Forecasting Real Time Series Data using Deep Belief Net and Reinforcement Learning

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Abstract

Hinton's deep auto-encoder (DAE) with multiple restricted Boltzmann machines (RBMs) is trained by the unsupervised learning of RBMs and fine-tuned by the supervised learning with error-backpropagation (BP). Kuremoto et al. proposed a deep belief network (DBN) with RBMs as a time series predictor, and used the same training methods as DAE. Recently, Hirata et al. proposed to fine-tune the DBN with a reinforcement learning (RL) algorithm named "Stochastic Gradient Ascent (SGA)" proposed by Kimura & Kobayashi and showed the priority to the conventional training method by a benchmark time series data CATS. In this paper, DBN with SGA is invested its effectiveness for real time series data. Experiments using atmospheric CO2 concentration, sunspot number, and Darwin sea level pressures were reported.

Keywords: deep learning, restricted Boltzmann machine, stochastic gradient ascent, reinforcement learning, error-backpropagation

1. Introduction

Deep learning (DL) is the novel kernel technique of artificial intelligence (AI) developed rapidly in nowadays. As the training method of artificial neural networks (ANNs), in 2006, DL firstly is introduced by Hinton's deep auto-encoder (DAE) [1], which has multiple stacked restricted Boltzmann machines (RBMs). The learning process of DAE is divided into two phases: firstly, pretraining, which is a kind of unsupervised learning using the gradient of network energy of RBMs, and secondly fine-tuning using the supervised learning: error-backpropagation (BP) [2].

To deal with the adaptive behavior acquisition problem in unknown environment, reinforcement learning (RL), which is a kind of machine learning method adjusting is output by the rewards/punishment from the environment when a learner (system) changed its state by the policy of output, has been studied for decades [3] [4]. Recently, RL is also introduced into deep neural networks [5]-[7]. In [5], a deep Q-network (DQN) is proposed and applied to game (named ATARI) control and reached human level. In [6], a computer software named AlphaGo, using a deep neural network and RL, won the world champion of the game Go. In [7], we adopted a policy gradient RL algorithm [8] [9] into a deep belief net (DBN) proposed by Kuremoto et al. [10]-[13] instead of its fine-tuning method BP. And using a benchmark data CATS which is used by time series forecasting competition with ANNs [14] [15], the DBN with RL showed the highest prediction precision comparing to all conventional methods in the competition and the conventional DBN with BP learning [12] [13].

In this paper, we concentrate to investigate the effectiveness of the DBN with RL for real time series forecasting. Three kinds of real time series data which are weekly average of CO2 concentration in atmosphere at Hawaii, monthly average of sea level pressures at Darwin, the number of sunspot monthly provided by

Aalto University [16] were used in the forecasting experiments, and the prediction precision was compared to the conventional BP learning method. And as the results, DBN with RL showed the higher performance than the conventional DBN with BP in the process of fine-tuning of the network.

which are parameters of Gaussian distribution function used in the case of SGA learning method [4] [7].

2.2. *BP learning for DBN*

Let E is the mean squared error (MSE) between the output of DBN and the teacher signal, the weight of

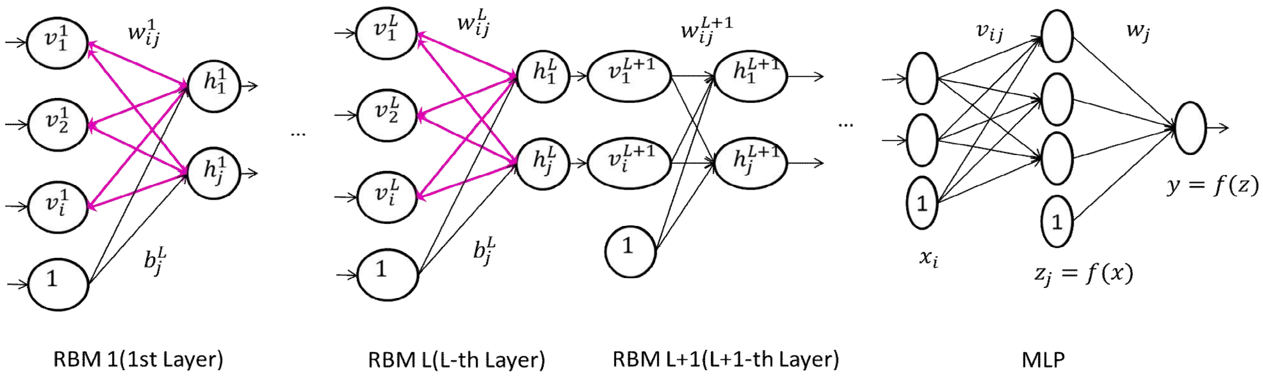

Fig.1. A structure of DBN composed by RBMs and a MLP

2. DBN with BP

In [10] [11], Kuremoto et al. firstly applied Hinton & Slakhutdinov's deep belief net (DBN) with restricted Boltzmann machines (RBMs) to the field of time series forecasting. In [12] and [13], Kuremoto, Hirata, et al. constructed a DBN with RBMs and a multi-layer perceptron (MLP) to improve the previous time series predictor with RBMs. In [7], Hirata et al. adopted a reinforcement learning named "stochastic gradient ascent" (SGA) [8] [9] into DBN instead of the BP learning used in the fine-tuning of the network. In this section, the structure of DBN and learning methods are introduced.

2.1. *DBN with RBMs and MLP*

As a neural predictor model, a DBN composed by multiple RBMs and a MLP is shown in Fig. 1 [7] [12] [13]. The visible layer of RBM 1 (1st Layer) are input with raw data of time series data (omitted in the figure). The hidden layer of RBM L+1 are used as the input layer of the MLP. The output of MLP is with one unit in the case of DBN using BP learning, and it has two units

connections w between layers of RBMs and MLP, and the bias of RBMs b are modified as following.

$$
\begin{aligned}
w_{ij}^{L\,new} &= w_{ij}^{L\,old} + \alpha \frac{\partial E}{\partial w_{ij}^{L\,old}} \\
&= w_{ij}^{L\,old} + \alpha \left(\sum_j \frac{\partial E}{\partial w_{ij}^{L+1\,old}} \cdot w_{ij}^{L+1\,old} \right) \cdot (1 - h_j^L) \cdot v_i^L \qquad (1)
\end{aligned}
$$

$$
\begin{aligned}
b_j^{L\,new} &= b_j^{L\,old} + \alpha \frac{\partial E}{\partial b_j^{L\,old}} \\
&= b_j^{L\,old} + \alpha \left(\sum_j \frac{\partial E}{\partial w_{ij}^{L+1\,old}} \cdot w_{ij}^{L+1\,old} \right) \cdot (1 - h_j^L) \qquad (2)
\end{aligned}
$$

where a is the learning rate.

2.3. *SGA learning for DBN*

The SGA algorithm and the learning rule for the weight of DBN's layers and parameters of the stochastic policy (Gaussian distribution function) were introduced in [7].

3. Prediction Experiments and Results

We predicted three types of natural phenomenon time series data given by Aalto University [16].

- CO2: Atmospheric CO2 from continuous air samples Weekly averages atmospheric CO2 concentration derived from continuous air samples, Hawaii, 2225 values

- Sea level pressures: Monthly values of the Darwin Sea Level Pressure series, 1882-1998, 1300 values
- Sunspot Number: Monthly averages of sunspot numbers from 1749 through the present, 3078 values

In Fig. 2 to Fig. 4, the one-ahead prediction results of DBN with BP and DBN with SGA were shown. In Table 1, the comparison of forecasting precision (MSE) of these different learning methods for DBN was given. The DBN with SGA showed its priority to the DBN with BP in all cases of real time series data. In Table 2, the number of samples and structures of different DBNs

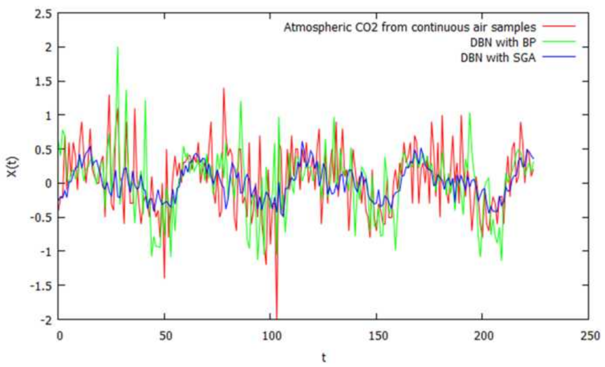

Fig.2. Prediction result of CO2 data

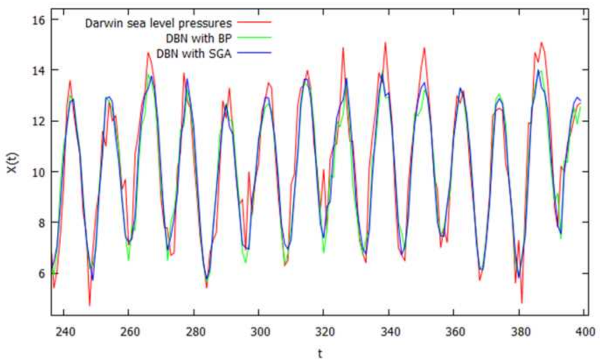

Fig.3. Prediction result of Sea level pressure data

Table.1. Prediction MSE of real time series data [16]

	DBN with BP	**DBN with SGA**
CO2	0.2671	**0.2047**
Sea level pressure	0.9902	**0.9003**
Sun spot number	733.51	**364.05**

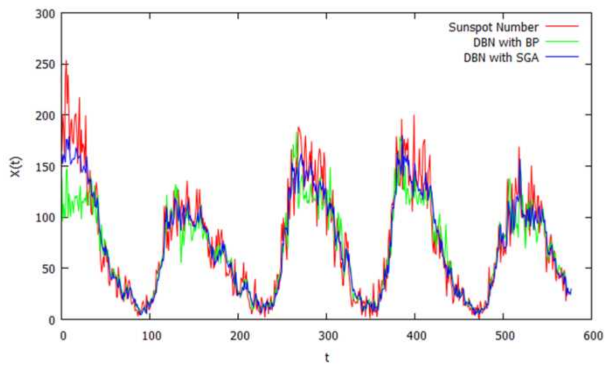

Fig.4. Prediction result of Sun spot number data

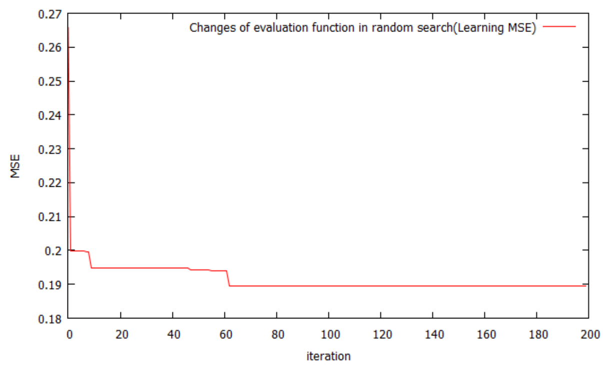

Fig.5. Changes of evaluation function in random search [17] (CO2, DBN with SGA)

were listed. To decide the number of RBMs, and the number of units on different layers of RBMs and MLP, random search (RS) [17] was used in the experiments. As an optimization method, RS used random values of parameter vector spaces to find the lower forecasting error (MSE). The change of evaluation function in the

Table.2. Sizes of time series data and structures of prediction networks

Series	Total size	Testing size	DBN with BP	DBN with SGA
CO2	2225	225	15-17-17-1	20-18-7-2
Sea level pressure	1400	400	16-18-18-1	16-20-8-7-2
Sun spot number	3078	578	20-20-17-18-1	19-19-20-10-2

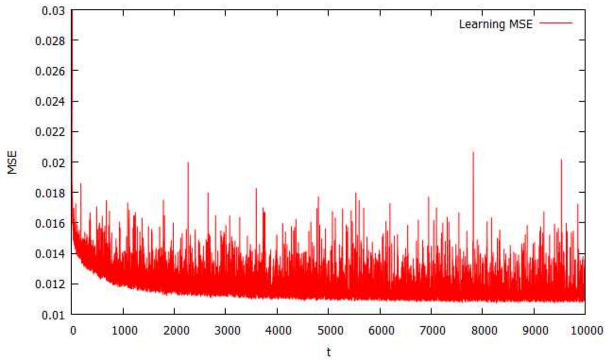

Fig.6. Changes in learning MSE (CO2, DBN with SGA)

case of DBN with SGA for CO2 forecasting is shown in Fig. 5 as a sample. In Fig. 6, the change of MSE in SGA learning process is shown. As a stochastic forecasting method of RL, the vibration of MSE needs to be reduced by tuning learning rates and rewards and we leave it as a future work.

4. Conclusion

In this paper, a reinforcement learning (RL) method "stochastic gradient ascent (SGA)" for fine-tuning of a deep belief net (DBN) with multiple restricted Boltzmann machines (RBMs) and a multi-layer perceptron (MLP) was compared to the conventional method error backpropagation (BP) in the case of real time series forecasting. Different to the supervised learning method which uses learning error exhaustively, RL a reward function which allows a range of errors between the output of the model and the teach signal and it may raise the forecasting precision for the real time series data.

Acknowledgements

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