Design Neural Network for Stock Market Volatility: Accuracy Measurement

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Abstract:

Artificial Neural Networks (ANNs) are very powerful tool in modern quantitative finance and have emerged as a powerful statistical modeling technology. This paper focuses on the problem of estimation of volatility of Indian Stock market. It begins with volatility calculation by Auto Regressive Conditional Heteroscedastic (ARCH), & Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models of financial computation. At last the accuracy of using Artificial Neural Network for it is examined and concluded that ANN can be used as a best choice for measuring the volatility of stock market.

Keywords: ARCH, GARCH, ANN

Introduction:

The main characteristic of any financial asset is its return. Return is typically considered to be a random variable. An asset’s volatility, which describes the spread of outcomes of this variable, plays an important role in numerous financial applications. Its primary usage is to estimate the value of market list. Volatility is also a key parameter for pricing evaluation. It is also used for risk management applications and in general portfolio management. This is crucial for financial institutions not only to know the current value of the volatility of managed assets, but also to be able to estimate their future values. Volatility measuring & forecasting is especially important for institution involved in options trading and portfolio management.

Different Mathematical Modeling Techniques are used by the researchers & practitioners to calculate it. But Artificial Neural Networks (or Neural Networks) are popular statistic techniques for machine learning. Originally, they were created as an attempt to model the biological neuron system. This attempt was made to create a new approach to the computing, and to possible mimic the behavior of human brain. This field of a science was created in a late 1950s, and was extensively developed in 1980s. Now a days ANNs techniques are used to calculate the value of volatility & forecasting for Stock Market.
Empirical Research on Volatility Modeling

Stock market analysis is an area of financial application. Detecting trends of stock market data is a difficult task as they have complex, nonlinear, dynamic and chaotic behavior.

More specifically, at first Mandelbrot [1963] observed that volatility of stock prices exhibits ‘clustering’, where periods of large returns are followed by period of small returns. Later popular models of volatility clustering were developed by Engle [1982] and Bollerslev [1986]. The autoregressive conditional heteroskedastic (ARCH) models Engle, [1982] and generalized ARCH (GARCH) models Bollerslev et al [1986] have been extensively used in capturing volatility clustering in financial time series data. The superiority of GARCH of models in volatility predictions over naïve models like historical average, moving average and exponentially weighted moving average (EWMA) has been confirmed in several empirical studies Akgiray [1989], West et al [1993]. GARCH models are claimed to work better under the conditions of such non-normality. Working with daily data from 1990-1998, Varma [1999, 2002] showed the superiority of the GARCH (1,1) model over EWMA model for predicting volatility. [Dev et al [2003], Karmakar [2005] and Kakati and Kakati [2006] also confirm the superiority of GARCH (1,1) model for volatility prediction. Banerjee and Sarkar [2006] claim that Indian stock market exhibits volatility clustering and hence GARCH type models can better predict the market volatility. The GARCH models are however subject to certain weaknesses (Brooks, 2002). One of the primary restrictions imposed by the GARCH models is that they enforce a symmetric response of positive and negative shocks. However, it has been reported that volatility in a falling market is more than volatility in a rising market. This asymmetry is typically attributed to leverage effect (Black, 1976, Christie, 1982). Empirical evidence on leverage effect can also be found in Nelson (1991), Gallant et al (1992), Campbell and Kyle (1993) and Engle and Ng (1993). Nelson (1991) also proposed an Exponential GARCH (EGARCH) framework to model volatility under the conditions of leverage or asymmetry. Many financial time series data possess the characteristics of persistence. IGARCH (Integrated GARCH) model proposed by Engle & Bollerslev (1986) has taken care of the current shock on the conditional volatility which does not die out asymptotically. Pandey (2005), on the other hand claimed that extreme value estimators perform better than the conditional volatility estimators.

But, White [1988] was the first who had used Neural Networks for forecasting stock market volatility. However, Ripley [1993] claims that although comparison of ANNs to other models are rare, however, when done carefully, often show that statistical methods can outperform the state-of the art ANNs. His paper includes a comment from Aharnian [1992] on ANNs as financial applications. Sarle [1994] concludes that ANNs will supersede statistical methodology as he believes that applied statistic is highly unlikely to be reduced to an automatic process or expert system. They were also successfully used for the

Volatility Estimation By Using ARCH ,GARCH Group & ANN Models

ARCH Model

The ARCH model was formulated by Robert F. Engle in 1982. The underlying principle of the model is that the variance of a dependent variable is expressed as a function of its own past value. The clustering of large moves and small moves of either sign in the price process was one of the first documented features of the volatility process of asset prices. Mandelbrot (1963) and Fama (1965) both reported evidence that large changes in the price of an asset are often followed by small changes. The principal implication of such volatility clustering is that volatility shock to-day will influence the volatility many periods in future.

Accordingly, conditional variance under ARCH(q) model is a linear combination of squared past errors of specified lag.

This is

\[ \sigma_i^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \]

\[ \alpha_i \geq 0 \]

\[ \alpha_0 > 0 \]

\( \sigma_i^2 \) = Conditional variance of return at time ‘t’ which depends on the squared disturbances at time lag of ‘ i’ where i varies from 1,2,3……..

\( \alpha_0 = \) Intercept

\( \alpha_i = \) Coefficient of the lagged squared error terms

\( u_{t-i}^2 = \) lagged lagged squared error terms

It is very difficult to decide the number of lags (q ) of the squared residual in the model. But the study has used lagged squared residuals up to three periods.

Other things being equal, the more the parameters in the conditional variance equations as stated above in equation , the more likely it is that one or more of them will have negative estimated value.

GARCH Model

ARCH model has the limitation with respect to the violation of non-negativity constraints. To overcome these limitation,GARCH model was developed independently by T. Bollerslev in 1986 and S. J. Taylor in 1987. They suggested that the conditional variance be specified through GARCH (q, p) model as

\[ \sigma_i^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i u_{t-i}^2) + \sum_{j=1}^{p} (\beta_j \sigma_{t-j}^2) \]

Where, \( \sigma_i^2 = \) conditional variance
With constraints

\[ \alpha_0 > 0; \alpha_i \geq 0, \text{ for } i=1,2,\ldots,q \]
\[ \beta_j \geq 0, \text{ for } j=1,2,\ldots,p \]

to ensure a positive conditional variance.

Thus, the volatility is expressed as a function of \( \alpha_0 \), a constant, \( u_{t-i}^2 \), news about volatility from the previous period \( t-i \) (the ARCH term) and \( \sigma_{t-j}^2 \), the previous period forecast variance (The GARCH term). The unconditional variance can be expressed under GARCH \((q, p)\) as

\[
\text{Var}(u_t) = \frac{\alpha_0}{1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j}
\]

Thus, for the unconditional variance to exist, the GARCH model requires a restriction on \( \alpha_i + \beta_i < 1 \) in case of GARCH(1,1)

If \( \sum \alpha_i + \sum \beta_i = 1 \), it is known as a ‘unit root invariance’ and is termed as Integrated GARCH.

If \( \sum \alpha_i + \sum \beta_i \geq 1 \), the unconditional variance of \( u_i \) is not defined and this would be termed as non-stationarity in variance.

Banarjee and Sarkar (2006) claim that the Indian stock market exhibits volatility clustering and hence, GARCH type of models can better predict the market volatility.

In the present study, GARCH \((1, 1)\), GARCH \((2, 2)\) and GARCH \((3, 3)\) are used to estimate the volatility of BSE SENSEX and NSE NIFTY.

**ANN model**

Neural Network learning methods provide a robust approach to approximating real-valued, discrete-valued and vector-value target functions. For certain types of problems, such as learning to interpret complex real-world sensor data, artificial neural networks (ANNs) are among the most effective learning methods currently known, Mitchell, [1997]. The study of ANNs has been inspired in part by the observation that biological learning systems are built of very complex webs of interconnected neurons. In rough analogy, ANNs are built out of a densely interconnected set of sample units, where each unit takes a number of real-valued inputs (possibly the outputs of other units) and produces a single real-valued output, which may become input to other units, Mitchell, [1997]. One motivation for ANN systems is to capture this kind of highly parallel computation based on distributed representations. Most ANN software runs on sequential machines emulating distributed processes, although faster versions of the algorithms have also been implemented on highly parallel machines and on specialized hardware designed specifically for ANN applications. Here we have used the Multilayer Perceptron Model (MLP) to calculate the volatility of stock market of India (BSE Sensex and NSE Nifty), Mantri et al.[2010]

**Comparison Analysis:**

Here we will go to present the ANN structure implemented for the Data (High, Low, Open & close indices of BSE SENSEX and NSE NIFTY) that resulted in
a minimum error. Also the results of ARCH(1), ARCH(2), ARCH(3), GARCH(1,1), GARCH(2,2), GARCH(3,3), and ANN models are described for comparison.

At first, the study has three different specifications such as ARCH (1), ARCH (2) and ARCH(3). The study does not go beyond the order three because of the parsimonious representation of higher order ARCH models. The order of the lag ‘q’ determines the length of time for which a shock persists in conditioning the variance of the subsequent errors.

Table-1 shows year-wise volatility calculation of BSE SENSEX and NSE NIFTY using ARCH models.

Table-2 shows, GARCH (1, 1), GARCH (2, 2) and GARCH (3, 3) are used to estimate the volatility of BSE SENSEX and NSE NIFTY year wise.

Table-3 shows the volatility under ANNs model calculated under multilayer perceptron (MLP) model and R-squared value of ANN and GARCH models.

Finally, it is concluded from table-1 and table-2 that in both the indices, time varying volatility is present. Also volatilities except 2009 and 2010 are nearly same for Sensex & Nifty by considering ARCH & GARCH models.

Table-3 shows the volatility under ANNs model calculated under multilayer perceptron (MLP) model and R-squared value of ANN and GARCH models.
Table 3

<table>
<thead>
<tr>
<th>Year</th>
<th>Sensex Volatility</th>
<th>Nifty Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MISO R-squared</td>
<td>GARCH R-squared</td>
</tr>
<tr>
<td>2006</td>
<td>1.256</td>
<td>0.9827</td>
</tr>
<tr>
<td>2007</td>
<td>1.479</td>
<td>0.9903</td>
</tr>
<tr>
<td>2008</td>
<td>2.510</td>
<td>0.9845</td>
</tr>
<tr>
<td>2009</td>
<td>2.217</td>
<td>0.9911</td>
</tr>
<tr>
<td>2010</td>
<td>1.015</td>
<td>0.9831</td>
</tr>
</tbody>
</table>

MISO: Multiple Inputs Single Output.

The Volatility under ANN model is less than that of the volatility from GARCH model. The GARCH model is symmetric in nature and therefore gives equal weightage to both positive and negative shocks while calculating volatility. For this above reason, volatility under GARCH model may not appropriately find a place in option valuation and portfolio selection models. It is the volatility under ANN model which may be used for option pricing and portfolio selection as it takes care of non-linearity in data by removing outliers and sentiments of the traders.

The graphical representation of the volatilities of SENSEX and NIFTY (Fig-1) using ARCH(1), ARCH(2), ARCH(3), GARCH(1,1), GARCH(2,2), GARCH(3,3), and ANN are shown below. It shows that except two years all the values nearly same for respective indices.

The R-squared value (in table 3) represents the proportion of variation in the dependent variable, that is explained by the independence variables. The better the model explains variation in the dependent variable, the higher the R-squared value. Without further comparison, the Neural network best explains variation in the dependent variable, followed by the GARCH model (the Regression...
Hence ANN model though differs from the model ranking due to R squared values as it performs better than other model.

**Conclusion:**

This research examined and analyzed the use of Artificial Neural Networks for calculating the volatilities of Indian stock market. We can conclude that ANNs has the capabilities to measure the volatilities more accurately than other mathematical models. For future research work, Fuzzy logic, Natural language processing, and Wavelet analysis, Pattern recognition can be used with ANN to calculate and forecast the volatility of Stock market.

**Reference:**


