

INDIAN INSTITUTE OF TECHNOLOGY, JODHPUR



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School of Artificial Intelligence and Data Science **(Augmented Reality and Virtual Reality)**

PSYCHOPHYSICS

CODING ASSIGNMENT 2

Student Details:

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Objective

Understanding and Analysis of human perception of material properties like roughness across different sensory modalities.

Introduction

Human perception of material properties like roughness is a complex interplay between various sensory modalities.

Experiment Overview

The experiment involved comparing materials based on roughness, utilising a scale of 1 to 9 for both auditory and visual modalities. The comparisons were between 33 objects, leading to ${}^{33}C_2 = 528$ comparisons. The value of 1 on this scale meant that the objects were dissimilar, and the value of 9 indicated that the things were similar. The experiment was conducted by different participants, and the combined dataset was used for analysis.

Methodology, Observations and Analysis

Method:

The collected similarity ratings were transformed into normalised dissimilarities by subtracting each rating from nine and dividing them by 8, as suggested by Vardar et al. in “Fingertip Interaction Metrics Correlate with Visual and Haptic Perception of Real Surfaces” [1]. After converting ratings to dissimilarities, the dissimilarity values corresponding to ratings given by different participants were averaged for each comparison of materials to get a single data point for each comparison. Thus, a matrix of 33x33 was created.

$$dissimilarity = \frac{9 - rating}{8} \quad (1)$$

$$Average\ dissimilarity = \frac{\sum_{i=1}^{participants} dissimilarity^i}{participants} \quad (2)$$

Method:

Spearman correlation coefficients were calculated, and heatmaps were plotted to determine the correlation within and between participants.

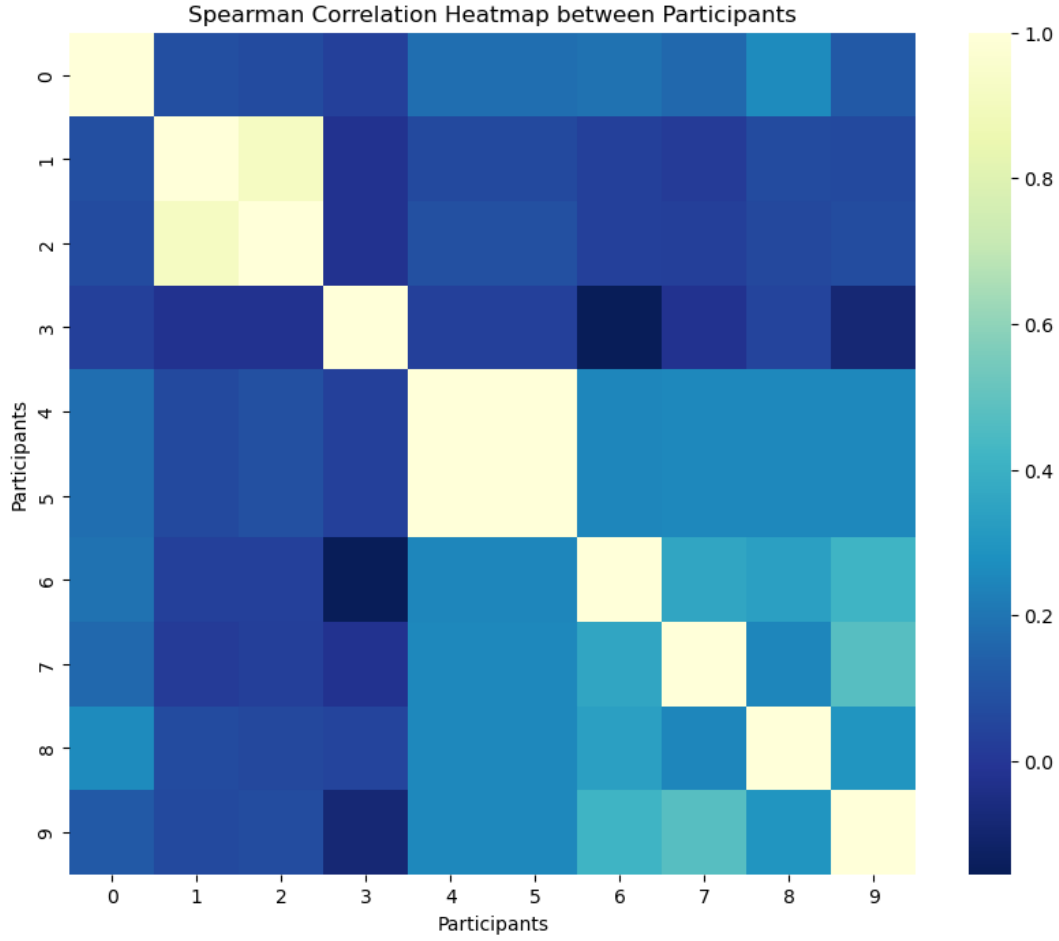
Observations:

Fig. 1. Heatmap showing consistencies within and between participants

Method:

The average dissimilarities between different objects were converted to disparities using a monotonic function to preserve the order. Let dissimilarity be denoted by d and disparity be denoted by d^* . Then, a monotonic function was used to transform the rating from dissimilarity to disparity such that if $d_{ij} < d_{kl}$, then $d_{ij}^* < d_{kl}^*$.

For NMDS, we need a stress function. So, a stress function was used, as mentioned in the equation below.

$$Stress = \sqrt{\frac{\sum_{i < j}^n (|x_i - x_j| - d_{ij}^*)^2}{\sum_{i < j}^n (x_i - x_j)^2}} \quad (3)$$

This x_i refers to a point in perceptual space predicted using NMDS. The stress values corresponding to different dimensions of a point in perceptual space were recorded, and an optimal stress value was chosen. The perceptual space points thus obtained from NMDS, corresponding to that dimension and optimal stress value, were retained.

Implementation of NMDS: NMDS is non-metric multi-dimensional scaling. NMDS aims to cluster objects based on distances while preserving the order of dissimilarities and minimising stress. In this, random coordinates were first assigned to data points in the reduced space and updated as the stress was minimised. The stress values and the number of dimensions were recorded. Then, a graph was plotted between stress

values and number of dimensions, and the elbow point was chosen as an optimal number of dimensions corresponding to optimal stress. The coordinates predicted corresponding to this optimal dimension and stress were retained and used in further analysis.

Observations:

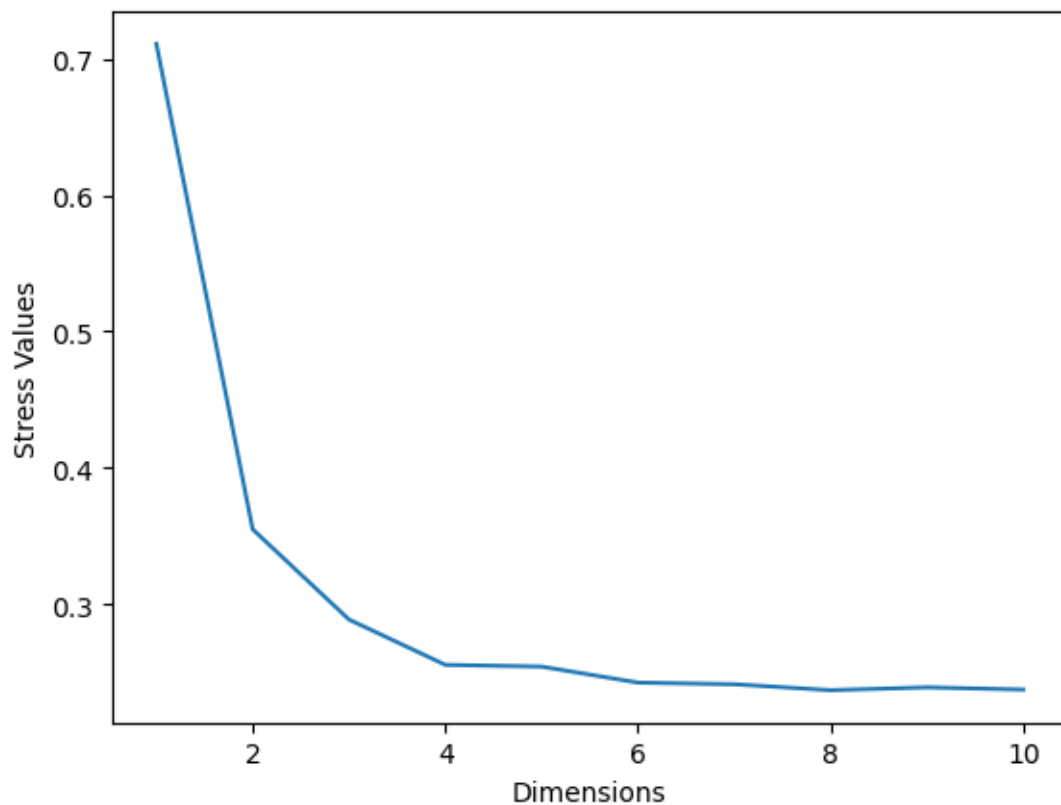


Fig. 2. Stress vs Dimensions

Analysis:

The optimal dimension corresponding to the optimal stress value is the elbow point of the graph shown in Fig. 2. Here, the Optimum Stress was 0.35, corresponding to two dimensions. So, the proximity plot will be projected across two dimensions. The coordinates obtained using these values of stress and number of dimensions were plotted on a 2D graph since the number of optimal dimensions is 2.

Method:

The Euclidean distances between the points obtained from NMDS corresponding to optimal stress value and optimal number of dimensions (two dimensions in this case) were calculated, and a matrix was created representing the Euclidean distances between the points in the perceptual space, and a heatmap was generated based on this Euclidean distance-based matrix,

Observations:

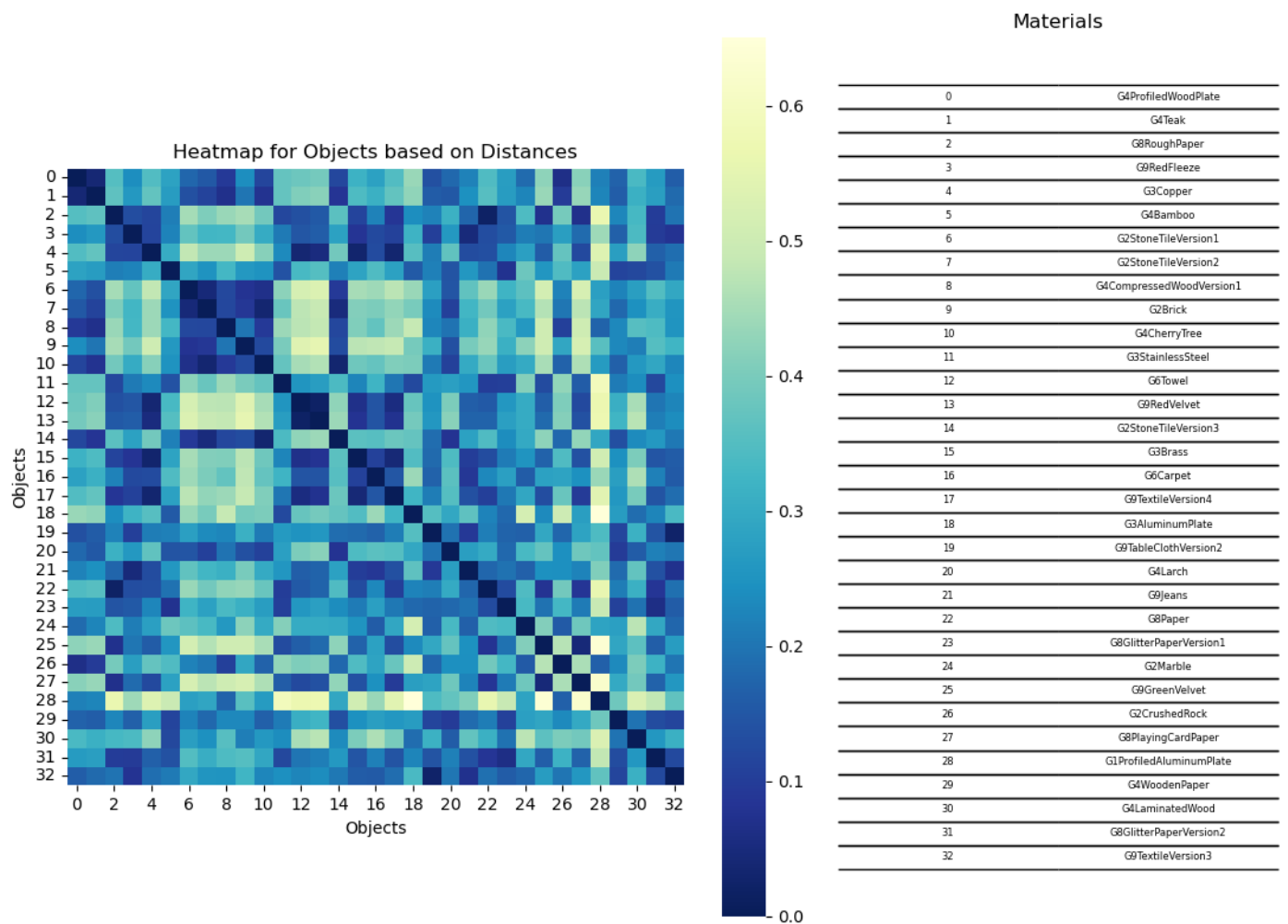


Fig. 3. Heatmap corresponding to distance-based Matrix

Analysis:

The heatmap shows that the objects close to each other are perceptually similar and are shown with colours corresponding to smaller distance values. The Euclidean distance between these objects (those marked with similar colours) is less and suggests that the objects appear perceptually the same. For example:

- Consider the point (1,0), (represented in heatmap by dark blue colour) the distance between them is shown in a colour corresponding to a smaller distance value, which means that the materials 'G4Teak' (index 1) 'G4ProfiledWoodPlate' (index 0) are perceptually similar
- Similarly, consider the points (9,13) (represented in the heatmap by a light green colour) which means ('G2Brick', 'G9RedVelvet') have a higher distance value, and suggest that they are perceptually different.

The matrix based on distances corresponding to this heatmap is shown in Fig. 4 while the matrix based on originality dissimilarity is shown in Fig. 5. For ease of analysis, the distance matrix also contains an index row and index column. For clarity, the matrices for both distances and dissimilarities were exported as CSV files 'distance_matrix.csv', 'dissimilarity_matrix.csv' and 'final_adjacency_matrix_edges.csv' and are attached with the report. The comparison of heatmaps for dissimilarity matrix and distance matrix are shown in Fig. 6. The proximity threshold was kept at 0.075, and the clusters were obtained based on this proximity threshold. Edges were drawn between objects of the same cluster.

Distance Matrix

i	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31		
0	0	0.04	0.15	0.24	0.35	0.28	0.18	0.15	0.09	0.24	0.12	0.37	0.38	0.39	0.32	0.32	0.28	0.35	0.44	0.14	0.18	0.22	0.35	0.27	0.38	0.42	0.27	0.42	0.22	0.17	0.34	0.27	0.16	
1	0.04	0	0.36	0.36	0.37	0.27	0.14	0.11	0.07	0.20	0.08	0.37	0.41	0.42	0.08	0.34	0.31	0.37	0.43	0.16	0.15	0.25	0.36	0.27	0.22	0.43	0.38	0.43	0.23	0.16	0.31	0.27	0.18	
2	0.35	0.36	0	0.15	0.12	0.21	0.45	0.40	0.44	0.45	0.39	0.12	0.14	0.15	0.36	0.11	0.22	0.08	0.24	0.22	0.31	0.17	0.02	0.14	0.34	0.07	0.40	0.07	0.56	0.23	0.13	0.10	0.20	
3	0.24	0.26	0.15	0	0.11	0.22	0.37	0.33	0.33	0.39	0.30	0.21	0.15	0.18	0.28	0.08	0.12	0.11	0.32	0.30	0.26	0.05	0.15	0.15	0.21	0.20	0.27	0.18	0.44	0.17	0.34	0.09	0.08	
4	0.35	0.37	0.32	0.11	0	0.30	0.48	0.44	0.44	0.50	0.41	0.23	0.04	0.05	0.39	0.05	0.13	0.03	0.35	0.21	0.37	0.13	0.13	0.23	0.27	0.16	0.37	0.12	0.53	0.27	0.42	0.17	0.19	
5	0.28	0.27	0.21	0.22	0.30	0	0.29	0.25	0.33	0.26	0.25	0.14	0.33	0.35	0.22	0.28	0.34	0.28	0.16	0.22	0.14	0.28	0.20	0.08	0.38	0.25	0.34	0.28	0.49	0.11	0.12	0.14	0.21	
6	0.38	0.14	0.45	0.37	0.48	0.29	0	0.04	0.32	0.08	0.07	0.42	0.52	0.33	0.08	0.45	0.44	0.47	0.44	0.28	0.35	0.37	0.44	0.32	0.36	0.31	0.32	0.52	0.28	0.22	0.27	0.35	0.29	
7	0.15	0.11	0.40	0.33	0.44	0.25	0.04	0	0.12	0.08	0.05	0.38	0.48	0.49	0.05	0.41	0.48	0.43	0.40	0.24	0.11	0.33	0.39	0.28	0.33	0.47	0.20	0.47	0.29	0.18	0.25	0.31	0.25	
8	0.09	0.07	0.44	0.33	0.44	0.33	0.12	0.12	0	0.20	0.09	0.44	0.47	0.48	0.12	0.41	0.37	0.44	0.49	0.23	0.20	0.31	0.43	0.34	0.26	0.31	0.11	0.30	0.17	0.23	0.35	0.34	0.25	
9	0.24	0.20	0.45	0.39	0.50	0.38	0.08	0.09	0.20	0	0.12	0.40	0.54	0.55	0.13	0.47	0.48	0.49	0.39	0.31	0.14	0.48	0.43	0.31	0.42	0.50	0.28	0.52	0.36	0.23	0.22	0.35	0.32	
10	0.12	0.08	0.39	0.30	0.41	0.25	0.07	0.03	0.09	0.12	0	0.17	0.45	0.46	0.03	0.39	0.37	0.41	0.40	0.21	0.11	0.38	0.38	0.27	0.30	0.45	0.17	0.46	0.27	0.17	0.38	0.29	0.23	
11	0.37	0.37	0.12	0.21	0.23	0.14	0.42	0.38	0.44	0.40	0.37	0	0.25	0.27	0.34	0.23	0.32	0.20	0.12	0.26	0.28	0.25	0.10	0.10	0.41	0.12	0.45	0.16	0.39	0.21	0.24	0.12	0.24	
12	0.38	0.41	0.14	0.35	0.05	0.33	0.52	0.48	0.47	0.54	0.45	0.25	0	0.02	0.45	0.07	0.54	0.06	0.38	0.25	0.40	0.36	0.15	0.28	0.30	0.16	0.41	0.12	0.57	0.31	0.45	0.28	0.23	
13	0.39	0.42	0.15	0.16	0.05	0.35	0.33	0.49	0.48	0.55	0.46	0.27	0.02	0	0.44	0.08	0.14	0.07	0.19	0.26	0.42	0.17	0.17	0.28	0.30	0.18	0.41	0.14	0.17	0.32	0.47	0.22	0.24	
14	0.12	0.08	0.36	0.28	0.39	0.22	0.08	0.05	0.12	0.13	0.03	0.34	0.43	0.44	0	0.36	0.35	0.38	0.37	0.19	0.08	0.28	0.35	0.24	0.29	0.42	0.18	0.43	0.29	0.13	0.24	0.26	0.20	
15	0.32	0.34	0.11	0.08	0.03	0.38	0.45	0.41	0.41	0.47	0.39	0.23	0.07	0.08	0.36	0	0.31	0.04	0.35	0.38	0.34	0.38	0.13	0.21	0.25	0.17	0.34	0.14	0.51	0.25	0.40	0.35	0.16	
16	0.28	0.31	0.22	0.12	0.13	0.34	0.44	0.40	0.37	0.48	0.37	0.32	0.34	0.14	0.35	0.11	0	0.35	0.44	0.17	0.36	0.09	0.23	0.28	0.16	0.28	0.28	0.25	0.43	0.27	0.46	0.22	0.16	
17	0.35	0.37	0.08	0.11	0.05	0.28	0.47	0.43	0.44	0.49	0.41	0.28	0.08	0.07	0.39	0.04	0.15	0	0.32	0.21	0.25	0.34	0.38	0.15	0.38	0.18	0.54	0.26	0.40	0.14	0.19	0.21		
18	0.44	0.43	0.24	0.32	0.35	0.16	0.44	0.40	0.49	0.39	0.40	0.12	0.38	0.39	0.37	0.35	0.44	0.32	0	0.35	0.29	0.36	0.22	0.18	0.51	0.23	0.50	0.27	0.45	0.27	0.19	0.23	0.34	
19	0.14	0.16	0.22	0.10	0.21	0.22	0.28	0.24	0.23	0.31	0.21	0.26	0.25	0.26	0.19	0.18	0.17	0.21	0.35	0	0.19	0.09	0.22	0.17	0.17	0.29	0.18	0.28	0.34	0.12	0.31	0.14	0.02	
20	0.38	0.15	0.11	0.26	0.37	0.24	0.35	0.11	0.20	0.34	0.11	0.28	0.40	0.42	0.08	0.34	0.38	0.25	0.29	0.19	0	0.27	0.30	0.38	0.33	0.37	0.34	0.38	0.37	0.08	0.36	0.22	0.20	
21	0.22	0.25	0.17	0.05	0.13	0.26	0.37	0.33	0.33	0.31	0.40	0.30	0.25	0.16	0.17	0.28	0.10	0.09	0.14	0.36	0.09	0.27	0	0.18	0.19	0.17	0.24	0.24	0.22	0.41	0.18	0.37	0.14	0.07
22	0.35	0.36	0.02	0.13	0.13	0.10	0.20	0.44	0.39	0.43	0.43	0.38	0.10	0.35	0.17	0.35	0.13	0.23	0.10	0.22	0.22	0.30	0.18	0	0.33	0.34	0.08	0.39	0.09	0.56	0.21	0.31	0.09	0.19
23	0.27	0.27	0.14	0.35	0.23	0.08	0.32	0.28	0.34	0.31	0.27	0.10	0.28	0.28	0.24	0.21	0.28	0.20	0.18	0.17	0.18	0.39	0.33	0	0.33	0.19	0.33	0.21	0.49	0.11	0.39	0.06	0.16	
24	0.18	0.22	0.34	0.21	0.27	0.38	0.36	0.33	0.26	0.42	0.30	0.41	0.30	0.30	0.29	0.25	0.18	0.29	0.11	0.17	0.33	0.17	0.34	0.33	0	0.41	0.16	0.39	0.28	0.28	0.47	0.29	0.18	
25	0.42	0.43	0.07	0.20	0.16	0.25	0.51	0.47	0.51	0.50	0.45	0.12	0.16	0.18	0.42	0.17	0.28	0.13	0.23	0.29	0.17	0.24	0.08	0.19	0.41	0	0.47	0.04	0.84	0.29	0.36	0.16	0.27	
26	0.07	0.10	0.40	0.27	0.37	0.34	0.22	0.20	0.31	0.28	0.17	0.43	0.41	0.41	0.38	0.34	0.28	0.38	0.50	0.38	0.24	0.24	0.39	0.53	0.38	0.47	0	0.46	0.17	0.23	0.48	0.32	0.20	
27	0.42	0.43	0.07	0.18	0.12	0.28	0.32	0.47	0.50	0.52	0.46	0.16	0.32	0.14	0.43	0.14	0.25	0.30	0.27	0.28	0.38	0.22	0.09	0.21	0.39	0.04	0.46	0	0.62	0.50	0.39	0.17	0.26	
28	0.22	0.23	0.56	0.44	0.53	0.48	0.28	0.29	0.37	0.36	0.27	0.59	0.57	0.57	0.29	0.51	0.43	0.54	0.65	0.34	0.37	0.41	0.56	0.49	0.28	0.64	0.17	0.62	0	0.39	0.53	0.48	0.37	
29	0.17	0.16	0.23	0.17	0.27	0.31	0.22	0.18	0.23	0.23	0.17	0.21	0.31	0.32	0.33	0.25	0.27	0.26	0.27	0.32	0.09	0.38	0.21	0.11	0.28	0.29	0.23	0.30	0.39	0	0.20	0.13	0.12	
30	0.34	0.31	0.33	0.34	0.42	0.12	0.27	0.25	0.35	0.22	0.26	0.24	0.45	0.47	0.24	0.40	0.46	0.40	0.19	0.31	0.16	0.37	0.31	0.19	0.47	0.36	0.40	0.39	0.53	0.20	0	0.26	0.31	
31	0.27	0.27	0.10	0.09	0.17	0.34	0.35	0.31	0.34	0.35	0.29	0.12	0.20	0.22	0.26	0.15	0.22	0.14	0.23	0.14	0.22	0.34	0.09	0.38	0.39	0.16	0.32	0.17	0.48	0.32	0.26	0	0.12	
32	0.16	0.18	0.20	0.08	0.18	0.21	0.29	0.25	0.25	0.32	0.23	0.24	0.23	0.24	0.20	0.16	0.18	0.19	0.34	0.02	0.20	0.07	0.19	0.16	0.18	0.27	0.20	0.26	0.37	0.32	0.31	0.12	0	

Materials

0	G4ProfiledWoodPlate
1	G4Teak
2	G8RoughPaper
3	G9RedFleeze
4	G3Copper
5	G4Bamboo
6	G2StoneTileVersion1
7	G2StoneTileVersion2
8	G4CompressedWoodVersion1
9	G2Brick
10	G4CherryTree
11	G3StainlessSteel
12	G6Towel
13	G9RedVelvet
14	G2StoneTileVersion3
15	G3Brass
16	G6Carpet
17	G9TextileVersion4
18	G3AluminumPlate
19	G9TableClothVersion2
20	G4Larch
21	G9Jeans
22	G8Paper
23	G8GlitterPaperVersion1
24	G2Marble
25	G9GreenVelvet
26	G2CrushedRock
27	G8PlayingCardPaper
28	G1ProfiledAluminumPlate
29	G4WoodenPaper
30	G4LaminatedWood
31	G8GlitterPaperVersion2
32	G9TextileVersion3

Fig. 4. Distance Matrix

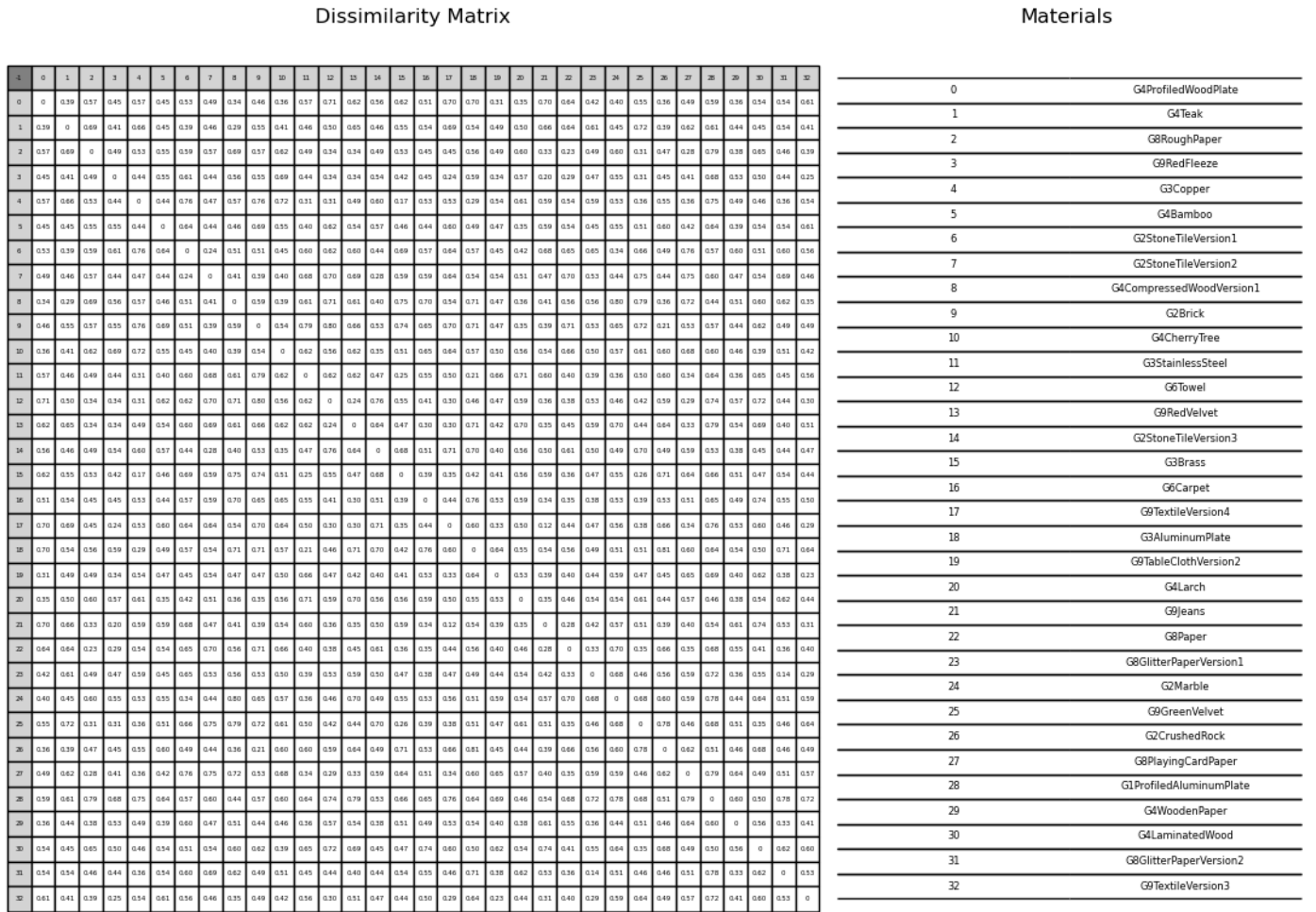


Fig. 5. Original Dissimilarity Matrix

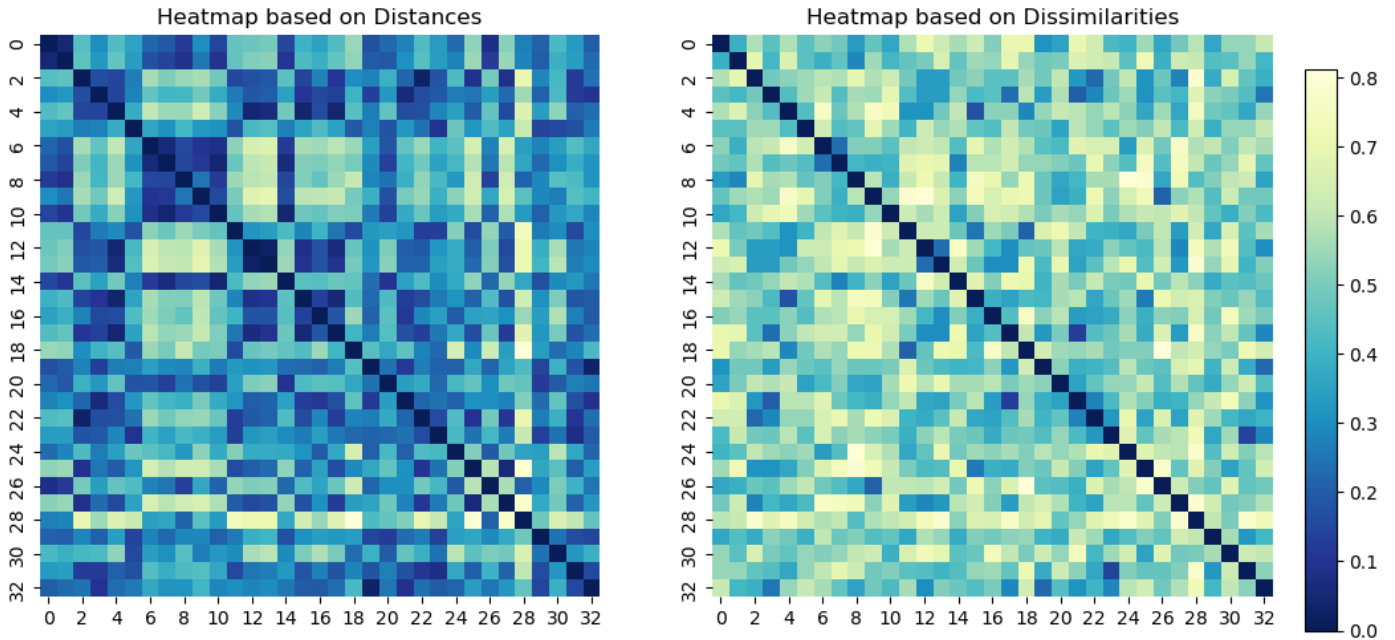


Fig. 6. Heatmaps for both Distance and Dissimilarity Matrices

The heatmaps in Fig. 6. shows that **the order of dissimilarities and distances is preserved by NMDS.**

Observations regarding proximity plot:

The proximity plots across projected dimensions were also plotted as shown in Fig 5.

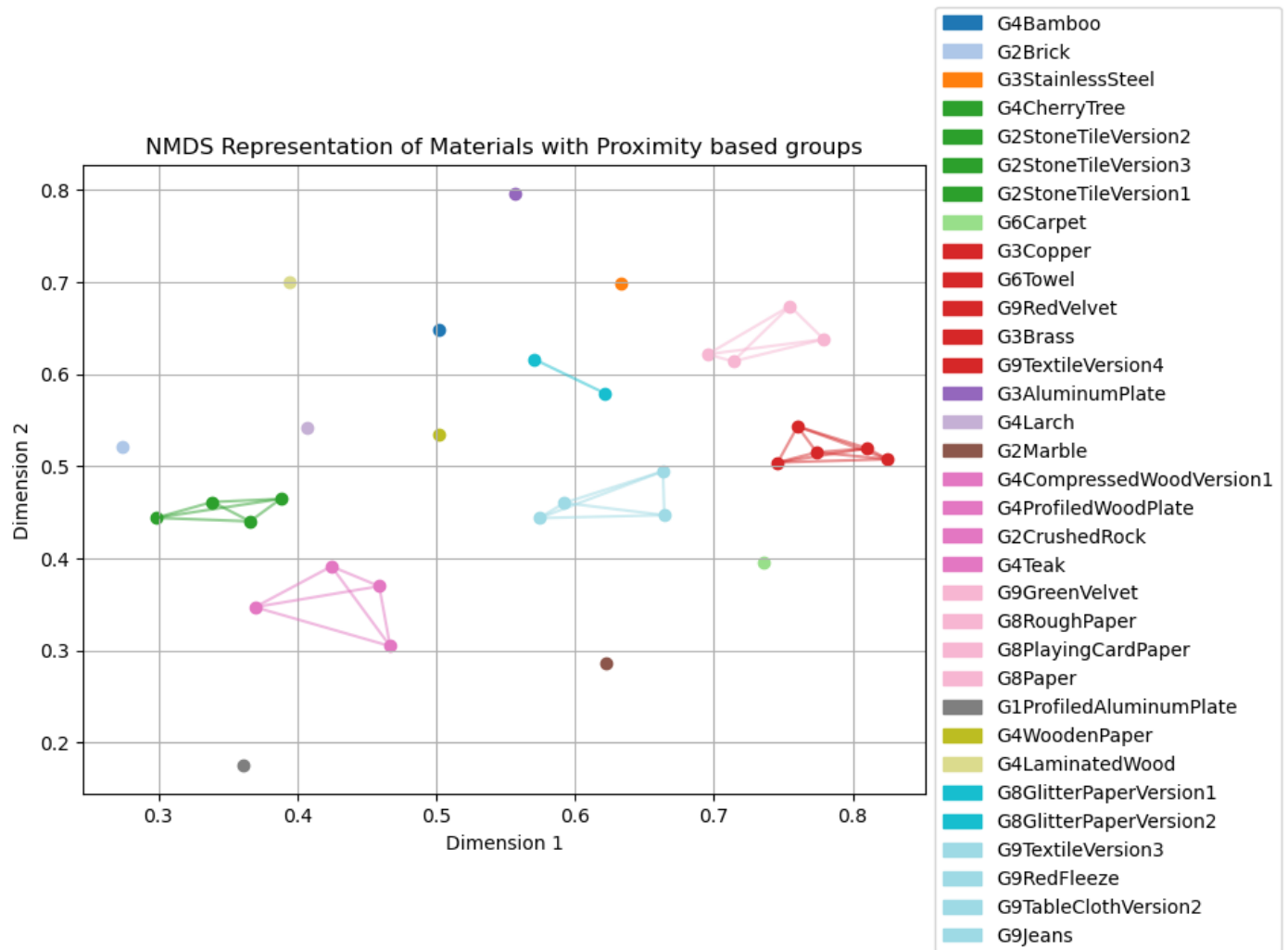


Fig. 7. Proximity Plot in projected dimensions

Analysis:

The perceptually similar objects were clustered in the same cluster. For example, 'G3Copper', 'G6Towel', 'G9RedVelvet' and 'G3Brass' were clustered in the same group. Similarly, materials like 'G2StoneTileVersion1' and 'G2StoneTileVersion2' were placed in same cluster. However, materials like 'G2Brick' and 'G9RedVelvet' were placed in different clusters suggesting that they are perceptually dissimilar.

Observations:

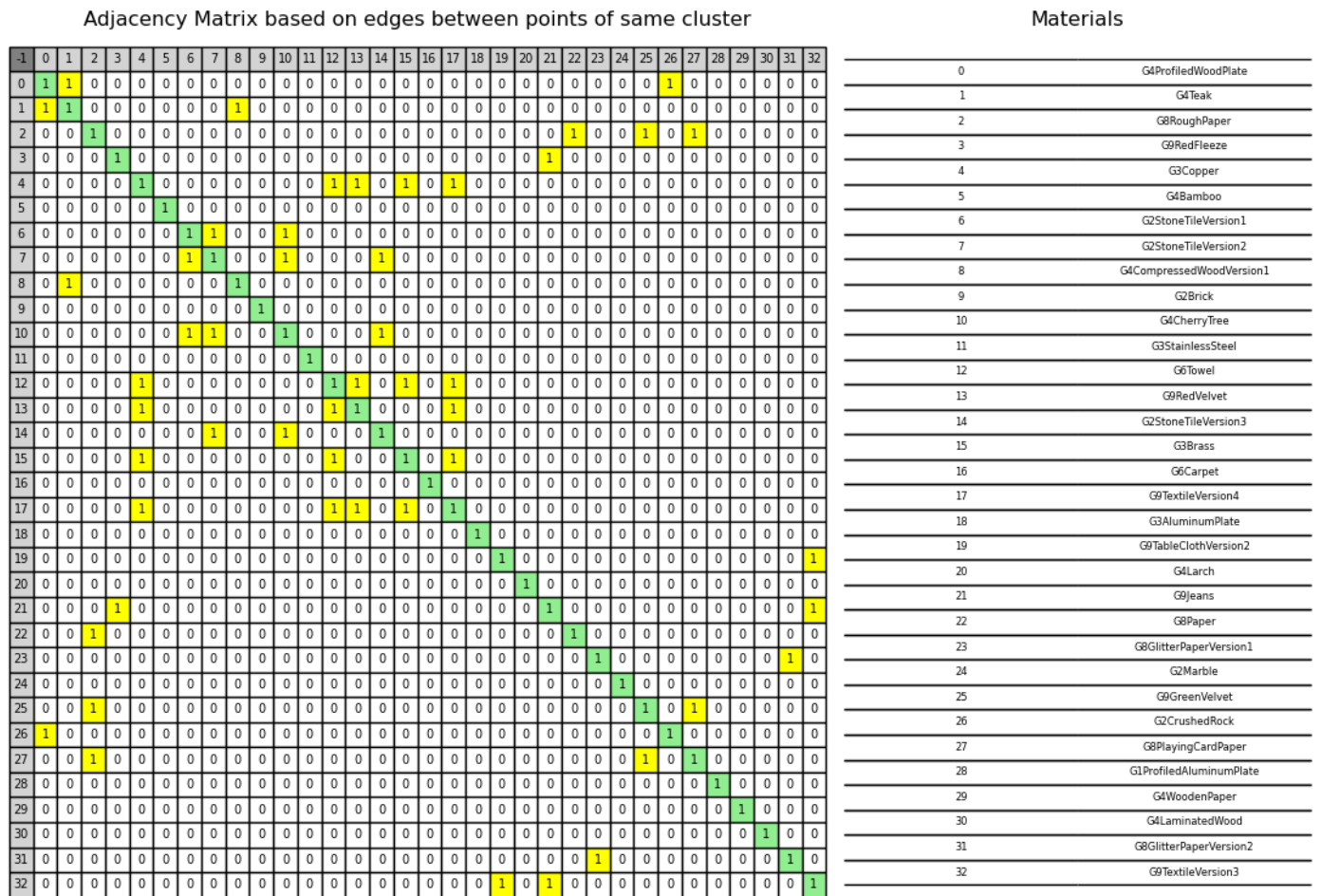


Fig. 8. Adjacency Matrix based on edges between objects of the same cluster

Observations:

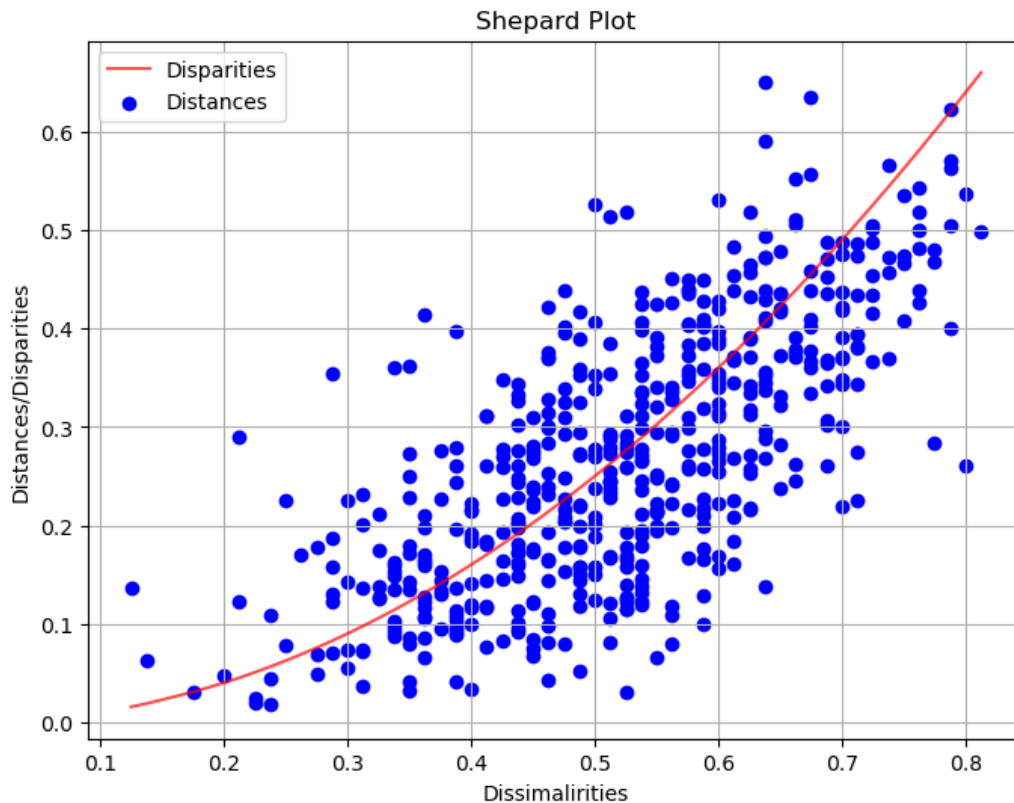


Fig. 9. Shepard Plot

The Shepard plot indicates that the NMDS algorithm has preserved the order of the dissimilarities well, as most of the data points are close to the disparities, representing that NMDS has fitted data well. The plot also shows that the data points have a positive correlation between dissimilarities and distances, meaning that the more dissimilar two points are in the original space, the farther apart they are in the reduced space. This is desirable for NMDS, as **it preserves the order of relative distances of the data points**. That means if, between two points i and j , dissimilarities are represented by d_{ij} , disparities are represented by d_{ij}^* and Euclidean distances are represented by $|x_i - x_j|$, then the order of these values is preserved.

$$d_{ij} < d_{kl} \Rightarrow d_{ij}^* < d_{kl}^* \Rightarrow |x_i - x_j| < |x_k - x_l| \quad (4)$$

The plot does not exhibit any obvious outliers or anomalies except a few, such as the one of the data points at the right most corner, which has a high dissimilarity but a low distance. This could indicate some noise or error in the data or the NMDS algorithm.

Running the Code:

The code (both Python and Jupyter notebooks are attached with this report). For Python or Jupyter Notebook file, the python file or Jupyter Notebook need to be placed in the same folder that contains the data folder, where “For Group A” folder need to be renamed as “data”, and the code can be run. The necessary libraries will be installed automatically.

References

- [1] Y. Vardar, C. Wallraven and K. J. Kuchenbecker, "Fingertip Interaction Metrics Correlate with Visual and Haptic Perception of Real Surfaces," in *2019 IEEE World Haptics Conference (WHC)*, 2019.