EDA 2

In [416]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler
%matplotlib inline
```

In [417]:
```
# Random Seed
SEED = 42
np.random.seed = SEED
```

In [418]:
```
dataurl = '../datasets/high_diamond_ranked_10min.csv'
```

In [419]:
```
df = pd.read_csv(dataurl)
df.head()
```

Out[419]:

	gameId	blueWins	blueWardsPlaced	blueWardsDestroyed	blueFirstBlood	blueKills	blueDea
0	4519157822	0	28	2	1	9	
1	4523371949	0	12	1	0	5	
2	4521474530	0	15	0	0	7	
3	4524384067	0	43	1	0	4	
4	4436033771	0	75	4	0	6	

5 rows × 40 columns

In [420]:
```
print('Shape of Data, # of Rows {} and # of Columns {}'.format(df.shape[0], df.sh
```

```
Shape of Data, # of Rows 9879 and # of Columns 40
```

In [421]:
```
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
```

In [422]:
```
df.iloc[:, 2:20].columns
```

Out[422]:
```
Index(['blueWardsPlaced', 'blueWardsDestroyed', 'blueFirstBlood', 'blueKills',
       'blueDeaths', 'blueAssists', 'blueEliteMonsters', 'blueDragons',
       'blueHeralds', 'blueTowersDestroyed', 'blueTotalGold', 'blueAvgLevel',
       'blueTotalExperience', 'blueTotalMinionsKilled',
       'blueTotalJungleMinionsKilled', 'blueGoldDiff', 'blueExperienceDiff',
       'blueCSPerMin'],
      dtype='object')
```

In [423]:
```
df.iloc[:, 21:].columns
```

Out[423]:
```
Index(['redWardsPlaced', 'redWardsDestroyed', 'redFirstBlood', 'redKills',
       'redDeaths', 'redAssists', 'redEliteMonsters', 'redDragons',
       'redHeralds', 'redTowersDestroyed', 'redTotalGold', 'redAvgLevel',
       'redTotalExperience', 'redTotalMinionsKilled',
       'redTotalJungleMinionsKilled', 'redGoldDiff', 'redExperienceDiff',
       'redCSPerMin', 'redGoldPerMin'],
      dtype='object')
```

The data is found on Kaggle. The data set contained 9879 observations with 40 features. there are 19 features per team except gameid and the target variable as indicated above.
Data Source: [https://www.kaggle.com/bobbyscience/league-of-legends-diamond-ranked-games-10-min (https://www.kaggle.com/bobbyscience/league-of-legends-diamond-ranked-games-10-min)](https://www.kaggle.com/bobbyscience/league-of-legends-diamond-ranked-games-10-min)

Checking gameid uniqueness to acertain all games are independent.

In [424]:
```
len(df['gameId'].unique()) == df.shape[0]
```

Out[424]:
```
True
```

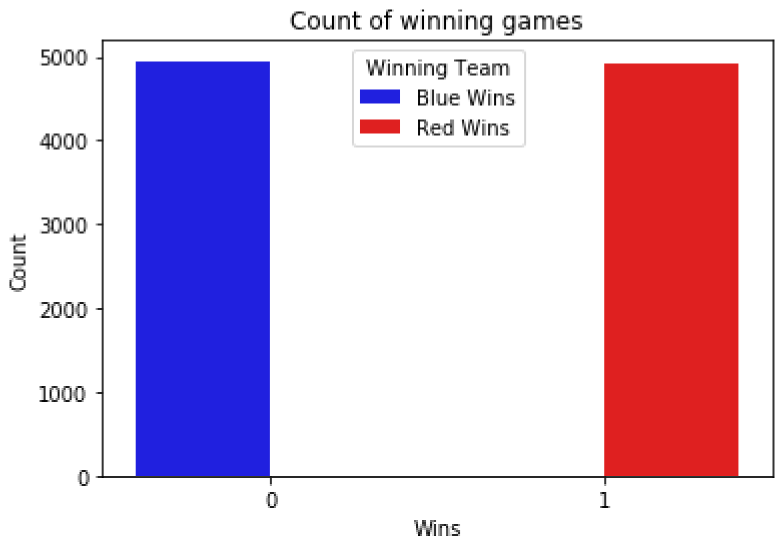
Distribution of wins

In [425]:
```
df['blueWins'].value_counts()
```

Out[425]:
```
0    4949
1    4930
Name: blueWins, dtype: int64
```

blueWins is our target variable, we want to make sure the data is balanced.

In [426]:
```
ax = sns.countplot(df['blueWins'], hue=df['blueWins'], palette=['blue', 'red'])
ax.set(xlabel='Wins', ylabel='Count')
ax.legend(title='Winning Team', loc='upper center', labels=['Blue Wins', 'Red Wir
ax.set_title('Count of winning games')
plt.show()
```



Data Cleaning

Dropping `gameId` since it is a unique value for each observation.

In [427]:
```
df = df.drop(columns='gameId')
```

In [428]:
```
corr = df.corr()
```

Checking correlation between features

In [429]:
```
columns = df.columns
for i in columns:
    for j in columns:
        if abs(df[i].corr(df[j])) >= 0.95:
            if i != j:
                print([i, j, df[i].corr(df[j])])
                columns = columns.drop(i)
```

```
['blueFirstBlood', 'redFirstBlood', -1.0]
['blueKills', 'redDeaths', 1.0]
['blueDeaths', 'redKills', 1.0]
['blueTotalGold', 'blueGoldPerMin', 1.0]
['blueTotalMinionsKilled', 'blueCSPerMin', 1.0]
['blueGoldDiff', 'redGoldDiff', -1.0]
['blueExperienceDiff', 'redExperienceDiff', -1.0]
['redTotalGold', 'redGoldPerMin', 1.0]
['redTotalMinionsKilled', 'redCSPerMin', 0.9999999999999996]
```

In [430]:
```
print((df['blueKills'] == df['redDeaths']).value_counts())

print((df['blueDeaths'] == df['redKills']).value_counts())
```

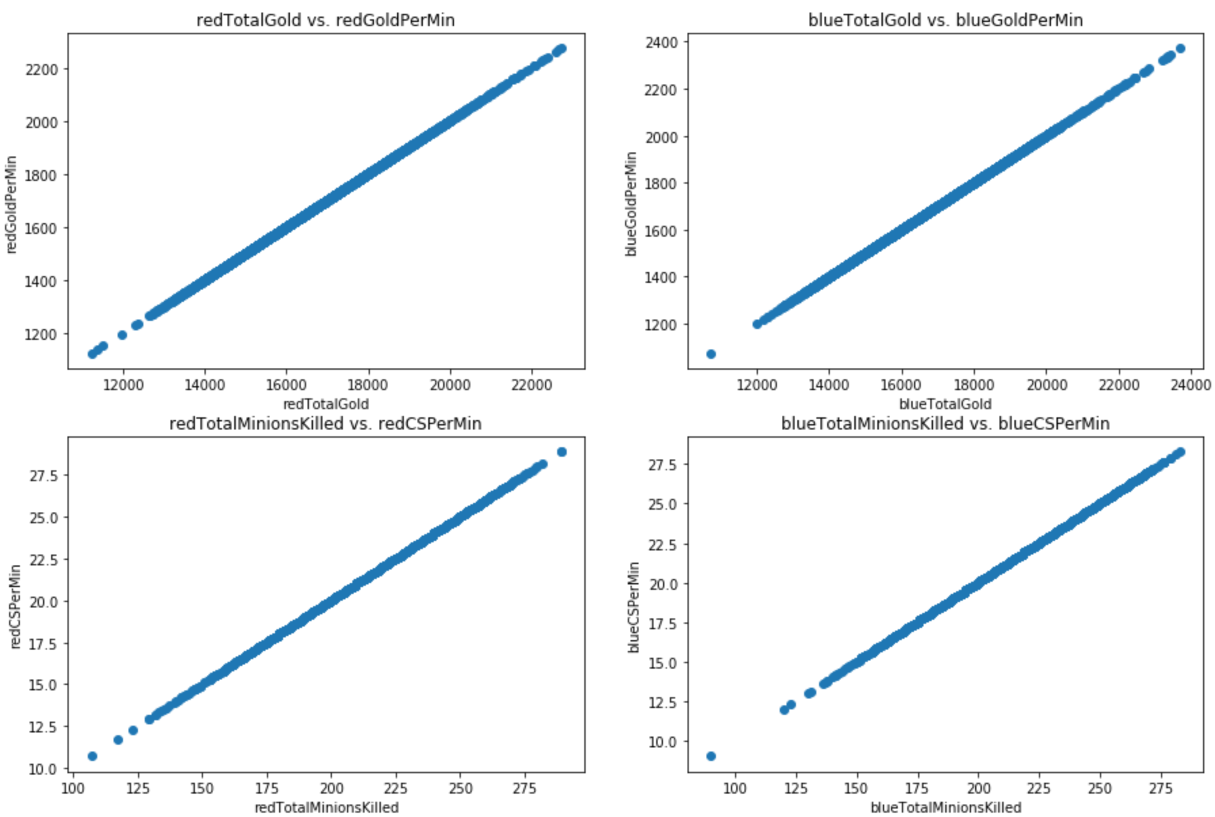
```
True    9879
dtype: int64
True    9879
dtype: int64
```

In [431]:
```
print((df['redTotalGold'] / 10 == df['redGoldPerMin']).value_counts())
print((df['blueTotalGold'] / 10 == df['blueGoldPerMin']).value_counts())
print((df['redTotalMinionsKilled'] / 10 == df['redCSPerMin']).value_counts())
print((df['blueTotalMinionsKilled'] / 10 == df['blueCSPerMin']).value_counts())
print((df['redEliteMonsters'] == (df['redDragons'] + df['redHeralds'])).value_cou
print((df['blueEliteMonsters'] == (df['blueDragons'] + df['blueHeralds'])).value_
print((df['blueGoldDiff'] == (df['blueTotalGold'] - df['redTotalGold'])).value_co
print((df['redGoldDiff'] == (df['redTotalGold'] - df['blueTotalGold'])).value_cou
print((df['blueExperienceDiff'] == (df['blueTotalExperience'] - df['redTotalExper
print((df['redExperienceDiff'] == (df['redTotalExperience'] - df['blueTotalExperi
```

```
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
True    9879
dtype: int64
```

we can see above that variables with correlation of 1 or -1 are repeated, so we can minimize them later

In [432]:
```
fig, ax = plt.subplots(2, 2, figsize=(15, 10))


ax[0,0].scatter('redTotalGold','redGoldPerMin', data=df)
ax[0,0].set_title('redTotalGold vs. redGoldPerMin')
ax[0,0].set_ylabel('redGoldPerMin')
ax[0,0].set_xlabel('redTotalGold')

ax[0,1].scatter('blueTotalGold','blueGoldPerMin', data=df)
ax[0,1].set_title('blueTotalGold vs. blueGoldPerMin')
ax[0,1].set_ylabel('blueGoldPerMin')
ax[0,1].set_xlabel('blueTotalGold')

ax[1,0].scatter('redTotalMinionsKilled','redCSPerMin', data=df)
ax[1,0].set_title('redTotalMinionsKilled vs. redCSPerMin')
ax[1,0].set_ylabel('redCSPerMin')
ax[1,0].set_xlabel('redTotalMinionsKilled')

ax[1,1].scatter('blueTotalMinionsKilled','blueCSPerMin', data=df)
ax[1,1].set_title('blueTotalMinionsKilled vs. blueCSPerMin')
ax[1,1].set_ylabel('blueCSPerMin')
ax[1,1].set_xlabel('blueTotalMinionsKilled')

plt.show()
```



Dealing with features with high correlation

- `blueFirstBlood` and `redFirstBlood` are inversely correlated since only one team can score first blood in the game. Dropping one feature
- `blueKills` and `redDeaths` , and `blueDeaths` and `redKills` are perfectly correlated and have same data since the game is only between two teams.
- `redCSPerMin` , `redGoldPerMin` , `redExperienceDiff` , `redGoldDiff` , `blueGoldDiff` , `blueCSPerMin` , `blueExperienceDiff` , `redEliteMonsters` , `blueEliteMonsters` and `blueGoldPerMin` , are all derived values

In [433]:
```
df = df.drop(columns=['redFirstBlood', 'redDeaths', 'redKills', 'redGoldPerMin',
```

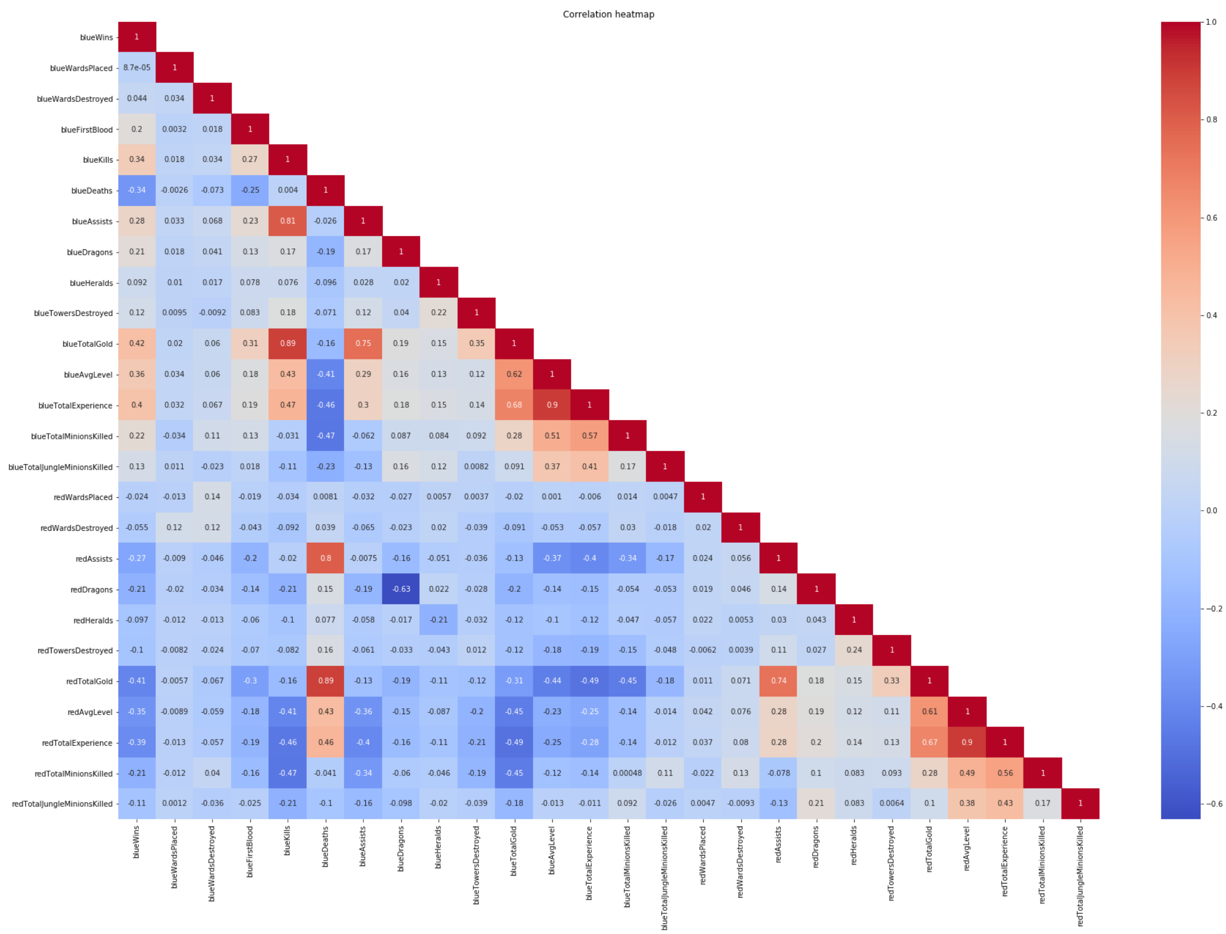
In [434]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9879 entries, 0 to 9878
Data columns (total 26 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   blueWins                      9879 non-null   int64  
 1   blueWardsPlaced               9879 non-null   int64  
 2   blueWardsDestroyed            9879 non-null   int64  
 3   blueFirstBlood                9879 non-null   int64  
 4   blueKills                     9879 non-null   int64  
 5   blueDeaths                    9879 non-null   int64  
 6   blueAssists                   9879 non-null   int64  
 7   blueDragons                   9879 non-null   int64  
 8   blueHeralds                   9879 non-null   int64  
 9   blueTowersDestroyed           9879 non-null   int64  
 10  blueTotalGold                 9879 non-null   int64  
 11  blueAvgLevel                  9879 non-null   float64
 12  blueTotalExperience           9879 non-null   int64  
 13  blueTotalMinionsKilled        9879 non-null   int64  
 14  blueTotalJungleMinionsKilled  9879 non-null   int64  
 15  redWardsPlaced                9879 non-null   int64  
 16  redWardsDestroyed             9879 non-null   int64  
 17  redAssists                    9879 non-null   int64  
 18  redDragons                    9879 non-null   int64  
 19  redHeralds                    9879 non-null   int64  
 20  redTowersDestroyed            9879 non-null   int64  
 21  redTotalGold                  9879 non-null   int64  
 22  redAvgLevel                   9879 non-null   float64
 23  redTotalExperience            9879 non-null   int64  
 24  redTotalMinionsKilled         9879 non-null   int64  
 25  redTotalJungleMinionsKilled   9879 non-null   int64  
dtypes: float64(2), int64(24)
memory usage: 2.0 MB
```

In [435]:
```
clean_corr = df.corr()
clean_corr['blueWins'].sort_values(ascending=False)
```

Out[435]:
```
blueWins                        1.000000
blueTotalGold                   0.417213
blueTotalExperience             0.396141
blueAvgLevel                    0.357820
blueKills                       0.337358
blueAssists                     0.276685
blueTotalMinionsKilled          0.224909
blueDragons                     0.213768
blueFirstBlood                  0.201769
blueTotalJungleMinionsKilled    0.131445
blueTowersDestroyed             0.115566
blueHeralds                     0.092385
blueWardsDestroyed              0.044247
blueWardsPlaced                 0.000087
redWardsPlaced                 -0.023671
redWardsDestroyed              -0.055400
redHeralds                     -0.097172
redTowersDestroyed             -0.103696
redTotalJungleMinionsKilled    -0.110994
redDragons                     -0.209516
redTotalMinionsKilled          -0.212171
redAssists                     -0.271047
blueDeaths                     -0.339297
redAvgLevel                    -0.352127
redTotalExperience             -0.387588
redTotalGold                   -0.411396
Name: blueWins, dtype: float64
```

In [436]:
```
f, ax = plt.subplots(figsize= (30, 20))
lower = clean_corr.where(np.tril(np.ones(clean_corr.shape)).astype(np.bool))
hmap=sns.heatmap(lower,cmap="coolwarm", annot=True)
ax.set_title('Correlation heatmap')
plt.savefig('clean-corr-half.png')
```



['blueTotalGold' , 'blueTotalExperience', blueAvgLevel, 'blueKills', 'blueAssists', 'blueTotalMinionsKilled', 'blueDragons', 'blueFirstBlood'], those feature have more higher corrlation than other features with blueWins

Identify Missing Data

In [437]:
```
df.describe()
```

Out[437]:

	blueWins	blueWardsPlaced	blueWardsDestroyed	blueFirstBlood	blueKills	blueDeatl
count	9879.000000	9879.000000	9879.000000	9879.000000	9879.000000	9879.00000
mean	0.499038	22.288288	2.824881	0.504808	6.183925	6.13766
std	0.500024	18.019177	2.174998	0.500002	3.011028	2.93381
min	0.000000	5.000000	0.000000	0.000000	0.000000	0.00000
25%	0.000000	14.000000	1.000000	0.000000	4.000000	4.00000
50%	0.000000	16.000000	3.000000	1.000000	6.000000	6.00000
75%	1.000000	20.000000	4.000000	1.000000	8.000000	8.00000
max	1.000000	250.000000	27.000000	1.000000	22.000000	22.00000

8 rows × 26 columns

In [438]:
```
df.isnull().sum().sum()
```

Out[438]: 0

In [439]:
```
df.head()
```

Out[439]:

	blueWins	blueWardsPlaced	blueWardsDestroyed	blueFirstBlood	blueKills	blueDeaths	blueAss
0	0	28	2	1	9	6	
1	0	12	1	0	5	5	
2	0	15	0	0	7	11	
3	0	43	1	0	4	5	
4	0	75	4	0	6	6	

5 rows × 26 columns

In [440]:
```
df.applymap(np.isreal).all().sum()
```

Out[440]: 26

In [441]:
```
df.applymap(lambda x: isinstance(x, (int, float))).all().sum()
```
Out[441]:
```
26
```

For missing value, first see use df.describe() to see min/max in each columns. ensure each feature in right range. Then, we use df.isnull() to see pandas that can identify any missing value. Since our data contain all numeric features, we also use applymap function with np.isreal or isinstance, search for each row and each column to see if there any missing value can find. Base on the result, our data do not have any missing values.

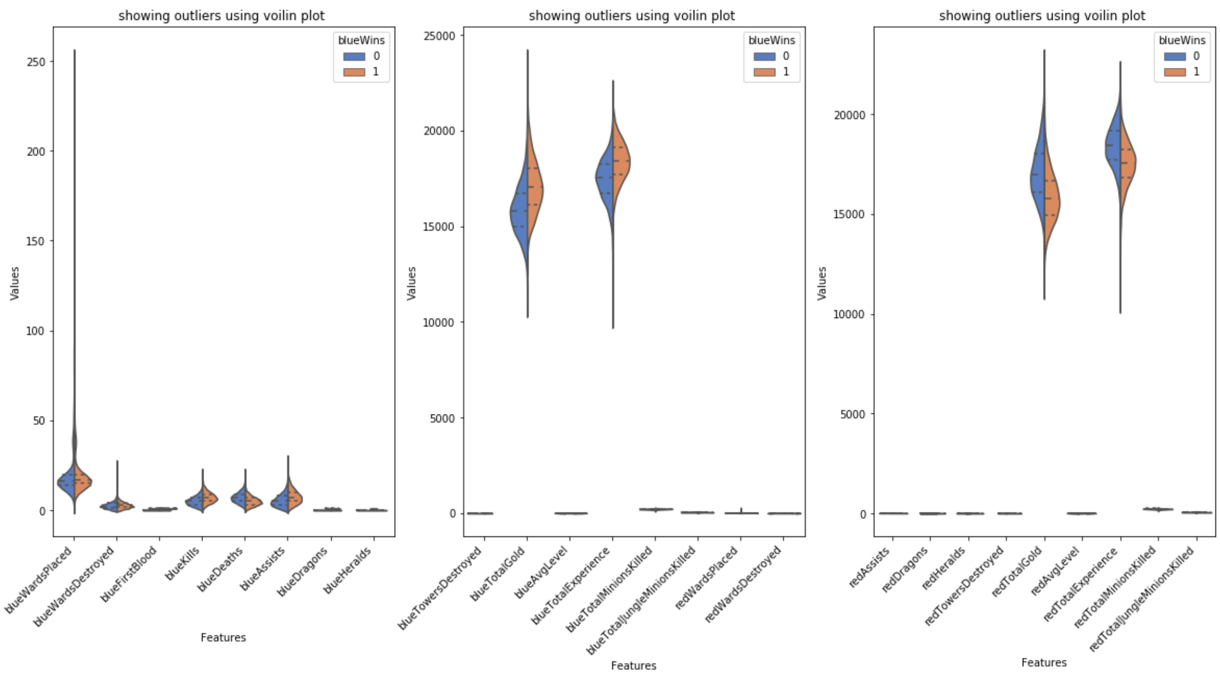
In [442]:
```
print('Lenght of columms {}'.format(len(df.columns)))
```
```
Lenght of columms 26
```

In [443]:
```
df.columns
```
Out[443]:
```
Index(['blueWins', 'blueWardsPlaced', 'blueWardsDestroyed', 'blueFirstBlood',
       'blueKills', 'blueDeaths', 'blueAssists', 'blueDragons', 'blueHeralds',
       'blueTowersDestroyed', 'blueTotalGold', 'blueAvgLevel',
       'blueTotalExperience', 'blueTotalMinionsKilled',
       'blueTotalJungleMinionsKilled', 'redWardsPlaced', 'redWardsDestroyed',
       'redAssists', 'redDragons', 'redHeralds', 'redTowersDestroyed',
       'redTotalGold', 'redAvgLevel', 'redTotalExperience',
       'redTotalMinionsKilled', 'redTotalJungleMinionsKilled'],
      dtype='object')
```

Outliers

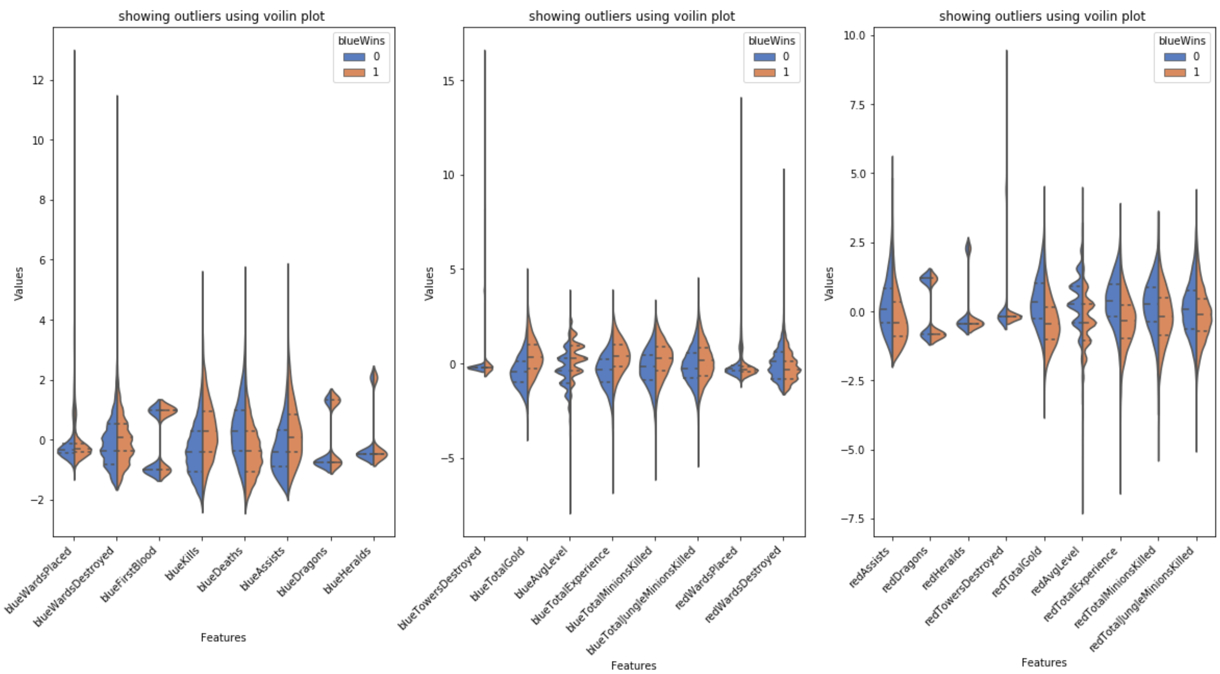
In [444]:
```
def plot_violinplot(df,ax_key):
    df = pd.melt(df, id_vars='blueWins', var_name='Features', value_name='Values'
    sns.violinplot(x='Features', y='Values', hue='blueWins', data=df, split=True,
                   inner='quart', ax=ax[ax_key], palette='muted').set_title('showing
    fig.autofmt_xdate(rotation=45)
```

In [445]:
```
fig, ax = plt.subplots(1,3,figsize=(20,10))
data = df.loc[:, df.columns != 'blueWins']
data = pd.DataFrame(data = data, columns = data.columns)
data1 = pd.concat([df.blueWins, data.iloc[:, 0:8]], axis=1)
plot_violinplot(data1,0)
data2 = pd.concat([df.blueWins, data.iloc[:, 8:16]], axis=1)
plot_violinplot(data2,1)
data3 = pd.concat([df.blueWins, data.iloc[:, 16:]], axis=1)
plot_violinplot(data3,2)
plt.show()
```



let's plot with standardized value to see better visualization

In [446]:
```
fig, ax = plt.subplots(1,3,figsize=(20,10))
data = df.loc[:, df.columns != 'blueWins']
data_std = StandardScaler().fit_transform(data)
data_std = pd.DataFrame(data = data_std, columns = data.columns)
data1 = pd.concat([df.blueWins, df_std.iloc[:, 0:8]], axis=1)
plot_violinplot(data1,0)
data2 = pd.concat([df.blueWins, df_std.iloc[:, 8:16]], axis=1)
plot_violinplot(data2,1)
data3 = pd.concat([df.blueWins, df_std.iloc[:, 16:]], axis=1)
plot_violinplot(data3,2)
plt.show()
```



Our data contain outliers. But since those are about game performance for each group, like red group performed well in one game, but performance bad in other games. we decide to keep those outliers since there is no unit. and these outliers could better give feedback on which team will win the game.

In [447]:
```
from sklearn.model_selection import train_test_split
```

In [448]:
```
y = df['blueWins']
X = df.loc[:, df.columns != 'blueWins']
```

In [449]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, stratify
```

In [450]:
```
test_df = pd.concat([X_test, y_test], axis=1)
```

In [451]:
```
train_df = pd.concat([X_train, y_train], axis=1)
```

In [452]:
```
train_df.to_csv('../datasets/train.csv', index=False)
test_df.to_csv('../datasets/test.csv', index = False)
```

In [453]:
```
print('Labels count in y: ', np.bincount(y))
print('Labels count in y_train ', np.bincount(y_train))
print('Labels count in y_test', np.bincount(y_test))
```

```
Labels count in y:  [4949 4930]
Labels count in y_train  [3464 3451]
Labels count in y_test [1485 1479]
```

The data has been split into training and testing set. The training data contain 6915 observations and the test data contain 2964 observations. we also use stratify=y to eunsures that both training and test datasets have the same class proportions as the original dataset.

In [ ]: