DataAnalysis

April 26, 2022

1 PUBG Finish Placement Prediction

[1]:
```
# Imports
import sys
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import random
import gc

random.seed(16)
```

[2]:
```
# Read data to dataframe
df = pd.read_csv("data/train_V2.csv")
df_types = pd.read_csv("data/types.csv")
```

[3]:
```
# 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
```

[4]:
```
#center figures
from IPython.core.display import HTML
HTML("""
<style>
.output_png {
    display: table-cell;
    text-align: center;
    vertical-align: middle;
}
</style>
""")
```

[4]:
```
<IPython.core.display.HTML object>
```

[5]:
```
# 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
```

[6]:
```
# 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
```

[7]:
```
# 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
```

[8]:
```
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.

[9]:
```
df[df.isnull().any(axis=1)]
```

[9]:
```
                    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
```

[10]:
```
df = df[pd.notnull(df['winPlacePerc'])]
df[df.isnull().any(axis=1)]
```

[10]:
```
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.

[11]:
```
validStartCount = len(df)
validStartCount
```

[11]:
```
4446965
```

We have this many valid rows

1.1.2 Removing custom games

- flaretpp
- flarefpp
- crashtpp
- crashfpp

[12]:
```
df[(df['matchType'] == "flaretpp") |
   (df['matchType'] == "flarefpp") |
   (df['matchType'] == "crashtpp") |
   (df['matchType'] == "crashfpp")].head(5)
```

[12]:
```
                  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
```

[13]:
```
df.drop(df[(df['matchType'] == "flaretpp") |
           (df['matchType'] == "flarefpp") |
           (df['matchType'] == "crashtpp") |
```

```
            (df['matchType'] == "crashfpp")]
        .index, inplace=True)

customDropCount = len(df)
```

[14]:
```
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.

[15]:
```
df[df['walkDistance'] == 0].head(5)
```

[15]:

	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	0.000000	0	0	0.0
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	0.000000	0	847	0.0
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	0.000000	0	765	0.0
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	0.000000	0	1510	0.0
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	0.000000	0	0	0.0

```
0.0           0           0.0           0                 0           0.0
0           0       0.127686
```

[16]:
```
df.drop(df[df['walkDistance'] == 0].index, inplace=True)
noWalkDropCount = len(df)
```

[17]:
```
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

[18]:
```
df[['walkDistance', 'rideDistance', 'swimDistance']].describe()
```

[18]:

	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

[19]:
```
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)
```

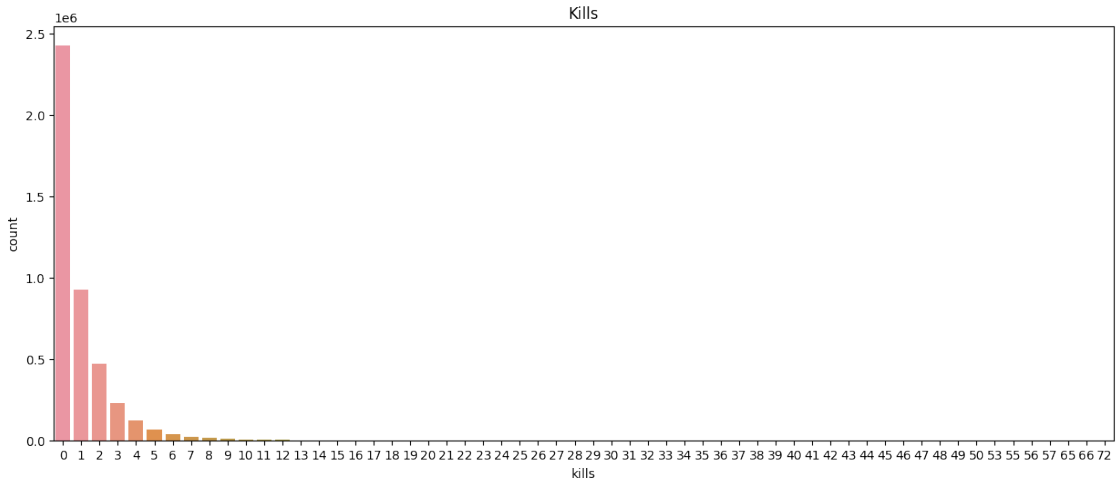
[20]:
```
print(potentialCheatsDropCount)
print("Dropped:", noWalkDropCount - potentialCheatsDropCount)
```

```
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.

[21]:
```
plt.figure(figsize=(15,6))
sns.countplot(data=df, x=df['kills']).set_title('Kills')
plt.show()
```



[22]:
```
display(df[df['kills'] > 40].shape)
```

```
(32, 29)
```

[23]:
```
df[df['kills'] >= 40].head(5)
```

[23]:

	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.

[24]:
```
df.drop(df[df['kills'] >= 40].index, inplace=True)
largeKillsDropCount = len(df)
```

[25]:
```
print(largeKillsDropCount)
print("Dropped:", potentialCheatsDropCount - largeKillsDropCount)
```

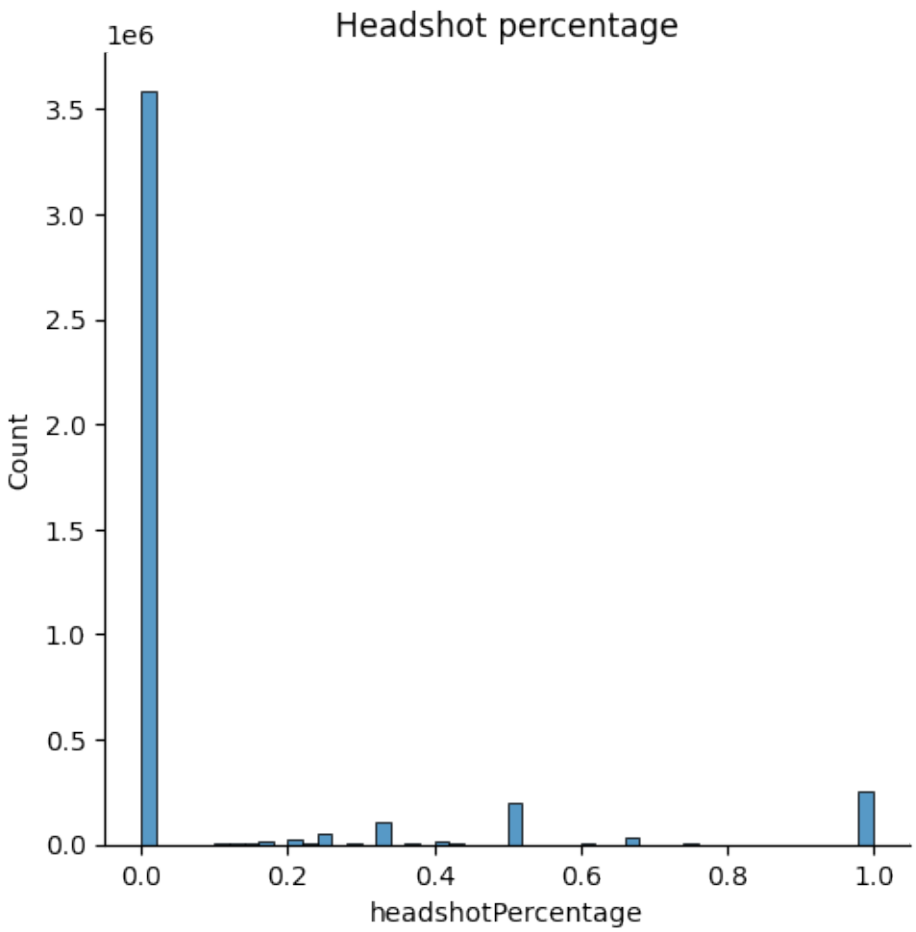
```
4337436
Dropped: 36
```

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

[26]:
```
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.

[27]:
```
df[(df['headshotKills'] == df['kills']) & (df['kills'] >= 10)].head(5)
```

[27]:
```
                    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
1535.0     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
```

[28]:
```
df.drop(df[(df['headshotKills'] == df['kills']) & (df['kills'] >= 10)].index,␣
↪inplace=True)
highHSrateDropCount = len(df)
```

[29]:
```
print(highHSrateDropCount)
print("Dropped:", largeKillsDropCount - highHSrateDropCount)
```

```
4337412
Dropped: 24
```

Altogether we dropped

[30]:
```
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

[31]:
```
df_train, df_test = split_into_train_test_sets(df, 0.2)
```

1.2.1 Train data

Brief look at the train data

[32]:
```
df_train.head()
```

[32]:
```
               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
```

[33]:
```
df_train.describe()
```

[33]:
```
            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

[34]:
```
df_test.head()
```

[34]:
```
                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
```

[35]:
```
df_test.describe()
```

[35]:
```
             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

[36]:
```
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.

[37]:
```
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

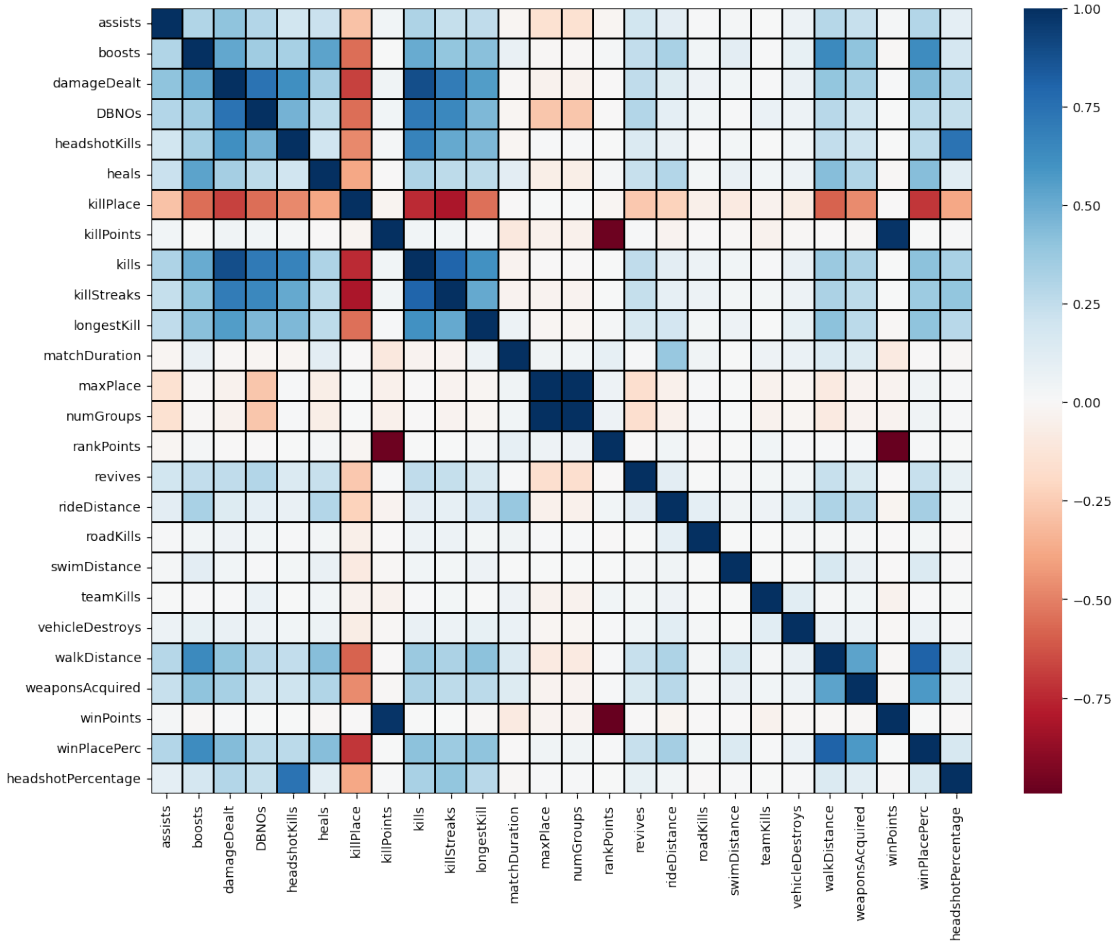
1.3.1 Correlation of feature

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

[38]:
```
# 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:

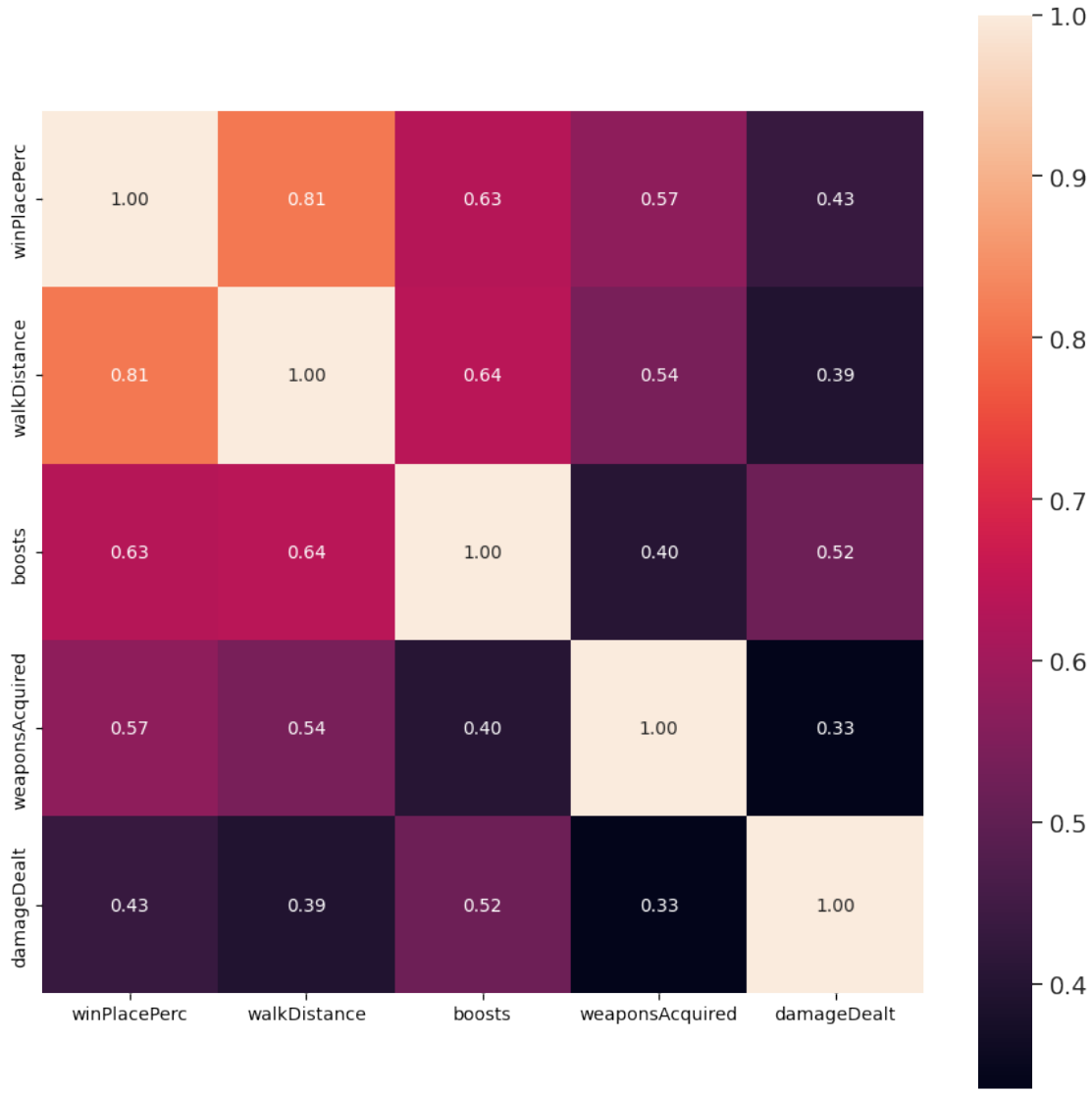
[39]:
```
corr_pairs = corr.unstack().sort_values(ascending=False).drop_duplicates()
corr_pairs[corr_pairs >= 0.45]
```

[39]:
```
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

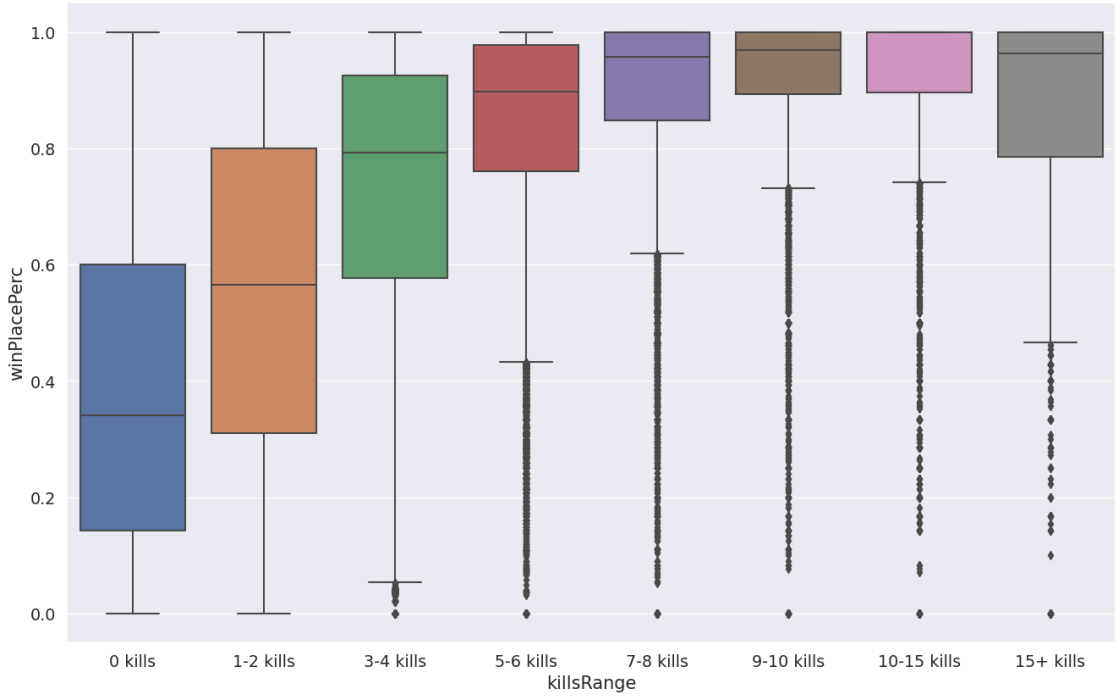
[40]:
```
f,ax = plt.subplots(figsize=(11, 11))
cols = df.corr().nlargest(5, 'winPlacePerc')['winPlacePerc'].index
cm = np.corrcoef(df[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f',␣
 ↪annot_kws={'size': 10}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```



1.3.2 Impactof kills made on final position

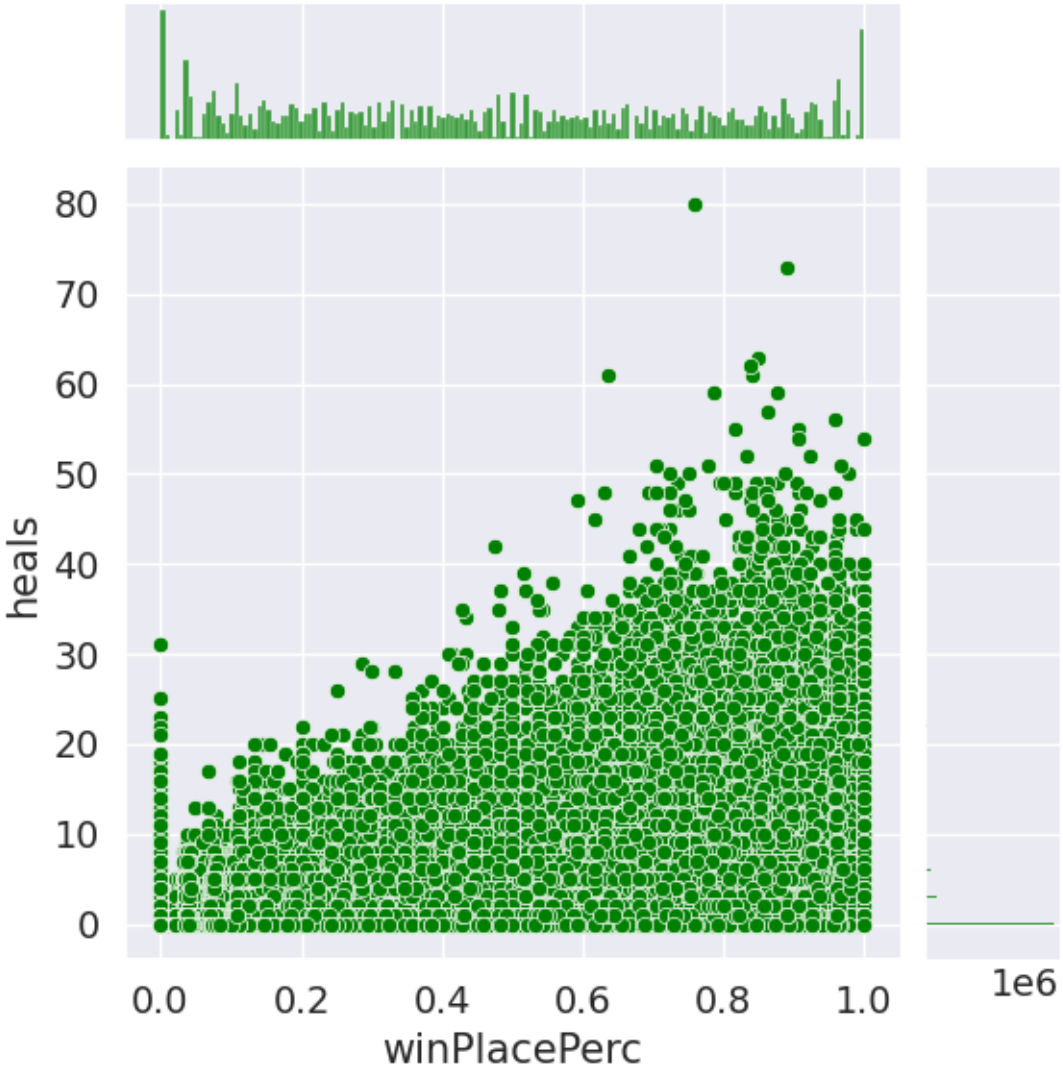
[ ]:

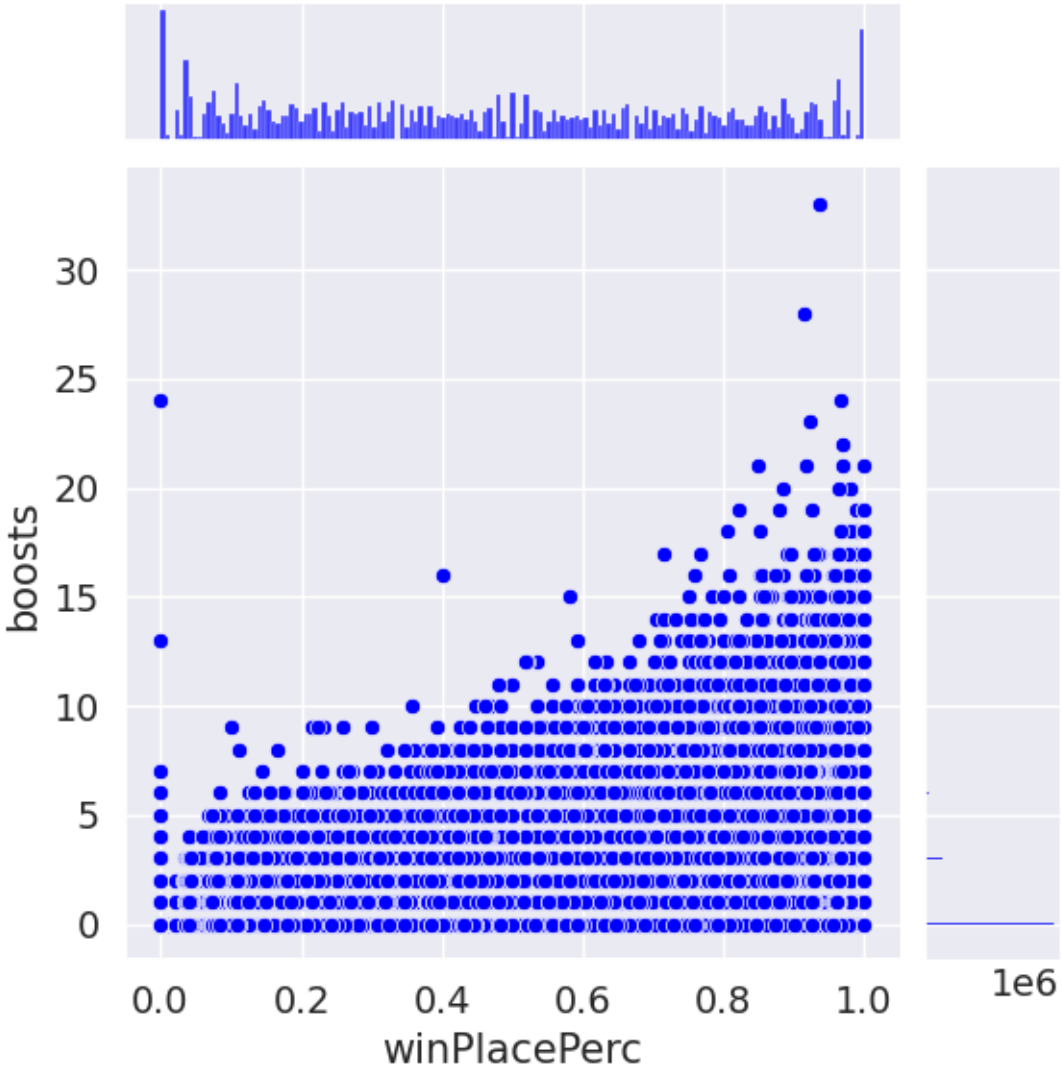
[41]:
```
df['killsRange'] = pd.cut(df['kills'], [-1, 0, 2, 4, 6, 8, 10, 15, 100],
                                        labels=['0 kills','1-2 kills', '3-4␣
 ↪kills', '5-6 kills',
                                                '7-8 kills', '9-10␣
 ↪kills','10-15 kills', '15+ kills'])
plt.figure(figsize=(16,10))
sns.boxplot(x='killsRange', y='winPlacePerc', data=df)
df.drop(['killsRange'],axis=1,inplace=True)
```



1.3.3 Boosts and heals importance

[42]:
```
sns.jointplot(x='winPlacePerc', y='heals', data=df, color='green')
sns.jointplot(x='winPlacePerc', y='boosts', data=df, color='blue')
plt.show()
```


heals
80
70
60
50
40
30
20
10
0
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.

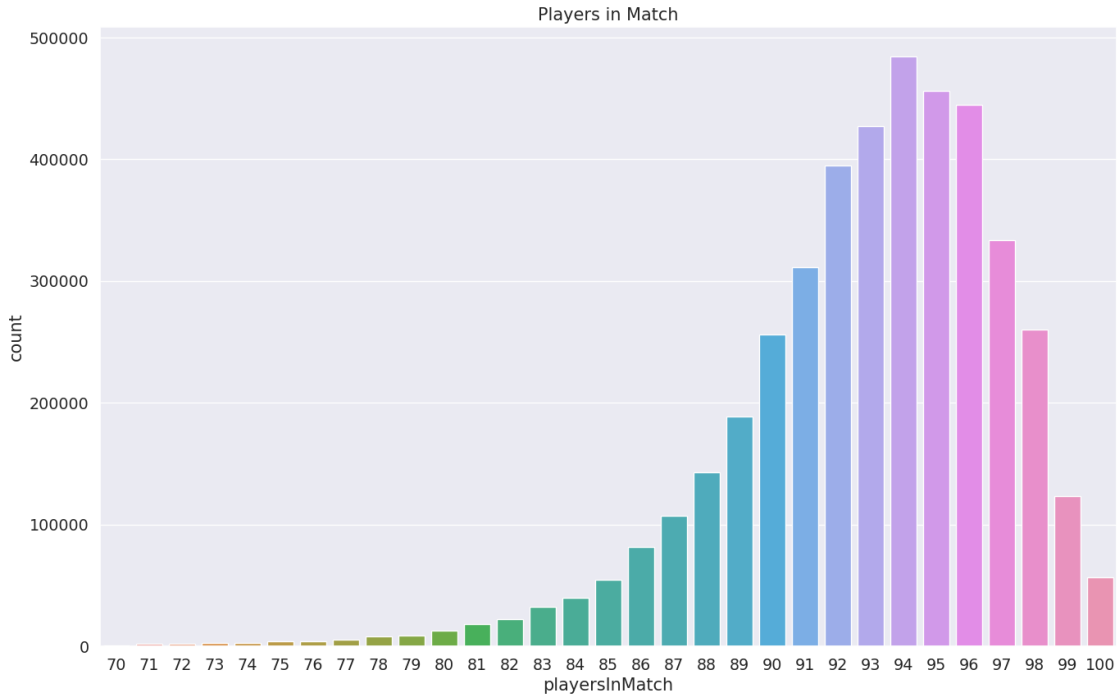
Now we will consider some other options.

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.

[43]:
```
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"

[44]:
```
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()
```

[44]:

	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

[45]:
```
df['totalDistance'] = df['rideDistance'] + df['swimDistance'] +␣
↪df['walkDistance']
df['totalDistance'].describe()
```

[45]:
```
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.

[46]:
```
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

[47]:
```
results = []
def resultsAppend(name,val):
    results.append({'name': name, 'error': val} )
```

[48]:
```
colsToDrop = ['Id','groupId','matchId','matchType']
colsNorm = ['killsNorm','damageDealtNorm','assistsNorm','DBNOsNorm']
colsNoNorm = ['kills', 'damageDealt','assists', 'DBNOs']
```

[49]:
```
def scoreMetrices(true,predicted):
      return mean_squared_error(true,predicted)
```

[50]:
```
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.

[51]:
```
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.

[52]:
```
df['items'] = df['heals'] + df['boosts']
resultsAppend('items', tryDataLinear(df[defaultCols+['items']]))
```

[53]:
```
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']]))
```

[54]:
```
resultsAppend('all', tryDataLinear(df))
```

[55]:
```
gc.collect()
pd.DataFrame(results)
```

[55]:

	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.

[56]:
```
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_
```

[57]:
```
err, importances = tryDataRandomFor(df)
err
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 3 concurrent workers.
[Parallel(n_jobs=-1)]: Done  44 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed:  2.9min finished
[Parallel(n_jobs=3)]: Using backend ThreadingBackend with 3 concurrent workers.
```

```
ready, predicting...
```

```
[Parallel(n_jobs=3)]: Done  44 tasks      | elapsed:    6.2s
[Parallel(n_jobs=3)]: Done  50 out of  50 | elapsed:    7.0s finished
```

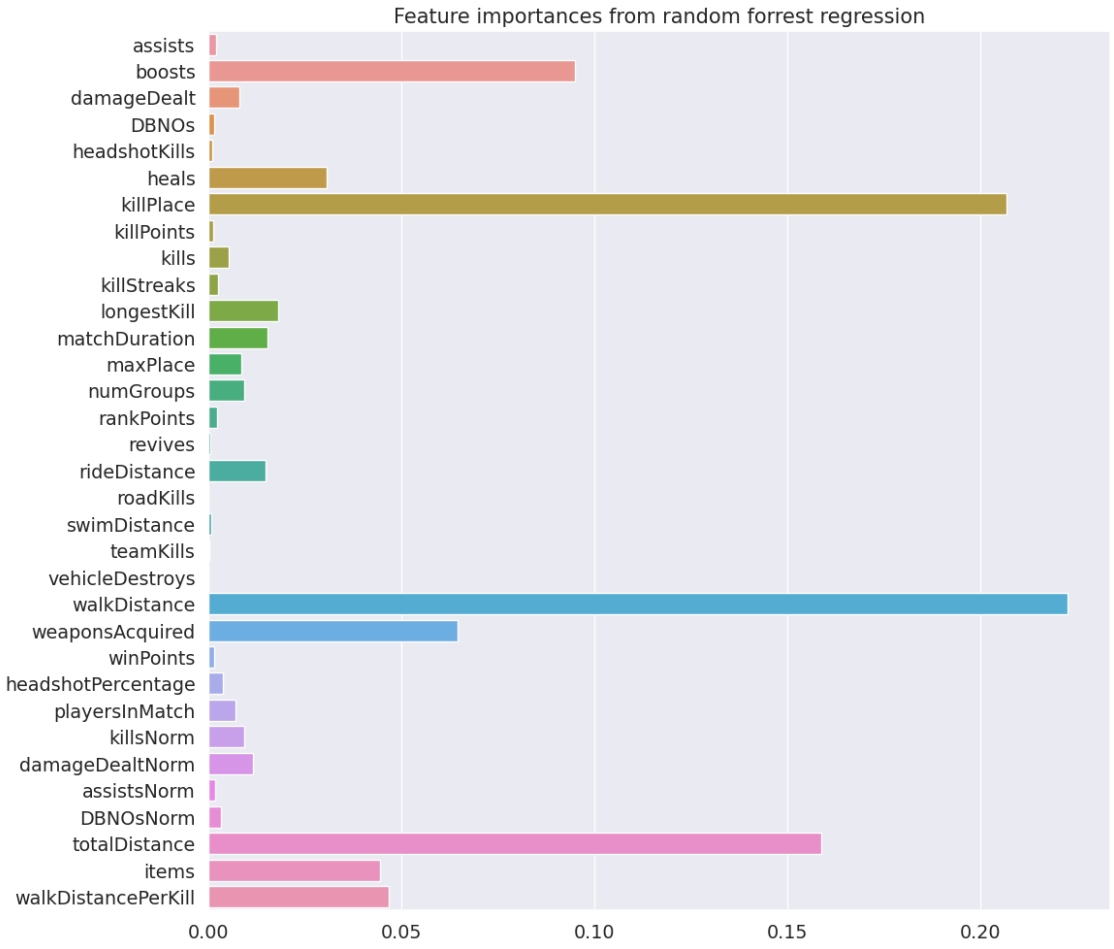
```
[1.96188931e-03 9.49342500e-02 8.05289155e-03 1.63502346e-03
 9.24685222e-04 3.06395964e-02 2.07024049e-01 1.17194793e-03
 5.31039372e-03 2.56074178e-03 1.81659757e-02 1.54229028e-02
 8.48489584e-03 9.35906241e-03 2.18529340e-03 4.49193914e-04
 1.48008009e-02 3.14675069e-05 8.81232136e-04 1.81357033e-04
 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]
```

[57]:
```
0.007329174284615545
```

[58]:
```
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)
```



[58]:

	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.

[59]:
```
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)
```

[60]:
```
tryDataMLP(df)
```

```
Iteration 1, loss = 13.65986295
Iteration 2, loss = 0.24759344
Iteration 3, loss = 0.02581661
Iteration 4, loss = 0.00623266
Iteration 5, loss = 0.00427271
Iteration 6, loss = 0.00396272
Iteration 7, loss = 0.00392776
Iteration 8, loss = 0.00385521
Iteration 9, loss = 0.00381902
Iteration 10, loss = 0.00378070
Iteration 11, loss = 0.00375663
Iteration 12, loss = 0.00374898
Iteration 13, loss = 0.00374274
Iteration 14, loss = 0.00373668
Iteration 15, loss = 0.00372678
Iteration 16, loss = 0.00371403
Iteration 17, loss = 0.00370302
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs.
Stopping.
```

[60]:
```
0.007185331653201 43
```

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.

[61]:
```
import sys
import gc
ipython_vars = ['In', 'Out', 'exit', 'quit', 'get_ipython', 'ipython_vars']
gc.collect()

# Get a sorted list of the objects and their sizes
sorted([(x, sys.getsizeof(globals().get(x))/1024/1024) for x in dir() if not x.
↪startswith('_') and x not in sys.modules and x not in ipython_vars],␣
↪key=lambda x: x[1], reverse=True)
```

[61]:
```
[('df', 1677.1969003677368),
 ('df_train', 1089.6036710739136),
 ('df_test', 272.4516773223877),
 ('corr_pairs', 0.008527755737304688),
```

```
('corr', 0.007859230041503906),
('df_types', 0.00635528564453125),
('forest_importances', 0.0023908615112304688),
('MLPRegressor', 0.00191497802734375),
('RandomForestRegressor', 0.00191497802734375),
('LinearRegression', 0.00140380859375),
('ElasticNet', 0.00101470947265625),
('GridSearchCV', 0.00101470947265625),
('HTML', 0.00101470947265625),
('Lasso', 0.00101470947265625),
('SelectFromModel', 0.00101470947265625),
('importances', 0.00035858154296875),
('cols', 0.00034046173095703125),
('cols_to_fit', 0.0003204345703125),
('cm', 0.00031280517578125),
('defaultCols', 0.000274658203125),
('cross_val_score', 0.00012969970703125),
('explained_variance_score', 0.00012969970703125),
('mean_absolute_error', 0.00012969970703125),
('mean_squared_error', 0.00012969970703125),
('reduce_mem_usage', 0.00012969970703125),
('resultsAppend', 0.00012969970703125),
('scoreMetrices', 0.00012969970703125),
('split_into_train_test_sets', 0.00012969970703125),
('tryDataLinear', 0.00012969970703125),
('tryDataMLP', 0.00012969970703125),
('tryDataRandomFor', 0.00012969970703125),
('results', 0.00011444091796875),
('colsNoNorm', 8.392333984375e-05),
('colsNorm', 8.392333984375e-05),
('colsToDrop', 8.392333984375e-05),
('cols_to_drop', 8.392333984375e-05),
('np', 6.866455078125e-05),
('pd', 6.866455078125e-05),
('plt', 6.866455078125e-05),
('sns', 6.866455078125e-05),
('ax', 4.57763671875e-05),
('f', 4.57763671875e-05),
('hm', 4.57763671875e-05),
('err', 3.0517578125e-05),
('customDropCount', 2.6702880859375e-05),
('highHSrateDropCount', 2.6702880859375e-05),
('largeKillsDropCount', 2.6702880859375e-05),
('noWalkDropCount', 2.6702880859375e-05),
('potentialCheatsDropCount', 2.6702880859375e-05),
('validStartCount', 2.6702880859375e-05)]
```

1.5.4 K-means

K means is a clustering algorithm. It allows to identify similar objects by grouping them together.

[62]:
```
def get(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 = KMeans(n_clusters=1000)

    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)
```

[63]:
```
def tryDataKmeans(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 = KMeans(n_clusters=1000)

    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)
```