EECS731-League-of-Legends

November 25, 2020

[1]:
```python
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

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 sns
import plotly as py
import plotly.graph_objs as go
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import graphviz
from sklearn import tree
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory
import os

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

0.0.1 Importing data

[2]:
```python
leg_data = pd.read_csv('Data/games.csv')
leg_data.head(5)
```

[2]:

	gameId	creationTime	gameDuration	seasonId	winner	firstBlood	\
0	3326086514	1504279457970	1949	9	1	2	
1	3229566029	1497848803862	1851	9	1	1	
2	3327363504	1504360103310	1493	9	1	2	
3	3326856598	1504348503996	1758	9	1	1	
4	3330080762	1504554410899	2094	9	1	2	

```
   firstTower  firstInhibitor  firstBaron  firstDragon  …  t2_towerKills  \
0           1               1           1            1  …              5
1           1               1           0            1  …              2
2           1               1           1            2  …              2
3           1               1           1            1  …              0
4           1               1           1            1  …              3

   t2_inhibitorKills  t2_baronKills  t2_dragonKills  t2_riftHeraldKills  \
0                  0              0               1                   1
1                  0              0               0                   0
2                  0              0               1                   0
3                  0              0               0                   0
4                  0              0               1                   0

   t2_ban1  t2_ban2  t2_ban3  t2_ban4  t2_ban5
0      114       67       43       16       51
1       11       67      238       51      420
2      157      238      121       57       28
3      164       18      141       40       51
4       86       11      201      122       18

[5 rows x 61 columns]
```

0.0.2 Data processing

remove seasonId, hero banlist

[3]:
```
leg_data.drop(['t2_ban1','t2_ban2','t2_ban3','t2_ban4','t2_ban5'],inplace=True,␣
 ↪axis=1)
```

[4]:
```
leg_data.head(5)
```

[4]:
```
       gameId   creationTime  gameDuration  seasonId  winner  firstBlood  \
0  3326086514  1504279457970          1949         9       1           2
1  3229566029  1497848803862          1851         9       1           1
2  3327363504  1504360103310          1493         9       1           2
3  3326856598  1504348503996          1758         9       1           1
4  3330080762  1504554410899          2094         9       1           2

   firstTower  firstInhibitor  firstBaron  firstDragon  …  t2_champ4_sum1  \
0           1               1           1            1  …              14
1           1               1           0            1  …               4
2           1               1           1            2  …               4
3           1               1           1            1  …               4
4           1               1           1            1  …               4

   t2_champ4_sum2  t2_champ5id  t2_champ5_sum1  t2_champ5_sum2  t2_towerKills  \
```

```
0                 4          412                 4                 3                 5
1                14           92                 4                 7                 2
2                11           22                 7                 4                 2
3                14           22                 4                 7                 0
4                12           51                 4                 7                 3

   t2_inhibitorKills  t2_baronKills  t2_dragonKills  t2_riftHeraldKills
0                  0              0               1                   1
1                  0              0               0                   0
2                  0              0               1                   0
3                  0              0               0                   0
4                  0              0               1                   0

[5 rows x 56 columns]
```

0.0.3 Data analyzing

Single impact of different resources on winning rate

1. Team side choice

2. game duration

3. First kill

4. inhibitorKills

5. firstBaron

6. dragonKills

7. towerkills

[5]:
```
Winning_team = go.Pie(labels=leg_data['winner'].value_counts().values,
                values=leg_data['winner'].value_counts().values,
                )

layout = go.Layout(title='winning condition')

l_data = [Winning_team]
fig = go.Figure(l_data).show()
fig
```

[6]:
```
leg_data['game_duration'] = round(leg_data['gameDuration'] / 60)

x1 = leg_data[leg_data['winner'] == 1]['game_duration']
x2 = leg_data[leg_data['winner'] == 2]['game_duration']
```

```
team1_time = go.Histogram(x=x1, bingroup=25, name='team1', opacity=0.9)
team2_time = go.Histogram(x=x2, bingroup=25, name='team2', opacity=0.9)
bg = go.Layout(title='game_duration')

data = [team1_time, team2_time]
fig = go.Figure(data, bg).show()
fig
```

[7]:
```
def plot_bar_vertical(input_col: str, target_col: str, title_name: str):
    cross_table = round(pd.crosstab(leg_data[input_col], leg_data[target_col],␣
 ↪normalize='index')*100, 2)
    index_0 = cross_table.columns.tolist()[0]
    index_1 = cross_table.columns.tolist()[1]
    t1 = go.Bar(x=cross_table.index.tolist(),y=cross_table[index_0].values.
 ↪tolist(),name=index_0,orientation='v', marker=dict(color='rgb(250,520,250)')
                   )
    t2 = go.Bar(x=cross_table.index.tolist(), y=cross_table[index_1].values.
 ↪tolist(), name=index_1,orientation='v',marker=dict(color='rgb(100,300,200)'))

    data = [t1, t2]
    layout = go.Layout(title=title_name, bargap=0.4, barmode='stack')

    fig = go.Figure(data=data, layout=layout)
    return fig
```

[8]:
```
plot_bar_vertical('firstBlood', 'winner', 'First blood winning rate').show()
```

[9]:
```
plot_bar_vertical(input_col='t2_inhibitorKills', target_col='winner',␣
 ↪title_name='inhibitor related to winning')
```

[10]:
```
plot_bar_vertical(input_col='firstBaron', target_col='winner',␣
 ↪title_name='First baron r')
```

[11]:
```
plot_bar_vertical(input_col='t1_dragonKills', target_col='winner',
                  title_name='T1 dragon related to winning')
```

[12]:
```
plot_bar_vertical(input_col='t1_towerKills', target_col='winner',␣
 ↪title_name='Tower kill realted to winning')
```

ML training

Predict the outcome with multiple important attributes of Machine learning Training

1. remove game with too short game duration

2. Select feature, and importing Decsion Tree.

[13]:
```
leg_data = leg_data[(leg_data['gameDuration'] >= 900)]
```

[14]:
```
leg_data_model = leg_data[['winner', 'firstBaron', 't1_towerKills',␣
↪'t1_inhibitorKills','t1_baronKills','t1_dragonKills', 't2_towerKills',␣
↪'t2_inhibitorKills', 't2_baronKills', 't2_dragonKills'
              ]]
```

[15]:
```
x = leg_data_model.drop('winner', axis=1)
y = leg_data_model['winner']

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪stratify=y, random_state=0)
```

[16]:
```
clf = DecisionTreeClassifier(random_state=0)
clf.fit(X_train,y_train)
print("score:", clf.score(X_test,y_test))
```

```
score: 0.9666234930756202
```

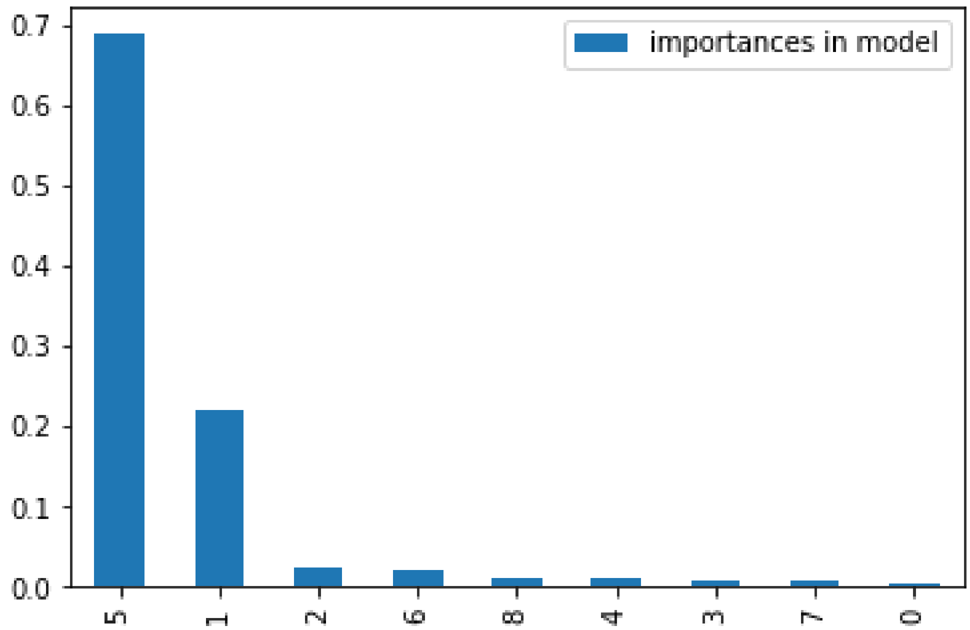
[17]:
```
importance_weight = pd.DataFrame(list(zip(X_train.columns, clf.
↪feature_importances_)))
importance_weight.columns = ['columns', 'importances in model']
importance_weight = importance_weight.sort_values('importances in model',␣
↪ascending=False)
importance_weight
```

[17]:

	columns	importances in model
5	t2_towerKills	0.687272
1	t1_towerKills	0.219558
2	t1_inhibitorKills	0.026110
6	t2_inhibitorKills	0.021998
8	t2_dragonKills	0.012767
4	t1_dragonKills	0.012384
3	t1_baronKills	0.008227
7	t2_baronKills	0.007846
0	firstBaron	0.003837

[18]:
```
importance_weight.plot.bar()
```

[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x205bf740f08>
```



1 How does game result effected by first 10 mins performance

[19]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

[20]:
```
data = pd.read_csv("Data/high_diamond_ranked_10min.csv")
data = data.drop('gameId',axis=1)
data
```

[20]:
```
      blueWins  blueWardsPlaced  blueWardsDestroyed  blueFirstBlood  \
0            0               28                   2               1
1            0               12                   1               0
2            0               15                   0               0
3            0               43                   1               0
4            0               75                   4               0
…          …                …                   …              …
9874         1               17                   2               1
9875         1               54                   0               0
9876         0               23                   1               0
9877         0               14                   4               1
9878         1               18                   0               1
```

	blueKills	blueDeaths	blueAssists	blueEliteMonsters	blueDragons	\
0	9	6	11	0	0	
1	5	5	5	0	0	
2	7	11	4	1	1	
3	4	5	5	1	0	
4	6	6	6	0	0	
…	…	…	…	…	…	
9874	7	4	5	1	1	
9875	6	4	8	1	1	
9876	6	7	5	0	0	
9877	2	3	3	1	1	
9878	6	6	5	0	0	

	blueHeralds	…	redTowersDestroyed	redTotalGold	redAvgLevel	\
0	0	…	0	16567	6.8	
1	0	…	1	17620	6.8	
2	0	…	0	17285	6.8	
3	1	…	0	16478	7.0	
4	0	…	0	17404	7.0	
…	…	…	…	…	…	
9874	0	…	0	15246	6.8	
9875	0	…	0	15456	7.0	
9876	0	…	0	18319	7.4	
9877	0	…	0	15298	7.2	
9878	0	…	0	15339	6.8	

	redTotalExperience	redTotalMinionsKilled	redTotalJungleMinionsKilled	\
0	17047	197	55	
1	17438	240	52	
2	17254	203	28	
3	17961	235	47	
4	18313	225	67	
…	…	…	…	
9874	16498	229	34	
9875	18367	206	56	
9876	19909	261	60	
9877	18314	247	40	
9878	17379	201	46	

	redGoldDiff	redExperienceDiff	redCSPerMin	redGoldPerMin
0	-643	8	19.7	1656.7
1	2908	1173	24.0	1762.0
2	1172	1033	20.3	1728.5
3	1321	7	23.5	1647.8
4	1004	-230	22.5	1740.4
…	…	…	…	…

```
9874        -2519              -2469         22.9         1524.6
9875         -782               -888         20.6         1545.6
9876         2416               1877         26.1         1831.9
9877          839               1085         24.7         1529.8
9878         -927                 58         20.1         1533.9

[9879 rows x 39 columns]
```

[21]:
```
data.shape
```

[21]:
```
(9879, 39)
```

[22]:
```
data.columns
```

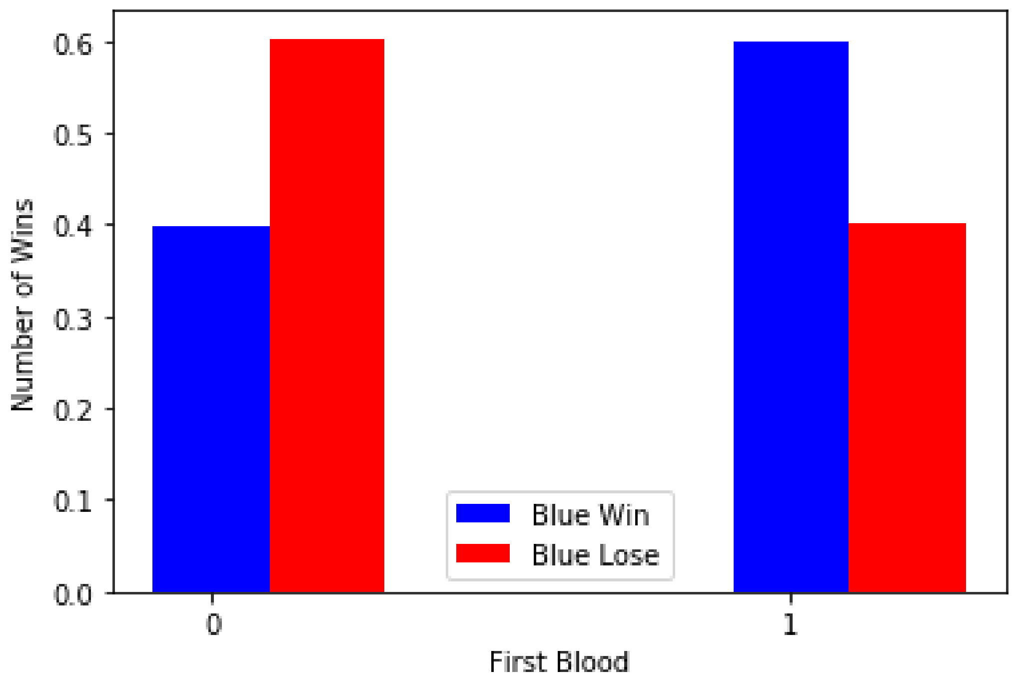
[22]:
```
Index(['blueWins', 'blueWardsPlaced', 'blueWardsDestroyed', 'blueFirstBlood',
       'blueKills', 'blueDeaths', 'blueAssists', 'blueEliteMonsters',
       'blueDragons', 'blueHeralds', 'blueTowersDestroyed', 'blueTotalGold',
       'blueAvgLevel', 'blueTotalExperience', 'blueTotalMinionsKilled',
       'blueTotalJungleMinionsKilled', 'blueGoldDiff', 'blueExperienceDiff',
       'blueCSPerMin', 'blueGoldPerMin', 'redWardsPlaced', 'redWardsDestroyed',
       'redFirstBlood', 'redKills', 'redDeaths', 'redAssists',
       'redEliteMonsters', 'redDragons', 'redHeralds', 'redTowersDestroyed',
       'redTotalGold', 'redAvgLevel', 'redTotalExperience',
       'redTotalMinionsKilled', 'redTotalJungleMinionsKilled', 'redGoldDiff',
       'redExperienceDiff', 'redCSPerMin', 'redGoldPerMin'],
      dtype='object')
```

2 Simple features

Looking for how does the first blood effects blue win

[23]:
```
tempData = data[['blueWins','blueFirstBlood','redFirstBlood']]
tempData['redWins'] = 1-tempData.blueWins

inBlueFirst = tempData.set_index(['blueFirstBlood'])
blueFirstWin = inBlueFirst['blueWins'].groupby(['blueFirstBlood']).sum().
 ↪reset_index()
#blueFirstWin['blueWinPerc'] = blueFirstWin['blueWins']/
 ↪blueFirstWin['blueWins'].sum()

inRedFirst = tempData.set_index(['blueFirstBlood'])
redFirstWin = inRedFirst['redWins'].groupby(['blueFirstBlood']).sum().
 ↪reset_index()
#redFirstWin['redWinPerc'] = redFirstWin['redWins']/redFirstWin['redWins'].sum()

bluePrec0 = blueFirstWin['blueWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
```

```
bluePrec1 = blueFirstWin['blueWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
blueFirstWin['blueWinPerc'] = [bluePrec0, bluePrec1]

redPrec0 = redFirstWin['redWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
redPrec1 = redFirstWin['redWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
redFirstWin['redWinPerc'] = [redPrec0,redPrec1]

plt.figure()
plt.bar(blueFirstWin.blueFirstBlood, blueFirstWin.blueWinPerc,color='b',width =␣
 ↪0.2,label='Blue Win')
plt.bar(redFirstWin.blueFirstBlood+0.2, redFirstWin.redWinPerc,color='r',width␣
 ↪= 0.2,label='Blue Lose')
plt.xlabel('First Blood')
plt.xticks([0,1])
plt.ylabel('Number of Wins')
plt.legend()
plt.show()
```

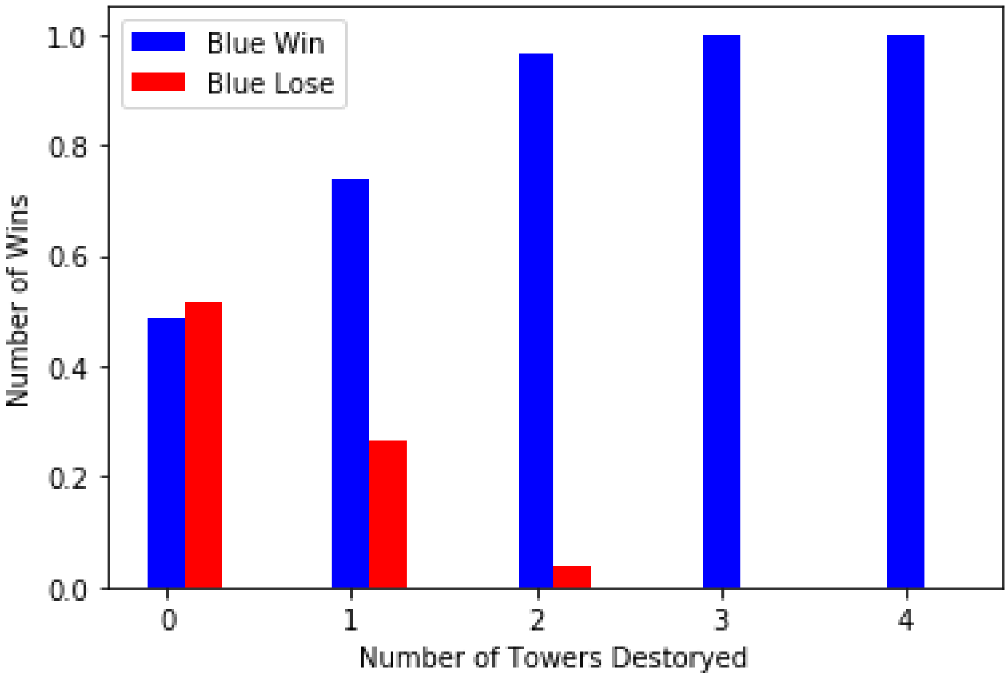


How does blue wins effected by whether they get bouns from boss or not

[24]:

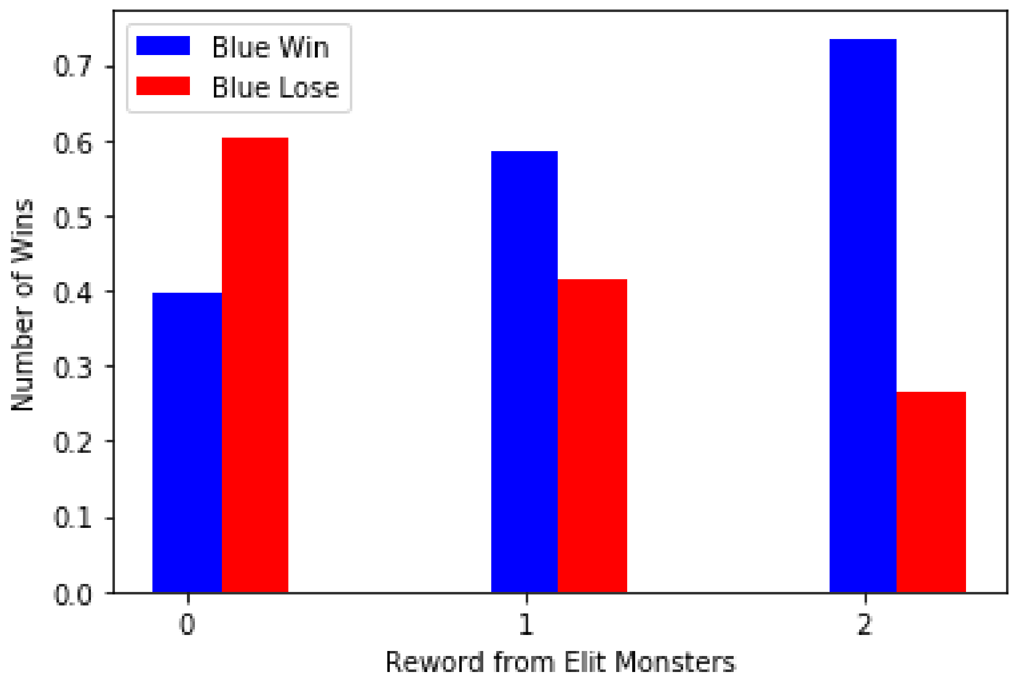
```
tempData = data[['blueWins','blueTowersDestroyed','redTowersDestroyed']]
tempData['redWins'] = 1-tempData.blueWins

inBlueFirst = tempData.set_index(['blueTowersDestroyed'])
blueFirstWin = inBlueFirst['blueWins'].groupby(['blueTowersDestroyed']).sum().
↪reset_index()
blueFirstWin['blueWinPerc'] = blueFirstWin['blueWins']/blueFirstWin['blueWins'].
↪sum()

inRedFirst = tempData.set_index(['blueTowersDestroyed'])
redFirstWin = inRedFirst['redWins'].groupby(['blueTowersDestroyed']).sum().
↪reset_index()
redFirstWin['redWinPerc'] = redFirstWin['redWins']/redFirstWin['redWins'].sum()

bluePrec0 = blueFirstWin['blueWins'][0]/(blueFirstWin['blueWins'][0] +␣
↪redFirstWin['redWins'][0])
bluePrec1 = blueFirstWin['blueWins'][1]/(blueFirstWin['blueWins'][1] +␣
↪redFirstWin['redWins'][1])
bluePrec2 = blueFirstWin['blueWins'][2]/(blueFirstWin['blueWins'][2] +␣
↪redFirstWin['redWins'][2])
bluePrec3 = blueFirstWin['blueWins'][3]/(blueFirstWin['blueWins'][3] +␣
↪redFirstWin['redWins'][3])
bluePrec4 = blueFirstWin['blueWins'][4]/(blueFirstWin['blueWins'][4] +␣
↪redFirstWin['redWins'][4])
blueFirstWin['blueWinPerc'] = [bluePrec0,␣
↪bluePrec1,bluePrec2,bluePrec3,bluePrec4]

redPrec0 = redFirstWin['redWins'][0]/(blueFirstWin['blueWins'][0] +␣
↪redFirstWin['redWins'][0])
redPrec1 = redFirstWin['redWins'][1]/(blueFirstWin['blueWins'][1] +␣
↪redFirstWin['redWins'][1])
redPrec2 = redFirstWin['redWins'][2]/(blueFirstWin['blueWins'][2] +␣
↪redFirstWin['redWins'][2])
redPrec3 = redFirstWin['redWins'][3]/(blueFirstWin['blueWins'][3] +␣
↪redFirstWin['redWins'][3])
redPrec4 = redFirstWin['redWins'][4]/(blueFirstWin['blueWins'][4] +␣
↪redFirstWin['redWins'][4])
redFirstWin['redWinPerc'] = [redPrec0,redPrec1,redPrec2,redPrec3,redPrec4]

plt.figure()
plt.bar(blueFirstWin.blueTowersDestroyed, blueFirstWin.
↪blueWinPerc,color='b',width = 0.2,label='Blue Win')
plt.bar(redFirstWin.blueTowersDestroyed+0.2, redFirstWin.
↪redWinPerc,color='r',width = 0.2,label='Blue Lose')
plt.xlabel('Number of Towers Destoryed')
plt.xticks([0,1,2,3,4])
```

```
plt.ylabel('Number of Wins')
plt.legend()
plt.show()
```



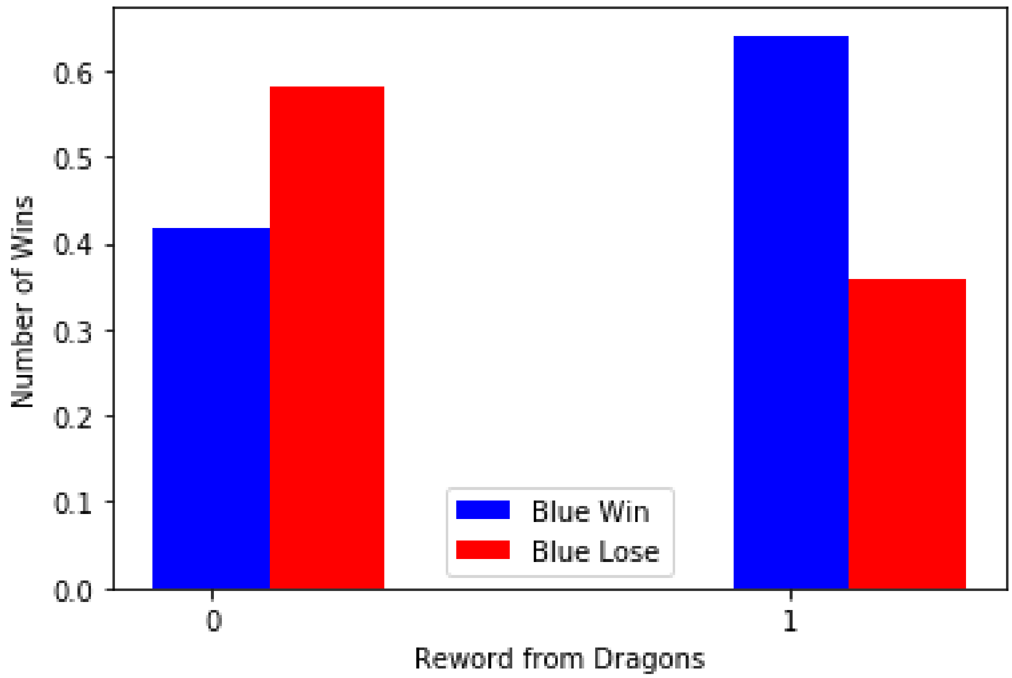
[25]:
```
tempData = data[['blueWins','blueEliteMonsters','redEliteMonsters']]
tempData['redWins'] = 1-tempData.blueWins

inBlueFirst = tempData.set_index(['blueEliteMonsters'])
blueFirstWin = inBlueFirst['blueWins'].groupby(['blueEliteMonsters']).sum().
 ↪reset_index()
#blueFirstWin['blueWinPerc'] = blueFirstWin['blueWins']/
 ↪blueFirstWin['blueWins'].sum()

inRedFirst = tempData.set_index(['blueEliteMonsters'])
redFirstWin = inRedFirst['redWins'].groupby(['blueEliteMonsters']).sum().
 ↪reset_index()
#redFirstWin['redWinPerc'] = redFirstWin['redWins']/redFirstWin['redWins'].sum()

bluePrec0 = blueFirstWin['blueWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
bluePrec1 = blueFirstWin['blueWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
bluePrec2 = blueFirstWin['blueWins'][2]/(blueFirstWin['blueWins'][2] +␣
 ↪redFirstWin['redWins'][2])
```

```
blueFirstWin['blueWinPerc'] = [bluePrec0, bluePrec1,bluePrec2]

redPrec0 = redFirstWin['redWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
redPrec1 = redFirstWin['redWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
redPrec2 = redFirstWin['redWins'][2]/(blueFirstWin['blueWins'][2] +␣
 ↪redFirstWin['redWins'][2])
redFirstWin['redWinPerc'] = [redPrec0,redPrec1,redPrec2]

plt.figure()
plt.bar(blueFirstWin.blueEliteMonsters, blueFirstWin.
 ↪blueWinPerc,color='b',width = 0.2,label='Blue Win')
plt.bar(redFirstWin.blueEliteMonsters+0.2, redFirstWin.
 ↪redWinPerc,color='r',width = 0.2,label='Blue Lose')
plt.xlabel('Reword from Elit Monsters')
plt.xticks([0,1,2])
plt.ylabel('Number of Wins')
plt.legend()
plt.show()
```



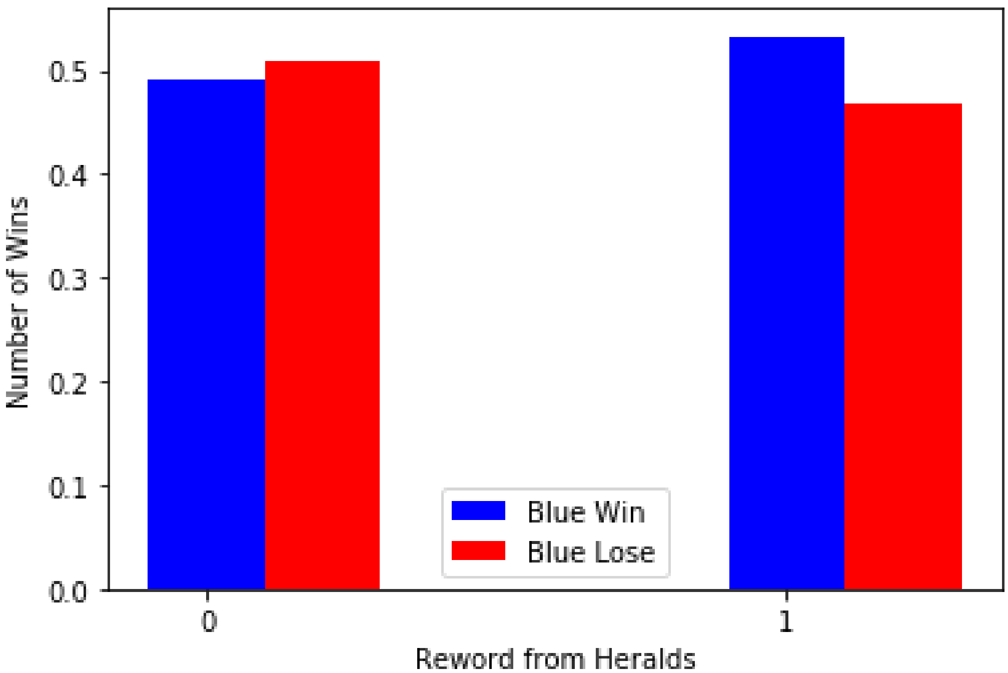
[26]:
```
tempData = data[['blueWins','blueDragons','redDragons']]
tempData['redWins'] = 1-tempData.blueWins
```

```
inBlueFirst = tempData.set_index(['blueDragons'])
blueFirstWin = inBlueFirst['blueWins'].groupby(['blueDragons']).sum().
 ↪reset_index()
#blueFirstWin['blueWinPerc'] = blueFirstWin['blueWins']/
 ↪blueFirstWin['blueWins'].sum()

inRedFirst = tempData.set_index(['blueDragons'])
redFirstWin = inRedFirst['redWins'].groupby(['blueDragons']).sum().reset_index()
#redFirstWin['redWinPerc'] = redFirstWin['redWins']/redFirstWin['redWins'].sum()

bluePrec0 = blueFirstWin['blueWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
bluePrec1 = blueFirstWin['blueWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
blueFirstWin['blueWinPerc'] = [bluePrec0, bluePrec1]

redPrec0 = redFirstWin['redWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
redPrec1 = redFirstWin['redWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
redFirstWin['redWinPerc'] = [redPrec0,redPrec1]

plt.figure()
plt.bar(blueFirstWin.blueDragons, blueFirstWin.blueWinPerc,color='b',width = 0.
 ↪2,label='Blue Win')
plt.bar(redFirstWin.blueDragons+0.2, redFirstWin.redWinPerc,color='r',width = 0.
 ↪2,label='Blue Lose')
plt.xlabel('Reword from Dragons')
plt.xticks([0,1])
plt.ylabel('Number of Wins')
plt.legend()
plt.show()
```



[27]:
```
tempData = data[['blueWins','blueHeralds','redHeralds']]
tempData['redWins'] = 1-tempData.blueWins

inBlueFirst = tempData.set_index(['blueHeralds'])
blueFirstWin = inBlueFirst['blueWins'].groupby(['blueHeralds']).sum().
 ↪reset_index()
#blueFirstWin['blueWinPerc'] = blueFirstWin['blueWins']/
 ↪blueFirstWin['blueWins'].sum()

inRedFirst = tempData.set_index(['redHeralds'])
redFirstWin = inRedFirst['redWins'].groupby(['redHeralds']).sum().reset_index()
#redFirstWin['redWinPerc'] = redFirstWin['redWins']/redFirstWin['redWins'].sum()

bluePrec0 = blueFirstWin['blueWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
bluePrec1 = blueFirstWin['blueWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
blueFirstWin['blueWinPerc'] = [bluePrec0, bluePrec1]

redPrec0 = redFirstWin['redWins'][0]/(blueFirstWin['blueWins'][0] +␣
 ↪redFirstWin['redWins'][0])
redPrec1 = redFirstWin['redWins'][1]/(blueFirstWin['blueWins'][1] +␣
 ↪redFirstWin['redWins'][1])
redFirstWin['redWinPerc'] = [redPrec0,redPrec1]
```

```
plt.figure()
plt.bar(blueFirstWin.blueHeralds, blueFirstWin.blueWinPerc,color='b',width = 0.
 ↪2,label='Blue Win')
plt.bar(redFirstWin.redHeralds+0.2, redFirstWin.redWinPerc,color='r',width = 0.
 ↪2,label='Blue Lose')
plt.xlabel('Reword from Heralds')
plt.xticks([0,1])
plt.ylabel('Number of Wins')
plt.legend()
plt.show()
```

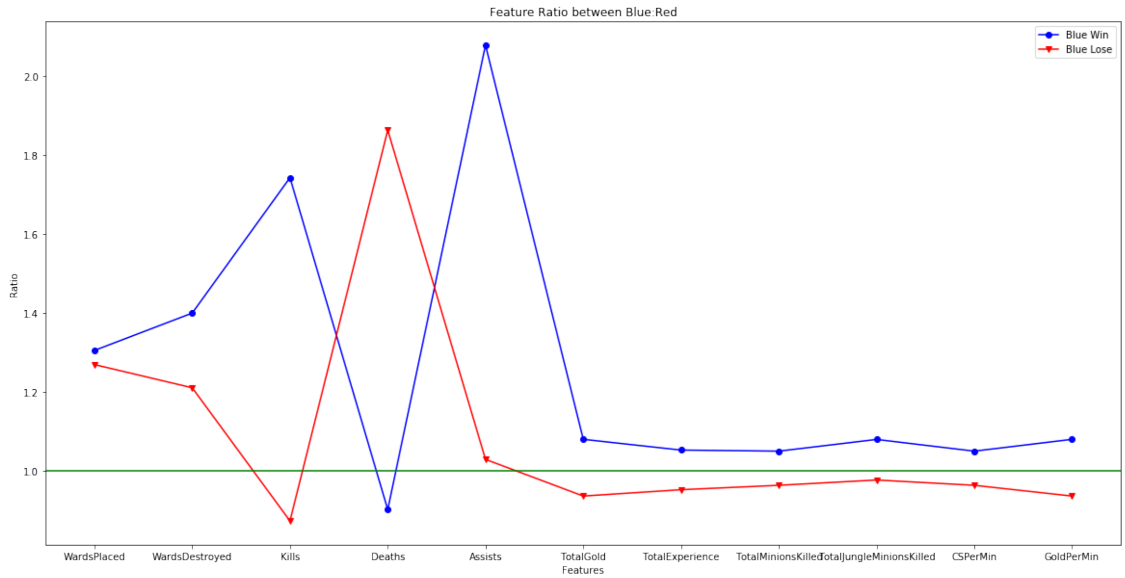


3 Looking for other effective features

Calculate the ratio of blue:red for each features, and plot the average ratio for blue wins and blue lose. If the value of the feature in blue is higher than the value of the feature in red, then the ratio is greater than 1, otherwise 0. We can see in this graph, the ratio gap between blue win and blue lose is very large in feature Kills, Death and Assistants, so we think these three features may have high effective of blue wins.

[28]:
```
diff_blue_red = pd.DataFrame(data['blueWins'])
diff_blue_red['WardsPlaced'] = data['blueWardsPlaced'] / data['redWardsPlaced']
diff_blue_red['WardsDestroyed'] = data['blueWardsDestroyed'] /␣
 ↪data['redWardsDestroyed']
```

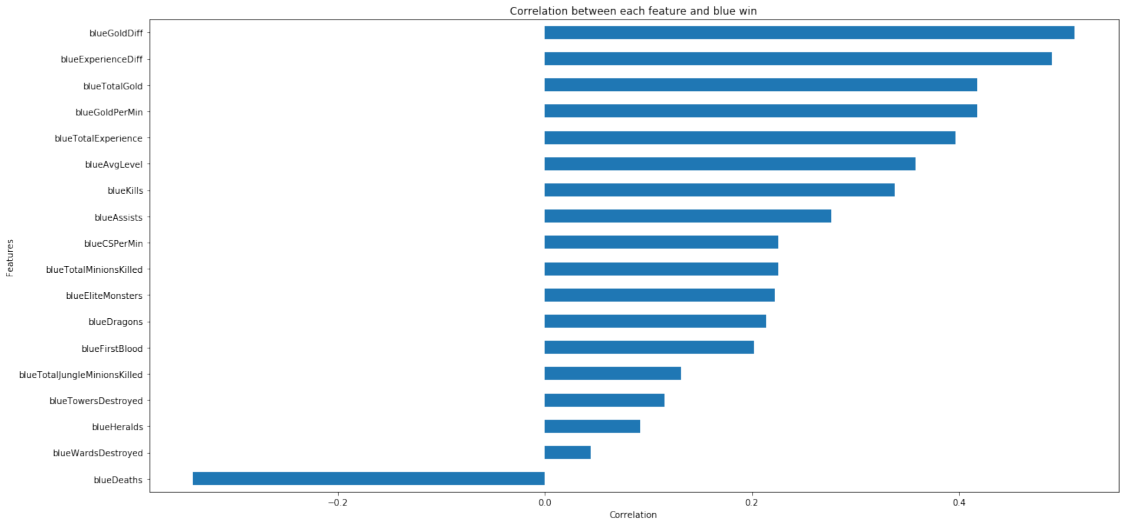
```
diff_blue_red['Kills'] = data['blueKills'] / data['redKills']
diff_blue_red['Deaths'] = data['blueDeaths'] / data['redDeaths']
diff_blue_red['Assists'] = data['blueAssists'] / data['redAssists']
diff_blue_red['TotalGold'] = data['blueTotalGold'] / data['redTotalGold']
diff_blue_red['TotalExperience'] = data['blueTotalExperience'] /␣
 ↪data['redTotalExperience']
diff_blue_red['TotalMinionsKilled'] = data['blueTotalMinionsKilled'] /␣
 ↪data['redTotalMinionsKilled']
diff_blue_red['TotalJungleMinionsKilled'] =␣
 ↪data['blueTotalJungleMinionsKilled'] / data['redTotalJungleMinionsKilled']
diff_blue_red['CSPerMin'] = data['blueCSPerMin'] / data['redCSPerMin']
diff_blue_red['GoldPerMin'] = data['blueGoldPerMin'] / data['redGoldPerMin']
diff_blue_red = diff_blue_red.replace([np.inf, -np.inf], np.nan)
diff_blue_red = diff_blue_red.dropna()
diff_blue_red

blueWin = diff_blue_red.loc[diff_blue_red['blueWins'] == 1]
blueWin = blueWin.drop('blueWins',axis=1)
blueLose = diff_blue_red.loc[diff_blue_red['blueWins'] == 0]
blueLose = blueLose.drop('blueWins',axis=1)

blueWinAve = blueWin.mean(axis=0)
blueLoseAve = blueLose.mean(axis=0)

plt.figure(figsize = (20,10))
plt.plot(blueWinAve,'bo-',label='Blue Win')
plt.plot(blueLoseAve,'rv-',label='Blue Lose')
plt.axhline(y=1, color='g', linestyle='-')
plt.xlabel('Features')
plt.ylabel('Ratio')
plt.title('Feature Ratio between Blue:Red')
plt.legend()
plt.show()
```



3.1 Correlations between features and blue wins

This graph shows the correlations between all the features and blue wins, we can see that the most correlated features are gold differece and experience difference between two team. Then the next is number of total gold and total experience, and then Kills, Death, and Assistance. So we think the total gold difference and the experience difference also have high effective for blue win. And then we will mainly focus on the five features: Kills, Death, Assitance, and difference in gold and experence.

[29]:
```
blueWin_cor = data[data.columns[2:20]].apply(lambda x: x.corr(data['blueWins']))
blueWin_cor = blueWin_cor.sort_values()

plt.figure(figsize=(20,10))
blueWin_cor.plot.barh()
plt.title('Correlation between each feature and blue win')
plt.xlabel('Correlation')
plt.ylabel('Features')
plt.show()
```

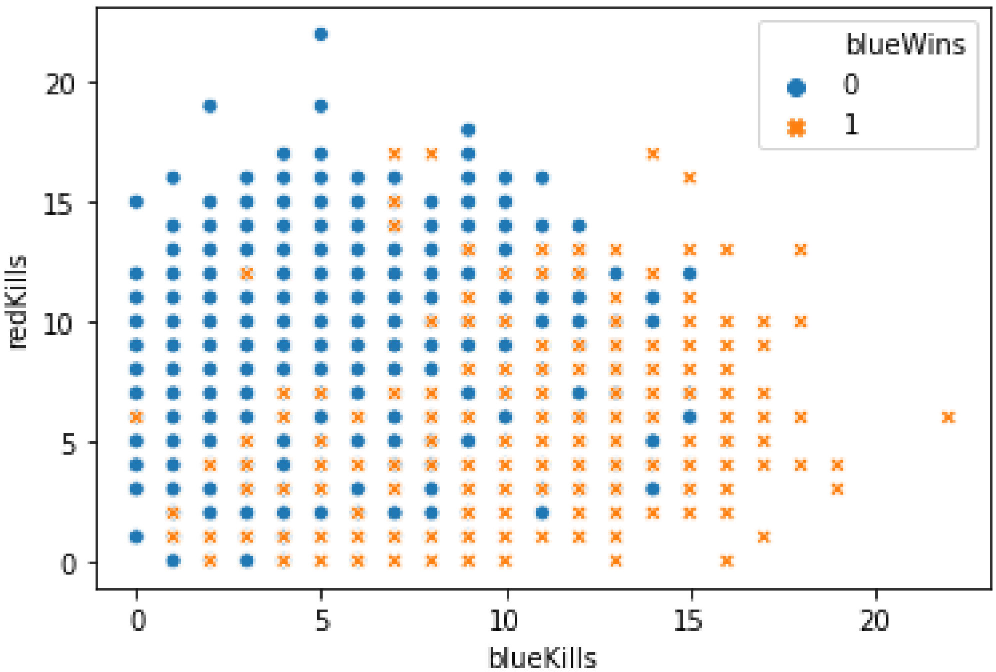


4 Kills, Death, Assist

The following figures plot the number of kills by both teams. The figure shows that when blue team have more than 15 kills in first 10 mins, they have 100% to win the game. Also the winning probablity will increase while the team have more number of kills

[30]:
```
sns.
 ↪scatterplot(data=data,x='blueKills',y='redKills',hue='blueWins',style='blueWins')
```

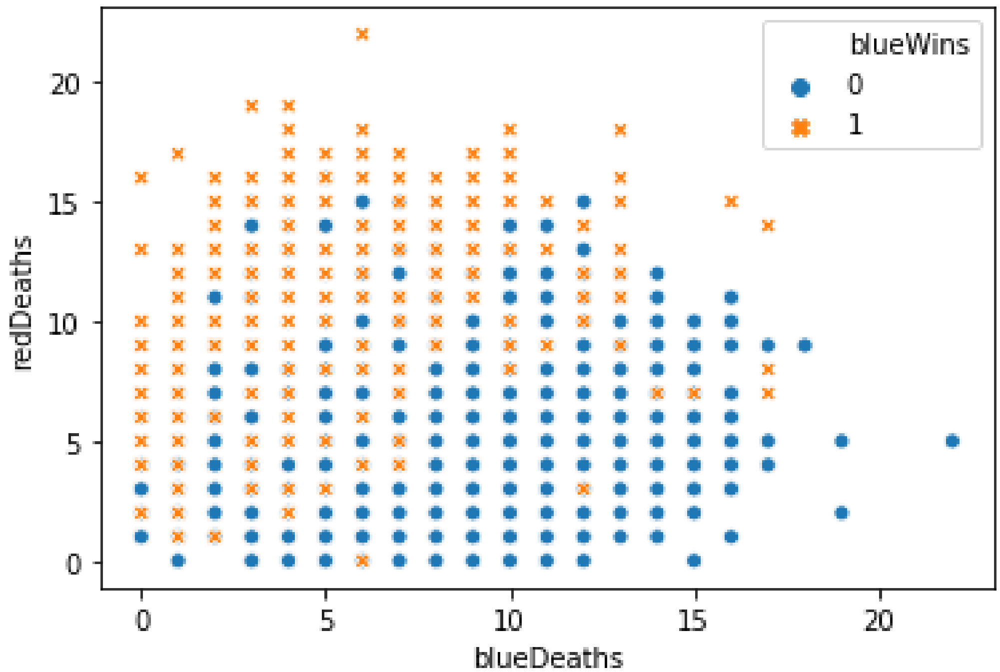
[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x205bfb37ac8>
```



This figures shows all Deaths in both team, it is opposite with the figure of kills, so when a team has less death in first 10 mins, then they will have higher probability to win the game.

[31]:
```
sns.
↪scatterplot(data=data,x='blueDeaths',y='redDeaths',hue='blueWins',style='blueWins')
```

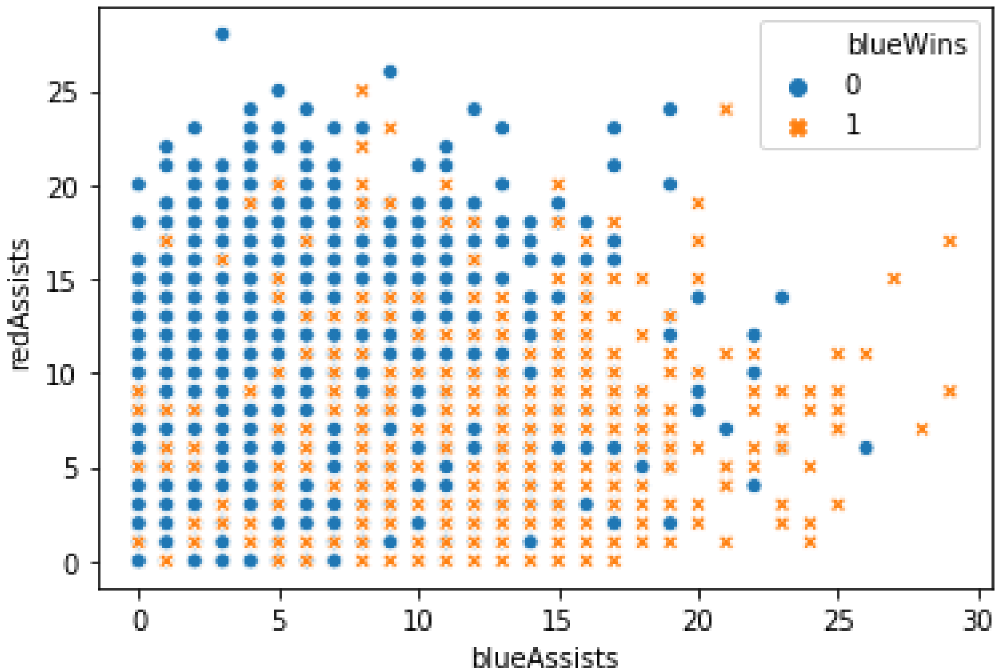
[31]: <matplotlib.axes._subplots.AxesSubplot at 0x205bfc3f648>



This figure shows all the Assistance from each team, it did not have very obvious result than other two, but it still briefly showed that when a team have more assistance, it will have high probability to win the game.

[32]:
```
sns.
↪scatterplot(data=data,x='blueAssists',y='redAssists',hue='blueWins',style='blueWins')
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x205c0727508>

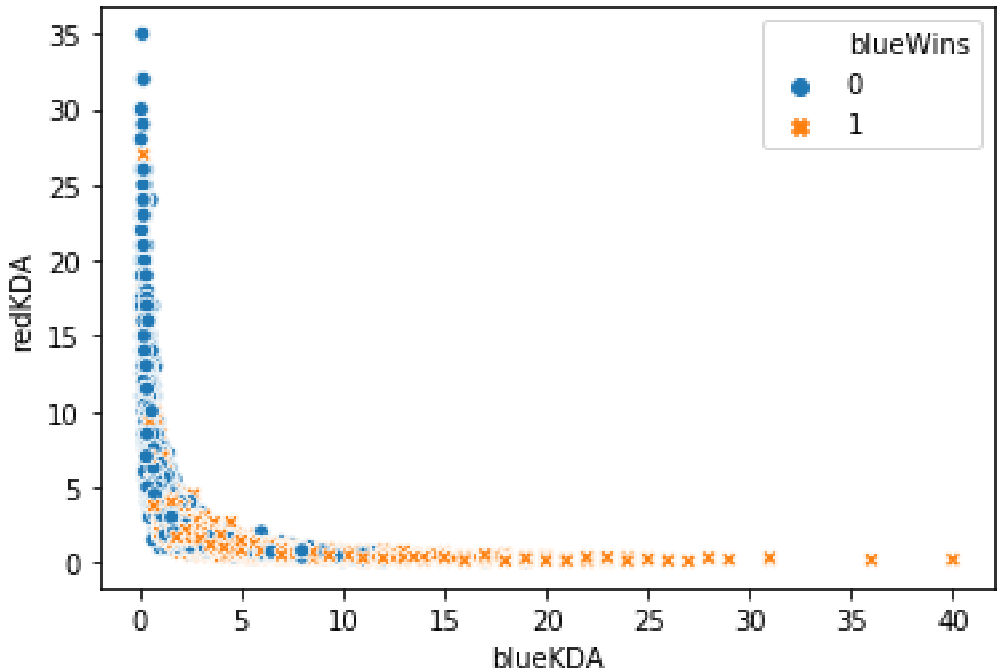


4.1 KDA rate

Now let's look at the KDA rate, KDA rate = (#Kills + #Assistance) / #Death. The first figure shows all the KDA for both team, the second figure shows the relationship between KDA rate of blue team and the game results, and we can see that when the KDA rate for blue team is higher than 15, then blue team will have more than 90% to win, and if the KDA rate is more than 20, then the blue team will have 100% probability to win the game. Also in figure 1, we can learn that if a team have high KDA rate, then another team will have low KDA rate.

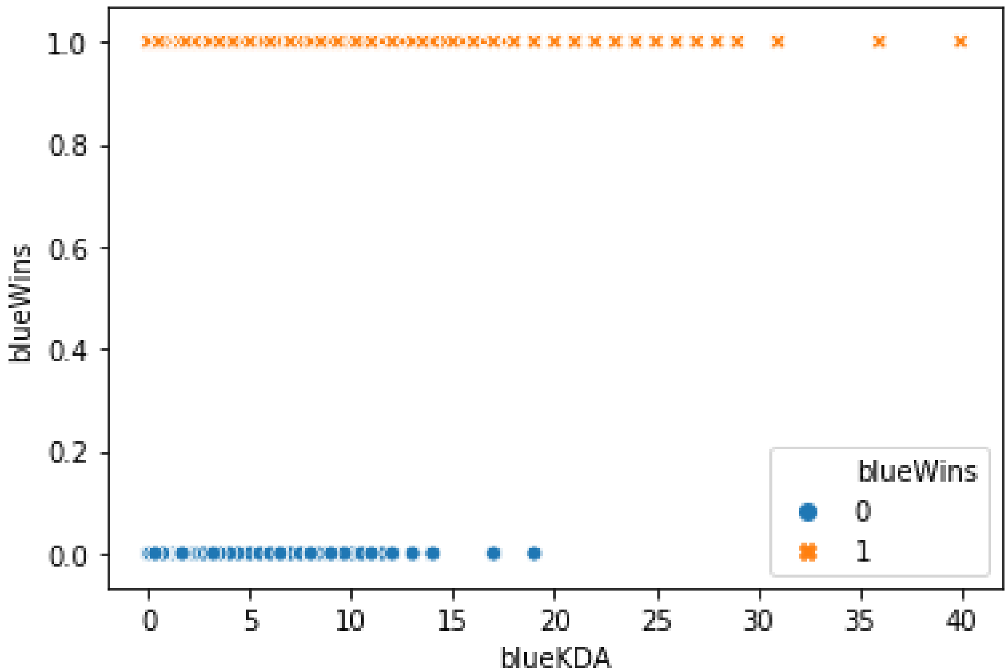
[33]:
```
KDA = pd.DataFrame(data['blueWins'])
KDA['blueKDA'] = (data['blueKills'] + data['blueAssists']) / data['blueDeaths']
KDA['redKDA'] = (data['redKills'] + data['redAssists']) / data['redDeaths']


sns.scatterplot(data=KDA,x='blueKDA',y='redKDA',hue='blueWins',style='blueWins')
```

[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x205c07bd948>
```



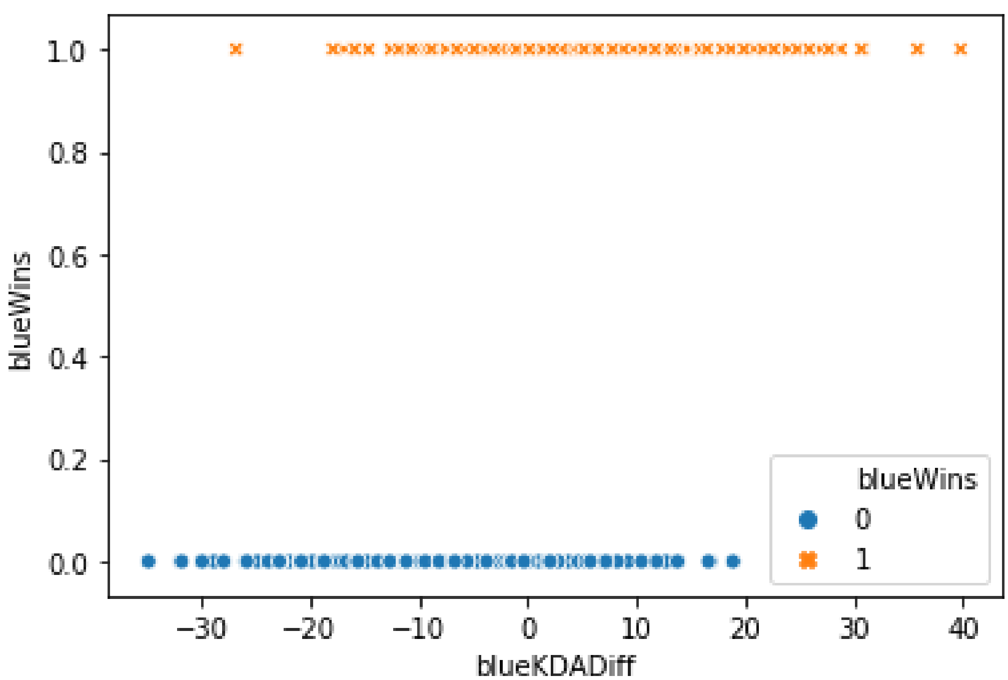
[34]:
```
inBlueKDA = KDA[['blueKDA','blueWins']]
inBlueKDA['blueKDADiff'] = KDA['blueKDA'] - KDA['redKDA']
sns.
 ↪scatterplot(data=inBlueKDA,x='blueKDA',y='blueWins',hue='blueWins',style='blueWins')
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x205c0824a88>



[35]:
```
sns.
→scatterplot(data=inBlueKDA,x='blueKDADiff',y='blueWins',hue='blueWins',style='blueWins')
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x205c08c9608>

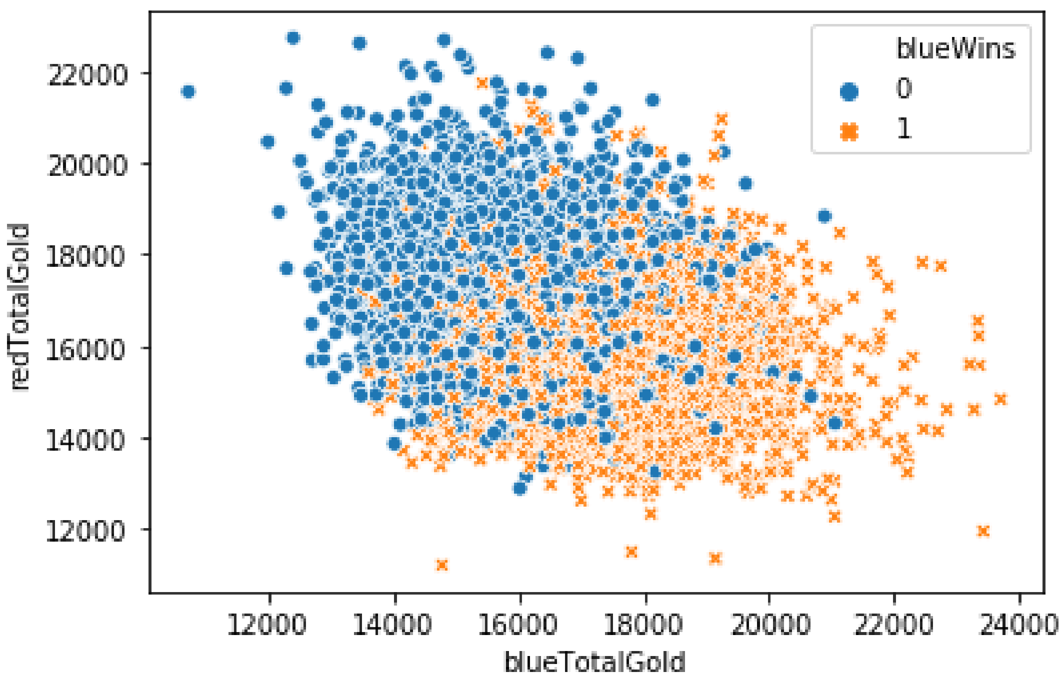


5 Total Gold Difference

Then I plotted the all the total gold for both teams, and obviously in the figure, when the blue team get more than 21000 gold in first 10 mins, they will have 100% probability to win the game.

[36]:
```
sns.
 ↪scatterplot(data=data,x='blueTotalGold',y='redTotalGold',hue='blueWins',style='blueWins')
```

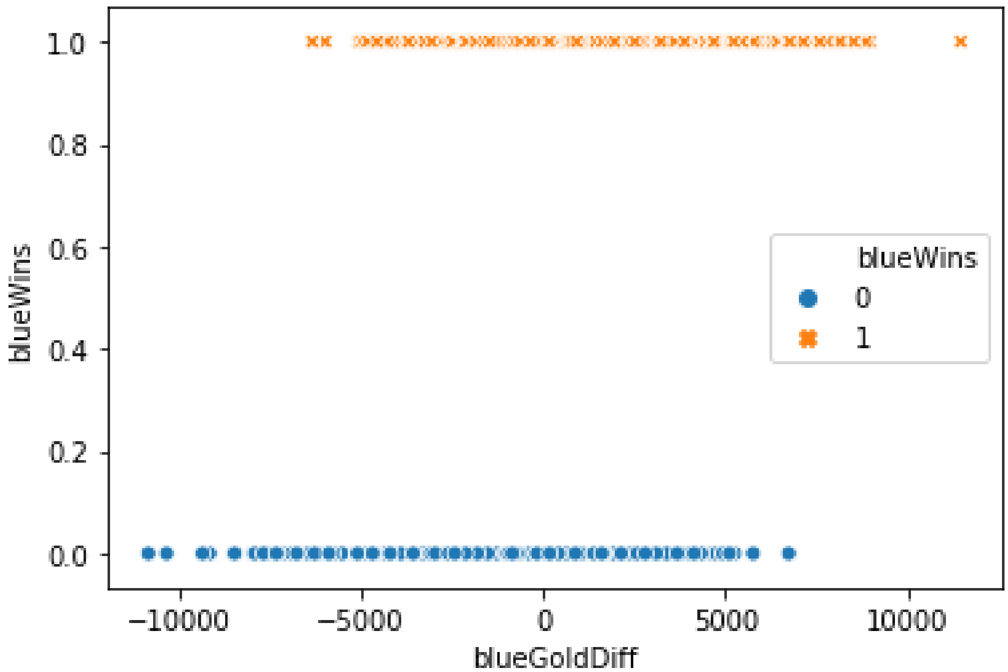
[36]: <matplotlib.axes._subplots.AxesSubplot at 0x205bfa5fbc8>



The following plot is the relationship between gold difference in first 10 mins and the game result, and we can see that when blue team gets approx. 7000 gold more than red team, then blue team will win the game.

[37]:
```
sns.
 ↪scatterplot(data=data,x='blueGoldDiff',y='blueWins',hue='blueWins',style='blueWins')
```

[37]: <matplotlib.axes._subplots.AxesSubplot at 0x205bf9d6788>

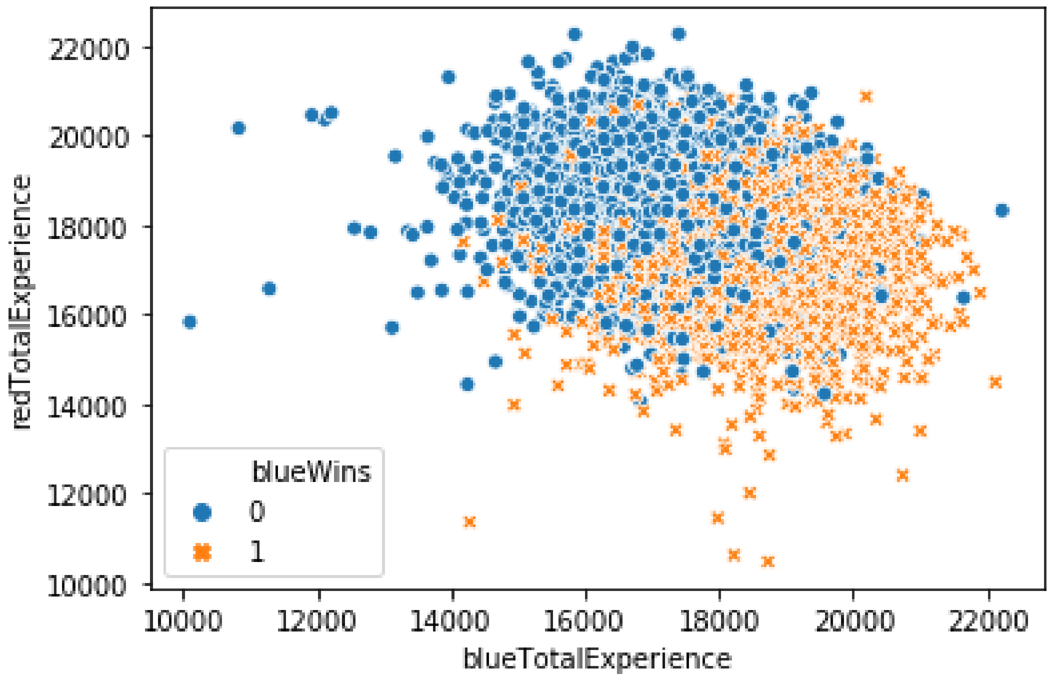


6 Experience Difference

Then the plot of all experience of both team, and the second figure is the relationship between experience difference in first 10 mins and the result of the games. It is hard to conclud anything from the first figure, but from the second figure, we can see that when blue team has approx. 6000 experience more than red team, then blue team wins the game.

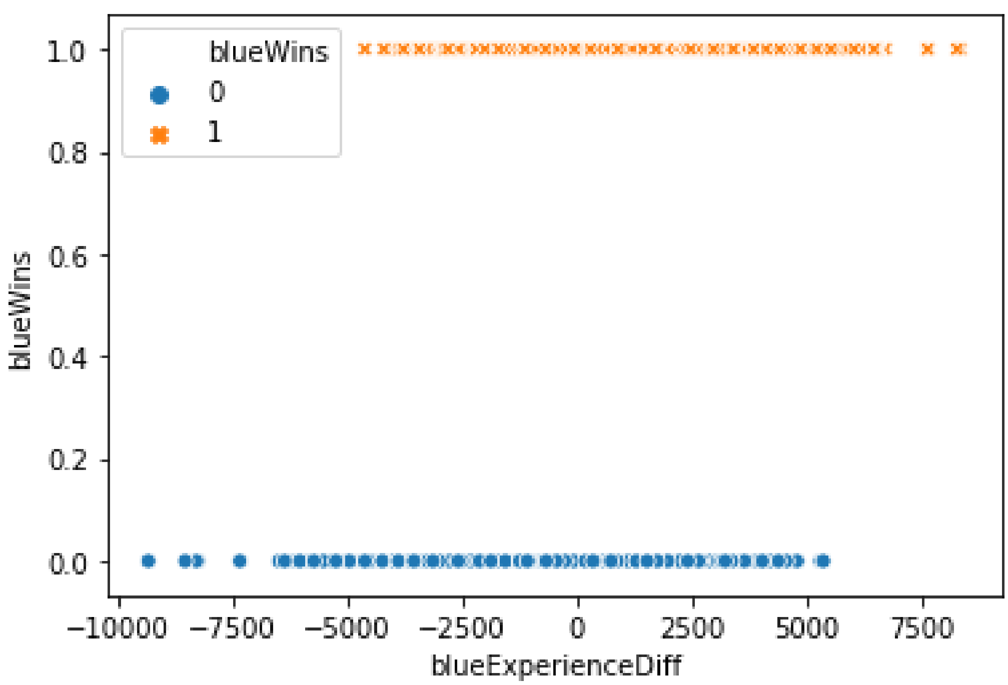
[38]:
```
sns.
→scatterplot(data=data,x='blueTotalExperience',y='redTotalExperience',hue='blueWins',style='
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x205bf804248>




```
[39]: sns.
      ↪scatterplot(data=data,x='blueExperienceDiff',y='blueWins',hue='blueWins',style='blueWins')
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x205bf8a2308>



7 Prediction of game result

[40]:
```
data['blueKDA'] = KDA['blueKDA'].round(1)
data['redKDA'] = KDA['redKDA'].round(1)
data = data.replace([np.inf, -np.inf], np.nan)
data = data.dropna()
data
```

[40]:
```
      blueWins  blueWardsPlaced  blueWardsDestroyed  blueFirstBlood  \
0            0               28                   2               1
1            0               12                   1               0
2            0               15                   0               0
3            0               43                   1               0
4            0               75                   4               0
…          …                …                   …               …
9874         1               17                   2               1
9875         1               54                   0               0
9876         0               23                   1               0
9877         0               14                   4               1
9878         1               18                   0               1

      blueKills  blueDeaths  blueAssists  blueEliteMonsters  blueDragons  \
0             9           6           11                  0            0
1             5           5            5                  0            0
2             7          11            4                  1            1
3             4           5            5                  1            0
4             6           6            6                  0            0
…           …           …            …                  …            …
9874          7           4            5                  1            1
9875          6           4            8                  1            1
9876          6           7            5                  0            0
9877          2           3            3                  1            1
9878          6           6            5                  0            0

      blueHeralds  …  redAvgLevel  redTotalExperience  \
0               0  …          6.8               17047
1               0  …          6.8               17438
2               0  …          6.8               17254
3               1  …          7.0               17961
4               0  …          7.0               18313
…             …  …          …                 …
9874            0  …          6.8               16498
9875            0  …          7.0               18367
9876            0  …          7.4               19909
```

```
9877              0  ...          7.2               18314
9878              0  ...          6.8               17379

      redTotalMinionsKilled  redTotalJungleMinionsKilled  redGoldDiff  \
0                       197                           55         -643
1                       240                           52         2908
2                       203                           28         1172
3                       235                           47         1321
4                       225                           67         1004
...                     ...                          ...          ...
9874                    229                           34        -2519
9875                    206                           56         -782
9876                    261                           60         2416
9877                    247                           40          839
9878                    201                           46         -927

      redExperienceDiff  redCSPerMin  redGoldPerMin  blueKDA  redKDA
0                     8         19.7         1656.7      3.3     1.6
1                  1173         24.0         1762.0      2.0     1.4
2                  1033         20.3         1728.5      1.0     3.6
3                     7         23.5         1647.8      1.8     3.8
4                  -230         22.5         1740.4      2.0     2.2
...                 ...          ...            ...      ...     ...
9874              -2469         22.9         1524.6      3.0     1.6
9875               -888         20.6         1545.6      3.5     1.2
9876               1877         26.1         1831.9      1.6     3.0
9877               1085         24.7         1529.8      1.7     2.0
9878                 58         20.1         1533.9      1.8     1.7

[9744 rows x 41 columns]
```

Then I build some models to predict the game result with first 10 mins performance. All the models are have around 70% accuracy.

[41]:
```python
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

sample = data.drop('blueWins',axis=1)
label = data['blueWins']
sample_train, sample_test, label_train, label_test = train_test_split(sample, label, test_size=0.1)
```

[42]:
```python
from sklearn.linear_model import LogisticRegression
LRmodel = LogisticRegression(C=0.01)
LRmodel.fit(sample_train,label_train)
pred_LR = LRmodel.predict(sample_test)
acc_LR = accuracy_score(pred_LR, label_test)
```

```
print('Logistic Regression Prediction Accuracy: ' + str(acc_LR))
```

Logistic Regression Prediction Accuracy: 0.7364102564102564

[43]:
```
from sklearn.tree import DecisionTreeClassifier
DTmodel = DecisionTreeClassifier(criterion='entropy',max_depth=5)
DTmodel.fit(sample_train,label_train)
pred_DT = DTmodel.predict(sample_test)
acc_DT = accuracy_score(pred_DT,label_test)

print('Decision Tree Classifier Prediction Accuracy: ' + str(acc_DT))
```

Decision Tree Classifier Prediction Accuracy: 0.7343589743589743

[44]:
```
from sklearn.ensemble import RandomForestClassifier
RFmodel = RandomForestClassifier(max_depth=6)
RFmodel.fit(sample_train,label_train)
pred_RF = RFmodel.predict(sample_test)
acc_RF = accuracy_score(pred_RF,label_test)

print('Random Forest Classifier Prediction Accuracy: ' + str(acc_RF))
```

Random Forest Classifier Prediction Accuracy: 0.7364102564102564

[45]:
```
from sklearn.neighbors import KNeighborsClassifier
KNNmodel = KNeighborsClassifier(n_neighbors=45)
KNNmodel.fit(sample_train,label_train)
pred_KNN = KNNmodel.predict(sample_test)
acc_KNN = accuracy_score(pred_KNN,label_test)

print('KNN Classifier Prediction Accuracy: ' + str(acc_KNN))
```

KNN Classifier Prediction Accuracy: 0.72

[46]:
```
from sklearn.ensemble import AdaBoostClassifier
ABmodel = AdaBoostClassifier(n_estimators=40)
ABmodel.fit(sample_train,label_train)
pred_AB = ABmodel.predict(sample_test)
acc_AB = accuracy_score(pred_AB,label_test)

print('Ada Boost Classifier Prediction Accuracy: ' + str(acc_AB))
```

Ada Boost Classifier Prediction Accuracy: 0.7323076923076923

[ ]:
```

```

[47]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
```

```
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

8 How Champions Selection Influence the Game?

8.1 Load the Library and Data

8.1.1 Take a look for all data

[48]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

champs = pd.read_csv('Data/champs.csv')
matches = pd.read_csv('Data/matches.csv')
participants1 = pd.read_csv('Data/participants.csv')
stats1 = pd.read_csv('Data/stats1.csv')
stats2 = pd.read_csv('Data/stats2.csv')
teambans = pd.read_csv('Data/teambans.csv')
teamstats = pd.read_csv('Data/teamstats.csv')

champs.head()
```

[48]:

	name	id
0	Jax	24
1	Sona	37
2	Tristana	18
3	Varus	110
4	Fiora	114

[49]:
```
teambans.head()
```

[49]:

	matchid	teamid	championid	banturn
0	10	100	11	1
1	10	100	117	3
2	10	100	120	5
3	10	200	84	2
4	10	200	201	4

[50]:
```
teamstats.head()
```

[50]:

	matchid	teamid	firstblood	firsttower	firstinhib	firstbaron	\
0	10	100	0	1	0	0	
1	10	200	1	0	1	1	
2	11	100	1	0	0	0	
3	11	200	0	1	1	0	
4	12	100	1	0	0	0	

	firstdragon	firstharry	towerkills	inhibkills	baronkills	dragonkills	\
0	0	0	5	0	0	0	
1	1	1	10	3	1	3	
2	0	0	2	0	0	0	
3	1	0	10	3	0	2	
4	0	0	1	0	0	0	

	harrykills
0	0
1	1
2	0
3	0
4	0

[51]:
```
matches.head()
```

[51]:

	id	gameid	platformid	queueid	seasonid	duration	creation	\
0	10	3187427022	EUW1	420	8	1909	1495068946860	
1	11	3187425281	EUW1	420	8	1693	1495066760778	
2	12	3187269801	EUW1	420	8	1482	1495053375889	
3	13	3187252065	EUW1	420	8	1954	1495050993613	
4	14	3187201038	EUW1	420	8	2067	1495047893400	

	version
0	7.10.187.9675
1	7.10.187.9675
2	7.10.187.9675
3	7.10.187.9675
4	7.10.187.9675

8.1.2 Combine Champion Name and Bans with Champion Id

[52]:
```
teambans = pd.merge(teambans,champs,how='left',left_on = 'championid', right_on
↪= 'id')
teambans.head()
```

[52]:

	matchid	teamid	championid	banturn	name	id
0	10	100	11	1	Master Yi	11
1	10	100	117	3	Lulu	117
2	10	100	120	5	Hecarim	120
3	10	200	84	2	Akali	84
4	10	200	201	4	Braum	201

8.1.3 Tranlate the Roles and Position

[53]:
```
def PositionTranfer(row):
    if row['role'] in ('DUO_SUPPORT', 'DUO_CARRY'):
        return row['role']
    else:
        return row['position']

participants1['adjP'] = participants1.apply(PositionTranfer, axis = 1)
```

8.1.4 Checking Datasets Size Before Merging Data

[54]:
```
participants1['team'] = participants1['player'].apply(lambda x: '1' if x <= 5
↪else '2')
participants1['team_role'] = participants1['team'] + '-' + participants1['adjP']
participants1.shape
```

[54]: (1834520, 11)

[55]:
```
game_info=stats1.append(stats2)
game_info.shape
```

[55]: (1834517, 56)

8.1.5 Finish Merging

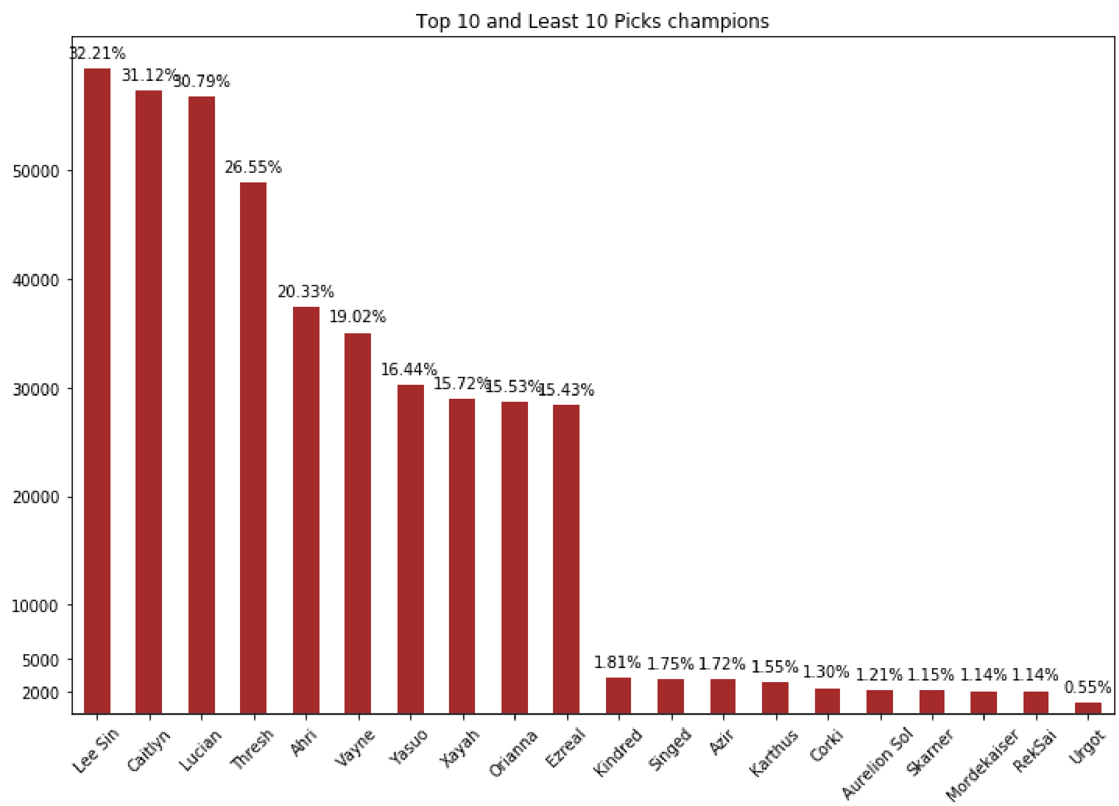
[56]:
```
df = pd.merge(participants1, game_info, how = 'left', on = ['id'])
df = pd.merge(df, champs, how = 'left', left_on = 'championid', right_on = 'id')
df = pd.merge(df, matches, how = 'left', left_on = 'matchid', right_on = 'id')
df['teamid']= df['player'].apply(lambda x: '1' if x <= 5 else '2')
df.shape
```

[56]: (1834520, 77)

8.2 Let's Take a Look at Champions Selection

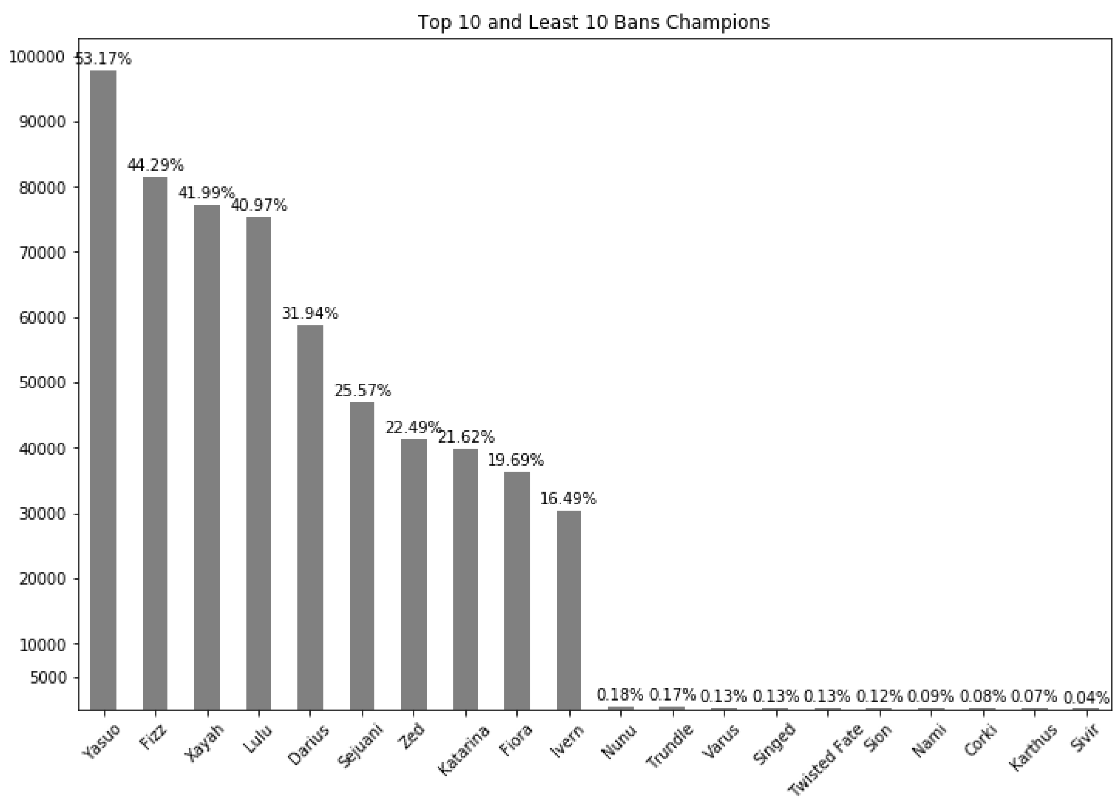
[57]:
```
sort_val=df.name.value_counts().sort_values(ascending=False)
total_records=len(matches)
```

[58]:
```
fig,ax = plt.subplots(figsize=(12,8))
plt.title('Top 10 and Least 10 Picks champions')
ax =pd.concat((sort_val.head(10),sort_val.tail(10))).plot(kind='bar', color =␣
↪'brown')
for p in ax.patches:
    level = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,level + 1000,'{:.2f}%'.format(level/
↪total_records*100),ha="center",rotation=0)

plt.yticks([2000,5000,10000,20000,30000,40000,50000])
plt.xticks(rotation = 45)
plt.show()
```



This is the top ten and the least ten picks champions. There are four shooters, two magicians, and only one support (Thresh) in top ten champions. Comparing to other position in the game, support is not the first choice for most people. This role has less health and low damage. Thresh must very good among all other supports. Urgot only has 0.5% picks means this champion is very bad. If you want to win, you won't choose this champion. The Riot company redesign this champion in 2017 to save this champion's career.

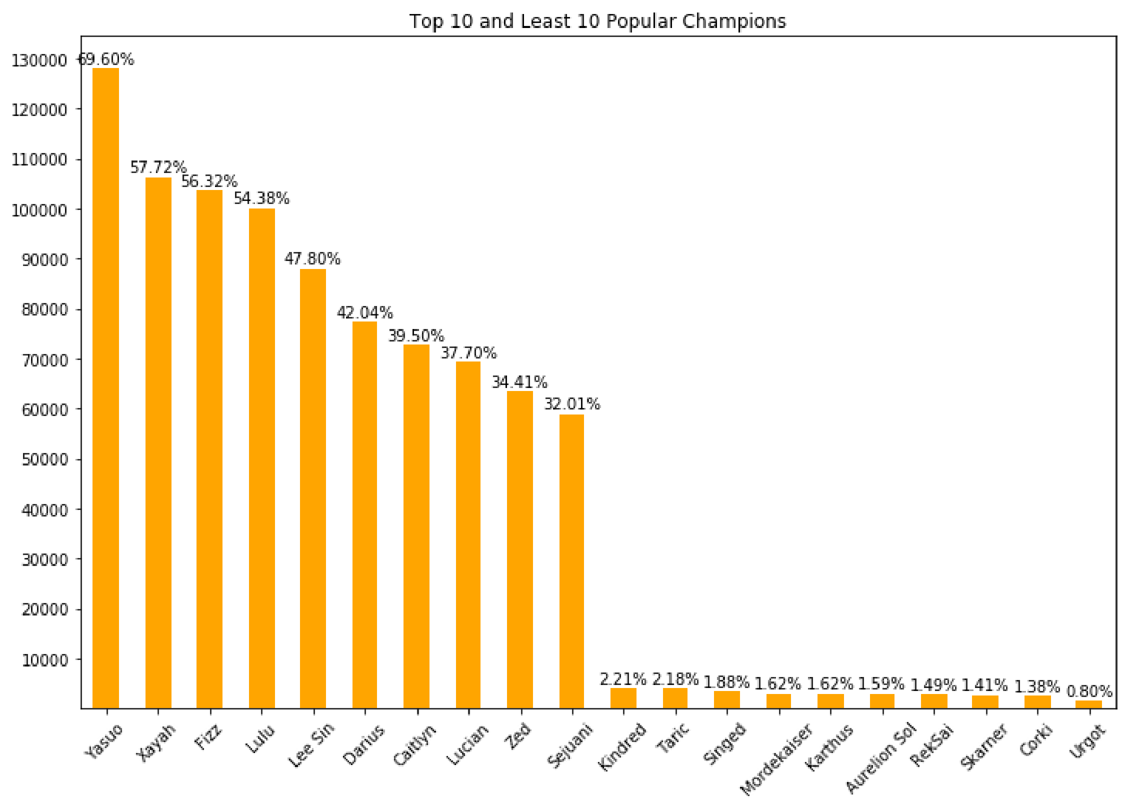
[59]:
```
sort_val=teambans.name.value_counts().sort_values(ascending=False)
fig,ax = plt.subplots(figsize=(12,8))
plt.title('Top 10 and Least 10 Bans Champions')
ax=pd.concat((sort_val.head(10),sort_val.tail(10))).plot(kind='bar',color =␣
↪'gray')
for p in ax.patches:
    level = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,level + 1000,'{:.2f}%'.format(level/
↪total_records*100),ha="center",rotation=0)

plt.yticks([5000,10000,20000,30000,40000,50000,60000,70000,80000,90000,100000])
plt.xticks(rotation = 45)
plt.show()
```



This is the top ten and the least ten bans champions. In each ranked game, each team could choose to ban 5 champions for the other team, so the opponent cannot choose restrained champions, and vice versa. In top ten ban rate side, Yasuo is far ahead of other hearos, with a ban rate of 53%, which mean that every two games will have to ban Yasuo. For those champions with the lowest ban rate, I won't be surprised because they are not strong at all and there's not need to waste ban for them.

```
[60]: val1=teambans.name.value_counts().sort_values(ascending=False)
val2=df.name.value_counts().sort_values(ascending=False)
sort_val = (val1 + val2).sort_values(ascending=False)
```

```
[61]: fig,ax = plt.subplots(figsize=(12,8))
plt.title('Top 10 and Least 10 Popular Champions')
ax=pd.concat((sort_val.head(10),sort_val.tail(10))).plot(kind='bar',color =␣
 ↪'orange')
for p in ax.patches:
    level = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,level + 1000,'{:.2f}%'.format(level/
 ↪total_records*100),ha="center",rotation=0)

plt.
 ↪yticks([10000,20000,30000,40000,50000,60000,70000,80000,90000,100000,110000,120000,130000])
plt.xticks(rotation = 45)
plt.show()
```



This is most popular champions. I use formula bans rate + picks rate = popular rate. With not surprise, Yasuo is the most popular one. As lone as opponent did not ban it, player will choose him. These top ten popular champions are not only strong, but also have special mechanism to provide good feedback to players. When we stand on game designer' perspective, designers can also learn their customer and balanced the game. For example, they can remake the champions to bring more favor for the weak one. As a long-term game. They do not want people always choose same type of champion all the time.

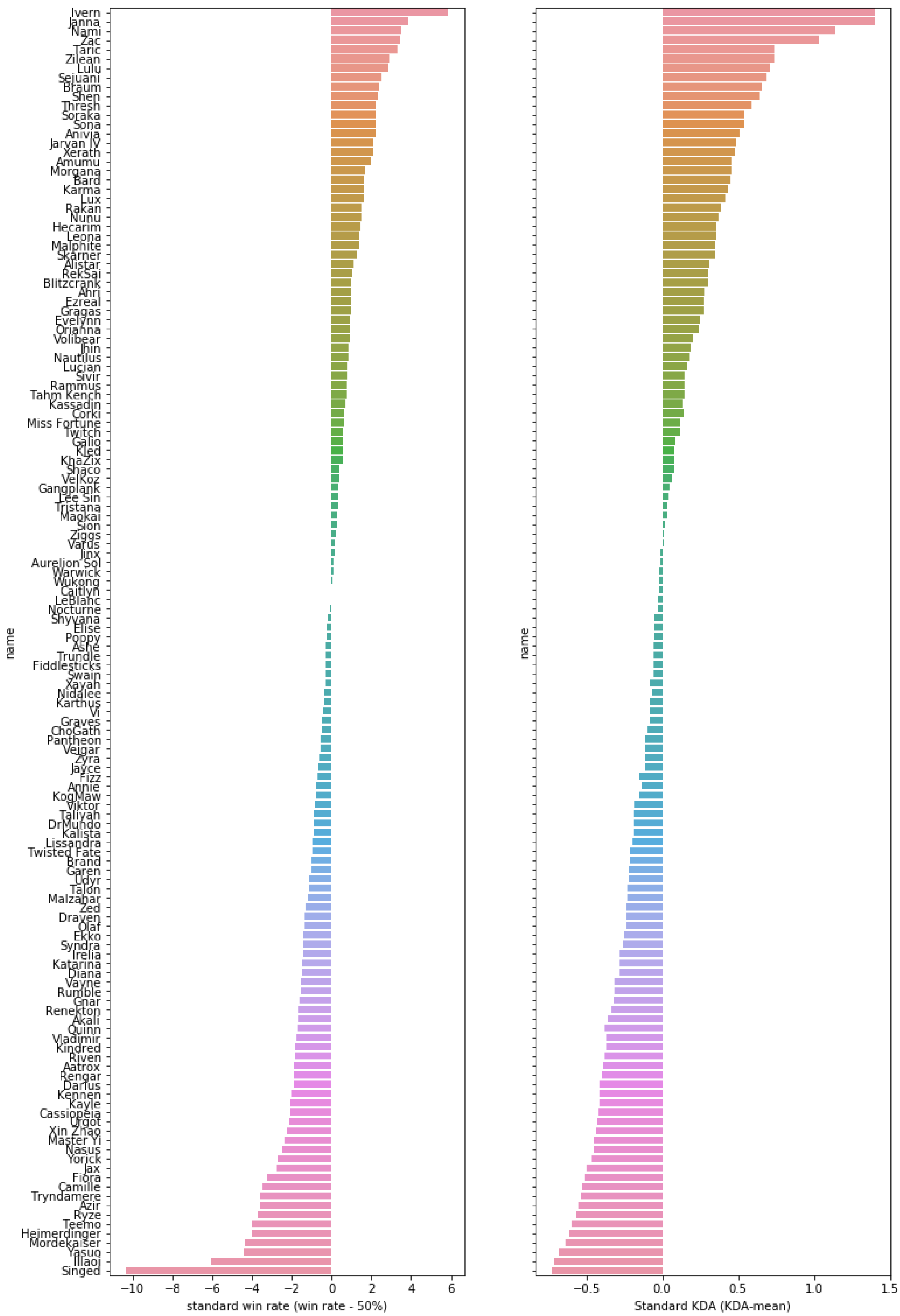
8.3 Let's take a look at total KDA and Win rate

[62]:
```
CS = df.groupby('name').agg({'win': 'sum','name': 'count','kills':
↪'mean','deaths':'mean','assists':'mean'})
CS.columns = ['win' , 'total matches', 'K', 'D', 'A']

#mean KDA
CS['KDA'] = (CS.K + CS.A)/CS.D
CS['Standard KDA (KDA-mean)'] = CS['KDA'] - CS.KDA.mean()

#50% win ratio
CS['win rate']  = CS.win/CS['total matches'] * 100
CS['standard win rate (win rate - 50%)']  = CS['win rate'] - 50.0

CS = CS.round(2)
CS.reset_index(inplace=True)
CS.sort_values(by='win rate', ascending = False).head(10)
```

[62]:
```
         name      win  total matches     K     D      A   KDA  \
40      Ivern   4578.0           8194  2.61  4.09  12.98  3.81
5      Anivia   4194.0           7785  6.23  4.66   7.39  2.92
127    Xerath   3357.0           6273  7.09  5.34   8.36  2.89
99       Sona   7529.0          14090  2.93  5.57  13.52  2.95
1        Ahri  19949.0          37424  7.08  5.43   7.51  2.69
41      Janna  12856.0          24296  0.86  3.94  14.15  3.81
98    Skarner   1116.0           2111  4.71  4.95   8.95  2.76
80   Pantheon   5934.0          11305  7.87  6.31   6.63  2.30
4       Amumu   7118.0          13585  4.59  5.30  10.65  2.88
22     Draven  10633.0          20327  7.62  6.41   6.30  2.17

     Standard KDA (KDA-mean)  win rate  standard win rate (win rate - 50%)
40                      1.40     55.87                                5.87
5                       0.51     53.87                                3.87
127                     0.48     53.52                                3.52
99                      0.54     53.44                                3.44
1                       0.28     53.31                                3.31
41                      1.40     52.91                                2.91
98                      0.35     52.87                                2.87
80                     -0.11     52.49                                2.49
4                       0.46     52.40                                2.40
22                     -0.24     52.31                                2.31
```

[63]:
```
win_rate = CS.sort_values(by='win rate',ascending=False)
KDA_data = CS.sort_values(by='KDA',ascending=False)

fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True, figsize=(12, 20))
sns.barplot(x='standard win rate (win rate - 50%)', y='name', data=win_rate,␣
↪ax=ax1)
sns.barplot(x='Standard KDA (KDA-mean)', y='name', data=KDA_data, ax=ax2)
```

[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x205836156c8>
```



name
standard win rate (win rate - 50%)
Standard KDA (KDA-mean)
Ivern
Janna
Nami
Zac
Taric
Zilean
Lulu
Sejuani
Braum
Shen
Thresh
Soraka
Sona
Anivia
Jarvan IV
Xerath
Amumu
Morgana
Bard
Karma
Lux
Rakan
Nunu
Hecarim
Leona
Malphite
Skarner
Alistar
RekSai
Blitzcrank
Ahri
Ezreal
Gragas
Evelynn
Orianna
Volibear
Jhin
Nautilus
Lucian
Sivir
Rammus
Tahm Kench
Kassadin
Corki
Miss Fortune
Twitch
Galio
Kled
KhaZix
Shaco
VelKoz
Gangplank
Lee Sin
Tristana
Maokai
Sion
Ziggs
Varus
Jinx
Aurelion Sol
Warwick
Wukong
Caitlyn
LeBlanc
Nocturne
Shyvana
Elise
Poppy
Ashe
Trundle
Fiddlesticks
Swain
Xayah
Nidalee
Karthus
Vi
Graves
ChoGath
Pantheon
Veigar
Zyra
Jayce
Fizz
Annie
KogMaw
Viktor
Taliyah
DrMundo
Kalista
Lissandra
Twisted Fate
Brand
Garen
Udyr
Talon
Malzahar
Zed
Draven
Olaf
Ekko
Syndra
Irelia
Katarina
Diana
Vayne
Rumble
Gnar
Renekton
Akali
Quinn
Vladimir
Kindred
Riven
Aatrox
Rengar
Darius
Kennen
Kayle
Cassiopeia
Urgot
Xin Zhao
Master Yi
Nasus
Yorick
Jax
Fiora
Camille
Tryndamere
Azir
Ryze
Teemo
Heimerdinger
Mordekaiser
Yasuo
Illaoi
Singed
−10
−8
−6
−4
−2
0
2
4
6
−0.5
0.0
0.5
1.0
1.5

There are half of the champions that has positive win rate and those top win rate champions cannot surpass 60%-win rate. Kda(kill death, and assist rate) is a very interesting feature. It high kda means the champion (kills + assists) a lot, but rarely death. However, high KDA doesn't 100% means high damage in real game. Mean kda is about 2.4. but the highest kdi has 3.9. the top three, there two supports and one's role is in the jungle. Because these heroes are easier to get assists in the early stages of the game and their self-protection ability is often relatively strong, and the weight of kill and assists in the KDA calculation is the same, so heroes with weak survivability such as shooters and wizards are often not easy Get a high KDA. But neither the win rate nor the KDA can explain the strength of a hero, because this is still related to the characteristic of each hero.

8.4 Champ Selection in Different Lane

I made a hero's laning restraint table based on the hero's laning win rate, but only analyzed the mid lane and top lane, because the bottom road is a two-player road, you can't just watch one hero, and the jungler also cooperates with the top lane more, so we do not need to made these graphs.Before I do That, I will clean the data and remove those games duo on top lane and mid lane.

8.4.1 Data Cleaning

[64]:
```
DuoGame = df[df['team_role'] == '1-MID'].groupby('matchid').agg({'team_role':
 ↪'count'})
DuoGame[DuoGame['team_role'] != 1].index.values

NeedRemoved = []
for i in ('1-DUO_SUPPORT', '1-TOP', '2-DUO_CARRY', '1-JUNGLE', '2-MID',␣
 ↪'1-DUO_CARRY', '1-MID', '2-TOP', '2-DUO_SUPPORT', '2-JUNGLE'):
    DuoGame = df[df['team_role'] == i].groupby('matchid').agg({'team_role':
 ↪'count'})
    NeedRemoved.extend(DuoGame[DuoGame['team_role'] != 1].index.values)

NeedRemoved.extend(df[df['adjP'] == 'BOT']['matchid'].unique())
NeedRemoved = list(set(NeedRemoved))

print(f'Before Cleaning: {df.matchid.nunique()}')
df_cleaned = df[~df['matchid'].isin(NeedRemoved)]
print(f'After Cleaning: {df_cleaned.matchid.nunique()}')
```

```
Before Cleaning: 184069
After Cleaning: 148638
```

We remove over 30000 ranked game data.

8.4.2 Match up

Now we are focus on how top and mid lane champions compete. We will match up the champions with their games id.**

[65]:
```
df_shift = df_cleaned.sort_values(['matchid', 'adjP'], ascending = [1, 1])
df_shift['shift 1'] = df_shift['name'].shift()
df_shift['shift -1'] = df_shift['name'].shift(-1)
```

8.4.3 shift the position to measure the chapions in regions behaviors

[66]:
```
def get_matchup(x):
    if x['player'] > 5:
        if x['name'] >= x['shift 1']:
            matchup = x['shift 1'] + ' vs ' + x['name']
        else:
            matchup = x['name'] + ' vs ' + x['shift 1']
    else:
        if x['name'] >= x['shift -1']:
            matchup = x['shift -1'] + ' vs ' + x['name']
        else:
            matchup = x['name'] + ' vs ' + x['shift -1']
    return matchup
```

[67]:
```
match_up = df_shift.apply(get_matchup, axis=1)
df_shift.insert(7, 'pattern', match_up)
df_shift = df_shift.drop(['platformid','queueid','role','position','shift␣
↪1','shift -1'], axis=1)
df_shift.head(10)
```

[67]:

	id_x	matchid	player	championid	ss1	ss2	pattern	\
2	11	10	3	119	7	4	Draven vs Jinx	
8	17	10	9	222	7	4	Draven vs Jinx	
1	10	10	2	267	3	4	Nami vs VelKoz	
9	18	10	10	161	14	4	Nami vs VelKoz	
0	9	10	1	19	4	11	Skarner vs Warwick	
5	14	10	6	72	11	4	Skarner vs Warwick	
4	13	10	5	112	4	3	Ahri vs Viktor	
7	16	10	8	103	14	4	Ahri vs Viktor	
3	12	10	4	114	12	4	Fiora vs Galio	
6	15	10	7	3	4	12	Fiora vs Galio	

	adjP	team	team_role	…	firstblood	name	id_y	id	\
2	DUO_CARRY	1	1-DUO_CARRY	…	0.0	Draven	119	10	
8	DUO_CARRY	2	2-DUO_CARRY	…	1.0	Jinx	222	10	
1	DUO_SUPPORT	1	1-DUO_SUPPORT	…	0.0	Nami	267	10	
9	DUO_SUPPORT	2	2-DUO_SUPPORT	…	0.0	VelKoz	161	10	
0	JUNGLE	1	1-JUNGLE	…	0.0	Warwick	19	10	
5	JUNGLE	2	2-JUNGLE	…	0.0	Skarner	72	10	
4	MID	1	1-MID	…	0.0	Viktor	112	10	
7	MID	2	2-MID	…	0.0	Ahri	103	10	
3	TOP	1	1-TOP	…	0.0	Fiora	114	10	

```
6          TOP    2          2-TOP  …         0.0    Galio     3  10

       gameid  seasonid  duration       creation        version  teamid
2  3187427022         8      1909  1495068946860  7.10.187.9675       1
8  3187427022         8      1909  1495068946860  7.10.187.9675       2
1  3187427022         8      1909  1495068946860  7.10.187.9675       1
9  3187427022         8      1909  1495068946860  7.10.187.9675       2
0  3187427022         8      1909  1495068946860  7.10.187.9675       1
5  3187427022         8      1909  1495068946860  7.10.187.9675       2
4  3187427022         8      1909  1495068946860  7.10.187.9675       1
7  3187427022         8      1909  1495068946860  7.10.187.9675       2
3  3187427022         8      1909  1495068946860  7.10.187.9675       1
6  3187427022         8      1909  1495068946860  7.10.187.9675       2

[10 rows x 74 columns]
```

[68]:
```python
winner= df_shift.apply(lambda x: x['win'] if x['name'] == x['pattern'].split(' vs ')[0] else 0, axis = 1)
df_shift.insert(8, 'winner', winner)
df_shift.head(10)
```

[68]:
```
   id_x  matchid  player  championid  ss1  ss2             pattern  \
2    11       10       3         119    7    4      Draven vs Jinx
8    17       10       9         222    7    4      Draven vs Jinx
1    10       10       2         267    3    4      Nami vs VelKoz
9    18       10      10         161   14    4      Nami vs VelKoz
0     9       10       1          19    4   11  Skarner vs Warwick
5    14       10       6          72   11    4  Skarner vs Warwick
4    13       10       5         112    4    3      Ahri vs Viktor
7    16       10       8         103   14    4      Ahri vs Viktor
3    12       10       4         114   12    4      Fiora vs Galio
6    15       10       7           3    4   12      Fiora vs Galio

          adjP  winner  team  … firstblood     name  id_y  id      gameid  \
2    DUO_CARRY     0.0     1  …        0.0   Draven   119  10  3187427022
8    DUO_CARRY     0.0     2  …        1.0     Jinx   222  10  3187427022
1  DUO_SUPPORT     0.0     1  …        0.0     Nami   267  10  3187427022
9  DUO_SUPPORT     0.0     2  …        0.0   VelKoz   161  10  3187427022
0       JUNGLE     0.0     1  …        0.0  Warwick    19  10  3187427022
5       JUNGLE     1.0     2  …        0.0  Skarner    72  10  3187427022
4          MID     0.0     1  …        0.0   Viktor   112  10  3187427022
7          MID     1.0     2  …        0.0     Ahri   103  10  3187427022
3          TOP     0.0     1  …        0.0    Fiora   114  10  3187427022
6          TOP     0.0     2  …        0.0    Galio     3  10  3187427022

   seasonid  duration       creation        version  teamid
2         8      1909  1495068946860  7.10.187.9675       1
```

```
8          8      1909   1495068946860   7.10.187.9675       2
1          8      1909   1495068946860   7.10.187.9675       1
9          8      1909   1495068946860   7.10.187.9675       2
0          8      1909   1495068946860   7.10.187.9675       1
5          8      1909   1495068946860   7.10.187.9675       2
4          8      1909   1495068946860   7.10.187.9675       1
7          8      1909   1495068946860   7.10.187.9675       2
3          8      1909   1495068946860   7.10.187.9675       1
6          8      1909   1495068946860   7.10.187.9675       2

[10 rows x 75 columns]
```

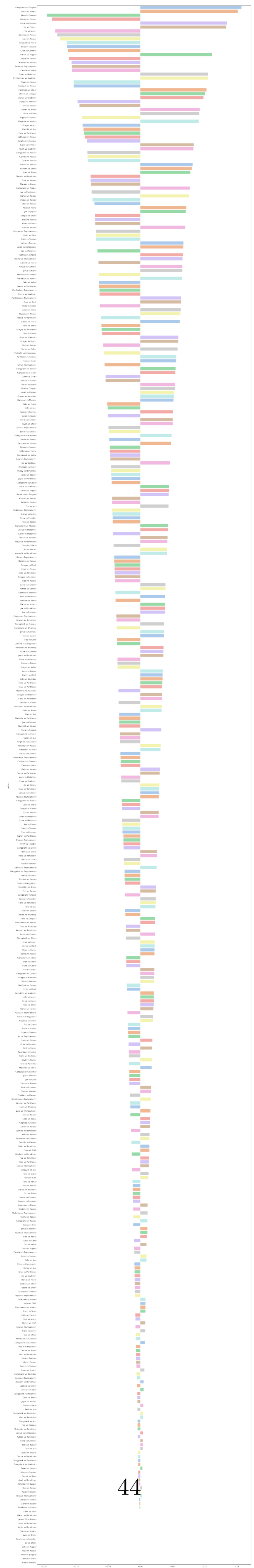
8.4.4 Top Lane

[69]:
```
df_top = df_shift[df_shift['adjP']=='TOP']

counter_top = df_top.groupby('pattern').agg({'win': 'count', 'winner': 'sum'})
counter_top.reset_index(inplace=True)
counter_top.columns = ['pattern', 'total matchs', 'total first win']
counter_top['total matchs'] = counter_top['total matchs'] / 2
counter_top['counter rate'] = counter_top['total first win'] /␣
↪counter_top['total matchs']
counter_top['counter rate compared 50%'] = counter_top['total first win'] /␣
↪counter_top['total matchs'] - 0.5

counter_top['abs'] = abs(counter_top['counter rate compared 50%'])
counter_top = counter_top[(counter_top['total matchs']>100) &␣
↪(counter_top['total first win']>0)].sort_values(by='abs', ascending=False)
counter_top.reset_index(inplace=True)

counter_top.head()
```

[69]:
```
   index              pattern  total matchs  total first win  counter rate  \
0   1920  Gangplank vs Singed         102.0             67.0      0.656863
1   4993       Yasuo vs Yorick         109.0             71.0      0.651376
2   4573         Shen vs Teemo         189.0             67.0      0.354497
3   3751        Maokai vs Yasuo         113.0             41.0      0.362832
4   2502      Irelia vs Kennen         186.0            118.0      0.634409

   counter rate compared 50%       abs
0                   0.156863  0.156863
1                   0.151376  0.151376
2                  -0.145503  0.145503
3                  -0.137168  0.137168
4                   0.134409  0.134409
```

[70]:
```
plt.figure(figsize=(20, 150))
sns.barplot(x="counter rate compared 50%", y="pattern", data=counter_top,
 ↪palette='pastel')
```

[70]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x205871711c8>
```



The graph is huge. There are more than 300 distinct patterns that generate on this graph and all these patters appeared more than 100 times in the whole dataset, so I think these patterns are classic. If you played Ganplank in the Top lane and the opponent plays Singed, there are very high change that you may lost in the end. If you played as Shen and your opponent choose Teemo, you have very high change to win. We can definitely check these graph before the game to increase your win rate a little bit.

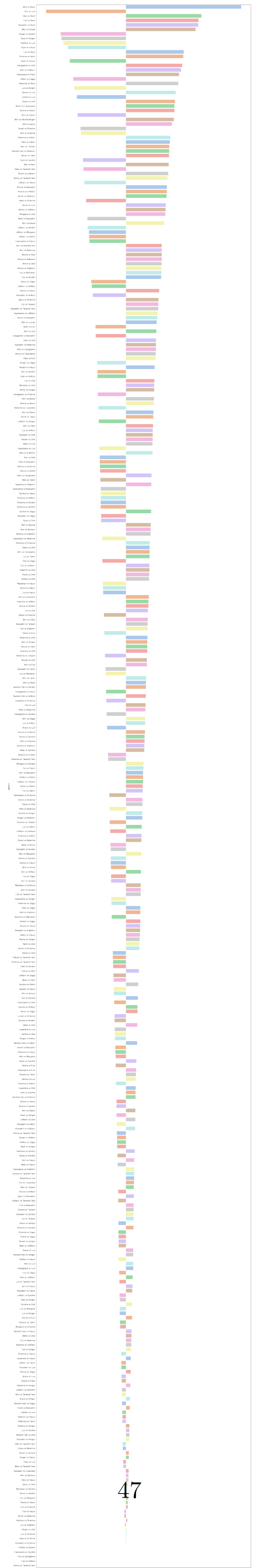
8.4.5 Mid Lane

[71]:
```
df_mid = df_shift[df_shift['adjP']=='MID']

counter_mid = df_mid.groupby('pattern').agg({'win': 'count', 'winner': 'sum'})
counter_mid.reset_index(inplace=True)
counter_mid.columns = ['pattern', 'total matchs', 'total first win']
counter_mid['total matchs'] = counter_mid['total matchs'] / 2
counter_mid['counter rate'] = counter_mid['total first win'] /␣
 ↪counter_mid['total matchs']
counter_mid['counter rate compared 50%'] = counter_mid['total first win'] /␣
 ↪counter_mid['total matchs'] - 0.5

counter_mid['abs'] = abs(counter_mid['counter rate compared 50%'])
counter_mid = counter_mid[(counter_mid['total matchs']>100) &␣
 ↪(counter_mid['total first win']>0)].sort_values(by='abs', ascending=False)
counter_mid.reset_index(inplace=True)

counter_mid.head()
```

[71]:
```
   index          pattern  total matchs  total first win  counter rate  \
0     96      Ahri vs Ryze         319.0            227.0      0.711599
1    568       Azir vs Lux         150.0             53.0      0.353333
2   1192      Ekko vs Ryze         130.0             83.0      0.638462
3   1443      Fizz vs Ryze         158.0            100.0      0.632911
4   2092  Kassadin vs Ryze         147.0             93.0      0.632653

   counter rate compared 50%       abs
0                   0.211599  0.211599
1                  -0.146667  0.146667
2                   0.138462  0.138462
3                   0.132911  0.132911
4                   0.132653  0.132653
```

[72]:
```
plt.figure(figsize=(20, 150))
sns.barplot(x="counter rate compared 50%", y="pattern", data=counter_mid,␣
 ↪palette='pastel')
```

[72]: <matplotlib.axes._subplots.AxesSubplot at 0x205871d9a08>



8.5 Wardsplaced and Kills

We select most of recent Games, Season 8

[73]:
```
season8 = df_cleaned[['id', 'matchid', 'player', 'name', 'adjP', 'team_role',␣
↪'win', 'kills', 'deaths', 'assists',␣
↪'turretkills','totminionskilled','totdmgtaken', 'inhibkills','wardsplaced',␣
↪'duration', 'platformid', 'seasonid']]
season8 = season8[season8['seasonid'] == 8]
print('Season 8: ',season8.matchid.nunique())
season8.head(10)
```

```
Season 8:  140403
```

[73]:

	id	matchid	player	name	adjP	team_role	win	kills
0	10	10	1	Warwick	JUNGLE	1-JUNGLE	0.0	6.0
1	10	10	2	Nami	DUO_SUPPORT	1-DUO_SUPPORT	0.0	0.0
2	10	10	3	Draven	DUO_CARRY	1-DUO_CARRY	0.0	7.0
3	10	10	4	Fiora	TOP	1-TOP	0.0	5.0
4	10	10	5	Viktor	MID	1-MID	0.0	2.0
5	10	10	6	Skarner	JUNGLE	2-JUNGLE	1.0	3.0
6	10	10	7	Galio	TOP	2-TOP	1.0	4.0
7	10	10	8	Ahri	MID	2-MID	1.0	13.0
8	10	10	9	Jinx	DUO_CARRY	2-DUO_CARRY	1.0	15.0
9	10	10	10	VelKoz	DUO_SUPPORT	2-DUO_SUPPORT	1.0	4.0

	deaths	assists	turretkills	totminionskilled	totdmgtaken	inhibkills
0	10.0	1.0	0.0	42.0	41446.0	0.0
1	2.0	12.0	1.0	17.0	17769.0	0.0
2	8.0	5.0	0.0	205.0	25627.0	0.0
3	11.0	2.0	3.0	164.0	31705.0	0.0
4	8.0	2.0	1.0	235.0	20585.0	0.0
5	3.0	9.0	1.0	28.0	22708.0	0.0
6	5.0	11.0	2.0	187.0	21719.0	0.0
7	4.0	8.0	3.0	183.0	19174.0	0.0
8	3.0	9.0	2.0	191.0	17655.0	2.0
9	5.0	19.0	0.0	72.0	13443.0	0.0

	wardsplaced	duration	platformid	seasonid
0	10.0	1909	EUW1	8
1	17.0	1909	EUW1	8
2	13.0	1909	EUW1	8
3	3.0	1909	EUW1	8
4	10.0	1909	EUW1	8
5	8.0	1909	EUW1	8

```
6           7.0       1909        EUW1          8
7           8.0       1909        EUW1          8
8           6.0       1909        EUW1          8
9          25.0       1909        EUW1          8
```

8.5.1 The feature of'wardsplaced' is the number of insertions.

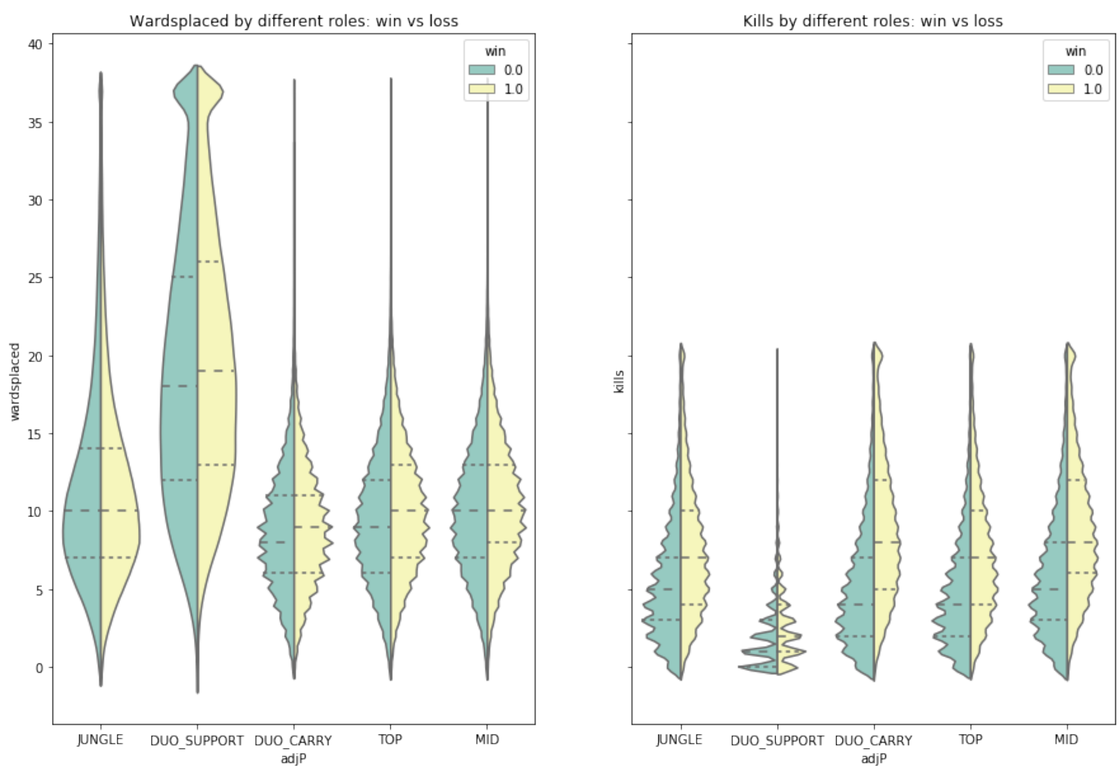
[74]:
```
pd.set_option('display.max_rows', None)
pd.set_option('display.float_format', lambda x: '%.4f' % x)

wardsplaced = season8['wardsplaced'].value_counts().sort_index() / len(df)
wardsplaced.cumsum()
kills = season8['kills'].value_counts().sort_index() / len(season8)
kills.cumsum()
```

[74]:
```
0.0000     0.0645
1.0000     0.1580
2.0000     0.2595
3.0000     0.3593
4.0000     0.4541
5.0000     0.5419
6.0000     0.6214
7.0000     0.6916
8.0000     0.7525
9.0000     0.8041
10.0000    0.8469
11.0000    0.8817
12.0000    0.9098
13.0000    0.9318
14.0000    0.9491
15.0000    0.9623
16.0000    0.9723
17.0000    0.9798
18.0000    0.9854
19.0000    0.9896
20.0000    0.9926
21.0000    0.9948
22.0000    0.9964
23.0000    0.9975
24.0000    0.9982
25.0000    0.9988
26.0000    0.9992
27.0000    0.9994
28.0000    0.9996
29.0000    0.9997
30.0000    0.9998
31.0000    0.9999
```

```
32.0000    0.9999
33.0000    0.9999
34.0000    1.0000
35.0000    1.0000
36.0000    1.0000
37.0000    1.0000
38.0000    1.0000
39.0000    1.0000
41.0000    1.0000
42.0000    1.0000
43.0000    1.0000
44.0000    1.0000
Name: kills, dtype: float64
```

[75]:
```
season8['wardsplaced'] = season8['wardsplaced'].apply(lambda x: x if x<=37 else␣
 ↪37)
season8['kills'] = season8['kills'].apply(lambda x: x if x<=20 else 20)
```

[76]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, sharey=True, figsize=(15, 10))
sns.violinplot(x='adjP', y='wardsplaced', hue="win", data=season8,␣
 ↪palette='Set3', split=True, inner='quartile', ax=ax1)
sns.violinplot(x="adjP", y="kills", hue="win", data=season8, palette='Set3',␣
 ↪split=True, inner='quartile', ax=ax2)
ax1.title.set_text('Wardsplaced by different roles: win vs loss')
ax2.title.set_text('Kills by different roles: win vs loss')
```



- Left graph is wardplaced by different roles. Wardsplanced means open a hidden region for all teammates, so they can know if any enemy pass by or set a trap in the grass. In the left graph, we can see the Duo support most time do these stuffs for the team. Carry rarely warsplaced for team because they need to spend most of their time on kill amines and return home to buy equipment.
- Right graph is kills made by different roles. we can see the support rarely kills enemy especially when game over 20 minutes, the carries's equipment are shield and they cannot do much damage for enemy team. All other roles have pretty good kill number but the win team. The winner teams have more kill than loss team.