D212 Performance Assessment Task 2

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0.0.1 A. Purpose of Analysis

A1. Relevant Question Can we reduce the dimensionality of our dataset while keeping the most important variables?

Our dataset was high dimensional since we had 50 columns. Most of these columns did not explain the variability of the data. We wanted to reduce the columns with little to no variance. A smaller number of dimensions made the data less complex to analyze and a lower chance of model overfitting (Boeye, 2022).

A2. Analysis Goal The main goal of this analysis was to reduce the dataset to only the important variables that explained most of the variability in the data.

0.0.2 B. Technique Justification

B1. Explanation of PCA Principal Component Analysis (PCA) worked by calculating the covariance matrix of the dimensions in a dataset. For example, if the dataset had 2 dimensions `x` and `y`, then the covariance matrix would be:

$$Matrix(Covariance) = \begin{bmatrix} Cov(x,x) & Cov(x,y) \\ Cov(y,x) & Cov(y,y) \end{bmatrix}$$

This matrix represents the correlations between the dimensions. The PCA algorithm computed the eigenvectors, the directions of the axes with the most variance, and eigenvalues, the coefficients of those directions. The pricipal components were the directions of the data that contained the most information. By ranking these principal components, we could identify which components explained the most variance about our dataset (Jaadi, 2022).

B2. PCA Assumption PCA assumes that all variables have a linear relationship. It uses this assumption of correlations to calculate the eigenvectors and eigenvalues.

0.0.3 C. Data Preparation

C1. Initial Dataset The intial dataset contained 19 continuous variables: `Population`, `Children`, `Age`, `Income`, `Outage_sec_perweek`, `Email`, `Contacts`, `Yearly_equip_failure`, `Tenure`, `MonthlyCharge`, `Bandwidth_GB_Year`, and `Item1` through `Item8` of the survey responses.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

[2]:
```
# Import dataset
churn = pd.read_csv('churn_clean.csv')
```

[3]:
```
# Create new dataframe with relevant continuous variables
df = churn[['Population', 'Children', 'Age', 'Income', 'Outage_sec_perweek',␣
 ↪'Email',
            'Contacts', 'Yearly_equip_failure', 'Tenure', 'MonthlyCharge',␣
 ↪'Bandwidth_GB_Year',
            'Item1', 'Item2', 'Item3', 'Item4', 'Item5', 'Item6', 'Item7',␣
 ↪'Item8']].copy()
```

[4]:
```
# Rename survey responses columns
df.rename(columns={
    'Item1': 'SurveyResponse',
    'Item2': 'SurveyFixes',
    'Item3': 'SurveyReplacements',
    'Item4': 'SurveyReliability',
    'Item5': 'SurveyOptions',
    'Item6': 'SurveyRespect',
    'Item7': 'SurveyCourteous',
    'Item8': 'SurveyListening'
}, inplace=True)
```

C2. Standardize Variables

[5]:
```
# Create scaler object
scaler = StandardScaler()

# Standardize data and assign values back to dataframe
df.loc[:, :] = scaler.fit_transform(df)

df.head()
```

[5]:
```
   Population  Children       Age    Income  Outage_sec_perweek     Email  \
0   -0.673405 -0.972338  0.720925 -0.398778           -0.679978 -0.666282
```

```
1    0.047772 -0.506592 -1.259957 -0.641954            0.570331 -0.005288
2   -0.417238  0.890646 -0.148730 -1.070885            0.252347 -0.996779
3    0.284537 -0.506592 -0.245359 -0.740525            1.650506  0.986203
4    0.110549 -0.972338  1.445638  0.009478           -0.623156  1.316700

   Contacts  Yearly_equip_failure    Tenure  MonthlyCharge  Bandwidth_GB_Year  \
0 -1.005852              0.946658 -1.048746      -0.003943          -1.138487
1 -1.005852              0.946658 -1.262001       1.630326          -1.185876
2 -1.005852              0.946658 -0.709940      -0.295225          -0.612138
3  1.017588             -0.625864 -0.659524      -1.226521          -0.561857
4  1.017588              0.946658 -1.242551      -0.528086          -1.428184

   SurveyResponse  SurveyFixes  SurveyReplacements  SurveyReliability  \
0        1.454307     1.444922            1.471896          -0.485004
1       -0.472948     0.478354           -0.473770          -0.485004
2        0.490679     0.478354           -1.446603           0.489878
3        0.490679     0.478354            0.499063          -1.459886
4        0.490679     0.478354            0.499063          -0.485004

   SurveyOptions  SurveyRespect  SurveyCourteous  SurveyListening
0       0.494844       0.486389        -0.495406         0.490384
1       0.494844      -0.481165         0.476931         0.490384
2       0.494844      -0.481165        -0.495406        -0.481828
3       1.470674       0.486389        -0.495406        -0.481828
4       0.494844       0.486389         0.476931         1.462596
```

[6]:

```python
# Export copy of standardized dataset
df.to_csv('churn_standardized.csv', index=False)
```

0.0.4 D. Perform PCA

D1. Components Matrix

[7]:

```python
# Adapted from Dimensionality Reduction in Python (Boeye, 2022)
# https://app.datacamp.com/learn/courses/dimensionality-reduction-in-python

# Create PCA object and apply to dataset
pca = PCA(n_components=df.shape[1])
pca.fit_transform(df)

# PCA matrix
pca_cols = [f'PC {i + 1}' for i in range(pca.n_components_)]
matrix = pd.DataFrame(
    pca.components_.T,
    columns=pca_cols,
    index=df.columns)
matrix
```

[7]:

```
                         PC 1      PC 2      PC 3      PC 4      PC 5  \
Population          -0.002109 -0.005463  0.014732 -0.292151  0.264958
Children             0.004072  0.015862  0.028393  0.510569  0.345310
Age                  0.006459  0.000294 -0.029319 -0.455297 -0.417933
Income               0.001038  0.006035  0.025865  0.252065 -0.285030
Outage_sec_perweek  -0.017516  0.003927 -0.014363 -0.220115  0.339482
Email                0.008744 -0.020609 -0.003459 -0.190450  0.519450
Contacts            -0.008761  0.003318 -0.011853 -0.420731 -0.124577
Yearly_equip_failure -0.007688  0.017604  0.008199  0.167516 -0.373155
Tenure              -0.016320  0.702323 -0.063085 -0.005355 -0.007568
MonthlyCharge        0.000930  0.039858 -0.009499 -0.298690  0.113921
Bandwidth_GB_Year   -0.016845  0.703831 -0.062132  0.005068  0.022808
SurveyResponse       0.458670  0.031340  0.280974 -0.010952 -0.002667
SurveyFixes          0.433847  0.038755  0.282381 -0.020122 -0.002284
SurveyReplacements   0.400488  0.035504  0.280527 -0.004108  0.013294
SurveyReliability    0.145802 -0.039380 -0.568452  0.015142  0.001544
SurveyOptions       -0.175698  0.056278  0.587090 -0.038899 -0.023275
SurveyRespect        0.405080 -0.006648 -0.183525 -0.000910  0.002245
SurveyCourteous      0.358246  0.002051 -0.181337  0.031194 -0.022614
SurveyListening      0.308733 -0.013634 -0.131655 -0.028435 -0.001573

                         PC 6      PC 7      PC 8      PC 9     PC 10  \
Population           0.402355  0.355864  0.329128  0.161654  0.580378
Children            -0.089376  0.119069  0.226847  0.155912 -0.175953
Age                  0.183902  0.152752 -0.024113  0.346066 -0.180481
Income              -0.084983 -0.429611  0.581477  0.449649  0.219833
Outage_sec_perweek  -0.591284  0.273527  0.262607 -0.149557  0.125521
Email                0.319498 -0.103117  0.170129  0.290785 -0.592268
Contacts            -0.146366 -0.275202  0.508824 -0.434373 -0.248703
Yearly_equip_failure -0.147092  0.686465  0.241921  0.114547 -0.334113
Tenure               0.048576  0.000016  0.007554 -0.028780 -0.001590
MonthlyCharge       -0.537631 -0.112559 -0.284655  0.562547  0.029519
Bandwidth_GB_Year    0.005063 -0.009132 -0.001688  0.001654  0.001271
SurveyResponse      -0.016377  0.018684 -0.013618 -0.012424 -0.012899
SurveyFixes         -0.022966  0.000550 -0.001653 -0.014345 -0.006536
SurveyReplacements   0.022177  0.008048 -0.032817 -0.017965 -0.011038
SurveyReliability    0.013909  0.010808 -0.024875 -0.020863 -0.000102
SurveyOptions        0.008693 -0.010701 -0.011610 -0.013280  0.001989
SurveyRespect        0.002666  0.000918  0.025175  0.009562 -0.007608
SurveyCourteous      0.010414 -0.059311  0.048238 -0.001604 -0.022373
SurveyListening     -0.034953  0.044129  0.010774  0.014507  0.097526

                        PC 11     PC 12     PC 13     PC 14     PC 15  \
Population           0.167295  0.229022 -0.057130  0.019142 -0.016176
Children             0.655599 -0.241974  0.017020 -0.012250 -0.014011
Age                  0.234748 -0.590829 -0.045336  0.002513 -0.002495
Income              -0.252659 -0.057674 -0.020484 -0.079018 -0.007573
```

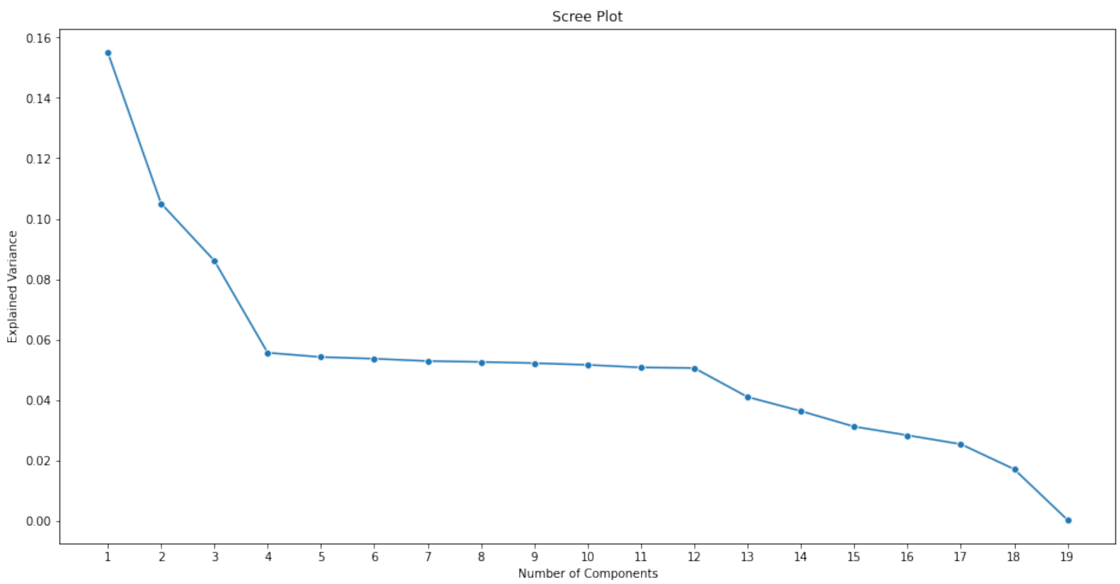
Outage_sec_perweek	-0.319263	-0.439536	-0.089844	0.016926	-0.008716
Email	-0.328652	0.061145	0.061158	-0.017175	-0.016342
Contacts	0.371468	0.241548	0.044032	-0.035285	-0.003279
Yearly_equip_failure	-0.146136	0.365394	0.020739	0.006446	-0.015853
Tenure	-0.028600	-0.027147	0.005940	-0.003507	0.006548
MonthlyCharge	0.228176	0.375187	-0.005920	0.014551	-0.016508
Bandwidth_GB_Year	-0.000743	0.008874	0.010520	-0.003326	0.005612
SurveyResponse	0.007946	0.022275	-0.069228	-0.116810	-0.046422
SurveyFixes	0.009542	-0.013865	-0.111545	-0.170010	-0.066139
SurveyReplacements	-0.020962	0.000952	-0.176045	-0.249291	-0.147591
SurveyReliability	0.008042	0.023763	-0.173905	-0.480655	-0.442505
SurveyOptions	-0.008550	-0.014829	0.137294	0.057896	-0.206302
SurveyRespect	0.001311	0.017187	-0.060350	0.062041	0.759347
SurveyCourteous	-0.005070	0.011386	-0.170669	0.804890	-0.377415
SurveyListening	-0.018232	-0.065755	0.921694	-0.018911	-0.113107

	PC 16	PC 17	PC 18	PC 19
Population	0.001210	-0.005661	-0.002356	-0.000322
Children	0.014490	0.020915	-0.000948	-0.021615
Age	-0.009405	0.005784	0.013696	0.022421
Income	-0.002561	0.005301	0.013466	-0.000910
Outage_sec_perweek	0.013529	0.018262	0.013516	0.000361
Email	0.006449	-0.017253	0.000961	0.000226
Contacts	-0.026498	0.020255	-0.000813	-0.000948
Yearly_equip_failure	-0.001308	0.007488	-0.021448	-0.000145
Tenure	-0.007773	-0.004625	0.007519	-0.705251
MonthlyCharge	-0.000068	0.021494	-0.012007	-0.045778
Bandwidth_GB_Year	-0.006119	-0.002188	0.001815	0.706780
SurveyResponse	0.025057	-0.240545	0.792965	0.002979
SurveyFixes	0.073917	-0.590696	-0.573547	-0.001144
SurveyReplacements	-0.395875	0.673812	-0.176863	0.000077
SurveyReliability	0.431933	0.088483	0.018686	0.000105
SurveyOptions	0.694089	0.264886	-0.041819	-0.000811
SurveyRespect	0.400452	0.229253	-0.063809	-0.000593
SurveyCourteous	0.071323	0.066812	-0.041324	0.000486
SurveyListening	-0.045658	0.045412	-0.043235	-0.001994

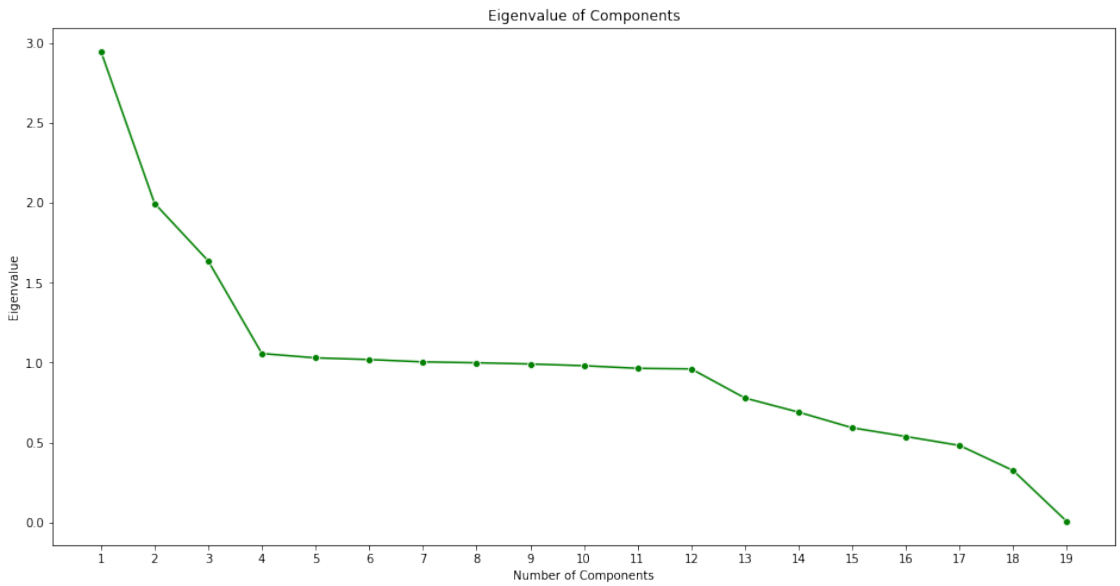
D2. Number of Components

[8]:
```python
# Adapted from How to Perform PCA in Python (Middleton, 2021)
# https://my.wgu.edu/courses/course/23720006/course-material

# Create scree plot showing component variance
pca_values = np.arange(pca.n_components_) + 1
plt.figure(figsize=(16, 8))
sns.lineplot(x=pca_values, y=pca.explained_variance_ratio_, marker='o')
plt.title('Scree Plot')
```

```
plt.xlabel('Number of Components')
plt.ylabel('Explained Variance')
plt.xticks(range(1, 20))
plt.show()
```



[9]:
```
# Calculate the covariance and eigenvalues of each component
cov_values = np.dot(df.T, df) / df.shape[0]
eigenvalues = [np.dot(eigenvector.T, np.dot(cov_values, eigenvector)) for␣
↪eigenvector in pca.components_]

# Plot eigenvalues for Kaiser criterion
plt.figure(figsize=(16, 8))
# plt.plot(pca_values, eigenvalues, 'o-', color='green')
sns.lineplot(x=pca_values, y=eigenvalues, marker='o', color='green')
plt.title('Eigenvalue of Components')
plt.xlabel('Number of Components')
plt.ylabel('Eigenvalue')
plt.xticks(range(1, 20))
plt.show()
```



Using the scree plot and the elbow rule, we identified the number of principal components to be four. However, the total explained variance appeared to be relatively low with only four components. Instead, we plotted the eigenvalue of each component and used the Kaiser criterion for additional insight. With this criteria, all components with eigenvalues greater than one were selected. This method gave us 12 principal components and provided more total explained variance.

D3. Variance of Components

[10]:
```
print('Principal Components Explained Variance:')

# Percentage of variance explained by each component
for index, var in enumerate(pca.explained_variance_ratio_):
    print(f'- PC {index + 1}: {round(var * 100, 2)}%')
    # Break out of loop at 12 components
    if index == 11:
        break
```

```
Principal Components Explained Variance:
- PC 1: 15.52%
- PC 2: 10.51%
- PC 3: 8.61%
- PC 4: 5.56%
- PC 5: 5.42%
- PC 6: 5.36%
- PC 7: 5.29%
- PC 8: 5.26%
- PC 9: 5.22%
- PC 10: 5.16%
- PC 11: 5.08%
```

- PC 12: 5.06%

D4. Total Variance

[11]:
```
# Sum of variance for 12 principal components
total = sum(pca.explained_variance_ratio_[:12])
print(f'Total Explained Variance: {round(total * 100, 2)}%')
```

```
Total Explained Variance: 82.05%
```

D5. Analysis Results We used PCA to reduce the dimensions of our dataset and retained 12 principal components. These components explained 82.05% of the total variability. This meant that the other 38 variables only contributed 17.95% to the explained variance. By focusing our analyses on these important features, we could significantly reduce the resources required and avoid overfitting our models. An added value of this analysis was that we could also use all 19 components to explain the maximum variance possible. However, we would need to consider the trade-offs if we decided to pursue this option.

0.0.5 E. Third-Party Code

Middleton, K. (2021). Lesson 7: Principal Component Analysis (PCA). Western Governors University. Retrieved July 11, 2022. https://my.wgu.edu/courses/course/23720006/course-material

0.0.6 F. References

Boeye, J. (2022). Dimensionality Reduction in Python. DataCamp. Retrieved July 10, 2022, from https://app.datacamp.com/learn/courses/dimensionality-reduction-in-python

Jaadi, Z. (2022, July 14). A Step-by-Step Explanation of Principal Component Analysis (PCA). Built In. Retrieved July 11, 2022, from https://builtin.com/data-science/step-step-explanation-principal-component-analysis