DataAnalysis

June 4, 2022

1 PUBG Finish Placement Prediction

[ ]:
```
# Imports
import sys
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import lightgbm as lgb
import random
import gc
import graphviz

random.seed(16)
```

[ ]:
```
# Read data to dataframe
df = pd.read_csv("data/train_V2.csv")
df_types = pd.read_csv("data/types.csv")
```

[ ]:
```
# Initial settings
pd.set_option('display.max_rows',500)
pd.set_option('display.max_columns',500)
pd.set_option('display.width',2000)

plt.rcParams['figure.dpi'] = 100
```

[ ]:
```
#center figures
from IPython.core.display import HTML
HTML("""
<style>
.output_png {
    display: table-cell;
    text-align: center;
    vertical-align: middle;
}
</style>
""")
```

[ ]: <IPython.core.display.HTML object>

[ ]:
```
# Memory saving function credit to https://www.kaggle.com/gemartin/
↪load-data-reduce-memory-usage
def reduce_mem_usage(df):
    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)
    return df
```

[ ]:
```
# Reducing memory usage
print(str(sys.getsizeof(df)/1024/1024) + " MB")
df = reduce_mem_usage(df)
df_types = reduce_mem_usage(df_types)
print(str(sys.getsizeof(df)/1024/1024) + " MB")
```

```
2024.0970821380615 MB
1328.5800914764404 MB
```

[ ]:
```
# Function to split data into two sets
# Data is grouped by "matchId" which means that games are not mixed up between␣
↪sets.
```

```
def split_into_train_test_sets(df, test_set_size=0.2):
    match_ids = df['matchId'].unique().tolist()
    train_size = int(len(match_ids) * (1 - test_set_size))
    train_match_ids = random.sample(match_ids, train_size)

    train = df[df['matchId'].isin(train_match_ids)]
    test = df[-df['matchId'].isin(train_match_ids)]

    return train, test
```

[ ]:
```
defaultCols = list(df.columns)
```

1.1 Cleaning data

1.1.1 Incorrect Match

In the data set there is one row of data where the variable we are going to predict is missing. We need to drop it.

[ ]:
```
df[df.isnull().any(axis=1)]
```

[ ]:
```
                         Id          groupId          matchId  assists  boosts
damageDealt  DBNOs  headshotKills  heals  killPlace  killPoints  kills
killStreaks  longestKill  matchDuration matchType  maxPlace  numGroups
rankPoints  revives  rideDistance  roadKills  swimDistance  teamKills
vehicleDestroys  walkDistance  weaponsAcquired  winPoints  winPlacePerc
2744604  f70c74418bb064  12dfbede33f92b  224a123c53e008        0       0
0.0      0              0       0          1            0       0            0
0.0              9  solo-fpp          1           1         1574         0
0.0          0            0.0           0                 0            0.0
0           0             NaN
```

[ ]:
```
df = df[pd.notnull(df['winPlacePerc'])]
df[df.isnull().any(axis=1)]
```

[ ]:
```
Empty DataFrame
Columns: [Id, groupId, matchId, assists, boosts, damageDealt, DBNOs,
headshotKills, heals, killPlace, killPoints, kills, killStreaks, longestKill,
matchDuration, matchType, maxPlace, numGroups, rankPoints, revives,
rideDistance, roadKills, swimDistance, teamKills, vehicleDestroys, walkDistance,
weaponsAcquired, winPoints, winPlacePerc]
Index: []
```

Row where winPlacePerc is missing is gone.

[ ]:
```
validStartCount = len(df)
validStartCount
```

```
[ ]: 4446965
```

We have this many valid rows

1.1.2 Removing custom games

- flaretpp
- flarefpp
- crashtpp
- crashfpp

```python
[ ]: df[(df['matchType'] == "flaretpp") |
        (df['matchType'] == "flarefpp") |
        (df['matchType'] == "crashtpp") |
        (df['matchType'] == "crashfpp")].head(5)
```

```
[ ]:                   Id         groupId         matchId  assists  boosts
damageDealt  DBNOs  headshotKills  heals  killPlace  killPoints  kills
killStreaks  longestKill  matchDuration matchType  maxPlace  numGroups
rankPoints  revives  rideDistance  roadKills  swimDistance  teamKills
vehicleDestroys  walkDistance  weaponsAcquired  winPoints  winPlacePerc
1093  c8ed6a171536e3  84748458aba82a  d4f1811cf6a04b        1       3
187.3750      0              1      6          27            0      1            1
0.800781             904  crashfpp         50          45         1500         0
0.00           0           0.0           0                 0   1342.000000
1          0      0.489746
1207  fb785deb59f2bc  4438f77ac9f2e6  33d976b454b843        0       4
577.0000      7              2      4           6            0      4            2
208.500000           1947  flaretpp         26          25         1500         1
2548.00          0           0.0           0                 1   2564.000000
6          0      0.799805
1276  d3c4dd2e585d21  6af9bb6b56b722  16e6befa897b44        0       0
0.0000      0              0      0          88            0      0            0
0.000000             892  crashfpp         47          45         1500         0
0.00           0           0.0           0                 0      0.000000
0          0      0.000000
1524  b0fbbe07014fcd  7ce6194a5dd609  e330f44c528e6f        0       0
20.9375      0              0      0          55            0      0            0
0.000000            2031  flarefpp         17          17         1500         0
0.00           0           0.0           0                 0     13.640625
1          0      0.062500
1790  28390372a2cc4f  c529d05da4597b  be945f2803814a        0       0
0.0000      0              0      0          76            0      0            0
0.000000             915  crashfpp         50          50         1500         0
393.75          0           0.0           0                 0    459.500000
0          0      0.204102
```

[ ]:
```
df.drop(df[(df['matchType'] == "flaretpp") |
           (df['matchType'] == "flarefpp") |
           (df['matchType'] == "crashtpp") |
           (df['matchType'] == "crashfpp")]
        .index, inplace=True)

customDropCount = len(df)
```

[ ]:
```
print(customDropCount)
print("Dropped:", validStartCount - customDropCount)
```

```
4437084
Dropped: 9881
```

We dropped this many rows

1.1.3 AFKs and cheaters

Removing players who haven't moved throughout the match. We are trying to identify cheaters and AFKs.

[ ]:
```
df[df['walkDistance'] == 0].head(5)
```

[ ]:
```
                 Id         groupId         matchId  assists  boosts  \
damageDealt  DBNOs  headshotKills  heals  killPlace  killPoints  kills  \
killStreaks  longestKill  matchDuration  matchType  maxPlace  numGroups  \
rankPoints  revives  rideDistance  roadKills  swimDistance  teamKills  \
vehicleDestroys  walkDistance  weaponsAcquired  winPoints  winPlacePerc
29   ac5b57ff39979c  857cc55b2b6001  e019e04dee4f19        0       0
0.0      0              0      0         87           0      0            0
0.0           1530         duo         46          44        1534         0
0.0           0           0.0           0                0           0.0
0          0      0.000000
116  6adb021f5165ff  58e5500bd40898  de5c692fe25a73        0       0
0.0      0              0      0         68         311      0            0
0.0           1414         duo         41          36           0         0
0.0           0           0.0           0                0           0.0
0        847      0.000000
151  a2bbe20aa8789d  926e8a09bab249  e36e4203ed4831        0       0
0.0      0              0      0         92         309      0            0
0.0           1377         duo         48          41          -1         0
0.0           0           0.0           0                0           0.0
0        765      0.000000
237  baaa694658e085  d034728f22cff7  fa71620624d3e7        0       0
0.0      0              0      0         94        1397      0            0
0.0           1358   squad-fpp         29          26          -1         0
0.0           0           0.0           0                0           0.0
0       1510      0.000000
```

```
283  3ab8128e6bcbe6  bb52a209f2e938  aabd2650b129e2        0        0
0.0      0               0       0          84            0       0             0
0.0           1797          duo          48          47          1500        0
0.0           0            0.0           0                 0             0.0
0           0       0.127686
```

```
[ ]: df.drop(df[df['walkDistance'] == 0].index, inplace=True)
     noWalkDropCount = len(df)
```

```
[ ]: print(noWalkDropCount)
     print("Dropped:", customDropCount - noWalkDropCount)
```

```
4337720
Dropped: 99364
```

1.1.4 Potential cheats

Removing players who traveled great distances (potential speed cheat) - walked more than 10km - rode more than 30km - swam more than 2km

```
[ ]: df[['walkDistance', 'rideDistance', 'swimDistance']].describe()
```

```
[ ]:        walkDistance  rideDistance  swimDistance
     count  4.337720e+06  4.337720e+06     4337720.0
     mean            NaN           NaN           NaN
     std             NaN           NaN           NaN
     min    1.000166e-04  0.000000e+00           0.0
     25%    1.722500e+02  0.000000e+00           0.0
     50%    7.335000e+02  0.000000e+00           0.0
     75%    2.010000e+03  7.756250e+01           0.0
     max    2.577600e+04  4.070400e+04        3824.0
```

```
[ ]: df.drop(df[df['walkDistance'] >= 10000].index, inplace=True)
     df.drop(df[df['rideDistance'] >= 30000].index, inplace=True)
     df.drop(df[df['swimDistance'] >= 2000].index, inplace=True)
     potentialCheatsDropCount = len(df)
```

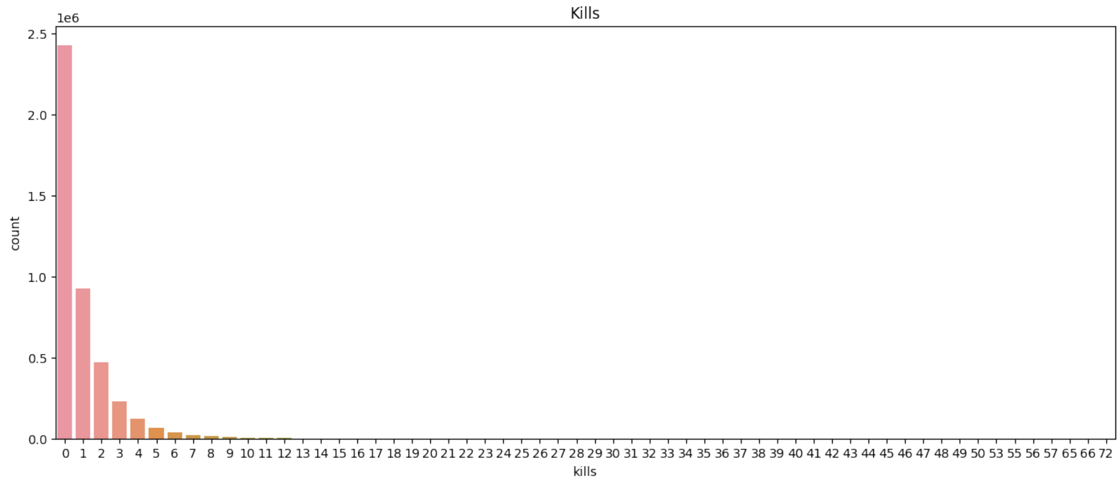
```
[ ]: print(potentialCheatsDropCount)
     print("Dropped:", noWalkDropCount - potentialCheatsDropCount)
```

```
4337472
Dropped: 248
```

Large Number of Kills Removing players who have more than 40 kills.

Let's plot the total kills for every player first.

[ ]:
```
plt.figure(figsize=(15,6))
sns.countplot(data=df, x=df['kills']).set_title('Kills')
plt.show()
```



[ ]:
```
display(df[df['kills'] > 40].shape)
```

```
(32, 29)
```

[ ]:
```
df[df['kills'] >= 40].head(5)
```

[ ]:
```
                        Id         groupId         matchId  assists  boosts
damageDealt  DBNOs  headshotKills  heals  killPlace  killPoints  kills
killStreaks  longestKill  matchDuration         matchType  maxPlace  numGroups
rankPoints  revives  rideDistance  roadKills  swimDistance  teamKills
vehicleDestroys  walkDistance  weaponsAcquired  winPoints  winPlacePerc
156599  746aa7eabf7c86  5723e7d8250da3  f900de1ec39fa5       21       0
5480.0      0             12      7          4          0     48            6
81.9375           1798   normal-solo-fpp         11          11         1500
0           0.0           0           0.0          0                0
23.703125                61           0      0.700195
160254  15622257cb44e2  1a513eeecfe724  db413c7c48292c        1       0
4032.0      0             40      0          1       1000     42            5
266.2500           844   normal-squad-fpp          8           8           -1
0           0.0           0           0.0          1                0
718.500000                16        1500      1.000000
334400  810f2379261545  7f3e493ee71534  f900de1ec39fa5       20       0
6616.0      0             13      5          1          0     65            7
73.8750           1798   normal-solo-fpp         11          11         1500
0           0.0           0           0.0          0                0
1036.000000                60           0      1.000000
672993  da31f191ace8ed  ce9a3c4950a8f2  17dea22cefe62a       10       0
```

```
5792.0       0              5      2           1           0     57            5
104.1875           1798     normal-duo-fpp        15         12         1500
0            0.0           0           0.0          0                0
24.265625               56           0       1.000000
770454   2ade4369bccd12  9f9e64a3db8384  e024bf51bf1799       12        0
5556.0       0              7      4           1           0     55            6
74.8125           1798    normal-solo-fpp        19         18         1500
0            0.0           0           0.0          0                0
85.562500               66           0       1.000000
```

It doesn't look like there are too many outliers. We decide to remove those.

```
[ ]: df.drop(df[df['kills'] >= 40].index, inplace=True)
     largeKillsDropCount = len(df)
```

```
[ ]: print(largeKillsDropCount)
     print("Dropped:", potentialCheatsDropCount - largeKillsDropCount)
```

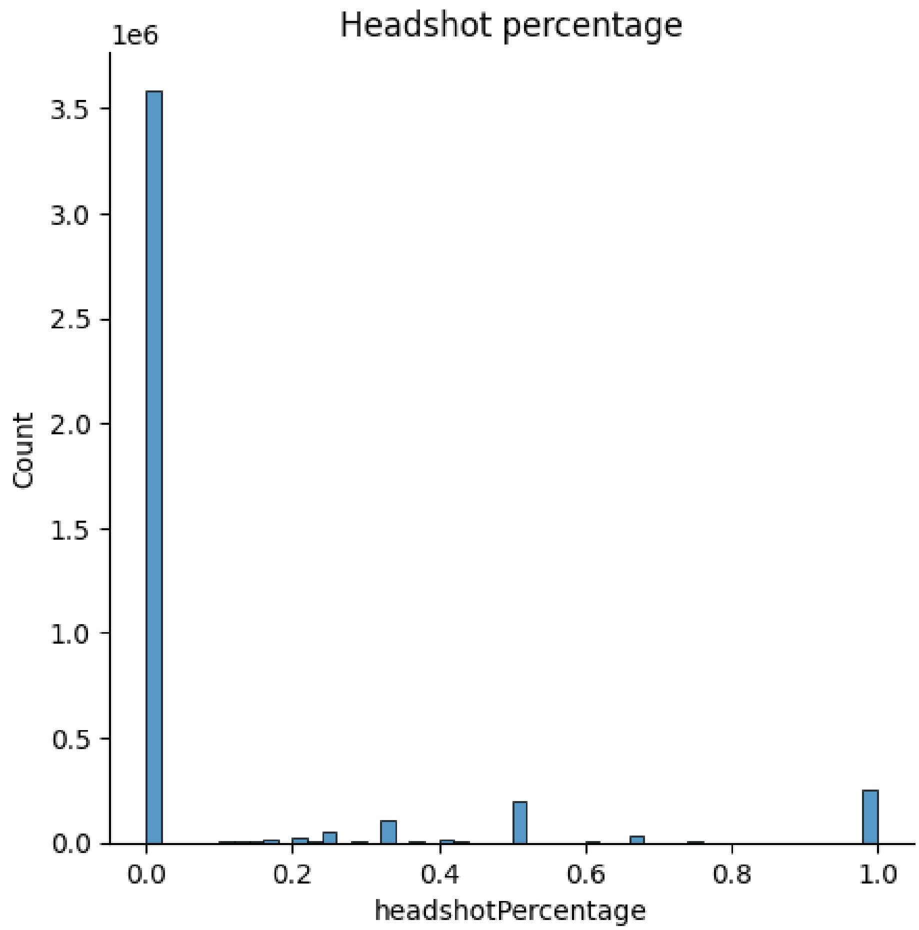
```
4337436
Dropped: 36
```

Potential Aim Bot We will create a new feature 'headshotRate' and plot of it

```
[ ]: df['headshotPercentage'] = df['headshotKills'] / df['kills']
     df['headshotPercentage'] = df['headshotPercentage'].fillna(0)

     plt.figure(figsize=(12, 4))
     sns.displot(df['headshotPercentage'], bins=50)
     plt.title('Headshot percentage')
     plt.show()
```

```
<Figure size 1200x400 with 0 Axes>
```



Not every player with 100% headshot has to be cheater. They might be just goog players.n That's why we will remove only players who have more than 10 kills and 100% headshots.

```
[ ]: df[(df['headshotKills'] == df['kills']) & (df['kills'] >= 10)].head(5)
```

```
[ ]:                    Id          groupId          matchId  assists  boosts
damageDealt  DBNOs  headshotKills  heals  killPlace  killPoints  kills
killStreaks  longestKill  matchDuration  matchType  maxPlace  numGroups
rankPoints  revives  rideDistance  roadKills  swimDistance  teamKills
vehicleDestroys  walkDistance  weaponsAcquired  winPoints  winPlacePerc
headshotPercentage
281570  ab9d7168570927  add05ebde0214c  e016a873339c7b        2       3
1212.0      8             10      0          1            0      10             4
159.25          1423  squad-fpp        27         25         1564          1
0.0           0            0.0           0                 0         2940.0
5          0       0.846191                   1.0
346124  044d18fc42fc75  fc1dbc2df6a887  628107d4c41084        3       5
1620.0     13             11      3          1         1424      11             2
```

```
633.50           1727      squad        27          26          -1         3
4720.0          0          0.0          0                  0        3422.0
8        1560      1.000000                  1.0
871244   e668a25f5488e3   5ba8feabfb2a23   f6e6581e03ba4f        0       4
1365.0      9             13      0          1        1579     13            2
353.75           1255      squad        27          27          -1         0
0.0          0          0.0          0                 0        2104.0
5        1587      1.000000                  1.0
908815   566d8218b705aa   a9b056478d71b2   3a41552d553583        2       5
1365.0      10            10      3          1        1393     10            3
533.00           1838   squad-fpp       28          24          -1         0
5188.0          0          0.0          2                  0        2760.0
7        1519      0.962891                  1.0
963463   1bd6fd288df4f0   90584ffa22fe15   ba2de992ec7bb8        2       6
1355.0      12            10      2          1        1543     10            2
277.00           1417      squad        27          26          -1         0
1018.0          0          0.0          0                  0        2458.0
4        1562      1.000000                  1.0
```

[ ]:
```python
df.drop(df[(df['headshotKills'] == df['kills']) & (df['kills'] >= 10)].index,
 inplace=True)
highHSrateDropCount = len(df)
```

[ ]:
```python
print(highHSrateDropCount)
print("Dropped:", largeKillsDropCount - highHSrateDropCount)
```

```
4337412
Dropped: 24
```

Altogether we dropped

[ ]:
```python
print("Dropped:", validStartCount - highHSrateDropCount)
```

```
Dropped: 109553
```

1.2 Train data and test data

Source of data: https://www.kaggle.com/c/pubg-finish-placement-prediction

Our data contains around 4.5 millions rows.

We are going to split it into two sets: - train set, - test set

[ ]:
```python
df_train, df_test = split_into_train_test_sets(df, 0.2)
```

1.2.1 Train data

Brief look at the train data

[ ]:
```python
df_train.head()
```

[ ]:
```
               Id         groupId         matchId  assists  boosts  damageDealt
DBNOs  headshotKills  heals  killPlace  killPoints  kills  killStreaks
longestKill  matchDuration  matchType  maxPlace  numGroups  rankPoints  revives
rideDistance  roadKills  swimDistance  teamKills  vehicleDestroys  walkDistance
weaponsAcquired  winPoints  winPlacePerc  headshotPercentage
0  7f96b2f878858a  4d4b580de459be  a10357fd1a4a91        0       0      0.00000
0              0      0         60        1241      0            0      0.00000
1306  squad-fpp        28         26          -1        0      0.000000
0      0.000000           0                 0        244.75                 1
1466      0.444336                 0.0
1  eef90569b9d03c  684d5656442f9e  aeb375fc57110c        0       0     91.50000
0              0      0         57           0      0            0      0.00000
1777  squad-fpp        26         25        1484        0      0.004501
0     11.039062           0                 0       1434.00                 5
0      0.640137              0.0
2  1eaf90ac73de72  6a4a42c3245a74  110163d8bb94ae        1       0     68.00000
0              0      0         47           0      0            0      0.00000
1318        duo        50         47        1491        0      0.000000
0      0.000000           0                 0        161.75                 2
0      0.775391              0.0
3  4616d365dd2853  a930a9c79cd721  f1f1f4ef412d7e        0       0     32.90625
0              0      0         75           0      0            0      0.00000
1436  squad-fpp        31         30        1408        0      0.000000
0      0.000000           0                 0        202.75                 3
0      0.166748              0.0
4  315c96c26c9aac  de04010b3458dd  6dc8ff871e21e6        0       0    100.00000
0              0      0         45           0      1            1     58.53125
1424   solo-fpp        97         95        1560        0      0.000000
0      0.000000           0                 0         49.75                 2
0      0.187500              0.0
```

[ ]:
```
df_train.describe()
```

[ ]:
```
            assists        boosts    damageDealt         DBNOs   headshotKills
heals     killPlace     killPoints         kills   killStreaks   longestKill
matchDuration      maxPlace      numGroups    rankPoints        revives
rideDistance     roadKills  swimDistance     teamKills  vehicleDestroys
walkDistance  weaponsAcquired     winPoints  winPlacePerc  headshotPercentage
count  3.469847e+06  3.469847e+06  3.469847e+06  3.469847e+06   3.469847e+06
3.469847e+06  3.469847e+06  3.469847e+06  3.469847e+06  3.469847e+06
3.469847e+06   3.469847e+06  3.469847e+06  3.469847e+06  3.469847e+06
3.469847e+06   3469847.000  3.469847e+06     3469847.0  3.469847e+06
3.469847e+06  3.469847e+06     3.469847e+06  3.469847e+06  3.469847e+06
3.469847e+06
mean   2.383901e-01  1.131767e+00           NaN  6.718607e-01   2.316344e-01
1.402385e+00  4.682020e+01  5.064362e+02  9.446624e-01  5.557087e-01
NaN   1.580254e+03  4.450200e+01  4.304152e+01  8.922022e+02  1.682633e-01
```

```
NaN  3.084286e-03           NaN  2.396071e-02     7.964328e-03           NaN
3.734484e+00  6.076616e+02           NaN        1.054396e-01
std    5.927108e-01  1.727558e+00           NaN  1.153240e+00   6.027012e-01
2.705222e+00  2.705407e+01  6.284574e+02  1.561952e+00  7.132730e-01
NaN   2.572401e+02  2.377867e+01  2.321655e+01  7.368644e+02  4.768281e-01
NaN  6.590024e-02           NaN  1.680334e-01     9.259659e-02           NaN
2.415307e+00  7.404351e+02  0.000000e+00        2.628985e-01
min    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00   0.000000e+00
0.000000e+00  1.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
0.000000e+00   1.330000e+02  2.000000e+00  1.000000e+00 -1.000000e+00
0.000000e+00         0.000  0.000000e+00           0.0  0.000000e+00
0.000000e+00  1.000166e-04     0.000000e+00  0.000000e+00  0.000000e+00
0.000000e+00
25%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00   0.000000e+00
0.000000e+00  2.300000e+01  0.000000e+00  0.000000e+00  0.000000e+00
0.000000e+00   1.367000e+03  2.800000e+01  2.700000e+01 -1.000000e+00
0.000000e+00         0.000  0.000000e+00           0.0  0.000000e+00
0.000000e+00  1.722500e+02     2.000000e+00  0.000000e+00  2.143555e-01
0.000000e+00
50%    0.000000e+00  0.000000e+00  8.818750e+01  0.000000e+00   0.000000e+00
0.000000e+00  4.700000e+01  0.000000e+00  0.000000e+00  0.000000e+00
0.000000e+00   1.438000e+03  3.000000e+01  3.000000e+01  1.444000e+03
0.000000e+00         0.000  0.000000e+00           0.0  0.000000e+00
0.000000e+00  7.340000e+02     3.000000e+00  0.000000e+00  4.680176e-01
0.000000e+00
75%    0.000000e+00  2.000000e+00  1.897500e+02  1.000000e+00   0.000000e+00
2.000000e+00  7.000000e+01  1.174000e+03  1.000000e+00  1.000000e+00
2.231250e+01   1.851000e+03  4.900000e+01  4.700000e+01  1.500000e+03
0.000000e+00        81.625  0.000000e+00           0.0  0.000000e+00
0.000000e+00  2.009000e+03     5.000000e+00  1.495000e+03  7.500000e-01
0.000000e+00
max    1.700000e+01  3.300000e+01  4.240000e+03  3.900000e+01   2.700000e+01
7.300000e+01  1.010000e+02  2.170000e+03  3.900000e+01  1.800000e+01
1.094000e+03   2.237000e+03  1.000000e+02  1.000000e+02  5.910000e+03
3.200000e+01      29424.000  1.800000e+01        1980.0  1.200000e+01
5.000000e+00  9.984000e+03     2.360000e+02  2.013000e+03  1.000000e+00
1.000000e+00
```

1.2.2 Test data

[ ]:
```
df_test.head()
```

[ ]:
```
                 Id        groupId        matchId  assists  boosts  damageDealt
DBNOs  headshotKills  heals  killPlace  killPoints  kills  killStreaks
longestKill  matchDuration  matchType  maxPlace  numGroups  rankPoints  revives
rideDistance  roadKills  swimDistance  teamKills  vehicleDestroys  walkDistance
weaponsAcquired  winPoints  winPlacePerc  headshotPercentage
```

```
7   311b84c6ff4390  eaba5fcb7fc1ae  292611730ca862        0       0     8.539062
0              0      0         48        1000      0            0     0.000000
1967   solo-fpp        96         92           -1         0        2004.0
0       0.00000          0                 0       1089.00                 6
1500      0.736816                0.00
19  71cbdbc3b263e5  7b61f74b51906c  a329ac99449ad7        0       1    65.250000
0              0      1         48        1349      0            0     0.000000
1322  squad-fpp        30         28           0         0          0.0
0       20.84375          0                 0       3310.00                 3
1479      0.931152                0.00
28  f9473c4f1cfdc4  8483976f3ba230  6057f846f3ed12        0       6   345.500000
2              1      1          6           0      4            1   105.187500
1339  squad-fpp        28         28         1339         0          0.0
0       0.00000          0                 0       3856.00                 4
0       0.962891             0.25
35  47143f942503e0  e17a8867a393ec  bc2faecb77e5ec        0       0   136.875000
0              0      0         37           0      1            1    22.828125
1425   solo-fpp        96         94         1500         0          0.0
0       0.00000          0                 0        270.75                 1
0      0.347412             0.00
40  ffd9e56f13438e  8df2112760f9e2  3f8b160eeee685        0       1    61.906250
1              0      1         31           0      1            1    48.406250
1303      squad        26         25         1472         0        529.0
0       0.00000          0                 0        327.25                 2
0      0.320068             0.00
```

[ ]:
```python
df_test.describe()
```

[ ]:
```
             assists         boosts  damageDealt          DBNOs  headshotKills
heals      killPlace     killPoints          kills    killStreaks    longestKill
matchDuration       maxPlace      numGroups     rankPoints        revives
rideDistance      roadKills  swimDistance      teamKills  vehicleDestroys
walkDistance  weaponsAcquired      winPoints   winPlacePerc  headshotPercentage
count  867565.000000  867565.000000   867565.000  867565.000000  867565.000000
867565.000000  867565.000000  867565.000000  867565.000000  867565.000000
867565.000000  867565.000000  867565.000000  867565.000000  867565.000000
867565.000000   867565.0000  867565.000000      867565.0  867565.000000
867565.000000   867565.0000    867565.000000  867565.000000  867565.000000
867565.000000
mean        0.238522       1.131575          NaN       0.675299       0.231425
1.392457      46.833276     515.209303       0.940653       0.556460
NaN    1580.545062      44.283254      42.829447     880.640411       0.169433
NaN      0.003108         NaN       0.023577        0.008021           NaN
3.720321      618.834212           NaN          0.105714
std         0.587974       1.724802          NaN       1.147718       0.600599
2.686267      27.049054     629.828682       1.542626       0.714488
NaN     257.405717      23.582118      23.000790     738.636207       0.476911
```

```
NaN      0.065496         NaN      0.165959        0.093134          NaN
2.352038    742.563683      0.000000          0.263227
min          0.000000      0.000000       0.000      0.000000      0.000000
0.000000      1.000000      0.000000      0.000000      0.000000
0.000000    312.000000      2.000000      1.000000     -1.000000
0.000000        0.0000      0.000000          0.0      0.000000
0.000000        0.0001        0.000000      0.000000      0.000000
0.000000
25%          0.000000      0.000000       0.000      0.000000      0.000000
0.000000     23.000000      0.000000      0.000000      0.000000
0.000000   1367.000000     28.000000     27.000000     -1.000000
0.000000        0.0000      0.000000          0.0      0.000000
0.000000      171.7500        2.000000      0.000000      0.214355
0.000000
50%          0.000000      0.000000      88.750      0.000000      0.000000
0.000000     47.000000      0.000000      0.000000      0.000000
0.000000   1438.000000     30.000000     30.000000   1438.000000
0.000000        0.0000      0.000000          0.0      0.000000
0.000000      731.5000        3.000000      0.000000      0.466797
0.000000
75%          0.000000      2.000000     189.625      1.000000      0.000000
2.000000     70.000000   1178.000000      1.000000      1.000000
22.296875    1851.000000     49.000000     47.000000   1500.000000
0.000000       59.6875      0.000000          0.0      0.000000
0.000000     2011.0000        5.000000   1497.000000      0.750000
0.000000
max         17.000000     23.000000    4080.000     26.000000     23.000000
80.000000    100.000000   2154.000000     38.000000     11.000000
1000.000000    2218.000000    100.000000    100.000000   5820.000000
39.000000    28448.0000      11.000000       1960.0      4.000000
3.000000     9992.0000       95.000000   2002.000000      1.000000
1.000000
```

1.2.3 Data Fields Descriptions

[ ]:
```python
print(df_types)
```

```
        Data field                                        Description     Type
0               Id                                        Player's Id   object
1          groupId                  ID to identify a group within a match   object
2          matchId                                  ID to identify match   object
3        matchType  String identifing the game mode that the data …   object
4          assists  Number of enemy players this player damaged th…    int64
5           boosts                           Number of boost items used    int64
6      damageDealt                                  Total damage dealt  float64
7            DBNOs                       Number of enemy players knocked    int64
8    headshotKills         Number of enemy players killed with headshots    int64
```

```
9              heals                           Number of healing items used    int64
10         killPlace  Ranking in match of number of enemy players ki…    int64
11        killPoints               Kills-based external ranking of player    int64
12       killStreaks  Max number of enemy players killed in a short …    int64
13             kills                        Number of enemy players killed    int64
14       longestKill  Longest distance between player and player kil…  float64
15     matchDuration                         Duration of match in seconds    int64
16        rankPoints                           Elo-like ranking of player    int64
17           revives      Number of times this player revived teammates    int64
18      rideDistance  Total distance traveled in vehicles measured i…    int64
19         roadKills                    Number of kills while in a vehicle    int64
20      swimDistance  Total distance traveled by swimming measured i…  float64
21         teamKills      Number of times this player killed a teammate    int64
22  vehicleDestroys                         Number of vehicles destroyed    int64
23      walkDistance  Total distance traveled on foot measured in me…  float64
24  weaponsAcquired                          Number of weapons picked up    int64
25         winPoints                 Win-based external ranking of player    int64
26         numGroups     Number of groups we have data for in the match    int64
27          maxPlace      Worst placement we have data for in the match    int64
28      winPlacePerc                            The target of prediction  float64
```

We have total 28 predictors where 24 of them is numerical. Id, groupId, matchId and matchType are objects. The three ids identify the players information of each group in each match the participated. The match type indicates one of the 16 game types.

[ ]:
```
print(df_train["matchType"].unique())
```

```
['squad-fpp' 'duo' 'solo-fpp' 'squad' 'duo-fpp' 'solo' 'normal-squad-fpp'
 'normal-solo-fpp' 'normal-duo-fpp' 'normal-duo' 'normal-squad'
 'normal-solo']
```

Players playing solo-match have their own placement, while the players from the same group share the same placement.

1.3 Looking for best strategy

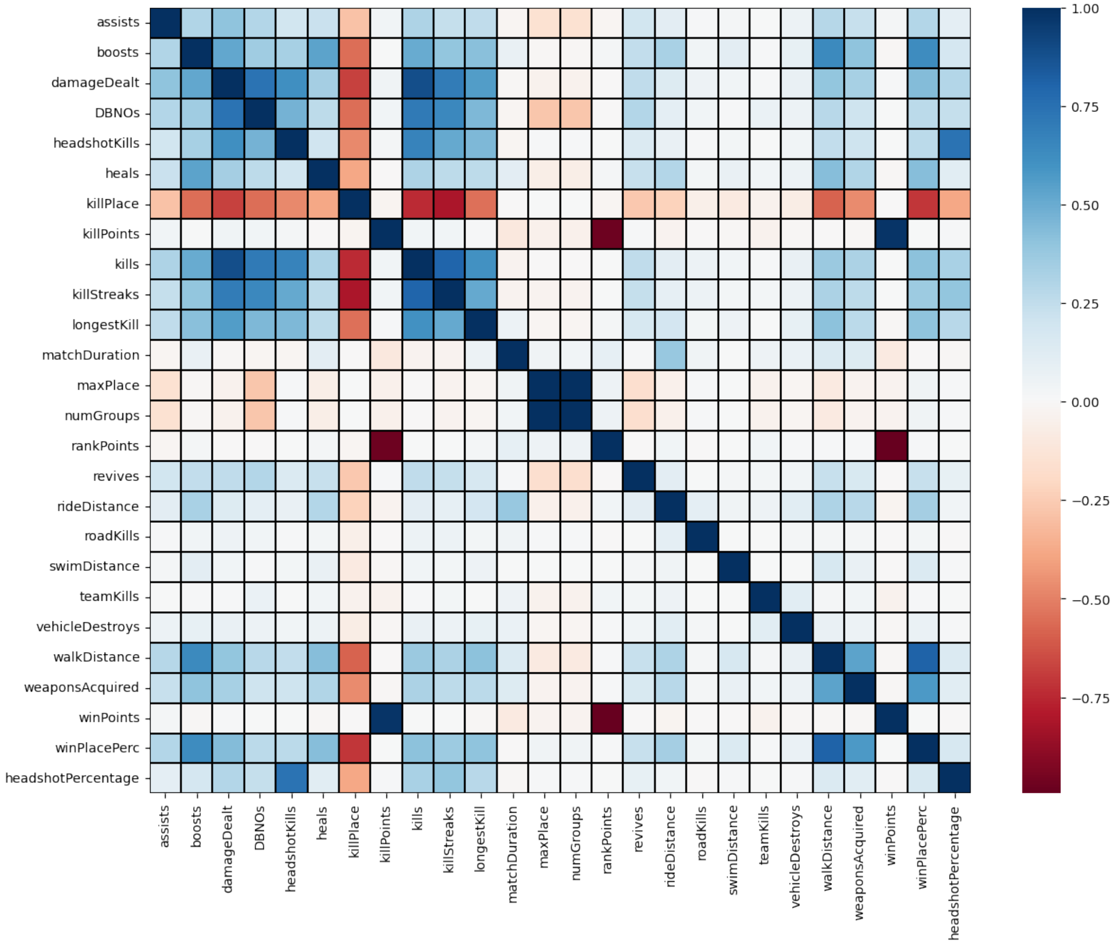
1.3.1 Correlation of feature

A correlation matrix is a table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables.

[ ]:
```
# We do not use columns containing Id and matchType. Only numerical values.
cols_to_drop = ['Id', 'groupId', 'matchId', 'matchType']
cols_to_fit = [col for col in df.columns if col not in cols_to_drop]
corr = df[cols_to_fit].corr()

plt.figure(figsize=(14,11))
sns.heatmap(
    corr,
    xticklabels=corr.columns.values,
```

```
    yticklabels=corr.columns.values,
    linecolor='black',
    linewidths=0.1,
    cmap="RdBu"
)
plt.show()
```



As we can see there are some pairs of value that are highly correlated. It is possible that the highly correlated variables such as might be the most important features in predicting winPlacePerc.

Pairs with correlation >= 0.45:

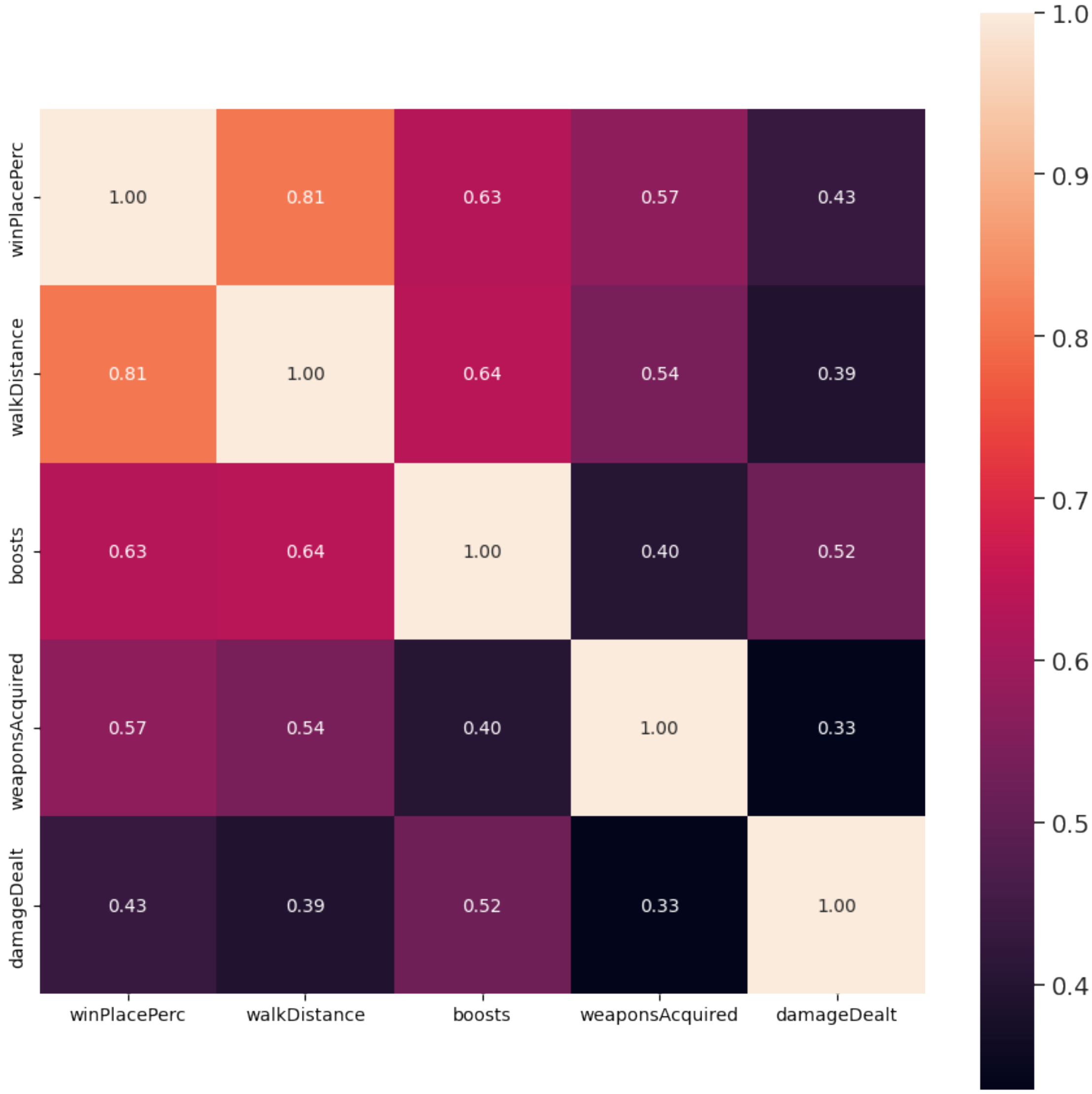
[ ]:
```
corr_pairs = corr.unstack().sort_values(ascending=False).drop_duplicates()
corr_pairs[corr_pairs >= 0.45]
```

[ ]:
```
assists             assists          1.000000
maxPlace            numGroups        0.998236
winPoints           killPoints       0.983452
```

```
damageDealt          kills            0.887425
winPlacePerc         walkDistance     0.810390
kills                killStreaks      0.803082
damageDealt          DBNOs            0.737639
headshotPercentage   headshotKills    0.737256
kills                DBNOs            0.709956
killStreaks          damageDealt      0.701581
kills                headshotKills    0.671712
killStreaks          DBNOs            0.644889
boosts               walkDistance     0.637142
winPlacePerc         boosts           0.632603
headshotKills        damageDealt      0.610699
kills                longestKill      0.603579
weaponsAcquired      winPlacePerc     0.573229
damageDealt          longestKill      0.563338
weaponsAcquired      walkDistance     0.537947
boosts               heals            0.532803
                     damageDealt      0.521317
killStreaks          longestKill      0.512229
                     headshotKills    0.511868
kills                boosts           0.502377
DBNOs                headshotKills    0.470472
dtype: float64
```

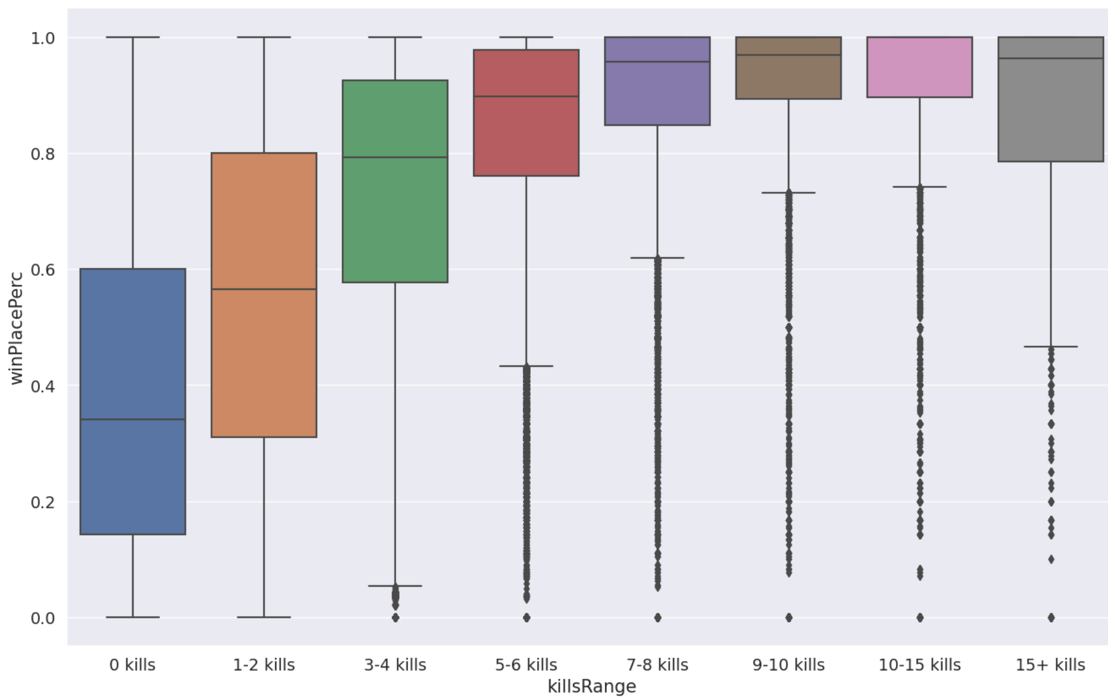
Highlt correlated Let's take a closer look at 6 most correlated variables with the target

[ ]:
```
f,ax = plt.subplots(figsize=(11, 11))
cols = df.corr().nlargest(5, 'winPlacePerc')['winPlacePerc'].index
cm = np.corrcoef(df[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f',␣
↪annot_kws={'size': 10}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```



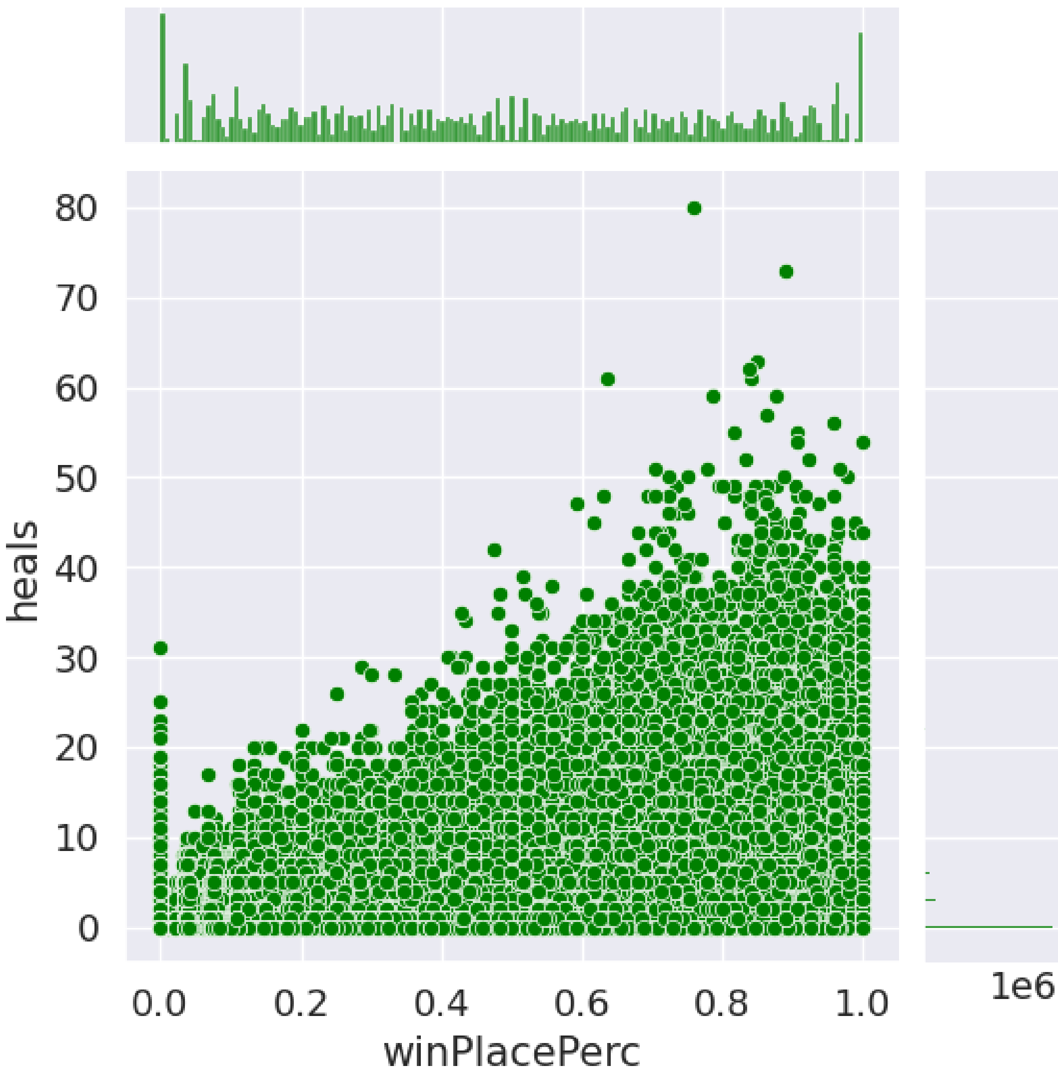
1.3.2 Impact of kills made on final position

[ ]:
```
df['killsRange'] = pd.cut(df['kills'], [-1, 0, 2, 4, 6, 8, 10, 15, 100],
                                            labels=['0 kills','1-2 kills', '3-4␣
 ↪kills', '5-6 kills',
                                                    '7-8 kills', '9-10␣
 ↪kills','10-15 kills', '15+ kills'])
plt.figure(figsize=(16,10))
sns.boxplot(x='killsRange', y='winPlacePerc', data=df)
df.drop(['killsRange'],axis=1,inplace=True)
```

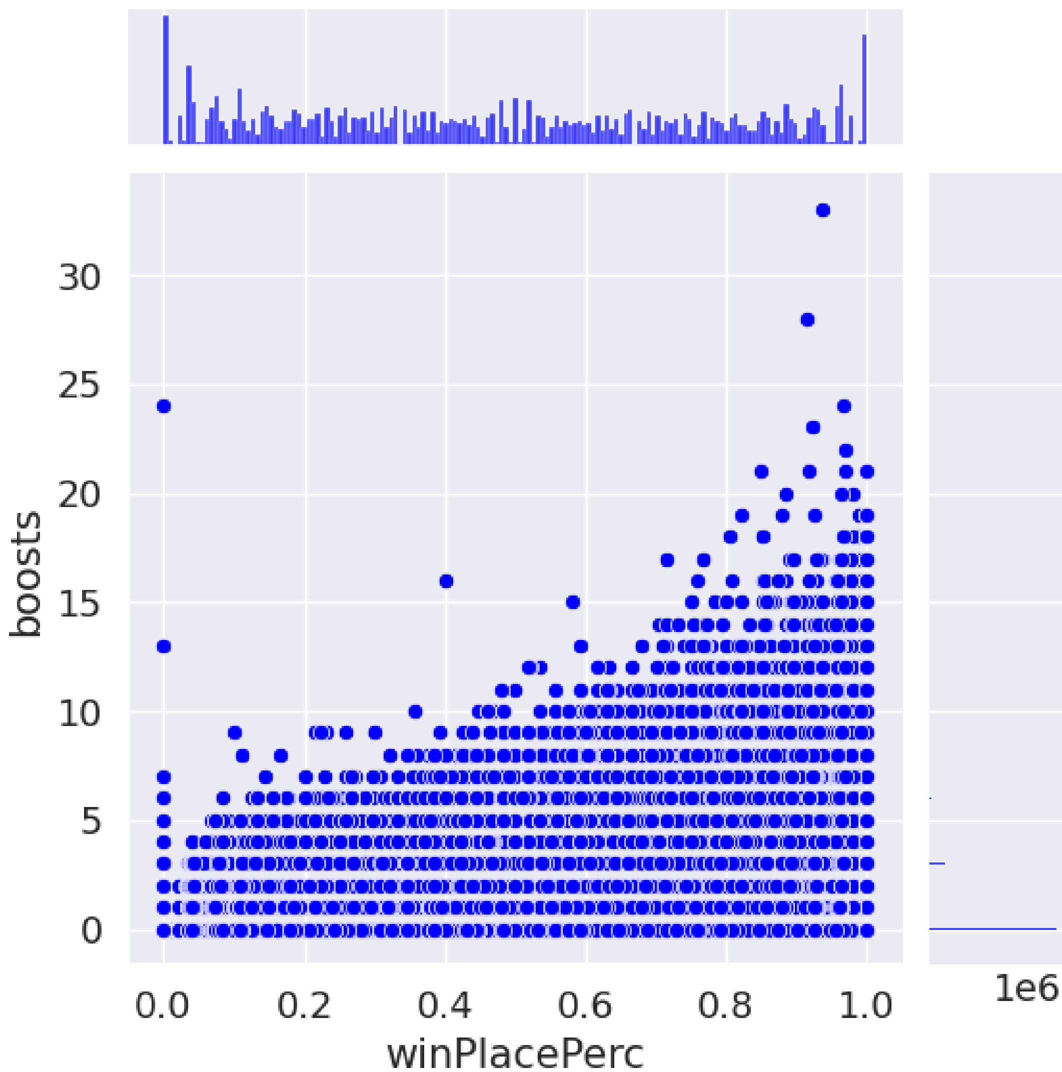


1.3.3 Boosts and heals importance

[ ]:
```
sns.jointplot(x='winPlacePerc', y='heals', data=df, color='green')
sns.jointplot(x='winPlacePerc', y='boosts', data=df, color='blue')
plt.show()
```



80
70
60
50
40
30
20
10
0
heals
0.0
0.2
0.4
0.6
0.8
1.0
winPlacePerc
1e6



1.4 New Features

We already created 'headshotPercentage' and 'totalDistance' features during cleaning stage.

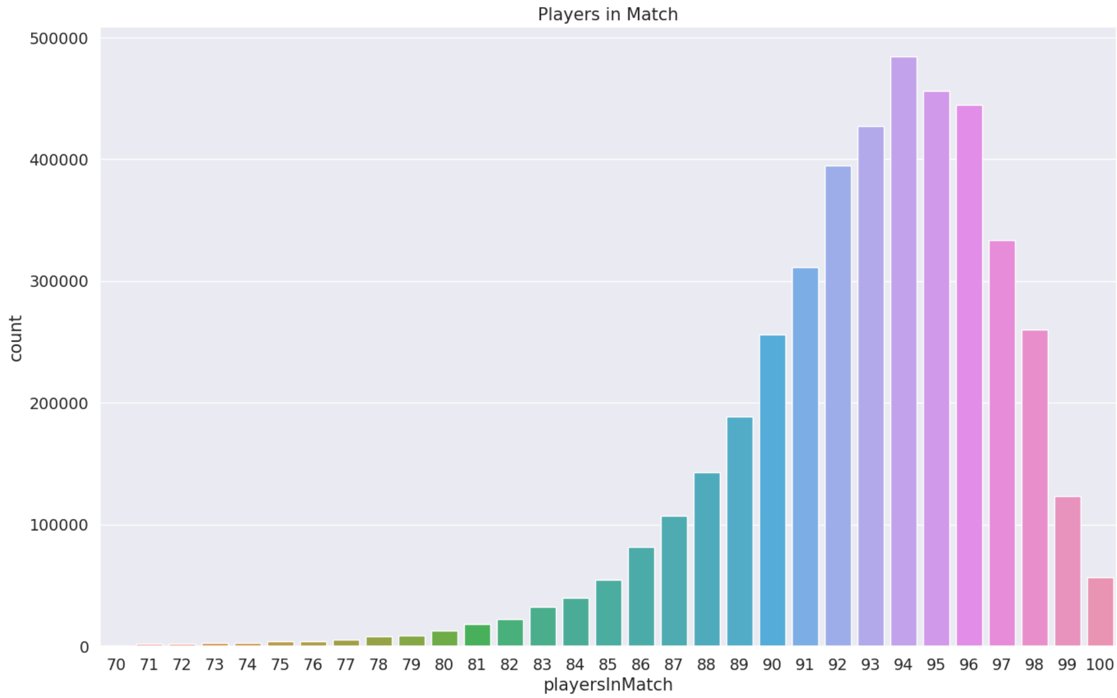
Now we will consider some other options.

1.4.1 Players in match

This features will let as know how many people are in a match. Thanks to that we can normalize some features.

[ ]:
```
df['playersInMatch'] = df.groupby('matchId')['matchId'].transform('count')
plt.figure(figsize=(16,10))
sns.countplot(x=df[df['playersInMatch']>=70]['playersInMatch'])
plt.title('Players in Match')
```

```
plt.show()
```



Most of the matches are nearly full.

Normalization Based on the "playersInMatch" feature we can create (or change) a lot of others to normalize their values. Since the number of players in game is not const and when there are 100players in the game it might be easier to find someone we can create the "killsNorm", "damageDealtNorm"

[ ]:
```
df['killsNorm'] = df['kills']*((100-df['playersInMatch'])/100 + 1)
df['damageDealtNorm'] = df['damageDealt']*((100-df['playersInMatch'])/100 + 1)
df['assistsNorm'] = df['assists']*((100-df['playersInMatch'])/100 + 1)
df['DBNOsNorm'] = df['DBNOs']*((100-df['playersInMatch'])/100 + 1)

df[['playersInMatch', 'kills', 'killsNorm', 'damageDealt', 'damageDealtNorm',␣
↪'assists', 'assistsNorm', 'DBNOs', 'DBNOsNorm']].head()
```

[ ]:
```
   playersInMatch  kills  killsNorm  damageDealt  damageDealtNorm  assists
assistsNorm  DBNOs  DBNOsNorm
0               94      0       0.00      0.00000         0.000000        0
0.00      0         0.0
1               90      0       0.00     91.50000       100.650000        0
0.00      0         0.0
2               93      0       0.00     68.00000        72.760000        1
1.07      0         0.0
```

```
3               91       0        0.00      32.90625         35.867812         0
0.00       0         0.0
4               94       1        1.06     100.00000        106.000000         0
0.00       0         0.0
```

1.4.2 Total Distance

[ ]:
```
df['totalDistance'] = df['rideDistance'] + df['swimDistance'] +␣
 ↪df['walkDistance']
df['totalDistance'].describe()
```

[ ]:
```
count    4.337412e+06
mean              NaN
std               NaN
min      1.000166e-04
25%      1.755000e+02
50%      8.560000e+02
75%      2.770000e+03
max      3.030400e+04
Name: totalDistance, dtype: float64
```

1.5 New Features Evaluation |For 21.04

We will create new features and analyze their impact. To do that we will create a simple linear model for each set of features and compare them.

[ ]:
```
from sklearn.linear_model import LinearRegression, Lasso, ElasticNet
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
 ↪explained_variance_score
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestRegressor
```

1.5.1 Linear Regression

[ ]:
```
results = []
def resultsAppend(name,val):
    results.append({'name': name, 'error': val} )
```

[ ]:
```
colsToDrop = ['Id','groupId','matchId','matchType']
colsNorm = ['killsNorm','damageDealtNorm','assistsNorm','DBNOsNorm']
colsNoNorm = ['kills', 'damageDealt','assists', 'DBNOs']
```

[ ]:
```
def scoreMetrices(true,predicted):
      return (mean_squared_error(true,predicted),)
```

```
[ ]: def tryDataLinear(data):
         random.seed(42)
         data_train,data_test = split_into_train_test_sets(data)
         data_train = data_train.drop(colsToDrop,axis=1)
         data_test = data_test.drop(colsToDrop,axis=1)

         model = LinearRegression(n_jobs=-1)
         model.fit(data_train.
      ↪drop(['winPlacePerc'],axis=1),data_train['winPlacePerc'])
         pred = model.predict(data_test.drop(['winPlacePerc'],axis=1))
         return scoreMetrices(data_test['winPlacePerc'],pred)
```

We are checking already added features.

```
[ ]: results = []
     resultsAppend('default', tryDataLinear(df[defaultCols]))
     resultsAppend('normalized w/', tryDataLinear(df[defaultCols + colsNorm]))
     resultsAppend('normalized w/o', tryDataLinear(df[defaultCols + colsNorm].
      ↪drop(colsNoNorm,axis=1)))
     resultsAppend('total distance', tryDataLinear(df[defaultCols +␣
      ↪['totalDistance']]))
     resultsAppend('hs percentage', tryDataLinear(df[defaultCols +␣
      ↪['headshotPercentage']]))
```

We are adding new features.

```
[ ]: df['items'] = df['heals'] + df['boosts']
     resultsAppend('items', tryDataLinear(df[defaultCols+['items']]))
```

```
[ ]: df['walkDistancePerKill'] = df['walkDistance'] / df['kills']
     df['walkDistancePerKill'].fillna(0, inplace=True)
     df['walkDistancePerKill'].replace(np.inf, 0, inplace=True)
     resultsAppend('walk dist per kill',␣
      ↪tryDataLinear(df[defaultCols+['walkDistancePerKill']]))
```

```
[ ]: resultsAppend('all', tryDataLinear(df))
```

```
[ ]: gc.collect()
     pd.DataFrame(results)
```

```
[ ]:                  name     error
     0             default  0.015742
     1       normalized w/  0.015623
     2      normalized w/o  0.015760
     3      total distance  0.015742
     4       hs percentage  0.015472
     5               items  0.015742
```

```
6  walk dist per kill  0.015717
7                 all  0.014732
```

We can see that all added features separately have little to no effect on MSE value but combined they decrease error value.

1.5.2 Random Forrest

We are going to create simple Random Forrest Regressor model on all added features and extract their importances.

```
[ ]: def tryDataRandomFor(data):
        random.seed(42)
        data_train,data_test = split_into_train_test_sets(data)
        data_train = data_train.drop(colsToDrop,axis=1)
        data_test = data_test.drop(colsToDrop,axis=1)

        model = RandomForestRegressor(max_depth=20, random_state = 123,␣
     ↪n_estimators=50,max_features='sqrt',verbose=1,n_jobs=-1)
        model.fit(data_train.
     ↪drop(['winPlacePerc'],axis=1),data_train['winPlacePerc'])
        print("ready, predicting...")
        pred = model.predict(data_test.drop(['winPlacePerc'],axis=1))
        gc.collect()
        print(model.feature_importances_)
        return scoreMetrices(data_test['winPlacePerc'],pred),model.
     ↪feature_importances_
```

```
[ ]: err, importances = tryDataRandomFor(df)
     err
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  2.2min finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
```

```
ready, predicting…
```

```
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    4.4s
[Parallel(n_jobs=4)]: Done  50 out of  50 | elapsed:    5.1s finished
```

```
[1.96188931e-03 9.49342500e-02 8.05289155e-03 1.63502346e-03
 9.24685222e-04 3.06395964e-02 2.07024049e-01 1.17194793e-03
 5.31039372e-03 2.56074178e-03 1.81659757e-02 1.54229028e-02
 8.48489584e-03 9.35906241e-03 2.18529340e-03 4.49193914e-04
 1.48008009e-02 3.14675069e-05 8.81232136e-04 1.81357033e-04
 5.72665215e-05 2.22661189e-01 6.45127010e-02 1.47509165e-03
 3.80463817e-03 6.97336086e-03 9.41051445e-03 1.15130708e-02
 1.87083502e-03 3.32803454e-03 1.58965349e-01 4.45503803e-02
```

```
4.66999179e-02]
```

[ ]: 0.007329174284615545

[ ]:
```
forest_importances = pd.DataFrame(importances, index = list(df.
↪drop(['winPlacePerc']+colsToDrop,axis=1).columns),columns=["importance"])

plt.figure(figsize=(12,12))
ax = sns.barplot(y =list(df.drop(['winPlacePerc']+colsToDrop,axis=1).columns),␣
↪x = importances)
plt.title('Feature importances from random forrest regression')
plt.show()
forest_importances.sort_values(by=['importance'],ascending=False)
```

[ ]:

	importance
walkDistance	0.222661
killPlace	0.207024
totalDistance	0.158965

```
boosts                 0.094934
weaponsAcquired        0.064513
walkDistancePerKill    0.046700
items                  0.044550
heals                  0.030640
longestKill            0.018166
matchDuration          0.015423
rideDistance           0.014801
damageDealtNorm        0.011513
killsNorm              0.009411
numGroups              0.009359
maxPlace               0.008485
damageDealt            0.008053
playersInMatch         0.006973
kills                  0.005310
headshotPercentage     0.003805
DBNOsNorm              0.003328
killStreaks            0.002561
rankPoints             0.002185
assists                0.001962
assistsNorm            0.001871
DBNOs                  0.001635
winPoints              0.001475
killPoints             0.001172
headshotKills          0.000925
swimDistance           0.000881
revives                0.000449
teamKills              0.000181
vehicleDestroys        0.000057
roadKills              0.000031
```

We can observe that normalized features have their importance almost twice as big as their unnormalized counterparts.

1.5.3 Multi-Layer Perceptron

We are adding a MLP model in order to check how well it performs compared to previously created models.

[ ]:
```
def tryDataMLP(data):
    random.seed(13)
    data_train,data_test = split_into_train_test_sets(data)
    data_train = data_train.drop(colsToDrop,axis=1)
    data_test = data_test.drop(colsToDrop,axis=1)

    model = MLPRegressor(hidden_layer_sizes=(100,50),verbose=True)
```

```
    model.fit(data_train.
↪drop(['winPlacePerc'],axis=1),data_train['winPlacePerc'])
    pred = model.predict(data_test.drop(['winPlacePerc'],axis=1))
    gc.collect()
    return scoreMetrices(data_test['winPlacePerc'],pred)
```

[ ]:
```
tryDataMLP(df)
```

```
Iteration 1, loss = 12.30300443
Iteration 2, loss = 0.44146175
Iteration 3, loss = 0.03553147
Iteration 4, loss = 0.00599401
Iteration 5, loss = 0.00521973
Iteration 6, loss = 0.00474776
Iteration 7, loss = 0.00444030
Iteration 8, loss = 0.00440045
Iteration 9, loss = 0.00439647
Iteration 10, loss = 0.00438827
Iteration 11, loss = 0.00438111
Iteration 12, loss = 0.00437673
Iteration 13, loss = 0.00437625
Iteration 14, loss = 0.00437320
Iteration 15, loss = 0.00437158
Iteration 16, loss = 0.00436945
Iteration 17, loss = 0.00437131
Iteration 18, loss = 0.00437096
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs.
Stopping.
```

[ ]: 0.008658087505028349

The MSE value is comparable to Random Forrest Regressor error value. We also checked wider and deeper MLP models but no significant decrease in error value was achived.

1.5.4 LightGBM | For 26.04

Next we will use tree based Light Gradient Boosting Machine model to see if we can still increase the performance.

LightGBM, unlike standard gradient boosting machines, uses growth in the vertical direction (leaf-wise) instead of growth in the horizontal direction (level-wise). Thanks to it model increases training speed and accuracy of received results for big volumes of data.

[ ]:
```
def tryDataLGBM(data):
    # random.seed(13)
    data_train, data_test = split_into_train_test_sets(data)
    data_train = data_train.drop(colsToDrop, axis=1)
    data_test = data_test.drop(colsToDrop, axis=1)
```

```
x_train = data_train.drop(['winPlacePerc'],axis=1)
y_train = data_train['winPlacePerc']
x_test = data_test.drop(['winPlacePerc'],axis=1)
y_test = data_test['winPlacePerc']

# laoding data
lgb_train = lgb.Dataset(x_train, y_train)
lgb_eval = lgb.Dataset(x_test, y_test, reference=lgb_train)

params = {
    'objective': 'regression',     # defines regression model
    'num_leaves': 50,              # max number of leafs in one tree
    'learning_rate': 0.03,         # shrinkage rate - rate of dropped trees
    'min_split_gain': 0.0001,      # min gain to perform split
    'bagging_fraction': 0.9,       # randomly select subset of features on␣
↪each iteration (without resampling)
    'min_data_in_leaf': 1000,      # min data in leaf
    'lambda_l2': 9,                # L2 regularization
    'metric': {'l2','l1'},         # list l1 (absolute loss) and l2 (square␣
↪loss) metrics
}

# fitting the model
# parameters:
# num_boost_round - maximum number of boosting iterations
# early_stopping - stopping after X iterations without notable increase
# log_evaluation - write down evaluation results every X iterations
model = lgb.train(params,
                  train_set=lgb_train,
                  valid_sets=lgb_eval,
                  num_boost_round = 1000,
                  callbacks=[lgb.early_stopping(stopping_rounds=30),
                            lgb.log_evaluation(period=100)])

# prediction
pred = model.predict(x_test)

# accuracy check
mse = mean_squared_error(y_test, pred)
rmse = mse**(0.5)
print("MSE: %.8f" % mse)
print("RMSE: %.8f" % rmse)

feature_importances_ = (model.feature_importance() / sum(model.
↪feature_importance()))
```

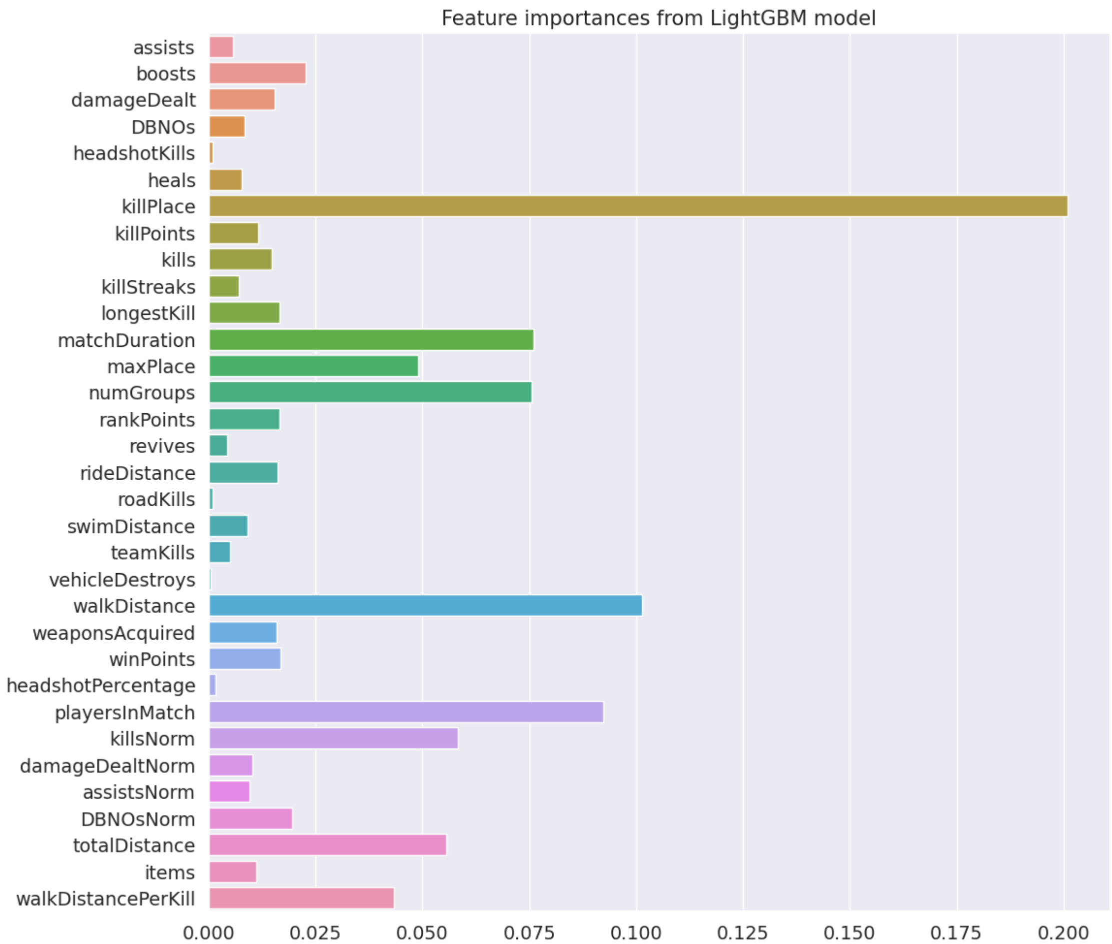
```
    return scoreMetrices(data_test['winPlacePerc'], pred), feature_importances_
```

[ ]:
```
err, importances = tryDataLGBM(df)
print("ERR: %f" % err)
```

```
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.240409 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 4510
[LightGBM] [Info] Number of data points in the train set: 3469771, number of
used features: 33
[LightGBM] [Info] Start training from score 0.482656
Training until validation scores don't improve for 30 rounds
[100]   valid_0's l1: 0.0652805 valid_0's l2: 0.00790295
[200]   valid_0's l1: 0.0587909 valid_0's l2: 0.00673547
[300]   valid_0's l1: 0.0574327 valid_0's l2: 0.00645155
[400]   valid_0's l1: 0.0568812 valid_0's l2: 0.00633338
[500]   valid_0's l1: 0.0565826 valid_0's l2: 0.00627215
[600]   valid_0's l1: 0.0563721 valid_0's l2: 0.00623257
[700]   valid_0's l1: 0.0562298 valid_0's l2: 0.00620531
[800]   valid_0's l1: 0.0561374 valid_0's l2: 0.00618638
[900]   valid_0's l1: 0.0560596 valid_0's l2: 0.00617229
[1000]  valid_0's l1: 0.0559976 valid_0's l2: 0.00616046
Did not meet early stopping. Best iteration is:
[1000]  valid_0's l1: 0.0559976 valid_0's l2: 0.00616046
MSE: 0.00616046
RMSE: 0.07848859
ERR: 0.006160
```

[ ]:
```
LGBM_importances = pd.DataFrame(importances, index = list(df.
 ↪drop(['winPlacePerc']+colsToDrop,axis=1).columns),columns=["importance"])

plt.figure(figsize=(12,12))
ax = sns.barplot(y =list(df.drop(['winPlacePerc']+colsToDrop,axis=1).columns),␣
 ↪x = importances)
plt.title('Feature importances from LightGBM model')
plt.show()
LGBM_importances.sort_values(by=['importance'],ascending=False)
```



[ ]:

	importance
killPlace	0.200878
walkDistance	0.101449
playersInMatch	0.092245
matchDuration	0.075959
numGroups	0.075571
killsNorm	0.058204
totalDistance	0.055571
maxPlace	0.049041
walkDistancePerKill	0.043245
boosts	0.022755
DBNOsNorm	0.019429
winPoints	0.016694
rankPoints	0.016612
longestKill	0.016490
rideDistance	0.016184
weaponsAcquired	0.015980
damageDealt	0.015367

```
kills                   0.014735
killPoints              0.011571
items                   0.011020
damageDealtNorm         0.010265
assistsNorm             0.009469
swimDistance            0.009041
DBNOs                   0.008347
heals                   0.007694
killStreaks             0.007061
assists                 0.005755
teamKills               0.005102
revives                 0.004388
headshotPercentage      0.001612
roadKills               0.001000
headshotKills           0.000816
vehicleDestroys         0.000449
```

1.5.5 Gradient Boost Regression Tree - GBRT

Gradient Boostred Regression Trees is a statistical learning technique. This section analyzes algorithm provided by sklearn library.

Model is defined in sklearn.tree namespace

[ ]:
```
from sklearn.tree import DecisionTreeRegressor
```

While defining model, only parameter that we provide is maximal depth of trees - we use 10, as it significantly improves accuracy of algorithm.

[ ]:
```
def tryDataGBRT(data):
    data_train,data_test = split_into_train_test_sets(data)
    data_train = data_train.drop(colsToDrop,axis=1)
    data_test = data_test.drop(colsToDrop,axis=1)
    model = DecisionTreeRegressor(max_depth=10)
    model.fit(data_train.
 ↪drop(['winPlacePerc'],axis=1),data_train['winPlacePerc'])
    pred = model.predict(data_test.drop(['winPlacePerc'],axis=1))
    gc.collect()
    return scoreMetrices(data_test['winPlacePerc'],pred)
```

This method has prediction accuracy around 99%

[ ]:
```
err = tryDataGBRT(df)
print("ERR: %f" % err)
```

```
ERR: 0.009002
```

1.5.6 XGboost

XGBoost is an open-source library providing implementation of gradient boosted decision trees algorithm. This library provies regression model, we will use model from scikit-learn wrapper classes.

First of all we need to import the necessary library and valid regression model from it

[ ]:
```
import xgboost
from xgboost import XGBRegressor
```

XGBRegressor is a class from scikit-learn, it is parameterizable. We specify the following parameters: - n_estimators: amount of trees used - 100 is optimal value, increase won't affect accuracy - max_depth: maximal depth of tree, biggest possible value is 10, we use 5 - eta: learnig rate, used to specify weight of models (- subsample: number of samples in a tree - we use 1 in order to use all samples - colsample_bytree - number of features in a tree - we use 1 to use all features

[ ]:
```
def tryDataXGBoost(data):
    data_train,data_test = split_into_train_test_sets(data)
    data_train = data_train.drop(colsToDrop,axis=1)
    data_test = data_test.drop(colsToDrop,axis=1)
    model = XGBRegressor(n_estimators=100, max_depth=5, eta=0.1, subsample=1,␣
 ↪colsample_bytree=1)
    model.fit(data_train.
 ↪drop(['winPlacePerc'],axis=1),data_train['winPlacePerc'])
    pred = model.predict(data_test.drop(['winPlacePerc'],axis=1))
    gc.collect()
    return scoreMetrices(data_test['winPlacePerc'],pred)
```

Now we train the model and predict the test set. This method is very accurate, its accuracy is more than 99%.

[ ]:
```
err = tryDataXGBoost(df)
print("ERR: %f" % err)
```

```
ERR: 0.006813
```

1.6 Conclusion

Summarising we collected all of the attained mean square errors for each model in a table below.

Metoda	Błąd średniokwadratowy
Multi-layer Perceptron	0.087
Gradient Boosted Regression Tree	0.0090
LightGBM	0.0062
XGboost	0.0068

As we can see we have achieved very precise results with an accuracy of 99%. The best models are LightGBM and XGboost.