**Inf2B Coursework 1 Report  
  
Task 1 – Anuran-Call analysis and classification**

**1.2) Findings from the correlation matrix:**

Upon analyzing the data within correlation matrix R I found it would be useful to visualize the data in 2 ways:

1. A collection of subplots to show the relationships between all feature vectors
2. A bar graph to show the average correlation value for each feature vector

I used bar graphs to represent both visualizations so it would be easy to recognize the highest/lowest correlations.

A close up of text on a white background

Description automatically generated**A collection of subplots to show the relationships between all feature vectors  
in the data set X**

*We must note that when analyzing these subplots all bars with correlation 1 represent the correlation between the same feature, and thereby do not represent anything significant.*

This visualization of correlation matrix R is convenient for determining the nature of how a given feature is correlated to other features. This can be useful for making predictions about an incomplete sample (does not have data for all features), in which we can predict the value for a given missing feature by using the existing data in the sample with appropriate weightings (weighting for a given feature F is directly proportional to the correlation value between the missing feature and F).

A screenshot of a cell phone

Description automatically generated

This visualization of correlation matrix R is convenient in order to determine which features are uniquely correlated. This is particularly useful as a supplement metric when predicting feature values for an incomplete sample as it can be used for the normalization of correlation values when equating weights.

A screenshot of a cell phone

Description automatically generated**1.3) b) Graph of cumulative variance**

**1.3) c) Plotting of data on 2D-PCA plane**  
A screenshot of a cell phone

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**1.4) b) Accuracy for CovKind = 1,2,3**

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Overall accuracy for a given class** | | | | | | | | | | |
| **CovKind** | **Class 1** | **Class 2** | **Class 3** | **Class 4** | **Class 5** | **Class 6** | **Class 7** | **Class 8** | **Class 9** | **Class 10** | **Average** |
| **1** | 0.3971 | 0.9972 | 0.9787 | 0.6035 | 0.8276 | 0.9919 | 0.8661 | 1 | 0.9920 | 0.9867 | **0.8641** |
| **2** | 0.2853 | 0.9823 | 0.7184 | 0.4000 | 0.0269 | 0.9899 | 0.8596 | 1 | 0.9444 | 0.5000 | **0.6707** |
| **3** | 0.3765 | 0.9963 | 0.9230 | 0.7139 | 0.8785 | 0.9879 | 0.8411 | 0.9765 | 0.9634 | 0.9267 | **0.8584** |
| **Average** | **0.3529** | **0.9919** | **0.8733** | **0.5725** | **0.5777** | **0.9899** | **0.8556** | **0.9922** | **0.9666** | **0.8044** | **0.7977** |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Overall accuracy for a given partition** | | | | | |
| **CovKind** | **Partition 1** | **Partition 2** | **Partition 3** | **Partition 4** | **Partition 5** | **Average** |
| **1** | 0.9122 | 0.9170 | 0.9063 | 0.9229 | 0.9146 | **0.9146** |
| **2** | 0.7960 | 0.7995 | 0.7900 | 0.8233 | 0.7947 | **0.8007** |
| **3** | 0.9146 | 0.9110 | 0.8992 | 0.9336 | 0.8997 | **0.9116** |
| **Average** | **0.8743** | **0.8758** | **0.8652** | **0.8932** | **0.8697** | **0.8756** |

**1.5) Classification accuracy VS epsilon**

**∑**-1 becomes unstable when |**∑**|is small. Solutions to this are either, reducing the dimensionality with PCA, or using regularisation.

In this case we used regularisation by adding a small positive number (epsilon) to the diagonal elements.  
**A close up of a logo

Description automatically generated**

**We can see that in the range the classification accuracy is greater than 90%.**

**\*Talk about the reason behind regularization in this situation and why a certain size of epsilon changes the accuracy**

**The covariance matrix is regularized by adding Epsilon to the diagonal.**

**Task 2 – Neural networks**

A close up of a map

Description automatically generated**2.3) Structure of the neural network**

**How weights were determined:**  
For this given neural network weights are created in order to classify data correctly using the given activation function (hNeuron).

**WEIGHTS: Input -> Hidden 1   
(All calculations within *task2\_find\_hNN\_A\_weights.m*)**

For the first layer of weights, the activation function classification is dependent on the coordinate of a point being within the boundaries of polygon A or not. Thereby we must calculate the functions of these boundaries and find how they can be converted to appropriate weights.

Given we are calculating weights we must ensure to account for every variable:

The sign of Y is negative after isolating all terms to one side of the equation, and the default coefficient of Y has a constant magnitude of 1 so we only need to calculate the gradient and y-intercept.

So firstly, I created a function *task2\_calcGrads(x)* which calculates the constants for all boundary functions of a given polygon x. It takes an input of a polygon coordinate matrix and produces an output of a boundary function matrix (where each row represents a boundary function and each column represents the associated gradient and y-intercept respectively). Implementing this function promotes much higher accuracy for boundary calculations than mere hardcoding.

Now, given we have the respective boundary function constants we must identify which boundaries are the maxima and minima of this polygon. This is very relevant as it denotes which side of the boundaries represents the polygon. I identified these maxima and minima by capitalizing on the order of polygon vertex input, in which the maximum Y vertex is always first and the other vertices follow in a clockwise/anti-clockwise fashion. In order to represent these maxima and minima boundaries we can just multiply the minima boundary functions by -1.

Given that we only account for points inside the polygon (not including the periphery) I deducted a tiny value (-1\*10-14) from the maxima boundaries and added a tiny weight (+ 1\*10-14) to the minima boundaries.

At this point, the only thing left to do is normalize the weights. So, I divided each weight vector by its associated maximum magnitude element.

**WEIGHTS: Hidden 1 -> Output**

Given that the first layer of neurons each output a 1 or a 0 to represent if the given point is within the given boundary, the rest of the neurons act like AND logic gates. This is because the point must be within all borders to be within the polygon.

So, in order to create a suitable weighting, I created a large negative bias which could only be overcome if both W1 and W2 inputs were 1.

**2.10) Difference in decision boundary calculations for *task2\_hNN\_AB()* & *task2\_sNN\_AB()***  
The only difference between the layout of these neural networks was the activation functions used. The first using a step function (hNeuron) and the second a sigmoid function (sNeuron).

The predominant difference I found in calculating these decision boundaries was that it was far more difficult to simulate logic gates using a sigmoid neuron. This is because in contrast to the step function which produces an output of 1 or 0 the output of a sigmoid is in the range from 0 to 1. In order to cater for this I decided it would be useful to use non-normalized weights for the sigmoid function, I did this by multiplying each weight vector by 10^8 this in effect creates a very large number if a > 0 as e-a -> 0 and thereby z = 1/1

and a very small number if a <= 0 ea -> INF and thereby z = 1/INF = 0

these in effect produces an output of 1 if a > 0 and an output of 0 if a <= 0.