Causal Maps: Theory, Implementation, and Practical Applications in Multiagent Environments

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Abstract—Analytical techniques are generally inadequate for dealing with causal interrelationships among a set of individual and social concepts. Usually, causal maps are used to cope with this type of interrelationships. However, the classical view of causal maps is based on an intuitive view with ad hoc rules and no precise semantics of the primitive concepts, nor a sound formal treatment of relations between concepts. In this paper, we solve this problem by proposing a formal model for causal maps with a precise semantics based on relation algebra and the software tool, CM-RELVIEW, in which it has been implemented. Then, we investigate the issue of using this tool in multiagent environments by explaining through different examples *how* and *why* this tool is useful for the following aspects: 1) the reasoning on agents' subjective views, 2) the qualitative distributed decision making, and 3) the organization of agents considered as a holistic approach. For each of these aspects, we focus on the computational mechanisms developed within CM-RELVIEW to support it.

Index Terms—Decision support, cognitive maps, knowledge base management, tools and supports, causal maps, agent and multiagent systems.

1 Introduction

Cognitive maps follow *personal construct theory*, first put forward by Kelly [19]. This theory provides a basis for representing an individual's multiple perspectives. Kelly suggests that understanding how individuals organize their environments requires that subjects themselves define the relevant dimensions of that environment. He proposed a set of techniques, known collectively as a *repertory grid*, in order to facilitate empirical research guided by the theory. The personal construct theory has spawned many fields and has been used as a first step in generating cognitive maps. Huff [17] has identified five generic "families" of cognitive maps:

1. *Maps that assess attention, association, and importance of concepts*. With these maps, the map maker searches for frequent use of related concepts as indicators of the strategic emphasis of a particular decision maker or organization, for example, and looks for the association of these concepts with others to infer mental connection between important strategic themes. She also might make judgments about the complexity of these relationships or differences in the use of concepts.
2. *Maps that show dimension of categories and cognitive taxonomies*. Here, the map maker investigates more complex relationships among concepts. She might dichotomize concepts and construct hierarchical relationships among broad concepts and more specific subcategories. Maps of this type have been used to define the competitive environment and to explore the range and nature of choices perceived by decision makers in a given setting.
3. *Maps that show influence, causality, and system dynamics (causal maps)*. These maps allow the map maker to focus on action; for example, how the respondent explains the current situation in terms of previous events and what changes she expects in the future. This kind of cognitive map is currently, has been, and is still the most popular mapping method.
4. *Maps that show the structure of argument and conclusion*. This type of map attempts to show the logic behind conclusions and decisions to act. Here, the map maker includes causal beliefs, but looks more broadly at the text as a whole to show the cumulative impact of varied evidence and the links between longer chains of reasoning.
5. *Maps that specify frames and perceptual codes*. This approach suggests that cognition is highly conditioned by previous experience and that experience is stored in memory as a set of structured expectations.

In this paper, we extend the causal map by providing a formal model for this type of map with a precise semantics based on relation algebra and the software tool, CM-RELVIEW, in which it has been implemented. Then, we investigate the issue of using this tool in multiagent environments by explaining through different examples *how* and *why* these maps are useful in those environments.

1.1 Causal Maps: Motivations Through an Example

Much attention has been recently directed toward the problem of strategic decision making in dynamic and open environments. The issues of this problem tend to become

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more complicated, unstructured, and not always readily quantifiable [33]. They particularly involve interacting variables that make them difficult to deal with. Analytical techniques have been used to handle well-defined problems, but they are inadequate for this type of problem. A causal map may be employed to cope with complicated problems because it offers to model interrelationships among a variety of concepts. Causal maps (CMs) make the following three assumptions about cognition in the context of decision [17]:

1. Causal associations are a major way in which decision problems can be described and understood.
2. Causality is the primary form of post hoc explanation of decision outcomes, and
3. Choice among alternative decision actions involves causal relations.

Causal maps are usually based on human "communications" collected by interviewing or found in documents such as corporate reports or memos. We are looking there for expressions having the general type:

- "Entity/phenomenon/concept A leads-to/causes/influences/etc./Entity/phenomenon/concept B" or
- "B is caused/effected/influenced/etc./ by A".

These are *causal assertions*, which are taken to indicate that the concerned subjects: 1) use concepts (A,B) to refer to some phenomena or concepts in their domains, and 2) think (believe, assume, know, argue, etc.) that there are certain relationships between these concepts.

We generally use causal maps for dealing with such cause-effect relations embedded in deciders' thinking. These maps are represented as directed graphs where the basic elements are simple. The concepts an individual (a decision-maker or a group of decision-makers) uses are represented as *points* and the causal links between these concepts are represented as *arrows* between these points. This representation gives a graph of points and arrows called a *causal map*. The strategic alternatives, all of the various causes and effects, goals, and the ultimate utility[1] of the decision maker can all be considfered as concept variables and represented as points in the CM. Causal relationships can take on different values based on the most basic values $+$ (positive), $-$ (negative), and 0 (neutral). Logical combinations of these three basic values give the following: "neutral or negative" ($\ominus$), "neutral or positive" ($\oplus$), "nonneutral" ($\pm$), "ambivalent" (a), and, finally, "positive, neutral, or negative" (i.e.,"universal") ($?$) [1], [7], [24].

The real power of this approach appears when a CM is pictured in graph form. It is then relatively easy to see how concepts and causal relationships are related to each other and to see the overall causal relationships of one concept with another, particularly if these concepts are the concepts of several agents.

For instance, the CM of Fig. 1, taken from [21], explains how the Japanese made the decision to attack Pearl Harbor. Indeed, this CM states that "remaining idle *promotes* the attrition of Japanese strength while *enhancing* the defensive

1. Utility means the unspecified best interests of a decision maker.

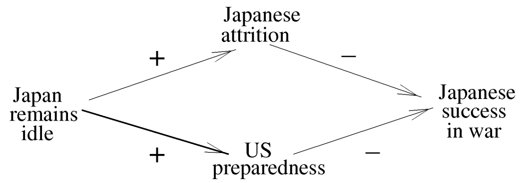

Fig. 1. An example of causal map (from [21]).

preparedness of the United States, both of which *decrease* Japanese prospects for success in war." Thus, a CM is a set of concepts as "Japan remains idle," "Japanese attrition," and so forth, and a set of signed edges representing causal relations like "promote(s)," "decrease(s)," and so forth.

Note that the concepts' domains are not necessarily defined precisely because there are no obvious scales for measuring "US preparedness," "success in war," and so forth. Nevertheless, it seems easy to catch the intended meaning of the signed relationships in this model [36]. As any causal map, the CM of Fig. 1 can be transformed in a matrix, called an adjacency or valency matrix, which is a square matrix with one row and one column for each concept. Thus, if a, b, c, and d represents "Japan remains idle," "Japanese attrition," "Japanese success in war," and "US preparedness," respectively, we obtain the following adjacency or valency matrix:

$$\begin{array}{c} \\ a \\ b \\ c \\ d \end{array} \begin{array}{c} \begin{array}{cccc} a & b & c & d \end{array} \\ \begin{pmatrix} 0 & + & 0 & + \\ 0 & 0 & - & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & - & 0 \end{pmatrix} \end{array}.$$

Inferences that we can draw from a CM are based on a qualitative reasoning similar to "friend's enemy is enemy, enemy's enemy is friend, and so forth." Thus, in the case of Fig. 1, remaining idle decreases the prospects for Japanese success in a war along two causal paths. Notice that the relationship between idleness and war prospects is negative because both paths agree. In these conditions, Japan has an interest in starting war as soon as possible if she believes that war is inevitable.

Thus, causal maps and the qualitative reasoning that it sustains serve generally as the modeling language for problem resolution through decision making, particularly in multiagent systems where decision emerges generally from interrelationships among agents' concepts. Such is the case for the previous example that reflects a multiagent system in the sense where "Japan" and "USA" are individual agents.

1.2 Related Work

As previously stated, causal maps appear to be the most widely used cognitive maps in practice. Causal maps have been used for decision analysis in the fields of international relations [1], [7], administrative sciences [28], management sciences [13], [32], and distributed group decision support [40]. In the latter context, Zhang and his colleagues provided the notions of NPN (negative-positive-neutral) logic, NPN relations, neurons, and neural networks. Based on these notions, they constructed D-POOL, a causal map architecture for the coordination of distributed cooperative agents. This architecture consists of a collection of distributed nodes, each node being a CM system coupled with a local expert system. To solve a problem, a local node first pools causal maps from relevant agents into a NPN relation that retains both negative and positive assertions. Then, new causal maps are derived and focuses of attention are generated. With the focuses, a solution is proposed by the local node and passed to the remote systems. Based on their viewpoints, the remote systems respond to the proposal and D-POOL strives for a cooperative or compromised solution through coherent communication and perspective sharing. Zhang [41] extended his approach by an NPN fuzzy set theory and an NPN qualitative algebra. In doing so, Zhang and his colleagues focused on quantitative models of CM, based on particular techniques for associating intervals with edges of directed graphs. In their model, quantities combine by propagation along paths, but there is no other connection to the original spirit of CMs, (i.e., the causal reasoning).

Except for Zhang's work [40], [41], all other approaches to CMs were based on simple inference mechanisms about the consequences of a CM. Thus, the definition of a precise semantic interpretation of qualitative causality has received very little attention. The only work that we are aware of in this context is Wellman's [36] and Nadkarni and Shenoy [23] approaches. The first author used an approach based on graphical dependency models for probabilistic reasoning, and sign algebras for qualitative reasoning. The second author used the Bayesian network approach to making inferences in causal maps. Thus, both used probability theory as is the case usually in artificial intelligence. However, their approaches are applicable only in the acyclic case because circular relations or causal loops, common in causal maps, violate the acyclic graphical structure required in a Bayesian network.

1.3 Our Contributions

In this paper, we propose a new approach for causal maps which takes into account the cyclic cases. More precisely, we present a formal model for CMs with a precise semantics based on relation algebra and the computational tool issued from this formal model: CM-RELVIEW. Then, we investigate some useful applications of CMs in the context of multiagent systems. Multiagent systems consist of intelligent entities (or agents) that work together to perform some tasks or satisfy some goals. Generally, these agents are more or less autonomous and are concerned with distributing and coordinating knowledge and actions in a distributed environment. In the field of multiagent systems, researchers explore methods that enable the *coherent interaction* of agents. More precisely, they seek to establish the basis for interagent negotiation, agreement, coordination, and cooperation in order to construct multiagent systems where agents interact productively with one another. To achieve this in an efficient way, researchers have been studying a broad range of issues related to the distribution and coordination of knowledge and actions in environments involving multiple agents. In this paper, we propose a new approach to one of those issues: the *causal reasoning* in a distributed environment. Causal reasoning in multiagent systems is about interrelationships between agents. It involves many relations among a variety of social and individual concepts and provides a foundation to

- predict some (expected or not) events,
- explain past events,
- make a decision, and
- analyze and compare the causal representations of agents.

All of these aspects can be useful for coordination, conflict resolution, and the emergence of cooperation between agents. In this paper, we mainly focus on the following aspects:

1. the reasoning on agents' subjective views,
2. the qualitative distributed decision making, and
3. the organization of agents considered as a holistic approach.

For each of these aspects, we provide illustrative examples that explain how CMs can be used as well as computational mechanisms which have been developed within CM-RELVIEW to support them.

1.4 Outline of this Paper

The paper is organized as follows: The next section presents our formal model for the CMs based on relation algebra. Section 3 gives an overview of the CM-RELVIEW tool, a machine support of relational computations. In Section 4, we explain in detail how CMs can be used for the causal reasoning in multiagent environments and how the CM-RELVIEW tool can be exploited in these type of environments. Finally, we present our conclusions and some possible future work in Section 5.

2 Causal Maps: A Formal Model Based on Relation Algebra

2.1 A Brief Overview of Classical Theory of CMs

As previously stated, eight causal relations are used in the context of CMs: $a, +, -, 0, \oplus, \ominus, \pm, ?$. Four operators are defined on $\mathcal{C}$ which is the set of those eight relations. They are *union* ($\cup$), *intersection* ($\cap$), *sum* ($|$), and *multiplication* ($*$). The laws of union and intersection are obtained by considering $a, +, -, 0, \oplus, \ominus, \pm$, and $?$ as shorthands for $\{\ \}, \{+\}, \{-\}, \{0\}, \{0,+\}, \{0,-\}, \{+,-\}$, and $\{+,0,-\}$, respectively. Thus, one has [1], [24]:

$$\begin{aligned} \oplus &= 0 \cup +, \\ \ominus &= 0 \cup -, \\ \pm &= + \cup -, \\ ? &= 0 \cup + \cup -, \\ a &= + \cap 0 = + \cap - = 0 \cap -. \end{aligned} \tag{1}$$

It can be seen that a denotes conflicting assertions about a given link. The laws of sum are given below (with "do" meaning "distributes over"):

For any $x, y \in \mathcal{C}$,

$$\begin{array}{ll} \text{(a)} & 0|y = y, \\ \text{(b)} & a|y = a, \\ \text{(c)} & y|y = y, \\ \text{(d)} & +|- = \ ?, \\ \text{(e)} & |\ \text{do} \cup, \\ \text{(f)} & x|y = y|x. \end{array} \tag{2}$$

The laws of multiplication $(*)$ are given below:
For any $x, y \in \mathcal{C}$,

$$\begin{array}{ll} \text{(a)} & + * y = y, \\ \text{(b)} & 0 * y = 0, \text{ if } y \neq a, \\ \text{(c)} & a * y = a, \\ \text{(d)} & - * - = +, \\ \text{(e)} & *\ \text{do} \cup \\ \text{(f)} & x * y = y * x. \end{array} \tag{3}$$

Let us explain what these operations are intended for. Multiplication is used to calculate *indirect effects*. For instance, from $v_i \xrightarrow{-} v_j \xrightarrow{-} v_k$, there is an indirect effect $v_i \xrightarrow{+} v_k$ (Equation (3d) is $- * - = +$). Given the set $\mathcal{C}$ of causal relations, the six rules of multiplication seem rather reasonable. For example, rule (3b) says that, if v_i has no effect on v_j, it is natural that v_i has no indirect effect on v_k through $v_j (0 * y = 0)$, no matter what the effect y of v_j on v_k is. Rule (3c) says that, if the effect from v_i to v_j is ambivalent, the indirect effect from v_i to v_k through v_j is also ambivalent $(a * y = a)$, even if the effect from v_j to v_k is not ambivalent. Rule (3f) states that $*$ is commutative.

The sum operator is used to accumulate *direct effects* from different paths. For example, if there is a path from v_i to v_j with indirect effect $+$ and another path with indirect effect $-$, the net effect is ?, according to law (2d).

The operators $*$ and $|$ can be lifted to matrices. Assume that V and W are square matrices of size n. Addition and multiplication of matrices are defined as follows:

$$(V|W)_{ij} = V_{ij}|W_{ij}, \tag{4}$$

$$(V * W)_{ij} = (V_{i1} * W_{1j})| \cdots |(V_{in} * W_{nj}). \tag{5}$$

The nth *power* of a square matrix V, for $n > 0$, is then naturally defined by

$$V^1 := V \quad \text{and} \quad V^n := V * V^{n-1}. \tag{6}$$

The total effect of one concept on another is calculated according to the *total effect matrix* V_t which is the matrix that has as its ijth entry the total effect of v_i on v_j; that is, $V_t = V|V^2|V^3| \ldots$. It is easy to check here that the sum operator is $\subseteq$-monotonic. This implies that there is a k such that:

$$V_t = V|V^2| \cdots |V^k. \tag{7}$$

In summary, it is important to notice that the classical view of causal maps, as shown so far, is an intuitive view with ad hoc rules and no precise meaning of the primitive concepts, nor a sound formal treatment of relations between concepts. These considerations brought us to develop the formal model presented in the next section. More details on this formal model can be found elsewhere [9].

2.2 Semantics for Causal Maps Based on Relation Algebra

We conventionally employ the symbols $(\vee, \wedge, \rightarrow)$ for *conjunction*, *disjunction*, and *implication* between predicates and truth values. We use $(\cup, \cap, \subseteq)$ for the *union*, *intersection*, and *inclusion* of sets. Finally, we use $(\sqcup, \sqcap, \sqsubseteq)$ to denote *union*, *intersection*, and *inclusion* of relations. Other symbols used in this text are: $\Longrightarrow$, $\Longleftrightarrow$ are metalevel implication and equivalence, respectively; $:=$ is the definitional equality; and $:\Longleftrightarrow$ is the definitional equivalence.

Notice that relations are sets and, consequently, we can consider their intersection, union, complementation, and inclusion. If we consider, relations R and S and F the set of all relations, then $R, S \sqsubseteq F \times F$. In these conditions, the usual basic operations on relations are:

1. union $R \sqcup S := \{(x, y) \mid (x, y) \in R \vee (x, y) \in S\}$,
2. intersection $R \sqcap S := \{(x, y) \mid (x, y) \in R \wedge (x, y) \in S\}$,
3. complement $\overline{R} := \{(x, y) \mid (x, y) \notin R\}$,
4. product, composition

$$R \circ S := \{(x, z) \mid \exists y \in F : (x, y) \in R \wedge (y, z) \in S\},$$

5. transposition $R^\top := \{(x, y) \mid (y, x) \in R\}$,
6. empty $O := \{(x, y) \mid \text{false}\} \sqsubseteq F \times F$,
7. identity $I := \{(x, y) \mid x = y\} \sqsubseteq F \times F$,
8. power $R^0 := I$ and $R^n = R \circ R^{n-1}$ if $n > 0$, and
9. inclusion $R \sqsubseteq S :\Longleftrightarrow \forall x, y : [(x, y) \in R \rightarrow (x, y) \in S]$.

Priority of operations. The unary operations as complement and transposition are performed first, followed by the binary operation $(\circ)$ and, finally, by the binary operations $(\sqcup, \sqcap)$. See [30] for more detail.

A finite relation R can be represented by a Boolean matrix, using the convention $R_{xy} = 1 \Longleftrightarrow (x, y) \in R$ and $R_{xy} = 0 \Longleftrightarrow (x, y) \notin R$. The definition of the relational operators for Boolean matrices follows: We use $\wedge$ and $\vee$ as operators on the set $\{0, 1\}$, considered as a set of truth values in the usual way.

$$\begin{array}{ll} (V \sqcup V')_{ik} := V_{ik} \vee V'_{ik}, & (\overline{V})_{ik} := \neg V_{ik} \\ (V \circ V')_{ik} := \bigvee_{j=1}^{n} V_{ij} \wedge V'_{jk}, & (V \sqcap V')_{ik} := V_{ik} \wedge V'_{ik}, \\ (V^\top)_{ik} := V_{ki}. & \end{array} \tag{8}$$

We are now ready to give our own representation of signs $+$, $-$, and 0. Let $\Delta := \{-1, 1\}$. Numbers in Δ are intended to represent changes (variations) in a concept variable, with -1 and 1 denoting decrease and increase, respectively. How these variations are measured and what exactly is varying does not concern us here; it could be, for example, the utility of a variable, an amount of something, etc. Next, we define the basic relations $+^\bullet, 0^\bullet, -^\bullet$ on the set Δ:

$$
\begin{aligned}
+^{\bullet} &:= \begin{array}{c|cc} & 1 & -1 \\ \hline 1 & 1 & 0 \\ -1 & 0 & 1 \end{array}, \\
0^{\bullet} &:= \begin{array}{c|cc} & 1 & -1 \\ \hline 1 & 0 & 0 \\ -1 & 0 & 0 \end{array}, \\
-^{\bullet} &:= \begin{array}{c|cc} & 1 & -1 \\ \hline 1 & 0 & 1 \\ -1 & 1 & 0 \end{array}.
\end{aligned} \tag{9}
$$

To label arrows of a relational causal map, we use sets of relations (SoR) as $\{+^{\bullet}\}$, $\{-^{\bullet}\}$, and $\{0^{\bullet}\}$. Such sets of relations, noted $+$, 0, and $-$, respectively, link cause variables to effect variables. Indeed, consider the representation $\{+^{\bullet}\}$. It is interpreted as follows: The relation for the label arrow considered is "$+$" and it means an increase in the cause variable (i.e., the origin of the arrow) causes an increase in the effect variable (i.e., the end of the arrow) and a decrease in the cause variable causes a decrease in the effect variable. Finally, $\{0^{\bullet}\}$ and $\{-^{\bullet}\}$ are interpreted similarly.

We use the primary representations $\{+^{\bullet}\}$, $\{-^{\bullet}\}$, and $\{0^{\bullet}\}$ to define: $\oplus$, $\ominus$, $\pm$, $?$, and a.

$$
\begin{aligned}
&\oplus := \{0^{\bullet}, +^{\bullet}\}, \\
&\ominus := \{0^{\bullet}, -^{\bullet}\}, \\
&\pm := \{+^{\bullet}, -^{\bullet}\}, \\
&? := \{+^{\bullet}, -^{\bullet}, 0^{\bullet}\}, \\
&a := \{+^{\bullet}\} \sqcap \{-^{\bullet}\} = \{\ \}.
\end{aligned}
$$

Now, we can formally define the cognitive maps as follows:

Definition 1. *A* cognitive map $CM := (C, A)$ *is a directed graph that represents an individual's (i.e., an agent, a group of agents, or an organization) assertions about its beliefs with respect to its environment. The components of this graph are a set of points C(the vertices) and a set of arrows A (the edges) between these points. The arrows are labeled by elements of the set* $\mathcal{C} := \{a, +, -, 0, \oplus, \ominus, \pm, ?\}$. *A point represents a* concept *(also called* concept variable *in the sequel), which may be a goal or an action option of any agent. It can also represent the utility of any agent or the utility of a group or an organization, or any other concept appropriate to multiagent reasoning. An arrow represents a causal relation between concepts, that is, it represents a causal assertion of how one concept variable affects another. The concept variable at the origin of an arrow is called a* cause variable *and that at the end point of the arrow is called the* effect variable. *A* path *from concept variable* v_1 *to concept variable* v_n *is a sequence of points* $v_1, v_2, \ldots, v_n$, *together with the nonzero arrows (i.e., arrows labeled by a relation different from 0* $v_1v_2, v_2v_3, \ldots, v_{n-1}v_n$. *A path is* trivial *if it consists of a single point. The* valency matrix *V of a cognitive map M is a square matrix of size n, where n is the number of concepts in M. The entry V_{ij} is the label of the arrow from v_i to v_j in M. If there is no such arrow, then $V_{ij} = 0$. Finally, sum ($|$) and multiplication ($*$) (as defined below) are used to calculate, respectively,* indirect effects *and* direct effects *between concepts.*

The laws of sum ($|$) are reviewed below (see (10)). Note that "do" means "distributes over." Thus, law (3) $|$ do "," means that $|$ distributes over "," as, for instance,

$$
\begin{aligned}
+|\oplus &= \{+^{\bullet}\}|\{+^{\bullet}, 0^{\bullet}\} = \{+^{\bullet} \sqcup +^{\bullet}, +^{\bullet} \sqcup 0^{\bullet}\} \\
&= \{+^{\bullet}, +^{\bullet}\} = \{+^{\bullet}\} = +.
\end{aligned}
$$

Finally, $\mathcal{C}_p$ is the set $\{+^{\bullet}, 0^{\bullet}, -^{\bullet}\}$.

$$
\begin{aligned}
&1)\ a|y = a \quad \forall y \in \mathcal{C}, \\
&2)\ x|y = \{x^{\bullet} \sqcup y^{\bullet}\}\ \forall x, y \in \mathcal{C}_p, \\
&3)\ |\ \text{do}\ '','' , \\
&4)\ x|y = y|x.
\end{aligned} \tag{10}
$$

Similarly, the laws of multiplication ($*$) are given below (see (11)). Here, also "do" means "distributes over."

$$
\begin{aligned}
&1)\ a * y = a \quad \forall y \in \mathcal{C}, \\
&2)\ x * y = \{x^{\bullet} \circ y^{\bullet}\}\ \forall x, y \in \mathcal{C}_p, \\
&3)\ *\ \text{do}\ '','' , \\
&4)\ x * y = y * x.
\end{aligned} \tag{11}
$$

Equations (10) and (11) show the result of the application of the relational operators $\sqcup, \sqcap, \circ$ to our own relations introduced in (9). These tables are constructed using (8). Thus, for instance, it is easy to verify that $- * - = \{-^{\bullet} \circ -^{\bullet}\} = +$ by multiplying the matrix representing $-^{\bullet}$ by itself.

Thus, our definition of primary causal relations $+$, 0, and $-$, based on $\{-1, 1\}$ denoting increase and decrease of concepts, respectively, provides a clear semantics of CMs which justifies the classical intuitive cause-effect relationships between concepts. Note that, in our approach, an $n \times n$ matrix whose entries are 2×2 matrices is a $2n \times 2n$ matrix. This implies that $V_t = V|V^2|\cdots|V^k$, as expressed by (7), can be computed in $O((2n)^3) = O(n^3)$ steps using the Roy-Warshall algorithm; better algorithms also exist [30].

Finally, it is important to point out that the causal map approach is generally based on two important assumptions: 1) pairwise influence and 2) superposition. The first assumption requires relations in a CM to be binary relations. The second means that the result of applying together C_1 and C_2 is the same as applying C_1 and C_2 sequentially.

3 CM-RELVIEW: An Implementation of the Relation Model of CMs

Our formal model has been implemented in a system used as a computational tool supporting the relational manipulations. This tool is called CM-RELVIEW and is built over the RELVIEW software,[2] a freeware package developed by Berghammer and Schmidt [2].

In the CM-RELVIEW system, all data are represented as binary relations, which the system visualizes in two different ways. For homogeneous relations, CM-RELVIEW offers a representation as cognitive maps, including several different algorithms for pretty-printing. As an alternative,

2. This software can be obtained by anonymous ftp from http://www.informatik.uni-kiel.de/~progsys/relview.html.

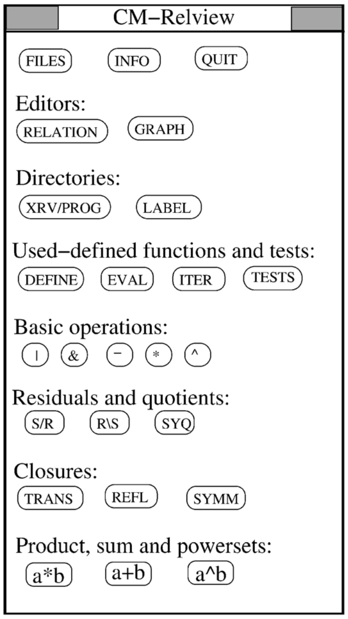

Fig. 2. The menu window of CM-RELVIEW.

an arbitrary relation may be displayed on the screen as a Boolean matrix. With matrix representation, we can visually edit and also discover various structural properties that are not evident from the causal map representation. The CM-RELVIEW system can manage as many graphs and matrices simultaneously as memory allows and the user may manipulate and analyze the relations behind these objects by combining them with the operators of relational algebra. The elementary operations can be accessed through a simple mouse-click, but they can also be combined into relational expressions, mapping, and imperative programs. CM-RELVIEW also allows users to store relations and CMs.

CM-RELVIEW offers a menu window (Fig. 2) that can be divided into different parts. The first part, deals with tasks as:

- FILES: opens the file-chooser window,
- INFO: helps users by giving some appropriate information, and
- QUIT: quits the system.

The "Editors" part includes the following:

- RELATION: opens the window of the relation editor and
- GRAPH: pops the window of the CMs editor.

By clicking onto the button RELATION, one opens the relation editor. One can then load a relation by simply selecting this relation in the first scroll list of the directory window. Typically, the window of the relation editor looks like a grid network in which a single entry of the relation unequivocal defined by a row and a column of a relation is represented by one of the set $\mathcal{C} := \{a, +, -, 0, \oplus, \ominus, \pm, ?\}$. If the mouse pointer is located on an item of a relation, the mouse buttons invoke the following different actions:

- the left mouse button sets the item if it was cleared, or clears it if it was set,
- the middle mouse button allows one to choose one relation (which is used by the left mouse to set) of the set $\mathcal{C} := \{a, +, -, 0, \oplus, \ominus, \pm, ?\}$, and, finally,
- the right mouse button pops up a menu where these appear:
  - NEW: It creates a new relation.
  - DELETE: It deletes the relation displayed in the relation editor window from the workspace (the causal map associated with the deleted relation is also deleted).
  - RELATION $\longrightarrow$ GRAPH: It creates a CM from homogeneous relation with the same name as the relation (such CM is displayed in the graph editor).

The window of the graph editor (i.e., CM editor) can be opened by pressing the button GRAPH in the menu window. Similar to relations, all actions within this menu are selected with the same right mouse button. By pressing such a button, we reach the graph menu within and we can particularly invoke the following actions:

- DELETE: It deletes all nodes of a causal map.
- NEW: It opens a dialog window which allows one to enter a name for a causal map.
- GRAPH $\longrightarrow$RELATION: It creates a relation from a causal map.
- GRAPH-DRAWING: It opens a submenu from which different graph algorithms can be chosen, particularly LAYER, which places the edges vertically, FOREST, which draws a directed forest, and WHOLISTIC-APPROACH, which draws a particular causal map that we will detail in Section 4.4.

CM-RELVIEW offers also a "directory" part which contains:

- XRV/PROG: It displays the directory window showing the state of the workspace and the reasoning on causal maps.
- LABEL: It opens the label directory listing label set, which is, in our case, $\mathcal{C} := \{a, +, -, 0, \oplus, \ominus, \pm, ?\}$.

The buttons in the "user-defined functions and tests" part are mostly needed while working with the CM-RELVIEW system:

- EVAL: pops up the evaluation window for entering a relational term (a relational term can be a relation, a function, or a relational program),
- TESTS: pops up a window for invoking tests. With this command, one can perform the following actions:
  1. TEST-1-R: to execute various kinds of tests on a relation (is it empty, injective, symmetric? etc.),
  2. TEST-2-R: to execute tests on two relations (are they equal, included? etc.),
  3. SUBJECTIVE VIEWS: to do tests on CMs in the case of the reasoning on subjective views (COMPARISON, PREDICTION, EXPLANATION, and NEGOTIATION) discussed in details in Section 4.2.7, and

4. WHOLISTIC-CM to execute some strategies of changes on the particular CMs representing an organization of agents as discussed in Section 4.4.

Finally, the other parts of the menu window offer a number of relational operations which are directly accessible via push buttons. Among those operations, TRANS allows one to calculate the transitive closure of a given relation.

4 Using Causal Maps in Multiagent Environments

4.1 Causal Maps in Multiagent Environments: Motivations

As stated in the introduction, in multiagent environments, causal reasoning involves many interacting concepts that make them difficult to deal with and for which classical methods are inadequate. Causal maps designed to show causal associations appear to be the most useful tool for coping with those interacting concepts. Indeed, causal maps are based on somewhat different assumptions about cognition than the classical methods, particularly the following:

- Causal associations constitute a privileged way to reason about a global view of agents.
- Causality allows explanation of past events.
- Causality allows prediction of future actions.
- Causality allows anticipation of effects of changes in multiagent environments.
- Causal evaluation could constitute a privileged way of choosing among alternative actions or goals.
- Causal maps allow one to represent and relate the subjective perceptions of agents.

In multiagent environments, all these ideas are important for negotiation or mediation between agents. Negotiation and mediation are notions most often stressed in multiagent systems [22] and are generally used to solve disparities and uncertainties which are generated by the *bounded vision* that each agent has because of its limited capacities. Note that, if these disparities and uncertainties are not solved, they can lead to conflicts between agents.

In the rest of this section, we detail how causal maps can be used in multiagent systems.

4.2 Modeling Agents' Subjective Views by Causal Maps

4.2.1 Need to Develop a New Approach Based on CMs for Subjective Views

In multiagent environments, each agent is conscious of only a portion of the world because its perception is limited. Each agent must represent its portion to reason about it and this representation process is generally subject to problems of incompleteness. In these conditions, agents have to be able to cope with differences between their respective views. Researchers in distributed systems have used different approaches for resolving such disparities between agents. Thus, Halpern et al. [14] have used *reasoning about knowledge* to study the knowledge of agents who reason about the world and each other's knowledge. Gmytrasiewics and Durfee [15] have elaborated on a recursive modeling method (RMM) based on a payoff matrix, which succinctly and completely expresses the subjective view of an agent about its environment, its capabilities, and its preferences. Other frameworks have been proposed for reconciliation of disparate views of situations, for example, the contract net protocol [31] or partial global plans [10], [12]. Finally, a negotiation mechanism as a process of improving agreement (reducing inconsistency and uncertainty) has also been used [29].

However, no one of these approaches deal with causality and what it sustains as prediction, explanation, reasoning, on interacting causal concepts, etc. Therefore, there is a need to develop a new approach that supports causal reasoning on others' views. In this section, we propose such an approach that we believe is promising, particularly for the reasoning on subjective views. The main reason is that, in an uncertain multiagent environment, it is fundamental to our common sense (and also to the personal construct theory of Kelly [19]) that every individual agent sees a situation through a unique set of perceptual filters that reflects its capabilities and its experience. Therefore, it is unusual for each agent to see a situation as others see it and it is necessary to consider the interactions of individuals or groups of individuals having different appreciations of a situation and, hence, different *CMs*. Evidently, different *CMs* might produce a conflict between agents. A *conflict* is considered here as a situation in which individuals possess *CMs* that cannot apparently be conciliated. One method to solve this type of conflict is to allow agents to *negotiate* or to go to *mediation* in order to develop more harmonious relations. Negotiation here means that some agents try to alter others' causal maps by persuading these agents that they have real interests to do these alterations, and, if this could be achieved, then more harmonious interactions could develop. On the other hand, mediation means appealing to a mediator who negotiates with each of the participants in conflict to arrive at a mutually satisfying arrangement. The role of this mediator consists of coming up with a negotiated agreement by proposing arrangements based on some arguments.

4.2.2 Representing Subjective Views

In the context of modeling subjective views by CMs, it is helpful to visualize the structure of a causal map by drawing it as a *graph*. This graph can be constructed by one or many agents, in order to perform a causality-based analysis where choices are made in terms of the consequences of believed courses of actions and can be explained in terms of antecedent circumstances. In fact, we can use causal maps at different levels to represent the subjective views of agents [5]. Thus, first-order *CMs* show the views of individuals (or groups of individuals) such as I and J, and second-order *CMs* show what agent I thinks agent Y is thinking and vice versa. Third-order maps show what agent I thinks agent Y thinks agent X is thinking and vice versa. Similarly, higher-order *CMs* can be constructed, but the reflections on reflections rapidly diminish like mirrors facing each other. Of course, higher-order causal maps are by no means the only method of depicting such structures. However, the method proposed in this section is relevant in those cases where some sort of causal belief structures appear to be helpful in thinking about interagent interaction.

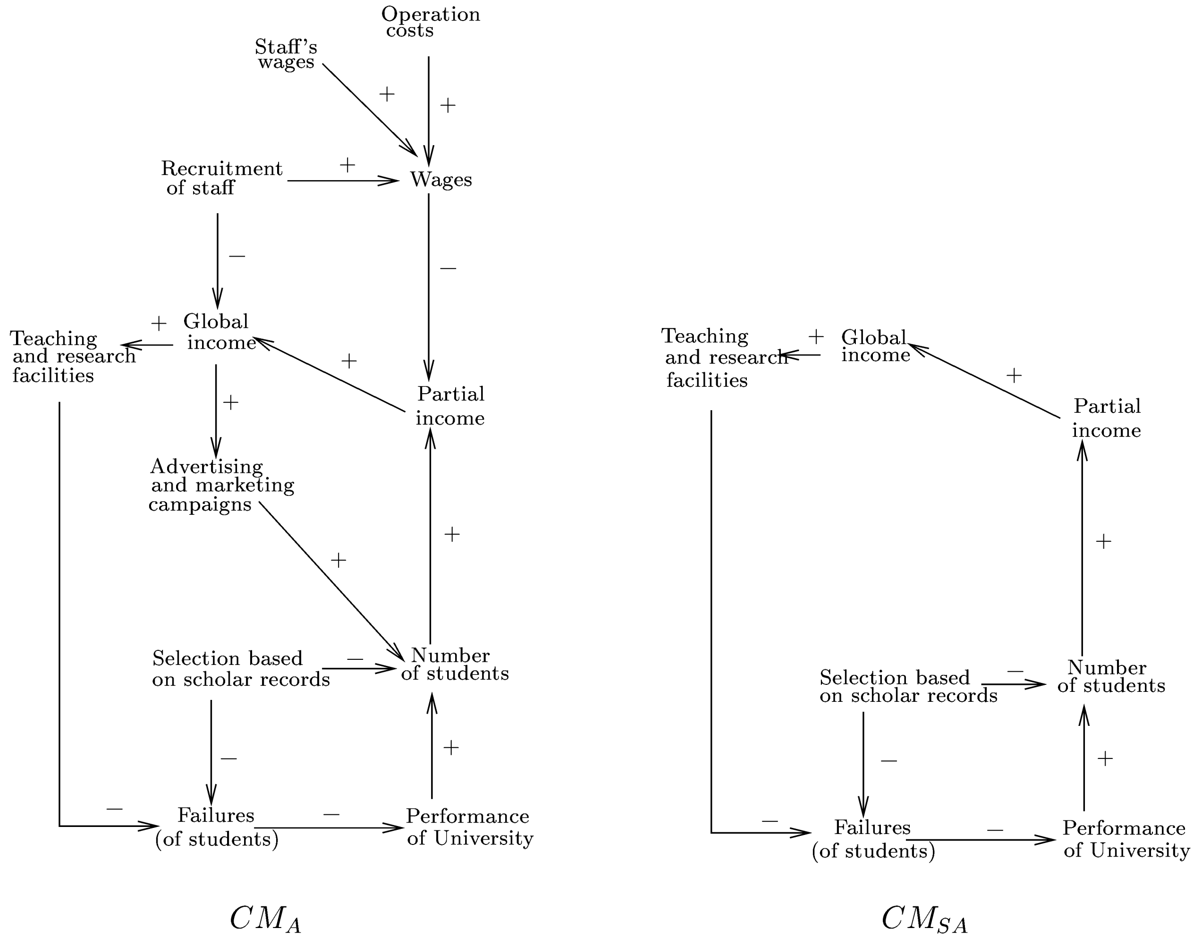

Fig. 3. CM_A reflects the adminstrators' causal map and CM_{SA} reflects the administrators' perceptions of the staff causal map.

4.2.3 *Illustrative Examples*

As illustrative examples, consider the maps in Figs. 3 and 4, which represent the first and second-order perception of a situation involving a typical interaction between administrators and the staff in a university. Note that, for the sake of simplicity and readability of causal maps, we have only considered here the three basic relationships ($+$, 0, $-$). In these conditions, Fig. 3a indicates the point of view of administrators and expresses that the global income of the university depends both on the number of students and upon supplementary sources of funds such as those provided by advertising and marketing campaigns. In Fig. 3b, administrators believe that the staff have a bounded vision of the overall situation and, particularly, administrators believe that the staff do not understand the importance of advertising and marketing campaigns for improving the number of students.

Members of the university staff have their point of view on the overall situation also, as indicated in Fig. 4a. Their causal map CM_S emphasizes the working facilities and the recruitment of other staff in order to improve teaching and research quality. Their causal map also shows that the global income promotes precarious jobs (i.e., unstable jobs) that, in turn, negatively influence global income. Thus, the staff's causal map specifies what is important for the staff: their working conditions and the recruitment of precarious staff, which has a negative indirect effect on the recruitment of the permanent staff. Finally, causal map CM_{AS} of Fig. 4b denotes the staff's perception of administrators. In this causal map, the staff believes that administrators do not see the importance of adequate working conditions of the staff and the worst thing is that administrators try to replace permanent staff by precarious staff with few advantages, in order to improve global income.

To summarize, the causal reasoning sustaining subjective views can bear on:

- trying to demonstrate to others the importance of some area of causal relationships between concepts (this generally leads to a negotiation between agents),
- trying to surround consensus and unilateral views between agents (a mediator, for instance, can do that in case of conflict), and
- predicting what others can do and/or explaining what others have done.

In the next sections, we describe all these aspects through our previous example on "Administrators" and "Members of the Staff," just for illustrating our approach. Note that the adopted example does not limit our approach which remains applicable to any environment of agents A, B, C, $\dots$ and, for which, we should compare their subjective views represented by the causal maps CM_A, CM_{BA}, CM_B, CM_{BA}, etc.

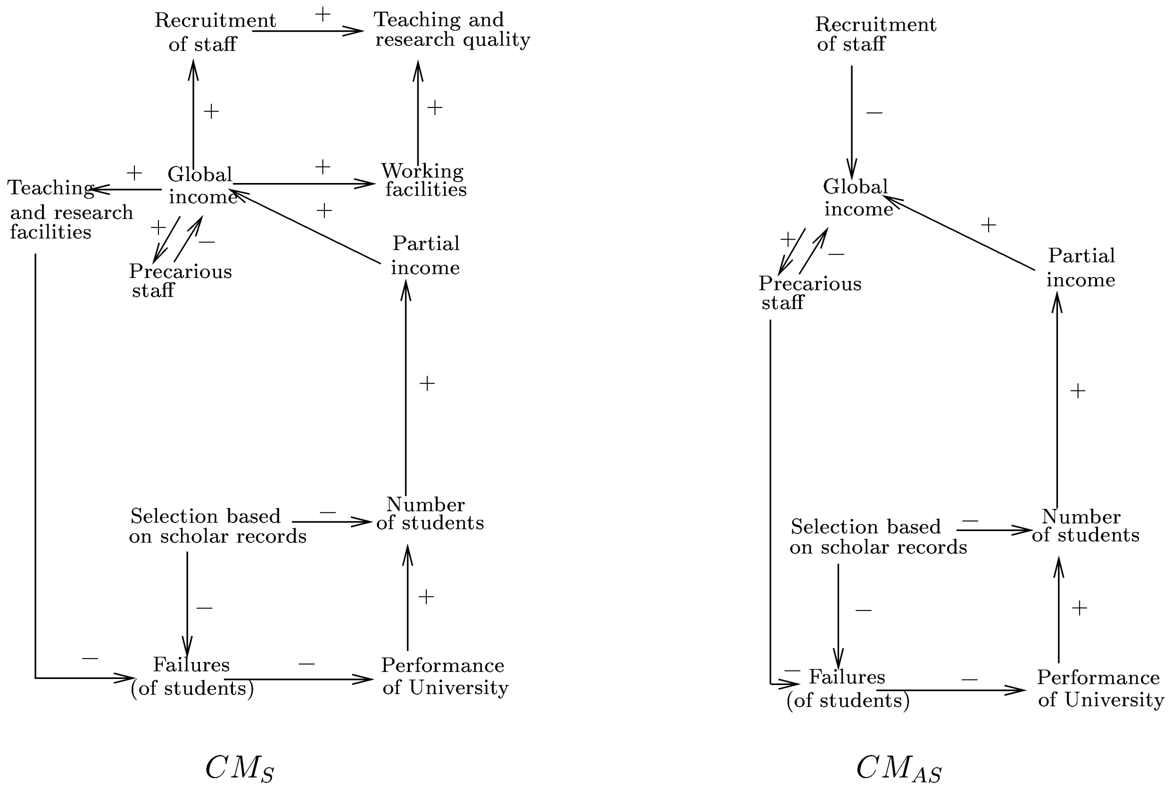

Fig. 4. CM_S reflects the staff's causal map and CM_{AS} reflects staff's perception of adminstrators' causal maps.

4.2.4 as Act between Parties with a View to Reconciling Differences

To facilitate the representation of causal maps, we code the concept variables as follows:

1. recruitment of staff,
2. staff's wages,
3. operation costs,
4. wages,
5. global income,
6. partial income,
7. advertising and marketing campaigns,
8. number of students,
9. selection based on school records,
10. performance of university,
11. teaching and research facilities,
12. teaching and research quality,
13. working facilities,
14. precarious staff, and
15. failure (of students).

In this case, CM_A, CM_{SA}, CM_S, and CM_{AS} can be easily transformed as square adjacency matrices of size 15×15, V_A, V_{SA}, V_S, and V_{AS}. In these matrices, each element $\{ij\}$ takes a value $\{+, 0, -\}$ as expressed in causal maps CM_A, CM_{SA}, and so forth. This matrix representation of CMs allows administrators and staff to construct new matrices A (merging the information from V_A and V_{SA}) and S (merging the information from V_S and V_{AS}). In matrix A (respectively, S), the notation $[x, y]$ in entry i, j expresses that the causal relation between C_i and C_j is x in the causal map CM_A (respectively, CM_S) and y in the causal map CM_{SA} (respectively, CM_{AS}). Thus, for example, the notation $[+, -]$ in A expresses that the relationship between C_i and C_j is $+$ in causal map CM_A and $-$ in causal map CM_{SA}. Entries consisting of 0,0 are left blank.

With A and S, each party can compare his causal relations with those of the other. When it becomes time for negotiations between both parties (administrators and staff) to renew their "social contract," matrix A permits administrators to see on what causal links they think they agree with the members of the staff (i.e., $[+, +]$ or $[-, -]$) and on what other causal links they think they disagree with them ($[+, 0]$ or $[-, 0]$). In the latter case, administrators try to convince members of the staff to alter their CMs so that the causal links $[+, 0]$ and $[-, 0]$ become $[+, +]$ and $[-, -]$. On the other hand, members of the staff defend their point of view which is based on matrix S. They try to convince administrators to change their beliefs so that causal links $[0, +]$ and $[0, -]$, as reflected in S, become $[+, +]$ and $[-, -]$. (See Figs. 5 and 6.)

4.2.5 Prediction from Subjective Views

We now examine the case where possible actions are considered by agents (prediction) and suppose that, in our context of university, administrators want to build a new building for services (including restaurants, banks, bars, libraries, movies, theater, etc.) to raise money. Administrators can view this action (through their causal map, CM_A) as a new contribution for improving the global income of the university, whereas the university staff can consider this idea (through their subjective view on the administrators' causal map, CM_{AS}) as a way to recruit more precarious staff. This case is a conflict and it can be solved by a negotiation between administrators and staff. To

$$A = \begin{array}{cc} & \begin{array}{ccccccccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \\ 11 \\ 12 \\ 13 \\ 14 \\ 15 \end{array} & \begin{pmatrix} & & & +,0 & -,0 & & & & & & & & & & \\ & & & +,0 & & & & & & & & & & & \\ & & & +,0 & & & & & & & & & & & \\ & & & & & -,0 & & & & & & & & & \\ & & & & & & +,0 & & & & +,+ & & & & \\ & & & & +,+ & & & & & & & & & & \\ & & & & & & & +,0 & & & & & & & \\ & & & & & +,+ & & & & & & & & & \\ & & & & & & & -,- & & & & & & & -,- \\ & & & & & & & +,+ & & & & & & & \\ & & & & & & & & & & & & & & -,- \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & & & & & \\ & & & & & & & & & -,- & & & & & \end{pmatrix} \end{array}$$

Fig. 5.

achieve this, administrators must try to alter CM_{AS} by persuading, with arguments, the staff that:

- the university community needs to have such a new building and
- the staff's belief about the recruitment of more precarious staff is a misperception.

The staff can counteract to demonstrate that it is just the opposite or that administrators want to make money, and so forth.

4.2.6 Mediation between Agents

Now, suppose that administrators and staff do not agree on a satisfying settlement at the time of discussions about their social contract. In this situation, both parties might agree on appealing to a mediator from another university to find a solution to this impasse. We assume that they agree on a mediator who knows very well the situation (e.g., the chosen person is a former professor who has been working in administration for 10 years). In these conditions, the chosen mediator knows the concepts which are relevant to this situation and, consequently, can construct a grid from those concepts that he/she communicates to both parties in order to collect their beliefs about causal links and, therefore, their CMs. After this collection, the mediator constructs A and S and analyzes them through a new matrix M to identify potential conflicts.

$$S = \begin{array}{cc} & \begin{array}{ccccccccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \\ 10 \\ 11 \\ 12 \\ 13 \\ 14 \\ 15 \end{array} & \begin{pmatrix} & & & & & & & & & & & +,0 & & & \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & +,0 & & +,0 & +,+ & \\ & & & & +,+ & & & & & & & & & & \\ & & & & & & & & & & & & & & \\ & & & & & +,+ & & & & & & & & & \\ & & & & & & & -,- & & & & & & & -,- \\ & & & & & & & +,+ & & & & & & & \\ & & & & & & & & & & & & & & -,- \\ & & & & & & & & & & & & & & \\ & & & & & & & & & & & +,0 & & & \\ & & & & -,- & & & & & & & & & & 0,- \\ & & & & & & & & & -,- & & & & & \end{pmatrix} \end{array}$$

Fig. 6.

$$
M = \begin{array}{cc}
 & \begin{array}{ccccccccccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \end{array} \\
\begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10\\11\\12\\13\\14\\15 \end{array} &
\begin{pmatrix}
 & & & \mathcal{U}_A & & & & & & & & \mathcal{U}_S & & & \\
 & & & \mathcal{U}_A & & & & & & & & & & & \\
 & & & \mathcal{U}_A & & & & & & & & & & & \\
 & & & & & \mathcal{U}_A & & & & & & & & & \\
 & & & & & & \mathcal{U}_A & & & & \mathcal{S}_A & & \mathcal{U}_S & \mathcal{O} & \\
 & & & & \mathcal{A} & & & & & & & & & & \\
 & & & & & & & \mathcal{U}_A & & & & & & & \\
 & & & & & \mathcal{A} & & & & & & & & & \\
 & & & & & & & \mathcal{A} & & & & & & & \mathcal{A} \\
 & & & & & & & \mathcal{A} & & & & & & & \\
 & & & & & & & & & & & & & & \mathcal{A} \\
 & & & & & & & & & & & & & & \\
 & & & & & & & & & & & \mathcal{U}_S & & & \\
 & & & & \mathcal{O}_B & & & & & & & & & & \mathcal{U}_{AS} \\
 & & & & & & & & & \mathcal{A} & & & & &
\end{pmatrix}
\end{array}
$$

Fig. 7.

The matrix M includes A and S and is based on Bryant's representation [6]. In this representation, the notation $[+, 0; +, 0]$ indicates that the causal relationship between concepts C_i and C_j is $+$ in the causal map CM_A, neutral in CM_{SA}, $+$ in CM_S, and neutral in CM_{AS}. In these conditions, $[+, +; +, +]$ and $[-, -; -, -]$ express a general *agreement* (noted $\mathcal{A}$) about a causal link. Similarly, $[+, 0; 0, 0]$ and $[-, 0; 0, 0]$ (noted $\mathcal{U}_A$) or $[0, 0; +, 0]$ and $[0, 0; -, 0]$ (noted $\mathcal{U}_S$) express an unilateral view of administrators or staff. In the same way, notations such as $[0, +; 0, 0]$ and $[0, -; 0, 0]$ (noted $\mathcal{U}_{SA}$) or $[0, 0; -, 0]$ and $[0, 0; +, 0]$ (noted $\mathcal{U}_{AS}$) specify an unilateral view on another agent. Other causal links include:

- $[+, +; +, 0]$, $[-, -; -, 0]$, $[-, 0; -, -]$, or $[+, 0; +, +]$;
- $[+, +; 0, 0]$, $[0, 0; +, +]$, $[-, -; 0, 0]$, or $[0, 0; -, -]$;
- $[+, 0; +, 0]$, $[-, 0; -, 0]$, $[0, -; 0, -]$, or $[0, +; 0, +]$.

In link 1, both parties see the same causal relationship and one side believes that the other side shares the same perception (noted $\mathcal{S}_A$ or $\mathcal{S}_B$). In link 2, one participant holds a point of view and believes the other does too (noted $\mathcal{O}_A$ or $\mathcal{O}_B$). Finally, in link 3, both parties see causal relations in the same way, but neither believes that the other shares this perception (noted $\overline{\mathcal{S}}$). (See Fig. 7.)

The matrix M allows the mediator to study the following:

- Areas of consensus between agents (such as, for instance, the negative relationship between the selection based on scholar records and the number of accepted students at the university, the negative relationship between teaching and research facilities, and students' failures, etc.).
- Unilateral views of administrators represented by $\mathcal{U}_A$.
- Unilateral views of the university staff, $\mathcal{U}_S$.

The problem of how the mediator reasons on these aspects to solve conflicts between both parties will be investigated in the future.

4.2.7 How the CM-RELVIEW Tool can be Used by Decision Makers (DMs) in the Case of Subjective Views

First of all, DMs elicit causal knowledge about their subjects from different sources, including documents (such as corporate reports or memos), questionnaires, interviews, grids, and interaction and communication between other agents. After that, they use the editor relation of CM-RELVIEW for filling matrices relatives to subjects's beliefs. Finally, they transform those matrices into graphs (causal maps) representing subjective views of their subjects, using the GRAPH button, as explained in Section 3. Finally, DMs use the button SUBJECTIVE VIEWS of the menu TESTS for analyzing their causal maps, as explained in Section 3. Thus, by pressing the SUBJECTIVE VIEWS button, they can reach the following menu:

- COMPARISON: With this menu, DMs can analyze and compare the agents' causal representations. Selecting this menu lets DMs know: 1) areas of consensus between agents' views (e.g., in the case of the previous example on administrators and the staff, the CM-RELVIEW tool gives: areas of consensus are: selection on scholar records—(-)—> number of students, teaching—(-)—> research facilities, etc.) and 2) unilateral view of an agent i (as, for example, unilateral view of administrators are: advertising and marketing campaigns—(+)—> the number of students, etc.).
- PREDICTION: This menu answers the "what if" questions of DMs. In the case of administrators, for instance, the answer to the "what if" question of building new building services (including restaurants, banks, etc.) is building services—(+)—> total income. Whereas, in the case of the staff, the same question produces building services—(+)—> administrators' profit.

- EXPLANATION: With this menu, the CM-RELVIEW tool supply DMs with explanations on what has happened in a given situation. Thus, for instance, if a decision maker asks the tool "why has the global income increased recently in the point of view of Administrators," the answer given by CM-RELVIEW might be one possible explanation is: the augmentation of students.
- NEGOTIATION: Negotiation here is between a decision maker (DM) and the CM-RELVIEW tool. Thus, for instance, if the tool plays the role of an administrator and the DM the role of a member of staff, one can obtain the following exchange:
  - DM: recruitment of staff—(−)—> global income,
  - CM-RELVIEW: I don't see the same relation, give me the reason(s),
  - DM: reason: recruitment of staff = 30 percent of global income during the last five years,
  - CM-RELVIEW: OK, recruitment of staff—(−)—> global income.

4.3 Causal Maps as a Tool for Qualitative Decision Making (QDM) in Multiagent Environments

Decision theory is becoming increasingly significant in artificial intelligence since it is being used to address important tasks (planning, diagnosis, learning, etc.), and serves as the basis for a new generation of "intelligent" softwares known as normative systems. In spite of this, decision analytic approaches have several limitations:

1. difficulties acquiring the numbers as probabilities and utilities;
2. computations needed to assess likelihoods and decide on actions can become unfeasible when there are too many numbers that must be taken into account; and
3. difficulties dealing with causal knowledge.

Qualitative decision analysis (QDA) aims to solve these problems. QDA is driven by the notion that precise numbers and exact numerical computations are often unnecessary and can be replaced by symbolic approaches that provide a number of advantages.

Several approaches that can be considered to be examples of QDA have been proposed, including *linguistic phrases* [16], *qualitative probabilistic networks (QPNs)* [35], *order of magnitude calculi* [27], [37], *qualitative logics of decision* [25], and *causal maps* [7].

In this section, we investigate the issue of using causal maps in multiagent environments where an agent or a group of agents considered as a whole should make a decision based on causal knowledge. An example of QDA using causal maps is given in Fig. 1 where "remaining idle" decreases the prospects for Japanese success in a war along two causal paths. Precisely, the relationship between idleness and war prospects is negative because both paths agree. In these conditions, Japan has interest in starting a war as soon as possible if she believes that war is inevitable.

4.3.1 An Algorithm for Solving the Undetermined Decision

The problem of QDA based on causal maps can be stated as follows: Given a causal map with one or more decision variables and a utility variable, which decision should be taken and which should be rejected? To achieve this, the concerned agent should calculate the total effect of each decision on the utility variable. Those decisions that have a $+$ or $\oplus$ total effect on utility should be chosen, and decisions that have a $-$ or $\ominus$ total effect should be rejected. Generally, no advice can be given about decisions with a, that is, an ambivalent, total effect on utility, whereas a $\pm$ or ? total effect on utility should not be rejected because it raises the undetermined decision problem.

The indetermination decision is a problem here and we propose to solve it by applying the principle of superposition adopted for causal maps. This principle stipulates that the result of applying together two concepts C_1 and C_2 is the same as applying C_1 and C_2 *in sequence*. (See Fig. 8.)

Thus, the positive and negative effects of C on C' are applied in sequence in order to evaluate which is the strongest. Obviously, this method might be limited, particularly in cases where knowledge for evaluating P_1 and P_2 does not exist. We will show below how this algorithm operates with a concrete example. Before that, we now illustrate the decision-making process in the context of multiagent environments using causal maps.

4.3.2 An Illustrative Example

To achieve this, consider, for example, the causal map of a professor P_1 (considered as an agent) shown in Fig. 9, who supervises a research group, called G_{12}, and who has to choose between two courses D_1 and D_2 (D_1 and D_2 are decision variables). The question now is how P_1 can choose between D_1 and D_2 knowing the facts reflected by the causal map, shown in Fig. 9. This causal map includes the following P_1 beliefs. D_1 favors the theoretical knowledge of G_{12}'s students. Greater theoretical knowledge gives a greater motivation to students. Greater motivation of students gives a better quality of research for group G_{12}, which gives a greater utility of G_{12}, which, in turn, has a positive result on utility of P_1. Finally, the second decision variable D_2 is an easy course that decreases the workload of P_1. Obviously, decreasing P_1's workload increases her utility.

In this case, how can P_1 make her choice between the two courses D_1 and D_2? Note that, in the context of our example, P_1 should reason about another agent, which is the group G_{12}, to make her decision. In other contexts and for other decisions, she can also collaborate with her group to develop her decision. In this sense, the decision-making process considered here is a multiagent process. To run this process, it might be useful to convert the causal map being analyzed to the form of a valency matrix V. With the valency matrix, P_1 can calculate indirect paths of length 2 (i.e., V^2), 3 (i.e., V^3), and so forth and the total effect matrix V_t (see Definition 7). In fact, V_t tells P_1 how the decision variables D_1 and D_2 affect her utility and G_{12}'s utility. This

Algorithm for solving the undetermined decision

1. For any concept C that has an undetermined result on the Utility U, calculate all the indirect effects between C and U; then separate those indirect effects in positive and negative paths (i.e., paths with "$+$" and "$-$" total indirect effect respectively).
2. Cut off all the negative paths and evaluate the effect of positive paths on U, then note P_1 this evaluation.
3. Repeat the previous step for the effect of negative paths on U (without taking into account the positive paths) and note P_2 this evaluation.
4. Compare P_1 and P_2
   (a) if P_1 is more valuable than P_2, then the sign between C and U is "$+$;"
   (b) else if P_1 is less valuable than P_2, then the sign between C and U is "$-$;"
   (c) else if P_1 is as valuable as P_2, then the sign between C and U is "0."

Fig. 8. Algorithm for solving the undetermined decision.

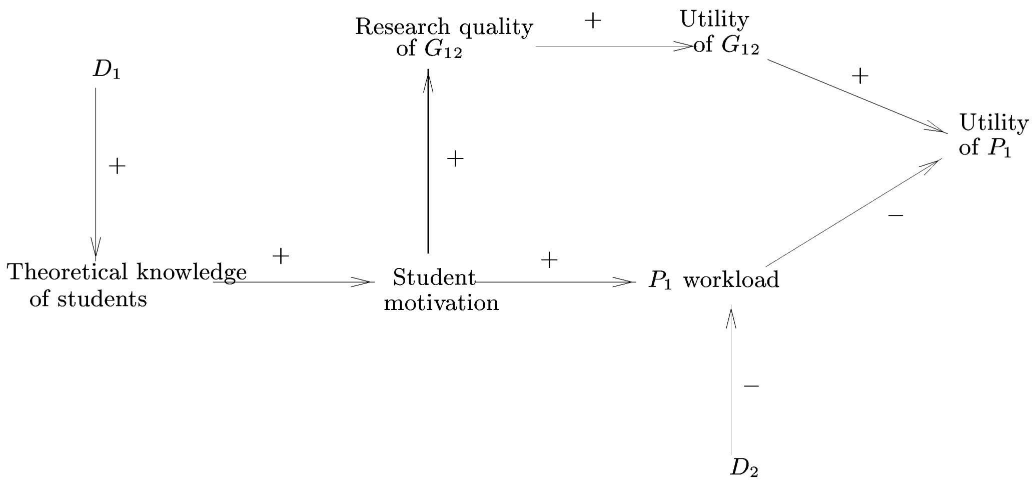

Fig. 9. An illustrative example for QDM in a multiagent environment.

gives the following matrix of size 2×2 (keeping only the relevant entries) involving two decision concepts (DC), D_1, and D_2, and two utilities considered as value concepts (VC), namely, utility of G_{12} and utility of P_1. (See Table 1.)

Thus, P_1 perceives:

1. decision D_1 as having a positive effect on utility of G_{12} and an undetermined effect on her utility, and
2. decision D_2 as having a neutral effect on utility of G_{12} and a positive effect on her utility.

TABLE 1
Table 1

$DC \backslash VC$	Utility of G_{12}	Utility of P_1
D_1	$+$	?
D_2	0	$+$

In these conditions, it is important to remove the undetermined result of the D_1 decision on P_1 utility. To achieve this, we apply the previous algorithm as follows:

1. To see the impact of giving the course D_1 on utility of G_{12}, we cut off the negative path produced by "Student motivation" —(+)—> "Workload of P_1" —(−)—> "Utility of P_1". Practically, this means that P_1 evaluates the following hypothetical situation: "if the course D_1 will be given by another colleague what will be the impact (I_1) of D_1 on my utility without taking into account the workload induced by D_1?"
2. Similarly, we cut off the positive path produced by "Student motivation" —(+)—>"Research quality of G_{12}" —(+)—> "Utility of G_{12}" —(+)—> "Utility of P_1". By doing so, we can see the impact (I_2) of giving the course D_1 on the workload (W_2) of P_1 without the positive impact induced by the group G_{12}. Practically, this means that P_1 evaluates the following hypothe-

TABLE 2
Table 2

$DC\backslash VC$	Utility of G_{12}	Utility of P_1
D_1	$+$	$+$
D_2	0	$+$

tical situation: "What will be the impact (I_2) on my utility if I give the course D_1 to another group that has no connection with me?"

3. Finally, if the impact I_1 a) compensates I_2, then D_1—(0)—> "Utility of P_1," b) if it is more valuable than I_2, then D_1 —(+)—> "Utility of P_1," and c) finally, if it is less valuable than I_2, then D_1—(−)—> "Utility of P_1."

Suppose that P_1 *believes* that the impact of giving the course D_1 produces effects on her utility, via her group of research, which are more valuable than what this course gives her as workload. In these conditions, please refer to Table 2.

Here, it is clear that decision D_1 would be preferred on decision D_2 because this decision has a positive impact on P_1's utility and on G_{12}'s utility. Conversely, D_2 has only limited impact because it only positively influences the utility of P_1.

Thus, causal maps might allow agents to choose among alternative actions. Such choice is based on causal evaluation of the different alternatives on agents' utilities.

4.3.3 How the CM-RELVIEW Tool can be Used by Decision Makers (DMs) for Their QDM

Here also, DMs elicit causal knowledge about their decision and utility variables from different sources, including documents (such as corporate reports or memos), questionnaires, interviews, grids, and interaction and communication between other agents. After that, they use the relation editor of CM-RELVIEW for filling matrices relative to this causal knowledge. Then, they use the GRAPH button for transforming those matrices, into graphs (causal maps). Finally, they analyze those causal maps using the TRANS button.

Here, how a decision maker (DM) can use this tool. By pressing the button TRANS in the menu window (Fig. 2), CM-RELVIEW, a decision maker (DM) can calculate the transitive closure, (i.e., the total effect that a decision has on the utility variable). In the case where there is an undetermined result, CM-RELVIEW applies the algorithm introduced previously and asks the DM to give it some guidance to solve the undetermined result. In particular, the DM is asked to supply 1) the impact of positive and negative paths and 2) the most valuable impact. A fully automated process for solving the undetermined result problem is scheduled in the agenda of our future work.

4.4 Causal Maps as a Tool for Representing a Dynamic Wholistic Approach of an Organization of Agents

4.4.1 Organization of Agents as a Dynamic View

Weick [34] suggested changing the prevalent static view of an organization of agents to a dynamic view which is sustained by *change*. Precisely, he proposed that organization and change are two sides of the same social phenomenon. His reasoning was that an organization is a process of coevolution of agents' perceptions, cognitions, and actions. In this context, Weick proposed a theory of organization and change based on the graphs of loops in evolving social systems. Recently, additional investigation guided by this approach [3], [4] tried to articulate how causal maps provide a way to identify the loops that produce and control an organization.

In multiagent systems, the study of an organization of agents has generally focused on some structural models such as the following:

- centralized and hierarchical organizations,
- organizations as authority structure,
- marketlike organizations, and
- organizations as communities with rules of behavior.

All of these structures missed dynamic aspects and influences that exist in an organization of agents. Generally, dynamic aspects and influences evolve through paths that close on themselves and form loops. We have realized that such loops are important for an organization of agents for two main reasons:

1. A change in an organization is the result of deviation amplifying loops.
2. The stability of an organization is the result of deviation countering loops [4].

4.4.2 An Illustrative Example

As an example, consider the organization that binds researchers, grant agencies, and qualified personnel in any (science and engineering) department. The causal map representing this organization is shown in Fig. 10. The meaning of this CM is clear and we shall not explain it further.

In this causal map, concepts link together to form loops, some of which are numbered 1 to 7. Loops 1, 4, 5, 6, and 7 are *deviation-amplifying* loops. The change in the organization is the result of such loops because any initial increase (or decrease) in any concept loops back to that concept as an additional increase (or decrease), which, in turn, leads to more increase (or decrease). Thus, in loop 5, an increase in research quality improves researcher satisfaction. An increase in researcher satisfaction allows, in turn, the improvement of the retention of the best researchers. Finally, the improvement of retention of the best researchers improves research quality.

Loops 2 and 3 are *deviation-countering* loops [4]. The stability of the organization is the result of such loops. In the case of loop 2, for instance, an increase of resources for research can lead to an increase of salaries which, in turn, reduces the resources allowed to research. If this reduction is not enough to compensate the initial increase

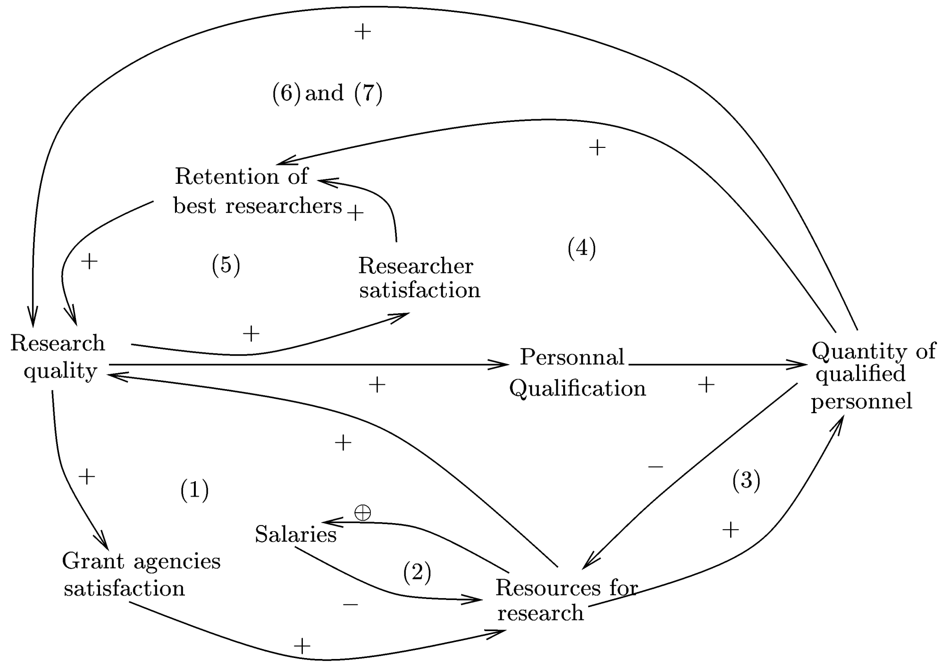

Fig. 10. An organization of agents as loops.

of resources, then a residual increase of salaries takes place, which, in turn, reduces the resources, and so on, until a balance between the initial increase of resources and salaries is reached. Thus, deviation-countering loops are useful for stabilizing the growth generated in an organization.

Note that, in a wholistic approach, the whole constrains the concepts and the relationships between them. With an organization of agents represented as a wholistic approach, we obtain a dynamic system in which deviation-amplifying loops are responsible for change and deviation-countering loops are responsible for stability in the organization. Using these loops, an individual strategist can direct strategic change in the desired directions. This can be achieved by choosing and changing a loop or choosing and changing a set of loops.

4.4.3 How the CM-RELVIEW Tool can be Used by DMs for the Reasoning on Organization Changes

Here also, DMs elicit causal knowledge about their organizations from different sources as reports, memos, questionnaires, interviews, etc. After that, they use the CM-RELVIEW for constructing causal maps reflecting this causal knowledge. Finally, they use the CM-RELVIEW tool for analyzing those causal maps.

As stated in Section 3, the submenu of the graph menu called WHOLISTIC-APPROACH allows DMs to draw a "wholistic" causal map, whereas the menu WHOLISTIC-CM of TEST allows them to test it by choosing and changing a loop. Obviously, the loop to be changed should be a weak loop loosely coupled to the system. CM-RELVIEW offers DMs the following actions for changing a loop (from deviation amplifying to deviation countering, or vice versa): ADD-NODE: adding a node; REM-NODE: removing a node; REP-NODE: replacing a node; CHG-LABEL: changing the label of a link.

As we note, CM-RELVIEW does not take into account the aspect of changing a set of loops which is more subtle and requires complex strategies in order to avoid conflicts between agents.

5 Conclusion and Future Work

We have first proposed a formal causal map representation of relationships between agents' beliefs. This formal representation, based on relation algebra

- defines a precise semantic interpretation of qualitative causalities,
- justifies most of the classical intuitive inference laws for reasoning from cause to effect, and
- provides a tool, CM-RELVIEW, for determining certain quantitative and qualitative features of causal maps.

Then, we have argued for the use of causal maps to reason about interrelationships among a set of individual and social concepts in the context of multiagent systems. In this context, we have investigated the following aspects:

1. reasoning on subjective views in multiagent systems,
2. qualitative distributed decision making, and
3. the organization of agents considered as a wholistic approach.

We have illustrated each of these aspects by an example in order to show the practicality of causal reasoning, and we have explained, finally, how the CM-RELVIEW tool can be used for each of them.

It is important to point out that the causal map approach adopted here is generally applicable to an environment that is not rapidly changing. In other words, the causal maps considered here are relatively stable. It is also convenient to point out that the approach adopted here seems inappropriate to open environments where agents enter and leave the group dynamically. The main reason is that it is very difficult to update causal maps and to assure coherence between concepts.

There are many directions in which the proposal made here can be extended:

1. The full possibilities of relation algebra have yet to be exploited. In particular, it allows equation solving, which would certainly be useful. An example of solving linear equations might be: Solve in X, the following equation $RX = S$, where R, S, and X are causal maps. Also, the relational operations of complementation and conversion offer ways of expressing relationships between concepts that are not available in the classical theory of causal maps. Another option is to study "fuzzy relations" between agents' concepts [8], [41]. Our approach might be extended in this direction to take into account many degrees and vague degrees of influence between agents such as none, very little, sometimes, a lot, usually, more or less, and so forth [20], [26].
2. Applications such as the following ones must be investigated in greater depth:
   - negotiation and mediation between agents in the case of reasoning about subjective views;
   - knowledge available to or necessary to agents in the case of nested causal maps;
   - reasoning about the wholistic approach; and
   - reasoning on social laws, particularly for qualitative decision making.
3. The connections of CMs with other causal approaches should also be investigated in greater depth, in particular:
   - connection with preference-based decision making [38],
   - connection with influence graphs [7], and
   - connection with belief networks [15].

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