

Multi-Layer Perceptron

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Outline

- Introduction
- Architecture & It's Implementation
- Learning Process & It's Implementation
- Training Set/Data Set
- Questions/Answers

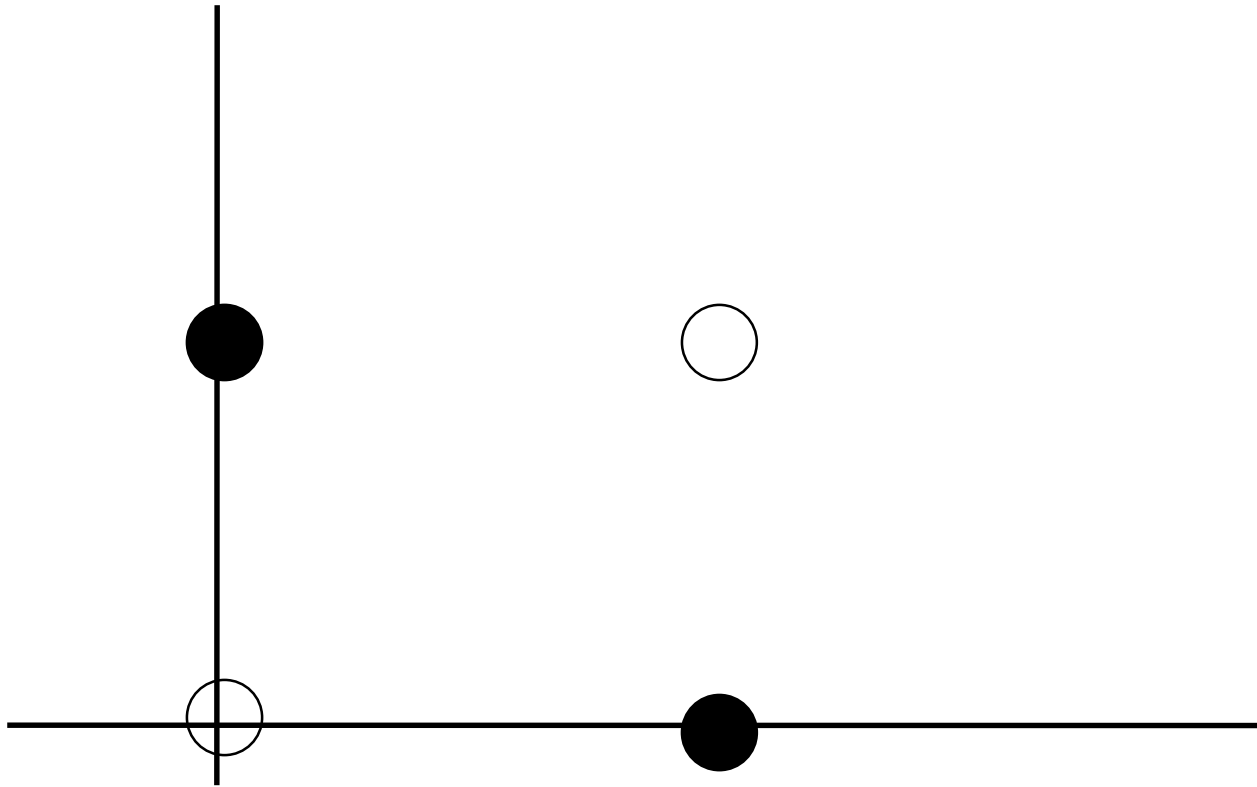
Introduction

- **Limitations in Perceptron:**

- 1) Can't solve X-OR Problems
- 2) Can't solve Non-Linearly Separable Problems

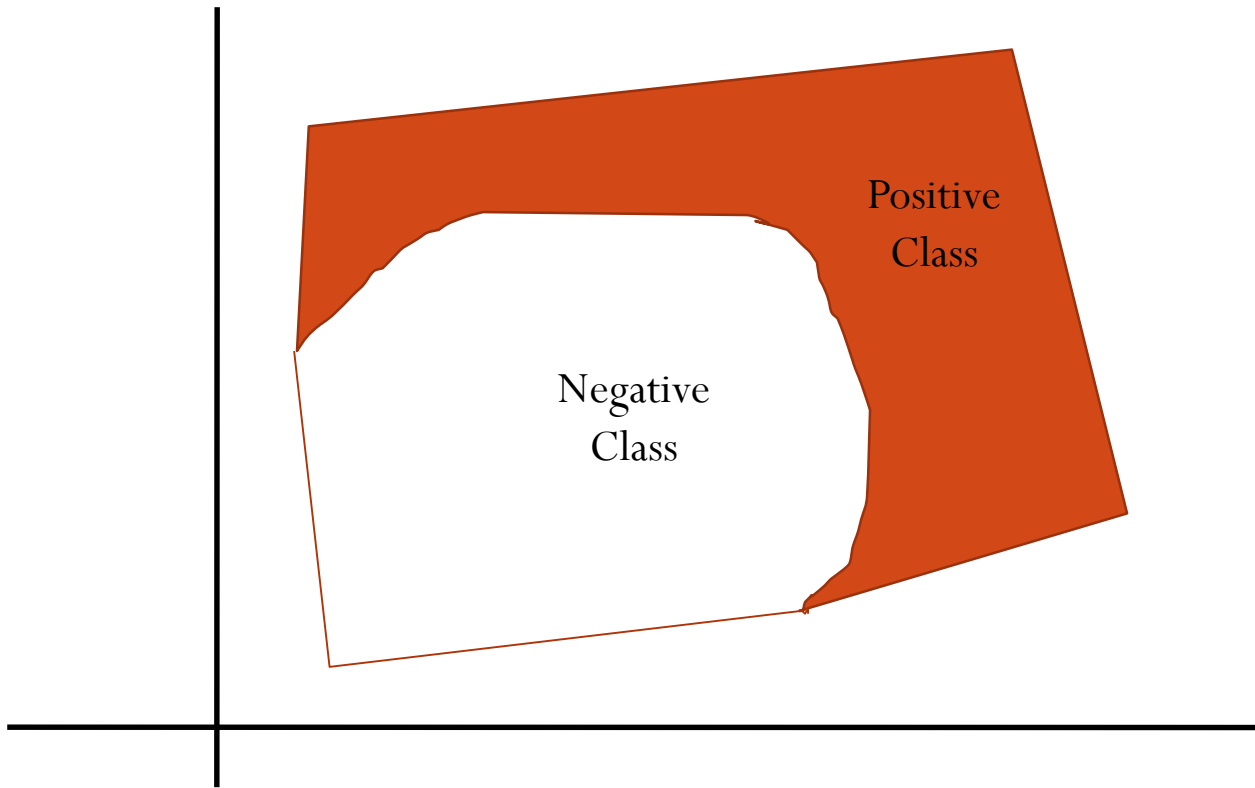
Introduction

- XOR Problem



Introduction

- Nonlinear Separable Problem

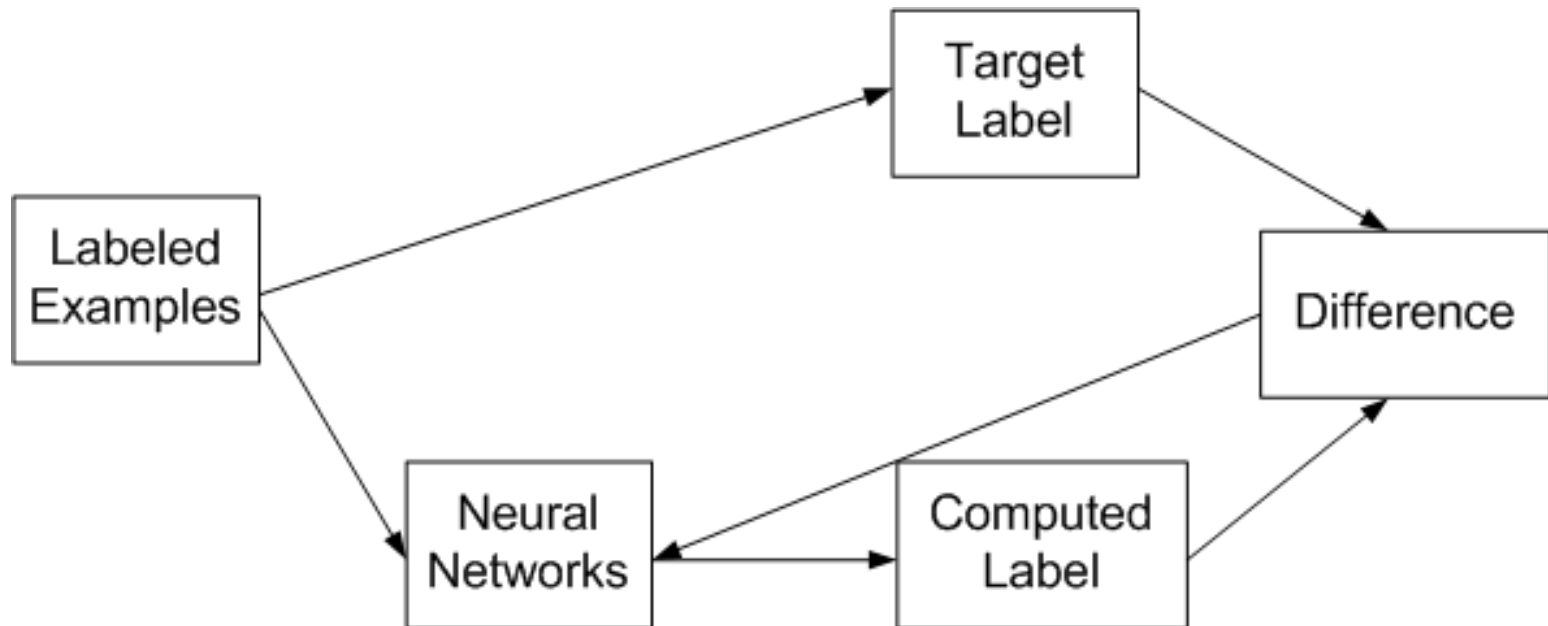


Motivations:

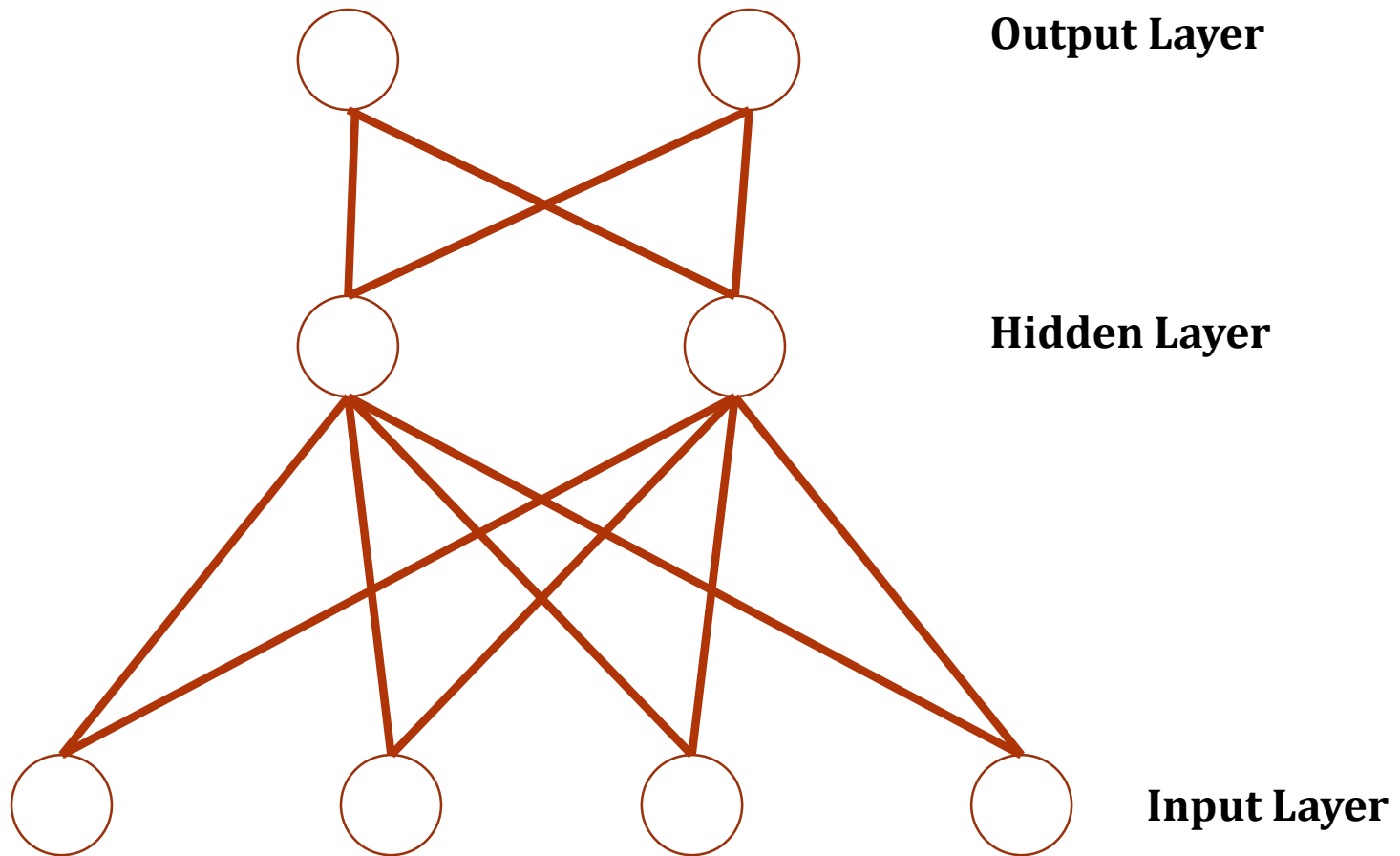
- 1) Addition of intermediate layer called hidden layer
- 1) Solvable even to Nonlinear Separable

Introduction: Multilayer Perceptron

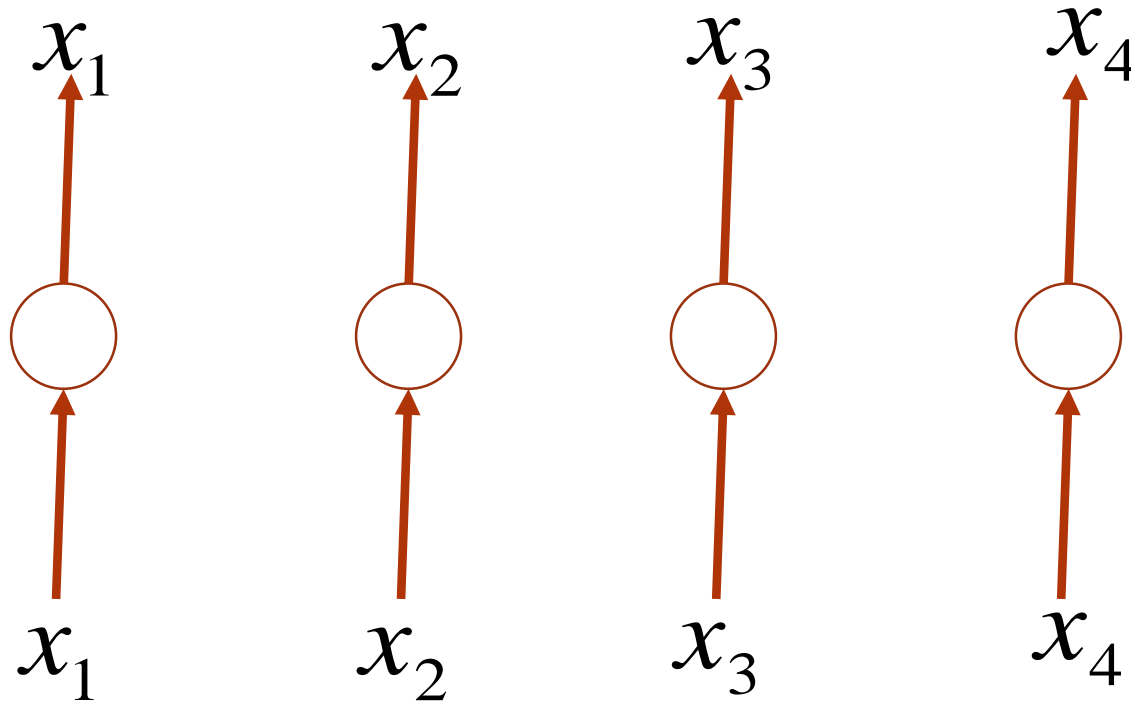
- Supervised Neural Networks



Architecture



Architecture: Input Node



Implementation : Input Layer

```
15     public class InputLayer implements Layer{
16         int dinput;
17         NeuralVector inputLayerValues;
18     public InputLayer(int inputLength){
19         //         inputNodes = nodes;
20             dinput=inputLength;
21     }
22
23     @Override
24     public void setInputNodesValues(NeuralVector inputVector) {
25         inputLayerValues = inputVector;
26     }
27
28     public NeuralVector getOutputValuesOfLayer() {
29         return inputLayerValues;
30     }
31
32 }
33
```

Implementation : Input Node

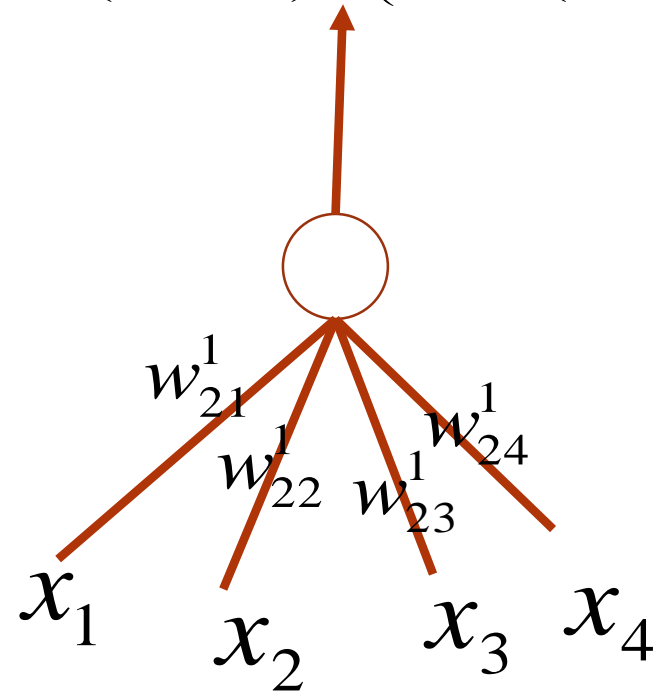
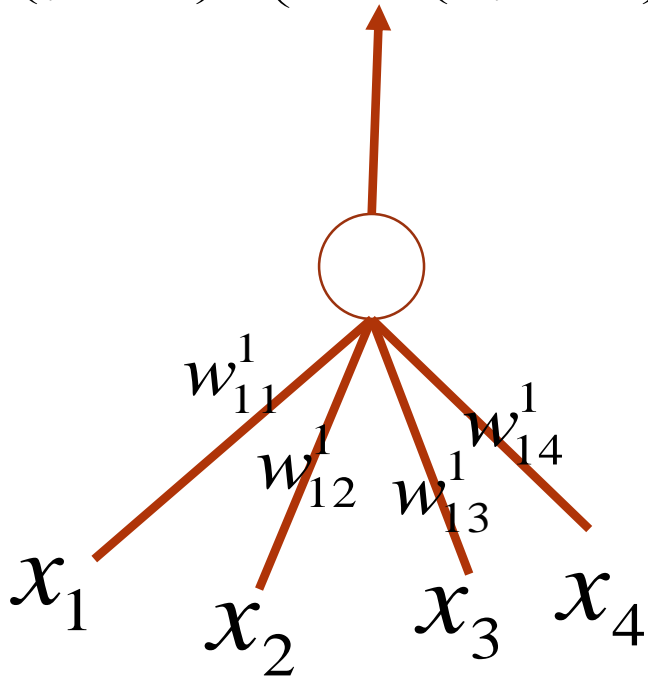
```
public void setValues(List<Double> value) {  
    input = (Vector) value ;  
}
```

```
@Override  
public List<Double> getValues() {  
    return input;  
}
```

```
@Override  
public double get(int i) {  
    return input.elementAt(i);  
}
```

Architecture: Hidden Node

$$h_1 = f\left(\sum_{i=1}^4 x_i w_{1i}^1\right) = \left(1 + \exp\left(-\sum_{i=1}^4 x_i w_{1i}^1\right)\right)^{-1} \quad h_2 = f\left(\sum_{i=1}^4 x_i w_{2i}^1\right) = \left(1 + \exp\left(-\sum_{i=1}^4 x_i w_{2i}^1\right)\right)^{-1}$$



Implementation :

Hidden Layer

```
16 public class HiddenLayer implements Layer {
17
18     List<HiddenNode> hiddenNodes;
19     InputLayer inputValues;
20     int dinput;
21     double learningRate;
22
23     int mhidden;
24
25     public HiddenLayer(int numberOfHiddenNodes, int inputLength, double hiddenLayerLearningRate, InputLayer inputLayerValue
26         dinput = inputLength;
27         inputValues = inputLayerValue;
28         learningRate = hiddenLayerLearningRate;
29         hiddenNodes = new Vector<HiddenNode>();
30         mhidden = numberOfHiddenNodes;
31
32         //      inputNodes=inputnodes;
33     }
```

Implementation :

Hidden Layer

```
34
35 public void initilize() {
36
37     for (int j = 0; j < mhidden; j++) {
38         for (int i = 0; i < dinput; i++) {
39             Random r = new Random();
40             MultiLayerPerceptron.hiddenLayerWeights[j][i] = ((r.nextDouble() * (-0.1)) + 0.1);
41         }
42     }
43
44     for (int i = 0; i < mhidden; i++) {
45         hiddenNodes.add(new HiddenNode(dinput, mhidden, this));
46     }
47
48
49
50
51
52
53
54
55
56
57 @Override
58 public NeuralVector getOutputValuesOfLayer() {
59     InputVector vectorFromInputLayer = (InputVector) inputValues.getOutputValuesOfLayer();
60     int nodeIndex = 0;
61     double[] hiddenLayerOutput = new double[mhidden];
62     for (HiddenNode hiddenNode : hiddenNodes) {
63         hiddenNode.calculateNetInput(vectorFromInputLayer, nodeIndex);
64         hiddenLayerOutput[nodeIndex] = hiddenNode.getOutput();
65         nodeIndex++;
66     }
67     return new HiddenLayerVector(hiddenLayerOutput);
68 }
69
70
71
72
73
74
75
76
77
78
79 }
80
81 }
82
```

Implementation :

Hidden Node

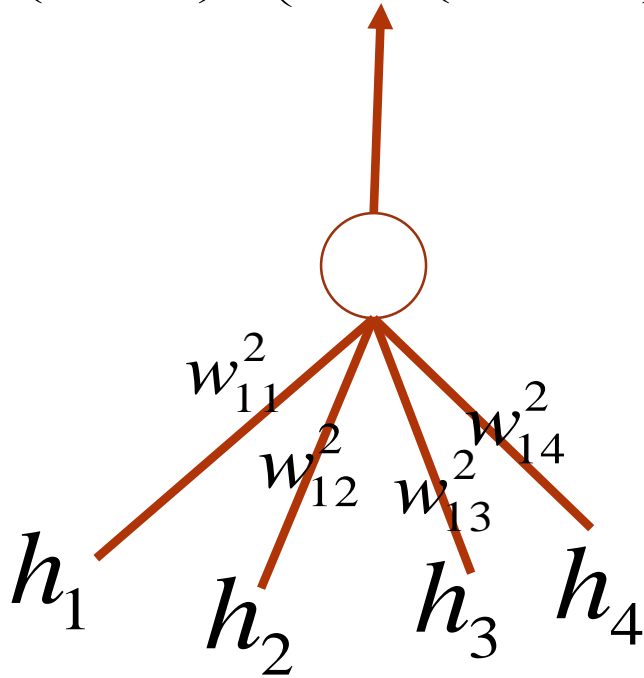
```
@Override
void calculateNetInput(NeuralVector input, int nodeSubscript) {
    netInput = 0;
    for (int i = 0; i < inputLayerSize; i++) {
        netInput += (input.get(i) * MultiLayerPerceptron.hiddenLayerWeights[nodeSubscript][i]);
    }
}

@Override
public double getOutput() {
    outPutOfCurrentNode = (1 / (1 + Math.exp(-(netInput))));
    return outPutOfCurrentNode;
}
```

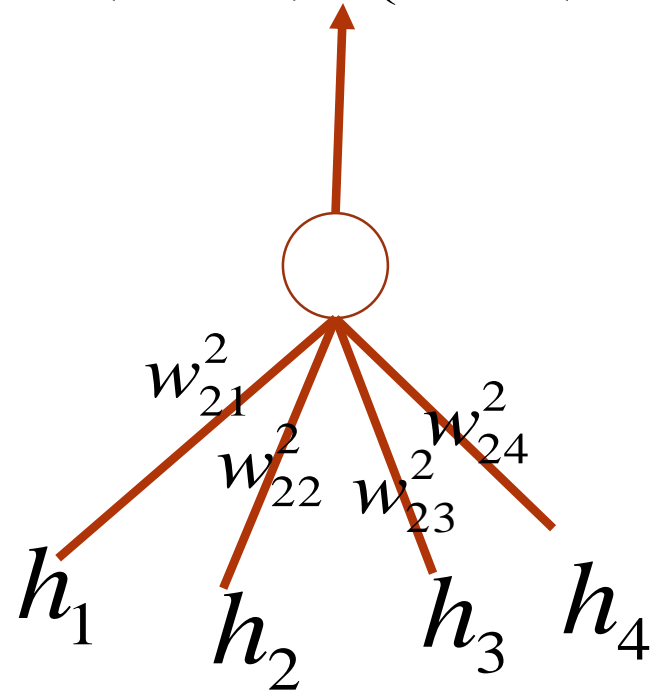
Architecture:

Output Node

$$o_1 = f\left(\sum_{i=1}^4 h_i w_{1i}^2\right) = \left(1 + \exp\left(-\sum_{i=1}^4 h_i w_{1i}^2\right)\right)^{-1}$$



$$o_2 = f\left(\sum_{i=1}^4 h_i w_{2i}^2\right) = \left(1 + \exp\left(-\sum_{i=1}^4 h_i w_{2i}^2\right)\right)^{-1}$$



Architecture: Output Layer

```
16 public class OutputLayer extends LearnableLayer {
17
18     List<OutputNode> outputNodes;
19     HiddenLayer hiddenLayer;
20     int mhidden;
21     int coutput;
22     //double[][] weights;
23     double learningRate;
24
25     public OutputLayer(int outputLength, int hiddenLength, double hiddenLayerLearningRate, HiddenLayer hiddenLayerValue)
26     {
27         mhidden = hiddenLength;
28         coutput = outputLength;
29         hiddenLayer = hiddenLayerValue;
30         learningRate = hiddenLayerLearningRate;
31         outputNodes = new Vector<OutputNode>();
32     }
33 }
```

Architecture: Output Layer

```
34 public void initialize() {
35
36
37     for (int j = 0; j < coutput; j++) {
38         for (int i = 0; i < mhidden; i++) {
39             Random r = new Random();
40             MultiLayerPerceptron.outputLayerWeight[j][i] = ((r.nextDouble() * (-0.1)) + 0.1);
41         }
42     }
43
44     for (int i = 0; i < coutput; i++) {
45         outputNodes.add(new OutputNode(/*hiddenLayerValue,*/mhidden, coutput, this,0.52));
46     }
47 }
48
49 @Override
50 public NeuralVector getOutputValuesOfLayer() {
51     HiddenLayerVector vectorFromHiddenLayer = (HiddenLayerVector) hiddenLayer.getOutputValuesOfLayer();
52     int nodeIndex = 0;
53     double[] finalOutput = new double[coutput];
54     for (OutputNode outputNode : outputNodes) {
55         outputNode.calculateNetInput(vectorFromHiddenLayer, nodeIndex);
56         finalOutput[nodeIndex] = outputNode.getActivationFunctionOutput();
57         nodeIndex++;
58     }
59     return new OutputVector(finalOutput);
60 }
```

Implementation :

Output Node

```
@Override
void calculateNetInput(NeuralVector input, int nodeSubscript) {
    netInput = 0;
    for (int i = 0; i < hiddenLayerSize; i++) {
        netInput += (input.get(i) * MultiLayerPerceptron.outputLayerWeight[nodeSubscript][i]);
    }
}
```

```
public double getActivationFunctionOutput(){

    activationFunctionOutput = (1 / (1 + Math.exp(-(netInput))));
    System.out.println("Finaloutput: " +outputOfCurrentNode+"Bias"+bias );
    return activationFunctionOutput;
}
```

Learning Rule: Back Propagation

- Update weight between output and hidden

$$E = \frac{1}{2} \sum_{k=1}^c (t_k - o_k)^2 \quad o_j = \left[1 + \exp(-net_j^o) \right]^{-1} \quad net_j^o = \sum_{k=1}^m h_k w_{jk}^2$$

$$\frac{\partial E}{\partial w_{ji}^2} = \frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial net_j^o} \frac{\partial net_j^o}{\partial w_{ji}^2}$$

$$\frac{\partial o_j}{\partial net_j^o} = \left[\left(1 + \exp(-net_j^o) \right)^{-1} \right]' = o_j(1 - o_j)$$

$$\frac{\partial E}{\partial o_j} = -(t_j - o_j) \quad \frac{\partial net_j^o}{\partial w_{ji}^2} = h_i$$

$$w_{ji}^2 = w_{ji}^2 + \eta(t_j - o_j)o_j(1 - o_j)h_i$$

Implementation : Learning Rule: Back Propagation

- Update weight between output and hidden

```
void learn(double expectedValue, int nodeSubscript, NeuralVector hiddenLayerOutput) {  
    getOutput();  
    for (int i = 0; i < hiddenLayerSize; i++) {  
        MultiLayerPerceptron.outputLayerWeight[nodeSubscript][i] += outputLayer.learningRate * (expectedValue  
- activationFunctionOutput) * activationFunctionOutput * (1 - activationFunctionOutput) * hiddenLayerOutput.get(i);  
    }  
}
```

Learning Rule: Back Propagation

- Update weight between hidden and input

$$\frac{\partial E}{\partial w_{ji}^1} = \sum_{k=1}^c \frac{\partial E}{\partial o_k} \frac{\partial o_k}{\partial net_k^o} \frac{\partial net_k^o}{\partial h_j} \frac{\partial h_j}{\partial net_j^h} \frac{\partial net_j^h}{\partial w_{ji}^1}$$

$$h_j = \left[1 + \exp(-net_j^h) \right]^{-1} \quad net_j^h = \sum_{i=1}^d x_i w_{ji}^1$$

$$\frac{\partial E}{\partial o_k} = -(t_k - o_k) \quad \frac{\partial o_k}{\partial net_k^o} = o_k (1 - o_k)$$

$$\sum_{k=1}^c \frac{\partial net_k^o}{\partial h_j} = \sum_{k=1}^c w_{kj}^2 \quad \frac{\partial h_j}{\partial net_j^h} = (1 - h_j) h_j \quad \frac{\partial net_i^h}{\partial w_{ji}^1} = x_i$$

$$w_{ji}^1 = w_{ji}^1 + \eta \sum_{k=1}^c (t_k - o_k) o_k (1 - o_k) w_{kj}^2 (1 - h_j) h_j x_i$$

Implementation : Learning Rule: Back Propagation

- Update weight between hidden and input

```
void learn(double[] expectedOutputValues, OutputVector outputValues, NeuralVector input, int nodeSubscript) {
    getOutput();
    for (int i = 0; i < inputLayerSize; i++) {
        double multipleOfLearningRate = 0;
        //Why no increment in output index?
        for(int outputIndex = expectedOutputValues.length - outputValues.length();
            outputIndex < expectedOutputValues.length; outputIndex++){//How we separate the target value ?
            int c=outputIndex-inputLayerSize;
            double outputValue = outputValues.get(c);//We don't iterating output?

            double expectedVale = expectedOutputValues[outputIndex];
            //System.out.println("c Index:"+c+"output Index:"+outputIndex );
            multipleOfLearningRate += (expectedVale - outputValue) * outputValue * (1 - outputValue) *
MultiLayerPerceptron.outputLayerWeight[c][nodeSubscript] * (1 - outPutOfCurrentNode)*outPutOfCurrentNode * input.get (i);
        }
    }
}
```

Learning Rule: Back Propagation

- Interactive Learning

Input: Training Examples

$$E = \sum_{i=1}^c (t_i - o_i)^2$$

Initialize Weights at Random

Iterate T times

```
for each training example{  
    compute values of hidden nodes  
    compute value of output nodes  
    compute average error  
    update weights between output and hidden  
    update weights between hidden and input  
}
```

Output: Optimized Weights

Implementation : Learning Rule Back Propagation

- Interactive Learning

```
public void train(ArrayList<double[]> trainingExamples, int trainingIterations) throws Exception {  
    if (trainingExamples.size() < 1) {  
        throw new Exception("training examples must have some values.");  
    }  
    if (trainingExamples.get(0).length != numberOfInputNodes + numberOfOutputNodes) {  
        throw new Exception("Length of training Example is not consistent with dimensions of MLP.");  
    }  
    //why this running for 1 time  
    for (int i = 0; i < trainingIterations; i++) { //How many time inner loop will this run?29  
        for (int j = 0; j < trainingExamples.size(); j++) {  
            InputVector iv = new InputVector(trainingExamples.get(j), numberOfInputNodes);  
            iv.printScreen();  
            inputLayer.setInputNodesValues(iv);  
            OutputVector ov = (OutputVector) outputLayer.getOutputValuesOfLayer();  
            outputLayer.learn(trainingExamples.get(j));  
            hiddenLayer.learn(trainingExamples.get(j), ov);  
            ov.printScreen();  
        }  
    }  
}
```





Training Data Set

```
1 traningExamples.add(new double[]{68, 29, 82, 0, 1, 0});
2 traningExamples.add(new double[]{43, 34, 42, 1, 0, 0});
3 traningExamples.add(new double[]{8, 91, 37, 0, 1, 1});
4 traningExamples.add(new double[]{71, 16, 95, 1, 0, 1});
5 traningExamples.add(new double[]{91, 15, 49, 1, 1, 1});
6 traningExamples.add(new double[]{26, 44, 24, 0, 0, 0});
7 traningExamples.add(new double[]{71, 94, 22, 1, 0, 0});
8 traningExamples.add(new double[]{74, 45, 64, 0, 1, 0});
9 traningExamples.add(new double[]{89, 37, 77, 1, 1, 1});
10 traningExamples.add(new double[]{69, 76, 53, 1, 0, 1});
```

```
1 traningExamples.add(new double[]{1,0 , 1});
2 traningExamples.add(new double[]{1,1 , 0});
3 traningExamples.add(new double[]{0,0 , 0});
4 traningExamples.add(new double[]{0,1 , 1});
5 traningExamples.add(new double[]{1,1 , 0});
6 traningExamples.add(new double[]{1,0 , 1});
7 traningExamples.add(new double[]{1,1 , 0});
8 traningExamples.add(new double[]{0,0 , 0});
9 traningExamples.add(new double[]{1,0 , 1});
10 traningExamples.add(new double[]{0,1 , 1});
```

```
24 traningExamples.add(new double[]{96, 95, -3, 1, 0, 0});
25 traningExamples.add(new double[]{102, 102, 3, 1, 0, 0});
26 traningExamples.add(new double[]{101, 100, -4, 1, 0, 0});
27 traningExamples.add(new double[]{97, 99, 2, 1, 0, 0});
28 traningExamples.add(new double[]{102, 96, -2, 1, 0, 0});
29 traningExamples.add(new double[]{3, 97, 105, 0, 1, 0});
30 🧠 traningExamples.add(new double[]{-5, 99, 97, 0, 1, 0});
31 traningExamples.add(new double[]{5, 105, 102, 0, 1, 0});
32 traningExamples.add(new double[]{0, 96, 101, 0, 1, 0});
33 traningExamples.add(new double[]{5, 101, 103, 0, 1, 0});
34 traningExamples.add(new double[]{0, 103, 98, 0, 1, 0});
35 traningExamples.add(new double[]{-1, 99, 95, 0, 1, 0});
36 traningExamples.add(new double[]{-4, 98, 96, 0, 1, 0});
```

Output Results:

Usages	Output - MLPClass (run) X
	output: 0.6839953832380323 0.3642024538651048 0.40010949319260186 input: 3.0 97.0 105.0
	output: 0.7057351234625642 0.33543245687028955 0.3660777840132758 input: -5.0 99.0 97.0
	output: 0.6581158773973538 0.3866311980137963 0.3370429308216462 input: 5.0 105.0 102.0
	output: 0.6065452744694959 0.4394678223552267 0.312281905431864 input: 0.0 96.0 101.0
	output: 0.5537139396911628 0.49094971515415603 0.2910963364126225 input: 5.0 101.0 103.0
	output: 0.5026116961376481 0.5385786839989182 0.27285714120695836 input: 0.0 103.0 98.0
	output: 0.4556111860254098 0.580937017863102 0.2570472789667228 input: -1.0 99.0 95.0
	output: 0.4139827115667947 0.6176641112638019 0.24323998286531912 input: -4.0 98.0 96.0
	output: 0.3779717638921623 0.6490972937388158 0.23109268716330417 input: 0.0 101.0 104.0
	output: 0.34717813780057244 0.6758940809817994 0.22032728310736738 input: 5.0 103.0 104.0
	output: 0.3209310531145426 0.6987737494083545 0.21072913641661511 input: -5.0 4.0 4.0
	output: 0.38618361104279814 0.6248748264376521 0.3206502693886243 input: 1.0 4.0 2.0
	output: 0.3656514870912087 0.618115878875692 0.3229143470810782 input: 0.0 -4.0 2.0
	output: 0.3795826670930059 0.5843807957618913 0.36554329913143646 input: -5.0 -5.0 1.0
	output: 0.40441740636236184 0.5537517723981625 0.4082931377424167 input: -5.0 -2.0 1.0
	output: 0.3945788979035574 0.5487902244378303 0.41128832012429584 input: 1.0 2.0 -1.0
	output: 0.34680598931904877 0.5571782741568988 0.38754313000128393 BUILD SUCCESSFUL (total time: 0 seconds)

Result

- Can be used as supervised network, or for classification.

Questions?

