Case Study on PUBG

Features (From kaggle)

PlayerUnknowns Battleground (Pubg) is a game where 100 playes drop onto a deserted island alone, with a partner, or with three others and seek to be the final one(s) standing. The goal is to predict the likelihood an individual will win based on a variety of statistics.

The features as taken from the compeition's data page is:

- **DBNOs** - Number of enemy players knocked.
- **assists** - Number of enemy players this player damaged that were killed by teammates.
- **boosts** - Number of boost items used.
- **damageDealt** - Total damage dealt. Note: Self inflicted damage is subtracted.
- **headshotKills** - Number of enemy players killed with headshots.
- **heals** - Number of healing items used.
- **Id** - Player's Id
- **killPlace** - Ranking in match of number of enemy players killed.
- **killPoints** - Kills-based external ranking of player. (Think of this as an Elo ranking where only kills matter.) If there is a value other than -1 in rankPoints, then any 0 in killPoints should be treated as a "None".
- **killStreaks** - Max number of enemy players killed in a short amount of time.
- **kills** - Number of enemy players killed.
- **longestKill** - Longest distance between player and player killed at time of death. This may be misleading, as downing a player and driving away may lead to a large longestKill stat.
- **matchDuration** - Duration of match in seconds.
- **matchId** - ID to identify match. There are no matches that are in both the training and testing set.
- **matchType** - String identifying the game mode that the data comes from. The standard modes are "solo", "duo", "squad", "solo-fpp", "duo-fpp", and "squad-fpp"; other modes are from events or custom matches.
- **rankPoints** - Elo-like ranking of player. This ranking is inconsistent and is being deprecated in the API's next version, so use with caution. Value of -1 takes place of "None".
- **revives** - Number of times this player revived teammates.
- **rideDistance** - Total distance traveled in vehicles measured in meters.
- **roadKills** - Number of kills while in a vehicle.
- **swimDistance** - Total distance traveled by swimming measured in meters.
- **teamKills** - Number of times this player killed a teammate.

- **vehicleDestroys** - Number of vehicles destroyed.
- **walkDistance** - Total distance traveled on foot measured in meters.
- **weaponsAcquired** - Number of weapons picked up.
- **winPoints** - Win-based external ranking of player. (Think of this as an Elo ranking where only winning matters.) If there is a value other than -1 in rankPoints, then any 0 in winPoints should be treated as a “None”.
- **groupId** - ID to identify a group within a match. If the same group of players plays in different matches, they will have a different groupId each time.
- **numGroups** - Number of groups we have data for in the match.
- **maxPlace** - Worst placement we have data for in the match. This may not match with numGroups, as sometimes the data skips over placements.
- **winPlacePerc** - The target of prediction. This is a percentile winning placement, where 1 corresponds to 1st place, and 0 corresponds to last place in the match. It is calculated off of maxPlace, not numGroups, so it is possible to have missing chunks in a match.

1 Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
import matplotlib.pyplot as plt
```

2 Reading data

In [2]:

```
train = pd.read_csv('train_V2.csv',nrows=500000)
```

In [3]:

```
train.head(5)
```

Out[3]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	revive
0	7f96b2f878858a	4d4b580de459be	a10357fd1a4a91	0	0	0.00	0	0	0	60	...	
1	eef90569b9d03c	684d5656442f9e	aeb375fc57110c	0	0	91.47	0	0	0	57	...	
2	1eaf90ac73de72	6a4a42c3245a74	110163d8bb94ae	1	0	68.00	0	0	0	47	...	
3	4616d365dd2853	a930a9c79cd721	f1f1f4ef412d7e	0	0	32.90	0	0	0	75	...	
4	315c96c26c9aac	de04010b3458dd	6dc8ff871e21e6	0	0	100.00	0	0	0	45	...	

5 rows × 29 columns

In [4]:

```
# Stats
train.describe()
```

Out[4]:

	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	killPoints	500
count	500000.000000	500000.000000	500000.000000	500000.000000	500000.000000	500000.000000	500000.000000	500000.000000	
mean	0.232488	1.109146	130.825331	0.657088	0.227080	1.368404	47.582600	507.064550	
std	0.587467	1.715940	171.117918	1.143812	0.600895	2.669700	27.467169	627.882529	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	24.000000	0.000000	

	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	killPoints
50%	0.000000	0.000000	84.580000	0.000000	0.000000	0.000000	47.000000	0.000000
75%	0.000000	2.000000	186.000000	1.000000	0.000000	2.000000	71.000000	1173.000000
max	21.000000	33.000000	6616.000000	32.000000	40.000000	52.000000	100.000000	2152.000000

8 rows × 25 columns

This kernel features:

- The Killers

```
- Kill without movement
- Road kils
- more than 30 kills
- 100% headshot
- longest kills
```

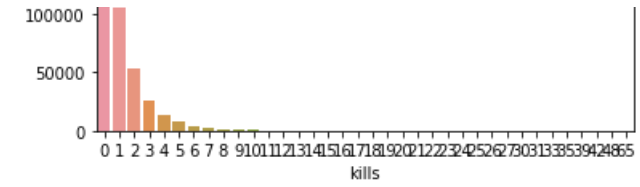
- walkDistance
- rideDistance
- swimDistance
- rideDistance
- Healers & Boosts
- weapons
- Solos, Duos and Squads

3. Data Exploration

3.1 The Killer

In [5]:

```
sns.countplot(train['kills']).set_title("Kills");
```



In [6]:

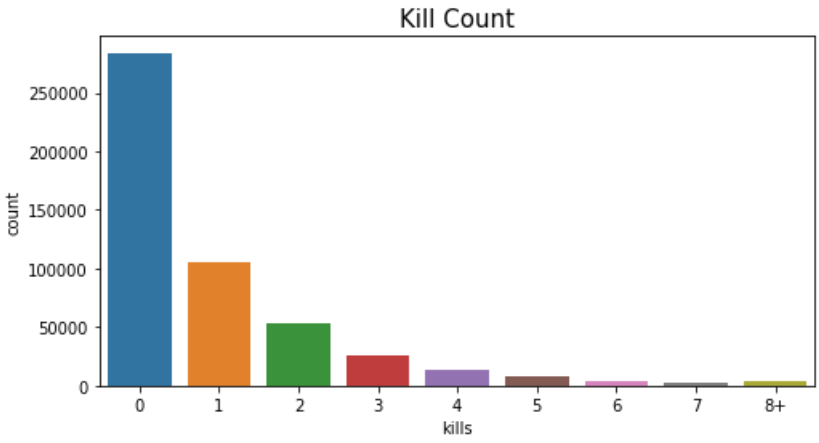
```
print("The average person kills {:.4f} players".format(train['kills'].mean()))

print("99% of people have {} kills or less".format(train['kills'].quantile(0.99)))

print("while the most kills ever recorded is {}.".format(train['kills'].max()))
```

```
The average person kills 0.9256 players
99% of people have 7.0 kills or less
while the most kills ever recorded is 65.
```

Let's plot the kill counts.

In [7]:

```
data = train.copy()
data.loc[data['kills'] > data['kills'].quantile(0.99)] = '8+'
plt.figure(figsize=(8,4))
sns.countplot(data['kills'].astype('str').sort_values())
plt.title("Kill Count",fontsize=15)
plt.show()
```



In [8]:

```
print("{} players ({:.4f}%) have won without a single kill!".format(len(data[data['winPlacePerc']==1]),
                                                                    100*len(data[data['winPlacePerc']==1])/len(train)))

data1 = train[train['damageDealt'] == 0].copy()

print("{} players ({:.4f}%) have won without dealing damage!".format(len(data1[data1['winPlacePerc']==1]),
                                                                    100*len(data1[data1['winPlacePerc']==1])/len(train)))
```

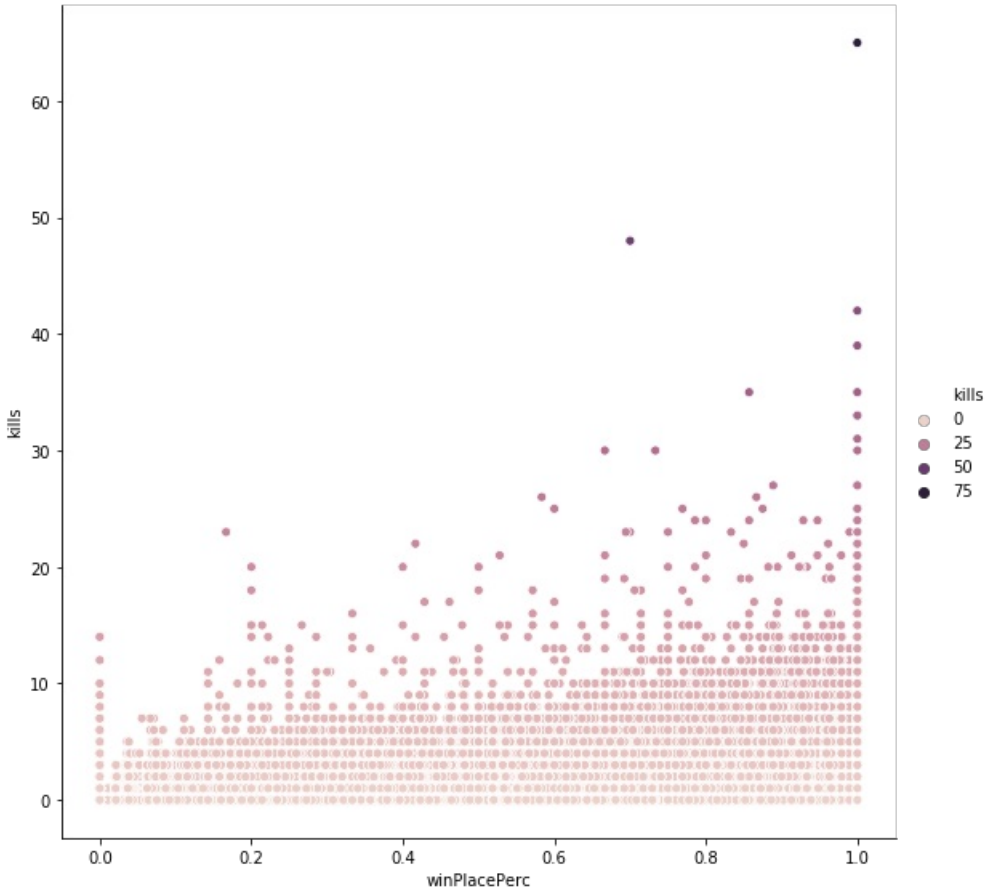
```
12689 players (2.5378%) have won without a single kill!
537 players (0.1074%) have won without dealing damage!
```

Plot win placement percentage vs kills.

In [9]:

```
sns.relplot(x="winPlacePerc", y="kills", data=train, hue='kills', height=8)
```

```
plt.show()
```



These things help from removing cheating players

In [10]:

```
# Create feature totalDistance
train['totalDistance'] = train['rideDistance'] + train['walkDistance'] + train['swimDistance']
# Create feature killsWithoutMoving
train['killsWithoutMoving'] = ((train['kills'] > 0) & (train['totalDistance'] == 0))
```

In [11]:

```
# Create headshot_rate feature
train['headshot_rate'] = train['headshotKills'] / train['kills']
train['headshot_rate'] = train['headshot_rate'].fillna(0)
```

Outlier Detection

3.1.2 Kills without movement

This is perhaps the most obvious sign of cheating in the game. It is already fishy if a player hasn't moved during the whole game, but the player could be AFK and got killed. However, if the player managed to get kills without moving it is most likely a cheater.

In [12]:

```
# Check players who kills without moving
display(train[train['killsWithoutMoving'] == True].shape)
train[train['killsWithoutMoving'] == True].head(5)
```

(179, 32)

(179, 32)

Out[12]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	s
1824	b538d514ef2476	0eb2ce2f43f9d6	35e7d750e442e2	0	0	593.0	0	0	3	18	...	
6673	6d3a61da07b7cb	2d8119b1544f87	904cecf36217df	2	0	346.6	0	0	6	33	...	
11892	550398a8f33db7	c3fd0e2abab0af	db6f6d1f0d4904	2	0	1750.0	0	4	5	3	...	
14631	58d690ee461e9d	ea5b6630b33d67	dbf34301df5e53	0	0	157.8	0	0	0	69	...	
15591	49b61fc963d632	0f5c5f19d9cc21	904cecf36217df	0	0	100.0	0	1	0	37	...	

5 rows × 32 columns

In [13]:

```
# Remove outliers
train.drop(train[train['killsWithoutMoving'] == True].index, inplace=True)
```

3.1.3 Roadkills Outliers detection

In [14]:

```
# Players who got more than 10 roadKills
train[train['roadKills'] > 10]
```

Out[14]:

Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	swimDistance	teamKills	vehicleDes

0 rows × 32 columns

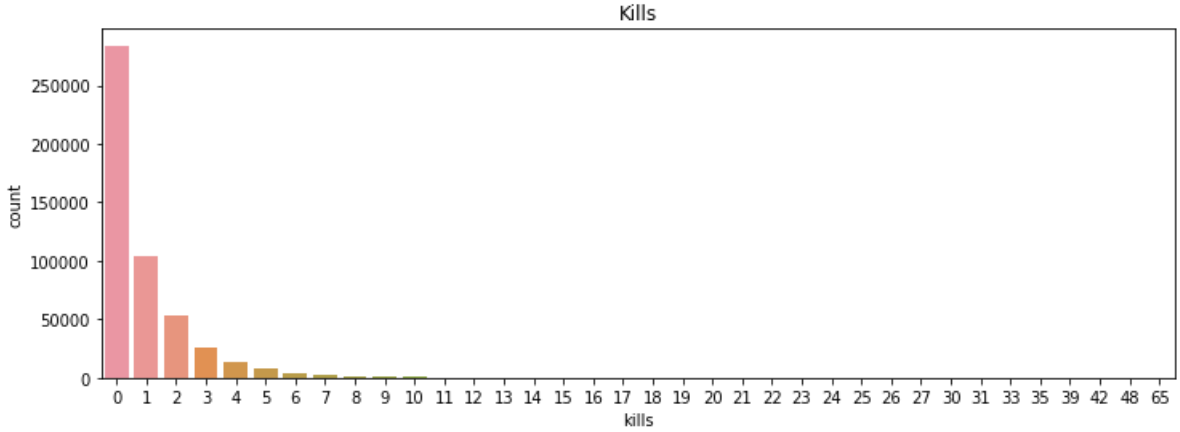
In [15]:

```
# Drop roadKill 'cheaters'
train.drop(train[train['roadKills'] > 10].index, inplace=True)
```

3.1.4 More than 30 kills Outliers detection

In [16]:

```
# Plot the distribution of kills
plt.figure(figsize=(12,4))
sns.countplot(data=train, x=train['kills']).set_title('Kills')
plt.show()
```



In [17]:

```
# Players who got more than 30 kills
display(train[train['kills'] > 30].shape)
train[train['kills'] > 30].head(10)
```

(9, 32)

Out[17]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...
57978	9d8253e21ccbbd	ef7135ed856cd8	37f05e2a01015f	9	0	3725.0	0	7	0	2	...
87793	45f76442384931	b3627758941d34	37f05e2a01015f	8	0	3087.0	0	8	27	3	...
156599	746aa7eabf7c86	5723e7d8250da3	f900de1ec39fa5	21	0	5479.0	0	12	7	4	...
160254	15622257cb44e2	1a513eeecfe724	db413c7c48292c	1	0	4033.0	0	40	0	1	...
180189	1355613d43e2d0	f863cd38c61dbf	39c442628f5df5	5	0	3171.0	0	6	15	1	...
334400	810f2379261545	7f3e493ee71534	f900de1ec39fa5	20	0	6616.0	0	13	5	1	...
353128	f3e9746e3ff151	4bc1f00f07b304	a9e84c456cc859	2	0	3834.0	0	9	5	1	...
457829	265e23756baa0b	9d94424171c2a1	664dee9ed8f646	3	0	2907.0	0	27	2	1	...
488335	31a0682922ef45	275a27a3ee4cc8	3037f74ef8a3a3	2	0	3055.0	0	9	0	1	...

9 rows × 32 columns

In [18]:

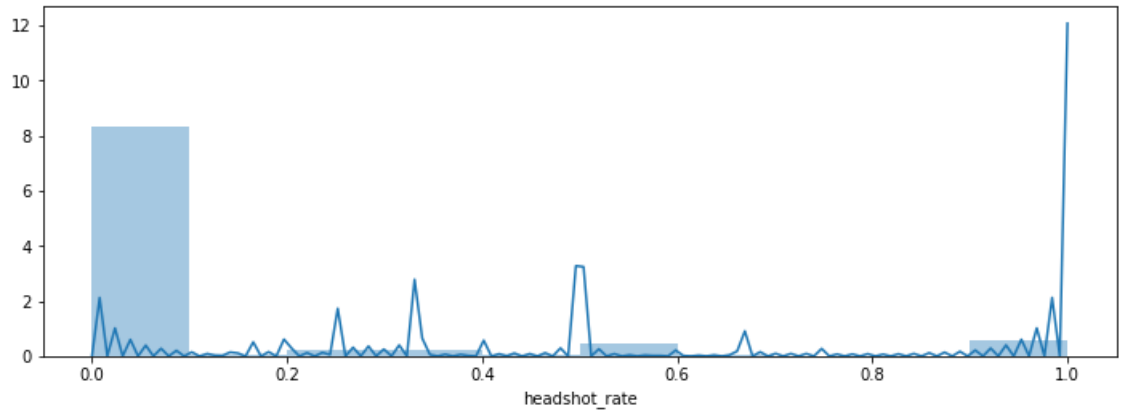
```
# Remove outliers
train.drop(train[train['kills'] > 30].index, inplace=True)
```

3.1.5 100% headshot rate Outliers detection

Again, we first take a look at the whole dataset and create a new feature 'headshot_rate'. We see that the most players score in the 0 to 10% region. However, there are a few anomalies that have a headshot_rate of 100% percent with more than 9 kills!

In [19]:

```
# Plot the distribution of headshot_rate
plt.figure(figsize=(12,4))
sns.distplot(train['headshot_rate'], bins=10)
plt.show()
```



In [20]:

```
# Players who made a minimum of 10 kills and have a headshot_rate of 100%
display(train[(train['headshot_rate'] == 1) & (train['kills'] > 9)].shape)
train[(train['headshot_rate'] == 1) & (train['kills'] > 9)].head(10)
```

(2, 32)

(2, 32)

Out[20]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...
281570	ab9d7168570927	add05ebde0214c	e016a873339c7b	2	3	1212.0	8	10	0	1	...
346124	044d18fc42fc75	fc1dbc2df6a887	628107d4c41084	3	5	1620.0	13	11	3	1	...

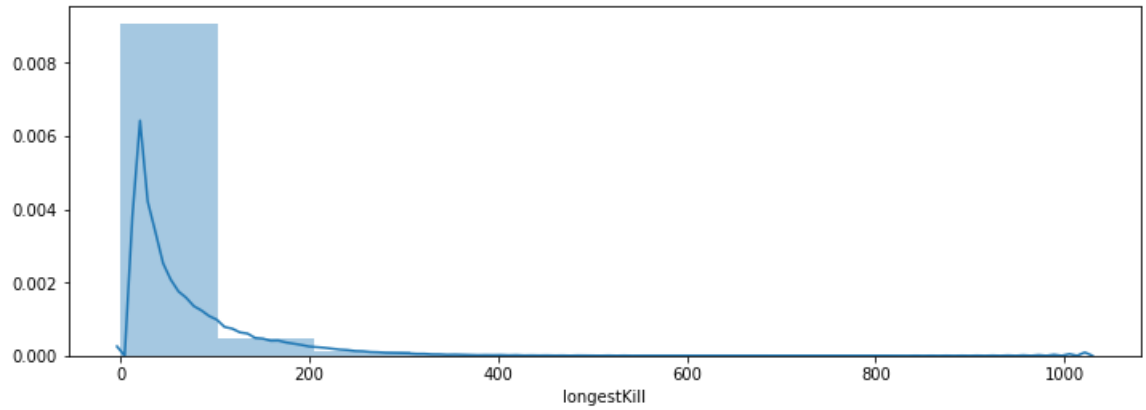
2 rows × 32 columns

3.1.6 Longest kill

Most kills are made from a distance of 100 meters or closer. There are however some outliers who make a kill from more than 1km away. This is probably done by cheaters.

In [21]:

```
# Plot the distribution of longestKill
plt.figure(figsize=(12,4))
sns.distplot(train['longestKill'], bins=10)
plt.show()
```



Let's take a look at the players who make these shots.

In [22]:

```
# Check out players who made kills with a distance of more than 1 km
display(train[train['longestKill'] >= 1000].shape)
train[train['longestKill'] >= 1000].head(10)
```

(3, 32)

Out[22]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...
202281	88e2af7d78af5a	34ddeede52c042	4346bc63bc67fa	0	3	783.9	5	1	1	5	...
240005	41c2f5c0699807	9faecf87ab4275	634edab75860b3	5	0	1284.0	8	5	7	18	...
324313	ef390c152bcc3d	30fd444be3bbc1	4f7f8d6cf558b4	2	0	1028.0	0	0	0	9	...

3 rows × 32 columns

In [23]:

```
# Remove outliers
train.drop(train[train['longestKill'] >= 1000].index, inplace=True)
```

3.2 walkDistance

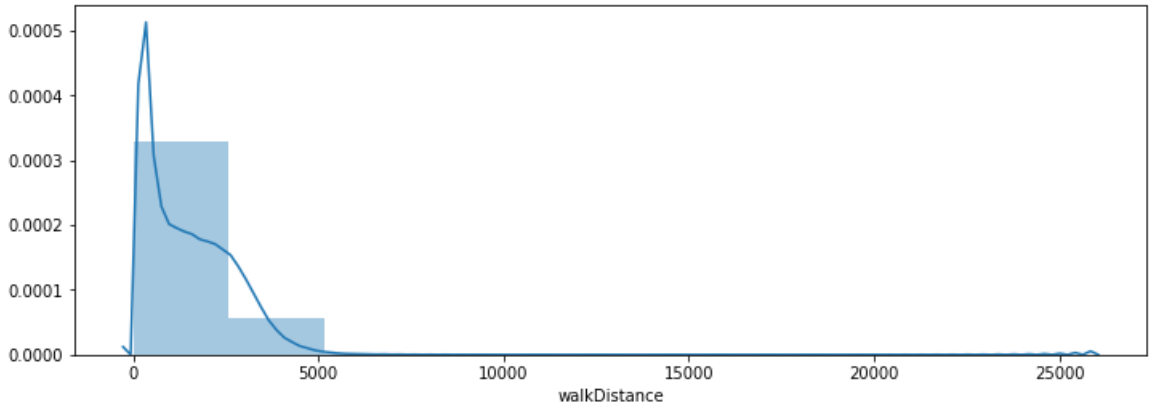
In [24]:

```
print("The average person walks for {:.1f}m".format(train['walkDistance'].mean()))

print("99% of people have walked {}m or less".format(train['walkDistance'].quantile(0.99)))

print("while the marathoner champion walked for {}m.".format(train['walkDistance'].max()))
```

```
The average person walks for 1155.5m
99% of people have walked 4397.0m or less
while the marathoner champion walked for 25780.0m.
```

In [25]:

```
# Plot the distribution of walkDistance
plt.figure(figsize=(12,4))
sns.distplot(train['walkDistance'], bins=10)
plt.show()
```



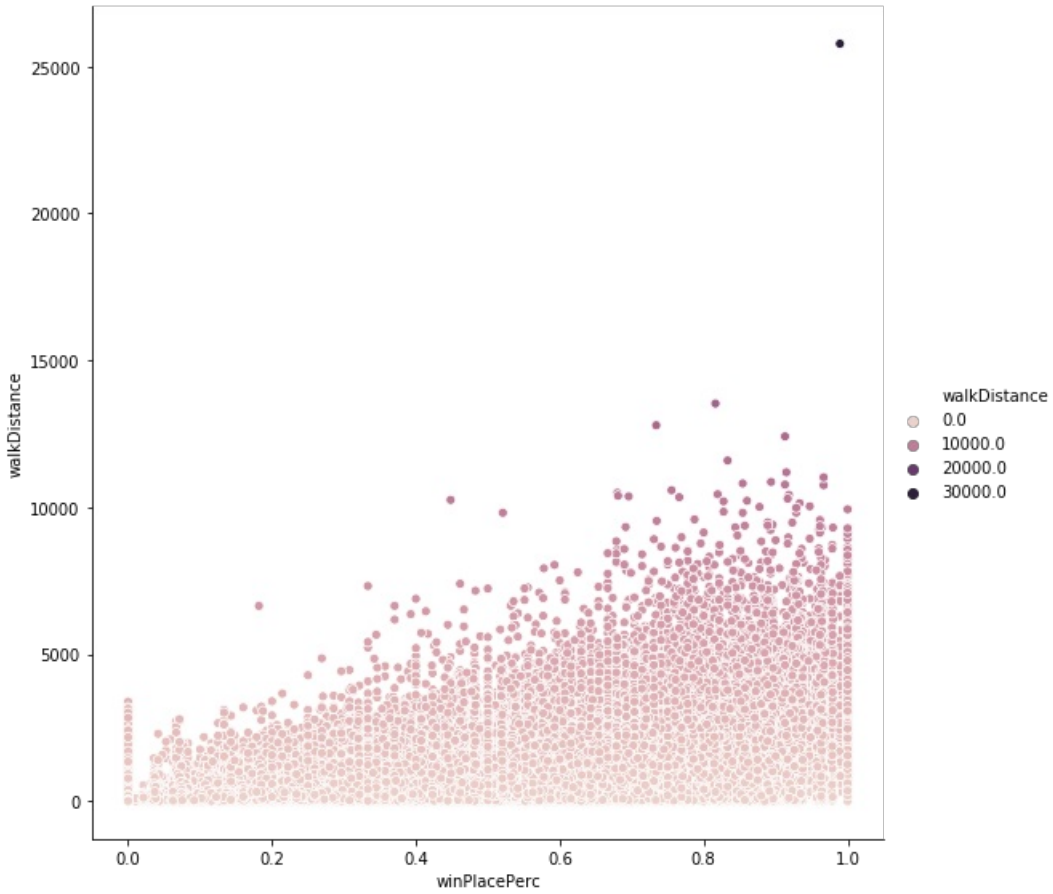
In [26]:

```
print("{} players ({:.4f}%) walked 0 meters.".format(len(data[data['walkDistance'] == 0]), 100*len(
data1[data1['walkDistance']==0])/len(train)))

print("This means that they die before even taking a step or they are afk (more possible)")
```

```
10988 players (2.0022%) walked 0 meters.
This means that they die before even taking a step or they are afk (more possible)
```

In [27]:

```
sns.relplot(x="winPlacePerc", y="walkDistance",  data=train,hue="walkDistance", height=8)
plt.show()
```



Apparently walking has a high correlation with winPlacePerc.

3.2.1 Outliers

In [28]:

```
# walkDistance anomalies
display(train[train['walkDistance'] >= 10000].shape)
train[train['walkDistance'] >= 10000].head(10)
```

```
(25, 32)
```

Out[28]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...
23026	8a6562381dd83f	23e638cd6eaf77	b0a804a610e9b0	0	1	0.00	0	0	0	44	...
34344	5a591ecc957393	6717370b51c247	a15d93e7165b05	0	3	23.22	0	0	1	34	...
49312	582685f487f0b4	338112cd12f1e7	d0afbf5c3a6dc9	0	4	117.20	1	0	1	24	...
68590	8c0d9dd0b4463c	c963553dc937e9	926681ea721a47	0	1	32.34	0	0	1	46	...
94400	d441bebd01db61	7e179b3366adb8	923b57b8b834cc	1	1	73.08	0	0	3	27	...
125103	db5a0cdc969dcb	50cc466757950e	c306a9745c4c1d	0	4	37.73	0	0	7	47	...
136421	955e60b09a96b1	30df08fe22a901	8669d01725f135	0	1	0.00	0	0	1	46	...
136476	0d75d05b5c988c	3da040ce77cd0b	65bc5211a569dd	0	3	0.00	0	0	0	41	...
154080	7e8a71d23381cd	e2c9f4f92840b2	a721de1aa05408	0	3	0.00	0	0	13	46	...
154128	32fdde4c716787	390ae9a51c11b8	82610ed1b4d033	0	4	52.16	0	0	7	25	

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...

10 rows × 32 columns

In [29]:

```
# Remove outliers
train.drop(train[train['walkDistance'] >= 10000].index, inplace=True)
```

3.3 rideDistance

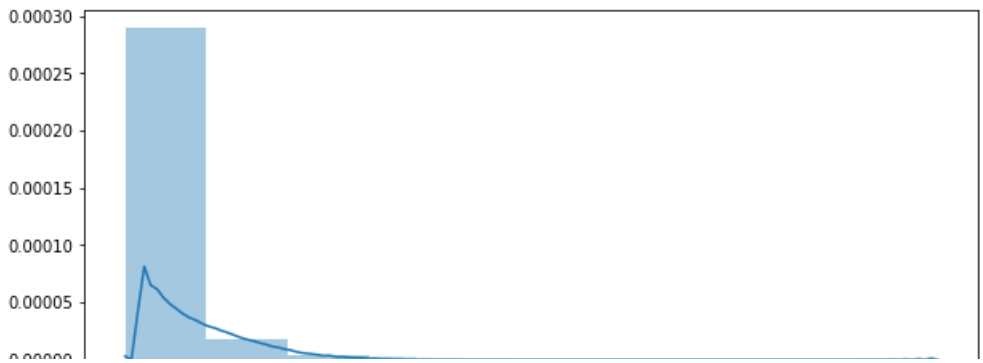
In [30]:

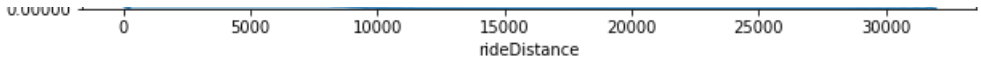
```
print("The average person drives for {:.1f}m".format(train['rideDistance'].mean()))

print("99% of people have drived {}m or less".format(train['rideDistance'].quantile(0.99)))

print("while the formula 1 champion drived for {}m.".format(train['rideDistance'].max()))
```

```
The average person drives for 605.9m
99% of people have drived 6925.0m or less
while the formula 1 champion drived for 31960.0m.
```

In [31]:

```
# Plot the distribution of rideDistance
plt.figure(figsize=(10,4))
sns.distplot(train['rideDistance'], bins=10)
plt.show()
```





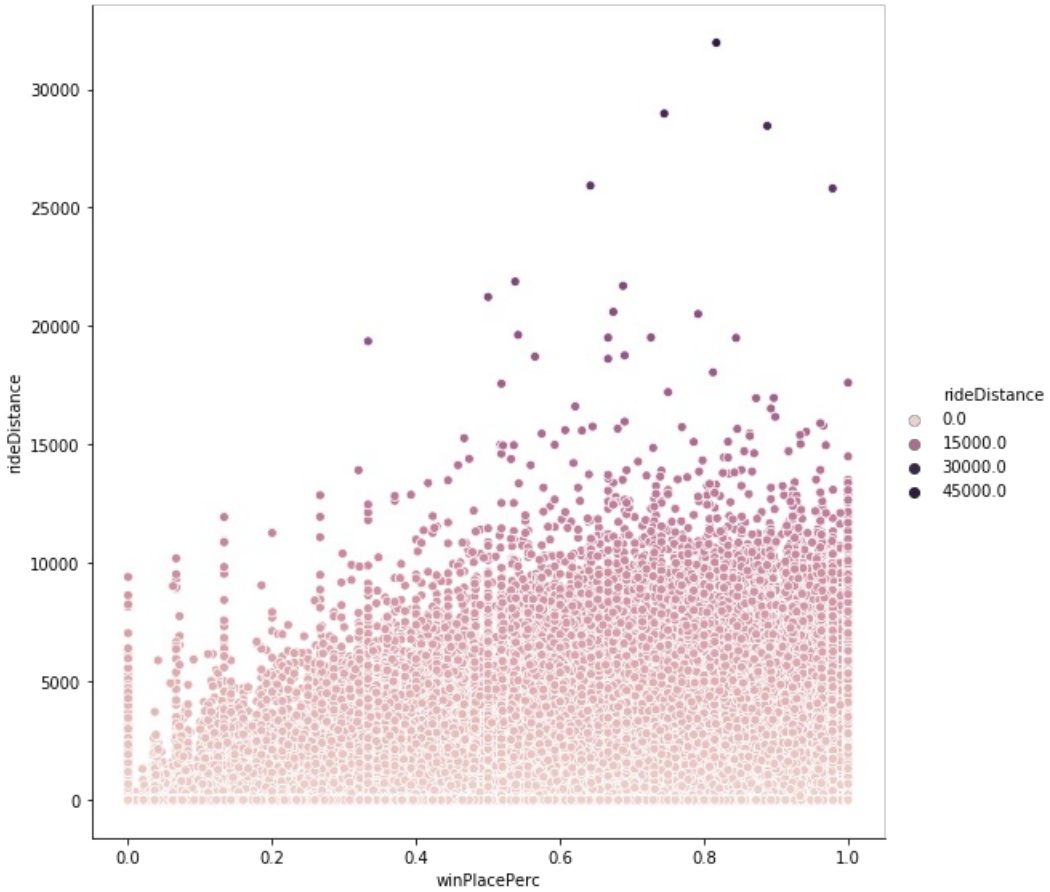
In [32]:

```
print("{} players ({:.4f}%) drived for 0 meters.".format(len(data[data['rideDistance'] == 0]),
                                                         100*len(data1[data1['rideDistance']==0])/l
(train)))

print("This means that they don't have a driving licence yet.")
```

```
370124 players (23.1538%) drived for 0 meters.
This means that they don't have a driving licence yet.
```

In [33]:

```
sns.relplot(x="winPlacePerc", y="rideDistance", data=train,hue="rideDistance", height=8)
plt.show()
```

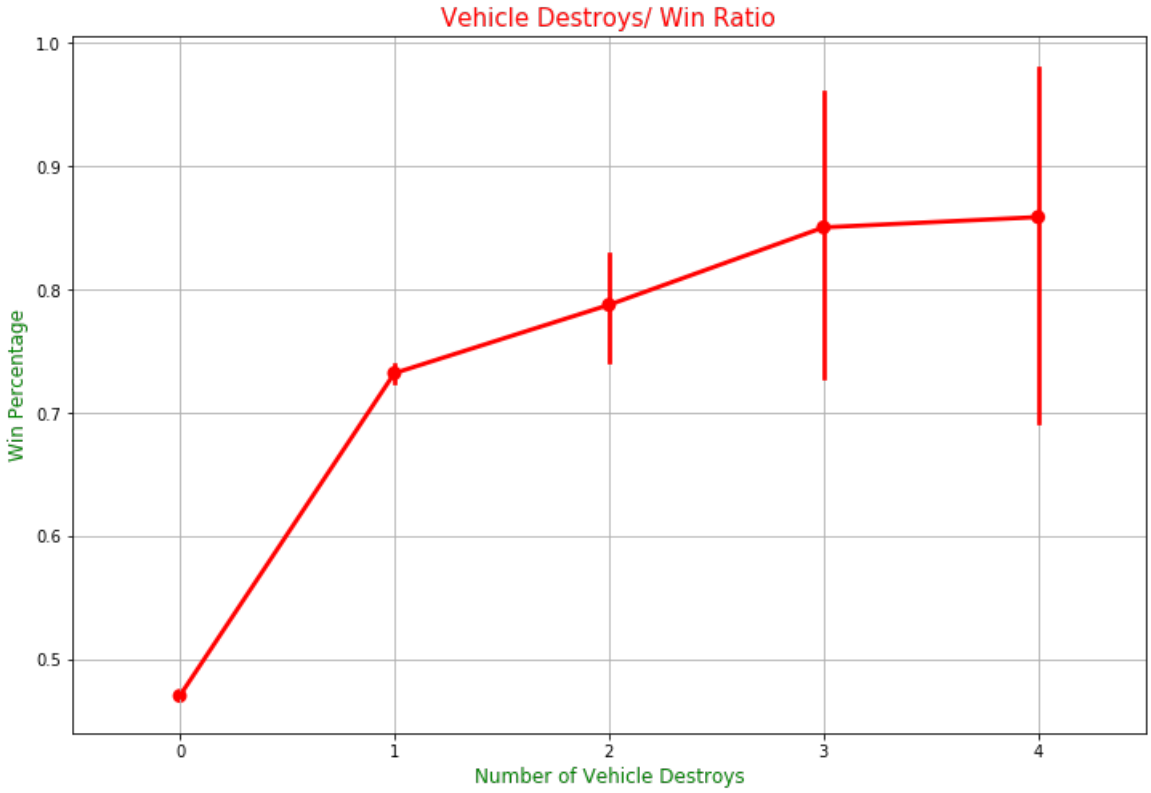


There is a small correlation between rideDistance and winPlacePerc.

Destroying a vehicle in my experience shows that a player has skills.

In [34]:

```
f,ax1 = plt.subplots(figsize =(12,8))

sns.pointplot(x='vehicleDestroys',y='winPlacePerc',data=train,color='red',alpha=0.8)

plt.xlabel('Number of Vehicle Destroys',fontsize = 12,color='green')
plt.ylabel('Win Percentage',fontsize = 12,color='green')
plt.title('Vehicle Destroys/ Win Ratio',fontsize = 15,color='red')

plt.grid()
plt.show()
```



My experience was correct. Destroying a single vehicle increases your chances of winning!

3.3.1 Outliers

In [35]:

```
# rideDistance anomalies
display(train[train['rideDistance'] >= 50000].shape)
train[train['rideDistance'] >= 50000].head(10)
```

```
(0, 32)
```

Out[35]:

Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	swimDistance	teamKills	vehicleDes

0 rows × 32 columns

In [36]:

```
# Remove outliers
train.drop(train[train['rideDistance'] >= 50000].index, inplace=True)
```

3.4 swimDistance

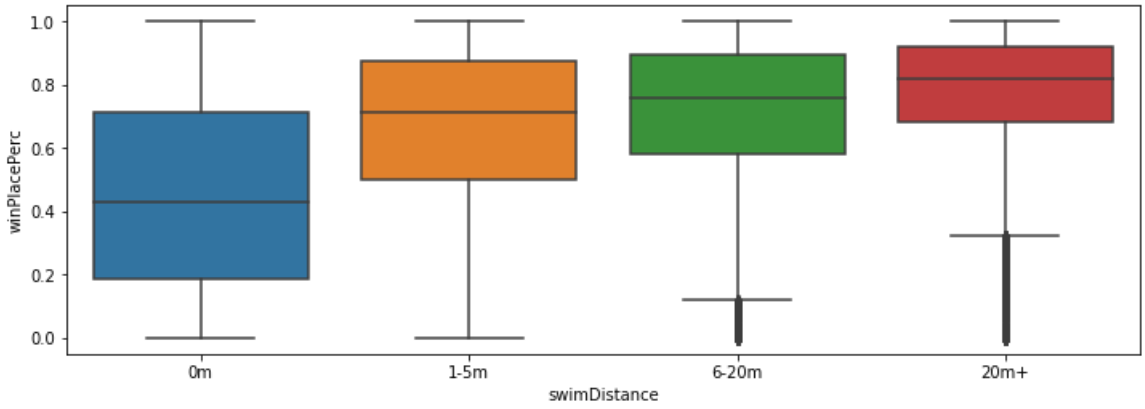
In [37]:

```
print("The average person swims for {:.1f}m.".format(train['swimDistance'].mean()))

print("99% of people have swimemd {}m or less".format(train['swimDistance'].quantile(0.99)))

print("while the olympic champion swimmed for {}m.".format(train['swimDistance'].max()))
```

```
The average person swims for 4.5m.
99% of people have swimemd 122.5m or less
while the olympic champion swimmed for 2295.0m.
```

In [38]:

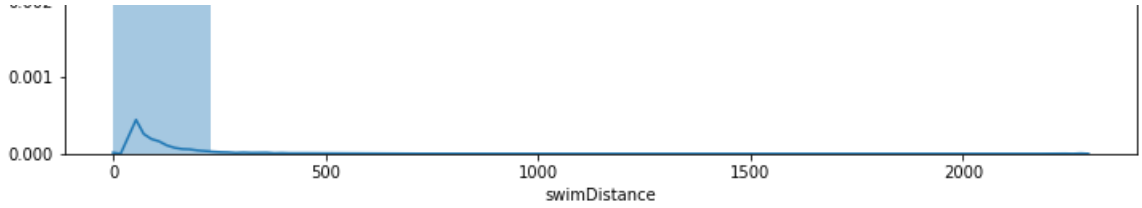
```
swim = train.copy()

swim['swimDistance'] = pd.cut(swim['swimDistance'], [-1, 0, 5, 20, 5286], labels=['0m','1-5m', '6-20m', '20m+'])

plt.figure(figsize=(12,4))
sns.boxplot(x="swimDistance", y="winPlacePerc", data=swim)
plt.show()
```



It seems that if you swim, you rise to the top. In PUBG there are currently 3 maps.

In [39]:

```
# Plot the distribution of swimDistance
plt.figure(figsize=(12,4))
sns.distplot(train['swimDistance'], bins=10)
plt.show()
```



3.4.1 Outliers

In [40]:

```
# Players who swam more than 2 km
train[train['swimDistance'] >= 2000]
```

Out[40]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	s
177973	c2e9e5631f4e54	23213058f83abe	f01eb1073ef377	0	5	78.12	1	0	1	47	...	
274258	ba5e3dfb5a0fa0	383db055216ec2	d6e13468e28ab4	0	4	53.32	0	0	16	39	...	

2 rows × 32 columns

In [41]:

```
# Remove outliers
train.drop(train[train['swimDistance'] >= 2000].index, inplace=True)
```

3.5 heals & boost

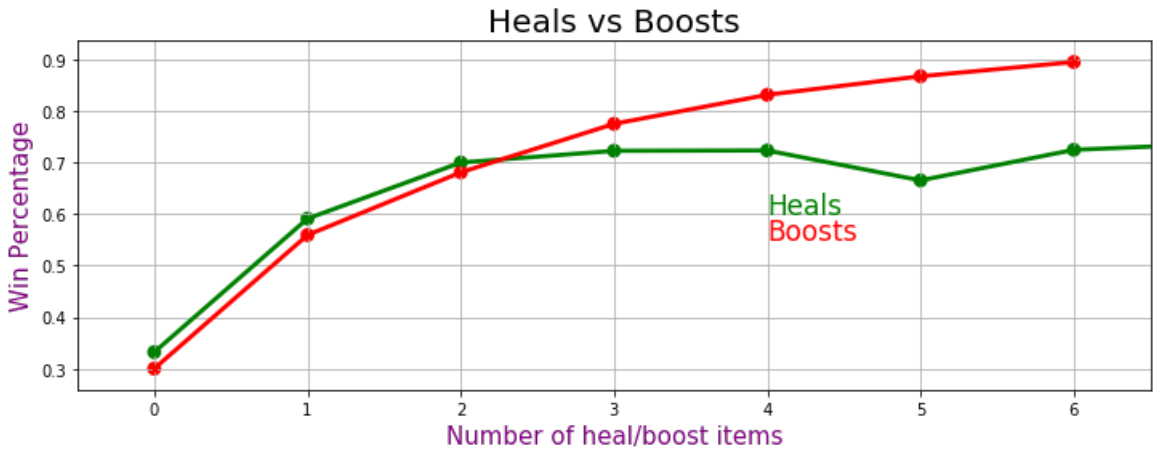
In [42]:

```
print("The average person uses {:.1f} heal items".format(train['heals'].mean()))

print("99% of people use {} or less".format(train['heals'].quantile(0.99)))

print("while the boost used {}.".format(train['boosts'].max()))
```

```
The average person uses 1.4 heal items
99% of people use 12.0 or less
while the boost used 33.
```

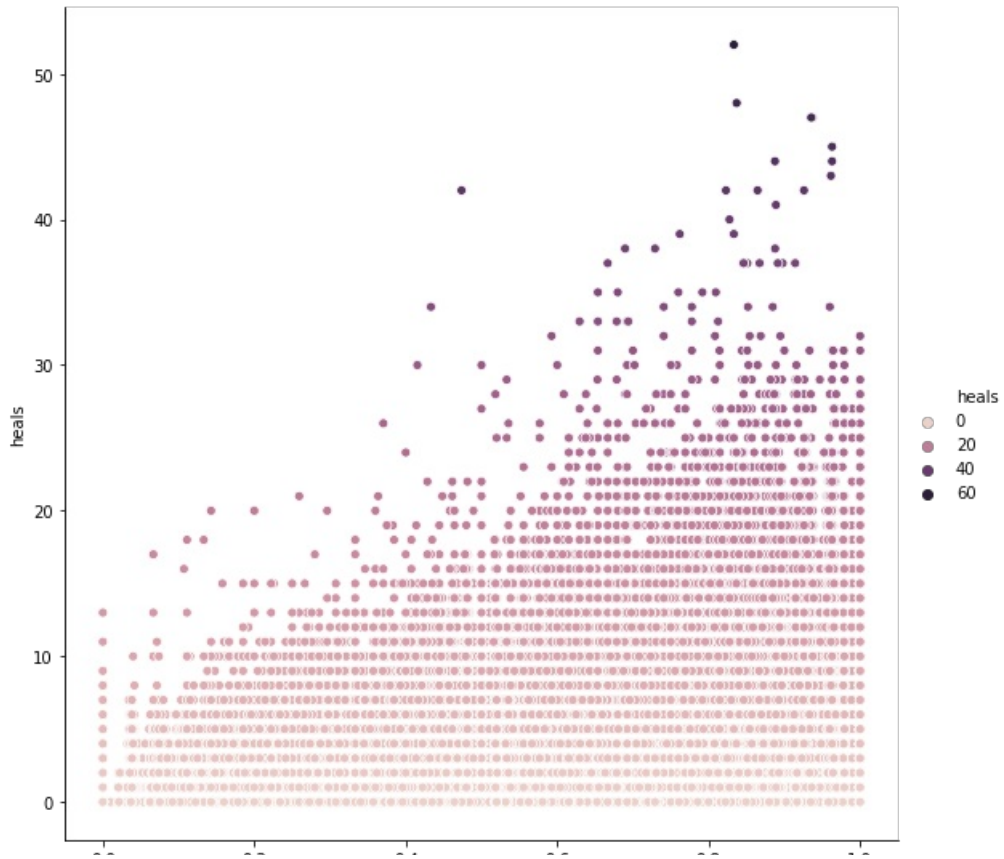
In [43]:

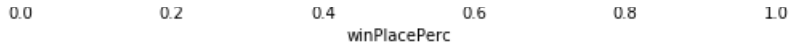
```
data = train.copy()
data = data[data['heals'] < data['heals'].quantile(0.99)]
data = data[data['boosts'] < data['boosts'].quantile(0.99)]

f,ax1 = plt.subplots(figsize =(12,4))
sns.pointplot(x='heals',y='winPlacePerc',data=data,color='green',alpha=0.8)
sns.pointplot(x='boosts',y='winPlacePerc',data=data,color='red',alpha=0.8)

plt.text(4,0.55,'Boosts',color='red',fontsize = 17)
plt.text(4,0.6,'Heals',color='green',fontsize = 17)

plt.xlabel('Number of heal/boost items',fontsize = 15,color='purple')
plt.ylabel('Win Percentage',fontsize = 15,color='purple')
plt.title('Heals vs Boosts',fontsize = 20,color='black')
plt.grid()
plt.show()
```



In [44]:

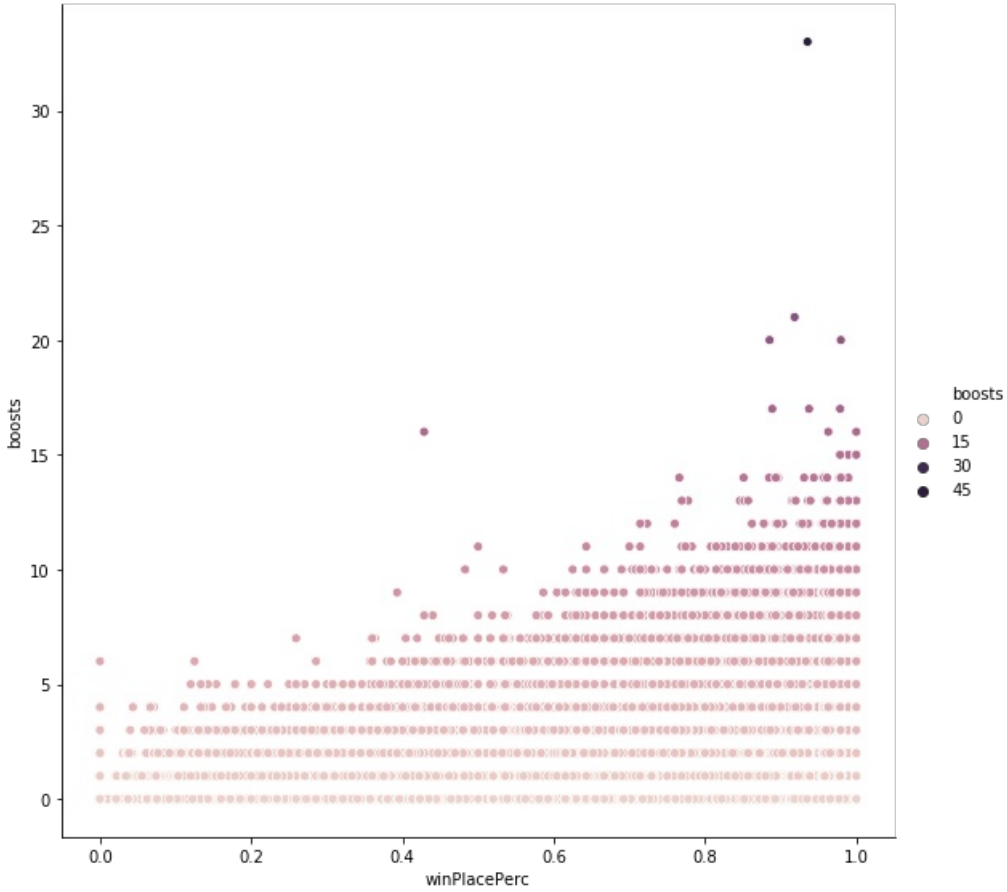
```
sns.relplot(x="winPlacePerc", y="heals", data=train,hue="heals" ,height=8)
plt.show()
```





In [45]:

```
sns.relplot(x="winPlacePerc", y="boosts", data=train,hue="boosts" ,height=8)
plt.show()
```



So healing and boosting, definitely are correlated with winPlacePerc. Boosting is more.

3.5.1 Outliers

In [46]:

```
# 40 or more healing items used
display(train[train['boosts'] >= 40].shape)
train[train['boosts'] >= 40].head(10)
```

(0, 32)

Out[46]:

Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	swimDistance	teamKills	vehicleDes

0 rows × 32 columns

In [47]:

```
# Remove outliers
train.drop(train[train['boosts'] >= 40].index, inplace=True)
```

3.5.2 Outliers

In [48]:

```
# 40 or more healing items used
display(train[train['heals'] >= 40].shape)
train[train['heals'] >= 40].head(10)
```

```
(14, 32)
```

Out[48]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...
18405	63ab976895d860	927eeba5614c4f	69473402649f11	0	2	0.0	0	0	47	43	...
54463	069ddee7c9d26a	58ab5a1ce8e06f	942416b6caf21e	1	4	182.0	0	1	43	21	...
126439	c45bd6917146e2	81ab9f863957cb	4335664c6716fa	0	2	0.0	0	0	52	49	...
259351	86910c38335c2f	2738398928d28c	7d2911e944bfaa	0	10	0.0	0	0	42	45	...
268747	a007734fbc6ebf	5bf702dfa1e5d4	ad6b5669d33a2c	0	5	0.0	0	0	48	43	...
269098	a0891dbc2950ea	dde848d90491ba	b4fd3348551b73	0	2	0.0	0	0	42	44	...
284195	91a2fb00455eb3	f639b09774c5b1	65b73c71653822	0	3	123.0	0	0	40	52	...
300204	1f4f2efc86bfcb	3d668492d1fca9	d3638466a43d38	0	6	175.0	2	1	47	25	...
349908	7725ad71ad2ff7	4b2a7cf86d1546	cfa2775c9ef944	3	0	2348.0	0	8	41	9	...
375156	d64866c78ebcb0	aa0f089ae6430c	4dbc4ebba33ec6	0	7	278.5	3	1	44	3	...

10 rows × 32 columns

In [49]:

```
# Remove outliers
train.drop(train[train['heals'] >= 40].index, inplace=True)
```

3.6 Weapons

In [50]:

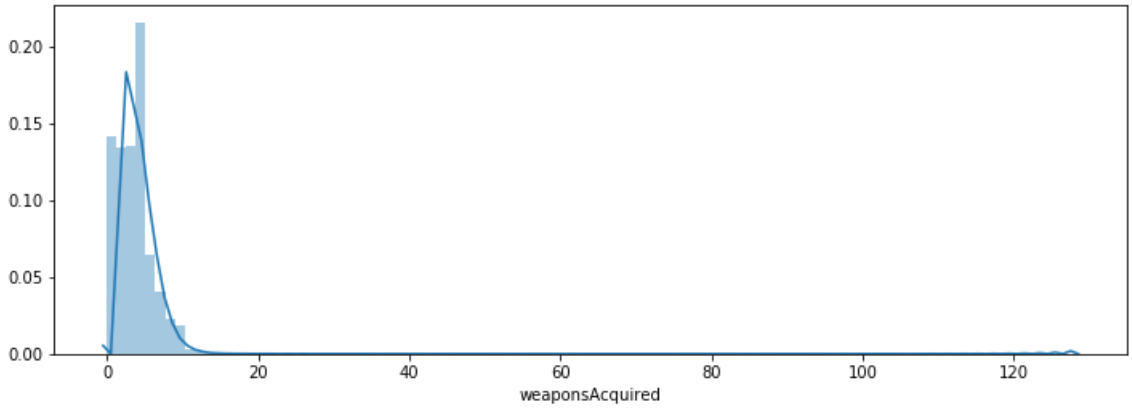
```
print("The average person uses {:.1f} weapons".format(train['weaponsAcquired'].mean()))

print("99% of people use {} or less".format(train['weaponsAcquired'].quantile(0.99)))
```

```
print("while the weapons used {}.".format(train['weaponsAcquired'].max()))
```

```
The average person uses 3.7 weapons
99% of people use 10.0 or less
while the weapons used 128.
```

In [51]:

```
# Plot the distribution of weaponsAcquired
plt.figure(figsize=(12,4))
sns.distplot(train['weaponsAcquired'], bins=100)
plt.show()
```



In [52]:

```
print("{} players ({:.4f}%) acquired weapons".format(len(data[data['weaponsAcquired'] == 0]),
                                                     100*len(data1[data1['weaponsAcquired']==0])/le
train)))

print("This means that they died beforer taking weapons")
```

```
25340 players (4.4140%) acquired weapons
This means that they died beforer taking weapons
```

3.6.1 Outliers

In [53]:

```
# Players who acquired more than 80 weapons
display(train[train['weaponsAcquired'] >= 80].shape)
train[train['weaponsAcquired'] >= 80].head()
```

```
(1, 32)
```

Out[53]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	...	sw
233643	7c8c83f5f97d0f	b33b210a52a2f8	2e8a0917a71c43	0	0	67.11	0	0	0	44	...	

1 rows × 32 columns

In [54]:

```
# Remove outliers
train.drop(train[train['weaponsAcquired'] >= 80].index, inplace=True)
```

3.7 Solos, Duos and Squads

There are 3 game modes in the game. One can play solo, or with a friend (duo), or with 3 other friends (squad). 100 players join the same server, so in the case of duos the max teams are 50 and in the case of squads the max teams are 25.

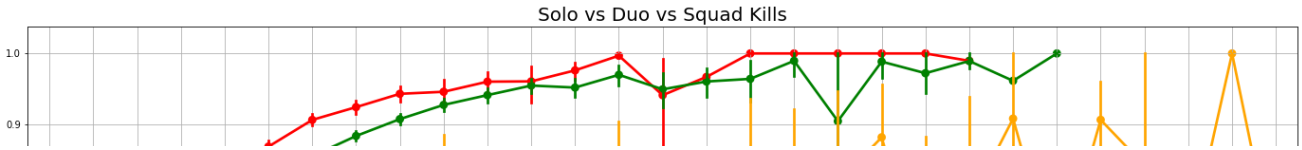
In [55]:

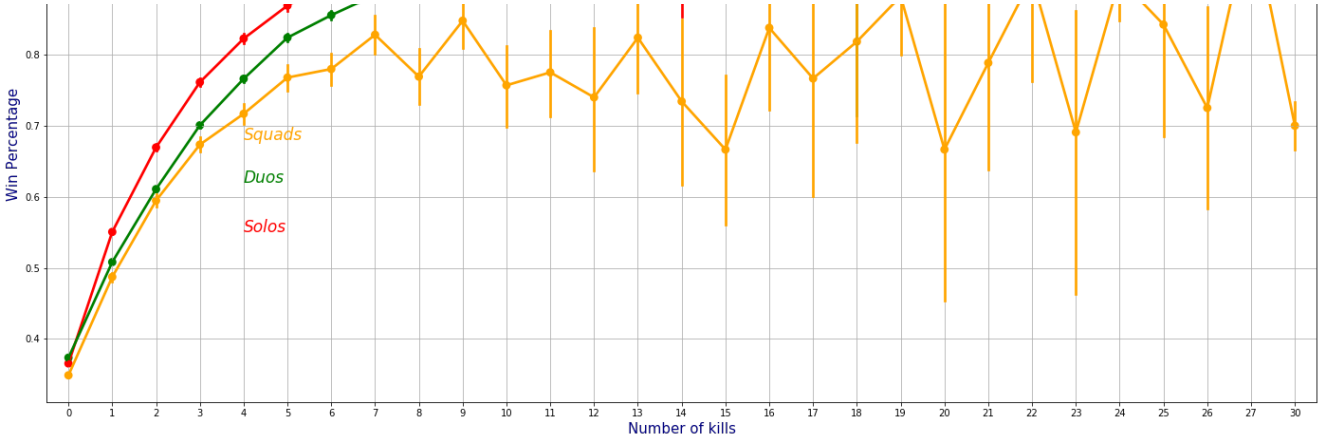
```
solos = train[train['numGroups']>50]
duos = train[(train['numGroups']>25) & (train['numGroups']<=50)]
squads = train[train['numGroups']<=25]

print("There are {} ({:.2f}%) solo games".format(len(solos), 100*len(solos)/len(train),))

print("There are {} ({:.2f}%) duo games".format(len(duos), 100*len(duos)/len(train)))

print("There are {} ({:.2f}%) squad games".format(len(squads), 100*len(squads)/len(train),))
```

```
There are 79478 (15.90%) solo games
There are 370635 (74.16%) duo games
There are 49654 (9.94%) squad games
```

In [56]:

```
plt.subplots(figsize=(24,10))
sns.pointplot(x='kills',y='winPlacePerc',data=solos,color='red',alpha=0.8)
sns.pointplot(x='kills',y='winPlacePerc',data=duos,color='green',alpha=0.8)
sns.pointplot(x='kills',y='winPlacePerc',data=squads,color='orange',alpha=0.8)

plt.text(4,0.55,'Solos',color='red',fontsize = 17,style = 'italic')
plt.text(4,0.62,'Duos',color='green',fontsize = 17,style = 'italic')
plt.text(4,0.68,'Squads',color='orange',fontsize = 17,style = 'italic')

plt.xlabel('Number of kills',fontsize = 15,color='navy')
plt.ylabel('Win Percentage',fontsize = 15,color='navy')
plt.title('Solo vs Duo vs Squad Kills',fontsize = 20,color='black')

plt.grid()
plt.show()
```





- Solos and duos behave the same, but when playing squads kills don't matter that much.

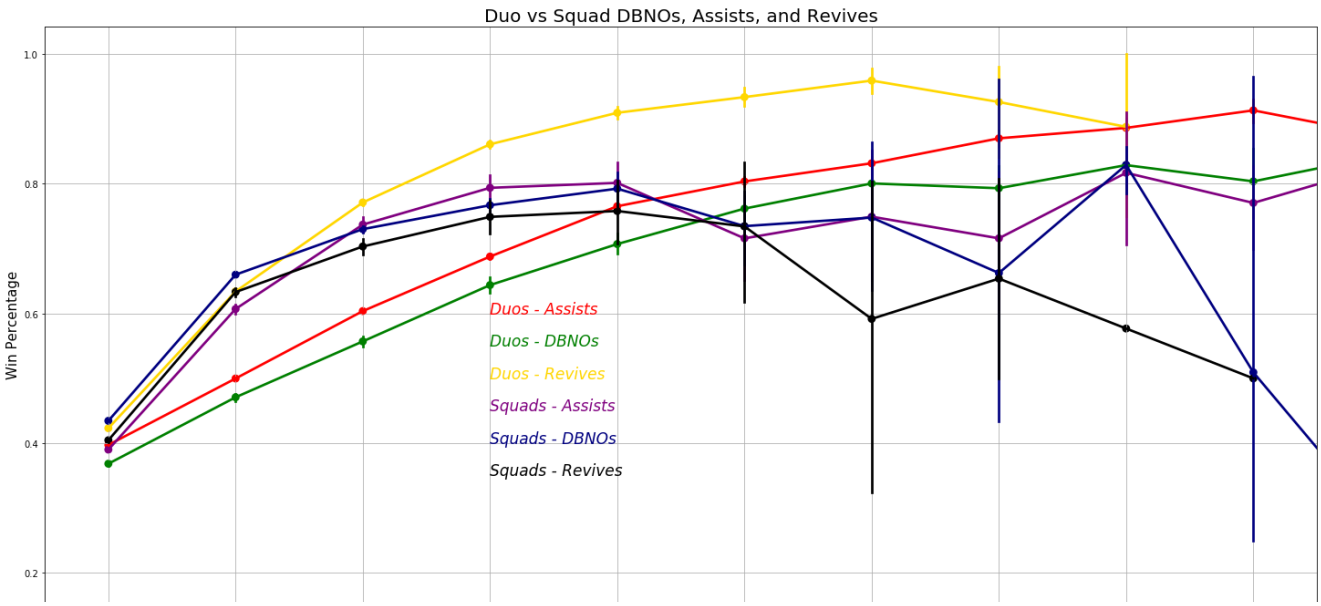
The attribute DBNOs means enemy players knocked. A "knock" can happen only in duos or squads, because the teammates have the chance to "revive" the knocked player in a given time. So a knocked player can be revived or die. If he is revived, the next time he will be knocked, his teammates will have less time to revive him.

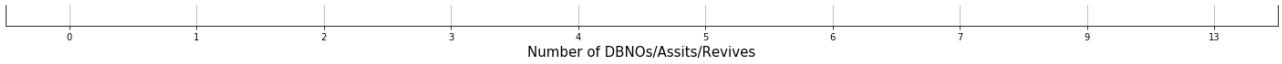
The attribute assist can also happen only in duos or squads. It generally means that the player had an involvement in a kill.

The attribute revive also happens in duos or squads.

In [57]:

```
f,ax1 = plt.subplots(figsize =(25,12))

sns.pointplot(x='DBNOs',y='winPlacePerc',data=duos,color='red',alpha=0.8)
sns.pointplot(x='DBNOs',y='winPlacePerc',data=squads,color='green',alpha=0.8)
sns.pointplot(x='assists',y='winPlacePerc',data=duos,color='gold',alpha=0.8)
sns.pointplot(x='assists',y='winPlacePerc',data=squads,color='purple',alpha=0.8)
sns.pointplot(x='revives',y='winPlacePerc',data=duos,color='navy',alpha=0.8)
sns.pointplot(x='revives',y='winPlacePerc',data=squads,color='black',alpha=0.8)

plt.text(3,0.6,'Duos - Assists',color='red',fontsize = 17,style = 'italic')
plt.text(3,0.55,'Duos - DBNOs',color='green',fontsize = 17,style = 'italic')
plt.text(3,0.50,'Duos - Revives',color='gold',fontsize = 17,style = 'italic')
plt.text(3,0.45,'Squads - Assists',color='purple',fontsize = 17,style = 'italic')
plt.text(3,0.40,'Squads - DBNOs',color='navy',fontsize = 17,style = 'italic')
plt.text(3,0.35,'Squads - Revives',color='black',fontsize = 17,style = 'italic')

plt.xlabel('Number of DBNOs/Assits/Revives',fontsize = 15,color='black')
plt.ylabel('Win Percentage',fontsize = 15,color='black')
plt.title('Duo vs Squad DBNOs, Assists, and Revives',fontsize = 20,color='black')
plt.grid()
plt.show()
```

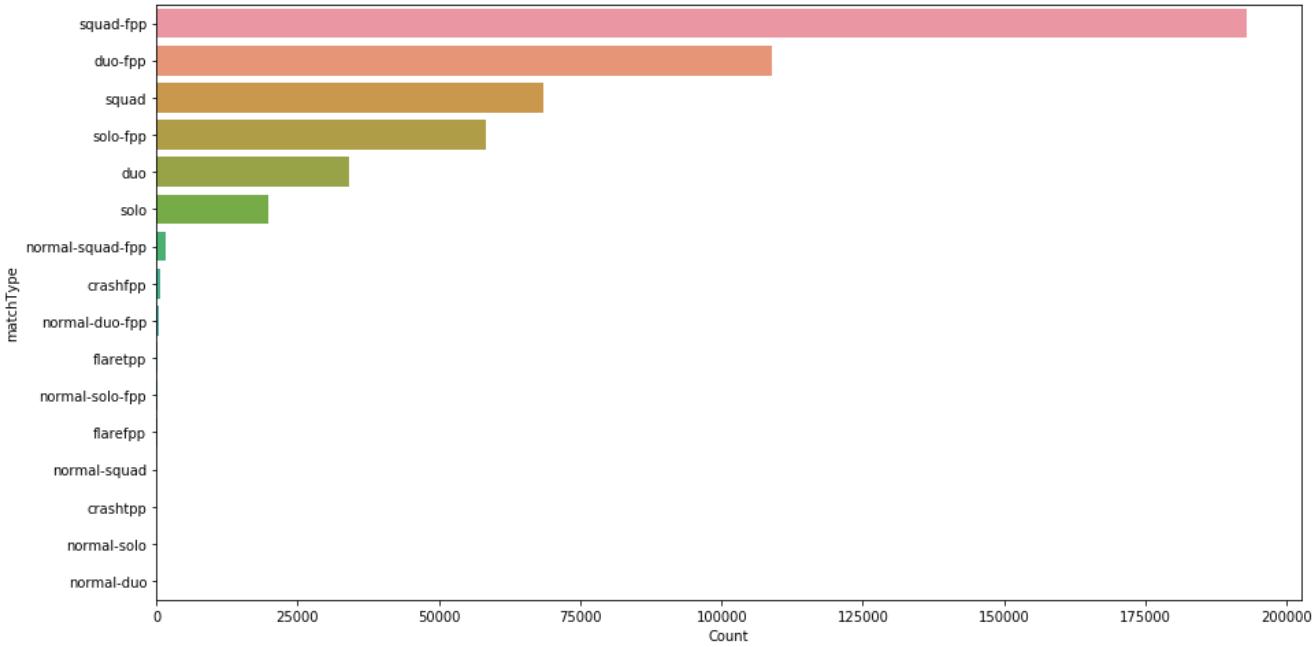




3.8 match type

In [58]:

```
f,ax = plt.subplots(figsize=(15,8))
sns.barplot(data.matchType.value_counts().values,data.matchType.value_counts().index)
plt.xlabel('Count')
plt.ylabel('matchType')
plt.show()
```



We will one hot encode the matchType

In [59]:

```
print('There are {} different Match types in the dataset.'.format(train['matchType'].nunique()))
```

```
There are 16 different Match types in the dataset.
```

3.8.1 one hot encoding matchtype on train

In [60]:

```
# One hot encode matchType
train = pd.get_dummies(train, columns=['matchType'])

# Take a look at the encoding
matchType_encoding = train.filter(regex='matchType')
matchType_encoding.head()
```

Out[60]:

	matchType_crashfpp	matchType_crashtpp	matchType_duo	matchType_duo-fpp	matchType_flarefpp	matchType_flaretpp	matchType_n
0	0	0	0	0	0	0	
1	0	0	0	0	0	0	
2	0	0	1	0	0	0	

	matchType_crashfpp	matchType_crashtpp	matchType_duo	matchType_duo-fpp	matchType_flarefpp	matchType_flaretpp	matchType_n
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	

There are a lot of groupId's and matchId's so one-hot encoding them is computational suicide. We will turn them into category codes.

3.9 Removing unnecessary columns from trainig and test data set

In [61]:

```
# Drop Id column, because it probably won't be useful for our Machine Learning algorithm,
# because the test set contains different Id's

train.drop(columns=['groupId','Id', 'matchId'], inplace=True)
```

- Added features to train so we need to remove

In [62]:

```
train.drop(columns=['totalDistance','killsWithoutMoving', 'headshot_rate'], inplace=True)
```

In [63]:

```
# Check dimensions of data
print('train data shape: ', train.shape)
```

```
train data shape:  (499767, 41)
```

4 Preparation for Machine Learning

Feature Engineering

In [0]:

```
#Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import lightgbm as lgb
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error
import gc

#Figures Inline and Visualization style
%matplotlib inline
sb.set()
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
```

```
.....
Mounted at /content/drive
```

In [0]:

```
train = pd.read_csv('drive/My Drive/pubg/train_V2.csv')
test = pd.read_csv('drive/My Drive/pubg/test_V2.csv')
train.dropna(inplace=True)
```

In [4]:

```
train['matchType'].value_counts()
```

Out[4]:

```
squad-fpp            1756186
duo-fpp               996691
squad                 626526
solo-fpp              536761
duo                   313591
solo                  181943
normal-squad-fpp       17174
crashfpp                6287
normal-duo-fpp          5489
flaretpp                2505
normal-solo-fpp         1682
flarefpp                 718
normal-squad             516
crashtpp                 371
normal-solo              326
normal-duo               199
Name: matchType, dtype: int64
```

'groupId' and 'matchId' are available in the data. From these, no. of players in the team and total players entered in the match can be extracted.

In [0]:

```
train['teamPlayers']=train.groupId.map(train.groupId.value_counts())
test['teamPlayers']=test.groupId.map(test.groupId.value_counts())
train['gamePlayers']=train.matchId.map(train.matchId.value_counts())
test['gamePlayers']=test.matchId.map(test.matchId.value_counts())
```

new column with total enemy players . The players remaining other than the player's squad.

In [0]:

```
train['enemyPlayers']=train['gamePlayers']-train['teamPlayers']
test['enemyPlayers']=test['gamePlayers']-test['teamPlayers']
```

new column representing the total distance(ride+swim+walk) covered by the player in the game.

In [0]:

```
train['totalDistance']=train['rideDistance']+train['swimDistance']+train['walkDistance']
test['totalDistance']=test['rideDistance']+test['swimDistance']+test['walkDistance']
```

new column which is the sum of assists and kills.

In [0]:

```
train['enemyDamage']=train['assists']+train['kills']
test['enemyDamage']=test['assists']+test['kills']
```

new column containing total kills by the team.

In [0]:

```
totalKills = train.groupby(['matchId','groupId']).agg({'kills': lambda x: x.sum()})
totalKills.rename(columns={"kills": "squadKills"}, inplace=True)
train = train.join(other=totalKills, on=['matchId', 'groupId'])
totalKills = test.groupby(['matchId','groupId']).agg({'kills': lambda x: x.sum()})
totalKills.rename(columns={"kills": "squadKills"}, inplace=True)
test = test.join(other=totalKills, on=['matchId', 'groupId'])
```

In [0]:

```
train['medicKits']=train['heals']+train['boosts']
test['medicKits']=test['heals']+test['boosts']
```

In [0]:

```
train['medicPerKill'] = train['medicKits']/train['enemyDamage']
test['medicPerKill'] = test['medicKits']/test['enemyDamage']
```

In [0]:

```
train['distancePerHeals'] = train['totalDistance']/train['heals']
test['distancePerHeals'] = test['totalDistance']/test['heals']
```

In [0]:

```
train['headShotKillRatio']=train['headshotKills']/train['kills']
test['headShotKillRatio']=test['headshotKills']/test['kills']
```

In [0]:

```
train['headshotKillRate'] = train['headshotKills'] / train['kills']
test['headshotKillRate'] = test['headshotKills'] / test['kills']
```

In [0]:

```
train['killPlaceOverMaxPlace'] = train['killPlace'] / train['maxPlace']
test['killPlaceOverMaxPlace'] = test['killPlace'] / test['maxPlace']
```

In [0]:

```
train['kills/distance']=train['kills']/train['totalDistance']
test['kills/distance']=test['kills']/test['totalDistance']
```

In [0]:

```
train['kills/walkDistance']=train['kills']/train['walkDistance']
test['kills/walkDistance']=test['kills']/test['walkDistance']
```

In [0]:

```
train['avgKills'] = train['squadKills']/train['teamPlayers']
test['avgKills'] = test['squadKills']/test['teamPlayers']
```

In [0]:

```
train['damageRatio'] = train['damageDealt']/train['enemyDamage']
test['damageRatio'] = test['damageDealt']/test['enemyDamage']
```

In [0]:

```
train['distTravelledPerGame'] = train['totalDistance']/train['matchDuration']
test['distTravelledPerGame'] = test['totalDistance']/test['matchDuration']
```

In [0]:

In [0]:

```
train['killPlacePerc'] = train['killPlace']/train['gamePlayers']
test['killPlacePerc'] = test['killPlace']/test['gamePlayers']
```

In [0]:

```
train["playerSkill"] = train["headshotKills"]+ train["roadKills"]+train["assists"]-(5*train['teamKills'])
test["playerSkill"] = test["headshotKills"]+ test["roadKills"]+test["assists"]-(5*test['teamKills'])
```

In [0]:

```
train['gamePlacePerc'] = train['killPlace']/train['maxPlace']
test['gamePlacePerc'] = test['killPlace']/test['maxPlace']
```

if newly created features contains missing values and Infinity values in it. replace these with 0.

In [0]:

```
train.fillna(0,inplace=True)
train.replace(np.inf, 0, inplace=True)
test.fillna(0,inplace=True)
test.replace(np.inf, 0, inplace=True)
```

In [25]:

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4446965 entries, 0 to 4446965
Data columns (total 49 columns):
Id                      object
groupId                 object
matchId                 object
assists                 int64
boosts                  int64
damageDealt             float64
DBNOs                   int64
headshotKills           int64
heals                   int64
killPlace               int64
killPoints              int64
kills                   int64
killStreaks             int64
longestKill             float64
matchDuration           int64
matchType               object
maxPlace                int64
numGroups               int64
rankPoints              int64
revives                 int64
rideDistance            float64
roadKills               int64
swimDistance            float64
teamKills               int64
vehicleDestroys         int64
walkDistance            float64
weaponsAcquired         int64
winPoints               int64
winPlacePerc            float64
teamPlayers             int64
gamePlayers             int64
enemyPlayers            int64
totalDistance           float64
enemyDamage             int64
squadKills              int64
medicKits               int64
medicPerKill            float64
distancePerHeals        float64
headShotKillRatio       float64
```

```
headshotKillRate          float64
killPlaceOverMaxPlace     float64
kills/distance            float64
kills/walkDistance        float64
avgKills                  float64
damageRatio               float64
distTravelledPerGame      float64
killPlacePerc             float64
playerSkill               int64
gamePlacePerc             float64
dtypes: float64(19), int64(26), object(4)
memory usage: 1.7+ GB
```

From the heat map, killPoints, rankPoints, winPoints, maxPlace are found to be not having any significance in determining winPlacePerc. So let's remove these features from the data set.

In [0]:

```
train.drop(columns=['killPoints','rankPoints','winPoints','maxPlace'],inplace=True)
test.drop(columns=['killPoints','rankPoints','winPoints','maxPlace'],inplace=True)
```

In [0]:

```
def reduce_mem_usage(df):
    """ iterate through all the columns of a dataframe and modify the data type
        to reduce memory usage, took from Kaggle.
    """
    start_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage of dataframe is {:.2f} MB'.format(start_mem))

    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)

    end_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage after optimization is: {:.2f} MB'.format(end_mem))
    print('Decreased by {:.1f}%'.format(100 * (start_mem - end_mem) / start_mem))
    return df
```

In Pubg, if a player wins, his team mates are also winners. So instead on finding winPlacePerc for individual payers, let's find the winPlacePerc for each group in a match. Let's write a function that will create new columns that are the match wise and group wise mean, max, min of all the current features and also rank them.

In [0]:

```
def feature(df):
    features = list(df.columns)
    features.remove("Id")
    features.remove("matchId")
    features.remove("groupId")
    features.remove("matchType")
    condition='False'
```

```
    if 'winPlacePerc' in df.columns:
        y = np.array(df.groupby(['matchId','groupId'])['winPlacePerc'].agg('mean'), dtype=np.float6
4)
        features.remove("winPlacePerc")
        condition='True'

    print("get group mean feature")
    agg = df.groupby(['matchId','groupId'])[features].agg('mean')
    agg_rank = agg.groupby('matchId')[features].rank(pct=True).reset_index()
    df_out = agg.reset_index()[['matchId','groupId']]
    df_out = df_out.merge(agg.reset_index(), suffixes=["", ""], how='left', on=['matchId',
'groupId'])
    df_out = df_out.merge(agg_rank, suffixes=["_mean", "_mean_rank"], how='left', on=['matchId', 'g
roupId'])

    print("get group max feature")
    agg = df.groupby(['matchId','groupId'])[features].agg('max')
    agg_rank = agg.groupby('matchId')[features].rank(pct=True).reset_index()
    df_out = df_out.merge(agg.reset_index(), suffixes=["", ""], how='left', on=['matchId',
'groupId'])
    df_out = df_out.merge(agg_rank, suffixes=["_max", "_max_rank"], how='left', on=['matchId', 'gro
upId'])

    print("get group min feature")
    agg = df.groupby(['matchId','groupId'])[features].agg('min')
    agg_rank = agg.groupby('matchId')[features].rank(pct=True).reset_index()
    df_out = df_out.merge(agg.reset_index(), suffixes=["", ""], how='left', on=['matchId',
'groupId'])
    df_out = df_out.merge(agg_rank, suffixes=["_min", "_min_rank"], how='left', on=['matchId', 'gro
upId'])

    print("get match mean feature")
    agg = df.groupby(['matchId'])[features].agg('mean').reset_index()
    df_out = df_out.merge(agg, suffixes=["", "_match_mean"], how='left', on=['matchId'])
    df_id=df_out[["matchId", "groupId"]].copy()
    df_out.drop(["matchId", "groupId"], axis=1, inplace=True)

    del df, agg, agg_rank
    gc.collect()
    if condition=='True':
        return df_out,pd.DataFrame(y),df_id
    else:
        return df_out,df_id
```

In [29]:

```
x,y,id_train=feature(reduce_mem_usage(train))
x_test,id_test=feature(reduce_mem_usage(test))
```

```
Memory usage of dataframe is 1560.67 MB
Memory usage after optimization is: 436.82 MB
Decreased by 72.0%
get group mean feature
get group max feature
get group min feature
get match mean feature
Memory usage of dataframe is 649.29 MB
Memory usage after optimization is: 171.55 MB
Decreased by 73.6%
get group mean feature
get group max feature
get group min feature
get match mean feature
```

In [30]:

```
del train,test
gc.collect()
```

Out[30]:

```
21
```

GRADIENT BOOSTING MODEL

Split the data into train and validation set

In [31]:

```
x['matchId']=id_train['matchId']
x['groupId']=id_train['groupId']
# Train test split
x_train,x_val,y_train,y_val=train_test_split(reduce_mem_usage(x),y,test_size=.1)
x_test=reduce_mem_usage(x_test)
id_val=x_val[['matchId','groupId']]
x_val.drop(['matchId','groupId'],axis=1,inplace=True)
x_train.drop(['matchId','groupId'],axis=1,inplace=True)
x.drop(['matchId','groupId'],axis=1,inplace=True)
del y
gc.collect()
```

```
Memory usage of dataframe is 2957.27 MB
Memory usage after optimization is: 1055.34 MB
Decreased by 64.3%
Memory usage of dataframe is 1279.61 MB
Memory usage after optimization is: 447.10 MB
Decreased by 65.1%
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/frame.py:3940: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  errors=errors)
```

Out[31]:

```
7
```

In [0]:

```
params = {
        "objective" : "regression",
        "metric" : "mae",
        "num_leaves" : 149,
        "learning_rate" : 0.03,
        "bagging_fraction" : 0.9,
        "bagging_seed" : 0,
        "num_threads" : 4,
        "colsample_bytree" : 0.5,
        'min_data_in_leaf':1900,
        'min_split_gain':0.00011,
        'lambda_l2':9
}
```

In [0]:

```
# create dataset for lightgbm
lgb_train = lgb.Dataset(x_train, y_train,
                        free_raw_data=False)
lgb_eval = lgb.Dataset(x_val, y_val, reference=lgb_train,
                       free_raw_data=False)
```

In [34]:

```
model = lgb.train(params,
                  lgb_train,
                  num_boost_round=22000,
                  valid_sets=lgb_eval,
                  early_stopping_rounds=10,
                  verbose_eval=1000)
```

```
Training until validation scores don't improve for 10 rounds.
[1000] valid_0's l1: 0.0279616
[2000] valid_0's l1: 0.0272089
[3000] valid_0's l1: 0.0268065
[4000] valid_0's l1: 0.0265105
[5000] valid_0's l1: 0.0263117
Early stopping, best iteration is:
[5943] valid_0's l1: 0.0261426
```

Now that we have trained the model, let' have a look if we can make some tweaks in the predicted data so that the predicted value can be improved. First let's merge the predicted value with appropriate gamer Id in the train data.

In [35]:

```
y_pred_val = model.predict(x, num_iteration=model.best_iteration)
id_train['win_pred']=y_pred_val
id_train.set_index(['matchId','groupId'])
train = reduce_mem_usage(pd.read_csv("drive/My Drive/pubg/train_V2.csv"))

df=pd.merge(train,id_train,on=['matchId','groupId'],how='right')
df.head()
```

```
Memory usage of dataframe is 983.90 MB
Memory usage after optimization is: 288.39 MB
Decreased by 70.7%
```

Out[35]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	killPoints
0	7f96b2f878858a	4d4b580de459be	a10357fd1a4a91	0	0	0.00	0	0	0	60	1241
1	7516514fbd1091	4d4b580de459be	a10357fd1a4a91	0	0	0.00	0	0	0	62	1232
2	c56d45be16aa86	4d4b580de459be	a10357fd1a4a91	0	0	318.00	2	1	0	6	1185
3	100eef17c4d773	4d4b580de459be	a10357fd1a4a91	0	0	90.75	0	0	0	61	1344
4	eef90569b9d03c	684d5656442f9e	aeb375fc57110c	0	0	91.50	0	0	0	57	0

In [36]:

```
print('The mae score is {}'.format(mean_absolute_error(df['winPlacePerc'],df['win_pred'])))
df = df[["Id", "matchId", "groupId", "maxPlace", "numGroups",'winPlacePerc', 'win_pred']]
```

```
The mae score is 0.020879417399560927
```

In [0]:

```
df_grouped = df.groupby(["matchId", "groupId"]).first().reset_index()
df_grouped["team_place"] = df_grouped.groupby(["matchId"])["win_pred"].rank()
```

In [0]:

```
df_grouped["win_perc"] = (df_grouped["team_place"] - 1) / (df_grouped["numGroups"]-1)
df = df.merge(df_grouped[["win_perc","matchId", "groupId"]], on=["matchId", "groupId"], how="left"
)
```

In [0]:

```
df.loc[df['maxPlace'] == 0, "win_perc"] = 0
df.loc[df['maxPlace'] == 1, "win_perc"] = 1
df.loc[(df['maxPlace'] > 1) & (df['numGroups'] == 1), "win_perc"] = 0
df.loc[df['win_perc'] < 0,"win_perc"] = 0
df.loc[df['win_perc'] > 1,"win_perc"] = 1
df['win_perc'].fillna(df['win_pred'],inplace=True)
```

In [40]:

```
df_grouped[df_grouped['maxPlace']>1]
[['winPlacePerc','win_perc','maxPlace','numGroups','team_place']]
```

Out[40]:

	winPlacePerc	win_perc	maxPlace	numGroups	team_place
0	0.333252	0.333333	28	28	10.0
1	0.036987	0.037037	28	28	2.0
2	0.000000	0.000000	28	28	1.0
3	0.370361	0.370370	28	28	11.0
4	1.000000	0.925926	28	28	26.0
5	0.592773	0.592593	28	28	17.0
6	0.777832	0.851852	28	28	24.0
7	0.703613	0.629630	28	28	18.0
8	0.259277	0.259259	28	28	8.0
9	0.666504	0.703704	28	28	20.0
10	0.518555	0.518519	28	28	15.0
11	0.629395	0.666667	28	28	19.0
12	0.185181	0.185185	28	28	6.0
13	0.111084	0.111111	28	28	4.0
14	0.296387	0.296296	28	28	9.0
15	0.852051	0.777778	28	28	22.0
16	0.407471	0.407407	28	28	12.0
17	0.740723	0.740741	28	28	21.0
18	0.814941	0.814815	28	28	23.0
19	0.888672	1.000000	28	28	28.0
20	0.481445	0.481481	28	28	14.0
21	0.962891	0.962963	28	28	27.0
22	0.444336	0.444444	28	28	13.0
23	0.148071	0.148148	28	28	5.0
24	0.925781	0.888889	28	28	25.0
25	0.222168	0.222222	28	28	7.0
26	0.074097	0.074074	28	28	3.0
27	0.555664	0.555556	28	28	16.0
28	0.296387	0.269231	28	27	8.0
29	0.629395	0.615385	28	27	17.0
...	...	...	...	...	...
2026714	0.729004	0.739130	49	47	35.0
2026715	0.107117	0.107143	29	29	4.0
2026716	0.856934	0.857143	29	29	25.0
2026717	0.571289	0.571429	29	29	17.0
2026718	0.321289	0.321429	29	29	10.0
2026719	0.357178	0.357143	29	29	11.0
2026720	0.893066	0.892857	29	29	26.0
2026721	0.214355	0.178571	29	29	6.0
2026722	0.535645	0.535714	29	29	16.0
2026723	0.285645	0.250000	29	29	8.0
2026724	0.071411	0.071429	29	29	3.0
2026725	0.606934	0.678571	29	29	20.0
2026726	0.785645	0.785714	29	29	23.0
2026727	0.392822	0.392857	29	29	12.0

	winPlacePerc	win_perc	maxPlace	numGroups	team_place
2026728	0.821289	0.821429	29	29	24.0
2026729	0.178589	0.285714	29	29	9.0
2026730	0.035706	0.035714	29	29	2.0
2026731	0.964355	0.964286	29	29	28.0
2026732	0.142944	0.142857	29	29	5.0
2026733	0.678711	0.714286	29	29	21.0
2026734	0.750000	0.750000	29	29	22.0
2026735	0.714355	0.642857	29	29	19.0
2026736	1.000000	1.000000	29	29	29.0
2026737	0.500000	0.500000	29	29	15.0
2026738	0.428711	0.428571	29	29	13.0
2026739	0.643066	0.607143	29	29	18.0
2026740	0.928711	0.928571	29	29	27.0
2026741	0.000000	0.000000	29	29	1.0
2026742	0.250000	0.214286	29	29	7.0
2026743	0.464355	0.464286	29	29	14.0

2026744 rows × 5 columns

In [0]:

```
subset = df.loc[df['maxPlace'] > 1]
gap = 1 / (subset['maxPlace'].values-1)
new_perc = np.around(subset['win_perc'].values / gap) * gap
df.loc[df.maxPlace > 1, "win_perc"] = new_perc
```

In [42]:

```
print('The new mae score is {}'.format(mean_absolute_error(df['winPlacePerc'],df['win_perc'])))
```

```
The new mae score is 0.01777692776241997
```

In [43]:

```
del x,train,df
gc.collect()
```

Out[43]:

```
28
```

Submission

In [44]:

```
y_pred = model.predict(x_test, num_iteration=model.best_iteration)
id_test['win_pred']=y_pred
id_test.set_index(['matchId','groupId'])
del x_train,x_val,y_train,y_val,x_test
gc.collect()

test = reduce_mem_usage(pd.read_csv("drive/My Drive/pubg/test_V2.csv"))
df=pd.merge(test,id_test,on=['matchId','groupId'],how='right')
del id_test,test
gc.collect()
df.head()
```

```
Memory usage of dataframe is 413.18 MB
Memory usage after optimization is: 121.74 MB
Decreased by 70.5%
```

Out[44]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotKills	heals	killPlace	killPoints
0	9329eb41e215eb	676b23c24e70d6	45b576ab7daa7f	0	0	51.46875	0	0	0	73	0
1	d6267a32c5709c	676b23c24e70d6	45b576ab7daa7f	0	0	0.00000	0	0	0	71	0
2	b896f8954a92e2	676b23c24e70d6	45b576ab7daa7f	1	0	74.18750	1	0	0	72	0
3	2f134f2c7be198	676b23c24e70d6	45b576ab7daa7f	0	0	0.00000	0	0	0	70	0
4	639bd0dcd7bda8	430933124148dd	42a9a0b906c928	0	4	179.12500	0	0	2	11	0

In [0]:

```
df = df[["Id", "matchId", "groupId", "maxPlace", "numGroups",'win_pred']]
```

In [0]:

```
df_grouped = df.groupby(["matchId", "groupId"]).first().reset_index()
df_grouped["team_place"] = df_grouped.groupby(["matchId"])["win_pred"].rank()
```

In [0]:

```
df_grouped["win_perc"] = (df_grouped["team_place"] - 1) / (df_grouped["numGroups"]-1)
df = df.merge(df_grouped[["win_perc", "matchId", "groupId"]], on=["matchId", "groupId"],
how="left")
```

In [0]:

```
df.loc[df.maxPlace == 0, "win_perc"] = 0
df.loc[df.maxPlace == 1, "win_perc"] = 1
df.loc[(df.maxPlace > 1) & (df.numGroups == 1), "win_perc"] = 0
df.loc[df['win_perc'] < 0,"win_perc"] = 0
df.loc[df['win_perc'] > 1,"win_perc"] = 1
df['win_perc'].fillna(df['win_pred'],inplace=True)
```

In [0]:

```
subset = df.loc[df['maxPlace'] > 1]
gap = 1 / (subset['maxPlace'].values-1)
new_perc = np.around(subset['win_perc'].values / gap) * gap
df.loc[df.maxPlace > 1, "win_perc"] = new_perc
df['winPlacePerc']=df['win_perc']
```

In [0]:

```
df=df[['Id','winPlacePerc']]
df.to_csv("drive/My Drive/pubg/submission_final.csv", index=False)
```

In [ ]:

```
```

Conclusion

- we seen kernel features
- killer
  - Kill without movement
  - Road kils
  - more than 30 kills
  - 100% headshot
  - longest kills features and removed the outlier features of this killers and plotted the killer features
- we seen the walkDistance feature and most winners are walk more than others and plotted this and removed the ouliers
- we plot rideDistance distance and removed the outliers
- swimDistance most of them winners are not much swim than 2000 meters and removed the outliers
- most of the winners are rideDistance more than 5000 meters and removed the outliers

- all players are Healers & Boosts used much
- most of the winners are used less than 10 weapons and removed outliers
- players are played Solos, Duos and Squads with other players
- and one hot encoded match type
- we split the data train and test data
- and lastly perform the machine learning models on train and test data
- above the Random Forest perform very well on data

In [ ]: