HW1_RA_LAB 1_ITDSIU21095

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[1]:
```
import pandas as pd, numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

[2]:
```
df = pd.read_csv('APPENC02.txt',
                 sep='\s+',
                 header=None,
                 names=[' Id_number',' County','State',
                        'Landarea','Total_population',
                        'Percent_of_population_18-34_',
                        'Percent_of_population_65_or_older',
                        'Number_of_active_physicians',
                        'Number_of_hospital_beds',
                        'Total_serious_crimes',
                        'Percent_high_school_graduates',
                        'Percent_bachelor's_degrees',
                        'Percent_below_poverty_level',
                        'Percent_unemployment','Per_capita_income',
                        'Total_personal_income',' Geographic_region'])
df.head()
```

[2]:
```
    Id_number       County State  Landarea  Total_population  \
0           1  Los_Angeles    CA      4060           8863164
1           2         Cook    IL       946           5105067
2           3       Harris    TX      1729           2818199
3           4    San_Diego    CA      4205           2498016
4           5       Orange    CA       790           2410556

   Percent_of_population_18-34_  Percent_of_population_65_or_older  \
0                          32.1                                9.7
1                          29.2                               12.4
2                          31.3                                7.1
```

```
3                         33.5                             10.9
4                         32.6                              9.2

   Number_of_active_physicians  Number_of_hospital_beds  Total_serious_crimes  \
0                        23677                    27700                688936
1                        15153                    21550                436936
2                         7553                    12449                253526
3                         5905                     6179                173821
4                         6062                     6369                144524

   Percent_high_school_graduates  Percent_bachelor's_degrees  \
0                           70.0                        22.3
1                           73.4                        22.8
2                           74.9                        25.4
3                           81.9                        25.3
4                           81.2                        27.8

   Percent_below_poverty_level  Percent_unemployment  Per_capita_income  \
0                         11.6                   8.0              20786
1                         11.1                   7.2              21729
2                         12.5                   5.7              19517
3                          8.1                   6.1              19588
4                          5.2                   4.8              24400

   Total_personal_income  Geographic_region
0                 184230                  4
1                 110928                  2
2                  55003                  3
3                  48931                  4
4                  58818                  4
```

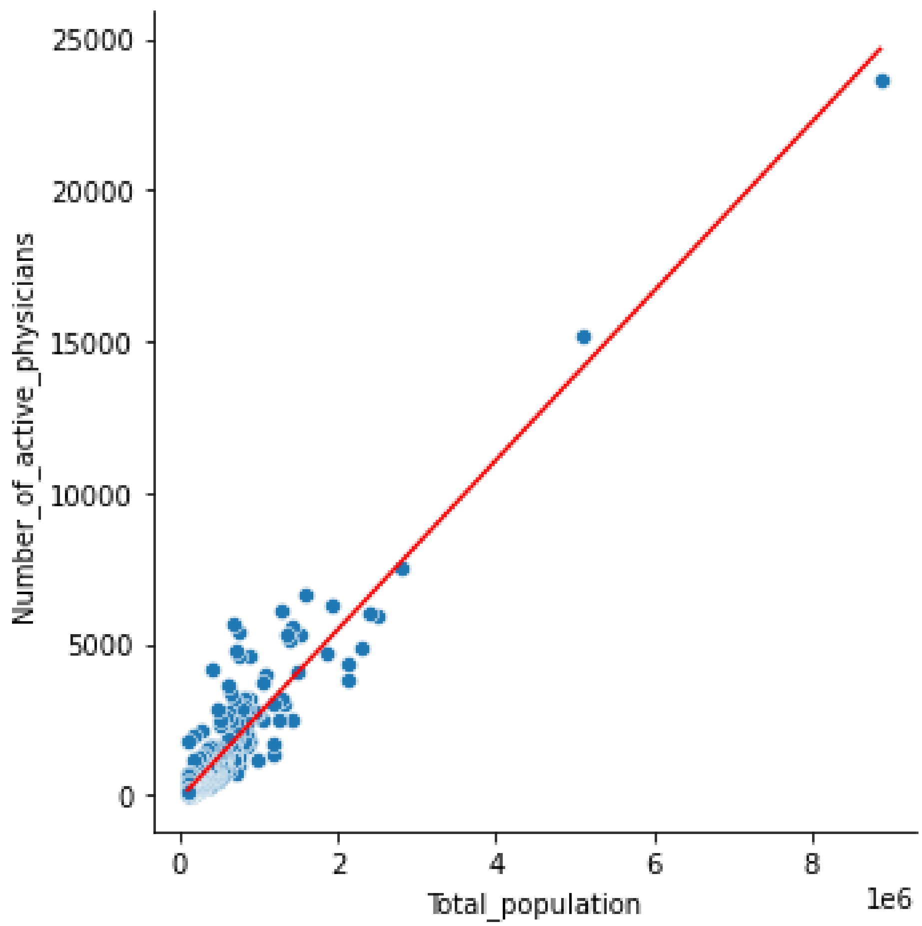
[3]:
```
y = df['Number_of_active_physicians']
y_mean = np.mean(y)
y_err = y -y_mean

x1 = df['Total_population']
x1_mean = np.mean(x1)
x1_err = x1 -x1_mean

x2 = df['Number_of_hospital_beds']
x2_mean = np.mean(x2)
x2_err = x2 -x2_mean

x3 = df['Total_personal_income']
x3_mean = np.mean(x3)
x3_err = x3 -x3_mean
```

[4]:
```
b1_x1 = np.sum(x1_err*y_err) / np.sum(x1_err**2)
b0_x1 = y_mean - b1_x1*x1_mean
print(b1_x1, b0_x1)
```

```
0.0027954248783588946 -110.6347772326377
```

- The linear regression model for Toluca dataset is: Y1 = -110.63 + 0.003 * X1 + where (0,).
- The linear regression model for Toluca dataset is: { 1 } = -110.63 + 0.003 ∗ 1.

[5]:
```
sns.relplot(x='Total_population', y='Number_of_active_physicians', data=df)
sns.lineplot(x=x1, y=b0_x1+b1_x1*x1, color='red')
plt.show()
```

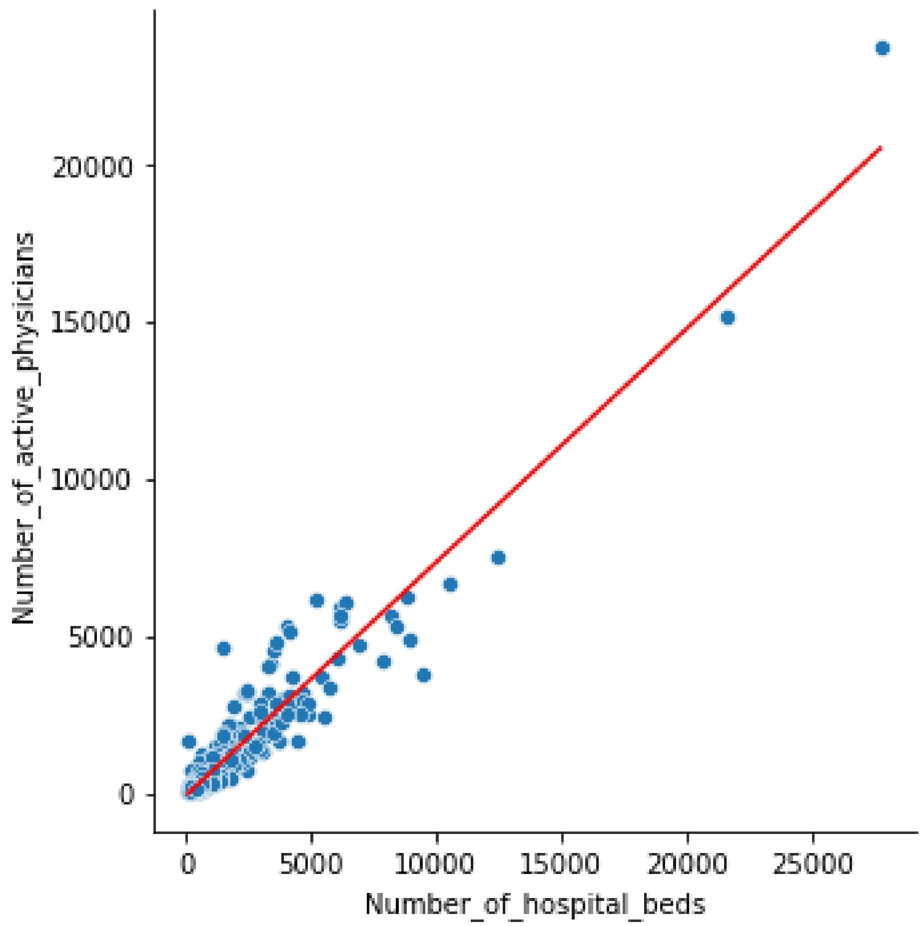


[6]:
```
b1_x2 = np.sum(x2_err*y_err) / np.sum(x2_err**2)
b0_x2 = y_mean - b1_x2*x2_mean
print(b1_x2, b0_x2)
```

```
0.7431164439874645 -95.9321847394973
```

- The linear regression model for Toluca dataset is: Y2 = -95.93 + 0.74 * X2 + where (0,).
- The linear regression model for Toluca dataset is: { 2 } = -95.93 + 0.74 ∗ 2.

[7]:
```
sns.relplot(x='Number_of_hospital_beds', y='Number_of_active_physicians',␣
 ↪data=df)
sns.lineplot(x=x2, y=b0_x2+b1_x2*x2, color='red')
plt.show()
```

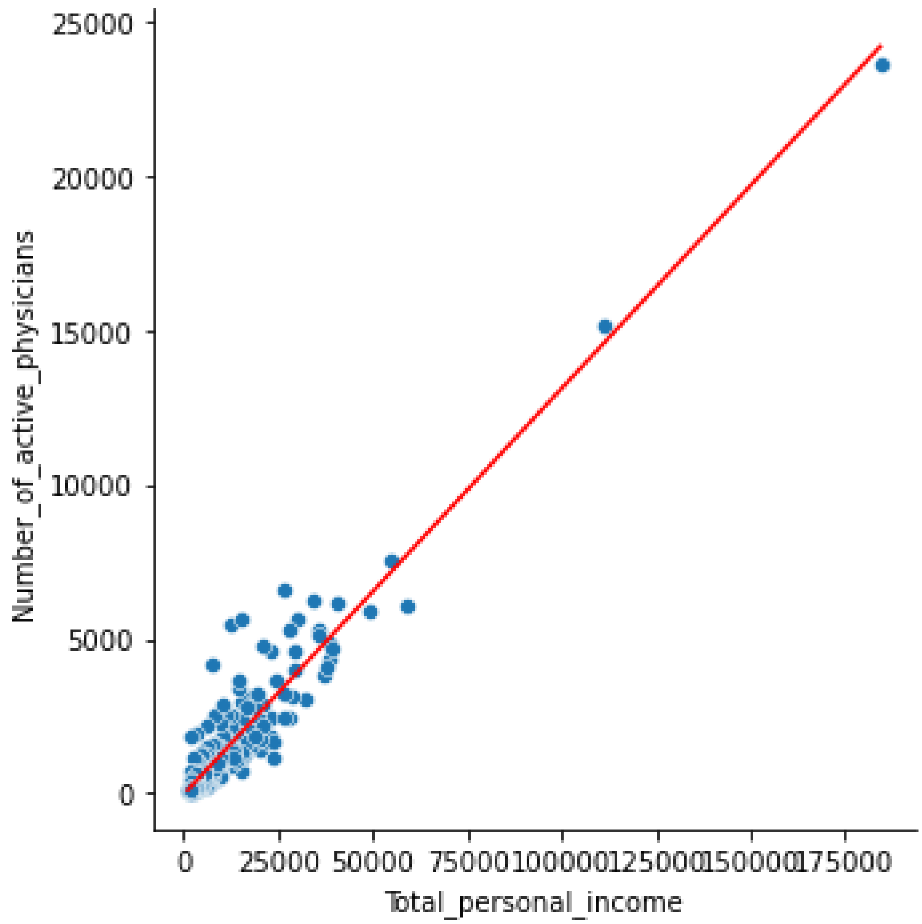


[8]:
```
b1_x3 = np.sum(x3_err*y_err) / np.sum(x3_err**2)
b0_x3 = y_mean - b1_x3*x3_mean
print(b1_x3, b0_x3)
```

```
0.13170118918365611 -48.39484891960376
```

- The linear regression model for Toluca dataset is: 3 = -48.4 + 0.13 ∗ 3 + where (0,).
- The linear regression model for Toluca dataset is: { 3 } = -48.4 + 0.13 ∗ 3.

[9]:
```
sns.relplot(x='Total_personal_income', y='Number_of_active_physicians', data=df)
sns.lineplot(x=x3, y=b0_x3+b1_x3*x3, color='red')
plt.show()
```



[10]:
```
model_1 = smf.ols('y ~ x1', data=df)
results_1 = model_1.fit()
results_1.summary()
```

[10]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.884
Model:                            OLS   Adj. R-squared:                  0.884
Method:                 Least Squares   F-statistic:                     3340.
Date:                Fri, 07 Oct 2022   Prob (F-statistic):          4.66e-207
Time:                        11:08:01   Log-Likelihood:                -3445.3
No. Observations:                 440   AIC:                             6895.
```

```
Df Residuals:                     438   BIC:                             6903.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   -110.6348     34.746     -3.184      0.002    -178.924     -42.345
x1             0.0028   4.84e-05     57.793      0.000       0.003       0.003
==============================================================================
Omnibus:                      265.471   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2775.183
Skew:                           2.437   Prob(JB):                         0.00
Kurtosis:                      14.297   Cond. No.                     8.58e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 8.58e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[11]:
```
n1= len(x1)
y_hat_1 = b0_x1 + b1_x1*x1
resid_1 = y - y_hat_1
print(np.sum(resid_1))
print((np.sum((resid_1 - np.mean(resid_1))**2)))
print(np.var(resid_1, ddof=1)*(n1-1))
```

```
1.0913936421275139e-11
163025135.15359497
163025135.15359482
```

[12]:
```
SSE_1 = np.sum((y - y_hat_1)**2)
MSE_1 = SSE_1 / (n1-2)
print(MSE_1, SSE_1)
resid_dev_1 = np.sqrt(MSE_1)
resid_dev_1
```

```
372203.5049168835 163025135.15359497
```

[12]:
```
610.0848341967562
```

[13]:
```
model_2 = smf.ols('y ~ x2', data=df)
results_2 = model_2.fit()
results_2.summary()
```

[13]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.903
Model:                            OLS   Adj. R-squared:                  0.903
Method:                 Least Squares   F-statistic:                     4095.
Date:                Fri, 07 Oct 2022   Prob (F-statistic):          2.14e-224
Time:                        11:08:01   Log-Likelihood:                -3405.2
No. Observations:                 440   AIC:                             6814.
Df Residuals:                     438   BIC:                             6823.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -95.9322     31.494     -3.046      0.002    -157.830     -34.034
x2             0.7431      0.012     63.995      0.000       0.720       0.766
==============================================================================
Omnibus:                      193.985   Durbin-Watson:                   2.028
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2549.058
Skew:                           1.524   Prob(JB):                         0.00
Kurtosis:                      14.391   Cond. No.                     3.22e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.22e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[14]:
```python
n2= len(x2)
y_hat_2 = b0_x2 + b1_x2*x2
resid_2 = y - y_hat_2
print(np.sum(resid_2))
print((np.sum((resid_2 - np.mean(resid_2))**2)))
print(np.var(resid_2, ddof=1)*(n2-1))
```

```
6.639311322942376e-11
135864044.99064988
135864044.99064988
```

[15]:
```python
SSE_2 = np.sum((y - y_hat_2)**2)
MSE_2 = SSE_2 / (n2-2)
print(MSE_2, SSE_2)
resid_dev_2 = np.sqrt(MSE_2)
resid_dev_2
```

```
310191.8835402965 135864044.99064988
```

[15]:
```
556.9487261322146
```

[16]:
```
model_3 = smf.ols('y ~ x3', data=df)
results_3 = model_3.fit()
results_3.summary()
```

[16]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.899
Model:                            OLS   Adj. R-squared:                  0.899
Method:                 Least Squares   F-statistic:                     3895.
Date:                Fri, 07 Oct 2022   Prob (F-statistic):          4.28e-220
Time:                        11:08:01   Log-Likelihood:                -3415.2
No. Observations:                 440   AIC:                             6834.
Df Residuals:                     438   BIC:                             6843.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -48.3948     31.833     -1.520      0.129    -110.960      14.170
x3             0.1317      0.002     62.409      0.000       0.128       0.136
==============================================================================
Omnibus:                      285.860   Durbin-Watson:                   2.139
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4009.832
Skew:                           2.571   Prob(JB):                         0.00
Kurtosis:                      16.866   Cond. No.                     1.77e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.77e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

[17]:
```
n3= len(x3)
y_hat_3 = b0_x3 + b1_x3*x3
resid_3 = y - y_hat_3
print(np.sum(resid_3))
print((np.sum((resid_3 - np.mean(resid_3))**2)))
print(np.var(resid_3, ddof=1)*(n3-1))
```

```
3.001332515850663e-11
```

```
142148254.43029362
142148254.43029377
```

[18]:
```
SSE_3 = np.sum((y - y_hat_3)**2)
MSE_3 = SSE_3 / (n3-2)
print(MSE_3, SSE_3)
resid_dev_3 = np.sqrt(MSE_3)
resid_dev_3
```

```
324539.39367646945 142148254.43029362
```

[18]:
```
569.6835908436099
```

- MSE_1= 372203.5049168835
- SSE_1= 163025135.15359497
- MSE_2= 310191.8835402965
- SSE_2= 135864044.99064988
- MSE_3= 324539.39367646945
- SSE_3= 142148254.43029362

Hence: MSE of model (X2, Y) is the smallest, so the fitted regression line is the line(X2,Y)

1 Homework LAB_1

1.0.1 4.

[26]:
```
SSTO_1 = np.sum((y - b0_x1)**2)
print(SSTO_1)
SSTO_2 = np.sum((y - b0_x2)**2)
print(SSTO_2)
SSTO_3 = np.sum((y - b0_x3)**2)
print(SSTO_3)
```

```
1937283386.178249
1923164082.8258522
1878814510.671821
```

[36]:
```
R2_1= 1 - SSE_1/SSTO_1
R2_2= 1 - SSE_2/SSTO_2
R2_3= 1 - SSE_3/SSTO_3
print(R2_1,'\n',R2_2,'\n',R2_3)
```

```
0.9158485865740063
 0.9293538985030261
 0.9243415176842207
```

- The variation in the number of active physicians is reduced by 91.6% when total population is considered.
- The variation in the number of active physicians is reduced by 92.9% when number of hospital beds is considered.

- The variation in the number of active physicians is reduced by 92.4% when total person income is considered. ##### Thus: By using coefficient of determination R^2 as the criterion, the number of hospital beds accounts for the largest reduction in the variability in the number of active physicians.

1.0.2 5.

[37]:
```
# 90 percent confidence coefficient in each case.
alpha = 0.1
```

Case 1:

[38]:
```
s2_b1_x1 = MSE_1/ np.sum(x1_err**2)
s_b1_x1 = np.sqrt(s2_b1_x1)
s_b1_x1
```

[38]: 4.8369416072151935e-05

[39]:
```
t_x1 = stats.t.ppf(q = 1 - alpha/2,df = len(x1)-2)
t_x1
```

[39]: 1.6483399665616618

[40]:
```
L1 = b1_x1 - t_x1 * s_b1_x1
U1 = b1_x1 + t_x1 * s_b1_x1
print(L1,U1)
```

```
0.0027156956366879165 0.0028751541200298728
```

- With confident coefficient .90, we estimate that mean number of active physicians increase by somewhere between 0.00271 and 0.00287 for each additional person in the total population.

Case 2:

[41]:
```
s2_b1_x2 = MSE_2/ np.sum(x2_err**2)
s_b1_x2 = np.sqrt(s2_b1_x2)
s_b1_x2
```

[41]: 0.011612125334784671

[42]:
```
t_x2 = stats.t.ppf(q = 1 - alpha/2,df = len(x2)-2)
t_x2
```

[42]: 1.6483399665616618

[48]:
```
L2 = b1_x2 - t_x2 * s_b1_x2
U2 = b1_x2 + t_x2 * s_b1_x2
print(L2,U2)
```

```
0.7239757137014157 0.7622571742735132
```

- With confident coefficient .90, we estimate that mean number of active physicians increase by somewhere between 0.72397 and 0.76225 for each additional bed in the number of hospital beds.

Case 3:

[45]:
```
s2_b1_x3 = MSE_3/ np.sum(x3_err**2)
s_b1_x3 = np.sqrt(s2_b1_x3)
s_b1_x3
```

[45]:
```
0.002110279102147496
```

[46]:
```
t_x3 = stats.t.ppf(q = 1 - alpha/2,df = len(x3)-2)
t_x3
```

[46]:
```
1.6483399665616618
```

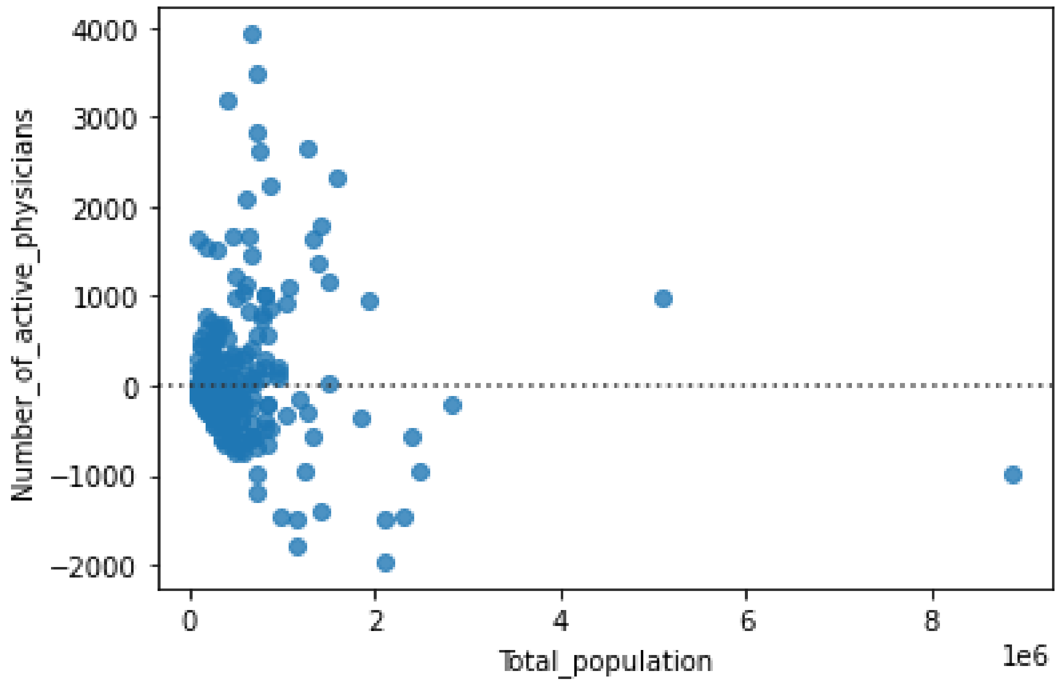
[47]:
```
L3 = b1_x3 - t_x3 * s_b1_x3
U3 = b1_x3 + t_x3 * s_b1_x3
print(L3,U3)
```

```
0.12822273179898655 0.13517964656832568
```

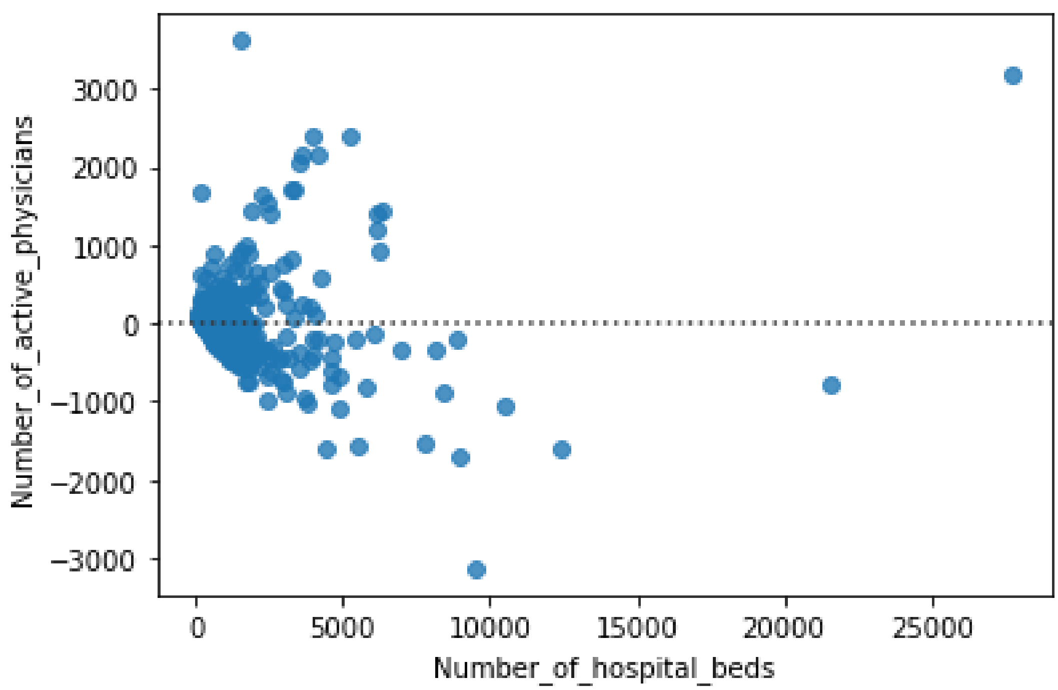
- With confident coefficient .90, we estimate that mean number of active physicians increase by somewhere between 0.72397 and 0.76225 for each additional personal income in the total personal income.

1.0.3 6.

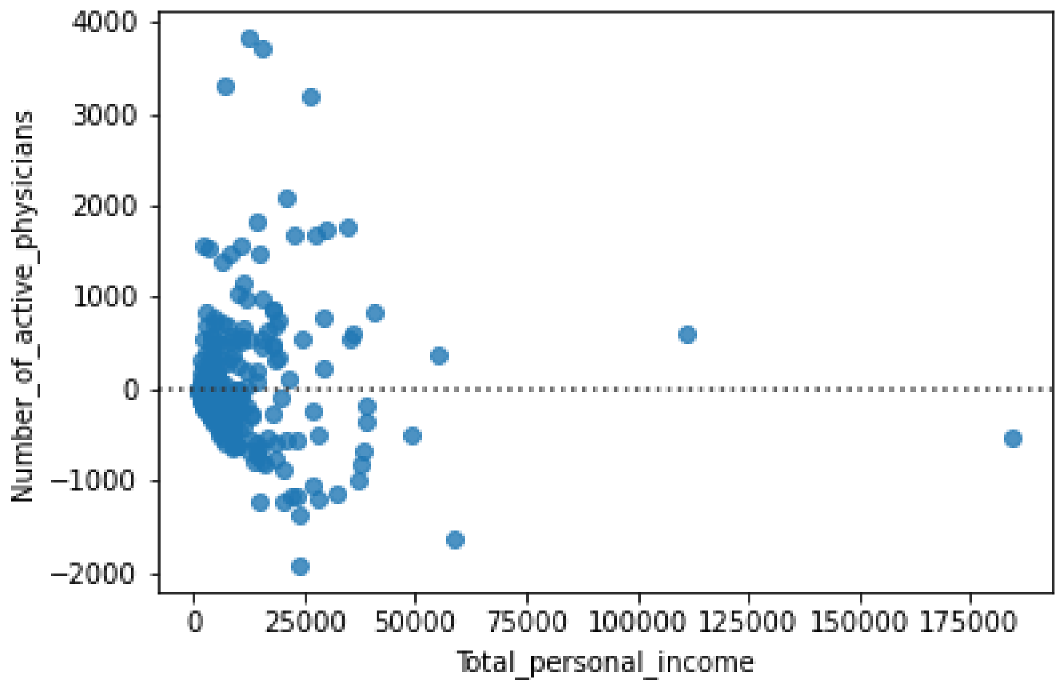
[49]:
```
sns.residplot(x=x1, y=y, data=df);
```



[50]:
```
sns.residplot(x=x2, y=y, data=df);
```



[51]:
```
sns.residplot(x=x3, y=y, data=df);
```



- In summary, three plots exhibit the same trend. Nevertheless, the data points in graph 2 had the greatest tendency to surround the zero point among the three plots. Furthermore, normal linear regression are strongly fitted than residual plots.

7.

- Yes,there are various outliers.
- if we omit the outliers, they sometimes could negatively impact the model and could make the model change much.