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Categorization of Emotion Based on Causality

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Abstract

Background: Emotions come in all shapes and forms. Some of them can be external, visible, and clearly comprehensible, while others can seemingly be coming out of thin air. Knowing what causes an emotion is crucial for better therapy and mental health. Therefore, in this manuscript, we address the problem of emotions causality.

Methods: We propose a comparison of three traditional clustering models: Gaussian mixture model, HDBSCAN, and fuzzy c-means, to categorize each emotion described in the DEAP database. It contains over 1700 points, and has no prior label as to which type of stressor the subject's emotion is generated from. This labelling task has been conducted by a psychiatrist.

Results: The fuzzy c-means yields the highest results, with an accuracy of 57.13%, followed by the Gaussian mixture model at 39.49% and the HDBSCAN method with only 18.86%. Another score computed is the mutual information score which shows how homogenous the clusters are for each model.

Conclusion: The data from DEAP is very heterogeneous and its density is stable, which may indicate that classification would be the better option, in terms of accuracy and homogeneity of the clusters.

Keywords: Emotions, Causality, Psychiatry, Artificial Intelligence.

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1. Introduction

Emotions have been seen as spiritual states, personality traits, neural pathways and chemical reactions throughout history. We often do not even know where these feelings come from, or how they come to be.

Over the centuries, multiple theories have emerged. One of them is the Cannon-Bard theory. It states that the emotion and the arousal happen at the same time, caused by a stimulus, or what we would call a stressor. This theory has been backed by scientific evidence, in which they observed using modern medicine that upon detection of the stressor, signals are sent to the amygdala and the brain cortex at the exact same time [1].

Earlier in the 19th century, there were two schools of thought. The modular and discrete way of thinking was pushed by Darwin, stating that emotions are separate entities, no one overlapping the other; while Wundt went for a spectrum-like approach, on two different scales: pleasantness and arousal levels [2].

We could argue that the latter was the first attempt at categorizing them. While putting things in boxes is a human instinct helping us understand the world around us, in the field of emotions, facial expression is the aspect that has been studied in detail, rather than the physiological part of it [3]. As Ekman said, after conducting a survey on a large population of emotion scientists, "[twenty] years of research

has been productive, but as this short survey revealed, there are still many aspects of emotion that deserve further scrutiny to reduce the disagreements that still persist.” [2]
We aim to bridge the gap in that lacking research, more specifically in the field of emotion stimuli. The goal is to flesh out a tool that could potentially sort emotions based on the stressor that caused it. It is vital to specify that in this work, a stressor will be referred to as a stimulus, because the former has been taking the meaning of negative stress in literature. This tool could become essential for researchers and psychologists alike, helping them identify what are the potential causes of the patient’s emotion, thus making the therapy process seamless for both parties.
And so, the first step towards this well-rounded tool is clustering the data. We need to see clearly how it presents and if there are any major clusters that we could then categorize. This is what is done in this paper.

2. Materials and Methods

2.1 Environment Setup

2.1.1 The Dataset

The choice of dataset was based on availability. Not enough databases had a wide variety of emotions. The DEAP database contains multiple datasets. The one we chose to work with is the online ratings. Other dataset files had metadata such as familiarity of the video watched by the subject, their personal data, and even their mental health history. Access to this database was provided by a researcher at the CDTA, and was the best candidate due to the sheer quantity of data.

Table I: View of the first few lines of the dataset.

ID	V	A	D	E	I	Type
1	4	4	3	11	3	3
1	8	3	3	3	4	1
1	5	1	1	3	2	1
1	5	3	5	3	1	1
1	7	1	7	7	1	2
1	7	5	5	3	2	1
1	9	8	8	3	4	1
1	6	7	7	2	3	1
1	7	2	6	8	3	1
1	9	8	6	2	4	1
1	6	6	5	3	1	1

The online ratings dataset contains the three dimensions of the electroencephalography (EEG) signal measured on the subjects and the emotion they reported feeling with the intensity: valence, dominance and arousal. It has over 1700 entries, and was deemed enough for the task at hand.
The data was collected in the following way: the subjects watched a video, while EEG signals were being recorded. After watching, they reported on which emotion they felt, and how intense it was on a scale from 1 to 4. The emotions were picked from a numbered list from 1 to 16: pride, elation, joy, satisfaction, relief, hope, interest, surprise, sadness, fear, shame, guilt, envy, disgust, contempt and anger. Those 5 features needed further analysis, so feature extraction techniques have been investigated [4].

Table II: Emotions categorized into multiple stimulus types

Emotion	Catastrophe	Major life	Microstressor	Ambient
1. Pride		X		
2. Elation		X		
3. Joy		X		
4. Satisfaction			X	X
5. Relief		X	X	
6. Hope		X		
7. Interest			X	
8. Surprise		X	X	
9. Sadness	X	X		X
10. Fear	X	X		X
11. Shame			X	X
12. Guilt		X	X	X
13. Envy			X	
14. Disgust	X		X	X
15. Contempt		X		X
16. Anger	X	X	X	X

2.1.2 Labelling Stimulus Types

Causes of emotions are categorized into four types: catastrophic events, major life events, microstressors and ambient stressors. Catastrophic events are the negatively intense type of events a human can experience, such as natural disasters. Major life events can be negative or positive; one example of this is a graduation ceremony, or a family death. A microstressor could be a traffic jam, but also an encounter with irritable people. The last category is ambient stressors; they are usually subconsciously perceived, irritating noises, or thoughts in the back of our minds [5].

Each emotion can have multiple possible causes. This fact pushed for a search for an overlapping clustering algorithm. With the help of a licensed psychiatrist, Dr Chikhi, each emotion was put in the stimulus category it belonged to.

Table III: Emotions categorized into single stimulus types

Emotion	Catastrophe	Major life	Microstressor	Ambient
1. Pride		X		
2. Elation		X		
3. Joy		X		
4. Satisfaction			X	
5. Relief			X	
6. Hope		X		
7. Interest			X	
8. Surprise		X		
9. Sadness	X			
10. Fear	X			
11. Shame				X
12. Guilt		X		
13. Envy			X	
14. Disgust	X			
15. Contempt				X
16. Anger	X			

Then, each emotion was put into the most probable category, as seen in table III. This step was crucial. The search for overlapping clustering models on the python language was unsuccessful, so the data had to be labeled again, stripping down each emotion to pertain to only one type of stimulus. This way any clustering model encountered could be tested on this newly labeled data.

2.1.3 Coding

Python is the language used, with access to multiple packages installed through the pip command. The first limitation we had was novelty. To create a new AI clustering model was an advanced task. It has been decided that for a start, to outline a prototype, premade functions from packages were to be used.

```
import pandas as pd
part=["V","A","D","E","I"]
dat=pd.read_csv("data.csv", usecols=part)
data=dat[dat["I"]!=0]
cdata=pd.read_csv("data.csv", usecols=["Type"])
cdata=cdata.dropna()
```

The data was read by python using the "pandas" package. The columns included were the three dimensions of the EEG signal, the emotion reported, and its intensity. Of course, our added labels were omitted. Since a handful of subjects had reported nothing, their rows were eliminated from the data, by replacing the data read by itself, without all the rows in which the intensity was equal to zero.

```
import plotly.express as px
graph=px.scatter(data, y="E", color=cdata)
graph.show()
graph3D=px.scatter_3d(data, x="V", y="A", z="D",
    color=cdata)
graph3D.show()
```

The data was read a second time, but solely the stimulus type column. As for the empty cells, corresponding to the zero values previously mentioned, have been eliminated using the "dropna()" function, to ensure the same length of data. This reading was done to be able to visualize the actual categorization and compare it easily with the results.

As for the plotting, the "plotly.express" package was used, since it has the ability to plot data on three dimensions with a good amount of customization. This is the sole instance where the "cdata" array is used, to be the label for each point. This was done on 2D and 3D, giving some flexibility as to how we could analyze the results later. On a 2D plot, the emotion number was the y-axis, and each row was on the x-axis. However, on 3D plots, the three axes were the three dimensions of the EEG signal, making for a more heterogeneous visualization.

2.2 Gaussian Mixture Model

The first algorithm was the Gaussian mixture model (GMM). In image processing, the Gaussian based filter is the most effective, so it was tried first in this data clustering. It is implicitly a soft clustering algorithm, because it is not based on binary values of belonging. Its algorithm does however manipulate probabilistic values, and uses a certain threshold to give out a clear result. Another important element to the GMM is the Expectation-Maximization (EM) algorithm. It is used in the Gaussian mixture model to calculate the right mean and variance for the dataset. It can also be useful for incomplete data [6].

```
from sklearn.mixture import GaussianMixture
gmm=GaussianMixture(n_components=4,random_state=0,
    max_iter=15)
gmm=gmm.fit(data)
pred=gmm.predict(data)
```

In a practical sense, the Gaussian mixture model was implemented through the "SciKit Learn" package. This clustering model is semi-supervised, due to the user having to choose the number of clusters when implementing it. So, "n_components" was set to the same number of stimulus types we have, 4. Another parameter of the function was the randomizer, "random_state". It was enabled by default, making the data handled differently every time the model was fitted and executed. So, it was turned off, to have the same baseline clustering for each different run, with different parameters changed. On the first run, the parameter responsible for maximum expectation-maximization iterations "max_iter" was untouched, setting it by default to 100. Then, the model was fitted to the data, and the clustering labels were assigned into the "pred" variable, which will be used as the colors of each stimulus type.

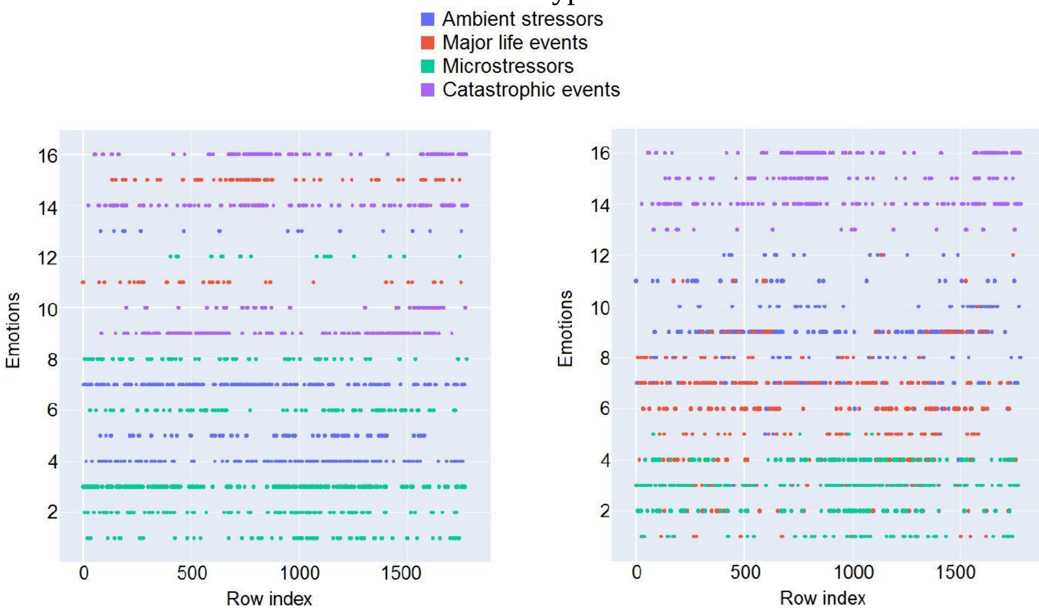

Fig. 1: 2D plots, on the y-axis, the emotion number, on the x-axis, the index row. (a) Labeled data. (b) GMM's first run.

2.3 HDBSCAN

The second model implemented was the HDBSCAN model. It is based on the DBSCAN, which stands for "Density-Based Spatial Clustering of Applications with Noise". As the name suggests, it is most well suited for data containing a lot of noise. That aspect was not interesting for this dataset. However, HDBSCAN's hierarchical algorithm was the point of interest. Because each emotion could pertain to multiple stimulus types, a hierarchical model could work with this overlapping aspect.

```
import hdbscan
from hdbscan import flat
predhdb=flat.HDBSCAN_flat(data, n_clusters=4)
labels=predhdb.labels_
proba=predhdb.probabilities_
```

After importing the HDBSCAN package, and a function called flat, the next steps were streamlined. The latter was the function used for the prediction model. This was mainly because prior setting of the number of clusters was needed. This also led to not using the hierarchical distance computations that were available, thus this usage of HDBSCAN made it like other simple single-cluster clustering techniques. The number of clusters was set and the predicted labels were extracted. Furthermore, as seen in the code, the probability for each point to belong to the stimulus type it was clustered into was extracted and saved in the "proba" variable for future visualizing.

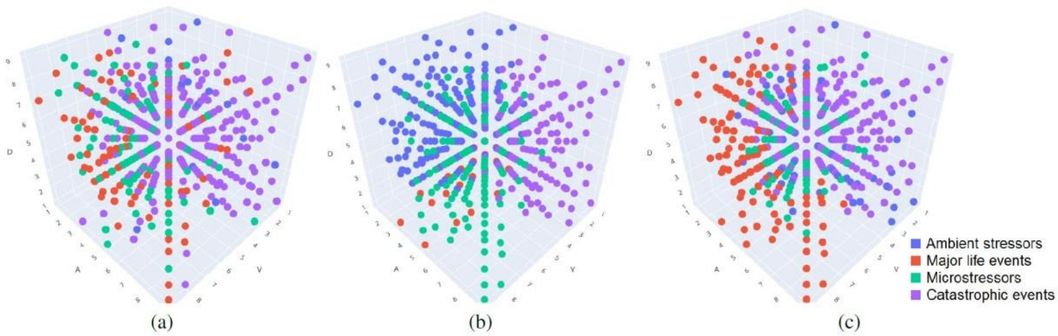

Fig. 2: 3D plots for the labeled data (a), the GMM excluding emotion and intensity (b) and all-inclusive GMM (c).

2.4 Fuzzy C-Means

In artificial intelligence, particularly in clustering, the word "fuzzy" signifies "imprecise" or even "non-absolute". Contrary to traditional hard-threshold clustering techniques, this model assigns a degree of membership to each point. The "c" in the name is the center of each cluster [7]. The initialization step is quite similar to the k-means algorithm, especially if the centers are chosen at random. The next step is calculating each point and its membership to each cluster, which makes it slower than the k-means algorithm.

```
import numpy as np
from fcmeans import FCM
from sklearn.cluster import KMeans
datanp=np.array(data)
my_model=FCM(n_clusters=4)
my_model.fit(datanp)
centers=my_model.centers
fcmpred=my_model.predict(datanp)
```

After importing the corresponding packages, the data was converted to the "numpyarray" format, making it compatible with the fuzzy c-means algorithm function. When executed, the number of clusters is set, and a model is generated. This model is then fit to the data. The centers of each cluster are also extracted for future reference. The last step in this implementation is the prediction of the clusters, which are found using the fitted model and the data.

3. Results

3.1 Visualization

While trying the Gaussian mixture model successfully for the first time, the dimensionality of the plotting tools was not taken into consideration, due to ignorance of how representative each column was of the data. This observation leads to a number of findings, which were inadvertently displayed. This happened on accident, but proved to give an interesting viewpoint of each model tried.

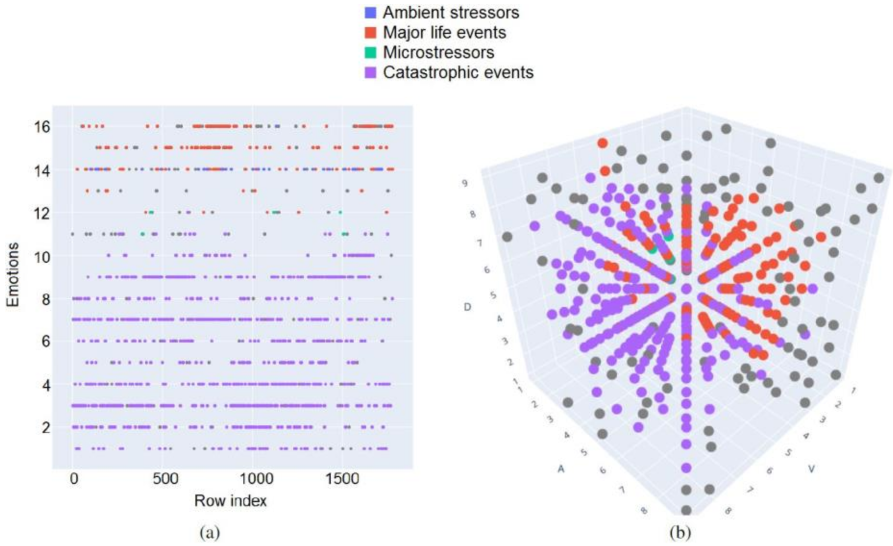

Fig. 3: Results of the HDBSCAN flat prediction model. (a) 2D plot. (b) 3D plot.

3.1.1 Gaussian Mixture Model

On the first run, the results were quite promising. The default set value for the “max_iter” parameter seemed to be optimal for the dataset. In figure 1, there is a clear gradient of colors happening. From bottom to top, green to yellow, then yellow to blue, then completely red. With the y-axis displaying the emotion number and it being the sole column of the plot, it shows how the emotion number was treated as an integer, calculated, not as a discrete value or object. This may be the case for the other models. Since the model’s reliance on the emotion value was a crutch, a second run was executed, using only the three dimensions of the EEG. This gave drastically different results.

Three zones are distinguishable at first glance: low arousal (blue), high arousal high valence (green), and high arousal low valence (purple). The dominance of the signal does not seem to have any correlation with the emotion in this model, apart from a few outliers seen in red (figure 2b). Therefore, all columns were included once again, giving the prediction results we can see on the right side of the figure.

Comparing it to the 2D plot, the 3D one seems to clarify how each dimension of the data was computed. We can argue that this model put the majority of high-valence points into the same category. However, the more the other two values increased, the more it diversified its prediction. The high arousal high valence data points zone became smaller, by excluding the low dominance points altogether.

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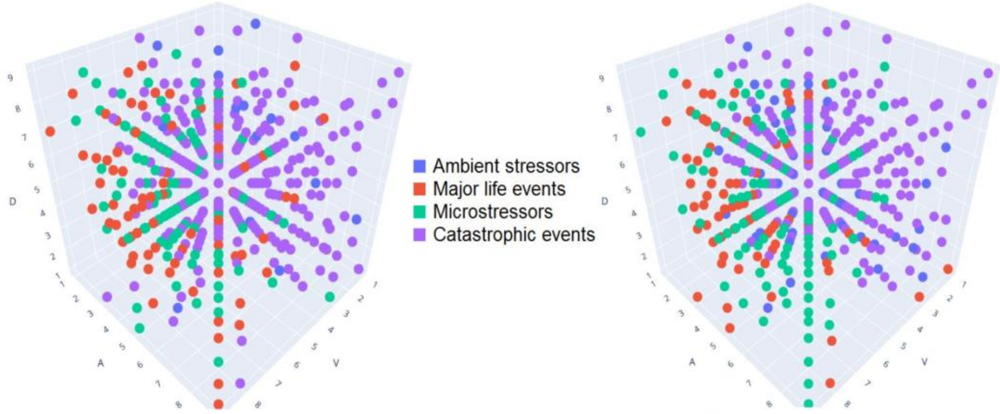

(a) (b)

Fig. 4: Side-by-side comparison of 3D plots for the labeled data (a) and the Fuzzy c-Means prediction model (b).

3.1.2 HDBSCAN

While running the “HDBSCAN_flat” function with only the EEG signal columns, there was a recurring error: “RuntimeError: Could not find epsilon”. This was probably caused by the choice of number of clusters, because the module uses it to find the most adequate epsilon (i.e. the maximum distance between two points in a cluster). It may also have been due to the number of data columns changing, because keeping all columns gave a concrete result.

For HDBSCAN in general, when data points are labeled, outliers are given a separate label, which are colored in gray on figure 3. For emotions from 1 to 10, the model labeled them all as one stimulus type. Only two types are visible here, colored in red and purple. On figure 3b, the unlabeled points form the majority of the outer layer of the scatter plot. It seems like the threshold for excluding points from stimulus types was not strict enough. Some points have a different label to them, which can be easily seen in green on the 3D plot. Trying “HDBSCAN_flat” was a trial of a function that was modified from the start to let us choose the number of clusters. Its core weakness was the lack of parameters that could be tweaked.

3.1.3 Fuzzy c-Means

At first glance, the fuzzy c-means algorithm has some promise (figure 4b). The high valence side of the plot, mostly populated by green and red-labeled points, seemed to be less monochromatic than the Gaussian mixture model. There is not much to be discussed here, since it was expected for a model based on a reliable algorithm like k-means to be performing this well. One noticeable point here is the high-arousal high-valence axis seems to be all grouped together in the green label.

3.2 Performance

While observing the data points on different plot in 2D and 3D is quite helpful for understanding how each model's algorithm works, calculating their efficiency might prove to bring out more insights. Since this is a case study that stands between classification (due to having the ground truth and its categories), and clustering, due to the models used, two types of performance scores had to be computed.

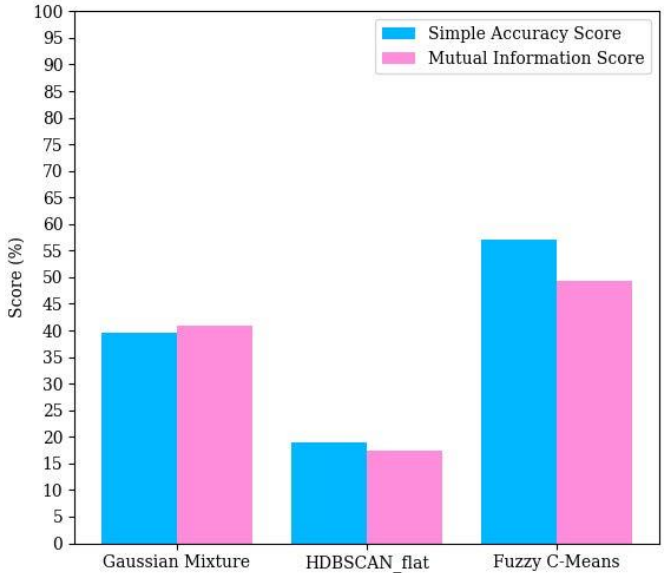

Fig. 5: Performance of the clustering models.

The first way to do it would be to get the simple accuracy score for each model, which is calculated using a fairly straightforward formula (see equation 1 below). The accuracy scores that the models have obtained are represented in figure 5 in blue. It is how most classification models are first evaluated, for a clear overview of their performance. Even though was what done was not classification, a simple accuracy score could prove to be helpful in assessing the precision of the models tried.

$$Accuracy = \frac{CorrectPredictions}{TotalDataPoints} \qquad (1)$$

The other scoring method is a more suitable one for clustering models. It was the mutual information score. According to the documentation for the sklearn.metrics package, it is a "measure of the similarity between two labels of the same data" [8], and is also symmetrical, which makes it easier for models that assign different labels every time they are executed. This was the case with the fuzzy c-means for the simple accuracy score, so repeating the calculation until there was a clear higher score was needed.

$$MI(U,V) = \sum_{i=1}^{|U|}\sum_{j=1}^{|V|} \frac{|U_i \cap V_j|}{N} \log \frac{N|U_i \cap V_j|}{|U_i||V_j|} \qquad (2)$$

The two scores yielded close results, with the GMM having 39.49% of accuracy and 40.84% on the mutual information score. HDBSCAN_flat had the lowest scores with 18.86% and 17.84% on accuracy and mutual information respectively, and finally fuzzy c-means with the highest scores, 57.13% and 49.28%. Interestingly, it has the biggest difference between scores, seeing that the difference for GMM is 1.35%, which is quasi equal to HDBSCAN_flat's score difference, at 1.38%, while for fuzzy c-means, it is 7.85%. One reason as to why this is happening may be the heterogeneity of each cluster. It is true that the labeled data did not have that many homogeneous zones; it is then possible that its closeness to the ground truth could have been a factor. We could even suppose or predict that the closer the model to the truth, the bigger the gap between the scores would be.

4. Discussion

With the low classification and clustering scores, the performance graph (figure 5) clearly states that clustering may not be the path to take in this emotion categorization project.

For the Gaussian mixture model, it has been tried twice, with and without the emotion and intensity taken as input, and the results were drastically different. When only the three dimensions of the EEG signal are taken as input, the model has a tendency to cluster as if there were only 3 clusters, even though it is a parameter set by the user beforehand. Those three zones are clearly cut, which is not optimal. Adding the emotion and intensity back into the equation had arranged things, even though the score for the GMM was subpar. It gets the three first emotions right, as seen in figure 1b. The rest of the emotions do not get clustered properly, until the three last ones seen at the top in red, where there is emotion number 15 which was incorrectly combined into this cluster due to its positioning in the plot.

On the topic of HDBSCAN flat, if the case study was truly a clustering problem, i.e. if the data was more homogeneous, results would have changed drastically. There would be no obligation to set the number of clusters, so there would be no need for a modified version of HDBSCAN. However, it was the case here. Most of the outliers were clustered separately, which could have been caused by a previously mentioned too low of a threshold. Another notable thing is that only two clusters are visible, one dominating the majority of the data points. The green cluster shows less than 5 points, while the blue one does not even appear. The original model DBSCAN works better on datasets with varying densities. Throughout, it was not the case for this study. Also, it does not contain much noise, which could explain the unsuited clustering of outliers in gray. All in all, the HDBSCAN flat model was ill-fitted for the DEAP ratings dataset.

The best model here, the fuzzy c-means, showed some promise, until the scores were calculated. On the 3D plot, it seemed to have performed at 80-85% accuracy, but the scores convey otherwise. As a clustering algorithm, seeing how big of a difference there was between its accuracy score and mutual information score, it does not perform well. As a classification algorithm, it can be refined. 57% accuracy has the potential to increase to 75%, with prior training on a portion of the set, as part of a machine learning model. It could even be argued that it can be added on a classification algorithm, or be taken as a blueprint to improve upon.

4.1 Classification as an alternative

Firstly, the accuracy score shows that 2 out of the 3 models tried cannot predict half of the points' stimulus type correctly. This score is a result of the models being used for clustering, and not for classification. Also, when observing the ground truth data, labeled, there may not be any real cluster. In figure 1a, only one major cluster can be seen, from emotion 1 to 3. This begs the question: would there be any clustering model that could surpass the fuzzy c-means accuracy? The answer to this question is most likely to be no.

Secondly, the mutual information score, especially for fuzzy c-means, being as low as it was, showed mathematically the lack of homogeneity in the data. Clustering is absolutely not like this data should be predicted. Since the accuracy score is a precision score for classification models, let us see which one could be the most suitable. The simplest models to try would be a linear regression or k-nearest neighbors. It can be said that the latter could have a worse result than the former, because it is based on how similar the neighboring points, and as stated earlier, the data points are not really homogeneous. Another interesting one would be a random forest decision tree, but a one-time prediction would not hold up to the standards wanted. A training set, a testing set and a classification model would be the main pillars of a bettered version of what was attempted.

4.2 Multi-label classification

A very important detail that was completely omitted during the clustering, and during this whole paper, was the fact that the labels were originally multiple labels for each emotion (see table II). In this instance, the next step would be multi-label classification, where the target labels are a vector. It is a non-exclusive classification technique that is well-suited for datasets like this [9]. For instance, emotion number 5 (relief) can be caused by major life events and microstressors, so the label vector would be [0, 1, 1, 0].

5. Conclusions

This study, with its trials and errors, marks the beginning of a potential better understanding of where emotions come from. The Gaussian mixture model depended too much on the emotion number, but was a good starting point. It helped gauge how the clusters should look like, since it was the first model tried. The HDBSCAN flat model, on the other hand, was a failure, excluding a big part of the data and putting all the rest into one type. This model was very random. Last but not least, the fuzzy c-means model has detected quite well, but not perfectly, the major clusters in the data. They were properly sized, but still failed to be totally accurate.

Since the methods tried were clustering techniques, the labelling, especially in HDBSCAN flat's case, was quite arbitrary. The random parameter for the GMM had to be turned off or else it would have changed label numbers every time it ran. These two details bring up the point that the qualitative aspect of each emotion and how it fits in each stimulus type was not included in this study. They were represented by numbers, and only seen as such. This showed particularly well in the 2D figures (1a, 1b, and 3a).

This first round of testing and evaluating clustering models has shown that with this dataset, the best way to find a prediction model that fits would be to turn to classification models, preferably a multi-label model. It is true that overlapping clustering models have not been tried, and even the fuzzy c-means model that originally has a soft clustering algorithm, was used in a hard clustering context. This means that a step is added to this endeavor, which is figuring out how to get closer to the ground truth, the one with multiple labels for each emotion.

To reiterate, the DEAP database contains multiple datasets, which could prove to be useful for a more fleshed out model, taking into consideration personal information about the subjects. For example, the age of the subject would be weighted highly if the number is high, due to supposed emotional maturity, which could help confirm the validity of the emotion in their case. Another observation that would be useful is their mental health history, which could modify the value of the intensity in calculations based on which illness they had or currently have.

This could also help the model see the emotions and their stimulus type as qualitative data and not quantitative.
On a more precise level, creating a multi-label classification model from scratch which would emulate the functioning of already established models while adding specific parameters and using all useful datasets in the database could be the best plan in sight. It would be a quite difficult task, but could produce the best results nonetheless.

6. Acknowledgments

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7. Conflict of interest statement

We certify that there is no conflict of interest with any financial organization in the subject matter or materials discussed in this manuscript.

8. Authors' biography

Farah Benayad, obtained her Master of science degree in Computer science from Université de Grenoble-Alpes, France. Interested in human emotions and its exploration via artificial intelligence techniques. Coming from a double field herself, artificial intelligence applied to health, she wanted to touch more on mental health, thus exploring the road less taken.
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Pr Djamel bouchaffra, Director of Research, Head of the ASM Division, Head of the Design and Implementation of Intelligent Machines Group, Former Professor of Computer Science (USA), Founding Member of the Algerian Academy of Science and Technology. Research interest: Pattern Recognition and Machine Learning, Computer Vision, Artificial Intelligence, Cognitive Computing, Image and Signal Processing, Soft Computing.

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