# **Project Report on WSNN**

By group: 17

**LIBRARIES USED:** To implement this question, we have used numpy, and random.

- **1.) NUMPY:** Numpy is a python library used when we want to work with arrays.
- 2.) **RANDOM:** It is an inbuilt module of python that is used to generate random numbers.

# 1. Building our Neural Network

1a) Preprocess: Use this module to preprocess the data and divide into train and test.

```
# For making compatibility we do one hot encoding
def oneHotEncoding(y):
    if y == 1:
        return [0, 0, 0]
    elif y == 2:
        return [0, 1, 0]
    else:
        return [0, 0, 1]

# print(y)
def split_data(X, y, split_ratio = 0.8):
    indexes = [i for i in range(len(X))]
    train_size = len(indexes) * split_ratio
    train_index = np.random.choice(indexes, size=int(train_size), replace=False)

X_train = []
    X_test = []
    y_test = []
    for i in range(len(X)):
    if i in train_index:
        X_train.append(X[i])
        y_train.append(oneHotEncoding(y[i]))

else:
        X_test.append(X[i])
        y_test.append(oneHotEncoding(y[i]))

return X_train, X_test, y_train, y_test
```

1b) **Data loader**: Use this module to load all datasets and create mini-batches, with each minibatch having 32 training examples.

```
# Load the data set
def load_dataset():

# open the data set
file = open("seeds_dataset.txt")
lines = file.readlines()
data_set = []

for line in lines:
    x = []
    line = line.strip().split()
    for elem in line:
        x.append(float(elem))
    data_set.append(x)

return data_set

data_set = load_dataset()
```

1c) Weight initializer: This module should initialize all weights randomly between -1 and 1.

```
# Function that initializes weights between -1 and 1
def Initialize_Weights(self, size1, size2):
    return np.random.uniform(low=-1, high=1, size=(size1, size2))
```

1d) **Forward pass**: Define the forward() function where you do a forward pass of the neural network.

```
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def forward(self, X):

# For ANN Specification 1
if self.no_of_hidden_layer == 1:

# Hidden layer
self.zl = np.dot(X, self.weight_I_H1) + self.bias_1
self.al = self.sigmoid(self.zl)

# Output layer
self.z2 = np.dot(self.al, self.weights_H1_0) + self.bias_2
self.a2 = self.softmax(self.z2)

return self.a2

else:

# Hidden layer 1
self.zl = np.dot(X, self.weight_I_H1) + self.bias_1
self.al = self.relu(self.zl)

# Hidden layer 2
self.z2 = np.dot(self.al, self.weights_H1_H2) + self.bias_2
self.a2 = self.relu(self.z2)

# output layer
self.z3 = np.dot(self.a2, self.weights_H2_0) + self.bias_3
self.a3 = self.softmax(self.z3)

return self.a3
```

1e) **Backpropagation**: Define a backward() function where you compute the loss and do a backward pass (backpropagation) of the neural network and update all weights.

```
def backward(self, X, y, y_hat, learning_rate = 0.01):
     # For ANN Specification 1
     if self.no_of_hidden_layer == 1:
          # Compute gradients
          m = y.shape[0]
         delta2 = y_hat - y
          dW2 = np.dot(self.al.T, delta2) / m
db2 = np.sum(delta2, axis=0, keepdims=True) / m
          delta1 = np.dot(delta2, self.weights_H1_0.T) * self.a1 * (1 - self.a1)
          dW1 = np.dot(X.\(\bigcup_{\text{(parameter)}}\) learning_rate: float
db1 = np.sum(de (parameter))
          # Now update the weights
          self.weights_H1_0 -= learning_rate * dW2
          self.bias_2 -= learning_rate * db2
self.weight_I_H1 -= learning_rate * dW1
          self.bias_1 -= learning_rate * db1
      # compute graients
          y.shape[0]
      delta3 = y_hat - y
      dW3 = np.dot(self.a2.T, delta3) / m
      db3 = np.sum(delta3, axis=0, keepdims=True) / m
      delta2 = (np.dot(delta3, self.weights_H2_0.T) * (self.a2 > 0)) / m
      dW2 = np.dot(self.a1.T, delta2)
db2 = np.sum(delta2, axis=0, keepdims=True)
      delta1 = (np.dot(delta2, self.weights_H1_H2.T) * (self.a1 > 0)) / m
dW1 = np.dot(X.T, delta1)
db1 = np.sum(delta1, axis=0, keepdims=True)
      # Now update the weights
      self.weight_I_H1 -= learning_rate * dW1
      self.bias_1 -= learning_rate * db1
       self.weights_H1_H2 -= learning_rate * dW2
       self.bias_2 -= learning_rate * db2
      self.weights_H2_0 -= learning_rate * dW3
self.bias_3 -= learning_rate * db3
```

1f) **Training**: Implement a simple mini batch SGD loop and train your neural network, using forward and backward passes.

```
def train(self, X_train, y_train, X_test, y_test, epochs = 200, batch_size = 32):
     # Calulate the number of batches
     num_batch = X_train.shape[0] // batch_size
train_acc = []
test_acc = []
      for i in range(epochs):
         # Shuffle training data
          perm = np.random.permutation(X_train.shape[0])
          X_train = X_train[perm]
y_train = y_train[perm]
                start = j * batch_size
end = (j + 1) * batch_size
                batch_X = X_train[ (variable) start: Any
batch_y = y_train[start : end]
                # print(batch_X, batch_y)
                # Forward pass
y_hat = self.forward(batch_X)
# print(y_hat)
                # Backward pass
                self.backward(batch_X, batch_y, y_hat)
           # Compute the accuracy on every 10 epochs
             # Forward pass

# Forward pass

y_hat = self.forward(batch_X)

# print(y_hat)
             # Backward pass
        # Compute the accuracy on every 10 epochs if i % 10 == 0:
             acc_train = self.predict(X_train, y_train)
acc_test = self.predict(X_test, y_test)
             \label{eq:print(f"Epoch: $$\{i\} \to Training\ Accuracy: \{acc\_train\},\ Testing\ Accuracy: \{acc\_test\}")$$ train_acc.append(acc\_train)
   test_acc.append(acc_test)
return train_acc, test_acc
```

1g) **Predict**: To test the learned model weights to predict the classes of the test set.

```
# Function to calculate the accuracy
def accuracy(self, y_pred, y):
    acc = np.mean(y_pred == np.argmax(y, axis=1))
    return acc

# Function that predict the output
def predict(self, X, y):
    y_hat = self.forward(X)
    y_pred = np.argmax(y_hat, axis=1)
    acc = self.accuracy(y_pred, y)
    return acc
```

```
else:
    # Initialize weight and bias between input and hidden layer 1
    self.weight_IH1 = self.Initialize_Weights(self.input_size, self.hidden1_size)
    self.bias_1 = np.zeros((1, self.hidden1_size))

# Initialize weight and bias between hidden layer 1 and hidden layer 2
    self.weights_H1_H2 = self.Initialize_Weights(self.hidden1_size, self.hidden2_size)
    self.bias_2 = np.zeros((1, self.hidden2_size))

# Initialize weight and bias between hidden layer 2 and output layer
    self.weights_H2_0 = self.Initialize_Weights(self.hidden2_size, self.output_size)
    self.bias_3 = np.zeros((1, self.output_size))

def Info(self):
    print(f"number of hidden layer : {self.no_of_hidden_layer}")
    print(f"input size of neural network : {self.input_size}")
    print(f"output size of neural network : {self.output_size}")
    print(f"hidden layer 1 size of neural network : {self.hidden1_size}")
    print(f"hidden layer 2 size of neural network : {self.hidden2_size}")

# Function that initializes weights between -1 and 1
def Initialize_Weights(self, size1, size2):
    return np.random.uniform(low=-1, high=1, size=(size1, size2))

# Sigmoid activation function
def sigmoid(self, y):
    return 1 / (1 + np.exp(-y))
```

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```

```
# compute graients

m = y.shape[0]
delta3 = y_hat - y
dW3 = np.dot(self.a2.T, delta3) / m
db3 = np.sum(delta3, axis=0, keepdims=True) / m

delta2 = (np.dot(delta3, self.weights_H2_0.T) * (self.a2 > 0)) / m
dW2 = np.dot(self.a1.T, delta2)
db2 = np.sum(delta2, axis=0, keepdims=True)

delta1 = (np.dot(delta2, self.weights_H1_H2.T) * (self.a1 > 0)) / m
dW1 = np.dot(X.T, delta1)
db1 = np.sum(delta1, axis=0, keepdims=True)

# Now update the weights
self.weight_I_H1 -= learning_rate * dW1
self.bias_1 -= learning_rate * db1
self.weights_H1_H2 -= learning_rate * db2
self.bias_2 -= learning_rate * db2
self.weights_H2_0 -= learning_rate * db3

def train(self, X_train, y_train, X_test, y_test, epochs = 200, batch_size = 32):

# Calulate the number of batches
num_batch = X_train.shape[0] // batch_size
```

```
print(f"Epoch : {i} -> Training Accuracy : {acc_train}, Testing Accuracy : {acc_test}")
train_acc.append(acc_train)
test_acc.append(acc_test)
return train_acc, test_acc

# Function to calculate the accuracy
def accuracy(self, y_pred, y):
    acc = np.mean(y_pred == np.argmax(y, axis=1))
    return acc

def predict(self, X, y):
    y_hat = self.forward(X)
    y_pred = np.argmax(y_hat, axis=1)
    acc = self.accuracy(y_pred, y)
    return acc
```

### ANN Specification 1

- No of hidden layers: 1
- No. of neurons in hidden layer: 32
- Activation function in the hidden layer: Sigmoid
- 3 neurons in the output layer.

 Activation function in the output layer: Softmax Activation Function in hidden layer: Sigmoid

```
# Sigmoid activation function
def sigmoid(self, y):
    return 1 / (1 + np.exp(-y))

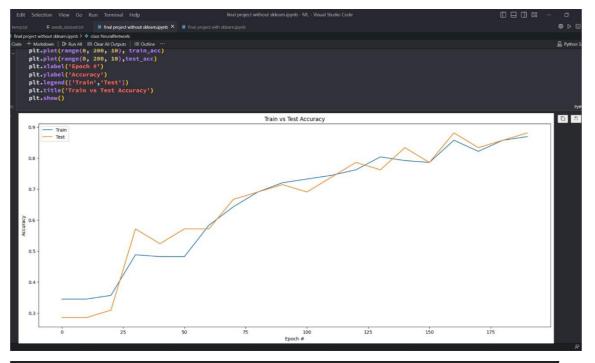
# Soft max activation function
def softmax(self, y):
    exp_y = np.exp(y)
    return exp_y / np.sum(exp_y, axis=1, keepdims=True)
```

- Optimisation algorithm: Mini Batch Stochastic Gradient Descent (SGD)
- Loss function: categorical cross-entropy loss

```
# Cross Entropy loss function
def cross_entropy_loss(self, y_true, y_pred):
    num_samples = y_true.shape[0]
    loss = -np.sum(y_true * np.log(y_pred)) / num_samples
    # print(loss)
    return loss
```

• Learning rate: 0.01

```
train_acc, test_acc = clf.train(X_train, y_train, X_test, y_test)
Epoch: 0 -> Training Accuracy: 0.34523809523809523, Testing Accuracy: 0.2857142857142857
Epoch: 10 -> Training Accuracy: 0.34523809523809523, Testing Accuracy: 0.2857142857142857
Epoch : 20 -> Training Accuracy : 0.35714285714285715, Testing Accuracy : 0.30952380952380953
Epoch: 30 -> Training Accuracy: 0.4880952380952381, Testing Accuracy: 0.5714285714285714
Epoch: 40 -> Training Accuracy: 0.48214285714285715, Testing Accuracy: 0.5238095238095238
Epoch : 50 -> Training Accuracy : 0.48214285714285715, Testing Accuracy : 0.5714285714285714
Epoch : 60 -> Training Accuracy : 0.58333333333334, Testing Accuracy : 0.5714285714285714
Epoch : 70 -> Training Accuracy : 0.6428571428571429, Testing Accuracy : 0.66666666666666
Epoch : 80 -> Training Accuracy : 0.6904761904761905, Testing Accuracy : 0.6904761904761905
Epoch : 90 -> Training Accuracy : 0.7202380952380952, Testing Accuracy : 0.7142857142857143
Epoch : 100 -> Training Accuracy : 0.7321428571428571, Testing Accuracy : 0.6904761904761905
Epoch: 110 -> Training Accuracy: 0.7440476190476191, Testing Accuracy: 0.7380952380952381
Epoch: 120 -> Training Accuracy: 0.7619047619047619, Testing Accuracy: 0.7857142857142857
Epoch: 130 -> Training Accuracy: 0.8035714285714286, Testing Accuracy: 0.7619047619047619
Epoch : 150 -> Training Accuracy : 0.7857142857142857, Testing Accuracy : 0.7857142857142857
Epoch: 160 -> Training Accuracy: 0.8571428571428571, Testing Accuracy: 0.8809523809523809
Epoch: 170 -> Training Accuracy: 0.8214285714285714, Testing Accuracy: 0.83333333333333333
Epoch: 180 -> Training Accuracy: 0.8571428571428571, Testing Accuracy: 0.8571428571428571
Epoch : 190 -> Training Accuracy : 0.8690476190476191, Testing Accuracy : 0.8809523809523809
   import matplotlib.pyplot as plt
  plt.rcParams["figure.figsize"]=(20,8)
plt.plot(range(0, 200, 10), train_acc)
   plt.plot(range(0, 200, 10),test_acc)
```



### 3. ANN Specification 2

- No of hidden layers: 2
- No. of neurons in the 1st hidden layer: 64
- No. of neurons in the 2nd hidden layer: 32
- 3 neurons in the output layer.

• Activation function in both the hidden layers: ReLU

```
# Relu activation function
def relu(self, y):
    return np.maximum(0, y)

def relu_der(self, y):
    y[y <= 0] = 0
    y[y > 0] = 1

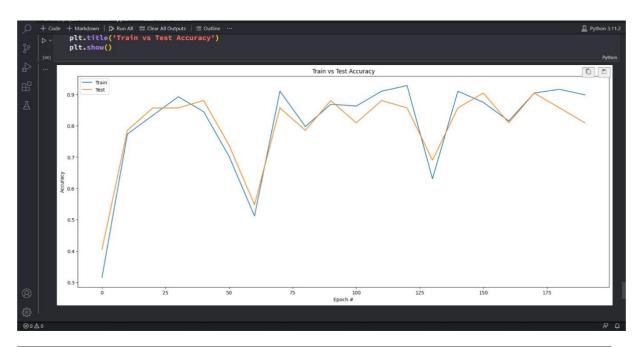
    return y
```

• Activation function in the output layer: Softmax

```
# Soft max activation function
def softmax(self, y):
    exp_y = np.exp(y)
    return exp_y / np.sum(exp_y, axis=1, keepdims=True)
```

- Optimisation algorithm: Mini Batch Stochastic Gradient Descent (SGD)
- Loss function: categorical cross-entropy loss
- Learning rate: 0.01
- No. of epochs = 200

```
train_acc, test_acc = clf.train(X_train, y_train, X_test, y_test)
Epoch : 0 -> Training Accuracy : 0.31547619047619047, Testing Accuracy : 0.40476190476190477
Epoch: 10 -> Training Accuracy: 0.7738095238095238, Testing Accuracy: 0.7857142857142857
Epoch : 20 -> Training Accuracy : 0.8333333333333333, Testing Accuracy : 0.8571428571428571
Epoch: 30 -> Training Accuracy: 0.8928571428571429, Testing Accuracy: 0.8571428571428571
Epoch : 40 -> Training Accuracy : 0.8452380952380952, Testing Accuracy : 0.8809523809523809
Epoch: 50 -> Training Accuracy: 0.7023809523809523, Testing Accuracy: 0.7380952380952381
Epoch: 60 -> Training Accuracy: 0.5119047619047619, Testing Accuracy: 0.5476190476190476
Epoch : 70 -> Training Accuracy : 0.9107142857142857, Testing Accuracy : 0.8571428571428571
Epoch: 80 -> Training Accuracy: 0.7976190476190477, Testing Accuracy: 0.7857142857142857
Epoch: 90 -> Training Accuracy: 0.8690476190476191, Testing Accuracy: 0.8809523809523809
Epoch : 100 -> Training Accuracy : 0.8630952380952381, Testing Accuracy : 0.8095238095238095
Epoch : 110 -> Training Accuracy : 0.9107142857142857, Testing Accuracy : 0.8809523809523809
Epoch : 120 -> Training Accuracy : 0.9285714285714286, Testing Accuracy : 0.8571428571428571
Epoch: 130 -> Training Accuracy: 0.6309523809523809, Testing Accuracy: 0.6904761904761905
Epoch: 140 -> Training Accuracy: 0.9107142857142857, Testing Accuracy: 0.8571428571428571
Epoch : 150 -> Training Accuracy : 0.875, Testing Accuracy : 0.9047619047619048
Epoch : 160 -> Training Accuracy : 0.8154761904761905, Testing Accuracy : 0.8095238095238095
Epoch: 170 -> Training Accuracy: 0.9047619047619048, Testing Accuracy: 0.9047619047619048
Epoch : 180 -> Training Accuracy : 0.91666666666666666666, Testing Accuracy : 0.8571428571428571
Epoch: 190 -> Training Accuracy: 0.8988095238095238, Testing Accuracy: 0.8095238095238095
```



## 4. Implementation with scikit learn

- 4a) Use the MLP implementation of scikit learn.
- 4b) Use the specifications from Part 2 and Part 3, and use the same training and test data.

#### STEPS:

- 1 We created a with MLPClassifier with 1 hidden layer and 32 neurons
- 2 Then, we trained the model and computed the accuracy of ANN specification 1 and 2, which was 85.71 and 66.67, respectively.

