# Arrythmia ECG Classification using ANN

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## 1 Low Level Neural Network for ECG Classification

In this notebook we implement a 3-layer ANN for classifying ECG signals using PSD and Energy as input. Our three layers consist of: Layer 1: 2 neurons to input the PSD and Energy. Layer 2: In Layer 2 we used a variable amount of neurons ,namely from one to 30 neurons and we obtained the best metrics by using a 16 neuron layer. Layer 3: 2 neurons to output the probability of a patient having a Normal sinus or an arrythmia.

The Network is implemented from scratch to mimic the flow of the process on low-level hardware.

```
In [8]: # Library imports
        import numpy as np
        import matplotlib
        import csv
        from matplotlib import pyplot as plt
        from matplotlib.pyplot import figure
```

### 1.1 Loading datasets

We load the arrythmia and normal sinus datasets from https://physionet.org/physiobank/database/#ecg MIT-BIH and split the data into two sets, a training set and a post-training test set. We also perform normalization of data to decrease the training speed when using the gradient descent optimization.

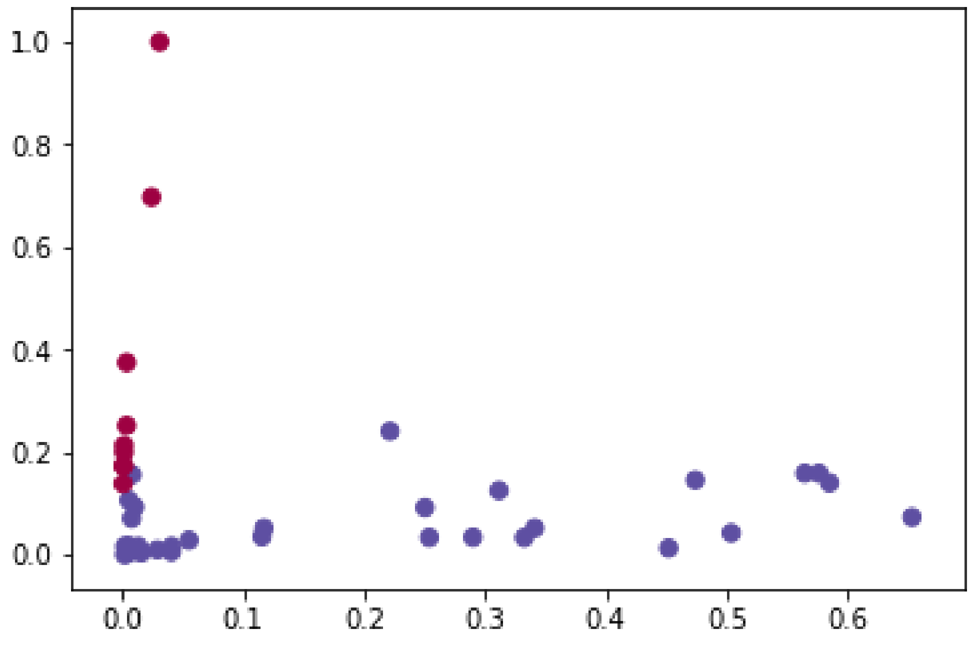
```
In [9]: # Load dataset and plot a scatter-graph
        np.random.seed(0)
        X1_init= []
        y_init= []
        max1 = 0
        max2 = 0
        min1 = 99999999
        min2 = 99999999

        with open('database.csv', 'rt') as csvfile:
            lines = csv.reader(csvfile)
            for row in lines:
                dummy = []
                dummy.append(float(row[1])*1e10)
                dummy.append(float(row[2])/1e5)
                max1 = max(max1, dummy[0])
                max2 = max(max2, dummy[1])
                min1 = min(min1, dummy[0])
                min2 = min(min2, dummy[1])
                X1_init.append(dummy)
                y_init.append(int(row[3]))

        X_init = []
        for val in X1_init:
            dumbo = []
            v1 = (val[0]- min1)/(max1-min1)
            v2 = (val[1]- min2)/(max2-min2)
            dumbo.append(v1)
            dumbo.append(v2)
            X_init.append(dumbo)
        Xt = np.array(X_init[len(X_init)-11:])
        yt = np.array(y_init[len(X_init)-11:])
        X = np.array(X_init[0:len(X_init)-12])
        y = np.array(y_init[0:len(X_init)-12])
        print (yt)
        plt.scatter(X[:,0], X[:,1], s=40, c=y, cmap=plt.cm.Spectral)
```

```
[0 0 1 1 0 0 0 1 1 0 0]
```

```
Out[9]: <matplotlib.collections.PathCollection at 0x1e2ed38e518>
```



There are two labels (healthy sinus and arrythmia) denoted as red and blue points in the above graph

Our goal is to train an ML classifier that predicts if the patient is healthy or not.

```
In [10]: # Helper function to plot a decision boundary.
         # If you don't fully understand this function don't worry, it just generates the contou
         def plot_decision_boundary(pred_func):
             # Set min and max values and give it some padding
             x_min, x_max = -2, 4
             y_min, y_max = 0, 50
             h = 0.1
             # Generate a grid of points with distance h between them
             xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
             # Predict the function value for the whole gid
             Z = pred_func(np.c_[xx.ravel(), yy.ravel()])
             Z = Z.reshape(xx.shape)
             # Plot the contour and training examples
             figure(num=None, figsize=(7, 5), dpi=80, facecolor='w', edgecolor='k')
             plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral)
             plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Spectral)
             plt.ylim(0,2)
             plt.xlim(-0.1,1)
```

## 1.2 Network Architecture and Training

Firstly, we will build our 3 layer network, with one input layer (dimensionality = 2 ; PSD & Energy), hidden layer (dimensionality = 16 ; which corrosponds to the perceptrons) and the output layer which takes from the hidden layer the inputs and maps them to our classes(2: Normal Wave or not). Furthermore, if we need to expand our network, our architecture is modular and can be scaled to occupy more classes and feautures.

The choice of the number of perceptrons in the hidden layer reflects the complexity and the ability to comprehend more feautures. Moreover, there is a tradeoff for chosing high dimensionality in the hidden layer, which is the computional cost. In spiderman, there was a saying "With great power comes great responsibility"; and that exactly what happens with a neural network with more power(perceptrons), comes greater responsibility(computional cost).

Secondly, in order to transfer the output of the layers to closer values, we need activation functions and specially non-linear activiation functions. Some of the most important and used activation functions are the tanh,RELU, sigmoid and softmax.

### 1.2.1 ANN's Prediction

Our network makes predictions using *forward propagation*, which is basically matrix multiplications and the application of the activation functions we mentioned earlier. If $x$ is the 2-dimensional input(PSD & Energy) to our network, then we compute our prediction $\hat{y}$ (also two-dimensional) as follows:

$$\begin{aligned}
z_1 &= xW_1 + b_1 \\
a_1 &= \tanh(z_1) \\
z_2 &= a_1 W_2 + b_2 \\
a_2 &= \hat{y} = \mathrm{softmax}(z_2)
\end{aligned}$$

$z_i$ is the weighted sum of inputs of layer $i$ (bias included) and $a_i$ is the output of layer $i$ after applying the activation function. $W_1, b_1, W_2, b_2$ are parameters of our network, which we need to learn from our training data. You can think of them as matrices transforming data between layers of the network.

### 1.2.2 Learning the Parameters

Learning the parameters for our network means finding parameters ($W_1, b_1, W_2, b_2$) that minimize the error on our training data. But how do we define the error? We call the function that measures our error the *loss function*. A common choice with the softmax output is the cross-entropy loss. If we have $N$ training examples and $C$ classes then the loss for our prediction $\hat{y}$ with respect to the true labels $y$ is given by:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{n \in N} \sum_{i \in C} y_{n,i} \log \hat{y}_{n,i}$$

The equation basically calculates the error by summing the values of the test data and approximates the error, by checking the wrongly classified points.

Our objective is to minimize the loss function mentioned earlier, thus we will use a simple gradient descent algorithm. Moreover, we will need to define the below equation to be used.

$$\begin{aligned}
\delta_3 &= \hat{y} - y \\
\delta_2 &= (1 - \tanh^2 z_1) \circ \delta_3 W_2^T \\
\frac{\partial L}{\partial W_2} &= a_1^T \delta_3 \\
\frac{\partial L}{\partial b_2} &= \delta_3 \\
\frac{\partial L}{\partial W_1} &= x^T \delta_2 \\
\frac{\partial L}{\partial b_1} &= \delta_2
\end{aligned}$$

### 1.2.3 Implementation

Now we are ready for our implementation. We start by defining some useful variables and parameters for gradient descent:

```
In [11]: num_examples = len(X) # training set size
         nn_input_dim = 2 # input layer dimensionality
         nn_output_dim = 2 # output layer dimensionality

         # Gradient descent parameters (I picked these by hand)
```

```
        epsilon = 0.01 # learning rate for gradient descent
        reg_lambda = 0.01 # regularization strength
```

First let's implement the loss function we defined above. We use this to evaluate how well our model is doing:

```
In [12]: # Helper function to evaluate the total loss on the dataset
         def calculate_loss(model):
             W1, b1, W2, b2 = model['W1'], model['b1'], model['W2'], model['b2']
             # Forward propagation to calculate our predictions
             z1 = X.dot(W1) + b1
             a1 = np.tanh(z1)
             z2 = a1.dot(W2) + b2
             exp_scores = np.exp(z2)
             probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True)
             # Calculating the loss
             corect_logprobs = -np.log(probs[range(num_examples), y])
             data_loss = np.sum(corect_logprobs)
             # Add regulatization term to loss (optional)
             data_loss += reg_lambda/2 * (np.sum(np.square(W1)) + np.sum(np.square(W2)))
             return 1./num_examples * data_loss
```

We also implement a helper function to calculate the output of the network. It does forward propagation as defined above and returns the class with the highest probability.

```
In [13]: # Helper function to predict an output (0 or 1)
         def predict(model, x):
             W1, b1, W2, b2 = model['W1'], model['b1'], model['W2'], model['b2']
             # Forward propagation
             z1 = x.dot(W1) + b1
             a1 = np.tanh(z1)
             z2 = a1.dot(W2) + b2
             exp_scores = np.exp(z2)
             probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True)
             #print("Probs: \n",probs)
             return np.argmax(probs, axis=1)
```

```
In [58]: # This function learns parameters for the neural network and returns the model.
         # - nn_hdim: Number of nodes in the hidden layer
         # - num_passes: Number of passes through the training data for gradient descent
         # - print_loss: If True, print the loss every 20000 iterations
         def build_model(nn_hdim, num_passes=300, print_loss=False):

             # Initialize the parameters to random values. We need to learn these.
             np.random.seed(1)
             W1 = np.random.randn(nn_input_dim, nn_hdim) / np.sqrt(nn_input_dim)
             b1 = np.zeros((1, nn_hdim))
             W2 = np.random.randn(nn_hdim, nn_output_dim) / np.sqrt(nn_hdim)
             b2 = np.zeros((1, nn_output_dim))
```

```
# This is what we return at the end
model = {}

# Gradient descent. For each batch...
for i in range(0, num_passes):

    # Forward propagation
    z1 = X.dot(W1) + b1
    a1 = np.tanh(z1)
    z2 = a1.dot(W2) + b2
    exp_scores = np.exp(z2)
    probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True)

    # Backpropagation
    delta3 = probs
    delta3[range(num_examples), y] -= 1
    dW2 = (a1.T).dot(delta3)
    db2 = np.sum(delta3, axis=0, keepdims=True)
    delta2 = delta3.dot(W2.T) * (1 - np.power(a1, 2))
    dW1 = np.dot(X.T, delta2)
    db1 = np.sum(delta2, axis=0)

    # Add regularization terms (b1 and b2 don't have regularization terms)
    dW2 += reg_lambda * W2
    dW1 += reg_lambda * W1

    # Gradient descent parameter update
    W1 += -epsilon * dW1
    b1 += -epsilon * db1
    W2 += -epsilon * dW2
    b2 += -epsilon * db2

    # Assign new parameters to the model
    model = { 'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}

    # Optionally print the loss.
    best = 1000
    losses=calculate_loss(model)
    if best>losses:
        best = losses
        BW1 = W1
        Bb1 = b1
        BW2 = W2
        Bb2 = b2
    W1A = []
    W2A = []
    b1A = []
```

```
                b2A = []
                for i in Bb1:
                    for j in i:
                        b1A.append(j)
                for i in Bb2:
                    for j in i:
                        b2A.append(j)
                for j in BW1:
                    for i in j:
                        W1A.append(i)
                for j in BW2:
                    for i in j:
                        W2A.append(i)
                b1A = np.array(b1A)
                b2A = np.array(b2A)
                W2A = np.array(W2A)
                W1A = np.array(W1A)
                np.savetxt("bestWeights/BW1.csv", W1A)
                np.savetxt("bestWeights/b1.csv", b1A)
                np.savetxt("bestWeights/BW2.csv", W2A)
                np.savetxt("bestWeights/b2.csv", b2A)
        #     print ("Weights of edges of Input layer to hidden layer (2x16): ",W1, "\n")
        #     print ("biases of hidden layer (x16): ",b1, "\n")
        #     print ("Weights of edges of hidden layer to output layer (16x2): ",W2, "\n")
        #     print ("biases of output layer (x2): ",b2, "\n")
            print(best)
            return model
```

### 1.2.4 Selected hidden layer neurons size(16)

Based on the hidden layer neurons count variant training we chose 16.

```
In [59]: # Build a model with a 16-dimensional hidden layer
         model = build_model(16, print_loss=True)
```

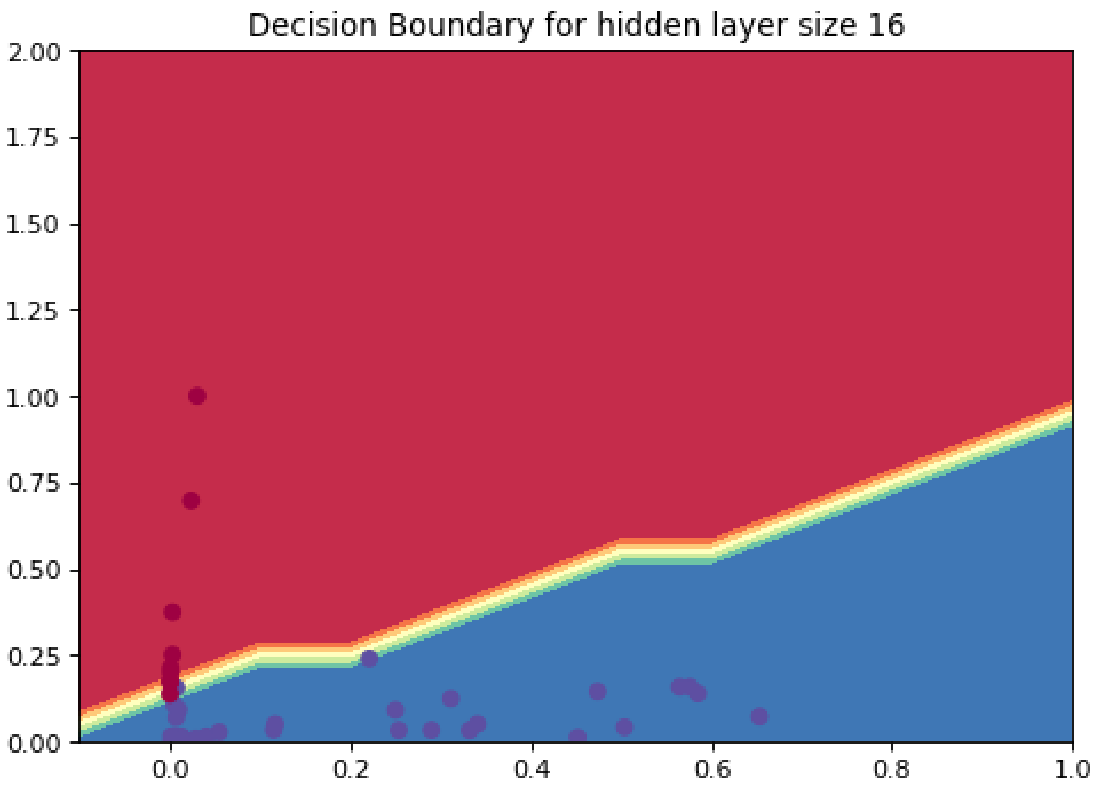
```
0.08991451839856202
```

```
In [60]: scores = 0
         for i in range(0, 11, 1):
             if predict(model,Xt[i]) == yt[i]:
                 print (yt[i])
                 scores+=1
         print("the accuracy is : ",scores/10)
         # Plot the decision boundary
         plot_decision_boundary(lambda x: predict(model, x))
         plt.title("Decision Boundary for hidden layer size 16")
```

```
0
1
```

```
1
0
0
0
1
1
the accuracy is :  0.8
```

```
Out[60]: Text(0.5,1,'Decision Boundary for hidden layer size 16')
```

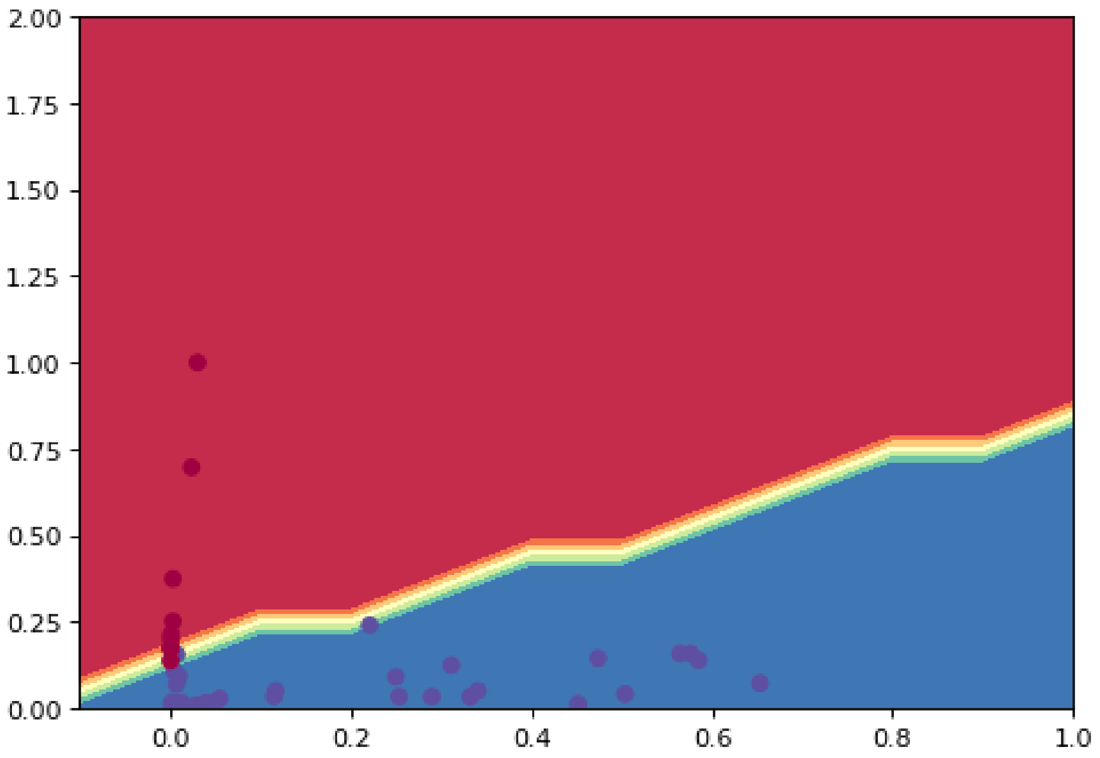


Varying the hidden layer size

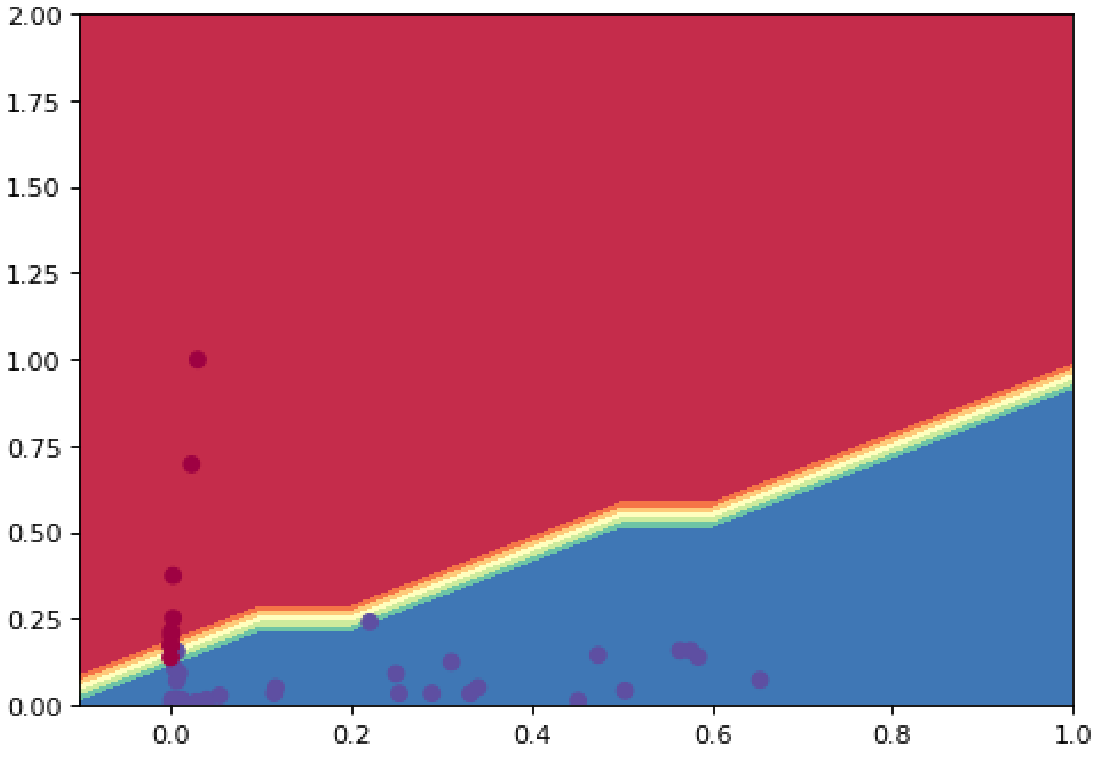
In the example above we picked a hidden layer size of 16. Let's now get a sense of how varying the hidden layer size affects the result.

```
In [65]: hidden_layer_dimensions = [1,16,2000]
         for i, nn_hdim in enumerate(hidden_layer_dimensions):
             print("Model",i+1,"With %d perceptrons\n Loss = "%nn_hdim,end="")
             model = build_model(nn_hdim, print_loss=True)
             print('\n')
             plot_decision_boundary(lambda x: predict(model, x))
             plt.show()
```

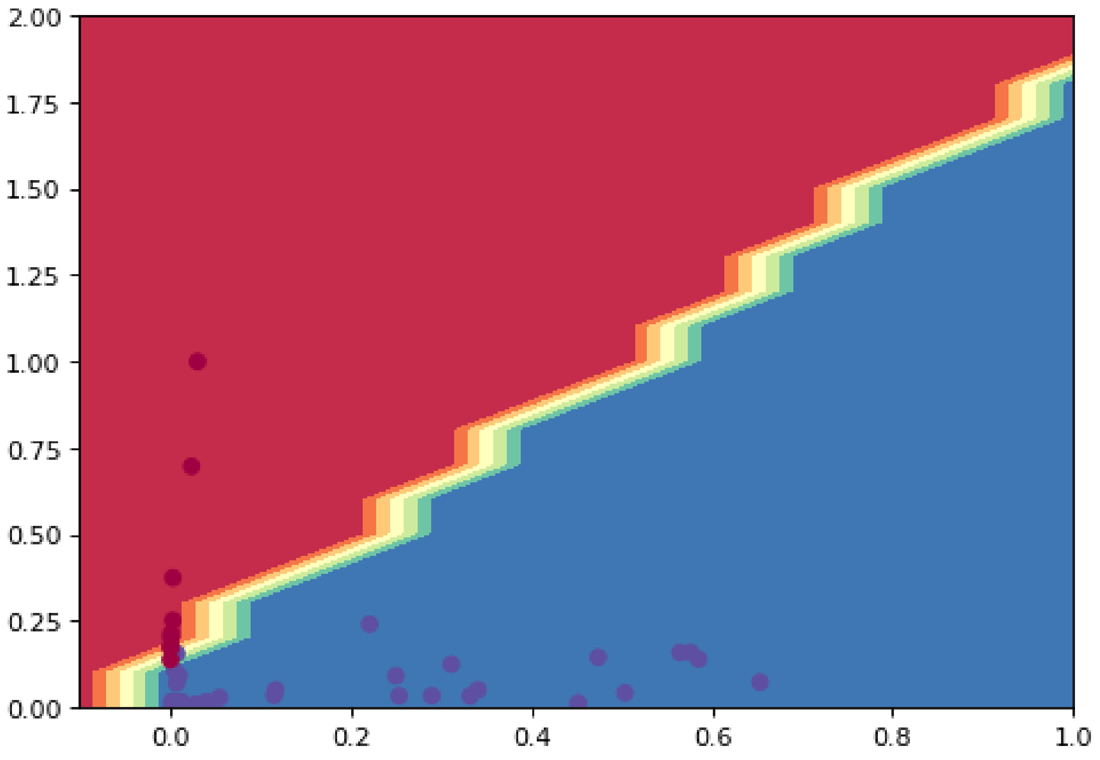
```
Model 1 With 1 perceptrons
 Loss = 0.09983589374395352
```



```
Model 2 With 16 perceptrons
 Loss = 0.08991451839856202
```



```
Model 3 With 2000 perceptrons
 Loss = 0.2782942615519288
```



2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0