TEAM PROJECT 3

Course: Customer Analysis

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Abstract

We analyzed all the data sets and had insights on them. In the report, we analyze each consumer's preferences and restaurant perceptions based on the attributes. Then we will derive insights based on the perception maps we have created.

Team3 – New Bees

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Executive Summary

We analyzed all the data sets, and we gain insights about characteristics of each restaurant and analyze the similarities between the customers who prefer the same restaurants. Based on our analysis, we find out that our restaurant, Ti Amo, rates high on atmosphere, libations, and location. From there, we find out that customers who scatter closer to Ti Amo generally have high incomes and a smaller number of children. Based on our observations, we give strategies such as increasing the prices a little bit, making the atmosphere nicer for our customers to have a fine dining experience. Thus, it will ensure the privacy of customers and separate them from family dining experiences.

For comparing the results of different function of unfolding analysis, we performed a series of unfolding analysis using R. We first run the function of **interval Scaling with Row Conditionality(figure4-1) and interval Scaling with Matrix Conditionality(figure5-1)**, then we performed the function of **Ordinal Scaling with Row Conditionality(figure7-1) and Ordinal Scaling with Matrix Conditionality(figure8-1)**, What we found is that the Ordinal Scaling with Row Conditionality shows the lowest stress. we get the results of stress value and iterations for different functions.

According to the preference dataset, you can see some customers did the exactly same ratings to different restaurants making ties in restaurant ranking, for example, customer 4 they rating restaurant Mildreds and Shoneys both are 6.5. After we run the function of treatment of ties using R,with a specification “ties= secondary”in unfolding function, the stress level for the secondary specification is lower than the primary ones because it has more constraints.

The joint configuration plots for different configurations reveal how restaurants are grouped based on consumer preferences. For both ordinal and interval scaling with matrix and row conditionality show similar pattern, based on joint configuration plots (Figure 4-2, 5-2, 7-2,8-2) we get some points:

- **Paramount, TheTop**, **Mildreds**, and **Emilianos** tend to be grouped together with high stress value on Dimension2 and low stress value on Dimension1.
- **Carrabbas**, **Las Margaritas**, and **Shoney’s** should be grouped together with relatively low stress value on Dimension 1 and moderate stress value on Dimension2 .
- **BeefOBradys**, **Bistro1245**, and **TheSwamp** seems can be put together to a same group with moderate stress value on Dimension 1 and and low stress value on Dimension 2.

The reversed stress decomposition charts (Figure7-3) further confirm the grouping of restaurants by showing the stress proportion contributed by each restaurant. Notable findings include:

- Restaurants like **Emilianos** and **Leo's 706** contribute more stress, indicating they are more out of alignment with the rest of the restaurants.
- On the other hand, **Paramount Grill** and **Las Shoney's** contribute significantly less stress, which suggests they are more aligned with consumer preferences.

The Shepard diagrams for different configurations show how well the configurations fit the dissimilarities between the restaurants. A good fit would show a straight line, indicating that the model has accurately preserved the distances between objects:

- This interval scaling(Figure 4-4) seems to show a slightly curved line, which indicates that some discrepancies remain between the original dissimilarities and the configuration distances.
- For ordinal scaling(Figure 7-4), the lines are more tightly grouped around the straight line, indicating a better fit. The spread between the data points is smaller, which suggests that the ordinal scaling might have captured the underlying preferences more effectively than the interval scaling.

After reviewing different configurations, The **Ordinal Scaling with Row Conditionality** configuration seems to be the most representative, as it yields the lowest stress value and appears to provide the clearest separation between restaurants. According to figure 7, 7-1, 7-2, 7-3 and 7-4, we can see that teh configuration plot shoes nondegenrate plot since you can easily derives insights from the plot. The stress level is also low compared to other types of unfolding process. As shown in the shepard diagram, all the points are on the lines and shows good fit.

We finally chose the **Ordinal Scaling with Row Conditionality** configuration. From the **Joint Configuration Plot (Figure 7-1)**, we found that the brands that are expected to be close based on their attributes and consumer preferences are indeed placed close to each other in the plot.

For example, **Paramount Grill**, **The Top**, and **Mildred's** are positioned closely together on the left side of the plot, indicating that they share similar high preference scores in both **food quality** and **location** factors (Dimension 1). **Carrabbas**, **Las Margaritas**, and **Shoney's** are positioned towards the lower-right part of the plot, suggesting that while they have lower rankings on core preference factors, they have moderate to high scores on secondary factors, such as **affordability** or **parking** (Dimension2**)**. This clustering aligns with the expectation that these brands share similar traits, even if they're not as highly ranked in terms of food and location.

The plot also shows that customers with similar preferences are indeed close to one another in the configuration. The **blue and red dots** represent customer groups, with red indicating high preference for certain restaurants and blue indicating lower preference.

For example, Customers who prefer **Paramount Grill** or **The Top** (restaurants on the high-preference side) tend to cluster together, which suggests that their preferences for food quality and location. Similarly, customers who rate **Carrabbas** or **Shoney's** lower on preferences are also grouped together. These customers likely value factors like **price** and **parking** more than food or location.

According to the preference map (figure 9), you can clearly see that some customers are gathering close to specific restaurants, and some are dawdling in the middle where no restaurants are nearby. For example, customers 16, 20, 23, 30 are very close to each other and restaurants Mildred's and Bistro1245 are near them. They probably have similar preferences in terms of choosing restaurants to dine in. As shown in figure 18, Restaurants Mildred's and Bristo 1245 positioned on the same vertical coordinate on the map. In figure1, From the restaurant attribute table: Mildred's ratings are as follows: High Price (7), Low Location Score (1), High Food Rating (7), Moderate Atmosphere (2), Good Parking (6). And for Bistro 1245, it has Balanced Scores Across Factors: Food (4), Price (4), Atmosphere (3), Seating (7), Libations (7), Parking

(2). Then we check customers 16, 20, 23, and 30 preferences: they rate **atmosphere** and **food quality highly** (values around 9-11), they rate seating and **libations** relatively high (similar to Bistro 1245 and Mildred's), and they do not prioritize affordability, suggesting they prefer premium dining experiences. These restaurants share attributes that **these customers value**, particularly **high food quality, good seating, and premium ambiance**. **Mildred's** is a **higher-end restaurant with good parking**, attracting customers who don't mind higher prices for better food. **Bistro 1245** has a **balanced offering of good food and a comfortable seating experience**, aligning with their preferences. In conclusion, Customers **16, 20, 23, and 30** are close to **Mildred's and Bistro 1245** because: **they prioritize food quality and seating comfort, they are less price-sensitive, preferring premium dining**, and **their ratings indicate a preference for a more upscale, balanced experience.**

On the other hand, Customer 11 is not close to any restaurant brands on the preference map, which suggests that their preferences do not strongly align with any single restaurant's attributes. We can see that **Customer 11's ratings are more extreme and varied**, meaning they have a unique set of preferences that don't match any restaurant perfectly: Customer 11 gives very high scores (9-12) for certain attributes, she also gives significantly lower ratings (e.g., 1-4) to some aspects. This suggests that their expectations may be **too specific or diverse**, making it hard for any restaurant to fully match them. People like Customer 11 will make restaurant managers go to therapy. Why? Because no matter how hard they tried, they could never make their customers "appetize"!

Based on Figure 9, customers can be broadly segmented into three major clusters by analyzing the Preference Map based on all demographic characteristics (Figures 10-14), with black circles indicating the following groups:

Cluster 1: Characterized by fewer children, middle-to-high income, and relatively younger age, with a high preference for atmosphere.

Cluster 2: Defined by high income and fewer children, with higher spending levels and a strong emphasis on atmosphere.

Cluster 3: Comprised of low-income, more children, and younger individuals, with a lower emphasis on atmosphere.

Additionally, there are two highly similar sub-clusters (red circles):

Sub-cluster (3, 15, 13): This group shares similarities in terms of younger age and middle-to-upper income, forming a distinct cluster.

Sub-cluster (23, 30, 20, 16): These individuals exhibit similarities in the number of children and income levels, with few children and high income as their key defining characteristics.

It is evident that Sub-cluster (23, 30, 20, 16) is primarily driven by similarities in income and family size, while Sub-cluster (3, 15, 13) is formed based on younger age and middle-to-upper income levels.

By analyzing the distance relationships between Ti Amo and various customers on the preference map (figure 9), it is evident that Ti Amo is positioned closely to customer segments 22, 9, and Sub-cluster (23, 30, 20, 16). Given that this cluster includes customers with the highest income levels, reaching up to $125,000, it presents a high-profit potential.

Therefore, our strategy is to shift TiAmo’s position closer to this cluster, aligning its offerings with the preferences of high-income consumers with fewer children to maximize profitability. So, we have the following strategy for Targeting Sub-cluster (23, 30, 20, 16):

Enhancing Atmosphere:

Upgrade the restaurant’s ambiance with modern, stylish décor, improved lighting, and a more sophisticated dining environment to match the expectations of high-income customers.

Introduce background music, private dining areas, and elegant table settings to create an upscale experience.

Slightly Increasing Prices:

Since this group has high income, a moderate price increase is feasible if it is accompanied by perceived value improvements (e.g., premium ingredients, refined presentation, better service).

Implement tiered pricing strategies, offering premium menu options while still keeping some affordable selections.

Strategy for Number of Children (Fewer Kids):

Offer a more adult-oriented dining experience, with fewer distractions for children (e.g., no noisy play areas). Maybe at that time, our customer will say: “Why doesn’t your restaurant have a kids' menu?” And our waiter will say with smiling: “Oh, we do! It’s just very exclusive… you have to be at least 18 to order from it.”

Position the restaurant as an ideal place for date nights, business meetings, and sophisticated social gatherings, rather than a family-focused venue.

Introduce exclusive promotions for couples and small groups, reinforcing the idea of a refined dining space tailored to those without large families.

By elevating the atmosphere, optimizing pricing, and catering to a more adult-oriented clientele, we can effectively position the restaurant to attract Sub-cluster (23, 30, 20, 16) while maximizing profitability.

Appendix:

Note: we have deleted the extra cell (the header) in the dataset TP3_ResPercep and we changed "#OfNumberChildren" into "Number of Children? In Customer_Data for the convenience of R coding.

	Location	Food	Price	Atmosphere	Seating	Libations	Parking
Bistro 1245	3	4	4	3	7	7	2
The Swamp	6	7	1	5	6	6	7
Carrabbas	6	5	3	4	1	1	3
Las Margaritas	2	4	2	3	3	6	6
Beef O'Bradys	4	6	1	6	6	1	3
Mildred's	1	1	7	2	4	6	6
The Top	3	2	5	3	7	1	3
Paramount Grill	2	1	7	2	7	3	2
Shoney's	2	7	1	6	2	2	1
Ti Amo	3	2	7	5	1	1	5
Emiliano's	4	2	6	1	4	5	5
Leo's 706	4	3	5	4	4	5	5

Figure 1: Reverse Coded Restaurant Perception

	Paramount	TheTop	Bistro1245	TheSwamp	Mildreds	Emilianos	Leos706	BeefOBradys
[1,]	1	2.0	3	7	5.0	6	4	8.0
[2,]	1	2.0	6	7	4.0	5	3	10.0
[3,]	2	3.0	4	7	6.0	5	3	9.0
[4,]	12	10.0	11	9	6.5	3	4	8.0
[5,]	1	2.0	5	7	4.0	6	3	9.0
[6,]	8	3.5	3	2	10.0	7	5	3.5
[7,]	12	11.0	10	8	9.0	7	5	4.0
[8,]	12	9.0	8	6	11.0	7	5	3.0
[9,]	12	10.0	11	9	8.0	6	5	7.0
[10,]	12	11.0	10	6	9.0	7	5	4.0
[11,]	3	1.0	2	4	7.0	6	5	8.0
[12,]	11	7.0	6	2	10.0	9	4	1.0
[13,]	5	1.0	2	6	7.0	4	3	8.0
[14,]	12	11.0	10	9	8.0	7	4	6.0
[15,]	2	1.0	3	7	6.0	4	5	8.0
[16,]	3	4.0	6	10	2.0	1	5	11.0
[17,]	1	4.0	6	9	2.0	3	5	11.0
[18,]	12	11.0	10	8	9.0	7	4	5.0
[19,]	12	11.0	10	6	9.0	7	5	4.0
[20,]	7	8.0	11	12	2.0	3	5	10.0
[21,]	12	11.0	9	6	10.0	7	4	5.0
[22,]	9	11.0	12	10	5.0	4	7	8.0
[23,]	2	5.0	7	10	1.0	3	4	11.0
[24,]	8	3.0	1	2	10.0	5	7	4.0
[25,]	11	5.0	2	3	8.5	1	7	4.0
[26,]	6	2.0	1	3	9.0	5	7	4.0
[27,]	1	2.0	5	7	3.0	4	6	10.0
[28,]	4	2.0	6	7	5.0	3	1	9.0
[29,]	12	11.0	10	9	8.0	7	5	6.0
[30,]	6	4.0	9	11	3.0	1	2	10.0

	TiAmo	Carrabbas	LasMargaritas	Shoneys
[1,]	10.0	11.0	9	12.0
[2,]	9.0	11.0	8	12.0
[3,]	10.5	10.5	8	12.0
[4,]	5.0	1.0	2	6.5
[5,]	10.0	11.0	8	12.0
[6,]	12.0	11.0	6	9.0
[7,]	6.0	2.0	3	1.0
[8,]	10.0	4.0	1	2.0
[9,]	4.0	1.0	2	3.0
[10,]	8.0	3.0	2	1.0
[11,]	11.0	10.0	9	12.0
[12,]	12.0	8.0	3	5.0
[13,]	11.0	10.0	9	12.0
[14,]	5.0	1.0	3	2.0
[15,]	11.0	10.0	9	12.0
[16,]	7.0	9.0	8	12.0
[17,]	7.0	10.0	8	12.0
[18,]	6.0	2.0	3	1.0
[19,]	8.0	3.0	2	1.0
[20,]	1.0	4.0	6	9.0
[21,]	8.0	3.0	2	1.0
[22,]	1.0	2.0	3	6.0
[23,]	6.0	8.0	9	12.0
[24,]	12.0	11.0	6	9.0
[25,]	12.0	8.5	6	10.0
[26,]	12.0	11.0	8	10.0
[27,]	8.0	11.0	9	12.0
[28,]	12.0	10.0	8	11.0
[29,]	4.0	1.0	3	2.0
[30,]	8.0	7.0	5	12.0

Figure 2- Reverse Coded Customer Preference

```
Call: unfolding(delta = pref_reverse_matrix, type = "interval")

Model:                 Rectangular smacof
Number of subjects:    30
Number of objects:     12
Transformation:        interval
Conditionality:        matrix

Stress-1 value:    0.164483
Penalized Stress:  0.00111
Number of iterations: 1632
```

Figure 3-1: interval unfolding model

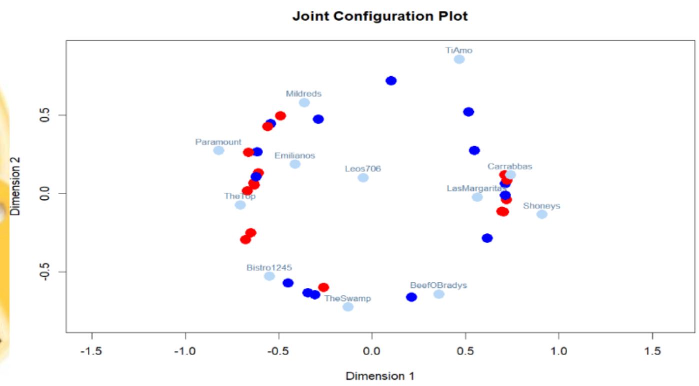

Figure 3-2: interval unfolding model: joint config plot

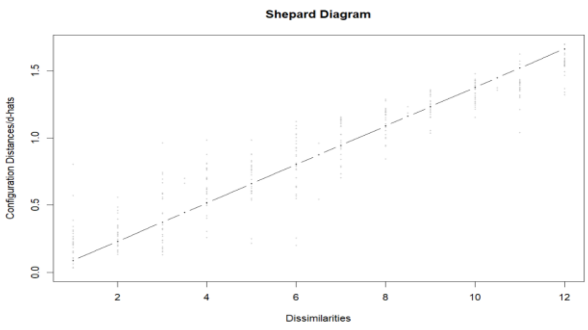

Figure 3-3: interval unfolding - Shepard Diagram

```
Call: unfolding(delta = pref_reverse_matrix, type = "interval", conditionality = "row")

Model:               Rectangular smacof
Number of subjects:  30
Number of objects:   12
Transformation:      interval
Conditionality:      row

Stress-1 value:     0.087094
Penalized Stress:   0.519606
Number of iterations: 10000
```

Figure 4-1: Interval Row-Conditional Unfolding Model

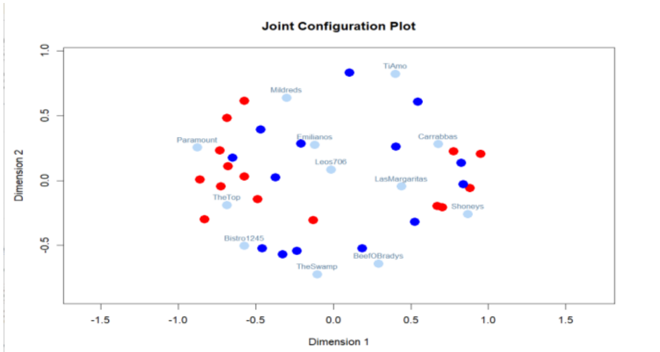

Figure 4-2: interval row conditional Unfolding Model-joint config plot

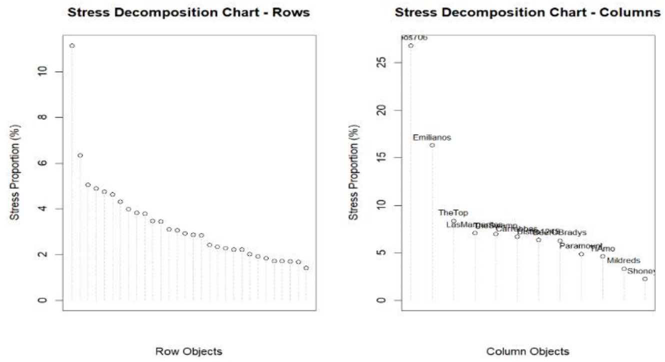

Figure 4-3: interval row conditional unfolding model- stress plot

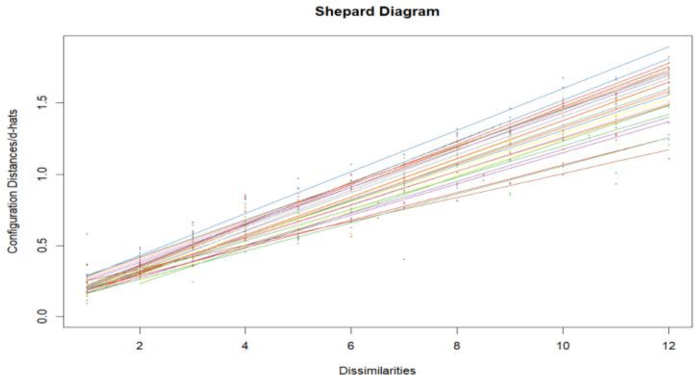

Figure 4-4: Interval Row-Conditional Unfolding Model- shepherd

```
Call: unfolding(delta = pref_reverse_matrix, type = "interval", conditionality = "matrix")

Model:               Rectangular smacof
Number of subjects:  30
Number of objects:   12
Transformation:      interval
Conditionality:      matrix

Stress-1 value:     0.164483
Penalized Stress:   0.00111
Number of iterations: 1632
```

Figure 5-1: Interval Matrix-Conditional Unfolding Model

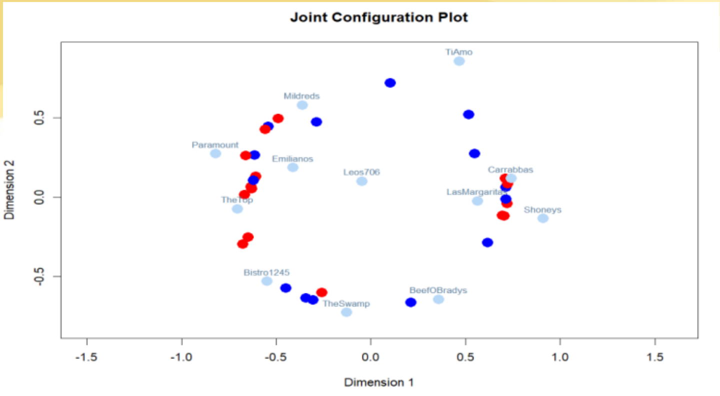

Figure 5-2: Interval Matrix-Conditional Unfolding Model- joint Config plot

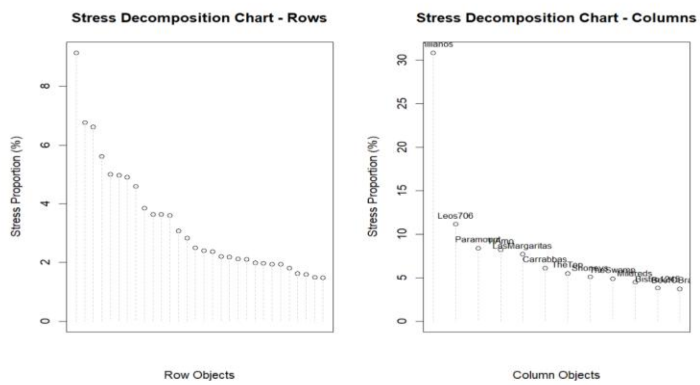

Figure 5-3: Interval Matrix-Conditional Unfolding Model- Stress

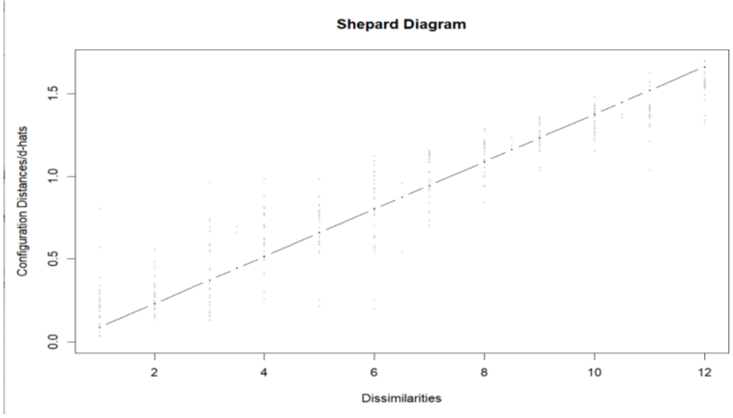

Figure 5-4: Interval Matrix-Conditional Unfolding Model- Shepard

```
Call: unfolding(delta = pref_reverse_matrix, type = "ordinal")

Model:                  Rectangular smacof
Number of subjects:     30
Number of objects:      12
Transformation:         ordinalp
Conditionality:         matrix

Stress-1 value:     0.085273
Penalized Stress:   1.652697
Number of iterations: 63
```

Figure 6-1: Ordinal Unfolding Model

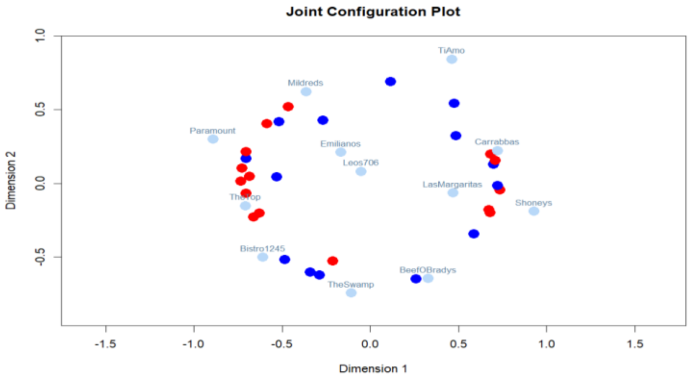

Figure 6-2: ordinal unfolding - joint config plot

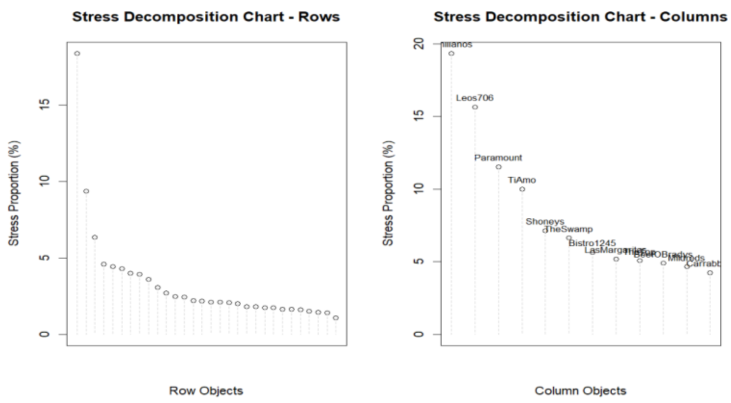

Figure6-3: ordinal unfolding- stress

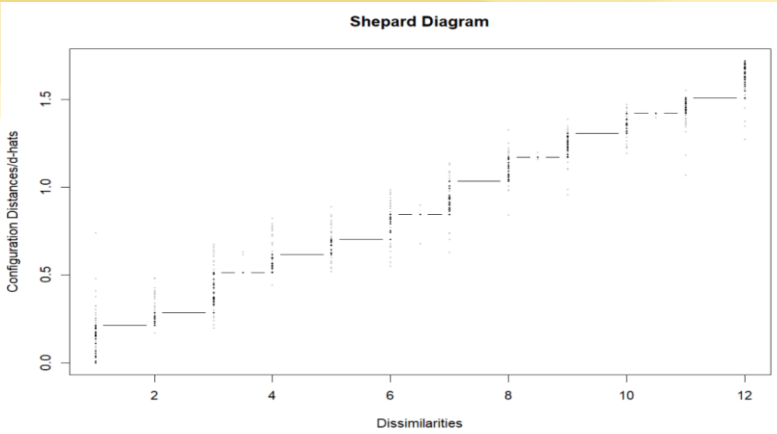

Figure 6-4: Ordinal Unfolding Model

```
Call: unfolding(delta = pref_reverse_matrix, type = "ordinal", conditionality = "row")

Model:               Rectangular smacof
Number of subjects:  30
Number of objects:   12
Transformation:      ordinalp
Conditionality:      row

Stress-1 value:    0.00596
Penalized Stress:  1.886149
Number of iterations: 10000
```

Figure 7-1 Ordinal Row-Conditional Unfolding Model

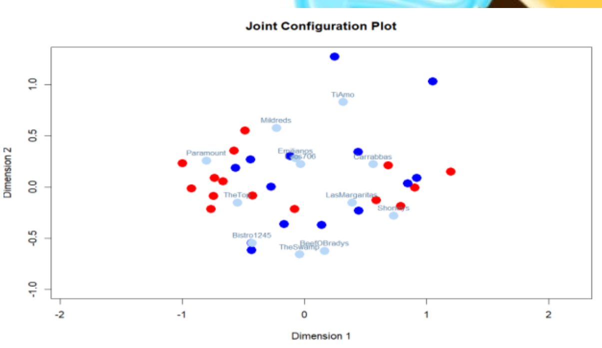

Figure 7-2: Ordinal Row-Conditional Unfolding Model- joint config plot

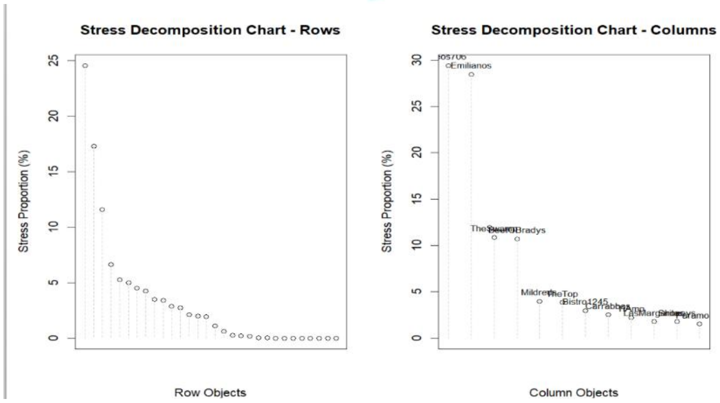

Figure 7-3: Ordinal Row-Conditional Unfolding Model- stress

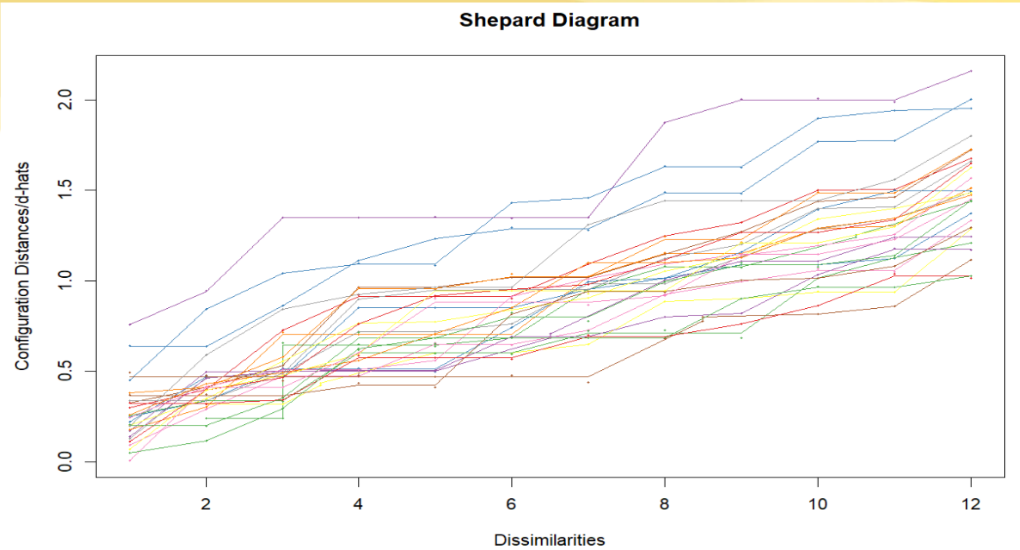

Figure 7-4: Ordinal Row-Conditional Unfolding Model- shepherd

```
Call: unfolding(delta = pref_reverse_matrix, type = "ordinal",
conditionality = "matrix")

Model:               Rectangular smacof
Number of subjects:  30
Number of objects:   12
Transformation:      ordinalp
Conditionality:      matrix

Stress-1 value:    0.085273
Penalized Stress:  1.652697
Number of iterations: 63
```

Figure 8-1: Ordinal Matrix-Conditional Unfolding Model

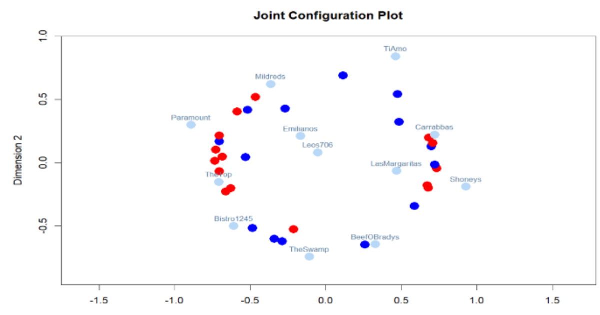

Figure 8-2: Ordinal Matrix-Conditional Unfolding Model- joint config plot

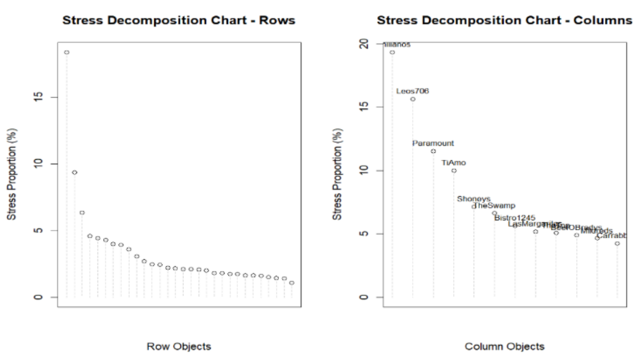

Figure 8-3: Ordinal Matrix-Conditional Unfolding Model- stress

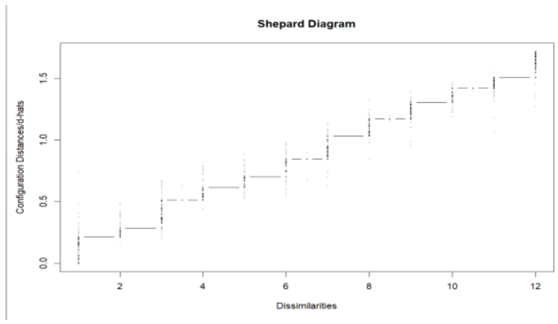

Figure 8-4: Ordinal Matrix-Conditional Unfolding Model- Shepard

Figure 9- Preference Map for Restaurants and Customers Using MDS

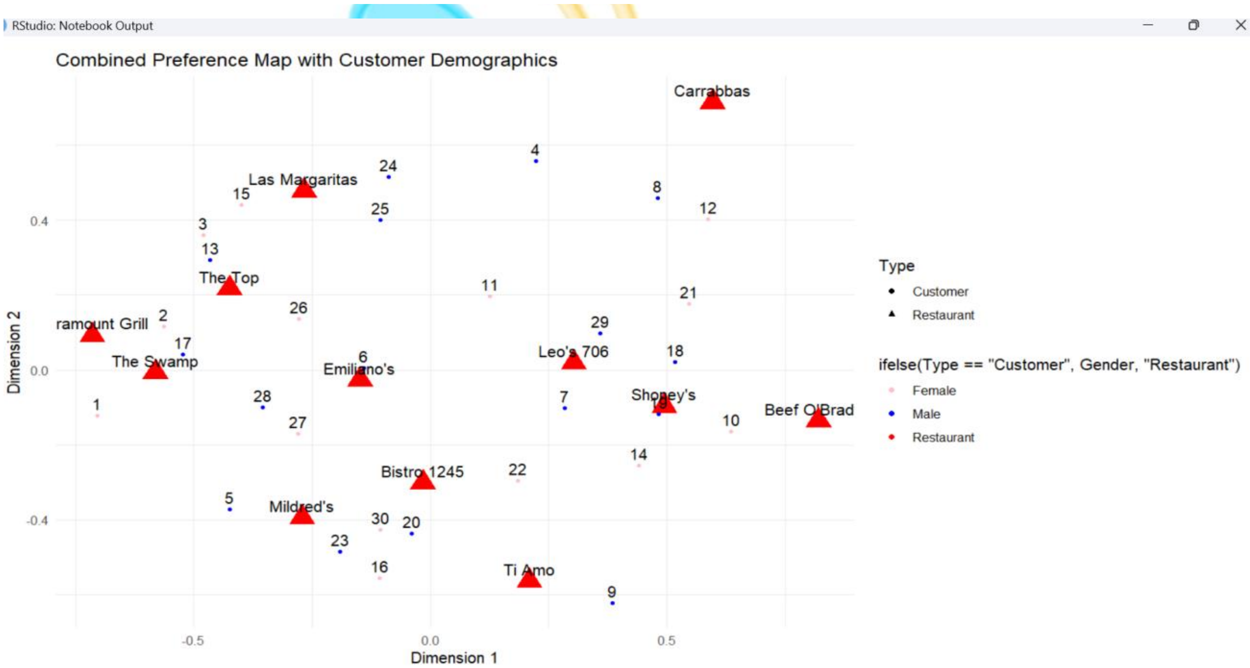

Figure 10 - Preference Map based on Gender

Figure 11- Preference Map based on Age

Figure 13- Preference Map based on Income

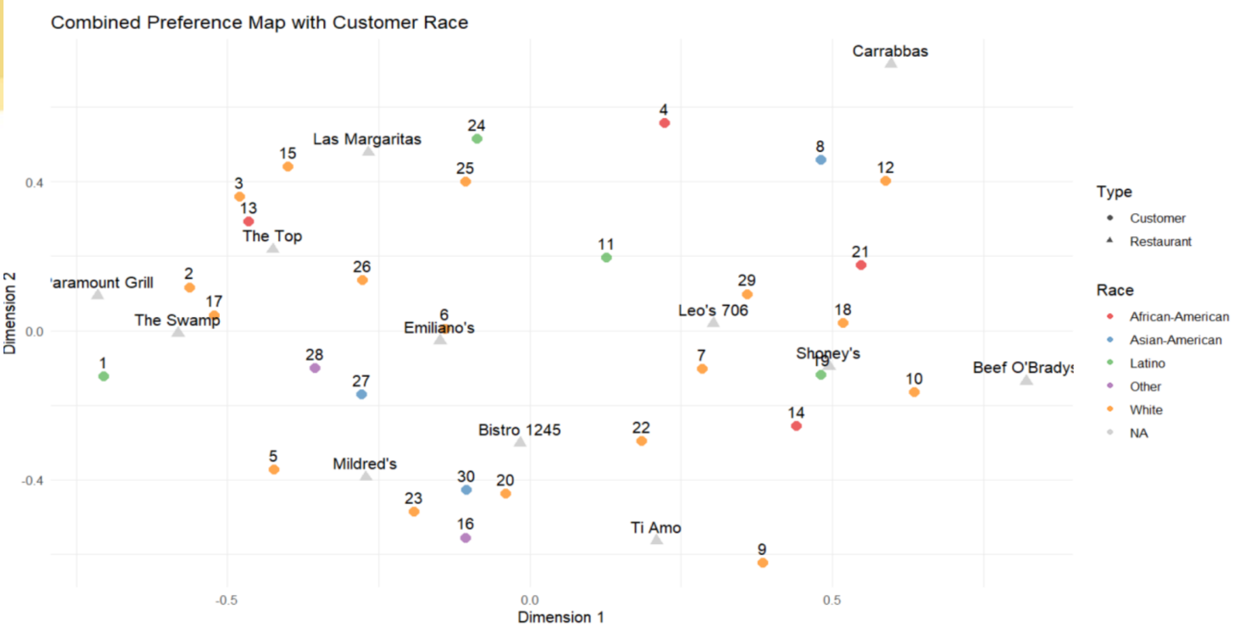

Figure 14- Preference Map based on Race

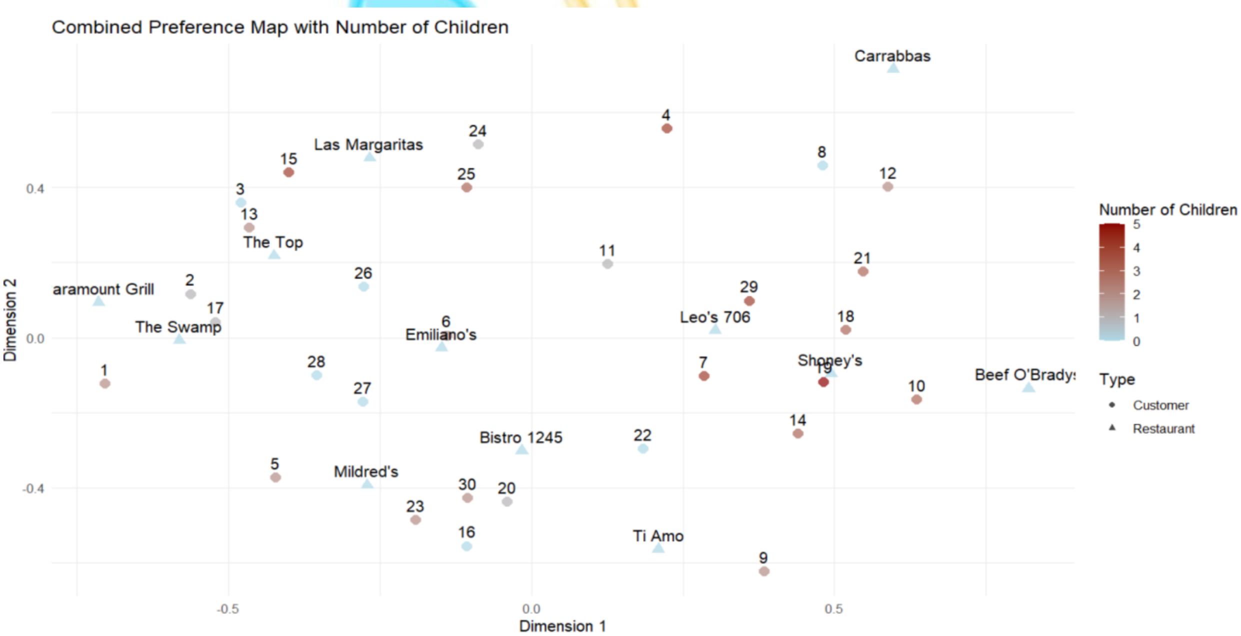

Figure15 Preference Map Based on Number of Children

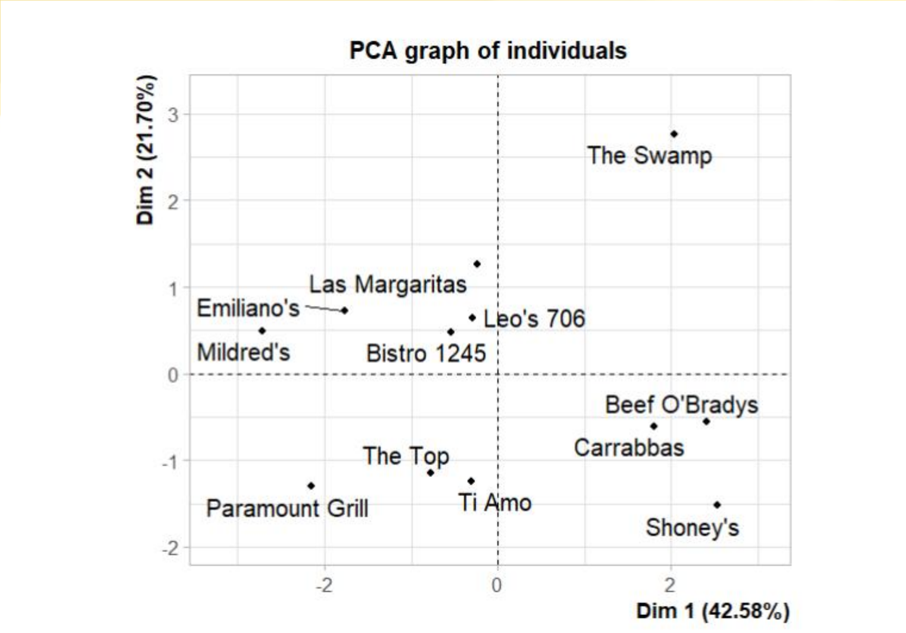

Figure 16- PCA Graph of Restaurants

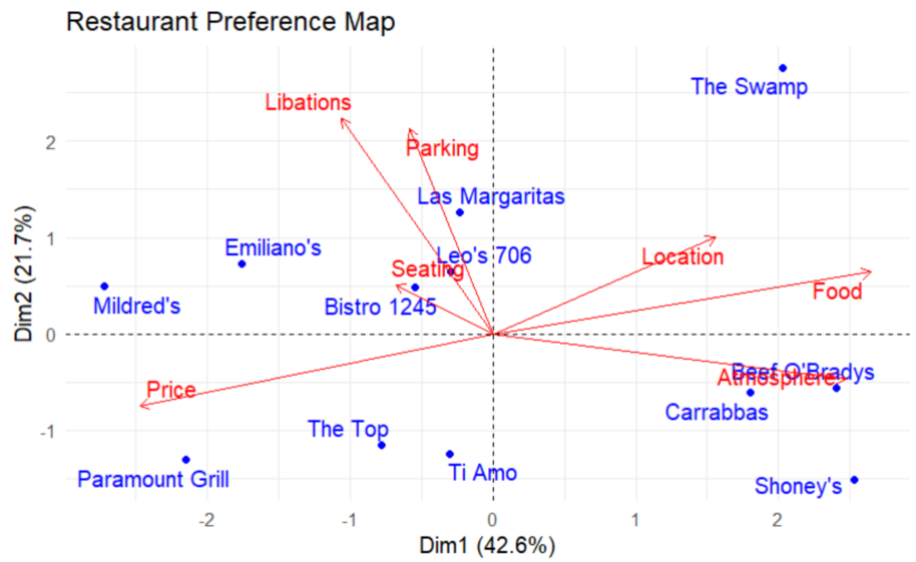

Figure 17- Restaurant Preference Map

```
Call: unfolding(delta = pref_reverse_matrix, type = "ordinal",
conditionality = "matrix",
    ties = "secondary")

Model:                Rectangular smacof
Number of subjects:   30
Number of objects:    12
Transformation:       ordinals
Conditionality:       matrix

Stress-1 value:    0.144163
Penalized Stress:  0.001059
Number of iterations: 1491
```

Figure 18- 1: Ordinal Matrix-Conditional Unfolding Model- Secondary

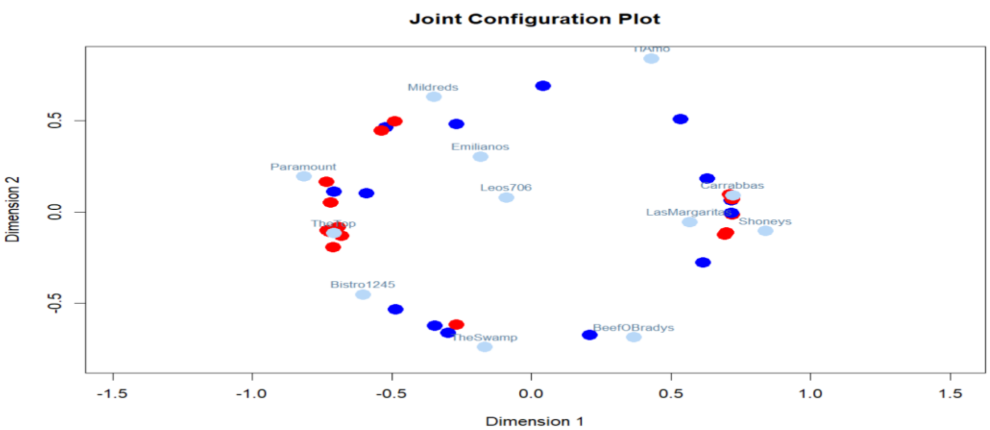

*Figure18-2 Ordinal Matrix-Conditional Unfolding Model- Joint Config- **Secondary***

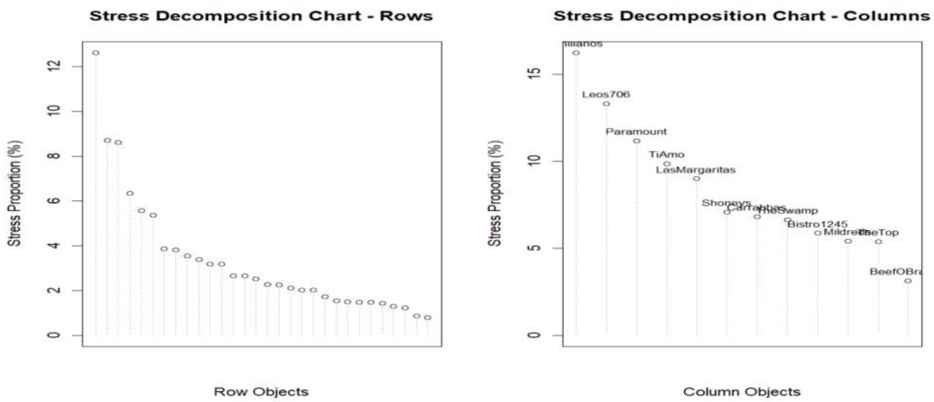

*Figure 18-2 Ordinal Matrix-Conditional Unfolding Model-Stress- **Secondary***

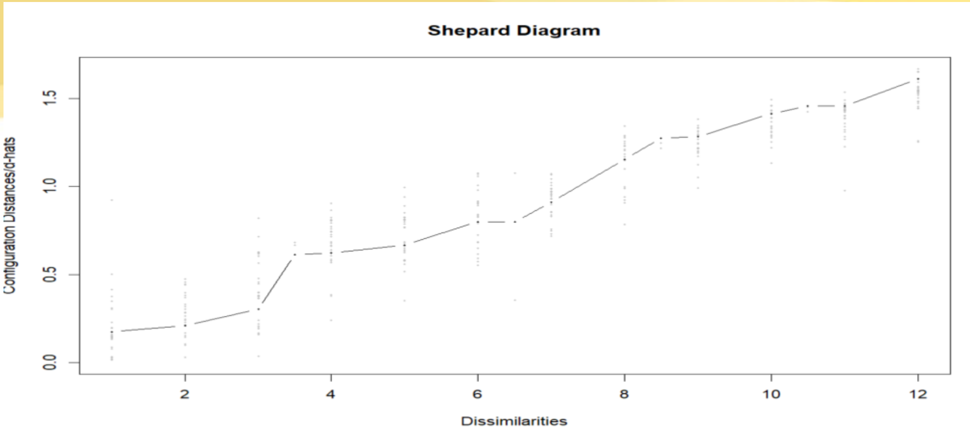

Figure 18- Ordinal Matrix-Conditional Unfolding Model-Shepard- Secondary

Customer#	favorite	rank	disfavourite	rank
1	Paramount	1	Shoneys	12
2	Paramount	1	Shoneys	12
3	Paramount	2	Shoneys	12
4	Carrabbas	1	Shoneys	6.5
5	Paramount	1	Shoneys	12
6	TheSwamp	2	Shoneys	9
7	Shoneys	1	Paramount	12
8	LasMargaritas	1	Paramount	12
9	Carrabbas	1	Paramount	12
10	Shoneys	1	Paramount	12
11	TheTop	1	Shoneys	12
12	BeefOBradys	1	TheTop	12
13	TheTop	1	Shoneys	12
14	Carrabbas	1	Paramount	12
15	TheTop	1	Shoneys	12
16	Carrabbas	1	Paramount	12
17	Carrabbas	1	Paramount	12
18	Shoneys	1	Paramount	12
19	Shoneys	1	Paramount	12
20	TiAmo	1	Shoneys	9
21	Shoneys	1	Paramount	12
22	TiAmo	1	Paramount	12
23	TheSwamp	1	Shoneys	12
24	BeefOBradys	1	Paramount	12
25	BeefOBradys	1	Paramount	12
26	BeefOBradys	1	Paramount	12
27	Paramount	1	Shoneys	12
28	Paramount	2	Shoneys	11
29	Carrabbas	1	Paramount	12
30	TheSwamp	1	Shoneys	12

Figure 19- Customer Preference Detail Chart