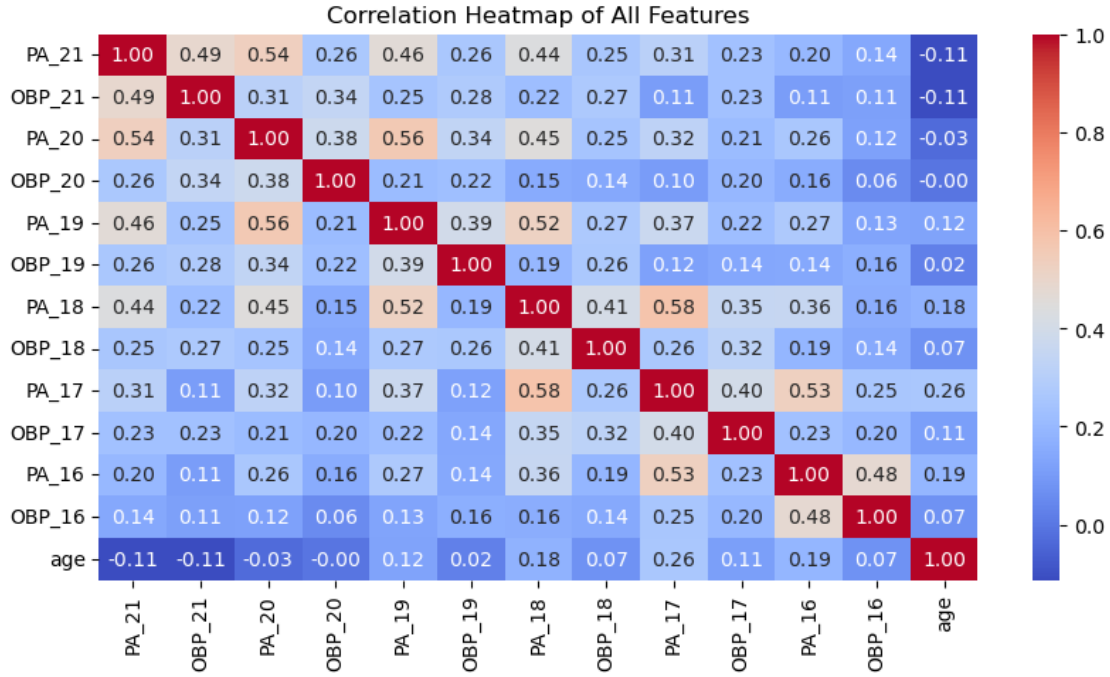
[64]:
```
# Filter out players with fewer than 150 total plate appearances across multiple␣
↪seasons
df = df[df[['PA_16', 'PA_17', 'PA_18', 'PA_19', 'PA_20']].sum(axis=1) >= 150]

# Replace missing values in both OBP and PA columns with their respective medians
years = ['16', '17', '18', '19', '20', '21']
for year in years:
    df[f'OBP_{year}'] = df[f'OBP_{year}'].fillna(df[f'OBP_{year}'].median())
    df[f'PA_{year}'] = df[f'PA_{year}'].fillna(df[f'PA_{year}'].median())

# Calculate player's age in 2021 by subtracting birth year from 2021
df['age'] = 2021 - pd.to_datetime(df['birth_date']).dt.year
```

3 Correlation Analysis in Subsequent Steps.

Next, I created a heatmap to visualize and hopefully see any features that have the most weight in the prediction and or if there's a trend



4 Feature Engineering

Based on the heatmap I saw a correlation of various factors that I believed should be given weights to help strengthen our prediction. I think the most recent season should have the most weight and slowly lessen the weight as prior season are then taken account for. Additionally, I added another features that takes in account how there performance various between two season.

[23]:
```
# Generate a weighted OBP metric, giving more significance to recent years
df['OBP_weighted'] = (df['OBP_16'] * 0.1 + df['OBP_17'] * 0.2
                      + df['OBP_18'] * 0.25 + df['OBP_19'] * 0.3
                      + df['OBP_20'] * 0.35)

# Calculate OBP trends to reflect how performance changes between consecutive␣
 ↪seasons
df['OBP_trend_1920'] = df['OBP_20'] - df['OBP_19']
df['OBP_trend_1819'] = df['OBP_19'] - df['OBP_18']
```

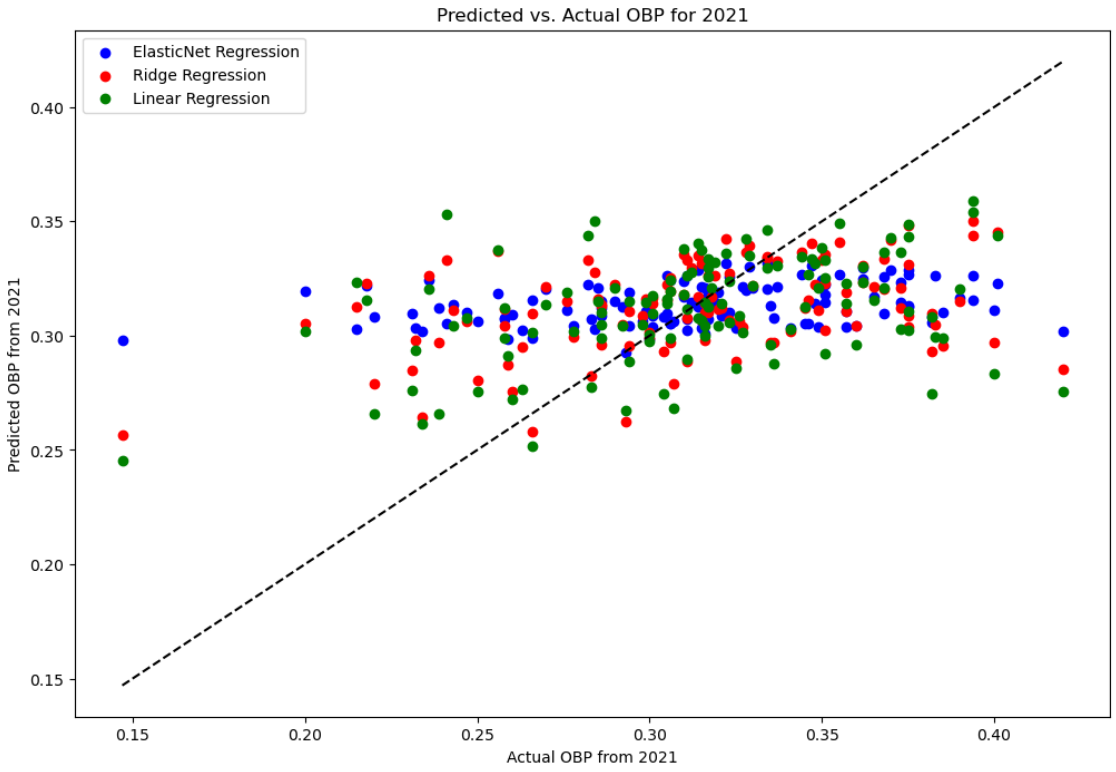
4.1 Model Training

Here I have created a dictionary to test all of our models and see which ones have the highest and most accurate score in regards to MSE and R2. You will see the three best models are 'ElasticNet Regression', 'Ridge Regression', and 'Linear Regression'. Ultimatley, I decided to go with the Ridge Regression Model

4.2 Model Evaluation

```
Evaluating Linear Regression:
MSE: 0.0020 and R2: 0.1372
Evaluating Ridge Regression:
MSE: 0.0020 and R2: 0.1515
Evaluating Lasso Regression:
MSE: 0.0022 and R2: 0.0524
Evaluating Random Forest Regression:
MSE: 0.0021 and R2: 0.1066
Evaluating Decision Tree Regressor:
MSE: 0.0032 and R2: -0.3641
Evaluating Gradient Boosting:
MSE: 0.0025 and R2: -0.0630
Evaluating AdaBoost:
MSE: 0.0020 and R2: 0.1401
Evaluating ElasticNet Regression:
MSE: 0.0021 and R2: 0.0807
Evaluating XGBoost:
MSE: 0.0024 and R2: -0.0285
```

4.3 Comparison of Model Predictions



5 Final Predictions of All OBP

After optimizing the Ridge Regression We are ready for our final predictions. You will see that the list is arranged for lowest error to highest

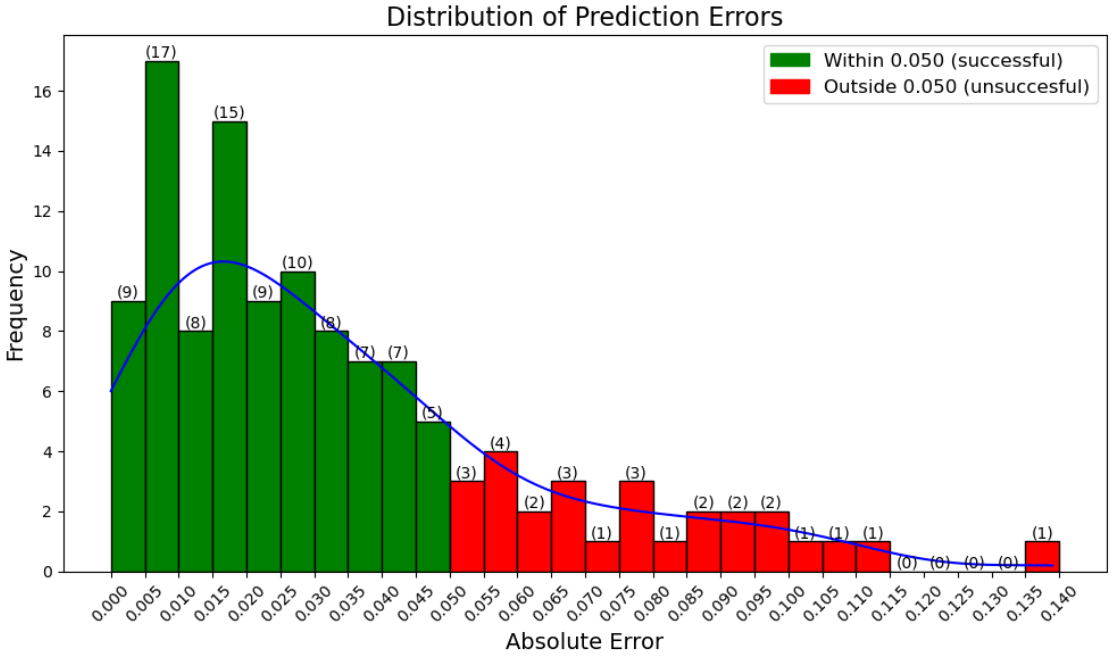
	Player	Actual	Predicted	Error
112	Mitch Haniger	0.318	0.318	0.000
222	Joey Wendle	0.319	0.320	0.001
333	Oscar Mercado	0.300	0.299	0.001
441	Elvis Andrus	0.294	0.295	0.001
287	Miguel Cabrera	0.316	0.318	0.002
138	Eduardo Escobar	0.314	0.312	0.002
322	Jake Lamb	0.306	0.303	0.003
382	Jon Berti	0.311	0.315	0.004
232	Joc Pederson	0.310	0.314	0.004
218	Colin Moran	0.334	0.329	0.005
245	Brett Phillips	0.300	0.295	0.005
86	Willy Adames	0.337	0.332	0.005
440	Stephen Vogt	0.283	0.277	0.006
97	Avisail Garcia	0.330	0.324	0.006
296	Abraham Toro	0.315	0.308	0.007
157	Brad Miller	0.321	0.314	0.007
87	Jorge Polanco	0.323	0.331	0.008
313	Tucker Barnhart	0.317	0.309	0.008
417	Juan Lagares	0.266	0.258	0.008
107	Trevor Story	0.329	0.338	0.009
193	Jonathan Schoop	0.320	0.311	0.009
61	Pete Alonso	0.344	0.335	0.009
154	Luke Voit	0.328	0.337	0.009
133	Alex Bregman	0.355	0.346	0.009
84	Manny Machado	0.347	0.338	0.009
62	Salvador Perez	0.316	0.307	0.009
49	Marcus Semien	0.334	0.324	0.010
383	Cole Tucker	0.298	0.308	0.010
354	Clint Frazier	0.317	0.329	0.012
291	Christian Walker	0.315	0.327	0.012
384	Gerardo Parra	0.292	0.304	0.012
406	Carter Kieboom	0.301	0.314	0.013
278	Whit Merrifield	0.317	0.331	0.014
495	Jarrod Dyson	0.260	0.274	0.014
348	Tom Murphy	0.304	0.289	0.015
68	Jose Altuve	0.350	0.335	0.015
282	Rowdy Tellez	0.305	0.320	0.015
212	Ryan Zimmerman	0.286	0.302	0.016
301	Josh Naylor	0.301	0.317	0.016
228	Eddie Rosario	0.305	0.321	0.016
130	Ozzie Albies	0.310	0.326	0.016
368	Nick Senzel	0.323	0.306	0.017

267	Max Kepler	0.306	0.323	0.017
141	Alex Verdugo	0.351	0.333	0.018
341	Guillermo Heredia	0.311	0.293	0.018
265	Sean Murphy	0.306	0.324	0.018
223	Francisco Lindor	0.322	0.340	0.018
339	Isiah Kiner-Falefa	0.312	0.331	0.019
174	Ramon Laureano	0.317	0.336	0.019
165	Danny Jansen	0.299	0.319	0.020
217	Sam Hilliard	0.294	0.314	0.020
275	Anthony Santander	0.286	0.306	0.020
123	Jordan Luplow	0.326	0.305	0.021
229	Kyle Farmer	0.316	0.294	0.022
88	Joey Gallo	0.351	0.329	0.022
475	Mike Ford	0.278	0.301	0.023
285	Brett Gardner	0.327	0.303	0.024
196	Dansby Swanson	0.311	0.335	0.024
319	Nick Solak	0.314	0.340	0.026
505	Tim Locastro	0.263	0.290	0.027
139	Ji-Man Choi	0.348	0.321	0.027
45	Yordan Alvarez	0.346	0.319	0.027
360	Rene Rivera	0.293	0.266	0.027
544	Matt Adams	0.250	0.278	0.028
111	Luis Urias	0.345	0.317	0.028
48	Xander Bogaerts	0.370	0.342	0.028
358	Travis Shaw	0.286	0.314	0.028
22	Trea Turner	0.375	0.346	0.029
144	Brandon Drury	0.307	0.277	0.030
526	Andrew Romine	0.234	0.265	0.031
34	Max Muncy	0.368	0.336	0.032
471	Jake Bauers	0.290	0.322	0.032
19	Nick Castellanos	0.362	0.330	0.032
427	Willians Astudillo	0.259	0.292	0.033
338	Hunter Dozier	0.285	0.318	0.033
363	Miguel Andujar	0.284	0.318	0.034
178	Matt Duffy	0.357	0.320	0.037
177	Josh Rojas	0.341	0.303	0.038
92	Michael Brantley	0.362	0.324	0.038
249	Leury Garcia	0.335	0.297	0.038
183	Kevin Plawecki	0.349	0.311	0.038
328	Rob Refsnyder	0.325	0.286	0.039
18	Joey Votto	0.375	0.336	0.039
21	Aaron Judge	0.373	0.333	0.040
390	Jose Peraza	0.266	0.307	0.041
433	Adam Eaton	0.282	0.325	0.043
448	David Bote	0.276	0.319	0.043
72	Adam Engel	0.336	0.293	0.043
8	Ronald Acuna Jr.	0.394	0.350	0.044
126	Nathaniel Lowe	0.357	0.313	0.044

167	Nicky Lopez	0.365	0.320	0.045
76	Ty France	0.368	0.322	0.046
542	Dustin Fowler	0.239	0.285	0.046
490	Erik Gonzalez	0.258	0.305	0.047
411	Didi Gregorius	0.270	0.319	0.049
10	Jesse Winker	0.394	0.344	0.050
80	Evan Longoria	0.351	0.300	0.051
531	Jay Bruce	0.231	0.284	0.053
445	Shed Long Jr.	0.258	0.313	0.055
42	Cedric Mullins II	0.360	0.305	0.055
6	Vladimir Guerrero Jr.	0.401	0.345	0.056
518	Austin Hedges	0.220	0.278	0.058
485	David Dahl	0.247	0.309	0.062
79	Delino DeShields	0.375	0.311	0.064
36	Brandon Crawford	0.373	0.308	0.065
508	Austin Wynns	0.232	0.301	0.069
512	Rio Ruiz	0.243	0.312	0.069
33	Buster Posey	0.390	0.317	0.073
83	Tony Kemp	0.382	0.305	0.077
59	Yuli Gurriel	0.383	0.306	0.077
28	C.J. Cron	0.375	0.298	0.077
482	Keston Hiura	0.256	0.339	0.083
524	Jackie Bradley Jr.	0.236	0.323	0.087
25	Darin Ruf	0.385	0.298	0.087
539	Chance Sisco	0.241	0.333	0.092
65	Luke Maile	0.382	0.288	0.094
364	Renato Nunez	0.218	0.316	0.098
547	Andrew Knapp	0.215	0.314	0.099
560	Todd Frazier	0.200	0.303	0.103
561	Scott Schebler	0.147	0.256	0.109
0	Trayce Thompson	0.400	0.289	0.111
3	Chris Owings	0.420	0.281	0.139

5.1 Distribution of Errors based on predictions

Here I have provided a graph depicting what I believe is a successful prediction! I have anything labeled in green that has less than a 0.050 error and anything in red that is greater. As you can see there's 78% success rate in the predictions


Distribution of Prediction Errors
Within 0.050 (successful)
Outside 0.050 (unsuccesful)
Frequency
Absolute Error
(17)
(15)
(10)
(9)
(9)
(8)
(8)
(7)
(7)
(5)
(4)
(3)
(3)
(3)
(2)
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(0)
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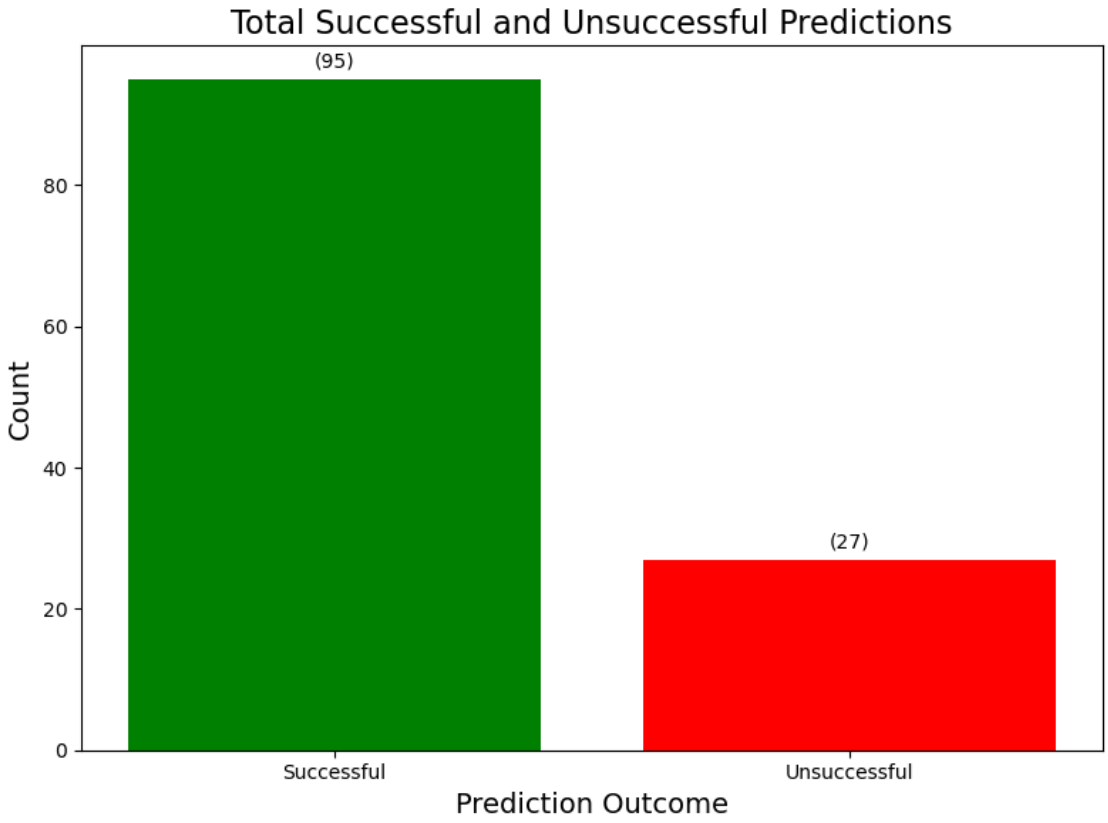
(0)


Total Successful and Unsuccessful Predictions
Count
Prediction Outcome
(95)
(27)
Successful
Unsuccessful

6 Concluding

Predicting on-base percentage for the 2021 season only having a batters on-base percentage and plate appearances was definitely a challenging task. Based on my predictions with a 78% success rate I'd say it was a good job. Without additional information and baseball being such a complex games that various little values can skew the odds I'd say that a majority of batters were predicted with a correct OBP!