UFC_MachineLearning_Project

January 11, 2025

#UFC Prediction Project

[1]:
```
from IPython.core.display import display, HTML

# adjust output cell width
display(HTML("""
<style>
.output_subarea {
    max-width: 50% !important; /* Set the width to half the screen */
    margin: 0 auto;            /* Center the output */
}
</style>
"""))
```

```
<IPython.core.display.HTML object>
```

[2]:
```
# this command installs the kagglehub library, which provides easy access to␣
 ↪datasets on Kaggle.
!pip install kagglehub
```

```
Requirement already satisfied: kagglehub in /usr/local/lib/python3.10/dist-
packages (0.3.6)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from kagglehub) (24.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from kagglehub) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from kagglehub) (4.67.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->kagglehub) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->kagglehub) (2024.12.14)
```

[3]:
```
# downloading the dataset from kaggle
import kagglehub
```

```
path = kagglehub.dataset_download("maksbasher/
 ↪ufc-complete-dataset-all-events-1996-2024")
print("path is", path)
```

path is /root/.cache/kagglehub/datasets/maksbasher/ufc-complete-dataset-all-events-1996-2024/versions/6

[4]:
```
import os

# define the directory path where the dataset is stored
dir_path = "/root/.cache/kagglehub/datasets/maksbasher/
 ↪ufc-complete-dataset-all-events-1996-2024/versions/6"

# create the full path to the UFC dataset folder
ufc_dataset_path = os.path.join(dir_path, "UFC dataset")

# check if the specified path is a valid directory and list its contents
if os.path.isdir(ufc_dataset_path):
    print("Contents of UFC dataset directory:", os.listdir(ufc_dataset_path))
else:
    print("UFC dataset is not a directory or does not exist.")
```

Contents of UFC dataset directory: ['Urls', 'Small set', 'Large set', 'Fighter stats', 'Medium set']

[5]:
```
import os

# define the directory path where the dataset is stored
ufc_dataset_path = "/root/.cache/kagglehub/datasets/maksbasher/
 ↪ufc-complete-dataset-all-events-1996-2024/versions/6/UFC dataset"

# iterate through all files and subdirectories in the dataset directory
for sub_dir in os.listdir(ufc_dataset_path):
    sub_dir_path = os.path.join(ufc_dataset_path, sub_dir)
    if os.path.isdir(sub_dir_path):
        print(f"Contents of '{sub_dir}':", os.listdir(sub_dir_path))
    else:
        print(f"File: {sub_dir}")
```

```
Contents of 'Urls': ['event_urls.txt', 'fighter_urls.txt', 'fight_urls.txt']
Contents of 'Small set': ['upcoming_events_small.csv',
'completed_events_small.csv']
Contents of 'Large set': ['large_dataset.csv']
Contents of 'Fighter stats': ['fighter_stats.csv', 'fighters_stats.txt']
Contents of 'Medium set': ['medium_dataset.csv']
```

[6]:
```python
# to load the fighter statistics data from the fighter_stats.csv file into a␣
↪pandas dataframe for analysis.
csv_file_path = os.path.join(ufc_dataset_path, "Fighter stats", "fighter_stats.
↪csv")

import pandas as pd
fighter_stats = pd.read_csv(csv_file_path)
print(fighter_stats.head())
```

```
               name  wins  losses  height  weight   reach    stance   age  \
0      Amanda Ribas  12.0     5.0  160.02   56.70  167.64  Orthodox  30.0
1    Rose Namajunas  13.0     6.0  165.10   56.70  165.10  Orthodox  31.0
2     Karl Williams  10.0     1.0  190.50  106.59  200.66  Orthodox  34.0
3       Justin Tafa   7.0     4.0  182.88  119.75  187.96  Southpaw  30.0
4  Edmen Shahbazyan  13.0     4.0  187.96   83.91  190.50  Orthodox  26.0

   SLpM  sig_str_acc  SApM  str_def  td_avg  td_acc  td_def  sub_avg
0  4.63         0.40  3.40     0.61    2.07    0.51    0.85      0.7
1  3.69         0.41  3.51     0.63    1.38    0.47    0.59      0.5
2  2.87         0.52  1.70     0.60    4.75    0.50    1.00      0.2
3  4.09         0.54  5.02     0.47    0.00    0.00    0.50      0.0
4  3.60         0.52  4.09     0.45    2.24    0.38    0.63      0.6
```

[7]:
```python
# to load the fight-level dataset from large_dataset.csv into a Pandas␣
↪DataFrame for further exploration, preprocessing, and modeling.
csv_file_path = os.path.join(ufc_dataset_path, "Large set", "large_dataset.
↪csv")  # Adjust subdirectory if needed

import pandas as pd
master_ufc = pd.read_csv(csv_file_path)
print(master_ufc.head())
```

```
                             event_name           r_fighter         b_fighter  \
0  UFC Fight Night: Ribas vs. Namajunas        Amanda Ribas    Rose Namajunas
1  UFC Fight Night: Ribas vs. Namajunas       Karl Williams       Justin Tafa
2  UFC Fight Night: Ribas vs. Namajunas    Edmen Shahbazyan         AJ Dobson
3  UFC Fight Night: Ribas vs. Namajunas      Payton Talbott   Cameron Saaiman
4  UFC Fight Night: Ribas vs. Namajunas  Billy Quarantillo     Youssef Zalal

  winner       weight_class  is_title_bout gender               method  \
0   Blue  Women's Flyweight              0  Women  Decision - Unanimous
1    Red        Heavyweight              0    Men  Decision - Unanimous
2    Red       Middleweight              0    Men                KO/TKO
3    Red       Bantamweight              0    Men                KO/TKO
4   Blue      Featherweight              0    Men            Submission

   finish_round  total_rounds  …  weight_diff reach_diff  SLpM_total_diff  \
0             5           5.0  …         0.00       2.54             0.94
```

```
1            3          3.0  ...       -13.16      12.70            -1.22
2            1          3.0  ...         0.00      -2.54            -0.69
3            2          3.0  ...         0.00       7.62             2.73
4            2          3.0  ...         0.00      -5.08             4.48

   SApM_total_diff  sig_str_acc_total_diff  td_acc_total_diff  \
0            -0.11                   -0.01               0.04
1            -3.32                   -0.02               0.50
2            -1.22                    0.06              -0.37
3            -0.60                    0.08              -0.28
4             3.84                    0.07              -0.11

   str_def_total_diff  td_def_total_diff  sub_avg_diff  td_avg_diff
0               -0.02               0.26           0.2         0.69
1                0.13               0.50           0.2         4.75
2               -0.01              -0.02           0.3         0.57
3                0.00               0.43          -0.2        -0.91
4               -0.22               0.01          -0.2        -1.04

[5 rows x 95 columns]
```

[8]:

```python
# dropped columns such as event_name and referee because they are not necessary in our prediction model, they have unsigfincant value.
columns_to_drop = ['event_name', 'referee']
master_ufc.drop(columns=columns_to_drop, inplace=True)

print(master_ufc.columns)
```

```
Index(['r_fighter', 'b_fighter', 'winner', 'weight_class', 'is_title_bout',
       'gender', 'method', 'finish_round', 'total_rounds', 'time_sec', 'r_kd',
       'r_sig_str', 'r_sig_str_att', 'r_sig_str_acc', 'r_str', 'r_str_att',
       'r_str_acc', 'r_td', 'r_td_att', 'r_td_acc', 'r_sub_att', 'r_rev',
       'r_ctrl_sec', 'r_wins_total', 'r_losses_total', 'r_age', 'r_height',
       'r_weight', 'r_reach', 'r_stance', 'r_SLpM_total', 'r_SApM_total',
       'r_sig_str_acc_total', 'r_td_acc_total', 'r_str_def_total',
       'r_td_def_total', 'r_sub_avg', 'r_td_avg', 'b_kd', 'b_sig_str',
       'b_sig_str_att', 'b_sig_str_acc', 'b_str', 'b_str_att', 'b_str_acc',
       'b_td', 'b_td_att', 'b_td_acc', 'b_sub_att', 'b_rev', 'b_ctrl_sec',
       'b_wins_total', 'b_losses_total', 'b_age', 'b_height', 'b_weight',
       'b_reach', 'b_stance', 'b_SLpM_total', 'b_SApM_total',
       'b_sig_str_acc_total', 'b_td_acc_total', 'b_str_def_total',
       'b_td_def_total', 'b_sub_avg', 'b_td_avg', 'kd_diff', 'sig_str_diff',
       'sig_str_att_diff', 'sig_str_acc_diff', 'str_diff', 'str_att_diff',
       'str_acc_diff', 'td_diff', 'td_att_diff', 'td_acc_diff', 'sub_att_diff',
       'rev_diff', 'ctrl_sec_diff', 'wins_total_diff', 'losses_total_diff',
       'age_diff', 'height_diff', 'weight_diff', 'reach_diff',
       'SLpM_total_diff', 'SApM_total_diff', 'sig_str_acc_total_diff',
       'td_acc_total_diff', 'str_def_total_diff', 'td_def_total_diff',
```

```
       'sub_avg_diff', 'td_avg_diff'],
      dtype='object')
```

[9]:
```
# checking for columns that have missing values
missing_columns = master_ufc.columns[master_ufc.isnull().sum() > 0]
print("Columns with missing values:", missing_columns)
```

```
Columns with missing values: Index(['total_rounds', 'r_age', 'r_reach',
'r_stance', 'b_age', 'b_reach',
       'b_stance', 'age_diff', 'reach_diff'],
      dtype='object')
```

[10]:
```
# the dataset master_ufc has 93 features
print("Number of columns:", master_ufc.shape[1])
```

```
Number of columns: 93
```

[11]:
```
# removing duplicated columns
master_ufc = master_ufc.loc[:, ~master_ufc.columns.duplicated()]
```

[12]:
```
# calculate the number of NaN values in each column
nan_counts = master_ufc.isnull().sum()

# filter columns that have one or more missing values
nan_columns = nan_counts[nan_counts > 0]

# print columns with missing values and their counts
print("Columns with NaN values and their counts:")
print(nan_columns)
```

```
Columns with NaN values and their counts:
total_rounds      31
r_age             76
r_reach          412
r_stance          26
b_age            190
b_reach          888
b_stance          68
age_diff         213
reach_diff      1038
dtype: int64
```

[13]:
```
# merge fighter statistics for red corner fighters
master_ufc = master_ufc.merge(
    fighter_stats,            # Fighter stats dataset
    left_on="r_fighter",      # Match red corner fighter name
    right_on="name",          # Match fighter stats 'name' column
    how="left"                # Left join to keep all rows from master_ufc
)
```

```
# rename the columns from fighter_stats to distinguish red corner stats
master_ufc = master_ufc.rename(columns={col: f"r_{col}" for col in␣
↪fighter_stats.columns if col != "name"})

# merge fighter statistics for blue corner fighters
master_ufc = master_ufc.merge(
    fighter_stats,            # Fighter stats dataset
    left_on="b_fighter",      # Match blue corner fighter name
    right_on="name",          # Match fighter stats 'name' column
    how="left"                # Left join to keep all rows from master_ufc
)

# rename the columns from fighter_stats to distinguish blue corner stats
master_ufc = master_ufc.rename(columns={col: f"b_{col}" for col in␣
↪fighter_stats.columns if col != "name"})
```

[14]:
```
# removed duplicated columns
master_ufc = master_ufc.loc[:, ~master_ufc.columns.duplicated()]
```

[15]:
```
# removed unnecessary columns
master_ufc = master_ufc.drop(columns=['name_x', 'name_y'])

print("Updated columns:", master_ufc.columns)
```

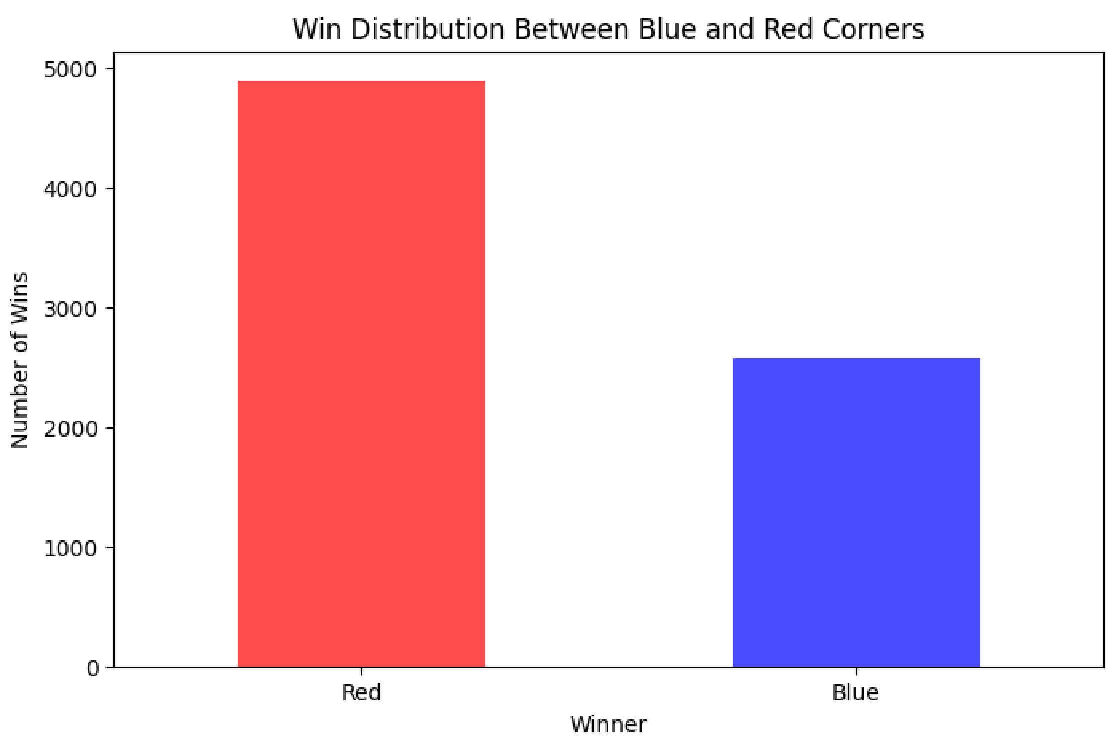
```
Updated columns: Index(['r_fighter', 'b_fighter', 'winner', 'weight_class',
'is_title_bout',
       'gender', 'method', 'finish_round', 'total_rounds', 'time_sec',
       …
       'r_SLpM', 'r_SApM', 'r_str_def', 'r_td_def', 'b_wins', 'b_losses',
       'b_SLpM', 'b_SApM', 'b_str_def', 'b_td_def'],
      dtype='object', length=105)
```

[16]:
```
# calculate the total number of missing values in each column of the DataFrame
nan_counts = master_ufc.isnull().sum()

# filter columns with more than 0 missing values
nan_columns = nan_counts[nan_counts > 0]

print("Columns with NaN values and their counts:")
print(nan_columns)
```

```
Columns with NaN values and their counts:
total_rounds      33
r_age             81
r_reach          420
r_stance          28
b_age            200
```

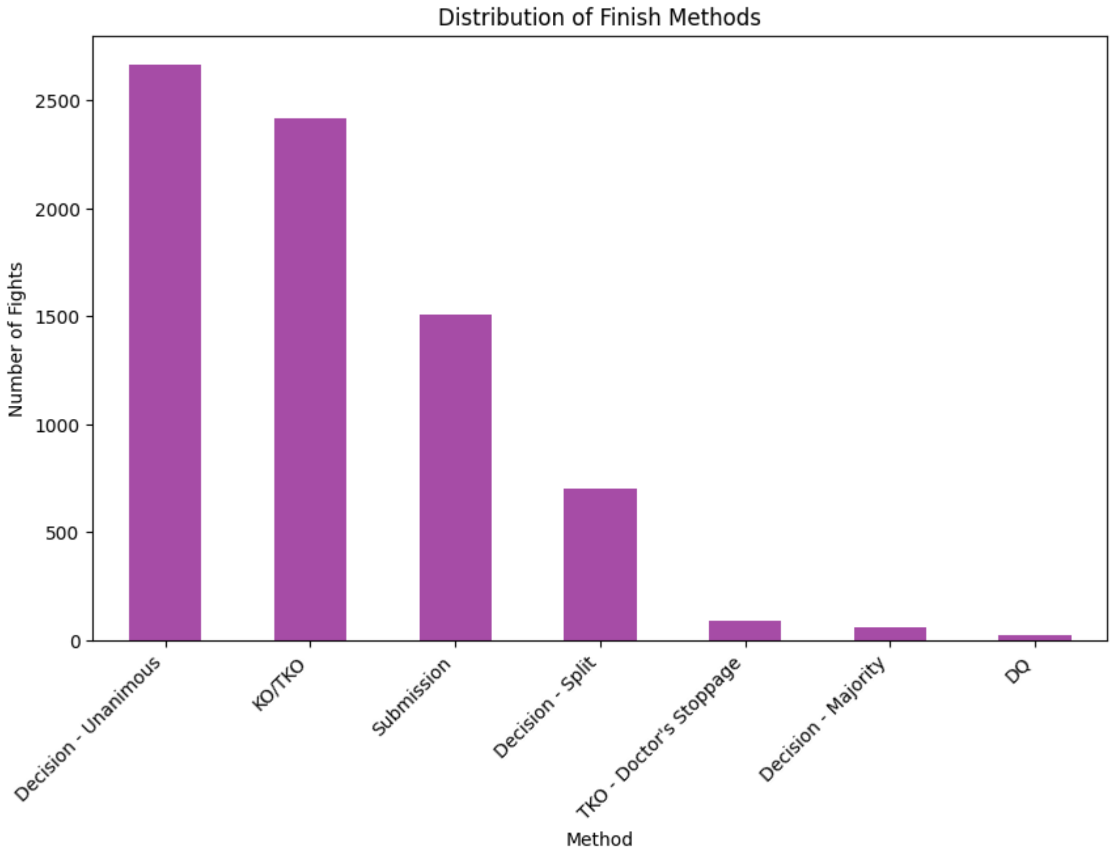
```
b_reach          898
b_stance          72
age_diff         223
reach_diff      1048
dtype: int64
```

[17]:
```
# import the matplotlib library
import matplotlib.pyplot as plt

# size
plt.figure(figsize=(8, 5))

# plot a bar chart for the 'winner' column value counts
# 'color' specifies Red and Blue for each category, 'alpha' adds transparency
master_ufc['winner'].value_counts().plot(kind='bar', color=['red', 'blue'],␣
↪alpha=0.7)

plt.title('Win Distribution Between Blue and Red Corners')
plt.xlabel('Winner')
plt.ylabel('Number of Wins')
plt.xticks(rotation=0)
plt.show()
```



[18]:

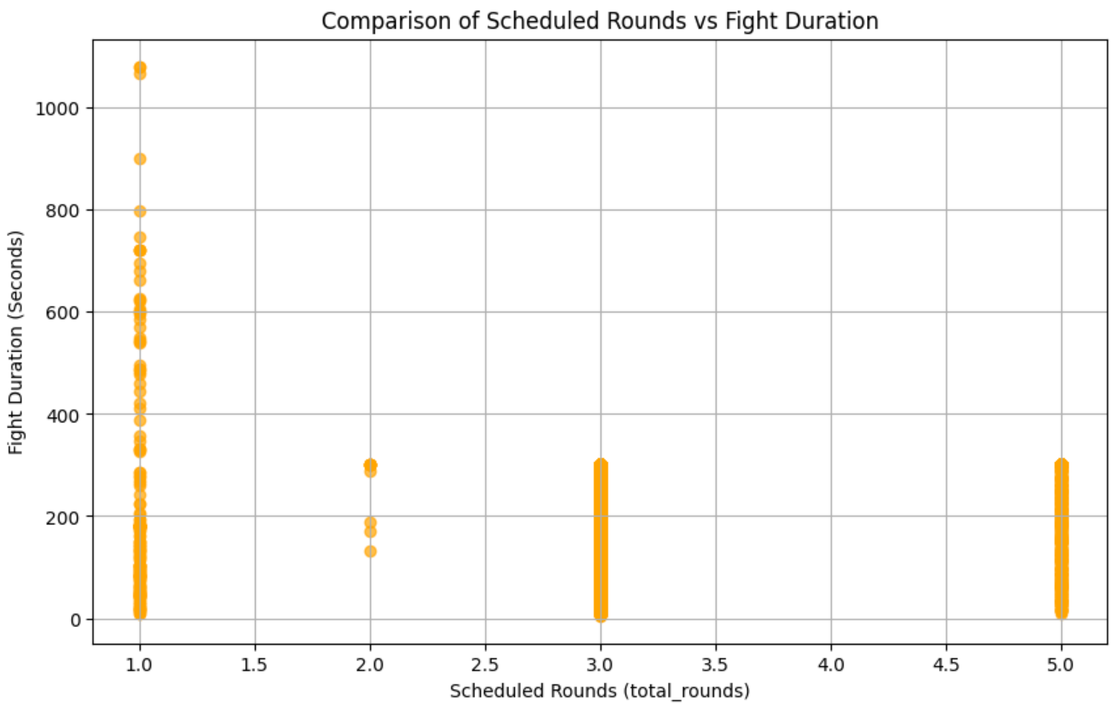
```
plt.figure(figsize=(10, 6))

# plot the distribution of the 'method' column as a bar chart
master_ufc['method'].value_counts().plot(kind='bar', color='purple', alpha=0.7)

plt.title('Distribution of Finish Methods')
plt.xlabel('Method')
plt.ylabel('Number of Fights')

# rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

plt.show()
```



[19]:

```
plt.figure(figsize=(10, 6))

# Create a scatter plot to compare scheduled rounds and fight duration
plt.scatter(master_ufc['total_rounds'], master_ufc['time_sec'], alpha=0.7,␣
 ↪color='orange')
```

```python
# Add a title and axis labels for context
plt.title('Comparison of Scheduled Rounds vs Fight Duration')
plt.xlabel('Scheduled Rounds (total_rounds)')
plt.ylabel('Fight Duration (Seconds)')

plt.grid(True)

plt.show()
```



[20]:
```python
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
import pandas as pd

def predict_missing_numeric_values(df, target_column, exclude_columns):
    """
    Predict missing numeric values for a specific column using Random Forest␣
↪Regressor.
    """
    known_data = df[~df[target_column].isnull()]
    unknown_data = df[df[target_column].isnull()]

    if unknown_data.empty:
        print(f"No missing values to predict for {target_column}")
        return df
```

```
    # prepare training and prediction data
    X_train = known_data.drop(columns=exclude_columns)
    y_train = known_data[target_column]
    X_unknown = unknown_data.drop(columns=exclude_columns)

    # convert categorical features to numerical using dummy encoding
    X_train = pd.get_dummies(X_train, drop_first=True)
    X_unknown = pd.get_dummies(X_unknown, drop_first=True)

    # align columns to ensure matching structure
    X_unknown = X_unknown.reindex(columns=X_train.columns, fill_value=0)

    # train Random Forest Regressor
    model = RandomForestRegressor(random_state=42)
    model.fit(X_train, y_train)

    # predict missing values and update the dataframe
    predictions = model.predict(X_unknown)
    df.loc[df[target_column].isnull(), target_column] = predictions

    return df


def predict_missing_categorical_values(df, target_column, exclude_columns):
    """
    Predict missing categorical values using Random Forest Classifier.
    """
    known_data = df[~df[target_column].isnull()]
    unknown_data = df[df[target_column].isnull()]

    if unknown_data.empty:
        print(f"No missing values to predict for {target_column}")
        return df

    # prepare training and prediction data
    X_train = known_data.drop(columns=exclude_columns)
    y_train = known_data[target_column]
    X_unknown = unknown_data.drop(columns=exclude_columns)

    # convert categorical features to numerical using dummy encoding
    X_train = pd.get_dummies(X_train, drop_first=True)
    X_unknown = pd.get_dummies(X_unknown, drop_first=True)

    # align columns to ensure matching structure
    X_unknown = X_unknown.reindex(columns=X_train.columns, fill_value=0)

    # train Random Forest Classifier
```

```python
    model = RandomForestClassifier(random_state=42)
    model.fit(X_train, y_train)

    # predict missing values and update the DataFrame
    predictions = model.predict(X_unknown)
    df.loc[df[target_column].isnull(), target_column] = predictions

    return df


# define numeric and categorical columns with missing values
numeric_columns = [
    'total_rounds', 'r_age', 'r_reach', 'b_age', 'b_reach', 'age_diff',
    'reach_diff'
]

categorical_columns = [
    'r_stance', 'b_stance',
]

# predict and fill missing values for numeric columns
for column in numeric_columns:
    print(f"Predicting missing values for numeric column: {column}")
    master_ufc = predict_missing_numeric_values(
        master_ufc,
        target_column=column,
        exclude_columns=['r_fighter', 'b_fighter', 'winner', column]
    )

print("Remaining missing values in numeric columns:")
print(master_ufc[numeric_columns].isnull().sum())

# predict and fill missing values for categorical columns
for column in categorical_columns:
    print(f"Predicting missing values for categorical column: {column}")
    master_ufc = predict_missing_categorical_values(
        master_ufc,
        target_column=column,
        exclude_columns=['r_fighter', 'b_fighter', 'winner', column]
    )

print("Remaining missing values in categorical columns:")
print(master_ufc[categorical_columns].isnull().sum())
```

```
Predicting missing values for numeric column: total_rounds
Predicting missing values for numeric column: r_age
Predicting missing values for numeric column: r_reach
Predicting missing values for numeric column: b_age
```

```
Predicting missing values for numeric column: b_reach
Predicting missing values for numeric column: age_diff
Predicting missing values for numeric column: reach_diff
Remaining missing values in numeric columns:
total_rounds    0
r_age           0
r_reach         0
b_age           0
b_reach         0
age_diff        0
reach_diff      0
dtype: int64
Predicting missing values for categorical column: r_stance
Predicting missing values for categorical column: b_stance
Remaining missing values in categorical columns:
r_stance    0
b_stance    0
dtype: int64
```

[21]:
```python
# downloading the dataset for the upcoming fights
path = kagglehub.dataset_download("jaredcarmona/upcomingdatasetproject")
print("path is", path)
```

```
path is
/root/.cache/kagglehub/datasets/jaredcarmona/upcomingdatasetproject/versions/1
```

[22]:
```python
import os

# define the path to the dataset directory
dataset_path = "/root/.cache/kagglehub/datasets/jaredcarmona/
↪upcomingdatasetproject/versions/1"

# list and print all files and directories in the specified dataset path
print("Files in the dataset directory:", os.listdir(dataset_path))
```

```
Files in the dataset directory: ['upcomingproject382.csv']
```

[23]:
```python
dataset_file = os.path.join(dataset_path, "upcomingproject382.csv")  #␣
↪construct the file path

# read the CSV file into a into a pandas dataframe
upcoming_fights = pd.read_csv(dataset_file, encoding='latin1')

# display the contents of the DataFrame
upcoming_fights
```

[23]:

	r_fighter	b_fighter
0	Erin Blanchfield	Manon Fiorot

```
1          Vicente Luque   Joaquin Buckley
2          Chris Weidman       Bruno Silva
3     Nursulton Ruziboev   Sedriques Dumas
4             Bill Algeo       Kyle Nelson
..                   ...               ...
377         Sean Woodson  Fernando Padilla
378          Miles Johns       Felipe Lima
379      Miranda Maverick   Jamey-Lyn Horth
380          Davey Grant     Ramon Tavares
381    Josefine Knutsson   Piera Rodriguez

[382 rows x 2 columns]
```

[24]:
```
master_ufc.head() # showing the head of the whole dataset of historical fights
```

[24]:
```
           r_fighter        b_fighter winner       weight_class  \
0       Amanda Ribas   Rose Namajunas   Blue  Women's Flyweight
1      Karl Williams      Justin Tafa    Red        Heavyweight
2   Edmen Shahbazyan        AJ Dobson    Red       Middleweight
3     Payton Talbott  Cameron Saaiman    Red       Bantamweight
4  Billy Quarantillo    Youssef Zalal   Blue      Featherweight

   is_title_bout gender                method  finish_round  total_rounds  \
0              0  Women  Decision - Unanimous             5           5.0
1              0    Men  Decision - Unanimous             3           3.0
2              0    Men                KO/TKO             1           3.0
3              0    Men                KO/TKO             2           3.0
4              0    Men            Submission             2           3.0

   time_sec  …  r_SLpM  r_SApM  r_str_def  r_td_def  b_wins  b_losses  \
0       300  …    4.63    3.40       0.61      0.85    13.0       6.0
1       300  …    2.87    1.70       0.60      1.00     7.0       4.0
2       273  …    3.60    4.09       0.45      0.63     7.0       3.0
3        21  …    8.05    3.58       0.51      0.90     9.0       2.0
4       110  …    7.36    5.57       0.43      0.61    14.0       5.0

   b_SLpM  b_SApM  b_str_def  b_td_def
0    3.69    3.51       0.63      0.59
1    4.09    5.02       0.47      0.50
2    4.29    5.31       0.46      0.65
3    5.32    4.18       0.51      0.47
4    2.88    1.73       0.65      0.60

[5 rows x 105 columns]
```

[25]:
```
upcoming_fights.head() # showing the head of the whole dataset of  upcoming
 ↪fights
```

[25]:
```
             r_fighter        b_fighter
0     Erin Blanchfield     Manon Fiorot
1        Vicente Luque  Joaquin Buckley
2        Chris Weidman      Bruno Silva
3  Nursulton Ruziboev  Sedriques Dumas
4           Bill Algeo      Kyle Nelson
```

[26]:
```python
import pandas as pd

def align_and_combine(master_ufc, upcoming_fights):
    """
    Aligns the upcoming fights dataset with the master UFC dataset structure
    and combines them into a single DataFrame.

    Parameters:
    ----------
    master_ufc : pd.DataFrame
        The historical UFC dataset containing fight records and fighter␣
↪statistics.
    upcoming_fights : pd.DataFrame
        The dataset containing upcoming fights information.

    Returns:
    -------
    combined_dataset : pd.DataFrame
        A DataFrame combining both historical and upcoming fight data.
    """
    # create an empty DataFrame with the same columns as master_ufc
    aligned_upcoming = pd.DataFrame(columns=master_ufc.columns)

    # fill 'r_fighter' and 'b_fighter' columns with values from the upcoming␣
↪fights dataset
    aligned_upcoming[['r_fighter', 'b_fighter']] =␣
↪upcoming_fights[['r_fighter', 'b_fighter']]

    # concatenate the historical data and upcoming fight data into a single␣
↪dataset
    combined_dataset = pd.concat([master_ufc, aligned_upcoming], axis=0,␣
↪ignore_index=True)

    return combined_dataset

# combine historical UFC dataset with upcoming fights
ufc_combined = align_and_combine(master_ufc, upcoming_fights)

# print the last rows of the combined dataset to see the merge
print("Combined UFC Dataset:")
```

```
print(ufc_combined.tail())
```

```
Combined UFC Dataset:
              r_fighter          b_fighter winner weight_class is_title_bout  \
7841       Sean Woodson  Fernando Padilla    NaN          NaN           NaN
7842         Miles Johns       Felipe Lima    NaN          NaN           NaN
7843   Miranda Maverick   Jamey-Lyn Horth    NaN          NaN           NaN
7844         Davey Grant    Ramon Tavares    NaN          NaN           NaN
7845  Josefine Knutsson   Piera Rodriguez    NaN          NaN           NaN

     gender method finish_round  total_rounds time_sec  … r_SLpM r_SApM  \
7841    NaN    NaN          NaN           NaN      NaN  …    NaN    NaN
7842    NaN    NaN          NaN           NaN      NaN  …    NaN    NaN
7843    NaN    NaN          NaN           NaN      NaN  …    NaN    NaN
7844    NaN    NaN          NaN           NaN      NaN  …    NaN    NaN
7845    NaN    NaN          NaN           NaN      NaN  …    NaN    NaN

     r_str_def  r_td_def b_wins b_losses  b_SLpM b_SApM b_str_def  b_td_def
7841       NaN       NaN    NaN      NaN     NaN    NaN       NaN       NaN
7842       NaN       NaN    NaN      NaN     NaN    NaN       NaN       NaN
7843       NaN       NaN    NaN      NaN     NaN    NaN       NaN       NaN
7844       NaN       NaN    NaN      NaN     NaN    NaN       NaN       NaN
7845       NaN       NaN    NaN      NaN     NaN    NaN       NaN       NaN

[5 rows x 105 columns]

<ipython-input-26-fb5c46e152ff>:27: FutureWarning: The behavior of DataFrame
concatenation with empty or all-NA entries is deprecated. In a future version,
this will no longer exclude empty or all-NA columns when determining the result
dtypes. To retain the old behavior, exclude the relevant entries before the
concat operation.
  combined_dataset = pd.concat([master_ufc, aligned_upcoming], axis=0,
ignore_index=True)
```

[27]:
```
import pandas as pd

def fill_fighter_stats(combined_df, exclude_columns):
    """
    Fills NaN values for numeric and non-numeric stats of fighters
    in the upcoming fights using their historical values from past fights.

    Parameters:
    ----------
    combined_df : pd.DataFrame
        The combined dataset containing both historical and upcoming fight data.
    exclude_columns : list
        A list of columns to exclude from the filling process.

```

```
    Returns:
    -------
    pd.DataFrame
        The updated DataFrame with missing fighter statistics filled using␣
↪historical values.
    """
    for role in ['r', 'b']:
        fighter_col = f"{role}_fighter"  # column indicating fighter names

        # identify relevant stats columns for the given fighter role
        stats_columns = [
            col for col in combined_df.columns
            if col.startswith(role) and col not in exclude_columns
        ]

        # separate columns into numeric and non-numeric stats
        non_numeric_columns = [col for col in stats_columns if combined_df[col].
↪dtype == 'object']
        non_numeric_columns.extend(['weight_class', 'is_title_bout', 'gender'])␣
↪ # additional non-numeric columns
        numeric_columns = [col for col in stats_columns if col not in␣
↪non_numeric_columns]
        numeric_columns.append('total_rounds')  # include 'total_rounds' as a␣
↪numeric column

        # fill missing numeric stats with the mean value from past fights
        for stat_col in numeric_columns:
            combined_df[stat_col] = combined_df.apply(
                lambda row: combined_df.loc[
                    (combined_df[fighter_col] == row[fighter_col]) &
                    (~combined_df[stat_col].isna()), stat_col
                ].mean() if pd.isna(row[stat_col]) else row[stat_col], axis=1
            )

        # fill missing non-numeric stats with the most common value from past␣
↪fights
        for stat_col in non_numeric_columns:
            combined_df[stat_col] = combined_df.apply(
                lambda row: (
                    combined_df.loc[
                        (combined_df[fighter_col] == row[fighter_col]) &
                        (~combined_df[stat_col].isna()), stat_col
                    ].value_counts().idxmax()
                    if not combined_df.loc[
                        (combined_df[fighter_col] == row[fighter_col]) &
                        (~combined_df[stat_col].isna()), stat_col
```

```
                    ].empty else None
                ) if pd.isna(row[stat_col]) else row[stat_col], axis=1
            )

    return combined_df

# columns to exclude from the filling process
exclude_columns = ['winner', 'time_sec', 'b_td', 'r_td', 'r_sig_str',␣
 ↪'b_sig_str']

# fill missing fighter statistics using historical data
ufc_combined_filled = fill_fighter_stats(ufc_combined, exclude_columns)
```

[28]:

```
print(ufc_combined_filled.tail())
```

```
               r_fighter         b_fighter winner         weight_class  \
7841        Sean Woodson  Fernando Padilla    NaN        Featherweight
7842         Miles Johns       Felipe Lima    NaN         Bantamweight
7843     Miranda Maverick   Jamey-Lyn Horth    NaN     Women's Flyweight
7844         Davey Grant    Ramon Tavares    NaN         Bantamweight
7845   Josefine Knutsson   Piera Rodriguez    NaN  Women's Strawweight

      is_title_bout gender method finish_round  total_rounds time_sec  …  \
7841            0.0    Men    NaN          NaN           3.0      NaN  …
7842            0.0    Men    NaN          NaN           3.0      NaN  …
7843            0.0  Women    NaN          NaN           3.0      NaN  …
7844            0.0    Men    NaN          NaN           3.0      NaN  …
7845            0.0  Women    NaN          NaN           3.0      NaN  …

      r_SLpM r_SApM  r_str_def  r_td_def  b_wins  b_losses  b_SLpM b_SApM  \
7841    5.40   4.00       0.58      0.84    16.0       5.0    6.48   5.25
7842    3.28   2.55       0.68      0.85     NaN       NaN     NaN    NaN
7843    3.80   2.60       0.59      0.40     6.0       1.0    3.97   3.53
7844    4.77   3.82       0.55      0.61     NaN       NaN     NaN    NaN
7845    3.73   1.33       0.64      1.00     9.0       1.0    3.46   2.98

      b_str_def  b_td_def
7841       0.53      1.00
7842        NaN       NaN
7843       0.57      0.70
7844        NaN       NaN
7845       0.57      0.66

[5 rows x 105 columns]
```

[29]:

```
# define columns where NaN values are allowed
allowed_nan_columns = [
```

```
    'winner', 'finish_round', 'time_sec', 'b_td', 'r_td', 'r_sig_str',␣
 ↪'b_sig_str', 'method'
]

# identify fighter-specific statistic columns that are not in the allowed NaN␣
 ↪list, this happens
# due to special fighters having weird characters in their name we just␣
 ↪avoiding for simplicity
fighter_stats_columns = [
    col for col in ufc_combined_filled.columns
    if (col.startswith('r_') or col.startswith('b_')) and col not in␣
 ↪allowed_nan_columns
]

# drop rows where any fighter stats or gender columns have missing values
ufc_cleaned = ufc_combined_filled.dropna(
    subset=['gender'] + fighter_stats_columns,
    how='any'
)

print("Cleaned Dataset:")
from IPython.display import display
display(ufc_cleaned.tail())
```

```
Cleaned Dataset:

              r_fighter         b_fighter winner         weight_class  \
7839    Michael Johnson    Ottman Azaitar    NaN          Lightweight
7840       Joel Alvarez     Drakkar Klose    NaN          Lightweight
7841       Sean Woodson  Fernando Padilla    NaN        Featherweight
7843   Miranda Maverick   Jamey-Lyn Horth    NaN     Women's Flyweight
7845  Josefine Knutsson   Piera Rodriguez    NaN  Women's Strawweight

      is_title_bout gender method finish_round  total_rounds time_sec  …  \
7839            0.0    Men    NaN          NaN      3.105263      NaN  …
7840            0.0    Men    NaN          NaN      3.000000      NaN  …
7841            0.0    Men    NaN          NaN      3.000000      NaN  …
7843            0.0  Women    NaN          NaN      3.000000      NaN  …
7845            0.0  Women    NaN          NaN      3.000000      NaN  …

      r_SLpM r_SApM  r_str_def  r_td_def  b_wins  b_losses  b_SLpM b_SApM  \
7839    4.27   3.83       0.57      0.81    13.0       2.0    5.73   4.96
7840    3.65   3.37       0.50      0.11    14.0       2.0    4.33   3.40
7841    5.40   4.00       0.58      0.84    16.0       5.0    6.48   5.25
7843    3.80   2.60       0.59      0.40     6.0       1.0    3.97   3.53
7845    3.73   1.33       0.64      1.00     9.0       1.0    3.46   2.98

      b_str_def  b_td_def
```

```
7839        0.48      1.00
7840        0.52      0.68
7841        0.53      1.00
7843        0.57      0.70
7845        0.57      0.66

[5 rows x 105 columns]
```

[30]:
```
ufc_cleaned.tail()
```

[30]:
```
               r_fighter         b_fighter winner         weight_class  \
7839     Michael Johnson    Ottman Azaitar    NaN          Lightweight
7840        Joel Alvarez     Drakkar Klose    NaN          Lightweight
7841        Sean Woodson  Fernando Padilla    NaN       Featherweight
7843    Miranda Maverick   Jamey-Lyn Horth    NaN   Women's Flyweight
7845  Josefine Knutsson   Piera Rodriguez    NaN  Women's Strawweight

      is_title_bout gender method finish_round  total_rounds time_sec  …  \
7839            0.0    Men    NaN          NaN      3.105263      NaN  …
7840            0.0    Men    NaN          NaN      3.000000      NaN  …
7841            0.0    Men    NaN          NaN      3.000000      NaN  …
7843            0.0  Women    NaN          NaN      3.000000      NaN  …
7845            0.0  Women    NaN          NaN      3.000000      NaN  …

      r_SLpM r_SApM  r_str_def  r_td_def  b_wins  b_losses  b_SLpM b_SApM  \
7839    4.27   3.83       0.57      0.81    13.0       2.0    5.73   4.96
7840    3.65   3.37       0.50      0.11    14.0       2.0    4.33   3.40
7841    5.40   4.00       0.58      0.84    16.0       5.0    6.48   5.25
7843    3.80   2.60       0.59      0.40     6.0       1.0    3.97   3.53
7845    3.73   1.33       0.64      1.00     9.0       1.0    3.46   2.98

      b_str_def  b_td_def
7839       0.48      1.00
7840       0.52      0.68
7841       0.53      1.00
7843       0.57      0.70
7845       0.57      0.66

[5 rows x 105 columns]
```

[31]:
```
# list of base statistics to compute differences
base_stats = [
    'kd', 'sig_str', 'sig_str_att', 'sig_str_acc', 'str', 'str_att', 'str_acc',
    'td', 'td_att', 'td_acc', 'sub_att', 'ctrl_sec', 'wins_total',␣
↪'losses_total',
    'age', 'height', 'weight', 'SLpM_total', 'SApM_total', 'sig_str_acc_total',
    'td_acc_total', 'str_def_total', 'td_def_total', 'sub_avg', 'td_avg'
```

```
]

# calculate the difference for each statistic between red and blue corner␣
 ↪fighters
for stat in base_stats:
    diff_col = f"{stat}_diff"  # new column for the difference
    red_col = f"r_{stat}"      # column name for red corner fighter stats
    blue_col = f"b_{stat}"     # column name for blue corner fighter stats

    # check if the stat exists for both red and blue corner in the dataset
    if red_col in ufc_cleaned.columns and blue_col in ufc_cleaned.columns:
        # compute the difference and store it in the new column
        ufc_cleaned[diff_col] = ufc_cleaned[red_col] - ufc_cleaned[blue_col]

# print the updated dataset with new difference columns
print("Updated dataset with calculated difference columns:")
from IPython.display import display
display(ufc_cleaned.tail())
```

```
Updated dataset with calculated difference columns:
```

```
<ipython-input-31-247bf4c10e6c>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[diff_col] = ufc_cleaned[red_col] - ufc_cleaned[blue_col]
```

```
             r_fighter         b_fighter winner         weight_class  \
7839    Michael Johnson    Ottman Azaitar    NaN          Lightweight
7840       Joel Alvarez     Drakkar Klose    NaN          Lightweight
7841       Sean Woodson  Fernando Padilla    NaN        Featherweight
7843    Miranda Maverick   Jamey-Lyn Horth    NaN    Women's Flyweight
7845  Josefine Knutsson   Piera Rodriguez    NaN  Women's Strawweight

      is_title_bout gender method finish_round  total_rounds time_sec  …  \
7839            0.0    Men    NaN          NaN      3.105263      NaN  …
7840            0.0    Men    NaN          NaN      3.000000      NaN  …
7841            0.0    Men    NaN          NaN      3.000000      NaN  …
7843            0.0  Women    NaN          NaN      3.000000      NaN  …
7845            0.0  Women    NaN          NaN      3.000000      NaN  …

      r_SLpM r_SApM  r_str_def  r_td_def  b_wins  b_losses  b_SLpM b_SApM  \
7839    4.27   3.83       0.57      0.81    13.0       2.0    5.73   4.96
7840    3.65   3.37       0.50      0.11    14.0       2.0    4.33   3.40
7841    5.40   4.00       0.58      0.84    16.0       5.0    6.48   5.25
7843    3.80   2.60       0.59      0.40     6.0       1.0    3.97   3.53
7845    3.73   1.33       0.64      1.00     9.0       1.0    3.46   2.98
```

```
      b_str_def  b_td_def
7839       0.48      1.00
7840       0.52      0.68
7841       0.53      1.00
7843       0.57      0.70
7845       0.57      0.66

[5 rows x 105 columns]
```

[32]:
```python
# calculate the total number of missing values in each column
missing_values = ufc_cleaned.isna().sum()

# Filter columns with more than 0 missing values
missing_columns = missing_values[missing_values > 0]

print("Columns with missing values and their counts:")
print(missing_columns)
```

```
Columns with missing values and their counts:
winner          201
method          201
finish_round    201
time_sec        201
r_sig_str       201
r_td            201
b_sig_str       201
b_td            201
sig_str_diff    201
td_diff         201
dtype: int64
```

[33]:
```python
#this is what exactly the number of fights we want to predict
```

[34]:
```python
targets = ['winner', 'method', 'finish_round', 'time_sec', 'r_sig_str', 'r_td',␣
↪'b_sig_str', 'b_td']
```

[35]:
```python
from sklearn.preprocessing import LabelEncoder
import numpy as np

# dictionary to store labelencoder for each target variable
label_encoders = {}

# loop through all target variables and encode them if they are not numeric
for target in targets:
    if target in ufc_cleaned.columns and not pd.api.types.
↪is_numeric_dtype(ufc_cleaned[target]):
        le = LabelEncoder()  # initialize labelencoder
```

```
        non_null_values = ufc_cleaned[target].dropna()  # Exclude missing␣
↪values for fitting the encoder
        le.fit(non_null_values)  # fit the encoder to the unique non-null values

        # apply the encoder to the column keeping missing values
        ufc_cleaned[target] = ufc_cleaned[target].apply(
            lambda x: le.transform([x])[0] if pd.notna(x) else np.nan
        )

        # store the encoder for future decoding or usage
        label_encoders[target] = le
        print(f"'{target}' converted to numeric with NaNs preserved.")
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'winner' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'method' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'finish_round' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'time_sec' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'r_sig_str' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'r_td' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

```
'b_sig_str' converted to numeric with NaNs preserved.
'b_td' converted to numeric with NaNs preserved.
```

```
<ipython-input-35-19e9e9093884>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  ufc_cleaned[target] = ufc_cleaned[target].apply(
```

[36]:
```
import pandas as pd
from IPython.display import display

# select only the numeric columns from the 'ufc_cleaned' DataFrame
numeric_data = ufc_cleaned.select_dtypes(include=['number'])

# dictionary to store correlation results
correlation_results = {}

# iterate through the list of target variables
```

```python
for target in targets:
    if target in numeric_data.columns:
        # calculate correlations and sort them
        top_correlations = numeric_data.corr()[target].
 ↪sort_values(ascending=False).head(10)
        correlation_results[target] = top_correlations
    else:
        print(f"'{target}' is not numeric or not in the dataset.")

# display correlations as tables
for target, correlations in correlation_results.items():
    print(f"\nTop Correlations with '{target}':")
    corr_df = correlations.reset_index()
    corr_df.columns = ['Feature', 'Correlation']  # Rename columns
    display(corr_df.style.format({'Correlation': '{:.4f}'}))
```

```
Top Correlations with 'winner':

<pandas.io.formats.style.Styler at 0x7a8d4d44dd80>


Top Correlations with 'method':

<pandas.io.formats.style.Styler at 0x7a8d4d44e020>


Top Correlations with 'finish_round':

<pandas.io.formats.style.Styler at 0x7a8d4d44ceb0>


Top Correlations with 'time_sec':

<pandas.io.formats.style.Styler at 0x7a8d4d44eb30>


Top Correlations with 'r_sig_str':

<pandas.io.formats.style.Styler at 0x7a8d4d44df90>


Top Correlations with 'r_td':

<pandas.io.formats.style.Styler at 0x7a8d4d44e020>


Top Correlations with 'b_sig_str':

<pandas.io.formats.style.Styler at 0x7a8d4d44ceb0>


Top Correlations with 'b_td':

<pandas.io.formats.style.Styler at 0x7a8d4d44eb30>
```

[37]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import accuracy_score, mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
import pandas as pd

# define target variables and their associated features for prediction
target_features = {
    'winner': ['sig_str_diff', 'str_diff', 'sig_str_acc_diff', 'kd_diff',␣
↪'str_acc_diff',
               'str_att_diff', 'td_diff', 'r_td', 'ctrl_sec_diff'],
    'method': ['winner', 'r_sub_avg', 'sig_str_diff', 'r_sub_att', 'td_diff',
               'b_td', 'r_sig_str_acc', 'sub_att_diff', 'r_td'],
    'finish_round': ['r_str_att', 'b_str_att', 'b_str', 'b_sig_str_att',␣
↪'r_str',
                     'r_sig_str_att', 'b_td', 'r_td', 'time_sec'],
    'time_sec': ['finish_round', 'b_td', 'b_str_att', 'b_str', 'r_str_att',
                 'b_sig_str_att', 'r_td', 'r_sig_str_att', 'r_str'],
    'r_sig_str': ['finish_round', 'r_str_att', 'r_sig_str_att', 'b_sig_str',␣
↪'r_str',
                  'b_sig_str_att', 'b_str_att', 'r_td', 'b_td'],
    'r_td': ['td_diff', 'r_td_att', 'r_ctrl_sec', 'ctrl_sec_diff', 'r_td_acc',
             'td_att_diff', 'finish_round', 'r_td_avg', 'td_acc_diff'],
    'b_sig_str': ['finish_round', 'b_str_att', 'b_sig_str_att', 'b_str', 'b_td',
                  'r_sig_str_att', 'r_str_att', 'r_sig_str', 'b_SLpM_total'],
    'b_td': ['b_ctrl_sec', 'b_td_att', 'finish_round', 'b_td_acc', 'b_td_avg',
             'b_str', 'time_sec', 'b_sig_str', 'b_str_att']
}

# dictionaries to store results and encoders
model_results = {}
label_encoders = {}
results_table = []  # List to store results for table display

# loop through each target variable and its associated features
for target, features in target_features.items():
    print(f"\nTraining model to predict '{target}' using features: {features}")

    # drop rows with missing target values
    data = ufc_cleaned.dropna(subset=[target])
    X = data[features]  # Feature matrix
    y = data[target]    # Target variable

    # encode categorical targets if necessary
    if target in ['winner', 'method']:
        le = LabelEncoder()
        y = le.fit_transform(y)  # transform categories to numeric labels
```

```
        label_encoders[target] = le

    # splitiing data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # selecting  model type: classifier for categorical, regressor for numeric targets
    if target in ['winner', 'method']:
        model = RandomForestClassifier(random_state=42)
        model_type = 'Classification'
    else:
        model = RandomForestRegressor(random_state=42)
        model_type = 'Regression'

    # train the model
    model.fit(X_train, y_train)

    # make predictions
    predictions = model.predict(X_test)

    # evaluate model performance
    if target in ['winner', 'method']:
        accuracy = accuracy_score(y_test, predictions)
        print(f"Accuracy for '{target}': {accuracy:.4f}")
        results_table.append({
            'Target': target,
            'Model': model_type,
            'Accuracy': round(accuracy, 4),
            'R²': 'N/A',
            'MSE': 'N/A'
        })
    else:
        mse = mean_squared_error(y_test, predictions)
        r2 = r2_score(y_test, predictions)
        print(f"R² for '{target}': {r2:.4f}, MSE: {mse:.4f}")
        results_table.append({
            'Target': target,
            'Model': model_type,
            'Accuracy': 'N/A',
            'R²': round(r2, 4),
            'MSE': round(mse, 4)
        })

print("\nAll models have been trained and evaluated!")

results_df = pd.DataFrame(results_table)
```

```
display(results_df.style.set_caption("Model Performance Summary"))
```

```
Training model to predict 'winner' using features: ['sig_str_diff', 'str_diff',
'sig_str_acc_diff', 'kd_diff', 'str_acc_diff', 'str_att_diff', 'td_diff',
'r_td', 'ctrl_sec_diff']
Accuracy for 'winner': 0.8480

Training model to predict 'method' using features: ['winner', 'r_sub_avg',
'sig_str_diff', 'r_sub_att', 'td_diff', 'b_td', 'r_sig_str_acc', 'sub_att_diff',
'r_td']
Accuracy for 'method': 0.6457

Training model to predict 'finish_round' using features: ['r_str_att',
'b_str_att', 'b_str', 'b_sig_str_att', 'r_str', 'r_sig_str_att', 'b_td', 'r_td',
'time_sec']
R² for 'finish_round': 0.8118, MSE: 0.1948

Training model to predict 'time_sec' using features: ['finish_round', 'b_td',
'b_str_att', 'b_str', 'r_str_att', 'b_sig_str_att', 'r_td', 'r_sig_str_att',
'r_str']
R² for 'time_sec': 0.5734, MSE: 3673.0353

Training model to predict 'r_sig_str' using features: ['finish_round',
'r_str_att', 'r_sig_str_att', 'b_sig_str', 'r_str', 'b_sig_str_att',
'b_str_att', 'r_td', 'b_td']
R² for 'r_sig_str': 0.9754, MSE: 24.6589

Training model to predict 'r_td' using features: ['td_diff', 'r_td_att',
'r_ctrl_sec', 'ctrl_sec_diff', 'r_td_acc', 'td_att_diff', 'finish_round',
'r_td_avg', 'td_acc_diff']
R² for 'r_td': 0.9905, MSE: 0.0314

Training model to predict 'b_sig_str' using features: ['finish_round',
'b_str_att', 'b_sig_str_att', 'b_str', 'b_td', 'r_sig_str_att', 'r_str_att',
'r_sig_str', 'b_SLpM_total']
R² for 'b_sig_str': 0.9715, MSE: 26.7956

Training model to predict 'b_td' using features: ['b_ctrl_sec', 'b_td_att',
'finish_round', 'b_td_acc', 'b_td_avg', 'b_str', 'time_sec', 'b_sig_str',
'b_str_att']
R² for 'b_td': 0.9960, MSE: 0.0088

All models have been trained and evaluated!
```

```
<pandas.io.formats.style.Styler at 0x7a8d4d7f6ef0>
```

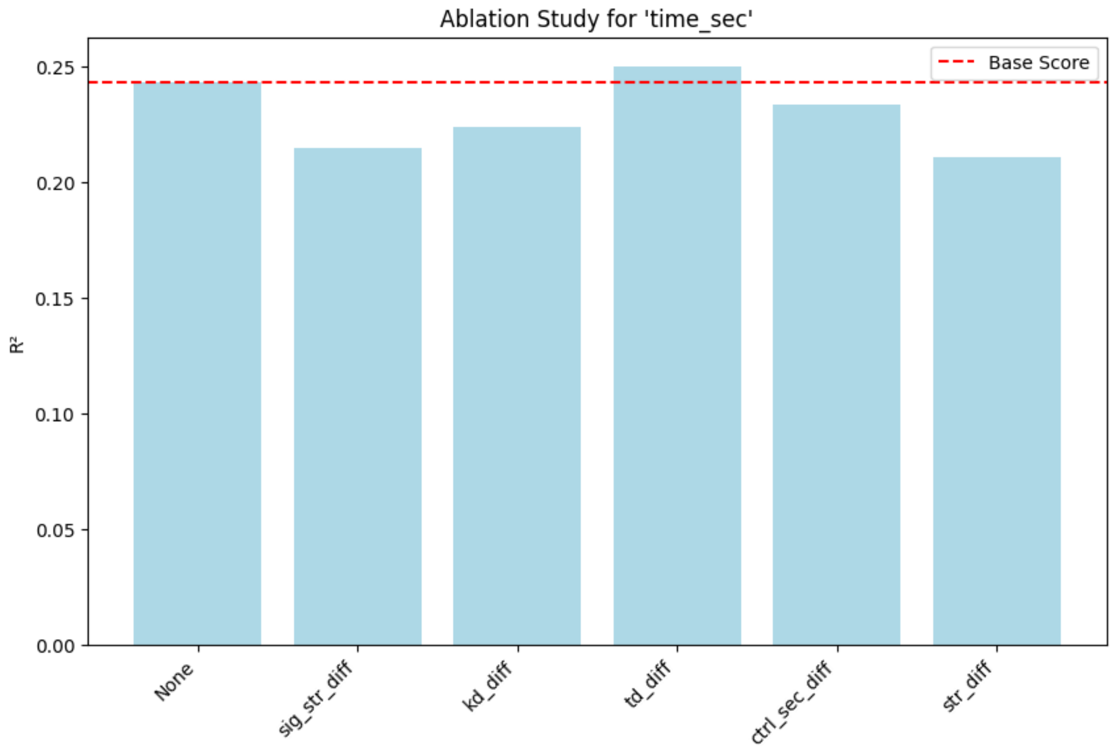
[38]:

```
import pandas as pd
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score
from xgboost import XGBRegressor, XGBClassifier
import matplotlib.pyplot as plt

def ablation_study(target, base_features, model_type='regressor',␣
↪remove_features=None):
    """
    Perform ablation study by evaluating model performance when specific␣
↪features are removed.

    Parameters:
    - target: str, the target variable to predict.
    - base_features: list, the full list of features to use.
    - model_type: str, 'regressor' or 'classifier'.
    - remove_features: list, features to remove one at a time for ablation.

    Returns:
    - results_df: pd.DataFrame, a DataFrame with performance metrics for each␣
↪feature removed.
    """
    # drop rows with missing target values
    data = ufc_cleaned.dropna(subset=[target])

    # ensure all features are numeric
    X = data[base_features].apply(pd.to_numeric, errors='coerce')
    y = data[target]

    # drop rows with invalid or missing  data after conversion
    X = X.dropna()
    y = y[X.index]

    # train-test split
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

    # initialize base model
    model = XGBRegressor(random_state=42) if model_type == 'regressor' else␣
↪XGBClassifier(random_state=42)
    base_model = model.fit(X_train, y_train)
    base_pred = base_model.predict(X_test)

    # base performance
    if model_type == 'regressor':
        base_score = r2_score(y_test, base_pred)
        score_type = 'R²'
    else:
```

```
        base_score = accuracy_score(y_test, base_pred.round())
        score_type = 'Accuracy'

    print(f"Base model performance ({score_type}): {base_score:.4f}")

    # start ablation study
    results = [{'Feature Removed': 'None', 'Performance': base_score}]
    for feature in remove_features:
        print(f"Removing feature: {feature}")
        reduced_features = [f for f in base_features if f != feature]

        # subset data
        X_reduced_train = X_train[reduced_features]
        X_reduced_test = X_test[reduced_features]

        # train reduced model
        model.fit(X_reduced_train, y_train)
        reduced_pred = model.predict(X_reduced_test)

        # evaluate reduced performance
        if model_type == 'regressor':
            reduced_score = r2_score(y_test, reduced_pred)
        else:
            reduced_score = accuracy_score(y_test, reduced_pred.round())

        results.append({'Feature Removed': feature, 'Performance':␣
↪reduced_score})
        print(f"Performance after removing {feature}: {reduced_score:.4f}")

    results_df = pd.DataFrame(results)
    results_df['Performance'] = results_df['Performance'].round(4)

    print("\nAblation Study Results:")
    display(results_df)

    plt.figure(figsize=(10, 6))
    plt.bar(results_df['Feature Removed'], results_df['Performance'],␣
↪color='lightblue')
    plt.axhline(y=base_score, color='r', linestyle='--', label='Base Score')
    plt.title(f"Ablation Study for '{target}'")
    plt.ylabel(score_type)
    plt.xticks(rotation=45, ha='right')
    plt.legend()
    plt.show()

    return results_df
```

```python
#usage for time_sec since it did poorly
target = 'time_sec'
features = ['sig_str_diff', 'kd_diff', 'td_diff', 'ctrl_sec_diff', 'str_diff']
remove_features = ['sig_str_diff', 'kd_diff', 'td_diff', 'ctrl_sec_diff',␣
 ↪'str_diff']

# using the ablation study function for regression task
ablation_results = ablation_study(target, features, model_type='regressor',␣
 ↪remove_features=remove_features)
```

```
Base model performance (R²): 0.2431
Removing feature: sig_str_diff
Performance after removing sig_str_diff: 0.2145
Removing feature: kd_diff
Performance after removing kd_diff: 0.2237
Removing feature: td_diff
Performance after removing td_diff: 0.2500
Removing feature: ctrl_sec_diff
Performance after removing ctrl_sec_diff: 0.2336
Removing feature: str_diff
Performance after removing str_diff: 0.2104

Ablation Study Results:

  Feature Removed  Performance
0            None       0.2431
1    sig_str_diff       0.2145
2         kd_diff       0.2237
3         td_diff       0.2500
4   ctrl_sec_diff       0.2336
5        str_diff       0.2104
```



[39]:
```
!pip install scikit-learn==1.5.2
```

```
Requirement already satisfied: scikit-learn==1.5.2 in
/usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn==1.5.2) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn==1.5.2) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn==1.5.2) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn==1.5.2) (3.5.0)
```

[40]:
```
# import required libraries the XGB
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
import pandas as pd

# initialize the XGBoost Regressor
xgb = XGBRegressor(random_state=42)

# define the grid of hyperparameters to tune
param_grid = {
```

```
    'n_estimators': [100, 200, 300],  # number of boosting trees
    'max_depth': [3, 5, 7],           # maximum tree depth
    'learning_rate': [0.01, 0.05, 0.1]  # learning rate
}

# set up GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(
    estimator=xgb,          # model to tune
    param_grid=param_grid, # grid of hyperparameters
    cv=5,                  # 5-fold cross-validation
    scoring='r2',          # r-squared score for evaluation
    verbose=1,             # show progress logs
    n_jobs=-1              # use all CPU cores for faster computation
)

# fit GridSearchCV to the training data
grid_search.fit(X_train, y_train)

# extract GridSearch results as a DataFrame
results_df = pd.DataFrame(grid_search.cv_results_)

# select and rename columns for better readability
results_df = results_df[['param_n_estimators', 'param_max_depth',␣
↪'param_learning_rate',
                         'mean_test_score', 'std_test_score',␣
↪'rank_test_score']]
results_df.columns = ['n_estimators', 'max_depth', 'learning_rate',
                      'Mean R² Score', 'Std Dev R²', 'Rank']

# sort results by rank (best score first)
results_df = results_df.sort_values(by='Rank')

print("Grid Search Results:")
display(results_df.style.set_caption("Hyperparameter Tuning Results"))
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
Grid Search Results:

<pandas.io.formats.style.Styler at 0x7a8d4c402050>
```

[41]:

```
# import required libraries
from xgboost import XGBRegressor  # XGBoost model for regression tasks
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score ␣
↪# regression evaluation metrics
import numpy as np  # for numerical operations
import pandas as pd  # for table display
```

```
# initialize the XGBoost Regressor with hyperparameters optimized through␣
↪GridSearch or prior tuning
xgb_final = XGBRegressor(
    learning_rate=0.1,  # step size shrinkage to prevent overfitting
    max_depth=3,        # maximum depth of each tree
    n_estimators=300,   # number of boosting rounds (trees)
    random_state=42     # ensures reproducibility
)

# train the XGBoost model on the training data
xgb_final.fit(X_train, y_train)  # X_train: training features, y_train:␣
↪training target variable

# predicting the target variable on the test data
y_pred = xgb_final.predict(X_test)  # X_test: test features, y_pred: model␣
↪predictions

# evaluate the model using various regression metrics
mae = mean_absolute_error(y_test, y_pred)  # mean Absolute Error
mse = mean_squared_error(y_test, y_pred)   # mean Squared Error
rmse = np.sqrt(mse)                        # root Mean Squared Error
r2 = r2_score(y_test, y_pred)              # r-squared Score

# create a table with the performance metrics
metrics_table = pd.DataFrame({
    'Metric': ['Mean Absolute Error (MAE)', 'Mean Squared Error (MSE)',
               'Root Mean Squared Error (RMSE)', 'R² Score'],
    'Value': [round(mae, 4), round(mse, 4), round(rmse, 4), round(r2, 4)]
})

print("Model Performance on Test Set:")
display(metrics_table.style.set_caption("XGBoost Model Performance").
↪set_table_styles(
    [{'selector': 'th', 'props': [('font-size', '12pt'), ('text-align',␣
↪'center')]}]
))
```

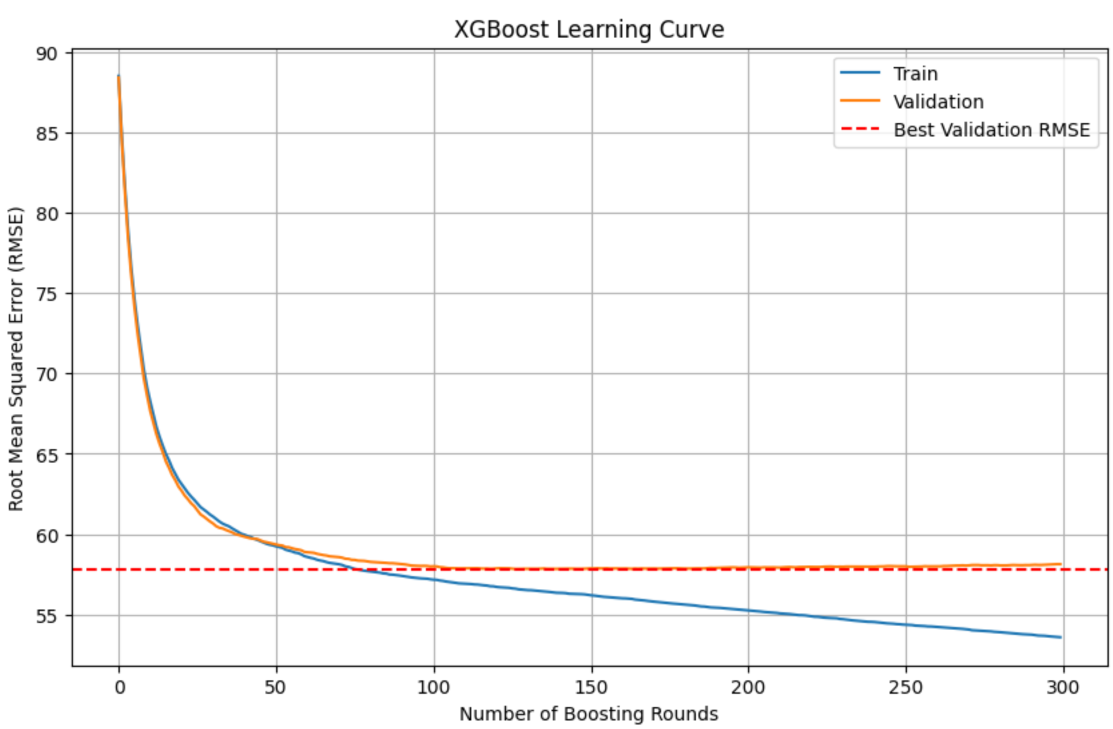
```
Model Performance on Test Set:

<pandas.io.formats.style.Styler at 0x7a8d4c9bd570>
```

[42]:

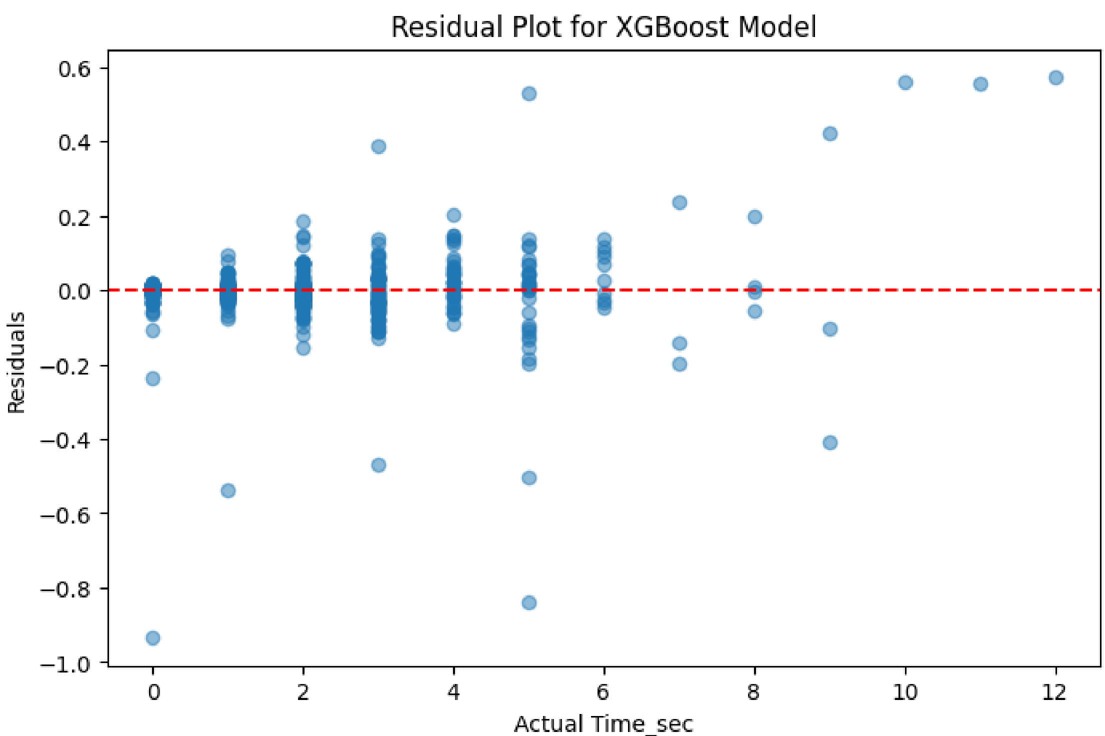
```
from xgboost import XGBRegressor
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# function to plot XGBoost learning curve
```

```python
def plot_xgboost_learning_curve(X, y, model_params, test_size=0.2,␣
↪random_state=42):
    """
    Trains an XGBoost model and plots the learning curve for training and␣
↪validation datasets.

    Parameters:
    - X: Feature matrix
    - y: Target variable
    - model_params: Dictionary of hyperparameters for the XGBoost model
    - test_size: Proportion of the dataset to use as test set
    - random_state: Random state for reproducibility
    """
    # split the data into train and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y,␣
↪test_size=test_size, random_state=random_state)

    # add eval_metric to model parameters
    model_params['eval_metric'] = 'rmse'

    # initialize the XGBoost Regressor with given hyperparameters
    model = XGBRegressor(**model_params)

    # set up evaluation datasets for training and validation
    eval_set = [(X_train, y_train), (X_test, y_test)]

    # train the model with evaluation set to track error metrics
    model.fit(X_train, y_train,
              eval_set=eval_set,
              verbose=False)  # Suppress training logs

    # extract the learning curve data
    results = model.evals_result()
    epochs = len(results['validation_0']['rmse'])
    x_axis = range(0, epochs)

    # ploting the learning curve
    plt.figure(figsize=(10, 6))
    plt.plot(x_axis, results['validation_0']['rmse'], label='Train')  #␣
↪Training error
    plt.plot(x_axis, results['validation_1']['rmse'], label='Validation')  #␣
↪Validation error
    plt.axhline(y=np.min(results['validation_1']['rmse']), color='r',␣
↪linestyle='--', label='Best Validation RMSE')
    plt.xlabel('Number of Boosting Rounds')
    plt.ylabel('Root Mean Squared Error (RMSE)')
```

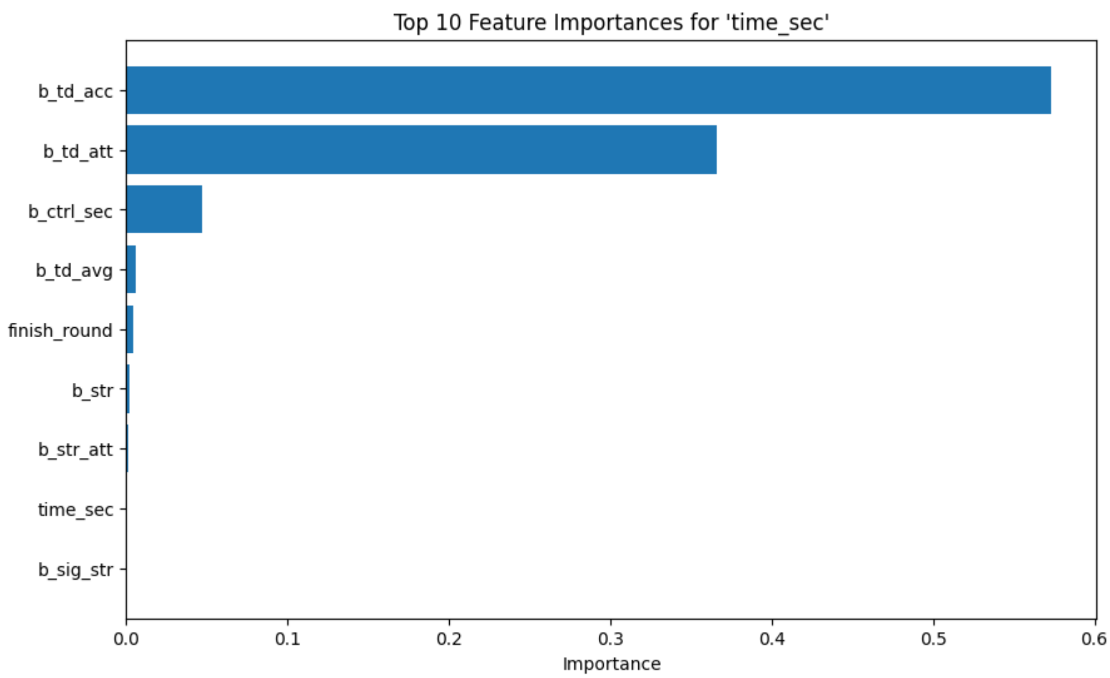
```python
    plt.title('XGBoost Learning Curve')
    plt.legend()
    plt.grid()
    plt.show()

# define target and features
target = 'time_sec'
features = ['finish_round', 'b_td', 'b_str_att', 'b_str', 'r_str_att',
 ↪'r_sig_str_att', 'b_sig_str_att', 'r_td']

# prepare the data
data = ufc_cleaned.dropna(subset=[target])
X = data[features]
y = data[target]

# define XGBoost hyperparameters
xgb_params = {
    'learning_rate': 0.1,
    'n_estimators': 300,
    'max_depth': 3,
    'random_state': 42
}

# plot the learning curve
plot_xgboost_learning_curve(X, y, xgb_params)
```



[43]:
```python
import matplotlib.pyplot as plt  # import Matplotlib for visualization

# calculate residuals: difference between actual and predicted values
residuals = y_test - y_pred

# create a new figure with a specified size
plt.figure(figsize=(8, 5))

# scatter plot: Actual target values (x-axis) vs Residuals (y-axis)
plt.scatter(y_test, residuals, alpha=0.5)

# add a horizontal reference line at y=0 to indicate zero residuals
plt.axhline(y=0, color='r', linestyle='--')  # Red dashed line at y=0

plt.xlabel("Actual Time_sec")

plt.ylabel("Residuals")

plt.title("Residual Plot for XGBoost Model")

plt.show()
```



[44]:
```
import pandas as pd  #import Pandas for data manipulation
import matplotlib.pyplot as plt  # import Matplotlib for visualization

# extract feature importance scores from the trained XGBoost model
feature_importance = xgb_final.feature_importances_

# create a DataFrame to associate features with their importance scores
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance':␣
↪feature_importance})

# sort the feature importance values in descending order
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# create a horizontal bar plot for the top 10 most important features
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'].head(10), importance_df['Importance'].
↪head(10))  # plot top 10 features

# invert the y-axis so the most important feature appears at the top
plt.gca().invert_yaxis()

plt.xlabel("Importance")

plt.title("Top 10 Feature Importances for 'time_sec'")

plt.show()
```



[45]:
```python
# calculate the total number of missing (NaN) values in each column
missing_values = ufc_cleaned.isna().sum()

# filter to keep only columns with missing values (greater than 0)
missing_columns = missing_values[missing_values > 0]

print("Columns with missing values and their counts:")
print(missing_columns)
```

```
Columns with missing values and their counts:
winner          201
method          201
finish_round    201
time_sec        201
r_sig_str       201
r_td            201
b_sig_str       201
b_td            201
sig_str_diff    201
td_diff         201
dtype: int64
```

[46]:
```python
all_predicted_values = pd.DataFrame()  # initialize an empty DataFrame to store␣
 ↪predicted values

def train_and_predict_missing(target, features):
    """
    Trains a model to predict and fill missing values for a target column using␣
 ↪specified features.
    Updates the cleaned dataset with predicted values and stores the results.
    """
    print(f"\nTraining model to predict '{target}' using features: {features}")
    global ufc_cleaned, all_predicted_values  # Use global variables for the␣
 ↪cleaned dataset and predictions log

    # prepare the dataset: Drop rows where the target variable is missing
    data = ufc_cleaned.dropna(subset=[target])
    X = data[features]  # Feature matrix
    y = data[target]    # Target variable

    # check if the target is categorical (classification task)
    is_classification = target in ['winner', 'method']
    if is_classification:
        le = LabelEncoder()  # initialize LabelEncoder for categorical targets
        y = le.fit_transform(y)  # encode target labels to numeric values
```

```
        label_encoders[target] = le  # save the encoder for future decoding

    # split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

    # select the appropriate model based on the target variable
    if target == 'time_sec':
        model = XGBRegressor(learning_rate=0.1, n_estimators=300, max_depth=3,␣
↪random_state=42)  # XGBoost for 'time_sec'
    elif is_classification:
        model = RandomForestClassifier(random_state=42)  # Random Forest␣
↪Classifier for categorical targets
    else:
        model = RandomForestRegressor(random_state=42)  # Random Forest␣
↪Regressor for numeric targets

    # train the model
    model.fit(X_train, y_train)

    # predict missing values for rows where the target is NaN
    missing_data = ufc_cleaned[ufc_cleaned[target].isnull()]
    if not missing_data.empty:
        X_missing = missing_data[features].fillna(0)  # Replace NaN in features␣
↪with 0 for prediction
        predicted_values = model.predict(X_missing)

        # decode predicted values if the target is categorical
        if is_classification:
            predicted_values = le.inverse_transform(predicted_values)

        # ppdate the main DataFrame with predicted values
        ufc_cleaned.loc[ufc_cleaned[target].isnull(), target] = predicted_values
        print(f"Missing values for '{target}' have been filled.")

        # store the predicted rows in the 'all_predicted_values' DataFrame
        predicted_rows = missing_data.copy()
        predicted_rows[target] = predicted_values
        predicted_rows['target_column'] = target

        all_predicted_values = pd.concat([
            all_predicted_values,
            predicted_rows[['r_fighter', 'b_fighter', target, 'target_column']]
        ], ignore_index=True)

        # display the predicted rows
        print(f"\nPredicted values for '{target}':")
```

```
        display(predicted_rows[['r_fighter', 'b_fighter', target,␣
↪'target_column']])

# loop through each target variable and its associated features to predict and␣
↪fill missing values
for target, features in target_features.items():
    train_and_predict_missing(target, features)
```

```
Training model to predict 'winner' using features: ['sig_str_diff', 'str_diff',
'sig_str_acc_diff', 'kd_diff', 'str_acc_diff', 'str_att_diff', 'td_diff',
'r_td', 'ctrl_sec_diff']
Missing values for 'winner' have been filled.

Predicted values for 'winner':

<ipython-input-46-74a21deb7b75>:40: FutureWarning: Downcasting object dtype
arrays on .fillna, .ffill, .bfill is deprecated and will change in a future
version. Call result.infer_objects(copy=False) instead. To opt-in to the future
behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_missing = missing_data[features].fillna(0)  # Replace NaN in features with 0
for prediction

              r_fighter          b_fighter  winner target_column
7464    Erin Blanchfield      Manon Fiorot     1.0        winner
7465       Vicente Luque   Joaquin Buckley     1.0        winner
7466       Chris Weidman       Bruno Silva     0.0        winner
7468          Bill Algeo       Kyle Nelson     1.0        winner
7469      Chidi Njokuani       Rhys McKee     1.0        winner
…                 …                 …     …           …
7839     Michael Johnson    Ottman Azaitar     1.0        winner
7840        Joel Alvarez     Drakkar Klose     1.0        winner
7841        Sean Woodson  Fernando Padilla     0.0        winner
7843    Miranda Maverick   Jamey-Lyn Horth     1.0        winner
7845   Josefine Knutsson   Piera Rodriguez     1.0        winner

[201 rows x 4 columns]


Training model to predict 'method' using features: ['winner', 'r_sub_avg',
'sig_str_diff', 'r_sub_att', 'td_diff', 'b_td', 'r_sig_str_acc', 'sub_att_diff',
'r_td']
Missing values for 'method' have been filled.

Predicted values for 'method':

<ipython-input-46-74a21deb7b75>:40: FutureWarning: Downcasting object dtype
arrays on .fillna, .ffill, .bfill is deprecated and will change in a future
version. Call result.infer_objects(copy=False) instead. To opt-in to the future
```

```
behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_missing = missing_data[features].fillna(0)  # Replace NaN in features with 0
for prediction

             r_fighter         b_fighter  method target_column
7464   Erin Blanchfield      Manon Fiorot     4.0        method
7465      Vicente Luque   Joaquin Buckley     4.0        method
7466      Chris Weidman       Bruno Silva     4.0        method
7468         Bill Algeo       Kyle Nelson     4.0        method
7469     Chidi Njokuani        Rhys McKee     4.0        method
…                   …               …     …             …
7839    Michael Johnson    Ottman Azaitar     4.0        method
7840       Joel Alvarez     Drakkar Klose     5.0        method
7841       Sean Woodson  Fernando Padilla     4.0        method
7843   Miranda Maverick   Jamey-Lyn Horth     4.0        method
7845  Josefine Knutsson   Piera Rodriguez     4.0        method

[201 rows x 4 columns]


Training model to predict 'finish_round' using features: ['r_str_att',
'b_str_att', 'b_str', 'b_sig_str_att', 'r_str', 'r_sig_str_att', 'b_td', 'r_td',
'time_sec']
Missing values for 'finish_round' have been filled.

Predicted values for 'finish_round':

             r_fighter         b_fighter  finish_round target_column
7464   Erin Blanchfield      Manon Fiorot          2.83  finish_round
7465      Vicente Luque   Joaquin Buckley          2.38  finish_round
7466      Chris Weidman       Bruno Silva          1.84  finish_round
7468         Bill Algeo       Kyle Nelson          2.20  finish_round
7469     Chidi Njokuani        Rhys McKee          1.64  finish_round
…                   …               …           …             …
7839    Michael Johnson    Ottman Azaitar          1.48  finish_round
7840       Joel Alvarez     Drakkar Klose          1.08  finish_round
7841       Sean Woodson  Fernando Padilla          2.04  finish_round
7843   Miranda Maverick   Jamey-Lyn Horth          2.47  finish_round
7845  Josefine Knutsson   Piera Rodriguez          2.04  finish_round

[201 rows x 4 columns]


Training model to predict 'time_sec' using features: ['finish_round', 'b_td',
'b_str_att', 'b_str', 'r_str_att', 'b_sig_str_att', 'r_td', 'r_sig_str_att',
'r_str']
Missing values for 'time_sec' have been filled.

Predicted values for 'time_sec':
```

```
                r_fighter         b_fighter    time_sec target_column
7464   Erin Blanchfield      Manon Fiorot  293.060699      time_sec
7465      Vicente Luque   Joaquin Buckley  276.723877      time_sec
7466      Chris Weidman       Bruno Silva  190.074600      time_sec
7468         Bill Algeo       Kyle Nelson  263.400574      time_sec
7469     Chidi Njokuani        Rhys McKee  200.727386      time_sec
…                   …                 …           …            …
7839    Michael Johnson    Ottman Azaitar  168.073898      time_sec
7840       Joel Alvarez     Drakkar Klose  115.154816      time_sec
7841       Sean Woodson  Fernando Padilla  230.117477      time_sec
7843   Miranda Maverick   Jamey-Lyn Horth  261.566467      time_sec
7845  Josefine Knutsson   Piera Rodriguez  256.690521      time_sec

[201 rows x 4 columns]


Training model to predict 'r_sig_str' using features: ['finish_round',
'r_str_att', 'r_sig_str_att', 'b_sig_str', 'r_str', 'b_sig_str_att',
'b_str_att', 'r_td', 'b_td']
Missing values for 'r_sig_str' have been filled.

Predicted values for 'r_sig_str':

                r_fighter         b_fighter  r_sig_str target_column
7464   Erin Blanchfield      Manon Fiorot      59.18     r_sig_str
7465      Vicente Luque   Joaquin Buckley      79.09     r_sig_str
7466      Chris Weidman       Bruno Silva      34.69     r_sig_str
7468         Bill Algeo       Kyle Nelson      66.47     r_sig_str
7469     Chidi Njokuani        Rhys McKee      25.23     r_sig_str
…                   …                 …          …            …
7839    Michael Johnson    Ottman Azaitar      19.60     r_sig_str
7840       Joel Alvarez     Drakkar Klose       3.55     r_sig_str
7841       Sean Woodson  Fernando Padilla      75.86     r_sig_str
7843   Miranda Maverick   Jamey-Lyn Horth      25.46     r_sig_str
7845  Josefine Knutsson   Piera Rodriguez      79.50     r_sig_str

[201 rows x 4 columns]


Training model to predict 'r_td' using features: ['td_diff', 'r_td_att',
'r_ctrl_sec', 'ctrl_sec_diff', 'r_td_acc', 'td_att_diff', 'finish_round',
'r_td_avg', 'td_acc_diff']
Missing values for 'r_td' have been filled.

Predicted values for 'r_td':

<ipython-input-46-74a21deb7b75>:40: FutureWarning: Downcasting object dtype
arrays on .fillna, .ffill, .bfill is deprecated and will change in a future
version. Call result.infer_objects(copy=False) instead. To opt-in to the future
behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

```
  X_missing = missing_data[features].fillna(0)  # Replace NaN in features with 0
for prediction

              r_fighter         b_fighter  r_td target_column
7464   Erin Blanchfield      Manon Fiorot  4.59          r_td
7465       Vicente Luque   Joaquin Buckley  1.00          r_td
7466       Chris Weidman       Bruno Silva  3.40          r_td
7468          Bill Algeo       Kyle Nelson  1.00          r_td
7469     Chidi Njokuani         Rhys McKee  0.00          r_td
…                    …                 …    …           …
7839    Michael Johnson    Ottman Azaitar  1.00          r_td
7840        Joel Alvarez     Drakkar Klose  0.00          r_td
7841        Sean Woodson  Fernando Padilla  1.00          r_td
7843   Miranda Maverick   Jamey-Lyn Horth  1.00          r_td
7845  Josefine Knutsson   Piera Rodriguez  3.00          r_td

[201 rows x 4 columns]


Training model to predict 'b_sig_str' using features: ['finish_round',
'b_str_att', 'b_sig_str_att', 'b_str', 'b_td', 'r_sig_str_att', 'r_str_att',
'r_sig_str', 'b_SLpM_total']
Missing values for 'b_sig_str' have been filled.

Predicted values for 'b_sig_str':

              r_fighter         b_fighter  b_sig_str target_column
7464   Erin Blanchfield      Manon Fiorot      94.50     b_sig_str
7465       Vicente Luque   Joaquin Buckley      69.91     b_sig_str
7466       Chris Weidman       Bruno Silva      20.64     b_sig_str
7468          Bill Algeo       Kyle Nelson      78.98     b_sig_str
7469     Chidi Njokuani         Rhys McKee      73.66     b_sig_str
…                    …                 …         …           …
7839    Michael Johnson    Ottman Azaitar       9.73     b_sig_str
7840        Joel Alvarez     Drakkar Klose      15.80     b_sig_str
7841        Sean Woodson  Fernando Padilla      14.20     b_sig_str
7843   Miranda Maverick   Jamey-Lyn Horth      40.85     b_sig_str
7845  Josefine Knutsson   Piera Rodriguez      12.61     b_sig_str

[201 rows x 4 columns]


Training model to predict 'b_td' using features: ['b_ctrl_sec', 'b_td_att',
'finish_round', 'b_td_acc', 'b_td_avg', 'b_str', 'time_sec', 'b_sig_str',
'b_str_att']
Missing values for 'b_td' have been filled.

Predicted values for 'b_td':

              r_fighter         b_fighter  b_td target_column
```

```
7464   Erin Blanchfield      Manon Fiorot  1.30          b_td
7465      Vicente Luque   Joaquin Buckley  1.00          b_td
7466      Chris Weidman       Bruno Silva  1.00          b_td
7468         Bill Algeo       Kyle Nelson  0.00          b_td
7469     Chidi Njokuani        Rhys McKee  0.00          b_td
…                  …                …    …             …
7839    Michael Johnson    Ottman Azaitar  0.00          b_td
7840       Joel Alvarez     Drakkar Klose  2.39          b_td
7841       Sean Woodson  Fernando Padilla  0.00          b_td
7843   Miranda Maverick   Jamey-Lyn Horth  1.00          b_td
7845  Josefine Knutsson   Piera Rodriguez  1.00          b_td

[201 rows x 4 columns]
```

[ ]:
```
# drop the 'target_column' column if it exists in all_predicted_values
final_combined_predictions = all_predicted_values.
 ↪drop(columns=['target_column'], errors='ignore')

# reshape the data using a pivot table to combine predictions for each fighter␣
 ↪pair
final_combined_predictions = final_combined_predictions.pivot_table(
    index=['r_fighter', 'b_fighter'],  # group data by red and blue fighters
    aggfunc='first'                    # use the first non-null value for each␣
 ↪group
).reset_index()                        # reset the index to convert it back to␣
 ↪a DataFrame

print("Final Combined Predictions Without 'target_column':")
display(final_combined_predictions)
```

[ ]:
```
# define a mapping for method predictions to descriptive labels
method_mapping = {
    0.0: 'DQ',                          # Disqualification
    1.0: 'Decision - Majority',         # Majority decision
    2.0: 'Decision - Split',            # Split decision
    4.0: 'Decision - Unanimous',        # Unanimous decision
    5.0: 'KO/TKO',                      # Knockout/Technical Knockout
    6.0: "TKO - Doctor's Stoppage",     # Doctor's stoppage for TKO
    3.0: 'Submission'                   # Submission victory
}

# define a mapping for winner predictions to descriptive corner labels
winner_mapping = {
    0: 'Blue Corner',                   # Blue corner fighter won
    1: 'Red Corner'                     # Red corner fighter won
}
```

```python
# decode 'method' column using the method_mapping dictionary
final_combined_predictions['method'] = final_combined_predictions['method'].
 ↪map(method_mapping)

# decode 'winner' column using the winner_mapping dictionary
final_combined_predictions['winner'] = final_combined_predictions['winner'].
 ↪map(winner_mapping)

print("Manually Decoded Final Combined Predictions:")
display(final_combined_predictions)
```

[49]:
```python
# add a new column 'winner_fighter' with the name of the winning fighter
final_combined_predictions['winner_fighter'] = final_combined_predictions.apply(
    lambda row: row['r_fighter'] if row['winner'] == 'Red Corner' else␣
 ↪row['b_fighter'],
    axis=1
)

# print the updated DataFrame with the 'winner_fighter' column
print("Updated Final Combined Predictions with Winner's Name:")
display(final_combined_predictions)
```

```
Updated Final Combined Predictions with Winner's Name:

           r_fighter            b_fighter  b_sig_str  b_td  finish_round  \
0       Adrian Yanez        Daniel Marcos      46.49   1.0          1.65
1       Adrian Yanez    Vinicius Salvador      77.90   1.0          1.71
2       Alex Caceres         Sean Woodson      82.79   1.0          2.60
3       Alex Pereira         Jamahal Hill     165.44   0.0          2.34
4       Alexa Grasso  Valentina Shevchenko     77.07   1.0          2.88
..               …                    …        …    …             …
192    Vitor Petrino        Dustin Jacoby      89.05   0.0          1.81
193  Volkan Oezdemir        Carlos Ulberg     118.83   0.0          1.56
194    William Gomis     Joanderson Brito      10.71   1.0          1.39
195      Yana Santos     Chelsea Chandler      62.45   1.0          2.57
196  Yazmin Jauregui         Ketlen Souza       0.10   0.0          1.89

                  method  r_sig_str  r_td    time_sec      winner  \
0    Decision - Unanimous      30.27  0.00  187.573776  Red Corner
1    Decision - Unanimous      29.16  0.00  209.285477  Red Corner
2    Decision - Unanimous      83.01  1.00  266.243988  Red Corner
3    Decision - Unanimous     108.38  0.00  165.843246  Red Corner
4    Decision - Unanimous     153.85  1.00  291.207123  Red Corner
..                     …        …    …           …           …
192  Decision - Unanimous      26.18  2.81  193.640701  Red Corner
193  Decision - Unanimous      22.24  1.00  236.108627  Red Corner
194                KO/TKO      49.89  1.00  169.792755  Red Corner
195  Decision - Unanimous      93.38  1.00  275.622620  Red Corner
```

```
196  Decision - Unanimous      86.48  0.00  226.683182  Red Corner

      winner_fighter
0       Adrian Yanez
1       Adrian Yanez
2       Alex Caceres
3       Alex Pereira
4       Alexa Grasso
..               …
192     Vitor Petrino
193  Volkan Oezdemir
194     William Gomis
195       Yana Santos
196  Yazmin Jauregui

[197 rows x 11 columns]
```

[50]:

```
from google.colab import files  # Import the Colab file utility module
#downloading the whole dataset with all the fighters
final_combined_predictions.to_csv("final_combined_predictions.csv", index=False)

files.download("final_combined_predictions.csv")
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>
```