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Факультет «Информатика и управление»

Кафедра ИУ5. Курс «Технологии машинного обучения»

Отчет по лабораторной работе №1:
«Разведочный анализ данных. Исследование и визуализация данных»

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Подпись и дата:

Проверил:

Подпись и дата:

Москва, 2019 г.

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=',', thousands=',')
```

In [3]:
```
data.shape
```

Out[3]:
```
(27820, 12)
```

In [4]:
```
data.columns
```

Out[4]:
```
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 [5]:
```
data.dtypes
```

Out[5]:
```
country                 object
year                     int64
sex                     object
age                     object
suicides_no              int64
population               int64
suicides/100k pop      float64
country-year            object
HDI for year           float64
 gdp_for_year ($)        int64
gdp_per_capita ($)       int64
generation              object
dtype: object
```

In [6]:
```python
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]:
```python
# удалим пустые значения
data = data.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)
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 - 0
 gdp_for_year ($)  - 0
gdp_per_capita ($) - 0
generation - 0
```

In [8]:
```
data.describe()
```

Out[8]:

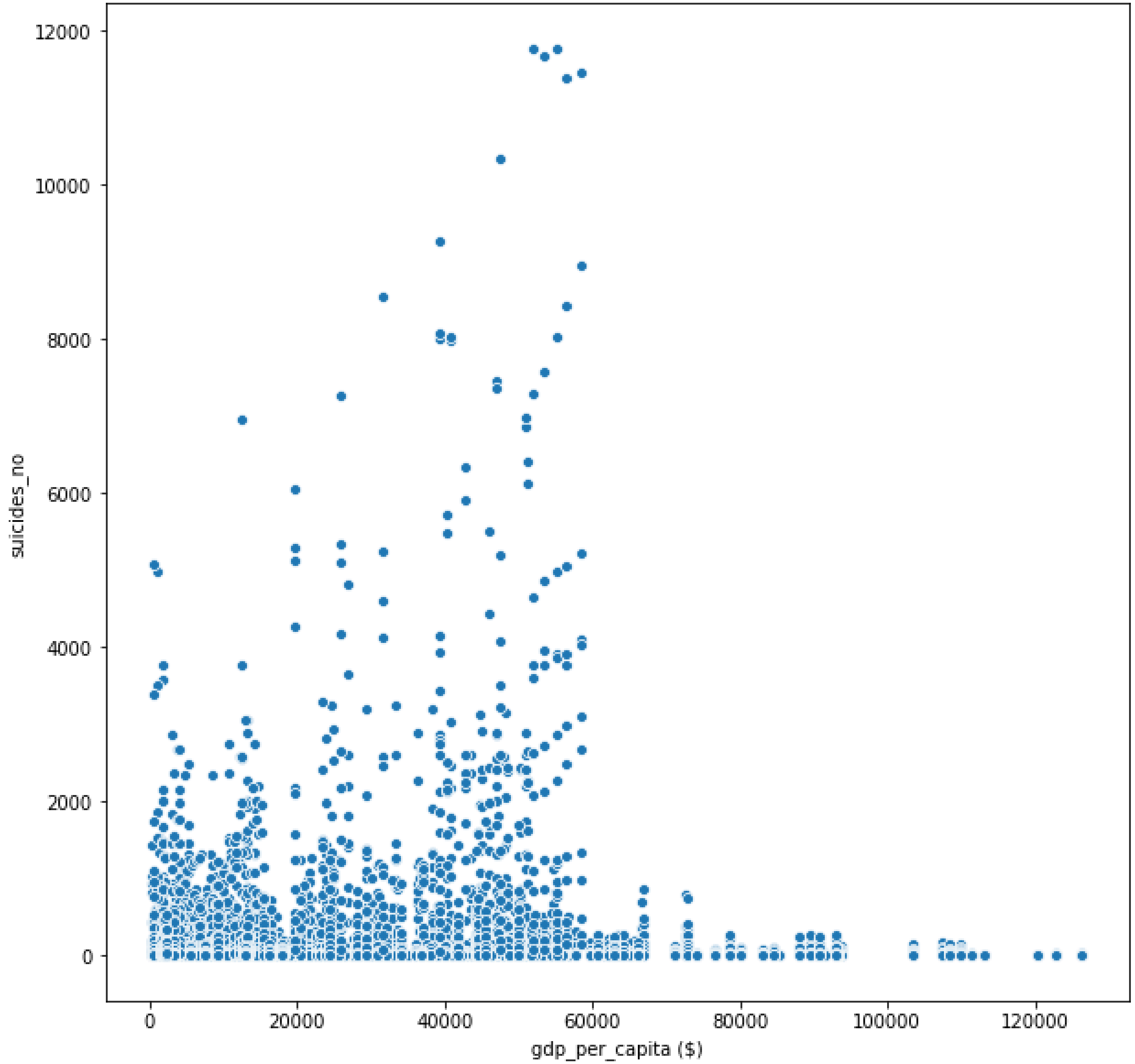
	year	suicides_no	population	suicides/100k pop	HDI for year	gdp_for_year ($)	gdp_per_capita ($)
count	8364.000000	8364.000000	8.364000e+03	8364.000000	8364.000000	8.364000e+03	8364.000000
mean	2005.348637	206.124342	1.852173e+06	11.991936	0.776601	5.476639e+11	21074.371593
std	8.803020	681.004457	3.969754e+06	17.361772	0.093367	1.720106e+12	22579.186968
min	1985.000000	0.000000	8.750000e+02	0.000000	0.483000	3.962700e+08	313.000000
25%	2000.000000	3.000000	1.216425e+05	1.040000	0.713000	1.430751e+10	4862.000000
50%	2010.000000	27.000000	4.722505e+05	5.720000	0.779000	6.175779e+10	12584.000000
75%	2012.000000	127.250000	1.500290e+06	15.442500	0.855000	3.115395e+11	30271.000000
max	2014.000000	11767.000000	4.350934e+07	187.060000	0.944000	1.742761e+13	126352.000000

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)
```

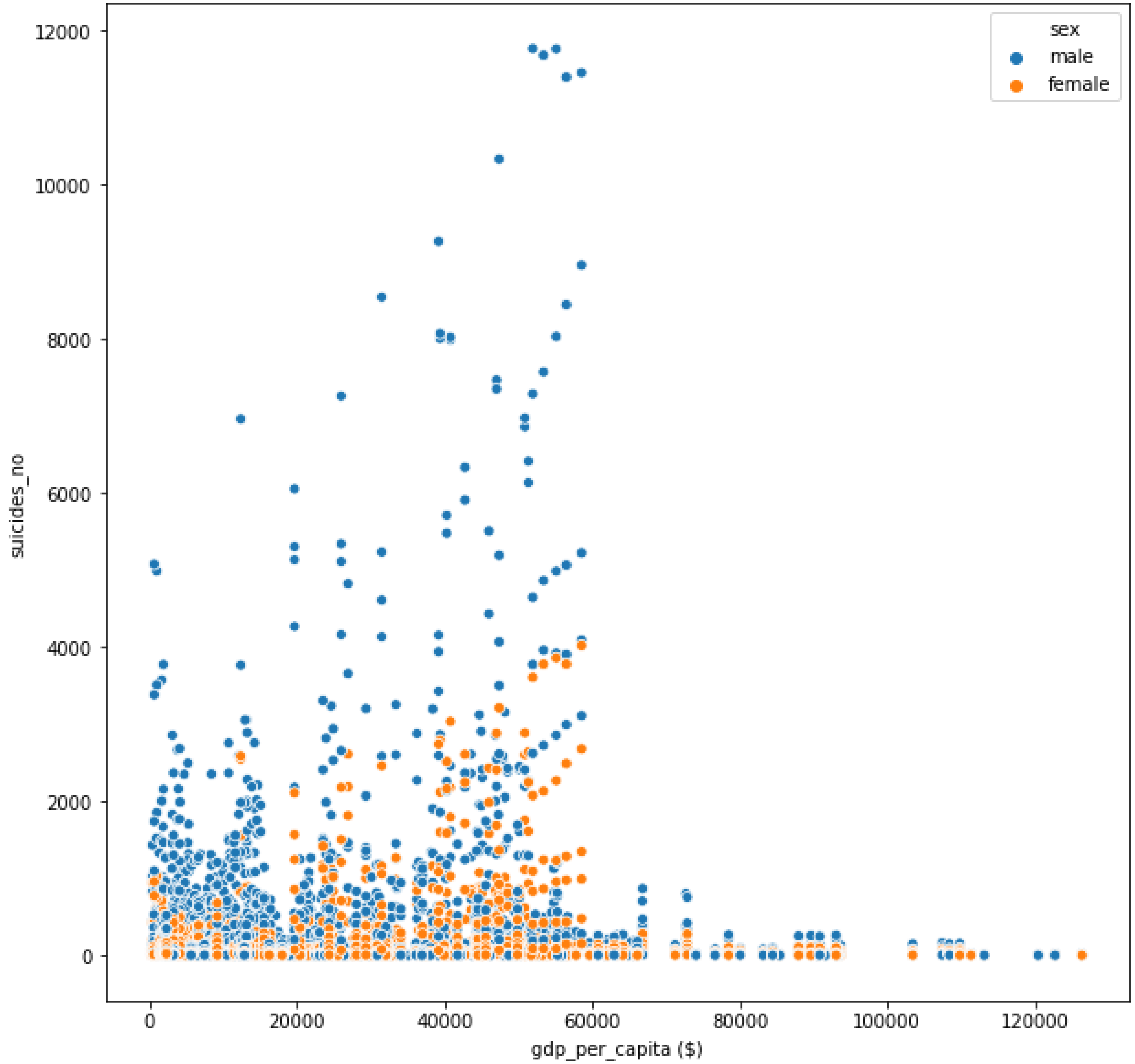
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x120a72b00>



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 0x120fe56a0>

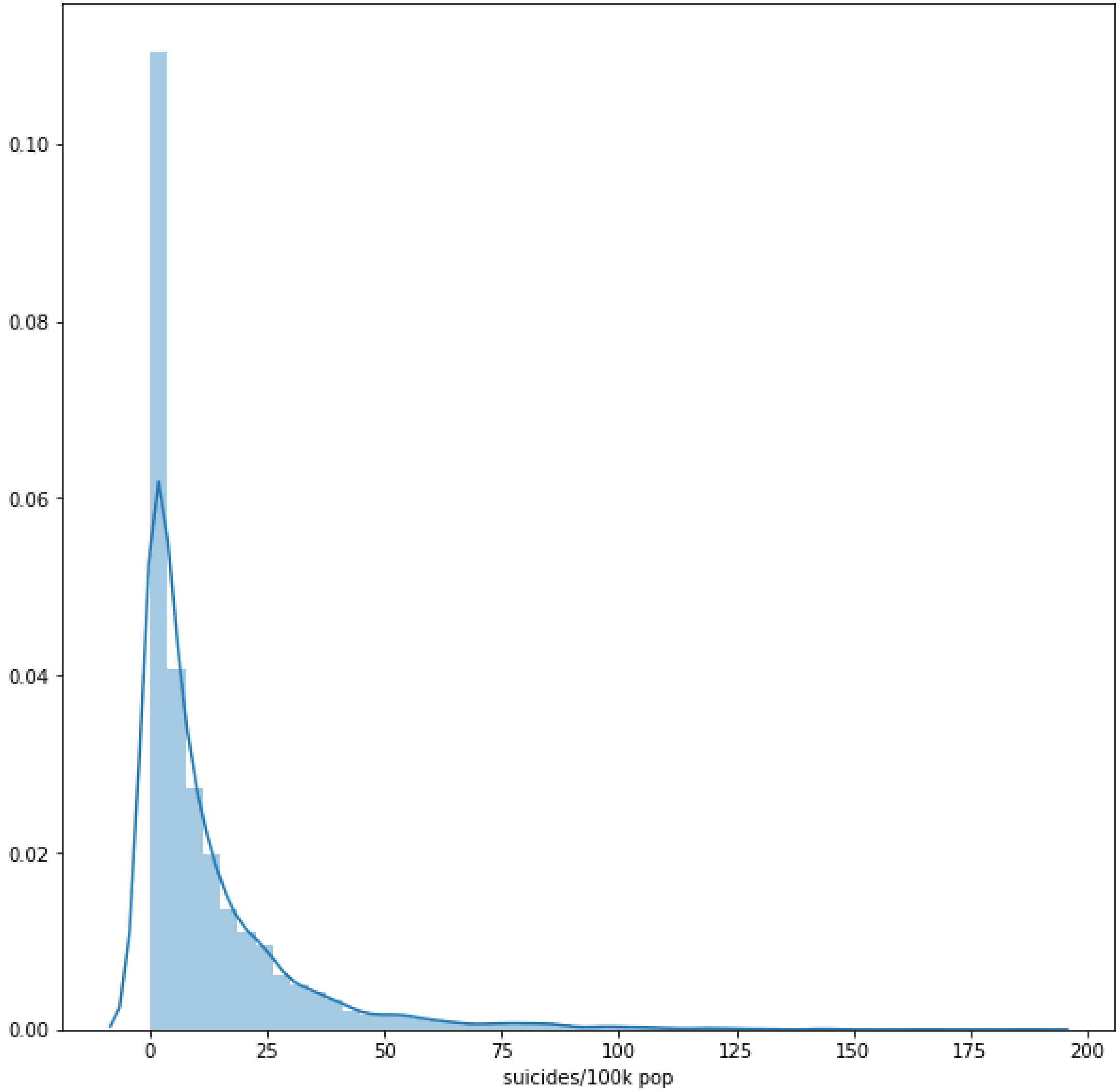


Больше самоубийств среди мужчин.

Гистограмма

In [11]:
```
# плотность вероятности распределения
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['suicides/100k pop'])
```

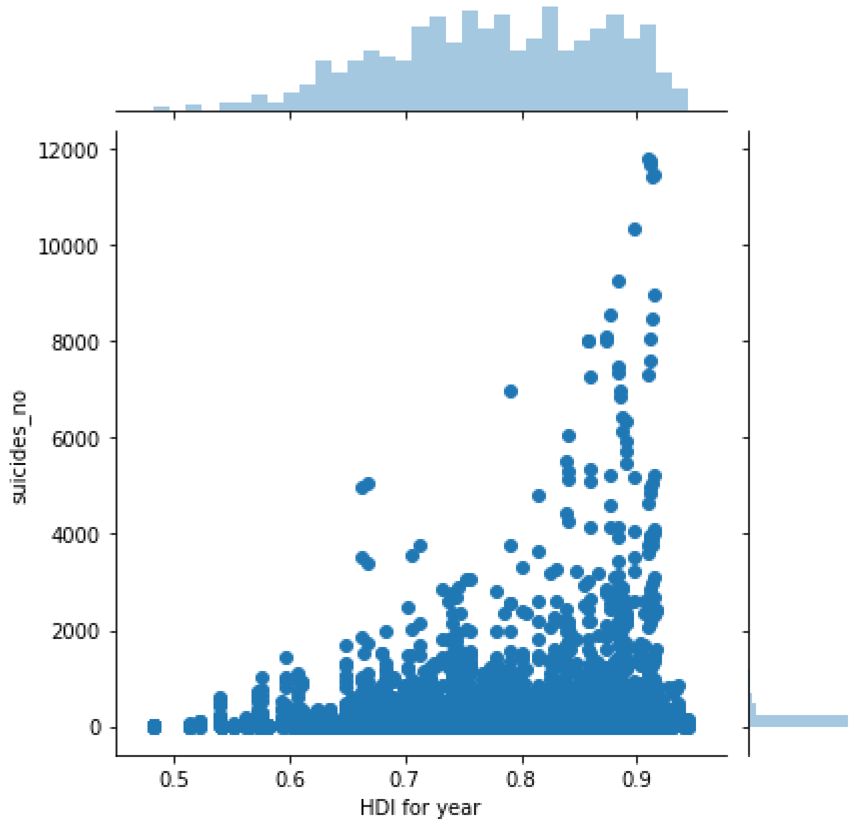
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x12142bf60>



Jointplot

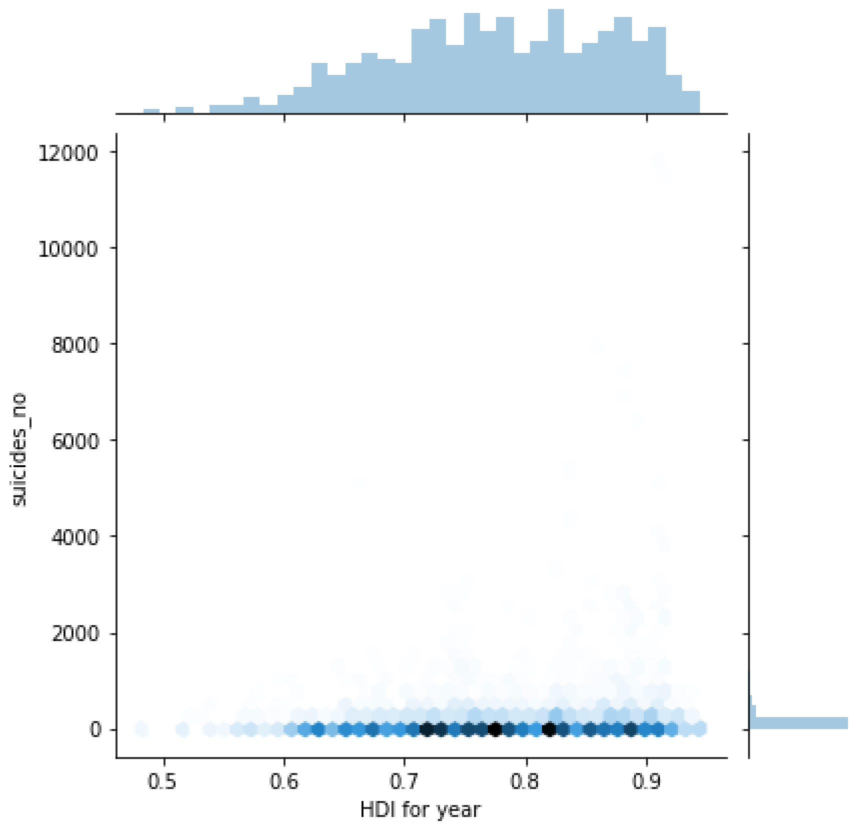
In [12]:
```
sns.jointplot(x='HDI for year', y='suicides_no', data=data)
```

Out[12]: <seaborn.axisgrid.JointGrid at 0x12143a6a0>



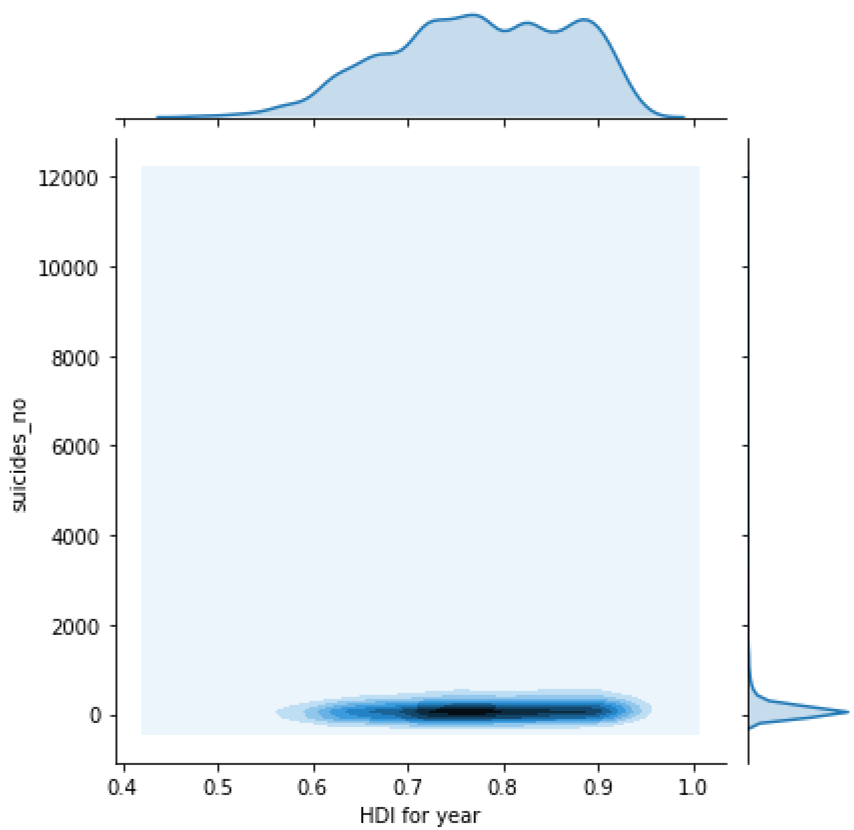
```
In [13]: sns.jointplot(x='HDI for year', y='suicides_no', data=data, kind='hex')
```

```
Out[13]: <seaborn.axisgrid.JointGrid at 0x125ae4da0>
```



In [14]:
```
sns.jointplot(x='HDI for year', y='suicides_no', data=data, kind='kde')
```

Out[14]: <seaborn.axisgrid.JointGrid at 0x125c533c8>

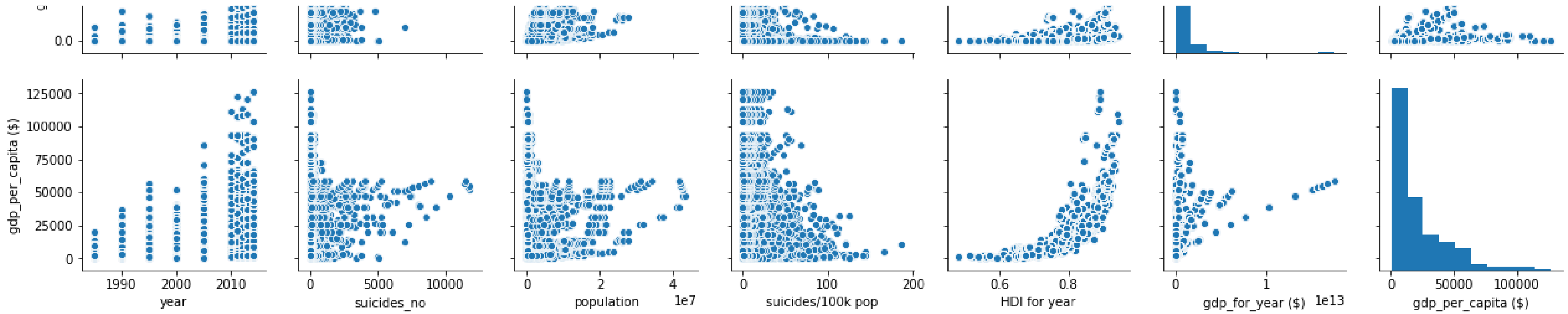


"Парные диаграммы"

In [15]:
```
sns.pairplot(data)
```

```
Out[15]: <seaborn.axisgrid.PairGrid at 0x125e60630>
```

year
suicides_no
population
1e7
suicides/100k pop
HDI for year
gdp_for_year ($)
1e13

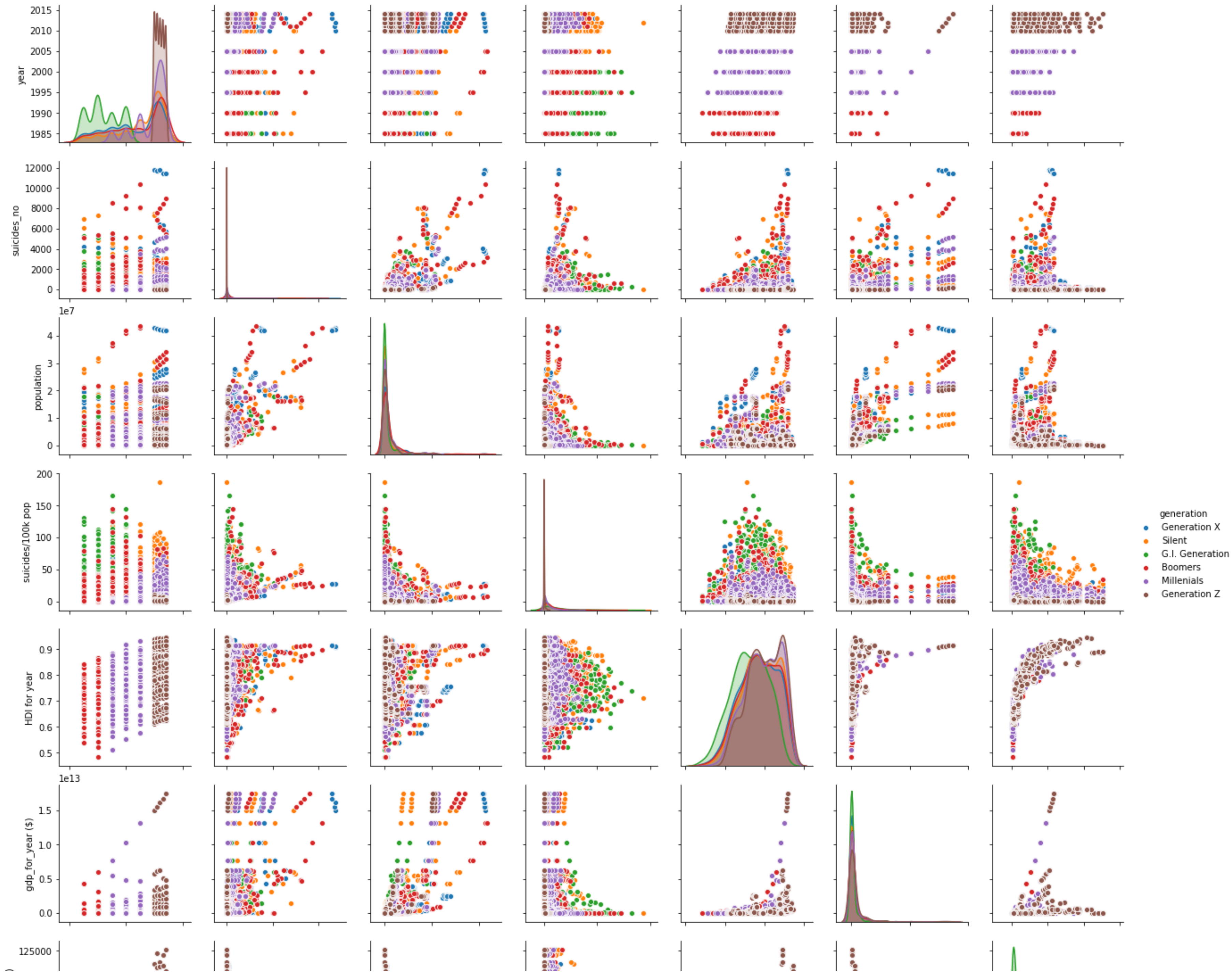


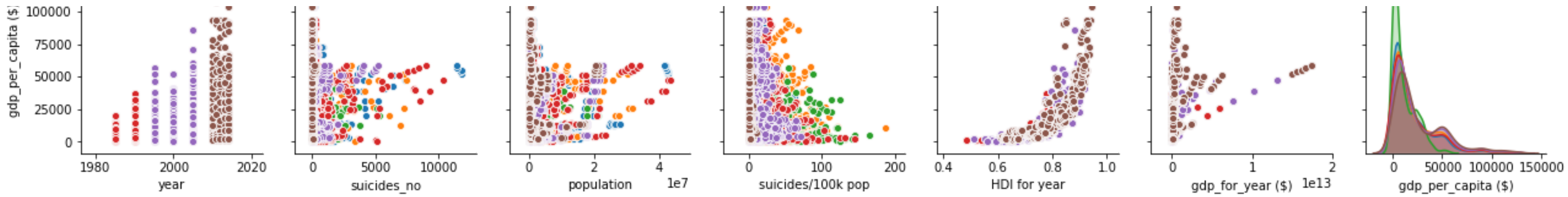
0.0
gdp_per_capita ($)
125000
100000
75000
50000
25000
0
1990
2000
2010
year
0
5000
10000
suicides_no
0
2
4
population
1e7
0
100
200
suicides/100k pop
0.6
0.8
HDI for year
0
1
gdp_for_year ($)
1e13
0
50000
100000
gdp_per_capita ($)

In [16]:

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

```
Out[16]: <seaborn.axisgrid.PairGrid at 0x12738b780>
```

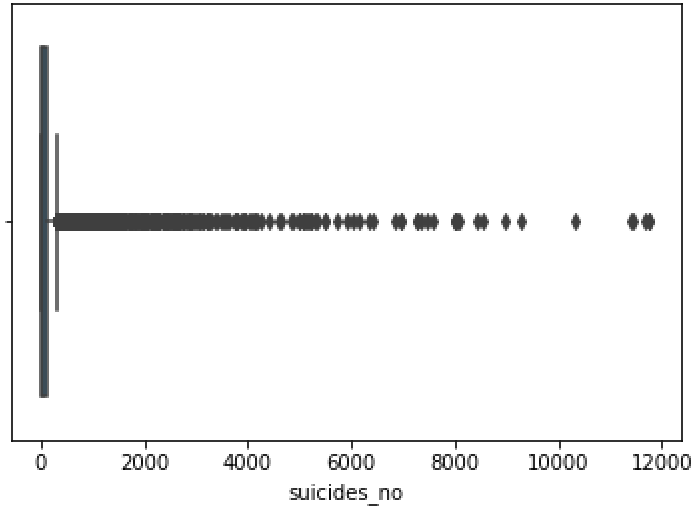

year
suicides_no
population
suicides/100k pop
HDI for year
gdp_for_year ($)
1e7
1e13
generation
Generation X
Silent
G.I. Generation
Boomers
Millenials
Generation Z



Ящик с усами

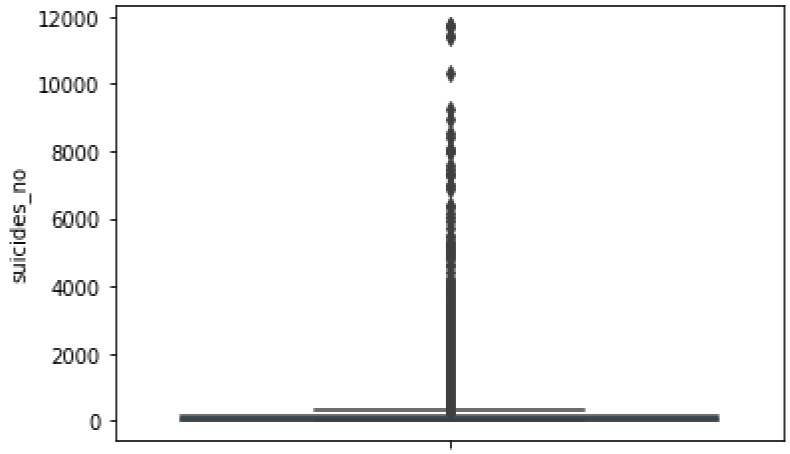
In [17]:
```
sns.boxplot(x=data['suicides_no'])
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x12a438b70>



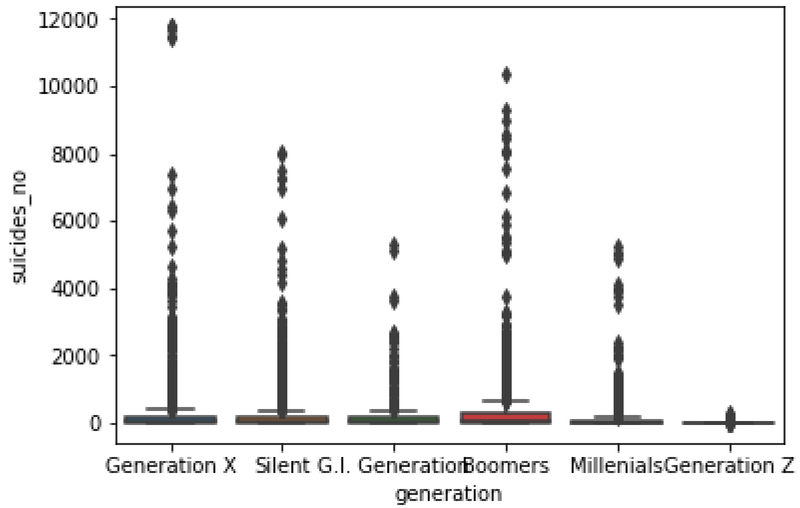
```
In [18]: sns.boxplot(y=data['suicides_no'])
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x12a3ed0b8>




```
In [19]: sns.boxplot(x='generation', y='suicides_no', data=data)
```

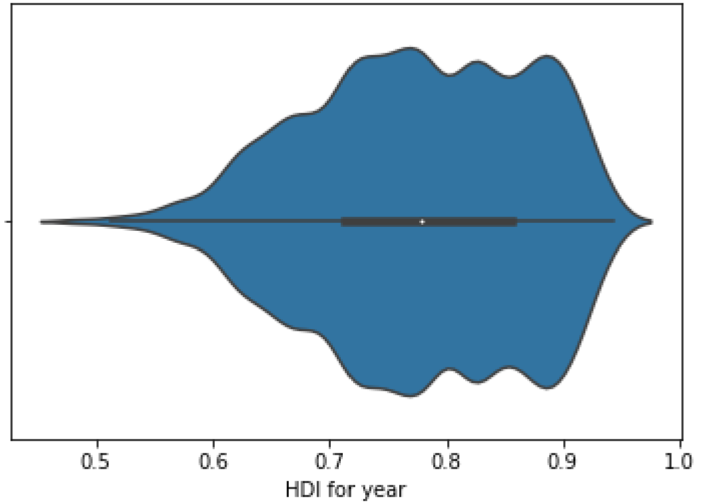
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x12ad7d550>



Violin plot

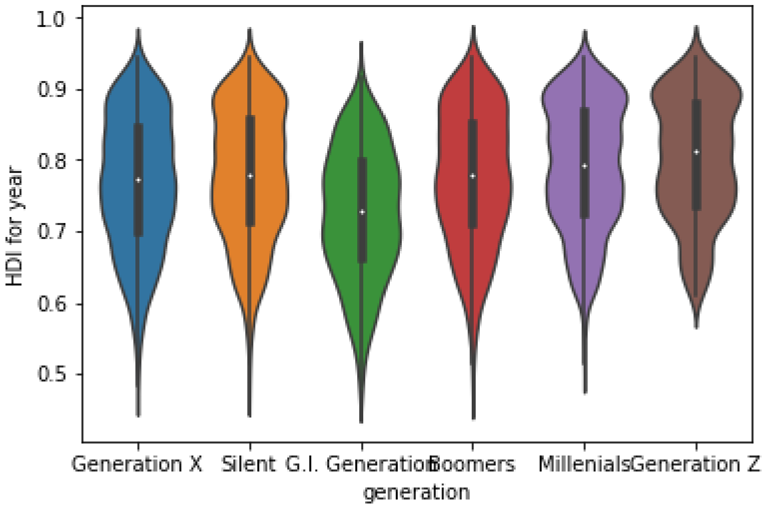
In [20]:
```
sns.violinplot(x=data['HDI for year'])
```

Out[20]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12adf5630>
```



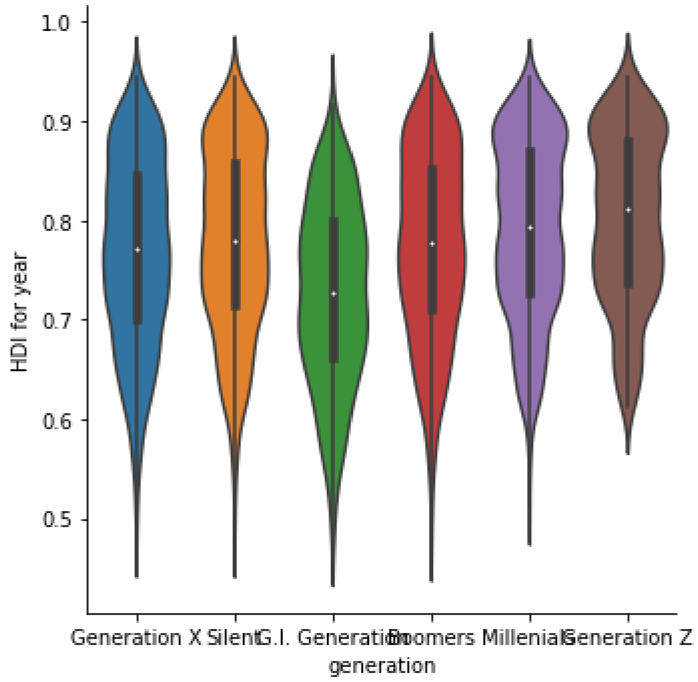
In [21]:
```
sns.violinplot(x='generation', y='HDI for year', data=data)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x12aeadf98>



In [22]:
```
sns.catplot(x='generation', y='HDI for year', data=data, kind="violin", split=True)
```

Out[22]: <seaborn.axisgrid.FacetGrid at 0x12aead940>



4) Информация о корреляции признаков

In [23]:
```
data.corr()
```

Out[23]:

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

In [24]:
```
data.corr(method='pearson') # по умолчанию
```

Out[24]:

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

In [25]:
```
data.corr(method='kendall')
```

Out[25]:

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

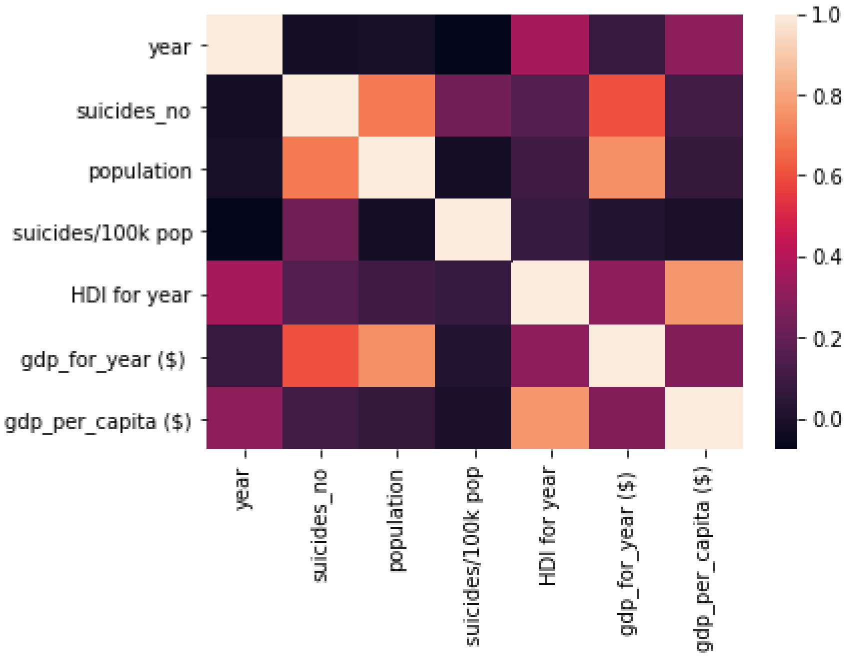
In [26]:
```
data.corr(method='spearman')
```

Out[26]:

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

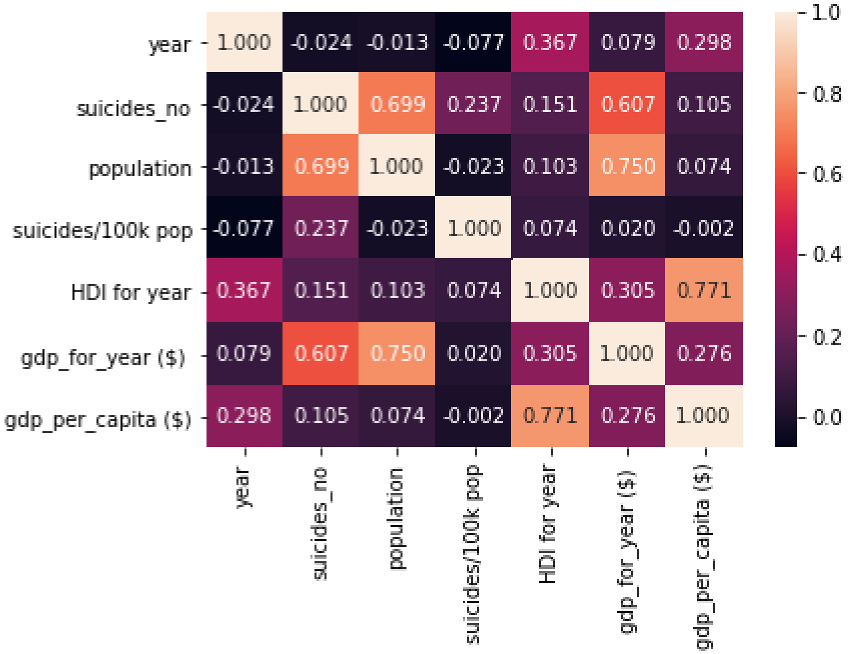
In [27]:
```
sns.heatmap(data.corr())
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x12b201d30>



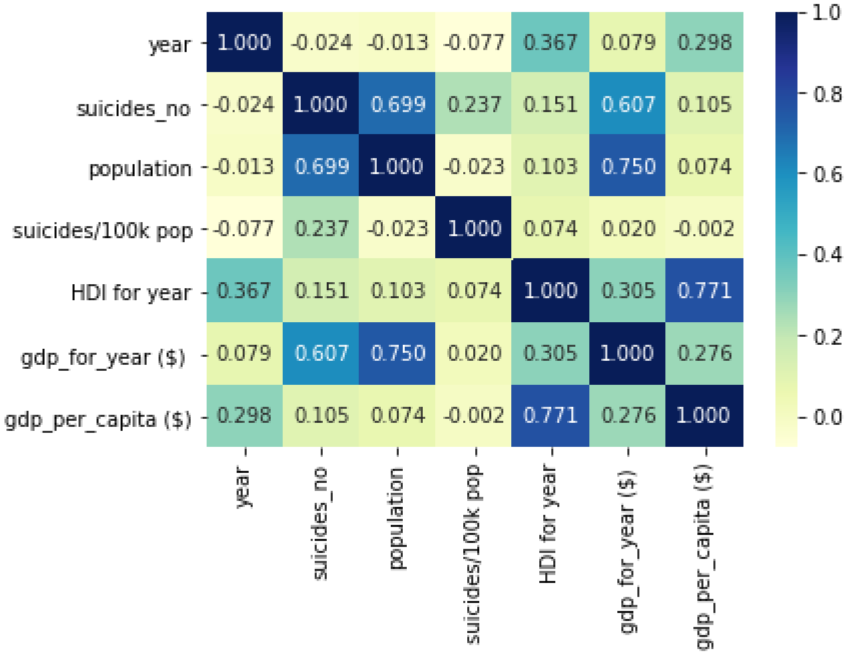
In [28]:
```python
sns.heatmap(data.corr(), annot=True, fmt='.3f')
```

Out[28]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12b3537b8>
```



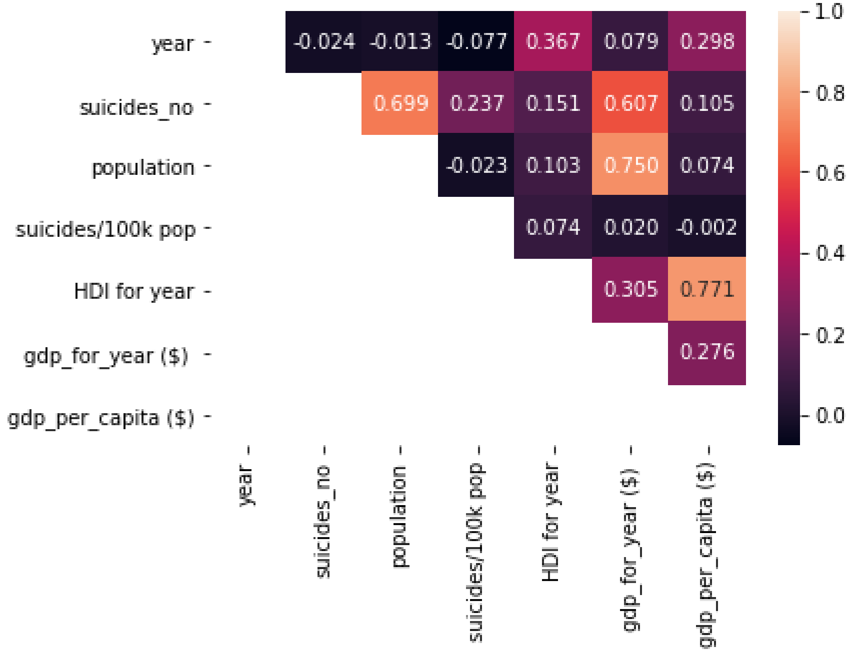
In [29]:
```
sns.heatmap(data.corr(), cmap='YlGnBu', annot=True, fmt='.3f')
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x12b33c1d0>



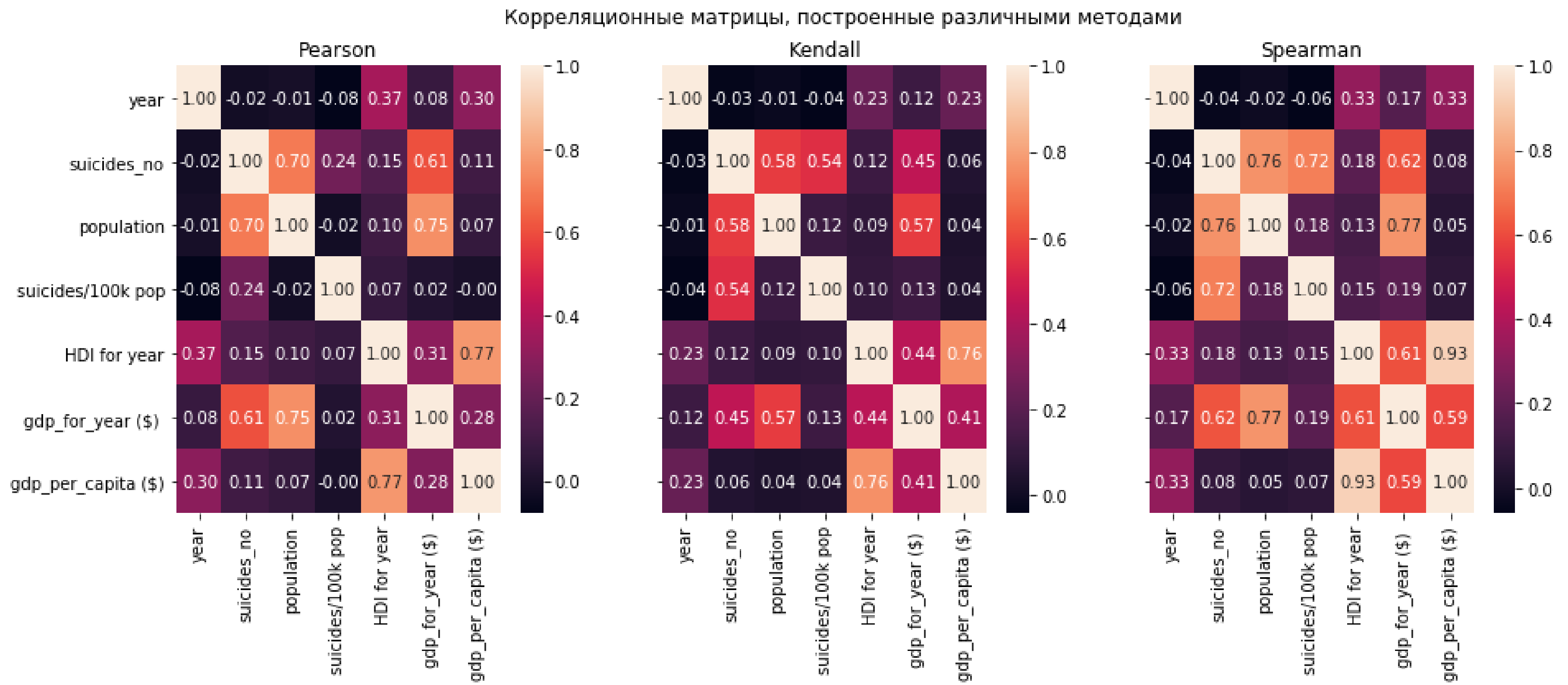
In [30]:
```python
mask = np.zeros_like(data.corr(), dtype=np.bool)
mask[np.tril_indices_from(mask)] = True
sns.heatmap(data.corr(), mask=mask, annot=True, fmt='.3f')
```

Out[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12b0a2048>
```



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.