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# Stock Market Prediction System with Modular Neural Networks

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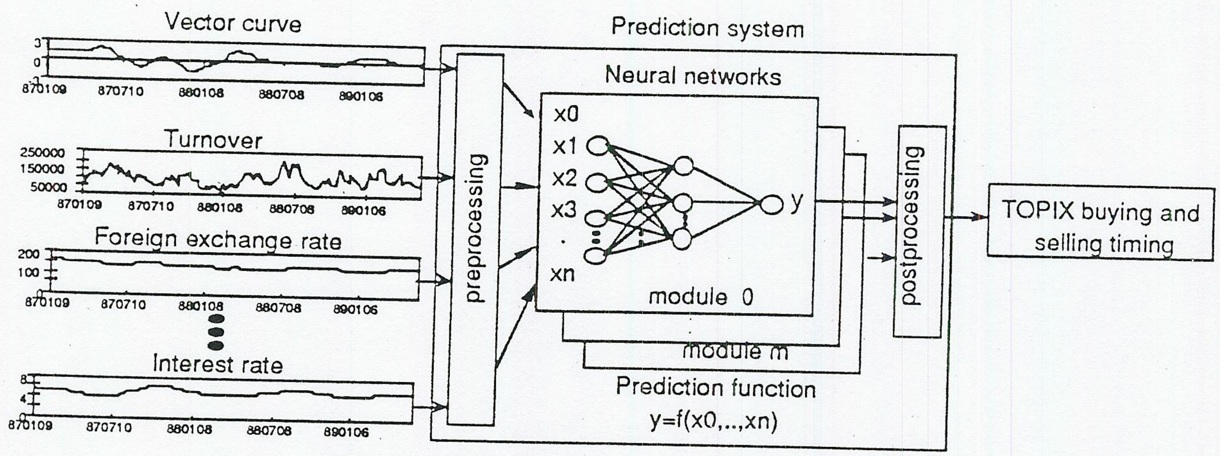



Figure 1 Basic architecture of prediction system

### 2.2.2 High-speed Learning Algorithm

The error back propagation method proposed by Rumelhart[3] is a representative

Input Hidden Output

... according to the prediction system. Use of the system showed an excellent profit.

Portfolio Value

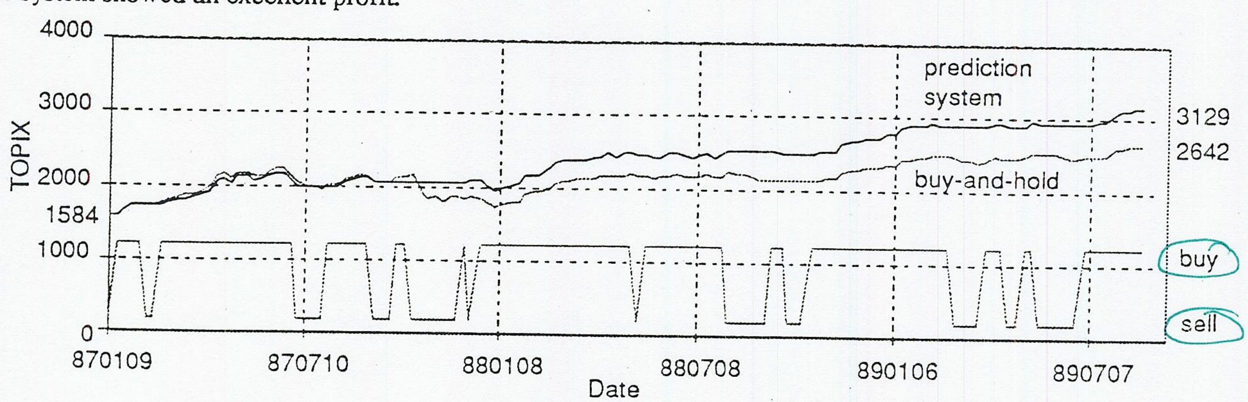



Figure 4 Performance of the prediction system

## 4. Analysis

### 4.1 Comparison with Multiple Regression Analysis

The timing for when to buy and sell stocks is not linear, so statistical methods are not effective for creating a model. We compared modeling with the neural network and with multiple regression analysis. Weekly learning data from January 1985 to September 1989 was used for modeling. Since the objectives of this test were comparison of learning capabilities and internal analysis of the network after learning, the network learned 100,000 iterations.

The hierarchical network that had five units of hidden layers learned the relationships between various

INVESTNG TOOL

## You *can* do this at home

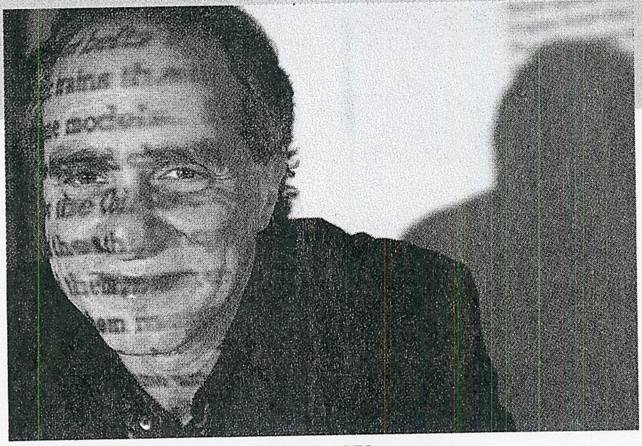
Artificial intelligence isn't just for elite Manhattan hedge-fund managers. Amateur investors can fashion their own AI war room. AIQ Systems ($99 for monthly subscription and real-time data) sells expert system software for picking individual stocks. Tradetrek.com offers a "Live Stock Commentary Engine" ($39.95 a month), which tracks fundamental and technical characteristics of stocks and then "writes" an analysis. And Ward Systems sells neural-network software ($1,045) that can be programmed for investing. Real-time data from a provider like eSignal or myTrack might cost you an additional $100 a month.

So it's not hard to see how you can easily spend a couple grand a year on this stuff. But that price tag can eliminate one advantage of do-it-yourself investing vs. mutual funds. That $2,000 means you would need to invest at least $147,000 to achieve an expense ratio equal to the average mutual fund's, about 1.4 percent. If you invest half that, your cost of doing business would double—and that comes right out of your return. And don't think expenses are irrelevant compared with the huge profits you will be making. "We're into risk management, not 600 percent returns," says Jim Ackles, president of LBS Capital Management in Clearwater, Fla., which manages $50 million ($25,000 minimum) using AI programs.

**Tools for change.** Most AI tools available to individuals are really geared to either full-time day-traders or people who invest as a hobby. But Andrew Lo, director of MIT's Laboratory for Financial Engineering, predicts AI tools will soon veer away from such a hands-on approach. "It will be like radio," he says. "Who builds their own radios anymore other than hobbyists?"

For individuals, Lo foresees AI systems that would monitor your portfolio and quietly rebalance it to maintain a desired asset allocation. Or how about "SmartIndexes," which would take into account all your myriad financial goals and alert you if your portfolio returns deviated from them. *–J.M.P.*

C. J. GUNTHER—SIPA



**Inventor Ray Kurzweil is a big fan of AI programs.**

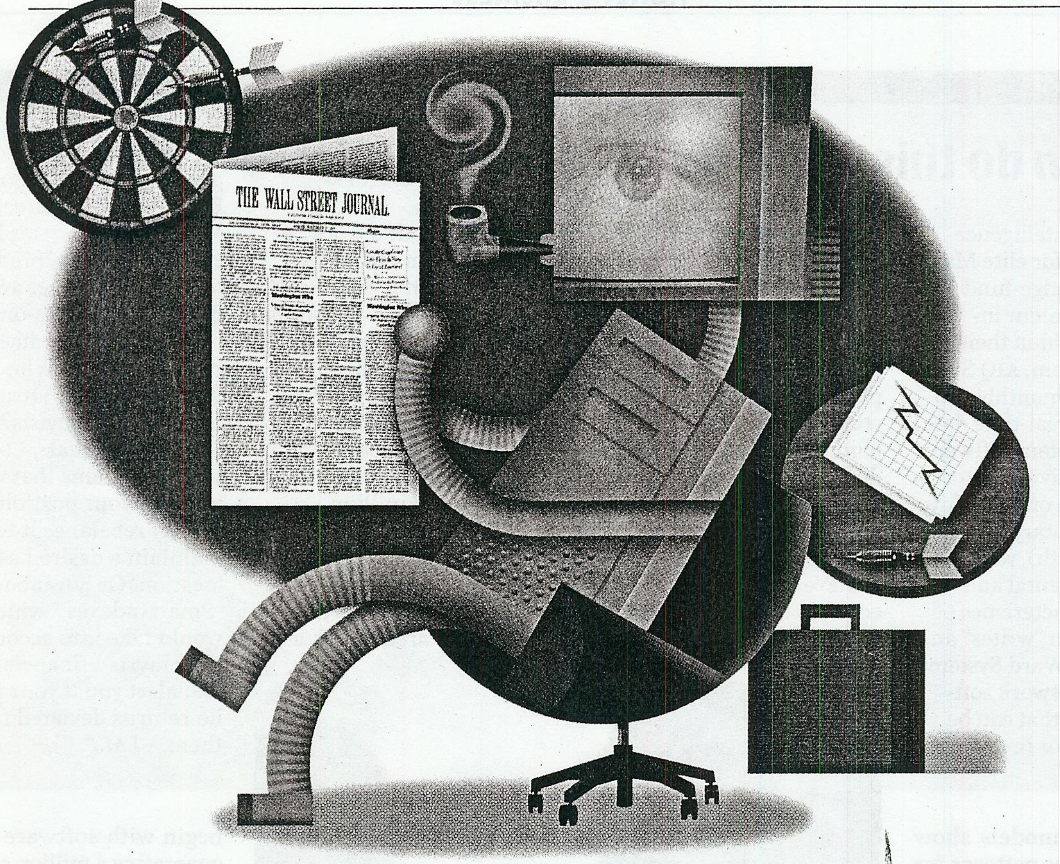
est rates), AIT's models show valuation and price patterns for the stock similar to those that have been bullish in the past. AIT's AllCap large-stock portfolio has beaten the overall market by an average of 3 percentage points a year since 1999. Those strong, though not otherworldly, results back up Case's cautionary contention that while AI is a formidable investing tool, "it's not some holy grail."

Still, the results can sometimes be astounding. Standard & Poor's uses a neural net to compile its Neural Fair Value 20 portfolio—available in its *Outlook* newsletter for $19.50 a month—which gained 29 percent last year, compared with a 13 percent loss for the S&P 500. The network constantly looks back six months to find the factors that seem to affect stock prices to predict the best performers over the next six months. Among the stocks in the portfolio are Computer Associates, PacifiCare Health Systems, and Tommy Hilfiger.

The VirtualHamilton presents a more tantalizing use of the technology. Why not also a VirtualBuffett or VirtualLynch? These digital doppelgängers might beat the originals by quantifying the unconscious intuition of these fabled investors. Just as an Ichiro Suzuki doesn't run trajectory and velocity calculations before catching a fly ball, many managers probably don't fully understand how they analyze stocks. Digitize a superstar manager's moves, and you might be able to hack his financial mind. "That's called reverse engineering," says Yale finance professor William Goetzmann. "And I suspect it is scaring some managers away from using a single broker who can view all of their trades." Using available information, Goetzmann himself has been attempting to reverse engineer the decisions made by managers of some unnamed mutual funds. "The idea being to see what makes managers trade, what signals they use, and if there is a magic formula," he says.

**Math whiz.** If there's a wild card in this investing arms race, it may be FatKat. The company may sound like a villain in a James Bond flick, but it's really a fledgling investment firm in Wellesley, Mass., founded by inventor and AI evangelist Ray Kurzweil. Although he's currently mum on FatKat, Kurzweil has written about the potential of mathematical formulas known as genetic algorithms to beat the market. The Darwinist process would begin with software randomly generating a million sets of rules for buying and selling stocks. Each set is a financial organism with the rules constituting its DNA. The ones that can't beat the market are killed, while the stock-savvy survivors mutate and breed until the population is back to a million. Rinse and repeat 100,000 times. "The surviving software creatures should be darn smart investors," he writes in *The Age of Spiritual Machines*.

How smart might AI programs get? By the year 2050, perhaps, investment software programs may be able to "come up with their own investment hypotheses, test them out, and implement them," says Andrew Lo, director of MIT's Laboratory for Financial Engineering. For now, though, humans still have a big role to play in the AI investment process. While the numbers are being crunched, the world keeps spinning and you need humans to keep track of it. At AIT, it takes all weekend to download data and update investment models. You also need humans to monitor the world for events that aren't reflected immediately in the data, such as terrorist attacks. And what happens if supersmart computers eventually get so good at the prediction game that all investors are made of silicon rather than carbon? Then the computers, as Kurzweil puts it, "will be trying to outpredict each other." ●




# Robotrading 101

Sophisticated computer programs take the human element out of picking winners on Wall Street

BY JAMES M. PETHOKOUKIS

William Peter Hamilton, former editor of the *Wall Street Journal*, was a market timer extraordinaire. Hamilton's investment instincts beat the market by nearly 3 percentage points a year between 1930 and 1997. There's just one hitch—Hamilton died in 1929. His results are real, but he is not—at least not any longer.

Those sparkling returns were produced by a VirtualHamilton neural network—a branch of artificial intelligence whereby software programs "learn" through trial and experience—created by a team from New York University and Yale. The real Hamilton ran the *Journal* in the early 1900s, but the academics mined his writings to replicate the pundit's mind. They then fed the VirtualHamilton seven decades of market data to see how it performed.

Techies joke that AI is a technology that is supposed to make real computers act as they do in movies such as *2001: A Space Odyssey* and last summer's *A.I.* Wall Street's AI can't yet match Hollywood's version of thinking, self-aware computers, but as much as $250 billion is currently being managed using sophisticated computer tools. These include neural nets, expert systems (investment acumen distilled into rules of thumb), and genetic algorithms (stock strategies digitally converted into cyberspace creatures that mutate and evolve like human DNA).

"We all have the same data, and the question is what the hell are we going to do with it," says Doug Case, chief investment officer at Advanced Investment Technology in Clearwater, Fla. Case sees AI as the key to decrypting high-velocity, information-saturated financial markets. "AI can deal with that data and handle these disorderly global markets," says Case, whose $1 billion firm is majority owned by State Street Global Advisors. There's even a chance that as AI filters down to amateur stock pickers (box, Page 24), the result may be warp-speed markets where using this technology will be a must. "In this escalating arms race, the humans with better information and more powerful AI tools will be able to fight the more competitive battle," says John Moody, a professor of computer science at the Oregon Graduate Institute and a hedge-fund manager.

**"Skunk Works."** At PanAgora Asset Management in Boston, researchers in the firm's advanced products division (nicknamed the "Skunk Works" as homage to the secretive Lockheed Martin unit that developed the Stealth fighter) have created a hedge fund where stocks are traded by a "virtual securities analyst." It uses an expert system to try to mimic human analysts by converting their smarts into a string of programmed if/then statements. (If a company's cash flow is less than the sector average, then the quality of that cash flow is low.) A summary of these statements then produces a buy/sell decision. "Real analysts think what they do is some sort of art, but it can really be reduced to rules," says Edgar Peters, the firm's chief investment officer. Why not just hire a real analyst? A human analyst can analyze only a small number of stocks. An AI analyst can cover them all—and without a fat expense account or million-dollar salary.

Neural networks function more like the human brain. They can compare existing stock-trading patterns with previous situations and eventually "learn" what works and what doesn't as the program digests more data. Unlike traditional financial models, neural nets capture interconnections among financial variables. At Case's AIT, neural nets search out linkages between stock performance and variables such as price momentum, free cash flow, and the state of the overall economy.

AIT's neural nets have discovered, for instance, that with some stocks, the price-earnings ratio is a key indicator of its future return during good economic times. But when the economy is slowing, the stock's price momentum becomes more critical. Gaming company Aztar is one of AIT's largest positions. With low inflation and a steepening yield curve (a widening gap between short- and long-term inter-

ILLUSTRATION BY GORDON STUDER FOR *USN&WR*

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# Predicting box-office success of motion pictures with neural networks

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## Abstract

Predicting box-office receipts of a particular motion picture has intrigued many scholars and industry leaders as a difficult and challenging problem. In this study, the use of neural networks in predicting the financial performance of a movie at the box-office before its theatrical release is explored. In our model, the forecasting problem is converted into a classification problem-rather than forecasting the point estimate of box-office receipts, a movie based on its box-office receipts in one of nine categories is classified, ranging from a 'flop' to a 'blockbuster.' Because our model is designed to predict the expected revenue range of a movie before its theatrical release, it can be used as a powerful decision aid by studios, distributors, and exhibitors. Our prediction results is presented using two performance measures: average percent success rate of classifying a movie's success exactly, or within one class of its actual performance. Comparison of our neural network to models proposed in the recent literature as well as other statistical techniques using a 10-fold cross validation methodology shows that the neural networks do a much better job of predicting in this setting.



*Keywords:* Forecasting; Prediction; Motion pictures; Box-office receipts; Neural networks; Logistic regression; CART; Sensitivity analysis

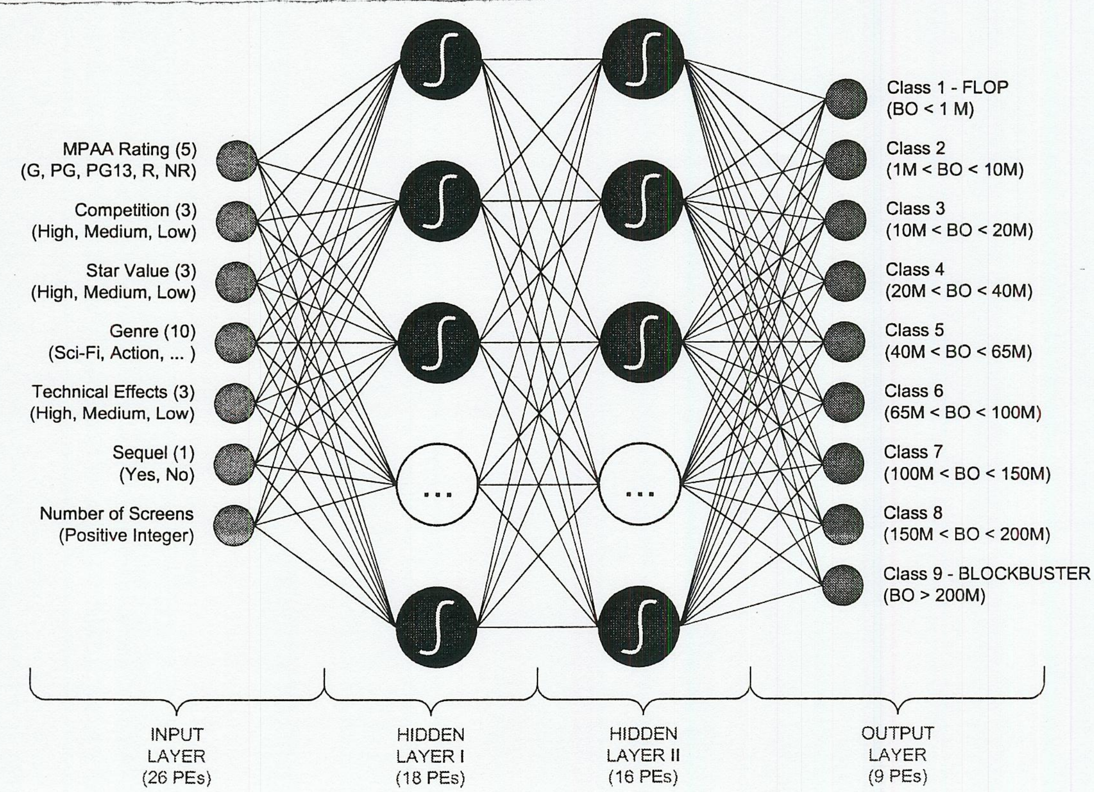


Fig. 2. Graphical representation of our MLP neural network model.

# A Neural Network for Tornado Prediction Based on Doppler Radar–Derived Attributes

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ABSTRACT

The National Severe Storms Laboratory's (NSSL) mesocyclone detection algorithm (MDA) is designed to search for patterns in Doppler velocity radar data that are associated with rotating updrafts in severe thunderstorms. These storm-scale circulations are typically precursors to tornados and severe weather in thunderstorms, yet not all circulations produce such phenomena.

A neural network has been designed to diagnose which circulations detected by the NSSL MDA yield tornados. The data used both for the training and the testing of the network are obtained from the NSSL MDA. In particular, 23 variables characterizing the circulations are selected to be used as the input nodes of a feed-forward neural network. The output of the network is chosen to be the existence/nonexistence of tornados, based on ground observations. It is shown that the network outperforms the rule-based algorithm existing in the MDA, as well as statistical techniques such as discriminant analysis and logistic regression. Additionally, a measure of confidence is provided in terms of probability functions.

ticular volume scan of radar data (the sampling rate of a radar volume scan is approximately 6 min) can be associated with a report of a tornado, hail greater than 1.9 cm in diameter, and/or winds in excess of 25 m s$^{-1}$. These three occurrences all classify a circulation as being "severe," and the occurrence of a tornado (either alone or in combination with other severe weather phenomena) renders the circulation "tornadic." If a circulation is detected within 20 min prior to a ground report of severe weather or a tornado or 5 min after a report, the circulation is classified as a "prediction" of severe weather or a tornado (depending on the ground report). The neural network is then trained to determine whether a circulation will produce a tornado within the next 20 min, a suitable "lead time" for advanced severe weather warnings by the NWS.

The particular NN program used in this study is a modified version of one obtained from Masters (1993). The original source codes, written in C++, were designed to be compiled and executed on DOS machines. For our purposes the source codes were modified to run in the UNIX environment. The modified version allows us to use a large number of nodes on each layer, as well as to view the network's weights. Usually the weights are uninterpretable due to the presence of hidden layers and the nonlinearity of the activation function. Even with no hidden layers, linear correlations in the input data (nodes) can render the weights uninterpretable. However, with proper care one can still gain nontrivial information from the weights (see the appendix).

Also, the statistical method of discriminant analysis (see the appendix) is performed to provide a comparison with the results of the NN. Logistic regression (i.e., NN with no hidden nodes—see the appendix) also provides for an additional comparison. The NN, discriminant analysis, and logistic regression will all be compared to the rule-based algorithm present in the MDA.

is included:

1) base (m),
2) depth (m),
3) "strength rank" (0–9),
4) low-altitude diameter (m),
5) maximum diameter (m),
6) height of maximum diameter (m),
7) low-altitude rotational velocity (m s$^{-1}$),
8) maximum rotational velocity (m s$^{-1}$),
9) height of maximum rotational velocity (m),
10) low-altitude shear (m s$^{-1}$ km$^{-1}$),
11) maximum shear (m s$^{-1}$ km$^{-1}$),
12) height of maximum shear (m),
13) low-altitude gate-to-gate velocity difference (m s$^{-1}$),
14) maximum gate-to-gate velocity difference (m s$^{-1}$),
15) height of maximum gate-to-gate velocity difference (m),
16) core base (m),
17) core depth (m),
18) age (s),
19) strength index (MSI) weighted by avg density of integrated layer,
20) strength index (MSIr) "rank,"
21) relative depth (%),
22) low-altitude convergence (m s$^{-1}$),
23) midaltitude convergence (m s$^{-1}$).

These attributes are all based on Doppler velocity data; the inclusion of reflectivity data and/or near-storm environmental (sounding) data is currently under consideration.

As mentioned above, the energy surface whose minimum is to be found is well known for being infested with local minima. For this study we employed simulated annealing (see the appendix), both for initiating a set of weights that could then be evolved according