Dimension Reduction of Telcom Customer Churn Data

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D212: Data Mining II

Task 2: Dimension Reduction

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Revision 6

Abstract

Telecom customer data will be analyzed for feature selection using principal component analysis (PCA). The dataset consists of 50 features associated with 10,000 customer records. The purpose of this analysis is reduce number of features by finding and removing irrelevant data. The analysis will reduce the number of principal components to 39. While using Kaiser criterion, the analysis will reduce the number of principal components to 26.

Keywords: Telecom. Churn. Data Mining. Dimension Reduction. PCA.

Scenario 1

One of the most critical factors in customer relationship management that directly affects a company's long-term profitability is understanding its customers. When a company can better understand its customer characteristics, it is better able to target products and marketing campaigns for customers, resulting in better profits for the company in the long term.

You are an analyst for a telecommunications company that wants to better understand the characteristics of its customers. You have been asked to use principal component analysis (PCA) to analyze customer data to identify the principal variables of your customers, ultimately allowing better business and strategic decision-making.

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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 using principal component analysis (PCA)

What are the most influential features of the Telecom customer data related to churn?

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.

Use principal component analysis (PCA) to reduce dimensionality of the problem set to a more manageable number of principal components. The primary dataset consists of 10,000 customer records with 50 attributes each, which by definition is a high dimension dataset. The overall steps to the analysis are below:

Part II: Method Justification

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

B1. Explain how the PCA analyzes the selected the selected dataset. Include expected outcomes.

According to Vadapalli (2020), “Principal component analysis (PCA) is a statistical method used to transform a large number of possibly correlated variables into a much smaller number of uncorrelated variables referred to as principal components. PCA can be used as a data reduction technique as it allows us to find the most important variables that are needed to describe a dataset. PCA can also be used to reduce the dimensionality of the data space in order to get insight on the inner structure of the data. This is helpful when dealing with large datasets.”

The expected outcome of the reduction analysis is the appropriate number of principal components and total variance for each component.

B2. Summarize one assumption of PCA.

PCA is dependent on having numeric, scaled data. If any one feature is not scaled and has large values, the PCA will give more weight to those higher values. In order to place equal weight of all features, all of the data should be scaled such that the mean of the feature is 0 and the standard deviation is 1.

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.

The list of continuous features that will be used for the PCA is shown in Figure 1 and Figure 2. They are:

- Children
- Population
- Age
- Income
- Tenure
- Email
- Contacts
- Outage_sec_perweek
- MonthlyCharge
- Bandwidth_GB_Year
- Lat
- Lng

All remaining data is either categorical or discreet and will not be used for the PCA.

Figure 1

Define continuous features

Define continuous features

In [39]:
```
feature_names=[]
```

In [40]:
```
feature_names.append('Children') # Nbr of children
feature_names.append('Population') # Population within a mile radius
feature_names.append('Age') # Age of customer
```

In [41]:
```
feature_names.append('Income') # Annual income
feature_names.append('Tenure') # Nbr of months with service
```

In [42]:
```
feature_names.append('Email') # Nbr of emails sent to customer
feature_names.append('Contacts') # Nbr of times customer contacted support
```

In [43]:
```
feature_names.append('Outage_sec_perweek') # Ave seconds/week of system outage
```

In [44]:
```
feature_names.append('MonthlyCharge') # customer's monthly charge
feature_names.append('Bandwidth_GB_Year') # ave amount of data used
```

In [45]:
```
feature_names.append('Lat') # GPS coordinates of customer residence
feature_names.append('Lng') # GPS coordinates of customer residence
```

In [46]:
```
feature_names
```

Out[46]:
```
['Children',
 'Population',
 'Age',
 'Income',
 'Tenure',
 'Email',
 'Contacts',
 'Outage_sec_perweek',
 'MonthlyCharge',
 'Bandwidth_GB_Year',
 'Lat',
 'Lng']
```

Notes.

Table 1

First 5 rows of the original dataset

	0	1	2	3	4
Children	0.000	1.000	4.000	1.000	0.000
Population	38.000	10446.000	3735.000	13863.000	11352.000
Age	68.000	27.000	50.000	48.000	83.000
Income	28561.990	21704.770	9609.570	18925.230	40074.190
Tenure	6.796	1.157	15.754	17.087	1.671
Email	10.000	12.000	9.000	15.000	16.000
Contacts	0.000	0.000	0.000	2.000	2.000
Outage_sec_perweek	7.978	11.699	10.753	14.914	8.147
MonthlyCharge	172.456	242.633	159.948	119.957	149.948
Bandwidth_GB_Year	904.536	800.983	2054.707	2164.579	271.493
Lat	56.251	44.329	45.356	32.967	29.380
Lng	-133.376	-84.241	-123.247	-117.248	-95.807

Notes. Info():
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Children            10000 non-null  int64  
 1   Population          10000 non-null  int64  
 2   Age                 10000 non-null  int64  
 3   Income              10000 non-null  float64
 4   Tenure              10000 non-null  float64
 5   Email               10000 non-null  int64  
 6   Contacts            10000 non-null  int64  
 7   Outage_sec_perweek  10000 non-null  float64
 8   MonthlyCharge       10000 non-null  float64
 9   Bandwidth_GB_Year   10000 non-null  float64
 10  Lat                 10000 non-null  float64
 11  Lng                 10000 non-null  float64
dtypes: float64(7), int64(5)
memory usage: 937.6 KB
```

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

Scaled data is critical to the PCA. If not scaled properly, larger values will tend to dominate the PCA. Table 2 shows the first five rows of the scaled data. The StandardScaler was used to fit and transform the raw data.

Table 2

First 5 rows of the scaled data

```
                       0      1      2      3      4
Children           -0.972 -0.507  0.891 -0.507 -0.972
Population         -0.673  0.048 -0.417  0.285  0.111
Age                 0.721 -1.260 -0.149 -0.245  1.446
Income             -0.399 -0.642 -1.071 -0.741  0.009
Tenure             -1.049 -1.262 -0.710 -0.660 -1.243
Email              -0.666 -0.005 -0.997  0.986  1.317
Contacts           -1.006 -1.006 -1.006  1.018  1.018
Outage_sec_perweek -0.680  0.570  0.252  1.651 -0.623
MonthlyCharge      -0.004  1.630 -0.295 -1.227 -0.528
Bandwidth_GB_Year  -1.138 -1.186 -0.612 -0.562 -1.428
Lat                 3.217  1.025  1.214 -1.065 -1.725
Lng                -2.810  0.432 -2.142 -1.746 -0.332

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Children            10000 non-null  float64
 1   Population          10000 non-null  float64
 2   Age                 10000 non-null  float64
 3   Income              10000 non-null  float64
 4   Tenure              10000 non-null  float64
 5   Email               10000 non-null  float64
 6   Contacts            10000 non-null  float64
 7   Outage_sec_perweek  10000 non-null  float64
 8   MonthlyCharge       10000 non-null  float64
 9   Bandwidth_GB_Year   10000 non-null  float64
 10  Lat                 10000 non-null  float64
 11  Lng                 10000 non-null  float64
dtypes: float64(12)
memory usage: 937.6 KB
None
```

Notes. The data is available as an attached file located at tables\scaled_df.csv

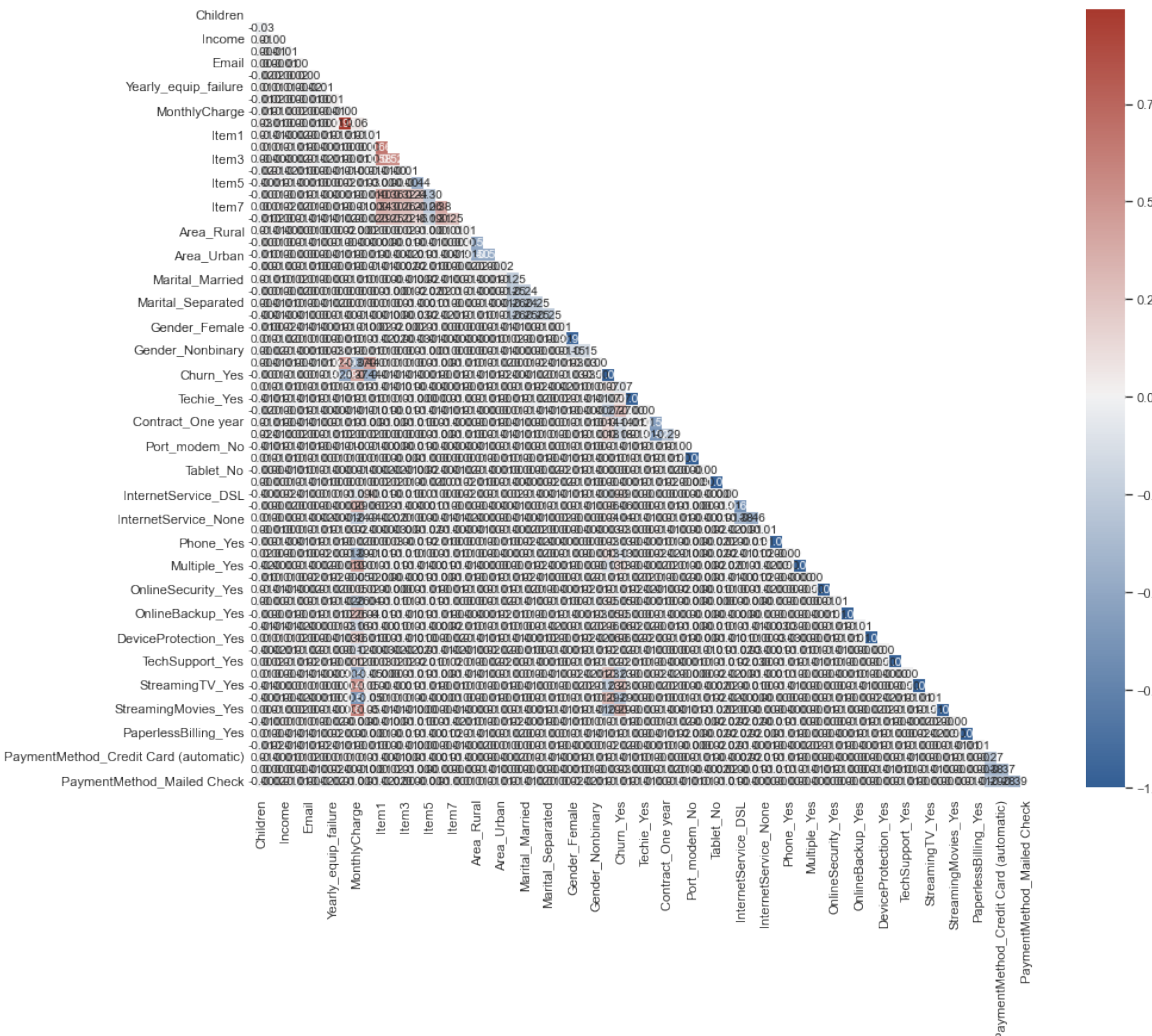
Part IV: Analysis

D. Perform the data analysis and report on the results by doing the following:

1. Determine the matrix of all the principal components. (Figure 1). Generate a correlation matrix of all numerical data, and look for correlation values greater than 0.70. Evaluate the highly correlated features and consider removing one or the other. (Bex, 2021)
2. Identify the total number of principal components using the elbow rule or the Kaiser criterion. Include a screenshot of the scree plot. (Figure 2). Use the PCA components, eigenvalues and variance values to generate a scree plot. Evaluate where on the plot represents the optimum number of components. Consider the Kaiser criterion which says to drop features where the eigenvalue is less than 1.
3. Identify the variance of each of the principal components identified in part D2. (Figure 3). Using the PCA components and variance values, generate a plot showing amount of variance for each principal component.
4. Identify the total variance captured by the principal components identified in part D2. (Figure 4). Using the PCA component variance, generate a cumulative plot of total variance. Find the minimum number of principal components that exceed a total variance of 85%, 90% or 95%.
5. Summarize the results of your data analysis.

Figure 2

D1. Determine matrix of all the principal components



Notes. Figure 1 is the correlation matrix for all numerical data, including the newly created categorical dummy features. To help identify the features with high correlation, the names of the features with correlation above 0.7 are listed in the figure notes.

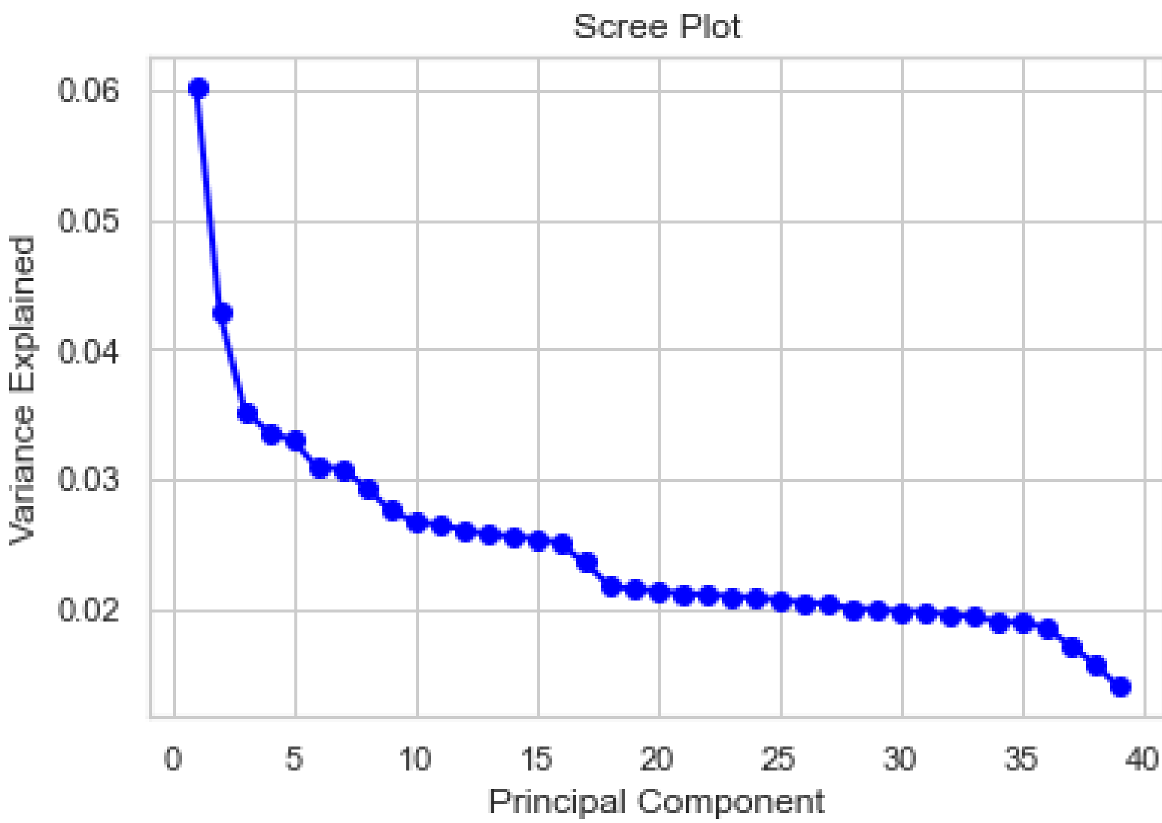
```
['Tenure', 'Gender_Female']
```

Here is the adapted code to generate the correlation matrix in Figure 1 (Bex, 2021):

```
# Create a mask
# adapted code (Bex, 2021)
matrix = D.corr()
plt.figure(figsize=(16,12))
cmap = sns.diverging_palette(250, 15, s=75, l=40,
            n=9, center="light", as_cmap=True)
mask = np.triu(np.ones_like(matrix, dtype=bool))
sns.heatmap(matrix, mask=mask, center=0, annot=True,
             fmt='.2f', square=True, cmap=cmap)
```

Figure 3

D2. Use scree plot to identify variance for each component




```
(10000, 52)
(10000, 39)
```

Notes. Figure 2 shows the scree plot. PCA was able to successfully reduce the problem dimension from 52 to 39. Although the first two components have the most explained variance, it takes all of the 39 components to explain 95% (see Figure 3).

Here is the code to create the scree plot:

```
# PCA - keep 90% of variance (Boyle, 2019)
pca = PCA(0.95)
principal_components = pca.fit_transform(X)
principal_df = pd.DataFrame(data = principal_components)
print(A.shape)
print(principal_df.shape)
```

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

The explained variance ratios for each principal component:

```
array([0.43319022, 0.06947163, 0.02696186, 0.02574512, 0.02300794,
       0.02293276, 0.02062869, 0.01795037, 0.01764734, 0.01757722,
       0.01734662, 0.01708094, 0.01696258, 0.01688812, 0.01679839,
       0.01648529, 0.0163014 , 0.01589637, 0.01569515, 0.01559179,
       0.0152735 , 0.01520301, 0.0146579 , 0.01424522, 0.01403923,
       0.01363732, 0.01341701, 0.01315427])
```

Code used to calculated these ratios:

```
pca.explained_variance_ratio_
```

The explained variance for each principal component also known as the eigenvalues:

array([**2.95331466, 2.09708838, 1.72647177, 1.6464298 , 1.6158704 ,
1.51286066, 1.5089432 , 1.4396131 , 1.35090479, 1.31073554,
1.29621584, 1.28024198, 1.25996635, 1.25322462, 1.24445112,
1.22687776, 1.15499185, 1.06679257, 1.05330037, 1.04799724,
1.03641008, 1.03441197, 1.02859453, 1.022224 , 1.01408408,
1.00405837**, 0.99857262, 0.98238462, 0.97787214, 0.97041187,
0.96866228, 0.95769867, 0.95013982, 0.93132333, 0.92690545,
0.90929756, 0.84158254, 0.77122477, 0.68610635])

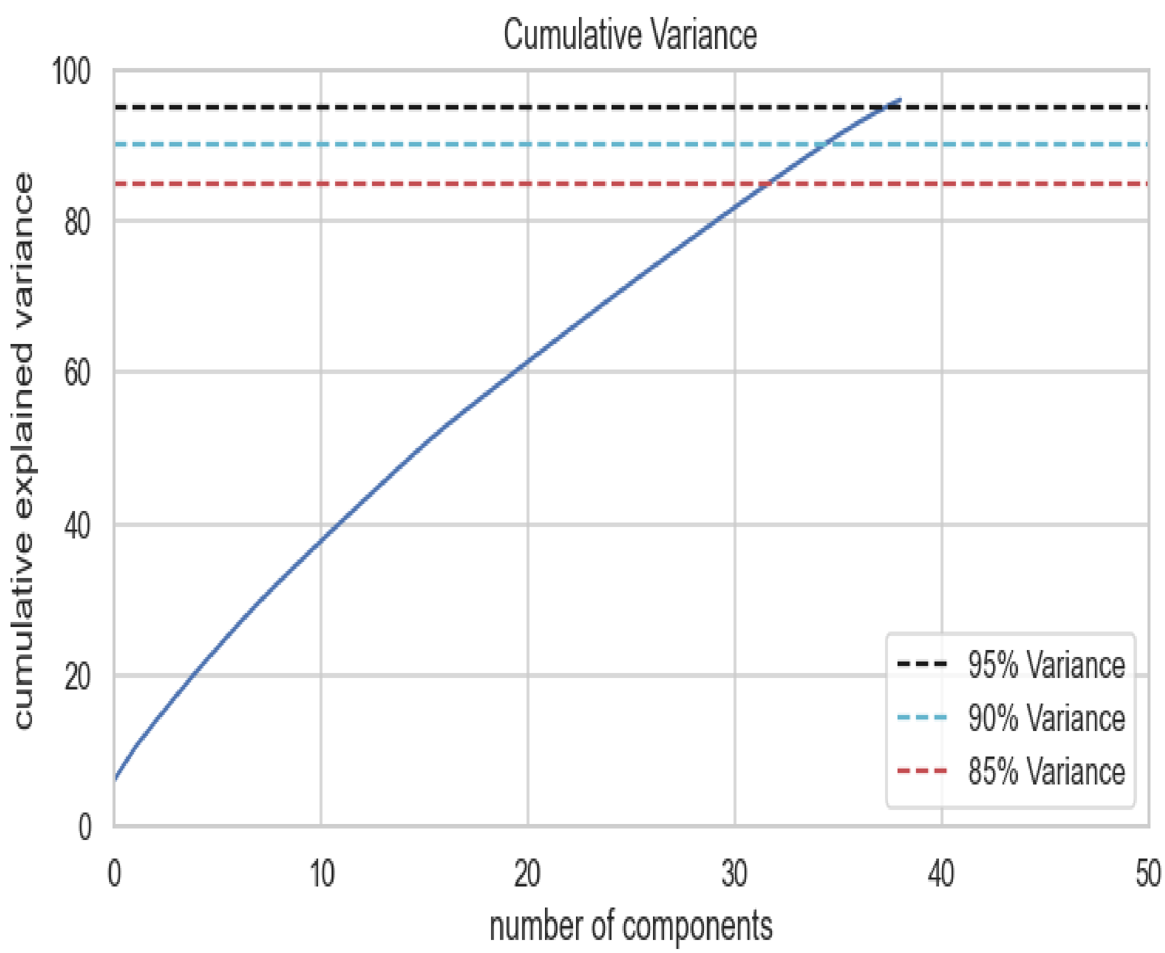
Notes. The Kaiser criterion suggests that you select eigenvalues above 1, which are the ones highlighted, so it would suggest using 26 principal components.

Code used to calculated these eigenvalues:

```
pca.explained_variance_
```

Figure 4

D4. Use cumulative variance to identify total variance as function of components



Notes.
Code used to generate Figure 3 (Tripathi, 2019):

```
# create cumulative variance plot (Tripathi, 2019)
%matplotlib notebook
plt.figure(figsize = (8,4))
plt.plot(np.cumsum(pca.explained_variance_ratio_*100))
plt.xlim(xmax = 50, xmin = 0)
plt.ylim(ymax = 100, ymin = 0)
plt.title('Cumulative Variance')
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
plt.axhline(y = 95, color='k', linestyle='--', label = '95% Variance')
plt.axhline(y = 90, color='c', linestyle='--', label = '90% Variance')
plt.axhline(y = 85, color='r', linestyle='--', label = '85% Variance')
```

D5. Summarize the results of your data analysis.

Figure 3 shows a total variance of 95% using 39 principal components, a nice reduction in overall dimensionality from the original 50 attributes. However, using the Kaiser criterion, the reduction should be 26 principal components with an overall total variance of about 70%.

In addition, Table 2 below shows the load factors of each of the first four principal components for consideration. Table 2 is now available to analyze for further considerations.

Table 3

Load factors using first four principal components

	PC-1	PC-2	PC-3	PC-4
Children	0.004287	-0.011847	0.056988	-0.007169
Age	0.006379	0.010735	-0.040605	-0.002853
Income	0.001256	-0.012560	0.006080	0.015310
Outage_sec_perweek	-0.017785	0.028091	0.012807	-0.009239
Email	0.008474	0.003132	-0.011032	-0.007576
Contacts	-0.008854	0.010380	-0.003544	-0.008951
Yearly_equip_failure	-0.007175	-0.010055	0.016260	-0.002627
MonthlyCharge	0.004897	0.651798	0.017227	0.006228
Bandwidth_GB_Year	-0.008765	0.042386	0.067694	0.007396
Item1	0.458462	0.002105	0.065232	0.266118
Item2	0.433380	-0.006572	0.063387	0.271625
Item3	0.400054	-0.017077	0.075854	0.261363
Item4	0.145856	0.000282	-0.138714	-0.538065
Item5	-0.175411	-0.008643	0.151248	0.553502
Item6	0.404361	-0.000385	-0.041612	-0.174481
Item7	0.357802	-0.010872	-0.038490	-0.173017
Item8	0.307872	-0.003411	-0.047196	-0.110907
Techie	0.007654	0.005402	0.012696	0.025636
Port_modem	0.001061	0.003508	-0.018632	-0.010168
Tablet	0.016664	0.005912	0.032047	-0.005458
Phone	0.005372	-0.024208	0.025749	0.020751
Multiple	0.000647	0.239813	0.047058	0.002902
OnlineSecurity	0.001275	0.046507	0.024437	-0.020494
OnlineBackup	-0.004294	0.155624	0.004595	0.038125
DeviceProtection	-0.003015	0.112385	0.005802	0.016252
TechSupport	0.024767	0.049147	0.006000	-0.011838
StreamingTV	0.000668	0.284363	0.047628	-0.019655
StreamingMovies	-0.005987	0.365867	-0.002556	-0.013579
PaperlessBilling	0.005735	0.006693	0.007231	-0.014428
Area_Rural	0.014564	-0.001592	0.019460	-0.011710

	PC-1	PC-2	PC-3	PC-4
Area_Suburban	-0.002729	-0.005928	0.012699	-0.056373
Area_Urban	-0.011831	0.007529	-0.032177	0.068163
Marital_Divorced	-0.005619	-0.003829	-0.026831	-0.060881
Marital_Married	-0.002297	-0.013400	-0.010474	0.021426
Marital_Never Married	0.014242	0.010585	-0.015655	-0.065502
Marital_Separated	0.008360	0.020935	0.014914	-0.005697
Marital_Widowed	-0.014461	-0.014349	0.037958	0.110955
Gender_Male	-0.011993	0.010563	-0.002120	0.004230
Gender_Nonbinary	0.007434	-0.000591	0.016339	-0.011388
Contract_Month-to-month	-0.005073	-0.032387	-0.715505	0.189692
Contract_One year	0.005451	0.018520	0.370886	-0.082303
Contract_Two Year	0.000710	0.019972	0.477510	-0.141793
InternetService_DSL	-0.004315	-0.194057	0.139568	-0.016785
InternetService_Fiber Optic	0.016730	0.390904	-0.127339	0.038016
InternetService_None	-0.015276	-0.248552	-0.007776	-0.026597
PaymentMethod_Bank Transfer(automatic)	-0.004483	0.007619	0.023450	-0.015990
PaymentMethod_Credit Card (automatic)	-0.002710	0.031776	-0.026254	-0.048399
PaymentMethod_Electronic Check	0.010785	-0.026531	0.026856	0.112633
PaymentMethod_Mailed Check	-0.005098	-0.008351	-0.028126	-0.064348

Notes. For example, the first principal component (PC-1) has its strongest loadings from the following six features:

- Item1
- Item2
- Item3
- Item 6
- Item 7
- Item 8

The sign of the loading value doesn't matter, but just the magnitude (abs(x)). For PC-2, the strongest loadings come from the following six features:

- MonthlyCharge
- Multiple
- OnlineSecurity
- StreamingMovies
- Internet_Fiber
- Internet_None

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. (see References below)

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

G. Demonstrate professional communication in the content and presentation of your submission.

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