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Fuzzy Logic and Investment Strategy

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In this article we try to find a complementarity between efficiency theory and behavioural finance concerning investment strategy using a fuzzy logic. To accomplish this goal, we use daily data of 25 firms quoted on the Tunisian Stock Exchange from January 2001 to December 2008. We find that the fuzzy logic give as a best results with a degree of precision of 93.26%.So, despite the debate between efficiency theory an behavioural finance, we can assert that it exist a fuzzy complementarity between these two theories in decision making that is means a fuzzy complementarity between fundamental and behavioural data.

Keywords: Fuzzy logic, investment strategy, complementarity, efficiency theory, behavioural finance

1. Introduction

Decision-making is a complex activity. It can be defined as the process of choosing a particular alternative from a number of alternatives. It is an activity that follows after proper evaluation of all the alternatives. Two principal theories are until on debate according to investment strategy: the efficiency theory and the behavioural finance.

The efficiency theory suggest that investors act rationally and consider all available information in the decision- making process, and hence investment markets are efficient, reflecting all available information in security prices (Fama 1965).It identify three forms of market efficiency: the weak, semi strong, and strong form.(Fama 1969). The choice of an active or passive investment policy is based on the acceptance concerning the market efficiency. A refusal of the market efficiency hypothesis results logically in an active investment strategy. However, a passive investment strategy is based on the acceptance of efficient markets.

The behavioural finance have uncovered a surprisingly large amount of evidence of irrationality and repeated errors in judgement. Its field has evolved that attempts to better understand and explain how emotions and cognitive errors influence investors and the decision-making process. Kahneman and Tversky (1979), Shefrin and Statman (1994), Shiller (1995) and Shleifer (2000) are among the leading researchers that have utilised theories of psychology and other social sciences to shed light on the efficiency of financial markets as well as explain many stock market anomalies, bubbles and crashes.

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Between these two theories, some researches, using classical logic, have tried to find an eventual relationship using heterogeneous approach (Henrik 2007). However, the classical logic has been widely criticized on the modeling the relationship between fundamental and behavioural data concerning investment strategy. The critics concern essentially the representation of each anticipation (so far to the reality), the linearity problem (ignorance of the no linearity), the complexity of the parameters (qualitative data)…

So and to overcome those critics, the goal of this paper is to model the investment decision through the fuzzy complementarity between fundamental and behavioural data. In fact, classical (two-valued) logic deals with propositions that are either true or false. In many-valued logic, a generalization of the classical logic, the propositions have more than two truth values. Fuzzy logic is an extension of the many-valued logic in the sense of incorporating fuzzy sets and fuzzy relations as tools into the system of many-valued logic. Fuzzy logic provides a methodology for dealing with linguistic variables and describing modifiers like very, fairly, not, etc. Fuzzy logic facilitates common sense reasoning with imprecise and vague propositions dealing with natural language and serves as a basis for decision analysis and control actions (Bojadziev and Bojadziev (2007)).

The paper is organized as follows. The second section gives a short summary of the three forms of efficiency theory; the investor's feeling measures and a brief idea of fuzzy logic. The third section presents our database and the used methodology. The fourth section presents the results. Finally, the last section concludes.

2. Literature review

2.1 Empirical Evidence of the three forms of efficiency

The three forms of efficiency are the weak, semi-strong and strong form.

2.1.1: *The weak form efficiency*

According to the weak form efficiency theory, the utilization of technical analysis is deemed void. Canadian evidence of weak form efficiency was seen in a study conducted by Zhang and Kyrzanowksi. Their study proved the "overreaction theory" does not work in Canadian markets. The overreaction theory assumes that knowing past stock returns enables investors to predict future returns. According to Zhang & Kyrzanowski the theory did not replicate similar results when tested with TSX listed stocks over the same time period of 38 years (Zhang and Kyrzanowksi, 1992).

2.1.2: The semi-strong form efficiency

Evidence of semi-strong form efficiency can be seen in examples such as stock splits, dividend announcements, IPOs' and overall reaction to the news and media. A study conducted in 2003 looked at 12,747 stock splits from 1927-1996. The study concluded that although a very small portion of those stock splits allowed investors to yield a substantial return, the overall results suggest that the buyers and sellers of stock splits do not yield extensive gains (Byun & Rozeff 2003). In addition, a study conducted by Fama indicated that markets seem to anticipate any information substantially in advance, and after the news is released the price of securities stabilize and do not experience extraordinary fluctuations (Fama, 1969). The same can be witnessed when a company announces a dividend. Although most dividend announcements coincide with earnings announcements, studies have concluded that the market adjusts accordingly, thus supporting the overall theory of an efficient market (Cleary et al 2005).

2.1.3: *The strong form efficiency*

In order to test strong-form market efficiency the assumption that industry insiders and investing professionals have an advantage should be thoroughly analyzed. In a research study conducted by Jensen, approximately one hundred and fifteen mutual funds were observed from 1955 to 1964. During this ten year period, eighty nine of those funds had average negative returns of -14.6%. If management fees, loading charges and other transactional costs were to be excluded, then fifty eight of the funds posted an average return of -2.5% (Fama, 1969). According to the results found in the research study, it is fair to conclude that evidence for strong-form efficiency exists, and even professional industry insiders are not able to beat the market and post abnormal gains.

In another study conducted on market efficiency called article “Volatility forecasting and the efficiency of the Toronto 35 index options market,” Craig Doidge found evidence for efficiency. This study focused on factors that determine option prices in the Toronto 35 option market. The study basically found that no substantial profits could be made after considering transaction costs and other fees thus concluding that the Toronto 35 option market is indeed efficient. Evidence of market efficiency from overseas markets was also observed. In a study conducted on the Nikkei index called, “Market efficiency: Experiences with Nikkei put warrants,” by Jason Wei looked at whether abnormal profits could be made by exploiting market lags. Wei concluded that the markets were efficient and that no consistent profits could be derived from utilizing such a strategy (Doidge 1998).

2.2 Measures of investor’s feeling

In the literature, we find two types of investor’s feeling measures: the direct measures and the indirect measures.

The direct measures of investor’s anticipations are generated by the gallup poll, for example investor’s investigation, circumstance’s (situation) investigation…

The indirect method supposes that some economic and financial variables, as closed funds below par rating, stock exchange introduction data, by-product…contain anticipations not justified by the economic fundamental.

2.3 fuzzy logic

The term "fuzzy logic" emerged in the development of the theory of fuzzy sets by Lotfi Zadeh (1965). The model developed by this author converts the subjective values into objective values. A fuzzy set does not have specific and limited boundaries; the distinction between belonging or not does not exist, but a degree of pertinence. Fuzzy logic is a system of concepts, principals and methods of dealing with modes of reasoning that are approximate rather than exact. It is particularly good at handling uncertainty, vagueness and imprecision and it is specially useful where a problem can be described linguistically (using words).In fuzzy logic the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values {true, false} as in classic predicate logic (Constantin (1995)).

3. Data and Methodology

3.1. Database

In our study, we use daily data for 25 firms quoted on the Tunisian Stock Exchange belonging to the banking and non banking sector. The historical data is obtained from the www.bvmt.com.tn Website of the Tunisian stock market and covers the period from 2/01/2001 to 31/12/2008. So we have 50025 observations.
Our variables are a combination between fundamental data and behavioural data.
For every firm, we calculate the following variables every day during the period January 2001-December 2008:

* Fundamental data (efficiency theory's variables): these variables are taken from the weak form of efficiency especially from the technical analyse:

- Return= $\frac{R_i}{E(R_i)}$

where R_i is the observed return and $E(R_i)$ is the expected return.

- Oss= the stochastic oscillator. It gives a signal for investor to decide, buy or sell, according to market trend. It tries to maintain the market trend by measuring the difference between the closing price, the lowest price of the last x days and the highest price of the last x days.

His measure is as follow:

$$Oss_{(xdays)} = 100 \times \frac{C - Lx}{Hx - Lx}$$

where C= The closing price, Lx= the lowest price of the last x days, Hx= the highest price of the last x days.

- Mom: the momentum. It represents the prices evolution speed. So, it constitutes a signal for investor to sell or to buy.

$$Mom = C_t - C_{t-x}$$

where C_t is the price of the day t and C_{t-x} is the price of the last x days.

* Bihavioural data (behavioural variables): those variables are the investor's feeling measures (Brown and cliff (2004)):

- $Sent_1 = \frac{ADV_t}{DEC_t}$

where ADV_t is the number of securities that know an augmentation of the price at the date t and DEC_t is the number of securities that know a diminution of the price at the date t.

- $Sent_2 = \frac{HI}{LO}$

where HI is the number of the new augmentations and LO is the number of the new diminutions. For the bihavioural data, we calculate the two variables (Sent $_1$ and Sent $_2$) every day for all firms not for every firm.

Table1: summary of data

Firms		Fundamental data	Behavioural data	Period
Banking sector	Non banking sector	Return= $\frac{R_i}{E(R_i)}$	Sent $_1$= $\frac{ADV_t}{DEC_t}$	January 2001-december 2008
AMEN BANK	ATL	Oss$_{(xdays)}$= $100 \times \frac{C - Lx}{Hx - Lx}$	Sent $_2$= $\frac{HI}{LO}$	
ATB	CIL	Mom = C_t-C_{t-x}		
ATTIJARI BANK	ELECTROSTAR			
BH	MAGASIN GENERAL			
BIAT	MONOPRIX			
BNA	SFBT			
BT	SIAME			
BTE(ADP)	SIMPAR			
STB	SIPHAT			
UIB	SOTETEL			
	SOTRAPIL			
	SOTUVER			
	SPDIT-SICAF			
	STAR			
	TUNINVEST-SICAR			

3.2. Methodology

We apply a fuzzy logic using software FuzzyTech®, where the model is divided into three main parts (figure 1):

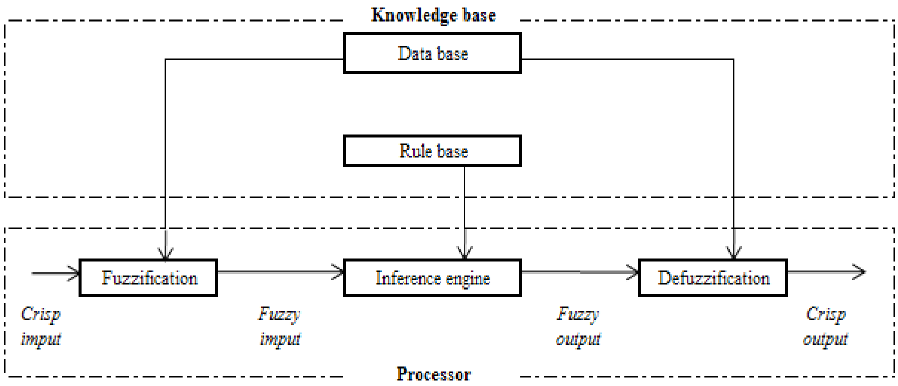

Fig 1. A fuzzy inference system

-Fuzzification: where numerical crisp variables are transformed to linguistic variables, which become a fuzzy impute for the inference rules.
- Inference engine: where the fuzzy impute is transformed by the rules of inference to fuzzy output.
- Defuzzification: where the linguistic language are changed into numerical value to become the output of the system.

a- Definition of data set for training and testing
The first 25012 daily data sets are used for in-sample estimation, covering the period from January 2001 to December 2004. The second half that covers the remainder period is used for out of-sample evaluation.

b- Fuzzification
All numerical input variables must be converted to linguistic variables. In this work, the input linguistic variables adopted were “low”, “high” and “medium”. To accomplish this task, membership functions are developed. Figure 2 show these pertinence functions for the variable Sent $_1$. This figure shows statistical membership functions which have been based on historical occurrences of the variable defining “low”, “high” and “medium” as above or below the 25th and 75th quartiles of the data. This definition naturally implies the trapezoidal shaped membership functions illustrated.

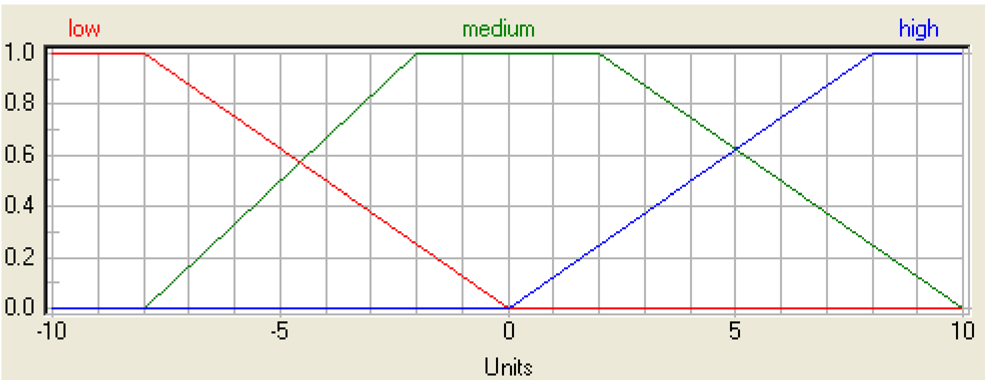

Fig 2: Membership functions for the variable *"sent$_1$"*

We define a membership function as follow (see annex 1):

$$\mu_{F^{Tr}}(u) = \begin{cases} 0 & if\ u \leq a \\ \dfrac{(u-a)}{(b-a)} & if\ a < u \leq b \\ \dfrac{(c-u)}{(c-b)} & if\ b < u \leq c \\ 0 & if\ u \geq c \end{cases}$$

C- Inference rules

Once the fuzzification of all input values has been done, the next step involves the establishment of inference rules. These rules represent the manner in which humans make decisions, inferring from linguistics premises. Inference rules were created with the help of the software FuzzyTech®. These rules are logical statements, and to each rule it can be assigned a value from zero to one, called Degree of Support (DoS), that depends on the characteristics of based sample. When a rule is assigned with a DoS equal to zero (one), the rule is considered insignificant (significant). The DoS also allows for values between zero and one for partial significant rule.

Within FuzzyTech, the DoS can be identified by the user as a fixed value or randomly determined by the software. The program also provides artificial neural networks (ANNs) that can be used to extract data for the rule base. ANNs perform repetitive evaluation of the known results and incrementally strengthen/weaken the influence of the rule on the modeling result; referred to as the 'DoS' in fuzzy models (The DoS is equivalent to rule weightings in an ANN for this application).
Below is an example of one of the used rules in our model.

If (Sent $_1$= 'low' ***and*** Sent $_2$= 'low' ***and*** Rent= 'low' ***and*** Oss='low' ***and*** Mom= 'low')
Then Strategy= 'Buy' with DoS= 0.84.

Initially, some difficulties were encountered in calibrating the fuzzy model, because of inconsistencies in the data. To address this problem, fuzzy cluster analysis which is part of FuzzyTech is used to identify discrepancies contained in data. Fuzzy clustering is a method of processing the data to remove redundant or conflicting data to increase the speed of training (Tsoukalas and Uhrig (1996)).For this reason, we remove conflicting data but we reserve them for the model validation.

In order to establish the inference rules, from the 25012 training sets, 18520 characteristics sets were selected. These characteristics sets had the values of *Return* associated to 100% "high" or 100% "low" or 100% "medium", the values of *oss* associated to 100% "high" or 100% "low" or 100% "medium", the values of *mom* associated to 100%"high" or 100% "low" or 100% "medium", the values of $sent_1$ associated to 100% "high" or 100% "low" or 100% "medium" and the values of $sent_2$ associated to 100% "high" or 100% "low" or 100% "medium" (see annex 2).

Same as before, these sets had the values of *Return* associated to 100% “high” or 100% “low” or 100% “medium”, the values of *oss* associated to 100% “high” or 100% “low” or 100% “medium”, the values of *mom* associated to 100%“high” or 100% “low” or 100% “medium”, the values of $sent_1$ associated to 100% “high” or 100% “low” or 100% “medium” and the values of $sent_2$ associated to 100% “high” or 100% “low” or 100% “medium” (see annex 3).

Based on the probability distribution, the inference rules were developed using FuzzyTech® (see annex 4).

d- Output variables
The output of our model is denominated *Strategy*, which represents investor’s decision making. The output of the linguistic values adopted was: buy, sell, and no trade. In this work the defuzzification was not necessary. The linguistic values were used as output variables, corresponding to the probability of the index showing a buy, sell, or no trade behavior.

For a preliminary verification of the model it was selected, from the 18520 test sets, 18141 characteristics sets.

The output variable *Strategy* can be represented as a vector of dimension 3x1 as shown below:

$$S = \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix}$$

Where S_1 is the linguistic component “buy” of output *Strategy*, S_2 is the linguistic component “notrade” of output *Strategy*, and S_3 is the linguistic component “sell” of output *Strategy*.

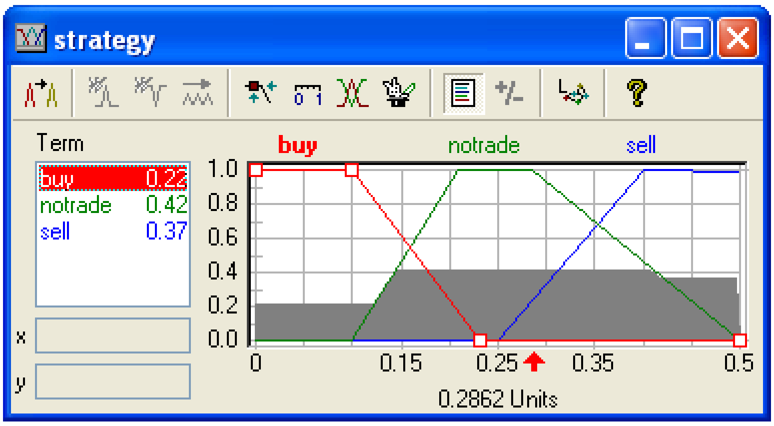

Fig 3. Example of output linguistic value

4. Results

When we have divided our period into two equal subsets, for training data (January 2001-december 2004) and for test data (January 2005-december 2008), we have find ε = 6.74% that's means that our model give as a best results with a degree of precision of 93.26%.

So, we can conclude that the fuzzy logic shows that there is a relationship between fondamental data (technical analyse's variables: return, momentum, stochastic oscillator) and behavioural data (investor's feeling measures: $Sent_1$ and $sent_2$) concerning investment strategy. So, we can say that there is a *fuzzy complementarity* between efficiency theory and behavioural finance concerning investment strategy.

5. Conclusion

In this study we present a model based on fuzzy logic to know the investor's investment strategy (sell, buy or no trade) using the FuzzyTech® software. The sampled period comprised 50025 daily observations of five variables that constitute fundamental data and behavioural data of 25 firms quoted on the Tunisian Stock Exchange from January 2001 to December 2008. The proposed model returns a non exact answer, with a probabilistic output. Despite of this imprecision, the model output give as a best results that let's as conclude, despite the present debate between efficiency theory and behavioural finance, that is a *fuzzy colmplementarity* between those two theories concerning investment strategy. Also, the proposed model, with its probabilistic output, can be used as a support to other decisions as the herding behaviour. One of the shortcomings of this work is the short period of study, and the small number of variables and firms used. There are many new researches possibilities that could be derived from this work. One of them is to add other input variables (fundamental variables and behavioural variables) and linguistic terms, increase the number of firms that constitute the sample and make the comparison between the classical logic and the fuzzy logic concerning decision making. Also other artificial intelligence techniques, as ANN, could be associated with models based on fuzzy logic.

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Annex 1

Example of a membership function: the variable Sent $_1$(The same work is done for the other input variables (Return, Oss, Mom and sent $_2$)):

Sent1

$$\mu_x \text{ (low)} = \begin{cases} 1 \text{ if } x < 0.6 \\ (1.4-x)/0.8 \text{ if } 0.6<x<1.4 \\ 0 \text{ if } x>1.4 \end{cases}$$

$$\mu_x \text{ (high)} = \begin{cases} 0 \text{ if } x <0.6 \\ (1.4+x)/2 \text{ if } 6<x<1.4 \\ 1 \text{ if } x>1.4 \end{cases}$$

$$\mu_x \text{ (medium)} = \begin{cases} 0 \text{ if } x <0.6 \text{ M } x>1.4 \\ 1 \text{ if } 0.8<x<1.2 \\ (0.8-x)/0.2 \text{ if } 0.6<x<0.8 \\ (1.4+x)/0.6 \text{ if } 0.8<x<1.4 \end{cases}$$

Annex 2

Table 1: Example of selected training data

$sent_1$	$sent_2$	Return	Oss	Mom	Sets
Low	low	low	low	low	100
Low	low	low	low	low	195
Low	low	low	low	low	180
Low	low	low	low	high	56
Low	low	low	low	high	143
Low	low	low	low	high	80
Low	low	low	medium	low	142
Low	low	low	medium	low	90
Low	low	low	medium	low	150
Low	low	low	medium	high	30
Low	low	low	medium	high	140
Low	low	low	medium	high	23
Low	low	low	high	low	47
Low	low	low	high	low	151
Low	low	low	high	low	158
Low	low	low	high	high	51
Low	low	low	high	high	69
Low	low	low	high	high	95
Low	low	medium	low	low	60
Low	low	medium	low	low	78
Low	low	medium	low	low	192
Low	low	medium	low	high	78
Low	low	medium	low	high	58
Low	low	medium	low	high	93
Low	low	medium	medium	low	114
low	low	medium	medium	low	86
low	low	medium	medium	low	123
low	low	medium	medium	high	47
low	low	medium	medium	high	58
low	low	medium	medium	high	56
low	low	medium	high	low	69
low	low	medium	high	low	71
low	low	medium	high	low	56
low	low	medium	high	high	123
low	low	medium	high	high	58
low	low	medium	high	high	25
low	low	high	low	low	90
low	low	high	low	low	179
low	low	high	low	low	158
low	low	high	low	high	69
low	low	high	low	high	17
low	low	high	low	high	64
low	low	high	medium	low	159
low	low	high	medium	low	157
low	low	high	medium	low	186
low	low	high	medium	high	64
low	low	high	medium	high	67
low	low	high	medium	high	49
low	low	high	high	low	79
low	low	high	high	low	73

low	low	high	high	low	96
low	low	high	high	high	176
low	low	high	high	high	145
low	low	high	high	high	97
low	medium	low	low	low	100
low	medium	low	low	low	162
low	medium	low	low	low	45
low	medium	low	low	high	54
low	medium	low	low	high	115
low	medium	low	low	high	178
low	medium	low	medium	low	147
low	medium	low	medium	low	69
low	medium	low	medium	low	48
low	medium	low	medium	high	137
low	medium	low	medium	high	186
low	medium	low	medium	high	147
low	medium	low	high	low	58
low	medium	low	high	low	96
low	medium	low	high	low	68
low	medium	low	high	high	179

Annex 3

Table 2: Example of selected testing data

$sent_1$	$sent_2$	Return	Oss	Mom	Sets
Low	low	low	low	low	100
Low	low	low	low	low	185
Low	low	low	low	low	180
Low	low	low	low	high	40
Low	low	low	low	high	143
Low	low	low	low	high	78
Low	low	low	medium	low	142
Low	low	low	medium	low	90
Low	low	low	medium	low	150
Low	low	low	medium	high	25
Low	low	low	medium	high	125
Low	low	low	medium	high	23
Low	low	low	high	low	47
Low	low	low	high	low	99
Low	low	low	high	low	158
Low	low	low	high	high	51
Low	low	low	high	high	61
Low	low	low	high	high	95
Low	low	medium	low	low	60
Low	low	medium	low	low	65
Low	low	medium	low	low	192
Low	low	medium	low	high	78
Low	low	medium	low	high	40
Low	low	medium	low	high	93
Low	low	medium	medium	low	85
Low	low	medium	medium	low	86
Low	low	medium	medium	low	94
Low	low	medium	medium	high	47
Low	low	medium	medium	high	58
Low	low	medium	medium	high	39

Low	low	medium	high	low	69
Low	low	medium	high	low	71
Low	low	medium	high	low	56
Low	low	medium	high	high	120
Low	low	medium	high	high	58
Low	low	medium	high	high	25
Low	low	high	low	low	88
low	low	high	low	low	179
low	low	high	low	low	158
low	low	high	low	high	64
low	low	high	low	high	17
low	low	high	low	high	64
low	low	high	medium	low	133
low	low	high	medium	low	147
low	low	high	medium	low	180
low	low	high	medium	high	64
low	low	high	medium	high	61
low	low	high	medium	high	49
low	low	high	high	low	79
low	low	high	high	low	70
low	low	high	high	low	96
low	low	high	high	high	176
low	low	high	high	high	145
low	low	high	high	high	97
low	medium	low	low	low	85
low	medium	low	low	low	162
low	medium	low	low	low	45
low	medium	low	low	high	54
low	medium	low	low	high	105
low	medium	low	low	high	178
low	medium	low	medium	low	147
low	medium	low	medium	low	69
low	medium	low	medium	low	48
low	medium	low	medium	high	129
low	medium	low	medium	high	186
low	medium	low	medium	high	147
low	medium	low	high	low	58
low	medium	low	high	low	96
low	medium	low	high	low	64
low	medium	low	high	high	179

Annex 4

Table 3: Example of Inference rules

IF					THEN	
sent1	**sent2**	**rent**	**oss**	**mom**	**DoS**	**strategy**
Low	low	low	low	low	0.84	buy
Low	low	low	low	low	0.03	notrade
Low	low	low	low	low	0.75	sell
Low	low	low	low	high	0.77	buy
Low	low	low	low	high	0.26	notrade
Low	low	low	low	high	0.22	sell
Low	low	low	medium	low	0.42	buy
Low	low	low	medium	low	0.17	notrade
Low	low	low	medium	low	0.55	sell
Low	low	low	medium	high	0.04	buy
Low	low	low	medium	high	0.69	notrade
Low	low	low	medium	high	0.79	sell
Low	low	low	high	low	0.41	buy
Low	low	low	high	low	0.09	notrade
Low	low	low	high	low	0.01	sell
Low	low	low	high	high	0.10	buy
Low	low	low	high	high	0.60	notrade
Low	low	low	high	high	0.25	sell
Low	low	medium	low	low	0.91	buy
Low	low	medium	low	low	0.45	notrade
Low	low	medium	low	low	0.73	sell
Low	low	medium	low	high	0.27	buy
Low	low	medium	low	high	0.90	notrade
Low	low	medium	low	high	0.59	sell
Low	low	medium	medium	low	0.28	buy
low	low	medium	medium	low	0.87	notrade
low	low	medium	medium	low	0.77	sell
low	low	medium	medium	high	0.77	buy
low	low	medium	medium	high	0.09	notrade
low	low	medium	medium	high	0.47	sell
low	low	medium	high	low	0.03	buy
low	low	medium	high	low	0.66	notrade
low	low	medium	high	low	1.00	sell
low	low	medium	high	high	0.25	buy
low	low	medium	high	high	0.32	notrade
low	low	medium	high	high	0.20	sell
low	low	high	low	low	0.10	buy
low	low	high	low	low	0.72	notrade
low	low	high	low	low	0.43	sell
low	low	high	low	high	0.67	buy
low	low	high	low	high	0.20	notrade
low	low	high	low	high	0.33	sell

IF					THEN	
low	low	high	medium	low	0.98	buy
low	low	high	medium	low	0.80	Notrade
low	low	high	medium	low	0.84	Sell
low	low	high	medium	high	0.45	Buy
low	low	high	medium	high	0.16	Notrade
low	low	high	medium	high	0.56	Sell
low	low	high	high	low	0.79	Buy
low	low	high	high	low	0.23	Notrade
low	low	high	high	low	0.77	Sell
low	low	high	high	high	0.37	Buy
low	low	high	high	high	0.05	Notrade
low	low	high	high	high	0.58	sell
low	medium	low	low	low	0.87	buy
low	medium	low	low	low	0.10	notrade
low	medium	low	low	low	0.30	sell
low	medium	low	low	high	0.93	buy
low	medium	low	low	high	0.21	notrade
low	medium	low	low	high	0.95	sell
low	medium	low	medium	low	0.09	buy
low	medium	low	medium	low	0.82	notrade
low	medium	low	medium	low	0.98	sell
low	medium	low	medium	high	0.35	buy
low	medium	low	medium	high	0.51	notrade
low	medium	low	medium	high	0.14	sell
low	medium	low	high	low	0.80	buy
low	medium	low	high	low	0.18	notrade
low	medium	low	high	low	0.50	sell
low	medium	low	high	high	0.04	buy