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Multiple Kernel Learning for Stock Price Direction Prediction

Amit Kumar Sirohi, Pradeep Kumar Mahato, Dr. Vahida Attar
Department of Computer Engineering and IT
College of Engineering
Pune, India
sirohiaa12.comp@coep.ac.in

***Abstract*— Unstable and assumptive aspects of the securities makes it hard to predict the next day stock prices. There is no absolute indicator for financial forecasting but there are many technical indicators like simple moving average, exponential moving average, stochastic fast and slow, on balance volume for better accomplishment. It is important to have a significant and well-constructed set of features to elaborate stock trends. In this paper, we have proposed a Multiple Kernel Learning Model which predicts the daily trend of stock prices such as up or down, it comprises of 2-tier framework. In first tier, we extracted some technical indicators based on five raw elements- opening price, daily high price, daily low price, closing price and trading volume. In second tier, we built different base kernels on the extracted feature set and then combined these base kernels through Multiple Kernel learning, we have trained the model through walk forward method and predicted the movement of daily stock trend such as up or down, and then evaluated its performance. Experiment results shows that our proposed solution performs well consistently than baseline methods (Support Vector Machine) in terms of prediction accuracy for two commodities in stock market.**

Keywords- Multiple Kernel L*earning; Stock Price Prediction; *Time Series Data

I. INTRODUCTION

In financial market, stock market plays a vigilant role. From the perspective of Efficient Market Hypothesis [1], stock market is hard to predict, stock price at any given time gives large amount of previous public information up to that time. To solve this start the work by limiting the boundary of the problem to binary classification problem. During a period of last ten years, many researchers applied machine learning algorithms such as Neural Networks (NNs), Genetic Algorithm (GA),or Support Vector Machine(SVM) for prediction of financial values in the assets or stock market; e.g., from related work[2] SVM used to predict the prices for time series data and achieved better results. In past years, many researchers have applied a method to solve an issue for choosing appropriate kernels for distinct featured sets. It called as Multiple Kernel Learning (MKL) [3]. An advantage of MKL is that it gives us a flexibility to combine different type of kernels on distinct input features. Few researchers have used MKL for prediction of prices in stock or FX market; In [4] used MKL on limit order book for predicting and trading in the FX market; In [5] used text classification for predicting the abnormal returns from news by MKL; In [6] used MKL for the prediction of prices on the Taiwan stock market, results seems to be little good than some conventional methods.

Our contribution is here twofold. First we extract some technical features form historical stock data and trading volume. Second, we used a MKL framework to optimally combine different base kernels on featured sets. Due to fluctuations in stock market, we have made our model in such a way that it can accumulate to changes in stock prices .And for this we have used walk forward (window-shift) method for training and testing.

The rest of the paper is organized as follows. Section II describes the definition of MKL. Section III explains our proposed model. Section IV gives Experimental design. Section V describes some methods and performance metric. Section VI shows the results and analysis. Section VII gives conclusion and some future research directions.

II. MULTIPLE KERNEL LEARNING

It aims to construct a kernel model where fixed base kernels are combined linearly to build a kernel. The success of SVM depends on good kernel choices, which are hand crafted and prepared in advance. MKL kernels learn from training data. Usually for single kind of feature, a SVM is applied. But in our experiments, we use MKL to integrate various types of kernels. In the Multiple kernel learning frameworks, by manufacturing a weighted linear combination of M base kernels, the optimal kernel is learned. Combined Kernel is :

$$K_{comb}(x,y) = \sum_{j=1}^{K} \beta_j K_j(x,y) \qquad (1)$$

$$with\ \beta_j \geq 0, \quad \sum_{j=1}^{K} \beta_j = 1 \qquad (2)$$

Where weights β_j is used to combine different sub-kernels $K_j(x,y)$. Optimal weights can be evaluated by MKL from training data. We can get an optimal combined kernel by making a sub-kernel for each feature set and by evaluating weights using MKL and norms used in MKL to regularize kernel weights [8]. An accomplished algorithm of MKL classification was contended by Sonnenburg et al. [7] to evaluate optimal weights and SVM parameters concurrently by reoccurring training steps of a normal SVM. MKL library accommodated in SHOGUN toolbox were used in our experiments.

III. Proposed Model

The proposed model is made up of 3 components shown in figure 1.

A. Preprocessing Component:

In preprocessing component, firstly we collected the raw data from the market and processed it and then extracted some technical features or indicators based on the historical stock prices and trading volume and then we finally normalized the whole features set.

B. Prediction Component:

In Prediction Component , first we built different base kernels(RBF and Poly kernel)on normalized data set and then combined these base kernels through MKL and then set a norm to predict the movement of daily's stock trend such as up or down for the next trading day from the previous day.

C. Performance Component:

In Performance Component, we compute prediction accuracy to evaluate the performance of proposed and baseline methods.

IV. Experimental Design

A. Data Set

We collected the historical daily stock prices and trading volume from the market. We use a proprietary dataset for our experiments so not mention too much detail about it. Table1 refer experimental data.

TABLE I. EXPERIMENTAL DATA

	Number of rows
S Data	2734
N Data	2744

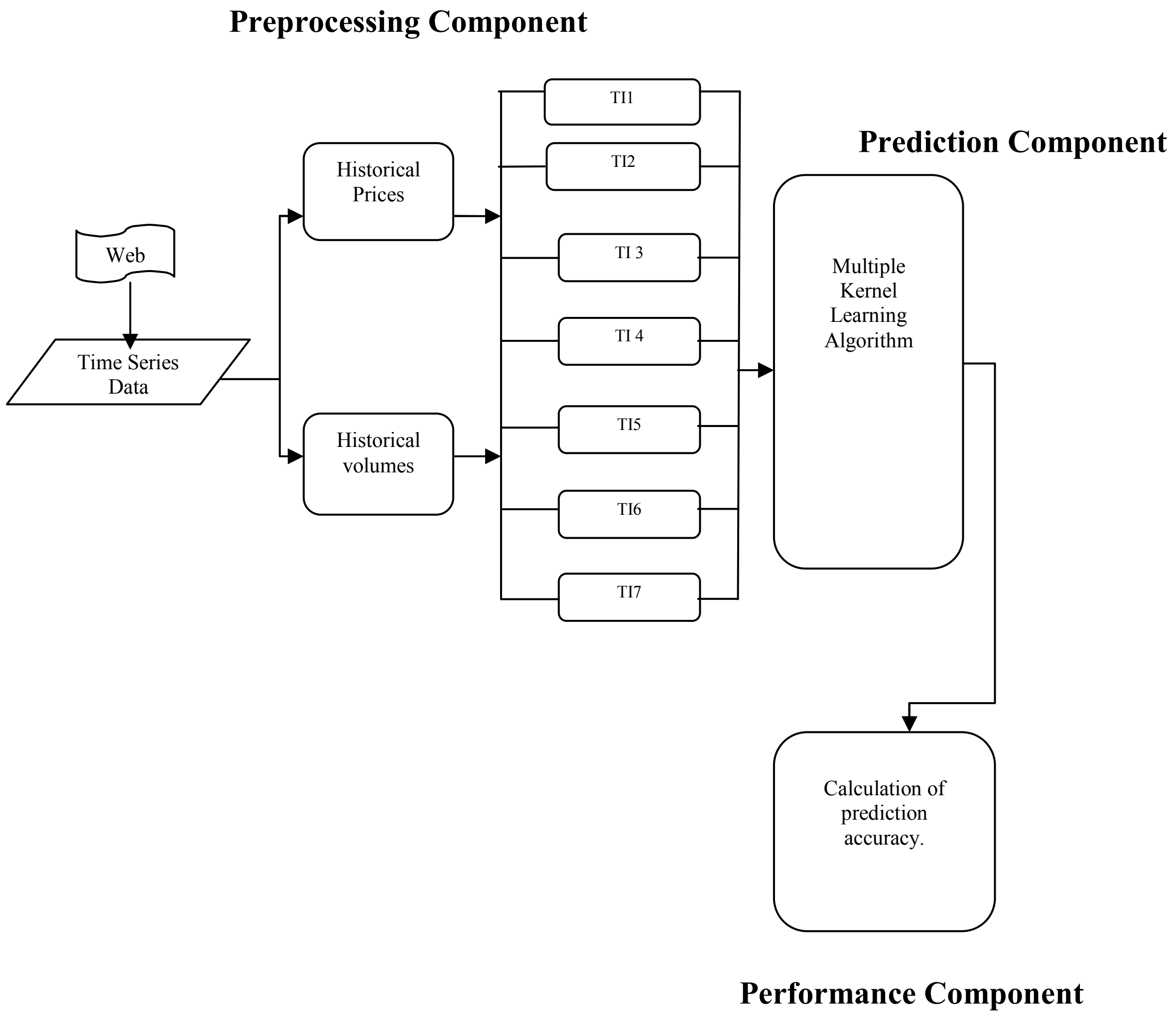

Fig. 1. Proposed Model

B. Input and Output

We have used raw data to calculate some of the technical indicators and used as a input to a model to predict the movement of daily stock trend. The features are extracted from historical stock price and trading volume. Our model prediction is one day ahead and the output is in the form of Binary classification.

C. Walk forward Method for Training and Testing

We used walk forward method for training and testing since underlying dynamics might change rapidly in stock markets. In Walk Forward method, we made a window of k rows, first we trained on k rows and then predicted next day stock price. It will show movement (up or down) from previous day stock price. Now, we moved the window 1 row ahead, we have taken the k rows again and trained again. In our experiment, for walk forward method we have used a window size 750 training rows and testing window of 1 row ahead., then we performed different MKL combination and ,computed their performance at different norms.

V. BASELINE METHODS AND EVALUATION METRIC

A. Baseline Methods

Table 2 shows the proposed and baseline methods. MKL-2 is our proposed method and SVM is a baseline method.

TABLE II. LIST OF METHODS FOR EXPERIMENTS

Abbreviations	Description
MKL-1	5 Gaussian Kernels with sigma 2.5, 5, 10, 20, 40
MKL-2	7 Gaussian kernels with sigma .25,1,2.5,4,10,16,20 and 3 poly kernels with degree 1,3,5
SVM	Support Vector Machine with default values.

B. Evaluation Metric

In Performance component of our proposed model, we have used an accuracy metric to evaluate the performance of our proposed and baseline methods. It computes from confusion matrix. In confusion matrix the predictions are obtained by the column and actual class by the row of the matrix. Diagonal represents correct predictions. Prediction Accuracy is used to evaluate the classifier.

VI. EXPERIMENTAL ANALYSIS

All experiments are conducted with Shogun 2.1 on a 2.4 GHZ Intel® Core ™2 Duo PC running Ubuntu 12.10with 4GB main memory. Figure3&4 shows the Prediction Accuracy of different methods over different norms with window size 750 in walk forward approach for each commodity. Table 3,4 & 5 shows the results. Rows represent the accuracy of methods and columns represent different norms.

Our experimental results shows that our proposed method , combining of different Base kernels(RBF and Poly kernel) through MKL framework achieves higher degree of accuracy and lower degree of false prediction than baseline method SVM for all stock data.

TABLE III. N DATA RESULTS

Norms	1	1.2	1.3	1.6
MKL-1	0.55309	0.557654	0.556064	0.553744
MKL-2	0.557462	0.563756	0.563705	0.564051

TABLE IV. S DATA RESULTS

Norms	1	1.2	1.3	1.6
MKL-1	0.554665	0.554907	0.555576	0.56052
MKL-2	0.596375	0.597714	0.596729	0.590762

TABLE V. SVM RESULTS

Metrics	N Data	S Data
Accuracy	0.510949	0.507101

Fig. 3: Accuracy results for S Data for Proposed and baseline methods

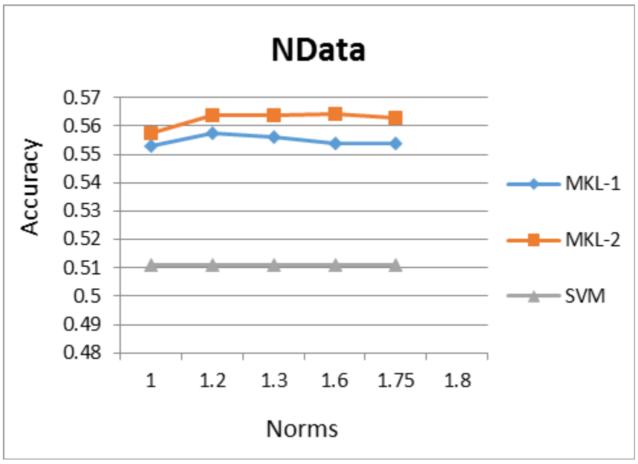

Fig. 4: Accuracy results for N Data for Proposed and baseline methods

VII. CONCLUSION AND- FUTURE WORK

We have presented a combination of different base kernels to market predictability analysis and prediction based on multiple kernel learning frameworks. We found that MKL gives better prediction as compared to single kernel function SVM when predicting daily stock direction with testing accuracy around 55-60%. Some of the future scope would be to implement the approach for parallel computing platform for training MKL which would help reduce the time required for the approach and integrate the sentimental analysis of the news contents with the historical prices of the stocks.

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