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Data mining for financial prediction and trading: application to single and multiple markets

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Abstract

An alluring aspect of financial investment lies in the opportunity for respectable returns even in the absence of prediction. For instance, a portfolio tied to the S and P500 would have yielded a compound annual return in the teens over the last half century. Over the same period, a portfolio tracking the fast-growth economies of the Far East would have provided even higher returns. Previous researches in learning methods has focused on predictability based on comparative evaluation even these techniques may be employed to forecast financial markets as a prelude to intelligent trading systems.

This paper explores the effect of a number of possible scenarios in this context. The alternative combinations of parameters include the selection of a learning method, whether a neural net or case based reasoning; the choice of markets, whether in one country or two; and the deployment of a passive or active trading strategy. When coupled with a forecasting system, however, a trading strategy offers the possibility for returns in excess of a passive buy-and-hold approach. In this study, we investigated the implications for portfolio management using an implicit learning technique (neural nets) and an explicit approach (CBR)

Keywords: Portfolio investment; Trading strategy; Knowledge discovery; Neural network; Case based reasoning

1. Motivation

A central issue in business and economics lies in the prediction of financial variables. This is especially true for the realms of monetary policy, investment analysis, and risk management. Since the trajectory of a stock market depends on both macroeconomic and microeconomic variables, a systematic approach to knowledge discovery for stock market analysis must be able to accommodate disparate types of information. To this end, a battery of techniques from the field of data mining may be harnessed to the predictive task. A key advantage of a multistrategy approach to discovery and forecasting lies in the ability to merge data available in disparate formats.

In recent years, data mining techniques such as neural networks (NN) have been applied extensively to the task of predicting financial variables. This paper explores the implications for portfolio management using an implicit learning technique (neural nets) and an explicit approach (CBR).

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2. Background

A versatile approach to self-organization lies in NN (Anderson & Rosenfeld, 1988; Grossberg, 1976; Hebb, 1949; Hopfield, 1982; Kohonen, 1991; Rosenblatt, 1962; Rumelhart, Hinton, & Williams, 1986). NN are characterized by learning capability, the ability to improve performance over time. A closely related feature is that of generalization, relating to the recognition of new objects, which are similar but not identical to previous ones. An additional characteristic relates to graceful degradation: the network fails gradually rather than catastrophically when it suffers partial damage.

Backpropagation neural network. The most popular neural method for practical applications is found in the backpropagation (BPN) algorithm. Unfortunately, BPN models suffer from protracted training periods. Hundreds or thousands of trials are usually required for satisfactory performance in various tasks. The time and effort required for training have hindered their widespread application to practical domains. Fortunately, certain other learning techniques such as case based reasoning (CBR) offer much swifter response.

Case based reasoning and composite neighbors. Conventional methods of prediction based on discrete logic usually seek the single best instance, or a weighted combination of a small number of neighbors in the observational space. For instance, the rule of thumb in CBR is to seek the nearest neighbor to a target case. In an analogous way, certain algorithms in NN seek a small number of the closest neighbors; this approach is illustrated by the use of self-organizing maps for pattern recognition tasks (Kohonen, 1991).

An intelligent learning algorithm should therefore take account of a 'virtual' or composite neighbor whose parameters are defined by some weighted combination of actual neighbors in the case base. In this way, the algorithm can utilize the knowledge reflected in a larger subset of the case base than the immediate collection of proximal neighbors (Kim, 1995).

The key to the composite approach lies in the determination of the most effective set of weights to use in order to construct the virtual neighbor. Learning the optimal set of weights is the primary challenge, and the particular values of the weights may well evolve over time as the experience base expands. A promising way to address this task lies in simulated annealing: the weights for constructing the composite neighbor may be perturbed randomly and the advantageous trends pursued, as in the quest for effective parameters in a neural network algorithm.

3. Methodology

The study examined the effect of coupling learning techniques with various trading strategies. The learning methods relate to CBR or to NN using the BPN algorithm.

The random walk model of financial markets in its most plausible form assumes that all public information is already incorporated in the price of a security or the level of a market index. Consequently, no advantage can be gained through active trading. In light of transaction costs the optimal strategy is to establish a position and maintain it through the vicissitudes of the financial markets.

Further, according to the capital asset pricing model (CAPM), the fluctuation in market prices entails a risk which should be compensated by returns superior to a riskfree approach such as the purchase of US Treasury bills. According to financial orthodoxy, the optimal strategy to superior returns lies in a constant long position. This buy-and-hold (BH) policy serves as a baseline for comparing the mean return and risk using alternative strategies.

Trading in a single market. Most investors in financial markets favor long positions or none at all. Such an investor may buy a security, then later sell the instrument to effect a cash position; he or she has no interest in establishing a short position. This type of investment behavior might be called the 'long-none' strategy. Further, if transaction costs were negligible, the strategy might be named the 'long-none-free' approach. In this study, the label has been shortened to the 'LFree' policy.

On the other hand, when transaction costs are considered, the strategy might be called 'LCost'. The study assumed a transaction cost of 0.1% of the amount traded, whether for opening or closing a position. A round-turn cost of 0.2% (corresponding to a 0.1% loss with each opening or closing of a position) might be optimistic for an individual investor. However, certain institutional investors can conduct operations at significantly lower cost.

An experienced trader may well choose to assume short as well as long positions. This type of fully active trading, in conjunction with transaction costs of 0.1% of the traded amount, is labeled the 'LSCost' strategy.

To summarize, the trading strategies were as follows.

- *Risk-Free (RFree)*. Hold US Treasury bills to avoid default risk. Profit is based on the average rate of return for 3 month Treasury bills from May 1, 1996 through September 15, 1996.
- *Buy-Hold (BH)*. Buy at the beginning of the trial period, then make no trades.
- *Long-Free (LFree)*. Buy if the prognosis is bullish; sell to hold cash if bearish. Assumes zero transaction costs.
- *Long-Cost (LCost)*. Buy if the prognosis is bullish and the anticipated increase exceeds transaction cost. Assume a transaction cost of 0.1% of the amount traded.
- *Long-Short-Cost (LSCost)*. Hold current position if anticipated change (Up or Down) is less than the transaction cost. Otherwise, if the prognosis is bullish, open a long position and close any short positions. Do the converse if the prognosis is bearish. Assumes transaction costs of 0.1% of the traded amount for each opening or closing of a position.

As noted earlier, the buy-and-hold strategy corresponds to the random walk model which assumes perfect market efficiency.

Trading in Multiple Markets. A common way to reduce risk is to diversify a portfolio. In a diversified holding, the fraction of a portfolio allocated to one instrument or market over the others may vary over time.

The diversified buy-hold (DBH) strategy allocates equal amounts of the initial budget to each market. The positions are then maintained indefinitely, without rebalancing despite fluctuations in the value of one instrument or market versus another.

To highlight the differences among active trading strategies, this study employs an all-or-none approach to a single market. For instance, all available funds are committed at a particular time to one country or another, rather than splitting the portfolio across multiple economies. The 'DLSFree' strategy involves a portfolio which may contain long or short positions in markets, although not