3a. Logistic Regression - Serve Statistics

Using logistic regression, the three serve statistics are tested to see their correlation with the likelihood of winning a match on the ATP tour. Statistics for the winner and loser were created and a new variable was added (1 for a match won and 0 for a match lost). The two dataframes were then combined and are ready for the regression.

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Step 1: Load and Verify Data

```
import pandas as pd
import os
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
import matplotlib.pyplot as plt
import seaborn as sns

#Set Path
path = r'/Users/tristansavella/Desktop/Important Things/Data
Analytics/CareerFoundry/Data Immersion/Achievement 6/Master Folder
ATP/02 Data'

#Import df_matchstats
df_matchstats = pd.read_pickle(os.path.join(path, 'Prepared
Data','df_matchstats.pkl'))

# Set the option to display all rows
pd.set_option('display.max_rows', None)
```

```
# Set the option to display all columns
pd.set_option('display.max_columns', None)

df_matchstats.head()
```

```
       tourney_id  Year tourney_name surface tourney_level
winner_id  \
119317   2000-301  2000     Auckland    Hard             A    103163

119318   2000-301  2000     Auckland    Hard             A    102607

119319   2000-301  2000     Auckland    Hard             A    103252

119320   2000-301  2000     Auckland    Hard             A    103507

119321   2000-301  2000     Auckland    Hard             A    102103


       winner_ioc          winner_name  winner_age  winner_rank
winner_ht  \
119317        GER           Tommy Haas        21.7         11.0
188.0
119318        ESP        Juan Balcells        24.5        211.0
190.0
119319        ESP       Alberto Martin        21.3         48.0
175.0
119320        ESP  Juan Carlos Ferrero        19.9         45.0
183.0
119321        USA         Michael Sell        27.3        167.0
180.0

       loser_id loser_ioc           loser_name  loser_rank
loser_ht  \
119317   101543       USA        Jeff Tarango        63.0     180.0

119318   102644       ARG     Franco Squillari        49.0     183.0

119319   102238       ESP  Alberto Berasategui        59.0     173.0

119320   103819       SUI        Roger Federer        61.0     185.0

119321   102765       FRA       Nicolas Escude        34.0     185.0


        loser_age best_of round  minutes  w_#ServeGames  w_#aces
w_#dfs  \
119317       31.1       3   R32    108.0           17.0     18.0
4.0
119318       24.3       3   R32     85.0           12.0      5.0
3.0
119319       26.5       3   R32     56.0            8.0      0.0
```

```
0.0
119320       18.4      3   R32     68.0           10.0      5.0
1.0
119321       23.7      3   R32    115.0           13.0      1.0
2.0

        w_#ServePoints  w_#1stServesIn  w_#2ndServePoints  w_
%1stServesIn  \
119317            96.0            49.0               47.0
51
119318            76.0            52.0               24.0
68
119319            55.0            35.0               20.0
63
119320            53.0            28.0               25.0
52
119321            98.0            66.0               32.0
67

        w_#1stWon  w_%1stWon  w_#2ndWon  w_%2ndWon  w_bpSaved
w_#bpFaced  \
119317       39.0         79       28.0         59        3.0
5.0
119318       39.0         75       13.0         54        5.0
6.0
119319       25.0         71       12.0         60        1.0
1.0
119320       26.0         92       15.0         60        0.0
0.0
119321       39.0         59       14.0         43        6.0
11.0

        l_#ServeGames  l_#aces  l_#dfs  l_#ServePoints  l_#1stServesIn
\
119317           17.0      7.0     8.0           106.0            55.0

119318           12.0      5.0    10.0            74.0            32.0

119319            8.0      0.0     6.0            56.0            33.0

119320           10.0     11.0     2.0            70.0            43.0

119321           12.0      8.0     8.0            92.0            46.0


        l_#2ndServePoints  l_%1stServesIn  l_#1stWon  l_%1stWon
l_#2ndWon  \
119317               51.0              51       39.0         70
29.0
119318               42.0              43       25.0         78
```

```
18.0
119319                23.0                 58        20.0            60
7.0
119320                27.0                 61        29.0            67
14.0
119321                46.0                 50        34.0            73
18.0

        l_%2ndWon  l_bpSaved  l_#bpFaced
119317         56        4.0         7.0
119318         42        3.0         6.0
119319         30        7.0        11.0
119320         51        6.0         8.0
119321         39        5.0         9.0

# Drop columns with NaN values
df_matchstats.dropna(axis=1, inplace=True)

# Verify initial columns
print("Initial Columns:", df_matchstats.columns.tolist())

Initial Columns: ['tourney_id', 'Year', 'tourney_name', 'surface',
'tourney_level', 'winner_id', 'winner_ioc', 'winner_name',
'winner_age', 'loser_id', 'loser_ioc', 'loser_name', 'best_of',
'round', 'w_#ServeGames', 'w_#aces', 'w_#dfs', 'w_#ServePoints',
'w_#1stServesIn', 'w_#2ndServePoints', 'w_%1stServesIn', 'w_#1stWon',
'w_%1stWon', 'w_#2ndWon', 'w_%2ndWon', 'w_bpSaved', 'w_#bpFaced',
'l_#ServeGames', 'l_#aces', 'l_#dfs', 'l_#ServePoints',
'l_#1stServesIn', 'l_#2ndServePoints', 'l_%1stServesIn', 'l_#1stWon',
'l_%1stWon', 'l_#2ndWon', 'l_%2ndWon', 'l_bpSaved', 'l_#bpFaced']
```

Step 2: Separate and Rename Columns

```
# Create separate DataFrames for winner and loser statistics
winners = df_matchstats.copy()
losers = df_matchstats.copy()

# Add a target variable to each DataFrame
winners['win'] = 1
losers['win'] = 0

# Rename columns for losers to ensure uniqueness
losers.rename(columns={
    'l_%1stServesIn': '1stServesIn',
    'l_%1stWon': '1stWon',
    'l_%2ndWon': '2ndWon'
}, inplace=True)
```

```
# Rename columns for winners to ensure consistency
winners.rename(columns={
    'w_%1stServesIn': '1stServesIn',
    'w_%1stWon': '1stWon',
    'w_%2ndWon': '2ndWon'
}, inplace=True)

# Extract relevant columns
winners_renamed = winners[['1stServesIn', '1stWon', '2ndWon', 'win']]
losers_renamed = losers[['1stServesIn', '1stWon', '2ndWon', 'win']]

# Verify the column names after renaming
print("Winners Renamed Columns:", winners_renamed.columns.tolist())
print("Losers Renamed Columns:", losers_renamed.columns.tolist())

Winners Renamed Columns: ['1stServesIn', '1stWon', '2ndWon', 'win']
Losers Renamed Columns: ['1stServesIn', '1stWon', '2ndWon', 'win']
```

Step 3: Combine the DataFrames

```
# Combine the DataFrames
combined_df = pd.concat([winners_renamed, losers_renamed],
ignore_index=True)

# Verify the combined DataFrame
print("Combined DataFrame Columns:", combined_df.columns.tolist())
print(combined_df.head())

Combined DataFrame Columns: ['1stServesIn', '1stWon', '2ndWon', 'win']
   1stServesIn  1stWon  2ndWon  win
0           51      79      59    1
1           68      75      54    1
2           63      71      60    1
3           52      92      60    1
4           67      59      43    1
```

Step 4: Train the Logistic Regression Model and Plot

```
# Define the features and target variable
features = combined_df[['1stServesIn', '1stWon', '2ndWon']]
target = combined_df['win']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(features, target,
test_size=0.2, random_state=42)
```

```python
# Train the logistic regression model
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train, y_train)
```

```
LogisticRegression(max_iter=1000)
```

```python
# Make predictions and evaluate the model
y_pred = log_reg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)

print(f'Classification Model Accuracy: {accuracy}')
print('Confusion Matrix:\n', conf_matrix)
print('Classification Report:\n', class_report)
```

```
Classification Model Accuracy: 0.7902606748760594
Confusion Matrix:
 [[9794 2606]
 [2640 9972]]
Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.79      0.79     12400
           1       0.79      0.79      0.79     12612

    accuracy                           0.79     25012
   macro avg       0.79      0.79      0.79     25012
weighted avg       0.79      0.79      0.79     25012
```

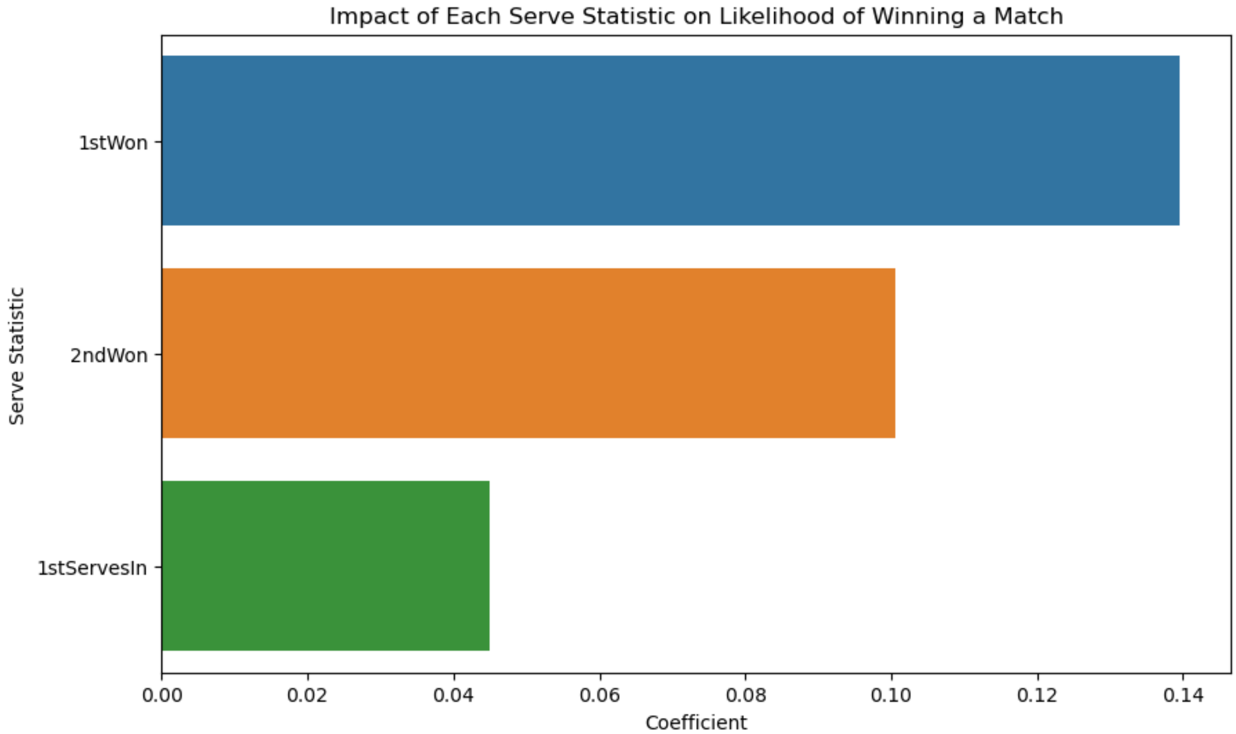
```python
# Get the coefficients of the logistic regression model
coefficients = log_reg.coef_[0]
feature_names = features.columns

# Create a DataFrame for feature importance (coefficients)
importance_df = pd.DataFrame({'Serve Statistic': feature_names,
'Coefficient': coefficients})
importance_df = importance_df.sort_values(by='Coefficient',
ascending=False)
print(importance_df)
```

```
  Serve Statistic  Coefficient
1          1stWon     0.139635
2          2ndWon     0.100579
0     1stServesIn     0.044955
```

```python
# Plot the feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Coefficient', y='Serve Statistic', data=importance_df)
plt.title('Impact of Each Serve Statistic on Likelihood of Winning a
```

```
Match')
plt.show()
```



Step 5: Export Combined Dataset

```
combined_df.to_pickle(os.path.join(path, 'Prepared
Data','combined_df.pkl'))

#as CSV
combined_df.to_csv(os.path.join(path,'Prepared Data
CSV','combined_df.csv'))

importance_df.head()
```

	Serve Statistic	Coefficient
1	1stWon	0.139635
2	2ndWon	0.100579
0	1stServesIn	0.044955