

PUBG Finish Placement Prediction

July 19, 2021

Import Packages

```
[1]: import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
sns.set

pd.set_option('display.max_columns', 500)
```

Load Data

```
[2]: raw_training_data = pd.read_csv(r'C:\Users\amind\Downloads\train_V2.csv')
raw_test_data = pd.read_csv(r'C:\Users\amind\Downloads\test_V2.csv')

# Reference: memory usage reduction code from https://www.kaggle.com/nms2016145/
# ↳ gbr-lightgbm-test
def reduce_mem_usage(df):
    """ iterate through all the columns of a dataframe and modify the data type
    to reduce memory usage.
    """
    start_mem = df.memory_usage().sum()

    for col in df.columns:
        col_type = df[col].dtype

        if col_type != object:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).
↳ max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.
↳ int16).max:
```

```

        df[col] = df[col].astype(np.int16)
        elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.
↪int32).max:
            df[col] = df[col].astype(np.int32)
            elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.
↪int64).max:
                df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.
↪float16).max:
                    df[col] = df[col].astype(np.float16)
                    elif c_min > np.finfo(np.float32).min and c_max < np.finfo(np.
↪float32).max:
                        df[col] = df[col].astype(np.float32)
                    else:
                        df[col] = df[col].astype(np.float64)
                else:
                    df[col] = df[col].astype('category')

    end_mem = df.memory_usage().sum()

    return df

raw_training_data = reduce_mem_usage(raw_training_data)
raw_test_data = reduce_mem_usage(raw_test_data)

training_data = raw_training_data
test_data = raw_test_data

```

Explore Data

```

[3]: # Split Numerical and Categorical Variables
numerical_data = training_data[['assists', 'boosts', 'damageDealt', 'DBNOs',
↪'headshotKills', 'heals', 'kills',
    'killStreaks', 'longestKill', 'matchDuration', 'revives', 'rideDistance',
↪'roadKills', 'swimDistance',
    'teamKills', 'vehicleDestroys', 'walkDistance', 'weaponsAcquired']]

categorical_data = training_data[['killPlace', 'killPoints', 'matchType',
↪'maxPlace', 'numGroups', 'rankPoints',
    'winPoints', 'winPlacePerc']]

[4]: numerical_data.describe().apply(lambda x: x.apply('{0:.3f}'.format))

```

```

[4]:
      assists      boosts  damageDealt      DBNOs  headshotKills  \
count  4446966.000  4446966.000  4446966.000  4446966.000  4446966.000

```

mean	0.234	1.107	nan	0.658	0.227
std	0.589	1.716	nan	1.146	0.602
min	0.000	0.000	0.000	0.000	0.000
25%	0.000	0.000	0.000	0.000	0.000
50%	0.000	0.000	84.250	0.000	0.000
75%	0.000	2.000	186.000	1.000	0.000
max	22.000	33.000	6616.000	53.000	64.000

	heals	kills	killStreaks	longestKill	matchDuration	\
count	4446966.000	4446966.000	4446966.000	4446966.000	4446966.000	
mean	1.370	0.925	0.544	nan	1579.506	
std	2.680	1.558	0.711	nan	258.740	
min	0.000	0.000	0.000	0.000	9.000	
25%	0.000	0.000	0.000	0.000	1367.000	
50%	0.000	0.000	0.000	0.000	1438.000	
75%	2.000	1.000	1.000	21.312	1851.000	
max	80.000	72.000	20.000	1094.000	2237.000	

	revives	rideDistance	roadKills	swimDistance	teamKills	\
count	4446966.000	4446966.000	4446966.000	4446966.000	4446966.000	
mean	0.165	nan	0.003	nan	0.024	
std	0.472	nan	0.073	nan	0.167	
min	0.000	0.000	0.000	0.000	0.000	
25%	0.000	0.000	0.000	0.000	0.000	
50%	0.000	0.000	0.000	0.000	0.000	
75%	0.000	0.191	0.000	0.000	0.000	
max	39.000	40704.000	18.000	3824.000	12.000	

	vehicleDestroys	walkDistance	weaponsAcquired
count	4446966.000	4446966.000	4446966.000
mean	0.008	nan	3.660
std	0.093	nan	2.457
min	0.000	0.000	0.000
25%	0.000	155.125	2.000
50%	0.000	685.500	3.000
75%	0.000	1976.000	5.000
max	5.000	25776.000	236.000

```
[5]: categorical_data.describe().apply(lambda x: x.apply('{0:.3f}'.format))
```

	killPlace	killPoints	maxPlace	numGroups	rankPoints	\
count	4446966.000	4446966.000	4446966.000	4446966.000	4446966.000	
mean	47.599	505.006	44.505	43.008	892.010	
std	27.463	627.505	23.828	23.289	736.648	
min	1.000	0.000	1.000	1.000	-1.000	
25%	24.000	0.000	28.000	27.000	-1.000	
50%	47.000	0.000	30.000	30.000	1443.000	

75%	71.000	1172.000	49.000	47.000	1500.000
max	101.000	2170.000	100.000	100.000	5910.000

	winPoints	winPlacePerc
count	4446966.000	4446965.000
mean	606.460	nan
std	739.700	0.000
min	0.000	0.000
25%	0.000	0.200
50%	0.000	0.458
75%	1495.000	0.741
max	2013.000	1.000

```
[6]: # Find how many observations for each match type
training_data['matchType'].value_counts()
```

```
[6]: squad-fpp          1756186
duo-fpp              996691
squad                626526
solo-fpp             536762
duo                  313591
solo                 181943
normal-squad-fpp     17174
crashfpp              6287
normal-duo-fpp       5489
flaretp              2505
normal-solo-fpp      1682
flarefpp              718
normal-squad         516
crashtp              371
normal-solo          326
normal-duo           199
Name: matchType, dtype: int64
```

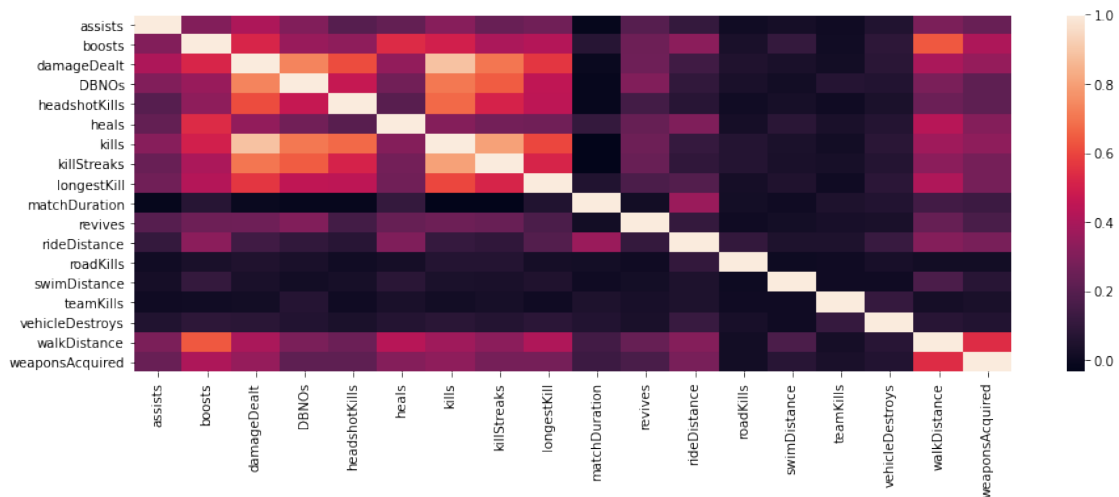
```
[7]: # Add "normal - ..." matchTypes to the larger 'matchType' options
training_data = training_data.replace(to_replace='normal-duo', value='duo')
training_data = training_data.replace(to_replace='normal-solo', value='solo')
training_data = training_data.replace(to_replace='normal-squad', value='squad')
training_data = training_data.replace(to_replace='normal-solo-fpp',
    ↪value='solo-fpp')
training_data = training_data.replace(to_replace='normal-duo-fpp',
    ↪value='duo-fpp')
training_data = training_data.replace(to_replace='normal-squad-fpp',
    ↪value='squad-fpp')

test_data = test_data.replace(to_replace='normal-duo', value='duo')
test_data = test_data.replace(to_replace='normal-solo', value='solo')
```

```
test_data = test_data.replace(to_replace='normal-squad', value='squad')
test_data = test_data.replace(to_replace='normal-solo-fpp', value='solo-fpp')
test_data = test_data.replace(to_replace='normal-duo-fpp', value='duo-fpp')
test_data = test_data.replace(to_replace='normal-squad-fpp', value='squad-fpp')
```

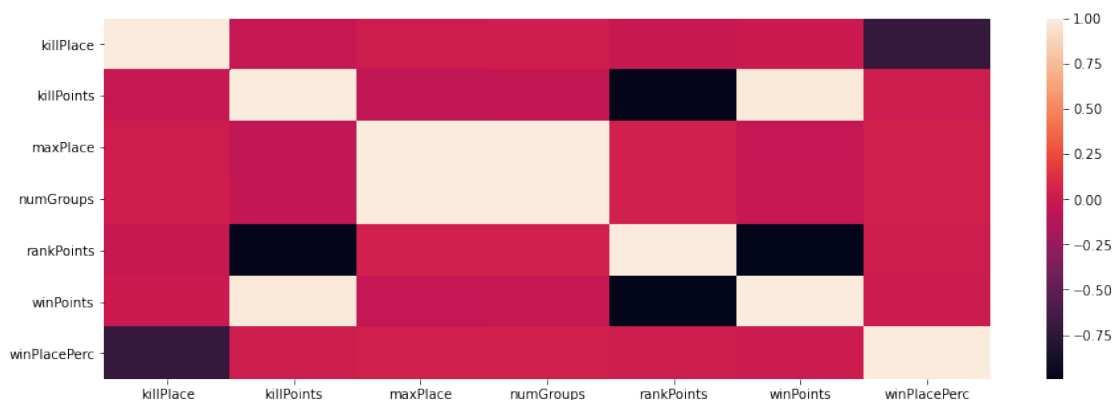
```
[8]: # Find correlation for numerical data
fig_dims = (15, 5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.heatmap(ax=ax, data=numerical_data.corr())
```

[8]: <AxesSubplot:>

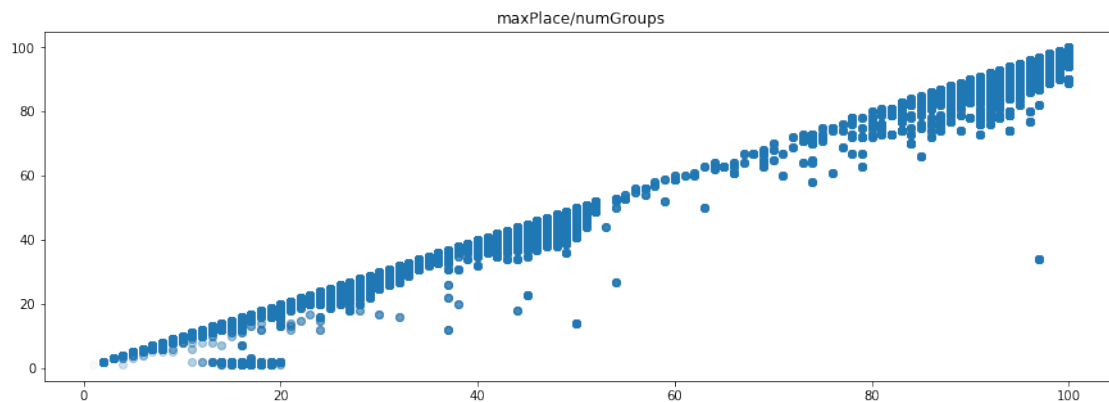
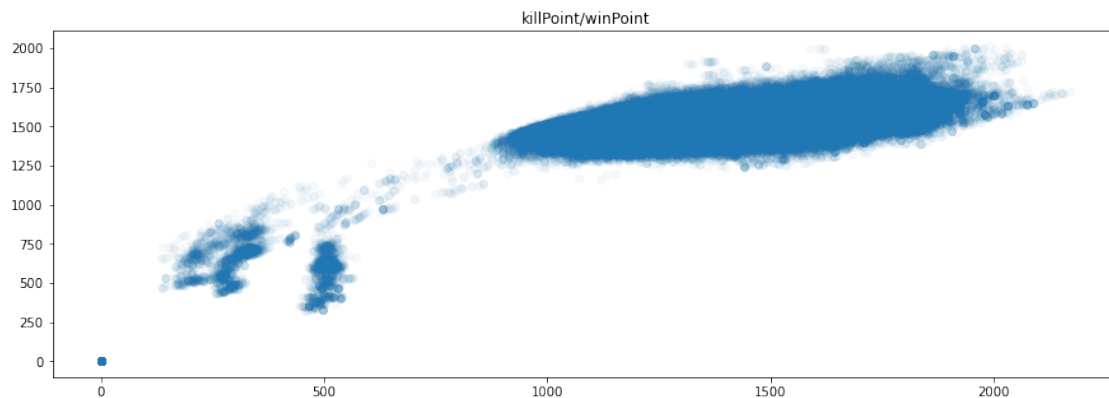


```
[9]: # Find correlation for categorical data
fig_dims = (15, 5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.heatmap(ax=ax, data=categorical_data.corr())
```

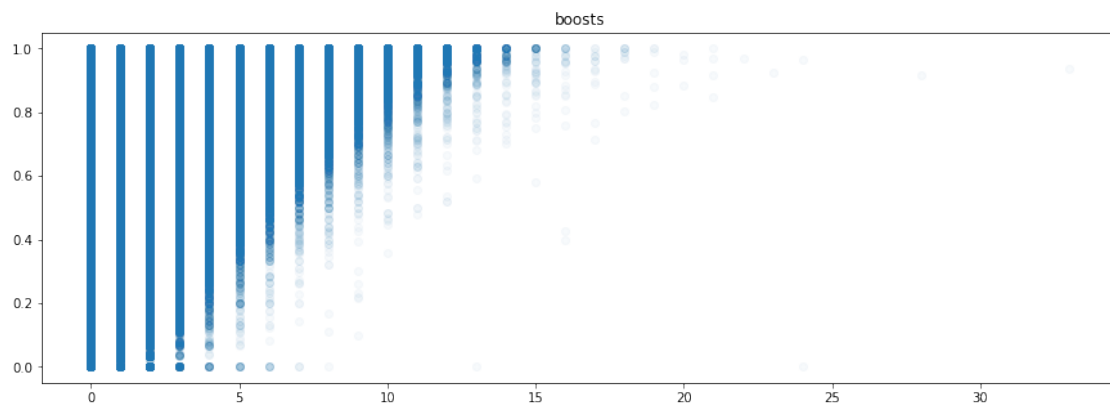
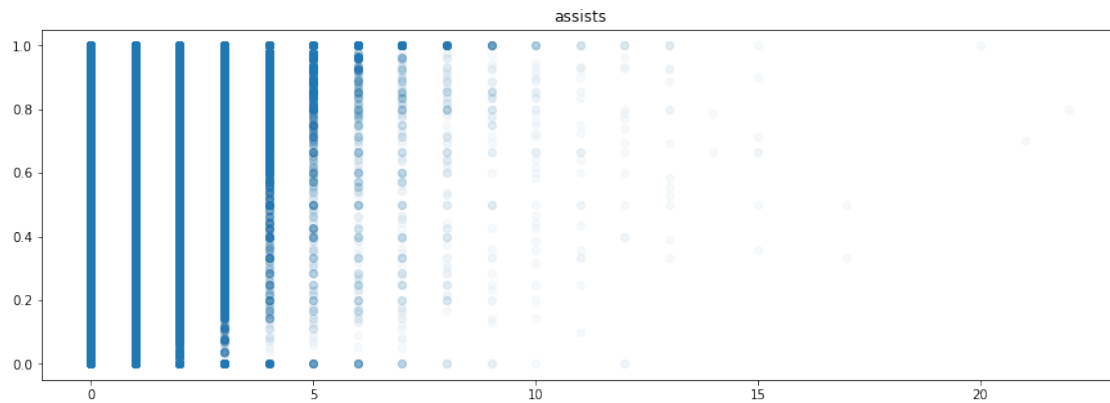
[9]: <AxesSubplot:>

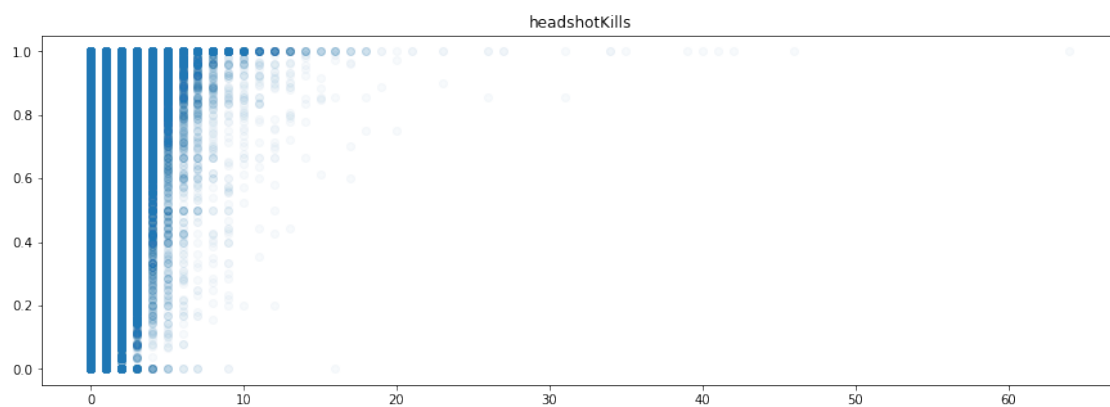
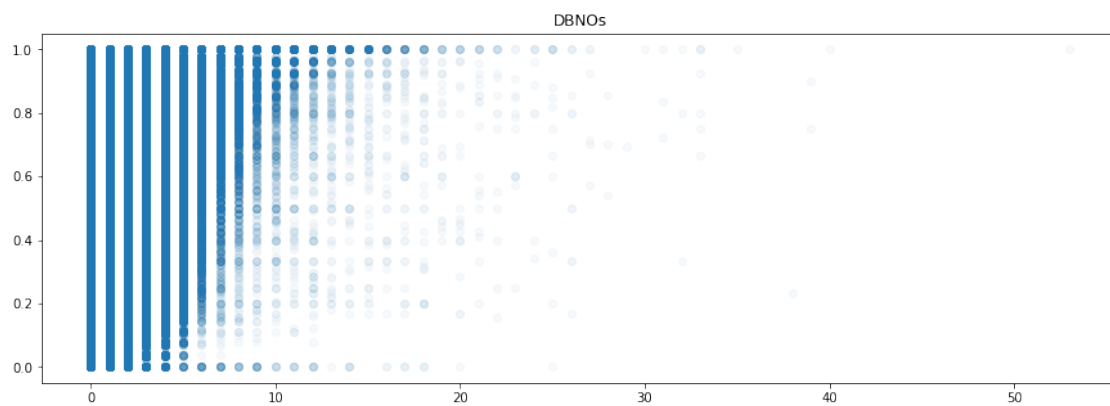
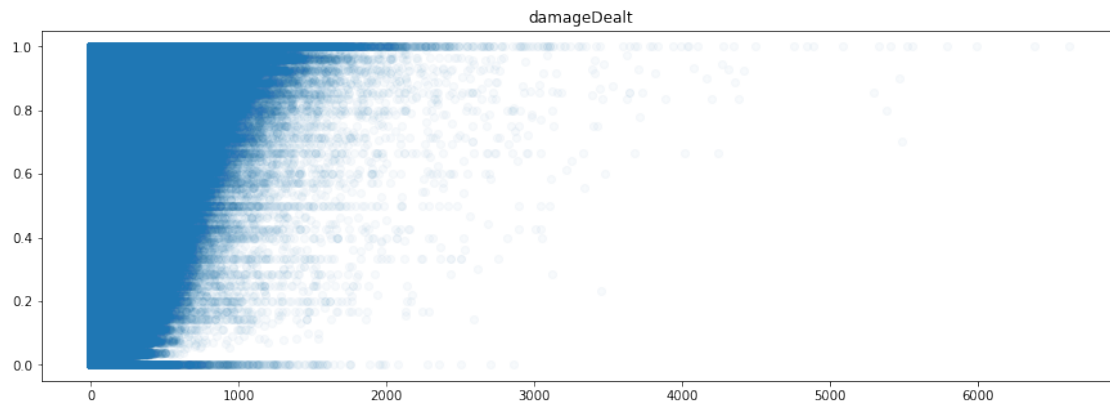


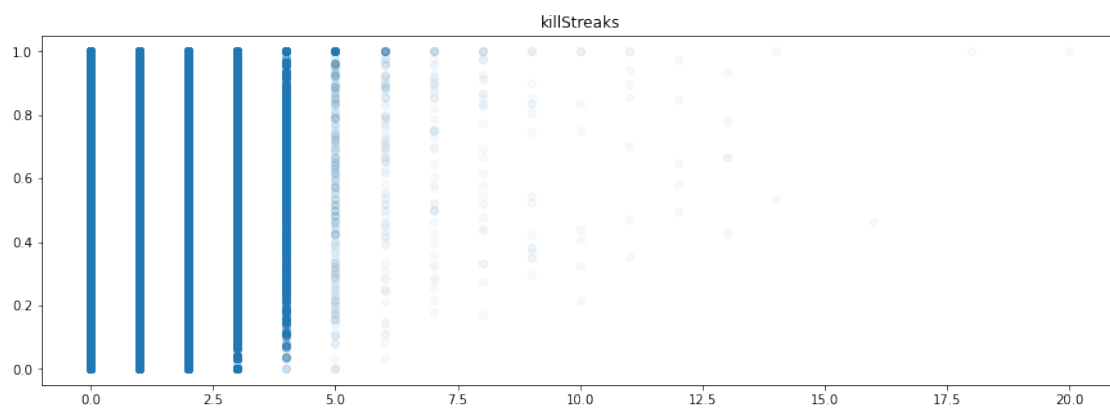
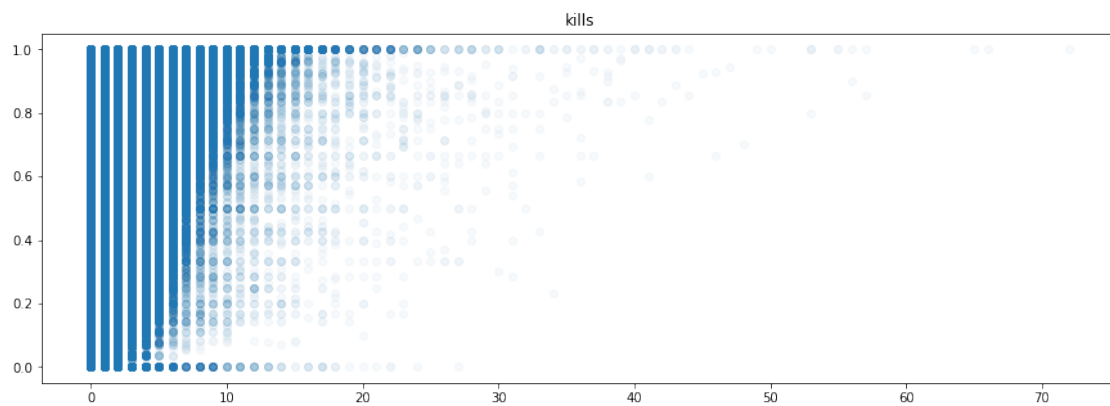
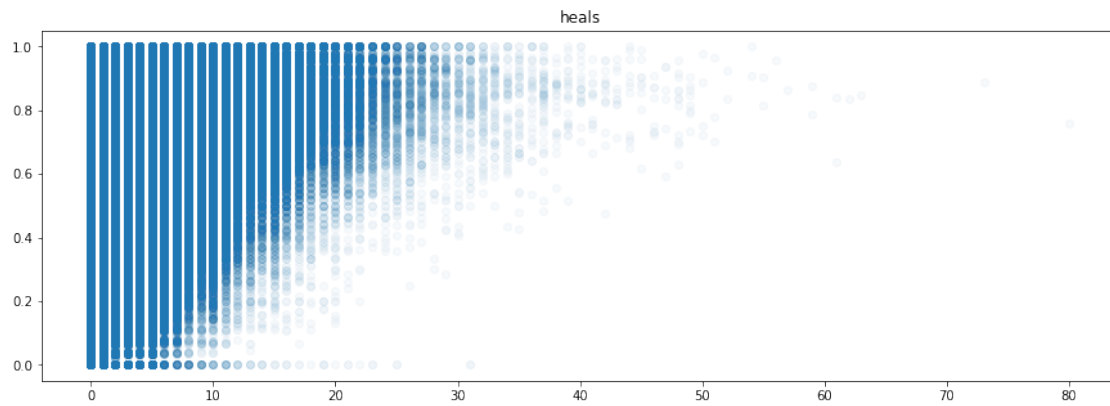
```
[10]: # Look into high correlation between 'killPoints'/'winPoints' and 'maxPlace'/'
      ↪ 'numGroups'
for i in range(1):
    plt.figure(figsize=(15,5))
    plt.scatter(x=training_data['killPoints'], y=training_data['winPoints'],
    ↪ alpha=0.03)
    plt.title('killPoint/winPoint')
    plt.show()
    plt.figure(figsize=(15,5))
    plt.scatter(x=training_data['maxPlace'], y=training_data['numGroups'],
    ↪ alpha=0.03)
    plt.title('maxPlace/numGroups')
    plt.show()
```

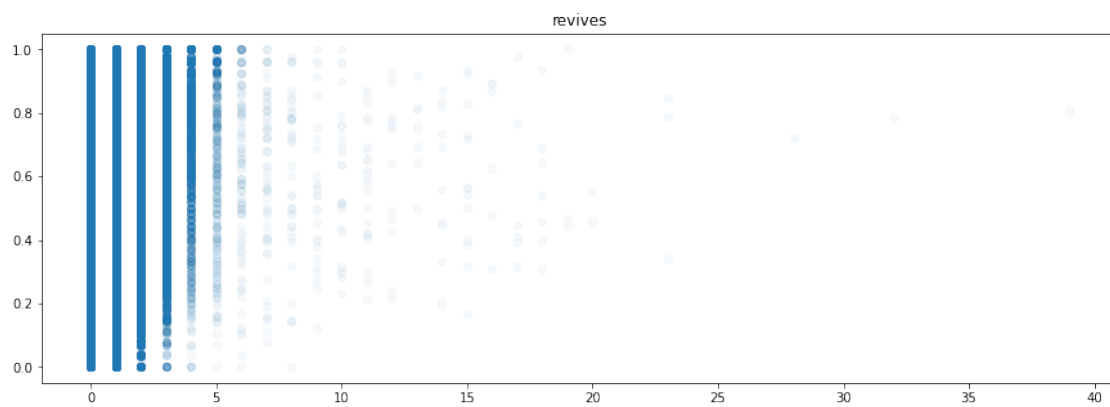
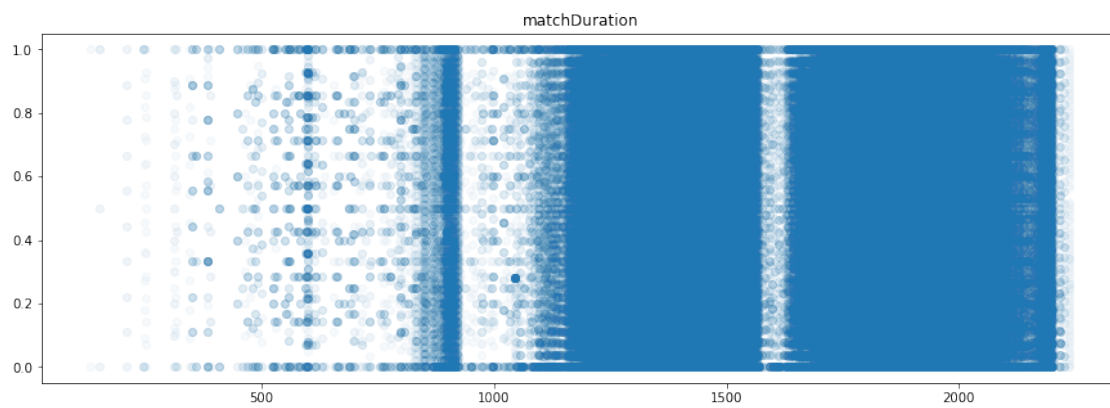
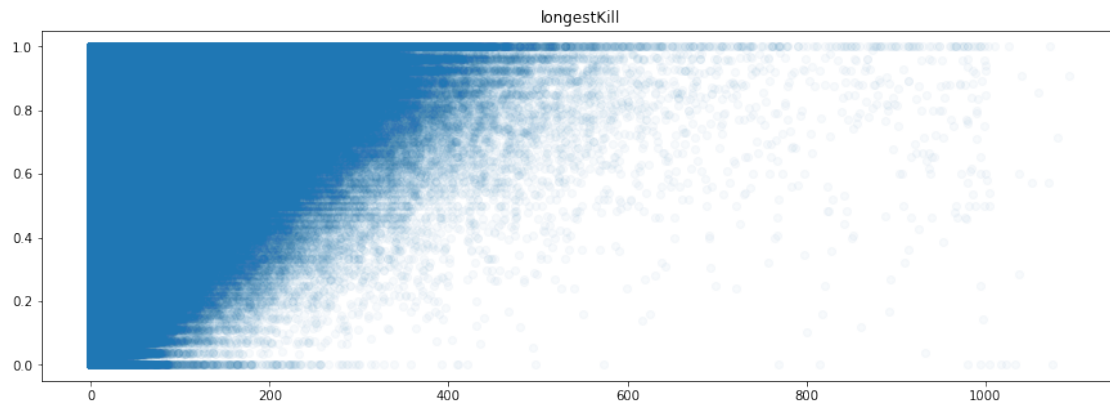


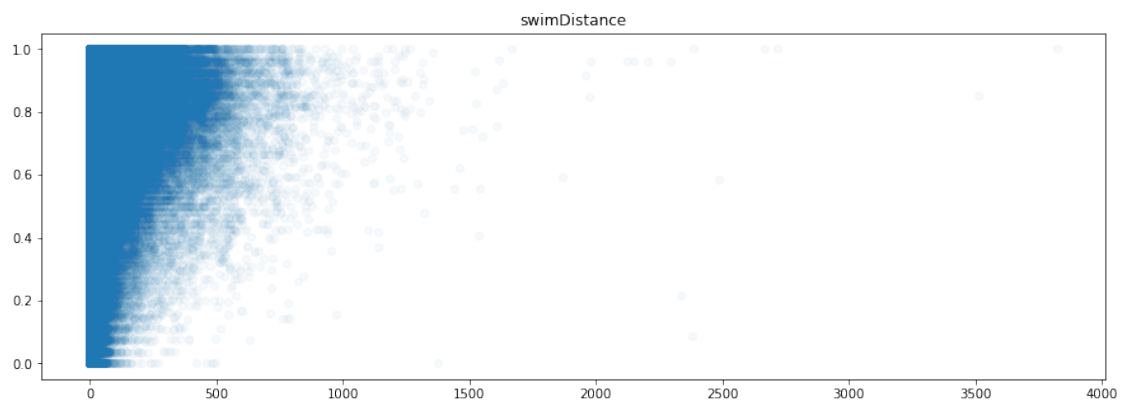
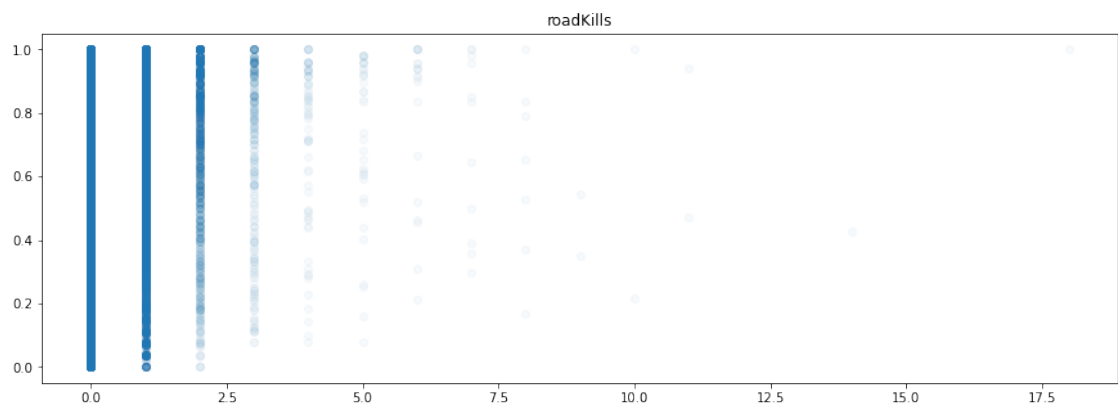
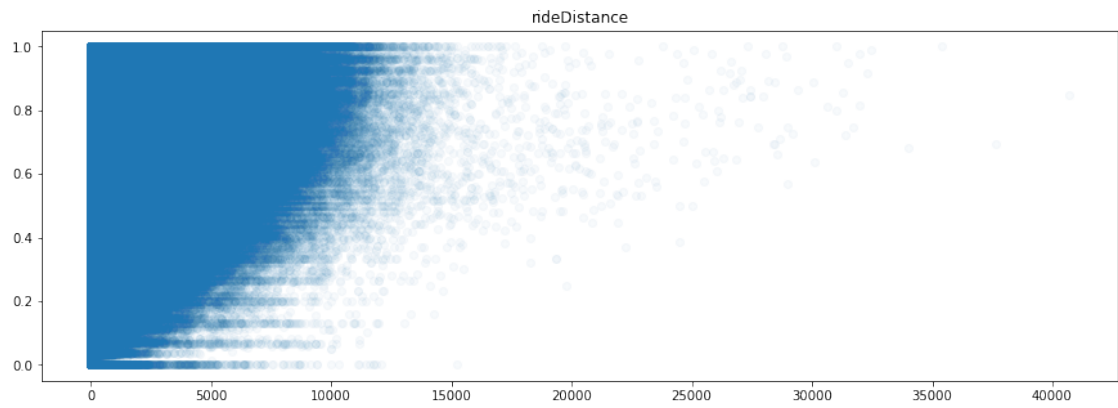
```
[11]: # Look into how 'winPlacePerc' varies with numerical inputs
for i in range(len(numerical_data.columns)):
    var_name = str(numerical_data.columns[i])
    plt.figure(figsize=(15, 5))
    plt.scatter(x=training_data[var_name], y=training_data['winPlacePerc'],
        ↪alpha=0.03)
    plt.title(var_name)
    plt.show()
```

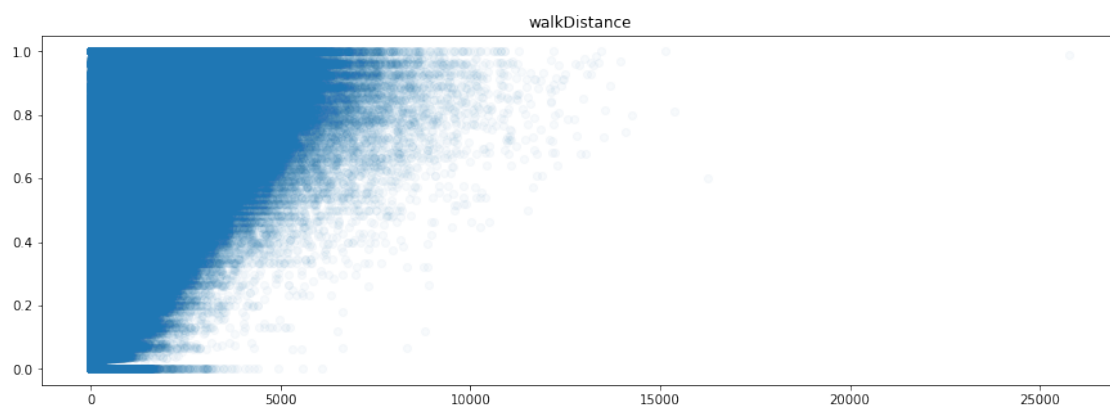
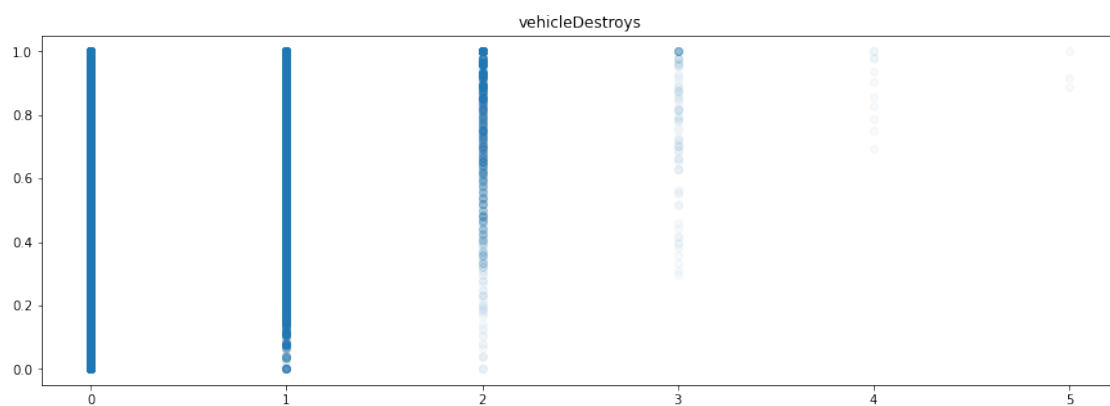
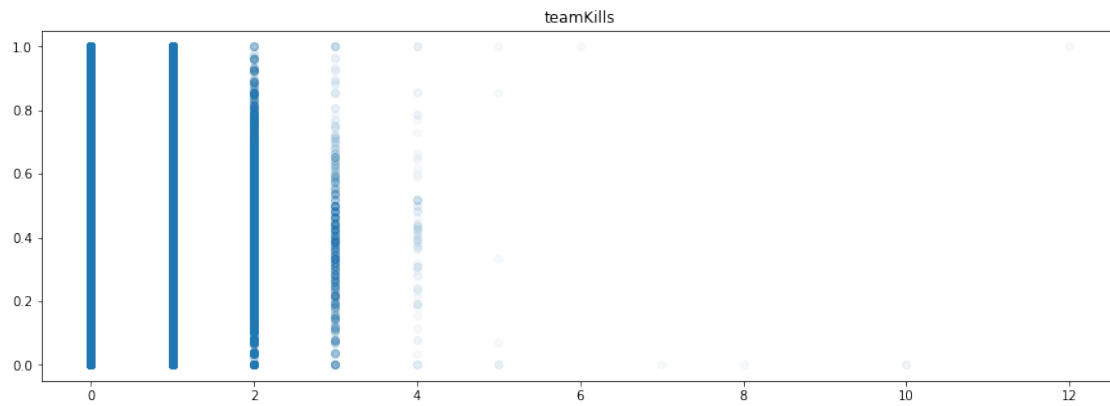


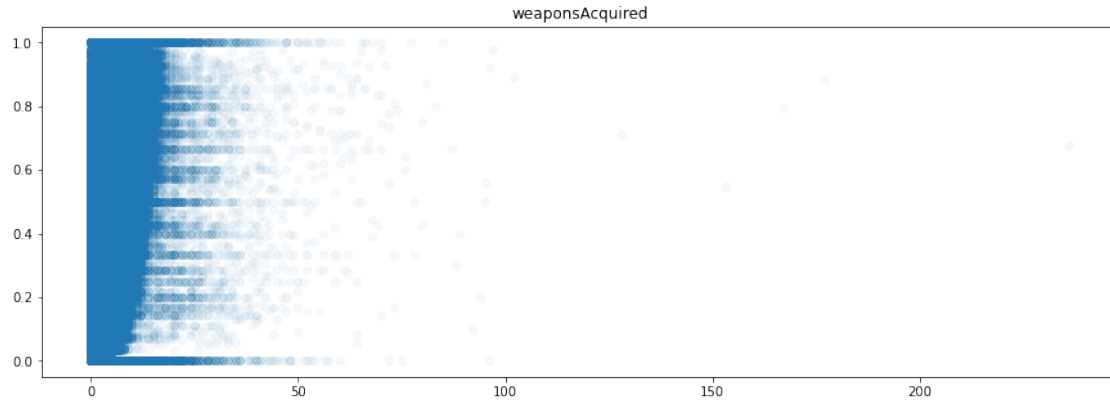




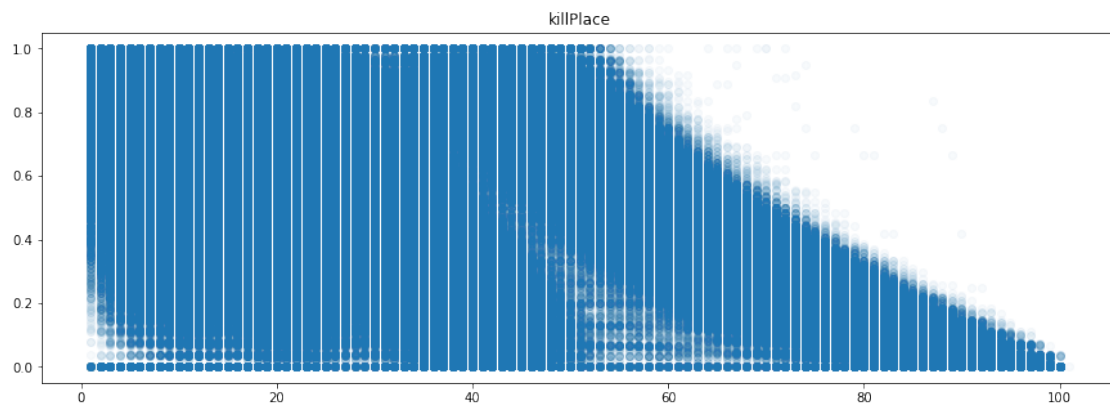


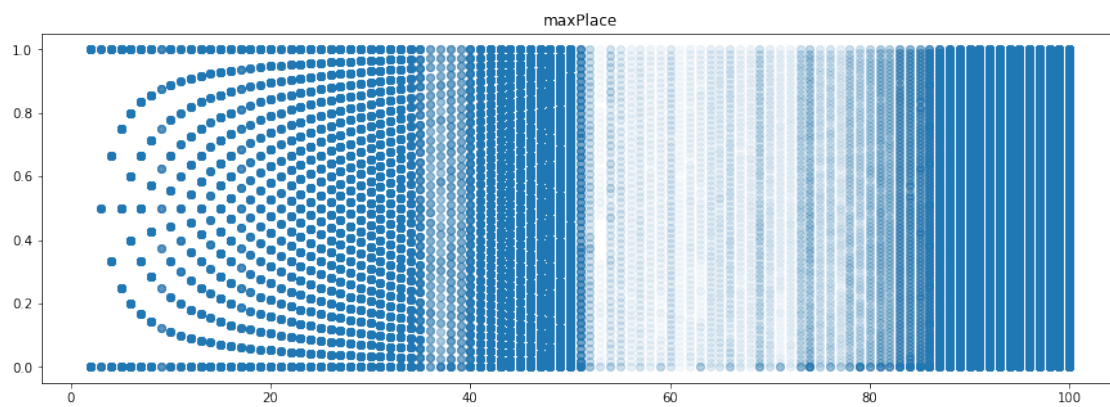
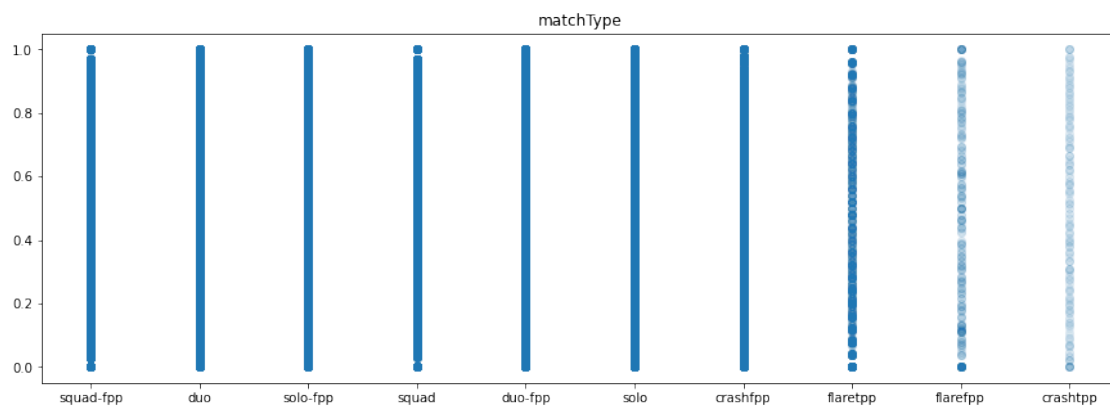
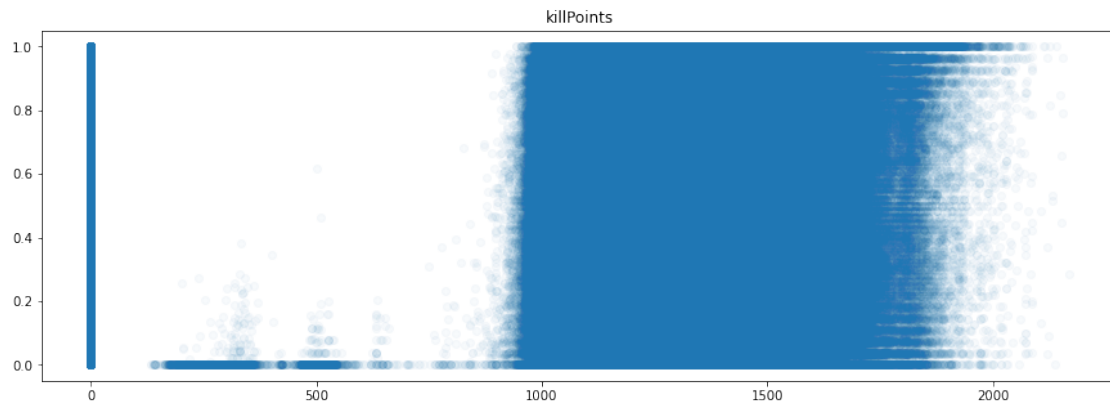


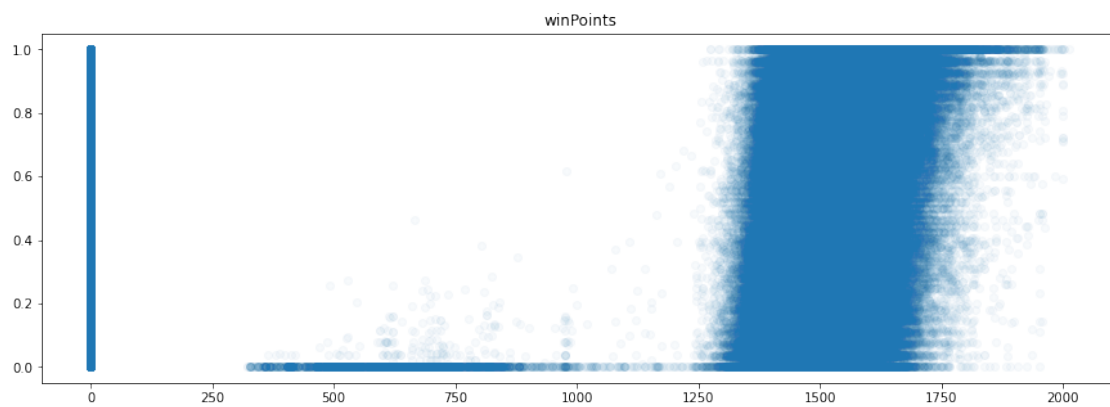
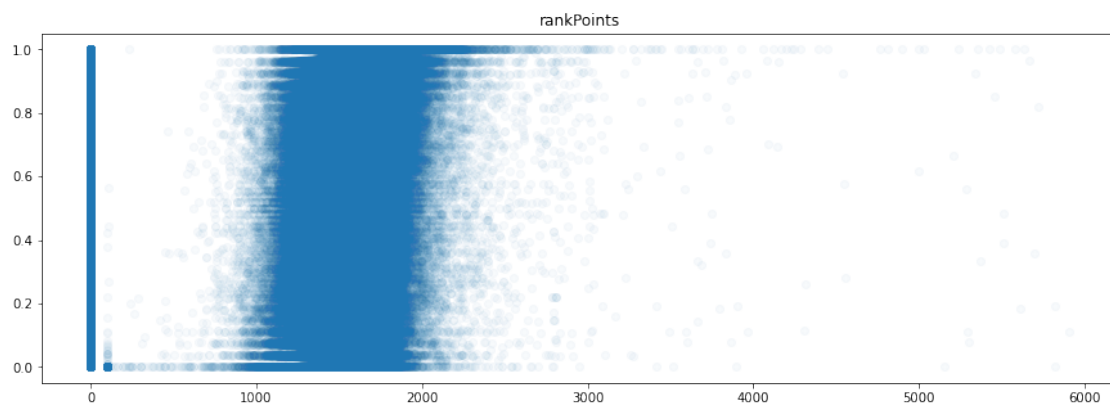
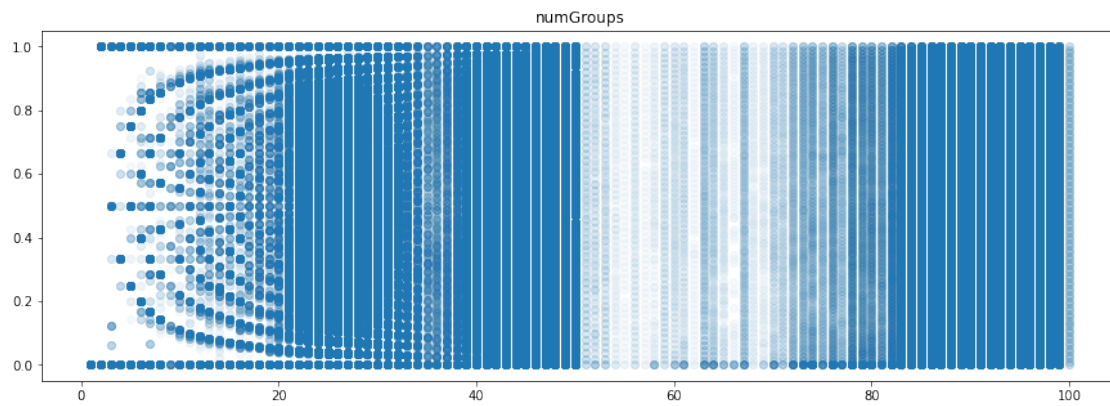


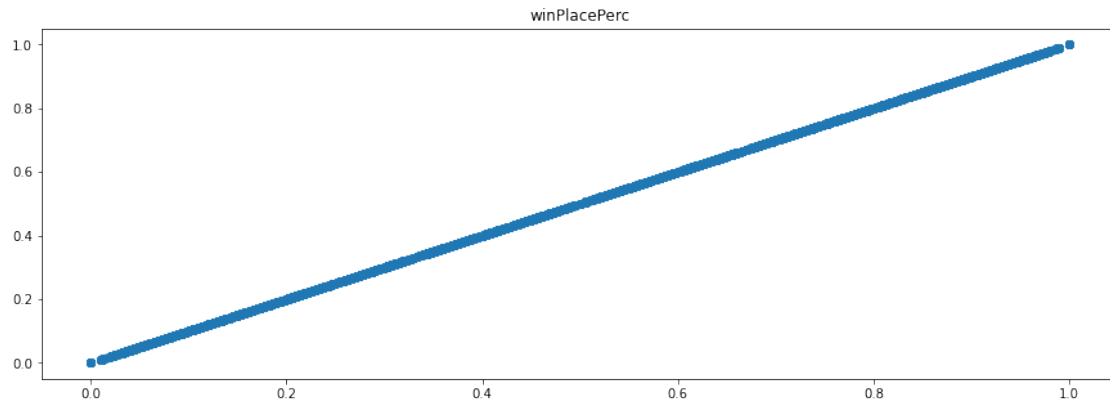


```
[12]: # Look into how 'winPlacePerc' varies with categorical inputs
for i in range(len(categorical_data.columns)):
    var_name = str(categorical_data.columns[i])
    plt.figure(figsize=(15, 5))
    plt.scatter(x=training_data[var_name], y=training_data['winPlacePerc'],
    ↪alpha=0.03)
    plt.title(var_name)
    plt.show()
```

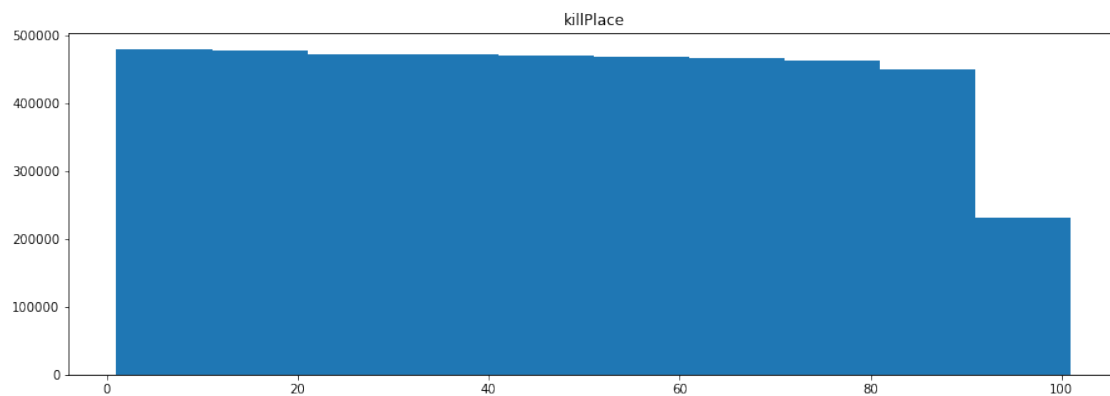


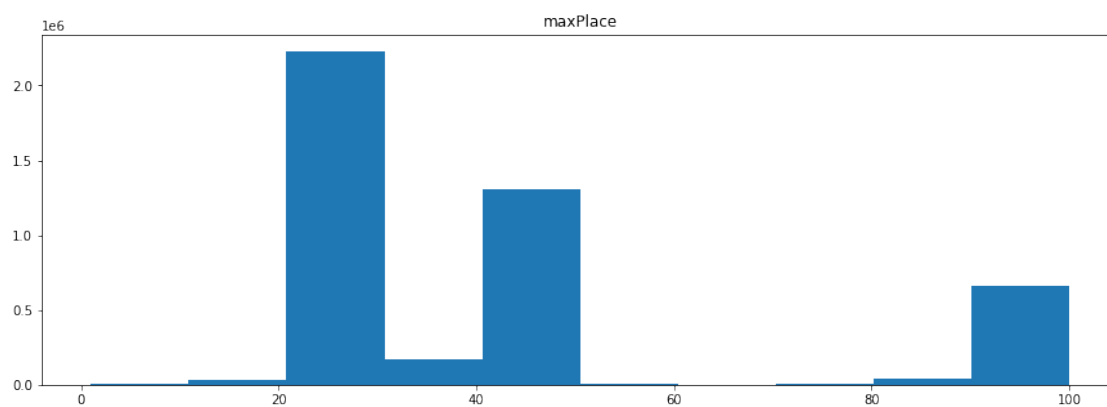
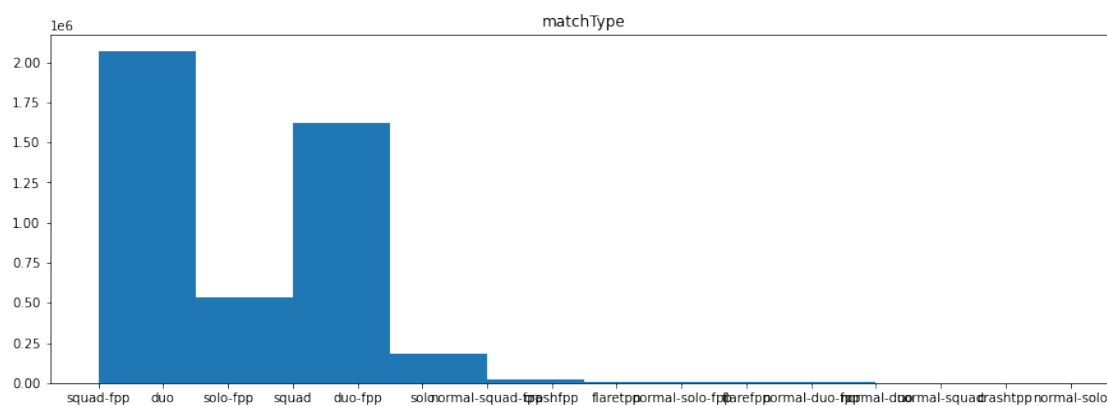
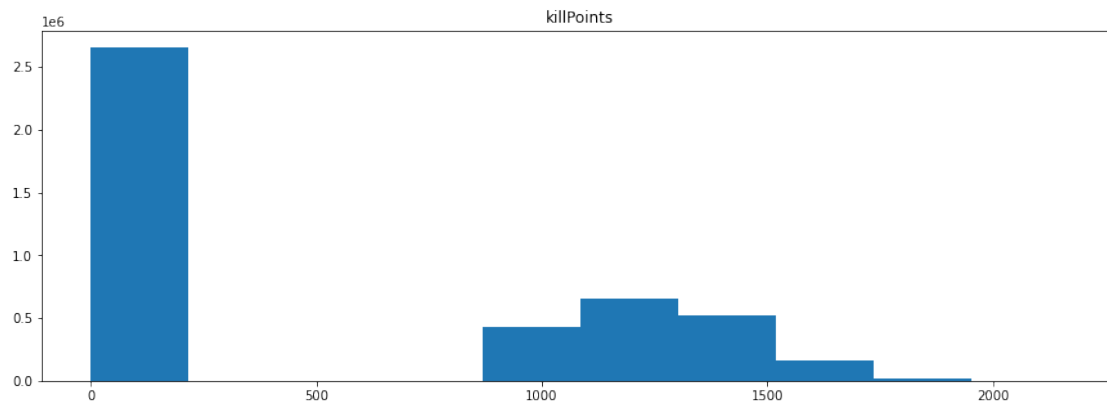


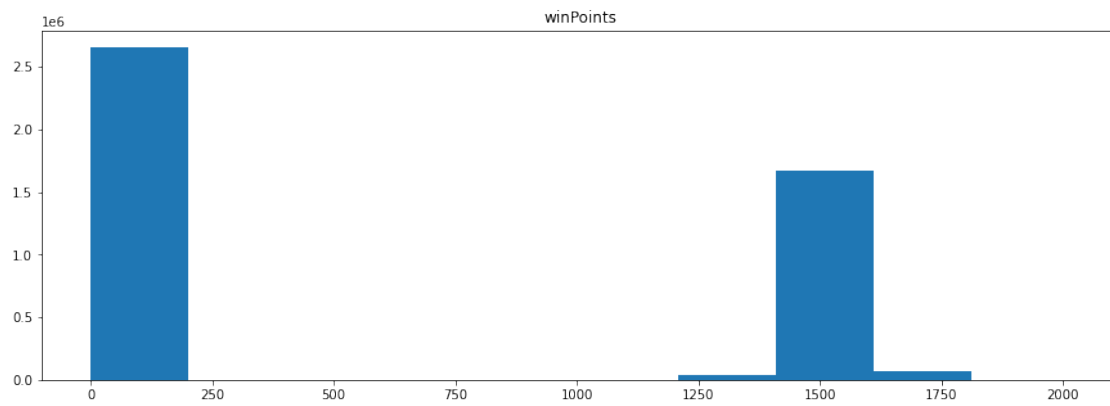
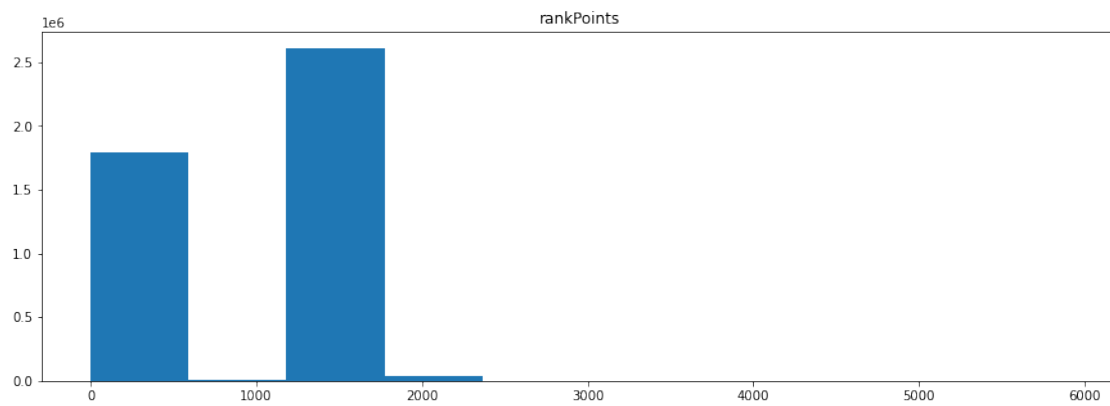
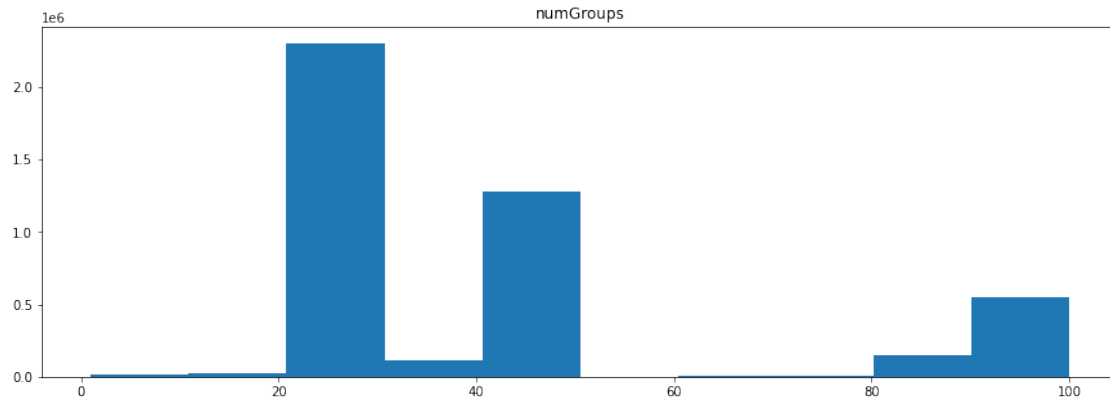


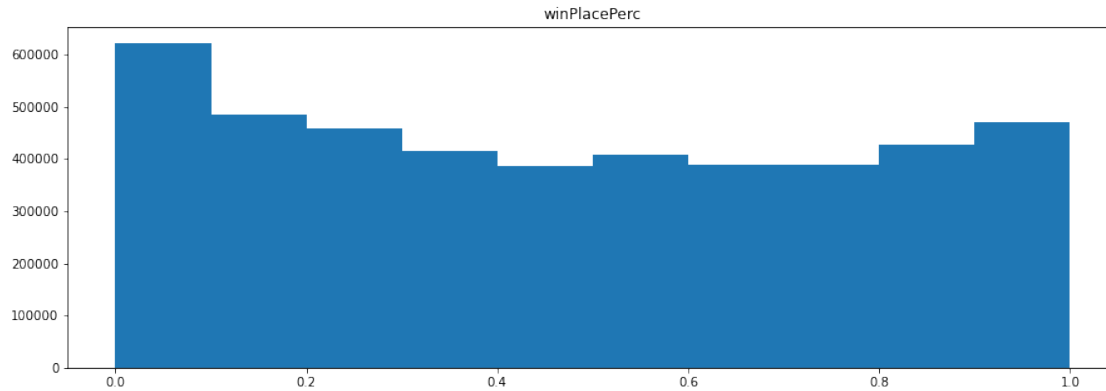


```
[13]: # See how catergorical data is skewed
for i in range(len(categorical_data.columns)):
    var_name = str(categorical_data.columns[i])
    plt.figure(figsize=(15,5))
    plt.hist(categorical_data[var_name])
    plt.title(var_name)
    plt.show()
```









```
[14]: # Find observations with only one numGroups
empty_games = training_data.loc[(training_data['numGroups'] == 1)]
empty_games['winPlacePerc'].value_counts()
```

```
[14]: 0.0    1146
      Name: winPlacePerc, dtype: int64
```

Preprocess Data

```
[15]: # Drop single observation missing 'winPlacePerc' from training data
training_data = training_data.dropna()

# Drop 'maxPlace' since it highly correlated with 'numGroups'
training_data = training_data.drop('maxPlace', axis=1)
test_data = test_data.drop('maxPlace', axis=1)

# Drop 'rankPoints' as this ranking is inconsistent and is being deprecated in
↳ the API's next version
training_data = training_data.drop('rankPoints', axis=1)
test_data = test_data.drop('rankPoints', axis=1)

# Drop 'Id', 'groupId', 'matchId'
training_data = training_data.drop('Id', axis=1)
training_data = training_data.drop('groupId', axis=1)
training_data = training_data.drop('matchId', axis=1)
test_data = test_data.drop('Id', axis=1)
test_data = test_data.drop('groupId', axis=1)
test_data = test_data.drop('matchId', axis=1)
```

```
[16]: # Standardize inputs
scaled_training_data = training_data
scaled_test_data = test_data
```

```

def standardize_data(df):
    for i in range(len(df.columns)):
        var_name = str(df.columns[i])
        if var_name != 'matchType':
            scaler = MinMaxScaler()
            scaled_training_data[var_name] = scaler.fit_transform(np.
↪array(training_data[var_name]).reshape(4446965,1))
    return scaled_training_data

scaled_training_data = standardize_data(training_data)
scaled_test_data = standardize_data(test_data)

```

```

[17]: # Get dummies for 'matchType'
final_training_data = pd.get_dummies(data=scaled_training_data,
↪drop_first=True, columns=['matchType'])
final_test_data = pd.get_dummies(data=scaled_test_data, drop_first=True,
↪columns=['matchType'])

```

```

[18]: # split data
Y = final_training_data.pop('winPlacePerc')
X = final_training_data

train_x, test_x, train_y, test_y = train_test_split(X, Y, test_size=0.20,
↪random_state=1)

```

```

[19]: train_x.to_csv('train_x.csv', index=False)
test_x.to_csv('test_x.csv', index=False)
train_y.to_csv('train_y.csv', index=False)
test_y.to_csv('test_y.csv', index=False)

```