A Comparative Review on Computational Modeling Paradigms. A Study on Case-Based Modeling and Political Terrorism

Voinea, Camelia Florela

A COMPARATIVE REVIEW ON COMPUTATIONAL MODELING PARADIGMS. A STUDY ON CASE-BASED MODELING AND POLITICAL TERRORISM

CAMELIA FLORELA VOINEA

We review the advances in Case-Based Computational Modeling on Political Analysis issues. Starting in early '70s, the research on *political terrorism* has been challenged by the latest advances of *terrorism computational modeling research*. Nowadays Political Analysis community has a wider perspective over the *terrorism* research aims, methodology and instruments. Widening up this perspective is not a matter of political analysis and research only, it is as well a long-term effect of an interdisciplinary style which has been adopted within the area by acknowledging the scientific advances and support of the *Computational Modeling and Simulation* as a specific scientific research method. Computational Modeling includes several research frameworks. The *Case-Based Modeling* is analysed and evaluated on a comparative basis with *Agent-Based Modeling* in a study on *political terrorism* phenomena.

1. Introduction

Terrorism appears to nowadays Artificial Intelligence researchers as a collection of facts and information regarding situations and contexts which make the subject of political, military, economic and social concern almost all over the world, especially after *September 11*. In spite of the international efforts to control it, the *political terrorism phenomena* still represent an area of scarce conceptual and decision making experience which makes difficult the process of understanding, defining, and modeling it (Crenshaw, 2000; Cooper, 2001), not to speak about the strong necessity of preventing and controlling it. Progresses have been made and reported ever since *September 11*, 2001, nevertheless *terrorism* is far from being completely understood and even less properly defined. Governments along with experts in Political Science, Social Sciences, Economic and Decision Sciences are currently focusing their research on finding the proper ways to approach this type of phenomena by means of interdisciplinary paradigms.

After almost 30 years of research on *political terrorism* (Crenshaw, 2002), the Political Analysis community has a wider perspetive over the terrorism research aims, methodology and instruments. Widening up this perspective is not a matter of political analysis and research only, it is as well an effect of an interdisciplinary style which has been adopted within PA area. It therefore acknowledges the scientific advances and support of the *Computational Modeling and Simulation* as a specific scientific investigation philosophy and method.

Computational Modeling

In spite of the extreme social, political, military and philosophical challenges raised by the *terrorism* phenomena, these challenges are rather driving us up to the idea that unusual as it is as a social phenomena, from a scientific research perspective it is at the same time a prototype of social change and a social emergence scenario. It therefore has to be approached as a new area of scientific interdisciplinary research for which new philosophical, cognitive, economic, military and social concepts and processes have to be defined. More than the social and political challenges *terrorism* has raised so far, *terrorism* is a scientific challenge itself. It either requiers a new science to be created and developed such that these phenomena could be approached and well-understood or it requires that several existing sciences employ their actual and potential resources in order to tackle the challenges of the *terrorism* phenomena.

Beyond all the other questions connected to the issues above, *terrorism* has raised one more fundamental question: the question of the appropriateness of current scientific research instruments in defining terrorism. *Computational Modeling* is considered one of these sophisticated research instruments. However, its scientific status and its potential capacity to respond several fundamental epistemological questions in the area of scientific research, go beyond the status of an instrument and make of the computational modeling a best choice as a scientific research technology. From this perspective, it seems that *terrorism* opens up a research area for which we do not have so far the appropriate semantic primitives, the fundamental concepts, reasoning schema and knowledge representation: *terrorism computational modeling and simulation*. And it is this point that our approach has decided to start with: the role and substance of the computational modeling aimed at *defining, describing, explaining* and *predicting terrorism phenomena* in the area of Political Analysis.

Nevertheless, in the area of Political Analysis, the *terrorism* issue as well as the issue of computational modeling of socio-political phenomena (*terrorism* included) are not at all new issues of research. For more than 15 years, there have been systematically developed researches in several areas of mathematical and computational modeling which have focused on different aspects of *terrorism* and associated conflict, political violence, unconventional security affairs and war phenomena: the nature and patterns of terrorism, societal construction of terrorist ideology, organization and action, type of terrorist weapons, strategies, decision-making and agents, to name but a few. The area of computational modeling and simulations on political analysis issues has become a virtual field of research able to offer the scholars a way of scientifically investigating the *terrorism* phenomena. There are several classes of *terrorism* concepts and phenomena which could be roughly identified with the following research approaches on computational models of *terrorism*:

(1) *epistemological*: definition, basic concepts and type of societal construction of terrorism;

(2) *cultural*: context of terrorism (ideology, religion, ethnicity)

(3) *instrumental*: structure of terrorist organization, type of terrorist strategy, weapon and action, terrorist case databases;

(4) *operational*: military training games, strategic behavior, retaliation against terrorism, terrorist and guerilla warfare.

Following this classification, several types of computational approaches may be identified:

– *mathematical and computational models of decision making* in terrorist organizations and agents based on Decision Theory, Markov Decision Processes and repeated Bayesian Games (Weaver *et al.*, 2001);

– *mathematical models* based on the Graph Theory of the structure, organisation and action of the terrorist cells (Peterson, 2004; Farley, 2003);

– *emotion models* in the development of computational models and agent-based simulations of terrorist behavior and terrorist decision making organizations and agents in the area of military training games (Johns and Silverman, 2001);

– *case-based models* and databases of terrorist operations, organizations, types of weapons, types of security, ideology and agents (Dupuy, 1988);

– *agent-based computational models* of the relation between ethnicity and conflict (Cederman, 2005), of the geo-cultural logic of nationalist insurgency and civil wars (Cederman, 2004), of the pacifying effect of peace-keeping forces on secession and ethnic inter-group conflicts (Epstein, Steinbruner and Parker, 2001), of the ethnic genocide in Rwanda (Bhavnani and Backer, 2000) and of the globalisation and the ethnic conflict (Van der Veen, 2001).

Though some of the above-mentioned computational models succeed to provide for explanations of nationalist insurgency in terms of geopolitical and geocultural contexts using the theory of complex adaptive systems (Cederman, 2005), there is no computational model or there are only scarce research resources employed so far which could provide a basis for an explanation of the emergence of terrorism (Cerderman, 2001), for defining *terrorism* or for the development of a conceptual model able to explain the roots of *terrorism* as a philosophy of action and choice.

Each of these classes of computational modeling approaches has focused on some particular aspect of terrorism and some of these models succeeded to offer a comprehensive perspective over these phenomena. The advantages of these models reside in their capacity to "mimick" the reality and provide for a chance to investigate these phenomena in artificial worlds/societies.

We will approach in this paper on a comparative basis a conceptual modeling framework which succeeds to bring a Cognitive Science paradigm – *modeling* – and an Artificial Intelligence paradigm – *Concept Learning* – back to our memory and in the service of Computational Modeling and Simulation in Political Analysis: the **Case-Based Reasoning paradigm**.

Case-Based Reasoning (or simply *CBR*) is a classical reasoning paradigm used in the area of problem solving. It is based on analogy, reminding and the use of explanative past experience in order to solve new problems. So far so good. There is nothing special so far in CBR with regard to the computational modeling issue in Political Science we have introduced above, not to say that CBR is regarded as already an old-fashioned Artificial Intelligence paradigm created by late '70s and forgotten soon after its first performances in the area of *Expert Systems*. There is however a clue to an argument which makes it suddenly valuable again: CBR works with ill-structured domain theories and it has been the only paradigm of the Artificial Intelligence which has acknowledged the term of *creative hypothesis development* by means of *adaptive explanations* – the terminology belongs to Alex Kass (Kass, 1990) – provided by the past experience, understanding and remembering. The connection between these intriguing attributes and the issue of conceptual constructivism in Political Science might now appear straightforward: CBR paradigm provides a framework for using the past experience for conceptual construction in ill-structured domains. The limitations of ill-structured domain theories underlying systems building on past experience weaken the explanation structure and expressiveness. Therefore the explanative power of such conceptual constructs is strongly dependent on the knowledge representation, reasoning and learning strategy.

The aim of reaching a powerful explanation framework by cognitive modeling might look limited itself given the technical limitations invoked above, but it still is the aim we go for. The reason is that the complexity of phenomena might be approached from two perspectives: (a) we can either explain things by growing up a *simulation model* whose outcomes could imitate in a "believable" way the real processes (Epstein, 1999), or (b) we can *explain* things *by having well-structured domain knowledge*, which we can get by learning and conceptual construction.

One might argue that the explanation power heavily depends on the completeness and soundness of the knowledge in the domain theory, and having to deal with ill-structured domains, the aim of a powerful explanation framework might never be reached. There is no complete and sound knowledge in either of these alternate perspectives – *simulation model* or *explanative conceptual knowledge*. There is nevertheless an undoubtedly *complementarity* between the two: one can grow up a simulation model knowing as much as possible about the underlying reality or one can construct a *corpus* of conceptual knowledge which can make the simulations be understood in real terms.

Case-Based Reasoning

The classical AI Case-Based Reasoning approach has been introduced by Roger Schank in 1982 (Schank, 1982). At that time, CBR was meant to be a unifying paradigm for knowledge representation and concept learning, and for almost a decade it focused everybody's attention, being rapidly developed and scaled up to more complex capabilities like the problem solving. Nevertheless it has been forgotten soon afterwards. Why ?

The answer concerns the very essence of the CBR paradigm, which suits very well the requirements of a conceptual model able to start from *ill-structured domain theories*, and to further build up expertise by interleaving learning and reasoning into an integrated framework of different past experiences.

One main advantage of CBR-type computational modeling is its capacity of conceptual construction from contingent knowledge. The Knowledge Base of a CBR-based systems is able to grow up as a *corpus* of domain knowledge by means of *learning*. Such a system is able to abstractize from contingent data by means of inductive (example-based generalizations), deductive (explanation-based learning) or abductive (by the use of plausible reasoning) learning techniques. Past experience is used as a resource for building up abstract conceptual constructs: once conceptual construction enriched with new concept, the system's cognitive competence increses influecing its cognitive modeling performances. As new cases are encountered, they are easily classified. The other major advantage of CBR-based systems is the *problem solving capacity*: past experience is used to extract explanations or solutions of known cases and to solve new problems. The analogy-based transfer of problem solving competence from the past cases to new cases make of CBR a paradigm for the understanding models and for the development of creative hypothesis by adaptive explanations.

The initial limitations of the classical CBR paradigm have been induced – on the one hand – by the computer memory and programming technical limitations and – on the other hand – by the limited representation power of the knowledge representation structures like the scripts and frames used at that time. Once these do not operate anymore as technical limitations cutting down the CBR theoretical capabilities, CBR could become the appropriate paradigm to approach conceptual constructisvism in Political Science, due to its considerable conceptual representation, learning and explaining power. The considerable enhancement provided by the Internet technologies and associated intelligent technologies, like the KDD (see *Section 4*), are now available and most appropriate to replace the classical in CBR dynamical memory with advanced memory access techniques.

2. Early and OnGoing Research Work in Case-Based Reasoning

We have traced back the case-based modeling paradigm along a period of time of 30 years, since Roger Schank had first reported research results on the Scripts' Theory and on a new theory of case-based knowledge representation and learning. We have classified research work in three stages: (1) the pioneering work of Schank and the classical CBR systems of early and mid' 80's; (2) the CBR inspired research work developed within the area of Knowledge and Data Discovery; (3) the case-based modeling research work developed within the area of Agent-Based Modeling in social and political sciences.

The way **Case-Based Reasoning (CBR)** came into being as a distinct AI problem solving and learning paradigm is connected – on the one hand – to the theories of computability and symbolic representation in computers (Simon and Newell, 1972) and – on the other hand – to the cognitive science theories on expert problem solving by analogy (Gentner, 1983; Carbonnell, 1983; Carbonnell and Lenat, 1986).

In the twentieth century, by the mid 70's, several research communities reported research results concerning an interesting transfer of philosophy and cognitive psychology models of human mind and human associational learning towards the theory of computability and the area of Artificial Intelligence and Machine Learning sciences. All this has represented the starting point for the development of the theories concerning the knowledge representations in humans and machines (Dreyfus, 1986). The "conceptual engine" which proved able to move on the philosophy of the human mind and cognition towards the computing machinery was the idea that we can draw a parallel between the human mind and the computing machine at the level of the modeling capacity. Philippe N. Johnson-Laird, in his seminal work on *Mental Models. Towards a Cognitive Science of Language, Inference, and Consciousness* (1983), had proved out that symbolic representations in the computer memory refer to the world inasmuch human perception "is the construction of the world" (Johnson-Laird, 1983, p.156). As humans "are unable to compare this perceptual representation directly with the world" since "it *is* their world" (Johnson-Laird, 1983, p.156), and use references to their mental models to make this comparison, so does the computers: "The programmer can solve problems in terms of arrays and can entirely ignore the detailed machinery on which they rely. There is no reason to suppose that the human mind is organized on different lines. It, too, needs to develop new procedures and it can do so very much more easily if it can work directly with high-level structures, such as spatial representations, ignoring the details of their ultimate representation in the brain" (Johnson-Laird, 1983, p.153-154).

John R. Anderson, in his early work on *Arguments concerning representations for mental imagery* (1978) and further developed in his book on *Cognitive psychology and its implications* (1985) proves the idea that mental representations of the perceived world or imagery can be mimicked (the Mimicry Theorem) by different kind of representations and constructs which are able to behave in an equivalent way. This basic idea has turned later on to be useful as a background to the transferring of Cognitive Psychology theories concerning the associational character of the human expert problem solving into a theory of knowledge representation and modeling of contingency experiences in computers.

On the other hand, studies of expert problem solving by analogy showed that human experts make oftenly use of their past experience in problem solving to adapt the solutions to previoulsy encountered problems to currently encountered problems which prove to be equivalent or just similar to the old problems encountered in the past by means of analogy-based schemata transfer (Gentner, 1983).

Roger Schank associated these theories with the evidence that computers may store a huge amount of problem solving experiences (cases) and could therefore be used as an artificial intelligent expert systems in problem solving. The problem of making the computer do the same as the human experts was not so much a problem of model building in an artificial environment like the computer's memory (a problem already studied and solved by excellence by Simon and Newell in their book in 1972), but a problem of building a past experience storage which could be accessed and inspected in a dynamic manner as it apparently happens with the human experts's memory in such situations. After a long time when computers' artificial intelligence have been designed to learn in many possible ways – from domain or model theories, from examples and counterexamples, or by means of heuristic rules and production systems – Schank himself combined the theories previously developed with his new theory on machine learning: learning from the solutions provided by the past experiences stored and retrieved in a dynamically accessed memory of previously solved problems (or past "cases").

Schank had been the pioneer of the Case-Based Problem Solving and Learning Theory (also known as the Schank's MOP Theory of human problem solving and learning). He theoretized and actually developed together with his students at the Yale University several AI systems based on the storage of conceptual and factual knowledge from past experiences (or past cases) in a case memory from which both knowledge and reasoning schemata can be retrieved and further used for problem solving and concept learning purposes: CYRUS (Kolodner, 1983), JULIA (Kolodner, 1993; Hinrichs, 1992), CHEF (Hammond, 1986). Their example and research experience has been further developed in the following years: the CASEY system developed at the M.I.T.

(Koton, 1989), the PROTOS system developed at the University of Texas, Austin (Porter and Bareiss, 1986), the CREEK system developed at the University of Trondheim and the Norwegian Institute of Technology (Aamodt, 1991), the XP adaptive explanation system developed at the Institute for the Learning Sciences and Northwestern University (Kaas, 1991) and the SEA system developed at the Romanian Research Institute for Informatics (Voinea, 1991a).

Schank's original work concerned a particular type of schema-based theories, called the Script Theory (Schank, 1977; Minsky, 1975), which concentrate an explanation extracted from a past case in a stereotype knowledge structure which can be instantiated to explain new cases. Scripts and frames provided the appropriate knowledge structures to implement Schank' Scripts Theory. The Case Memory is organized as a hierarchy network in which the nodes contain generalized knowledge structures called *Generalized Episodes* (GE) or *Episodic-Memory Organization Packets* (E-MOPs). Each GE is a knowledge structure which generalises the episodes sharing similar properties like norms. The GEs are discriminated by means of their associated indices (name and values). The instances of GEs are stored as individual cases. The GEs are used as an indexing structure for matching and retrieval of cases. A particular case is retrieved by matching its features against the GEs: the *best match* identifies the GE with most features in common with the matching case (Schank, 1982).

CHEF is a planning system which combines model-based reasoning and explanation-based learning. The cases are goal-oriented plans stored in a planning memory where the *best match* provides the plan which best suits the achievement of a certain pre-defined goal. The system uses a causal knowledge model to adapt plans from the planning memory to the current goal (Hammond, 1986).

CASEY is a system of causal reasoning which combines two types of reasoning – associational (case-based) and interpretative (model-based) – with a causal knowledge model. The Case Memory consists of cases stored together with a causal explanation. The *problem solving* task is achieved by matching a current case against the Case Memory and extract a causal explanation which is used for classification. The learning task consists in storing the cases and their associated causal explanations in the Case Memory (Koton, 1989).

PROTOS is designed as a case-based system aimed at classification and concept learning from a collection of examples (instance cases). A current case is described as a set of attributes which are used to identify in the case memory the case which best matches the current case. The examples (instances) are stored as the nodes in a semantic network of domain knowledge and the connections between the nodes describe the taxonomy relations. A new concept is *learned* by generalisations of the instances with the same attributes. The *problem solving* task is achieved by analogy-based solution transfer from the "best match" case in the case memory to the current case (Porter, 1986; Bareiss, 1988).

CREEK (Case-based Reasoning through Extensive Explicit Knowledge) is a knowledge intensive approach to problem solving and learning which combines several paradigms of reasoning and learning in an unifying view. It uses a knowledge base which contains both general and specific domain knowledge, allowing for using model-based, rule-based, case-based and experienced-based reasoning and learning (Aamodt, 1991).

SEA (Semantics and Explanations vs. Ambiguity) is a CBR system (Voinea, 1991a) which addreses the problem of hypothesis choice from among a set of explanatory hypotheses by integrating both explanatory and semantic principles of coherence. The hypotheses choice operates on a combined model-based and case-based reasoning schema in empirical or abduction-based learning. The explanatory hypotheses extracted from some domain theory or from the past experience which prove to form a coherent hypotheses set are further used in problem solving tasks of new cases (Voinea, 1991b).

The Adaptation-Based Theory of Explanation – the XP system (Kaas, 1991) is an extension of the schema-based theory, in particular of the Script/Frame Theory, to story understanding by developing creative hypotheses. While the Schank' script theory applied stereotype schema extracted from the Case Memory as general knowledge structure called MOPs to the new cases problem solving tasks, the Kaas' approach is an extension of the script theory to the problems solving of new cases to which a stereotype schema extracted from the Case Memory does not apply: such atypical cases need that the solution schema gets adapted by means of causal reasoning models. Instead of stereotype knowledge structures like MOPs, the adaptation-based explaining system uses XPs (Explanation Patterns) which explicitly encode causal reasoning and causal coherence mechanisms able to explain the schema and adapt it to fit new problem solving instances. The Case Memory is replaced with an Explanation Patterns Memory which can provide causal explanations of the solution'structure needed by a new case. The organizing principle is not centered anymore on matching and retrieval mechanisms and on the temporal sequencing of the events describing a case (MOPs), but on inference chains and explicit representation of the causal relationship between the elements of a solution structure (XPs). The steps in developing an explanation are: XP retrieval, extraction from the XP Memory and application to the new case at hand. If the retrieved XP successfully explains the case at hand, the explanation process is reduced to a script application. Otherwise, if the retrieved XP fails matching the new case due to its incompleteness, inconsistancies, invalid assumptions or wrong type of knowledge with respect to the new case, the explanation (XP) is adapted in a creative way by producing a new *variation* on the retrieved XP. After creating an acceptable explanation, the adapted XP is stored in the XP Memory. The adaptation strategies involved in producing *variations* of the retrieved XPs by replacing the components of the explanations (i.e., the development of the creative hypotheses) include:

replacing an inappropriate action/agent, generalising a constraint, refining a slot-filler description, adding a sub-explanation.

The limitations of CBR as a problem solving and learning paradigm come from external constraints: one regards the memory support and indexing system and the other one regards the representation memory structures. Neither of these have had the proper charateristics for a really dynamically evolving memory structures, as it has been proved later on as new memory concepts and principles have been developed[1].

Regardless of its limitations, the fundamental characteristics of the classical CBR which made it a valuable theoretical experience concern two main aspects: (i) the use of the *conceptual knowledge models* and *generalisation* techniques for the case-based concept learning, (ii) and the use of *explanation* as a means of mapping the solutions to past problem solving experiences onto newly encountered problem solving cases. These characteristics represent in a nutshell the most precious idea which CBR brought to the light: model semantics and explanation power as the means of knowledge extraction from contingent cognitive experience.

3. Classical CBR Modeling Paradigm

The Case-Based Reasoning Model

The general structure of the CBR Models consists of a Cognitive Model underlining the Knowledge Model, a Case Memory associated with a set of case indexing techniques, and a collection of cases. The Knowledge Model consists of the *general domain knowledge* describing the conceptual knowledge, and the *domain specific knowledge* describing the experiential knowledge level. It also includes control knowledge, rules, inferencial engines.

The Case-Based Reasoning Process

The general CBR process can be described as a four step process (Schank, 1983; Kolodner, 1983; Hammond, 1986; Porter and Bareiss, 1986; Kaas, 1990; Aamodt, 1991):

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[1] See WALTER FREEMAN’s *Societies of Brains* (1995), ROGER PENROSE’s *The Emperor’s New Mind* (1989), HUMBERTO R. MATURANA and FRANCISCO VARELA’s *Autopoiesis and Cognition*: *The Realisation of the Living* (1980), the RICHARD DAWKINS’ *Selfish Gene* (1989), DANIEL DENNETT’ *Consciousness Explained* (1991) and JOHN BROCKMAN’s *Third Culture* (1995) for an extended history of Computer Science and Artificial Intelligence Science.

The first step may be described as the "comprehension step", since it concerns the identification of the current case with its relevant characteristics, which can be immediately matched against similar characteristics of the cases already recorded in the Case Memory (see *Figure 3.1.*);

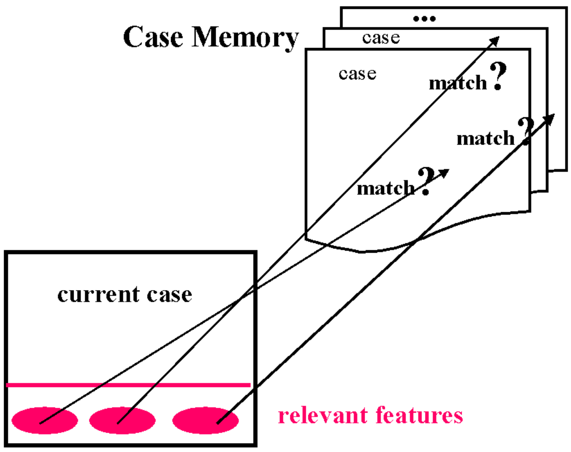

Figure 3.1. Classical CBR Process. The Comprehension Stage

The second step may be described as the "solution transfer", since it concerns the analogy-based transfer of the solution extracted from the best match case found in the Case Memory to the current case; the solution extracted from the Case Memory may be adapted in order to make it fit the particularities of the current case;

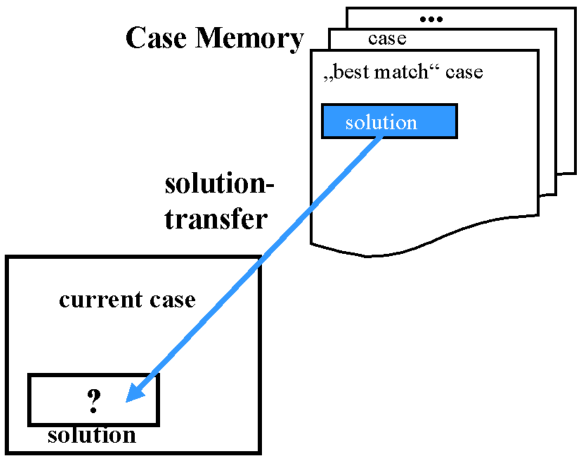

Figure 3.2. Classical CBR Process. The Solution Transfer Stage

The third step may be described as the "solution acknowledgement", since it concerns the evaluation of the way the transferred solution performs as the solution of the current case and the quality of the results; this two steps could be iterated until the imported solution is completely adapted to the current case;

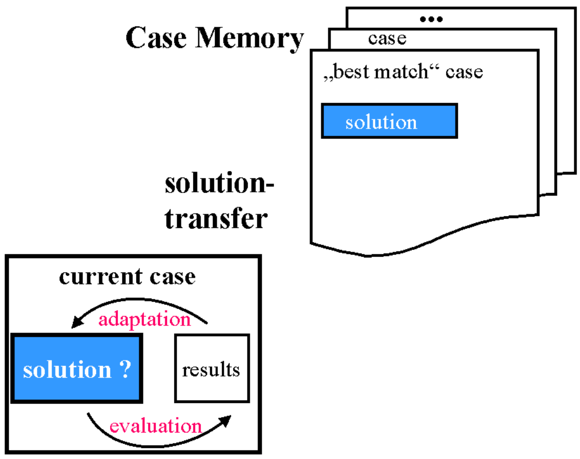

Figure 3.3. Classical CBR Process. The Solution Acknowledgement Stage

The forth step may be described as the "learning" step, since it concerns the storage of the current case together with its solution in the Case Memory.

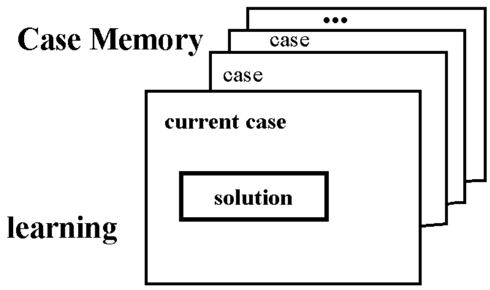

Figure 3.4. Classical CBR Process. The Learning Stage

The Knowledge Representation Framework

The *knowledge representation* issue is of a particular relevance for the CBR paradigm since it represents one of the three dimensions of cognitive and problem solving performances of the CBR systems: (a) the expertise model, (b) the reasoning model, and (c) the learning model. Depending on the approach on each of these research fundamental dimensions, a CBR system may prove capacity to understand past experience, to extract from it the relevant knowledge necessary to solve newly appeared problem solving tasks, and, finally, to update and enrich its knowledge and problem solving experience by learning from each new experience. The development of researches on CBR paradigms has overlapped in time with researches on knowledge acquisition and representation models like the Schank's scripts/frame dynamic memory model, frames (Winograd, 1975), semantic networks (Brachman, 1979, 1983; Brachman and Levesque, 1985), Wilensky (1986), KADS (Breuker and Wielinga, 1989) and expert systems (Waterman, Hayes-Roth and Lenat, 1983) (and others, but an analysis of this area does not make the subject of this paper). Classical CBR systems usually embedd integrated representational frameworks for knowledge modeling, problem solving and learning, oftenly combining multiple reasoning models: model-based, rule – or constraint-based, case-based, and causal or explanation-based *understanding* and *reasoning* models.

The classical CBR systems have powerful descriptive and reasoning capacities based on:

(1) the knowledge model, including the expertise model and the representational model,

(2) the inferencial power of the (oftenly, combined) reasoning models and their impact on the problem solving processes,

(3) the generalisation power of the learning model.

The Knowledge Model

A typical CBR Knowledge Representation Model is based on the modeler's *cognitive model* of the world and consists of two fundamental levels (Minsky, 1975, 1988; Johnson-Laird, 1983; Jansson, 1986; Kaas, 1990; Aamodt, 1991):

(1^{st} level) the Conceptual Level, i.e. the modeling level of the (modeler's perception of the) real world; at this level, the set of *semantic primitives* are used to construct a real world model (the *ontology* level),

(2^{nd} level) the Representational Level, i.e. the level consisting of the representational constructs; at this level, a set of *representational primitives* are used to construct a semantical correspondence between the objects of the two levels, i.e., to map the artificial (computational) world objects on the representational level to the corresponding objects on the conceptual level (the *epistemology* level) (Brachman, 1979).

The cognitive performances of a knowledge representation frameworks and, implicitly, of any CBR system relying on such representational platforms reside in the capacity of such knowledge models to construct an operational correspondence between the set of the semantic primitives describing the real world (examples of semantic primitives: *time*, *space*) and the set of the representational primitives (examples of representational primitives: *symbol*, *entity*, *value*, *relation)*

In other research approaches, a knowledge representation model consists of more representational levels, each modeling level corresponding to a different layer of representational primitives and constructs (Breuker and Wielinga, 1986, 1989; Newell, 1982, 1990;).

The major part of the CBR research is mainly based on a class of knowledge models which use the *taxonomic* representation. Representation of taxonomies is based on the generalisation-specialisation hierarchies. Such hierarchies use two types of taxonomic relationships: (i) relationships between intensionally described concepts and instances (*generalisation-of / specialisation-of*), and (ii) relationships between extensionally described concepts and instances (*element-of/subset-of*).

The structure and contents of the Knowledge Representation Model concern the knowledge *types*, the representational *terms* and the knowledge *representations* for the domain theory, cases, and explanation structures.

The *Knowledge Types* are categories of representational knowledge and are used to describe the representational constructs. The CBR systems work with several knowledge types:

(1) types concerning the meaning of knowledge, like *level*, *depth*, *role* and (degree of) *generality*: the *role* type concerns the *descriptive* and *operational* knowledge, the (degree of) generality type concerns the *general* knowledge (domain theory knowledge) and *specific* knowledge (instances, exemplars, cases, plans, rules and constraints), the *level* type concerns the object level (descriptive) and control level (procedural) knowledge, and the *depth* type concerns the deep knowledge models (domain theory, rules) and shallow knowledge models (cases, observations) .

(2) types concerning the *form* of knowledge, like *concepual*, *procedural*, and *control* knowledge.

The *Representation Terms* concern the set of representational primitives and the representational constructs. These terms include general domain knowledge structures like *scripts*, *frames*, *semantic networks*, indexing structures like *names*, *remindings* and *difference links*, case representation structures like *MOPs* (CASEY), *TOPs* (CHEF), *exemplars* (PROTOS, SEA), *plans* (JULIA), *experiences* and *explanations* (XP).

The Reasoning Model

The artificial intelligent systems developed under the CBR paradigm are generally aimed at *problem solving*. The specific past experiences stored as associational (index, case, solution) knowledge structures are usually inspected (matched against the current case) in order to find similarities with the problem solving task at hand and, if such a case similarity is found in the Case Memory, the respective case-solution is extracted, adapted (if necessary), and applied to the current case. This *general problem solving framework* has three phases: "understanding the problem" – "generating the plausible solutions" – "selecting a good solution" (Newell and Simon, 1972; Aamodt, 1991).

The "understanding" phase is strongly dependent on the *cognitive model* (Schank, 1982; Johnson-Laird, 1983; Minsky, 1988; Newell, 1990) underlying the knowledge representation, reasoning and learning framework used by a CBR system. It is important because it is the phase which provide the candidate solutions that can potentially be applied to the problem solving tasks of a new case. The description of the problem at hand is interpreted on the basis of the general domain knowledge and/or experience knowledge structures and reasoning mechanisms characterizing this cognitive model. The problem's attribute description is matched against the case descriptions in the Case Memory. The matching process is aimed at identifying the similarities and/or differences between the current description and the other descriptions existing for other cases stored in the Case Memory. The understanding model and the case matching process in a CBR system are of a particular releveance for the CBR philosophy: they provide for a knowledge selection process which undergoes the *explanation* construction. This explanation is necessary if the retrieved candidate solutions should be reduced in order to get the most appropriate candidate solution (*best match*) for the problem solving task at hand. The term "explanation" has the meaning of "justification" and concerns both a *body of knowledge* extracted from the case base by means of search, retrieval and matching, and an inferential *process* aimed at proving the coherence of the extracted knowledge with the current case attribute description and problem solving tasks.

There is a significant difference between the Understanding Models and the Reasoning Models: while the reasoning models are used to extract solutions and apply them to new problem solving, the understanding models are used to extract causal relationships between knowledge items and buildup explanations.

There are three schools of thought: first, the so-called "retrieve and apply" school of explanation construction (Minsky, 1975; Schank and Abelson, 1977), which views the whole process as a memory-driven retrieval and application process of the knowledge schema in the case memory to any equivalent or, at least, similar new case. The second, the "plausible inferences chaining" school of thought (Rieger, 1975; Wilensky, 1978) views the explanation construction as an inference process which uses a large plausible inference rules base to build up a solution for any new case. Finally, the "creative hypothesis" school of explanation construction (Kaas, 1990) which has been considered as a revolutionary approach to the CBR paradigm. This school of thought assumes that new cases are rarely equivalent or similar enough to past cases such that a knowledge schema could be applied for successful problem solving purposes. While previous approaches put the burden on the memory use making the explanation construction to appear as a process of indexing and retrieval of knowledge schema from a memory of past experiences, this approach highlighted the role of the *reasoning models*. It views the explanation construction as a process of explanation adaptation based on the development of creative hypotheses for the situations in which the extracted knowledge from the case base is either irrelevant, or not appropriate enough for the problem solving tasks.

It is this approach which seems of major relevance to our research purposes, since understanding terrorism is oftenly a situation of either lack of past experience or scarce past experience, both perspectives being in no way sufficient to find knowledge schema and solutions for any new terrorism case.

The *reasoning model* is one of the components of a general problem solving process and its role concerns the projection of the goal constraints onto the inference chain in the problem solving context specified by the particular problem at hand. The result of this projection is what we call in the computational environment an *explanation*, i.e. a computational justification of the reasoning process outcomes. The reasoning model is characterized by the *reasoning type* (model-based reasoning, rule-based reasoning, case-based reasoning, explanation-based reasoning, constraint-based reasoning, causal reasoning, common-sense reasoning, etc.) and by the *inference methods*.

A typical *case-based reasoning process* can be described itself as a multi-phase process depending on the school of thought its general problem solving model belongs to:

(1) for the *retrieve and apply knowledge schema* type of framework, the reasoning process may be described as a sequence of two steps:

1st step: "coherence-based extraction of the knowledge schema"

2nd step: "application of the extracted knowledge schema to the current case";

(2) for the *plausible inference chaining* type of framework, the reasoning process may be described as a bottom-up process which uses a large base of plausible inference rules to build up explanations by dynamically chaining these inference rules together each time a new case needs a solution:

1st step: "use the input case description to follow up any plausible inference rule which apply to the input case"

2nd step: "inference chaining"

3rd step: "focus on a solution"

Aamodt describes this process as a sequence of three reasoning steps: "activating knowledge structures" – "explaining candidate facts" – "focusing on a conclusion" (Aamodt, 1991; Aamodt and Plaza, 1994). The "activating"

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phase concerns the retrieval of knowledge schemata extracted from the similar cases in the Case Memory: the indexing structures are instantiated with the relevant attributes of the current case so that they can be used for the searching, identification and extraction of the cases having similar attribute descriptions with the current case. The retrieved cases are used as a potential knowledge and/or solution source for the current case. To this aim, these candidate cases are matched against the current case so that a *best match* case can be found. This selection process can be interpreted as an *explanation* process since the match-based selection methods are actually inference methods able to justify the selection or rejection of a candidate case: they check if the extracted knowledge is coherent with the current case knowledge description. Finally, the solution of the *best match case* is *applied* and/or *adapted* for the current case problem solving task.

The type of reasoning used in the classical CBR is highly dependent on the case representation and retrieval, but the most important characteristics which makes the difference between CBR and other reasoning models is the adaptation of a retrieved solution to a new problem solving context. From this point of view, the case-based reasoning model includes several theories from philosophy and cognitive psychology which regard the use of general background knowledge in order to derive a model of the world or to derive a solution to a problem solving task. It must be emphasized however that the case-based reasoning model has many similarities with other reasoning paradigms, like exemplar-based reasoning, memory-based reasoning or analogy-based reasoning. The main similarity with the exemplar-based reasoning model is the learning of new abstract concepts using extensional descriptions of concepts: in this type of scenario, a CBR task is mainly a classification task in which the class of the most similar (*best match*) past case retrieved in the Case Base becomes the class of the solution to a current classification problem. The main similarity with the memory-based reasoning is the use of a case memory and the definition of the case-based reasoning process in terms of searching and retrieving a particular case in the case memory using memory indexing techniques (Schank, 1982) or general domain knowledge (Kolodner, 1983). The main similarity with the analogy-based reasoning is that both models use methods to solve new problems by means of solutions to past similar problems. Here, the major difference is that analogy-based reasoning use past cases from a different domain (called "source" or "base") to solve current problem (called "Target"), while the CBR uses past cases from the same domain (Carbonnell and Lenat, 1986).

The Learning Model

Case-Based Learning is defined as a process of retaining the new solution or the new problem solving plan into the Case Memory for later retrieval and use. The learning process is not a simply memory storage process, it involves several types of learning tasks: (1) the *selecting* task concerns the type, form and structure of the new case information to be retained in the Case Base; (2) the *indexing* task concerns the way of using case similarity and features for identification and retrieval, (3) the integration of new cases in the Case Base structure.

The CBR learning can be described as a three-step process (Aamodt, 1991):

1st step: extract the past case(s) which provide for the learning source,
2nd step: construct new knowledge structures, and
3rd step: store and index the new case in the Case Memory.

Case-Based Learning concerns three major areas. The first regards **concept learning**, which aims at learning new abstract concept from exemplars provided by past cases, from instances of the same concept provided by the past cases or from combined general domain knowledge and domain specific knowledge. The basic idea for this learning area is provided by the theories concerning concept formation from extensional concept descriptions developed by Wittgenstein. These theories allow the use of a set of instances of some concept provided by several particular cases for the concept learning purposes. The idea has been extensivelly used in Machine Learning.

The second regards **problem solving**, which aims at learning the problems solving plans or the solutions to new cases using the past cases.

The third regards **decision making** learning which aims at learning the rational decision structure (goal, alternatives, choice rules) and operational architecture.

Case-Based Reasoning Model has appeared as a very interesting research paradigm in Artificial Intelligence due to its capacity of building up solutions to problem solving tasks in terms of **explanations**. These explanations are constructs based on the inference rules and mechanisms used by the CBR Model and on the general domain knowledge and the cognitive model which underline a particular CBR approach.

As a learning paradigm, **explanation-based learning** concerns the learning process of a problem solving task using an example of a solved problem as a problem solving method of a new unsolved problem. It is basically an analytic learning method and requires one example in order to learn a problem solving method for anjy other similar problem. For this reason, it has been approached as a fundamental issue in the research area of CBR. Explanation-based learning is a foundational paradigm of the Machine Learning science and it has been created as a means of making artefacts able to learn as humans do. From this perspective, a CBR Model which uses Explanation-Based Generalisation and Learning represents a necessary condition for concept construction and learning in areas where only scarce experiential knowledge is available.

4. Knowledge Extraction: The Meeting of the CBR's Dynamical Memory Utopia with the *Web* Technology

Classical CBR, as it was first created by Roger Schank, has been inspired by the way humans think and remember. Its initial target – the automated learning and problem solving systems – was designed to replicate the human thought and to achieve the performances of the human reasoning. On the long term, this was an wining idea, but the concrete way to implement it at that time had faced too hard a calculus complexity problem than the computational memory technologies and AI itself were prepared to approach.

CBR's most prominent achievement was the idea of imitating human memory and reminding mechanisms in an artificial operational Dynamic Memory system. The Dynamic Memory was nevertheless its major limitation, since the AI implementation based on scripts and frames – the most advanced knowledge structures at that time – have not succeeded to increase the computational performances of this beautiful idea. On the contrary, the Dynamic Memory worked as a bumerang and hit back its own AI paradigmatic system. For several decades afterwards, both Artificial Intelligence (AI) and Machine Learning (ML) had kept this idea as a lost war still bleeding wound and faught rather tacitly the dynamic memory failure gost until an unexpected, aparently irrelevant for AI, idea had arose: the *web* as a huge storage of easy-retrieval information. Meeting it had turned into a true change of destiny, at least for CBR and its dynamic memory problem, if not for AI itself.

The *web* is a simple idea, but always the simple ideas have succeeded to move the world small steps forward. It has a simple mechanism to link one piece of information to another in, at least theoretically, endless chains within a huge, say "hyper", multidimensional space of information. The link is bidirectional – it works both forward and backward on each connection – and, moreover, each piece of information can be linked to, theoretically, infinitely many others. Following each alternative chaining would mean to get several different perspectives to, eventually, the same "bag" of information. Going one step further with this piece of simple reasoning, understanding and interpreting this information, depending on what one chaining or another have provided at first glance, would result in as many "stories" as the semantics of one such "bag" of information can support. But this needs a human mind to make both the understanding and the interpretation, since computers are not able to understand this knowledge, while humans are quite lazy and unpatient at analyzing – piece by piece, chain by chain – huge, barren, apparently irrelevant amounts of information.

The idea basically resembles the old, almost defeated (technologically speaking), idea of the dynamic memory. Schank himself finally understood this fascinating similarity, but meanwhile many others did. A new true dynamic memory idea was born. And it makes possible revisiting CBR.

One might ask why “revisiting” and not trying something really new? – The true answer is that CBR was, undoubtedly, forgotten or just left aside for a while, but it has never been exhausted as a potential cognitive resource and as a computational philosophy, and this seems to be the reason why we witness its revival from time to time.

The idea of making CBR and *web* meet was not advocated by neither of them. It was a rather commercial impulse which moved things towards making them joining: How to discover and extract the potential knowledge likely to be provided by the information in the old databases which have been abandoned world wide as soon as the new *web* technologies offered a huge information storage space and easy information retrieval services ? The *Knowledge and Data Discovery* (KDD) scientific area has been created exactly for this purpose. But it served much more.

Developed as an intelligent knowledge engineering technique around mid 90’s, the KDD made possible the analysis of huge heterogeneous collections of data, left in the commercial and institutional databases all over the world. The approach on discovering regularity patterns and significant relationships in these data collections has oriented these researches towards the construction of large knowledge bases on the *web*. Original KDD has developed afterwards into a class of knowledge extraction researches and advanced technologies: *information extraction, extraction of relational knowledge from the web, text classification, construction of world wide web knowledge bases, text data mining, web data mining, data mining on symbolic knowledge extracted from the web*, to name but a few.

Each of these research areas are systematically developed approaches on *knowledge extractors* aimed at making the

> “computer-retrievable information intended for human consumption a data source in computer-understandable form [...which means] to have computers not only gather and represent knowledge existing on the Web, but also to use that knowledge for planning, acting, and creating new knowledge “[2]

A *web knowledge base* in a computer-understandable form which mirrors the contents of the WWW is created by a *knowledge extractor*. There are various types of knowledge extractors: feature extractors like hand-written wrappers, learned information extractors, text feature extractors, text classifiers and extractors of learned relations (Craven *et al.*, 1998).

A *knowledge extractor* is organized as a *generative mechanism*: it is initially designed or trained to recognize and classify a given type of *web* items. It is then let work as a „recognition-selection-and-collect“ engine on the *web*.

[2] GHANI, R., JONES, R., MLADENIC, D., NIGAM, K., SLATTERY, S., *Data Mining on Symbolic Knowledge Extracted from the Web,* 2000.

The outcome of a knowledge base generative mechanism is a conceptual construct which emerges as the knowledge base grows up: it is usually an automatically generated, populated and maintained *topical taxonomy*. Such topical taxonomies or descriptive hierarchies are used to provide for multiple set of indexes which provide the support for learning in ill-structured domains and constructivism (Nigam, 2001; Schmidt, 2004). Perhaps the best example of a generative mechanism in text classification is the parametric generative model for dependencies between *web* text documents and their corresponding *web* class labels. This generative model is trained with unlabeled document examples easily extracted from the *web* and then used for text classification tasks involving online data sources, such as web pages and email. The model is actually a statistical process which encodes which words are encountered more frequently in one class than another and which then use this information to create new *web* labeled documents (Nigam, 2001).

Though KDD has represented a powerful conceptual and technological change within the Artificial Intelligence, Machine Learning and Knowledge Engineering – the CBR paradigm keeps being what we use to call a “scientific challenge”: while the knowledge representation, search and retrieval problems in classical CBR have found in the KDD techniques some excellent solutions, the CBR still remains an open problem. KDD has provided different means for knowledge discovering in databases on the *web*, but KDD alone cannot fully provide for the explanation and creative explanation-based hypotheses development for problem solving tasks of new and atypically cases.

From a philosophy of science point of view, the major KDD’s merit is that it has induced to the modern Artificial Intelligence the necessity of revisiting its own conceptual history very much like people do when they start building up a new house using the bricks of the old house. What does CBR gain from revisiting its own history? – The actual gain is two folded: it realizes in the first place that it still is an open problem, surviving due to its best ideas, and, secondly, it realizes that its limitations are not just technical, but theoretical too. The theoretical limitations reside in the perspective over the role of the dynamic memory.

The CBR’s Dynamical Memory initially worked on the principle that any automated learning and problem solving system needs a memory of its own as *a place to store, re-organize and construct new knowledge*. From this point of view, the Dynamic Memory in CBR system works as a *resource* which makes possible the storage and retrieval of past experience. The better the resource, the better the system’s performances. The larger the contents of the resource, the higher the cognitive capacity of the system. The difficulty comes from indexing the past experience in such a way that it can be not only easily retrieved, but retreived on multiple search keys, thus providing an automated reasoner (an inference engine) with multiple potential inference chains and cognitive flexibility. The classical CBR’s dynamic memory failed to approach this aspects for large memories and multiple indexing levels.

A CBR system which would use the *web* as an extrinsec dynamic memory or implement a *web*-like dynamic memory, works on a different principle: a flexible dynamic web-like memory works as a *generative mechanism* for constructing new knowledge. The CBR's dynamic memory system would therefore work as a conceptual constructor and not as a "search-and-retrieve" servant.

The difference between these two perspectives over the role of the dynamic memory is fundamental since it transforms the CBR paradigm from a *model-theoretic paradigm* into a *constructivist paradigm* based on *cognitive generative mechanisms*. This paradigmatic shift subsequently supports an epistemological shift since the generative mechanisms are likely to become the essential attribute of the *artificial societies* if these are expected to replicate the key issue of the human societies and to be thus used as highly cognitive instruments for investigating complex emerging societal phenomena.

As far as the KDD and data mining technologies involves learning and knowledge extraction from text, the research on *political terrorism* has been offered the chance of extracting specific knowledge from *web* text using knowledge extractors and case-based reasoning modeling (Kass, 1990, 1991; Riloff and Lehnert, 1884; Cardie, 1999; Schmidt, 2004).

As an example, the original *terrorist* scenarios used by Kass to develop a framework of creative hypotheses – the **Pan Am** and the **Suicide Bomber** scenarios – have been used as a basis for knowledge extraction from the *web* and for *web* text classification.

The Original Pan Am Scenario (Kass, 1991)

„The **Pan Am flight 103** exploded in mid air over Lockerbie, Scotland, on December 21st, 1988, killing all aboard. It was en route to NYC from Frankfurt, Germany, via London, Great Britain" (Kass, 1991).

The Original Suicide Bomber Scenario (Kass, 1991)

„a teenage girl exploded a car bomb at a joint point of israeli troops and pro-israeli militiamen in southern Lebanon. The bomber and a number of israeli soldiers were killed by the blast" (Kass, 1991).

Kass analysed a set of five sample anomalies and associated explanations[3]. In particular, of a special interest for our approach, the Pan Am and the Suicide Bomber stories are good examples of how the XP technique can provide a creative explanation by adapting the explanations found in the Terrorist Bombing XP: the adaptation by means of creative use of the past experience explanation-based structures in order to explain new cases. Each of the original scenarios and the

[3] KASS, A. M., *Question Asking, Artificial Intelligence, and Human Creativity*, Technical Report #11, Institute for the Learning Sciences, Northwestern University, U.S.A., 1991, pp. 18-19.

explaining schema can be mapped onto one or all of the new terrorist scenarios we would like to get from the *web knowledge extractor* and approach with CBR.

5. The Generative Mechanism-Based vs. Case-Based Modeling

The power of the *generative mechanisms*, no matter at what level are they used in the architecture of an artificial system – be it an artificial actor or an artificial world – resides in their capacity to explain *emergence* and *complexity* – two key attributes of the real complex systems like those concerning the human living, belief, attitude, free will, history, society, and civilisation. If these issues are to be computationally modeled, then a generative mechanism is the best way to buildup realistic models.

The generative mechanisms have been intensively used initially within the Arificial Life research areas and then extended to the *Social Simulation* domains and recently to Political Science domain and to whatever subdomain of these sciences which might be concerned with the processes underlying the emergence of new, unknown or unexpected forms of life and societal phenomena.

The *generative mechanism* is a computational modeling and simulation method to:

(1) automatically generate research data with the help of artificial worlds (societies) in order to study potential emergent phenomena, (Social Simulation),

(2) automatically construct topic hierarchies and taxonomies with the help of knowledge extractors, classifiers and constructors in order to support conceptual constructivism, (KDD and *Web* knowledge technologies),

(3) automatically create artificial agents and agenthood in order to study society and social life emergence, (Artificial Autonomous Agent research areas), and least but not last,

(4) automatically generate normative social scenarios and agent societies in order to study societal issues like reputation, social action, collective misbelief, ethnic conflicts, emergence of new geopolitical powers and international relations, (Social and Political Sciences, see (Conte, 1996; Conte and Castelfranchi, 1995).

Note that the researches based on generative mechanisms are mainly in the area of the artificial life and artificial society and only scarcely in the area of simulation with cognitive agents and of conceptual thinking. This observation is relevant if we are to understand the worth of revisiting CBR.

A generative mechanism is just a *research tool* if the application keeps the human expert in the role of the reasoner. Thus the human expert would be the only one able to transform the simulation outcomes into explanations and able to reason with this background knowledge.

Now, if an application based on a generative mechanism uses an automated reasoner which takes on the reasoning role of the human expert, then the generative mechanism itself becomes the "*living kernel*" of an artificially generated world or society. A CBR system which would make its knowledge base computer-understandable *would support a variety of intelligent knowledge-based agents.* Today social simulations are mainly based on agents which are not cognitive agents. In simulations using cellular automata, they are simple cells in a grid and have no knowledge and no reasoning capacity with respect to the societal scenarios in which they are involved by the simulation generative mechanisms. It is the case of the ongoing *Social Simulation* researches which are facing a challenging debate on this epistemological issue. This observation is only meant to highlight the perspective that social simulations based on agents which are able to know, understand and reason would provide for different results and validation issues. Currently used social simulation agents have such a simple design that nobody can guarantee if the simulation results are a true side-effect of the generative mechanism or a random outcome of the computational resources used to program and operate these agents. The epistemological debate is unavoidable under the given circumstances, though a cognitive agent literature has been developed during the past half of a century, but unfortunately ignored by the ongoing social simulation researches.

We are not going to fall into the old dilemma of the worth of getting an artificial mind competing with a human mind, since this is not our purpose here. We would just like to note that evaluating the research results provided by the systems based on generative mechanisms is not a matter of evaluation in terms of "advantage-disadvantage", which obviously can be done at a certain point. It is in the first place a matter of evaluation in terms of what exactly is generated? – A *gain* improving method? An *would-be world*? An ontology? An epistemology?

If we are to evaluate what has been generated then we are able to make a distinction between the worth of revisiting CBR and the worth of doing the same thing with the current Agent-Based Computational Modeling paradigm used in the ongoing *Social Simulation* researches. Actually this is the question to which this paper is trying to give an answer. And the answer is:

Revisiting CBR would allow a new generative paradigm to be developed, aimed at providing the framework for conceptual construction in ill-structured domains.

The *Agent-Based Models* use *artificial life generative mechanisms* and the simulation outcome of such a computational modeling would be an *artificial society* whose attributes are still to be understood since the generative mechanisms is not based on cognitive agents: these agents are not able to know while they are involved in a simulation generative mechanism. The cognitive issue and the knowledge is still an attribute of the human expert who is finally analyzing the results, but the simulations did not take into account during their execution any of the knowledge the human experts is able to extract from the simulation analysis. The debate is generated by the fact that the human expert knows only and knows all, while the agents involved in a generative mechanism know not and know nothing while simulating a dynamically evolving scenario.

6. The Agent-Based vs. Case-Based Computational Modeling and Simulation

One theoretical issue which made CBR survive and value is the quest of *explanation*. Learning and reasoning by (creatively) explaining things is one of the most fundamental issues of human intelligence and one of the major proofs in the artificial intelligence. The answer to this quest did not come from Computer Science, as expected, and not even from the Artificial Intelligence, as it should, but from the Social Sciences: *Computational Agent-Based Modeling*.

The Agent-Based Computational Modeling and Simulation in Social Sciences is what Nigel Gilbert called

> "... not just a new method to add to the social researcher's armoury, but a new way of thinking about society, and especially social processes [...] The simulation would thus have to model both the emergence of societal level properties from individual actions and the effect of societal level properties on individual actions. [...] One of the present-day challenges for simulation in the social sciences is to develop convincing examples of such models"[4]

Agent-Based Models – as they have been conceived by the computational research in social sciences – are less devoted to the aim at providing heuristics and explanations in the model-theoretical *top-down* style (Axtell, 1997b; Gilbert, 1995) using classical inductive or deductive methods (Axelrod, 1997b). They are *bottom-up* approaches aimed at the understanding of the complex social processes in terms of artefact constructs able to replicate at both individual and societal level a class of phenomena in a virtual environment which is similar to the real environment in many respects. Following the retroductive principles of the scientific realism (Miller, 1987), the main goal of this computational modeling paradigm is to extract the generative mechanisms of the emergent phenomena by setting up at the micro level an artificial construct which can be grown up such that it can provide for the emergence of certain patterns of the complex processes at the macro level (Epstein, 1999).

The *social micro-macro link generative mechanisms* are actually computational constructs of parameter values and environmental contextual configurations of micro elements (individuals, relations between individuals, relations between

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[4] GILBERT, N., *Simulation: an emergent perspective*, text of a lecture first given at the conference on New Technologies in the Social Sciences, 27-29th October, 1995, Bournemouth, UK and then at LAFORIA, Paris, 22nd January 1996.

individuals and groups, norms, etc.) which are let to evolve in conditions which are similar to the reality. The construct is aimed at explicitly setup a virtual replication of some phenomenon and at aggregating the underlying processes which are assumed to support this phenomenon in reality. The conditions and configurations of elements are themselves selected and their parameters values are setup by experts in social sciences whose high-level expertise can guarantee the validity of the selection. The simulation outcomes of these evolutive constructs are used as hypotheses on the nature and potential evolution of the real micro-macro links at the social level. The data provided by the simulation consists in the values of the modified parameters and the regularity patterns and significant relationships discovered in this data. The data is analyzed again by the experts who use their knowledge and past experience to evaluate the "realism" and the scientific validity of the presumed social phenomena. The human experts may eventualy get an understanding of the evolution of this artefact constructs and associate it with patterns of real phenomena and their contingent evolutions. Experts' understanding may thus finally become expert knowledge and used to hypothetically explain emergent complex phenomena.

There is a special class of Agent-Based Models: *Case-Based Models*. Case-Based Models are one of the three categories of Agent-Based Models found by Boero and Squazzoni in their study on methodological issues on ABM for analytical social sciences: *case-based models*, *typifications* and *theoretical abstractions* (Boero and Squazzoni, 2005). Though it looks like we should actually be interested in the Case-Based Models as an equivalent for the classical AI Case-Based Reasoning Models, Boero and Squazzoni's study shows that things should be taken rather as distinct non-equivalent categories. The Case-Based Model is defined by Boero and Squazzoni as an

> "... *ad hoc* construct made by the model maker with respect to a target [which] is a specific empirical phenomenon with a circumscribed space-time nature"[5]

As such, a Case-Based Model is what Max Weber called a "*historical individual*"[6] and

> "it would allow ... explaining the specificity of the case, and sometimes to build upon it realistic scenarios"[7]

Rather than achieving generality as it usually happens in the CBR Models, such Case-Based Models would help at "*appreciating complexity*"[8]. They

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[5] BOERO and SQUAZZONI, „Does Empirical Embeddedness Matter? Methodological Issues on Agent-Based Models for Analytical Social Science", *JASSS*, 8, 4, 2005.

[6] MAX WEBER, *Objectivity of Social Science and Social Policy* (1904), in SHILS, E., FINCH, H. (eds.), The Methodology of Social Sciences, Free Press, NY, 1949.

[7] BOERO and SQUAZZONI, *op. cit.*

[8] RAGIN, C.C., *The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies*, Berkeley: University of California Press, 1987.

would provide for a means to achieve generality only if they can be related to a typification in the sense this is defined in the Boero and Squazzoni's study:

> "As Weber argues (1904), the relevance of a case-based model, as well as the condition of its possibility, depends on its relation with a theoretical typification [...] Typifications are theoretical constructs intended to investigate some properties that apply to a wide range of empirical phenomena that share some common features. They are heuristic models that allow understanding some mechanisms that operate within a specific class of empirical phenomena [...] cases are nothing but a synonymous for instances of a broader class. The selection can be done just under empirical and theoretical prior knowledge and following some theoretical hypotheses. This is why typifications models can be useful."[9]

We could understand that isolating empirical phenomena and simulating them as Case-Based Models might provide the means to generalize specific aspects of those phenomena if some reference to a theoretical defined typed could be used or if the simulation results could be compared with previous classifications of those phenomena. Things look very much similar with the classical Case-Based Reasoning where arbitrary cases (MOPs) are generalized to a *Generalized Episode (GE)* (Schank, 1982) and retrieval of further cases which might fall within the same class could only "reinforce the generality level of the Generalized Episode" (Aamodt, 1991). When a Case-Based Model's outcomes and/or conclusions (in the Boero and Squazzoni'sense) are theoretically validated by one or more abstractions (in the same sense), then the Case-Based Model may be appreciated as an ultimate instance of the general social reality described by the theoretical abstractions:

> "[...] if case-based models are 'veridicality'-based models, aiming at reaching accuracy and empirical descriptions, theoretical abstractions are 'transparency'-based models aiming at reaching simplicity and generalization."[10]

This *continuum* of the three possible stages of a "carefully selected" case-based model suggests that the Case-Based Models could be used for the general purposes of case-based reasoning and learning under the constraint that there is a previously defined validating domain theory (or theoretical model) to which any reference has the value of a theory proof.

King, Verba and Keohane support this conclusion by making a distinct difference between the statistical inference tools (heavily used in analytical social sciences for almost a century in generalising empirical cases) and the methods of scientific inference based on analogy:

> "... one of the traditional ways of generalising empirical case studies is to use methods of scientific inference also to study systematic patterns in similar parallel events [...] This is what is done in statistical research: generalising from the sample to the

9 BOERO and SQUAZZONI, *op. cit.*

10 *Ibid.*

universe, trying to test the significance of particular findings with respect to the universe. But empirical case studies profoundly differ from statistical surveys."[11]

Following the epistemological reference framework elaborated by Becker, Niehaves and Klose (2005), we could distinguish an essential diference between the AI CBR models and the *Social Simulation* Case-Based models: while the classical CBR is an empirical, inductive paradigm, the CBM is a kantian, deductive paradigm:

"Models are used as the core of the method, to - at least partly - representing and/or aiming at a "real world" object system or problem. In fact, here, models are used in two ways. At first, researchers try to identify universal principles and processes of the "real world" which they formalize in the forms of models. Afterwards, the models derived, are in turn used within the simulation process in order to receive new cognitions. Obviously, the construction of the simulation model is a fundamental step for the validity of the simulation results."[12]

This interesting parallel between the CBR revisited paradigm and the Agent Case-Based Modeling paradigm highlights their resemblance in many respects. Their resemblance is provided by the fact that both of them use particular past experience in order to acquire more general classification and problem solving experience.

Beyond this resemblance (which is important and relevant up to a certain point), there is however a fundamental difference at the level of their generative mechanisms: while the generative mechanisms in the AI CBR are meant to support the conceptual constructivism, the generative mechanisms in the *Social Simulation* Case-Based Models are meant to support the structural complexity constructivism. The models which could be generated even from single cases (case-based models) are viewed as

"generative tools, because they allow formalising a representation of the micro-macro mechanisms responsible for social outcomes to be brought about"[13]

Their specific purposes are targeting constructivism obstinately, but at different levels, in different ways and with different theoretical implications. The former builds up abstract conceptual knowledge and use it in a *top-down* manner in order to provide for explanations, while the later builds up an artefact construct and use it in a *bottom-up* manner to provide for explanations.

[11] KING, G., VERBA, S., and KEOHANE, R.O., *Designing Social Inquiry: Scientific Inference in Qualitative Research,* Princeton Univ. Press, 1994.

[12] BECKER, J., NIEHAVES, B., and KLOSE, K., „A Framework for Epistemological Perspectives on Simulation", in *Journal of Artificial Societies and Social Simulation*, 8, 4, 2005.

[13] HEDSTRÖM, P. and SWEDBERG, R. (eds.), *Social mechanisms: An Analytical Approach to Social Theory*, Cambridge University Press, 1998.

This comparative perspective does show that beyond resemblance and discrepance between these two paradigms, there is a basic **complementarity** between them. Their fundamental attributes provide for a *necessary* and, in some sense, *expected* paradigmatic complementarity. The *necessity* follows from their both supporting constructivism at complementary levels: the structural level and the conceptual level. The *expectedness* follows from both of them building up on contingent knowledge and reaching a generalized knowledge level. We might say that each of them is a oneway ticket to achieving an integrated computational modeling and simulation framework in ill-structured domains: just that one if for the way to (the *bottom-up* way), and the other is for the way back (the *top-down* way).

7. Conclusions

Case Based Reasoning and *Modeling* is a classical Artificial Intelligence paradigm for learning and problem solving in ill-structured domains. This research framework is particulary useful for ill-structured domains which have weak domain theories or which have only scarce ill-structured typical knowledge. The AI Case-Based Reasoning paradigm provides the appropriate support for constructivism and advanced learning in political analysis.

Political Terrorism is characterized by an ill-structured domain theory. For almost 15 years, the Case-Based Reasoning and Modeling paradigm has been employed in researches on *political terrorism*: data mining and web text classification or constructivist frameworks concerning explanative hypotheses. This powerful computational modeling paradigm has provided the conceptual support for advances in the direction of conceptual constructivism in the analysis and modeling of the *terrorism* phenomena.

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