JOONE - Java Object Oriented Neural Engine

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Abstract

I would like to present the objectives that I had in mind when I started to write the first lines of code for Joone. My dream was (and still is) to create the necessary framework to enable the implementation of a new approach to the use of neural networks. I felt this necessity because the biggest (and unresolved until now) difficulty is to find the fittest network for a given problem, without falling into local minima, thus allowing one to discover the best neural network architecture for the problem. Okay - you'll say - this is what we can do simply by training some randomly initialized neural network with a supervised or unsupervised algorithm. Yes, that is true, but this is just scholastic theory, because training only one neural network, especially for the hard problems found in real life situations, is rarely enough to permit the discovery of optimal solutions. In addition, finding the best neural network can be a daunting task simply because we need to determine numerous parameters for any given network. Parameters such as the number of the layers, number of neurons for each layer, the transfer function, the value of the learning rate and the momentum may all require extensive manipulation while searching for problem solutions. This difficulty often leads to many frustrating failures. That being said my basic idea is to provide an environment which will facilitate the training of many neural networks in parallel, initialised with different weights different parameters and different architectures, enabling investigators an opportunity to find the best neural network simply by selecting the fittest neural network after the training processes. In addition these processes could continue retraining the selected neural networks until some final parameter is reached (e.g. a low RMSE value). Similar to distillation processes the best architecture would be distilled by Joone, not by the user! Many programs in existence today permit the selection of the fittest neural network by the application of genetic algorithms. I want to go beyond this. My goal is to build a flexible environment programmable by the end user, thereby permitting the implementation of any currently existing or newly discovered global optimisation algorithm. This is why Joone has its own distributed training environment and why it is based on a cloneable engine. Moreover, my dreams do not terminate with a flexible environment but extend to providing the ability for Joone end users to not only use but also distribute trained neural networks to others for their use. For example, I'm imagining an assurance company that continuously trains many neural networks on customer risk evaluations1 (perhaps using the results of historical cases), distributing the best 'distilled' (or genetically evolved) neural network to its sales force, so that they can use optimized neural networks on their mobile devices. This is why neural networks built with Joone are serializable, remotely transportable and easily runnable using simple, small and generalized programs using any wired or wireless protocol. It also means that my dream can become a more solid reality thanks to the advent of handheld devices like mobile phones and PDAs which contain Java virtual machines. Joone is ready to run on them. I sincerely

hope you will find our work interesting and useful and I thank you for giving Joone a try.
Paolo Marrone and the Joone team

Contents

Chapter 1

Introduction

1.1 Intended Audience

This paper describes the technical concepts underlying the core engine of Joone, explaining in detail the architectural design that is at its foundation. This paper is intended to provide programers - or anyone interested in using Joone - with knowledge of the basic mechanisms of the core engine thereby enabling anyone to understand how to use and expand Joone to resolve their individual needs.

A basic knowledge of the concepts underlying artificial neural networks is required for the understanding and use of Joone, consequently, those who do not possess such know-how should read some good introductory books on the field.

1.2 What is Joone

Joone http://www.joone.org is a Java framework to build and run Artificial Intelligence (AI) applications based on neural networks. Joone applications can be built on a local machine, they can be trained on a distributed environment (DTE http://www.linktothedte) and they can be run on any device that contains a Java Virtual machine. Joone consists of a modular architecture based on linkable components that can be extended to build new learning algorithms and neural network architectures.

All the components have some basic specific features such as persistence, multithreading, serialization and parameterisation. These features guarantee scalability, reliability and expansibility. Such features are mandatory for reaching the final goal of having Joone represent the future standard in the AI world.

Joone applications are built out of components. Components are pluggable, reusable, persistent code modules. Components are written by developers. AI experts and designers can build applications by gluing together components with graphical editors while controlling the logic of the applications with scripts.

Since all the modules and applications written with Joone are based on, and will be built around, components, Joone can be used to build Custom Systems, adopted in an *Embedded* manner. These custom systems can be used to enhance existing applications or employed while building applications for *Mobile Devices*.

1.2.1 Custom systems

A great need present in the industrial market is finding suitable resolutions to business problems using neural network technologies and innovations (or with AI applications in general). Joone represents an optimal solution in building applications to satisfy these industrial market needs (e.g. bank loan assessment, sales forecasting, etc.).

Joone's characteristics are optimal when it comes to building custom applications driven by the user's needs particularly where it is important to have flexibility, scalability and portability. In addition, each enhancement of Joone will be compatible with the necessity of building applications more quickly. This will enable Joone to gain in popularity as it saves both development time and development dollars, thereby providing a business advantage to those who utilize its neural network frameworks.

1.2.2 Embedded systems

Joone's core engine contains components which are the bricks used to build whatever neural network architecture one desires. They provide the programmer with the ability to create AI applications writing Java code that uses the Joone API. In the spirit of the goal that aims for wide market adoption of Joone the license of the core engine is the Lesser General Public License (LGPL), so anyone can freely embed the engine into existing or new applications. **This will never change**.

The business model of Joone anticipates for the possibility of providing more components to satisfy future user needs of creating several neural network architectures and algorithms, so they can embed Joone into whatever application desired (e.g. data mining systems, automatic categorization for search engines, customer classification, etc.)

1.2.3 Mobile Devices

Another long-term goal for Joone is to have it become the basic framework for providing a computational engine to AI applications suitable for mobile devices (phones, PDA, etc.). The demand for software products for such devices is growing thus creating a new market for applications using Joone technologies. This demand is gaining the interest of the industrial world. Joone wants to be present in that market and represent the main framework to distribute and run personal or corporate AI applications (e.g. handwriting and voice recognition, support to the sales force, sales or financial forecasting, etc.). The core engine of Joone is poised and ready to meet these market demands since it is ideally suited for

small devices because Joone has a small memory footprint and is runnable on Personal Java environments (JME).

1.3 About this guide

This guide is composed of the following chapters (the asterisks indicate the skills required to correctly understand the concepts utilized in each chapter).

- **Chapter 1 Introduction**
  This Chapter contains a brief description of what Joone is and also provides ideas for potential applications in several fields of the professional world.

- **Chapter 2 Getting and installing Joone**
  This Chapter contains the starter guide which provides the information required to learn how to download and install all of the Joone API packages, framework as well as additional instructions for obtaining a runnable version from Joone's source code.

- **Chapters 3-7 Concepts and technical details**
  These chapters illustrate the basic concepts underlying Joone's core engine. They explain the main features of the core engine from a functional point of view. Also, for whose that are interested in the technical implementation, each chapter ends with a paragraph named Ôtechnical detailsÕ where a more detailed look at the described features and how they have been implemented is given.

- **Chapter 8 Common Architectures**
  This chapter is a practical guide to building the most common neural network architectures. Architectures such as the temporal, recurrent, unsupervised and combinations are explained. For each architecture an example is built using the visual editor. This Chapter is intended as a complement to the Editor User Guide, and its goal is to give a first look at some potential applications of Joone.
  TO BE COMPLETED .

- **Chapter 9 Applying Joone**
  This Chapter explains the main features of Joone using concrete and useful examples written in Java code. Applying the programming techniques described in this chapter anyone can build a custom Java application that uses Joone as its internal neural network engine.
  TO BE COMPLETED .

1.3.1 Acknowledgements

Joone was made possible thanks to the many people that have supported my initial idea and have extended the initial code by adding new ideas, suggestions and, mainly, good and

often documented source code. This is a demonstration that complex fields like Artificial Intelligence approached under the Open Source model can obtain the collaboration of many skilled programmers thereby enabling the building of a complete, stable and powerful framework.

Paolo Marrone, the founder and project manager of Joone, wants to thank all the guys who have contributed continuously and for a long period of time, writing good Java code, and also giving great support represented by their very interesting proposals and suggestions. They are (listed in alphabetical order):

Andrea Corti, Huascar Fiorletta, Harry Glasgow, Boris Jansen, Julien Norman, Paul Sinclair, Thomas Lionel Smets

Thanks also to the following people for their valuable contribution:

Gavin Alford, Mark Allen, Jan Boonen, Yan Cheng Cheok, Ka-Hing Cheung, Pascal Deschenes, Jan Erik Garshol, Jack Hawkins, Nathan Hindley, Olivier Hussenet, Shen Linlin, Casey Marshall, Richard Ouimet, Christian Ribeaud, Anat Rozenzon, Trevis Silvers, Jerry R. Vos

Do you want to see your name listed above? Join us: any contribution is always welcome, therefore if you have built some new component, new feature, or you have fixed some bug, contact me (mailto:pmarrone@users.sourceforge.net) and I'll be very happy to insert your name in the above list of contributors. You can also contact me even if you're not a Java developer, but, as an expert on neural networks, you'd like to help me to implement some new component or new training algorithm. Of course the Forums on the web site and my email address are always available for any idea or suggestion. Thank you.

I want also to thank all the authors of the following O.S. external packages used by Joone:

JHotDraw	http://sourceforge.net/projects/jhotdraw
BeanShell	http://sourceforge.net/projects/beanshell
jEdit-Syntax	http://sourceforge.net/projects/jedit-syntax
Log4J	http://jakarta.apache.org/log4j
HSSF-POI	http://jakarta.apache.org/poi
NachoCalendar	http://nachocalendar.sourceforge.net
XStream	http://xstream.codehaus.org
VisAD	http://www.ssec.wisc.edu/~billh/visad.html
additional packages ...	...

A particular acknowledgment to:

SourceForge.net	http://sourceforge.net/	thanks to which all this has been possible
Zero G Software	http://urltozerogsoftware	for their installer used by Joone

Chapter 2

Getting and Installing Joone

2.1 Platform and requirements

Joone is written in 100 % pure Java and can run on any platform for which a Java Runtime Environment version 1.6 is available. Due to his direct experience and because he has received information from other users, the author can assure the compatibility of Joone with the following operating systems:

- Linux
- Mac OS X
- Windows 2000
- Windows XP
- SUN Solaris

Memory requirements depend on the complexity of the neural network used, however, generally the availability of at least 256MB of RAM, even if not mandatory, is strongly recommended. Due to its small footprint, a minimal version of Joone's core engine can also run on mobile devices (e.g. PDAs) running JME CLDC with the Personal Profile (The author has run, without problems, the sample XOR neural network on a HP-Compaq IPAQ device provided with 32MB of flash memory successfully on both Jeode and IBM J9 JVMs.)

2.2 Installing the binary distribution

Joone is distributed both in source and compiled forms. The compiled distribution (named also the binary distribution) is available both for the core engine and the GUI editor. The following explains how to download and install them on your particular machine.

2.2.1 The core engine

The compiled form of the core engine can be useful to run any application written in Java that uses the Joone's engine API, as extensively described in the next chapters. All the classes are contained in a library jar file entitled joone-engine.jar. This library cannot run stand-alone since it does not contain any main class. The libraries of classes must be put into the classpath of the application that will use Joone. In addition, and depending on which of Joone's engine packages are used, you may also need to add one or more external packages (provided in a separate downloadable file) into the applications classpath.

The following are the necessary steps to execute to correctly install the core engine's libraries:

1. Download the core engine's binary distribution file joone-engine-x.y.z.zip (where x, y and z are respectively the major/minor version and the build number of the last available distribution).

2. Download joone-ext.zip, the file containing the necessary external libraries. Unzip both the above files into a predefined directory of your file system. At this point you should have a directory tree as below (we omitted the unessential files):

   - *-Base Directory-*
     - Jonne-engine.jar
     - ....
     - *-ext-*
       - bsh.jar
       - crimson.jar
       - jakarta-poi.jar
       - log4j.jar
       - ....
     - *-samples-*

   ...

3. Put the joone-engine.jar and also the <ext>*.jar files into your classpath

4. Run your own application

Depending on which of the engine's packages your application uses you will need to place the necessary libraries in your classpath, as depicted in the following table:

Library	Purpose	When used
joone-engine.jar	The Joone core engine	**Mandatory**
log 4j.jar	The configurable logger	**Mandatory**
bsh.jar	The BeanShell interpreter	**Optional** Needed only if you want to use the scripting features
jakarta-poi.jar	The Jakarta Excel libraries	**Optional** Needed only if you use the Excel Input/Output synapses
jh.jar	The Java Help libraries	**Never** Used only in conjunction with the GUI editor contained into the *joone-editor.jar* file
jhotdraw.jar	The drawing framework	**Never** Used only in conjunction with the GUI editor contained into the *joone-editor.jar* file
visad.jar	The external graphic library to plot graphs	**Never** Used only in conjunction with the GUI editor contained into the *joone-editor.jar* file

As you can see, only the first two libraries have to be present into your classpath, whereas the next two are needed only if you use specific features of the core engine. The last three libraries are used only in conjunction with the GUI editor contained in the joone-editor.jar file; however, in that case, you donÕt need to install the editor manually. You can use an auto-installer as described in the following paragraph.

2.2.2 The GUI Editor

We have prepared package installers for the following platforms: Do we really need these installers?

- Linux
- Windows
- Platform Independent

By using the first two installers you need not be concerned about the installation of the Java runtime environment as these installers are available both with and without an

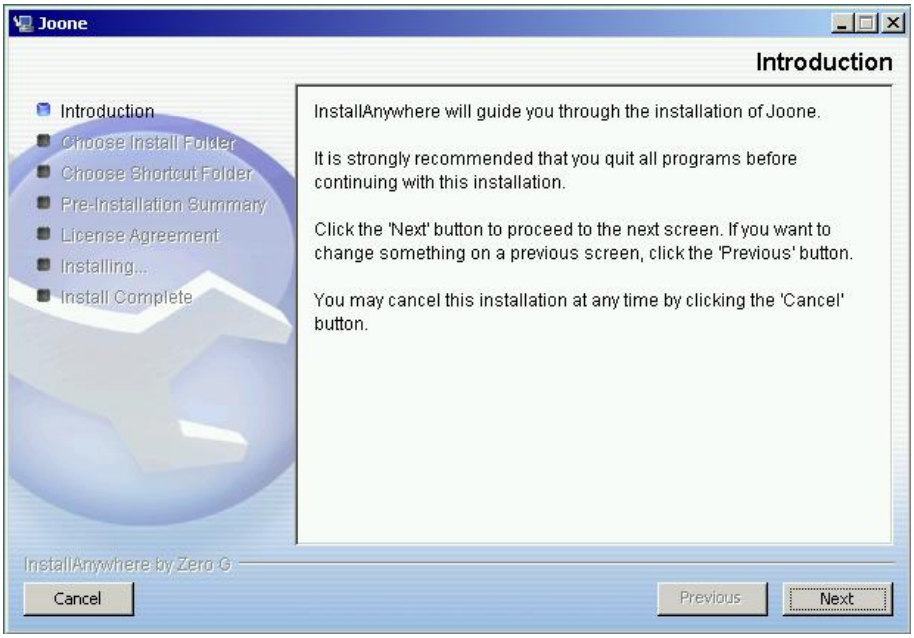
embedded Java virtual machine. All you need to do is download the appropriate installer depending on your platform and run it as described below:

- **Linux Instructions:**
  After downloading open a shell and, cd to the directory where you downloaded the installer. At the prompt type: sh ./JooneEditorX_Y_Z.bin If you do not have a Java virtual machine installed be sure to download the package which includes one. Otherwise you may need to download one from Sun's Java web site or contact your OS manufacturer.

- **Windows Instructions:**
  After downloading double-click JooneEditorX.Y.Z.exe If you do not have a Java virtual machine installed be sure to download the package which includes one.

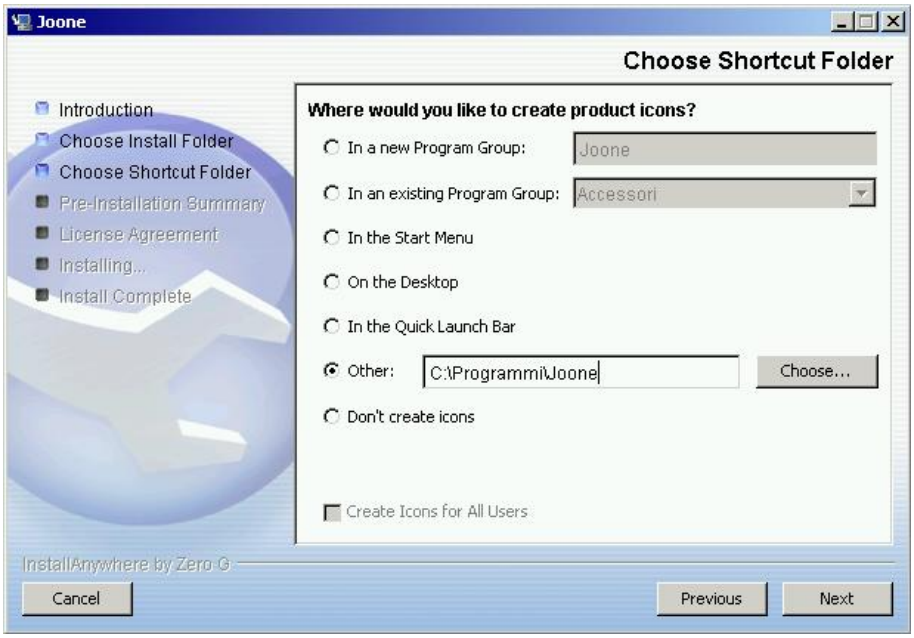
- **Platform Independent Instructions:**
  After downloading, expand JooneEditorX.Y.Z-All.zip into a directory (requires a JRE 1.4.2 or later installed), cd to that directory and launch ./RunEditor.sh (Linux/Unix/MacOSX) or RunEditor.bat (Windows).

If you have downloaded the Linux or Windows auto-installer after the launch you should see the following panel:

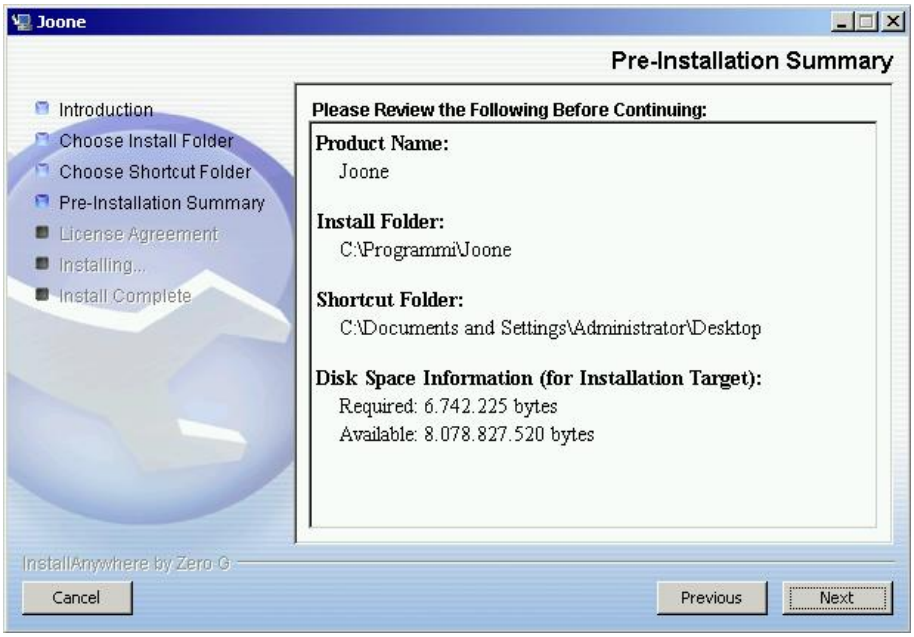


By clicking on the Next button you can advance in the installation process. At any moment, by pressing the Cancel button, you can abort and exit from the installation.

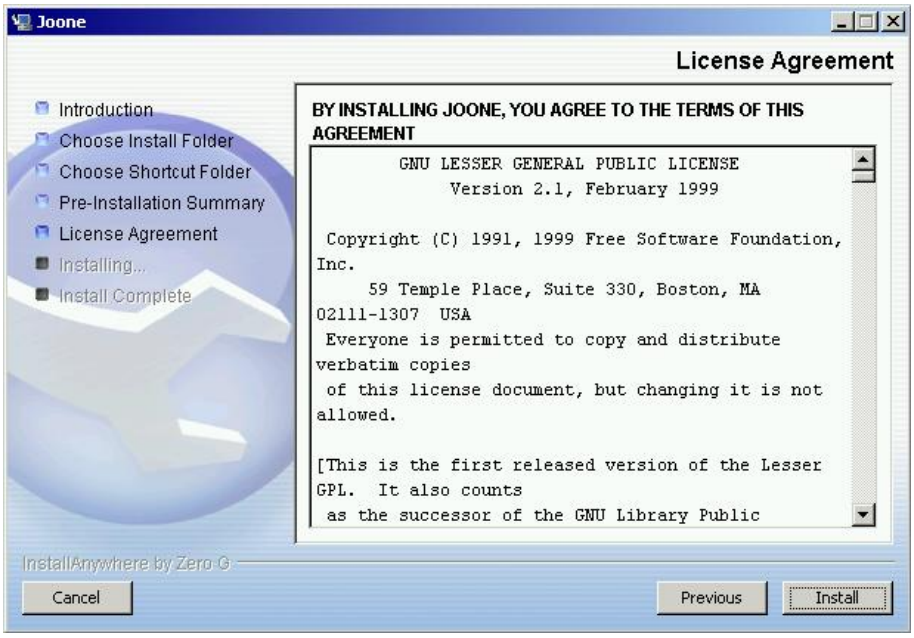
In this panel you must specify the directory where you want to install Joone. The Choose button will open an explorer window, where you can make the choice, whereas by using the 'Restore Default Folder' button you can reset the directory to its initial value.



Here you can choose where to put the Joone launcher's icon. This panel can contain several available choices depending on the platform you are installing Joone on. By checking the 'Create Icon for All Users' box - if not greyed - you will make the icon visibility to all the users of the system.



At this point a panel showing the summary of the choices made will appear. If your satisfied with your choices press the Next button, otherwise, pressing the Previous button allows you to go back to the previous panels and review or change any parameter



Finally the panel showing the GNU LESSER GENERAL PUBLIC LICENSE appears. This is the license under which Joone is released.

Be aware: Open Source doesn't mean 'no license', hence, before you continue, you must carefully read the license agreement. Press the 'Install' button only if you agree to the terms of the license. A copy of the LGPL license is contained in the last chapter of this guide.

If you choose to continue the installation process starts and a panel indicating the progress will appear. At the end a panel indicating the success of the operation similar to the following will be shown.

Press Done to exit.

After the installation you should found a file named Joone (or Joone.bat for the Windows platforms) has been placed in the chosen installation directory. You must execute it (a double click from within the file explorer should work on all the platforms) to run the editor. Alternatively, if you have chosen to add a shortcut to the Start Menu or to the Desktop you can press these to start the application.

2.3 Building from the source distribution

In this paragraph we will demonstrate how to build Joone starting from the source distribution. This will require the installation of some useful tools to your system.

2.3.1 Prerequistes

You need to have installed on your system:

1. a Java Development Kit version 1.6 or above (`http://java.sun.com`)
2. the ANT build tool v. 1.5.1 or above (`http://ant.apache.org`)
3. the source code for Joone which can either be the last released version or you can download the last (unstable) code from the CVS repository.

The instructions to get Java SDK and ANT installed and running on your system go beyond the scope of this document. You may find and read a great deal of documentation on these subjects on the Internet. Now we'll show you how to get Joone's source code.

2.3.2 Getting the last released source code

The released version is preferable if you need to use a stable and tested version of Joone without being worried about possible unknown or uncorrected bugs. To do this open your preferred browser and simply go to the download page of Jooneathttp://sourceforge.net/project/showfiles.php?group_id=22635 and obtain the files joone-engine-x.y.z.zip (the core engine), joone-editor-x.y.z.zip (the GUI editor) and joone-ext.zip (the external libraries). *Note: x, y and z are respectively the major/minor version and the build number of the last available distribution.* Unzip them on a directory of your file system (say c:\joone for Windows or /joone for Linux).

2.3.3 Getting the CVS sources

If you need to use some new feature of Joone which has not been released you can get the last developed source code from the CVS repository. To do this you need to have a cvs client installed on your system. Unix/Linux systems normally have a cvs client pre-installed. For windows system go to http://www.cvshome.org/ and download a suitable version for your OS. Of course most users prefer GUI for CVS operations: You may have a look at standalone clients like TortoiseCVS or SmartCVS or the ones integrated in IDEs like Eclipse or Netbeans.
By the way there's no standard IDE for Joone, but checked out to Eclipse it should compile without any changes.
The CVS repository of Joone is hosted at SourceForge. Here is an extract from the instructions given at the SourceForge cvs page:

"...This project's SourceForge.net CVS repository can be checked out through anonymous (pserver) CVS with the following instruction set. The module you wish to check out must be specified as the modulename. When prompted for a password for anonymous, simply press the Enter key.

cvs -d:pserver:anonymous@joone.cvs.sourceforge.net:/cvsroot/joone login

cvs -z3 -d:pserver:anonymous@joone.cvs.sourceforge.net:/cvsroot/joone co joone

Information about accessing this CVS repository may be found in our document titled, "Basic Introduction to CVS and SourceForge.net (SF.net) Project CVS Services" (http://sourceforge.net/docman/display_doc.php?docid=14033&group_id=1). Updates from within the module's directory do not need the -d parameter. NOTE: UNIX file and directory names are case sensitive. The path to the project CVSROOT must be specified using lowercase characters (i.e. /cvsroot/joone)"

You will need to download the file containing the external libraries (joone-ext.zip) and unzip it into the same directory where you have placed the cvs (review the previous chapter on how to download it).

2.3.4 Compiling

Regardless of which repository you have decided to download from you should end up with the following directory tree on your file system:

- *<base_dir>*
  - *joone*
    - *lib*
    - *org*
    - *joone*
      - *data*
      - *edit*
      - *engine*
      - *exception*
      - *io*
      - *net*
      - *samples*
      - *script*
      - *util*

Before you start the build process you will need to edit the build.xml file found in the root installation directory. Open it with a text editor and search for the following line:
⟨ property name="base" value=/usr/SourceForge/"⟩ change the path into the quotes with your previous chosen installation directory (e.g. c:\joone or /joone) and save the file. Assuming you have the Java JDK and ANT correctly installed and running (in order to verify, try to launch the commands 'javac' and 'ant' in a console) you need to cd into the installation directory and launch the command 'ant' at the prompt. At the end of the operation, provided no error have occured, under the installation directory you should have a subdirectory named 'build' containing all the compiled classes.
At this point to run the GUI editor you need to:

1. Put the <base_dir>/build directory and all the <base_dir>/lib/*.jar files in your classpath
2. Open a console and launch the following command: java org.joone.edit.JoonEdit

The main window of the Joone editor should appear.

Chapter 3

Inside the Core Engine

3.1 Basic Concepts

Each neural network (NN) is composed of a number of components (layers) joined together by specific connections (synapses). Several neural network architectures can be created (feed forward NN, recurrent NN, etc) depending on how these components are linked together. This section deals with feed forward neural networks (FFNN) for simplicity's sake, but it is possible to build whatever neural network architecture is required with Joone. A FFNN is composed of a number of consecutive layers with each one connected to the next by a synapse. In a FFNN recurrent connections from a layer to a previous one are not permitted. Consider figure 3.1. This is a sample FFNN with two layers fully connected with synapses. Each layer is composed of a certain number of neurons, each of which have the same characteristics (transfer function, learning rate, etc). A neural net built with Joone can be composed of any number of layers belonging to different typologies (linear, sigmoid, etc). Each layer processes its input signal by applying a transfer function and sending the resulting pattern to the synapses that connect it to the next layer. So a neural network can process an input pattern and transferring that pattern from an input layer to an output layer. This is the basic concept upon which the entire engine is based.

3.2 The Transport Mechanism

Ferra made some big changes for the recurrent networks, so this section must probably be rewritten completely!

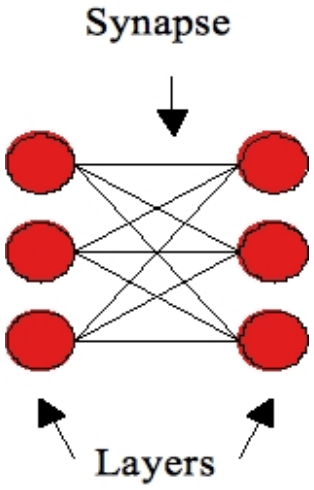


Figure 3.1: Feed Forward Network

INFO

Note: as of Joone v. 2.0 a new single-thread engine has been written in order to improve the performances on machines with multi-core CPUs. As a consequence, the Layer no longer runs within its own separate thread and so the concepts described below, though still accurate when the network is launched in multi-thread mode, do not apply completely when the new single-thread engine is used.

In order to ensure that it is possible to build any neural network architecture one requires with Joone a method to transfer the patterns through the net is required that does not depend on a central point of control. To accomplish this goal each layer of Joone is implemented as a Runnable object. As a result each layer runs independently from every other layer while getting the input pattern, applying a transfer function to the pattern and placing the resulting pattern on the output synapses where the next layer can receive and process the pattern. This is depicted by illustration 3.2:

Where for each neuron N:

$$X_N = (I_1 * W_N 1) + \ ... \ + (I_P * W_{NP}) + bias \tag{3.1}$$

$$Y_N = f(X_N) \tag{3.2}$$

X_N : The weighted net input of each neuron
X_N: The output value of each neuron
f(X): The transfer function (which is dependant on the layer type)

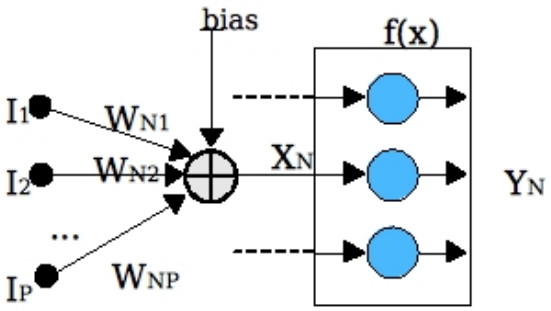


Figure 3.2: Runnable Layer

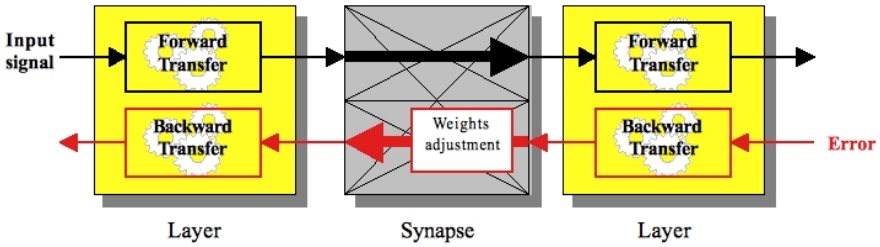


Figure 3.3: Transport Mechanism

This basic transport mechanism is also used to bring the error from the output layers to the input layers during the training phases. This allows the weights and biases to change according to the chosen learning algorithm (e.g. backprop algorithm). In other words, the layer objects alternately 'pump' the input signal from the input synapses to the output synapses, and the error pattern from the output synapses to the input synapses. This pumping action is accomplish by each layer having two opposing transport mechanisms, one from the input to the output to transfer the input pattern during the recall phase, and another from the output to the input to transfer the learning error during the training phase. This is depicted in figure 3.3:

Complex neural network architectures can be easily built, either linear or recursive, because there is no necessity for a global controller of the net. Imagine each layer acting as a pump that 'pushes' the signal (the pattern) from its input to its output, where one or more synapses connect it to the next layers, regardless of the number, the sequence, or the nature of the layers connected. This is the main characteristic of Joone and is guaranteed by the fact that each layer runs on its own thread and represents the unique active element of any neural network based on JooneÕs core engine. Look at figure 3.4 (the arrows represent the synapses): Any kind of neural network architecture can be built

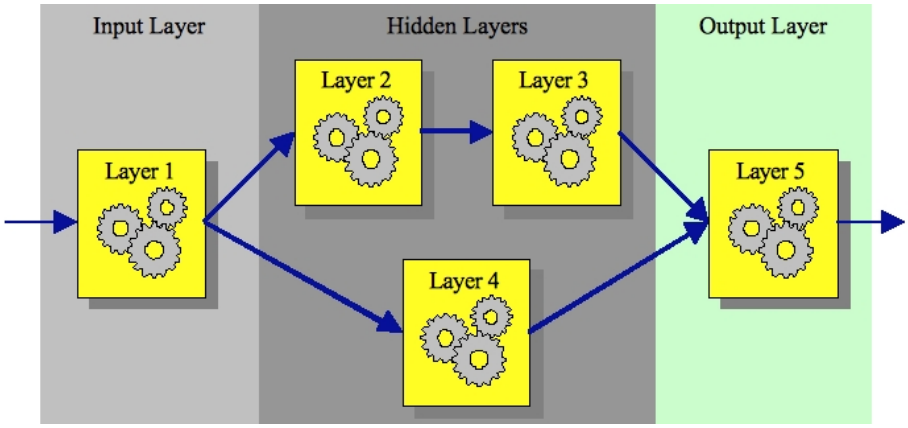


Figure 3.4: Transport Mechanism

in this manner. To build a neural network one simply connects each layer to another as required using synapses and the net will run without problems. Each layer (running in its own thread) will read it's input, apply a transfer function, and write the result to it's output synapses. This action can be recursively applied as many times as desired, creating many threads, while creating any neural network required. Joone allows any kind of net to be built thanks to its modular architecture much like a LEGO©bricks system

This is due mainly to the following characteristics:

- The engine is flexible: you can build any architecture you want simply by connecting each layer to another with a synapse, without being concerned about the overall interaction of the architecture. Each layer will run independently, processing the signal on its input and writing the results to its output, where any connected synapses will transfer the signal to the next layers, ad infinitum.
- The engine is scalable: if you need more computational power, simply add more CPUs to the system. Each layer, running on a separate thread, will be processed by a different CPU which will enhancing the speed of the computation.
- The engine closely mirrors reality: conceptually, the net is not far from a real system (the brain), where each neuron can work independently from any other even while part of a larger interconnected system.

All the above characteristics are valid for the single-thread engine also, introduced with version 2.0 of Joone, where the layers do not run within separate threads but instead are invoked from a unique external thread which is instantiated and handled by the NeuralNet object. The redesigning of the core engine has been carefully implemented in order to

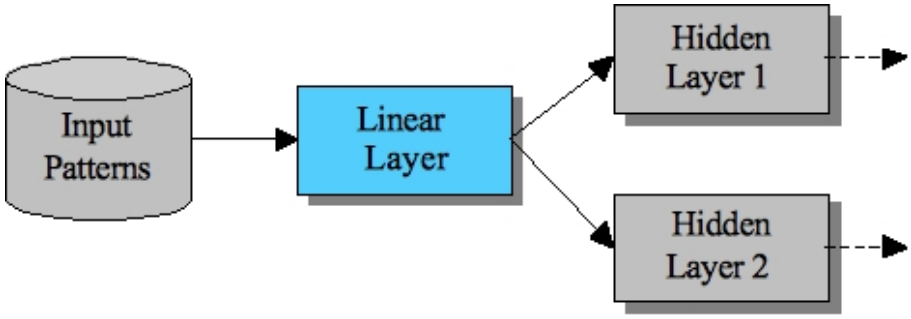


Figure 3.5: Using the Linear Layer as a Router

provide the same features of the multi-thread version thereby maintaining almost complete compatibility with previou releases.

3.3 The Processing Elements

We will now describe the principal types of layers and synapses implemented in the core engine. For each type we will show the transfer function and the most common usage.

3.3.1 The Layers

The layer object is the basic element that forms any neural network constructed in Joone. A layer object is composed of neurons which all have the same characteristics. By executing a transfer function the layer component transfers the input pattern to the output pattern.

The output pattern is sent to a vector of synapse objects which are attached to the layer's output. The vector of synapse objects is the active element of a neural network created in Joone, in fact the vector runs in a separate thread (it implements the java.lang.Runnable interface) so that it can run independently from other layers in the neural network.

The Linear Layer

Description The Linear Layer is the simplest kind of layer in Joone. It simply transfers the input pattern to the output side while applying a linear transformation, i.e. multiplying it by a constant term, the Beta term. If this term is equal to 1 (one), then the input pattern is transferred without modification. The Linear Layer is commonly used as a buffer. By being added, for instance, as the first layer of a neural network, the linear layer permits sending an unmodified copy of the input pattern to several hidden layers. This is depicted in figure 3.5.

Without a Linear Layer in this network, or those like it, it would be impossible to send the same input pattern to many subsequent layers because the input component (the InputSynapse here represented by a cylinder) can only be attached one layer.

Transfer Function

$$y = \beta * x \tag{3.3}$$

β : The factor by which the activation function multplies the input

The Biased Linear Layer

Description The Biased Linear Layer is an extension of the Linear Layer. It also applies a linear transfer function to its input pattern, but differs from the Linear Layer in two important ways:

- The Biased Linear Layer, as its name suggests, uses biases. The biases can/will be adjusted during the
- training phase It has no scalar beta parameter

This layer can be used wherever you need a layer having a linear transfer function which also has an adjustable parameter - the bias - that adapts the response of the layer according to the gradient. This provides back-propagated during the learning process.

Transfer Function

$$y = x + bias_n \tag{3.4}$$

$bias_n$: the bias of the n_t neuron

The Sigmoid Layer

Description The Sigmoid Layer applies a sigmoid transfer function to its input patterns and represents a good non-linear element to build the hidden layers of a neural network. Sigmoid layers can be used to build any layer of a neural network. Its output is smoothly limited within the range of 0 and 1.

Transfer Function

$$y = \frac{1}{1 + e^{-x}} \tag{3.5}$$

The Tanh Layer

Description The Tanh Layer is similar to the Sigmoid Layer except that the applied function is a hyperbolic tangent function which limits its output to the range of -1 and +1.

Transfer Function

$$y = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3.6}$$

The SoftMax Layer

This layer is also similar to the Sigmoid Layer as the output of each node ranges from between 0 and 1. It differs in that the sum of all the nodes is always 1. Due to this characteristic the output values of the SoftMax layer can be interpreted as a posterior probability. The activation of each output node represents the probability that the input pattern belongs to the corresponding output class (represented by each output node). This class is used in supervised networks to implement the 1 of C classification (by contrast with the SigmoidLayer which is normally used for binary classification). Statisticians usually call softmax a "multiple logistic" function as it reduces to a logistic function when there are only two output categories. TODO: Give an example when this can be used ect.

Transfer Function

$$y = \frac{e^x}{\sum_{j=1}^{C} e^{x_j}} \tag{3.7}$$

j: The classification ...

TODO: Document this properly ...

The Logarithmic Layer

Description This layer applies a logarithmic transfer function to its input patterns. This results in an output that, unlike the two previous layers described, ranges from 0 to ∞. This behaviour allows one to avoid saturating the processing elements of a layer in the presence of multiple input synapses. It also avoids saturation that may occur in the presence of input values very near to the limits of 0 and 1, where the sigmoid and tanh layers have a response curve that is very flat.

Transfer Function

$$y = \log(1 + x) \text{ if } x \geq 0 \tag{3.8}$$

$$y = \log(1 - x) \text{ if } x < 0 \tag{3.9}$$

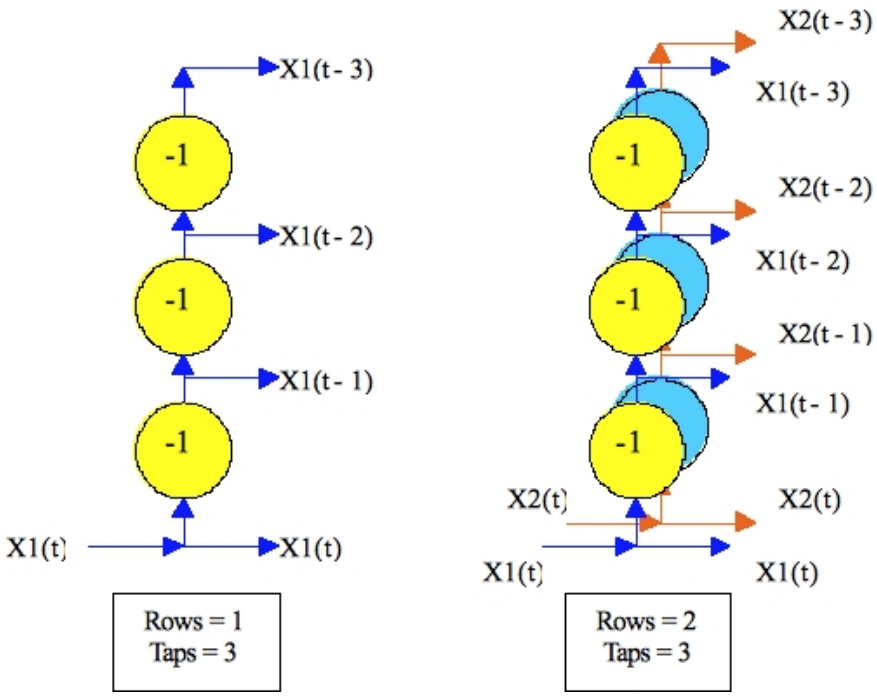


Figure 3.6: Delay Layer

The Sine Layer

Description The output of a Sine Layer neuron is the sum of the weighted input values applied to a sine x sin(x) - transfer function. Neurons with a sine activation function might be useful when dealing with problems with periodicity.

Transfer Function

$$y = \sin x \tag{3.10}$$

The Delay Layer

Description The delay layer applies the sum of the input values to a delay line. The output of each neuron is delayed the number of iterations specified by the taps parameter. To understand the meaning of the taps parameter see figure 3.6. The diagram contains two different delay layers, one with 1 row and 3 taps, and another with 2 rows and 3 taps:

A delay layer contains:

- a number of inputs equal to the rows parameter
- a number of outputs equal to rows · (taps + 1)

The taps parameter indicates the number of cycles the output is delayed for each row of neurons plus one. The addition of an extra cycle is due to the fact that the delayed layer also presents the actual input signal Xn(t) to the output. During the training phase error values are fed backwards through the delay layer as required.

This layer is very useful in training a neural network to predict a time-series, in effect giving the network a 'temporal window' on the raw data being input.

Transfer Function

$$y_N = x_{t-N} \tag{3.11}$$

x <N≤ taps

The Context Layer

Description The context layer is similar to the linear layer except that it contains an auto-recurrent connection between its output and input as depicted in figure 3.7. The recurrent weight w is named 'timeConstant' both because it is a constant value less than one and because it back-propagates the past output signals. Since the timeConstant has a value of less than one the contribution of the past output signal decays slowly toward zero as cycles are completed. As a result of these features a context layer has it's own 'memory' embedding mechanism.

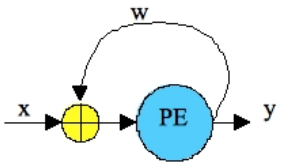


Figure 3.7: ContextLayer

The context layer is used in recurrent neural networks like the Jordan-Elman networks. These are network topologies produced by the researchers Micheal I. Jordan and Jeffrey Elman. TODO: Write an example which uses this layer in a recurrent network!

Transfer Function

$$y = \beta \cdot (x + y_{(t-1)\cdot w} \tag{3.12}$$

β: the beta parameter (inherited from the linear layer)
w: the fixed weight of the recurrent connection (not learned)

The GaussLayer

Description The output of a GaussLayer neuron is the sum of the weighted input values applied to a gaussian function. It is useful whenever a layer must respond to a particular set of input patterns (e.g. those having their coords within the center of the gaussian curve). This layer has a curve centered on zero, and its size is not adjustable. If you're searching for a gaussian component to use in a RBF or Kohonen network, see the note below.

Transfer Function

$$y = e^{(-x \cdot x)} \tag{3.13}$$

INFO

Note: do not confuse this layer with the GaussianLayer or with the RBFGaussianLayer. The former is used as output map of a Kohonen SOM whereas the latter must be used as a hidden layer of a RBF network.

The RBFGaussianLayer

This class implements the nonlinear layer in Radial Basis Function (RBF) networks using Gaussian functions. Its output, like the GaussLayer described above, is the sum of the weighted input values applied to a gaussian function. The difference is represented by the gaussian curve itself which will have adjustable its own center according to predefined parameters. The center of the gaussian curve can be adjusted using two different techniques:

1. **Random** - each node will be assigned a randomly chosen center according to the input data. In order to obtain this a new plugin - the RbfRandomCenterSelector - has been built. This plugin must be attached to the input synapse of the network where it will calculate the mean (center) as well as the standard deviation for each node of the layer.

2. **Custom** - whereby each node is assigned a predefined center. To do this a new component - the RbfGaussianParameters - has been built. The calling application must set the mean (center) and the standard deviation for each node of the layer before starting the training phase.

Transfer Function

$$y = e^{\frac{D^2}{-\sigma(x) \cdot \sigma(x)}} \tag{3.14}$$

D^2: the squared euclidean distance and $\sigma(x)$ is the standard deviation calculated on the input patterns.

INFO

Note: the XOR_static_RBF.java class in the org.joone.samples.engine.xor.rbf package contains a complete example that shows how to build and use a RBF network.

The actual implementation of the RBF network is not complete. It represents only a starting point (a good starting point, I think, thanks to Boris Jansen) and therefore anyone interested in completing this work is welcome.

The WinnerTakeAllLayer

Description The WinnerTakeAll layer is one of the components - along with the GaussianLayer and the KohonenSynapse - useful in the building of unsupervised self-organized-map (SOM) networks. This kind of networks learns without an external teacher simply by detecting the similarities of the input patterns and categorizing (i.e. projecting) them on a dimensionally reduced (1D or 2D) map.

This layer implements the Winner Takes All SOM strategy. The layer expects to receive Euclidean distances between the previous synapse (the KohonenSynapse) weights and it's input. The layer simply works out which node is the winner and passes 1.0 for that node and 0.0 for the others.

In this manner the attached KohonenSynapse can adjust its own weights according to the winning neuron thereby updating the internal connections so that whenever a similar input is presented the same neuron will be activated (or one near it, depending on how much that pattern is similar to the one seen during the learning phase).

Transfer Function

$$y_n = 1 \text{ if n is the most active neuron} \tag{3.15}$$

$$y_n = 0 \text{ otherwhise} \tag{3.16}$$

D^2: the squared euclidean distance and $\sigma(x)$ is the standard deviation calculated on the input patterns.

The Gaussian Layer

Description The Gaussian layer performs work similar to the WTA layer, however in this case it activates the output neurons in accord with a gaussian shape centered around the most active neuron (the winner). This layer implements the Gaussian Neighborhood SOM strategy. It receives the Euclidean distances between the input vector and weights and calculates the distance fall off between the winning node and all other nodes. These

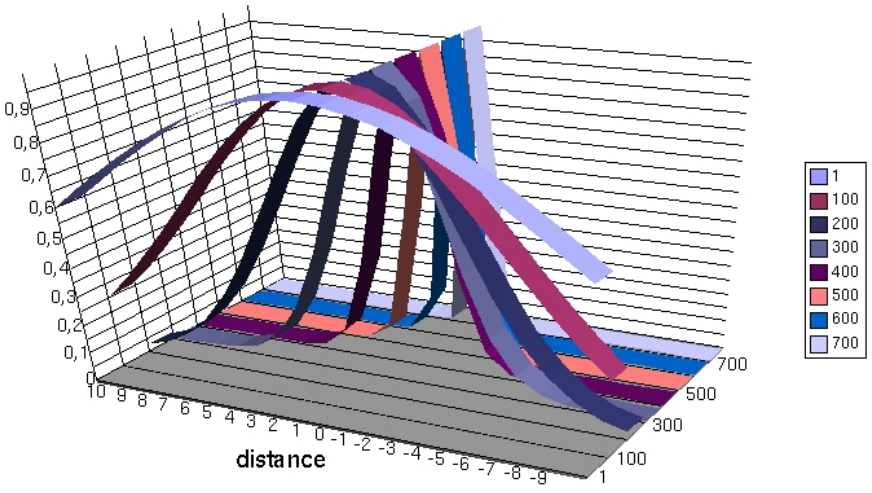


Figure 3.8: Gaussian Function

values are passed back and allow the previous synapse (the KohonenSynapse) to adjust it's weights. The distance fall off is calculated according to a Gaussian distribution from the winning node. In this manner, inside the KohonenSynapse, both the weights feeding the winning neuron and it's neighbors' weights will be adjusted with a strength inversely proportional to the distance from the winning neuron.

Transfer Function Rather than representing the transfer function by a complex formula we can represent this function graphically whereby output values correspond to both the distance from the winning node and the actual epoch. The neighborhood around the winning node starts very large and then is reduced following a gaussian curve as depicted in figure 3.8: the curves represent how the neighborhood function changes during the training epochs; the X axis represents the distance from the winning node (in this example), the Y axis contains the output values of the layer, and the numbers in the legend (put on the Z axis) represent the number of epochs (from 1 to 700 in this example). As you can see an initial phase exists within which the algorithm maintains a large neighborhood size to permit a large number of weights to participate in the adjustments (this phase is named ordering phase), after which a small neighborhood is maintained (the weights are frozen after they have chosen the input vectors to which to respond). A similar mechanism is implemented into the KohonenSynapse object.

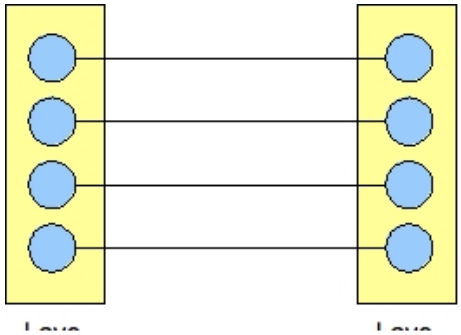


Figure 3.9: Direct Synapse

3.3.2 The Synapses

The Synapse represents the connection between two layers which permits a pattern to be passed from one layer to another. The Synapse is also the 'memory' of a neural network. During the training process the weigh of each connection is modified in accord with the implemented learning algorithm. Remember that, as described above, a synapse is both the output synapse of a layer and the input synapse of the next connected layer in the neural network. Hence, a synapse represents a shared resource between two Layers (no more than two since a Synapse can be attached only once as an input and once as an output of a Layer).

In order to avoid the problem of a layer trying to read the pattern from its input synapse before the other layer has written it the shared synapse in synchronized; in other words a semaphore based mechanism prevents two Layers from simultaneously accessing a shared Synapse.

The Direct Synapse

The DirectSynapse represents a 1 to 1 connection between the nodes of the two connected layers as depicted in figure 3.9: Each connection has a weight equal to 1 which does not change during the learning phase. A DirectSynapse can only connect layers having the same numbers of neurons or nodes.

The Full Synapse

The FullSynapse connects each node of one layer with every node of the other layer as depicted in the figure 3.10: This is the most common type of synapse used in a neural network. Its weights change during the learning phase in accord with the implemented learning algorithm. It can connect layers having any number of neurons. The number of

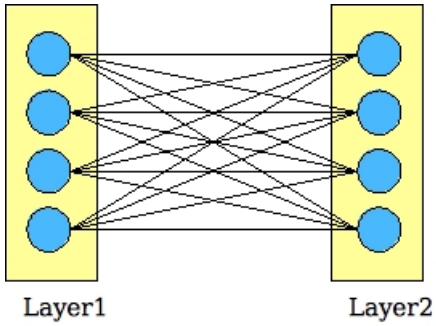


Figure 3.10: Full Synapse

weights contained is equal to N1 x N2, where Nx is the number of nodes of the Layerx

The Delayed Synapse

This Synapse has an architecture similar to the FullSynapse, however each connection is implemented using a matrix of FIR Filter elements of size NxM. Figure 3.11 illustrates how a DelaySynapses can be represented: As you can see in the first figure, each connection - represented by the grey rectangle - is implemented as an FIR (Finite Impulse Response) filter and in the second figure the internal detail of an FIR filter is shown. An FIR Filter connection is a delayed connection that permits the implemention of a temporal back-propagation algorithm which is functionally equivalent to the TDNN (Time Delay Neural Network) but in a more efficient and elegant manner. To learn more about this kind of synapse I refer you to the article Time Series Prediction Using a Neural Network with Embedded Tapped Delay-Lines by Eric Wan. This article can be found in Time Series Prediction: Forecasting the Future and Understanding the Past, editors A. Weigend and N. Gershenfeld, Addison-Wesley, 1994. Also, at the following web site you can find some good examples that make use of FIR filters. http://www.cs.hmc.edu/courses/1999/fall/cs152/firnet/firnet.html

The Kohonen Synapse

The KohonenSynapse belongs to a special group of components that permit one to build unsupervised neural networks. In particular, the KohonenSynapse is the central element of SOM (Self Organizing Maps) networks. A KohonenSynapse must be followed, by necessity, by a WTALayer or a GaussianLayer component thereby forming a complete SOM. This is depicted in figure 3.12:

Typically an SOM is composed of three elements:

1. A LinearLayer that is used as an input layer

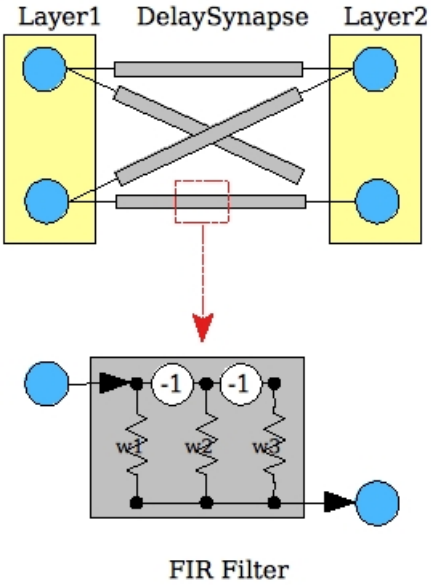


Figure 3.11: Delayed Synapse

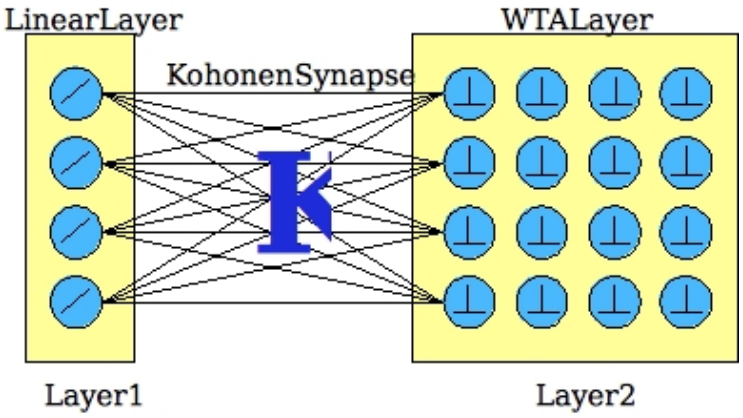


Figure 3.12: Kohonen Synapse

2. A WTALayer (or GaussianLayer) that's used as an output layer

3. A KohonenSynapse that connects the two previous layers

During the training phase the KohonenSynapse has it's weights adjusted to map the N-dimensional input patterns to the 2-dimensional map represented by the output synapse. This begs the question of "What is the difference between the WTA and the Gaussian layers?" The answer very simply depends on the precision of the response one would like from the network. If, for instance, one is using an SOM to make predictions, for example to forecast the next day's weather, one probably needs to use a GaussianLayer as output since one would like a response in terms of some probability centered around a given value (e.g. it will be cloudy and maybe it will rain). Alternatively, if one is using an SOM to recognize handwritten characters then one would need a precise response (i.e. 'the character is A', NOT 'the character could be A or B'). For these precise evaluations one would need to use a WTALayer which activates one (and only one) neuron for each input pattern.

The Sanger Synapse

The SangerSynapse serves in the building of unsupervised neural networks which apply the PCA (Principal Component Analysis) algorithm. The PCA is a well known and widely used technique that permits the extraction of the most important components from a given signal. The Sanger algorithm, in particular, extracts the components in ordered mode - from the most to the least meaningful - thereby permitting the separation of noise from true signal. This component, via reducing the number of input values without diminishing the useful signal, permits the training of the network on a given problem and reduces training time requirements considerably.. The SangerSynapse normally is poised between two LinearLayers where the output layer has less neurons than the input layer. This is depicted in the following figure: By using this synapse along with the Nested Neural Network component it becomes very easy to build modular neural networks where the first neural network acts as a pre-processing element that reduces the number of input columns and consequently noise.

3.4 The Monitor: a central point to control the neural network

A neural network cannot be composed of only layers and synapses. There is the necessity of controlling all the parameters associated with the training and running processes. For this purpose the Joone engine contains several other components designed to provide the neural network with a series of services. The main component that is ever present in each Joone based neural network is the Monitor object. The Monitor object represents a central containment point where all necessary parameters (such as the learning rate, the ,

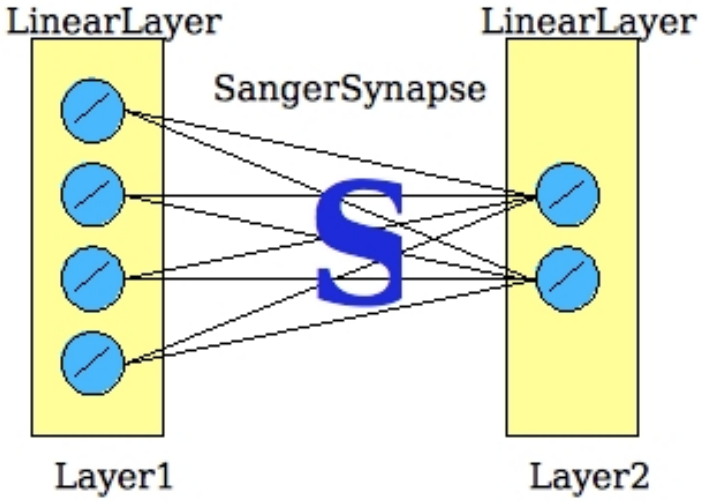


Figure 3.13: Sanger Synapse

the number of training epochs, the current cycle, etc) which other components may require can be accesses. Each component of a neural network (both the layers and synapses) receives a pointer to an instance of the monitor object. This instance can be different for each component but usually only a unique instance is created and used. By using a unique instance each component can access the same parameter settings for the entire neural network. This is depicted in figure 3.14: In this manner, when the user wants to change any of a neural networks parameters, s/he must simply change the corresponding value in the Monitor object; as a result each component of the neural network will receive the new value that has been applied to the parameter. The Monitor provides services to both the internal components of a neural network and to the external application that uses it. In fact, the Monitor object provides any external application with a notification mechanism based on several events raised when a particular action is performed. For instance, an external application can be advised when the neural network starts or stop the training epochs, when it finishes a cycle or when the value of the global error (the RMSE) changes during the training phase. In this manner any application using Joone can asynchronously perform a certain action in response to a specific event of the controlled neural network. For example, an application could stop the training when the desired RMSE is reached, or check the generalisation level of the net using a separate input validation set, or display, in some graphical window, the actual values of the parameters of the net. The following is a list of the Monitor object's features.

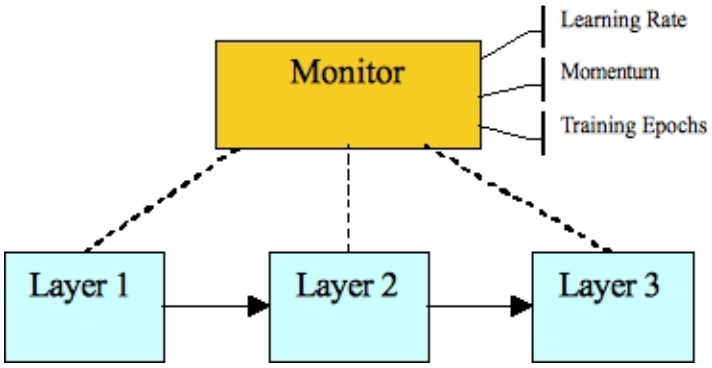


Figure 3.14: The Monitor

3.4.1 The Monitor as a container of the Network Parameters

The Monitor contains all the parameters needed during the training phases, e.g. the learning rate, the momentum, etc. Each parameter has its own getter and setter methods which conform to the JavaBeans specifications. These parameters can be used by an external application. For example an application could display the parameters in a user interface, or provide the parameters to an internal component to calculate the formulas used to implement the recall/training phases. This represents a standard and centralized mechanism for getting and setting the parameters needed for an applications work.

3.4.2 The Monitor as the Network Controller

TODO: This section (to 3.4.4 - How Patterns and the internal weights are represented) is probably no longer consistent with the implementation, especially because of the changes made to enable recurrent networks!

The Monitor object is also a central point for controlling the start/stop times of a neural network. A monitor object has several parameters that are useful in controlling the behaviour of a neural network such as the total number of epochs, the total number of the input patterns, etc. Before explaining how this works an explanation is required of how the input components of a neural network work.

When the first Layer of a neural network calls its connected InputSynapse component to read a pattern from an external source, (see the I/O components chapter), this object calls the neural networks monitor in order to advise it that a new cycle must be processed. The monitor, in accord with its internal state (current cycle, current epoch, etc.) verifies if the next input pattern must be normally processed. If the answer is yes the InputSynapse simply receives the permission to continue to elaborate the next pattern and all the counters internal to the monitor object are updated. If the answer is no (i.e. the net reached the

last epoch) the monitor object does not give the permission to continue and additionally it notifies all the external applications by raising an event that describes the nature of the notification.

In this manner the following services are made available by using the Monitor object:

1. The InputSynapse knows if it can read and process the next input pattern (otherwise it stops) by being advised by the returned Boolean value.

2. An external application (or the NeuralNet object itself) can start/stop a neural network simply by setting the initial parameters of the monitor. To simplify these actions some simple methods - Go (to start), Stop (to stop) and runAgain1 (to restore a previous stopped network to running) - have been added to the Monitor.

3. The observer objects (e.g. the main application) connected to the Monitor can be advised when a particular event raises such as when an epoch or the entire training process has finished. The monitor could either show the user the actual epoch number or the actual training error for example. To see how to manage the events of the Monitor and to access the parameters of the neural network read the following paragraph.

3.4.3 Managing the events

In order to explain how the events of the Monitor object can be used by an external application, this paragraph explains in detail what happens when a neural network is trained and when the last epoch is reached. Suppose one has a neural network composed, as depicted in the above figure 3.15, by three layers, an InputSynapse to read the training data, a TeacherSynapse to calculate the error for the back-propagation algorithm, and a Monitor object that controls the overall training process. As previously mentioned all the components of a neural network built with Joone obtain a reference to the Monitor object. This is represented in the figure by the dotted lines. Suppose the net is started in training mode. In the following figures all the phases involved in the process are shown when the end of the last epoch is reached. The numbers in the label boxes indicate the sequence of the processing (see figure 3.16): When the input layer calls the InputSynapse (1) the called object interrogates the monitor to know if the next pattern must be processed (2) (see figure 3.17). Since the current state is that the last epoch is finished (i.e. the last pattern of the last cycle has been elaborated) the monitor object raises a netStopped event (3) and returns a false Boolean value to the InputSynapse (4). The InputSynapse, because it has received a false value, creates a 'stop pattern' composed of a Pattern object with the counter set to -1 and injects it in the neural network (5) (see figure 3.18).

All the layers of the net stop their currently running threads and simply exit from the run() method when they receive a Ôstop patternÕ (6). The resulting behaviour is that the neural network is stopped and no further patterns are elaborated (see figure 3.19).

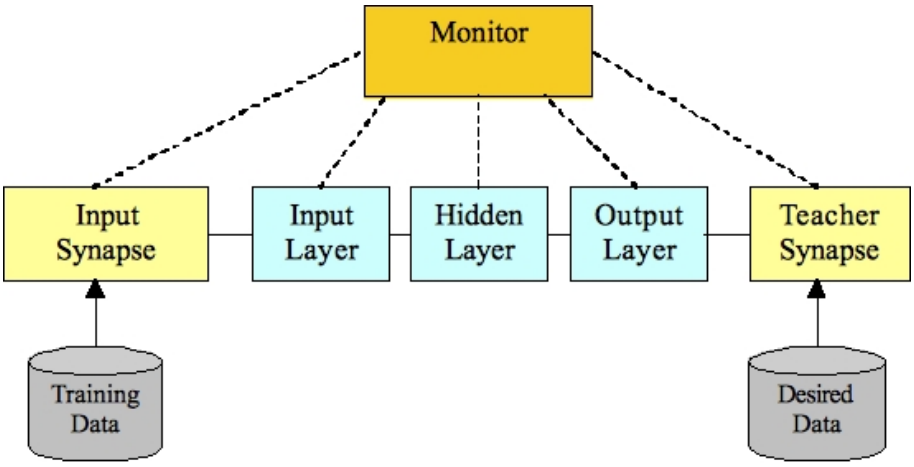


Figure 3.15: 3-layer network

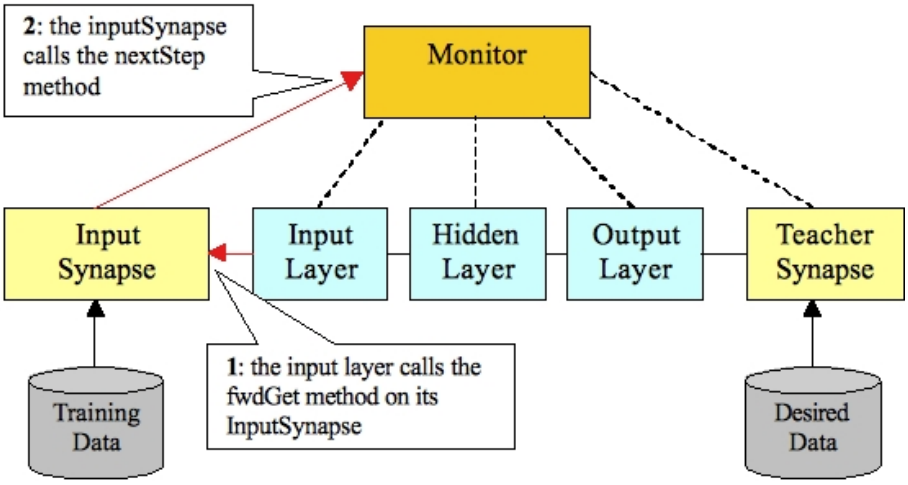


Figure 3.16: Operations in training model

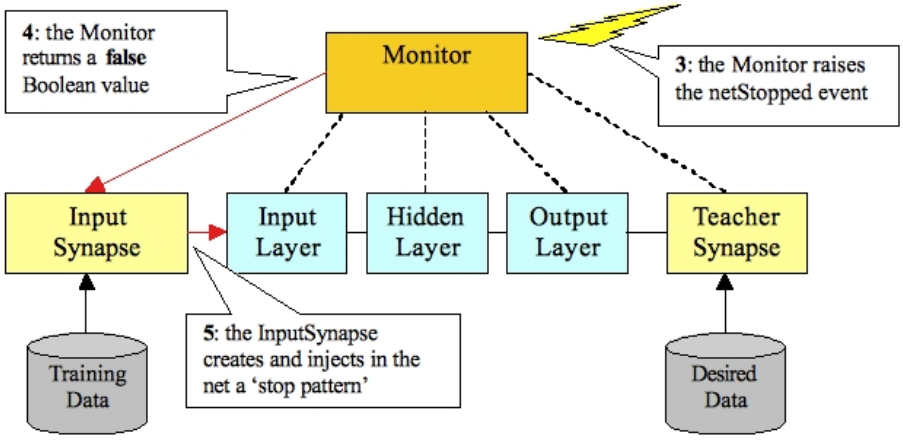


Figure 3.17: ....

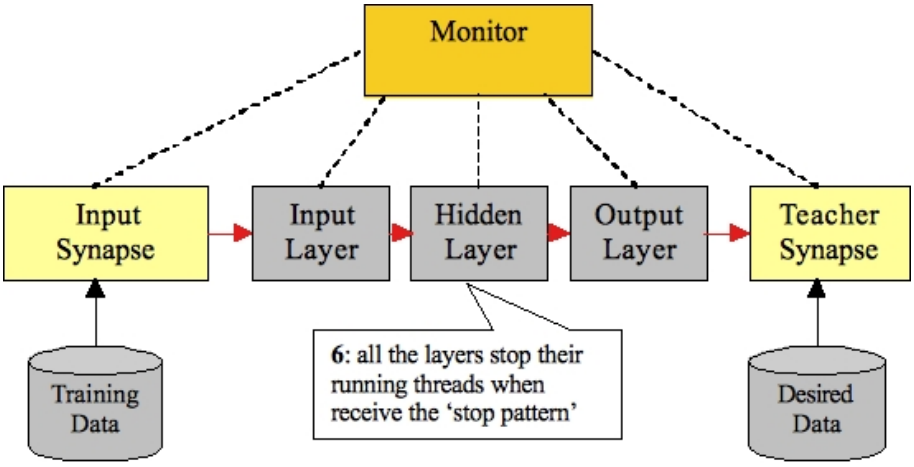


Figure 3.18: ....

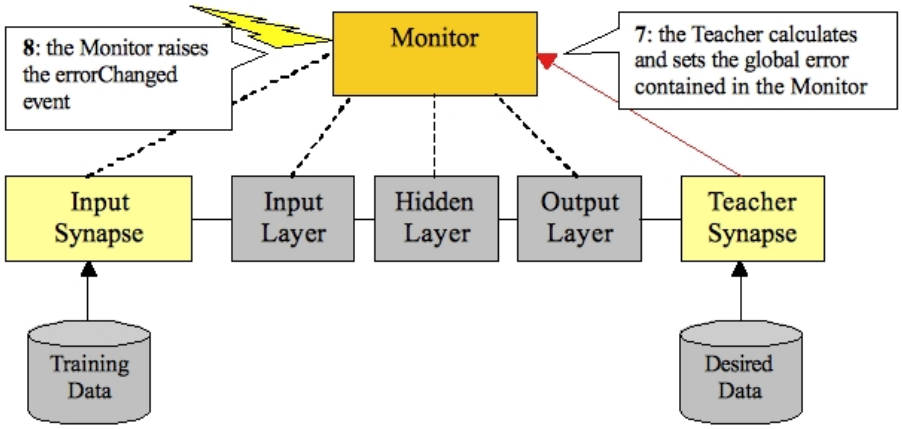


Figure 3.19: ....

When the stop pattern reaches the TeacherSynapse it causes the TeacherSynapse to calculates the global error and communicate this value to the monitor object (7), which raises an errorChanged event to its listeners (8).

WARNING

Note: As explained in the above process the netStopped event raised by the monitor cannot be used to read the last error value of the net, nor can it be used to read the resulting output pattern from a recall phase, because this event could be raised when the last input pattern is still travelling across the layers, i.e. before it reaches the last output layer of the neural network.

To insure the reading of the right values from the net the rules explained below must be followed:

Reading the RMSE: to read the last rmse of the neural network the errorChanged event must be waited for. Therefore, a neural network listener must be built so the last error of the training cycle can be read and elaborated at the end of the elaboration.

Reading the outcome: to insure one has received all the resulting patterns of a cycle from a recall phase a stop pattern from the output layer of the net must be waited for. To do this an object belonging to the I/O components family must be built with the code to manage the output pattern written into it. Appropriate actions can be taken by checking the 'count' parameter of the received Pattern. Some pre-built output synapse classes are provided with Joone and many others will be released in future versions.

However, as described in the next chapters, a neural network must always be used by instantiating a NeuralNet object that hides all these internal mechanisms and provides the user with several useful features to start-stop the neural network and to access its internal parameters in a safe manner.

3.4.4 How the patterns and the internal weights are represented

The pattern

The Pattern object is the 'container' of the data used to interrogate or train a neural network. It is composed of two parameters: an array of doubles to contain the values of the transported pattern, and an integer to contain the sequence number of that pattern (the counter). The dimensions of the array are set according to the dimensions of the pattern transported.

The Pattern object is also used to 'stop' all the Layers in the neural network. When its 'count' parameter contains the value -1 all the layers that had been receiving that pattern will exit from their 'running' state and will stop (the unique safe way to stop a thread in Java is to exit from its 'run' method). Using this simple mechanism the threads within which the Layer objects run can easily be controlled.

The Matrix

The matrix object simply contains a matrix of doubles to store the values of the weights of the connections and the biases. An instance of a matrix object is contained within both the Synapse (weights) and Layer (biases) components.

Each element of a matrix contains two values: the actual value of the represented weight and the corresponding delta value. The delta value is the difference between the actual value and the value of the previous cycle.

The delta value is useful during the learning phase as it permits the application of momentum to enable quickly finding the best minimum of the error surface. The momentum algorithm adds the previous variation to the actual calculated weight's value. See the literature for more information about the algorithm.

The NodesAndWeight class

TODO: The NodesAndWeight class introduces for recurrent learning algorithms should be documented.

3.5 Technical Details

The core engine of Joone is composed of a small number of interfaces and abstract classes. These classes form a nucleus of objects that implement the basic behaviours of neural

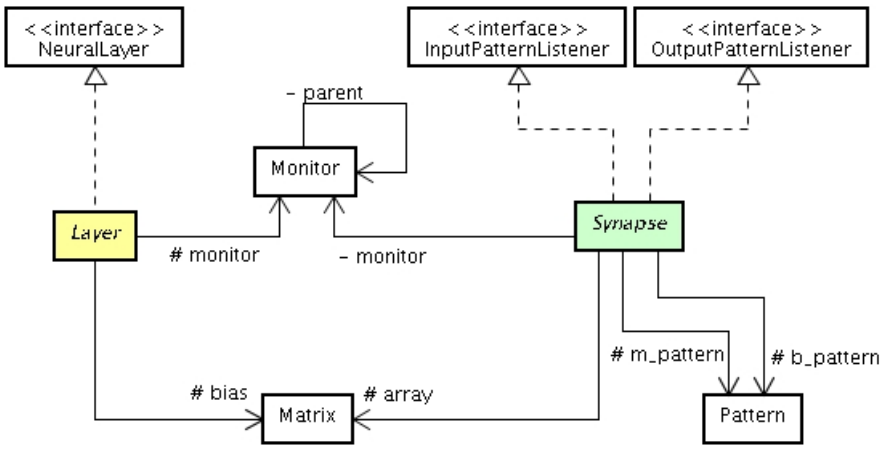


Figure 3.20: Joone Class Diagram

networks as illustrated in the previous chapter. The following UML class diagram in figure 3.20 contains the main objects constituting the model of the core engine of Joone: All the objects implement the java.io.Serializable interface. As a result each neural network built with Joone can be saved as a byte stream to be stored in a file system, a data base, or be transported to other machines to be used remotely. The two main components are represented by two abstract classes (both contained in the org.joone.engine package): the Layer and the Synapse objects.

3.5.1 The abstract Layer class

The Layer object is the basic element that is used to form any neural net. It is composed of any number of neurons all having the same characteristics. This component transfers the input pattern to the output pattern by executing a transfer function. The output pattern is sent to a vector of Synapse objects attached to the layer's output. It is the active element of a neural net in Joone and in fact it runs in a separate thread (it implements the java.lang.Runnable interface) so that it can run independently from other layers in the neural net. Its heart is represented by the method run (see listing 3.1):

```
1      public void run() {
2         while (running) {
3             int dimI = getRows();
4             int dimO = getDimension();
5             /* Recall phase */
6             {\color{green}{inps = new double[dimI];}}
7             this.fireFwdGet();
8             if (m_pattern != null) {
9                 forward(inps);
```

```
10                  m_pattern.setArray(outs);
11                  fireFwdPut(m_pattern);
12              }
13              if (step != -1)
14                  /* Checks if the next step is a learning step */
15                  m_learning = monitor.isLearningCicle(step);
16              else
17                  /* Stops the net */
18                  running = false;
19          /* Learning phase */
20              if ((m_learning) && (running)) {
21                  gradientInps = new double[dimO];
22                  this.fireRevGet();
23                  backward(gradientInps);
24                  m_pattern = new Pattern(gradientOuts);
25                  m_pattern.setCount(step);
26                  fireRevPut(m_pattern);
27              }
28          }  /* END while (running = false) */
29          myThread = null;
30      }
```

Listing 3.1: The abstract synapse's run method

The end of the cycle is controlled by the running variable, so the code loops until some ending event occurs.
TODO: This section to be updated with regard to the new singlethreaded mode!

The Recall Phase

The code in the first block reads all the input patterns from the input synapses (fireFwdGet). Each input pattern is added to the others to produce the inps vector of doubles. It then calls the Forward method which is an abstract method in the Layer object. In the forward method the inherited classes must implement the required formulas of the transfer function, read the input values from the inps vector and return the result in the outs vector of doubles. By using this mechanism based on the template pattern any new kind of layer can easily be built by extending the Layer object. After calling the forward method the code calls the fireFwdPut method to write the calculated pattern to the output synapses. Output synapses provide the pattern necessary for any subsequent layers to process the results in the same manner. In simpler terms layer objects behave like pumps that decant the liquid (the pattern) from one recipient (the synapse) to another.

The Learning Phase

After the recall phase, if the neural net is in a training cycle, the code calls the fireRevGet method to read the error obtained on the last pattern from the output synapses. The code then calls the abstract backward method where, like in the forward method, the inherited classes must implement the processing of the error to modify the biases of the

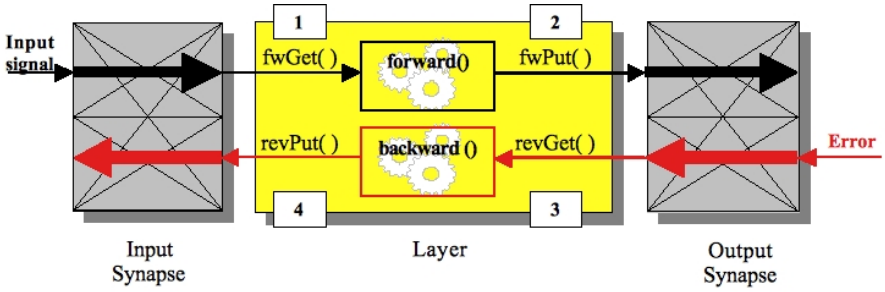


Figure 3.21: Learning phase

neurons constituting the layer. The code does this task by reading the error pattern in the gradientInps vector and writing the result to the gradientOuts vector. After this, the code writes the error pattern contained in the gradientOuts vector to the input synapses (fireRevPut), from which other layers can subsequently process the back propagated error signal. To summarize the concepts described above, the Layer object alternately 'pumps' the input signal from the input synapses to the output synapses, and the error pattern from the output synapses to the input synapses, as depicted in diagram 3.21 (the numbers indicate the sequence of the execution):

3.5.2 Connecting a Synapse to a Layer

To connect a synapse to a layer the program must call the Layer.addInputSynapse method for an input synapse or the Layer.addOutputSynapse method for an output synapse. These two methods, inherited from the NeuralLayer interface, are implemented in the Layer object as depicted in Listing 3.2:

```
1   /** Adds a new input synapse to the layer
2    * @param newListener neural.engine.InputPatternListner
3    */
4   public synchronized void addInputSynapse(InputPatternListener newListener) {
5       if (aInputPatternListener == null) {
6           aInputPatternListener = new java.util.Vector();
7       };
8       aInputPatternListener.addElement(newListener);
9       if (newListener.getMonitor() == null){
10          newListener.setMonitor(getMonitor());
11      }
12      this.setInputDimension(newListener);
13      notifyAll();
14  }
```

Listing 3.2: Connecting Synapses

The Layer object has two vectors containing the list of the input synapses and the list of the output synapses connected to it. In the fireFwGet and fireRevPut methods the Layer

scans the input vector and for each input synapse found it calls the fwGet and the revPut methods respectively (implemented by the input synapse from the InputPatternListener interface). Look at listing 3.3 that implements the fireFwGet method:

```
1   /**
2    * Calls all the fwdGet methods on the input synapses in order
3    * to get the input patterns
4    */
5   protected synchronized void fireFwdGet() {
6       double[] patt;
7       int currentSize = aInputPatternListener.size();
8       InputPatternListener tempListener = null;
9       for (int index = 0; index < currentSize; index++){
10          tempListener =
11      (InputPatternListener)aInputPatternListener.elementAt(index);
12          if (tempListener != null) {
13              m_pattern = tempListener.fwdGet();
14              if (m_pattern != null) {
15                  patt = m_pattern.getArray();
16                  if (patt.length != inps.length)
17                      inps = new double[patt.length];
18                  sumInput(patt);
19                  step = m_pattern.getCount();
20              }
21          };
22      };
23  }
```

Listing 3.3: fireFwGet() Method

In the bordered code there is a loop that scans the vector of input synapses. The same mechanism exists for the fireFwPut and fireRevGet methods applied to the vector of output synapses implementing the OutputPatternListener interface. This mechanism is derived from the Observer Design Pattern, where the Layer is the Subject and the Synapse is the Observer. Using these two vectors makes is possible to connect many synapses (both input and output) to a Layer and permits the building of complex neural net architectures.

3.5.3 The abstract Synapse class

The Synapse object represents the connection between two layers and permits the passing, from one layer to another, of a pattern. The Synapse is also the 'memory' of a neural network. During the training process the weighs of the synapse (contained in the Matrix object) are modified in accord with the implemented learning algorithm. As described above a synapse is both the output synapse of a layer and the input synapse of the next connected layer in the neural network. To enable this behavior the synapse object implements the InputPatternListener and the OutputPatternListener interfaces. These interfaces contain the methods fwGet, revPut, fwPut and revGet. Listing 3.4 describes how these methods are implemented in the Synapse object:

```
1   public synchronized void fwdPut(Pattern pattern) {
2       if (isEnabled()) {
```

```
3               count = pattern.getCount();
4               if ((count > ignoreBefore) || (count == -1)) {
5                   while (items > 0) {
6                       try {
7                           wait();
8                       } catch (InterruptedException e) {
9                           return; }
10                  }
11                  m_pattern = pattern;
12                  inps = (double[]) pattern.getArray();
13                  forward(inps);
14                  ++items;
15                  notifyAll();
16              }
17          }
18      }
19      public synchronized Pattern fwdGet() {
20          if (!isEnabled())
21              return null;
22          while (items == 0) {
23              try {
24                  wait();
25              } catch (InterruptedException e) {
26                  return null;
27              }
28          }
29          --items;
30          notifyAll();
31          m_pattern.setArray(outs);
32          return m_pattern;
33      }
```

Listing 3.4: Synapse Methods

The Synapse is the shared resource located between two Layers which run on two separate threads in the multi-thread mode. To avoid a layer trying to read the pattern from its input synapse before the other layer has written it the shared synapse in synchronized. In the code above the variable called 'items' represents the semaphore of this synchronization mechanism. After the first Layers calls the fwdPut method the items variable is incremented to indicate that the synapse is 'full'. Conversely, after the subsequent Layer calls the fwdGet method the variable 'items' is decremented indicating that the synapse is now empty.

Both the above methods control the 'items' variable when they are invoked:

1. If a layer tries to call the fwPut method when items is greater then zero, its thread falls in the wait state, because the synapse is already full.

2. In the fwGet method when a Layer tries to get a pattern while items is equal to zero (meaning that the synapse does not contain a pattern) then its corresponding thread falls in the wait state.

The notifyAll method call at the end of the two methods permits the 'awakening' of the other waiting layer, signalling that the synapse is ready to be read or written. After the

notifyAll at the end of the method the running thread releases the owned object which permits any other waiting thread to take ownership. Note that although all waiting threads are notified by notifyAll only one will acquire a lock and the other threads will return to a wait state. The synchronizing mechanism is the same in the corresponding revGet and revPut methods for the training phase of the neural network. The fwPut method calls the abstract forward method (at the same time as the revPut calls the abstract backward method) which permits the inherited classes to implement the recall and learning formulas respectively. This was previosuly described for the Layer object (according to the Template design pattern). By writing the appropriate code in these two methods the engine can be extended with new synapses and layers permitting the implementation of any learning algorithm and architecture that is required.

Starting with v.2.0 of Joone which contains a new single-thread engine the mechanism is very similar except that the xxxGet/Put methods are invoked by a single thread (instantiated by the NeuralNet object) therefore no conflict between concurrent threads is possible and a performance improvement of approximately 50% is realized.

Chapter 4

I/O components: a link with the external world

The I/O components of the core engine implement the mechanisms needed to connect a neural network to external sources of data. These mechanisms provide for the reading of patterns one wishes to elaborate and for the storing of a networks results to any output device required. All of the I/O components extend the Synapse object. They can be 'attached' to the input or the output of a generic Layer object since they expose the same interface required by any i/o listener of a Layer. Using these simple mechanisms a Layer is unaffected by the type of synapse connected to it because the I/O components all have the same interface. A Layer will continue to call the Get and Put methods without needing to know anything more about an I/O components specialization.

4.0.4 The input mechanism

To permit a user to utilize any source of data as input for a neural network a complete input mechanism has been designed into the core engine. The main concept underlying the input system is that a neural network elaborates ÔpatternsÕ. A pattern is composed by a row of values The neural network reads and elaborates, sequentially, all of the input rows (each one constituted by the same number of values - or columns). For each row it generates an output pattern representing the outcome of the entire process.

Two main features are required in order to reach the goal of making this mechanism as flexible as possible:

Firstly, to represent a row of values Joone uses an array of doubles therefore to permit the use of other data formats Joone requires a Ôformat converterÕ. The format converter is based on the concept that a neural network can elaborate only numerical data (integers or real numbers) hence a system to convert any external format to numerical values is provided. This system acts like a ÔpluggableÕ driver: provided with Joone is an interface and some basic drivers (for instance one to read ASCII values and another to read Excel

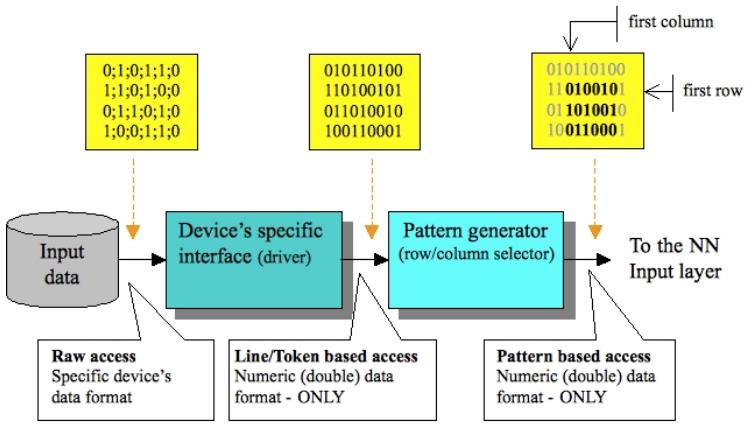


Figure 4.1: I/O Diagram

sheets) to convert the input values to a usable array of double. This mechanism is expansible so anyone can write new drivers implementing the provided interfaces to convert other data types.

Secondly, since not all the available rows and columns normally need to be used as input data a ÔselectionmechanismÕ for selecting the input values is provided. This second feature is implemented as a component interposed between the above mentioned driver and the first layer of the neural network. The selection of the needed input columns is made by using a paremeter named AdvancedColumnSelector. The advanced column selector specifies what columns from the input source should be presented to the next layer. For example, if an input file contains 5 columns a user could specify that only columns 1 and 3 be presented to the next layer. The selector must be a list of one or a comma delimeted list of multiple options. The options can be one column '2' or a range of columns '3-6'. The format for the selector is as follows ... For example if the input source has 5 columns and you would like to use column 1 and columns 3,4 and 5, you could specify the selector as '1,3-5' or '1,3,4,5'. For specific needs the same column can be read many times within the same pattern, simply specifying the same number more than once, like in the following example: '1,3,3,3,4'. A complete example of this feature can be found in Chapter 9.

The overall input system is depicted in diagram 4.1:

Note that the component connected to the first layer of the neural network, implemented within the StreamInputSynapse class, is built just like a synapse and implements the corresponding interface. Again we see that an input layer is not bothered about the kind of synapse attached to it.

This is one of the most important characteristics of Joone which permits the building of any architecture simply by gluing together several components. The StreamInputSynapse

class exposes several other parameters in addition to the AdvancedColumnSelector which are inherited by all xxxInputSynapses that extend the above abstract class:

- **Name** The name of the input synapse. It's always a good norm to set a name for each input synapse, in order to be able to manage them when attached to other I/O components (like, for instance, the InputSwitchSynapse).
- **Buffered** Determines whether the data should be buffered in memory rather than being read throughout the run. By default all the input synapses are buffered. This is due to the fact that buffering is a useful feature when a neural network has to be transported to another machine for remote training. When the input synapses are buffered all the input data is transported along with the neural network which avoids having to retrieve it remotely.
- **FirstRow** The first row of the file that contains useful information.
- **LastRow** The last row of the file that contains useful information. Default of zero uses all the rows.
- **Enabled** The component is working only when this property is true.
- **StepCounter** Input layers affect the running of the network. By default each time a line is read from an input layer the network monitor advances one step in the learning process. Note: If there are several input layers only one should have the step counter enabled.
- **MaxBufSize** Indicates the max buffer size used to store the input patterns. If equal to 0 (the default) the buffer size is set to 1MB (augment it only if your input data source exceeds such size). Also this is Used only if 'Buffered' = true, otherwise it is ignored. Must be equal or greater than the size of the input buffer expressed in bytes.

4.0.5 The FileInputSynapse

A file input synapse allows data to be presented to the network from a file. The file must contain columns of integer or real values delimited by a semicolon. For example the xor problem file should contain:

0 0 0
1 0 1
0 1 1
1 1 0

There is an extra property that can be set for file input layers:

- **FileName** The name of the file containing the data. E.g. c:\data\myFile.txt

4.0.6 The URLInputSynapse

This component allows data to be presented to the network from a URL. The protocols supported are HTTP and FTP. The file pointed by the URL must contain the same format accepted by the FileInputSynapse, numbers separated by a semicolon , . One extra property that should be set for URL input layers is:

- **URL** The name of the Unified Resource Locator containing the data.
  E.g. http//www.someServer.org/somepath/myData.txt or
  ftp://ftp.someServer.org/somePath/myData.txt.

4.0.7 The Excel Input Synapse

The Excel Input synapse permits the application of data from an Excel file to a neural network for processing. The extra properties that can be specified for Excel input layers are:

- **fileName** This parameter allows the specifying of the name of the file from which the input data is to be read.
- **Sheet** This parameter allows the name of the sheet to be chosen from which the input data is read. If left blank this defaults to the first available sheet.

4.0.8 The JDBCInput Synapse

The JDBCInputSynapse permits data from almost any database to be applied to a neural network for processing. To use this input synapse you should ensure that the required JDBC Type 4 Driver is in the class path of your application. It is possible to use other JDBC driver types although you will need to refer to the specific vendors documentation which may require the installation of extra software and may limit your distribution to certain Operating Systems. The extra properties that can be specified for JDBC input layers are:

- **driverName** The name of the database driver. For example if you were using the JdbcOdbc driver provided by Sun and already present in the java distribution then 'sun.jdbc.odbc.JdbcOdbcDriver'
- **dbURL** The database specification. This protocol is specific to the driver therefore you must check the protocol with the driver vendor. For example for the JdbcOdbc 'jdbc:mysql://localhost/MyDb'user=myuser&password=mypass'
- **SQLQuery**The query that you will use to extract information from the database. For example 'select input1,input2,output from xortable;'

Some commonly used driver protocols are shown below: Driver com.mysql.jdbc.Driver
Protocol jdbc:mysql://[hostname][,failoverhost...][:port]/[dbname][param1=value1][param2=value2].....
MySQL Protocol
Example jdbc:mysql://localhost/test?user=blah&password=blah
See http://www.mysql.com

Driver sun.jdbc.odbc.JdbcOdbcDriver
Protocol jdbc:odbc:[;=]* ODBC Protocol
Example jdbc:odbc:mydb;UID=me;PWD=secret
See http://www.java.sun.com

Data Types
Any fields selected from a database should contain a single integer of double or float format value. The data type is not so important it can be text or a number field so long as it contains just one integer of double or float format. E.g Correct = '2.31' Correct = '-15' Wrong= '3.45;1.21' and Wrong = 'hello'

4.0.9 The Image InputSynapse

This input synapse collects data from image files or image objects and feeds the data from the images into the Neural network. Images can be read either from the file system or from a predefined array of images. GIF, JPG and PNG image file formats can be read. The synapse operates in two modes: colour and grey scale.

- **Colour Mode** In colour mode ImageInputSynapse produces seperate RGB input values in the range 0 to 1 from the image. So using an image of width 10 and height 10 there will be 10x10x3 inputs in the range 0 to 1. The individual colour components are calculated by obtaining the RGB values from the image. These values are initially in an ARGB format. Transparency is removed and the RGB value extracted and normalized between 0 and 1.

- **Non Colour Mode / Grey Scale Mode** In this mode the synapse treats each input value as a grey scale value for each pixel. In this mode only Width*Height values are required. To produce the final image the red, green and blue components are set to this same value. The grey scale component is calculated by obtaining the RGB values from the image. These values are initially in an ARGB format. Transparency is removed and the RGB value extracted, averaged and normalised to produce one grey scale value between 0 and 1.

The following properties must be provided to this synapse:

- **ImageDirectory** This is the path to the directory that contains the images to elaborate. By default it's equal to the value of the Òuser.dirÓ system property.

- **FileFilter** A regex containing the filter used to read the image files from the file system. By default equal to the string ".*[jJ][pP][gG]" (.jpg and .JPG files)
- **ImageInput** (Optional property) Points to an array of Image objects. If this property is used the images will be read from the array and the above two properties will be ignored.
- **DesiredWidth/DesiredHeight** These two properties indicate the desired size of the images that will be used to feed the neural network. All the images will be rescaled in order to respect the indicated size (by default both the dimensions are set to 10 pixel)
- **ColourMode** A boolean value indicating the operating mode (see above). By default the synapse will operate in colour mode (ColourMode=true).

4.0.10 The YahooFinanceInputSynapse

The YahooFinanceInputSynapse provides support for financial data input from financial markets. The synapse contacts Yahoo Finance services and downloads historical data for the chosen symbol and date range. Finally the data is presented to the network in reverse date order (i.e. oldest first). The following properties must be provided to this synapse:

- **Symbol** This is the symbol of the specific stock (e.g TSCO.L for UK supermarket company Tescos). This must be one of symbols defined by Yahoo.
- **firstDate** This is the date of the oldest requested stock value. Note the dates should be in the following format YYYY.MM.DD where YYYY=4 Character year, MM=2 character month, DD=2 character day of the month.
- **lastDate** This is the date of the latest requested stock value. This uses the same format as First Date above.
- **Period** This is the period between stock values obtained from Yahoo, 'Daily' will obtain stock values recorded at the end of each day, 'Monthly' will obtain stock values recorded at the beginning of each month, 'Yearly' will obtain stock values recorded at the start of each year.

This synapse provides the following information for the particular stock symbol:

Open	column 1
High	column 2
Low	column 3
Close	column 4
Volume	column 5
Adjusted Close	column 6

You must set the Advanced Column Selector (ACS) in accord with these values. That is, if you wish to use as input the Open, High and Volume columns then you must write '1-2,5' into the ACS. Note the stock symbol must be one of the symbols defined by Yahoo. For a list of symbols see the Finance section of the Yahoo web site `http://finance.yahoo.com`.

4.0.11 The MemoryInputSynapse

The memoryInputSynapse allows data to be presented to the network from an array of doubles. This component is very useful when an external program needs to feed the network with data obtained from external or internal sources for which a specific xxxInputSynapse doesn't exist.

The following property must be provided to this synapse...

- **inputArray** This property must contain a pointer to the double[][] array containing the input data.

4.0.12 The Input Connector

When we need to train a network we need to use at least two input data sources, one as training input data and another as the desired data. If we then add another data source to validate the network we need to add another two data sources to our neural network. All those input synapses make the architecture of the neural network very complex and, if they are buffered, a huge amount of memory is required to store all of the implied data.

In order to resolve this large memory demand we have built a new input component called InputConnector. This component permits the sharing of input synapses across several uses as depicted in diagram 4.2 (created from a snapshot of the drawing area of the GUI Editor):

The InputConnectors are in the two red boxes in the diagram. As you can see, thanks to the InputConnector components, we have used only one input data source (the ExcelInputSynapse) and only one NormalizerPlugin which simplifies the entire architecture of the neural network.

The four InputConnectors are used to read from the Excel sheet:

- The input data for the training phase (InputTraining connector)
- The input data for the validation phase (InputValidation connector)
- The desired data for the training phase (DesiredTraining component)
- The desired data for the validation phase (DesiredValidation component)

The following are the main properties which must be set and utilized by these components:

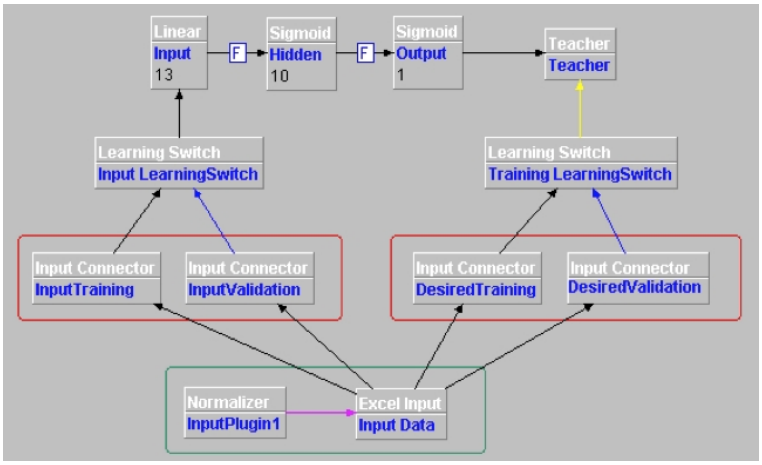


Figure 4.2: Inputconnector

- **advancedColumnSelector** Contains the columns to read from the connected input synapse
- **first/lastRow** This specifies the first and the last row we want to read from the input synapse
- **buffered** If set to true the InputConnector reads all the patterns from the connected input synapse when the network starts and stores them within an internal buffer (by default this property is set to false). Note: set to true ONLY when an input plugin is connected to the InputConnector (read below)

The above properties are set independently from the corresponding ones of the connected input synapse. In the above figure we could have the settings depicted in listing 4.1 (in this example we'll use the first 100 rows for training and the next 50 for validation; the first 13 columns are the independent variables and the col. 14 contains the target value):

```
1  /*The settings for the ExcelInputSynapse*/
2  ExcelInputSynapse.advancedColumnSelector = "1-14"
3  ExcelInputSynapse.firstRow = 1
4  ExcelInputSynapse.lastRow = 0
5  ExcelInputSynapse.buffered = true
6
7  /*settings for the InputConnector named 'InputTraining'*/
8  InputTraining.advancedColumnSelector = "1-13"
9  InputTraining.firstRow = 1
10 InputTraining.lastRow = 100
11 InputTraining.buffered = false
12
13 /*...the InputConnector named 'InputValidation':*/
14 InputValidation.advancedColumnSelector = Ò1-13Ó
```

```
InputValidation.firstRow = 101
InputValidation.lastRow = 150
InputValidation.buffered = false

/*...the InputConnector named 'DesiredTraining':*/
DesiredTraining.advancedColumnSelector = Ò14Ó
DesiredTraining.firstRow = 1
DesiredTraining.lastRow = 100
DesiredTraining.buffered = false

/*...and the InputConnector named 'DesiredValidation'*/
DesiredValidation.advancedColumnSelector = Ò14Ó
DesiredValidation.firstRow = 101
DesiredValidation.lastRow = 150
DesiredValidation.buffered = false
```

Listing 4.1: Sample Configurations

As illustrated in the example, the ExcelInputSynapse is buffered and contains all the rows and all the columns needed while each single InputConnector reads only the 'piece' of input data it needs according to its position and purpose within the neural network. The four InputConnectors are all unbuffered and thereby occupy only the amount of memory strictly necessary.

The 'buffered' property of the InputConnector class exists for the purpose of pre-process the data of a particular InputConnector using an InputPlugin. Inthis case we would set the buffered property to true. This is due to the fact that the input plugins work only for buffered synapses. In this manner we have the maximum flexibility and are able to 'cut' the input data as we want as well as being able to pre-process separately each single piece of data if necessary. Of course you must use a buffered InputConnector only when really necessary in order to avoid wasting valuable memory resources.

It is very simple to use the InputConnector class in a java program. Listing 4.2 shows how to do it:

```
// Create the InputSynapse
XLSInputSynapse inputSynapse = new XLSInputSynapse();
inputSynapse.setFileName(ÒmyData.xlsÓ);
inputSynapse.setAdvancedColumnSelector(Ò1-14Ó);
...
// Create the InputConnector
InputConnector inputTraining = new InputConnector();
inputTraining.setAdvancedColumnSelector(Ò1-13Ó);
...
// Connect the InputSynapse to the InputConnector
inputTraining.setInputSynapse(inputSynapse);
// Connect the InputConnector to the input layer of the network
LinearLayer inputLayer = new LinearLayer();
inputLayer.addInputSynapse(inputTraining);
...
```

Listing 4.2: Configuring an InputConnector

4.1 The Output: using the outcome of a neural network

The Output components allow a neural network to write output patterns to any storage fomat one wishes to support. These components write all the values of the pattern passed by the attached calling layer to an output stream thereby permitting the output patterns from an interrogation phase to be written in such formats as ASCII files, FTP sites, spreadsheets or even for charting visual components.

Joone has several real implementations of the output classes to write patterns in the following formats:

- Comma separated ASCII values
- Excel spreadsheets
- Images (JPG)
- RDBMS tables using JDBC
- Java Arrays - to write the output in a 2D array of doubles which can permit the use of the output of a neural network from an embedding or external application.

In the Chapter 9 some techniques to get and use the outcome of a neural network will be shown.

Many others output components may be added by simply extending the basic abstract classes provided with the core engine; in this manner Joone could be used to manipulate several physical devices such as robot arms, servomotors or regulator valves.

4.2 The switching mechanism

Sometimes it is useful to change the input source of a neural network depending on the network's state or on some other event. For example, it might become necessary to test a trained neural network on several different input patterns or to train a net using input patterns coming from several different sources. The same idea would also be useful on the output of a neural network because the user might need to dynamically change the destination of the network output stream.

A mechanism to accommodate these needs is shown in diagram 4.3:

Joone has just the mechanism to dynamically change the input source and the output destination of a neural network. This is based on two components: the Input Switch and the Output Switch.

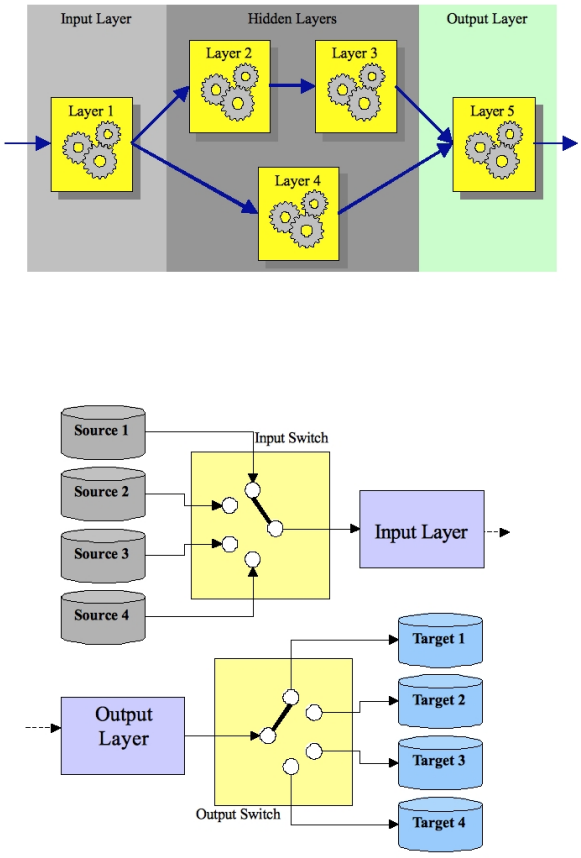


Figure 4.3: The InputSwitch

4.2.1 The InputSwitch

Any input synapse (any object capable of reading an external source of data) can be attached to this component. The InputSwitch permits the active input source (i.e. the input source attached to the neural network) to be changed dynamically simply by indicating the name of the input synapse that is to be made the active input of the neural network.

4.2.2 The OutputSwitchSynapse

Any output synapse can be attached to this component. An OutputSwitchSynapse permits the active output target to be dynamically changed simply by indicating the name of the output synapse that is to be made the active output of the neural network.

4.3 The Validation mechanism

Validating a neural network during its training cycles is very useful in determining the generalized capabilities of the net. This verification is made by measuring the error of the net using a set of patterns that have not been used by the net during the training cycles.

It is a good rule to reserve a certain number of rows of the training patterns to execute the validation check. The following outlines how this would be done with a neural network built with Joone. First, a mechanism is required to automatically switch between the training and the validation data sets. To accommodate this requirment an extension of the Input Switch has been built. The schema in figure illustrates the required architecture: 4.4

The LearningSwitch can change its state according to the value of the validation parameter of the Monitor object. Depending on the state of this parameter the switch will either connect the training or the validation data set to the input layer of the neural network.

INFO

The same schema must also be applied to the desired data sets by inserting a LearningSwitch between the training and validation desired data sets and the TeachingSynapse.

Once a neural network has been built in accord with to the described architecture the validation check can be performed in the following manner:

1. The neural network is trained for a certain number of cycles.
2. A clone of the neural network is obtained by calling the NeuralNet.cloneNet() method.
3. The Monitor of the cloned net is set to these values:
4. The totCycles parameter is set to 1.

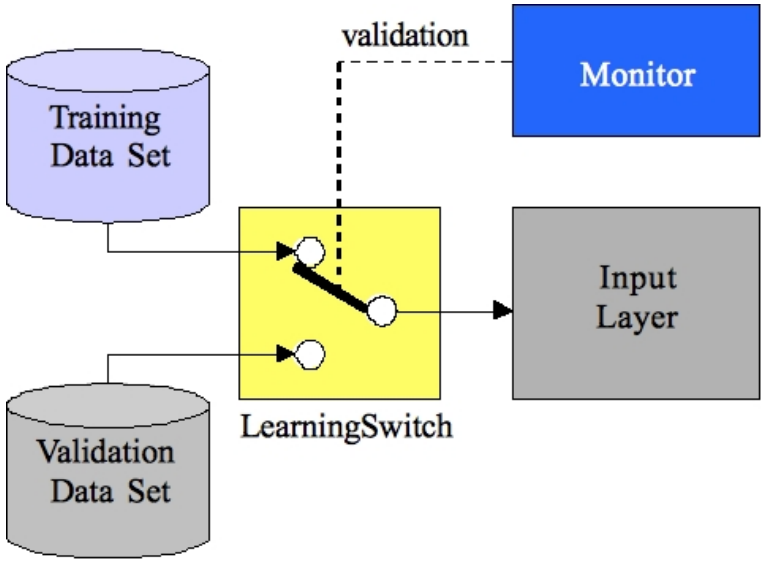


Figure 4.4: The LearningSwitch

5. The validation parameter is set to true.
6. The neural network is interrogated and the RMSE value is measured.
7. If the RMSE value is less than some desired threshold the training cycle is stopped, otherwise the cycle is repeated beginning with step 1.

Steps 2, 3, 4 and 5 can be performed in response to a cycleTerminated event of the trainee neural network. Note that it is not necessary to explicitly set the validation parameter of the net before step 1 because its default value is equal to false (i.e. the training data set is connected to the input layer). The cloning of the net in step 2 is performed to obtain a ÔdummyÕ neural network to change and use for the validation steps. This prevents the necessity of having to save and then restore the networks original state to correctly continue the training. A complete example demonstrating how to implement this technique is described in Chapter 9.

4.4 Technical Details

The I/O components of the core engine are stored in the org.joone.io package. They permit both the connection of a neural network to external sources of data and the storage of the results of the network to an output device as required. The object model is shown in figure 4.5: 4.4

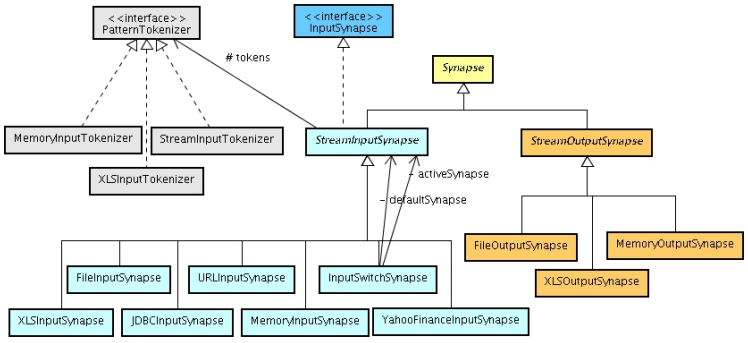


Figure 4.5: Inputmechanism Objectmodel

The abstract StreamInputSynapse and StreamOutputSynapse classes represent the core elements of the IO package. They extend the abstract Synapse class and can be ÔattachedÕ to the input or the output of a generic Layer object since they expose the same interface required by any i/o listener of a Layer. Using this simple mechanism the Layer is unaffected by the category of synapses connected to it because, as they all have the same interface, the Layer will continue to call the xxxGet and xxxPut methods without needing to know details about their specialization.

4.4.1 The StreamingInputSynapse

The StreamInputSynapse object is designed to provide a neural network with input data by providing a simple method to manage data that is organized as rows and columns, for instance as semicolon-separated ASCII input data streams. Each value in a row will be made available as an output of the input synapse and the rows will be processed sequentially by successive calls to fwdGet method.

As some files may contain information in addition to the required data the parameters firstRow, lastRow, and AdvancedColumnSelector, derived from the InputSynapse interface, may be used to define the range of usable data. The Boolean parameter stepCounter indicates if the object is to call the Monitor.nextStep() method for each pattern read.

By default it is set to TRUE but in some cases it must be set to FALSE. In any neural network that is to be trained we need to put at least two StreamInputSynapse objects: one to give the sample input patterns to the neural network and another to provide the network with the desired output patterns which are used to implement some supervised learning algorithm. Since the Monitor object is the same for all the components in a neural network built with Joone there can be only one input component that calls the Monitor.nextStep() method. Without this constraint the counters of the Monitor object will be modified twice (or more) for each cycle. To avoid this undesirable effect the stepCounter parameter of the

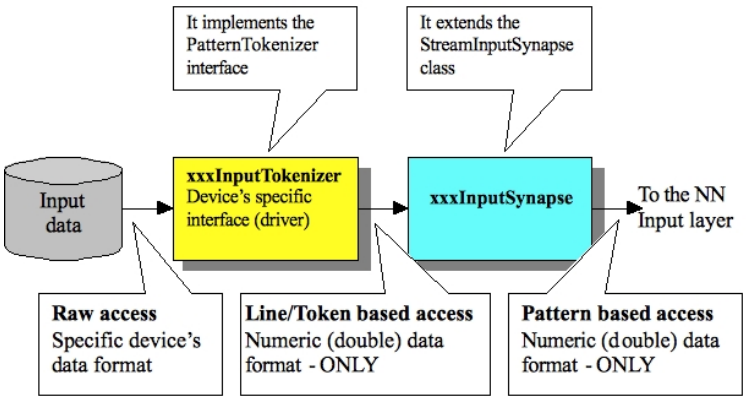


Figure 4.6: I/O Object Model

StreamInputSynapse which provides the desired output data to the neural network is set to FALSE.

A StreamInputSynapse can store its input data permanently by setting the buffered parameter to TRUE (the default). In this way an input component can be saved or transported along with its input data which permits a neural network to be used without the initial input file. This feature is very useful for remotely training a neural network in a distributed environment which is a capability provided by the Joone framework.

The FileInputSynapse and URLInputSynapse objects are real implementations of the abstract StreamInputSynapse class which read input patterns from files and http/ftp sockets respectively.

To extract all the values from a semicolon-separated input stream the above two classes use the StreamInputTokenizer object. These tokenizer objects are able to parse each line of the input data stream to extract all of the single values and return the values by using the getTokenAt and getTokensArray methods.

To better understand the concepts underlying the I/O model of Joone we must considerate that the I/O component package is based on two distinct tiers to logically separate the neural network from its input data.

Since a neural network can natively process only floating point values the I/O of Joone is based on this assumption. If the nature of the input data is already numeric, integer or float/double, the user need make no further format transformations on them. The I/O object model is based on two distinct and separated levels of abstraction as depicted in diagram 4.6. The two colored blocks represent the objects that must be written to add a new input data format and/or device to the neural network.

The first is the ÔdriverÕ that knows how to read the input data from the specific input device. The driver converts the specific input data format to the neural networkÕs

accepted numeric format of double and also exposes a line/token (e.g. row/column) based interface to provide the xxxInputSynapse with the patterns read.

The latter is the ÔadapterÕ that reads the data provided by the xxxInputTokenizer, selects only the desired columns and encapsulates them into one a Pattern object for each requested row. Each call to its fwdGet() method will provide the caller with a new read Pattern.

To add a new xxxInputSynapse that reads patterns from a different kind of input data to semicolon separated values you must:

1. Create a new class implementing the PatternTokenizer interface (e.g. xxxInputTokenizer)
2. Write all the code necessary to implement all the public methods of the inherited interface.
3. Create a new class inherited from StreamInputSynapse (e.g. xxxInputSynapse).
4. Override the abstract method initInputStream by writing the code necessary to initialise the ÔtokenÕ parameter of the inherited class. To do this you must call the method super.setToken from within initInputStream and pass the newly created xxxInputTokenizer after having initialised it. For more details see the implementation built into FileInputSynapse.

The actual implemented StreamInputTokenizer is an object used to transform semicolon separated ASCII values to numeric double values. It was the first implementation made because the most common format of data is contained in text files; if the input data are already contained in this ASCII format it can be used directly without implement any transformation.

For data contained in an array of doubles (i.e. for input provided from another application) we have built the MemoryInputTokenizer and the MemoryInputSynapse classes that implement the above two layers. This provides the neural network with data contained in a 2D array of doubles. To use these components simply create a new instance of the MemoryInputSynapse and set the input array by calling its setInputArray method Finally, connect it to the input layer of the neural network.

4.4.2 The StreamOutputSynapse

The StreamOutputSynapse object allows a neural network to write output patterns. It writes all the values of the pattern passed by the call to the fwdPut method to an output stream.

The values are written separated by the character contained in the separator parameter (the default is a semicolon) and each row is separated by a carriage return. By extending this class output patterns from an output device can be written as ASCII files, FTP sites, spreadsheets or charting visual components.

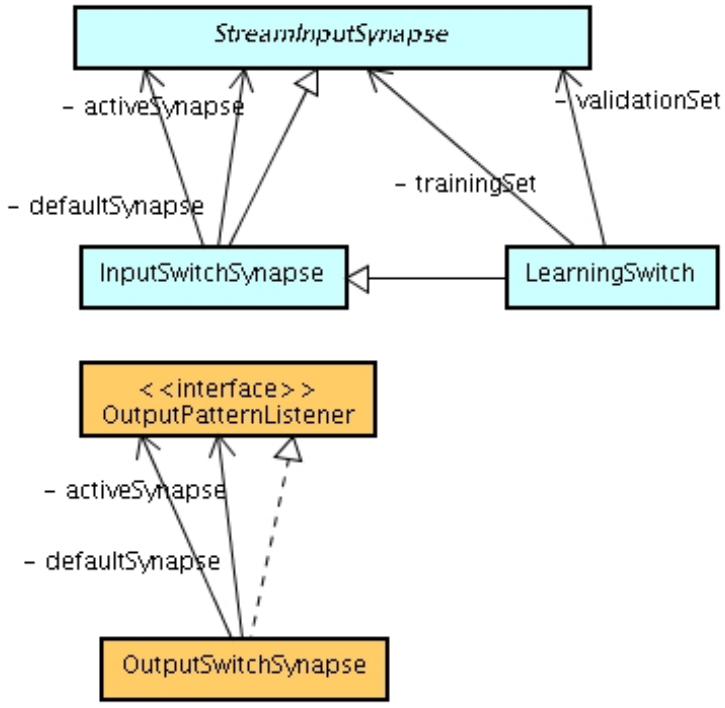


Figure 4.7: The Input Switch Object Model

4.4.3 The Switching mechanism's object model

Class diagram 4.7 shows the corresponding object model.

The InputSwitchSynapse

Using the addInputSynapse method any xxxInputSynapse (any object inheriting the StreamInputSynapse class) can be attached to this component. Since it acts as a switch the active input source can be changed dynamically simply by calling the setActiveInput(name) method and passing as a parameter the name of the input synapse that is to be made the active input of the neural network. Calling the setDefaultInput(name) method sets the default input connected to the net.

The OutputSwitchSynapse

By using the addOutputSynapse method any object inheriting the OutputPatternListener class can be attached to this component. Since it acts as an output switch the active

output target can be dynamically changed simply by calling the setActiveOutput(name) method and passing as a parameter the name of the output synapse that is to be made the active output of the neural network. As with the InputSwitchSynapse object calling the setDefaultOutput(name) method sets the default output connected to the net.

The LearningSwitch

As described above the LearningSwitch permits the dynamic changing of the input source connected to a neural network according to its validation flag.

By calling the addTrainingSet method any xxxInputSynapse (any object inheriting the StreamInputSynapse class) can be attached to this component containing the training input patterns. Calling the addValidationSet permits the setting of the xxxInputSynapse containing the validation patterns that will be used when the validation parameter is true.

Chapter 5

Teaching a neural network: supervised learning

To implement the supervised learning techniques some mechanism is needed to provide the neural network with the error for each input pattern. This error is expressed as the difference between the output generated by the pattern actually processed and the desired output value for that pattern.

5.1 The Teacher component

The function of this component (the TeacherSynapse) is to calculate the difference between the output of the neural network and the desired value obtained from some external data source. The calculated difference is injected backward into the neural network starting from the output layer of the net. Each component can process the error pattern and modify the internal connections by applying some learning algorithm.

The TeacherSynapse object, as its name suggests, implements the Synapse object so that it can be attached as the output synapse of the last layer in the neural network. This is a basic rule of thumb for all the main processing elements of Joone, permitting in this manner the easy attaching of each component to each other component (compatibly with their nature) without concern for any components particular specialization.

The internal composition of the Teacher object is depicted in diagram 5.1.

The TeacherSynapse object receives - as does any other Synapse - the pattern from the preceding Layer. The Teacher reads the desired pattern for that cycle from an InputSynapse and calculates the difference between the two patterns. The result of the calculation is made available to the connected Layer. The connected layer can receive and inject back into the neural network the result of the calculation. This is back-propagation of the measured error.

So the training cycle is complete! The error pattern can be transported from the last to

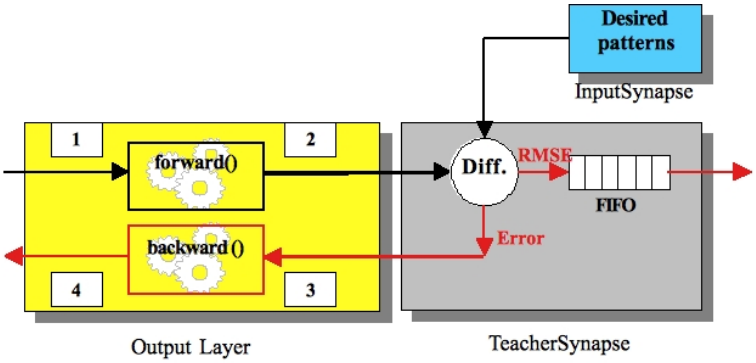


Figure 5.1: The Teachercomponent

the first layer of the neural network using the mechanism illustrated in the previous chapters of this paper. In this simple manner the output layer doesnÕt concern itself about the nature of the attached output synapse, since it continues to call the same methods known for the Synapse object.

To give to an external application the RMSE - root mean squared error - calculated on the last cycle, at the end of each cycle the TeacherSynapse pushes this value into a FIFO - First-In-First-Out - structure. From here any external application can get the resulting RMSE value in any moment during the training cycle. The use of a FIFO structure permits loose coupling between the neural network and the external thread that reads and processes the RMSE value, avoiding the training cycles having to wait before processing of the RMSE pattern.

INFO

Note: from the version 1.2 of the core engine, the TeacherSynapse is able to calculate also the MSE (mean squared error) instead of the RMSE. This depends on the value of the boolean property useRMSE. If false (the default), the MSE is calculated.

In fact, to get the RMSE values, simply connect another Layer - that runs on a separate Thread - to the output of the TeacherSynapse object, and connect to the output of this Layer, for instance, a FileOutputSynapse object, to write the RMSE values to an ASCII file, as depicted in figure 5.2. To simplify the construction of the above described chain - teacher -fifo -¿layer - a new object (called TeachingSynapse) has been built and inserted in the core engine.

This compound object is a fundamental example about how to use the basic components of Joone to built more complex components that implement some more sophisticated feature. In other words, this is an additional example of the simplicity of the

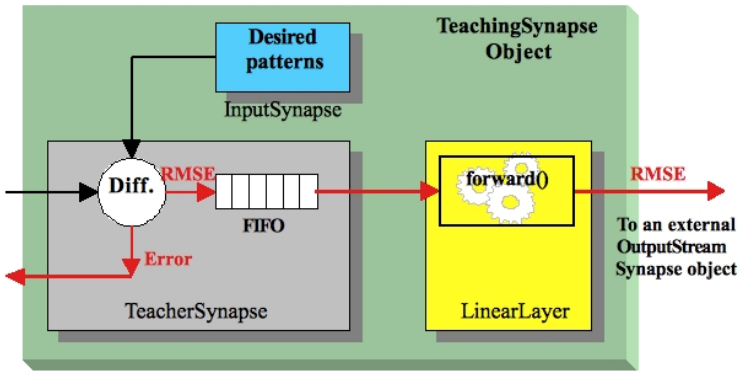


Figure 5.2: The TeachingSynapse

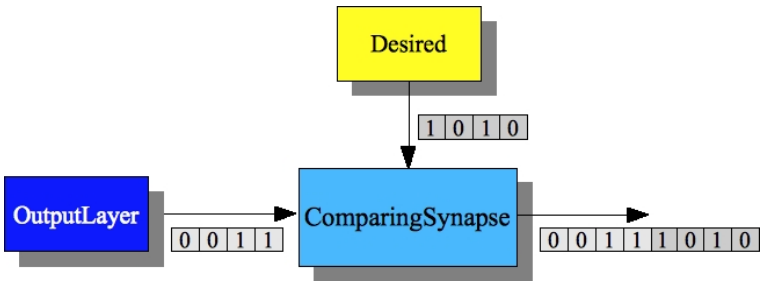


Figure 5.3: Comparing Mechanism

5.1.1 Comparing the desired with the output patterns

In some cases it should be useful to compare the actual output of the trainee neural network with the desired patterns used during the training phase. To do this, the ComparingSynapse has been built.

It implements the same interface of the TeachingSynapse class, so it can be used exactly like that component.

The unique difference is its output, represented by a pattern that is the composition of the two input patterns (that one coming from the output layer and the desired one), like depicted in figure 5.3

As you can see, the output pattern's length is the double of that of the two inputs, and contains the composition of their content.

This component can be used to plot, for instance, the two signals into the same chart component, or can be used to write the output+desired patterns as columns of the same output file for further uses.

5.2 The Supervised Learning Algorithms

As everybody already knows, in the supervised learning, a neural network learns to resolve a problem simply by modifying its internal connections (biases and weights) by back-propagating the difference between the current output of the neural network and the desired response.

In order to obtain that, each bias/weight of the network's components (both layers and synapses) is adjusted according to some specific algorithm.

Of course, as there isn't just one algorithm to change the internal weights of a neural network, we need a flexible mechanism in order to be able to set the training algorithm suitable for a determined problem. Joone provides the user with several learning algorithms, and in the following paragraphs we'll see them in detail.

INFO

Before to continue, I want to recall that there isn't any optimal algorithm that is good for whatever problem. You need to try several of them in order to find the best one for your own specific application. For this reason Joone comes with a distributed training environment - the DTE - to permit to train in parallel mode different neural networks in order to efficiently find the best one.

5.2.1 The basic On-Line BackProp algorithm

This is the most common used training algorithm. It adjusts the Layers' biases and the Synapses' weights according to the gradient calculated by the TeacherSynapse, and back-propagated by the backward-transportation mechanism already illustrated in the previous chapters.

It is called 'On-Line' because it adjusts the biases and weights after each input pattern is read and elaborated, so each new pattern will be elaborated using the new weights/biases calculated during the previous cycles.

The algorithm searches for a optimal combination of network's biases/weights by moving a virtual point along a multi-dimensional error surface, until a good minimum is found, like represented by figure 5.4(represented in three dimensions for the sake of semplicity).

The algorithm uses two parameters to work: the learning rate, that represents the 'speed' of the virtual point (the blue ball in the above figure) along the error surface (represented by the red grid), and the momentum, that represents the 'inertia' of that point. Both these parameters must be set to a value in the range [0, +1], and good values can be found only through several trials.

INFO

Remember that, while the momentum can be set to 0, the learning rate must be always set to a value greater than zero, otherwise the network cannot learn.

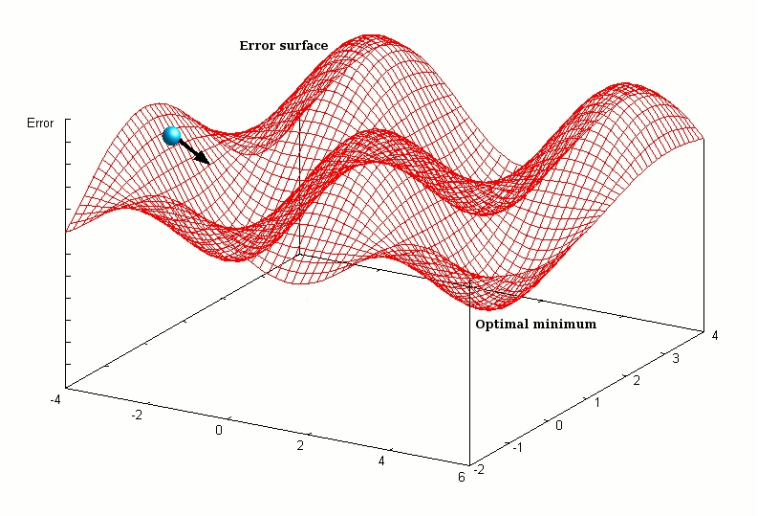


Figure 5.4: The error surface

5.2.2 The Batch BackProp algorithm

This is a variation of the on-line algorithm, because it works exactly like the above, except that the biases/weights adjustments are applied only at the end of each epoch (i.e. after all the input patterns of the training set have been elaborated). It works by storing in a separate array all the changes calculated for each pattern, and applying them only at the end of each epoch.

In this manner each pattern belonging to the same epoch will be elaborated using an unmodified copy of the weights/biases. This causes more memory to be consumed by the network, but in some cases the batch algorithm converges in less epochs.

This algorithm uses, beside the same parameters of the on-line version, also another parameter named batch size. It indicates the number of input patterns during which we want to use the batch mode, before to apply the on-line modification of the biases/weighs. This parameter, normally, is set to the number of training patterns, but by setting it to a smaller value, we can train our network also in mixed-mode.

5.2.3 The Resilient BackProp algorithm (RPROP)

This is an enhanced version of the batch backprop algorithm, and for several problems it converges very quickly.

It uses only the sign of the backpropagated gradient to change the biases/weights of the network, instead of the magnitude of the gradient itself.

This because, when a Sigmoid transfer function is used (characterized by the fact that

its slope approaches zero as the input gets large), the gradient can have a very small magnitude, causing small changes in the weights and biases, even though the weights and biases are far from their optimal values.

Based on this modified algorithm, Rprop is generally much faster than the standard steepest descent algorithm. As said, it is a batch training algorithm, and uses only the batch size property.

Note: even if the value of the learning rate and the momentum properties doesn't affect the calculus of the Rprop algorithm, you need to set the learning rate to 1.0 in order to use properly this training algorithm.

5.2.4 How to set the learning algorithm

In order to choose the needed learning algorithm of a neural network, the Monitor object exposes the getter/setter methods of the following properties:

Learners: it's an indexed list containing all the declared learners (i.e. objects implementing the org.joone.engine.Learner interface - see the technical details) learningMode: it's an integer containing the index of the chosen Learner object from the above list In order to set a learning algorithm you need to write the java code in listing 5.1 before to start the network.

```
1 Monitor.getLearners().add(0, "org.joone.engine.BasicLearner"); // On-line
2 Monitor.getLearners().add(1, "org.joone.engine.BatchLearner"); // Batch
3 Monitor.getLearners().add(2, "org.joone.engine.RpropLearner"); // RPROP
4 Monitor.getLearners().add(3, "<whatever_else_learner_class>"); // ...
5 Monitor.setLearningMode(1); // We have chosen the Batch learning in this case
```

Listing 5.1: Setting the learning algorithms

As you can see, you can add whatever learning modes you want, after that you can choose the current one simply by setting the learningMode property. Of course you need to declare only the learner objects you want to use, not all the existing ones! And if you need to use only the basic on-line mode, then you don't need to do anything, as that learning mode is the default learner, and it's activated whenever no learners have been declared.

5.3 Technical Details

5.3.1 The learning components object model

All the learning components are in the org.joone.engine.learning package, and its object model is represented in figure 5.5:

As you can see, all the above described components are represented. The TeachingSynapse is a compound object containing, other than a TeacherSynapse object, also a LinearLayer. When you put a TeachingSynapse within a neural network, you must simply

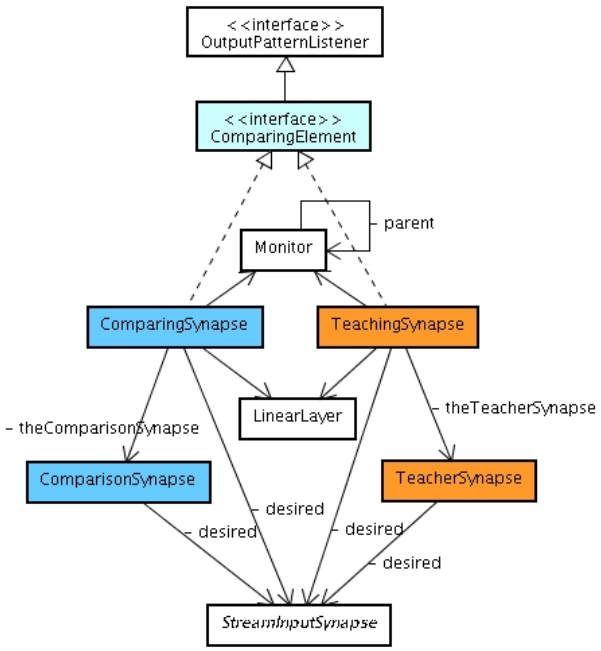


Figure 5.5: The learning components object model

connect it to the last Layer of the net (using Layer.addOutputSynapse) and set the desired property to the StreamInputSynapse object containing the desired output patterns.

Nothing else, as the TeachingSynapse will provide you with all the services needed to calculate the error to feed the neural network during the training supervised phase. The error is transmitted, by the LinearLayer, to the attached OutputPatternListener object.

The ComparingSynspase is also contained in this class diagram, and inherits the same interface of the TeachingSynapse class (the ComparingElement interface), hence it can be used in the same manner, permitting, in this case, to compose the two different input data sets - the output and the desired one - to compare them.

As you can see, both the two families of components - Theaching/Teacher and Comparing/Comparison -belong to the same class of components, and have the same internal composition. Both they read two external sources of data:

1. the output pattern from the output layer of the neural network and
2. the desired pattern from an external data source

Therefore the unique difference is represented by the pattern calculated as output:

1. The Teaching family calculates the difference between the two patterns (i.e. a scalar value representing the current training error of the neural network)
2. The Comparing family, instead, calculates the composite pattern obtained by combining the above two patterns (i.e. a vector containing the concatenation of the two patterns)

5.3.2 The Learners object model

Figure 5.6 is the scheme of the Learner/Learnable mechanism.

The org.joone.engine.Learner interface describes all the methods that each learner must implement. A Learner contains all the formulas that implement the corresponding learning algorithm, and, within each of them exist the implementations for both the Layer biases' changes (requestBiasUpdate) and the Synapse weights' changes (requestWeightUpdate).

Based on the content of the learningMode property of the Monitor, at the start of the neural network both the Layers and the Synapses receive a pointer to the active learner (represented by the 'myLearner' variable in the above diagram), so each component will be able to call the needed Learner's method according to its nature, in order to permit their biases/weights to be adjusted during the training phase.

Each component that can be manipulated by a Learner must implement the org.joone.engine.Leaneable interface and, as described by the above diagram, two Learnable objects exist: LeanableLayer - implemented by the Layer - and LearnableSynapse - implemented by the Synapse object.

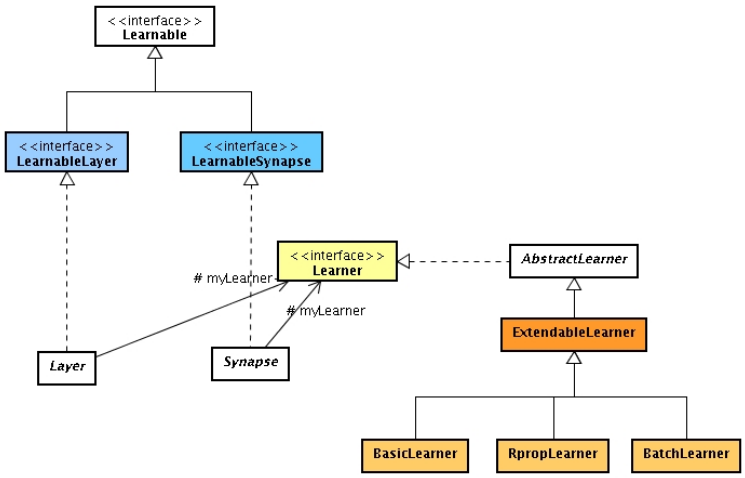


Figure 5.6: The Learners object model

5.3.3 The Extensible Learning Mechanism

Since the version 1.2 of the core engine (thanks to the great work made by Boris Jansen), the learners mechanism has been extended in order to permit to easily add whatever else learning algorithm, simply by extending the LearnerExtender abstract class, as depicted in figure 5.7.

The framework is based on so-called extenders, which implement a certain part of a learning algorithm. For example, certain extenders calculate the update value for the weights (e.g. standard back-propagation, RPROP, etc) other extenders implement the weight storage mechanism (e.g. online mode, batch mode, etc). By combining and creating extenders users can develop their own learning algorithms. Still, if a certain learning algorithm cannot be implemented by using the framework, for whatsoever reason, the user is still able to extend the Learner or AbstractLearner interface/class directly and build the learning algorithm from scratch.

However, one of the advantages of the learning framework is that user can use existing extenders to construct their learning algorithm and only focus on that part of the learning algorithm that differs from the functionality provided by the extenders. For example, if a user wants to implement a new learning algorithm that uses a different delta weight update rule, the user only has to implement a DeltaRuleExtender. By combining the new extender with an OnlineModeExtender the learning algorithm becomes an online training algorithm. By combining the new extender with a BatchModeLearner, the learning algorithm becomes a batch mode (offline) learning algorithm.

Yet another advantage is that not only certain basic functionality can be overwritten

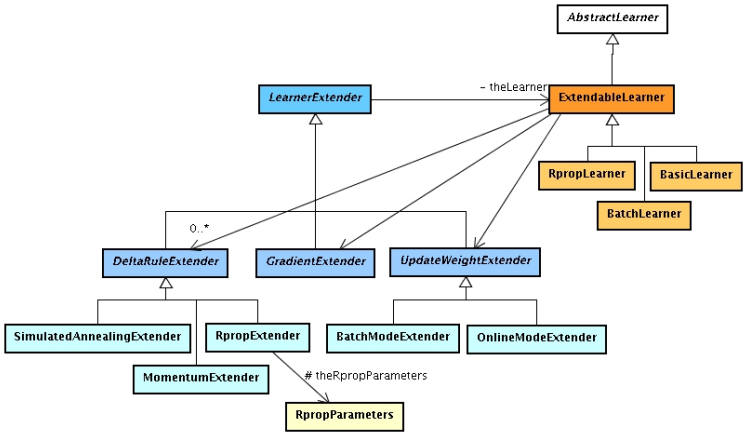


Figure 5.7: The extensible learning mechanism

by new extenders, it can also be combined. For example, a certain new DeltaRuleExtender can be combined with the MomentumExtender to provide the new learning algorithm with the momentum mechanism, or it can be combined with the SimulatedAnnealingExtender to provide the new learning algorithm with the simulated annealing mechanism.

The framework is very flexible and different techniques can be combined and easily implemented. Still the user has to verify if certain combinations of extender make sense. For example a DeltaRuleExtender implementing the RPROP delta weight update rule in combination with the OnlineModeExtender probably gives bad results, because the RPROP learning algorithm is a batch mode learning algorithm.

LetÕs look a little bit more in detail the learning algorithm extender framework: The class that provides the skeleton for learning algorithms based on extenders is the ExtendableLearner class. This class basically implements the standard BP algorithm, however the weights are not updated. In order to update the weights (that is to store the new values) one needs to set an UpdateWeightExtender, currently Joone provides two UpdateWeightExtenderÕs, a OnlineModeExtender and a BatchModeExtender.

Whenever errors are back-propagated thought the network, the methods requestWeight(or Bias)Update are called. The first thing the method does is to call the preWeight(or Bias)Update method on all the extenders that are set. This way it gives any extender the opportunity to perform some action before the weights will be updated.

Next all the DeltaRuleExtenders that are set are executed. The back propagated gradient error is passed to the DeltaRuleExtenders and the can calculate the new weight update value for the current weights (or biases). The new calculated value is passed to any next DeltaRuleExtender if more than one DeltaRuleExtender is set. This way it is possible to combine for example the standard BP together with the MomentumExten-

der and/or SimulatedAnnealingExtender. After the DeltaRuleExtenders have calculated the delta value, the WeightUpdateExtender is called, which stores the values according to some storage mechanism, e.g. the OnlineModeExtender or BatchModeExtender. Finally the postWeight(or Bias)Update method is called on all extenders to give them the opportunity to do some thing (clean up) after the weights are updated.

For example, to create a learner implementing the standard BP together with simulated annealing, all I have to do is create the class in listing 5.2:

```
1 public class MyLearner extends ExtendableLearner {
2    public BasicLearner() {
3       setUpdateWeightExtender(new OnlineModeExtender());
4       addDeltaRuleExtender(new SimulatedAnnealingExtender());
5    }
6 }
```

Listing 5.2: Subclassing the learner

If we look for example at the MomentumExtender all it does is add a momentum to the calculated delta weight update value (see listing 5.3).

```
1 public double getDelta(double[] currentGradientOuts, int j, double aPreviousDelta)
2 {
3  if(getLearner().getUpdateWeightExtender().storeWeightsBiases()) {
4     // the biases will be stored this cycle, add momentum
5     aPreviousDelta += getLearner().getMonitor().getMomentum() *
6     getLearner().getLayer().getBias().delta[j][0];
7  }
8  return aPreviousDelta;
9 }
```

Listing 5.3: The momentum extender

We think that in this manner we have created a very powerful framework which easies the implementation of different learning algorithms, and as Joone is an Open Source project, anyone can do it. **Send us your work, and we'll be very happy to publish it!**

Chapter 6

The Plugin based expansibility mechanism

The core Joone engine is built to be extended and controlled by any custom class implemented by the user. This extensibility is obtained by using plugins that can be attached to some components of the neural network. Three main kinds of plugins exist in Joone:

1. The **input** plugins
2. The **output** plugins
3. The **monitor** plugins

These are discussed in the following sections.

6.1 The Input Plugins

These plugins are very useful for implementing mechanisms to control the pre-processing of the input data for a neural network.

Several input plugins have been implemented:

- The **NormalizerPlugin** to limit the input data into a predefined range of values.
- The **CenterOnZeroPlugin** to center the input values around the origin, by subtracting their average value.
- The**MinMaxExtractorPlugin** to extract the turning points of a time series.
- The **MovingAveragePlugin** to calculate the average values of a time series.
- The **DeltaNormPlugin** to feed a network with the normalized 'delta' values of a time series.

- The **ShufflePlugin** to 'shuffle' the order of the input patterns at each epoch.
- The **ToBinaryPlugin** to convert the input values to binary format.
- New: The RbfRandomCenterSelector: TODO: Documentation
- New: The LogarithmicPlugin: TODO: Documentation
- New: The ColumSelectorPlugin: TODO: Documentation

Other pre-processing plugins can be built simply by extending the above classes.

6.1.1 The Output Plugins

The output plugins are very useful to post-process the outcome of a neural network. This could be useful to rescale an output signal to obtain a range equal to that of the original input patterns.

At this moment only one output plugin exists - the **UnNormalizerOutputPlugin** class. It, as already said, serves to rescale the output values to a predefined range, and it's useful when a NormalizerInputPlugin is used to normalize the input patterns. It can be used simply attaching it to an xxxOutputSynapse, and setting its OutDataMin and OutDataMax parameters to the desired min/max output range values. As for each other component in the joone's core engine, obviously also in this case it's possible to build new output plugins simply extending the basic ones.
The Unnormalizer should be coupled with the NormalizerPlugin so that the same scaling factor can be applied.

6.1.2 The Monitor Plugins

As mentioned in earlier, a notification mechanism has been implemented in Joone's core engine to inform all the interested objects about some events of the neural network (have a look at the NeuralNetListener Super interface too). Using this mechanism, a plugin system has been implemented that permits useful behaviour to be added in response to events raised by the net. This mechanism is very simple, and permits to provide the network with pre-built useful behaviours in response to particular events. The events that can be handled are:

- the **netStarted** event
- the **netStopped** event
- the **CycleTerminated** event
- the **ErrorChanged** event

They can be subdivided into two categories:

1. **One-time events**, like the netStarted and netStopped events
2. **Cyclic events**, like the CycleTerminated and ErrorChanged events

With Joone are delivered **two Monitor Plugins that permit to control some parameters of the neural network during the learning phase** by handling the cyclic ErrorChanged event:

- The Linear Annealing plugin changes the values of the learning rate (LR) and the momentum parameters linearly during training. The values vary from an initial value to a final value linearly, and the step is determined by the following formulas:

$$step = \text{(FinalValue - InitValue) / numberOfEpochs} \tag{6.1}$$
$$LR = LR - step \tag{6.2}$$

  The **Dynamic Annealing** plugin controls the change of the learning rate based on the difference between the last two global error (E) values as follows:

$$\text{If E(t)} > \text{E(t-1) then LR} = \text{LR} \cdot \text{(1 - step/100\%)} \tag{6.3}$$
$$\text{If E(t)} \leq \text{E(t-1) then LR remains unchanged.} \tag{6.4}$$

  The 'rate' parameter indicates how many epochs occur between an annealing change. These plugins are useful to implement the annealing (hardening) of a neural network, changing the learning rate during the training process.

  With the Linear Annealing plugin, the LR starts with a large value, allowing the network to quickly find a good minimum, and then the LR reduces permitting the found minimum to be fine tuned toward the best value, with little the risk of escaping from a good minimum by a large LR.

- The **Dynamic Annealing** plugin is an enhancement to the Linear concept, reducing the LR only as required, when the global error of the neural net augments are larger (worse) than the previous step's error. This may at first appear counter-intuitive, but it allows a good minimum to be found quickly and then helps to prevent its loss.

  To explain why the learning rate has to diminish as the error increases, look at figure 6.1.

  All the weights of a network represent an error surface of n-dimensions (for simplicity, in the figure there are only two dimensions). Training a network means to modify the connection weights so as to find the best group of values that give the minimum error for certain input patterns.

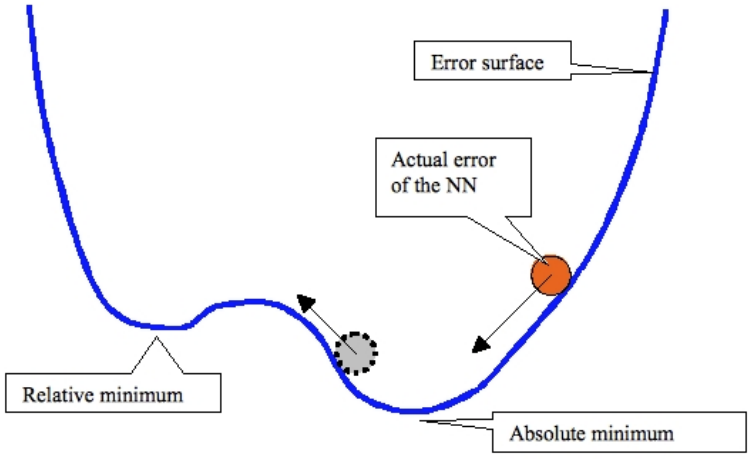


Figure 6.1: The learningrate adoption

In the above figure, the red ball represents the actual error. It 'runs' on the error surface during the training process, approaching the minimum error. Its speed is proportionate to the value of the learning rate, so if it is too high, the ball can overstep the absolute minimum and become trapped in a relative minimum.

To avoid this side effect, the speed (learning rate) of the ball needs to be reduced as the error becomes worse (see the grey ball).

With Joone 2, a few new plugins have been added:

- **ConvergenceObserver (DeltaBasedConvergenceObserver, ErrorBasedConvergenceObserver)**: TODO: Documentation
- **ErrorBasedTerminator**: TODO: Documentation
- **GroovyMacroPlugin**: TODO: Documentation
- **SnapshotPlugin and SnapshotRecorder**: TODO: Documentation

6.2 The Scripting Mechanism

Joone has its own scripting mechanism based on the BeanShell (`http://www.beanshell.org`) scripting engine. It takes advantage of the possibility of intercepting all the events raised by a neural network from within a Monitor plugin. To make possible the management of the neural network's events by an external script, a complete system has been implemented with the following features:

1. It is expansible, as makes possible the addition of new scripting interpreters simply by creating new classes inheriting a basic interface, without having to change any other class

2. The entire mechanism, being isolated by the rest of the core engine, does not depends on the BeanShell's libraries, making possible the distribution of a neural network without having to also distribute the scripting interpreter if the neural network does not use this feature.

3. It permits to write macros in response to any of the events raised by a neural network, permitting to implement whatever behaviour at run-time without the necessity to write and compile java code.

4. The macros are embedded in the neural network, and therefore they are stored/transported along with the neural network at which belong. This is a powerful mechanism capable to transport and remotely run some kind of 'custom logic' to control the run-time behaviour of a neural network.

The scripting mechanism contains two types of macros: event-driven and user-driven macros.

- **Event-driven macros** are all macros associated with the defined events of the neural network. It is possible to execute these scripts in response to a net event. It is impossible to add, remove or rename these macro because they are inherently connected to the events that a neural network can raise. The user can only set their text. If no action is required for an event, the corresponding text must be cleared (i.e. set to an empty string).

- **User-driven macros** are macros added by the user that are executed at the user's request by calling a method. These macros can be added, removed or renamed as they are not linked to any net's event.

Since version 2.0 Joone supports the Groovy (`http://groovy.codehaus.org/` scripting too. TODO: Documentation

6.3 Technical Details

6.3.1 The Input/Output Plugins object model

The mechanism, contained in the org.joone.util package, is based on the abstract classes **ConverterPlugin** and **OutputConverterPlugin**. Figure 6.2 depicts the object model of the input/output plugin mechanism.

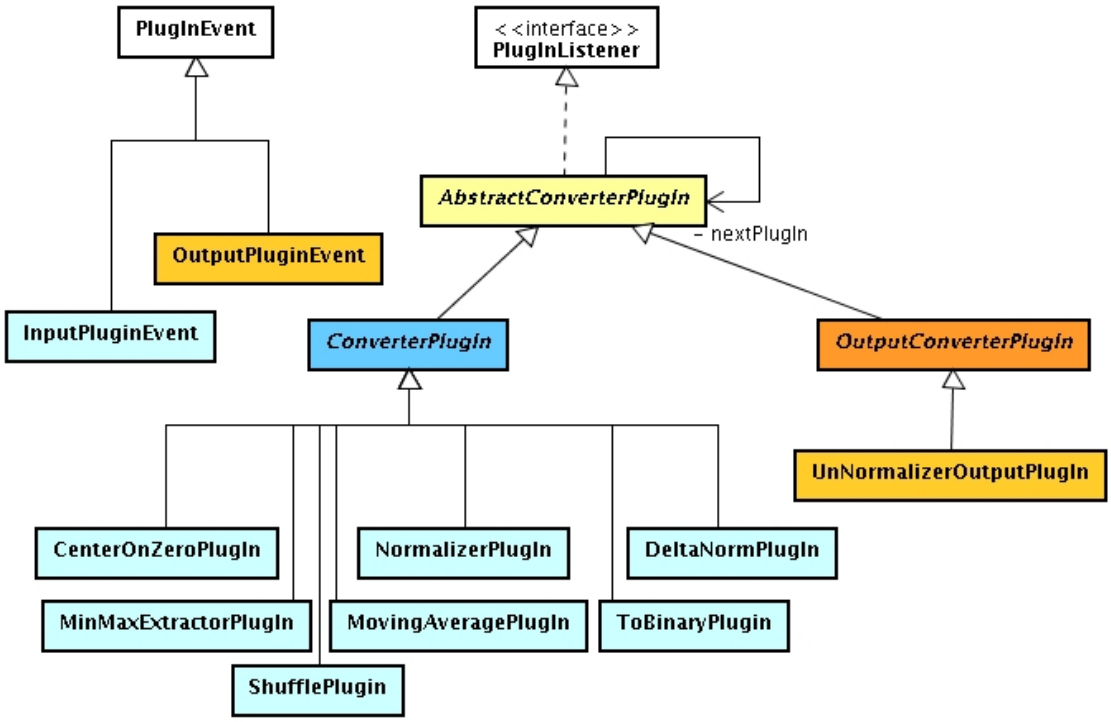


Figure 6.2: I/O Plugin mechanism

Any ConverterPlugin can be attached to a StreamInputSynapse with the setPlugIn() method, and can be extended to implement any required pre-processing of the input patterns read by the parent Input Synapse. To provide the processing, classes inheriting the ConverterPlugin must implement the abstract method convert() with the necessary code to pre-process the data.

The code for the NormalizerPlugin is shown in listing 6.1. This class normalizes the input pattern to a range delimited by the min and the max parameters.

```
1   protected void convert(int serie) {
2       int s = getInputVector().size();
3       int i;
4       double v, d;
5       double vMax = getValuePoint(0, serie);
6       double vMin = vMax;
7       Pattern currPE;
8   /* Calculates the max and the min values of the input patterns */
9       for (i = 0; i < s; ++i) {
10          v = getValuePoint(i, serie);
11          if (v > vMax)
12              vMax = v;
13          else
14              if (v < vMin)
15                  vMin = v;
16      }
17
18      d = vMax - vMin;
19  /* Calculates the new normalized values */
20      for (i = 0; i < s; ++i) {
21          if (d != 0.0) {
22              v = getValuePoint(i, serie);
23              v = (v - vMin) / d;
24              v = v * (getMax() - getMin()) + getMin();
25          }
26          else
27              v = getMin();
28          currPE = (Pattern) getInputVector().elementAt(i);
29          currPE.setValue(serie, v);
30      }
31  }
```

Listing 6.1: NormalizerPlugin

Firstly, in the first for-loop, the min and the max values of the input data are calculated, then in the second for-loop the new normalized values of the input data are calculated using the following formula:

$$norm(x) \quad = \quad \frac{x - min(x)}{max(x) - min(x)} \cdot (\text{UpperLimit - LowerLimit}) + \text{LowerLimit} \quad (6.5)$$

Note the methods used to read/write the input values:

- getValuePoint(row, serie) is used to extract an input value
- Pattern.setValue(serie, value) instead is used to write the new calculated value

The serie variable represents the column affected by the pre-processing action, and it is passed as a parameter to the convert method. Because many pre-processing calculations require all the values of the input data to be read before the data can actually be processed (as in the above example), the input plugins can be attached only to a buffered input synapse. So calling the setPlugIn method on an unbuffered synapse sets its state to 'buffered'.

To allow more than one pre-processing calculation to be applied to the input data, the input plugins can be attached in sequence, building a chain structure.

To do this, the AbstractConverterPlugin itself has a setPlugIn method, like the StreamInputSynapse class. This allows one plugin to be attached to another plugin, pre-processing the input data using as many as plugins are required. Note the auto-association link on the AbstractConverterPlugin class in the above object model. The chained input plugins will be invoked in the same order that they have been attached in the chain. To allow the input synapse and the attached plugins to be informed of changes to any parameter in any plugin constituting the chain, a notification mechanism based on the PluginEvent (do no longer use the InputPluginEvent, it is deprecated) object has been implemented.

Once an input plugin is attached to an input synapse or to another input plugin, the parent object is registered as a listener to the newly attached object. Any change made to any plugin attached to the chain raises an event to its parent, which is propagated up to the chain until it reaches the parent input synapse. Here, a new pre-processing action is invoked calling the convert() method on each attached input plugin. Thus the new pre-processed input data can be calculated.

INFO

Note: For this reason, when a new input plugin is implemented, the fireDataChanged method must be called from within the setXXX( ) method of any parameter that affects the pre-processing calculations.

As an example, consider the setMin() method of the NormalizerPlugin class (see listing **??**normplug).

```
1     /**
2      * Sets the min value of the normalization range
3      */
4     public void setMin(double newMin) {
5         min = newMin;
6         super.fireDataChanged();
7     }
```

Listing 6.2: NormalizerPlugin min() - Method

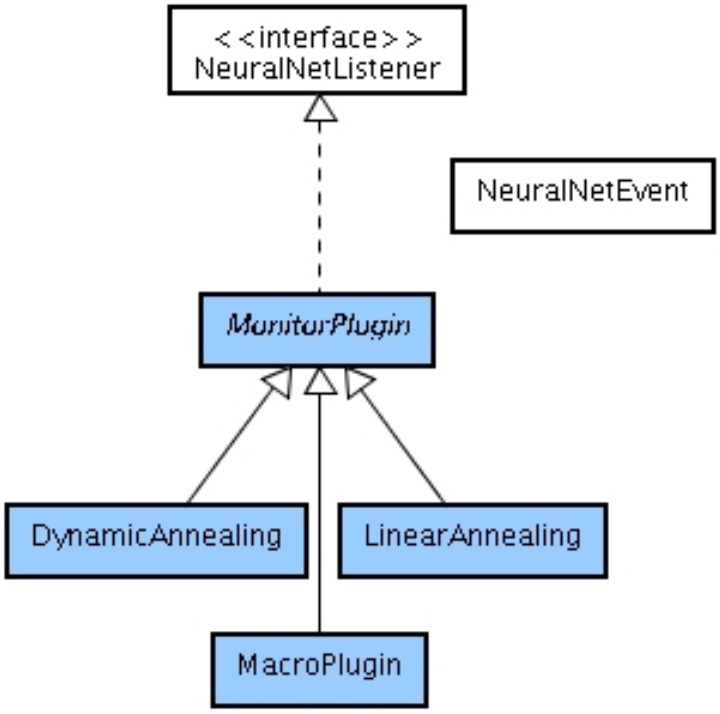


Figure 6.3: MonitorPlugin object model

6.3.2 The Monitor Plugin object model

Figure 6.3 illustrates the object model of the monitor plugin system contained in the org.joone.util package. As depicted in the above class diagram, the system is based around the MonitorPlugin object, which implements the NeuralNetListener interface. To attach a plugin to a Monitor object, the addNeuralNetListener method must be invoked, passing the object inheriting the MonitorPlugin as parameter.

To build a new plugin, the MonitorPlugin object must be extended. To implement the actions needed for each raised event, the corresponding manageXXX abstract method must be coded, where XXX is:

- **Start**: to manage the netStarted event
- **Stop**: to manage the netStopped event
- **Cycle**: to manage the CycleTerminated event
- **Error**: to manage the ErrorChanged event

The monitor plugins are very useful for dynamically controlling the parameters and/or the behaviour of a neural network.

For instance, to stop the training of a neural network when its RMSE is less than 0.01, an object could be written that extends the MonitorPlugin class as depicted in listing 6.3.

```
1 Public class StopCondition extends MonitorPlugin {
2   protected void manageError(Monitor mon) {
3     double rmse = mon.getGlobalError();
4     if (rmse < 0.01)
5           nnet.stop();
6   }
7 }
```

Listing 6.3: RMSE control - Method

The MonitorPlugin.rate parameter allows the interval (number of cycles) between two events' calls to be set. This is useful for the recurring events (the cycleTerminated and the errorChanged events) to avoid calling that event handler too often, which would reduce valuable CPU resource available to the running of the neural network.

6.3.3 The Scripting mechanism object model

The actual implementation of the scripting mechanism is based on the BeanShell scripting library, but indeed it has been built to be used with whatever else scripting library, simply by extending some basic interfaces. As far Joone 2.0, also the Groovy language is supported.

The complete object model, contained in the org.joone.script package, is depicted in the class diagram depitcted in figure 6.4.

The NeuralNet object has a pointer to the MacroInterface interface, which is implemented by the MacroPlugin object. This interface has been introduced to avoid having direct dependencies between the NeuralNet class and the BeanShell's libraries. There are two reasons for this:

- The MacroInterface makes the addition of new scripting interpreters possible simply by creating new classes inheriting that interface, without having to change any other class, as the MacroPlugin is the unique class that in this object model must reference.
- The NeuralNet object, pointing to an interface, does not depends on the BeanShellÕs libraries, making possible the distribution of a neural network without having to also distribute the scripting interpreter if the neural network doesn't need to use this feature.

The MacroManager object is a class 'container' of all the macros defined in the neural network. Each macro is represented by an instance of the Joone class, which contains the scriptÕs text that will be interpreted by the scripting engine when the corresponding macro will be executed. The MacroManager contains both the two defined types of macros: event-driven macros and user-driven macros.

The following rules are applied:

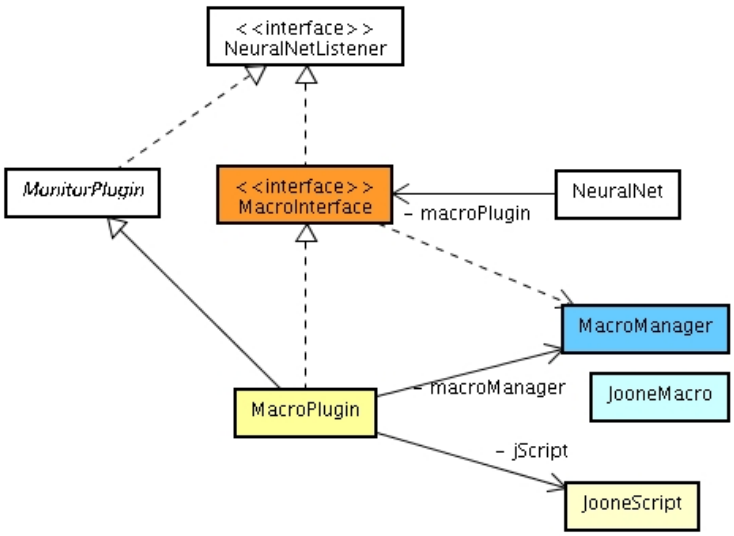


Figure 6.4: The scripting mechanism object model

- All the macros added with the addMacro method are inserted as user-driven macro
- Trying to remove or rename an event-driven macro results in a null action, and in this case the item corresponding method returns false
- Macros can be updated by passing the new text for an existing macro as a parameter of the addMacro method. This saves having to remove and then add that macro.

The MacroManager.isEventMacro(name) returns true if the string passed as parameter is the name of an event-driven macro.

Chapter 7

Using the Neural Network as a Whole

As we have seen, a neural network is composed by several components linked together to form a particular architecture suitable to resolve a given problem. In some circumstances, however, it's not convenient to handle the network as a group of single components when, for instance, we need to store, reload or transport it.

To elegantly resolve these needs, we have built an object that can contain a neural network, and in the meantime also it provides the developers with a set of useful features. This object is the NeuralNet object, and resides in the org.joone.net package.

IMPORTANT

Note: although the NeuralNet object has been initially conceived as an helper class to resolve the above needs, starting from Joone 2.0 the NeuralNet is became a fundamental class of the core engine, representing so a mandatory object to use in order to have at disposal all the features of the new engine (like for instance the single-thread mode).

7.1 The NeuralNet object

The NeuralNet object represents a container of a neural network, giving the developer the possibility of managing a neural network as a whole. With this component a neural network can be saved and restored using a unique write and read operation, without be concerned about its internal composition. Also by using a NeuralNet object, we can easily transport a neural network on remote machines and run it there by writing a small generalized Java program.

The NeuralNet provides the following services:

- **A neural network 'container'**
  The main purpose of the NeuralNet object is represented by the possibility to contain

a whole neural network. It exposes several methods useful to add, remove and get the layers constituting the contained neural network. The NeuralNet object, in fact, provides the user with some useful features to manage feed forward neural networks by exposing methods to add/remove layers (addLayer(layer) and removeLayer(layer)), to get a Layer by its name (getLayer(name)) and to extract the first and the last tier of a neural network (getInputLayer() and getOutputLayer()), giving either the declared input/output layers, or searching them following these simple rules:

1. A layer is an input layer if:
   - It has been added by using the NeuralNet.addLayer(layer, INPUT_LAYER) method, or...
   - It has not input synapses connected, or...
   - It has an input synapse belonging to the StreamInputSynapse or the InputSwitchSynapse classes
2. A layer is an output layer if:
   - It has been added by using the NeuralNet.addLayer(layer, OUTPUT_LAYER) method, or...
   - It has not output synapses connected, or...
   - It has an output synapse belonging to the StreamOutputSynapse or the OutputSwitchSynapse or the TeacherSynapse or TheachingSynapse classes

The knowledge of all these methods is very important to manage the input/output of a neural network, when, for instance, we want to dynamically change the connected I/O devices.

- **A neural network 'helper'**
  The NeuralNet object provides the contained neural network with some components useful to its work. Starting from the assumption that to build a neural network with Joone we must connect to it both a Monitor and a TeachingSynapse object (see the above chapters), the NeuralNet already contains internally these two objects. The NeuralNet creates an instance of the Monitor object and connects it automatically to any layer added to it. It also holds a pointer to a TeachingSynapse object and permits this to be externally set by calling the get/setTeacher methods.

- **A neural network 'manager'**
  The NeuralNet object is also the ÔmanagerÕ of all the behaviour of the contained neural network exposing methods like addNoise, Randomize, resetInput, etc. taking care to apply these methods to all its contained components.

Moreover, starting from Joone 2.0, the NeuralNet object exposes the methods needed to start/stop and restart a neural network (go, stop, and restore respectively). It manages

transparently all the code needed to run a network, both in multi and single thread modes. It also permits to run a network both in asynch and synch mode, the last one very useful in order to wait for the termination of all the network's running threads. It's very important to use it when we need to wait for the termination of the running of a neural network without the necessity to use CPU-consuming loops to interrogate the state of the network.

7.2 The NestedNeuralLayer object

This object is the fundamental component to use when we want to build a modular neural network, i.e. a neural network composed by several other neural networks. This feature is very useful when, for example, we want to use a neural network as a pre-processing layer of another one, or we want to teach separately several network to recognize particular aspects of the problem to solve.

The NestedNeuralLayer class, contained in the org.joone.net package, comes in our aid by providing a 'container' able to hold another entire neural network. It exposes a method - setNeuralNet(nnet) - that permits to set the embedded neural network by indicating as parameter the name of a file containing the serialized form of a NN (obtained, for instance by exporting a NN from the GUI Editor).

The NestedNeuralLayer class has a property named 'learning', used to determine if the embedded neural network's weights and biases must be changed during the training phase when inserted in the main neural network. When the 'learning' property is false, the weights of the embedded NN are not adjusted during the main neural network's training, and also the embedded NN ignores the 'randomize' and 'addNoise' commands given to the main neural network, in order to preserve the weights learned in the initial phase.

The purpose of this property becomes clear when we explain how the NestedNeural-Layer is normally used.

Let us want to use a PCA as pre-processing layer of a neural network, and we want to train the same NN until we find a good one having a low RMSE. In this case we need to execute the following steps:

1. Build a PCA NN (by using the SangerSynapse) and train it in unsupervised mode
2. Export it to a file in a serialized format (after having removed the i/o components used during the training)
3. Build the main neural network, and insert a NestedNeuralLeyer as first layers
4. Import the above serialized PCA NN into the NestedNeuralLayer
5. Set to false the 'learning' property of the NestedNeuralLayer (it should already be set to that value by default)
6. Set to true the learning mode of the main NN

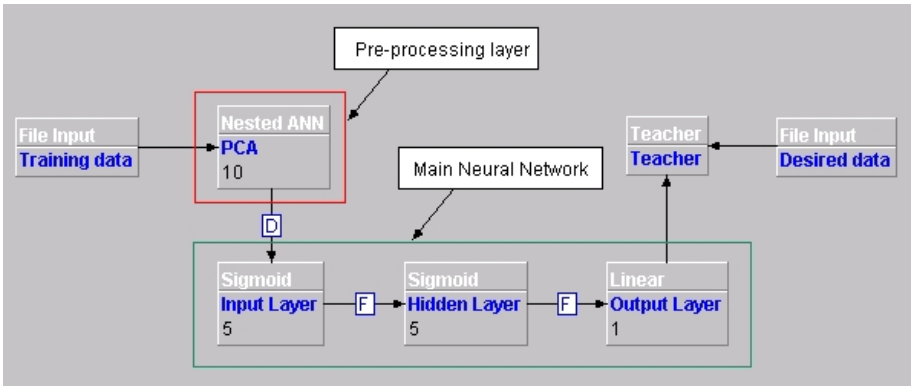


Figure 7.1: The NestedNeuralLayer in use

7. Randomize the weights of the main neural network
8. Start the training phase
9. Repeat the steps 7 and 8 until you get a good RMSE

As you can see, at the steps 7 and 8 we shuffle the weights and then train the main neural network several times, but we don't need to do so also for the embedded one, because we have already trained it at the step 1, hence at the step 5 we need to freeze the learned weights of the embedded NN.

Figure 7.1 depicts the final neural network as it would appear in the GUI Editor.

In this example the PCA is used to reduce the input layer's size from 10 to only 5 nodes, reducing in this manner the neural network's complexity.

In fact we need only to train 30 weights (5x5+5) instead of 55 (10x5+5), reducing in this manner the training time and limiting the curse of dimensionality.

7.3 Technical details

The diagram in figure 7.2 depicts the object model of the org.joone.net package, showing the NeuralNet and its link with other classes and interfaces of the core engine:

First of all, we must note that the NeuralNet object implements the NeuralLayer interface - the same implemented by the Layer object - making possible to use it as whatever else Layer in a neural network; in this manner it's possible to build very complex neural networks where each Layer could be represented itself by an entire neural network.

As you can see, the NeuralNet object contains a pointer to an embedded TeachingSynapse and a Monitor object, providing, in this manner, the objects necessary to buid correctly a neural network.

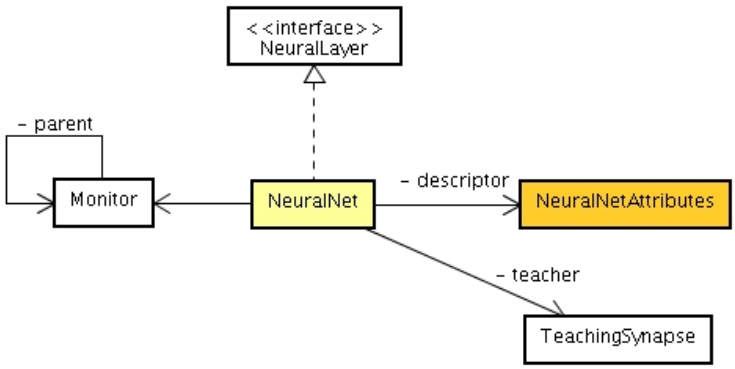


Figure 7.2: NeuralNet object model

The NeuralNet class, also, contains a pointer to the NeuralNetAttributes class. It contains several parameters of the attached neural network useful during the training or validation phases (like, for instance, the neural network's name and the last training and validation errors). This class, of course, can be extended adding new custom attributes.

Anyway if we need to add dynamically new attributes to a neural network without being constrained to write and compile new java classes, the NeuralNet object contains a mechanism to store custom parameters at run time, based on an Hashtable that stores key-value pairs.

They can be used calling the following methods:

- void setParam(String key, Object value) - to store a key-value pair
- Object getParam(String key) - to retrieve a saved parameter given its key

This possibility is very useful, for example, when the neural network is trained remotely in a distributed environment, because some parameters can be set during the remote training phase and then recalled and used by the central machine where the results must be collected.

This technique is made even more useful by the possibility to set/get these parameters from within the java scripting code. A good example of the use of this mechanism is shown in the MultipleValidation sample provided with the core engine distribution package.

Chapter 8

Common Architectures

8.1 Modular Neural Networks

As said in the previous chapters, Joone exposes a modular engine that permits to build any neural network architecture, and also it permits to build modular networks, i.e. neural networks composed by several other embedded neural networks. The central component of this feature is represented by the NestedNeuralLayer. In the following paragraph we'll illustrate a classical example by building a modular neural network to resolve the parity problem.

8.1.1 The Parity Problem

This is a classical problem, like the XOR, used to show the learning capabilities of the neural networks applied to non-linearly separable problems. The truth table of the 4-bits parity problem is depicted in table 9.1.

I1	I2	I3	I4	Output
0	0	0	0	0
0	0	0	0	0
0	0	0	1	1
0	0	1	0	1
0	0	1	1	0
0	1	0	0	1
0	1	0	1	0
0	1	1	0	0
0	1	1	1	1
1	0	0	0	1
1	0	0	1	0
1	0	1	0	0

I1	I2	I3	I4	Output
1	0	1	1	1
1	1	0	0	0
1	1	0	1	1
1	1	1	0	1
1	1	1	1	0

Table 8.1: Parity table

The 4-bit parity problem can be resolved by a feed forward neural network with one hidden layer, but if you try to do it, you'll notice that the training time is very long, and sometime the neural network will not learn to resolve the problem. A better approach is represented by a modular network composed by three XOR NNs, as depicted in figure 8.1.

The three XOR neural networks are marked with a red rectangle, and you can see that the output nodes of the first two neural networks are used as input nodes of the last one. Let us show now how to build the above architecture with joone.

1. First of all, build a XOR neural network with the GUI Editor and train it until the RMSE goes below 0.01
2. Export that neural network (by using the 'File-¿Export NeuralNet...Ó menu item), after having deleted all the i/o and the teacher components
3. Create a file named 'parity.txt' and write into it the parity truth table using semicolons as columns separator, like in the following example:

0;0;0;0;0
0;0;0;1;1
0;0;1;0;1
....
1;1;1;1;0

4. Build a neural network following the architecture shown in the figure:

You can recognize the three XOR NNs, bordered by the red boxes as in figure 8.2. Now perform the following tasks:

1. Import the above exported XOR neural network into the two NestedANN components (named 'XOR 1' and 'XOR 2' in the figure)

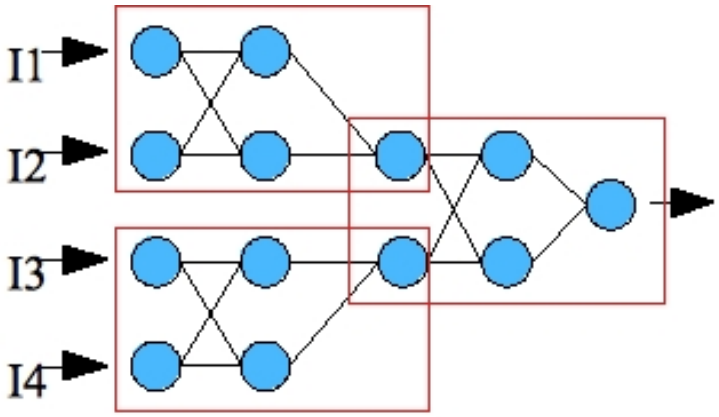


Figure 8.1: Composed Network

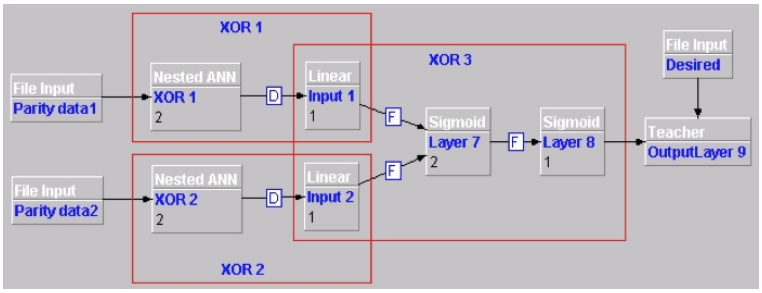


Figure 8.2: Composed XOR-Network

2. Set the two File Input components in order to read the parity.txt file, setting their advancedColumnSelector as follows: Ò1-2Ó for 'Parity Data1' and Ò3-4Ó for 'Parity Data2'. Remember also to set to false the 'stepCounter' parameter of 'Parity Data2'.

3. Set the desired File Input component in order to read the column 5 of the parity.txt file.

4. Open the ControlPanel and set:

   (a) learning = true

   (b) learning rate = 0.7

   (c) momentum = 0.7

   (d) training patterns = 16

   (e) epochs = 5000

5. Run the training phase.

You should see the a descending RMSE value, that demonstrates that the neural network is able to learn the parity problem by using a modular architecture.

8.2 Temporal Feed Forward Neural Networks

In this chapter we'll show some potential application of the neural networks in the field of the time series elaboration in order to predict the future values given the past history of the temporal series.

8.2.1 Time Series Forecasting

First of all, we want to warn about the difficulties that arise when we try to make time series prediction applied to problems of the real life, like weather or financial predictions.

Reading the emails that we receive from the users of Joone, we know that about the 60% of them want to use the neural networks to make financial predictions. Be aware: may people think that a neural network is like the Aladdin's lamp, but soon they discover that the reality is different, and that it's very difficult to obtain good results.

Don't waste time: very few people know that by using simply the past prices as training data is not enough. You must fight and eliminate your main enemy: the noise.

Therefore the following paragraphs want to give you just an initial knowledge about the most famous and used techniques, but you need to try many and many different architectures and pre-processing techniques in order to have some possibility to obtain some good result.

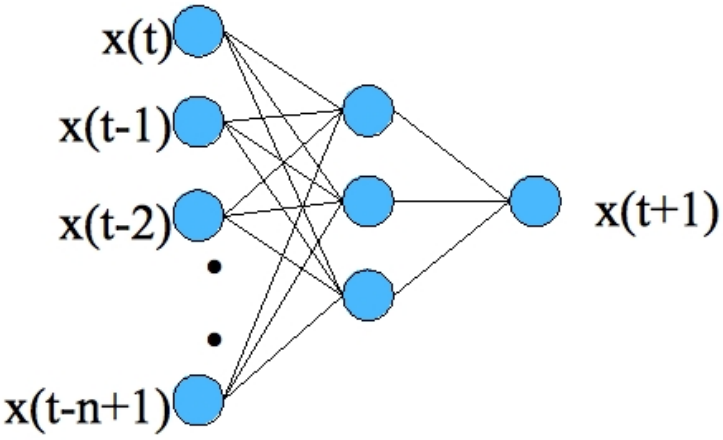


Figure 8.3: Delayed Network

Preprocessing

To make financial forecasting is one of the most famous applications of the neural networks. In this section we want to explain the use of a particular pre-processing technique useful to make trend predictions.

One of the most used techniques is to sample the time series at discrete moments (hourly, daily, weekly, etc.) and use the measured values as input patterns of the neural network.

Because a time series, to be predictable, needs to have an internal dependency on the past values (otherwise the time series would be just a noisily random sequence), a common pre-processing technique is represented by feeding a neural network with a temporal window of the time series, like depicted in figure 8.3. As you can see, each input pattern is composed by the values at times t, t-1, t-2,...,t-n+1 where n is the temporal window's size.

How to obtain a temporal window of a given size starting from a single-column stored time series? Joone provides the user with a component, the DelayLayer, useful to create a temporal window to feed the input layer of a neural network. Look at figure 8.4 containing an example built with the GUI editor of Joone.

As you can see, we have used a YahooFinance input component to get the stock prices time series from Yahoo, and have connected it to a Delay layer. The properties panel for this component, other than the rows, permits to set the 'taps' parameter, that indicates the size of the temporal window we'll use to feed our neural network. By setting taps to '5', we obtain a window of size 6 composed by the following values:

[x(t), x(t-1), x(t-2), x(t-3), x(t-4), x(t-5)]

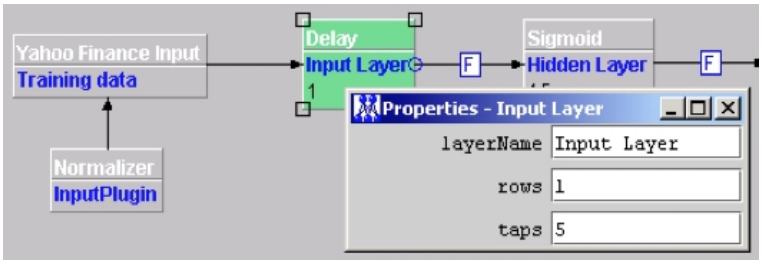


Figure 8.4: Delayed Network

INFO

Remember that the size of the temporal window is always equal to (taps+1), because the Delay layer outputs also the actual value x(t) of the time series.

Of course this is just an example, and you can experiment several configurations, either using windows of different size, and/or using as input not only the 'raw' data, but also some pre-elaborated values, as for instance the N-days' average (calculated by using the Moving Average Plugin component attached to the Yahoo Finance Input), as illustrated in figure 8.5.

In this example we want to train the neural network using the 15 and 50 days moving averages. The YahooFinance component has the setting depicted in figure 8.6.

As you can see, the AdvancedColumnSelector has been set to '4,4,4', so the fourth column (the Close value) will be extracted three times, and now we'll see why. As the data must be normalized, we have used a NormalizerPlugin having the following properties depicted in figure 8.7.

the AdvancedSerieSelector is equal to '1-3', thus we will normalize all the three input values between 0 and 1. The MovingAverage Plugin settings are depicted in figure 8.8. There you can see that we calculate the 15-days and the 50-days moving average (property Moving Average set to '15,50') respectively on the second and third column (property AdvancedSerieSelector set to '2,3').

The result is that we'll feed the neural network with the following three normalized values of the time series:

1. The raw daily Close values
2. The 15-days moving average of the Close values
3. The 50-days moving average of the Close values

Now it should be clear why we have extracted three times the same value from the YahooFinance component. Of course, in this case, the Delay Layer must have rows=3 and taps=5 (or the windows' size we have chosen to use).

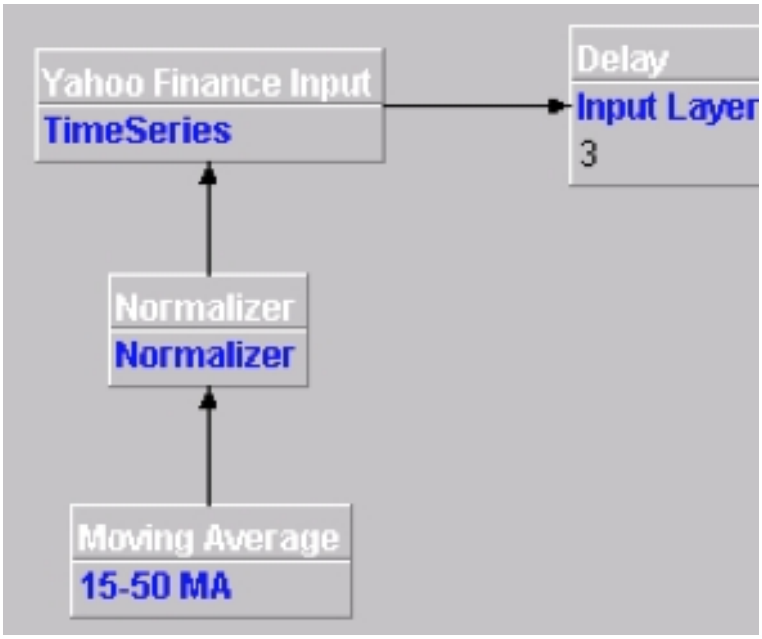


Figure 8.5: Yahoo Synapse

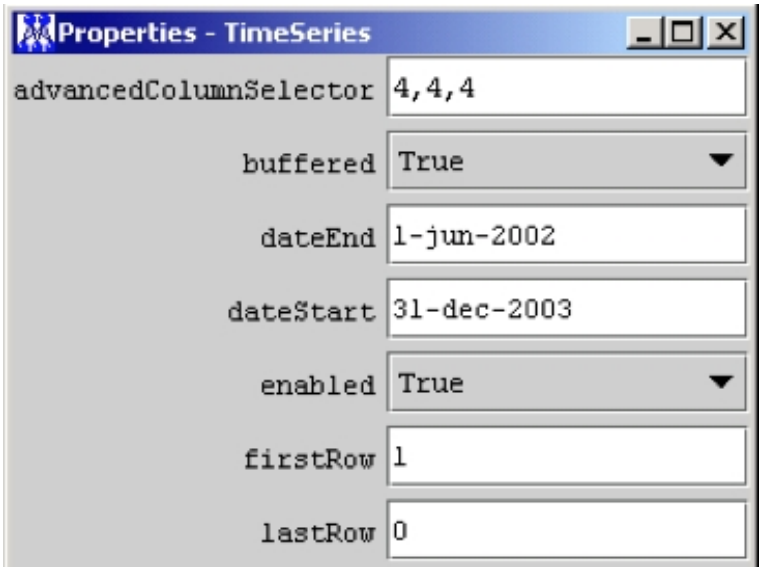


Figure 8.6: Yahoo Synapse Settings

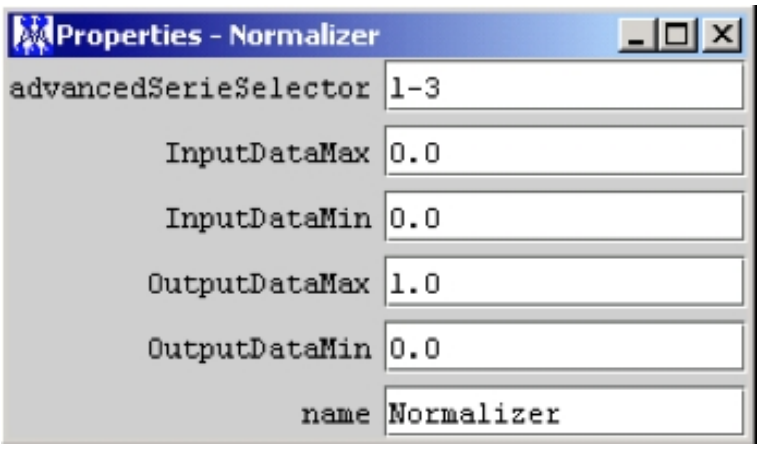


Figure 8.7: Normalizer Settings

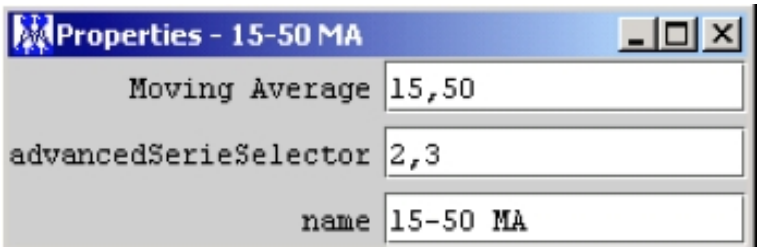


Figure 8.8: Moving Average Settings

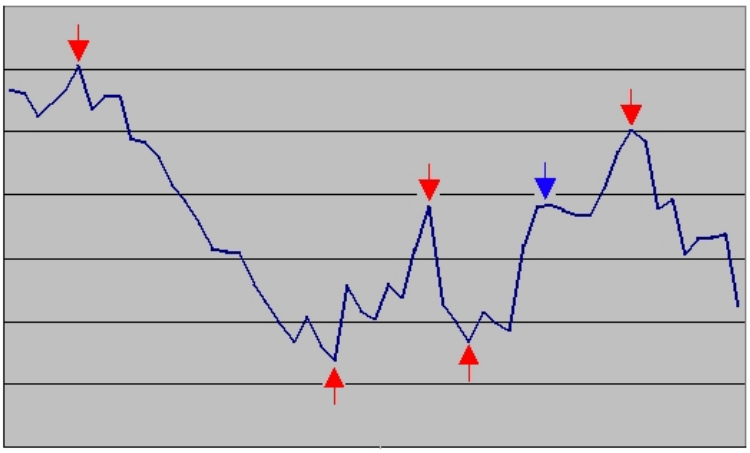


Figure 8.9: Chart

That said, we now need to decide how we'll train the neural network, and to do it, we must to set the desired data of our training phase. Normally, as desired data, the value at time t+1 is used, so the network is trained to predict the next value of the time series in base of the past n values.

Indeed it's very difficult to predict the exact value of a noisily time series, hence we want to explain a different technique to make trend predictions, instead of the next day's exact Open/Close/High/Low values prediction.

Trend Prediction

This technique tries to predict the future prices at a short-medium interval of time (from 2 to 10-15 days) using as input the past history of the prices. Using this technique, we don't need to know the value of the next day close, but simply the future direction (up or down) of the observed market, so to take a decision about our trading position (long/short - buy/sell).

The question is: how do we teach a neural network fed with the past history of a stock? The response is very simple. Remember that this paragraph deals with the trend prediction technique, hence we don't need to predict the exact close value of the next trading day, as we found our trading strategy on the predicted trend (up or down). What we need to predict, in other words, are the turning points of the market we're dealing with. Look at the following chart in figure 8.9.

We should trade in correspondence of the red arrows to make money, buying on the lowest values and selling at the highest ones. A good trading system should raise a signal only when a true turning point is reached, avoiding to generate false signals, as, for

instance, that one indicated by the blue arrow, where the market goes down only for a little percentage before to continue to raise. As you can see, we donÕt need to predict the exact values of the daily market closes, as weÕre interested to predict only the right turning points.

To do this, Joone owns the TurningPointExtractor plugin that calculates exactly the ideal trading signals, as explained in the above figure. It has a ÔMin change percentageÕ property that serves to indicate what is the minimum change between two turning points to generate the corresponding signals. It must be set to a value not too small, to avoid to generate too many signals (many of which could be false).

The algorithm is the following:

- When the market rises more than the desired change, the previous lower value is flagged as a 'buy' signal, and the corresponding output value is set to 0.
- When the market declines more than the desired change, the previous higher value is flagged as a 'sell' signal, and the corresponding output value is set to +1.
- The desired values for days between the above two points are normalized by interpolating to values within the interval 0 and +1.

The following two figures show the output of the turning point extractor plugin for a given time series. Their min. percent change parameter is set to 5% and 8% respectively.

As you can see in figure 8.10 and 8.11, setting the generation of buy/sell signals only when the output value is lower than 0.1 and higher than 0.9 respectively, the number of signals generated for the 5% setting is greater than those generated for the 8% case.

It doesn't exist a fixed rule to calculate the optimal percentage, and you need to try several configurations until you get good results in terms of good generalization capacity of the resulting neural network.

As we want to predict the turning points of the time series, we need to teach the network to recognize them, hence the TurningPointExtractor plugin must be connected to the desired input signal of our neural network, as depicted in figure 8.12.

In this manner the signals generated by the plugins will be used as the 'desired' data on which the neural network will be trained.

To summarize, we need to train a neural network teaching it to recognize the turning points of the observed market. To do this, we must feed the neural network with, for example, a temporal window of the normalized past input data, and we must use the turning point extractor to generate the desired values for the supervised learning phase. After that, we interrogate the net giving as input the last closes normalized with the same techniques seen above and, only when the output of the net is:

- lesser than 0.1, the signal is BUY
- greater than 0.9, the signal is SELL

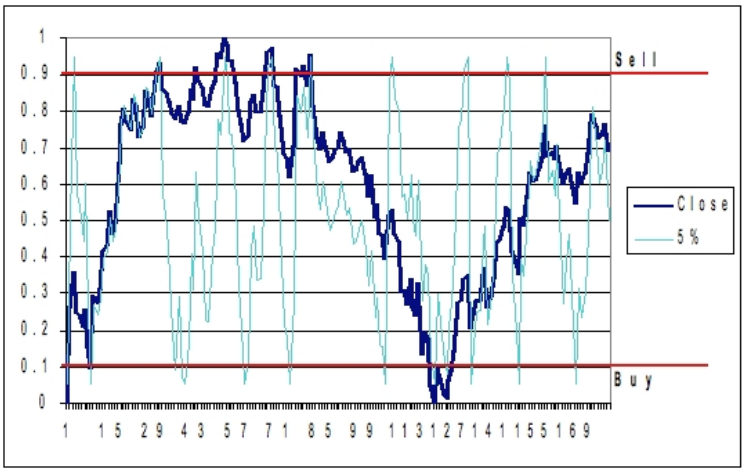


Figure 8.10: 5% limit

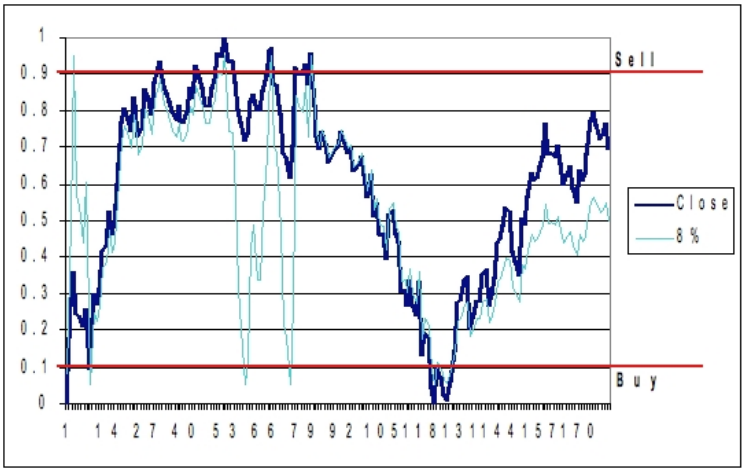


Figure 8.11: 8% limit

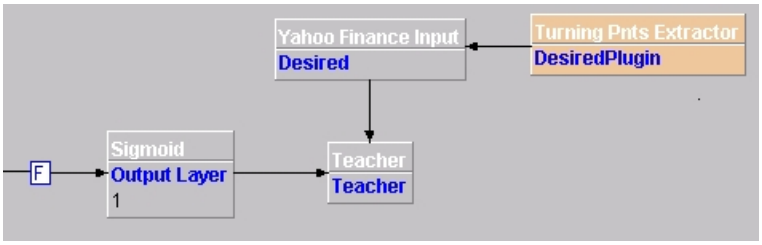


Figure 8.12: Turiningpoint Extractor Plugin

Of course, as already said, we must do several experiments to set both the above limits and the other parameters' right values, in order to obtain acceptable results. **Good luck! ...and if you obtain some good result, remember to make a donation to joone :o)**

Dynamic Control of the training parameters

The learning rate used to train a neural network is a crucial parameter, and the choose of the right value is determining to have good results, especially for noisily time-series prediction.

As said in the paragraph 6.3, the learning rate represents the 'speed' on the error surface with which we search the optimal minimum. A value too big would cause an oscillation around the minimum, while a value too low would cause a very long training time.

To resolve this dilemma, we can use the DynamicAnnealing plugin. Look at the neural network in figure 8.13.

It's a neural network to make financial predictions (it's just an example, of course), and in the Control Panel you can see all the settings we have used (note the learning rate and the momentum both set to 0.6, a relatively high value). When we train the above neural network we obtain a RMSE like the following:

That's horrible! Due to the wrong settings, the neural network has not been able to learn the time series we have used as input, and the final RMSE is really too bad. Now we'll insert a DynamicAnnealing plugin, as shown by the following figure:

the DynamicAnnealing's rate is set to 5 and the change to 15%. These values mean that the plugin will check the training RMSE value each 5 epochs, and when the last value is greater than the previous one, it will decrease the learning rate of 15%. Note that the Dynamic Annealing component is not attached to any component of the neural network. Figure 8.14 illustrates the resulting RMSE. Good! We have eliminated all those horrible oscillations, and the final RMSE after 3000 epochs is very small.

Of course this is just an example, and maybe you'll obtain different results with your own neural network, but remember that by trying different values for the DynamicAnneal-

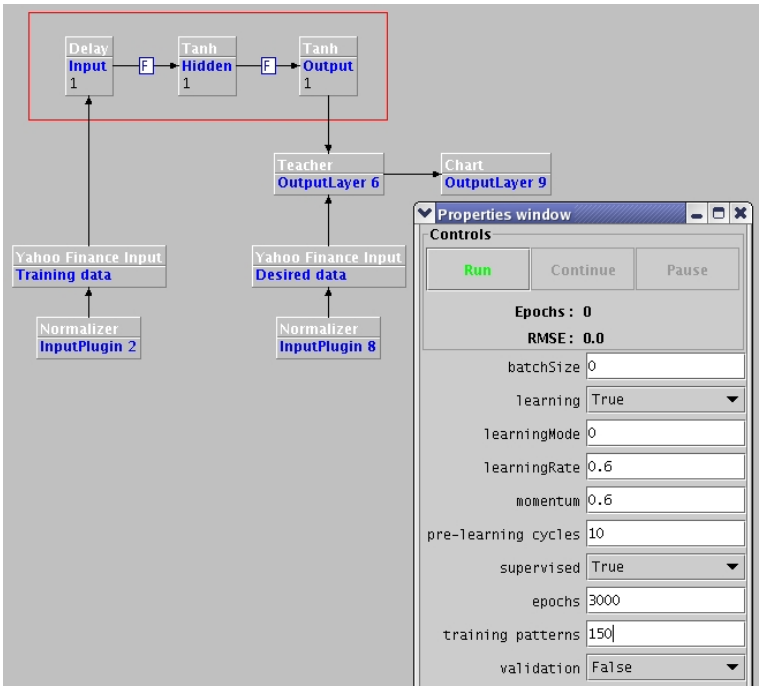


Figure 8.13: Dynamic Annealing Plugin

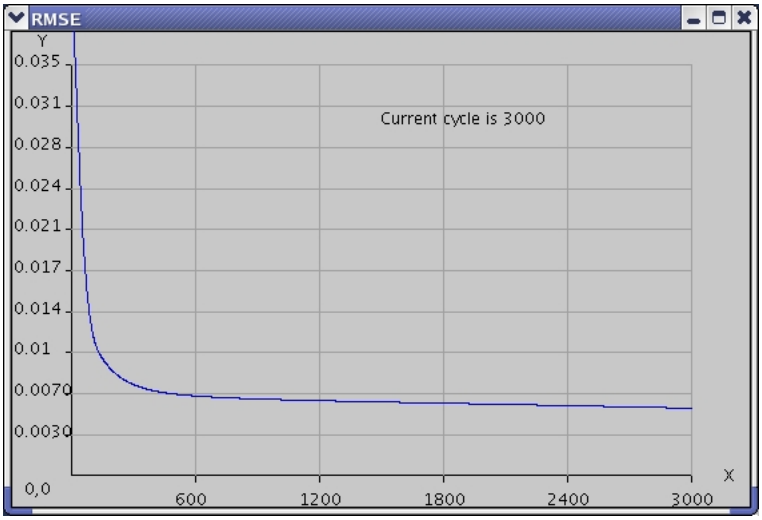


Figure 8.14: The resulting RMSE

ing's properties, you'll be always able to regularize the learning of your network in case of uncontrolled oscillations.

8.2.2 Optimising Forcasting FFNs

The following section is a stub!!!!

Some points to consider

- In [5] it is claimed that feedforward networks exceed recurrent neural networks as well as arima models in prediction of price levels and price direction (exchange rates). Those results should be considered carefully because a. the forecast step is quite large (1month compared to daily or even hourly steps) and b. they didn't even mention the training algorithmus used in the recurrent network (they used some third party software therefore).
- Kolmogorovs theorem that one neuron in the hidden layer is sufficient for universal approximation is not true for all functions.
- Using multiple hidden layers is theoretically advantageous but has practically no significant effect. The one layer networks have usually the lower average error and generalize better. If one uses multiple hidden layers, they should have an equal size.
- For a formula to calculate optimal number of neurons in the hidden layer, given the "outputdimension" of the network see [23] chapter 4.4.1.
- For a formula to calculate the required training patterns for a given network see [23] chapter 4.4.2.

Variable Selection

- Technical inputs: lagged values of the dependent variable
- Fundamental inputs: Influental economics variables
- Use of intermarket data: e.g crossrates when predicting currencies.
- Fundamental macroeconomic data like current account balance, wholesale price a.s.f.

Data Preprocessing

See [12].

- Precondiction: Data must be normalized into the bounds of the transfer function (usually [-1,1] or even [0,0])

- First differencing (change in variable): removes linear trend from data
- Taking natural log (converts multiplicativive or ratio relationships to additive which can improve the network training)
- Ratios of input variables: conserves degrees of freedom and highlights the important relationships
- Using moving averages see `http://openforecast.sourceforge.net/` or JFreeChart.
- Include technical analysis measures like oscillators, directional movement, volatility filters a.s.f.
- Empirical work on testing the efficient market hypothesis has found that prices exhibit time dependency that prices exhibit time dependency or positive autocorrelation while price changes around the trend are somewhat random [26]
- Sampling/filtering

Training, testing, validation

- Training set
- Test set: 10% - 30% of the available data, used to test the generalization ability of the network
- Validation set: Most recent oberservations
- Rigorous validation approach: walk-forward testing. see [12]

Neural network paradigms

- Number of hidden layers: To many hidden layers - reduces degrees of freedom - overfitting - loss of generalization capabilities [18, 3]. Possible approach: start with one or two layer network and extend to 4 layer network. if the 4 layer network doesn't produce good results, start changing input variables
- Number of hidden neurons:
  - three-layer network [18]: n input neurons, m output neurons - hidden layer should have sqrt(m*n) neurons
  - three-layer network [4]: number of hidden neurons in a three layer neural network should be 75% of the number of input neurons.
  - [13]: optimal number of hidden neurons between one-half to three times the number of input neurons

8.3 Construction and training of recurrent neural networks

8.3.1 Common recurrent network architectures

8.3.2 Implementation

8.3.3 Training recurrent networks

8.3.4 Training algorithms

8.3.5 Training the network

8.4 Unsupervised Neural Networks

8.4.1 Kohonen Self Organized Map

This tutorial is intended to give a basic example of how to perform image / character recognition using SOM / Kohonen neural network architectures.

Example: a character recognition system

This tutorial uses a basic application called org.joone.samples.editor.SOMImageTester, and you can launch it from within the GUI Editor simply by clicking on the 'Help - Examples - SOM Image Tester' menu item. You can use the sample application to draw basic black and white colour images and save the output into a file format that Joone recognises. The example presented in this tutorial teaches the user how to setup a network that recognises the characters 'A' and 'B'. The reader can use this technique to setup a network that will recognise an arbitrary number of characters.

Sample Application Quick Guide The sample application (see figure 8.15) is fairly self explanatory but you can use the guide below in order to use the application.

Features

- Drawing Area - The high resolution 'A' image shown above is where the user can draw custom images.
- Image ID - This is the identify of the image, you can use this number to mark what character the image is. Only numbers can be entered here. I.e a 1 could mean character 'A' and 2 could be 'B'.
- Down Sample - This allows you to preview the down sampled image after drawing. To obtain the down sample the application first crops the image in the draw area. The image is cropped by obtaining the left most black pixel , top most black pixel etc to find the bounds of the cropped image. See the image 8.16.

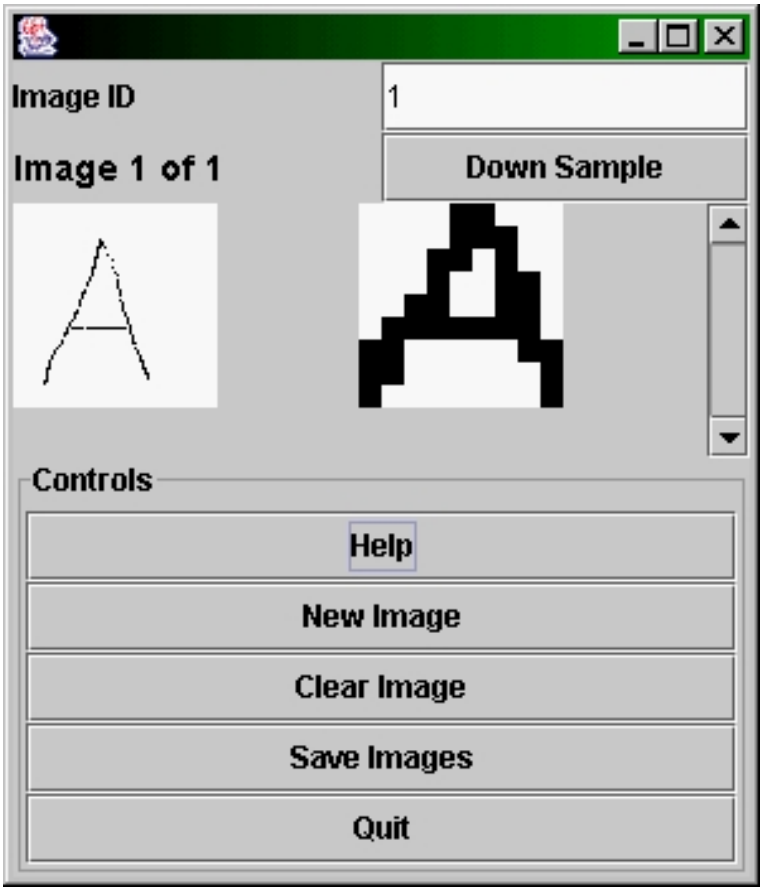


Figure 8.15: The sample application

Secondly the cropped image is scaled down to a 9x9 image. The image is scaled by splitting the cropped image into a series of grids relating to each pixel in the 9x9 down sampled image, then if a grid in the cropped image contains a black pixel then the relevant pixel in the 9x9 down sampled image will contain a black pixel. The application automatically down samples each image when the user saves the the images to a file.

- Help - This presents some basic help on the application.
- New Image - Creates a new image for drawing a character/image into.
- Clear Image - Removes all the black pixels from the current image.
- Save Images - Allows all images to be saved to a Joone format file for use in a File Input Synapse. The format is 81 pixel inputs followed by the image id.
- Quit - Allows you to quit the application.

Data Setup

- Start the example application SOMImageTester. See the basic guide above on how to use the application.
- First we need to create several 'A' character images and several 'B' character images that will be used in training and testing.
- Draw the 4 'A' characters in the drawing panel clicking on New Image when you have finished each one. The down sample button can be used to see what each character looks like down sampled. When you have finished drawing the 4 'A' characters then draw four 'B' characters. Then use the Save Images button to save them out to a file, remember the file name and location we will call this 4As4Bs.txt in this example.
- Note the more samples of a specific character you draw will mean the network is better able to recognise that character. ÊYou'll have noticed that the image gets cropped and down sampled, this is to stop the network from just recognising the character's size.
- We now need a couple of test character's. Close and re-open the application , draw one 'A' character and save it we will call this testA.txt. Close the application again and re-start, this time draw a 'B' character and save the file we will call this testB.txt.

Neural Network Setup

For the neural network we will be using SOM components thus the network will be unsupervised. We will need to input the previously produced file into a linear layer of 81 inputs.

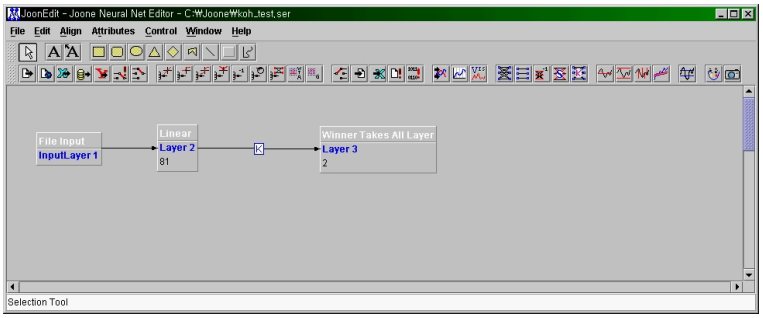


Figure 8.17: The network setup

This will by be fed to a Winner Takes All layer via a Kohonen Synapse. We can use a File Input Synapse to load the file. See the image 8.17. Note that the Winner Takes All layer has two neurons, this is to ensure it classifies out two characters.

Input Layer Properties
Note our input images have 81 inputs i.e the 9x9 down sampled image that the application made earlier (see figure 8.18.

Linear Layer Properties Note the rows here must match the inputs from the file input synapse (see figure 8.19).

Winner Takes All Layer Properties
Note the height or width should be 2 and 1, either can be 2 but not both. This ensure the layer contains 2 neurons for our two character classification (see figure 8.20)

Control Properties
The controlproperties are depicted in figure 8.21.

Training The Network
Ensure the network has been set up as in the previous section. The run the network. When it has finished10000 epochs it should have learned how to recognise the character 'A' and 'B'. We need to find out which neuron fires on an 'A' character and which one fires on a 'B'. We need to attach a file output synapse to the Winner Takes All Layer. Do this now and in the file output synapse set the file name to something like test.txt, in the control panel set the number of epochs to 1 and the learning property to false. Run the network again and examine the text.txt file, you should see 8 rows and two columns. The column represents the neuron and the row the character they are trying to recognise i.e 1-8. We now that the first four characters were the character 'A' and the lest four were 'B' characters. Check that the test.txt contains 1.0 in the same column for four rows then 1.0 in the other column for the last four rows. On hour network it came out like this ...

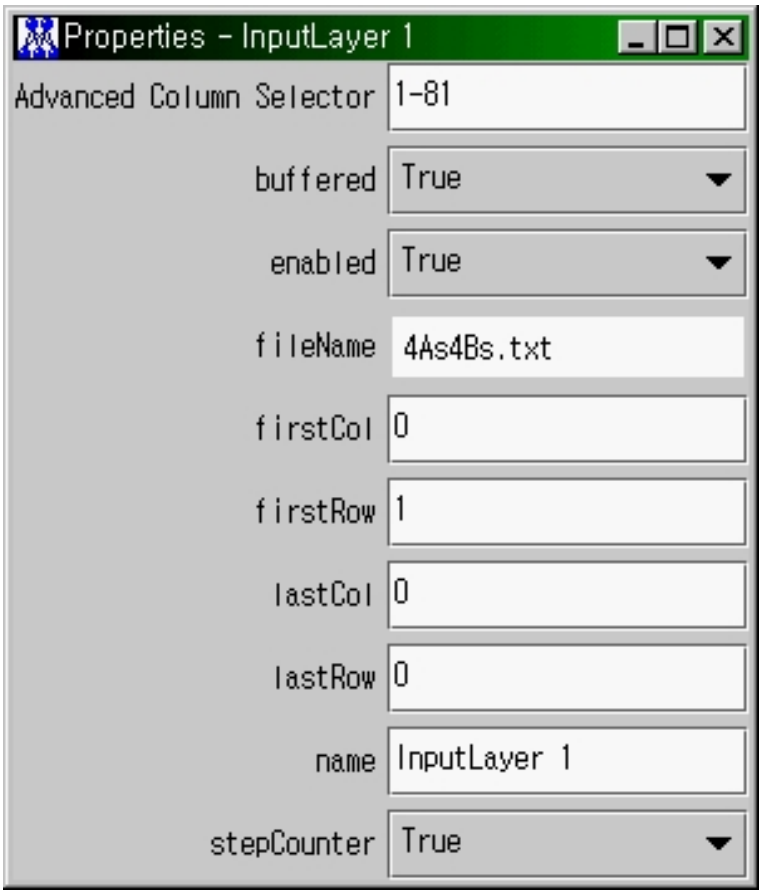


Figure 8.18: The input layer properties

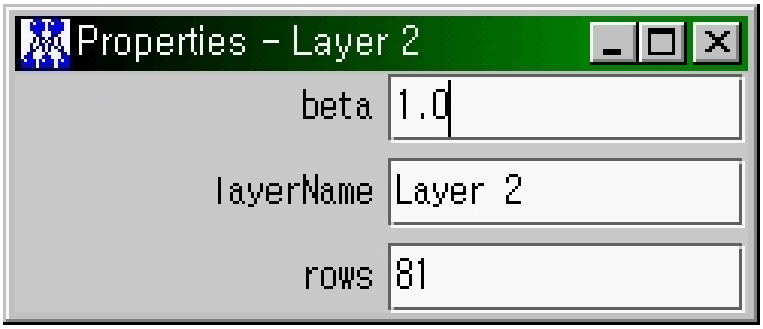


Figure 8.19: The linear layer properties

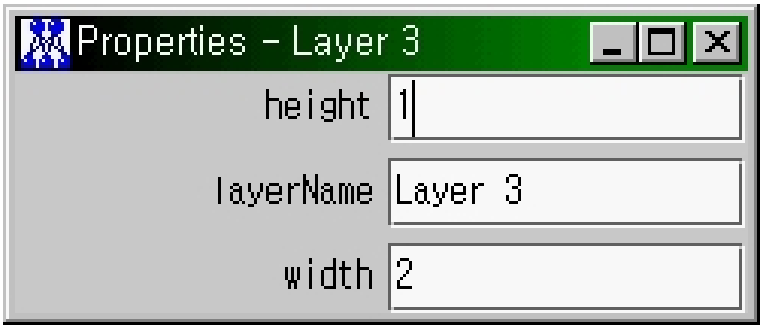


Figure 8.20: The winner takes all layer properties

0.0;1.0
0.0;1.0
0.0;1.0
0.0;1.0
1.0;0.0
1.0;0.0
1.0;0.0
1.0;0.0

So we now know that by looking at the first four rows neuron 2 fires for character 'A' and neuron 1 fires for character 'B'. It could be the other way round for you. If at this point the it is not clear i.e neuron 2 fires for both an 'A' and 'B' then you might not have setup the network correctly or it may need more training.

Testing The Network
To test the network, modify the file name in the file input synapse, select the testA.txt in order to test a character 'A'. We have only one character in this file so in the control panel set the validation patterns to 1 and the learning mode to false. Run the network again. Examine the test.txt file, check if the correct neuron fired. In our case it was correct ..

0.0;1.0

Neuron 2 fired indicating that the network thought it was a character 'A', it is correct. You can do the same for the testB.txt file.

Using The Network
It is possible to use this network in your own application but your custom application must present 81 inputs which are written as row1 x,x+1,x+2,x+3,...,x+9 , row2 x,x+1,x+2,x+3,....x+9 , row3 ..... , row9 x, x+1,x+2,...,x+9. Direct input from memory will require the Memory

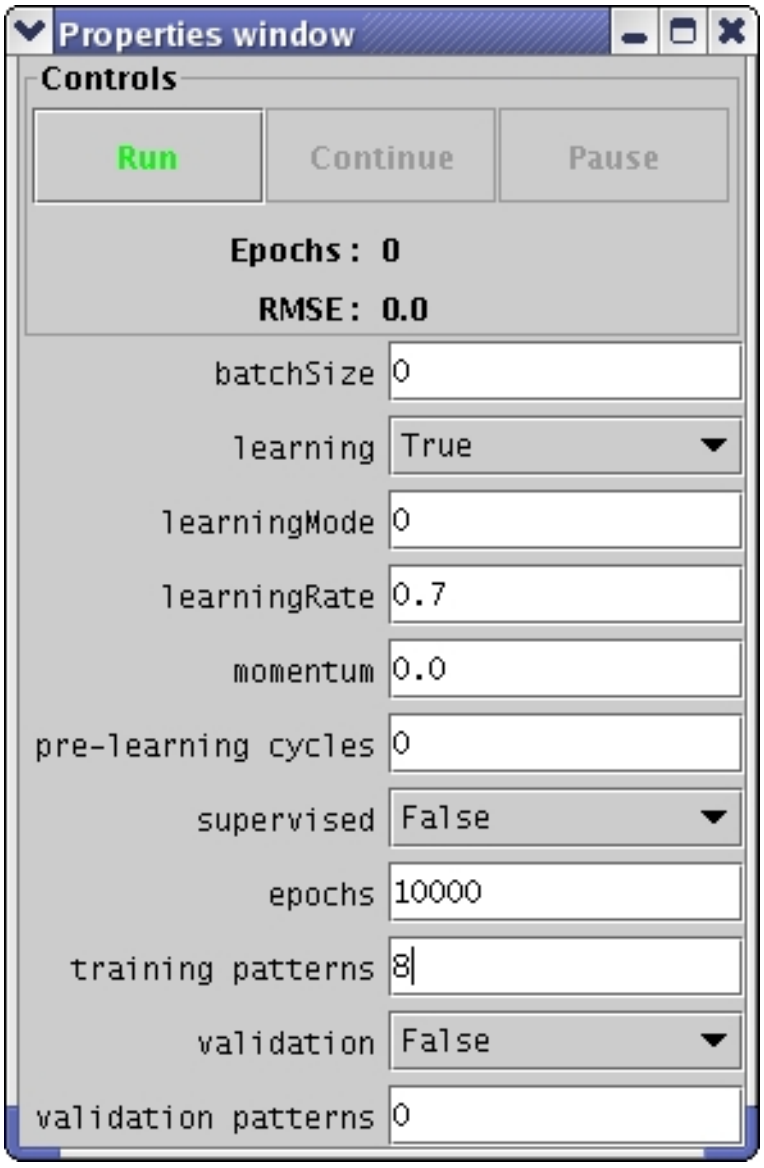


Figure 8.21: The control properties

Input Synapse. An on pixel is represented as 1.0 and off 0.0. The network can obviously not handle colour just black (on) and white (off). Your application will also have to crop the image and down sample it to the correct size.

Further Work

Image recognition is a fascinating field and you'll probably want to experiment in recognising different images / objects. It should be useful to produce an Image Input Synapse that will enable users to present images from files or Java images. If (and when) this will be available, then you could use this to easily load images into the network for training and running. Whatever contribution in this area is welcome, of course. Ê Something worth thinking about when looking at image recognition is things like colour , size , shape, texture etc. An extension to the this example might be to enable the net to recognise coloured characters but independent of the actual colour. If you always present 'A' in green and 'B' in blue and train it then when you come to test it might have just learned how to recognise the colours green and blue, then when you try and present a green 'B' it doesn't recognise it according to what you were thinking of. In this case you should present 'A' and 'B' in different colours. Ê In the classic tank hiding in jungle example a research team wanted to train a network to spot tanks hidden in a jungle. They went out an took pictures of tanks hiding in a jungle and pictures with no tanks. They trained the network and when they tested it the network worked very well. However to verify the network they went out a took more pictures and tested it again. This time it failed miserably. Why? For the training images the researchers took pictures of the tanks hiding in the jungle on sunny day and the ones where the tanks were not hiding on an overcast rainy day. The network had simply recognised that it was sunny or cloudy.

This example demonstrates that it's very important to apply good preprocessing techniques, in order to eliminate all the extraneous objects, colours and noise that could disturb the training of the network. Ê

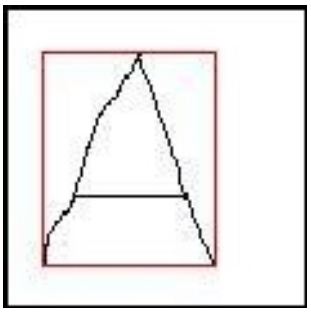


Figure 8.16: Sample file

Chapter 9

Applying Joone

9.1 Building your own first neural network

INFO

Even if the GUI Editor can be easily used to build, train and test neural networks, it's impractical to use within a real application to resolve your needs. To really capture and use all the power of the core engine you need to write java code.

Indeed, as we'll see in the following paragraphs, the Editor can be used as a starting point to build a neural network - due to its user friendly interface - and then we can write java code to embed the resulting neural network into our own application.

As of Joone 2.0, we have introduced an helper class, org.joone.helpers.factory.JooneTools, with which you can build & run a neural network in a very simple manner, by simply invoking some easy-to-use methods of the JooneTools class. So you can use either the 'standard' method, or the JooneTools class, depending of the kind of network you need to build.

9.2 The standard API

9.2.1 A simple (but useless) neural network

We will start by writing a simple toy neural network, and then will continue by building more complex architectures, until we'll be able to use almost all the features of the core engine. Consider a feed-forward neural network composed of three layers like depicted in figure 9.1

To build this net with Joone, three Layer objects and two Synapse objects are required (see figure 9.2). The code therefore can be found in listing 9.1.

```
1 /*The SigmoidLayer objects and the FullSynapse objects are real implementations of
      the abstract Layer   and Synapse objects.*/
2 SigmoidLayer layer1 = new SigmoidLayer();
```

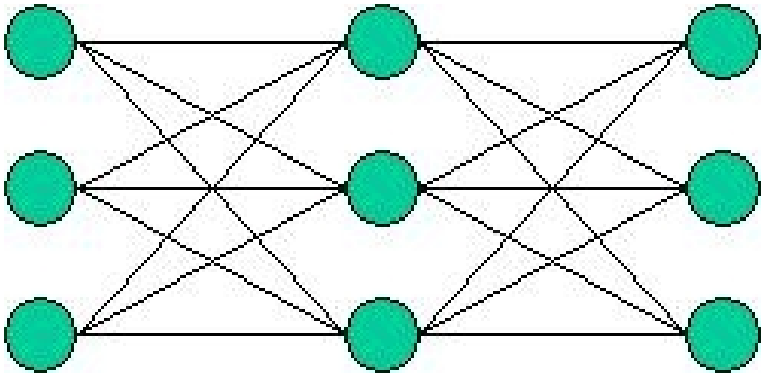


Figure 9.1: 3-Layer FFN

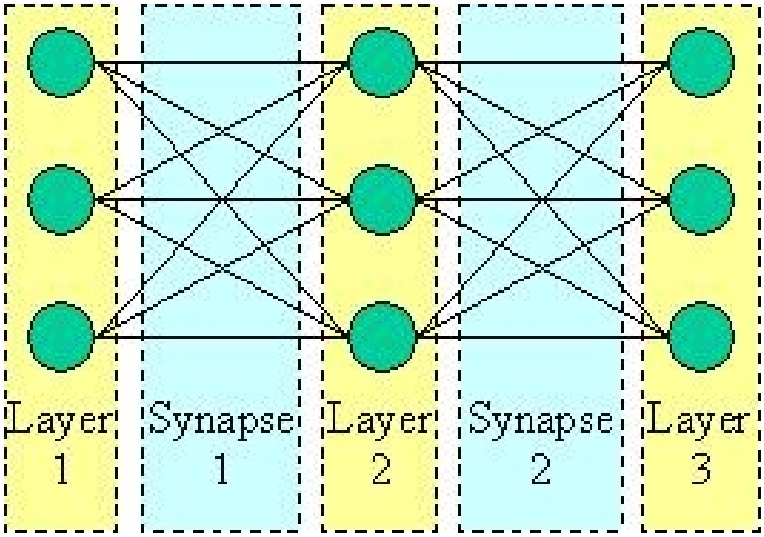


Figure 9.2: 3-Layer FFN with Joone

```
3  SigmoidLayer layer2 = new SigmoidLayer();
4  SigmoidLayer layer3 = new SygmoidLayer();
5  FullSynapse synapse1 = new FullSynapse();
6  FullSynapse synapse2 = new FullSynapse();
7
8  /*Set the dimensions of the layers*/
9  layer1.setRows(3);
10 layer2.setRows(3);
11 layer3.setRows(3);
12
13 /*Then complete the net, connecting the three layers with the synapses*/
14 layer1.addOutputSynapse(synapse1);
15 layer2.addInputSynapse(synapse1);
16 layer2.addOutputSynapse(synapse2);
17 layer3.addInputSynapse(synapse2);
```

Listing 9.1: Network construction

As you can see, each synapse is both the output synapse of one layer and the input synapse of the next layer in the net. This simple net is ready, but it can't do any useful work because there are no components to read or write the data. The next example shows how to build a real net that can be trained and used for a real problem.

9.2.2 A real implementation: the XOR problem

Suppose a net to teach on the classical XOR problem is required. In this example, the net has to learn the following XOR 'truth table' (see table **??**).

I1	I2	Output
0	0	0
0	1	1
1	0	1
1	1	0

Table 9.1: Parity table

Firstly, a file containing these values is created:

0.0;0.0;0.0
0.0;1.0;1.0
1.0;0.0;1.0
1.0;1.0;0.0

Each column must be separated by a semicolon. The decimal point is not mandatory if the numbers are integer. Write this file with a text editor and save it on the file system (for instance c:\joone\xor.txt in a Windows environment). Now build a neural net that has the following three layers:

- An input layer with 2 neurons, to map the two inputs of the XOR function

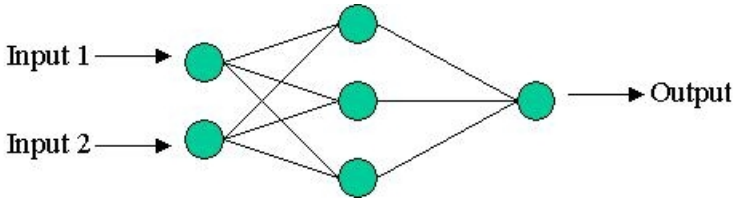


Figure 9.3: The XOR problem network

- A hidden layer with 3 neurons, a good value to assure a fast convergence
- An output layer with 1 neuron, to represent the XOR function's output

as shown by figure 9.3. The code therefore can be found in listing 9.2.

```
1  /*First, create the three layers (using the sigmoid transfer function for the hidden
       and the output layers)
2  LinearLayer input = new LinearLayer();
3  SigmoidLayer hidden = new SigmoidLayer();
4  SigmoidLayer output = new SigmoidLayer();
5  /*set their dimensions*/
6  input.setRows(2);
7  hidden.setRows(3);
8  output.setRows(1);
9
10 /*Now build the neural net connecting the layers by creating the two synapses using
       the FullSynapse class that connects all the neurons on its input with all the
       neurons on its output.*/
11 FullSynapse synapse_IH = new FullSynapse();  /* Input -> Hidden conn. */
12 FullSynapse synapse_HO = new FullSynapse(); /* Hidden -> Output conn. */
13 Next connect the input layer with the hidden layer:
14 input.addOutputSynapse(synapse_IH);
15 hidden.addInputSynapse(synapse_IH);
16
17 /*and then, the hidden layer with the output layer*/
18 hidden.addOutputSynapse(synapse_HO);
19 output.addInputSynapse(synapse_HO);
20
21 /*Now we need a NeuralNet object that will contain all the Layers of the network*/
22 NeuralNet nnet = new NeuralNet();
23 nnet.add(input, NeuralNet.INPUT_LAYER);
24 nnet.add(hidden, NeuralNet.HIDDEN_LAYER);
25 nnet.add(output, NeuralNet.OUTPUT_LAYER);
26
27 /*Now we'll set all the Monitor's parameters needed for the network to work*/
28 Monitor monitor = nnet.getMonitor();
29 monitor.setLearningRate(0.8);
30 monitor.setMomentum(0.3);
31
32 /*The application registers itself as a monitor's listener, so it can receive the
       notifications of termination from the net. To do this, the application must
       implement the org.joone.engine.NeuralNetListener interface.*/monitor.
       addNeuralNetListener(this);
```

```
33
34 /*Now define an input for the net, then create an org.joone.io.FileInputStream and
       give it all the parameters*/
35 FileInputSynapse inputStream = new FileInputSynapse();
36 /* The first two columns contain the input values */
37 inputStream.setAdvancedColumnSelector(Ò1,2Ó);
38 /* This is the file that contains the input data */
39 inputStream.setInputFile(new File("c:\\joone\\XOR.txt"));
40
41 /*Next add the input synapse to the first layer. The input synapse extends the
       Synapse object, so it can be attached to a layer like a synapse*/
42 input.addInputSynapse(inputStream);
43
44 /*A neural net can learn from examples, so it needs to be provided it with the right
        responses.
45 For each input the net must be provided with the difference between the desired
       response and the actual response gave from the net. The org.joone.engine.
       learning.TeachingSynapse is the object that has this task*/
46 TeachingSynapse trainer = new TeachingSynapse();
47 /* Setting of the file containing the desired responses, provided by a
       FileInputSynapse */
48 FileInputSynapse samples = new FileInputSynapse();
49 %samples.setInputFile(new File("c:\\joone\\XOR.txt"));
50 /* The output values are on the third column of the file */
51 samples.setAdvancedColumnSelector(Ò3Ó);
52 trainer.setDesired(samples);
53
54 /*The TeacherSynapse object extends the Synapse object. So it can be added as the
       output of the last layer of the net*/
55 output.addOutputSynapse(trainer);
56 /* We attach the teacher to the network */
57 nnet.setTeacher(trainer);
58
59 /*Set all the training parameters of the net: */
60 monitor.setTrainingPatterns(4); /* # of rows in the input file */
61 monitor.setTotCicles(10000); Ê/* How many times the net must be trained*/
62 monitor.setLearning(true); Ê/* The net must be trained */
63 nnet.go(); Ê/* The network starts the training phase */
```

Listing 9.2: NeuralNet construction

Here is an example describing how to handle the netStopped and cicleTerminated events. Remember: To be notified, the main application must implement the org.joone.NeuralNetListener interface and must be registered to the Monitor object by calling the Monitor.addNeuralNetListener(this) method (see listing 9.3).

```
1     public void netStopped(NeuralNetEvent e) {
2         System.out.println("Training finished");
3     }
4
5     public void cicleTerminated(NeuralNetEvent e) {
6         Monitor mon = (Monitor)e.getSource();
7         long c = mon.getCurrentCicle();
8         /* We want print the results every 100 epochs */
9         if (c \% 100 == 0)
10            System.out.println(c + " epochs remaining - RMSE = " +
```

```
11          mon.getGlobalError());
12      }
```

Listing 9.3: Notification

(Many examples showing the above technique can be found in the org.joone.samples.engine.xor package of the source distribution)

9.2.3 Saving and restoring a neural network

To have the possibility of reusing a neural network built with Joone, we need to save it in a serialized format. To accomplish this goal, all the core elements of the engine implement the Serializable interface, permitting a neural network to be saved in a byte stream, to store it on the file system or data base, or transport it on remote machines using any wired or wireless protocol.

A simple way to save a neural network is to serialize the entire NeuralNet by using an ObjectOutputStream object, like illustrated in listing 9.4 that extends the XOR java class:

```
1  public void saveNeuralNet(String fileName) {
2  try {
3  FileOutputStream stream = new FileOutputStream(fileName);
4  ObjectOutputStream out = new ObjectOutputStream(stream);
5  out.writeObject(nnet);
6  out.close();
7      } catch (Exception excp) {
8              excp.printStackTrace();
9      }
10 }
```

Listing 9.4: Extending the XOR class

The writeObject method recursively saves all the objects contained in the non-transient variables of the serialized class, also avoiding having to store the same objectÕs instance twice in case it is referenced by two separated objects -for instance a synapse connecting two layers. We can later restore the above neural network using the code in listing 9.5.

```
1  public NeuralNet restoreNeuralNet(String filename) {
2  try {
3  FileInputStream stream = new FileInputStream(fileName);
4  ObjectInputStream inp = new ObjectInputStream(stream);
5  return (NeuralNet)inp.readObject();
6      } catch (Exception excp) {
7          excp.printStackTrace();
8       return null;
9      }
10 }
```

Listing 9.5: Object serialization

As you can see, the above code is generic, as it doesn't depend on the internal structure of the saved/restored neural network.Due to this motive, we have written a utility class,

org.joone.net.NeuralNetLoader, that serves to reload a saved NeuralNet object, avoiding to write the above code whenever we need to load a serialized neural network. As listing 9.6 shows, it is quite easy.

```
1 /* We need just to provide the serialized NN file name */
2 NeuralNetLoader loader = new NeuralNetLoader(Ò/somepath/myNet.snetÓ);
3 NeuralNet myNet = loader.getNeuralNet();
4 ...
```

Listing 9.6: Easy serialization

so, by using only the above two simple lines of code, we're able to load in memory whatever serialized NeuralNet object, independently from its internal architecture.

9.3 Using the outcome of a neural network

After having learned how to train and save/restore a neural network, we will see how we can use the resulting patterns from a trained neural network. To do this, we must use an object inherited from the OutputStreamSynapse class, so that we will be able to manage all the output patterns of a neural network for both the following two cases:

1. UserÕs needs: to permit a user to read the results of a neural network, we must be able to write them onto a file, in some useful format, for instance, in ASCII format.
2. ApplicationÕs needs: to permit an embedding application to read the results of a neural network, we must be able to write them onto a memory buffer - a 2D array of type double, for instance - and to read them automatically at the end of the elaboration.

INFO

Note: The examples shown in the following two chapters use the serialized form of the XOR neural network. To obtain that file, you must first create the XOR neural network with the editor, as illustrated in the GUI Editor User Guide, and export it using the File-¿Export menu item.

9.3.1 Writing the results to an output file

The first example we will see is about how to write the results of a neural network into an ASCII file, so a user can read and use it in practice. To do this, we will use a FileOutputSynapse object, attaching it as the output of the last layer of the neural network. Assume that we have saved the XOR neural net from the previous example in a serialized form named Ôxor.snetÕ so we can use it by simply loading it from the file system and attaching to its last layer the output synapse. First of all, we write the code necessary to read a serialized NeuralNet object from an external application (see listing 9.7), then we write the code to use the restored neural network (see listing 9.8).

```
NeuralNet restoreNeuralNet(String fileName) {
NeuralNetLoader loader = new NeuralNetLoader(fileName);
NeuralNet nnet = loader.getNeuralNet();
return nnet;
}
```

Listing 9.7: Writing the results to an output file

```
NeuralNet xorNNet = this.restoreNeuralNet("/somepath/xor.snet");
if (xorNNet != null) {
// we get the output layer
Layer output = xorNNet.getOutputLayer();
// we create an output synapse
FileOutputSynapse fileOutput = new FileOutputSynapse();
FileOutput.setFileName("/somepath/xor_out.txt");
// we attach the output synapse to the last layer of the NN
output.addOutputSynapse(fileOutput);
// we run the neural network only once (1 cycle) in recall mode
xorNNet.getMonitor().setTotCicles = 1;
xorNNet.getMonitor().setLearning(false);
xorNNet.go();
}
```

Listing 9.8: Use a restored network

After the above execution, we can print out the obtained file, and, if the net is correctly trained, we will see a content like this:

0.016968769233825207 0.9798790621933134 0.9797402885436198 0.024205151360285334

This demonstrates the correctness of the previous training cycles.

9.3.2 Getting the results into an array

We now will see the use of a neural network from an embedding application that needs to use its results. The obvious approach in this case is to obtain the result of the recall phase into an array of doubles, so the external application can use it as needed. We will see two usages of a trained neural network:

1. The test of a net using a set of predefined patterns; in this case we want to interrogate the net with several patterns, all collected before to query the net

2. The test of a net using only one input pattern; in this case we need to interrogate the net with a pattern provided by an external asynchronous source of data

We will see an example of both the above methods.

Using multiple input patterns

To accomplish this goal we will use the org.joone.io.MemoryOutputSynapse object, as illustrated in listing 9.9.

```
    // The input array used for this example
    private double[][] inputArray = { {0, 0}, {0, 1}, {1, 0}, {1, 1} };

    private void Go(String fileName) {
        // We load the serialized XOR neural net
        NeuralNet xor = restoreNeuralNet(fileName);
        if (xor != null) {
            /* We get the first layer of the net (the input layer),
               then remove all the input synapses attached to it
               and attach a MemoryInputSynapse */
            Layer input = xor.getInputLayer();
            input.removeAllInputs();
            MemoryInputSynapse memInp = new MemoryInputSynapse();
            memInp.setFirstRow(1);
            memInp.setAdvancedColumnSelector(Ò1,2Ó);
            input.addInputSynapse(memInp);
            memInp.setInputArray(inputArray);

            /* We get the last layer of the net (the output layer),
               then remove all the output synapses attached to it
               and attach a MemoryOutputSynapse */
             Layer output = xor.getOutputLayer();
            // Remove all the output synapses attached to it...
            output.removeAllOutputs();
            //...and attach a MemoryOutputSynapse
            MemoryOutputSynapse memOut = new MemoryOutputSynapse();
            output.addOutputSynapse(memOut);
            // Now we interrogate the net
            xor.getMonitor().setTotCicles(1);
            xor.getMonitor().setTrainingPatterns(4);
            xor.getMonitor().setLearning(false);
            xor.go();
            for (int i=0; i < 4; ++i) {
                // Read the next pattern and print out it
                double[] pattern = memOut.getNextPattern();
              System.out.println("Output Pattern #"+(i+1)+" = "+pattern[0]);
            }
            xor.stop();
           System.out.println("Finished");          }
    }
```

Listing 9.9: Multiple Inputs

As illustrated in the above code, we load the serialized neural net (using the same restoreNeuralNet method used in the previous chapter), and then we attach a MemoryInputSynapse to its input layer and a MemoryOutputSynapse to its output layer. Before that, we have removed all the I/O components of the neural network, to be not aware of the I/O components used in the editor to train the net. This is a valid example about how to dynamically modify a serialized neural network to be used in a different environment respect to that used for its design and training.

To provide the neural network with the input patterns, we must call the MemoryInputSynapse.setInputArray method, passing a predefined 2D array of double. To get the resulting patterns from the recall phase we call the MemoryOutputSynapse.getNextPattern method; this method waits for the next output pattern from the net, returning an array of doubles containing the response of the neural network. This call is made for each input pattern provided to the net.

The above code must be written in the embedding application, and to simulate this situation, we can call it from a main() method (see listing 9.10.

```
1    public static void main(String[] args) {
2        EmbeddedXOR xor = new EmbeddedXOR();
3        xor.Go(Òorg/joone/samples/engine/xor/xor.snetÓ);
4    }
```

Listing 9.10: Main method

The complete source code of this example is contained in the EmbeddedXOR.java file in the org.joone.samples.xor package.

Using only one input pattern

We now will see how to interrogate the net using only an input pattern. We will show only the differences respect to the previous example in listing 9.12.

```
1    private void Go(String fileName) {
2        // We load the serialized XOR neural net
3        NeuralNet xor = restoreNeuralNet(fileName);
4        if (xor != null) {
5            /* We get the first layer of the net (the input layer),
6               then remove all the input synapses attached to it
7               and attach a DirectSynapse */
8            Layer input = xor.getInputLayer();
9            input.removeAllInputs();
10           DirectSynapse memInp = new DirectSynapse();
11           input.addInputSynapse(memInp);
12           ...
13           /* We get the last layer of the net (the output layer),
14              then remove all the output synapses attached to it
15              and attach a DirectSynapse */
16           Layer output = xor.getOutputLayer();
17           output.removeAllOutputs();
18           DirectSynapse memOut = new DirectSynapse();
19           ...
```

Listing 9.11: Interrogating the network

As you can read, we now use both as input and output a DirectSynapse instead of the MemoryInputSynapse object.
What are the differences?

1. The DirectSynapse object is not a I/O component, as it doesnÕt inherit the StreamInputSynapse class

2. Consequently, it doesnÕt call the Monitor.nextStep method, so the neural network is not more controlled by the MonitorÕs parameters (see the Chapter 3 to better understand these concepts). Now the embedding application is responsible of the control of the neural network (it must know when to start and stop it), whereas during the training phase the start and stop actions were determined by the parameters of the Monitor object, being that process not supervised (remember that a neural network can be trained on remote machines without a central control).

3. For the same reasons, we donÕt need to set the ÔTotCyclesÕ and ÔPatternsÕ parameters of the Monitor object.

Thus, to interrogate the net we can just write, after having invoked the NeuralNet.start method (see listing **??**).

```
1            xor.go(); // start the network
2            for (int i=0; i < 4; ++i) {
3                // Prepare the next input pattern
4                Pattern iPattern = new Pattern(inputArray[i]);
5                iPattern.setCount(1);
6                // Interrogate the net
7                memInp.fwdPut(iPattern);
8                // Read the output pattern and print out it
9                Pattern pattern = memOut.fwdGet();
10               System.out.println("Output#"+(i+1)+" = "+pattern.getArray()[0]);
11           }
```

Listing 9.12: Interrogating the network

In the above code we give the net only one pattern for each query, using the DirectSynapse.fwdPut method (note that this method accepts a Pattern object). As in the previous example, to retrieve the output pattern we call the MemoryOutputSynapse.getNextPattern method. The complete source code of this example is contained in the ImmediateEmbeddedXOR.java file in the org.joone.samples.xor package

9.4 Controlling the training of a neural network

9.4.1 Controlling the RMSE

In most cases it's very useful to control the behavior of a neural network at run time. One of these cases could be represented by the necessity to stop the training of a neural network when its global error (RMSE) goes below a given value.

As probably you have noticed, in Joone there isn't any internal predefined mechanism to stop a neural network before the last training cycle is reached1, hence it would be a wasting of time to continue to train the neural network after the RMSE became acceptable for our purposes.

The core engine comes in our aid by providing a notification mechanism based on events raised at the happening of certain facts. The behavior of a neural network can be controlled

by writing code in response of those neural network events; the code must be written into the corresponding event handler. As already described in a previous chapter, there are four neural networks events that are raised in correspondence of the following actions:

- netStarted
- netStopped
- cycleTerminated
- errorChanged

The last two are denominated 'cyclic events', and they are what we need to control the behavior of a neural network during its training (or querying) cycles.

If we need to stop the neural network when the RMSE reaches a given value, we can write the code in listing 9.13 into the errorChanged event handler:

```
1    public void errorChanged(NeuralNetEvent e) {
2        Monitor mon = (Monitor)e.getSource();
3    if (mon.getGlobalError() <= givenValue)
4    nnet.stop();
5    }
```

Listing 9.13: Catching the targeted rmse

We could also use this technique to write to the output console the current rmse every predetermined number of cycles, as described in listing 9.14

```
1    public void cicleTerminated(NeuralNetEvent e) {
2        Monitor mon = (Monitor)e.getSource();
3        long c = mon.getTotCicles() - mon.getCurrentCicle();
4
5        /* We want to print the result only every 1000 cycles */
6        if ((c \% 1000) == 0)
7            System.out.println("Cycle:"+c+" RMSE = " + mon.getGlobalError());
8    }
```

Listing 9.14: Tracking the rmse

As you can see, by calling the NeuralNetEvent.getSource() method, we can obtain a pointer to the Monitor object of the current neural network, thanks to which we can control (almost) any aspect of the running neural network.

IMPORTANT

Because all the above events are called synchronously by the threads running the neural network, avoid to make CPU intensive tasks within the event handler code. If you need to make some long elaboration, it would be better to instantiate a new thread, where the task could be executed without affecting the running of the neural network.

9.4.2 Cross Validation

Thanks to the possibility to execute java code in response of any events of the neural network, we can perform any kind of task, even if very complicated, as, for instance, the validation of a neural network 'on the fly' during the training phase, without the necessity to stop that phase. To do it, we need to use two LearningSwitch components, along with some code executed in response of the cicleTerminated event. In the example shown here we'll explain also some good programming techniques used to write a more readable and robust code, enhancing the code reuse. First of all, as we need to repeat the same configuration (i.e. the chain input–¿switch¡–desired, as described in the chapter 4) both for the training and the desired input data, we'll write a generalized piece of code where we'll initialize all the components needed to perform our task (see lisiting 9.15).

```
1   /** Creates a FileInputSynapse */
2   private FileInputSynapse createInput(String name, int firstRow, int firstCol, int
        lastCol) {
3       FileInputSynapse input = new FileInputSynapse();
4       input.setFileName(name);
5       input.setFirstRow(firstRow);
6       if (firstCol != lastCol)
7           input.setAdvancedColumnSelector(firstCol+"-"+lastCol);
8       else
9           input.setAdvancedColumnSelector(Integer.toString(firstCol));
10
11      // We normalize the input data in the range 0 - 1
12      NormalizerPlugIn norm = new NormalizerPlugIn();
13      if (firstCol != lastCol) {
14   String ass = "1-"+Integer.toString(lastCol-firstCol+1);
15      norm.setAdvancedSerieSelector(ass);
16  }
17      else
18          norm.setAdvancedSerieSelector("1");
19      input.setPlugIn(norm);
20      return input;
21  }
```

Listing 9.15: Cross Validation

The method in listing 9.15 creates and returns a FileInputSynapse with attached a NormalizerPlugin, simply by receiving as parameters the input file name, the first row, the first and last columns from which we must start to read the input data.

After that, we need to write a routine able to build the chain inputSynapse –¿ LearningSwitch ¡– DesiredSynapse (see listing 9.16).

```
1   /* Creates a LearningSwitch and attach to it both the training and
2      the desired input synapses */
3   private LearningSwitch createSwitch(StreamInputSynapse IT, StreamInputSynapse IV
        ) {
4       LearningSwitch lsw = new LearningSwitch();
5       lsw.addTrainingSet(IT);
6       lsw.addValidationSet(IV);
7       return lsw;
8   }
```

```
9
10 At this point we can simply call the above two methods to build the input and
       desired data components (see listing \ref{iandd}
11 \begin{lstlisting}[caption=Build input and desired data components, label=iandd,
       language=java]
12         /* Creates all the required input data sets:
13      * ITdata = input training data set
14      * IVdata = input validation data set
15      * DTdata = desired training data set
16      * DVdata = desired validation data set
17      */
18         FileInputSynapse ITdata = this.createInput(path+"/data.txt",1,2,14);
19         FileInputSynapse IVdata = this.createInput(path+"/data.txt",131,2,14);
20         FileInputSynapse DTdata = this.createInput(path+"/data.txt",1,1,1);
21         FileInputSynapse DVdata = this.createInput(path+"/data.txt",131,1,1);
22
23         /* Creates and attach the input learning switch */
24         LearningSwitch Ilsw = this.createSwitch(ITdata, IVdata);
25         InputLayer.addInputSynapse(Ilsw);
26
27         /* Creates and attach the desired learning switch */
28         LearningSwitch Dlsw = this.createSwitch(DTdata, DVdata);
29         TeachingSynapse ts = new TeachingSynapse(); // The teacher of the net
30         ts.setDesired(Dlsw);
31         OutputLayer.addOutputSynapse(ts);
```

Listing 9.16: Connecting InputSynapse and DesiredSynapse

In the above example we have used the first 130 rows as training patterns, and the remaining rows as validation data. Moreover, we use the columns from 2 to 14 as input data, and the first one as target value. As you can see in the above code, at the end we have attached the input and desired switches to the input layer and the teacher respectively (we have omitted the code to build the layers of the neural network, but you should be able to do it yourself without problems). Now we must add the code needed to perform the validation of the neural network at end of every training epoch. Of course, that code must be written into the cicleTerminated event handler (see listing 9.17).

```
1
2     public void cicleTerminated(NeuralNetEvent e) {
3     Monitor mon = (Monitor)e.getSource();
4
5         // Prints out the current epoch and the training error
6       int cycle = mon.getCurrentCicle()+1;
7         if (cycle \% 200 == 0) { // We validate the net every 200 cycles
8           System.out.println("Epoch #"+(mon.getTotCicles() - cycle));
9           System.out.println("    Training Error:"+mon.getGlobalError());
10
11          // Creates a copy of the neural network
12          net.getMonitor().setExporting(true);
13          NeuralNet newNet = net.cloneNet();
14          net.getMonitor().setExporting(false);
15
16          // Cleans the old listeners
17          // This is a fundamental action to avoid that the validating net
18          // calls the cicleTerminated method of this class
```

```
19            newNet.removeAllListeners();
20
21            // Set all the parameters for the validation
22            NeuralNetValidator nnv = new NeuralNetValidator(newNet);
23            nnv.addValidationListener(this);
24            nnv.start();  // Validates the net
25          }
26      }
```

Listing 9.17: Perform validation

Even if the code is rather self-explaining, we want to emphasize the following aspects:

You can notice that the main neural network is not stopped during the validation phase, and this is possible thanks to the cloning capacity of the NeuralNet object; as you can see, in fact, we validate a cloned copy of the neural network, while the main neural network continues to be trained. This offers some advantages, because we perform in parallel the validation phase, being so able to take advantage of the presence of a multiprocessor architecture.

To perform the validation task we use the NeuralNetValidator object. It runs on a separate thread and notifies the main application by issuing a netValidated event (to be notified, the main application must implement the NeuralValidationListener interface).

The code in listing 9.18 illustrates what we do in response of a netValidated event.

```
1  /* Validation Event */
2  public void netValidated(NeuralValidationEvent event) {
3    // Shows the RMSE at the end of the cycle
4    NeuralNet NN = (NeuralNet)event.getSource();
5   System.out.println("    Validation Error: "+NN.getMonitor().getGlobalError());
6  }
```

Listing 9.18: Capturing a validation event

As you can see, the variable passed as parameter of the method contains a pointer to the validated neural network (that one that we have cloned in the previous code), so we're able to access to all the parameters of the validation task from within the caller main application (in this example we use it to get the validation RMSE).

If you want to try yourself the above example, you can find the complete code into the org.joone.samples.engine.validation.SimpleValidationSample class, and if you run it, you'll get a result like the following:

Epoch #200 Training Error: 0.03634410057758484 Validation Error: 0.08310312916100844 Epoch #400 Training Error: 0.023295226557687492 Validation Error: 0.07643178777353665 Epoch #600 Training Error: 0.017832470096609952 Validation Error: 0.07457234059641271 ...

In this example we have just used the validated neural network to get and print the validation error, but you could perform whatever task as, for instance, to save in serialized format each validated neural network, or only those having a RMSE lower than a predefined value,

in order to be able to perform a selection of the best neural networks (i.e. those having the best generalization capacity) at the end of the training phase.

A good technique could be represented by the implementation of the following algorithm, also known as ÒEarly StoppingÓ:

1. When we start the main network, a variable named lastRMSE must be set to a high value, say 999
2. In response to the netValidated event, if the returned validation RMSE ¡ lastRMSE, then save the returned network and let lastRMSE = RMSE
3. Otherwise, do not save the network and stop the training phase. The last saved network is the best one.

When in the step 2 we notice that the validation error begins to increase, then we're sure that the last saved network is the best one (e.g. the neural network with the best generalization error), hence we stop the training phase.

Note: This technique is very powerful when used in conjunction with the distributed training environment, where you can run several copies of the same neural network (each one initialized with different random weights) by using different machines connected to a LAN, augmenting in this manner the probability to find a neural network having very good performances in terms of generalization capacity.

9.5 The JooneTools helper class

JooneTools is a class that exposes many useful static methods to build and run a neural network by hiding the complexity of the core engine's API. It can be used in a lot of circumstances, whenever the network you need to build belongs to one of the standard architectures supported by JooneTools (feed forward and SOM networks at the moment), and when the training or interrogation phases must be performed without any particular customization. By reading the following paragraphs, and reading the JooneTools API javadoc, you'll be able to understand when and how to use it.

9.5.1 Building and running a simple feed forward neural network

By using JooneTools, you can easily build, train and interrogate a feed forward neural network simply writing 3 (yes, three :-) rows of code! Look at the listing 9.19.

```
1 // Create an MLP network with 3 layers [2,2,1 nodes] with a logistic output layer
2 NeuralNet nnet = JooneTools.create_standard(new int[]{2,2,1},
3       JooneTools.LOGISTIC);
4
5 // Train the network for 5000 epochs, or until the rmse < 0.01
6 double rmse = JooneTools.train(nnet, inputArray, desiredArray,
7       5000,     // Max epochs
```

```
8         0.01,       // Min RMSE
9         0,          // Epochs between ouput reports
10        null,       // Std Output
11        false       // Asynchronous mode
12        );
13
14  // Interrogate the network
15  double[] output = JooneTools.interrogate(nnet, testArray);
```

Listing 9.19: Building a simple network

Let's explain the methods used:

- **JooneTools.create_standard**: this method creates and returns a new feed-forward neural network. The number of layers will be equal to the size of the array of integers passed as the first parameter; each element of the array indicates the nodes (or rows) contained in each layer. The first Layer will be always composed by a LinearLayer, the hidden nodes will be composed by SigmoidLayers, while the output layer kind is determined by the second parameter of the method, that can be one of the constants indicated in table 9.2.

Constant used	Kind of output layer	Problem to resolve
JooneTools.LINEAR6LinearLayer	Function approximation	
JooneTools.LOGISTIC	SigmoidLayer	Binary classification
JooneTools.SOFTMAX	SoftmaxLayer	1 of C classification

Table 9.2: Layer table

  You'll choose the kind of output layer depending on the kind of problem you need to resolve, as indicated in the table.

- **JooneTools.train**: this method trains a network in supervised mode, according to some parameters (listed in the order expected by the method):

  1. The neural network to train; it must contain only the input, hidden and output layers, without any I/O components attached (like that one returned by the create
  2. A 2D array of doubles containing the training input data. The array must have a number of columns equal to the number of network's input nodes and a number of rows equal to the number of training patterns to use.
  3. A 2D array of doubles containing the training desired data. The array must have a number of columns equal to the number of network's output nodes and a number of rows equal to the number of training patterns to use.
  4. The number of (max) training epochs.

5. The min RMSE; the network will be trained until its rmse will be greater than this parameter (if ¿0), otherwise the training will continue for the number of epochs indicated in the previous parameter.
6. The number of epochs between two notifications (see the next parameter). 0 if no notifications desired.
7. A pointer to the object that will receive the network's notifications. It can implement either a NeuralNetListener, or a PrintStream class, depending on the kind of the notification we want to receive. If the object is a NeuralNetListener, the corresponding methods will be invoked, otherwise, in case of a PrintStream class (like System.out, for instance), a preformatted text will be written. In both the cases, the interval of epochs between two notifications is determined by the content of the previous parameter. Null if no notifications needed.
8. A boolean indicating if the training must be executed in asynchronous mode. If true, the method will return immediately and the network will be trained in background, within a separate thread. If false, the method will return only after the training is terminated.

While almost all the above parameters have a clear meaning, maybe the 6th and 7th need a deeper explanation. JooneTools permits to monitor the training progress in two manners:

– By using a NeuralNetListener: this is the classic method, where the caller application needs to declare and pass a NeuralNetListener class, as in listing 9.20.

```
1   NeuralNetListener listener = new NeuralNetListener() {
2           public void netStarted(NeuralNetEvent e) { ... }
3           public void cicleTerminated(NeuralNetEvent e) { ... }
4           public void errorChanged(NeuralNetEvent e) { ... }
5           public void netStopped(NeuralNetEvent e) { ... }
6           public void netStoppedError(NeuralNetEvent e,String error) {
                ... }
7   }
8   double rmse = JooneTools.train(nnet, inputArray, desiredArray,
9       5000,     // Max epochs
10      0.01,     // Min RMSE
11      100,      // Epochs between notifications
12      listener,   // Notifications listener
13      false     // Asynchronous mode
14        );
```

Listing 9.20: Monitoring the training progress using the NeuralNetListener

In the above example the declared listener will be used, and its cyclic methods, like cycleTerminated and errorChanged, will be invoked each 100 epochs.

– By using a PrintStream class: when we don't need to execute custom code in response of a network's event, but we want anyway to be informed about the

training progress, we can pass as listener a simple PrintStream class (like, for instance, System.out, if we want the messages printed on the console). Look at listing 9.21.

```
double rmse = JooneTools.train(nnet, inputArray, desiredArray,
        5000,      // Max epochs
        0.01,      // Min RMSE
        200,       // Epochs between notifications
        System.out, // Output to the system console
        false      // Asynchronous mode
          );
```

Listing 9.21: Monitoring the training progress using the PrintStream

In this case all the network's events will be notified on the system console with a periodicity of 200 epochs:

Network started
Epoch n.200 terminated - rmse: 0.3552344523359257
Epoch n.400 terminated - rmse: 0.09979108423932816
Epoch n.600 terminated - rmse: 0.038605717897835144
Network stopped

Of course you can use whatever else class that extends PrintStream, in order to direct the output messages to a different media.

- **JooneTools.interrogate**: as the name indicates, this method is used to interrogate a trained network using a single input pattern. The method returns an array of double containing the outcome of the neural network. As parameters, it accept the NeuralNet object to interrogate, and an array of double containing the input data to use. The input array must have as many elements as the size of the output layer of the network. In the org.joone.samples.engine.helpers.XOR_using_helpers class you can find a complete example illustrating the use of JooneTools to build, train and interrogate a XOR network.

9.5.2 The JooneTools I/O helper methods

As previously illustrated, many methods of JooneTools expect an array of double as input data. In order to easily extract such an array from an input stream, in JooneTools we'll find the method getDataOnStream, that can be used as in listing 9.22.

```
    // Prepare the training and testing data set
    FileInputSynapse fileIn = new FileInputSynapse();
    fileIn.setInputFile(new File(fileName));
    fileIn.setAdvancedColumnSelector("1-14");

    // Input data normalized between -1 and +1
    NormalizerPlugIn normIn = new NormalizerPlugIn();
    normIn.setAdvancedSerieSelector("2-14");
```

```
    normIn.setMin(-1);
    normIn.setMax(1);
    fileIn.addPlugIn(normIn);

    // Target data normalized between 0 and 1
    NormalizerPlugIn normDes = new NormalizerPlugIn();
    normDes.setAdvancedSerieSelector("1");
    fileIn.addPlugIn(normDes);

    // Extract the training data
    double[][] inputTrain = JooneTools.getDataFromStream(fileIn,
            1, trainingRows, 2, 14);
    double[][] desiredTrain = JooneTools.getDataFromStream(fileIn,
            1, trainingRows, 1, 1);

    // Extract the testing data
    double[][] inputTest = JooneTools.getDataFromStream(fileIn,
            trainingRows+1, 178, 2, 14);
    double[][] desiredTest = JooneTools.getDataFromStream(fileIn,
            trainingRows+1, 178, 1, 1);
```

Listing 9.22: Using the I/O helper tools

In listing 9.22 we used a FileInputSynapse to read the input data, composed by 178 patterns, 14 columns each. We use the columns from 2 to 14 as input, while the first column contains the desired data the network must learn to recognize.

After having normalized both the input and desired data by using two NormalizerPlugins (as already described in the previous chapters), we use the resulting FileInputSynapse as input parameter for the invocation of the JooneTools.getDataFromStream method, passing each time all the parameters needed to extract the input&desired arrays of data, both for training and testing phases. Now, having extracted the corresponding four arrays of double, we can use them to train and interrogate the network, by comparing the results on the test data, as illustrated in listing 9.23.

```
    // Train the network
    JooneTools.train(nnet, inputTrain, desiredTrain,
                5000,   // Max # of epochs
                0.010,  // Stop RMSE
                100,    // Epochs between output reports
                this,   // The listener
                false); // Runs in synch mode

...
    // And now compare the results on the test set
    double[][] out = JooneTools.compare(nnet, inputTest,
                  desiredTest);
    System.out.println("Comparison of the last "+out.length+"
          rows:");
    int cols = out[0].length/2;
    for (int i=0; i < out.length; ++i) {
        System.out.print("\nOutput: ");
        for (int x=0; x < cols; ++x) {
            System.out.print(out[i][x]+" ");
        }
```

```
21          System.out.print("\tTarget: ");
22          for (int x=cols; x < cols*2; ++x) {
23              System.out.print(out[i][x]+" ");
24          }
25      }
```

Listing 9.23: Comparing the results with the desired output

By running the above example, (the complete source code is in org/joone/samples/engine/helpers/Validation_using_stream.java), you'll obtain an output like the following:

Network started
Comparion of the last 28 rows:
Output: 0.001644333042189837 Target: 0.0
Output: 9.292946600039575E-4 Target: 0.0
Output: 0.4855262175163008 Target: 0.5
Output: 0.9976350028550492 Target: 1.0
...
...
Output: 0.11104094434076456 Target: 0.5
Output: 0.6211928869659087 Target: 0.5
Network stopped

We have introduced here a new JooneTools method named 'compare', using which you can easily extract both the response of the network and the target values within the same array, in order to be able to make comparisons between them. The JooneTools.compare method, in fact, returns a 2D array of double containing the output+target data for each pattern (the resulting output array's number of columns is the double of the target array size).

9.5.3 Testing the performance of a network

Finally, you can also test the performances of a network (i.e. calculate the resulting RMSE for a specific input pattern) by using the JooneTools.test method. It accepts as parameters the NeuralNet object containing the network to test, the input test data and the corresponding desired data. All the data, as always, must be contained in an array of double, that you can obtain by invoking the JooneTools.getDataFromStream method, as seen in the previous paragraph. The test method returns a double indicating the RMSE obtained on the input patterns, compared with the given target data. This method is very useful, for example, to calculate the generalization capacity of a network on unseen data.

9.5.4 Builiding unsupervised (SOM) networks

JooneTools permits to create unsupervised Self Organized Map network by exposing the JooneTools.createUnsupervised method.

It accepts two parameters:

- nodes: An array of integer containing 3 elements, having the following meaning:
  - nodes[0] = Rows of the input layer
  - nodes[1] = Width of the output map
  - nodes[2] = Height of the output map
- outputType: an integer indicating the kind of output layer we need. It can contain one of the following two constants:
  - JooneTools.WTA - SOM with a WinnerTakeAll output layer
  - JooneTools.GAUSSIAN - SOM with a Gaussian output layer

Once we have created the SOM network, we can train it by using the JooneTools.train_unsupervised method. See the JooneTools API javadoc to read about the parameters accepted by this method.

9.5.5 Loading and saving a network with JooneTools

JooneTools exposes, of course, also some methods to save/load easily a neural network. You can use the following methods:

Method name	Purpose
save(NeuralNet network, String fileName)	Saves a network to a file
save_toStream(NeuralNet nnet, OutputStream stream)	Saves a network to an OutputStream
load(String fileName)	Loads a network from a file

The above methods save/load a network ONLY in java serialized format. The XML format is not still supported.

Chapter 10

The Joone Editor

Is there already some documentation about the editor? Maybe we should start to document it here.

10.1 User Manual

10.2 Technical Documentation

10.2.1 The Graphing Component

10.2.2 The Help System

Chapter 11

Miscellaneous

11.1 The Logging Configuration

11.2 The Serialization Mechanism

11.3 Some Mathematical Neural Network Theory And Its Implementation In Joone

11.3.1 Learning Algorithms

11.3.2 ...

11.4 The CVS Tree Structure

The CVS tree contains the following projects:

- forrest: What is the intend of forrest?
- html: contains the content for joones webpage. This version is identical with the one currently online, the new version should be commited back.
- joone: the main project. Contains the source code for the engine and the editor as well as the required third-party libraries and this documentation.
- Joone: seems to be an empty folder. can it be deleted ?
- jooneExamples: should probably contain some examples. Actually there's basically nothing. Either we transfer all samples in this project or we should delete it.
- jooneFarm: all lot of code ;-). Seems to have something to do with dte/terracota. Please document it.

- joonePad: seems to be the new editor for joone. Does anyone know something about its further developmnet? If see, please document it.
- jooneTests: contains some automatically generated unit-tests, without any testcases. There is also a unresolved project reference to a JINI project. Is the JINI development still going on?
- tools: some kind of network analysis tool. To be documented

11.5 The examples

There are two kind of examples: The ones created with the network editor and those directly coded in java. All of them can be found in the source distribution. TODO: All these examples should be documentated using the same template, e.g 1.) what is intend of the network, 2.) how is it implemented, 3.) which features of Joone are used (so that they can be reference from the rest of the documentation). For most of them it is probably sufficient to update the already existing documentation in the code files.

11.5.1 The Java Code/Engine Examples

The engine examples can be found in the org.joone.samples.engine.* packages.

Helpers examples

TODO: Update and documention

MultipleInput examples

TODO: Update and documention

Parity examples

TODO: Update and documention

Scripting examples

TODO: Update and documention

TimeSeries examples

TODO: Update and documention

Validation examples

TODO: Update and documention

XOR examples

TODO: Update and documention

XOR/InputConnector examples

TODO: Update and documention

RBF examples

TODO: Update and documention

11.5.2 The Editor Examples

TODO: To use simple serialization as persistence mechanism is a actually a bad idea, because it depends on binary compatibility, which is lost by every code change! We should switch to another persistence mechanism/framework! The editor examples can be found in the org.joone.samples.editor.* packages. They're *.ser files can be imported directly in the editor.

Charting Examples

TODO: Update and documention

PCA Example

TODO: Update and documention

Recurrent Network Examples

TODO: Update and documention

Scripting/Validation Examples

TODO: Update and documention

Scripting/InputConnector Example

TODO: Update and documention

SOM Example

TODO: Update and documention

Synapses Example

TODO: Update and documention

TuriningPtsExtractor, DelayLayerSample Example

TODO: Update and documention

Simple XOR Example

TODO: Update and documention

XOR InputConnector Example

TODO: Update and documention

11.6 Software Quality Control

11.6.1 The Unit Tests

11.6.2 The Findbugs™Report

11.7 Joone is not yet complete

11.7.1 BackPropagation Algorithm And Its Variations

Name	Description	State
Classical Backpropagation of Error	....	
Vogl's Method	....	
Delta-Bar Delta	....	
Silva and Almeida	....	
SuperSAB	....	
Rprop	....	
Quickprop	....	
Search Then Converge	....	
Fuzzy Control of Back-Propagation	....	

Name	Description	State
Gradient Reuse	....	
Gradient Correlation	....	

Table 11.1: Backpropagation And Its Variations

11.7.2 Optimization Techniques

Evaluation-Only Methods

Name	Description	State
Hooke-Jeeves Pattern	....	
Nelder-Mead Simplex Search	....	
Powell's Conjugate Direction Method	....	

Table 11.2: Evaluation-Only Methods

First-Order Gradient Methods

Name	Description	State
Gradient Descent	....	
Nelder-Mead Simplex Search	....	
Best-Step Steepest Descent	....	
Conjugate Gradient Descent	....	

Table 11.3: First-Order Gradient Methods

Second-Order Gradient Methods

Name	Description	State
Newton's Method	....	
Gauss-Newton	....	
The Levenberg-Marquardt Method	....	
Quasi-Newton Method (BFGS)	....	

Table 11.4: Second-Order Gradient Methods

Stochastic Evaluation-Only Methods

Name	Description	State
Simulated Annealing	....	
Genetic Algorithms	....	

Table 11.5: Stochastic Evaluation-Only Methods

11.7.3 Recurrent Network Training Methods

Name	Description	State
Real-time recurrent learning (RTRL)	....	
Offline recurrent learning	....	
Extended Kalman Filter (EFK)	....	
Back Propagation Through Time (BPTT)	....	

Table 11.6: Recurrent Network Training Methods

11.7.4 Pruning Algorithms

Name	Description	State
Brute Force Pruning	....	
Sensitivity Calculation Methods	....	
Penalty-Term Methods	....	
Interactive Pruning	....	
Local Bottlenecks	....	
Distributed Bottlenecks	....	
Principal Components Pruning	....	

Table 11.7: Pruning Algorithms

11.7.5 Generalization Prediction and Assesment

Name	Description	State
Cross Validation	....	
Bayesian Approach	....	
Akaike's Final Prediction Error	....	
PAC Learning and VC Dimension	....	

Table 11.8: Generalization Prediction and Assesment

Chapter 12

Frequently asked questions

Chapter 13

The LGPL Licence

Is it necessary to include the LGPL here?

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Bibliography

[1] James A. Anderson. *An Introduction to Neual Networks*. MIT Press, 1995.

[2] Martin Anthony and Peter L. Bartlett. *Neural network learning theoretical foundations*. na, na.

[3] E.B. Baum and D.Haussler. What size gives valid generalization? *Neural Computation*, 6:151 – 160, 1989.

[4] D.Baily and D.M Thompson. Developing neural network applications. *AI Expert*, na:33 – 41, 1990.

[5] Giovani Dematos, Milton S.Boyd, Bahman Kermanshahi, Nowruz Kohzadi, and Iebeling Kaastra. Feedforward versus recurrent neural networks for forecasting monthly japanese yen exchange rates. *Financial Engineering and the Japanese Markets*, 3:59–75, 1996.

[6] Stuart Duerson, Farhan Saleem Khan, Victor Kovalev, and Ali Hisham Malik. Reinforcement learning in online stock trading systems. *na*, na:na, na.

[7] O. Ersoy. Tutorial at hawaii international conference on systems sciences. *na*, na:na, 1990.

[8] Laurene Fausett. *Fundamentals of neural networks architectures, algorithms, and applications*. na, na.

[9] Box G.E.P. and Jenkins G.M. *Time Series Analysis - Forecasting and Control, San Francisco: Holden Day, 1970*. na, 1970.

[10] Carl Gold. Fx trading via recurrent reinforcement learning. *na*, na:na, 2003.

[11] Thorsten Hens and Peter Woehrmann. Strategic asset allocation and market timing: A reinforcement learining approach. *na*, na:na, 2006.

[12] Iebeling Kaastra and Milton Boyd. Designing a neural network for forecasting financial and economic time series. *Neurocomputing*, na:na, 1996.

[13] J.O. Katz. Developing neural network forecasters for trading. *Technical analysis of stocks and commodities*, na:58–70, 1992.

[14] C.C. Klimasaukas. Applying neural networks. *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real World Performance*, na:58 – 70, 1993.

[15] John F. Kolen. *A field guide to dynamical recurrent networks.* na, na.

[16] Burton G. Malkiel. The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, 17:59 – 82, 2003.

[17] Mandic. *Recurrent Neural Networks for Prediction.* Wiley, na.

[18] Timothy Masters. *Practical Neural Network Recipies in C++.* Academic Press, 1993.

[19] Timothy Masters. *Advanced algorithms for neural networks.* Katherine Schowalter, 1995.

[20] John Moody, Lizhong Yu, Yuangsong Liao, and Matthew Saffell. Performance functions and reinforcement learining for trading systems and portfolios. *Journal of Forecasting*, 17:441 – 470, 1998.

[21] na. *Backpropagation theory, architectures, and applications.* na, na.

[22] Ahmet Onat, Hajime Kita, and Yoshikazu Nisikawa. Recurrent neural networks for reinforcement learnin: Architecture, learning algorithms and internal representation. *IEE*, 1998.

[23] Russel D. Reed and Robert J.Marks. *Neural Smithing.* MIT Press, 1999.

[24] R. Sharda and R.B. Patil. A connectionist approach to time series prediction: An empirical test. *na*, na:na, 1994.

[25] Z. Tang, C. de Almeida, and P.A. Fishwick. Time series forecasting using neural networks vs. box-jenkins. *na*, na:na, 1990.

[26] William G. Tomak and Scott F. Querin. Random processes in prices and technical analysis. *Journal of Futures Markets*, 4:15–23, 1984.

[27] Paul J. Werbos. Backpropagation through time: What it does and how to do it. *Proceedings of the IEE*, 78, 1990.

[28] Stefan Zemke. On developing a financial prediction system: Pitfalls and possibilities. *na*, na:na, na.