Exploring Table Data

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1. Business Understanding

`About League of Legends:`

Developed by Riot Studios, League of Legends, or "LoL", is an online multiplayer video-game that is available to Windows/MacOS users. LoL consists 2 teams ('Blue & 'Red') facing each other, where the main objective is to destroy the opposing teams 'Nexus', or home base, while facing obstacles like destroying damage dealing towers & eliminating players throughout the way. Perks & gold are able to be obtained by players/teams through completing tasks such as eliminating players, enemy creeps, or dragons. Players then spend the gold to purchase items that help raise the power of their abilities.

League of Legends offers different game modes, such as ranked. In this game mode, players are given a rank based off of the number of wins + the number of games played. "Diamond" is one of the highest ranks a player may obtain and is known to be extremely competitive. A ranked game on average lasts 30-45 minutes. The dataset we will be using contains the first 10 minute analytics of each team for different diamond ranked matches.

`Measure of Success`

Once the data is analyzed, third parties, or teams/players, would be able to conceptualize the level of priority different attributes have during early stages of diamond ranked matches. With the first 10-minutes of each game being critical, they could then use this information to adjust their strategy to one proven to win matches. In order for this data to be useful and trusted by third parties in specific situations such as playing at professional level, the data would have to render at least a 70% accuracy. The reason for it being 70% and not any higher is because as mentioned this data only include the first 10 minutes of a game (average full game: 30-45 minutes). We leave a 30% error gap for any changes of pace the winning team might have for the remaining time of the game (~67%).

Additionally, players who are accustomed to playing as the 'jungle' role (a player role that focuses on obtaining objective eliminations within the jungle areas of the map) can use this analyzed data to better understand the impact elite monsters have on winning games.

Dataset [Kaggle]: [First 10 minutes of diamond ranked League of Legends matches]

Question Of Interest : As of the first 10 minutes, which team will win?

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2. Data Understanding

2.1 Data Description

In [1]:
```python
import pandas as pd

# Load in the dataset into a dataframe
df =
pd.read_csv('https://raw.githubusercontent.com/luisegarduno/MachineLearning_Projects/master/data/high_diamond_ran



df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9879 entries, 0 to 9878
Data columns (total 40 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   gameId                        9879 non-null   int64  
 1   blueWins                      9879 non-null   int64  
 2   blueWardsPlaced               9879 non-null   int64  
 3   blueWardsDestroyed            9879 non-null   int64  
 4   blueFirstBlood                9879 non-null   int64  
 5   blueKills                     9879 non-null   int64  
 6   blueDeaths                    9879 non-null   int64  
 7   blueAssists                   9879 non-null   int64  
 8   blueEliteMonsters             9879 non-null   int64  
 9   blueDragons                   9879 non-null   int64  
 10  blueHeralds                   9879 non-null   int64  
 11  blueTowersDestroyed           9879 non-null   int64  
 12  blueTotalGold                 9879 non-null   int64  
 13  blueAvgLevel                  9879 non-null   float64
 14  blueTotalExperience           9879 non-null   int64  
 15  blueTotalMinionsKilled        9879 non-null   int64  
 16  blueTotalJungleMinionsKilled  9879 non-null   int64  
 17  blueGoldDiff                  9879 non-null   int64  
 18  blueExperienceDiff            9879 non-null   int64  
 19  blueCSPerMin                  9879 non-null   float64
 20  blueGoldPerMin                9879 non-null   float64
 21  redWardsPlaced                9879 non-null   int64  
 22  redWardsDestroyed             9879 non-null   int64  
 23  redFirstBlood                 9879 non-null   int64  
 24  redKills                      9879 non-null   int64  
 25  redDeaths                     9879 non-null   int64  
```

```
 26  redAssists                    9879 non-null   int64
 27  redEliteMonsters              9879 non-null   int64
 28  redDragons                    9879 non-null   int64
 29  redHeralds                    9879 non-null   int64
 30  redTowersDestroyed            9879 non-null   int64
 31  redTotalGold                  9879 non-null   int64
 32  redAvgLevel                   9879 non-null   float64
 33  redTotalExperience            9879 non-null   int64
 34  redTotalMinionsKilled         9879 non-null   int64
 35  redTotalJungleMinionsKilled   9879 non-null   int64
 36  redGoldDiff                   9879 non-null   int64
 37  redExperienceDiff             9879 non-null   int64
 38  redCSPerMin                   9879 non-null   float64
 39  redGoldPerMin                 9879 non-null   float64
dtypes: float64(6), int64(34)
memory usage: 3.0 MB
```

Printing out the information about the dataframe we are able to see that there are a total of 9,879 instances, and 39 attributes.

Additionally we are able to see that there are 19 of the same attributes for each the blue & red team (columns 1-19 are the same as 20-38).

Attributes for each team includes :

- Wards placed & destroyed
- Total number of kills, deaths, & assists
- First Bloods (1st elimination of the game)
- Total : towers destroyed, gold, experience
- Average : level, CS per minute, & gold per minute
- Difference in gold & experience between the teams
- Objective eliminations : elite monsters(dragons, heralds), minions, & jungle minions

Attributes such as total gold, experience, objectives eliminations, towers destroyed, etc. will be of type integer (int64) because they will always be whole numbers. Attributes involving averages such as cs per minute, gold per minute, & level, should be the only of double-precision floating-point format (float64).

The data type for "blueWins" and "first bloods" could be changed to be of type boolean, but because we are wanting to visualize these attributes, optimally it is best to keep these as integer data types. As a result, the data types presented for each attribute are correct and should not be changed.

Below is a brief description of some of the key attributes.

In [2]:

```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# describe dataframe
df.describe()
```

Out[2]:

	gameId	blueWins	blueWardsPlaced	blueWardsDestroyed	blueFirstBlood	blueKills	blueDeaths	blueAssists	blueEliteM
count	9.879000e+03	9879.000000	9879.000000	9879.000000	9879.000000	9879.000000	9879.000000	9879.000000	9879
mean	4.500084e+09	0.499038	22.288288	2.824881	0.504808	6.183925	6.137666	6.645106	0
std	2.757328e+07	0.500024	18.019177	2.174998	0.500002	3.011028	2.933818	4.064520	0
min	4.295358e+09	0.000000	5.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0
25%	4.483301e+09	0.000000	14.000000	1.000000	0.000000	4.000000	4.000000	4.000000	0
50%	4.510920e+09	0.000000	16.000000	3.000000	1.000000	6.000000	6.000000	6.000000	0
75%	4.521733e+09	1.000000	20.000000	4.000000	1.000000	8.000000	8.000000	9.000000	1
max	4.527991e+09	1.000000	250.000000	27.000000	1.000000	22.000000	22.000000	29.000000	2

8 rows × 40 columns

Variable	Description	Type	Range
blueWins (target)	whether blue team won or not	Discrete	[0] red team won; [1] blue team won;
WardsPlaced / WardsDestroyed	number of total wards placed or destroyed by team	Continuous	[placed] 5 - 250; [destroyed] 0 - 27
FirstBlood	team with the first kill of game	Discrete	[0] did not get first kill; [1] team obtained first kill
Kills / Deaths / Assists	total number of kills, deaths, or assists of team	Continuous	[kills] 0 - 22; [deaths] 0 - 22; [assists] 0 - 29
TowersDestroyed	total number of towers destroyed by team	Continuous	0 - 2
TotalGold	total gold obtained by team	Continuous	11,000 - 25,000
AvgLevel	average level of all players on team	Continuous	4.5 - 8.5
TotalExperience	total experience points accumulated by team	Continuous	10,000 - 24,000
CSPerMin	average creep score per minute	Continuous	10.0 - 30.0
GoldPerMin	average gold obtained per minute	Continuous	1,100.0 - 2,000.0

2.2 Data Quality

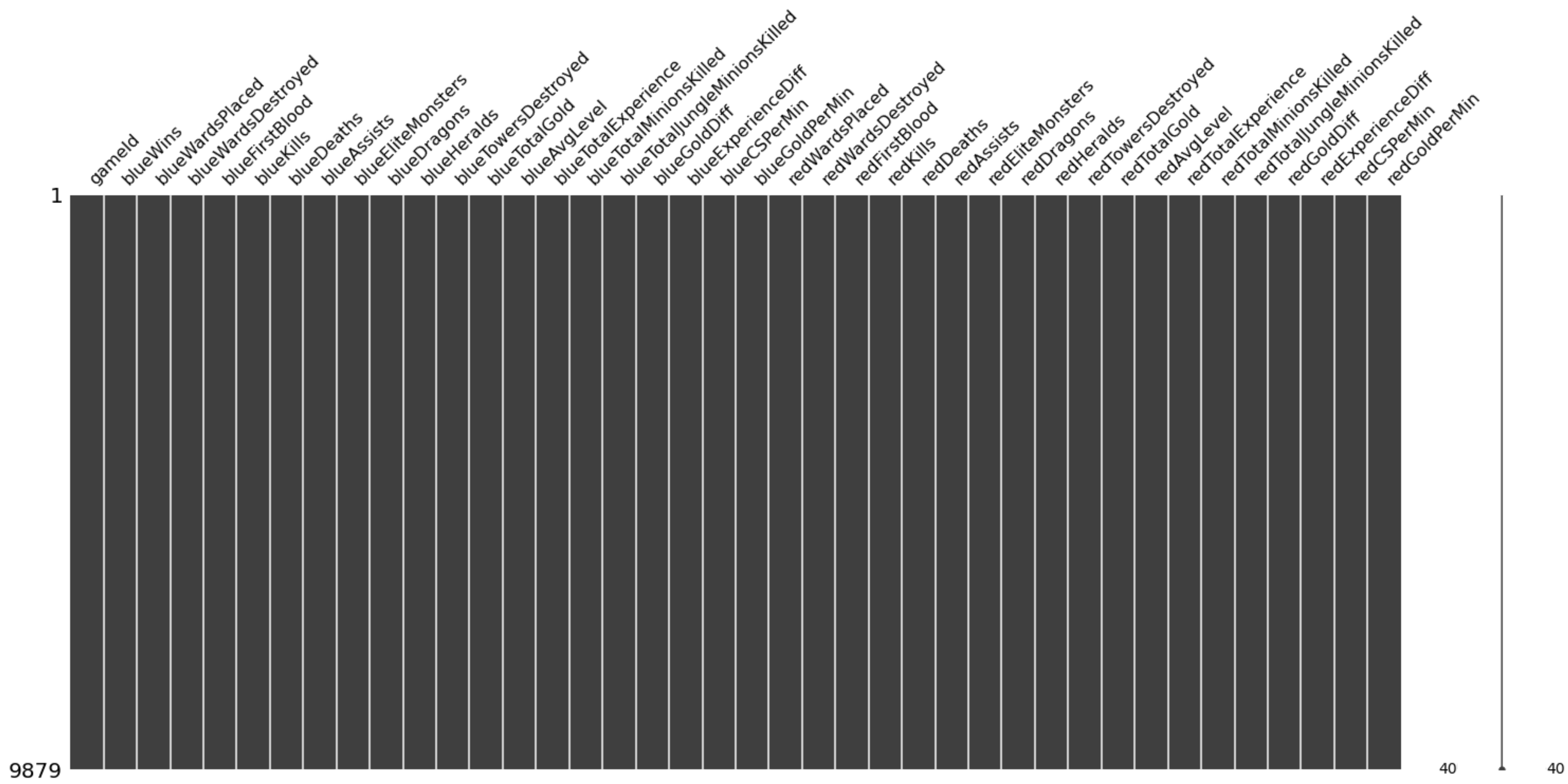
Using the `missingno` package, we are able to additionally confirm that all the data is complete and there is no missing entries with the dataset. If there was missing data, we could impute the missing values by using the k-nearest neighbor. But if an instance was missing a majority of its attributes, it would be removed from the dataset.

The number of unique values in the column "gameId" is printed to verify that all instances are weighted equally.

In [3]:

```python
import numpy as np
import missingno as mn

mn.matrix(df)

# Count unique values in column 'gameId' of the dataframe
print('Number of unique values in column "gameId" : ', df['gameId'].nunique())

dup_df = df.replace(to_replace=-1, value=np.nan)

dup_df = dup_df.duplicated()
print('Duplicates : ', len(df[dup_df]))
```

```
Number of unique values in column "gameId" :  9879
Duplicates :  0
```



2.3 Cleaning the Dataset

After confirming there are no duplicates in the data, the "gameId" column can be removed since it will have no impact on the results.

Using the correlation feature from the `pandas` package, for each team we find the names of attributes that correlate most with winning (correlation >= 7%). The names of these attributes are stored in a array for later use.

Lastly, two dataframes are created to hold the attributes at instances when blue team wins, and when blue team loses.

In [4]:

```python
del df['gameId']

red_col = df.corr()[df.corr()['blueWins'] <= -0.07].index.values
blue_col = df.corr()[df.corr()['blueWins'] >= 0.07].index.values

# Create dataframes for the 2 possible outcomes :
df_win   = df[df["blueWins"]==1]      # Blue Team Win  /  Red Team Lost
df_lose = df[df["blueWins"]==0]      # Red Team Win   /  Blue Team Lost
```

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3. Data Visualization

3.1 Data Exploration

3.1.1 Win rate by Team

Does being on a specific team have an impact on winning?

For context :

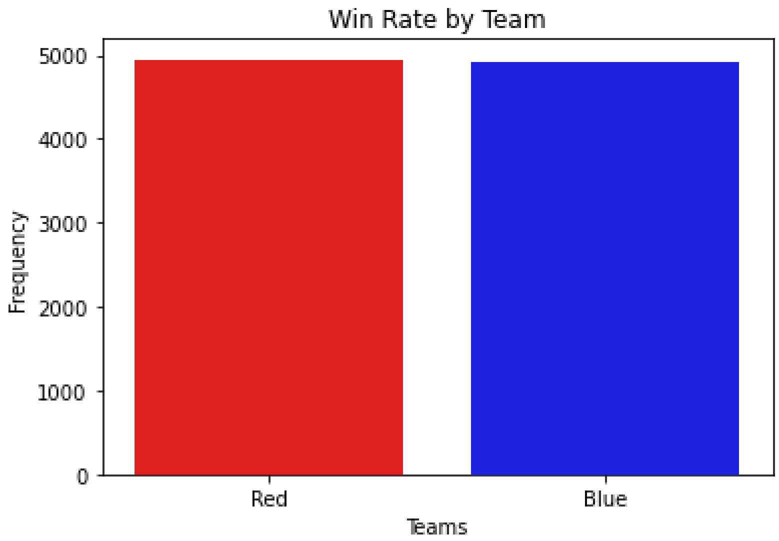
- Red team defends the top right Nexus
- Blue team defends the bottom left Nexus

In [5]:

```
ax = sns.countplot(x="blueWins", data=df, palette=['red', 'blue'])
ax.set_title('Win Rate by Team')
ax.set_xlabel('Teams')
ax.set_xticks([0,1])
ax.set_xticklabels(['Red', 'Blue'])
ax.set_ylabel('Frequency')
```

Out[5]:

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



Because each team puts you on a specific side of the map, some may think that having a specific perspective on the map may make an impact on your chances of winning. As shown above, the win rate for each team is symmetrical within the large dataset, meaning that defending a specific side of the map will likely not have an impact on the game outcome.

3.1.2 Win rate by kill/death/assist ratio

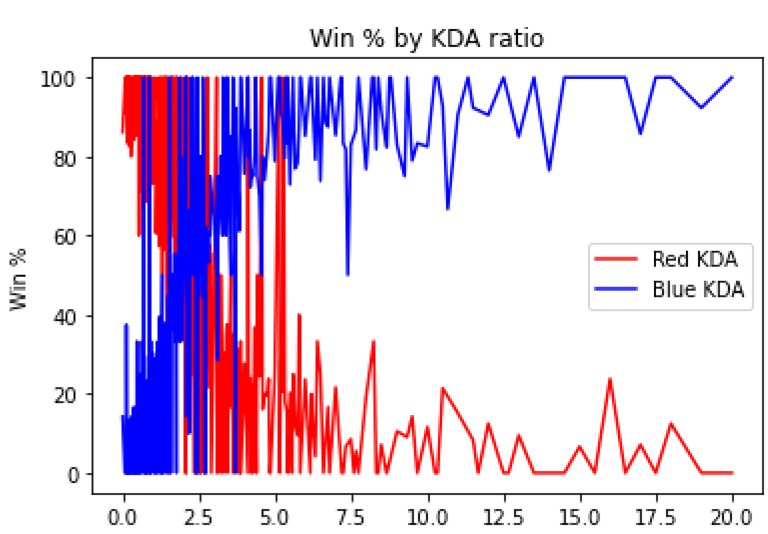
A KDA, or Kills/Deaths/Assists, ratio is highly significant when determining whether a team will win or not. A KDA ratio is calculated by using the formula shown in the code below(Kills + Assists / Deaths).

In [6]:

```
# Formula to calculate KDA ratio ------> KDA = (Kills + Assists) / Deaths
df['redKDA'] = ((df['redKills'] + df['redAssists']) / df['redDeaths'])
df['blueKDA'] = ((df['blueKills'] + df['blueAssists']) / df['blueDeaths'])

# Group all KDA's for each team
df_redKDA = df[(df['redKDA'] <= 20)].groupby(by=['redKDA'])
df_blueKDA = df[(df['blueKDA'] <= 20)].groupby(by=['blueKDA'])

# Calculate probability of winning according to KDA
# Frequency of winning according to KDA / Frequency for each KDA * 100
redKDA_rate = (df_redKDA.blueWins.sum() / df_redKDA.blueWins.count() * 100)
blueKDA_rate = (df_blueKDA.blueWins.sum() / df_blueKDA.blueWins.count() * 100)

ax = sns.lineplot(data=redKDA_rate, label='Red KDA', color='red')
sns.lineplot(data=blueKDA_rate, label='Blue KDA', color='blue')
ax.set_xlabel('KDA ratio')
ax.set_ylabel('Win %')
ax.set_title('Win % by KDA ratio')
```

Out[6]:

```
Text(0.5, 1.0, 'Win % by KDA ratio')
```

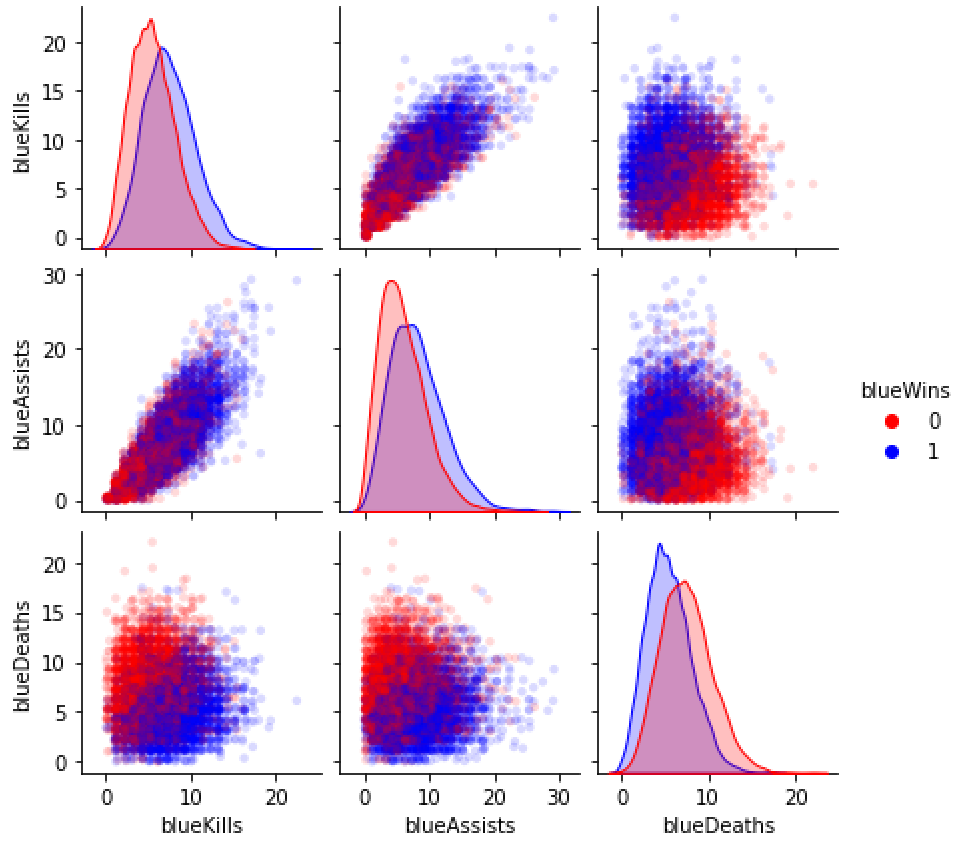


The line plot shown above helps us visualize the KDA's at instances where the blue team won. The x-axis represents the KDA obtained by a team. Meanwhile the y-axis represents the probability of winning according to a teams KDA ratio. When the dataframes are initially grouped according to blue/red team kda, only KDA's under 20 are taken into consideration since they are the most relevant/frequent data. The line plot does an excellent job at displaying the frequency of each KDA, i.e the interval 0.0 - 5.0 shows us the most common KDA ratios obtained within diamond ranked games. Additionally it helps teams/players see how when the blue team KDA ratio rises, the probability of red team winning rapidly declines.

In [7]:

```
jitter_values = ['blueKills','blueAssists','blueDeaths','blueWins']
```

```
df_jitter = df[jitter_values].copy()
df_jitter[['blueKills','blueAssists','blueDeaths']] += np.random.rand(len(df_jitter),3)/2
ax = sns.pairplot(df_jitter,hue="blueWins",height=2,plot_kws=dict(s=20,alpha=0.15,linewidth=0),palette=
['red','blue'])

plt.show()
```



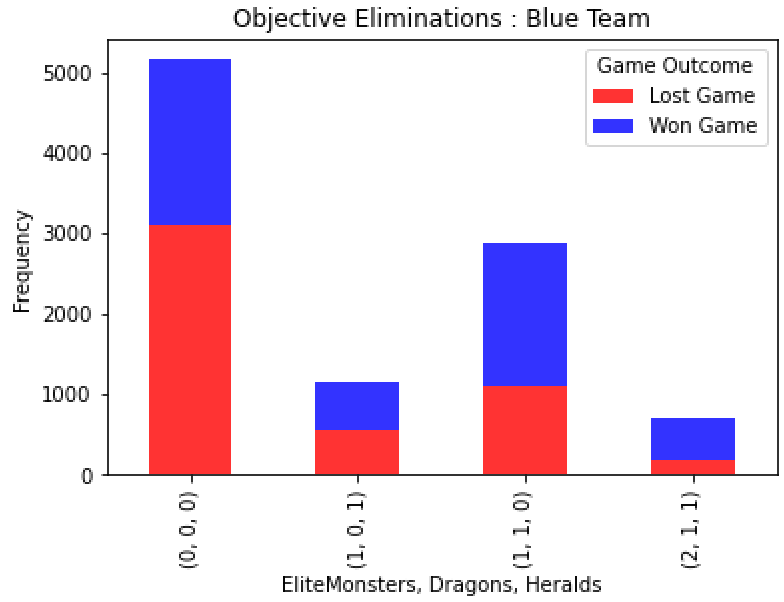
We additionally use a jitter plot to demonstrate KDA ratio, but we break down the ratio into the original attributes (blueKills, blueAssists, & blueDeaths). The bottom row of the jitter plot emphasizes the already known correlation deaths has with losing games. Players/teams should be expected to already know this since everytime a player on your team dies, the opposing team receives gold.

3.1.3 Win rate by objective eliminations

In [8]:
```
obj_blue = pd.crosstab([df['blueEliteMonsters'],df['blueDragons'],df['blueHeralds']],df.blueWins.astype(bool))

ax_blue = obj_blue.plot(kind='bar', stacked=True, label='Game Outcome', color=['red', 'blue'], alpha=0.8)
ax_blue.set_xlabel('EliteMonsters, Dragons, Heralds')
ax_blue.set_ylabel('Frequency')
ax_blue.set_title('Objective Eliminations : Blue Team')
ax_blue.legend(["Lost Game", "Won Game"], title="Game Outcome")

obj_blue
```

Out[8]:

		blueWins	False	True
blueEliteMonsters	**blueDragons**	**blueHeralds**		
0	**0**	**0**	3101	2055
1	**0**	**1**	564	583
	1	**0**	1096	1770
2	**1**	**1**	188	522



The stacked plot shown above contains values regarding objective eliminations for elite monsters. As mentioned in section `2.1`, these elite monsters are dragons, & heralds.

By eliminating these elite monsters, a team/player will gain perks that give you advantages such as increased damaged dealing, or regenerating health quicker. The stacked plots shown above, show the clear impact these elite monsters have on winning.

Breaking down the 'obj_blue' table into percentages:

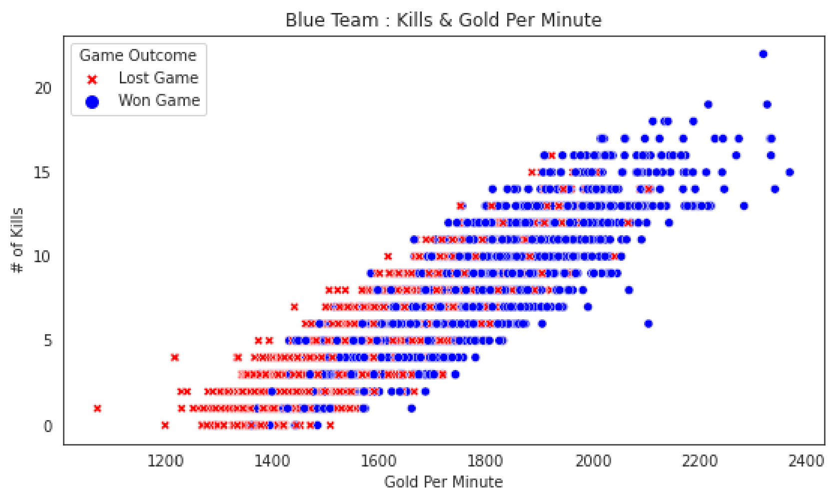
- 0 elite monsters : ~40% win rate
- 1 herald (0 dragons) : ~50% win rate
- 1 dragon (0 heralds) : ~60% win rate
- herald & dragon : ~70% win rate

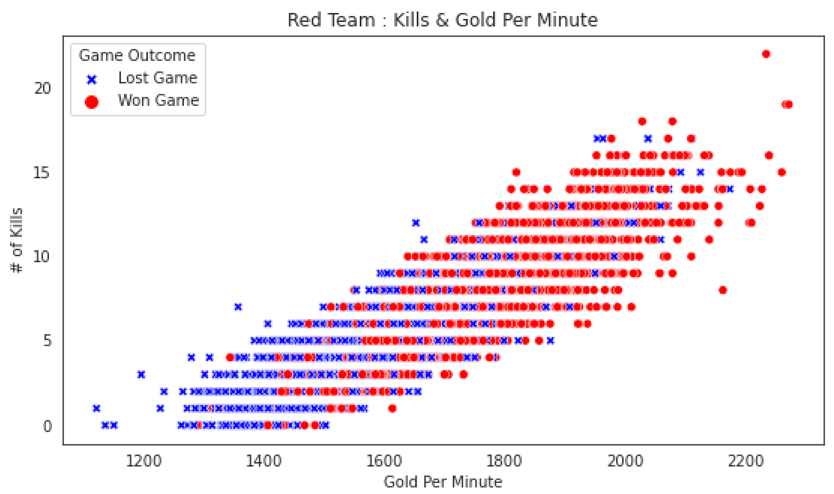
Players/Teams but mostly 'Jungle' role players should take note of these percentages. A couple things to point out:

- If no elite monsters are obtained within the first 10 minutes of playing, ~60% of the time they are shown to lose.
- A 'jungler' should prioritize on eliminating a dragon before a herald, as a dragon seems to yield a %60 win rate.
- Out of ~5,000 diamond ranked matches where blue team won, only in ~700 games was blue team able to eliminate both a dragon and herald within the first 10 minutes. Most importantly, in the games this occurred in, ~70% of them resulted in a win. So as a team it would be strongly advised to help your 'jungle' role player eliminate these elite monsters.

3.1.4 Win rate by Kills & GoldPerMinute

In [9]:
```
from matplotlib.lines import Line2D

mark1 = {0:"X", 1:"o"}
mark2 = {0:"o", 1:"X"}

legend_elements_1 = [Line2D([0],[0],marker='X',color='w',label='Lost Game',markerfacecolor='red',markersize=8),
                     Line2D([0],[0],marker='o',color='w',label='Won
Game',markerfacecolor='blue',markersize=10)]

legend_elements_2 = [Line2D([0],[0],marker='X',color='w',label='Lost
Game',markerfacecolor='blue',markersize=8),
                     Line2D([0],[0],marker='o',color='w',label='Won Game',markerfacecolor='red',markersize=10)]

plt.subplots(figsize=(20,5))
sns.set_style("white")

plt.subplot(1,2,1)
ax1 = sns.scatterplot(data=df,x='blueGoldPerMin',y='blueKills',hue='blueWins',palette=
['red','blue'],style='blueWins',markers=mark1)
ax1.set_title('Blue Team : Kills & Gold Per Minute')
ax1.set_xlabel('Gold Per Minute')
ax1.set_ylabel('# of Kills')
ax1.legend(title='Game Outcome', handles=legend_elements_1, loc='upper left')

plt.subplot(1,2,2)
ax2 = sns.scatterplot(data=df,x='redGoldPerMin',y='redKills',hue='blueWins',palette=
['red','blue'],style='blueWins',markers=mark2)
ax2.set_title('Red Team : Kills & Gold Per Minute')
ax2.set_xlabel('Gold Per Minute')
ax2.set_ylabel('# of Kills')
ax2.legend(title='Game Outcome',handles=legend_elements_2,loc='upper left')

plt.show()
```





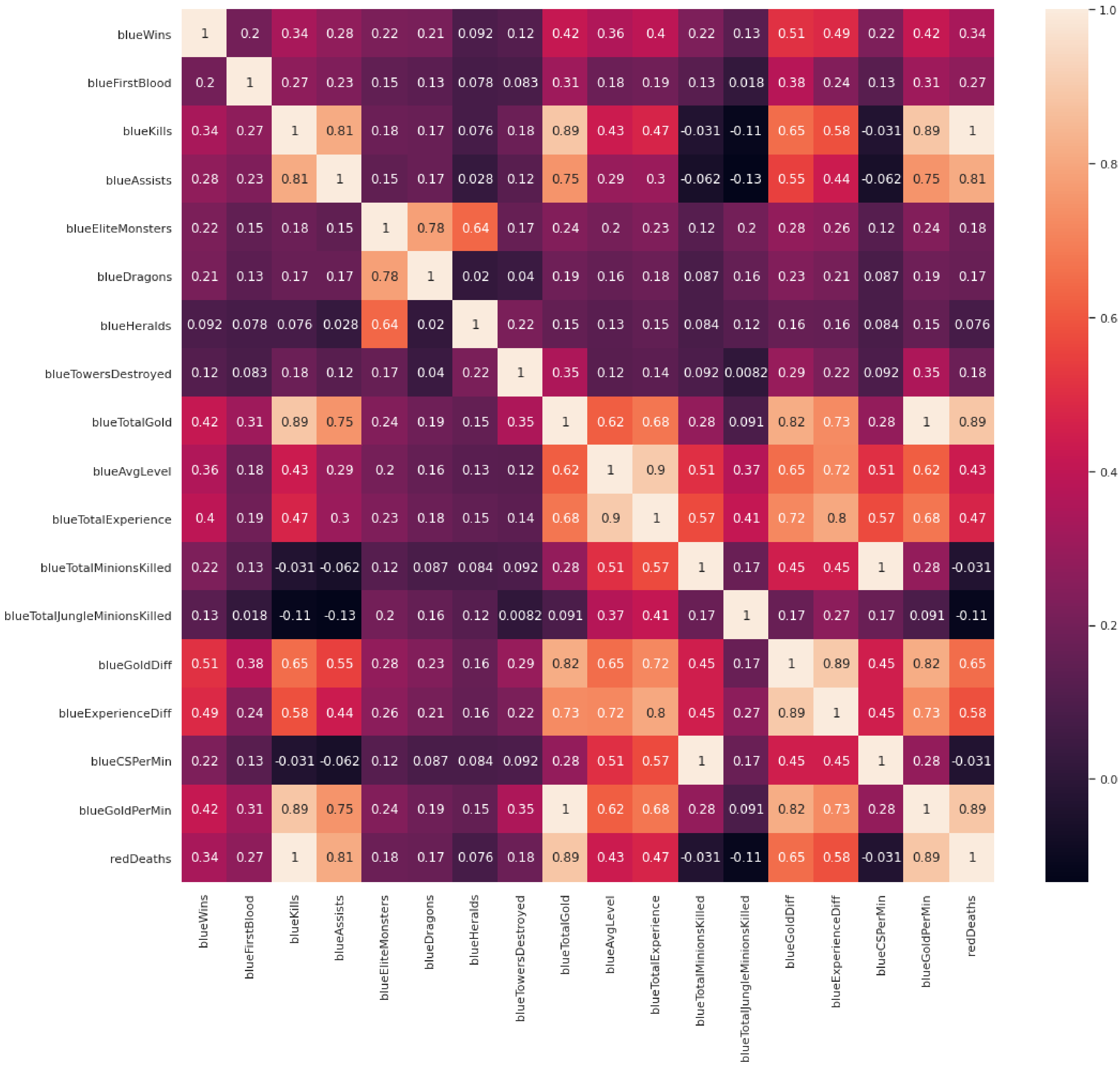
Above we have scatter plots for each teams performances during games that they won/lost. The x-axis represents the average gold per minute, & the y-axis represents the number of kills. In both scatter plots we see the same pattern of the higher number a kills & average gold per minute achieved by a team, will often lead to winning the game.

3.2 Data Relationship Exploration

3.2.1 Correlation Matrix

In [10]:
```
cmap = sns.set(style="darkgrid", palette="colorblind")
```

```python
plt.subplots(figsize=(17,15))
plt.pcolor(df[blue_col].corr())
plt.xticks(np.arange(0, len(blue_col), 1), blue_col)
plt.yticks(np.arange(0, len(blue_col), 1), blue_col)
plt.xticks(rotation=90)
sns.heatmap(df[blue_col].corr(),cmap=cmap,annot=True)
plt.show()
```



The heatmap printed above contains correlating values pertaining to the 'blueWins' attribute. We observe that there are 6 attributes with a correlation value of 1 ('blueWins' not included) :

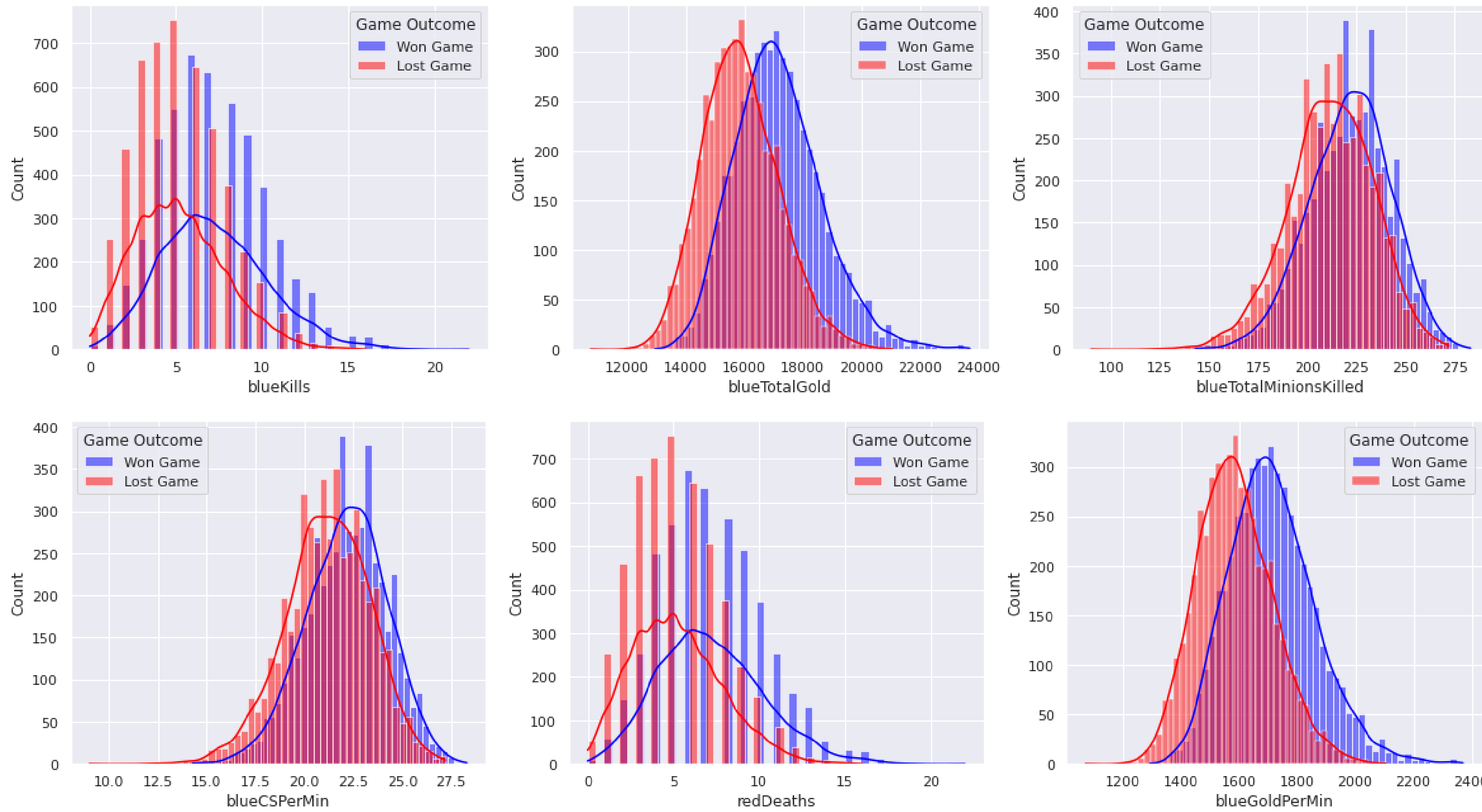
- 'redDeaths'
- 'blueKills'
- 'blueCSPerMin'
- 'blueTotalGold'
- 'blueGoldPerMin'
- 'blueTotalMinionsKilled'

3.2.2 Winning attributes

In [11]:

```python
corr_blue = ['blueKills', 'blueTotalGold', 'blueTotalMinionsKilled', 'blueCSPerMin', 'redDeaths',
'blueGoldPerMin']

c = 0
plt.subplots(figsize=(20,5))
for i in corr_blue:
    plt.subplot(1,3,c+1)
    sns.histplot(df_win[i],label='Won Game',color='blue', kde=True)
    sns.histplot(df_lose[i],label='Lost Game',color='red', kde=True)
    plt.legend(title='Game Outcome')
    c=c+1

    if c == 3:
        plt.show()
```

```
        if i != corr_blue[len(corr_blue) - 1]:
            plt.subplots(figsize=(20,5))
        c=0
```



Using the attributes we found in `3.2.1` with a correlation value of 1, we output the distribution plot (kernel density estimation + histogram) for each attribute to help us visualize how significantly important each of these are to winning.

The distribution plots shown above help teams/players visualize the importance of these attributes and how the higher these attribute values are, the greater chance a team has at winning the game. Players/teams can adjust their strategy by using the averaged values displayed in the plots above as a measure of success within their first 10 minutes of a game.

References

Kaggle. League of Legends Diamond Ranked Games (First 10 Minutes). https://www.kaggle.com/bobbyscience/league-of-legends-diamond-ranked-games-10-min (Accessed 2-8-2021)