In [40]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import statsmodels.formula.api as smf
df = pd.read_csv('suicide_rates.csv')
```

The project uses a data set of suicides number and many other factors to explore what factors has the most significant impact on the suicides rate.

In [41]:

```
df.columns = ['country', 'year', 'sex', 'age', 'suicides_no', 'population',
        'suicides_rate', 'country-year', 'HDI',
        'gdp_for_year', 'gdp_per_capita', 'generation']
```

In [42]:

```
# the data in year 2016 is not complete, so it should be dropped
df = df.loc[df['year']!=2016,:]
df['gdp_for_year'] = df['gdp_for_year'].str.replace(',','').astype(int)
df_year = df.groupby('year')['suicides_no'].sum()
```

In [43]:

```
df
```

Out[43]:

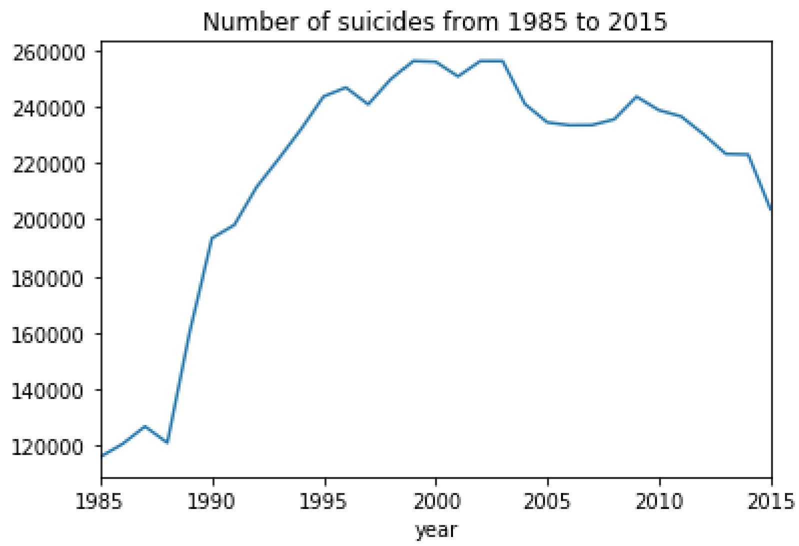
	country	year	sex	age	suicides_no	population	suicides_rate	country-year	HDI	gdp_for_yea
0	Albania	1987	male	15-24 years	21	312900	6.71	Albania1987	NaN	215662490
1	Albania	1987	male	35-54 years	16	308000	5.19	Albania1987	NaN	215662490
2	Albania	1987	female	15-24 years	14	289700	4.83	Albania1987	NaN	215662490
3	Albania	1987	male	75+ years	1	21800	4.59	Albania1987	NaN	215662490
4	Albania	1987	male	25-34 years	9	274300	3.28	Albania1987	NaN	215662490

In [44]:

```
# show the change in suicides number per year
fig, ax = plt.subplots()
df_year.plot(x='year', y='suicides_no', ax = ax)
ax.set_title('Number of suicides from 1985 to 2015')
```

Out[44]:

```
Text(0.5, 1.0, 'Number of suicides from 1985 to 2015')
```



In [45]:

```
df_country_year = df.groupby('country-year')['suicides_no'].sum()
df_population = df.groupby('country-year')['population'].sum()
df_country_pgdp = df.groupby('country-year')['gdp_per_capita'].sum()
df_country_gdp = df.groupby('country-year')['gdp_for_year'].sum()
```

In [46]:

```
# explore the relationship between gdp per capita and suicides rate
suicide_pgdp = pd.DataFrame()
```

In [47]:

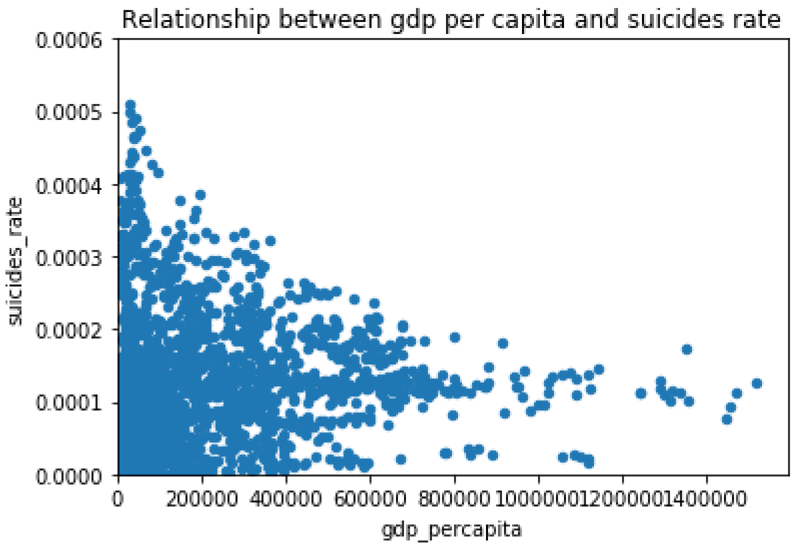
```
suicide_pgdp['gdp_percapita'] = df_country_pgdp
suicide_pgdp['suicides_rate'] = df_country_year / df_population
```

In [48]:

```
fig, ax = plt.subplots()
suicide_pgdp.plot.scatter(x='gdp_percapita', y='suicides_rate', ax=ax)
ax.set_ybound(lower=0, upper=0.0006)
ax.set_xbound(lower=0)
ax.set_title('Relationship between gdp per capita and suicides rate')
```

Out[48]:

```
Text(0.5, 1.0, 'Relationship between gdp per capita and suicides rat
e')
```



In [49]:

```
reg = smf.ols('suicides_rate ~ gdp_percapita', data=suicide_pgdp).fit()
print(reg.summary())
```

```
                            OLS Regression Results
======================================================================
========
Dep. Variable:          suicides_rate   R-squared:
0.004
Model:                            OLS   Adj. R-squared:
0.003
Method:                 Least Squares   F-statistic:
8.542
Date:                Thu, 19 Dec 2019   Prob (F-statistic):
0.00351
Time:                        10:21:21   Log-Likelihood:
18226.
No. Observations:                2305   AIC:                           -
3.645e+04
Df Residuals:                    2303   BIC:                           -
3.644e+04
Df Model:                           1
Covariance Type:            nonrobust
======================================================================
===========
                  coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept       0.0001   2.49e-06     45.227      0.000       0.000
0.000
gdp_percapita 2.397e-11    8.2e-12     2.923      0.004    7.89e-12
4.01e-11
======================================================================
========
Omnibus:                      440.100   Durbin-Watson:
0.125
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
783.348
Skew:                           1.199   Prob(JB):
7.91e-171
Kurtosis:                       4.550   Cond. No.
4.06e+05
======================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 4.06e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

The t-value and p-value told us that there is a relationship between suicides rate and gdp_percapita, but we can find that the R_squared is very lower, so we may conclude that the gdp_percapita does not influence the suicides rate a lot.

In [50]:

```
# explore the relationship between gdp and suicides rate
suicide_gdp = pd.DataFrame()
suicide_gdp['gdp'] = df_country_gdp
suicide_gdp['suicides_rate'] = df_country_year / df_population
suicide_gdp
```

Out[50]:

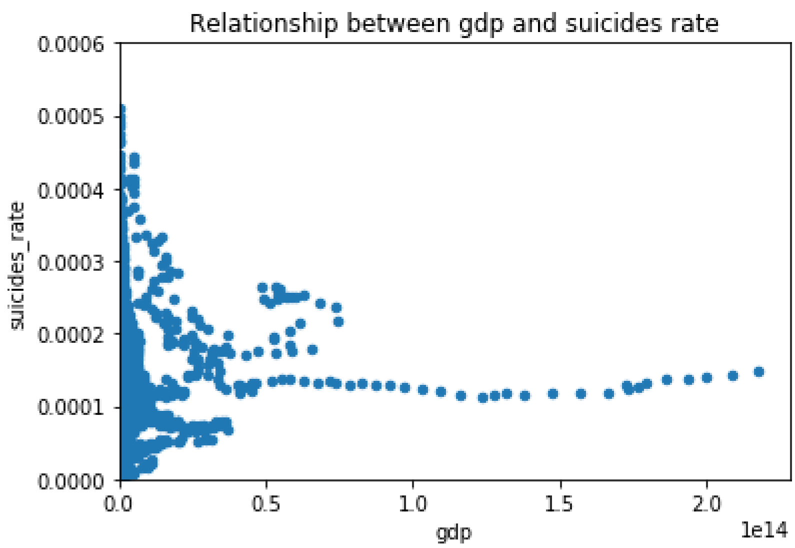
country-year	gdp	suicides_rate
Albania1987	25879498800	0.000027
Albania1988	25512000000	0.000023
Albania1989	28021499856	0.000024
Albania1992	8513431008	0.000017
Albania1993	14736852456	0.000026
Albania1994	23828085576	0.000018
Albania1995	29093988108	0.000030
Albania1996	39778779504	0.000030
Albania1997	28318837296	0.000057

In [51]:

```
fig, ax = plt.subplots()
suicide_gdp.plot.scatter(x='gdp', y='suicides_rate', ax=ax)
ax.set_ybound(lower=0, upper=0.0006)
ax.set_xbound(lower=0)
ax.set_title('Relationship between gdp and suicides rate')
```

Out[51]:

```
Text(0.5, 1.0, 'Relationship between gdp and suicides rate')
```



In [52]:

```
reg = smf.ols('suicides_rate ~ gdp', data=suicide_gdp).fit()
print(reg.summary())
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:          suicides_rate   R-squared:
0.005
Model:                            OLS   Adj. R-squared:
0.005
Method:                 Least Squares   F-statistic:
12.08
Date:                Thu, 19 Dec 2019   Prob (F-statistic):
0.000519
Time:                        10:21:24   Log-Likelihood:
18228.
No. Observations:                2305   AIC:                          -
3.645e+04
Df Residuals:                    2303   BIC:                          -
3.644e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept      0.0001   1.94e-06     59.445      0.000       0.000
0.000
gdp         3.686e-19   1.06e-19      3.476      0.001    1.61e-19
5.77e-19
==============================================================================
========
Omnibus:                      422.152   Durbin-Watson:
0.125
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
730.017
Skew:                           1.172   Prob(JB):
3.01e-159
Kurtosis:                       4.453   Cond. No.
1.91e+13
==============================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.91e+13. This might indicate that
there are
strong multicollinearity or other numerical problems.
```

The t-value and p-value told us that there is a relationship between suicides rate and gdp, but we can find that the R_squared is very lower, so we may conclude that the gdp does not influence the suicides rate a lot.

In [54]:

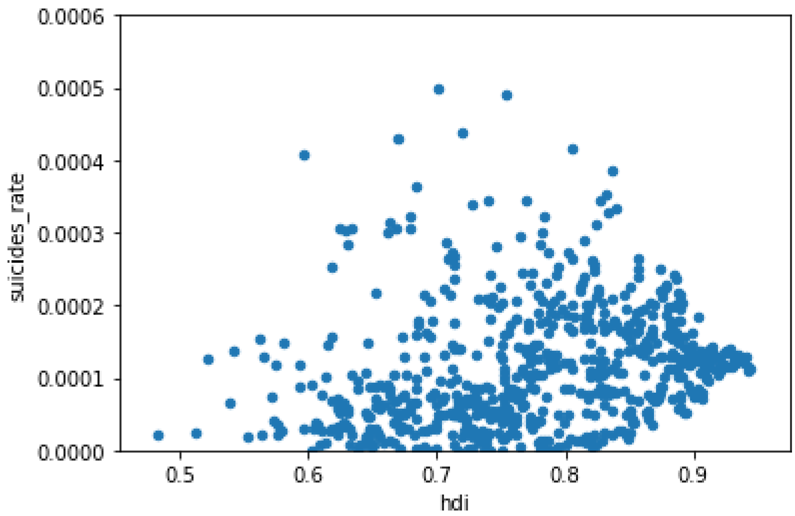
```
df2 = df.dropna()
df2_suicide_rate = df2.groupby('country-year')['suicides_no'].sum() / df2.groupby('c
df2_hdi = df2.groupby('country-year')['HDI'].mean()
```

In [55]:

```
# explore the relationship between hdi and suicides rate
suicide_hdi = pd.DataFrame()
suicide_hdi['hdi'] = df2_hdi
suicide_hdi['suicides_rate'] = df2_suicide_rate
```

In [56]:

```
fig, ax = plt.subplots()
suicide_hdi.plot.scatter(x='hdi', y='suicides_rate', ax=ax)
ax.set_ybound(lower=0, upper=0.0006)
```



In [57]:

```
reg = smf.ols('suicides_rate ~ hdi', data=suicide_hdi).fit()
print(reg.summary())
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:           suicides_rate   R-squared:
0.047
Model:                             OLS   Adj. R-squared:
0.046
Method:                  Least Squares   F-statistic:
34.23
Date:                 Thu, 19 Dec 2019   Prob (F-statistic):
7.54e-09
Time:                         10:21:49   Log-Likelihood:
5577.5
No. Observations:                  697   AIC:                        -
1.115e+04
Df Residuals:                      695   BIC:                        -
1.114e+04
Df Model:                            1
Covariance Type:             nonrobust
==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept  -3.629e-05   2.57e-05     -1.410      0.159   -8.68e-05
1.43e-05
hdi            0.0002   3.29e-05      5.851      0.000       0.000
0.000
==============================================================================
========
Omnibus:                       191.474   Durbin-Watson:
0.411
Prob(Omnibus):                   0.000   Jarque-Bera (JB):
470.773
Skew:                            1.424   Prob(JB):
5.93e-103
Kurtosis:                        5.846   Cond. No.
17.2
==============================================================================
========

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

The t-value and p-value told us that there is a relationship between suicides rate and hdi, and the R-square is higher, which is 0.047, but we still can not find a strong relationship between hdi and suicides rate.

In [58]:

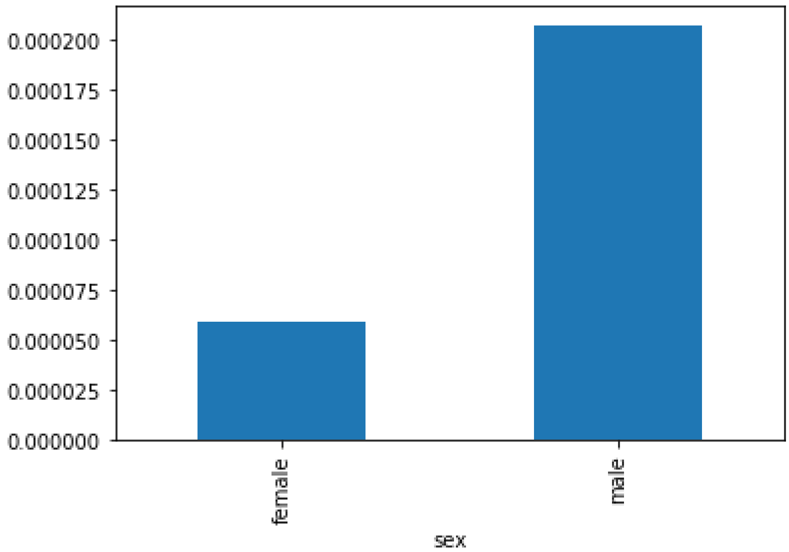
```
# explore the relationship between hdi and sex
male_female = df.groupby('sex')['suicides_no'].sum() / df.groupby('sex')['populatio
```

In [59]:

```
male_female.plot.bar()
```

Out[59]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a1a1c8e10>



We can find a clear distinction between the suicides rate of male and female, this tells us that male has four times the possibility of suicide than female.

In [60]:

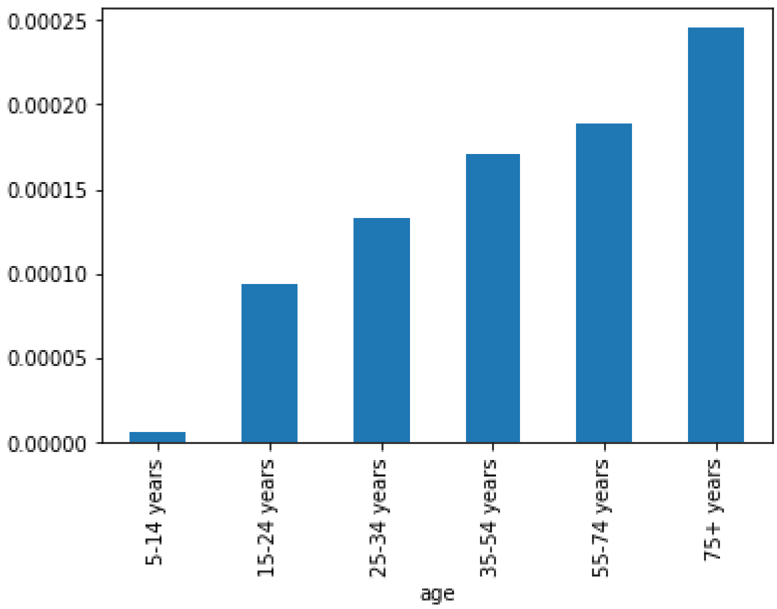
```
ages = df.groupby('age')['suicides_no'].sum() / df.groupby('age')['population'].sum(
```

In [61]:

```
ages.sort_values().plot.bar()
```

Out[61]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a1ac8a6d8>



We can also find a relationship between suicides rate and age, generally speaking, as age increases, the

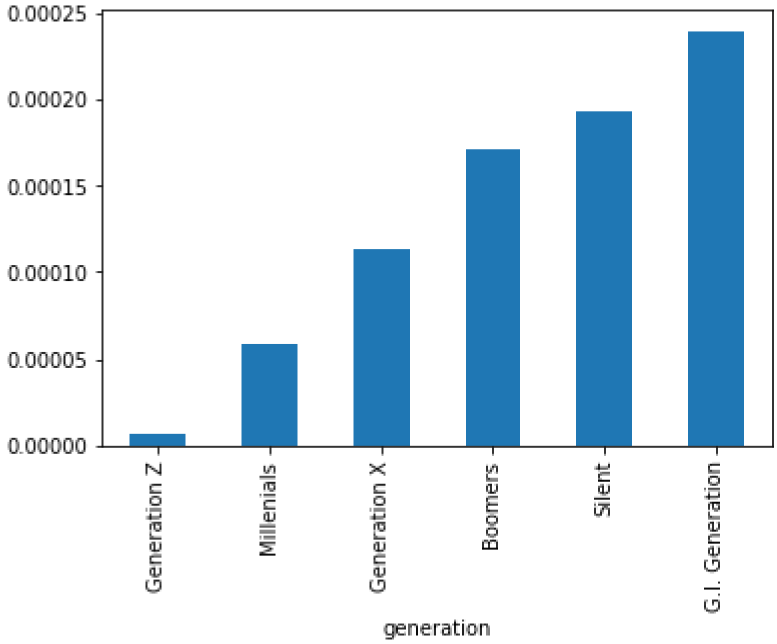
probability of suicide increases.

In [62]:

```
ages = df.groupby('generation')['suicides_no'].sum() / df.groupby('generation')['pop
ages.sort_values().plot.bar()
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1accf3c8>
```



The relationship between suicides rate and generation just corresponds to that between suicides rate and age.

We have found out that sex and age influence suicides the most, so we are going to use these two factors to build KNeighborsRegreessor model to predict the suicides rate.

In [66]:

```
from patsy import dmatrices
from sklearn.neighbors import KNeighborsRegressor as knn
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor as rf
```

In [67]:

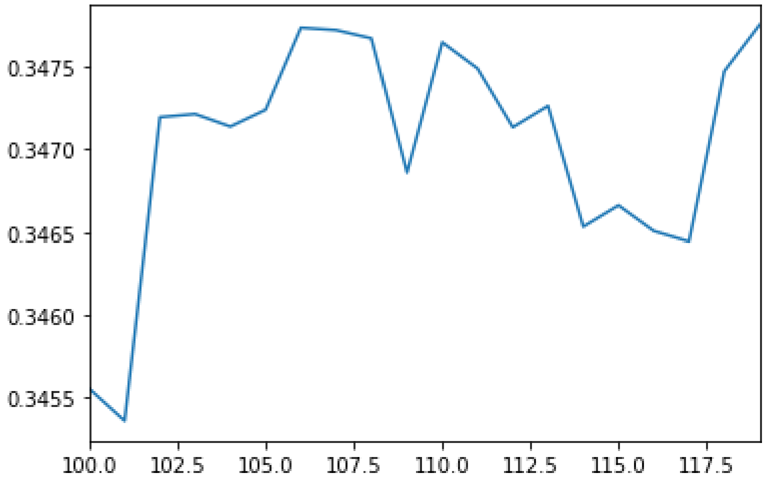
```
# y, X = dmatrices('suicides_rate ~ HDI + gdp_for_year + gdp_per_capita', df2)
y, X = dmatrices('suicides_rate ~ sex + age', df2)
```

In [68]:

```
knn_scores = pd.Series()
for i in range(100, 120, 1):
    knn_scores.loc[i] = cross_val_score(knn(n_neighbors=i),X,np.ravel(y),cv=2).mean(
knn_scores.plot()
```

Out[68]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a19fc9780>
```



In [69]:

```
# We can find that the model is most useful when n_neighbors is set to 106
cross_val_score(knn(n_neighbors=106),X,np.ravel(y),cv=2).mean()
```

Out[69]:

```
0.3477382747360774
```

In [70]:

```
knn(n_neighbors=106).fit(X,y).predict(X)
```

Out[70]:

```
array([[16.28245283],
       [26.47028302],
       [ 8.17698113],
       ...,
       [ 0.88415094],
       [ 0.52386792],
       [ 4.41745283]])
```