

Backpropagation algorithm

Back-propagation algorithm, Summary



Initialize the weights to small random values.

repeat

- for each training example $\langle (x_1, \dots, x_n), t \rangle$ Do
 - Input the instance (x_1, \dots, x_n) to the network and compute the outputs from each layer in the network : **(forward step)**
 - For output layer: $y_k = F(v_k)$, since $v_k = \sum w_{kh} y_h$
 - For hidden layer: $y_h = \Phi(v_h)$, since $v_h = \sum w_{hi} x_i$
 - Compute the errors signal δ_j in the output layer and propagate them to the hidden layer **(backward step)**:
 - For each output unit k
$$\delta_k = (t_k - y_k) F'(v_k),$$
 - For each hidden unit h
$$\delta_h = \Phi'(v_h) \sum_k w_{kh} \delta_k$$
 - Update the weights in both layers according to: **(forward step)**
$$\Delta w_{kh} = \eta \delta_k y_h, \quad \Delta w_{hi} = \eta \delta_h x_i$$

□ end for loop

until overall error E becomes acceptably low

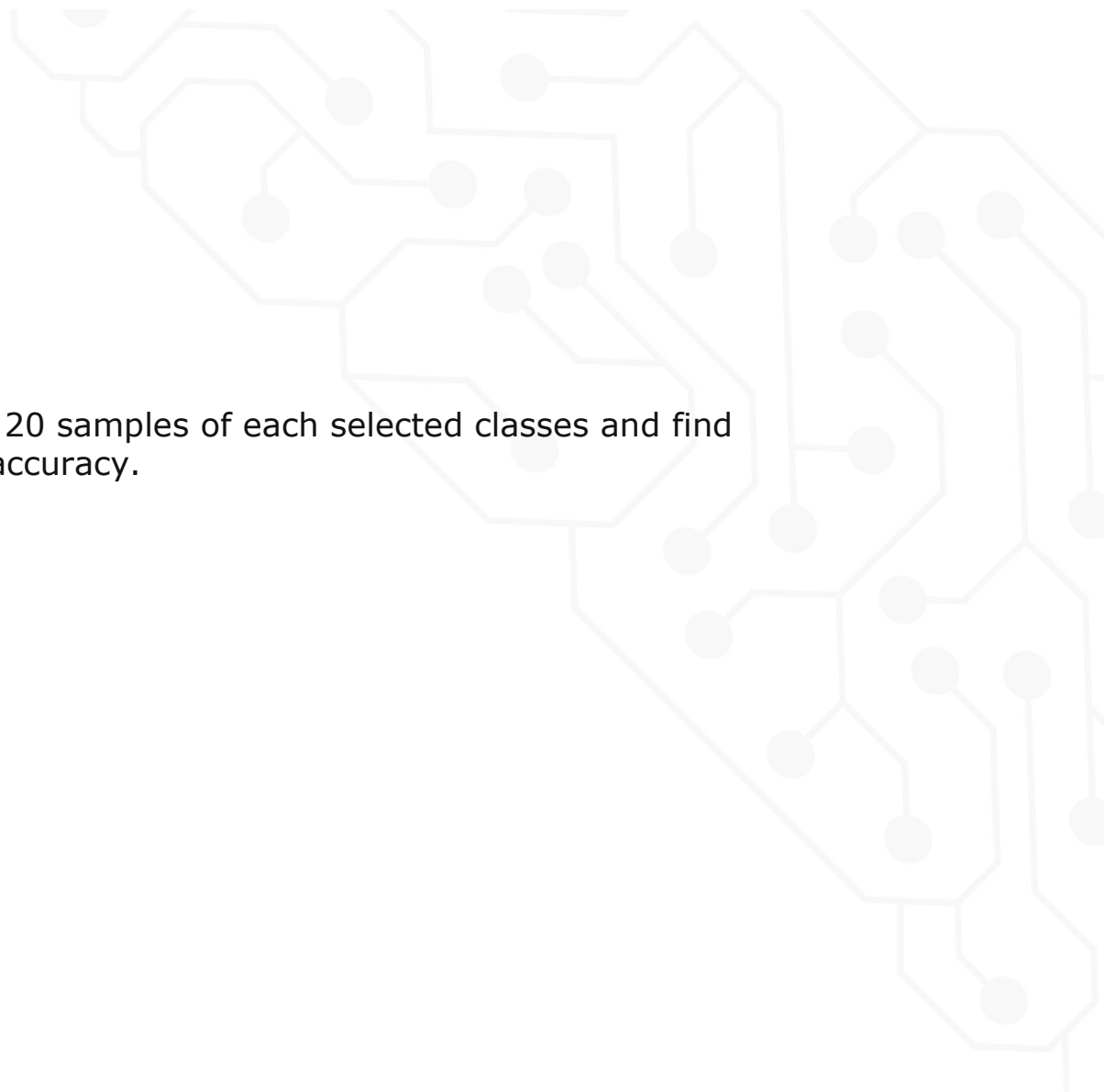
Task2 description

1. Implement the **Back-Propagation learning algorithm** on a multi-layer neural networks, which can be able to classify a stream of input data to one of a set of predefined classes.
- Use the dry beans data in both your training and testing processes. (Each class has 50 samples: train NN with the first 30 non-repeated samples, and test it with the remaining 20 samples)

Task2 description

2. After training

- Test the classifier with the remaining 20 samples of each selected classes and find confusion matrix and compute overall accuracy.



Task2 description

1. User Input:

- Enter number of hidden layers
- Enter number of neurons in each hidden layer
- Enter learning rate (η)
- Enter number of epochs (m)
- Add bias or not (Checkbox)
- Choose to use Sigmoid or Hyperbolic Tangent sigmoid as the activation function

2. Initialization:

- Number of features = 5
- Number of classes = 3
- Weights + Bias = small random numbers

3. Classification:

- Sample (single sample to be classified).

Task2 description

4. Workflow:

➤ Training Phase: (repeat the following m epochs)

Assuming that we have n training samples $\{sample_i: i = 1 \rightarrow n\}$




- Fetch features (x) of $sample_i$, and its desired output (d)
- **Forward step** for input signal from input layer towards output layer
 1. Calculate the net value (v) of each neuron,
 2. Calculate the output of each neuron using the selected activation function,
- **Backward step** for error signal from output layer towards input layer
Calculate error in each neuron
- **Update the weights**
 $new\ weights = old\ weights + eta * error * input$

Task2 description

4. Workflow:

➤ Testing Phase:

1. Given a sample x
2. **Forward step for input signal from input layer towards output layer**
 - a. Calculate the net value (v) of each neuron,
 - b. Calculate the output of each neuron using the selected activation function,
3. Reaching the output layer, calculate the actual output of each neuron. Set the maximum actual output to 1 and the other outputs to 0. (i.e. assign the sample x to the output neuron with the maximum actual output)
4. **Output: y** (Class ID).

Output Layer	Class1	Class2	Class3
	1	0	0
	0	1	0
	0	0	1

- ### ➤ Evaluation:
- build the confusion matrix and overall accuracy.

Task2 description

- Submit a report with your code. This report contains (with screenshots) the best accuracy you obtained using each activation function and what parameters were used for these results
- Example:

Activation Function	Train Accuracy	Test Accuracy	LR	Epochs	#Layers	#HiddenNodes
Sigmoid	70	50	0.01	1000	2	3,4
Tanh	60	40	0.001	5000	1	5