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Multiplayer Games and Competitive Business Models

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Abstract The paper is based on agent plan computing where the interaction amongst heterogeneous computing resources is via objects, multiagent AI and agent intelligent languages. Modeling, objectives, and planning issues are examined at an agent planning. A basis to model discovery and prediction planning is stated. The new AI agent computing business bases defined during the last several years can be applied to present precise decision strategies on multiplayer games with only perfect information between agent pairs. A new basis for business modelling with the new agent computing paradigms is essential to economic agent models. Multiplayer agnet game trees are introuced as the basis to ecenomic games The game trees are applied to attain models. The computing model is based on a novel competitive learning with agent multiplayer game tree planning. Specific agents are assigned to transform the models to reach goal plans where goals are satisfied based on competitive game tree learning. The planning applications include OR- Operations Research as goal satsfibility and micro-managing decision support with means-end analysis.

Keywords Multiplayter Game Trees, Management Sciences, Business Planning, Prediction, AI, Micro-Economics

1. INTRODUCION

Modeling, objectives, and planning issues are examined with agent planning and competitive models. Model discovery and prediction is applied to compare models and get specific confidence intervals to supply to goal formulas. Competitive model learning is presented starting with the new agent computing bases defined since 1994. The foundations are applied to present precise decision strategies on multiplayer games with only perfect information between agent pairs. The game tree model is applied to train models. The computing model is based on a novel competitive learning with agent multiplayer game tree planning. Specific agents are assigned to transform the models to reach goal plans where goals are satisfied based on competitive game tree learning. Intelligent and/or trees and means-end analysis is applied with agents as the hidden –step computations.

A novel multiplayer game model is presented where "intelligent" agent enriched languages can be applied to address game questions on models in the mathematical logic sense. The new MIS as an academic and business field might be depicted by the enclosed figure. Software agents are specific agents designed by a language that carry out specified tasks and define software functionality. Most agents defined by our examples are software agents. Academic MIS essentials might be redefined as the figure indicates. There is agent computing, cyberspace computing, intelligent multimedia and heterogeneous computing. Plans and goals are

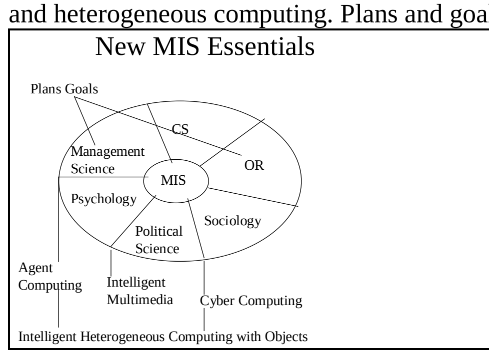

Figure 1 Agent-based Business and MIS Model[1]

A preliminary multimedia forecasting plan is put forth in the author's papers. The idea is to apply Morph-Gentzen logic as a basis for intelligent multimedia forecasting Nourani[10]. A graphics sequent is applied to predict the trends. Specifc market condition graphs are obtained by Morph Gentzen sequents from known stock market parameters.

2. Planning WITH Prediction

Modeling with agent planning is applied where uncertainty, including effector and sparameter uncertainty, are relegated to agents, where competitive learning on game trees determines a confidence interval. The incomplete knowledge modelling is treated with KR on predictive model diagrams. Model discovery at KB's are with specific techniques defined for trees. Model diagrams allow

[1] The specific agent business modeling techniques are the technical property of the author's businsess ventures associated with ProjectMETAAI. Commerical applications must be with proper credit and permission.

us to model-theoretically characterize incomplete KR. To key into the incomplete knowledge base we apply generalized predictive diagrams whereby specified diagram functions a search engine can select onto localized data fields. The predictive model diagrams Nourani [9] could be minimally represented by the set of functions {f1,fn} that inductively define the model. Data discovery from KR on diagrams might be viewed as satisfying a goal by getting at relevant data which instaniates a goal. The goal formula states what relevant data is sought. We propose methods that can be applied to planning Norman[11] with diagrams to implement discovery planning. In planning with G-diagrams that part of the plan that involves free Skolemized trees is carried along with the proof tree for a plan goal. Computing with diagram functions allows us to key to active visual databases with agents. Diagrams are well-known concepts in mathematical logic and model theory. The diagram of a structure is the set of atomic and negated atomic sentences that are true in that structure.

Models uphold to a deductive closure of the axioms modelled and some rules of inference. The generalized diagram (G-diagram) Nourani [10,11] is a diagram in which the elements of the structure are all represented by a specified minimal set of function symbols and constants, such that it is sufficient to define the truth of world formulas only for the terms generated by the minimal set of functions and constant symbols. Such assignment implicitly defines the diagram. It allows us to define a canonical model in terms of a minimal family of function symbols. The minimal set of functions that define a G-diagram are those with which a standard model could be defined. Formal definition of diagrams are stated here, generalized to G-diagrams, and applied in the sections to follow.

2.1 Prediction and Discovery

Minimal prediction is an artificial intelligence technique defined since the author's model-theoretic planning project. It is a cumulative approximation Norman[9] attained with completing model diagrams on what might be true in a model or knowledge base. A *predictive diagram* for a theory T is a diagram D (M), where M is a model for T, and for any formula q in M, either the function f: q $\rightarrow$ {0,1} is defined, or there exists a formula p in D(M), such that T U {p} proves q; or that T proves q by minimal prediction. A *generalized predictive diagram*, is a predictive diagram with D (M) defined from a minimal set of functions. The predictive diagram could be minimally represented by a set of functions {f1,...,fn} that inductively define the model. The free trees we had defined by the notion of provability implied by the definition, could consist of some extra Skolem functions {g1,...,gl} that appear at free trees. The f terms and g terms, tree congruences, and predictive diagrams then characterize partial deduction with free trees. The predictive diagrams are applied to discover models to the intelligent game trees. Prediction is applied to plan goal satisfiablity and can be combined with plausibility [11], probabilities, and fuzzy logic to obtain, for example, confidence intervals.

2.2 KR with Keyed Functions

Practical AI systems are designed by modelling AI with facts, rules, goals, strategies, knowledge bases. Patterns, schemas, AI Frames and viewpoints are the micro to aggregate glimpses onto the database and knowledge bases were masses of data and their relashionships-represenations, respectively, are stored. Schemas and frames are what might be defined with objects, the object classes, the object class inheritances, user-defined inheritance relations, and specific restrictions on the object, class, or frame slot types and behaviors.

A scheme might be
Intelligent Forecasting
IS-A Stock Forecasting Technique
Portfolios Stock, bonds, corporate assets
Member Management Science Techniques

Schemas allow brief descriptions on object surface properties with which high level inference and reasoning with incomplete knowledge can be carried out applying facts and the defined relationships amongst objects. Relationships: Visual Objects A and B have mutual agent visual message correspondence. Looking for patterns is a way some practical AI is a carried on with to recognize important features, situations, and applicable rules. From the proofs standpoint patterns are analogies to features as being leaves on computing trees. *Forward chaining* is a goal satisfaction technique, where inference rules are activated by data patterns, to sequentially get to a goal by apply the inference rules. The current pertinent rules are available at an *agenda store*. The carried out rules modify the database.

Backward chaining is an alternative based on opportunistic response to changing information. It starts with the goal and looks for available premises that might be satisfied to have gotten there. Goals are objects for which there is automatic goal generation of missing data at the goal by recursion backward chaining on the missing objects as sub-goals. Data unavailability implies search for new goal discovery.

Goal Directed Planning is carried out while planning with diagrams. That part of the plan that involving free Skolemized trees is carried along with the proof decision tree for a plan goal. If the free proof tree is constructed then the plan has a standard computable model in which the goals are satisfied. Let us see what predictive diagrams do for knowledge discovery knowledge management. Diagrams allow us to model-theoretically characterize incomplete KR. To key into the incomplete knowledge base. Selector functions Fi from an abstract view grid interfaced via an inference engine to a knowledge base and in turn onto a database. Generalized predictive diagrams whereby specified diagram functions a search engine can select onto localized data fields.

A G*eneralized Predictive Diagram* is a predictive diagram with D (M) defined from a minimal set of functions. The predictive diagram could be minimally represented by a set of functions {f1,fn} that inductively define the model. The functions are keyed onto the inference and knowledge base to select via the areas keyed onto.

Visual object views to active databases might be designed with the above. The trees defined by the notion of provability implied by the definition might consist of some extra Skolem functions {g1,...,gn}, that appear at free trees. The f terms and g terms, tree congruences, and predictive diagrams characterize deduction with virtual trees as intelligent predictive interfaces. Data discovery from KR on diagrams might be viewed as satisfying a goal by getting at relevant data which instantiates a goal. The goal formula states what relevant data is sought. We have presented planning techniques, which can be applied to implement discovery planning. In planning with G-diagrams that part of the plan that involves free Skolemized trees is carried along with the proof tree for a plan goal. The idea is that if the free proof tree is constructed then the plan has a model in which the goals are satisfied. The model is the standard model of the AI world for which the free Skolemized trees were constructed.

3. COMPETITIVE MODELS and GAMES

Planning is based on goal satisfaction at models. Multiagent planning, for example as Muller-Pischel [5] and Bazier et.al.[2], here is modeled as a competitive learning problem where the agents compete on game trees as candidates to satisfy goals hence realizing specific models where the plan goals are satisfied**.** When a specific agent group "wins" to satisfy a goal the group has presented a model to the specific goal, presumably consistent with an intended world model. For example, if there is a goal to put a spacecraft at a specific planet's orbit, there might be competing agents with alternate micro-plans to accomplish the goal. While the galaxy model is the same, the specific virtual worlds where a plan is carried out to accomplish a real goal at the galaxy via agents are not. Therefore, Plan goal selections and objectives are facilitated with competitive agent learning. The intelligent languages Norman[8] are ways to encode plans with agents and compare models on goal satisfaction to examine and predict via model diagrams why one plan is better than another or how it could fail. Virtual model planning is treated in the author's publications where plan comparison can be carried out at VR planning Nourani [16]. Games play an important role as a basis to economic theories. Here the import is brought forth onto decision tree planning with agents.

Intelligent tree computing theories we have defined since 1994 can be applied to present precise strategies and prove theorems on multliplayer games. Game tree degree with respect to models is defined and applied to prove soundness and completeness. The game is viewed as a multiplayer game with only perfect information between agent pairs. Upper bounds on determined games are presented. The author had presented a chess-playing basis [12] to a computing conference. For each chess piece a designating agent is defined. The player P makes its moves based on the board B it views. <P,B> might view chess as if the pieces on the board had come alive and were autonomous agents carrying out two-person games as in Alice in Wonderland. Game moves are individual tree operations.

3.1 Intelligent AND/OR Trees and Search

AND/OR trees Nilsson [18] are game trees defined to solve a game from a player's stand point.

```
        n          an OR node.
      /  |  \
        m         an AND node
     /__|__\
    /   |   \
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Formally a node problem is said to be solved if one of the following conditions hold.

1. The node is the set of terminal nodes (primitive problem- the node has no successor).
2. The node has AND nodes as successors and the successors are solved.
3. The node has OR nodes as successors and any one of the successors is solved.

A solution to the original problem is given by the subgraph of AND/OR graph sufficient to show that the node is solved. A program which can play a theoretically perfect game would have task like searching and AND/OR tree for a solution to a one-person problem to a two-person game. An intelligent AND/OR tree is and AND/OR tree where the tree branches are intelligent trees. The branches compute a Boolean function via agents. The Boolean function is what might satisfy a goal formula on the tree. An intelligent AND/OR tree is solved iff the corresponding Boolean functions solve the AND/OR trees named by intelligent functions on the trees. Thus node m might be f(a1,a2,a3) & g(b1,b2), where f and g are Boolean functions of three and two variables, respectively, and ai's and bi's are Boolean valued agents satisfying goal formulas for f and g.

```
          g      is on OR agent
        / | \
          |
       b1 | b2
           f                    f is an
AND agent
        /__|__\
       /   |   \
```

The chess game trees can be defined by agent augmenting AND/OR trees Nilsson [6]. For the intelligent game trees and the problem solving techniques defined, the same model can be applied to the game trees in the sense of two person games and to the state space from the single agent view. The two person game tree is obtained from the intelligent tree model, as is the state space tree for agents. To obtain the two-person game tree the cross-board-coboard agent computation is depicted on a tree. Whereas the sate-space trees for each agent is determined by the computation sequence on its side of the board-coboard. Thus a tree node m might be f(a1,a2,a3) & g(b1,b2), where f and g are Boolean functions of three and two variables, respectively, and ai's and bi's are Boolean valued agents satisfying goal formulas for f and g.

```
          g      is on OR agent
        / | \
          |
       b1 | b2
           f    f is an AND agent
        /__|__\
       /   |   \
     a1    a2   a3
```

A tree game degree is the game state a tree is at with respect to a model truth assignment, e.g. to the parameters to the Boolean functions above. Let generic diagram or G-diagrams be diagrams definable by specific functions. Intelligent signatures Nourani[15] are signatures with designated multiplayer game tree function symbols. A soundness and completeness theorem is proved on the intelligent signature language Nourani [10]. The techniques allowed us to present a novel model-theoretic basis to game trees, and generally to the new intelligent game trees. The following specifics are from Nourani[14]. Let N be the set of all functions from ω to ω. Let A be a subset of N. Gale-Stewart[3] associated with A a 2-person game of prefect information G<A>. Player I begins by choosing n0 in ω; player two chooses n1 in ω; then I chooses n2 in ω; so on. Let a(i) = ni. I wins G<A> if and only if a in A. We say that G<A> is determined if one of the players has a winning strategy. To get a glimpse onto the specifcs let us start with the following basics.

Proposition If G<A> is determined, the complexity upper bound on the number of moves to win is A's cardinality.

Theorem For every pair p of opposing agents there is a set A<p>$\subseteq$ N. The worse case bound for the number of moves for a determined game based on the intelligent game tree model is the sum ({|A<p>|:p agent pairs}.
Proof Sum over the proposition [14].

At the intelligent game trees the wining agents determine the specific model where the plan goals are satisfied.

3.2 Two-Person Games

From the game tree view point for what Shannon had estimated a complete tree carried to depth 6-three moves for each player- would already have one billion tip nodes. Yet from an abstract mathematical viewpoint only, the game is a two-person game with perfect information Gale-Stewart [3]. However, the two-person game view is not a mathematical model for any chess playing algorithm or machine. The real chess game, from the abstract viewpoint, might well be modeled as a multiagent game, being only a two-agent game with perfect information between mutually informable agents.

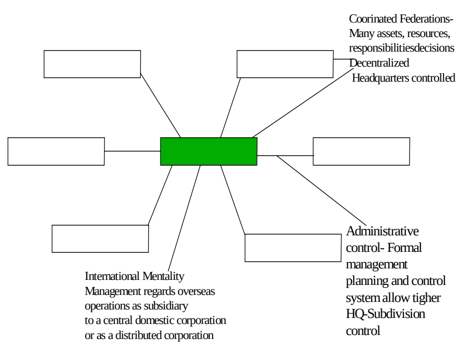
A multiagent chess design or chess computing by any technique does not in reality provide perfect information in a way, which can be applied. The perfect information overall is a massive amount of data to be examined. There are thousands of move trees computed for searches coming close to being exhaustive. The multiagent chess paradigm Nourani [12] is not based on an exhaustive two-person game with perfect information model. There is only minimal information for the multiagent plans across the board. The multiagent multiboard model is a realization where the game is partitioned and correlated amongst agents and boards, with a cognitive anthropomorphism to human player's mind. There is an abstract two-person game model, but it does not apply to define a chess-playing machine. It is there to make precise mathematical statements.

3.3 MANAGEMENT PROCESS MODELS

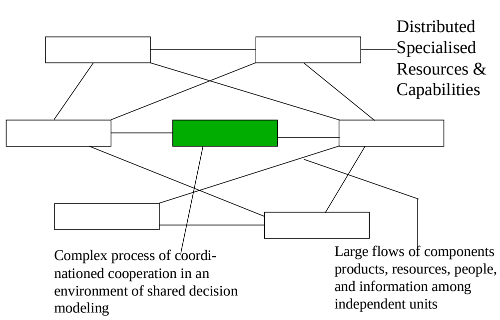
There are specific application areas for multiagent computing to Multinational corporation and their strategic management of multinational enterprises in [Nourani 1998a]. The areas to be applied to are global planning, external enterprise assessment, goal setting applications for operations research and market forcasting Nourani [11]. The figures indicate the specific models starting with a multi-business corporate model.

The figures indicate the specific models starting with a multinational business model.

Transnational Business Models Bases for Multiagent MIS



Dispersed, Specialized and Interdependent Organization
is what many companies might be employing



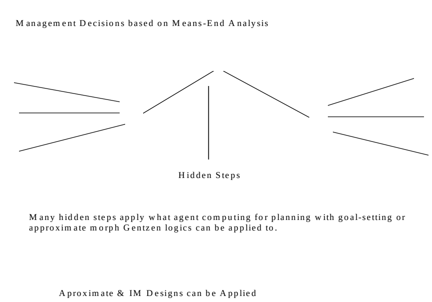
A Multiagent MIS Model

The orginzational knowledge van Heijst et.al. [2] is one of the main bases to competitive advantage. Enterprise modelling inculdes stock management, payroll, and advanced administrative tasks applying decision support. The follwing figure is a glimpse onto applying meas-end analysis decision support where teh hidden steps are desinged and computed with parameter agents.

3.4 DECISION TREES

We have defined specific application areas for multiagent computing to multinational corporations and their strategic management of multinational transactional business models appears in brief at (Nourani 1998a). The areas applied to are global planning, external enterprise assessment, and goal-setting applications for operations research and market forecasting (Nourani 1998b). A specific models starting with a transactional business model is in Nourani[16]. The organizational knowledge [2] is one of the main bases to competitive advantage. Enterprise modelling includes stock management, payroll, and advanced administrative tasks applying decision support. The following figure is a glimpse onto applying meas-end analysis decision support where the hidden steps are designed and computed with parameter agents. The obvious planning goal satisfaction applications are where agents apply backward chaining from objectives.

Specific Practical Areas to be Further Applied



4. CONCLUSIONS

A novel basis to decision-theoretic planning is presented classical and non-classical planning techniques, see for example [6,13] from artificial intelligence with games and decision trees providing a agent expressive planning model. We use a broad definition of decision-theoretic planning that includes planning techniques that deal with all types of uncertainty and plan evaluation. Planning with predictive model diagrams represented with keyed KR to knowledge bases is presented. Techniques for representing uncertainty, plan generation, plan evaluation, plan improvement, and are accommodate with agents, predictive diagrams, and competitive model learning. Modeling with effector and sensor uncertainty, incomplete knowledge of the current state, and how the world operates is treated with agents and competitive models. Bounds on game trees are presented as a measure on the complexity of model comparison and competitive learning. Applications to means-end analysis and decision support with goal planning is presented.

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