Advanced Neural Networks: Finance, Forecast, And Other Applications

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I dedicate this work to my family. Your continuous support is essential for me. Thank you!
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Executive Summary

The content summarized for the rushing executive in 150 words

My dissertation enhances the FAUN neurosimulator. It implements a grid computing client. With this client you can reuse spare computing capacity of user workstations. Remote wake up and shutdown saves power costs when the computers are not needed. I present and analyze a novel neural network topology, the shared layer perceptron. It is memory enabled and allows multi asset and multi step forecasts. Convergence is robust and not sensitive to meta parameters. Applications include modeling market value at risk, transaction decision support and investment. I use 25 financial time series spanning 10 years. The shared layer perceptron produces good or even very good results on equities, interest and exchange rates, and commodities. Multi step forecasts especially enable market timing with high accuracy. The distribution of returns allows to evaluate the probable path of the portfolio within confidence bands. Performance is robust over a time span of 8 years, without retraining.

The content summarized on 8 pages

My dissertation answers the research question «Can advanced neural networks provide sustainable and economic competitive edge in today’s financial markets?» I show that neural networks are indeed capable of adding value to financial applications. To achieve this requires several components working together. Figure 0.1 on the following page provides an overview.

My research question considers several important aspects:

- I investigate advanced neural networks. This is not a standard multi layer perceptron but a quite new topology, the shared layer perceptron, that allows easy modeling of multi dimensional financial time series.

- The models should be sustainable, i.e., more than just a statistical fluke, more than just a lucky hit. They should be robust over time.
Chapter 2 The FAUN grid computing client offers speedups of more than 95%.

Chapter 3 We meet the shared layer perceptron. A memory enabled neural network topology for multi asset multi time step forecasts.

\[
\vec{s}^{t+1} = \tanh(W \vec{s}^t).
\]

\[
\frac{\partial E}{\partial w_{i,j}} = \sum_{t=1}^{T} l_i \vec{s}_{j,t-1} - l_i.
\]

\[
\vec{l} = (1 \odot (\vec{s}^t)^2) \otimes (W' \vec{l}^{t+1} + \vec{e}^t).
\]

Chapter 4 We analyze different financial applications: market value at risk, transaction decision support, and investment.

Chapter 5 Conclusions. The shared layer perceptron topology

- is very robust. It performs regardless of asset or time span.
- adds economic value. It beats the benchmarks hands down.
- is versatile. It works well on a wide variety of financial applications.
- is easily parallelizable. It can be trained on off-the-shelf hardware.

Advanced neural networks provide sustainable and economic competitive edge in today’s financial markets.

Figure 0.1: Steps towards advanced neural networks for financial applications.
• Computational requirements should be low, i.e., economic. Especially, computation should not require special high performance computers.

• The modeled applications should not be simple forecasts. They should offer real competitive edge.

• I focus on financial markets.

Everything in my dissertation is linked to the FAUN neurosimulator, FAUN = Fast Approximation with Universal Neural Networks. Since my supervisor Michael H. Breitner started the FAUN project in 1996 there has been continuous development and improvement. You will find the following highlights:

• The FAUN neurosimulator now also uses fine-grained parallelization. This allows for easily achieved speedups on dual and quad core CPUs. End users are therefore enabled to utilize their workstation to full capacity without having to deal with the increased complexity of message passing software.

• FAUN now also features coarse-grained parallelization using an easy to install grid computing client. Via the web interface it is possible to use clusters of heterogeneous workstations. Spare computing capacity gets reused. Automatic wake up and shutdown saves power costs.

• FAUN is now well-equipped to handle time series problems. It uses a very innovative shared-layer perceptron architecture. I provide a detailed analysis of the computational requirements for the gradient calculation. The gradient calculation itself is presented extensively. Using reverse accumulation and matrix algorithms allows for very efficient computation.

• The examples are designed to provide a maximum of practicality. This includes not only the standard trading application but also market value at risk modeling and transaction decision support.

• The same dataset is used for different application. This offers the possibility to benchmark the performance of neural networks or more standard modeling procedures in different domains. The dataset spans 10 years. It includes bear and bull cycles and is not limited to a single up or down trend where most models perform well anyway. The models are very robust and work well without retraining over a period of 8 years.
Grid Computing

Successfully training neural networks is also a matter of having enough computing capacity available. Neural networks are ideally suited for coarse grained parallelization. Communication requirements are low. You can distribute every single neural network to a separate thread. With the FAUN grid computing client spare computing capacity on user workstations is reused. There is no need to install specialized message passing software. The client is self contained. The achievable speedup is above 95 percent, see figure 0.2. This means that 95 percent of theoretically available computing power compared to a single thread is used.

It is a waste of energy to leave computers running continually. The FAUN grid computing client allows to wake up and shutdown computers remotely.

The update procedure is simple because all functionality is hosted on the server. An important feature of my client and server is that they are totally platform independent. Working combinations include the last releases of Debian and Ubuntu Linux, Windows 7, Windows Vista and Windows XP. This functionality is normally only implemented in commercial message passing software which necessitates a much more complicated setup.

Figure 0.2: The FAUN grid computing client offers consistent speedup above 95 percent on networks of heterogeneous computers.
The Shared Layer Perceptron Topology

The shared layer perceptron provides an elegant method to build multi asset and multi step models, see figure 0.3 on the following page. It augments the observable states $s_1, \ldots, s_N$ by hidden states $s_{N+1}, \ldots, s_D$. Hidden states allow the model to build up memory. Philosophically the shared layer perceptron acknowledges an incomplete view of the world. You do not assume that your «variables» are a perfect description of what happens. Rather you explicitly allow other «hidden» variables to influence your model. Training a shared layer perceptron implicitly also involves finding the right trajectory through the state space: for observable and hidden variables.

At each time step the state space is squeezed through the common weight matrix $W$ and the following non linearity. This is an essential difference to standard multi layer perceptrons. Only a single weight matrix is used. This reduces the number of free parameters and also training times.

This topology produces at each time step all necessary input for the next time step. This simple mechanisms has two additional advantages. First, you automatically get forecasts for all your observables. Second, you can reuse the forecast at the next time step and produce multi step forecasts.

Financial Applications

My dataset includes 25 financial time series from July 1999 to July 2009, i.e., 10 years of data. The dataset is divided into four asset classes: equity indices, interest rates, currency exchange rates and commodities. Interest rates are generally proxied by using yield curves. This dataset is challenging because it includes the boom and bust of the new economy, the bull market up to the credit crisis of 2007, the subsequent sharp bear market and even a small part of the ongoing recovery. Contrary to other studies this dataset truly represents all market cycles.

The first application models market value at risk. We are interested in the worst expected portfolio value over the next 10 days. Figure 0.4 on page 12 shows a sample forecast for the FTSE 100 index. We are interested in modeling the worst returns as closely as possible. It turns out that the shared layer perceptron beats the benchmark historical simulation for every asset on a time span of 110 days. It still beats the benchmark without retraining on 8 years except for 5 cases. This allows institutions to reduce the margin of safety to an appropriate level.
Figure 0.3: The shared layer perceptron for multi asset multi step models.
Figure 0.4: The shared layer perceptron topology models the probably worst portfolio value over the next 10 days for the FTSE 100 equity index.

Figure 0.5 on the following page shows a 20 days ahead ensemble forecast for the Baltic Exchange Dry Index. The target is to find an appropriate low entry point within the next month to secure low freight rates. You note that the shared layer perceptron appropriately models the target: first down, then flat, then slightly up again. It does not exactly find the lowest price. However, the suggested lowest forecast is a sensible entry point. It is located before the index rises again. This models the typical challenge of a corporate treasurer: regular investments on a monthly basis. Again, the shared layer perceptron beats every fixed day strategy for every asset on 110 days. It is still very successful without retraining on 8 years.

The last application focuses on correctly forecasting the sign of next day returns. I benchmark the shared layer perceptron against a naive strategy and a moving average strategy. The shared layer perceptron performs well or very well across a broad range of assets. Results are especially satisfactory on equities and currencies. It does not always beat the benchmark strategies. But it is at worst second best and shows very consistent returns. The benchmarks, however, show fabulous gains followed by catastrophic losses. The shared layer perceptron works robustly on the shorter and longer time span.
Figure 0.5: The shared layer perceptron forecasts the path of the Baltic Exchange Dry Index over the next 20 days.

Conclusions

I show that the shared layer perceptron is a very robust model. It performs well over different asset classes. It also adapts to different market circumstances and shows consistent performance for long and short time spans without retraining. The shared layer perceptron offers a unique way to model a market ensemble:

- The multi step forecasts offer a complete view on the portfolio value path.
- A single model is used. With an expert topology you get every percentile of the underlying distribution for free.
- You will be more confident to use a model that works well over a broad range of assets. The shared layer perceptron works for all inputs by design.

Training the networks using coarse grained parallelization and the FAUN grid computing client provides a cost efficient and failsafe path to neural network modeling. Using the client does not require additional setup. The shared layer perceptron topology adds value to financial applications. I recommend it as an important addition in the modeler's and forecaster's toolbox.
Curriculum Vitae and Publications

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- *Multi-Objective Optimization for Planning of Central IT Resources with Focus on Green IT* in Valerie Belton, Erwin Pesch, Gerhard J. Woeginger (eds.): Proceedings of the 23rd European Conference on Operational Research, July 5–8, 2009, Universität Siegen, Bonn (with Marc Klages, and Michael H. Breitner)


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