0.) Import and Clean data

In [1]:
```
import pandas as pd
from google.colab import drive
import matplotlib.pyplot as plt
import numpy as np
```

In [2]:
```
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from sklearn.decomposition import PCA
```

In [3]:
```
drive.mount('/content/gdrive/', force_remount = True)
```

```
Mounted at /content/gdrive/
```

In [5]:
```
df = pd.read_csv("/content/gdrive/MyDrive/Country-data.csv", sep = ",")
```

In [6]:
```
df.head()
```

Out[6]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

In [7]:
```
df.columns
```

Out[7]:
```
Index(['country', 'child_mort', 'exports', 'health', 'imports', 'income',
       'inflation', 'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

In [27]:
```
names = df[["country"]]
X = df.drop(["country"], axis = 1)
```

In [28]:
```
scaler = StandardScaler().fit(X)
X_scaled = scaler.transform(X)
```

1.) Run a PCA Algorithm to get 2 Principle Components for the 9 X features

In [29]:
```
pca = PCA(n_components = 2)
X_pca = pca.fit_transform(X_scaled)
X_pca
```

Out[29]:
```
array([[-2.91302459e+00,  9.56205755e-02],
       [ 4.29911330e-01, -5.88155666e-01],
       [-2.85225077e-01, -4.55174413e-01],
       [-2.93242265e+00,  1.69555507e+00],
       [ 1.03357587e+00,  1.36658709e-01],
       [ 2.24072616e-02, -1.77918658e+00],
       [-1.01583737e-01, -5.68251724e-01],
       [ 2.34216461e+00, -1.98845915e+00],
       [ 2.97376366e+00, -7.34688659e-01],
       [-1.81486997e-01, -4.02865873e-01],
       [ 1.26874386e+00, -6.56588363e-01],
       [ 1.67099640e+00,  5.61162493e-01],
       [-1.12385093e+00, -9.61397405e-01],
       [ 1.08137420e+00, -4.81969530e-01],
       [ 5.80025152e-01,  5.35326834e-01],
       [ 3.14378596e+00,  6.63547921e-01],
       [ 2.11255447e-01,  6.99242662e-01],
       [-2.67231388e+00,  4.18172125e-01],
       [-1.56570962e-01,  7.77395617e-01],
```

In [30]:
```
X_pca[:,0] #every row and the first column
```

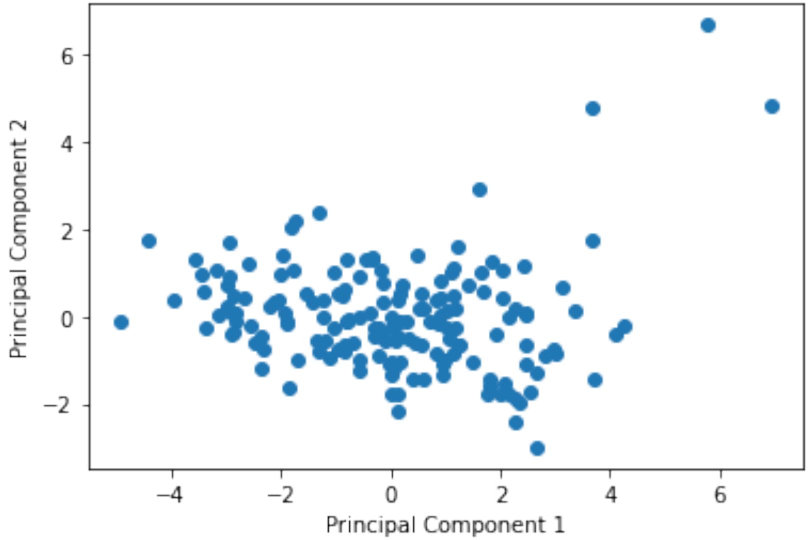
Out[30]:
```
array([-2.91302459e+00,  4.29911330e-01, -2.85225077e-01, -2.93242265e+00,
        1.03357587e+00,  2.24072616e-02, -1.01583737e-01,  2.34216461e+00,
        2.97376366e+00, -1.81486997e-01,  1.26874386e+00,  1.67099640e+00,
       -1.12385093e+00,  1.08137420e+00,  5.80025152e-01,  3.14378596e+00,
        2.11255447e-01, -2.67231388e+00, -1.56570962e-01, -7.93851561e-01,
        9.95867143e-01, -8.82087639e-01,  1.40781361e-01,  2.46008609e+00,
        9.06594515e-01, -3.12205344e+00, -2.89897068e+00, -5.82411867e-01,
       -2.80790857e+00,  2.54363055e+00, -1.55801452e-01, -3.96496402e+00,
       -3.55755520e+00,  9.51656055e-01,  5.74819803e-02,  1.21146120e-01,
```

```
       -2.09355643e+00, -3.17337012e+00, -1.72567641e+00,  9.37826615e-01,
       -2.58170623e+00,  1.14886344e+00,  2.17445492e+00,  2.05326329e+00,
        3.01049182e+00, -2.31102923e-01,  9.61833240e-03, -8.48186699e-01,
        8.18678445e-02, -1.29342284e+00, -2.47469590e+00,  1.65908340e+00,
       -1.88828409e-01,  2.45896019e+00,  2.25427080e+00, -1.42171455e+00,
       -2.21366958e+00,  3.21942207e-01,  2.67142195e+00, -2.05416693e+00,
        1.77949294e+00,  1.45504799e-01, -6.63503125e-01, -2.96952947e+00,
       -2.83361647e+00, -3.22781465e-01, -4.40971727e+00,  1.83916013e+00,
        2.48092396e+00, -1.34282579e+00, -9.54750124e-01, -1.06461193e-03,
       -1.02922816e+00,  3.66862804e+00,  1.48531666e+00,  2.16580995e+00,
        1.86093002e-02,  2.26588199e+00,  1.60142643e-01, -2.93346500e-01,
       -1.87470247e+00, -1.23921686e+00,  2.46565870e+00, -3.39969880e-01,
       -1.52776995e+00,  1.18883984e+00,  1.17199076e+00, -1.80315140e+00,
       -1.77358023e+00,  8.18943051e-01,  1.40978812e+00,  6.91775496e+00,
        7.33210319e-01, -2.13600867e+00, -2.97988525e+00,  1.23082842e+00,
        1.10860101e+00, -3.41225513e+00,  3.67954260e+00, -1.95392747e+00,
        8.99775055e-01, -3.80928795e-01,  5.09539453e-01, -9.44975538e-01,
        1.02668389e+00, -2.32870156e-01, -2.92054051e+00, -1.83719774e+00,
       -1.04337471e+00, -1.30708985e+00,  3.37915727e+00,  1.81574666e+00,
       -3.45016774e+00, -4.91206615e+00,  3.72119513e+00,  1.12738665e+00,
       -2.36034718e+00,  1.16378429e+00,  1.17846224e-01, -2.06354519e-02,
       -7.82745871e-01,  1.21782754e+00,  1.81406748e+00,  4.24229634e+00,
        5.72792704e-01,  1.63761544e-01, -1.67970356e+00, -5.62897632e-01,
        8.55935813e-01, -1.91217031e+00,  8.32420187e-01,  1.60259775e+00,
       -3.38162479e+00,  5.78337630e+00,  2.02972370e+00,  2.27949171e+00,
       -8.06209136e-01, -1.19183736e+00,  1.91806245e+00,  2.01919721e+00,
       -5.75572155e-01,  2.66234652e-02, -2.31942387e+00,  1.71674731e-01,
        2.81832286e+00,  4.08854413e+00, -1.24446436e+00, -2.55404919e+00,
        9.26092707e-01, -2.37197047e+00, -1.99764225e+00, -7.55008538e-01,
        6.02231612e-01,  4.01437705e-01, -4.63936165e-01, -2.85483624e+00,
        3.02299800e-01,  2.42714125e+00,  2.06798993e+00,  2.64120583e+00,
        6.17312598e-01, -8.53528944e-01, -8.20631131e-01, -5.51035564e-01,
        4.98524385e-01, -1.88745106e+00, -2.86406392e+00])
```

2.) Plot a Scatter plot of the PCs on the axis

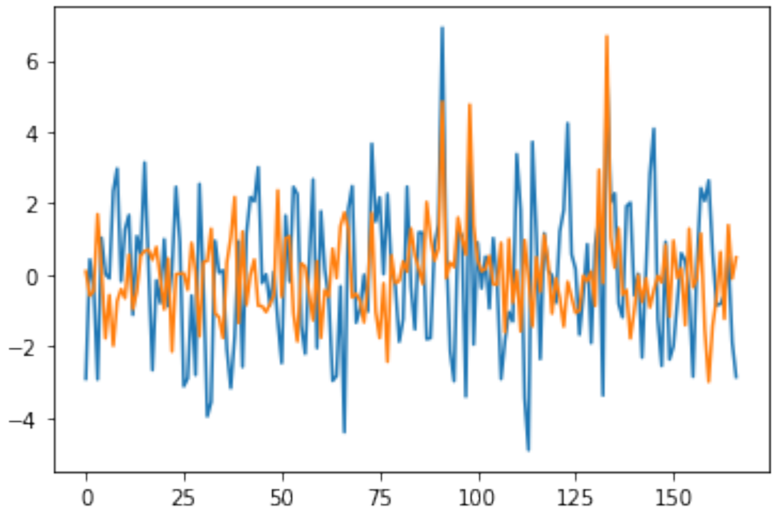
In [31]:
```
plt.scatter(X_pca[:,0], y = X_pca[:,1])
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
```

Out[31]:
```
Text(0, 0.5, 'Principal Component 2')
```



In [32]:
```
plt.plot(X_pca)
```

Out[32]:
```
[<matplotlib.lines.Line2D at 0x7f0224555820>,
 <matplotlib.lines.Line2D at 0x7f0224555880>]
```



3.) Rank the features in order of importance according to PCA

In [33]:
```
loadings = pca.components_
loadings
```

Out[33]:
```
array([[-0.41951945,  0.28389698,  0.15083782,  0.16148244,  0.39844111,
        -0.19317293,  0.42583938, -0.40372896,  0.39264482],
       [ 0.19288394,  0.61316349, -0.24308678,  0.67182064,  0.02253553,
        -0.00840447, -0.22270674,  0.15523311, -0.0460224 ]])
```

In [34]:
```
feature_importance = pd.DataFrame(np.sum(loadings**2, axis = 0))
```

In [35]:
```
feature_importance.index = df.columns[1:] #can add feature_names
feature_importance
```

Out[35]:

	0
child_mort	0.213201
exports	0.456567
health	0.081843
imports	0.477420
income	0.159263
inflation	0.037386
life_expec	0.230937
total_fer	0.187094
gdpp	0.156288

In [36]:
```
feature_importance.index.sort_values(0, ascending = False)
```

Out[36]:
```
Index(['total_fer', 'life_expec', 'inflation', 'income', 'imports', 'health',
       'gdpp', 'exports', 'child_mort'],
      dtype='object')
```

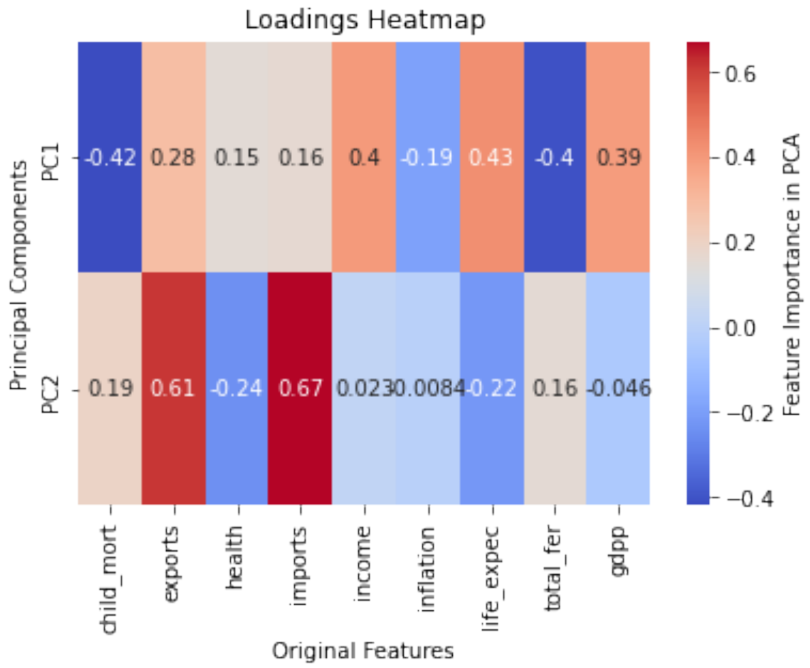
4.) Plot a heatmap of the feature importance (Fill in all parameters)

In [37]:
```
feature_names = df.columns[1:]
feature_names
```

Out[37]:
```
Index(['child_mort', 'exports', 'health', 'imports', 'income', 'inflation',
       'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

In [47]:
```
#sns.heatmap(, annot=, cmap='coolwarm', xticklabels=, yticklabels=[, ], cbar_kws={'label':''})
sns.heatmap(loadings, annot = True, cmap = 'coolwarm', xticklabels = feature_names, yticklabels = ["PC1"

plt.xlabel('Original Features')
plt.ylabel('Principal Components')
plt.title('Loadings Heatmap')
plt.show()
```



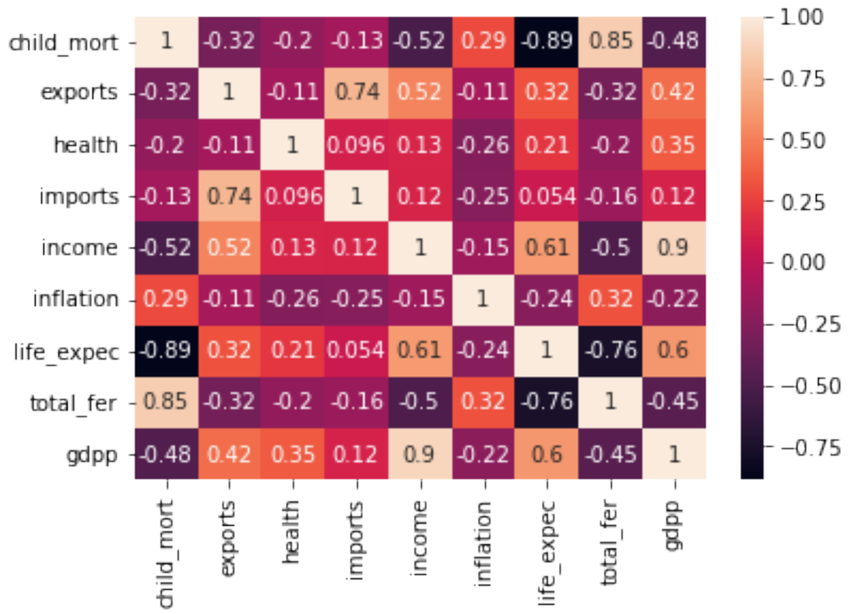
From the above graph, we see that there is the importance attached to imports and exports. In PC2, we can say that imports and exports have high importance attached. However, another important thing that we noticed is that if a particular feature is important in one PC, it is not necessary that it will also be important in another PC, because each PC explains a totally different line.

We see this in the graph above as well that althoug imports and exports are considered highly important in PC2, they are not really important in PC1.

5.) Plot a correlation plot of the original features. What do you notice between the graphs of 4 & 5?

In [40]:
```
sns.heatmap(X.corr(), annot = True)
plt.plot()
```

Out[40]: []



A very high correlation is observed between child mortality as well as imports and exports. Coincidenally, there is also high importance attached to both of these varibles. What we can understand from this is that if there is a high correlation, this means that a lot of the information is explained by those two variables and therefore it also comes out as a high importance for that variable.

Therefore, a high correlation between two variables explains why there might be high importance attached as well simply because they might be conveying a lot of information and hence have a lot of information.

6.) Run a PCA with 9 PCs. Plot a Cumulative Explained Variance Plot. How many PCs should we use if we want to retain 95% of the variance?

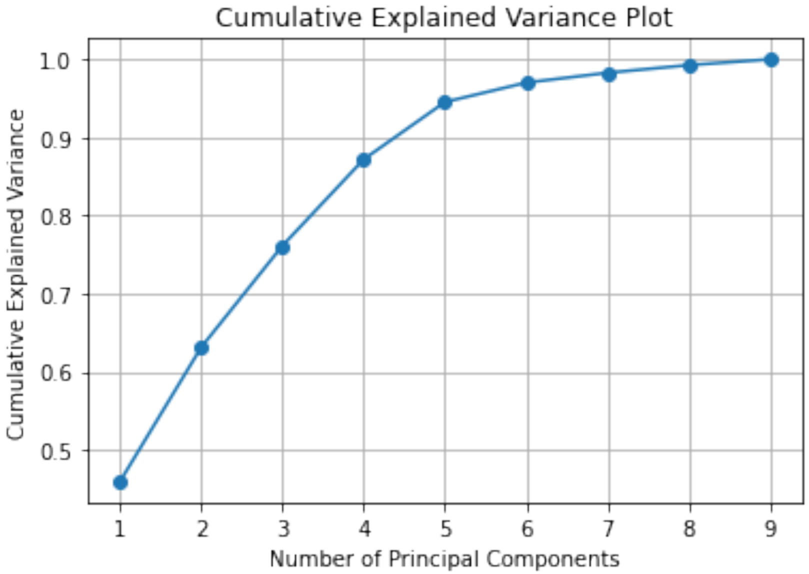
In [43]:
```
pca = PCA(n_components = 9)
X_pca = pca.fit_transform(X_scaled)
```

In [44]:
```
pca_explained = pca.explained_variance_ratio_
pca_explained
#amount that the data explains for each variable. so if 0.45, the data explained 45% of the variance
```

Out[44]:
```
array([0.4595174 , 0.17181626, 0.13004259, 0.11053162, 0.07340211,
       0.02484235, 0.0126043 , 0.00981282, 0.00743056])
```

In [46]:
```
cumulative_explained_variance = np.cumsum(pca_explained)

plt.plot(np.arange(1, len(cumulative_explained_variance) + 1), cumulative_explained_variance, marker='o'
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Cumulative Explained Variance Plot')
plt.grid()
plt.show()
```



In [48]:
```
cumulative_explained_variance
```

Out[48]:
```
array([0.4595174 , 0.63133365, 0.76137624, 0.87190786, 0.94530998,
       0.97015232, 0.98275663, 0.99256944, 1.        ])
```

By plotting the cumulative sum of explained variables, we see that if we take 5 PCs, the retained variance is 94.5%, which although very close to 95, does not touch 95%. Therefore, we would need 6 PCs to retain a variance of 95%.