OBTAINING THE MEMBERSHIP FUNCTION BY USING THE NEURAL NETWORK IN ISTANBUL STOCK EXCHANGE TO FIND THE RELATION BETWEEN THE LOW AND CLOSING PRICES

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Abstract

By using neural network, the relationship between the low price and the closing price in IMKB is developed by a fuzzy membership function.

Keywords: Fuzzy, membership function, neural network, IMKB, indexes, closing price, clustering.

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1 Introduction

The principal aim of this paper in to find the relation between the low and closing prices in Istanbul Stock Exchange by using neural network and fuzzy membership functions.

The theory of fuzzy sets for the representation of uncertainty was introduced by Lotfi A. Zadeh and has been studied and applied by many people in all over the world. Recently the theory of fuzzy numbers and fuzzy logics has been introduced and up to now a great development was provided.

Second section covers the fundamentals of fuzzy set theory, membership functions, their shapes and properties and also the methods of membership value assignments.

Neural Network's structure and working are mentioned in third section.

In section four, the basic information about Istanbul Stocks Exchange (IMKB) and also the basic information about clustering are given.

In last section, we are going to use this information while solving our problem.

2 Preliminaries

2.1 Definition

Let X be the universe of discourse (the universal set) and x be a generic element of X. In a crisp set (classical set) membership of an element x in set $A \subset X$ is described by a characteristic function $\mu_A(x)$ as in the following.

$$\mu_A(x) = \begin{cases} 1 & , \quad x \in A \\ 0 & , \quad x \notin A \end{cases}$$

For a fuzzy set, the characteristic function allows a various grades of membership in the interval [0, 1] of a given set. Fuzzy set theory is a generalization of crisp set theory. Definitions, theorems and proofs of fuzzy set theory always hold for crisp sets. Briefly a fuzzy set A on X, is a set of ordered-pairs $A = [(x, \mu_A(x))]$, $x \in X$ where $\mu_A(x) \in [0,1]$ and is called membership function.

A finite fuzzy set A on X is expressed as

$$\begin{aligned} A &= \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \ldots + \mu_A(x_n)/x_n \\ &= \sum_{i=1}^{x} \mu_A(x_i)/x_i. \end{aligned}$$

When X is not finite, fuzzy set A on X is expressed as

$$A = \int_x \mu_A(x)/x, [3].$$

2.2 Fuzzy Set Operations

Let A and B are two fuzzy subsets of X, with membership functions μ_A and μ_B respectively.

Union	: $\mu_{A \cup B}(x) = \mu_A(x) \vee \mu_B(x) = \max(\mu_A(x), \mu_B(x))$
Intersection	: $\mu_{A \cap B}(x) = \mu_A(x) \wedge \mu_B(x) = \min(\mu_A(x), \mu_B(x))$
Complement	: $\mu_{\bar{A}}(x) = 1 - \mu_A(x)$

Bounded sum : $A \oplus B = \int_x 1 \wedge (\mu_A(x) + \mu_B(x))/x$

Bounded difference : $A \Theta B = \int_x 0 \vee (\mu_A(x) - \mu_B(x))/x$

Also in fuzzy set theory $A \cup \bar{A} \neq X, A \cap \bar{A} \neq \emptyset$ are holds.

2.3 Membership Functions

Since fuzzy sets are described by membership functions, their descriptions are very important in fuzzy set theory. Membership functions are in the triangle, bell curve, trapezoid, monotonic and monolitic forms according to the properties of studying case.

2.4 Properties of Membership Functions

- The core of a membership function for some fuzzy set A is comprises those elements x of the universe such that $\mu_A(x) = 1$.
- The support of a membership function for some fuzzy set A is the set of points in X at which $\mu_A(x) > 0$.
- A *normal fuzzy set* is one whose membership function has at least one element in the universe where its membership value is equal to 1.
- For any $x, y, z \in A$, $x < y < z$ relation implies that $\mu_A(y) \geq \min(\mu_A(x), \mu_A(z))$, then A is said to be a *convex fuzzy set.*
- The *crossover point* of a membership function A is the point in X whose grade of membership in A is 0.5.
- The *heigh* of a fuzzy set is equal to $\max\{\mu_A(x)\}$.
- Convex and normal fuzzy set is said to be a *fuzzy number.*

2.5 Membership Value Assignments

There are possibly more ways to assign values or functions to fuzzy variables in literature. Intuition, inference, neural networks, genetic algorithms and fuzzy statistics are some of these methods.

3 Neural Networks

A neural network is a tecnique that seeks you builds an intelligent program using models to simulate the working network of the neurons in the human brain [4].

The concept of how neurons work in the human brain is utilized in performing computations on computers. The neurons are responsible for the human capacity to learn, and in this sense the physical structure is being emulated by a neural network to accomplish machine learning [4].

The variables $x_1, x_2, \ldots, x_n$ are the n inputs of the threshold element. The variables $w_1, w_2, \ldots, w_n$ are the weights associated with the impulse. When w_i is a positive input x_i acts as an excitatory otherwise acts as an inhibitory signal for the element.

The threshold element compares the sum $\sum w_i x_i$ to a prescribed threshold value and if the $\sum w_i x_i$ is greater than the threshold value computes an output using a nonlinear function, for example a sigmoid function $F(s) = \frac{1}{1+e^{-s}}$. The y output can be defined as $y = F(\sum w_i x_i - t)$ where t is a threshold value [4].

Figure 3.1 shows a simple neural network for a system with single input signal x and a corresponding single output signal $f(x)$. First layer has a single element that has a single input and the element sends its output to the other elements in the second layer. Second layer elements are single output elements and the last layer has one element that has four inputs. This is a $1 \times 4 \times 1$ neural network system. Neural network systems solve problems by adapting to the nature of the signal they receive. By doing, this neural network use a training-data set and a checking-data set of input and output signals.

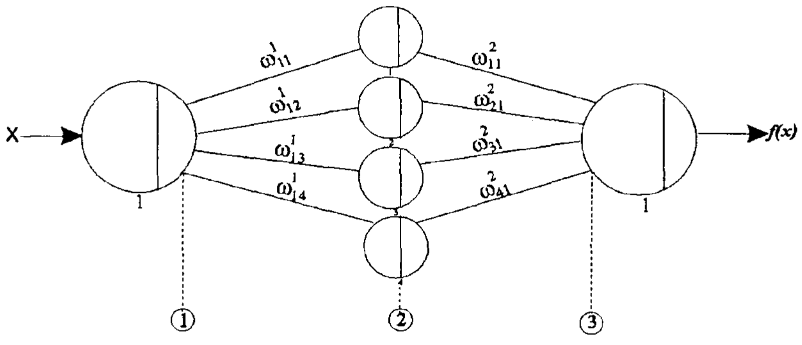

Figure 3.1. 1 x 4 x Neural network system

Randon assignment of weights w^i_{jk} is given to the paths joining the elements in the different layers. Later an input from the training-data set is passed through the neural network. Output value $f(x)$, computes by a neural network and the error measure δ is computed by $\delta = y - f(x)$. Then this error distribute to the hidden layers (layers other than first and last layer) using back-propagation technique. Let

δ_j : The error associated with the j th element
w_{nj} : The weight associated with the line from element n to the element j
I : input to unit n

The error for element n is computed by the formula $\delta_n = F'(I) w_{nj} \delta_j$ where $F(I) = 1/(1 + e^{-I})$ and also $F'(I) = F(I)(1 - F(I))$. Then the different weights w^i_{jk} are corrected so that they can approximate the final output. The associated weights may be updated by

$$w_i(new) = w_i(old) + \alpha \delta x_i$$

where

α : Learning constant
δ : Error measure
x_i : Input signal

Then input value x_i is passed through the neural network again and the errors are computed again. This technique is iterated until the error value of the final output is within the acceptable limits. This method is continued for all data in the training-data set. Finally a checking-data set is used to verify how well the neural network can simulate the nonlinear relationship [4].

4 Istanbul Stocks and Bonds Exchange (IMKB)

4.1 Definition of Exchange

According to the governing statutes, exchanges are the public associations, which provide the trade of stock and bonds admitted by the exchanges, in regular ways, and appropriate to the statue. They are established with the permission of ministry after the offer of Exchange Stock Market Council.

According to the statute, exchanges in which the means of stock market are mack procedure, are the foundations that are established in order to provide the stocks and bonds and other stock market means to be sold in a confidence and stability position and with the competition lack of restraint. Juristic persons manage these foundations.

4.2 Istanbul Stocks and Bonds Exchange (IMKB)

It is a governing association which is managed by jursitic persons and is established in order to the make functions given by statue written decree market 91 about Stocks and Bonds exchanges IMKB, is active during the official work days, also IMKB is also a profession establishment. It has member, like the other profession establishment.

4.3 Members of Exchange

1. Investment and propress banks
2. Commercial Banks
3. Medator Foundations

can be the members of exchanges, in order to be the member, they have to get authority certificate from stock market council.

General council is the top part of exchange it has members and decisions are taken there. General council chooses Executive Committee. The chief of Exchange is also the chief of executive committee and government with common written degree appoints him.

4.4 Function and Qualifications of IMKB

The main functions and qualifications of IMKB are as following:

- To make decisions an appraise about petitions which is wanted to be in Stock and Bonds Exchange.
- To want more documents and information to examine petitions according to the basis of internal written regulations.
- To open markets about money foreign exchange valuable mine, rocks and procedures having a fixed term after making lawful requirements.
- To make kinds of stocks and bonds markets for stocks and bonds being made procedure in exchange and publish them in exchange bulletin.
- To regulate place for markets in exchange building.
- To show the prices taken from the result of the procedure and total procedure amounts made due to these prices at the end of the sessions [1].

4.5 Indexes

Indexes that is used as a pointer in statistics can be defined as measurement of changes of one few variables in order to time, place the other properties, indexes are the tools which solves complex problems and gives information about them.

Indexes provide the facility of compare and continuity. In this way the directions of variable or variables, changes and directions can be determined. Indexes, which are especially used in scientific research, are generally used for matter, which are about management and economics. During the comparisons and measures of incomes of alternative investments, beneficial information can be provided from indexes.

The indexes of price of allotted portion which is general pointer of market gives information about general performance of market in order to the price of allotted portion. Indexes of price allotted portion generally shows temporary situation.

There are two main kinds of indexes, which measure the chances of prices of allotted portion. The first part of indexes is simple ones, which depends on geometric or arithmetic average.

This part of indexes ignores the partial importance of allotted portion. The other part is complex one, which contains large amount of allotted portion. The indexes of IMKB are also complex indexes.

IMKB was originated in order to the average price of market of 40 firms in 1986 with 100 starting point. Until on October 26 in 1987, indexes were calculated weekly. Then these indexes were calculated every day. Until the end of the 1989 indexes were calculated in order to the arithmetic average of changes of firms market prices. In 1990 the compound indexes of IMKB was started to calculate in order to the market price of companies. In 1991 it was started to calculate in order to the market price of the parts of the firm, which are vailable to public. The number of firms reached 100 by means of the increase of the companies, which are managed in indexes. And the compound indexes of IMKB were identified as 100.

4.6 The Characteristics of Indexes of IMKB

1. The indexes of IMKB depend on market prices.

2. The indexes of IMKB are continual.

3. The starting point of IMKB indexes is 100.

4. IMKB take into consideration of officially registered price.

5. IMKB compound indexes comprehensive and represent the big part of the market.

6. Compound indexes calculates again for every 15-second between the first sitting (10:00-12:00) and the second sitting (14:00-16:00). Maximum and minimum prices are demonstrated in Reuters Telerate, TRT - teleteks for all 15 seconds [1].

4.7 Generating a Fuzzy Membership Function Using Istambul Stock Exchange Data

We have tried to calculate the estimated closing price of paper in the following session by educating the related data of previous session by using an neural network system based on received data from Istanbul Stock Exchange. We have formed a fuzzy membership function by using neural network. Before passing our problem, we will explain why we needed to use fuzzy logic in the neural network and how we obtained the membership functions by using the neural network.

We can classify in and out data clusters in different fuzzy classes by using fuzzy logic in system where the relation between the inlet and outlet is not linear or not clearly known to classify the inlet and outlet data clusters into different fuzzy clusters. Moreover, fuzzy membership functions must be updated over and over in dynamic system of nature. In such system, neural network system will be the best method to use since it automatically modifies itself to provide the changes.

4.8 Obtaining Fuzzy Membership Function by Using Neural Network

We will describe how to obtain fuzzy membership functions for fuzzy classes for a let data cluster. First, a certain number of inlet data values are chosen and divided into different data clusters for education and control. Education data cluster is used for educating the neural network. Control data cluster is used to test the educated neural network. Data points are divided into different classes with clustering method.

When we consider data points are classified into two classes as $\mathbf{R_1}$ and $\mathbf{R_2}$, any data belonging to $\mathbf{R_1}$ class shall have 1 membership value and data belonging to $\mathbf{R_2}$ class shall have 0 membership value. This calculation shall be repeated for each and all data and 1 membership value appointed to data points for the classes they belongs in the beginning. In order to educate the relationship between the data coordinates and membership functions, a neural network are formed which use such data points and corresponding membership functions. Then performance of the neural network system is measured by using the control data cluster. After that we obtain the actual membership values of the data in above-mentioned classes by using the educated neural network [4].

5 Obtaining the Membership Function by Using the Neural Network in Istanbul Stock Exchange to Find the Relation between the Low and Closing Prices

For the solution of our problem, we have received weekly and session-by-session data from Istanbul Stock Exchange.

We have educated 30 of data on the neural network that we have selected randomly at the end of a session with a slightly different method from the one described above. We aimed at providing the intermediary agencies with the estimation for them to supply their customers whether a given security will close the next session at high or low value by using the values obtained from this educated neural network and thus to have them act accordingly during the closing. We have gathered a very high performance from our works. First, we have normalized the low, high and closing values of randomly selected 30 securities since we would use fuzzy clusters. Then, we have divided these values to through clustering method by using a pascal program. We have taken first of these as the "low" and the second as "high" class. See table 5.1 for related data.

Data obtained from 1^{st} session of Istanbul Stock Exchange on Friday, May 9, 1997 that we have used in educating the neural network and test its performance are indicated in Table 5.2. Whether a given security will close high or low at the end of second session of the same day is found by taking the closing value of that security in the first session and the lowest value of the same security taken by the intermediary agency in the second session as entry data and passing it through the educated neural network. Related data indicated in Table 5.3 to show how much of our estimations are true, the values of the subject securities in the second session are in table 5.4.

Table 5.1. Classification of educated 30 data to Low and High classes through clustering Methods.

Security $N°$	Low	High
1	0	1
2	0	1
3	1	0
4	0	1
5	0	1
6	0	1
7	1	0
8	0	1
9	1	0
10	0	1
11	0	1
12	0	1
13	1	0
14	0	1
15	0	1
16	0	1
17	1	0
18	0	1
19	0	1
20	1	0
21	1	0
22	0	1
23	0	1
24	0	1
25	0	1
26	0	1
27	1	0
28	0	1
29	0	1
30	0	1

Table 5.2. Normalized Values, which were obtanined in the 1^{st} session on Friday, May 9, 1997.

Security $N°$	Lowest Price	Highest Price	Closing Price
1	0.01275	0.01325	0.013
2	0.0975	0.105	0.1
3	0.44	0.45	0.445
4	0.2275	0.2325	0.2325
5	0.27	0.28	0.275
6	0.1375	0.14	0.14
7	0.5	0.51	0.51
8	0.2125	0.225	0.2175
9	0.57	0.58	0.58
10	0.11	0.1125	0.1125
11	0.105	0.1075	0.1075
12	0.1075	0.1125	0.1075
13	0.32	0.32	0.32
14	0.1425	0.1475	0.1425
15	0.145	0.15	0.1475
16	0.043	0.046	0.044
17	0.65	0.65	0.65
18	0.091	0.093	0.091
19	0.265	0.275	0.265
20	0.365	0.365	0.365
21	0.5	0.53	0.53
22	0.26	0.275	0.265
23	0.225	0.2325	0.2275
24	0.2125	0.2175	0.2125
25	0.12	0.125	0.125
26	0.01925	0.0195	0.01925
27	0.049	0.53	0.49
28	0.038	0.039	0.038
29	0.1375	0.14	0.14
30	0.2025	0.2025	0.2025

Table 5.3. Estimations for closing of some securities at the end of 2^{nd} session (normalized data).

Security	Lowest Value during 2^{nd} session	Closing Price at the end of 1^{st} session	Low Rate	High Rate
Alarko Holding	0.1825	0.1725	0	1
Borusan	0.069	0.07	0	1
Brisa	0.51	0.51	1	0
Ege Biracilik	0.365	0.36	0.998	0.002
Ereğli D. Çelik	0.1465	0.1425	0	1
Ist. Motor Pis.	0.1475	0.15	0	1
Koniteks	0.82	0.88	1	0
Raks Elektronik	0.3	0.3	0.632	0.368
Good-Year	0.65	0.65	1	0
Derimod	0.1225	0.125	0	1

Table 5.4. Values obtained for securities mentioned in Table 5.3 at the end of the 2^{nd} session on May 9, 1997.

Security $N°$	**Lowest Price**	**Highest Price**	**Closing Price**
Alarko Holding	0.18	0.185	0.1825
Borusan	0.068	0.07	0.07
Brisa	0.51	0.51	0.51
Ege Biracilik	0.36	0.365	0.365
Ereğli D. Çelik	0.1425	0.1475	0.1475
Ist. Motor Pis.	0.1475	0.15	0.1475
Koniteks	0.8	0.89	0.82
Raks Elektronik	0.295	0.305	0.305
Good-Year	0.65	0.65	0.65
Derimod	0.1225	0.1275	0.125

We have used $(2 \times 2 \times 1) - 3$ layer neural network model in solving problem. The model is drawn in Figure 5.1. By choosing weights randomly we have set the first data through neural network. While doing this, we have the following formula to calculate out of the knots. Starting value of t will also be selected randomly.

O : Output calculated for starting value by using sigmoid function.
x_i : Entrance value depending on the starting value.
w_i : Weight depending on x_i.
t : Starting value.

Output calculated through following formula:

$$O = \frac{1}{1 + \exp - (\sum x_i w_i - t)} \tag{5.1}$$

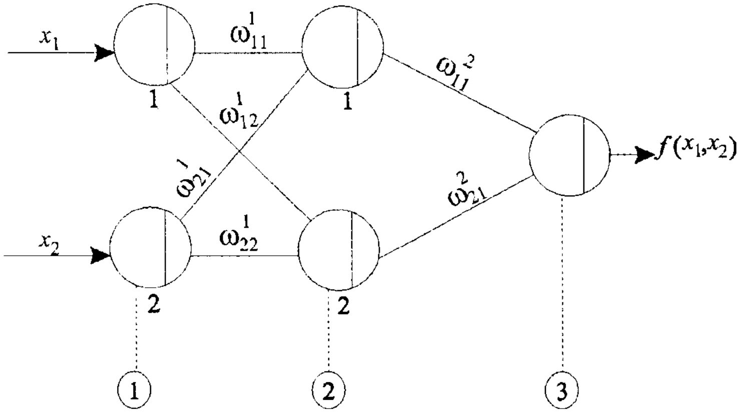

Figure 5.1. Neural Network Model in our problem $(2 \times 2 \times 1)$

Since output in the last layer is only one, and since we are only interested in "low" value, we will take the only output to consider the problem in the single dimension different from above mentioned method. For this, we will use only the low values in table 5.1.

$$D : E_1^3 = O_1^3 - O_1^3(\text{real}) \tag{5.2}$$

We will find O_1^3 (real) value is the value corresponding to low in the Table 5.4. Then we will change the weights by spreading the default backwards. While doing this we will use the following formula:

$$E_n^i = O_n^i(1 - O_n^i) \sum_j \omega_{nj}^i \, E_j^{i+1} \tag{5.3}$$

Then;

ω_{jk}^i : The weight which transfers element j of layer i to the element k of layer $(i+1)$.
α : Fixed learning value.
E_k^{i+1} : Default of element k of layer $(i+1)$.
O_j^i : Out from element j of layer i to the element k of layer $(j+1)$.

$$\omega_{jk}^i(son) = \omega_{jk}^i(ilk) + \alpha \, E_k^{i+1} \, O_j^i \tag{5.4}$$

With above formula the weights are changed. While changing the weights the default is distributed to hidden layer. In order to receive a better result, α is multiplied with a coefficient such as epsilon and out value. Also while weights are changed, starting value of t is changed by adding epsilon * alpha * (out value in the last layer) multiplication to the first t value. Different from the method of Ross we have described in the beginning, the solution is carried out by taking the second data not the first until the thirtieth data. For us, this is the end of 1^{st} iteration and in order to provide better education to neural network, we provided the iteration of 10000 consecutive repetition. After educating the system for each data as Ross suggested, we could not reach a solution for our problem. We have used a pascal program (which is using in neural network) with some changes to carry out the calculation. According to this, weights randomly selected for our first data (0.01275, 0.013) with which we would start to educate our neural network, out values we would obtain and new weights were as follows:

Random appointed first weights:

$\omega_{11}^{1} = 0.06$

$\omega_{12}^{1} = 0.08$

$\omega_{21}^{1} = 0.2$

$\omega_{22}^{1} = 0.09$

$\omega_{11}^{2} = 0.04$

$\omega_{21}^{2} = 0.11$

First out values:

$O_1^2 = 0.05004512$

$O_2^2 = 0.500929$

$O_1^3 = 0.45639$

Changed Weights:

$\omega_{11}^{1} = 0.059997$

$\omega_{12}^{1} = 0.07997$

$\omega_{21}^{1} = 0.199992$

$\omega_{22}^{1} = 0.089991$

$\omega_{11}^{2} = 0.02866$

$\omega_{21}^{2} = 0.098655$

Again, different from Ross, to test the performance of the educated neural network we used the data cluster that we have educated instead of a second data cluster.

Low and high values mentioned in Table 5.3, give the membership values of the data in the table. Figure 5.2 (a) shows monotonic membership functions obtained for Raks Electronic and Brisa.

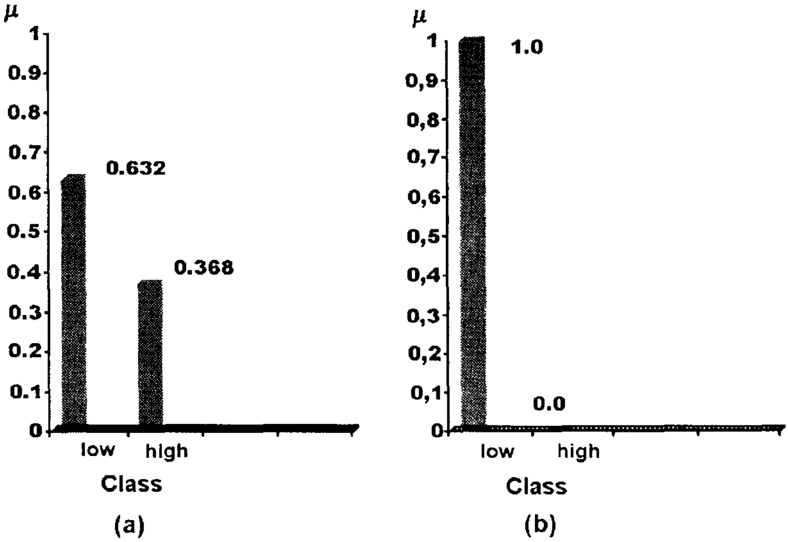

Figure 5.2 Membership function graphics for Raks Electronic (a) and Brisa (b)

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