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A high-dimensional semantic space of emotion representations support circumplex structure

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Abstract

Emotion space models are frameworks that represent emotions in a multidimensional space, providing a structured way to understand and analyze the complex landscape of human emotions. However, the dimensional representation of emotions is still debatable. In this work, we are probing the higher dimensional space constituted by emotion labeling done by participants from India on multimedia stimuli. Our approach formalizes the study of emotion in the investigation of representational state spaces capturing semantic variation in emotion-related response (including experience and expression, as well as associated physiology, cognition, and motivation). We have created a high-dimensional space of emotional ratings by participants to represent emotional stimuli. Using a prominent dimensional reduction technique, t-distribution-based stochastic neighbour embedding (t-SNE), we have projected the higher dimensional space into two dimensions. We observed that the structure of emotional categories and clusters formed of these emotional categories is similar to Russell's circumplex model. The transition from the blended complex emotional states to the discrete emotional states is projected out from the centre, and discrete emotional states occur in the periphery. Using advanced visualization and multidimensional technique, we show a continuity of emotional experiences to complement the existing knowledge based on V-A space with the information on how the transitions among emotion categories occur.
Keywords: Emotion Representation; Semantic Space Theory; Circumplex Model; Valence; Arousal

Introduction

Despite significant research on emotion representation, there has yet to be a clear consensus on the precise nature and structure of emotion representation. Emotion is a complex and multidimensional phenomenon, and scholars from various disciplines, including psychology, neuroscience, philosophy, and linguistics, have proposed different models and theories to explain how emotions are represented and organized. For instance, basic emotion theory by Paul Ekman (Ekman, 1992) discusses the concept of basic emotions and their universality. Some discuss how cultural factors influence the experience and expression of emotions (Mesquita & Frijda, 1992). Scherer's component process model (Scherer, 2009) highlights the dynamic and sequential nature of emotional processes. Barrett (Barrett, 2017) argues for the constructionist nature of emotions, challenging traditional views on discrete emotions, and presents a theory suggesting that emotions are constructed, dynamic, and context-dependent.

A dominant approach to representing emotional experience and expression revolves around Basic Emotion theory (BET). The basic emotion theory, rooted in the work of researchers such as Paul Ekman (Ekman, 1992) and Carroll Izard (Izard & Izard, 1977), proposes that there is a small set of fundamental and biologically innate emotions with clear boundaries (Lench, Flores, & Bench, 2011) that are universally recognized across different cultures. These basic emotions are considered to be distinct, with unique facial expressions, physiological responses, and behavioural patterns associated with each. The classic basic emotions often include happiness, sadness, anger, fear, surprise, and disgust (Ekman, 1992). Izard's Differential Emotions Theory (DET) is another influential framework within basic emotion theory (Izard & Izard, 1977). DET proposes ten primary emotions: joy, interest-excitement, surprise, anger, disgust, contempt, fear, shame, guilt, and distress. Izard's theory incorporates the idea that these primary emotions serve as the foundation for a wide range of secondary and tertiary emotions, forming a hierarchical structure. Efforts to determine the nature of emotions have focused on mapping six specific emotions (anger, disgust, fear, happiness, sadness, and surprise) to subjective experiences, expressions, and brain states. However, these mappings still need to provide a comprehensive understanding of the broader structure of emotions (Scarantino, 2012). The central focus on discrete categories is not able to explain the complex and dynamic nature of emotions. Alternative models, such as dimensional theories of emotion, have emerged to address some of these limitations by emphasizing the continuous and multifaceted nature of emotional experiences.

Dimensional theories, such as Russell's Circumplex Model (Russell, 1980), propose that emotions are better understood as points in a continuous space defined by dimensions such as valence and arousal. This allows for a more flexible and nuanced representation of emotional experiences. Dimensional models recognize individual differences in emotional experiences (Asif, Mishra, Vinodbhai, & Tiwary, 2023; Asif, Ali, Mishra, Dandawate, & Tiwary, 2024). Watson and Tellegen's model (Watson & Tellegen, 1985), for example, considers positive and negative affect as two independent dimensions, providing a framework for understanding variability in emotional experiences. Sociodynamic models, like the one proposed by Mesquita and Boiger (Mesquita & Boiger, 2014), highlight the importance of cultural and contextual factors in shaping emotional experiences. Dimensional theories can accommodate these variations without relying on a fixed set of universal emotions.

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Barrett's conceptual act theory (Barrett, 2006) challenges traditional views by proposing that emotions are not discrete, pre-wired entities but rather emergent experiences constructed by the brain based on contextual cues and conceptual knowledge. It suggests that emotions are complex psychological events emerging from the interplay of multiple psychological processes. It emphasizes the need to move beyond discrete categories. These challenge some assumptions of dimensional models of emotion, such as the Circumplex Model, which posits that emotions can be represented along a limited set of continuous dimensions (e.g., valence and arousal). Barrett's work, particularly the theory of constructed emotion, emphasizes the importance of language and cultural context in shaping emotional experiences. Semantic space models argue that the meaning of emotion labels and the experiences they represent are highly context-dependent (Barrett & Satpute, 2013; Barrett, 2017). Different cultures and individuals may use the same label to refer to different emotional experiences. This challenges the assumption of a universal and consistent mapping of emotions onto dimensional space. Barrett's theory of constructed emotion (Barrett, 2017) suggests that emotions are not pre-existing categories with fixed features but are constructed by the brain based on various contextual and sensory inputs. This challenges the notion that emotions can be neatly categorized along a few dimensions, as dimensional models often imply.

One approach to account for the variability in emotional experience is semantic space models (Cowen & Keltner, 2021), which uses computational methods to capture systematic variation in emotional behaviors and experiences. The dimensionality of a semantic space refers to the number of distinct varieties of emotion represented within a response modality, which essentially captures the cultural conceptualization and subjectivity of emotional experiences and expressions. Hence, studying a broader taxonomy of emotions can enrich our understanding of human experience. Semantic space models highlight the variability and flexibility of emotional experiences. Emotional states may involve a combination of various dimensions, and the same dimension may not consistently map onto a specific emotional category. This challenges the simplicity of dimensional models in capturing the diverse and dynamic nature of emotions. There are upwards of 25 distinct varieties of emotional experiences, which are high-dimensional, categorical, and often blended (Cowen & Keltner, 2017). In semantic space models, it is emphasized that specific emotions, rather than just valence and arousal, play a significant role in organizing emotional experiences, expressions, physiology and neural processing (Mishra, Srinivasan, & Tiwary, 2022a, 2022b). Hence, it is suggested that studying a broader taxonomy of emotions beyond the traditional six emotions or core dimensions can lead to a richer and more comprehensive understanding of the human experience.

Given these different approaches, it is essential to be able to look at emotion representations obtained using different methods. Semantic space models generally do obtain valence or arousal ratings, and it is not clear how models like circumplex models can be linked to other theories that postulate different ways of characterizing emotions. This paper makes an attempt to develop emotion representations based on a different analysis technique and see how it relates to a representation that is arrived at by explicitly obtaining valence and arousal ratings. Also, most studies use static stimuli like pictures, and it is not clear how that would generalize to our day-to-day social interactions. Hence, we use emotional multimedia videos to elicit emotional experiences.

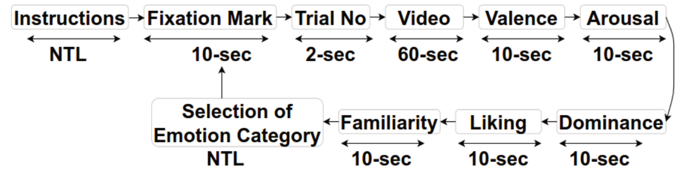


Figure 1: Experiment Paradigm. The figure is taken from (Mishra et al., 2023) with permission.

Methods

Participants

All the participants were recruited from the institute through advertisements and presentations in some classes. 271 participants participated in the study with mean age = 20.37 years (SD = 1.57 years). There were 231 males and 40 females.

Task

In total, sixty-nine multimedia emotional videos were used in the experiment. As part of the approval protocol, all stimuli were submitted to the review board and were approved for presentation in the study. Before the experiment, participants were given a presentation on a projector screen and briefed about the experiment. They were also told how to perform the experiment (i.e. how the experiment would progress and how they should give their ratings and responses). Response scales (as shown in figure-**??**. The figure is taken from (Mishra et al., 2023)) were also explained to participants. We had 69 video stimuli, which were divided into eight sets. Each participant saw only one set. The sets were recreated for every batch of participants by reassigning videos randomly and automatically to minimize potential grouping or selection biases. The experiment paradigm is shown in the figure-**??**. Participants watched a video and then provided valence, arousal, familiarity, dominance, and liking ratings. Then, they gave an emotion category out of a set of 19 possible emotion categories.

Data Visualization using t-SNE

We used the t-SNE method to visualise the structure in high-dimensional space into low dimensions. Unlike dimension reduction methods like PCA, the basic idea behind the t-SNE method is to preserve the local structure when projecting high-dimensional data into low-dimensional space.

As mentioned earlier, we had 19 emotion categories. Each clip is assigned the emotion category attributed by most of the participants. However, like in other datasets, for each stimulus, some other categories (though very similar, for example, happy is rated by one participant and joyous is rated by another participant) are also attributed. Hence, we calculated the ratio of participants who were assigned different emotion categories for each stimulus and created a matrix. In this matrix, rows represented the stimuli, columns represented the emotion categories, and cell values represented the ratio of participants who categorized a particular stimulus to a particular emotion category. In this high-dimensional space, we considered emotions as dimensions different from valence-arousal space, which considers valence and arousal as dimensions. So, if two stimuli had a similar configuration of the ratio for emotion categories, they would be close to each other.

t-SNE project data points from high-dimensional space to low-dimensional space. The Gaussian distribution of pairwise similarities of data points in high-dimensional space is calculated.

$$p_{ij} = \frac{\exp(\frac{-x_i - x_j^2}{2\sigma^2})}{\Sigma_k \Sigma_{l \neq k} \exp(\frac{-x_k - x_l^2}{2\sigma^2})}$$

To calculate the distribution in low-dimensional space, instead of the Gaussian distribution, t-distribution is used due to its heavy tail. The central idea is that if two points say a and b, are ten units apart in Gaussian distribution with the probability of 0.01, these points should have a larger distance between them to get the same probability in heavy tail t-distribution. So, with this trick, the dissimilar points are pushed further away in the low-dimensional space. To calculate the similarity distribution in low-dimensional space, the expression is

$$q_{ij} = \frac{\exp(-y_i - y_j^2)}{\Sigma_k \Sigma_{l \neq k} \exp(-y_k - y_l^2)}$$

The idea is that p_{ij} and q_{ij} should have as low a distance as possible. To ensure that the distance between these two distributions is optimized, gradient descent on k-l divergence is performed. The lower the distance, the better the similarity is preserved during projection. So, the objective function-/ is

$$\Sigma_i \Sigma_{j \neq i} p_{ij} \log \frac{p_{ij}}{q_{ij}}$$

We plotted the results on a 2-dimensional space (figure-3a) with perplexity value 65. In order to understand the smooth transitions among different emotion categories, we constructed the chromatic map by calculating the weighted interpolation of colours based on the percentage of different emotional experiences reported for any stimulus. In this way, we represented the gradient of emotional experience with a gradient of colours in this 2D space.

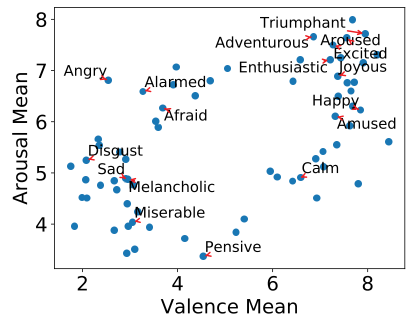


Figure 2: Representation of 69 stimuli using mean valence and arousal ratings (Permission from (Mishra et al., 2023)).

Calculating Ratio between Intra-cluster Emotions and Inter-cluster Emotions

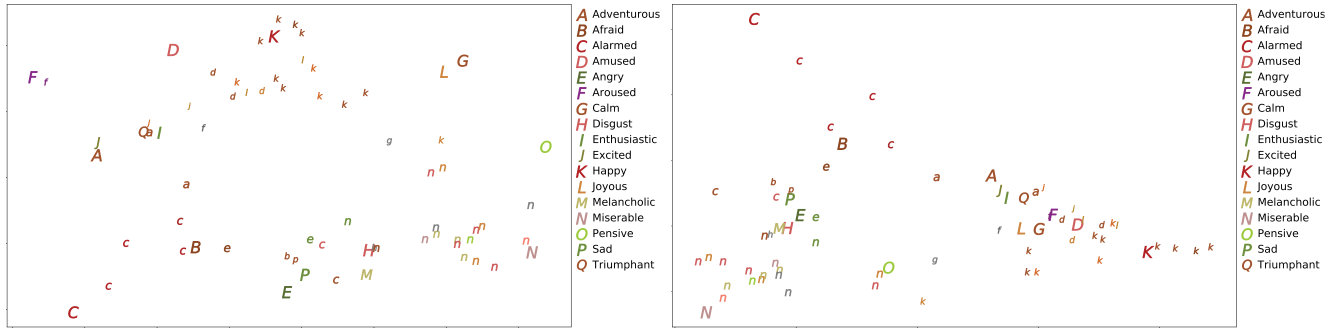
We have calculated the ratio between intra-cluster emotions and inter-cluster emotions for each emotion concept. We considered each emotion and calculated mean intra-cluster and inter-cluster distance using cluster information. It is calculated to compare the distribution of clusters in two different spaces.

Results

Visualization of Emotion Categories

Many of the applied dimensionality reduction methods (e.g. PCA) that have been used rely on explaining the variation in the data without preserving local structure. Likewise, we got the principle dimensions of variations after applying the PCA dimension reduction in our data. The low-dimensional representation formed using PCA does not agree well with the well-known valence-arousal space (compare figure-**??** and figure-3b). A possible reason might be the loss of local similarity structure of the data. This interpretation leads us to believe that if any method is able to preserve the local similarity structure, then we may be able to get a representation in low dimension while preserving the structure in high-dimensional space. Hence, we applied t-SNE, which preserves the local similarity structure of the data points.

Figure-3a represents a 2D map constructed by applying the t-SNE method on high-dimensional space constructed with 19 emotional experiences. Further, the overlay of the chromatic map represents the smooth gradients between different categories of emotions. The assurance that the local structure is preserved in the transformation of high-dimensional space to low-dimensional space comes from the value of Kullback–Leibler (KL) divergence. The best case is 0 (i.e. the similarity distribution in these two spaces is similar). When we projected the high-dimensional space to 2-dimensional space, we got a value of 0.007 for KL divergence in comparison to 0.807 for the 3-dimensional space. The low value of divergence ensures that projection to 2-dimensional space preserves the local structure and distribution better than the projection to 3-dimensional space.



(a) (b)

Figure 3: **Distribution of emotional experiences:** The high-dimensional data with 19 emotional dimensions is projected into two-dimensional space using the t-SNE method (a) and PCA dimension reduction method (b). The data points in the chromatic map represent video stimuli, and the smooth gradient of colour captures the varieties of emotional experiences reported by participants for any video. The upper-case labels are annotated on those data points, which represents the video stimuli with the maximum probability of associated emotional experience.

We observed that the structure of distribution of emotion experience in the low-dimensional space is similar to the circumplex model. We compared the calculated t-SNE space and V-A space further.

Comparison between calculated 2-dimensional t-SNE space and V-A Space

In the previous step, we created a 2-dimensional space in which emotion stimuli were presented and annotated by color gradient calculated based on a percentage of participants labelled different emotion category. We grouped these emotional stimuli based on the dominant labelling by the participants in both the spaces. If these two spaces differ, the comparison of emotion pairwise distances will reflect this difference. We calculated the pairwise euclidean distance between emotions represented in each space. We compared the t-SNE space and V-A space by comparing the pairwise euclidean distance between emotions. The mean square distance between the two spaces was 1.73. We performed a surrogate test by randomly shuffling pairwise euclidean distance vectors between emotions 1,00,000 times to create a null distribution of mean square distances. The proportion of mean square distances in the null distribution greater than the original mean square distance is considered as a p-value. We observed $p < 0.0000001$. Our results show that the true mean square distance between the t-SNE space and V-A space is significantly less. In the next step, we created clusters in these two spaces for qualitative comparison of clustering within these spaces.

Emotion Clustering in t-SNE space and V-A space

With the clustering, we wanted to further compare two spaces based on the ratio between intracluster and intercluster for each emotion category. It shows how closely an emotion is related to emotion within the cluster in comparison to emotions outside of the cluster. We clustered the emotions based on euclidean distance in t-SNE space (figure-4a) and V-A space (figure-4b). We used the clustering information from the presented dendrogram shown in figure-4 to form the clusters (two or four). We observed that similar emotions fall into two and four clusters of t-SNE and V-A spaces. The clusters are as follows:

- Two Clusters
  - V-A space
    1. Adventurous, Amused, Aroused, Calm, Enthusiastic, Excited, Happy, Joyous, Love, Peaceful, Pensive.
    2. Afraid, Alarmed, Angry, Disgust, Distress, Melancholic',' Miserable, Sad
  - t-SNE space
    1. Adventurous, Amused, Aroused, Calm, Enthusiastic',' Excited, Happy, Joyous, Love, Peaceful
    2. Afraid, Alarmed, Angry, Disgust, Distress, Melancholic',' Miserable, Pensive, Sad
- Four Clusters
  - V-A space
    1. Adventurous, Amused, Aroused, Enthusiastic, Excited, Happy, Joyous
    2. Calm, Love, Peaceful, Pensive
    3. Melancholic, Miserable, Sad
    4. Afraid, Alarmed, Angry, Disgust, Distress
  - t-SNE space
    1. Adventurous, Aroused, Enthusiastic, Excited
    2. Amused, Calm, Happy, Joyous, Love, Peaceful
    3. Miserable, Sad
    4. Afraid, Alarmed, Angry, Disgust, Distress, Melancholic

We developed representations of emotional experiences using two different methods from participants who watched emotional audiovisual stimuli. We can observe in figure-3a and figure-4 that some emotions are in close proximity to each other such that they may be considered as a meaningful cluster. For instance, happy, amused, joyous, love; aroused, excited, enthusiastic, adventurous; afraid, alarmed; angry, distress; miserable, melancholic, sad, disgust; calm, peaceful. We compared this t-SNE space with the V-A space (in figure-**??**) and found that these two spaces are similar to each other in a way that the relative positions of most emotional experiences match. These results show that the dimensional model constituted of valence and arousal dimensions captures the subjective semantic characteristic of emotion experiences.

Discussion

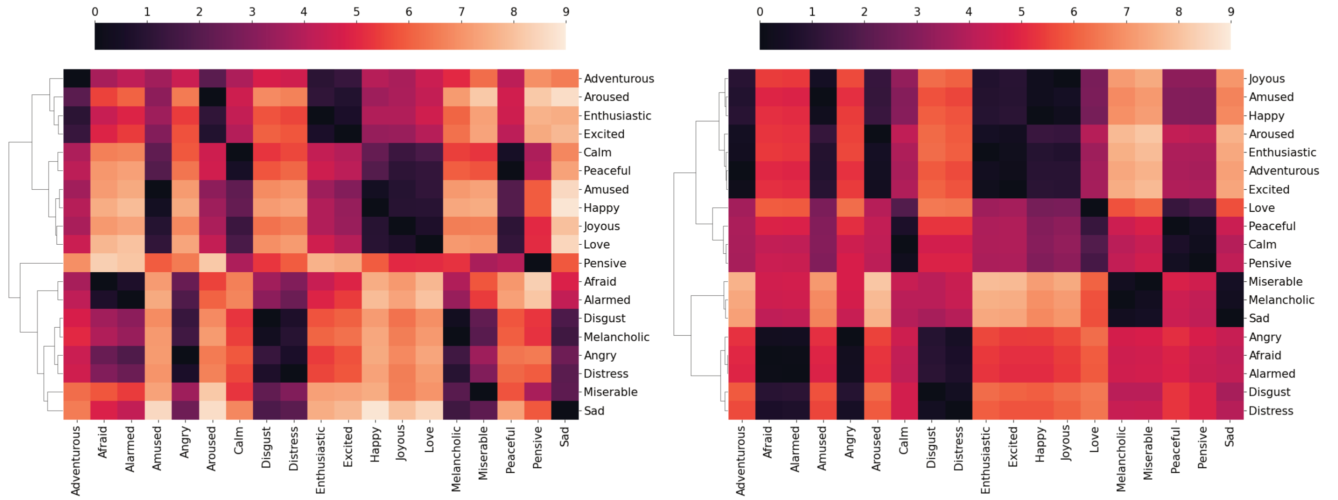
Compared with the Russell's grid (Russell, 1980), valence-arousal plot with Indian participants also show similar placement of emotion concepts. However, the placement and distance among emotion concepts differs slightly from those for the western population. For example, in the Russell's model, the emotions angry, alarmed and afraid were placed with higher arousal values than those with the Indian participants. Likewise, the arousal rating of miserable feeling is lesser for Indian participants than in the russell's model. However, there is relatively less difference on the placement of positive emotions suggesting more culutual variability with negative emotions than positive emotions. The specific variations due to cultural influences on positive and negative emotions would require further investigation.

Like multidimensional scaling methods (MDS), t-SNE also aims to preserve relationships while representing high-dimensional data into a lower-dimensional space. However, it is different from MDS since it introduces non-linearity and stochasticity to better capture the structure of the data. Hence, t-SNE may be a better method than MDS to analyze the high-dimensional structures for different perceptual attributes studied in cognitive science. In addition, the t-SNE space in our work allowed for the visualization of gradient and fluidity in emotional experiences. With the overlay of the chromatic map in t-SNE space, we can trace these transitional feelings. For instance, the chromatic map and the preserved local proximity show the transition from miserable feelings to melancholic, sad, and disgust feelings. Miserable feelings are also reported by some participants for stimuli that also elicited calm feelings. Alarmed, angry, and distress states also have a trace of continuity with the miserable state. The transition between afraid and alarmed states can also be observed.

In addition, the transition from positive to negative emotions and negative to positive emotions can be observed from data obtained using t-SNE. For example, there are transitions between afraid, adventurous, and enthusiastic states. On the positive sub-space side, happy, amused, joyous and love emotional states show transitions among each other. Love, joyous, peaceful and calm states are showing smooth transitions among each other. The calm state has continuity with positive states like happy, amused, peaceful and negative state like miserable. So, a calm state has mixed feelings of both positive and negative emotions. Likewise, adventurous has both the elements of afraid state and positive feelings like enthusiastic and excited. The t-SNE results show that by probing the structure of emotional experience with a different visualization method or approach, additional information can be obtained to enhance our understanding of emotional experiences. We suggest that instead of taking only using V-A space to understand the representational structure of emotion experiences, emotion researchers may also consider such high dimensional visualization techniques to not only understand the structure of emotional experience on V-A space but to complement this knowledge with information on transition from one emotion experience to other emotion experience. In other words, the lack of information about the dynamical changes in emotions can be obtained from such visualization techniques.

The work by (Cowen & Keltner, 2017) came up with a semantic space of 27 emotion categories as dimensions, which is far richer in capturing the reported emotion experience. Our aim was not to derive or validate distinct dimensions of the semantic space of emotions. Our aim in the paper was to visualize the higher dimensional semantic space of emotion categories using a small number of potentially basic dimensions and compare it with the circumplex structure of emotions. In addition, the present work has been performed with a sample from a different culture with culturally validated stimuli on Indian participants. Research shows that more collectivist (like Indian) and individualist (like American) cultures have differences in emotion expression and experience (von Suchodoletz & Hepach, 2021). However, the reported results for some emotion categories are in sync with the similarly reported in the low-dimensional t-SNE space from western culture (Cowen & Keltner, 2017). For instance, in line with the results in this work, the proximity of emotions, including angry and disgust; sadness and pain (melancholic in the current work); afraid and surprise (alarmed in the current work); calm and aesthetic appreciation (love in the current work); joyous and amused, is observed in work by (Cowen & Keltner, 2017). The similarity of emotions from different cultures in this nonlinear space shows that there might be some underlying similarity in the structure of emotion experiences across cultures. In the future, based on the cross-cultural research with the presented dataset, it would be interesting to see that how much the findings and theories from the west are generalizable to those from the Indian culture.

The continuous nature of emotion representation reflects the complexity and variability of human emotional experiences. Dimensional models, such as the circumplex model, allow for flexibility and accommodate individual differences in the experience and expression of emotions. This is crucial as emotional responses can vary widely among individuals (Russell, 2003). Continuous representations in the dimensional model capture nuanced and gradual changes in emotional states. Emotions are not binary or static; they can unfold and evolve over time. Continuous models provide a more detailed account of the dynamic nature of emotional experiences (Kuppens, Tuerlinckx, Russell, & Barrett, 2013). Di-



(a) (b)

Figure 4: **Emotion Clustering:** (a) t-SNE space (b) V-A space. The heatmap is created using the distance matrix. Each cell of the distance matrix is the pairwise euclidean distance. Then we performed dendogram based clustering on the distance matrix.

mensional models are well-suited to capture the contextual sensitivity of emotions. The same emotion may have different intensities or meanings in different situations, and continuous representations account for this variability (Barrett, 2006). Continuous models often integrate multiple dimensions (e.g., valence and arousal) to represent the diverse range of emotional experiences. This allows for a more comprehensive understanding of the multidimensional nature of emotions (Posner, Russell, & Peterson, 2005). Continuous models account for the overlap and blending of emotions, acknowledging that individuals can experience mixed or nuanced emotional states. This captures the richness of emotional experiences that may not fit neatly into discrete categories (Larsen & Diener, 1992). Neuroscience research also supports the continuous nature of emotion representation, as brain imaging studies have demonstrated patterns of activation corresponding to variations in emotional valence and arousal (Lindquist, Wager, Kober, Bliss-Moreau, & Barrett, 2012). Hence, the continuous nature of emotion representation is important for capturing the richness, variability, and individuality of human emotional experiences and provide a more nuanced and flexible framework that aligns with the complexities of emotions in real-life contexts. Given the cultural and individual life experience that influence emotional experiences, we would need to evaluate the structure of emotional experience across cultures and as a function of individual differences.

In conclusion, we started with the representation of emotional stimuli in the high-dimensional semantic space constituted of emotions as dimensions. After performing multidimensional scaling using t-SNE, we observed that the projection of stimuli from the higher dimensional space to the lower dimensional space is similar to the circumplex model of affective experience, which captures the dynamic and complex nature of emotions. Hence, the circumplex model of affect, including valence and arousal as dimensions, could represent the complex nature of emotions.

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