Dimension Reduction of Telcom Customer Churn Data

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D212: Data Mining II

Task 2: Dimension Reduction

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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 analysis looked at the 50 features and select 13 continuous features to be used by the PCA. PCA results indicate that 11 principal components are needed to explained approx. 95% of the total variance. 10 principal components are needed to explain approx. 85% of total variance. Eigenvalue analysis suggests using only the first six (6) PCs. The first principal component (PC1) has high correlation to the original features of Tenure and Bandwidth\_GB\_Year. The second principal component (PC2) has high correlation to population and location.

Keywords: Telecom. Churn. Data Mining. Dimension Reduction. PCA. Principal Components. Scree Plot. Load Factors.

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.

List of Tables

[Table 1 *Define continuous features* 8](#_Toc103809242)

[Table 2 *First 5 rows of the original dataset* 9](#_Toc103809243)

[Table 3 *First 5 rows of the scaled data* 11](#_Toc103809244)

[Table 4 *Loadings for each PC to original features* 16](#_Toc103809245)

[Table 5 *Total variance by principal component* 18](#_Toc103809246)

List of Figures

[Figure 1 *Correlation matrix of all 13 principal components with loadings to original features* 14](#_Toc103809247)

[Figure 2 *Scree plot to identify explained variance for each principal component* 15](#_Toc103809248)

[Figure 3 *Heatmap of loadings for each PC to original feature* 17](#_Toc103809249)

[Figure 4 *Bar plot/line plot of variance and cumulative variance for six (6) PCs* 19](#_Toc103809250)

# 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 best metrics when conducting dimension reduction using principal component analysis (PCA)?

## 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.

Reduce high dimension dataset (over 10 ) to a simpler, lower dimension dataset (less than 10 ) using principal component analysis (PCA).

# 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.

The cost or limitation of the PCA is model accuracy, you are giving up accuracy for simplicity. The PCA will determine a lower dimension dataset and the order of significance of the identified principal components so that the results can be visualized and understood by less technical team members. Often, it can be very easy to visualize a 2-dimension plot using just the first two principal components.

The PCA key metrisc are “explained variance” and “factor loading”. According to Schmalen, (Schmalen, 2020) “explained variance measures how much a model can reflect the variance of the whole data. Principle components try to capture as much of the variance as possible and this measure shows to what extent they can do that. It helps to see Components are sorted by explained variance, with the first one scoring highest and with a total sum of up to 1 across all components.” He continues, “factor loading indicates how much a variable correlates with a component.” Using these two metrics and some scree plots and bar plots, the results can be verified as to how effectively the PCA accomplished the dimension reduction.

## 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 Table 1 and Table 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.

Table   
Define continuous features

Table

Description automatically generated

Notes.

Table 2  
First 5 rows of the original dataset

Graphical user interface, text

Description automatically generated

Lat 56.251 44.329 45.356 32.967 29.380

Lng -133.376 -84.241 -123.247 -117.248 -95.807

Population 38.000 10446.000 3735.000 13863.000 11352.000

Children 0.000 1.000 4.000 1.000 0.000

Age 68.000 27.000 50.000 48.000 83.000

Income 28561.990 21704.770 9609.570 18925.230 40074.190

Outage\_sec\_perweek 7.978 11.699 10.753 14.914 8.147

Email 10.000 12.000 9.000 15.000 16.000

Contacts 0.000 0.000 0.000 2.000 2.000

Yearly\_equip\_failure 1.000 1.000 1.000 0.000 1.000

Tenure 6.796 1.157 15.754 17.087 1.671

MonthlyCharge 172.456 242.633 159.948 119.957 149.948

Bandwidth\_GB\_Year 904.536 800.983 2054.707 2164.579 271.493

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 10000 entries, 0 to 9999

Data columns (total 13 columns):

# Column Non-Null Count Dtype

--- ------ -------------- -----

0 Lat 10000 non-null float64

1 Lng 10000 non-null float64

2 Population 10000 non-null int64

3 Children 10000 non-null int64

4 Age 10000 non-null int64

5 Income 10000 non-null float64

6 Outage\_sec\_perweek 10000 non-null float64

7 Email 10000 non-null int64

8 Contacts 10000 non-null int64

9 Yearly\_equip\_failure 10000 non-null int64

10 Tenure 10000 non-null float64

11 MonthlyCharge 10000 non-null float64

12 Bandwidth\_GB\_Year 10000 non-null float64

dtypes: float64(7), int64(6)

memory usage: 1015.8 KB

None

(10000, 13)

Notes. Using the original dataset, it can be seen that there are 13 numerical features that comprise the dataset for the company’s 10,000 customer records. This will be the basis of the PCA.

## 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   
First 5 rows of the scaled data

|  |
| --- |
| 0 1 2 3 4  Lat 3.217 1.025 1.214 -1.065 -1.725  Lng -2.810 0.432 -2.142 -1.746 -0.332  Population -0.673 0.048 -0.417 0.285 0.111  Children -0.972 -0.507 0.891 -0.507 -0.972  Age 0.721 -1.260 -0.149 -0.245 1.446  Income -0.399 -0.642 -1.071 -0.741 0.009  Outage\_sec\_perweek -0.680 0.570 0.252 1.651 -0.623  Email -0.666 -0.005 -0.997 0.986 1.317  Contacts -1.006 -1.006 -1.006 1.018 1.018  Yearly\_equip\_failure 0.947 0.947 0.947 -0.626 0.947  Tenure -1.049 -1.262 -0.710 -0.660 -1.243  MonthlyCharge -0.004 1.630 -0.295 -1.227 -0.528  Bandwidth\_GB\_Year -1.138 -1.186 -0.612 -0.562 -1.428  <class 'pandas.core.frame.DataFrame'>  RangeIndex: 10000 entries, 0 to 9999  Data columns (total 13 columns):  # Column Non-Null Count Dtype  --- ------ -------------- -----  0 Lat 10000 non-null float64  1 Lng 10000 non-null float64  2 Population 10000 non-null float64  3 Children 10000 non-null float64  4 Age 10000 non-null float64  5 Income 10000 non-null float64  6 Outage\_sec\_perweek 10000 non-null float64  7 Email 10000 non-null float64  8 Contacts 10000 non-null float64  9 Yearly\_equip\_failure 10000 non-null float64  10 Tenure 10000 non-null float64  11 MonthlyCharge 10000 non-null float64  12 Bandwidth\_GB\_Year 10000 non-null float64  dtypes: float64(13)  memory usage: 1015.8 KB  None  (10000, 13) |

Notes. The data is available as an attached file located at tables\scaled\_df.csv. This is the final scaled dataset, it can be seen that we have the same 13 features from the original data, but now scaled and ready to be used in PCA.

# Part IV: Analysis

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

## D1. Determine the matrix of all the principal components.

Figure 2 shows the complete set of principal components and the factor loadings to the original features. It is called a correlation matrix with load factors and it shows how much each feature contributes towards each principal component.

## D2. Identify the total number of principal components using the elbow rule or the Kaiser criterion. Include a screenshot of the scree plot.

Figure 3 shows the scree plot for all principal components showing the cumulative sum of total explained variance for each of the principal components. The plot also has lines to indicate 85%, 90% and 95% of total explained variance. The scree plot can be effectively used to select the desired number of principal components to use in the final PCA model.

From the scree plot in Figure 3, and from the eigenvalue data, the appropriate number of components is somewhere between 6 and 10.

From the Eigenvalue calculations, you should select PCs with eigenvalues greater than 1, so PC6 would be the cutoff.

Table 4 and Figure 3 shows the PCA for six (6) principal components with the loadings to original features.

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

Table 5 shows the total variance for each of the principal components.

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

Graphical user interface, text, application

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The total explained variance for six (6) principal components is 56.6. Figure 4 shows a bar plot of total variance for each principal component as well as a line plot showing the cumulative total variance for all of the PCs up to that point.

Figure 1  
Correlation matrix of all 13 principal components with loadings to original features

Chart, treemap chart

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Notes. The correlation matrix for the initial PCA using all 13 PCs. Load factors or +/- .7 indicate a high load factor for that component.

Figure 2  
Scree plot to identify explained variance for each principal component

Table

Description automatically generatedChart, line chart

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Notes. The scaled dataset used for the initial PCA is using all of the original 13 features, so the scree plot should have 13 principal components, PC1 through PC13. It looks like it will take about 10 or 11 PCs to account for a 90% total variance. But, from the Eigenvalue data, select PCs with eigenvalues greater than 1, so PC1 through PC6.

Each PC: [15.344 9.493 8.105 8.035 7.871 7.774 7.686 7.635 7.573 7.398

7.388 5.656 0.042]

Cumulative Sum: [ 15.344 24.836 32.942 40.977 48.847 56.622 64.308 71.943 79.516

86.914 94.302 99.958 100. ]

Table   
Loadings for each PC to original features

Graphical user interface, application, table

Description automatically generated

Notes. Compare table to Figure 3 (next page) of heatmaps of same data.

Figure   
Heatmap of loadings for each PC to original feature

Chart, table

Description automatically generated

Notes.

Table 5  
Total variance by principal component

Graphical user interface, text

Description automatically generated

Notes.

Figure 4  
Bar plot/line plot of variance and cumulative variance for six (6) PCs

Chart

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Notes. Code adapted from Kumar (Kumar, 2020)

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

The first observation is that 12 PCs are required to achieve a total explained variance of 99.9%. That would be a dimension reduction but not quite what was hoped for.

The first 2 principal components have a total explained variance of 24.8%. A much simpler dimensional dataset, but at the extreme expense of all accuracy.

The first 3 principal components have a total explained variance of 32.9%. Not much better.

The first principal component (PC1) is highly correlated to tenure and bandwidth. Either experienced customers who prefer more bandwidth or possibly new customers with only limited bandwidth. But, the correlation for tenure and bandwidth are both above a impact threshold of 0.70.

The second principal component (PC2) is correlated to location and population count in the region nearest to each customer. There is a positive correlation to population and a negative correlation to the location.

Lastly, selecting six (6) principal components as determined by eigenvalue criteria, the total cumulative explained variance is only 56.6, not good at all. Future work should focus on getting more data or defining better continuous data to use in the PCA.

# 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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