Declarative vs. Procedural Memory: Roles in Second Language Acquisition

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Abstract

Memory is not a single faculty but is a combination of multiple distinct abilities (Schacter, 1987). The declarative-procedural distinction is used both with regard to knowledge and memory that stores this knowledge. Ellis (2008) used the terms explicit/implicit, and declarative/procedural interchangeably. In this article the researcher aims at identifying the different aspects of declarative/procedural memory, interaction between these two types of memory, and the role they may play in second language acquisition.

Keywords: Conscious memory, Declarative memory, Procedural memory

1. Introduction

According to Reber & Squire (1998) what distinguishes declarative (explicit) memory from non-declarative (implicit) memory is the point that declarative memory supports conscious memory of facts and events, and procedural memory supports a range of phenomena including habit learning, simple conditioning, and priming. As Squire (2007, as cited in Dornyei, 2009, p. 147) argued, declarative memory is representational, and what is learnt can be expressed through conscious recollection. "It involves the storage and retrieval of facts (e.g. semantic knowledge) and events (e.g. episodic knowledge)". It is the kind of memory used in everyday language.

According to Ullman (2004) an important feature of declarative memory system is that it enables us to learn very rapidly and flexibly, sometimes even based on a single stimulus presentation (i. e. a single exposure to the information to be learnt). In contrast, procedural memory is expressed through performance rather than conscious recollection. "It involves the storage and retrieval of sensori-motor and cognitive habits, skills, and other types of sequences, which can be as complex as playing an instrument or game". The unconscious memory system is related our experiences in interacting with the world, and it involves "gradual learning on a continuous basis during multiple representations of stimuli and responses" (Ullman, 2004).

Schumann (2004, as cited in Dornyei, 2009, p. 148) clarified an important aspect of procedural memory, and stated that procedural memory is "relatively inflexible and non-transferrable", that is, it is only available in contexts that are either identical or very similar to the original learning situation (e.g. the ability to play one string instrument cannot be transferred efficiently to playing another). However as Dornyei (2009, p. 148) stated this is compensated by the fact that procedural memory can be reserved much more than declarative memory in the elderly or in people with dementia which is an illness that affects the brain and memory, and makes you gradually lose the ability to think and behave normally.

2. Interaction between two memory systems in second language acquisition

Although, the two memory systems are largely autonomous, they may interact in a number of ways (McBride, 2007). For example, recent studies suggest that declarative knowledge may turn into procedural knowledge (proceduralization of declarative knowledge) and procedural (implicit) knowledge may be converted into declarative knowledge as a result of accumulating experience
Ullman (2001) also believed that the two systems are related to separate aspects of language. He argued that procedural memory is 'largely informationally encapsulated' and develops as a result of implicit, nonconscious processes of learning. It is specialized for sequences (i.e. linguistic chunks) and it has a rule system which includes "the representations of linguistic patterns extracted from input which has repeatedly stimulated the relevant neural circuits". It is associated with grammatical processing (both syntax and morphology) as this occurs in real time. He characterized the

declarative memory as 'an associative memory of distributed representations' which contains a mental lexicon, which is the sound and meanings of morphologically simple and complex words.

He illustrated this model with an example of the processing of morphological forms such as regular and irregular past-tense verb forms. He proposed that procedural memory is responsible for the computation of regular morphological features (for example, v-ed) by ordering the phonological forms of the base and an affix (for example, walk + ed = walked). In contrast declarative memory handles irregular forms.

According to Ellis (2008, p. 751) evidence for functional distinction of two memory systems come from studies of neurological injuries and neuroimaging studies. Dornyei (2009, p. 148) argued that "declarative memory is located in the medial temporal lobe, including the hippocampus, while procedural memory is usually associated a network of more diffuse brain structures placed in the frontal/basal-ganglia circuits".

As was referred earlier evidence for the differentiation between declarative and procedural memory systems comes from neurological impairment and neuroimaging studies. Ellis (2008) while referring to this issue stated that the nature of language loss in people with neurodegeneracy and neurodevelopmental disorders can be explained in terms of two separate systems, each with their own distinct functions. For example the implicit memory system is damaged in Parkinson's disease, and as a result grammatical processing deficiency would occur. The explicit memory system is damaged in Alzheimer's disease and Williams' Syndrome, which leads to difficulty in accessing lexical items. What is particularly strong evidence of the distinctiveness of the two systems is that damage to one system does not lead to loss of functions associated with the other system.

3. Conscious memory

The study of consciousness is often discussed in terms of intention and awareness. Memory researchers have also used these concepts to distinguish conscious and automatic memory forms of memory. According to McBride (2007) conscious memory processes involve either intentional retrieval of a previous episode, awareness of the retrieval of a previous episode, or both. An important goal of research on conscious and automatic memory in the past few decades has been the measurement of these processes in the retrieval of information. The distinction between intention and awareness has been important in the development of these measurement techniques. In some methods, subjects are asked to complete a task by intentionally retrieving a study episode (measuring conscious memory) or are asked to complete a task without intentional retrieval of a study episode (measuring automatic memory). In other methods, awareness that a study episode was previously experienced distinguishes conscious from automatic memory processes.

Sun et al. (2008) also confirmed this dichotomy and said that conscious memory (CM), involves intentional retrieval and self-awareness of memory, whereas unconscious memory (UM), which refers to the cognitive use of previous experiences without involving self-awareness of memory (Sun et al., 2008).

According to them a widely used method to illuminate CM and UM has been to compare differences in performance between explicit and implicit tests (i.e., the task-dissociation method). Explicit tests such as recall and recognition are assumed to tap CM. Implicit tests such as word-stem completion and word identification, in which participants are not instructed to make reference to studied words, are thought to reflect UM. It has been shown that the memories measured by the two types of test differ from each other in their sensitivity to experimental variables such as level-of-processing (LoP) and self-generation, which suggests that the two types of test measure different memory systems.

The human medial temporal lobe (MTL) system mediates memories that can be consciously recollected (Grunwald et al., 2003). However, the specific natures of the individual contributions of its various subregions to conscious memory processes remain vague. Grunwald et al. (2003) show a functional dissociation between the hippocampus proper and the parahippocampal region in conscious and unconscious memory as revealed by invasive recordings of limbic event-related brain potentials recorded during explicit and implicit word recognition: Only hippocampal and not parahippocampal neural activity exhibits sensitivity to the implicit versus explicit nature of the recognition memory task. Moreover, only within the hippocampus proper do the neural responses to repeated words differ not only from those to new words but also from each other as a function of recognition success. By contrast parahippocampal (rhinal) responses are sensitive to repetition independent of conscious recognition. These findings thus demonstrate that it is the hippocampus proper among the MTL structures that is specifically engaged during *conscious* memory processes.

4. Degree of availability of procedural memory to L2 learners

Procedural memory is less available to L2 learners: They have fewer items in their implicit linguistic competence than native speakers. (Paradis, 2009, p. 22). As predetermined in Paradis (2004, as cited in Paradis, 2009, p. 22), to the extent that there is a gap in their L2 implicit linguistic competence (the "rule" system), adult learners compensate by relying on their metalinguistic knowledge (concretely, if they cannot process the passive construction procedurally, they will consciously construct a passive sentence by applying the explicit rule they have learned); they therefore depend more than native speakers upon declarative memory.

According to him to the extent that a language has been internalized, its implicit grammatical competence is processed by procedural memory (and is available); to the extent that there are gaps in the implicit competence for one (or more) of the languages, the speaker will compensate for them by using explicit knowledge sustained by declarative memory (upon which the speaker is thus more dependent).

Procedural memory is not monolithic (Paradis, 2009, p. 24). There is procedural memory that sustains phonology, and procedural memory that sustains syntax, just as there is procedural memory dedicated to playing tennis and dedicated to playing the piano. Each procedural language module concerns a different set of objects, of a different nature, that engage a different type of implicit rule (procedures).

In addition, as Paradis (2009, p. 24) believed it is also the case that the availability of procedural memory for acquiring language as a whole decreases with age (though with different optimal periods for the development of various components: prosody, phonology, morphology, syntax, in that order).

5. There is no continuum from automatic to controlled processing

According to Paradis (2009, p. 26) there is no continuum between implicit competence and explicit knowledge, declarative memory and procedural memory, incidental acquisition and attentional learning, or automatic and controlled processing. Processing is either automatic or controlled. Controlled processing may be speeded-up but it remains qualitatively different from automatic processing. Conscious control may be involved in the deliberate decision to initiate an automatic process, but it is not involved in the processing itself (p. 26).

Paradis (2009, p. 26) argued that what may be considered as a continuum is the gradual replacement of the conscious use of metalinguistic knowledge by the automatic use of implicit linguistic competence. He provided the example that if you gradually replace meat by vegetable protein in your diet, meat does not become vegetable protein, and there is no continuum between meat and vegetables (except, possibly, phylogenetically over millions of years of evolution – but not in the context of the period and situation that concern us).

There is no continuum from automatic to controlled processing (i.e., no degrees of automaticity; a function is automatic or it is not); there is only a continuum ranging from predominant reliance on controlled processing to predominant reliance on automatic processing, or between the amount of controlled and automatic processing exerted on a particular function Paradis (2009, p. 26).

7. Concluding remarks

Studies of memory organization in non-human animals and humans have led to a consensus that memory is not a monolithic faculty, but rather is supported by multiple brain systems that differ in terms of the types of memory they mediate (Poldrack & Packard, 2003).

According to Cleerman (2003, as cited in Dornyei, 2009, p. 146) with the rapid development of cognitive neuroscience, many existing distinctions that were described in binary terms, such as the explicit-implicit or the declarative-procedural distinction, have been redefined in terms of graded characterizations. This is particularly applicable for declarative-procedural memory dichotomy. Since current memory frameworks identified more memory types, procedural memory has been replaced by 'non declarative memory', and procedural memory refers to only one constituent of declarative memory system. The exact number of different systems in the category of 'non declarative memory' has not been identified yet, but the main aspects referred to in literature which was mentioned by Dornyei (2009, p. 148), include for: (1) skills and habits (which is procedural memory in the narrow sense), (2) priming and perceptual learning, (3) classical conditioning, and (4) non-associative learning (i.e. behavioral change brought by repeated representation of one stimulus).

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Comparative study of Financial Time Series Prediction by Artificial Neural Network with Gradient Descent Learning

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Abstract

Financial forecasting is an example of a signal processing problem which is challenging due to Small sizes, high noise, non-stationarity, and non-linearity,but fast forecasting of stock market price is very important for strategic business planning.Present study is aimed to develop a comparative predictive model with Feedforward Multilayer Artificial Neural Network & Recurrent Time Delay Neural Network for the Financial Timeseries Prediction.This study is developed with the help of historical stockprice dataset made available by GoogleFinance.To develop this prediction model Backpropagation method with Gradient Descent learning has been implemented. Finally the Neural Net ,learned with said algorithm is found to be skillful predictor for non-stationary noisy Financial Timeseries.

Key Words: Financial Forecasting, Financial Timeseries Feedforward Multilayer Artificial Neural Network,Recurrent Timedelay Neural Network, Backpropagation, Gradient descent.

1. Introduction

Over past fifteen years, a view has emerged that computing based on models inspired by our understanding of the structure and function of the biological neural networks may hold the key to the success of solving intelligent tasks by machines like noisy time series prediction and more [1]. A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: Knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge[2]. Moreover, recently the Markets have become a more accessible investment tool, not only for strategic investors but for common people as well. Consequently they are not only related to macroeconomic parameters, but they influence everyday life in a more direct way. Therefore they constitute a mechanism which has important and direct social impacts. The characteristic that all Stock Markets have in common is the uncertainty, which is related with their short and long-term future state. This feature is undesirable for the investor but it is also unavoidable whenever the Stock Market is selected as the investment tool. The best that one can do is to try to reduce this uncertainty. Stock Market Prediction (or Forecasting) is one of the instruments in this process. We cannot exactly predict what will happen tomorrow, but from previous experiences we can roughly predict tomorrow. In this paper this knowledge based approach is taken.

The accuracy of the predictive system which is made by ANN can be tuned with help of different network architectures. Network is consists of input layer ,hidden layer & output layer of neuron, no of neurons per layer can be configured according to the needed result accuracy & throughput,there is no cut & bound rule for that.the network can be trained by using sample training data set,this neural network model is very much useful for mapping unknown functional dependencies between different input & output tuples.In this paper two types of neural network architecture,feed forward multilayer network & timedelay recurrent network is used for the prediction of the NASDAQ stock price.A comparative error study for both network architecture is introduced in this paper.

In this paper gradient descent backpropagation learning algorithm is used for supervised training of both network architectures. The back propagation algorithm was developed by Paul Werbos in 1974 and it is rediscovered independently by Rumelhart and Parker. In backpropagation learning atfirst the network weight is selected as random small value then the network output is calculated & it is compared with the desired output,difference between them is defined by error .The goal of efficient network training is to minimize this error by monotonically tuning the network weights by using gradient descent method.To compute the gradient of error surface it takes mathematical tools & it is a iterative process.

ANN is a powerful tool widely used in soft-computing techniques for forecasting stock price.The first stock forecasting approach was taken by White,1988 ,he used IBM daily stock price to predict the future stock value[3].When developing predictive model for forecasting Tokyo stock market, Kimoto, Asakawa, Yoda, and Takeoka 1990 have reported onthe effectiveness of alternative learning algorithms and prediction methods using ANN[4]. Chiang, Urban, and Baldridge 1996 have used ANN to forecast the end-of-year net asset value of mutual funds[5]. Trafalis (1999) used feed-forward ANN to forecast the change in the S&P(500) index. In that model, the input values were the univariate data consisting of weekly changes in 14 indicators[6].Forecasting of daily direction of change in the S&P(500) index is made by Choi, Lee, and Rhee 1995[7]. Despite the wide spread use of ANN in this domain, there are significant problems to be addressed. ANNs are data-driven model (White, 1989[8]; Ripley, 1993[9]; Cheng & Titterington, 1994[10]), and consequently, the underlying rules in the data are not always apparent (Zhang, Patuwo, & Hu, 1998[11]). Also, the buried noise and complex dimensionality of the stock market data makes it difficult to learn or re-estimate the ANN parameters (Kim & Han, 2000[12]). It is also difficult to come with an ANN architecture that can be used for all domains. In addition, ANN occasionally suffers from the overfitting problem (Romahi & Shen, 2000[13])[14].

2. Data analysis and problem description

This paper develops two comparative ANN models step-by-step to predict the stock price over financial time series, using data available at the website http://www.google.com/finance. The problem described in this paper is a predictive problem. In this paper four predictors have been used with one predictand. The four predictors are listed below

- Stock open price
- Stock price high
- Stock price low
- Stock close price
- Total trading volume

The predictand is next stock opening price.

All these four predictors of year X are used for prediction of stock opening price of year (X+1). Whole dataset comprises of 1460 days NASDAQ stock data. Now first subset contains early 730 days data (open,high,low,close,volume) which is the inputseries to the neural network predictor.Second subset has later 730 days data(only open) which is the target series to the neural network predictor.Now the network learns the dynamic relationship between those previous five parameters (open, high, low, close, volume)to the one final parameter(open),which it will predict in future.

Data Preprocessing

Once the historical stock prices are gathered ,now this is the time for data selection for training,testing and simulating the network.In this project we took 4 years historical price of any stock ,means total 1460 working days data.We done R/S analysis over these datafor predictability(Hurst exponent analysis).Now The Hurst exponent (H) is a statistical measure used to classify time series. H=0.5 indicates a random series while H>0.5 indicates a trend reinforcing series. The larger the H value is, the stronger trend. (1) H=0.5 indicates a random series. (2) 0<H<0.5 indicates an anti-persistent series. (3) 0.5<H<1 indicates a persistent series. An antipersistent series has a characteristic of “mean-reverting”, which means an up value is more likely followed by a down value, and vice versa. The strength of “meanreverting” increases as H approaches 0.0. A persistent series is trend reinforcing, which means the direction (up or down compared to the last value) of the next value imore likely the same as current value. The strength of trend increases as H approaches 1.0. Most economic and financial time series are persistent with H>0.5. Now we took the dataset timeseries having hurst exponent >0.5 for persistency in good predictability.

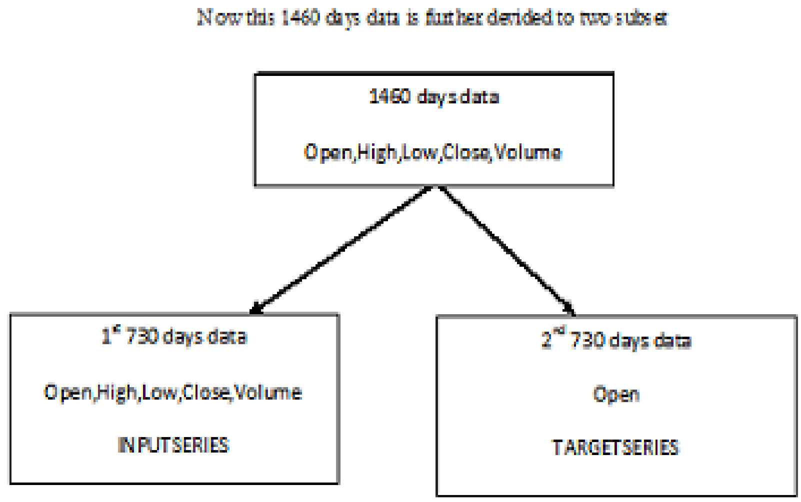

Figure 1. Data Division for NetworkTraining

Now first subset contains early 730 days data(open,high,low,close,volume) which is the inputseries to the neural network predictor.Second subset has later 730 days data(only open) which is the target series to the neural network predictor.Now the network learns the dynamic relationship between those previous five parameters (open,high,low,close,volume) to the one final parameter(open),which it will predict in future.

All five predictors are given to the network & also corresponding predictand is given by using backpropagation traing (gradient descent approach) the network will learn the abstract mapping between input & output & will minimize prediction error. After getting satisfactory minimization of mean square error over several epoch the training is said to be completed & the prediction system is ready for forecasting purpose.

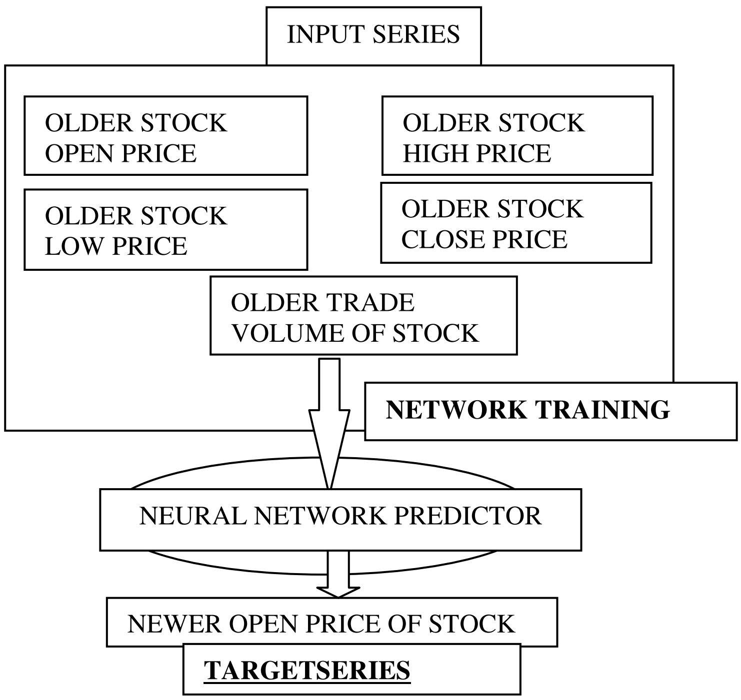

Figure 2.Flow Chart for Data preprocessing & Training

After these data processing job is done these are fed to the network fortraining and testing,80% of total data is used for training purpose and rest 20% data is used for testing purpose.

III. Methodology

This paper develops an ANN based comparative predictive model for NASDAQ stock prediction. The first ANN model is developed with Multi-Layer Feed forward Network Architecture & the second model is developed with Recurrent Neural Network Architecture. In this paper gradient descent based back propagation learning algorithm is used for the supervised learning of the predictive network. The mathematical model used in this paper is described below,

Algorithm

Initialize each weight w_i to some small random value.

- Until termination condition is met do ->
  - -For each training example do ->
    - Input it & compute network output Ok
      - For each output unit k

$$\delta k <-Ok\,(1-O)(Tk-Ok)$$

- For each hidden unit h

$$\delta h <-Oh\,(1-Oh\,)\,\sum_{k\epsilon outputs} \mathrm{wh,k}\,\delta\mathrm{k}$$

- For each network weight wi do –>

$$wi, <\text{-}\; wi,+\Delta wi,j$$

Where $\Delta wi, = \eta\delta jxi,$

Here the transfer function is sigmoid transfer function, it is used for its continuous nature. η is the learning rate & is the gradient.

At first the network is constructed. in this paper, sigmoidal function is used as the activation function of the ANN, it is chosen because of its continuous nature so the transfer function is eq(1),

$$f(x)=(1+e^{-x})^{-1} \quad (1)$$

Where x is the total summed input received at node k. At first all weights are allocated to some small random value w_i for ith layer. The successive weight is defined by eq(2),

$$w_{i+1}=w_i+\Delta w \quad (2)$$

The weight updating rule for gradient descent back propagation is eq (3),

$$\Delta wi, = \eta\delta jxi, \quad (3)$$

Here we use mean square error,because the error surface is a multi-variable function it is wise to take mean of them & it is defined by eq(4),

$$\text{Err}=\frac{1}{2}(\text{Target Output} - \text{Network Output})^2 \quad (4)$$

3. Implementation and results

The whole dataset is divided into training & test dataset, 80% of total data is used for training purpose & 20% of total data is used for test purpose. Using gradient descent backpropagation algorithm the data are trained two times up to 1000 epochs. After training ANN model is tested over test dataset. Both networks are trained in same manner, after completion of training comparison of their mean square error is presented by Table 1.

Table 1. Comparison of ERROR

Network Data	Feedforward NN	Timedelay Recurrent NN
Using Trainig Set	4.14%	3.01%
Using Testing Set	25%	15%

A regression model relates *Y* to a function of **X** and **β**.

$$Y \approx f(\mathbf{X}, \beta) \quad (5)$$

The **unknown parameters** denoted as **β**; this may be a scalar or a vector.
The **independent variables**, **X**.
The **dependent variable**, *Y*.

Regression model is very much useful for model relation between function of independent variables and unknown parameters with some dependent variable. This paper also compute and contrast the regression plot for both networks over same NASDAQ data forecasting problem.

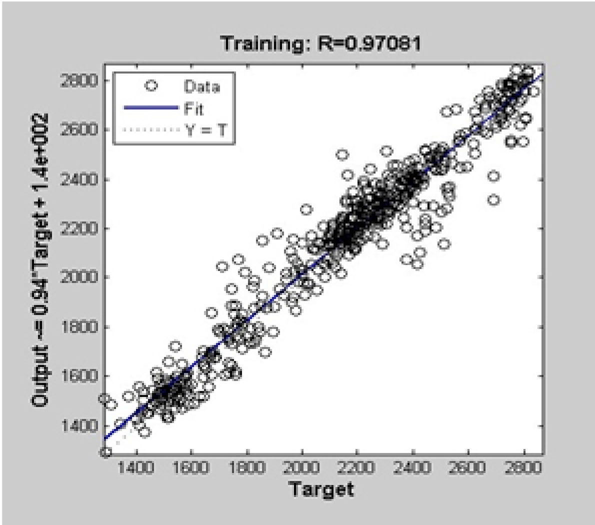

Figure 3. Regression plot for NASDAQ index (MLP)

Figure 3 depicts the regression plot for the feedforward MLP network, analyzing it we can say that Y=T regression is not so good.

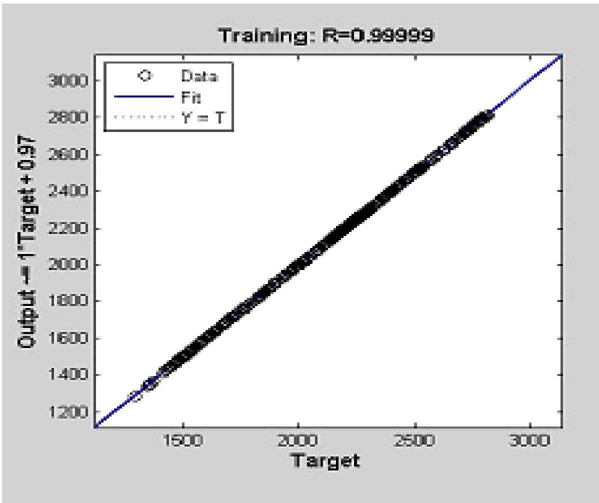

Figure 4. Regression plot for NASDAQ index (RNN)

Figure 4,depicts the regression plot for the Timedelay RNN network, analyzing it we can say that Y=T regression is totally fit.

This paper also comprises of comparative study of performance(mse) plot of both network.

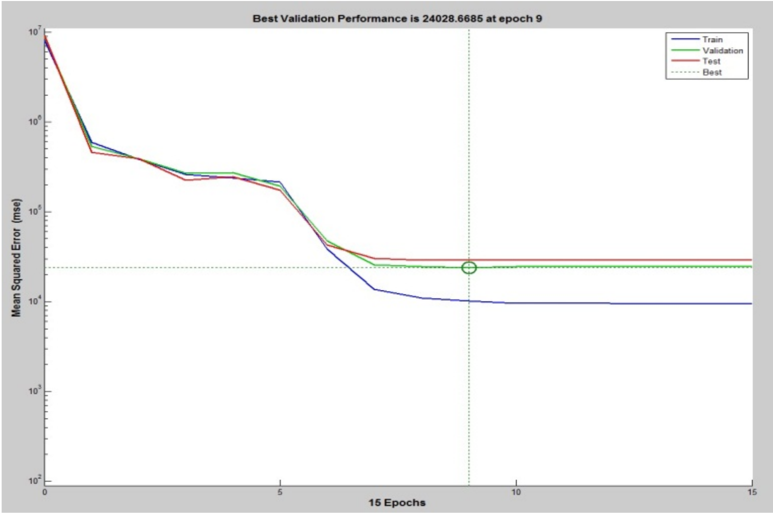

Figure 5. Performance plot for NASDAQ index (MLP)

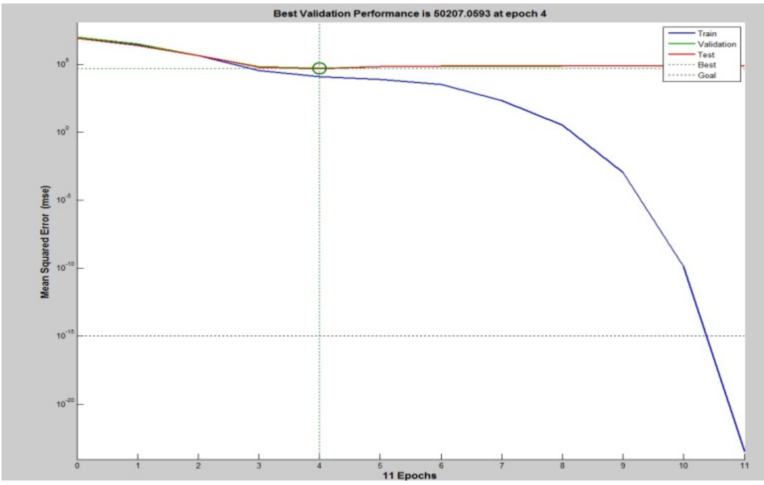

Figure 6. Performance plot for NASDAQ index (RNN)

Figure 5 we can see that the mse curve reaches the In performance goal but it does not decrease in that good manner,but in Figure 6 the mse is reduces widely. By analyzing all these results one can say that RNN is better choice than Feedforward MLP in prediction purpose.

Table2 represents the original stock value & predicted ones

4. Conclusion

This paper presented a hybrid neural-evolutionary methodology to forecast time-series. The methodology is hybrid because an evolutionary computation-based optimization process is used to produce a complete design of a neural network. The produced neural network, as a model, is then used to forecast the time-series. One of the advantages of the proposed scheme is that the design and training of the ANNs has been fully automated. This implies that the model identification does not require any human intervention. The model identification process involves data manipulation and a highly experienced statistician to do the work. This fact pushes the state of the art in automating the process of producing forecasting models. Compared to previous work, this paper approach is purely evolutionary, while others use mixed, mainly combined with back-propagation, which is known to get stuck in local optima. On the direction of model production, the evolutionary process automates the identification of input variables, allowing the user to avoid data pre-treatment and statistical analysis. The system is fully implemented in Matlab [15].

The study proves the nimbleness of ANN as a predictive tool for Financial Timeseries Prediction. Furthermore, Conjugate Gradient Descent is proved to be an efficient Backpropagation algorithm that can be adopted to predict the average stock price of NASDAQ.It is also revealed that temporal relationship between mapping is better learnt by RNN than FFMLP.

Table 2.Comparison between original stock price(TARGET) & Simulated price by ANN.

TARGET	SIMRNN	SIMMLP	TARGET	SIMRNN	SIMMLP
2519.1	2627	2183.8	2183.8	2627	2183.8
2514.8	5209.6	2379.7	2326.8	2352.8	2355.1
2500	3219	1921	2309.7	2355.3	2316.0
2473	3269.9	2215.3	2308.1	2353.4	2251.9
2509.4	2524.1	2083.9	2349.1	2416.2	2466.4
2528.5	2534.3	2534.3	2362.7	2420.3	2406.3
2483.2	2497.4	2124.7	2356.8	2356.8	2356.8
2436.7	2439.9	2141.6	2407.5	2456.4	2344.7
2444.9	2268.6	2309.9	2434.2	2412.8	2390.9
2414.4	2446.2	2086.0	2424.3	2521.9	2414.0
2423.0	2423.0	1961.4	2414.4	2462.8	2369.6
2443.1	2467.0	2018.2	2463.1	2463.1	2463.1
2481.2	2515.9	2239.5	2456.9	2363.3	2382.5
2444.9	2043.0	2223.8	2404.9	2501.4	2501.4
2416.5	2462.1	2107.2	2390.3	2438.9	2394.5
2375.8	2400.8	1992.4	2399.7	2435.9	2388.4
2388.4	2416.4	2227.8	2364.3	2888.2	2319.0
2365.8	2430.4	2119.0	2362.8	2412.8	2372.2
2319.6	2353.4	2173.1	2390.1	2444.5	2324.4
2312.4	2347.1	2120.1	2120.1	2441.5	2323.5
2274.2	2308.9	2102.5	2402.1	2468.7	2334.6
2311.5	2293.3	2242.3	2346.8	2421.8	2301.6
2261.7	2309.6	2251.3	2315.1	2315.1	2315.1
2263.6	2322.7	2089.0	2241.6	2312.9	2240.0
2244.9	2225.6	2337.0	2296.1	2369.7	2161.6
2290.6	2336.7	2204.6	2204.6	2204.6	2204.6
2239.9	2270.0	2102.5	2102.5	2102.5	2102.5
2102.5	2102.5	2463.1	2270.0	2463.1	2102.5
2456.9	2456.9	2270.0	2204.8	2102.5	2204.9
2308.9	2307.6	2308.9	2346.8	2102.5	2204
2362.8	2102.5	2390.1	2390.1	2270.0	2204
2362.8	2362.8	2270.0	2362.8	2390.1	2390.1
2362.8	2362.8	2364.3	2102.5	2270.0	2364.3
2501.4	2362.8	2270.0	2204	2204	2315.1
2362.8	2308.9	2089.0	2364.3	2315.1	2501.4
2501.4	2508.3	2362.8	2204	2102.5	2390.1

SIMRNN-simulated output using RNN model.
SIMMLP-simulated output using MLP model.

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