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701 E. Chocolate Avenue, Suite 200, Hershey PA 17033-1240, USA
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Chapter V

Application of Higher-Order Neural Networks to Financial Time-Series Prediction

John Fulcher, University of Wollongong, Australia

Ming Zhang, Christopher Newport University, USA

Shuxiang Xu, University of Tasmania, Australia

Abstract

Financial time-series data is characterized by nonlinearities, discontinuities, and high-frequency multipolynomial components. Not surprisingly, conventional artificial neural networks (ANNs) have difficulty in modeling such complex data. A more appropriate approach is to apply higher-order ANNs, which are capable of extracting higher-order polynomial coefficients in the data. Moreover, since there is a one-to-one correspondence between network weights and polynomial coefficients, higher-order neural networks (HONNs) — unlike ANNs generally — can be considered open-, rather than "closed-box" solutions, and thus hold more appeal to the financial community. After developing polynomial and trigonometric HONNs (P[T]HONNs), we introduce the concept of HONN groups. The latter incorporate piecewise continuous-activation

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functions and thresholds, and as a result are capable of modeling discontinuous (or piecewise-continuous) data, and what is more to any degree of accuracy. Several other PHONN variants are also described. The performance of P(T)HONN and HONN groups on representative financial time series is described (i.e., credit ratings and exchange rates). In short, HONNs offer roughly twice the performance of MLP/BP on financial time-series prediction, and HONN groups around 10% further improvement.

Financial Time Series Prediction

It is clear that there are pattern(s) underlying some time series. For example, the 11-year cycle observed in sunspot data (University of California, Irvine, 2005). Whether this is the case with financial time-series data is debatable. For instance, do underlying "forces" actually drive financial markets, and if so can their existence be deduced by observations of stock price and volume movements (Back, 2004)?

Alternatively, do so-called "market inefficiencies" exist, whereby it is possible to devise strategies to consistently "beat the market" in terms of return-on-investment (Edelman & Davy, 2004)? If this is in fact the case, then it runs counter to the so-called Efficient Markets Hypothesis, namely that the present pricing of a financial asset is a reflection of all the available information about that asset, whether this be private (insider), public, or previous pricing (if based *solely* on the latter, then this is referred to as the "weak form" of the EMH).

Market traders, by contrast, tend to base their decisions not only on the previous considerations, but also on many other factors, including hunches (intuition). Quantifying these often complex decision-making processes (expertise) is a difficult, if not impossible, task akin to the fundamental problem inherent in designing *any* Expert System. An overriding consideration is that any model (system) tends to break down in the face of singularities, such as stock market crashes (e.g., "Black Tuesday", October 1987), war, political upheaval, business scandals, rumor, panic buying, and so on.

"Steady-state" markets, on the other hand, tend to exhibit *some* predictability, albeit minor — for example, so-called "calendar effects": lower returns on Mondays, higher returns on the last day of the month and just prior to public holidays, higher returns in January, and so on (Kingdon, 1997).

Now, while it is possible that financial time-series data on occasion can be described by a linear function, most often it is characterized by nonlinearities, discontinuities, and high-frequency multipolynomial components.

If there *is* an underlying market model, then it has remained largely impervious to statistical (and other forms of) modeling. We can take a lead here from adaptive control systems and/or machine learning; in other words, if a system is too complex to model, try *learning* it. This is where techniques such as ANNs can play a role.

Many different techniques have been applied to financial time-series forecasting over the years, ranging from conventional, model-based, statistical approaches to more esoteric, data-driven, experimental ones (Harris & Sollis, 2003; Mills, 1993; Reinsel, 1997).

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