Financial Prediction, Some Pointers, Pitfalls, and Common Errors

Kevin Swingler

Center for Cognitive and Computational Neuroscience Stirling University

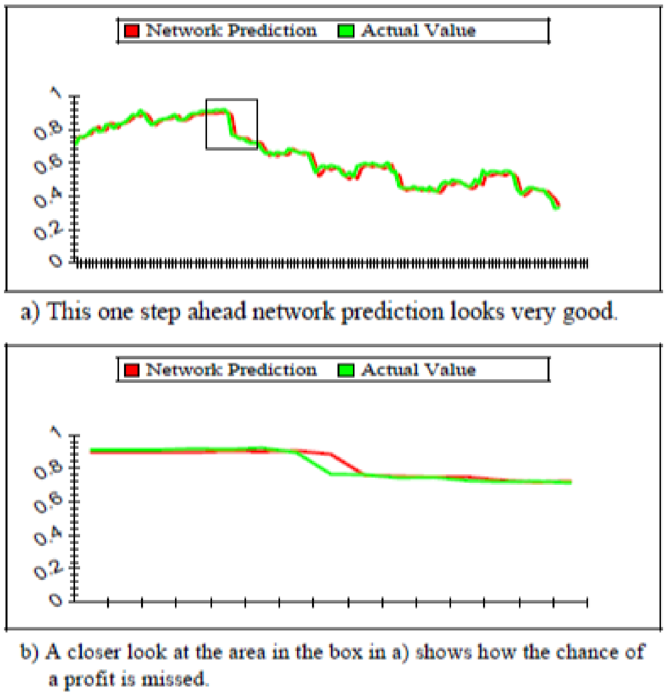
Ever since the evolution of Neuroscience started, the question that arose in everyone's mind was "Could this new innovation be a computer based crystal ball, capable of predicting the future?". This ever intimidating speculation of forecasting the unseen, made people think about the applications this technology, if implemented correctly, could have. The notion of making money throug h predicting the stock market changes based on its past behaviour seemed plausible even though it contradicted the well circulated *efficient markets hypothesis*[1]. This paper discusses the way around *efficient markets hypothesis*(EFM) by distinguishing between public availability and secretive availability of information, which contradicts the EFM. Also, it discusses how a perfect prediction "for all" would remove the discrepancies (on which the profit based market system works) and due to high transparency the opportunities for profits would ideally be lost.

The paper discusses two major neural network based approaches for forecasting the time series, namely time windowing and recurrent neural networks and proceeds on to tell the pitfalls and erorrs assosiated with predicting the stock market with the help of Neural Networks. With both of the approaches taking the current state of the stock market as the input and predciting the system's behaviour at some point in the future. Due to time series being autoregressive in nature, the outcome today depends on the past outcomes. So, the need for the temporal analysis is inevitable. One such way is converting the temporal dimensions into spacial vectors by taking the last n elements of the series by a method known as time windowing. There are various types of time windowing. The paper doesn't go in depth to discuss the concept of time windowing but it discusses the basics. The process basically consists of a feedforward network having n inputs till current state of time. The objective is to determine the value of the series at t+1, i.e one step prediction. To get many step ahead prediction, the single output (at t=t+1) is fed back to the input layer until when we reach the point in future we need to predict. The paper also marks that the predictions are only possible if there is some information to extract from the data sequence, as it is a statisitical based approach. The second method discussed is Recurrent Networks, which are now knowns as Recurrent Neural Networks (RNNs)[3]. The method consists of a feedforward network with one or more than one recurrent context layer which takes a copy of the network's hidden layer at time t-1 and re-uses it along with the input vector at the present moment (t=t). Throug this we are able to learn the temporal dependencies without changing the nature of the vector to spatial. RNN with a single recurrent layer is able to predict the one step ahead state and it can be extended to many step ahead prediction by feeding back the one-step ahead output back to the recurrent layer as an input. The inability of RNN to store data for a long time plays a huge role in letting us predict the outcomes.

The paper next talks about some common errors and pitfalls one should avoid while working with time series data in financial markets.

- **One Step Ahead Prediction-** Situations as shown in figure 1 a) and 1 b) are quite common if model is not implemented correctly. In 1 a) the output (at t=t+1) is being predicted the same as what it is right now. Overfitting, lack of training data and efficient market hypothesis are some reasons of such an anomality. In figure 1 b) we can see that the predicted output is'nt actually the future as the old information is reflected at a later time instant but in reality there is an opportunity being missed for profit gains. The main focus should be making sure that we are predicting ahead, not repititively.

- **Many Step Ahead Prediction[2**] While many step ahead prediction is quite complex and more reliable method, it is not uncommon to see a predictor predicting very general trends just by sheer coincidence. So, during each step in a multi step prediction, make sure the output is not a result of coincidence. Only when the predictor consistently forecasts the major turning points (like a major fall or rise), it can be considered successful. Also, we must not forget the actual profit gained by a person if he started with zero holding. Considering the profit in a transaction rather than the whole process may give us a false sense of success, which in reality is not actually success.



a) This one step ahead network prediction looks very good.

b) A closer look at the area in the box in a) shows how the chance of a profit is missed.

Figure 1: Predicting the hourly Dollar/Swiss France exchange rates [2].

The author next discusses about the ways to avoid wrong assumptions which people consider while formulating the predicting models. One such assumption is always relying on Mean Squared Error (MSE). We may be able to get the MSE down to 0.02 (standard), but if it remains constant or increases in further epochs, then our model has clearly failed. These small errors flatten the error gradients severely affecting the learning rate. Though the ways of getting a good loss function is not discussed in the paper, the ways of testing are discussed in the paper. Some of the methods discussed are:

- Reducing the number of hidden units/ layers or even using a perceptron (no hidden layers).

- Testing the network on totally unrelated functions(structures) like a sine curve, if the netowork still gives good results, then we have commited an error.

At last, the author discusses the use of neural networks. According to the technical analysts, all the market information is reflected in the price levels so these prices should be the only data that is required. But the speed of reflection is slow and by the time the data is publicly known, its too late and the price change flattens out after making a jump (which isn't forecasted before it happens). So, the assumptions of price levels being the only parameter, backfires. This implies we need more factors to predict the future state of the market [Hoptroff, 1992]. Also, one must not forget to take in account the trading costs and the frequencies of trading. The net profit must take in account the cost occuring in each trade. Trade frequency also plays a very major role to differenciate between the ideal and the actual situation. Theoritically we may get 60 transactions per hour, but practically it is too fast and must be accounted for.

[1]Burton G. Malkiel, Princeton University .The effecient market hypothesis and its critics. CEPS Working Paper No. 91.

[2]Kevn Swingler.Financial Prediction, Some Pointers, Pitfalls, and Common Errors.