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 [4]:
```
df = pd.read_csv("/content/gdrive/MyDrive/Country-data.csv", sep = ",")
```

In [5]:
```
df.head()
```

Out[5]:

	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 [6]:
```
df.columns
```

Out[6]:
```
Index(['country', 'child_mort', 'exports', 'health', 'imports', 'income',
       'inflation', 'life_expec', 'total_fer', 'gdpp'],
      dtype='object')
```

In [7]:
```
names = df[["country"]]
X = df.drop(["country"], axis = 1)
```

In [8]:
```
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 [12]:
```
pca = PCA(n_components = 2)
X_pca = pca.fit_transform(X_scaled)
```

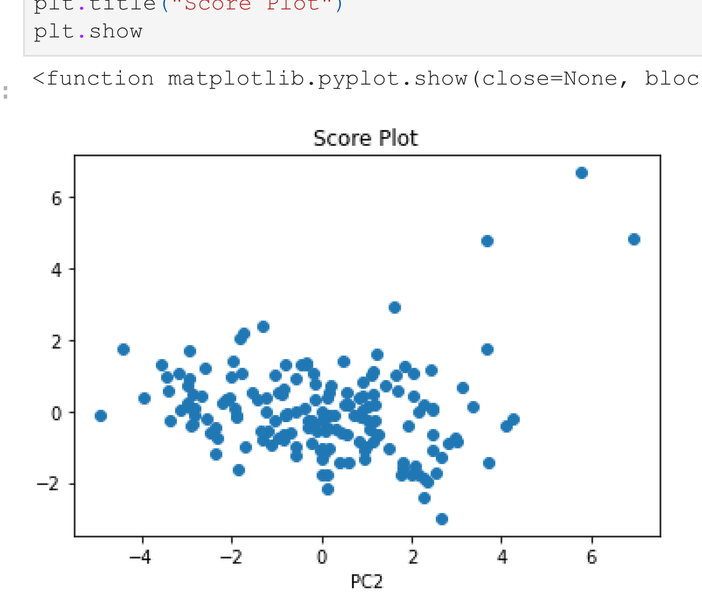
In [13]:
```
X_pca
```

Out[13]:
```
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],
       [-7.93851561e-01, -1.20261085e-01],
       [ 9.95867143e-01, -9.71888439e-01],
       [-8.82087639e-01,  4.57368180e-01],
       [ 1.40781361e-01, -2.15107731e+00],
       [ 2.46008609e+00,  1.64540436e-02],
       [ 9.06594515e-01,  3.02776054e-02],
       [-3.12205344e+00,  3.87749688e-02],
       [-2.89897068e+00, -4.22663328e-01],
       [-5.82411867e-01,  8.94820332e-01],
       [-2.80790857e+00,  7.86488969e-02],
       [ 2.54363055e+00, -1.72709470e+00],
       [-1.55801452e-01,  3.51235458e-01],
       [-3.96496402e+00,  3.86619319e-01],
       [-3.55755520e+00,  1.28912809e+00],
       [ 9.51656055e-01, -1.07642827e+00],
       [ 5.74819803e-02, -1.18999652e+00],
       [ 1.21146120e-01, -1.76890914e+00],
       [-2.09355643e+00,  3.43600988e-01],
       [-3.17337012e+00,  1.05038163e+00],
       [-1.72567641e+00,  2.17634895e+00],
       [ 9.37826615e-01, -1.35047238e+00],
       [-2.58170623e+00,  1.20787342e+00],
       [ 1.14886344e+00, -8.44812046e-01],
       [ 2.17445492e+00, -4.51044737e-03],
       [ 2.05326329e+00,  4.23198280e-01],
       [ 3.01049182e+00, -8.65548729e-01],
       [-2.31102923e-01, -8.80641302e-01],
       [ 9.61833240e-03, -1.04522097e+00],
       [-8.48186699e-01, -8.19818902e-01],
       [ 8.18678445e-02, -5.67803943e-01],
       [-1.29342284e+00,  2.36369455e+00],
       [-2.47469590e+00, -6.18025236e-01],
       [ 1.65908340e+00,  1.02156447e+00],
       [-1.88828409e-01,  1.07176458e+00],
       [ 2.45896019e+00, -1.07614294e+00],
       [ 2.25427080e+00, -1.86663813e+00],
       [-1.42171455e+00,  3.19723358e-01],
       [-2.21366958e+00,  2.23495896e-01],
       [ 3.21942207e-01, -5.18255225e-01],
       [ 2.67142195e+00, -1.27360990e+00],
       [-2.05416693e+00,  3.80034393e-01],
       [ 1.77949294e+00, -1.76539693e+00],
       [ 1.45504799e-01, -4.31336366e-01],
       [-6.63503125e-01, -6.13910837e-01],
       [-2.96952947e+00,  7.28533786e-01],
       [-2.83361647e+00, -9.11281950e-02],
       [-3.22781465e-01,  1.36134136e+00],
       [-4.40971727e+00,  1.74223049e+00],
       [ 1.83916013e+00,  1.27296493e+00],
       [ 2.48092396e+00, -6.34701926e-01],
       [-1.34282579e+00, -5.35138946e-01],
       [-9.54750124e-01, -7.32361786e-01],
       [-1.06461193e-03, -1.33434959e+00],
       [-1.02922816e+00, -2.83269323e-01],
       [ 3.66862804e+00,  1.72949317e+00],
       [ 1.48531666e+00, -1.04922436e+00],
       [ 2.16580995e+00, -1.77248548e+00],
       [ 1.86093002e-02, -2.38961304e-01],
       [ 2.26588199e+00, -2.43559383e+00],
       [ 1.60142643e-01,  5.41065172e-01],
       [-2.93346500e-01, -2.37525434e-01],
       [-1.87470247e+00, -1.71029967e-01],
       [-1.23921686e+00,  3.69138411e-01],
       [ 2.46565870e+00,  8.80497785e-02],
       [-3.39969880e-01,  1.29819641e+00],
       [-1.52776995e+00,  5.45786891e-01],
       [ 1.18883984e+00,  1.62040035e-01],
       [ 1.17199076e+00, -2.56295112e-01],
       [-1.80315140e+00,  2.03785098e+00],
       [-1.77358023e+00,  1.05339867e+00],
       [ 8.18943051e-01,  3.89841660e-01],
       [ 1.40978812e+00,  7.29833198e-01],
       [ 6.91775496e+00,  4.84984369e+00],
       [ 7.33210319e-01, -9.48674314e-02],
       [-2.13600867e+00,  3.42733042e-01],
       [-2.97988525e+00,  2.16622419e-01],
       [ 1.23082842e+00,  1.60174864e+00],
       [ 1.10860101e+00,  1.00931426e+00],
       [-3.41225513e+00,  5.61468514e-01],
       [ 3.67954260e+00,  4.76548605e+00],
       [-1.95392747e+00,  1.38338452e+00],
       [ 8.99775055e-01,  4.16479781e-01],
       [-3.80928795e-01,  1.01773629e-01],
       [ 5.09539453e-01,  1.61658340e-01],
       [-9.44975538e-01,  5.29799562e-01],
       [ 1.02668389e+00, -2.57641566e-01],
       [-2.32870156e-01, -2.81027769e-01],
       [-2.92054051e+00,  8.93270294e-01],
       [-1.83719774e+00, -1.61366899e+00],
       [-1.04337471e+00,  1.00284112e+00],
       [-1.30708985e+00, -7.89048631e-01],
       [ 3.37915727e+00,  1.15702442e-01],
       [ 1.81574666e+00, -1.58472369e+00],
       [-3.45016774e+00,  9.69922452e-01],
       [-4.91206615e+00, -9.44986846e-02],
       [ 3.72119513e+00, -1.44725498e+00],
       [ 1.12738665e+00,  4.91611136e-01],
       [-2.36034718e+00, -4.79399646e-01],
       [ 1.16378429e+00,  1.11527620e+00],
       [ 1.17846224e-01,  3.61031140e-01],
       [-2.06354519e-02, -1.08661741e+00],
       [-7.82745871e-01, -9.64980905e-02],
       [ 1.21782754e+00, -6.59168961e-01],
       [ 1.81406748e+00, -1.45088654e+00],
       [ 4.24229634e+00, -1.95603674e-01],
       [ 5.72792704e-01, -6.37384843e-01],
       [ 1.63761544e-01, -1.06667848e+00],
       [-1.67970356e+00, -1.00162862e+00],
       [-5.62897632e-01, -2.21043960e-02],
       [ 8.55935813e-01, -1.83440759e-01],
       [-1.91217031e+00,  9.15599347e-02],
       [ 8.32420187e-01, -8.69325996e-01],
       [ 1.60259775e+00,  2.93912057e+00],
       [-3.38162479e+00, -2.36301516e-01],
       [ 5.78337630e+00,  6.68209028e+00],
       [ 2.02972370e+00,  1.05040745e+00],
       [ 2.27949171e+00,  1.95275226e-01],
       [-8.06209136e-01,  1.30349059e+00],
       [-1.19183736e+00, -5.56757164e-01],
       [ 1.91806245e+00, -4.27468245e-01],
       [ 2.01919721e+00, -1.78438246e+00],
       [-5.75572155e-01, -9.97551478e-01],
       [ 2.66234652e-02, -1.60640815e-02],
       [-2.31942387e+00, -7.69407328e-01],
       [ 1.71674731e-01, -9.48076409e-02],
       [ 2.81832286e+00, -9.14480968e-01],
       [ 4.08854413e+00, -4.29461909e-01],
       [-1.24446436e+00, -2.89174316e-02],
       [-2.55404919e+00, -2.15027956e-01],
       [ 9.26092707e-01,  8.28230655e-01],
       [-2.37197047e+00, -1.17751295e+00],
       [-1.99764225e+00,  9.58361586e-01],
       [-7.55008538e-01, -8.78938568e-02],
       [ 6.02231612e-01,  1.73435708e-01],
       [ 4.01437705e-01, -1.41198973e+00],
       [-4.63936165e-01,  1.29187347e+00],
       [-2.85483624e+00, -3.52082382e-01],
       [ 3.02299800e-01, -9.75710669e-02],
       [ 2.42714125e+00,  1.15181307e+00],
       [ 2.06798993e+00, -1.53531349e+00],
       [ 2.64120583e+00, -2.99736446e+00],
       [ 6.17312598e-01, -1.43047723e+00],
       [-8.53528944e-01, -6.54485112e-01],
       [-8.20631131e-01,  6.39570072e-01],
       [-5.51035564e-01, -1.23388618e+00],
       [ 4.98524385e-01,  1.39074432e+00],
       [-1.88745106e+00, -1.09453015e-01],
       [-2.86406392e+00,  4.85997985e-01]])
```

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

In [17]:
```
plt.scatter(x = X_pca[:, 0], y = X_pca[:, 1])
plt.xlabel("PC1")
plt.xlabel("PC2")
plt.title("Score Plot")
plt.show
```

Out[17]:
```
&lt;function matplotlib.pyplot.show(close=None, block=None)&gt;
```



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

In [18]:
```
loadings = pca.components_
```

In [19]:
```
np.sum(loadings** 2 ,axis = 0 )
```

Out[19]:
```
array([0.21320078, 0.45656697, 0.08184323, 0.47741956, 0.15926317,
       0.03738641, 0.23093748, 0.18709439, 0.15628802])
```

In [20]:
```
feature_name = df.columns[1:]
```

In [21]:
```
features_importance = pd.DataFrame(np.sum(loadings** 2 ,axis = 0))
```

In [26]:
```
features_importance.index =  feature_name
```

In [29]:
```
features_importance.sort_values(0, ascending = False)
```

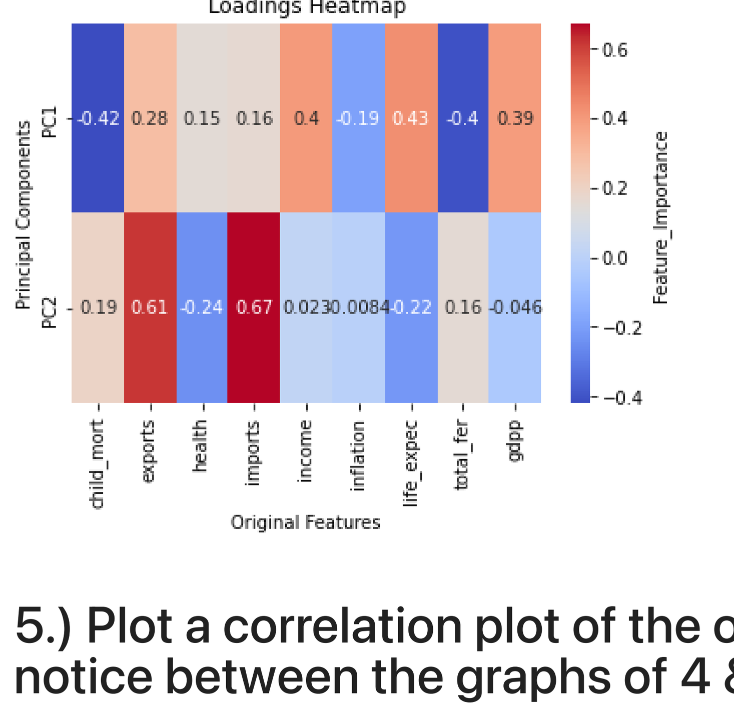
Out[29]:

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

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

In [30]:
```
feature_names = df.columns[1:]
```

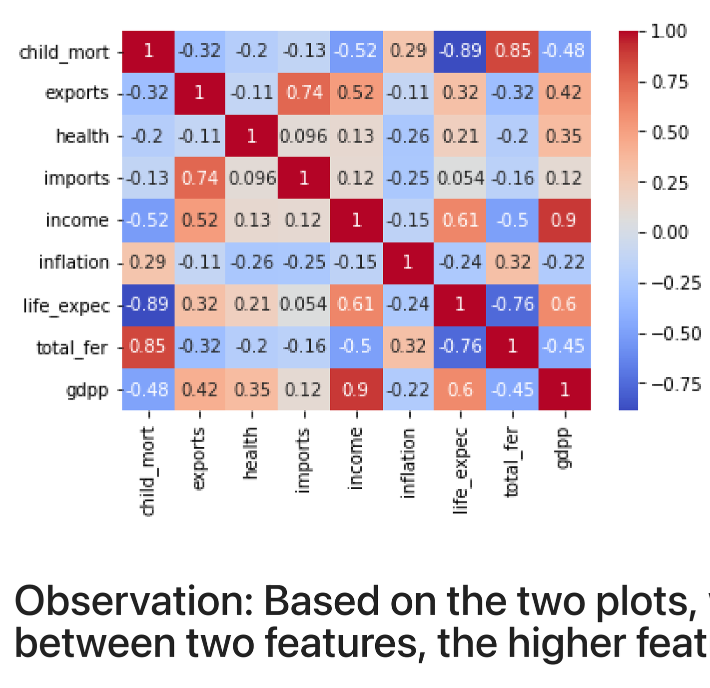
In [33]:
```
sns.heatmap(loadings, annot = True, cmap = 'coolwarm', xticklabels = feature_names, yticklabels = ["PC1", "PC2"
plt.xlabel('Original Features')
plt.ylabel('Principal Components')
plt.title('Loadings Heatmap')
plt.show()
```



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

In [34]:
```
sns.heatmap(X.corr(), cmap = 'coolwarm', annot = True)
plt.plot()
```

Out[34]:
```
[]
```



Observation: Based on the two plots, we could see that the higher correlation between two features, the higher feature importance it owns on the plot 5.

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?

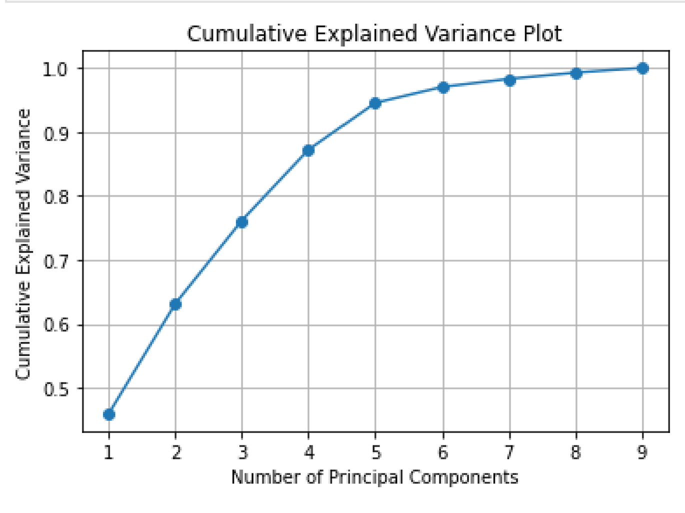
In [36]:
```
pca = PCA(n_components = 9)
X_pca = pca.fit_transform(X_scaled)
pca.explained_variance_ratio_
```

Out[36]:
```
array([0.4595174 , 0.17181626, 0.13004259, 0.11053162, 0.07340211,
       0.02484235, 0.0126043 , 0.00981282, 0.00743056])
```

In [42]:
```
cumulative_explained_variance = pca.explained_variance_ratio_.cumsum()

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()
```



From the plot above, we could see that with threshold of 0.95, the principal components would be 5.