

Neural Networks Project

What is this project all about?

- Artificial Neural Networks (ANNs) are one of the most versatile tools in the Machine Learning toolbox.
- Neural Nets are an attempt to model the way our own brains work. Such a network is a large number (maybe billions) of "neurons," each of which is incredibly simple.
- A neuron takes many inputs, combines them in some way, and generates an output. This output is either a final observable value, or it is the input to another neuron.

What are they good for?

- Mostly, neural nets are used for classification of some sort.
- Sounds a bit limiting!
- But the number of outputs can be large (can distinguish between many classes) and “deep learning” which is basically the use of multi-layer neural nets, with potentially lots of outputs,
- Neural nets are used for speech recognition, 3-D scene recognition (autonomous vehicles) and many, many other things!

Perceptron Classifier

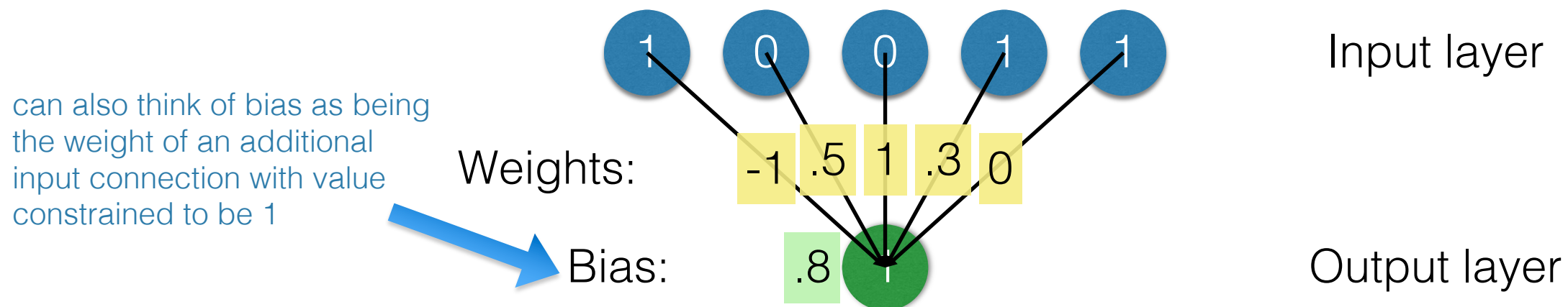
- What is a Perceptron?
 - A *perceptron* is a very simple form of ANN
 - with neurons arranged in layers such that its “feed-forward” connections are formed only between layers (not between neurons of the same layer)
 - each neuron outputs a binary signal (the “message”)
 - one of the first types of neural net to be built (1957)
 - and able to *classify* input sets with one or more (orthogonal) labels
 - for each neuron, output is calculated as follows:
 - $f(\mathbf{x}) = 1$ if $\mathbf{w} \cdot \mathbf{x} + b > 0$; otherwise 0
 - where \mathbf{w} is the weight vector of connections from the previous layer, and
 - where \mathbf{x} is the (binary) set of outputs at the previous layer,
 - and b is the bias



dot product

Training the perceptron

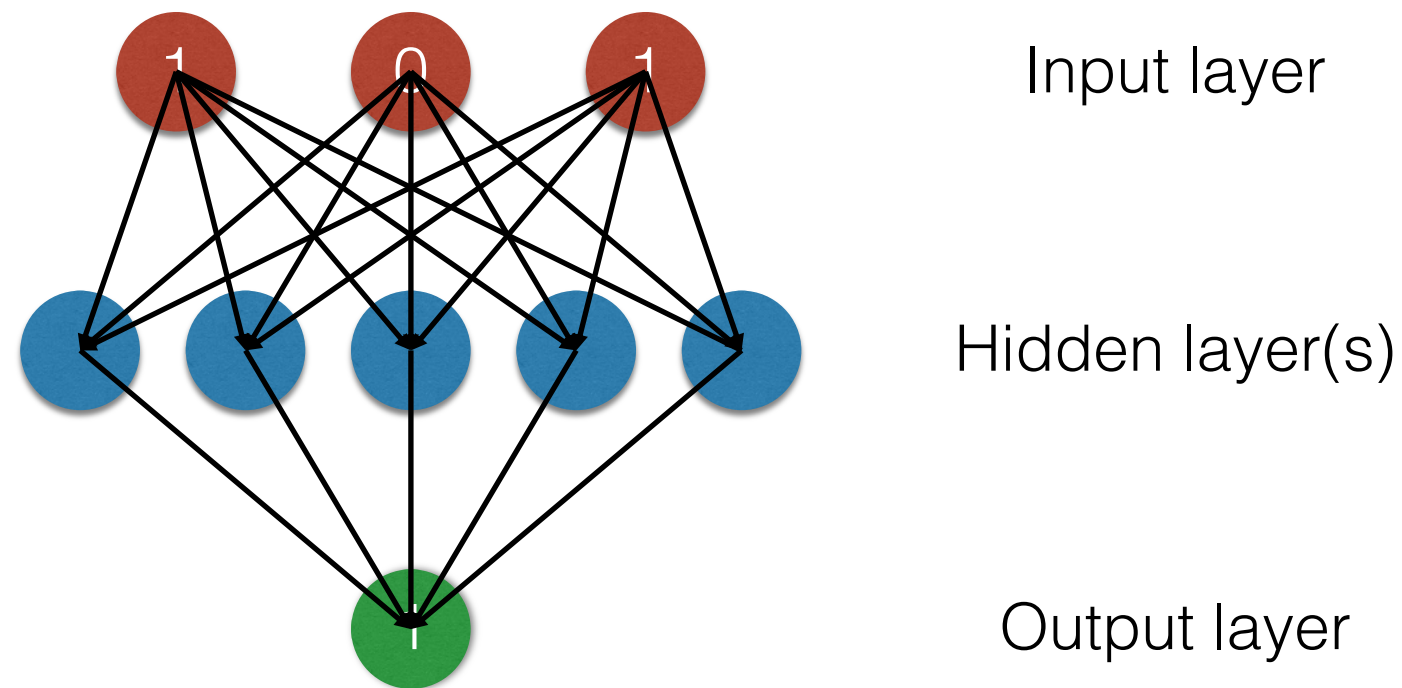
- Two-layer perceptron:



- The weights start out at random (and bias values usually zero):
 - As each new input set is labeled (supervised learning), the weights/bias are adjusted (by back-propagation of errors) until output values match as closely as possible.
 - Provided the input is *linearly separable**, the perceptron will converge (with some set of weights). The optimally stable solution is known as a *support vector machine*.
- * if a hyperplane can be drawn separating the inputs

Solving non-linearly-separable problems

- Use a multi-layer perceptron:



- Now you can solve problems such as XOR

Back-propagation, etc.

- Remember our Newton-Raphson convergence from the first week or two?
 - Essentially, perceptrons use an N-dimensional version of the same thing where N is the number of weights (including bias) that must be adjusted and where the function is linear.
- In practice, perceptrons aren't strictly binary at each neuron
 - Hidden neurons use “sigmoid” function;
 - Output neurons use “softmax” function.

Perceptron code

```
package edu.neu.coe.scala.spark.nn
import org.apache.spark.SparkConf
import org.apache.spark.SparkContext
import org.apache.spark.ml.classification.MultilayerPerceptronClassifier
import org.apache.spark.ml.evaluation.MulticlassClassificationEvaluator
import org.apache.spark.mllib.util.MLUtils
import org.apache.spark.sql.Row
object PerceptronClassifier extends App {
  val conf = new SparkConf().setAppName("perceptron")
  val sc = new SparkContext(conf)
  val sqlContext = new org.apache.spark.sql.SQLContext(sc)
  val sparkHome = "/Applications/spark-1.5.1-bin-hadoop2.6/"
  val trainingFile = "data/mllib/sample_multiclass_classification_data.txt"
  // this is used to implicitly convert an RDD to a DataFrame.
  import sqlContext.implicits._
  // Load training data
  val data = MLUtils.loadLibSVMFile(sc, s"$sparkHome$trainingFile").toDF()
  // Split the data into train and test
  val splits = data.randomSplit(Array(0.6, 0.4), seed = 1234L)
  val train = splits(0)
  val test = splits(1)
  // specify layers for the neural network:
  // input layer of size 4 (features), two intermediate of size 5 and 4 and output of size 3 (classes)
  val layers = Array[Int](4, 5, 4, 3)
  // create the trainer and set its parameters
  val trainer = new MultilayerPerceptronClassifier()
    .setLayers(layers)
    .setBlockSize(128)
    .setSeed(1234L)
    .setMaxIter(100)
  // train the model
  val model = trainer.fit(train)
  // compute precision on the test set
  val result = model.transform(test)
  val predictionAndLabels = result.select("prediction", "label")
  val evaluator = new MulticlassClassificationEvaluator()
    .setMetricName("precision")
  println("Precision:" + evaluator.evaluate(predictionAndLabels))
}
```

input file: label followed by four
input neuron values

```
1 1:-0.222222 2:0.5 3:-0.762712 4:-0.833333
1 1:-0.555556 2:0.25 3:-0.864407 4:-0.916667
1 1:-0.722222 2:-0.166667 3:-0.864407 4:-0.833333
1 1:-0.722222 2:0.166667 3:-0.694915 4:-0.916667
0 1:0.166667 2:-0.416667 3:0.457627 4:0.5
1 1:-0.833333 3:-0.864407 4:-0.916667
2 1:-1.32455e-07 2:-0.166667 3:0.220339 4:0.0833333
2 1:-1.32455e-07 2:-0.333333 3:0.0169491 4:-4.03573e-08
1 1:-0.5 2:0.75 3:-0.830508 4:-1
0 1:0.611111 3:0.694915 4:0.416667
```

result:

prediction	label
1.0	1.0
1.0	1.0
1.0	1.0
1.0	1.0
1.0	1.0
2.0	2.0
2.0	2.0
2.0	2.0
2.0	2.0
2.0	0.0
2.0	2.0
0.0	2.0
1.0	1.0
0.0	0.0
1.0	1.0
1.0	1.0
0.0	0.0
2.0	2.0
1.0	1.0
0.0	0.0
0.0	0.0

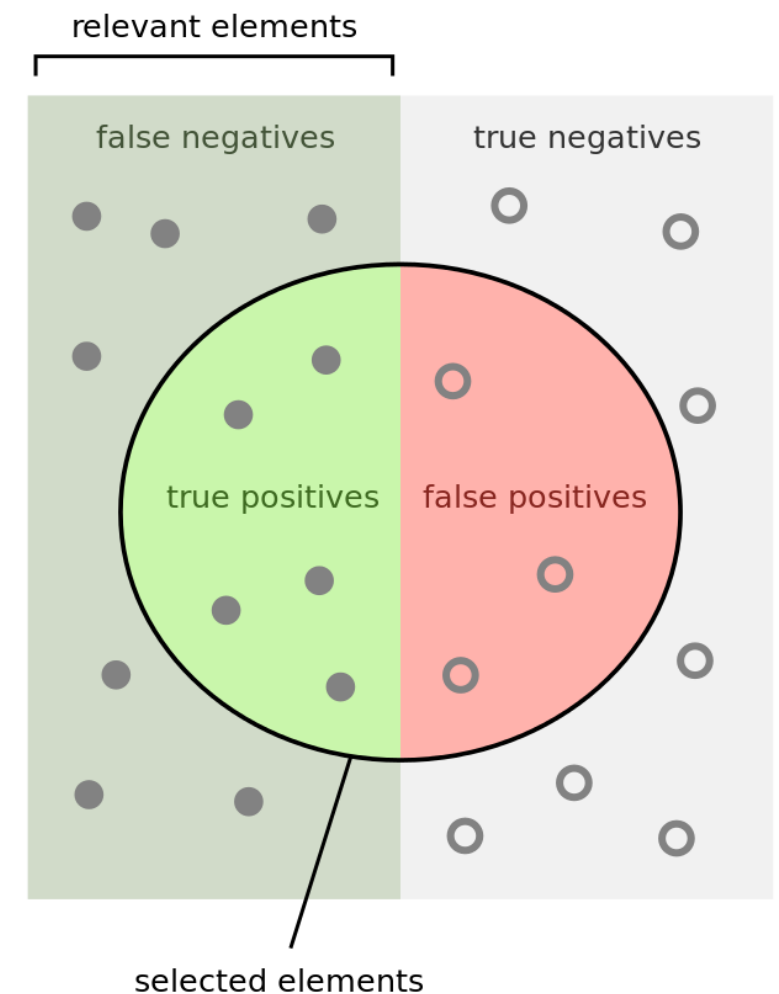
only showing top 20 rows

Why Neural Nets?

- I believe that ANNs are primarily useful because they:
 - are very general;
 - do not require much advance modeling thought;
 - are resistant to mutual information (co-variance);
 - can be used with very large feature sets and training sets—
 - in fact, multi-layer ANNs essentially do the feature selection for you;
 - can be used to gain insights for better modeling.
- What to avoid:
 - without sophisticated optimization (gradient descent, etc.) algorithms, convergence may be slow—or worse
 - MLlib uses L-BFGS (limited memory version of Broyden–Fletcher–Goldfarb–Shanno algorithm)

Classification

- Measurements
 - Precision/Recall (applicable for two classes)
 - e.g. for a recall of 50%, we want a precision of 60%
 - Confusion matrix (for > two classes)



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

What you have to do

- Form up in pairs;
- Build a neural net implementation:
 - Code (proper project structure using maven);
 - Unit tests (important);
 - Committed to github.
- Create an application/dataset for it and demonstrate its capabilities for .
- Write a report discussing your findings
- Submit before the deadline. Aug 9th.