

Title

In [239...]

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, MinMaxScaler, StandardScaler
from sklearn.metrics import roc_auc_score, classification_report, confusion_matrix
import shap
import warnings

warnings.simplefilter(action='ignore', category=FutureWarning)
df = pd.read_csv('/Users/mallorygo/Desktop/DATA1030/data1030-fall2025/final reports/ufc-master.csv')
pd.set_option("display.max_columns", None, "display.max_rows", None)

print(df.head())
```

	RedFighter	BlueFighter	RedOdds	BlueOdds	RedExpectedValue	\
0	Alexandre Pantoja	Kai Asakura	-250.0	215.0	40.0000	
1	Shavkat Rakhmonov	Ian Machado Garry	-210.0	295.0	47.6190	
2	Ciryl Gane	Alexander Volkov	-380.0	300.0	26.3158	
3	Bryce Mitchell	Kron Gracie	-950.0	625.0	10.5263	
4	Nate Landwehr	Dooho Choi	-130.0	110.0	76.9231	
BlueExpectedValue	Date	Location	Country	Winner	\	
0	215.0	2024-12-07	Las Vegas, Nevada, USA	USA	Red	
1	295.0	2024-12-07	Las Vegas, Nevada, USA	USA	Red	
2	300.0	2024-12-07	Las Vegas, Nevada, USA	USA	Red	
3	625.0	2024-12-07	Las Vegas, Nevada, USA	USA	Red	
4	110.0	2024-12-07	Las Vegas, Nevada, USA	USA	Blue	
TitleBout	WeightClass	Gender	NumberOfRounds	BlueCurrentLoseStreak	\	
0	True	Flyweight	MALE	5	0	
1	False	Welterweight	MALE	3	0	
2	False	Heavyweight	MALE	3	0	
3	False	Featherweight	MALE	3	2	
4	False	Featherweight	MALE	3	0	
BlueCurrentWinStreak	BlueDraws	BlueAvgSigStrLanded	BlueAvgSigStrPct	\		
0	0	0	0.00	0.00		
1	8	0	5.50	0.55		
2	4	0	5.13	0.57		
3	0	0	3.74	0.44		
4	1	1	4.41	0.53		
BlueAvgSubAtt	BlueAvgTDLanded	BlueAvgTDPct	BlueLongestWinStreak	\		
0	0.0	0.00	0.00	0		
1	0.3	0.77	0.55	8		
2	0.2	0.45	0.63	4		
3	0.5	0.47	0.25	1		
4	0.8	0.75	0.37	3		
BlueLosses	BlueTotalRoundsFought	BlueTotalTitleBouts	\			
0	0	0	0			
1	0	20	0			
2	4	44	0			
3	2	7	0			
4	3	15	0			

	BlueWinsByDecisionMajority	BlueWinsByDecisionSplit	\		
0	0	0			
1	0	1			
2	0	1			
3	0	0			
4	0	0			
	BlueWinsByDecisionUnanimous	BlueWinsByKO	BlueWinsBySubmission	\	
0	0	0	0		
1	4	3	0		
2	4	6	1		
3	0	0	1		
4	0	4	0		
	BlueWinsByTK0DoctorStoppage	BlueWins	BlueStance	BlueHeightCms	\
0	0	0	Orthodox	172.72	
1	0	8	Orthodox	190.50	
2	0	12	Orthodox	200.66	
3	0	1	Southpaw	175.26	
4	0	4	Orthodox	177.80	
	BlueReachCms	BlueWeightLbs	RedCurrentLoseStreak	RedCurrentWinStreak	\
0	175.26	125	0	6	
1	187.96	170	0	6	
2	203.20	250	0	1	
3	177.80	145	1	0	
4	177.80	145	0	1	
	RedDraws	RedAvgSigStrLanded	RedAvgSigStrPct	RedAvgSubAtt	\
0	0	4.41	0.49	0.8	
1	0	4.12	0.61	1.8	
2	0	5.49	0.60	0.5	
3	0	2.30	0.58	1.6	
4	0	6.25	0.46	1.0	
	RedAvgTDLanded	RedAvgTDPct	RedLongestWinStreak	RedLosses	\
0	2.61	0.47	6	3	
1	1.49	0.29	6	0	
2	0.58	0.21	7	2	
3	3.45	0.41	6	2	
4	1.00	0.41	3	3	

	RedTotalRoundsFought	RedTotalTitleBouts	RedWinsByDecisionMajority	\				
0	42	3	0					
1	11	0	0					
2	33	3	0					
3	22	0	1					
4	17	0	1					
	RedWinsByDecisionSplit	RedWinsByDecisionUnanimous	RedWinsByKO	\				
0	2	4	2					
1	0	0	1					
2	0	3	4					
3	0	5	0					
4	0	1	1					
	RedWinsBySubmission	RedWinsByTKODoctorStoppage	RedWins	RedStance	\			
0	4	0	12	Orthodox				
1	5	0	6	Orthodox				
2	2	0	9	Orthodox				
3	1	0	7	Southpaw				
4	2	0	5	Orthodox				
	RedHeightCms	RedReachCms	RedWeightLbs	RedAge	BlueAge	LoseStreakDif	\	
0	165.10	170.18	125	34	31	0		
1	185.42	195.58	170	30	27	0		
2	193.04	205.74	245	34	36	0		
3	177.80	177.80	145	30	36	1		
4	175.26	182.88	145	36	33	0		
	WinStreakDif	LongestWinStreakDif	WinDif	LossDif	TotalRoundDif	\		
0	-6	-6	-12	-3	-42			
1	2	2	2	0	9			
2	3	-3	3	2	11			
3	0	-5	-6	0	-15			
4	0	0	-1	0	-2			
	TotalTitleBoutDif	KODif	SubDif	HeightDif	ReachDif	AgeDif	SigStrDif	\
0	-3	-2	-4	7.62	5.08	-3	-4.41	
1	0	2	-5	5.08	-7.62	-3	1.38	
2	-3	2	-1	7.62	-2.54	2	-0.36	
3	0	0	0	-2.54	0.00	6	1.44	
4	0	3	-2	2.54	-5.08	-3	-1.84	

	AvgSubAttDif	AvgTDDif	EmptyArena	BMatchWCRank	RMatchWCRank	\
0	-0.8	-2.61	NaN	NaN	0.0	
1	-1.5	-0.72	NaN	7.0	3.0	
2	-0.3	-0.13	NaN	3.0	2.0	
3	-1.1	-2.98	NaN	NaN	13.0	
4	-0.2	-0.25	NaN	NaN	NaN	
	RWFlyweightRank	RWFeatherweightRank	RWStrawweightRank			\
0	NaN	NaN	NaN			
1	NaN	NaN	NaN			
2	NaN	NaN	NaN			
3	NaN	NaN	NaN			
4	NaN	NaN	NaN			
	RWBantamweightRank	RHeavyweightRank	RLightHeavyweightRank	\		
0	NaN	NaN	NaN			
1	NaN	NaN	NaN			
2	NaN	2.0	NaN			
3	NaN	NaN	NaN			
4	NaN	NaN	NaN			
	RMiddleweightRank	RWelterweightRank	RLightweightRank	RFeatherweightRank	\	
0	NaN	NaN	NaN	NaN	NaN	
1	NaN	3.0	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	13.0	
4	NaN	NaN	NaN	NaN	NaN	
	RBantamweightRank	RFlyweightRank	RPFPRank	BWFlyweightRank	\	
0	NaN	0.0	11.0	NaN		
1	NaN	NaN	NaN	NaN		
2	NaN	NaN	NaN	NaN		
3	NaN	NaN	NaN	NaN		
4	NaN	NaN	NaN	NaN		
	BWFlyweightRank	BWStrawweightRank	BWBantamweightRank	\		
0	NaN	NaN	NaN			
1	NaN	NaN	NaN			
2	NaN	NaN	NaN			
3	NaN	NaN	NaN			
4	NaN	NaN	NaN			

	BHeavyweightRank	BLightHeavyweightRank	BMiddleweightRank	\\			
0	NaN	NaN	NaN				
1	NaN	NaN	NaN				
2	3.0	NaN	NaN				
3	NaN	NaN	NaN				
4	NaN	NaN	NaN				
	BWelterweightRank	BLightweightRank	BFeatherweightRank	BBantamweightRank	\\		
0	NaN	NaN	NaN	NaN			
1	7.0	NaN	NaN	NaN			
2	NaN	NaN	NaN	NaN			
3	NaN	NaN	NaN	NaN			
4	NaN	NaN	NaN	NaN			
	BFlyweightRank	BPPFRank	BetterRank	Finish	FinishDetails	FinishRound	\\
0	NaN	NaN	Red	SUB	Rear Naked Choke	2.0	
1	NaN	NaN	Red	U-DEC	NaN	5.0	
2	NaN	NaN	Red	S-DEC	NaN	3.0	
3	NaN	NaN	Red	KO/TKO	Elbows	3.0	
4	NaN	NaN	neither	KO/TKO	Elbows	3.0	
	FinishRoundTime	TotalFightTimeSecs	RedDecOdds	BlueDecOdds	RSub0dds	\\	
0	2:05	425.0	300.0	800.0	150.0		
1	5:00	1500.0	250.0	650.0	180.0		
2	5:00	900.0	-160.0	450.0	1100.0		
3	0:39	639.0	-200.0	1100.0	380.0		
4	3:21	801.0	275.0	550.0	500.0		
	BSub0dds	RK00dds	BK00dds				
0	2500.0	400.0	350.0				
1	3000.0	240.0	700.0				
2	3000.0	350.0	1100.0				
3	1400.0	500.0	4000.0				
4	700.0	300.0	250.0				

```
In [240]: import os
output_folder = "/Users/mallorygo/Desktop/DATA1030/data1030-fall2025/data1030_final/figurefolder"
#fig_path = os.path.join(output_folder, f"{fig_name}.png")
```

```
In [241]: pd.set_option("display.max_columns", None, "display.max_rows", None)

print(df.dtypes)
```

```
# How many rows and columns do we have in df_merge?  
print(df.shape[0]) # number of rows  
print(df.shape[1]) # number of rows  
  
print(len(df))
```

RedFighter	object
BlueFighter	object
RedOdds	float64
BlueOdds	float64
RedExpectedValue	float64
BlueExpectedValue	float64
Date	object
Location	object
Country	object
Winner	object
TitleBout	bool
WeightClass	object
Gender	object
NumberOfRounds	int64
BlueCurrentLoseStreak	int64
BlueCurrentWinStreak	int64
BlueDraws	int64
BlueAvgSigStrLanded	float64
BlueAvgSigStrPct	float64
BlueAvgSubAtt	float64
BlueAvgTDLanded	float64
BlueAvgTDPct	float64
BlueLongestWinStreak	int64
BlueLosses	int64
BlueTotalRoundsFought	int64
BlueTotalTitleBouts	int64
BlueWinsByDecisionMajority	int64
BlueWinsByDecisionSplit	int64
BlueWinsByDecisionUnanimous	int64
BlueWinsByKO	int64
BlueWinsBySubmission	int64
BlueWinsByTKODoctorStoppage	int64
BlueWins	int64
BlueStance	object
BlueHeightCms	float64
BlueReachCms	float64
BlueWeightLbs	int64
RedCurrentLoseStreak	int64
RedCurrentWinStreak	int64
RedDraws	int64
RedAvgSigStrLanded	float64
RedAvgSigStrPct	float64

RedAvgSubAtt	float64
RedAvgTDLanded	float64
RedAvgTDPct	float64
RedLongestWinStreak	int64
RedLosses	int64
RedTotalRoundsFought	int64
RedTotalTitleBouts	int64
RedWinsByDecisionMajority	int64
RedWinsByDecisionSplit	int64
RedWinsByDecisionUnanimous	int64
RedWinsByKO	int64
RedWinsBySubmission	int64
RedWinsByTKODoctorStoppage	int64
RedWins	int64
RedStance	object
RedHeightCms	float64
RedReachCms	float64
RedWeightLbs	int64
RedAge	int64
BlueAge	int64
LoseStreakDif	int64
WinStreakDif	int64
LongestWinStreakDif	int64
WinDif	int64
LossDif	int64
TotalRoundDif	int64
TotalTitleBoutDif	int64
KODif	int64
SubDif	int64
HeightDif	float64
ReachDif	float64
AgeDif	int64
SigStrDif	float64
AvgSubAttDif	float64
AvgTDDif	float64
EmptyArena	float64
BMatchWCRank	float64
RMatchWCRank	float64
RWFlyweightRank	float64
RWFeatherweightRank	float64
RWStrawweightRank	float64
RWBantamweightRank	float64

```
RHeavyweightRank          float64
RLightHeavyweightRank     float64
RMiddleweightRank         float64
RWelterweightRank         float64
RLightweightRank          float64
RFeatherweightRank        float64
RBantamweightRank         float64
RFlyweightRank            float64
RPFPRank                 float64
BWFlyweightRank           float64
BwFeatherweightRank       float64
BWStrawweightRank         float64
BwBantamweightRank        float64
BHeavyweightRank          float64
BLightHeavyweightRank     float64
BMiddleweightRank         float64
BWelterweightRank         float64
BLightweightRank          float64
BFeatherweightRank        float64
BBantamweightRank         float64
BFlyweightRank            float64
BPFPRank                 float64
BetterRank                object
Finish                   object
FinishDetails             object
FinishRound               float64
FinishRoundTime           object
TotalFightTimeSecs        float64
RedDecOdds                float64
BlueDecOdds               float64
RSubOdds                  float64
BSubOdds                  float64
RK00dds                   float64
BK00dds                   float64
dtype: object
6528
118
6528
```

```
In [242]: comm_drop = [
    'Date', 'Location', 'Country'
]
```

```
df.drop(comm_drop, axis=1, inplace = True)

print(df.dtypes)
print(df.shape[0]) # number of rows
print(df.shape[1]) # number of rows

print(len(df))
```

RedFighter	object
BlueFighter	object
RedOdds	float64
BlueOdds	float64
RedExpectedValue	float64
BlueExpectedValue	float64
Winner	object
TitleBout	bool
WeightClass	object
Gender	object
NumberOfRounds	int64
BlueCurrentLoseStreak	int64
BlueCurrentWinStreak	int64
BlueDraws	int64
BlueAvgSigStrLanded	float64
BlueAvgSigStrPct	float64
BlueAvgSubAtt	float64
BlueAvgTDLanded	float64
BlueAvgTDPct	float64
BlueLongestWinStreak	int64
BlueLosses	int64
BlueTotalRoundsFought	int64
BlueTotalTitleBouts	int64
BlueWinsByDecisionMajority	int64
BlueWinsByDecisionSplit	int64
BlueWinsByDecisionUnanimous	int64
BlueWinsByKO	int64
BlueWinsBySubmission	int64
BlueWinsByTKODoctorStoppage	int64
BlueWins	int64
BlueStance	object
BlueHeightCms	float64
BlueReachCms	float64
BlueWeightLbs	int64
RedCurrentLoseStreak	int64
RedCurrentWinStreak	int64
RedDraws	int64
RedAvgSigStrLanded	float64
RedAvgSigStrPct	float64
RedAvgSubAtt	float64
RedAvgTDLanded	float64
RedAvgTDPct	float64

RedLongestWinStreak	int64
RedLosses	int64
RedTotalRoundsFought	int64
RedTotalTitleBouts	int64
RedWinsByDecisionMajority	int64
RedWinsByDecisionSplit	int64
RedWinsByDecisionUnanimous	int64
RedWinsByKO	int64
RedWinsBySubmission	int64
RedWinsByTKODoctorStoppage	int64
RedWins	int64
RedStance	object
RedHeightCms	float64
RedReachCms	float64
RedWeightLbs	int64
RedAge	int64
BlueAge	int64
LoseStreakDif	int64
WinStreakDif	int64
LongestWinStreakDif	int64
WinDif	int64
LossDif	int64
TotalRoundDif	int64
TotalTitleBoutDif	int64
KODif	int64
SubDif	int64
HeightDif	float64
ReachDif	float64
AgeDif	int64
SigStrDif	float64
AvgSubAttDif	float64
AvgTDDif	float64
EmptyArena	float64
BMatchWCRank	float64
RMatchWCRank	float64
RWFlyweightRank	float64
RWFeatherweightRank	float64
RWStrawweightRank	float64
RWBantamweightRank	float64
RHeavyweightRank	float64
RLightHeavyweightRank	float64
RMiddleweightRank	float64

```
RWelterweightRank          float64
RLightweightRank           float64
RFeatherweightRank         float64
RBantamweightRank          float64
RFlyweightRank              float64
RPFPRank                   float64
BWFlyweightRank             float64
BWFeatherweightRank        float64
BWS strawweightRank        float64
BWBantamweightRank         float64
BHeavyweightRank            float64
BLightHeavyweightRank      float64
BMiddleweightRank           float64
BWelterweightRank           float64
BLightweightRank             float64
BFeatherweightRank          float64
BBantamweightRank           float64
BFlyweightRank               float64
BPFPRank                   float64
BetterRank                  object
Finish                      object
FinishDetails                object
FinishRound                 float64
FinishRoundTime              object
TotalFightTimeSecs          float64
RedDecOdds                  float64
BlueDecOdds                  float64
RSubOdds                     float64
BSubOdds                     float64
RK00dds                      float64
BK00dds                      float64
dtype: object
6528
115
6528
```

```
In [243]: #Separating the features based on their data types
cat_col = [col for col in df.columns if df[col].dtypes == 'object']
num_col = [col for col in df.columns if col not in cat_col]
print(df['Winner'].value_counts(dropna=False))
```

```
Winner
Red      3787
Blue     2741
Name: count, dtype: int64
```

```
In [244...]: #take care of missingness in Winner
print("Unique values in Winner column:", df['Winner'].unique())
# Strip spaces and lowercase all values
df['Winner'] = df['Winner'].astype(str).str.strip().str.capitalize()
print("Cleaned Winner values:", df['Winner'].unique())
df = df[df['Winner'].isin(['Red', 'Blue'])]
print("Rows remaining after filtering:", len(df))
```

```
Unique values in Winner column: ['Red' 'Blue']
Cleaned Winner values: ['Red' 'Blue']
Rows remaining after filtering: 6528
```

```
In [245...]: unique_categorieswc = df['WeightClass'].unique()
print(unique_categorieswc)
```

```
['Flyweight' 'Welterweight' 'Heavyweight' 'Featherweight'
 'Light Heavyweight' 'Catch Weight' 'Lightweight' 'Bantamweight'
 "Women's Strawweight" "Women's Flyweight" 'Middleweight'
 "Women's Bantamweight" "Women's Featherweight"]
```

```
In [246...]: from sklearn.preprocessing import LabelEncoder
print(df['Winner'].value_counts(dropna=False))
# Convert 'Red' and 'Blue' winner string to binary label (1 = Red wins, 0 = Blue wins)
df = df[df['Winner'].isin(['Red', 'Blue'])] # filter out 'Draw' or 'No Contest'
print("Rows remaining after filtering:", len(df))

cat_col = ['RedFighter', 'BlueFighter', 'WeightClass', 'Gender']

from sklearn.preprocessing import LabelEncoder

enc = LabelEncoder()

for col in cat_col:
    if col in df.columns:
        df[col] = enc.fit_transform(df[col].astype(str))
    else:
        print(f"Warning: Column {col} not found in dataframe.")
```

```
print(df['Winner'].value_counts())
#Series([], Name: count, dtype: int64)

# result =
# Series([], Name: count, dtype: int64)
# Rows remaining after filtering: 0
# Series([], Name: count, dtype: int64)
```

```
Winner
Red      3787
Blue     2741
Name: count, dtype: int64
Rows remaining after filtering: 6528
Winner
Red      3787
Blue     2741
Name: count, dtype: int64
```

```
In [247...]: win_counts = df['Winner'].value_counts()
# Display the frequency table
print("Frequency Table for 'Winner' column:")
print(win_counts)
```

```
Frequency Table for 'Winner' column:
Winner
Red      3787
Blue     2741
Name: count, dtype: int64
```

```
In [248...]: for column in df.columns:
    if df[column].isnull().sum() != 0:
        print(f"NaN in {column}: {df[column].isnull().sum()}")
```

Nan in RedOdds: 227
Nan in BlueOdds: 226
Nan in RedExpectedValue: 227
Nan in BlueExpectedValue: 226
Nan in BlueAvgSigStrLanded: 930
Nan in BlueAvgSigStrPct: 765
Nan in BlueAvgSubAtt: 832
Nan in BlueAvgTDLanded: 833
Nan in BlueAvgTDPct: 842
Nan in BlueStance: 3
Nan in RedAvgSigStrLanded: 455
Nan in RedAvgSigStrPct: 357
Nan in RedAvgSubAtt: 357
Nan in RedAvgTDLanded: 357
Nan in RedAvgTDPct: 367
Nan in EmptyArena: 1486
Nan in BMatchWCRank: 5328
Nan in RMatchWCRank: 4749
Nan in RWFlyweightRank: 6432
Nan in RWFeatherweightRank: 6519
Nan in RWStrawweightRank: 6382
Nan in RWBantamweightRank: 6374
Nan in RHeavyweightRank: 6342
Nan in RLightHeavyweightRank: 6344
Nan in RMiddleweightRank: 6346
Nan in RWelterweightRank: 6337
Nan in RLightweightRank: 6344
Nan in RFeatherweightRank: 6351
Nan in RBantamweightRank: 6347
Nan in RFlyweightRank: 6340
Nan in RPFPRank: 6275
Nan in BWFlyweightRank: 6455
Nan in BWFeatherweightRank: 6527
Nan in BWStrawweightRank: 6428
Nan in BWBantamweightRank: 6421
Nan in BHeavyweightRank: 6380
Nan in BLightHeavyweightRank: 6408
Nan in BMiddleweightRank: 6391
Nan in BWelterweightRank: 6409
Nan in BLightweightRank: 6408
Nan in BFeatherweightRank: 6404
Nan in BBantamweightRank: 6409

```
Nan in BFlyweightRank: 6398
Nan in BPFPRank: 6461
Nan in Finish: 238
Nan in FinishDetails: 3636
Nan in FinishRound: 622
Nan in FinishRoundTime: 622
Nan in TotalFightTimeSecs: 622
Nan in RedDecOdds: 1087
Nan in BlueDecOdds: 1116
Nan in RSubOdds: 1336
Nan in BSubOdds: 1359
Nan in RK00dds: 1334
Nan in BK00dds: 1360
```

In [249...]

```
#force numeric WeightClass
df['WeightClass'] = pd.to_numeric(df['WeightClass'], errors='coerce')

weightclass_labels = {
    0: 'Flyweight',
    1: 'Welterweight',
    2: 'Heavyweight',
    3: 'Featherweight',
    4: 'Light Heavyweight',
    5: 'Catch Weight',
    6: 'Lightweight',
    7: 'Bantamweight',
    8: "Women's Strawweight",
    9: "Women's Flyweight",
    10: "Middleweight",
    11: "Women's Bantamweight",
    12: "Women's Featherweight"
}

df['WeightClassLabel'] = df['WeightClass'].map(weightclass_labels)

#check
missing_wtclass = df['WeightClass'].isnull().sum()
print(f"✓ WeightClass mapped. Missing values: {missing_wtclass}")

✓ WeightClass mapped. Missing values: 0
```

```
In [250...]: # Basic descriptive statistics
print(df.describe())

# Check class balance
sns.countplot(x='Winner', data=df)
plt.title('Fight Winner Distribution (Red = 1, Blue = 0)')
fig_name = "fight_winner_dist"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

# Missing data heatmap
sns.heatmap(df.isnull(), cbar=False)
plt.title("Missing Data Heatmap")
fig_name = "missing_data_heatmap1"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```

	RedFighter	BlueFighter	RedOdds	BlueOdds	RedExpectedValue	\
count	6528.000000	6528.000000	6301.000000	6302.000000	6301.000000	
mean	819.761795	942.707874	-115.711474	59.793240	96.658224	
std	476.188466	556.368724	277.225783	253.117416	85.891109	
min	0.000000	0.000000	-2100.000000	-1200.000000	4.761900	
25%	419.000000	462.000000	-255.000000	-150.000000	39.215700	
50%	806.000000	922.500000	-150.000000	130.000000	66.666700	
75%	1241.250000	1427.000000	130.000000	215.000000	130.000000	
max	1660.000000	1921.000000	775.000000	1300.000000	775.000000	
	BlueExpectedValue	WeightClass	Gender	NumberOfRounds	\	
count	6302.000000	6528.000000	6528.000000	6528.000000		
mean	165.054566	5.503370	0.877298	3.185509		
std	137.689177	3.200274	0.328120	0.577441		
min	8.333300	0.000000	0.000000	3.000000		
25%	66.666700	3.000000	1.000000	3.000000		
50%	130.000000	6.000000	1.000000	3.000000		
75%	215.000000	8.000000	1.000000	3.000000		
max	1300.000000	12.000000	1.000000	5.000000		
	BlueCurrentLoseStreak	BlueCurrentWinStreak	BlueDraws	\		
count	6528.000000	6528.000000	6528.000000			
mean	0.501072	0.957567	0.023131			
std	0.794303	1.406786	0.156327			
min	0.000000	0.000000	0.000000			
25%	0.000000	0.000000	0.000000			
50%	0.000000	0.000000	0.000000			
75%	1.000000	1.000000	0.000000			
max	6.000000	12.000000	2.000000			
	BlueAvgSigStrLanded	BlueAvgSigStrPct	BlueAvgSubAtt	BlueAvgTDLanded	\	
count	5598.000000	5763.000000	5696.000000	5695.000000		
mean	19.841810	0.453059	0.500202	1.320536		
std	20.315307	0.110787	0.672859	1.356491		
min	0.000000	0.000000	0.000000	0.000000		
25%	3.880000	0.400000	0.000000	0.330000		
50%	9.280000	0.460000	0.300000	1.000000		
75%	32.666700	0.513000	0.800000	1.970000		
max	154.000000	1.000000	8.400000	10.860000		
	BlueAvgTDPct	BlueLongestWinStreak	BlueLosses	BlueTotalRoundsFought	\	
count	5686.000000	6528.000000	6528.000000	6528.000000		

mean	0.325419	1.923407	1.863664	11.872396
std	0.239174	1.949952	2.170130	13.845139
min	0.000000	0.000000	0.000000	0.000000
25%	0.150000	0.000000	0.000000	3.000000
50%	0.330000	1.000000	1.000000	7.000000
75%	0.470000	3.000000	3.000000	17.000000
max	1.000000	17.000000	16.000000	111.000000
count	6528.000000	6528.000000	6528.000000	6528.000000
mean	0.251685	0.017770	0.133278	0.000000
std	1.085122	0.000000	0.000000	0.000000
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000
max	16.000000	2.000000	2.000000	2.000000
count	6528.000000	6528.000000	6528.000000	6528.000000
mean	0.279871	1.093597	1.066330	1.723951
std	0.595123	1.613288	1.723951	1.723951
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	2.000000	1.250000	1.250000
max	5.000000	11.000000	20.000000	20.000000
count	6528.000000	6528.000000	6528.000000	6528.000000
mean	0.626532	0.022212	3.145680	3.145680
std	1.258249	0.153494	3.712852	3.712852
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	2.000000	2.000000
75%	1.000000	0.000000	5.000000	5.000000
max	13.000000	2.000000	31.000000	31.000000
count	6528.000000	6528.000000	6528.000000	6528.000000
mean	177.822068	182.162155	163.183977	0.622243
std	9.105099	11.168891	34.599386	0.872301

min	152.400000	0.000000	115.000000	0.000000
25%	170.180000	175.260000	135.000000	0.000000
50%	177.800000	182.880000	155.000000	0.000000
75%	185.420000	190.500000	185.000000	1.000000
max	210.820000	213.360000	265.000000	7.000000

	RedCurrentWinStreak	RedDraws	RedAvgSigStrLanded	RedAvgSigStrPct	\
count	6528.000000	6528.000000	6073.000000	6171.000000	
mean	1.101562	0.031097	21.152766	0.460321	
std	1.760767	0.187999	19.882916	0.098315	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	4.160000	0.403000	
50%	0.000000	0.000000	15.666700	0.460000	
75%	2.000000	0.000000	34.000000	0.516000	
max	18.000000	2.000000	141.000000	1.000000	

	RedAvgSubAtt	RedAvgTDLanded	RedAvgTDPct	RedLongestWinStreak	\
count	6171.000000	6171.000000	6161.000000	6528.000000	
mean	0.536907	1.399962	0.341467	2.679994	
std	0.693125	1.308340	0.220986	2.242687	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.450000	0.200000	1.000000	
50%	0.333300	1.030000	0.338000	2.000000	
75%	0.800000	2.000000	0.470000	4.000000	
max	8.400000	12.500000	1.000000	18.000000	

	RedLosses	RedTotalRoundsFought	RedTotalTitleBouts	\
count	6528.000000	6528.000000	6528.000000	
mean	2.566789	17.408548	0.553462	
std	2.703546	17.846748	1.544962	
min	0.000000	0.000000	0.000000	
25%	1.000000	5.000000	0.000000	
50%	2.000000	12.000000	0.000000	
75%	4.000000	25.000000	0.000000	
max	21.000000	448.000000	16.000000	

	RedWinsByDecisionMajority	RedWinsByDecisionSplit	\
count	6528.000000	6528.000000	
mean	0.026961	0.400888	
std	0.163862	0.702801	
min	0.000000	0.000000	
25%	0.000000	0.000000	

50%	0.000000	0.000000
75%	0.000000	1.000000
max	2.000000	5.000000

	RedWinsByDecisionUnanimous	RedWinsByKO	RedWinsBySubmission	\
count	6528.000000	6528.000000	6528.000000	
mean	1.612286	1.563879	0.934589	
std	1.972295	2.156770	1.608402	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	
50%	1.000000	1.000000	0.000000	
75%	2.000000	2.000000	1.000000	
max	11.000000	21.000000	16.000000	

	RedWinsByTKODoctorStoppage	RedWins	RedHeightCms	RedReachCms	\
count	6528.000000	6528.000000	6528.000000	6528.000000	
mean	0.035539	4.628064	177.802399	182.410954	
std	0.199492	4.505498	9.182963	11.130395	
min	0.000000	0.000000	152.400000	147.320000	
25%	0.000000	1.000000	170.180000	175.260000	
50%	0.000000	3.000000	177.800000	182.880000	
75%	0.000000	7.000000	185.420000	190.500000	
max	2.000000	33.000000	210.820000	214.630000	

	RedWeightLbs	RedAge	BlueAge	LoseStreakDif	WinStreakDif	\
count	6528.000000	6528.000000	6528.000000	6528.000000	6528.000000	
mean	163.621324	30.359528	29.805607	0.059283	-0.143842	
std	34.846543	4.180712	3.959623	1.024000	1.874732	
min	115.000000	18.000000	19.000000	-6.000000	-18.000000	
25%	135.000000	27.000000	27.000000	0.000000	-1.000000	
50%	155.000000	30.000000	30.000000	0.000000	0.000000	
75%	185.000000	33.000000	32.000000	0.000000	0.000000	
max	265.000000	47.000000	47.000000	6.000000	10.000000	

	LongestWinStreakDif	WinDif	LossDif	TotalRoundDif	\
count	6528.000000	6528.000000	6528.000000	6528.000000	
mean	-0.756587	-1.482384	0.075061	-5.536152	
std	2.025886	4.182192	3.129140	17.995648	
min	-12.000000	-28.000000	-20.000000	-448.000000	
25%	-2.000000	-3.000000	-1.000000	-12.000000	
50%	-1.000000	-1.000000	0.000000	-3.000000	
75%	0.000000	0.000000	2.000000	2.000000	

max	14.000000	23.000000	16.000000	87.000000		\
count	TotalTitleBoutDif	KODif	SubDif	HeightDif	ReachDif	\
mean	6528.000000	6528.000000	6528.000000	6528.000000	6528.000000	
std	-0.301777	-0.510876	-0.308058	-0.006679	-0.299271	
min	1.681080	2.149365	1.844810	6.770956	9.132413	
25%	-16.000000	-21.000000	-16.000000	-187.960000	-187.960000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	5.080000	5.080000	
max	15.000000	14.000000	10.000000	30.480000	30.480000	
count	AgeDif	SigStrDif	AvgSubAttDif	AvgTDDif	EmptyArena	\
mean	6528.000000	6528.000000	6528.000000	6528.000000	5042.000000	
std	0.096814	-2.663342	-0.071094	-0.171371	0.153114	
min	5.201719	19.583493	0.892257	1.754354	0.360133	
25%	-17.000000	-118.000000	-8.400000	-11.000000	0.000000	
50%	-3.000000	-7.895850	-0.444400	-1.010000	0.000000	
75%	0.000000	-0.304750	0.000000	0.000000	0.000000	
max	4.000000	2.100000	0.282400	0.700000	0.000000	
count	17.000000	128.222200	7.800000	10.860000	1.000000	
count	BMatchWCRank	RMatchWCRank	RWFlyweightRank	RWFeatherweightRank		\
mean	1200.000000	1779.000000	96.000000	9.0		
std	8.339167	6.953345	7.291667	0.0		
min	4.202839	4.657029	4.975554	0.0		
25%	1.000000	0.000000	0.000000	0.0		
50%	5.000000	3.000000	3.000000	0.0		
75%	9.000000	7.000000	7.000000	0.0		
max	12.000000	11.000000	12.000000	0.0		
count	15.000000	15.000000	15.000000	0.0		
count	RWStrawweightRank	RWBantamweightRank	RHeavyweightRank			\
mean	146.000000	154.000000	186.000000			
std	7.047945	7.097403	6.881720			
min	4.616809	4.803008	4.404787			
25%	0.000000	0.000000	0.000000			
50%	3.000000	3.000000	3.000000			
75%	7.000000	7.000000	7.000000			
max	11.000000	11.750000	10.000000			
count	15.000000	15.000000	15.000000			

	RLightHeavyweightRank	RMiddleweightRank	RWelterweightRank	\
count	184.000000	182.000000	191.000000	
mean	7.119565	7.351648	7.130890	
std	4.638500	4.711274	4.705947	
min	0.000000	0.000000	0.000000	
25%	4.000000	4.000000	3.000000	
50%	7.000000	7.000000	7.000000	
75%	11.000000	11.750000	11.000000	
max	15.000000	15.000000	15.000000	

	RLightweightRank	RFeatherweightRank	RBantamweightRank	\
count	184.000000	177.000000	181.000000	
mean	7.032609	6.983051	6.972376	
std	4.662257	4.653291	4.709837	
min	0.000000	0.000000	0.000000	
25%	3.000000	3.000000	3.000000	
50%	6.000000	7.000000	7.000000	
75%	11.000000	11.000000	11.000000	
max	15.000000	15.000000	15.000000	

	RFlyweightRank	RPFPRank	BWFlyweightRank	BWFeatherweightRank	\
count	188.000000	253.000000	73.000000	1.0	
mean	6.590426	6.913043	8.410959	0.0	
std	4.621192	4.195655	4.009834	NaN	
min	0.000000	1.000000	1.000000	0.0	
25%	2.000000	3.000000	6.000000	0.0	
50%	7.000000	6.000000	9.000000	0.0	
75%	10.250000	10.000000	12.000000	0.0	
max	15.000000	15.000000	15.000000	0.0	

	BWStrawweightRank	BWBantamweightRank	BHeavyweightRank	\
count	100.000000	107.000000	148.000000	
mean	8.170000	8.476636	8.641892	
std	4.192478	4.254511	4.090823	
min	1.000000	0.000000	1.000000	
25%	5.000000	5.000000	5.000000	
50%	9.000000	9.000000	9.000000	
75%	12.000000	12.000000	12.000000	
max	15.000000	15.000000	15.000000	

	BLightHeavyweightRank	BMiddleweightRank	BWelterweightRank	\
count	120.000000	137.000000	119.000000	

mean	8.483333	8.554745	8.386555
std	4.152519	4.311271	4.405523
min	0.000000	0.000000	1.000000
25%	6.000000	5.000000	4.500000
50%	9.000000	9.000000	9.000000
75%	12.000000	12.000000	12.000000
max	15.000000	15.000000	15.000000

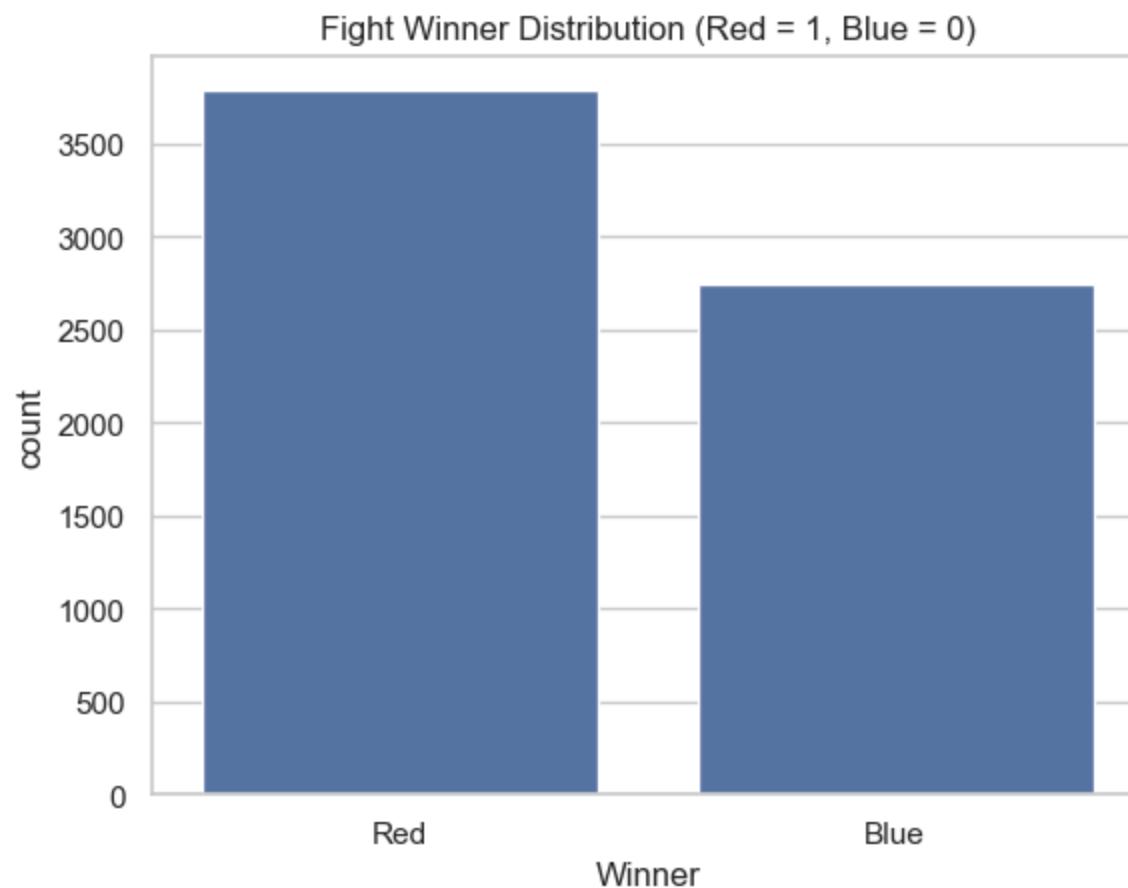
	BLightweightRank	BFeatherweightRank	BBantamweightRank	\
count	120.000000	124.000000	119.000000	
mean	8.150000	7.967742	8.268908	
std	4.076269	4.462919	4.354420	
min	1.000000	0.000000	0.000000	
25%	5.000000	4.000000	4.000000	
50%	8.000000	8.500000	9.000000	
75%	11.250000	12.000000	12.000000	
max	15.000000	15.000000	15.000000	

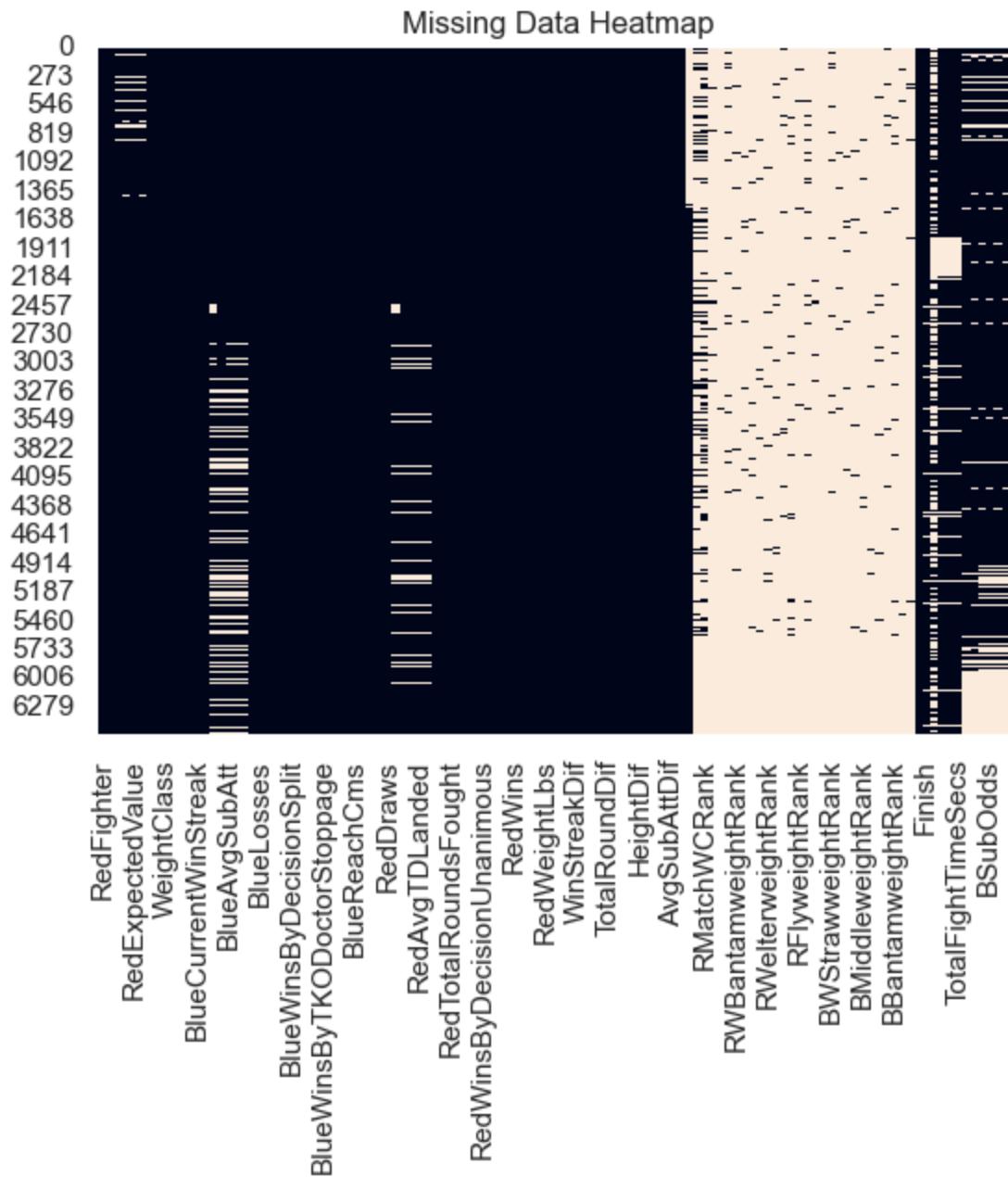
	BFlyweightRank	BPFPRank	FinishRound	TotalFightTimeSecs	\
count	130.000000	67.000000	5906.000000	5906.000000	
mean	8.407692	9.194030	2.424145	657.536234	
std	4.307369	4.352773	1.007887	360.383418	
min	1.000000	1.000000	1.000000	5.000000	
25%	5.000000	5.000000	1.000000	299.000000	
50%	8.000000	10.000000	3.000000	900.000000	
75%	12.000000	13.500000	3.000000	900.000000	
max	15.000000	15.000000	5.000000	1500.000000	

	RedDecOdds	BlueDecOdds	RSubOdds	BSubOdds	RK00dds	\
count	5441.000000	5412.000000	5192.000000	5169.000000	5194.000000	
mean	308.333395	425.870288	884.048151	1100.497775	510.891606	
std	250.750088	325.940028	601.826547	671.106177	426.563458	
min	-440.000000	-200.000000	-370.000000	-1250.000000	-550.000000	
25%	170.000000	222.000000	439.750000	600.000000	225.000000	
50%	250.000000	350.000000	750.000000	1000.000000	420.000000	
75%	400.000000	550.000000	1200.000000	1450.000000	700.000000	
max	2400.000000	3000.000000	4665.000000	5000.000000	4000.000000	

	BK00dds
count	5168.000000
mean	636.463235
std	465.014634

min	-400.000000
25%	310.000000
50%	525.000000
75%	875.000000
max	4000.000000





In [25]:

```
import numpy as np
df["BlueHeight"] = df["BlueHeightCms"] / 2.54
df['BlueReach']= df['BlueReachCms'] / 2.54
```

```
df['RedHeight'] = df['RedHeightCms'] / 2.54
df['RedReach']= df['RedReachCms'] / 2.54
df.drop(columns = ['BlueHeightCms', 'BlueReachCms', 'RedHeightCms', 'RedReachCms'], axis = 1, inplace = True)

df['ROver35'] = df['RedAge'].apply(lambda x: int(x > 35))
df['BOver35'] = df['BlueAge'].apply(lambda x: int(x > 35))

df['RWinPct'] = df['RedWins'] / (df['RedWins'] + df['RedLosses'])
df['BWinPct'] = df['BlueWins'] / (df['BlueWins'] + df['BlueLosses'])

df['RedStrikingRatio'] = df['RedAvgSigStrLanded'] / (df['RedAvgSigStrLanded'] + df['BlueAvgSigStrLanded'])
df['BlueStrikingRatio'] = df['BlueAvgSigStrLanded'] / (df['RedAvgSigStrLanded'] + df['BlueAvgSigStrLanded'])

df['RedTotalFights'] = df['RedWins'] + df['RedLosses']
df['BlueTotalFights'] = df['BlueWins'] + df['BlueLosses']

df['RedIsGrappler'] = (df['RedAvgTDLanded'] > 3.5).astype(int)
df['BlueIsGrappler'] = (df['BlueAvgTDLanded'] > 3.5).astype(int)

df['RedIsStriker'] = (df['RedAvgSigStrLanded'] > 6.0).astype(int)
df['BlueIsStriker'] = (df['BlueAvgSigStrLanded'] > 6.0).astype(int)

df['RGrapplerVBStriker'] = ((df['RedIsGrappler'] == 1) & (df['BlueIsStriker'] == 1)).astype(int)
df['BGrapplerVRStriker'] = ((df['BlueIsGrappler'] == 1) & (df['RedIsStriker'] == 1)).astype(int)

df['RedStrikingEfficiency'] = df['RedAvgSigStrLanded'] * df['RedAvgSigStrPct']
df['BlueStrikingEfficiency'] = df['BlueAvgSigStrLanded'] * df['BlueAvgSigStrPct']

df['RedTDEfficiency'] = df['RedAvgTDLanded'] * df['RedAvgTDPct']
df['BlueTDEfficiency'] = df['BlueAvgTDLanded'] * df['BlueAvgTDPct']

df['RedEffectiveTD'] = 1 / (df['RedAvgTDLanded'] / df['RedAvgSubAtt'])
df['BlueEffectiveTD'] = 1 / (df['BlueAvgTDLanded'] / df['BlueAvgSubAtt'])
df['EffectiveTDDif'] = df['BlueEffectiveTD'] - df['RedEffectiveTD']

df['RedSize'] = df['RedHeight'] + df['RedReach']
df['BlueSize'] = df['BlueHeight'] + df['BlueReach']

df['Favorite'] = (df['RedOdds'] < df['BlueOdds']).astype(int)

df['Favorite'] = df['Favorite'].map({0 : 'Blue', 1 : 'Red'})
```

```
df['FavoriteWins'] = (df['Favorite'] == df['Winner']).astype(int)
```

In [252...]: df.head()

Out[252...]:

	RedFighter	BlueFighter	RedOdds	BlueOdds	RedExpectedValue	BlueExpectedValue	Winner	TitleBout	WeightClass
0	66	1009	-250.0	215.0	40.0000	215.0	Red	True	3
1	1441	718	-210.0	295.0	47.6190	295.0	Red	False	8
2	307	67	-380.0	300.0	26.3158	300.0	Red	False	4
3	221	1071	-950.0	625.0	10.5263	625.0	Red	False	2
4	1183	524	-130.0	110.0	76.9231	110.0	Blue	False	2

In [253...]:

```

df['draw_diff'] = (df['BlueDraws']-df['RedDraws'])
df['avg_sig_str_pct_diff'] = (df['BlueAvgSigStrPct']-df['RedAvgSigStrPct'])
df['avg_TD_pct_diff'] = (df['BlueAvgTDPct']-df['RedAvgTDPct'])
df['win_by_Decision_Majority_diff'] = (df['BlueWinsByDecisionMajority']-df['RedWinsByDecisionMajority'])
df['win_by_Decision_Split_diff'] = (df['BlueWinsByDecisionSplit']-df['RedWinsByDecisionSplit'])
df['win_by_Decision_Unanimous_diff'] = (df['BlueWinsByDecisionUnanimous']-df['RedWinsByDecisionUnanimous'])
df['win_by_TKO_Doctor_Stoppage_diff'] = (df['BlueWinsByTKODoctorStoppage']-df['RedWinsByTKODoctorStoppage'])
df['odds_diff'] = (df['BlueOdds']-df['RedOdds'])
df['ev_diff'] = (df['BlueExpectedValue']-df['RedExpectedValue'])

blue_win = df[df['Winner'] == 'Blue']
red_win = df[df['Winner'] == 'Red']

blue_win_percent = len(blue_win) / len(df)
red_win_percent = len(red_win) / len(df)
df.head()

```

Out [253...]

	RedFighter	BlueFighter	RedOdds	BlueOdds	RedExpectedValue	BlueExpectedValue	Winner	TitleBout	WeightClass
0	66	1009	-250.0	215.0	40.0000	215.0	Red	True	3
1	1441	718	-210.0	295.0	47.6190	295.0	Red	False	8
2	307	67	-380.0	300.0	26.3158	300.0	Red	False	4
3	221	1071	-950.0	625.0	10.5263	625.0	Red	False	2
4	1183	524	-130.0	110.0	76.9231	110.0	Blue	False	2

In [254...]

```
print(df.shape[0]) # number of rows
print(df.shape[1]) # number of columns
```

6528

150

In [255...]

```
df.BlueStance.unique()
#It has one spelling mistake
df['BlueStance'].loc[df['BlueStance']=='Switch '] = 'Switch'
#R_Stance doesn't have this error, so we're cool

print(df['BlueStance'].value_counts())
```

BlueStance

Orthodox	4844
Southpaw	1274
Switch	406
Open Stance	1
Name: count, dtype: int64	

In [256...]

```
red_win_percent_high_TDDif = len(red_win[red_win['AvgTDDif'] < -1]) / len(df[df['AvgTDDif'] < -1])
print("Red Win Percentage Increase (w/ +1 more TDs): " + str(red_win_percent_high_TDDif - red_win_percent))

blue_win_percent_high_TDDif = len(blue_win[blue_win['AvgTDDif'] > 1]) / len(df[df['AvgTDDif'] > 1])
print("Blue Win Percentage Increase (w/ +1 more TDs): " + str(blue_win_percent_high_TDDif - blue_win_percent))

print('\n')

red_win_percent_highTD_v_lowTD = len(red_win[(red_win['RedAvgTDLanded'] > 2.5) & (red_win['BlueAvgTDLanded'] < 1)])
print("Red Win Percentage Increase (w/ +1 more TDs): " + str(red_win_percent_highTD_v_lowTD - red_win_percent))
```

```
print("Red Win Percentage Increase (w/ Red TD > 2.5, Blue TD < 1): " + str(red_win_percent_highTD_v_lowTD))

blue_win_percent_highTD_v_lowTD = len(blue_win[(blue_win['BlueAvgTDLanded'] > 2.5) & (blue_win['RedAvgTDLanded'] < 1)]) / len(blue_win)
print("Blue Win Percentage Increase (w/ Blue TD > 2.5, Red TD < 1): " + str(blue_win_percent_highTD_v_lowTD))

print('\n')

red_old_win_percent = len(df[(df['ROver35'] == 1) & (df['Winner'] == 'Red')]) / len(df[df['ROver35'] == 1])
print("Decrease in Win Percentage When Red Fighter > 35 y.o.: " + str(red_old_win_percent - red_win_percent))
blue_old_win_percent = len(df[(df['BOver35'] == 1) & (df['Winner'] == 'Blue')]) / len(df[df['BOver35'] == 1])
print("Decrease in Win Percentage When Blue Fighter > 35 y.o.: " + str(blue_old_win_percent - blue_win_percent))

df.to_csv('df.csv')

print(df['FavoriteWins'].sum() / len(df))
print("Blue Corner Win Percentage: " + str(blue_win_percent))
print("Red Corner Win Percentage: " + str(red_win_percent))

fig, ax = plt.subplots(1, 2)
ax[0].hist(red_win['RedOdds'], alpha=0.7, color='red')
ax[0].hist(red_win['BlueOdds'], alpha=0.7, color='blue')
ax[0].set_title('Odds for Red Wins')
ax[1].hist(blue_win['RedOdds'], alpha=0.7, color='red')
ax[1].hist(blue_win['BlueOdds'], alpha=0.7, color='blue')
ax[1].set_title('Odds for Blue Wins')
fig_name = "odds"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

sns.scatterplot(x='WinDif', y='LossDif', data=df, hue='RedAvgSigStrLanded')
fig_name = "strikes_and_wins"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```

Red Win Percentage Increase (w/ +1 more TDs): 0.06798639360885117

Blue Win Percentage Increase (w/ +1 more TDs): 0.0755971117904845

Red Win Percentage Increase (w/ Red TD > 2.5, Blue TD < 1): 0.11768577623357035

Blue Win Percentage Increase (w/ Blue TD > 2.5, Red TD < 1): 0.13643041474268885

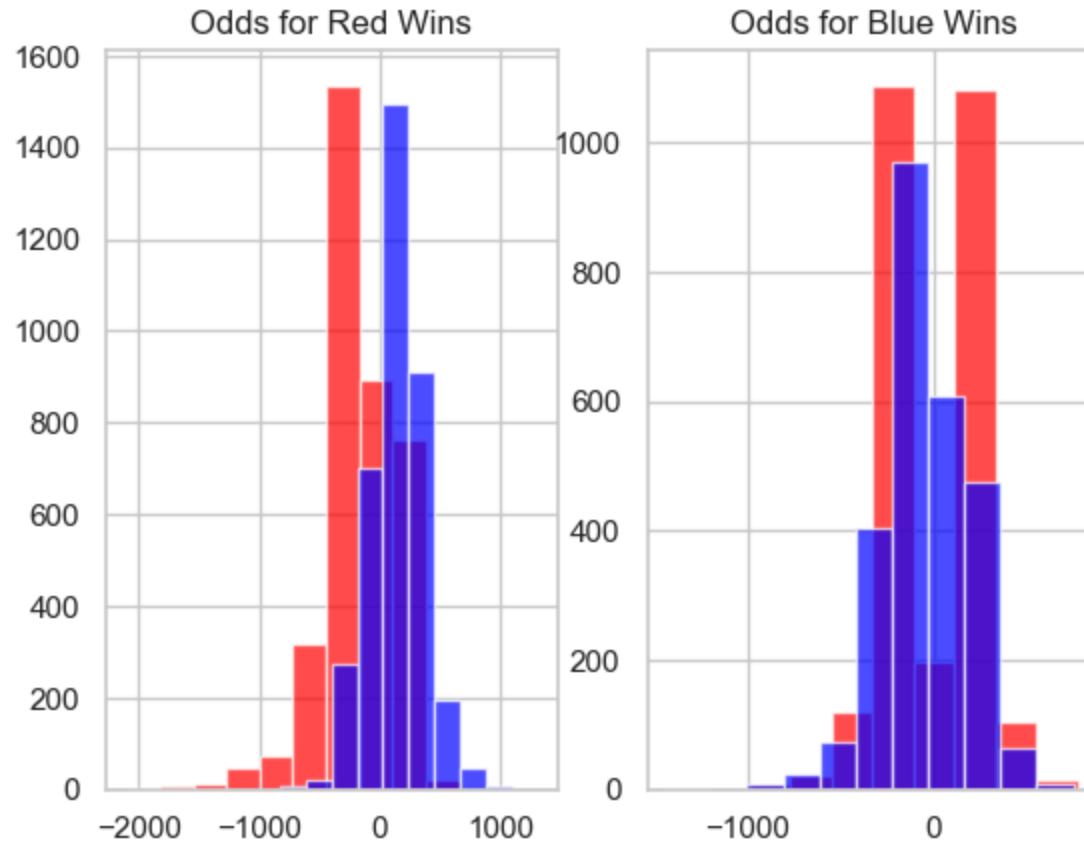
Decrease in Win Percentage When Red Fighter > 35 y.o.: -0.1215602718360071

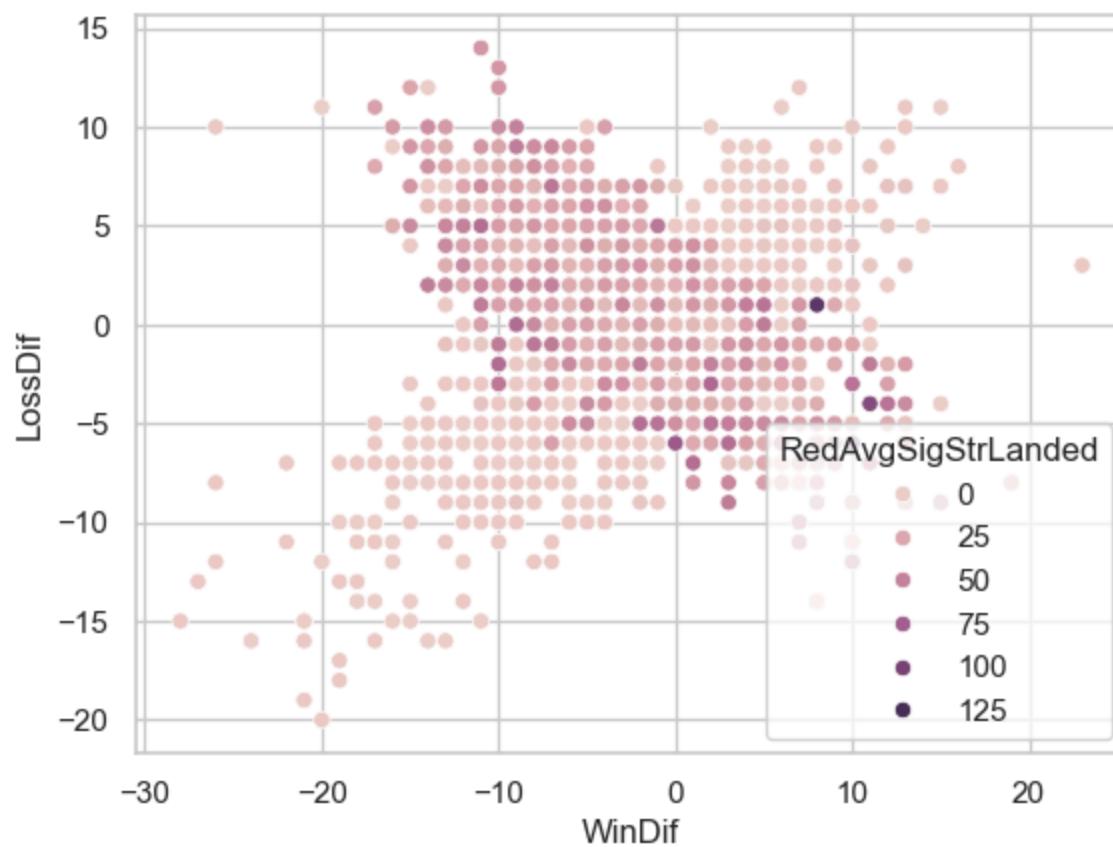
Decrease in Win Percentage When Blue Fighter > 35 y.o.: -0.08955866868408013

0.6499693627450981

Blue Corner Win Percentage: 0.41988357843137253

Red Corner Win Percentage: 0.5801164215686274





In [257]:

```
#calc missing proportions
missing_proportions = df.isnull().sum() / len(df)
print("Proportion of missing values per column:")
print(missing_proportions)

#calc missing percentages
missing_percentages = df.isnull().sum() * 100 / len(df)
print("\nPercentage of missing values per column:")
print(missing_percentages)
```

Proportion of missing values per column:

RedFighter	0.000000
BlueFighter	0.000000
RedOdds	0.034773
BlueOdds	0.034620
RedExpectedValue	0.034773
BlueExpectedValue	0.034620
Winner	0.000000
TitleBout	0.000000
WeightClass	0.000000
Gender	0.000000
NumberOfRounds	0.000000
BlueCurrentLoseStreak	0.000000
BlueCurrentWinStreak	0.000000
BlueDraws	0.000000
BlueAvgSigStrLanded	0.142463
BlueAvgSigStrPct	0.117188
BlueAvgSubAtt	0.127451
BlueAvgTDLanded	0.127604
BlueAvgTDPct	0.128983
BlueLongestWinStreak	0.000000
BlueLosses	0.000000
BlueTotalRoundsFought	0.000000
BlueTotalTitleBouts	0.000000
BlueWinsByDecisionMajority	0.000000
BlueWinsByDecisionSplit	0.000000
BlueWinsByDecisionUnanimous	0.000000
BlueWinsByKO	0.000000
BlueWinsBySubmission	0.000000
BlueWinsByTKODoctorStoppage	0.000000
BlueWins	0.000000
BlueStance	0.000460
BlueWeightLbs	0.000000
RedCurrentLoseStreak	0.000000
RedCurrentWinStreak	0.000000
RedDraws	0.000000
RedAvgSigStrLanded	0.069700
RedAvgSigStrPct	0.054688
RedAvgSubAtt	0.054688
RedAvgTDLanded	0.054688
RedAvgTDPct	0.056219
RedLongestWinStreak	0.000000

RedLosses	0.000000
RedTotalRoundsFought	0.000000
RedTotalTitleBouts	0.000000
RedWinsByDecisionMajority	0.000000
RedWinsByDecisionSplit	0.000000
RedWinsByDecisionUnanimous	0.000000
RedWinsByKO	0.000000
RedWinsBySubmission	0.000000
RedWinsByTKODoctorStoppage	0.000000
RedWins	0.000000
RedStance	0.000000
RedWeightLbs	0.000000
RedAge	0.000000
BlueAge	0.000000
LoseStreakDif	0.000000
WinStreakDif	0.000000
LongestWinStreakDif	0.000000
WinDif	0.000000
LossDif	0.000000
TotalRoundDif	0.000000
TotalTitleBoutDif	0.000000
KODif	0.000000
SubDif	0.000000
HeightDif	0.000000
ReachDif	0.000000
AgeDif	0.000000
SigStrDif	0.000000
AvgSubAttDif	0.000000
AvgTDDif	0.000000
EmptyArena	0.227635
BMatchWCRank	0.816176
RMatchWCRank	0.727482
RWFlyweightRank	0.985294
RWFeatherweightRank	0.998621
RWStrawweightRank	0.977635
RWBantamweightRank	0.976409
RHeavyweightRank	0.971507
RLightHeavyweightRank	0.971814
RMiddleweightRank	0.972120
RWelterweightRank	0.970741
RLightweightRank	0.971814
RFeatherweightRank	0.972886

RBantamweightRank	0.972273
RFlyweightRank	0.971201
RPFPRank	0.961244
BWFlyweightRank	0.988817
BWFeatherweightRank	0.999847
BWStrawweightRank	0.984681
BWBantamweightRank	0.983609
BHeavyweightRank	0.977328
BLightHeavyweightRank	0.981618
BMiddleweightRank	0.979013
BWelterweightRank	0.981771
BLightweightRank	0.981618
BFeatherweightRank	0.981005
BBantamweightRank	0.981771
BFlyweightRank	0.980086
BPFPRank	0.989737
BetterRank	0.000000
Finish	0.036458
FinishDetails	0.556985
FinishRound	0.095282
FinishRoundTime	0.095282
TotalFightTimeSecs	0.095282
RedDecOdds	0.166513
BlueDecOdds	0.170956
RSubOdds	0.204657
BSubOdds	0.208180
RK00dds	0.204350
BK00dds	0.208333
WeightClassLabel	0.000000
BlueHeight	0.000000
BlueReach	0.000000
RedHeight	0.000000
RedReach	0.000000
ROver35	0.000000
BOver35	0.000000
RWinPct	0.070619
BWinPct	0.170037
RedStrikingRatio	0.161152
BlueStrikingRatio	0.161152
RedTotalFights	0.000000
BlueTotalFights	0.000000
RedIsGrappler	0.000000

```
BlueIsGrappler          0.000000
RedIsStriker            0.000000
BlueIsStriker           0.000000
RGrapplerVBStriker     0.000000
BGrapplerVRStriker    0.000000
RedStrikingEfficiency   0.069700
BlueStrikingEfficiency  0.142463
RedTDEfficiency         0.056219
BlueTDEfficiency        0.128983
RedEffectiveTD          0.142616
BlueEffectiveTD         0.250000
EffectiveTDDif          0.314338
RedSize                 0.000000
BlueSize                0.000000
Favorite                0.000000
FavoriteWins             0.000000
draw_diff                0.000000
avg_sig_str_pct_diff    0.135876
avg_TD_pct_diff          0.145987
win_by_Decision_Majority_diff 0.000000
win_by_Decision_Split_diff 0.000000
win_by_Decision_Unanimous_diff 0.000000
win_by_TKO_Doctor_Stoppage_diff 0.000000
odds_diff                0.036458
ev_diff                  0.036458
dtype: float64
```

Percentage of missing values per column:

```
RedFighter              0.000000
BlueFighter              0.000000
RedOdds                 3.477328
BlueOdds                3.462010
RedExpectedValue         3.477328
BlueExpectedValue        3.462010
Winner                  0.000000
TitleBout                0.000000
WeightClass              0.000000
Gender                   0.000000
NumberOfRounds           0.000000
BlueCurrentLoseStreak   0.000000
BlueCurrentWinStreak    0.000000
BlueDraws                0.000000
```

BlueAvgSigStrLanded	14.246324
BlueAvgSigStrPct	11.718750
BlueAvgSubAtt	12.745098
BlueAvgTDLanded	12.760417
BlueAvgTDPct	12.898284
BlueLongestWinStreak	0.000000
BlueLosses	0.000000
BlueTotalRoundsFought	0.000000
BlueTotalTitleBouts	0.000000
BlueWinsByDecisionMajority	0.000000
BlueWinsByDecisionSplit	0.000000
BlueWinsByDecisionUnanimous	0.000000
BlueWinsByKO	0.000000
BlueWinsBySubmission	0.000000
BlueWinsByTKODoctorStoppage	0.000000
BlueWins	0.000000
BlueStance	0.045956
BlueWeightLbs	0.000000
RedCurrentLoseStreak	0.000000
RedCurrentWinStreak	0.000000
RedDraws	0.000000
RedAvgSigStrLanded	6.969975
RedAvgSigStrPct	5.468750
RedAvgSubAtt	5.468750
RedAvgTDLanded	5.468750
RedAvgTDPct	5.621936
RedLongestWinStreak	0.000000
RedLosses	0.000000
RedTotalRoundsFought	0.000000
RedTotalTitleBouts	0.000000
RedWinsByDecisionMajority	0.000000
RedWinsByDecisionSplit	0.000000
RedWinsByDecisionUnanimous	0.000000
RedWinsByKO	0.000000
RedWinsBySubmission	0.000000
RedWinsByTKODoctorStoppage	0.000000
RedWins	0.000000
RedStance	0.000000
RedWeightLbs	0.000000
RedAge	0.000000
BlueAge	0.000000
LoseStreakDif	0.000000

WinStreakDif	0.000000
LongestWinStreakDif	0.000000
WinDif	0.000000
LossDif	0.000000
TotalRoundDif	0.000000
TotalTitleBoutDif	0.000000
KODif	0.000000
SubDif	0.000000
HeightDif	0.000000
ReachDif	0.000000
AgeDif	0.000000
SigStrDif	0.000000
AvgSubAttDif	0.000000
AvgTDDif	0.000000
EmptyArena	22.763480
BMatchWCRank	81.617647
RMatchWCRank	72.748162
RWFlyweightRank	98.529412
RWFeatherweightRank	99.862132
RWStrawweightRank	97.763480
RWBantamweightRank	97.640931
RHeavyweightRank	97.150735
RLightHeavyweightRank	97.181373
RMiddleweightRank	97.212010
RWelterweightRank	97.074142
RLightweightRank	97.181373
RFeatherweightRank	97.288603
RBantamweightRank	97.227328
RFlyweightRank	97.120098
RPFPRank	96.124387
BWFlyweightRank	98.881740
BWFeatherweightRank	99.984681
BWStrawweightRank	98.468137
BWBantamweightRank	98.360907
BHeavyweightRank	97.732843
BLightHeavyweightRank	98.161765
BMiddleweightRank	97.901348
BWelterweightRank	98.177083
BLightweightRank	98.161765
BFeatherweightRank	98.100490
BBantamweightRank	98.177083
BFlyweightRank	98.008578

BPFPRank	98.973652
BetterRank	0.000000
Finish	3.645833
FinishDetails	55.698529
FinishRound	9.528186
FinishRoundTime	9.528186
TotalFightTimeSecs	9.528186
RedDecOdds	16.651348
BlueDecOdds	17.095588
RSubOdds	20.465686
BSubOdds	20.818015
RK00dds	20.435049
BK00dds	20.833333
WeightClassLabel	0.000000
BlueHeight	0.000000
BlueReach	0.000000
RedHeight	0.000000
RedReach	0.000000
ROver35	0.000000
BOver35	0.000000
RWinPct	7.061887
BWinPct	17.003676
RedStrikingRatio	16.115196
BlueStrikingRatio	16.115196
RedTotalFights	0.000000
BlueTotalFights	0.000000
RedIsGrappler	0.000000
BlueIsGrappler	0.000000
RedIsStriker	0.000000
BlueIsStriker	0.000000
RGrapplerVBStriker	0.000000
BGrapplerVRStriker	0.000000
RedStrikingEfficiency	6.969975
BlueStrikingEfficiency	14.246324
RedTDEfficiency	5.621936
BlueTDEfficiency	12.898284
RedEffectiveTD	14.261642
BlueEffectiveTD	25.000000
EffectiveTDDif	31.433824
RedSize	0.000000
BlueSize	0.000000
Favorite	0.000000

```
FavoriteWins           0.000000
draw_diff              0.000000
avg_sig_str_pct_diff  13.587623
avg_TD_pct_diff       14.598652
win_by_Decision_Majority_diff 0.000000
win_by_Decision_Split_diff   0.000000
win_by_Decision_Unanimous_diff 0.000000
win_by_TKO_Doctor_Stoppage_diff 0.000000
odds_diff               3.645833
ev_diff                 3.645833
dtype: float64
```

```
In [258...]: #count columns with any missing data
columns_with_missing_data = df.isna().any()
number_of_columns_with_missing_data = columns_with_missing_data.sum()
number_of_columns_with_missing_data
```

```
Out[258...]: np.int64(70)
```

```
In [259...]: print(df.shape[0]) # number of rows
print(df.shape[1]) # number of rows
#% of missing values per column
missing_percentage = df.isnull().sum() * 100 / len(df)
print(missing_percentage)
```

6528
150
RedFighter 0.000000
BlueFighter 0.000000
RedOdds 3.477328
BlueOdds 3.462010
RedExpectedValue 3.477328
BlueExpectedValue 3.462010
Winner 0.000000
TitleBout 0.000000
WeightClass 0.000000
Gender 0.000000
NumberOfRounds 0.000000
BlueCurrentLoseStreak 0.000000
BlueCurrentWinStreak 0.000000
BlueDraws 0.000000
BlueAvgSigStrLanded 14.246324
BlueAvgSigStrPct 11.718750
BlueAvgSubAtt 12.745098
BlueAvgTDLanded 12.760417
BlueAvgTDPct 12.898284
BlueLongestWinStreak 0.000000
BlueLosses 0.000000
BlueTotalRoundsFought 0.000000
BlueTotalTitleBouts 0.000000
BlueWinsByDecisionMajority 0.000000
BlueWinsByDecisionSplit 0.000000
BlueWinsByDecisionUnanimous 0.000000
BlueWinsByKO 0.000000
BlueWinsBySubmission 0.000000
BlueWinsByTKODoctorStoppage 0.000000
BlueWins 0.000000
BlueStance 0.045956
BlueWeightLbs 0.000000
RedCurrentLoseStreak 0.000000
RedCurrentWinStreak 0.000000
RedDraws 0.000000
RedAvgSigStrLanded 6.969975
RedAvgSigStrPct 5.468750
RedAvgSubAtt 5.468750
RedAvgTDLanded 5.468750
RedAvgTDPct 5.621936

RedLongestWinStreak	0.000000
RedLosses	0.000000
RedTotalRoundsFought	0.000000
RedTotalTitleBouts	0.000000
RedWinsByDecisionMajority	0.000000
RedWinsByDecisionSplit	0.000000
RedWinsByDecisionUnanimous	0.000000
RedWinsByKO	0.000000
RedWinsBySubmission	0.000000
RedWinsByTKODoctorStoppage	0.000000
RedWins	0.000000
RedStance	0.000000
RedWeightLbs	0.000000
RedAge	0.000000
BlueAge	0.000000
LoseStreakDif	0.000000
WinStreakDif	0.000000
LongestWinStreakDif	0.000000
WinDif	0.000000
LossDif	0.000000
TotalRoundDif	0.000000
TotalTitleBoutDif	0.000000
KODif	0.000000
SubDif	0.000000
HeightDif	0.000000
ReachDif	0.000000
AgeDif	0.000000
SigStrDif	0.000000
AvgSubAttDif	0.000000
AvgTDDif	0.000000
EmptyArena	22.763480
BMatchWCRank	81.617647
RMatchWCRank	72.748162
RWFlyweightRank	98.529412
RWFeatherweightRank	99.862132
RWStrawweightRank	97.763480
RWBantamweightRank	97.640931
RHeavyweightRank	97.150735
RLightHeavyweightRank	97.181373
RMiddleweightRank	97.212010
RWelterweightRank	97.074142
RLightweightRank	97.181373

RFeatherweightRank	97.288603
RBantamweightRank	97.227328
RFlyweightRank	97.120098
RPFPRank	96.124387
BWFlyweightRank	98.881740
BWFeatherweightRank	99.984681
BWStrawweightRank	98.468137
BWBantamweightRank	98.360907
BHeavyweightRank	97.732843
BLightHeavyweightRank	98.161765
BMiddleweightRank	97.901348
BWelterweightRank	98.177083
BLightweightRank	98.161765
BFeatherweightRank	98.100490
BBantamweightRank	98.177083
BFlyweightRank	98.008578
BPFPRank	98.973652
BetterRank	0.000000
Finish	3.645833
FinishDetails	55.698529
FinishRound	9.528186
FinishRoundTime	9.528186
TotalFightTimeSecs	9.528186
RedDecOdds	16.651348
BlueDecOdds	17.095588
RSubOdds	20.465686
BSubOdds	20.818015
RK00dds	20.435049
BK00dds	20.833333
WeightClassLabel	0.000000
BlueHeight	0.000000
BlueReach	0.000000
RedHeight	0.000000
RedReach	0.000000
ROver35	0.000000
BOver35	0.000000
RWinPct	7.061887
BWinPct	17.003676
RedStrikingRatio	16.115196
BlueStrikingRatio	16.115196
RedTotalFights	0.000000
BlueTotalFights	0.000000

```

RedIsGrappler           0.000000
BlueIsGrappler          0.000000
RedIsStriker            0.000000
BlueIsStriker           0.000000
RGrapplerVBStriker     0.000000
BGrapplerVRStriker     0.000000
RedStrikingEfficiency   6.969975
BlueStrikingEfficiency  14.246324
RedTDEfficiency         5.621936
BlueTDEfficiency        12.898284
RedEffectiveTD          14.261642
BlueEffectiveTD         25.000000
EffectiveTDDif          31.433824
RedSize                 0.000000
BlueSize                0.000000
Favorite                0.000000
FavoriteWins             0.000000
draw_diff               0.000000
avg_sig_str_pct_diff    13.587623
avg_TD_pct_diff         14.598652
win_by_Decision_Majority_diff 0.000000
win_by_Decision_Split_diff 0.000000
win_by_Decision_Unanimous_diff 0.000000
win_by_TKO_Doctor_Stoppage_diff 0.000000
odds_diff               3.645833
ev_diff                 3.645833
dtype: float64

```

```

In [260... # y = df['Winner']
# X = df.drop(columns=['Winner'])

# # Encode target variable labels as integers
# le = LabelEncoder()
# y = le.fit_transform(y)

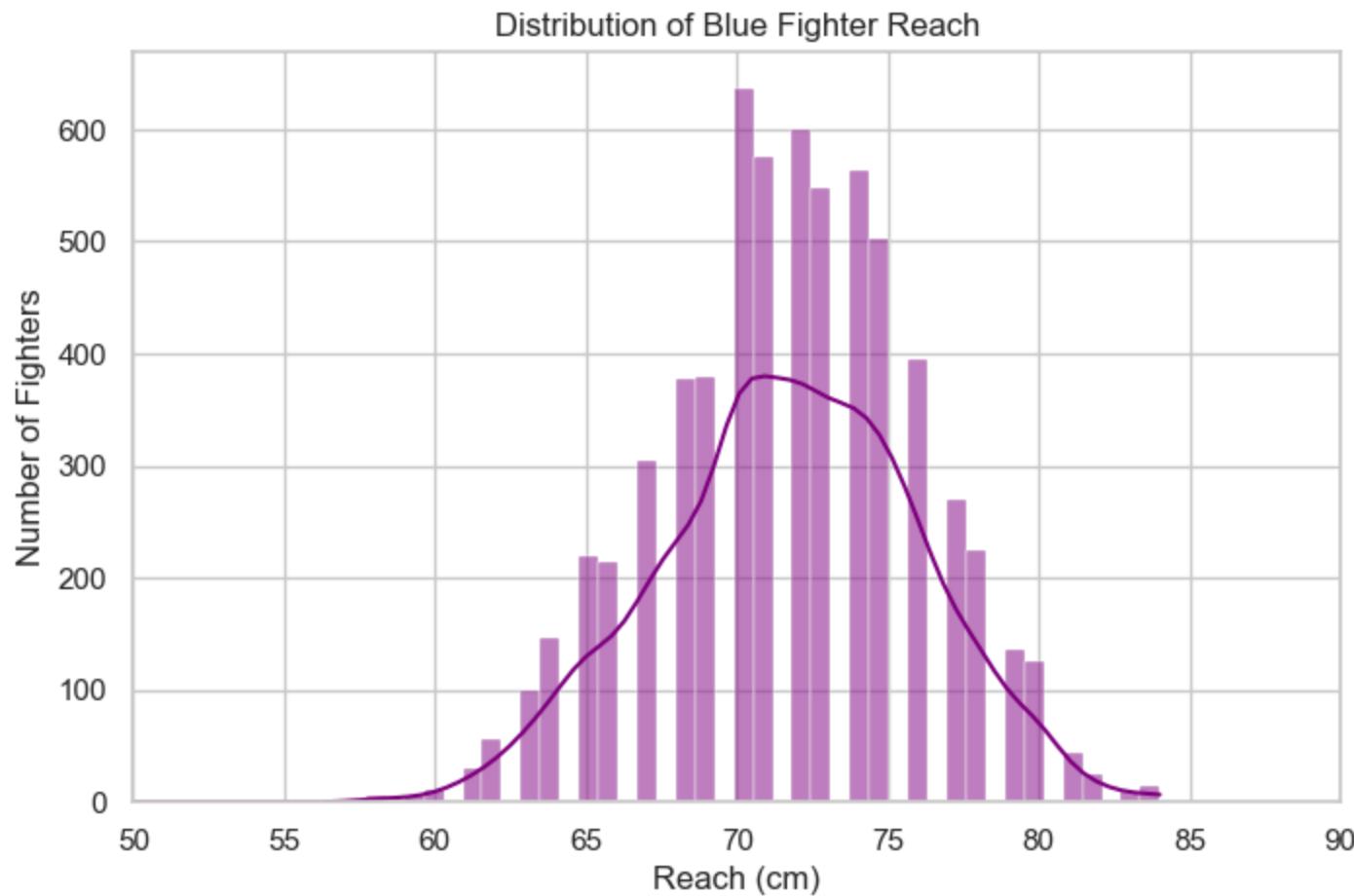
```

```

In [261... plt.figure(figsize=(8, 5))
sns.histplot(df['BlueReach'], kde=True, color='purple')
plt.title('Distribution of Blue Fighter Reach')
plt.xlabel('Reach (cm)')
plt.ylabel('Number of Fighters')
plt.xlim(50, 90) # limit x-axis range to be reasonable bc who has a 20in reach?
fig_name = "dist_blue_reach"

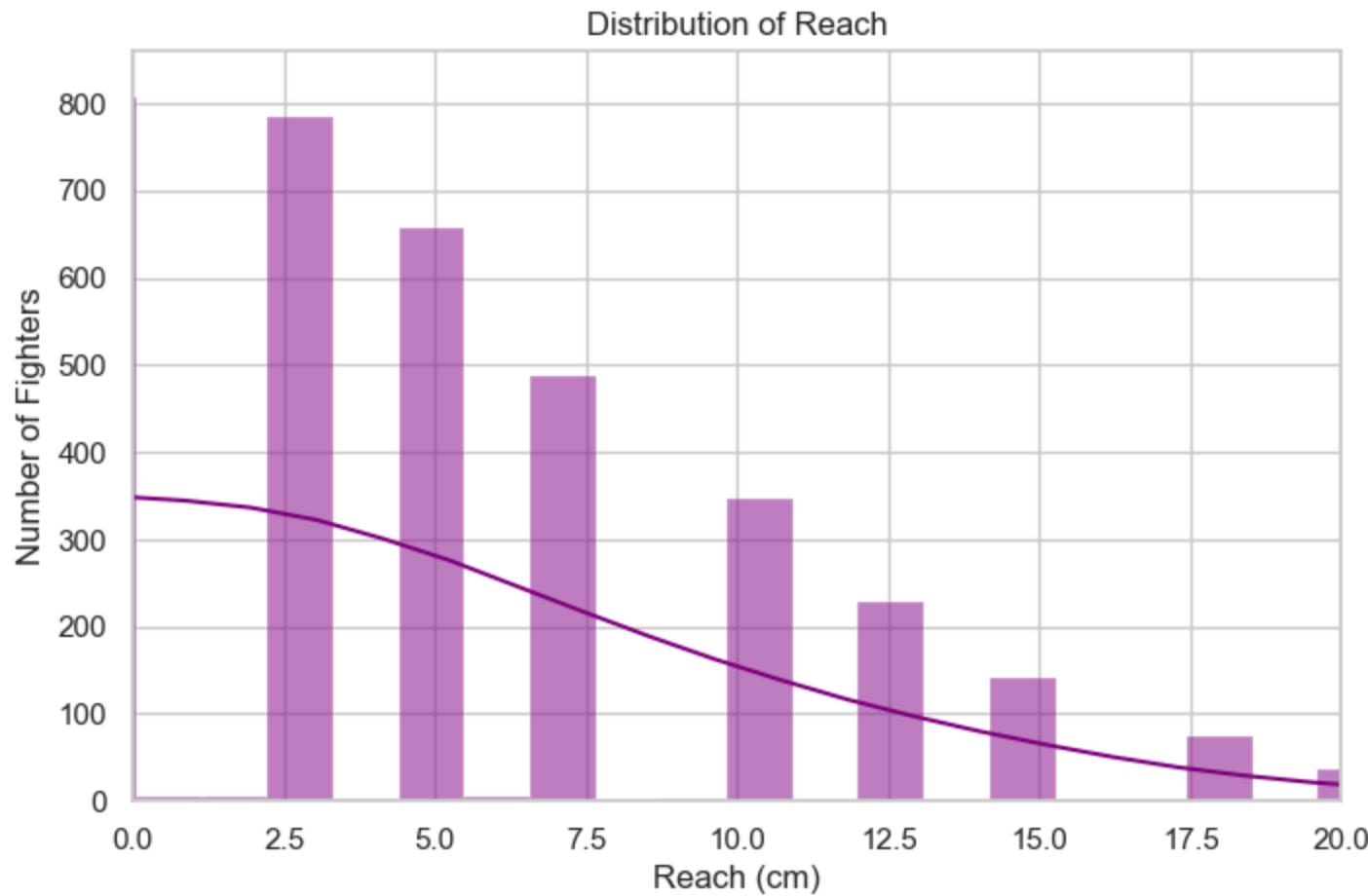
```

```
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



```
In [262]: plt.figure(figsize=(8, 5))
sns.histplot(df['ReachDiff'], kde=True, color='purple')
plt.title('Distribution of Reach')
plt.xlabel('Reach (cm)')
plt.ylabel('Number of Fighters')
plt.xlim(0, 20) # limit x-axis range to be reasonable bc who has a 20in reach?
fig_name = "dist_reach"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
```

```
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



```
In [263...]: df['StanceCombo'] = df['RedStance'].astype(str) + ' vs ' + df['BlueStance'].astype(str)

plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='RWinPct', y='BWinPct', hue='StanceCombo', palette='Set2', alpha=0.7)
plt.title('Red Win % vs Blue Win % by Stance Matchup')
plt.xlabel('Red Win Percentage')
plt.ylabel('Blue Win Percentage')
plt.legend(title='Stance Matchup', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
```

```
fig_name = "stance_combo"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



```
In [264]: print(df.dtypes)
```

RedFighter	int64
BlueFighter	int64
RedOdds	float64
BlueOdds	float64
RedExpectedValue	float64
BlueExpectedValue	float64
Winner	object
TitleBout	bool
WeightClass	int64
Gender	int64
NumberOfRounds	int64
BlueCurrentLoseStreak	int64
BlueCurrentWinStreak	int64
BlueDraws	int64
BlueAvgSigStrLanded	float64
BlueAvgSigStrPct	float64
BlueAvgSubAtt	float64
BlueAvgTDLanded	float64
BlueAvgTDPct	float64
BlueLongestWinStreak	int64
BlueLosses	int64
BlueTotalRoundsFought	int64
BlueTotalTitleBouts	int64
BlueWinsByDecisionMajority	int64
BlueWinsByDecisionSplit	int64
BlueWinsByDecisionUnanimous	int64
BlueWinsByKO	int64
BlueWinsBySubmission	int64
BlueWinsByTKODoctorStoppage	int64
BlueWins	int64
BlueStance	object
BlueWeightLbs	int64
RedCurrentLoseStreak	int64
RedCurrentWinStreak	int64
RedDraws	int64
RedAvgSigStrLanded	float64
RedAvgSigStrPct	float64
RedAvgSubAtt	float64
RedAvgTDLanded	float64
RedAvgTDPct	float64
RedLongestWinStreak	int64
RedLosses	int64

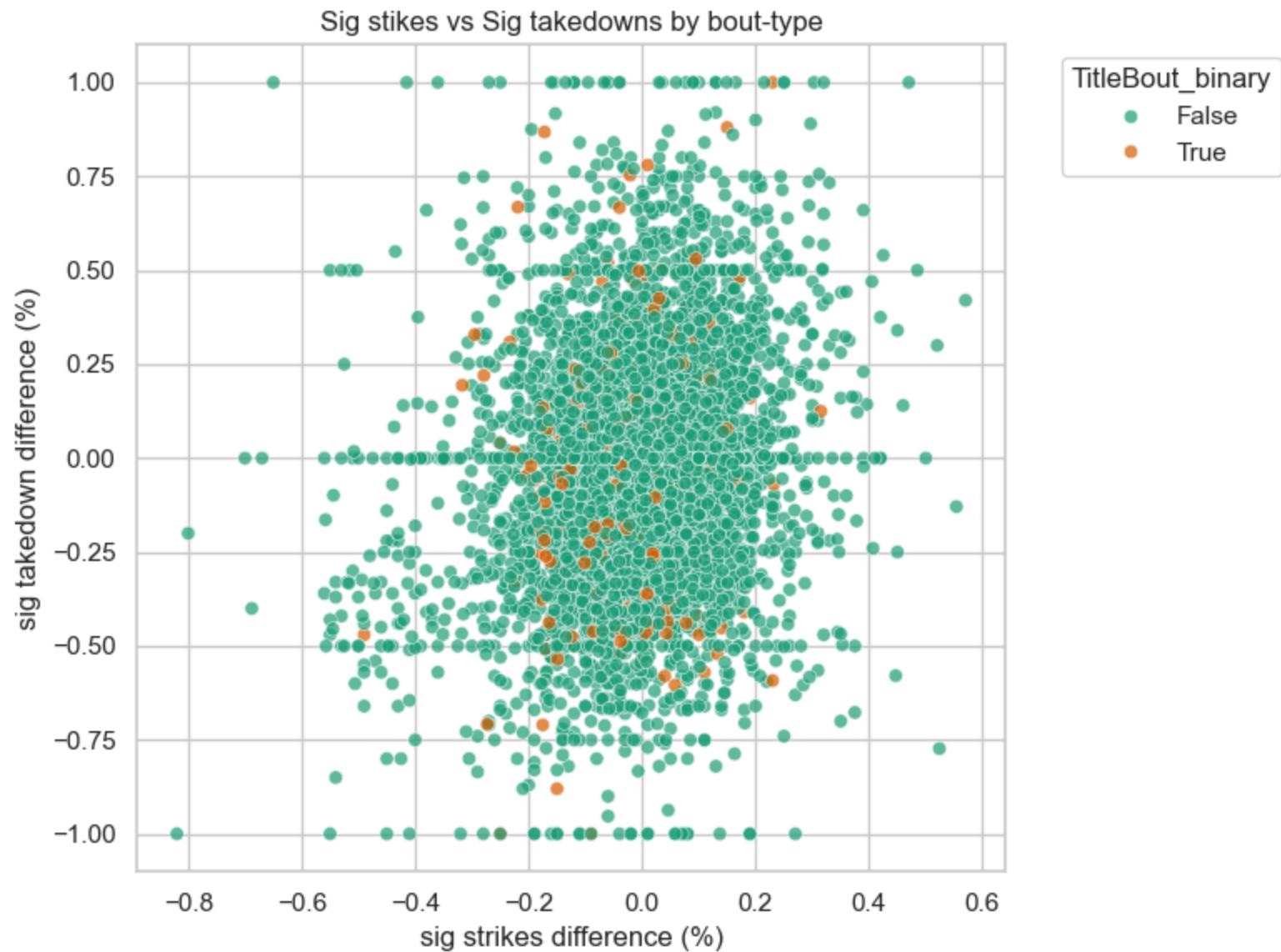
RedTotalRoundsFought	int64
RedTotalTitleBouts	int64
RedWinsByDecisionMajority	int64
RedWinsByDecisionSplit	int64
RedWinsByDecisionUnanimous	int64
RedWinsByKO	int64
RedWinsBySubmission	int64
RedWinsByTKODoctorStoppage	int64
RedWins	int64
RedStance	object
RedWeightLbs	int64
RedAge	int64
BlueAge	int64
LoseStreakDif	int64
WinStreakDif	int64
LongestWinStreakDif	int64
WinDif	int64
LossDif	int64
TotalRoundDif	int64
TotalTitleBoutDif	int64
KODif	int64
SubDif	int64
HeightDif	float64
ReachDif	float64
AgeDif	int64
SigStrDif	float64
AvgSubAttDif	float64
AvgTDDif	float64
EmptyArena	float64
BMatchWCRank	float64
RMatchWCRank	float64
RWFlyweightRank	float64
RWFeatherweightRank	float64
RWStrawweightRank	float64
RWBantamweightRank	float64
RHeavyweightRank	float64
RLightHeavyweightRank	float64
RMiddleweightRank	float64
RWelterweightRank	float64
RLightweightRank	float64
RFeatherweightRank	float64
RBantamweightRank	float64

RFlyweightRank	float64
RPFPRank	float64
BWFlyweightRank	float64
BWFeatherweightRank	float64
BWStrawweightRank	float64
BWBantamweightRank	float64
BHeavyweightRank	float64
BLightHeavyweightRank	float64
BMiddleweightRank	float64
BWelterweightRank	float64
BLightweightRank	float64
BFeatherweightRank	float64
BBantamweightRank	float64
BFlyweightRank	float64
BPFPRank	float64
BetterRank	object
Finish	object
FinishDetails	object
FinishRound	float64
FinishRoundTime	object
TotalFightTimeSecs	float64
RedDecOdds	float64
BlueDecOdds	float64
RSubOdds	float64
BSubOdds	float64
RK00dds	float64
BK00dds	float64
WeightClassLabel	object
BlueHeight	float64
BlueReach	float64
RedHeight	float64
RedReach	float64
ROver35	int64
BOver35	int64
RWinPct	float64
BWinPct	float64
RedStrikingRatio	float64
BlueStrikingRatio	float64
RedTotalFights	int64
BlueTotalFights	int64
RedIsGrappler	int64
BlueIsGrappler	int64

```
RedIsStriker           int64
BlueIsStriker          int64
RGrapplerVBStriker    int64
BGrapplerVRStriker    int64
RedStrikingEfficiency float64
BlueStrikingEfficiency float64
RedTDEfficiency       float64
BlueTDEfficiency      float64
RedEffectiveTD         float64
BlueEffectiveTD        float64
EffectiveTDDif         float64
RedSize                float64
BlueSize               float64
Favorite               object
FavoriteWins            int64
draw_diff               int64
avg_sig_str_pct_diff   float64
avg_TD_pct_diff        float64
win_by_Decision_Majority_diff int64
win_by_Decision_Split_diff   int64
win_by_Decision_Unanimous_diff int64
win_by_TKO_Doctor_Stoppage_diff int64
odds_diff               float64
ev_diff                 float64
StanceCombo             object
dtype: object
```

```
In [265]: plt.figure(figsize=(8, 6))
sns.scatterplot(
    data=df,
    x='avg_sig_str_pct_diff',
    y='avg_TD_pct_diff',
    hue='TitleBout',
    palette='Dark2',
    alpha=0.7
)
plt.title('Sig strikes vs Sig takedowns by bout-type')
plt.xlabel('sig strikes difference (%)')
plt.ylabel('sig takedown difference (%)')
plt.legend(title='TitleBout_binary', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
fig_name = "sigstrikes_sigtakedowns"
```

```
fig_path = os.path.join(output_folder, f'{fig_name}.png')
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



```
In [266]: # a list of all fighter names from the red and blue corner
all_fighters_df = pd.concat([df.RedFighter, df.BlueFighter], ignore_index = True)
```

```
# how many unique names there are
all_fighters_nbr = all_fighters_df.nunique()
print(all_fighters_nbr)

# a list of all fighter names from the red and blue corner
all_fighters_df = pd.concat([df.RedFighter, df.BlueFighter], ignore_index = True)

#check how many unique names there are
all_fighters_nbr = all_fighters_df.nunique()
print(all_fighters_nbr)

df['WeightClass'].value_counts()
```

1922

1922

Out[266...]: WeightClass

6	1074
8	1026
7	783
2	754
0	679
5	501
4	496
3	353
12	320
11	239
9	213
1	61
10	29

Name: count, dtype: int64

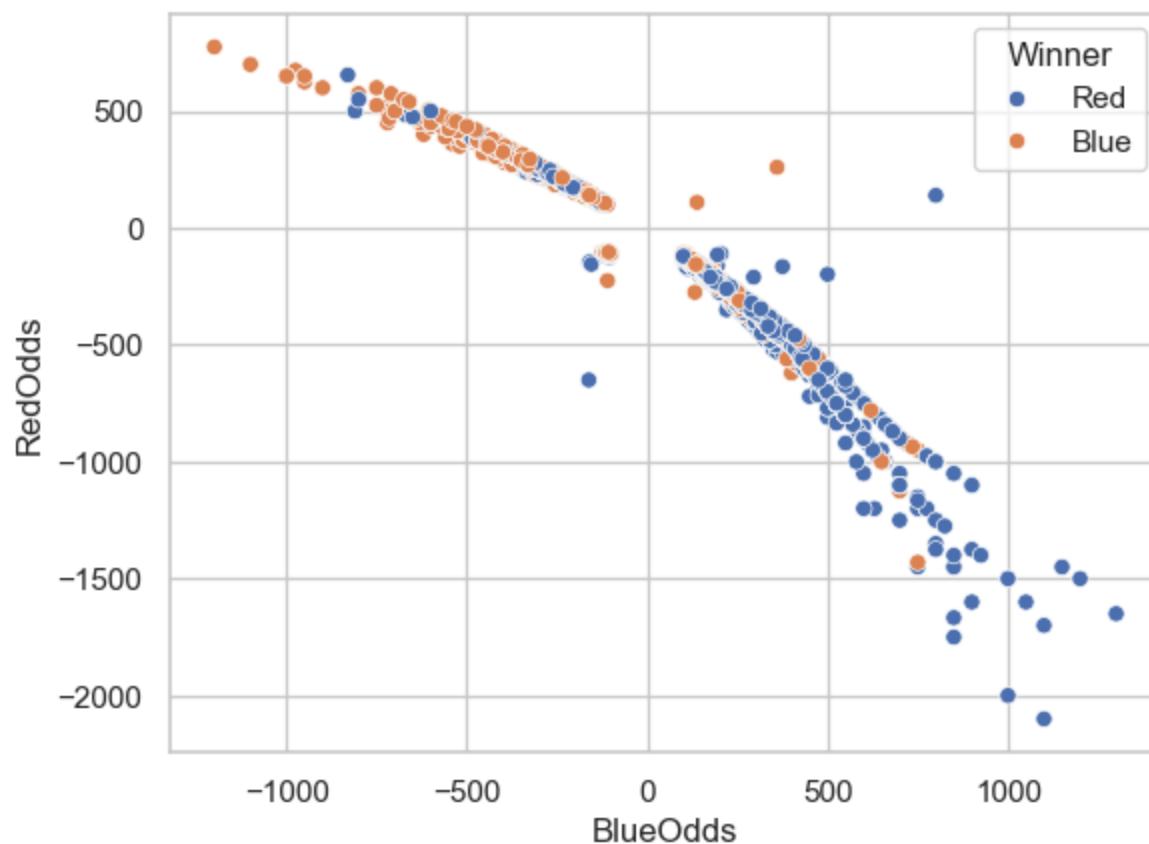
In [267...]:

```
#remove possible leading and trailing spaces in all 'object' columns
ufc_obj = df.select_dtypes(['object'])
df[ufc_obj.columns] = ufc_obj.apply(lambda x: x.str.strip()) # Apply over every column function lambda
#categorical
print(df['Finish'].value_counts())
#filtering
kos_by_round = df[['Finish', 'FinishRound']].query('Finish == "KO/TKO"') # Create new filtered dataframe
# kos_by_round
```

```
Finish
U-DEC      2404
K0/TK0     2009
SUB        1157
S-DEC      654
M-DEC      46
DQ         18
Overturned  2
Name: count, dtype: int64
```

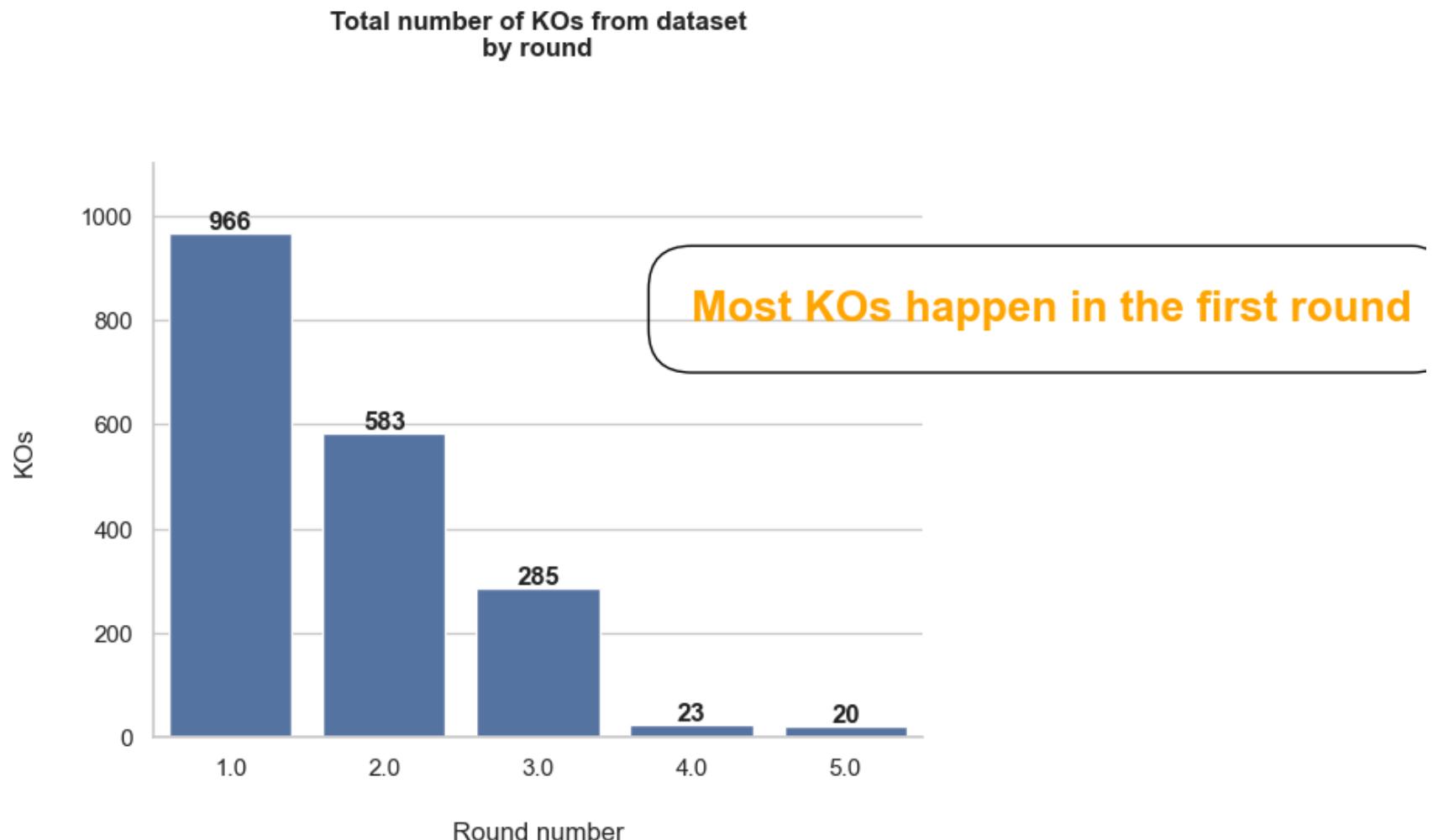
```
In [268...]: #Analysing "_odds" variables
sns.scatterplot(x="BlueOdds", y="RedOdds", hue="Winner", data = df)
df["Winner"].loc[df["BlueOdds"]>1].value_counts()
```

```
Out[268...]: Winner
Red      2659
Blue     1159
Name: count, dtype: int64
```



In [269]:

```
K0s = sns.countplot(x = kos_by_round['FinishRound']);
plt.title('Total number of KOs from dataset\nby round', pad = 50, weight = 'bold') # \n for line break. S:
plt.xlabel('Round number', labelpad = 20) # Label weight set to bold in general settings
plt.ylabel('KOs', labelpad = 20)
sns.despine() # Remove top and right border
plt.ylim([0,1100])
plt.bar_label(K0s.containers[0], weight = 'bold') # Add number labels on top of bars
plt.text(x = 3, y = 800, s = 'Most KOs happen in the first round', fontdict = {'size' : 20, 'weight' : 'bo'}
```



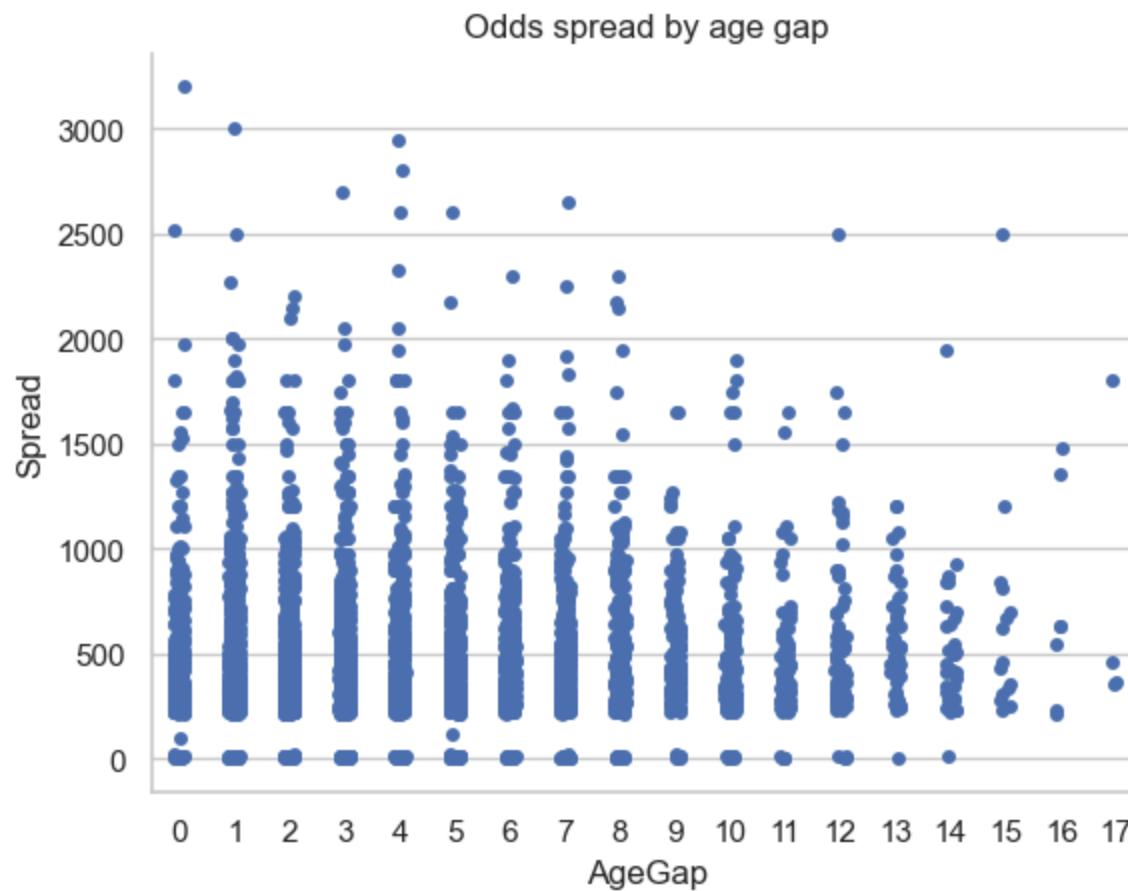
```
In [270...]: # Calculate the age gap
df['AgeGap'] = abs(df['RedAge'] - df['BlueAge'])
# df[['AgeGap', 'RedAge', 'BlueAge']]
```

```
In [271...]: # Create a function to calculate the spread as positive number
def spread_calculation(RedOdds, BlueOdds):
    if RedOdds > 0 and BlueOdds > 0:
        return max(RedOdds, BlueOdds) - min(RedOdds, BlueOdds)
    else:
        return abs(RedOdds - BlueOdds)
```

```
# Create column that holds the spread
df['Spread'] = df.apply(lambda row: spread_calculation(row['RedOdds'], row['BlueOdds']), axis=1)

# Check results
# df[['RedOdds', 'BlueOdds', 'Spread']]
```

```
In [272...]: sns.stripplot(data = df, x = 'AgeGap', y = 'Spread').set(title = 'Odds spread by age gap')
sns.despine()
```



```
In [273...]: # Create a frequency table
win_counts = df['Winner'].value_counts()
# Display the frequency table
```

```
print("Frequency Table for 'Winner' column:")
print(win_counts)
```

```
Frequency Table for 'Winner' column:
Winner
Red      3787
Blue     2741
Name: count, dtype: int64
```

```
In [274...]: # To get proportions instead of counts
check_win = df['Winner'].value_counts(normalize=True)
print("\nProportion Table for 'Winner' column:")
print(check_win)
```

```
Proportion Table for 'Winner' column:
Winner
Red      0.580116
Blue     0.419884
Name: proportion, dtype: float64
```

```
In [275...]: print(df.dtypes)
# How many rows and columns do we have in df_merge?
print(df.shape[0]) # number of rows
print(df.shape[1]) # number of rows

print(len(df))
df.head()
```

RedFighter	int64
BlueFighter	int64
RedOdds	float64
BlueOdds	float64
RedExpectedValue	float64
BlueExpectedValue	float64
Winner	object
TitleBout	bool
WeightClass	int64
Gender	int64
NumberOfRounds	int64
BlueCurrentLoseStreak	int64
BlueCurrentWinStreak	int64
BlueDraws	int64
BlueAvgSigStrLanded	float64
BlueAvgSigStrPct	float64
BlueAvgSubAtt	float64
BlueAvgTDLanded	float64
BlueAvgTDPct	float64
BlueLongestWinStreak	int64
BlueLosses	int64
BlueTotalRoundsFought	int64
BlueTotalTitleBouts	int64
BlueWinsByDecisionMajority	int64
BlueWinsByDecisionSplit	int64
BlueWinsByDecisionUnanimous	int64
BlueWinsByKO	int64
BlueWinsBySubmission	int64
BlueWinsByTKODoctorStoppage	int64
BlueWins	int64
BlueStance	object
BlueWeightLbs	int64
RedCurrentLoseStreak	int64
RedCurrentWinStreak	int64
RedDraws	int64
RedAvgSigStrLanded	float64
RedAvgSigStrPct	float64
RedAvgSubAtt	float64
RedAvgTDLanded	float64
RedAvgTDPct	float64
RedLongestWinStreak	int64
RedLosses	int64

RedTotalRoundsFought	int64
RedTotalTitleBouts	int64
RedWinsByDecisionMajority	int64
RedWinsByDecisionSplit	int64
RedWinsByDecisionUnanimous	int64
RedWinsByKO	int64
RedWinsBySubmission	int64
RedWinsByTKODoctorStoppage	int64
RedWins	int64
RedStance	object
RedWeightLbs	int64
RedAge	int64
BlueAge	int64
LoseStreakDif	int64
WinStreakDif	int64
LongestWinStreakDif	int64
WinDif	int64
LossDif	int64
TotalRoundDif	int64
TotalTitleBoutDif	int64
KODif	int64
SubDif	int64
HeightDif	float64
ReachDif	float64
AgeDif	int64
SigStrDif	float64
AvgSubAttDif	float64
AvgTDDif	float64
EmptyArena	float64
BMatchWCRank	float64
RMatchWCRank	float64
RWFlyweightRank	float64
RWFeatherweightRank	float64
RWStrawweightRank	float64
RWBantamweightRank	float64
RHeavyweightRank	float64
RLightHeavyweightRank	float64
RMiddleweightRank	float64
RWelterweightRank	float64
RLightweightRank	float64
RFeatherweightRank	float64
RBantamweightRank	float64

RFlyweightRank	float64
RPFPRank	float64
BWFlyweightRank	float64
BWFeatherweightRank	float64
BWStrawweightRank	float64
BWBantamweightRank	float64
BHeavyweightRank	float64
BLightHeavyweightRank	float64
BMiddleweightRank	float64
BWelterweightRank	float64
BLightweightRank	float64
BFeatherweightRank	float64
BBantamweightRank	float64
BFlyweightRank	float64
BPFPRank	float64
BetterRank	object
Finish	object
FinishDetails	object
FinishRound	float64
FinishRoundTime	object
TotalFightTimeSecs	float64
RedDecOdds	float64
BlueDecOdds	float64
RSubOdds	float64
BSubOdds	float64
RK00dds	float64
BK00dds	float64
WeightClassLabel	object
BlueHeight	float64
BlueReach	float64
RedHeight	float64
RedReach	float64
ROver35	int64
BOver35	int64
RWinPct	float64
BWinPct	float64
RedStrikingRatio	float64
BlueStrikingRatio	float64
RedTotalFights	int64
BlueTotalFights	int64
RedIsGrappler	int64
BlueIsGrappler	int64

RedIsStriker	int64
BlueIsStriker	int64
RGrapplerVBStriker	int64
BGrapplerVRStriker	int64
RedStrikingEfficiency	float64
BlueStrikingEfficiency	float64
RedTDEfficiency	float64
BlueTDEfficiency	float64
RedEffectiveTD	float64
BlueEffectiveTD	float64
EffectiveTDDif	float64
RedSize	float64
BlueSize	float64
Favorite	object
FavoriteWins	int64
draw_diff	int64
avg_sig_str_pct_diff	float64
avg_TD_pct_diff	float64
win_by_Decision_Majority_diff	int64
win_by_Decision_Split_diff	int64
win_by_Decision_Unanimous_diff	int64
win_by_TKO_Doctor_Stoppage_diff	int64
odds_diff	float64
ev_diff	float64
StanceCombo	object
AgeGap	int64
Spread	float64
dtype: object	
6528	
153	
6528	

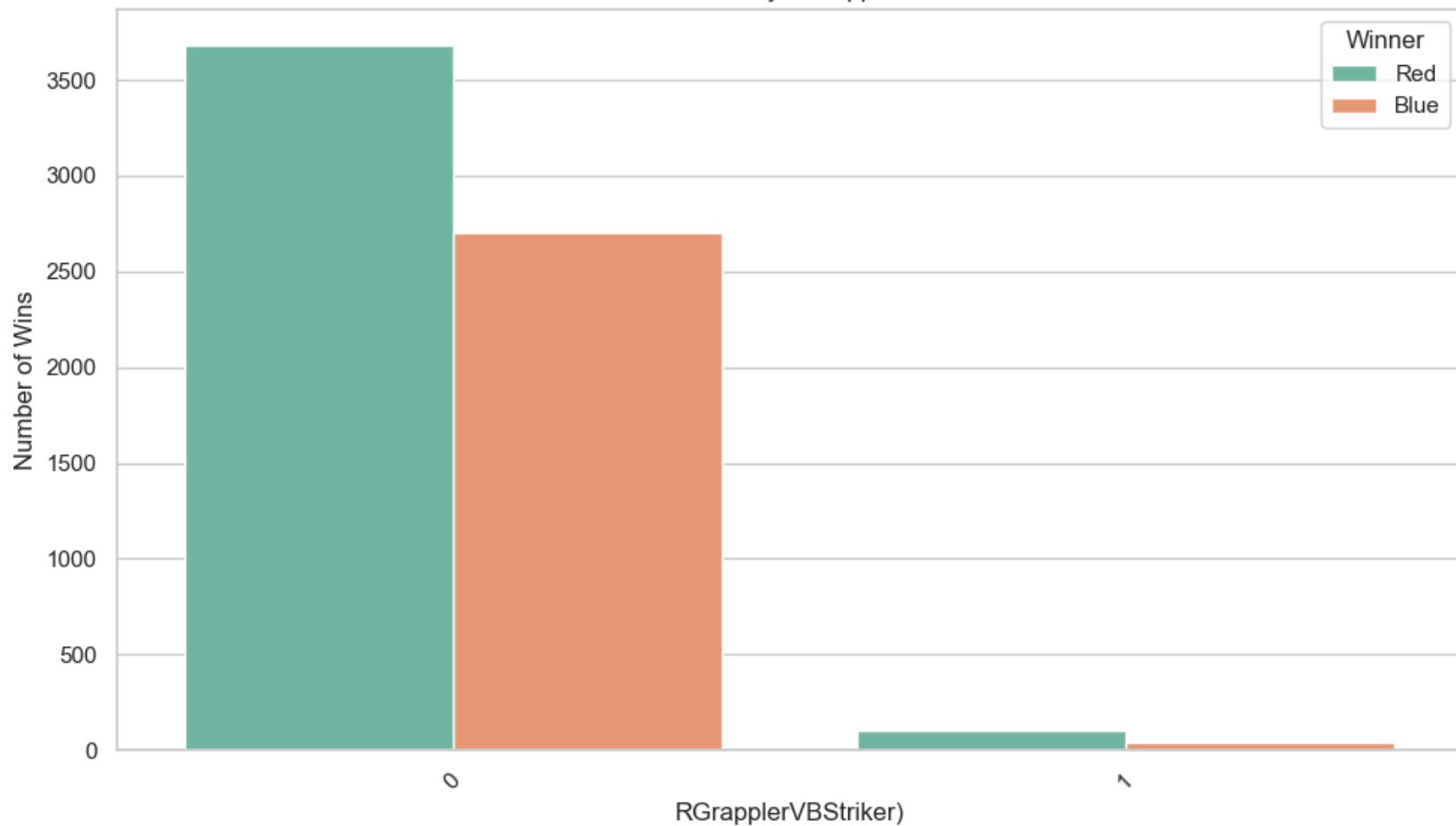
Out [275...]

	RedFighter	BlueFighter	RedOdds	BlueOdds	RedExpectedValue	BlueExpectedValue	Winner	TitleBout	WeightClass
0	66	1009	-250.0	215.0	40.0000	215.0	Red	True	3
1	1441	718	-210.0	295.0	47.6190	295.0	Red	False	8
2	307	67	-380.0	300.0	26.3158	300.0	Red	False	4
3	221	1071	-950.0	625.0	10.5263	625.0	Red	False	2
4	1183	524	-130.0	110.0	76.9231	110.0	Blue	False	2

In [276...]

```
# Plot: Count of Winners per Matchup type
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='RGrapplerVBStriker', hue='Winner', palette='Set2')
plt.title('Match Outcome by RGrapplerVBStriker')
plt.xlabel('RGrapplerVBStriker')
plt.ylabel('Number of Wins')
plt.xticks(rotation=45)
plt.tight_layout()
fig_name = "grappler_v_striker"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```

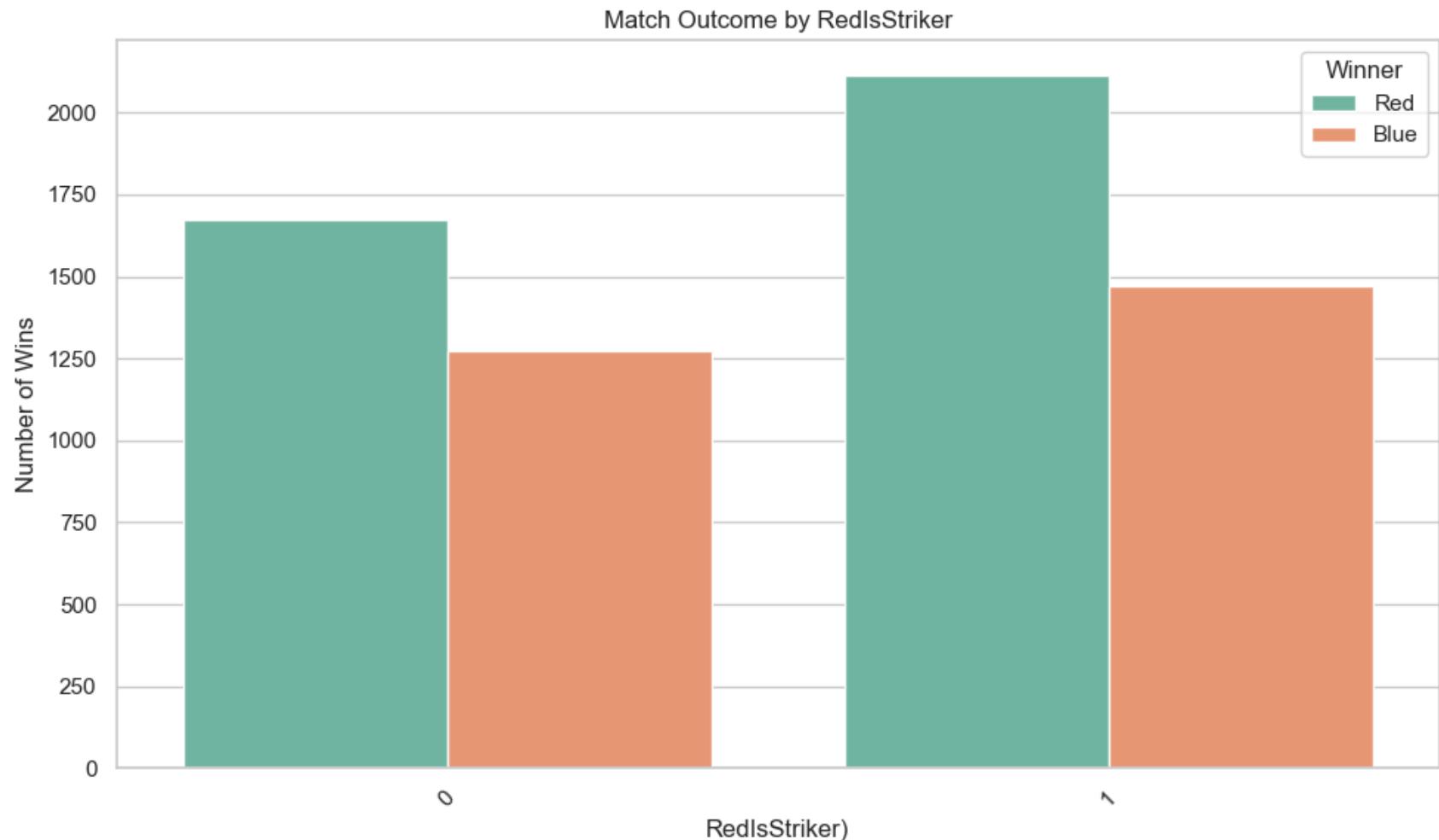
Match Outcome by RGrapplerVBStriker



```
In [277]: # Create a new combined column for Red vs Blue matchup  
#df['Matchup'] = df['RGrapplerVBStriker'].astype(str)
```

```
# Plot: Count of Winners per Matchup type  
plt.figure(figsize=(10, 6))  
sns.countplot(data=df, x='RedIsStriker', hue='Winner', palette='Set2')  
plt.title('Match Outcome by RedIsStriker')  
plt.xlabel('RedIsStriker')  
plt.ylabel('Number of Wins')  
plt.xticks(rotation=45)  
plt.tight_layout()
```

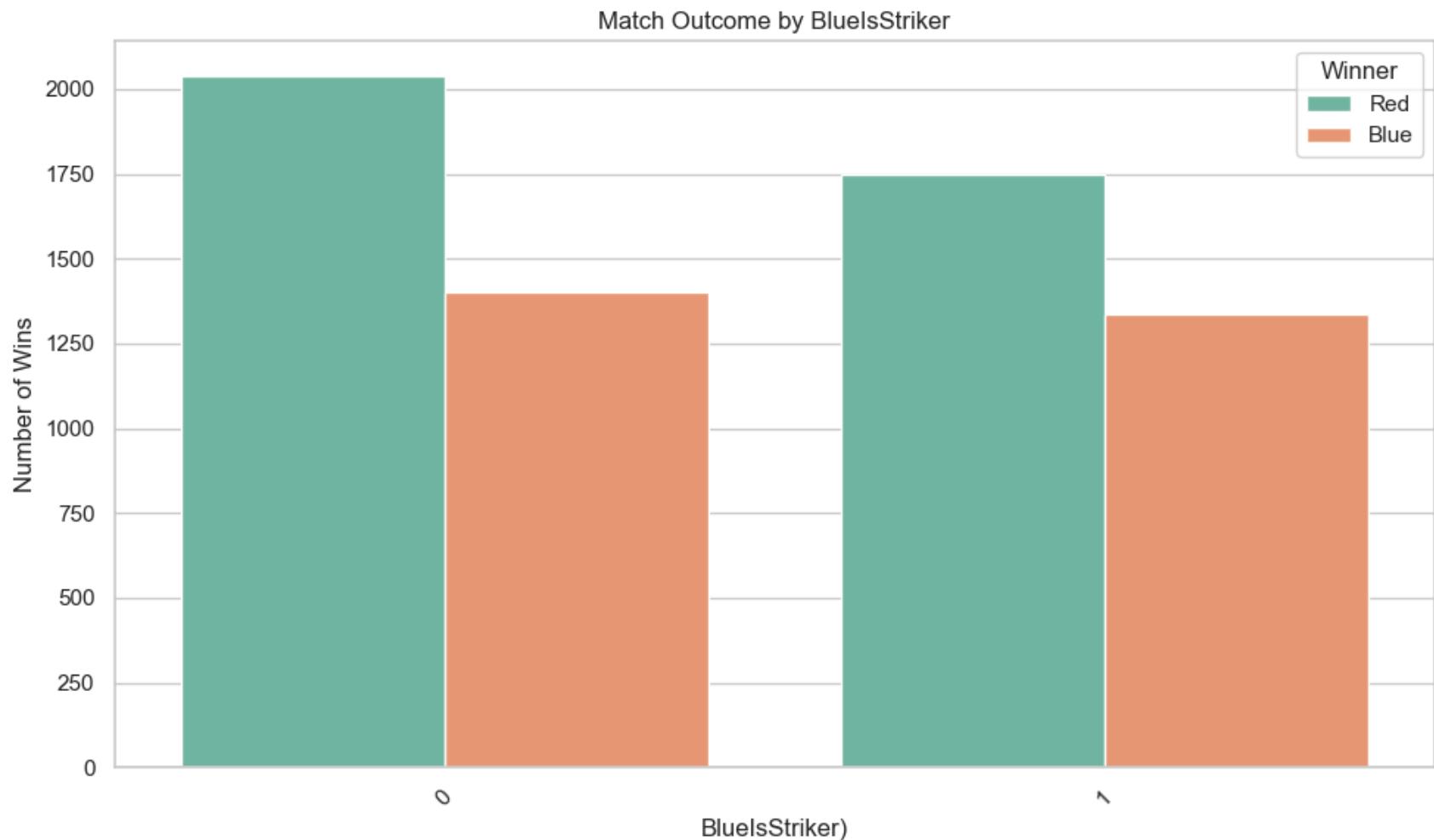
```
fig_name = "redstriker"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



In [278...]

```
# Plot: Count of Winners per Matchup type
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='BlueIsStriker', hue='Winner', palette='Set2')
plt.title('Match Outcome by BlueIsStriker')
plt.xlabel('BlueIsStriker')
```

```
plt.ylabel('Number of Wins')
plt.xticks(rotation=45)
plt.tight_layout()
fig_name = "bluestriker"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```



In [279]:
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline

```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder, LabelEncoder
from sklearn.compose import ColumnTransformer
import numpy as np

# Convert TitleBout to string "True"/"False" for encoding
if 'TitleBout' in df.columns:
    df['TitleBout'] = df['TitleBout'].astype(str)

categorical_nominal = [
    'Country', 'BlueStance', 'RedStance', 'BetterRank',
    'Finish', 'FinishDetails', 'FinishRoundTime',
    'Favorite', 'StanceCombo', 'TitleBout', "WeightClass"
]

numeric_features = [
    'RedOdds', 'BlueOdds', 'RedExpectedValue', 'BlueExpectedValue',
    'NumberOfRounds', 'BlueCurrentLoseStreak', 'BlueCurrentWinStreak', 'BlueDraws',
    'BlueAvgSigStrLanded', 'BlueAvgSigStrPct', 'BlueAvgSubAtt', 'BlueAvgTDLanded', 'BlueAvgTDPct',
    'BlueLongestWinStreak', 'BlueLosses', 'BlueTotalRoundsFought', 'BlueTotalTitleBouts',
    'BlueWinsByDecisionMajority', 'BlueWinsByDecisionSplit', 'BlueWinsByDecisionUnanimous',
    'BlueWinsByKO', 'BlueWinsBySubmission', 'BlueWinsByTKODoctorStoppage', 'BlueWins',
    'BlueWeightLbs', 'BlueAge',

    'RedCurrentLoseStreak', 'RedCurrentWinStreak', 'RedDraws',
    'RedAvgSigStrLanded', 'RedAvgSigStrPct', 'RedAvgSubAtt', 'RedAvgTDLanded', 'RedAvgTDPct',
    'RedLongestWinStreak', 'RedLosses', 'RedTotalRoundsFought', 'RedTotalTitleBouts',
    'RedWinsByDecisionMajority', 'RedWinsByDecisionSplit', 'RedWinsByDecisionUnanimous',
    'RedWinsByKO', 'RedWinsBySubmission', 'RedWinsByTKODoctorStoppage', 'RedWins',
    'RedWeightLbs', 'RedAge',

    'LoseStreakDif', 'WinStreakDif', 'LongestWinStreakDif', 'WinDif', 'LossDif', 'TotalRoundDif', 'TotalTi-
    'KODif', 'SubDif', 'HeightDif', 'ReachDif', 'AgeDif', 'SigStrDif', 'AvgSubAttDif', 'AvgTDDif',
    'EmptyArena',

    'BMatchWCRank', 'RMatchWCRank',
    'RWFlyweightRank', 'RwFeatherweightRank', 'RWStrawweightRank', 'RWBantamweightRank', 'RHeavyweightRank',
    'RLightHeavyweightRank', 'RMiddleweightRank', 'RWelterweightRank', 'RLightweightRank', 'RFeatherweight
]
```

```

'RBantamweightRank', 'RFlyweightRank', 'RPFPRank',
'BWFlyweightRank', 'BWFeatherweightRank', 'BWStrawweightRank', 'BWBantamweightRank', 'BHeavyweightRank',
'BLightHeavyweightRank', 'BMiddleweightRank', 'BWelterweightRank', 'BLightweightRank', 'BFeatherweightRank',
'BBantamweightRank', 'BFlyweightRank', 'BPFPRank',

'FinishRound', 'TotalFightTimeSecs',
'RedDecOdds', 'BlueDecOdds', 'RSubOdds', 'BSubOdds', 'RK00dds', 'BK00dds',
'BlueHeight', 'BlueReach', 'RedHeight', 'RedReach',
'ROver35', 'BOver35',
'RWinPct', 'BWinPct',
'RedStrikingRatio', 'BlueStrikingRatio',
'RedTotalFights', 'BlueTotalFights',
'RedIsGrappler', 'BlueIsGrappler', 'RedIsStriker', 'BlueIsStriker',
'RGrapplerVBStriker', 'BGrapplerVRStriker',
'RedStrikingEfficiency', 'BlueStrikingEfficiency',
'RedTDEfficiency', 'BlueTDEfficiency',
'RedEffectiveTD', 'BlueEffectiveTD',
'EffectiveTDDif',
'RedSize', 'BlueSize',
'FavoriteWins', 'draw_diff',
'avg_sig_str_pct_diff', 'avg_TD_pct_diff',
'win_by_Decision_Majority_diff', 'win_by_Decision_Split_diff', 'win_by_Decision_Unanimous_diff',
'win_by_TKO_Doctor_Stoppage_diff', 'odds_diff', 'ev_diff'
]

# Replace infinite values with NaN in numeric features ---
df[numeric_features] = df[numeric_features].replace([np.inf, -np.inf], np.nan)

# numeric_transformer = Pipeline([
#     ('imputer', SimpleImputer(strategy='mean')),
#     ('scaler', StandardScaler())
# ])

# categorical_nominal_transformer = Pipeline([
#     ('imputer', SimpleImputer(strategy='most_frequent')),
#     ('onehot', OneHotEncoder(sparse_output=False, handle_unknown='ignore'))
# ])

```

```
# categorical_ordered_transformer = Pipeline([
#     ('imputer', SimpleImputer(strategy='most_frequent')),
#     # ('ordinal', OrdinalEncoder(categories=ordinal_cats))
# ])

# processor = ColumnTransformer(
#     transformers=[
#         ('num', numeric_transformer, numeric_features),
#         ('cat', categorical_nominal_transformer, categorical_nominal)
#     ])

# prep = Pipeline(steps=[('processor', processor)])
```

In [280...]

```
print(df.dtypes)
print(df.shape[0]) # number of rows
print(df.shape[1]) # number of columns
print(len(df))
df.head()
for column in df.columns:
    unique_values = df[column].unique()
    print(f"Unique values in column '{column}': {unique_values}")
    print(f"Number of unique values in column '{column}': {len(unique_values)}\n")
```

RedFighter	int64
BlueFighter	int64
RedOdds	float64
BlueOdds	float64
RedExpectedValue	float64
BlueExpectedValue	float64
Winner	object
TitleBout	object
WeightClass	int64
Gender	int64
NumberOfRounds	int64
BlueCurrentLoseStreak	int64
BlueCurrentWinStreak	int64
BlueDraws	int64
BlueAvgSigStrLanded	float64
BlueAvgSigStrPct	float64
BlueAvgSubAtt	float64
BlueAvgTDLanded	float64
BlueAvgTDPct	float64
BlueLongestWinStreak	int64
BlueLosses	int64
BlueTotalRoundsFought	int64
BlueTotalTitleBouts	int64
BlueWinsByDecisionMajority	int64
BlueWinsByDecisionSplit	int64
BlueWinsByDecisionUnanimous	int64
BlueWinsByKO	int64
BlueWinsBySubmission	int64
BlueWinsByTKODoctorStoppage	int64
BlueWins	int64
BlueStance	object
BlueWeightLbs	int64
RedCurrentLoseStreak	int64
RedCurrentWinStreak	int64
RedDraws	int64
RedAvgSigStrLanded	float64
RedAvgSigStrPct	float64
RedAvgSubAtt	float64
RedAvgTDLanded	float64
RedAvgTDPct	float64
RedLongestWinStreak	int64
RedLosses	int64

RedTotalRoundsFought	int64
RedTotalTitleBouts	int64
RedWinsByDecisionMajority	int64
RedWinsByDecisionSplit	int64
RedWinsByDecisionUnanimous	int64
RedWinsByKO	int64
RedWinsBySubmission	int64
RedWinsByTKODoctorStoppage	int64
RedWins	int64
RedStance	object
RedWeightLbs	int64
RedAge	int64
BlueAge	int64
LoseStreakDif	int64
WinStreakDif	int64
LongestWinStreakDif	int64
WinDif	int64
LossDif	int64
TotalRoundDif	int64
TotalTitleBoutDif	int64
KODif	int64
SubDif	int64
HeightDif	float64
ReachDif	float64
AgeDif	int64
SigStrDif	float64
AvgSubAttDif	float64
AvgTDDif	float64
EmptyArena	float64
BMatchWCRank	float64
RMatchWCRank	float64
RWFlyweightRank	float64
RWFeatherweightRank	float64
RWStrawweightRank	float64
RWBantamweightRank	float64
RHeavyweightRank	float64
RLightHeavyweightRank	float64
RMiddleweightRank	float64
RWelterweightRank	float64
RLightweightRank	float64
RFeatherweightRank	float64
RBantamweightRank	float64

RFlyweightRank	float64
RPFPRank	float64
BWFlyweightRank	float64
BWFeatherweightRank	float64
BWStrawweightRank	float64
BWBantamweightRank	float64
BHeavyweightRank	float64
BLightHeavyweightRank	float64
BMiddleweightRank	float64
BWelterweightRank	float64
BLightweightRank	float64
BFeatherweightRank	float64
BBantamweightRank	float64
BFlyweightRank	float64
BPFPRank	float64
BetterRank	object
Finish	object
FinishDetails	object
FinishRound	float64
FinishRoundTime	object
TotalFightTimeSecs	float64
RedDecOdds	float64
BlueDecOdds	float64
RSubOdds	float64
BSubOdds	float64
RK00dds	float64
BK00dds	float64
WeightClassLabel	object
BlueHeight	float64
BlueReach	float64
RedHeight	float64
RedReach	float64
ROver35	int64
BOver35	int64
RWinPct	float64
BWinPct	float64
RedStrikingRatio	float64
BlueStrikingRatio	float64
RedTotalFights	int64
BlueTotalFights	int64
RedIsGrappler	int64
BlueIsGrappler	int64

```

RedIsStriker           int64
BlueIsStriker          int64
RGrapplerVBStriker    int64
BGrapplerVRStriker    int64
RedStrikingEfficiency float64
BlueStrikingEfficiency float64
RedTDEfficiency        float64
BlueTDEfficiency        float64
RedEffectiveTD          float64
BlueEffectiveTD          float64
EffectiveTDDif          float64
RedSize                 float64
BlueSize                 float64
Favorite                object
FavoriteWins             int64
draw_diff                int64
avg_sig_str_pct_diff    float64
avg_TD_pct_diff          float64
win_by_Decision_Majority_diff int64
win_by_Decision_Split_diff   int64
win_by_Decision_Unanimous_diff int64
win_by_TKO_Doctor_Stoppage_diff int64
odds_diff                float64
ev_diff                  float64
StanceCombo              object
AgeGap                   int64
Spread                   float64
dtype: object
6528
153
6528
Unique values in column 'RedFighter': [ 66 1441 307 ... 237 487 499]
Number of unique values in column 'RedFighter': 1661

Unique values in column 'BlueFighter': [1009 718 67 ... 781 1667 313]
Number of unique values in column 'BlueFighter': 1922

Unique values in column 'RedOdds': [-250. -210. -380. -950. -130. -650. -238. 150. -112. 142.
700. -550. -305. -198. nan 215. -225. 190. 102. 380.
-310. -144. -245. -265. -1350. 235. -1000. -105. 195. -1450.
-170. 250. 550. 205. 360. -485. -180. -155. -192. -270.
-375. 200. -340. -166. -108. -800. -575. -148. -218. -162.]

```

```

455. 170. -258. 330. 240. -290. 124. -425. 185. 154.
-500. 210. 245. 160. -520. -125. -102. -625. -360. 105.
100. -205. 110. -535. 225. -2100. 140. 220. -298. 120.
260. -142. 600. -325. 180. -900. -120. -445. 320. 114.
-135. -1050. 152. -720. 280. -345. -140. -160. -230. -475.
-220. -110. -175. -188. -410. -115. -145. -200. -1750. -810.
-395. 230. 450. 136. -215. -285. 130. -122. -152. -118.
390. 295. 145. -455. -440. -185. -1600. 350. 285. 370.
410. 164. 270. 300. 400. 625. -355. 500. -620. -470.
-195. 175. -920. -350. -700. -315. 290. 115. -240. 125.
-590. -104. 126. 188. -300. 128. -116. 310. -172. -260.
-138. -275. -164. -124. -1200. 132. -190. 122. -235. 166.
-335. -158. 106. -146. -255. -174. 116. -165. -132. 104.
184. 194. -490. -420. -156. 108. -184. -450. 148. -390.
138. 112. 440. -196. 134. 146. 176. -126. 172. -560.
-850. -530. -168. -600. -1400. -750. 155. -320. -365. 255.
-1250. 165. 675. -540. -150. 135. -280. 340. -1150. -580.
-645. -295. -330. 265. 275. -460. 520. -610. -435. 650.
575. -630. -760. -400. -2000. 385. 375. -525. 435. -1125.
-675. -1375. -129. -107. -106. -143. -136. -177. -134. 117.
-114. -137. -178. 127. -127. -147. -117. 157. 178. -370.
-430. -157. -278. -253. -487. -447. -103. 325. -139. -167.
-286. -1667. -835. -770. 315. 119. 277. -159. 133. 321.
-480. 111. -109. -186. 470. -182. -385. 306. -1430. 131.
-141. 271. -715. 168. -570. -870. -133. 655. 129. -641.
-181. -151. -303. -640. -1100. -670. 525. 415. 158. -515.
365. 425. -1500. -840. -680. 335. 305. 173. 243. 345.
485. -1165. 475. 775. -1700. -1275. -980. -660. -705. -925.
-815. -975. 540. 167. 505. -860. 420. -740. -405. 480.
-605. -510. -690. 149. -910. -935. 460. -545. 423. -735.
177. 355. 248. -875. -161. -131. -615. -710. 211. -171.
-121. -1650. -415. -153. 123. 101. -191. -176. 118. -173.
121. 163. -752. 181. -119. 107. -780.]
```

Number of unique values in column 'RedOdds': 377

```

Unique values in column 'BlueOdds': [ 215. 295. 300. 625. 110. -162. 195. -180. -108. -170.
-1100. 410. 245. 164. -230. 750. -265. 210. -122. -490.
250. 136. 200. 800. -290. 650. -115. -238. 850. 142.
-310. nan -800. -250. -470. 370. 150. 130. 160. 220.
-245. 270. 140. -112. 550. 425. 124. 180. -625. -205.
-425. -298. 235. -148. 330. -225. -185. 380. -258. 185.
-305. -192. 390. 105. -118. 455. 285. -125. -120. 170.
```

```

-130.  400.  -278.  1100.  -166.  -270.  240.  -142.  -325.  120.
-900.  260.  -218.  600.  100.  310.  -260.  -410.  -145.  -160.
 450.  -395.  -540.  -345.  175.  -110.  -195.  325.  145.  320.
-105.  114.  154.  500.  205.  290.  -285.  -720.  165.  230.
 102.  -150.  128.  -102.  -520.  -355.  -200.  -280.  -375.  -175.
-135.  350.  900.  -455.  -155.  -360.  -485.  -550.  190.  -198.
-340.  -380.  -620.  -950.  280.  -810.  360.  -500.  340.  188.
-535.  125.  -215.  -240.  -190.  135.  430.  -154.  168.  -405.
 176.  -255.  460.  -152.  -390.  144.  196.  108.  132.  106.
-156.  -144.  194.  184.  134.  -124.  -275.  -116.  152.  146.
-136.  112.  -220.  -235.  122.  630.  -510.  -300.  198.  660.
-168.  -176.  138.  -164.  -132.  -590.  -158.  -174.  -210.  -196.
-134.  -184.  420.  -106.  590.  186.  -146.  115.  -295.  265.
 155.  -350.  225.  -600.  255.  -975.  -365.  700.  510.  -165.
-435.  -675.  440.  480.  275.  -320.  -330.  -140.  -315.  -475.
 525.  435.  1000.  -525.  385.  -630.  -1000.  -335.  -400.  475.
 575.  580.  -186.  162.  153.  113.  187.  -139.  -167.  355.
-114.  -177.  375.  117.  157.  -147.  107.  127.  -103.  335.
-137.  178.  345.  415.  365.  137.  228.  -107.  174.  -129.
-182.  -117.  -143.  -560.  -159.  -420.  356.  277.  296.  131.
 169.  317.  -141.  103.  342.  246.  151.  253.  -715.  233.
 286.  227.  315.  239.  -109.  387.  333.  148.  161.  129.
 305.  635.  485.  158.  585.  610.  -830.  -151.  484.  159.
 234.  470.  -750.  328.  -460.  -570.  -370.  445.  465.  775.
 570.  490.  313.  -440.  -430.  243.  177.  -670.  -640.  -450.
 163.  1200.  -650.  925.  -700.  383.  -1200.  825.  640.  1050.
 540.  -710.  725.  248.  645.  -660.  -178.  -605.  675.  535.
 595.  167.  568.  1150.  123.  505.  -126.  -179.  560.  166.
 405.  710.  735.  423.  -480.  318.  555.  378.  685.  121.
 126.  -101.  258.  -231.  111.  1300.  133.  143.  -133.  680.
 181.  -111.  -530.  348.  -128.  -131.  -445.  -173.  -193.  602.
 109.  620.]
```

Number of unique values in column 'BlueOdds': 382

Unique values in column 'RedExpectedValue': [40. 47.619 26.3158 10.5263 76.9231 15.3846 42.0168 150.
89.2857 142. 700. 18.1818 32.7869 50.5051 nan 215.
44.4444 190. 102. 380. 32.2581 69.4444 40.8163 37.7358
7.4074 235. 10. 95.2381 195. 6.8966 58.8235 250.
550. 205. 360. 20.6186 55.5556 64.5161 52.0833 37.037
26.6667 200. 29.4118 60.241 92.5926 12.5 17.3913 67.5676
45.8716 61.7284 455. 170. 38.7597 330. 240. 34.4828

124.	23.5294	185.	154.	20.	210.	245.	160.
19.2308	80.	98.0392	16.	27.7778	105.	100.	48.7805
110.	18.6916	225.	4.7619	140.	220.	33.557	120.
260.	70.4225	600.	30.7692	180.	11.1111	83.3333	22.4719
320.	114.	74.0741	9.5238	152.	13.8889	280.	28.9855
71.4286	62.5	43.4783	21.0526	45.4545	90.9091	57.1429	53.1915
24.3902	86.9565	68.9655	50.	5.7143	12.3457	25.3165	230.
450.	136.	46.5116	35.0877	130.	81.9672	65.7895	84.7458
390.	295.	145.	21.978	22.7273	54.0541	6.25	350.
285.	370.	410.	164.	270.	300.	400.	625.
28.169	500.	16.129	21.2766	51.2821	175.	10.8696	28.5714
14.2857	31.746	290.	115.	41.6667	125.	16.9492	96.1538
126.	188.	33.3333	128.	86.2069	310.	58.1395	38.4615
72.4638	36.3636	60.9756	80.6452	8.3333	132.	52.6316	122.
42.5532	166.	29.8507	63.2911	106.	68.4932	39.2157	57.4713
116.	60.6061	75.7576	104.	184.	194.	20.4082	23.8095
64.1026	108.	54.3478	22.2222	148.	25.641	138.	112.
440.	51.0204	134.	146.	176.	79.3651	172.	17.8571
11.7647	18.8679	59.5238	16.6667	7.1429	13.3333	155.	31.25
27.3973	255.	8.	165.	675.	18.5185	66.6667	135.
35.7143	340.	8.6957	17.2414	15.5039	33.8983	30.303	265.
275.	21.7391	520.	16.3934	22.9885	650.	575.	15.873
13.1579	25.	5.	385.	375.	19.0476	435.	8.8889
14.8148	7.2727	77.5194	93.4579	94.3396	69.9301	73.5294	56.4972
74.6269	117.	87.7193	72.9927	56.1798	127.	78.7402	68.0272
85.4701	157.	178.	27.027	23.2558	66.	45.	63.
35.9712	39.5257	20.5339	22.3714	97.0874	63.6943	325.	71.9424
59.8802	34.965	5.9988	11.976	13.986	315.	119.	277.
62.8931	133.	321.	20.8333	111.	91.7431	53.7634	470.
54.9451	25.974	306.	6.993	131.	70.922	12.987	168.
17.5439	11.4943	75.188	655.	129.	15.6006	55.2486	66.2252
33.0033	15.625	9.0909	14.9254	525.	415.	158.	19.4175
365.	425.	6.6667	11.9048	14.7059	335.	305.	173.
243.	345.	485.	8.5837	475.	775.	5.8824	7.8431
10.2041	15.1515	14.1844	10.8108	12.2699	10.2564	540.	167.
505.	11.6279	420.	13.5135	24.6914	480.	16.5289	19.6078
14.4928	149.	10.989	10.6952	460.	18.3486	423.	13.6054
177.	355.	248.	11.4286	62.1118	76.3359	16.2602	14.0845
211.	58.4795	82.6446	6.0606	24.0964	65.3595	123.	101.
52.356	56.8182	118.	57.8035	121.	163.	13.2979	181.
84.0336	107.	12.8205]					

Number of unique values in column 'RedExpectedValue': 379

Unique values in column 'BlueExpectedValue': [215. 295. 300. 625. 110. 61.7284
 195.

55.5556	92.5926	58.8235	9.0909	410.	245.	164.
43.4783	750.	37.7358	210.	81.9672	20.4082	250.
136.	200.	800.	34.4828	650.	86.9565	42.0168
850.	142.	32.2581	nan	12.5	40.	21.2766
370.	150.	130.	160.	220.	40.8163	270.
140.	89.2857	550.	425.	124.	180.	16.
48.7805	23.5294	33.557	235.	67.5676	330.	44.4444
54.0541	380.	38.7597	185.	32.7869	52.0833	390.
105.	84.7458	455.	285.	80.	83.3333	170.
76.9231	400.	35.9712	1100.	60.241	37.037	240.
70.4225	30.7692	120.	11.1111	260.	45.8716	600.
100.	310.	38.4615	24.3902	68.9655	62.5	450.
25.3165	18.5185	28.9855	175.	90.9091	51.2821	325.
145.	320.	95.2381	114.	154.	500.	205.
290.	35.0877	13.8889	165.	230.	102.	66.6667
128.	98.0392	19.2308	28.169	50.	35.7143	26.6667
57.1429	74.0741	350.	900.	21.978	64.5161	27.7778
20.6186	18.1818	190.	50.5051	29.4118	26.3158	16.129
10.5263	280.	12.3457	360.	20.	340.	188.
18.6916	125.	46.5116	41.6667	52.6316	135.	430.
64.9351	168.	24.6914	176.	39.2157	460.	65.7895
25.641	144.	196.	108.	132.	106.	64.1026
69.4444	194.	184.	134.	80.6452	36.3636	86.2069
152.	146.	73.5294	112.	45.4545	42.5532	122.
630.	19.6078	33.3333	198.	660.	59.5238	56.8182
138.	60.9756	75.7576	16.9492	63.2911	57.4713	47.619
51.0204	74.6269	54.3478	420.	94.3396	590.	186.
68.4932	115.	33.8983	265.	155.	28.5714	225.
16.6667	255.	10.2564	27.3973	700.	510.	60.6061
22.9885	14.8148	440.	480.	275.	31.25	30.303
71.4286	31.746	21.0526	525.	435.	1000.	19.0476
385.	15.873	10.	29.8507	25.	475.	575.
580.	53.7634	162.	153.	113.	187.	71.9424
59.8802	355.	87.7193	56.4972	375.	117.	157.
68.0272	107.	127.	97.0874	335.	72.9927	178.
345.	415.	365.	44.	33.	74.	46.
54.	137.	228.	93.4579	174.	77.5194	54.9451
85.4701	69.9301	17.8571	62.8931	23.8095	356.	277.
296.	131.	169.	317.	70.922	103.	342.

```
246.    151.    253.    13.986  233.    286.    227.  
315.    239.    91.7431  387.    333.    148.    161.  
129.    305.    635.    485.    158.    585.    610.  
12.0482 66.2252 484.    159.    234.    470.    13.3333  
328.    21.7391  17.5439  27.027  445.    465.    775.  
570.    490.    313.    22.7273  23.2558 243.    177.  
14.9254 15.625   22.2222  163.    1200.   15.3846 925.  
14.2857 383.    8.3333  825.    640.    1050.   540.  
14.0845 725.    248.    645.    15.1515  56.1798 16.5289  
675.    535.    595.    167.    568.    1150.   123.  
505.    79.3651  55.8659  560.    166.    405.    710.  
735.    423.    20.8333  318.    555.    378.    685.  
121.    126.    99.0099  258.    43.29   111.    1300.  
133.    143.    75.188   680.    181.    90.0901 18.8679  
348.    78.125   76.3359  22.4719  57.8035  51.8135 602.  
109.    620.    ]
```

Number of unique values in column 'BlueExpectedValue': 387

Unique values in column 'Winner': ['Red' 'Blue']

Number of unique values in column 'Winner': 2

Unique values in column 'TitleBout': ['True' 'False']

Number of unique values in column 'TitleBout': 2

Unique values in column 'WeightClass': [3 8 4 2 5 1 6 0 12 11 7 9 10]

Number of unique values in column 'WeightClass': 13

Unique values in column 'Gender': [1 0]

Number of unique values in column 'Gender': 2

Unique values in column 'NumberOfRounds': [5 3 4]

Number of unique values in column 'NumberOfRounds': 3

Unique values in column 'BlueCurrentLoseStreak': [0 2 1 3 4 5 6]

Number of unique values in column 'BlueCurrentLoseStreak': 7

Unique values in column 'BlueCurrentWinStreak': [0 8 4 1 3 2 6 5 7 10 9 12]

Number of unique values in column 'BlueCurrentWinStreak': 12

Unique values in column 'BlueDraws': [0 1 2]

Number of unique values in column 'BlueDraws': 3

Unique values in column 'BlueAvgSigStrLanded': [0. 5.5 5.13 ... 32.8333 16.8333 13.7]
Number of unique values in column 'BlueAvgSigStrLanded': 1702

Unique values in column 'BlueAvgSigStrPct': [0. 0.55 0.57 0.44 0.53 0.49 0.61 0.52 0.47 0.5 0. 0.54 0.36

0.46 0.56 0.43 0.42 0.66 0.45 0.31 0.35 0.37 0.38 0.41 0.48
0.34 0.39 0.58 0.1 0.4 0.59 0.6 0.51 0.64 0.7 0.8 0.33
0.23 0.28 0.63 0.65 0.71 0.18 0.29 0.62 0.67 0.27 0.32 0.21
0.3 0.68 0.69 0.26 0.25 0.79 0.2 0.88 0.73 0.24 0.74 0.72
0.19 0.77 0.76 0.397 0.529 0.377 0.526 0.522 0.317 0.616 0.556 0.667
0.348 0.599 0.642 0.362 0.376 0.467 0.445 0.413 0.474 0.391 0.342 0.502
0.436 0.487 0.559 0.417 0.507 0.412 0.456 0.571 0.503 0.575 0.466 0.399
0.496 0.499 0.454 0.536 0.567 0.345 0.562 0.587 0.335 0.495 0.515 0.549
0.597 0.464 0.433 0.463 0.358 0.504 0.398 0.514 0.455 0.477 0.353 0.395
0.451 0.361 nan 0.605 0.497 0.462 0.434 0.525 0.544 0.367 0.662 0.437
0.573 0.426 0.472 0.288 0.483 0.475 0.583 0.543 0.405 0.465 0.505 0.664
0.537 0.488 0.453 0.165 0.435 0.352 0.16 0.457 0.363 0.425 0.371 0.485
0.545 0.368 0.359 0.527 0.885 0.563 0.427 0.382 0.593 0.366 0.523 0.651
0.486 0.383 0.442 0.375 0.409 0.447 0.13 0.394 0.566 0.484 0.492 0.374
0.333 0.347 0.324 0.459 0.612 0.388 0.518 0.452 0.343 0.326 0.423 0.476
0.513 0.565 0.336 0.432 0.438 0.263 0.552 0.248 0.307 0.542 0.561 0.501
0.357 0.385 0.655 0.325 0.553 0.319 0.387 0.491 0.618 0.602 0.431 0.332
0.356 0.75 0.424 0.443 0.378 0.441 0.538 0.386 0.554 0.393 0.471 0.705
0.574 0.615 0.479 0.428 0.411 0.685 0.578 0.22 0.675 0.235 0.444 0.511
0.372 0.516 0.603 0.558 0.365 0.531 0.524 0.448 0.392 0.446 0.364 0.577
0.509 0.401 0.285 0.283 0.601 0.478 0.384 0.429 0.355 0.402 0.346 0.396
0.403 0.535 0.506 0.473 0.354 0.596 0.389 0.713 0.458 0.407 0.338 0.757
0.315 0.406 0.555 0.533 0.418 0.275 0.468 0.304 0.416 0.414 0.737 0.337
0.419 0.339 0.379 0.421 0.493 0.598 0.585 0.517 0.267 0.215 0.519 0.494
0.489 0.592 0.408 0.586 0.314 0.637 0.373 0.606 0.78 0.308 0.498 0.645
0.404 0.327 0.607 0.15 0.619 0.693 0.344 0.539 0.481 0.313 0.633 0.551
0.305 0.259 0.692 0.422 0.609 0.613 0.469 0.625 0.512 0.643 0.415 0.665
0.12 0.795 0.237 0.568 0.309 0.17 0.635 0.634 0.439 0.541 0.627 0.381
0.759 0.638 0.564 0.295 0.547 0.743 0.461 0.449 0.294 0.322 0.328 0.175
0.508 0.534 0.646 0.703 0.207 0.628 0.763 0.296 0.745 0.528 0.653 0.238
0.11 0.482 0.225 0.591 0.334 0.688 0.331 0.83 0.588 0.608 0.742 0.253
0.569 0.243 0.589 0.707 0.548 0.695 0.611 0.579 1. 0.81 0.14 0.727
0.172 0.279 0.297 0.369 0.595 0.715 0.329 0.255 0.623 0.244 0.657 0.302
0.805 0.268 0.303 0.205 0.725 0.245 0.185 0.157 0.227 0.269 0.323 0.09
0.223 0.532 0.272 0.252 0.217 0.614 0.648 0.604 0.242 0.318 0.293 0.622]

Number of unique values in column 'BlueAvgSigStrPct': 432

Unique values in column 'BlueAvgSubAtt': [0.
 4
 1. 1.9 1.2 1.5 0.4 1.3 0.9 1.1 2.8 1.7
 1.6 2. 2.4 2.2 1.8 2.1 8.4 2.5 3.7 2.6
 3.9 4.3 2.7 3. 4.1 4. 3.4 5.2 3.2 3.6
 3.5 2.9 3.8 5.8 0.64 1.37 1.75 0.24 0.52 0.14
 0.16 0.88 0.15 0.23 0.96 2.07 0.35 0.45 0.25 1.68
 0.78 3.3 3.1 0.3548 0.6667 nan 0.3636 0.3333 0.1667 0.7857
 1.0909 0.7619 0.75 0.3571 0.2609 0.4167 0.5385 0.3667 0.375 0.5714
 0.619 0.1429 0.125 0.2857 0.05 2.3333 0.4667 0.7273 0.0556 0.7143
 0.0909 0.2222 0.4545 0.1111 0.0588 0.2143 0.2727 0.1818 0.8182 1.0952
 6. 0.0625 1.1667 0.0769 0.3793 1.2857 1.1429 0.5556 0.7778 5.
 1.1053 0.8889 0.625 0.5625 0.4286 0.4615 0.4444 0.8571 0.5455 0.7895
 0.5263 0.8333 0.4706 0.55 1.6667 1.125 0.6364 0.6154 0.875 1.3158
 0.6429 0.0714 0.6296 1.25 0.1538 0.3478 0.9167 0.4737 1.3333 0.2083
 0.3704 0.6538 0.2941 0.6087 0.5333 0.7647 0.6923 0.2174 0.5833 0.9231
 0.381 1.4444 1.5714 0.5909 1.1111 0.5294 0.3158 0.4375 0.0667 2.25
 0.72 0.2778 1.2941 1.8333 1.1333 0.1333 1.44 0.5217 1.0455 0.3529
 0.3913 0.5789 1.0833 1.375 1.5217 0.0833 0.7222 0.4211 0.9412 0.2105
 0.4091 0.8235 1.15 0.2632 1.1875 0.5238 0.8077 1.0714 0.2667 0.3077
 0.3889 0.7368 0.2308 0.8667 0.3846 0.9375 0.84 1.4615 1.1538 1.4167
 0.3125 0.2917 0.7059 1.2222 0.3043 0.913 1.4375 0.7333 0.6957 1.2105
 1.2727 0.2381 1.1818 1.4286 1.8235 0.8125 1.2308 0.8462 0.9286 0.0952
 2.5714 0.5882 1.2778 0.8421 1.3125 0.9091 1.6154 0.1053 2.6667 1.4545
 0.1765 0.9333 1.3846 1.0526 1.5385 1.8182 2.3636 1.8571 1.5833 1.5789
 0.4783 7. 1.7273 1.3889 0.1176 0.4118 0.6111 1.4706 1.7143 0.6471]
 Number of unique values in column 'BlueAvgSubAtt': 250

Unique values in column 'BlueAvgTDLanded': [0.
 0.96
 1.79 1.62 1.45 2.74 1.08 0.56 0.72 4.67 1.6
 1.7 1.74 1.59 1.52 2.79 2.3 1.51 2.16 4.37
 0.44 6.39 1.97 2.68 0.92 0.59 2.17 0.84 1.39
 1.46 1.27 2.5 1.07 0.48 2.34 1.02 1.1 2.18
 2.53 0.25 4.31 0.66 0.99 0.19 1.95 5.36 0.5
 0.81 0.78 1. 2.63 0.23 1.42 5.08 1.13 0.49
 2.73 1.85 0.91 3.38 0.34 3.97 1.04 2.07 2.
 2.48 1.81 1.92 0.83 2.75 1.96 2.4 0.95 1.09
 0.57 1.14 1.67 3.08 3.85 2.39 1.18 0.36 0.8
 2.88 3.53 6.09 0.64 1.21 1.72 0.76 1.2 3.49
 0.4 1.06 4.36 4.8 3.26 3.44 0.41 2.02 9.63
 1.56 2.99 2.2 1.16 2.14 1.57 0.05 0.73 4.52

2.77	2.94	1.5	1.75	4.63	3.09	2.62	4.2	3.98
1.68	3.35	2.95	1.23	0.63	0.65	0.85	2.28	5.69
0.21	1.93	0.54	0.15	2.29	0.86	2.26	1.03	1.61
1.73	2.04	0.7	2.49	2.09	1.12	2.41	2.33	0.55
3.91	0.98	1.33	2.37	2.15	1.38	1.82	1.78	1.01
3.24	0.71	0.68	0.67	3.3	1.11	0.88	0.89	2.45
4.08	1.48	0.27	1.24	4.17	2.23	3.	1.47	1.22
1.37	0.6	0.2	4.12	0.33	7.44	1.58	2.78	3.59
0.38	3.6	3.25	4.42	1.89	1.53	2.84	1.17	1.69
0.93	1.31	1.83	2.97	4.98	6.62	1.55	0.28	0.79
1.49	6.06	0.13	2.22	0.82	0.51	4.76	6.85	1.44
1.65	6.68	5.29	1.26	3.06	4.65	1.86	2.54	2.32
3.99	1.8	1.99	2.43	0.22	0.61	0.31	3.04	4.75
1.94	2.25	3.15	3.79	0.26	3.45	4.6	0.29	4.23
0.39	2.19	3.11	5.19	0.17	3.27	3.73	2.86	2.65
2.05	3.29	1.76	3.41	5.25	1.54	0.35	3.69	0.58
1.9	1.34	1.35	0.9	6.2	3.13	1.66	0.11	1.4
1.19	4.07	0.69	2.61	1.15	3.61	4.43	4.34	2.12
0.42	0.16	1.71	3.43	0.62	3.01	4.04	1.84	0.09
2.24	2.59	5.2	0.87	1.91	0.52	0.97	0.43	2.82
3.96	1.77	6.43	2.27	5.4	0.94	2.72	4.55	3.72
6.63	2.83	3.76	5.28	1.88	5.24	0.24	1.3	3.66
2.51	3.17	0.18	4.77	3.19	0.74	1.25	6.	3.1
4.18	3.63	4.28	4.45	0.14	3.22	2.35	3.71	3.87
3.14	6.75	4.16	3.93	2.9	2.85	5.03	2.11	2.13
2.44	3.83	3.5	7.3	2.6	3.31	5.57	4.14	2.58
0.53	1.05	4.33	2.93	2.08	1.32	6.46	1.87	1.63
1.36	1.29	5.35	3.81	0.3	2.01	4.83	4.11	2.03
2.1	3.12	3.78	6.86	2.8	10.61	3.92	4.97	7.84
8.93	4.91	5.52	2.56	4.	2.98	3.65	1.98	10.86
3.54	6.91	2.21	0.32	5.27	3.37	2.57	3.7	4.51
2.64	3.28	3.16	2.55	1.28	2.76	4.27	5.	3.03
2.71	3.02	1.41	7.17	4.24	8.67	3.82	6.77	8.7
4.84	3.74	3.34	1.43	3.18	4.26	2.46	9.93	5.78
3.55	3.67	3.23	2.91	nan	6.66	7.02	3.39	4.5
4.48	0.37	2.42	5.48	6.53	3.32	2.69	3.84	0.6774
0.3333	0.5833	1.125	0.3636	0.8333	1.3333	2.1667	1.5238	2.3571
0.1304	2.6667	0.375	0.6667	1.0833	2.4231	7.3333	0.5556	0.8571
1.1667	1.1429	1.875	1.6667	0.5333	1.0909	2.3333	0.2778	0.5714
0.6364	2.1111	0.9091	4.4444	5.75	0.4118	0.4286	2.4286	0.2727
1.4545	1.9091	2.9048	0.1364	0.0625	0.0833	2.4615	0.6897	1.2857
1.5455	4.3333	3.2	0.7273	0.9167	0.7778	0.1429	0.1818	1.4444

0.1667	2.0526	0.4444	1.625	8.	1.1818	0.125	3.0909	1.7692
1.2222	1.3636	3.6667	0.8889	0.1	1.4211	0.1333	0.1111	0.5652
1.9474	0.6923	0.7143	4.6667	0.2857	0.875	0.9412	3.75	0.9643
0.625	4.0909	0.3846	0.6154	1.7778	4.5556	4.8333	3.4	1.3684
0.0714	3.1111	3.8	1.4286	0.6087	1.375	0.7857	0.1538	2.875
2.0909	0.2222	2.625	1.1111	0.0909	0.8125	7.	1.8889	2.125
5.5	3.2308	0.4706	2.0588	1.7391	1.0667	0.5294	2.8571	1.0769
1.7273	4.1429	1.6154	1.0714	3.2222	5.125	2.2727	2.7143	1.8182
3.8889	2.5833	0.7083	1.4167	0.8182	6.5	1.8333	1.2308	1.8235
3.2105	3.3333	4.7143	1.8571	0.6818	5.3333	1.3913	1.1538	4.375
3.2857	1.2941	3.625	3.1667	2.5556	0.5385	2.2667	1.1304	0.4167
1.0455	0.2353	5.6667	2.1429	2.8333	1.5714	1.1739	0.4667	1.1053
0.8235	1.7143	0.7619	0.7692	2.3529	0.5263	1.5385	2.7727	0.2308
1.2273	2.2941	4.2857	0.1053	2.5714	2.6316	2.3077	0.3571	1.0952
0.8077	2.5385	1.2381	1.7857	2.4118	1.4667	1.7647	0.5455	0.7222
1.5263	2.2308	2.1818	2.3846	2.1538	1.1905	10.	0.9333	2.7778
2.4167	1.8462	1.2143	2.0833	1.6111	0.5789	4.25	0.3158	2.3636
1.6364	1.9333	1.6957	3.4167	0.8696	0.4545	0.3125	1.2667	0.6111
3.4783	1.7059	2.0714	0.7895	2.375	2.2857	2.7	1.8667	1.1765
3.7143	1.3529	1.3889	1.6875	2.2222	3.4615	1.3846	5.8	1.2727
1.0588	1.4118	0.1765	3.2727	2.8462	1.5556	2.7273	3.6316	2.9167
0.7368	3.7273	3.1818	1.9286	1.5294	0.3077	0.8667	2.1154	1.9231
0.5625	0.9286	1.5833	3.4286	0.9231	3.125	3.1429	3.5714	1.5625
7.5	0.4737	0.8824	3.8333	2.2609	0.7059	1.9412	1.2778	4.3636
1.2353	0.8462	4.7	3.0833]					

Number of unique values in column 'BlueAvgTDLanded': 715

Unique values in column 'BlueAvgTDPct': [0.													
0.55 0.63 0.25 0.37 0.26 0.65 0.27 0.23 0.41 0.24													
0.5													
0.34	0.32	0.18	0.75	0.58	0.14	1.	0.21	0.2	0.33	0.35	0.38		
0.66	0.39	0.12	0.11	0.43	0.16	0.36	0.4	0.53	0.46	0.52	0.51		
0.6	0.44	0.47	0.45	0.29	0.56	0.3	0.57	0.68	0.64	0.28	0.61		
0.13	0.8	0.48	0.42	0.72	0.54	0.31	0.17	0.22	0.62	0.73	0.59		
0.07	0.76	0.19	0.77	0.83	0.06	0.69	0.49	0.71	0.15	0.9	0.09		
0.05	0.86	0.7	0.08	0.78	0.1	0.79	0.417	0.091	0.518	0.381	0.312		
0.182	0.375	nan	0.225	0.295	0.288	0.233	0.125	0.165	0.241	0.096	0.228		
0.357	0.393	0.455	0.315	0.625	0.415	0.524	0.457	0.094	0.277	0.363	0.343		
0.305	0.266	0.453	0.264	0.323	0.107	0.221	0.333	0.473	0.163	0.254	0.466		
0.335	0.314	0.523	0.329	0.735	0.187	0.066	0.144	0.313	0.583	0.215	0.605		
0.498	0.287	0.258	0.167	0.497	0.194	0.164	0.085	0.123	0.398	0.435	0.553		
0.153	0.106	0.399	0.255	0.162	0.075	0.214	0.433	0.136	0.678	0.166	0.451		
0.318	0.063	0.332	0.387	0.592	0.322	0.319	0.083	0.281	0.325	0.282	0.396		

```

0.548 0.235 0.099 0.273 0.428 0.527 0.243 0.047 0.146 0.151 0.374 0.248
0.195 0.366 0.356 0.267 0.133 0.334 0.193 0.304 0.436 0.239 0.198 0.385
0.222 0.331 0.143 0.093 0.407 0.081 0.208 0.494 0.262 0.426 0.154 0.486
0.353 0.276 0.309 0.383 0.493 0.224 0.056 0.347 0.421 0.202 0.437 0.071
0.249 0.192 0.82 0.487 0.272 0.503 0.362 0.539 0.067 0.253 0.395 0.284
0.213 0.545 0.365 0.132 0.283 0.124 0.645 0.405 0.256 0.179 0.514 0.246
0.219 0.394 0.271 0.506 0.612 0.418 0.104 0.328 0.447 0.326 0.403 0.475
0.563 0.355 0.419 0.321 0.777 0.244 0.595 0.212 0.479 0.432 0.444 0.077
0.443 0.541 0.481 0.141 0.183 0.567 0.538 0.178 0.055 0.376 0.286 0.316
0.238 0.369 0.119 0.522 0.307 0.229 0.667 0.234 0.665 0.516 0.535 0.468
0.301 0.448 0.543 0.172 0.558 0.588 0.411 0.364 0.263 0.373 0.346 0.097
0.109 0.425 0.943 0.371 0.404 0.729 0.368 0.354 0.293 0.569 0.422 0.577
0.484 0.439 0.581 0.294 0.408 0.715 0.424 0.292 0.177 0.044 0.261 0.615
0.298 0.111 0.502 0.041 0.188 0.227 0.653 0.429 0.205 0.412 0.306 0.574
0.086 0.269 0.454 0.915 0.358 0.647 0.508 0.413 0.643 0.341 0.402 0.472
0.585 0.175 0.482 0.135 0.291 0.137 0.197 0.265 0.533 0.458 0.626 0.495
0.714 0.512 0.308 0.467 0.367 0.351 0.456 0.279 0.04 0.103 0.587 0.673
0.324 0.537 0.207 0.118 0.232 0.388 0.562 0.176 0.278 0.344 0.438 0.105
0.303 0.159 0.833 0.753 0.465 0.349 0.223 0.074 0.065 0.382 0.631 0.601
0.131 0.463 0.679 0.218 0.478 0.311 0.477 0.378 0.441 0.632 0.359 0.226
0.446 0.098 0.505 0.639 0.379 0.676 0.607 0.302 0.174 0.471 0.317 0.337
0.416 0.339 0.361 0.406 0.474 0.117 0.633 0.705 0.464 0.274 0.529 0.532
0.336 0.462 0.622 0.126 0.414 0.115 0.148 0.555 0.145 0.184 0.559 0.685
0.203 0.598 0.623 0.275 0.531 0.606 0.297 0.196 0.517 0.746 0.526 0.372
0.431 0.231 0.766 0.571 0.513 0.338 0.392 0.573 0.185 0.237 0.576 0.391
0.85 0.142 0.342 0.627 0.507 0.546 0.245 0.492 0.423 0.808 0.236 0.345
0.211 0.084 0.088 0.958 0.476 0.169 0.611 0.575 0.057 0.128 0.401 0.856
0.268 0.247 0.189 0.773 0.578 0.483 0.568 0.289 0.257 0.775 0.445 0.552
0.663 0.386 0.259 0.867 0.442 0.053 0.677 0.087 0.873 0.191 0.81 0.635
0.875 0.251 0.296 0.591 0.812 0.525 0.173 0.171 0.501 0.515 0.596 0.452
0.129 0.618 0.674 0.157 0.742 0.122 0.593 0.629 0.511 0.488 0.534 0.149
0.803 0.561 0.572]

```

Number of unique values in column 'BlueAvgTDPct': 543

Unique values in column 'BlueLongestWinStreak': [0 8 4 1 3 9 2 5 6 13 7 10 12 15 17 16]
Number of unique values in column 'BlueLongestWinStreak': 16

Unique values in column 'BlueLosses': [0 4 2 3 12 1 8 5 6 9 7 14 13 10 16 11 15]
Number of unique values in column 'BlueLosses': 17

Unique values in column 'BlueTotalRoundsFought': [0 20 44 7 15 63 12 57 16 14 23 22 26 9
13 2 6 4

```
3 11 46 34 8 5 30 37 52 24 17 32 51 18 98 49 111 19  
25 21 1 27 53 29 31 78 45 65 33 10 60 41 48 28 40 54  
75 50 47 71 42 36 93 39 96 61 108 58 70 56 38 59 103 67  
69 55 77 35 64 101 43 80 104 72 62 79 91 94 87 86 89 68  
97 66 83 73]
```

Number of unique values in column 'BlueTotalRoundsFought': 94

Unique values in column 'BlueTotalTitleBouts': [0 1 5 6 8 7 9 4 3 11 2 10 15 13 14 12 16]
Number of unique values in column 'BlueTotalTitleBouts': 17

Unique values in column 'BlueWinsByDecisionMajority': [0 1 2]

Number of unique values in column 'BlueWinsByDecisionMajority': 3

Unique values in column 'BlueWinsByDecisionSplit': [0 1 2 3 5 4]

Number of unique values in column 'BlueWinsByDecisionSplit': 6

Unique values in column 'BlueWinsByDecisionUnanimous': [0 4 1 3 7 2 5 8 11 6 9 10]
Number of unique values in column 'BlueWinsByDecisionUnanimous': 12

Unique values in column 'BlueWinsByKO': [0 3 6 4 7 1 2 5 9 11 8 12 10 14 20]

Number of unique values in column 'BlueWinsByKO': 15

Unique values in column 'BlueWinsBySubmission': [0 1 6 4 2 3 7 5 8 10 12 9 11 13]

Number of unique values in column 'BlueWinsBySubmission': 14

Unique values in column 'BlueWinsByTKODoctorStoppage': [0 1 2]

Number of unique values in column 'BlueWinsByTKODoctorStoppage': 3

Unique values in column 'BlueWins': [0 8 12 1 4 15 16 6 7 2 13 3 14 9 5 11 10 22 21 23 26 18 17 2
0
19 29 31]

Number of unique values in column 'BlueWins': 27

Unique values in column 'BlueStance': ['Orthodox' 'Southpaw' 'Switch' nan 'Open Stance']

Number of unique values in column 'BlueStance': 5

Unique values in column 'BlueWeightLbs': [125 170 250 145 205 185 155 236 135 115 240 254 246 265 252 242 2
60 235
264 262 249 256 230 245 253 257 243 255 241 140 220 238 258 225 231 248
247 251 263]

Number of unique values in column 'BlueWeightLbs': 39

Unique values in column 'RedCurrentLoseStreak': [0 1 2 3 4 7 6 5]

Number of unique values in column 'RedCurrentLoseStreak': 8

Unique values in column 'RedCurrentWinStreak': [6 1 0 8 3 2 18 5 4 7 10 12 13 9 11 17 15 14 16]

Number of unique values in column 'RedCurrentWinStreak': 19

Unique values in column 'RedDraws': [0 1 2]

Number of unique values in column 'RedDraws': 3

Unique values in column 'RedAvgSigStrLanded': [4.41 4.12 5.49 ... 12.75 30.7273 33.1]

Number of unique values in column 'RedAvgSigStrLanded': 2025

Unique values in column 'RedAvgSigStrPct': [0.49 0.61 0.6 0.58 0.46 0.5 0.52 0.48 0.47 0.45 0.4

0.33

0.54 0.55 0.38 0.39 0.43 0.29 0.63 0.59 0.42 0.41 0.56 0.44

0.53 0.51 0.65 0.57 0.37 0.64 0.67 0.62 0.36 0.32 0.28 0.34

0.7 0.24 0.23 0.69 0.35 0.66 0.31 0.3 0.75 0.72 0.68 0.77

0. 0.86 0.1 0.78 0.95 0.79 0.82 0.27 0.81 0.74 0.399 0.464

0.533 0.426 0.522 0.574 0.318 0.431 0.466 0.427 0.405 0.541 0.512 0.381

0.459 0.489 0.505 0.653 0.348 0.368 0.373 0.73 0.457 0.553 0.417 0.789

0.667 0.25 0.576 0.366 0.545 0.638 0.478 0.403 0.257 0.295 0.385 0.537

0.456 0.498 0.467 nan 0.465 0.317 0.453 0.434 0.511 0.484 0.555 0.485

0.408 0.496 0.303 0.443 0.494 0.432 0.428 0.335 0.528 0.445 0.439 0.488

0.337 0.495 0.582 0.461 0.507 0.523 0.414 0.454 0.413 0.386 0.479 0.372

0.689 0.525 0.288 0.444 0.387 0.557 0.458 0.527 0.543 0.321 0.343 0.363

0.449 0.415 0.365 0.605 0.513 0.473 0.452 0.493 0.487 0.378 0.305 0.416

0.411 0.554 0.435 0.384 0.338 0.536 0.393 0.499 0.22 0.481 0.379 0.383

0.544 0.369 0.438 0.333 0.519 0.437 0.579 0.425 0.508 0.357 0.347 0.352

0.565 0.402 0.468 0.418 0.9 0.647 0.514 0.358 0.451 0.578 0.344 0.535

0.422 0.476 0.552 0.643 0.323 0.595 0.442 0.423 0.521 0.462 0.325 0.354

0.486 0.327 0.546 0.678 0.725 0.472 0.483 0.855 0.407 0.549 0.695 0.361

0.455 0.563 0.591 0.312 0.419 0.652 0.475 0.446 0.491 0.376 0.382 0.429

0.516 0.517 0.396 0.374 0.397 0.547 0.412 0.587 0.394 0.275 0.421 0.404

0.509 1. 0.469 0.436 0.526 0.581 0.502 0.256 0.328 0.583 0.566 0.538

0.463 0.265 0.497 0.685 0.353 0.518 0.448 0.395 0.424 0.367 0.377 0.597

0.406 0.441 0.477 0.388 0.375 0.501 0.359 0.635 0.339 0.534 0.585 0.356

0.433 0.561 0.326 0.558 0.603 0.515 0.506 0.341 0.297 0.471 0.568 0.331

0.277 0.607 0.362 0.584 0.524 0.315 0.722 0.503 0.573 0.531 0.389 0.304

0.84 0.626 0.324 0.319 0.492 0.575 0.572 0.409 0.283 0.371 0.588 0.322

0.223 0.398 0.655 0.345 0.26 0.621 0.14 0.598 0.474 0.392 0.308 0.482

0.273 0.567 0.551 0.316 0.401 0.735 0.255 0.569 0.644 0.733 0.355 0.532

0.656 0.589 0.616 0.447 0.391 0.266 0.609 0.213 0.688 0.306 0.634 0.292

```

0.648 0.195 0.612 0.624 0.604 0.296 0.548 0.539 0.675 0.205 0.628 0.613
0.08 0.756 0.623 0.683 0.599 0.055 0.267 0.676 0.577 0.723 0.622 0.18
0.649 0.775 0.197 0.504 0.21 0.145 0.564 0.313 0.346 0.349 0.627 0.264
0.364 0.278 0.291 0.556 0.713 0.2 0.342 0.596 0.85 0.529 0.668 0.8
0.307 0.336 0.665 0.727 0.253 0.602 0.17 0.254 0.329 0.677 0.249 0.83
0.294 0.738 0.651 0.765 0.311 0.703 0.697 0.592 0.282 0.301 0.276 0.773
0.71 0.704 0.245 0.625 0.562 0.251 0.571 0.825 0.185 0.299 0.334 0.15
0.332 0.614 0.12 0.698 0.717 0.268 0.606 0.187 0.633 0.235 0.09 0.805
0.155 0.11 0.718 0.204 0.351 0.617 0.238 0.608 0.314 0.559 0.728 0.286
0.262 0.284 0.619 0.749 0.793 0.03 0.248 0.298]

```

Number of unique values in column 'RedAvgSigStrPct': 464

	0.8	1.8	0.5	1.6	1.	0.3	0.6	0.2	0.9	0.1
0.	2.3	2.4	2.7	3.6	0.7	1.7	1.5	0.4	1.4	
1.1	1.2	1.3	2.1	5.3	4.4	2.5	7.3	3.9	1.9	
4.3	2.6	2.	2.2	2.8	7.5	5.4	3.	8.4	3.7	
3.8	3.2	3.3	7.2	5.	2.9	8.3	3.1	6.9	4.5	
4.	6.2	6.	0.35	1.25	1.23	1.58	1.35	0.98	0.19	
0.42	0.58	0.26	0.44	0.83	0.62	1.64	0.74	0.71	1.83	
1.71	0.92	0.31	3.93	0.4286	0.75	0.6667	0.1667	0.3333	0.1818	
nan	0.5556	0.6154	1.2609	0.25	0.0833	0.2308	0.24	0.4615	0.2143	
0.125	0.0909	1.1429	0.4667	0.5294	0.1786	1.2903	0.1429	0.3684	0.2778	
0.05	1.375	0.2857	0.1111	0.4783	1.7273	0.5263	0.3448	0.7143	0.6429	
0.9524	0.5833	0.2222	0.4545	0.4444	0.6842	0.1538	0.8571	1.2727	0.5714	
0.48	0.8462	0.0526	1.3333	0.3889	0.5385	0.0588	0.45	0.56	0.2667	
0.1176	0.2632	0.3846	0.5455	0.3571	1.5556	0.7692	1.625	0.625	1.0714	
0.2941	0.6316	0.0667	0.4118	0.0625	0.1923	1.3448	0.0556	1.3571	0.7059	
0.1333	0.7778	0.2727	1.125	0.2353	1.1667	0.375	0.7222	0.3704	0.6364	
0.0769	0.2105	1.1579	1.7143	0.8889	0.32	0.8947	0.4348	1.3929	0.875	
0.5789	1.16	0.8333	1.0526	0.4167	0.6923	1.3077	0.3636	1.1765	2.6667	
1.1111	1.2778	0.6111	1.0435	1.2083	0.1852	0.9231	0.9091	0.9444	0.3125	
0.7273	0.4375	0.5238	0.6087	0.2273	0.4706	0.4762	1.75	1.2174	1.3636	
0.5625	1.8571	0.2381	1.2273	0.9167	2.1429	0.3529	0.8235	0.5333	1.2632	
0.3077	0.5882	1.4583	1.1176	0.8125	1.2857	1.1875	1.2381	1.1364	1.0909	
1.0952	1.2143	1.4444	1.5714	0.7826	1.5909	1.6667	0.9545	2.3333	0.8182	
0.3158	0.8667	0.6471	1.1333	1.3684	0.55	1.2667	0.64	3.5	0.1765	
0.1053	0.95	1.2222	1.7895	0.2174	0.6875	0.7857	0.4211	1.7222	0.65	
1.5294	1.0833	0.4737	0.7619	1.875	0.8421	1.4667	1.9333	0.3182	0.9286	
1.0625	1.2941	1.1818	0.0714	2.25	0.7647	2.0769	1.6364	1.7778	1.8182	
0.1875	1.8889	0.7333	1.8333	1.0556	1.1538	1.4286	0.2609	1.5333	1.4167	
1.4615	1.5455	0.6957	2.4286	0.4091	0.6818	1.3125	5.5	1.0667		

Number of unique values in column 'RedAvgSubAtt': 289

Unique values in column 'RedAvgTDLanded': [2.61 1.49 0.58 3.45 1. 0.35 4.75 0.72
3.44
4.36 3.35 3.13 1.61 0.92 0.42 1.16 0.5 0.
1.65 0.37 2.42 0.84 1.89 2.25 3.61 1.86 0.38
1.52 0.73 1.42 1.15 2.21 0.93 2.12 2.01 0.78
1.8 0.31 0.7 1.01 2.17 3.46 1.53 1.59 0.52
0.21 2.27 0.16 0.34 3.22 4.49 0.68 2.02 0.8
1.78 0.56 3.84 3.12 3.97 1.6 3.95 6.64 0.33
2.86 1.22 1.88 1.23 1.29 2.03 0.75 0.74 3.65
0.59 5.02 4.89 1.11 2.95 0.14 0.83 0.49 1.33
1.39 0.25 0.28 1.54 1.32 3.28 1.87 0.88 1.05
2.47 1.28 4.04 3.21 1.7 0.27 5.36 2.24 0.39
2.11 0.29 0.44 1.07 0.18 1.13 0.15 2.26 4.02
2.1 2.23 1.17 1.45 1.85 5.15 3.54 3.91 0.76
2.15 0.63 4.08 3.66 3.04 0.61 5.25 1.19 0.43
5.66 2.34 0.26 0.97 1.68 1.2 2.33 0.51 0.62
1.03 0.77 2.63 1.31 1.25 3.27 1.56 1.84 5.29
2.67 1.94 0.9 2.43 4.65 0.69 1.55 0.67 2.92
1.69 1.62 2.39 3.41 0.66 0.99 0.46 0.64 1.04
5.45 5.2 1.1 0.45 1.97 5.5 2.04 0.55 4.8
5.08 2.5 2. 0.89 0.36 1.47 1.79 2.22 3.19
6.85 1.18 2.65 3.11 1.99 0.41 0.57 1.96 0.96
0.54 2.99 1.27 3.1 1.73 1.14 2.73 0.65 1.9
2.83 0.22 0.17 2.51 0.11 7.46 0.87 0.79 2.37
1.74 1.06 1.82 4.52 1.91 2.07 4.45 3.38 2.05
2.29 4.07 4.2 1.24 2.77 1.02 3. 9.69 2.14
5.03 1.77 1.48 2.62 5.69 4.17 3.98 1.38 0.2
1.66 2.32 3.26 1.37 1.75 3.17 3.43 3.76 6.43
6.62 1.4 3.72 4.18 1.26 1.76 3.01 2.49 1.71
2.48 0.94 1.72 3.96 0.91 3.71 3.73 1.83 2.35
3.29 1.58 1.09 1.08 5.24 0.82 2.59 4.12 2.82
0.98 2.85 0.23 1.12 4.39 2.09 1.5 0.05 0.95
2.31 1.51 4.76 2.41 3.6 0.86 2.74 3.59 1.67
2.68 3.08 4.6 0.24 3.03 3.85 4.84 3.18 1.3
3.25 1.81 1.92 2.28 0.47 0.6 1.93 3.3 2.56
3.14 4.23 6.2 6. 2.19 2.13 1.21 3.63 0.13
0.09 2.4 4.15 4.16 0.71 5.4 3.99 1.46 0.81
6.9 0.06 3.16 1.95 6.75 4.43 1.34 4.34 1.44
3.53 2.78 2.6 4.38 5.64 4.06 3.79 4.63 1.35
2.45 2.54 2.55 4.32 3.39 4.48 1.57 0.53 6.27
2.9 7.17 0.19 4.56 4.13 3.15 4.47 0.4 4.55

0.07	2.76	0.12	3.24	2.36	3.62	2.66	0.48	2.75
3.2	3.31	5.77	2.16	2.58	3.47	2.06	4.	2.89
2.64	2.57	4.7	2.44	2.7	3.69	3.02	7.38	6.96
7.1	6.11	1.63	2.79	3.9	4.28	1.41	4.01	2.69
2.38	2.81	3.7	7.07	6.05	6.61	0.32	4.98	5.
0.3	0.85	6.41	1.64	5.35	1.98	3.32	3.33	8.4
8.33	4.91	4.81	2.2	4.59	2.08	2.8	4.5	5.09
4.29	4.31	2.98	4.67	6.63	7.8	3.58	2.52	4.14
6.53	3.23	2.71	12.5	4.77	5.23	3.74	2.72	7.05
2.46	3.93	5.22	1.43	3.06	4.42	3.4	3.5	2.53
3.42	3.34	6.77	2.4286	0.625	0.1111	1.0667	0.1667	0.2727
0.3333	nan	0.5556	0.7143	1.7308	2.7778	1.3043	2.8333	0.125
0.9231	0.0909	0.8889	0.6667	0.9286	0.6875	0.1818	1.3333	0.8571
1.0833	1.8571	1.3125	0.1176	0.3214	2.7143	1.1613	1.7857	0.2667
2.1667	1.5714	1.6667	0.2632	0.6429	4.1667	6.1667	0.3846	4.125
1.4167	0.4286	0.3125	0.2857	0.913	0.7273	0.2222	1.3636	1.9474
0.4167	0.8421	0.7778	0.931	1.4286	3.75	1.1071	8.	2.3333
0.3571	3.4545	0.4737	2.0909	0.8333	1.4667	1.1667	2.2667	0.375
2.1429	1.3182	0.5417	2.1111	1.0625	1.1429	2.875	0.4667	1.8462
0.5385	2.4615	0.3684	3.875	2.3	1.4444	0.2941	0.4118	3.9091
0.4706	4.7143	0.2143	2.1579	1.7692	3.7273	1.2222	0.6923	1.1111
2.7692	0.4211	3.1111	1.7778	4.9	0.5294	2.6316	0.0667	1.3571
0.9412	0.4375	0.2692	8.5	0.4545	2.5385	5.6667	3.1667	1.037
1.2069	0.4444	4.2941	0.7333	0.1429	1.7143	1.0909	1.375	2.6667
1.2353	1.6429	0.5833	0.9167	0.9375	0.7037	0.5625	0.8182	0.2308
3.8571	2.4091	1.2105	3.1053	2.2778	1.625	2.2222	0.875	1.6842
0.3889	2.913	1.8333	1.2143	11.	1.2632	0.9545	4.7778	3.0455
0.3158	2.0556	1.9167	1.4615	0.1538	3.3333	0.7308	0.5455	1.8889
0.6522	0.6364	3.8889	2.7857	1.3077	2.2727	1.0385	2.1765	4.875
0.4615	1.5556	0.8462	0.5714	0.2353	0.5333	3.2778	1.0556	0.963
3.05	1.1818	2.3077	3.2857	2.8571	4.0625	0.0833	1.125	2.1875
3.5556	2.4167	2.9231	3.6667	1.0769	1.6316	2.6522	0.1364	3.1429
0.3636	4.375	1.0714	1.2174	1.8235	4.2667	0.5238	1.1875	1.875
2.7273	4.1429	3.3889	0.9091	3.4706	1.2857	0.7391	1.4091	1.2273
2.125	3.2353	0.1333	0.7727	3.4286	4.2143	1.2941	2.2941	5.2857
1.6364	1.381	1.2727	0.8824	1.4375	2.2857	1.4545	3.375	0.1
3.7143	2.3913	1.0588	1.0952	4.3333	2.0714	0.6842	2.0526	0.2778
1.2667	2.3636	2.0625	4.5385	5.8333	0.7222	3.8	1.6923	0.1579
2.0769	0.6471	1.1176	1.9375	2.381	0.0769	0.3077	2.2308	4.5833
0.5882	0.5263	1.2778	1.1304	1.1579	0.7647	3.2941	0.7368	2.2632
3.2143	1.3529	2.5833	2.5455	2.6364	1.2308	1.4211	3.0769	3.0625
0.7692	0.7857	7.	3.4091	1.1538	2.8421	3.381	3.0667	4.4444

1.5833	1.9333	1.9286	1.3684	1.3158	2.375	0.8125	0.8636	2.5714
2.625	0.8095	3.55	2.3846	2.8824	1.7727	0.8667	2.4545	1.5882
0.9048	0.1875	0.3529	2.1818	3.7222	0.8235	3.9474	1.7619	3.4118
3.8235	3.8333	1.5385	1.5333	0.8947	1.2381	0.6154	3.7778	3.9333
0.9333	3.1818	3.125	1.7895	3.4615	2.0833	3.4667	2.5556	4.0714
1.9091	3.5714	1.9583	2.3478	2.0667	3.1538	0.7059	4.1538	3.8824
1.3846	4.25	2.0435	4.4167	4.0909	3.625	2.3182	3.2727	2.1364
9.	1.8125	2.2381	4.6667]					

Number of unique values in column 'RedAvgTDLanded': 805

Unique values in column 'RedAvgTDPct': [0.47 0.29 0.21 0.41 0.28 0.53 0.46 0.39 0.42 0.5 0.51

0.36

0.45	0.49	0.73	0.3	0.	0.75	0.33	0.16	0.31	0.25	0.4	0.43
0.35	0.44	0.2	0.32	0.24	0.38	1.	0.22	0.57	0.37	0.55	0.56
0.14	0.61	0.54	0.64	0.34	0.23	0.11	0.18	0.26	0.65	0.8	0.27
0.52	0.66	0.62	0.69	0.12	0.15	0.48	0.63	0.17	0.71	0.91	0.72
0.59	0.6	0.77	0.68	0.58	0.9	0.07	0.09	0.76	0.19	0.13	0.06
0.78	0.05	0.1	0.7	0.83	0.81	0.85	0.08	0.88	0.319	0.222	0.539
0.313	0.714	0.429	0.506	0.833	0.387	0.167	0.462	0.571	0.125	0.433	nan
0.458	0.601	0.277	0.104	0.818	0.418	0.056	0.301	0.111	0.303	0.091	0.132
0.333	0.231	0.151	0.297	0.483	0.108	0.478	0.638	0.219	0.067	0.558	0.183
0.375	0.316	0.875	0.215	0.102	0.379	0.121	0.268	0.364	0.118	0.129	0.453
0.423	0.278	0.267	0.368	0.341	0.529	0.79	0.211	0.226	0.312	0.127	0.237
0.398	0.348	0.193	0.063	0.415	0.546	0.513	0.141	0.584	0.357	0.555	0.274
0.448	0.221	0.438	0.292	0.165	0.208	0.163	0.244	0.171	0.225	0.305	0.557
0.342	0.351	0.135	0.463	0.615	0.248	0.214	0.161	0.468	0.228	0.503	0.119
0.275	0.587	0.282	0.073	0.254	0.198	0.362	0.454	0.467	0.665	0.367	0.509
0.216	0.189	0.389	0.383	0.577	0.194	0.338	0.261	0.466	0.329	0.249	0.444
0.437	0.152	0.224	0.255	0.535	0.643	0.288	0.608	0.289	0.296	0.286	0.472
0.206	0.455	0.397	0.526	0.308	0.227	0.114	0.197	0.667	0.179	0.287	0.449
0.475	0.683	0.419	0.583	0.291	0.542	0.339	0.517	0.371	0.354	0.294	0.373
0.143	0.173	0.556	0.374	0.245	0.238	0.882	0.298	0.602	0.285	0.311	0.095
0.259	0.425	0.356	0.314	0.235	0.213	0.496	0.113	0.565	0.138	0.083	0.432
0.479	0.229	0.417	0.353	0.204	0.212	0.035	0.473	0.404	0.071	0.525	0.186
0.242	0.304	0.393	0.498	0.177	0.474	0.416	0.344	0.693	0.647	0.403	0.192
0.241	0.093	0.323	0.302	0.349	0.201	0.166	0.355	0.188	0.322	0.625	0.153
0.265	0.258	0.047	0.064	0.887	0.154	0.262	0.271	0.377	0.203	0.413	0.414
0.508	0.281	0.136	0.915	0.566	0.327	0.209	0.688	0.243	0.395	0.232	0.543
0.279	0.236	0.318	0.381	0.122	0.055	0.572	0.434	0.402	0.385	0.392	0.409
0.039	0.564	0.376	0.345	0.205	0.272	0.147	0.328	0.594	0.361	0.037	0.346
0.251	0.596	0.284	0.176	0.435	0.427	0.412	0.239	0.233	0.384	0.785	0.456
0.172	0.247	0.257	0.407	0.568	0.253	0.677	0.042	0.264	0.476	0.502	0.306

```
0.452 0.283 0.062 0.406 0.494 0.378 0.156 0.075 0.307 0.653 0.382 0.553
0.648 0.428 0.273 0.694 0.234 0.332 0.343 0.446 0.045 0.669 0.712 0.115
0.185 0.369 0.325 0.408 0.266 0.436 0.592 0.295 0.522 0.411 0.646 0.405
0.719 0.336 0.359 0.605 0.358 0.493 0.386 0.459 0.581 0.324 0.256 0.451
0.223 0.182 0.148 0.133 0.066 0.053 0.464 0.337 0.365 0.699 0.317 0.331
0.335 0.426 0.162 0.293 0.372 0.347 0.058 0.527 0.532 0.175 0.263 0.658
0.276 0.441 0.321 0.733 0.269 0.181 0.528 0.545 0.246 0.465 0.611 0.094
0.309 0.164 0.586 0.515 0.158 0.054 0.137 0.863 0.187 0.424 0.363 0.67
0.604 0.721 0.077 0.773 0.334 0.352 0.421 0.447 0.442 0.178 0.168 0.533
0.326 0.388 0.461 0.603 0.481 0.202 0.817 0.613 0.574 0.486 0.443 0.707
0.184 0.491 0.749 0.471 0.445 0.765 0.117 0.678 0.497 0.128 0.523 0.718
0.505 0.492 0.401 0.562 0.612 0.504 0.641 0.217 0.422 0.777 0.144 0.485
0.632 0.544 0.623 0.576 0.366 0.507 0.196 0.074 0.736 0.801 0.521 0.534
0.431 0.131 0.146 0.516 0.139 0.487 0.775 0.768 0.519 0.488 0.74 0.107
0.394 0.633 0.661 0.396 0.315 0.484 0.563 0.155 0.595 0.573 0.674 0.514
0.145 0.123 0.098 0.585 0.551 0.793 0.606 0.391 0.207 0.743 0.569 0.511
0.469 0.579 0.645 0.399 0.758 0.94 0.626 0.607 0.537 0.618 0.616 0.659
0.518 0.652 0.644 0.567 0.614 0.116 0.499 0.495 0.489 0.157 0.547 0.477
0.591 0.682 0.524 0.748 0.593 0.457 0.675 0.627 0.82 0.575 0.767 0.716
0.126 0.552 0.666 0.554 0.843 0.541 0.092 0.732 0.751]
```

Number of unique values in column 'RedAvgTDPct': 609

Unique values in column 'RedLongestWinStreak': [6 7 3 8 4 9 2 1 18 11 5 0 15 12 10 13 17 14 16]
 Number of unique values in column 'RedLongestWinStreak': 19

Unique values in column 'RedLosses': [3 0 2 4 6 5 7 19 1 10 17 8 11 9 12 13 21 15 16 20 18 14]
 Number of unique values in column 'RedLosses': 22

Unique values in column 'RedTotalRoundsFought': [42 11 33 22 17 21 47 24 43 46 41 105 31 45 3
 4 23 2 8
 6 4 1 12 74 63 35 39 99 14 49 88 5 13 40 26 37 53
 19 9 29 36 20 15 16 64 30 10 25 72 3 65 7 54 90 60
 44 59 57 0 73 87 18 48 27 66 58 75 28 79 103 56 76 62
 32 61 38 51 71 84 93 100 55 102 52 68 69 50 81 96 78 92
 98 85 70 89 67 97 77 94 95 91 83 86 80 448 82]

Number of unique values in column 'RedTotalRoundsFought': 105

Unique values in column 'RedTotalTitleBouts': [3 0 2 5 1 4 16 6 15 7 8 9 11 10 12 14 13]
 Number of unique values in column 'RedTotalTitleBouts': 17

Unique values in column 'RedWinsByDecisionMajority': [0 1 2]
 Number of unique values in column 'RedWinsByDecisionMajority': 3

```
Unique values in column 'RedWinsByDecisionSplit': [2 0 1 4 3 5]
Number of unique values in column 'RedWinsByDecisionSplit': 6

Unique values in column 'RedWinsByDecisionUnanimous': [ 4  0  3  5  1  7  6  9  2 10 11  8]
Number of unique values in column 'RedWinsByDecisionUnanimous': 12

Unique values in column 'RedWinsByK0': [ 2  1  4  0  8  3  6  5 11  7 10  9 14 13 12 21 20 19]
Number of unique values in column 'RedWinsByK0': 18

Unique values in column 'RedWinsBySubmission': [ 4  5  2  1  0  3  7  6 16 12 11  8  9 10 15 14 13]
Number of unique values in column 'RedWinsBySubmission': 17

Unique values in column 'RedWinsByTK0DoctorStoppage': [0 1 2]
Number of unique values in column 'RedWinsByTK0DoctorStoppage': 3

Unique values in column 'RedWins': [12  6  9  7  5 15  8 13 20  2  1  3 21 22 10 26  4 17 18  0 11 14 19 25
16 24 27 23 29 33 32]
Number of unique values in column 'RedWins': 31

Unique values in column 'RedStance': ['Orthodox' 'Southpaw' 'Switch' 'Open Stance']
Number of unique values in column 'RedStance': 4

Unique values in column 'RedWeightLbs': [125 170 245 145 205 185 155 135 115 248 249 250 262 240 264 254 26
5 256
239 257 260 235 242 253 246 230 243 255 258 225 140 238 231 241 263 247]
Number of unique values in column 'RedWeightLbs': 36

Unique values in column 'RedAge': [34 30 36 33 40 37 42 32 31 35 26 28 29 25 24 41 39 27 38 19 23 22 45 20
44 18 21 43 47]
Number of unique values in column 'RedAge': 29

Unique values in column 'BlueAge': [31 27 36 33 35 30 37 23 39 25 32 29 40 34 28 22 42 38 24 26 41 21 43 20
44 45 19 46 47]
Number of unique values in column 'BlueAge': 29

Unique values in column 'LoseStreakDif': [ 0  1 -1 -2  2 -3  3 -4 -6  4  5 -5  6]
Number of unique values in column 'LoseStreakDif': 13

Unique values in column 'WinStreakDif': [ -6   2   3   0  -1   4  -7  -2 -18  -5   5  -3   1  -4 -10   8 -1
2   6
7  -9 -11  -8  10 -16   9 -13]
```

Number of unique values in column 'WinStreakDif': 26

Unique values in column 'LongestWinStreakDif': [-6 2 -3 -5 0 -2 1 -1 -7 3 -12 -8 6 -4 -9
4 5 9
7 -10 8 11 -11 14 12 10]

Number of unique values in column 'LongestWinStreakDif': 26

Unique values in column 'WinDif': [-12 2 3 -6 -1 8 -11 -7 -4 -2 -13 4 1 0 -18 -20 -9 7
-5 -10 -3 5 15 13 -8 -14 -17 6 9 -15 10 -21 12 -16 -24 -19
-26 11 16 -22 -27 23 -28 14 19]

Number of unique values in column 'WinDif': 45

Unique values in column 'LossDif': [-3 0 2 8 -5 4 -4 1 -16 -1 3 -7 -12 -2 -8 -11 -9 -6
5 7 10 6 -10 -20 12 11 -14 -19 9 -15 -13 -17 -18 14 16 13]

Number of unique values in column 'LossDif': 36

Unique values in column 'TotalRoundDif': [-42 9 11 -15 -2 42 -35 33 -27 -10 3 -82 -17
-1
-12 7 -18 0 -9 -28 -49 28 -34 -69 -14 -43 -13 -81
24 12 -31 -40 -21 -24 -5 -4 34 -22 4 1 5 82
-52 -11 29 81 6 -25 -16 -45 -41 -7 25 8 -70 32
-32 -29 56 10 -30 17 -3 -8 23 -6 14 -38 -44 2
15 -54 -74 20 -19 -33 16 -65 13 -20 -37 18 -90 -60
-26 41 19 31 -61 60 -47 -23 -53 26 -51 -46 -50 65
22 -48 37 -62 87 21 -68 -79 -67 -89 49 51 44 -59
36 53 43 -36 46 63 27 39 -66 -92 -75 -58 -39 62
-57 -64 -77 -72 -55 40 50 38 -83 52 -76 -86 45 -80
54 80 48 -71 59 30 -448 -56 47 -73 55 -84 35 57
58]

Number of unique values in column 'TotalRoundDif': 155

Unique values in column 'TotalTitleBoutDif': [-3 0 -1 5 -5 -2 2 -8 -6 7 8 -4 4 1 -15
9 10 -7
6 -9 -10 -11 -13 3 15 -12 13 14 -14 11 -16]

Number of unique values in column 'TotalTitleBoutDif': 31

Unique values in column 'KODif': [-2 2 0 3 -7 -6 -1 1 4 -5 -3 7 -4 -10 6 5 -8 9
-14 10 -9 12 -12 -20 8 -11 -17 -21 14 -13 11]

Number of unique values in column 'KODif': 31

Unique values in column 'SubDif': [-4 -5 -1 0 -2 5 4 -3 -7 1 -6 -15 2 -10 -11 7 3 8
9 -16 -8 -9 6 10 -13 -12]

Number of unique values in column 'SubDif': 26

Unique values in column 'HeightDif': [7.62 5.08 -2.54 2.54 0. -5.08 15.24 -10.16 -7.
62 -12.7 12.7 10.16 -20.32 17.78 -15.24 20.32 -17.78 22.86
-22.86 -187.96 -5.5 -25.4 -27.94 -33.02 30.48 27.94]

Number of unique values in column 'HeightDif': 26

Unique values in column 'ReachDif': [5.0800e+00 -7.6200e+00 -2.5400e+00 0.0000e+00 -5.0800e+00 2.5400e+00
0 1.0160e+01 -1.2700e+01 -1.7780e+01 1.5240e+01 -1.0160e+01 2.0320e+01
7.6200e+00 1.2700e+01 1.7780e+01 -1.5240e+01 -2.0320e+01 -2.2860e+01
2.2860e+01 -2.5400e+01 2.5400e+01 -1.8796e+02 -1.6002e+02 -1.3400e+00
-2.3400e+00 8.8900e+00 -1.3970e+01 -1.9050e+01 6.3500e+00 1.2700e+00
-1.6510e+01 -6.3500e+00 -3.8100e+00 -1.2700e+00 -1.7960e+01 4.0000e-02
-4.2800e+00 2.5800e+00 -8.9800e+00 -4.2000e-01 -8.1000e+00 7.6000e+00
-1.0440e+01 2.7400e+00 1.6600e+00 1.0640e+01 -1.8260e+01 2.7940e+01
-8.0400e+00 -9.9600e+00 -4.9800e+00 -3.0480e+01 -2.7940e+01 8.9300e+00
1.2820e+01 1.0000e-01 -5.1800e+00 -9.6000e-01 7.2000e+00 1.8000e-01
5.2800e+00 2.5000e+00 2.8000e-01 -5.4200e+00 3.6600e+00 2.3400e+00
-5.2000e+00 -2.8200e+00 -9.8000e+00 -5.5000e+00 2.0000e-01 -7.5000e+00
-7.5800e+00 -4.8800e+00 -1.0420e+01 -4.9600e+00 2.2800e+00 1.1200e+00
-7.4200e+00 4.9000e+00 -4.8000e+00 1.0500e+01 2.0580e+01 1.0000e+01
4.6600e+00 5.2000e+00 -1.3120e+01 -7.2600e+00 -7.8800e+00 -3.4000e-01
8.0400e+00 -1.2260e+01 -1.0040e+01 7.2800e+00 1.2960e+01 1.5120e+01
-1.0120e+01 5.5000e+00 -1.2800e+00 1.2900e+01 -5.0400e+00 -1.4800e+01
-2.5800e+00 -3.3020e+01 4.0000e+00 2.6600e+00 -1.5280e+01 1.2000e-01
-2.0000e+00 -2.0580e+01 1.2500e+01 1.8200e+01 1.4040e+01 4.5800e+00
1.5280e+01 -1.5340e+01 -4.0000e-02 -2.1200e+00 1.4740e+01 -7.7200e+00
3.0480e+01 -1.3000e+00]

Number of unique values in column 'ReachDif': 122

Unique values in column 'AgeDif': [-3 2 6 0 5 -4 -10 -17 -6 -1 8 -8 -2 7 3 -7 4 -5
1 -15 -9 9 -11 12 -12 10 13 11 -13 -16 14 15 -14 16 17]

Number of unique values in column 'AgeDif': 35

Unique values in column 'SigStrDif': [-4.41 1.38 -0.36 ... -7.1091 -15.55 -22.35]

Number of unique values in column 'SigStrDif': 3007

Unique values in column 'AvgSubAttDif': [-8.0000e-01 -1.5000e+00 -3.0000e-01 -1.1000e+00 -2.0000e-01 3.000
0e-01 0.0000e+00 5.0000e-01 -1.0000e-01 -7.0000e-01 -9.0000e-01 1.7000e+00

1.3000e+00	1.0000e-01	-2.0000e+00	-5.0000e-01	-2.2000e+00	1.0000e+00
-2.1000e+00	1.2000e+00	4.0000e-01	-6.0000e-01	8.0000e-01	7.0000e-01
-4.0000e-01	1.4000e+00	9.0000e-01	2.0000e-01	1.1000e+00	2.8000e+00
-2.4000e+00	-1.2000e+00	6.0000e-01	-1.3000e+00	-4.8000e+00	-2.5000e+00
-7.3000e+00	1.8000e+00	-1.6000e+00	2.4000e+00	-3.9000e+00	1.9000e+00
-1.7000e+00	2.6000e+00	-2.3000e+00	-1.0000e+00	-3.6000e+00	7.8000e+00
-1.8000e+00	-2.8000e+00	-6.6000e+00	2.1000e+00	3.3000e+00	-1.4000e+00
1.5000e+00	-5.0000e+00	2.2000e+00	-3.0000e+00	3.4000e+00	2.0000e+00
-8.4000e+00	-2.6000e+00	-1.9000e+00	1.6000e+00	-4.6000e+00	-7.5000e+00
-4.3000e+00	2.5000e+00	3.5000e+00	-5.4000e+00	-7.4000e+00	3.8000e+00
-2.9000e+00	-3.8000e+00	2.7000e+00	2.3000e+00	4.1000e+00	-2.7000e+00
2.9000e+00	5.2000e+00	3.1000e+00	-3.2000e+00	-6.4000e+00	3.6000e+00
-8.3000e+00	-3.3000e+00	-4.9000e+00	3.0000e+00	4.8000e+00	-4.0000e+00
-5.9000e+00	-6.0000e+00	2.9000e-01	-1.2500e+00	1.4000e-01	-1.5800e+00
-9.8000e-01	2.4000e-01	1.0000e-02	-4.4000e-01	6.2000e-01	-6.8000e-01
-3.9000e-01	-7.4000e-01	-7.1000e-01	2.0700e+00	-1.4800e+00	-1.2600e+00
-6.7000e-01	-1.5000e-01	-2.2500e+00	7.8000e-01	-5.1000e+00	2.7140e-01
-6.4520e-01	2.5000e-01	1.6670e-01	-8.3300e-02	-6.6670e-01	3.3330e-01
3.0300e-02	-1.8180e-01	-2.2220e-01	1.7030e-01	1.3333e+00	-1.7000e-01
-7.5000e-01	-2.5000e-01	6.7860e-01	-3.9290e-01	2.6090e-01	2.6920e-01
-2.4000e-01	8.1820e-01	-3.3333e+00	7.6900e-02	1.1670e-01	-2.1430e-01
7.5000e-02	-9.0900e-02	-1.1429e+00	-2.9170e-01	-5.2940e-01	-1.7860e-01
-4.2860e-01	-9.5700e-01	1.4290e-01	2.3800e-02	-3.3330e-01	2.5060e-01
5.7100e-02	-2.3800e-02	3.2220e-01	-1.6670e-01	1.2500e-01	-5.0000e-02
2.8570e-01	-1.1670e-01	-8.3330e-01	-1.3750e+00	-4.1670e-01	6.6670e-01
1.8333e+00	-8.7500e-01	4.6670e-01	2.2730e-01	3.8100e-01	5.5600e-02
6.0320e-01	-4.0910e-01	-2.5600e-01	-5.4550e-01	-1.2273e+00	-1.4290e-01
-1.2500e-01	-1.2630e-01	-2.7800e-02	8.8890e-01	7.2730e-01	6.5520e-01
-7.1430e-01	1.1110e-01	1.1571e+00	-2.4120e-01	-5.7740e-01	-5.8330e-01
4.8050e-01	-7.9000e-03	1.3556e+00	-6.8420e-01	-1.9440e-01	8.0950e-01
-1.3330e-01	2.2700e-02	5.0000e+00	-3.9375e+00	1.1667e+00	9.6200e-02
8.3300e-02	-8.5710e-01	-1.2727e+00	6.8890e-01	-2.6670e-01	-1.7310e-01
4.2860e-01	3.7930e-01	-2.8570e-01	3.5710e-01	-1.9840e-01	6.0600e-02
4.4620e-01	2.0000e-02	-1.5380e-01	-5.7340e-01	2.4740e-01	-4.7600e-02
-1.1110e-01	-6.3330e-01	6.6700e-02	7.5400e-01	1.6150e-01	-1.3750e-01
5.7780e-01	-5.8800e-02	3.7780e-01	-4.5000e-01	2.1210e-01	-4.4440e-01
-3.1000e-01	7.3330e-01	-1.1760e-01	-2.6320e-01	3.9100e-01	-3.8460e-01
6.3890e-01	-6.2500e-01	3.4290e-01	-3.5710e-01	-1.5556e+00	-4.2000e-02
1.0260e-01	-9.5830e-01	5.6250e-01	-7.1400e-02	2.2220e-01	-5.2600e-02
3.5040e-01	4.4440e-01	2.0590e-01	-3.4290e-01	9.0900e-02	4.6840e-01
7.7780e-01	-6.6700e-02	1.3330e-01	-9.6670e-01	3.7770e-01	-8.1820e-01
7.5000e-01	9.3750e-01	7.7000e-03	5.2630e-01	8.3330e-01	-1.2020e+00

4.4400e-02	8.5700e-02	2.1538e+00	4.7060e-01	6.5000e-01	-1.1071e+00
-5.8090e-01	-2.7780e-01	5.5000e-01	8.4400e-02	1.5000e-01	1.5833e+00
1.4700e-02	-6.2500e-02	-8.5700e-02	-5.5000e-01	-3.3300e-02	3.2500e-01
-1.1667e+00	-3.7500e-01	6.3640e-01	-1.8460e-01	4.0480e-01	4.0280e-01
-7.2220e-01	1.8520e-01	3.6360e-01	5.5560e-01	4.3333e+00	-3.6110e-01
-7.6900e-02	-2.8210e-01	2.1430e-01	7.5580e-01	4.3230e-01	7.1400e-02
-1.1579e+00	6.2960e-01	-4.6430e-01	2.7800e-02	-5.7140e-01	-6.0320e-01
-1.0710e-01	6.8060e-01	-5.4620e-01	1.6667e+00	-8.9470e-01	8.6110e-01
-2.9190e-01	-5.7890e-01	-9.7400e-02	-1.3571e+00	-3.2630e-01	-6.0710e-01
-1.4440e-01	-1.1600e+00	-3.2140e-01	8.7880e-01	-8.4430e-01	8.7500e-01
-3.5560e-01	-5.2780e-01	1.7040e-01	-2.7380e-01	-4.4400e-02	4.3590e-01
-6.9230e-01	-7.3630e-01	2.6667e+00	-2.1000e-02	-1.8060e-01	-2.7270e-01
-3.6360e-01	1.1429e+00	-2.0830e-01	7.8570e-01	-7.4600e-01	1.4091e+00
-9.6200e-02	-1.1176e+00	-4.4120e-01	-2.1667e+00	-3.9820e-01	-1.1111e+00
6.0870e-01	2.1540e-01	5.7140e-01	1.0462e+00	3.7500e-01	3.6670e-01
-1.1180e-01	4.1270e-01	-9.4440e-01	-1.0333e+00	-1.1900e-02	7.6470e-01
-1.7140e-01	-3.5120e-01	2.1740e-01	-2.1970e-01	9.1010e-01	9.2310e-01
-2.5000e-02	1.0820e-01	-6.7310e-01	-5.7100e-02	1.0444e+00	8.7180e-01
-3.6670e-01	9.4640e-01	-8.7900e-02	-9.0910e-01	2.1370e-01	-3.7880e-01
-2.3810e-01	1.7780e-01	1.8180e-01	2.7840e-01	3.8890e-01	1.1111e+00
-1.1900e-01	1.2500e+00	7.0830e-01	5.6670e-01	9.1670e-01	-1.3333e+00
7.6000e-01	4.1670e-01	1.6727e+00	-9.1670e-01	-1.1030e-01	-4.8480e-01
2.0190e-01	-4.3750e-01	2.6980e-01	-7.7780e-01	-1.5910e-01	1.1364e+00
-1.5480e-01	-5.5560e-01	-2.0800e-01	2.4840e-01	-2.2730e-01	-1.8490e-01
3.7140e-01	7.1430e-01	1.7140e-01	-1.5710e-01	1.0420e-01	2.7540e-01
-3.2480e-01	3.2100e-02	1.7860e-01	-4.6150e-01	6.9050e-01	-1.7500e+00
3.8670e-01	-6.1740e-01	9.4290e-01	2.5000e-02	3.3300e-02	-3.4720e-01
1.2941e+00	1.3462e+00	2.6670e-01	4.3750e-01	1.4583e+00	-3.4620e-01
6.4290e-01	3.6400e-02	1.0710e-01	-2.3100e-02	6.3330e-01	4.6150e-01
4.7600e-02	-3.0710e-01	8.7750e-01	3.2140e-01	-1.7650e-01	7.9170e-01
-1.8571e+00	1.4860e-01	1.1900e-02	8.6670e-01	-5.2530e-01	1.1778e+00
-8.7830e-01	2.7270e-01	-1.5290e-01	-8.2350e-01	3.2000e+00	-1.2632e+00
5.9090e-01	4.1700e-02	-4.1700e-02	8.5710e-01	7.3810e-01	-1.0770e-01
4.0110e-01	4.1180e-01	-3.0300e-02	1.5290e-01	-4.0900e-02	-5.1790e-01
-8.7000e-03	1.1230e-01	-1.1583e+00	4.8330e-01	-3.0560e-01	4.3060e-01
1.0180e-01	-9.5100e-01	2.3480e-01	5.2730e-01	1.1540e-01	-1.0667e+00
2.0630e-01	-8.1250e-01	-6.6070e-01	-3.9000e-02	-1.1875e+00	1.9440e-01
7.9000e-03	5.8330e-01	2.8360e-01	1.9050e-01	-1.1364e+00	1.0590e-01
-3.4920e-01	-8.9290e-01	-5.1950e-01	-8.4520e-01	-2.5710e-01	-6.4290e-01
-3.5000e-01	-2.7500e-01	-1.4444e+00	-1.0714e+00	-4.1430e-01	4.6100e-02
5.1740e-01	-1.5909e+00	9.4120e-01	-5.6250e-01	2.2500e+00	-6.3160e-01
-1.8950e-01	-1.5714e+00	1.0833e+00	3.6540e-01	4.2060e-01	-3.1250e-01

-4.4290e-01	-1.0303e+00	-2.2500e-01	-3.5470e-01	1.0910e-01	4.9020e-01
3.1430e-01	-6.1900e-01	1.9550e-01	2.6320e-01	1.1875e+00	-4.0280e-01
-2.1150e-01	-3.0360e-01	-2.1333e+00	-1.6667e+00	2.8890e-01	3.5700e-02
6.1540e-01	-3.7300e-01	5.2380e-01	-2.6667e+00	7.1680e-01	1.0952e+00
-7.2730e-01	6.9230e-01	8.4850e-01	-1.0750e-01	-2.4440e-01	3.8160e-01
-2.4680e-01	7.6200e-02	-8.6670e-01	-3.0770e-01	-1.8400e-02	-4.5450e-01
-2.3330e-01	-3.8500e-02	2.3330e-01	-7.6670e-01	1.4100e-01	4.5450e-01
1.1760e-01	2.7780e-01	-1.9230e-01	1.1500e+00	1.7430e-01	-9.0260e-01
4.4000e-02	-2.6260e-01	8.2310e-01	-5.0180e-01	-1.6920e-01	-9.8570e-01
1.8460e-01	-2.6920e-01	-5.3330e-01	2.0240e-01	-1.7900e-02	-3.1820e-01
-2.7500e+00	-3.0670e-01	2.7080e-01	1.3640e-01	-3.5000e+00	-1.9050e-01
-7.6000e-03	5.4590e-01	1.0449e+00	7.0910e-01	1.5690e-01	8.9470e-01
-8.5000e-01	-8.8890e-01	-1.5395e+00	1.8200e-02	9.3650e-01	6.2500e-01
-4.0480e-01	-7.7220e-01	-9.3570e-01	7.8950e-01	-1.3890e-01	-3.3040e-01
5.1950e-01	-6.3680e-01	2.7380e-01	4.2900e-02	-4.5390e-01	-4.1180e-01
1.3070e-01	4.5710e-01	-1.3640e-01	3.8330e-01	2.5670e-01	-1.7780e-01
3.7270e-01	9.7200e-02	3.2890e-01	5.6800e-02	-9.2220e-01	7.7140e-01
-2.2630e-01	-6.5000e-01	-3.9470e-01	-4.8610e-01	7.9370e-01	7.3600e-02
1.2154e+00	9.1300e-01	1.2375e+00	1.1250e+00	1.0667e+00	-1.1008e+00
-6.3640e-01	-1.1540e-01	3.8070e-01	6.9570e-01	8.2350e-01	-5.8970e-01
1.9840e-01	1.3500e+00	-9.3940e-01	4.6050e-01	1.4615e+00	-1.9190e-01
1.7500e+00	7.9900e-01	-2.3210e-01	3.5000e-01	-1.2857e+00	9.2300e-02
4.5500e-02	-1.1500e+00	9.1430e-01	-3.8890e-01	-4.6670e-01	-5.9500e-02
-6.0600e-02	-3.3640e-01	-8.4620e-01	5.5680e-01	5.3850e-01	-7.8570e-01
7.4440e-01	1.4389e+00	-3.6190e-01	1.4550e-01	6.8750e-01	-1.3490e-01
1.6071e+00	-2.6300e-02	-1.0909e+00	1.2090e-01	4.7500e-01	-4.1070e-01
-8.8900e-02	8.3080e-01	2.8600e-02	-1.4550e-01	8.4620e-01	-1.8750e+00
1.3750e+00	7.9400e-02	-9.2300e-02	3.3090e-01	2.2333e+00	-1.0833e+00
-1.0202e+00	1.2120e-01	9.2860e-01	-3.4210e-01	9.5200e-02	2.9170e-01
6.5710e-01	1.7381e+00	4.0000e+00	-3.5700e-02	1.0500e+00	5.8820e-01
-5.8170e-01	1.6250e+00	-1.2167e+00	-6.4710e-01	-6.8330e-01	-4.7500e-01
-4.7620e-01	5.3600e-02	1.1900e-01	1.1905e+00	1.4375e+00	-2.2080e-01
5.8550e-01	-6.4550e-01	3.0770e-01	8.9090e-01	5.1590e-01	-1.0420e-01
-7.8800e-02	1.5150e-01	-1.0625e+00	-1.0227e+00	9.6000e-03	4.5000e+00
-4.7730e-01	5.2940e-01	-1.5240e-01	4.2100e-02	5.2780e-01	-2.9090e-01
-1.7143e+00	1.1154e+00	-4.4020e-01	-5.8820e-01	-9.2310e-01	4.2500e-01
6.9640e-01	1.5450e-01	2.3939e+00	2.8330e-01	-4.7060e-01	3.8180e-01
1.4545e+00	2.9370e-01	5.1500e-02	-1.2941e+00	-1.2143e+00	1.4286e+00
-1.5790e-01	5.9520e-01	-1.1818e+00	2.0910e-01	3.2860e-01	-2.0833e+00
1.2820e-01	1.6860e-01	5.0980e-01	8.2910e-01	-1.4580e-01	-1.0910e-01
-2.0590e-01	-7.1800e-02	-5.2630e-01	6.9440e-01	5.0000e-02	2.2860e-01
7.6920e-01	-9.5200e-02	-1.4300e-02	8.4440e-01	-1.9090e-01	-1.0530e-01

```
1.0556e+00 5.2860e-01 -2.0800e-02 -1.2250e+00 -1.6364e+00 -1.6970e-01
2.0800e-02 9.5240e-01 -2.7450e-01 -1.5682e+00 7.6190e-01 -1.8750e-01
-2.2860e-01 -2.6370e-01 1.6042e+00 1.1100e-02 1.3940e-01 5.4170e-01
2.1667e+00 1.0714e+00 1.0526e+00 1.6429e+00 1.5380e-01 2.7500e-01
-1.0278e+00 -4.5830e-01 -2.3080e-01 1.7143e+00 1.2260e+00 3.0300e-01
1.3182e+00 -1.8889e+00 6.0200e-02 2.2970e+00 1.0909e+00 1.0536e+00
-1.9000e-02 -1.4333e+00 -5.5600e-02 -7.0000e-02 -6.9400e-02 -1.1250e+00
5.8570e-01 -7.6920e-01 3.2310e-01 3.0360e-01 1.8286e+00 -4.3180e-01
-8.6360e-01 2.3080e-01 5.6667e+00 -1.1538e+00 4.6210e-01 2.0510e-01
2.8210e-01 -4.9210e-01 4.1667e+00 1.1504e+00 -1.2820e-01 3.4560e-01
1.0273e+00 7.2500e-02 1.2857e+00 -7.0830e-01 -1.5333e+00 8.1430e-01
-7.3330e-01 -8.0950e-01 1.2222e+00 1.2143e+00 5.6410e-01 -3.2170e-01
1.0889e+00 -3.3770e-01 6.0000e+00 1.9700e-01 8.6060e-01 -3.0130e-01
-1.4143e+00 1.3889e+00 -5.4900e-01 1.9167e+00 -4.7270e-01 5.5710e-01
-9.6320e-01 -8.9010e-01 4.9230e-01 1.0222e+00 -4.3430e-01 -8.4500e-02
-1.1786e+00 9.3180e-01 -1.8940e-01 4.7140e-01 4.6030e-01 -6.1540e-01
-7.5890e-01 7.0140e-01 3.8640e-01 2.4240e-01 8.8100e-01 6.9090e-01
-2.4286e+00 3.9710e-01 1.7900e-02 -3.7690e-01 -5.1280e-01 9.6360e-01
6.9320e-01 1.8750e-01 -5.5000e+00 7.4550e-01 9.8570e-01 -4.0180e-01
6.0710e-01 2.3333e+00 -1.2667e+00 1.4444e+00 -2.8330e-01 1.5910e-01
1.2730e-01]
```

Number of unique values in column 'AvgSubAttDif': 889

Unique values in column 'AvgTDDif': [-2.61 -0.72 -0.13 ... 1.9545 -0.9818 -4.6667]
Number of unique values in column 'AvgTDDif': 1796

Unique values in column 'EmptyArena': [nan 0. 1.]
Number of unique values in column 'EmptyArena': 3

Unique values in column 'BMatchWCRank': [nan 7. 3. 13. 9. 5. 10. 8. 11. 14. 15. 2. 12. 1. 6. 4.]
Number of unique values in column 'BMatchWCRank': 16

Unique values in column 'RMatchWCRank': [0. 3. 2. 13. nan 12. 14. 5. 8. 9. 15. 1. 10. 7. 6. 11. 4.]
Number of unique values in column 'RMatchWCRank': 17

Unique values in column 'RWFlyweightRank': [nan 3. 13. 0. 15. 6. 12. 2. 8. 4. 9. 14. 11. 5. 10. 7. 1.]
Number of unique values in column 'RWFlyweightRank': 17

Unique values in column 'RWFeatherweightRank': [nan 0.]
Number of unique values in column 'RWFeatherweightRank': 2

```
Unique values in column 'RWStrawweightRank': [nan  2.  13.  6.  9.  7.  3.  14.  11.  0.  5.  10.  12.  15.  8.  4.  1.]  
Number of unique values in column 'RWStrawweightRank': 17  
  
Unique values in column 'RWBantamweightRank': [nan  0.  2.  15.  5.  12.  8.  3.  11.  6.  13.  4.  9.  7.  1.  14.  10.]  
Number of unique values in column 'RWBantamweightRank': 17  
  
Unique values in column 'RHeavyweightRank': [nan  2.  0.  9.  13.  10.  8.  1.  3.  7.  12.  5.  15.  6.  14.  4.  11.]  
Number of unique values in column 'RHeavyweightRank': 17  
  
Unique values in column 'RLightHeavyweightRank': [nan  12.  8.  1.  0.  14.  10.  7.  15.  11.  3.  9.  13.  5.  6.  2.  4.]  
Number of unique values in column 'RLightHeavyweightRank': 17  
  
Unique values in column 'RMiddleweightRank': [nan  3.  13.  10.  4.  5.  0.  1.  6.  15.  11.  8.  14.  2.  7.  1.  2.  9.]  
Number of unique values in column 'RMiddleweightRank': 17  
  
Unique values in column 'RWelterweightRank': [nan  3.  14.  15.  10.  9.  6.  12.  0.  7.  11.  13.  4.  8.  5.  1.  2.]  
Number of unique values in column 'RWelterweightRank': 17  
  
Unique values in column 'RLightweightRank': [nan  2.  11.  5.  15.  0.  1.  10.  3.  6.  13.  4.  12.  14.  8.  7.  9.]  
Number of unique values in column 'RLightweightRank': 17  
  
Unique values in column 'RFeatherweightRank': [nan  13.  5.  0.  12.  3.  6.  8.  4.  11.  10.  1.  9.  15.  2.  14.  7.]  
Number of unique values in column 'RFeatherweightRank': 17  
  
Unique values in column 'RBantamweightRank': [nan  3.  13.  10.  0.  2.  4.  8.  7.  15.  6.  9.  11.  12.  1.  5.  14.]  
Number of unique values in column 'RBantamweightRank': 17  
  
Unique values in column 'RFlyweightRank': [ 0.  nan  14.  2.  7.  1.  11.  4.  6.  5.  9.  12.  10.  3.  15.  8.  13.]  
Number of unique values in column 'RFlyweightRank': 17  
  
Unique values in column 'RPFPRank': [11.  nan  3.  7.  4.  2.  8.  6.  1.  12.  14.  10.  15.  5.  13.  9.]
```

Number of unique values in column 'RPFPRank': 16

Unique values in column 'BWFlyweightRank': [nan 11. 5. 14. 1. 8. 13. 3. 6. 9. 4. 12. 10. 15. 7. 2.]

Number of unique values in column 'BWFlyweightRank': 16

Unique values in column 'BWFeatherweightRank': [nan 0.]

Number of unique values in column 'BWFeatherweightRank': 2

Unique values in column 'BWStrawweightRank': [nan 10. 14. 11. 5. 15. 12. 1. 6. 7. 13. 2. 9. 4. 8. 3.]

Number of unique values in column 'BWStrawweightRank': 16

Unique values in column 'BWBantamweightRank': [nan 3. 8. 14. 11. 7. 10. 9. 13. 15. 5. 6. 12. 1. 4. 2. 0.]

Number of unique values in column 'BWBantamweightRank': 17

Unique values in column 'BHeavyweightRank': [nan 3. 8. 15. 12. 9. 4. 5. 13. 10. 7. 14. 1. 11. 6. 2.]

Number of unique values in column 'BHeavyweightRank': 16

Unique values in column 'BLightHeavyweightRank': [nan 13. 10. 8. 15. 9. 1. 7. 11. 3. 12. 5. 6. 14. 4. 2. 0.]

Number of unique values in column 'BLightHeavyweightRank': 17

Unique values in column 'BMiddleweightRank': [nan 13. 14. 8. 12. 2. 10. 7. 6. 11. 5. 4. 1. 15. 9. 3. 0.]

Number of unique values in column 'BMiddleweightRank': 17

Unique values in column 'BWelterweightRank': [nan 7. 15. 11. 8. 2. 14. 10. 3. 6. 4. 13. 5. 1. 9. 12.]

Number of unique values in column 'BWelterweightRank': 16

Unique values in column 'BLightweightRank': [nan 7. 5. 15. 11. 4. 13. 8. 9. 3. 12. 6. 10. 1. 14. 2.]

Number of unique values in column 'BLightweightRank': 16

Unique values in column 'BFeatherweightRank': [nan 9. 2. 14. 13. 10. 4. 3. 0. 12. 8. 15. 1. 5. 6. 7. 11.]

Number of unique values in column 'BFeatherweightRank': 17

Unique values in column 'BBantamweightRank': [nan 5. 12. 11. 1. 10. 6. 2. 7. 3. 15. 14. 13. 8. 9.

4. 0.]

Number of unique values in column 'BBantamweightRank': 17

Unique values in column 'BFlyweightRank': [nan 3. 13. 14. 5. 15. 7. 8. 10. 12. 2. 11. 1. 6. 9. 4.]
Number of unique values in column 'BFlyweightRank': 16

Unique values in column 'BPFPRank': [nan 6. 11. 3. 13. 10. 14. 15. 8. 2. 4. 5. 1. 9. 7. 12.]
Number of unique values in column 'BPFPRank': 16

Unique values in column 'BetterRank': ['Red' 'neither' 'Blue']

Number of unique values in column 'BetterRank': 3

Unique values in column 'Finish': ['SUB' 'U-DEC' 'S-DEC' 'KO/TKO' 'M-DEC' 'DQ' nan 'Overturned']
Number of unique values in column 'Finish': 8

Unique values in column 'FinishDetails': ['Rear Naked Choke' nan 'Elbows' 'Punches' 'Anaconda Choke' 'Armbar'
'Punch' 'Kick' 'Elbow' 'Spinning Back Kick' 'Guillotine Choke'
'Arm Triangle' "D'Arce Choke" 'Spinning Back Fist' 'Knee' 'Heel Hook'
'Triangle Choke' 'Knees' 'Triangle Armbar' 'Spinning Back Elbow'
'Flying Knee' 'Neck Crank' 'Kimura' 'Slam' 'Kicks' 'Ezekiel Choke'
'Twister' 'Other - Lock' 'Kneebar' 'Inverted Triangle' 'Von Flue Choke'
'Keylock' 'Scarf Hold' 'Straight Armbar' 'Ankle Lock' 'Other - Choke'
'Peruvian Necktie' 'Omoplata' 'North-South Choke' 'Injury']

Number of unique values in column 'FinishDetails': 40

Unique values in column 'FinishRound': [2. 5. 3. 1. 4. nan]

Number of unique values in column 'FinishRound': 6

Unique values in column 'FinishRoundTime': ['2:05' '5:00' '0:39' '3:21' '4:46' '0:52' '4:51' '1:56' '3:41'
'3:49'
'2:25' '2:36' '0:46' '1:28' '4:29' '2:44' '2:55' '0:40' '4:50' '1:44'
'1:15' '0:51' '4:19' '1:23' '1:20' '2:28' '4:28' '3:43' '0:59' '1:34'
'3:34' '4:52' '1:30' '3:14' '4:27' '2:22' '4:33' '1:42' '2:50' '4:06'
'2:15' '2:12' '4:32' '2:17' '1:35' '3:19' '3:47' '0:27' '2:59' '3:52'
'4:02' '3:02' '3:59' '0:29' '4:14' '3:28' '1:14' '1:49' '4:39' '4:12'
'1:02' '3:38' '4:04' '4:56' '0:48' '2:39' '1:55' '3:44' '3:36' '3:18'
'4:45' '1:00' '3:22' '3:12' '3:23' '4:48' '1:36' '2:58' '1:05' '3:58'
'4:49' '0:20' '0:18' '3:27' '1:46' '0:13' '1:58' '1:25' '1:22' '0:19'
'2:27' '1:52' '1:50' '2:00' '4:47' '2:42' '2:47' '3:50' '0:37' '3:16'
'0:49' '0:12' '3:00' '0:54' '2:10' '3:35' '4:42' '2:16' '2:09' '1:29'
'4:59' '3:17' '1:47' '4:11' '2:13' '3:06' '2:18' '4:00' '4:43' '0:22'

```
'1:32' '0:21' '2:45' '2:52' '4:08' '3:54' '4:23' '1:43' '1:38' '0:15'
'2:32' '0:36' '1:01' '0:26' '4:41' '1:57' '4:36' '0:58' '2:04' '0:44'
'3:32' '1:41' '1:18' '2:43' '0:55' '4:03' '0:32' '2:03' '4:21' '1:17'
'3:25' '4:55' '3:29' '1:03' '4:31' '3:42' '4:25' '0:56' '1:04' '2:49'
'4:10' '4:17' '1:11' '0:38' '3:53' '4:24' '1:31' '1:09' '3:15' '3:08'
'4:01' '2:14' '2:07' '1:13' '3:03' '2:26' '1:06' '2:23' '0:33' '4:40'
'4:15' '3:26' '4:44' '4:37' '3:46' '2:20' '3:51' '0:23' '1:24' '3:01'
'4:16' '2:40' '2:19' '3:11' '4:54' '2:37' '2:11' '4:57' '4:26' '4:05'
'1:07' '0:34' '3:10' '0:17' '4:20' '2:54' '4:13' '1:48' '1:45' '2:57'
'4:09' '0:14' '1:10' '1:40' '4:34' '4:22' '2:51' '1:37' '3:13' '2:02'
'3:05' '2:56' '0:28' '3:04' '2:29' '4:30' '3:20' '3:24' '1:27' '2:01'
'3:37' '2:30' '3:33' '0:47' '0:08' '4:07' '1:33' '0:30' '3:55' '1:53'
'2:21' '2:24' '0:16' '3:39' '1:39' '2:31' '3:57' '3:09' '2:46' '4:38'
'0:45' '0:42' '4:58' '1:08' '1:12' '2:38' '4:35' '1:16' '2:35' '0:41'
'2:48' '3:56' '2:34' '3:45' '2:33' '0:57' '2:06' '0:25' '3:07' '1:21'
'3:31' '0:53' '1:51' '3:48' '1:54' '3:40' '0:35' '1:59' '0:07' nan '4:18'
'2:53' '2:41' '1:26' '0:05' '0:09' '0:50' '0:43' '1:19' '4:53' '2:08'
'0:24' '3:30' '0:31' '0:11']
```

Number of unique values in column 'FinishRoundTime': 295

Unique values in column 'TotalFightTimeSecs': [425. 1500. 900. 639. 801. 586. 52. 591. 716. 221. 291. 229.

529.	145.	156.	646.	688.	869.	164.	600.	175.	640.	290.	704.
75.	51.	259.	83.	380.	748.	268.	523.	359.	694.	214.	592.
90.	794.	267.	1342.	873.	402.	170.	246.	435.	432.	1172.	300.
737.	95.	199.	527.	327.	779.	232.	242.	182.	239.	329.	554.
559.	208.	374.	409.	390.	279.	552.	62.	1118.	244.	542.	296.
648.	159.	104.	415.	224.	816.	498.	285.	60.	202.	792.	203.
588.	96.	478.	518.	65.	238.	289.	620.	18.	207.	406.	313.
418.	85.	382.	19.	109.	747.	148.	675.	479.	712.	710.	994.
120.	442.	20.	287.	1362.	94.	147.	167.	230.	223.	637.	496.
649.	12.	891.	480.	37.	54.	430.	515.	282.	395.	436.	129.
756.	273.	689.	194.	1499.	497.	407.	89.	551.	599.	433.	486.
738.	198.	240.	283.	420.	622.	692.	339.	321.	410.	165.	135.
472.	248.	234.	563.	403.	98.	615.	452.	823.	336.	61.	1200.
326.	881.	417.	276.	658.	106.	724.	137.	44.	512.	503.	101.
678.	163.	655.	288.	543.	218.	197.	299.	32.	892.	885.	492.
123.	861.	377.	462.	805.	295.	509.	252.	63.	571.	596.	117.
222.	378.	565.	212.	356.	656.	539.	361.	355.	64.	169.	703.
550.	557.	371.	638.	178.	833.	534.	889.	564.	91.	548.	69.
495.	188.	49.	573.	241.	363.	434.	186.	127.	73.	783.	780.
446.	66.	743.	33.	280.	423.	572.	192.	255.	506.	584.	577.

82.	132.	499.	59.	524.	226.	740.	231.	623.	84.	181.	256.
589.	351.	103.	459.	160.	522.	139.	251.	821.	227.	391.	491.
360.	894.	333.	457.	731.	115.	580.	597.	566.	206.	245.	585.
367.	34.	859.	443.	38.	822.	190.	17.	560.	77.	55.	174.
797.	553.	456.	408.	110.	899.	250.	366.	23.	105.	661.	555.
475.	177.	429.	249.	715.	14.	860.	140.	448.	130.	501.	1270.
469.	388.	131.	215.	157.	125.	400.	853.	561.	796.	195.	470.
544.	567.	872.	112.	136.	883.	383.	124.	1174.	857.	862.	865.
471.	595.	397.	193.	133.	422.	344.	185.	791.	260.	253.	545.
476.	437.	438.	328.	196.	733.	184.	465.	530.	749.	763.	490.
581.	570.	500.	404.	546.	806.	362.	663.	204.	687.	1321.	365.
720.	121.	200.	80.	217.	150.	654.	813.	67.	725.	294.	47.
308.	349.	484.	92.	247.	587.	866.	88.	122.	93.	30.	568.
488.	257.	387.	235.	713.	439.	1072.	741.	277.	444.	863.	669.
316.	594.	1444.	274.	219.	1037.	699.	213.	179.	1051.	721.	837.
116.	874.	489.	690.	513.	15.	466.	578.	508.	1218.	790.	493.
739.	45.	392.	42.	598.	68.	72.	1472.	152.	74.	541.	458.
275.	485.	832.	671.	142.	502.	76.	317.	134.	155.	41.	851.
78.	168.	836.	590.	698.	945.	237.	454.	225.	153.	57.	243.
58.	126.	325.	582.	644.	338.	346.	507.	389.	700.	264.	421.
569.	708.	504.	278.	16.	146.	216.	778.	113.	645.	487.	662.
201.	48.	381.	270.	108.	830.	318.	482.	211.	314.	886.	511.
742.	755.	777.	653.	583.	254.	411.	1140.	746.	875.	158.	450.
265.	776.	879.	895.	205.	272.	284.	676.	455.	528.	431.	525.
1058.	714.	820.	35.	401.	451.	574.	330.	97.	774.	119.	7.
nan	393.	626.	269.	657.	189.	372.	258.	449.	1404.	141.	758.
824.	773.	161.	764.	876.	162.	22.	114.	370.	111.	183.	39.
1264.	520.	817.	1419.	628.	154.	414.	398.	40.	789.	517.	616.
70.	1450.	1496.	633.	376.	849.	86.	629.	841.	29.	723.	834.
166.	494.	771.	726.	266.	579.	1149.	176.	709.	706.	46.	187.
5.	399.	505.	71.	642.	674.	9.	419.	1127.	107.	447.	804.
50.	25.	854.	172.	481.	757.	292.	36.	441.	26.	233.	53.
354.	236.	722.	852.	100.	759.	341.	643.	679.	261.	845.	427.
1056.	286.	463.	766.	1083.	379.	660.	843.	81.	461.	342.	118.
526.	43.	87.	882.	297.	593.	369.	352.	533.	138.	775.	761.
271.	1356.	220.	730.	1338.	180.	460.	933.	736.	998.	228.	263.
752.	453.	298.	768.	632.	293.	650.	102.	839.	473.	870.	728.
685.	718.	128.	819.	842.	1395.	79.	753.	24.	445.	556.	171.
576.	810.	686.	562.	825.	751.	424.	474.	343.	353.	1131.	1267.
28.	607.	516.	210.	467.	719.	21.	659.	826.	799.	149.	324.
890.	634.	765.	477.	1122.	385.	426.	831.	732.	624.	262.	781.
880.	143.	745.	618.	13.	340.	538.	682.	173.	871.	347.	696.

1410.	394.	334.	691.	386.	323.	782.	697.	850.	1092.	1345.	558.
191.	627.	651.	549.	898.	647.	99.	760.	935.	56.	1260.	877.
701.	348.	670.	281.	384.	1367.	795.	695.	838.	858.	8.	547.
1138.	514.	897.	510.	846.	413.	31.	357.	412.	681.	1340.	416.
151.	320.	827.	957.	521.	144.	856.	829.	976.	767.	625.	1346.
786.	803.	350.	612.	440.	1389.	531.	335.	798.	808.	630.	954.
1020.	1423.	537.	744.	887.	641.	613.	884.	1096.	693.	540.	1137.
364.	536.	575.	664.	711.	619.	967.	311.	332.	532.	668.	814.
1134.	464.	27.	717.	735.	1390.	375.	322.	893.	772.]		

Number of unique values in column 'TotalFightTimeSecs': 862

Unique values in column 'RedDecOdds': [300. 250. -160. -200. 275. 450. -135. 400. 150. 200. 1200. 10.

nan	-110.	500.	800.	480.	185.	700.	180.	215.	550.	350.	1100.
600.	130.	140.	225.	-115.	-175.	120.	650.	100.	-105.	750.	240.
-150.	1400.	-140.	165.	1000.	900.	175.	330.	-165.	430.	-120.	125.
370.	380.	-125.	425.	1600.	2000.	320.	2200.	1300.	850.	280.	210.
410.	360.	420.	460.	190.	440.	105.	270.	135.	260.	195.	220.
310.	160.	170.	390.	340.	2400.	290.	230.	1500.	950.	470.	145.
1800.	475.	188.	333.	235.	525.	285.	385.	375.	575.	-145.	155.
115.	325.	-180.	625.	-130.	-185.	515.	245.	1050.	305.	211.	580.
710.	265.	539.	167.	345.	255.	181.	437.	925.	395.	349.	151.
560.	545.	490.	335.	129.	355.	-121.	491.	1065.	-107.	178.	465.
-155.	163.	-132.	317.	205.	855.	442.	168.	509.	510.	415.	315.
-103.	405.	153.	690.	635.	685.	246.	-225.	429.	256.	313.	177.
520.	540.	585.	257.	579.	112.	670.	142.	660.	162.	219.	147.
179.	156.	199.	365.	334.	378.	-104.	201.	174.	229.	553.	488.
463.	-195.	286.	166.	262.	328.	-325.	284.	547.	222.	207.	566.
109.	137.	251.	234.	228.	134.	128.	352.	226.	157.	148.	1460.
169.	412.	454.	223.	432.	164.	149.	435.	455.	306.	565.	504.
294.	1265.	118.	574.	448.	655.	570.	709.	214.	172.	309.	447.
705.	116.	189.	249.	610.	485.	316.	1040.	-220.	1475.	106.	196.
1094.	213.	278.	139.	-172.	399.	108.	495.	252.	640.	271.	517.
216.	457.	775.	184.	382.	362.	287.	247.	727.	595.	860.	242.
562.	-116.	323.	237.	603.	667.	176.	-153.	-117.	738.	-108.	103.
445.	459.	-114.	561.	221.	675.	825.	423.	-101.	743.	292.	535.
538.	-170.	1310.	208.	131.	-127.	891.	505.	204.	544.	1125.	696.
940.	588.	119.	526.	496.	209.	173.	755.	1075.	-112.	268.	481.
680.	-154.	605.	363.	725.	144.	203.	620.	132.	331.	785.	159.
277.	-138.	133.	111.	702.	354.	197.	383.	146.	346.	626.	-123.
875.	730.	438.	830.	227.	1350.	302.	530.	318.	659.	307.	101.
648.	348.	324.	263.	259.	114.	182.	198.	254.	296.	295.	276.

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-118. 272. -146. 244. 154. 507. 113. 122. 117. 404. 187. 123.
723. 143. 261. 304. 243. 141. -113. 206. 506. 413. 549. 436.
885. -128. 787. 569. 314. 1190. 477. 1209. 1175. 347. 1201. 386.
634. 529. 751. 381. 493. 192. 359. 351. 630. 232. 961. -148.
718. 449. 303. 543. 499. -111. 297. 183. 804. 191. 161. -102.
236. 472. 291. 1390. 1450. 1080. 138. 451. 233. 554. 642. 1550.
289. -124. 288. -137. 373. 706. 282. 1420. 311. 818. 194. 171.
274. 258. 422. 1025. 434. 337. 212. 293. 476. 721. 224. 102.
609. 152. 193. 584. 469. 1440. 1250. 253. 1008. 158. 266. 1090.
845. 267. 202. 564. 443. 651. 589. 674. 557. 124. 444. 518.
336. 398. 541. 394. 401. 890. 353. 241. 645. 416. 1150. 951.
358. 406. 441. 555. 615. 218. 633. 599. 372. 327. 767. 369.
301. 753. 498. 567. 798. 377. 239. 299. 894. 269. -440. 1365.
1085. 473. 217. 341. 402. 656. 321. 417. 840. 468. 329. 552.
548. 1195. 503. 631. 281. 388. 339. 487. 248. 708. 666. 613.
464. 357. 1019. 121. 868. 387. 644. 127. 695. 497. 638. 606.
1003. 572. 264. 596. 136. 471. 581. 524. 1358. 1005. 186. 652.
104. 733. 686. 407. 322. 837. 716. 424. 326. 344. 384. 534.
1260. 1700.]
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Number of unique values in column 'RedDec0dds': 578

Unique values in column 'BlueDec0dds': [800. 650. 450. 1100. 550. 750. 130. 275. 185. 200. 250. 225.

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700. 215. 175. 1000. 240. 1400. nan 150. -195. 3000. 100. 1200.
300. -150. 180. 500. -110. 350. 400. 140. -125. -115. 1800. 120.
165. 110. -160. 330. 2800. 600. -120. 230. 900. 2000. -105. 195.
-135. 125. 425. 320. 1600. 850. 2200. 475. 380. 1300. 220. 310.
155. 270. 170. 420. 210. 340. 950. 1500. 460. 260. 410. 360.
290. 190. 280. 430. 470. 115. 135. 145. 480. 1900. 2600. -190.
105. -200. 2500. -140. 375. -165. 525. 625. 325. 255. 675. 235.
575. 295. 365. -175. 160. 725. 383. 645. 740. 285. 248. 1040.
925. 1166. -170. 1250. 423. -185. -145. 1075. 345. 355. 251. 540.
655. 1165. 265. 485. 415. 510. 524. 570. 177. 560. 724. 258.
245. 422. 257. 945. 335. 435. 975. 205. -182. 168. 565. 244.
315. 515. 535. 382. 440. 370. 674. 520. 445. 390. 783. -130.
211. 1150. 279. 1217. 385. 465. 317. 588. 223. 163. 326. -128.
585. 127. 432. 875. 506. 316. 690. 259. 274. 156. 349. -123.
640. 138. 143. 698. 328. 158. 284. 442. 174. 218. 169. 1309.
760. 348. 286. 494. 192. 221. 775. 241. 484. 592. 141. 839.
323. 281. 159. 299. 735. 395. 391. 705. 289. 503. 514. 519.
183. 882. 294. 293. 116. 424. 273. 178. 555. 1025. 715. 243.
237. 171. 202. -142. -136. 249. 329. 176. 204. 630. 499. 233.
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-172. 680. 509. 660. 474. 920. 942. 137. 479. 1350. 589. 726.
 635. 108. 217. 572. 164. 1700. 444. -155. 336. 333. 551. 402.
 505. 102. 426. 271. 371. 522. 157. 363. 1050. 327. 236. 405.
 111. 246. 287. 865. 610. 711. 161. 148. 153. 187. 825. 377.
 782. 1235. 1750. -103. 539. 688. 347. 254. 563. 512. 227. 264.
 139. 427. 128. 679. 129. 282. 203. 1255. 229. -104. 890. 272.
 835. 107. 529. 595. 748. 112. 576. 481. 777. 232. 126. 252.
 2300. 1650. 940. 1225. 785. 401. 916. 545. 437. 678. 214. -112.
 278. 860. 1125. 603. 222. 228. 314. 791. 692. 172. 490. 452.
 431. 376. 590. 805. 301. -121. 720. 730. 197. 142. 304. 662.
 792. 1110. 253. 298. 312. 580. -101. 491. 283. 318. 477. 234.
 343. 615. 547. 710. 291. 344. -114. 351. 483. 605. 242. 626.
 219. 467. 369. 247. 616. 937. 268. 922. 536. 352. 461. 541.
 324. 308. 917. 1108. 904. 508. 1450. 121. 332. 446. 364. 1270.
 179. 1015. 419. 266. 454. 561. 118. 1189. 334. 831. 584. 397.
 632. 403. 408. 362. 830. 620. 753. 502. 543. 113. 429. 1271.
 486. 822. 1149. 166. 305. 199. 418. 2100. 765. 1441. 434. 463.
 338. 1420. 146. -180. 109. 269. 495. 594. 386. 778. 207. 1005.
 1487. 880. 577. 530. 1262. 648. 378. 346. 1065. 162. 353. 361.
 411. 1002. 216. 1550. 149. 517. 224. 154. 196. 593. 191. 553.
 1055. 358. 459. 381. 621. 321. 606. 456. 262. 554. 1440. 194.
 990. 763. 201. 1090. 492. 957. 910. 609. 104. 357. 1133. 1155.
 1252. 421. 167. 319. 331. 1272. 671. 614. 416. 379. 438. 1030.
 523. 556. 842. 528. 855. 845. 1395. 374. 721. 354. -124. 624.
 209. 677. 723. 685. 549. 433. 436. 297. 1850. 1185. 658. 114.
 356. 288. 1081. 1160. -161. 306. 885. 1372. 181. 747. 193. 738.
 1175. 516. 768. 847. 802. 184. 261. 367. 341. 188. 695. 776.
 404. 591. 231. 546. 573. 417. 239. 1370. 277. 1445. 569. 173.
 226. 406. -108. 412. 716. 206. 359. 1022. 368. 389. 147. 366.
 568. 471. 1385. 256. 722. 769. 303. 384. 428. 119. 1394. 117.
 1335. 761. 488. 396. 526. 238. 263. 829. 489. 212. 439. 213.
 1006. 372. 1406. 1142. 322. 1430. 1312. 1117. 186. 1123. 394. 578.
 513. 814. 1950. 123. 732. 874. 665. 739.]

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Number of unique values in column 'BlueDecOdds': 632

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Unique values in column 'RSubOdds': [ 150. 180. 1100. 380. 500. 1200. 450. 1600. 1000. 550. 350. 280
0.
 700. 2000. nan 460. 600. 2100. 800. 490. 200. 130. 175. 1400.
 900. 275. 300. 3000. 2200. 1800. 215. 2500. 400. 3500. 650. 250.
 440. 240. 750. 110. 165. 850. 280. -135. 330. 120. 4000. 225.
 100. -145. 140. -200. -125. 950. 230. 2900. 420. 2600. 170. 360.
 210. 1300. 1500. 220. 1700. 340. 125. -110. 270. 2300. 310. 260.

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145. 290. 185. 155. -105. 430. -175. -115. 475. -140. 333. 575.
375. 625. 675. 775. 425. 325. 285. 725. 525. 135. -240. 235.
1475. 1325. 730. 1275. 1415. 652. 115. 190. 1125. 1250. 205. 160.
-150. 1150. 1020. 630. 435. 1365. 470. 610. 567. 421. 432. 448.
1030. 1375. 1083. 1015. 580. 405. -160. 948. 659. 4665. 1440. 617.
1025. 1050. 540. 825. 1090. 602. 2050. 581. 505. 845. 365. 320.
385. 642. 667. 245. 1850. -230. -170. 1008. 1422. 2750. 545. 680.
1065. 1425. 1340. 315. 2105. 2250. 2550. 1075. 1905. 312. 515. 172.
410. 1483. 1575. 1465. 465. 1120. 587. 585. 940. 1240. 1533. 885.
1650. 975. 595. 1265. 565. 1355. 335. 1825. 1720. 1550. -130. 705.
765. 925. 715. 1428. 1403. 1350. 1675. 685. 970. 1450. 664. 345.
690. 434. 1445. 875. 179. 677. 1190. 1225. 382. 755. 2400. 1460.
645. 265. 746. 760. 859. 1655. 520. 559. 1183. 429. 1467. 1278.
571. 1195. 1805. 815. 217. 615. 334. 1285. 1055. 2150. 560. 614.
2625. 927. 739. 1915. 337. 796. 870. 485. 535. 355. 1950. 779.
105. 711. 1525. 2025. 1545. 1419. 2665. 880. 2320. 480. 901. 370.
424. 542. 267. 684. 284. 1625. 1390. 1105. 920. 720. 1167. 2390.
770. 1555. 751. 1160. 1208. 665. 1018. 865. 510. 431. -280. 1645.
1900. 1145. 1042. -165. 634. 1175. 419. 701. 569. 1245. 745. 1060.
2850. 2450. 1615. 1750. 154. 1875. 1205. 1735. 945. 1855. 1070. 524.
794. 955. 539. 930. 1035. 1315. 3200. 735. 1455. 820. 1180. 852.
1710. 412. 795. 459. 1865. 889. 1085. 402. 2160. 734. -120. 2350.
390. 683. 1288. 1385. 519. 157. 740. 197. 169. 1165. 1435. 537.
935. 830. 501. 1520. 219. 1155. 837. 1530. 635. 2125. 268. 2700.
1135. 305. 1092. 1215. 278. 1490. 1010. 1320. 495. 1005. 679. 392.
778. 826. 468. 1880. 551. 882. 1775. 1360. 620. 951. 854. 1347.
504. 749. 805. 1255. 2225. 781. 176. 660. 457. 1095. 572. 1370.
1995. 789. 563. 914. 960. 824. 924. 804. 1170. 349. 827. 195.
511. 1910. -155. 1363. 556. 621. 1130. 1405. 1142. 674. 1755. 483.
454. 941. 967. 1185. 487. 627. 761. 699. 554. 547. 1670. 639.
892. 931. 631. 633. 703. 1080. 590. 328. 243. 810. 724. 273.
493. 952. 916. 1117. 478. 586. 527. 295. 913. 1140. 806. 404.
1115. 840. 514. 456. 544. 502. 822. 121. 1253. 655. 777. 1920.
331. 488. 754. 710. 2005. 708. 1108. 1335. 1343. 965. 876. 442.
1310. 536. 605. 415. 1510. 561. 1975. 194. 771. 244. 1045. 1620.
426. -111. 474. 939. 1695. 811. 1955. 1725. 681. 607. 758. 646.
1220. 351. 928. 414. 449. 910. 670. 202. 768. 1940. 721. 788.
1303. 1470. 682. 932. 526. -185. 445. 1705. 366. 453. 718. 2055.
329. 2075. 416. 521. 2115. -180. 254. 286. 640. 626. 1408. 596.
451. 255. 531. 1570. 1480. 649. 1505. 241. 878. 1290. 354. 1110.
582. 594. 362. 1295. 706. 689. 693. 1820. 1760. 861. 417. 324.
1595. 401. 619. 588. 1067. 1447. 439. 395. 506. 530. 766. 253.

344. 628. 1980. 443. 376. 306. 386. 1430. 507. 943. 784. 313.
 346. 1481. 576. 1990. 555. 743. 477. 558. 471. 629. 713. 222.
 570. 1260. 1860. 1630. 1330. 2770. 455. 656. 304. 1305. 562. 1270.
 688. 589. 842. 1230. 311. 1685. 801. 1790. 1835. 484. 654. 722.
 906. 942. 785. 422. 1235. 835. 1970. 479. 2760. 1268. 807. 178.
 1040. 1845. 319. 601. 873. 1210. 1380. 1895. 1478. -275. 695. 606.
 1665. 926. 2020. 897. 896. 1680. 2640. 1795. 1433. -300. 129. 272.
 428. 258. 1640. 336. 1456. 1410. 874. 134. 199. 3300. 361. 1770.
 -370. 323. 973. 1387. 242. 387. 2295. 564. 2830. 989. 2470. 1263.
 236. 676. 637. 1133. 1280. 3450. 522. 1367.]

Number of unique values in column 'RSub0dds': 692

Unique values in column 'BSub0dds': [2500. 3000. 1400. 700. 1200. 900. 1100. 550. 1800. 800.
 -165. 1600. nan 400. 1000. 3500. 300. 4000. 2200. 165.
 110. 600. 450. 2000. 2800. 240. 350. 500. 225. 650.
 5000. 175. 250. 120. 750. 275. 125. 180. 1900. 1500.
 140. 4500. 200. 100. 330. 150. 950. 460. 1300. 280.
 2600. 380. 260. 390. 2300. 850. 1700. 3100. 210. -105.
 440. 270. 320. 470. 3200. 340. 3300. 370. 420. 190.
 -110. 3400. 215. -125. 925. 425. 375. 325. 675. 575.
 170. 525. 475. 775. 825. 625. 185. 1625. 1465. 445.
 1125. 875. 1250. 605. 1365. -145. 2150. 725. 785. 970.
 1750. 2400. 244. 405. 567. 1370. 1045. 955. 534. -140.
 455. 1285. 1350. 2050. 4785. 860. 3550. 505. 385. 885.
 614. 930. 1278. 335. 1150. 535. 4200. 1225. 2550. 360.
 1450. 1440. 1575. 1360. 665. 590. 502. 2250. 1815. 1310.
 730. 1065. 1995. 830. 1550. 2875. 640. 1675. 1095. 1408.
 1008. 3600. 965. 195. 935. 1660. 1050. 1670. 715. 410.
 1422. 1330. 1075. 2475. 602. 720. 585. 2750. 2320. 1055.
 1305. 555. -115. 205. 934. 1425. 1475. 1005. 680. 1615.
 285. 1480. 160. 1795. 310. 705. 1275. 515. 685. 1175.
 1240. 2090. 1745. 615. 545. 435. 315. 1680. 815. 542.
 464. 645. 1565. 510. 760. 635. 855. 1165. 977. 954.
 915. 2100. 1270. 1155. 1705. 601. 489. 577. 1655. 1025.
 1505. 1263. 451. 895. 1755. 387. 1455. 1850. 1185. 1340.
 364. 840. 2450. 1015. 941. 962. 757. 1535. 735. 1820.
 1375. 1315. 2015. 173. -175. 245. 740. 660. 920. 522.
 557. 1431. 1650. 743. 698. 1040. 345. 1515. 395. 1458.
 1397. 619. 1980. 710. 1260. 869. 584. 1145. 520. 1833.
 905. 3425. 1115. 1355. 1120. 485. 690. 1325. 870. 2900.
 1495. 1785. 1780. 1445. 220. 1570. 1135. 365. 611. 620.
 457. 1845. 1265. 1345. 610. 789. 290. 995. 1435. 820.

| | | | | | | | | | |
|-------|-------|-------|-------|-------|--------|-------|-------|-------|-------|
| 940. | 1205. | -130. | 810. | 465. | 865. | 570. | 630. | 415. | 1983. |
| 1387. | 1530. | 530. | 495. | 898. | 265. | -120. | 701. | 2350. | 958. |
| 1430. | 1486. | 416. | 787. | 129. | 684. | 441. | 540. | 765. | 1060. |
| 906. | 564. | 695. | 115. | 1010. | 980. | 1410. | 1775. | 493. | 1245. |
| 945. | 1085. | 755. | 724. | 772. | 158. | 541. | 776. | 366. | 1195. |
| 1220. | 1825. | 617. | 1630. | 382. | 1695. | 823. | 277. | 1067. | 975. |
| 2020. | 1170. | 226. | 586. | 1353. | 878. | 430. | 1335. | 1390. | 1190. |
| 321. | 131. | 230. | 1470. | 174. | 295. | 433. | 556. | 1405. | 155. |
| 655. | 429. | 921. | 1255. | 880. | 1585. | 539. | 1110. | 862. | 1142. |
| 1160. | 2165. | 686. | 612. | 1080. | 722. | 444. | 1605. | 346. | 2700. |
| 717. | 459. | 714. | 349. | 446. | 319. | 177. | 235. | 419. | 842. |
| 1725. | 311. | 835. | 1683. | 1105. | 609. | 595. | 507. | 571. | 504. |
| 946. | 514. | 1235. | 592. | 1092. | 846. | 872. | 652. | 606. | 558. |
| 516. | 1580. | 582. | 537. | 845. | 524. | 481. | 960. | 1280. | 436. |
| 1950. | 422. | 1210. | 916. | 745. | 756. | 939. | 716. | 363. | 1295. |
| 1378. | 670. | 2275. | 1945. | 837. | 682. | 1130. | 983. | 371. | 649. |
| 284. | 2950. | 1665. | 953. | 565. | 910. | 985. | 2675. | 866. | 432. |
| 490. | 636. | 467. | 1485. | 1510. | 461. | 1930. | 1520. | 2825. | 911. |
| 1635. | 769. | 2045. | 1905. | 2255. | 1920. | 1720. | 576. | 859. | 1955. |
| 2155. | 1290. | 1208. | 754. | 768. | 2425. | 974. | 951. | 316. | 1090. |
| 1467. | 651. | 1318. | 2295. | 1395. | 604. | 468. | 1033. | 1030. | 1380. |
| 672. | 713. | 1180. | 562. | 731. | 942. | 795. | 642. | 304. | 546. |
| 1765. | 2740. | 737. | 1835. | 676. | 358. | 709. | 914. | 384. | 551. |
| 770. | 1545. | 626. | 353. | 952. | -1250. | 2095. | 1975. | 1908. | 2640. |
| 766. | 634. | 2615. | 326. | 791. | 2105. | 889. | 1420. | 873. | 1215. |
| 808. | 781. | 1935. | 1385. | 1970. | 1880. | 874. | 2355. | 482. | 792. |
| 538. | 381. | 2360. | 1307. | 664. | 2665. | 531. | 414. | 2365. | 2530. |
| 479. | 1610. | 2860. | 1462. | 1640. | 1460. | 105. | 856. | 628. | 454. |
| 1770. | 1965. | 959. | 2170. | 805. | 135. | 574. | 1860. | 1303. | 242. |
| 2030. | 403. | 2120. | 1910. | 834. | 580. | 2040. | 1915. | 1790. | 2540. |
| 972. | 1540. | 790. | 202. | 2650. | 563. | 1620. | 1035. | 1472. | 431. |
| 596. | 990. | 2785. | 2830. | 402. | 944. | 913. | 1865. | 1242. | 1042. |
| 501. | 1140. | 599. | 931. | 832. | 578. | 788. | 1805. | 1735. | 526. |
| 145. | 305. | 1415. | 666. | 764. | 2065. | 484. | 1685. | 2220. | 2240. |
| 1608. | 809. | 2525. | 591. | 294. | 423. | 469. | 763. | 739. | 271. |
| 2205. | 264. | 2125. | 2575. | 411. | 573. | 583. | 899. | 497. | 2445. |
| 1369. | 547. | 3375. | 2775. | 747. | 699. | 632. | 631. | 2625. | 332.] |

Number of unique values in column 'BSub0dds': 670

Unique values in column 'RK00dds': [400. 240. 350. 500. 300. -125. 600. 550. 450. 650. 900. 1600. 2200. -150. 200. nan 280. -185. 1100. 3600. 130. 700. 120. 215. 2000. -120. 1200. 1400. 380. -250. 800. 225. 165. 150. -175. 250.

180. -225. -295. 4000. -200. 185. 275. 1000. 340. 750. 100. 175.
1800. 110. 330. -165. -140. -190. -135. 140. 2500. -300. -110. -145.
-230. 950. 115. 850. 135. -130. 290. 270. 470. 195. 420. 155.
1700. 460. 145. 210. 320. 390. 310. 125. -180. 160. 360. 170.
-115. 440. 480. 260. 410. 370. 1500. 190. 230. 220. 1300. 490.
475. 425. 333. 163. 525. 295. 325. 375. 235. 435. 625. 285.
575. 675. -160. -275. 105. 205. 315. 725. 1025. 825. 2100. 585.
305. 615. 1125. -155. 1250. -210. -170. 780. 1405. 1450. 560. -105.
960. 926. 495. 255. 508. -245. 655. 584. 1230. 515. 642. -122.
875. 1050. 1350. 686. 705. 124. 640. 620. 539. 1180. 201. 415.
364. 1035. 405. 245. 794. 935. 1265. 1565. 667. 1145. 1150. 870.
660. 434. 499. 1675. 565. 775. 317. 1175. 1325. 1900. 513. 685.
1550. 830. 605. 737. 335. 1020. 430. 485. 925. 1375. 915. 510.
599. 1075. 1215. 690. 276. 520. -365. 1275. 529. 942. 277. 302.
-260. 710. 681. 626. 213. 975. 612. 835. 1345. 1390. 692. 1415.
534. 1315. 545. 1635. 439. 540. 899. 1318. 1010. 1208. 643. 999.
590. 251. 421. 595. 342. 306. 1293. 254. 2255. 630. 166. 868.
283. 552. 473. 102. 236. 345. 384. 1040. 311. 507. 758. 402.
933. 970. 385. 1695. 815. 535. 1490. 714. 265. 1080. 381. 127.
-147. 1290. 613. 521. 592. -400. -111. 1260. 580. 1445. 796. 506.
1110. 1380. 1655. 1875. 484. 1220. 249. 884. 514. 527. 111. 109.
-107. -128. 294. 777. 2335. 708. 178. 422. 855. 1245. 173. 1650.
1105. 985. 444. 680. 365. 1030. 411. 1225. 1065. 412. 1330. 1425.
940. 129. 805. 635. 1465. 252. 792. 303. 324. 890. 781. 1015.
1665. 1235. 148. 319. 447. 765. 820. 912. 464. 454. 2075. 1158.
1965. 1460. 610. 1280. 346. 945. 1540. 279. 119. 957. 670. 930.
1710. 395. 658. 357. 1625. 799. 366. 530. 1170. 1070. 1447. 811.
1085. 562. 810. 272. 158. 790. 952. 860. 171. 452. -108. 465.
845. 1130. 401. 489. 1268. 459. 449. 882. 596. -162. 1115. 570.
911. 574. 1120. 547. 683. 224. 437. 924. 394. 1408. 1745. 1045.
1455. 445. 716. 207. 631. 665. 840. 271. 348. 397. 467. 463.
505. 524. 542. 941. -240. 461. 1090. 259. 879. 588. 770. 719.
956. 877. 1210. 910. 706. 1008. 668. 378. 664. 387. 334. 785.
322. 501. 955. 312. 177. 307. 809. 273. 865. 423. 257. 455.
466. 885. 488. 688. 1417. -146. 907. 114. 204. 731. 715. 571.
1670. 1520. 226. -270. -103. 696. 676. 1135. 1475. 281. 554. 991.
608. 332. 798. 581. 229. 2305. 2300. 1530. 451. 1060. 179. 2675.
652. 2370. 1340. 904. 474. 172. 301. 377. 286. 755. 1195. 1033.
349. 274. 555. 1410. 151. 1610. 1420. 1160. 189. 482. 771. 632.
379. 242. 424. 1255. 448. 169. 347. 1295. 1780. 734. 678. 704.
462. 1486. 1525. 363. -320. 438. 543. 654. 821. 849. 645. -550.
483. 778. 181. 1005. 1285. 323. 371. 353. 1385. -131. 786. 2225.

```

601. 1880. 1720. 289. 1055. 814. 112. 813. 457. 735. 243. 1185.
1431. 905. 1360. -127. 2195. 627. -119. 328. 1095. 760. 1740. 901.
1915. 839. 2475. 745. 1042. 880. 2650. 304. 187. 1750. 1242. -380.
589. 1440. 436. 1320. 182. -106. 293. 856. 1155. 578. 149. 1515.
1117. 672. 416. 874. 359. 533. 282. -265. 649. 1690. 427. 1270.
-121. 843. 1392. 604. 634. 990. 1480. 628. 253. 893. 141. 894.
689.]
```

Number of unique values in column 'RK00dds': 613

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Unique values in column 'BK00dds': [ 350. 700. 1100. 4000. 250. 800. 450. 1600. 300. 380. 225. 1200.
1000. 1800. 200. 2200. 130. nan 550. 750. 3000. 500. 165. -400.
650. 175. 240. 900. 330. 600. -250. 280. 1400. 2000. -110. 120.
2500. 400. 180. 275. -160. 230. 475. -280. -190. 110. 185. -120.
320. 425. 215. 140. -225. 150. 105. -175. -125. -105. 100. -150.
440. 260. 220. 420. 135. 190. 470. 460. 950. 310. 210. 125.
360. 270. 850. 1300. 390. 2100. 115. 340. 160. 1700. 370. 155.
1500. 145. 290. 2300. 2800. -165. -135. 170. 333. 265. 1250. -145.
775. 325. 285. 235. 205. 725. 375. 575. 625. -130. 315. 525.
-220. 675. 365. 435. 1085. 402. 737. 515. 921. 1375. 540. 795.
1125. 1900. 417. 1145. 295. -115. 483. 245. 1120. 247. 410. 865.
805. 683. 353. 335. 695. 560. 905. 305. 492. 382. 1180. 965.
890. 765. 780. 520. -116. 767. 570. 1405. 860. 490. 1385. 1745.
1050. 415. 1265. 1450. 455. 640. 1425. 1190. 345. 1675. 445. 480.
545. 505. 880. 590. 1750. 430. 510. 2150. -210. 499. 875. 960.
935. 1195. 1369. 1215. 534. 355. 1280. 1150. 715. 1350. 820. 404.
1230. 1075. 485. 1550. 1565. 1715. 1010. 576. 1315. 385. 1485. 484.
620. 177. 1515. 1160. 1387. 565. 138. 178. 508. 594. 1030. 1055.
1590. 985. 255. 316. 663. 779. 945. 1263. 278. 555. 328. 405.
853. 660. 1170. 1472. 845. 236. 1525. 760. 495. -138. 1183. 331.
1353. 482. 352. 467. 302. 228. 1275. 599. 710. 645. 434. -122.
1135. 1025. 2065. 1365. 1095. 1950. 1940. 1282. 615. 535. 119. 870.
790. 1455. 199. 753. 585. 1430. 248. 2060. -140. 273. 1775. 1475.
579. 1645. 942. 610. 1270. 971. 451. 121. 2020. 179. 658. 401.
1245. 2975. 569. 1020. 927. 649. 2400. -215. 1445. 1260. 453. 3200.
168. 258. 637. 798. 1760. 1325. 764. 1105. 1340. 1885. 1130. 118.
1360. -126. 840. 785. 1855. 770. 395. 925. 641. 446. 712. 1285.
617. 665. -155. 915. 655. 1155. 609. 735. 293. 472. 137. 132.
626. 1035. 1140. 670. 1845. 825. 174. 259. 465. 1380. 1370. 1440.
990. 975. -230. 142. 881. 1288. -169. 702. 616. 206. -185. -149.
1330. 509. 481. 1740. 1175. 885. 372. 436. 463. 716. 195. 1045.
676. 516. 136. 2550. 263. 878. 479. 1335. 471. 842. -123. 815.
1165. 244. 639. 830. 911. 448. -172. 751. 685. 855. 2700. 396.
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2350. 605. 634. 595. 117. 872. 728. 506. 1560. 524. 251. 112.
1635. 745. 1255. 1090. 1185. 1520. -200. 332. 541. 948. 602. 653.
1060. 644. 601. 636. 1225. 632. 920. 816. 1205. 504. 257. 547.
167. 201. 421. 172. 877. 409. 354. 684. 1220. 679. 294. 588.
635. 862. 329. 692. 774. 580. 503. 813. 720. 539. -240. 680.
951. 1395. 216. 787. 243. 910. 1410. 464. 727. 2105. 607. 930.
686. 705. 1875. 1725. 1615. 582. 542. 348. 530. 571. 1390. 1108.
690. 1625. 2455. -180. 1435. 731. 1850. 2005. 981. 2170. 242. 1005.
1305. 474. 1650. 391. 1080. 1930. 598. 980. 1995. 687. 755. 1555.
1320. 689. 1575. 486. 1580. 1680. 847. 841. 317. 630. 109. 2250.
859. 1378. -275. 1040. 894. 1065. 810. 2075. 442. 253. 307. 698.
2050. 1655. -131. 1470. 707. 769. 718. 2025. 603. 361. 2110. 1730.
336. 749. 721. 2525. 217. 1925. 2255. 2650. 730. 1412. 1115. 1905.
2225. 212. 1257. 426. 2145. 827. 869. 462. -195. 1420. 627. 187.
1332. 783. 662. -154. 276. 928. 291. 2470. 424. 514. 561. 366.
574. 529. 606. 586. 564. 1167. 254. 171. 1240. 469. 1431. 1486.
706. 2630.]
```

Number of unique values in column 'BK00dds': 590

Unique values in column 'WeightClassLabel': ['Featherweight' "Women's Strawweight" 'Light Heavyweight' 'Heavyweight'
 'Catch Weight' 'Welterweight' 'Lightweight' 'Flyweight'
 "Women's Featherweight" "Women's Bantamweight" 'Bantamweight'
 "Women's Flyweight" 'Middleweight']

Number of unique values in column 'WeightClassLabel': 13

Unique values in column 'BlueHeight': [68. 75. 79. 69. 70. 76.
 73. 67. 65. 71. 61. 66.
 72. 64. 62. 78. 74. 63.
 77. 60. 67.71653543 83. 80.]

Number of unique values in column 'BlueHeight': 23

Unique values in column 'BlueReach': [69. 74. 80. 70. 76. 77.
 71. 75. 65. 78. 68. 61.
 66. 79. 67. 73. 72. 63.
 81. 62. 84. 58. 64. 60.
 59. 83. 82. 67.71653543 0. 70.47244094
 70.07874016 75.5 68.5 71.5 77.5 78.5
 74.01574803 80.31496063 72.83464567 61.81102362 62.99212598 71.65354331
 72.04724409 64.96062992 75.98425197 68.11023622 70.86614173 72.44094488
 66.14173228 68.8976378 66.92913386 81.1023622 77.16535433 64.17322835
 79.52755906 74.80314961 69.5 70.98425197 74.48818898]

Number of unique values in column 'BlueReach': 59

Unique values in column 'RedHeight': [65. 73. 76. 70. 69. 71.
67. 75. 74. 77. 72. 66.
62. 64. 68. 63. 78. 61.
60. 79. 83. 77.16535433]

Number of unique values in column 'RedHeight': 22

Unique values in column 'RedReach': [67. 77. 81. 70. 72. 75.
78. 83. 63. 71. 66. 73.
60. 84. 74. 76. 68. 64.
80. 69. 62. 79. 65. 82.
59. 61. 58. 78.5 74.5 70.5
67.5 66.5 75.5 72.5 84.5 71.5
83.07086614 66.53543307 68.11023622 61.81102362 77.16535433 64.96062992
76.37795276 66.92913386 70.07874016 72.04724409 75.98425197 70.86614173
66.14173228 72.83464567 68.50393701 74.01574803]

Number of unique values in column 'RedReach': 52

Unique values in column 'ROver35': [0 1]

Number of unique values in column 'ROver35': 2

Unique values in column 'BOver35': [0 1]

Number of unique values in column 'BOver35': 2

Unique values in column 'RWinPct': [0.8 1. 0.81818182 0.77777778 0.625 0.63636364
0.71428571 0.72222222 0.63157895 0.6 0.51282051 0.64285714
0.69230769 0.72727273 0.57142857 0.66666667 0.5 0.95454545
0.6875 0.54545455 0.60465116 0.52941176 0.53846154 0.33333333
0.85714286 0.41666667 0.46153846 0.75 0.77272727 0.90909091
0.61538462 0.58823529 0.55555556 0.7 0. 0.25
0.88888889 0.75862069 0.44444444 0.45454545 0.4 0.91666667
0.68181818 0.62962963 0.83333333 nan 0.48 0.53333333
0.64705882 0.76923077 0.65217391 0.875 0.5862069 0.58333333
0.42857143 0.14285714 0.60869565 0.57692308 0.61290323 0.54347826
0.76190476 0.93333333 0.61904762 0.70588235 0.9 0.62068966
0.78571429 0.5625 0.68 0.375 0.70967742 0.47619048
0.61111111 0.16666667 0.60606061 0.52631579 0.73333333 0.65
0.46666667 0.86666667 0.46428571 0.67741935 0.6097561 0.42105263
0.84615385 0.43478261 0.92857143 0.88235294 0.3 0.68421053
0.74074074 0.56521739 0.73684211 0.2 0.65384615 0.92307692
0.78947368 0.68965517 0.84210526 0.41176471 0.56818182 0.59090909

```

0.56      0.55172414 0.82352941 0.8125      0.70833333 0.73076923
0.59259259 0.54054054 0.95238095 0.675      0.52777778 0.30769231
0.57894737 0.7037037 0.58139535 0.72413793 0.64516129 0.60526316
0.35714286 0.76      0.28571429 0.45833333 0.64      0.54285714
0.76470588 0.72      0.63333333 0.59459459 0.73913043 0.56097561
0.60714286 0.69565217 0.38461538 0.55      0.46875   0.47058824
0.65909091 0.4375      0.47826087 0.36363636 0.65517241 0.71052632
0.52173913 0.68085106 0.59375   0.52380952 0.61764706 0.7027027
0.5483871  0.80952381 0.9375      0.48387097 0.80769231 0.95
0.70731707 0.47368421 0.67857143 0.94736842 0.65625   0.58064516
0.89473684 0.51724138 0.54166667 0.35294118 0.82608696 0.7826087 ]

```

Number of unique values in column 'RWinPct': 168

```

Unique values in column 'BWinPct': [       nan 1.          0.75      0.33333333 0.57142857 0.55555556
0.8      0.85714286 0.5      0.7      0.8125      0.63636364
0.875    0.          0.6      0.77777778 0.52941176 0.54545455
0.4      0.66666667 0.64705882 0.6875      0.375      0.53846154
0.52631579 0.625      0.71428571 0.28571429 0.75862069 0.61111111
0.44444444 0.81818182 0.41666667 0.42857143 0.65      0.53333333
0.64285714 0.69230769 0.46153846 0.61764706 0.5625      0.53571429
0.86666667 0.83333333 0.55      0.61904762 0.61538462 0.58333333
0.2      0.82352941 0.76470588 0.45454545 0.16666667 0.3
0.52380952 0.73333333 0.72727273 0.25      0.74193548 0.68421053
0.76923077 0.63157895 0.45833333 0.78947368 0.68181818 0.27272727
0.59259259 0.92857143 0.60714286 0.57692308 0.38461538 0.73684211
0.57894737 0.9      0.58823529 0.56      0.48148148 0.52
0.62962963 0.9375      0.88888889 0.91666667 0.72      0.84615385
0.76      0.64444444 0.42105263 0.61290323 0.78571429 0.65384615
0.60869565 0.73913043 0.57575758 0.47058824 0.54166667 0.63333333
0.68      0.76190476 0.53125   0.7037037 0.65217391 0.62068966
0.75609756 0.77272727 0.46666667 0.9047619 0.70833333 0.7826087
0.6744186  0.73076923 0.6969697  0.90909091 0.36363636 0.56666667
0.72222222 0.47619048 0.70588235 0.72413793 0.51851852 0.14285714
0.69565217 0.79166667 0.56521739 0.64      0.52173913 0.59090909
0.80952381 0.94117647 0.47368421]

```

Number of unique values in column 'BWinPct': 129

```

Unique values in column 'RedStrikingRatio': [1.          0.42827443 0.51694915 ... 0.79846449 0.54915217 0.3
3098615]

```

Number of unique values in column 'RedStrikingRatio': 5189

```

Unique values in column 'BlueStrikingRatio': [0.          0.57172557 0.48305085 ... 0.20153551 0.45084783 0.

```

66901385]
Number of unique values in column 'BlueStrikingRatio': 5192

Unique values in column 'RedTotalFights': [15 6 11 9 8 21 18 19 10 39 14 13 2 3 1 4 5 22 32 43 20 1
2 33 17
7 28 24 29 16 27 0 25 23 26 31 46 30 41 45 38 35 40 44 37 36 34 42 48
47]
Number of unique values in column 'RedTotalFights': 49

Unique values in column 'BlueTotalFights': [0 8 16 3 7 27 5 20 10 6 11 1 2 18 17 4 13 19 29 9 35
12 15 14
22 34 28 21 31 24 42 26 33 25 32 45 23 30 41 43]
Number of unique values in column 'BlueTotalFights': 40

Unique values in column 'RedIsGrappler': [0 1]
Number of unique values in column 'RedIsGrappler': 2

Unique values in column 'BlueIsGrappler': [0 1]
Number of unique values in column 'BlueIsGrappler': 2

Unique values in column 'RedIsStriker': [0 1]
Number of unique values in column 'RedIsStriker': 2

Unique values in column 'BlueIsStriker': [0 1]
Number of unique values in column 'BlueIsStriker': 2

Unique values in column 'RGrapplerVBStriker': [0 1]
Number of unique values in column 'RGrapplerVBStriker': 2

Unique values in column 'BGrapplerVRStriker': [0 1]
Number of unique values in column 'BGrapplerVRStriker': 2

Unique values in column 'RedStrikingEfficiency': [2.1609 2.5132 3.294 ... 9.9 16.4025
9.2120196]
Number of unique values in column 'RedStrikingEfficiency': 4748

Unique values in column 'BlueStrikingEfficiency': [0. 3.025 2.9241 ... 3.57975 11.305017 1
4.566682]
Number of unique values in column 'BlueStrikingEfficiency': 4240

Unique values in column 'RedTDEfficiency': [1.2267 0.4321 0.1218 ... 0.5625368 3.686693 0.120828
5]

Number of unique values in column 'RedTDEfficiency': 3145

Unique values in column 'BlueTDEfficiency': [0. 0.4235 0.2835 ... 1.3125 0.6864 0.82875]
Number of unique values in column 'BlueTDEfficiency': 2543

Unique values in column 'RedEffectiveTD': [0.30651341 1.20805369 0.86206897 ... 0.5000175 0.16663611 0.21428418]

Number of unique values in column 'RedEffectiveTD': 1767

Unique values in column 'BlueEffectiveTD': [nan 0.38961039 0.44444444 ... 0.29731132 0.58333333 0.06668]

Number of unique values in column 'BlueEffectiveTD': 1423

Unique values in column 'EffectiveTDDif': [nan -0.8184433 -0.41762452 ... 0.82352941 -1.93362003 -1.200012]

Number of unique values in column 'EffectiveTDDif': 3180

Unique values in column 'RedSize': [132. 150. 157. 140. 141.
153. 146. 139. 152. 134.
148. 137. 160. 128. 143.
149. 122. 138. 131. 144.
145. 155. 136. 124. 127.
130. 147. 135. 154. 133.
142. 158. 125. 156. 124.
159. 123. 151. 126. 129.
121. 163. 167. 154.5 146.5
141.5 132.5 131.5 148.5 143.5
167.5 139.5 149.5 161. 160.23622047
142.5 132.53543307 120. 135.11023622 128.81102362
152.16535433 129.96062992 150.37795276 131.92913386 136.07874016
143.04724409 149.98425197 143.86614173 133.14173228 144.04724409
143.83464567 135.50393701 149.16535433 146.01574803 141.86614173
138.07874016 145.01574803 145.83464567]

Number of unique values in column 'RedSize': 78

Unique values in column 'BlueSize': [137. 149. 159. 139. 140.
152. 150. 138. 148. 130.
147. 154. 133. 122. 141.
132. 153. 155. 131. 135.
134. 136. 156. 151. 145.
142. 144. 128. 125. 157.
146. 129. 126. 163. 143.]

```
127.      121.      119.      123.      160.  
124.      158.      124.      135.43307087 66.  
138.47244094 135.07874016 149.5      133.5      137.5  
151.5      154.5      134.5      135.5      144.01574803  
148.01574803 155.31496063 140.83464567 128.81102362 126.99212598  
167.      140.07874016 161.      142.65354331 120.  
139.07874016 146.01574803 143.04724409 129.96062992 144.83464567  
137.07874016 149.98425197 135.11023622 143.86614173 143.44094488  
132.14173228 140.04724409 136.8976378 142.04724409 135.8976378  
138.07874016 131.92913386 159.1023622 141.83464567 137.8976378  
141.04724409 145.83464567 133.14173228 139.86614173 151.16535433  
130.17322835 142.07874016 145.01574803 139.8976378 158.52755906  
146.80314961 131.96062992 150.5      140.5      137.98425197  
148.48818898 152.16535433]
```

Number of unique values in column 'BlueSize': 102

Unique values in column 'Favorite': ['Red' 'Blue']
Number of unique values in column 'Favorite': 2

Unique values in column 'FavoriteWins': [1 0]
Number of unique values in column 'FavoriteWins': 2

Unique values in column 'draw_diff': [0 1 -1 -2 2]
Number of unique values in column 'draw_diff': 5

Unique values in column 'avg_sig_str_pct_diff': [-0.49 -0.06 -0.03 ... -0.134 -0.138 -0.128]
Number of unique values in column 'avg_sig_str_pct_diff': 1206

Unique values in column 'avg_TD_pct_diff': [-0.47 0.26 0.42 ... 0.361 0.161 0.572]
Number of unique values in column 'avg_TD_pct_diff': 1669

Unique values in column 'win_by_Decision_Majority_diff': [0 -1 1 -2]
Number of unique values in column 'win_by_Decision_Majority_diff': 4

Unique values in column 'win_by_Decision_Split_diff': [-2 1 0 -1 2 -4 -3 3 4 5 -5]
Number of unique values in column 'win_by_Decision_Split_diff': 11

Unique values in column 'win_by_Decision_Unanimous_diff': [-4 4 1 -5 -1 0 2 -2 -3 -7 -6 -10
6 -9 10 -8 3 5
7 8 -11 11 9]
Number of unique values in column 'win_by_Decision_Unanimous_diff': 23

Unique values in column 'win_by_TKO_Doctor_Stoppage_diff': [0 -1 1 -2 2]
Number of unique values in column 'win_by_TKO_Doctor_Stoppage_diff': 5

Unique values in column 'odds_diff': [4.650e+02 5.050e+02 6.800e+02 1.575e+03 2.400e+02 4.880e+02
4.330e+02 -3.300e+02 4.000e+00 -3.120e+02 -1.800e+03 9.600e+02
5.500e+02 3.620e+02 nan 1.700e+03 -4.800e+02 4.350e+02
-4.200e+02 -2.240e+02 -8.700e+02 5.600e+02 2.800e+02 4.450e+02
4.800e+02 2.150e+03 -5.250e+02 1.650e+03 -1.000e+01 -4.330e+02
2.300e+03 3.120e+02 -5.600e+02 -1.350e+03 -4.550e+02 -8.300e+02
8.550e+02 3.300e+02 2.850e+02 3.520e+02 -4.400e+02 4.900e+02
6.700e+02 -4.450e+02 6.100e+02 3.060e+02 -4.000e+00 1.350e+03
1.000e+03 2.720e+02 3.980e+02 2.980e+02 -1.080e+03 -3.750e+02
4.680e+02 -7.550e+02 -5.380e+02 5.250e+02 -2.720e+02 7.550e+02
-4.100e+02 -3.390e+02 8.800e+02 -4.680e+02 4.100e+02 -5.500e+02
-3.520e+02 9.100e+02 2.300e+02 -1.600e+01 1.080e+03 6.450e+02
-2.300e+02 -2.200e+02 3.750e+02 -2.400e+02 9.350e+02 -5.030e+02
3.200e+03 -3.060e+02 -4.900e+02 5.380e+02 -2.620e+02 -5.850e+02
2.620e+02 -1.500e+03 5.850e+02 -3.980e+02 1.500e+03 2.200e+02
-5.180e+02 -7.300e+02 -2.590e+02 -2.840e+02 -3.320e+02 7.250e+02
1.170e+03 -6.750e+02 5.950e+02 -9.000e+02 2.500e+02 2.960e+02
-5.950e+02 2.200e+03 2.840e+02 4.050e+02 1.000e+01 4.700e+02
8.000e+02 3.900e+02 3.200e+02 3.330e+02 0.000e+00 7.300e+02
2.590e+02 -2.000e+01 3.540e+02 -4.180e+02 2.490e+02 2.600e+03
4.180e+02 1.310e+03 4.550e+02 7.050e+02 -3.450e+02 7.000e+02
-3.200e+02 -5.150e+02 -1.170e+03 -2.980e+02 6.200e+02 3.800e+02
5.180e+02 5.150e+02 -2.960e+02 2.240e+02 -2.700e+02 1.600e+01
-9.100e+02 -6.350e+02 -3.540e+02 -6.700e+02 -2.490e+02 8.050e+02
3.390e+02 -4.080e+02 2.500e+03 -8.050e+02 -2.850e+02 -6.450e+02
-8.550e+02 2.890e+02 6.600e+02 -9.600e+02 4.200e+02 -3.620e+02
-6.100e+02 -6.800e+02 -1.020e+03 -1.575e+03 6.350e+02 6.980e+02
-1.310e+03 1.020e+03 8.300e+02 3.450e+02 1.150e+02 -8.800e+02
-4.050e+02 1.470e+03 3.550e+02 5.700e+02 1.200e+03 8.700e+02
6.750e+02 7.800e+02 5.450e+02 4.060e+02 -9.350e+02 2.700e+02
-4.000e+02 -2.500e+02 6.550e+02 3.250e+02 9.000e+02 -3.250e+02
2.600e+02 -2.800e+02 -3.500e+02 2.900e+02 -8.000e+00 -2.740e+02
3.680e+02 -4.130e+02 -7.250e+02 3.860e+02 -4.650e+02 1.400e+01
-7.000e+02 4.130e+02 3.160e+02 4.560e+02 2.380e+02 2.460e+02
4.070e+02 3.440e+02 1.950e+03 -2.880e+02 3.500e+02 -2.660e+02
4.290e+02 -3.640e+02 6.050e+02 4.040e+02 2.920e+02 -5.000e+02
-1.400e+01 3.320e+02 3.950e+02 2.220e+02 -2.520e+02 2.730e+02
1.000e+02 2.440e+02 -2.260e+02 -4.040e+02 -4.290e+02 2.660e+02
-2.220e+02 1.830e+03 -5.450e+02 7.500e+02 2.860e+02 4.380e+02

| | | | | | |
|------------|------------|------------|------------|------------|------------|
| -2.440e+02 | 1.660e+03 | -3.100e+02 | 3.380e+02 | 7.900e+02 | -3.240e+02 |
| 6.300e+02 | 2.800e+01 | -3.020e+02 | 3.020e+02 | -1.030e+03 | -2.180e+02 |
| 3.600e+02 | -2.920e+02 | -2.380e+02 | -3.860e+02 | -3.600e+02 | 2.340e+02 |
| 2.880e+02 | -2.480e+02 | 8.100e+02 | 4.750e+02 | -3.770e+02 | -4.500e+02 |
| -3.380e+02 | 9.800e+02 | 1.440e+03 | 3.150e+02 | 8.900e+02 | 4.310e+02 |
| 3.100e+02 | 1.050e+03 | 2.250e+03 | 3.050e+02 | -4.600e+02 | -4.250e+02 |
| -7.400e+02 | 1.300e+03 | 4.000e+02 | -3.150e+02 | 9.300e+02 | -3.350e+02 |
| -5.400e+02 | -3.900e+02 | 4.600e+02 | 6.400e+02 | 6.650e+02 | 3.350e+02 |
| -6.400e+02 | -1.050e+03 | 3.700e+02 | 2.050e+03 | -1.650e+03 | -6.650e+02 |
| 1.750e+03 | 7.100e+02 | 1.450e+03 | 7.650e+02 | -2.900e+02 | -3.800e+02 |
| 5.750e+02 | -7.650e+02 | 4.150e+02 | -6.900e+02 | 4.400e+02 | -4.150e+02 |
| 1.210e+03 | -3.050e+02 | -3.700e+02 | 4.500e+02 | 1.900e+03 | -7.850e+02 |
| 6.900e+02 | -1.175e+03 | 1.125e+03 | 5.400e+02 | -5.050e+02 | -6.200e+02 |
| -6.050e+02 | -2.600e+02 | -5.750e+02 | 1.600e+03 | -1.240e+03 | 1.070e+03 |
| 7.850e+02 | 9.900e+02 | 4.250e+02 | -6.300e+02 | -1.600e+03 | -1.375e+03 |
| 3.000e+02 | 5.200e+02 | -7.200e+02 | 4.950e+02 | 1.285e+03 | -3.000e+02 |
| 8.250e+02 | -3.650e+02 | 1.035e+03 | -4.350e+02 | 3.850e+02 | -4.700e+02 |
| 3.000e+03 | 1.015e+03 | -8.850e+02 | 7.200e+02 | -4.950e+02 | -1.035e+03 |
| 5.350e+02 | 8.500e+02 | 5.550e+02 | -5.550e+02 | 7.450e+02 | -1.500e+01 |
| -3.850e+02 | 2.350e+02 | -2.950e+02 | -2.750e+02 | -5.350e+02 | 1.825e+03 |
| -7.450e+02 | -5.200e+02 | 1.150e+03 | -5.700e+02 | 5.900e+02 | -1.220e+03 |
| 2.175e+03 | 1.425e+03 | 9.500e+02 | 9.850e+02 | 2.290e+02 | 1.580e+03 |
| -3.400e+02 | -3.360e+02 | -1.200e+01 | 3.480e+02 | 2.560e+02 | 4.270e+02 |
| 6.500e+02 | 3.170e+02 | -2.250e+02 | -3.310e+02 | -2.510e+02 | 2.750e+02 |
| 2.390e+02 | -4.850e+02 | -2.650e+02 | 4.280e+02 | -6.000e+00 | 2.270e+02 |
| 2.950e+02 | 1.200e+01 | -3.170e+02 | -2.390e+02 | 3.090e+02 | 2.540e+02 |
| 4.300e+02 | 2.740e+02 | -3.550e+02 | -3.340e+02 | -2.640e+02 | 3.040e+02 |
| 5.800e+02 | -3.930e+02 | 5.650e+02 | -2.540e+02 | 5.100e+02 | 3.930e+02 |
| 7.750e+02 | 6.000e+02 | 5.000e+02 | 9.400e+02 | 2.940e+02 | 4.930e+02 |
| 3.400e+02 | 2.000e+01 | 5.060e+02 | 3.790e+02 | 4.630e+02 | -3.220e+02 |
| 8.520e+02 | 7.870e+02 | -2.150e+02 | -2.410e+02 | 2.580e+02 | 2.250e+02 |
| -2.580e+02 | -2.350e+02 | -9.500e+02 | -2.680e+02 | -2.870e+02 | 9.050e+02 |
| 3.220e+02 | -2.890e+02 | 9.750e+02 | 2.510e+02 | 4.850e+02 | 2.470e+02 |
| -5.800e+02 | 5.110e+02 | 2.517e+03 | 2.970e+02 | 6.950e+02 | 1.360e+03 |
| 2.420e+02 | 1.270e+03 | -7.500e+02 | 8.560e+02 | 6.520e+02 | -2.670e+02 |
| 6.960e+02 | -6.950e+02 | 3.130e+02 | 3.840e+02 | -6.520e+02 | 7.520e+02 |
| -2.560e+02 | -3.110e+02 | 3.650e+02 | -7.760e+02 | 2.280e+02 | 8.220e+02 |
| 5.810e+02 | -5.000e+00 | 3.370e+02 | 5.880e+02 | -1.185e+03 | -2.370e+02 |
| -3.010e+02 | -2.470e+02 | 6.710e+02 | 5.220e+02 | -7.260e+02 | -2.970e+02 |
| 3.270e+02 | 5.540e+02 | 5.000e+00 | 4.010e+02 | 5.030e+02 | -4.280e+02 |
| 2.180e+03 | -2.330e+02 | 9.470e+02 | 7.880e+02 | 8.200e+02 | 3.340e+02 |
| 6.250e+02 | 2.370e+02 | -3.270e+02 | 4.980e+02 | 3.610e+02 | -2.930e+02 |

```

2.530e+02 -6.460e+02 1.190e+03 -2.420e+02 -4.300e+02 3.240e+02
1.435e+03 1.060e+03 -3.630e+02 -6.000e+02 2.640e+02 2.100e+02
3.140e+02 1.455e+03 1.530e+03 -1.485e+03 2.430e+02 5.370e+02
8.450e+02 1.110e+03 -5.100e+02 1.800e+03 1.155e+03 1.005e+03
-6.600e+02 1.275e+03 -1.275e+03 1.065e+03 6.930e+02 -6.500e+02
-9.400e+02 9.250e+02 -8.250e+02 -5.650e+02 -8.450e+02 -1.005e+03
-9.750e+02 1.095e+03 1.975e+03 1.410e+03 2.275e+03 -5.900e+02
6.880e+02 -3.780e+02 -7.900e+02 7.400e+02 -7.950e+02 -5.280e+02
-7.750e+02 5.280e+02 3.690e+02 -1.155e+03 -1.110e+03 -8.100e+02
-6.850e+02 7.670e+02 3.630e+02 2.700e+03 1.230e+03 1.915e+03
-2.100e+02 -1.125e+03 2.325e+03 -1.200e+03 8.630e+02 -1.975e+03
2.800e+03 2.100e+03 -7.100e+02 1.620e+03 2.650e+03 -1.285e+03
1.460e+03 1.535e+03 -8.950e+02 1.185e+03 1.335e+03 7.950e+02
8.950e+02 1.268e+03 6.850e+02 1.100e+03 2.000e+03 -3.460e+02
1.250e+03 -3.080e+02 3.430e+02 8.600e+02 1.670e+03 -1.000e+03
9.030e+02 1.010e+03 -1.225e+03 -9.030e+02 1.325e+03 -3.690e+02
6.680e+02 1.235e+03 -8.500e+02 8.030e+02 1.560e+03 2.520e+02
5.300e+02 8.000e+00 5.430e+02 -4.420e+02 2.320e+02 2.780e+02
2.950e+03 2.760e+02 5.730e+02 2.260e+02 1.550e+03 3.770e+02
-2.120e+02 3.670e+02 -2.940e+02 -9.850e+02 3.420e+02 -2.860e+02
7.380e+02 -2.460e+02 3.360e+02 -2.000e+00 3.180e+02 -1.100e+03
-8.000e+02 6.000e+00 -3.710e+02 1.354e+03 4.160e+02 1.225e+03
1.400e+03]

```

Number of unique values in column 'odds_diff': 619

Unique values in column 'ev_diff': [175. 247.381 273.6842 ... 607.1795 459.6154 534.6154]
Number of unique values in column 'ev_diff': 1067

Unique values in column 'StanceCombo': ['Orthodox vs Orthodox' 'Southpaw vs Southpaw' 'Southpaw vs Orthodox'
'Orthodox vs Southpaw' 'Switch vs Orthodox' 'Orthodox vs Switch'
'Southpaw vs Switch' 'Switch vs Switch' 'Switch vs Southpaw'
'Orthodox vs nan' 'Southpaw vs nan' 'Open Stance vs Orthodox'
'Southpaw vs Open Stance' 'Open Stance vs Southpaw']
Number of unique values in column 'StanceCombo': 14

Unique values in column 'AgeGap': [3 2 6 0 5 4 10 17 1 8 7 15 9 11 12 13 16 14]
Number of unique values in column 'AgeGap': 18

Unique values in column 'Spread': [4.650e+02 5.050e+02 6.800e+02 1.575e+03 2.400e+02 4.880e+02 4.330e+02
3.300e+02 4.000e+00 3.120e+02 1.800e+03 9.600e+02 5.500e+02 3.620e+02
nan 1.700e+03 4.800e+02 4.350e+02 4.200e+02 2.240e+02 8.700e+02

| | | | | | | |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 5.600e+02 | 2.800e+02 | 4.450e+02 | 2.150e+03 | 5.250e+02 | 1.650e+03 | 1.000e+01 |
| 2.300e+03 | 1.350e+03 | 4.550e+02 | 8.300e+02 | 8.550e+02 | 2.850e+02 | 3.520e+02 |
| 4.400e+02 | 4.900e+02 | 6.700e+02 | 6.100e+02 | 3.060e+02 | 1.000e+03 | 2.720e+02 |
| 3.980e+02 | 2.980e+02 | 1.080e+03 | 3.750e+02 | 4.680e+02 | 7.550e+02 | 5.380e+02 |
| 4.100e+02 | 3.390e+02 | 8.800e+02 | 9.100e+02 | 2.300e+02 | 1.600e+01 | 6.450e+02 |
| 2.200e+02 | 9.350e+02 | 5.030e+02 | 3.200e+03 | 2.620e+02 | 5.850e+02 | 1.500e+03 |
| 5.180e+02 | 7.300e+02 | 2.590e+02 | 2.840e+02 | 3.320e+02 | 7.250e+02 | 1.170e+03 |
| 6.750e+02 | 5.950e+02 | 9.000e+02 | 2.500e+02 | 2.960e+02 | 2.200e+03 | 4.050e+02 |
| 4.700e+02 | 8.000e+02 | 3.900e+02 | 3.200e+02 | 3.330e+02 | 0.000e+00 | 2.000e+01 |
| 3.540e+02 | 4.180e+02 | 2.490e+02 | 2.600e+03 | 1.310e+03 | 7.050e+02 | 3.450e+02 |
| 7.000e+02 | 5.150e+02 | 6.200e+02 | 3.800e+02 | 2.700e+02 | 6.350e+02 | 8.050e+02 |
| 4.080e+02 | 2.500e+03 | 2.890e+02 | 6.600e+02 | 1.020e+03 | 6.980e+02 | 1.150e+02 |
| 1.470e+03 | 3.550e+02 | 5.700e+02 | 1.200e+03 | 7.800e+02 | 5.450e+02 | 4.060e+02 |
| 4.000e+02 | 6.550e+02 | 3.250e+02 | 2.600e+02 | 3.500e+02 | 2.900e+02 | 8.000e+00 |
| 2.740e+02 | 3.680e+02 | 4.130e+02 | 3.860e+02 | 1.400e+01 | 3.160e+02 | 4.560e+02 |
| 2.380e+02 | 2.460e+02 | 4.070e+02 | 3.440e+02 | 1.950e+03 | 2.880e+02 | 2.660e+02 |
| 4.290e+02 | 3.640e+02 | 6.050e+02 | 4.040e+02 | 2.920e+02 | 5.000e+02 | 3.950e+02 |
| 2.220e+02 | 2.520e+02 | 2.730e+02 | 1.000e+02 | 2.440e+02 | 2.260e+02 | 1.830e+03 |
| 7.500e+02 | 2.860e+02 | 4.380e+02 | 1.660e+03 | 3.100e+02 | 3.380e+02 | 7.900e+02 |
| 3.240e+02 | 6.300e+02 | 2.800e+01 | 3.020e+02 | 1.030e+03 | 2.180e+02 | 3.600e+02 |
| 2.340e+02 | 2.480e+02 | 8.100e+02 | 4.750e+02 | 3.770e+02 | 4.500e+02 | 9.800e+02 |
| 1.440e+03 | 3.150e+02 | 8.900e+02 | 4.310e+02 | 1.050e+03 | 2.250e+03 | 3.050e+02 |
| 4.600e+02 | 4.250e+02 | 7.400e+02 | 1.300e+03 | 9.300e+02 | 3.350e+02 | 5.400e+02 |
| 6.400e+02 | 6.650e+02 | 3.700e+02 | 2.050e+03 | 1.750e+03 | 7.100e+02 | 1.450e+03 |
| 7.650e+02 | 5.750e+02 | 4.150e+02 | 6.900e+02 | 1.210e+03 | 1.900e+03 | 7.850e+02 |
| 1.175e+03 | 1.125e+03 | 1.600e+03 | 1.240e+03 | 1.070e+03 | 9.900e+02 | 1.375e+03 |
| 3.000e+02 | 5.200e+02 | 7.200e+02 | 4.950e+02 | 1.285e+03 | 8.250e+02 | 3.650e+02 |
| 1.035e+03 | 3.850e+02 | 3.000e+03 | 1.015e+03 | 8.850e+02 | 5.350e+02 | 8.500e+02 |
| 5.550e+02 | 7.450e+02 | 1.500e+01 | 2.350e+02 | 2.950e+02 | 2.750e+02 | 1.825e+03 |
| 1.150e+03 | 5.900e+02 | 1.220e+03 | 2.175e+03 | 1.425e+03 | 9.500e+02 | 9.850e+02 |
| 2.290e+02 | 1.580e+03 | 3.400e+02 | 3.360e+02 | 1.200e+01 | 3.480e+02 | 2.560e+02 |
| 4.270e+02 | 6.500e+02 | 3.170e+02 | 2.250e+02 | 3.310e+02 | 2.510e+02 | 2.390e+02 |
| 4.850e+02 | 2.650e+02 | 4.280e+02 | 6.000e+00 | 2.270e+02 | 3.090e+02 | 2.540e+02 |
| 4.300e+02 | 3.340e+02 | 2.640e+02 | 3.040e+02 | 5.800e+02 | 3.930e+02 | 5.650e+02 |
| 5.100e+02 | 7.750e+02 | 6.000e+02 | 9.400e+02 | 2.940e+02 | 4.930e+02 | 5.060e+02 |
| 3.790e+02 | 4.630e+02 | 3.220e+02 | 8.520e+02 | 7.870e+02 | 2.150e+02 | 2.410e+02 |
| 2.580e+02 | 2.680e+02 | 2.870e+02 | 9.050e+02 | 9.750e+02 | 2.470e+02 | 5.110e+02 |
| 2.517e+03 | 2.970e+02 | 6.950e+02 | 1.360e+03 | 2.420e+02 | 1.270e+03 | 8.560e+02 |
| 6.520e+02 | 2.670e+02 | 6.960e+02 | 3.130e+02 | 3.840e+02 | 7.520e+02 | 3.110e+02 |
| 7.760e+02 | 2.280e+02 | 8.220e+02 | 5.810e+02 | 5.000e+00 | 3.370e+02 | 5.880e+02 |
| 1.185e+03 | 2.370e+02 | 3.010e+02 | 6.710e+02 | 5.220e+02 | 7.260e+02 | 3.270e+02 |
| 5.540e+02 | 4.010e+02 | 2.180e+03 | 2.330e+02 | 9.470e+02 | 7.880e+02 | 8.200e+02 |

```
6.250e+02 4.980e+02 3.610e+02 2.930e+02 2.530e+02 6.460e+02 1.190e+03
1.435e+03 1.060e+03 3.630e+02 2.100e+02 3.140e+02 1.455e+03 1.530e+03
1.485e+03 2.430e+02 5.370e+02 8.450e+02 1.110e+03 1.155e+03 1.005e+03
1.275e+03 1.065e+03 6.930e+02 9.250e+02 1.095e+03 1.975e+03 1.410e+03
2.275e+03 6.880e+02 3.780e+02 7.950e+02 5.280e+02 3.690e+02 6.850e+02
7.670e+02 2.700e+03 1.230e+03 1.915e+03 2.325e+03 8.630e+02 2.800e+03
2.100e+03 1.620e+03 2.650e+03 1.460e+03 1.535e+03 8.950e+02 1.335e+03
1.268e+03 1.100e+03 2.000e+03 3.460e+02 1.250e+03 3.080e+02 3.430e+02
8.600e+02 1.670e+03 9.030e+02 1.010e+03 1.225e+03 1.325e+03 6.680e+02
1.235e+03 8.030e+02 1.560e+03 5.300e+02 5.430e+02 4.420e+02 2.320e+02
2.780e+02 2.950e+03 2.760e+02 5.730e+02 1.550e+03 2.120e+02 3.670e+02
3.420e+02 7.380e+02 2.000e+00 3.180e+02 3.710e+02 1.354e+03 4.160e+02
1.400e+03]
```

Number of unique values in column 'Spread': 400

In [281... df.head()

| | RedFighter | BlueFighter | RedOdds | BlueOdds | RedExpectedValue | BlueExpectedValue | Winner | TitleBout | WeightClass |
|---|------------|-------------|---------|----------|------------------|-------------------|--------|-----------|-------------|
| 0 | 66 | 1009 | -250.0 | 215.0 | 40.0000 | 215.0 | Red | True | 3 |
| 1 | 1441 | 718 | -210.0 | 295.0 | 47.6190 | 295.0 | Red | False | 8 |
| 2 | 307 | 67 | -380.0 | 300.0 | 26.3158 | 300.0 | Red | False | 4 |
| 3 | 221 | 1071 | -950.0 | 625.0 | 10.5263 | 625.0 | Red | False | 2 |
| 4 | 1183 | 524 | -130.0 | 110.0 | 76.9231 | 110.0 | Blue | False | 2 |

In [282... pd.set_option('display.max_columns', None)

```
print(df.columns)
print(df.columns.tolist())
```

```
Index(['RedFighter', 'BlueFighter', 'RedOdds', 'BlueOdds', 'RedExpectedValue',
       'BlueExpectedValue', 'Winner', 'TitleBout', 'WeightClass', 'Gender',
       ...
       'avg_TD_pct_diff', 'win_by_Decision_Majority_diff',
       'win_by_Decision_Split_diff', 'win_by_Decision_Unanimous_diff',
       'win_by_TKO_Doctor_Stoppage_diff', 'odds_diff', 'ev_diff',
       'StanceCombo', 'AgeGap', 'Spread'],
      dtype='object', length=153)
['RedFighter', 'BlueFighter', 'RedOdds', 'BlueOdds', 'RedExpectedValue', 'BlueExpectedValue', 'Winner', 'TitleBout', 'WeightClass', 'Gender', 'NumberOfRounds', 'BlueCurrentLoseStreak', 'BlueCurrentWinStreak', 'BlueDraws', 'BlueAvgSigStrLanded', 'BlueAvgSigStrPct', 'BlueAvgSubAtt', 'BlueAvgTDLanded', 'BlueAvgTDPct', 'BlueLongestWinStreak', 'BlueLosses', 'BlueTotalRoundsFought', 'BlueTotalTitleBouts', 'BlueWinsByDecisionMajority', 'BlueWinsByDecisionSplit', 'BlueWinsByDecisionUnanimous', 'BlueWinsByKO', 'BlueWinsBySubmission', 'BlueWinsByTKODoctorStoppage', 'BlueWins', 'BlueStance', 'BlueWeightLbs', 'RedCurrentLoseStreak', 'RedCurrentWinStreak', 'RedDraws', 'RedAvgSigStrLanded', 'RedAvgSigStrPct', 'RedAvgSubAtt', 'RedAvgTDLanded', 'RedAvgTDPct', 'RedLongestWinStreak', 'RedLosses', 'RedTotalRoundsFought', 'RedTotalTitleBouts', 'RedWinsByDecisionMajority', 'RedWinsByDecisionSplit', 'RedWinsByDecisionUnanimous', 'RedWinsByKO', 'RedWinsBySubmission', 'RedWinsByTKODoctorStoppage', 'RedWins', 'RedStance', 'RedWeightLbs', 'RedAge', 'BlueAge', 'LoseStreakDif', 'WinStreakDif', 'LongestWinStreakDif', 'WinDif', 'LossDif', 'TotalRoundDif', 'TotalTitleBoutDif', 'KODif', 'SubDif', 'HeightDif', 'ReachDif', 'AgeDif', 'SigStrDif', 'AvgSubAttDif', 'AvgTDDif', 'EmptyArena', 'BMatchWCRank', 'RMatchWCRank', 'RWFlyweightRank', 'RWFeatherweightRank', 'RWStrawweightRank', 'RWBantamweightRank', 'RHeavyweightRank', 'RLightHeavyweightRank', 'RMiddleweightRank', 'RWelterweightRank', 'RLightweightRank', 'RFeatherweightRank', 'RBantamweightRank', 'RFlyweightRank', 'RPFPRank', 'BWFlyweightRank', 'BWFeatherweightRank', 'BWStrawweightRank', 'BWBantamweightRank', 'BHeavyweightRank', 'BLightHeavyweightRank', 'BMiddleweightRank', 'BWelterweightRank', 'BLightweightRank', 'BFeatherweightRank', 'BBantamweightRank', 'BFlyweightRank', 'BPFPRank', 'BetterRank', 'Finish', 'FinishDetails', 'FinishRound', 'FinishRoundTime', 'TotalFightTimeSecs', 'RedDecOdds', 'BlueDecOdds', 'RSubOdds', 'BSubOdds', 'RK0Odds', 'BK0Odds', 'WeightClassLabel', 'BlueHeight', 'BlueReach', 'RedHeight', 'RedReach', 'ROver35', 'BOver35', 'RWinPct', 'BWinPct', 'RedStrikingRatio', 'BlueStrikingRatio', 'RedTotalFights', 'BlueTotalFights', 'RedIsGrappler', 'BlueIsGrappler', 'RedIsStriker', 'BlueIsStriker', 'RGrapplerVBStriker', 'BGrapplerVRStriker', 'RedStrikingEfficiency', 'BlueStrikingEfficiency', 'RedTDEfficiency', 'BlueTDEfficiency', 'RedEffectiveTD', 'BlueEffectiveTD', 'EffectiveTDDif', 'RedSize', 'BlueSize', 'Favorite', 'FavoriteWins', 'draw_diff', 'avg_sig_str_pct_diff', 'avg_TD_pct_diff', 'win_by_Decision_Majority_diff', 'win_by_Decision_Split_diff', 'win_by_Decision_Unanimous_diff', 'win_by_TKO_Doctor_Stoppage_diff', 'odds_diff', 'ev_diff', 'StanceCombo', 'AgeGap', 'Spread']
```

In [283...]

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Convert 'Winner' to binary (Red=1, Blue=0), and drop others
df = df[df['Winner'].isin(['Red', 'Blue'])] # Keep only valid outcomes
```

```
df['Winner'] = df['Winner'].map({'Red': 1, 'Blue': 0}) # Binary conversion

# Check value counts for the 'Winner' column (including NaNs)
print(df['Winner'].value_counts(dropna=False))

# Basic descriptive statistics
print(df.describe())


# -----
# columns with excessive missingness
# -----
cols_missing = [
    'BMatchWCRank', 'RMatchWCRank', 'RWFlyweightRank', 'RWFeatherweightRank',
    'RWStrawweightRank', 'RBantamweightRank', 'RHeavyweightRank',
    'RLightHeavyweightRank', 'RMiddleweightRank', 'RWelterweightRank',
    'RLightweightRank', 'RFeatherweightRank', 'RBantamweightRank',
    'RFlyweightRank', 'RPFPRank', 'BWFlyweightRank', 'BWFeatherweightRank',
    'BWStrawweightRank', 'BWBantamweightRank', 'BHeavyweightRank',
    'BLightHeavyweightRank', 'BMiddleweightRank', 'BWelterweightRank',
    'BLightweightRank', 'BFeatherweightRank', 'BBantamweightRank',
    'BFlyweightRank', 'BPFPRank'
]

# -----
# columns to drop due to data leakage
# -----
cols_leakage = [
# Red fighter stats
'RedAvgSigStrLanded', 'RedAvgSigStrPct', 'RedAvgSubAtt',
'RedAvgTDLanded', 'RedAvgTDPct', 'RedLongestWinStreak',
'RedTotalRoundsFought', 'RedTotalTitleBouts',
'RedWinsByDecisionMajority', 'RedWinsByDecisionSplit', 'RedWinsByDecisionUnanimous',
'RedWinsByKO', 'RedWinsBySubmission', 'RedWinsByTKODoctorStoppage',
'RedWins', 'RedStrikingRatio', 'RedStrikingEfficiency', 'RedTDEfficiency',
'RedEffectiveTD', 'RedExpectedValue', 'RedDecOdds', 'RSubOdds', 'RK0Odds',

# Blue fighter stats
'BlueAvgSigStrLanded', 'BlueAvgSigStrPct', 'BlueAvgSubAtt',
'BlueAvgTDLanded', 'BlueAvgTDPct', 'BlueLongestWinStreak',
'BlueTotalRoundsFought', 'BlueTotalTitleBouts',
'BlueWinsByDecisionMajority', 'BlueWinsByDecisionSplit', 'BlueWinsByDecisionUnanimous',
]
```

```
'BlueWinsByKO', 'BlueWinsBySubmission', 'BlueWinsByTKODoctorStoppage',
'BlueWins', 'BlueStrikingRatio', 'BlueStrikingEfficiency', 'BlueTDEfficiency',
'BlueEffectiveTD', 'BlueExpectedValue', 'BlueDecOdds', 'BSubOdds', 'BKOOdds',
'Finish', 'FinishDetails', 'FinishRound', 'FinishRoundTime', 'TotalFightTimeSecs', 'Favorite', 'FavoriteWin',
# Derived features (includes current fight outcome)
'SigStrDif', 'AvgSubAttDif', 'AvgTDDif', 'LoseStreakDif', 'WinStreakDif', 'LongestWinStreakDif',
'WinDif', 'LossDif', 'TotalRoundDif', 'TotalTitleBoutDif', 'KODif', 'SubDif',
'NumberOfRounds', 'EffectiveTDDif', 'draw_diff', 'avg_sig_str_pct_diff', 'avg_TD_pct_diff',
'win_by_Decision_Majority_diff', 'win_by_Decision_Split_diff', 'win_by_Decision_Unanimous_diff', 'win_by_TI'
]

# -----
# REMOVE LEAKAGE / FUTURE-ONLY FEATURES FROM TRAINING DATA
# -----



all_leakage = cols_missing + cols_leakage

df = df.drop(columns=all_leakage, errors='ignore')

print("\nTraining dataset shape after leakage removal:", df.shape)
```

Winner

```
1    3787
0    2741
```

Name: count, dtype: int64

| | RedFighter | BlueFighter | RedOdds | BlueOdds | RedExpectedValue | \ |
|-------|-------------|-------------|--------------|--------------|------------------|---|
| count | 6528.000000 | 6528.000000 | 6301.000000 | 6302.000000 | 6301.000000 | |
| mean | 819.761795 | 942.707874 | -115.711474 | 59.793240 | 96.658224 | |
| std | 476.188466 | 556.368724 | 277.225783 | 253.117416 | 85.891109 | |
| min | 0.000000 | 0.000000 | -2100.000000 | -1200.000000 | 4.761900 | |
| 25% | 419.000000 | 462.000000 | -255.000000 | -150.000000 | 39.215700 | |
| 50% | 806.000000 | 922.500000 | -150.000000 | 130.000000 | 66.666700 | |
| 75% | 1241.250000 | 1427.000000 | 130.000000 | 215.000000 | 130.000000 | |
| max | 1660.000000 | 1921.000000 | 775.000000 | 1300.000000 | 775.000000 | |

| | BlueExpectedValue | Winner | WeightClass | Gender | \ |
|-------|-------------------|-------------|-------------|-------------|---|
| count | 6302.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | 165.054566 | 0.580116 | 5.503370 | 0.877298 | |
| std | 137.689177 | 0.493577 | 3.200274 | 0.328120 | |
| min | 8.333300 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 66.666700 | 0.000000 | 3.000000 | 1.000000 | |
| 50% | 130.000000 | 1.000000 | 6.000000 | 1.000000 | |
| 75% | 215.000000 | 1.000000 | 8.000000 | 1.000000 | |
| max | 1300.000000 | 1.000000 | 12.000000 | 1.000000 | |

| | NumberOfRounds | BlueCurrentLoseStreak | BlueCurrentWinStreak | \ |
|-------|----------------|-----------------------|----------------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | 3.185509 | 0.501072 | 0.957567 | |
| std | 0.577441 | 0.794303 | 1.406786 | |
| min | 3.000000 | 0.000000 | 0.000000 | |
| 25% | 3.000000 | 0.000000 | 0.000000 | |
| 50% | 3.000000 | 0.000000 | 0.000000 | |
| 75% | 3.000000 | 1.000000 | 1.000000 | |
| max | 5.000000 | 6.000000 | 12.000000 | |

| | BlueDraws | BlueAvgSigStrLanded | BlueAvgSigStrPct | BlueAvgSubAtt | \ |
|-------|-------------|---------------------|------------------|---------------|---|
| count | 6528.000000 | 5598.000000 | 5763.000000 | 5696.000000 | |
| mean | 0.023131 | 19.841810 | 0.453059 | 0.500202 | |
| std | 0.156327 | 20.315307 | 0.110787 | 0.672859 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.000000 | 3.880000 | 0.400000 | 0.000000 | |
| 50% | 0.000000 | 9.280000 | 0.460000 | 0.300000 | |
| 75% | 0.000000 | 32.666700 | 0.513000 | 0.800000 | |

| | | | | | |
|-------|-----------------------------|-----------------------------|----------------------------|-----------------------------|---|
| max | 2.000000 | 154.000000 | 1.000000 | 8.400000 | |
| count | BlueAvgTDLanded | BlueAvgTDPct | BlueLongestWinStreak | BlueLosses | \ |
| mean | 5695.000000 | 5686.000000 | 6528.000000 | 6528.000000 | |
| std | 1.320536 | 0.325419 | 1.923407 | 1.863664 | |
| min | 1.356491 | 0.239174 | 1.949952 | 2.170130 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.330000 | 0.150000 | 0.000000 | 0.000000 | |
| 75% | 1.000000 | 0.330000 | 1.000000 | 1.000000 | |
| max | 1.970000 | 0.470000 | 3.000000 | 3.000000 | |
| | 10.860000 | 1.000000 | 17.000000 | 16.000000 | |
| count | BlueTotalRoundsFought | BlueTotalTitleBouts | BlueWinsByDecisionMajority | BlueWinsByDecisionSplit | \ |
| mean | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| std | 11.872396 | 0.251685 | 0.017770 | 0.595123 | |
| min | 13.845139 | 1.085122 | 0.133278 | 0.000000 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 3.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 75% | 7.000000 | 0.000000 | 0.000000 | 0.000000 | |
| max | 17.000000 | 0.000000 | 0.000000 | 0.000000 | |
| | 111.000000 | 16.000000 | 2.000000 | 5.000000 | |
| count | BlueWinsByDecisionSplit | BlueWinsByDecisionUnanimous | BlueWinsByKO | BlueWinsBySubmission | \ |
| mean | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| std | 0.279871 | 1.093597 | 1.066330 | 0.626532 | |
| min | 0.595123 | 1.613288 | 1.723951 | 0.000000 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 75% | 0.000000 | 2.000000 | 1.250000 | 0.000000 | |
| max | 5.000000 | 11.000000 | 20.000000 | 13.000000 | |
| count | BlueWinsByTKODoctorStoppage | BlueWins | BlueWinsBySubmission | BlueWinsByTKODoctorStoppage | \ |
| mean | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| std | 0.022212 | 3.145680 | 0.626532 | 0.022212 | |
| min | 0.153494 | 3.712852 | 0.258249 | 0.153494 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.000000 | 2.000000 | 0.000000 | 0.000000 | |
| 75% | 0.000000 | 5.000000 | 1.000000 | 0.000000 | |
| max | 2.000000 | 31.000000 | 13.000000 | 2.000000 | |

| | BlueWeightLbs | RedCurrentLoseStreak | RedCurrentWinStreak | RedDraws | \ |
|-------|----------------------------|---------------------------|------------------------|----------------------------|---|
| count | 6528.00000 | 6528.00000 | 6528.00000 | 6528.00000 | |
| mean | 163.183977 | 0.622243 | 1.101562 | 0.031097 | |
| std | 34.599386 | 0.872301 | 1.760767 | 0.187999 | |
| min | 115.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 135.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 155.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 75% | 185.000000 | 1.000000 | 2.000000 | 0.000000 | |
| max | 265.000000 | 7.000000 | 18.000000 | 2.000000 | |
| | | | | | |
| | RedAvgSigStrLanded | RedAvgSigStrPct | RedAvgSubAtt | RedAvgTDLanded | \ |
| count | 6073.00000 | 6171.00000 | 6171.00000 | 6171.00000 | |
| mean | 21.152766 | 0.460321 | 0.536907 | 1.399962 | |
| std | 19.882916 | 0.098315 | 0.693125 | 1.308340 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 4.160000 | 0.403000 | 0.000000 | 0.450000 | |
| 50% | 15.666700 | 0.460000 | 0.333300 | 1.030000 | |
| 75% | 34.000000 | 0.516000 | 0.800000 | 2.000000 | |
| max | 141.000000 | 1.000000 | 8.400000 | 12.500000 | |
| | | | | | |
| | RedAvgTDPct | RedLongestWinStreak | RedLosses | RedTotalRoundsFought | \ |
| count | 6161.00000 | 6528.00000 | 6528.00000 | 6528.00000 | |
| mean | 0.341467 | 2.679994 | 2.566789 | 17.408548 | |
| std | 0.220986 | 2.242687 | 2.703546 | 17.846748 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.200000 | 1.000000 | 1.000000 | 5.000000 | |
| 50% | 0.338000 | 2.000000 | 2.000000 | 12.000000 | |
| 75% | 0.470000 | 4.000000 | 4.000000 | 25.000000 | |
| max | 1.000000 | 18.000000 | 21.000000 | 448.000000 | |
| | | | | | |
| | RedTotalTitleBouts | RedWinsByDecisionMajority | RedWinsByDecisionSplit | RedWinsByDecisionUnanimous | \ |
| count | 6528.00000 | 6528.00000 | 6528.00000 | 6528.00000 | |
| mean | 0.553462 | 0.026961 | 0.400888 | 0.000000 | |
| std | 1.544962 | 0.163862 | 0.702801 | 0.000000 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 75% | 0.000000 | 0.000000 | 1.000000 | 0.000000 | |
| max | 16.000000 | 2.000000 | 5.000000 | 0.000000 | |
| | | | | | |
| | RedWinsByDecisionUnanimous | RedWinsByKO | RedWinsBySubmission | RedWinsByUnconscious | \ |
| count | 6528.00000 | 6528.00000 | 6528.00000 | 6528.00000 | |

| | | | |
|------|-----------|-----------|-----------|
| mean | 1.612286 | 1.563879 | 0.934589 |
| std | 1.972295 | 2.156770 | 1.608402 |
| min | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 0.000000 | 0.000000 |
| 50% | 1.000000 | 1.000000 | 0.000000 |
| 75% | 2.000000 | 2.000000 | 1.000000 |
| max | 11.000000 | 21.000000 | 16.000000 |

| | RedWinsByTKO | DoctorStoppage | RedWins | RedWeightLbs | RedAge | \ |
|-------|--------------|----------------|-------------|--------------|-------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | 0.035539 | 4.628064 | 163.621324 | 30.359528 | | |
| std | 0.199492 | 4.505498 | 34.846543 | 4.180712 | | |
| min | 0.000000 | 0.000000 | 115.000000 | 18.000000 | | |
| 25% | 0.000000 | 1.000000 | 135.000000 | 27.000000 | | |
| 50% | 0.000000 | 3.000000 | 155.000000 | 30.000000 | | |
| 75% | 0.000000 | 7.000000 | 185.000000 | 33.000000 | | |
| max | 2.000000 | 33.000000 | 265.000000 | 47.000000 | | |

| | BlueAge | LoseStreakDif | WinStreakDif | LongestWinStreakDif | \ |
|-------|-------------|---------------|--------------|---------------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | 29.805607 | 0.059283 | -0.143842 | -0.756587 | |
| std | 3.959623 | 1.024000 | 1.874732 | 2.025886 | |
| min | 19.000000 | -6.000000 | -18.000000 | -12.000000 | |
| 25% | 27.000000 | 0.000000 | -1.000000 | -2.000000 | |
| 50% | 30.000000 | 0.000000 | 0.000000 | -1.000000 | |
| 75% | 32.000000 | 0.000000 | 0.000000 | 0.000000 | |
| max | 47.000000 | 6.000000 | 10.000000 | 14.000000 | |

| | WinDif | LossDif | TotalRoundDif | TotalTitleBoutDif | \ |
|-------|-------------|-------------|---------------|-------------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | -1.482384 | 0.075061 | -5.536152 | -0.301777 | |
| std | 4.182192 | 3.129140 | 17.995648 | 1.681080 | |
| min | -28.000000 | -20.000000 | -448.000000 | -16.000000 | |
| 25% | -3.000000 | -1.000000 | -12.000000 | 0.000000 | |
| 50% | -1.000000 | 0.000000 | -3.000000 | 0.000000 | |
| 75% | 0.000000 | 2.000000 | 2.000000 | 0.000000 | |
| max | 23.000000 | 16.000000 | 87.000000 | 15.000000 | |

| | KODif | SubDif | HeightDif | ReachDif | AgeDif | \ |
|-------|-------------|-------------|-------------|-------------|-------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | -0.510876 | -0.308058 | -0.006679 | -0.299271 | 0.096814 | |
| std | 2.149365 | 1.844810 | 6.770956 | 9.132413 | 5.201719 | |

| | | | | | |
|-----|------------|------------|-------------|-------------|------------|
| min | -21.000000 | -16.000000 | -187.960000 | -187.960000 | -17.000000 |
| 25% | -1.000000 | -1.000000 | -5.080000 | -5.080000 | -3.000000 |
| 50% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 75% | 0.000000 | 0.000000 | 5.080000 | 5.080000 | 4.000000 |
| max | 14.000000 | 10.000000 | 30.480000 | 30.480000 | 17.000000 |

| | SigStrDif | AvgSubAttDif | AvgTDDif | EmptyArena | BMatchWCRank | \ |
|-------|-------------|--------------|-------------|-------------|--------------|---|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 5042.000000 | 1200.000000 | |
| mean | -2.663342 | -0.071094 | -0.171371 | 0.153114 | 8.339167 | |
| std | 19.583493 | 0.892257 | 1.754354 | 0.360133 | 4.202839 | |
| min | -118.000000 | -8.400000 | -11.000000 | 0.000000 | 1.000000 | |
| 25% | -7.895850 | -0.444400 | -1.010000 | 0.000000 | 5.000000 | |
| 50% | -0.304750 | 0.000000 | 0.000000 | 0.000000 | 9.000000 | |
| 75% | 2.100000 | 0.282400 | 0.700000 | 0.000000 | 12.000000 | |
| max | 128.222200 | 7.800000 | 10.860000 | 1.000000 | 15.000000 | |

| | RMatchWCRank | RWFlyweightRank | RWFeatherweightRank | RWStrawweightRank | \ |
|-------|--------------|-----------------|---------------------|-------------------|------------|
| count | 1779.000000 | 96.000000 | | 9.0 | 146.000000 |
| mean | 6.953345 | 7.291667 | | 0.0 | 7.047945 |
| std | 4.657029 | 4.975554 | | 0.0 | 4.616809 |
| min | 0.000000 | 0.000000 | | 0.0 | 0.000000 |
| 25% | 3.000000 | 3.000000 | | 0.0 | 3.000000 |
| 50% | 7.000000 | 7.000000 | | 0.0 | 7.000000 |
| 75% | 11.000000 | 12.000000 | | 0.0 | 11.000000 |
| max | 15.000000 | 15.000000 | | 0.0 | 15.000000 |

| | RWBantamweightRank | RHeavyweightRank | RLightHeavyweightRank | \ |
|-------|--------------------|------------------|-----------------------|---|
| count | 154.000000 | 186.000000 | 184.000000 | |
| mean | 7.097403 | 6.881720 | 7.119565 | |
| std | 4.803008 | 4.404787 | 4.638500 | |
| min | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 3.000000 | 3.000000 | 4.000000 | |
| 50% | 7.000000 | 7.000000 | 7.000000 | |
| 75% | 11.750000 | 10.000000 | 11.000000 | |
| max | 15.000000 | 15.000000 | 15.000000 | |

| | RMiddleweightRank | RWelterweightRank | RLightweightRank | \ |
|-------|-------------------|-------------------|------------------|---|
| count | 182.000000 | 191.000000 | 184.000000 | |
| mean | 7.351648 | 7.130890 | 7.032609 | |
| std | 4.711274 | 4.705947 | 4.662257 | |
| min | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 4.000000 | 3.000000 | 3.000000 | |

| | | | |
|-----|-----------|-----------|-----------|
| 50% | 7.000000 | 7.000000 | 6.000000 |
| 75% | 11.750000 | 11.000000 | 11.000000 |
| max | 15.000000 | 15.000000 | 15.000000 |

| | RFeatherweightRank | RBantamweightRank | RFlyweightRank | RPFPRank | \ |
|-------|--------------------|-------------------|----------------|------------|---|
| count | 177.000000 | 181.000000 | 188.000000 | 253.000000 | |
| mean | 6.983051 | 6.972376 | 6.590426 | 6.913043 | |
| std | 4.653291 | 4.709837 | 4.621192 | 4.195655 | |
| min | 0.000000 | 0.000000 | 0.000000 | 1.000000 | |
| 25% | 3.000000 | 3.000000 | 2.000000 | 3.000000 | |
| 50% | 7.000000 | 7.000000 | 7.000000 | 6.000000 | |
| 75% | 11.000000 | 11.000000 | 10.250000 | 10.000000 | |
| max | 15.000000 | 15.000000 | 15.000000 | 15.000000 | |

| | BWFlyweightRank | BWFeatherweightRank | BWStrawweightRank | \ |
|-------|-----------------|---------------------|-------------------|---|
| count | 73.000000 | 1.0 | 100.000000 | |
| mean | 8.410959 | 0.0 | 8.170000 | |
| std | 4.009834 | NaN | 4.192478 | |
| min | 1.000000 | 0.0 | 1.000000 | |
| 25% | 6.000000 | 0.0 | 5.000000 | |
| 50% | 9.000000 | 0.0 | 9.000000 | |
| 75% | 12.000000 | 0.0 | 12.000000 | |
| max | 15.000000 | 0.0 | 15.000000 | |

| | BWBantamweightRank | BHeavyweightRank | BLightHeavyweightRank | \ |
|-------|--------------------|------------------|-----------------------|---|
| count | 107.000000 | 148.000000 | 120.000000 | |
| mean | 8.476636 | 8.641892 | 8.483333 | |
| std | 4.254511 | 4.090823 | 4.152519 | |
| min | 0.000000 | 1.000000 | 0.000000 | |
| 25% | 5.000000 | 5.000000 | 6.000000 | |
| 50% | 9.000000 | 9.000000 | 9.000000 | |
| 75% | 12.000000 | 12.000000 | 12.000000 | |
| max | 15.000000 | 15.000000 | 15.000000 | |

| | BMiddleweightRank | BWelterweightRank | BLightweightRank | \ |
|-------|-------------------|-------------------|------------------|---|
| count | 137.000000 | 119.000000 | 120.000000 | |
| mean | 8.554745 | 8.386555 | 8.150000 | |
| std | 4.311271 | 4.405523 | 4.076269 | |
| min | 0.000000 | 1.000000 | 1.000000 | |
| 25% | 5.000000 | 4.500000 | 5.000000 | |
| 50% | 9.000000 | 9.000000 | 8.000000 | |
| 75% | 12.000000 | 12.000000 | 11.250000 | |

| | | | | | | |
|-------|----------------------------------|-----------------------------------|------------------------------|----------------------------|--------------------------|---|
| max | 15.000000 | 15.000000 | 15.000000 | | | \ |
| count | BFeatherweightRank
124.000000 | BBantamweightRank
119.000000 | BFlyweightRank
130.000000 | BPFPRank
67.000000 | | |
| mean | 7.967742 | 8.268908 | 8.407692 | 9.194030 | | |
| std | 4.462919 | 4.354420 | 4.307369 | 4.352773 | | |
| min | 0.000000 | 0.000000 | 1.000000 | 1.000000 | | |
| 25% | 4.000000 | 4.000000 | 5.000000 | 5.000000 | | |
| 50% | 8.500000 | 9.000000 | 8.000000 | 10.000000 | | |
| 75% | 12.000000 | 12.000000 | 12.000000 | 13.500000 | | |
| max | 15.000000 | 15.000000 | 15.000000 | 15.000000 | | |
| count | FinishRound
5906.000000 | TotalFightTimeSecs
5906.000000 | RedDecOdds
5441.000000 | BlueDecOdds
5412.000000 | RSubOdds
5192.000000 | \ |
| mean | 2.424145 | 657.536234 | 308.333395 | 425.870288 | 884.048151 | |
| std | 1.007887 | 360.383418 | 250.750088 | 325.940028 | 601.826547 | |
| min | 1.000000 | 5.000000 | -440.000000 | -200.000000 | -370.000000 | |
| 25% | 1.000000 | 299.000000 | 170.000000 | 222.000000 | 439.750000 | |
| 50% | 3.000000 | 900.000000 | 250.000000 | 350.000000 | 750.000000 | |
| 75% | 3.000000 | 900.000000 | 400.000000 | 550.000000 | 1200.000000 | |
| max | 5.000000 | 1500.000000 | 2400.000000 | 3000.000000 | 4665.000000 | |
| count | BSubOdds
5169.000000 | RK00dds
5194.000000 | BK00dds
5168.000000 | BlueHeight
6528.000000 | BlueReach
6528.000000 | \ |
| mean | 1100.497775 | 510.891606 | 636.463235 | 70.008688 | 71.717384 | |
| std | 671.106177 | 426.563458 | 465.014634 | 3.584685 | 4.397201 | |
| min | -1250.000000 | -550.000000 | -400.000000 | 60.000000 | 0.000000 | |
| 25% | 600.000000 | 225.000000 | 310.000000 | 67.000000 | 69.000000 | |
| 50% | 1000.000000 | 420.000000 | 525.000000 | 70.000000 | 72.000000 | |
| 75% | 1450.000000 | 700.000000 | 875.000000 | 73.000000 | 75.000000 | |
| max | 5000.000000 | 4000.000000 | 4000.000000 | 83.000000 | 84.000000 | |
| count | RedHeight
6528.000000 | RedReach
6528.000000 | ROver35
6528.000000 | BOver35
6528.000000 | RWinPct
6067.000000 | \ |
| mean | 70.000944 | 71.815336 | 0.114583 | 0.084865 | 0.631346 | |
| std | 3.615340 | 4.382045 | 0.318543 | 0.278702 | 0.256596 | |
| min | 60.000000 | 58.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 67.000000 | 69.000000 | 0.000000 | 0.000000 | 0.500000 | |
| 50% | 70.000000 | 72.000000 | 0.000000 | 0.000000 | 0.666667 | |
| 75% | 73.000000 | 75.000000 | 0.000000 | 0.000000 | 0.777778 | |
| max | 83.000000 | 84.500000 | 1.000000 | 1.000000 | 1.000000 | |

| | BWinPct | RedStrikingRatio | BlueStrikingRatio | RedTotalFights | \ |
|-------|-----------------------|------------------------|--------------------|----------------|---|
| count | 5418.000000 | 5476.000000 | 5476.000000 | 6528.000000 | |
| mean | 0.591404 | 0.513428 | 0.486572 | 7.194853 | |
| std | 0.298916 | 0.158090 | 0.158090 | 6.761721 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.500000 | 0.414774 | 0.395959 | 2.000000 | |
| 50% | 0.625000 | 0.507965 | 0.492035 | 5.000000 | |
| 75% | 0.800000 | 0.604041 | 0.585226 | 10.000000 | |
| max | 1.000000 | 1.000000 | 1.000000 | 48.000000 | |
| | | | | | |
| | BlueTotalFights | RedIsGrappler | BlueIsGrappler | RedIsStriker | \ |
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 | |
| mean | 5.009344 | 0.062653 | 0.059743 | 0.548866 | |
| std | 5.502321 | 0.242357 | 0.237028 | 0.497644 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 1.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 3.000000 | 0.000000 | 0.000000 | 1.000000 | |
| 75% | 7.000000 | 0.000000 | 0.000000 | 1.000000 | |
| max | 45.000000 | 1.000000 | 1.000000 | 1.000000 | |
| | | | | | |
| | BlueIsStriker | RGrapplerVBStriker | BGrapplerVRStriker | \ | |
| count | 6528.000000 | 6528.000000 | 6528.000000 | | |
| mean | 0.472733 | 0.022212 | 0.025429 | | |
| std | 0.499294 | 0.147384 | 0.157436 | | |
| min | 0.000000 | 0.000000 | 0.000000 | | |
| 25% | 0.000000 | 0.000000 | 0.000000 | | |
| 50% | 0.000000 | 0.000000 | 0.000000 | | |
| 75% | 1.000000 | 0.000000 | 0.000000 | | |
| max | 1.000000 | 1.000000 | 1.000000 | | |
| | | | | | |
| | RedStrikingEfficiency | BlueStrikingEfficiency | RedTDEfficiency | \ | |
| count | 6073.000000 | 5598.000000 | 6161.000000 | | |
| mean | 9.729212 | 9.149099 | 0.626869 | | |
| std | 9.535491 | 9.800691 | 0.756785 | | |
| min | 0.000000 | 0.000000 | 0.000000 | | |
| 25% | 1.906100 | 1.761800 | 0.110000 | | |
| 50% | 6.600000 | 4.076800 | 0.380800 | | |
| 75% | 15.500186 | 14.755537 | 0.888000 | | |
| max | 81.180000 | 78.540000 | 8.330000 | | |
| | | | | | |
| | BlueTDEfficiency | RedEffectiveTD | BlueEffectiveTD | EffectiveTDDif | \ |
| count | 5686.000000 | 5347.000000 | 4608.000000 | 4078.000000 | |

| | | | | |
|------|----------|-----------|-----------|------------|
| mean | 0.605154 | 0.552095 | 0.538713 | -0.010168 |
| std | 0.810902 | 0.902846 | 0.876956 | 1.243102 |
| min | 0.000000 | 0.000000 | 0.000000 | -10.732888 |
| 25% | 0.062500 | 0.052627 | 0.000000 | -0.380948 |
| 50% | 0.330000 | 0.293332 | 0.285700 | 0.000000 |
| 75% | 0.831017 | 0.666667 | 0.666667 | 0.353956 |
| max | 9.000000 | 11.212121 | 11.212121 | 11.170016 |

| | | | | |
|-------|-------------|-------------|-------------|-------------|
| count | 6528.000000 | 6528.000000 | 6528.000000 | 6528.000000 |
| mean | 141.816281 | 141.726072 | 0.649969 | -0.007966 |
| std | 7.797873 | 7.744036 | 0.477016 | 0.232091 |
| min | 120.000000 | 66.000000 | 0.000000 | -2.000000 |
| 25% | 136.000000 | 136.000000 | 0.000000 | 0.000000 |
| 50% | 142.000000 | 142.000000 | 1.000000 | 0.000000 |
| 75% | 147.000000 | 147.000000 | 1.000000 | 0.000000 |
| max | 167.500000 | 167.000000 | 1.000000 | 2.000000 |

| | | | | |
|-------|-------------|-------------|-------------------------------|-----------|
| count | 5641.000000 | 5575.000000 | win_by_Decision_Majority_diff | \ |
| mean | -0.008139 | -0.019948 | | -0.009191 |
| std | 0.138355 | 0.311780 | | 0.208392 |
| min | -0.820000 | -1.000000 | | -2.000000 |
| 25% | -0.080000 | -0.210000 | | 0.000000 |
| 50% | 0.000000 | 0.000000 | | 0.000000 |
| 75% | 0.077000 | 0.161000 | | 0.000000 |
| max | 0.570000 | 1.000000 | | 1.000000 |

| | | | | |
|-------|-------------|----------------------------|--------------------------------|------------|
| count | 6528.000000 | win_by_Decision_Split_diff | win_by_Decision_Unanimous_diff | \ |
| mean | -0.121017 | | | -0.518689 |
| std | 0.873700 | | | 2.107779 |
| min | -5.000000 | | | -11.000000 |
| 25% | 0.000000 | | | -1.000000 |
| 50% | 0.000000 | | | 0.000000 |
| 75% | 0.000000 | | | 0.000000 |
| max | 5.000000 | | | 11.000000 |

| | | | | | | |
|-------|-------------|---------------------------------|------------|------------|----------|---|
| count | 6528.000000 | win_by_TKO_Doctor_Stoppage_diff | odds_diff | ev_diff | AgeGap | \ |
| mean | -0.013327 | | 175.464229 | 68.482524 | 4.142463 | |
| std | 0.247506 | | 525.482605 | 203.186608 | 3.147162 | |

| | | | | |
|-----|-----------|--------------|-------------|-----------|
| min | -2.000000 | -1975.000000 | -766.666700 | 0.000000 |
| 25% | 0.000000 | -280.000000 | -63.333300 | 2.000000 |
| 50% | 0.000000 | 280.000000 | 63.333300 | 3.000000 |
| 75% | 0.000000 | 470.000000 | 175.784300 | 6.000000 |
| max | 2.000000 | 3200.000000 | 1293.939400 | 17.000000 |

| | Spread |
|-------|-------------|
| count | 6290.000000 |
| mean | 457.442607 |
| std | 312.470074 |
| min | 0.000000 |
| 25% | 280.000000 |
| 50% | 370.000000 |
| 75% | 550.000000 |
| max | 3200.000000 |

Training dataset shape after leakage removal: (6528, 51)

```
In [284...]: #shiyu
# To follow up on our previous discussion:
# You can keep all 152 variables – that's perfectly fine.
# Just make sure to check for highly correlated features and remove or combine
# any that show strong correlations (for example, |r| > 0.9),
# so your model doesn't suffer from redundancy.
```

```
In [285...]: # for i in random_states:

#     - split the data
#     - preprocess it
#     - decide which hyperparameters you'll tune and what values you'll try
#     - for combo in hyperparameters:
#         - train your ML algo
#         - calculate training scores
#         - calculate validation scores
#     - select best model based on the mean and std validation scores
#     - predict the test set using the best model
#     - return your test score (generalization error)
#     - return the best model
```

```
In [286...]: df.isnull().sum().sort_values(ascending=False)
```

| | | |
|--------------|---------------------------------|------|
| Out [286...] | BWinPct | 1110 |
| | RWinPct | 461 |
| | Spread | 238 |
| | ev_diff | 238 |
| | odds_diff | 238 |
| | RedOdds | 227 |
| | BlueOdds | 226 |
| | BlueStance | 3 |
| | BlueIsGrappler | 0 |
| | RedHeight | 0 |
| | RedReach | 0 |
| | ROver35 | 0 |
| | BOver35 | 0 |
| | RedTotalFights | 0 |
| | BlueTotalFights | 0 |
| | RedIsGrappler | 0 |
| | RGrapplerVBStriker | 0 |
| | RedIsStriker | 0 |
| | BlueIsStriker | 0 |
| | BlueHeight | 0 |
| | BGrapplerVRStriker | 0 |
| | RedSize | 0 |
| | BlueSize | 0 |
| | win_by_TKO_Doctor_Stoppage_diff | 0 |
| | StanceCombo | 0 |
| | AgeGap | 0 |
| | BlueReach | 0 |
| | RedFighter | 0 |
| | WeightClassLabel | 0 |
| | RedCurrentLoseStreak | 0 |
| | Winner | 0 |
| | TitleBout | 0 |
| | WeightClass | 0 |
| | Gender | 0 |
| | BlueCurrentLoseStreak | 0 |
| | BlueCurrentWinStreak | 0 |
| | BlueDraws | 0 |
| | BlueLosses | 0 |
| | BlueWeightLbs | 0 |
| | RedCurrentWinStreak | 0 |
| | BlueFighter | 0 |
| | RedDraws | 0 |

```
RedLosses          0
RedStance          0
RedWeightLbs       0
RedAge             0
BlueAge            0
HeightDif          0
ReachDif           0
AgeDif             0
BetterRank          0
dtype: int64
```

In [287...]

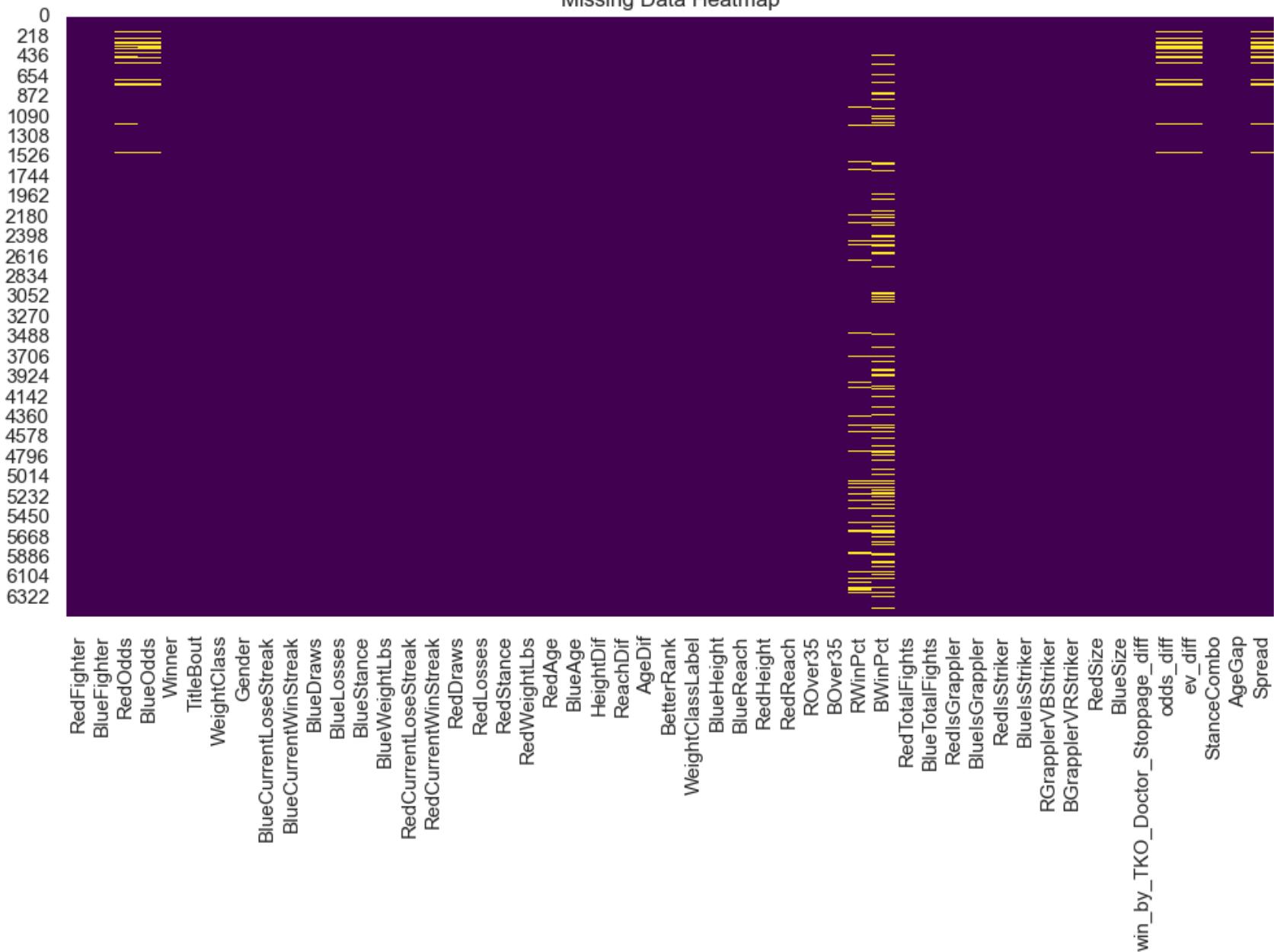
```
# Plot missing values heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(df.isnull(), cbar=False, cmap="viridis")
plt.title("Missing Data Heatmap")
fig_name = "missing_data_heatmap2"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

# Missing values per column (%)
missing_percent = df.isnull().sum() * 100 / len(df)
print("Missing percentages per column:\n", missing_percent)

# Class balance
plt.figure(figsize=(6, 4))
sns.countplot(x='Winner', data=df)
plt.title('Class Balance: Winner')
fig_name = "class_balance_winner"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

# Display proportions
print("Class proportions:")
print(df['Winner'].value_counts(normalize=True))
```

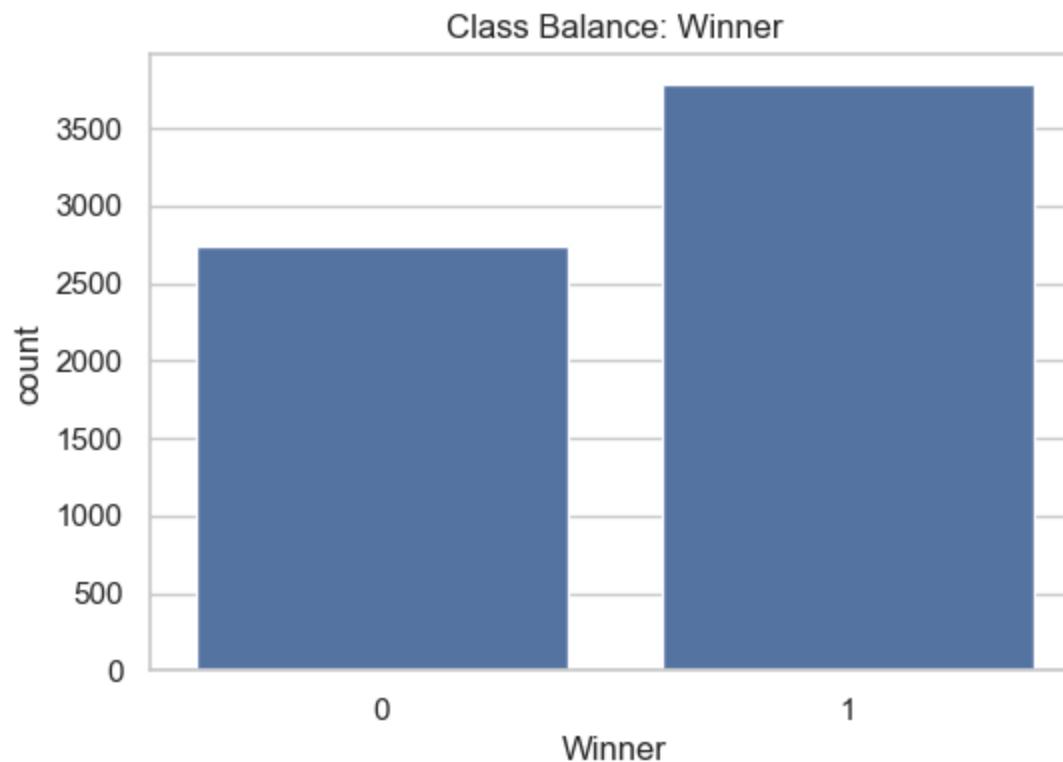
Missing Data Heatmap



Missing percentages per column:

| | |
|-----------------------|-----------|
| RedFighter | 0.000000 |
| BlueFighter | 0.000000 |
| RedOdds | 3.477328 |
| BlueOdds | 3.462010 |
| Winner | 0.000000 |
| TitleBout | 0.000000 |
| WeightClass | 0.000000 |
| Gender | 0.000000 |
| BlueCurrentLoseStreak | 0.000000 |
| BlueCurrentWinStreak | 0.000000 |
| BlueDraws | 0.000000 |
| BlueLosses | 0.000000 |
| BlueStance | 0.045956 |
| BlueWeightLbs | 0.000000 |
| RedCurrentLoseStreak | 0.000000 |
| RedCurrentWinStreak | 0.000000 |
| RedDraws | 0.000000 |
| RedLosses | 0.000000 |
| RedStance | 0.000000 |
| RedWeightLbs | 0.000000 |
| RedAge | 0.000000 |
| BlueAge | 0.000000 |
| HeightDif | 0.000000 |
| ReachDif | 0.000000 |
| AgeDif | 0.000000 |
| BetterRank | 0.000000 |
| WeightClassLabel | 0.000000 |
| BlueHeight | 0.000000 |
| BlueReach | 0.000000 |
| RedHeight | 0.000000 |
| RedReach | 0.000000 |
| ROver35 | 0.000000 |
| BOver35 | 0.000000 |
| RWinPct | 7.061887 |
| BWinPct | 17.003676 |
| RedTotalFights | 0.000000 |
| BlueTotalFights | 0.000000 |
| RedIsGrappler | 0.000000 |
| BlueIsGrappler | 0.000000 |
| RedIsStriker | 0.000000 |
| BlueIsStriker | 0.000000 |

```
RGrapplerVBStriker      0.000000
BGrapplerVRStriker     0.000000
RedSize                 0.000000
BlueSize                0.000000
win_by_TKO_Doctor_Stoppage_diff 0.000000
odds_diff               3.645833
ev_diff                 3.645833
StanceCombo              0.000000
AgeGap                  0.000000
Spread                  3.645833
dtype: float64
```



Class proportions:
Winner
1 0.580116
0 0.419884
Name: proportion, dtype: float64

In [288...]

```
# Separate categorical and numerical columns
cat_cols = df.select_dtypes(include=['object']).columns.tolist()
num_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
num_cols.remove('Winner') if 'Winner' in num_cols else None

print("Categorical columns:", cat_cols)
print("Numerical columns:", num_cols)
```

Categorical columns: ['TitleBout', 'BlueStance', 'RedStance', 'BetterRank', 'WeightClassLabel', 'StanceCombO']

Numerical columns: ['RedFighter', 'BlueFighter', 'RedOdds', 'BlueOdds', 'WeightClass', 'Gender', 'BlueCurrentLoseStreak', 'BlueCurrentWinStreak', 'BlueDraws', 'BlueLosses', 'BlueWeightLbs', 'RedCurrentLoseStreak', 'RedCurrentWinStreak', 'RedDraws', 'RedLosses', 'RedWeightLbs', 'RedAge', 'BlueAge', 'HeightDif', 'ReachDif', 'AgeDif', 'BlueHeight', 'BlueReach', 'RedHeight', 'RedReach', 'ROver35', 'BOver35', 'RWinPct', 'BWinPct', 'RedTotalFights', 'BlueTotalFights', 'RedIsGrappler', 'BlueIsGrappler', 'RedIsStriker', 'BlueIsStriker', 'RGrapplerVBStriker', 'BGrapplerVRStriker', 'RedSize', 'BlueSize', 'win_by_TKO_Doctor_Stoppage_diff', 'odds_diff', 'ev_diff', 'AgeGap', 'Spread']

In [289...]

```
#DummyClassifier = baseline to compare better model's performance later
# base_model = DummyClassifier(random_state=42)
# base_model.fit(X_train,y_train)
# preds = base_model.predict(X_valid)
# accuracy_score(y_valid, preds)
```

In [290...]

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

# -----
# drop strongly corr ftrs  (|r| ≥ 0.50)
# -----


num_df = df.select_dtypes(include=['int64','float64'])
corr_matrix = num_df.corr().abs()

# Keep only upper triangle
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Strong correlation pairs
strong_pairs = (
    upper.stack()
```

```
.reset_index()
    .rename(columns={"level_0": "Feature_1", "level_1": "Feature_2", 0: "Correlation"})
)
strong_pairs = strong_pairs[strong_pairs["Correlation"] >= 0.50]

print("\nSTRONGLY CORRELATED PAIRS (|r| ≥ 0.50)")
print(strong_pairs.sort_values("Correlation", ascending=False))

# Choose lower variance feature from each pair
to_drop_corr = set()
for f1, f2, corr_val in strong_pairs.values:
    var1 = num_df[f1].var()
    var2 = num_df[f2].var()
    drop_feature = f1 if var1 < var2 else f2
    to_drop_corr.add(drop_feature)

print("\nDropping correlated features:")
print(to_drop_corr)

# Drop from df_clean
df_clean = df.drop(columns=list(to_drop_corr), errors='ignore')

# Rebuild num_df using cleaned df
num_df = df_clean.select_dtypes(include=['int64', 'float64'])

# -----
# Load features + target
# -----
X = df_clean.drop(columns=['Winner'])
y = df_clean['Winner']

print("Raw feature columns:")
print(X.columns.tolist())


print("\nFeatures considered for modeling:")
print(X.columns.tolist())

# -----
# EDA
# -----
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

sns.set(style="whitegrid")

print("\n====")
print(" BASIC DATA OVERVIEW")
print("====")
print(df_clean.head())
print("\nShape:", df_clean.shape)
print("\nData types:\n", df_clean.dtypes)
print("\nMissing values per column:\n", df_clean.isna().sum().sort_values(ascending=False))

# -----
# Target variable distribution
# -----
plt.figure(figsize=(6,4))
sns.countplot(x=df_clean['Winner'])
plt.title("Distribution of Winner")
plt.xlabel("Winner (0 = Blue, 1 = Red)")
fig_name = "dist_winner_rb"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

num_df = X.select_dtypes(include=['int64', 'float64'])
cat_df = X.select_dtypes(include=['object', 'category'])

print("\nUpdated feature count after removing correlated vars:")
print("Numeric:", len(num_df.columns))
print("Categorical:", len(cat_df.columns))

# rebuild cleaned num_df
num_df = df_clean.select_dtypes(include=['int64', 'float64'])

plt.figure(figsize=(10,4))
sns.histplot(num_df.isna().sum(), bins=20)
```

```
plt.title("Missing Values Distribution (Numeric Columns)")
fig_name = "numeric_missing"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

print("\nNumeric Summary Stats:\n")
display(num_df.describe().T)

# -----
# Correlation Heatmap (top 20 strongest correlations)
# -----
plt.figure(figsize=(14,12))
corr = num_df.corr()

# keep strongest correlations with target
if 'Winner' in corr.columns:
    target_corr = corr['Winner'].abs().sort_values(ascending=False)[1:21]
    top_corr_cols = target_corr.index.tolist()
else:
    top_corr_cols = num_df.columns[:20]

sns.heatmap(num_df[top_corr_cols].corr(), annot=False, cmap='viridis')
plt.title("Correlation Heatmap (Top Correlated Numeric Features)")
fig_name = "corr_heatmap_num"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()

# -----
# Distribution plots for key variables
# -----

cols_to_plot = [
    'ReachDif', 'HeightDif', 'Oddsdiff',
    'ev_diff', 'AgeGap'
]
```

```
cols_to_plot = [c for c in cols_to_plot if c in df_clean.columns]

for col in cols_to_plot:
    plt.figure(figsize=(7,4))
    sns.histplot(df_clean[col], kde=True)
    plt.title(f"Distribution: {col}")
    fig_name = "dist_cols_to_plot"
    fig_path = os.path.join(output_folder, f"{fig_name}.png")
    plt.savefig(fig_path, bbox_inches="tight", dpi=300)
    plt.show()
    plt.close()

# -----
# Boxplots of numeric variables by Winner
# -----
for col in cols_to_plot:
    plt.figure(figsize=(7,4))
    sns.boxplot(x=df_clean["Winner"], y=df_clean[col])
    plt.title(f"{col} by Winner")
    fig_name = "boxplot_winner"
    fig_path = os.path.join(output_folder, f"{fig_name}.png")
    plt.savefig(fig_path, bbox_inches="tight", dpi=300)
    plt.show()
    plt.close()

# -----
# Categorical feature frequencies
# -----
cat_df = df_clean.select_dtypes(include=['object', 'category'])

for col in cat_df.columns:
    plt.figure(figsize=(9,4))
    sns.countplot(y=df_clean[col], order=df_clean[col].value_counts().index)
    plt.title(f"Value Counts: {col}")
    plt.tight_layout()
    fig_name = "last_edu"
    fig_path = os.path.join(output_folder, f"{fig_name}.png")
    plt.savefig(fig_path, bbox_inches="tight", dpi=300)
    plt.show()
    plt.close()
```

```
print("\n-----")
print("EDA COMPLETE")
print("-----")
```

STRONGLY CORRELATED PAIRS ($|r| \geq 0.50$)

| | Feature_1 | Feature_2 | Correlation |
|-----|----------------|--------------------|-------------|
| 125 | RedOdds | odds_diff | 0.991816 |
| 166 | BlueOdds | odds_diff | 0.990186 |
| 984 | odds_diff | ev_diff | 0.984505 |
| 812 | RedReach | RedSize | 0.979474 |
| 126 | RedOdds | ev_diff | 0.976921 |
| 774 | BlueReach | BlueSize | 0.975792 |
| 167 | BlueOdds | ev_diff | 0.974324 |
| 793 | RedHeight | RedSize | 0.969695 |
| 433 | BlueWeightLbs | RedWeightLbs | 0.965231 |
| 87 | RedOdds | BlueOdds | 0.964238 |
| 753 | BlueHeight | BlueSize | 0.963343 |
| 780 | RedHeight | RedReach | 0.900542 |
| 569 | RedLosses | RedTotalFights | 0.895224 |
| 415 | BlueLosses | BlueTotalFights | 0.887705 |
| 737 | BlueHeight | BlueReach | 0.881352 |
| 605 | RedWeightLbs | RedSize | 0.809872 |
| 591 | RedWeightLbs | RedHeight | 0.806387 |
| 456 | BlueWeightLbs | BlueSize | 0.803452 |
| 439 | BlueWeightLbs | BlueHeight | 0.802761 |
| 455 | BlueWeightLbs | RedSize | 0.799574 |
| 441 | BlueWeightLbs | RedHeight | 0.794270 |
| 606 | RedWeightLbs | BlueSize | 0.793032 |
| 589 | RedWeightLbs | BlueHeight | 0.792587 |
| 592 | RedWeightLbs | RedReach | 0.775875 |
| 442 | BlueWeightLbs | RedReach | 0.767546 |
| 969 | RedSize | BlueSize | 0.767207 |
| 752 | BlueHeight | RedSize | 0.764074 |
| 440 | BlueWeightLbs | BlueReach | 0.760556 |
| 794 | RedHeight | BlueSize | 0.759768 |
| 738 | BlueHeight | RedHeight | 0.758014 |
| 590 | RedWeightLbs | BlueReach | 0.750499 |
| 813 | RedReach | BlueSize | 0.738414 |
| 739 | BlueHeight | RedReach | 0.734285 |
| 773 | BlueReach | RedSize | 0.728262 |
| 759 | BlueReach | RedHeight | 0.720101 |
| 760 | BlueReach | RedReach | 0.701839 |
| 927 | BlueIsGrappler | BGrapplerVRStriker | 0.640823 |
| 935 | RedIsStriker | BlueIsStriker | 0.638930 |
| 620 | RedAge | ROver35 | 0.636553 |
| 665 | HeightDif | ReachDif | 0.627953 |

| | | | |
|-----|-----------------------|--------------------|----------|
| 210 | WeightClass | Gender | 0.622688 |
| 647 | BlueAge | BOver35 | 0.593329 |
| 915 | RedIsGrappler | RGrapplerVBStriker | 0.582975 |
| 624 | RedAge | RedTotalFights | 0.547067 |
| 556 | RedLosses | RedAge | 0.544640 |
| 308 | BlueCurrentLoseStreak | BWinPct | 0.544207 |
| 344 | BlueCurrentWinStreak | BWinPct | 0.538211 |
| 128 | RedOdds | Spread | 0.533459 |
| 281 | Gender | BlueSize | 0.533012 |
| 280 | Gender | RedSize | 0.521222 |
| 265 | Gender | BlueReach | 0.521174 |
| 267 | Gender | RedReach | 0.518583 |
| 988 | ev_diff | Spread | 0.517156 |
| 264 | Gender | BlueHeight | 0.512167 |

Dropping correlated features:

```
{'ROver35', 'ev_diff', 'HeightDif', 'RedSize', 'BWinPct', 'Gender', 'RedLosses', 'BlueReach', 'BGrapplerVRS
triker', 'BlueWeightLbs', 'RedAge', 'BlueOdds', 'BOver35', 'BlueSize', 'BlueLosses', 'BlueHeight', 'RGrappl
erVBStriker', 'RedHeight', 'RedIsStriker', 'RedReach', 'RedOdds'}
```

Raw feature columns:

```
['RedFighter', 'BlueFighter', 'TitleBout', 'WeightClass', 'BlueCurrentLoseStreak', 'BlueCurrentWinStreak',
'BlueDraws', 'BlueStance', 'RedCurrentLoseStreak', 'RedCurrentWinStreak', 'RedDraws', 'RedStance', 'RedWeig
htLbs', 'BlueAge', 'ReachDif', 'AgeDif', 'BetterRank', 'WeightClassLabel', 'RWinPct', 'RedTotalFights', 'Bl
ueTotalFights', 'RedIsGrappler', 'BlueIsGrappler', 'BlueIsStriker', 'win_by_TKO_Doctor_Stoppage_diff', 'odd
s_diff', 'StanceCombo', 'AgeGap', 'Spread']
```

Features considered for modeling:

```
['RedFighter', 'BlueFighter', 'TitleBout', 'WeightClass', 'BlueCurrentLoseStreak', 'BlueCurrentWinStreak',
'BlueDraws', 'BlueStance', 'RedCurrentLoseStreak', 'RedCurrentWinStreak', 'RedDraws', 'RedStance', 'RedWeig
htLbs', 'BlueAge', 'ReachDif', 'AgeDif', 'BetterRank', 'WeightClassLabel', 'RWinPct', 'RedTotalFights', 'Bl
ueTotalFights', 'RedIsGrappler', 'BlueIsGrappler', 'BlueIsStriker', 'win_by_TKO_Doctor_Stoppage_diff', 'odd
s_diff', 'StanceCombo', 'AgeGap', 'Spread']
```

BASIC DATA OVERVIEW

| | RedFighter | BlueFighter | Winner | TitleBout | WeightClass | \ |
|---|------------|-------------|--------|-----------|-------------|---|
| 0 | 66 | 1009 | 1 | True | 3 | |
| 1 | 1441 | 718 | 1 | False | 8 | |
| 2 | 307 | 67 | 1 | False | 4 | |
| 3 | 221 | 1071 | 1 | False | 2 | |
| 4 | 1183 | 524 | 0 | False | 2 | |

| | BlueCurrentLoseStreak | BlueCurrentWinStreak | BlueDraws | BlueStance | \ | |
|------------------------|---------------------------------|----------------------|---------------|----------------|------------------|---------------------|
| 0 | 0 | 0 | 0 | 0 | Orthodox | |
| 1 | 0 | 8 | 0 | 0 | Orthodox | |
| 2 | 0 | 4 | 0 | 0 | Orthodox | |
| 3 | 2 | 0 | 0 | 0 | Southpaw | |
| 4 | 0 | 1 | 1 | 1 | Orthodox | |
| RedCurrentLoseStreak | RedCurrentWinStreak | RedDraws | RedStance | \ | | |
| 0 | 0 | 6 | 0 | 0 | Orthodox | |
| 1 | 0 | 6 | 0 | 0 | Orthodox | |
| 2 | 0 | 1 | 0 | 0 | Orthodox | |
| 3 | 1 | 0 | 0 | 0 | Southpaw | |
| 4 | 0 | 1 | 0 | 0 | Orthodox | |
| RedWeightLbs | BlueAge | ReachDif | AgeDif | BetterRank | WeightClassLabel | \ |
| 0 | 125 | 31 | 5.08 | -3 | Red | Featherweight |
| 1 | 170 | 27 | -7.62 | -3 | Red | Women's Strawweight |
| 2 | 245 | 36 | -2.54 | 2 | Red | Light Heavyweight |
| 3 | 145 | 36 | 0.00 | 6 | Red | Heavyweight |
| 4 | 145 | 33 | -5.08 | -3 | neither | Heavyweight |
| RWinPct | RedTotalFights | BlueTotalFights | RedIsGrappler | BlueIsGrappler | \ | |
| 0 0.800000 | 15 | 0 | 0 | 0 | | |
| 1 1.000000 | 6 | 8 | 0 | 0 | | |
| 2 0.818182 | 11 | 16 | 0 | 0 | | |
| 3 0.777778 | 9 | 3 | 0 | 0 | | |
| 4 0.625000 | 8 | 7 | 0 | 0 | | |
| BlueIsStriker | win_by_TKO_Doctor_Stoppage_diff | odds_diff | \ | | | |
| 0 0 | 0 | 465.0 | | | | |
| 1 0 | 0 | 505.0 | | | | |
| 2 0 | 0 | 680.0 | | | | |
| 3 0 | 0 | 1575.0 | | | | |
| 4 0 | 0 | 240.0 | | | | |
| StanceCombo | AgeGap | Spread | | | | |
| 0 Orthodox vs Orthodox | 3 | 465.0 | | | | |
| 1 Orthodox vs Orthodox | 3 | 505.0 | | | | |
| 2 Orthodox vs Orthodox | 2 | 680.0 | | | | |
| 3 Southpaw vs Southpaw | 6 | 1575.0 | | | | |
| 4 Orthodox vs Orthodox | 3 | 240.0 | | | | |

Shape: (6528, 30)

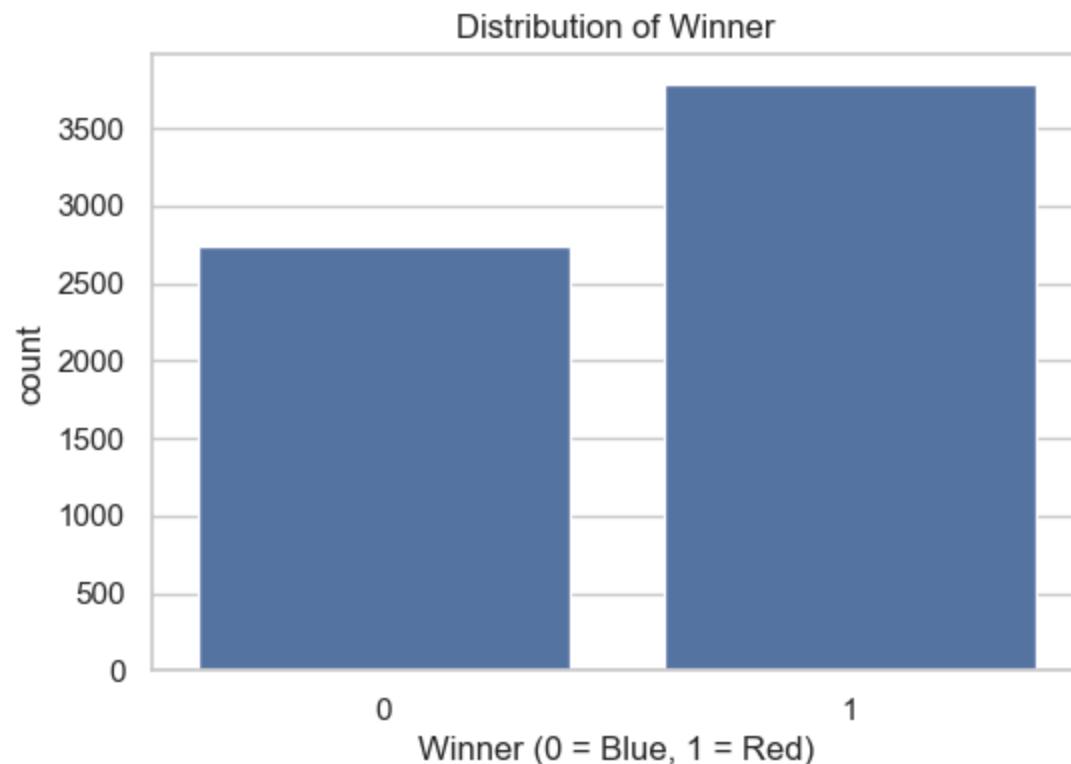
Data types:

| | |
|---------------------------------|---------|
| RedFighter | int64 |
| BlueFighter | int64 |
| Winner | int64 |
| TitleBout | object |
| WeightClass | int64 |
| BlueCurrentLoseStreak | int64 |
| BlueCurrentWinStreak | int64 |
| BlueDraws | int64 |
| BlueStance | object |
| RedCurrentLoseStreak | int64 |
| RedCurrentWinStreak | int64 |
| RedDraws | int64 |
| RedStance | object |
| RedWeightLbs | int64 |
| BlueAge | int64 |
| ReachDif | float64 |
| AgeDif | int64 |
| BetterRank | object |
| WeightClassLabel | object |
| RWinPct | float64 |
| RedTotalFights | int64 |
| BlueTotalFights | int64 |
| RedIsGrappler | int64 |
| BlueIsGrappler | int64 |
| BlueIsStriker | int64 |
| win_by_TKO_Doctor_Stoppage_diff | int64 |
| odds_diff | float64 |
| StanceCombo | object |
| AgeGap | int64 |
| Spread | float64 |
| dtype: object | |

Missing values per column:

| | |
|------------|-----|
| RWinPct | 461 |
| Spread | 238 |
| odds_diff | 238 |
| BlueStance | 3 |
| AgeDif | 0 |

| | |
|---------------------------------|-------|
| AgeGap | 0 |
| StanceCombo | 0 |
| win_by_TKO_Doctor_Stoppage_diff | 0 |
| BlueIsStriker | 0 |
| BlueIsGrappler | 0 |
| RedIsGrappler | 0 |
| BlueTotalFights | 0 |
| RedTotalFights | 0 |
| WeightClassLabel | 0 |
| BetterRank | 0 |
| RedFighter | 0 |
| BlueFighter | 0 |
| BlueAge | 0 |
| RedWeightLbs | 0 |
| RedStance | 0 |
| RedDraws | 0 |
| RedCurrentWinStreak | 0 |
| RedCurrentLoseStreak | 0 |
| BlueDraws | 0 |
| BlueCurrentWinStreak | 0 |
| BlueCurrentLoseStreak | 0 |
| WeightClass | 0 |
| TitleBout | 0 |
| Winner | 0 |
| ReachDif | 0 |
| dtype: | int64 |

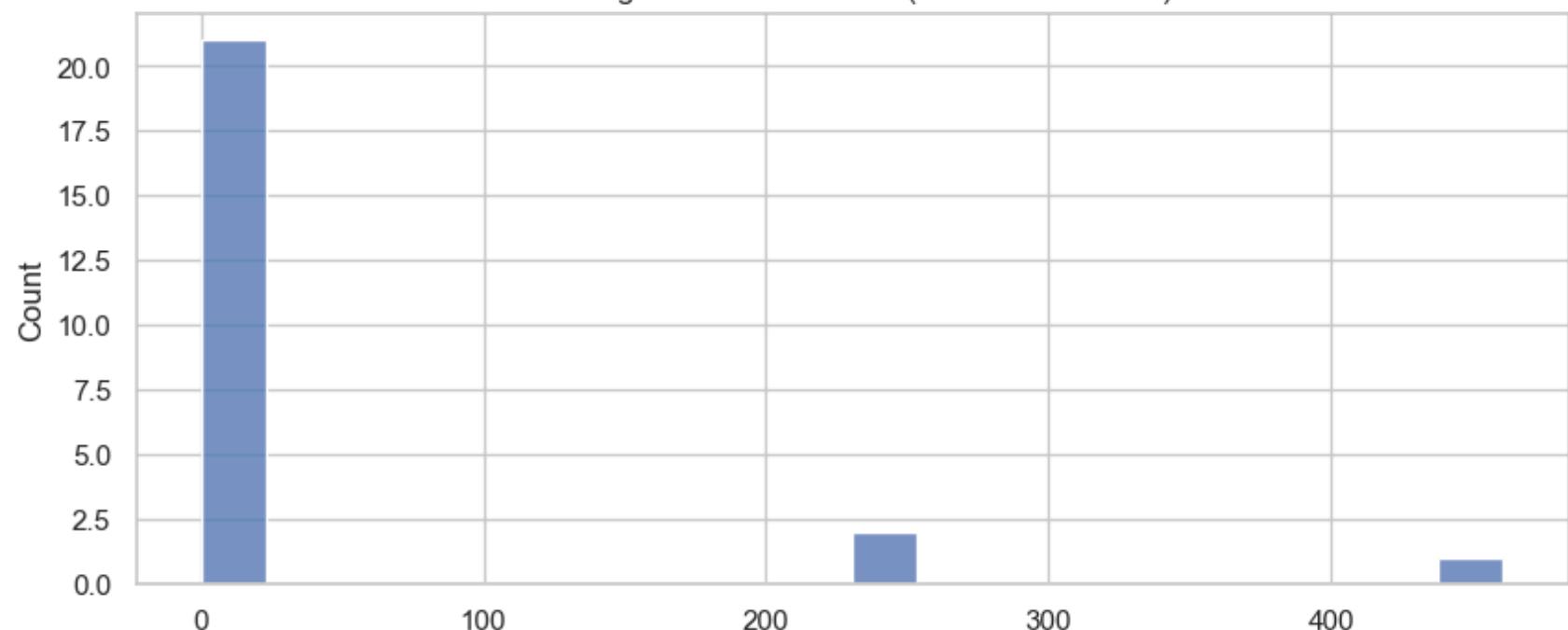


Updated feature count after removing correlated vars:

Numeric: 23

Categorical: 6

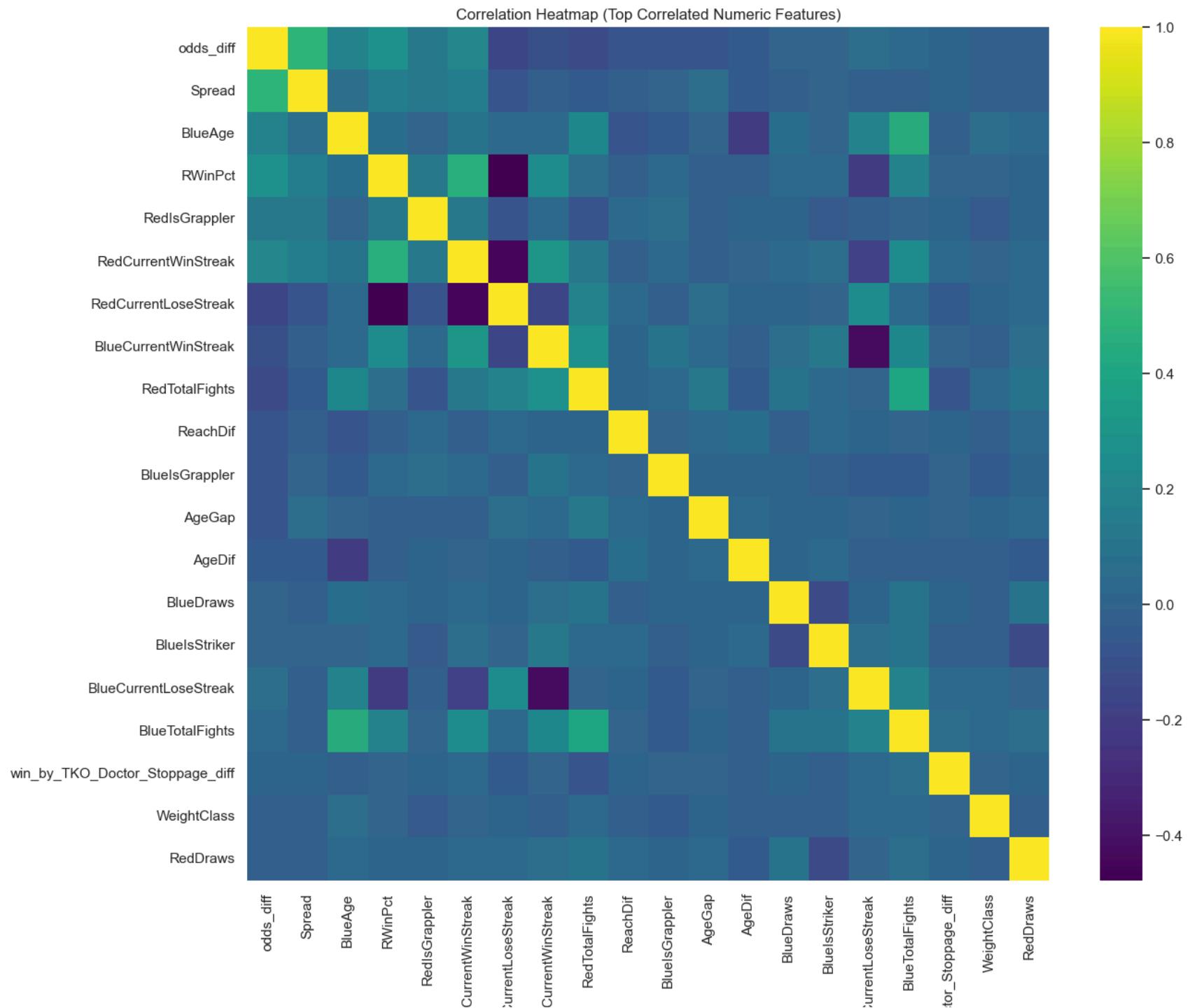
Missing Values Distribution (Numeric Columns)



Numeric Summary Stats:

| | | count | mean | std | min | 25% | 50% | 75% | max |
|--|--|--------|------------|------------|----------|---------|------------|-------------|---------|
| | RedFighter | 6528.0 | 819.761795 | 476.188466 | 0.00 | 419.00 | 806.000000 | 1241.250000 | 1660.00 |
| | BlueFighter | 6528.0 | 942.707874 | 556.368724 | 0.00 | 462.00 | 922.500000 | 1427.000000 | 1921.00 |
| | Winner | 6528.0 | 0.580116 | 0.493577 | 0.00 | 0.00 | 1.000000 | 1.000000 | 1.00 |
| | WeightClass | 6528.0 | 5.503370 | 3.200274 | 0.00 | 3.00 | 6.000000 | 8.000000 | 12.00 |
| | BlueCurrentLoseStreak | 6528.0 | 0.501072 | 0.794303 | 0.00 | 0.00 | 0.000000 | 1.000000 | 6.00 |
| | BlueCurrentWinStreak | 6528.0 | 0.957567 | 1.406786 | 0.00 | 0.00 | 0.000000 | 1.000000 | 12.00 |
| | BlueDraws | 6528.0 | 0.023131 | 0.156327 | 0.00 | 0.00 | 0.000000 | 0.000000 | 2.00 |
| | RedCurrentLoseStreak | 6528.0 | 0.622243 | 0.872301 | 0.00 | 0.00 | 0.000000 | 1.000000 | 7.00 |
| | RedCurrentWinStreak | 6528.0 | 1.101562 | 1.760767 | 0.00 | 0.00 | 0.000000 | 2.000000 | 18.00 |
| | RedDraws | 6528.0 | 0.031097 | 0.187999 | 0.00 | 0.00 | 0.000000 | 0.000000 | 2.00 |
| | RedWeightLbs | 6528.0 | 163.621324 | 34.846543 | 115.00 | 135.00 | 155.000000 | 185.000000 | 265.00 |
| | BlueAge | 6528.0 | 29.805607 | 3.959623 | 19.00 | 27.00 | 30.000000 | 32.000000 | 47.00 |
| | ReachDif | 6528.0 | -0.299271 | 9.132413 | -187.96 | -5.08 | 0.000000 | 5.080000 | 30.48 |
| | AgeDif | 6528.0 | 0.096814 | 5.201719 | -17.00 | -3.00 | 0.000000 | 4.000000 | 17.00 |
| | RWinPct | 6067.0 | 0.631346 | 0.256596 | 0.00 | 0.50 | 0.666667 | 0.777778 | 1.00 |
| | RedTotalFights | 6528.0 | 7.194853 | 6.761721 | 0.00 | 2.00 | 5.000000 | 10.000000 | 48.00 |
| | BlueTotalFights | 6528.0 | 5.009344 | 5.502321 | 0.00 | 1.00 | 3.000000 | 7.000000 | 45.00 |
| | RedIsGrappler | 6528.0 | 0.062653 | 0.242357 | 0.00 | 0.00 | 0.000000 | 0.000000 | 1.00 |
| | BlueIsGrappler | 6528.0 | 0.059743 | 0.237028 | 0.00 | 0.00 | 0.000000 | 0.000000 | 1.00 |
| | BlueIsStriker | 6528.0 | 0.472733 | 0.499294 | 0.00 | 0.00 | 0.000000 | 1.000000 | 1.00 |
| | win_by_TKO_Doctor_Stoppage_diff | 6528.0 | -0.013327 | 0.247506 | -2.00 | 0.00 | 0.000000 | 0.000000 | 2.00 |
| | odds_diff | 6290.0 | 175.464229 | 525.482605 | -1975.00 | -280.00 | 280.000000 | 470.000000 | 3200.00 |
| | AgeGap | 6528.0 | 4.142463 | 3.147162 | 0.00 | 2.00 | 3.000000 | 6.000000 | 17.00 |

| | count | mean | std | min | 25% | 50% | 75% | max |
|---------------|--------|------------|------------|------|--------|------------|------------|---------|
| Spread | 6290.0 | 457.442607 | 312.470074 | 0.00 | 280.00 | 370.000000 | 550.000000 | 3200.00 |



Red

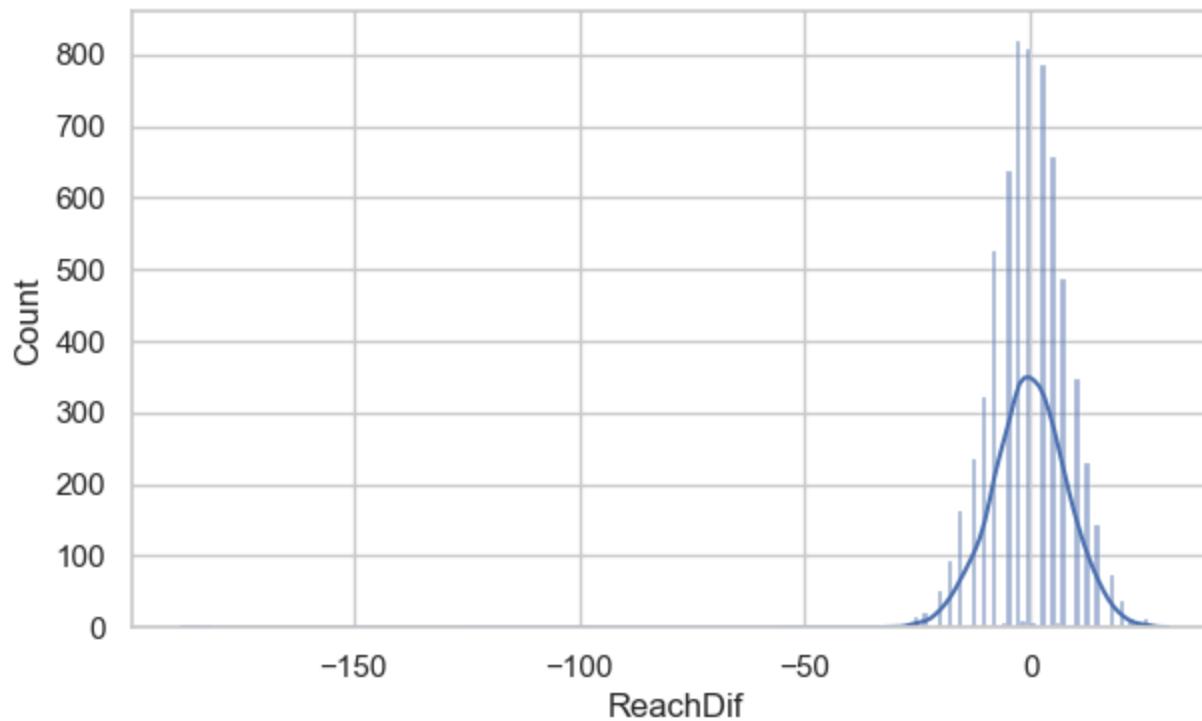
RedC

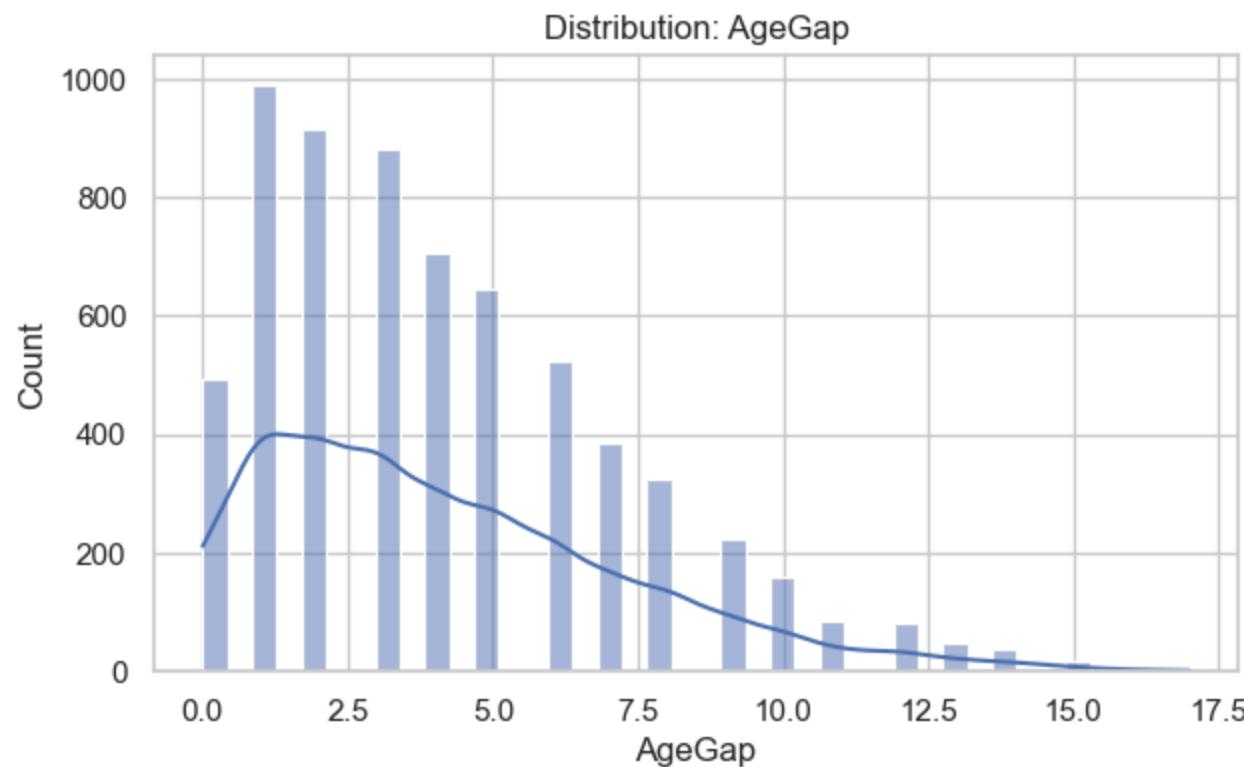
Blue

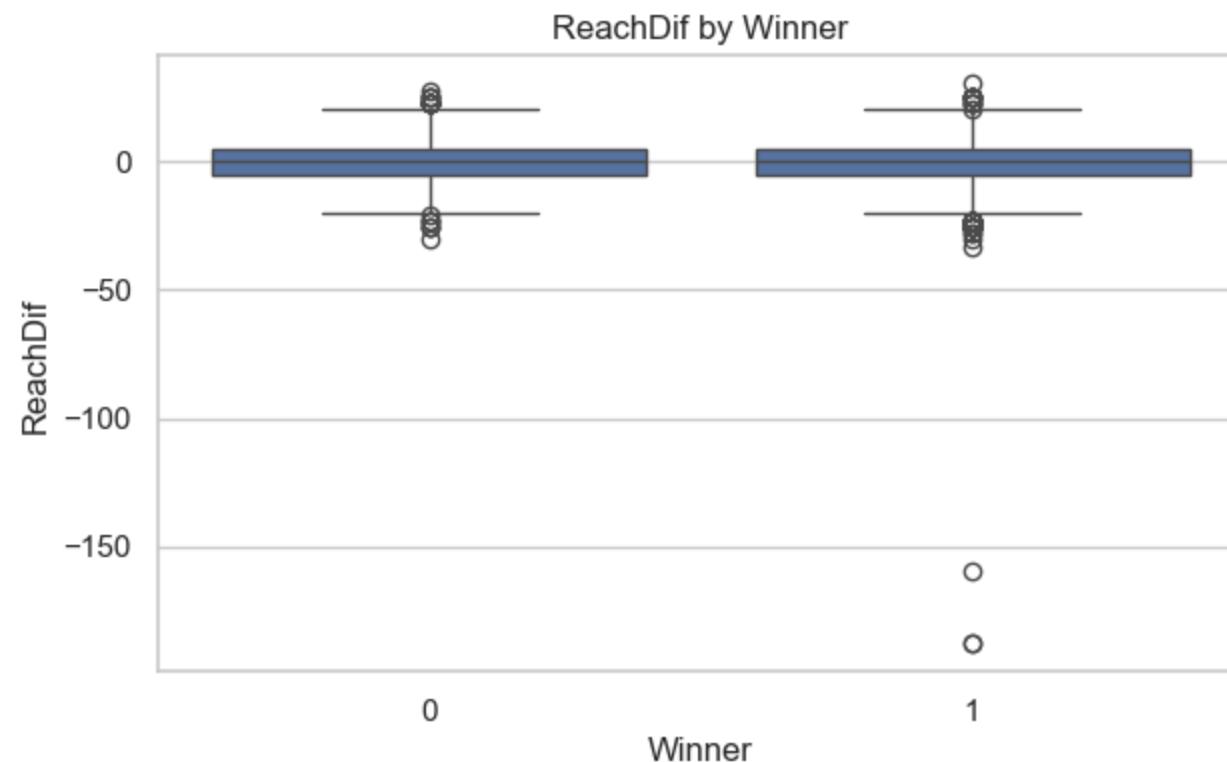
BlueC

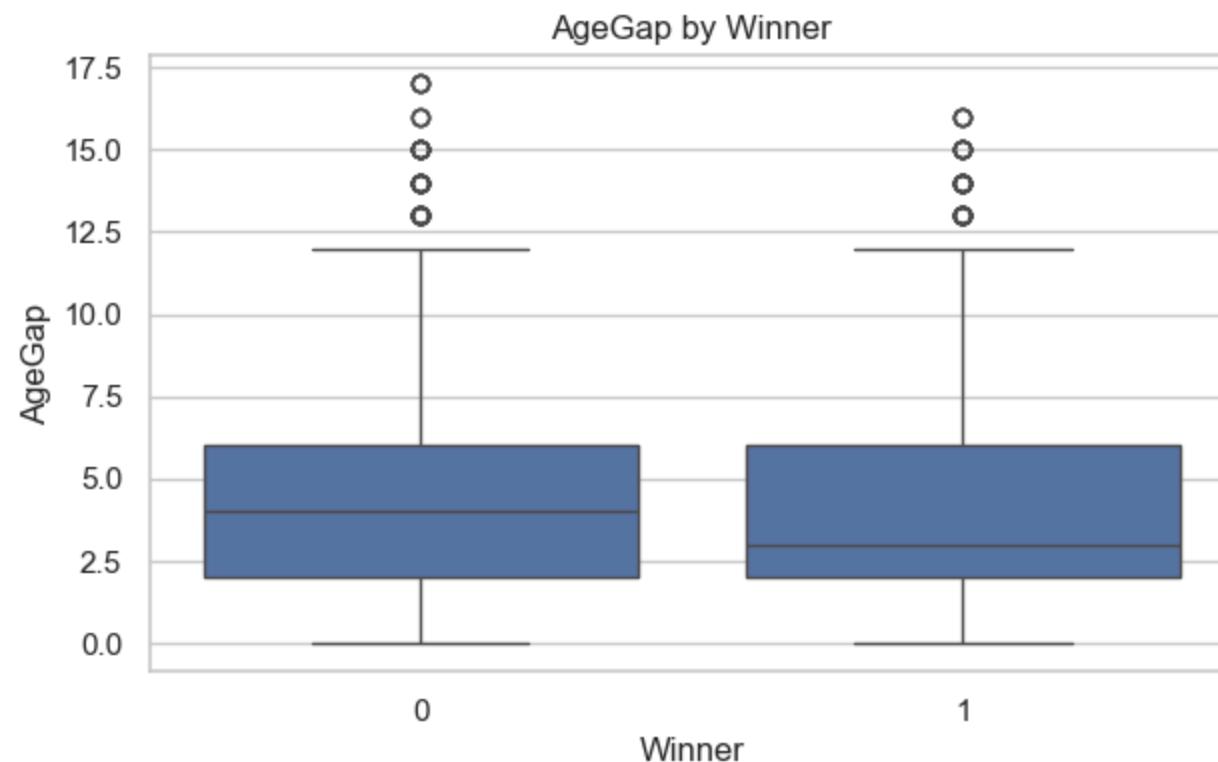
win_by_TKO_Doc

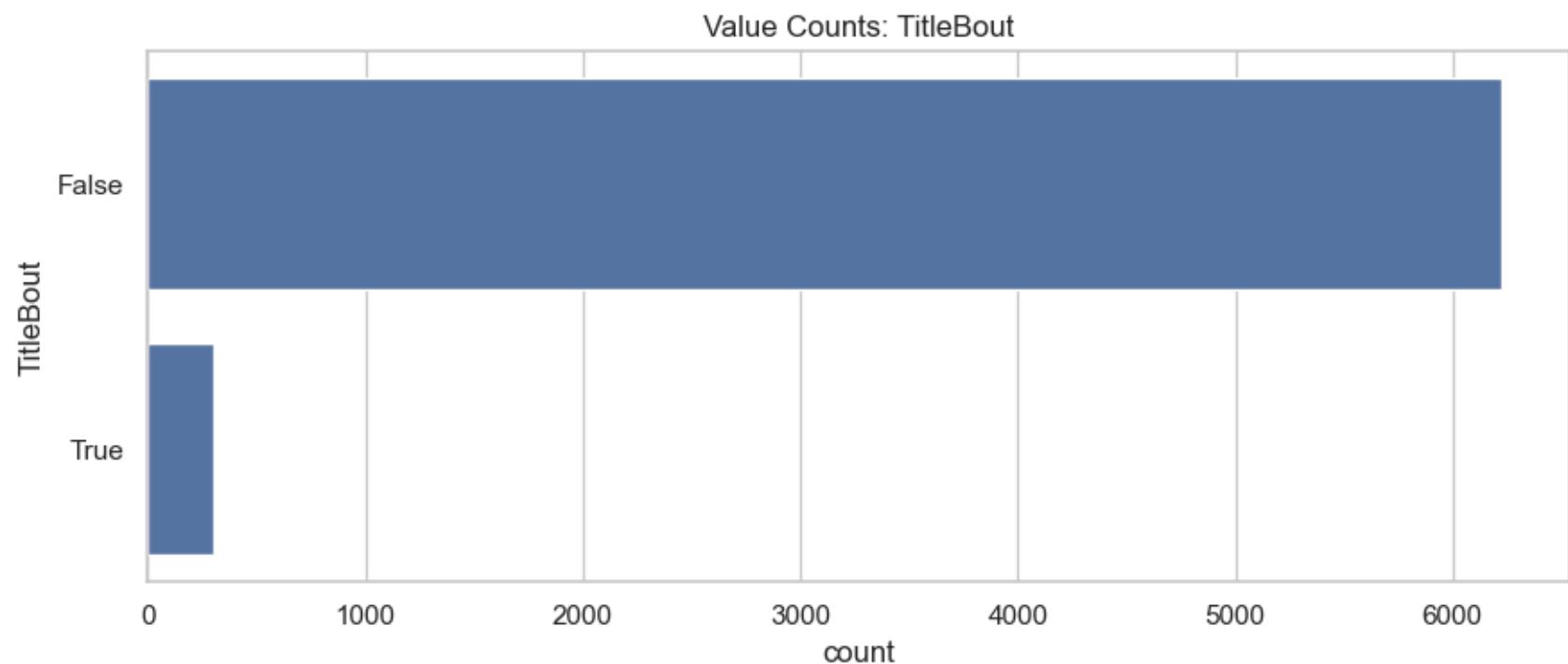
Distribution: ReachDif

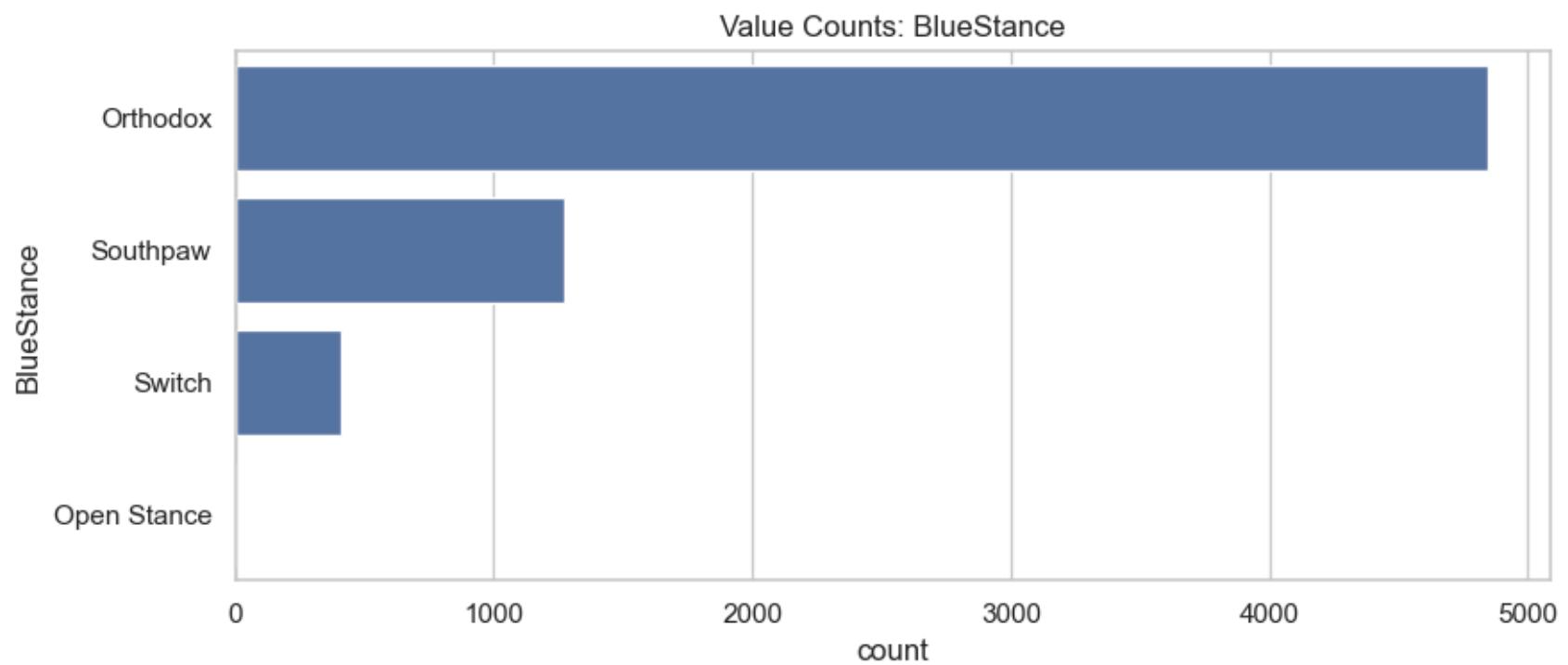


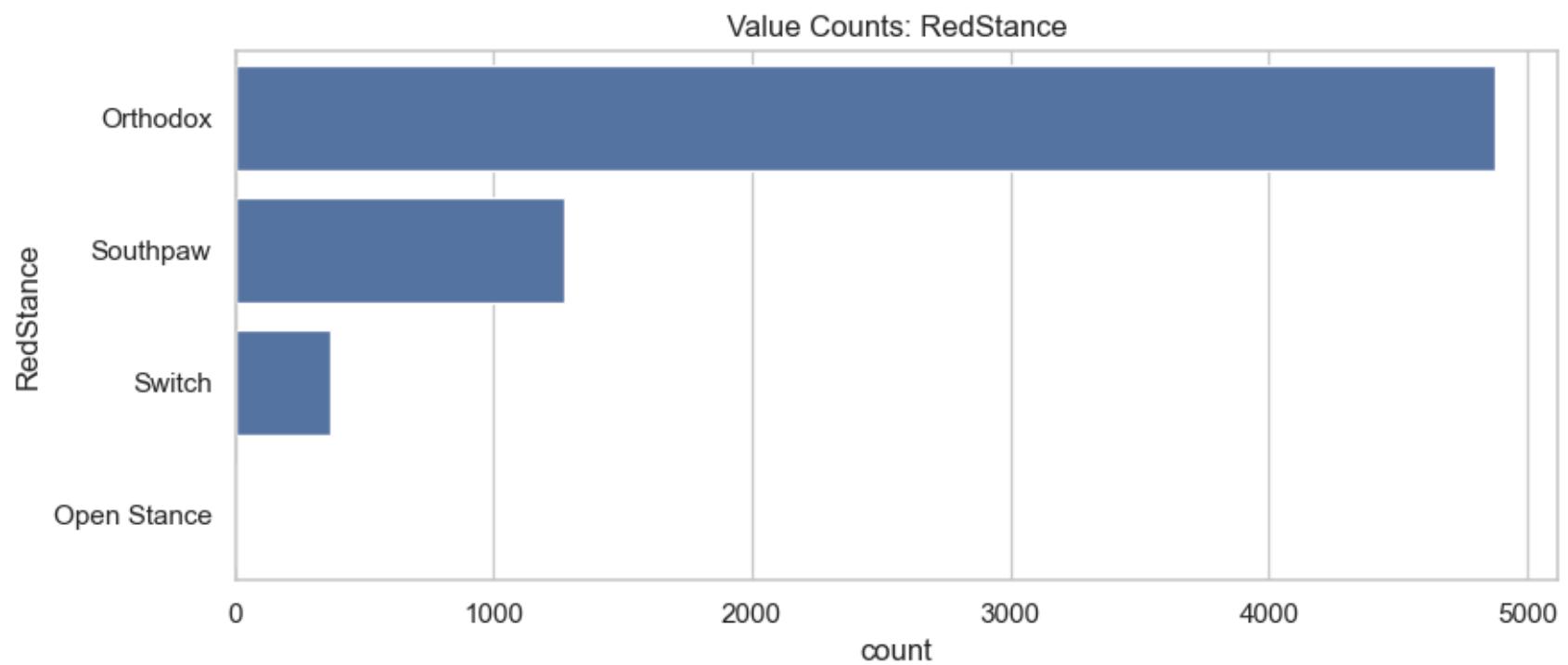


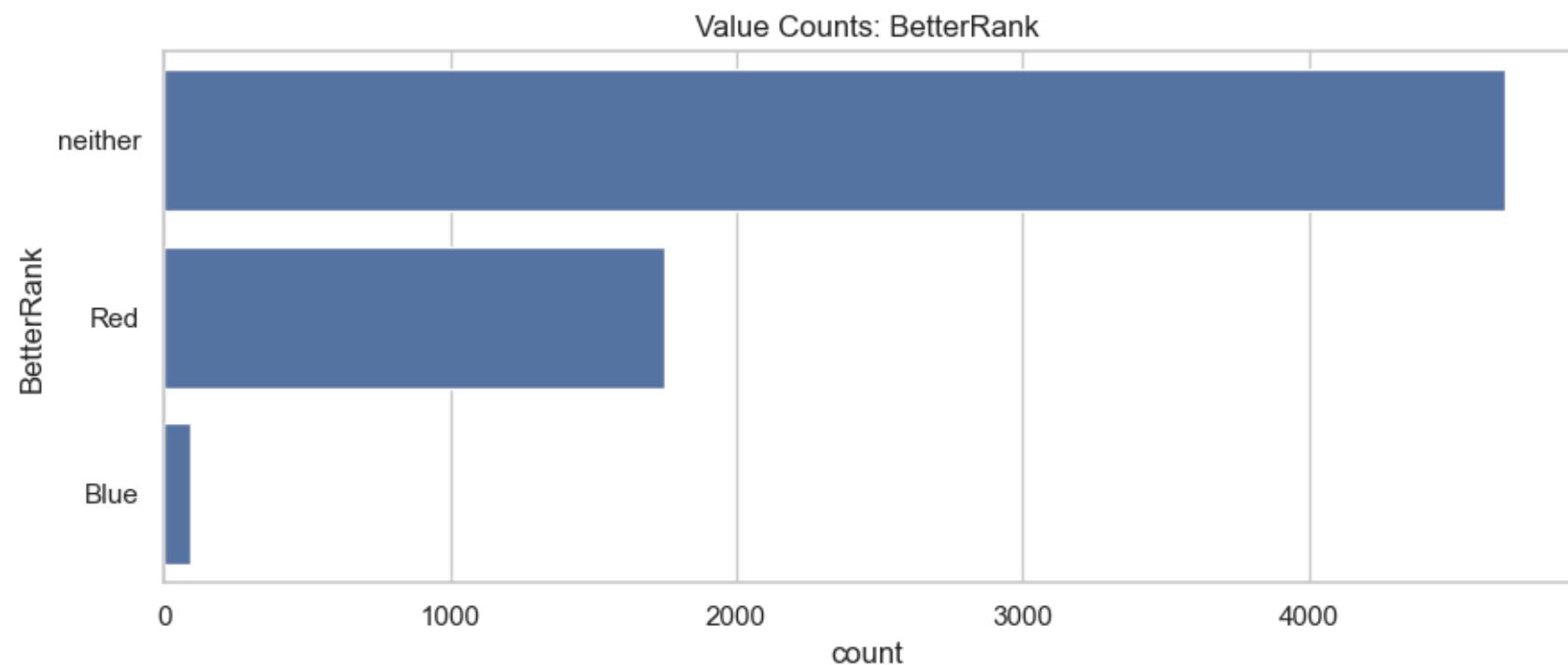


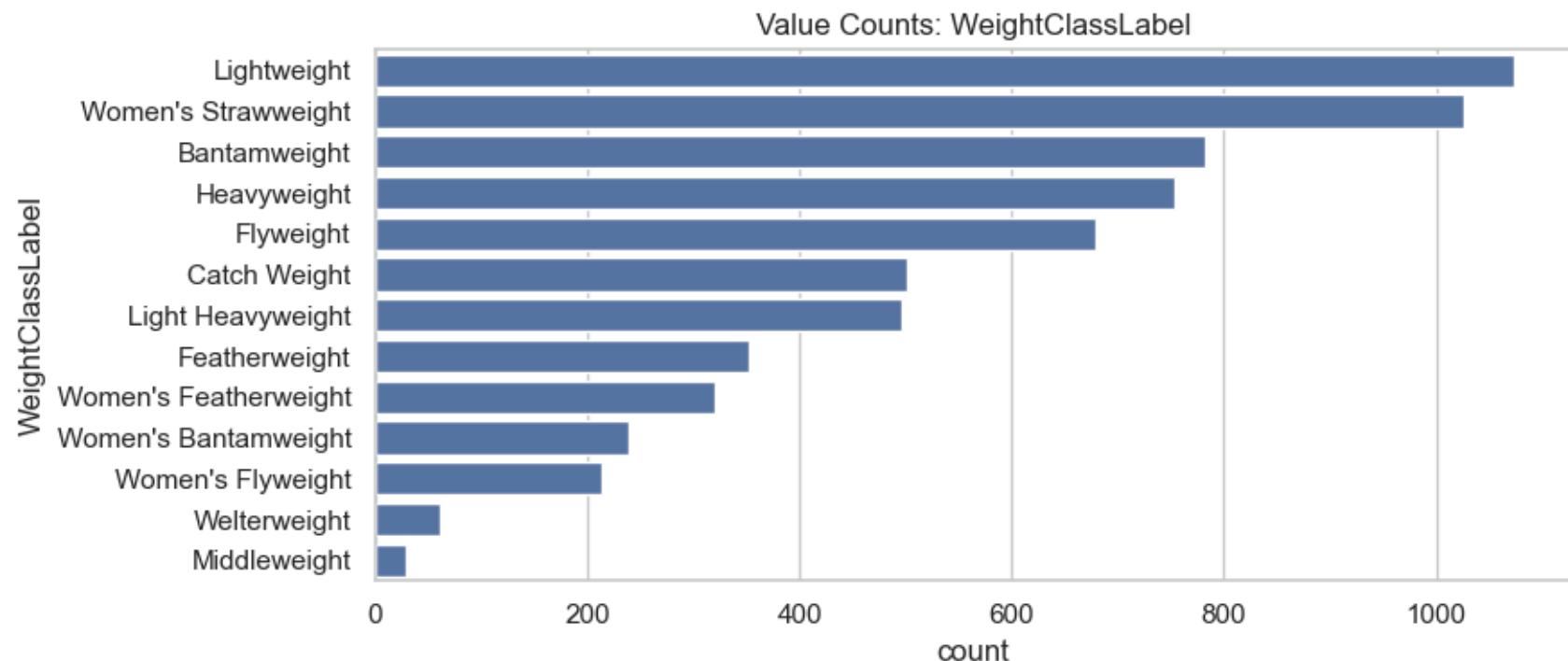


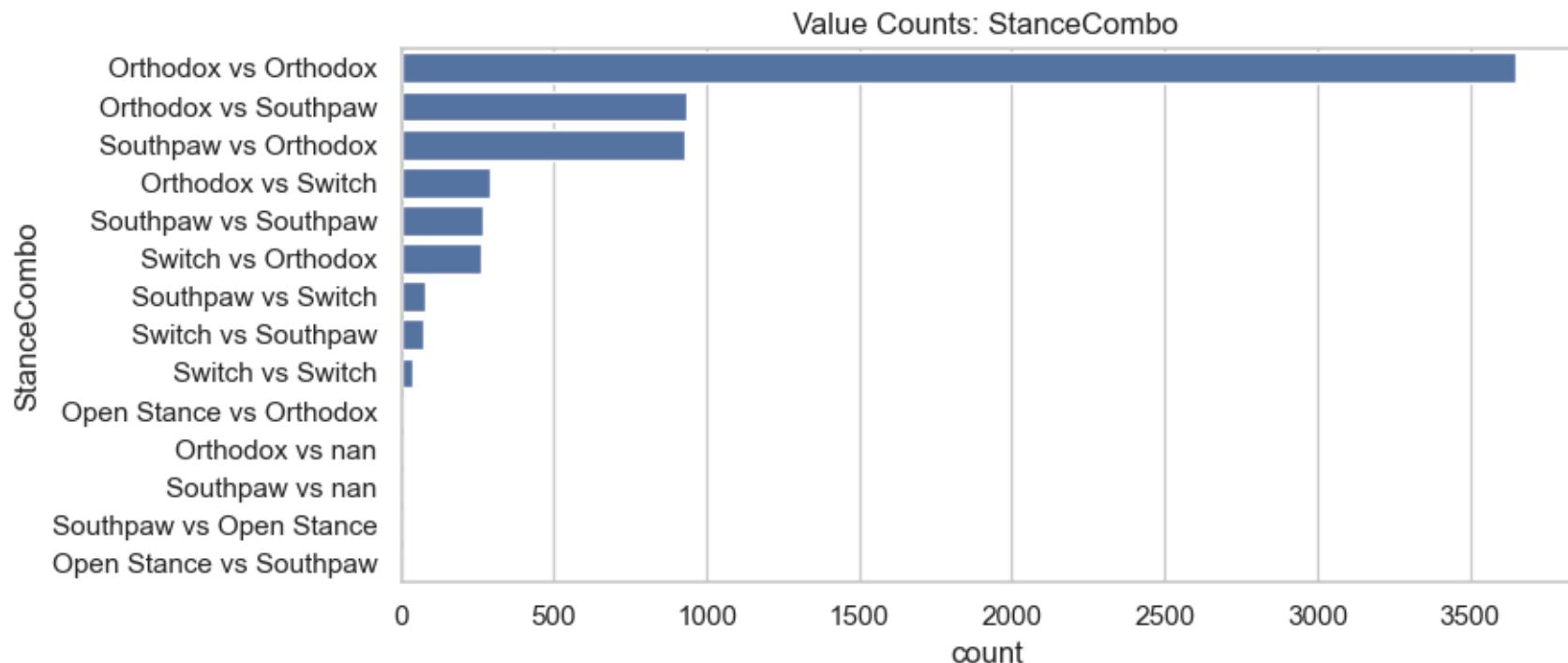












EDA COMPLETE

```
In [291]: # -----
# MICE and preprocess
# -----
# -----
#   split - matchup safe - for leakage
# -----
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GroupShuffleSplit

print("\n-----")
print(" Creating matchup-safe split")
print("-----")

# Encode target
le = LabelEncoder()
y_enc = le.fit_transform(df_clean["Winner"])
```

```
# Build matchup ID
df_clean["MatchupID"] = df_clean.apply(
    lambda row: "_".join(sorted([
        str(row.get("RedFighter", "")),
        str(row.get("BlueFighter", ""))
    ])),
    axis=1
)

# Build X and y
X = df_clean.drop(columns=["Winner"])
y = y_enc

# Group-based split
gss = GroupShuffleSplit(n_splits=1, test_size=0.20, random_state=42)
train_idx, test_idx = next(gss.split(X, y, groups=df_clean["MatchupID"]))

X_train = X.iloc[train_idx].reset_index(drop=True)
X_test = X.iloc[test_idx].reset_index(drop=True)
y_train = y[train_idx]
y_test = y[test_idx]

# Drop identifiers (not allowed in model)
drop_cols = ["RedFighter", "BlueFighter", "MatchupID", "win_by_TKO_Doctor_Stoppage_diff"] #win_by_TKO_Doctor_Stoppage_diff
X_train = X_train.drop(columns=[c for c in drop_cols if c in X_train.columns])
X_test = X_test.drop(columns=[c for c in drop_cols if c in X_test.columns])

# -----
# Recompute num and cat cols
# -----
num_cols = X_train.select_dtypes(include=["int64", "float64"]).columns.tolist()
cat_cols = X_train.select_dtypes(include=["object", "category"]).columns.tolist()

print("\nUpdated numeric columns:", len(num_cols))
print("Updated categorical columns:", len(cat_cols))

# -----
# MICEFOREST - for num training data
# -----
import miceforest as mf
```

```
print("\nRunning MICE-Forest Imputation on TRAINING numeric columns...")  
  
# Extract numeric-only  
X_train_num = X_train[num_cols].reset_index(drop=True)  
X_test_num = X_test[num_cols].reset_index(drop=True)  
  
# Ensure column names strings  
X_train_num.columns = X_train_num.columns.astype(str)  
X_test_num.columns = X_test_num.columns.astype(str)  
  
# ---- FIT MICE ON TRAIN ONLY ----  
kernel = mf.ImputationKernel(  
    data=X_train_num,  
    save_all_iterations_data=True,  
    random_state=42  
)  
  
kernel.mice(  
    iterations=3,  
    n_estimators=50  
)  
  
# ---- COMPLETE TRAIN ----  
completed_train = kernel.complete_data()  
  
# ---- IMPUTE TEST USING THE TRAINING KERNEL ----  
completed_test = kernel.impute_new_data(X_test_num).complete_data()  
  
# Put imputed values back  
X_train[num_cols] = completed_train.values  
X_test[num_cols] = completed_test.values  
  
print("MICE Imputation Completed (train-fit only).\n")  
  
# -----  
# preprocessing pipeline  
# -----  
from sklearn.pipeline import Pipeline  
from sklearn.compose import ColumnTransformer  
from sklearn.preprocessing import StandardScaler, OneHotEncoder  
from sklearn.impute import SimpleImputer
```

```
num_transformer = Pipeline(steps=[  
    ('scaler', StandardScaler())  
])  
  
cat_transformer = Pipeline(steps=[  
    ('imputer', SimpleImputer(strategy='constant', fill_value='Missing')),  
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))  
])  
  
preprocessor = ColumnTransformer(  
    transformers=[  
        ('num', num_transformer, num_cols),  
        ('cat', cat_transformer, cat_cols)  
    ]  
)
```

Creating matchup-safe split

Updated numeric columns: 20
Updated categorical columns: 6

Running MICE–Forest Imputation on TRAINING numeric columns...
MICE Imputation Completed (train-fit only).

In [292]

```
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
import seaborn as sns  
import shap  
import warnings  
warnings.filterwarnings('ignore')  
  
from sklearn.base import clone  
from sklearn.model_selection import StratifiedKFold, GridSearchCV  
from sklearn.model_selection import (  
    train_test_split, GridSearchCV, KFold  
)  
from sklearn.pipeline import Pipeline  
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

```
from sklearn.compose import ColumnTransformer
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.metrics import (
    accuracy_score, confusion_matrix, roc_auc_score, classification_report
)
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.model_selection import GroupKFold

# -----
# Machine Learning Pipelines
# -----
pipelines = {
    'LogisticRegression': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', LogisticRegression(max_iter=1000))
    ]),

    'RandomForest': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', RandomForestClassifier(random_state=42))
    ]),

    'SVM': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', SVC(probability=True))
    ]),

    'XGBoost': Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', XGBClassifier(eval_metric='logloss'))
    ])
}

# -----
# Hyperparameter Grids
# -----
#shifted LR parameters down as 0.1 was best performing in first run
#ended up shifting several parameters down post-ppt
```

```
param_grids = {
    'LogisticRegression': {'classifier_C': [0.0001, 0.001, 0.01, 0.1]},
    'RandomForest': {
        'classifier_n_estimators': [100, 300],
        'classifier_max_depth': [None, 10, 20],
        'classifier_min_samples_split': [5, 10]
    },
    'SVM': {
        'classifier_C': [0.001, 0.01, 0.1],
        'classifier_kernel': ['rbf', 'linear']
    },
    'XGBoost': {
        'classifier_n_estimators': [100, 300],
        'classifier_max_depth': [1, 3],
        'classifier_learning_rate': [0.001, 0.01]
    }
}
```

In [293...]

```
# -----
# (3 seeds x 5-fold CV)
# -----
import joblib

nr_states = 3
kf_splits = 5
results_summary = {}

for name, base_pipeline in pipelines.items():

    print(f"\n-----")
    print(f"Training {name}")
    print(f"-----")

    test_scores = []
    best_param_list = []
    final_models = []

    for seed in range(1, nr_states + 1):

        print(f"\n--- Random State {seed} ---")
```

```
# Clone pipeline to ensure fresh model each iteration
pipeline = clone(base_pipeline)

# Ensure reproducibility for models that support random_state
if name in ["RandomForest", "XGBoost", "LogisticRegression"]:
    pipeline.named_steps["classifier"].set_params(random_state=seed)

# CV strategy
cv = StratifiedKFold(
    n_splits=kf_splits, shuffle=True, random_state=seed
)

# Grid search
grid = GridSearchCV(
    estimator=pipeline,
    param_grid=param_grids[name],
    scoring="accuracy",
    cv=cv,
    n_jobs=-1
)

grid.fit(X_train, y_train)

# Store best estimator for this seed
best_model = grid.best_estimator_
final_models.append(best_model)
best_param_list.append(grid.best_params_)

# Evaluate on test set
y_pred = best_model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
test_scores.append(acc)

print(f"Best params: {grid.best_params_}")
print(f"CV accuracy: {grid.best_score_:.4f}")
print(f"Test accuracy: {acc:.4f}")

# -----
# Aggregate results across random seeds - need average
# -----
avg_test_score = np.mean(test_scores)
```

```
std_test_score = np.std(test_scores)
best_test_score = np.max(test_scores)

print(f"\nAverage Test Accuracy for {name}: {avg_test_score:.4f}")

results_summary[name] = {
    "test_scores": test_scores,
    "avg_test_score": avg_test_score,
    "std_test_score": std_test_score,
    "best_test_score": best_test_score,
    "best_params": best_param_list,
    "models": final_models
}

# -----
# Save best model (pick the seed with highest test accuracy) for results in git repo
# -----
best_model_idx = np.argmax(test_scores)
best_model_overall = final_models[best_model_idx]

save_path = f"best_model_{name}.pkl"
joblib.dump(best_model_overall, save_path)

print(f"Saved best {name} model → {save_path}")

# -----
#          COMPILE FINAL RESULTS TABLE
# -----
results_table = []

for model_name, info in results_summary.items():

    rows = {
        "Algorithm": model_name,
        "Best params (seed 1)": info["best_params"][0],
        "Mean test accuracy": round(info["avg_test_score"], 4),
        "Std test accuracy": round(info["std_test_score"], 4),
        "Best test accuracy (across seeds)": round(info["best_test_score"], 4)
    }
```

```
results_table.append(rows)

results_table = pd.DataFrame(results_table)

print("\n\n-----")
print("      FINAL RESULTS TABLE")
print("-----\n")
print(results_table)
```

Training LogisticRegression

--- Random State 1 ---
Best params: {'classifier__C': 0.1}
CV accuracy: 0.6560
Test accuracy: 0.6458

--- Random State 2 ---
Best params: {'classifier__C': 0.01}
CV accuracy: 0.6595
Test accuracy: 0.6489

--- Random State 3 ---
Best params: {'classifier__C': 0.01}
CV accuracy: 0.6556
Test accuracy: 0.6489

Average Test Accuracy for LogisticRegression: 0.6478
Saved best LogisticRegression model → best_model_LogisticRegression.pkl

Training RandomForest

--- Random State 1 ---
Best params: {'classifier__max_depth': 10, 'classifier__min_samples_split': 5, 'classifier__n_estimators': 300}
CV accuracy: 0.6512
Test accuracy: 0.6473

--- Random State 2 ---
Best params: {'classifier__max_depth': 10, 'classifier__min_samples_split': 10, 'classifier__n_estimators': 300}
CV accuracy: 0.6508
Test accuracy: 0.6450

--- Random State 3 ---
Best params: {'classifier__max_depth': 20, 'classifier__min_samples_split': 10, 'classifier__n_estimators': 300}
CV accuracy: 0.6455

Test accuracy: 0.6405

Average Test Accuracy for RandomForest: 0.6443

Saved best RandomForest model → best_model_RandomForest.pkl

Training SVM

--- Random State 1 ---

Best params: {'classifier__C': 0.1, 'classifier__kernel': 'linear'}

CV accuracy: 0.6564

Test accuracy: 0.6557

--- Random State 2 ---

Best params: {'classifier__C': 0.01, 'classifier__kernel': 'linear'}

CV accuracy: 0.6564

Test accuracy: 0.6534

--- Random State 3 ---

Best params: {'classifier__C': 0.1, 'classifier__kernel': 'linear'}

CV accuracy: 0.6539

Test accuracy: 0.6557

Average Test Accuracy for SVM: 0.6550

Saved best SVM model → best_model_SVM.pkl

Training XGBoost

--- Random State 1 ---

Best params: {'classifier__learning_rate': 0.01, 'classifier__max_depth': 3, 'classifier__n_estimators': 300}

CV accuracy: 0.6562

Test accuracy: 0.6534

--- Random State 2 ---

Best params: {'classifier__learning_rate': 0.01, 'classifier__max_depth': 1, 'classifier__n_estimators': 300}

CV accuracy: 0.6548

Test accuracy: 0.6618

```
--- Random State 3 ---
Best params: {'classifier__learning_rate': 0.01, 'classifier__max_depth': 1, 'classifier__n_estimators': 10
}
CV accuracy: 0.6543
Test accuracy: 0.6618

Average Test Accuracy for XGBoost: 0.6590
Saved best XGBoost model → best_model_XGBoost.pkl
```

FINAL RESULTS TABLE

| | Algorithm | Best params (seed 1) \ |
|---|--------------------|--|
| 0 | LogisticRegression | {'classifier__C': 0.1} |
| 1 | RandomForest | {'classifier__max_depth': 10, 'classifier__min... |
| 2 | SVM | {'classifier__C': 0.1, 'classifier__kernel': '... |
| 3 | XGBoost | {'classifier__learning_rate': 0.01, 'classifie... |
| | | Mean test accuracy Std test accuracy Best test accuracy (across seeds) |
| 0 | 0.6478 | 0.0014 0.6489 |
| 1 | 0.6443 | 0.0029 0.6473 |
| 2 | 0.6550 | 0.0011 0.6557 |
| 3 | 0.6590 | 0.0040 0.6618 |

In [294...]

```
# -----
# Plot: Mean Test Accuracy by Model Algorithm
#
import seaborn as sns
import matplotlib.pyplot as plt

print(results_table.columns)
print(results_table.head())
plt.figure(figsize=(10,6))
sns.barplot(
    data=results_table,
    x="Algorithm",           # check corrected column name - check
    y="Mean test accuracy",  # check corrected column name - check
    ci=None
)
```

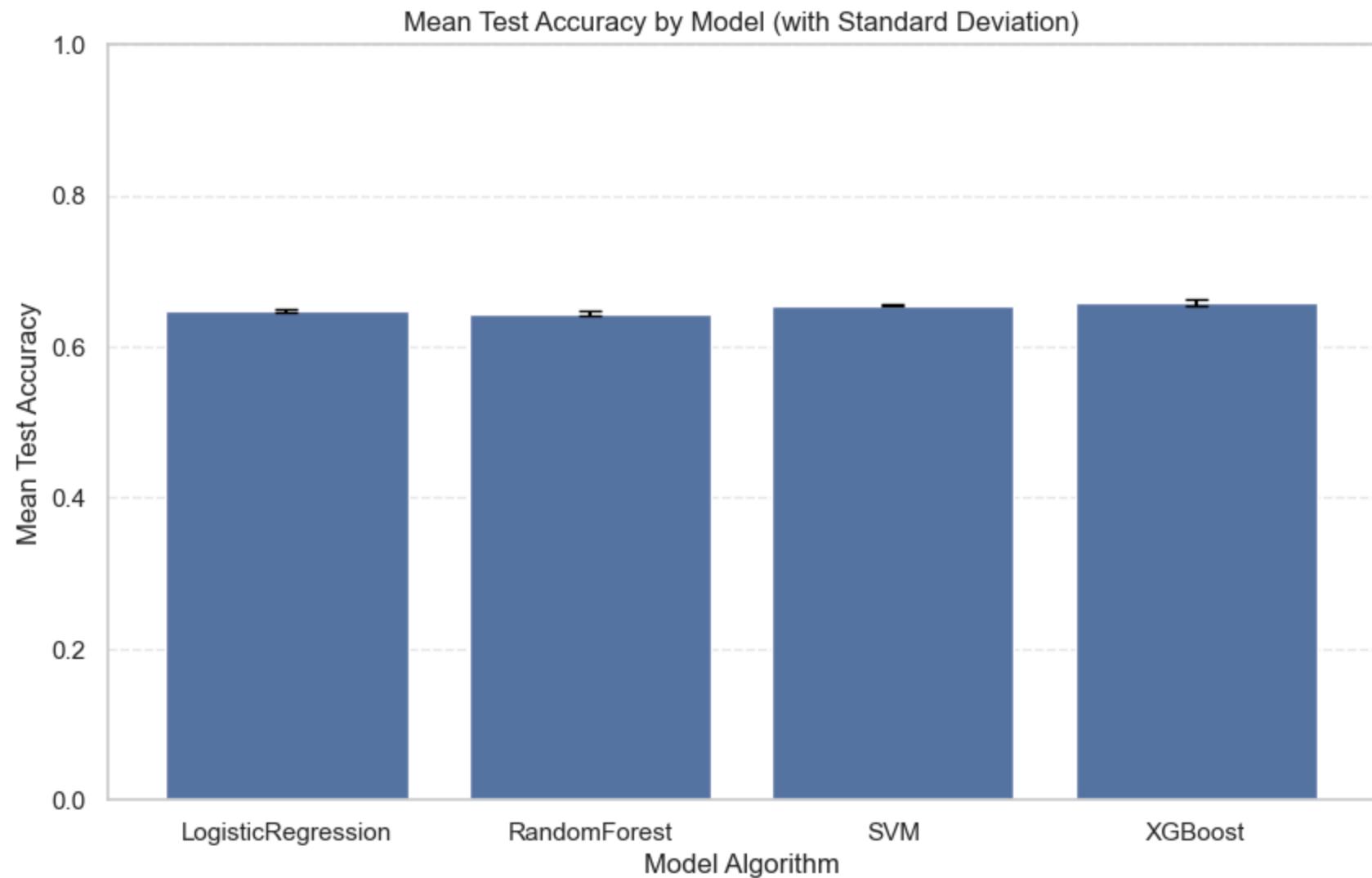
```
# Add error bars manually using standard deviation
for i, row in results_table.iterrows():
    plt.errorbar(
        i,
        row["Mean test accuracy"], # check corrected column name - check
        yerr=row["Std test accuracy"], # check corrected column name - check
        fmt="none",
        capsize=5,
        color="black"
    )

plt.title("Mean Test Accuracy by Model (with Standard Deviation)")
plt.xlabel("Model Algorithm")
plt.ylabel("Mean Test Accuracy")
plt.ylim(0, 1)
plt.grid(axis='y', linestyle='--', alpha=0.4)
fig_name = "test_acc_mean"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```

Index(['Algorithm', 'Best params (seed 1)', 'Mean test accuracy',
 'Std test accuracy', 'Best test accuracy (across seeds)'],
 dtype='object')

| | Algorithm | Best params (seed 1) |
|---|--------------------|--|
| 0 | LogisticRegression | {'classifier_C': 0.1} |
| 1 | RandomForest | {'classifier_max_depth': 10, 'classifier_min... |
| 2 | SVM | {'classifier_C': 0.1, 'classifier_kernel': '... |
| 3 | XGBoost | {'classifier_learning_rate': 0.01, 'classifie... |

| | Mean test accuracy | Std test accuracy | Best test accuracy (across seeds) |
|---|--------------------|-------------------|-----------------------------------|
| 0 | 0.6478 | 0.0014 | 0.6489 |
| 1 | 0.6443 | 0.0029 | 0.6473 |
| 2 | 0.6550 | 0.0011 | 0.6557 |
| 3 | 0.6590 | 0.0040 | 0.6618 |



In [295...]

```
# -----
#   metrics
# -----
```



```
import numpy as np
import shap
from sklearn.metrics import accuracy_score, fbeta_score, f1_score
from sklearn.inspection import permutation_importance
```

```
print("\n\n-----")
print("      BASELINES + CHECK SHAP/PERMUTATION INPUTS")
print("-----\n")

# -----
# FINAL FITTED PREPROCESSOR of the BEST MODEL
# -----
best_global_model_name = max(results_summary, key=lambda m: results_summary[m]["avg_test_score"])
best_pipeline = results_summary[best_global_model_name]["models"][0]
fitted_preprocessor = best_pipeline.named_steps["preprocessor"]

# Feature names from trained processor
try:
    feature_names = fitted_preprocessor.get_feature_names_out()
except:
    feature_names = X_train.columns.tolist()

# Preprocessed matrices (same one SHAP will use)
X_train_trans = fitted_preprocessor.transform(X_train)
X_test_trans = fitted_preprocessor.transform(X_test)

# Convert sparse → dense only if necessary as per error messages
X_train_dense = X_train_trans.toarray() if hasattr(X_train_trans, "toarray") else np.asarray(X_train_trans)
X_test_dense = X_test_trans.toarray() if hasattr(X_test_trans, "toarray") else np.asarray(X_test_trans)

print("Shapes after preprocessing:")
print("  X_train_trans:", X_train_trans.shape)
print("  X_test_trans :", X_test_trans.shape)

# -----
# baseline metrics
# -----
(unique, counts) = np.unique(y_train, return_counts=True)
majority_label = unique[np.argmax(counts)]
baseline_preds = np.full_like(y_test, fill_value=majority_label)

baseline_acc = accuracy_score(y_test, baseline_preds)
baseline_f05 = fbeta_score(y_test, baseline_preds, beta=0.5, average='macro', zero_division=0)
baseline_f1 = f1_score(y_test, baseline_preds, average='macro', zero_division=0)
baseline_f2 = fbeta_score(y_test, baseline_preds, beta=2, average='macro', zero_division=0)
```

```
print("\n==== BASELINE (majority class) ===")
print(f"Majority label: {majority_label}")
print(f"Accuracy: {baseline_acc:.4f}")
print(f"F0.5 (macro): {baseline_f05:.4f}")
print(f"F1 (macro): {baseline_f1:.4f}")
print(f"F2 (macro): {baseline_f2:.4f}")

# Non-1D columns would break SHAP/permuation importance
bad_cols = [
    c for c in X_train.columns
    if isinstance(X_train[c].iloc[0], (list, dict, tuple))
]

if bad_cols:
    print("⚠️ Removing non-1D columns:", bad_cols)
    X_train = X_train.drop(columns=bad_cols, errors="ignore")
    X_test = X_test.drop(columns=bad_cols, errors="ignore")

# -----
# shiyu note from meeting: check shape
# -----
for model_name, info in results_summary.items():
    model_check = info["models"][0]
    try:
        preds_check = model_check.predict(X_test)
        print(f"{model_name} prediction length: {len(preds_check)} | y_test: {len(y_test)}")
        if len(preds_check) != len(y_test):
            print("❌ MISMATCH! Predictions don't align with y_test.")
        else:
            print("✅ OK – predictions match test labels.")
    except Exception as e:
        print(f"{model_name} prediction failed: {e}")

print("\n----- Completed SHAP/Permutation Prep Block -----\\n")
```

```
-----  
BASELINES + CHECK SHAP/PERMUTATION INPUTS  
-----n  
Shapes after preprocessing:  
X_train_trans: (5218, 60)  
X_test_trans : (1310, 60)  
  
== BASELINE (majority class) ==  
Majority label: 1  
Accuracy: 0.5947  
F0.5 (macro): 0.3236  
F1 (macro): 0.3729  
F2 (macro): 0.4400  
LogisticRegression prediction length: 1310 | y_test: 1310  
✓ OK – predictions match test labels.  
RandomForest prediction length: 1310 | y_test: 1310  
✓ OK – predictions match test labels.  
SVM prediction length: 1310 | y_test: 1310  
✓ OK – predictions match test labels.  
XGBoost prediction length: 1310 | y_test: 1310  
✓ OK – predictions match test labels.
```

----- Completed SHAP/Permutation Prep Block -----

```
In [296]: # -----  
# Compare models to baseline; compute permutation importance + impurity + SHAP  
# -----  
summary_rows = []  
global_importances_all = []  
  
for model_name, info in results_summary.items():  
    print(f"\n\n----- ANALYZING {model_name} -----")  
  
    # Best model (first index in stored list)  
    pipeline_best = info["models"][0]  
    classifier = pipeline_best.named_steps["classifier"]  
  
    # ----- Metrics -----  
    y_test_pred = pipeline_best.predict(X_test)
```

```
acc = accuracy_score(y_test, y_test_pred)
f05 = fbeta_score(y_test, y_test_pred, beta=0.5, average="macro", zero_division=0)
f1 = f1_score(y_test, y_test_pred, average="macro", zero_division=0)
f2 = fbeta_score(y_test, y_test_pred, beta=2, average="macro", zero_division=0)

mean_test = info.get("avg_test_score", np.mean(info["test_scores"]))
std_test = np.std(info["test_scores"]) if "test_scores" in info else np.nan

z_score = (mean_test - baseline_acc) / std_test if std_test and std_test > 0 else np.nan

print(f"Mean CV/Test (avg across states): {mean_test:.4f} (std: {std_test:.4f})")
print(f"Test accuracy: {acc:.4f}")
print(f"F0.5/F1/F2: {f05:.4f} / {f1:.4f} / {f2:.4f}")
print(f"Z-score above baseline: {z_score if not np.isnan(z_score) else 'N/A'}")

# ----- Impurity Importance -----
impurity_df = None
if hasattr(classifier, "feature_importances_"):
    try:
        impurity_df = (
            pd.DataFrame({
                "feature": feature_names,
                "impurity_importance": classifier.feature_importances_
            }).sort_values("impurity_importance", ascending=False)
        )
        print("Impurity importance computed.")
    except Exception as e:
        print("Impurity importance failed:", e)

# ----- Permutation Importance -----
perm_df = None
try:
    classifier = pipeline_best.named_steps["classifier"]
    preprocessor = pipeline_best.named_steps["preprocessor"]

    X_test_trans = preprocessor.transform(X_test)

    #parameters for times sake
    perm = permutation_importance(
        classifier,
        X_test_trans,
        y_test,
```

```
n_repeats=20,
random_state=42,
n_jobs=-1,
scoring="accuracy"
)

feature_names = preprocessor.get_feature_names_out()

perm_df = pd.DataFrame({
    "feature": feature_names,
    "perm_mean": perm.importances_mean,
    "perm_std": perm.importances_std
}).sort_values("perm_mean", ascending=False)

print("Permutation importance computed.")
print("\nTop 10 permutation importances:")
print(perm_df.head(10))
except Exception as e:
    print("Permutation importance failed:", e)

# ----- Transform Train/Test Once -----
pre = pipeline_best.named_steps["preprocessor"]

X_train_trans = pre.transform(X_train)
X_test_trans = pre.transform(X_test)

# convert to dense
X_train_dense = X_train_trans.toarray() if hasattr(X_train_trans, "toarray") else X_train_trans
X_test_dense = X_test_trans.toarray() if hasattr(X_test_trans, "toarray") else X_test_trans

# ----- SHAP Global Importance -----
shap_df = None
explainer = None

try:
    X_shap_background = X_train_dense[:200]

    explainer = shap.Explainer(
        classifier,
        X_shap_background,
        feature_names=feature_names
```

```
)  
  
    shap_values = explainer(X_train_dense[:500])  
    vals = shap_values.values  
  
    # multiclass = list of arrays → average abs val over classes  
    if isinstance(vals, list) or (hasattr(vals, "dtype") and vals.dtype == object):  
        arrs = [np.abs(v).mean(axis=0) for v in vals]  
        mean_abs_shap = np.mean(arrs, axis=0)  
    else:  
        mean_abs_shap = np.abs(vals).mean(axis=0)  
  
    shap_df = pd.DataFrame({  
        "feature": feature_names,  
        "shap_mean_abs": mean_abs_shap  
    }).sort_values("shap_mean_abs", ascending=False)  
  
    print("SHAP global importance computed.")  
except Exception as e:  
    print("SHAP global importances failed:", e)  
  
# ----- Combine importances -----  
imp_combined = pd.DataFrame({"feature": feature_names})  
  
if impurity_df is not None:  
    imp_combined = imp_combined.merge(impurity_df, on="feature", how="left")  
  
if perm_df is not None:  
    imp_combined = imp_combined.merge(perm_df[["feature", "perm_mean"]], on="feature", how="left")  
  
if shap_df is not None:  
    imp_combined = imp_combined.merge(shap_df, on="feature", how="left")  
  
# Normalize  
for col in ["impurity_importance", "perm_mean", "shap_mean_abs"]:  
    if col in imp_combined.columns:  
        col_vals = imp_combined[col].fillna(0).values  
        imp_combined[col + "_norm"] = (  
            col_vals / col_vals.max() if col_vals.max() > 0 else 0  
        )  
  
norm_cols = [c for c in imp_combined.columns if c.endswith("_norm")]
```

```

if norm_cols:
    imp_combined["aggregate_score"] = imp_combined[norm_cols].mean(axis=1)
    imp_combined = imp_combined.sort_values("aggregate_score", ascending=False)

global_importances_all.append((model_name, imp_combined))

# ----- Local SHAP -----
local_shap_out = None
if explainer is not None and shap_values is not None:
    try:
        n_local = min(3, X_test_dense.shape[0])
        local_vals = explainer(X_test_dense[:n_local])
        local_shap_out = {
            "instance_indices": list(range(n_local)),
            "local_values": local_vals.values,
            "expected_value": local_vals.base_values
        }
        print(f"Computed local SHAP for {n_local} samples.")

    # Print top 5 features per instance
    for i in range(n_local):
        instance_df = pd.DataFrame({
            "feature": feature_names,
            "shap_value": local_vals.values[i]
        }).sort_values("shap_value", key=abs, ascending=False)
        print(f"\nInstance {i} top 5 SHAP features:")
        print(instance_df.head(5))
    except Exception as e:
        print("Local SHAP failed:", e)

# ----- Collect summary row -----
summary_rows.append({
    "Algorithms": model_name,
    "Best parameters (example)": info["best_params"][0] if info.get("best_params") else None,
    "Mean test score": round(mean_test, 4),
    "Std test score": round(std_test, 4) if not np.isnan(std_test) else None,
    "Test accuracy (best model)": round(acc, 4),
    "Test F0.5": round(f05, 4),
    "Test F1": round(f1, 4),
    "Test F2": round(f2, 4),
    "Z_score_above_baseline": round(z_score, 4) if not np.isnan(z_score) else None,
    "Top feature (aggregate)": imp_combined["feature"].iloc[0] if not imp_combined.empty else None,
})

```

```
"Least feature (aggregate)": imp_combined["feature"].iloc[-1] if not imp_combined.empty else None,  
"local_shap_example": local_shap_out  
})
```

----- ANALYZING LogisticRegression -----

Mean CV/Test (avg across states): 0.6478 (std: 0.0014)

Test accuracy: 0.6458

F0.5/F1/F2: 0.6282 / 0.6265 / 0.6254

Z-score above baseline: 36.9463293169982

Permutation importance computed.

Top 10 permutation importances:

| | | feature | perm_mean | perm_std |
|----|--|--|-----------|----------|
| 17 | | num__odds_diff | 0.092137 | 0.010744 |
| 32 | | cat__BetterRank_Red | 0.002481 | 0.001944 |
| 50 | | cat__StanceCombo_Orthodox vs Switch | 0.002214 | 0.000634 |
| 11 | | num__RWinPct | 0.001183 | 0.001610 |
| 5 | | num__RedCurrentWinStreak | 0.001031 | 0.001965 |
| 34 | | cat__WeightClassLabel_Bantamweight | 0.001031 | 0.001624 |
| 14 | | num__RedIsGrappler | 0.000802 | 0.002334 |
| 21 | | cat__TitleBout_True | 0.000725 | 0.000743 |
| 10 | | num__AgeDif | 0.000649 | 0.000437 |
| 43 | | cat__WeightClassLabel_Women's Bantamweight | 0.000611 | 0.000857 |

SHAP global importance computed.

Computed local SHAP for 3 samples.

Instance 0 top 5 SHAP features:

| | | feature | shap_value |
|----|--|---------------------------|------------|
| 17 | | num__odds_diff | 0.735632 |
| 2 | | num__BlueCurrentWinStreak | -0.140735 |
| 8 | | num__BlueAge | 0.139484 |
| 32 | | cat__BetterRank_Red | 0.106626 |
| 7 | | num__RedWeightLbs | 0.080405 |

Instance 1 top 5 SHAP features:

| | | feature | shap_value |
|----|--|-------------------------|------------|
| 17 | | num__odds_diff | 1.941565 |
| 19 | | num__Spread | 0.224957 |
| 8 | | num__BlueAge | 0.139484 |
| 29 | | cat__RedStance_Southpaw | 0.120034 |
| 32 | | cat__BetterRank_Red | 0.106626 |

Instance 2 top 5 SHAP features:

| | | feature | shap_value |
|----|--|----------------|------------|
| 17 | | num__odds_diff | -1.352854 |

```
8          num__BlueAge   -0.238962
9          num__ReachDif  -0.121905
0          num__WeightClass -0.105519
25 cat__BlueStance_Southpaw  0.097518
```

----- ANALYZING RandomForest -----

Mean CV/Test (avg across states): 0.6443 (std: 0.0029)

Test accuracy: 0.6473

F0.5/F1/F2: 0.6243 / 0.6189 / 0.6171

Z-score above baseline: 17.37198072430765

Impurity importance computed.

Permutation importance computed.

Top 10 permutation importances:

| | | feature | perm_mean | perm_std |
|----|--|------------------------------------|-----------|----------|
| 17 | | num__odds_diff | 0.081870 | 0.009784 |
| 46 | cat__WeightClassLabel_Women's Strawweight | | 0.002634 | 0.001698 |
| 16 | | num__BlueIsStriker | 0.002252 | 0.001765 |
| 26 | | cat__BlueStance_Switch | 0.001870 | 0.000511 |
| 24 | | cat__BlueStance_Orthodox | 0.001489 | 0.001038 |
| 30 | | cat__RedStance_Switch | 0.001489 | 0.000818 |
| 50 | cat__StanceCombo_Orthodox vs Switch | | 0.001412 | 0.000651 |
| 34 | | cat__WeightClassLabel_Bantamweight | 0.001260 | 0.000735 |
| 48 | cat__StanceCombo_Orthodox vs Orthodox | | 0.001107 | 0.001265 |
| 43 | cat__WeightClassLabel_Women's Bantamweight | | 0.001069 | 0.000611 |

99% | ===== | 988/1000 [00:29<00:00]

SHAP global importances failed: Per-column arrays must each be 1-dimensional
 Computed local SHAP for 3 samples.
 Local SHAP failed: Per-column arrays must each be 1-dimensional

----- ANALYZING SVM -----

Mean CV/Test (avg across states): 0.6550 (std: 0.0011)
 Test accuracy: 0.6557
 F0.5/F1/F2: 0.6328 / 0.6264 / 0.6243
 Z-score above baseline: 55.861435713737386
 Permutation importance computed.

Top 10 permutation importances:

| | | feature | perm_mean | perm_std |
|----|-----------------------------------|--------------------------|-----------|----------|
| 17 | | num__odds_diff | 0.147748 | 0.010390 |
| 19 | | num__Spread | 0.015458 | 0.006694 |
| 40 | cat__WeightClassLabel_Lightweight | | 0.002634 | 0.000614 |
| 10 | | num__AgeDif | 0.001832 | 0.000978 |
| 18 | | num__AgeGap | 0.001756 | 0.000545 |
| 16 | | num__BlueIsStriker | 0.001603 | 0.000867 |
| 5 | | num__RedCurrentWinStreak | 0.001336 | 0.000585 |
| 0 | | num__WeightClass | 0.001221 | 0.001217 |
| 9 | | num__ReachDif | 0.001107 | 0.000918 |
| 14 | | num__RedIsGrappler | 0.000916 | 0.000890 |

SHAP global importance computed.

Computed local SHAP for 3 samples.

Instance 0 top 5 SHAP features:

| | | feature | shap_value |
|----|---|-------------------|------------|
| 17 | | num__odds_diff | 1.093114 |
| 19 | | num__Spread | -0.247060 |
| 7 | | num__RedWeightLbs | 0.037935 |
| 48 | cat__StanceCombo_Orthodox vs Orthodox | | 0.030171 |
| 39 | cat__WeightClassLabel_Light Heavyweight | | -0.029046 |

Instance 1 top 5 SHAP features:

| | | feature | shap_value |
|----|--------------------------|----------------|------------|
| 17 | | num__odds_diff | 2.885071 |
| 19 | | num__Spread | -1.909985 |
| 29 | cat__RedStance_Southpaw | | 0.076576 |
| 24 | cat__BlueStance_Orthodox | | 0.042962 |
| 28 | cat__RedStance_Orthodox | | -0.038900 |

Instance 2 top 5 SHAP features:

| | feature | shap_value |
|----|---------------------------------------|------------|
| 17 | num__odds_diff | -2.010276 |
| 19 | num__Spread | -0.600084 |
| 24 | cat__BlueStance_Orthodox | 0.042962 |
| 48 | cat__StanceCombo_Orthodox vs Orthodox | -0.038399 |
| 8 | num__BlueAge | -0.033158 |

----- ANALYZING XGBoost -----

Mean CV/Test (avg across states): 0.6590 (std: 0.0040)

Test accuracy: 0.6534

F0.5/F1/F2: 0.6318 / 0.6268 / 0.6249

Z-score above baseline: 16.263455967290525

Impurity importance computed.

Permutation importance computed.

Top 10 permutation importances:

| | feature | perm_mean | perm_std |
|----|-------------------------------------|-----------|----------|
| 17 | num__odds_diff | 0.119885 | 0.010302 |
| 8 | num__BlueAge | 0.001641 | 0.002969 |
| 9 | num__ReachDif | 0.001603 | 0.001205 |
| 0 | num__WeightClass | 0.001489 | 0.000886 |
| 29 | cat__RedStance_Southpaw | 0.000802 | 0.000614 |
| 16 | num__BlueIsStriker | 0.000534 | 0.000350 |
| 12 | num__RedTotalFights | 0.000496 | 0.000774 |
| 11 | num__RWinPct | 0.000382 | 0.002027 |
| 2 | num__BlueCurrentWinStreak | 0.000267 | 0.001493 |
| 57 | cat__StanceCombo_Switch vs Orthodox | 0.000153 | 0.000305 |

SHAP global importance computed.

Computed local SHAP for 3 samples.

Instance 0 top 5 SHAP features:

| | feature | shap_value |
|----|---------------------|------------|
| 17 | num__odds_diff | 0.854119 |
| 19 | num__Spread | 0.294339 |
| 12 | num__RedTotalFights | -0.035756 |
| 8 | num__BlueAge | 0.025057 |
| 10 | num__AgeDif | -0.022076 |

Instance 1 top 5 SHAP features:

| | feature | shap_value |
|----|--------------------------|------------|
| 17 | num__odds_diff | 1.143060 |
| 19 | num__Spread | 0.560455 |
| 15 | num__BlueIsGrappler | 0.029522 |
| 24 | cat__BlueStance_Orthodox | -0.029412 |
| 12 | num__RedTotalFights | -0.029180 |

Instance 2 top 5 SHAP features:

| | feature | shap_value |
|----|--------------------------|------------|
| 17 | num__odds_diff | -1.061218 |
| 19 | num__Spread | -0.339018 |
| 5 | num__RedCurrentWinStreak | 0.083631 |
| 11 | num__RWinPct | 0.056465 |
| 8 | num__BlueAge | -0.041240 |

In [297...]

```
# -----
# Summary DataFrame
# -----
model_perf_df = pd.DataFrame(summary_rows)
print("\n\n==== Model performance summary vs baseline ===")
display(model_perf_df)

# -----
# Barplot of mean test score with error bars
# -----
plt.figure(figsize=(8,5))

# Create barplot
sns.barplot(
    data=model_perf_df,
    x='Algorithms',
    y='Mean test score',
    ci=None,
    palette='Set2'
)

# Add error bars
y_err = model_perf_df['Std test score'].fillna(0).values
plt.errorbar(
    x=np.arange(len(model_perf_df)),
    y=model_perf_df['Mean test score'].values,
    yerr=y_err,
```

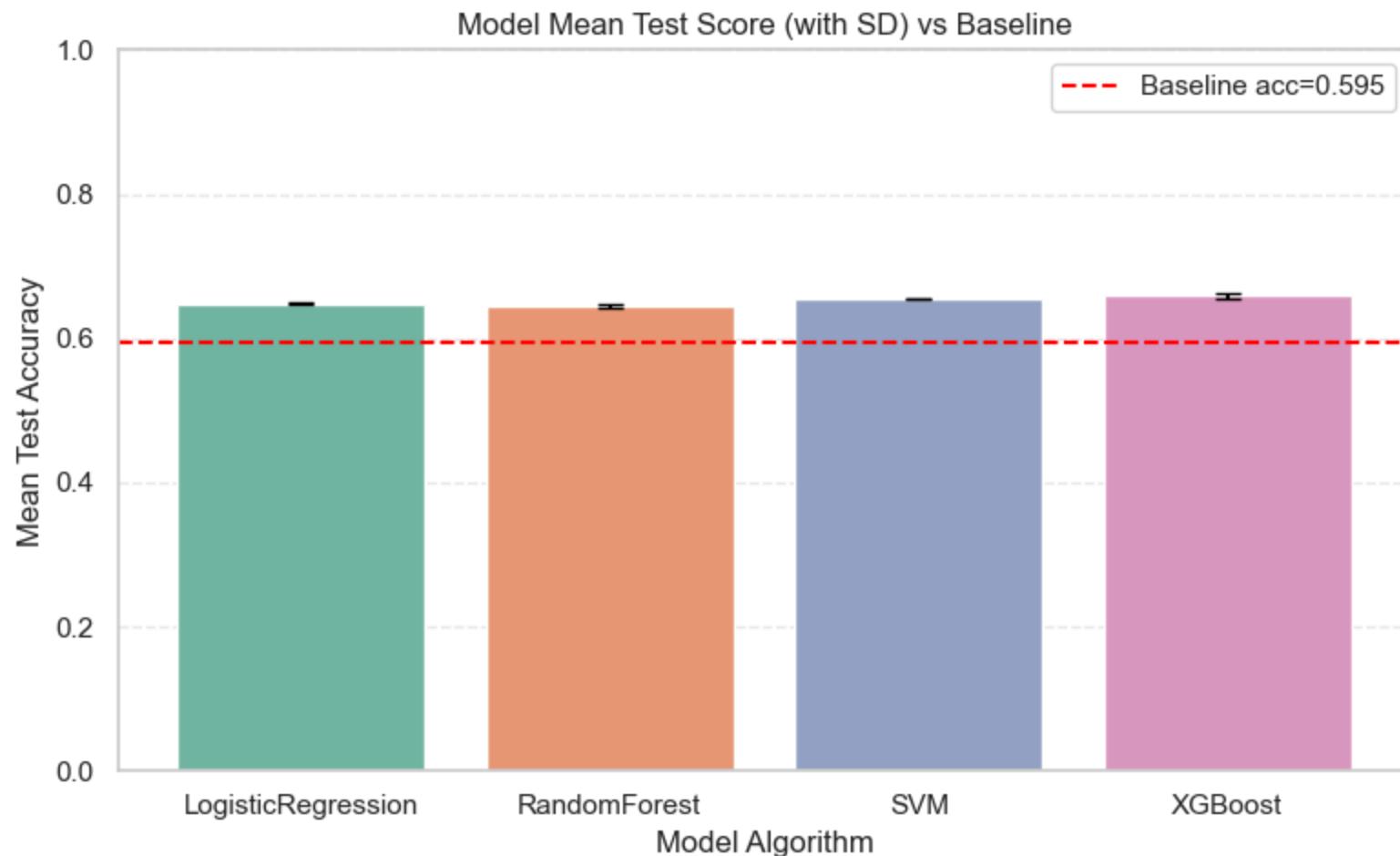
```
        fmt='none',
        capsizes=5,
        color='black'
    )

# Baseline accuracy line
plt.axhline(baseline_acc, color='red', linestyle='--', label=f'Baseline acc={baseline_acc:.3f}')

# Labels and styling
plt.title("Model Mean Test Score (with SD) vs Baseline")
plt.ylabel("Mean Test Accuracy")
plt.xlabel("Model Algorithm")
plt.ylim(0, 1)
plt.grid(axis='y', linestyle='--', alpha=0.4)
plt.legend()
plt.tight_layout()
fig_name = "mean_test_acc_model"
fig_path = os.path.join(output_folder, f"{fig_name}.png")
plt.savefig(fig_path, bbox_inches="tight", dpi=300)
plt.show()
plt.close()
```

==== Model performance summary vs baseline ===

| | Algorithms | Best parameters
(example) | Mean
test
score | Std
test
score | Test
accuracy
(best
model) | Test
F0.5 | Test
F1 | Test
F2 | Z_score_above_baseline |
|---|--------------------|--|-----------------------|----------------------|-------------------------------------|--------------|------------|------------|------------------------|
| 0 | LogisticRegression | {'classifier__C': 0.1} | 0.6478 | 0.0014 | 0.6458 | 0.6282 | 0.6265 | 0.6254 | 36.9463 |
| 1 | RandomForest | {'classifier__max_depth':
10, 'classifier__min...} | 0.6443 | 0.0029 | 0.6473 | 0.6243 | 0.6189 | 0.6171 | 17.3720 |
| 2 | SVM | {'classifier__C': 0.1,
'classifier__kernel': '...'} | 0.6550 | 0.0011 | 0.6557 | 0.6328 | 0.6264 | 0.6243 | 55.8614 |
| 3 | XGBoost | {'classifier__learning_rate':
0.01, 'classifie...'} | 0.6590 | 0.0040 | 0.6534 | 0.6318 | 0.6268 | 0.6249 | 16.2635 |

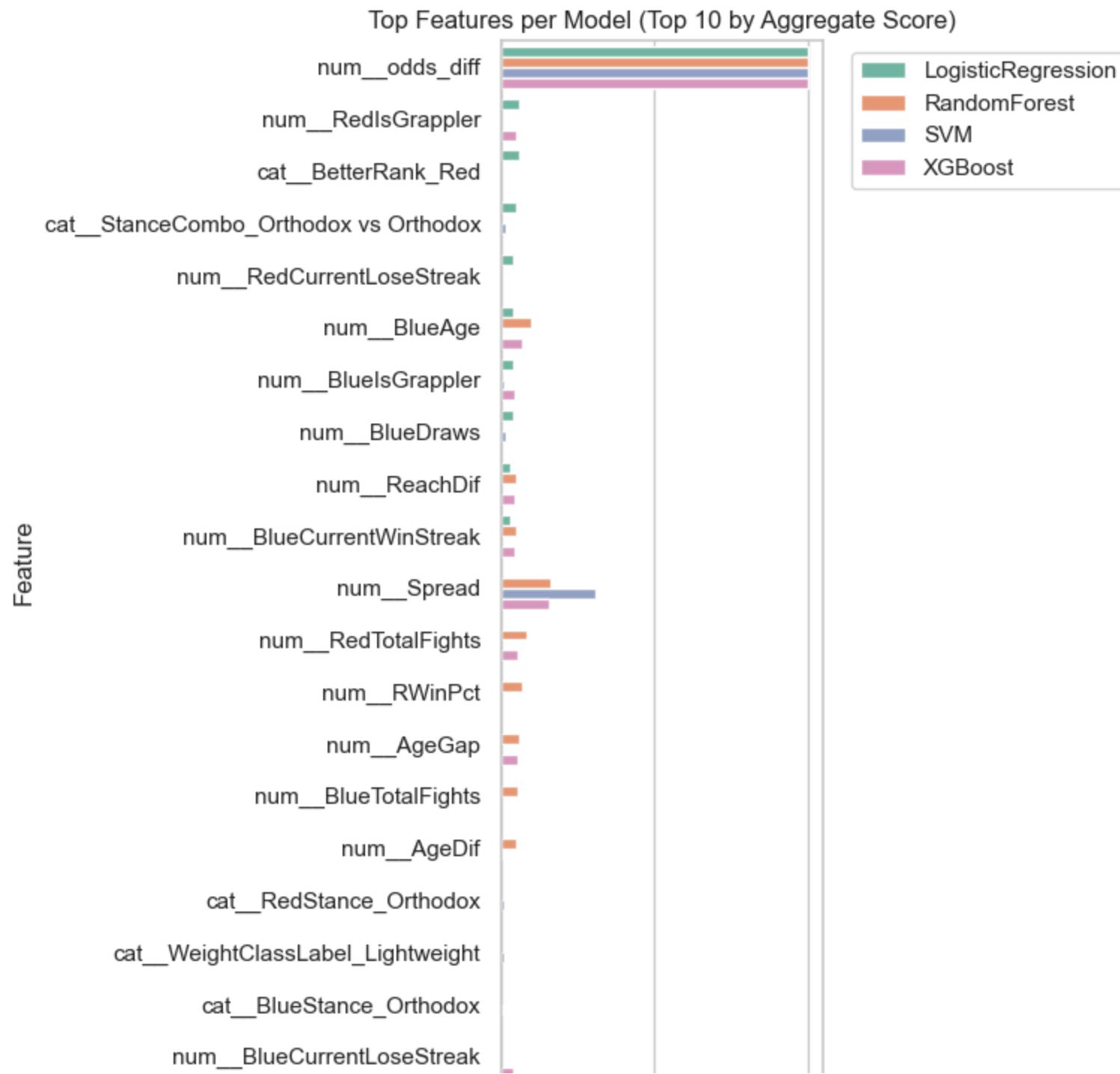


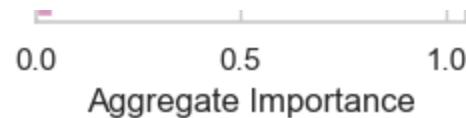
```
In [298...]: # -----
# Top features across models (aggregate)
# -----
import os
top_feats_list = []

for model_name, imp_df in global_importances_all:
    # Use aggregate_score if available, otherwise fallback to SHAP
    score_col = 'aggregate_score' if 'aggregate_score' in imp_df.columns else 'shap_mean_abs'

    if score_col in imp_df.columns:
        top_feats = (
```

```
    imp_df.nlargest(10, score_col)[['feature', score_col]]  
    .rename(columns={score_col: 'aggregate_score'})  
    .assign(model=model_name)  
)  
top_feats_list.append(top_feats)  
  
if top_feats_list:  
    top_feats_all = pd.concat(top_feats_list, ignore_index=True)  
  
    plt.figure(figsize=(8,8))  
    sns.barplot(  
        data=top_feats_all,  
        x='aggregate_score',  
        y='feature',  
        hue='model',  
        palette='Set2'  
    )  
    plt.title("Top Features per Model (Top 10 by Aggregate Score)")  
    plt.xlabel("Aggregate Importance")  
    plt.ylabel("Feature")  
    plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')  
    plt.tight_layout()  
    fig_name = "top_features_per_model"  
    fig_path = os.path.join(output_folder, f"{fig_name}.png")  
    plt.savefig(fig_path, bbox_inches="tight", dpi=300)  
    plt.show()  
    plt.close()  
else:  
    print("No feature importance data available to plot.")
```





In [299...]

```

# -----
# Ensure dense inputs for SHAP/tree models - may be redundant but i'm paranoid
# -----
X_train_dense = X_train_trans.toarray() if hasattr(X_train_trans, "toarray") else np.asarray(X_train_trans)
X_test_dense = X_test_trans.toarray() if hasattr(X_test_trans, "toarray") else np.asarray(X_test_trans)

# -----
# SHAP fx
# -----
def run_shap(pipeline_model, classifier, model_name, feature_names, X_sample=None):
    if X_sample is None:
        X_sample = X_test_dense[:200] # subset for speed

    try:
        if model_name in ["RandomForest", "XGBoost"]:
            explainer = shap.TreeExplainer(classifier)
            shap_values = explainer.shap_values(X_sample)
        elif model_name == "LogisticRegression":
            masker = shap.maskers.Independent(X_sample)
            explainer = shap.KernelExplainer(classifier.predict_proba, masker)
            shap_values = explainer.shap_values(X_sample, nsamples=200)
        elif model_name == "SVM":
            print("Skipping SHAP for SVM - KernelExplainer too slow.")
            return
        else:
            print(f"SHAP not supported for {model_name}.")
            return

        shap.summary_plot(shap_values, X_sample, feature_names=feature_names, show=True)
        plt.title(f"SHAP Summary Plot - {model_name}")
        fig_name = "shap_summary_plot_{model_name}"
        fig_path = os.path.join(output_folder, f"{fig_name}.png")
        plt.savefig(fig_path, bbox_inches="tight", dpi=300)
        plt.show()
        plt.close()
    except Exception as e:

```

```
print(f"SHAP failed for {model_name}: {e}")

# -----
# Ftr importance for rubric
# -----
def extract_feature_importance(classifier, model_name, feature_names):
    if hasattr(classifier, "feature_importances_"):      # Tree-based
        importances = classifier.feature_importances_
    elif hasattr(classifier, "coef_"):                      # Linear models
        importances = np.abs(classifier.coef_).flatten()
    else:
        print(f"{model_name} does not support feature importances.")
        return None

    return pd.DataFrame({
        "Feature": feature_names,
        "Importance": importances,
        "Model": model_name
    })

# -----
# CONFUSION MATRIX + AUROC
# -----
def run_confusion(pipeline_model, model_name):
    preds = pipeline_model.predict(X_test)
    cm = confusion_matrix(y_test, preds)
    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.xlabel("Predicted Labels")
    plt.ylabel("True Labels")
    plt.title(f"{model_name} - Confusion Matrix")
    fig_name = f"{model_name}_confusion_matrix"
    fig_path = os.path.join(output_folder, f"{fig_name}.png")
    plt.savefig(fig_path, bbox_inches="tight", dpi=300)
    plt.show()
    plt.close()

from sklearn.preprocessing import LabelBinarizer
```

```
def run_auroc(pipeline_model, model_name):
    y_true = y_test.copy() # 1D integer labels
    if y_true.ndim > 1:
        #y_test is one-hot, convert to single integer labels
        y_true = np.argmax(y_true, axis=1)

    try:
        if hasattr(pipeline_model, "predict_proba"):
            probs = pipeline_model.predict_proba(X_test)
            if probs.shape[1] > 2:
                # multiclass
                auc = roc_auc_score(y_true, probs, multi_class="ovr")
            else:
                auc = roc_auc_score(y_true, probs[:,1])
        else:
            probs = pipeline_model.decision_function(X_test)
            auc = roc_auc_score(y_true, probs)

        print(f"{model_name} AUROC: {auc:.4f}")
        print(classification_report(y_true, pipeline_model.predict(X_test)))
    except Exception as e:
        print(f"{model_name} AUROC failed: {e}")

# -----
# RUN ANALYSIS FOR ALL MODELS - home stretch
# -----
all_fi = []

for model_name, info in results_summary.items():
    print("\n\n-----")
    print(f" FINAL ANALYSIS: {model_name}")
    print("-----")

    pipeline_model = info["models"][0] # best model
    classifier = pipeline_model.named_steps["classifier"]

    # Feature names from pipeline
    try:
        feature_names = pipeline_model.named_steps["preprocessor"].get_feature_names_out()
    except:
```

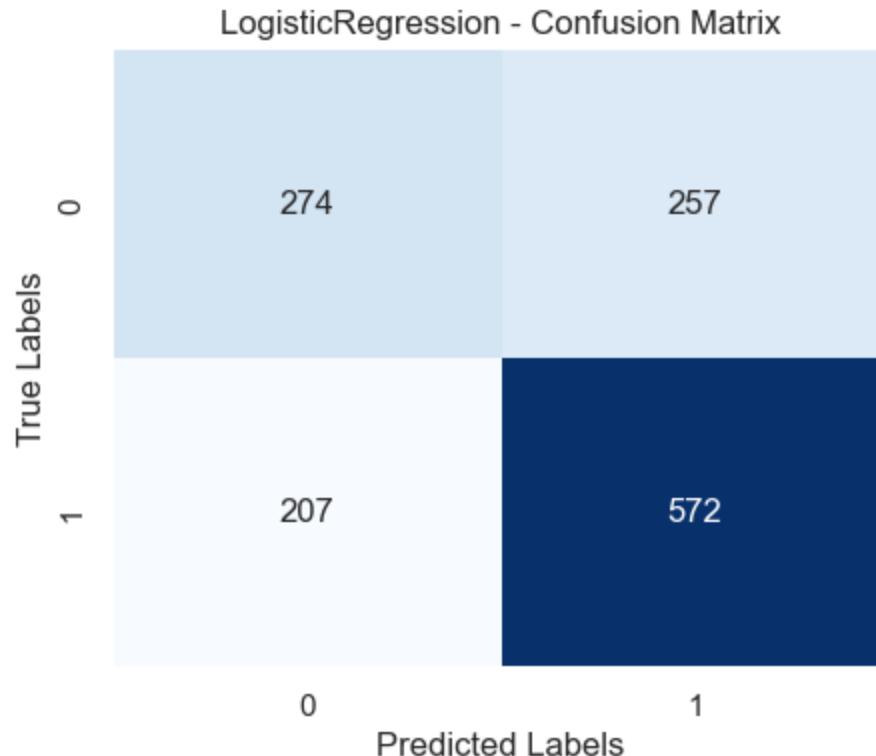
```
feature_names = X_train.columns.tolist()

# Confusion matrix & AUROC
run_confusion(pipeline_model, model_name)
run_auroc(pipeline_model, model_name)

# Feature importance
fi_df = extract_feature_importance(classifier, model_name, feature_names)
if fi_df is not None:
    all_fi.append(fi_df)

# SHAP summary
run_shap(pipeline_model, classifier, model_name, feature_names)
```

FINAL ANALYSIS: LogisticRegression



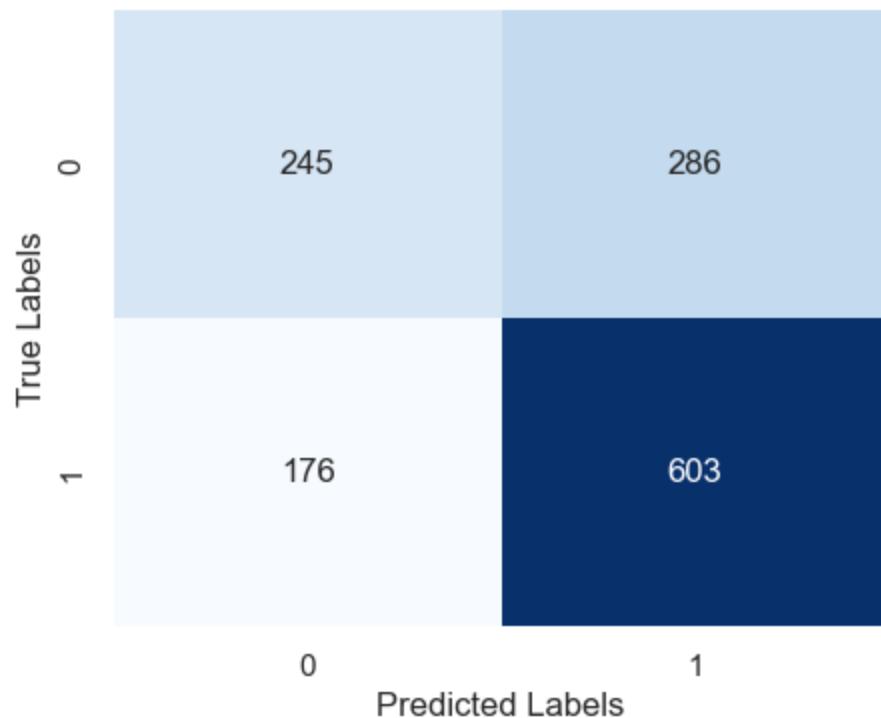
LogisticRegression AUROC: 0.6974

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.57 | 0.52 | 0.54 | 531 |
| 1 | 0.69 | 0.73 | 0.71 | 779 |
| accuracy | | | 0.65 | 1310 |
| macro avg | 0.63 | 0.63 | 0.63 | 1310 |
| weighted avg | 0.64 | 0.65 | 0.64 | 1310 |

SHAP failed for LogisticRegression: Unknown type passed as data object: <class 'shap.maskers._tabular.Independent'>

FINAL ANALYSIS: RandomForest

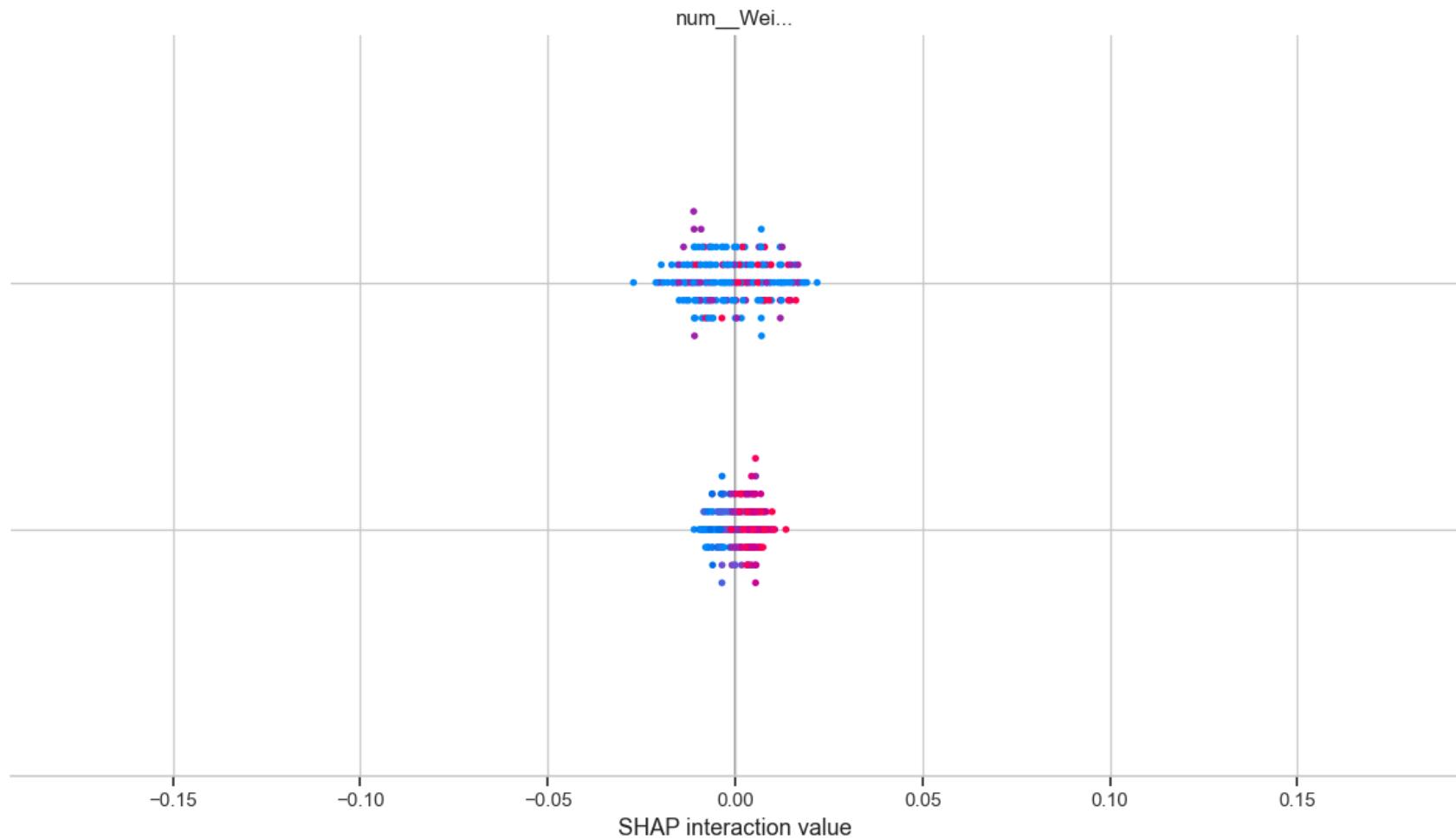
RandomForest - Confusion Matrix

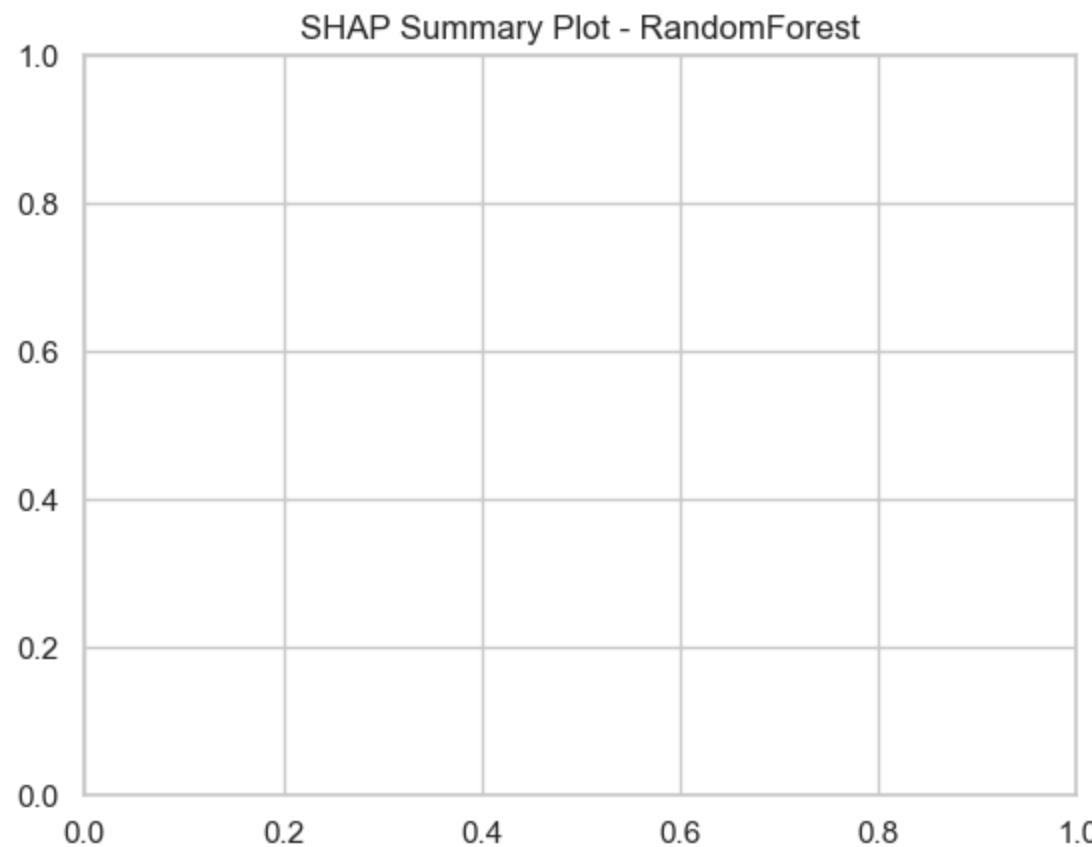


RandomForest AUROC: 0.6928

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.58 | 0.46 | 0.51 | 531 |
| 1 | 0.68 | 0.77 | 0.72 | 779 |
| accuracy | | | 0.65 | 1310 |
| macro avg | 0.63 | 0.62 | 0.62 | 1310 |
| weighted avg | 0.64 | 0.65 | 0.64 | 1310 |

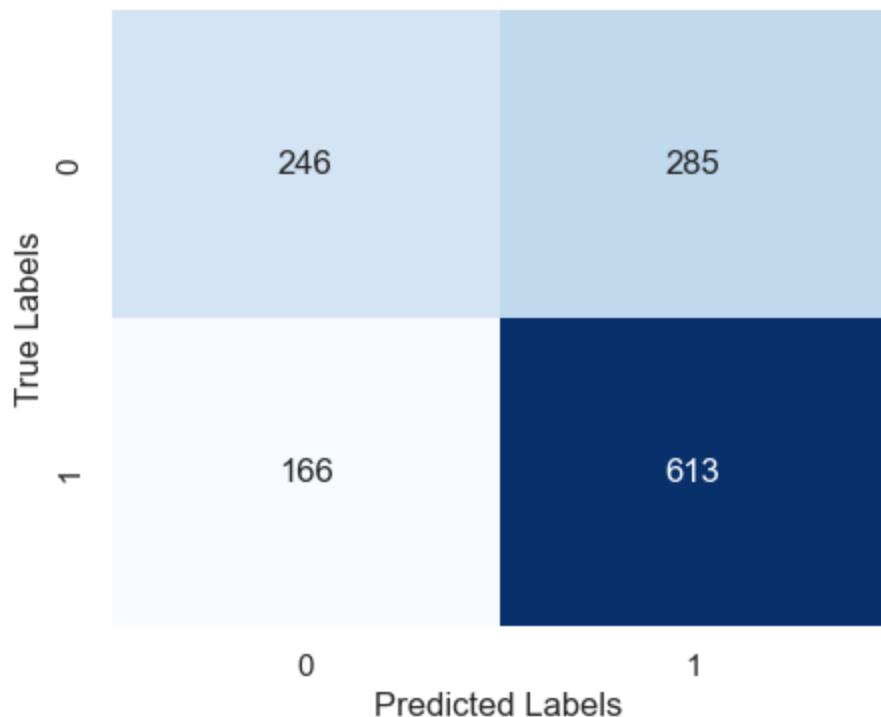
<Figure size 640x480 with 0 Axes>





FINAL ANALYSIS: SVM

SVM - Confusion Matrix

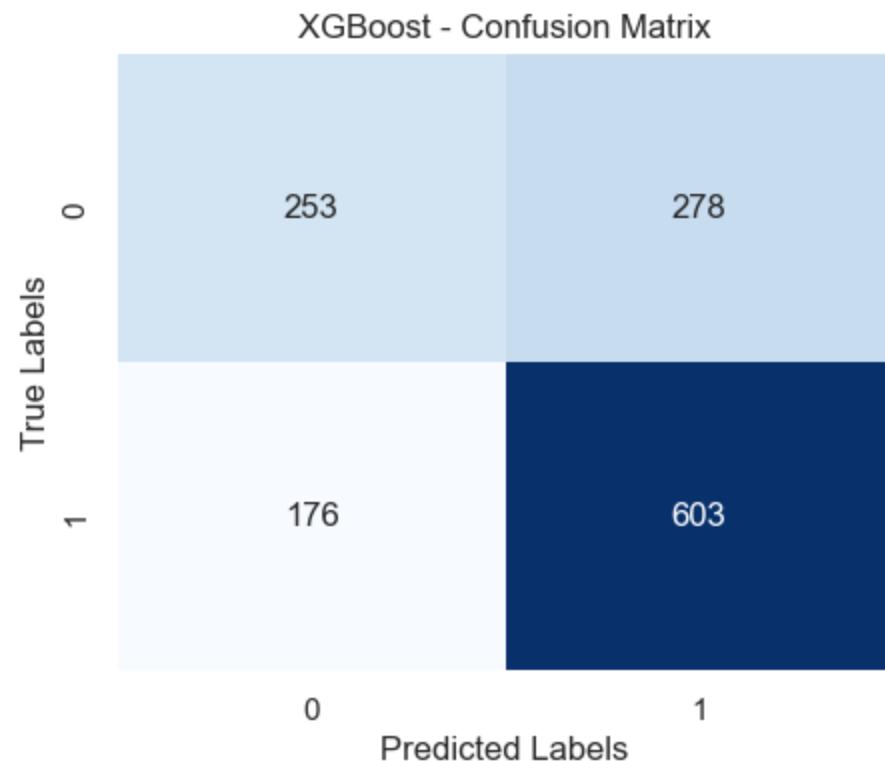


SVM AUROC: 0.6921

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.60 | 0.46 | 0.52 | 531 |
| 1 | 0.68 | 0.79 | 0.73 | 779 |
| accuracy | | | 0.66 | 1310 |
| macro avg | 0.64 | 0.63 | 0.63 | 1310 |
| weighted avg | 0.65 | 0.66 | 0.65 | 1310 |

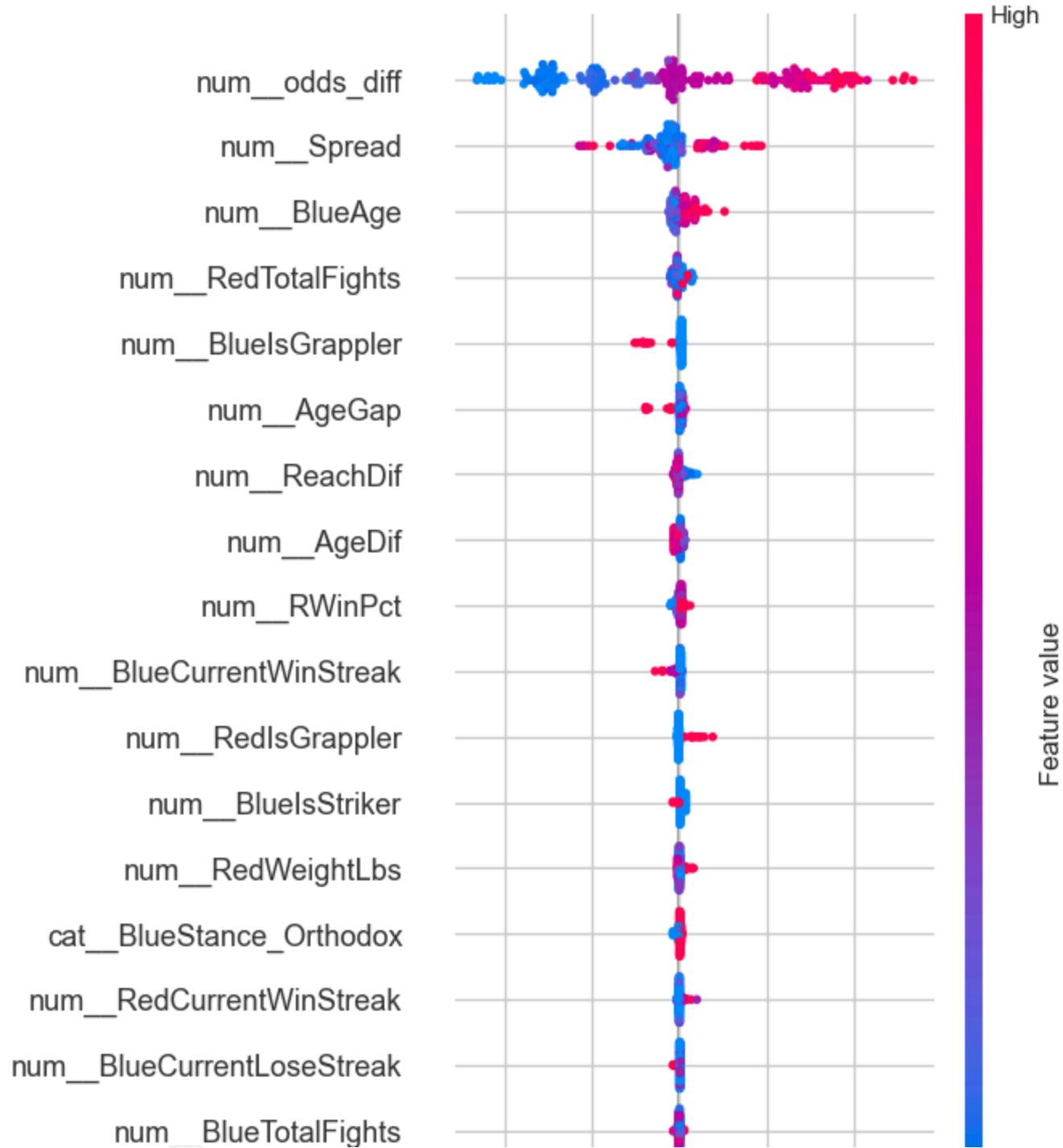
Skipping SHAP for SVM – KernelExplainer too slow.

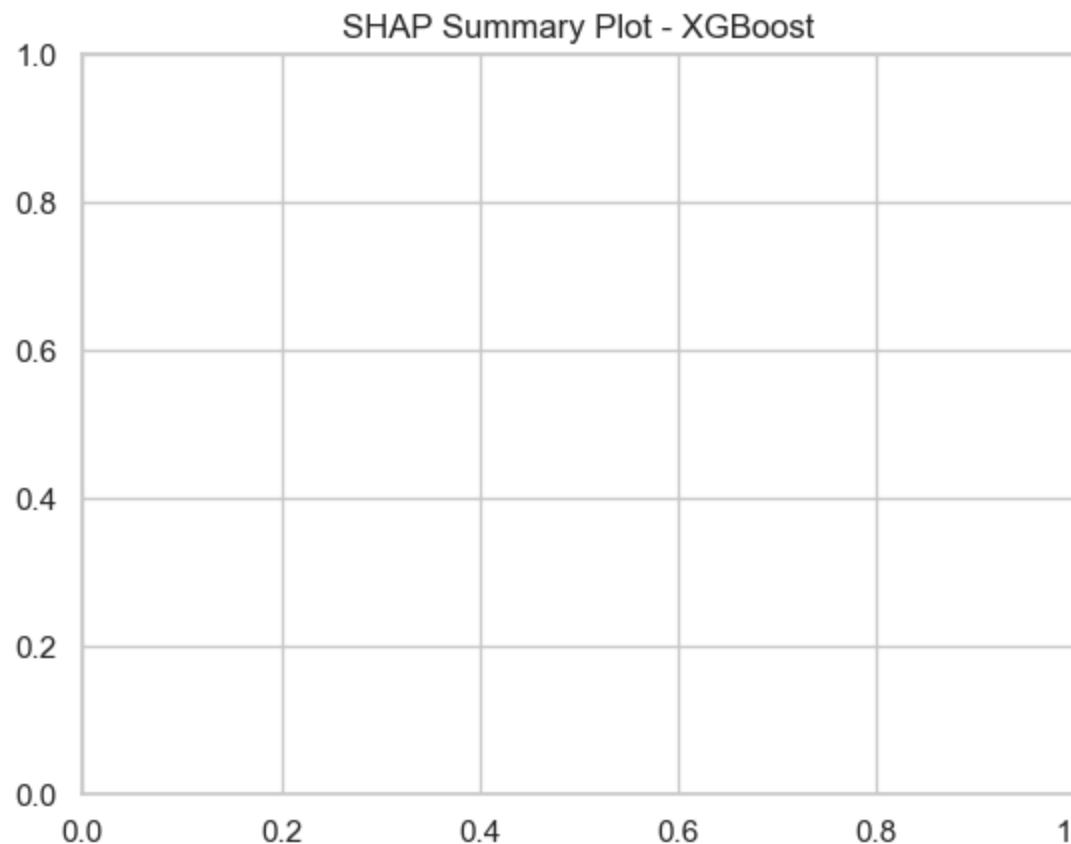
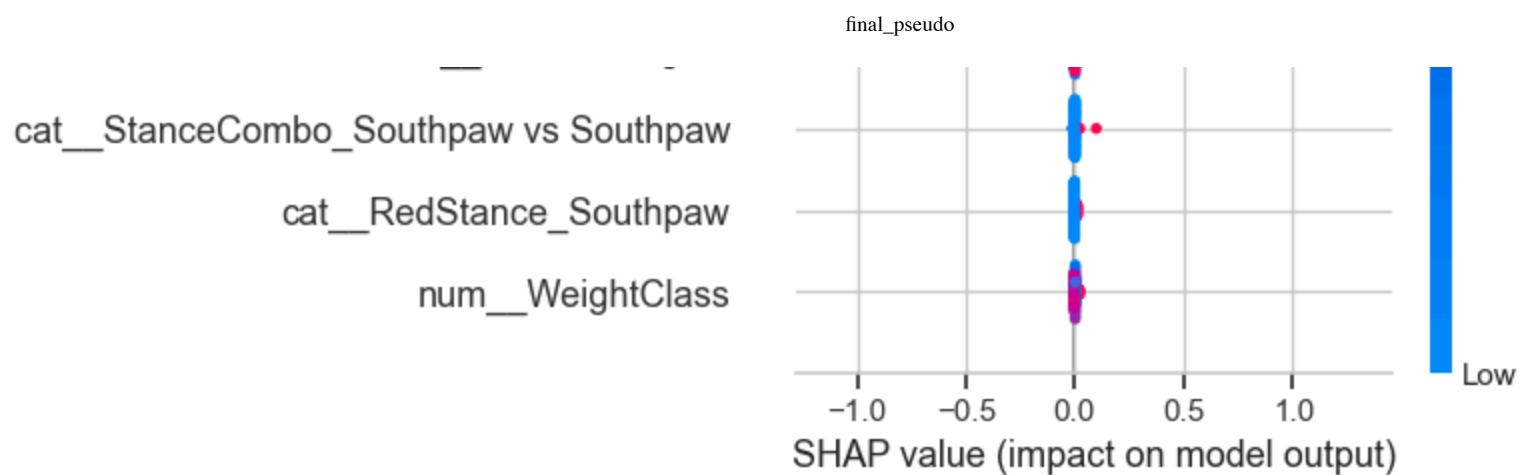
FINAL ANALYSIS: XGBoost



XGBoost AUROC: 0.6998

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.59 | 0.48 | 0.53 | 531 |
| 1 | 0.68 | 0.77 | 0.73 | 779 |
| accuracy | | | 0.65 | 1310 |
| macro avg | 0.64 | 0.63 | 0.63 | 1310 |
| weighted avg | 0.65 | 0.65 | 0.65 | 1310 |





In [300...]

```
# -----  
# XGBOOST-SPECIFIC ADVANCED ANALYSIS – BEST MODEL I KNEW IT
```

```
# -----
if "XGBoost" in results_summary:
    model_name = "XGBoost"
    pipeline_model = results_summary[model_name]["models"][0]
    classifier = pipeline_model.named_steps["classifier"]
    preprocessor = pipeline_model.named_steps["preprocessor"]

    # Get feature names (post-preprocessing)
    feature_names = preprocessor.get_feature_names_out()

    print("\n===== XGBoost - Baseline vs Model =====")

    # ---- majority baseline ----
    unique, counts = np.unique(y_train, return_counts=True)
    majority_class = unique[counts.argmax()]

    baseline_preds = np.full(len(y_test), majority_class)
    baseline_acc = accuracy_score(y_test, baseline_preds)
    baseline_f1 = f1_score(y_test, baseline_preds, average="macro")

    model_preds = pipeline_model.predict(X_test)
    model_acc = accuracy_score(y_test, model_preds)
    model_f1 = f1_score(y_test, model_preds, average="macro")

    print(f"Baseline acc: {baseline_acc:.4f}, Model acc: {model_acc:.4f}")
    print(f"Baseline F1: {baseline_f1:.4f}, Model F1: {model_f1:.4f}")

    # ---- PERMUTATION IMPORTANCE (must use transformed X_test) ----
    X_test_trans = preprocessor.transform(X_test)
    X_test_dense = (
        X_test_trans.toarray() if hasattr(X_test_trans, "toarray")
        else np.asarray(X_test_trans)
    )

    perm = permutation_importance(
        classifier,
        X_test_dense,
        y_test,
        n_repeats=15,
        random_state=42,
        n_jobs=-1,
        scoring="accuracy"
```

```
)\n\nperm_df = pd.DataFrame({\n    "Feature": feature_names,\n    "Importance": perm.importances_mean,\n    "Std": perm.importances_std\n}).sort_values("Importance", ascending=False)\n\nprint("\nTop 15 Permutation Importances:")\nprint(perm_df.head(15))\n\n# ---- XGBoost Internal Importance - I chose: gain / cover / weight ----\nbooster = classifier.get_booster()\n\ngain = booster.get_score(importance_type="gain")\ncover = booster.get_score(importance_type="cover")\nweight = booster.get_score(importance_type="weight")\n\ndef map_booster_keys(score_dict):\n    return {\n        feature_names[int(k[1:])]: v\n        for k, v in score_dict.items()\n    }\n\ngain_map = map_booster_keys(gain)\ncover_map = map_booster_keys(cover)\nweight_map = map_booster_keys(weight)\n\ngain_df = pd.DataFrame({\n    "Feature": list(gain_map.keys()),\n    "Gain": list(gain_map.values()),\n    "Cover": [cover_map.get(f, 0) for f in gain_map.keys()],\n    "Weight": [weight_map.get(f, 0) for f in gain_map.keys()],\n}).sort_values("Gain", ascending=False)\n\nprint("\nXGBoost Gain / Cover / Weight:")\nprint(gain_df.head(20))\n\n# ---- SHAP Global ----\nX_shap_global = X_test_dense[:200]\n\nexplainer = shap.TreeExplainer(classifier)
```

===== XGBoost – Baseline vs Model =====

Baseline acc: 0.5947, Model acc: 0.6534

Baseline F1: 0.3729, Model F1: 0.6268

Top 15 Permutation Importances:

| | | Feature | Importance | Std |
|----|--|---|------------|----------|
| 17 | | num__odds_diff | 0.121221 | 0.009547 |
| 9 | | num__ReachDif | 0.001730 | 0.001291 |
| 0 | | num__WeightClass | 0.001374 | 0.000798 |
| 8 | | num__BlueAge | 0.001272 | 0.002811 |
| 29 | | cat__RedStance_Southpaw | 0.000763 | 0.000683 |
| 16 | | num__BlueIsStriker | 0.000560 | 0.000338 |
| 12 | | num__RedTotalFights | 0.000458 | 0.000873 |
| 2 | | num__BlueCurrentWinStreak | 0.000356 | 0.001692 |
| 57 | | cat__StanceCombo_Switch vs Orthodox | 0.000102 | 0.000259 |
| 1 | | num__BlueCurrentLoseStreak | 0.000051 | 0.000190 |
| 55 | | cat__StanceCombo_Southpaw vs Switch | 0.000000 | 0.000000 |
| 45 | | cat__WeightClassLabel_Women's Flyweight | 0.000000 | 0.000000 |
| 34 | | cat__WeightClassLabel_Bantamweight | 0.000000 | 0.000000 |
| 35 | | cat__WeightClassLabel_Catch Weight | 0.000000 | 0.000000 |
| 37 | | cat__WeightClassLabel_Flyweight | 0.000000 | 0.000000 |

XGBoost Gain / Cover / Weight:

| | | Feature | Gain | Cover | Weight |
|----|--|---------------------------------------|-----------|------------|--------|
| 17 | | num__odds_diff | 57.722713 | 883.203125 | 537.0 |
| 19 | | num__Spread | 14.390915 | 468.717590 | 441.0 |
| 18 | | num__AgeGap | 7.698019 | 451.328674 | 71.0 |
| 8 | | num__BlueAge | 7.328346 | 453.039642 | 158.0 |
| 1 | | num__BlueCurrentLoseStreak | 6.852878 | 281.897278 | 18.0 |
| 15 | | num__BlueIsGrappler | 6.804818 | 827.483093 | 71.0 |
| 7 | | num__RedWeightLbs | 6.611917 | 409.421082 | 44.0 |
| 28 | | cat__StanceCombo_Switch vs Orthodox | 6.583469 | 320.493195 | 9.0 |
| 26 | | cat__StanceCombo_Orthodox vs Switch | 6.393301 | 271.613617 | 7.0 |
| 12 | | num__RedTotalFights | 6.311788 | 350.288300 | 87.0 |
| 14 | | num__RedIsGrappler | 6.126726 | 662.121399 | 48.0 |
| 2 | | num__BlueCurrentWinStreak | 6.066645 | 437.866760 | 49.0 |
| 25 | | cat__WeightClassLabel_Lightweight | 5.799694 | 79.841141 | 1.0 |
| 21 | | cat__RedStance_Southpaw | 5.544939 | 775.471252 | 6.0 |
| 27 | | cat__StanceCombo_Southpaw vs Southpaw | 5.305297 | 124.942085 | 54.0 |
| 9 | | num__ReachDif | 5.227875 | 376.921967 | 110.0 |
| 10 | | num__AgeDif | 5.171468 | 182.773819 | 79.0 |
| 20 | | cat__BlueStance_Orthodox | 5.062984 | 202.173096 | 22.0 |

| | | | | |
|----|-----------------------------------|----------|------------|------|
| 13 | num__BlueTotalFights | 5.008529 | 91.695442 | 37.0 |
| 24 | cat__WeightClassLabel_Heavyweight | 4.836949 | 300.554871 | 6.0 |