Prediction based – High Frequency Trading on Financial Time Series

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Abstract: In this paper we investigate prediction based trading on financial time series assuming general AR(J) models and mean reverting portfolios. A suitable nonlinear estimator is used for predicting the future values of a financial time series will be provided by a properly trained FeedForward Neural Network (FFNN) which can capture the characteristics of the conditional expected value. In this way, one can implement a simple trading strategy based on the predicted future value of an asset price or a portfolio and comparing it to the current value. The method is tested on FOREX data series and achieved a considerable profit on the mid price. In the presence of the bid-ask spread, the gain is smaller but it still ranges in the interval 2-6 percent in 6 months without using any leverage. FFNNs were also used to predict future values of mean reverting portfolios after identifying them as Ornstein-Uhlenbeck processes. In this way, one can provide fast predictions which can give rise to high frequency trading on intraday data series.

1 INTRODUCTION

In the advent high speed computation and ever increasing computational power, algorithmic trading has been receiving a considerable interest (A Hanif, 2012) (Pole, 2007) (Kissell, 2006) (Peter Bergan, 2005). The main focus of research is to develop real-time algorithms which can cope with portfolio optimization and price estimation within a very small time interval enabling high frequency, intraday trading. In this way, fast identification of favorable patterns on time series becomes feasible on small time scales which can give rise to profitable trading where asset prices follow each other in sec or msec range.

Several papers have been dealt with algorithmic trading by using fast prediction algorithms (Naik et al., 2012); (Y. Zuo, 2012) or by identifying mean reverting portfolios (J.W., 2002) (D'Aspremont, 2011) (Balvers et al., 2000). The paper (L., 2012) uses linear prediction which however proves to be poor to capture the complexity of the underlying time series. Other methods (D'Aspremont, 2011); (Balvers et al., 2000) are focused on identifying mean reverting portfolios and launch a trading action (e.g. buy) if the portfolio is out of the mean and taking the opposite action when it returns to the mean.

In our approach, we focus on prediction based trading by estimating the future price of the time series by using a nonlinear predictor in order to capture the underlying structure of the time series.

The investigated time series can either refer to foreign exchange rates, single asset prices or the value of a previously optimized portfolio. By using FFNNs, which exhibit universal representation capabilities, one can model the nonlinear AR(J) process (the current value of the time series depends on J previous values and corrupted by additive Gaussian noise). Assuming the price series to be a nonlinear AR(J) process, we first develop the optimal trading strategy and then approximate the parameters of nonlinear AR(J) by an FFNN.

In this way, one can obtain a fast adaptive trading procedure which, in the first stage, runs a learning algorithm for parameter optimization based on some observed prices and then, in the second stage, provides near optimal estimation of future prices. The numerical results obtained on Forex rates have demonstrated that the method is profitable and achieves more than 1% profit in one month with leverage 1:1 which can be much bigger if we use leverage.

The paper treats this material in the following structure:

- In section 2, the model is outlined;
- In section 3 the optimal strategy is derived first for trading on mid-prices and then it is extended to

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trading in the presence of bid-ask spread;

- In section 4 numerical results and performance analysis is given;
- In section 5 some conclusions are drawn.

2 THE MODEL

Let us assume that we trade on the mid prices, the corresponding asset price time series is denoted by x_n and follows a nonlinear AR(J) process

$$x_n = F\left(x_{n-1,\dots,}x_{n-J}\right) + \nu_n \qquad (2.1)$$

where F is a Borel measurable function and $\nu_n \sim N\left(0,\sigma\right)$ i.i.d.r.v.-s, being independent of x_n. For trading, we construct an estimator

$$\tilde{x}_n = Net\left(x_{n-1},\dots,x_{n-J},w_1,\dots,w_M\right) = Net\left(\mathbf{x},\mathbf{w}\right), \qquad (2.2)$$

where

$$\tilde{x}_n = Net\left(\mathbf{x},\mathbf{w}\right) = \varphi\left(\sum_i w_i^{(L)}\varphi\left(\sum_j w_{ij}^{(L-1)}\dots\varphi\left(\sum_m w_{nm}^{(1)}x_{n-m}\right)\dots\right)\right)$$

is a Feedforward neural Network (FFNN) depicted by Figure 2.1 and vector $\mathbf{w}$ denotes the free parameters subject to training.

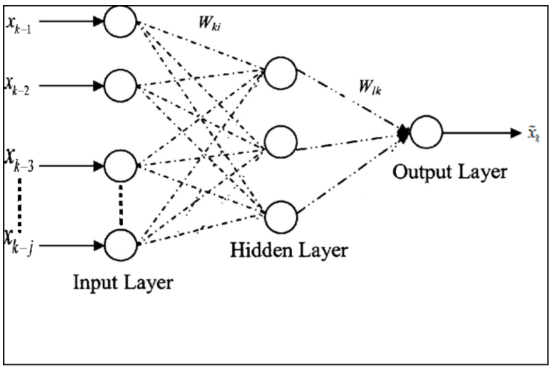

Figure 2.1: The structure of feed forward neural network (FFNN).

Trading is performed as follows:

Stage 1. Observing a historical time series and forming a training set $\tau^{(n)} = \left\{\left(\mathbf{x}^{(n)},x_n\right), n = 1,\dots,N\right\}$ where $\mathbf{x}^{(n)} = \left(x_{n-J},\dots,x_{n-1}\right)$.

Stage 2. Training the weights by minimizing the objective function $\min_{\mathbf{w}} \frac{1}{N}\left(x_n - Net\left(\mathbf{x}^{(n)},\mathbf{w}\right)\right)^2$ by the back propagation (BP) algorithm.

Stage 3. Trading on the real data as follows:

Calculate $\tilde{x}_n = Net\left(\mathbf{x}^{(n)},\mathbf{w}\right)$,where $\mathbf{x}^{(n)} = \left(x_{n-J},\dots,x_{n-1}\right)$ and we are in time instant $n-1$.

If $\tilde{x}_n > x_{n-1}$ then buy at time instant $n-1$ and sell at time instant n. (2.3)

If $\tilde{x}_n < x_{n-1}$ then sell at time instant $n-1$ and buy at time instant n. (2.4)

It can be easily proven that this is the optimal strategy, as far as the expected profit maximization is concerned.

3 PORTFOLIO OPTIMIZATION BY MEAN REVERSION

We view the asset prices as a first order, vector autoregressive VAR (1) process. Let $s_{i,t}$ denote the price of asset i at time instant t, where $i = 1,\dots,n$ and $t = 1,\dots,m$ are positive integers and assume that $\mathbf{s}_t^T = (s_{1,t},\dots,s_{n,t})$ is subject to a first order vector autoregressive process, VAR (1), defined as follows:

$$\mathbf{s}_t = \mathbf{A}\mathbf{s}_{t-1} + \mathbf{W}_t, \qquad (3.5)$$

where $\mathbf{A}$ is an $n\times n$ matrix and $\mathbf{W}_t \sim N(0,\sigma I)$ are i.i.d. noise terms for some $\sigma > 0$.

One can introduce a portfolio vector $\mathbf{r}^T = (r_1,\dots,r_n)$, where component r_i denotes the amount of asset i held. In practice, assets are traded in discrete units, so $r_i \in \{0,1,2,\dots\}$ but for the purposes of our analysis we allow r_i to be any real number, including negative ones which denote the ability to short sell assets. Multiplying both sides by vector r (in the inner product sense), we obtain

$$\mathbf{r}^T\mathbf{s}_t = \mathbf{r}^T\mathbf{s}_{t-1}\mathbf{A} + \mathbf{r}^T\mathbf{W}_t \qquad (3.6)$$

Following the treatment in (Box and Tiao, 1977) and (D'Aspremont, 2011), we define the predictability of the portfolio as

$$\nu(\mathbf{r}) := \frac{\mathrm{var}(\mathbf{r}^T\mathbf{A}\mathbf{s}_{t-1})}{\mathrm{var}(\mathbf{r}^T\mathbf{s}_t)} = \frac{E(\mathbf{r}^T\mathbf{A}\mathbf{s}_{t-1}\mathbf{s}_{t-1}^T\mathbf{A}^T\mathbf{r})}{E\left(\mathbf{r}^T\mathbf{s}_t\mathbf{s}_t^T\mathbf{r}\right)}, \qquad (3.7)$$

provided that $E(\mathbf{s_t}) = 0$, so the asset prices are normalized on each time step. The intuition behind this portfolio predictability is that the greater this ratio is, the more $\mathbf{s}_{t-1}$ dominates the noise and therefore the more predictable $\mathbf{s}_t$ becomes.

Therefore, we will use this measure as a proxy for the portfolio's mean reversion parameter λ. Maximizing this expression will yield the following optimization problem for finding the best portfolio vector $r_{\mathbf{opt}}$:

$$\mathbf{r}_{\text{opt}} = \arg\max_{\mathbf{r}} \nu(\mathbf{r}) = \arg\max_{\mathbf{r}} \frac{\mathbf{r}^T \mathbf{A}\mathbf{G}\mathbf{A}^T \mathbf{r}}{\mathbf{r}^T \mathbf{G}\mathbf{r}}, \tag{3.8}$$

where $\mathbf{G}$ is the stationary covariance matrix of process $\mathbf{s}_t$. This optimization can be performed by gradient or stochastic search.

4 NUMERICAL RESULTS

We have tested the proposed method for predicting the price of a single asset and then the value of a selected mean reverting portfolio in three different cases:

- In the first case we predict the future price based on mid-price and we also trade on mid-price;
- In the second case we still predict by using the mid-price but we trade in the presence of Bid/Ask spread.
- In third case we predict by using Bid/Ask and also trade in presence of Bid/Ask spread.

The testing parameters (period length, timeframe J, initial deposit,...) are the same in all 3 cases and taken to be: period length = 1 Month (2012.06.01-2012.07.02); J=5; average training period=20; timeframe=M15; single asset(EURUSD); Portfolio(EURUSD,GBPUSD,AUDUSD,NZDUSD; initial deposit=1000

In the figures the number of trades is shown in the horizontal axis, while the account balance is indicated on the vertical axis.

4.1 Prediction and Trading on mid Price

As was mentioned before, in the first case we only predict and trade on the mid-price. The results are indicated by figures 4.1.1 and 4.1.2, respectively.

One can see that the we can achieve a 3 % or in quantity profit= \$30.29; Profit=3% ; MAX Drawdown=0.5%.

One can see that the we can achieve a 3.9 % or in quantity profit= \$39.70; Profit=3.9%; MAX Drawdown=0.24%.

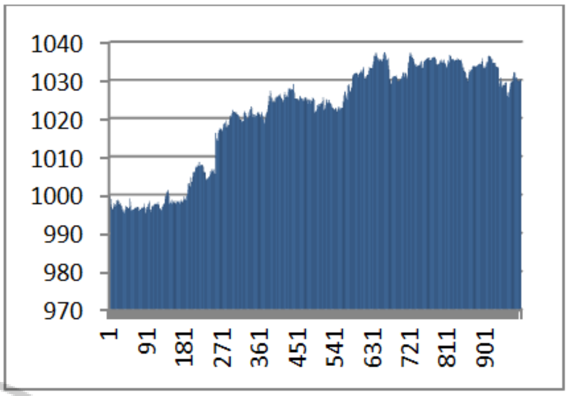

Figure 4.1.1: Balance with respect to time (single asset).

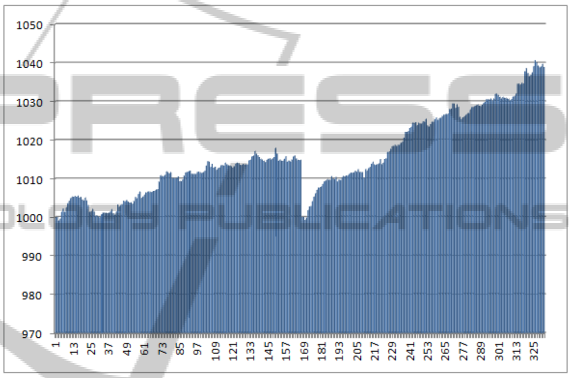

Figure 4.1.2: Balance with respect to time (Portfolio).

4.2 Training on the mid Price and Trading on Bid/Ask

In this case we use mid-price for prediction but we trade on Bid/Ask. Here on horizontal axis we have the same number of trades as in the previous figure.

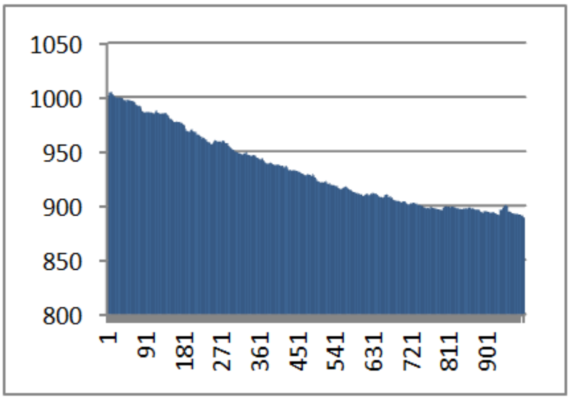

Figure 4.2.1: Balance with respect to time (single asset).

The achieved profits are negative -10.70%,-5.8% (Profit: -110.70\$, -58\$) MAX Drawdown=3.4%, 2.1%.

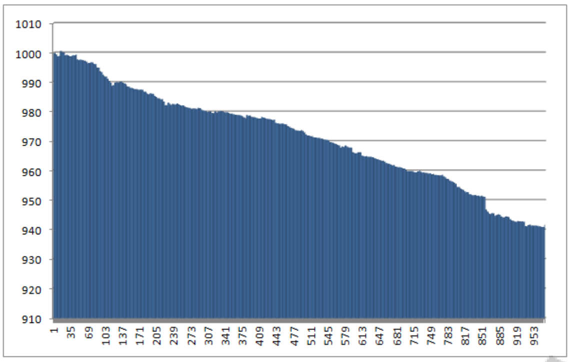

Figure 4.2.2: Balance with respect to time (Portfolio).

The result is not so good as we have negative balance growth on vertical axis. However, as expected this is due to the fact we have not exploited the information given in the bid and ask series.

4.3 Training on the Bid/Ask and Trading on the Bid/Ask

In this case, we use following model to cover the spread.

$$\tilde{x}_k = Net^{Bid}(\mathrm{y}, \mathrm{x}, \mathrm{w}) \quad (4.9)$$

$$\tilde{y}_k = Net^{Ask}(\mathrm{y}, \mathrm{x}, \mathrm{u}) \quad (4.10)$$

$$\tilde{x}_k > y_{k-1} \rightarrow \text{BUY}$$

$$\tilde{y}_k < x_{k-1} \rightarrow \text{SELL}$$

In the figure bellow we have smaller number of trades on horizontal axis in comparison to previous cases because it might happen that the predicted value is not greater than Ask Price or it is not even less than Bid Price, therefore in some cases we do not trade. Again on the vertical axis we have account balance but this time we have some positive growth.

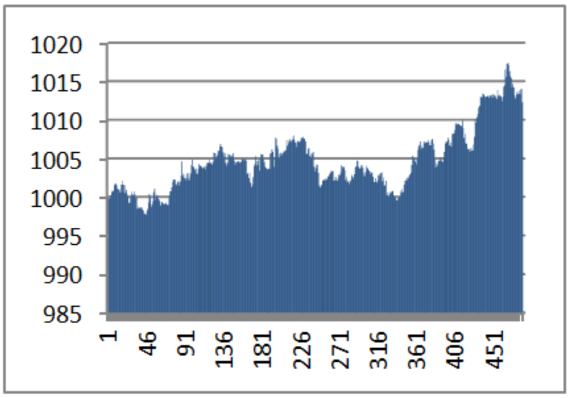

Figure 4.3.1: Balance with respect to time (single asset).

The achieved profit 1.23 %(Profit: $12.30) which is good in the presence of bid-ask spread.

MAX Drawdown=0.85%. One can see that even in the presence of bid-ask spread the method can materialize profit.

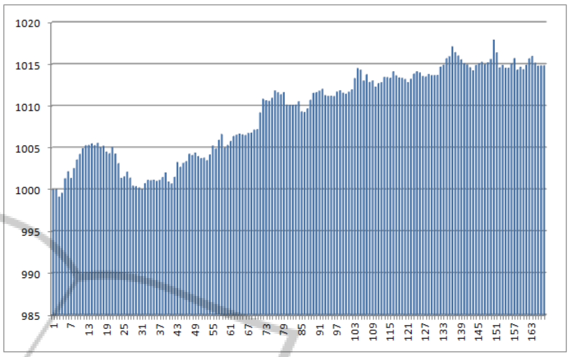

Figure 4.3.2: Balance with respect to time (Portfolio).

The achieved profit is 1.48 %(Profit:$14.8)which is good in the presence of bid-ask spread. Max Drawdown=0.29%.

5 OPTIMIZING THE STEP

So far in our main model we only predicted the next candle(time instant), but we can also predict more than one candle. It can help us to better cover the spread and possibly extend our profit, as we let the price series change more dominantly to get out of the spread and materializing more profit. Here our goal is to find the optimal step parameter, where the step is defined as how many candles in the future we predict.

The next figure shows the result regarding the step parameter, i.e. the account profit in percentage (optimization period is 6 months) is plotted as a function of the step parameter.

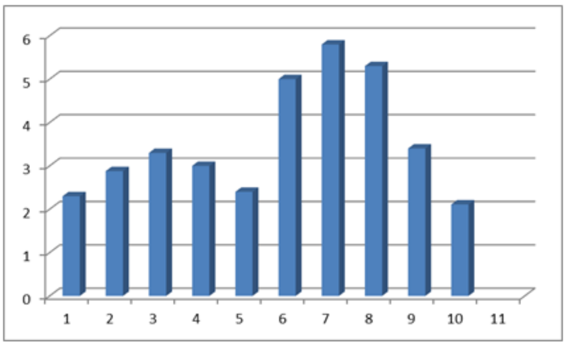

Figure 5.1: Profit as a function of prediction step.

From Figure 5.1, one can conclude that the optimal step parameter is 7.

6 CONCLUSIONS AND FURTHER WORK

In this paper we used FFNN based prediction for trading on financial time series. The optimal trading strategy has been derived by using the fact that FFNN can represent the conditional expected value. Furthermore, we have optimized the prediction step parameter numerically. In the case of trading on the mid-price a considerable amount of profit can be accumulated. In the case of trading in the presence of bid-ask spread the method is still profitable but the achieved profit is more modest.

The methods presented here can pave the way towards high frequency, intraday trading.

Furthermore, in our tests we did not use leverage, but with these low drawdowns which we had, we can easily use bigger leverages to magnify our profit. Although the ability to earn significant profits by using leverage is substantial, leverage can also work against investors. For example, if the currency underlying one of the trades moves in the opposite direction of what the investor believed would happen, leverage will greatly amplify the potential losses. To avoid such a catastrophe, Forex traders usually use money management techniques.

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