

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sb
import warnings
warnings.filterwarnings('ignore')
```

Project Introduction

I'll analyze my performance during the matches for this project. I'll try to figure out which agents I play best with and which maps I have the best win rate on. What is the best agent for each map, and finally, a small machine learning model that can predict whether a match will win or lose.

In [2]:

data=pd.read_csv("C:/Users/LITE/Documents/Valorant_Analysis/Lite.csv")

In [3]:

data.head()

Out [3]:

| | Date | Map Name | Match Result | Agent Name | kills | headshots | deaths | assists | damage | damageReceived | plants | defuses | firstBloods | kdRatio | placement | rank |
|---|-------------------------------|----------|--------------|------------|-------|-----------|--------|---------|--------|----------------|--------|---------|-------------|----------|-----------|----------|
| 0 | 2021-11-08T15:49:57.865-05:00 | Icebox | defeat | Jett | 5 | 1 | 14 | 3 | 1327 | 2447 | 0 | 0 | 0 | 0.357143 | 9 | Silver 1 |
| 1 | 2021-11-07T17:06:44.201-05:00 | Fracture | victory | Killjoy | 12 | 5 | 9 | 1 | 2169 | 1871 | 9 | 0 | 2 | 1.333333 | 7 | Silver 1 |
| 2 | 2021-11-07T16:28:18.945-05:00 | Breeze | defeat | Yoru | 3 | 1 | 17 | 2 | 895 | 3077 | 0 | 0 | 1 | 0.176471 | 9 | Silver 1 |
| 3 | 2021-11-07T15:32:01.224-05:00 | Haven | victory | Jett | 11 | 6 | 19 | 6 | 2685 | 3633 | 1 | 0 | 0 | 0.578947 | 9 | Silver 1 |
| 4 | 2021-11-07T13:40:04.085-05:00 | Ascent | defeat | Breach | 15 | 8 | 20 | 3 | 2925 | 3671 | 0 | 0 | 1 | 0.750000 | 4 | Silver 1 |

Data Cleaning

In this section, I'll split the date column into two columns: datetime and hour.

In [4]:

hour=[]
for i in range(len(data['Date'])):
 hour.append(data['Date'][i].split('T')[1].split('.')[0])
data.insert(1,'hour',hour)

day=pd.to_datetime(data['Date'])
for i in range(len(day)):
 day[i]=day[i].date()
data['Date']=day

Out [5]:

data.head()

Out [5]:

| | Date | hour | Map Name | Match Result | Agent Name | kills | headshots | deaths | assists | damage | damageReceived | plants | defuses | firstBloods | kdRatio | placement | rank |
|---|------------|----------|----------|--------------|------------|-------|-----------|--------|---------|--------|----------------|--------|---------|-------------|----------|-----------|----------|
| 0 | 2021-11-08 | 15:49:57 | Icebox | defeat | Jett | 5 | 1 | 14 | 3 | 1327 | 2447 | 0 | 0 | 0 | 0.357143 | 9 | Silver 1 |
| 1 | 2021-11-07 | 17:06:44 | Fracture | victory | Killjoy | 12 | 5 | 9 | 1 | 2169 | 1871 | 9 | 0 | 2 | 1.333333 | 7 | Silver 1 |
| 2 | 2021-11-07 | 16:28:18 | Breeze | defeat | Yoru | 3 | 1 | 17 | 2 | 895 | 3077 | 0 | 0 | 1 | 0.176471 | 9 | Silver 1 |
| 3 | 2021-11-07 | 15:32:01 | Haven | victory | Jett | 11 | 6 | 19 | 6 | 2685 | 3633 | 1 | 0 | 0 | 0.578947 | 9 | Silver 1 |
| 4 | 2021-11-07 | 13:40:04 | Ascent | defeat | Breach | 15 | 8 | 20 | 3 | 2925 | 3671 | 0 | 0 | 1 | 0.750000 | 4 | Silver 1 |

Data Visualisation

Top Agent kills

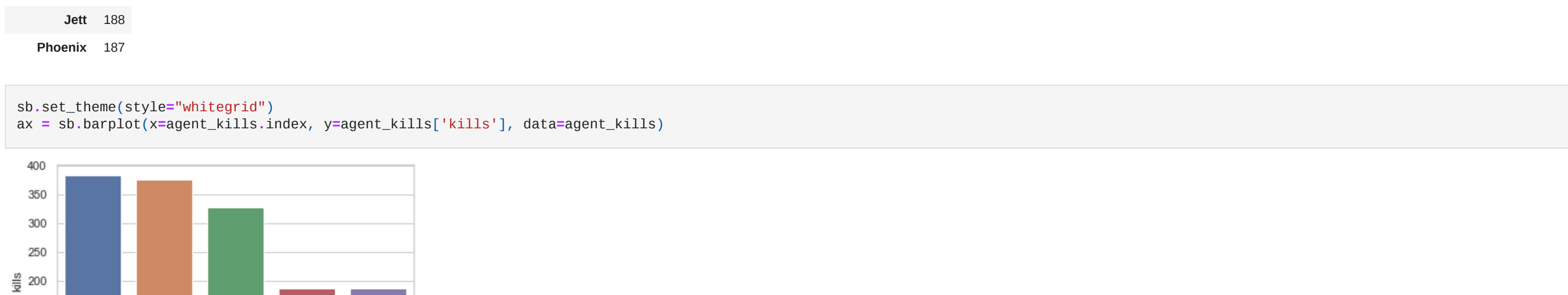
In this section, I'm looking for the agent with the most kills across all competitive matches.

In [6]:

agent_kills=data[['Agent Name','kills']]
agent_kills=agent_kills.set_index('Agent Name')
agent_kills=agent_kills.groupby('Agent Name').sum()
agent_kills=agent_kills.sort_values(by='kills',ascending=False)
agent_kills=agent_kills.head()

Out [6]:

| | kills |
|------------|-------|
| Agent Name | |
| Omen | 383 |
| Sage | 375 |
| Cypher | 327 |
| Jett | 188 |
| Phoenix | 187 |



Based on this bar chart, we can conclude that Omen (type: controller), Sage (type: sentinelle), and Cypher (type: sentinelle) are the top three agents in terms of kills, followed by two dualists, Jett and Phoenix. But is it enough to say that you're the best agent I've ever played with? Let's dig deeper to see what we can find.

Best Agent performance

We are calculating the kd ratio for each agent, which is: the number of kills + the number of deaths / the number of times that agent has been played.

In [8]:

agent_ADR_Count=data[['Agent Name']]
agent_ADR_Count=agent_ADR_Count['Agent Name'].groupby(agent_ADR_Count['Agent Name']).tolist().size().reset_index().\
 rename(columns={0:'records'})
agent_ADR_Count.rename(columns = {'index': 'Agent Name', 'Agent Name': 'Count'}, inplace = True)
agent_ADR_Count.sort_values('Agent Name')
agent_ADR_Count=agent_ADR_Count.set_index('Agent Name')

Out [8]:

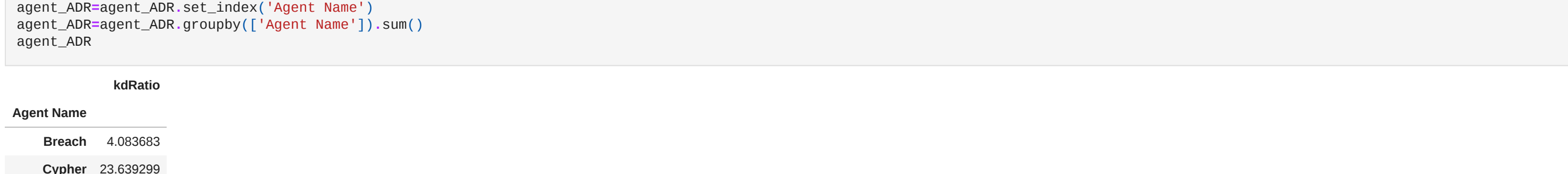
| | kdRatio |
|------------|-----------|
| Agent Name | |
| Breach | 4.083683 |
| Cypher | 23.639299 |
| Jett | 10.136627 |
| Killjoy | 11.782649 |
| Omen | 25.622963 |
| Phoenix | 10.666659 |
| Reyna | 14.548084 |
| Sage | 25.082575 |
| Skye | 1.090909 |
| Sova | 2.802438 |
| Yoru | 0.176471 |

In [10]:

agent_ADR_mean= pd.concat([agent_ADR_Count, agent_ADR], axis=1)
agent_ADR_mean[['kdRatio']]>agent_ADR_mean[['kdRatio']/agent_ADR_mean['Count']]
agent_ADR_mean=agent_ADR_mean.drop('Skye')
agent_ADR_mean=agent_ADR_mean.sort_values(by='kdRatio',ascending=False)
agent_ADR_mean=agent_ADR_mean.head()

Out [10]:

| | Count | kdRatio |
|------------|-------|----------|
| Agent Name | | |
| Reyna | 13 | 1.119083 |
| Killjoy | 14 | 0.841618 |
| Omen | 31 | 0.826548 |
| Cypher | 31 | 0.762558 |
| Sage | 33 | 0.760078 |



As we can see, there are additional results: Reyna, a dualist, has the highest kd ratio of 1.119, followed by Killjoy, a sentinelle, with 0.84, and then Omen, Cypher, and Sage. As a result, we have three sentinelle , one controller, and one dualist.

Match Results Base Map

In [12]:

Match_Stats=data[['Map Name','Match Result']]
Match_Stats['Match Result'].replace({'victory', 'defeat'}, (1, 0), inplace=True)
Match_Stats=Match_Stats.groupby(['Map Name']).sum()
Match_Stats=Match_Stats.sort_values(by='Match Result',ascending=False)
Match_Stats

Out [12]:

| | Map Name | |
|----------|----------|--|
| Ascent | 16 | |
| Haven | 15 | |
| Bind | 12 | |
| Split | 9 | |
| Fracture | 8 | |
| Icebox | 8 | |
| Breeze | 7 | |

In [13]:

sb.set_theme(style="whitegrid")
ax = sb.barplot(x=Match_Stats.index, y=Match_Stats['Match Result'], data=Match_Stats)

According to the graph, the most popular maps with a high win rate are Ascent, Haven, and Bind. Actually, as a valorant player, these maps are the first ones that come with the game, so I am very familiar with them. Split, on the other hand, is a cursed map.

In [14]:

Match_Stats=Match_Stats.head(4)

Out [14]:

| | Map Name | |
|--------|----------|--|
| Ascent | 16 | |
| Haven | 15 | |
| Bind | 12 | |
| Split | 9 | |

Agent and Map

In this part of analysis, I am going to conclude the performance of the agent that I play and there win rate in the maps

In [15]:

Map_Agent=data[['Map Name','Agent Name']]
Map_Agent=Map_Agent.groupby(['Map Name','Agent Name']).count()
Map_Agent=Map_Agent.to_frame()

Map_Agent=Map_Agent.rename(columns={'Agent Name':'N° of Play'})
Map_Agent_KD_Ratio=data[['Map Name','Agent Name','kdRatio']]
Map_Agent_KD_Ratio=Map_Agent_KD_Ratio.groupby(['Map Name','Agent Name'])['kdRatio'].sum()
Map_Agent_KD_Ratio=Map_Agent_KD_Ratio.to_frame()
Map_Agent_KD_Ratio.Normalized= pd.concat([Map_Agent, Map_Agent_KD_Ratio], axis=1)
Map_Agent_KD_Ratio.Normalized['kdRatio']=Map_Agent_KD_Ratio.Normalized['kdRatio']/Map_Agent_KD_Ratio.Normalized['N° of Play']
Map_Agent_KD_Ratio.Normalized

Match_Stats_By_Agent=data[['Map Name','Agent Name','Match Result']]
Match_Stats_By_Agent['Match Result'].replace({'victory', 'defeat'}, (1, 0), inplace=True)
Match_Stats_By_Agent=Match_Stats_By_Agent.groupby(['Map Name','Agent Name'])['Match Result'].sum()
Match_Stats_By_Agent=Match_Stats_By_Agent.to_frame()
Match_Stats_By_Agent

Player_Performance_based_Map_and_Agent= pd.concat([Map_Agent_KD_Ratio.Normalized, Match_Stats_By_Agent], axis=1)
Player_Performance_based_Map_and_Agent

Out [15]:

| | | N° of Play | kdRatio | Match Result |
|----------|------------|------------|----------|--------------|
| Map Name | Agent Name | | | |
| Ascent | Breach | 3 | 0.826389 | 1 |
| | Cypher | 6 | 0.521119 | 3 |
| | Jett | 3 | 0.826087 | 1 |
| | Killjoy | 4 | 0.644841 | 3 |
| | Omen | 4 | 0.648510 | 0 |
| | Phoenix | 5 | 0.712692 | 2 |
| | Reyna | 3 | 2.126984 | 1 |
| | Sage | 9 | 0.727167 | 5 |
| Bind | Breach | 1 | 0.571429 | 0 |
| | Cypher | 9 | 0.953159 | 4 |
| | Jett | 3 | 0.829714 | 1 |
| | Killjoy | 1 | 0.909091 | 1 |
| | Omen | 3 | 1.062530 | 2 |
| | Phoenix | 2 | 0.528708 | 0 |
| | Reyna | 1 | 0.800000 | 1 |
| | Sage | 6 | 0.636338 | 1 |
| | Sova | 2 | 0.717105 | 2 |
| Breeze | Jett | 2 | 0.500000 | 2 |
| | Killjoy | 1 | 0.928571 | 1 |
| | Omen | 5 | 0.734324 | 2 |
| | Phoenix | 3 | 0.511586 | 0 |
| | Sage | 3 | 0.710395 | 1 |
| | Sova | 2 | 0.420956 | 1 |
| | Yoru | 1 | 0.176471 | 0 |
| Fracture | Cypher | 3 | 1.079365 | 1 |
| | Killjoy | 1 | 1.333333 | 1 |
| | Omen | 8 | 0.891876 | 5 |
| | Reyna | 1 | 1.307692 | 1 |
| Haven | Breach | 2 | 0.516544 | 0 |
| | Cypher | 4 | 0.745705 | 3 |
| | Jett | 2 | 0.422807 | 1 |
| | Killjoy | 1 | 0.846154 | 1 |
| | Omen | 7 | 0.780013 | 3 |
| | Phoenix | 3 | 0.748718 | 3 |
| | Reyna | 1 | 0.636364 | 0 |
| | Sage | 8 | 0.739086 | 4 |
| | Sova | 1 | 0.526316 | 0 |
| Icebox | Cypher | 1 | 0.636364 | 0 |
| | Jett | 4 | 0.580952 | 1 |
| | Killjoy | 6 | 0.864356 | 4 |
| | Omen | 4 | 0.893661 | 1 |
| | Phoenix | 2 | 0.658750 | 0 |
| | Sage | 4 | 1.047078 | 2 |
| Split | Cypher | 8 | 0.634609 | 1 |
| | Jett | 1 | 1.000000 | 1 |
| | Phoenix | 1 | 0.947368 | 1 |
| | Reyna | 7 | 0.774725 | 3 |
| | Sage | 3 | 0.829261 | 2 |
| | Skye | 1 | 1.090909 | 1 |

In [16]:

Player_Performance_based_Map_and_Agent.sort_values(by='Match Result',ascending=False)
Player_Performance_based_Map_and_Agent

Out [16]:

| | Map Name | Agent Name | N° of Play | kdRatio | Match Result |
|---|----------|------------|------------|----------|--------------|
| 1 | Ascent | Sage | 9.0 | 0.727167 | 5.0 |
| 2 | Fracture | Omen | 8.0 | 0.891876 | 5.0 |
| 4 | Icebox | Killjoy | 6.0 | 0.864356 | 4.0 |
| 0 | Ascent | Killjoy | 4.0 | 0.644841 | 3.0 |
| 3 | Haven | Cypher | 4.0 | 0.745705 | 3.0 |

This table provides all of the information that I require; as we can see, I am a **sentinelle** type of player who does not play aggressively as a **dualist**. I enjoy playing **Ascent**, **Haven**, **Fracture**, and **Icebox** Ascent, Haven, Fracture, and Icebox. My main as a controller is **omen** omen.

Machine Learning

In this machine learning section, I will use a model called linear regression to predict the kd ratio for the agent and the map. Logistic regression is used to predict win-loss outcomes for the agent and the map.

In [17]:

data_ML=data

Out [17]:

| | Date | hour | Map Name | Match Result | Agent Name | kills | headshots | deaths | assists | damage | damageReceived | plants | defuses | firstBloods | kdRatio | placement | rank |
|-----|------------|----------|----------|--------------|------------|-------|-----------|--------|---------|--------|----------------|--------|---------|-------------|----------|-----------|----------|
| 0 | 2021-11-08 | 15:49:57 | 5 | 0 | 7 | 5 | 1 | 14 | 3 | 1327 | 2447 | 0 | 0 | 0 | 0.357143 | 9 | Silver 1 |
| 1 | 2021-11-07 | 17:06:44 | 4 | 1 | 1 | 12 | 5 | 9 | 1 | 2169 | 1871 | 9 | 0 | 2 | 1.333333 | 7 | Silver 1 |
| 2 | 2021-11-07 | 16:28:18 | 6 | 0 | 9 | 3 | 1 | 17 | 2 | 895 | 3077 | 0 | 0 | 1 | 0.176471 | 9 | Silver 1 |
| 3 | 2021-11-07 | 15:32:01 | 1 | 1 | 7 | 11 | 6 | 19 | 6 | 2685 | 3633 | 1 | 0 | 0 | 0.578947 | 9 | Silver 1 |
| 4 | 2021-11-07 | 13:40:04 | 0 | 0 | 0 | 15 | 8 | 20 | 3 | 2925 | 3671 | 0 | 0 | 1 | 0.750000 | 4 | Silver 1 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 161 | 2021-07-16 | 15:05:30 | 2 | 1 | 1 | 10 | 5 | 11 | 8 | 2270 | 2012 | 2 | 1 | 0 | 0.909091 | 6 | Bronze 3 |
| 162 | 2021-07-16 | 09:44:52 | 2 | 0 | 5 | 8 | 2 | 14 | 3 | 1440 | 2130 | 0 | 0 | 1 | 0.571429 | 8 | Bronze 3 |
| 163 | 2021-07-16 | 07:13:18 | 3 | 0 | 4 | 14 | 7 | 16 | 3 | 2907 | 2687 | 3 | 0 | 1 | 0.875000 | 9 | Bronze 3 |
| 164 | 2021-07-15 | 15:02:45 | 0 | 1 | 4 | 10 | 4 | 14 | 5 | 1810 | 2577 | 8 | 1 | 1 | 0.714286 | 10 | Bronze 3 |
| 165 | 2021-07-15 | 14:15:02 | 1 | 0 | 5 | 11 | 8 | 19 | 2 | 2204 | 3279 | 4 | 0 | 2 | 0.578947 | 10 | Bronze 3 |

166 rows × 17 columns

In [28]:

data_ML=data_ML[['Map Name','Agent Name','kdRatio','Match Result']]
data_ML

Out [28]:

| | Map Name | Agent Name | kdRatio | Match Result |
|-----|----------|------------|----------|--------------|
| 0 | 5 | 7 | 0.357143 | 0 |
| 1 | 4 | 1 | 1.333333 | 1 |
| 2 | 6 | 9 | 0.176471 | 0 |
| 3 | 1 | 7 | 0.578947 | 1 |
| 4 | 0 | 0 | 0.750000 | 0 |
| ... | ... | ... | ... | ... |
| 161 | 2 | 1 | 0.909091 | 1 |
| 162 | 2 | 5 | 0.571429 | 0 |
| 163 | 3 | 4 | 0.875000 | 0 |
| 164 | 0 | 4 | 0.714286 | 1 |
| 165 | 1 | 5 | 0.578947 | 0 |

166 rows × 4 columns

In [35]:

X_Result=data_ML[['Map Name','Agent Name']]
Y_Result=data_ML[['Match Result']]
X_kd=data_ML[['Map Name','Agent Name']]
Y_kd=data_ML[['kdRatio']]

Out [35]:

| | Map Name | Agent Name |
|-----|----------|------------|
| 0 | 5 | 7 |
| 1 | 4 | 1 |
| 2 | 6 | 9 |
| 3 | 1 | 7 |
| 4 | 0 | 0 |
| ... | ... | ... |
| 161 | 2 | 1 |
| 162 | 2 | 5 |
| 163 | 3 | 4 |
| 164 | 0 | 4 |
| 165 | 1 | 5 |

166 rows × 2 columns

In [36]:

from sklearn.model_selection import train_test_split
X_train_R,X_test_R,Y_train_R,Y_test_R=train_test_split(X_Result,Y_Result,test_size=0.3,random_state=0)
X_train_KD,X_test_KD,Y_train_KD,Y_test_KD=train_test_split(X_kd,Y_kd,test_size=0.4,random_state=0)

Out [36]:

| | Map Name | Agent Name |
|-----|----------|------------|
| 0 | 5 | 7 |
| 1 | 4 | 1 |
| 2 | 6 | 9 |
| 3 | 1 | 7 |
| 4 | 0 | 0 |
| ... | ... | ... |
| 161 | 2 | 1 |
| 162 | 2 | 5 |
| 163 | 3 | 4 |
| 164 | 0 | 4 |
| 165 | 1 | 5 |

166 rows × 2 columns

In [37]:

from sklearn.linear_model import LogisticRegression, LinearRegression
model_R=LogisticRegression()
model_R.fit(X_train_R,Y_train_R)
model_KD=LinearRegression()
model_KD.fit(X_train_KD,Y_train_KD)

Out [37]:

| | Map Name | Agent Name |
|-----|----------|------------|
| 0 | 5 | 7 |
| 1 | 4 | 1 |
| 2 | 6 | 9 |
| 3 | 1 | 7 |
| 4 | 0 | 0 |
| ... | ... | ... |
| 161 | 2 | 1 |
| 162 | 2 | 5 |
| 163 | 3 | 4 |
| 164 | 0 | 4 |
| 165 | 1 | 5 |

166 rows × 2 columns

In [42]:

y_pred_R=model_R.predict(X_test_R)
y_pred_KD=model_KD.predict(X_test_KD)

Out [42]:

| | Map Name | Agent Name |
|-----|----------|------------|
| 0 | 5 | 7 |
| 1 | 4 | 1 |
| 2 | 6 | 9 |
| 3 | 1 | 7 |
| 4 | 0 | 0 |
| ... | ... | ... |
| 161 | 2 | 1 |
| 162 | 2 | 5 |
| 163 | 3 | 4 |
| 164 | 0 | 4 |
| 165 | 1 | 5 |

166 rows × 2 columns

Finally, those models could not provide a good prediction because there are so many features that should be implemented in the ML input, such as ping(latency is the technically more correct term) means the time it takes for a small data set to be transmitted from your device to a server on the Internet and back to your device again.) packet loss, computer configuration, team mmr... those features will provide a good prediction with high accuracy.

In []:

Data_for_report=data
Data_for_report.replace(to_replace=['defeat', 'victory'], value=[0, 1])
Data_for_report.to_csv('Valorant_Lite Performance.csv')
Best_agent_based_map.to_csv('Best_agent_based_map.csv')

Out []:

| | Map Name | Agent Name |
|-----|----------|------------|
| 0 | 5 | 7 |
| 1 | 4 | 1 |
| 2 | 6 | 9 |
| 3 | 1 | 7 |
| 4 | 0 | 0 |
| ... | ... | ... |
| 161 | 2 | 1 |
| 162 | 2 | 5 |
| 163 | 3 | 4 |
| 164 | 0 | 4 |