Emerging Technologies

Case-based Reasoning and Multiple-agent Systems for Accounting Regulation Systems with Extensions

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Abstract One of the areas of judgment research in accounting and financial applications is that of accounting regulation. Previously, artificial intelligence efforts at modeling human judgment in accounting regulation systems have concentrated on rule-based expert systems. In those systems, general heuristic knowledge was captured using 'if ... then ...' rules in order to model particular decision processes. Recent developments in artificial intelligence have focused on case-based reasoning (CBR) and multiple-agent intelligent systems (MAIS). The ideas behind CBR are that 'if it worked once then remember to use it again' and 'if it did not work before, then remember to not use it again'. MAIS assumes that many organizational systems can be treated as computational models of multiple-interacting intelligent agents. Typically, solutions may be derived using some form of negotiations between agents to accomplish single global or separate individual interacting goals. This paper argues that many accounting regulation judgment processes can be modeled using CBR and MAIS. As a result, it summarizes some examples of both CBR and MAIS useful in accounting regulation and extends those to other accounting applications. In addition, it describes the results of some previously developed systems that employ CBR or MAIS.

Introduction

This paper discusses the application of recent research in artificial intelligence (AI) to accounting regulation systems (ARS). In addition, some other applications in accounting and finance are also described.

Accounting Regulation

Accounting regulation is the study of the governmental and self-regulation of accounting decisions. These decisions include determining what information should be disclosed, how it should be disclosed, which companies should disclose it and what disclosures mean to different decision makers. It is influenced by a number of institutions, including the courts, legislatures, stock exchanges and professional organizations (such as the American Institute of Certified Public Accountants—AICPA). The impact is felt in litigation, the number of business failures, competitive pressures and in the public trust of business.

There is substantial pressure for the regulatory and accounting professions to exploit the available technologies. For example, Parker and Previts (1987, p. 3), note that:

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> it is no longer adequate to be reactive. The [accounting and regulation] profession must, to the best of its ability, anticipate the future needs of society and the pressures of regulatory institutions, and react to the future—i.e., be proactive.

One tool that appears to offer substantial ability to assist the regulation and accounting professions to anticipate needs and to react to pressures of the future is AI.

Artificial Intelligence

Previously, researchers have made substantial use of rule-based expert systems that employ general heuristics (typically of the form 'if . . . then . . .') to model some accounting regulation processes (O-Leary, 1987). However, there are approaches to the representation of intelligence other than rule-based expert systems that can prove useful in some accounting and financial situations. It is two of these approaches that are the concern of this paper: case-based reasoning (CBR) and multiple-agent intelligent systems (MAIS).

Generally, CBR is the use of previous experiences (referred to and stored as 'cases') in reasoning and problem solving. It is based on the notions (Hammond, 1988, p. 17) that 'if it worked once before then remember and use it again' and 'if it did not work before then remember and to not use it'.

MAIS often are used to model organizational systems by capturing the interactive behavior of intelligent agents. These systems are representations of the agents and their interactions. One of the primary concerns of MAIS is the co-ordination of and negotiation between the agents. The goals of the agents may be either some single global goal or interacting individual ones. Often the system output is a solution that is a negotiated settlement between those intelligent agents.

Research Contributions of Artificial Intelligence to ARS

The use of artificial intelligence research has four primary contributions for ARS. First, the development of descriptive cognitive models in accounting regulation allows us to elicit and study human cognitive models and decision making. The analysis of these cognitive models can assist in understanding cognition, as in the study of cognitive models of other tasks (e.g. Peters, 1991).

Second, these models could prove useful in understanding accounting regulation and the extent to which experts representing different constituencies in accounting regulation differ from each other. Limitations in those descriptive models can assist in the determination of the content of new models for accounting regulation. So-called 'gaps' in the knowledge of accounting regulation could be found.

Third, descriptive models of AI provide the basis to investigate the interaction of organizations and agents within those organizations. Models can allow us to understand how the agents will act in making decisions or taking actions. Experiments can focus on the impact of alternative objectives, such as how to enable agents to act coherently, how to facilitate communication between agents and a variety of other questions.

Fourth, artificial intelligence models can assist in the development and support of decisions. The computational strength of the computer can be harnessed through the use of artificial intelligence. Artificial intelligence models can provide the ability to assist in the analysis of difficult or extensive database search and analysis. Such models could prove useful in processing, in a timely manner, all the data available to the decision maker in computer-based format, e.g. cases within NEXIS or LEXIS (commonly used financial information databases).

Although a number of rule-based approaches have been used to analyze specific problems, the potential contributions of CBR and MAIS have received little attention in some areas of accounting, finance and management. This is in spite of the fact that these contributions have been exploited in some closely related areas such as law.

In part, the lack of direct contributions to accounting regulation may be the result of the technology itself. For example, most of the research in accounting regulation and other aspects of accounting to date has been with rule-based expert systems (O'Leary, 1987). However, single knowledge base, rule-based systems do not necessarily characterize the nature of many accounting regulation problems. Instead, many of the problems faced in accounting regulation are based on the analysis and investigation of particular cases, e.g. legal cases. In addition, problems are generally concerned with interacting agents and not a single set of rule-based heuristics. As a result, many researchers could have argued that many of the problems faced in accounting regulation are not necessarily well suited to a rule-based technology.

Layout of This Paper

This paper is concerned with the application of case-based reasoning and multiple-agent intelligent systems to accounting regulation. In order to accomplish this objective we will provide some examples of case-based reasoning and multiple-agent intelligent systems in accounting regulation-based systems. The paper will:

(1) Provide a brief overview of artificial intelligence (including rule-based systems, case-based reasoning and multiple-agent systems);
(2) Discuss some related applications of applications of case-based reasoning and multiple-agent intelligent systems;
(3) Investigate some examples of case-based reasoning in accounting regulation;
(4) Investigate some examples of multiple-agent systems in accounting regulation;
(5) Briefly discuss some extensions to other applications in accounting and finance;
(6) Summarize the results.

Artificial Intelligence

Newell and Simon (1972, p. 6) have defined AI as '. . . the part of computer science devoted to getting computers (or other devices) to perform tasks requiring intelligence'. Three areas of artificial intelligence that are receiving attention in accounting and finance, and the closely related area of law, are rule-based expert systems, case-based reasoning and multiple-agent intelligent systems.

Rule-based Expert Systems and their Limitations

Rule-based expert systems are that part of AI that have received the most attention in accounting and financial applications. These systems are distinguished by their use of heuristic rules of thumb to represent expertise and knowledge. A typical configuration of such a rule is 'if *a* then *b*', where *a* is some condition and *b* is the resulting consequence. Rule-based expert systems are particularly appropriate for those situations where a good or parsimonious set of rules can be developed. Typically, the situation needs to be one where the problem can be solved using a sequence or hierarchy of such rules.

Rules are limited in their ability to communicate and explain. Often in human communication, we hear the phrase 'give me an example'. The example provides analogical understanding. Rules do not provide such reasoning capabilities.

Rules capture 'what to do', not why (Chandrasekaran and Mittal, 1982). A rule that says 'if a firm has negative cash flow then it will ultimately go bankrupt' does not capture the why. Instead, it simply says what will likely happen.

Another problem with rules is that the knowledge ends up being scattered into hundreds of individual pieces (Reisbeck and Schank, 1989, p. 31). This seems to be a difficult way to model large processes. Instead, we might expect that related pieces of knowledge would be close to each other.

In many cases the rules that are used are the result of empirical evidence. The rules that emerge are the average of a number of different occurrences. Average behavior is not appropriate for all situations, particularly where there is averaging of inconsistent views.

Further, if a single rule-base is used then that indicates that alternative views on the knowledge in the system have been consolidated into a single one. Often this means that various trade-offs have been made on different positions in order to arrive at a single position. Although this may be effective in some situations, in others it may be more effective to have these trade-offs or negotiations clearly established at the time they are made, with the use of the system.

Case-based Reasoning

Cased-based reasoning involves the process of making decisions based on what has occurred in the past rather than just a set of rules. Previous cases or plans are stored for use in solving future problems. In addition, means of adapting previous plans to work in different decision-making problems are saved. By making previous solutions available to decision makers, the decision maker can anticipate variables of concern and alternative solutions. In addition, past mistakes can be avoided, while short-cuts can be made available. As noted by Hammond (1988, p. 17):

> The ideas behind case based planning rise out of the simple principle:
> If it worked, use it again.
> and a corollary
> If it works, don't worry about it.
> The refinements of the basic idea come out of a second, equally simple, principle:
> If it didn't work, remember not to do it again.
> to which is added
> If it doesn't work, fix it.

Further, Ashley and Rissland (1988, p. 70), note that CBR is used '. . . to capture expertise in domains where rules are ill-defined, incomplete, or inconsistent'. Generally, cases are appropriate for those situations where explanation is by examples or where the domain is precedence-based. Cases are useful where there are many exceptions to rules or where seemingly contradictory rules are present for different situations. In addition, they are useful where solutions can be constructed or modified from altering previous solutions.

At the most basic level, making a case-based inference entails a number of different elements (e.g. Kolodner, 1988a). First, the cases themselves must be chosen for the use of the system. This typically can require the existence of a database of cases and an expert to assist in choosing those cases that are appropriate for the system (e.g. Reisbeck, 1988). Second, the case-base representation must be established. Key elements of the cases are determined so that memory is organized to meet the demands placed upon it. In terms of implementation, this means that the cases are indexed or some other structure is used to organize the cases so that various patterns in the cases can be established. For example, in Selfridge and Cuthill (1989) a legal clerk system was designed so that different patterns were represented in the system. Specifically, the legal knowledge patterns included legal conflict patterns, legal interpretation patterns and legal argument strategies. Third, there must be an inference process that allows sorting through the cases. This must permit the ability to focus on the appropriate parts of the cases and then allow for the use of those parts of the previous case that enable the appropriate construction of a new case. Kolodner (1988a) has outlined a number of different approaches. For example, when a single case can meet the needs of a situation, then the solution associated with that case is the system's recommendation. If there is not a case that exactly meets the needs of the current situation, then the system can modify a previous solutions based on differences between it and the current case.

Multiple-agent Intelligent Systems

As noted by Gasser and Hill (1990, p. 204):

> For many years, the field of AI has been concerned with the study of problem solving by people and machines. Yet until recently, problem solving in AI has been conceived almost wholly from the perspective of individual 'intelligent agents' solving individual problems. We find this a bit strange, given the observable fact that so much human activity is social in nature. In general, it seems that most if not all human problem solving has social components. Even individual 'expert' automated problem solvers take input from other agents, give output to other agents, and in general are designed, constructed and invested with goals by numerous other agents.

Bond and Gasser (1988b) state that MAIS research is concerned with the co-ordination of behavior among a collection of intelligent agents. That co-ordination includes their knowledge, goals, skills and plans. The agents may have a single goal or individual subgoals that are perhaps contradictory.

Multiple-agent systems are a part of the subfield of AI referred to as 'Distributed Artificial Intelligence' (DAI). DAI is divided by Bond and Gasser (1988b) into three areas: distributed problem solving (determining how the work of solving a specific problem can be divided among a number of modules); parallel AI (concerned with developing architectures, languages, etc. for AI in parallel computing environments); and multiple-agent intelligent systems.

MAIS is closely related to the problems of other issues. For example, Multiple Criteria Decision Making (MCDM) addresses decision making in those situations where there are multiple goals to optimize using a mathematical programming approach (Zeleny, 1982). Further, although team theory (Marschak and Radner, 1973) analyzes teams, generally a quadratic decision function is assumed for the team. Similarly, Dantzig (1963) has addressed some multiple-agent issues in his analysis of decomposition analysis for linear programming. However, these authors assume a linear set of constraints and objective.

Integrated Case-based and MAIS Systems

There are some situations where the case-based approach and the MAIS have been integrated (e.g. Sycara, 1987, 1988, 1989). As would be expected, those situations employ multiple agents and those agents use case-based reasoning. The integration of these two technologies can form a powerful medium for the representation of problems in accounting, finance and management.

Some Legal Applications of Case-based Reasoning

Although there have been very few applications of CBR to accounting regulation, accounting or finance, one of the primary sources of case-based reasoning systems to date has been in the closely related legal domain. This section summarizes some of these applications and some of them are discussed in more detail in Riesbeck and Schank (1989).

HYPO (Ashley and Rissland, 1986, 1988)

HYPO is a CBR system that analyzes trade secret law. The system takes a set of facts from the user and retrieves relevant cases in order to generate either plausible defence or prosecution arguments.

As of 1988 the system contained about 30 cases on trade secrets and related problems. Each case in the system is an actual one that has resulted in a published opinion. The case representations describe the main aspects of the case, including plaintiff, defendant, prevailing party, etc. Factual predicates indicate if a legal fact is true or not (e.g. the employee has switched employers). 'Dimensions' are used to capture the legal relevance of a fact cluster and allow the system to view the cases from different perspectives. The dimensions are frame-like forms of knowledge representation.

For example, six of the thirteen implemented dimensions include (Ashley and Rissland, 1988, p. 72):

(1) Brought-tools—The Plaintiff's former employees brought the plaintiff's notes, diagrams and tools to the defendant;
(2) Competitive advantage—The defendant's access to the plaintiff's secret information gave the defendant a competitive advantage;
(3) Disclose secrets—The plaintiff did not voluntarily disclose his secrets to outsiders;
(4) Noncompete agreement—The plaintiff's employees had entered into nondisclosure agreements;
(5) Bribe employee—The defendant bribed the plaintiff's employees to switch employment;
(6) Vertical knowledge—The plaintiff's secrets were not simply about customer business methods.

Then the current fact situation (cfs) is compared to the existing cases along these dimensions in order to find the case or cases that are most like the cfs. That comparison produces a case analysis record, including (1) applicable fact matches, (2) applicable dimensions, (3) near-miss dimensions, (4) potential claims and (5) relevant cases from the case base.

JUDGE (Bain, 1986)

JUDGE is a system in the domain of criminal sentencing, which is aimed at determining sentencing of those convicted of crimes. As is the situation in a court room setting, the system takes as input the events behind the case, the charge, the relevant legal statutes, parole conditions and range of imprisonment allowed.

There is no iteration between the user and the system. As long as the sentence is within the relevant range the system's response is not 'wrong'. Initially, the JUDGE has an empty case library and a set of heuristics. Over time, JUDGE develops a case library that contains the previous crimes and sentences that it investigates.

MEDIATOR (Simpson, 1985)

MEDIATOR is designed for the domain of dispute resolution. If there is goal conflict then it proposes potential compromises. Unlike JUDGE, if that proposal fails to solve all parties then the system generates a new proposal. Failures are saved and used to mitigate the potential for failure in the future.

PERSUADER (Sycara, 1987, 1988, 1989)

PERSUADER is a system that acts as a labor mediator. The system integrates case-based reasoning with an analytic tool based on multi-attribute utility theory. The input is a set of conflicting goals (such as wages, pensions, management rights and seniority language), and the context of the dispute (e.g. economic conditions of industry and general economic conditions). The output is a single plan or an indication of the basis of the failure.

As in MEDIATOR, proposed solutions that fail are changed and new solutions are proposed. This leads to a re-use of plans in those situations where they best fit. In order to perform its task, PERSUADER brings to bear knowledge of the negotiation process.

LAWCLERK (Selfridge and Cuthill, 1989)

LAWCLERK was designed to study a dynamic memory-based approach to CBR. As Selfridge and Cuthill (1989, p. 313) note, 'the ultimate purpose of LAWCLERK is to read a new case in natural language, retrieve relevant, possible out-of-context cases, and propose possible legal arguments for the new case by adapting arguments employed in the retrieved cases'. LAWCLERK uses five different memory structures: Episodes and Memory Organization Packets (MOPS) to represent general world knowledge; and Legal Interpretation Patterns, Legal Conflict Patterns and Legal Argument Strategies to represent specialized legal knowledge. Qualitative models of legal thought are embedded in the legal specific knowledge. Current efforts with LAWCLERK are aimed at understanding how to chose the most relevant cases, rather than employing an extensive search.

Summary of CBR

These cases provide a number of insights that will be useful to the development of such systems in accounting regulation. First, the structure and capture of relevant information about the cases in summarized form of slot information is essential. Second, choosing from among similar cases can employ a number of approaches. Third, in some situations (e.g. sentence length) traditional mathematical operations such as averaging can prove useful at providing feasible solutions. Fourth, there is often an explicit or implicit negotiation process in case-based systems. Fifth, there is often both general and specific knowledge embedded in the system. Sixth, there is typically some qualitative model embedded either in the slots or in the relationships between the cases or through some other device.

Some Applications of MAIS

There have been a number of applications in MAIS, as summarized in Bond and Gasser (1988a) and Gasser and Huhns (1989a). Some of those applications have implications for accounting and financial applications, including the following.

PERSUADER (Sycara, 1987, 1988, 1989)

PERSUADER was discussed above as a case-based reasoning system. In addition, it makes use of multiple intelligent agents (Sycara, 1989). In particular, PERSUADER consists of three agents: a company, a union and its mediator, whose job is to reach an appropriate compromise. The mediator is in parallel negotiations with the union and the company, generating a proposal and a counterproposal based on feedback from the dissenting party. Typically, two of the agents, the company and the union, will have multiple, conflicting goals. If both the union and the company accept the proposal then it is the final compromise.

During negotiations messages are sent containing the following information:

The proposed compromise;
Supporting persuasive arguments;
Agreement or disagreement with the compromises;
Additional information requests;
Agents preferences associated with issues for which agreement has not been reached.

Loan Quality (Price, 1990)

Price (1990) has suggested a related approach for the study of loan quality. She proposes that a model that includes multiple expert systems rule bases be used to represent three different sets of experts: loan review officers; auditors; and the regulatory agency (e.g. the Federal Deposit Insurance Corporation). The rationale for the multiple-expert system knowledge bases is that the different sets of agents each have different experience and requirements. In addition, each of the sets of agents has a different set of objectives. As a result, Price (1990) suggests the development of an expert system that incorporates knowledge from the three different sources. As is the case with the different sets of agents, the different knowledge bases may derive different solutions. In this case there would be the need to have a conflict-resolution device to determine which advice should be followed. She proposes a method based on Fraser *et al.* (1989) for resolution of these negotiation problems.

Office Information Systems (Hewitt, 1986) and Co-ordination Theory (Malone, 1987)

Development of a multiple-agent perspective in two closely related areas is worth discussion. Hewitt (1986) proposed that 'due process' was a central activity in organizational information processing. That perspective stresses the importance of negotiations and mediation, with particular emphasis on the role of the computer in that process. In addition, he suggested that computer systems would begin to acquire more of the structure of human organizations.

Malone (1987) examined some of those structures in more detail, concentrating on four different forms (product hierarchy, functional hierarchy, centralized markets and decentralized markets), examining different 'co-ordination trade-offs'. He suggested that these trade-offs could be characterized by co-ordination costs (proportional to the number of agents and connections), production costs (proportional to organizational capacity) and vulnerability costs (unavoidable costs).

Summary of MAIS

MAIS are used to model multiple-agent systems. Typically, in these systems there is a conflict of goals between those agents and in the plans to satisfy those goals. Systems have employed cases, analytical tools and rules as the basis of representing knowledge of the agents. There is apparently substantial reason to assert that office information systems in general can be represented using such a multiple-agent format. In addition, there are some basic structures that have been found to be useful in representing multiple-agent problems.

Case-based Reasoning in Accounting Regulation and Extensions

There is substantial reason to assert that case-based reasoning is already being used in accounting regulation. Computerization of this reasoning could have advantages for accessing a broad base of cases and reasoning consistently about these cases. This section summarizes some of those opportunities for the development of CBR ARS.

Common Law Accounting

Common law accounting is necessarily a case-based part of accounting regulation. Consider the 'case' of goodwill, as discussed by Johnson (1987, p. 59):

> More than 1,000 cases with decisions and data on accounting were screened with these criteria in mind. More than 50 cases were identified with content reflecting current goodwill accounting. . .These cases, as well as prior court precedents cited in them, include a variety of causes and a variety of remedies. The private legal actions were based on tort claims of fraud, misrepresentation, conversion of property and unfair competition; . . . Remedies sought by the plaintiffs included recovery of purchase price; damages; and injunction. Some cases were decided on the merits of evidence and substantive law. . . Collectively these cases of private litigation created general purpose accounting for goodwill.

This discussion is characteristic of the type of relationships that could be established as a model of accounting regulation. The 50 cases referenced here could become part of a case base and could be characterized as different types of legal actions. Cases would also include information about the remedies and how they were decided.

Securities and Exchange Commission (SEC) Enforcements

Kunitake (1987) used cases in an analysis of SEC enforcement actions. In a review of SEC enforcement activity brought against independent auditors and certified public accounting firms (CPAs), 116 releases documented the investigation of 130 CPAs and 47 CPA firms for the period 1934–85. In those situations roughly 15% of the firms were permanently suspended or dissolved, 40% received temporary suspensions and 28% were sited for censure.

Design of a CBR system for SEC enforcement actions could use those SEC releases as the basis for the cases. Causal models of the SEC enforcement process would be employed to assess the essential case features and the knowledge that needed to be built into the system.

Auditing Regulation and Accounting Principles

Accounting policies must be chosen that correspond to so-called 'generally accepted accounting principles', promulgated by a number of regulatory agencies, including the SEC and AICPA. Thus, auditors and accountants are often in a position of finding what accounting principles have 'worked' for other firms in similar industries. Auditors make use of an accounting databases such as NEXIS in order to find case situations that meet a certain set of requirements. As a result, this is also a CBR situation.

Here, each firm that has 'generally accepted accounting policies' could become a case. The firm's context (e.g. industry), their auditors, the corresponding accounting principles, the specific accounting policy, the current portfolio of accounting principles, previous accounting policy before the current policy, existing portfolio of accounting policies and a host of other variables could form the basis of the representation of the cases.

Summary of CBR for ARS

There are a number of situations in accounting and finance where decisions are heavily contingent on previous cases, but only a few have been examined here. In these situations it may be dysfunctional to attempt to distill the general principles in those cases into a few rules. Instead, a CBR approach that includes the key aspects of those cases would appear more appropriate.

Extensions to other Accounting and Finance Applications

As noted above, CBR has been suggested for those situations where if it worked, then use it again. That reasoning permeates a number of accounting and financial applications, some of which are discussed here.

Credit Decisions

Another application could be in the credit decision. To structure the credit decision as a CBR problem it is assumed that credit decisions are based on previous cases. Clearly, this assumption is a research issue.

For this problem, each previous credit-granting case or some subset would form the case base. The dimensions could include resulting regularity of repayment of credit, credit customer characteristics, environmental characteristics at time of the credit decision and other factors.

Capital Investment

Capital investment is another area that could be treated using a CBR. As with credit decisions, it is assumed that in some cases capital investment decisions are based on previous cases. It is reasonable to assume that the capital investment decision involves multiple forms of reasoning. For example, in order to be eligible to be financed, projects must meet certain rule-based requirements (e.g. rate of return is greater than some prespecified percentage). However, if there are more projects than funds available, then once a project is eligible, then case-based reasoning could be used to differentiate between projects.

In this problem-solving environment the case decisions would be made up of the set of investment decisions (both for and against). Dimensions could include the budgeted and actual rates of return, who was manager on the project, the nature of the project, the manager's history of success with previous projects and other project-based factors.

Auditing

Denna and Meservy (1990) have investigated the use of CBR in one auditing problem, assessing audit risk. The system was designed to assess the impact of a truck strike on an audit client.

Multiple-agent Intelligent Systems in Accounting Regulation and Extensions

MAIS can be used in a number of different models of accounting regulation, accounting and finance. The following applications are not meant to be all-inclusive but merely suggestive of some applications.

In order to facilitate discussion of the different applications we will treat them as four distinct types: multiple agents with different knowledge (e.g. different regulation agencies); multiple agents with different information (e.g. situation assessment in multiple locations); multiple agents for task sharing to facilitate problem solution (e.g. to multiple processors); and multiple agents for behind-the-scenes housekeeping (e.g. providing an alerting function for executive information systems).

Multiple Agents with Different Knowledge

One approach to MAIS is to have agents represent alterantive knowledge perspectives. For example, in a predictive model of accounting regulation there are a number of organizational forces, including the Security and Exchange Commission; American Institute of Certified Public Accountants; and others (e.g. Parker and Previts, 1987). Associated with each of those organizations is different knowledge, goals and plans to accomplish their objectives, and thus a need for negotiation for those decisions where those organizations interact with each other or with their constituencies.

The knowledge may be in the form of rules, cases, analytic techniques, etc. For example, as noted above, in many regulation situations there is the need to establish precedence based on previous cases, and rules may not be appropriate. Thus, accounting regulation could benefit from a combination of case-based reasoning and multiple agents.

In management accounting there also are a number of multiple-agent issues (e.g. that of transfer pricing). Typically, in a decentralized firm, managers are given authority to buy resources from either internal or external sources. Although the actual price they pay may be less for an external source, it may be beneficial to the firm as a whole to have the purchase from the internal source. Often there is a negotiation process between the internal source and the manager before the purchase would be made from the external source. That negotiation process may be through a central arbitrator or directly between the two managers. This type of application is appropriate for an MAIS application, since the different actors have different knowledge, goals and information and typically there is a negotiated price.

The use of multiple independent intelligent agents in accounting information system databases was proposed by O'Leary (1991) for a number of purposes, including determining which transactions are related to other transactions. In that application, those agents each have an objective of determining if a transaction is an accounting event or if there are other transactions related to it that make up the event. For example, in the case of the purchase of $1000 of computer software, where the purchaser has a $500 spending limit, without authorization, two $500 transactions may be used to achieve the total $1000 billing (the actual event). It would be the agent's job to determine that the two transactions are one event.

If the agent finds that it appears that two transactions are related then it must determine if some other agent indicates that it thinks that one of the two transactions are related to a different transaction that it is trying to match. In some cases there will be no conflict—no other agent will be trying to join those events into a single transaction. In others there will be conflict. In cases of conflict, solution knowledge can be derived from the conflict. If there is conflict then it may be that all three transactions should be treated as an event. In other cases, the fact that another agent has a better match can be used by the other agent to determine that two transactions are not related.

Multiple Agents with Different Information

In some situations agents may have the same knowledge but also have access to different information. These information differences may relate to geographic location, time (e.g. days) or people.

For example, in the case of an international firm with multiple geographic locations, different agents at different locations would have access to different information. A MAIS auditing system could have different agents examine information in each of those locations. Then interaction between the agents would be necessary to determine the overall assessment (e.g. of the company). There may, for example, be frauds that are ascertainable only by being able to consider both sides of a transaction. Transactions may appear legitimate if only one party's activity is analyzed. However, by having access to both sides, through the agents' interaction, additional insight may be provided.

A number of insurance companies have developed expert systems to search for fraud in a number of situations. For example, Lockheed has developed a system for checking the validity of claims received by its medical insurance program (Holsapple *et al.*, 1988). Such an analysis of fraud could be extended to a multiple-agent system. For example, in the case of insurance claims another set of agents each could be responsible for auto, life and homeowners' insurance. Those agents could then periodically review each other's findings in an effort to discover additional frauds that crossed the domain of multiple types of insurance claims against the company.

Another source of applications is based on different agents associated with different time periods. An application of artificial intelligence in internal auditing is the audit of foreign currency transactions (O'Leary and Watkins, 1991). One structure to that audit is to audit individual days for unusual transactions and then to audit between days for unusual transactions. From a multiple-agent perspective, this can be structured by employing one agent for each day and then using a negotiation and discussion between agents to discover unusual transactions occurring across multiple days.

Multiple Agents for Task Allocation

In other situations, multiple agents may represent multiple processing capabilities. Virtually any task for which a single processor can be used to solve a multiple-processor approach (where each of those multiple processors has the same capability as the single one) can be employed to speed solution. This is particularly important for those applications where a rapid response is necessary to exploit the situation.

There are a number of cases in accounting and financial applications where such speed would provide substantial dividends. Probably one of the most apparent is portfolio analysis. Models of portfolio selection are typically computationally intensive and highly dependent on rapid response to exploit environmental situations. In addition, the ability to provide a rapid response could have substantial value in the portfolio development.

The Role of Multiple Agents—Direct or Behind the Scenes

The role of agents may differ from one system to another. In many situations, such as those discussed above, this role is the primary focus of the system. In other cases agents may perform a role behind the scenes, bringing information to the attention of the user only in extreme situations, such as in executive information systems (EIS) (King, 1990). In EIS, agents are often used to monitor specified activities and domains, and then report on those activities only when certain default values are reached. For example, if liquidity is too low on a potential investment, an agent could report to that effect in order to bring it to the attention of the user.

Summary

This paper has addressed the use of three facets of artificial intelligence (rule-based expert systems, case-based reasoning and multiple-agent intelligent systems) in accounting regulation. It does not appear that any one of the individual facets of artificial intelligence discussed is better than any other approach. Instead, each seem to have their own particular uses in accounting regulation systems.

Rule-based expert systems are of particular use in a situation where there is a well-established set of rules or where a set of rules can be developed. Case-based reasoning is helpful when the reasoning uses precedence cases. Multiple intelligent agents are useful in those situations where there are multiple objectives, multiple sets of knowledge or multiple agents, and the behavior of those multiple agents must be co-ordinated.

As a result, rather than systems that employ a single approach it appears that those that use multiple approaches could solve a broader base of problems. In addition, such integrated approaches are likely to provide solutions that better model cognitive models of accounting regulators and provide better decisions.

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