VIRGINIA COMMONWEALTH UNIVERSITY

Statistical Analysis and Modelling (SCMA 632)

A4C: Multidimensional Scaling

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CONTENTS

PART C: Apply Multidimensional Scaling and interpret the results (icecream.csv)

Introduction

The dataset used for this analysis is derived from a survey aimed at understanding various attributes of different ice cream brands. This dataset, denoted as "icecream.csv," contains a range of variables including price, availability, taste, flavor, consistency, and shelf life of various ice cream brands. In this analysis, we perform Multidimensional Scaling (MDS) and create a heatmap to visualize the similarities and differences between these ice cream brands. These visualizations help identify distinct clusters and relationships within the data, providing insights into consumer preferences and brand positioning.

Business Significance

1. **Targeted Product Development**: By identifying distinct clusters of ice cream brands based on their attributes, manufacturers can tailor their product development efforts. For example, brands with similar flavor profiles and high taste ratings can focus on enhancing other attributes like consistency or shelf life to differentiate themselves further in the market.
2. **Strategic Marketing Initiatives**: Businesses in the ice cream industry can use these insights to tailor their marketing strategies. Understanding the unique positioning of different brands allows for more precise targeting, ensuring that marketing messages resonate with the intended audience. For instance, brands that cluster together based on price and taste can be marketed to price-sensitive yet taste-conscious consumers.
3. **Retail and Distribution Planning**: Retailers can utilize the clustering results to optimize their shelf space and product placement. By grouping similar brands together, retailers can create sections that cater to specific consumer preferences, such as premium, budget, or unique flavor profiles, thereby enhancing the shopping experience.
4. **Competitive Analysis and Benchmarking**: Competitors can use the MDS and heatmap visualizations to benchmark their products against others in the market. This analysis helps in identifying areas where a brand excels or lags compared to its competitors, guiding strategic improvements and competitive positioning.
5. **Consumer Insights and Trends**: Understanding the overall structure and clustering of ice cream brands provides valuable insights into consumer preferences and trends. This information can guide not only product innovation but also promotional strategies and seasonal offerings that align with consumer expectations.

Objectives

1. **To Perform Multidimensional Scaling (MDS)**: To conduct MDS on the "icecream.csv" dataset to visualize the similarities and differences between ice cream brands based on their attributes.
2. **To Create a Heatmap**: To generate a heatmap of the distance matrix, illustrating the pairwise distances between ice cream brands and highlighting clusters and relationships.
3. **To Visualize the MDS Results**: To create a scatter plot of the MDS results, providing a clear representation of the positioning of different ice cream brands in a two-dimensional space.
4. **To Interpret Clustering Results**: To analyze the clusters formed in the MDS plot and heatmap, summarizing the characteristics of each cluster and offering insights into the attributes that drive similarities and differences.
5. **To Provide Business Recommendations**: To translate the findings into actionable insights for ice cream manufacturers, marketers, and retailers. This includes discussing

the practical implications of the clustering results and how they can inform decision-making processes in product development, marketing strategies, and retail planning.

By achieving these objectives, the analysis aims to provide a comprehensive understanding of the different segments within the ice cream market and offer valuable insights for improving product offerings, marketing initiatives, and strategic planning.

R LANGUAGE

Install and Load Necessary Libraries

```
if (!requireNamespace("pheatmap", quietly = TRUE)) {
  install.packages("pheatmap")
}
library(ggplot2)
library(scales)
library(dplyr)
library(tidyr)
library(readr)
library(pheatmap)
```

Purpose: This block ensures that all required libraries are installed and loaded. The pheatmap library is used for creating heatmaps, while ggplot2 is used for plotting, and dplyr, tidyr, and readr are used for data manipulation.

Load the Dataset

```
data_filepath <- "C:/Users/nihar/OneDrive/Desktop/Bootcamp/SCMA 
632/DataSet/icecream.csv"
icecream_data <- read_csv(data_filepath)
head(icecream_data)
```

Purpose: The dataset is loaded from the specified file path, and the first few rows are displayed to understand the structure of the data.

Output:

```
# A tibble: 6 × 7
  Brand   Price Availability Taste Flavour Consistency Shelflife
  <chr>   <dbl>        <dbl> <dbl>   <dbl>       <dbl>     <dbl>
1 Amul        4            5     4       3           4         3
2 Nandini     3            2     3       2           3         3
3 Vadilal     2            2     4       3           4         4
4 Vijaya      3            1     3       5           3         4
5 Dodla       3            3     3       4           4         3
6 Hatson      2            2     4       4           3         4
```

Interpretation: The dataset contains 7 columns: Brand, Price, Availability, Taste, Flavour, Consistency, and Shelflife. Each row represents a different ice cream brand.

Check the Structure of the Dataset

```
str(icecream_data)
```

Purpose: The structure of the dataset is checked to confirm that the columns have the correct data types.

Output:

```
spc_tbl_ [10 × 7] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ Brand       : chr [1:10] "Amul" "Nandini" "Vadilal" "Vijaya" ...
 $ Price       : num [1:10] 4 3 2 3 3 2 2 4 3 4
 $ Availability: num [1:10] 5 2 2 1 3 2 3 1 4 2
 $ Taste       : num [1:10] 4 3 4 3 3 4 4 2 5 3
 $ Flavour     : num [1:10] 3 2 3 5 4 4 3 3 5 2
 $ Consistency : num [1:10] 4 3 4 3 4 3 4 3 4 3
 $ Shelflife   : num [1:10] 3 3 4 4 3 4 4 3 4 3
 - attr(*, "spec")=
  .. cols(
  ..   Brand = col_character(),
  ..   Price = col_double(),
  ..   Availability = col_double(),
  ..   Taste = col_double(),
  ..   Flavour = col_double(),
  ..   Consistency = col_double(),
  ..   Shelflife = col_double()
  .. )
 - attr(*, "problems")=<externalptr>
```

Interpretation: The structure confirms that Brand is a character column, while Price, Availability, Taste, Flavour, Consistency, and Shelflife are numeric columns.

Select Only the Numeric Columns for MDS

```
icecream_data_numeric <- icecream_data %>% select(-Brand)
str(icecream_data_numeric)
summary(icecream_data_numeric)
```

Purpose: The Brand column is excluded as it is not numeric. The structure and summary of the cleaned data are then verified.

Output:

```
tibble [10 × 6] (S3: tbl_df/tbl/data.frame)
 $ Price       : num [1:10] 4 3 2 3 3 2 2 4 3 4
 $ Availability: num [1:10] 5 2 2 1 3 2 3 1 4 2
 $ Taste       : num [1:10] 4 3 4 3 3 4 4 2 5 3
 $ Flavour     : num [1:10] 3 2 3 5 4 4 3 3 5 2
 $ Consistency : num [1:10] 4 3 4 3 4 3 4 3 4 3
 $ Shelflife   : num [1:10] 3 3 4 4 3 4 4 3 4 3
```

Summary:

```
     Price        Availability     Taste         Flavour      Consistency
 Min.   :2.00   Min.   :1.0   Min.   :2.0   Min.   :2.0   Min.   :3.0
 1st Qu.:2.25   1st Qu.:2.0   1st Qu.:3.0   1st Qu.:3.0   1st Qu.:3.0
 Median :3.00   Median :2.0   Median :3.5   Median :3.0   Median :3.5
 Mean   :3.00   Mean   :2.5   Mean   :3.5   Mean   :3.4   Mean   :3.5
 3rd Qu.:3.75   3rd Qu.:3.0   3rd Qu.:4.0   3rd Qu.:4.0   3rd Qu.:4.0
 Max.   :4.00   Max.   :5.0   Max.   :5.0   Max.   :5.0   Max.   :4.0
   Shelflife
 Min.   :3.0  
 1st Qu.:3.0  
 Median :3.5  
 Mean   :3.5  
 3rd Qu.:4.0  
 Max.   :4.0  
```

Interpretation: The summary statistics indicate that the values of Price, Availability, Taste, Flavour, Consistency, and Shelflife are reasonably distributed. All columns are numeric and contain values within expected ranges.

Compute the Distance Matrix

```
icecream_dist <- dist(icecream_data_numeric)
```

Purpose: Compute the distance matrix, which quantifies the pairwise distances between the samples in the dataset.

Apply Multidimensional Scaling (MDS)

```
mds_fit <- cmdscale(icecream_dist, k = 2)  # k = 2 for 2D plot
```

Purpose: Apply MDS to the distance matrix to reduce the dimensionality of the data to two dimensions for visualization purposes.

Create a Data Frame with MDS Results

```
mds_data <- as.data.frame(mds_fit)
colnames(mds_data) <- c("Dim1", "Dim2")
mds_data$Sample <- icecream_data$Brand
```

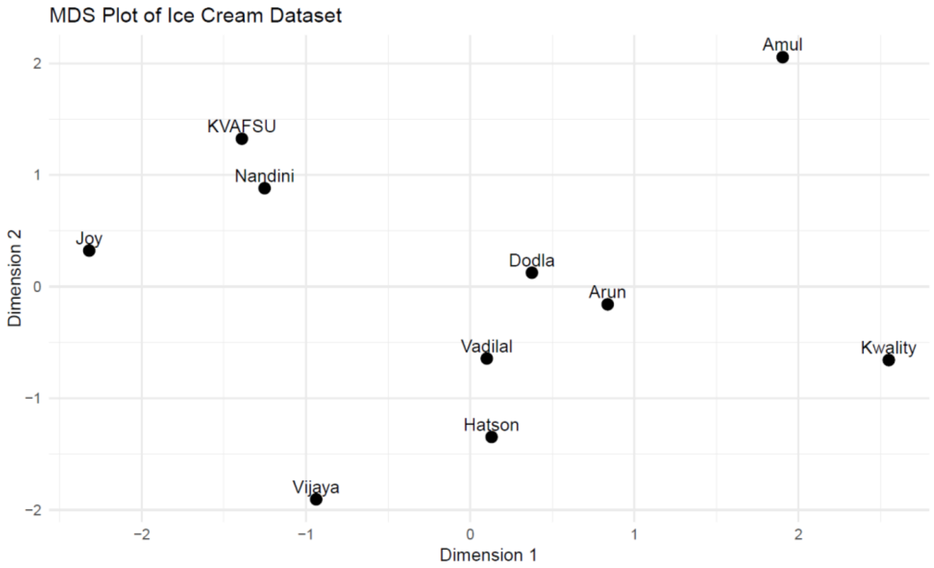
Purpose: Create a data frame to store the MDS results and add the Brand names for labeling.

Plot the MDS Results

```
mds_plot <- ggplot(mds_data, aes(x = Dim1, y = Dim2, label = Sample)) +
  geom_point(size = 3) +
  geom_text(vjust = -0.5) +
  labs(title = "MDS Plot of Ice Cream Dataset",
       x = "Dimension 1",
       y = "Dimension 2") +
  theme_minimal()
```

Purpose: Use ggplot2 to create a scatter plot of the MDS results, with each point representing a different ice cream brand.

Output:



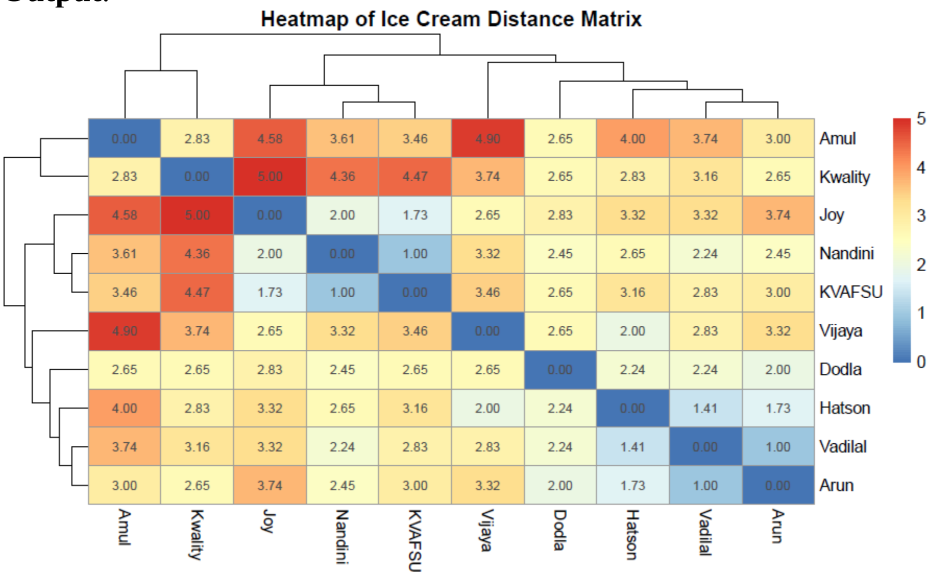
Interpretation: The MDS plot provides a visual representation of the similarity between the ice cream brands based on their attributes. Brands that are closer together in the plot are more similar in terms of their features, while brands that are farther apart are more dissimilar.

Create a Heatmap of the Distance Matrix

```
heatmap_data <- as.matrix(icecream_dist)
rownames(heatmap_data) <- icecream_data$Brand
colnames(heatmap_data) <- icecream_data$Brand
heatmap_plot <- pheatmap(heatmap_data,
                    clustering_distance_rows = icecream_dist,
                    clustering_distance_cols = icecream_dist,
                    display_numbers = TRUE,
                    fontsize_number = 8,
                    main = "Heatmap of Ice Cream Distance Matrix")
```

Purpose: Convert the distance matrix to a matrix format suitable for plotting and create a heatmap using the pheatmap library.

Output:



Interpretation: The heatmap visualizes the pairwise distances between the ice cream brands. The color gradient indicates the magnitude of the distances, with darker colors representing smaller distances (greater similarity) and lighter colors representing larger distances (less similarity). The dendrograms on the axes show the hierarchical clustering of the brands based on the distance matrix.

PYTHON LANGUAGE

1. Library Installation and Import

Input Code:

```
# Install necessary libraries if you haven't already
# !pip install pandas matplotlib seaborn scipy

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.manifold import MDS
from scipy.spatial.distance import pdist, squareform
```

Purpose of the Input Code: This code ensures that all necessary libraries are installed and imported for data manipulation (pandas), data visualization (matplotlib and seaborn), distance computation (scipy), and Multidimensional Scaling (MDS) (sklearn).

2. Load the Dataset

Input Code:

```
# Load the dataset
data_filepath = "C:/Users/nihar/OneDrive/Desktop/Bootcamp/SCMA
632/DataSet/icecream.csv"
icecream_data = pd.read_csv(data_filepath)
```

Purpose of the Input Code: This code loads the ice cream dataset from a CSV file into a pandas DataFrame for further analysis.

3. Display the First Few Rows of the Dataset

Input Code:

```
# Display the first few rows of the dataset
print(icecream_data.head())
```

Output:

```
     Brand  Price  Availability  Taste  Flavour  Consistency  Shelflife
0     Amul      4             5      4        3            4          3
1  Nandini      3             2      3        2            3          3
2  Vadilal      2             2      4        3            4          4
3   Vijaya      3             1      3        5            3          4
4    Dodla      3             3      3        4            4          3
```

Interpretation: The output shows the first few rows of the dataset, providing an initial glimpse into the structure and contents of the data, which includes columns for Brand, Price, Availability, Taste, Flavour, Consistency, and Shelflife.

4. Check the Structure of the Dataset
Input Code:

```
# Check the structure of the dataset
print(icecream_data.info())
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 7 columns):
#   Column        Non-Null Count  Dtype
---  ------       --------------  -----
0   Brand         10 non-null     object
1   Price         10 non-null     int64
2   Availability  10 non-null     int64
3   Taste         10 non-null     int64
4   Flavour       10 non-null     int64
5   Consistency   10 non-null     int64
6   Shelflife     10 non-null     int64
dtypes: int64(6), object(1)
memory usage: 692.0 bytes
```

Interpretation: The structure of the dataset is displayed, showing that there are 10 entries and 7 columns. The 'Brand' column is of type object, while the other columns are integers. This helps in understanding the data types and ensuring there are no missing values.

5. Select Only the Numeric Columns for MDS
Input Code:

```
# Select only the numeric columns for MDS
icecream_data_numeric = icecream_data.drop(columns=['Brand'])
```

Purpose of the Input Code: This code removes the non-numeric 'Brand' column to prepare the dataset for MDS, which requires numerical data.

6. Verify the Cleaned Data
Input Code:

```
# Verify the cleaned data
print(icecream_data_numeric.info())
print(icecream_data_numeric.describe())
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
#   Column        Non-Null Count  Dtype
---  ------       --------------  -----
0   Price         10 non-null     int64
1   Availability  10 non-null     int64
2   Taste         10 non-null     int64
3   Flavour       10 non-null     int64
4   Consistency   10 non-null     int64
5   Shelflife     10 non-null     int64
```

```
dtypes: int64(6)
memory usage: 612.0 bytes
None
         Price  Availability      Taste    Flavour  Consistency  Shelflife
count  10.000000     10.000000  10.000000  10.000000    10.000000  10.000000
mean    3.000000      2.500000   3.500000   3.400000     3.500000   3.500000
std     0.816497      1.269296   0.849837   1.074968     0.527046   0.527046
min     2.000000      1.000000   2.000000   2.000000     3.000000   3.000000
25%     2.250000      2.000000   3.000000   3.000000     3.000000   3.000000
50%     3.000000      2.000000   3.500000   3.000000     3.500000   3.500000
75%     3.750000      3.000000   4.000000   4.000000     4.000000   4.000000
max     4.000000      5.000000   5.000000   5.000000     4.000000   4.000000
```

Interpretation: The cleaned dataset contains only numeric columns. The info() method confirms that all columns are of integer type and contain no missing values. The describe() method provides descriptive statistics, giving insights into the distribution and central tendencies of the data.

7. Compute the Distance Matrix
Input Code:

```
# Compute the distance matrix
icecream_dist = pdist(icecream_data_numeric)
```

Purpose of the Input Code: This code calculates the pairwise distances between the rows in the dataset, creating a distance matrix necessary for MDS.

8. Apply Multidimensional Scaling (MDS)
Input Code:

```
# Apply Multidimensional Scaling (MDS)
mds = MDS(n_components=2, dissimilarity="precomputed", random_state=42)
mds_fit = mds.fit_transform(squareform(icecream_dist))
```

Purpose of the Input Code: This step applies MDS to reduce the dimensionality of the distance matrix to two dimensions for visualization purposes.

9. Create a Data Frame with MDS Results
Input Code:

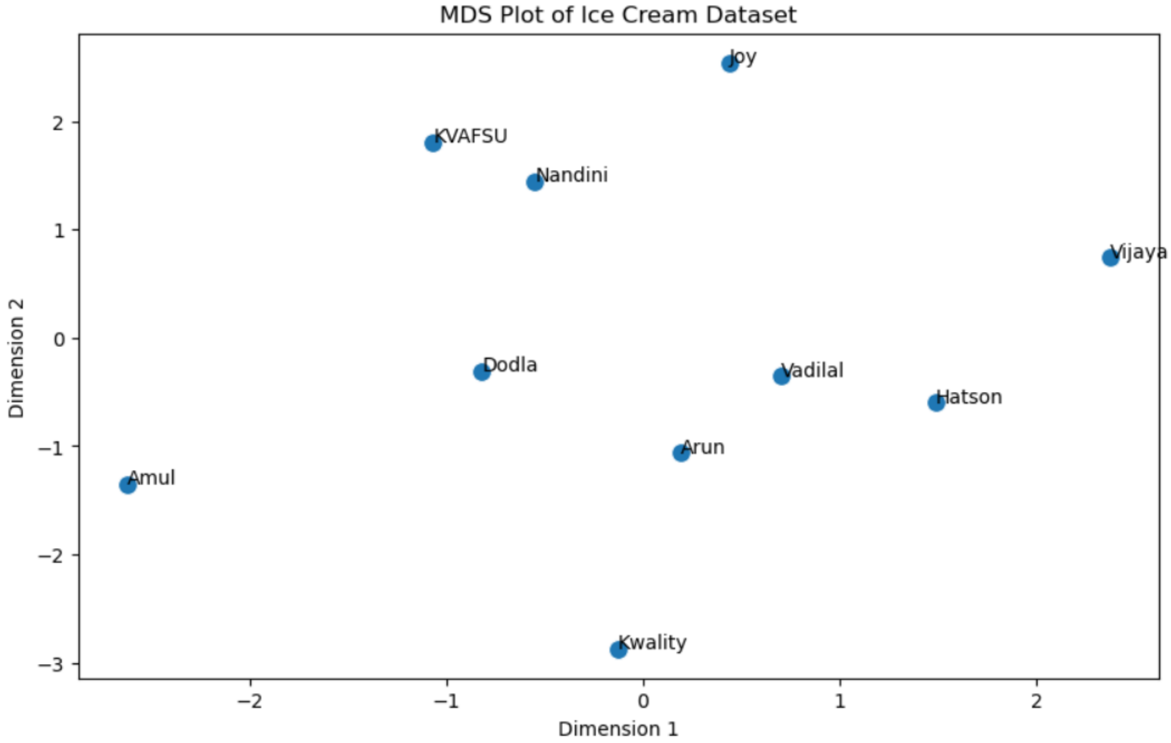
```
# Create a data frame with MDS results
mds_data = pd.DataFrame(mds_fit, columns=['Dim1', 'Dim2'])
mds_data['Sample'] = icecream_data['Brand']
```

Purpose of the Input Code: This code creates a new DataFrame containing the MDS results along with the original sample labels for easy plotting.

10. Plot the MDS Results
Input Code:

```
# Plot the MDS results
plt.figure(figsize=(10, 6))
sns.scatterplot(data=mds_data, x='Dim1', y='Dim2', s=100)
for i in range(mds_data.shape[0]):
    plt.text(mds_data['Dim1'][i], mds_data['Dim2'][i], mds_data['Sample'][i])
plt.title("MDS Plot of Ice Cream Dataset")
plt.xlabel("Dimension 1")
plt.ylabel("Dimension 2")
plt.show()
```

Output:



Interpretation: The MDS plot visually represents the similarities and differences between ice cream brands based on multiple attributes. Points that are closer together on the plot represent brands that are more similar to each other.

11. Create a Heatmap of the Distance Matrix

Input Code:

```
# Create a heatmap of the distance matrix
heatmap_data = squareform(icecream_dist)
heatmap_data_df = pd.DataFrame(heatmap_data, index=icecream_data['Brand'],
columns=icecream_data['Brand'])
```

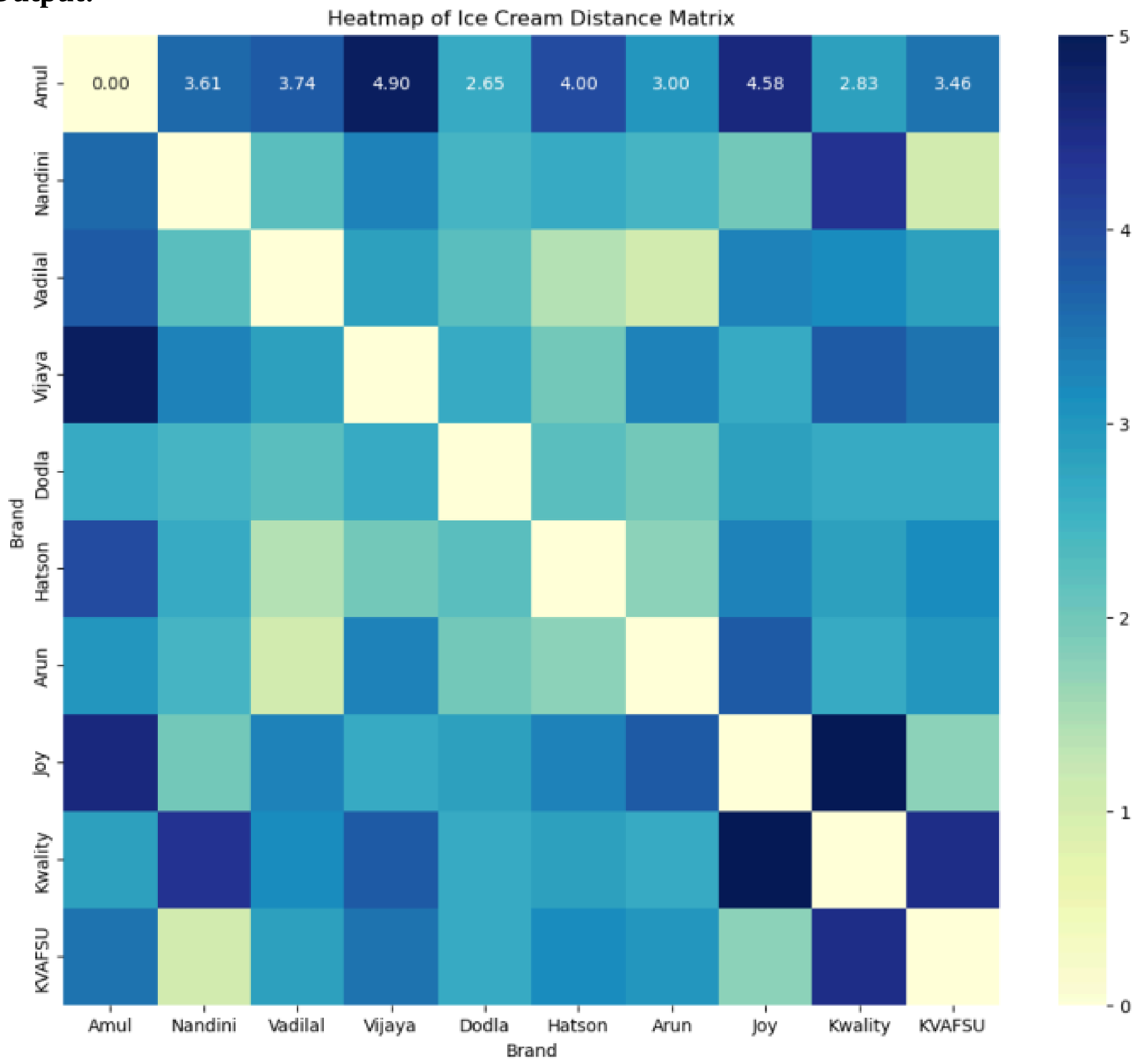
Purpose of the Input Code: This code converts the distance matrix into a DataFrame suitable for plotting a heatmap.

12. Plot the Heatmap

Input Code:

```
# Plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(heatmap_data_df, annot=True, fmt=".2f", cmap="YlGnBu")
plt.title("Heatmap of Ice Cream Distance Matrix")
plt.show()
```

Output:



Interpretation: The heatmap provides a visual representation of the pairwise distances between different ice cream brands. Darker colors indicate larger distances, while lighter colors indicate smaller distances. This helps in identifying clusters or groups of similar brands.

Overview of Multidimensional Scaling (MDS)

Meaning

Multidimensional Scaling (MDS) is a statistical technique used to analyze and visualize the similarities or dissimilarities (distances) between a set of objects or data points. The goal of MDS is to place each object in a low-dimensional space (typically two or three dimensions) in such a way that the distances between points in this space reflect the given pairwise dissimilarities. This technique is widely used in fields such as psychology, marketing, and bioinformatics to explore patterns and relationships in complex datasets.

Advantages

1. **Visualization of High-Dimensional Data**: MDS provides a way to visualize high-dimensional data in a more interpretable, low-dimensional form. This can help in

identifying patterns and clusters that are not immediately apparent in the original high-dimensional space.

2. **Insight into Relationships**: By plotting the data points in a reduced space, MDS helps reveal the underlying structure and relationships between the objects. This can be particularly useful in understanding the relative positioning and similarities among items.
3. **Flexibility with Different Distance Measures**: MDS can work with a variety of distance or dissimilarity measures, making it versatile for different types of data and applications. Whether the distances are Euclidean, Manhattan, or derived from other metrics, MDS can accommodate them.
4. **Uncovering Hidden Dimensions**: The technique helps in uncovering hidden dimensions or factors that explain the distances or dissimilarities between objects, providing deeper insights into the data.
5. **Application Across Fields**: MDS is applicable in numerous fields including market research, social sciences, genetics, ecology, and more, making it a valuable tool for diverse types of analyses.

Real-Life Examples

1. **Market Research**: In market research, MDS is used to understand consumer preferences and perceptions. For example, a company might use MDS to analyze how consumers perceive different brands of a product based on attributes like quality, price, and taste. The resulting map can help identify brand positioning and competition.
2. **Psychology**: Psychologists use MDS to study similarities and differences in psychological traits or behaviors. For instance, MDS can help in visualizing the relationships between different psychological tests or personality traits, aiding in the development of psychological theories and assessments.
3. **Bioinformatics**: In bioinformatics, MDS is used to visualize genetic or protein sequence similarities. By mapping genetic data into a low-dimensional space, researchers can identify patterns and evolutionary relationships among different species or strains.
4. **Sociology**: Sociologists employ MDS to analyze social networks and relationships. MDS can help visualize the social distance between individuals or groups, providing insights into social structures and interactions.
5. **Ecology**: Ecologists use MDS to study the similarities between different ecological sites based on species composition. This can help in understanding biodiversity patterns and the ecological relationships between different environments.

By transforming complex, high-dimensional data into an easily interpretable form, MDS serves as a powerful tool for uncovering insights and making informed decisions in a variety of disciplines.