

Lab 6 – Classification & Prediction #2
Data Mining, Spring 2017

- Remember the deadline: Monday April 17th
- Feel free to use today's lab on the assignment
- Also feel free to ask questions
 - Either now at the lab
 - On the Q&A forum on learnIT
 - Or via email: malw@itu.dk / dafr@itu.dk (email both of us)

Today's Lab: Neural Networks and Backpropagation

Classification & Prediction #2

- Today you will create a digital brain capable of learning!
- Two options
 - A perceptron
 - Neural network with backpropagation (advanced, but well explained in the book)



Overview of the two approaches

Perceptron

- One of the simplest neural networks
- Binary input/output
- Topology:
 - One node which is fed variable amount of inputs, and produces a single output
- Activation function = step function
- Best for two class label problems
- Ignored by the book
 - Info available at: <https://en.wikipedia.org/wiki/Perceptron>

$$f(x) = \begin{cases} 1 & \text{if } \sum(\text{weight} \cdot \text{input}) + \text{bias} > 0 \\ 0 & \text{otherwise} \end{cases}$$

Overview of the two approaches

Neural Network with Backpropagation

- Advanced neural network
- More topology choices decided by you
 - Input/output
 - Number of nodes
 - Activation function
- Can be used in many different scenarios
- Detailed walkthrough of the algorithm in the book, chapter 9.2

Plan of attack

Perceptron

- Implement necessary data structures to build the perceptron
- Construct your perceptron
 - Try first with two inputs
 - Then implement weight updating
 - Example with results available in help slides

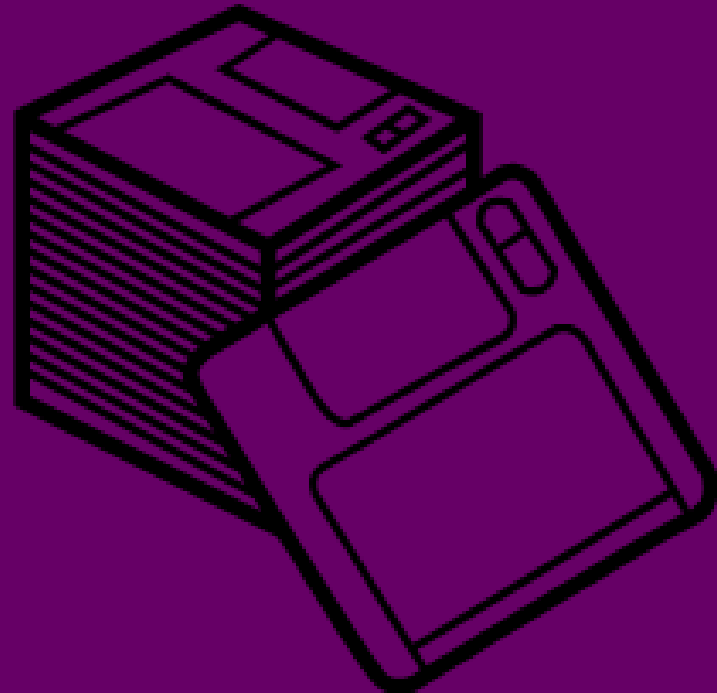
Plan of attack

Neural Network with Backpropagation

- You will be building a digital brain to predict which class different Iris flowers belong to.
- Code is provided to help you load in the data.
- Then start working on your neural network
 - First step: Normalize data!
 - Then construct the neural network:
 - Data structure to store layers
 - Topology?
- Then implement Backpropagation
- After implementing the perceptron use k-fold cross validation (chapter 8.5.3) with $k = 10$ to measure prediction accuracy. (*optional*)

The Data

- Same data as clustering #1
- The iris data can be found in the iris.csv file in the java-project.
- Attributes:
 - Sepal length
 - Sepal width
 - Petal length
 - Petal width
 - Class
- Possible values: Iris-setosa, Iris-versicolor and Iris-virginica



Code Provided

- Iris class used to store data for each Iris flower in data.
- Data loading and conversion to Iris-objects
 - Done by the CSVFileReader and DataLoader class.
- Main-class contains Main-function
 - Currently it calls the LoadData method of the DataLoader which returns an ArrayList of all Iris objects loaded in from the data file.

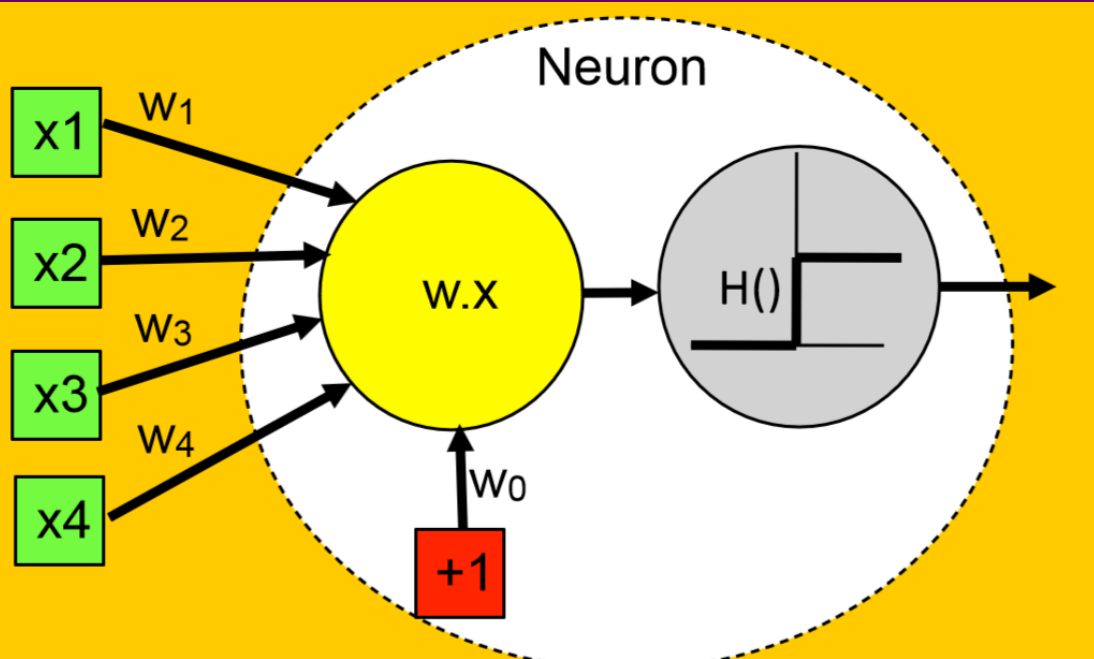
Thanks for listening!
Help Slides available below

Help!!!

Perceptron

- To simplify the topology in regards to the output layer consider making two perceptrons instead of one.
- E.g.
 - One to classify between Class 1 and Class 2
 - Another to classify between Class 2 and Class 3.
- If you do this, you will only need one output neuron.
- Requires you to split data

Neural networks 101



- Inputs (X)
- Connection Weights (W)
- Threshold/bias
- Weighted Sum
- Activation function
- Output

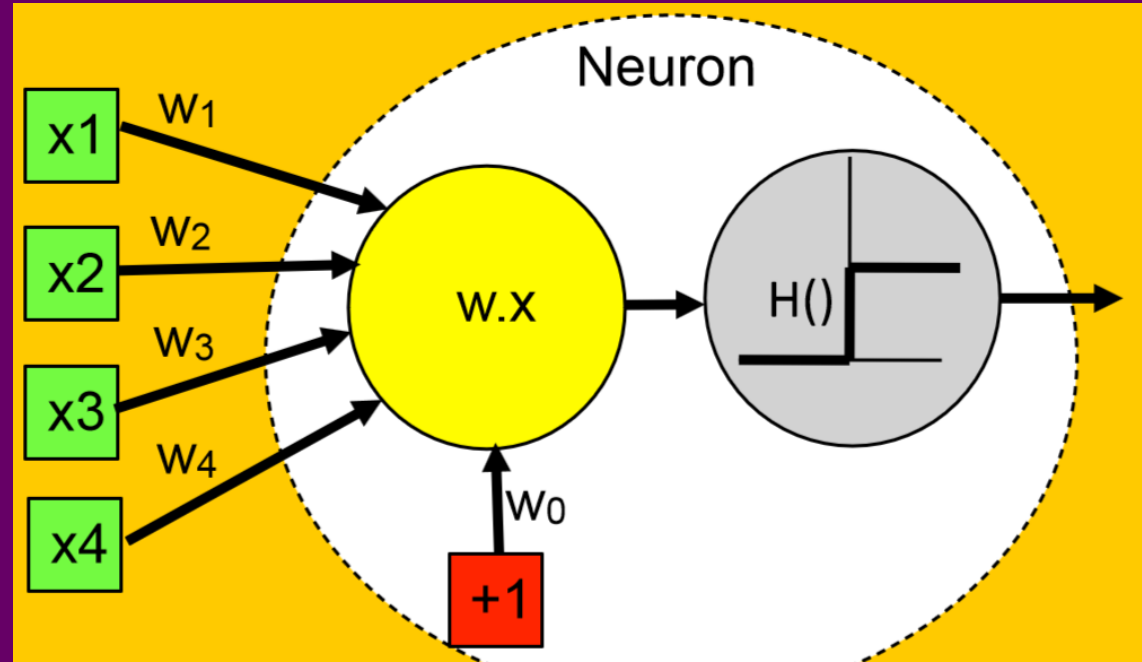
Slide from a lecture given by Hector P. Martinez in the course Modern AI for Games, Fall 2012

Perceptron algorithm

1. Initialize perceptron with random weights $[0...1]$ and bias value $[0...1]$, or with your own values (e.g. bias = 0)
2. For each set of inputs
 - Compute actual output, a_p , from perceptron using the activation function (more on next slide)
 - Update all weights with Δw_j
3. If no changes to weights, then stop
4. Otherwise go back to 2

Perceptron algorithm – weight update

- $\Delta w_j = \text{Learning rate} \cdot x_j \cdot (d_j - a_j)$
- Example with w_1 , learning rate = 0.5, $d_j = 0$, $a_j = 1$:
 - $\Delta w_1 = 0.5 \cdot x_1 \cdot (0 - 1)$
- x_j = input to neuron x_j
- d_j = desired output
- a_j = actual output



Perceptron example

Threshold = Bias

Slide from a lecture given by Hector P. Martinez in the course Modern AI for Games, Fall 2012

Epoch	Inputs		Desired output d^p	Initial weights		Actual output a^p	Error E^p	Final weights	
	x_1	x_2		w_1	w_2			w_1	w_2
1	0	0	0	0.3	-0.1	0	0	0.3	-0.1
	0	1	0	0.3	-0.1	0	0	0.3	-0.1
	1	0	0	0.3	-0.1	1	-1	0.2	-0.1
	1	1	1	0.2	-0.1	0	1	0.3	0.0
2	0	0	0	0.3	0.0	0	0	0.3	0.0
	0	1	0	0.3	0.0	0	0	0.3	0.0
	1	0	0	0.3	0.0	1	-1	0.2	0.0
	1	1	1	0.2	0.0	1	0	0.2	0.0
3	0	0	0	0.2	0.0	0	0	0.2	0.0
	0	1	0	0.2	0.0	0	0	0.2	0.0
	1	0	0	0.2	0.0	1	-1	0.1	0.0
	1	1	1	0.1	0.0	0	1	0.2	0.1
4	0	0	0	0.2	0.1	0	0	0.2	0.1
	0	1	0	0.2	0.1	0	0	0.2	0.1
	1	0	0	0.2	0.1	1	-1	0.1	0.1
	1	1	1	0.1	0.1	1	0	0.1	0.1
5	0	0	0	0.1	0.1	0	0	0.1	0.1
	0	1	0	0.1	0.1	0	0	0.1	0.1
	1	0	0	0.1	0.1	0	0	0.1	0.1
	1	1	1	0.1	0.1	1	0	0.1	0.1
Threshold: $w_0 = -0.2$; learning rate $\eta = 0.1$									