Augmented Learning and Data Filtering: Knowledge Management and Discovery

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Abstract. Ever since the author's publications on frontiers of decision trees, forecasting, and business ecosystems, over a decade the techniques for enterprise business systems planning and design with predictive models have become an attention focus. Heuristics on predictive analytics are developed with novel applications to decision trees. Augmented world and priority-based decision trees are new applications for machine learning and big data filtering. The areas addressed include designing predictive modeling with strategic decision systems with applications to analytics, enterprise modeling, and cognitive social media business interfaces. The areas explored range from plan goal decision tree satisfiability with competitive business models to predictive analytics models that accomplish goals on 3-tier glimpse to business systems. Example decision support application for AI KM with applications is presented. Augmented learning decisions is how AI enhances the decision-making process with more comprehensive cognitive views to business models and infrastructures.

Keywords: Augmented model learning, data analytics, decision trees, predictive analytics, enterprise modeling, cognitive spanning.

1. Introduction

The areas presented in this paper range from plan goal decision tree satisfiability with competitive business models to predictive analytics models that accomplish goals on a 3-tier business systems design models. The decision-making process and business analytics are explored with an augmentation of decision processes to accomplish goals modeled. Attention spanning trees are applied to focus on plan goal models that can be processed on a vector state machine coupled with a database pre-processor data mining interfaces (Nourani 200? Pedersen 200?). Modeling, objectives, and planning issues are examined to present precise decision strategies. Competitive decision tree models are applied to agent learning. Enterprise systems stage sequence communications with business objects and basic content management with multi-tier interfaces are being explored, focusing on attention spanning (Nourani-Lauth-Pedersen 2013) with specific examples developed in (Lauth-Nourani-Pederson-Bloom 2013), (Lauth 2013). The field of automated learning and discovery has obvious financial and organizational memory applications. There are basic applications to data discovery and model discovery. Augmentation is a process that enhances decision making by providing cognitive decision support that provides AI argumentation that affects behavior and sentiments to make sensible decisions. Hence it does not replace the human decision-making process with an automated machine.

A competitive business modeling technique, based on the first author's planning techniques are stated in brief. Systemic decisions are based on common organizational goals, and as such business planning and resource assignments should strive to satisfy such goals. Heuristics on predictive analytics are examined with brief applications to decision trees. The basic multi-tiered designs are based on the following layers. The presentation layer contains components dealing with user interfaces and user interaction. Example a visual JAVA standalone application. A business logic layer contains components that work together to solve business problems. The data layer is caused by the business logic layer to persist state permanently. More and more enterprises recognize that in the electronically archived databases a there is a potential for knowledge that could be processed up to now only insufficiently example application for competitive models appears in the transactional business models. Alternate models can be designed based on where assets, resources, and responsibility are assigned; how to control and coordination are distributed; and where the plan goals are set. A transactional international business model might comprise a coordinated federation with many assets and resources. The overseas operations are considered a subsidiary to a domestic central corporation. However, decisions and responsibilities are decentralized. Administrative formal management planning and control systems are how headquarters-subdivision controls are managed. Section outlines are as follows: section 2 presents the basics of competitive goals and models. Agent and/or trees are applied as primitives on decision trees to be satisfied by competitive models. Planning with predictive models and goals are presented with stock forecasting examples from the first author's newer decade's publications. The section concludes with the entrepreneurial cognitive augmented decision processes implications. Section 3 briefs on goals, plans, and realizations with databased and knowledge bases. There a function key interface to the database is presented with applications to model discovery and data mining. Competitive model goal satisfiability with model diagrams is briefed with examples. Section 4 presents the applications to decision trees and practical systems design with splitting agent decisions trees. Cognitive spanning with decision trees and state vector machine computations applications are presented. Section 5 presents spanning applications with multitier business interfaces. Social media applications with Gatesense example from the accompanying author's is briefed. The paper concludes with heuristics for competitive models and goals for decision tree accomplishment from the first author's newer game decision tree bases since (Nourani-Schulte 2014).

2 Competitive Models and Goals

The massive data without data filtering techniques is very prohibitive for business analytics. The process is not based on statistical models for massive data. It is AI AI that can filter based on data patterns. There is domain knowledge built up from years of experience or technology experts who may be well-versed in data, analytics, or AI. An important AI technique is planning that is based on goal satisfaction at business models. Multiagent planning, for example, as (Muller and Pischel 1994, Bazier et.al. 1997), in the paper 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 (Nourani 1996,1998) 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. Games play an important role as a basis for economic theories. Here the import is brought forth onto decision tree planning. An agent AND/OR tree is an AND/OR tree e,g. (Nourani, 1999), with And/or trees from (Nielsen 1967, Genesereth-Nielsen 1987) 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 are Boolean valued agents satisfying goal formulas for f and g.

2.1 Predictive Models

Predictive modeling is an artificial intelligence technique defined since the first author’s model-theoretic planning project over a decade before. It is a cumulative nonmonotonic approximation 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 ∪ {p} proves q; or that T proves q by minimal prediction. Prediction involves constructing hypotheses, where each hypothesis is a set of atomic literals; such that when some particular theory T is augmented with the hypothesis, it entails the set of goal literals G. The hypotheses must be a subset of a set of ground atomic predictable. The logical theory augmented with the hypothesis must be proved consistent with the model diagram. Prediction is minimal when the hypothesis sets are the minimal such sets. Plan goal selections and objectives are facilitated with competitive agent learning. The intelligent languages (Nourani 1996,1998) 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. Games play an important role as a basis for economic theories. Here the import is brought forth onto decision tree planning. Newer tree computing techniques are applied to present precise strategies and prove theorems on multiplayer games. Game tree degree concerning models is defined and applied to prove soundness and completeness.

2.3 How Augmented Model Decisions are permeated

Augmented intelligence combines person and machine intelligence when filtering data for value creation. Augmenting instincts and intuition with AI algorithms render rapid data-driven predictive insights. These insights can help people redesign functions, detect patterns find strategic opportunities, and turn data into action. We have seen some specifics on the preceding sections intended to extend human cognitive abilities, augmented intelligence is different from straight automation.

Augmented world cognitive decision-making involves a creative mix of data, analytics, and artificial intelligence (AI), with a clever person-machine ambient interaction. The consequent is augmented intelligence with the analytical power and speed of AI managing the big data towards agile, smarter decisions and discovering patterns. The analytics that is deployed at major companies are not yet at the stage that one can state examples for augmented, that is an abstraction, for example to bussiness processes to which one can apply machine intelligence to address lower lever decisions in infrastructure, for example. fall short of their potential. We present some techniques, for example, cognitive spanning for decision making.

2.4 Entreprenurship Behavior and Decisions Example

Entrepreneurship research (Shönberger 2016) focuses on what type of personality entrepreneurs have. Since the activities are new in certain respects the uncertainty and unpredictability are central characteristics of entrepreneurship. Research has shown that certain personality traits correlate to the propensity to engage in entrepreneurship. (Gartner 1989) presents bases that behavior, rather than personality traits, that permeate entrepreneurial decision making: to engage or not to engage decisions in certain entrepreneurial activities. When AI and behavior are the considerations the paradigm shift in how man and machine will work together is behavior-driven, therefore, amenable to argumentation. Equally important, you need to have the right models and processes in place, i.e. the recipes for success.

One would like to have APS that processes data with AI and create predictive models to make predictive recommendations e.g. (Nourani 2017- TUB EM). But these models do not exist in a vacuum. They involve inputs and outputs that impact the rest of your business. You have to think about how these models fit in and how to prioritize the insights from data. Moreover, you need governance over augmented intelligence to see that the automation is working and people know their role in the new man-meets-machine workforce. The innovation ecosystem is based on decision processes that are augmentation critical. Self-regulated innovations inn self-managing teams are additionally important areas for the behavior and decision examples (Caremla´-Annosi, Brunetta, Magnusen 2017) and (Mercier-Laurent 2017) are example overviews for the ecosystem processes on innovations. (Bullard and Duffy 1998) and (Nourani-Lauth-Pedersen 206) are the past glimpses to the economies for decision processes considered here.

3 Goals, Plans, and Knowledge Bases

Practical systems are designed by modeling with information, rules, goals, strategies, and information onto the data and knowledge bases, where masses of data and their relationships and representations are stored respectively. Example analytics systems on the agenda are Watson Analytics: a cognitive system that sifts through massive data to discover insights that can help its users answers to the most complex of questions. It can reach for relevant answers in the context of questions. Furthermore can become smarter, learning from each interaction with users, and each piece of data it interacted with. Watson can "think" or "reason" similar to a real person. It processes information, draws conclusions, and learns from its experiences.

With our agent augmented decision trees with forward chaining, that is a goal satisfaction technique where inference rules are activated by data patterns, to sequentially get to a goal by applying the inference rules, allows decisions on the surface meta-data on an augmented abstraction with keyed data functions. The current pertinent rules are available at an 'agenda' store. The rules carried out will modify the database. Backward chaining is an alternative based on an 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 a search for new goal discovery.

A basis to model discovery and prediction planning is presented in (Nourani 2002) and is briefed here. 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. The game trees are applied to improve models. The computing model is based on 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- ERP and EM as goal satisfiability. Minimal prediction is an artificial intelligence technique defined since the author's model-theoretic planning project. It is a cumulative nonmonotonic approximation attained with completing model diagrams on what might be true in a model or knowledge base.

3.1 Decision-Theoretic Planning

A novel basis to decision-theoretic planning with competitive models was presented in (Nourani 2005) and (Nourani-Schulte 2013) with classical and non-classical planning techniques, see for example, (Hedeler et.al. 1990, Wilkins 1984) from artificial intelligence with games and decision trees providing an 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 accommodated 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 were developed based on the first author's preceding publications on game trees generalizations on VMK to on (Nourani- Schulte 2013). Partial deductions in this approach correspond to proof trees that have free Skolemized trees in their representation. Our past decade developments have applied diagrams do for knowledge discovery knowledge management. Diagrams allow us to model-theoretically characterize incomplete KR. To key into the incomplete knowledge base. The following figure depicts selector functions Fi from an abstract view grid interfaced via an inference engine to a knowledge base and in turn onto a database.

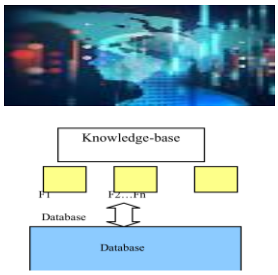

Figure 3 Keyed Data Functions, Inference, and Model Discovery
Adapted from (Nourani 2014) & Cognitive MIT Sloan Reviews

Generalized predictive diagrams are defined, whereby specified diagram functions and the search engine can select onto localized data fields. A Generalized Predictive Diagram, is a predictive diagram where D (M) is 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 to, designated as Si's in figure 1, and data is retrieved Nourani [20]. 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 then characterize deduction with virtual trees Nourani [12] as intelligent predictive interfaces. Data discovery from knowledge 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.

3.2 Competitive Models and Goal Satisfiability

Business intelligence interfaces might apply automated learning and discovery-often called data mining, machine learning, or advanced data analysis has new w-interface relevance. There are obvious financial and organizational memory applications. E-business, trustworthiness, usability, Human-Computer Interaction, cognitive ergonomics, user interface design, ease of use, interaction design, and online marketing, are the business user modeling issues areas to address. Consider an example ERP system to optimize a business plan with task assignments based on team-play compatibility. Generic model diagrams are basic function-based data modeling techniques the first author put forth over a decade ago to characterize a business domain, with for example (Nourani-Loo 1999), business objects on a minimal function base**.**

Remark: The functions above are those by which a business model could be characterized by some schemes, e.g. stock forecasting scheme example e.g. (Nourani. 2018). The computing specifics are based on creating models from generic model diagram functions where basic models can be piece-meal designed and diagrams completed starting from incomplete descriptions at times. Models uphold to a deductive closure of the axioms modeled and some rules of inference, depending on the theory. By the definition of a diagram, they are a set of atomic and negated atomic sentences. Thus the diagram might be considered as a basis for a model, provided we can by algebraic extesion, define the truth value of arbitrary formulas instantiated with arbitrary terms.

4. Decision Trees and Vector Spanning Cognitive Spaces

Game theory is the study of rational behavior in situations in which choices have a mutual effect on one's business and competitors. The best decision depends on what others do, and what others do may depend on what they think you do. Hence games and decisions are intertwined. A second stage business plan needs to specify how to assign resources concerning the decisions, ERP plans, and apply that to elect supply chain policies, which can in part specify how the business is to operate. The splitting agent decision trees have been developed independently by (Nourani ECAI 1994). The computing model is based on novel competitive learning with agent multiplayer game tree planning. For example, when arranging team playing, there are many permutations on where the players are positioned. Every specific player arrangement is a competitive model. There is a specific arrangement that does best in a specific game. What model is best can be determined with agent player competitive model learning.

4.1 Cognitive learning-based decisions

Cognitive agents are software agents included in the higher-level performance of autonomous intelligent systems. They belong to the class of autonomous agents which are complex computing entities active in some kind of environment without the direct intervention of humans or other virtual systems. For an overview on what was our beginning, examples are (Nourani 2005) (Nourani, Lauth, et.al. 2017). To design intelligent agents systems, flexible problem-solving behavior, and adequate knowledge about the beliefs regarding the environment and its changing conditions is required. We refer here to humans, as well as to virtual systems and we try to look at some general characteristics of new cyber-physical systems. Multi-agent planning 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. Example agenda can distinguish and prioritize Commitments: Committed plans Committed goals Intended goals and Intended plans, (Kinny, Georgeff, and Rao 1996).

4.2 Approaches to cognitive systems

Three broad approaches have been adopted so far for implementing cognitive concepts into autonomously acting systems: Data modeling approach that infers the cognitive concepts from the modular data structures to means-end reasoning system through a theorem prover. An example is a cognitive agent system called Artimis[18], an intentional system designed for human interaction and applied in a spoken-dialog interface for human information access. Procedural approaches that use explicit representations of cognitive contents approach based on the BID: belief, intention, desire agent models and can be instantiated in a procedural reasoning system (PRS), like e.g. MARS [18]. Most cognitive systems fall into this second category. The newest approach is the "situated automata" approach that has no explicit representations of the cognitive concepts and therefore seems to perform better than other approaches in settings where higher performance is expected. Cognitive agents are present in complex applications trying to solve efficiently: context-sensitive behavior, adaptive reasoning, ability to monitor and respond to a situation in real-time (immersive agents), and modeling capabilities based on an understanding of human cognitive behavior, like innovation management, generation of new insights, e.g. new ways of thinking. Further application areas are ubiquitous computing so far as person-machine exchanges might be perceived (Cadrina Lauth,, Berendt, B. et.al). Example research on cognitive agents are on the first author`s publications at CBS Copenhagen, e.g. (Nourani 2005) on affective haptic logic, and (Huhn and Sihng 1988).

4.3 Splitting Trees and the CART Model

The following examples from (Nourani 2010) can be motivating for business applications. Example: A business manager has 6 multitalented players, designed with personality codes indicated with codes on the following balls. The plan is to accomplish 5 tasks with persons with matching personality codes to the task, constituting a team. Team competitive models can be generated by comparing teams on specific assignments based on the task area strength. The optimality principles outlined on the first author's publications might be to accomplish the goal with as few a team grouping as possible, thereby minimizing costs. The following section presents new agent game trees the author had put forth [26]. Applying game theory to business is tantamount to interactive decision theory. Decisions are based on the world as given. However, the best decision depends on what others do, and what others do may depend on what they think you do. Hence games and decisions are intertwined. A second stage business plan needs to specify how to assign resources concerning the decisions, ERP plans, and apply that to elect supply chain policies, which can in part specify how the business is to operate. A tactical planning model that plans critical resources up to sales and delivery is a business planner's dream. Planning and tasking require a definition of their respective policies and processes; and the analyses of supply chain parameters. The above are the key elements of a game, anticipating behavior, and acquiring an advantage. The players on the business planned must know their options, the incentives, and how do the competitors think.

Example premises: Strategic Interactions Strategies :{ Advertise, Do Not Advertise} Payoffs: Companies' Profits Advertising costs Euro million. The And vs. Or principle is carried out on the above trees with the System to design ERP systems and manage as Cause principle decisions. The agent business modeling techniques the author had introduced [25,28] apply the exact 'system as cause' and 'system as symptom' based on models (assumptions, values, etc.) and the 'system vs. symptom' principle via tracking systems behavior with cooperating computational agent trees. The design might apply agents splitting trees, where splitting trees is a well-known decision tree technique. Surrogate agents are applied to splitting trees. The technique is based on the first author's intelligent tree project ECAI 1994 and European AI Communication journal are based on agent splitting tree decisions like what is designed later on the CART system: The ordinary splitting tree decisions are regression-based, developed at Berkeley and Stanford (Brieman, Friedman, et.al. 1984), (Breiman 1996).

CART system deploys a binary recursive partitioning that for our system is applications for the agent and/or trees (Nourani 1999) The term "binary" implies that each group is represented by a "node" in a decision tree, can only be split into two groups. Thus, each node can be split into two child nodes, in which case the original node is called a parent node. The term "recursive" refers to the fact that the binary partitioning process can be applied over and over again. Thus, each parent node can give rise to two child nodes and, in turn, each of these child nodes may themselves be split, forming additional children. The term "partitioning" refers to the fact that the dataset is split into sections or partitioned. CART trees are much simpler to interpret than the multivariate logistic regression model, making it more likely to be practical in a clinical setting. Secondly, the inherent "logic" in the tree is easily apparent.

The agent splitting decision trees have been developed independently since (Nourani 1994-ECAI). For new directions in forecasting and business planning (Nourani 2002). Team coding example diagram from reach plan optimal games where a project is managed with a competitive optimality principle is to achieve the goals minimizing costs with the specific player code rule first author and company 2005.

More recent areas are optimized decisions based on goal reachability (CFNourani-Cadrina Lauth 2018).

4.4 Designing an Augmented Learning Model Decision Support Systems

The formal compositional framework for modeling multi-agent tasks DESIRE is introduced here. The following aspects are modeled and specified: (1) a task (de)composition,(2) information exchange, (3) sequencing of (sub)tasks, (4) subtask delegation, (5) knowledge structures. Information required/produced by a (sub) task is defined by input and output signatures of a component. The signatures used to name the information are defined in predicate logic with a hierarchically ordered sort structure (order-sorted predicate logic). Units of information are represented by the ground atoms defined in the signature. The role information plays within reasoning is indicated by the level of an atom within a signature: different (meta) levels may be distinguished.

In a two-level situation, the lowest level is termed object-level information, and the second level meta-level information. Some specifics and a mathematical basis to such models with agent signatures might be obtained from [34]. Meta-level information contains information about object-level information and reasoning processes; for example, for which atoms the values are still unknown (epistemic information). Similarly, tasks that include reasoning about other tasks are modeled as meta-level tasks with respect to object-level tasks. Often more than two levels of information and reasoning occur, resulting in meta-meta-information and reasoning. Information exchange between tasks is specified as information links between components. Each information link relates to output of one component to the input of another, by specifying which truth-value of a specific output atom is linked with which truth value of a specific inputs.

5. Spanning and the Multitier Models

5.1 Spanning Attention on Decision Trees

When a specific agent group "wins" to satisfy a goal, the agent group is presenting a model consistent with an intended world model for that goal. 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 [38]. 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 based on the attention spans with competitive agent learning. This technique can be also used to solve highly interacting communication problems in a complex web application, web intelligence settings. The intelligent languages (Nourani 1996,1997) 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. The state space agent modeling present techniques to span the attention state space, where specific agents with internal state set I can distinguish their membership. State vector machines-SVM, agent vectors, and data mining referring to the sections above are applied to design cognitive spanning. SVM creates a set of hyper-planes in N-dimensional space that is used for classification, regression, and spanning in our approach. The SVM algorithms create the largest minimum distance to have competitive goals satisfied on models.

The BID-architectures upon which specifications for compositional multi-agent systems are based are the result of analysis of the tasks performed by individual agents and groups of agents. Task (de)compositions include specifications of interaction between subtasks at each level within a task (de)composition, making it possible to explicitly model tasks that entail interaction between agents. The formal compositional framework for modeling multi-agent tasks DESIRE is introduced here. The following aspects are modeled and specified: (Brazier- Dunin-Keplic., Jennings, Truer 1997)

(1) a task (de)composition,(2) information exchange, (3) sequencing of (sub)tasks, (4) subtask delegation, (5) knowledge structures. Information required/produced by a (sub) task is defined by input and output signatures of a component. The signatures used to name the information are defined in a predicate logic with a hierarchically ordered sort structure (order-sorted predicate logic). Units of information are represented by the ground atoms defined in the signature. The role information plays within reasoning is indicated by the level of an atom within a signature: different (meta) levels may be distinguished. In a two-level situation, the lowest level is termed object-level information, and the second level meta-level information. Some specifics and a mathematical basis to such models with agent signatures might be obtained.

Meta-level information contains information about object-level information and reasoning processes; for example, for which atoms the values are still unknown (epistemic information). Similarly, tasks that include reasoning about other tasks are modeled as meta-level tasks with respect to object-level tasks. Often more than two levels of information and reasoning occur, resulting in meta-meta-information and reasoning. Information exchange between tasks is specified as information links between components. Each information link relates output of one component to input of another, by specifying which truth-value of a specific output atom is linked with which truth value of a specific input atom. For a multi-agent object information exchange model, see, for example (Nourani 1996).

5.2 Multitier Business Models

From e.g. (Nourani 2012) Presentation Layer o Runs with the address space if one or more web servers. Business Logic layer Runs with the address space of one or more application servers, and a Backend and DataBase layer.

The presentation layer contains components dealing with user interfaces and user interaction. Example a visual JAVA standalone application. A business logic layer contains components that work together to solve business problems. The components can be high -performance engines. Data layer is used by the business logic layer to persist state permanently. Control f the data layer is one or more databases that home the standalone. From an example content processing prototype (Nourani 2007,2013) we can glimpse on the applications for the above section. A basic keyed database view provides the presentation of the model. It is the look The presentation of the model. It is the look of the application. We apply predefined user know functions on the view to present the applications look. The view should be notified when changes to the model.

The business logic updates the state of the model and helps control the flow of the application. With Struts, this is done with an Action class as a thin wrapper to the actual business logic. The model represents the world model for the actual business state of the application. The business objects update the application state. application. The business objects update the Ap. Action Form bean represents the Model state at a session or request level, bean represents the Model state at a session or request level, and not at a persistent level. The JSP file reads information from the om the ActionForm bean using JSP tags. Our design applies the same functions that are presented on the that are the view for specific application to generate a content model for specific applications.

6. Augmented Learning and Knowledge Management

6.1 Augmented learning with smart data

Competitive model planning above selects big data segments spanning infinite data. Possible big data is encoded on model diagrams with nondeterminism minimizing data segment spans. Big Data has a big value, it also takes organizations big effort to manage well and an effective governance discipline can fulfill its purpose. The Big Data Exponentials: Content, Apps: Consumers have been pledging their love for data visualizations for a while now, and data mining with multimedia discovery is the area being explored. Big data is a popular term used to describe the exponential growth and availability of data, both structured and unstructured. More accurate analyses may lead to more confident decision making. And better decisions can mean greater operational efficiencies, cost reductions, and reduced risk. Our novel techniques apply non-deterministic data model diagram filters to span big data spaces. Smart data is big data turned into actionable data that is available in real-time. Smart Data: What Purpose,

Users, Processes, Platform.
Users with data analysis, IT and marketing knowledge, can define processes, enabling processes to take advantage of smart data analytics platforms that can be deployed for the benefits of SmartData : efficiently scalable over many marketing processes. With smart data, we focus on valuable data and often smaller data sets that can be turned into actionable data and effective outcomes to address customer and business challenges. On our decision tree spanning techniques (Nourani and CBS group: Nourani-Ina Lauth-Rassmus Pedersen 2015) a specific cooperating group “wins” to satisfy a goal, the agent group is presenting a model consistent with an intended world model for that goal. The value of big data is only multiplied by good data governance. Our techniques are in part analogical augmented learning applied to model discovery and data management. Eric Klopfer on an MIT press book 2011 describes the largely untapped potential of mobile learning Klopfer argues that the strengths of the mobile platform—its portability, context sensitivity, connectivity, and ubiquity—make it ideal for learning in schools. These games—either participatory (which require interaction with other players) or augmented reality (which augment the real world with virtual information. Our data modeling and discovery techniques apply competitive model diagrams with cooperating learning agents acting on game trees to manage knowledge.

6.2 Competitive Model Learning Heurísticus

The first author had developed free proof tree techniques since projects at TU Berlin, 1994. Free proof trees allow us to carry on Skolemized tress on game tree computing models, for example, that can have unassigned variables. The techniques allow us to carry on predictive model diagrams realized on plans with free proof trees (Nourani 1994-2007). Thus essentially the basic heuristics here are satisfying nodes on agent AND./OR game trees. The general heuristics to accomplish that is a game tree deductive technique based on computing game tree unfoldings projected onto predictive model diagrams. Newer areas are on a volume chapter (Nourani 2018, editor), for example (Nourani-Lauth 2018) on impact competitive decision tree models. The soundness and completeness of these techniques, e,g, heuristics as a computing logic are published since (Nourani 1994) at several events e.g. AISB 1995, and Systems and Cybernetics 2005), (Nourani 2015). In computer science, specifically in algorithms related to pathfinding, a heuristic function is said to be admissible if it never overestimates the cost of reaching the goal, i.e. the cost it estimates to reach the goal is not higher than the lowest possible cost from the current point in the path. [1] An admissible heuristic is also known as an optimistic heuristic.

An admissible heuristic is used to estimate the cost of reaching the goal state in an informed search algorithm. The heuristic nomenclature indicates that a heuristic function is called an admissible- heuristic if it never overestimates the cost of reaching the goal, i.e. the cost it estimates to reach the goal is not higher than the lowest possible cost from the current point in the path. An admissible heuristic is also known as an optimistic heuristic (Russell and Norvig 2002). We shall use the term optimistic heuristic from now on to save ambiguity with admissible sets from mathematics, e.g. first author's publications on descriptive computing, for the time being. What is the cost estimate on satisfying a goal on an unfolding projection to model diagrams, for example with SLNDF, to satisfy a goal? Our heuristics are based on satisfying nondeterministic Skolemized trees. The heuristics aim to decrease the unknown assignments on the trees. Since at least one path on the tree must have all assignments defined to T or F, and at most one such assignment closes the search, the "cost estimate," is no more than the lowest. To become more specific how game tree node degrees can be ranked, we state one example linear measure proposition since (Nourani-Schulte 2015). That was further extrapolated for big data heuristics in (Nourani-Fähndrich 2017). The big Data Sparse Heuristics,e.g (Nourani 2016) ,(Nourani-Fähndrich 2017:TU Berlin) agent state vectors are spanning with models for diagram values that either, true, false, or X- undetermined. The cross product with the model diagram for vectors is a matrix. That matrix is sparse coding to bigdata with the X's sparsing the matrix (Nourani 1992, ScandinviaAI), thus minimizing reaches for bigdata: hence sparse heuristics are entailed.

7. Conclusions

New bases for augmented model decision techniques with splitting decision tree for enterprise modeling and business planning with predictive analytics models were presented. Decision tree applications to analytics towards designing cognitive augmented business interfaces with applications to social media were presented. Augmented reasoning on business systems reflect on the innovation ecosystems. Data filtering is applied with function keyed knowledge bases for goal satisfiability with competitive business models coupled with predictive analytics models accomplish goals on business models. Spanning trees focus on plan goal models that can be processed on a vector state machine coupled with database preprocessor interfaces. Cognitive views and augmented models with heuristics on predictive analytics are developed based on ranked game trees from the first authors preceding publications on economic games and big data towards newer applications to decision tree heuristics. Newer areas on predictive analytics and impact competitive models are on an edited volume (Nourani 2018, editor).

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