

```
In [1]: #Import data and packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.decomposition import PCA

file = 'C:/Users/cdric/OneDrive/Desktop/School/d212/medical_clean.csv'
data = pd.read_csv(file, na_values='NA') #replace NA values with NaN
data.head()
```

```
Out[1]:
```

	CaseOrder	Customer_id	Interaction	UID	City	State	Co
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Mc
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Ja
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minne
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	W
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	W

5 rows × 50 columns

```
In [2]: #Make sure that there are no null values
print(data.isnull().sum())
```

```

CaseOrder      0
Customer_id    0
Interaction    0
UID            0
City           0
State          0
County         0
Zip            0
Lat            0
Lng            0
Population     0
Area           0
TimeZone       0
Job            0
Children       0
Age            0
Income         0
Marital        0
Gender         0
ReAdmis        0
VitD_levels    0
Doc_visits     0
Full_meals_eaten 0
vitD_supp      0
Soft_drink     0
Initial_admin  0
HighBlood      0
Stroke         0
Complication_risk 0
Overweight     0
Arthritis      0
Diabetes       0
Hyperlipidemia 0
BackPain       0
Anxiety        0
Allergic_rhinitis 0
Reflux_esophagitis 0
Asthma         0
Services       0
Initial_days   0
TotalCharge    0
Additional_charges 0
Item1          0
Item2          0
Item3          0
Item4          0
Item5          0
Item6          0
Item7          0
Item8          0
dtype: int64

```

```

In [3]: #These columns appear to be unique to the patient and procedures so we are checking if
print(data['CaseOrder'].is_unique)
print(data['Customer_id'].is_unique)
print(data['Interaction'].is_unique)
print(data['UID'].is_unique)

```

True  
True  
True  
True

```
In [4]: #https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=60fa4159-94ba-4f41-9ba8-c
##Steps: 1) Standardize, 2) Compute covariance, 3) Compute eigen vectors and values 4)
```

```
In [5]: #Create set with only continuous variables
##Population, Income, VitD_levels, Initial_days, TotalCharge, Additional_charges, Age

cont_data=data[['Population', 'Income', 'VitD_levels', 'Initial_days', 'TotalCharge',
print(cont_data)
```

	Population	Income	VitD_levels	Initial_days	TotalCharge	\
0	2951	86575.93	19.141466	10.585770	3726.702860	
1	11303	46805.99	18.940352	15.129562	4193.190458	
2	17125	14370.14	18.057507	4.772177	2434.234222	
3	2162	39741.49	16.576858	1.714879	2127.830423	
4	5287	1209.56	17.439069	1.254807	2113.073274	
...	...	...	...	...	...	...
9995	4762	45967.61	16.980860	51.561220	6850.942000	
9996	1251	14983.02	18.177020	68.668240	7741.690000	
9997	532	65917.81	17.129070	70.154180	8276.481000	
9998	271	29702.32	19.910430	63.356900	7644.483000	
9999	41524	62682.63	18.388620	70.850590	7887.553000	

	Additional_charges	Age
0	17939.403420	53
1	17612.998120	51
2	17505.192460	53
3	12993.437350	78
4	3716.525786	22
...	...	...
9995	8927.642000	25
9996	28507.150000	87
9997	15281.210000	45
9998	7781.678000	43
9999	11643.190000	70

[10000 rows x 7 columns]

```
In [6]: #Scale Data

scaler=StandardScaler()
scaled_data = scaler.fit_transform(cont_data)
scaled_data = pd.DataFrame(scaled_data, columns = ['Population', 'Income', 'VitD_level',
'TotalCharge', 'Additional_charges',
print(scaled_data.head())
```

	Population	Income	VitD_levels	Initial_days	TotalCharge \
0	-0.473168	1.615914	0.583603	-0.907310	-0.727185
1	0.090242	0.221443	0.483901	-0.734595	-0.513228
2	0.482983	-0.915870	0.046227	-1.128292	-1.319983
3	-0.526393	-0.026263	-0.687811	-1.244503	-1.460517
4	-0.315586	-1.377325	-0.260366	-1.261991	-1.467285

	Additional_charges	Age
0	0.765005	-0.024795
1	0.715114	-0.121706
2	0.698635	-0.024795
3	0.009004	1.186592
4	-1.408991	-1.526914

```
In [7]: #Extract cleaned data from Jupyter to desktop
scaled_data.to_csv(r'C:\Users\cdric\OneDrive\Desktop\School\d212\D212Task 2\scaled_mec
```

```
In [8]: #Perform PCA
pca_all = PCA(n_components = 7, random_state=42)
pc=pca_all.fit_transform(scaled_data)
print(pc)
```

```
[[-1.12949397  0.65171606  0.70603764 ...  1.60387358 -0.56744533
  0.09987943]
 [-0.82819815  0.52529657 -0.14860596 ...  0.39259784 -0.5969337
  0.1261863 ]
 [-1.63037103  0.68340864 -0.61460571 ... -0.82203778 -0.49984235
 -0.16371901]
 ...
 [ 1.86880505 -0.27460709  0.84720546 ...  0.62818536 -0.55110214
 -0.01949778]
 [ 1.40213738 -1.04930053 -1.04038589 ...  0.64869864  0.18497355
 -0.00593244]
 [ 1.8843154  0.13434397  0.73373261 ... -0.10636015  0.74145682
 -0.11558188]]
```

```
In [9]: #Create a dataframe to explain all continuous variable features.
pc_df = pd.DataFrame(pc,columns = ['PC1','PC2','PC3','PC4','PC5','PC6','PC7'])
print(pc_df)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
0	-1.129494	0.651716	0.706038	0.100780	1.603874	-0.567445	0.099879
1	-0.828198	0.525297	-0.148606	0.332045	0.392598	-0.596934	0.126186
2	-1.630371	0.683409	-0.614606	0.350770	-0.822038	-0.499842	-0.163719
3	-1.807875	1.068282	0.387090	-0.694423	-0.301055	0.833054	-0.120546
4	-2.142475	-1.799882	-0.932004	-0.621448	-1.008335	-0.084879	-0.134660
...	...	...	...	...	...	...	...
9995	0.771136	-1.516410	0.385633	-0.506705	-0.013706	-0.549460	0.026960
9996	2.037951	2.638300	-0.691467	-0.624637	-0.292485	-0.538032	-0.176982
9997	1.868805	-0.274607	0.847205	-0.612837	0.628185	-0.551102	-0.019498
9998	1.402137	-1.049301	-1.040386	-0.357959	0.648699	0.184974	-0.005932
9999	1.884315	0.134344	0.733733	2.118223	-0.106360	0.741457	-0.115582

[10000 rows x 7 columns]

```
In [10]: #Contribution to each of the PCs, D1
load = pd.DataFrame(pca_all.components_.T, columns = ['PC1','PC2','PC3','PC4','PC5','PC6','PC7'])
load
```

Out[10]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
<b>Population</b>	0.023764	-0.027794	0.139508	0.913250	-0.380757	0.014048	-0.000910
<b>Income</b>	-0.020681	-0.019072	0.717051	0.171784	0.674929	0.002157	0.001291
<b>VitD_levels</b>	-0.001640	0.019142	-0.682130	0.368144	0.631501	-0.001922	-0.001545
<b>Initial_days</b>	0.701091	-0.089764	0.005694	-0.015491	0.018090	0.031477	-0.706274
<b>TotalCharge</b>	0.702221	-0.079253	0.003713	-0.012829	0.017349	-0.031550	0.706491
<b>Additional_charges</b>	0.084934	0.701346	0.025860	0.022484	-0.008450	-0.705905	-0.036789
<b>Age</b>	0.084541	0.701622	0.018925	0.004898	-0.001245	0.706758	0.026259

```
In [11]: #Calc variance explained by all PCs
print('Variance explained by all 7 principal components = ', sum(pca_all.explained_variance_ratio_))

Variance explained by all 7 principal components = 100.0
```

```
In [12]: #Captured variance, less than one is not important and can be dropped
vary = pca_all.explained_variance_ratio_*100
var_df1 = pd.DataFrame(vary.round(2), columns = ['Captured Variance Per PC'], index =
var_df1
```

Out[12]:

Captured Variance Per PC	
<b>PC1</b>	28.47
<b>PC2</b>	24.49
<b>PC3</b>	14.47
<b>PC4</b>	14.30
<b>PC5</b>	14.06
<b>PC6</b>	4.05
<b>PC7</b>	0.17

```
In [13]: #Eigenvalues to determine PCs
eigenvalues = pca_all.explained_variance_
eigen_df = pd.DataFrame(eigenvalues.round(4), columns = ['Eigenvalues per PC'], index =
eigen_df
```

Out[13]:

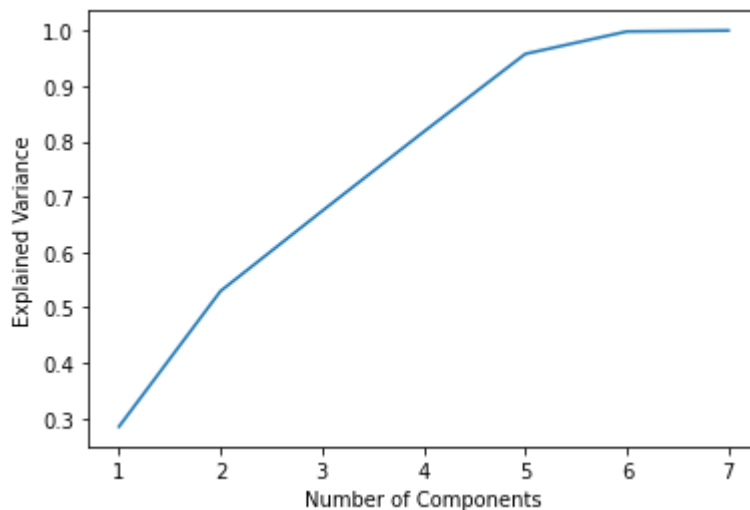
Eigenvalues per PC	
<b>PC1</b>	1.9929
<b>PC2</b>	1.7141
<b>PC3</b>	1.0128
<b>PC4</b>	1.0014
<b>PC5</b>	0.9842
<b>PC6</b>	0.2836
<b>PC7</b>	0.0117

```
In [14]: #Cumulative sum
np.cumsum(pca_all.explained_variance_ratio_*100)
```

```
Out[14]: array([ 28.46708594,  52.95208953,  67.41897126,  81.72330206,
        95.78202088,  99.83258854, 100.          ])
```

```
In [15]: #Scree plot
#Components 1-5 are most significant

plt.plot(np.cumsum(pca_all.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Explained Variance')
plt.xticks(np.arange(len(np.cumsum(pca_all.explained_variance_ratio_)),
                    np.arange(1, len(np.cumsum(pca_all.explained_variance_ratio_))+1)))
plt.show()
```



```
In [16]: #Explaining the PC variability.
print('Variance explained by the first pc =', np.cumsum(pca_all.explained_variance_ratio_)[0])
print('Variance explained by the first 2 pcs =', np.cumsum(pca_all.explained_variance_ratio_)[1])
print('Variance explained by the first 3 pcs =', np.cumsum(pca_all.explained_variance_ratio_)[2])
print('Variance explained by the first 4 pcs =', np.cumsum(pca_all.explained_variance_ratio_)[3])
print('Variance explained by all the pcs =', np.cumsum(pca_all.explained_variance_ratio_)[4])
```

```
Variance explained by the first pc = 28.467085941027054
Variance explained by the first 2 pcs = 52.95208953266629
Variance explained by the first 3 pcs = 67.41897125612338
Variance explained by the first 4 pcs = 81.72330206422662
Variance explained by all the pcs = 95.78202087830768
```

```
In [17]: #Feature reduction to 5 variables since it makes up ~95.8% of variance
pc_5 = PCA(n_components = 5, random_state=42)
pc_5.fit(scaled_data)
var_pc5=pc_5.transform(scaled_data)

pca_5 =pc_5.explained_variance_ratio_*100
var_df1 = pd.DataFrame(pca_5.round(2), columns = ['Captured Variance per PC'],
                    index = ['PC1','PC2','PC3','PC4','PC5'])
var_df1
```

Out[17]: **Captured Variance per PC**

<b>PC1</b>	28.47
<b>PC2</b>	24.49
<b>PC3</b>	14.47
<b>PC4</b>	14.30
<b>PC5</b>	14.06

In [19]: `load = pd.DataFrame(pc_5.components_.T, columns = ['PC1', 'PC2', 'PC3', 'PC4', 'PC5'], index=load.index)`

	<b>PC1</b>	<b>PC2</b>	<b>PC3</b>	<b>PC4</b>	<b>PC5</b>
<b>Population</b>	0.023764	-0.027794	0.139508	0.913250	-0.380757
<b>Income</b>	-0.020681	-0.019072	0.717051	0.171784	0.674929
<b>VitD_levels</b>	-0.001640	0.019142	-0.682130	0.368144	0.631501
<b>Initial_days</b>	0.701091	-0.089764	0.005694	-0.015491	0.018090
<b>TotalCharge</b>	0.702221	-0.079253	0.003713	-0.012829	0.017349
<b>Additional_charges</b>	0.084934	0.701346	0.025860	0.022484	-0.008450
<b>Age</b>	0.084541	0.701622	0.018925	0.004898	-0.001245

In [ ]: