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Several novel evaluation measures for rank-based ensemble pruning with applications to time series prediction

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ABSTRACT

Ensemble pruning is a desirable and popular method to overcome the deficiency of high computational costs of traditional ensemble learning techniques. Among various of ensemble pruning methods, rank-based pruning is conceptually the simplest and possesses performance advantage. While four evaluation measures for rank-based ensemble pruning specifically for time series prediction are proposed by us in this paper. The first one, i.e. Complementarity measure for time series prediction (ComTSP), is properly modified from Complementarity measure (COM) for classification. The design idea of ComTSP is, if the error made by the subensemble for a pruning sample is larger than that by the candidate predictor to a certain extent, it is assumed that the predictor is complementary to the subensemble. And the predictor which minimizes the error rate of subensemble on the pruning set will be selected at each selection step. The second one, i.e. Concurrency thinning for time series prediction (ConTSP), is correctly transformed from Concurrency measure (CON) for classification. With ConTSP, a predictor is rewarded for obtaining a good performance, and rewarded more for obtaining a good performance when the subensemble performs badly. A predictor is penalized when both the subensemble and itself perform poorly. The measure ReTSP-Value is specifically designed for Reduce Error (RE) pruning for time series prediction. However, ReTSP-Value and ComTSP have the same flaw that, they could not guarantee the remaining predictor which supplements the subensemble the most will be selected. The cause of this flaw is that the predictive error in time series prediction is directional. It is not reasonable for these measures to take reducing error as the only goal while ignore the error direction. While our finally proposed measure ReTSP-Trend overcomes this defect, taking into consideration the trend of time series and the direction of forecasting error. It could indeed guarantee that the remaining predictor which supplements the subensemble the most will be selected. The comparison experiments on four benchmark financial time series datasets show that the measure ReTSP-Trend outperforms the other measures, which can remarkably improve the predictive ability and promote the generalization capability of the pruned ensembles for time series forecasting.

1. Introduction

Time series can be defined as a set of sequential observations, of a variable of interest, recorded over a predefined period of time. In general, time series involves a subject of research interest in various areas of knowledge such as: economy (stock prices, unemployment rate, and industrial production), epidemiology (rate of cases of an infectious diseases), medicine (electrocardiogram, and electroencephalogram), and meteorology (temperature, wind velocity and pluviometric precipitation) (Neto et al., 2009). Financial time series forecasting is one of the most active areas in time series prediction. A major challenge confronted with speculators, investors and businesses is how to accurately forecast price movements in financial and commodity markets (Abu-Mostafa & Atiya, 1996). While many factors might influence the trend of a stock market, including political events, general economic conditions, and trader's expectations (Abu-Mostafa & Atiya, 1996), and consequently, it is a challenging task to predict the stock market trend, due to its high volatility and noisy environment.

Motivated by that an ensemble of individual predictors usually performs better than a single predictor, lots of papers (Khashei & Bijari, 2012; Kim & Kim, 1997; Lai, Yu, Wang, & Wei, 2006; Qian & Rasheed, 2010) investigate the use of ensemble methods to improve financial time series forecasting performance. However

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an important shortcoming of ensemble methods is that, in many problems of practical interest, many constituent predictors are needed for the ensemble to achieve good generalization performance. While, obviously, large ensembles require more storage spaces and take longer to make predictions (Hernández-Lobato, Martínez-Muñoz, & Suárez, 2011).

Ensemble pruning is a competitive approach to alleviate the above problems of traditional ensemble methods. Moreover, there exists another benefit that, the generalization performance of the pruned ensemble may be even better than the original ensemble consisting of all the given individual learners. This approach has shown to be effective in classification and regression problems. It can achieve better performance than, or nearly the same level of performance as, the entire ensemble in these tasks (Banfield, Hall, Bowyer, & Kegelmeyer, 2005; Caruana et al., 2004; Margineantu & Dietterich, 1997; Martínez-Muñoz & Suárez, 2006; Martínez-Muñoz & Suárez, 2007; Martınez-Munoz & Suárez, 2004; Prodromidis & Stolfo, 2001; Zhou & Tang, 2003). However, there are few works studying the performance of ensemble pruning technique on time series forecasting problems. But it could be foreseen that the ensemble pruning technique could perform well on this task. As first of all, ensemble pruning technique could be used to enhance the robustness and accuracy of time series forecasting model. Second, time series forecasting is similar to regression problems, and according to the certification given by Zhou, Wu, and Tang (2002), it can be concluded that pruned ensemble could be better than the original entire ensemble in a regression task.

Ensemble pruning methods could be organized into four categories: rank-based methods, clustering-based methods, optimization-based methods and others which do not fall into any of the previous categories (Tsoumakas, Partalas, & Vlahavas, 2009). Among the four categories of ensemble pruning methods, rank-based methods are conceptually the simplest. They order the remaining models in the original ensemble according to an evaluation measure, and incorporate the model which ranks the first into the selected subensemble at each selection step, and this procedure will be executed iteratively until the size of subensemble reaches the expectation. The main issue among the methods of this category is the evaluation measure used for models ranking. In Partalas, Tsoumakas, Hatzikos, and Vlahavas (2008), the authors found that using just the best single model performs quite well and outperforms most of the ensemble pruning methods, apart from the pruning method using Root-Mean-Square-Error (RMSE) as the evaluation measure, when applied to water quality prediction in their work. It could be found that the measure RMSE used for ensemble pruning in time series prediction task has its design prototype in classification task. It corresponds to the Reduce-Error (RE) pruning measure used in classification task.

Inspired by this discovery, we propose four evaluation measures taken those for ensemble pruning in classification task as prototypes and apply them to financial time series forecasting task. Specifically, our proposed four evaluation measures are: Complementarity measure for time series prediction (ComTSP); Concurrency thinning for time series prediction (ConTSP); and ReTSP-Value and ReTSP-Trend for RE pruning for time series prediction (ReTSP).

As can be clearly identified, ComTSP is specifically modified for time series prediction task with its prototype being Complementarity measure (COM) for classification task. However, we modify the definition of COM appropriately according to the requirement of time series forecasting problems. If the error made by the subensemble for a specific pruning sample is larger than that by the candidate model for a certain degree, it is assumed that the candidate model is complementary to the subensemble. The candidate predictor which can minimize the error rate of subensemble on the selection dataset will be selected at each selection step. However, we found ComTSP has its inherent defect that it cannot guarantee the most complementary predictor will be selected.

And ConTSP is specifically modified from Concurrency (CON) measure in classification task for time series prediction task. A learner is rewarded for obtaining a good performance, and rewarded more for obtaining a good performance when the subensemble performs badly. A learner is penalized in the event both the subensemble and learner perform badly.

The RE pruning approach cannot be directly applied to time series prediction task, either. Since the way of estimating the predictive error is different in time series prediction task. Actually, there exists several error estimating criterions. Our proposed evaluation measure ReTSP-Value is similar to the evaluation measure Root Mean Square Error (RMSE), which has been used in Partalas et al. (2008). However, the predictive error in time series prediction task is directional. It is not very reasonable to only focus on decreasing the value of forecasting error while ignore its direction. This can be understood as a consideration to the diversity of ensemble, while the ensemble diversity here for time series prediction task is apparently different from that for classification task. The proposed measure ReTSP-Value also has the same defect as ComTSP that, it could not guarantee the remaining learner which supplements the subensemble the most will be selected. While our finally proposed measure ReTSP-Trend overcomes this defect, taking into consideration the direction of forecasting error. It could indeed guarantee that the remaining learner which supplements the subensemble the most will be selected into the subensemble at each selection step.

And another contribution of this work consists in, a smart time window size selection procedure is proposed based on ensemble learning paradigm. Moreover, we carry out investigation to study whether there exists great difference among different sizes of original homogenous ensembles with respect to their predicting performance after pruning. And the homogeneous models of the original ensemble are generated with support vector regression (SVR) learning algorithm.

Experimental results demonstrate that using the measure ReTSP-Trend to order the learners in the ensemble has powerful advantages over the other measures, which could significantly improve the predictive accuracy of the pruned ensembles for time series prediction task. And it is demonstrated through experiments that there did not exist any great differences among different sizes of the original ensemble with respect to their predictive performance after pruning.

The rest of this paper is organized as follows. Section 2 presents a theoretical analysis on ensemble pruning for time series forecasting task. The details of the four proposed measures for rank-based ensemble methods are presented in Section 3. Section 4 gives a presentation of the data-driven time window size selection procedure based on ensemble pruning methods. Section 5 takes a review of support vector regression (SVR) learning algorithm. Section 6 describes the setup of empirical study and Section 7 reports and discusses the experimental results. Finally, Section 8 summarizes this paper.

2. Theoretical analysis on ensemble pruning for time series forecasting task

If we consider an equidistant sampled time series $\{\alpha_v\}_{v=1,...,N}$, we can construct a m-dimensional state space vector γ_t in the form

$$\gamma_t = \left(\alpha_{(t-(m-1))}, \alpha_{(t-(m-2))}, \ldots, \alpha_t\right) \tag{1}$$

$$\hat{\alpha}_{(t+s)} = f(\gamma_t) \tag{2}$$