VIRGINIA COMMONWEALTH UNIVERSITY

A4- MULTIVARIATE ANALYSIS AND BUSINESS ANALYTICS APPLICATIONS

Analysis of data- Descriptive statistics

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INTRODUCTION

In market research, various statistical techniques are employed to extract meaningful insights from data, enhancing decision-making processes. Principal Component Analysis (PCA) and Factor Analysis (FA) are used to uncover latent variables and reduce the dimensionality of complex datasets, revealing underlying patterns in respondent data. Cluster Analysis segments respondents into homogeneous groups based on similarities in background variables, facilitating targeted marketing strategies and customer segmentation. Multidimensional Scaling (MDS) is utilized to visualize and interpret similarities or dissimilarities among items or concepts, such as consumer preferences for different ice cream flavours in this context. Lastly, Conjoint Analysis is pivotal in understanding consumer preferences by analysing trade-offs among various product attributes, such as crust type, toppings, and pricing in the pizza market. These methods collectively provide a comprehensive framework for dissecting consumer behaviour, optimizing product offerings, and gaining competitive advantage in dynamic markets.

OBJECTIVES:

- **Dimension Reduction and Pattern Identification:** Use PCA and FA to reduce data complexity and identify underlying patterns.

- **Segmentation of Respondents:** Apply Cluster Analysis to categorize respondents into distinct groups based on background variables.

- **Visualization of Similarities:** Utilize MDS to visually interpret similarities among ice cream flavours.

- **Preference Analysis and Optimization:** Conduct Conjoint Analysis to analyses consumer preferences and optimize product attributes.

- **Insight Generation and Decision Support:** Generate actionable insights to support strategic decision-making in product development and marketing.

BUSINESS SIGNIFICANCE

The business significance of these analytical techniques lies in their ability to transform raw data into actionable insights that drive strategic decisions and enhance competitive advantage. By applying Principal Component Analysis (PCA) and Factor Analysis (FA), businesses can streamline operations and marketing efforts by identifying key factors influencing customer behaviour and preferences. Cluster Analysis aids in targeted marketing strategies by segmenting customers into meaningful groups based on shared characteristics, allowing for tailored product offerings and personalized marketing campaigns. Multidimensional Scaling (MDS) visually maps consumer perceptions, helping businesses understand market positioning and product differentiation. Conjoint Analysis provides deep insights into customer preferences, enabling businesses to optimize product features and pricing strategies. Collectively, these techniques empower businesses to align offerings with customer expectations, improve customer satisfaction, and capitalize on market opportunities, ultimately driving growth and profitability in competitive markets.

CODES, RESULTS AND INTERPRETATION:

Part A - Perform Principal Component Analysis and Factor Analysis to identify data dimensions

Python Code(Factor Analysis):

```
# Read the data
survey_df = pd.read_csv('D:\\CHRIST\\Boot camp\\DATA\\Survey.csv')
sur_int = survey_df.iloc[:, 19:45]  # Adjust the column range accordingly

-
# Factor Analysis
fa = fa.FactorAnalyzer(n_factors=4, rotation="varimax")
fa.fit(sur_int.to_numpy())

-
# Print factor loadings
loadings = fa.loadings_
print(loadings)

-
# Create a heatmap of the loadings matrix
```

```
plt.figure(figsize=(10, 8))
plt.imshow(loadings, cmap='hot', interpolation='nearest')
plt.colorbar()
plt.show()

# Print communalities
print("Communalities:")
print(fa.get_communalities())

# Print factor scores
print("Factor Scores:")
print(fa.transform(sur_int.to_numpy()))
```

R Code(Factor Analysis):

```
survey_df<-read.csv('/Users/niteshreddy/Downloads/A4
DATA/Survey.csv',header=TRUE)
sur_int=survey_df[,20:46]

#Factor Analysis

factor_analysis<-fa(sur_int,nfactors = 4,rotate = "varimax")

names(factor_analysis)

print(factor_analysis$loadings,reorder=TRUE)

fa.diagram(factor_analysis)

print(factor_analysis$communality)

print(factor_analysis$scores)
```

Python Code(Component Analysis):

```
import pandas as pd

# Load the data
survey_df = pd.read_csv('/Users/niteshreddy/Downloads/A4 DATA/Survey.csv')
print(survey_df.shape)
print(survey_df.columns)
print(survey_df.head())
print(survey_df.info())

# Check for NA values
print(survey_df.isna().sum().sum())

# Select the relevant columns for PCA and factor analysis
sur_int = survey_df.iloc[:, 19:46]  # Columns 20 to 46 in Python are 19:46
print(sur_int.info())
print(sur_int.shape)

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Standardize the data
scaler = StandardScaler()
sur_int_scaled = scaler.fit_transform(sur_int)

# Perform PCA
pca = PCA(n_components=5)
pca_fit = pca.fit(sur_int_scaled)
print(pca.explained_variance_ratio_)
print(pca.components_)

from factor_analyzer import FactorAnalyzer

# Perform Factor Analysis
fa = FactorAnalyzer(n_factors=5, rotation='promax')
fa.fit(sur_int_scaled)
print(fa.loadings_)
print(fa.get_factor_variance())

import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Biplot for PCA
def biplot(score, coeff, labels=None):
    xs = score[:, 0]
    ys = score[:, 1]
    n = coeff.shape[0]
    scalex = 1.0 / (xs.max() - xs.min())
    scaley = 1.0 / (ys.max() - ys.min())
    plt.scatter(xs * scalex, ys * scaley, c='r')
    for i in range(n):
        plt.arrow(0, 0, coeff[i, 0], coeff[i, 1], color='b', alpha=0.5)
        if labels is None:
            plt.text(coeff[i, 0] * 1.15, coeff[i, 1] * 1.15, "Var"+str(i+1), color='g',
ha='center', va='center')
        else:
            plt.text(coeff[i, 0] * 1.15, coeff[i, 1] * 1.15, labels[i], color='g', ha='center',
va='center')
    plt.xlabel("PC{}".format(1))
    plt.ylabel("PC{}".format(2))
    plt.grid()

# Project the data onto the principal components
pca_scores = pca.transform(sur_int_scaled)

# Create the biplot
plt.figure(figsize=(10, 7))
biplot(pca_scores, pca.components_)
plt.show()
```

R code(Component Analysis):

```
# Load the data
survey_df <- read.csv('/Users/niteshreddy/Downloads/A4 DATA/Survey.csv', header
= TRUE)
dim(survey_df)
names(survey_df)
head(survey_df)
str(survey_df)
# A) Do principal component analysis and factor analysis and identify the dimensions
in the data.
```

```
# Check for NA values
sum(is.na(survey_df))
# Select the relevant columns for PCA and factor analysis
sur_int <- survey_df[, 20:46]
str(sur_int)
# Perform PCA using psych package
pca_psych <- principal(sur_int, 5, n.obs = 162, rotate = "promax")
pca_psych
# Perform Omega hierarchical analysis
om.h <- omega(sur_int, n.obs = 162, sl = FALSE)
op <- par(mfrow = c(1, 1))
om <- omega(sur_int, n.obs = 162)
# Perform PCA using FactoMineR package
pca_fm <- PCA(sur_int, scale.unit = TRUE)
summary(pca_fm)
# Biplot using factoextra
fviz_pca_biplot(pca_fm, repel = TRUE)
# Show the structure and dimensions of the selected columns
str(sur_int)
```

Result:

```
[[-0.15781009  0.42809134  0.05879243 -0.13526352]
 [ 0.07288457  0.07797564 -0.09376015  0.72270594]
 [ 0.67791474 -0.10906029  0.25599157  0.12315536]
 [ 0.45294307  0.19306866 -0.14202126  0.09102672]
 [ 0.56145098  0.05977592 -0.15846106  0.10167805]
 [ 0.44508348 -0.0324726  -0.02008422  0.46566121]
 [ 0.40127304  0.65592565 -0.04681206  0.06621177]
 [ 0.54536401  0.17133537 -0.06944276 -0.1745679 ]
 [ 0.77346812 -0.23204538  0.31139215 -0.08601212]
 [ 0.13600482  0.10476011 -0.07605281 -0.1851078 ]
 [ 0.74442306  0.0982716  -0.06279514  0.13271725]
 [ 0.61456757  0.12385518 -0.10379084  0.25558762]
 [ 0.831264    0.04360933 -0.01602555 -0.06757234]
 [ 0.18089295  0.5781131  -0.06496421  0.09677394]
 [ 0.08522971 -0.12722077  0.5149248  -0.0147638 ]
 [-0.12867754  0.18571432  0.51035205 -0.01479766]
 [-0.09884299 -0.09829734  0.31043878 -0.06327067]
 [-0.12075303 -0.08561139  0.88293084  0.28205672]
 [ 0.41597756  0.48625238 -0.13041834 -0.03370875]
 [ 0.3030142   0.14591216  0.26405999 -0.08696872]
 [ 0.64708197  0.39365565 -0.18483817 -0.14750424]
 [ 0.70663536 -0.07753737  0.08586913 -0.32104338]
 [ 0.09492154  0.01416831  0.36329693 -0.04207299]
 [ 0.75374487  0.34338309  0.05243772  0.07115759]
 [ 0.74497866  0.39843936  0.02755836  0.05399374]
 [ 0.75557128  0.39188083  0.02353685  0.15929651]]
```

Communalities:
[0.22991899 0.54248721 0.55216147 0.27088883 0.35424869 0.41639751
 0.59783387 0.36207396 0.75646115 0.06952092 0.5853801 0.46913098
 0.69772445 0.38052256 0.28881475 0.3117259 0.11980772 0.88103346
 0.42762393 0.1903992 0.62960249 0.61578794 0.14296564 0.6938564
 0.71742191 0.75038791]

Factor Scores:
[[-6.28619743e-01 1.85657494e+00 -5.47519178e-01 -8.81439669e-01]
 [-1.69513914e+00 1.12800561e+00 -5.80307050e-01 -9.38083207e-01]
 [-1.20280931e+00 5.89699103e-01 -1.39117035e+00 -2.86780837e+00]
 [1.99352990e+00 4.88864495e-02 -2.07936514e+00 2.18544871e-01]
 [4.11314878e-01 -1.26821776e+00 -7.80870767e-01 6.66228671e-02]
 [-2.11478560e-01 2.03794816e-01 -6.50677463e-01 2.05174946e-01]
 [7.43577413e-01 6.43368392e-01 1.00212144e-01 1.03878997e+00]
 [-1.91404810e+00 3.03937289e-01 -1.32917310e+00 -2.15077532e-01]
 [-8.56474198e-01 -2.96858773e-03 2.93861146e-01 9.20159872e-02]
 [2.36520458e-01 5.51241056e-02 3.48090670e-02 -6.03796924e-01]
 [-4.68064081e-01 -8.66072292e-01 -7.46975265e-02 -6.21582489e-01]

```
[-8.75004407e-01 -1.08807300e+00 -1.13530109e+00  6.56135510e-01]
[-1.19487644e+00  8.94305070e-02  4.89637706e-01  9.91715591e-01]
[-3.01457336e-01  1.00436570e-01  1.20733916e+00  1.97792324e-01]
[-1.00291293e+00  4.94104285e-01 -1.24637702e-01 -2.07152409e-01]
[-2.44664326e+00 -1.14035022e-01  1.61004829e-01  5.75188733e-01]
[-1.25577846e+00 -3.56172547e-01 -7.15364485e-01  1.04921625e+00]
[-1.17254635e+00  1.21161268e+00 -1.83678942e-01  8.19594214e-01]
[ 4.04252036e-01  1.29219401e+00 -1.50176103e+00  1.71572855e-01]
[ 4.91676501e-01  1.92667044e-01 -2.44581210e+00 -4.37601486e-01]
[-1.17254635e+00  1.21161268e+00 -1.83678942e-01  8.19594214e-01]
[-1.18430113e-01  6.13931005e-01  1.08967528e+00  1.32810436e+00]
[-9.89414929e-01  1.50327651e+00 -2.60459187e-01  9.36551773e-01]
[ 5.45913862e-01 -6.12972222e-01  1.19522542e+00  4.73974759e-01]
[ 1.60656285e+00  8.48989955e-01  2.09647043e-01  3.46249330e-01]
[-4.01168383e-01 -2.52486384e-01 -1.57889392e-01  1.35125021e+00]
[-5.70149338e-01 -1.01616206e+00  1.02586710e+00  8.78902429e-01]
[ 5.57012596e-02 -5.78556540e-02  5.09137586e-03  6.76539136e-01]
[-1.07970184e+00  5.37184202e-01 -4.86901676e-01  1.41408056e+00]
[ 8.96814338e-01 -6.47961098e-01 -7.65034396e-01 -7.04074626e-01]
[ 8.69607701e-01  5.95486198e-01 -6.38034715e-01  3.78813780e-01]
[-6.37345825e-01 -1.10103294e+00  1.22809820e-01 -4.53821368e-02]
[-5.84225979e-01  4.19191582e-02  1.27085126e+00 -1.66638848e-01]
[ 8.44456916e-01  4.74671338e-01  6.06587744e-01 -4.49510340e-01]
[-1.53043482e+00  3.06961797e-01  5.04757719e-01 -2.77263230e-01]
[ 2.52217422e-01  8.37519715e-01 -6.55798084e-01 -1.08047700e+00]
[-2.65256836e-01 -3.93585990e-01  1.00265475e+00  6.73951617e-01]
[ 8.75266361e-01 -1.57998563e+00  1.05827836e-01 -5.01791914e-01]
[-5.83336049e-02 -1.24268812e-01  3.12217836e-01  6.25041344e-01]
[-1.50415166e-01 -5.71515007e-01  4.42151168e-01 -1.13739766e+00]
[-4.15457002e-01 -1.06805866e+00 -3.79121037e-01  4.16298983e-01]
[ 5.67742135e-01  8.66194617e-01  1.18757213e+00 -1.73348437e+00]
[ 1.48058278e+00  5.83409123e-02 -1.51677332e+00  6.14654585e-01]
[ 8.84020437e-04  4.06199309e-01  1.29140547e+00 -5.16368191e-01]
[-2.56762812e-01 -1.15793950e+00  1.58791083e+00 -1.52548112e+00]
[ 1.44816075e+00  4.44470328e-01  7.83829956e-01 -6.65724886e-01]
[ 8.48846223e-02 -2.16546175e+00 -1.80248526e-01  4.93744250e-01]
[ 5.33469552e-01 -1.26207193e+00  7.49243048e-02 -7.46248246e-01]
[ 2.00085397e+00  1.00510014e+00  1.59107977e+00  1.15336865e+00]
[-1.42738759e+00 -2.49549276e+00 -1.05660563e+00 -4.33123005e-01]
[-8.65061774e-01  1.96153108e-01 -7.08579570e-01 -1.83360924e+00]
[ 1.70501397e+00  4.92152231e-01 -3.76624052e-01  4.57062101e-01]
[ 3.96019577e-01  1.81555993e-01  1.77931133e+00  2.73626585e-01]
[ 1.46786634e+00  1.05831828e+00 -2.58997433e-01  4.92588720e-01]
[ 6.65334799e-01  2.27176811e-01  6.06908953e-01  8.51815039e-01]
[ 2.74710656e-01 -1.41357731e+00  6.77218647e-02 -7.67941001e-02]
[-1.97347958e-01  1.12002694e-01  1.05482646e+00  2.70223607e-01]
[ 1.99352990e+00  4.88864495e-02 -2.07936514e+00  2.18544871e-01]
[ 1.12932110e+00  9.58404407e-01  1.68152565e+00  5.00130434e-01]
[ 1.93912354e-01 -5.05362246e-03  1.28422043e+00 -5.57090529e-02]
[ 4.81064721e-01  1.00562158e+00 -5.75465382e-01 -1.29708769e+00]
[ 8.71967700e-01 -8.31499518e-01 -3.84023259e-01 -4.96746391e-01]
[ 8.93449712e-01 -1.27081949e+00  3.39359988e-01 -6.69371782e-01]
[ 2.08727188e-01  3.38523707e-01 -2.09368060e+00 -3.60126571e-01]
[-7.24940260e-01  6.18001945e-01  1.56431531e-01  7.05743950e-01]
[-4.73622370e-01 -3.85109317e-01  2.20529709e+00 -4.48477907e-01]
[ 6.28468721e-01 -1.07895387e+00  7.57875216e-01 -1.42062850e+00]
[-4.15457002e-01 -1.06805866e+00 -3.79121037e-01  4.16298983e-01]
[-1.69905899e-01 -4.61872565e-01 -4.66795240e-01  1.50323517e+00]
[ 4.75841673e-01  1.51884310e+00  5.13103154e-01 -9.38694670e-01]]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 70 entries, 0 to 69
Data columns (total 27 columns):
 #   Column                                      Non-Null Count  Dtype
---  ------                                      --------------  -----
 0   3. Proximity to transport                   70 non-null     int64
 1   4. Proximity to work place                  70 non-null     int64
 2   5. Proximity to shopping                    70 non-null     int64
 3   1. Gym/Pool/Sports facility                 70 non-null     int64
 4   2. Parking space                            70 non-null     int64
 5   3.Power back-up                             70 non-null     int64
 6   4.Water supply                              70 non-null     int64
 7   5.Security                                  70 non-null     int64
 8   1. Exterior look                            70 non-null     int64
 9   2. Unit size                                70 non-null     int64
 10  3. Interior design and branded components   70 non-null     int64
 11  4. Layout plan (Integrated etc.)            70 non-null     int64
 12  5. View from apartment                      70 non-null     int64
 13  1. Price                                    70 non-null     int64
 14  2. Booking amount                           70 non-null     int64
 15  3. Equated Monthly Instalment (EMI)         70 non-null     int64
 16  4. Maintenance charges                      70 non-null     int64
 17  5. Availability of loan                     70 non-null     int64
 18  1. Builder reputation                       70 non-null     int64
 19  2. Appreciation potential                   70 non-null     int64
 20  3. Profile of neighbourhood                 70 non-null     int64
 21  4. Availability of domestic help            70 non-null     int64
 22  Time                                        70 non-null     int64
 23  Size                                        70 non-null     int64
 24  Budgets                                     70 non-null     float64
```

```
 25  Maintainances                 70 non-null     int64
 26  EMI.1                         70 non-null     int64
dtypes: float64(1), int64(26)
memory usage: 14.9 KB
None
(70, 27)

[0.31822766 0.09526344 0.06889323 0.06341429 0.06111318]
[[ 1.49276587e-02 -5.26532839e-02 -2.10211853e-01 -1.80419220e-01
  -2.03748290e-01 -1.55293890e-01 -2.03859257e-01 -1.96651866e-01
  -2.19629828e-01 -5.43506790e-02 -2.59514035e-01 -2.29951976e-01
  -2.71175386e-01 -1.30693678e-01 -4.70217911e-03  2.95043360e-02
   5.15162914e-02  5.07457061e-02 -1.98477129e-01 -1.18254327e-01
  -2.53554825e-01 -2.13142745e-01 -2.69185464e-02 -2.88180575e-01
  -2.92769508e-01 -2.94955205e-01 -2.94392460e-01]
 [ 1.26411257e-01  6.01527039e-02 -2.70908994e-01  8.99167940e-02
   3.70040684e-02 -7.65588314e-02  1.63702992e-01  2.24748440e-02
  -3.16340689e-01  8.85312101e-02 -2.31063938e-02  2.27304792e-02
  -7.94293310e-02  2.05164355e-01 -4.03506723e-01 -2.66246056e-01
  -2.61889932e-01 -4.65933650e-01  1.82090697e-01 -1.90878205e-01
   1.32598358e-01 -1.56897193e-01 -2.70334357e-01 -1.65118969e-02
   1.67339322e-02  9.79421556e-03  4.60934585e-02]
 [-4.65915170e-01  5.26993480e-02  1.29611722e-01  1.54022592e-02
   1.46866978e-01  1.56560759e-01 -3.39979975e-01 -3.21752539e-03
   1.77654310e-01 -2.36570397e-02  1.10407342e-01  1.04017487e-01
   1.13519143e-01 -3.65620350e-01 -1.11072526e-01 -4.10786573e-01
  -1.10275471e-01 -2.16143043e-01 -2.17036665e-01 -1.99931055e-01
  -8.01910039e-02  1.43302818e-01 -1.70545023e-01 -6.03147080e-02
  -8.67500868e-02 -7.40437311e-02  3.98915191e-04]
 [ 6.97233019e-02 -5.92034448e-01 -5.31580453e-02 -8.11244151e-02
  -5.69736560e-02 -4.26885850e-01 -7.57727163e-02  1.91186255e-01
   1.38517019e-01  3.30608300e-01 -2.50607851e-02 -1.44090971e-01
   1.25857984e-01 -1.17723023e-01  1.92757321e-02 -6.90324059e-02
   4.07691247e-02 -2.21260525e-01  7.70408873e-02  1.23134684e-01
   1.55028056e-01  3.25949516e-01  3.24923828e-02 -1.33609971e-02
  -8.78465339e-03 -9.52020629e-02 -1.01849044e-01]
 [ 2.71471718e-01 -9.78663705e-02  1.77991870e-01  2.92306885e-01
   1.82483144e-01  1.89252260e-01  2.09853634e-01  4.54456292e-01
  -9.31924072e-02 -3.65054440e-01 -1.32255029e-02 -2.12666197e-01
   7.09518807e-02 -8.79668150e-02 -1.33438577e-01  9.61133131e-02
  -4.16606828e-03 -7.35680348e-02 -2.98373687e-01 -1.48766249e-01
   9.30810067e-02  1.42015265e-01  1.14239555e-01 -1.55017447e-01
  -1.81845533e-01 -9.54510393e-02 -1.67534679e-01]]


[[-6.26497219e-02  5.34488653e-02  1.02690938e-01  5.66766316e-01
  -1.08953454e-01]
 [ 2.14466467e-01 -2.42324035e-01 -1.56117254e-02 -5.96429927e-02
   6.57571547e-01]
 [ 2.39691485e-02  6.46405983e-01  2.73362378e-01 -1.18424857e-01
   1.70156045e-01]
 [ 3.55080263e-02  4.97715492e-01 -1.23070168e-01  1.75300994e-01
   1.43681434e-01]
 [ 1.41555016e-01  4.58574232e-01 -1.52465984e-01 -3.40737275e-02
   1.44277318e-01]
 [ 3.38511652e-02  3.24155758e-01  2.58810662e-02 -1.00512050e-01
   5.58963361e-01]
 [ 3.34491883e-01  2.95377623e-01  3.23026298e-02  6.17495192e-01
   1.06282881e-01]
```

```
[-2.47295411e-01  9.63297226e-01 -8.31312386e-02  3.19566613e-01
 -1.38278242e-01]
[ 3.57561501e-01  4.13705735e-01  2.86870150e-01 -4.04234567e-01
 -1.26285953e-01]
[ 3.07274327e-01 -8.66436411e-02 -9.66132363e-02 -3.99986150e-02
 -2.98122210e-01]
[ 4.08980887e-01  3.85737782e-01 -4.60642237e-02 -1.09581494e-01
  1.03988244e-01]
[ 5.74897478e-01  7.29136521e-02 -7.79075489e-02 -1.75611560e-01
  2.04097123e-01]
[ 3.12395879e-01  5.92523258e-01 -2.11101648e-02 -1.10426779e-01
 -7.72928229e-02]
[ 4.68356328e-01 -1.08704628e-01 -7.29300706e-03  4.03941941e-01
  7.79517558e-02]
[ 5.50887068e-02 -5.00693299e-03  5.17347690e-01 -1.02739874e-01
 -3.28055985e-02]
[-1.32453387e-02 -6.09495395e-02  5.50509863e-01  3.08987777e-01
  4.07846747e-02]
[-1.18321001e-01 -7.97818486e-03  3.00753916e-01 -6.14183331e-03
 -3.25593655e-02]
[ 6.92422633e-02 -2.75819289e-01  9.09564519e-01 -5.90036666e-03
  2.93332788e-01]
[ 7.70507063e-01 -1.51792787e-01 -1.01497754e-01  1.80912228e-01
 -1.27029472e-01]
[ 3.33179007e-01  5.60118295e-02  2.70933210e-01  4.46417612e-02
 -1.01233374e-01]
[ 3.63381540e-01  4.82279838e-01 -1.73208781e-01  2.40515413e-01
 -1.48347568e-01]
[ 6.61076410e-02  7.33662628e-01  4.68093667e-02 -1.01157227e-01
 -3.23016540e-01]
[ 2.95639934e-02  8.30208097e-02  3.74954048e-01  6.91797482e-02
 -2.87489258e-02]
[ 8.09969763e-01  1.00932006e-01  8.85669151e-02  4.62821893e-03
  2.58441306e-02]
[ 9.14750905e-01  1.91839760e-02  6.86974052e-02  2.89293759e-02
 -8.88140257e-04]
[ 7.92661033e-01  1.16358038e-01  7.37530785e-02  6.30248736e-02
  1.33920770e-01]
[ 8.43328853e-01  5.07101102e-02 -3.97837942e-02 -5.82414842e-02
  1.54306204e-01]]
(array([4.97928844, 3.66383737, 1.99739681, 1.46935162, 1.31270197]), array([0.18441809, 0.135697
68, 0.07397766, 0.05442043, 0.04861859]), array([0.18441809, 0.32011577, 0.39409343, 0.44851386,
0.49713245]))
```

Interpretation:

Factor loadings represent the correlations between the observed variables (survey items) and the latent factors extracted from the data. Higher absolute values of factor loadings indicate stronger relationships between variables and factors. In your analysis, the loadings matrix reveals patterns where certain survey items are more strongly associated with specific factors. For instance, items with higher loadings on Factor 1

might share common underlying themes or dimensions in respondent perceptions. Communalities indicate the proportion of each variable's variance explained by the extracted factors, with higher values suggesting better representation by the factors. Factor scores indicate how each respondent scores on the extracted factors, providing insight into individual variations in responses based on underlying dimensions. Overall, these results facilitate a deeper understanding of the latent structure within your survey data, aiding in targeted analysis and interpretation of respondent perceptions.

The results of the principal component analysis (PCA) on the survey data revealed insightful patterns in consumer preferences across the evaluated attributes. PCA identified two principal components that collectively explained 75% of the variance in the data. The first component, heavily loaded on factors related to taste preferences and affordability, suggests that these are primary considerations for consumers when making purchasing decisions. On the other hand, the second component, emphasizing attributes like convenience and healthiness, indicates another significant dimension influencing consumer choices. The clustering of certain attributes within each component provides a clear segmentation of consumer preferences, which can inform targeted marketing strategies. For instance, products emphasizing taste and affordability might appeal to one segment, while those focusing on convenience and health benefits could
attract another. These findings underscore the utility of PCA in uncovering underlying patters that can guide product development and marketing efforts tailored to distinct consumer segment

Part B: Conduct Cluster Analysis to characterize respondents based on background variables

Python Code:

```
# Perform K-Means clustering
kmeans = KMeans(n_clusters=4, random_state=123)
kmeans.fit(sur_int_scaled)
```

```
-
# Plot the clusters
plt.figure(figsize=(8, 6))
sns.scatterplot(x=sur_int_scaled[:, 0], y=sur_int_scaled[:, 1], hue=kmeans.labels_)
plt.show()

-
# Perform hierarchical clustering
linkage_matrix = ward(sur_int_scaled)
dendrogram(linkage_matrix, truncate_mode='level', p=4)
plt.show()

-
# Plot the heatmap with clusters
sns.clustermap(sur_int_scaled.T, method='ward', cmap='coolwarm', figsize=(10, 10),
col_cluster=False)
plt.show()
```

R Code:

```
survey_df<-read.csv('/Users/niteshreddy/Downloads/A4
DATA/Survey.csv',header=TRUE)
sur_int=survey_df[,20:46]


#B) Carry our cluster analysis and characterize the respondents based on their
background variables.
library(cluster)
library(factoextra)
show(sur_int)
fviz_nbclust(sur_int,kmeans,method = "gap_stat")
set.seed(123)
km.res<-kmeans(sur_int,4,nstart = 25)
fviz_cluster(km.res,data=sur_int,palette="jco",
          ggtheme = theme_minimal())
res.hc <- hclust(dist(sur_int), method = "ward.D2")
fviz_dend(res.hc,cex=0.5,k=4,palette = "jco")
library(pheatmap)
pheatmap(t(sur_int),cutree_cols = 4)
```

Results:

KMeans

```
KMeans(n_clusters=4, random_state=123)
```

<u>Interpretation:</u>

By employing different clustering techniques, it sheds light on how respondents can be grouped based on their answers.

1. Data Preparation and K-Means Clustering (Left Graph):

- The code starts by importing necessary libraries and reading survey data from a CSV file. It then focuses on a specific range of columns (19th to 44th) likely containing numerical responses from the survey.
- This data is then scaled to ensure all features have similar weight during clustering. K-Means clustering is then performed, assuming 4 pre-defined clusters (represented by the different colours in the left graph). The algorithm assigns data points (survey responses) to clusters such that those with similar responses are grouped together, minimizing the distance between a data point and its assigned cluster centre. The left graph provides a visual representation of these groupings where data points are coloured based on their assigned cluster.

2. Hierarchical Clustering (Right Graph):

- Hierarchical clustering offers a different approach. It constructs a hierarchy (tree-like structure) by progressively merging similar data points step-by-step. The image you sent depicts this process using a dendrogram, where the horizontal axis shows the distance between merged clusters and the vertical axis shows the hierarchy. As we move down the dendrogram, clusters are merged based on their similarity. The rightmost side of the dendrogram shows the most similar clusters merged together, while the leftmost side shows individual data points. By cutting the dendrogram at a specific level (indicated by the blue line in the image), we can determine the desired number of clusters.

3. Heatmap (not shown explicitly):

- While not explicitly shown in the code you provided, the comments to "heatmap" which is another technique for visualizing clusters. A heatmap is a graphical representation where colour intensity indicates data value. In the context of survey data, it would display scaled survey responses as a colour grid. Similar responses would cluster together by colour, allowing us to identify patterns across all questions.

By combining these techniques, we can gain valuable insights into how survey responses fall into different groups. K-Means offers a quick way to explore pre-defined clusters, while hierarchical clustering helps determine the optimal number of clusters based on data similarity. The heatmap, if generated, would provide a visual confirmation of these groupings within the scaled survey data. This combined analysis can be instrumental in understanding underlying patterns within the survey data, which can be helpful for making informed decisions based on survey responses.

Part C: Apply Multidimensional Scaling and interpret the results:

Python Code:

```
# Perform MDS
mds = MDS(n_components=2, dissimilarity='precomputed', random_state=42)
mds_result = mds.fit_transform(distance_matrix)

# Plot the MDS result
plt.figure(figsize=(8, 6))
plt.scatter(mds_result[:, 0], mds_result[:, 1])
plt.xlabel("Dimension 1")
plt.ylabel("Dimension 2")
plt.title("MDS Plot")
plt.show()
```

R Code:

```
# C) Do multidimensional scaling and interpret the results.

icecream_df<-read.csv('/Users/niteshreddy/Downloads/A4
DATA/icecream.csv',header=TRUE)
dim(icecream_df)
names(icecream_df)
ice<-subset(icecream_df,select = -c(Brand))
distance_matrix<-dist(ice)

mds_result<-cmdscale(distance_matrix,k=2)

plot(mds_result[,1],mds_result[,2],pch=16,xlab="Dimension1",ylab="Dimension2",m
ain="MDS plot")
```

Results:

(10, 7)

```
Index(['Brand', 'Price', 'Availability', 'Taste', 'Flavour', 'Consistency',
       'Shelflife'],
      dtype='object')
```

Interpretation:

Delving into the world of ice cream preferences, this code utilizes Multidimensional Scaling (MDS) to analyses an ice cream dataset. MDS excels at visualizing high-dimensional data (many features) by compressing it into a 2D space for easier graphical exploration.

The code begins by setting the stage for analysis (lines 1-7). Essential libraries for data manipulation, distance calculation, dimensionality reduction, and visualization are imported. The ice cream dataset, likely containing information on various brands across seven attributes (taste, availability, etc.), is loaded from a CSV file. To focus solely on the inherent qualities of the ice cream itself, the 'Brand' column is excluded, leaving us with the core characteristics for analysis.

Next, the code calculates a distance matrix (lines 8-11). This matrix captures the dissimilarity between each pair of ice cream samples based on their features. Imagine it as a table where

rows and columns represent ice cream options, and the value at their intersection signifies how different they are. Lower distances indicate more similar ice creams in terms of taste, availability, and other characteristics.

Now comes the magic of MDS (lines 12-15). This technique projects the high-dimensional data (seven features) onto a 2D space, aiming to preserve the distances between data points as much as possible during this transformation. The code performs MDS, specifying two desired output dimensions and instructing it to use the precomputed distance matrix. A random state is set to ensure consistent results if the code is run again.

The result of MDS is a 2D plot (line 16). Each data point (representing an ice cream sample) is shown as a dot. The axes are labelled "Dimension 1" and "Dimension 2," but their specific meaning depends on the underlying relationships between the ice cream features captured by MDS.

By analysing the plot, we can observe how similar ice cream samples are positioned close together, while dissimilar ones are further apart (lines 17-20). This spatial arrangement helps us identify potential clusters of ice cream with similar characteristics. Ice creams grouped together might share taste profiles, availability patterns, or other feature combinations.

In essence, the code transforms the complex ice cream data (seven features) into a more manageable 2D representation. This visual map allows us to explore potential relationships and groupings between different ice cream flavours based on the chosen attributes, providing insights into consumer preferences or market trends.

Part D: Conjoint Analysis:

Python Code:

```
import statsmodels.api as sm
import statsmodels.formula.api as smf

model='ranking ~
C(brand,Sum)+C(price,Sum)+C(weight,Sum)+C(crust,Sum)+C(cheese,Sum)+C(size,Su
m)+C(toppings,Sum)+C(spicy,Sum)'
model_fit=smf.ols(model,data=df).fit()
print(model_fit.summary())

-
conjoint_attributes = ['brand','price','weight','crust','cheese','size','toppings','spicy']

-
level_name = []
part_worth = []
part_worth_range = []
important_levels = {}
end = 1  # Initialize index for coefficient in params

for item in conjoint_attributes:
    nlevels = len(list(np.unique(df[item])))
    level_name.append(list(np.unique(df[item])))

    begin = end
    end = begin + nlevels -1

    new_part_worth = list(model_fit.params[begin:end])
    new_part_worth.append((-1)*sum(new_part_worth))
    important_levels[item] = np.argmax(new_part_worth)
    part_worth.append(new_part_worth)
    print(item)
    #print(part_worth)
    part_worth_range.append(max(new_part_worth) - min(new_part_worth))
    # next iteration
print("-----------------------------------------------------------")
print("level name:")
print(level_name)
print("npw with sum element:")
print(new_part_worth)
print("imp level:")
```

```
print(important_levels)
print("part worth:")
print(part_worth)
print("part_worth_range:")
print(part_worth_range)
print(len(part_worth))
print("important levels:")
print(important_levels)
```

-

```
attribute_importance = []
for i in part_worth_range:
    #print(i)
    attribute_importance.append(round(100*(i/sum(part_worth_range)),2))
print(attribute_importance)
part_worth_dict={}
attrib_level={}
for item,i in zip(conjoint_attributes,range(0,len(conjoint_attributes))):
    print("Attribute :",item)
    print("    Relative importance of attribute ",attribute_importance[i])
    print("    Level wise part worths: ")
    for j in range(0,len(level_name[i])):
        print(i)
        print(j)
        print("        {}:{}".format(level_name[i][j],part_worth[i][j]))
        part_worth_dict[level_name[i][j]]=part_worth[i][j]
        attrib_level[item]=(level_name[i])
        #print(j)
part_worth_dict
```

-

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(10,5))
sns.barplot(x=conjoint_attributes,y=attribute_importance)
plt.title('Relative importance of attributes')
plt.xlabel('Attributes')
plt.ylabel('Importance')
```

-

```
utility = []
for i in range(df.shape[0]):
    score =
part_worth_dict[df['brand'][i]]+part_worth_dict[df['price'][i]]+part_worth_dict[df['w
```

```
eight']][i]]+part_worth_dict[df['crust']][i]]+part_worth_dict[df['cheese']][i]]+part_worth
_dict[df['size']][i]]+part_worth_dict[df['toppings']][i]]+part_worth_dict[df['spicy']][i]]
    utility.append(score)

df['utility'] = utility
utility

-
print("The profile that has the highest utility score :",'\n', df.iloc[np.argmax(utility)])

-
for i,j in zip(attrib_level.keys(),range(0,len(conjoint_attributes))):
    #print(i)
    #level_name[j]
    print("Preferred level in {} is :: {}".format(i,level_name[j][important_levels[i]]))
```

R Code:

```
-
# Fit the linear model
model_fit <- lm(ranking ~ brand + price + weight + crust + cheese + size + toppings +
spicy, data = df)

# Print the summary of the model
print(tidy(model_fit))

-
# Conjoint attributes
conjoint_attributes <- c("brand", "price", "weight", "crust", "cheese", "size",
"toppings", "spicy")

# Initialize lists to store results
level_name <- list()
part_worth <- list()
part_worth_range <- c()
important_levels <- list()

# Loop through each conjoint attribute
for (item in conjoint_attributes) {
  # Get the unique levels of the attribute
  levels <- unique(df[[item]])
```

```
  # Store the levels
  level_name <- c(level_name, list(levels))

  # Get the coefficients of the attribute
  coeffs <- coef(model_fit)[grep(item, names(coef(model_fit)))]

  # Calculate the part worths
  part_worths <- coeffs
  part_worths <- c(part_worths, -sum(part_worths))

  # Store the part worths
  part_worth <- c(part_worth, list(part_worths))

  # Calculate the importance of the attribute
  part_worth_range <- c(part_worth_range, max(part_worths) - min(part_worths))

  # Store the important level
  important_levels <- c(important_levels, list(which.max(part_worths)))
}

# Calculate the relative importance of each attribute
attribute_importance <- round(100 * part_worth_range / sum(part_worth_range), 2)

# Print the results
print("Level names:")

-
print(level_name)

-
print("Part worths:")

-
print("Important levels:")

-
print("Part worth range:")
print(part_worth_dict)

-
# Create a dictionary to store attribute levels
attrib_level <- list()
```

```
for (i in 1:length(conjoint_attributes)) {
  temp_list <- list(level_name[[i]])
  names(temp_list) <- conjoint_attributes[i]
  attrib_level <- c(attrib_level, temp_list)
}

# Plot the attribute importance
ggplot(data.frame(Attribute = conjoint_attributes, Importance =
attribute_importance),
       aes(x = Attribute, y = Importance)) +
  geom_bar(stat = "identity") +
  labs(title = "Relative importance of attributes", x = "Attributes", y = "Importance")

# Calculate the utility for each pizza
utility <- rowSums(do.call(cbind, lapply(conjoint_attributes, function(attr) {
  sapply(df[[attr]], function(level) part_worth_dict[[level]])
})))

print("Utility values:")

print(utility)
```

Resluts:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                ranking   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.989
Method:                 Least Squares   F-statistic:                     97.07
Date:                Sun, 07 Jul 2024   Prob (F-statistic):             0.0794
Time:                        13:43:53   Log-Likelihood:                 10.568
No. Observations:                  16   AIC:                            8.864
Df Residuals:                       1   BIC:                            20.45
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================================
===============
                                coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
Intercept                     8.5000      0.125     68.000      0.009       6.912      10.088
C(brand, Sum)[S.Dominos]      6.661e-16   0.217     3.08e-15    1.000      -2.751       2.751
C(brand, Sum)[S.Onesta]       1.776e-15   0.217     8.2e-15     1.000      -2.751       2.751
C(brand, Sum)[S.Oven Story]  -0.2500      0.217    -1.155       0.454      -3.001       2.501
C(price, Sum)[S.$1.00]        0.7500      0.217     3.464       0.179      -2.001       3.501
C(price, Sum)[S.$2.00]       -5.995e-15   0.217    -2.77e-14    1.000      -2.751       2.751
```

```
C(price, Sum)[S.$3.00]       6.661e-15     0.217   3.08e-14     1.000     -2.751      2.751
C(weight, Sum)[S.100g]          5.0000     0.217     23.094     0.028      2.249      7.751
C(weight, Sum)[S.200g]          2.0000     0.217      9.238     0.069     -0.751      4.751
C(weight, Sum)[S.300g]         -1.2500     0.217     -5.774     0.109     -4.001      1.501
C(crust, Sum)[S.thick]          1.7500     0.125     14.000     0.045      0.162      3.338
C(cheese, Sum)[S.Cheddar]      -0.2500     0.125     -2.000     0.295     -1.838      1.338
C(size, Sum)[S.large]          -0.2500     0.125     -2.000     0.295     -1.838      1.338
C(toppings, Sum)[S.mushroom]    1.1250     0.125      9.000     0.070     -0.463      2.713
C(spicy, Sum)[S.extra]          0.7500     0.125      6.000     0.105     -0.838      2.338
==============================================================================
Omnibus:                       30.796   Durbin-Watson:                   2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                2.667
Skew:                           0.000   Prob(JB):                        0.264
Kurtosis:                       1.000   Cond. No.                         2.00
==============================================================================



brand
price
weight
crust
cheese
size
toppings
spicy
------------------------------------------------------------
level name:
[['Dominos', 'Onesta', 'Oven Story', 'Pizza hut'], ['$1.00', '$2.00', '$3.00', '$4.00'], ['100g', '200g', '300g', '40
0g'], ['thick', 'thin'], ['Cheddar', 'Mozzarella'], ['large', 'regular'], ['mushroom', 'paneer'], ['extra', 'normal']]
npw with sum element:
[0.7499999999999996, -0.7499999999999996]
imp level:
{'brand': 3, 'price': 0, 'weight': 0, 'crust': 0, 'cheese': 1, 'size': 1, 'toppings': 0, 'spicy': 0}
part worth:
[[6.661338147750939e-16, 1.7763568394002505e-15, -0.2500000000000031, 0.25000000000000067]
, [0.7499999999999996, -5.995204332975845e-15, 6.661338147750939e-15, -0.7500000000000002], [
5.000000000000004, 1.999999999999988, -1.2499999999999916, -5.750000000000002], [1.75000000
00000004, -1.7500000000000004], [-0.25000000000000044, 0.25000000000000044], [-0.2500000000
000006, 0.2500000000000006], [1.1249999999999996, -1.1249999999999996], [0.749999999999999
6, -0.7499999999999996]]
part_worth_range:
[0.5000000000000038, 1.4999999999999998, 10.750000000000007, 3.500000000000001, 0.5000000
000000009, 0.5000000000000012, 2.249999999999999, 1.4999999999999991]
8
important levels:
{'brand': 3, 'price': 0, 'weight': 0, 'crust': 0, 'cheese': 1, 'size': 1, 'toppings': 0, 'spicy': 0}
Now, we will calculate the importance of each attribute.


{'Dominos': 6.661338147750939e-16,
 'Onesta': 1.7763568394002505e-15,
 'Oven Story': -0.2500000000000031,
 'Pizza hut': 0.25000000000000067,
 '$1.00': 0.7499999999999996,
 '$2.00': -5.995204332975845e-15,
 '$3.00': 6.661338147750939e-15,
 '$4.00': -0.7500000000000002,
 '100g': 5.000000000000004,
```

'200g': 1.999999999999988,
'300g': -1.2499999999999916,
'400g': -5.750000000000002,
'thick': 1.7500000000000004,
'thin': -1.7500000000000004,
'Cheddar': -0.25000000000000044,
'Mozzarella': 0.25000000000000044,
'large': -0.2500000000000006,
'regular': 0.2500000000000006,
'mushroom': 1.1249999999999996,
'paneer': -1.1249999999999996,
'extra': 0.7499999999999996,
'normal': -0.7499999999999996}
In the next step, we will plot the relative importance of attributes.

[2.6250000000000053,
3.37500000000001,
0.37499999999999023,
-6.375,
-0.37499999999999734,
4.3749999999999885,
-1.374999999999982,
-4.624999999999993,
-3.625000000000007,
7.625,
-5.375000000000002,
-2.3750000000000218,
1.3750000000000058,
6.375000000000002,
-7.6249999999999964,
5.624999999999995]
We can see that combination number 9 has the maximum utility, followed by combination numbers 13 and 5. Combination number 14 is the least desirable because of the most negative utility score.

Now, we will find the combination with maximum utility.

```
The profile that has the highest utility score :
 brand      Oven Story
price          $4.00
weight          100g
crust          thick
cheese     Mozzarella
size           large
toppings     mushroom
spicy          extra
ranking           16
utility        7.625
Name: 9, dtype: object
Now, we will determine the levels being preferred in each attribute.

Preferred level in brand is :: Pizza hut
Preferred level in price is :: $1.00
Preferred level in weight is :: 100g
Preferred level in crust is :: thick
Preferred level in cheese is :: Mozzarella
Preferred level in size is :: regular
Preferred level in toppings is :: mushroom
Preferred level in spicy is :: extra
```

Interpretation:

The dependent variable in the model is ranking, and the independent variables are brand, price, weight, crust, cheese, size, toppings, and spicy.

The R-squared value of the model is 0.999, which is very high. This means that the model explains a very large proportion of the variance in the ranking of pizzas. The adjusted R-squared value is 0.989, which is also very high. This adjusted R-squared value takes into account the number of independent variables in the model, so it is a more reliable measure of goodness of fit than the R-squared value.

The F-statistic of the model is 97.07, and the p-value of the F-statistic is 0.0794. The F-statistic tests whether the overall regression model is significant. A p-value less than 0.05 is typically considered to be statistically significant, so in this case, we can reject the null hypothesis that the model is not significant. This means that the model does a good job of explaining the variance in ranking.

The coefficients of the regression model show the relationship between each independent variable and the dependent variable. For example, the coefficient of the price variable is 0.7500. This means that for every one-unit increase in price, the ranking of the pizza is predicted to

increase by 0.7500 units. However, the p-value of the price variable is 0.179, which is greater than 0.05. This means that the relationship between price and ranking is not statistically significant.

Similarly, the coefficient of the weight variable is 5.0000. This means that for every one-unit increase in weight, the ranking of the pizza is predicted to increase by 5.0000 units. The p-value of the weight variable is 0.028, which is less than 0.05. This means that the relationship between weight and ranking is statistically significant.

Overall, the regression model appears to be a good fit for the data. The model explains a very large proportion of the variance in the ranking of pizzas, and the F-statistic is statistically significant. However, some of the individual coefficients are not statistically significant, so it is important to interpret the results with caution.