Categorising and Comparing Different Fighting Styles to Compare What is Most Effective for Self Defence Using Data from Fights in the UFC

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Abstract

Violence is part of society that unfortunately will remain, and human nature has shown that people will engage each other physically. There will be people who want to fight other people. Often times, the best way of dealing with these types of people is to walk away. However, sometimes that isn't possible. Thus, there have been many different fighting styles that have looked at what the most effective way of engaging in physical combat – Boxing, Jiu Jitsu, Wrestling, Kickboxing, Muay Thai, etc. People have consistently debated these questions. [1] This project attempts to use data analysis on data from the UFC to answer this question.

Keywords – ANOVA, Kruskal Wallis, Regression, Classification, K Means, Principal Component Analysis

I. Introduction

A. Background on UFC and MMA

This report is based on research into the question: "what is the most effective fighting style for self-defence". The dataset used for this research contains data from fights throughout Ultimate Fighting Championship's history [2]. The fighting styles listed include Striking, Wrestling and Jiu Jitsu. [3]

Given that the UFC is the closest current approximation to a self-defence situation someone may find themselves in, looking at what is successful in the UFC should give an indication of what will work if someone was put into that situation. [4]

B. Project Aims

This aim was to be achieved by transforming and comparing datasets that would then be analysed in a multitude of different ways with the aim of answering the above question. The techniques used in undertaking these comparisons included:

- One Way ANOVA
- Kruskal Wallis
- Mann Whitney U
- Two Way ANOVA
- Expected Value Testing & Chi Squared
- Multiple Linear Regression & Model Selection
- Logarithmic Regression & Variable Selection

C. Notes on the Project's Limits

It should be noted here that while Wrestling and Jiu-Jitsu seem somewhat similar in that they are both grappling styles, they function in different ways. Wrestling focuses on strength and aggression, whereas Jiu Jitsu focuses on technique, space, and leverage. [5]

It should also be noted that the purpose of this project is to look at which style they lean into the most. This is important to remember as each fighter will have a certain degree of mastery over the other fighting styles. Thus, it would be expected that the ideal skillset would be expertise over the three styles. But this is unfeasible for the normal person, so the project focuses on selecting one style for each fighter, with a secondary style added.

There were some other deficiencies within the data that should be noted. Given that the statistics analysed are on professional fighting, there will also be some deviation from the approximation of street fighting amongst normal people. For example, each fighter will typically be fighting someone of a similar skill level. Similarly, fighters fight at an agreed upon weight class with a maximum permitted weight [6]. These do not apply to real world situations.

There was approximation occurring in the analysis, as fighters were categorised solely by their output, and while there were some preventative measures (such as separating fighters who won and fighters who lost), there may have been exceptions where certain fights were miscategorised. However, the aggregation into fighter lists would have dealt with a lot of this, but the reader should still be mindful.

Data Description

The dataset provided contained 13522 and 530 columns. These columns included various different numerical and categorical columns – fighter, opponent, winner, division, method of victory, significant strikes, control time, etc. It should be noted that this dataset did not include the fighting style of the fighter. Thus, the fighting style would have to be calculated, based on various different columns. It should also be noted that each fight contained 2 rows of data per each fighter, so there were 6761 fights overall.

II. Literature Review

A. Introduction

The question of what the best fighting style is has been around for a very long time. Sports like Boxing [7] and Wrestling [8] are both thousands of years old, and while Jiu Jitsu is only hundreds of years old [9], it is another, very relevant style.

B. Prediction Models

A review of the literature of the subject suggests that most of the relevant research on this topic of mixed martial arts has focused on prediction of results [10], [11], [12]. From literature reviewed, it was found that fighting style was not mentioned, neither as a factor or an initial variable. Thus, there is an element of uniqueness to this project, as this project categorises the variables and then compares them. There classification models were helpful in the creation of the classification model used in this dataset for the purpose of seeing which variables were impactful.

C. Comparisons in Boxing and MMA

There was also valuable study published in 2008 which looked the Technical and Tactical aspects that lead to victory in boxing, however this mostly focused on descriptive statistics [13]. A further study was also completed in which used ANOVA to test for significant differences across a range of high ranked boxers [14]. There was also paper which looked at aggression and its impact on winning a decision in the UFC, which had a small amount of overlap with this study [15].

III. Methodology

A. Data Cleaning & Transformations

The data was loaded, and each column was then investigated. 530 columns was excessive, so some irrelevant columns were immediately dropped, and others were renamed. A new column for gender was created.

This data was then tested for which columns had missing variables. It was found that variables with missing values were height, age, reach, stance, referee, and anything with “precomp” or “recent” in the column name. This is expected as fighters with no previous bouts would not have previous stats. Since these variables were not used in the analysis, it was decided to ignore the missing values.

Given that the project was only focusing on fights that had been clearly won, all fights that didn’t have a clear winner, such as draws and disqualifications were then excluded. Outcomes such as majority decision, split decision or unanimous decision were simplified to ‘Decisions’.

The relevant data was then calculated to the number of events per minute, opposed to overall events. This was done by dividing the events by the total competition time. There were also some new columns made which included compiling all standing strikes, compiling all ground strikes, and compiling both of those to create total strikes per minute.

This data was then used to create an Evaluation dataframe. This only contained the relevant information for calculating the fighting style of each fight – 'Attempted Takedowns Per Minute', 'Total Strikes Attempted per Minute', etc. All fights with no output were then dropped, as they could not be successfully categorised into a fighting style.

Evaluation was then split into Fights Won and Fights Lost, as the output of a fighter who had won would generally be higher than the output of a fighter who had lost. By separating them then, the evaluation process was much easier for creating the list of fights data into a list of fighters data.

The evaluation process entailed ranking each relevant column using the rank function. From these rankings, an overall ranking of striking vs grappling was calculated. As mentioned previously, jiu jitsu and wrestling function differently. However, the decision was made to evaluate between striking and grappling, and then evaluate from grappling into wrestling and jiu jitsu. This process was repeated for Fights Won and Fights Lost.

From this, a list of fighters was calculated as well as their records in the UFC. The fighters' genders were also calculated, and any exceptions were altered. The number of each fight evaluation from each fighter was then assigned to each fighter so that each fighter had a percentage of how many fights were evaluated as striking, wrestling and ground game.

B. K Means Algorithm

The data was then fed to a K Means algorithm which computed which style each fighter would be. A secondary fighting style was also calculated, using a manual, handwritten algorithm.

C. Weight Class Categorisation

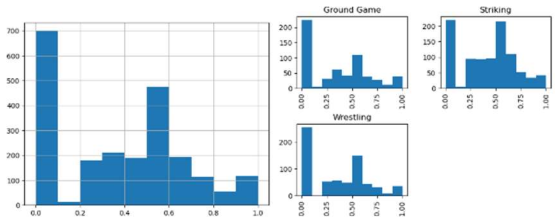
The mean weight each fighter fought at was then calculated and this mean weight was used to categorise each fighter into an average weight class. It was decided to define the weight class limits as the midpoints between weight classes. So lightweight at 155 was calculated as between 150 (half way to featherweight at 145) and 162.5(half way to welterweight at 170). This was because a fighter with 8 fights at lightweight and one at welterweight would be categorised as a middleweight if using the max limit of 155.

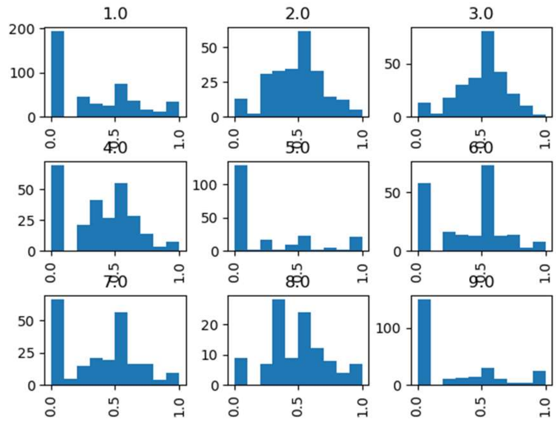
The data was tested and found that the maximum weight classes each fighter had fought at was 4. Open weight classes were not included as there was no weight information.

D. Test Assumptions

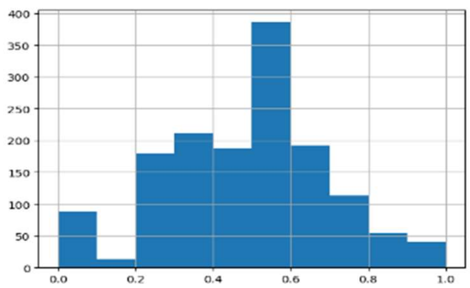
This dataframe was then used for the Kruskal Wallis for Primary Styles and the Kruskal Wallis Primary and Secondary Pairings. Histograms were produced to test whether the assumptions for this test was met. In particular, that the assumption that the data had similar distributions.

It was found that there were bimodal distributions with peaks occurring around Win Rates of 0 and 0.5. There was some deviation within the height of the peaks in the pairing data, but each histogram had the same format, so the assumption of similar distributions was accepted. The other assumptions (random sampling, independence, and ordinal variables) were also met by the nature of the data.





A second dataframe was created containing fighters with three fights or more. This had an approximately normal win rate, so was used as the data for the One- and Two-Way ANOVA tests, weight class and gender being included. Following the creation of a histogram to confirm approximate normality, Levene's test was carried out to confirm homogeneity of variances. It was found that the variances were not significantly different form each other, p = 0.502. The other assumptions were met by the nature of the data.

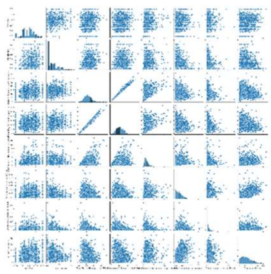


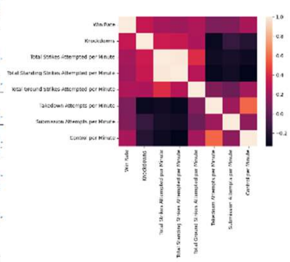
A third dataframe was created as a copy of the Kruskal Wallis dataframe, but converted Wrestling and Ground Game back into Grappling, for the purpose of a Mann Whitney U test. The assumptions of this test were met by the nature of the data, so no tests were carried out. A fourth dataframe, named EVOV, was created containing the number of fights of each style against the other styles. This was then used to calculate the expected values and how well each style did against each other. Each of these dataframes were then converted to csv files for analysis via Excel and SPSS.

A fifth dataframe was created with contained a list of fighters and the mean number of strikes, takedowns, submissions and control they had per fight, as well as their win rate. This dataframe was then used to create a multiple linear regression model.

E. Multiple Linear Regression Model

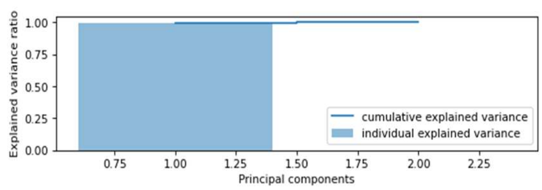
This dataset also only used fighters that had more than 3 fights in the UFC to ensure normality. A pair plot was created to test for linearity. It was found that while there wasn't perfect linearity, there was limited enough structure to justify creating the model anyway. A correlation heatmap was created. This showed that there was limited correlation between the predictor and dependent variables. However, it was decided to continue with the model anyway. The correlation plot also showed multicollinearity, particularly between 'Standing Strikes' and 'Total Strikes', and 'Takedowns' and 'Control'. It was decided to remove 'Total Strikes' from the model.





F. Principal Component Analysis

It was decided to perform dimension reduction on 'Takedowns' and 'Control' via Principal Component Analysis. The resulting PCA variable was then combined with the remaining variables for the regression model.



G. Classification Model

Given that there was inadequacies in the Multiple Linear Regression model, a Binary Logistic Regression model was also created. Correlations were tested to see which variables had a relevant relationship with the Result. These were then tested for multicollinearity and reduced where necessary.

The assumption of size was then tested. The guideline stated that there should be 10 rows for each variable used and divided by the least common expected output. Given that the result was binary, there were 8 variables being used, this was calculated as 160, which was much lower than the 13,000 rows in use.

IV. Results

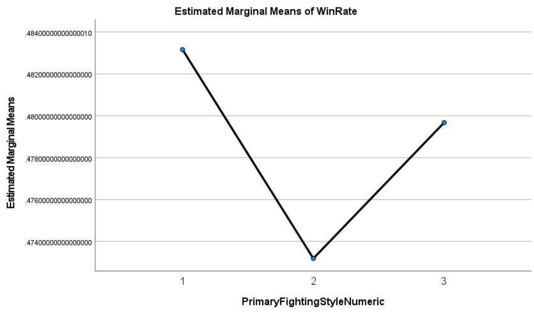
The purpose of the project was to answer the question: “what is the most effective fighting style for the purpose of winning a fight”. Thus, the first method of looking at this was to compare each style. Initially, a One-Way ANOVA test was run. All tests were run at $\alpha = 0.05$.

A. ANOVA Test

A One-Way ANOVA test was run was the relevant dataset. The hypotheses were:

- H0: There was no mean difference between the win rates of striking, wrestling and ground game.
- H1: There was a mean difference between the win rates of striking, wrestling and ground game.

It was found that there was no significant mean difference between win rates on the basis of fighting styles, $F_{stat}(2,2241) = 0.264$, $p = 0.768$. Thus, the null hypothesis failed to be rejected. From the Estimated Marginal Means Plot, there was a very marginal increase in striking, however, not nearly enough to be considered significant.



A. Mann Whitney U

A Mann Whitney U test was then run. The hypotheses were:

- H0: There was no median difference between striking and grappling.
- H1: There was a median difference between striking and grappling.

It was found that there was a significant median difference between striking and the grappling styles, $z_{stat}(1465) = -5.974$, $p < 0.01$.

Thus, the null hypothesis was rejected. Looking at the means between the two, the test followed the logic of the previous one. That is, there was a significant increase in striking than in grappling.

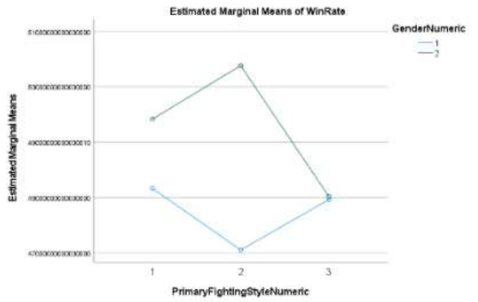
B. Two Way ANOVAs

Two Two-Way ANOVA Tests were then run. These were similar to the prior ANOVA test, accounting for interaction based on different variables. Again, they only used fighters with more than 3 fights in the UFC. The first variable to be tested was gender. The hypotheses were:

- $H_{1,0}$: There was no mean difference on win rate when accounting for fighting styles.
  $H_{1,1}$: There was a mean difference on win rate when accounting for fighting styles.
- $H_{2,0}$: There was no mean difference on win rate when accounting for gender.
  $H_{2,1}$: There was a mean difference on win rate when accounting for gender.
- $H_{3,0}$: There was no interaction effect between fighting styles and gender.
  $H_{3,1}$: There was an interaction effect between fighting styles and gender.

It was found that there was no mean difference on win rate when accounting for fighting style, $F_{stat}(2, 1465) = 0.056$, $p = 0.946$. There was also no mean difference on win rate when accounting for gender, $F_{stat}(1, 1465) = 0.530$, $p = 0.467$. There was also no significant interaction effect between fighting style and weight class, $F_{stat}(2, 1465) = 0.163$, $p = 0.850$.

Thus, all null hypotheses failed to be rejected. As can be seen from the estimated means plot below, whilst there is deviation in the shape, this deviation all lies within a win rate differential of 3%, which means that the deviation is not significant.

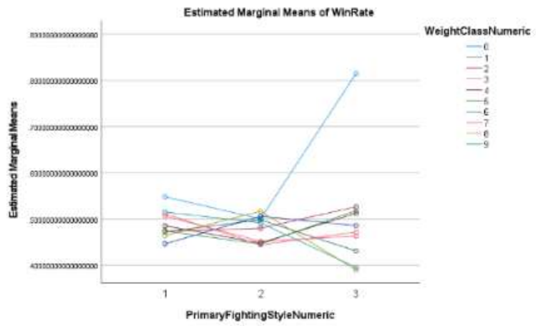


The second variable to be tested was weight class. The hypotheses were:

- $H_{1,0}$: There was no mean difference on win rate when accounting for fighting styles.
  $H_{1,1}$: There was a mean difference on win rate when accounting for fighting styles.
- $H_{2,0}$: There was no mean difference on win rate when accounting for weight class.
  $H_{2,1}$: There was a mean difference on win rate when accounting for weight class.
- $H_{3,0}$: There was no interaction effect between fighting styles and weight class.
  $H_{3,1}$: There was an interaction effect between fighting styles and weight class.

It was found that there was no mean difference on win rate when accounting for fighting style, $F_{stat}(2, 1465) = 0.410$, $p = 0.664$. There was also no mean difference on win rate when accounting for weight class, $F_{stat}(9, 1465) = 0.695$, $p = 0.714$. However, there was a significant interaction effect between fighting style and weight class, $F_{stat}(18, 1465) = 1.693$, $p = 0.034$.

Specifically, it was found that there was some interaction between weight class and fighting style, but that generally speaking, there was no difference across the means. The one exception occurred in open weight, where ground game had a significantly higher mean win rate than other ground game fighters in different weight classes and also open weight strikers and wrestlers.

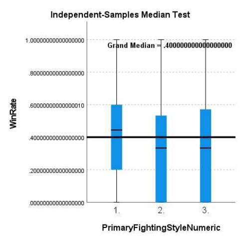


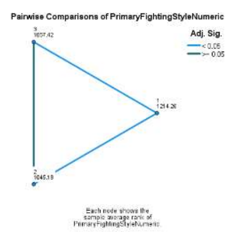
C. Kruskal Wallis

A Kruskal Wallis test was run. The hypotheses were:

- H0: There was no median difference between the win rates of striking, wrestling and ground game.
- H1: There was a median difference between the win rates of striking, wrestling and ground game.

It was found that there was a significant difference between the medians of the three groups, $F_{stat}(2, 2241) = 24.913$, $p < 0.001$. A Tukey Post Hoc Test was then run. The Tukey test found that Striking had a higher likelihood of winning than wrestlers or jiu jitsu practitioners. The tests also found that there was no significant difference between Wrestling and Jiu Jitsu.





D. Kruskal Wallis (9 way)

A 9-way Kruskal Wallis was run. This was to test whether there was a significant difference between style pairings. The pairings were set into groups 1 to 9. It was felt that the positioning of the primary fighting style was significant, so the combinations such as Striking-Wrestling and Wrestling-Striking were kept separate.

	Fighter	Number of Wins	Number of Losses	Total Fights	Gender	Gender Numeric	Percentage of Wrestling Evals	Percentage of Striking Evals	Percentage of Ground Game Evals	Win Rate	Primary Fighting Style	Primary Fighting Style Numeric	Secondary Fighting Style	Secondary Fighting Style Numeric	Weight Class
0	Scott Morris	1.0	1.0	2.0	Men	1	0.000000	0.000000	100.0	0.500000	Ground Game	3.0	Ground Game	3.0	Open Weight
1	Patrick Smith	4.0	1.0	5.0	Men	1	20.000000	40.000000	40.0	0.800000	Ground Game	3.0	Striking	1.0	Open Weight
2	Johnny Rhodes	2.0	1.0	3.0	Men	1	33.333333	66.666667	0.0	0.666667	Striking	1.0	Wrestling	2.0	Open Weight
3	Frank Hamaker	1.0	0.0	1.0	Men	1	0.000000	0.000000	100.0	1.000000	Ground Game	3.0	Ground Game	3.0	Open Weight
4	Orlando Wiet	1.0	1.0	2.0	Men	1	0.000000	50.000000	50.0	0.500000	Ground Game	3.0	Striking	1.0	Open Weight

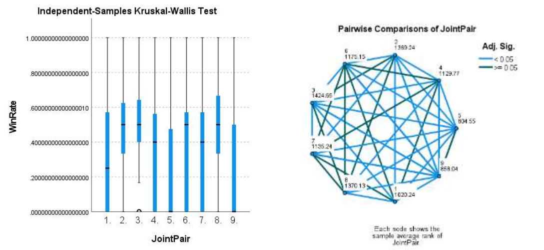
```
KruskalWallisTest['Combined Fighting Style Numeric'] = (KruskalWallisTest['Primary Fighting Style Numeric']*3+
                                                        KruskalWallisTest['Secondary Fighting Style Numeric']-3)
KruskalWallisTest.hist(column='Win Rate', by=['Combined Fighting Style Numeric'])
```

Only writing for the general hypothesis, the hypotheses were:

- H0: There was no median difference on win rate when accounting for two given pairings of fighting styles.
  H1: There was a median difference on win rate when accounting for two given pairings of fighting styles.

Most of the results here were significant. Of the 36 relationships, 24 were found to be significant enough to reject the null hypothesis. 7 were found to not be sufficiently significant and so these null hypotheses failed to be rejected. However, when the results were adjusted to account for Bonferroni's rule, it was found that there were 12 relationships that were not significant. In particular, it was found that there was no significant differences between: 2 and 3, 2 and 8, 3 and 8, 6 and 8, 7 and 6, 4 and 6, 4 and 7, 1 and 6, 1 and 7, 1 and 4, 5 and 9, and, 7 and 8. All other pairings had significant differences.

There seemed to be a generally lower score for pairings that had two of the same style. It was found that a combination of striking with ground game was the highest scorer, with striking & wrestling, and wrestling & ground game also having noticeably higher scores.



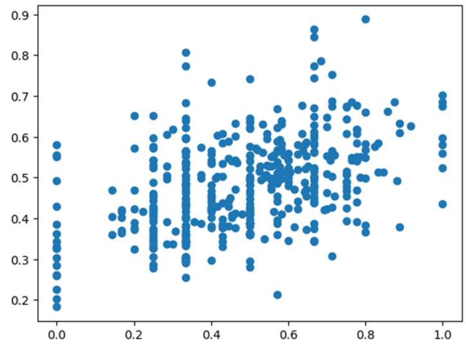
E. Expected Values vs Observed Values

A test was conducted to compare how each fighting style did against another. This test was quite crude, and looked purely at how many times each style fought each other and what proportion of each style won. This was calculated using the EVOV dataset. It was found that, more often than not, ground game fighters beat Strikers and Wrestlers, and Strikers fared better against Wrestlers. The results were that Ground beat Strikers 54% of the time, Ground beat Wrestlers 52% of the time and Strikers beat Wrestlers 53% of the time.

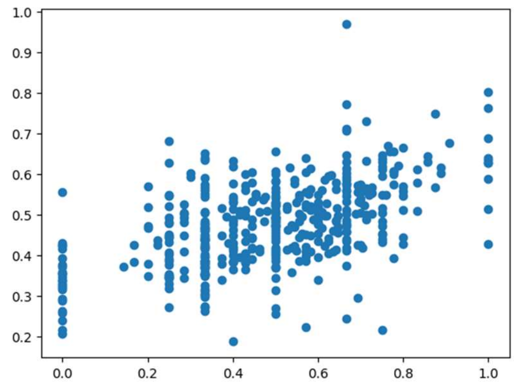
F. Multiple Linear Regression

Subsequent to the means and median testing, a multiple linear regression model was calculated. The model used the mean number of total strikes, standing strikes, and ground strikes attempted per minute, knockdowns, submissions attempted per minute, control per minute and takedowns attempted per minute for each fighter. The model only used data from fighters with more than 3 fights, so that the data would be approximately normal.

The model was then calculated. As to be expected, the model was poor. While it was homoscedastic, the residuals were quite spread out and there were some outliers. The programme also outputted differently effective models every time it was run. The adjusted R Squared Value for these models hovered between 0.19 and 0.27. It was found that the most substantial factors were the number of attempted submissions and the number of knockdowns per fighter.



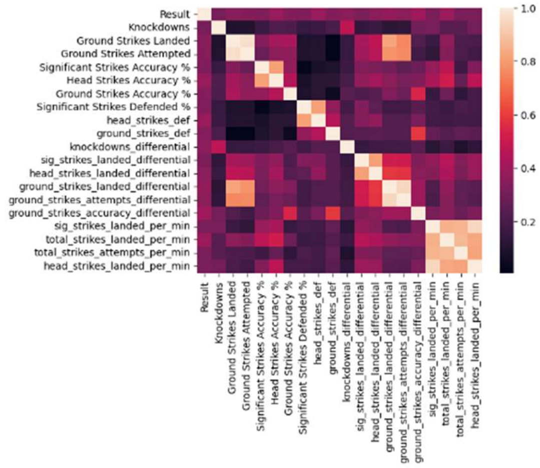
The model was attempted to be improved by utilising backwards stepwise regression, which recommended the removal of Ground Strikes. A further model was created excluding this variable, which slightly improved the model. Again, these figures jumped around, but the Adjusted R Squared Values hovered between of 0.23 and 0.29.



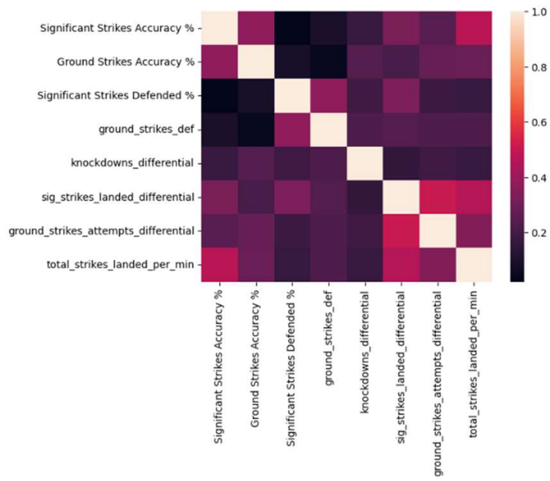
G. Classification Model

Further to the poor results from the linear regression, a logistic regression model was created on the full UFC Data. The goal of this model was to test it's effectiveness and what variables would be contributory. It was crucial to reduce these variables from 530. Thus, the full correlation matrix was calculated into a dataframe was made out of this correlation matrix. The variables that had correlation with Win Rate above 0.3 was then taken out. These were then tested for multicollinearity.

The most notable thing here was that the variables with the highest correlation with results were all striking data. There were multicollinearity issues, so some of these variables were dropped. Examples included 'Ground Strikes Attempted' and 'Ground Strikes Landed', and 'Significant Strikes Per Min', 'Head Strikes Per Minute' and 'Strikes Attempted Per Minute' and 'Strikes Landed Per Minute'.



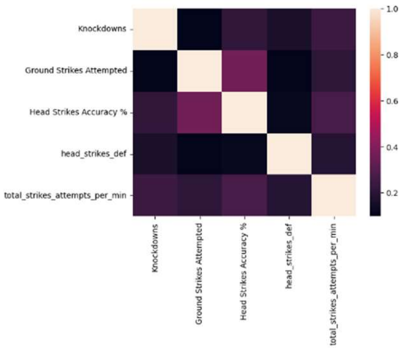
Given that the previous multiple linear regression model had focused on attempts, it was decided to focus on differentials here. The data was split into 70% training and 30% evaluation. A model was made using the data in the correlation matrix below. This model had minimal multicollinearity.



The model was then evaluated using the test data with an F1 score of 0.81, showing that the model was very good at predicting each result from this data. However, contextually, this would be expected as the variables included differentials – how many more strikes were engaged in by the winner vs the loser.

	precision	recall	f1-score	support
0	0.80	0.83	0.81	1957
1	0.82	0.79	0.80	1957
accuracy			0.81	3914
macro avg	0.81	0.81	0.81	3914
weighted avg	0.81	0.81	0.81	3914

Thus, another model was created using the remaining variables. These models were then tested for multicollinearity. A model was made using the data in the correlation matrix below.



This model was then evaluated with an F1 score of 0.8. Thus, while the previous data had the caveat of only using differentials, this dataset focused solely on objective output by each fighter and had a similarly strong model.

	precision	recall	f1-score	support
0	0.78	0.82	0.80	1957
1	0.81	0.77	0.79	1957
accuracy			0.80	3914
macro avg	0.80	0.80	0.80	3914
weighted avg	0.80	0.80	0.80	3914

V. Conclusions

It was found that striking is the most effective style for physical combat based on the analysis shown. It was found from the Kruskal Wallis test that when accounting for only experienced fighters (with more than three fights), fighters who primarily used striking had higher win rates than fighters who primarily used wrestling and ground game. It was also found in the Pairing Kruskal Wallis test that the best pairings was striking with ground game, with striking and wrestling and wrestling and ground game being the next best.

Furthermore, the regression and classification models show that striking variables made up a significant proportion of the models. In particular, the classification models, which were much more effective predictors, were consisted of almost exclusively striking variables, the minor exception being ground strikes which could be applicable to wrestling and ground game.

However, it was found that ground game fighters were the most effective when looking at observed vs expected results, with better results against wrestlers and strikers. Ground game was also the most effective style when looking at open weight competitions, meaning that this may be more effective for a smaller person. This is also supported by the Ground Game encompassing the most effective pairing.

VI. Acknowledgements

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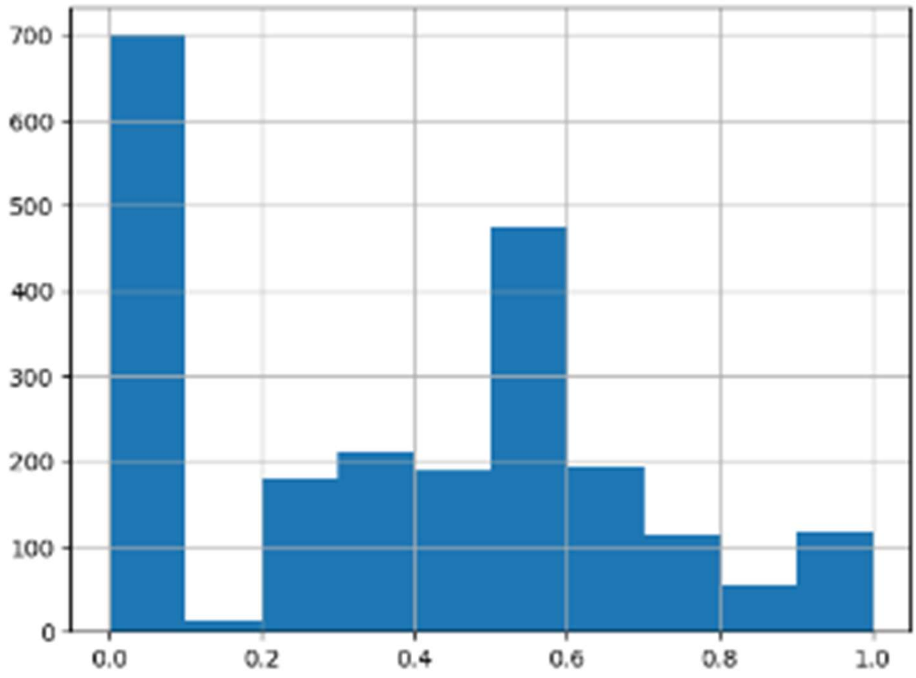
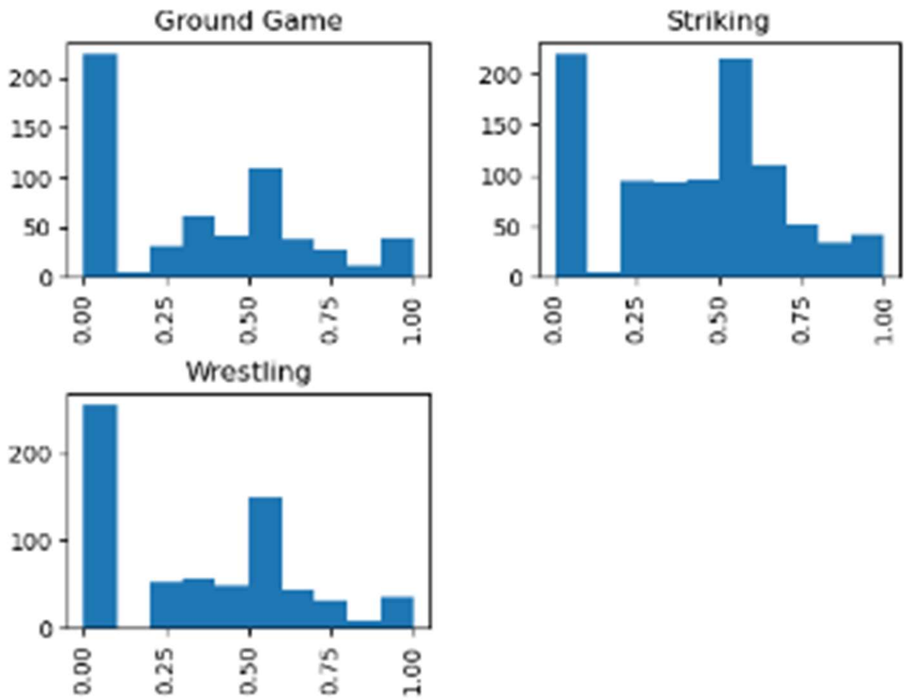
VIII. Appendices

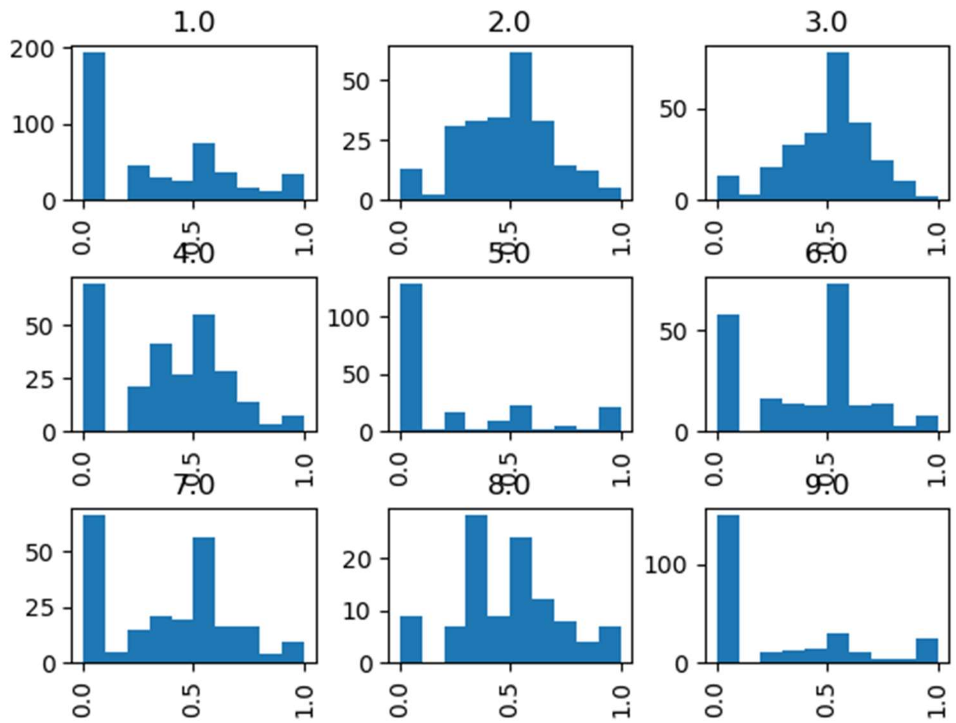
Kruskal wallis Histogram



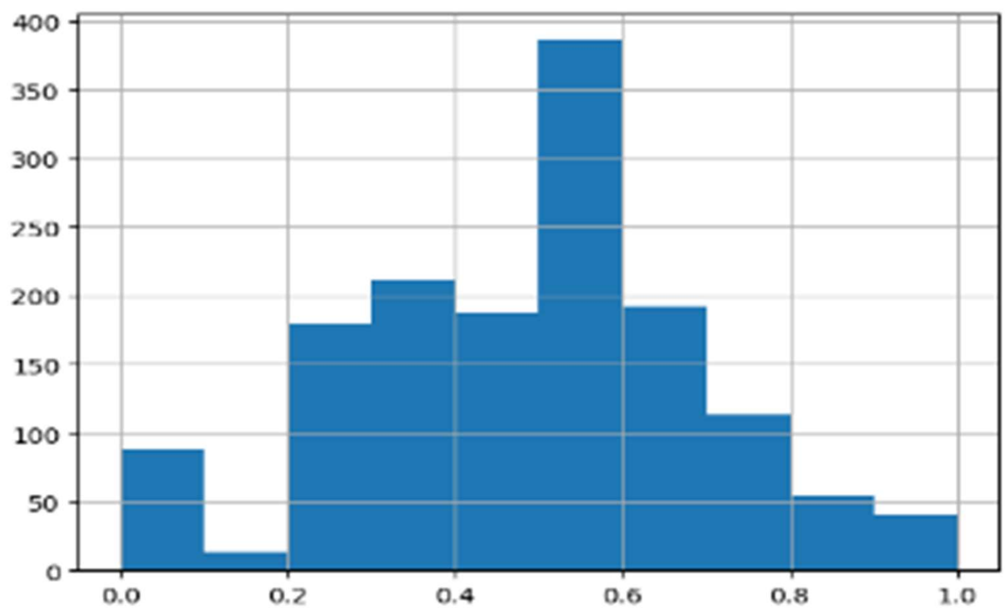
Kruskal Wallis Histogram by Fighting Style



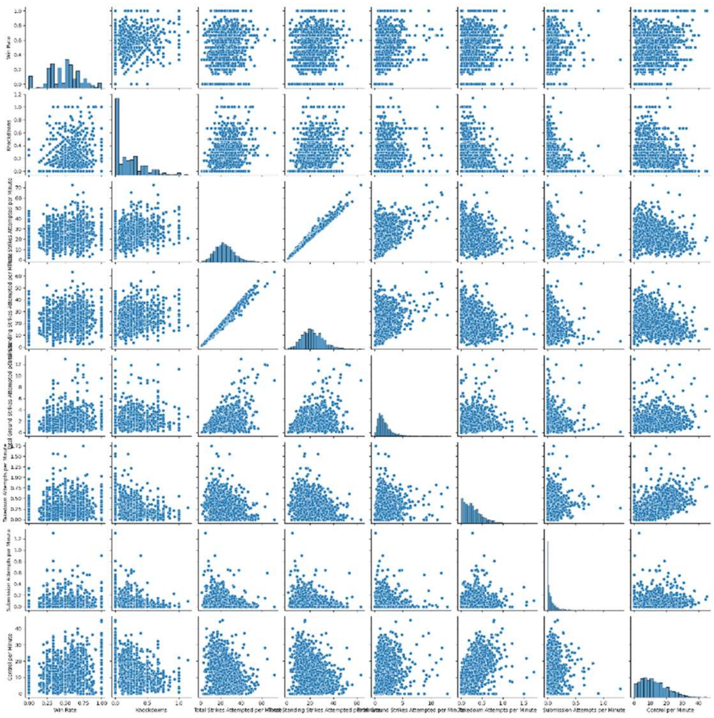
Kruskal Wallis Histogram by Primary and Secondary Fighting Style Pairing



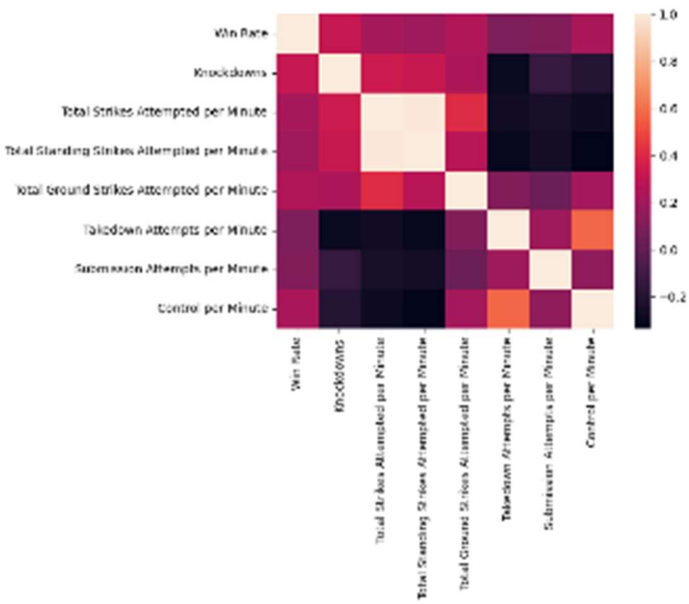
ANOVA Histogram



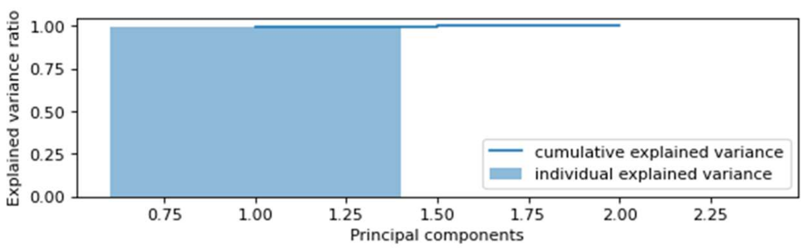
Pairplot for Regression Model

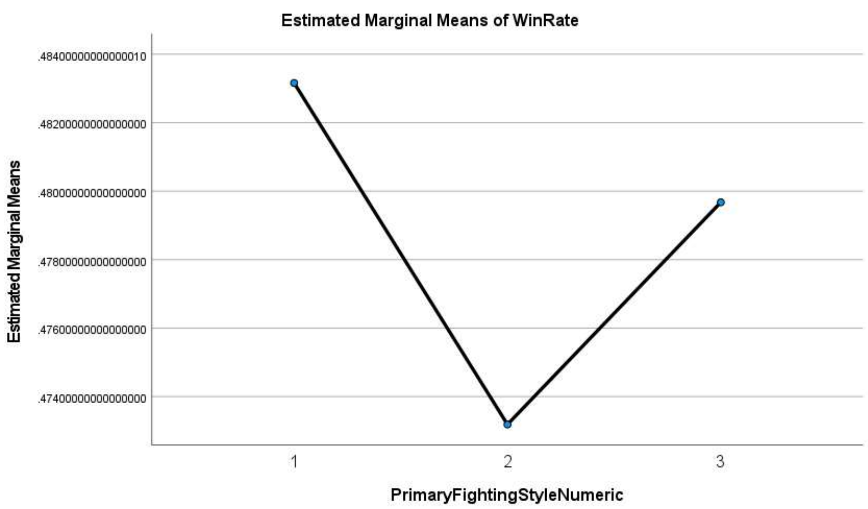


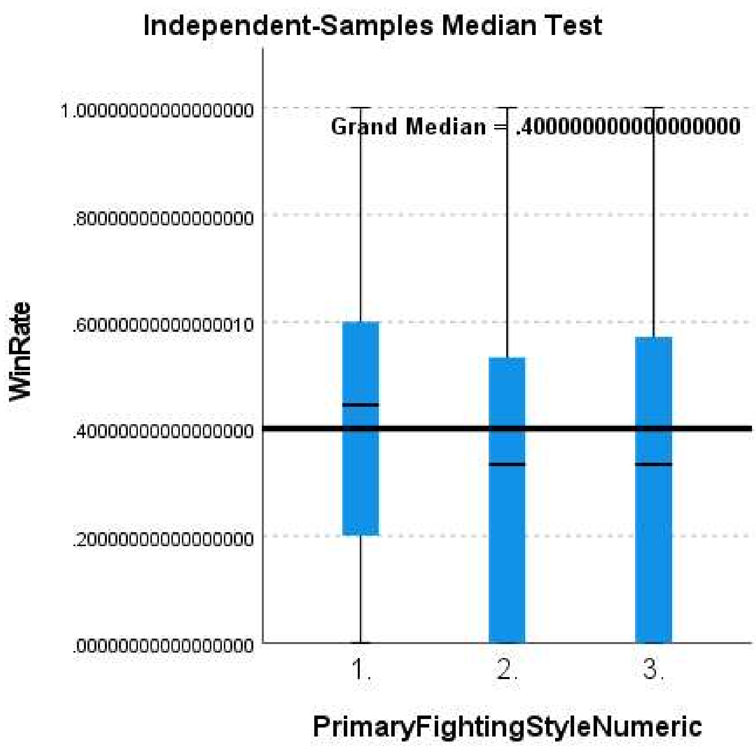
Correlation Plot for Regression Model

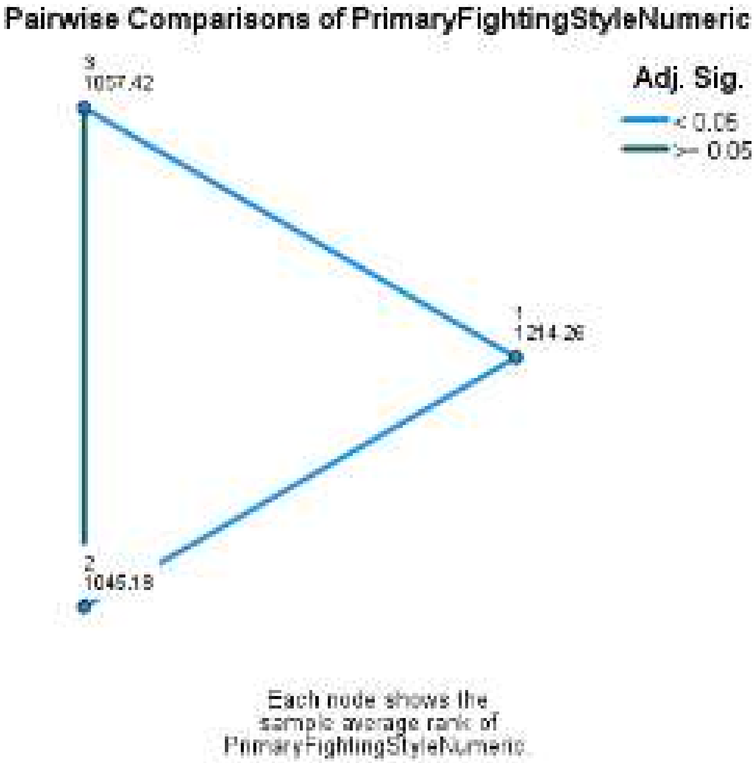


PCA Cumulative Plot

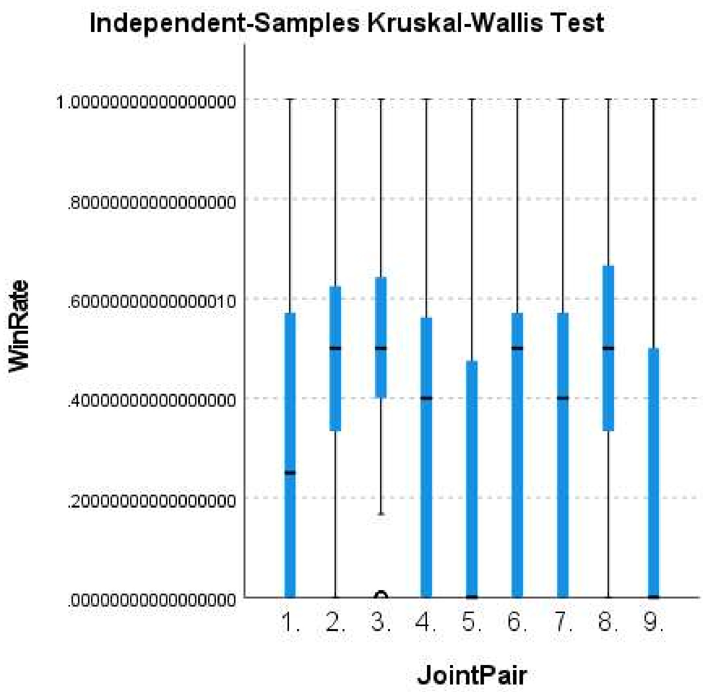



Estimated Marginal Means of WinRate
Estimated Marginal Means
.48400000000000010
.48200000000000000
.48000000000000000
.47800000000000000
.47600000000000000
.47400000000000000
1
2
3
PrimaryFightingStyleNumeric


Independent-Samples Median Test
Grand Median = .400000000000000000
WinRate
1.00000000000000000
.800000000000000000
.600000000000000010
.400000000000000000
.200000000000000000
.000000000000000000
1.
2.
3.
PrimaryFightingStyleNumeric



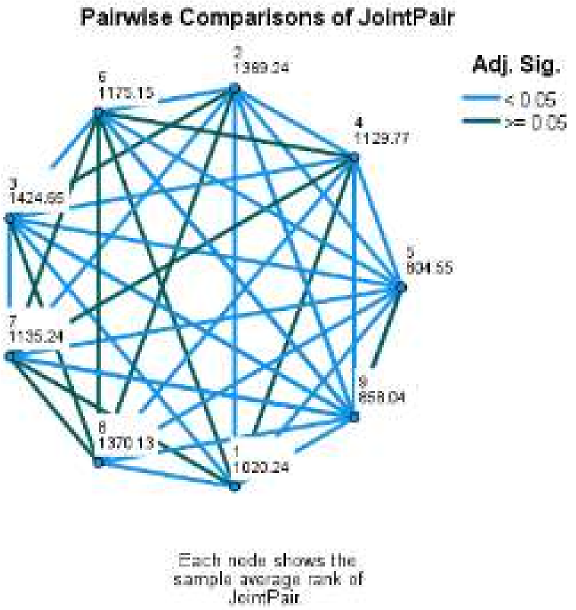
Pairwise Comparisons of PrimaryFightingStyleNumeric
3
1057.42
Adj. Sig.
< 0.05
>= 0.05
1
1214.26
2
1045.19
Each node shows the sample average rank of PrimaryFightingStyleNumeric.

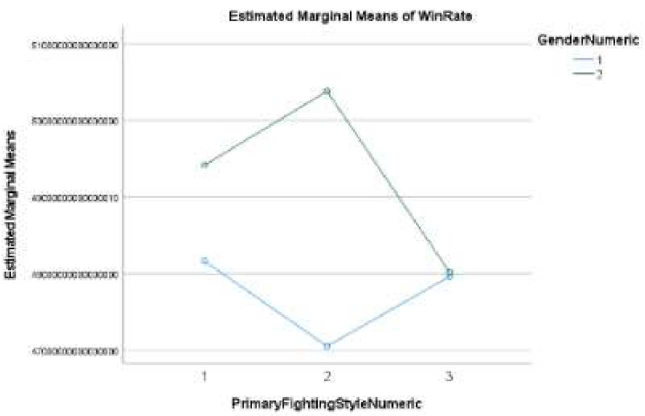


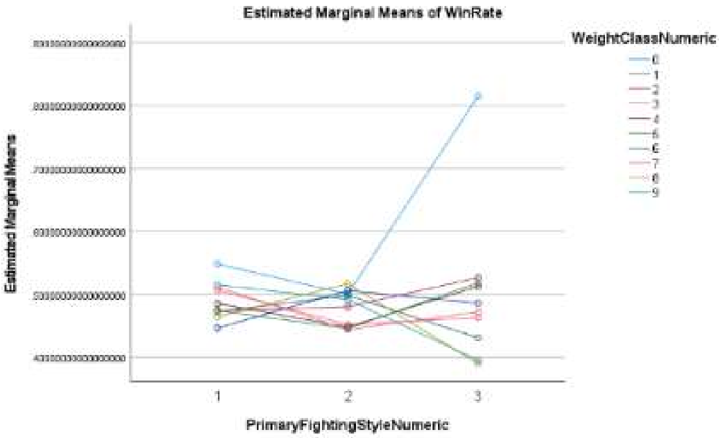
Independent-Samples Kruskal-Wallis Test
1.00000000000000000
.80000000000000000
.60000000000000010
.40000000000000000
.20000000000000000
.00000000000000000
WinRate
1. 2. 3. 4. 5. 6. 7. 8. 9.
JointPair

	Fighter	Number of Wins	Number of Losses	Total Fights	Gender	Gender Numeric	Percentage of Wrestling Evals	Percentage of Striking Evals	Percentage of Ground Game Evals	Win Rate	Primary Fighting Style	Primary Fighting Style Numeric	Secondary Fighting Style	Secondary Fighting Style Numeric	Weight Class
0	Scott Morris	1.0	1.0	2.0	Men	1	0.000000	0.000000	100.0	0.500000	Ground Game	3.0	Ground Game	3.0	Open Weight
1	Patrick Smith	4.0	1.0	5.0	Men	1	20.000000	40.000000	40.0	0.800000	Ground Game	3.0	Striking	1.0	Open Weight
2	Johnny Rhodes	2.0	1.0	3.0	Men	1	33.333333	66.666667	0.0	0.666667	Striking	1.0	Wrestling	2.0	Open Weight
3	Frank Hamaker	1.0	0.0	1.0	Men	1	0.000000	0.000000	100.0	1.000000	Ground Game	3.0	Ground Game	3.0	Open Weight
4	Orlando Wiet	1.0	1.0	2.0	Men	1	0.000000	50.000000	50.0	0.500000	Ground Game	3.0	Striking	1.0	Open Weight

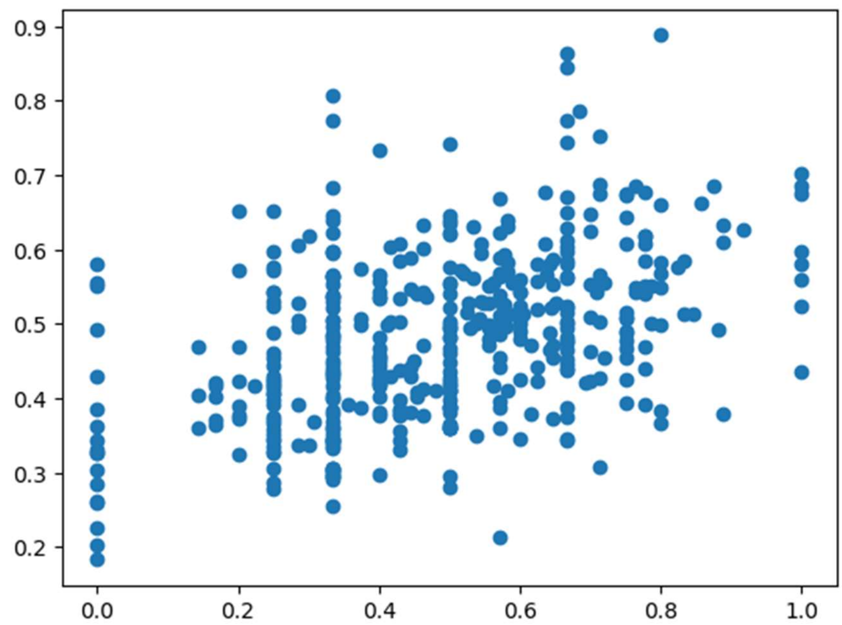
```
KruskalWallisTest['Combined Fighting Style Numeric'] = (KruskalWallisTest['Primary Fighting Style Numeric']*3+
                                                        KruskalWallisTest['Secondary Fighting Style Numeric']-3)
KruskalWallisTest.hist(column='Win Rate', by=['Combined Fighting Style Numeric'])
```



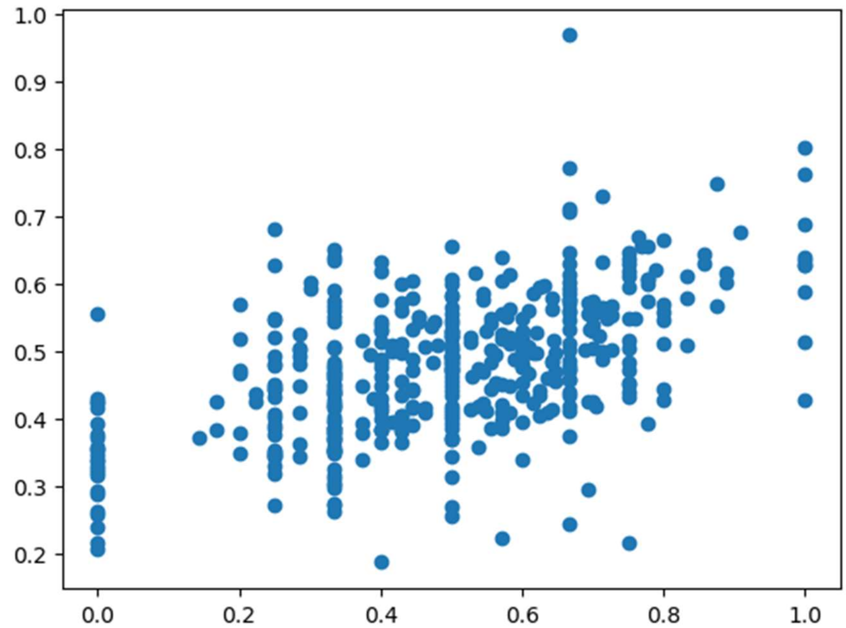



Estimated Marginal Means of WinRate
Estimated Marginal Means
1
2
3
PrimaryFightingStyleNumeric
WeightClassNumeric
1
2
3
4
6
7
9

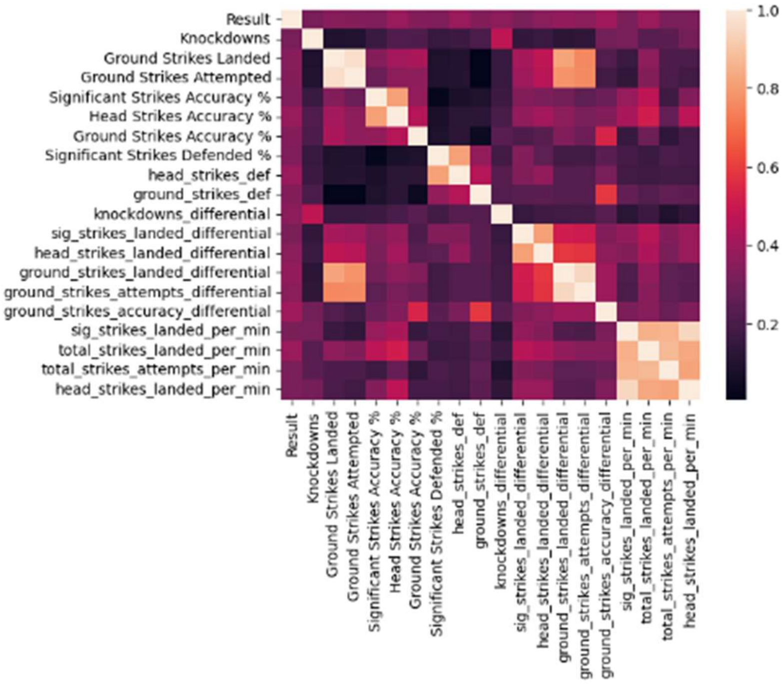
Residual Plot vs Fitted Values for First Regression Model



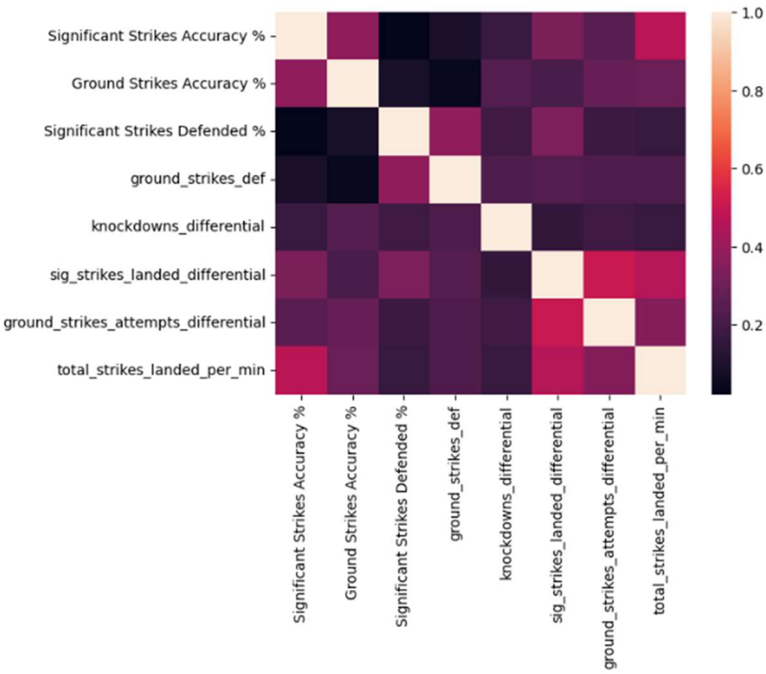
Residual Plot vs Fitted Values for Second Regression Model



Correlation Plot for all relevant Variables in Classification



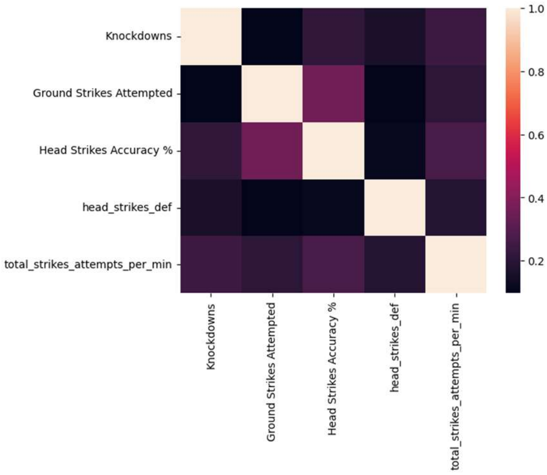
Correlation Plot for Classification Model 1



Classification Report for Classification Model 1

	precision	recall	f1-score	support
0	0.80	0.83	0.81	1957
1	0.82	0.79	0.80	1957
accuracy			0.81	3914
macro avg	0.81	0.81	0.81	3914
weighted avg	0.81	0.81	0.81	3914

Correlation Plot for Classification Model 2



Classification Report for Classification Model 1

	precision	recall	f1-score	support
0	0.78	0.82	0.80	1957
1	0.81	0.77	0.79	1957
accuracy			0.80	3914
macro avg	0.80	0.80	0.80	3914
weighted avg	0.80	0.80	0.80	3914