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A Predictive Tableaux Visual Analytics with Data Learning Discovery Applications

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A novel sequent visual tableaux analytics computation system with a specific mathematical basis is developed. Applications to designing stock forecasting analytics are examined. Morph Gentzen logic from the authors' 1977 basis is applied towards forecasting analytics. The presents novel model computing techniques with model diagrams for the tableaux with the applications to predictive modeling, forecasting, game tree planning, and predictive analytics support systems.

Introduction

Computing based on Intelligent Forecasting, and Model discovery [5] was studied by this author since [4], [8], [27]. Multiagent business objects and Intelligent Multimedia applications for Management Science and IT were defined. Amongst the areas treared were agent computing, modern portfolios, heterogeneous [32] computing, business objects, intelligent databases, intelligent objects, and decision science. The author presented new views to MIS with agent computing and intelligent multimedia in [9], [26], for example. Interaction amongst heterogeneous computing resources are via objects, multiagent AI [28] and agent intelligent languages. New applications to business with intelligent object languages were presented in brief. Intelligent multimedia and the new Morph Gentzen logic from this author [1] are being applied since as a basis for to forecasting analytics. The paper applies presents novel model computing techniques with model diagrams for the tableaux [18] with the applications to predictive modeling, forecasting, game tree planning, and predictive analytics support systems. New sequent visual tableaux analytics computation system with a specific mathematical basis developed here. Applications to designing stock forecasting analytics that were presented since [4] is outlined.

Plans And Uncertainty

Modeling with agent planning is applied where uncertainty is relegated to agents, where competitive learning on game trees determines a confidence interval. The incomplete knowledge modeling is treated with KR on predictive model diagrams. Model discovery at KB's are with specific techniques defined for trees. Model diagrams allow 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 [15] 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 instantiates a goal. The goal formula states what relevant data is sought. 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.

Prediction and Discovery

Minimal prediction is an artificial intelligence technique defined since the author's model-theoretic planning project. It is a cumulative nonmontonic 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 → {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. 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. 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. Prediction involves constructing hypotheses, where each hypothesis is a set of atomic literals f_i; such that when some particular theory T is augmented with f_i, it entails the set of goal literals G, i.e. $T \cup f_i$ logically implies G, written $f_i \models G$ (Shoenfield 1967). f_i must be a subset of a set of ground atomic predictables A. It addition we must ensure $T \cup f_i$ is consistent. The set of all possible hypotheses is $f = \{f_i\}$. Prediction is minimal when the f_i are the minimal such sets.

Goals and Plans

Practical systems are designed by modeling with information, rules, goals, strategies, and knowledge bases. Patterns, schemas, and viewpoints are the 'micros' to aggregate information onto the data and knowledge bases, where masses of data and their relationships and representations are stored respectively. Forward chaining is a goal satisfaction technique where inference rules are activated by data patterns, to sequentially get to a goal by applying the inference rules. The current pertinent rules are available at an 'agenda' store. 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. The new AI agent computing business bases defined during the last several years can be applied to present precise decision strategies on multiplayer games [11], [12], [14], [27]. The game trees are applied to improve models. The computing model is based on a novel competitive learning with agent multiplayer game tree planning. Minimal prediction is a cumulative nonmontonic approximation attained with completing model diagrams.

The Stock Traders Interface Predictive Computing Model

The basis for forecasting is put forth at preliminary stages in the author's publications since 1998. The idea is to apply Morph-Gentzen logic as a basis for intelligent multimedia forecasting. The figure indicates a graphics sequent for predicting the fourth quarter earnings from the second and third combined with a market condition graph. The way a market condition graph is designed is a propriety issue. It is obtained by Morph Gentzen sequents from known stock market parameters. The enclosed are example stock trading and forecasting interfaces, cf. [4], [10]

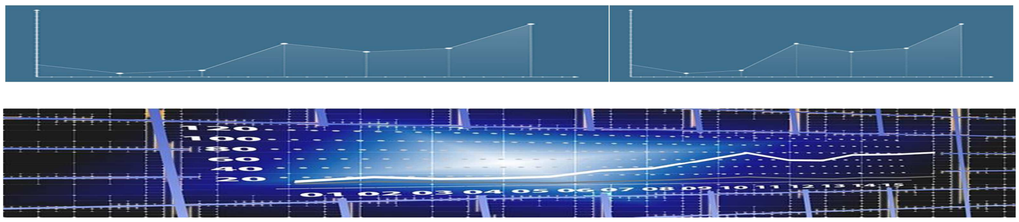

Figure 1. *Stock Forecasting.*

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.

A scheme might be Intelligent Forecasting { IS-A Stock Forecasting Technique} Portfolios

Stock, bonds, corporate assets Member Management Science Techniques.

The above scheme with the basic logical rules, can form a basic theory T to reason about a stock forecasting technique. To do predictive analysis we add hypotheses, for example, the atomic literals based on the following:

p1. Asset (Stocks); p2. Stock (x) => Asset (x) p3. S&P100 (x) => Stock (x). From the definitions 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 → {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. The predictive diagram for T is constructed starting with p1 =True, p2(f) = true for f ranging over stock symbols, p3 is true for all x=f, where f is a stock symbols in S&P100.

A Visual Computing Logic and Learning

A problem-solving paradigm was presented for the author's visualization techniques entitled Double Vision Computing [23]. Agents at each world compliment one with object co-object pairs: Problem solving is carried on boards by cooperating agents from the pairs. The IM Hybrid Multimedia Programming techniques have a computing logic is mathematical logic where a new morph Gentzen resembling a visual natural deduction systems is defined by taking multimedia objects coded by diagram functions. By transforming hybrid picture's corresponding functions a new hybrid picture is deduced. Multimedia objects are viewed as syntactic objects defined by functions, to which the deductive system is applied. The formal AI and mathematics appear in the first author's mathematical logic publications since 1997 and applied to business areas. The intelligent syntax languages are applied with Morph Gentzen is presented in brief with a soundness and completeness theorem in [3] from the author's 1994 and applied to intelligent business object computing. Learning the relationships amongst visual stored data is another important area, which can benefit from our project. Most existing learning algorithms [21] detect only correlations, but are unable to model causality and hence fail to predict the effect of external controls. Visualization and interactive discovery [8] data mining is a process which involves automated data analysis and control decisions by an expert of the domain. For example, patterns in many large-scale business system databases might be discovered interactively, by a human expert looking at the data, as it is done with medical data e.g. leaning and data bases [24], [25]. The techniques have been applied to design intelligent business objects, c.f. [4], [6], for example. AII techniques have been applied to Heterogeneous [32] KB Design and implementation. The application areas include support for highly responsive planning. The applied fields are, for example, intelligent business systems, aerospace, AI for robots, and multimedia.

Visual Model Discovery

Model diagrams allow us to 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 [3, 4] 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 instantiates a goal. The goal formula states what relevant data is sought. Model diagrams allow us to model-theoretically characterize incomplete Knowledge Representation. 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 Active Intelligent Database designs outline is presented in TAIM [29]. 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. Let us see what predictive diagrams do for knowledge discovery knowledge management. Generalized predictive diagrams are defined, whereby specified diagram functions and 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 [20]. Visual object views to active databases might be designed with the above, cf. [13], [16].

Data Filtering on Keyed Functions

Let us see what predictive diagrams do for knowledge discovery knowledge management. Diagrams allow us to model-theoretically characterize incomplete KR. To 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. From Nourani [14] example

Schema: A Stock Forecasting Technique Portfolios Stock, bonds, corporate assets Member Management Science Techniques

Schemas [32] 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 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. IM's basis for forecasting is put forth at preliminary stages in (Nourani. The Morph-Gentzen logic with predictive model diagrams has been applied as a basis for intelligent forecasting Nourani [4], [14]. There are graphics sequents for predicting the quarter earnings from the second and third combined with a market condition graph. The way a market condition graph is designed is a propriety issue. It is obtained by Morph Gentzen sequents from known stock market parameters. Data discovery from KR on diagrams might be viewed as satisfying a goal by getting at relevant data which instantiates a goal.

Morph Gentzen

The IM Morphed Computing Logic Logics for computing for multimedia are new projects with important computing applications since [1] and [20]. The basic principles are a mathematical logic where a Gentzen [2] or natural deduction systems [30] is defined by taking arbitrary structures coded by diagram functions. The techniques can be applied to arbitrary topological structures. Thus we define a syntactic morphing to be a technique by which infinitary definable structures are homomorphically mapped via their defining functions to new structures. The deduction rules are a Gentzen system augmented by two rules Morphing, and Trans-morphing. The Morph Rule - A structure defined by the functional n-tuple <f1,..., fn> can be Morphed to a structures definable by the functional n-tuple <h(f1),..., h(fn)>, provided h is a homomrphism of abstract signature structures [1],[26]. The Trans Morph Rules- A set of rules whereby combining structures A1,..., An defines an Event {A1, A2,..., An} with a consequent structure B. Thus the combination is an impetus event. The deductive theory is a Gentzen system in which structures named by parameterized functions; augmented by the morph and trans-morph rules. The structures we apply the Morph logic to are definable by positive diagrams. The idea is to do it at abstract models syntax trees without specifics for the shapes and topologies applied.

Theorem 1 Soundness and Completeness- Morphed Gentzen Logic is sound and complete.

Proof (c.f. Nourani [26]) outline Plain Morph Gentzen Logical Completeness has two proofs: A-There is a direct proof which applies positive diagrams, and canonical models for the infinitary language $L_{\omega1,\omega}$ fragments as the authors' papers in mathematical logic. B- There is a conventional proof route whereby we start with the completenss theorem for ordinary Gentzen systems. Form it we can add on the morph rules and carryout a proof based on what the morph rules preserve on models. Again intricate models are designed with positive diagrams.

Virtual Tree Plan Sequent Models

Canonical Models from models to set theory had been stated for arbitrary structures as follows. Generic diagrams, denoted by G-diagrams, were what the first author had defined over a decade ago 1980's to be diagrams for models defined by a specific function set, for example Σ_1 Skolem functions. The idea is that if the free proof tree is constructed for a goal formula, the G-diagram defines a model satisfying the goal formula satisfied.

Theorem 2 For the virtual proof trees defined for a goal formula from the G-diagram there is an initial model satisfying the goal formulas. It is the initial model definable by the G-diagram.

Proof (e.g. Nourani [26]).

Partial deductions, e.g. [31] in the present approach correspond to proof trees that have free Skolemized trees in their representation [32]. The free proof tree technique, as we shall further define, leaves could be virtual, where virtual leaves are free Skolemized trees. The model is the initial model of the AI world for which the free Skolemized trees were constructed. For plans with free Skolmized trees we can apply the Hilbert epsilon technique to define computing models We have planning applications with VR in which there is goal formula to be satisfied with perhaps existential quantifiers. Since we are interested in model theoretic techniques for handling proofs with the method of free proof trees we propose the following model-theoretic view, which we refer to by the Hilbert Model Theorem for Skolemized virtual tree computing.

Theorem 3 The Hilbert's epsilon technique implies there is a model M for the set of formulas such that we can take an existentially quantified formula w[X] and have it instantiated by a Skolem function which can answer the satisfiability question for the model.

Proof (Nourani [26]).

A Preface to Sequent Analytic Tableaux

The project is towards a new analytics based on Tableaux [23] computable Morph Gentzen sequent proofs. In the papers diagrams for cognitive modeling is applied and scientific techniques applied towards a discovery science, e.g., this author's [4]. Morph Gentzen comes close to human experience in attaining proofs. At the base of its empirical intuition lies a pure intuition which is a priori. Frege's basic logical ideas and Hilbert's program separate carrying out pure mathematics from the physical cognition perceptions of what is carried out as an end. Frege's "concept and object" and on "sense and meaning," is where carrying out logic for objects named by a language had started being distinguished from the object sense perception. Hilbert's program, aside from its being left to reconcile with Kant's transcendental idealism on concepts, were to arithmatize the entire mathematics. Hence there is a systematic basis to carryout concept-object descriptions for machine discovery.

Proposition A structure models a morph sequent iff (a) the structure models the intial antecedent to the sequent and (b) the sequent is explicitly definable by $\Phi\{P1,..., Pn\}$, where $\Phi\{P1,..., Pn\}$ is the set if sentences of the language $L \cup \{P1,..., Pn\}$; and P1,..., Pn are n- placed relation symbols for relations defining the Skolem functions available on the structure, applied by the sequent.

Theorem 4 A set of formula Λ's validity is preserved by an arbitrary morph sequent with functions appearing in Λ iff Λ is provable on a the tableaux for the respective language.

Proof Applies the proposition and theorem 1-3.

Conclusion: Example Forecasting Analytics

Let us probe an application with the value (example developed in the preceding sections. The predictive diagram for T is constucted starting with p1 =True, p2(f) = true for f ranging over stock symbols, p3 is true for all x=f, where f is a stock symbols in S&P100. To predict if the stock f is due to icrease in value might be infered with a predictive diagram that includes hypothes p3 on the stock symbol and that the average value of S&P100 is due to increase based on the stocks on the specific sector. For example, a predicate p4 that stock symol f1 is in Sector S1 and the sector S1 is due an increase. New hypothesis: p4. stock (f1) => S1(f) p5. S1(x); An observation $g \in \wedge$ is reconcilable if there exits ground hypotheses $\Re \subseteq W$ such that: => 25% increase average value (x). Thus T U p5 $\models$ increase value (f), i.e. the stock symbol f is predicted to appreciate. Example forecasting theory T based on the above is as follows. Defaults W: possible hypotheses, that we accept as part of a forecast and observations $\wedge$ which are to be reconciled. 1. T U $\Re \models$ g and 2. T U $\Re$ Is consistent. The author's publications [23] have proved that a set of first order observations $\wedge$ are reconcilable with the model iff there exists a predictive diagram for the logical consequences to $\wedge$. ■

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