Table of Contents

Introduction

The Labs for this course are completed using Intellij. Your instructor will have provided either instructions for setting up Intellij or you will have a Virtual Machine with Intellij pre-installed and configured.

1. Maven

We recommend you familiarize yourself with at least the basics of Maven for managing your DeepLearning4J projects.

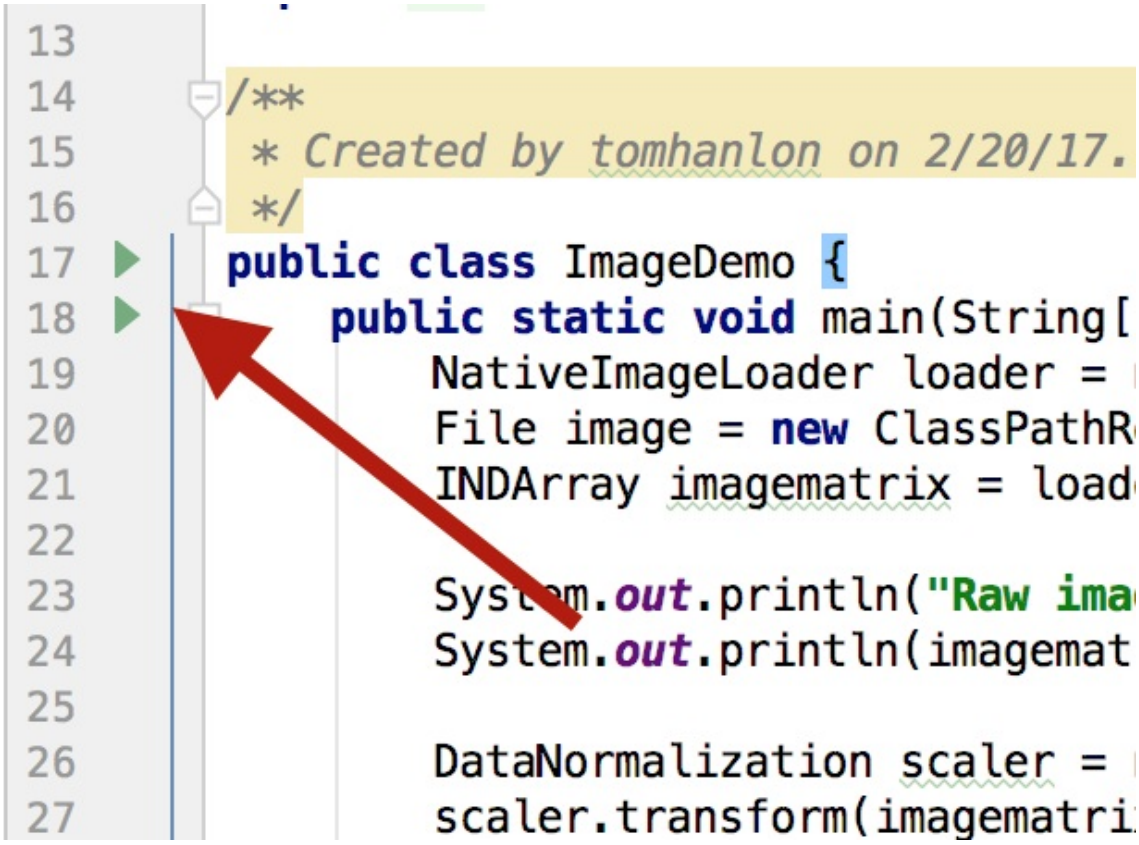
Maven uses a pom.xml file to manage dependencies.

If exploring the pom.xml file for the lab project note that there are two levels, training-parent/pom.xml and training-parent/training-labs/pom.xml

1. Running and stopping code

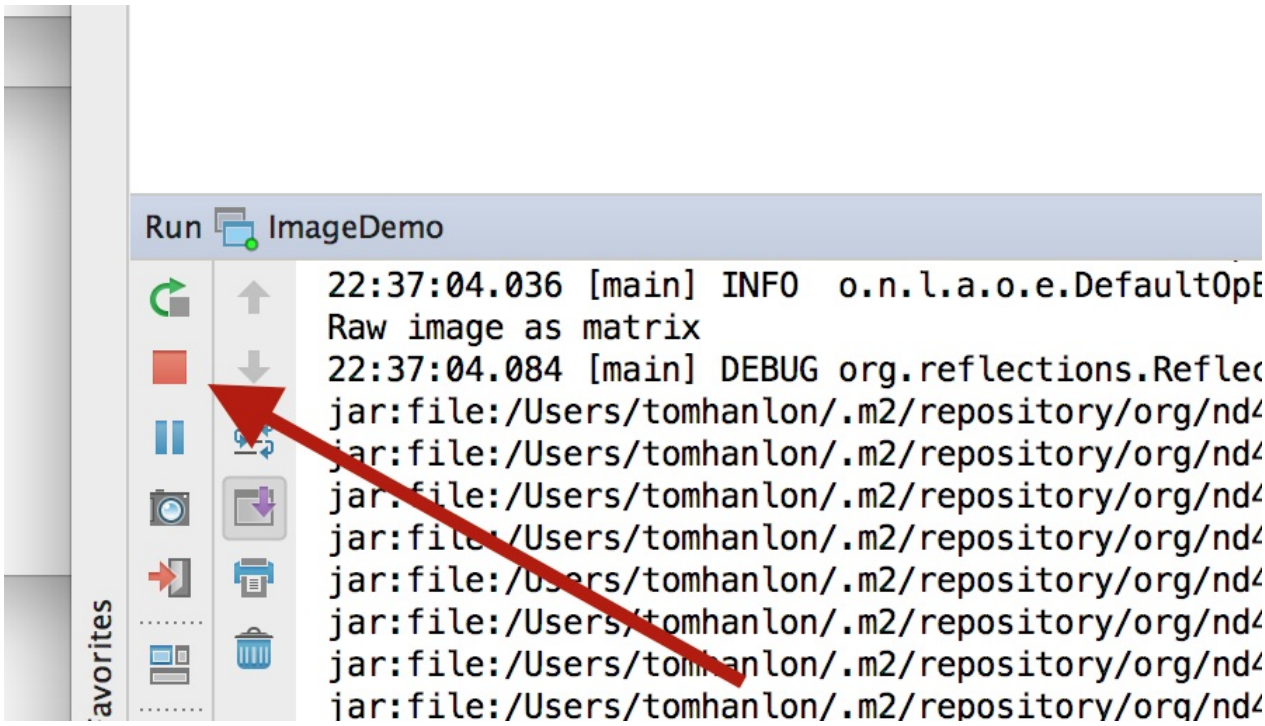
When editing or creating a java class you can run it at any time by hitting the green arrow next to your main class.

- Run your code



- Stop your code

To stop the code you can hit the red button.



1. Common issues

A code problem anywhere is a problem everywhere. If the project fails to compile then you will not be able to run other classes that do compile. Running a class causes the whole project to compile, and if another broken class fails to compile, your working class will fail to run.

Solution, if you have an unfinished class or something that won't compile, you need to either fix it, or comment out the offending section

1. Work at your own pace.
2. Too Hard

There is a solution directory, use it as a last resort. If the Lab is too challenging remember you can work as far as you can, save the class in a working state or comment it out to the point where it at least compiles and move on.

- Too Easy

You are welcome to start a blank project and work from scratch. If your questions are related to the course materials or the topic the instructor will happily answer your questions

Simplest Neural Network

In this Lab you will explore a very simple Neural Network. The Neural Network will consist of

- One input
- One expected numeric output
- One Hidden Layer with a single neuron

The Neural Net will receive the input of 0.5, the expected output will be 0.8 .

The Neural Net will train for 100 epochs with the goal of improving it's score, how close it gets to 0.8 .

Goals of this lab

- To familiarize the user with DeepLEarning4J code.
    - MultiLayer Network
        - fit
    - Parameters
        - Number of Epochs
        - Training Rate
        - Optimization Algorithm
        - Updater
    - UI server

Step 1

- Open up IntelliJ Open up IntelliJ and navigate to the Labs folder

Step 2

- Open the SimplestNetwork class

Click on SimplestNetwork.java to open up the java class in the editor

Step 3

- Review the Java Code

Note the parameters set at the top.

```
int seed = 123;
```

This is a hardcoded random seed to allow repeatable results. The Neural Net begins by assigning random weights to the matrix(?). If we want repeatable results then using a pre configured seed allows that.

If you change the seed, your networks behavior will change slightly as well.

```
int numInputs = 1;
int numOutputs = 1;
```

Xavier, why Xavier

In short, it helps signals reach deep into the network.

If the weights in a network start too small, then the signal shrinks as it passes through each layer until it’s too tiny to be useful. If the weights in a network start too large, then the signal grows as it passes through each layer until it’s too massive to be useful. Xavier initialization makes sure the weights are ‘just right’, keeping the signal in a reasonable range of values through many layers.

To go any further than this, you’re going to need a small amount of statistics - specifically you need to know about random distributions and their variance.

STOCHASTIC GRADIENT DESCENT

Note that the Optimiaztion Algoithm is Stochastic Gradient Descent.

As Neural Netowrks have been researched over the years the challenge of updating large matrices with modified weights to lead to less error(better answers) has been significant. The numerical computation in particular. SGD meets this challenge by making random choices in some way, research this further.

Updater Nesterovs

Without going into the updater in detail Note that momentum may be a hyperparameter that will need tuning on more complex networks. The problem in this demo is linear (? is it) but in a more complex graph with potential local minima momentum helps break through that. How deep do I go here?

Layer 0 activation tanh

The activation function of a Layer determines the signal it sends to connected neurons.

Choices are sigmoid, smooth curve output 0-1 as x increases.

tanh similar to sigmoid output -1-> +1 depending on value of x

Stepwise output 0 or 1 depending on value of X

Etc going to deep here.

Layer1 this is our output layer.

Note the activation is identity.

This determines that the output will be linear, a range of numeric values, .1, .2, .3 etc. VS 0 or 1, vs Class A, B or C

STEP 3

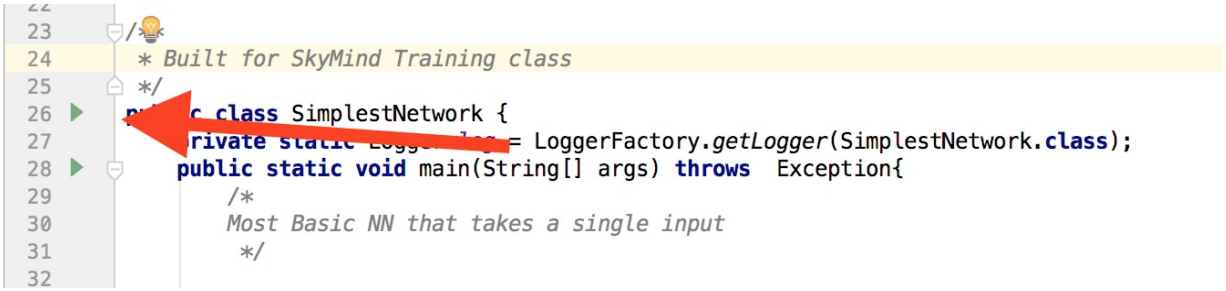
Run the code

In this step you will run the code.

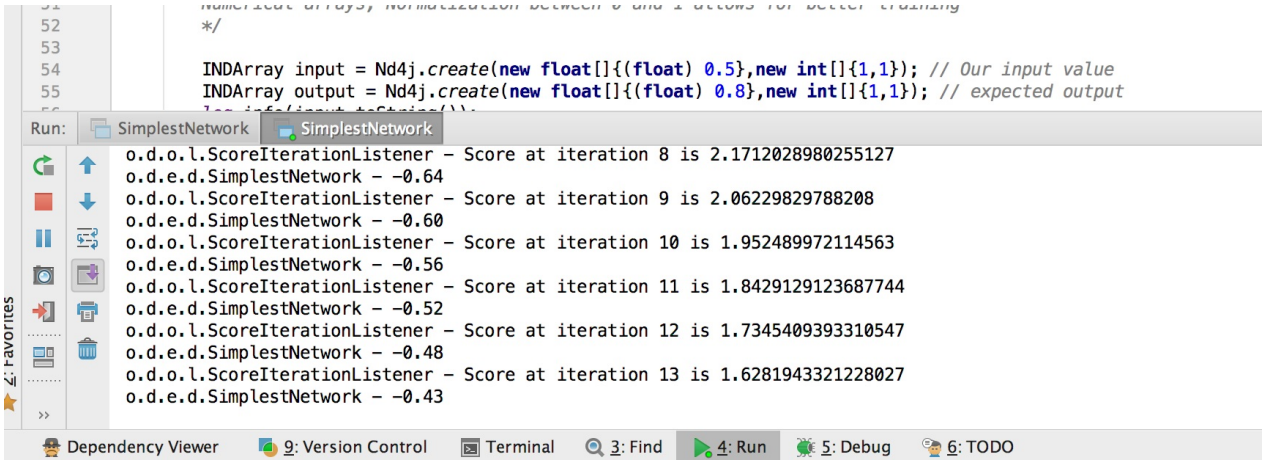
When the code executes it will create a UI that can be accessed with a web browser.

It will also print output to the output window at the bottom of intellij as it runs

Click on this green arrow to execute the code

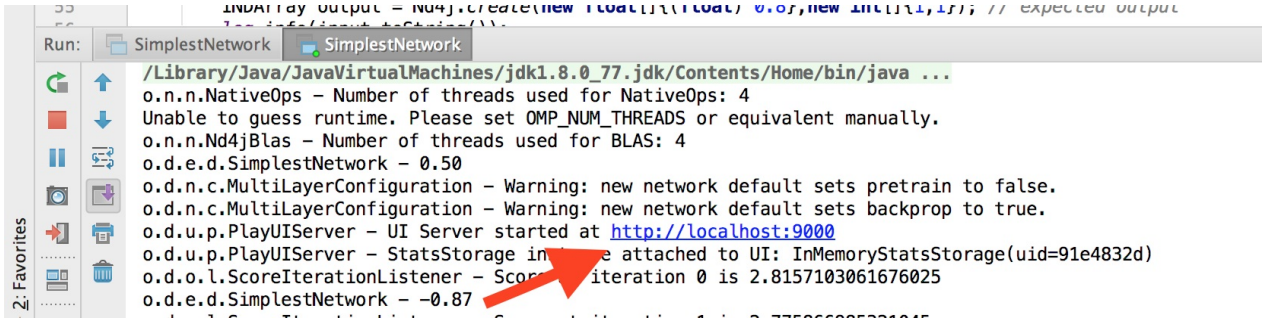


View the output in the console while the class runs



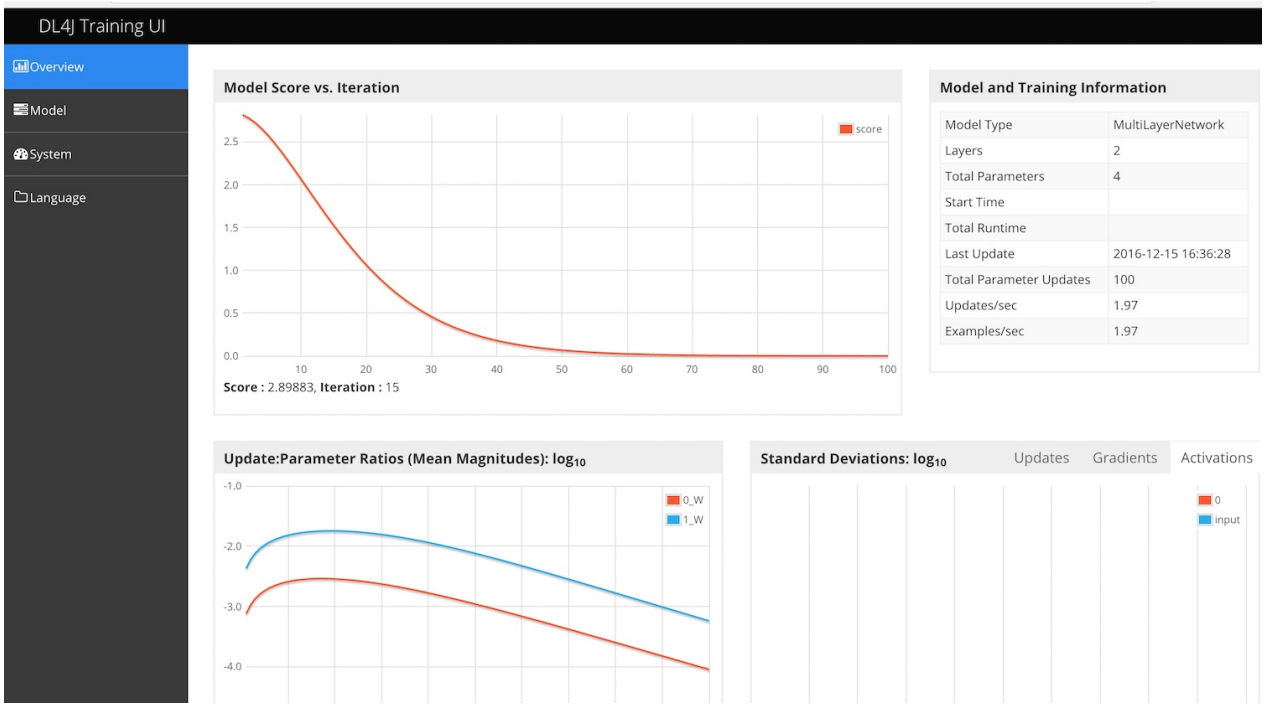
View the UI

When the code executes and the UI is created, a line is generated in the console output with the url



Open that URL in a browser

You should see this



Explanation of the output

Console Output.

The following block of code is what begins the training process.

```
for( int i=0; i<nEpochs; i++ ){
            model.fit(input,output);
            INDArray output2 = model.output(input);
            log.info(output2.toString());
            Thread.sleep(500);
        }
```

What is an Epoch?

It is a loop for the total number of Epochs. Or total passes through the training dataset, in this case our single input, but in real use cases it might be something like thousands of text reviews, or hundreds of thousands of images, or milllions od lines from log files.

What is Model.fit?

This is where the model trains. Data is ingested, random weights are assigned, output is evaluated against expected and weights are adjusted to lessen the error.

What output should look like

This section

```
INDArray output2 = model.output(input);
            log.info(output2.toString());
```

Generates these lines in our console output.

```
o.d.e.d.SimplestNetwork - -0.87
o.d.e.d.SimplestNetwork - -0.85
```

The "correct" output, or "expected" output is 0.80, you will see that the network is consistently getting closer to that goal as it trains.

This line in the console output

```
o.d.o.l.ScoreIterationListener - Score at iteration 1 is 2.775866985321045
```

Is generated by this line

```
model.setListeners(new StatsListener(statsStorage),new ScoreIterationListener(1));
```

STEP 4

In this step you will modify some of the parameters and see the effect on the training process.

Note that anytime you re-run this code you will have to terminate the previous running process. The webserver serving the UI will have a handle on a socket and the second example will try to grab that same socket, fail and return an error.

Kill the running process by clickin on the red square, top right.

Some parameters that you could tune.

Before you change things, note the current performance. How many iterations till it got to within .05 of the target? In 100 iterations how close did it get? Mine got to .78 after 100, and reached .75 at iteration 80

Settings you may change with reasonable results

Hidden Nodes

- Number of hidden nodes
  - Would provide more attempts towards the correct answer, more random weights, and may train quicker

Number of Epochs

- Number of Epochs
  - If the network is converging on the target, then more epochs should allow it to get there, in time
  - Note that to prevent things going to fast to visualize,I put a sleep .5 seconds in the loop.
  - Remove that if you set to large number of Epochs.

Learning Rate

Learning Rate Determines how far to adjust the weights given the error.

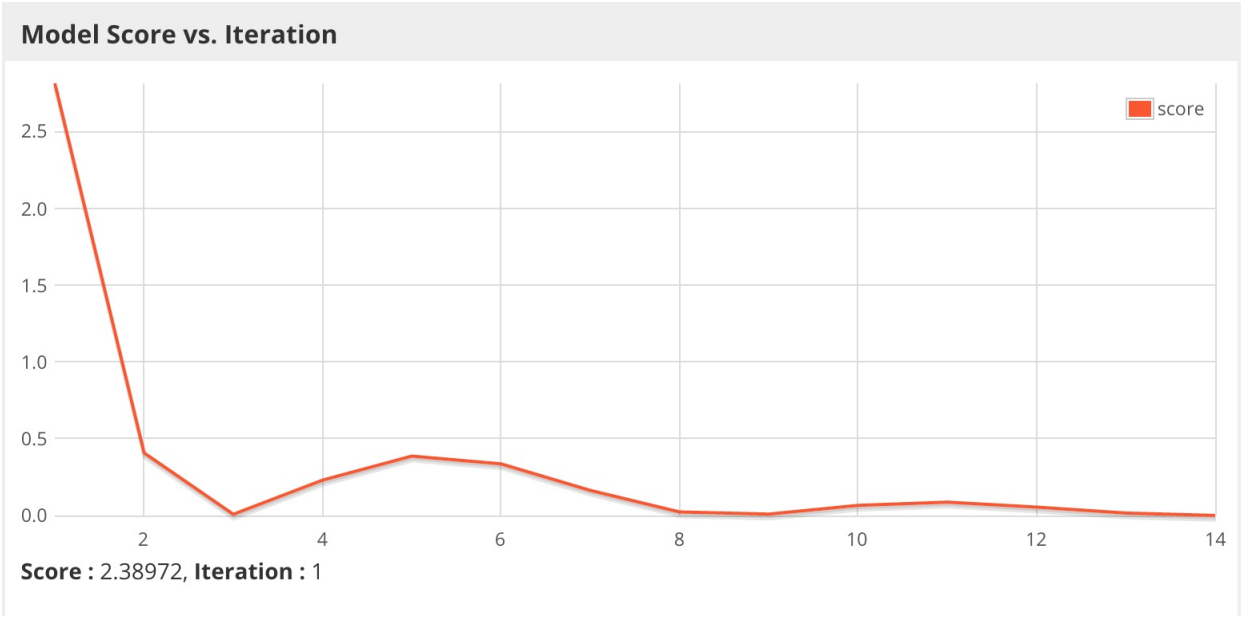
A range for learning rates would be ???

```
double learningRate = 0.001;
```

Change to perhaps...

```
double learningRate = 0.01;
```

Note that an aggressive learning rate may cause the network to overshoot the target before converging.



Overview of the functioning of a single node

The Output of a perceptron or node in our neural network is determined with what is actually a simple process. It is the combination of variables and the number of parameters that allow the neural network to learn complex patterns and generate complex outputs. Here is some review of Simple Network output.

Example Training Output from Simple Network

Settings

Activation Function = IDENTITY Number of Hidden Nodes = 1

Output of model.paramTable()

The weights and biases are randomly set initally.

{0_W=1.99, 0_b=-0.06, 1_W=-0.13, 1_b=0.23}

The input is .5.

First Calculation

(sum of inputs * Weight) + Bias

(.5 * 1.99) - 0.06 = 0.935

Activation function is identity so output remains 1.005 and is passed to connected neurons.

Second Calculation at output Layer.

(sum of inputs * Weight) + Bias

(.935 * -0.13) + .23 = 0.10845

Output is 0.11

Next iteration Weights Change

{0_W=1.99, 0_b=-0.06, 1_W=-0.13, 1_b=0.24}

Output is .12

Next Iteration Weights Change

{0_W=1.99, 0_b=-0.06, 1_W=-0.12, 1_b=0.25}

Output is 0.13

Lab questions

1. What parameters may need adjusting in a Neural Net?
2. The output of a neuron is determined by

a. The input

b. The activation Function

c. The Weights

d. The Biases

e. All of the Above

Answers

1. The most commonly adjusted parameter would be Learning Rate.
2. All of the above, the output of a neuron is output of the activation function applied to (sum of inputs * weights + bias)

END OF SIMPLEST NETWORK LAB

DataVec Lab

Using DataVec to ingest a CSV dataset

In this lab you will import data from a CSV file into a format suitable for a Neural Network.

Goals of this lab

- DataVec Introduction

Step 1

- Open up IntelliJ Open up IntelliJ and navigate to the Labs folder

Step 2

- Open the DataVecLab class

Click on DataVecLab.java to open up the java class in the editor

Step 3

- Review the Java Code

In this case the Neural Network has already been built. The goal of this Lab is to work through the Data ETL process using DataVec.

- Understand the Challenge

The Iris.txt file has 150 records of measurements of 3 Irises. Iris Setosa, Iris Virginica, Iris versicolor. Measurements are Petal Length, Petal Width,Sepal Length, Sepal Width.

The data is stored with numeric representation of the species, 0=> Setosa, 1 => Versicolor,2=> Virginica

STEP 3

Review the needed steps.

1. Read the File
2. Parse the Lines
3. Specify Label fields vs measurements
4. Create a DataSet object to pass into our Neural Network.

DataVec Classes that will be used.

https://deeplearning4j.org/datavecdoc/org/datavec/api/records/reader/RecordReader.html
https://deeplearning4j.org/datavecdoc/org/datavec/api/records/reader/impl/csv/CSVRecordReader.html

DeepLearning4J class that will be used

https://deeplearning4j.org/doc/org/deeplearning4j/datasets/datavec/RecordReaderDataSetIterator.html

Full DataVec JavaDoc https://deeplearning4j.org/datavecdoc/

Full DeepLEarning4J JavaDoc. https://deeplearning4j.org/doc/

Advanced users are welcome at this point to open up the stub and go for it.

Everyone else please follow along with the instructions

STEP 3 Set some parameters

CSVRecordReader is designed to be able to ignore the first x number of lines in a file. The assumption is the file may have header information or comments.

Take a look at Iris.txt and confirm that it has no headers.

CSVRecordReader is configurable in terms of how the data records are delimited. Verify that the file is comma delimeted.

** Note bad data is a frequent problem, in this clean sterilized lab environment you can trust the data, in real world I always run some verication scripts to verify every line has the same amount of commas, at the very least.

After verifying that there are no header lines, and the delimiter is a comma, add the following code to the stub program.

```
int numLinesToSkip = 0;
String delimiter = ",";
```

Create a RecordReader

Add this line to the code stub

```
RecordReader recordReader = new CSVRecordReader(numLinesToSkip,delimiter);
```

Initialize the RecordReader and pass it a file.

For portability the file is put in the resources folder. This makes it available as a ClassPathResource. If you chose to get the path to the file and use that instead that is fine.

This code snippet allows easy access to a file on the classpath `new ClassPathResource(fileName).getFile()`

Initialize your record Reader and passed it a FileSplit.

A FileSplit can point to a directory and the Record Reader can read all the files in the directory, or in this case it will point to a single file.

```
recordReader.initialize(new FileSplit(new ClassPathResource("iris.txt").getFile())
);
```

Optional Step

Verify the Record Reader.

You may want to verify the the Record Reader code is functional.

The Record Reader returns an Iterator over a set of Records.

Each call to next method returns an java.util.ArrayList of values.

Some code to explore that would be.

```
while( recordReader.hasNext()) {
            log.info(recordReader.next().toString());
            log.info(recordReader.next().getClass().toString());
        }
        recordReader.reset();
```

You would then run the code and see the records in the console window.

Set some parameters for the DataSetIterator that you will create in the next step

```
int labelIndex = 4;
//5 values in each row of the iris.txt CSV:
//4 input features followed by an integer label (class) index.
// Labels are the 5th value (index 4) in each row


int numClasses = 3;
//3 classes (types of iris flowers) in the iris data set.
//Classes have integer values 0, 1 or 2

int batchSize = 150;
//Iris data set: 150 examples total.
//We are loading all of them into one DataSet
//(not recommended for large data sets)
```

Create a DataSet Iterator

A Record Reader returns an iterator over a List of Writables. Writables are an efficient serialization method inspired by Hadoop Writables.

A Neural Net requires input as an Array of Numeric values. To do that use DataSetIterator.

A DataSet will contain an INDArray of features, and an INDArray of Labels.

Add the following code to the DataVecLab class.

```
DataSetIterator iterator = new RecordReaderDataSetIterator(recordReader,batchSize,
labelIndex,numClasses);
DataSet allData = iterator.next();
```

Shuffle the Data

Typically a Neural network trains over the results of a minibatch. Suppose a minibatch of Ten. Ten records are passed through the error between expected value and observed output is calculated and the weights of the network are updated to reduce the error. Now

look are our iris data set. All one species, followed by another species. If the records in a mini-batch are skewed towards one class then the network will train first in one direction then another. This is not good, shuffle your data.

Add this code to the class.

```
allData.shuffle();
```

Split Train and Test

For supervised learning a network is trained on a collection of records and then tested on records it has not seen before. Split the data into test and train.

Add the following code to the DataVecLab class.

```
    SplitTestAndTrain testAndTrain = allData.splitTestAndTrain(0.65);  //Use 65% o
f data for training
    DataSet trainingData = testAndTrain.getTrain();
    DataSet testData = testAndTrain.getTest();
```

Extra Credit

Normalize the DataSet

You should always Normalize/standardize your data. DeepLearning4J has tools to do that.

http://nd4j.org/doc/org/nd4j/linalg/dataset/api/preprocessor/DataNormalization.html

Extra Credit

Your data may be organized in many different ways. See the resources/irisData directory for some examples.

Parent Path Label Generator:

Labels can be extracted based on the name of the parent directory using ParentPathLabelGenerator. The irisData directory has 3 folders one for iris virginica, one for iris setosa and one for iris versicolor.

Write a datavec pipeline that extracts the label from the parent directory.

DataVec Spark Transform

Your data may have string labels instead of numeric values. DataVec has tools to build a Schema as read from the file, and then a target schema that transforms columns. In this case you would want to transform categorical to integer.

An example of Spark Transform is available in demos/AbaloneDataTransform

In that demo the data has String Labels for Gender, M(male),F(Female),I(Infant)

A similar format for Iris Data is in the resources folder,
`/resources/IrisData/iris_with_names.csv`

END OF IRIS DATAVEC LAB

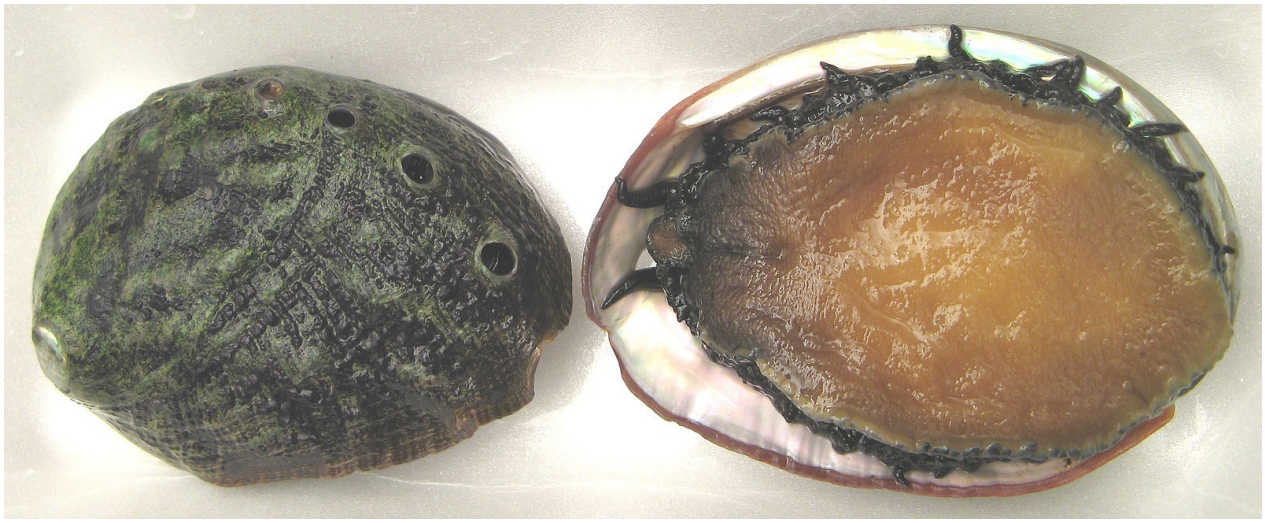
Lab: Using a FeedForward Network as Classifier

- Abalone data
  - Gender
  - Weight
  - Height etc
- Question for the Neural Network
  - Given that data can we predict age
  - Otherwise age is calculated by killing the abalone and counting rings

Data Source

- University of California at Irvine
- Large collection of DataSets
  - http://archive.ics.uci.edu/ml/datasets.html

What is an Abalone



More about Abalone

- Tasty Seafood
- High harvest demand needs to be managed
- Populations are studied
- Therefore we have a dataset

Dataset Details

- Total Records 4177
  - Not a lot of data
  - Question: How much Data do I need?
  - Answer: More, is always better
- Data structure

DataSet Details

- Sex / nominal / -- / M, F, and I (infant)
- Length / continuous / mm / Longest shell measurement
- Diameter / continuous / mm / perpendicular to length
- Height / continuous / mm / with meat in shell
- Whole weight / continuous / grams / whole abalone
- Shucked weight / continuous / grams / weight of meat
- Viscera weight / continuous / grams / gut weight (after bleeding)
- Shell weight / continuous / grams / after being dried
- Rings / integer / -- / +1.5 gives the age in years

Specifics

- DataSet has number of rings, not age
- Rings +1.5 gives age
- More straighttforwad to predict rings, extrapolate age

Loading our data

- Gender M/F/I, first column, needs to be converted to numeric
- Last column is our label, number of rings
- All other columns doubles

Data considerations

- Better performance when values normalized/scaled between 0 and 1
  - Are our values normalized?
  - Run then through datavec to get statistics
  - Also convert string to categorical

note the data has been prepared and split, the raw data and the process are available in resources folder

Analyzing the Data

- See Demos/AbaloneDataTransform.java
- Loads data
- Transforms M/F/I to 0,1,2
- Uses Spark RDD's for transform (RDD Docs)[http://spark.apache.org/docs/latest/programming-guide.html#resilient-distributed-datasets-rdds]
- You can run that code, it places summaries in /tmp/Abalonexxx

STEP 1

- Run the code in Demos/AbaloneDataTransform.java

STEP 2

- Examine the files in /tmp/abalone_data_xxxx
  - the xxxx will be replaced with the minute of the day to allow the code to run more than once without error
- Examine /tmp/abalone_data_xxxx/analysis.tx
  - Is the data normalized, are the values between 0-1?
- Examine the directory /tmp/abalone_data_xxxx/original/
  - Question: Why are there two files?
  - Answer: Spark is distributed by design, although it is run locally here it still has two process each on a split of the data. You can not have two processes write to same file, so spark/hadoop output is a directory containing maining files.
- Examine a part file: "less /tmp/abalone_data_xxx/original/part-00000"
  - Is the data Numeric?
- Examine a part file: "less /tmp/abalone_data_xxx/processed/part-00000"
  - Is the data Numeric?

STEP 3

In this step you will begin writing code to process the data. The data has been converted into numeric values for the Gender column, and split into Train (resources/abalone/abalone_train.csv)and Test(resources/abalone/abalone_test.csv) sets.

- Create File objects traindata and testdata

```
File traindata = new ClassPathResource("abalone/abalone_train.csv").getFile();
File testdata = new ClassPathResource("abalone/abalone_test.csv").getFile();
```

STEP 4

- Create a Recordreader for the Test data and one for the Train data.
- Initialize each
- You will need four lines of code.

STEP 5

- Create a DataSetIterator fore each RecordReader, remember to use the constructor with batchSize, LabelIndex and the other needed fields.

STEP 6

- Uncomment the code for the Neural Network

STEP 7

- Uncomment the code to run the model

Final Notes

- This Data does not give enough information for particularly accurate age predictions. Too much variabilty in growth patterns. Take a look at the output and it gets withing a few years for most.
- The Neural Net could most likely be improved and results improved but this is real data and the correlation between age and the measruments provides is present, but not particularly strong.

Extra Credit

Larger ranges for years

- Divide the data in another way, perhaps age 0-5,5-10,10->maxvalue, and see how well the measurments can target the broader age groups.
    - Hint: Note the relationship between number of inputs, number of outputs and number of classes when you make this change

Single continuous output

- Reconfigure the network to have a single output node delivering a continuous value. Instead of age = 1 of class 0-30, have age = continuous value 0-30
- Loss Function
    - For the regression output layer loss function we have multiple valid choices.
    - The most common are mean squared error (MSE) or sum of squared errors(L2)
- Activation Function
    - In this case we use the identity (linear) output function

END OF ABALONE LAB

Character Generation LSTM Lab

In this lab you will work on a Java Class that implements an LSTM Recurrent Neural Network. Long Short Term Memory Recurrent Networks are modelled after the work done by Graves (note source). Unlike a simple Multi Layer Perceptron, the computation nodes of an LSTM have the ability to recognize patterns in time series data. Useful for many Time Series applications, this lab treats a weather forecast as a sequential series of characters and predicts the next character.

Goals of this lab

- To familiarize the user with LSTM network configuration and use.

Lab Overview

This Lab will train a Neural Network to generate weather forecasts.

The Weather Forecast training data is gathered from actual National Weather service station Forecast Products.

Here is a sample forecast product.

```
WVZ015-171700-
KANAWHA-
INCLUDING THE CITIES OF...CHARLESTON...SOUTH CHARLESTON...
SAINT ALBANS
932 PM EST FRI DEC 16 2016

.REST OF TONIGHT...CLOUDY. RAIN LIKELY. NOT AS COLD WITH LOWS AROUND
30. TEMPERATURE RISING INTO THE LOWER 40S. SOUTH WINDS 10 TO 15 MPH
WITH GUSTS UP TO 25 MPH. CHANCE OF RAIN 70 PERCENT.
.SATURDAY...CLOUDY. RAIN LIKELY IN THE MORNING...THEN A CHANCE OF
SHOWERS IN THE AFTERNOON. MUCH WARMER WITH HIGHS IN THE LOWER 60S.
SOUTHWEST WINDS 10 TO 15 MPH WITH GUSTS UP TO 25 MPH. CHANCE OF RAIN
70 PERCENT.
.SATURDAY NIGHT...SHOWERS...MAINLY AFTER MIDNIGHT. LOWS IN THE UPPER
30S. SOUTHWEST WINDS 10 TO 15 MPH. CHANCE OF RAIN NEAR 100 PERCENT.
.SUNDAY...RAIN SHOWERS IN THE MORNING...THEN SNOW SHOWERS LIKELY IN
THE AFTERNOON. MUCH COOLER WITH HIGHS IN THE LOWER 40S. TEMPERATURE
FALLING TO AROUND 30 IN THE AFTERNOON. WEST WINDS 5 TO 10 MPH.
CHANCE OF PRECIPITATION 90 PERCENT.
.SUNDAY NIGHT...MOSTLY CLOUDY. A SLIGHT CHANCE OF SNOW SHOWERS IN
THE EVENING. MUCH COLDER WITH LOWS IN THE LOWER 20S. NORTHWEST WINDS
5 TO 10 MPH. CHANCE OF SNOW 20 PERCENT.
.MONDAY AND MONDAY NIGHT...PARTLY CLOUDY. HIGHS IN THE LOWER 30S.
LOWS IN THE LOWER 20S.
.TUESDAY THROUGH WEDNESDAY...MOSTLY CLEAR. HIGHS IN THE MID 40S.
LOWS IN THE MID 20S.
.WEDNESDAY NIGHT...PARTLY CLOUDY IN THE EVENING...THEN BECOMING
MOSTLY CLOUDY. LOWS IN THE MID 30S.
.THURSDAY AND THURSDAY NIGHT...MOSTLY CLOUDY. A CHANCE OF RAIN
SHOWERS. HIGHS IN THE MID 40S. LOWS IN THE LOWER 30S. CHANCE OF RAIN
40 PERCENT.
.FRIDAY...MOSTLY SUNNY. HIGHS IN THE MID 40S.

$$
```

Details worth noting

The Text is not exactly proper english. Looks like "." at begining of line denotes begining of phrase, no "." at begining of line denotes continuation of line, "$$" denotes end of product.

How our net will receive the data

The data will be delivered as a sequence of single characters. It will attempt to predict the next character, evaluate the results update the weights and repeat.

It will begin to learn to sound sort of like a weather forecast.

The output will be started with this sequence.

```
WVZ006-171700-
CABELL-
INCLUDING THE CITY OF...HUNTINGTON
932 PM EST FRI DEC 16 2016
```

And the neural net will generate the rest

Here is a sample of a first attempt.

```
.TODAY...MOSTLY CLOUDY. A CHANCE OF RAIN. NOT0 10 TO 16. NOUTHWEST WINDS 30 TOR 10
0. LOWS AROUND 30. WEST WINDS AROUND
5 MPH. CHANCE OF RAIN 60 PERCENT.
.SATURDAY...CLOUDY. HIGHS IN THE LOWER 30S. CHANCE OF PRECIPITATION 60 PERCENT.
.SUNDAY NIGHT...MOSTLY CLOUDY IN THE MORNING...THEN BECOMING
MOSTLY
CLOURNG WITH A 40 PERCENT CHANCE OF SHOW SHOWERS. COLD WITH HIGHS IN THE LOWER 40S
.
.FRIDAY NIGHT...MOSTLY CLOUDY. A SLIGHT CHANCE OF RAIN
IN THE AFTERNOON.
COOL WITH HIGHS IN THE MID 40S.



WVZ028-020150-
WROING-
INCLUDING THE CITY OF...GASTAY...CLEAN...BESPARAY HIGE 5GHT A
COOL WITH HIGHS IN THE UPPER 40S. CHANCE OF SNOW 30 PERCENT.
.SUNDAY NIGHT...A CHANCE OF SNOW. NOT AS COOL NH T A CHANCE OF SNOW SHOWERS. COLD
WITH LOWS IN THE UPPENNOG...TUEN ANOVVEATUR HISH A MOND 10. NORTHWEST WINDS
AROUND
5 MPM.
CHANCE OF R0E C0MPERATURE IN
THE MID AST.
.FRIDAY...CLOUDY. A SLIGHT CHANCE OF SNOW AND RAIN THIS LOWS IN THE AFTERNOON. MUC
H COOLER. NEAR STE LID 30 PM.
.THURSDAY...SUNNY. COLDER. NEAR STEADY TEMPERATURE IN THE
LOWER 30S.
.SUNDAY...MOSTLY SUNNY. HIGHS IN THE MIDNIGHT. COLD WITH HIGHS IN THE LOWER 20S.
.SUNDAY NIGHT...RAIN. NOT AS COOL WITH LOWS IN THE MPR 30T. CHANCE OF PREC
```

Most of the output is words. Some not so much. Seems to have learned the begining of line sequence. Will it ever learn the order of days?

Step 1

- Open up IntelliJ Open up IntelliJ and navigate to the Labs folder

Step 2

- Open the GravesLSTMCharModellingWeatherForecasts
- Open up the java class in the editor

Step 3

- Review the Java Code

Note the parameters set at the top.

```
int lstmLayerSize = 200;                    //Number of units in each GravesLSTM l
ayer
int miniBatchSize = 32;                        //Size of mini batch to use when  t
raining
int exampleLength = 4000;                     //Length of each training example seq
uence to use. This could certainly be increased
int tbpttLength = 50;                        //Length for truncated backpropagation
 through time. i.e., do parameter updates ever 50 characters
int numEpochs = 1;                             //Total number of training epochs
int generateSamplesEveryNMinibatches = 10;  //How frequently to generate samples f
rom the network? 1000 characters / 50 tbptt length: 20 parameter updates per minib
atch
int nSamplesToGenerate = 4;                    //Number of samples to generate aft
er each training epoch
int nCharactersToSample = 1200;                //Length of each sample to generate
// String generationInitialization = null;        //Optional character initializat
ion; a random character is used if null
String generationInitialization = "WVZ006-171700-\n" +
    "CABELL-\n" +
    "INCLUDING THE CITY OF...HUNTINGTON\n" +
    "932 PM EST FRI DEC 16 2016";
// Above is Used to 'prime' the LSTM with a character sequence to continue/complet
e.
// Initialization characters must all be in CharacterIterator.getMinimalCharacterS
et() by default
Random rng = new Random(12345);
```

Each Parameter Described

- lstmLayerSize = 200
  - Each of the lstm layers will have 200 nodes
- miniBatchSize = 32;
  - Number of characters
- exampleLength = 4000;
- tbpttLength = 50;
  - Parameter updates every 50 characters
- generateSamplesEveryNMinibatches = 10;
  - How oftern to generate a sample
- nSamplesToGenerate = 4
  - Number of samples to generate after each training epoch
- nCharactersToSample = 1200;
  - Length of each sample to generate
- Random rng = new Random(12345);

- Consistent Random Seed for consistent results

String generationInitialization

WVZ006-171700-CABELL- INCLUDING THE CITY OF...HUNTINGTON 932 PM EST FRI DEC 16 2016

LAB STEP 1

- Set up your LSTM Neural Network

Create a MultiLayerNetworkConfiguration Object

Here is a starting Line, use the Builder method and add

MultiLayerConfiguration conf = new NeuralNetConfiguration.Builder() .optimizationAlgo(OptimizationAlgorithm.STOCHASTIC_GRADIENT_DESCENT).iterations(1)

Add a learning rate of(0.1) Set rmsDecay to 0.95 Set seed to 12345 Set regularization to true Set l2 0.001 Set weightInit to Xavier Set updater RMSPROP Add .list()

Lab Step 2

Add 3 new Layers

```
.layer(0, new GravesLSTM.Builder().nIn(iter.inputColumns()).nOut(lstmLayerSize)
                    .activation(Activation.TANH).build())
.layer(1, new GravesLSTM.Builder().nIn(lstmLayerSize).nOut(lstmLayerSize)
                    .activation("tanh").build())
.layer(2, new RnnOutputLayer.Builder(LossFunction.MCXENT).activation("softmax")

                    .nIn(lstmLayerSize).nOut(nOut).build())
```

Lab Step 3

Configure the BackPropagation settings for the Neural Network/

LSTM use Backprop through Time to update the weights. Remember in the slides the discussion of an RNN being a "stacked" FeedForward Network for each timestamp with constraints? In this case use updataer BackpropType.TruncatedBPTT, use tbpttLength that is set to 50 for the forward and backwardLength

Set Pretrain to false, pretrain only applies to VAE and RBM's.

Set backprop to true.

```
.backpropType(BackpropType.TruncatedBPTT).tBPTTForwardLength(tbpttLength).tBPTTBac
kwardLength(tbpttLength)
            .pretrain(false).backprop(true)
            .build();
```

Lab Step 4

Add the following code to create a MultiLayer Network from the configuration created above.

Initialize the Neural Net and attach a Listener so you can view progress

```
MultiLayerNetwork net = new MultiLayerNetwork(conf);
net.init();
net.setListeners(new ScoreIterationListener(1));
```

Xavier, why Xavier

In short, it helps signals reach deep into the network.

If the weights in a network start too small, then the signal shrinks as it passes through each layer until it’s too tiny to be useful. If the weights in a network start too large, then the signal grows as it passes through each layer until it’s too massive to be useful. Xavier initialization makes sure the weights are ‘just right’, keeping the signal in a reasonable range of values through many layers.

To go any further than this, you’re going to need a small amount of statistics - specifically you need to know about random distributions and their variance.

STOCHASTIC GRADIENT DESCENT

Note that the Optimization Algoithm is Stochastic Gradient Descent.

As Neural Networks have been researched over the years the challenge of updating large matrices with modified weights to lead to less error(better answers) has been significant. The numerical computation in particular. SGD meets this challenge by making random choices in some way, research this further.

Updater RMSPROP

Without going into the updater in detail Note that momentum may be a hyperparameter that will need tuning on more complex networks. The problem in this demo is linear (? is it) but in a more complex graph with potential local minima momentum helps break through that. How deep do I go here?

Layer 0 activation tanh

The activation function of a Layer determines the signal it sends to connected neurons.

Choices are sigmoid, smooth curve output 0-1 as x increases.

tanh similar to sigmoid output -1-> +1 depending on value of x

Stepwise output 0 or 1 depending on value of X

Etc going to deep here.

Layer1 this is our output layer.

Note the activation is identity.

This determines that the output will be linear, a range of numeric values, .1, .2, .3 etc. VS 0 or 1, vs Class A, B or C

STEP 3

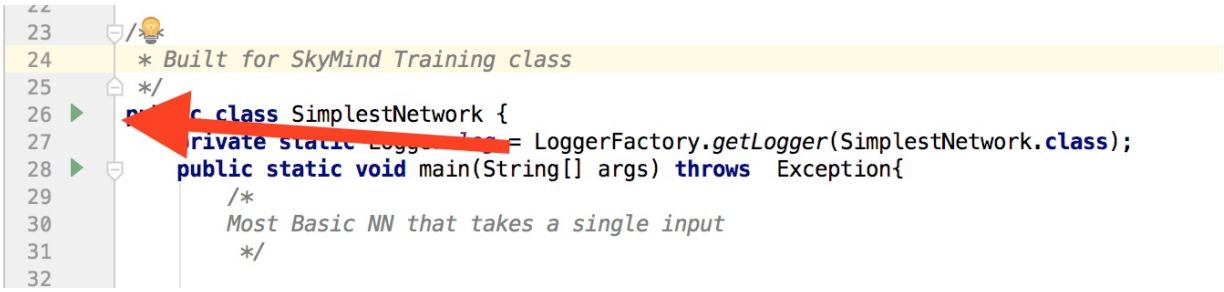
Run the code

In this step you will run the code.

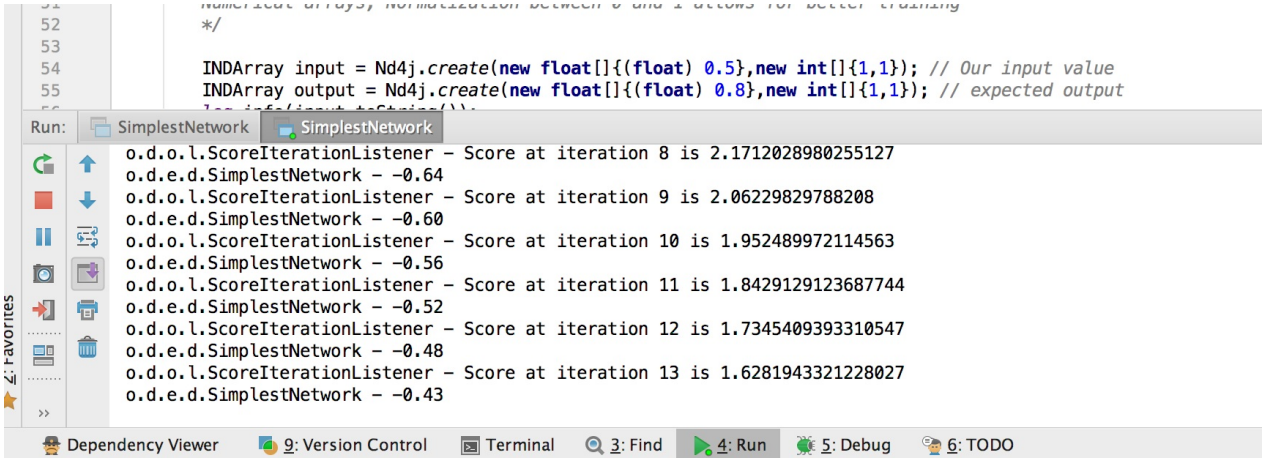
When the code executes it will create a UI that can be accessed with a web browser.

It will also print output to the output window at the bottom of intellij as it runs

Click on this green arrow to execute the code

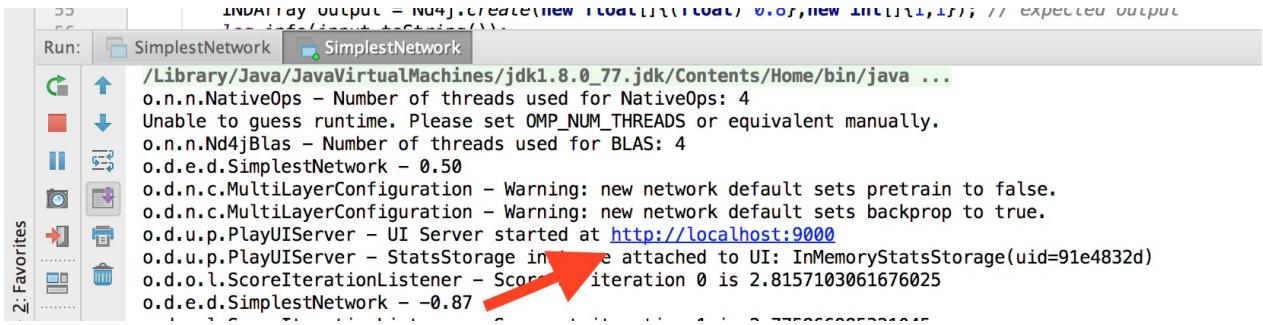


View the output in the console while the class runs



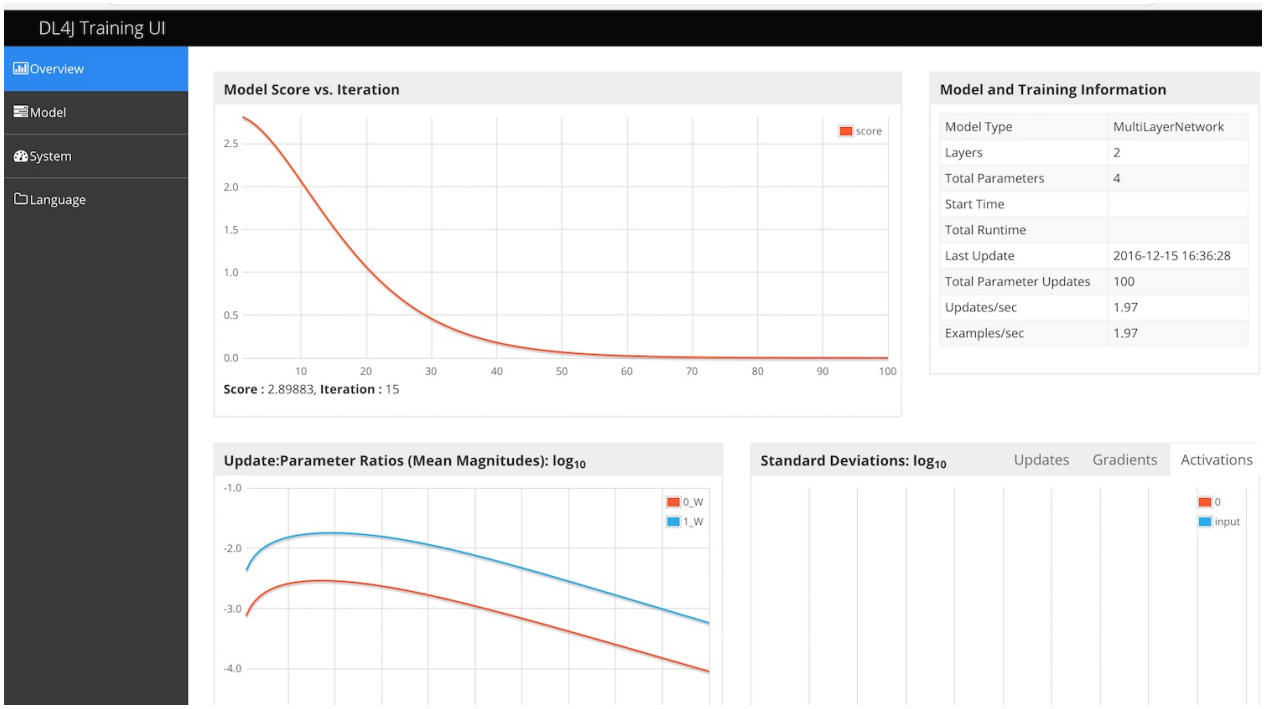
View the UI

When the code executes and the UI is created, a line is generated in the console output with the url



Open that URL in a browser

You should see this



Explaination of the output

Console Output.

The following block of code is what begins the training process.

```
for( int i=0; i<nEpochs; i++ ){
            model.fit(input,output);
            INDArray output2 = model.output(input);
            log.info(output2.toString());
            Thread.sleep(500);
        }
```

What is an Epoch?

It is a loop for the total number of Epochs. Or total passes through the training dataset, in this case our single input, but in real use cases it might be something like thousands of text reviews, or hundreds of thousands of images, or milllions od lines from log files.

What is Model.fit?

This is where the model trains. Data is ingested, random weights are assigned, output is evaluated against expected and weights are adjusted to lessen the error.

What output should look like

This section

```
INDArray output2 = model.output(input);
            log.info(output2.toString());
```

Generates these lines in our console output.

```
o.d.e.d.SimplestNetwork - -0.87
o.d.e.d.SimplestNetwork - -0.85
```

The "correct" output, or "expected" output is 0.80, you will see that the network is consistently getting closer to that goal as it trains.

This line in the console output

```
o.d.o.l.ScoreIterationListener - Score at iteration 1 is 2.775866985321045
```

Is generated by this line

```
model.setListeners(new StatsListener(statsStorage),new ScoreIterationListener(1));
```

STEP 4

In this step you will modify some of the parameters and see the effect on the training process.

Note that anytime you re-run this code you will have to terminate the previous running process. The webserver serving the UI will have a handle on a socket and the second example will try to grab that same socket, fail and return an error.

Kill the running process by clickin on the red square, top right.

Some parameters that you could tune.

Before you change things, note the current performance. How many iterations till it got to within .05 of the target? In 100 iterations how close did it get? Mine got to .78 after 100, and reached .75 at iteration 80

Settings you may change with reasonable results

Hidden Nodes

- Number of hidden nodes
  - Would provide more attempts towards the correct answer, more random weights, and may train quicker

Number of Epochs

- Number of Epochs
  - If the network is converging on the target, then more epochs should allow it to get there, in time
  - Note that to prevent things going to fast to visualize,I put a sleep .5 seconds in the loop.
  - Remove that if you set to large number of Epochs.

Learning Rate

Learning Rate Determines how far to adjust the weights given the error.

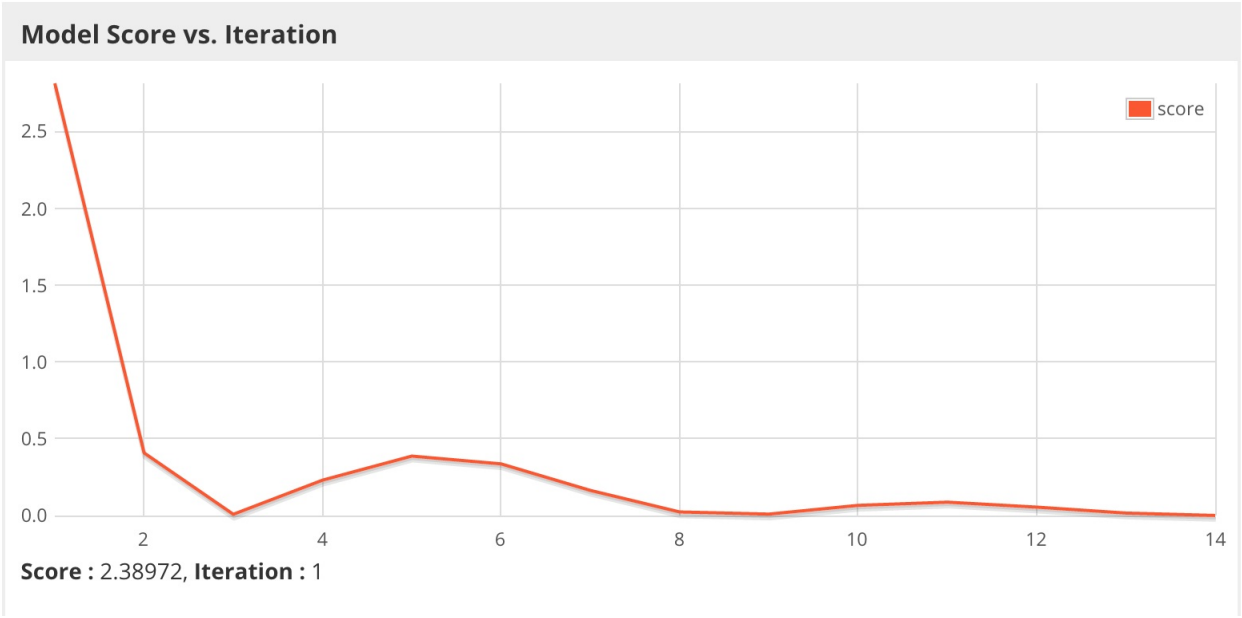
A range for learning rates would be ???

```
double learningRate = 0.001;
```

Change to perhaps...

```
double learningRate = 0.01;
```

Note that an aggressive learning rate may cause the network to overshoot the target before converging.



Lab questions

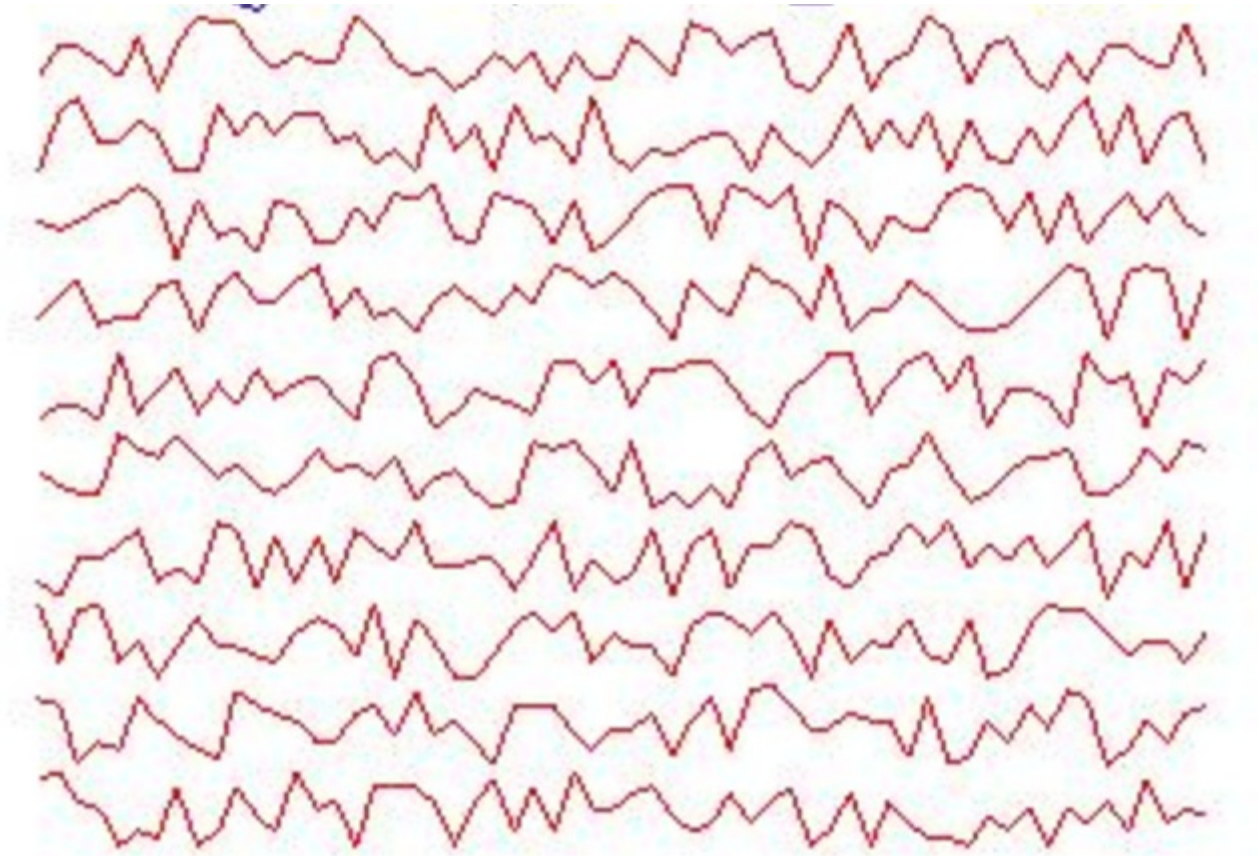
1. What parameters may need adjusting in a Neural Net
2.

Sequence Classification Lab

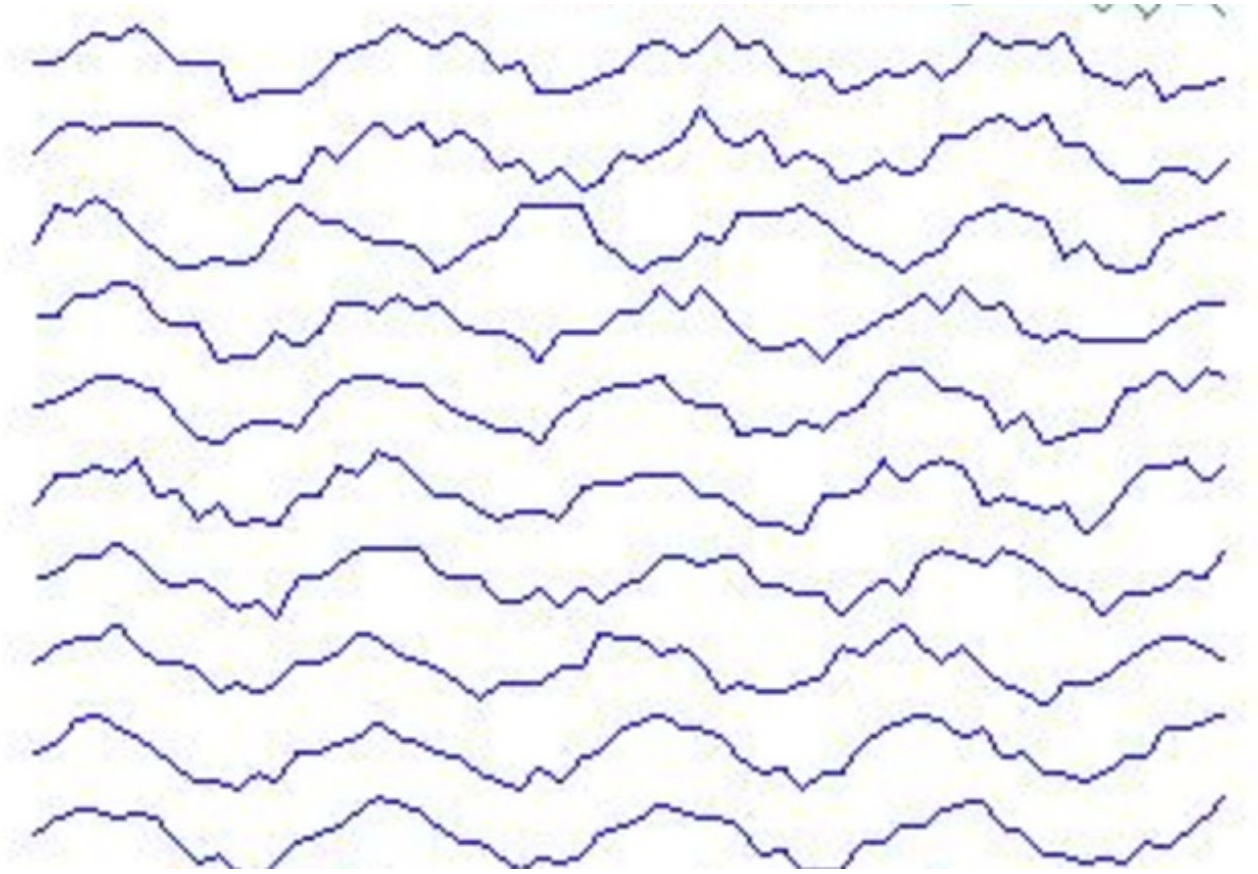
This Lab uses an LSTM Recurrent Neural Network to classify Sequence Data into 6 different classes.

The classes are:

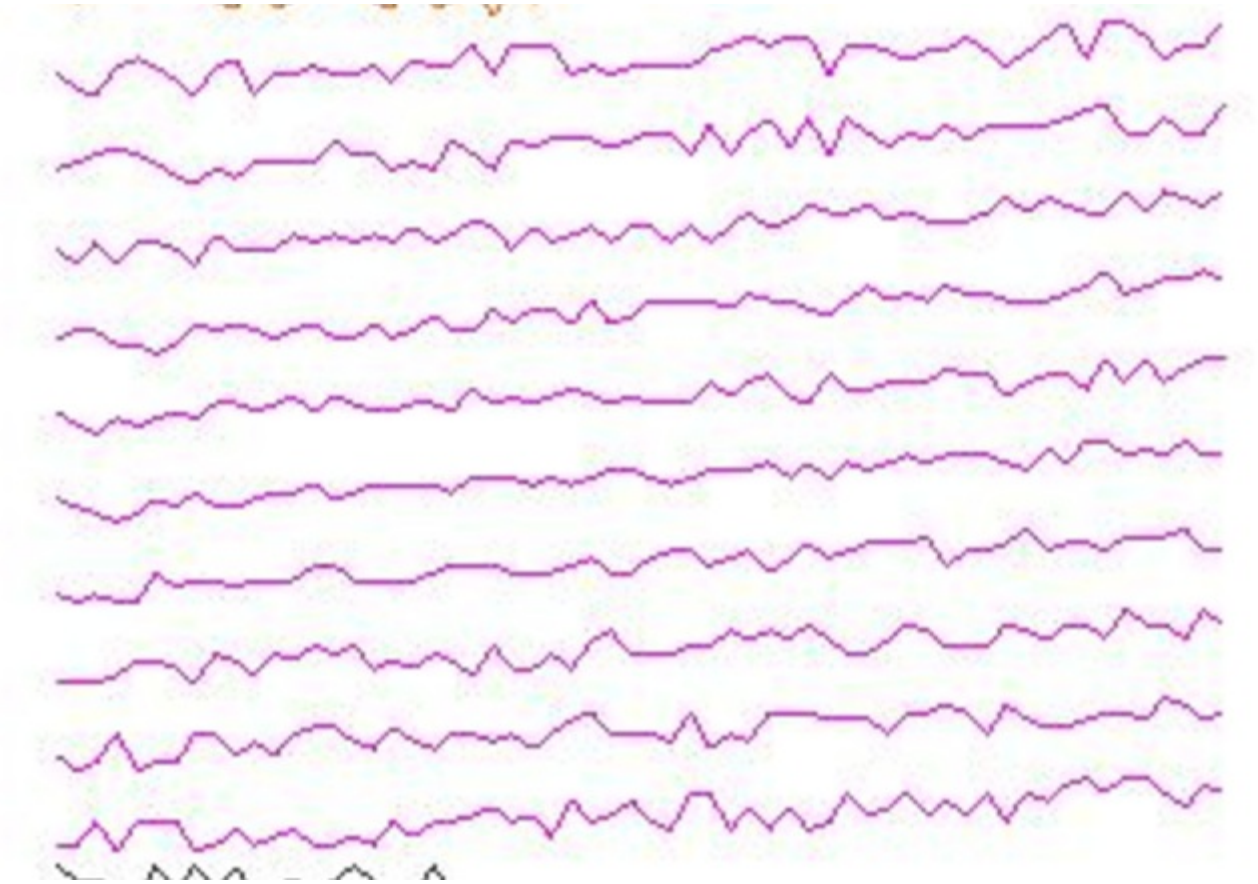
Normal



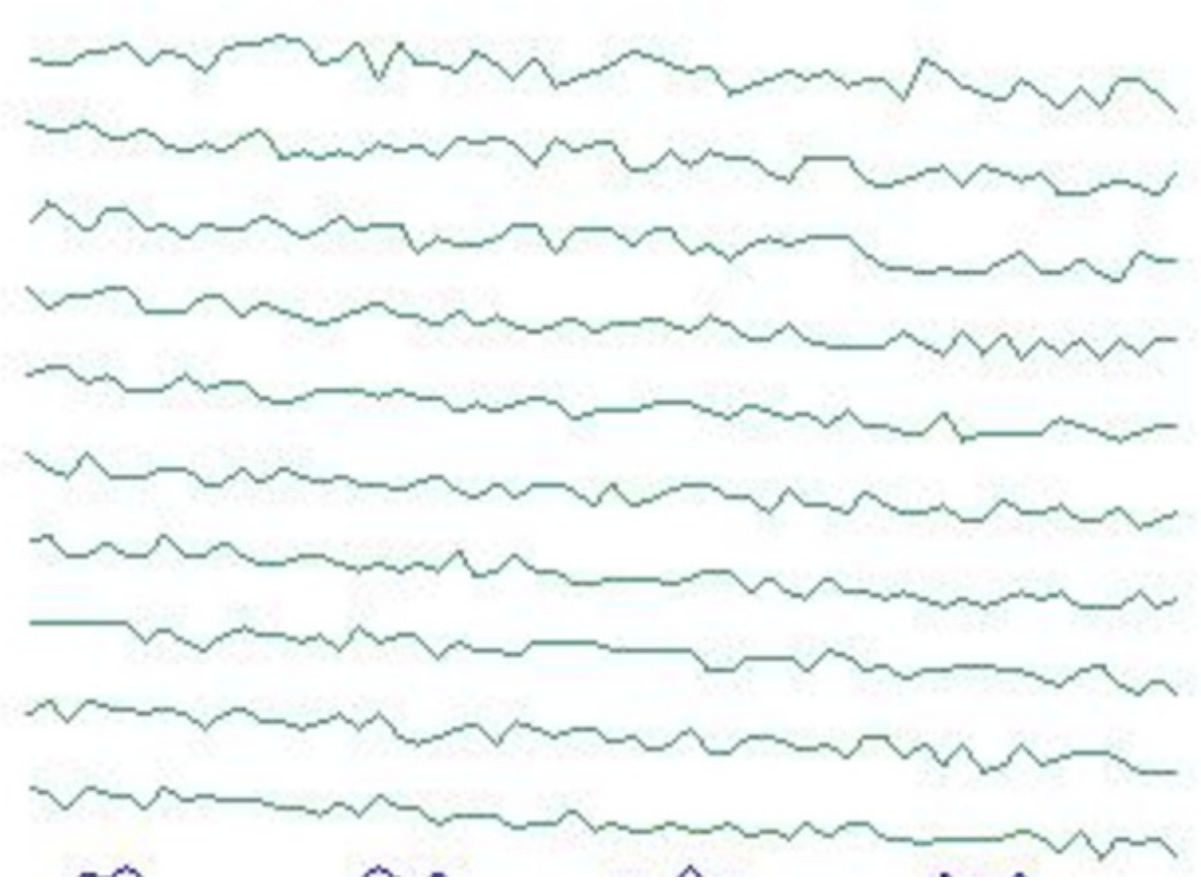
Cyclic



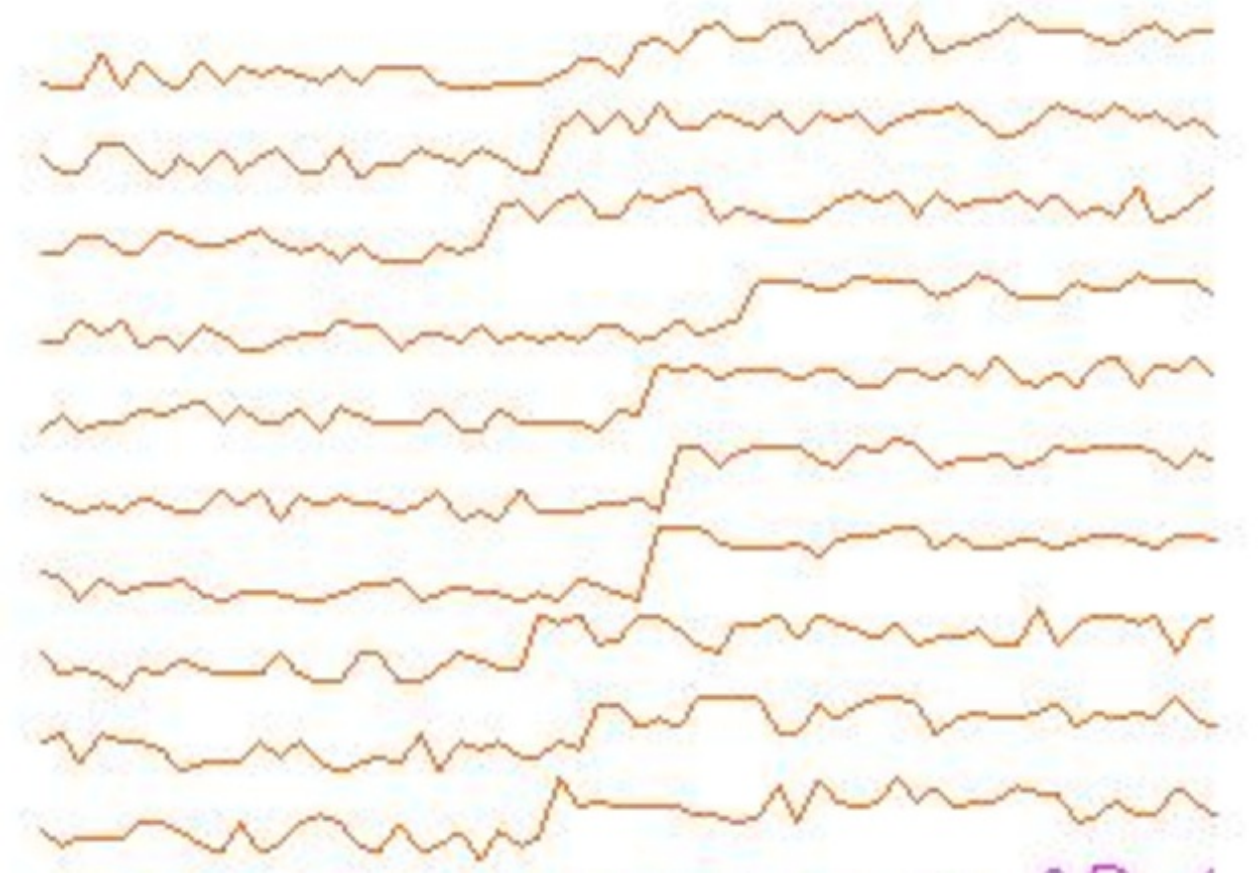
Increasing trend



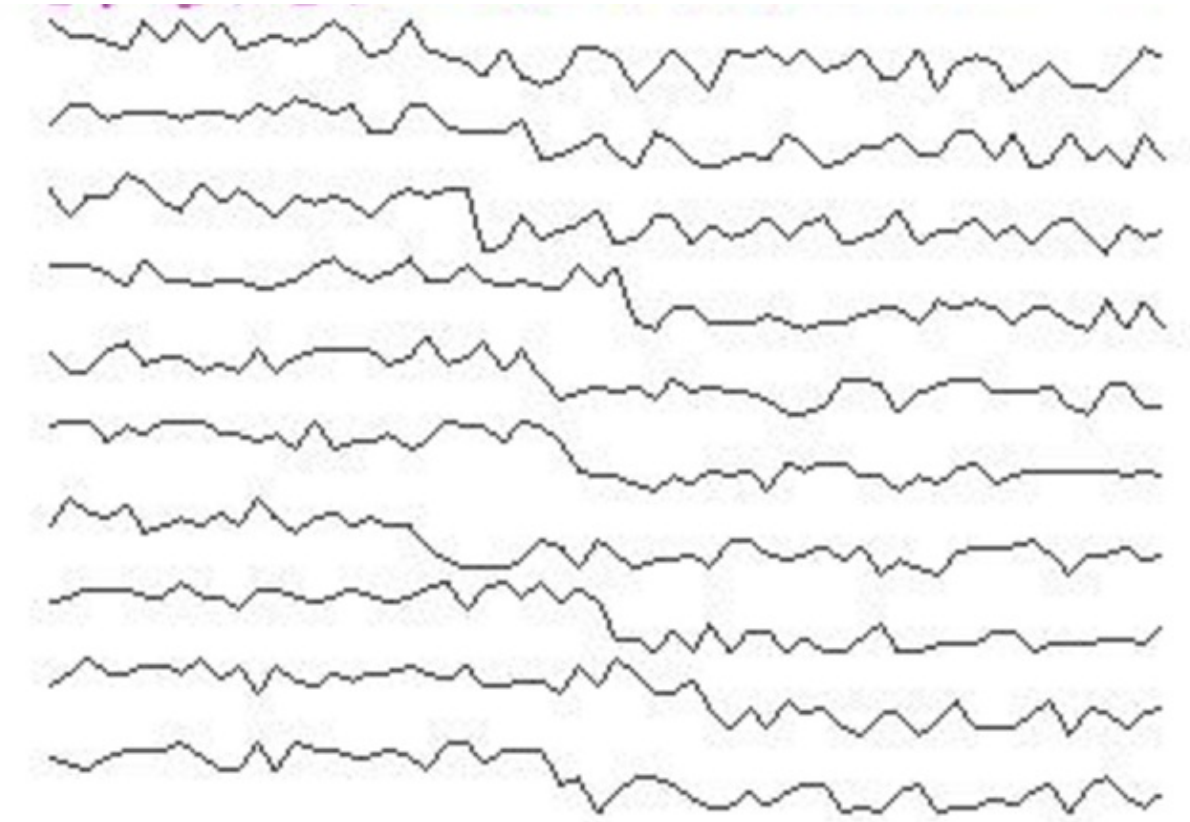
Decreasing trend



Upward shift



Downward shift



Lab Overview

- UCIdata.java
  - Utility class to download dataset
  - DO NOT EDIT UCIdata.java
- UCISequenceClassificationExample
  - The class you will edit for this lab

Lab Step 1

Navigate to the UCISequenceClassificationExample and add a line to call the UCIData class that downloads the data. ***Note*** the download takes time, once downloaded another call to UCIData verifies the download has occured and does NOT download again. It is safe to run the download twice.

Add this line to the class.

```
UCIData.download();
```

Lab Step 2

Set up the Record Readers for the Test and Train Data.

Add this line to the class.

```
SequenceRecordReader trainFeatures = new CSVSequenceRecordReader();
        trainFeatures.initialize(new NumberedFileInputSplit(ai.skymind.training.so
lutions.UCIData.featuresDirTrain.getAbsolutePath() + "/%d.csv", 0, 449));
        SequenceRecordReader trainLabels = new CSVSequenceRecordReader();
        trainLabels.initialize(new NumberedFileInputSplit(ai.skymind.training.solu
tions.UCIData.labelsDirTrain.getAbsolutePath() + "/%d.csv", 0, 449));
```

Lab Step 3

Set the miniBatchSize and the number of classes.

Add these lines to the class.

```
int miniBatchSize = 10;
int numLabelClasses = 6;
```

Lab Step 4

Create a DataSetIterator for the training Data.

The JavaDoc for the needed class is here, https://deeplearning4j.org/datavecdoc/org/datavec/api/records/reader/impl/csv/CSVSequenceRecordReader.html

Add this line to the class.

```
DataSetIterator trainData = new SequenceRecordReaderDataSetIterator(trainFeatures,
 trainLabels, miniBatchSize, numLabelClasses,false, SequenceRecordReaderDataSetIte
rator.AlignmentMode.ALIGN_END);
```

Lab Step 5

Normalize the data.

Add the following lines to the class.

```
DataNormalization normalizer = new NormalizerStandardize();
normalizer.fit(trainData);
trainData.setPreProcessor(normalizer);
```

Lab Step 6

Set up the Test Data.

Add the following lines to the class.

```
 SequenceRecordReader testFeatures = new CSVSequenceRecordReader();
 testFeatures.initialize(new NumberedFileInputSplit(ai.skymind.training.solutions.
UCIData.featuresDirTest.getAbsolutePath() + "/%d.csv", 0, 149));
 SequenceRecordReader testLabels = new CSVSequenceRecordReader();
 testLabels.initialize(new NumberedFileInputSplit(UCIData.labelsDirTest.getAbsolut
ePath() + "/%d.csv", 0, 149));
 DataSetIterator testData = new SequenceRecordReaderDataSetIterator(testFeatures,
testLabels, miniBatchSize, numLabelClasses,false, SequenceRecordReaderDataSetItera
tor.AlignmentMode.ALIGN_END);
 testData.setPreProcessor(normalizer);
```

Lab Step 7

Set up the Neural Network

Add the following lines of code to the class.

```
MultiLayerConfiguration conf = new NeuralNetConfiguration.Builder()
    .seed(123)
    .optimizationAlgo(OptimizationAlgorithm.STOCHASTIC_GRADIENT_DESCENT).iteration
s(1)
    .weightInit(WeightInit.XAVIER)
    .updater(Updater.NESTEROVS).momentum(0.9)
    .learningRate(0.005)
    .gradientNormalization(GradientNormalization.ClipElementWiseAbsoluteValue)
    .gradientNormalizationThreshold(0.5)
    .list()
        .layer(0, new GravesLSTM.Builder().activation("tanh").nIn(1).nOut(10).buil
d())
        .layer(1, new RnnOutputLayer.Builder(LossFunctions.LossFunction.MCXENT)
            .activation("softmax").nIn(10).nOut(numLabelClasses).build())
            .pretrain(false).backprop(true).build();

        MultiLayerNetwork net = new MultiLayerNetwork(conf);
        net.init();
```

Lab Step 8

Add a UI

Add the following lines to the class.

```
UIServer uiServer = UIServer.getInstance();
StatsStorage statsStorage = new InMemoryStatsStorage();
net.setListeners(new StatsListener(statsStorage));
uiServer.attach(statsStorage);
```

Lab Step 9

Train the network.

Add the following lines to the class.

```
int nEpochs = 40;
    String str = "Test set evaluation at epoch %d: Accuracy = %.2f, F1 = %.2f";
    for (int i = 0; i < nEpochs; i++) {
        net.fit(trainData);
        Evaluation evaluation = net.evaluate(testData);
        log.info(String.format(str, i, evaluation.accuracy(), evaluation.f1()));
        testData.reset();
        trainData.reset();
}
        log.info("----- Example Complete -----");
```

-

Physionet Multivariate TimeSeries Classification Lab

In this lab you will build a Neural Network to predict patient mortality based on 2 days worth of data from a stay at the Intensive Care Unit.

Goals of this lab

This Lab introduces the following

- Using DataVec to ingest Multivariate Sequence Data
- Building an LSTM for classification of MultiVariate Sequence Data

Step 1

- Open up IntelliJ Open up IntelliJ and navigate to the Labs folder

Step 2 : Review the Data

The Data is stored in the **Top Level** resources folder "src/main/resources". It is easy to confuse this with the "training-labs/src/main/resources" folder.

The Labels

The goal is to predict mortality, wether the patient lived or died. The folder "mortality" has one file for patient. Each file has a single line with either a 0 or 1 depending on life or death of the patient

This label will be what we train our neural network to learn to predict. The neural network will predict a label and the predicted label will be compared with the actual label.

The Features

Patient data was recorded at differing intervals for each metric,some data was recorded once upon arrival, other data was recorded once a day, other data more frequently. The original dataset was stored with timestamp, field, value. For our purposes the data has been reorganized in two ways.

Resampled Data

The directory "resampled" will have the data resampled to one hour intervals with values averaged over the one hour period. Each file will have 49 lines, one header line and one line with values for each of the 48 time steps. This dataset only has two days worth of data per patient.

Data Masking

An additional Field was added to each field, in order to deal with timesteps with a field that was not measured at that timestep a previous value or an imputed value, when a non-measured value is repeated or substituded the flag is set to 1, when a measured value is present the flag is set to 0.

Sequence Data

The Directory "sequence" contains the sequence data. The first column 'Time'is in hours since patient is admitted to ICU. The second column 'Elapsed' is the time in hours since the last timestep. Each timestep in the time series is of different length of time. For example, the time between the first and second timestep could be 1 hour, while the time between the second and third timestep could be 2 hours.

Note that the solution provides a flag for choosing wether or not to include the first two time related columns.

Set remove = 0 to use the original dataset minus the Time and Elapsed columns (84 features) Set remove = 1 to use the original dataset minus the Time column (85 features) Set remove = 2 to use the original datset minus the Elapsed column (85 features) Set remove to another integer to use the original dataset (86 features, including Time and Elapsed columns)

Step 3

- Review the Java Code

STEP 4

Set the number of epochs to 25. An epoch is a full pass through the test data. How many epochs are enough? You want the network to train to a point that it generalizes well and has not "overfit" the training data. Using the webui is helpful and comparing with a validation set is also helpful, when scores against the validation test quit improving any further training would lead to overfitting.

25 epochs was chosen as a reasonable length of time for this class lab. When training a model for production use over a large dataset it make take hours or days to train. In that case it would be a good idea to save a model using modelserializer every so often so you can save your work and start from a pre-trained model.

```
public static final int NB_EPOCHS = 25;
```

STEP 5: Set additional parameters

Set the following:

Random Seed

for reproducable results.

learning Rate.

Learning Rate settings will depend on the network and the data, reasonable values would be in a range from 0.1 to 0.000001. Through trial and error we found 0.032 to be a reasonable value for this network.

Batch Size

The batch size is the number of training samples your training will use in order to make one update to the model parameters.Too large a batch size may use too much memory. Smaller batch size converges less smoothly. In this case it is set to 40.

LSTM Layer Size

Our network will have a single LSTM layer, set it to a size of 200. Generally if the network is too large it has a greater risk of overfitting and takes more resources to calculate each parameter update.If the network is too small it wont have enough parameters to learn the features of the training set.

```
public static final int RANDOM_SEED = 1234;
public static final double LEARNING_RATE = 0.032;
public static final int BATCH_SIZE = 40;
public static final int lstmLayerSize = 200;
```

Step 6: Create DataSet Iterators for Train Validation and Test Datasets

A Record Reader returns an iterator over a List of Writables. Writables are an efficient serialization method inspired by Hadoop Writables.

A Neural Net requires input as an Array of Numeric values. DataSetIterator creates a DataSet tht contains an INDArray of Features and an INDArray of Labels.

```
DataSetIterator trainData;
DataSetIterator validData;
DataSetIterator testData;
```

Step 7: Create and initialize SequenceRecordReaders for the Train, Validation and Test Data

The measurments are stored in a file in one directory, the labels are stored in files in another directory. The correlation between the two is the number in the filename. To read the data use SequenceRecordReader, to read the Labels use SequenceRecordReader. To build a dataset with both Labels and Features use SequenceRecordReaderDataSetIterator.

```
// Load the Features
SequenceRecordReader trainFeatures = new CSVSequenceRecordReader(1, ",");
trainFeatures.initialize( new NumberedFileInputSplit(featuresDir.getAbsolutePath()
 + "/%d.csv", 0, NB_TRAIN_EXAMPLES - 1));

// Load the Labels
    SequenceRecordReader trainLabels = new CSVSequenceRecordReader();
    trainLabels.initialize(new NumberedFileInputSplit(labelsDir.getAbsolutePath()
+ "/%d.csv", 0, NB_TRAIN_EXAMPLES - 1));
// Combine Labels and Features into DataSet
    trainData = new SequenceRecordReaderDataSetIterator(trainFeatures, trainLabels
,
        BATCH_SIZE, numLabelClasses, false, SequenceRecordReaderDataSetIterator.Al
ignmentMode.ALIGN_END);


// Load validation data
    SequenceRecordReader validFeatures = new CSVSequenceRecordReader(1, ",");
    validFeatures.initialize(new NumberedFileInputSplit(featuresDir.getAbsolutePat
h() + "/%d.csv", NB_TRAIN_EXAMPLES , NB_TRAIN_EXAMPLES + NB_VALID_EXAMPLES  - 1));

// Load the Validation Labels
    SequenceRecordReader validLabels = new CSVSequenceRecordReader();
    validLabels.initialize(new NumberedFileInputSplit(labelsDir.getAbsolutePath()
+ "/%d.csv", NB_TRAIN_EXAMPLES , NB_TRAIN_EXAMPLES + NB_VALID_EXAMPLES  - 1));

// Combine the Validation Labels and Features into a DataSet
    validData = new SequenceRecordReaderDataSetIterator(validFeatures, validLabels
,
        BATCH_SIZE, numLabelClasses, false,SequenceRecordReaderDataSetIterator.Ali
gnmentMode.ALIGN_END);

// Load test data
// Load the Features
    SequenceRecordReader testFeatures = new CSVSequenceRecordReader(1, ",");
        testFeatures.initialize(new NumberedFileInputSplit(featuresDir.getAbsolute
Path() + "/%d.csv", NB_TRAIN_EXAMPLES+ NB_VALID_EXAMPLES, NB_TRAIN_EXAMPLES + NB_V
ALID_EXAMPLES + NB_TEST_EXAMPLES - 1));

// Load the Labels
    SequenceRecordReader testLabels = new CSVSequenceRecordReader();
        testLabels.initialize(new NumberedFileInputSplit(labelsDir.getAbsolutePath
() + "/%d.csv", NB_TRAIN_EXAMPLES+ NB_VALID_EXAMPLES, NB_TRAIN_EXAMPLES + NB_VALID
_EXAMPLES + NB_TEST_EXAMPLES - 1));

// Combine the Labels and Features into a DataSet
    testData = new SequenceRecordReaderDataSetIterator(testFeatures, testLabels,
        BATCH_SIZE, numLabelClasses, false, SequenceRecordReaderDataSetIterator.Al
ignmentMode.ALIGN_END);
```

Step 8: Configure a Neural Network

For this Neural Network we will start with a ComputationGraph Configuration. A Computation Graph allows for more options that a MultiLayerNetwork.

Add the following code to your class.

```
ComputationGraphConfiguration conf = new NeuralNetConfiguration.Builder()
                .seed(RANDOM_SEED)
                .optimizationAlgo(OptimizationAlgorithm.STOCHASTIC_GRADIENT_DESCEN
T)
                .learningRate(LEARNING_RATE)
                .weightInit(WeightInit.XAVIER)
                .updater(Updater.ADAM)
                .graphBuilder()
                .addInputs("trainFeatures")
                .setOutputs("predictMortality")
                .addLayer("L1", new GravesLSTM.Builder()
                                .nIn(NB_INPUTS)
                                .nOut(lstmLayerSize)
                                .activation(Activation.TANH)
                                .build(),
                        "trainFeatures")
                .addLayer("predictMortality", new RnnOutputLayer.Builder(LossFunct
ions.LossFunction.XENT)
                        .activation(Activation.SOFTMAX)
                        .weightInit(WeightInit.XAVIER)
                        .nIn(lstmLayerSize).nOut(numLabelClasses).build(),"L1")
                .pretrain(false).backprop(true)
                .build();
```

Step 9: Build a Neural Net and add listener

Build a Computation Graph and pass it the configuration built in step 8. Initialize the network and set a Listener. A listener reports progress, in this case for each 10 parameter updates our listener will log the score of the network's loss function.

```
ComputationGraph model = new ComputationGraph(conf);
    model.init();
    model.setListeners(new ScoreIterationListener(10));
```

Step 10: Remove the comments to run the code

The last section of code has been commented out, remove the comments, fix any errors you may find and run the code.

To uncomment find the lines, and remove the "/*" *and the* "*/"

// STEP #10 REMOVE THE COMMENT BELOW

Extra Credit

Attach a UI server to the network so you can visualize the training process.

Hint Copy code from SimplestNetwork.

END OF Physionet MultiVariate Time Series Lab

Building a Convolutional Neural Network

A convolutional Neural Network differs from a Feed Forward Neural Network by having Convolutional Layers, followed by MaxPooling Layers.

A convolutional Layer looks at a subset of the image in a moving window across the complete image. As each region of the window is evaluated the model learns to detect useful features, regardless of where they occur in the image.

A MaxPooling Layer is used after a Convolutional layer. Pooling Layers function to reduce the spatial size of the representation to reduce the amount of parameters and computation in the network.

Lab Step 1:

Open the Class ConvNeuralNet and uncomment/delete the two lines with

<-- DELETE THIS LINE --> .

The open comment line

```
/* <-- DELETE THIS LINE -->
```

and the close comment line

```
 <-- DELETE THIS LINE --> */
```

Lab Step 2:

Most of the code here is exactly the same as the FeedForward Neural Network Example.

The Network will be modified and the two hiddel layers will be replaced with a Convolutional Layer a MaxPooling Layer. The Output Layer will remain more or less the same.

Add the Convolutional Layer.

```
.layer(0, new ConvolutionLayer.Builder(5, 5)
    //nIn and nOut specify depth. nIn here is the nChannels and nOut is the number
 of filters to be applied
        .nIn(channels)
        .stride(1,1)
        .nOut(20)
        .activation(Activation.IDENTITY)
        .build())
```

Lab Step 3:

Add the MaxPooling Layer.

```
.layer(1, new SubsamplingLayer.Builder(SubsamplingLayer.PoolingType.MAX)
    .kernelSize(2,2)
    .stride(2,2)
    .build())
```

Lab Step 4:

Add the Output Layer

Note that this is very similar to the output Layer used in the FeedForward Network.

```
.layer(2, new OutputLayer.Builder(LossFunctions.LossFunction.NEGATIVELOGLIKELIHOOD
)
                        .nOut(outputNum)
                        .activation(Activation.SOFTMAX)
                        .build())
```

Lab Step 5:

Run the Convolutional Neural Network and compare the accuracy to the accuracy of the FeedForward Network.

In a single epoch run the convnet may misclassify a 5 as a 6, or a 3 as an 8.

Extra Credit:

Try to improve the performance of the Convolutional Network.

- Add more Layers

The Very Succesful Image Recognition Neural Networks have 16 or more layers.

Add one or more pairs of Convolutional Layer followed by maxPooling Layers.

- Modify the size of the Convolution Layers

This line `ConvolutionLayer.Builder(5, 5)` Specifies a 5 pixel by 5 pixel window will be examined, and this line `.stride(1,1)` specifies to move the window over 1 pixel and repeat till end of line and then down one pixel.

Modifying those settings and see if you can get better results.

Saving and Loading a Trained Model

In this lab you will

1. Attach a UI instance to a model
2. Save the model
3. Load the saved model

Goals of the Lab

- Label Generation with ParentPathLabelGenerator
- Attaching a UIServer
- Saving a Trained model
- Loading a Trained model

Step 1

- Open up IntelliJ Open up IntelliJ and navigate to the Labs folder

Step 2

- Open the MnistImageSave class

This example uses the classic Machine Learning challenge of recognizing handwritten digits.

Step 3

- Review the Input

The data is in the following directories resources/mnist_png/testing, resources/mnist_png/training.

Open one of the directories and note that it contains subdirectories 0-9 each containing24*24 pixel gray scale images of digits.

STEP 4

- Attach a UI instance to the Neural Network.

See the SumplestNetwork for an example.

Step 5

- Save the Model

The Javadoc for ModelSerializer is here
https://deeplearning4j.org/doc/org/deeplearning4j/util/ModelSerializer.html

You want to use ModelSerializer.writeModel with the constructor that takes(modelname,location_to_save, boolean saveUpdater)

The modelname will be the name of the model in this example.

The location to save is already defined. File locationToSave = new File("trained_mnist_model.zip");

SaveUpdater is used when you want to train the model further or simply use it for inference.

some models train for days or weeks, with any longrunning process it is important to save progress in case of disaster. Running ModelSerializer.writeModel allows you to save the model, perhaps every few hours.

Step 6

Run the code

Step 7

Load the Trained model.

Create a class named MnistImageLoad

add a Logger

```
    private static Logger log = LoggerFactory.getLogger(MnistImageLoad.class);
```

Add a Main method

```
public static void main(String[] args) throws Exception {

}
```

Set three Int objects height, width, channels.

Set values to 28,28 and 1.

Move the saved model to the resources folder so it is in the classpath.

Create two file objects one for the trained_mnist_model.zip file and one for the image that will be classified by the model, number.png.

```
File modelSave =  new ClassPathResource("trained_mnist_model.zip").getFile();
```

```
File imageToTest = new ClassPathResource("number.png").getFile();
```

Create a MultiLayerNetwork model using ModelSerializer.restoreMultiLaerNetwork([File Object for the model]);

To read a single image to pass into the saved network for evaluation use the NativeImageLoader Class.

```
NativeImageLoader loader = new NativeImageLoader(height, width, channels);
```

Get the image into an INDarray

```
INDArray image = loader.asMatrix(imageToTest);
```

For expected results the image must be processed in the same way as the images that the network trained on were processed.

Create a DataNormalization scaler to scale pixel values to values between 0 and 1.

```
DataNormalization scaler = new ImagePreProcessingScaler(0,1);
```

Transform the image with the transform method of the DataNormalization scaler.

```
scaler.transform(image);
```

Pass the transformed image matrix to neural Net.

```
INDArray output = model.output(image);
```

Print the output to the console.

```
log.info(output.toString());
```

Run your code to verify.