Matthew Morgan
Student ID: 010471280
Data Mining II - 212
Task 2: Dimensionality Reduction Methods
Western Governor's University
Program Mentor: Mandy Rasmuson

Part I: Research Question

A. Describe the purpose of this data mining report by doing the following:

A1. Propose one question relevant to a real-world organizational situation that you will answer by using principal component analysis (PCA).

My research question for this project will be the following. Can we use PCA to reduce the dimensionality of this dataset to gain a better understanding of our patients?

A2. Define one goal of the data analysis. Ensure that your goal is reasonable within the scope of the scenario and is represented in the available data.

The ultimate goal of this performance assessment is to reduce the dimensionality of the dataset to gain a better understanding of our patients. This can hopefully lead to better decision-making for the hospital.

Part II: Method Justification

B. Explain the reasons for using PCA by doing the following:

B1. Explain how PCA analyzes the selected data set. Include expected outcomes.

PCA is a way we can reduce dimensions within a dataset. This can be done through feature extraction. Feature extraction involves combining multiple features into one datapoint. This new datapoint is then evaluated to determine how important it is by how it effects the variance within the dataset. Components that explain the most variance are considered important and those are kept. We can evaluate what to keep by using a Scree Plot of eigen values. Components that fall below 1 eigen value are dropped before continuing.

The expected outcome is to create a number of principal components equal to the number of variables we evaluate as part of the PCA. Then through using the Kaiser criterion we can reduce the dimensionality of the dataset to make it more manageable.

B2. Summarize one assumption of PCA.

One assumption of PCA provided by Datacamp is that, "the principal components having the highest variance are more important than those which don't." (Keita, 2023) Because we'll be taking the variance scores of the different principal components we will be guided towards what to keep and what we can eliminate based on that assumption.

Part III: Data Preparation

C. Perform data preparation for the chosen dataset by doing the following:

C1. Identify the continuous dataset variables that you will need in order to answer the PCA question proposed in part A1.

Variable # Continuous Variable Dictionary
1 Latitude
2 Longitude
3 Population
4 Number of Children in Household
5 Age
6 Income of Patient
7 Patient's Vit D Level
8 Number of Physician Visits
9 Number of full meals eaten 9 Number of Vit D Supplements
10 Length of initial stay
11 Average daily amount charged for hospitalization
12 Average daily amount charged for additional charges

C2. Standardize the continuous dataset variables identified in part C1. Include a copy of the cleaned dataset.

In [105]:
```
#DataCleaning

#Import Packages needed for data cleaning and PCA
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import accuracy_score

#Loading the CSV of the default dataset, index_col to prevent duplicated column
df = pd.read_csv(r'C:\Users\mmorg\WGU\D212\medical_clean.csv', index_col=0)
#Get overiew of dataset such as # of columns, names, and size
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 1 to 10000
Data columns (total 49 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Customer_id         10000 non-null  object 
 1   Interaction         10000 non-null  object 
 2   UID                 10000 non-null  object 
 3   City                10000 non-null  object 
 4   State               10000 non-null  object 
 5   County              10000 non-null  object 
 6   Zip                 10000 non-null  int64  
 7   Lat                 10000 non-null  float64
 8   Lng                 10000 non-null  float64
 9   Population          10000 non-null  int64  
 10  Area                10000 non-null  object 
 11  TimeZone            10000 non-null  object 
 12  Job                 10000 non-null  object 
 13  Children            10000 non-null  int64  
 14  Age                 10000 non-null  int64  
 15  Income              10000 non-null  float64
 16  Marital             10000 non-null  object 
 17  Gender              10000 non-null  object 
 18  ReAdmis             10000 non-null  object 
 19  VitD_levels         10000 non-null  float64
 20  Doc_visits          10000 non-null  int64  
 21  Full_meals_eaten    10000 non-null  int64  
 22  vitD_supp           10000 non-null  int64  
 23  Soft_drink          10000 non-null  object 
 24  Initial_admin       10000 non-null  object 
 25  HighBlood           10000 non-null  object 
 26  Stroke              10000 non-null  object 
 27  Complication_risk   10000 non-null  object 
 28  Overweight          10000 non-null  object 
 29  Arthritis           10000 non-null  object 
 30  Diabetes            10000 non-null  object 
 31  Hyperlipidemia      10000 non-null  object 
 32  BackPain            10000 non-null  object 
 33  Anxiety             10000 non-null  object 
 34  Allergic_rhinitis   10000 non-null  object 
 35  Reflux_esophagitis  10000 non-null  object 
 36  Asthma              10000 non-null  object 
 37  Services            10000 non-null  object 
 38  Initial_days        10000 non-null  float64
 39  TotalCharge         10000 non-null  float64
 40  Additional_charges  10000 non-null  float64
 41  Item1               10000 non-null  int64  
 42  Item2               10000 non-null  int64  
 43  Item3               10000 non-null  int64  
 44  Item4               10000 non-null  int64  
 45  Item5               10000 non-null  int64  
 46  Item6               10000 non-null  int64  
 47  Item7               10000 non-null  int64  
 48  Item8               10000 non-null  int64  
dtypes: float64(7), int64(15), object(27)
memory usage: 3.8+ MB
```

In [106]:
```
# More exploration to spot any potential problems with the dataset and what might need cleaned up
pd.set_option("display.max_columns", None)
df.head(5)
```

Out[106]:

CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng	Population	
1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	-86.72508	2951	Sub
2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	-85.22907	11303	
3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	-96.63772	17125	Sub
4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	-93.51479	2162	Sub
5	C544523	5885f56b-d6da-43a3-8760-83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	-76.88958	5287	

In [107]:
```
#Because we are only using continuous variables, not much cleaning needs to be done and we can remove columns
#that are categorical or don't apply to the PCA

# Assign all continuous variables for PCA to X variable
X = df[["Lat", "Lng", "Population", "Children", "Age", "Income", "VitD_levels", "Doc_visits",
        "Full_meals_eaten", "vitD_supp",  "Initial_days", "TotalCharge", "Additional_charges"]].copy()
# Define list of column headers
X_columns = list(X.columns)
# Assign patient re-admissions column to y variable
y = df["ReAdmis"]
```

In [108]:
```
# Standardize X by instantiating the StandardScaler(), then fitting and transforming to X
X_stand = StandardScaler().fit_transform(df[["Lat", "Lng", "Population", "Children", "Age", "Income", "VitD_levels", "Do
        "Full_meals_eaten", "vitD_supp",  "Initial_days", "TotalCharge", "Additional_charges"]].copy())
# New dataframe with standardized values for verification
X_stand_df = pd.DataFrame(X_stand, columns=X_columns)
```

In [109]:
```
#Verifying the means of each column, should be 0 to confirm standardization
X_stand_means = X_stand_df.agg(['mean']).round(2)

print(X_stand_means)
```

```
      Lat  Lng  Population  Children  Age  Income  VitD_levels  Doc_visits  \
mean -0.0  0.0        -0.0      -0.0  0.0     0.0         -0.0         0.0

      Full_meals_eaten  vitD_supp  Initial_days  TotalCharge  \
mean               0.0       -0.0          -0.0         -0.0

      Additional_charges
mean                -0.0
```

In [110]:
```
#Verifying the standard deviation of each column, should be 1 to confirm standardization
X_stand_stddv = X_stand_df.agg(['std']).round(2)

print(X_stand_stddv)
```

```
     Lat  Lng  Population  Children  Age  Income  VitD_levels  Doc_visits  \
std  1.0  1.0         1.0       1.0  1.0     1.0          1.0         1.0

     Full_meals_eaten  vitD_supp  Initial_days  TotalCharge  \
std               1.0        1.0           1.0          1.0

     Additional_charges
std                 1.0
```

In [111]:
```
#Checking correlations to determine redundant components
X_stand_df.corr()
```

Out[111]:

	Lat	Lng	Population	Children	Age	Income	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	Initial_day
Lat	1.000000	-0.112348	-0.207572	0.006373	-0.007270	-0.019369	0.001493	0.008380	0.003401	0.001285	-0.00882
Lng	-0.112348	1.000000	-0.031979	-0.014114	0.007493	-0.006665	-0.006389	0.000754	-0.014231	-0.001961	-0.00929
Population	-0.207572	-0.031979	1.000000	0.002462	-0.018987	0.005426	0.002651	0.012646	-0.025608	0.009781	0.01746
Children	0.006373	-0.014114	0.002462	1.000000	0.009836	0.007176	0.009487	-0.002292	0.003835	-0.004319	0.02246
Age	-0.007270	0.007493	-0.018987	0.009836	1.000000	-0.012228	0.010315	0.006898	0.008555	0.010014	0.01626
Income	-0.019369	-0.006665	0.005426	0.007176	-0.012228	1.000000	-0.013115	0.013464	-0.011365	0.001253	-0.01246
VitD_levels	0.001493	-0.006389	0.002651	0.009487	0.010315	-0.013115	1.000000	0.010210	0.023223	-0.007203	-0.00364
Doc_visits	0.008380	0.000754	0.012646	-0.002292	0.006898	0.013464	0.010210	1.000000	-0.002767	0.005681	-0.00675
Full_meals_eaten	0.003401	-0.014231	-0.025608	0.003835	0.008555	-0.011365	0.023223	-0.002767	1.000000	-0.019980	-0.01726
vitD_supp	0.001285	-0.001961	0.009781	-0.004319	0.010014	0.001253	-0.007203	0.005681	-0.019980	1.000000	0.01597
Initial_days	-0.008820	-0.009292	0.017469	0.022467	0.016264	-0.012465	-0.003642	-0.006754	-0.017267	0.015974	1.00000
TotalCharge	-0.010759	-0.008830	0.019188	0.024100	0.016876	-0.014345	-0.001403	-0.005043	-0.014306	0.016924	0.98764
Additional_charges	-0.002283	0.000079	-0.004820	0.013548	0.716854	-0.009825	0.008290	0.008072	0.018763	0.010327	0.00440

In [112]:
```
#As shown Initial_days and TotalCharge are highly correlated and redundant.
#As I have done in previous classes, I dropped TotalCharge as they both basically represent the same data.
#Longer stays lead to more initial charges.

#Re-creating X variable and X_columns with this in mind
X = X_stand_df[["Lat", "Lng", "Population", "Children", "Age", "Income", "VitD_levels", "Doc_visits",
        "Full_meals_eaten", "vitD_supp",  "Initial_days", "Additional_charges"]].copy()
# Define list of column headers
X_columns = list(X.columns)
# Standardize X by instantiating the StandardScaler(), then fitting and transforming to X
X_stand = StandardScaler().fit_transform(df[["Lat", "Lng", "Population", "Children", "Age", "Income", "VitD_levels", "Do
        "Full_meals_eaten", "vitD_supp",  "Initial_days", "Additional_charges"]].copy())
# New dataframe with standardized values for verification
X_stand_df = pd.DataFrame(X_stand, columns=X_columns)
```

In [113]:
```
#Verifying the means of each column, should be 0 to confirm standardization
X_stand_means = X_stand_df.agg(['mean']).round(2)

print(X_stand_means)
```

```
      Lat  Lng  Population  Children  Age  Income  VitD_levels  Doc_visits  \
mean -0.0  0.0        -0.0      -0.0  0.0     0.0         -0.0         0.0

      Full_meals_eaten  vitD_supp  Initial_days  Additional_charges
mean               0.0       -0.0          -0.0                -0.0
```

In [114]:
```
#Verifying the standard deviation of each column, should be 1 to confirm standardization
X_stand_stddv = X_stand_df.agg(['std']).round(2)

print(X_stand_stddv)
```

```
     Lat  Lng  Population  Children  Age  Income  VitD_levels  Doc_visits  \
std  1.0  1.0         1.0       1.0  1.0     1.0          1.0         1.0

     Full_meals_eaten  vitD_supp  Initial_days  Additional_charges
std               1.0        1.0           1.0                 1.0
```

In [115]:
```
# Provide a copy of the cleaned Data Set, index=False prevents the creation of an additional column
X_stand_df.to_csv(r'C:\Users\mmorg\WGU\D212\Task 2\Cleaned212Task2data.csv', index=False)
```

Part IV: Analysis

D. Perform PCA by doing the following:

D1. Determine the matrix of all the principal components.

Now that the data is standardized, we can use PCA to reduce dimensionality. We can use fit_transform() to combine both of these steps into one function.

After creating the matrix we can examine what weight each feature contributes to each of the principal components generated. For example PC1 is primarily based on Initial_days, whereas PC2 is influenced by Longitude and Initial_days. The higher the numbers on this matrix mean that those

In [116]:

```
# Instantiating data
pca = PCA(n_components = 12, random_state = 0)
# Fit and transform the PCA to X_stand
X_pca = pca.fit_transform(X_stand)
# Create PCA Matrix, shows the weight that a feature contributes to each Principal Component
X_pca_matrix = pd.DataFrame(pca.components_,
                                columns = ["PC1", "PC2", "PC3", "PC4", "PC5", "PC6",
                                               "PC7", "PC8", "PC9", "PC10", "PC11", "PC12"],
                            index=X_columns)
X_pca_matrix
```

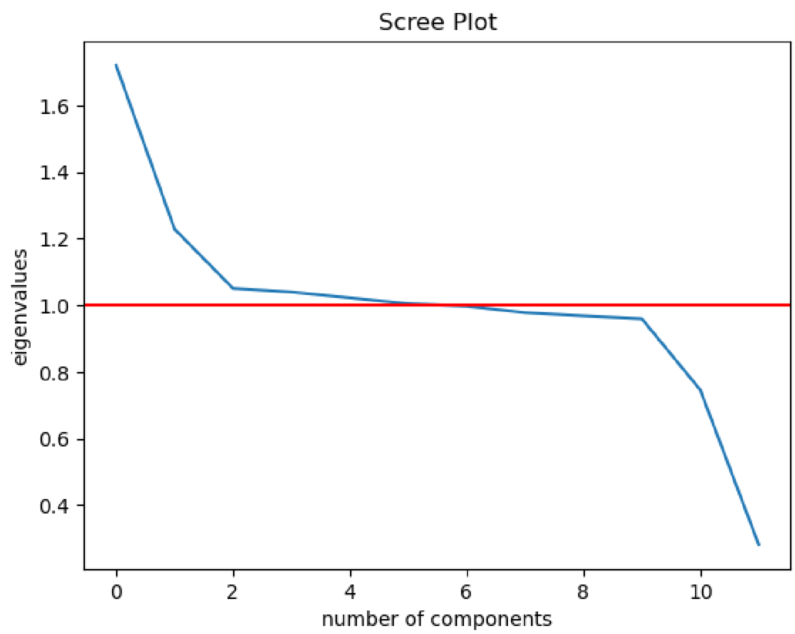
Out[116]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Lat	-0.003058	0.007652	-0.022811	0.023338	0.705901	-0.022410	0.019598	0.013893	0.027481	0.019038	0.020315	0.705664
Lng	-0.712542	0.265927	0.629684	-0.023013	0.008656	0.069845	-0.021974	0.013776	-0.111319	0.037972	0.070488	0.010325
Population	0.129259	-0.564164	0.253543	0.350595	-0.003164	0.088519	-0.080655	0.053630	-0.299785	0.338816	0.505879	-0.001590
Children	-0.064795	-0.343004	0.234772	0.291952	-0.022226	-0.137444	0.560328	0.048673	0.531893	-0.343571	-0.032595	-0.007786
Age	0.041323	-0.235515	0.102756	-0.120302	0.009154	0.617901	-0.011810	0.586993	-0.028745	0.007754	-0.435667	0.022723
Income	-0.042849	0.001443	-0.052169	0.448856	0.013231	0.477300	-0.391113	-0.420891	0.033011	-0.483289	-0.030242	0.016962
VitD_levels	0.007356	-0.528847	0.273410	-0.545779	0.017394	-0.128018	-0.297966	-0.412969	0.118341	-0.039959	-0.234668	0.030821
Doc_visits	-0.057235	0.073339	-0.067841	0.135775	-0.014133	0.326654	0.193909	-0.411312	0.351625	0.698886	-0.206142	-0.007117
Full_meals_eaten	-0.052112	0.052695	-0.008722	0.068395	-0.020392	-0.129952	-0.592420	0.354429	0.655825	0.142106	0.213063	-0.013102
vitD_supp	-0.002282	0.049267	-0.111711	-0.503772	0.006684	0.463827	0.219518	-0.064247	0.196984	-0.145438	0.635462	-0.006324
Initial_days	0.679482	0.384103	0.614897	-0.006411	-0.001120	0.056180	-0.003230	-0.056510	0.074130	-0.018554	0.003061	0.020499
Additional_charges	0.008854	-0.005042	0.016922	0.003751	0.707038	0.002297	-0.002533	0.000685	0.010346	0.000585	-0.011905	-0.706705

```
D2.  Identify the total number of principal components using the elbow rule or the Kaiser criterion.

Now that we have our 12 principal components we can start working on reducing those that have little influence. To do
this we can create a plot and use the eigen value to satisfy the Kaiser criterion. Below you can see the plot and it
starts to below 1 at PC 5. Because it starts at 0, and the 0 is referring to PC1, this means that we want to keep up
to PC 5, which means we keep 6 principal components heading forward.
```

In [117]:
```
test_pca = X_stand_df
test_pca_normalized=(test_pca-test_pca.mean())/test_pca.std()
pca = PCA(n_components=test_pca.shape[1])
pca.fit(test_pca_normalized)
print(pca)

test_pca2 = pd.DataFrame(pca.transform(test_pca_normalized),columns=['PC1','PC2','PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC
                                                                     'PC10', 'PC11', 'PC12'])


loadings = pd.DataFrame(pca.components_.T,
columns = ['PC1','PC2','PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8', 'PC9','PC10', 'PC11', 'PC12'],
index=test_pca_normalized.columns)

cov_matrix = np.dot(test_pca_normalized.T, test_pca_normalized) / test_pca.shape[0]
eigenvalues = [np.dot(eigenvector.T, np.dot(cov_matrix, eigenvector)) for eigenvector in pca.components_]

plt.plot(eigenvalues)
plt.xlabel('number of components')
plt.ylabel('eigenvalues')
plt.axhline(y=1, color="red")
plt.title('Scree Plot')
plt.show()
```

```
PCA(n_components=12)
```



D3. Identify the variance of each of the principal components identified in part D2.

To identify the variance of each PCA identified in D2 we have to run the PCA again with only 6 components and produce a new matrix. Once we have the PCA created we can then assign the explained_variance_ratio_ attribute. The numbers provided are percentage of variation of each principal component in decimal format.

In [118]:
```
# Instantiating data
reduced_pca = PCA(n_components = 6, random_state = 0)
# Fit and transform the PCA to X_stand
reduced_pca.fit(X_stand)
final_pca = reduced_pca.transform(X_stand)
# Create PCA Matrix, shows the weight that a feature contributes to each Principal Component
final_pca_matrix = pd.DataFrame(reduced_pca.components_.T,
                               columns = ["PC1", "PC2", "PC3", "PC4", "PC5", "PC6"],
                                index=X_columns)
final_pca_matrix
```

Out[118]:

	PC1	PC2	PC3	PC4	PC5	PC6
Lat	-0.003058	-0.712542	0.129259	-0.064795	0.041323	-0.042849
Lng	0.007652	0.265927	-0.564164	-0.343004	-0.235515	0.001443
Population	-0.022811	0.629684	0.253543	0.234772	0.102756	-0.052169
Children	0.023338	-0.023013	0.350595	0.291952	-0.120302	0.448856
Age	0.705901	0.008656	-0.003164	-0.022226	0.009154	0.013231
Income	-0.022410	0.069845	0.088519	-0.137444	0.617901	0.477300
VitD_levels	0.019598	-0.021974	-0.080655	0.560328	-0.011810	-0.391113
Doc_visits	0.013893	0.013776	0.053630	0.048673	0.586993	-0.420891
Full_meals_eaten	0.027481	-0.111319	-0.299785	0.531893	-0.028745	0.033011
vitD_supp	0.019038	0.037972	0.338816	-0.343571	0.007754	-0.483289
Initial_days	0.020315	0.070488	0.505879	-0.032595	-0.435667	-0.030242
Additional_charges	0.705664	0.010325	-0.001590	-0.007786	0.022723	0.016962

In [119]:
```
list(reduced_pca.explained_variance_ratio_)
```

Out[119]:
```
[0.14329551589301728,
 0.10240073568553089,
 0.08757786111482167,
 0.08667044956990405,
 0.08521515256145144,
 0.08373292555920943]
```

D4. Identify the total variance captured by the principal components identified in part D2.

Provided below is a running total of the variance of each principal component. This shows that the 6 principal components are responsible for 59% of total variance.

In [120]:
```
list(reduced_pca.explained_variance_ratio_.cumsum())
```

Out[120]:
```
[0.14329551589301728,
 0.24569625157854819,
 0.3332741126933699,
 0.4199445622632739,
 0.5051597148247253,
 0.5888926403839347]
```

```
D5.  Summarize the results of your data analysis.

After running PCA on the continuous variables in the dataset we find that we can reduce the dimensionality from 12
variables to 6 principal compoents. This was verified by using the Kaiser rule and dropping components that fell below
an eigen value of 1. The purpose of this assignment was to reduce the dimensionality of our dataset and I was
successfully able to do that.

According to a source, "it is sometimes though that a good factor analysis should explain two-thirds of the variance."
(Kaiser Rule - Displayr, n.d.) In this analysis we got close to that two-thirds mark while still satisfying our Kaiser
rule. Having said that, our 6 components only explained 59% of the variance. So I got close, but not close enough. I
would attribute that to the dataset not being entirely realistic. The dataset is also incomplete in this regard. I
robust medical system would have many more data points available on their patients than what we are provided.
```

Part V: Attachments

E. Record the web sources used to acquire data or segments of third-party code to support the analysis. Ensure the web sources are reliable.

I used information from the Datacamp modules, and my previous submissions in D206 and D212 Task 1 to help complete the coding in this assignment.

F. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

Keita, Z. (2023). Principal Component Analysis in R Tutorial. https://datacamp.com/tutorial/pca-analysis-r (https://datacamp.com/tutorial/pca-analysis-r)

Kaiser Rule - Displayr. (n.d.). https://docs.displayr.com/wiki/Kaiser_Rule (https://docs.displayr.com/wiki/Kaiser_Rule)