Assignment 3 - ADS 1 - Clustering & Fitting

Laveen Kirupakaran, 18049379

In [1]:
```
import os
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import time


from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.metrics import silhouette_score


from numpy import sin
from numpy import sqrt
from numpy import arange
from scipy.optimize import curve_fit
```

In [2]:
```
"""from urllib.request import urlretrieve
urlretrieve('https://github.com/laveen98/ADS/blob/main/main_WBdata.csv', 'main_WBdata.csv')
urlretrieve('https://github.com/laveen98/ADS/blob/main/Sri_Lanka.csv', 'Sri_Lanka.csv')
urlretrieve('https://github.com/laveen98/ADS/blob/main/colombia.csv', 'colombia.csv')
"""
```

Out[2]:
```
"from urllib.request import urlretrieve\nurlretrieve('https://github.com/laveen98/ADS/blob/main/main_WBdata.csv',
'main_WBdata.csv')\nurlretrieve('https://github.com/laveen98/ADS/blob/main/Sri_Lanka.csv', 'Sri_Lanka.csv')\nurlr
etrieve('https://github.com/laveen98/ADS/blob/main/colombia.csv', 'colombia.csv')\n"
```

https://github.com/laveen98/ADS

The dataset and selected 20 indicators from year 1990 to 2019 for 159 counteries

In [3]:
```
data = pd.read_csv('main_WBdata.csv')
data = data.sort_values(by=['Series Name', 'Country Name'])
data = data.set_index('Series Name')
```

Reference: dataset obtained from https://github.com/jakebobu/world-bank

In [4]:
```
#Preiliminary data exploration and selections
indicators = sorted(set(data.index))
climates = sorted(set(data['Country Name']))
num_econ = len(climates)
columns = list(data.columns)
columns = columns[1:]
years = columns[2:]
yearlist = []

data = data[columns]
```

In [5]:
```
#set up a dataframe
df = pd.DataFrame(index = indicators, columns = climates)
datalog = pd.DataFrame(index = indicators)
```

In [6]:
```
#Reference: code obtained from https://github.com/jakebobu/world-bank
#construct an usable dataframe
for indicator in indicators:

    year = 0

    #filtering out the indicators that too few countries provide
    for i in range(len(years)):
        if list(data.loc[indicator][years[i]] != '..').count(False) <= 35:
            if (year != 0) and (year != 1):
                if list(data.loc[indicator][years[i]] != '..').count(False) <= list(data.loc[indicator][years[yea
```

```
                year = i
            else:
                year = i

    #print the indicators and their latest years
    print(indicator, '-', years[year])
    yearlist.append(years[year])

    for climate in climates:
        try:
            #print(data.loc[data['Country Name'] == climate].loc[indicator].loc[years[year]])
            df.at[indicator, climate] = data.loc[data['Country Name'] == climate].loc[indicator].loc[years[year]]
        except:
            df.at[indicator, climate] = np.nan
```

```
Access to electricity, rural (% of rural population) - 2015 [YR2015]
Access to electricity, urban (% of urban population) - 2018 [YR2018]
Agriculture, forestry, and fishing, value added (% of GDP) - 2013 [YR2013]
CO2 emissions (metric tons per capita) - 2014 [YR2014]
Current health expenditure (% of GDP) - 2011 [YR2011]
Death rate, crude (per 1,000 people) - 2014 [YR2014]
Employment in agriculture (% of total employment) (modeled ILO estimate) - 2019 [YR2019]
Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate) - 2019 [YR2019]
GDP growth (annual %) - 2014 [YR2014]
GDP per capita growth (annual %) - 2014 [YR2014]
Individuals using the Internet (% of population) - 2017 [YR2017]
Labor force participation rate for ages 15-24, female (%) (modeled ILO estimate) - 2019 [YR2019]
Labor force participation rate for ages 15-24, male (%) (modeled ILO estimate) - 2019 [YR2019]
Mobile cellular subscriptions (per 100 people) - 2015 [YR2015]
Mortality rate, infant (per 1,000 live births) - 2018 [YR2018]
People using at least basic drinking water services (% of population) - 2013 [YR2013]
Rural population (% of total population) - 2011 [YR2011]
Secure Internet servers (per 1 million people) - 2017 [YR2017]
Trade in services (% of GDP) - 2014 [YR2014]
Vulnerable employment, total (% of total employment) (modeled ILO estimate) - 2019 [YR2019]
```

In [7]:

```
#print the indicators and their years
datalog['Year'] = yearlist
#print(yearlist.count(years[0]))

datalog_selected = datalog[datalog['Year'] != years[0]]
indicators_selected = list(datalog_selected.index)

df_selected = df.loc[indicators_selected]

indicators_count = []

for climate in climates:
    indicators_count.append(list(df_selected[climate] == '..').count(False))
    print(climate, '-', list(df_selected[climate] == '..').count(False))

print(indicators_count.count(datalog_selected.size))

count = dict(zip(climates, indicators_count))
```

```
Afghanistan - 20
Albania - 19
Algeria - 20
American Samoa - 6
Andorra - 12
Angola - 20
Antigua and Barbuda - 15
Argentina - 20
Armenia - 20
Aruba - 12
Australia - 20
Austria - 20
Azerbaijan - 20
Bahamas, The - 20
Bahrain - 20
Bangladesh - 20
Barbados - 19
Belarus - 20
Belgium - 20
Belize - 20
Benin - 20
Bermuda - 10
Bhutan - 20
Bolivia - 20
Bosnia and Herzegovina - 20
Botswana - 20
Brazil - 20
British Virgin Islands - 8
Brunei Darussalam - 20
Bulgaria - 20
```

Burkina Faso - 19
Burundi - 20
Cabo Verde - 20
Cambodia - 20
Cameroon - 20
Canada - 20
Cayman Islands - 12
Central African Republic - 19
Chad - 19
Channel Islands - 8
Chile - 20
China - 20
Colombia - 20
Comoros - 20
Congo, Dem. Rep. - 19
Congo, Rep. - 20
Costa Rica - 20
Cote d'Ivoire - 20
Croatia - 20
Cuba - 19
Curacao - 13
Cyprus - 20
Czech Republic - 20
Denmark - 20
Djibouti - 20
Dominica - 14
Dominican Republic - 20
Ecuador - 20
Egypt, Arab Rep. - 20
El Salvador - 20
Equatorial Guinea - 19
Eritrea - 14
Estonia - 20
Eswatini - 20
Ethiopia - 20
Faroe Islands - 10
Fiji - 20
Finland - 20
France - 20
French Polynesia - 14
Gabon - 20
Gambia, The - 20
Georgia - 20
Germany - 20
Ghana - 20
Gibraltar - 7
Greece - 20
Greenland - 12
Grenada - 14
Guam - 14
Guatemala - 20
Guinea - 20
Guinea-Bissau - 20
Guyana - 20
Haiti - 20
Honduras - 20
Hong Kong SAR, China - 18
Hungary - 20
Iceland - 20
India - 20
Indonesia - 20
Iran, Islamic Rep. - 19
Iraq - 20
Ireland - 20
Isle of Man - 8
Israel - 20
Italy - 20
Jamaica - 20
Japan - 20
Jordan - 20
Kazakhstan - 20
Kenya - 20
Kiribati - 15
Korea, Dem. People’s Rep. - 14
Korea, Rep. - 20
Kosovo - 9
Kuwait - 20
Kyrgyz Republic - 20
Lao PDR - 20
Latvia - 20
Lebanon - 20
Lesotho - 20
Liberia - 20
Libya - 18
Liechtenstein - 9
Lithuania - 20
Luxembourg - 20
Macao SAR, China - 17
Madagascar - 19

Malawi - 20
Malaysia - 20
Maldives - 20
Mali - 20
Malta - 20
Marshall Islands - 14
Mauritania - 20
Mauritius - 20
Mexico - 20
Micronesia, Fed. Sts. - 15
Moldova - 20
Monaco - 11
Mongolia - 20
Montenegro - 19
Morocco - 20
Mozambique - 20
Myanmar - 20
Namibia - 20
Nauru - 14
Nepal - 20
Netherlands - 20
New Caledonia - 14
New Zealand - 20
Nicaragua - 20
Niger - 20
Nigeria - 20
North Macedonia - 20
Northern Mariana Islands - 7
Norway - 20
Oman - 20
Pakistan - 20
Palau - 14
Panama - 20
Papua New Guinea - 20
Paraguay - 20
Peru - 20
Philippines - 20
Poland - 20
Portugal - 20
Puerto Rico - 16
Qatar - 20
Romania - 20
Russian Federation - 20
Rwanda - 20
Samoa - 20
San Marino - 12
Sao Tome and Principe - 20
Saudi Arabia - 20
Senegal - 20
Serbia - 20
Seychelles - 15
Sierra Leone - 20
Singapore - 20
Sint Maarten (Dutch part) - 10
Slovak Republic - 20
Slovenia - 20
Solomon Islands - 19
Somalia - 15
South Africa - 20
South Sudan - 19
Spain - 20
Sri Lanka - 20
St. Kitts and Nevis - 15
St. Lucia - 20
St. Martin (French part) - 4
St. Vincent and the Grenadines - 20
Sudan - 20
Suriname - 20
Sweden - 20
Switzerland - 20
Syrian Arab Republic - 16
Tajikistan - 20
Tanzania - 20
Thailand - 20
Timor-Leste - 20
Togo - 20
Tonga - 20
Trinidad and Tobago - 20
Tunisia - 20
Turkey - 20
Turkmenistan - 19
Turks and Caicos Islands - 10
Tuvalu - 12
Uganda - 20
Ukraine - 20
United Arab Emirates - 19
United Kingdom - 20
United States - 20
Uruguay - 20

```
Uzbekistan - 20
Vanuatu - 20
Venezuela, RB - 20
Vietnam - 20
Virgin Islands (U.S.) - 14
West Bank and Gaza - 19
Yemen, Rep. - 20
Zambia - 20
Zimbabwe - 20
158
```

In [8]:

```python
# displaying selected and excluded climates

climates_selected = {key: count[key] for key in count if (count[key] == datalog_selected.size)}

climates_dropped = {key: count[key] for key in count if (count[key] < datalog_selected.size) and (count[key] >= c

df_final= df_selected[climates_selected.keys()]
df_final = df_final.astype(float)

df_dropped = df_selected[climates_dropped.keys()]
df_dropped
```

Out[8]:

	Albania	Barbados	Burkina Faso	Central African Republic	Chad	Congo, Dem. Rep.	Cuba	Equatorial Guinea	Hong Kong SAR, China	Iran, Isla F
Access to electricity, rural (% of rural population)	100	100	..	10.60398446	0.522862551	..	97.59200933	6.700125869	100	99.94255
Access to electricity, urban (% of urban population)	100	100	62.3	55.24568558	41.83586121	50.70074081	100	90.36400604	100	
Agriculture, forestry, and fishing, value added (% of GDP)	19.56517622	..	23.64109279	32.25890625	50.04519248	19.31666763	3.924923524	1.19199068	0.057288366	9.753665
CO2 emissions (metric tons per capita)	1.90006971	4.40310366	0.168273976	0.064892841	0.073267221	0.063330889	2.443066279	6.512062095	6.3281682	8.421686
Current health expenditure (% of GDP)	..	6.899338961	5.229732767	3.822655603	3.910466284	3.431640565	11.31298617	1.553575136	..	6.607250
Death rate, crude (per 1,000 people)	7.219	8.708	9.105	14.164	13.053	10.424	8.338	10.245	6.2	4.
Employment in agriculture (% of total employment) (modeled ILO estimate)	36.69100189	2.630000114	25.22500038	77.32299805	76.55599976	65.43099976	17.50799942	42.35699844	0.171000004	17.9489
Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate)	22.00600052	31.66500092	47.02799988	52.52899933	53.37599945	32.48699951	35.91600037	27.21199989	36.98400116	19.9829
GDP growth (annual %)	1.774486785	-0.124547101	4.326845613	0.081070515	6.899985045	9.470288097	1.047576632	0.415066302	2.762391998	4.60341
GDP per capita growth (annual %)	1.985426103	-0.310043861	1.282101661	-0.282852498	3.433016822	5.895886034	0.831466817	-3.68850197	2.043147647	3.274962
Individuals using the Internet (% of population)	71.8470405	81.76077839	16	4.339254945	6.49999812	8.619904916	57.14840432	26.23999996	89.41594465	64.04397
Labor force participation rate for ages 15-24, female (%) (modeled ILO estimate)	23.93400002	43.19300079	44.30400085	52.88899994	55.65000153	38.51399994	28.68199921	28.03300095	42.25799942	11.89599
Labor force participation rate for ages 15-24, male	36.77000046	47.47600174	58.03499985	58.52000046	54.50500107	32.11199951	45.81399918	33.47200012	39.98799896	42.70500

(%) (modeled ILO estimate)										
Mobile cellular subscriptions (per 100 people)	117.6592183	117.337483	79.77028842	27.65294881	38.73436811	49.51538827	29.45174834	45.64013391	232.7365615	94.55563
Mortality rate, infant (per 1,000 live births)	7.8	11.3	49	84.5	71.4	68.2	3.7	62.6	..	
People using at least basic drinking water services (% of population)	89.46108788	98.4544419	49.48736677	46.03780207	39.32389462	41.23186089	94.9238056	63.67151493	99.8937928	95.0687
Rural population (% of total population)	46.753	68.3	74.804	60.865	77.946	59.456	23.311	32.512	0	
Secure Internet servers (per 1 million people)	443.0203758	768.6045984	1.927757647	0.435158358	0.599329829	2.555321356	8.466161678	0	10484.86816	225.6986
Trade in services (% of GDP)	34.4802978	43.9729304	12.64750088	..	..	9.460013313	..	..	62.06220431	
Vulnerable employment, total (% of total employment) (modeled ILO estimate)	52.85199928	15.84099954	86.41899872	91.37900162	93.02399826	79.67399788	23.0979991	77.29000092	5.717000008	41.42499

Correlation Analysis of Inidicators

In [9]:

```python
#Correlation Analysis of Inidicators
corr = df_final.head(10).T.corr()

corr.style.background_gradient(cmap='Spectral')
```

Out[9]:

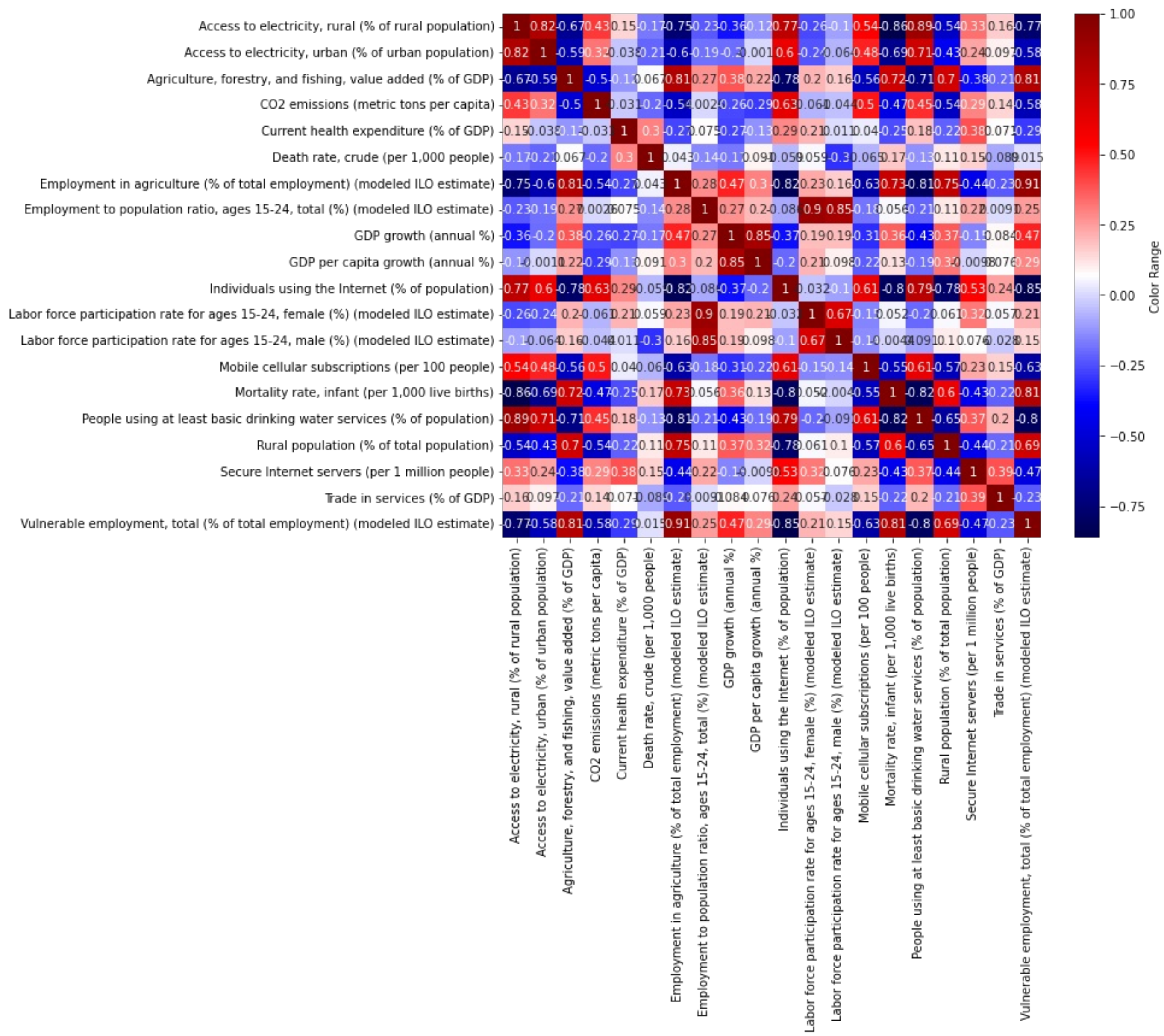
	Access to electricity, rural (% of rural population)	Access to electricity, urban (% of urban population)	Agriculture, forestry, and fishing, value added (% of GDP)	CO2 emissions (metric tons per capita)	Current health expenditure (% of GDP)	Death rate, crude (per 1,000 people)	Employment in agriculture (% of total employment) (modeled ILO estimate)	Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate)	GDP growth (annual %)	GDP per capita growth (annual %)
Access to electricity, rural (% of rural population)	1.000000	0.823420	-0.671903	0.433066	0.148118	-0.173204	-0.753470	-0.228211	-0.364153	-0.124567
Access to electricity, urban (% of urban population)	0.823420	1.000000	-0.591377	0.320155	-0.038313	-0.207164	-0.595886	-0.188021	-0.197253	-0.001107
Agriculture, forestry, and fishing, value added (% of GDP)	-0.671903	-0.591377	1.000000	-0.499447	-0.119159	0.066900	0.809546	0.272167	0.380246	0.223809
CO2 emissions (metric tons per capita)	0.433066	0.320155	-0.499447	1.000000	-0.030658	-0.202656	-0.542282	0.002572	-0.263262	-0.290608
Current health expenditure (% of GDP)	0.148118	-0.038313	-0.119159	-0.030658	1.000000	0.298587	-0.270811	0.075230	-0.268091	-0.130054
Death rate, crude (per 1,000 people)	-0.173204	-0.207164	0.066900	-0.202656	0.298587	1.000000	0.043255	-0.141138	-0.173251	0.091026
Employment in agriculture (% of total employment) (modeled ILO estimate)	-0.753470	-0.595886	0.809546	-0.542282	-0.270811	0.043255	1.000000	0.278098	0.471356	0.296064

Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate)	-0.228211	-0.188021	0.272167	0.002572	0.075230	-0.141138	0.278098	1.000000	0.268518	0.195906
GDP growth (annual %)	-0.364153	-0.197253	0.380246	-0.263262	-0.268091	-0.173251	0.471356	0.268518	1.000000	0.850731
GDP per capita growth (annual %)	-0.124567	-0.001107	0.223809	-0.290608	-0.130054	0.091026	0.296064	0.195906	0.850731	1.000000

In [10]:

```
#Plot correlation matrix of indicators
plt.figure(figsize=(10,8))
corrMatrix = df_final.T.corr()
sns.heatmap(corrMatrix, annot=True, cbar_kws={'label': 'Color Range'}, cmap="seismic")
```

Out[10]: <AxesSubplot:>

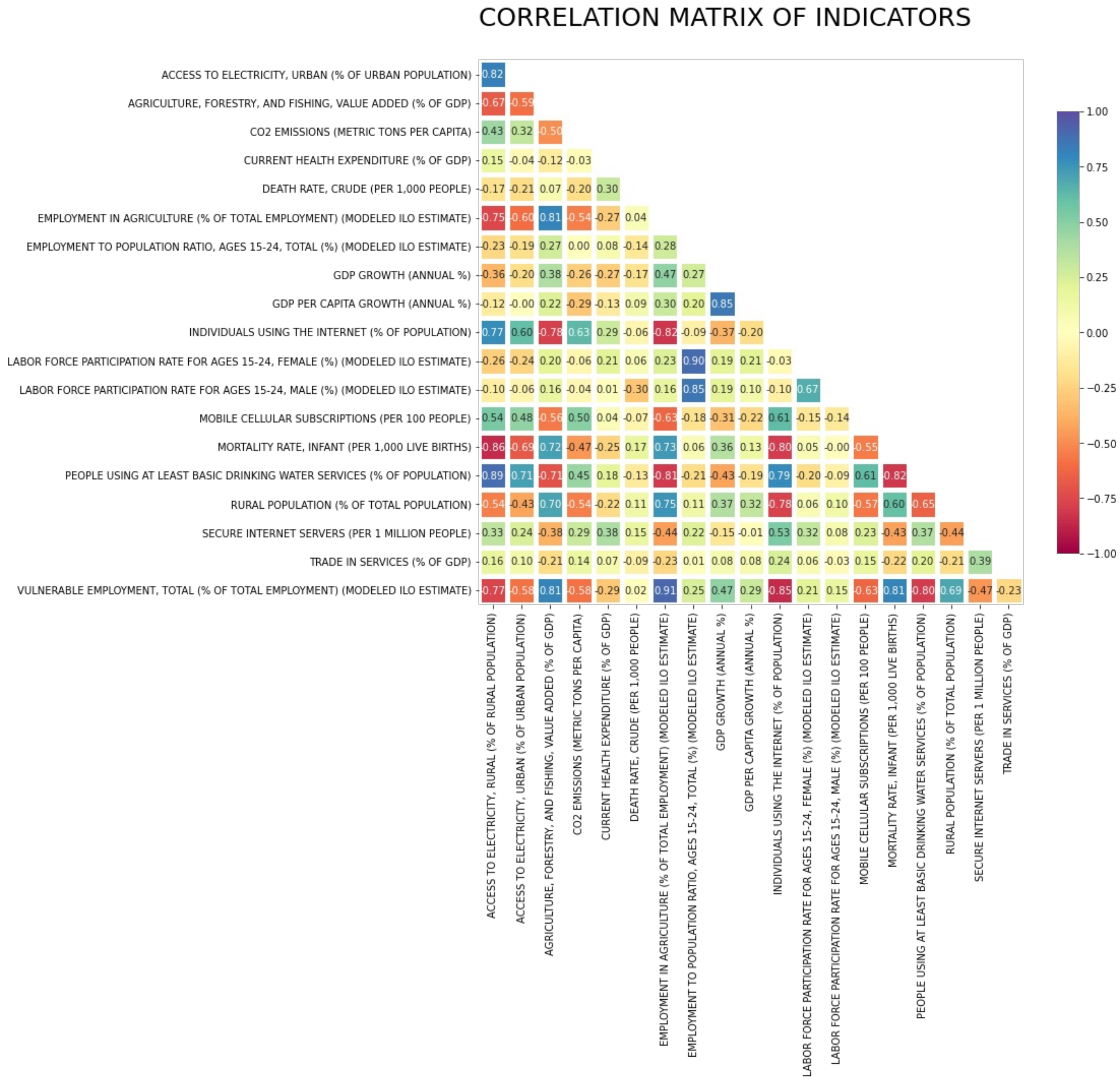


In [11]:

```
corrMatrix = df_final.T.corr()

fig, ax = plt.subplots(figsize=(12, 10))
# mask
mask = np.triu(np.ones_like(corrMatrix, dtype=np.bool))
# adjust mask and df
mask = mask[1:, :-1]
corr = corrMatrix.iloc[1:,:-1].copy()
# color map
cmap = sns.color_palette("Spectral", as_cmap=True)
# plot heatmap
sns.heatmap(corr, mask=mask, annot=True, fmt=".2f",
           linewidths=5, cmap=cmap, vmin=-1, vmax=1,
```

```python
            cbar_kws={"shrink": .8}, square=True)
# ticks
yticks = [i.upper() for i in corr.index]
xticks = [i.upper() for i in corr.columns]
plt.yticks(plt.yticks()[0], labels=yticks, rotation=0)
plt.xticks(plt.xticks()[0], labels=xticks)
# title
title = 'CORRELATION MATRIX OF INDICATORS\n'
plt.title(title, loc='left', fontsize=25)
plt.show()
```

```
/var/folders/dp/2ms1d3nx6nq459ycjnlz_p740000gn/T/ipykernel_5408/4272676397.py:5: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bool` by itself. Doing this will not modify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  mask = np.triu(np.ones_like(corrMatrix, dtype=np.bool))
```



K-means Cluster Analysis

In [12]:

```python
#standardization along columns
df_final_std=(df_final.T-df_final.T.mean())/df_final.T.std()

df_final_std.head(5)
```

Out[12]:

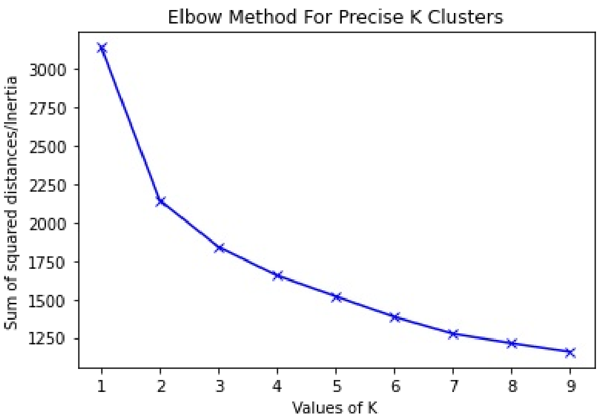
Access to electricity,	Access to electricity,	Agriculture, forestry, and	CO2 emissions	Current	Death rate,	Employment in agriculture	Employment to population ratio, ages	GDP	GDP per capita	Individu using t

	rural (% of rural population)	urban (% of urban population)	fishing, value added (% of GDP)	(metric tons per capita)	health expenditure (% of GDP)	crude (per 1,000 people)	(% of total employment) (modeled ILO estimate)	15-24, total (%) (modeled ILO estimate)	growth (annual %)	growth (annual %)	Internet populatic
Afghanistan	-0.343706	0.496160	1.126010	-0.705926	0.855704	-0.235424	0.947575	-0.255572	-0.277066	-1.050870	-1.5278
Algeria	0.689428	0.496160	-0.097492	-0.142934	-0.391623	-1.127714	-0.647515	-1.325894	0.112104	-0.123090	-0.2639
Angola	-2.127431	-1.734139	-0.413229	-0.477789	-1.384310	0.613206	1.312265	0.740532	0.482156	-0.314689	-1.4968
Argentina	0.641639	0.496160	-0.456147	-0.005111	0.793102	-0.048307	-1.119712	-0.565777	-2.172212	-2.188594	0.7194
Armenia	0.696340	0.496160	0.712866	-0.439959	1.163888	0.738684	0.309162	-1.007101	0.039731	0.408966	0.3664

Finding the optimal number of k clusters.

In [13]:

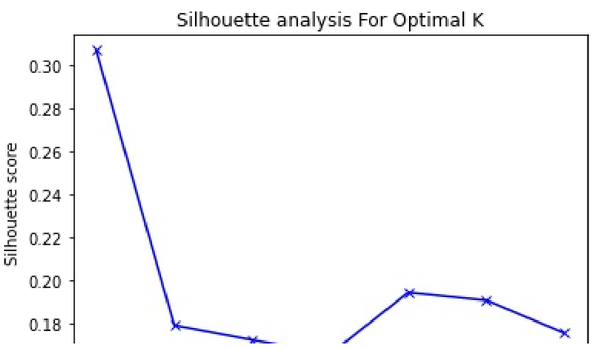
```
#Elbow method
Sum_of_squared_distances = []
K = range(1,10)
for num_clusters in K :
 kmeans = KMeans(n_clusters=num_clusters)
 kmeans.fit(df_final_std)
 Sum_of_squared_distances.append(kmeans.inertia_)
plt.plot(K,Sum_of_squared_distances,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Sum of squared distances/Inertia')
plt.title('Elbow Method For Precise K Clusters')
plt.show()
```

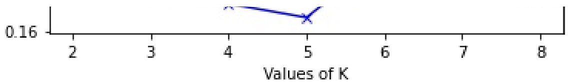


Silhouette analysis

In [14]:

```
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
silhouette_avg = []
for num_clusters in range_n_clusters:

 # initialise kmeans
 kmeans = KMeans(n_clusters=num_clusters)
 kmeans.fit(df_final_std)
 cluster_labels = kmeans.labels_

 # silhouette score
 silhouette_avg.append(silhouette_score(df_final_std, cluster_labels))
plt.plot(range_n_clusters,silhouette_avg,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Silhouette score')
plt.title('Silhouette analysis For Optimal K')
plt.show()
```





From both methods we find that k=2

In [15]:
```
# defining the kmeans function with initialization as k-means++
kmeans = KMeans(n_clusters=2, init='k-means++')

# fitting the k means algorithm on scaled data
kmeans.fit(df_final_std)
```

Out[15]:
```
KMeans(n_clusters=2)
```

In [16]:
```
# inertia on the fitted data
kmeans.inertia_
```

Out[16]:
```
2143.990677496662
```

Prediction

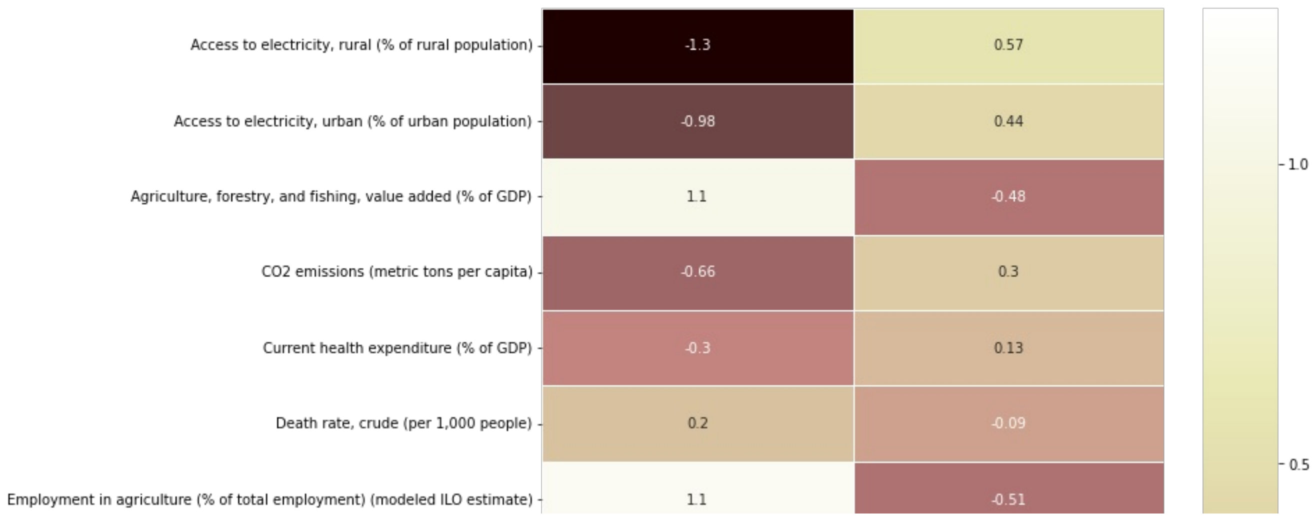
In [17]:
```
pred = kmeans.predict(df_final_std)

frame = pd.DataFrame(df_final_std)
frame['cluster'] = pred
frame['cluster'].value_counts()
```

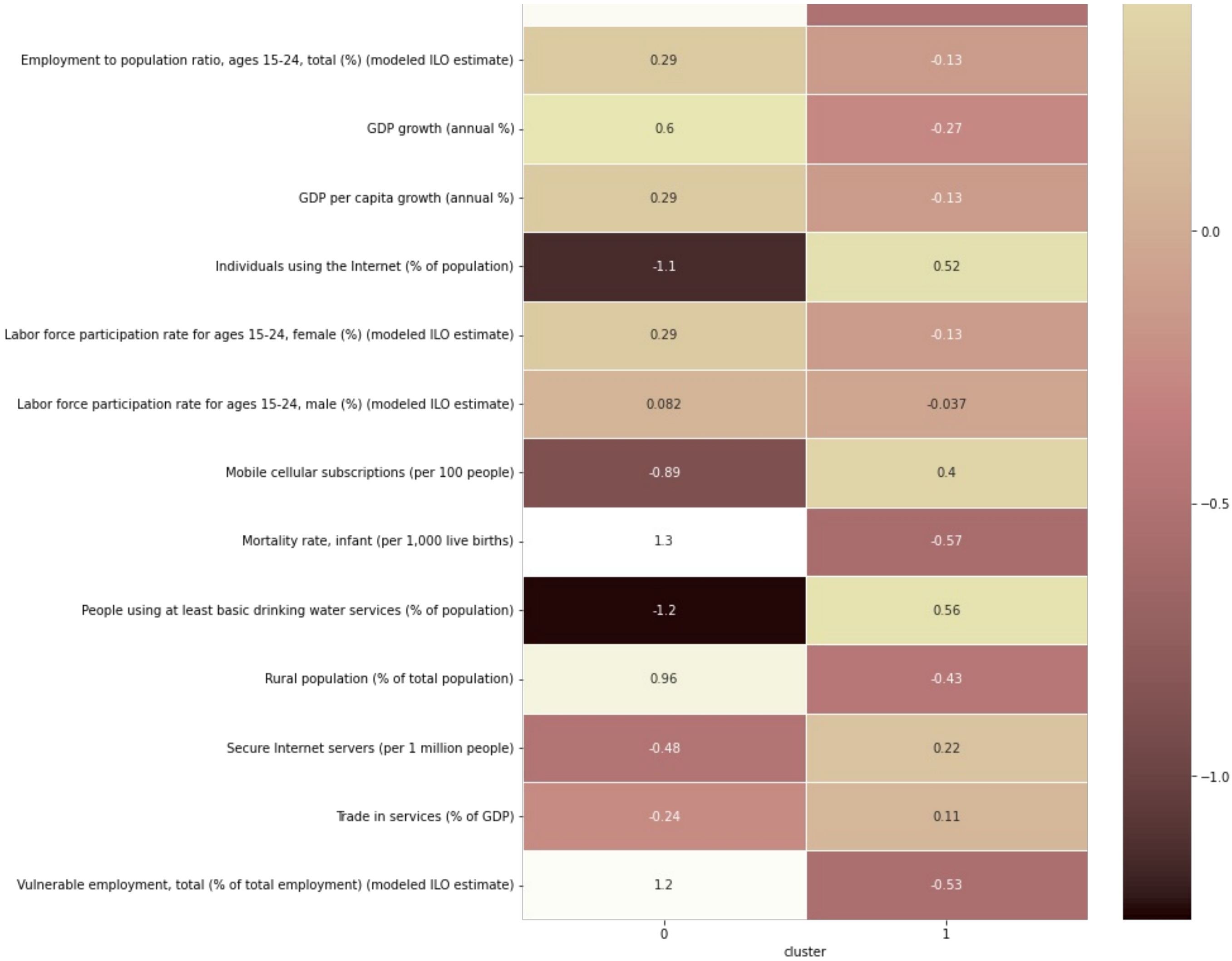
Out[17]:
```
1    109
0     49
Name: cluster, dtype: int64
```

In [18]:
```
df_final_T = df_final.T
df_final_T['cluster'] = pred
df_final_T.sort_values("cluster", inplace = True, ascending=True)

df_final_std['cluster'] = pred
df_final_std.sort_values("cluster", inplace = True, ascending=True)

df_cluster = df_final_T.groupby('cluster').mean()
df_cluster_std = df_final_std.groupby('cluster').mean()

df_final_T.to_csv('clusters.csv')
```

Heatmap of cluster characteristics

In [19]:
```
#Heatmap of cluster characteristics
plt.figure(figsize=(10,20))
sns.heatmap(df_cluster_std.T, annot=True, cmap="pink", linewidths=.5)
plt.savefig('hk.png')
```





In [20]:

```
# counting the number of clustering nations
num_of_countries = []
for n in range(len(set(pred))):
    num_of_countries.append(sum(df_final_T['cluster'] == n))

df_cluster['num of countries'] = num_of_countries
df_cluster_std['num of countries'] = num_of_countries

columns = list(df_cluster.columns)
columns = columns[-1:] + columns[:-1]

df_cluster = df_cluster.reindex(columns=columns)
df_cluster_std = df_cluster_std.reindex(columns=columns)

df_cluster
```

Out[20]:

	num of countries	Access to electricity, rural (% of rural population)	Access to electricity, urban (% of urban population)	Agriculture, forestry, and fishing, value added (% of GDP)	CO2 emissions (metric tons per capita)	Current health expenditure (% of GDP)	Death rate, crude (per 1,000 people)	Employment in agriculture (% of total employment) (modeled ILO estimate)	Employment to population ratio, ages 15-24, total (%) (modeled ILO estimate)	GDP growth (annual %)	...	Individuals using the Internet (% of population)
cluster												
0	49	33.234733	82.576516	22.131848	0.532720	5.509491	8.328694	46.865204	40.976388	5.138433	...	23.816908
1	109	95.631871	99.343446	5.828059	6.457169	6.658022	7.537202	12.627046	35.046486	2.749259	...	68.773614

2 rows × 21 columns

Curve Fitting

In [21]:

```
#Load data of cluster 2 countries for Year vs GDP Growth
data_SL = pd.read_csv('Sri_Lanka.csv')
```

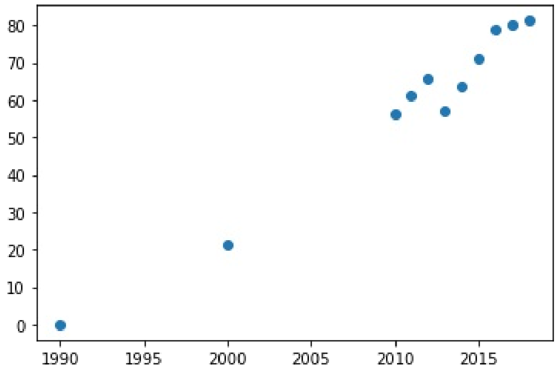
```
data_SL
```

Out[21]:

	Year	Internet
0	1990	0.000000
1	2000	21.384731
2	2010	56.300000
3	2011	61.000000
4	2012	65.800000
5	2013	57.057512
6	2014	63.665426
7	2015	71.064068
8	2016	78.788310
9	2017	80.140479
10	2018	81.201049

In [22]:

```
x, y = data_SL['Year'], data_SL['Internet']

# plot input vs output
plt.scatter(x, y)
plt.show()
```



In [23]:

```
# define the true objective function
def objective(x, a, b):
        return a * x + b

# curve fit
popt, _ = curve_fit(objective, x, y)

# summarize the parameter values
a, b = popt
print('y = %.5f * x + %.5f' % (a, b))
```

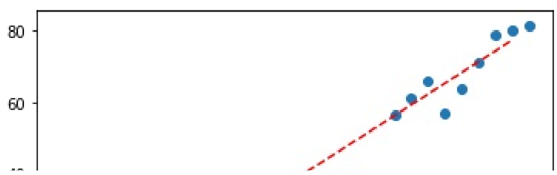
```
y = 2.99132 * x + -5956.33368
```

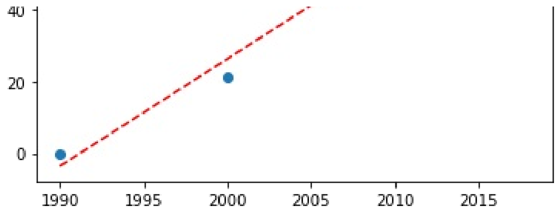
In [24]:

```
# compare input and output by plotting
# between the smallest and greatest known inputs, define a sequence of inputs.
# generate a line graph for the mapping function
# compute the output for the specified range
plt.scatter(x, y)

x_line = arange(min(x), max(x), 1)

y_line = objective(x_line, a, b)

plt.plot(x_line, y_line,'--', color='red')
```

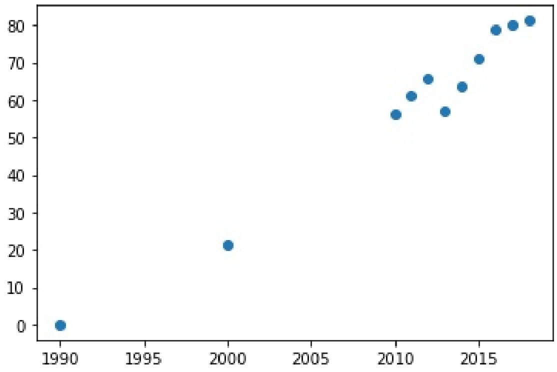
Out[24]:

```
[<matplotlib.lines.Line2D at 0x7fdbf8479b80>]
```





In [25]:
```
#Load data of cluster 2 countries for Year vs GDP Growth
data_colombia = pd.read_csv('colombia.csv')

x, y = data_colombia['Year'], data_SL['Internet']

# compare input and output by plotting
plt.scatter(x, y)
plt.show()
```



In [26]:
```
# define the true objective function
def objective(x, a, b, c):
        return a * x + b * x**2 + c

# curve fit
popt, _ = curve_fit(objective, x, y)

# the summary of parameter values
a, b, c = popt
print('y = %.5f * x + %.5f * x^2 + %.5f' % (a, b, c))
```

```
y = -115.75491 * x + 0.02962 * x^2 + 113037.91216
```

In [27]:
```
# compare input and output
# between the smallest and greatest known inputs, define a sequence of inputs.
#compute the outcome for the specified range
# generate a line graph for the mapping function
plt.scatter(x, y)

x_line = arange(min(x), max(x), 1)

y_line = objective(x_line, a, b, c)

plt.plot(x_line, y_line, '--', color='red')
plt.show()
```