An Investigation In To The Variables That Make a Fighter Successful in the Ultimate Fighting Championship

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1.0 Introduction and Research Questions

Statistical analysis of sports data to understand important variables for match predictions has been a study of the machine learning literature in the last 10 years[1], [2]. Predominantly focused on well established sports, more niche sports like mixed martial arts (MMA) have been largely ignored [3]. MMA presents an interesting problem, as a fighters skill set appears to be an important predictor of the winner of a fight (28 current champions are wrestlers, whilst 6 are kickboxers). All martial arts specialise in one method of winning either knockouts (from standing position) or submissions (from ground position). As both are permitted in MMA, a successful fighter must amalgamate two or more traditional martial arts categories to be successful. As there is currently no accurate way to describe a fighters style or understanding of the success of a style the first research question is:

1: Can infight statistics and a fighters physical attributes be used to define styles and what is the difference in win rate of each style?

Additionally if styles are considered important predictors for a fight, differences between the attributes used to define styles are likely to provide important information in to what makes a fighter successful, prompting the second research question:

2. What are the important physical attribute and skill differences between fighters when predicting the outcome of a fight?

1.1 Data Sources and Analytical Process

This experiment defined the style of a fighter as their physical attributes, age/height/weight, plus their proficiency in martial arts. Defining proficiency in a quantitative fashion is difficult as it can change across a fighters career, with the potential of fighters to show different styles against different opponents. Additionally, unlike traditional sports where matches our played on an almost weekly basis, a fighter may only have 5 to 10 fights in his career, making consideration of individual fighters statistically insignificant. To circumvent this, data was anonymised of fighters and each fight considered as two skill data points, with infight statistics representing a fighters proficiency in martial arts. Two data sets were merged a kaggle data set[4] containing fight statistics e.g punches thrown and a second webscaped dataset from “sherdog.com” containing physical attributes of a fighter, yielding 8282 rows of data with 39 fields. Web Scraping was achieved by manipulating a web scraping tool[5] available on GitHub. Unsupervised clustering methods were compared on the dataset, the resulting clusters were defined using domain knowledge and the average win rate for each cluster plotted.

The dataset was manipulated, to answer the second research question, forming cumulative differences in fighter level statistics up until the point of the fight and features engineered. The dataset from question 1 was not used as predicting a winner from infight statistics, would be using future knowledge to predict past events. Dataset were shuffled to remove bias of favourite (present in the original dataset) and models fitted and evaluated for feature importance.

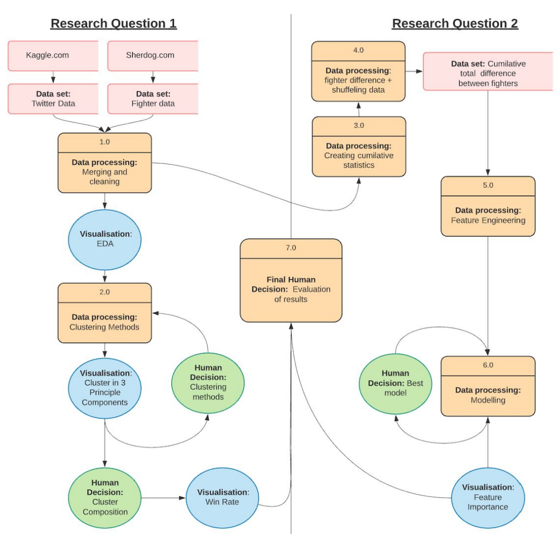

Figure 1: Research steps followed.

2.0 Findings and Discussion

2.1 Can infight statistics and a fighters physical attributes be used to define styles? what is the difference in win rate of each style?

Modeling method of winning as a crude approximation of style by weight class highlighted that weight was likely a factor in determining style. Higher weight divisions showed an increased likelihood fights would be won by knockout early and decreased the likelihood a fight would go to a decision.

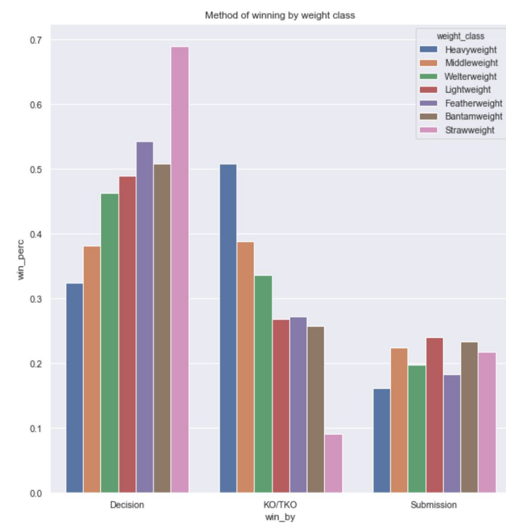

Figure 2: Winning method by weight class.

Conceptually this made sense as the more weight behind a punch the harder the hit. Examining physical attribute differences showed that older fighters were less likely to win a fight, with no observable difference in height within a weight class between winners and losers.

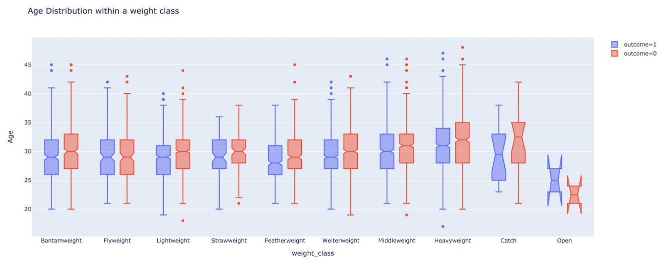

Figure 3: Distribution of age by win or loss

Infight statistics were highly correlated with one another showing the first hint of skills, i.e a fighter that threw a large number of punches to the head also through a large number of punches to the body, indicating he/she was a skilled striker.

Clustering algorithms were applied to low correlation features and evaluated over the 3 main principle components.

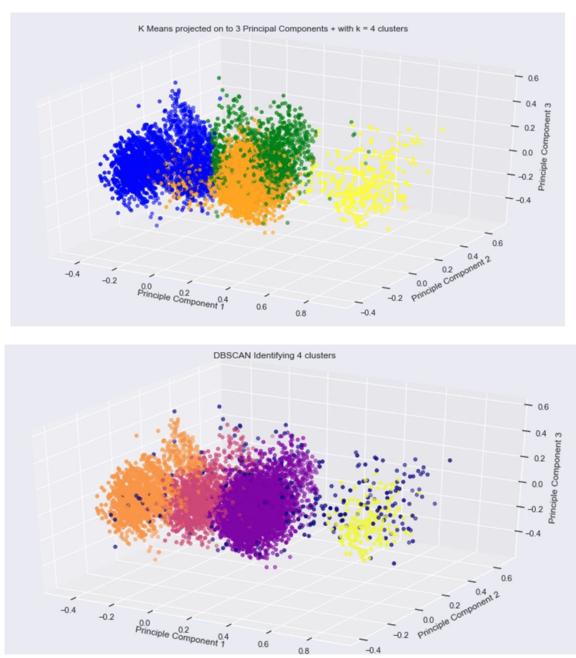

Figure 4: *top* 4 clusters identified using K means, *bottom* 4 clusters identified with DBSCAN and unclassified data points in dark blue.

K-means was unable to resolve clusters effectively whilst DBSCAN showed better resolutions with a small number of unclassified points, the averages of each cluster from DBSCAN were plotted on a parallel coordinates map, figure 5 and 4 distinct fighting styles defined in Figure 6.

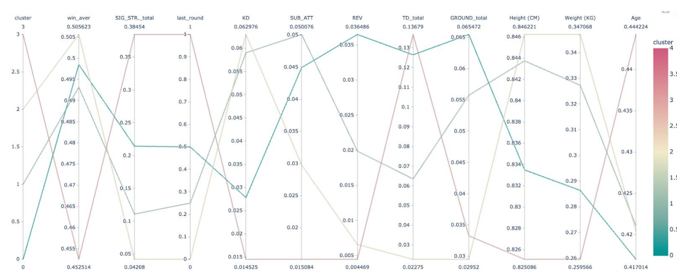

Figure 5: Cluster averages across variables.

Cluster Number	Description
Cluster 0: Generalists	• Good striking ability (High significant strikes) • High reversals and summission_att show good ground game • Cross between striking (muay thai/boxing) and BJJ (grappling)
Cluster 1: Excessively Offensive	• High knock downs and high submissions show very offensive • Lower win rate and no reversals shows poor defensive game • Striking athletes that go for a finish often but have poor defenses
Cluster 2: Power Athletes	• high body weight, high knock downs, high win rate, fights finish early • Few strikes thrown but are effective when they land • Poor grappling game, mainly heavy boxers
Cluster 3: Older Wrestlers	• Large number of takedowns (wrestler) but can't submit people • Fights are won by decision not knockout • Older athletes with lower win ratio

Figure 6: Cluster descriptions.

Interestingly the points that DBSCAN was not able to classify were also added to the parallel coordinates with the next two highest win averages but outperformed them by 15%, as well as showing significantly better infight variables. Although this behaviour seems bizarre DBSCAN is noted in literature for it anomaly detection ability[6]. When evaluating fighters in this smaller cluster it appeared to contain the majority of the UFC champions.

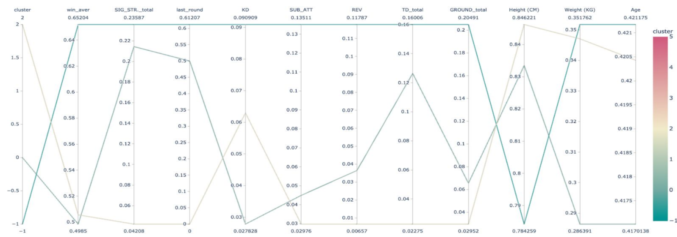

Figure 7: Anomalies from DBSCAN (cluster -1) with the next two highest win rate clusters.

Finally plotting the win rate of all the clusters (and the noise) to answer question 1 showed no significant difference in styles win rate with the exception of the outliers cluster, which had a significantly higher performance and was thus defined as a 'Champion' Cluster.

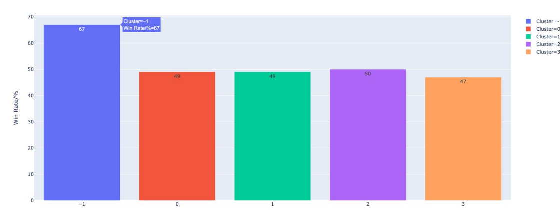

Figure 8: Average win rate by cluster.

2.2 What are the important physical attribute and skill differences between fighters when attempting to predict the outcome of a fight?

Models were fitted on cumulative difference between engineered skill features to find feature importance and direction. Logistic regression's poor R squared before and after backward elimination(significance of 0.01), led to a tree ensembles with depth limited to 3 (to aid explability) being used.

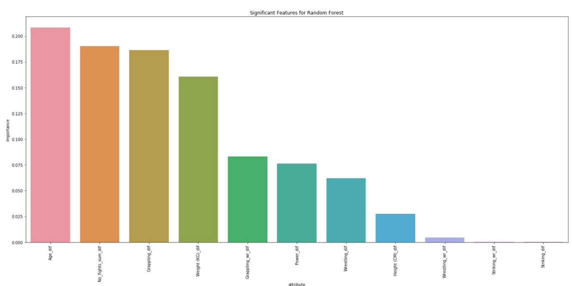

Figure 9: Feature importance for Random Forest.

Age and number of fights were the most important variables, with relationships in opposite directions, confusingly younger fighters are more likely to win, as are more experienced fighters. Showing gaining experience in MMA as a young age is essential. Difference in grappling ability was a large skill predictor for fight reconfirming the statistic from the introduction (majority of UFC champions are grapplers).

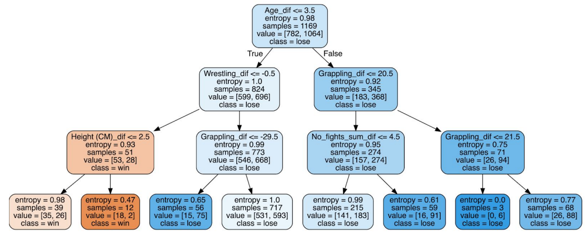

Figure 10: Random Tree from the random forest.

2.3 Application of Findings

For analysts attempting to predict fights findings are quite clear, basic information on fighters e.g. age, are hugely important for fight prediction. Secondly although striking is important in MMA (as fighter start from a standing position) the levels are fairly high for all fighters and difference are rarely significant, making it less important for prediction. Instead more niche wrestling skills are actually better predictors, thought to be due to the large disparity between fighters. Finally weight classes provide important skill clustering information and methods of finishing. Analyst looking at heavier weight classes need to weight predictive models to increase the importance of power statistics as power skill clusters are concentrated here, with knockouts being a significant method of finishing a fight. Champions are normally identified as complete outliers to the dataset and dominant across all skill categories, identifying these through cluster and including them as a variable of weighted importance is likely to improve models.

2.4 Potential Limitations and Biases

Weights of the athletes showed little variation and it was identified that a number of fighters had the weight of the weight class they competed in.

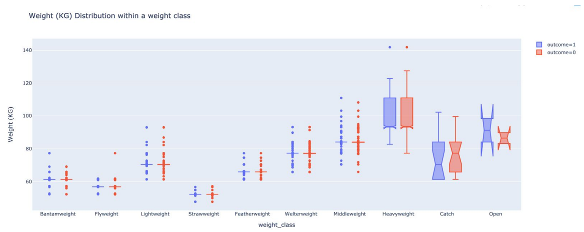

Figure 11: Distribution of fighters weights.

Its thought the reason for this is that fighters are weighed in a day prior to a fight, to make sure they are under a maximum limit. However it's a poor approximation of an athlete's weight as combat sports are notorious for “weight cutting”, with athletes losing as much as 30 lbs of water weight before a fight to weigh in, only to rehydrate and put the weight back on for the fight [7]. Secondly the distribution of fights by weight class was not even, with fewer fights for lower weight classes, biasing clustering styles towards heavier weight classes.

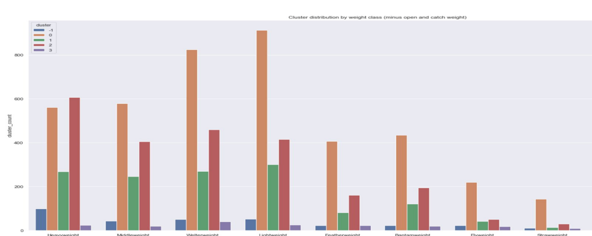

Figure 12: Clusters by weight class

Finally in the DBSCAN, the anomaly cluster showed quite significant overlap with another cluster unfortunately no amount of adjustment of epsilon could improve this.

3.0 Appendix

3.1 Future work-The role of a club

Clear distinctions in clubs win rates can be seen in figure 13. Interesting future work would be to see how the skills of a fighter change based on the club he/she is part of. A club is likely to have skill leak from one fighter to another, as well as coaches at the club transfering similar skills to their fighters. Firstly seeing if certain skill clusters were represented highly at certain clubs and secondly if a fighters skill cluster changed when he/she changed club.

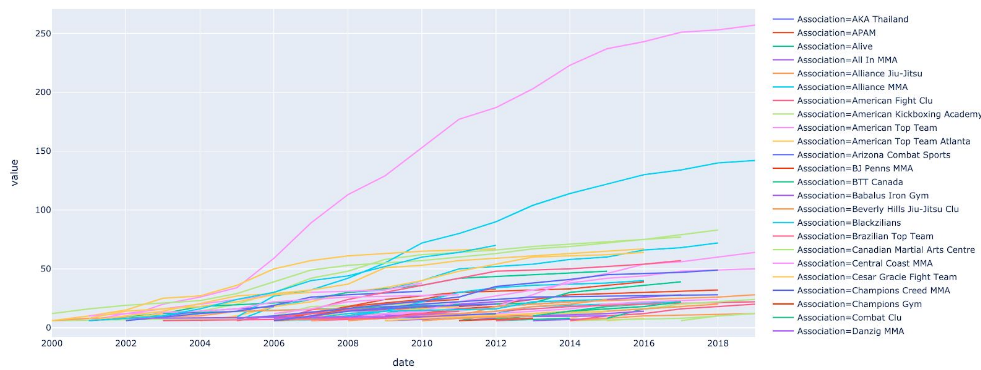

Figure 13: Count of Club wins over time.

4.0 References

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[4] Kaggle UFC fight data: https://www.kaggle.com/rajeevw/ufcdata#raw_total_fight_data.csv

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