MounicaSubramani_HW2_DS5500

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0.0.1 Problem 1

- Akhil Nair
- Mounica Subramani
- Mrinal Soni
- SuRui Yang

0.0.2 Problem 2

The visualization I chose to compare and review for Problem 2 of HW1 is by Bishishta.

https://github.com/bishishta/Information-Visualization/tree/master/DS5500_HW1

The visualization is about the distribution of GPA per Capita across countries over time. Her plot was a clear static line plot. There were 20 sub plots for 193 countries where 10 countries were represented in each plot. We have "Year" in X-axis and GDP per Capita in the y axis.

There was also another plot representing GDP/Capita across continents over time which is again a simple static 2D lne plot.

The plot that I have mode for problem 2 was similar to the one that represents GDP/capita across continents over time from Bishishta's plots. However the clear representation of distribution of GDP/capita across countries was interesting and it is easy to interpret. It also does justice to the actual question. Her plot was able to explain what was asked in the problem and interpretations were clear. Interpretations based on the second plot for both of us were kind of similar

0.0.3 Problem 3

The visualization I chose to compare and review for Problem 3 of HW1 is by Monica Mishra.

https://colab.research.google.com/drive/1v8EY74vQxPubjXHywpDUYo7a3FMj-GuB#scrollTo=KXfw0fJqJwab

The visualization is about the relationship between income (GDP / capita), life expectancy, and child mortality over time. We both have split the problem into three parts and plotted each feature relationship and used interactive dynamic plots for the problem. She also used the Google colab effectively for all her visualization plots. both of us have represented 4 continents instead of six.

The visualizations are easily interpretable. Her interpretations were also clear and did answer the questions in problem 3.

0.0.4 Problem 4

[94]:
```
import numpy as np
import pandas as pd
import plotly
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
```

[84]:
```
gdpc_income = pd.read_csv("C:/Users/mouni/Downloads/DS5500/HW2/
 ↪ddf--datapoints--income_per_person_gdppercapita_ppp_inflation_adjusted--by--geo--time.
 ↪csv")
life_exp = pd.read_csv("ddf--datapoints--life_expectancy_years--by--geo--time.
 ↪csv")
```

[85]:
```
gdpc_income.head()
```

[85]:
```
   geo  time  income_per_person_gdppercapita_ppp_inflation_adjusted
0  afg  1800                                                     603
1  afg  1801                                                     603
2  afg  1802                                                     603
3  afg  1803                                                     603
4  afg  1804                                                     603
```

[86]:
```
gdpc_income = gdpc_income.
 ↪rename(columns={"income_per_person_gdppercapita_ppp_inflation_adjusted":␣
 ↪"income_per_person"})
gdpc_income.head()
```

[86]:
```
   geo  time  income_per_person
0  afg  1800                603
1  afg  1801                603
2  afg  1802                603
3  afg  1803                603
4  afg  1804                603
```

[17]:
```
life_exp.head()
```

[17]:
```
   geo  time  life_expectancy_years
0  abw  1800                  34.42
1  abw  1801                  34.42
2  abw  1802                  34.42
3  abw  1803                  34.42
4  abw  1804                  34.42
```

[18]:
```
merge_df = pd.merge(gdpc_income,life_exp, on = ['geo', 'time'])
merge_df.head()
```

[18]:
```
   geo  time  income_per_person  life_expectancy_years
0  afg  1800                603                  28.21
```

```
1  afg  1801                 603                  28.20
2  afg  1802                 603                  28.19
3  afg  1803                 603                  28.18
4  afg  1804                 603                  28.17
```

[19]:
```
merge_df['log_gdp_income'] = np.log(merge_df.income_per_person)
```

[20]:
```
merge_df.head()
```

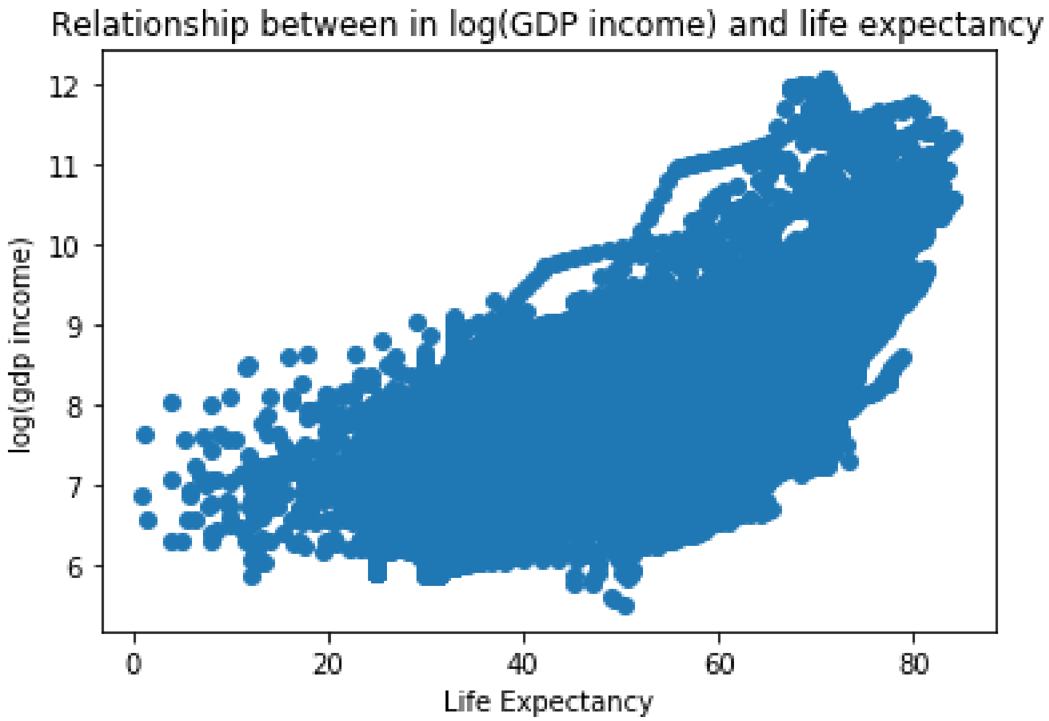
[20]:
```
   geo  time  income_per_person  life_expectancy_years  log_gdp_income
0  afg  1800                603                  28.21        6.401917
1  afg  1801                603                  28.20        6.401917
2  afg  1802                603                  28.19        6.401917
3  afg  1803                603                  28.18        6.401917
4  afg  1804                603                  28.17        6.401917
```

0.0.5 Linear Regression Model

Find correlation between the feature variables for better modelling.

[56]:
```
plt.scatter(merge_df["life_expectancy_years"],merge_df["log_gdp_income"])
plt.title("Relationship between in log(GDP income) and life expectancy")
plt.xlabel("Life Expectancy")
plt.ylabel("log(gdp income)")
```

[56]:
```
Text(0, 0.5, 'log(gdp income)')
```



There is a positive correlation between increase in gdp per capita income and life expectancy over years. The relationship is quite linear from pot that made out of mean values. So, trying a linear regression model on this data will be a good idea.

[29]:
```
X = merge_df["life_expectancy_years"].values.reshape(-1,1)
Y = merge_df["log_gdp_income"].values.reshape(-1,1)
xTrain, xTest, yTrain, yTest = train_test_split(X,Y, test_size=0.25,␣
 ↪random_state=0)

linear_reg = LinearRegression()
fit = linear_reg.fit(xTrain, yTrain)
print(fit)

coeff = linear_reg.coef_
print(coeff)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
[[0.05623936]]
```

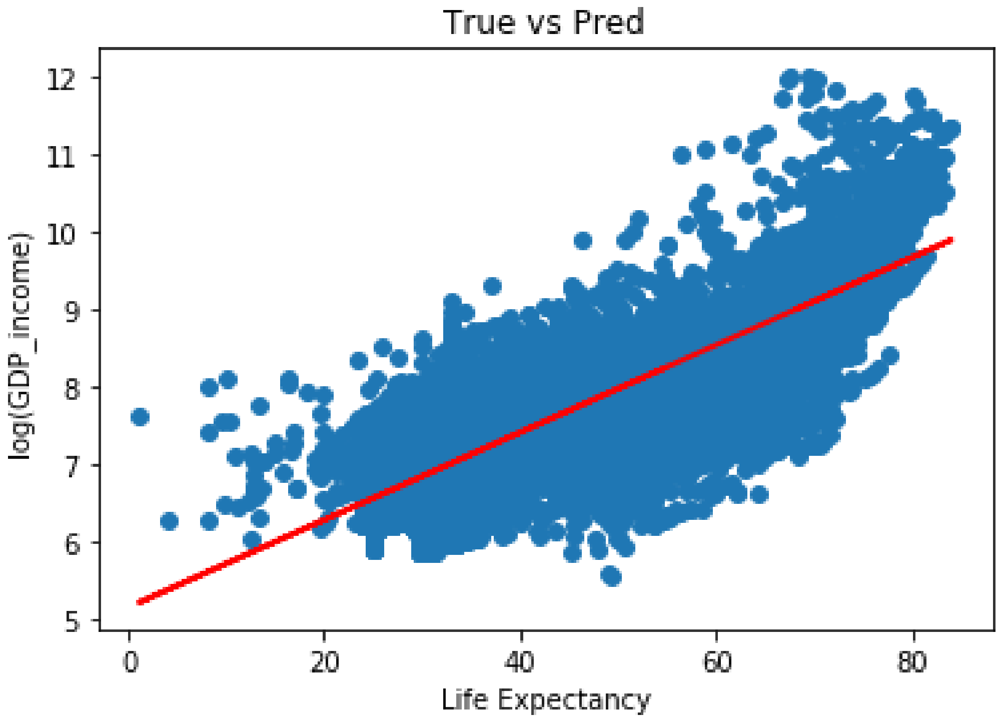
[37]:
```
y_pred = linear_reg.predict(xTest)
y_pred
```

[37]:
```
array([[8.24279466],
       [6.9335424 ],
       [7.02914931],
       ...,
       [7.84630719],
       [8.43063412],
       [9.00146361]])
```

[41]:
```
err = metrics.mean_squared_error(yTest,y_pred)
acc = 1 - err
print("Accuracy of the model: ", acc)
print("Error of the model: ", err)
```

```
Accuracy of the model:  0.5920870405134402
Error of the model:  0.40791295948655987
```

[74]:
```
plt.scatter(xTest, yTest)
plt.plot(xTest, y_pred, color='red', linewidth=2)
plt.title("True vs Pred")
plt.ylabel("log(GDP_income)")
plt.xlabel("Life Expectancy")
plt.show()
```



[50]:
```
err = metrics.mean_squared_error(yTest,y_pred)
acc = 1 - err
print("Accuracy: ", acc)
print("Error: ", err)
```

```
Accuracy:  0.5920870405134402
Error:  0.40791295948655987
```

It is observed that the accuracy of the model is not at its best and also the predicted line doesn't seem to be a best fit for the model and from the abouve graph it's not clear about model predictions too.

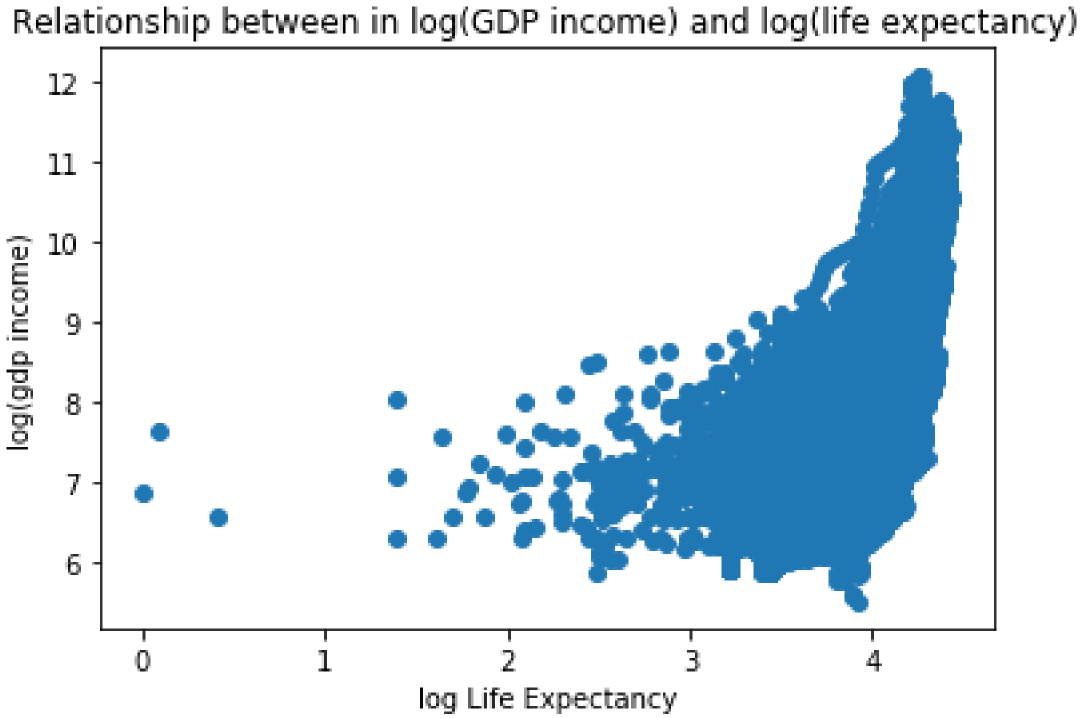
[55]:
```
merge_df['log_life_exp'] = np.log(merge_df.life_expectancy_years)
merge_df.head()
```

[55]:
```
   geo  time  income_per_person  life_expectancy_years  log_gdp_income  \
0  afg  1800                603                  28.21        6.401917
1  afg  1801                603                  28.20        6.401917
2  afg  1802                603                  28.19        6.401917
3  afg  1803                603                  28.18        6.401917
4  afg  1804                603                  28.17        6.401917

   log_life_exp
0      3.339677
1      3.339322
2      3.338967
```

```
3      3.338613
4      3.338258
```

[57]:
```
plt.scatter(merge_df["log_life_exp"],merge_df["log_gdp_income"])
plt.title("Relationship between log(GDP income) and log(life expectancy)")
plt.xlabel("log Life Expectancy")
plt.ylabel("log(gdp income)")
```

[57]:
```
Text(0, 0.5, 'log(gdp income)')
```



[58]:
```
X1 = merge_df["log_life_exp"].values.reshape(-1,1)
Y1 = merge_df["log_gdp_income"].values.reshape(-1,1)
xTrain1, xTest1, yTrain1, yTest1 = train_test_split(X1,Y1, test_size=0.25,␣
 ↪random_state=0)

linear_reg = LinearRegression()
fit = linear_reg.fit(xTrain1, yTrain1)
print(fit)

coeff = linear_reg.coef_
print(coeff)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
[[2.45250957]]
```

[59]:

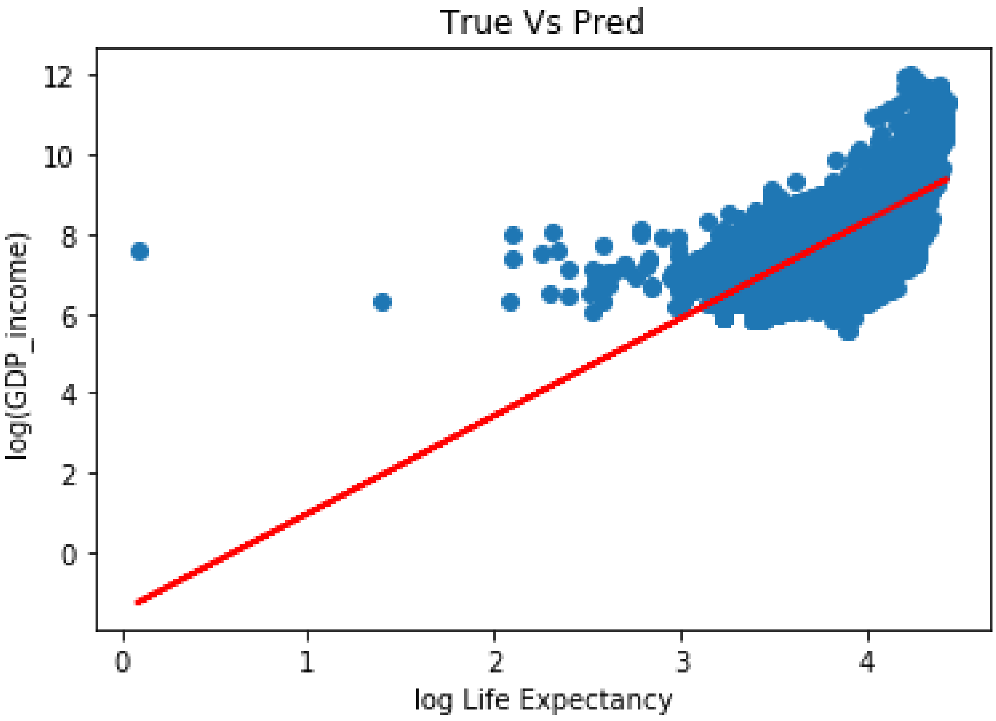
```
y_pred1 = linear_reg.predict(xTest1)
y_pred1
```

[59]:

```
array([[8.3354401 ],
       [6.9783743 ],
       [7.10728392],
       ...,
       [7.99757004],
       [8.48059108],
       [8.87534848]])
```

[72]:

```
plt.scatter(xTest1, yTest1)
plt.plot(xTest1, y_pred1, color='red', linewidth=2)
plt.title("True Vs Pred")
plt.ylabel("log(GDP_income)")
plt.xlabel("log Life Expectancy")
plt.show()
```



[61]:

```
err = metrics.mean_squared_error(yTest1,y_pred1)
acc = 1 - err
print("Accuracy: ", acc)
print("Error: ", err)
```

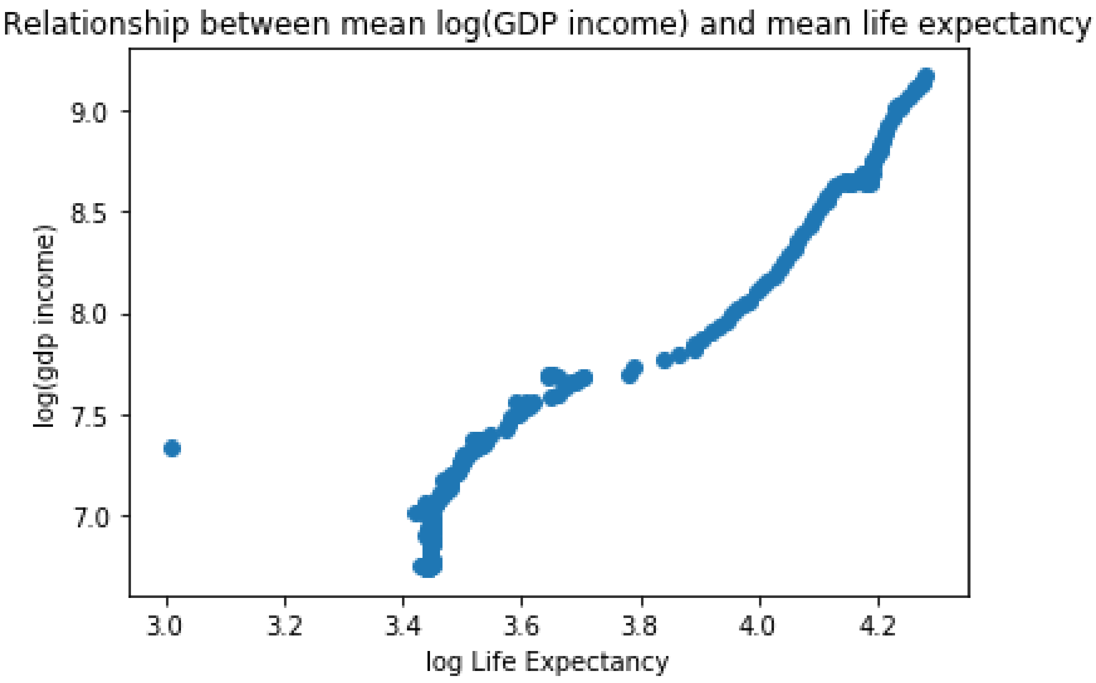
```
Accuracy:  0.5176426578739037
Error:  0.48235734212609627
```

[63]:
```
merge_df1 = merge_df.groupby("time").mean()
merge_df1.head()
```

[63]:
```
      income_per_person  life_expectancy_years  log_gdp_income  log_life_exp
time
1800         944.940217              31.503261        6.744176      3.442714
1801         945.375000              31.462717        6.744875      3.441401
1802         948.407609              31.478641        6.746483      3.441492
1803         948.119565              31.384620        6.746919      3.438252
1804         949.793478              31.459891        6.747735      3.440877
```

[108]:
```
plt.scatter(merge_df1["log_life_exp"],merge_df1["log_gdp_income"])
plt.title("Relationship between mean log(GDP income) and mean life expectancy")
plt.xlabel("log Life Expectancy")
plt.ylabel("log(gdp income)")
```

[108]:
```
Text(0, 0.5, 'log(gdp income)')
```



[65]:
```
X2 = merge_df1["life_expectancy_years"].values.reshape(-1,1)
Y2 = merge_df1["log_gdp_income"].values.reshape(-1,1)
xTrain2, xTest2, yTrain2, yTest2 = train_test_split(X2,Y2, test_size=0.25,␣
 ↪random_state=0)

linear_reg = LinearRegression()
fit = linear_reg.fit(xTrain2, yTrain2)
print(fit)
```

```
coeff = linear_reg.coef_
print(coeff)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
[[0.05107109]]
```

[66]:

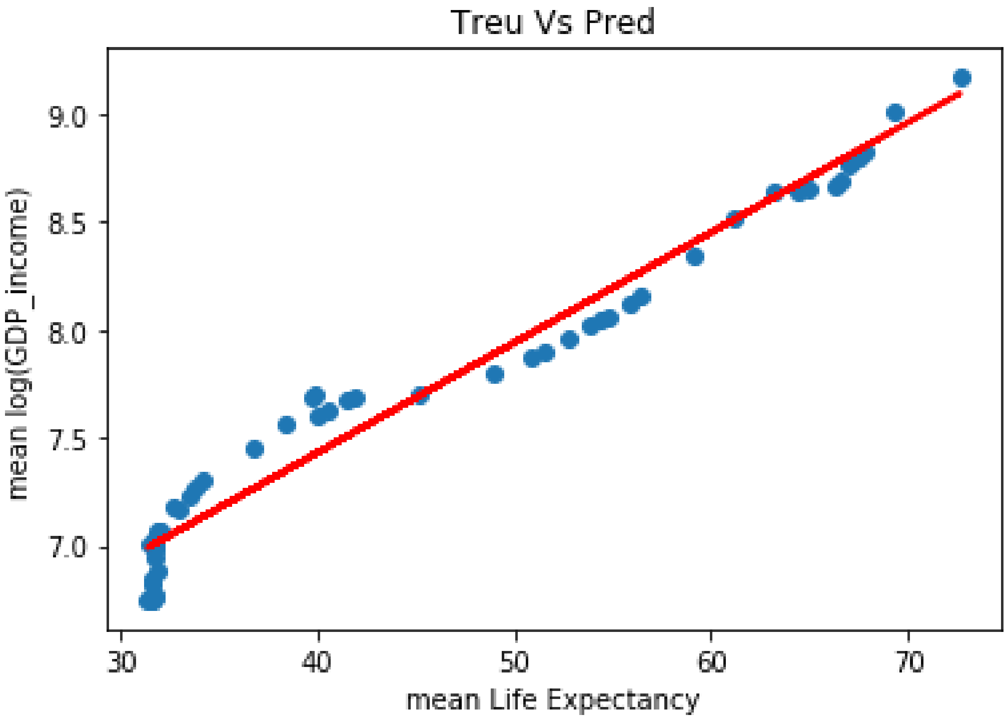
```
y_pred2 = linear_reg.predict(xTest2)
y_pred2
```

[66]:

```
array([[7.98620155],
       [7.02185732],
       [7.00916172],
       [8.24341386],
       [8.26699537],
       [7.42574912],
       [7.0089813 ],
       [8.01901472],
       [9.09748062],
       [7.43296846],
       [7.88727075],
       [7.00011048],
       [7.0574683 ],
       [8.40735204],
       [8.84762461],
       [8.77197113],
       [8.83708813],
       [7.09490008],
       [7.13260941],
       [7.01597027],
       [7.00804315],
       [6.99510051],
       [8.13428827],
       [7.00525644],
       [7.0011208 ],
       [7.34657506],
       [7.11362707],
       [7.00969186],
       [6.98974638],
       [7.0007905 ],
       [8.6164583 ],
       [7.00484565],
       [7.52517953],
       [7.00070168],
       [7.26683477],
       [8.18840419],
       [7.4586178 ],
       [7.41582079],
       [8.80968453],
       [8.08284803],
       [6.99668538],
       [7.0002104 ],
       [7.06895375],
       [8.16566368],
       [8.79034579],
       [8.51439806],
       [8.7070808 ],
       [8.92603648],
       [7.00373541],
       [7.50922259],
       [8.82478464],
       [7.69174066],
       [7.00901183],
       [8.6798875 ],
       [7.01477954]])
```

[70]:

```
plt.scatter(xTest2, yTest2)
plt.plot(xTest2, y_pred2, color='red', linewidth=2)
plt.title("Treu Vs Pred")
plt.ylabel("mean log(GDP_income)")
plt.xlabel("mean Life Expectancy")
plt.show()
```



[75]:

```
err = metrics.mean_squared_error(yTest2,y_pred2)
acc = 1 - err
print("Accuracy: ", acc)
print("Error: ", err)
```

```
Accuracy:  0.9788814825692786
Error:  0.02111851743072136
```

The linear regression model doesn't perform well on the actual data but taking mean of the features and log of gdp income did help in getting the best fit line of the model.

The hypothesis tried are: - Life Expectancy ~ log(gdp_income) + err - log(life expectancy) ~ log(gdp_income) + err - mean(life expectancy) ~ mean(log(gdp_income)) + err

The third hypothesis worked fine for the model.

0.0.6 Problem 5

[87]:

```
child_mort = pd.read_csv("C:/Users/mouni/Downloads/DS5500/HW2/
 ↪ddf--datapoints--child_mortality_0_5_year_olds_dying_per_1000_born--by--geo--time.
 ↪csv")
```

[88]:

```
merged_df_q5 = pd.merge(child_mort, gdpc_income, on = ['geo', 'time'])

merged_df_q5.head()
```

[88]:

```
   geo  time  child_mortality_0_5_year_olds_dying_per_1000_born  \
0  afg  1800                                             468.58
1  afg  1801                                             468.58
2  afg  1802                                             468.58
3  afg  1803                                             468.58
4  afg  1804                                             468.58

   income_per_person
0                603
1                603
2                603
3                603
4                603
```

[89]:

```
merged_df_q5 = merged_df_q5.
 ↪rename(columns={"child_mortality_0_5_year_olds_dying_per_1000_born":
 ↪"child_mort_rate"})
merged_df_q5.head()
```

[89]:

```
   geo  time  child_mort_rate  income_per_person
0  afg  1800           468.58                603
1  afg  1801           468.58                603
2  afg  1802           468.58                603
3  afg  1803           468.58                603
4  afg  1804           468.58                603
```

[90]:
```
merged_df_q5.corr()['income_per_person'].sort_values(ascending=False)
```

[90]:
```
income_per_person    1.000000
time                 0.415972
child_mort_rate     -0.514889
Name: income_per_person, dtype: float64
```

[91]:
```
merge_df2 = merged_df_q5.groupby("time").mean()
merge_df2.head()
```

[91]:
```
      child_mort_rate  income_per_person
time
1800       424.585598         944.940217
1801       423.930755         945.375000
1802       423.295315         948.407609
1803       422.893000         948.119565
1804       422.515913         949.793478
```

[92]:
```
merge_df2.corr()['income_per_person'].sort_values(ascending=False)
```

[92]:
```
income_per_person    1.000000
child_mort_rate     -0.946659
Name: income_per_person, dtype: float64
```

It is observed that there is a strong negative correlation between child mortality rate and gdp per capita income. Linear model can be fit to this data.

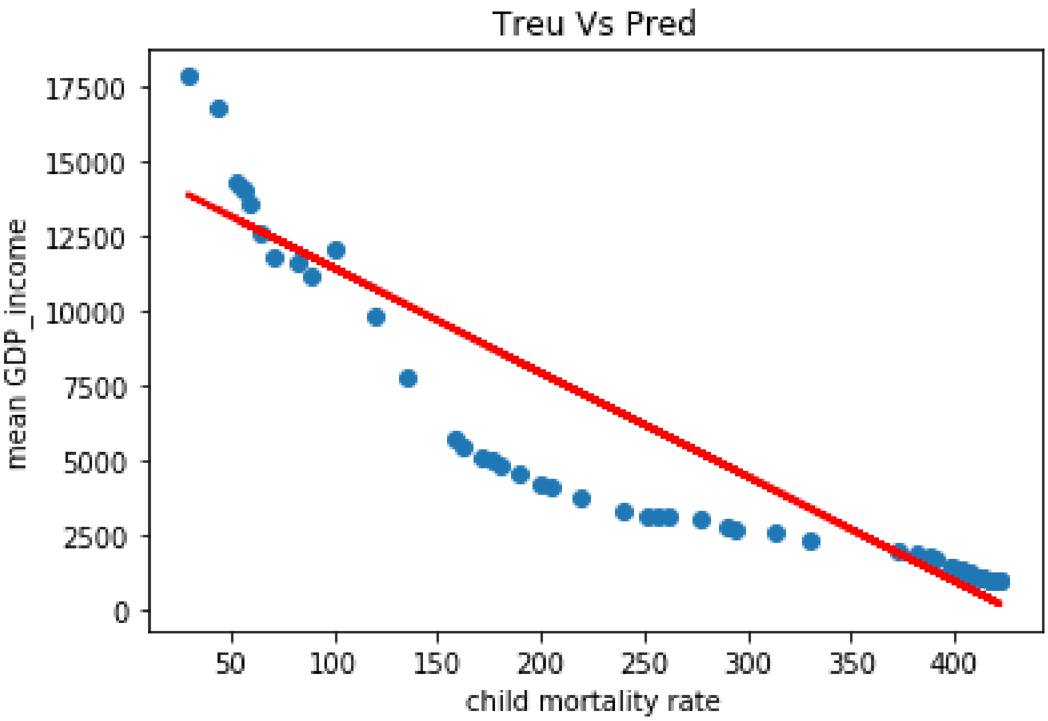
[96]:
```
X3 = merge_df2["child_mort_rate"].values.reshape(-1,1)
Y3 = merge_df2["income_per_person"].values.reshape(-1,1)
xTrain3, xTest3, yTrain3, yTest3 = train_test_split(X3,Y3, test_size=0.25,␣
 ↪random_state=0)

linear_reg = LinearRegression()
fit1 = linear_reg.fit(xTrain3, yTrain3)
print(fit1)

coeff1 = linear_reg.coef_
print(coeff1)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
[[-34.8652511]]
```

[97]:
```
y_pred3 = linear_reg.predict(xTest3)
y_pred3
```

[97]:
```
array([[ 7769.82499242],
       [ 1020.75293579],
       [  981.37092931],
       [ 9220.20321568],
       [ 9382.15268192],
       [ 5766.5017717 ],
[  830.30585983],
[ 7942.30054732],
[13875.79561609],
[ 4639.54866028],
[ 7266.04921043],
[  186.53472558],
[ 1299.2698255 ],
[10166.50442665],
[13055.70326852],
[12430.9468727 ],
[12981.52880168],
[ 1389.38342512],
[ 1915.49153734],
[ 1027.57932457],
[  690.13352852],
[  264.61469747],
[ 8597.68901061],
[  835.97013673],
[  512.8842765 ],
[ 3996.09946115],
[ 1605.51690637],
[  782.68201116],
[  207.03170353],
[  331.3426194 ],
[11406.93625817],
[  303.70376005],
[ 5226.29634996],
[  206.59399304],
[ 3386.3426006 ],
[ 8908.49944789],
[ 4797.53997717],
[ 5938.48087574],
[12832.50261501],
[ 8278.50692158],
[  869.54669994],
[  464.52806808],
[ 1365.62048268],
[ 8761.11040087],
[12668.26542382],
[10735.64889136],
[12034.31399546],
[13400.86925438],
[  317.39291875],
[ 6118.45757572],
[12908.43822866],
[ 6537.00221964],
[  372.75647418],
[11812.46233909],
[  640.91118389]])
```

[105]:
```
plt.scatter(xTest3, yTest3)
plt.plot(xTest3, y_pred3, color='red', linewidth=2)
plt.title("Treu Vs Pred")
plt.ylabel("mean GDP_income")
plt.xlabel("child mortality rate")
plt.show()
```



[106]:
```
err = metrics.mean_squared_error(yTest3,y_pred3)
acc = 1 - err
print("Accuracy: ", acc)
print("Error: ", err)
```

```
Accuracy:  -4003954.6158150965
Error:  4003955.6158150965
```

The best fit line of the model isn't that accurate. So we try some log function on the gdp per capita income variable.

[100]:
```
merge_df2['log_gdp_income'] = np.log(merge_df2.income_per_person)
merge_df2.head()
```

[100]:
```
      child_mort_rate  income_per_person  log_gdp_income
time
1800       424.585598         944.940217        6.851122
1801       423.930755         945.375000        6.851582
1802       423.295315         948.407609        6.854784
1803       422.893000         948.119565        6.854481
1804       422.515913         949.793478        6.856245
```

[101]:
```
X4 = merge_df2["child_mort_rate"].values.reshape(-1,1)
Y4 = merge_df2["log_gdp_income"].values.reshape(-1,1)
xTrain4, xTest4, yTrain4, yTest4 = train_test_split(X4,Y4, test_size=0.25,␣
 ↪random_state=0)

linear_reg = LinearRegression()
fit1 = linear_reg.fit(xTrain4, yTrain4)
print(fit1)

coeff1 = linear_reg.coef_
print(coeff1)
```

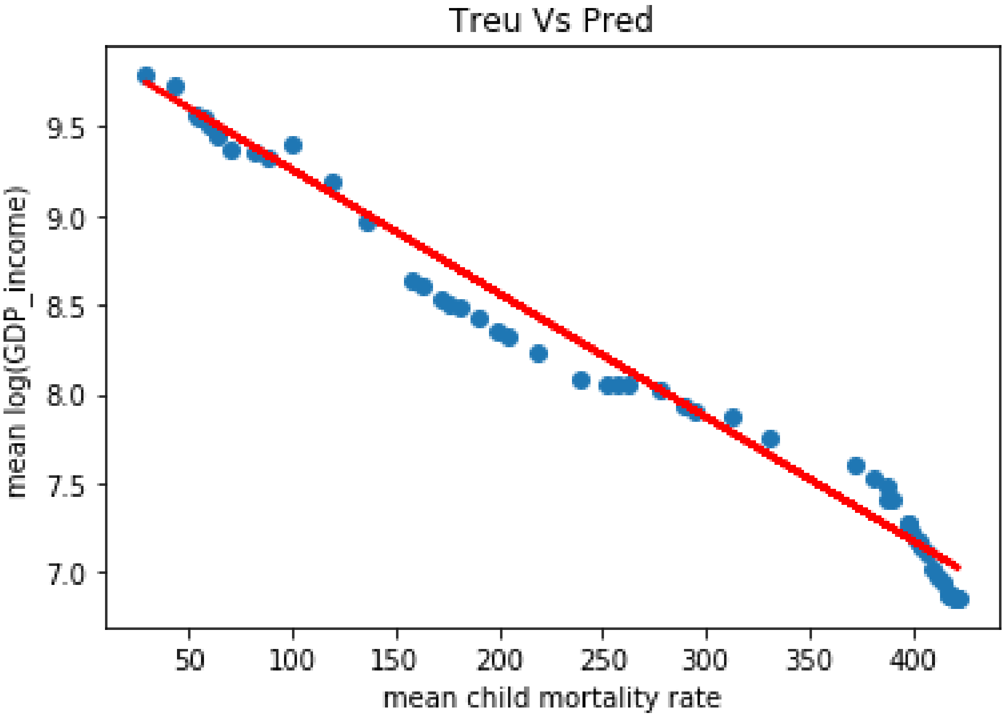
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
[[-0.00693673]]
```

[102]:
```
y_pred4 = linear_reg.predict(xTest4)
y_pred4
```

[102]:
```
array([[8.53404197],
       [7.19125853],
       [7.18342316],
       [8.82260665],
       [8.85482783],
       [8.13546433],
       [7.15336752],
       [8.5683574 ],
       [9.74887508],
       [7.91124773],
       [8.43381163],
       [7.02528395],
       [7.24667176],
       [9.01088107],
       [9.58571096],
       [9.46141053],
       [9.57095334],
       [7.2646006 ],
       [7.36927414],
       [7.1926167 ],
       [7.12547908],
       [7.04081861],
       [8.69875233],
       [7.15449447],
       [7.09021388],
       [7.78322821],
       [7.30760214],
       [7.14389236],
       [7.029362  ],
       [7.05409468],
       [9.25767519],
       [7.0485957 ],
       [8.02798601],
       [7.02927491],
       [7.66191207],
       [8.76059062],
       [7.9426814 ],
       [8.16968098],
       [9.54130335],
       [8.63524843],
       [7.16117481],
       [7.08059302],
       [7.25987277],
       [8.73126636],
       [9.50862701],
       [9.12411705],
       [9.38249716],
       [9.65438457],
       [7.05131927],
       [8.20548883],
       [9.55641137],
       [8.28876173],
       [7.0623343 ],
       [9.33835794],
       [7.11568589]])
```

[104]:

```
plt.scatter(xTest4, yTest4)
plt.plot(xTest4, y_pred4, color='red', linewidth=2)
plt.title("Treu Vs Pred")
plt.ylabel("mean log(GDP_income)")
plt.xlabel("mean child mortality rate")
plt.show()
```



[107]:
```
err = metrics.mean_squared_error(yTest4,y_pred4)
acc = 1 - err
print("Accuracy: ", acc)
print("Error: ", err)
```

```
Accuracy:  0.9803815832460806
Error:  0.019618416753919 39
```

The hypothesis tried are: - mean child mort rate ~ mean(gdp_income) + err - mean child mort rate ~ log(mean(gdp_income)) + err