Dimension Reduction of Telcom Customer Churn Data

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D212: Data Mining II

Task 2: Dimension Reduction

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Revision 5

Abstract

Telecom customer data has 50 attributes defining each customer, this analysis will use dimension reduction techniques to identify the most influential variables. Data source: Wgu.edu Telecom Churn data (N: 10,000).

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

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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.

# 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?

## 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 identify the most influential features of the customer data. The primary dataset consists of 10,000 customer records with 50 attributes each. The overall steps to the analysis are below:

Explore Data:

1. R <= import .csv file
2. S <= Drop unwanted data from R
3. Describe S’s numerical data
4. Describe S’s categorical data

PCA Pseudo Code:

1. target <= ‘Churn’
2. Y <= S.loc[:, S.columns == target]
3. X <= S.loc[:, S.columns != target]
4. D <= create dummy variables from X
5. Z <= standardize D
6. A<= feature selection
7. Create covariance matrix
8. Calculate Eigenvalues
9. Sort Eigenvalues

# Part II: Technique 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.

From the t

Here is the code used to create Figure 1:

# create scatter plot of lost customer data

fig**,** ax **=** plt**.**subplots**(**figsize **=(**7**,** 5**))**

plt**.**plot**(**df**[**"TEN"**],** df**[**"MCH"**],** marker**=**"x"**,** linestyle**=**""**)**

plt**.**xlabel**(**"Tenure"**)**

plt**.**ylabel**(**"Monthly Charge"**)**

plt**.**title**(**"Lost Customers (Churn='Yes')"**)**

fig**.**savefig**(**"figures/fig\_1"**,** dpi**=**150**)**

## B2. Summarize one assumption of PCA.

Data scie

# 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.

Using data preparation and exploratory data analysis, the following list of variables were determined to be relevant to the analysis. Using a helper function, these numerical variables are described showing whether it is continuous or categorical data:

# describe variables as continuous or categorical

describe\_dataframe\_type**(**df\_numerical**)**

1. INC **is** numerical **(**CONTINUOUS**)** **-** **type:** float64**.**

Min**:** 348.670 Max**:** 189938.400 Std**:** 28623.988

2. OUT **is** numerical **(**CONTINUOUS**)** **-** **type:** float64**.**

Min**:** 0.232 Max**:** 21.207 Std**:** 2.970

3. TEN **is** numerical **(**CONTINUOUS**)** **-** **type:** float64**.**

Min**:** 1.000 Max**:** 71.646 Std**:** 15.577

4. MCH **is** numerical **(**CONTINUOUS**)** **-** **type:** float64**.**

Min**:** 92.455 Max**:** 290.160 Std**:** 41.268

5. BAN **is** numerical **(**CONTINUOUS**)** **-** **type:** float64**.**

Min**:** 248.179 Max**:** 7096.495 Std**:** 1375.370

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

The cleaned dataset is saved to an external text file. Table 1 is a list of the file showing the first 10 rows:

Table

Cleaned Dataset (First 10 rows)

Source: cleaned.csv

Step 7. Find highly correlated variables using a correlation matrix

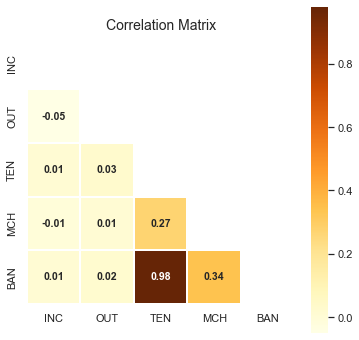


Figure Correlation Matrix

Here is the code to generate the correlation matrix:

# use heatmap graph to identify highly correlated variables

**def** Generate\_heatmap\_graph**(**corr**,** chart\_title**,** mask\_uppertri**=False** **):**

""" Based on features , generate correlation matrix """

mask **=** np**.**zeros\_like**(**corr**)**

mask**[**np**.**triu\_indices\_from**(**mask**)]** **=** mask\_uppertri

fig**,**ax **=** plt**.**subplots**(**figsize**=(**6**,**6**))**

sns**.**heatmap**(**corr

**,** mask **=** mask

**,** square **=** **True**

**,** annot **=** **True**

**,** annot\_kws**={**'size'**:** 10.5**,** 'weight' **:** 'bold'**}**

**,** cmap**=**plt**.**get\_cmap**(**"YlOrBr"**)**

**,** linewidths**=**.1**)**

plt**.**title**(**chart\_title**,** fontsize**=**14**)**

plt**.**show**()**

Generate\_heatmap\_graph**(**

**round(**df\_numerical**.**corr**(),**2**),**

chart\_title **=** 'Correlation Matrix'**,**

mask\_uppertri **=** **True)**

Step 9. Standardize remaining numerical data

# standardize remaining numerical data

scaler **=** StandardScaler**()**

scaled\_features **=** scaler**.**fit\_transform**(**df\_final**.**values**)**

df\_standardized **=** pd**.**DataFrame**(**scaled\_features**,**

index**=**df\_final**.**index**,**

columns**=**df\_final**.**columns**)**

df\_standardized**.**describe**().round(**2**)**

**+-------+---------+---------+---------+---------+**

**|** STD **|** INC **|** OUT **|** TEN **|** MCH **|**

**+-------+---------+---------+---------+---------+**

**|** count **|** 2650.00 **|** 2650.00 **|** 2650.00 **|** 2650.00 **|**

**|** mean **|** **-**0.00 **|** 0.00 **|** **-**0.00 **|** **-**0.00 **|**

**|** std **|** 1.00 **|** 1.00 **|** 1.00 **|** 1.00 **|**

**|** **min** **|** **-**1.39 **|** **-**3.29 **|** **-**0.78 **|** **-**2.59 **|**

**|** 25**%** **|** **-**0.73 **|** **-**0.67 **|** **-**0.58 **|** **-**0.77 **|**

**|** 50**%** **|** **-**0.23 **|** **-**0.01 **|** **-**0.34 **|** 0.02 **|**

**|** 75**%** **|** 0.49 **|** 0.66 **|** 0.04 **|** 0.81 **|**

**|** **max** **|** 5.24 **|** 3.77 **|** 3.76 **|** 2.20 **|**

**+-------+---------+---------+---------+---------+**

Here is the code to create the boxplot:

# use boxplot to look for outliers

fig**,** ax **=** plt**.**subplots**(**figsize **=(**7**,** 5**))**

ax **=** df\_standardized**.**boxplot**(**vert**=False)**

# 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.

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

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

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

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

# 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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