Associating Financial Trading Volume Volatility and Information Volume based on Neural Network and Support Vector Machine

Nan Li, Xun Liang
Institute of Computer Science and Technology, Peking University, Beijing, China, 100871
{linan, liangxun@icst.pku.edu.cn}

Abstract

Within the stock markets, the trading volumes and the asset prices are considered to be highly changeable and unpredictable. However, effective forecasting of the way how they will change guarantees constructive advice for financial practitioners. There are various factors that may have an impact on the movements, one of which is the financial information. On the other hand, financial volatility, be it exhibited by the trading volume or the stock price, is regarded to hold its very importance within stock markets. In this paper, we attempt to employ two approaches to forecast the stock market volatility using the online financial information. Particularly, we delve into the associations between the trading volume volatility and the online financial information volume. GARCH theory is adopted in conjunction with artificial neural network and support vector machine to achieve modified non-linear GARCH-based mining models. Most importantly, financial information downloaded from the Internet is fed into the models as an exogenous input. Relying on these models, we conduct experiments onto the data collected from the US stock markets. As indicated by the comparative study based on the experimental results, while both approaches are eligible enough to obtain acceptable forecasting performances for the volatility, SVM outweighs ANN in this regard, whereas ANN is capable to achieve a more promising forecasting result for the volatility trend. In order to further qualitatively substantiate the impact online financial information has on financial volatility, a series of disturbance experiments are conducted under both the ANN and the SVM settings, whose results show that a noticeable correlation does exist between the aforementioned two.

Keywords: Financial information, GARCH, neural network, support vector machine, time series, trading volume, volatility.

1. Introduction

Within the stock market, due to its undeniable changeability at a fast speed, effectively forecasting the stock market movement has been considerably appealing. Meanwhile, it is also a difficult task to various financial practitioners. Besides, a typical term reflecting the movement serves to be the financial volatility, which is a required parameter for pricing different kinds of financial assets and derivatives. Additionally, it is well acknowledged that financial volatility implies financial risk. Therefore, an accurate prediction of financial volatility is of critical significance. Nonetheless, how to efficiently predict financial volatility has been one of the unsolved issues under investigation within the current literature. In this paper, we aim to establish a scalable and customizable mathematical model to realize this forecast to an acceptable extent.

One important step involved in this attempt is to find out those potential factors that may have an impact on the stock market movement. In this sense, some researchers have observed that financial information has become increasingly influential, especially in this new information era nowadays. People tend to investigate into whether there is an association between this and the financial volatility and whether this association will further help predict the latter. In fact, already-adopted exogenous inputs for forecasting financial volatility include consumable prices, interest rates, foreign exchange rates, etc. [1]. In this paper, we dig into the associations between the trading volume volatility and the financial information volume, relying on GARCH-based [2] mathematical mining models utilizing both artificial neural network (ANN) [3, 4, 5] and support vector machine (SVM) [6, 7] approaches. Once these associations have been captured and recorded using our models, we intend to further carry out forecasts for the volatility.

GARCH has been widely implemented into financial time series investigation [8]. Despite that several traditional time series models and statistical methods have been employed to forecast financial volatility, GARCH model comparatively outplays
these approaches in modeling financial time series because it is more capable of capturing features such as fat tail, volatility-clustering, asymmetry, time-varying variance, leverage effect, etc. Both ANN and SVM have been adopted in our approach as the self-learning predicting tools while a comparative study targeting at their forecast performances is subsequently carried out. Till now, ANN and SVM have been pervasively studied and implemented into financial forecasting applications [1, 5, 9, 10, 11, 12, 13]. Our approach is characteristic of applying these three methodologies together into the forecasting for the trading volume volatility.

Accordingly, we implement two forecast approaches, namely the ANN-based one and the SVM-based one, to forecast the trading volume volatility with the online financial information volume as one exogenous input. Empirical studies have firmly substantiated that the ANN-based model is capable enough to provide a satisfying prediction for the volatility trend and is scalable enough to be applied into different stocks or indices by appropriately modifying the parameters, while the SVM-based model outweighs the ANN counterpart in forecasting the volatility itself.

The rest part of this paper is organized as follows. Section 2 briefly explains the architecture of our overall approach, while section 3 details the underlying theoretical and mathematical bases. How to utilize the ANN and the SVM to implement a dynamic training and forecasting is presented in section 4 and empirical studies are covered in section 5. Section 6 concludes this paper.

2. Our Approach

Considering that the fluctuation of trading volume, just like that of the stock price, vividly reflects the market behavior, we probe into the associations between the trading volume volatility and the online information volume, aimed at forecasting the former. GARCH model is introduced as our theoretical basis. The primary reason for this preference is that GARCH is sufficient to capture the various effects exhibited by financial time series. Furthermore, GARCH model can be applied on any time series that has exhibited GARCH effects, as illustrated by [8]. In our approach, we have substantiated that both the daily changing rate of the financial trading volume and the online financial information volume time series exhibit GARCH effects.

Online financial information volume has been considered, in our approach, as an important element that affects the financial trading volume volatility. We carry out the forecasting for the volatility, partly relying on the online information, using an ANN-based approach and an SVM-based approach, respectively. Eventually, we conduct a comparison between these two to observe the different forecast performances. The basic architecture of our approach can be visualized in Fig. 1.

We download the online financial information from Google Finance (http://finance.google.com) as shown in Fig. 1, and thereafter post-process the data to acquire the daily information volumes for various stocks and indices. Table 1 below shows a snippet of the post-processing result, with each sub-row on top indicating the date and the one below the volume of the news.

Table 1: The information volumes calculated from Google Finance. N, D, M, I, A, G stand for NASDAQ, DOW, MSFT, INTC, AAPL and GOOG, respectively. 0629 stands for the 29th, June 2006.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>D</th>
<th>M</th>
<th>I</th>
<th>A</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>0629</td>
<td>0630</td>
<td>0703</td>
<td>0704</td>
<td>0705</td>
<td>0706</td>
<td>0707</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>4</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>0630</td>
<td>0703</td>
<td>0704</td>
<td>0705</td>
<td>0706</td>
<td>0707</td>
<td>0708</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>0628</td>
<td>0629</td>
<td>0630</td>
<td>0701</td>
<td>0703</td>
<td>0704</td>
<td>0705</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>8</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>0703</td>
<td>0705</td>
<td>0706</td>
<td>0707</td>
<td>0710</td>
<td>0711</td>
<td>0712</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>0630</td>
<td>0701</td>
<td>0703</td>
<td>0705</td>
<td>0706</td>
<td>0707</td>
<td>0710</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>1</td>
<td>4</td>
<td>3</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>0717</td>
<td>0718</td>
<td>0719</td>
<td>0720</td>
<td>0721</td>
<td>0724</td>
<td>0725</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>8</td>
<td>7</td>
<td>4</td>
</tr>
</tbody>
</table>

3. Volatility Model and Modified Non-linear GARCH Model

Financial time series exhibits specific features [9], which renders GARCH model a preferable alternative over the other counterparts. We assume that the volatility of financial trading volume shares similar characteristics as that of stock price, in the level of
exhibiting GARCH effects. Further proof is realized via the tools provided by MATLAB. It is demonstrated by Fig. 2 that the daily changing rates of the trading volumes of NASDAQ index within the period from Oct 11th, 1984 to Oct 16th, 2006 exhibits volatility-clustering feature. Besides, a Kurtosis value of 11.53 calculated from it also implies that there exists an underlying fat tail effect. In parallel, we’ve discovered obvious GARCH effects exhibited by online financial information volume time series as well, via tests conducted on more than 100 stocks in the U.S. stock markets.

![Fig. 2: Daily changing rates of the trading volumes of NASDAQ index within the period from Oct 11th, 1984 to Oct 16th, 2006.](image)

In this paper, we define the variance of the trading volume’s daily changing rates within a certain period as the volatility. For a specific stock or index, let $v_t$ denote its trading volume on day $t$, the daily changing rate $y_t$ of the trading volume is denoted as

$$ y_t = \ln \frac{v_t}{v_{t-1}}. $$

(1)

If $D$ is defined as the width of the calculating window, the volatility $\sigma^2_t$ can be calculated by computing the variance of the $y_t$ within the $(t-D+1)$th and the $t$th day as

$$ \sigma^2_t = \frac{1}{D-1} \sum_{i=0}^{D-1} (y_{t-i} - \mu_t)^2. $$

(2)

where

$$ \mu_t = \frac{\sum_{i=0}^{D-1} y_{t-i}}{D}. $$

(3)

The GARCH model, proposed by Bollerslev in 1986, can be formulated as

$$ y_t = \mu_t + \epsilon_t, $$

(4)

$$ \epsilon_t \mid \psi_{t-1} \sim N(0, \sigma^2_t), $$

(5)

$$ \sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon^2_{t-i} + \sum_{j=1}^{q} \beta_j \psi^2_{t-j}, $$

(6)

where $\alpha_0 > 0$, $\alpha_i, \beta_j \geq 0$, $y_t$ represents the daily stock return, $\psi_{t-j}$ represents the information set available at time $t$ and $\epsilon_t$ denotes the disturbance, also known as the shock, forecast error, residual, innovation, etc. [9, 14]. $\sigma^2_t$ serves as the time-varying variance of both $y_t$ and $\epsilon_t$. In our approach, we substitute $y_t$ with the daily changing rate of the trading volume.

GARCH model has indicated that $\epsilon_t$ is a function of those exogenous inputs, which somewhat affect the financial volatility. GARCH model bases its conditional distribution on the information set available at time $t$ and Freisleben and Ripper (1997) point out that the parameter $\beta_i$ in equation (6) describes the stock return’s immediate reaction to new events in the market, mostly in the form of financial news [9]. In the meanwhile, the fast development of Internet enables us to acquire the online financial information in a most real-time and exhaustive fashion. Considering these factors, to designate the financial information volume as one variate of $\epsilon_t$ is justifiable.

Therefore we formulize $\epsilon_t$ using the following two equations,

$$ \epsilon_t = y_t - \zeta, $$

(7)

$$ \epsilon_t = f_t(W_t, \epsilon'_t) = g_t(W_t') + \theta \epsilon' t, $$

(8)

where $\zeta$ is a constant and $W_t$ is the online financial information volume on day $t$. Consequently a modified GARCH model can be expressed as

$$ y_t = \mu_t + \epsilon_t, $$

(9)

$$ \epsilon_t \mid \psi_{t-1} \sim N(0, \sigma^2_t), $$

(10)

$$ \sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon^2_{t-i} + \sum_{j=1}^{q} \beta_j \psi^2_{t-j} + \sum_{k=1}^{r} \gamma_k (W^2_{t-k}), $$

(11)

where $p, q, r$ represent the three time lags, the three unknown functions, $\chi_{t-i}, \varphi_{t-j}$, and $\phi_{t-k}$ represent the undetermined non-linear correlations.

4. Non-linear Forecast Approaches based on ANN and SVM

4.1. ANN-based forecast approach
As shown in Fig. 3, the ANN adopted in our approach is a three-layer feed-forward neural network and $\sigma_i^2$ represents the forecast volatility on day $t$. The input elements $\sigma_{t-1}^2$ to $\sigma_{t-p}^2$ constitute the auto-regressive part of the model while the elements $y_{t-1}^2$ to $W_{t-r}^2$ represent the moving average part. The size of the input vector amounts to $p+q+r$, there are $H$ units in the hidden layer and the size of the output vector is 1. The training algorithms used in our approach consist of the Bayesian regularization back-propagation, BFGS quasi-Newton back-propagation [15] and the Levenberg-Marquardt back-propagation [16], with the former two able to effectively impede the over-fitting effect while the third characteristic of fast convergence.

![Fig. 3: The ANN architecture in our approach.](image)

4.2. SVM-based forecast approach

The SVM is based on statistical learning theory, and the training of SVM leads to a quadratic programming (QP) problem. Proposed by Vapnik [6], SVM has become a promising data mining technique to overcome problems such as over-fitting and local minimum while to provide high generalization [12, 13]. SVM has been vastly applied into various fields such as classification [12, 14, 17], regression [13, 18], image retrieval [19], text categorization [20], time series analysis [21], etc. It is worth mentioning that SVM has also been adopted by many researchers in the financial field to forecast financial time series [10].

In our paper, SVM has been employed to realize function approximation and regression estimation. We presume that there exists some unknown non-linear correlation between online financial information and trading volume volatility, and afterwards utilize the SVM to approximate this unknown correlation as shown in Fig. 4. The basic idea of regression SVM is to nonlinearly map the input training data via mapping function into a higher dimensional feature space and then a linear regression problem is obtained and solved in this feature space [6, 7].

![Fig. 4: The SVM architecture in our approach.](image)

4.3. Dynamic training approach

Since financial data is inherently characteristic of being noisy, stochastic and non-stationary [11], we adopt a special training process, namely a “dynamic” training process, in order to prevent over-fitting. This methodology is applied to both ANN-based and SVM-based approaches. If a training cycle refers to the training process for a specific ANN or SVM, then we select the data acquired within the closest period to the current time point as the training samples for each cycle as in [11]. Specifically, within one certain training cycle, if we want to forecast the volatility on day $t$, provided that the size of the training samples amounts to $C$, we first train an ANN or SVM via...
supervised predictions for the volatilities from day \( t-C \) to day \( t-1 \). Thereafter, forecast for the volatility on the day \( t \) is carried out using the trained ANN or SVM. In a nutshell, the dynamic training refers to an iterative process within which the forecasting for the volatility on a certain day always utilizes a newly-trained ANN or SVM trained by data attained in most immediate past.

To further demonstrate the dynamic training, let \( C \) denote the size of the training samples for one training cycle. In addition, we use a matrix tuple \(<P, T>\) to denote the training samples for one training cycle, thus we have

\[
P = \begin{bmatrix}
\sigma_{t-C-1}^2 & \sigma_{t-C}^2 & \sigma_{t-C+1}^2 & \ldots & \sigma_{t-2}^2 \\
\sigma_{t-C-2}^2 & \sigma_{t-C-1}^2 & \sigma_{t-C}^2 & \ldots & \sigma_{t-3}^2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\sigma_{t-C-p}^2 & \sigma_{t-C-p+1}^2 & \sigma_{t-C-p+2}^2 & \ldots & \sigma_{t-1-p}^2 \\
y_{t-C-1}^2 & y_{t-C}^2 & y_{t-C+1}^2 & \ldots & y_{t-2}^2 \\
y_{t-C-2}^2 & y_{t-C-1}^2 & y_{t-C}^2 & \ldots & y_{t-3}^2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
y_{t-C-q}^2 & y_{t-C-q+1}^2 & y_{t-C-q+2}^2 & \ldots & y_{t-q}^2 \\
W_{t-C-1}^2 & W_{t-C}^2 & W_{t-C+1}^2 & \ldots & W_{t-2}^2 \\
W_{t-C-2}^2 & W_{t-C-1}^2 & W_{t-C}^2 & \ldots & W_{t-3}^2 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
W_{t-C-r}^2 & W_{t-C-r+1}^2 & W_{t-C-r+2}^2 & \ldots & W_{t-r}^2 
\end{bmatrix}
\]

and

\[
T = \begin{bmatrix}
\sigma_{t-C}^2 & \sigma_{t-C+1}^2 & \sigma_{t-C+2}^2 & \ldots & \sigma_{t-1}^2 
\end{bmatrix}
\]

\[
(12)
\]

\[
(13)
\]

The trained ANN or SVM is then used to forecast the volatility on the day \( t \), which is referred as the testing process. Likewise, we denote the testing samples by another matrix tuple \(<P', T'>\) as

\[
P' = \begin{bmatrix}
\sigma_{t-1}^2 \\
\sigma_{t-2}^2 \\
\vdots \\
\sigma_{t-p}^2 \\
y_{t-1}^2 \\
y_{t-2}^2 \\
\vdots \\
y_{t-q}^2 \\
W_{t-1}^2 \\
W_{t-2}^2 \\
\vdots \\
W_{t-r}^2
\end{bmatrix},
\]

\[
T' = \begin{bmatrix}
\sigma_{t}^2 
\end{bmatrix},
\]

\[
(14)
\]

\[
(15)
\]

where \( T' \) stands for the real volatility on the day \( t \).

5. Empirical Studies and Discussions

5.1. ANN-based and SVM-based forecast approaches

We utilize both the ANN and SVM to carry out the forecast for the volatilities. In addition, we introduce a forecasting measure based on volatility-clustering to be benchmarked by these two approaches. The SVM toolbox adopted in this paper is the LS-SVMlab (http://www.esat.kuleuven.ac.be/sista/lssvmlab/). LS-SVM [18, 22], namely the least squares SVM, is a reformulation of the regular SVM. Besides, the kernel function selected in our approach is the RBF function. In [23], only 15 web-pages are downloaded from a constant set of news sources on the morning of the current day, whereas in our approach, we based our experiments on the financial information acquired from Google Finance (http://finance.google.com), which collects a comprehensive set of online financial information within the past three months from more than 500 financial portals online. Besides, historical trading data is gathered from Yahoo Finance (http://finance.yahoo.com). The widths of the calculating windows, namely the \( D \), in both phases are set to 20 days.

As has been mentioned previously, we employ a comparative measure using the volatility-clustering
feature (denoted as “benchmark” in Table 2), to be benchmarked by both the ANN-based and the SVM-based approaches. If we use $\sigma_i^2$ and $\hat{\sigma}_i^2$ to denote the actual and the forecast volatility on the day $t$, we are able to obtain

$$\hat{\sigma}_i^2 = \sigma_i^2.$$  \hspace{1cm} (16)

Similarly, if we let $\Delta \sigma_i^2$ and $\Delta \hat{\sigma_i^2}$ denote the actual and the forecast volatility trend on the day $t$, first we assume that

$$\Delta \sigma_i^2 = \begin{cases} 1, & \sigma_i^2 > \sigma_i^{t-1} \\ 0, & \sigma_i^2 = \sigma_i^{t-1} \\ -1, & \sigma_i^2 < \sigma_i^{t-1} \end{cases},$$ \hspace{1cm} (17)

and then we can also obtain

$$\Delta \hat{\sigma_i^2} = \Delta \hat{\sigma_i^2}.$$ \hspace{1cm} (18)

Two criteria to measure the forecasting performance have been employed, namely the average forecast error $\bar{e}$ and the volatility trend forecast accuracy ratio. If we define $e_i$ as the forecast error for the day $t$, we have

$$e_i = \frac{|\sigma_i^2 - \hat{\sigma_i^2}|}{\sigma_i^2},$$ \hspace{1cm} (19)

$$- \bar{e} = \frac{1}{t_1 - t_0 + 1} \sum_{r=t_0}^{t_1} e_i,$$ \hspace{1cm} (20)

where $t_0$ and $t_1$ represent the beginning and ending day for the forecasting. Besides, the ratio is defined as the percentage of the days on which the forecast volatility trend is equivalent to the real one.

We conduct our experiments on two indices, NASDAQ and DOW, and two stocks, MSFT and INTC, with the time span as from Jun 30th, 2006 to Sept 30th, 2006, from Jun 29th, 2006 to Sept 26th, 2006, from Jun 28th, 2006 to Sept 26th, 2006 and from Jul 3rd, 2006 to Sep 28th, 2006, respectively.

The optimal parameters for RBF in SVM, namely the regularization parameter gam and the bandwidth sig2, are set as sig2=50 and gam=10. The results of these experiments are shown in Table 2.

Table 2: The forecast results of ANN-based and SVM-based approaches. s/i stand for stock/index. N, D, M, I stand for NASDAQ, DOW, MSFT, INTC, respectively. C represents the size of the samples, H the number of the hidden nodes and p, q, r the 3 time lags.

<table>
<thead>
<tr>
<th>s/i</th>
<th>model</th>
<th>C</th>
<th>H</th>
<th>p</th>
<th>q</th>
<th>r</th>
<th>$\bar{e}$ (%)</th>
<th>ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>ANN</td>
<td>20</td>
<td>5</td>
<td>4</td>
<td>9</td>
<td>1</td>
<td>11.08</td>
<td>83.33</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>20</td>
<td>--</td>
<td>4</td>
<td>9</td>
<td>1</td>
<td>9.60</td>
<td>58.33</td>
</tr>
<tr>
<td></td>
<td>benchmark</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.32</td>
<td>30.77</td>
</tr>
<tr>
<td></td>
<td>ANN</td>
<td>10</td>
<td>5</td>
<td>5</td>
<td>8</td>
<td>2</td>
<td>9.33</td>
<td>73.91</td>
</tr>
</tbody>
</table>

5.2. Disturbance experiments

We further justify the correlation between online financial information volume and the financial trading volume volatility by conducting disturbance experiments on the well-trained ANN and SVM during the testing process. To accomplish this, we consecutively adjust each element of the input vector $[\sigma_{t-1}^2, ..., \sigma_{t-p}^2, y_{t-1}^2, ..., y_{t-q}^2, W_{t-1}^2, ..., W_{t-r}^2]$ from 75% to 125% of the original value, by a predetermined step-length, and thereafter observe and record the corresponding changing rate of the output incurred.

Let $\Delta_{t}^{i,j}$ denote the changing rate of the forecast volatility on day $t$ caused by adjusting the value of the $i$th element in the input vector by $j$ step-lengths, $\bar{\Delta_{t}^{i,j}}$ the average changing rate of the output caused by the above action within the day $t_0$ and the day $t_1$, and we have

$$\bar{\Delta_{t}^{i,j}} = \frac{1}{t_1 - t_0 + 1} \sum_{r=t_0}^{t_1} \Delta_{t}^{i,j},$$ \hspace{1cm} (21)

where

$$\Delta_{t}^{i,j} = \hat{\sigma}_{t}^{i,j} - \sigma_{t}^{i,j}.$$ \hspace{1cm} (22)
configuration as Table 3: The ANN-based disturbance experiment

table NASDAQ within the period elements. rows in grey indicate the changing rates of the input elements.

\[ \sigma_i^2 \] in (22) represents the changed forecast volatility when the \( i \)th element of the input vector has been modified by \( j \) step-lengths.

Table 3 demonstrates the values of \( \Delta_{i,j} \) we have acquired when conducting the ANN-based disturbance experiment on the index NASDAQ within the period from Jun 30th, 2006 to Sept 28th, 2006. The specific configurations regarding the parameters are \( p=3 \), \( q=6 \), \( r=4 \), \( C=12 \) and \( H=7 \).

Table 4: The SVM-based disturbance experiment results for the index NASDAQ within the period from Jun 30th, 2006 to Sept 28th, 2006 with the configuration as \( p=3 \), \( q=6 \), \( r=4 \) and \( C=12 \). The rows in grey indicate the changing rates of the input elements.

<table>
<thead>
<tr>
<th>( \sigma_i^2 )</th>
<th>0.75</th>
<th>0.80</th>
<th>0.85</th>
<th>0.90</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma_{i,1}^2 )</td>
<td>-0.05204</td>
<td>-0.03886</td>
<td>-0.02643</td>
<td>-0.01663</td>
<td>-0.00860</td>
</tr>
<tr>
<td>( \sigma_{i,2}^2 )</td>
<td>-0.01961</td>
<td>-0.01332</td>
<td>-0.00773</td>
<td>-0.00359</td>
<td>-0.00105</td>
</tr>
<tr>
<td>( \sigma_{i,3}^2 )</td>
<td>-0.03693</td>
<td>-0.02941</td>
<td>-0.02142</td>
<td>-0.01382</td>
<td>-0.00661</td>
</tr>
<tr>
<td>( \sigma_{i,4}^2 )</td>
<td>-0.00144</td>
<td>-0.00114</td>
<td>-0.00084</td>
<td>-0.00055</td>
<td>-0.00027</td>
</tr>
<tr>
<td>( \sigma_{i,5}^2 )</td>
<td>0.00320</td>
<td>0.00260</td>
<td>0.00198</td>
<td>0.00134</td>
<td>0.00068</td>
</tr>
<tr>
<td>( \sigma_{i,6}^2 )</td>
<td>-0.00123</td>
<td>-0.00100</td>
<td>-0.00077</td>
<td>-0.00052</td>
<td>-0.00027</td>
</tr>
<tr>
<td>( \sigma_{i,7}^2 )</td>
<td>0.00029</td>
<td>0.00018</td>
<td>0.00010</td>
<td>0.00005</td>
<td>0.00001</td>
</tr>
<tr>
<td>( \sigma_{i,8}^2 )</td>
<td>-0.00117</td>
<td>-0.00089</td>
<td>-0.00063</td>
<td>-0.00039</td>
<td>-0.00018</td>
</tr>
<tr>
<td>( \sigma_{i,9}^2 )</td>
<td>0.00040</td>
<td>0.00026</td>
<td>0.00015</td>
<td>0.00007</td>
<td>0.00002</td>
</tr>
<tr>
<td>( \sigma_{i,10}^2 )</td>
<td>-0.00369</td>
<td>-0.00305</td>
<td>-0.00236</td>
<td>-0.00162</td>
<td>-0.00083</td>
</tr>
<tr>
<td>( \sigma_{i,11}^2 )</td>
<td>-0.00256</td>
<td>-0.00202</td>
<td>-0.00149</td>
<td>-0.00098</td>
<td>-0.00049</td>
</tr>
<tr>
<td>( \sigma_{i,12}^2 )</td>
<td>0.00247</td>
<td>0.00194</td>
<td>0.00143</td>
<td>0.00094</td>
<td>0.00046</td>
</tr>
<tr>
<td>( \sigma_{i,13}^2 )</td>
<td>-0.00009</td>
<td>-0.00008</td>
<td>-0.00007</td>
<td>-0.00005</td>
<td>-0.00003</td>
</tr>
</tbody>
</table>

\[ \Delta_i \]

\[ t \]

\[ y \]

\[ \Delta_{i,j}^2 \]

\[ W_{i,1}^2 \] 0.00004 0.00008 0.00013 0.00018 0.00024

Table 4 demonstrates the values of \( \Delta_{i,j}^2 \) we have acquired when conducting the SVM-based disturbance experiment on the same index within the same period of time with the configurations \( p=3 \), \( q=6 \), \( r=4 \) and \( C=12 \).

Table 4: The SVM-based disturbance experiment results for the index NASDAQ within the period from Jun 30th, 2006 to Sept 28th, 2006 with the configuration as \( p=3 \), \( q=6 \), \( r=4 \) and \( C=12 \). The rows in grey indicate the changing rates of the input elements.

```
<table>
<thead>
<tr>
<th>( \sigma_i^2 )</th>
<th>0.75</th>
<th>0.80</th>
<th>0.85</th>
<th>0.90</th>
<th>0.95</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma_{i,1}^2 )</td>
<td>-0.04033</td>
<td>-0.03486</td>
<td>-0.02777</td>
<td>-0.01931</td>
<td>-0.00988</td>
</tr>
<tr>
<td>( \sigma_{i,2}^2 )</td>
<td>-0.01064</td>
<td>-0.00827</td>
<td>-0.00579</td>
<td>-0.00346</td>
<td>-0.00150</td>
</tr>
<tr>
<td>( \sigma_{i,3}^2 )</td>
<td>-0.02244</td>
<td>-0.01865</td>
<td>-0.01447</td>
<td>-0.00984</td>
<td>-0.00406</td>
</tr>
<tr>
<td>( \sigma_{i,4}^2 )</td>
<td>-0.00168</td>
<td>-0.00134</td>
<td>-0.00100</td>
<td>-0.00066</td>
<td>-0.00033</td>
</tr>
<tr>
<td>( \sigma_{i,5}^2 )</td>
<td>0.00158</td>
<td>0.00125</td>
<td>0.00092</td>
<td>0.00060</td>
<td>0.00030</td>
</tr>
<tr>
<td>( \sigma_{i,6}^2 )</td>
<td>-0.00082</td>
<td>-0.00068</td>
<td>-0.00052</td>
<td>-0.00036</td>
<td>-0.00018</td>
</tr>
<tr>
<td>( \sigma_{i,7}^2 )</td>
<td>-0.00005</td>
<td>-0.00006</td>
<td>-0.00006</td>
<td>-0.00005</td>
<td>-0.00003</td>
</tr>
<tr>
<td>( \sigma_{i,8}^2 )</td>
<td>-0.00036</td>
<td>-0.00032</td>
<td>-0.00026</td>
<td>-0.00019</td>
<td>-0.00010</td>
</tr>
<tr>
<td>( \sigma_{i,9}^2 )</td>
<td>-0.00057</td>
<td>-0.00047</td>
<td>-0.00036</td>
<td>-0.00024</td>
<td>-0.00012</td>
</tr>
<tr>
<td>( \sigma_{i,10}^2 )</td>
<td>-0.00225</td>
<td>-0.00183</td>
<td>-0.00139</td>
<td>-0.00094</td>
<td>-0.00047</td>
</tr>
<tr>
<td>( \sigma_{i,11}^2 )</td>
<td>-0.00223</td>
<td>-0.00179</td>
<td>-0.00135</td>
<td>-0.00090</td>
<td>-0.00045</td>
</tr>
<tr>
<td>( \sigma_{i,12}^2 )</td>
<td>-0.00021</td>
<td>-0.00018</td>
<td>-0.00015</td>
<td>-0.00011</td>
<td>-0.00006</td>
</tr>
<tr>
<td>( \sigma_{i,13}^2 )</td>
<td>-0.00161</td>
<td>-0.00131</td>
<td>-0.00100</td>
<td>-0.00068</td>
<td>-0.00034</td>
</tr>
</tbody>
</table>
```

\[ 2 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]

\[ 1 \]

\[ 0 \]
Results shown in Tab.3 and Tab.4 clearly demonstrate that online financial information (indicated by $w_{i-h}^2$) volume does have a certain influence on the output, which can be considered as of the same magnitude of significance as that of the other input factors.

### 5.3. Comparative study and discussions

According to the experiment results shown in Table 2, it is observable that both ANN-based and SVM-based forecast approaches are capable to forecast the trading volume volatility, under the setting that online financial information volume has been designated as one exogenous input while GARCH model serves as the theoretical basis. Basically, in forecasting the volatility itself, the SVM-based approach comparatively beats the ANN counterpart. This is primarily due to that SVM is characteristic of the use of kernels, the absence of local minima, the sparseness of the solution and the capacity control obtained by optimising the margin, which enables its better generality in overcoming over-fitting phenomenon. In addition, SVM is a preferable solution especially for small-scaled sample set, with our experiment as a case in point. Nonetheless, considering the forecast for volatility trend, ANN-based approach considerably outplays the other two.

Second of all, the disturbance experiments conducted on both approaches disclose the fact that online financial information does have an influence on the trading volume volatility, which can be considered as of the same magnitude as those caused by volatilities and daily changing rates within the immediate past. Therefore, our work firmly warrants the existence of the associations between online financial information and trading volume volatility.

We have also applied our models upon the stock price return time series. Empirical studies show that if we take online information volume as an exogenous input, the forecasting performance for the trading volume volatility considerably outplays that for the price return volatility. Therefore trading volume is more inclined to be affected by online financial information. In addition, we’ve found out that the larger the value of $D$ is, the smaller the average forecast error becomes, which further proves the volatility clustering feature of financial time series. Additionally, better forecast performance can be achieved if we square the moving average part of the input vector, which substantiates one of the GARCH theory’s conclusions that there is a significant correlation between the squared residuals of financial time series.

### 6. Conclusion and Future Work

In this paper, we have introduced GARCH-based mathematical models utilizing both ANN and SVM to investigate the correlations between financial trading volume volatility and online information volume to forecast the former. According to the experimental results, ANN-based approach is capable to achieve an acceptable forecasting performance for the volatility and an excellent one for the volatility trend compared to the other two methodologies and SVM-based approach outweighs ANN-based approach in forecasting the volatility itself. To some level, our research work effectively discloses and depicts the micro-structure of financial markets. Furthermore, the empirical studies in this paper are advisory and helpful for financial investors, portfolio holders, academicians, etc. in the sense that they provide an alternative tool to forecast the volatility and the trend thereof.

However, some future work is still considered to be necessary. First of all, the data set used in the empirical studies is somewhat inconsistent and small. A larger and more complete one is vastly expected for the next phase of our investigation. Second of all, how to combine the favorable features of both ANN and SVM in order to achieve the best results for both volatility and its trend forecast is regarded as the most important research target in the near future.

### 7. References


