In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
train = pd.read_csv('trainV2.csv')
```

- **groupId** - Integer 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.
- **matchId** - Integer ID to identify match. There are no matches that are in both the training and testing set.
- **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.
- **DBNOs** - Number of enemy players knocked.
- **headshotKills** - Number of enemy players killed with headshots.
- **heals** - Number of healing items used.
- **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.)
- **kills** - Number of enemy players killed.
- **killStreaks** - Max number of enemy players killed in a short amount of time.
- **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.
- **maxPlace** - Worst placement we have data for in the match. This may not match with numGroups, as sometimes the data skips over placements.
- **numGroups** - Number of groups we have data for in the match.
- **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.)
- **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.

Kill count investigation

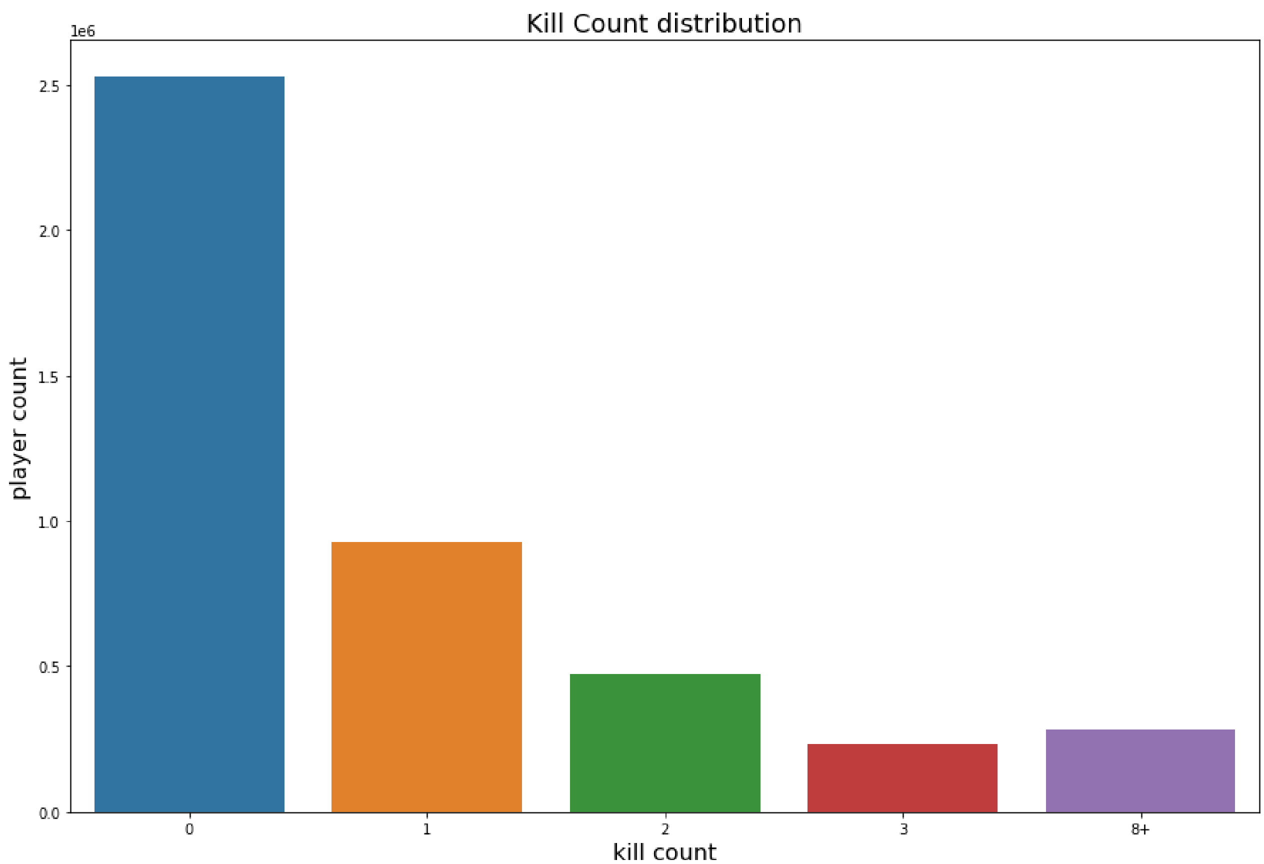
In [3]:

```
print("The average kill count in this dataset is: {:.3f}.\n90% of people have {} kills
```

```
The average kill count in this dataset is: 0.925.
90% of people have 3.0 kills or less.
The highest kill count is 72.
```

In [4]:

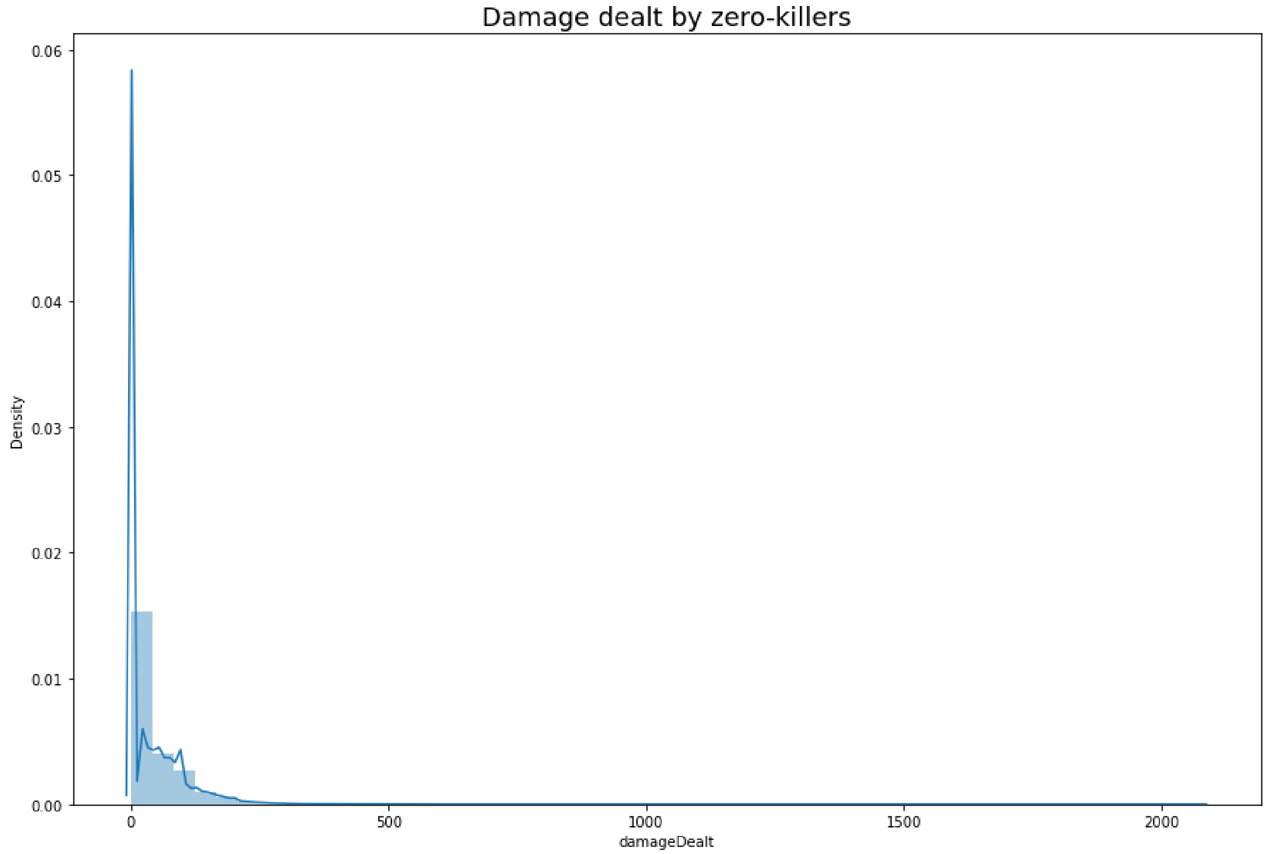
```
data = train.copy()
data.loc[data['kills'] > data['kills'].quantile(0.90)] = '8+' #those kills that're high
plt.figure(figsize=(15,10))
sns.countplot(data['kills'].astype('str').sort_values())
plt.title("Kill Count distribution", fontsize=18)
plt.xlabel('kill count',fontsize=16)
plt.ylabel('player count',fontsize=16)
plt.show()
```



Apparently, the majority of players didn't get to make a single kill. Let's investigate how much damage is dealt by them.

In [5]:

```
data = train.copy()
data = data[data['kills']==0] #pick zero-killers only
plt.figure(figsize=(15,10))
sns.distplot(data['damageDealt'])
plt.title('Damage dealt by zero-killers', fontsize=18)
plt.show()
```



Apparently, there're alot of zero-killers aren't able to damage other player without killing.

But, wouldn't it be interesting if there's someone who wins by chance without getting any kills or didn't deal any damage?

Let's investigate the exceptions!

In [6]:

```
print("Players who win without killing: {} ({:.2f}%)".format(len(data[data['winPlacePer
```

```
Players who win without killing: 16666 (0.37%)
```

In [7]:

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

In [8]:

```
print("Players who win without damaging: {} ({:.2f}%)".format(len(data1[data1['winPlace
```

```
Players who win without damaging: 4770 (0.11%)
```

In [9]:

```
data_superkillers = train.copy()
data_superkillers = data_superkillers[data_superkillers['kills'] > data_superkillers['k
print("The average damage dealt by top killers is approximately: {}({:.2f}%)".format(le
```

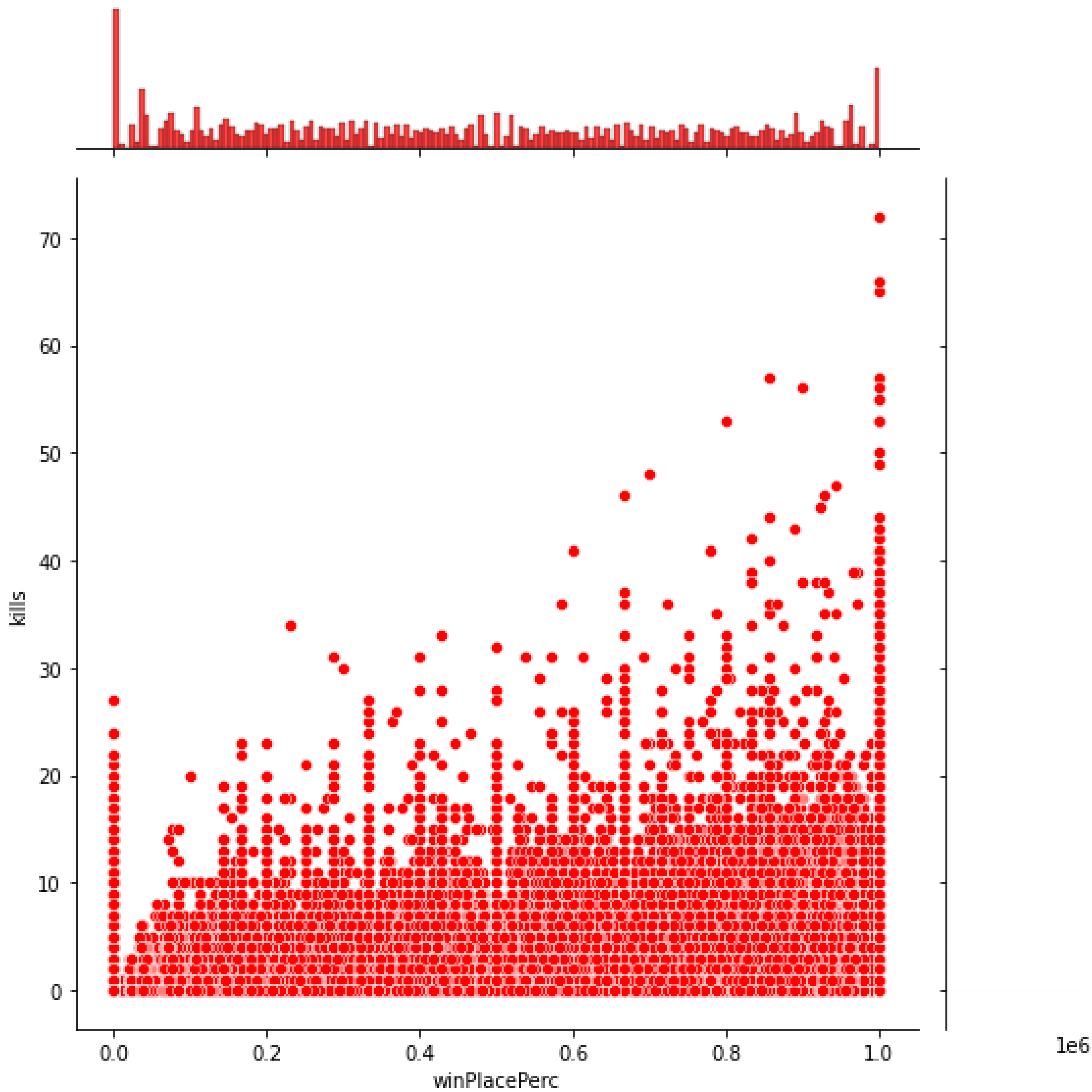
```
The average damage dealt by top killers is approximately: 55289(1.24%)
```

Kills VS Win placement

In [10]:

```
sns.jointplot(x="winPlacePerc", y="kills", data = train, height=8, color='r')
```

Out[10]: <seaborn.axisgrid.JointGrid at 0x21fcdf73160>

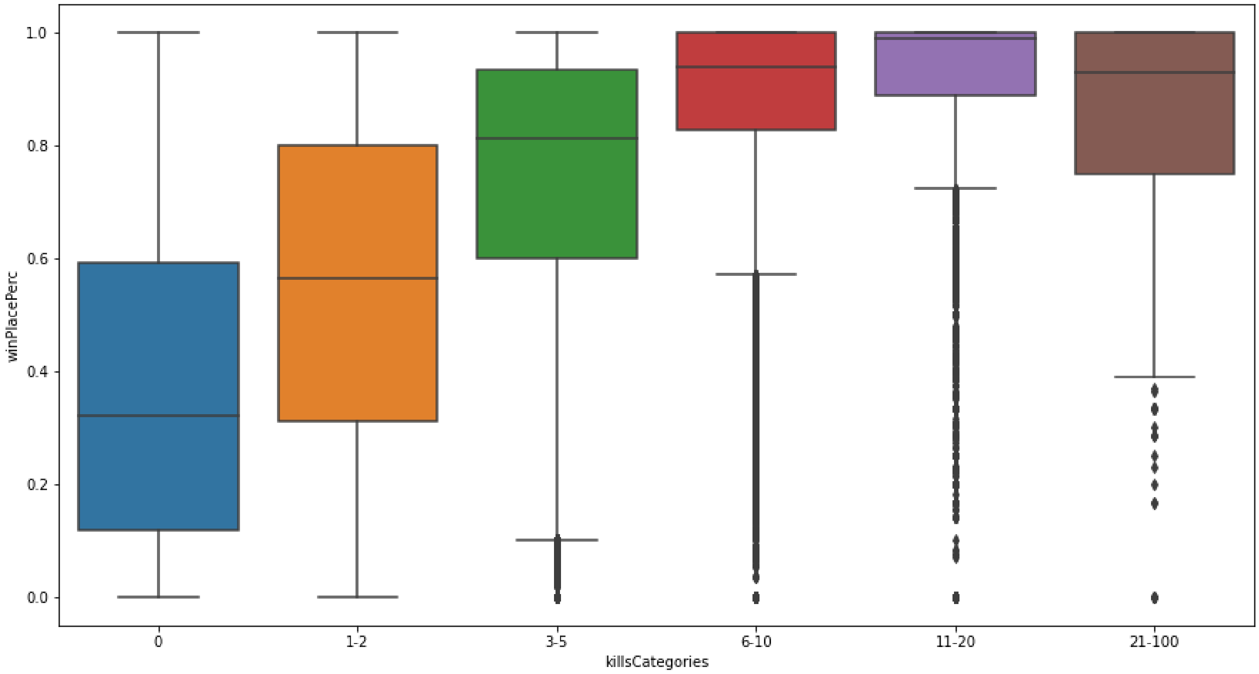


To put it simply, it's more likely for the player to win if he/she kills more.

Let's group players based on kill counts(0, 1-2, 3-5, 6-10, 10+).

In [11]:

```
kills = train.copy()
bins = [-1,0,2,5,10,20,100]
group_names = ['0','1-2','3-5','6-10','11-20','21-100']
kills['killsCategories'] = pd.cut(kills['kills'], bins, labels=group_names)
plt.figure(figsize=(15,8))
sns.boxplot(x="killsCategories", y="winPlacePerc", data=kills)
plt.show()
```



Distance walked investigation

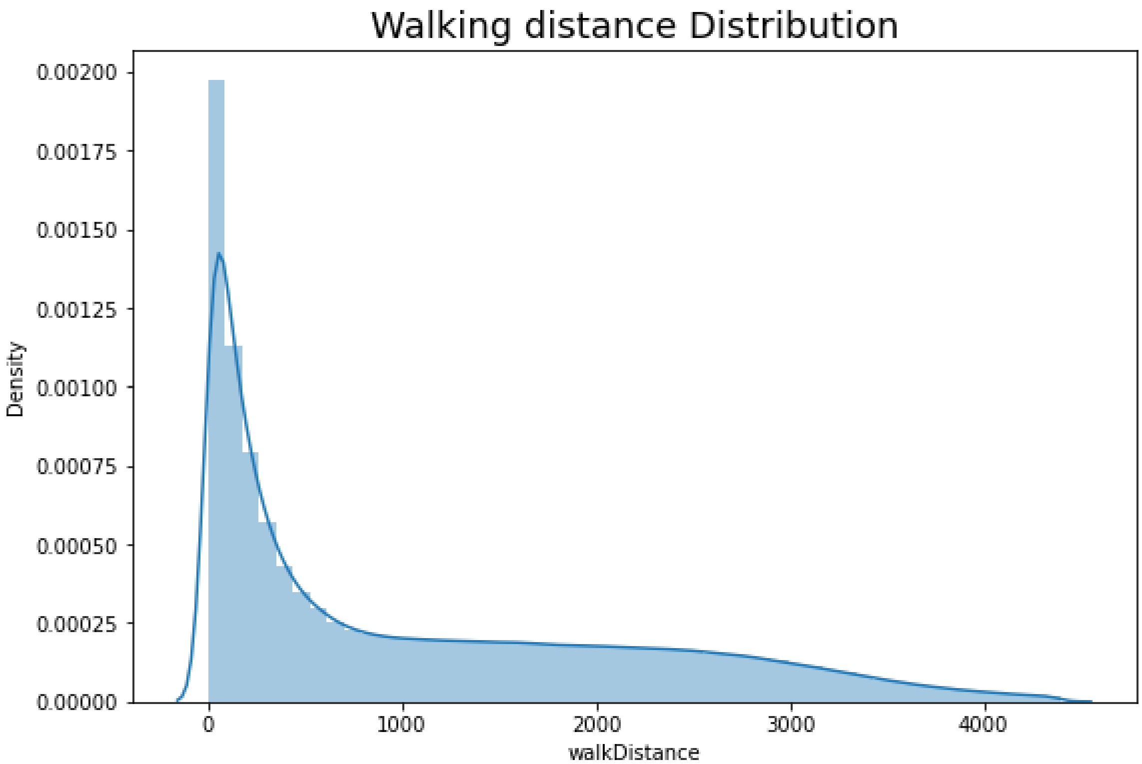
In [12]:

```
print("The average distance walked is: {:.3f}m\n99% of people have walked {:.3f}m\nLong
```

```
The average distance walked is: 1154.218m
99% of people have walked 4396.000m
Longest distance walked: 25780.000m
```

In [13]:

```
data = train.copy()
data = data[data['walkDistance']<train['walkDistance'].quantile(0.99)]
#pick top 1% of walker only,
#the .copy() makes sure we don't mess with the original data
plt.figure(figsize=(9,6))
plt.title("Walking distance Distribution",fontsize=18)
sns.distplot(data['walkDistance'])
plt.show()
```



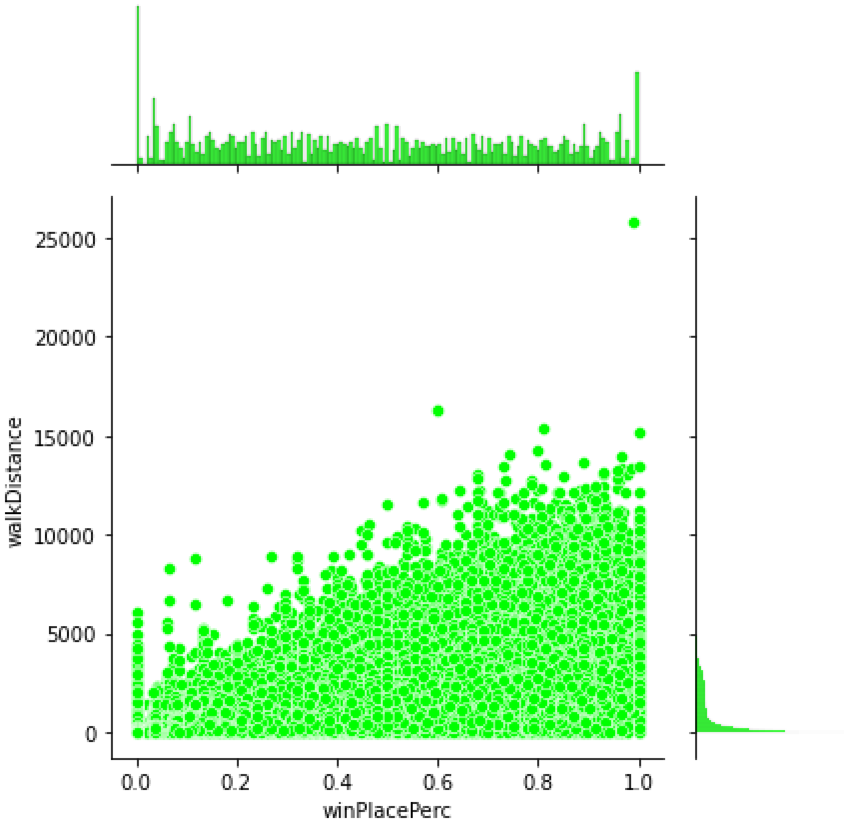
In [14]:

```
print("{} players({:.2f}%) walked 0m.\nWhich is utter nonsense because they die before
```

```
99603 players(2.24%) walked 0m.
Which is utter nonsense because they die before taking a step.
It's more likely they left the game early.
```

In [15]:

```
sns.jointplot(x="winPlacePerc", y="walkDistance",  data=train, height=6, ratio=3, color
plt.show()
```



It's very likely that the champion walks a lot.

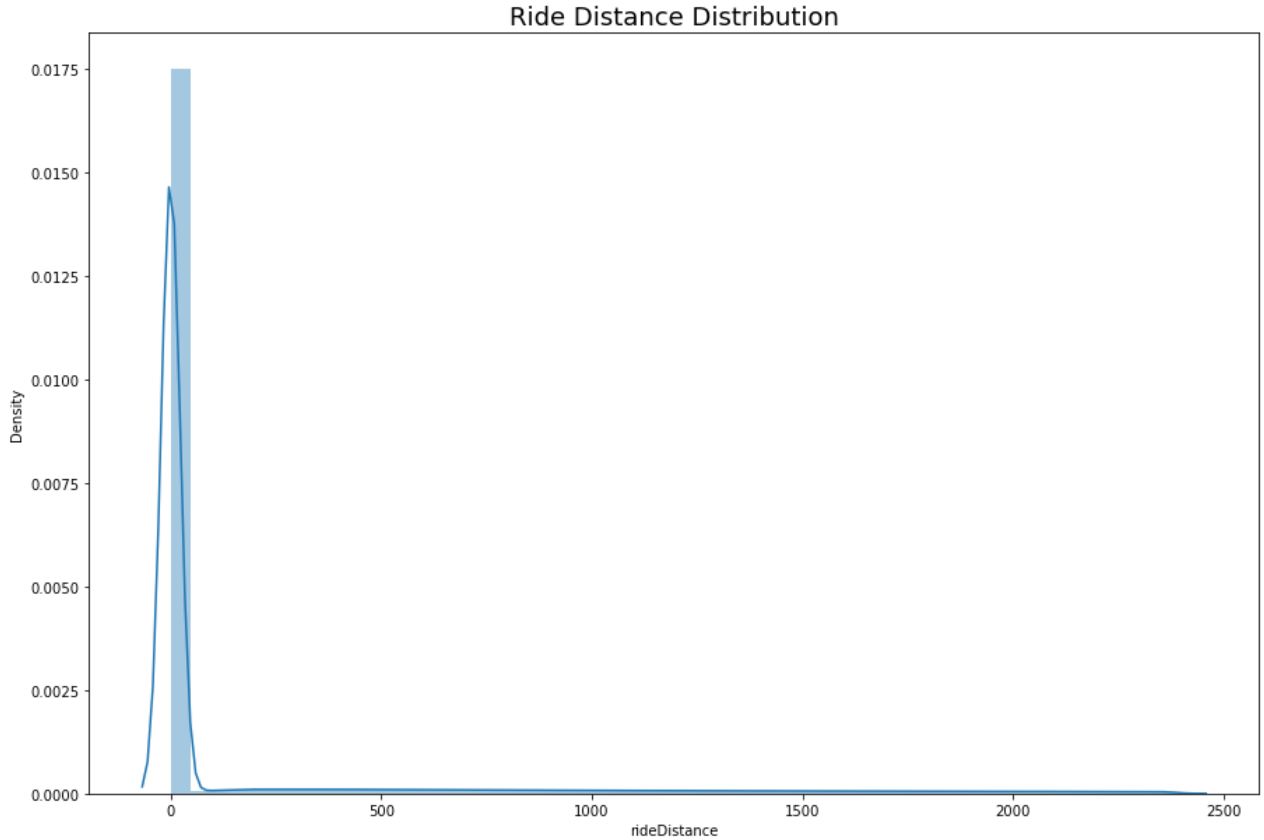
In [16]:

```
print("The average distance driven: {:.2f}m\n99% of players have driven: {}m or less\nT
```

```
The average distance driven: 606.12m
99% of players have driven: 6966.0m or less
The longest distance driven: 40710.00m
```

In [17]:

```
data = train.copy()
data = data[data['rideDistance']<train['rideDistance'].quantile(0.9)] #top10%
plt.figure(figsize=(15,10))
plt.title("Ride Distance Distribution", fontsize=18)
sns.distplot(data['rideDistance'])
plt.show()
```



wow, so many people drive so little distance. How many are they?

In [18]:

```
print("{} players ({:.2f}%) have driven for 0m.".format(len(data[data['rideDistance']==
```

```
3309429 players (74.42%) have driven for 0m.
```

Healers and Boosters

In [19]:

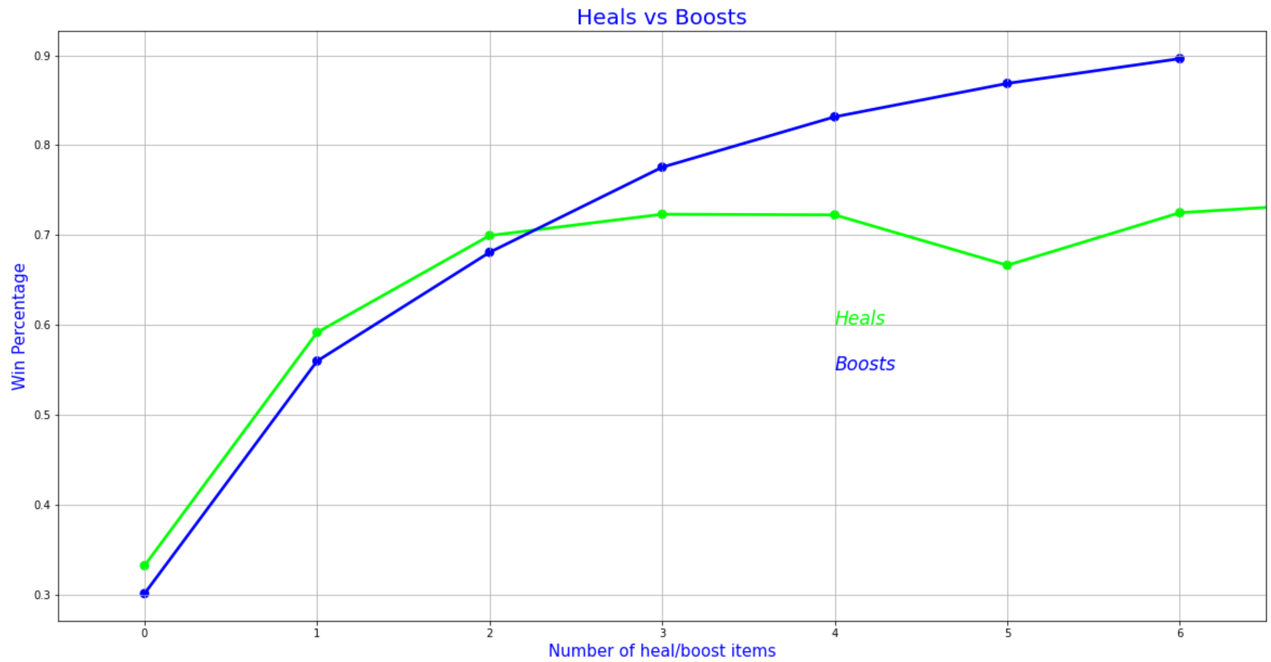
```
print("The average person uses {:.1f} heal items, 99% of people use {} or less.".format
print("The average person uses {:.1f} boost items, 99% of people use {} or less.".forma
```

```
The average person uses 1.4 heal items, 99% of people use 12.0 or less.
The average person uses 1.1 boost items, 99% of people use 7.0 or less.
```

In [20]:

```
data = train.copy()
data = data[data['heals'] < data['heals'].quantile(0.99)] #pick 99%
data = data[data['boosts'] < data['boosts'].quantile(0.99)]

f,ax1 = plt.subplots(figsize =(20,10))
sns.pointplot(x='heals',y='winPlacePerc',data=data,color='lime',alpha=0.8)
sns.pointplot(x='boosts',y='winPlacePerc',data=data,color='blue',alpha=0.8)
plt.text(4,0.6,'Heals',color='lime',fontsize = 17,style = 'italic')
plt.text(4,0.55,'Boosts',color='blue',fontsize = 17,style = 'italic')
plt.xlabel('Number of heal/boost items',fontsize = 15,color='blue')
plt.ylabel('Win Percentage',fontsize = 15,color='blue')
plt.title('Heals vs Boosts',fontsize = 20,color='blue')
plt.grid()
plt.show()
```



So healing and boosting, definitely are correlated with winPlacePerc. Boosting is more. In every plot, there is an abnormal behavior when values are 0.

In [21]:

```
train['boosts_per_walking_distance'] = train['boosts']/(train['walkDistance']+1)
train['boosts_per_walking_distance'].fillna(0, inplace=True)
train['heals_per_walking_distance'] = train['heals']/(train['walkDistance']+1)
train['heals_per_walking_distance'].fillna(0, inplace=True)
train[['walkDistance','boosts','boosts_per_walking_distance','heals','heals_per_walking
```

Out[21]:

	walkDistance	boosts	boosts_per_walking_distance	heals	heals_per_walking_distance
40	327.30	1	0.003046	1	0.003046
41	128.80	0	0.000000	0	0.000000
42	52.52	0	0.000000	0	0.000000
43	534.10	1	0.001869	0	0.000000
44	2576.00	4	0.001552	6	0.002328

Solos, Duos and Squads

In [22]:

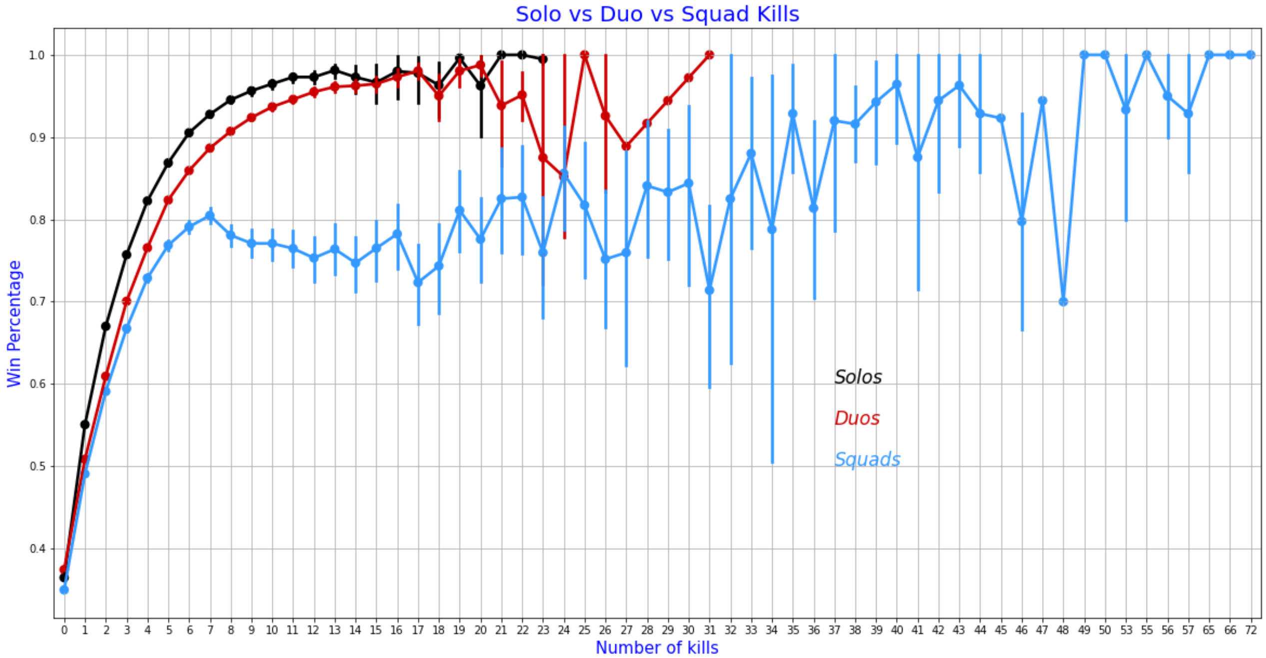
```
solos = train[train['numGroups']>50]
duos = train[(train['numGroups']>25) & (train['numGroups']<=50)]
squads = train[train['numGroups']<=25]
print("There are {} ({:.2f}%) solo games, {} ({:.2f}%) duo games and {} ({:.2f}%) squad
```

```
There are 709111 (15.95%) solo games, 3295326 (74.10%) duo games and 442529 (9.95%) squa
d games.
```

In [23]:

```
f,ax1 = plt.subplots(figsize =(20,10))
sns.pointplot(x='kills',y='winPlacePerc',data=solos,color='black',alpha=0.8)
sns.pointplot(x='kills',y='winPlacePerc',data=duos,color='#CC0000',alpha=0.8)
sns.pointplot(x='kills',y='winPlacePerc',data=squads,color='#3399FF',alpha=0.8)
```

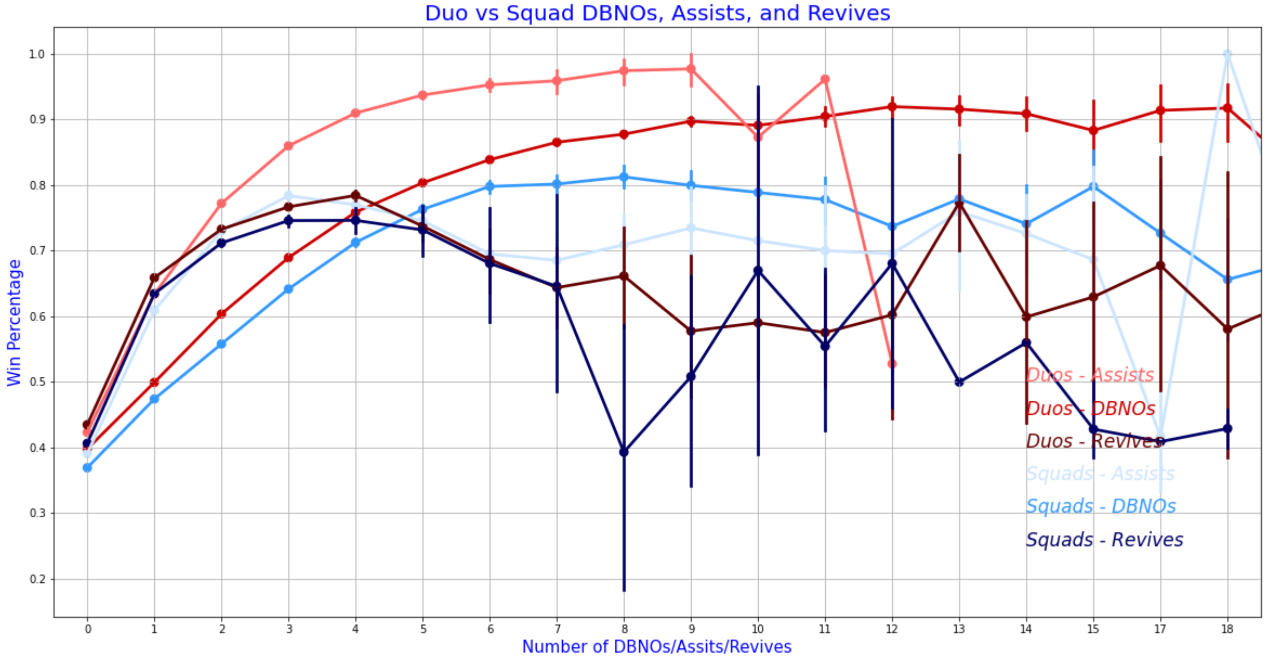
```
plt.text(37,0.6,'Solos',color='black',fontsize = 17,style = 'italic')
plt.text(37,0.55,'Duos',color='#CC0000',fontsize = 17,style = 'italic')
plt.text(37,0.5,'Squads',color='#3399FF',fontsize = 17,style = 'italic')
plt.xlabel('Number of kills',fontsize = 15,color='blue')
plt.ylabel('Win Percentage',fontsize = 15,color='blue')
plt.title('Solo vs Duo vs Squad Kills',fontsize = 20,color='blue')
plt.grid()
plt.show()
```



As you can see, as the number of kills increases, the win% increases generally.

In [24]:

```
f,ax1 = plt.subplots(figsize =(20,10))
sns.pointplot(x='DBNOs',y='winPlacePerc',data=duos,color='#CC0000',alpha=0.8)
sns.pointplot(x='DBNOs',y='winPlacePerc',data=squads,color='#3399FF',alpha=0.8)
sns.pointplot(x='assists',y='winPlacePerc',data=duos,color='#FF6666',alpha=0.8)
sns.pointplot(x='assists',y='winPlacePerc',data=squads,color='#CCE5FF',alpha=0.8)
sns.pointplot(x='revives',y='winPlacePerc',data=duos,color='#660000',alpha=0.8)
sns.pointplot(x='revives',y='winPlacePerc',data=squads,color='#000066',alpha=0.8)
plt.text(14,0.45,'Duos - DBNOs',color='#CC0000',fontsize = 17,style = 'italic')
plt.text(14,0.5,'Duos - Assists',color='#FF6666',fontsize = 17,style = 'italic')
plt.text(14,0.4,'Duos - Revives',color='#660000',fontsize = 17,style = 'italic')
plt.text(14,0.3,'Squads - DBNOs',color='#3399FF',fontsize = 17,style = 'italic')
plt.text(14,0.35,'Squads - Assists',color='#CCE5FF',fontsize = 17,style = 'italic')
plt.text(14,0.25,'Squads - Revives',color='#000066',fontsize = 17,style = 'italic')
plt.xlabel('Number of DBNOs/Assits/Revives',fontsize = 15,color='blue')
plt.ylabel('Win Percentage',fontsize = 15,color='blue')
plt.title('Duo vs Squad DBNOs, Assists, and Revives',fontsize = 20,color='blue')
plt.grid()
plt.show()
```



If your partner/teammate who shares the identical matchId as you gets DBNOs/ revives/assists it indirectly contributes to the win%.

In [25]:
```
train['team'] = [1 if i>50 else 2 if (i>25 & i<=50) else 4 for i in train['numGroups']]
```

In [26]:
```
train.head()
```

Out[26]:

	Id	groupId	matchId	assists	boosts	damageDealt	DBNOs	headshotI
0	7f96b2f878858a	4d4b580de459be	a10357fd1a4a91	0	0	0.00	0	
1	eef90569b9d03c	684d5656442f9e	aeb375fc57110c	0	0	91.47	0	
2	1eaf90ac73de72	6a4a42c3245a74	110163d8bb94ae	1	0	68.00	0	
3	4616d365dd2853	a930a9c79cd721	f1f1f4ef412d7e	0	0	32.90	0	
4	315c96c26c9aac	de04010b3458dd	6dc8ff871e21e6	0	0	100.00	0	

5 rows × 32 columns

Thank you for reading my project. I know it looks shabby, because it's my first personal project. Once again, much thanks!