Pattern Recognition Coursework 2023

A. Data Preparation

Task 1 The loaded data set contains tactile data, including High-Frequency Fluid Vibrations, Low-Frequency Fluid Pressure, and Core Temperature(PVT) of several objects. In order to choose a time slot that could identify the difference between objects, the PVT data is observed to determine the difference. For all objects, the High-Frequency Fluid Vibrations all start with rapid growth and become steady as time increases. Fig.1 and Fig.9 shown in the appendix give an example of acrylic and black foam vibrations. It can be seen that both objects tend to keep a 2300 vibration magnitude as time increases, the only difference occurs when the finger is just touching the objects, as it generates a peak in black foam. The magnitude of the peak could be used to determine the difference of the object, so that the 30-time instance is chosen, which is the time of the peak. So that it can provide a large differentiation between objects in the Vibration dimension. If the time instance chosen is large, the vibration variance between objects would be small, making it hard to identify the objects according to vibrations.

Task 2 After choosing the time, the PVT data at that time slot could be collected for each trial of the objects. The size of the PVT data is 10x3x6 (trials x PVT data x objects). The collected data is stored in F1_PVT.mat.

Task 3 The 3D scatter plot (Fig.21) is shown by plotting the mat data collected.

Different objects are plotted with different colors. It can be seen that the gaps between each object are variable, making it possible to identify each object in the 30-time slot.

B. Principal Component Analysis

Task 1.a Principle Component Analysis (PCA) is achieved by projecting the data orthogonally onto the dimension in which the variance of the total data points is the largest. The first step is to compute the covariance matrix, which is the autocorrelation matrix of the data, the result is shown in Eq. 1 in the appendix.

It can be seen that all the diagonal elements of the covariance matrix are all one, which means all object properties are fully self-correlated. and the other elements are all negative, which means the object properties are negatively correlated. Then it is possible to calculate the eigenvalues of the covariance matrix to visualize the variance of each Principal component which corresponds to the eigenvectors of the covariance matrix, as shown in Eq. 2 in the appendix.

Task 1.b The plot is shown in Fig.1. It is known that the means of each object property are different, which would cause errors in PCA. So it is necessary to normalize the data before reducing the dimensions. The normalized principle components should be the same as the original PCs.The normalized data with the principle components are plotted below, it is noticeable that all principle components are orthogonal with each other:

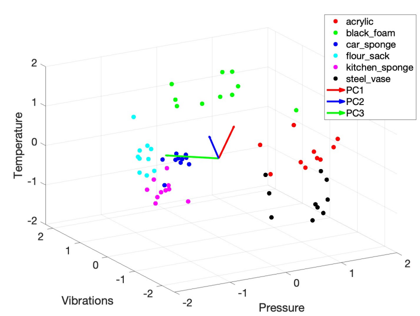


Figure 1. 3D plot PVT data with feature vectors

Task 1.c By selecting approximate pairs of principle components(eigenvectors) that commonly correspond to the largest eigenvalues. The data points could be projected onto the principle component axes. which is shown in Fig.16:

Task 1.d As shown in Fig.2. Repeating the same PCA process, the data points could be projected onto 1 dimension. It can be seen that PC1 performs generally the greatest variation in data. That is because the eigenvalue of the principle components 1 is the largest. It is also possible to see some potential for discriminating in PC1, which corresponds to the visualized variance of the data.

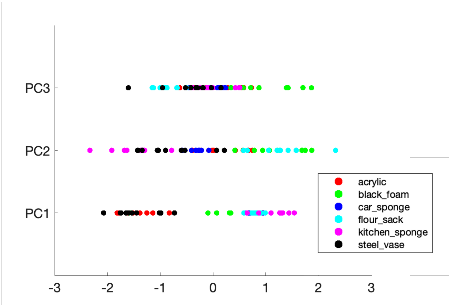


Figure 2. PVT data reduce to 1D

Task 1.e From the PCA result. It can be seen that PCA is really helpful in reducing the dimensions of the data, making it possible to visualize data points. However, as the dimensions decrease, all data would be projected together, which makes it becomes harder to identify the objects from the reduced dimensional data.

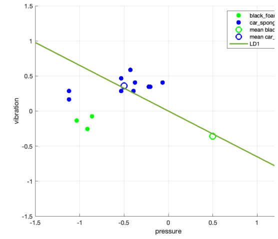
Task 2.a Each sensor contains 19 electrodes, which builds a data matrix with 19 dimensions. PCA can be used to reduce the data to lower dimensions. The variances of each principal component are determined by the eigenvalues of the covariance matrix. From the Scree plots (Fig.10), the 'elbow' in the data can be used to find the number of principle components should be 3 as there are only 3 eigenvalues with the large numbers, which means reducing the dimensions to 3 would not cause the data points to be too close to each other.

Task 2.b In order to visualize the difference between the electrodes of objects, PCA is used to reduce the dimensions to 3 principal components with the largest variance (eigenvalues). Then a 3D scatter figure could be plotted shown in Fig.11:

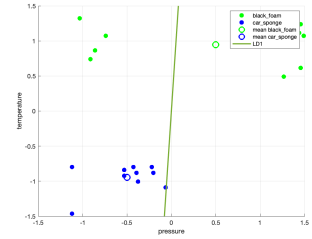
Task 2.c By observing the figure, it can be seen that most of the objects have data points with small variances, which makes it possible to be identified. However, the variances of the acrylic and the steel vase are large and the data points are combined with each other, which might cause errors in distinguishing these two objects.

C. Linear Discriminant Analysis (LDA)

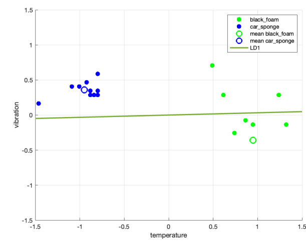
Task 1.a LDA is a supervised clustering algorithm, mainly achieved by maximizing the Fisher's Criteria3. The experiment results towards *black foam* and *car sponge* in 2D were shown in Fig.3. The clustering is obviously distinct among *temperature* and *vibration* when projecting the points onto the LD line, as shown in Fig.22



(a) vibration vs. pressure



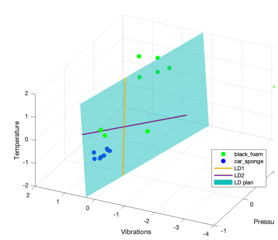
(b) temperature vs. pressure



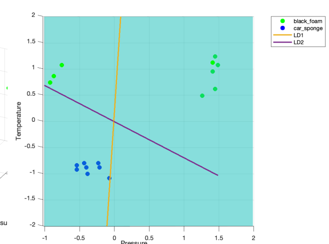
(c) vibration vs. temperature

Figure 3. 2D plot of black foam and car sponge points

Task 1.b The experiment results towards *black foam* and *car sponge* in 3D was shown in Fig.4



(a) 3D view



(b) feature plane view

Figure 4. 3D plot of black foam and car sponge points

Task 1.c Out of three sets of experiments conducted in 2D space, the best-performing ones were those that distinguished between *temperature* and *pressure*, as well as between *temperature* and *vibration*, as shown in Fig.3 (b) and Fig.3 (c). However, the attempt to separate *temperature* and *vibration* was unsuccessful as shown in Fig.3 (a).

A more comprehensive overview can be obtained by analyzing the data in 3-dimensional space, as depicted in Fig.4. The following characteristics can be observed: *1.*There's a distinct temperature boundary between two objects at around 0; *2.*The vibration reaction of the foam is more random when applied different forces, the sponge's variance of vibration is much smaller than the foam's. *3.* When viewed in the Linear Discriminant plane (Fig.15), the *vibration* dimension has been ignored by the plane.

These phonemes could be explained by their different texture features and Thermodynamics.

As per [5], Biotac sensor detects vibration through micro-vibrations and high-frequency signals produced while moving on a surface, with surface texture influencing the reading. Based on prior experiments in Figure 15, sponge and foam have similar cellular structures with tightly packed open ducts, but foam cells are denser. Hence, sliding the sensor on these materials is expected to produce similar vibration frequencies, with slightly stronger readings from foam.

The most distinct dimension separating foam and sponge is temperature, according to BioTac's product manual [1]. The sensor detects temperature changes through its thermistor when it touches objects with different thermal conductivity, causing thermal gradients. Studies by [6] and [3] indicate that as the density of foam and sponge decreases, so does their thermal conductivity. Therefore, BioTac can distinguish between the two materials based on their distinct thermal conductivity properties.

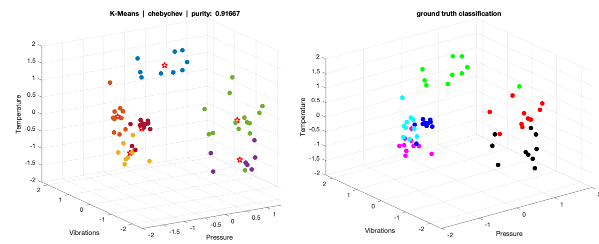
Task 1.d Given the results of the previous experiment, one observation is that when applying the same sliding touch process, similar textures on objects may lead to discrimination failure on the vibration dimension. To further prove this hypothesis, we selected two objects with a dramatic difference in the texture feature, expecting the data points will present a clear discrimination on the *pressure* vs. *vibration* dimensions. Therefore, *flour sack* and *steel vase* are selected.

Figure 17 presents the outcome of Linear Discriminant Analysis. In contrast to the clustered data in Fig.3 (a), the data points were separated into two distinct clusters when projected onto the LD1 vector in the *pressure* and *vibration* dimension.

D. Clustering & Classification

Task 1.a K-means, which updates the centroids points of each cluster iteratively, has a much smaller time complexity (O(mnk)) compared with the Hierarchy method (O(n^3m)), thus it was picked. The clustering result is shown in Fig.5

Task 1.b The K-means algorithm accurately clustered *black foam* and *flour sack* with 100% accuracy, and the *acrylic* and *flour sack* group had the longest distance between adjacent centroids. However, minor mistakes occurred among *car sponge* and *Kitech Sponge* groups, mainly near the boundary of these two groups. The majority of errors were observed among *acrylic* and *steel vase*, which have close centroids and large variances.



(a) K-means clustering (b) Ground-truth clustering

Figure 5. The clustering result (a): K-means result with Chebyshev distance; (b) The ground-truth clusters

Task 1.c K-means clustering is dependent on the calculation of distances, different distance-calculating methods would result in different results.

To quantify the evaluation matrices, the purity index [7] was taken to evaluate the clustering results in different distance calculation methods, where:

$$purity(\Omega, C) = 1/N \sum_k \max_j |C_k \cap W_j|$$

in which $\Omega = \{W_1, W_2, \cdots, W_j\}$ and $C = \{C_1, C_2, \cdots, C_k\}$ is the set of clusters. Bad clusterings have purity values close to 0, and perfect clustering has a purity of 1. The complete experiment results can be found in the appendix.

Tests showed that the Chebyshev distance measure gives the most accurate similarity groupings with a purity index of 0.92. It's more sensitive to differences in a single dimension than the Euclidean distance measure because it calculates the largest distance along any dimension. This makes it effective in separating data clusters within a single plane.

Task 2.a The number of trees and bags used in the model was determined by evaluating the out-of-bag error, which can be seen in Figure 18. It was discovered that using 23 trees resulted in the lowest out-of-bag error for the first time.

Task 2.b Tree 1 and Tree 15 were displayed in Fig.6 and Fig.20

Task 2.c The confusion matrix is shown in Fig.7. *Recall Rate*, *Precison* and *F1-score* are all calculated as 0.875. It indicates that this model achieved a robust prediction with a decent estimation of both precision and accuracy.

Task 2.d Misclassifications were observed among steel and acrylic, which is empirically difficult to distinguish on the 3D electrode data.PCA step plays an important role in bootstrap aggregation. The original dimensions of the electrodes are 19, after applying PCA, the reduced dimensions

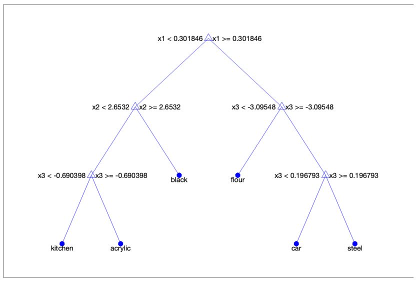


Figure 6. Decision Tree 1

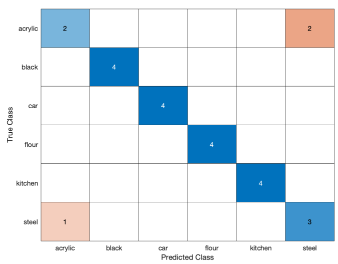


Figure 7. Confusion Matrix

are 3. So that in the bagging process, it just needs to consider 3 variables in the decision trees. If the original electrode data is applied to the bootstrap aggregation, it has to consider 19 variables to build the decision tree, which increases the complexity of the model.

E. Summarize

Task a Each pattern recognition algorithm helps the analyzing of the data in different ways: Principle Component Analysis (PCA) is often used to achieve the dimensional reduction of the data with the variance of all the data points being maximum. The benefit of that is the complexity of the data would be simplified. However, as the dimensions decrease, it might be hard to discriminate the data.

Linear Discriminant Analysis (LDA) could maximize the separations of given objects when the information of objects is provided. If the mean of data points is shared between the objects, it is not possible for LDA to generate a linear space or axis to separate the objects.

Clustering is used to group the data with their similarities, which is useful to identify the objects when the information is not provided. However, if the centroids are generated far from the data points, the results would be poor.

Bagging is a pattern recognition with the decision tree method. The tested samples are trained with trees that contain varying randomly selected data. By averaging the trees together to form a stronger classifier, the effect of over-fitting would be reduced. However, the randomly selected samples might cause an out-of-bag error, which would cause an error in the voting.

Task b For most of the objects, the K-mans clustering can exactly group the objects. However, misclassification errors are observed when the centroids of two groups of data are close while both variances are large. This resulted in a more random updating process in Kmeans. The larger the variance of the data points, the harder it becomes possible to cluster the data points into one group.

Task c According to plotting the data all combinations of 2 object properties as Fig.1, Fig.1, Fig.14. Table 1 can be plotted to show if LDA could successfully separate the two objects on the 2D plane it can be seen that most of the data points could be separated by the LDA function in terms of Pressure vs. Temperature. So that if the sensing modality is reduced to two, which means there are only two dimensions, it is still possible to identify several objects based on LDA of pressure and temperature, which makes temperature the most important object property.

If the sensing modalities of tactile data decrease to one dimension, the data points would be overlapped with each other making it hard to identify the objects. So the electrode would be a more important measurement than the Biotech data. That is because the initial dimensions of the electrodes are 19, which means lower one or few dimensions would still get very similar classification results, making it still possible to achieve clustering.

Task d Current pattern recognition is only based on one signal time slot. One alternative method for better pattern recognition is If the time collecting period is increased, like collecting the data from 30 to 100-time period.

The advantage of collecting the data during a time period is that the slope of the data could be used to identify the object. For example, it is known that touching the steel vase (metal) and flour sack (fabric) would cause different decreasing rates of temperature because of thermal conductivity. So that the temperature change could be used as one dimension in distinguishing the objects.

The alternative approach has drawbacks, as more data collection increases cost and model complexity. Also, initial temperature differences of the objects may cause variance in collecting temperature change data.

References

[1] Biotac product manual, August, 2018, V21.

[2] N. Asanuma, Y. Aita, and Y. Nonomura. Tactile texture of cosmetic sponges and their friction behavior under accelerated movement. *Journal of Oleo Science*, 67(9):1117–1122, 2018.

[3] T. L. Bergman, T. L. Bergman, F. P. Incropera, D. P. Dewitt, and A. S. Lavine. *Fundamentals of heat and mass transfer*. John Wiley & Sons, 2011.

[4] K. Carney, M. Melis, E. L. Fasanella, K. H. Lyle, and J. Gabrys. Material modeling of space shuttle leading edge and external tank materials for use in the columbia accident investigation. In *8th International LS-DYNA Users Conference*, 2004.

[5] J. A. Fishel and G. E. Loeb. Sensing tactile microvibrations with the biotac—comparison with human sensitivity. In *2012 4th IEEE RAS & EMBS international conference on biomedical robotics and biomechatronics (BioRob)*, pages 1122–1127. IEEE, 2012.

[6] S. Jiang, J. Y. Cheong, J. S. Nam, I.-D. Kim, S. Agarwal, and A. Greiner. High-density fibrous polyimide sponges with superior mechanical and thermal properties. *ACS applied materials & interfaces*, 12(16):19006–19014, 2020.

[7] C. D. Manning. *Introduction to information retrieval*. Syngress Publishing,, 2008.

1. Appendix

Additional results and discussions can be included here

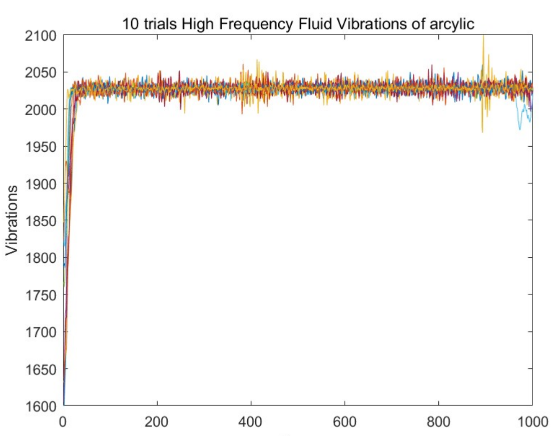


Figure 8. 10 trials High Frequency Fluid Vibrations of arcylic

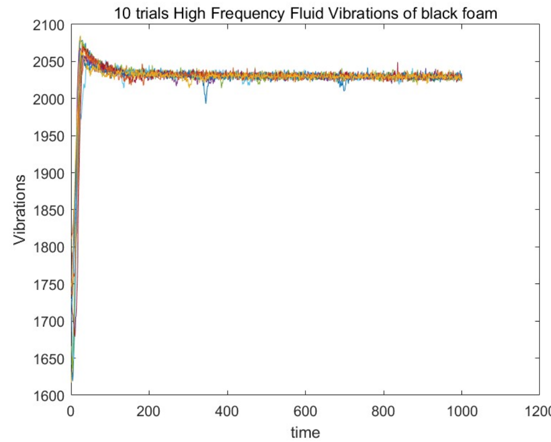


Figure 9. 10 trials High Frequency Fluid Vibrations of black foam

$$cov = \begin{bmatrix} 1.0000 & -0.2951 & -0.2195 \\ -0.2951 & 1.0000 & -0.2189 \\ -0.2195 & -0.2189 & 1.0000 \end{bmatrix} \tag{1}$$

$$\begin{array}{cc} eigenvalues & eigenvectors \\ \begin{bmatrix} 0.591 \\ 1.1958 \\ 1.2951 \end{bmatrix} & \begin{bmatrix} 0.5981 & -0.3751 & -0.7083 \\ 0.5977 & -0.3801 & 0.7059 \\ 0.5340 & 0.8455 & 0.0032 \end{bmatrix} \end{array} \tag{2}$$

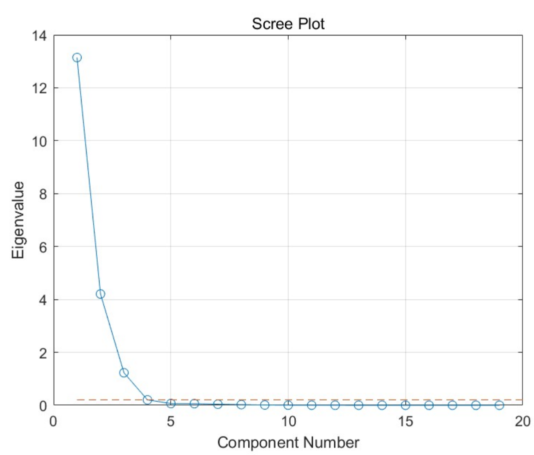


Figure 10. Scree Plots

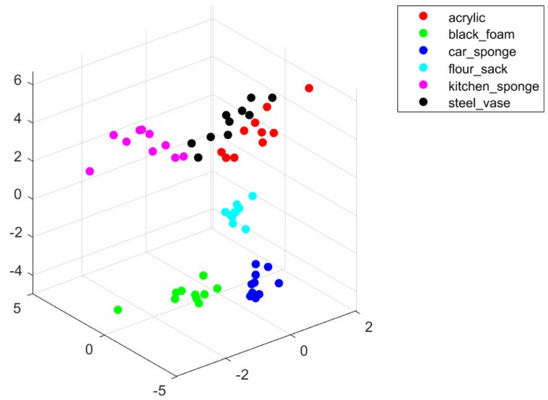


Figure 11. 3D electrodes data

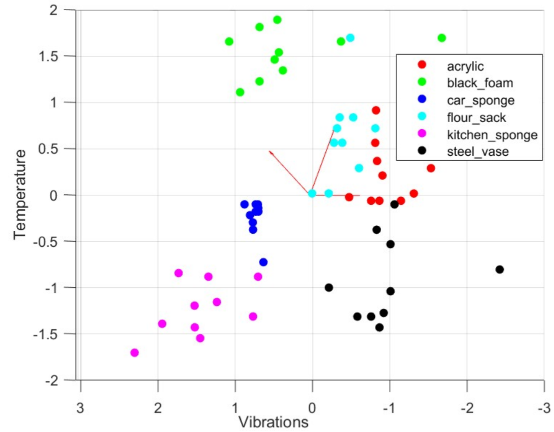


Figure 14. Data points with only Vibration and Temperature

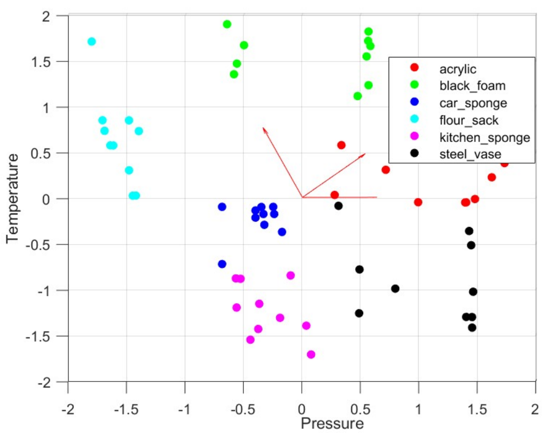
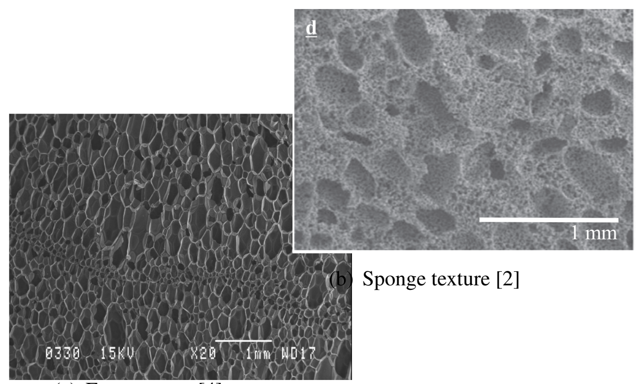


Figure 12. Data points with only Pressure and Temperature



(b) Sponge texture [2]

(a) Foam texture[4]

Figure 15. SEM images of typical foam and sponge material. The regularity of foam cells and the distribution of the open ducts in the foam cells form a dense surface texture

$$J(w) = \frac{|\widehat{m_1} - \widehat{m_2}|^2}{\hat{s_1}^2 - \hat{s_2}^2} \tag{3}$$

m for projected group means , s for group scatters

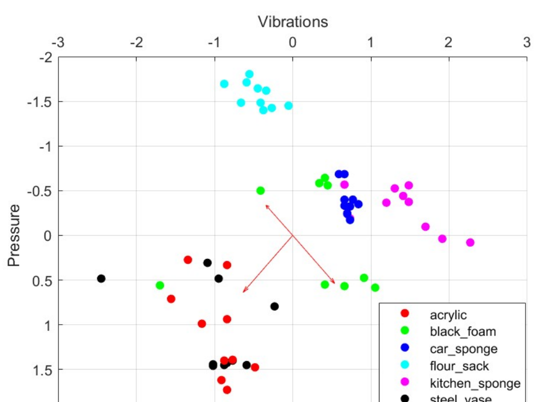


Figure 13. Data points with only Pressure and Vibration

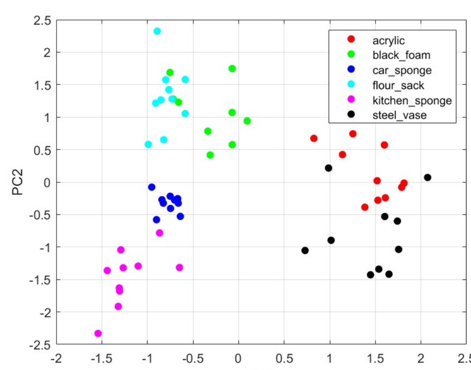


Figure 16. PVT data reduce to 2D

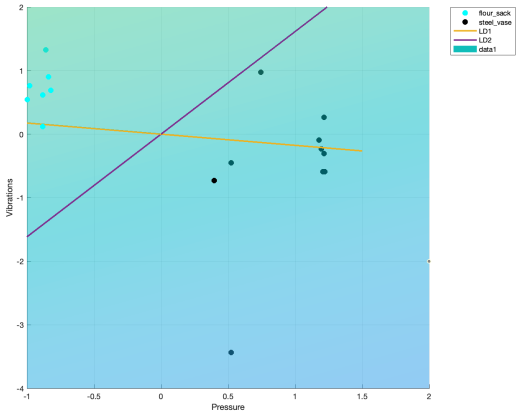


Figure 17. LDA results of *flour sack* and *steel vase* on the *pressure* & *vibration* dimension

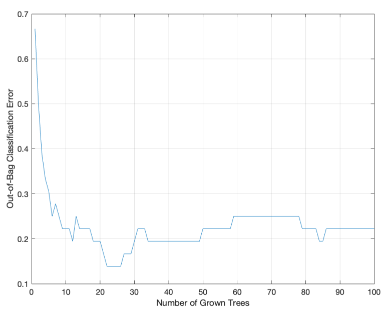


Figure 18.
Figure 19. out-off-bag error vs. number of trees

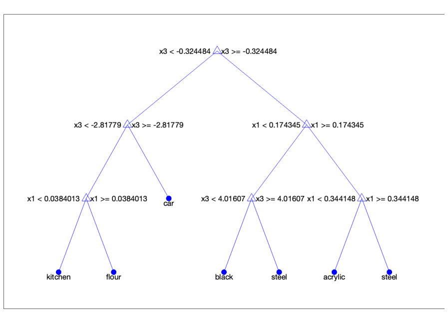


Figure 20. Decision Tree 15

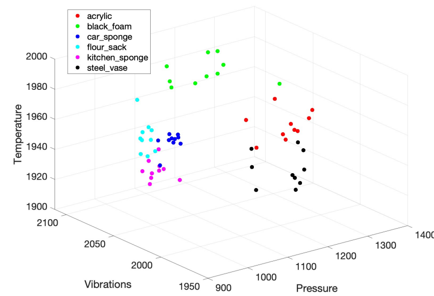


Figure 21. 3D plot of PVT data

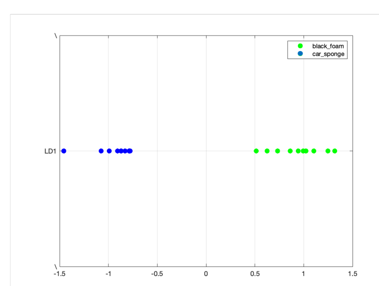


Figure 22. 3D plot of PVT data

	acrylic	black_foam	car_sponge	flour_sack	kitchen_sponge	steel_vase
acrylic	/	PT	PVT	PT	PV	PVT
black_foam	PT	/	PT	PVT	PVT	PVT
car_sponge	PVT	PT	/	PVT	VT	PVT
flour_sack	PT	PVT	PVT	/	PVT	PT,PV
kitchen_sponge	PV	PVT	VT	PVT	/	PV, TV
steel_vase	PVT	PVT	PVT	PT,PV	PV, TV	/