Iria Quintero García 254373
Norbert Tomàs Escudero 242695
Javier González Otero 243078

Lab 3: Emotions

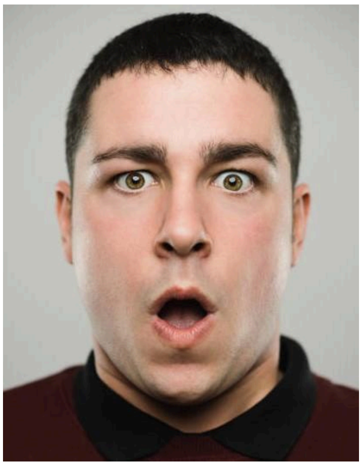
Introduction and justification

Facial expression analysis has been extensively studied in psychology, neuroscience, and artificial intelligence, with theories like Darwin's (1872) proposing the universality of emotions and Ekman and Friesen's (1976) studies identifying six basic emotions. More recent research suggests that emotional perception is influenced by cultural and contextual factors, challenging the idea of strictly universal expressions (Jack et al., 2012) [1]. While advances in computer vision have enabled automatic emotion recognition, challenges remain in distinguishing spontaneous from posed expressions and aligning computational models with human perception (Barrett et al., 2019) [2].

This project aims to understand how people subjectively perceive emotions by constructing a similarity matrix, a dissimilarity matrix derived from it, and a consistency matrix to assess annotation reliability. Additionally, multidimensional scaling (MDS) will be applied to extract the main underlying dimensions in emotional perception. By analyzing clustering patterns and inconsistencies in annotations, this study will contribute to a better understanding of how emotions are categorized and how computational models can be improved to better reflect human perception.

Dataset description

The dataset used in this project consists of 24 images with dimensions of 419x540 pixels, representing eight primary emotions: angry, boredom, disgusted, friendly, laughter, happiness, sadness, and surprise. Each emotion is represented by three images, allowing for an analysis of variability within each emotional category. Three samples of the dataset are shown in images 1 (laughter), 2 (surprise) and 3 (friendly).


Images 1, 2, 3: Dataset samples

Procedure

The experimental procedure began with the annotation of similarity scores for pairs of facial expression images. A graphical interface was provided to us through the *generate_similarity_v3.m* matlab function, displaying two images side by side and allowing us to rate their similarity on a scale from 1 to 9. The scoring criteria ranged from "not similar at all" to "identical." A total of 276 unique image pairs were evaluated. And ratings were used to form the **similarity matrix**.

Additionally, to assess the consistency of the annotations, the function randomly repeated 24 image pairs throughout the experiment, to check whether we always provide the same rating. This process allowed for the generation of the **consistency matrix**, which helped verify the reliability of the annotations.

Once the similarity matrix was obtained, we obtained the analogous **dissimilarity matrix** using a standard transformation formula (1) provided in the statement:

$$d_{ij} = \sqrt{c_{ii} - 2c_{ij} + c_{jj}} \tag{1}$$

where . This step ensured that higher similarity scores corresponded to shorter distances in the final representation. The dissimilarity matrix served as the input for the Multidimensional Scaling (MDS) analysis, which aimed to map the emotional perceptions into a lower-dimensional space.

The **MDS procedure** [3] involved computing the double-centered matrix B, derived from the squared dissimilarity matrix. The eigenvalues and eigenvectors of B were then extracted and sorted in descending order. The two most significant eigenvectors were selected to construct the Y matrix, representing the emotional expressions in a 2D coordinate system. To facilitate visualization, the coordinates were normalized and converted into polar coordinates, ensuring that all points fit within a unit circle.

The final step consisted of plotting the circular representation of emotions within the circumplex model of emotions (Posner et al., 2005) [4]. The transformed coordinates were assigned colors based on their respective emotion categories, enhancing interpretability. A reference circle was drawn to provide a structured layout, and labels were added to indicate emotional dimensions such as valence (positive vs. negative) and arousal (active vs. passive), following established models of affect. The resulting plot provided insights into the perceptual organization of facial expressions, highlighting similarities and differences in how emotions are subjectively interpreted

Iria Quintero García 254373
Norbert Tomàs Escudero 242695
Javier González Otero 243078

Result Analysis and interpretation

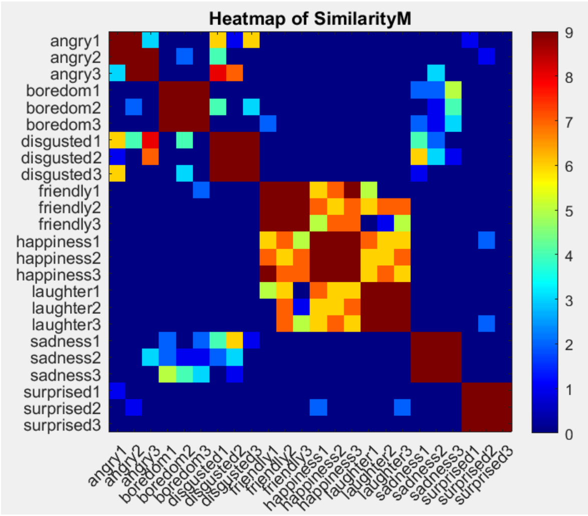


Image 4: Similarity heatmap

Image 4 presents a heatmap of the similarity matrix, showing how we rated the resemblance between facial expressions. Dark red areas (value 9) indicate high similarity, while blue regions (near 0) signify low similarity.

Emotions like *happiness, friendliness,* and *laughter* form a strong cluster, reflecting their shared positive affect.

We can also find two more clusters, the first one between *disgust* and *anger*, the second one for *sadness, boredom* and *disgust.* However, apparently these two clusters seem to be weaker than the first one formed by positive emotions.

Besides that, two distinct blue blocks highlight the clear separation between positive and negative clusters of emotions.

Surprise emotion doesn't seem to be well aligned with any other expression.

Since dissimilarity is the inverse of similarity, the corresponding heatmap will swap blue for red, emphasizing these distinctions.

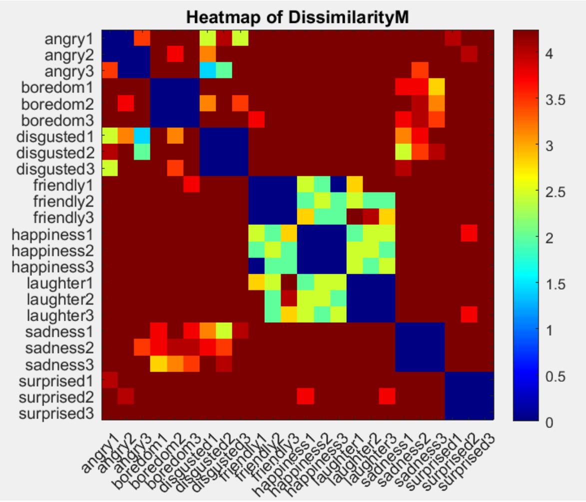


Image 5: Dissimilarity heatmap

Image 5 shows the dissimilarity matrix, which is essentially the inverse of the similarity heatmap, confirming that where similarity was high, dissimilarity is now low, and vice versa, emphasizing the psychological structure underlying facial emotion recognition.

where dark red indicates highly different expressions and blue represents similar ones. As expected, the strong cluster of positive emotions: *happiness*, *friendliness*, and *laughter*, now appears as a clear region, confirming their perceived similarity. The weaker clusters of anger with disgust and sadness with boredom remain visible.

The clear separation between positive and negative emotions in the similarity matrix is now highlighted by red regions, emphasizing their perceptual contrast. Surprise remains isolated, reinforcing its ambiguous nature.

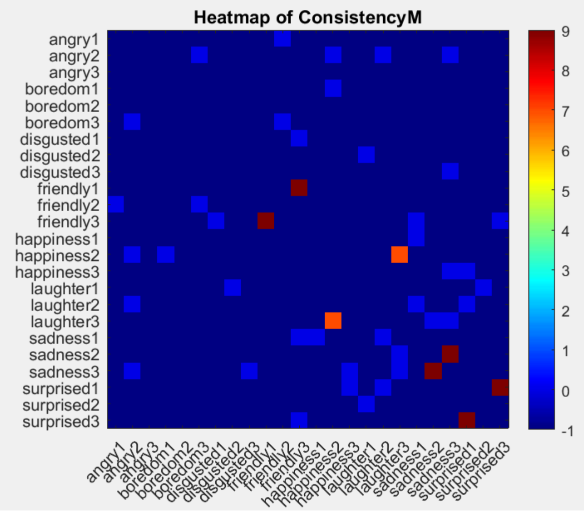


Image 6: Consistency heatmap

Image 6 represents the consistency matrix, showing how similarity scores were assigned to repeated images. Unlike previous heatmaps, the dark blue areas (value -1) indicate pairs that were not evaluated as duplicates, while the remaining colors directly reflect user input—red representing high similarity and lighter blue indicating dissimilarity.

This matrix is intended to be compared with the similarity heatmap. Ideally, repeated images should receive similar scores across different instances, meaning the patterns here should align closely with those in the similarity matrix. However, any noticeable discrepancies could indicate inconsistencies in user perception, where identical images were rated differently depending on the context in which they appeared.

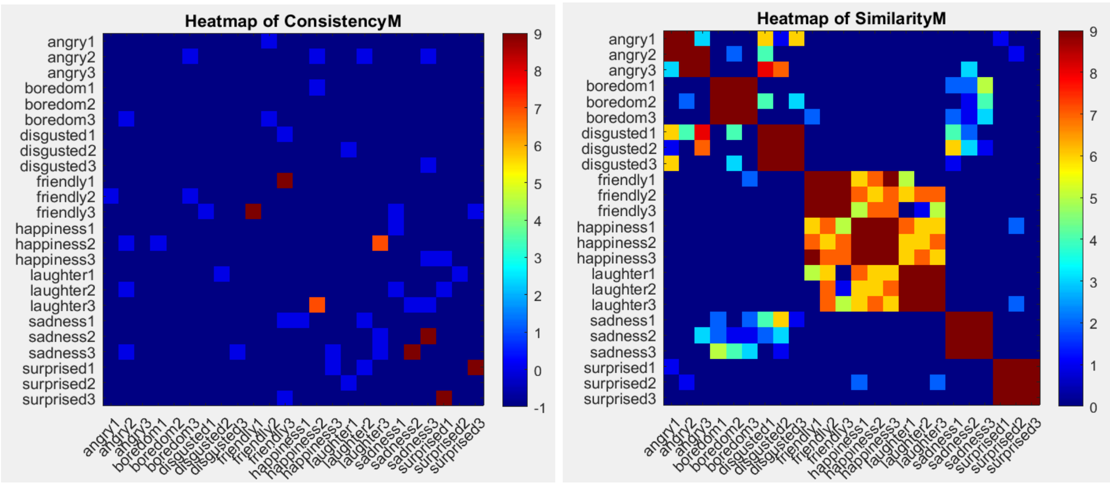


Image 7: Consistency vs similarity heatmaps

If we perform the comparison as in **Image 7**, we can see that we perform a quite conscious job setting the ratings since for repeated images, the obtained score is the same for consistency matrix and similarity matrix.

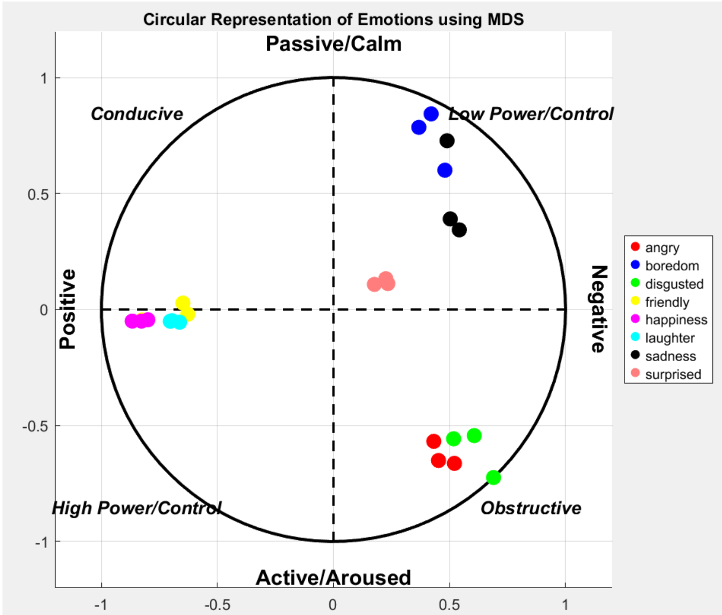


Image 8: Circular representation of emotions using MDS

Image 8 represents a circular mapping of emotions using Multidimensional Scaling (MDS) as described in the *procedure* section. The positioning of emotions in this 2D space preserves their perceptual distances and aligns with psychological models such as the Circumplex Model of Emotions (Posner et al., 2005) [4], which organizes emotions along two main axes: valence (positive vs. negative) and arousal (calm vs. active).

On the left side of the circle, positive emotions such as happiness, laughter, and friendliness cluster together, indicating that they are perceived as similar.

In contrast, negative emotions such as boredom and sadness are grouped in the upper-right quadrant, which corresponds to low-arousal but negative-valence emotions. Their proximity suggests they are both perceived as passive emotional states.

Anger and disgust, on the other hand, appear in the lower-right quadrant, where highly arousing and negative emotions are positioned. Their close placement reflects their shared intensity and strong negative connotation. These emotions contrast sharply with those in the upper-left quadrant.

Surprise is positioned near the center of the circle, slightly leaning toward the passive/negative region. This intermediate placement suggests that surprise could be perceived as either positive or negative depending on the context, making it a more ambiguous emotion compared to others in the diagram.

The structure of this MDS visualization aligns well with the patterns observed in the similarity and dissimilarity heatmaps. The strong clustering of happiness, laughter, and friendliness further supports

that they are perceived similarity. The proximity of anger and disgust suggests a perceptual overlap often found in emotion recognition studies. This visualization effectively captures the relationships between facial expressions and provides insight into how people categorize emotions based on their perceived differences.

How to run the script - display_matrices_mds.m

To execute the matlab code *display_matrices_mds.m* add the path to your images FOLDER in line 2 as seen in **Image 9**. Then run the code.

```
1   % --- Define the image directory ---
2   img_path = ''; %ADD YOUR PATH TO THE IMAGES !!!
```

Image 9: image path definition

References

[1] R.E. Jack, O.G.B. Garrod, H. Yu, R. Caldara, & P.G. Schyns, Facial expressions of emotion are not culturally universal, *Proc. Natl. Acad. Sci. U.S.A.* 109 (19) 7241-7244, https://doi.org/10.1073/pnas.1200155109 (2012).

[2] Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., & Pollak, S. D. (2019). Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements. *Psychological science in the public interest : a journal of the American Psychological Society*, *20*(1), 1–68. https://doi.org/10.1177/1529100619832930

[3] AGC2025. (2025). *Facial expressions & emotions [Class 5 lecture slides]*.

[4] Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology*, *17*(3), 715–734. https://doi.org/10.1017/S0954579405050340