Homework - 1

In [1]:
```
# importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
%matplotlib inline
```

In [30]:
```
# Importing Dataset
path = "Utilities.csv"
df=pd.read_csv(path)
```

1. Compute the minimum, maximum, mean, median, and standard deviation for each of the numeric variables. Which variable(s) has the largest variability? Explain your answer

In [2]:
```
df.describe().transpose()[['min','max','mean','50%','std' ]].transpose()
```

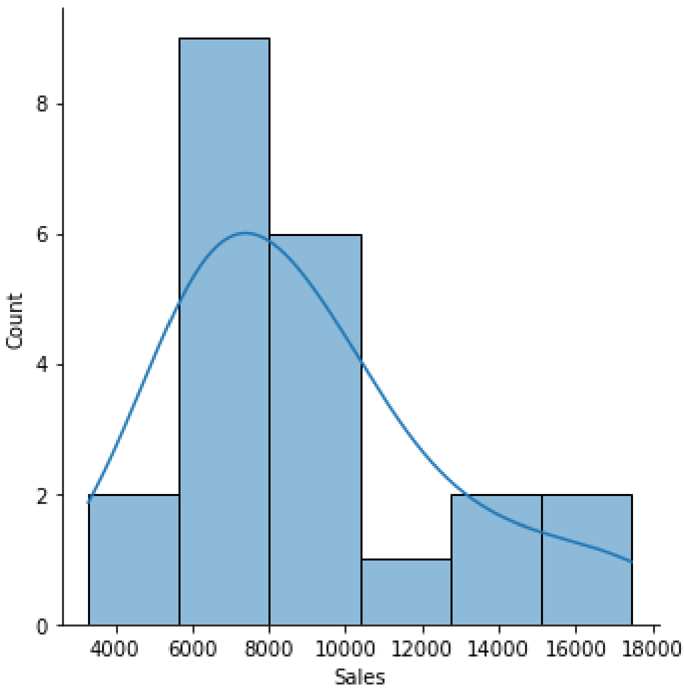
Out[2]:

	Fixed_charge	RoR	Cost	Load_factor	Demand_growth	Sales	Nuclear	Fuel_Cost
min	0.750000	6.400000	96.000000	49.800000	-2.200000	3300.000000	0.00000	0.309000
max	1.490000	15.400000	252.000000	67.600000	9.200000	17441.000000	50.20000	2.116000
mean	1.114091	10.736364	168.181818	56.977273	3.240909	8914.045455	12.00000	1.102727
50%	1.110000	11.050000	170.500000	56.350000	3.000000	8024.000000	0.00000	0.960000
std	0.184511	2.244049	41.191349	4.461148	3.118250	3549.984031	16.79192	0.556098

In [3]:
```
# Distribution Graph for Sales Variable

sns.displot(df, x="Sales", kde=True)
```

Out[3]: <seaborn.axisgrid.FacetGrid at 0x1eb67a9cbb0>



The above data frame describes the statistics of the given dataset. It can be seen that Sales variable has the highest variability followed by Cost and Nuclear. Their standard deviations are, 3549.98, 41.19 and 16.79 respectively. The range among these three as seen above is also high.

2. Create boxplots for each of the numeric variables. Are there any extreme values for any of the variables? Which ones? Explain your answer

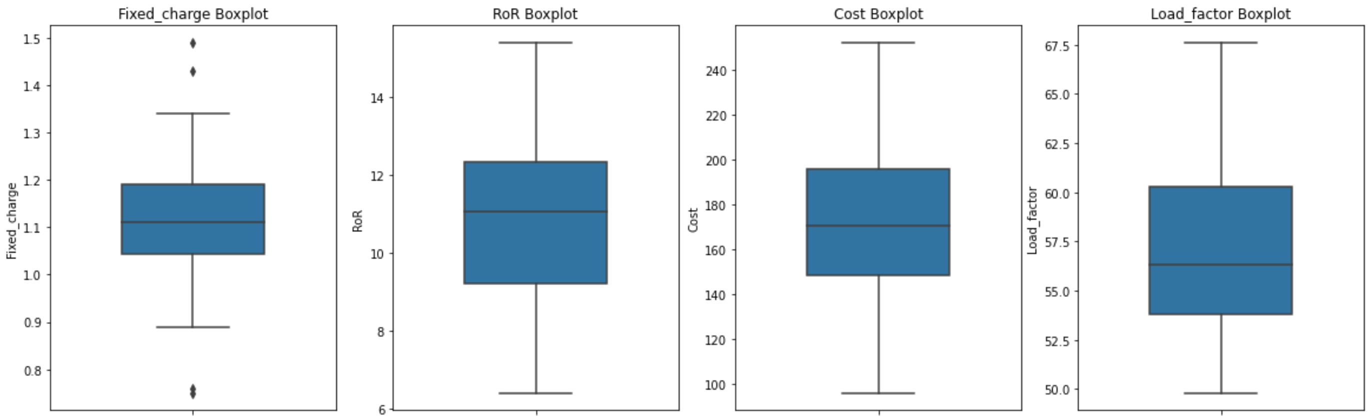
In [4]:
```
plt.figure(figsize=(10,6))
f, axes = plt.subplots(1, 4,figsize=(20,6))

sns.boxplot(y='Fixed_charge', data=df,  orient='v' , ax=axes[0],width=.5)
sns.boxplot(  y="RoR",  data=df,  orient='v' , ax=axes[1],width=.5)
sns.boxplot(  y="Cost",  data=df,  orient='v' , ax=axes[2],width=.5)
sns.boxplot(  y="Load_factor", data=df,  orient='v' , ax=axes[3], width=.5)


axes[0].set_title('Fixed_charge Boxplot')
axes[1].set_title('RoR Boxplot')
axes[2].set_title('Cost Boxplot')
axes[3].set_title('Load_factor Boxplot')
```

Out[4]:
```
Text(0.5, 1.0, 'Load_factor Boxplot')

<Figure size 720x432 with 0 Axes>
```

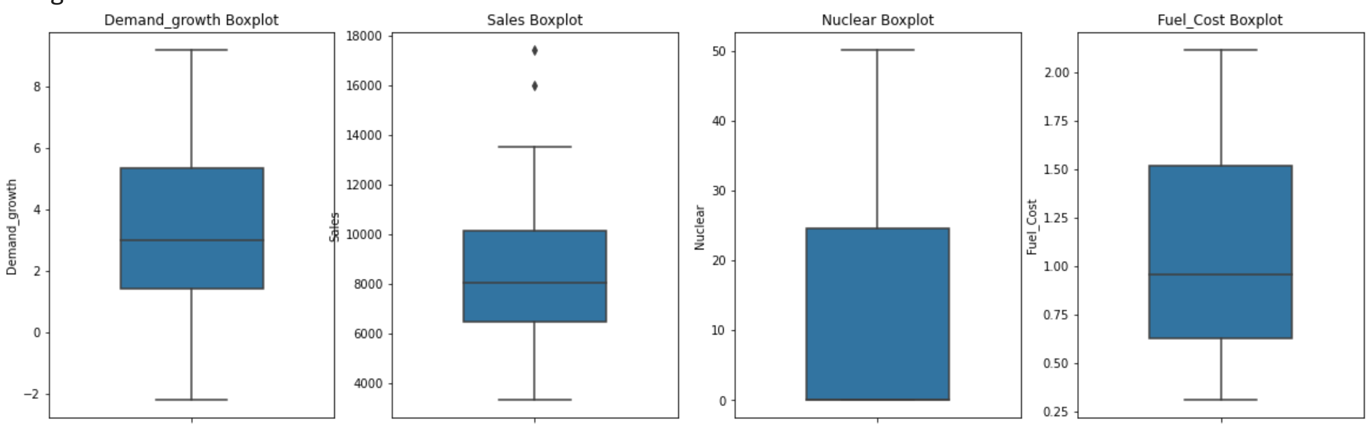


In [5]:
```
plt.figure(figsize=(10,6))
f, axes1 = plt.subplots(1, 4,figsize=(20,6))
sns.boxplot(  y="Demand_growth",  data=df,  orient='v' , ax=axes1[0], width=.5)
sns.boxplot(  y="Sales",  data=df,  orient='v' , ax=axes1[1], width=.5)
sns.boxplot(  y="Nuclear",  data=df,  orient='v' , ax=axes1[2], width=.5)
sns.boxplot(  y="Fuel_Cost",  data=df,  orient='v' , ax=axes1[3], width=.5)

axes1[0].set_title('Demand_growth Boxplot')
axes1[1].set_title('Sales Boxplot')
axes1[2].set_title('Nuclear Boxplot')
axes1[3].set_title('Fuel_Cost Boxplot')
```

Out[5]:
```
Text(0.5, 1.0, 'Fuel_Cost Boxplot')

<Figure size 720x432 with 0 Axes>
```



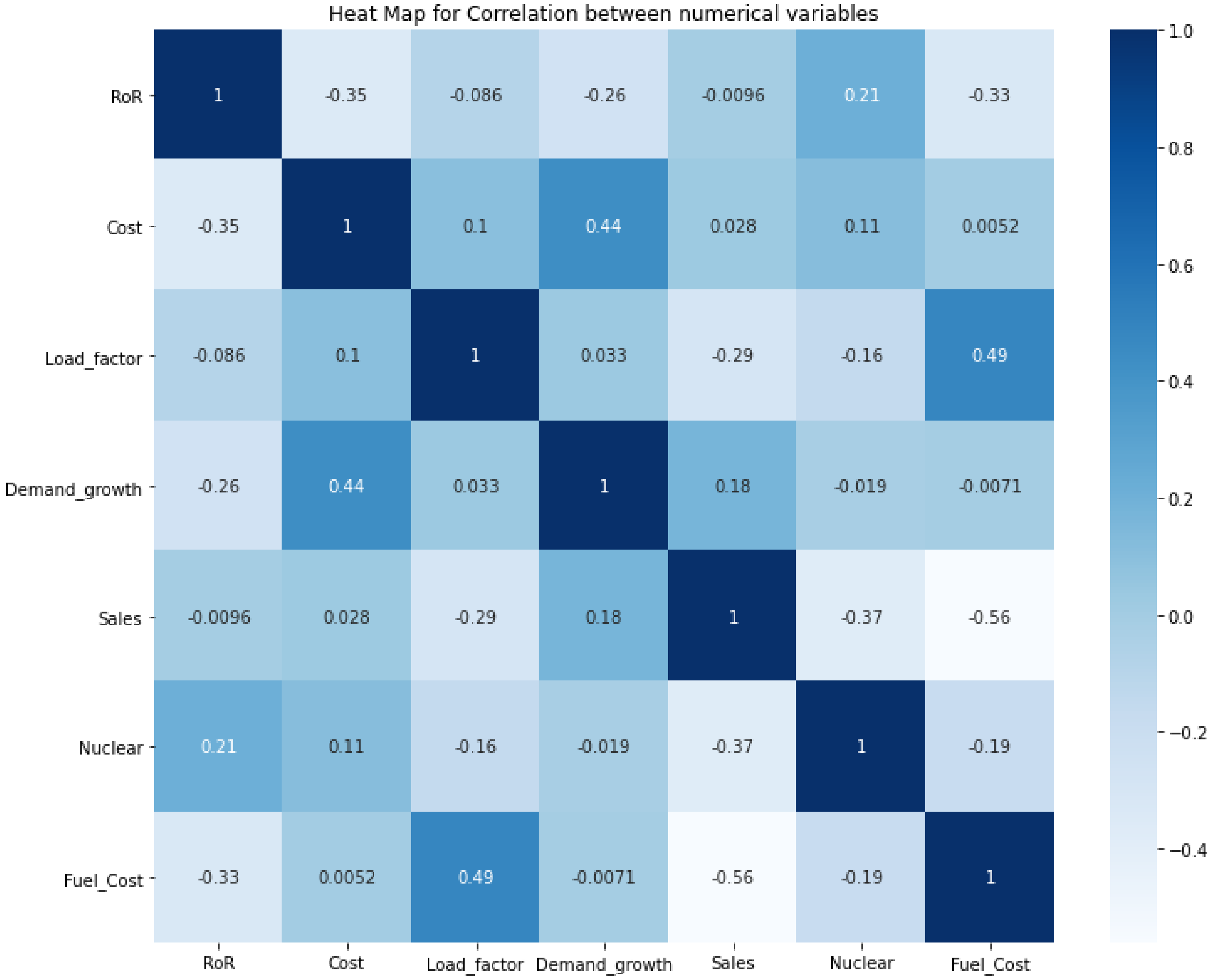
The box plot is a useful graphical display for describing the behavior of the data in the middle as well as at the ends of the distribution. In this extreme value is defined as being any point of data that lies over 1.5 Interquartile Ranges(IQRs) below the first quartile (Q1) or above the third quartile (Q3)in a dataset. From the boxplots above, it can be deduced that, there exists extreme values for Fixed Charge and Sales variables.

3. Create a heatmap for the numeric variables. Discuss any interesting trend you see in this chart

In [6]:
```python
df_corr = df[['RoR', 'Cost', 'Load_factor','Demand_growth', 'Sales', 'Nuclear', 'Fuel_Cost']].c
```

In [7]:
```python
plt.figure(figsize=(12, 10))
plt.title("Heat Map for Correlation between numerical variables")
sns.heatmap(df_corr, annot=True, cmap = 'Blues')
```

Out[7]:
```
<AxesSubplot:title={'center':'Heat Map for Correlation between numerical variables'}>
```



Heatmap defines a graphical representation of data using colours to visualize the values of the matrix. From the generated Heat Map, it is observed that there is no high correlation between any two variables of the given data.

Few trends observed are as below:

1. Increase in Fuel_Cost will reduce the Sales.

2. Demand_growth is directly proportional to Cost.

4. Run principal component analysis using unscaled numeric variables in the dataset. How do you interpret the results from this model?

In [8]:
```python
from sklearn.decomposition import PCA
```

In [9]:
```python
# Considering the Data Frame with Numeric Columns
df_numeric=df[['Fixed_charge','RoR', 'Cost', 'Load_factor','Demand_growth', 'Sales', 'Nuclear',
```

In [10]:
```python
# Creating a PCA instance
pca_unscaled = PCA(random_state=123)
```

In [11]:
```python
# Fitting the PCA instance with the Numeric Data
pca_unscaled.fit_transform(df_numeric)
```

Out[11]:
```
array([[ 1.62970630e+02, -1.79353052e+01, -1.04572018e+01,
         3.45164170e+00, -6.54123147e-01, -1.46872249e+00,
         6.05027764e-01,  5.41851733e-02],
       [-3.82605202e+03,  3.53468643e+01,  4.52867453e+00,
         4.99144559e-01, -1.52416994e+00, -3.20465032e-01,
        -1.83225799e-01, -2.73741800e-01],
       [ 2.97958767e+02, -5.59421815e+01, -7.69274676e+00,
         3.80099450e+00,  1.25021270e+00,  4.40941092e+00,
        -2.30122351e-01,  1.66194069e-02],
       [-2.49108077e+03,  1.56709874e+00,  1.79505003e+01,
         3.20756246e-01, -2.42465371e+00, -7.50899921e-01,
         3.36218996e-01, -8.81526806e-02],
       [-5.61403289e+03,  2.51097679e+01, -7.05996451e+00,
         8.93521908e+00, -1.49844508e+00, -1.30312403e+00,
        -5.61027235e-01,  2.83879542e-01],
       [ 2.21291169e+03, -5.71046945e+01,  1.73498478e+01,
        -5.97553893e+00, -4.25704055e+00, -6.88402991e-02,
        -5.50734312e-01,  9.54513477e-02],
       [-1.27202393e+03,  6.43211222e+00, -1.54785295e+01,
        -8.61767985e+00, -1.95418714e+00,  1.60281377e+00,
        -9.92682538e-02,  8.22658656e-03],
       [ 4.16799372e+03,  7.50283565e+01, -9.07500063e+00,
         3.59218407e-01, -3.06392932e+00, -3.23017743e-01,
         5.25780843e-01,  6.23794772e-02],
       [-5.08024060e+02, -6.50881316e-01, -1.30335875e+01,
        -2.26929595e+00,  3.24168342e+00,  3.50235074e+00,
         3.91198582e-01,  1.36381467e-01],
       [-2.45907862e+03,  3.07986333e+01,  2.15585111e+01,
         3.17412804e+00, -1.18725482e+00,  1.22149429e+00,
         1.81027954e-01, -9.80142037e-02],
       [ 8.52696540e+03,  2.32096246e+00,  3.01947693e+00,
         2.09466580e+00,  2.61674027e+00, -2.77194700e+00,
        -2.77558614e-01, -1.23260787e-01],
       [-2.76001819e+03,  9.76449461e+00, -1.77573127e+01,
        -2.26995422e+00,  1.71294191e-01,  1.03644026e+00,
        -2.64758118e-01, -7.04403307e-02],
       [-1.73509831e+03,  3.34046424e+01,  3.35554803e+01,
         8.81822918e-01,  2.21425665e+00,  1.71746615e+00,
         1.21605041e-01, -1.60262633e-02],
       [ 7.58953376e+02, -7.30389300e+01, -5.74507057e+00,
         6.65057627e+00,  6.78323754e-01,  5.05500002e-01,
         3.34559422e-01, -7.15714489e-02],
       [-2.44602546e+03, -4.27725517e+00, -1.56580548e+01,
        -2.65393294e+00, -2.43151054e+00, -3.21604336e+00,
         3.89217527e-01,  2.05281054e-02],
       [ 7.07699230e+03,  8.15366228e+01, -4.31876036e+00,
        -4.05567296e-01,  1.93551935e+00,  1.31952852e+00,
        -9.74203835e-02,  9.32051000e-02],
       [-3.20004487e+03, -3.12880153e+01, -8.09977852e+00,
        -3.63862639e+00,  7.88094675e+00, -3.19458468e+00,
         6.11298091e-02, -2.23102810e-02],
       [ 1.22596778e+03, -1.91694489e+01, -8.64675333e+00,
         4.16945938e-01, -4.93375384e-01,  1.81197455e+00,
        -9.90369117e-02, -1.91236352e-01],
       [ 4.59294741e+03, -6.59683526e+01,  5.94538082e-02,
         8.01241530e-01, -3.73687641e+00, -9.97696280e-01,
         9.08910370e-03,  3.32148971e-02],
       [-1.62710168e+03, -1.80364971e+01,  2.69716662e+01,
        -5.20172473e+00,  1.00644553e+00, -3.23353946e-01,
         2.88055212e-01,  1.60976761e-01],
       [-2.26401026e+03,  3.56149728e+01, -1.83694048e+01,
        -1.00109768e+00, -4.99696236e-01, -9.14805707e-01,
        -4.40749541e-01, -6.93541315e-02],
       [ 1.17893000e+03,  6.48703367e+00,  1.63985547e+01,
         6.47062978e-01,  2.72983967e+00, -1.47347874e+00,
        -4.39008735e-01,  5.90604146e-02]])
```

In [12]:
```
# Explained Variance of all the components
pca_unscaled.explained_variance_
```

Out[12]:
```
array([1.26024294e+07, 1.70314141e+03, 2.40006760e+02, 1.60079553e+01,
       7.74357721e+00, 3.90691089e+00, 1.22582078e-01, 1.49908933e-02])
```

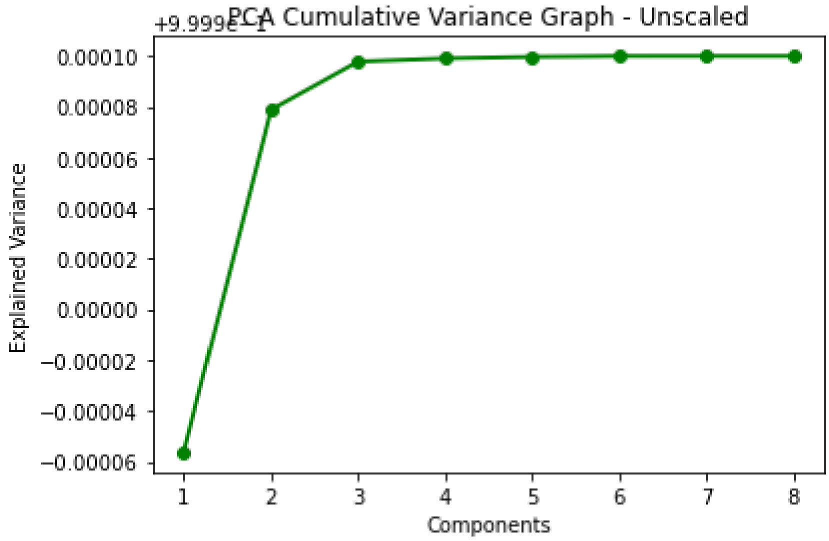
In [13]:
```
# Explained Variance Ratio of all the components
pca_unscaled.explained_variance_ratio_
```

Out[13]:
```
array([9.99843630e-01, 1.35122764e-04, 1.90415057e-05, 1.27002911e-06,
       6.14355068e-07, 3.09964043e-07, 9.72533993e-09, 1.18933808e-09])
```

In [14]:
```
# Cumulative Explained Variance Ratio of all the components
pca_unscaled.explained_variance_ratio_.cumsum()
```

Out[14]:
```
array([0.99984363, 0.99997875, 0.99999779, 0.99999906, 0.99999968,
       0.99999999, 1.        , 1.        ])
```

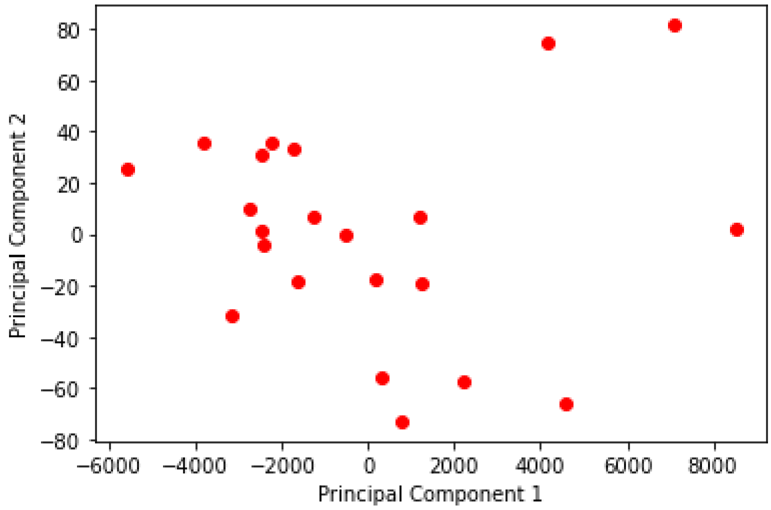
In [15]:
```
comp_count = np.arange(pca_unscaled.n_components_) + 1
plt.plot(comp_count, pca_unscaled.explained_variance_ratio_.cumsum(), 'o-', linewidth=2, color=
plt.title('PCA Cumulative Variance Graph - Unscaled')
plt.xlabel('Components')
plt.ylabel('Explained Variance')
plt.show()
```



In [16]:
```
pca_unscaled_main = PCA(n_components=2, random_state=123)

#Plotting the PCA components without scaling the numeric variables
pca_components = pca_unscaled_main.fit_transform(df_numeric)
pca_componentsDF=pd.DataFrame(data=pca_components, columns=['principal component 1', 'principal
plt.scatter('principal component 1', 'principal component 2', data=pca_componentsDF, color='r')
plt.ylabel('Principal Component 2')
plt.xlabel('Principal Component 1')
```

Out[16]:
```
Text(0.5, 0, 'Principal Component 1')
```



In [17]:
```
print(pca_unscaled_main.explained_variance_ratio_)
```

```
[9.99843630e-01 1.35122764e-04]
```

PCA is a great technique for visualization and a tool for reducing data dimensionality while preseving the information as much information as possible. In implementing the PCA above, we selected two Principal Components. From the visualization above, there exists there exists two 'clusters' where over 99% of the data points lies in one cluster. As show above, PC1 accounts for 99.98% of the information in the dataset, hence a single component could be used.

5. Next, run principal component model after scaling the numeric variables.

In [18]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [19]:
```
# Creating a MinMax Scaler instance
scaler = MinMaxScaler()
```

In [20]:
```
# Scaling the Numeric Data
data_scaled = scaler.fit_transform(df_numeric)
```

In [21]:
```
# Creating a PCA instance
pca_scaled = PCA(random_state=123)
```

In [22]:
```
# Fitting the instance with Scaled Data
pca_scaled.fit_transform(data_scaled)
```

Out[22]:
```
array([[-7.84533084e-02,  2.27673248e-01, -2.09358938e-01,
        -2.16632333e-01,  1.07613332e-01,  5.93883378e-02,
        -1.97107444e-01, -1.09005190e-01],
       [ 2.26870009e-01, -2.59091795e-01,  3.65289555e-01,
        -1.92290539e-01,  3.59000122e-02,  1.14001293e-01,
        -3.16056011e-02,  2.31994952e-01],
       [-3.97205792e-01, -1.52721777e-01, -5.16955881e-01,
         3.16407999e-01,  1.12740316e-02, -3.56177948e-01,
        -3.48144358e-02,  8.68811046e-02],
       [-3.43182747e-01, -2.26297655e-01,  2.83338908e-01,
        -2.72440993e-01, -2.95134313e-02,  1.85636059e-01,
        -8.23199859e-02,  2.87405722e-02],
       [ 1.81856735e-01, -5.42278797e-01,  3.84897689e-02,
         1.23055849e-01,  7.18325434e-01, -1.63008069e-01,
         4.99609598e-02, -1.30032094e-01],
       [-3.59141140e-01, -4.61902638e-01, -3.66519399e-01,
        -5.15520576e-02, -1.54164010e-01,  1.54677018e-01,
         3.28541791e-01, -4.28612154e-02],
       [ 3.98542610e-01, -3.22457776e-01, -2.71358849e-01,
         3.20894318e-01, -2.64949105e-01,  2.44641018e-01,
         3.41074633e-02,  1.79981436e-02],
       [-5.03794851e-02,  5.93979022e-01,  6.71941463e-02,
         1.86254905e-01,  1.53331758e-01,  4.22670070e-01,
```

```
        -9.60592504e-02, -5.50220980e-02],
       [-2.41163383e-02,  6.44882102e-02, -1.45222835e-01,
         5.15833918e-01, -2.04219163e-01, -1.37706355e-01,
        -1.70376767e-01, -9.27981529e-02],
       [-4.85518612e-01, -1.63346602e-01,  4.74066558e-01,
        -2.42221978e-02,  7.72166263e-02,  5.94467256e-02,
        -8.68373545e-02,  1.00330431e-01],
       [ 1.10674719e-01,  9.09642174e-01,  3.65497536e-02,
        -3.23479038e-01,  1.56781798e-02, -1.27997540e-01,
         1.95335681e-01,  5.79637151e-02],
       [ 5.01570991e-01, -2.52140666e-01, -1.32591815e-01,
         1.75904594e-01, -3.73138484e-02, -1.15933736e-02,
        -1.66630037e-02,  9.46960519e-02],
       [-5.54054016e-01, -1.02714872e-01,  7.37386529e-01,
         1.22293814e-01, -8.50241420e-02, -1.04878291e-01,
        -1.69979230e-02,  2.36198128e-02],
       [-4.05143407e-01,  1.52404260e-01, -4.46670296e-01,
        -2.87141058e-01,  5.51769316e-02, -2.48482578e-01,
        -1.71660119e-01,  3.32344598e-02],
       [ 4.60351920e-01, -1.16507925e-01, -1.57571146e-01,
        -2.96902243e-01, -1.47925731e-04,  2.85181108e-01,
        -1.10764573e-01, -1.06293366e-01],
       [ 5.81006088e-02,  8.00735190e-01,  2.06951826e-01,
         5.00067997e-01,  6.80038010e-02,  5.38968566e-02,
         1.05143888e-01, -1.89639973e-02],
       [ 8.30142138e-01,  3.78192147e-02,  2.49151289e-01,
        -2.97763435e-01, -3.03900230e-01, -3.82675695e-01,
        -5.16415346e-02, -1.17455811e-01],
       [-2.15989680e-02,  7.65920869e-02, -2.80994161e-01,
         3.29342506e-03, -9.29800894e-02, -3.90642936e-02,
        -2.88987590e-02,  1.86590383e-01],
       [-4.05311045e-01,  1.21837669e-01, -6.17781973e-01,
        -2.77677148e-01,  2.32795633e-02,  1.08294305e-01,
         9.83735535e-02, -3.96378154e-02],
       [-3.79740508e-01, -3.02319378e-01,  3.42071710e-01,
        -8.38871482e-03, -2.79393897e-01,  3.28953125e-02,
         3.60429036e-02, -1.92306018e-01],
       [ 7.14478093e-01, -1.49905255e-01,  2.89736444e-03,
         5.56374127e-02,  1.33488009e-01,  5.58703311e-02,
         5.33960445e-02,  8.97099536e-02],
       [ 2.12575415e-02,  6.65140612e-02,  3.41637885e-01,
        -7.11544742e-02,  5.23181625e-02, -2.05014291e-01,
         1.94844465e-01, -4.73838221e-02]])
```

In [23]:
```
# Explained Variance of all the components
pca_scaled.explained_variance_
```

Out[23]:
```
array([0.15962678, 0.13850169, 0.12242111, 0.06788535, 0.0434142 ,
       0.04136963, 0.01676391, 0.01133132])
```

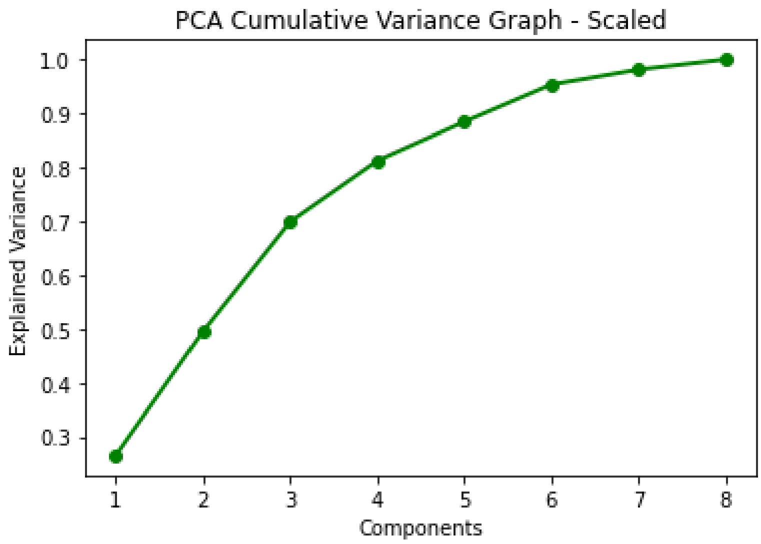
In [24]:
```
# Explained Variance Ratio of all the components
pca_scaled.explained_variance_ratio_
```

Out[24]:
```
array([0.26546327, 0.23033172, 0.20358933, 0.11289501, 0.07219888,
       0.06879872, 0.0278788 , 0.01884427])
```

In [25]:
```
# Cumulative Explained Variance Ratio of all the components
pca_scaled.explained_variance_ratio_.cumsum()
```

Out[25]:
```
array([0.26546327, 0.495795  , 0.69938432, 0.81227933, 0.88447821,
       0.95327693, 0.98115573, 1.        ])
```

In [26]:
```
comp_count = np.arange(pca_scaled.n_components_) + 1
plt.plot(comp_count, pca_scaled.explained_variance_ratio_.cumsum(), 'o-', linewidth=2, color='g
plt.title('PCA Cumulative Variance Graph - Scaled')
plt.xlabel('Components')
plt.ylabel('Explained Variance')
plt.show()
```

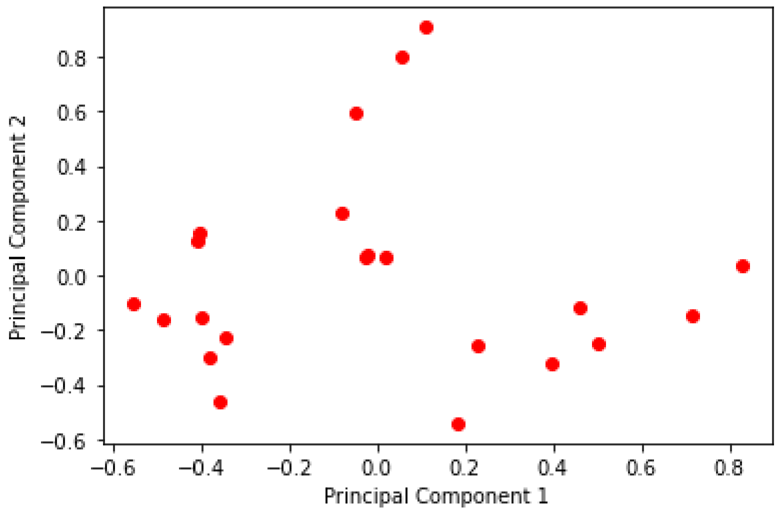


From the above Graph, it is understood that almost 90% of the Explained Variance can be obtained by the first five components. The Cumulative Sum of the Explained Variance for these components is 88.44. Hence, a new PCA instance is created with n_components = 5 and fit with scaled data.

In [27]:
```
pca_scaled_main = PCA(n_components=5, random_state=123)

#Plotting the PCA components without scaling the numeric variables
pca_components_scaled = pca_scaled_main.fit_transform(data_scaled)
pca_components_scaled_DF=pd.DataFrame(data=pca_components_scaled, columns=['principal component
plt.scatter('principal component 1', 'principal component 2', data=pca_components_scaled_DF, co
plt.ylabel('Principal Component 2')
plt.xlabel('Principal Component 1')
```

Out[27]:
```
Text(0.5, 0, 'Principal Component 1')
```



In [28]:
```
print(pca_scaled_main.explained_variance_ratio_)
```

```
[0.26546327 0.23033172 0.20358933 0.11289501 0.07219888]
```

Did the results/interpretations change? How so? Explain your answers.

The results/Interpretations changed.

With the unscaled data, 99% of the Explained Variance is obtained by one component itself.

But, 90% of the Explained Variance for the Scaled data is achieved by five components.

For this dataset, the dimensionality reduction using PCA performed better without scaling the data.