Kinney_DSC550_Final

February 1, 2020

0.1 D. Kinney DSC 550 Final Project

0.1.1 Part 1: Graph Analysis

---

[46]:
```
import warnings
warnings.filterwarnings("ignore")
```

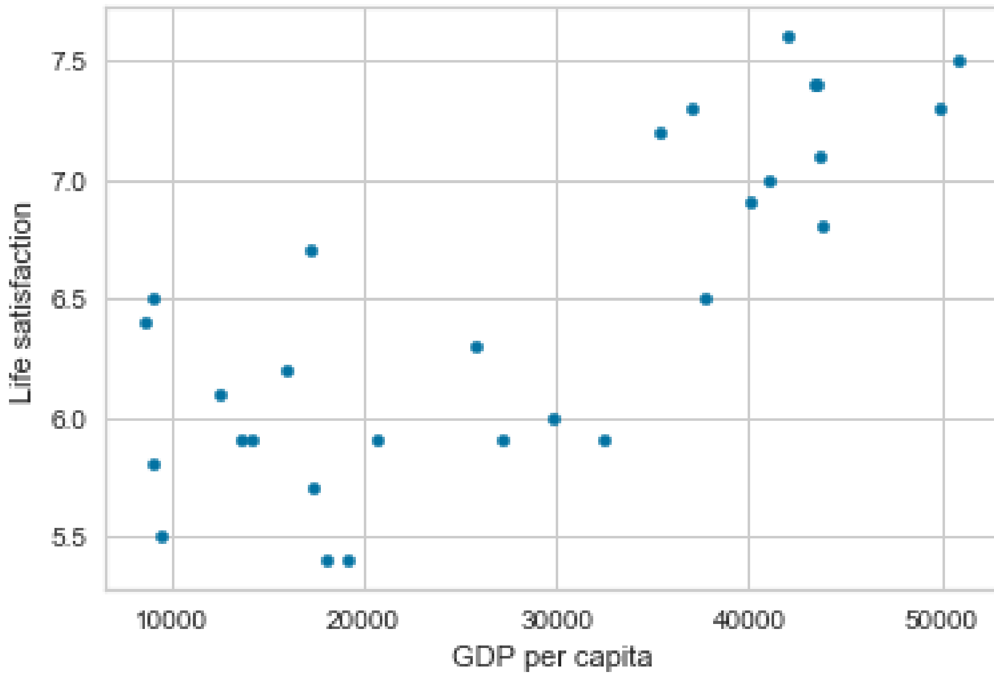
[47]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import sklearn.linear_model
import statsmodels.formula.api as smf

from pandas.plotting import scatter_matrix
from plotnine import *

pd.set_option('display.max_columns', None)

%matplotlib inline
```

[48]:
```
def prepare_country_stats(oecd_bli, gdp_per_capita):
    oecd_bli = oecd_bli[oecd_bli["INEQUALITY"]=="TOT"]
    oecd_bli = oecd_bli.pivot(index="Country", columns="Indicator",␣
 ↪values="Value")
    gdp_per_capita.rename(columns={"2015": "GDP per capita"}, inplace=True)
    gdp_per_capita.set_index("Country", inplace=True)
    full_country_stats = pd.merge(left=oecd_bli, right=gdp_per_capita,
                                  left_index=True, right_index=True)
    full_country_stats.sort_values(by="GDP per capita", inplace=True)
    remove_indices = [0, 1, 6, 8, 33, 34, 35]
    keep_indices = list(set(range(36)) - set(remove_indices))
    return full_country_stats[["GDP per capita", 'Life satisfaction']].
 ↪iloc[keep_indices]
```

Step 1: Load data into dataframe

[49]:
```
# Load the data
oecd_bli = pd.read_csv("data/oecd_bli_2015.csv", thousands=',')
gdp_per_capita = pd.read_csv("data/gdp_per_capita.
 ↪csv",thousands=',',delimiter='\t',
                             encoding='latin1', na_values="n/a")

# Prepare the data
country_stats = prepare_country_stats(oecd_bli, gdp_per_capita)
X = np.c_[country_stats["GDP per capita"]]
y = np.c_[country_stats["Life satisfaction"]]

# Visualize the data
country_stats.plot(kind='scatter', x="GDP per capita", y='Life satisfaction')
plt.show()

# Select a linear model
model = sklearn.linear_model.LinearRegression()

# Train the model
model.fit(X, y)

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus' GDP per capita
print(model.predict(X_new)) # outputs [[ 5.96242338]]
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
'x' & 'y'.  Please use a 2-D array with a single row if you really want to
specify the same RGB or RGBA value for all points.
```




```
[[6.25984414]]
```

Step 2: check the dimension of the table

[50]:
```
print("The dimension of the table is: ", oecd_bli.shape)
```

```
The dimension of the table is:  (2368, 17)
```

Step 3: Look at the data

[51]:
```
print(oecd_bli.head(5))
```

```
  LOCATION         Country INDICATOR                   Indicator MEASURE  \
0      AUS       Australia   JE_LMIS  Labour market insecurity       L
1      AUT         Austria   JE_LMIS  Labour market insecurity       L
2      BEL         Belgium   JE_LMIS  Labour market insecurity       L
3      CAN          Canada   JE_LMIS  Labour market insecurity       L
4      CZE  Czech Republic   JE_LMIS  Labour market insecurity       L

  Measure INEQUALITY Inequality Unit Code        Unit  PowerCode Code  \
0   Value        TOT      Total        PC  Percentage              0
1   Value        TOT      Total        PC  Percentage              0
2   Value        TOT      Total        PC  Percentage              0
3   Value        TOT      Total        PC  Percentage              0
4   Value        TOT      Total        PC  Percentage              0
```

```
  PowerCode  Reference Period Code  Reference Period  Value  Flag Codes  Flags
0     Units                    NaN               NaN    5.4         NaN    NaN
1     Units                    NaN               NaN    3.5         NaN    NaN
2     Units                    NaN               NaN    3.7         NaN    NaN
3     Units                    NaN               NaN    6.0         NaN    NaN
4     Units                    NaN               NaN    3.1         NaN    NaN
```

[52]:
```
oecd_bli.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2368 entries, 0 to 2367
Data columns (total 17 columns):
LOCATION                 2368 non-null object
Country                  2368 non-null object
INDICATOR                2368 non-null object
Indicator                2368 non-null object
MEASURE                  2368 non-null object
Measure                  2368 non-null object
INEQUALITY               2368 non-null object
Inequality               2368 non-null object
Unit Code                2368 non-null object
Unit                     2368 non-null object
PowerCode Code           2368 non-null int64
PowerCode                2368 non-null object
Reference Period Code    0 non-null float64
Reference Period         0 non-null float64
Value                    2368 non-null float64
Flag Codes               0 non-null float64
Flags                    0 non-null float64
dtypes: float64(5), int64(1), object(11)
memory usage: 314.6+ KB
```

Looking at the results of the "info" method, there are a number of empty columns that can be removed.
There are also some with the same value throughout.

[53]:
```
# Remove empty columns
oecd_bli.dropna(axis=1, inplace=True)

# Looks liks some other variables have the same value from top to bottom,
# so really don't need them...
print(oecd_bli['MEASURE'].value_counts())
print(oecd_bli['PowerCode Code'].value_counts())
oecd_bli.drop(['MEASURE', 'Measure', 'PowerCode Code'], axis = 1, inplace=True)

# Remove space from Unit Code
oecd_bli.rename(columns={'Unit Code': 'UnitCode'})
```

```
print(oecd_bli.info())
```

```
L    2368
Name: MEASURE, dtype: int64
0    2368
Name: PowerCode Code, dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2368 entries, 0 to 2367
Data columns (total 10 columns):
LOCATION      2368 non-null object
Country       2368 non-null object
INDICATOR     2368 non-null object
Indicator     2368 non-null object
INEQUALITY    2368 non-null object
Inequality    2368 non-null object
Unit Code     2368 non-null object
Unit          2368 non-null object
PowerCode     2368 non-null object
Value         2368 non-null float64
dtypes: float64(1), object(9)
memory usage: 185.1+ KB
None
```

[54]:
```
oecd_bli.sample(5)
```

[54]:
```
     LOCATION          Country INDICATOR                    Indicator  \
748       CAN           Canada  SC_SNTWS   Quality of support network
696       SVK  Slovak Republic   JE_LTUR  Long-term unemployment rate
1645      HUN          Hungary   HS_SFRH          Self-reported health
1786      FIN          Finland   HS_SFRH          Self-reported health
1791      IRL          Ireland   HS_SFRH          Self-reported health

     INEQUALITY Inequality Unit Code        Unit PowerCode  Value
748         TOT      Total        PC  Percentage     Units  93.00
696         WMN      Women        PC  Percentage     Units   4.63
1645        TOT      Total        PC  Percentage     Units  60.00
1786         LW        Low        PC  Percentage     Units  57.00
1791         LW        Low        PC  Percentage     Units  72.00
```

Using pandas.pivot_table, transform dataframe into a more human-friendly format…

[55]:
```
df_table = pd.pivot_table(oecd_bli, values='Value', index='Country',␣
 ↪columns=['INDICATOR'])

# I also need a 'Country' column. I know this is probably not the right way to␣
 ↪go about this...
df_table['country'] = df_table.index.astype('str')
```

```
# Drop this row, it's not a country...
indexNames = df_table[df_table['country'] == 'OECD - Total'].index
df_table.drop(indexNames , inplace=True)

print(df_table.sample(5))

# For reference, create a dictionary of Indicators
print("LIST OF INDICATOR KEYS AND DESCRIPTIONS")
print("========================================")
df_indicators = oecd_bli.groupby('INDICATOR')['Indicator'].agg('min')
print(df_indicators.sort_values())
```

```
INDICATOR        CG_SENG  CG_VOTO  EQ_AIRP   EQ_WATER    ES_EDUA   ES_EDUEX  \
Country
Ireland              1.3     65.0      7.0  85.000000  82.000000  18.100000
Netherlands          2.6     82.0     14.0  93.000000  78.333333  18.666667
Norway               2.2     78.0      5.0  97.666667  82.000000  18.333333
Hungary              1.2     70.0     19.0  77.000000  84.000000  16.433333
Slovak Republic      3.0     60.0     21.0  84.666667  91.333333  15.766667

INDICATOR        ES_STCS  HO_BASE  HO_HISH  HO_NUMR     HS_LEB  HS_SFRH  \
Country
Ireland            509.8      1.0     20.0      2.1  81.766667     82.8
Netherlands        509.6      0.1     19.0      1.9  81.600000     75.8
Norway             504.8      0.0     17.0      2.1  82.466667     77.2
Hungary            475.0      4.7     19.0      1.2  76.166667     61.0
Slovak Republic    463.4      1.2     23.0      1.1  77.266667     68.6

INDICATOR        IW_HADI   IW_HNFW    JE_EMPL  JE_LMIS   JE_LTUR  JE_PEARN  \
Country
Ireland          25310.0  217130.0  67.333333    8.784  3.203333   47653.0
Netherlands      29333.0  157824.0  75.666667    4.930  1.976667   52877.0
Norway           35725.0  228936.0  74.000000      NaN  0.656667   51212.0
Hungary              NaN  104458.0  68.000000    5.256  1.726667   22576.0
Slovak Republic  20474.0       NaN  66.000000   21.376  4.773333   24328.0

INDICATOR        PS_FSAFEN   PS_REPH  SC_SNTWS  SW_LIFS   WL_EWLH    WL_TNOW  \
Country
Ireland          76.000000  0.666667      95.0    7.050  5.260000        NaN
Netherlands      82.066667  0.600000      91.0    7.500  0.413333        NaN
Norway           90.033333  0.400000      94.0    7.620  2.886667  15.563333
Hungary          56.700000  1.000000      85.5    5.680  2.976667        NaN
Slovak Republic  63.700000  0.800000      91.5    6.425  4.073333        NaN

INDICATOR                country
Country
```

```
Ireland                      Ireland
Netherlands              Netherlands
Norway                        Norway
Hungary                      Hungary
Slovak Republic  Slovak Republic
LIST OF INDICATOR KEYS AND DESCRIPTIONS
=======================================
INDICATOR
EQ_AIRP                                                Air pollution
HO_BASE                           Dwellings without basic facilities
ES_EDUA                                       Educational attainment
WL_EWLH                            Employees working very long hours
JE_EMPL                                              Employment rate
PS_FSAFEN                        Feeling safe walking alone at night
PS_REPH                                                Homicide rate
IW_HADI                      Household net adjusted disposable income
IW_HNFW                                         Household net wealth
HO_HISH                                          Housing expenditure
JE_LMIS                                     Labour market insecurity
HS_LEB                                               Life expectancy
SW_LIFS                                            Life satisfaction
JE_LTUR                                  Long-term unemployment rate
JE_PEARN                                           Personal earnings
SC_SNTWS                                 Quality of support network
HO_NUMR                                             Rooms per person
HS_SFRH                                         Self-reported health
CG_SENG           Stakeholder engagement for developing regulations
ES_STCS                                               Student skills
WL_TNOW                     Time devoted to leisure and personal care
CG_VOTO                                                 Voter turnout
EQ_WATER                                               Water quality
ES_EDUEX                                          Years in education
Name: Indicator, dtype: object
```

[56]:
```
df_table.describe()
```

[56]:
```
INDICATOR    CG_SENG   CG_VOTO    EQ_AIRP   EQ_WATER    ES_EDUA   ES_EDUEX  \
count      38.000000  40.00000  40.000000  40.000000  39.000000  39.000000
mean        2.160526  69.57500  13.325000  82.333333  77.717949  17.547863
std         0.577291  12.21157   5.770782  10.492977  15.136134   1.412720
min         1.200000  47.00000   3.000000  55.333333  37.666667  14.100000
25%         1.725000  60.75000   9.750000  74.250000  75.000000  16.550000
50%         2.200000  69.50000  14.000000  83.833333  82.000000  17.666667
75%         2.575000  79.00000  16.500000  91.083333  87.833333  18.350000
max         3.200000  91.00000  28.000000  98.666667  94.000000  20.966667

INDICATOR    ES_STCS    HO_BASE    HO_HISH    HO_NUMR     HS_LEB    HS_SFRH  \
count      39.000000  37.000000  38.000000  37.000000  40.000000  37.000000
```

```
mean       485.707692   5.075676  20.657895   1.632432  79.567500  67.493243
std         33.787972   8.448320   2.528500   0.431441   4.669642  14.331584
min        398.200000   0.000000  15.000000   0.900000  57.500000  33.000000
25%        475.800000   0.300000  19.000000   1.200000  77.916667  60.800000
50%        492.800000   0.900000  21.000000   1.600000  81.366667  70.200000
75%        506.800000   6.700000  22.750000   1.900000  82.366667  76.000000
max        528.800000  37.000000  26.000000   2.600000  84.066667  89.250000

INDICATOR       IW_HADI        IW_HNFW    JE_EMPL    JE_LMIS    JE_LTUR  \
count         29.000000      27.000000  40.000000  33.000000  38.000000
mean       27807.310345  289780.185185  68.533333   7.706970   2.855789
std         7055.262661  165673.432787   7.882253   6.234572   3.622899
min        16275.000000   70160.000000  43.333333   0.662000   0.050000
25%        21453.000000  180100.000000  65.833333   4.392000   1.011667
50%        29333.000000  259667.000000  69.666667   5.396000   1.776667
75%        31304.000000  379777.000000  74.000000   8.784000   3.196667
max        45284.000000  769053.000000  85.666667  29.200000  16.643333

INDICATOR      JE_PEARN   PS_FSAFEN    PS_REPH   SC_SNTWS    SW_LIFS  \
count         35.000000  40.000000  40.000000  40.000000  40.000000
mean       39817.514286  68.463333   3.481667  90.193333   6.577208
std        13108.329748  13.960934   6.459861   4.384954   0.762724
min        15314.000000  35.866667   0.166667  78.333333   4.700000
25%        25971.500000  60.108333   0.600000  88.300000   5.938333
50%        40863.000000  70.483333   0.950000  91.350000   6.510000
75%        49400.500000  78.500000   2.166667  93.062500   7.243750
max        63062.000000  90.033333  27.000000  98.000000   7.660000

INDICATOR    WL_EWLH    WL_TNOW
count      38.000000  22.000000
mean        7.789649  15.048939
std         7.585983   0.672978
min         0.140000  13.826667
25%         3.150833  14.560833
50%         4.981667  14.885000
75%        10.571667  15.600833
max        31.043333  16.336667
```

[57]:
```
corr_matrix = df_table.corr()
corr_matrix["SW_LIFS"].sort_values(ascending=False)
```

[57]:
```
INDICATOR
SW_LIFS      1.000000
JE_PEARN     0.731418
IW_HADI      0.713008
EQ_WATER     0.682587
JE_EMPL      0.678344
SC_SNTWS     0.667896
```

```
HS_SFRH       0.656817
PS_FSAFEN     0.600163
HO_NUMR       0.597502
HS_LEB        0.568044
CG_VOTO       0.368598
ES_EDUEX      0.324655
ES_EDUA       0.293395
IW_HNFW       0.292887
HO_HISH       0.286334
WL_TNOW       0.199424
ES_STCS       0.197223
CG_SENG       0.180861
WL_EWLH      -0.195136
PS_REPH      -0.259378
JE_LMIS      -0.452874
HO_BASE      -0.528167
EQ_AIRP      -0.551376
JE_LTUR      -0.567002
Name: SW_LIFS, dtype: float64
```

Step 4: Think about some questions that might help you predict what indicators most influence the Life Satisfaction score: The central point of this dataset is the so-called, **"Life Satisfaction Index"**. In other words, do indicators in the categories of housing, income, jobs, community, education, environment, civic engagement, health, etc. really lead to a better, more satisfied life? Let's focus on a few high-level categories to see how the indicators correlate with the LSI…

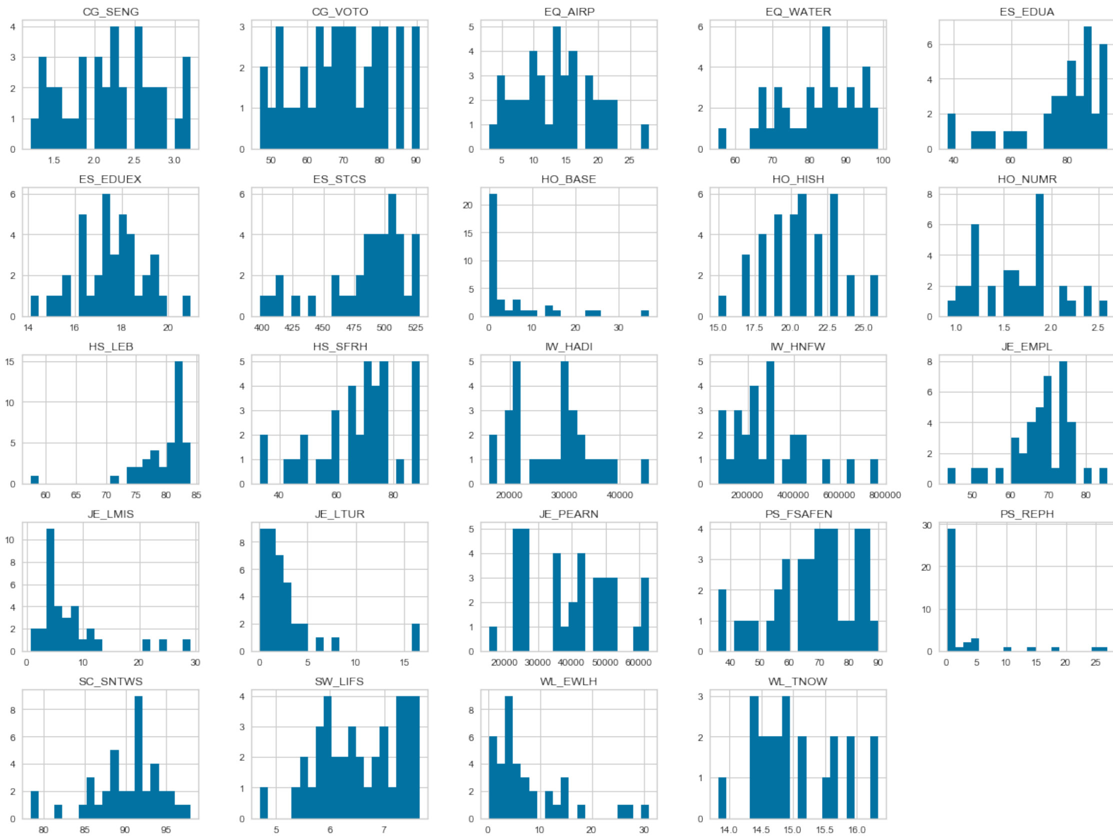
- **Wealth** Net Wealth, Labor Market Insecurity, Employment rate
- **Environment** Air pollution, Homicide rate, Water quality
- **Health** Life expectancy, Self-reported health, Long work hours

My observations are based on the **graph analysis** below.

First, there does not seem to be any noticeable normal distribution amongst any of the indicators, although some–such as HS_LEB (Life Expectancy) exhibit *normal-ish* distribution on a skewed scale.

- **Wealth** - somewhat surprisingly, Net Wealth does not appear to be as important as labor market security and the employment rate. Having said that, removing the data points above $500,000 might tell a different story.
- **Environment** - Air and water quality seem to factor higher than the homicide rate, which shows almost no effect on the LSI.
- **Health** - Life expectancy seems like an obvious factor, but I was also satisfied to see long work hours affect the index as well.

[58]:
```
df_table.hist( bins = 20, figsize =( 20,15))
plt.show()
```



[59]:

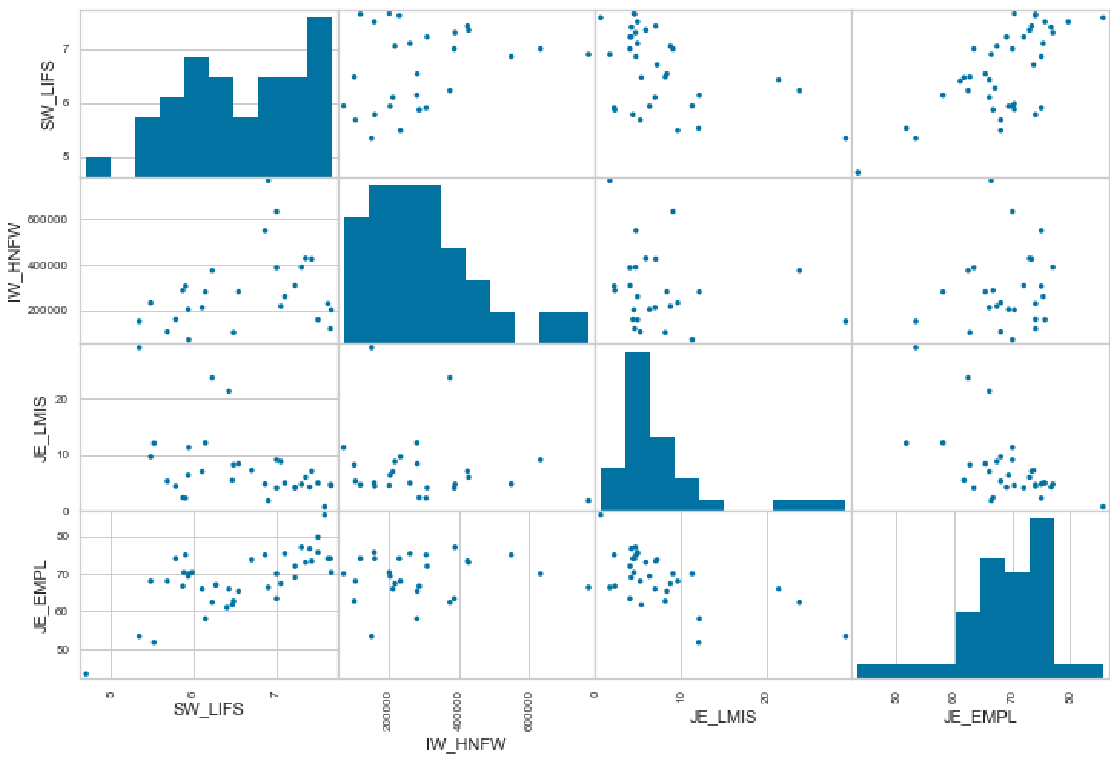
```python
results = smf.ols('SW_LIFS ~ IW_HNFW + JE_LMIS + JE_EMPL', data=df_table).fit()
print("Money: Net Wealth, Labor Market Insecurity, Employment rate")
print(results.summary())
```

```
Money: Net Wealth, Labor Market Insecurity, Employment rate
                            OLS Regression Results
==============================================================================
Dep. Variable:                SW_LIFS   R-squared:                       0.327
Model:                            OLS   Adj. R-squared:                  0.235
Method:                 Least Squares   F-statistic:                     3.564
Date:                Sat, 01 Feb 2020   Prob (F-statistic):             0.0306
Time:                        13:14:13   Log-Likelihood:                -22.710
No. Observations:                  26   AIC:                             53.42
Df Residuals:                      22   BIC:                             58.45
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.7241      2.217      1.229      0.232      -1.873       7.321
IW_HNFW      1.13e-06    7.6e-07      1.486      0.151   -4.47e-07    2.71e-06
```

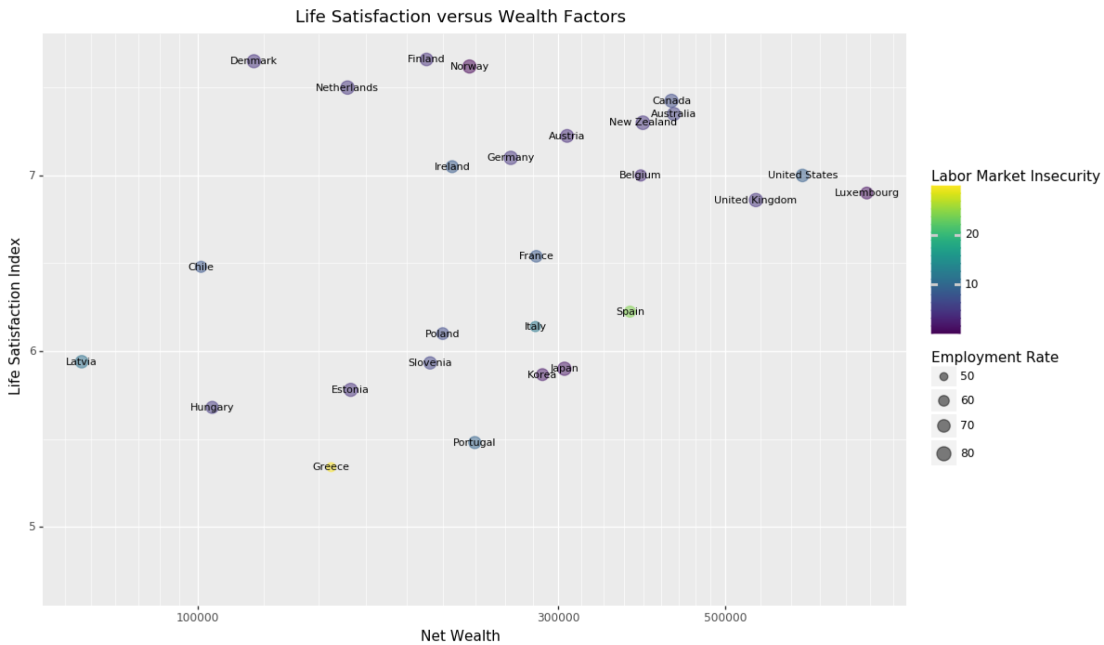
```
JE_LMIS       -0.0085      0.028     -0.304      0.764     -0.067      0.050
JE_EMPL        0.0523      0.030      1.763      0.092     -0.009      0.114
==============================================================================
Omnibus:                        0.953   Durbin-Watson:                   1.785
Prob(Omnibus):                  0.621   Jarque-Bera (JB):                0.831
Skew:                          -0.167   Prob(JB):                        0.660
Kurtosis:                       2.190   Cond. No.                     6.02e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 6.02e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[60]:
```python
attributes = ['SW_LIFS', 'IW_HNFW', 'JE_LMIS', 'JE_EMPL']
scatter_matrix(df_table[attributes], alpha=1.0, figsize=(12, 8))
```

[60]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E299AD30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2982700>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E29FAEE0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2A11730>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2A24F70>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2A3C7F0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2A44700>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2A5FFA0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2AA7EE0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4F1C970>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4F54FA0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4F7AA30>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4FB22B0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4FDBAF0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E56A1370>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E56CABB0>]],
      dtype=object)
```

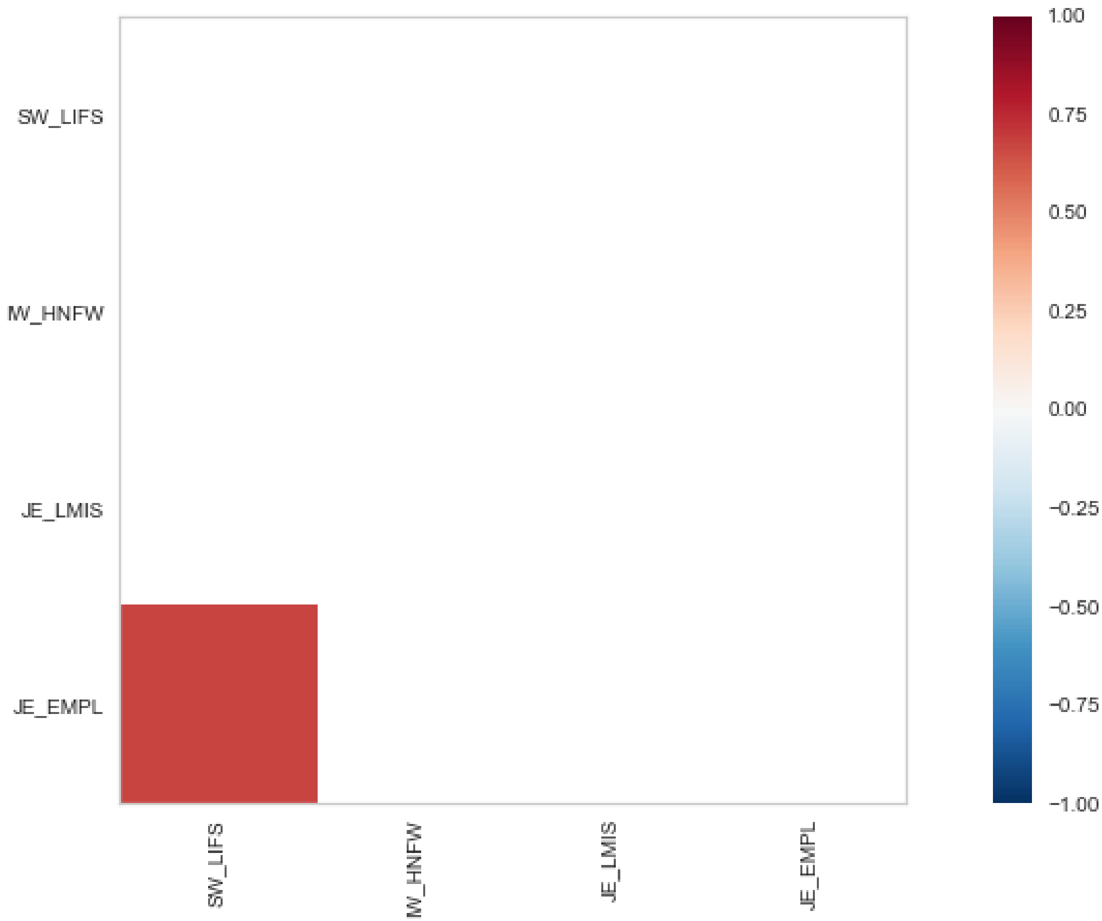


[61]:
```
(ggplot(df_table, aes(x='IW_HNFW', y='SW_LIFS', color='JE_LMIS',␣
↪size='JE_EMPL')) +
        geom_point(alpha=0.5) +
        scale_x_log10() +
        geom_text(aes(x='IW_HNFW', y='SW_LIFS', label='country'),
                  color="black",
                  size=8,
                  data=df_table) +
         theme(figure_size = (12.0, 8.0)) +
        labs(title="Life Satisfaction versus Wealth Factors",x="Net␣
↪Wealth",y="Life Satisfaction Index",size="Employment Rate",color="Labor␣
↪Market Insecurity")
)
```



[61]: <ggplot: (156738463305)>

[62]:
```
import yellowbrick
from yellowbrick.features import Rank2D
from yellowbrick.features import ParallelCoordinates
from yellowbrick.style import set_palette

#set up the figure size
plt.rcParams['figure.figsize'] = (15, 7)
num_features = ['SW_LIFS', 'IW_HNFW', 'JE_LMIS', 'JE_EMPL']
# extract the numpy arrays from the data frame
X = df_table[num_features].as_matrix()

# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X)                    # Fit the data to the visualizer
visualizer.transform(X)                 # Transform the data

plt.show()
```



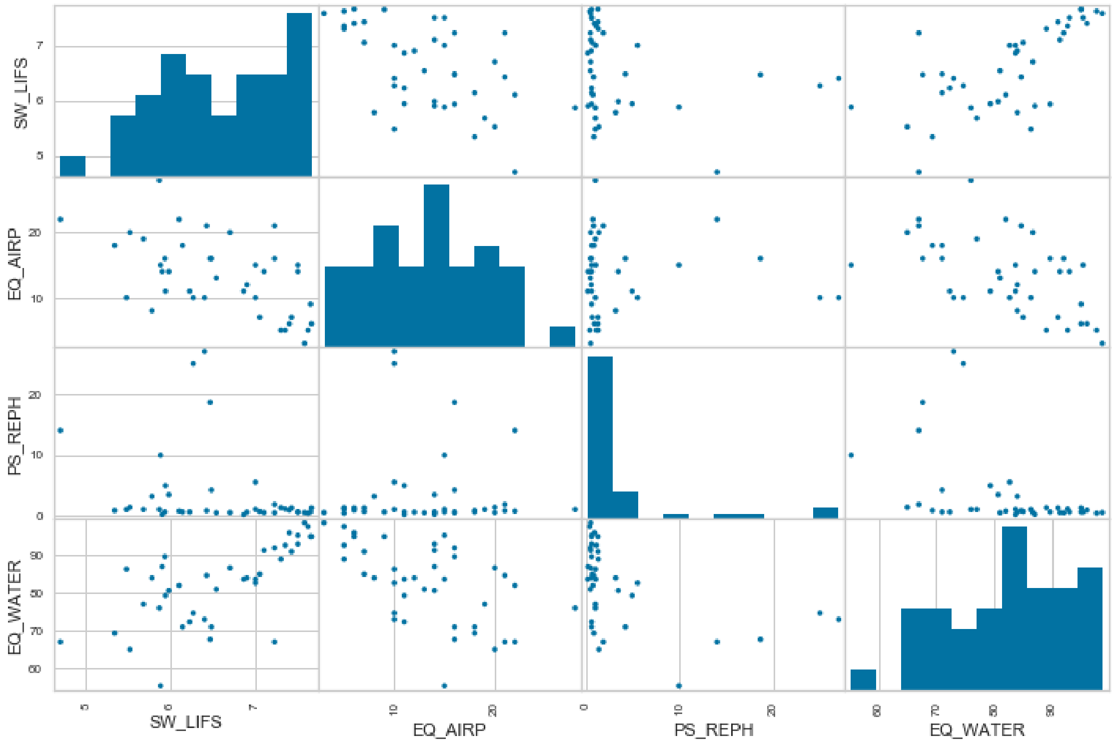
[63]:
```python
results = smf.ols('SW_LIFS ~ EQ_AIRP + PS_REPH + EQ_WATER', data=df_table).fit()
print("Environment: Air pollution, Homicide rate, Water quality")
print(results.summary())
```

```
Environment: Air pollution, Homicide rate, Water quality
                            OLS Regression Results
==============================================================================
Dep. Variable:                SW_LIFS   R-squared:                       0.512
Model:                            OLS   Adj. R-squared:                  0.471
Method:                 Least Squares   F-statistic:                     12.57
Date:                Sat, 01 Feb 2020   Prob (F-statistic):           8.92e-06
Time:                        13:14:15   Log-Likelihood:                -31.080
No. Observations:                  40   AIC:                             70.16
Df Residuals:                      36   BIC:                             76.92
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

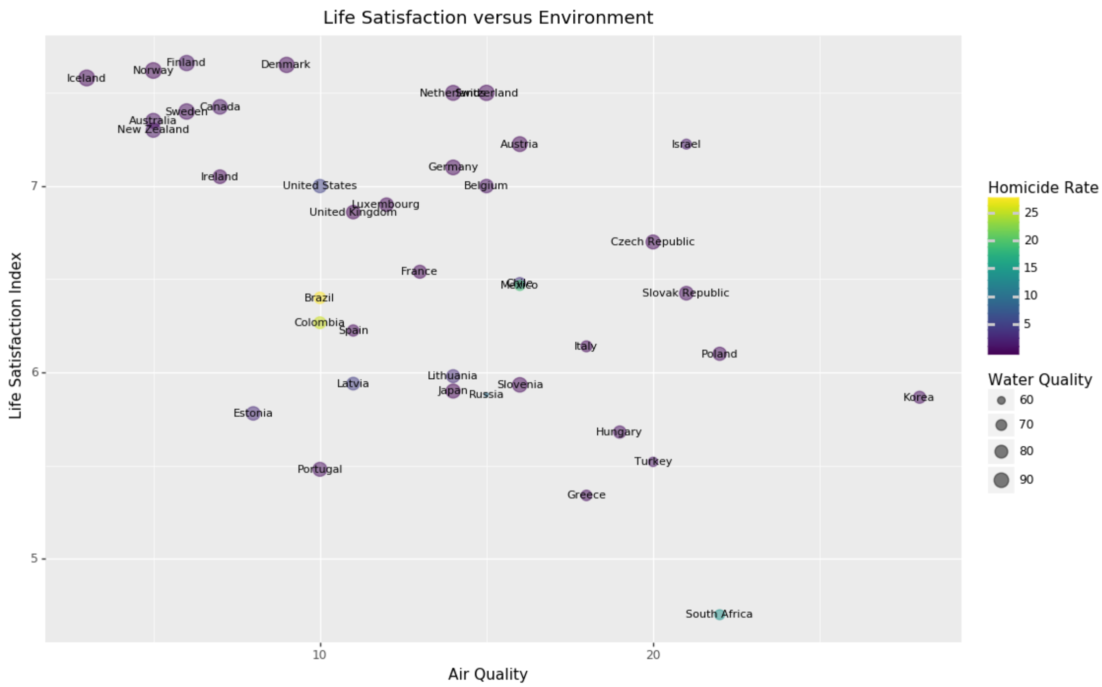
```
Intercept       3.8394      1.218      3.152      0.003       1.369       6.310
EQ_AIRP        -0.0343      0.020     -1.751      0.088      -0.074       0.005
PS_REPH        -0.0015      0.017     -0.093      0.926      -0.035       0.032
EQ_WATER        0.0389      0.012      3.193      0.003       0.014       0.064
==============================================================================
Omnibus:                        3.892   Durbin-Watson:                   1.767
Prob(Omnibus):                  0.143   Jarque-Bera (JB):                2.842
Skew:                          -0.368   Prob(JB):                        0.241
Kurtosis:                       4.079   Cond. No.                     1.17e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.17e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[64]:
```python
attributes = ['SW_LIFS', 'EQ_AIRP', 'PS_REPH', 'EQ_WATER']
scatter_matrix(df_table[attributes], alpha=1.0, figsize=(12, 8))
```

[64]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4E78130>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E27BF460>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E28BF970>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E29575B0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5229E50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247CBA952E0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2C34730>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E51012B0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E2818040>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E28DE820>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4C29D00>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4A53FA0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4C1B400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E49AFA30>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E4C4DAF0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E285DB80>]],
      dtype=object)
```

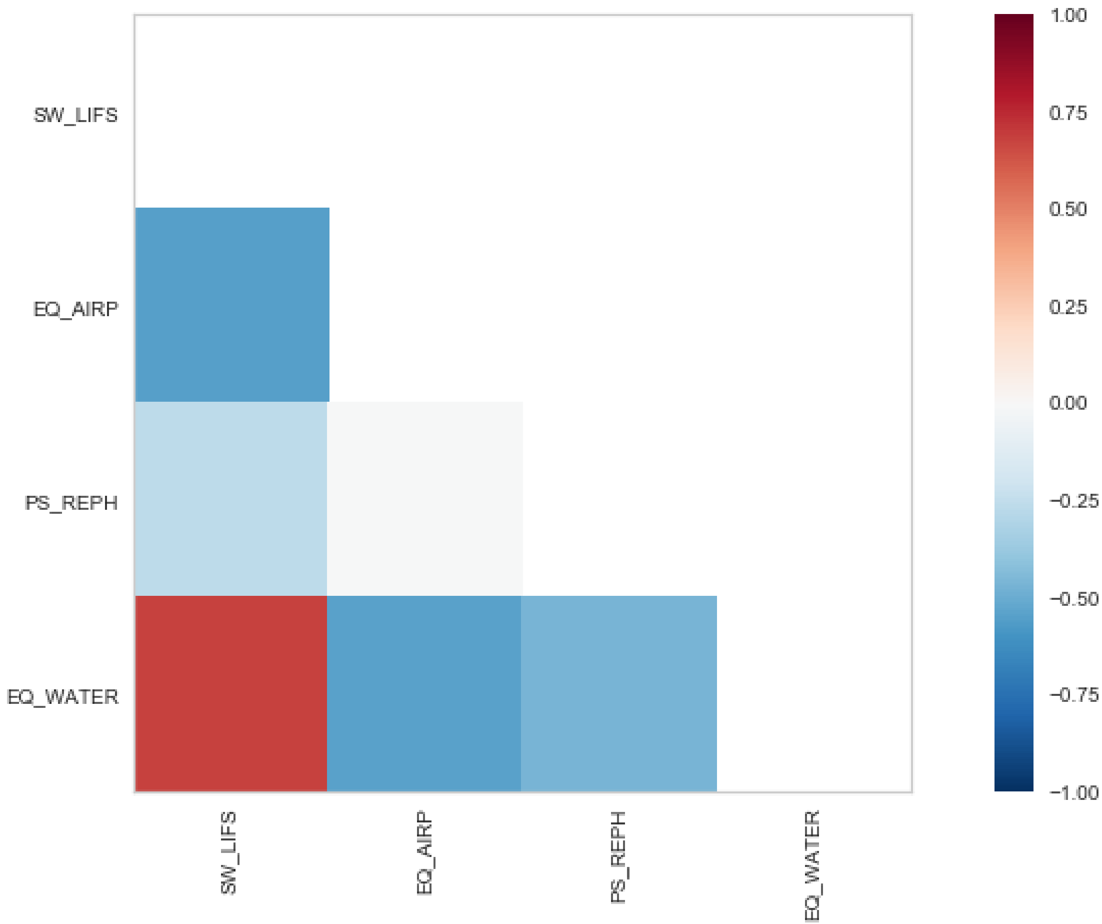


[65]:
```
(ggplot(df_table, aes(x='EQ_AIRP', y='SW_LIFS', color='PS_REPH',␣
↪size='EQ_WATER')) +
        geom_point(alpha = 0.5) +
         geom_text(aes(x='EQ_AIRP', y='SW_LIFS', label='country'),
                  color="black",
                  size=8,
                  data=df_table) +
        theme(figure_size = (12.0, 8.0)) +
        labs(title="Life Satisfaction versus Environment",x="Air␣
↪Quality",y="Life Satisfaction Index",size="Water Quality",color="Homicide␣
↪Rate")
)
```



[65]: <ggplot: (156737894614)>

[66]:
```
#set up the figure size
plt.rcParams['figure.figsize'] = (15, 7)
num_features = ['SW_LIFS', 'EQ_AIRP', 'PS_REPH', 'EQ_WATER']
# extract the numpy arrays from the data frame
X = df_table[num_features].as_matrix()

# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X)                    # Fit the data to the visualizer
visualizer.transform(X)                 # Transform the data

plt.show()
```



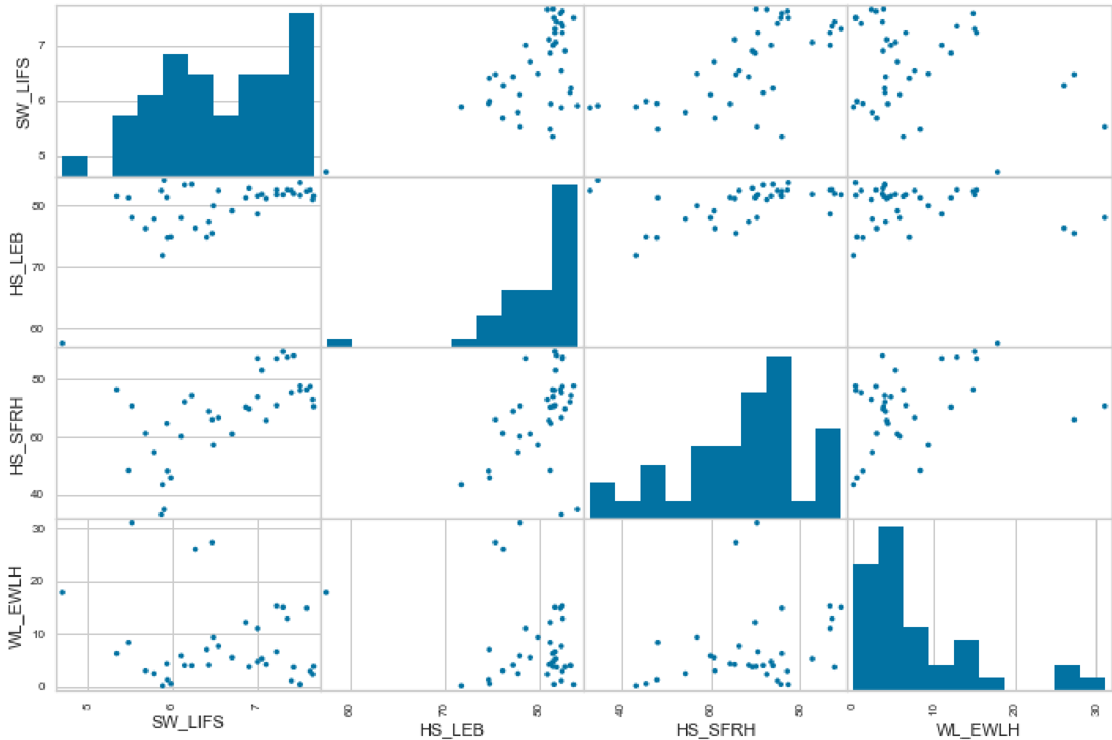
[67]:
```python
results = smf.ols('SW_LIFS ~ HS_LEB + HS_SFRH + WL_EWLH', data=df_table).fit()
print("Health: Life expectancy, Self-reported health, Long work hours")
print(results.summary())
```

```
Health: Life expectancy, Self-reported health, Long work hours
                            OLS Regression Results
==============================================================================
Dep. Variable:                SW_LIFS   R-squared:                       0.484
Model:                            OLS   Adj. R-squared:                  0.434
Method:                 Least Squares   F-statistic:                     9.707
Date:                Sat, 01 Feb 2020   Prob (F-statistic):           0.000114
Time:                        13:14:16   Log-Likelihood:                -26.111
No. Observations:                  35   AIC:                             60.22
Df Residuals:                      31   BIC:                             66.44
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

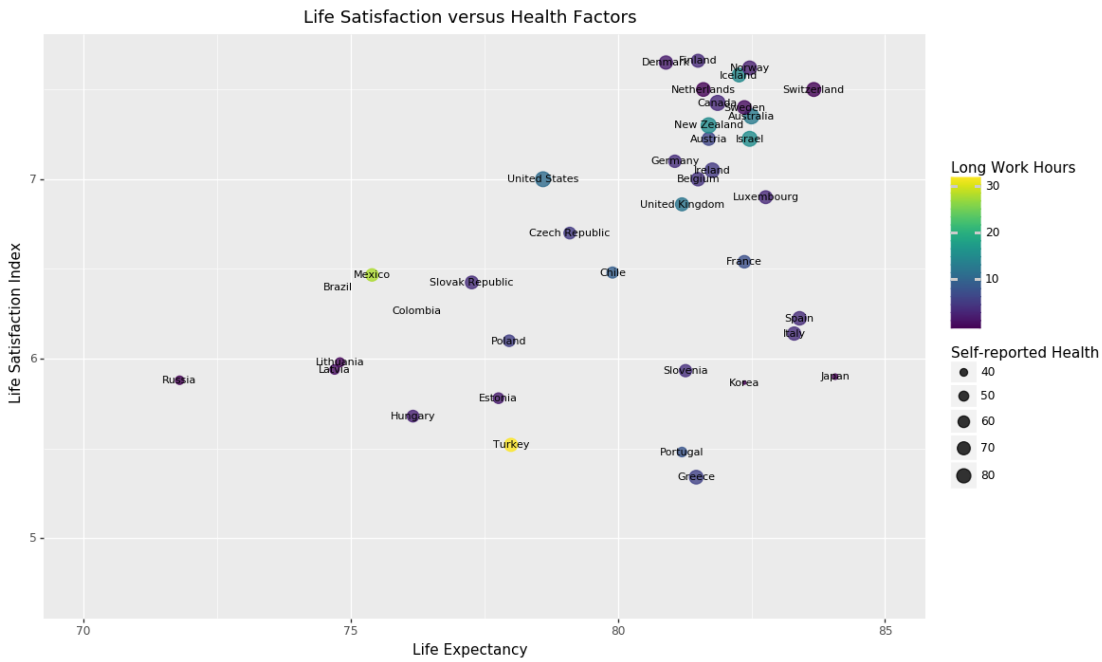
```
Intercept      2.3807      3.176      0.750      0.459     -4.096      8.858
HS_LEB         0.0227      0.046      0.499      0.621     -0.070      0.116
HS_SFRH        0.0382      0.011      3.403      0.002      0.015      0.061
WL_EWLH       -0.0250      0.014     -1.737      0.092     -0.054      0.004
==============================================================================
Omnibus:                        8.285   Durbin-Watson:                   2.096
Prob(Omnibus):                  0.016   Jarque-Bera (JB):                6.935
Skew:                          -0.902   Prob(JB):                       0.0312
Kurtosis:                       4.227   Cond. No.                     3.70e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.7e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[68]:
```python
attributes = ['SW_LIFS', 'HS_LEB', 'HS_SFRH', 'WL_EWLH']
scatter_matrix(df_table[attributes], alpha=1.0, figsize=(12, 8))
```

[68]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E542DC10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5047460>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E53D2C40>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E510CD90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5171F70>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E527A6D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5469520>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247DF9CEA00>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5302490>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E538E910>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5227D90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E51CC310>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x00000247DFD57B50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E52D83D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5339C10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x00000247E5520490>]],
      dtype=object)
```

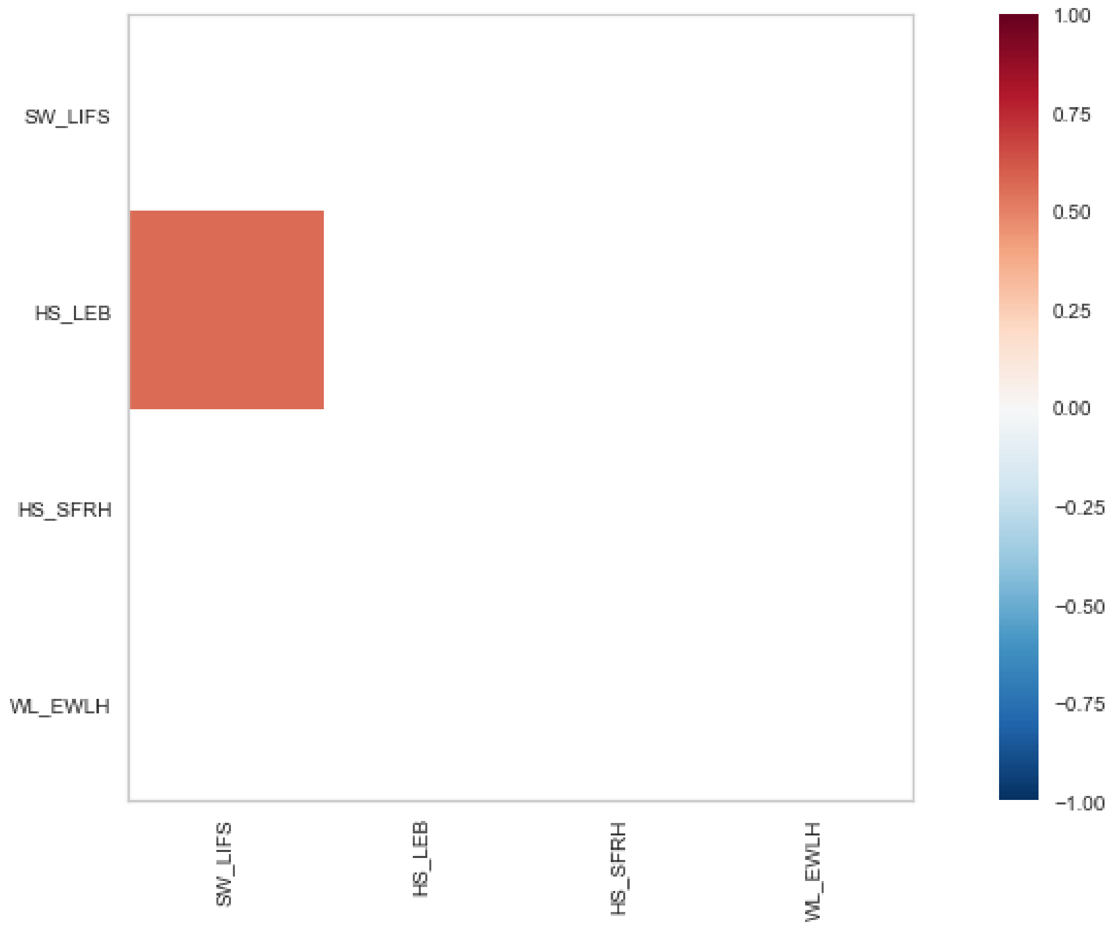


[69]:
```
(ggplot(df_table[df_table['HS_LEB'] > 70], aes(x='HS_LEB', y='SW_LIFS',␣
↪color='WL_EWLH', size='HS_SFRH')) +
        geom_point(alpha = 0.8) +
        scale_x_continuous(limits=[70,85]) +
        geom_text(aes(x='HS_LEB', y='SW_LIFS', label='country'),
                  color="black",
                  size=8,
                  data=df_table) +
        theme(figure_size = (12.0, 8.0)) +
        labs(title="Life Satisfaction versus Health Factors",x="Life␣
↪Expectancy",y="Life Satisfaction Index",size="Self-reported␣
↪Health",color="Long Work Hours")
)
```



[69]: <ggplot: (156737931379)>

[70]:
```
#set up the figure size
plt.rcParams['figure.figsize'] = (15, 7)
num_features = ['SW_LIFS', 'HS_LEB', 'HS_SFRH', 'WL_EWLH']
# extract the numpy arrays from the data frame
X = df_table[num_features].as_matrix()

# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X)                    # Fit the data to the visualizer
visualizer.transform(X)                 # Transform the data

plt.show()
```



Part 2: Dimensionality and Feature Reduction

[71]:
```
# What kind of data are we dealing with?
df_table.describe()
```

[71]:
```
INDICATOR    CG_SENG   CG_VOTO    EQ_AIRP   EQ_WATER    ES_EDUA   ES_EDUEX  \
count      38.000000  40.00000  40.000000  40.000000  39.000000  39.000000
mean        2.160526  69.57500  13.325000  82.333333  77.717949  17.547863
std         0.577291  12.21157   5.770782  10.492977  15.136134   1.412720
min         1.200000  47.00000   3.000000  55.333333  37.666667  14.100000
25%         1.725000  60.75000   9.750000  74.250000  75.000000  16.550000
50%         2.200000  69.50000  14.000000  83.833333  82.000000  17.666667
75%         2.575000  79.00000  16.500000  91.083333  87.833333  18.350000
max         3.200000  91.00000  28.000000  98.666667  94.000000  20.966667

INDICATOR    ES_STCS    HO_BASE    HO_HISH    HO_NUMR     HS_LEB    HS_SFRH  \
count      39.000000  37.000000  38.000000  37.000000  40.000000  37.000000
```

```
mean       485.707692   5.075676  20.657895   1.632432  79.567500  67.493243
std         33.787972   8.448320   2.528500   0.431441   4.669642  14.331584
min        398.200000   0.000000  15.000000   0.900000  57.500000  33.000000
25%        475.800000   0.300000  19.000000   1.200000  77.916667  60.800000
50%        492.800000   0.900000  21.000000   1.600000  81.366667  70.200000
75%        506.800000   6.700000  22.750000   1.900000  82.366667  76.000000
max        528.800000  37.000000  26.000000   2.600000  84.066667  89.250000

INDICATOR       IW_HADI        IW_HNFW    JE_EMPL    JE_LMIS    JE_LTUR  \
count         29.000000      27.000000  40.000000  33.000000  38.000000
mean       27807.310345  289780.185185  68.533333   7.706970   2.855789
std         7055.262661  165673.432787   7.882253   6.234572   3.622899
min        16275.000000   70160.000000  43.333333   0.662000   0.050000
25%        21453.000000  180100.000000  65.833333   4.392000   1.011667
50%        29333.000000  259667.000000  69.666667   5.396000   1.776667
75%        31304.000000  379777.000000  74.000000   8.784000   3.196667
max        45284.000000  769053.000000  85.666667  29.200000  16.643333

INDICATOR      JE_PEARN  PS_FSAFEN    PS_REPH   SC_SNTWS    SW_LIFS  \
count         35.000000  40.000000  40.000000  40.000000  40.000000
mean       39817.514286  68.463333   3.481667  90.193333   6.577208
std        13108.329748  13.960934   6.459861   4.384954   0.762724
min        15314.000000  35.866667   0.166667  78.333333   4.700000
25%        25971.500000  60.108333   0.600000  88.300000   5.938333
50%        40863.000000  70.483333   0.950000  91.350000   6.510000
75%        49400.500000  78.500000   2.166667  93.062500   7.243750
max        63062.000000  90.033333  27.000000  98.000000   7.660000

INDICATOR    WL_EWLH    WL_TNOW
count      38.000000  22.000000
mean        7.789649  15.048939
std         7.585983   0.672978
min         0.140000  13.826667
25%         3.150833  14.560833
50%         4.981667  14.885000
75%        10.571667  15.600833
max        31.043333  16.336667
```

Proposed Steps for Dimensionality and Feature Reduction

- The *variance* between features varies greatly, For example, CG_SENS ranges from 1.2 to 3.2 while SC_SNTWS ranges from 4.38 to 98. I will start by setting a variance threshold and eliminating features below the threshold. In theory, this should eliminate variables with low variance, which likely will not contribute greatly to the model.
- Due to the quantitative nature of these variables, there exists wide discrepancies of units. For instance, Household Net Wealth can be in the thousands of US dollars, while Employment Rate is a percentage. I will apply both aa simple `min-max rescaler` to normalize all variables, and a `standard scaler` to standardize the variables.

- I suspect that variables such as air pollution and water quality probably are highly correlated. I will apply a correlation matrix and will consider dropping one of the correlated features.
- Lastly, I'd like to automatically select the best features to keep by leveraging scikit-learn's `recursive feature elimination functionality`.

VarianceThreshold

[72]:
```
# Make a features DataFrame by dropping the target variable--SW_LIFS--and␣
↪assigning that to a target Series,
features = df_table.drop(['country','SW_LIFS'], axis=1)
target = df_table['SW_LIFS']
```

[73]:
```
# Apply a Variance Threshold to remove those features with low variance
from sklearn.feature_selection import VarianceThreshold

# Make a features dataset by dropping the target variable--SW_LIFS
features = df_table.drop(['country','SW_LIFS'], axis=1)
target = df_table['SW_LIFS']

# Create thresholder
thresholder = VarianceThreshold(threshold=5.0)

# Create high variance feature matrix
features_high_variance = thresholder.fit_transform(features)

features_vt = features.loc[:, thresholder.get_support()]
features_vt.head()
```

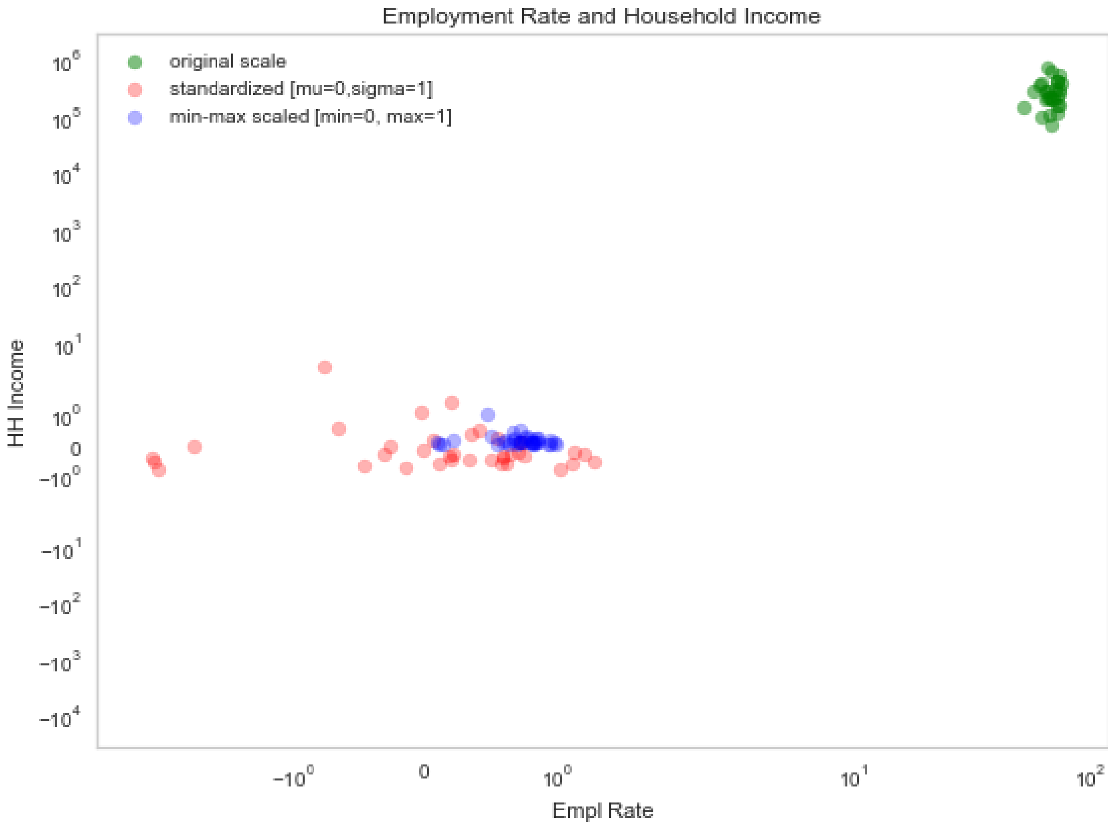
[73]:
```
INDICATOR  CG_VOTO  EQ_AIRP   EQ_WATER    ES_EDUA  ES_STCS  HO_BASE  HO_HISH  \
Country
Australia     91.0      5.0  92.666667  81.000000    411.2      NaN     20.0
Austria       80.0     16.0  92.000000  85.000000    492.8      0.9     21.0
Belgium       89.0     15.0  83.666667  77.000000    503.8      1.9     21.0
Brazil        79.0     10.0  73.000000  49.000000    398.2      6.7      NaN
Canada        68.0      7.0  91.000000  91.333333    523.2      0.2     22.0

INDICATOR     HS_LEB  HS_SFRH  IW_HADI    IW_HNFW    JE_EMPL  JE_LMIS  \
Country
Australia  82.500000    87.25  32759.0  427064.0  73.000000    5.922
Austria    81.700000    70.60  33541.0  308325.0  72.000000    4.076
Belgium    81.500000    73.60  30364.0  386006.0  63.333333    4.052
Brazil     74.766667      NaN      NaN        NaN  61.000000      NaN
Canada     81.866667    87.80  30854.0  423849.0  73.333333    7.048

INDICATOR   JE_LTUR  JE_PEARN  PS_FSAFEN   PS_REPH  SC_SNTWS    WL_EWLH
Country
Australia  1.306667   49126.0  64.133333  1.100000     95.25  12.840000
Austria    1.830000   50349.0  80.700000  0.466667     92.00   6.590000
Belgium    3.533333   49675.0  70.266667  1.033333     92.00   4.703333
```

Brazil	NaN	NaN	35.866667	27.000000	89.25	7.006667
Canada	0.763333	47622.0	82.500000	1.266667	93.25	3.673333

Not terribly surprising to see which features the `Variance Thesholder` dropped:
Stakeholder engagement for developing regulations
Years in education
Rooms per person
Time devoted to leisure and personal care

[74]:
```
from sklearn import preprocessing

# Standardizing
std_scale = preprocessing.StandardScaler().fit(features_vt)
df_std = std_scale.transform(features_vt)
standardized_df = pd.DataFrame(df_std, index=features_vt.index,␣
 ↪columns=features_vt.columns)

#Min-max scaling (normalization)
minmax_scale = preprocessing.MinMaxScaler().fit(features_vt)
df_minmax = minmax_scale.transform(features_vt)
scaled_features_df = pd.DataFrame(df_minmax, index=features_vt.index,␣
 ↪columns=features_vt.columns)
```

[75]:
```
def plot():
    plt.figure(figsize=(8,6))

    plt.scatter(df_table['JE_EMPL'], df_table['IW_HNFW'],
            color='green', label='original scale', alpha=0.5)

    plt.scatter(df_std[:,4], df_std[:,13], color='red',
            label='standardized [mu=0,sigma=1]', alpha=0.3)

    plt.scatter(df_minmax[:,4], df_minmax[:,13],
            color='blue', label='min-max scaled [min=0, max=1]', alpha=0.3)

    plt.title('Employment Rate and Household Income')
    plt.xlabel('Empl Rate')
    plt.ylabel('HH Income')
    plt.legend(loc='upper left')
    plt.xscale('symlog')
    plt.yscale('symlog')
    plt.grid()

    plt.tight_layout()

plot()
plt.show()
```



At this point I made a more or less arbitrary decision to go with the `standardized` feature set over the `min max scaled`…

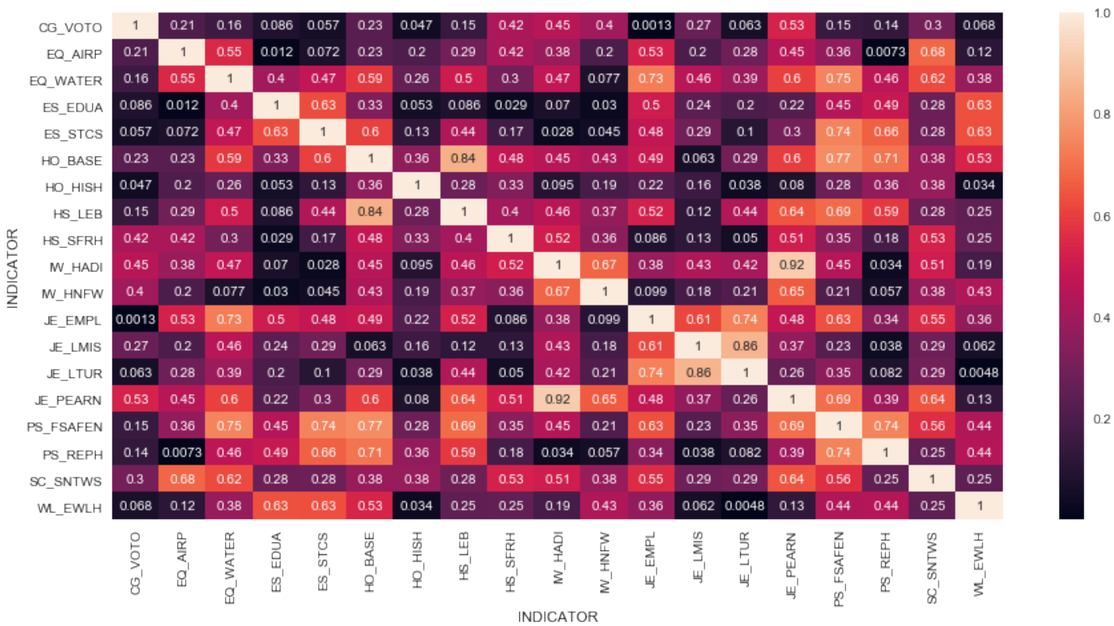
[82]:
```
# Create correlation matrix
corr_matrix = standardized_df.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape),
                          k=1).astype(np.bool))
upper.fillna(0, inplace=True)

# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]

# Drop features
standardized_df.drop(standardized_df.columns[to_drop], axis=1, inplace=True)
features = standardized_df
print(features.shape)
features.sample(5)
```

```
(40, 19)
```

[82]:
```
INDICATOR        CG_VOTO   EQ_AIRP  EQ_WATER   ES_EDUA   ES_STCS   HO_BASE  \
Country
Czech Republic -0.711149  1.171425  0.418236  1.067459  0.194660 -0.525079
Mexico         -0.545283  0.469447 -1.415567 -2.680661 -2.090062  2.450908
France          0.449910 -0.057036 -0.128688  0.041188  0.350573 -0.549079
New Zealand     0.864574 -1.460990  0.643439  0.063498  0.614426       NaN
Lithuania      -1.540476  0.118459 -0.160860  1.000529 -0.273078  1.022914

INDICATOR        HO_HISH    HS_LEB   HS_SFRH   IW_HADI   IW_HNFW   JE_EMPL  \
Country
Czech Republic  1.339516 -0.101390 -0.473470 -0.916590       NaN  0.659549
Mexico         -0.263684 -0.903836 -0.129209       NaN       NaN -0.882253
France          0.137116  0.607076 -0.077334  0.504387 -0.056141 -0.411147
New Zealand     2.141117  0.462491  1.539039       NaN  0.607307  1.087827
Lithuania      -0.664485 -1.033963 -1.548694 -0.886731       NaN  0.231270

INDICATOR        JE_LMIS   JE_LTUR  JE_PEARN  PS_FSAFEN   PS_REPH  SC_SNTWS  \
Country
Czech Republic -0.081274 -0.503264 -1.118099   0.295242 -0.467448  0.359524
Mexico         -0.376417 -0.780194 -1.896599  -1.922093  2.375390 -1.984698
France          0.109625  0.319134  0.304766   0.162250 -0.472674 -0.275610
New Zealand    -0.489784 -0.592776  0.017453  -0.159348 -0.342029  1.398835
Lithuania            NaN -0.044511 -1.202079  -0.887176 -0.007577 -0.414184

INDICATOR        WL_EWLH
Country
Czech Republic -0.306323
Mexico          2.603747
France         -0.017765
New Zealand     0.968140
Lithuania      -0.967601
```

[83]:
```python
import seaborn as sns
# print(corr_matrix)
sns.heatmap(corr_matrix, annot=True)
```

[83]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x247e2c8a0d0>
```



There are no features with a correlation of > 95%. If I drop the threshold to 90% there is one: JE_PEARN and IW_HADI (Personal Income and Household disposable income)
Although not surprising as they are similar measurements, I will leave them both in.

[86]:
```python
# Apply Recursive Feature Elimination

# Load libraries
import warnings
from sklearn.feature_selection import RFECV
from sklearn.ensemble import RandomForestRegressor

# Suppress an annoying but harmless warning
warnings.filterwarnings(action="ignore", module="scipy",
                        message="^internal gelsd")

# Need to fix the NaN's before we can successfully apply a model
features = features.fillna(features.median())
randomforest = RandomForestRegressor(random_state=0, n_jobs=-1)

# Recursively eliminate features
rfecv = RFECV(estimator=randomforest, step=1, scoring="neg_mean_squared_error")
rfecv.fit(features, target)
rfecv.transform(features)
```

```
Number of features we should keep: 15
```

[97]:
```python
# Once we have conducted RFE, we can see the number of features we should keep:
# Number of best features
print("Number of features we should keep: {}".format(rfecv.n_features_))
print()

# We can also see which of those features we should keep:
# Which categories are best
print(rfecv.support_)

# Rank features best (1) to worst
print(rfecv.ranking_)

df_rfecv = pd.DataFrame(features.columns, rfecv.ranking_)
print(df_rfecv.sort_values)
```

```
Number of features we should keep: 15

[False False  True  True  True  True  True  True  True  True False  True
  True  True  True  True False  True  True]
[5 3 1 1 1 1 1 1 1 1 4 1 1 1 1 1 2 1 1]
<bound method DataFrame.sort_values of    INDICATOR
5     CG_VOTO
3     EQ_AIRP
1    EQ_WATER
1     ES_EDUA
1     ES_STCS
1     HO_BASE
1     HO_HISH
1      HS_LEB
1     HS_SFRH
1     IW_HADI
4     IW_HNFW
1     JE_EMPL
1     JE_LMIS
1     JE_LTUR
1    JE_PEARN
1   PS_FSAFEN
2     PS_REPH
1    SC_SNTWS
1     WL_EWLH>
```

I have mixed feelings about these results, so I opted to drop the two with the lowest ranking: `CG_VOTO` (Voter Turnout) and `IW_HNFW` (Household Net Wealth).

[101]:
```python
features.drop(['CG_VOTO', 'IW_HNFW'], axis=1, inplace=True)
features.sample(3)
```

[101]:
```
INDICATOR          EQ_AIRP  EQ_WATER   ES_EDUA   ES_STCS   HO_BASE   HO_HISH  \
Country
```

```
Slovak Republic  1.346919  0.225204  0.911288 -0.668857 -0.465079  0.938716
Poland           1.522413 -0.032172  0.955908  0.590439 -0.249080  0.537916
Luxembourg      -0.232530  0.160860 -0.070363 -0.009226 -0.549079  0.137116

INDICATOR          HS_LEB   HS_SFRH   IW_HADI   JE_EMPL   JE_LMIS   JE_LTUR  \
Country
Slovak Republic -0.498999  0.078290 -1.057808 -0.325491  2.226451  0.536389
Poland          -0.347184 -0.530060 -1.153011 -0.325491 -0.117759 -0.375522
Luxembourg       0.693827  0.134881  1.652593 -0.282664 -0.974849 -0.143348

INDICATOR        JE_PEARN  PS_FSAFEN   PS_REPH  SC_SNTWS   WL_EWLH
Country
Slovak Republic -1.198906  -0.345537 -0.420416  0.301785 -0.496468
Poland          -0.988529  -0.072299 -0.430868 -0.968483 -0.262683
Luxembourg       1.799149   0.537045 -0.456997  0.648222 -0.540999
```

0.1.2 Part 3: Model Evaluation and Selection

Model Selection

I've decided to start with a **Random Forest Regression** model, leveraging scikit-learn's `RandomForestRegressorer`. This model takes advantage of the *ensemble learning method*, where multiple decision trees are trained, although each tree only receives a "bootstrapped" sample of observations. [1]

In order to "dial in" my model, I plan to leverage the **feature_importances_** of the RandomForestClassifier model, as well as **SelectFromModel** method from scikit-learn's `feature_selection` library.

Model Evaluation

This topic can get a little overwhelming, as, from the reading I've done, there appears to be a bewildering number of approaches to model evaluation. Given the constraints of one semester's worth of time, I'm going to focus on the following:

- Calculate the **Mean Squared Error**
- Calculate the **Coefficient of Determination *(R squared)***

References

[1] Albon, Chris. Machine Learning with Python Cookbook: Practical Solutions from Preprocessing to Deep Learning (p. 238). O'Reilly Media. Kindle Edition.

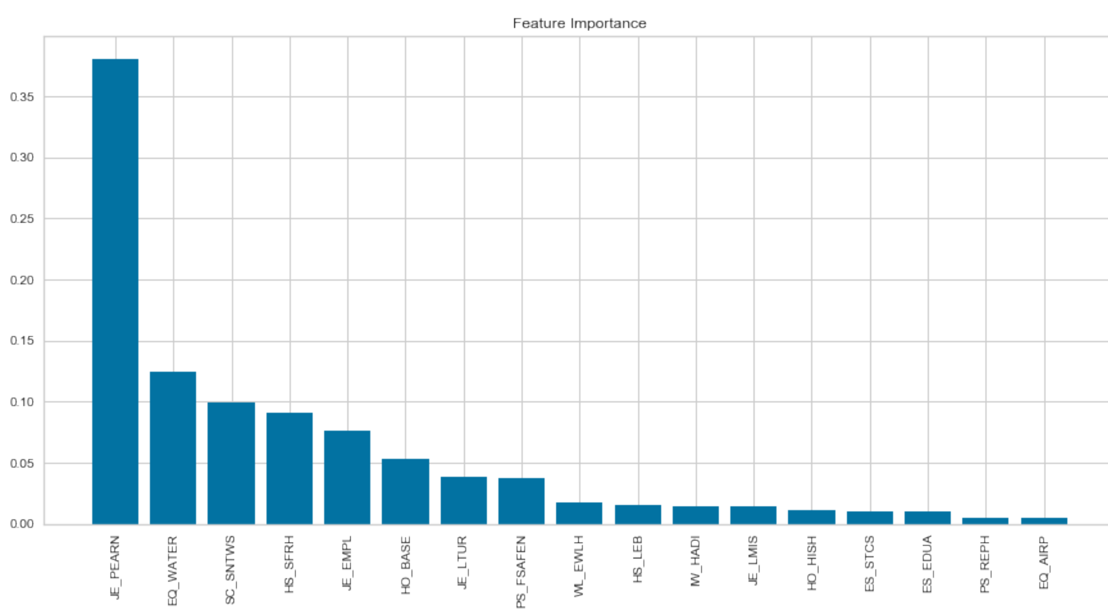
Model Selection

[102]:
```
# Apply a Random Forest Regressor Model and train (fit) it.
from sklearn.ensemble import RandomForestRegressor

# Create random forest classifier object
randomforest = RandomForestRegressor(random_state=0, n_jobs=-1)

# Train model
```

```
model = randomforest.fit(features, target)
```

[103]:
```
# Calculate feature importances
importances = model.feature_importances_

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

# Rearrange feature names so they match the sorted feature importances
names = [features.columns[i] for i in indices]
```

[104]:
```
# Create plot
plt.figure()

# Create plot title
plt.title("Feature Importance")

# Add bars
plt.bar(range(features.shape[1]), importances[indices])

# Add feature names as x-axis labels
plt.xticks(range(features.shape[1]), names, rotation=90)

# Show plot
plt.show()
```



Based on the results above, I'm dropping all but the highest rated columns above 0.5.

Interesting observation. I've been resisting dropping `EQ_AIRP`–Air Quality–because I just can't believe it's not important. But many of the calculations I've run have suggested eliminating it.

[107]:
```
new_features = ['JE_PEARN', 'EQ_WATER', 'SC_SNTWS', 'HS_SFRH', 'JE_EMPL',␣
 ↪'HO_BASE']
features_final = features[new_features]

# Re-train the model on the new feature set
model = randomforest.fit(features_final, target)
```

[ ]:
```
```

SelectFromModel is returning dubious results (I'm sure it's something I'm doing wrong) so dropping this for now…

[ ]:
```
```

[ ]:
```
# from sklearn.feature_selection import SelectFromModel

# # Create object that selects features with importance greater
# # than or equal to a threshold
# selector = SelectFromModel(randomforest, threshold=0.3)

# # Feature new feature matrix using selector
# features_important = selector.fit_transform(features, target)

# # Sort feature importances in descending order
# indices = np.argsort(features_important)[::-1]

# # Rearrange feature names so they match the sorted feature importances
# names = [features.columns for i in indices]

# # Create plot
# plt.figure()

# # Create plot title
# plt.title("Feature Importance")

# # Add bars
# plt.bar(range(features.shape[1]), features_important[indices])

# # Add feature names as x-axis labels
# plt.xticks(range(features.shape[1]), names, rotation=90)

# # Show plot
# plt.show()

# Train random forest using most important features
# model = randomforest.fit(features_important, target)
```

Model Evaluation

[125]:

```
# Cross-validate the random forest regression using (negative) MSE, RMSE and␣
↪R-squared
from sklearn.model_selection import cross_val_score
scorers = ['neg_mean_absolute_error', 'neg_root_mean_squared_error', 'r2']

for scorer in scorers:
    cvs = cross_val_score(randomforest, features, target, scoring=scorer)
    print("{}\t\t{}".format(scorer, cvs))
```

```
neg_mean_absolute_error         [-0.2856625  -0.46934375 -0.3044625  -0.28794583
-0.47037917]
neg_root_mean_squared_error             [-0.33881842 -0.5923367  -0.49264287
-0.35860543 -0.66774549]
r2              [0.36472877 0.56892412 0.16964655 0.76679536 0.46711817]
```

References http://sebastianraschka.com/Articles/2014_about_feature_scaling.html#standardization-and-min-max-scaling

Albon, Chris. Machine Learning with Python Cookbook: Practical Solutions from Preprocessing to Deep Learning . O'Reilly Media. Kindle Edition.