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AN ONE DAY AHEAD PREDICTION SYSTEM FOR STOCK MARKET MOVEMENTS

SYSTEM TWORZENIA JEDNODNIOWYCH PROGNOZ RUCHU CEN NA GIEŁDZIE PAPIERÓW WARTOŚCIOWYCH

A b s t r a c t

To build the next day investment decision system we propose to use wavelets analysis as a consistent tool for raw data preprocessing. Then wavelets coefficients that it returns are fed into SOM neural networks for clustering. For every cluster the measure of the next day forecast of share price movement is calculated. Test made on shares of PKOBP bank, shows good effectiveness of the method.

Keywords: *wavelets decomposition, artificial neural networks, stock market*

S t r e s z c z e n i e

Proponujemy wykorzystanie analizy falkowej do przygotowania danych dla sieci neuronowej SOM. Sieć dokonuje grupowania danych w postaci współczynników falkowych. Dla każdej grupy obliczana jest miara zmiany cen w następnym dniu. Testy przeprowadzone na akcjach banku PKOBP wskazują na skuteczność opisanej metody.

Słowa kluczowe: *dekompozycja falkowa, sztuczne sieci neuronowe, giełda papierów wartościowych*

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1. Introduction

Forecasting price movement of stock market, at least a one day ahead has been a goal of many traders. The motivation is obvious – financial gain. There has been essentially two approaches used to predict market: fundamental analysis and technical analysis. In the present paper we are going to present an approach which belongs to the second category. We make an attempt to predict future price movement solely on past prices of assets and other trading data, i.e. we want to apply a kind of technical analysis. Of course there have been many predecessors, majority of them failed as only a few of techniques used has proven to be successful enough. However the hope already exists that the next approach will outperforms former ones.

Among many tasks where artificial neural networks have been applied is time series analysis, in particular time series forecasting. Common exploratory time series analysis relies on linear models of stationary generating data processes . Parameters of the particular model are derived from the frequency spectrum, autocorrelation function and others. However many interesting processes generate non stationary time series. It is not reasonable to apply methods mentioned to non stationary processes, because e.g. empirical autocorrelation function has no interpretation for them.

On the contrary, artificial neural net of suitable chosen architecture is capable to approximate any reasonable function with arbitrary accuracy, in particular time series, not necessarily stationary or linear [3]. The usage of neural networks for time series analysis relies on the historical data and a process called network learning. Neural networks application in time series involves following steps:

Data collection and preprocessing (data analysis and transformation).

Choice of networks architecture. Among the most frequently used are the multilayer perceptron network and self organized map (SOM) of Kohonen [4].

Training and testing. Training is done on a set of historical data. They are introduced to the network, so that the network can adjust its weights. In the case of perceptron architecture the corresponding historical outputs have to be introduced as well. Weights are adjusted in such a way that difference between predicted and real output is as low as possible. It is not the case for SOM neural net which do not follow any predefined rules but finds its own rules as it is trained according to unsupervised procedure. Due to that property SOM neural networks are highly accomplished in finding and recognizing patterns.

Training of neural nets for time series prediction uses a method called windowing. The basic idea is that two windows are used with assumption that the sequence of values in both windows are somehow related one to another and this relation ship is defined entirely by the dataset. In the course of training process both windows are shifted along the time series.

The training process can be done once with the training data or the network can be retrained every time the new data comes. The ability of the network to retrain itself in the process of its usage is particularly useful in application of the network in stock market prediction. When training process is completed the net have to be tested on a set of test data which are not included to the set of training data.

The application of neural networks to stock market trading is relatively new [6], it emerged in early 1990s. The early studies used neural nets of various architecture to accurately predict the stock market price and direction of its movement [1]. Neural net, SOM in particular, not only can detect complex patterns in data but also make results of pattern analysis independent of trader interpretation. Besides, many techniques can be used to preprocess raw data from market as well as from fundamental analysis, with aim to fed their results into neural networks as input.

Common believe states that almost every significant, real process is chaotic in the sense that part of the process it is deterministic and part of it is random. A neural networks ability to capture deterministic as well as random features of the stock market processes make it ideal tool for technical analysis. The mathematical theorem has been proved that the correctly configured neural networks can approximate any function once right data are given, put it in another words, it can model any input-output relationships. This statement is in favor of neural networks as a promising element of tools to support technical analysis. However in spite of expectation the early studies to use neural networks of various architecture to accurately predict the stock market price and direction of its movement were not very successful. Now it is clear that market returns can be predicted but only to a certain degree.

In the present paper we restrict ourselves to a system which can be used by traders as a tool, predicting with some probability a short time trading signal. We suggest that it have to be a hybrid trading system consisting of three parts which perform: preprocessing raw data, cluster analysis, investment decision.

2. Raw data preprocessing

Data preprocessing describes any type of process performed on raw data in order to improve the efficiency of another processing procedure, the cluster analysis in our case. For training neural networks we need a set of patterns each corresponding to the input values on a particular day. In general (but not always) the greater number of patterns the better performance of training neural net is. It is however difficult to decide of how many inputs a single data pattern should consist. The single pattern data should capture all trends affecting particular day stock prices. The data of stock market quotations is huge so the number of inputs may be very large. On the other hand it has been shown, e.g. [6], that many of the inputs are unnecessary as their effect on system performance appears to be negligible. Besides, performance of cluster analysis is better when single pattern consists of least amount of input data. Usually the set of these inputs is selected arbitrary, as e.g. in [7].

Traditional technical analysis of stock market prices uses charts – the graphical representation of the history of price movements and other trading data. Technical analysis practitioners (chartists) claim that chart form the main (if not unique) basis for decisions made by traders. No wonder that graph allows trader to see much, however information provided by graph is only qualitative and unfortunately it has highly subjective nature, as different peoples can interpret picture in different manners.

Charts are often used to detect trends. Prices tend to move in trend, and once trend is established it continues until something happens to break monotonous price changes. One can believe that it is enough to follow saying “The trend is your friend” to be successful trader. However market at the same time is subject to many trends of different duration from minutes to – may be – years. Each trend may experience corrections of different reasons.

There are a variety of technical indicators derived from chart analysis which can be formalized into trading rule or used as inputs to neural networks. Each index has its own meaning and interpretation. Which of them are used for technical analysis and prediction depends on particular market participant.

Instead, we propose a wavelets analysis and reconstruction [2] as a consistent tool to built a single pattern data inputs. Wavelets allow a time series to be viewed in multiple resolutions. Each resolution represents a particular frequency component of the time series. The wavelet technique breaks down the signal into spectrum consisting of averages and differences of a signal terms. In application we are interested, the wavelet algorithms work on set of terms cut off from signal by window of length a power of two. Each step of the wavelet transform produces two sets of values: a set of averages and a set of differences which are referred to as wavelet coefficients. Each step produces a set of averages and coefficients that is half the size of the input data. For example, if window contains 16 terms of the time series, the first step will produce 8 averages and 8 coefficients. The averages then become the input for the next step (e.g., 8 averages resulting in a new set of 4 averages and 4 coefficients). This continues until one average and one coefficient (e.g., 20) is calculated. We say that the set of data from the window has been decomposed. To decompose long series of input data the window is shifted one term each time until last data term is reached. There are a variety of wavelet basis functions in use. The simplest is the Haar wavelets family. Which wavelet family works better for particular application depends on the nature of the data analyzed.

The analysis consists of wavelet decomposition of the data set (stock prices or/and volume), thresholding (if possible) wavelets coefficient, an then use the wavelet reconstruction as the estimate of the raw data. Pruned wavelets coefficients that reconstruct data set with good enough accuracy are inputs to neural nets for the cluster analysis. In conclusion wavelet preprocessing enables reduction amount of data by removing irrelevant or weakly relevant attributes, and data compression as well.

3. Pattern data clustering

There are number of neuro-computational approaches for pattern clustering. The unsupervised weight adapting algorithms are usually based on some form of global competition between the neurons. Competitive learning procedure divides a set of input patterns in clusters that are inherent to the input data.

In approach presented in the paper, SOM artificial neural network is used for clustering single pattern data. The principle behind SOM is competitive learning; the output neurons of the network compete among themselves with the result that only neuron is activated at a time. Unlike perceptron types of network, the SOM does not need a target output to be specified. Instead, if the weights of neurons in an area of net are close to the input vector, that area is selectively optimized to more closely resemble the data. In the basic version, starting from random initial distribution of weights, after many iterations only one neuron (winner) corresponding to each input is activated at a time. After many inputs is presented in the course of learning process the locations of the responses in the array of neurons tend to become ordered as if some nonlinear coordinate system for the different input features is created over the network. The neurons become selectively tuned to various classes of input patterns in the course of a competitive learning process Therefore SOM appears to be a clustering tool because similar data samples tend to be mapped on to one class (corresponding to neuron or nearby neurons). In another words particular locations of the neurons in the lattice are indicative of intrinsic statistical features contained in the input patterns. That's why SOM is nowadays often used, among others, as a statistical tool for multivariate analysis. The patterns in our case are vectors of wavelets coefficients, that wavelet tool returns when it is fed with logarithmic one-day returns of share prices.

4. Investment decision strategy

In our approach, the neural network works solely as an information system that would generate predictive information (trading signals) concerning next day stock price. A full--blown system would use a neural network as part of a hybrid trading system whose other part is relatively simple rule saying what a decision the trader should made. In that part we follow the paper [7]. Ones the training data are clustered we proceed as follows. For each data belonging to cluster, the next day return rates r_i are collected, statistically analyzed and finally represented by Sharpe ratio

$$s = \frac{\mathrm{mean}(r_i)}{\text{standard deviation } (r_i)},$$

which is believed to be a measure of investments efficiency.

That is done for each cluster separately, so that now we have collection of Sharpe ratios for each cluster. Members of the collection can be normalized to unity and used as a measure of the next day forecast of stock price and a base for the next day investment decision on the stock as well.

Let us summarize details of the method. The raw data are mapped on to logarithmic one-day returns, which became terms of the time series fed into wavelet decomposition tool. Wavelet decomposition was performed with the use of Scilab packet – Wavelab_Scilab_ver_1.1, in particular the function FWT_PB – (Forward Wavelet Transform, Periodized, Biorthogonal). The function uses biorthogonal 1.1 wavelet family. As input it takes logarithmic one-day returns as time series terms from window of length 16 and level of decomposition which we set to 4, and returns 16 wavelets coefficients. In this way the data from the 16 term long window are mapped onto vector of 16 wavelets coefficients which becomes representative of last term of data from the window. One can experiment how many and which of wavelets coefficients should enter the pattern that becomes the input into clustering tool. We decided to utilize first eight of all sixteen.

Turning now to clustering of patterns consisting of wavelets coefficients, we adopted the same topology and size of the SOM as in [7] was done, i.e. grid topology and $4 \times 4 = 16$ neurons (therefore we have decided that the number of clusters equals to 16 as well). After clustering was done, the Sharpe's ratio was calculated, which when normalized varied in the range of (–1.1). As and indicator of the active investment decision we choose sign of s when $\mathrm{abs}(s) > 0.01$, otherwise we assume the best thing is to do nothing.

However in opposite to the paper [7] we decided to create trading indicators on-line, which means that the networks is retrained every time the new data comes, i.e. when the price of final transaction ("close") of day is known. We believe that it would be more suitable for application of the networks in financial analysis and prediction.

Having prediction of tomorrow close price in hand, trading decision can be made which can be as follows: If we have cash and system predicts that the price of shares will increase the decision is - buy them. If we have shares and prediction system says that tomorrow the daily closing price will decrease, the decision is – sell them. If none of the two cases take place the decision is – stand aside (do nothing).

To test the method, close daily prices of the PKOBP bank shares in the time range span from 2.01.2007 to 24.04.2009 (in total 577 trading days) as raw input data have been used. The assumption has been made that portfolio consists of PKOBP shares only. Portfolio value equals to number of shares times current price of the share or equivalent number of currency units in cache. Besides, once a day an investor can only buy the shares for all money available or sell all shares. Transaction cost has not been taken into account.

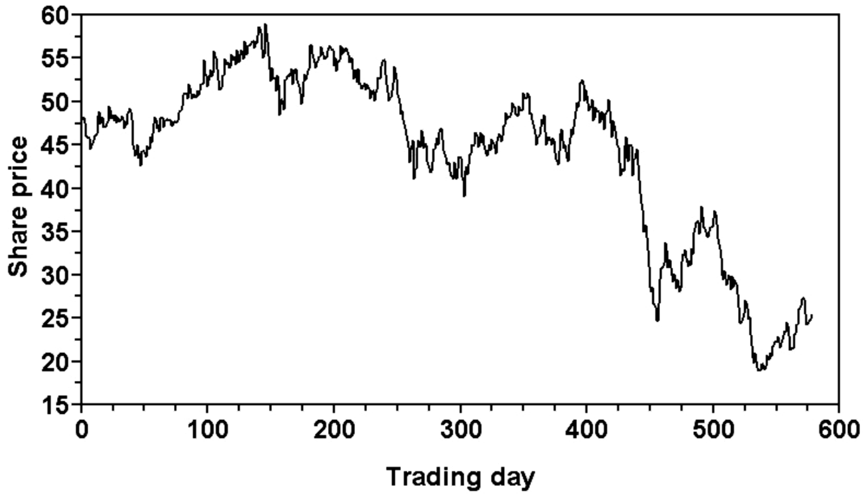

Fig. 1. Share price in the period of time since 2.01.2007 to 24.04.2009
Rys. 1. Cena akcji w okresie od 2.01.2007 do 24.04.2009

As a training data we used terms of data within sliding window of 64 terms long and predicted next day change of price for 150 trading days. The average number of correct predictions was about 60%, To illustrate effectiveness of proposed active investment strategy plots of portfolio value (worth of 100 currency units at the beginning) are done, one plot shows portfolio value changes when one follows our active investment strategy and second when one follows passive buy-and-hold strategy. We applied the method to two time periods of the same number – 150 of trading days. In the first one (since 2.08.2007 to 11.03.2008) share price fluctuate without any long time trend. Figure 2 shows evolution of portfolios value in that case.

In the second period (since 6.08.2008 to 11.03.2009) the rapid decrease of share price was observed. At the end of period considered, the share lost about 50% of its former value. Nevertheless active trading strategy was successful, it not only allow to avoid losses but even brought some gain.

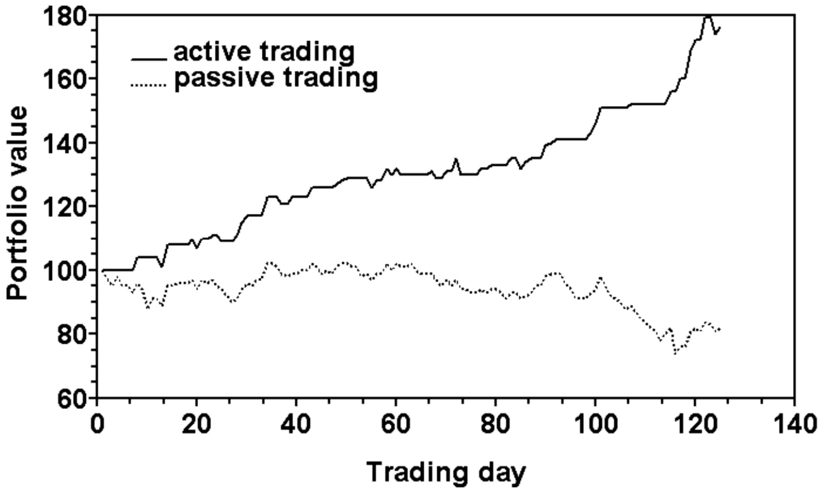

Fig. 2. Portfolio values in the period of time since 2.08.2007 to 4.02.2008
Rys. 2. Wartość portfela w okresie od 2.08.2007 do 4.02.2008

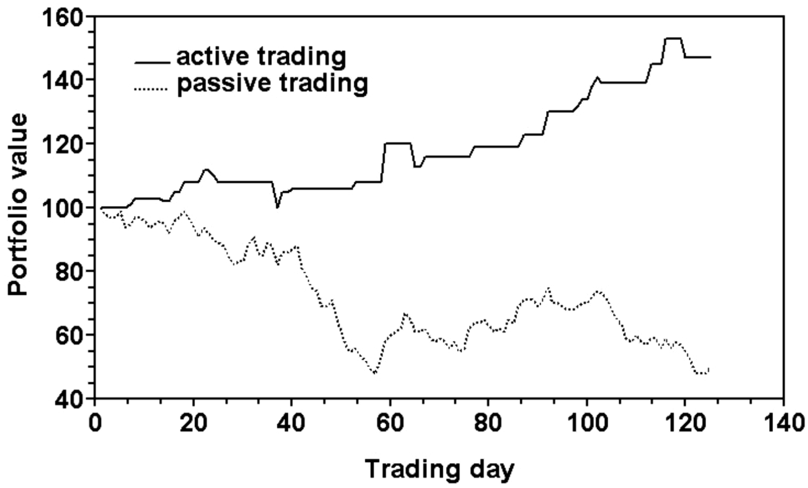

Fig. 3. Portfolio values in the period of time since 6.08.2008 to 6.02.2009
Rys. 3. Wartość portfela w okresie od 6.08.2008 do 6.02.2009

There is no doubt that the system based on wavelets preprocessing and neural networks clustering which we call active investments, outperforms a passive buy-and-hold strategy. The conclusion will stay true even if transaction cost (about 0.4% of turnover) is deducted from the total return.

5. Conclusion

Borrowing some ideas from papers [1] and [7] we propose a system of analysis time series data, in particular predicting its future values, based on wavelets preprocessing and neural networks clustering. We applied the system to predicting a one day ahead PKOBP share prices in two periods of time. In the first one stock market was not very bully and passive investment did not bring return. In the second one share price dropped strongly. Nevertheless the active investment in opposite to the passive one appears to be profitable in both cases.

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