

TEAM-BASED STRATEGY GAME

RED TEAM

Five Players per Team
Five Champions per Team
Objective: Destroy Blue team base

MINION

Bots: Supportive role / pawns

BLUE TEAM

Five Players per Team
Five Champions per Team
Objective: Destroy Red team base

CHAMPIONS

Over 140 champions
Different skills, strengths and weaknesses

TOWERS

Six towers per team (Forts)

Champion Roles

FARM. KITE. CARRY



AD CARRY

SMITE. GANK. TAX



SUPPORT

JUNGLE



PROTECT. HARASS.
DOMINATE

THE WORLD IS A DESERT.
I AM THE OASIS



TOP

MID



PUSH. CARRY. ROAM

CREATE A SUPERSQUAD

ANALYSIS WORKFLOW



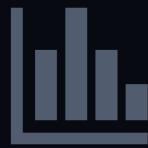
STEP1

Identify Data Source



STEP2

Clean and Explore Data



STEP3

Perform Initial Descriptive
Data Analysis



STEP4

Conduct Correlation
Analysis



STEP5

Create Algorithm to
Calculate Viability Score



Data Sources

Analysis Workflow

Champions

Season: ALL S4 S5 S6 S7 S8 S9 S10

Split: ALL Pre-Season Spring Summer

Tournament: -- ALL --

Game version: -- ALL --

Role: ALL TOP JUNGLE MID BOT SUPPORT

Leagues: TOP TIER2 NAT

Copy table to clipboard

| CHAMPION | PICKS | BANS | PRESENCE | AVG BT | WINS | LOSSES | WINRATE |
|--------------|-------|------|----------|--------|------|--------|---------|
| Aphelios | 259 | 170 | 86% | 4.7 | 140 | 119 | 54% |
| Varus | 38 | 326 | 73% | 2.5 | 19 | 19 | 50% |
| Kalista | 103 | 260 | 73% | 3.4 | 51 | 52 | 50% |
| Syndra | 117 | 242 | 72% | 4.2 | 60 | 57 | 51% |
| Ezreal | 219 | 130 | 70% | 4.8 | 110 | 109 | 50% |
| Twisted Fate | 119 | 210 | 66% | 4.6 | 71 | 48 | 60% |

User
Champion
Picks
2018-2020

GAMES OF LEGENDS eSPORTS



Data Sources

Analysis Workflow

Champion
stats for
majority of
analysis



Current Patch Statistics

Filter By Name Sort Role

| Rank | Champion | Role | Win Percent | Play Percent | Ban Rate | Playerbase Avg. Games | Kills | Deaths | Assists | Largest Killing Spree | Damage Dealt | Damage Taken | Total Healing | Minions Killed | Enemy Jungle CS | Team Jungle CS | Gold Earned | Role Position | Position Change ▾ |
|------|----------|---------|-------------|--------------|----------|-----------------------|-------|--------|---------|-----------------------|--------------|--------------|---------------|----------------|-----------------|----------------|-------------|---------------|-------------------|
| 1 | Swain | Middle | 54.04% | 0.80% | 0.27% | 9.81 | 6.87 | 5.64 | 9.15 | 6 | 23692 | 29502 | 10086 | 152.0 | 1.29 | 3.79 | 11090 | 7 | 0 |
| 2 | Skarner | Top | 45.27% | 0.21% | 0.03% | 12.75 | 4.24 | 5.31 | 7.56 | 4 | 13155 | 22879 | 2086 | 138.5 | 1.64 | 2.60 | 9951 | 45 | 0 |
| 3 | Senna | ADC | 52.09% | 2.04% | 1.32% | NaN | 5.89 | 5.18 | 11.29 | 7 | 19715 | 17444 | 10538 | 156.3 | 0.96 | 4.14 | 11301 | 16 | 0 |
| 4 | Riven | Support | 49.44% | 0.54% | 0.15% | 54.61 | 3.22 | 3.44 | 1.69 | 4 | 6865 | 10187 | 866 | 101.4 | 1.10 | 1.05 | 6440 | 64 | 0 |
| 5 | Lillia | Jungle | 42.73% | 7.09% | 1.94% | NaN | 5.91 | 5.82 | 7.77 | 9 | 17111 | 28494 | 9469 | 42.7 | 7.07 | 84.67 | 10596 | 17 | 0 |
| 6 | Lillia | Top | 45.09% | 1.48% | 1.94% | NaN | 5.13 | 6.14 | 6.65 | 7 | 19620 | 26316 | 4748 | 159.0 | 1.78 | 3.36 | 10667 | 36 | 0 |
| 7 | Karthus | ADC | 55.00% | 0.48% | 1.57% | 34.85 | 9.01 | 7.73 | 9.93 | 8 | 30765 | 21845 | 5654 | 177.7 | 3.04 | 11.23 | 13017 | 1 | 0 |
| 8 | Veigar | Support | 50.68% | 0.51% | 0.11% | 7.59 | 3.94 | 5.24 | 6.28 | 6 | 10897 | 12055 | 1067 | 68.1 | 0.58 | 1.12 | 7744 | 45 | ↑22 |
| 9 | Illaoi | Top | 50.14% | 1.14% | 0.37% | 5.35 | 5.26 | 6.28 | 4.67 | 6 | 23148 | 30556 | 8819 | 191.2 | 1.31 | 1.30 | 11686 | 8 | ↑20 |
| 10 | Qiyana | Support | 54.94% | 0.26% | 0.11% | NaN | 4.77 | 3.40 | 2.86 | 7 | 8727 | 9615 | 1423 | 93.7 | 0.70 | 0.69 | 6716 | 32 | ↑19 |



Data Exploration and Cleaning

Analysis Workflow



```
reduced_champions_df = champions_df.groupby(["Champion"]).mean()

#reduced_champions_df.head()
new = reduced_champions_df.sort_values(["picks"], ascending=False)[["picks"]]
healing_graph = new.head(10).plot(kind="bar")
healing_graph.set_ylabel("picks")
plt.title("Highest Picks: From 2018 to 2020")
plt.show()
```





Data Exploration and Cleaning

Analysis Workflow

```
#Columns in the dataset  
stack_df.columns  
  
#Search for null values, number of non-null values, data types  
stack_df.info()  
  
#Identify Null Values  
df_null = stack_df[stack_df.isnull().any(axis=1)]  
  
#Drop weird rows with no Champion listed & check non-null values  
df2 = stack_df.dropna(subset = ['Champion'])  
df2.info()  
  
## === Notice that playerbase avg games still has less data (898) === ##
```

| | Rank | Champion | Role | Win Percent | Play Percent | Ban Rate | Playerbase Avg. Games | Kills | Deaths |
|-----|---|----------|---------|-------------|--------------|----------|-----------------------|-------|--------|
| 0 | 1 | Aatrox | Top | 46.90% | 2.06% | 0.42% | 2.58 | 5.49 | |
| 1 | 2 | Ahri | Middle | 51.84% | 3.33% | 0.30% | 2.91 | 6.82 | |
| 2 | 3 | Akali | Middle | 43.79% | 3.49% | 0.77% | 2.98 | 8.45 | |
| 3 | 4 | Akali | Top | 46.67% | 1.27% | 0.77% | 3.98 | 7.21 | |
| 4 | 5 | Alistar | Support | 51.76% | 2.43% | 0.07% | 2.41 | 2.02 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 183 | 184 | Zilean | Support | 51.21% | 1.74% | 0.12% | 3.05 | 2.57 | |
| 184 | 185 | Zoe | Middle | 46.81% | 1.85% | 0.31% | NaN | 6.62 | |
| 185 | 186 | Zyra | Support | 52.83% | 2.61% | 0.27% | 4.01 | 3.75 | |
| 186 | Champion.gg isn't endorsed by Riot Games and doesn't have a ban rate. | | | NaN | NaN | NaN | NaN | NaN | NaN |
| 187 | Blitz App · FortniteMaster · StatsRealmRoyale | | | NaN | NaN | NaN | NaN | NaN | NaN |



9 rows × 21 columns

YIKES!!





Data Exploration and Cleaning

Analysis Workflow

```
#Columns in the dataset
stack_df.columns

#Search for null values, number of non-null values, data types
stack_df.info()

#Identify Null Values
df_null = stack_df[stack_df.isnull().any(axis=1)]

#Drop weird rows with no Champion listed & check non-null values
df2 = stack_df.dropna(subset = ['Champion'])
df2.info()

## === Notice that playerbase avg games still has less data (898) === ##
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 989 entries, 0 to 187
Data columns (total 21 columns):
 #   Column           Non-Null Count Dtype  
 ---  -- 
 0   Rank              989 non-null   object  
 1   Champion          979 non-null   object  
 2   Playerbase        979 non-null   float64 
 3   Win Percent       979 non-null   object  
 4   Play Percent      979 non-null   object  
 5   Ban Rate           979 non-null   object  
 6   Playerbase Avg. Games 898 non-null   float64 
 7   Kills              979 non-null   float64 
 8   Deaths             979 non-null   float64 
 9   Assists            979 non-null   float64 
 10  Largest Killing Spree 979 non-null   float64 
 11  Damage Dealt       979 non-null   float64 
 12  Damage Taken       979 non-null   float64 
 13  Total Healing       979 non-null   float64 
 14  Minions Killed     979 non-null   float64 
 15  Enemy Jungle CS    979 non-null   float64 
 16  Team Jungle CS     979 non-null   float64 
 17  Gold Earned         979 non-null   float64 
 18  Role Position       979 non-null   float64 
 19  Position Change     979 non-null   float64 
 20  League              989 non-null   object  
dtypes: float64(14), object(7)
```





Data Exploration and Cleaning

Analysis Workflow

```
#Percentage values showing up as OBJECTS,  
#problematic, need to remove the % for calculations!  
champ_df = df2.groupby(["Champion"]).mean()  
champ_df.head()  
  
## === Notice there are NO stats for these metrics === ##
```

| Champion | Playerbase | Avg. Games | Kills | Deaths | Assists | Largest Killing Spree | Damage Dealt |
|----------|------------|------------|----------|-----------|----------|-----------------------|--------------|
| Aatrox | 8.174286 | 4.644286 | 4.957143 | 4.828571 | 6.000000 | 15734.857143 | 2 |
| Ahri | 8.608333 | 6.106667 | 5.121667 | 7.061667 | 6.666667 | 18547.666667 | 1 |
| Akali | 12.318333 | 6.916667 | 5.678333 | 4.551667 | 7.500000 | 17378.416667 | 2 |
| Alistar | 3.300000 | 1.910000 | 5.650000 | 12.508000 | 3.800000 | 7564.200000 | 2 |
| Amumu | 2.844000 | 4.554000 | 5.704000 | 9.666000 | 6.800000 | 13318.600000 | 2 |



```
#Create a function to convert percent to float  
def convert_percent(val):  
    """  
    Convert the percentage string to an actual floating point percent  
    - Remove %  
    - Divide by 100 to make decimal  
    """  
    new_val = val.replace('%', '')  
    return float(new_val) / 100  
  
# Created a new column that applies the function to convert percentage to float  
df2['win_percent'] = df2["Win Percent"].apply(convert_percent)  
df2['ban_rate'] = df2["Ban Rate"].apply(convert_percent)  
df2['play_percent'] = df2["Play Percent"].apply(convert_percent)  
  
# Drop extra columns  
df2.drop(columns=['Win Percent', 'Play Percent', 'Ban Rate'])
```





Data Exploration and Cleaning

Analysis Workflow

```
#Create a function to convert percent to float
def convert_percent(val):
    """
    Convert the percentage string to an actual floating point percent
    - Remove %
    - Divide by 100 to make decimal
    """
    new_val = val.replace('%', '')
    return float(new_val) / 100

# Created a new column that applies the function to convert percentage to float
df2['win_percent'] = df2['Win Percent'].apply(convert_percent)
df2['ban_rate'] = df2['Ban Rate'].apply(convert_percent)
df2['play_percent'] = df2['Play Percent'].apply(convert_percent)

# Drop extra columns
df2.drop(columns=['Win Percent', 'Play Percent', 'Ban Rate'])
```



| Rank | Champion | Role | League | win_percent | ban_rate | play_percent | Kills | Deaths | Assists | Largest Killing Spree |
|------|----------|---------|---------|-------------|----------|--------------|--------|--------|---------|-----------------------|
| 0 | 1 | Aatrox | Top | Bronze | 0.4690 | 0.0042 | 0.0206 | 5.49 | 5.90 | 5.96 |
| 1 | 2 | Ahri | Middle | Bronze | 0.5184 | 0.0030 | 0.0333 | 6.82 | 5.69 | 7.73 |
| 2 | 3 | Akali | Middle | Bronze | 0.4379 | 0.0077 | 0.0349 | 8.45 | 6.61 | 5.48 |
| 3 | 4 | Akali | Top | Bronze | 0.4667 | 0.0077 | 0.0127 | 7.21 | 6.06 | 4.82 |
| 4 | 5 | Alistar | Support | Bronze | 0.5176 | 0.0007 | 0.0243 | 2.02 | 5.84 | 12.80 |



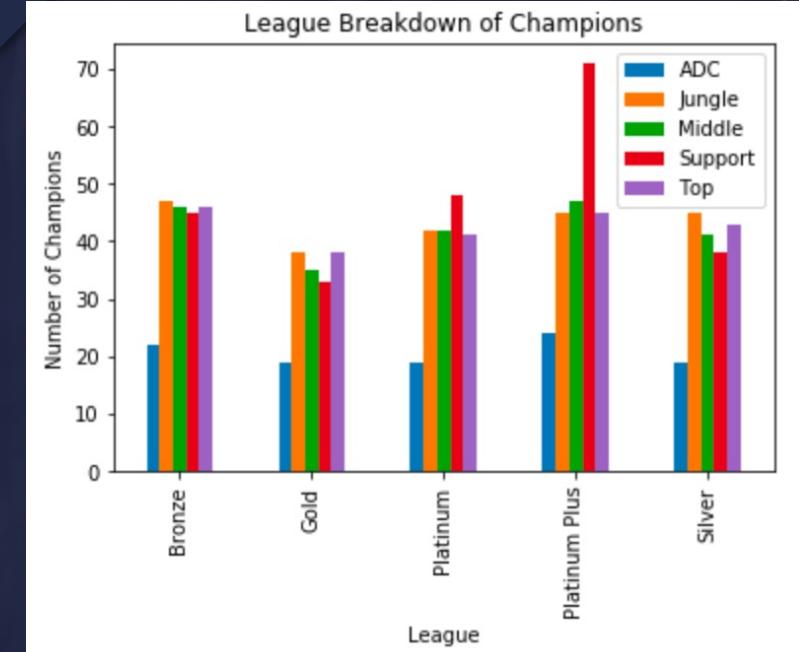


Data Exploration and Cleaning

Analysis Workflow

| | Feature | Unique values |
|----|-----------------------|---------------|
| 0 | Role | 5 |
| 1 | League | 5 |
| 2 | Largest Killing Spree | 10 |
| 3 | Position Change | 21 |
| 4 | Role Position | 71 |
| 5 | Champion | 148 |
| 6 | ban_rate | 215 |
| 7 | Rank | 232 |
| 8 | Deaths | 287 |
| 9 | play_percent | 470 |
| 10 | Kills | 515 |
| 11 | Assists | 547 |
| 12 | win_percent | 552 |
| 13 | Minions Killed | 645 |
| 14 | Gold Earned | 869 |
| 15 | Total Healing | 922 |
| 16 | Damage Dealt | 947 |
| 17 | Damage Taken | 950 |

```
#Explore Unique Values in the Dataset
ind_list = []
unique_count = []
for col in df2.columns:
    ind_list.append(len(df2[col].unique()))
    unique_count.append(len(df2[col].unique()))
final_series = pd.DataFrame({'Feature':ind_list,'Unique values':unique_count})
final_series = final_series[['Feature','Unique values']].sort_values(by='Unique values',ascending=True).reset_index(drop=True).style.bar()
```



```
#Create a graph that shows the number of Champions per Role with League as the X axis
role_chart = df2.groupby(["League", "Role"]).count()["Rank"].unstack().plot(kind = "bar")
role_chart.set_ylabel("Number of Champions")
plt.title("League Breakdown of Champions")
plt.legend(loc="best")
plt.show()
```





Descriptive Data Analysis

Data Workflow

Support

- ❖ High total healing
- ❖ High damage taken
- ❖ High minion kills
- ❖ Low death
- ❖ High assist

ADC

- ❖ High gold earned
- ❖ High damage taken
- ❖ High damage dealt

Middle

- ❖ High kills
- ❖ Low deaths
- ❖ High assist
- ❖ High minions kills

Jungle

- ❖ High minion kills
- ❖ High enemy jungle
- ❖ High team jungle cs
- ❖ High kills
- ❖ High assist
- ❖ High position change

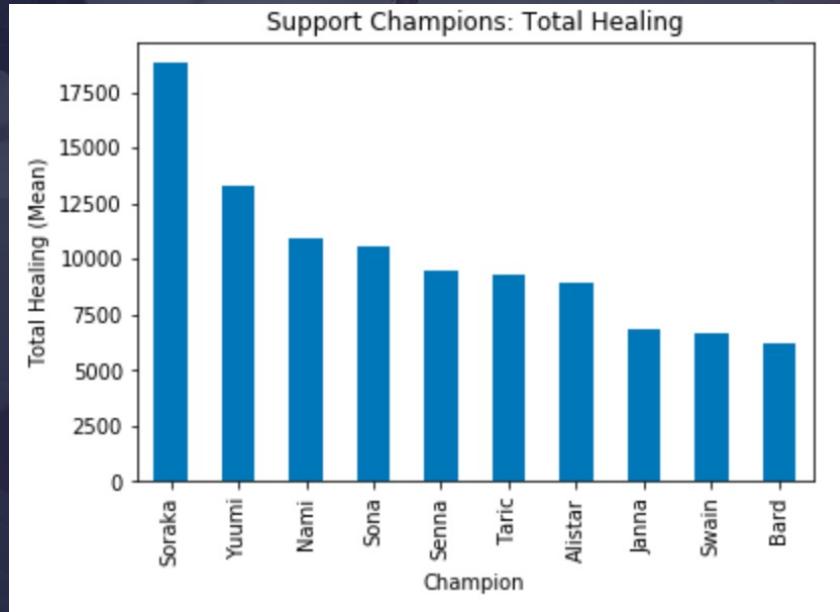
Top

- ❖ High kills
- ❖ High kills spree
- ❖ High minions kills
- ❖ Low deaths

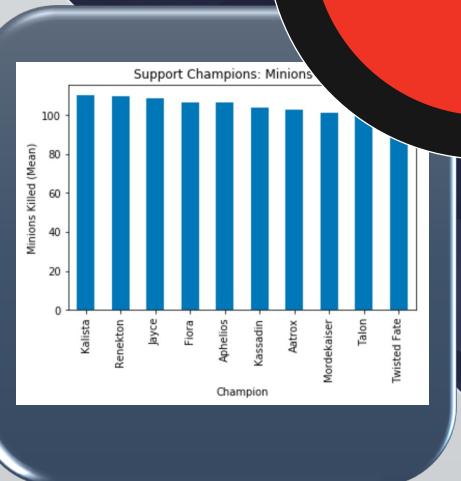


Descriptive Data Analysis

Data Workflow



```
#Bar chart for healing
healing = champ_support.sort_values(["Total Healing"], ascending=False)[["Total Healing"]]
healing_graph = healing.head(10).plot(kind="bar")
healing_graph.set_ylabel("Total Healing (Mean)")
plt.title("Support Champions: Total Healing")
plt.show()
```



No ONE Champion stands out

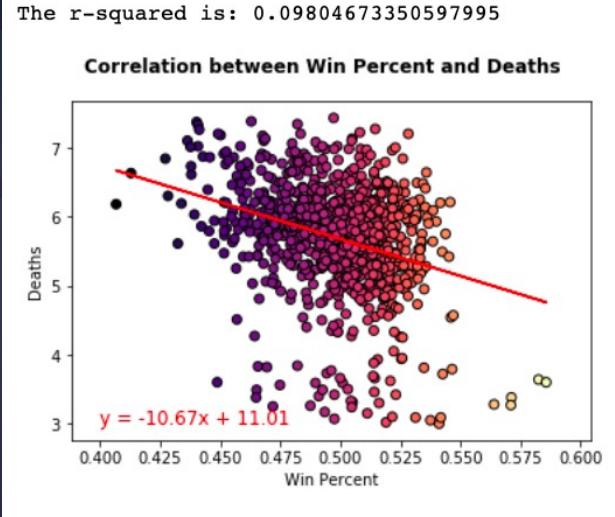


Pearson's

Correlation Data Analysis

Analysis Workflow

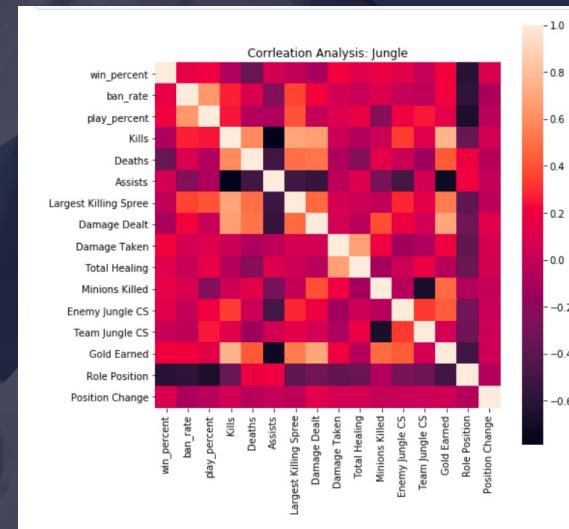
No Strong Correlation
Win Percent x Single Metric



```

1 x_win = df2["win_percent"]
2 y_deaths = df2["Deaths"]
3
4 #log calculation
5 (slope, intercept, rvalue, pvalue, stderr) = linregress(x_win, y_deaths)
6 regress_values = x_win * slope + intercept
7 line_eq = "y = " + str(round(slope,2)) + "x + " + str(round(intercept,2))
8 plt.ylabel('Deaths')
9 plt.xlabel('Win Percent')
10
11 t*x_win
12 plt.scatter(x_win, y_deaths, marker="o", edgecolor = "black", c=cwt, cmap='magma')
13 plt.suptitle("Correlation between Win Percent and Deaths", fontweight = "bold")
14 plt.plot(x_win, regress_values, "-r")
15 plt.annotate(line_eq,(0.4,3),fontsize=12, color = "red")
16
17
18
19 print(f"The r-squared is: {(rvalue**2)}")
20 plt.show()

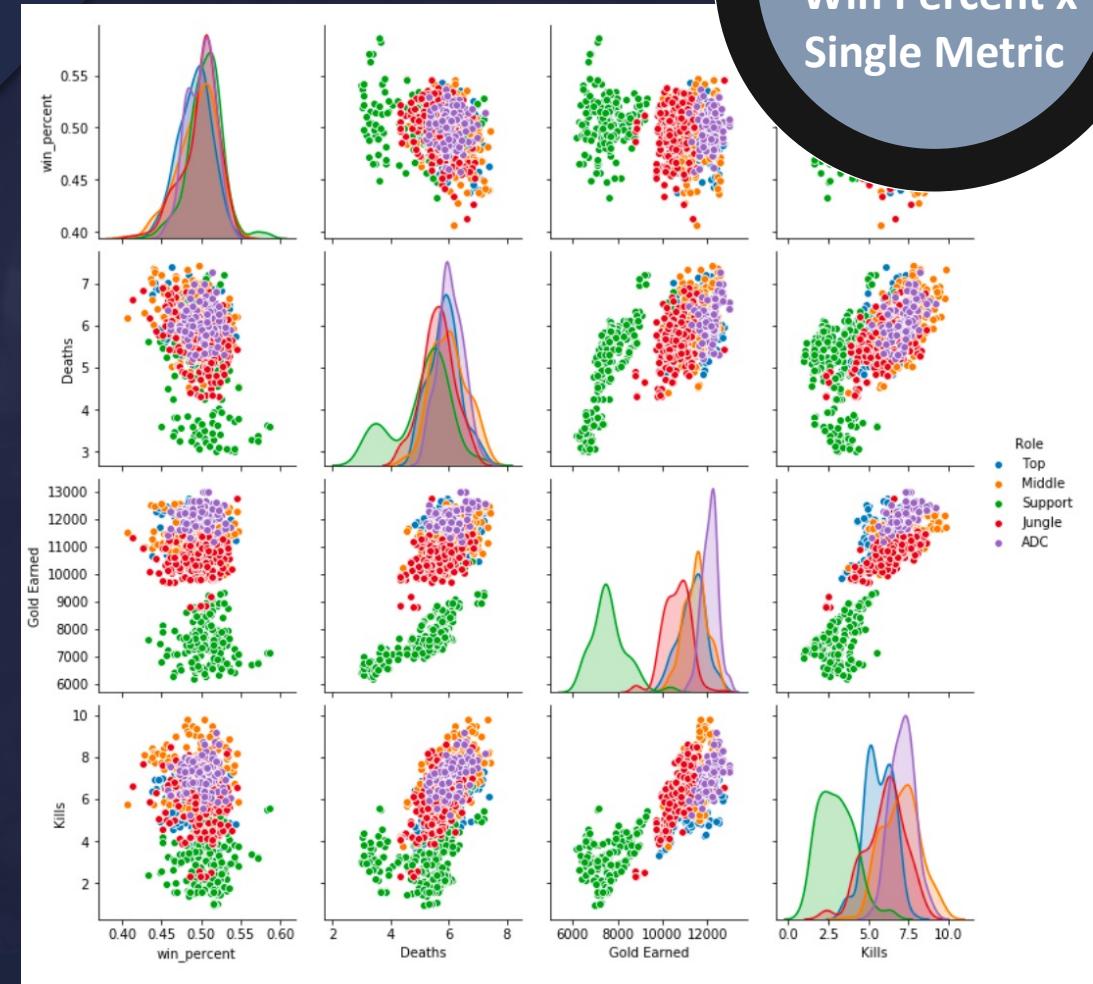
```



```

1 jungle = df2.loc[df2["Role"] == "Jungle"]
2 plt.figure(figsize=(8,8))
3 sns.heatmap(jungle.corr(), annot=False, square=True)
4 plt.title("Correlation Analysis: Jungle")
5 plt.show()

```



```

#Subset of Data for Presentation
sub2_df2 = df2[["win_percent", "Role", "Deaths", "Gold Earned", "Kills"]]
sns.pairplot(sub2_df2, hue="Role")

```



Viability Score

Analysis Workflow

```
# Running calc to find the most viable Support
top_score = 0
top_name = ''
current_score = 0
for index, row in support.iterrows():
    current_score = (row['Minions Killed'] - row['Deaths']
                     + row['Total Healing'] + row['Damage Taken']
                     + row['Assists'])

    if current_score > top_score :
        top_score = current_score
        top_name = row['Champion']
print(f'{top_name} is the most viable Support with a score of {int(top_score)}')

Soraka is the most viable Support with a score of 31853
```

```
# Running calc to find most viable Top
top_score = 0
top_name = ''
current_score = 0
for index, row in top.iterrows():
    current_score = (row['Minions Killed'] - row['Deaths']
                     + row['Kills'] + row['Largest Killing Spree'])

    if current_score > top_score :
        top_score = current_score
        top_name = row['Champion']
print(f'{top_name} is the most viable Top with a score of {int(top_score)}')

Irelia is the most viable Top with a score of 208
```

This equation was designed to take the most important metrics and use them to create an overall viability score. Using this score we can find the most effective champion in their respective role.



Super Squad

Middle



Karthus

Top



Irelia

Jungler



Signed

ACD



Kog'Maw

Support



Soraka

Analysis Summary

Conclusions and Post-Mortem



Dataset

Utilized Kaggle datasets from second-hand APIs
Required mild cleaning and merging of datasets



Viability Score

Rather than look at single metric, we combined our knowledge of the game with key metrics to create a viability score



Analysis

Top 10 analysis did not identify obvious champions
Correlation analysis provided insight into roles but no strong correlation with win percent



Improving Analysis

1. Utilize Riot API for real-time data
2. More statistics on game play rather than character attributes

