In [ ]:

```
# i took dataset of suicide rate overview from 1985 to 2016
```

In [3]:

```
import numpy as np
import pandas as pd
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:

```
#reading the file
df = pd.read_csv (r'master.csv')
```

In [5]:

```
df.head()
```

Out[5]:

	country	year	sex	age	suicides_no	population	suicides/100k pop	country-year	HDI for year	gdp
0	Albania	1987	male	15-24 years	21	312900	6.71	Albania1987	NaN	2,15
1	Albania	1987	male	35-54 years	16	308000	5.19	Albania1987	NaN	2,15
2	Albania	1987	female	15-24 years	14	289700	4.83	Albania1987	NaN	2,15
3	Albania	1987	male	75+ years	1	21800	4.59	Albania1987	NaN	2,15
4	Albania	1987	male	25-34 years	9	274300	3.28	Albania1987	NaN	2,15

In [4]:

```
print(df)
```

```
          country  year     sex          age  suicides_no  population  \
0         Albania  1987    male  15-24 years           21      312900
1         Albania  1987    male  35-54 years           16      308000
2         Albania  1987  female  15-24 years           14      289700
3         Albania  1987    male    75+ years            1       21800
4         Albania  1987    male  25-34 years            9      274300
...           ...   ...     ...          ...          ...         ...
27815  Uzbekistan  2014  female  35-54 years          107     3620833
27816  Uzbekistan  2014  female    75+ years            9      348465
27817  Uzbekistan  2014    male   5-14 years           60     2762158
27818  Uzbekistan  2014  female   5-14 years           44     2631600
27819  Uzbekistan  2014  female  55-74 years           21     1438935

       suicides/100k pop    country-year  HDI for year  gdp_for_year ($)   \
0                   6.71     Albania1987           NaN    2,156,624,900
1                   5.19     Albania1987           NaN    2,156,624,900
2                   4.83     Albania1987           NaN    2,156,624,900
3                   4.59     Albania1987           NaN    2,156,624,900
4                   3.28     Albania1987           NaN    2,156,624,900
...                  ...             ...           ...              ...
27815               2.96  Uzbekistan2014         0.675   63,067,077,179
27816               2.58  Uzbekistan2014         0.675   63,067,077,179
27817               2.17  Uzbekistan2014         0.675   63,067,077,179
27818               1.67  Uzbekistan2014         0.675   63,067,077,179
27819               1.46  Uzbekistan2014         0.675   63,067,077,179

       gdp_per_capita ($)       generation
0                     796     Generation X
1                     796           Silent
2                     796     Generation X
3                     796  G.I. Generation
4                     796          Boomers
...                   ...              ...
27815                2309     Generation X
27816                2309           Silent
27817                2309     Generation Z
27818                2309     Generation Z
27819                2309          Boomers

[27820 rows x 12 columns]
```

In [6]:

```
#Here RV function will be suicide_no,population,suicides/100k pop,HDI for year,gdp_for_year
#DVS will be {country,year,sex ,age,suicides_no,population,suicides/100k pop,country-year,H
#Iam taking Three numerical features: suicides_no,population,gdp_per_capita ($)
import matplotlib.pyplot as plt
```

In [7]:

```
df.columns
```

Out[7]:

```
Index(['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides/100k pop', 'country-year', 'HDI for year',
       ' gdp_for_year ($) ', 'gdp_per_capita ($)', 'generation'],
      dtype='object')
```

In [8]:

```
df.describe()
```

Out[8]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_per_capita ($)
count	27820.000000	27820.000000	2.782000e+04	27820.000000	8364.000000	27820.000000
mean	2001.258375	242.574407	1.844794e+06	12.816097	0.776601	16866.464414
std	8.469055	902.047917	3.911779e+06	18.961511	0.093367	18887.576472
min	1985.000000	0.000000	2.780000e+02	0.000000	0.483000	251.000000
25%	1995.000000	3.000000	9.749850e+04	0.920000	0.713000	3447.000000
50%	2002.000000	25.000000	4.301500e+05	5.990000	0.779000	9372.000000
75%	2008.000000	131.000000	1.486143e+06	16.620000	0.855000	24874.000000
max	2016.000000	22338.000000	4.380521e+07	224.970000	0.944000	126352.000000

In [9]:

```
df.shape
```

Out[9]:

```
(27820, 12)
```

In [10]:

```
df.isnull().any()
```

Out[10]:

```
country                False
year                   False
sex                    False
age                    False
suicides_no            False
population             False
suicides/100k pop      False
country-year           False
HDI for year            True
 gdp_for_year ($)      False
gdp_per_capita ($)     False
generation             False
dtype: bool
```

In [11]:

```
df.isnull().values.any()
```

Out[11]:

```
True
```

In [12]:

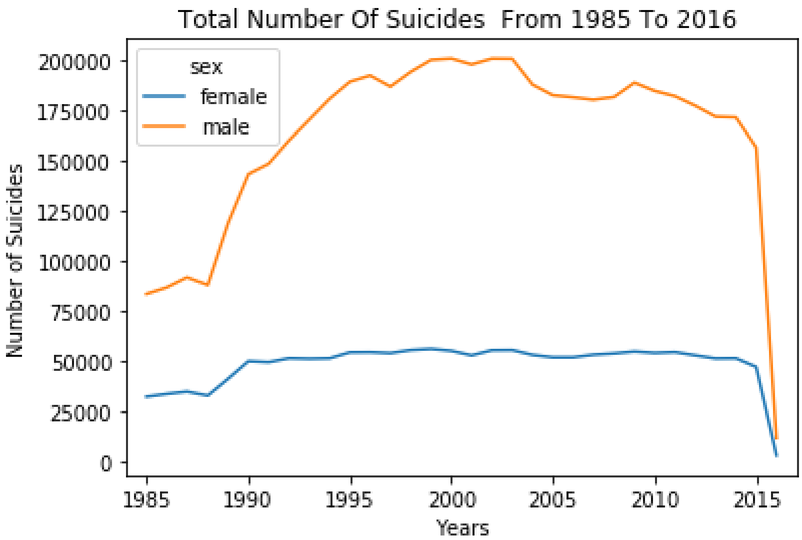
```
df.isnull().sum()
```

Out[12]:

```
country                   0
year                      0
sex                       0
age                       0
suicides_no               0
population                0
suicides/100k pop         0
country-year              0
HDI for year          19456
 gdp_for_year ($)         0
gdp_per_capita ($)        0
generation                0
dtype: int64
```

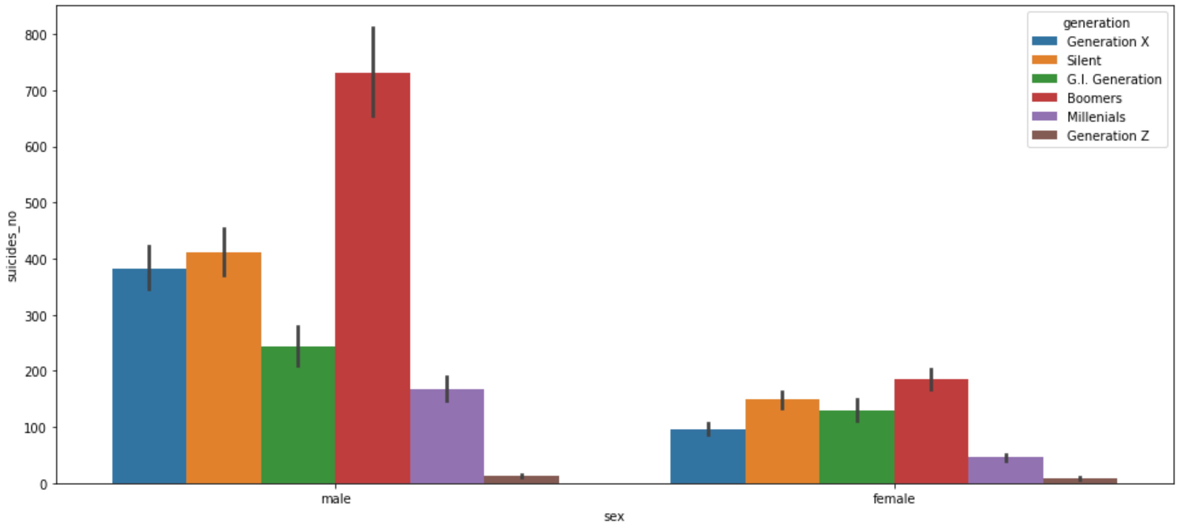
In [21]:

```
df.pivot_table('suicides_no', index='year', columns='sex', aggfunc='sum').plot()
plt.title('Total Number Of Suicides  From 1985 To 2016 ')
plt.ylabel('Number of Suicides')
plt.xlabel('Years')
plt.xlim((df.year.min() - 1), (df.year.max() + 1))
plt.show()
```



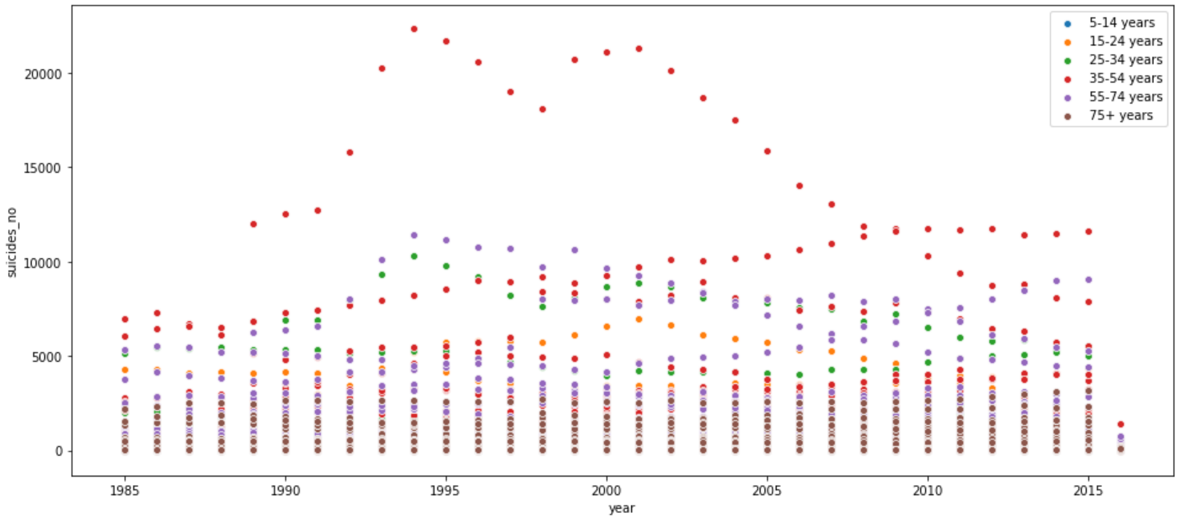
In [26]:

```
plt.figure(figsize=(16,7))
bar_gen = sns.barplot(x = 'sex', y = 'suicides_no', hue = 'generation',data = df)
```



In [27]:

```
###we store a range of age group in variables so we can do easily lineplot
age_5 = df.loc[df.loc[:, 'age']=='5-14 years',:]
age_15 = df.loc[df.loc[:, 'age']=='15-24 years',:]
age_25 = df.loc[df.loc[:, 'age']=='25-34 years',:]
age_35 = df.loc[df.loc[:, 'age']=='35-54 years',:]
age_55 = df.loc[df.loc[:, 'age']=='55-74 years',:]
age_75 = df.loc[df.loc[:, 'age']=='75+ years',:]

### Set figure size
plt.figure(figsize=(16,7))
####Now lets plot a line plot
age_5_lp = sns.scatterplot(x='year', y='suicides_no', data=age_5)
age_15_lp = sns.scatterplot(x='year', y='suicides_no', data=age_15)
age_25_lp = sns.scatterplot(x='year', y='suicides_no', data=age_25)
age_35_lp = sns.scatterplot(x='year', y='suicides_no', data=age_35)
age_55_lp = sns.scatterplot(x='year', y='suicides_no', data=age_55)
age_75_lp = sns.scatterplot(x='year', y='suicides_no', data=age_75)

##Now make the legend
leg = plt.legend(['5-14 years', '15-24 years', '25-34 years', '35-54 years', '55-74 years',
```



In [40]:

```
suicides_no=[]
for country in df.country.unique():
    suicides_no.append(sum(df[df['country']==country].suicides_no))
```

In [65]:

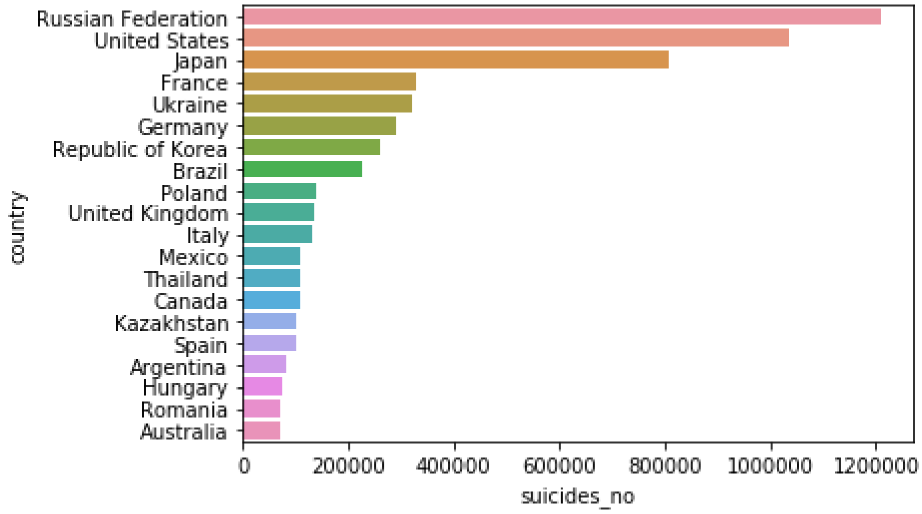
```
suicides_no=pd.DataFrame(suicidesNo,columns=['suicides_no'])
country=pd.DataFrame(df.country.unique(),columns=['country'])
data_suicide_countr=pd.concat([suicides_no,country],axis=1)
```

In [66]:

```
data_suicide_countr=data_suicide_countr.sort_values(by='suicides_no',ascending= False)
```

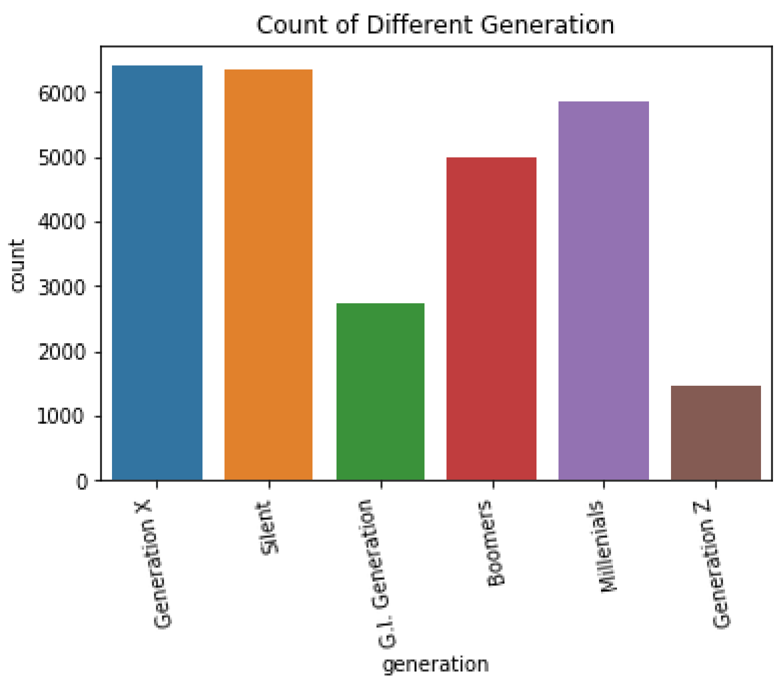
In [72]:

```
sns.barplot(y=data_suicide_countr.country[:20],x=data_suicide_countr.suicides_no[:20])
plt.show()
```



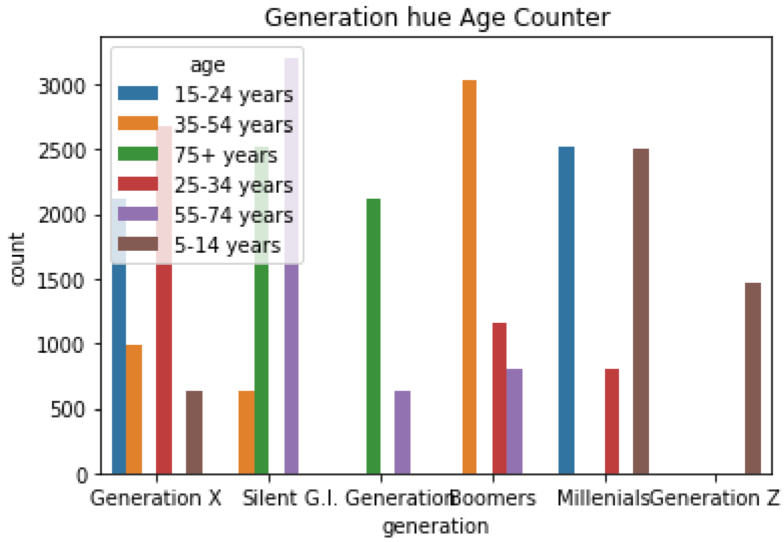
In [96]:

```
sns.countplot(df.generation)
plt.title('Count of Different Generation')
plt.xticks(rotation=100)
plt.show()
```



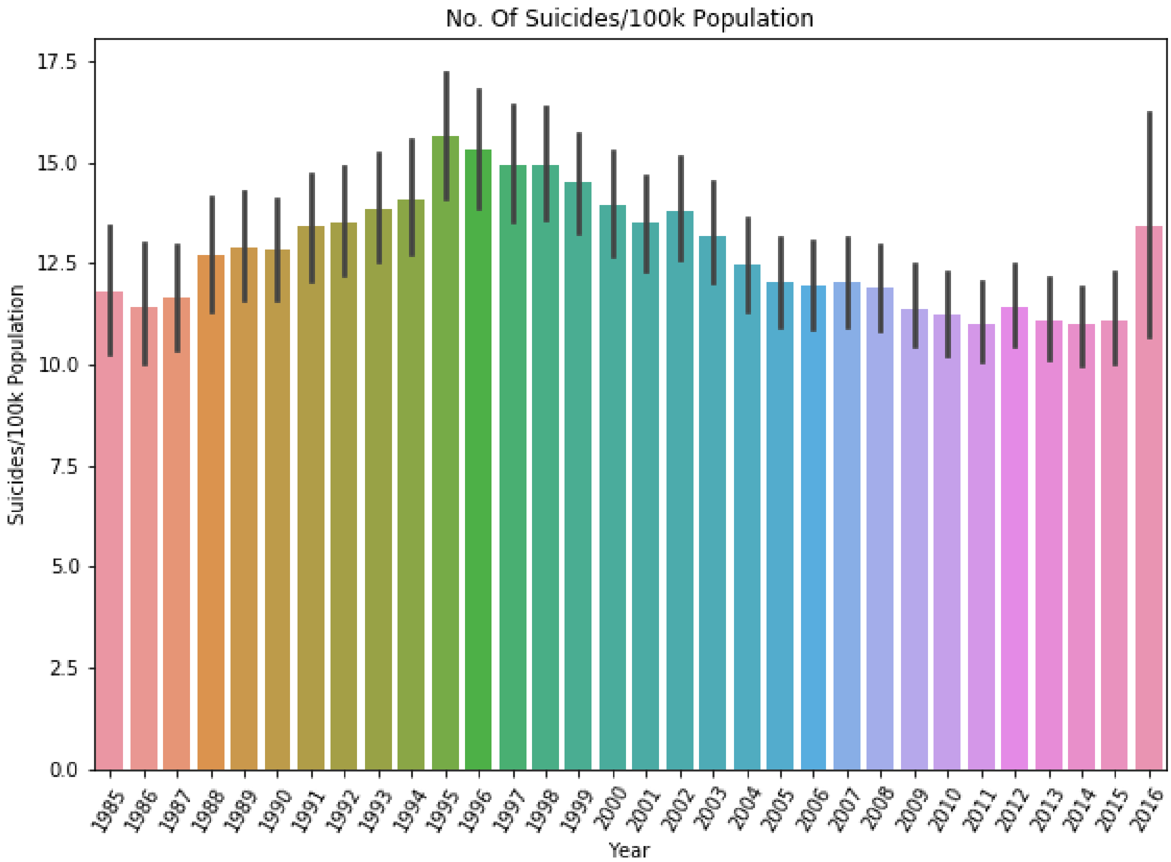
In [97]:

```
sns.countplot(df.generation,hue=df.age)
plt.title('Generation hue Age Counter')
plt.show()
```



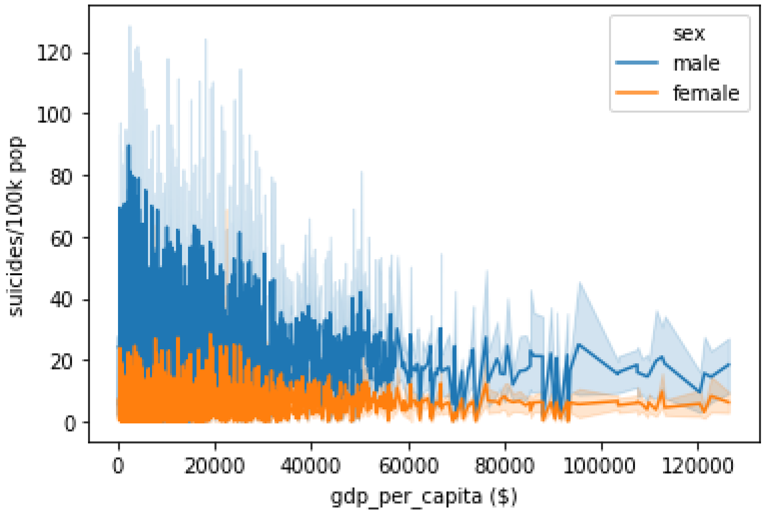
In [16]:

```
plt.figure(figsize=(10,7))
sns.barplot(x="year", y='suicides/100k pop', data=df)
plt.title('No. Of Suicides/100k Population')
plt.xlabel('Year')
plt.ylabel('Suicides/100k Population')
plt.xticks(rotation=60)
plt.show()
```



In [34]:

```
sns.lineplot(x="gdp_per_capita ($)", y="suicides/100k pop",
             hue="sex",data=df.sort_values(by='suicides/100k pop',ascending=False))
plt.show()
```



In [6]:

```
df.keys()
```

Out[6]:

```
Index(['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides/100k pop', 'country-year', 'HDI for year',
       ' gdp_for_year ($) ', 'gdp_per_capita ($)', 'generation'],
      dtype='object')
```

In [9]:

```
df.shape
```

Out[9]:

```
(27820, 12)
```

In [10]:

```
from sklearn.preprocessing import StandardScaler
```

In [18]:

```
df.drop(['country', 'sex', 'country-year','generation','HDI for year','age','year'], axis=1
```

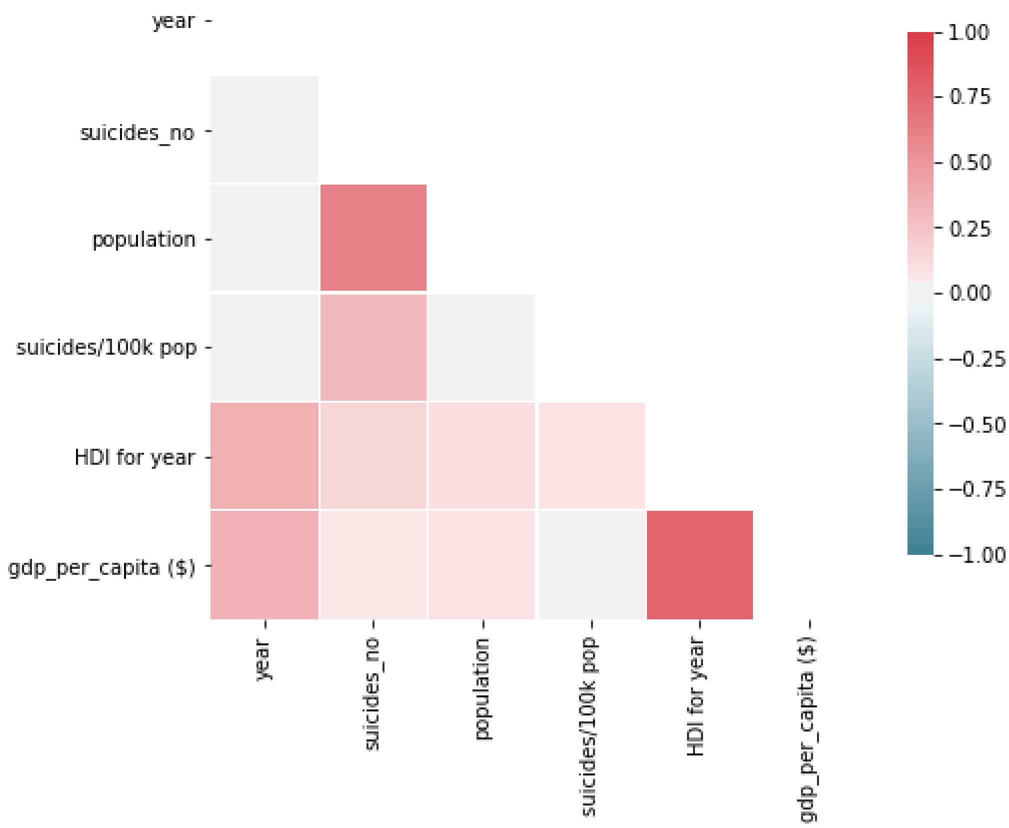
Out[18]:

	suicides_no	population	suicides/100k pop	gdp_for_year ($)	gdp_per_capita ($)
0	21	312900	6.71	2,156,624,900	796
1	16	308000	5.19	2,156,624,900	796
2	14	289700	4.83	2,156,624,900	796
3	1	21800	4.59	2,156,624,900	796
4	9	274300	3.28	2,156,624,900	796
...	...	...	...	...	...
27815	107	3620833	2.96	63,067,077,179	2309
27816	9	348465	2.58	63,067,077,179	2309
27817	60	2762158	2.17	63,067,077,179	2309
27818	44	2631600	1.67	63,067,077,179	2309
27819	21	1438935	1.46	63,067,077,179	2309

27820 rows × 5 columns

In [36]:

```
corr = df.corr()

# Generate a mask for the upper triangle

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(8, 6))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, vmin=-1, center=0,
            square=True, linewidths=0.2, cbar_kws={"shrink": 0.8});
```



In [50]:

```
columns = ['country', 'year', 'sex', 'age','population',
       'suicides/100k pop', 'country-year', 'generation']
target = df['suicides_no']
```

In [51]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import cross_val_predict
from sklearn.preprocessing import LabelEncoder
from sklearn.decomposition import PCA
```

In [52]:

```
le = LabelEncoder()
df['country'] = le.fit_transform(df['country'])
df['year'] = le.fit_transform(df['year'])
df['sex'] = le.fit_transform(df['sex'])
df['age'] = le.fit_transform(df['age'])
df['population'] = le.fit_transform(df['population'])
df['suicides/100k pop'] = le.fit_transform(df['suicides/100k pop'])
df['country-year'] = le.fit_transform(df['country-year'])
df['generation'] = le.fit_transform(df['generation'])
```

In [61]:

```
pca = PCA()
principalComponents_breast = pca.fit_transform(df[columns])
print(principalComponents_breast)
```

```
[[-2.31684505e+03 -4.53767702e+02  1.11999354e+03 ... -1.96117148e+00
  -1.07058042e+00 -4.63567807e-01]
 [-2.43358026e+03 -6.04235343e+02  1.11216061e+03 ... -2.28749710e+00
  -1.02630525e+00 -5.09103315e-01]
 [-2.91094103e+03 -6.34515173e+02  1.10626850e+03 ... -1.90114131e+00
  -1.04977949e+00  5.03890558e-01]
 ...
 [ 8.20582523e+03 -9.28808305e+02 -1.12575230e+03 ...  1.01996017e+00
  -2.58438260e-01 -7.18348912e-01]
 [ 8.08026418e+03 -9.77266079e+02 -1.12911135e+03 ...  1.06034728e+00
  -2.37513236e-01  2.72296037e-01]
 [ 6.25422584e+03 -9.76491580e+02 -1.14644126e+03 ...  3.69772770e+00
  -2.39223403e-01  2.02973656e-01]]
```

In [54]:

```
clf = DecisionTreeClassifier()
clf.fit(df[columns], target)
```

Out[54]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [55]:

```
clf.feature_importances_
```

Out[55]:

```
array([0.02654578, 0.08812791, 0.01008352, 0.02727822, 0.2886141 ,
       0.44604726, 0.08645713, 0.02684608])
```

In [58]:

```
target_pred = cross_val_predict(clf,df[columns],target,cv=6)
print('accuracy: ', accuracy_score(target, target_pred))
print('confusion matrix:')
print(confusion_matrix(target, target_pred))
print('classification report:')
print(classification_report(target, target_pred))
```

```
C:\Users\natha\anaconda3\lib\site-packages\sklearn\model_selection\_split.
py:667: UserWarning: The least populated class in y has only 1 members, wh
ich is less than n_splits=6.
  % (min_groups, self.n_splits)), UserWarning)
```

In [34]:

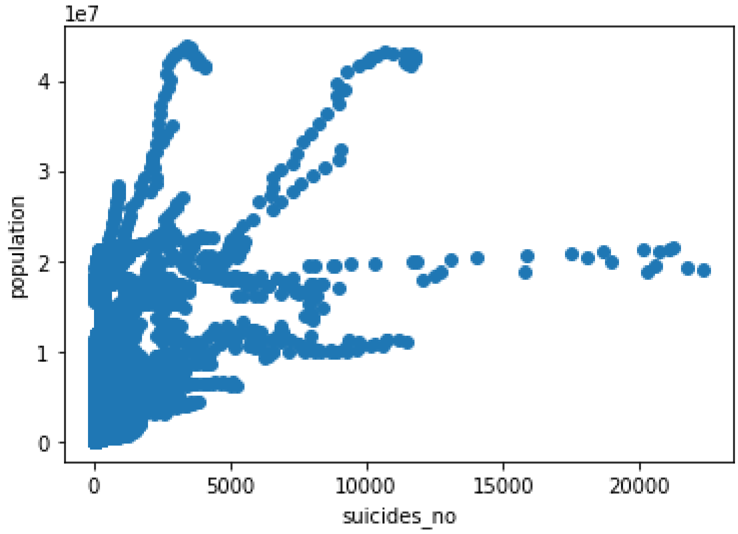
```
#scatter plot for suicides_no  and population
y = df['population'];
x = df['suicides_no']
```

In [35]:

```
a =plt.xlabel('suicides_no');
b =plt.ylabel('population')
plt.scatter(x,y)
```

Out[35]:

```
<matplotlib.collections.PathCollection at 0x1a12decbd48>
```



In [37]:

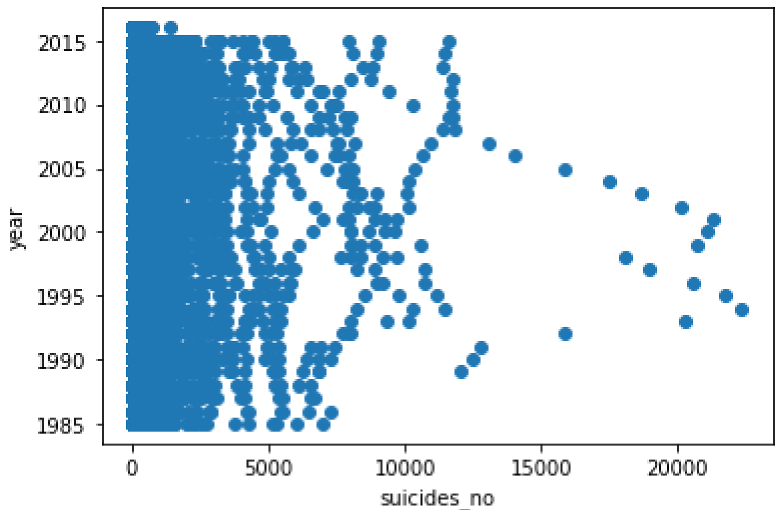
```
#scatter plot for suicides_no  and population
y = df['year'];
x = df['suicides_no']
```

In [38]:

```
a =plt.xlabel('suicides_no');
b =plt.ylabel('year')
plt.scatter(x,y)
```

Out[38]:

```
<matplotlib.collections.PathCollection at 0x1a130ee4448>
```

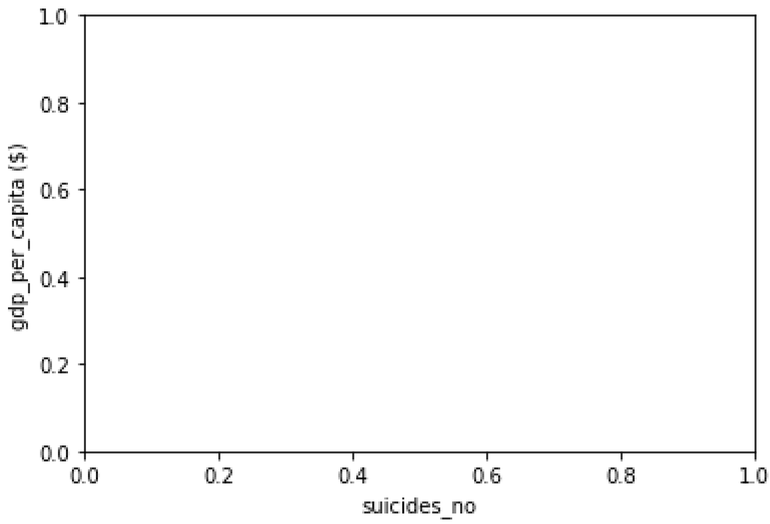


In [56]:

```
plt.xlabel('suicides_no');
plt.ylabel('gdp_per_capita ($)')
```

Out[56]:

```
Text(0, 0.5, 'gdp_per_capita ($)')
```

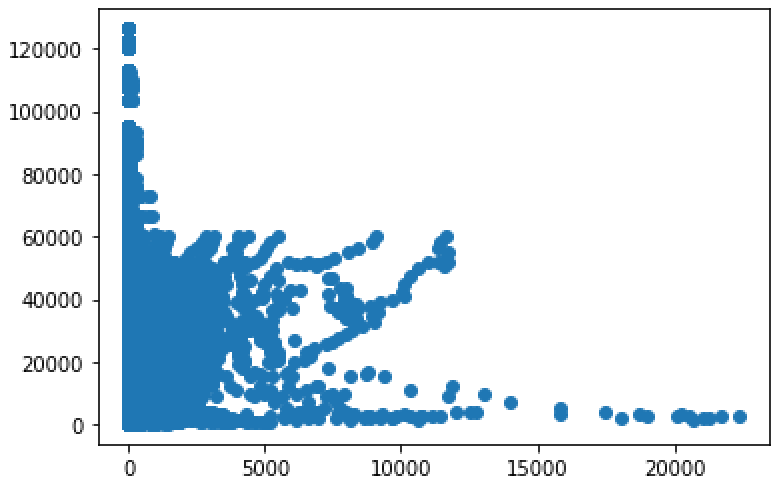


In [57]:

```
plt.scatter(x,y)
```

Out[57]:

<matplotlib.collections.PathCollection at 0x2f214972f88>



In [28]:

```
#finding pearson coefficient for each of the features
import scipy
from scipy.stats.stats import pearsonr
```

In [83]:

```
y = df['population'];
x = df['gdp_per_capita ($)']
```

In [84]:

```
pearson_correlation,p_value =pearsonr(x, y)
```

In [85]:

```
pearson_correlation
```

Out[85]:

```
0.08150985822280538
```

In [76]:

```
y = df['population'];
x = df['suicides_no']
```

In [77]:

```
pearson_correlation,p_value =pearsonr(x, y)
```

In [78]:

```
pearson_correlation
```

Out[78]:

```
0.6161622675219284
```

In [79]:

```
x = df['gdp_per_capita ($)'];
y = df['suicides_no']
```

In [80]:

```
pearson_correlation,p_value =pearsonr(x, y)
```

In [81]:

```
pearson_correlation
```

Out[81]:

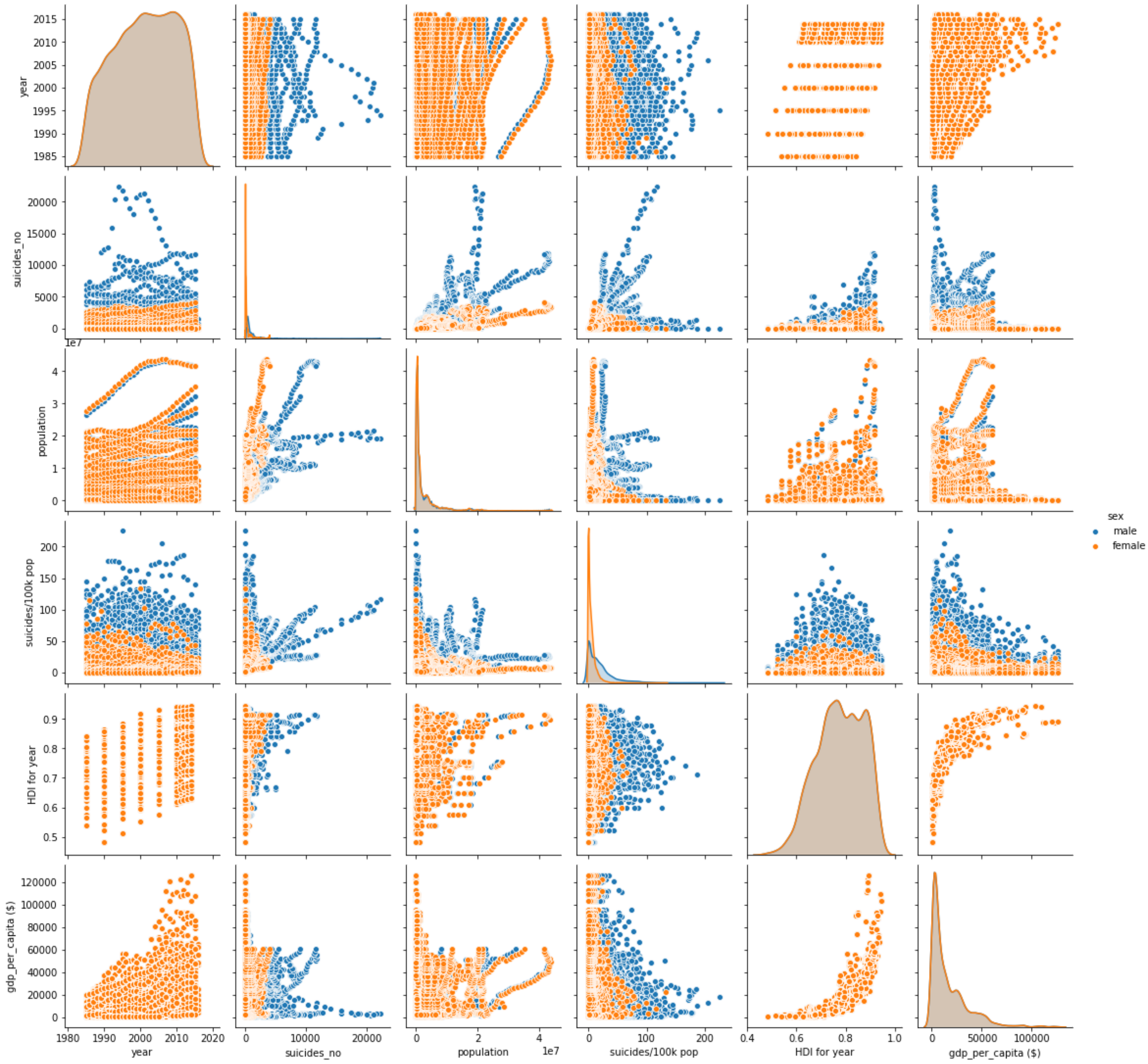
```
0.06132974884024557
```

In [52]:

```
#finding scatter matrix for RV functions
df_features=df[['age','suicides_no','population','suicides/100k pop','HDI for year',' gdp_f
```

In [21]:

```
sns.pairplot(df, hue="sex")
plt.show()
```



In [16]:

```
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import mean_absolute_error, accuracy_score
from sklearn.metrics import classification_report, confusion_matrix

from sklearn.model_selection import train_test_split
```

In [17]:

```
df.rename(columns={'HDI for year': 'HDI_for_year', 'country-year':'country_year', 'suicides
```

In [18]:

```
data = df.copy()
```

In [19]:

```
data.generation.replace(['Boomers', 'Generation X', 'Generation Z', 'G.I. Generation', 'Mil
                        ['0', '1', '2', '3', '4', '5'], inplace=True)

data.sex.replace(['male', 'female'], ['0', '1'], inplace=True)

data['gdp_for_year'] = data['gdp_for_year'].str.replace(',','')

def means(arr):
    return str(np.array(arr).mean())
data.age.replace(['15-24 years', '25-34 years', '35-54 years', '5-14 years', '55-74 years',
                 [means([15, 24]), means([25, 34]), means([35, 54]),
                  means([5, 14]), means([55, 74]), means([75])], inplace=True)
```

In [20]:

```
data.drop(['country', 'year', 'country_year'], 1, inplace=True)
```

In [21]:

```
pd.to_numeric(data['generation']);
pd.to_numeric(data['sex']);
pd.to_numeric(data['gdp_for_year']);
```

In [22]:

```
data['fatality_rate'] = np.where(data['suicides/100k_pop']>data['suicides/100k_pop'].mean()
                                 1, 0)
```

In [23]:

```
data.head()
```

Out[23]:

	sex	age	suicides_no	population	suicides/100k_pop	HDI_for_year	gdp_for_year	gdp_per_
0	0	19.5	21	312900	6.71	NaN	2156624900	
1	0	44.5	16	308000	5.19	NaN	2156624900	
2	1	19.5	14	289700	4.83	NaN	2156624900	
3	0	75.0	1	21800	4.59	NaN	2156624900	
4	0	29.5	9	274300	3.28	NaN	2156624900	

In [28]:

```
X = np.array(data.drop(['fatality_rate','HDI_for_year', 'suicides/100k_pop'], 1))
y = np.array(data.fatality_rate)
```

In [29]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)
```

In [30]:

```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

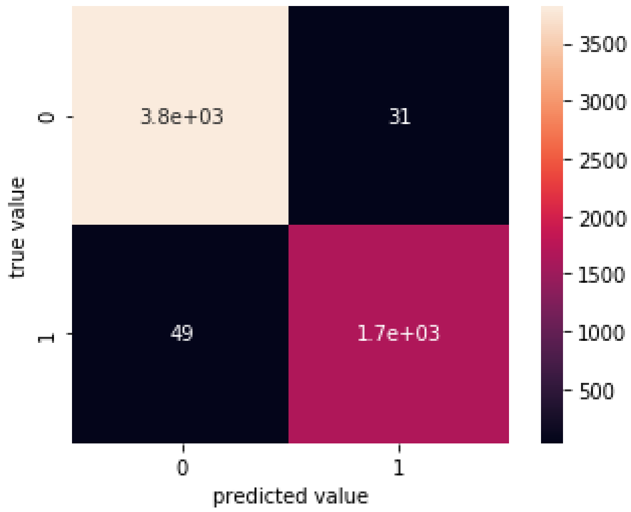
In [31]:

```
print("Model accuracy is: {0:.2f}".format(accuracy_score(y_test, y_pred) * 100))
```

```
Model accuracy is: 98.56
```

In [32]:

```
mat = confusion_matrix(y_test, y_pred)

sns.heatmap(mat, square=True, annot=True, cbar=True)

plt.xlabel('predicted value')
plt.ylabel('true value');
```



In [33]:

```
print(classification_report(y_pred, y_test))
```

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      3865
           1       0.97      0.98      0.98      1699

    accuracy                           0.99      5564
   macro avg       0.98      0.98      0.98      5564
weighted avg       0.99      0.99      0.99      5564
```

In [87]:

```
#plotting of pearsion correlation of each feature
gf =df[['suicides_no','population','gdp_per_capita ($)']]
```

In [88]:

```
corr = gf.corr()
```

In [89]:

```
corr
```

Out[89]:

	suicides_no	population	gdp_per_capita ($)
suicides_no	1.000000	0.616162	0.06133
population	0.616162	1.000000	0.08151
gdp_per_capita ($)	0.061330	0.081510	1.00000

In [7]:

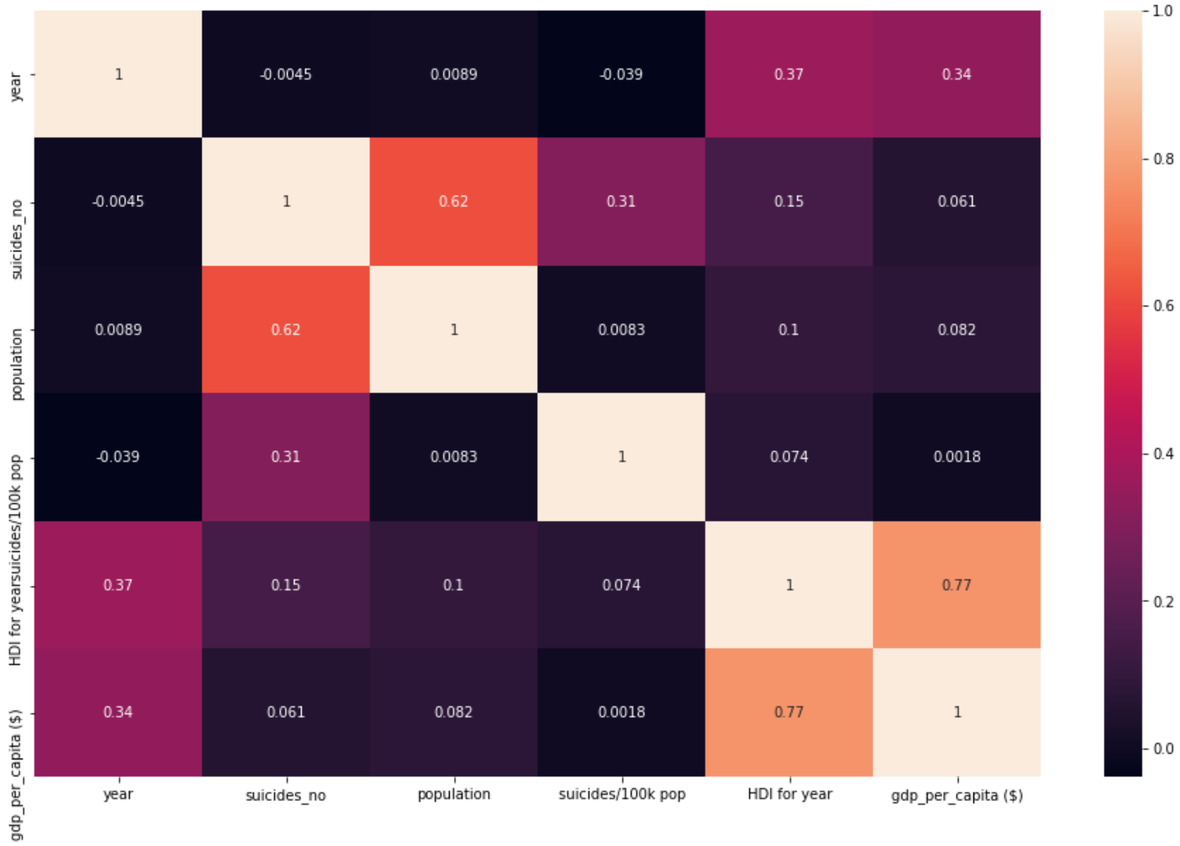
```
df.corr()
```

Out[7]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_per_capita ($)
year	1.000000	-0.004546	0.008850	-0.039037	0.366786	0.339134
suicides_no	-0.004546	1.000000	0.616162	0.306604	0.151399	0.061330
population	0.008850	0.616162	1.000000	0.008285	0.102943	0.081510
suicides/100k pop	-0.039037	0.306604	0.008285	1.000000	0.074279	0.001785
HDI for year	0.366786	0.151399	0.102943	0.074279	1.000000	0.771228
gdp_per_capita ($)	0.339134	0.061330	0.081510	0.001785	0.771228	1.000000

In [10]:

```
plt.figure(figsize=(16,10))
sb.heatmap(df.corr(),annot= True)
plt.show()
```



In [ ]:

In [ ]:

```

```