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Integrating spectral clustering with wavelet based kernel partial least square regressions for financial modeling and forecasting

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ABSTRACT

Traditional forecasting models are not very effective in most financial time series. To address the problem, this study proposes a novel system for financial modeling and forecasting. In the first stage, wavelet analysis transforms the input space of raw data to a time-scale feature space suitable for financial modeling and forecasting. A spectral clustering algorithm is then used to partition the feature space into several disjointed regions according to their time series dynamics. In the second stage, multiple kernel partial least square regressors ideally suited to each partitioned region are constructed for final forecasting. The proposed model outperforms neural networks, SVMs, and traditional GARCH models, significantly reducing root-mean-squared forecasting errors.

1. Introduction

Stock index predictions are a challenging application of modern time series forecasting, essential for the success of many businesses and financial institutions. On the other hand, with the continued liberalization of cross-border cash flow, international financial markets have become increasingly interdependent. Investors are highly susceptible to exchange risk and fluctuations in equity prices throughout the world. Consequently, numerous techniques have been developed to provide investors with more precise forecasting models.

The tight correlations among financial markets provide investors with valuable information to make accurate forecasts regarding the co-movements of stock indices. However, international investors are a diverse group, operating on very different time scales. As a result, the correlation pattern between international market indices are not fixed between each time scale. The objective of this paper was to implement a new forecasting strategy capable of extracting key features of multiple financial markets to enable more accurate predictions.

Wavelet analysis is a powerful tool for the extraction of time series features from among various time scales. Wavelets are capable of localizing data in time-scale space. At high scales (shorter time intervals), the wavelets have a short time support making them well suited to focusing on short lived, strong transients like discontinuities, ruptures and singularities. At low scales (longer time intervals), the time support of wavelets time support is longer, making them suitable for identifying long periodic features. Additionally, wavelets characterize physical properties of data in an intuitive manner. At low scales, the wavelet characterizes the coarse structure of data; its long-run trend and pattern. By gradually increasing the scale, the wavelet begins revealing more and more of the details within data, zooming in on the behavior at a point in time.

Wavelet analysis is relatively new in economics and finance. Applications in these fields include the following studies: Ramsey and Zhang [33] analyzed foreign exchange data using waveform dictionaries; Davidson et al. [10] analyzed commodity price behavior using wavelet analysis; Ramsey and Lampart [34] used wavelet analysis to decompose economic relation-

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ships of expenditure and income; Pan and Wang [31] examined stock market inefficiency using wavelet analysis; Gençay et al. [13,15,16] used wavelet analysis to investigate scaling properties of foreign exchange volatility and systematic risk (the beta of an asset) in a capital asset pricing model. Recent applications of wavelet analysis in finance grow rapidly. The followings are some typical studies: In and Kim [20], Kim and In [24], Lee [26], Yamada [44], Mitra [27], and Mitra et al. [28].

For financial forecasting, Box and Jenkins' Auto-Regressive Integrated Moving Average (ARIMA) technique has been widely used for time series forecasting. However, ARIMA is a general univariate model based on the assumption that the time series being forecasted are linear and stationary. In recent years, neural networks (NN) have found useful applications in financial time series analysis and forecasting (e.g. [40,42,45,47,46,1]). In several applications, Tang and Fishwich [40], Jhee and Lee [21], Wang and Leu [42], Hill et al. [17], Kamruzzaman and Sarker [23] and many other researchers have shown that NNs perform better than ARIMA models, specifically, for more irregular series and for multiple-period-ahead forecasting.

Recently, the support vector machine (SVM) method (e.g., [41,7,38,19,18]), another form of neural networks, has been gaining popularity and has been generally regarded as a state-of-the-art technique for regression and classification applications. It is believed that the formulation of SVM embodies the structural risk minimization principle, thus combining excellent generalization properties with a sparse model representation. Despite these attractive features and the many good empirical results obtained using SVMs, data modeling participants have begun to realize that the ability of the SVM method to produce sparse models has perhaps been overstated. For example, it has been shown that the standard SVM technique is not always able to construct parsimonious models in system identification (e.g., Drezet and Harrison [11]).

Motivated by recent results in kernel-based learning and support vector machines, the nonlinear kernel-based partial least squares (KPLS) methodology was proposed by Rosipal and Trejo [37] and Rosipal [35]. In its general form, partial least square (PLS) methods [43,36] create score vectors (components, latent vectors) using existing covariances between input and output variables, while maintaining most of the variance of both data sets. PLS has proven useful in situations where the dimension of input variables is much greater than that of observations, or in situations where a high degree of multicollinearity exists among the input variables. This situation is also quite common in the case of kernel-based learning where the original data are mapped to a high-dimensional feature space with dimension much greater than the sample size.

Another problem in forecasting is that financial time series are usually non-stationary; namely, time series switch their dynamics between different regions. This leads to changes in the dependency structure between input and output variables. Consequently, it is difficult for a single predictor to capture such a switching input–output relationship. Inspired by the so-called "divide-and-conquer" principle that is often used to attack complex problems, the approaches of local modeling have emerged as one of the promising methods of time series prediction [30]. This study employed a spectral clustering algorithm [2,29] for partitioning the feature space into several disjointed regions for different time series dynamics. We then employed an architecture involving multiple experts to overcome the problem, namely, using different experts for different feature regions. Spectral clustering is outstanding at partitioning non-linearly separable problems of any data type. A detailed introduction to spectral clustering is provided in Chapter 3.2.

The major innovation of this paper lies in its combination of spectral clustering with wavelet-based kernel PLS regression for international stock index forecasting. In the first stage, wavelet analysis is used to transform the input space (raw data) to a time scale feature space suitable for financial forecasting, whereupon a spectral clustering algorithm is used to partition the feature space according to time series dynamics. In the second stage of the new method, multiple kernel PLS regressors that best fit partitioned regions are constructed for the final forecasting. Due to the high dimensionality of wavelet features in the first stage, a group of kernel PLS regressors were employed to create the most efficient subspace maintaining maximum covariance between wavelet features and the output in each regime, thereby accurately forecasting the movement of prices. The proposed model outperforms neural networks, SVMs, and traditional GARCH models by significantly reducing root-mean-squared forecasting error.

The remainder of the paper is organized as follows. Section 2 introduces prior research on stock index forecasting including the GARCH and pure SVM prediction model. Section 3 describes the new prediction model. Section 4 describes the data used in the study, and discusses the experimental findings. Conclusions are provided in Section 5.

2. Prior research

2.1. SVM models

The support vector machines (SVMs) were proposed by Vapnik [41]. Based on the structured risk minimization (SRM) principle, SVMs seek to minimize an upper bound of the generalization error instead of the empirical error as in other neural networks. The SVM regression function is formulated as follows:

$$t = \mathbf{w}^T\phi(\mathbf{x}) + b, \tag{1}$$

where $\phi(x)$ is called the feature. ϕ is a nonlinear mapping from the input space to the future space. The coefficients $\mathbf{w}$ and b are estimated by minimizing

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(r_i, t_i) + \frac{1}{2}\|\mathbf{w}\|^2, \tag{2}$$