Integration of Collective Knowledge in Financial Decision Support System

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Abstract. Execution of a process supporting making financial decisions using the multiagent system entails the need of permanent cooperation between a human (humans) and agent (agents) collectives. Their knowledge is acquired from autonomous and distributed sources and they use different decision support methods therefore certain level of heterogeneity characterizes knowledge of collectives. In the decision-making process one, final decision is required therefore knowledge of individual members of the collective shall be automatically integrated. The aim of the paper is to develop consensus method in order to integrate knowledge of human-agent collectives in a multiagent financial decision support system built with the use of cognitive agent architecture. The first part shortly presents the state-of-the-art in the considered field; next a Multiagent Cognitive Financial Decision Support System has been characterized. The last part of paper presents the consensus algorithm for knowledge integration.

Keywords: Multiagent systems · Financial decision support systems · Human-agent collectives · Knowledge integration · Consensus methods

1 Introduction

Making financial decisions is a continuous process, it is connected with multivariance due to its multicriteria nature, and consecutive decision-related situations appear in a chronological order, in near real-time, which are why it has become necessary to employ systems supporting decision making processes, including multiagent systems. The systems enable automatic and fast access to information of adequate value, on the basis of which one can draw conclusions [4].

Execution of a process supporting making financial decisions using the multiagent system entails the need of permanent cooperation between a human (humans) and a program agent (agents). There may be various forms of such cooperation. One of them may include a situation when agents generate different variants of a decision, and human make the final decision. Cooperation may also consist of agents making final decisions automatically on the basis of criteria defined by people and specifying the level of his or her satisfaction from the decision (the criteria may include, for example the level of return rate, the level of risk). The form of cooperation may also be connected with making decisions concerning final decisions on the basis of variants created by a human

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(an expert) and variants generated by an agent (where a human and an agent are treated equally while making decisions).

Each of the forms of cooperation leads to the emergence of human-agent collectives (collectives, groups) characterized by the fact that they have knowledge from autonomous and distributed sources and they use different decision support methods. For example, decisions made by humans (people) may be made with the use of fundamental analysis, on the basis of experts' opinions, whereas decisions of an agent (agents) may be made using technical analysis, on the basis of various types of indicators. Additionally, one of the members of a collective may for example perform analysis of securities of a given group of companies, and another one may analyze securities of a different group of companies. Consequently, decision variants presented by individual members of the collective may differ. A certain level of heterogeneity characterizes knowledge of these collectives. Since, however, in the decision-making process one, final decision is required, knowledge of individual members of the collective shall be automatically integrated. It may be done, for example by using certain criteria or functions of assessing knowledge of individual members of the collective. However, in case of an inadequate or imprecise indication of the criteria or functions, the risk of selecting a variant which does not guarantee the desired level of satisfaction increases. The employment of consensus methods, which also enable integration of knowledge, seems to be more reliable. The consensus methods, however, assume that each party is taken into account, each party to a conflict "loses" as little as possible, each party contributes to the consensus, all parties accept the consensus, and it constitutes the representation of all parties to a conflict. Any decision made using the methods does not have to be a decision formulated by any of the members of a collective. It may only closely resemble one of such decisions. Thus the consensus enables integration of knowledge in real-time, and it guarantees reaching a satisfactory compromise at a lower level of risk, which consequently may lead to making decisions which bring satisfactory benefits to decision makers.

The aim of the paper is to develop consensus method in order to integrate knowledge of human-agent collectives in a multiagent financial decision support system built with the use of cognitive program agent architecture [2]. The integration of knowledge will consequently enable selection of final decisions presented by the system to users. A particular attention has been paid to the form of cooperation consisting of establishing final decisions on the basis of variants created by humans (experts) and variants generated by program agents.

This paper is organized as follows: the first part shortly presents the state-of-the-art in the considered field; next a Cognitive Multiagent Financial Decision Support System has been characterized. The last part of paper presents the consensus algorithm for knowledge integration.

2 Related Works

One of the first solutions of a multiagent financial decision support system has been suggested in paper [12]. The system presented in the paper facilitates cooperation of a user with many specialized agents which have access to various financial patterns.

The agents analyze the situation on a financial market taking into account criteria specified by a user. Paper [2] describes a system in which agents have been divided into two groups, however agents from the first group make decisions based on fundamental analysis methods, whereas agents from the second group make decisions based on technical analysis. Article [7] presents a multiagent system facilitating the process of investing on FOREX currency exchange market, and the method of assessing investment strategies of selected agents. The differences between these two approaches rely on more openness of the second one (e.g. behavioral agents can be also implemented). Paper [8], on the other hand, presents methods of passive and active learning by financial decisions making agents.

It needs to be stressed that more and more often, in practical solutions as well as in various sources on the subject, cognitive program agents are used to build multiagent systems e.g. [4, 11]. The agents play cognitive and decisive roles, the same as the ones taking place in the human brain, thanks to which they are capable of understanding the real meaning of observed business phenomena and processes taking place also on financial markets.

Aspects of human-agent cooperation have been extensively illustrated also in the paper by Jennings et al. [6]. The authors have concluded that the cooperation may be realized in different forms and methods, and that human imagination is the only limitation here.

Works on the use of the consensus method in order to integrate knowledge have been carried out by numerous authors e.g. [12, 13]. In papers [9, 10], a formal mathematical model of knowledge integration has been suggested. It uses the function of knowledge integration based on the consensus model. The methodology has been employed in various types of information systems to solve conflicts and inconsistencies of knowledge and to integrate knowledge.

The solutions which have been suggested so far however do not focus much on the problem of integrating knowledge of a collective in situations when in a multiagent financial decision support system the human-agent cooperation consists of establishing final decisions on the basis of variants created by humans (experts) and variants generated by agents. The problem has been undertaken and discussed in the paper. Further considerations will focus on characterizing the functional architecture of a cognitive multiagent financial decision support system.

3 A Cognitive Multiagent Financial Decision Support System

The aim of the Cognitive Multiagent Financial Decisions Support System (CMFDSS) is to support investing in the Stock Exchange or currency exchange markets by generating automatic decisions concerning creation of a securities portfolio (mainly stock portfolio) or a currency portfolio.

The Learning Intelligent Distribution Agent (LIDA), developed by Franklin [3], was used to build the CMFDSS. One of the advantages of the architecture is its emergent and symbolic nature, thanks to which it is possible to process both, structured (numerical and symbolic) knowledge as well as the unstructured one (recorded in the natural language) [1].

The CMFDSS system is made up of the following elements (Fig. 1):

1. Human-agent collectives consisting of several experts (people) and some LIDA cognitive program agents. The job of members of a collective is to analyze markets and to select (generate) decisions (securities portfolio or currency portfolio). Each expert/agent uses a different method supporting decisions (fundamental analysis methods as well as technical analysis methods are used). Each collective makes decisions concerning a different market (for example Collective 1 makes decisions concerning the stock market, Collective 3 concerning the currency exchange market).
2. Knowledge integration module which with the help of the consensus method is responsible for integrating knowledge possessed by individual members of a collective, and for selecting one, final decision which is then presented to users.
3. Users – people, financial investors, or program agents investing on behalf of a human. Users execute taken decisions (buy and sell) on financial markets.

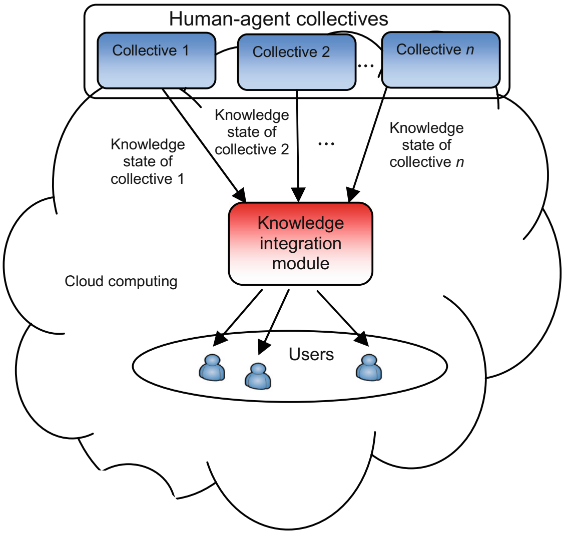

Fig. 1. Architecture of the CMFDSS.

One may notice that the CMFDSS can be viewed from a broader perspective. It is not just an information system as elements of sociological and social systems (experts-people groups) have been incorporated into its architecture. The level of satisfaction which the application of the consensus method to integrate knowledge should guarantee is specified by a user (decision maker), and it can be entered into a system in the form of parameters.

4 Integration of Knowledge in MCFDSS

Notice that each collective's knowledge state must be represented by using a concrete structure. Such structure was defined in previous work [5] as follows:

Definition 1. A knowledge structure representing decision P about finite set of financial instruments $E = \{e_1, e_2, \ldots, e_N\}$ is defined as a set:

$$P = \langle \{EW^+\}, \{EW^\pm\}, \{EW^-\}, Z, SP, DT \rangle$$

where:

(1) $EW^+ = \langle e_o, pe_o \rangle, \langle e_q, pe_q \rangle, \ldots, \langle e_p, pe_p \rangle$.
Couple $\langle e_x, pe_x \rangle$, where: $e_x \in E$ and $pe_x \in [0, 1]$ denote a financial instrument and this instrument's participation in set EW^+.
Financial instrument $e_x \in \langle e_x, pe_x \rangle$ is denoted by e_x^+ when $\langle e_x, pe_x \rangle \in EW^+$.
The set EW^+ is called a positive set; in other words, it is a set of financial instruments with respect to which an agent has the knowledge or information that they should be buy.

(2) $EW^\pm = \langle e_r, pe_r \rangle, \langle e_s, pe_s \rangle, \ldots, \langle e_t, pe_t \rangle$.
Couple $\langle e_x, pe_x \rangle$, where: $e_x \in E$ and $pe_x \in [0, 1]$ denote a financial instrument and this instrument's participation in set $EW^\pm$.
Financial instrument $e_x \in \langle e_x, pe_x \rangle$ is denoted by $e_x^\pm$ when $\langle e_x, pe_x \rangle \in EW^\pm$.
The set $EW^\pm$ is called a neutral set, in other words, it is a set of financial instruments, with respect to which an agent has no knowledge or information whether to buy or sell them. If these instruments are held by an investor, they should not be sold, or if they are not in the possession of the investor, they should not be bought.

(3) $EW^- = \langle e_u, pe_u \rangle, \langle e_v, pe_v \rangle, \ldots, \langle e_w, pe_w \rangle$.
Couple $\langle e_x, pe_x \rangle$, where: $e_x \in E$ and $pe_x \in [0, 1]$, denote a financial instrument and this instrument's participation in set EW^-.
Financial instrument $e_x \in \langle e_x, pe_x \rangle$ is denoted by e_x^- when $\langle e_x, pe_x \rangle \in EW^-$.
The set EW^- is called a negative set; in other words it is a set of financial instruments with respect to which an agent has the knowledge or information that they should be sell.

(4) $Z \in [0, 1]$ - decision rate of return forecast.

(5) $SP \in [0, 1]$ - degree of certainty of rate Z. It can be calculated on the basis of the level of risk related to the decision.

(6) DT- date of decision.

The percent of financial instrument's participation in positive, neutral or negative sets range <0, 1>. In our system, the financial decision consists of financial instruments, such as shares.

Integration of knowledge contained in human-agent collectives (realized in a module of knowledge integration) is performed in two stages. The concept of knowledge integration (Fig. 2) assumes that in the first stage a consensus is determined on the basis of knowledge status of all members of a collective, referred to as primary status of knowledge (primary profile in which the number of knowledge structures matches the number of all members of a given collective), and in the second stage an assessment of decisions of individual agents takes place.

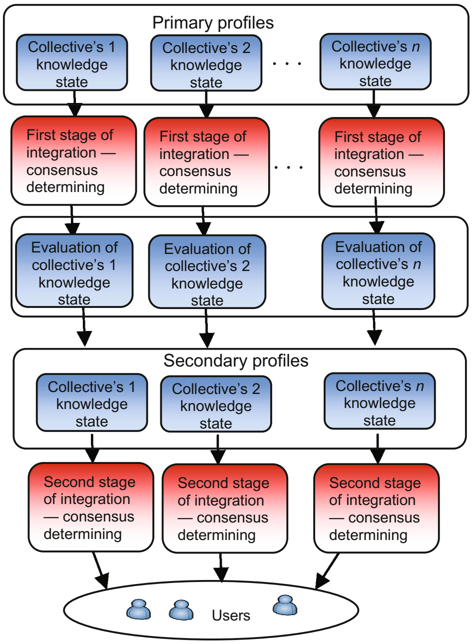

Fig. 2. A conception of knowledge integration process.

The assessment is performed by a separate agent performing evaluation on two levels:

- consistency of knowledge – various types of consistency evaluation functions are used; the evaluation is performed in such a way that decisions furthest from the consensus (in the sense of distances calculated according to different criteria) receive the worst score, and decision closest to the consensus receive the best score.
- efficiency (performance) of decisions made by members of a collective – a function of evaluation is used which takes into account performance and risk measurement indicators such as: return rate, number of profitable transactions, number of negative/loss transactions, costs of transactions, Sharpe ratio, etc.

A consensus algorithm for knowledge integration is as follows:

Algorithm 1.

Input: Profile $A = \{A^{(1)}, A^{(2)}, \ldots A^{(M)}\}$ consists of M structures of knowledge.
Result: Consensus $CON = \langle CON_+, CON_\pm, CON_-, CON_Z, CON_{SP}, CON_{DT} \rangle$ according A.
BEGIN
1: Procedure primary.
2: Evaluation of collectives members\` knowledge state and the elimination of lowest assessment knowledge states.
3: Procedure secondary.
END

Procedure primary:
1: Let $CON_+ = CON_\pm = CON_- = \emptyset$, $CON_Z, CON_{SP}, CON_{DT} = 0$.
2: j:=1.
3: i:=+.
4: If $t_i(j) > M/2$ then $CON_i := CON_i \cup \{e_j\}$. Go to:6.
// $t_i(j)$ - the number of occurrences of e_j element in sets EW^i of a profile.
5: If i= + then i:=±. If i=± to i:=- .
If i=- then go to: 6 else go to: 4.
6: If $j<Z$ then j:=j+1. Go to:3.If $j \geq Z$ then go to: 7.
7: i:=DT.
8: Determine $pr(i)$//ascending order.
9: $k_i^1 = (M+1)/2$, $k_i^2 = (M+2)/2$.
10: $k_i^1 \leq CON_i \leq k_i^2$.
End procedure

Procedure secondary:
1: Determining a profile $B = \{B^{(1)}, B^{(2)}, \ldots B^{(N)}\}$ consist of N structures.
2: Let CON is a consensus determined in the same way as in Procedure primary but for the profile B.
3: $CON_Z = \frac{1}{N}\sum_{i=1}^{N} Z^i$.
4: $CON_{SP} = \frac{1}{N}\sum_{i=1}^{N} SP^i$.
5: $CON_{DT} = \frac{1}{N}\sum_{i=1}^{N} DT^i$, let $d := \sum_{i=1}^{N}\left[\Psi\left(CON, A^{(i)}\right)\right]^2$ and j:=1.
6: If $e_j \in CON_+$ then

CON`:= $\langle CON_{+} \backslash \{e_j\}, CON_{\pm}, CON_{-}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$

Go to: 9,if $e_j \notin CON_{+}$ then go to: 7.

7: If $t_{+}(j)$ = 0 then go to:10,If $t_{+}(j)$ > 0 then go to:8.

8: If $e_j \cap CON \neq \emptyset$ and $e_j \in CON_{\pm}$ or $e_j \in CON_{\pm}$ then

CON`:= $\langle CON_{+} \cup \{e_j\}, CON_{\pm} \backslash \{e_j\}, CON_{-} \backslash \{e_j\}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$,

If $e_j \cap CON = \emptyset$ then

CON`:= $\langle CON_{+} \cup \{e_j\}, CON_{\pm}, CON_{-}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$**. Go to: 9.**

9: If $\sum_{i=1}^{N} \left[\Psi\left(CON', A^{(i)}\right)\right]^2 < d$ **then** $d := \sum_{i=1}^{N} \left[\Psi\left(CON', A^{(i)}\right)\right]^2$ **and**

CON: = CON`.

10: If $e_j \in CON_{\pm}$ then

CON`:= $\langle CON_{+}, CON_{\pm} \backslash \{e_j\}, CON_{-}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$ **and go to:**

24,if $e_j \notin CON_{\pm}$ then go to: 11.

11: If $t_{\pm}(j)$ = 0 then go to: 14,If $t_{\pm}(j)$>0 then go to: 12.

12: If $e_j \cap CON \neq \emptyset$ and $e_j \in CON_{+}$ or $e_j \in CON_{-}$ then

CON`:= $\langle CON_{+} \backslash \{e_j\}, CON_{\pm} \cup \{e_j\}, CON_{-} \backslash \{e_j\}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$,

If $e_j \cap CON = \emptyset$ then

CON`:= $\langle CON_{+}, CON_{\pm} \cup \{e_j\}, CON_{-}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$.

13: If $\sum_{i=1}^{M} \left[\Psi\left(CON', A^{(i)}\right)\right]^2 < d$ **then** $d := \sum_{i=1}^{M} \left[\Psi\left(CON', A^{(i)}\right)\right]^2$ **and**

CON: = CON`.

14: If $e_j \in CON_{-}$ then

CON`:= $\langle CON_{+}, CON_{\pm}, CON_{-} \backslash \{e_j\}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$ **and**

go to: 17.If $e_j \notin CON_{-}$ then go to: 14.

15: If $t_{-}(j)$=0 then go to: 18.If $t_{-}(j)$>0 then go to: 16.

16: If $e_j \cap CON \neq \emptyset$ and $e_j \in CON_{+}$ or $e_j \in CON_{\pm}$ then

CON`:= $\langle CON_{+} \backslash \{e_j\}, CON_{\pm} \backslash \{e_j\}, CON_{-} \cup \{e_j\}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$.

If $e_j \cap CON = \emptyset$ then

CON`:= $\langle CON_{+}, CON_{\pm}, CON_{-} \cup \{e_j\}, CON_{Z}, CON_{SP}, CON_{DT} \rangle$.

17: If $\sum_{i=1}^{N} \left[\Psi\left(CON', A^{(i)}\right)\right]^2 < d$ **then** $d := \sum_{i=1}^{N} \left[\Psi\left(CON', A^{(i)}\right)\right]^2$ **and**

CON: = CON`.

18: If j<Z then j:=j+1. Go to: 3.

End procedure.

Computational complexity of the algorithm equals: O(N^2M) + O(3NM).

It is worth noticing that in the second stage of knowledge integration determining a consensus is a NP-complete problem which is why the presented algorithm is a heuristic algorithm thanks to which its computational complexity is low.

The presented consensus determining algorithm allows agreeing on one decision presented by a system to a user taking into account evaluation of the status of knowledge of members of a collective. The algorithm is recalled automatically once all members of a collective have determined suggestions for decisions, and it is performed independently with respect to each collective.

On the basis of results of the preliminary research experiment performed by using 100 profiles it has been state, that in 92 cases consensus derived according to heuristic algorithm was in line with consensus derived by the optimal algorithm (compatibility level is 92 %). Consensus according to the optimal algorithm was calculated about 65 s, while the consensus heuristic algorithm in about 5 s. Therefore, the heuristic algorithm, developed in this paper, characterize a higher performance then performance of an optimal algorithm. Due to pages limitation of this paper, the wider research experiments will be presented in subsequent publication.

Knowledge integration allows for elimination of decisions generated by members of a collective whose knowledge status or condition has been assessed as being poor, which means that their decisions might not produce satisfactory benefits. Thanks to that, we are capable of eliminating the effect of such decisions on the final decision determined with the use of consensus methods and presented to a user. Additionally developed algorithm enables taking into account added knowledge of a collective as each individual status of knowledge of every member of a collective is taken into consideration.

5 Conclusions

Nowadays, in cognitive multiagent financial decision support systems, the cooperation of human-agent collectives is becoming more and more important. Authors of the paper have suggested implementing the collectives directly into the architecture of a system, thanks to which it is possible to automatically process collective knowledge. The problem of integration of knowledge of human-agent collectives, discussed in the paper, is also of great importance. Authors have pointed out that in order to solve the problem, consensus methods can be used. The developed consensus determining algorithm enables knowledge integration when there is cooperation between human and agents consisting of agreeing final decisions on the basis of variants created by experts (people) and variants generated by program agents. The algorithm includes the heterogenic nature of collective knowledge and enables generating added knowledge of a collective. In practical implementations it also allow also for decreasing risk level due to taking into consideration agents characterized by high level of knowledge. Consequently, it is possible to present to a user one satisfactory decision on the basis of which buy and sell transactions are made on financial markets. The developed consensus determining algorithm will also facilitate work of the creators of the multiagent financial decision support system as it can be directly implemented as a module of knowledge integration in the type of system. Consensus methods may also be used in order to integrate knowledge in decision support systems operating in others sectors (e.g. planning production, logistics, managing customers' relations). Since, however, knowledge structures differ with respect to each individual decision area, it is necessary to change the definition of the consensus algorithm.

Further research on the integration of knowledge of human-agent collectives shall focus, among other things, on verification of the effectiveness of the developed algorithm in systems functioning in practical environments, and on developing consistency evaluation function and on the assessment of knowledge of human-agent collectives in the cognitive multiagent financial decision support system.

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