Personal ADS Challenge of Filip Georgiev

The dataset used is "UFC-Fight historical data from 1993 to 2019" with the intention of trying to predict possible outcomes of fights.

In [1]:

```
#can be downloaded from https://www.kaggle.com/rajeevw/ufcdata
import pandas as pd
#remove restriction of max rows and columns when printing
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
ufc_data = pd.read_csv('D:\Programming\YEAR2\ADS\PersonalChallenge\data.csv', low_memor
y=False)
```

In [2]:

```
#remove future warning
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

EXPLORATORY DATA ANALYSIS

In [3]:

```
#seems that these columns are corrupted
print(ufc_data['B_draw'].value_counts(dropna = False))
print(ufc_data['R_draw'].value_counts(dropna = False))
```

```
0.0    5144
Name: B_draw, dtype: int64
0.0    5144
Name: R_draw, dtype: int64
```

In [4]:

```
#so we remove them
del ufc_data['B_draw']
del ufc_data['R_draw']
```

In [5]:

```
#use this for reference of the multitude of columns
ufc_data.head()
```

Out[5]:

	R_fighter	B_fighter	Referee	date	location	Winner	title_bout	weight_class	no_o
0	Henry Cejudo	Marlon Moraes	Marc Goddard	2019-06-08	Chicago, Illinois, USA	Red	True	Bantamweight	
1	Valentina Shevchenko	Jessica Eye	Robert Madrigal	2019-06-08	Chicago, Illinois, USA	Red	True	Women's Flyweight	
2	Tony Ferguson	Donald Cerrone	Dan Miragliotta	2019-06-08	Chicago, Illinois, USA	Red	False	Lightweight	
3	Jimmie Rivera	Petr Yan	Kevin MacDonald	2019-06-08	Chicago, Illinois, USA	Blue	False	Bantamweight	
4	Tai Tuivasa	Blagoy Ivanov	Dan Miragliotta	2019-06-08	Chicago, Illinois, USA	Blue	False	Heavyweight	

In [6]:

```
#look for null values and possible type mismatches
ufc_data.info(verbose=True, null_counts  = True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5144 entries, 0 to 5143
Data columns (total 143 columns):
R_fighter                     5144 non-null object
B_fighter                     5144 non-null object
Referee                       5121 non-null object
date                          5144 non-null object
location                      5144 non-null object
Winner                        5144 non-null object
title_bout                    5144 non-null bool
weight_class                  5144 non-null object
no_of_rounds                  5144 non-null int64
B_current_lose_streak         5144 non-null float64
B_current_win_streak          5144 non-null float64
B_avg_BODY_att                3879 non-null float64
B_avg_BODY_landed             3879 non-null float64
B_avg_CLINCH_att              3879 non-null float64
B_avg_CLINCH_landed           3879 non-null float64
B_avg_DISTANCE_att            3879 non-null float64
B_avg_DISTANCE_landed         3879 non-null float64
B_avg_GROUND_att              3879 non-null float64
B_avg_GROUND_landed           3879 non-null float64
B_avg_HEAD_att                3879 non-null float64
B_avg_HEAD_landed             3879 non-null float64
B_avg_KD                      3879 non-null float64
B_avg_LEG_att                 3879 non-null float64
B_avg_LEG_landed              3879 non-null float64
B_avg_PASS                    3879 non-null float64
B_avg_REV                     3879 non-null float64
B_avg_SIG_STR_att             3879 non-null float64
B_avg_SIG_STR_landed          3879 non-null float64
B_avg_SIG_STR_pct             3879 non-null float64
B_avg_SUB_ATT                 3879 non-null float64
B_avg_TD_att                  3879 non-null float64
B_avg_TD_landed               3879 non-null float64
B_avg_TD_pct                  3879 non-null float64
B_avg_TOTAL_STR_att           3879 non-null float64
B_avg_TOTAL_STR_landed        3879 non-null float64
B_longest_win_streak          5144 non-null float64
B_losses                      5144 non-null float64
B_avg_opp_BODY_att            3879 non-null float64
B_avg_opp_BODY_landed         3879 non-null float64
B_avg_opp_CLINCH_att          3879 non-null float64
B_avg_opp_CLINCH_landed       3879 non-null float64
B_avg_opp_DISTANCE_att        3879 non-null float64
B_avg_opp_DISTANCE_landed     3879 non-null float64
B_avg_opp_GROUND_att          3879 non-null float64
B_avg_opp_GROUND_landed       3879 non-null float64
B_avg_opp_HEAD_att            3879 non-null float64
B_avg_opp_HEAD_landed         3879 non-null float64
B_avg_opp_KD                  3879 non-null float64
B_avg_opp_LEG_att             3879 non-null float64
B_avg_opp_LEG_landed          3879 non-null float64
B_avg_opp_PASS                3879 non-null float64
B_avg_opp_REV                 3879 non-null float64
B_avg_opp_SIG_STR_att         3879 non-null float64
B_avg_opp_SIG_STR_landed      3879 non-null float64
B_avg_opp_SIG_STR_pct         3879 non-null float64
B_avg_opp_SUB_ATT             3879 non-null float64
B_avg_opp_TD_att              3879 non-null float64
B_avg_opp_TD_landed           3879 non-null float64
```

```
 B_avg_opp_TD_pct               3879 non-null float64
 B_avg_opp_TOTAL_STR_att        3879 non-null float64
 B_avg_opp_TOTAL_STR_landed     3879 non-null float64
 B_total_rounds_fought          5144 non-null float64
 B_total_time_fought(seconds)   3879 non-null float64
 B_total_title_bouts            5144 non-null float64
 B_win_by_Decision_Majority     5144 non-null float64
 B_win_by_Decision_Split        5144 non-null float64
 B_win_by_Decision_Unanimous    5144 non-null float64
 B_win_by_KO/TKO                5144 non-null float64
 B_win_by_Submission            5144 non-null float64
 B_win_by_TKO_Doctor_Stoppage   5144 non-null float64
 B_wins                         5144 non-null float64
 B_Stance                       4985 non-null object
 B_Height_cms                   5136 non-null float64
 B_Reach_cms                    4478 non-null float64
 B_Weight_lbs                   5138 non-null float64
 R_current_lose_streak          5144 non-null float64
 R_current_win_streak           5144 non-null float64
 R_avg_BODY_att                 4494 non-null float64
 R_avg_BODY_landed              4494 non-null float64
 R_avg_CLINCH_att               4494 non-null float64
 R_avg_CLINCH_landed            4494 non-null float64
 R_avg_DISTANCE_att             4494 non-null float64
 R_avg_DISTANCE_landed          4494 non-null float64
 R_avg_GROUND_att               4494 non-null float64
 R_avg_GROUND_landed            4494 non-null float64
 R_avg_HEAD_att                 4494 non-null float64
 R_avg_HEAD_landed              4494 non-null float64
 R_avg_KD                       4494 non-null float64
 R_avg_LEG_att                  4494 non-null float64
 R_avg_LEG_landed               4494 non-null float64
 R_avg_PASS                     4494 non-null float64
 R_avg_REV                      4494 non-null float64
 R_avg_SIG_STR_att              4494 non-null float64
 R_avg_SIG_STR_landed           4494 non-null float64
 R_avg_SIG_STR_pct              4494 non-null float64
 R_avg_SUB_ATT                  4494 non-null float64
 R_avg_TD_att                   4494 non-null float64
 R_avg_TD_landed                4494 non-null float64
 R_avg_TD_pct                   4494 non-null float64
 R_avg_TOTAL_STR_att            4494 non-null float64
 R_avg_TOTAL_STR_landed         4494 non-null float64
 R_longest_win_streak           5144 non-null float64
 R_losses                       5144 non-null float64
 R_avg_opp_BODY_att             4494 non-null float64
 R_avg_opp_BODY_landed          4494 non-null float64
 R_avg_opp_CLINCH_att           4494 non-null float64
 R_avg_opp_CLINCH_landed        4494 non-null float64
 R_avg_opp_DISTANCE_att         4494 non-null float64
 R_avg_opp_DISTANCE_landed      4494 non-null float64
 R_avg_opp_GROUND_att           4494 non-null float64
 R_avg_opp_GROUND_landed        4494 non-null float64
 R_avg_opp_HEAD_att             4494 non-null float64
 R_avg_opp_HEAD_landed          4494 non-null float64
 R_avg_opp_KD                   4494 non-null float64
 R_avg_opp_LEG_att              4494 non-null float64
 R_avg_opp_LEG_landed           4494 non-null float64
 R_avg_opp_PASS                 4494 non-null float64
 R_avg_opp_REV                  4494 non-null float64
 R_avg_opp_SIG_STR_att          4494 non-null float64
```

```
R_avg_opp_SIG_STR_landed        4494 non-null float64
R_avg_opp_SIG_STR_pct           4494 non-null float64
R_avg_opp_SUB_ATT               4494 non-null float64
R_avg_opp_TD_att                4494 non-null float64
R_avg_opp_TD_landed             4494 non-null float64
R_avg_opp_TD_pct                4494 non-null float64
R_avg_opp_TOTAL_STR_att         4494 non-null float64
R_avg_opp_TOTAL_STR_landed      4494 non-null float64
R_total_rounds_fought           5144 non-null float64
R_total_time_fought(seconds)    4494 non-null float64
R_total_title_bouts             5144 non-null float64
R_win_by_Decision_Majority      5144 non-null float64
R_win_by_Decision_Split         5144 non-null float64
R_win_by_Decision_Unanimous     5144 non-null float64
R_win_by_KO/TKO                 5144 non-null float64
R_win_by_Submission             5144 non-null float64
R_win_by_TKO_Doctor_Stoppage    5144 non-null float64
R_wins                          5144 non-null float64
R_Stance                        5010 non-null object
R_Height_cms                    5140 non-null float64
R_Reach_cms                     4828 non-null float64
R_Weight_lbs                    5141 non-null float64
B_age                           4972 non-null float64
R_age                           5080 non-null float64
dtypes: bool(1), float64(132), int64(1), object(9)
memory usage: 5.6+ MB
```

In [7]:

```
#fill numerical values with their average
ufc_data = ufc_data.fillna(ufc_data.mean())
ufc_data.info(verbose=True, null_counts  = True)
#not using referee so we won't fill him
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5144 entries, 0 to 5143
Data columns (total 143 columns):
R_fighter                    5144 non-null object
B_fighter                    5144 non-null object
Referee                      5121 non-null object
date                         5144 non-null object
location                     5144 non-null object
Winner                       5144 non-null object
title_bout                   5144 non-null bool
weight_class                 5144 non-null object
no_of_rounds                 5144 non-null int64
B_current_lose_streak        5144 non-null float64
B_current_win_streak         5144 non-null float64
B_avg_BODY_att               5144 non-null float64
B_avg_BODY_landed            5144 non-null float64
B_avg_CLINCH_att             5144 non-null float64
B_avg_CLINCH_landed          5144 non-null float64
B_avg_DISTANCE_att           5144 non-null float64
B_avg_DISTANCE_landed        5144 non-null float64
B_avg_GROUND_att             5144 non-null float64
B_avg_GROUND_landed          5144 non-null float64
B_avg_HEAD_att               5144 non-null float64
B_avg_HEAD_landed            5144 non-null float64
B_avg_KD                     5144 non-null float64
B_avg_LEG_att                5144 non-null float64
B_avg_LEG_landed             5144 non-null float64
B_avg_PASS                   5144 non-null float64
B_avg_REV                    5144 non-null float64
B_avg_SIG_STR_att            5144 non-null float64
B_avg_SIG_STR_landed         5144 non-null float64
B_avg_SIG_STR_pct            5144 non-null float64
B_avg_SUB_ATT                5144 non-null float64
B_avg_TD_att                 5144 non-null float64
B_avg_TD_landed              5144 non-null float64
B_avg_TD_pct                 5144 non-null float64
B_avg_TOTAL_STR_att          5144 non-null float64
B_avg_TOTAL_STR_landed       5144 non-null float64
B_longest_win_streak         5144 non-null float64
B_losses                     5144 non-null float64
B_avg_opp_BODY_att           5144 non-null float64
B_avg_opp_BODY_landed        5144 non-null float64
B_avg_opp_CLINCH_att         5144 non-null float64
B_avg_opp_CLINCH_landed      5144 non-null float64
B_avg_opp_DISTANCE_att       5144 non-null float64
B_avg_opp_DISTANCE_landed    5144 non-null float64
B_avg_opp_GROUND_att         5144 non-null float64
B_avg_opp_GROUND_landed      5144 non-null float64
B_avg_opp_HEAD_att           5144 non-null float64
B_avg_opp_HEAD_landed        5144 non-null float64
B_avg_opp_KD                 5144 non-null float64
B_avg_opp_LEG_att            5144 non-null float64
B_avg_opp_LEG_landed         5144 non-null float64
B_avg_opp_PASS               5144 non-null float64
B_avg_opp_REV                5144 non-null float64
B_avg_opp_SIG_STR_att        5144 non-null float64
B_avg_opp_SIG_STR_landed     5144 non-null float64
B_avg_opp_SIG_STR_pct        5144 non-null float64
B_avg_opp_SUB_ATT            5144 non-null float64
B_avg_opp_TD_att             5144 non-null float64
B_avg_opp_TD_landed          5144 non-null float64
```

```
B_avg_opp_TD_pct                5144 non-null float64
B_avg_opp_TOTAL_STR_att         5144 non-null float64
B_avg_opp_TOTAL_STR_landed      5144 non-null float64
B_total_rounds_fought           5144 non-null float64
B_total_time_fought(seconds)    5144 non-null float64
B_total_title_bouts             5144 non-null float64
B_win_by_Decision_Majority      5144 non-null float64
B_win_by_Decision_Split         5144 non-null float64
B_win_by_Decision_Unanimous     5144 non-null float64
B_win_by_KO/TKO                 5144 non-null float64
B_win_by_Submission             5144 non-null float64
B_win_by_TKO_Doctor_Stoppage    5144 non-null float64
B_wins                          5144 non-null float64
B_Stance                        4985 non-null object
B_Height_cms                    5144 non-null float64
B_Reach_cms                     5144 non-null float64
B_Weight_lbs                    5144 non-null float64
R_current_lose_streak           5144 non-null float64
R_current_win_streak            5144 non-null float64
R_avg_BODY_att                  5144 non-null float64
R_avg_BODY_landed               5144 non-null float64
R_avg_CLINCH_att                5144 non-null float64
R_avg_CLINCH_landed             5144 non-null float64
R_avg_DISTANCE_att              5144 non-null float64
R_avg_DISTANCE_landed           5144 non-null float64
R_avg_GROUND_att                5144 non-null float64
R_avg_GROUND_landed             5144 non-null float64
R_avg_HEAD_att                  5144 non-null float64
R_avg_HEAD_landed               5144 non-null float64
R_avg_KD                        5144 non-null float64
R_avg_LEG_att                   5144 non-null float64
R_avg_LEG_landed                5144 non-null float64
R_avg_PASS                      5144 non-null float64
R_avg_REV                       5144 non-null float64
R_avg_SIG_STR_att               5144 non-null float64
R_avg_SIG_STR_landed            5144 non-null float64
R_avg_SIG_STR_pct               5144 non-null float64
R_avg_SUB_ATT                   5144 non-null float64
R_avg_TD_att                    5144 non-null float64
R_avg_TD_landed                 5144 non-null float64
R_avg_TD_pct                    5144 non-null float64
R_avg_TOTAL_STR_att             5144 non-null float64
R_avg_TOTAL_STR_landed          5144 non-null float64
R_longest_win_streak            5144 non-null float64
R_losses                        5144 non-null float64
R_avg_opp_BODY_att              5144 non-null float64
R_avg_opp_BODY_landed           5144 non-null float64
R_avg_opp_CLINCH_att            5144 non-null float64
R_avg_opp_CLINCH_landed         5144 non-null float64
R_avg_opp_DISTANCE_att          5144 non-null float64
R_avg_opp_DISTANCE_landed       5144 non-null float64
R_avg_opp_GROUND_att            5144 non-null float64
R_avg_opp_GROUND_landed         5144 non-null float64
R_avg_opp_HEAD_att              5144 non-null float64
R_avg_opp_HEAD_landed           5144 non-null float64
R_avg_opp_KD                    5144 non-null float64
R_avg_opp_LEG_att               5144 non-null float64
R_avg_opp_LEG_landed            5144 non-null float64
R_avg_opp_PASS                  5144 non-null float64
R_avg_opp_REV                   5144 non-null float64
R_avg_opp_SIG_STR_att           5144 non-null float64
```

```
R_avg_opp_SIG_STR_landed        5144 non-null float64
R_avg_opp_SIG_STR_pct           5144 non-null float64
R_avg_opp_SUB_ATT               5144 non-null float64
R_avg_opp_TD_att                5144 non-null float64
R_avg_opp_TD_landed             5144 non-null float64
R_avg_opp_TD_pct                5144 non-null float64
R_avg_opp_TOTAL_STR_att         5144 non-null float64
R_avg_opp_TOTAL_STR_landed      5144 non-null float64
R_total_rounds_fought           5144 non-null float64
R_total_time_fought(seconds)    5144 non-null float64
R_total_title_bouts             5144 non-null float64
R_win_by_Decision_Majority      5144 non-null float64
R_win_by_Decision_Split         5144 non-null float64
R_win_by_Decision_Unanimous     5144 non-null float64
R_win_by_KO/TKO                 5144 non-null float64
R_win_by_Submission             5144 non-null float64
R_win_by_TKO_Doctor_Stoppage    5144 non-null float64
R_wins                          5144 non-null float64
R_Stance                        5010 non-null object
R_Height_cms                    5144 non-null float64
R_Reach_cms                     5144 non-null float64
R_Weight_lbs                    5144 non-null float64
B_age                           5144 non-null float64
R_age                           5144 non-null float64
dtypes: bool(1), float64(132), int64(1), object(9)
memory usage: 5.6+ MB
```

In [8]:

```
#Check Categorical columns
print(ufc_data['Winner'].value_counts(dropna = False))
print("--------------------------------------------------")
print(ufc_data['title_bout'].value_counts(dropna = False))
print("--------------------------------------------------")
print(ufc_data['weight_class'].value_counts(dropna = False))
print("--------------------------------------------------")
print(ufc_data['B_Stance'].value_counts(dropna = False))
print("--------------------------------------------------")
print(ufc_data['R_Stance'].value_counts(dropna = False))
print("--------------------------------------------------")
print(ufc_data['no_of_rounds'].value_counts(dropna = False))
```

```
Red      3470
Blue     1591
Draw       83
Name: Winner, dtype: int64
--------------------------------------------------
False    4809
True      335
Name: title_bout, dtype: int64
--------------------------------------------------
Lightweight              989
Welterweight             969
Middleweight             725
Heavyweight              507
Light Heavyweight        502
Featherweight            442
Bantamweight             379
Flyweight                187
Women's Strawweight      143
Women's Bantamweight     111
Open Weight               92
Women's Flyweight         50
Catch Weight              38
Women's Featherweight     10
Name: weight_class, dtype: int64
--------------------------------------------------
Orthodox       3829
Southpaw        975
Switch          168
NaN             159
Open Stance       9
Sideways          4
Name: B_Stance, dtype: int64
--------------------------------------------------
Orthodox       3807
Southpaw       1036
Switch          150
NaN             134
Open Stance      15
Sideways          2
Name: R_Stance, dtype: int64
--------------------------------------------------
3    4523
5     423
2      98
1      78
4      22
Name: no_of_rounds, dtype: int64
```

In [9]:

```
#most used stance, can be seen as median
ufc_data['R_Stance'] = ufc_data['R_Stance'].fillna('Orthodox')
ufc_data['B_Stance'] = ufc_data['B_Stance'].fillna('Orthodox')
```

In [10]:

```
#make categorical values numerical so that they may be use late for predictions/visuali
sations
ufc_data['RStance'] = ufc_data['R_Stance'].map( {'Orthodox': 1, 'Southpaw': 2,'Switch':
3, 'Open Stance': 4,'Sideways': 5} ).astype(int)
ufc_data['BStance'] = ufc_data['B_Stance'].map( {'Orthodox': 1, 'Southpaw': 2,'Switch':
3, 'Open Stance': 4,'Sideways': 5} ).astype(int)
ufc_data['WinnerInt'] = ufc_data['Winner'].map( {'Red': -1, 'Draw': 0,'Blue': 1} ).asty
pe(int)
```

VISUALISATIONS

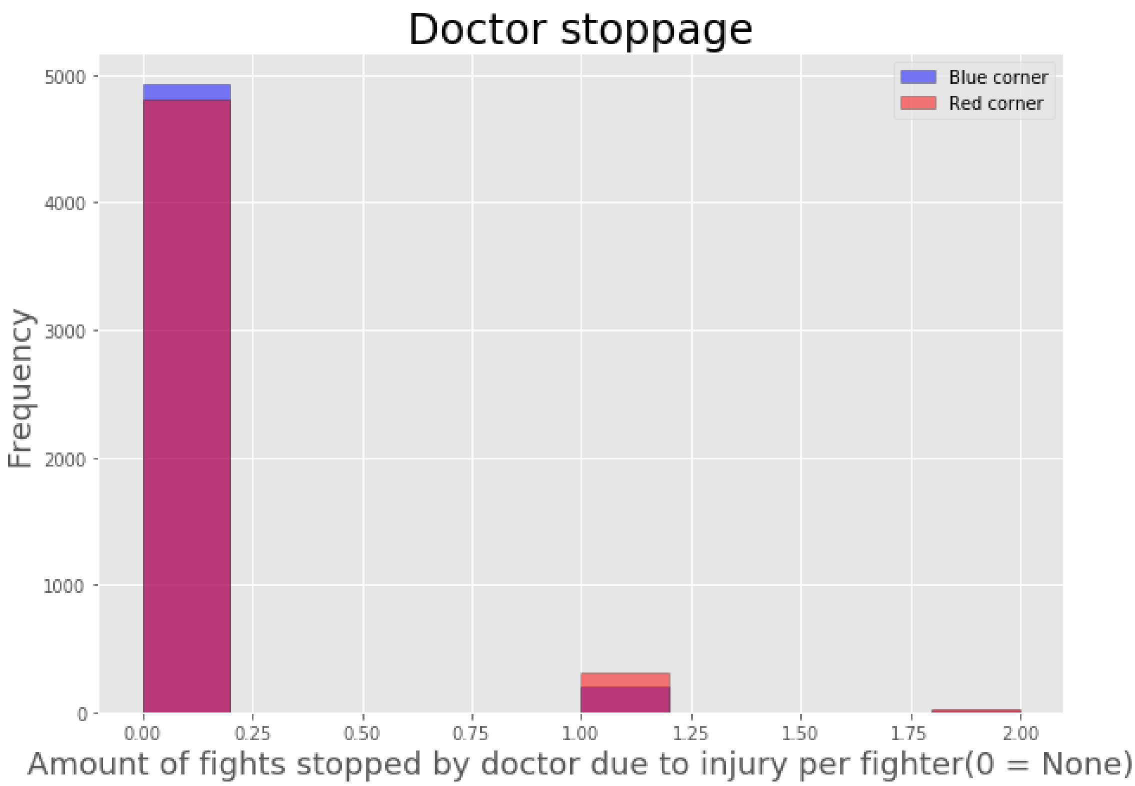
In [11]:

```
#visualise correlations between all numerical columns
import matplotlib.pyplot as plt
plt.style.use('ggplot')

import seaborn as sns
plt.figure(figsize=(100,100))
cor = ufc_data.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
#copy paste picture into paint for easier inspection
```

```
<Figure size 10000x10000 with 2 Axes>
```

In [12]:

```
# Histogram of the amount of wins by doctor stoppage
ufc_data['B_win_by_TKO_Doctor_Stoppage'].plot(kind='hist',color='blue',edgecolor='blac
k',alpha=0.5,figsize=(10,7))
ufc_data['R_win_by_TKO_Doctor_Stoppage'].plot(kind='hist',color='red',edgecolor='black'
,alpha=0.5,figsize=(10,7))
plt.legend(labels=['Blue corner','Red corner'])
plt.title('Doctor stoppage', size=24)
plt.xlabel('Amount of fights stopped by doctor due to injury per fighter(0 = None)', si
ze=18)
plt.ylabel('Frequency', size=18);
plt.show()
```

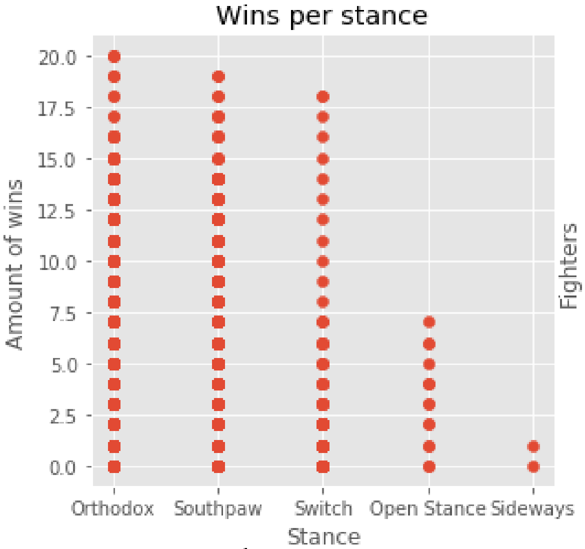


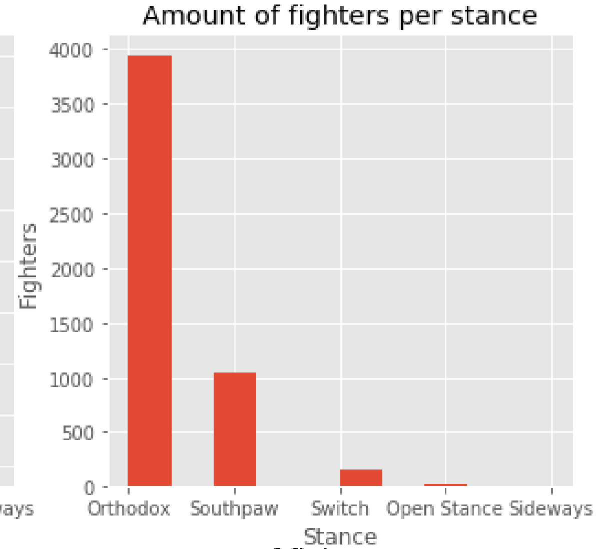
In [13]:

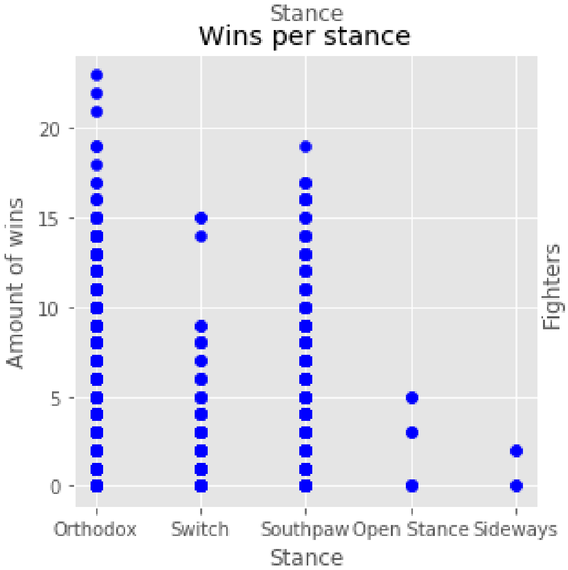
```
#check if stance used by fighter has any input on outcome
plt.figure(figsize=(10,10))

plt.subplot(2,2,1)
plt.scatter(ufc_data['R_Stance'], ufc_data['R_wins'] )
plt.xlabel('Stance')
plt.ylabel('Amount of wins')
plt.title('Wins per stance')

plt.subplot(2,2,2)
ufc_data['R_Stance'].hist()
plt.title('Amount of fighters per stance')
plt.xlabel('Stance')
plt.ylabel('Fighters')

plt.subplot(2,2,3)
plt.scatter(ufc_data['B_Stance'], ufc_data['B_wins'], color = 'blue' )
plt.xlabel('Stance')
plt.ylabel('Amount of wins')
plt.title('Wins per stance')

plt.subplot(2,2,4)
ufc_data['B_Stance'].hist(color = 'blue')
plt.title('Amount of fighters per stance')
plt.xlabel('Stance')
plt.ylabel('Fighters')
#a correlation between using a certain stance and winning can be seen, but then when co
mpared to amount of fighters using that
#specific stance it becomes clear that there are more winners with a widespread stance,
which makes this not a good predictor
```

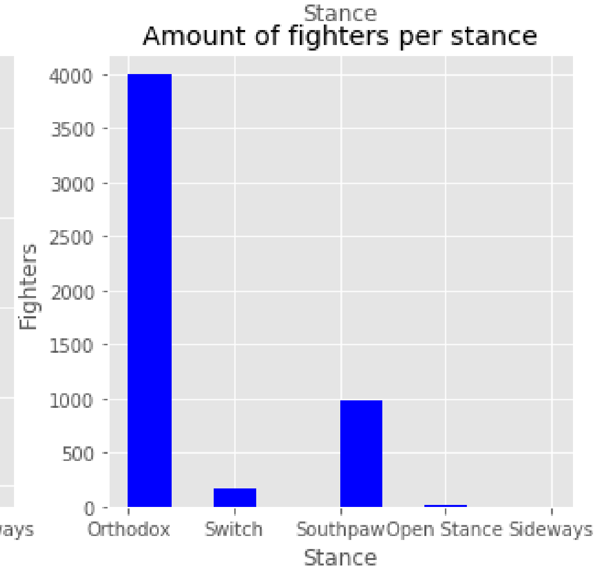
Out[13]:

```
Text(0, 0.5, 'Fighters')
```


Wins per stance
Amount of wins
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Orthodox
Southpaw
Switch
Open Stance
Sideways
Stance


Amount of fighters per stance
Fighters
4000
3500
3000
2500
2000
1500
1000
500
0
Orthodox
Southpaw
Switch
Open Stance
Sideways
Stance

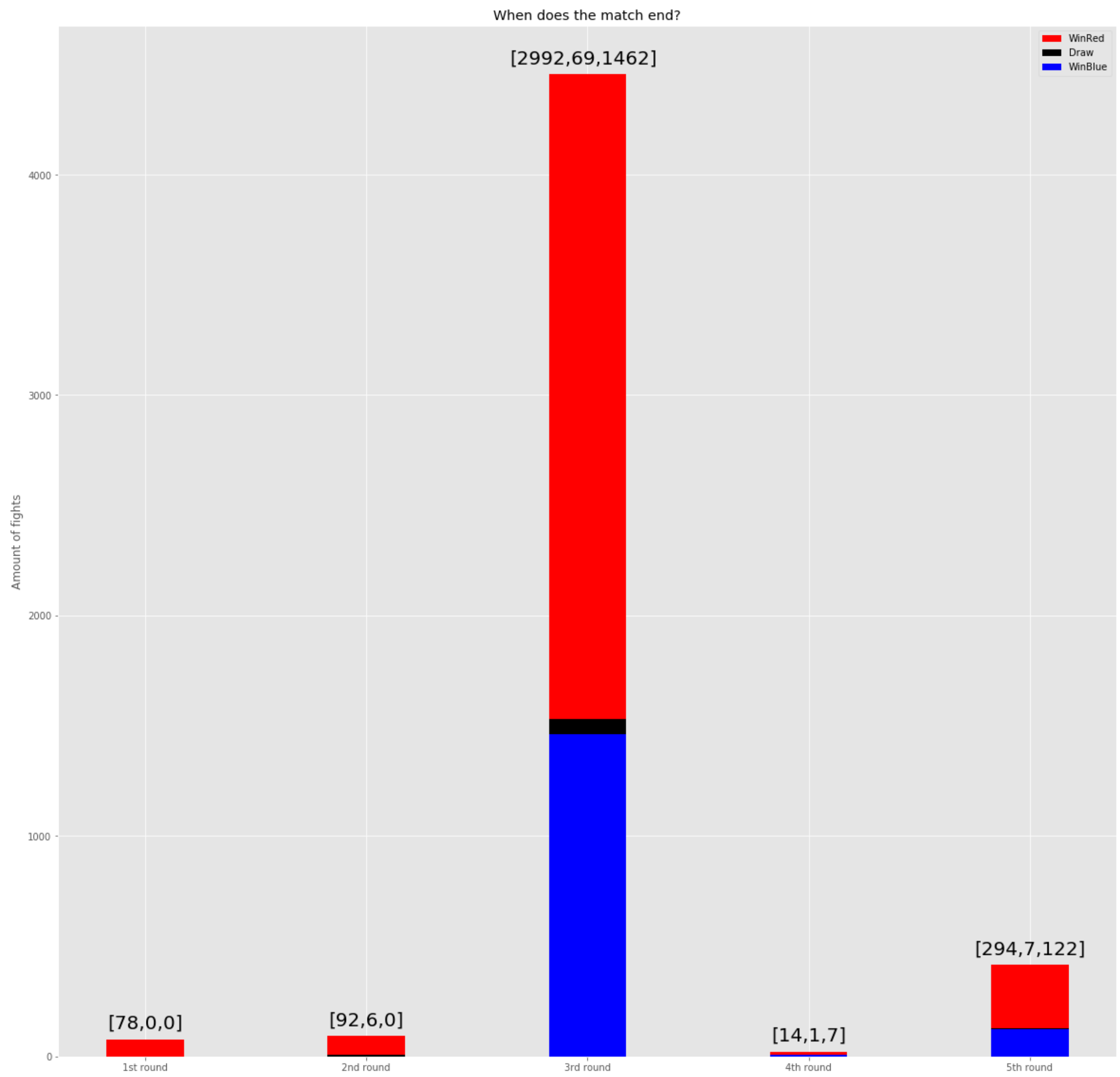

Wins per stance
Amount of wins
20
15
10
5
0
Orthodox
Switch
Southpaw
Open Stance
Sideways
Stance


Amount of fighters per stance
Fighters
4000
3500
3000
2500
2000
1500
1000
500
0
Orthodox
Switch
Southpaw
Open Stance
Sideways
Stance

In [14]:

```
#check whether the red corner fighter or the blue corner is more successfull usually an
d in what round
import numpy as np
firstRoundRed = ufc_data[(ufc_data['no_of_rounds'] == 1) & (ufc_data['WinnerInt'] == -1
)].shape[0]
firstRoundDraw = ufc_data[(ufc_data['no_of_rounds'] == 1) & (ufc_data['WinnerInt'] == 0
)].shape[0]
firstRoundBlue = ufc_data[(ufc_data['no_of_rounds'] == 1) & (ufc_data['WinnerInt'] == 1
)].shape[0]

secondRoundRed = ufc_data[(ufc_data['no_of_rounds'] == 2) & (ufc_data['WinnerInt'] == -
1)].shape[0]
secondRoundDraw = ufc_data[(ufc_data['no_of_rounds'] == 2) & (ufc_data['WinnerInt'] ==
0)].shape[0]
secondRoundBlue = ufc_data[(ufc_data['no_of_rounds'] == 2) & (ufc_data['WinnerInt'] ==
1)].shape[0]

thirdRoundRed = ufc_data[(ufc_data['no_of_rounds'] == 3) & (ufc_data['WinnerInt'] == -1
)].shape[0]
thirdRoundDraw = ufc_data[(ufc_data['no_of_rounds'] == 3) & (ufc_data['WinnerInt'] == 0
)].shape[0]
thirdRoundBlue = ufc_data[(ufc_data['no_of_rounds'] == 3) & (ufc_data['WinnerInt'] == 1
)].shape[0]

fourthRoundRed = ufc_data[(ufc_data['no_of_rounds'] == 4) & (ufc_data['WinnerInt'] == -
1)].shape[0]
fourthRoundDraw = ufc_data[(ufc_data['no_of_rounds'] == 4) & (ufc_data['WinnerInt'] ==
0)].shape[0]
fourthRoundBlue = ufc_data[(ufc_data['no_of_rounds'] == 4) & (ufc_data['WinnerInt'] ==
1)].shape[0]

fifthRoundRed = ufc_data[(ufc_data['no_of_rounds'] == 5) & (ufc_data['WinnerInt'] == -1
)].shape[0]
fifthRoundDraw = ufc_data[(ufc_data['no_of_rounds'] == 5) & (ufc_data['WinnerInt'] == 0
)].shape[0]
fifthRoundBlue = ufc_data[(ufc_data['no_of_rounds'] == 5) & (ufc_data['WinnerInt'] == 1
)].shape[0]

winRed = [firstRoundRed,secondRoundRed,thirdRoundRed,fourthRoundRed,fifthRoundRed]
draw = [firstRoundDraw,secondRoundDraw,thirdRoundDraw,fourthRoundDraw,fifthRoundDraw]
winBlue = [firstRoundBlue,secondRoundBlue,thirdRoundBlue,fourthRoundBlue,fifthRoundBlue
]

plt.figure(figsize=(20,20))
N = 5
p1 = plt.bar(np.arange(N), winRed, 0.35,bottom = winBlue, color = 'red')
p2 = plt.bar(np.arange(N), draw, 0.35,bottom=winBlue, color = 'black')
p3 = plt.bar(np.arange(N), winBlue, 0.35, color = 'blue')



plt.ylabel('Amount of fights')
plt.title('When does the match end?')
plt.xticks(np.arange(N), ('1st round', '2nd round', '3rd round', '4th round', '5th roun
d'))



plt.legend((p1[0], p2[0], p3[0]), ('WinRed', 'Draw', 'WinBlue'))
```

```
plt.text(x = -0.17 , y = firstRoundRed +firstRoundBlue + 50, s ='['+ str(winRed[0]) +
',' + str(draw[0]) + ','+ str(winBlue[0]) + ']' , size = 20)
plt.text(x = 1-0.17 , y = secondRoundRed +secondRoundBlue+ 50, s ='['+ str(winRed[1]) +
',' + str(draw[1]) + ','+ str(winBlue[1]) + ']' , size = 20)
plt.text(x = 2-0.35 , y = thirdRoundRed +thirdRoundBlue+ 50, s ='['+ str(winRed[2]) +
',' + str(draw[2]) + ','+ str(winBlue[2]) + ']' , size = 20)
plt.text(x = 3-0.17 , y = fourthRoundRed +fourthRoundBlue+ 50, s ='['+ str(winRed[3]) +
',' + str(draw[3]) + ','+ str(winBlue[3]) + ']' , size = 20)
plt.text(x = 4-0.25 , y = fifthRoundRed +fifthRoundBlue+ 50, s ='['+ str(winRed[4]) +
',' + str(draw[4]) + ','+ str(winBlue[4]) + ']' , size = 20)

plt.show()
#It can be seen that red corner fighters usually win more often than not, which may be
 due to the fact that the "champion",
#or favourite is assigned the red corner, while the underdog - the blue corner
```

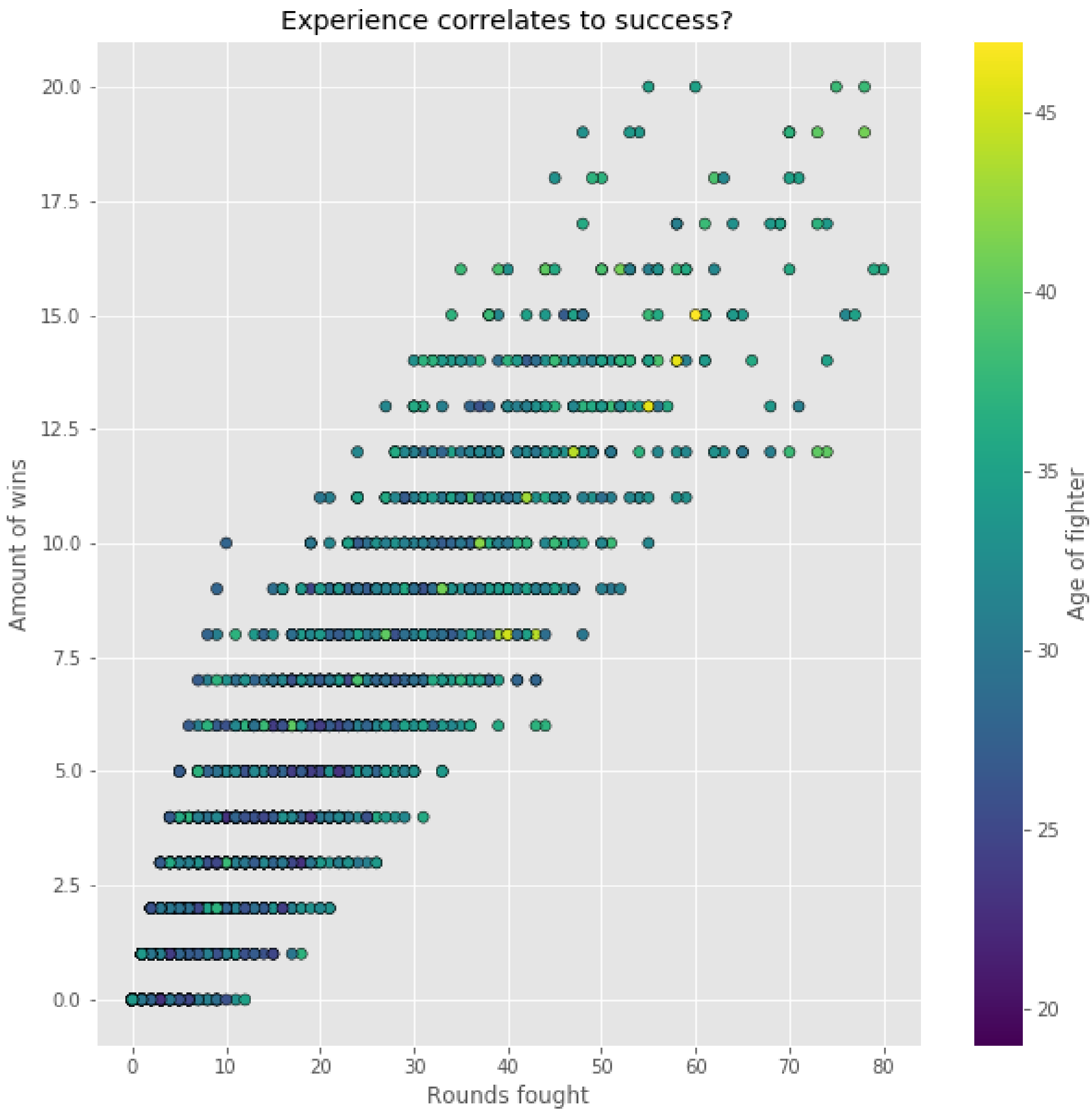


In [15]:

```
#check if the fighter being more experienced leads to a bigger win chance
plt.figure(figsize=(10,10))
pltExperience = plt.scatter(ufc_data['R_total_rounds_fought'], ufc_data['R_wins'], c =u
fc_data['R_age'], edgecolors='k' )
plt.xlabel('Rounds fought')
plt.ylabel('Amount of wins')
plt.title('Experience correlates to success?')
plt.colorbar(pltExperience, label = "Age of fighter")
#it can be seen that this is arguably true. Age has an effect as well, which is logical
as the older a fighter is, the more
#fights he has been in and hence has received more wins
```

Out[15]:

```
<matplotlib.colorbar.Colorbar at 0x205daaaa080>
```



MACHINE LEARNING ALGORITHMS AND PREDICTIONS

In [16]:

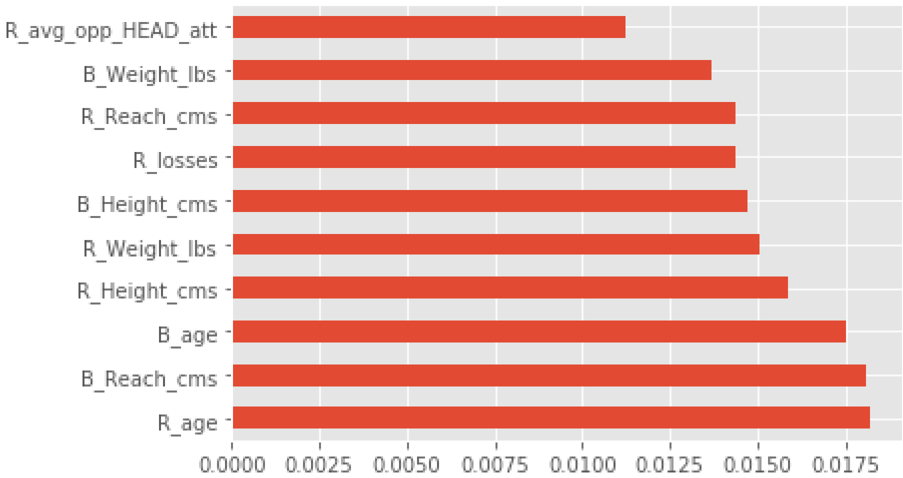
```
ufc_X = ufc_data.iloc[:,8:-1] # skip the strings and get all features till the one we w
ill predict
del ufc_X['B_Stance'] #delete object stance columns, as we have them in numerical value
s
del ufc_X['R_Stance']
ufc_y = ufc_data['WinnerInt'] #the label we would like to predict
```

In [17]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(ufc_X, ufc_y ,train_size = 0.7, tes
t_size=0.3)
random_state = 43
```

In [18]:

```
#use the extra tree classfier for its feature importance attribute. This will help us d
etermine which features to use
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
model.fit(X_train, y_train)
#plot feature importance
feat_importances = pd.Series(model.feature_importances_, index=ufc_X.columns)
feat_importances.nlargest(10).plot(kind='barh')
plt.show()
```

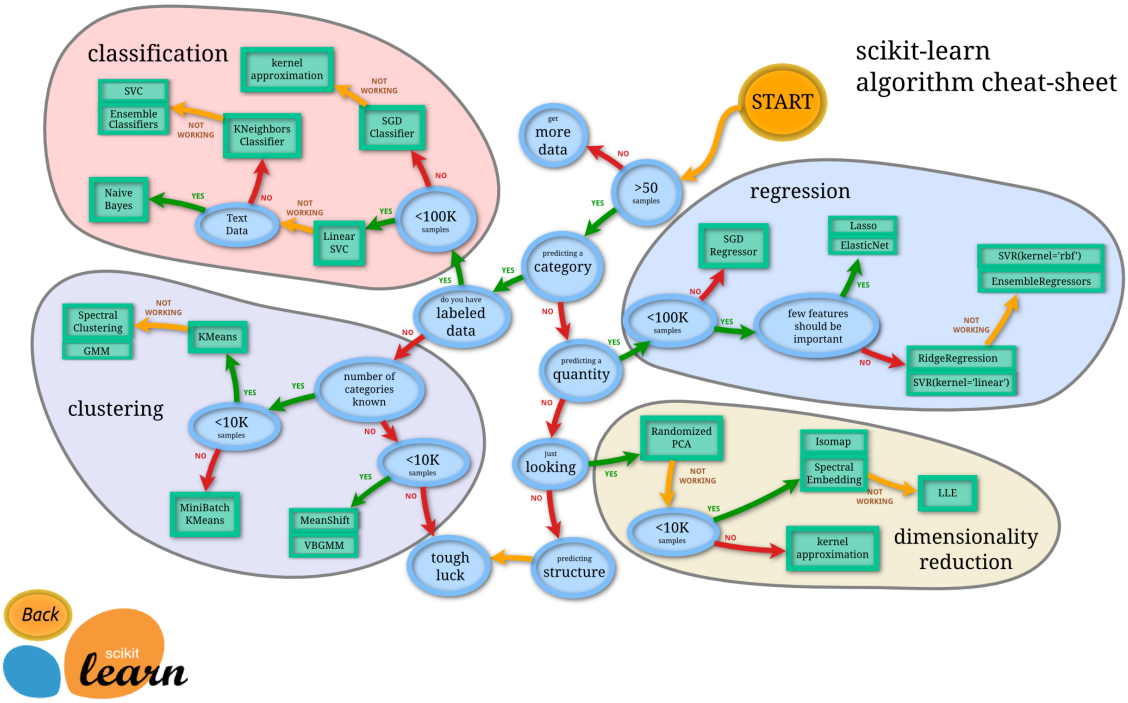


In [33]:

```
#use the best features on our models
ufc_X = ufc_data[['R_age','B_Reach_cms','R_Height_cms','B_age', 'R_Reach_cms', 'B_Weigh
t_lbs', 'B_Height_cms']]
ufc_y = ufc_data['WinnerInt']
X_train, X_test, y_train, y_test = train_test_split(ufc_X, ufc_y ,train_size = 0.7, tes
t_size=0.3)
```

In [20]:

```
#use cheat sheet to determine corect models
from IPython.core.display import Image, display
display(Image('https://scikit-learn.org/stable/_static/ml_map.png', width=1365, unconfi
ned=True))
```



In [21]:

```
#chose Decision Trees by intuition as it feels the best for this job. Use cheat sheet f
or furhter models
from sklearn import tree
from sklearn.metrics import accuracy_score, classification_report
clf = tree.DecisionTreeClassifier(criterion = 'entropy', max_depth = 5, min_samples_lea
f = 10, random_state = random_state)
clf.fit(X_train, y_train)
pred = clf.predict(X_test)
accTree = accuracy_score(pred, y_test)
print(accTree)
print(classification_report(y_test, pred))
#can't predict draws perhaps due to them being a very low amount or because they all go
to the test set
#no ROC_curve available, because prediction is multiclass
```

```
0.6897668393782384
              precision    recall  f1-score   support

          -1       0.71      0.93      0.81      1053
           0       0.00      0.00      0.00        25
           1       0.53      0.18      0.27       466

    accuracy                           0.69      1544
   macro avg       0.41      0.37      0.36      1544
weighted avg       0.64      0.69      0.63      1544


D:\Software\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:
1437: UndefinedMetricWarning: Precision and F-score are ill-defined and be
ing set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [36]:

```
# Implement a Random Forest classifier, does this improve the prediction?
# choose gini to be certain that random classifications are correct
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
clf = RandomForestClassifier(n_estimators = 100, criterion = 'gini', max_depth = 2, min
_samples_split = 10, random_state  =random_state)
clf = clf.fit(X_train, y_train)

random_pred = clf.predict(X_test)
accForest = accuracy_score(random_pred,y_test)
print(accForest)
```

```
0.6923575129533679
```

In [23]:

```
#tried distance as weight
#brute works best
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=4, algorithm  = 'brute')
neigh.fit(X_train, y_train)
accKNeigh = neigh.score(X_test,y_test)
print(accKNeigh)
```

```
0.667098445595855
```

In [24]:

```
from sklearn.svm import SVC
clf = SVC(gamma='auto',random_state =random_state)
clf.fit(X_train, y_train)
accSVC = clf.score(X_test,y_test)
print(accSVC)
```

```
0.6878238341968912
```

In [25]:

```
#learning rate = 2 makes it highly unstable
#algorithm choice makes no difference
clf = AdaBoostClassifier(n_estimators=100, random_state = random_state)
clf.fit(X_train, y_train)
accBoost = clf.score(X_test,y_test)
print(accBoost)
```

```
0.6813471502590673
```

In [26]:

```
#lbfgs because the dataset is relatively small yet adam performs better
#not using Shuffle makes it worse
from sklearn.neural_network import MLPClassifier
clf = MLPClassifier(hidden_layer_sizes=(30,30,30), activation ='tanh',learning_rate_ini
t=0.01, random_state = random_state)
clf.fit(X_train, y_train)
accNN = clf.score(X_test, y_test)
print(accNN)
```

```
0.6819948186528497
```

Make predictions for every weight class

In [27]:

```
#let's see if the predictions can be better if we furhter split our predictors by weigh
t class
weightDivision = ufc_data.groupby('weight_class', as_index = False) #group by weight
```

In [28]:

```
#Open weight division only has red winners
same = weightDivision.get_group('Open Weight')
same['Winner'].value_counts()
```

Out[28]:

```
Red    92
Name: Winner, dtype: int64
```

In [29]:

```
#Women's featherweight has only 10 recorded matches
same = weightDivision.get_group('Women\'s Featherweight')
same['Winner'].value_counts()
```

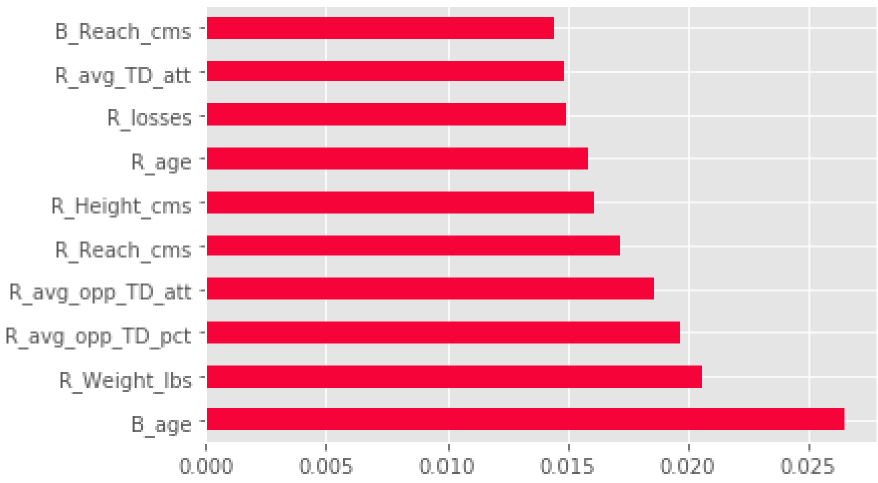
Out[29]:

```
Blue    6
Red     4
Name: Winner, dtype: int64
```

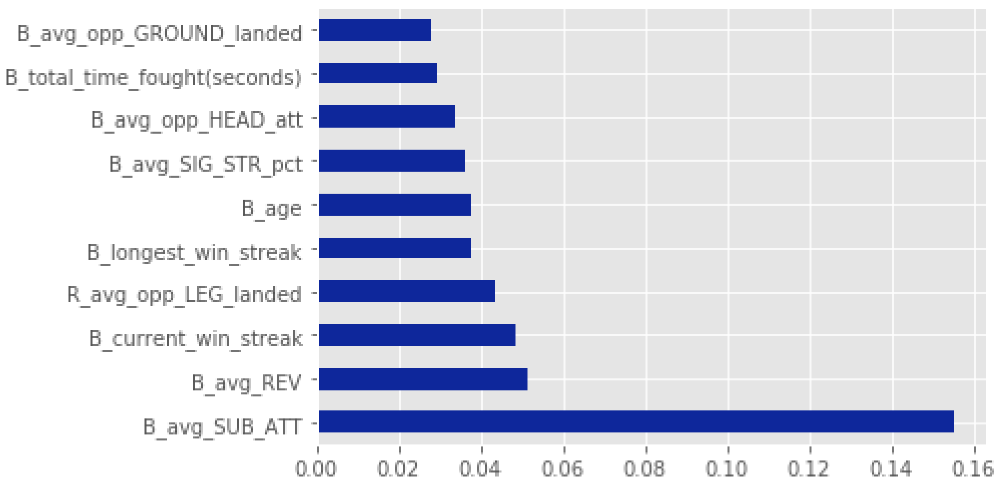
In [38]:

```
#for every weight class show the best features and use them to make a prediction using
 decision trees as they had the best results previously
for name, group in weightDivision:
    #skip Open and Women's featherweight
    if (name == 'Open Weight') | (name == 'Women\'s Featherweight'):
        continue
    print('\n************************\n' + name )
    x = weightDivision.get_group(name)
    ufc_X = x.iloc[:,8:-1] #use only valuable numerical featuees
    ufc_y = x['WinnerInt']
    del ufc_X['B_Stance'] #delete stances
    del ufc_X['R_Stance']

    #find best features
    X_train, X_test, y_train, y_test = train_test_split(ufc_X, ufc_y ,train_size = 0.7,
test_size=0.3)
    model = ExtraTreesClassifier()
    model.fit(X_train, y_train)
    #plot features
    feat_importances = pd.Series(model.feature_importances_, index=ufc_X.columns)
    feat_importances.nlargest(10).plot(kind='barh', color = np.random.rand(3,))
    plt.show()
    #use only top 10 features per weight class
    ufc_X = x[feat_importances.nlargest(10).keys()]
    X_train, X_test, y_train, y_test = train_test_split(ufc_X, ufc_y ,train_size = 0.7,
test_size=0.3)
    clf = tree.DecisionTreeClassifier(criterion = 'entropy', max_depth = 5, min_samples
_leaf = 10, random_state = random_state)
    clf.fit(X_train, y_train)
    pred = clf.predict(X_test)
    accTree = accuracy_score(pred, y_test)
    print('Accuracy of ' + name + ' class is ' + str(accTree))
```

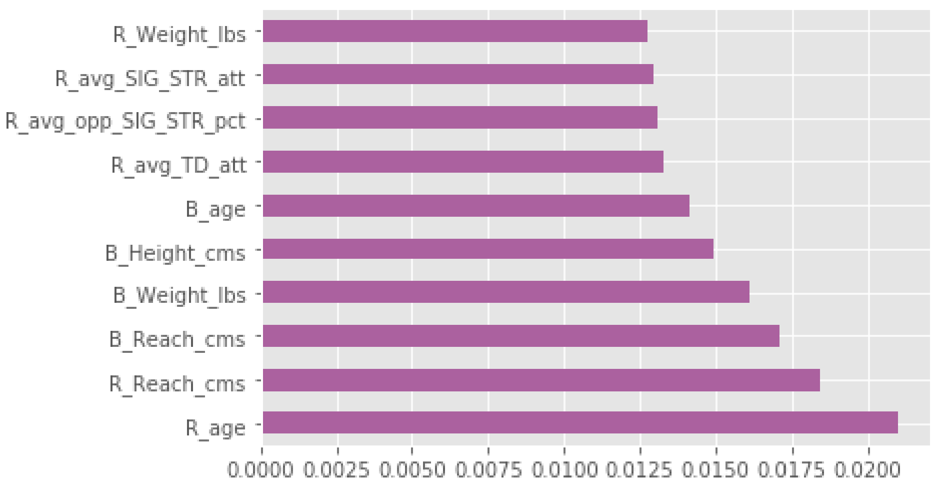
```
************************
Bantamweight
```



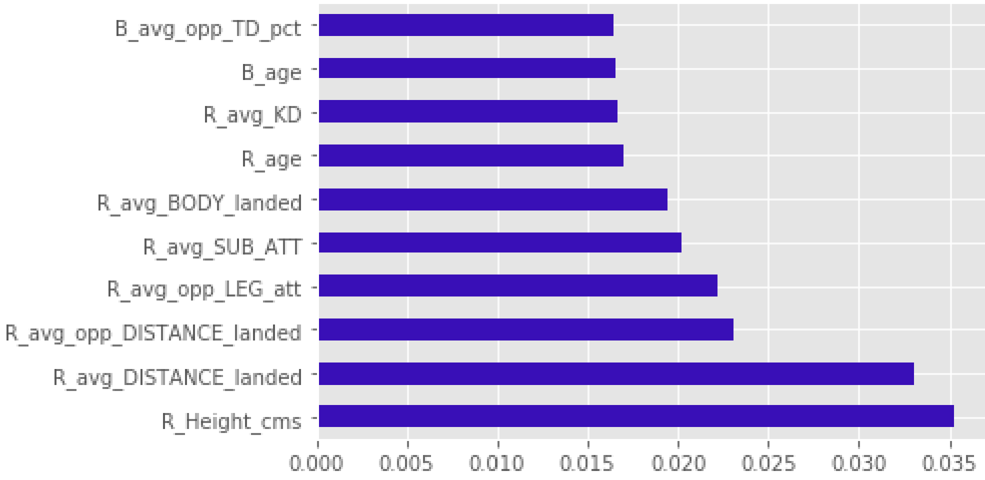

```
Accuracy of Bantamweight class is 0.543859649122807

************************
Catch Weight
```



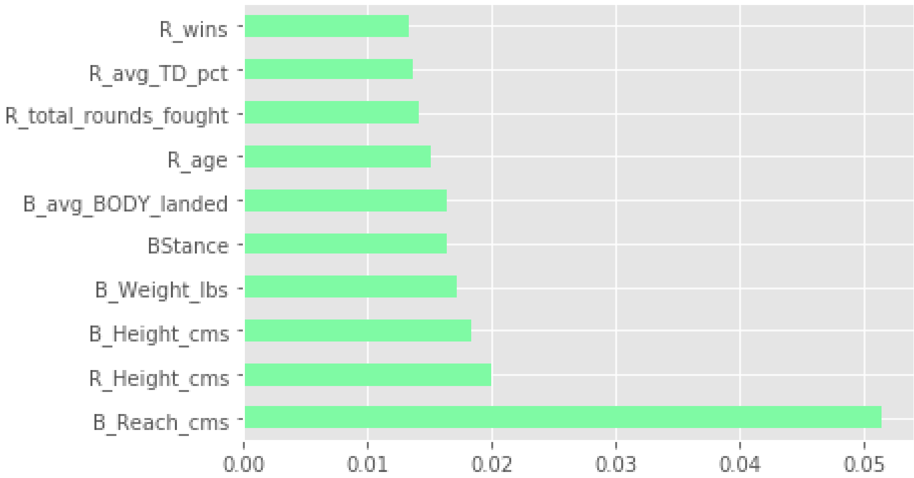

```
Accuracy of Catch Weight class is 0.8333333333333334

************************
Featherweight
```



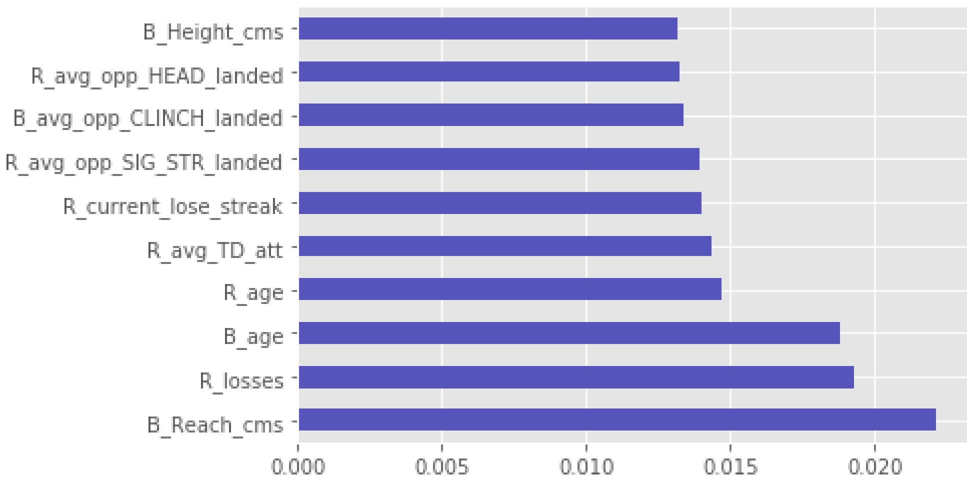
```
Accuracy of Featherweight class is 0.6090225563909775

*************************
Flyweight
```



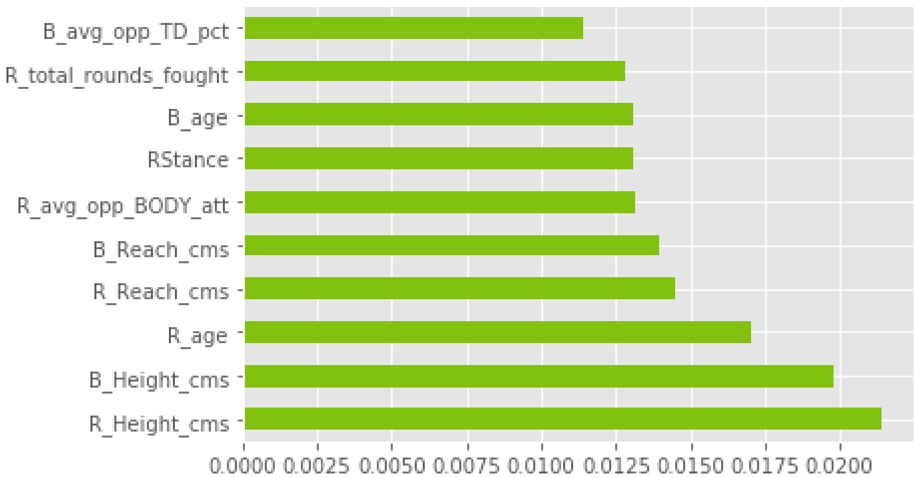

```
Accuracy of Flyweight class is 0.5263157894736842

*************************
Heavyweight
```



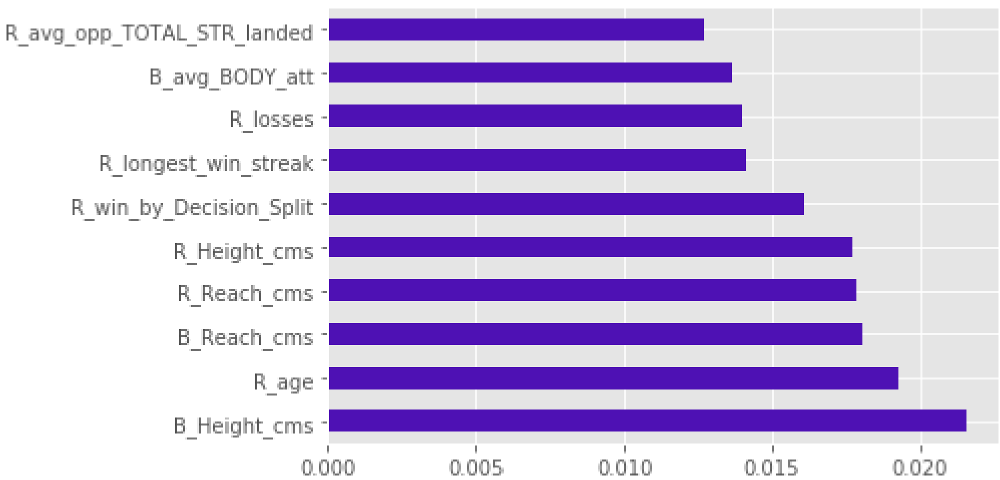

```
Accuracy of Heavyweight class is 0.738562091503268

*************************
Light Heavyweight
```



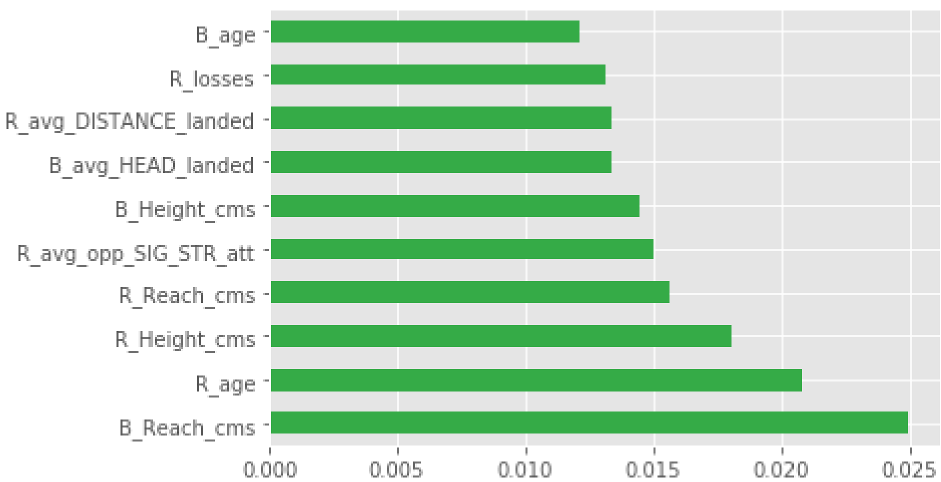
```
Accuracy of Light Heavyweight class is 0.7350993377483444

*************************
Lightweight
```



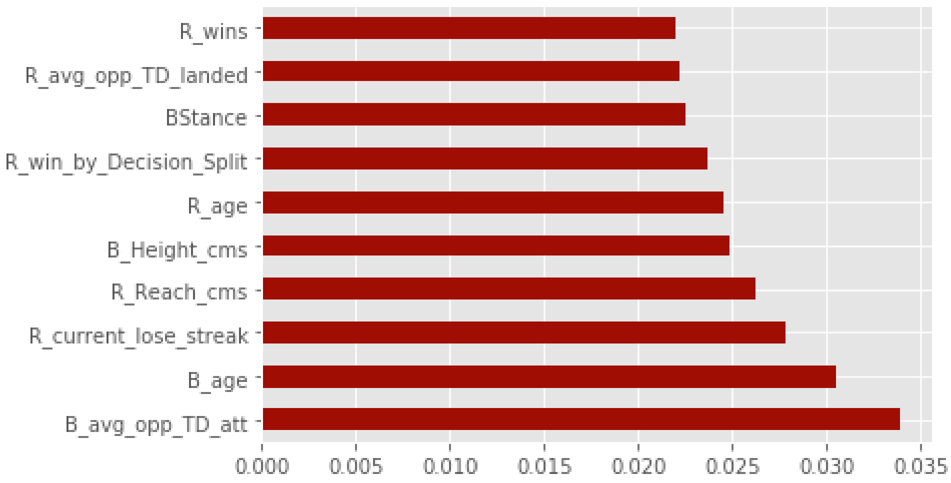

```
Accuracy of Lightweight class is 0.7104377104377104

*************************
Middleweight
```



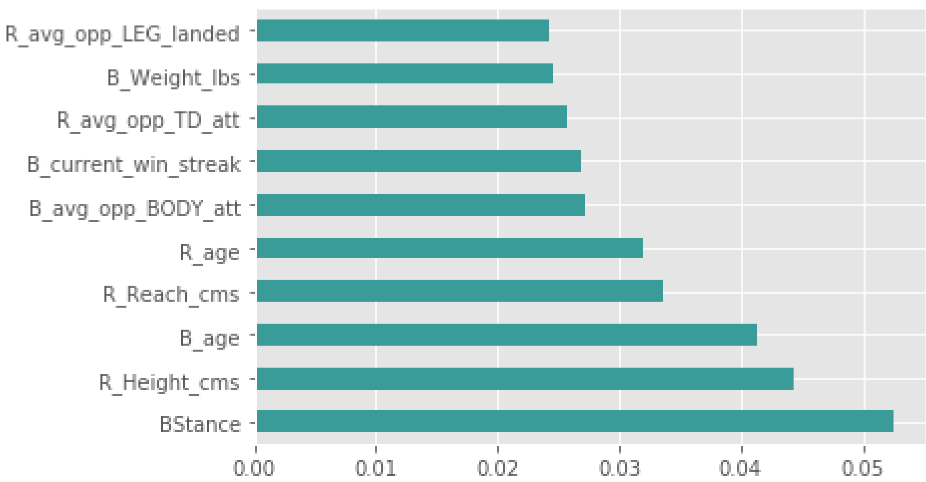

```
Accuracy of Middleweight class is 0.6513761467889908

*************************
Welterweight
```



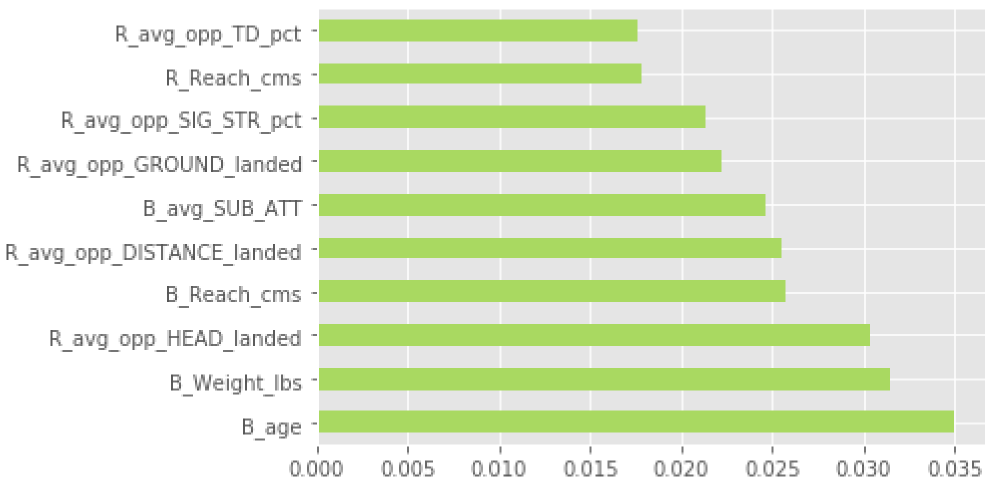
```
Accuracy of Welterweight class is 0.6666666666666666

*************************
Women's Bantamweight
```




```
Accuracy of Women's Bantamweight class is 0.5294117647058824

*************************
Women's Flyweight
```




```
Accuracy of Women's Flyweight class is 0.5333333333333333

*************************
Women's Strawweight
```



```
Accuracy of Women's Strawweight class is 0.5813953488372093
```