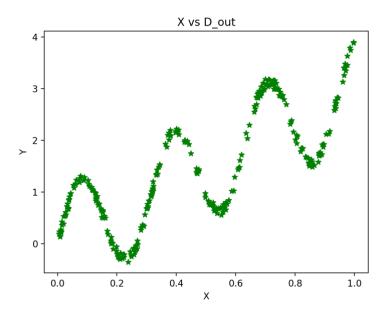
Name: Advait Pai Email: apai21@uic.edu

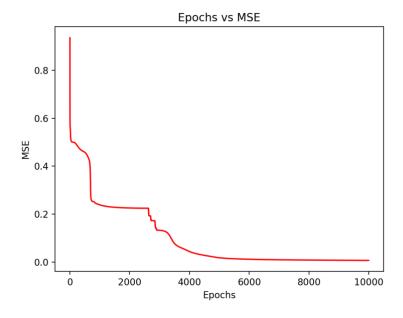
UIN: 677368201

Homework 4

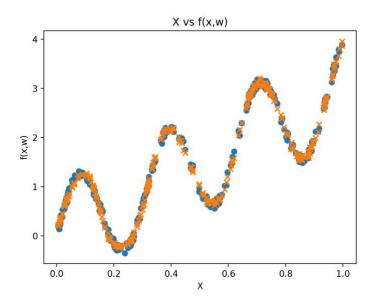
1. Graph of (xi, di)



2. Epoch vs MSE Graph



3. Fit to the curve



4. Final Results

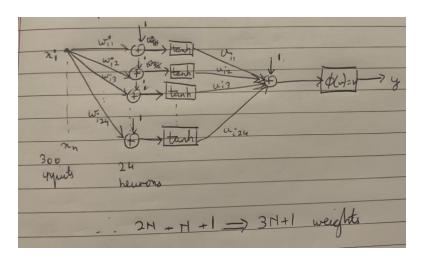
Epoch: 10000 Mean Squared Error: [0.00652244]

Algorithm:

1. Intiate values

```
X => 300 random numbers between [0,1]
V=> 300 random numbers between [-0.1,0.1]
Di => sin(20xi) + 3xi + vi, i = 1, ..., 300
W_list => 3N + 1 weights
Create a list W_list
Append array of 24 weights (for input layer)
Append array of 24 weights (for bias of neurons)
Append array of 24 weights (for output layer neurons
Append array of 1 weight (for output neuron bias)
```

2. Forward Propagation



Now we need to store two induced fields. The first induced field is for the inputs. Before the. Tanh boxes. The second induced field is of the output from the tanh functions into the output neuron. Once we have the second induced field, we can calculate the output y. A pseudo code is given below:

```
ind\_field\_list = [] \# Length \ of \ 2 \\ ind\_field\_list.append(np.dot(W\_list[0],1)+np.dot(W\_list[1],x)) \# Induced \ Field \ 1 \\ out\_tanh = np.tanh(ind\_field\_list[0]) \\ ind\_field\_list.append(out\_tanh) \# Output \ Layer \ 1 == Inputs \ for \ Output \ Layer \\ \# Hidden \ Layer -> Output \ Layer \\ output = 1*W\_list[3] \# Initialising \ output \ neuron \ using \ the \ weight \ of \ bias \ since \ bias == 1 \\ output=output+(np.dot(out\_tanh,W\_list[2])) \\ return \ ind\_field\_list,output
```

Here:

W[0] => Bias Weights for input layer

W[1] => Weights for Inputs

W[2]=> Weights for induced field after applying tanh activation

W[3]=> Bias Weight for output layer

x => input

Now we return the induced_field_list and the output. The induced field list will be used to calculate the backward propagation weight update and the output will be used for weight update and MSE calculations.

3. Backward Propagation

The generalised weight update for backpropagation is given as:

```
W \leftarrow W - learning rate * dE/dw
```

And

dE/dw = - (the signal before multiplication by w in the feedforward network) \times (the signal before dw multiplication by w in the feedback network)

Here is the pseudo-code to do the backpropagation step.

```
#Calculating de/dw

update_w3 = np.array((-1*1*(d-y))) # Output Layer Bias Weight Update

update_w2 = -1*((d-y)*(ind_fields[1])) # Output Layer Weights Update

update_w1 = -1*(der_tanh(ind_fields[0]))*(x)*(d-y)*W_list[2] #*ind_fields[1] # Input

Layer Weights Update

update_w0 = -1*(der_tanh(ind_fields[0]))*(1)*W_list[2]*(d-y)#*ind_fields[1] # Input Layer

Bias Weight Update

#Update Step

W_list[0] = W_list[0] - lr*(update_w0) # Input Bias

W_list[1] = W_list[1] - lr*(update_w1) # Input Weights

W_list[2] = W_list[2] - lr*(update_w2) # Hidden Layer Weights

W_list[3] = W_list[3] - lr*(update_w3) # Output Neuron Bias
```

Here we return the weights for the next input.

Return W list

- 4. Now we keep repeating this step for all values of x
- 5. We then calculate the MSE for all the outputs
- 6. With this one epoch is completed, now we keep doing steps 1 to 5 i.e. more epochs till we either reduce the MSE or we complete a set number of epochs.
- 7. Once 6 is complete, we plot the result we get f(x,y) and plot it against the original f(x,d) to see if the curve is a good fit

Code:

```
def calc_di(x,v):
        return np.\sin(20^*x) + (3^*x) + v
def der_tanh(val):
def der_output(val):
def create_weights(N):
        for n in N:
def forward_propagation(x,W_list):
        ind_field_list.append(np.dot(W_list[0],1)+np.dot(W_list[1],x)) # Induced Field 1
        out_tanh = np.tanh(ind_field_list[0])
        output = 1*W_list[3]# Initialising output neuron using the weight of bias since bias == 1
        output=output+(np.dot(out_tanh,W_list[2]))
        return ind field list, output
def backward_propogation(d,y,x,ind_fields,lr,W_list):
        update_w3 = np.array((-1*1*(d-y))) # Output Layer Bias Weight Update
        update_w2 = -1*((d-y)*(ind_fields[1])) # Output Layer Weights Update
        update\_w1 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w1 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(x)*(d-y)*(d-y)*W\_list[2] \\ \#'ind\_fields[1] \# Input Layer Weights Update \\ Update\_w2 = -1*(der\_tanh(ind\_fields[0]))*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-y)*(d-
        update\_w0 = -1*(der\_tanh(ind\_fields[0]))*(1)*W\_list[2]*(d-y)\#*ind\_fields[1] \# Input Layer Bias Weight Update
        W_list[0] = W_list[0] - Ir*(update_w0) # Input Bias
```

```
W_list[1] = W_list[1] - Ir*(update_w1) # Input Weights
  W_list[2] = W_list[2] - Ir*(update_w2) # Hidden Layer Weights
  W_list[3] = W_list[3] - Ir*(update_w3) # Output Neuron Bias
  return W_list
def main_algo(X,w,lr):
  for i in range(0,len(X)):
     ind_fields,y = forward_propagation(X[i],w_current)
     mse+=((D[i]-y)**2)
     w_update = backward_propogation(D[i],Y[i],X[i],ind_fields,lr,w_current)
  mse = mse/len(X)
  print("Mean Squared Error: ",mse)
N = [24,24,24,1] # 3N + 1 weights
D = [calc_di(X[i],V[i]) \text{ for } i \text{ in } range(len(X))]
plt.title("X vs D_out")
plt.ylabel("Y")
plt.scatter(X,D, marker='*',label='X',color ="green")
init_w,init_mse,Y_final = main_algo(X,W_list,lr_st)
```

```
mse_list = [init_mse]
while epoch < 10000:
  print("Epoch:",(epoch+1))
  init_w,init_mse,Y_final = main_algo(X,init_w,lr_st)
    print("MSE Limit Reached")
plt.xlabel("X")
plt.ylabel("f(x,w)")
plt.scatter(X,D,marker='o')
plt.scatter(X, Y_final,marker='x')
plt.show()
# Plotting Epochs vs MSE
plt.title("Epochs vs MSE")
plt.xlabel("Epochs")
plt.ylabel("MSE")
plt.plot([i for i in range(epoch+1)],mse_list,color="red")
plt.show()
```