**Inf2B Coursework 1 Report**

**Task 1 – Anuran-Call analysis and classification**

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

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**

he correlation matrix R contains information with regards to the relationships between every feature vector (column) in the data set X, I decided it would be useful to analyze these relationships. In

**1.3) b) Graph of cumulative variance**  
A screenshot of a cell phone

Description automatically generated

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

Description automatically generated

**1.4) Accuracy for CovKind = 1,2,3**Accuracy = correct classification rate.

**1.5) A graph of classification accuracy vs epsilon value**  
A close up of a logo

Description automatically generated

**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).