D212 Data Mining II - Principal Component Analysis

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A-1. Propose one question relevant to a real-world organizational situation that you will answer by using principal component analysis (PCA).

We are investigating the customer base for a telecom company, and trying to determine what factors lead to churn (the customer leaving for another company). Since compute resources are finite, and we will encounter a large number of records in our final dataset, we will ask if it is possible to perform dimensionality reduction via feature extraction with Principal Component Analysis.

A-2. 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 goal of this analysis is to reduce the number of variables that are used to predict churn. The reduction can result in faster compute times, but we will have to decide how much accuracy we are willing to lose in order to facilitate the performance gain.

B-1. Explain how PCA analyzes the selected data set. Include expected outcomes.

PCA begins by creating a matrix of how all of the variables are related to one another. This matrix contains direction and magnitude.

Next, PCA will realign the data so that one of the relational matrix components describes most of the variance, while the other is minimized. Finally, the "direction" with the least importance can be removed to reduce the variables that need to be processed. (Brems, 2019)

The expected outcome will be a dataset with less variables than the original, but still able to retain a majority of the accuracy. This will allow faster processing of predictions.

B-2. Summarize one assumption of PCA.

One of the core assumptions of PCA is linearity. This is the assumption that all variables in the dataset combine in a linear manner and exhibit relationships among themselves (Vadapalli, 2020).

C-1. Identify the continuous dataset variables that you will need in order to answer the PCA question proposed in part A1.

First we will review the full dataset and created a trimmed dataset with only the columns of interest.

In [1]:
```
import pandas as pd
import numpy as np

# Show all columns when reviewing
pd.options.display.max_columns = None

# Load the dataset
df = pd.read_csv('churn_clean.csv')
```

In [2]:
```
# describe will limit to the continuous variables
df.describe()
```

Out[2]:

	CaseOrder	Zip	Lat	Lng	Population	Children	
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000	10000.00
mean	5000.50000	49153.319600	38.757567	-90.782536	9756.562400	2.0877	53.07
std	2886.89568	27532.196108	5.437389	15.156142	14432.698671	2.1472	20.69
min	1.00000	601.000000	17.966120	-171.688150	0.000000	0.0000	18.00
25%	2500.75000	26292.500000	35.341828	-97.082813	738.000000	0.0000	35.00
50%	5000.50000	48869.500000	39.395800	-87.918800	2910.500000	1.0000	53.00
75%	7500.25000	71866.500000	42.106908	-80.088745	13168.000000	3.0000	71.00
max	10000.00000	99929.000000	70.640660	-65.667850	111850.000000	10.0000	89.00

> The initial set of variables that seems most relevant are the following:

Variable	Reasoning
Outage_sec_perweek	Poor service can drive a customer to leave
Email	This could be an indicator of the amount and service level being used
Yearly_equip_failure	Again, poor performance can drive customers away
Tenure	Loyalty would definitely impact the likelihood of leaving
Bandwith_GB_Year	This would be another indicator of usage and what internet service is being used

In [3]:
```python
# Create a dataframe limited to the variables we want to use
X = df[['Outage_sec_perweek', 'Email', 'Yearly_equip_failure', 'Tenure', 'B
X.head()
```

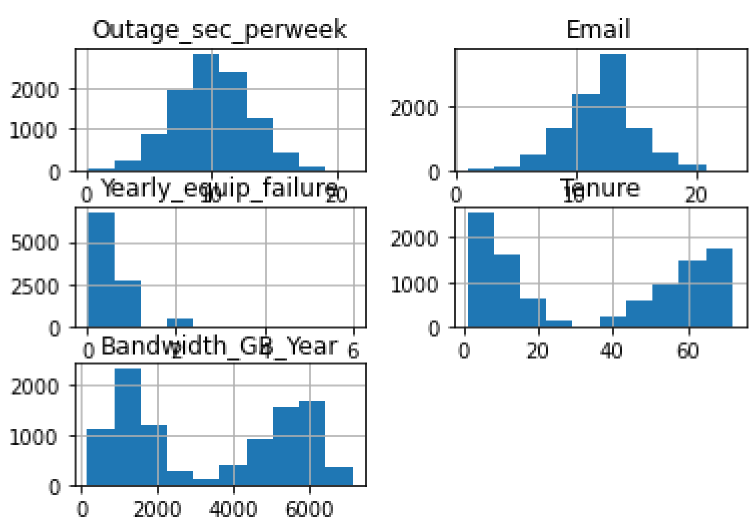
Out[3]:

	Outage_sec_perweek	Email	Yearly_equip_failure	Tenure	Bandwidth_GB_Year
0	7.978323	10	1	6.795513	904.536110
1	11.699080	12	1	1.156681	800.982766
2	10.752800	9	1	15.754144	2054.706961
3	14.913540	15	0	17.087227	2164.579412
4	8.147417	16	1	1.670972	271.493436

Check the histograms for outliers.

In [4]:
```python
X.hist()
```

Out[4]:
```
array([[<AxesSubplot:title={'center':'Outage_sec_perweek'}>,
        <AxesSubplot:title={'center':'Email'}>],
       [<AxesSubplot:title={'center':'Yearly_equip_failure'}>,
        <AxesSubplot:title={'center':'Tenure'}>],
       [<AxesSubplot:title={'center':'Bandwidth_GB_Year'}>,
        <AxesSubplot:>]], dtype=object)
```



In [5]:
```python
X.isna().sum()
```

Out[5]:
```
Outage_sec_perweek      0
Email                   0
Yearly_equip_failure    0
Tenure                  0
Bandwidth_GB_Year       0
dtype: int64
```

There do not appear to be any empty values or outliers in the data.

In [6]:
```
# Convert the target variable (Churn) to numeric and save it for training
# This is not covered in this document, but could be used with the resultin
conditions = [df['Churn'] == 'Yes', (df['Churn'] == 'No')]
values = [1,0]
new_churn_col = np.select(conditions, values)
df['ChurnBit'] = new_churn_col
y = df['ChurnBit']
y.describe()
```

Out[6]:
```
count    10000.000000
mean         0.265000
std          0.441355
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max          1.000000
Name: ChurnBit, dtype: float64
```

C-2. Standardize the continuous dataset variables identified in part C1. Include a copy of the cleaned dataset.

The resulting CSV will be included with the submitted paper.

In [7]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
df_scaled = pd.DataFrame(X_scaled, columns = X.columns)
df_scaled.describe()
```

Out[7]:

	Outage_sec_perweek	Email	Yearly_equip_failure	Tenure	Bandwidth_GB_Year
count	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04
mean	9.869883e-17	-1.802336e-16	-5.909051e-16	1.151235e-15	2.119283e-15
std	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00
min	-3.327464e+00	-3.640754e+00	-6.258635e-01	-1.267917e+00	-1.481263e+00
25%	-6.665728e-01	-6.662818e-01	-6.258635e-01	-1.006306e+00	-9.865847e-01
50%	5.615783e-03	-5.287951e-03	-6.258635e-01	3.420043e-02	-5.162246e-02
75%	6.611971e-01	6.557059e-01	9.466579e-01	1.019358e+00	1.003942e+00
max	3.765413e+00	3.630178e+00	8.809265e+00	1.417195e+00	1.723716e+00

In [8]:
```
df_scaled.to_csv('churn_scaled_task2.csv', index=False)
```

D-1. Determine the matrix of all the principal components.

Now that we have our scaled set of variables, we can fit PCA and **display the matrix of correlation.**

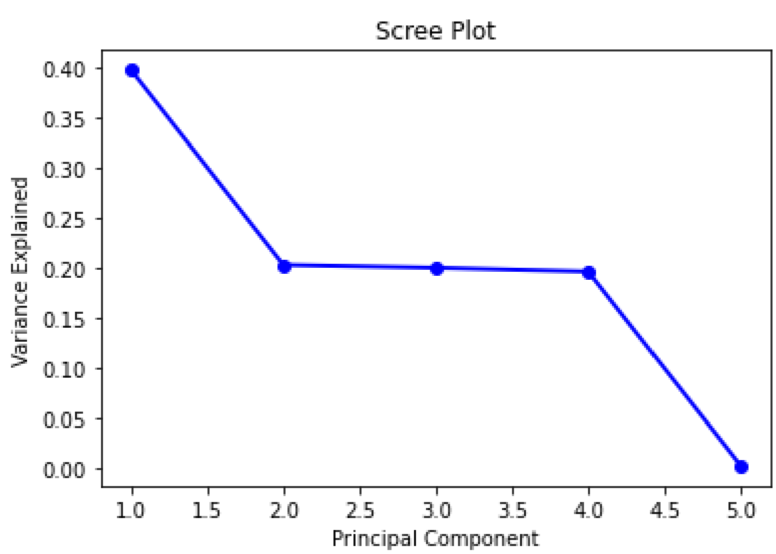
In [9]:
```
from sklearn.decomposition import PCA
pca = PCA()
pc = pca.fit_transform(X_scaled)
var = pca.explained_variance_ratio_

print(pc)
```

```
[[-1.51861441  1.21912925 -0.52435993  0.35656818 -0.06263709]
 [-1.71041258  0.67964671  0.77646513  0.47666944  0.0535953 ]
 [-0.89547685  1.38168689  0.32038223 -0.11736898  0.069119   ]
 ...
 [ 0.58974271  0.08753942 -1.34828218 -0.57251253 -0.09576276]
 [ 1.95119302 -0.99937644  0.60934155 -0.14983045  0.01672141]
 [ 1.52524621 -1.68663937  0.65477471  0.55899613  0.02634083]]
```

D-2. Identify the total number of principal components using the elbow rule or the Kaiser criterion. Include a screenshot of the scree plot.

Creating and elbow plot shows us that the **optimal number of principal components is 4**, due to the low amount of added variance explained with the 5th variable. While the first variable explains the most variance by far, we would still be leaving too much room for low accuracy with a single variable.

In [10]:
```
import matplotlib.pyplot as plt
PC_values = np.arange(pca.n_components_) + 1
plt.plot(PC_values, var, 'o-', linewidth=2, color='blue')
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Variance Explained')
plt.show()
```



D-3. Identify the variance of each of the principal components identified in part D2.

Below are the variances for each variable created by PCA.

In [11]:
```
print(var)
```

```
[0.39845184 0.20313488 0.20025551 0.19645698 0.00170079]
```

In [12]:
```
print(var.cumsum())
```

```
[0.39845184 0.60158672 0.80184223 0.99829921 1.        ]
```

D-4. Identify the total variance captured by the principal components identified in part D2.

The total variance captured with 4 variables is 0.9983.

D-5. Summarize the results of your data analysis.

Using PCA, we are able to remove one of the variables (down to 4) and should still be able to acheive an accuracy very close to the results with 5 variables. Although we didn't reduce further, we should still be able to more quickly train our models and predict with the reduction. This could allow faster results without increased spending for more resources.

Code References

Z. (2021, September 18). How to Create a Scree Plot in Python (Step-by-Step). Statology. Retrieved November 7, 2021, from https://www.statology.org/scree-plot-python/ (https://www.statology.org/scree-plot-python/)

References

Brems, M. (2019, December 10). A One-Stop Shop for Principal Component Analysis - Towards Data Science. Medium. Retrieved November 7, 2021, from https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c (https://towardsdatascience.com/a-one-stop-shop-for-principal-component-analysis-5582fb7e0a9c)

Vadapalli, P. (2020, November 12). PCA in Machine Learning: Assumptions, Steps to Apply & Applications. UpGrad Blog. Retrieved November 7, 2021, from https://www.upgrad.com/blog/pca-in-machine-learning/ (https://www.upgrad.com/blog/pca-in-machine-learning/)