1) Текстовое описание набора данных

Датасет: suicide-rates-overview-1985-to-2016.csv

Источник: https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016 (https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016)

Зависимость количества самоубийств по годам и странам от социальных (возраст, пол, поколение) и экономических составляющих (ИЧР, ВВП)

Колонки:

- country страна
- year год (1985 2016)
- sex пол
- age возраст (6 диапазонов)
- suicides_no кол-во самоубийств
- population кол-во людей в данном возрастном диапазоне
- suicides/100k pop suicides_no / (population / 100 000)
- country-year конкатенация страна + год
- HDI for year Human Development Index Индекс человеческого развития
- gdp_for_year (doll.) ВВП на год
- gdp per capita (doll.) ВВП на человека
- generation поколение (базируется на среднем значении для данного возраста) всего 6

2) Основные характеристики датасета

```
In [1]:
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

In [2]:
data = pd.read_csv('data/suicide-rates-overview-1985-to-2016.csv', sep=',', thou sands=',')

In [3]:
data.shape
Out[3]:
(27820, 12)
```

In [5]:

```
data.dtypes
```

Out[5]:

```
object
country
                         int64
year
sex
                        object
age
                        object
                         int64
suicides no
population
                         int64
suicides/100k pop
                       float64
country-year
                        object
                       float64
HDI for year
 gdp for year ($)
                         int64
gdp per capita ($)
                         int64
                        object
generation
dtype: object
```

dtype='object')

In [6]:

```
def count_empty_values(data):
    for col in data.columns:
        temp_null_count = data[data[col].isnull()].shape[0]
        print('{} - {}'.format(col, temp_null_count))
count_empty_values(data)
```

```
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
```

In [7]:

удалим пустые значения

```
data = data.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)
country - 0
year - 0
sex - 0
age - 0
suicides_no - 0
population - 0
suicides/100k pop - 0
country-year - 0
HDI for year - 0
gdp_for_year ($) - 0
gdp_per_capita ($) - 0
generation - 0
```

In [8]:

```
data.describe()
```

Out[8]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year (\$)	g
count	8364.000000	8364.000000	8.364000e+03	8364.000000	8364.000000	8.364000e+03	
mean	2005.348637	206.124342	1.852173e+06	11.991936	0.776601	5.476639e+11	
std	8.803020	681.004457	3.969754e+06	17.361772	0.093367	1.720106e+12	
min	1985.000000	0.000000	8.750000e+02	0.000000	0.483000	3.962700e+08	
25%	2000.000000	3.000000	1.216425e+05	1.040000	0.713000	1.430751e+10	
50%	2010.000000	27.000000	4.722505e+05	5.720000	0.779000	6.175779e+10	
75 %	2012.000000	127.250000	1.500290e+06	15.442500	0.855000	3.115395e+11	
max	2014.000000	11767.000000	4.350934e+07	187.060000	0.944000	1.742761e+13	1

3) Визуальное исследование датасета

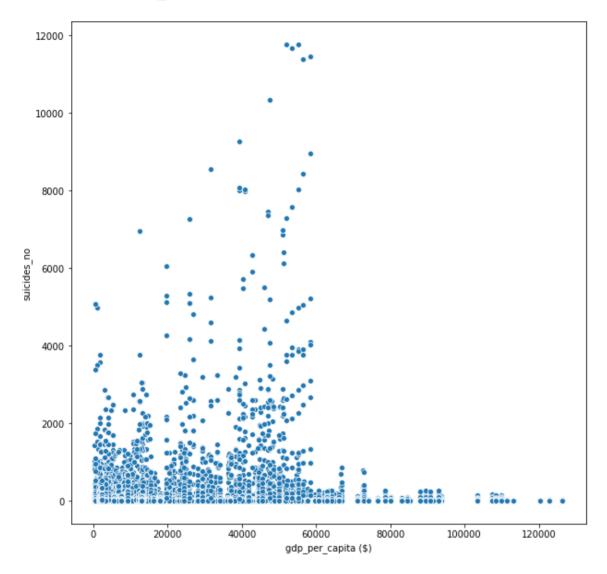
Диаграмма рассеяния

In [9]:

```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='gdp_per_capita ($)', y='suicides_no', data=data)
```

Out[9]:

<matplotlib.axes._subplots.AxesSubplot at 0x11d7ba390>



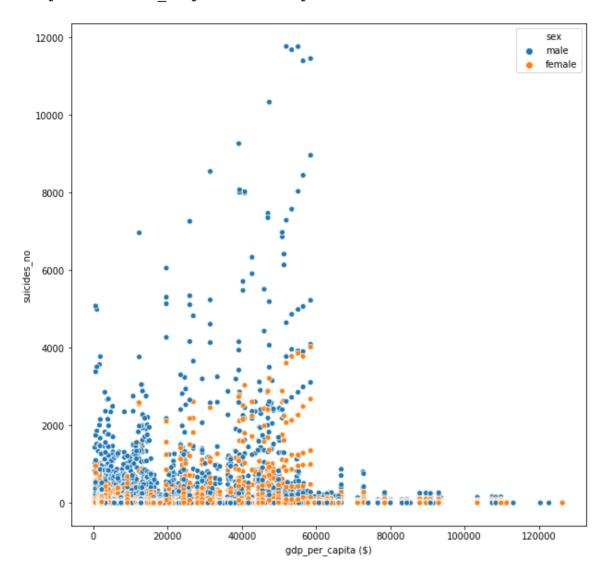
Очевидна обратная зависимость: чем больше ВВП на человека, тем меньше кол-во самоубийств.

In [10]:

```
fig, ax = plt.subplots(figsize=(10,10))
sns.scatterplot(ax=ax, x='gdp_per_capita ($)', y='suicides_no', data=data, hue=
'sex')
```

Out[10]:

<matplotlib.axes._subplots.AxesSubplot at 0x11d7fa9e8>



Больше самоубийств среди мужчин.

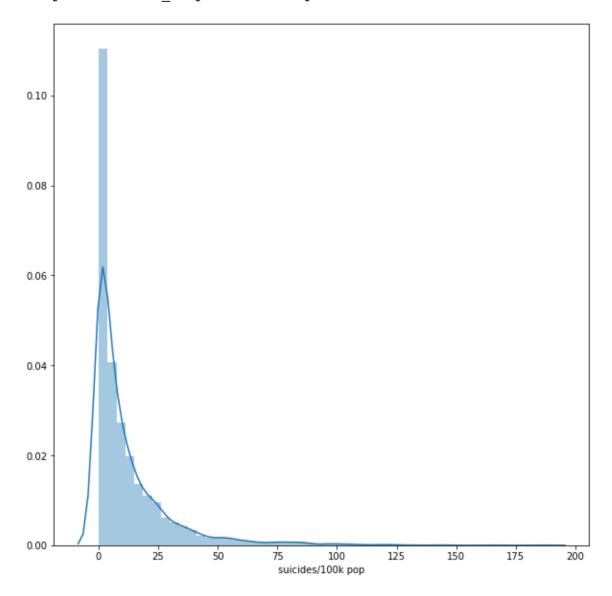
Гистограмма

In [11]:

```
# плотность вероятности распределения
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['suicides/100k pop'])
```

Out[11]:

<matplotlib.axes._subplots.AxesSubplot at 0x11da56978>



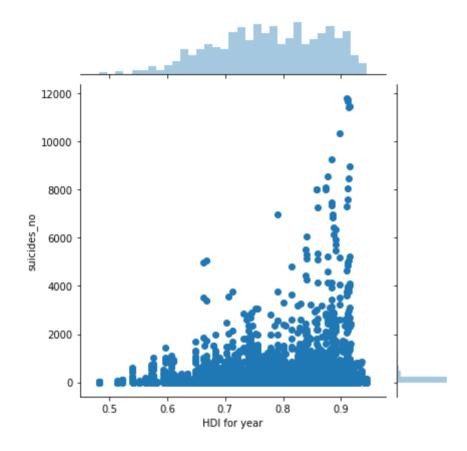
Jointplot

In [12]:

```
sns.jointplot(x='HDI for year', y='suicides_no', data=data)
```

Out[12]:

<seaborn.axisgrid.JointGrid at 0x11e186240>

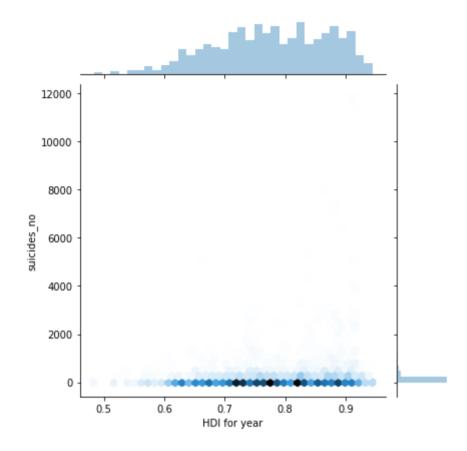


In [13]:

```
sns.jointplot(x='HDI for year', y='suicides_no', data=data, kind='hex')
```

Out[13]:

<seaborn.axisgrid.JointGrid at 0x1227b7f60>

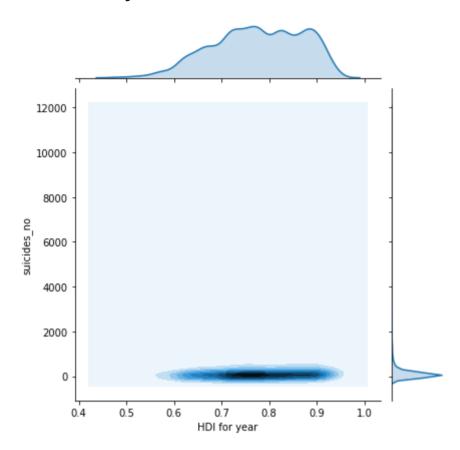


In [14]:

```
sns.jointplot(x='HDI for year', y='suicides_no', data=data, kind='kde')
```

Out[14]:

<seaborn.axisgrid.JointGrid at 0x1229fe630>



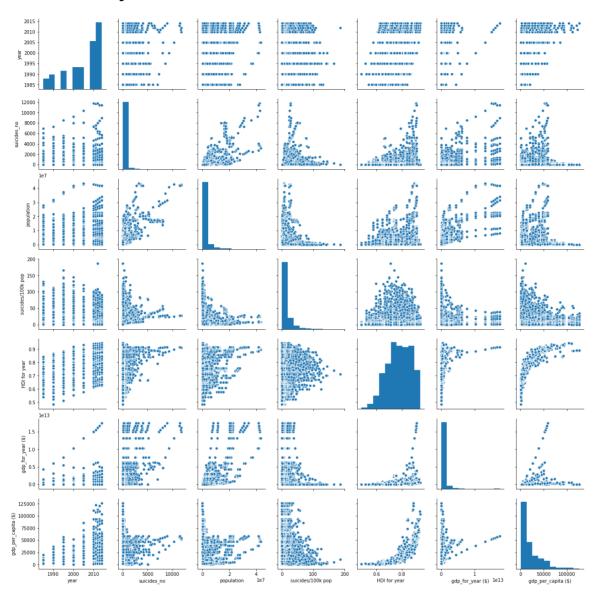
"Парные диаграммы"

In [15]:

sns.pairplot(data)

Out[15]:

<seaborn.axisgrid.PairGrid at 0x122b800f0>

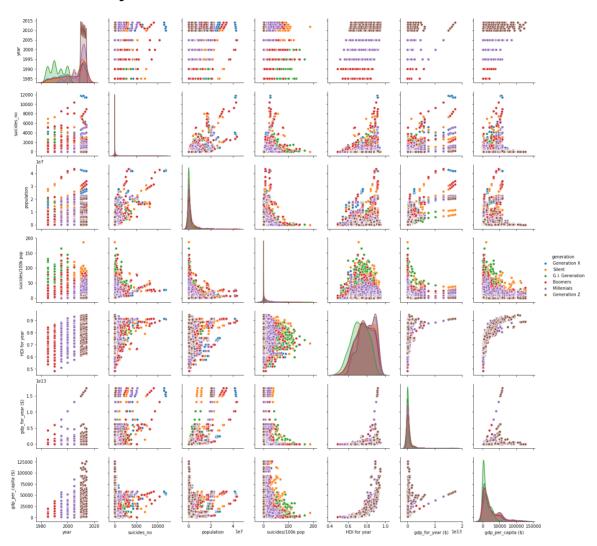


In [16]:

```
sns.pairplot(data, hue='generation')
```

Out[16]:

<seaborn.axisgrid.PairGrid at 0x124841e48>



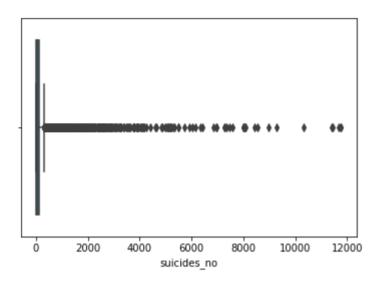
Ящик с усами

In [17]:

```
sns.boxplot(x=data['suicides_no'])
```

Out[17]:

<matplotlib.axes._subplots.AxesSubplot at 0x12674c6d8>

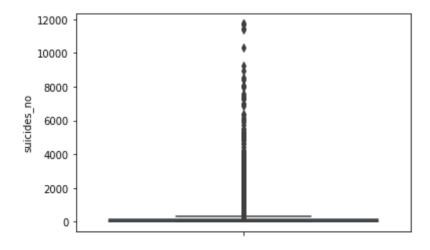


In [18]:

```
sns.boxplot(y=data['suicides_no'])
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x1265c7160>

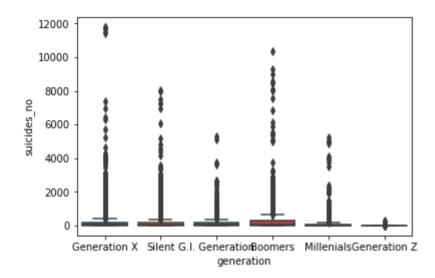


In [19]:

```
sns.boxplot(x='generation', y='suicides_no', data=data)
```

Out[19]:

<matplotlib.axes. subplots.AxesSubplot at 0x127ab8208>



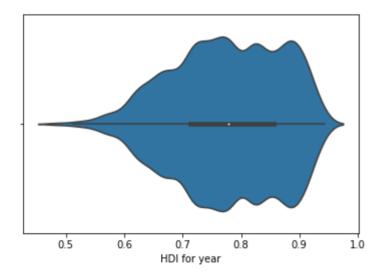
Violin plot

In [20]:

```
sns.violinplot(x=data['HDI for year'])
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x1278b1be0>

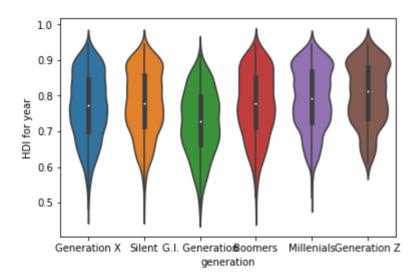


In [21]:

```
sns.violinplot(x='generation', y='HDI for year', data=data)
```

Out[21]:

<matplotlib.axes._subplots.AxesSubplot at 0x127bd0ac8>

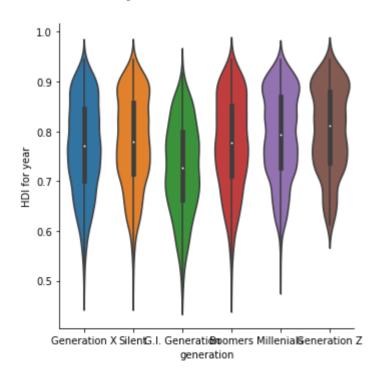


In [22]:

sns.catplot(x='generation', y='HDI for year', data=data, kind="violin", split=Tr
ue)

Out[22]:

<seaborn.axisgrid.FacetGrid at 0x127cb6748>



4) Информация о корреляции признаков

In [23]:

data.corr()

Out[23]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year (\$)	gdį
year	1.000000	-0.024297	-0.012628	-0.077410	0.366786	0.079105	
suicides_no	-0.024297	1.000000	0.698758	0.237169	0.151399	0.607203	
population	-0.012628	0.698758	1.000000	-0.023197	0.102943	0.750296	
suicides/100k pop	-0.077410	0.237169	-0.023197	1.000000	0.074279	0.020231	
HDI for year	0.366786	0.151399	0.102943	0.074279	1.000000	0.305193	
gdp_for_year (\$)	0.079105	0.607203	0.750296	0.020231	0.305193	1.000000	
gdp_per_capita (\$)	0.297888	0.105182	0.073701	-0.002339	0.771228	0.275643	

In [24]:

data.corr(method='pearson') # по умолчанию

Out[24]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year (\$)	gdį
year	1.000000	-0.024297	-0.012628	-0.077410	0.366786	0.079105	
suicides_no	-0.024297	1.000000	0.698758	0.237169	0.151399	0.607203	
population	-0.012628	0.698758	1.000000	-0.023197	0.102943	0.750296	
suicides/100k pop	-0.077410	0.237169	-0.023197	1.000000	0.074279	0.020231	
HDI for year	0.366786	0.151399	0.102943	0.074279	1.000000	0.305193	
gdp_for_year (\$)	0.079105	0.607203	0.750296	0.020231	0.305193	1.000000	
gdp_per_capita (\$)	0.297888	0.105182	0.073701	-0.002339	0.771228	0.275643	

In [25]:

data.corr(method='kendall')

Out[25]:

	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year (\$)	gdį
year	1.000000	-0.030382	-0.014514	-0.042359	0.234793	0.123667	
suicides_no	-0.030382	1.000000	0.575942	0.542566	0.121828	0.450226	
population	-0.014514	0.575942	1.000000	0.117592	0.090117	0.573964	
suicides/100k pop	-0.042359	0.542566	0.117592	1.000000	0.099305	0.126114	
HDI for year	0.234793	0.121828	0.090117	0.099305	1.000000	0.435299	
gdp_for_year (\$)	0.123667	0.450226	0.573964	0.126114	0.435299	1.000000	
gdp_per_capita (\$)	0.233916	0.055232	0.035116	0.043455	0.762445	0.409464	

In [26]:

data.corr(method='spearman')

Out[26]:

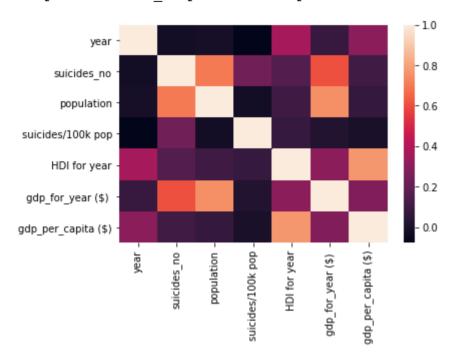
	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year (\$)	gdį
year	1.000000	-0.042841	-0.020724	-0.060357	0.329094	0.173595	
suicides_no	-0.042841	1.000000	0.762456	0.717508	0.184755	0.619786	
population	-0.020724	0.762456	1.000000	0.179320	0.133076	0.765920	
suicides/100k pop	-0.060357	0.717508	0.179320	1.000000	0.152627	0.187876	
HDI for year	0.329094	0.184755	0.133076	0.152627	1.000000	0.612349	
gdp_for_year (\$)	0.173595	0.619786	0.765920	0.187876	0.612349	1.000000	
gdp_per_capita (\$)	0.327475	0.084085	0.053653	0.067476	0.928608	0.591147	

In [27]:

sns.heatmap(data.corr())

Out[27]:

<matplotlib.axes._subplots.AxesSubplot at 0x127f1b4e0>

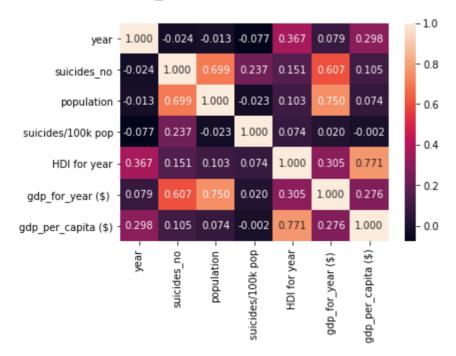


In [28]:

sns.heatmap(data.corr(), annot=True, fmt='.3f')

Out[28]:

<matplotlib.axes._subplots.AxesSubplot at 0x12804eac8>

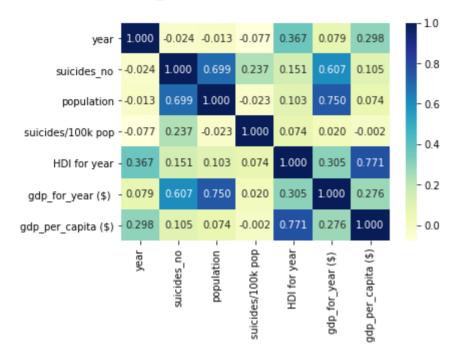


In [29]:

```
sns.heatmap(data.corr(), cmap='YlGnBu', annot=True, fmt='.3f')
```

Out[29]:

<matplotlib.axes. subplots.AxesSubplot at 0x127dbab38>

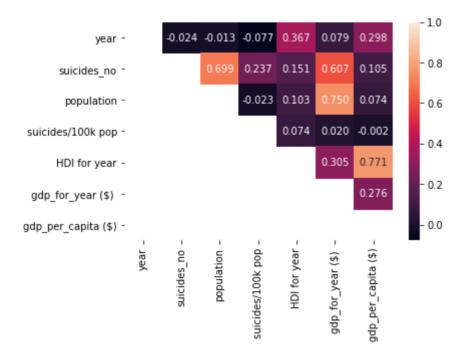


In [30]:

```
mask = np.zeros_like(data.corr(), dtype=np.bool)
mask[np.tril_indices_from(mask)] = True
sns.heatmap(data.corr(), mask=mask, annot=True, fmt='.3f')
```

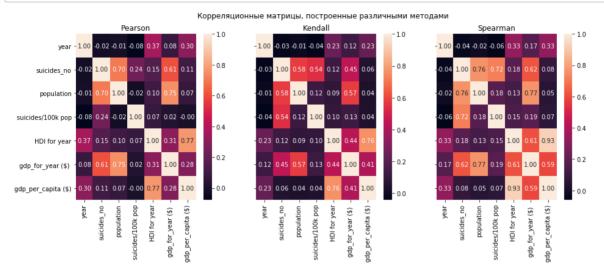
Out[30]:

<matplotlib.axes. subplots.AxesSubplot at 0x127dba828>



In [31]:

```
fig, ax = plt.subplots(1, 3, sharex='col', sharey='row', figsize=(15,5)) sns.heatmap(data.corr(method='pearson'), ax=ax[0], annot=True, fmt='.2f') sns.heatmap(data.corr(method='kendall'), ax=ax[1], annot=True, fmt='.2f') sns.heatmap(data.corr(method='spearman'), ax=ax[2], annot=True, fmt='.2f') fig.suptitle('Корреляционные матрицы, построенные различными методами') ax[0].title.set_text('Pearson') ax[1].title.set_text('Kendall') ax[2].title.set_text('Spearman')
```



Как видно, отличия между различными методами построения корреляционной матрицы незначительны.