final_project

December 19, 2019

[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')
```

1 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.

[41]:
```
df.columns = ['country', 'year', 'sex', 'age', 'suicides_no', 'population',
       'suicides_rate', 'country-year', 'HDI',
       'gdp_for_year', 'gdp_per_capita', 'generation']
```

[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()
```

[43]:
```
df
```

[43]:

	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	
5	Albania	1987	female	75+ years	1	35600	
6	Albania	1987	female	35-54 years	6	278800	
7	Albania	1987	female	25-34 years	4	257200	
8	Albania	1987	male	55-74 years	1	137500	
9	Albania	1987	female	5-14 years	0	311000	
10	Albania	1987	female	55-74 years	0	144600	
11	Albania	1987	male	5-14 years	0	338200	
12	Albania	1988	female	75+ years	2	36400	

13	Albania	1988	male	15-24 years	17	319200
14	Albania	1988	male	75+ years	1	22300
15	Albania	1988	male	35-54 years	14	314100
16	Albania	1988	male	55-74 years	4	140200
17	Albania	1988	female	15-24 years	8	295600
18	Albania	1988	female	55-74 years	3	147500
19	Albania	1988	female	25-34 years	5	262400
20	Albania	1988	male	25-34 years	5	279900
21	Albania	1988	female	35-54 years	4	284500
22	Albania	1988	female	5-14 years	0	317200
23	Albania	1988	male	5-14 years	0	345000
24	Albania	1989	male	75+ years	2	22500
25	Albania	1989	male	25-34 years	18	283600
26	Albania	1989	male	35-54 years	15	318400
27	Albania	1989	male	55-74 years	6	142100
28	Albania	1989	male	15-24 years	12	323500
29	Albania	1989	female	35-54 years	7	288600
...	...	...	...	...	...	...
27790	Uzbekistan	2012	female	25-34 years	148	2556673
27791	Uzbekistan	2012	female	35-54 years	89	3474788
27792	Uzbekistan	2012	male	5-14 years	67	2701361
27793	Uzbekistan	2012	female	55-74 years	25	1283060
27794	Uzbekistan	2012	female	75+ years	4	338557
27795	Uzbekistan	2012	female	5-14 years	16	2578408
27796	Uzbekistan	2013	male	35-54 years	481	3346411
27797	Uzbekistan	2013	male	25-34 years	328	2644648
27798	Uzbekistan	2013	female	15-24 years	323	3039740
27799	Uzbekistan	2013	male	15-24 years	320	3171202
27800	Uzbekistan	2013	male	55-74 years	119	1202790
27801	Uzbekistan	2013	male	75+ years	13	221002
27802	Uzbekistan	2013	female	25-34 years	146	2647820
27803	Uzbekistan	2013	female	35-54 years	99	3547895
27804	Uzbekistan	2013	female	75+ years	8	345180
27805	Uzbekistan	2013	male	5-14 years	61	2720938
27806	Uzbekistan	2013	female	55-74 years	21	1356298
27807	Uzbekistan	2013	female	5-14 years	31	2595000
27808	Uzbekistan	2014	male	35-54 years	519	3421300
27809	Uzbekistan	2014	male	25-34 years	318	2739150
27810	Uzbekistan	2014	female	15-24 years	347	2992817
27811	Uzbekistan	2014	male	55-74 years	144	1271111
27812	Uzbekistan	2014	male	15-24 years	347	3126905
27813	Uzbekistan	2014	male	75+ years	17	224995
27814	Uzbekistan	2014	female	25-34 years	162	2735238
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_rate    country-year    HDI  gdp_for_year  gdp_per_capita  \
0               6.71     Albania1987    NaN    2156624900             796
1               5.19     Albania1987    NaN    2156624900             796
2               4.83     Albania1987    NaN    2156624900             796
3               4.59     Albania1987    NaN    2156624900             796
4               3.28     Albania1987    NaN    2156624900             796
5               2.81     Albania1987    NaN    2156624900             796
6               2.15     Albania1987    NaN    2156624900             796
7               1.56     Albania1987    NaN    2156624900             796
8               0.73     Albania1987    NaN    2156624900             796
9               0.00     Albania1987    NaN    2156624900             796
10              0.00     Albania1987    NaN    2156624900             796
11              0.00     Albania1987    NaN    2156624900             796
12              5.49     Albania1988    NaN    2126000000             769
13              5.33     Albania1988    NaN    2126000000             769
14              4.48     Albania1988    NaN    2126000000             769
15              4.46     Albania1988    NaN    2126000000             769
16              2.85     Albania1988    NaN    2126000000             769
17              2.71     Albania1988    NaN    2126000000             769
18              2.03     Albania1988    NaN    2126000000             769
19              1.91     Albania1988    NaN    2126000000             769
20              1.79     Albania1988    NaN    2126000000             769
21              1.41     Albania1988    NaN    2126000000             769
22              0.00     Albania1988    NaN    2126000000             769
23              0.00     Albania1988    NaN    2126000000             769
24              8.89     Albania1989    NaN    2335124988             833
25              6.35     Albania1989    NaN    2335124988             833
26              4.71     Albania1989    NaN    2335124988             833
27              4.22     Albania1989    NaN    2335124988             833
28              3.71     Albania1989    NaN    2335124988             833
29              2.43     Albania1989    NaN    2335124988             833
...              ...             ...    ...           ...             ...
27790           5.79  Uzbekistan2012  0.668   51821573338            1964
27791           2.56  Uzbekistan2012  0.668   51821573338            1964
27792           2.48  Uzbekistan2012  0.668   51821573338            1964
27793           1.95  Uzbekistan2012  0.668   51821573338            1964
27794           1.18  Uzbekistan2012  0.668   51821573338            1964
27795           0.62  Uzbekistan2012  0.668   51821573338            1964
27796          14.37  Uzbekistan2013  0.672   57690453461            2150
27797          12.40  Uzbekistan2013  0.672   57690453461            2150
27798          10.63  Uzbekistan2013  0.672   57690453461            2150
27799          10.09  Uzbekistan2013  0.672   57690453461            2150
27800           9.89  Uzbekistan2013  0.672   57690453461            2150
27801           5.88  Uzbekistan2013  0.672   57690453461            2150
27802           5.51  Uzbekistan2013  0.672   57690453461            2150
```

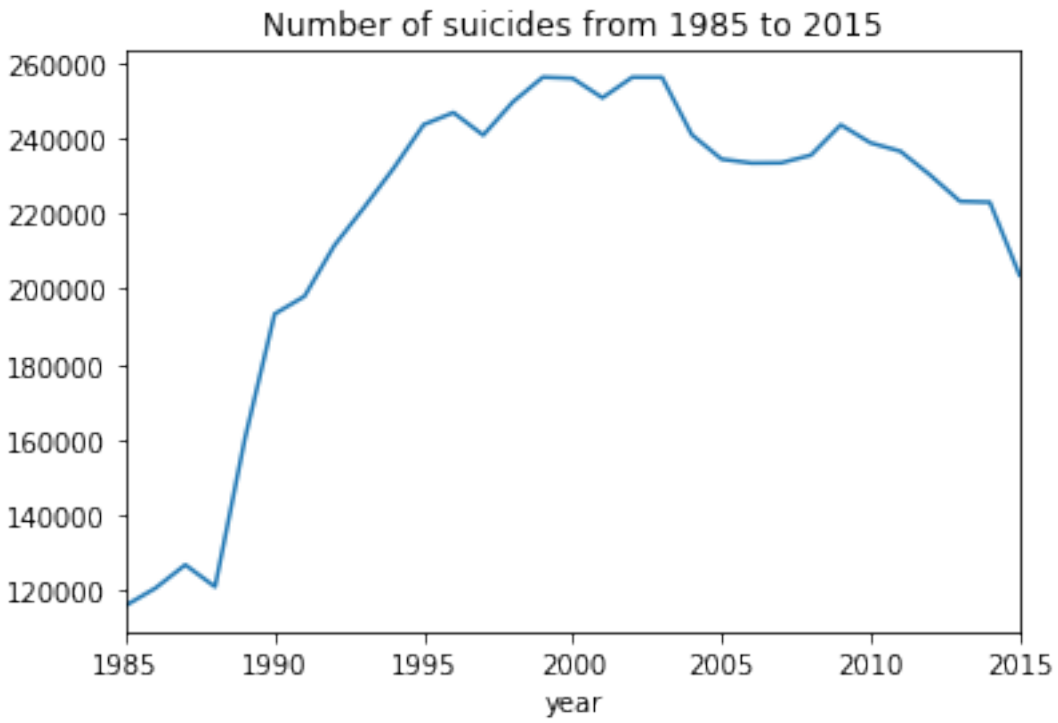
27803	2.79	Uzbekistan2013	0.672	57690453461	2150
27804	2.32	Uzbekistan2013	0.672	57690453461	2150
27805	2.24	Uzbekistan2013	0.672	57690453461	2150
27806	1.55	Uzbekistan2013	0.672	57690453461	2150
27807	1.19	Uzbekistan2013	0.672	57690453461	2150
27808	15.17	Uzbekistan2014	0.675	63067077179	2309
27809	11.61	Uzbekistan2014	0.675	63067077179	2309
27810	11.59	Uzbekistan2014	0.675	63067077179	2309
27811	11.33	Uzbekistan2014	0.675	63067077179	2309
27812	11.10	Uzbekistan2014	0.675	63067077179	2309
27813	7.56	Uzbekistan2014	0.675	63067077179	2309
27814	5.92	Uzbekistan2014	0.675	63067077179	2309
27815	2.96	Uzbekistan2014	0.675	63067077179	2309
27816	2.58	Uzbekistan2014	0.675	63067077179	2309
27817	2.17	Uzbekistan2014	0.675	63067077179	2309
27818	1.67	Uzbekistan2014	0.675	63067077179	2309
27819	1.46	Uzbekistan2014	0.675	63067077179	2309

	generation
0	Generation X
1	Silent
2	Generation X
3	G.I. Generation
4	Boomers
5	G.I. Generation
6	Silent
7	Boomers
8	G.I. Generation
9	Generation X
10	G.I. Generation
11	Generation X
12	G.I. Generation
13	Generation X
14	G.I. Generation
15	Silent
16	G.I. Generation
17	Generation X
18	G.I. Generation
19	Boomers
20	Boomers
21	Silent
22	Generation X
23	Generation X
24	G.I. Generation
25	Boomers
26	Silent
27	G.I. Generation

```
28        Generation X
29              Silent
...                ...
27790       Millenials
27791     Generation X
27792     Generation Z
27793          Boomers
27794           Silent
27795     Generation Z
27796     Generation X
27797       Millenials
27798       Millenials
27799       Millenials
27800          Boomers
27801           Silent
27802       Millenials
27803     Generation X
27804           Silent
27805     Generation Z
27806          Boomers
27807     Generation Z
27808     Generation X
27809       Millenials
27810       Millenials
27811          Boomers
27812       Millenials
27813           Silent
27814       Millenials
27815     Generation X
27816           Silent
27817     Generation Z
27818     Generation Z
27819          Boomers

[27660 rows x 12 columns]
```

[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')
```

[44]:
```
Text(0.5, 1.0, 'Number of suicides from 1985 to 2015')
```



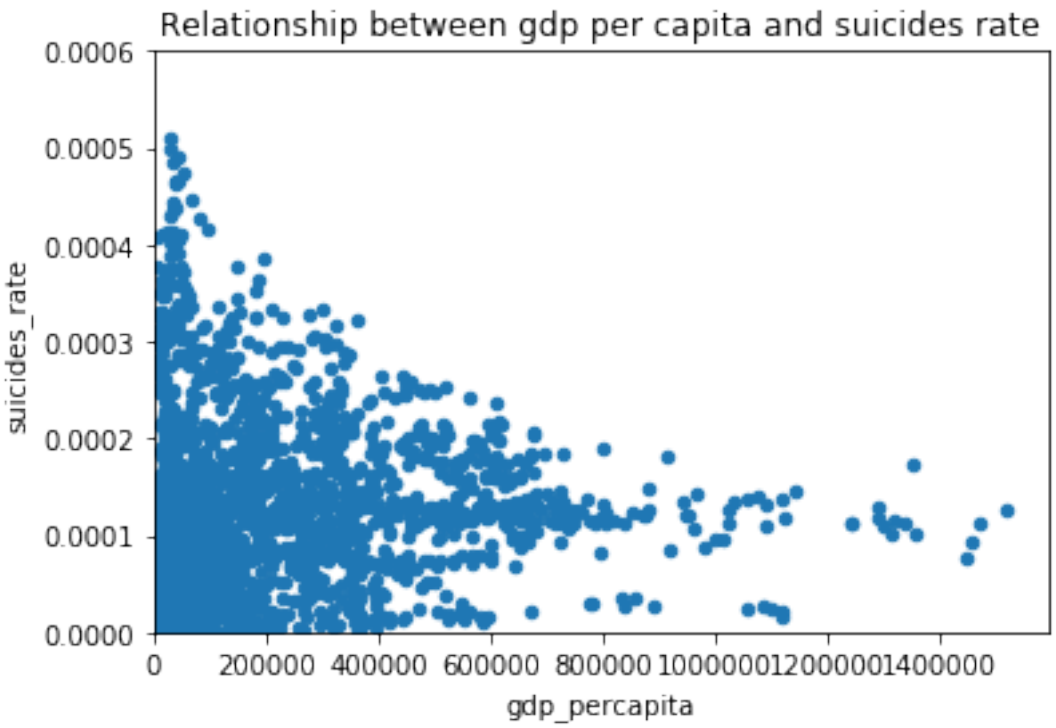
[45]:
```
df_country_year = df.groupby('country-year')['suicides_no'].sum()
df_population = df.groupby('country-year')['population'].sum()
df_country_pgdp = df.groupby('country-year')['gdp_per_capita'].sum()
df_country_gdp = df.groupby('country-year')['gdp_for_year'].sum()
```

[46]:
```
# explore the relationship between gdp per capita and suicides rate
suicide_pgdp = pd.DataFrame()
```

[47]:
```
suicide_pgdp['gdp_percapita'] = df_country_pgdp
suicide_pgdp['suicides_rate'] = df_country_year / df_population
```

[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')
```

[48]:
```
Text(0.5, 1.0, 'Relationship between gdp per capita and suicides rate')
```



[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.

[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
```

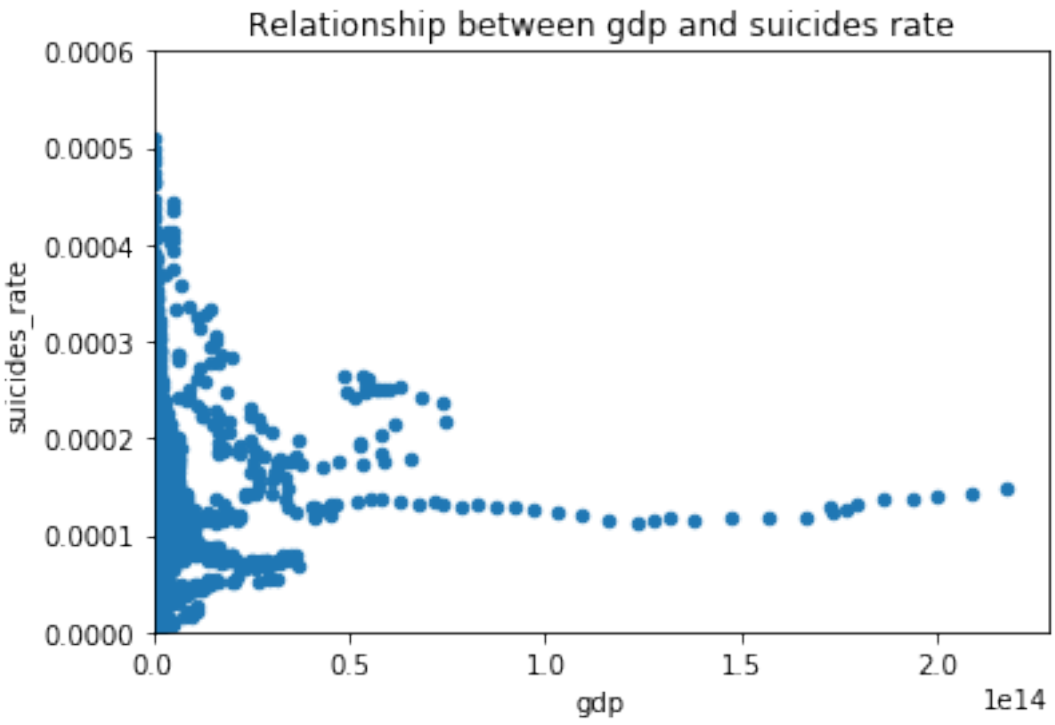
[50]:

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
Albania1998	32485485264	0.000051
Albania1999	40977130980	0.000046
Albania2000	43584526896	0.000019
Albania2001	48729105648	0.000043
Albania2002	53220943776	0.000047
Albania2003	68963350956	0.000044
Albania2004	87778382112	0.000051
Albania2005	97902584604	0.000000
Albania2006	107911708188	0.000000
Albania2007	128412142764	0.000045
Albania2008	154576232256	0.000058
Albania2009	144530554848	0.000000
Albania2010	143123439108	0.000035
Antigua and Barbuda1985	2891087112	0.000000
Antigua and Barbuda1986	3485281776	0.000000

```
Antigua and Barbuda1987    4046098224       0.000000
Antigua and Barbuda1988    4783652892       0.000000
Antigua and Barbuda1989    5265537336       0.000000
Antigua and Barbuda1990    5513628888       0.000017
Antigua and Barbuda1991    5780475996       0.000000
Antigua and Barbuda1992    5991373776       0.000000
...                               ...            ...
Uruguay2007              280926871608       0.000187
Uruguay2008              364394557428       0.000169
Uruguay2009              379930935324       0.000164
Uruguay2010              483413779824       0.000175
Uruguay2012              615172681392       0.000190
Uruguay2013              690374800212       0.000173
Uruguay2014              686832157032       0.000186
Uruguay2015              639291650664       0.000197
Uzbekistan1990           160327295016       0.000085
Uzbekistan1991           164131466664       0.000080
Uzbekistan1992           155295568512       0.000074
Uzbekistan1993           157188166032       0.000073
Uzbekistan1994           154789883892       0.000074
Uzbekistan1995           160205627004       0.000076
Uzbekistan1996           167386706592       0.000086
Uzbekistan1997           176935245288       0.000076
Uzbekistan1998           179867654532       0.000078
Uzbekistan1999           204941591784       0.000084
Uzbekistan2000           165124493856       0.000088
Uzbekistan2001           136816217040       0.000086
Uzbekistan2002           116255412660       0.000070
Uzbekistan2003           121537348812       0.000062
Uzbekistan2004           144360282576       0.000054
Uzbekistan2005           171690118068       0.000052
Uzbekistan2009           404270684076       0.000055
Uzbekistan2010           471993251148       0.000057
Uzbekistan2011           550982294268       0.000063
Uzbekistan2012           621858880056       0.000070
Uzbekistan2013           692285441532       0.000073
Uzbekistan2014           756804926148       0.000077

[2305 rows x 2 columns]
```

[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')
```

[51]:
```
Text(0.5, 1.0, 'Relationship between gdp and suicides rate')
```



[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
```

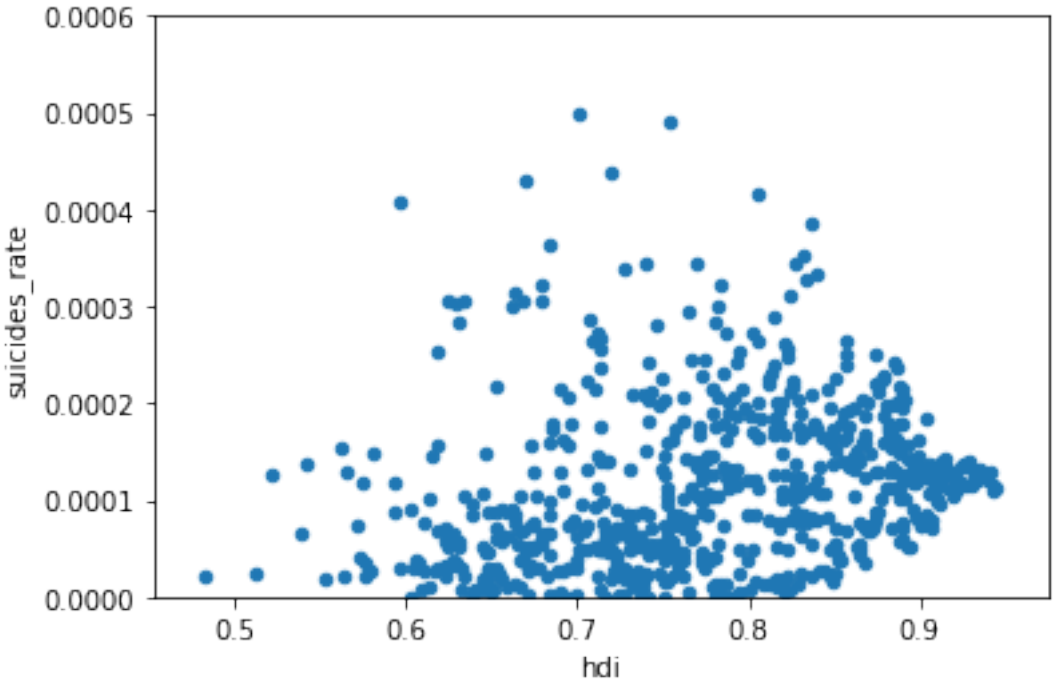
```
==============================================================================

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.

[54]:
```
df2 = df.dropna()
df2_suicide_rate = df2.groupby('country-year')['suicides_no'].sum() / df2.
 ↪groupby('country-year')['population'].sum()
df2_hdi = df2.groupby('country-year')['HDI'].mean()
```

[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
```

[56]:
```
fig, ax = plt.subplots()
suicide_hdi.plot.scatter(x='hdi', y='suicides_rate', ax=ax)
ax.set_ybound(lower=0, upper=0.0006)
```



[57]:
```
reg = smf.ols('suicides_rate ~ hdi', data=suicide_hdi).fit()
print(reg.summary())
```

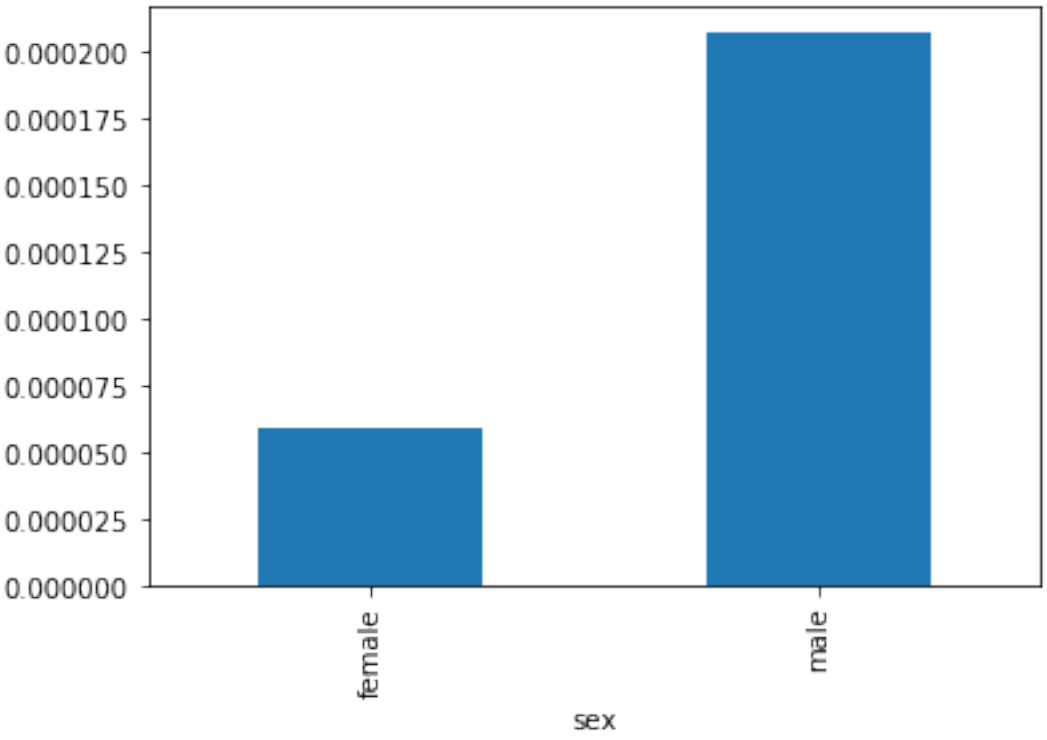
```
                            OLS Regression Results
==============================================================================
Dep. Variable:          suicides_rate   R-squared:                       0.047
Model:                            OLS   Adj. R-squared:                  0.046
Method:                 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.

[58]:
```
# explore the relationship between hdi and sex
male_female = df.groupby('sex')['suicides_no'].sum() / df.
 ↪groupby('sex')['population'].sum()
```

[59]:
```
male_female.plot.bar()
```

[59]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1a1c8e10>
```

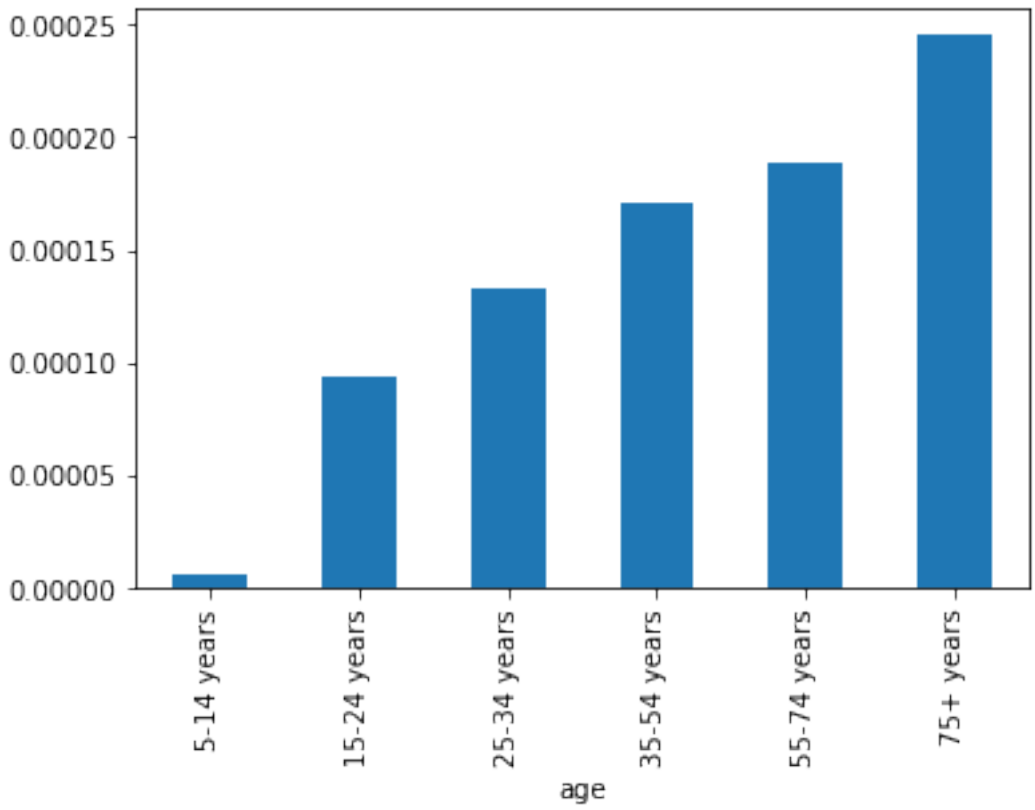


We can find a clear distinction between the suicides rate of male and female, this tells us that male has four times the possibility of suicide than female.

[60]:
```
ages = df.groupby('age')['suicides_no'].sum() / df.groupby('age')['population'].
↪sum()
```

[61]:
```
ages.sort_values().plot.bar()
```

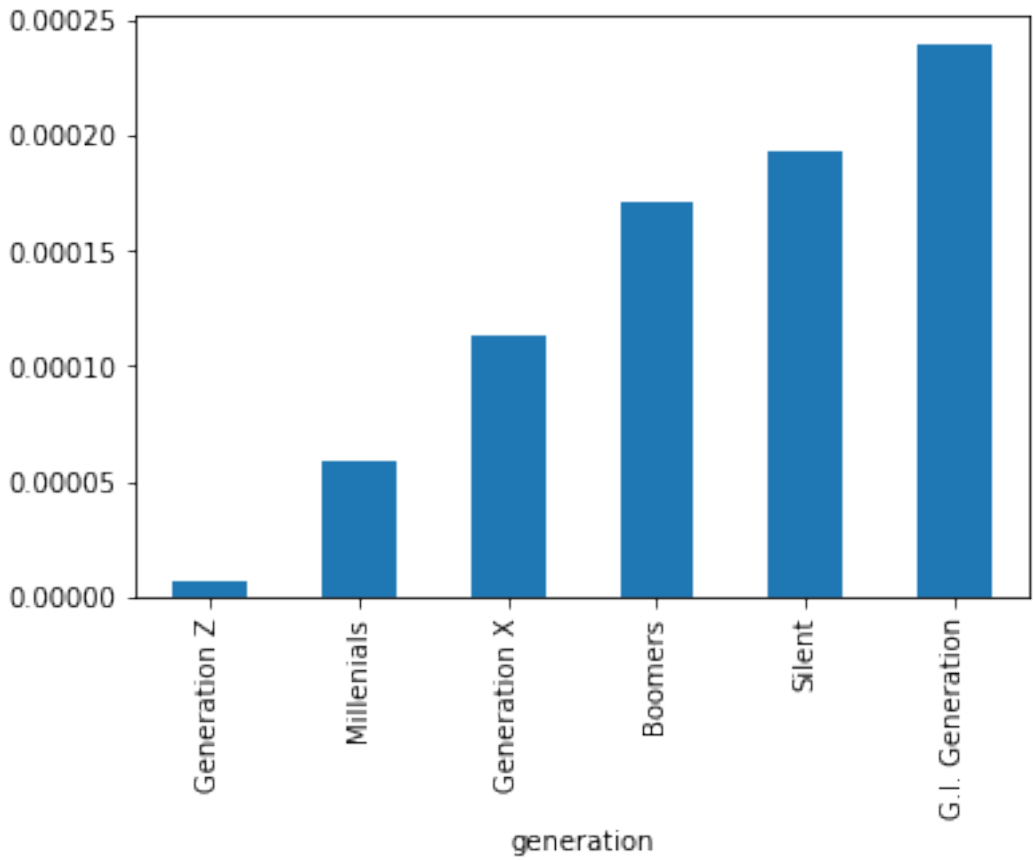
[61]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1ac8a6d8>
```



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

[62]:
```
ages = df.groupby('generation')['suicides_no'].sum() / df.
 ↪groupby('generation')['population'].sum()
ages.sort_values().plot.bar()
```

[62]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1accf3c8>
```



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

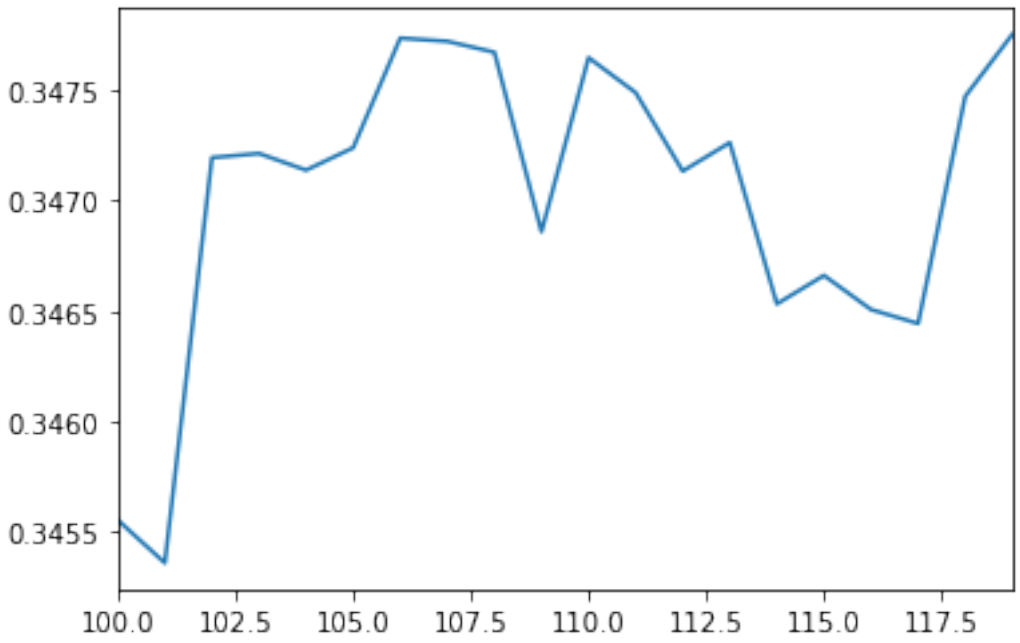
We have found out that sex and age influence suicides the most, so we are going to use these two factors to build KNeighborsRegreessor model to predict the suicides rate.

[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
```

[67]:
```
# y, X = dmatrices('suicides_rate ~ HDI + gdp_for_year + gdp_per_capita', df2)
y, X = dmatrices('suicides_rate ~ sex + age', df2)
```

[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()
```

[68]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a19fc9780>
```



[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()
```

[69]:
```
0.3477382747360774
```

[70]:
```
knn(n_neighbors=106).fit(X,y).predict(X)
```

[70]:
```
array([[16.28245283],
       [26.47028302],
       [ 8.17698113],
       ...,
       [ 0.88415094],
       [ 0.52386792],
       [ 4.41745283]])
```