SECONDARY MARKETING EXECUTIVE

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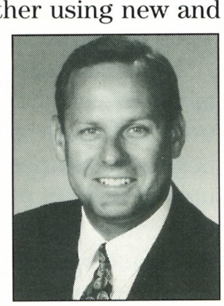
Turning On Neural Brain Network Tunes In Better Fallout Prediction

Through its technique of logic and learning, the neural network tool can chop mortgage pipeline prediction errors by 60% or more, this risk manager finds.

BY DEAN A. BROWN

Why bother with hedging? If a company's goal is to minimize risk and maximize gain on sale - that's why you pursue either. So why bother using new and better tools?



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Those tools may mean the difference between merely surviving and thriving.

Back in the dark ages of mortgage risk management, 10 to 15 years ago, the tools available to manage a mortgage pipeline were simplistic akin to a hammer and chisel.

An atypical secondary marketing executive might have had a 286 PC and Lotus 1-2-3 software if they were "high tech." With these tools, the manager would have manually entered and summed all of the locked loans, assigned a hedge ratio based on a regression analysis for each product type, and either used a Black-Sholes based option delta for the closing ratio or simply guessed what the probability of closing might be for the entire pipeline.

The tools available to the risk manager have progressed significantly since then for good reason:

- the mortgage market is 10 times more competitive today than it was back then,
- the financial markets are increasingly more volatile, and
- computer and software systems are much more sophisticated.

Collecting pipeline data

Let's focus on the difference in the way pipeline data can be collected.

Rather than rely on a manually entered locked loan listing, most firms have origination systems that feed data directly into the secondary marketing department's systems. Furthermore, most have a fairly sophisticated database tracking and data warehousing facility.

Hence, today no locks should be entered manually and most companies determine their expected closing ratios on a statistical basis. That is, they calculate historical closing ratios by source of business, by product type, processing status, mark-to-market, etc.

While this method is significantly better than the old methods, an even better technique has been developed using neural network technology.

An academically correct description of this new tool is:

A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs.

But a mortgage bankers' definition might be: "The equivalent to the most informed gut feel of the best secondary marketing executive with only a few loans to worry about."

This last definition is a play on words because even the most informed and best secondary manager cannot possibly keep up with a computer when it comes to calculating joint and matrix probabilities relating past experience with certain types of loans to current conditions.

Hence, a neural network employs the equivalent knowledge and experience used by a brain to determine an expected outcome.

For example, it automatically adjusts for source of loan and status data as discussed above and goes many steps further by developing a very sophisticated, effective, and easily generated fallout prediction by loan. Significant variables the

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model might employ include: LTV, loan amount, front and back ratios, loan type, status, time since original lock, and so on.

Works in layers

Unlike the iterative linear regression model that fits data to yield a least squared error representation of data, a neural network model captures interactions without upfront engineering.

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an activation function.

Patterns are presented to the network via the input layer, which communicates to one or more hidden layers where the actual processing is done via a system of weighted connections. The hidden layers then link to an output layer where the answer is output. Specifically:

- Input layers in the fallout model contain relevant data elements from the pipeline system that have been normalized for model input.
- Hidden layers contain the logic and learning area.
- The output layer contains the results of the analysis of the predicted fallout percentage.

Boosts secondary profits

The benefits of using neural network technology for fallout prediction are: increased profitability increased profitability, and increased profitability.

Enhanced profits arise from reduced hedging costs that are derived from significantly reduced fallout prediction error. The keys to unlocking the success of a neural network involve the method's ability to model data interactions, account for non-linearities, and provide a method that can produce accurate results quickly.

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In fact, our firm estimates that the neural network method can reduce fallout error by more than 60%, versus the weighted average method. It also delivers significant improvements over other techniques, depending on each firm's database integrity, types of business, and policies and procedures followed during the lock process.

An example...

The benefits of reduced fallout error prediction can be illustrated as follows:

Assume that your company has a $1 billion locked loan pipeline that is hedged employing a statistical bucketing method for forecasting fallout that generates an average 10% margin of error. This means that you are over- or under-hedging $100 million, given the degree of accuracy from the fallout analysis used.

Given this level of error, you would expect with perfect hedge construction and execution a correspondingly large gain on sale variance.

The expected gain on sale variance can be calculated using the following variables:

- the pipeline's weighted average price volatility,
- the weighted average time period each locked loan spends in the pipeline, and
- the margin of error calculated from your fallout analysis.

For example, if the weighted average annual price volatility is 6% and the average lock period in the pipeline is 60 days, the expected price volatility would be 1 point [(6%/12)*2].

Thus, a $100 million fallout forecast error multiplied by the -1.0 point expected price volatility equals a plus or minus $1 million expected gain on sale variance.

By comparison, employing the neural network to reduce your fallout prediction variance by 60%, the expected gain on sale volatility can be reduced accordingly to plus or minus $400 thousand, which is a $600 thousand reduction.

Note that a positive variance usually does not get noticed, or is attributed to trader performance, while negative variances are usually attributed to system problems. Hence, the true value of reducing your fallout forecast error by employing the neural network is the reduction of risk and the improvement of the hedging operation. Remember, a perfectly hedged position is one where neither unanticipated gains nor losses occur.

When the skillful application of neural network technology is employed, fallout prediction errors in the hedging risk equation can be significantly reduced. Thus, in conjunction with the other tools available today, your company can do more than simply survive - it can thrive. SME