Exploratory Factor Analysis

Name - Amith Korada

Course - AI & ML
(Batch - 4)

Duration - 12 Months

Problem Statement - Building a Machine Learning model for factor analysis on Airline Passenger Satisfaction Dataset.

Prerequisites -

What things you need to install the software and how to install them:

Python 3.6 This setup requires that your machine has the latest version of python. The following URL https://www.python.org/downloads/ can be referred to as download python.

The second and easier option is to download anaconda and use its anaconda prompt to run the commands. To install anaconda check this URL https://www.anaconda.com/download/ You will also need to download and install the below 3 packages after you install either python or anaconda from the steps above Sklearn (scikit-learn) numpy scipy if you have chosen to install python 3.6 then run the below commands in command prompt/terminal to install these packages pip install -U sci-kit-learn pip install NumPy pip install scipy if you have chosen to install anaconda then run the below commands in anaconda prompt to install these packages conda install -c sci-kit-learn conda install -c anaconda numpy conda install -c anaconda scipy.

Dataset Used - Airline Passenger Satisfaction Dataset

1. Importing required libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import os
```

2. Loading the dataset

```
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

```
train.shape
```

```
(103904, 25)
```

```
test.shape
```

```
(25976, 25)
```

3. Data Analysis

```
train.head()
```

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	...	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service
0	0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	...	5	4	3	4	4
1	1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	...	1	1	5	3	1
2	2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	...	5	4	3	4	4
3	3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	...	2	2	5	3	1
4	4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	...	3	3	4	4	3

5 rows × 25 columns

```
X_train = train.iloc[:,8:-3]
X_test = test.iloc[:,8:-3]
```

```
X_train.shape
```

```
(103904, 14)
```

```
X_test.shape
```

```
(25976, 14)
```

```
X_train.head()
```

	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness
0	3	4	3	1	5	3	5	5	4	3	4	4	5	5
1	3	2	3	3	1	3	1	1	1	5	3	1	4	1
2	2	2	2	2	5	5	5	5	4	3	4	4	4	5
3	2	5	5	5	2	2	2	2	2	5	3	1	4	2
4	3	3	3	3	4	5	5	3	3	4	4	3	3	3

```
train_target = train.iloc[:,-1:]
train_target.shape
```

```
(103904, 1)
```

```
np.unique(train_target, return_counts = True)
```

```
(array(['neutral or dissatisfied', 'satisfied'], dtype=object),
 array([58879, 45025], dtype=int64))
```

4. Zero Centering the data

```
x = X_train.values
x_mean = np.mean(x, axis=0)
x_n = x - np.matrix(x_mean)
x_n = x_n.T
x_n.shape
```

```
(14, 103904)
```

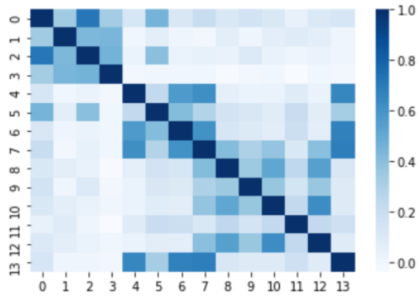
```
x_n
```

```
matrix([[ 0.27031683,  0.27031683, -0.72968317, ..., -1.72968317,
         -1.72968317, -1.72968317],
        [ 0.93970396, -1.06029604, -1.06029604, ..., -2.06029604,
         -2.06029604, -0.06029604],
        [ 0.2430994 ,  0.2430994 , -0.7569006 , ..., -1.7569006 ,
         -1.7569006 ,  0.2430994 ],
        ...,
        [ 0.6957095 , -2.3042905 ,  0.6957095 , ...,  1.6957095 ,
          1.6957095 ,  0.6957095 ],
        [ 1.3595723 ,  0.3595723 ,  0.3595723 , ...,  1.3595723 ,
          0.3595723 , -0.6404277 ],
        [ 1.71364914, -2.28635086,  1.71364914, ...,  0.71364914,
         -2.28635086, -2.28635086]])
```

5. Covariance and Correlation

```
c1 = np.cov(x_n)
c2 = np.corrcoef(x_n)
```

```
ax = sns.heatmap(c2, cmap='Blues')
```



6. Extracting the Eiigenvalues and Eigenvectors

```
eig_val, eig_vec = np.linalg.eig(c1)
eig_sorted = np.sort(eig_val)[::-1]
arg_sort = np.argsort(eig_val)[::-1]
```

```
eig_val
```

```
array([6.52815927, 4.47255915, 3.43215579, 1.98504987, 1.61162741,
       1.18057993, 1.02652179, 0.87877104, 0.32742411, 0.75170941,
       0.57857082, 0.47242866, 0.51571787, 0.51339277])
```

```
eig_vec_ls = []
eig_val_ls = []
```

```
imp_vec = arg_sort[:3]
print(imp_vec)
for i in imp_vec:
    eig_vec_ls.append(eig_vec[:,i])
    eig_val_ls.append(eig_val[i])
print(eig_vec_ls)
print(eig_val_ls)
```

```
[0 1 2]
[array([0.27033179, 0.15491373, 0.21598175, 0.09124768, 0.32248111,
       0.31012556, 0.35572388, 0.42488029, 0.24281505, 0.20346816,
       0.20154101, 0.16263595, 0.20267719, 0.36360393]), array([ 0.39021937,  0.49052653,  0.51498574,  0.37850549, -0.2026089
7,
        0.09688795, -0.1994409 , -0.22052189, -0.06650134, -0.02366476,
       -0.04491473, -0.04552343, -0.04930291, -0.2197468 ]), array([ 0.05306717, -0.00824977,  0.07508455,  0.06404967,  0.3194
0211,
        0.14576517,  0.27020783,  0.0037756 , -0.4376789 , -0.36397705,
       -0.42392401, -0.16410797, -0.43174682,  0.27201769])]
[6.528159273595769, 4.472559148142906, 3.432155786676286]
```

7. Estimating V (Factor Loading Matrix)

```
eig_val_arr = np.array(eig_val_ls)
lambda_i = np.diag(eig_val_arr)

eig_vec_mat = np.matrix(eig_vec_ls).T

V = eig_vec_mat@np.sqrt(lambda_i)
print(V)
```

```
[[ 0.69070483  0.82525254  0.09831266]
 [ 0.39580866  1.03738639 -0.01528359]
 [ 0.55183905  1.08911378  0.13910223]
 [ 0.23314023  0.80047953  0.11865892]
 [ 0.8239477  -0.42848608  0.59172685]
 [ 0.79237896  0.20490276  0.27004569]
 [ 0.90888385 -0.42178611  0.50058914]
 [ 1.08558032 -0.46636909  0.00699471]
 [ 0.62039882 -0.14063987 -0.81084737]
 [ 0.5198665  -0.05004723 -0.67430674]
 [ 0.51494257 -0.09498759 -0.78536494]
 [ 0.41553912 -0.09627489 -0.30402772]
 [ 0.51784555 -0.1042679  -0.79985753]
 [ 0.9290176  -0.46472989  0.50394211]]
```

8. Computing Variance of the important Eigenvectors and Estimating S (Source Vector)

```
var_ls = []
x_var = np.var(x_n, axis=1)
x_var = np.ravel(x_var)
print(x_var.shape)
print(x_var)
for i in range(V.shape[0]):
    s = np.sum(np.square(np.ravel(V[i,:])))
    sig_2 = x_var[i]-s
    var_ls.append(sig_2)
var_ls = np.array(var_ls)
S = np.diag(var_ls)
print(S)
```

```
(14,)
[1.76311414 2.32583197 1.95698483 1.63229974 1.76764022 1.82115689
 1.73997514 1.77684714 1.65984098 1.73079886 1.39451944 1.60121119
 1.38217027 1.72204345]
[[0.59533385 0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         1.09276337 0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.44694024 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.92309795 0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.55500941 0.
  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         1.07838266

  0.         0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.48541226 0.         0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.38081347 0.         0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.59769326 0.         0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         1.00334337 0.         0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.50353286 0.
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         1.32683672
  0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.46336238 0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.38903823]]
```

9. Dimensionality Reduction Transformation (Z - LAtent Factor Vector)

```
C1_inv = np.linalg.inv(c1)
W = V.T@C1_inv
print(W.shape)
print(W)
```

```
(3, 14)
[[ 0.10580392  0.06063097  0.08453211  0.03571301  0.1262144   0.12137862
   0.13922513  0.16629195  0.09503427  0.07963447  0.07888021  0.06365334
   0.0793249   0.14230927]
 [ 0.18451462  0.2319447   0.2435102   0.17897573 -0.09580334  0.04581331
  -0.09430532 -0.10427343 -0.03144506 -0.01118984 -0.02123786 -0.02152568
  -0.0233128  -0.10390693]
 [ 0.02864458 -0.00445306  0.04052911  0.03457271  0.17240676  0.07868107
   0.14585269  0.00203799 -0.23625016 -0.1964674  -0.22882555 -0.08858214
  -0.23304814  0.14682961]]
```

```
z = W@x_n
z1 = z.T
```

```
z.shape
```

```
(3, 103904)
```

```
z
```

```
matrix([[ 1.17813457, -1.64286334,  1.06568195, ..., -0.10159264,
         -1.87354186, -2.16462   ],
        [-0.77690998,  0.89139133, -1.37490904, ..., -1.73737597,
         -0.06824035,  0.64493744],
        [ 0.17824378, -0.56877708,  0.5429592 , ..., -0.01210009,
         -1.3963161 , -0.26353567]])
```