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AdaBoost-based long short-term memory ensemble learning approach for financial time series forecasting

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A hybrid ensemble learning approach is proposed for financial time series forecasting combining AdaBoost algorithm and long short-term memory (LSTM) network. First, LSTM predictor is trained using the training samples obtained by AdaBoost algorithm. Then, AdaBoost algorithm is applied to obtain the ensemble weights of each LSTM predictor. The forecasting results of all the LSTM predictors are combined using ensemble weights to generate our final results. Four major daily exchange rate datasets and two stock market index datasets are selected for model evaluation and model comparison. The empirical study demonstrates that the proposed AdaBoost-LSTM ensemble learning approach outperform other single forecasting models and other ensemble learning approach in terms of both level forecasting accuracy and directional forecasting accuracy. This suggests that the AdaBoost-LSTM ensemble learning approach is a highly promising for financial time rates forecasting.

Keywords: AdaBoost algorithm, ensemble learning, financial time series forecasting, long short-term memory network.

GLOBAL financial markets function in a complex and dynamic manner as high noisy data volatility is routine. Many factors impact the financial market, such as economic conditions, political events, and even traders' expectations. Hence, financial time series forecasting is usually regarded as one of the most challenging tasks among time series forecasting due to the high degrees of nonlinearity and irregularity. How to accurately forecast stock and exchange rate movement is still an open question with respect to the economic and social organization of modern society.

Many common econometric and statistical models have been applied to financial time series forecasting, such as linear regression models, autoregressive integrated moving average (ARIMA) models[1,2], co-integration models[3,4], generalized autoregressive conditional heteroscedasticity (GARCH) models[1,5], vector auto-regression (VAR) models[6,7] and error correction models (ECM)[4].

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Common forecasting models have failed to capture the nonlinearity and complexity of financial time series leading to poor forecasting accuracy. Therefore, exploring more effective forecasting models with high learning capacity is necessary for financial time series forecasting. Thus, nonlinear and more complex artificial intelligence methods are introduced for financial time series forecasting, such as artificial neural networks (ANN)[8–10], support vector regression (SVR)[11] and deep learning methods[12,13].

In recent years, deep learning methods have achieved state-of-the-art accuracy for many prediction tasks. A deep learning model automatically learns complex functions that map inputs to output. Therefore, some studies bring deep learning method into the domain of financial time series forecasting. Furao Shen[12] adopted an improved deep belief networks (DBN) by using continuous restricted Boltzmann machines for exchange rate forecasting. Sun[13] demonstrated that Stacked Denoising Auto-Encoders (SDAE) yields significant prediction power in stock market trend prediction[13].

However, the most widely used deep learning methods are convolutional neural networks (CNN) and recurrent neural network (RNN) while CNN is good at extracting position-invariant features. RNN is good at modelling sequence data. But neither have been no attempt used for financial time series forecasting. RNN is good at modelling sequence data and may be suitable for modelling financial time series with high nonlinearity and irregularity. Therefore, in this communication RNN is adopted to broaden the usage of deep learning methods in financial time series forecasting.

Though the nonlinear artificial intelligence methods have better forecasting performance than the common econometric and statistical models, they suffer from many shortcomings, such as parameter optimization and overfitting. Hence, many hybrid forecasting models with better forecasting performance were proposed for solving time series forecasting tasks[14–24].

Based on the above analysis, we found ANN to be the most common method for both single model forecasting and hybrid model forecasting which demonstrate that ANN are suitable for time series forecasting. Combining the advantages of different ANN may enhance the forecasting performance. Long short-term memory (LSTM) neural network is a kind of deep neural network, but it also possesses properties similar to RNN. Therefore, LSTM may be a better choice for financial time series forecasting. In addition, the above ensemble learning approach usually chooses AdaBoost to integrate different LSTM forecasters.

In this study, an AdaBoost-based LSTM ensemble learning approach is proposed for financial time series forecasting by combining AdaBoost ensemble algorithm and LSTM neural network. LSTM is considered as weak forecasters and AdaBoost is regarded as ensemble strategy. To the best of our knowledge, this is the first proposal of an AdaBoost-based LSTM ensemble learning approach for forecasting a financial time series.

The AdaBoost algorithm is a successful ensemble method proposed by Yoav Freund[25] which attempts to create a strong classifier from a number of weak classifiers. AdaBoost algorithm contains an iterative training process of weak classifiers and an ensemble process of weak classifiers. The steps of AdaBoost algorithm can be explained as follows: (i) Initialize the weight of each sample; (ii) update the weight of each sample according to the performance of the classifiers in previous iteration. If a sample is misclassified by the previous classifier, the weight of the sample will be increased which makes it more important in the next classifier; (iii) compute the ensemble weight of each weak classifier according to its performance. (iv) repeat step 2 until all the classifiers are obtained, and combine them according to ensemble weights.

LSTM network is a special kind of RNN[26]. It is capable of learning long-term dependencies which makes it suitable for time series forecasting problems.

LSTM includes input layer, hidden layer and output layer which is the same as traditional neural networks. But the hidden layer is different from other networks and more complicated. It contains four main parts, i.e. forget gate layer, input gate layer, cell state layer, and output gate layer. The main steps of hidden layer can be explained as follows: (i) Forget gate. The forget rate can be computed as

$$f_t = \sigma(w_f [h_{t-1}, x_t] + b_f), \tag{1}$$

where f_t is the forget rate, $\sigma(\cdot)$ the sigmoid activation function, h_{t-1} the output of last hidden layer, x_t the input of this hidden layer, w_f and b_f are the weights and bias of forget gate. (ii) Input gate. The input rate can be computed as

$$i_t = \sigma(w_i [h_{t-1}, x_t] + b_i), \tag{2}$$

where i_t is the forget rate, w_i and b_i are the weights and bias of input gate. (iii) Cell state layer. The cell state value can be computed as

$$\tilde{C}_t = \tanh(w_C [h_{t-1}, x_t] + b_C), \tag{3}$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t, \tag{4}$$

where $\tilde{C}_t$ is the candidate cell state value, $\tanh(\cdot)$ the tan h activation function, w_C and b_C are the weights and bias of cell state layer, C_{t-1} the cell state value of late hidden layer and C_t is the cell state value of this hidden layer. (iv) Output gate. The output rate and output of this hidden layer can be computed as

$$o_t = \sigma(w_o [h_{t-1}, x_t] + b_o), \tag{5}$$

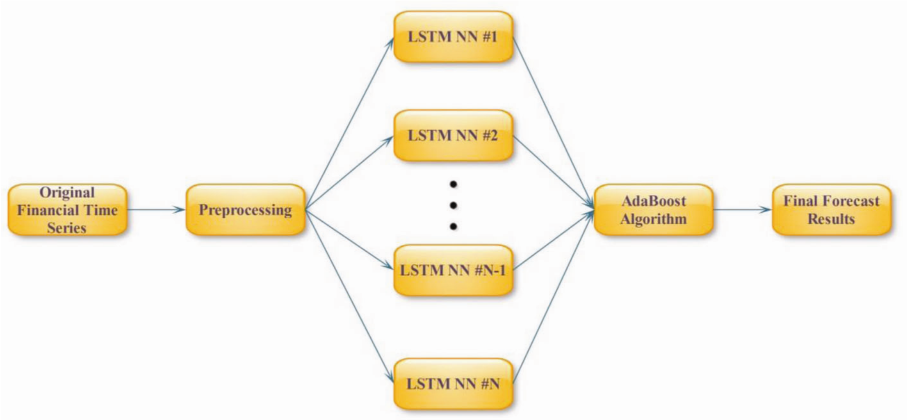

Figure 1. Flowchart of the AdaBoost-LSTM ensemble learning approach.

$$h_t = o_t \tan\mathrm{h}(C_t), \tag{6}$$

where o_t is the forget rate, w_o and b_o are the weights and bias of output gate and h_t is the output of this hidden layer.

For a time series $\{x_t\}_{t=1}^{T}$, the m-step is ahead of forecasting. Iterative forecasting strategy is implemented in this study, which can be expressed by

$$\hat{x}_{t+m} = f(x_t, x_{t-1}, \ldots, x_{t-(p-1)}), \tag{7}$$

where $\hat{x}$ is the forecast value, x_t the actual value in period t and p denotes the lag orders. In this study, the AdaBoost algorithm is introduced to combine a set of LSTM predictor which is a regression model[27]. An AdaBoost-LSTM ensemble learning approach is proposed for financial time series forecasting, and the flowchart is illustrated in Figure 1. The proposed AdaBoost-LSTM ensemble learning approach consists of six main steps as follows: (i) The sampling weights $\{D_n^t\}$ of training samples $\{x_t\}_{t=1}^{T}$ are calculated as

$$D_n^t = \frac{1}{N}, (n = 1,2,\ldots N; t = 1,2,\ldots,T), \tag{8}$$

where N is the number of LSTM predictors and T is the number of training samples. (ii) The LSTM predictor F_n is trained by the training samples which are sampled according to the weights D_n^t. (iii) The foresting error $\{e_n^t\}$ and ensemble weights $\{W_n\}$ of the LSTM predictor F_n are calculated as

$$e_n^t = \frac{|x_i - \hat{x}_i|}{x_i}, (n = 1,2,\ldots,N; t = 1,2,\ldots,T), \tag{9}$$

$$W_n = \frac{1}{2}\ln\left(\frac{1-\sum_{t=1}^{T} e_n^t}{\sum_{t=1}^{T} e_n^t}\right). \tag{10}$$

(iv) Update the sampling weights $\{D_{n+1}^t\}$ of the training samples $\{x_t\}_{t=1}^{T}$ as

$$D_{n+1}^t = \frac{D_n^t \beta_n^t}{\sum_{t=1}^{T} D_n^t \beta_n^t}, \tag{11}$$

where $\beta_n^t = \exp(e_n^t)$ is the update rate of training sample x_t. (v) Repeat the step ii–iv until all LSTM predictors are obtained. (vi) The forecasting results of all LSTM predictors are combined according to ensemble weights to generate a final forecasting result.

In this section on empirical studies, there are two main issues: (1) to evaluate the effectiveness of the proposed AdaBoost-LSTM ensemble learning approach for financial time series forecasting; and (2) to demonstrate the superiority of the proposed AdaBoost-LSTM ensemble learning approach in comparison with several other popular forecasting methods. To achieve these two tasks, four typical financial time series are adopted to test the proposed AdaBoost-LSTM learning approach.

The study data in this research comprises two typical stock indices (S&P 500 index and Shanghai composite index (SHCI)) and two main currency exchange rates (Euros versus US dollars (EURUSD) and US dollars versus Chinese yuan (USDCNY)). The historical data are collected daily from the wind database (http://www.wind.com.cn/), The datasets were then divided into in-sample subsets and out-of-sample subsets, as illustrated in Table 1. Table 2 shows the descriptive statistics of this data.

In order to evaluate the forecasting performance of the proposed AdaBoost-LSTM ensemble learning approach, mean absolute percentage error (MAPE) and directional symmetry (DS) were employed to evaluate the level forecasting accuracy and directional forecasting accuracy, respectively. MAPE is a measure of the deviation between the actual and forecasting values with smaller values indicating higher forecasting accuracy. DS is a measure of the performance in predicting the direction of

Table 1. In-sample and out-of-sample dataset of those exchange rates

Time series	Sample type	From	To	Sample size
S&P 500	In-sample	3 January 2011	30 June 2016	1383
	Out-of-sample	1 July 2016	30 June 2017	252
SHCI	In-sample	4 January 2011	30 June 2016	1334
	Out-of-sample	1 July 2016	30 June 2017	243
EUR/USD	In-sample	3 January 2011	30 June 2016	1434
	Out-of-sample	1 July 2016	30 June 2017	266
USD/CNY	In-sample	4 January 2011	30 June 2016	1332
	Out-of-sample	1 July 2016	30 June 2017	243

Table 2. Descriptive statistics of foreign exchange time series

Time series	Maximum	Minimum	Mean	Standard deviation	Skewness	Kurtosis
S&P 500	1099.2300	2453.4600	1778.4390	361.2504	–0.1252	1.7079
SHCI	1950.0100	5166.3500	2713.1580	611.2348	1.0975	4.3758
EURUSD	1.0388	1.4826	1.2447	0.1218	–0.1436	1.5706
USDCNY	6.0412	6.9557	6.3766	0.2345	0.8586	2.8220

value changes with higher values indicating better forecasting performance. MAPE and DS is defined as

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%, \tag{12}$$

$$\mathrm{DS} = \frac{1}{n-1}\sum_{i=2}^{n} d_i \times 100\%,$$

$$d_i = \begin{cases} 1 & \text{if} \quad (y_i - y_{i-1})(\hat{y}_i - y_{i-1}) \geq 0 \\ 0 & \text{otherwise} \end{cases}, \tag{13}$$

where $\hat{y}_i$ is the forecasting value, y_i the actual value, and n is the number of observation samples.

To evaluate the out-of-sample forecasting performance of the AdaBoost-LSTM learning approach, four single models including ARIMA, multi-layer perception neural networks (MLPNN), SVR, extreme learning machine (ELM), LSTM and three ensemble learning approaches including AdaBoost-MPLNN, AdaBoost-SVR, AdaBoost-ELM were implemented on four financial time series datasets for comparison.

In this study, it is worth noting that all approaches were implemented in Matlab computing environment. Autocorrelation function (ACF) and partial correlation function (PCF) were employed to determine the inputs of MLPNN, SVR, ELM and LSTM models, and trial-and-error testing was applied to determine the network structure of these AI models. The back-propagation algorithm was used to train the LSTM model. The learning rate, batch size and number of epochs are 0.05, 60 and 5000 respectively. The speed of convergence was controlled by the learning rate, which is a decreasing function of time. Setting the number of epochs and the learning rate to 5000 and 0.05 can achieve the convergence of the training.

The forecasting performances of single models and ensemble learning approaches are discussed in this section. Tables 3–6 show the comparison results of MAPE and DS evaluation criteria. The out-of-sample forecasting performance of the proposed AdaBoost-LSTM ensemble learning approach is better than that of the single forecasting models and other ensemble learning approaches, for the four financial time series data. This suggests that the proposed AdaBoost-LSTM ensemble learning approach is an effective tool to forecast financial time series rates.

As Tables 3–6 show, the proposed AdaBoost-LSTM ensemble learning approach significantly outperform all other benchmark models by level accuracy and directional accuracy for exchange rates forecasting. Overall, various ensemble learning approaches outperform the single models, while individual LSTM, ELM, SVR and MLP models consistently outperform ARIMA models in terms of MAPE and DS. Moreover, the proposed AdaBoost-LSTM ensemble learning approach produces 14.42–19.75% better directional forecasts than ARIMA models, reaching up to an accuracy rate of 76.54% in out-of-sample directional forecasting for the USD/CNY exchange rate series.

Some interesting findings can be summarized: (i) the proposed AdaBoost-LSTM outperforms all other benchmark models in different forecasting horizons, which implies that the AdaBoost-LSTM ensemble learning approach is a powerful learning approach for exchange rates forecasting in both level accuracy and directional

Table 3. Forecasting performance of different models for stock index

		S&P 500		SHCI	
	Models	MAPE (%)	DS (%)	MAPE (%)	DS (%)
Single forecasts	ARIMA	5.2473	53.5714	4.3652	57.6132
	MLPNN	3.4716	55.5556	1.9684	62.9630
	SVR	2.6158	57.1429	2.2156	61.7284
	ELM	2.0469	58.3333	1.8594	64.1975
	LSTM	1.9168	57.1428	1.1638	65.8436
Ensemble forecasts	AdaBoost-MLP	2.3633	60.3175	1.0269	66.6667
	AdaBoost-SVR	1.9859	65.0794	1.0124	65.8436
	AdaBoost-ELM	0.9044	69.0476	0.8169	68.7243
	AdaBoost-LSTM	0.8267	71.8254	0.4825	72.0164

Table 4. Forecasting performance of different models for exchange rates series

		EURUSD		USDCNY	
		MAPE (%)	DS (%)	MAPE (%)	DS (%)
Single forecasts	ARIMA	3.1463	57.8947	2.9584	56.7901
	MLPNN	2.1439	60.1504	2.0418	61.7384
	SVR	2.2417	63.1579	2.1036	64.6091
	ELM	2.0165	64.6617	1.5734	61.7284
	LSTM	1.8946	66.1654	1.2646	65.8436
Ensemble forecasts	AdaBoost-MLP	1.4364	72.5564	1.0464	69.1358
	AdaBoost-SVR	0.9695	71.8045	1.4471	73.2510
	AdaBoost-ELM	0.7912	73.6842	0.8838	72.8395
	AdaBoost-LSTM	0.4050	75.1880	0.3724	76.5432

Table 5. MAPE comparison with different ensemble forecasting approaches

		Number of forecasters				
	Ensemble models	$K = 10$	$K = 20$	$K = 30$	$K = 40$	$K = 50$
S&P 500	AdaBoost-MLP	2.3633	2.2687	2.2159	2.1987	2.2234
	AdaBoost-SVR	1.9859	1.9541	2.0126	2.0498	1.9743
	AdaBoost-ELM	0.9044	1.0238	0.9453	0.9268	0.9677
	AdaBoost-LSTM	0.8267	0.8957	0.8356	0.8943	0.8876
SHCI	AdaBoost-MLP	1.0269	1.0451	1.0147	1.1456	1.2136
	AdaBoost-SVR	1.0124	1.0245	0.9987	1.1223	1.0145
	AdaBoost-ELM	0.8169	0.8254	0.9131	1.0121	0.8345
	AdaBoost-LSTM	0.4825	0.4764	0.4901	0.5011	0.4918
EUR/USD	AdaBoost-MLP	1.4364	1.4269	1.3981	1.4457	1.5063
	AdaBoost-SVR	0.9695	1.0256	0.9785	1.0267	1.1246
	AdaBoost-ELM	0.7912	0.7846	0.8182	0.8049	0.8014
	AdaBoost-LSTM	0.4050	0.3778	0.3701	0.3786	0.4081
USD/CNY	AdaBoost-MLP	1.0464	1.4736	1.3629	1.2675	1.3516
	AdaBoost-SVR	1.4471	1.4359	1.4568	1.5026	1.4638
	AdaBoost-ELM	0.8838	0.9016	0.8957	0.9244	0.9016
	AdaBoost-LSTM	0.3724	0.3658	0.4193	0.5193	0.4084

accuracy; (ii) it clearly shows that the hybrid ensemble approach with AdaBoost is much better than the one without ensemble by means of level accuracy and directional accuracy, which reveals that AdaBoost is a more effective ensemble algorithm; (iii) the forecasting performance of hybrid ensemble learning approach is significantly better than single model. The possible reason is that the ensemble can dramatically improve the forecasting performance of single models.

This communication proposes an AdaBoost-LSTM ensemble learning approach which employs AdaBoost algorithm for ensemble forecasting and LSTM method for

Table 6. DS comparison with different ensemble forecasting approaches

		Number of forecasters				
		$K = 10$	$K = 20$	$K = 30$	$K = 40$	$K = 50$
S&P 500	AdaBoost-MLP	60.3175	60.7143	61.1111	59.9206	60.3175
	AdaBoost-SVR	65.0794	65.4762	64.6825	65.8730	66.2698
	AdaBoost-ELM	69.0476	69.8413	69.4444	68.6508	70.2381
	AdaBoost-LSTM	71.8254	72.2222	71.4286	72.6190	71.4286
SHCI	AdaBoost-MLP	66.6667	67.4897	67.0782	66.2551	67.9012
	AdaBoost-SVR	65.8436	67.0782	66.2551	67.4897	66.6667
	AdaBoost-ELM	68.7243	69.5473	69.1358	69.9588	68.3128
	AdaBoost-LSTM	72.0164	72.8395	72.4280	73.2510	73.6626
EUR/USD	AdaBoost-MLP	72.5564	73.6842	74.0602	73.3083	74.4361
	AdaBoost-SVR	71.8045	74.4361	74.8120	75.1880	73.6842
	AdaBoost-ELM	73.6842	75.5639	75.1880	75.9398	74.8120
	AdaBoost-LSTM	75.1880	78.1955	77.4436	77.8195	77.0677
USD/CNY	AdaBoost-MLP	69.1358	69.5473	68.3128	69.9588	67.9012
	AdaBoost-SVR	73.2510	72.8395	72.4280	72.0165	73.2510
	AdaBoost-ELM	72.8395	73.6626	73.2510	72.4280	72.8395
	AdaBoost-LSTM	76.5432	76.9547	76.1317	77.3663	75.7202

single forecasting. The proposed AdaBoost-LSTM ensemble learning approach is applied to forecast financial time series. For model evaluation and model comparison, four typical financial time series data are collected to test the model performance. The empirical results show that the proposed AdaBoost-LSTM ensemble learning approach can improve forecasting performance and outperform other single forecasting models and other ensemble learning approach in terms of both level and directional forecasting accuracy. This suggests that the AdaBoost-LSTM ensemble learning approach is promising for financial time series forecasting. Also, the proposed AdaBoost-LSTM ensemble learning approach can also be employed to solve other complex time series forecasting problems, such as crude oil price forecasting, wind speed forecasting, traffic flow forecasting, etc.

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