

Hybrid Intelligent Suite for Decision Support



State University of Pernambuco – Recife (Brazil)

Fernando B. de L. Neto
Flávio R. da S. Oliveira
Diogo F. Pacheco

Agenda

- I. Motivation & Problem
- II. Decision Support Systems
- III. Intelligent Techniques Utilized
- IV. Hybrid Intelligent Decision Suite (HIDS)
- V. Simulation & Results
 - a) *Applying HIDS to automobile evaluation*
 - b) *Applying HIDS to cardiologic diagnosis*
- VI. Conclusion



Part I

Motivation & Problem



Decision Making

- Decision making in dynamic environments is usually a difficult task because of:
 - Time variability
 - Non-availability of all necessary data
 - Conflicting interests (e.g. economical vs. technical)



Decision viewed as a Search

- A Decision Making process can be understood as a selection process, taken by the decision maker, which maximizes (or minimizes) a function over time.



The role of Artificial Intelligence

- AI techniques are known because of their ability to perform better in cases where regular techniques fail.
- AI techniques therefore can be employed to assist decision makers in tasks such as:
 - forecasting of future scenarios
 - searching for acceptable results
 - finding conditioning factors



Objectives

1. To propose a new kind of Decision Support System (DSS) which profits heavily on AI techniques to forecasting and searching in complex domains.
2. To test this concept in two distinct decision problems:
 - a) Diagnosis of cardiologic diseases
 - b) Automobile feature selection



Part II

Decision Support Systems (DSS)

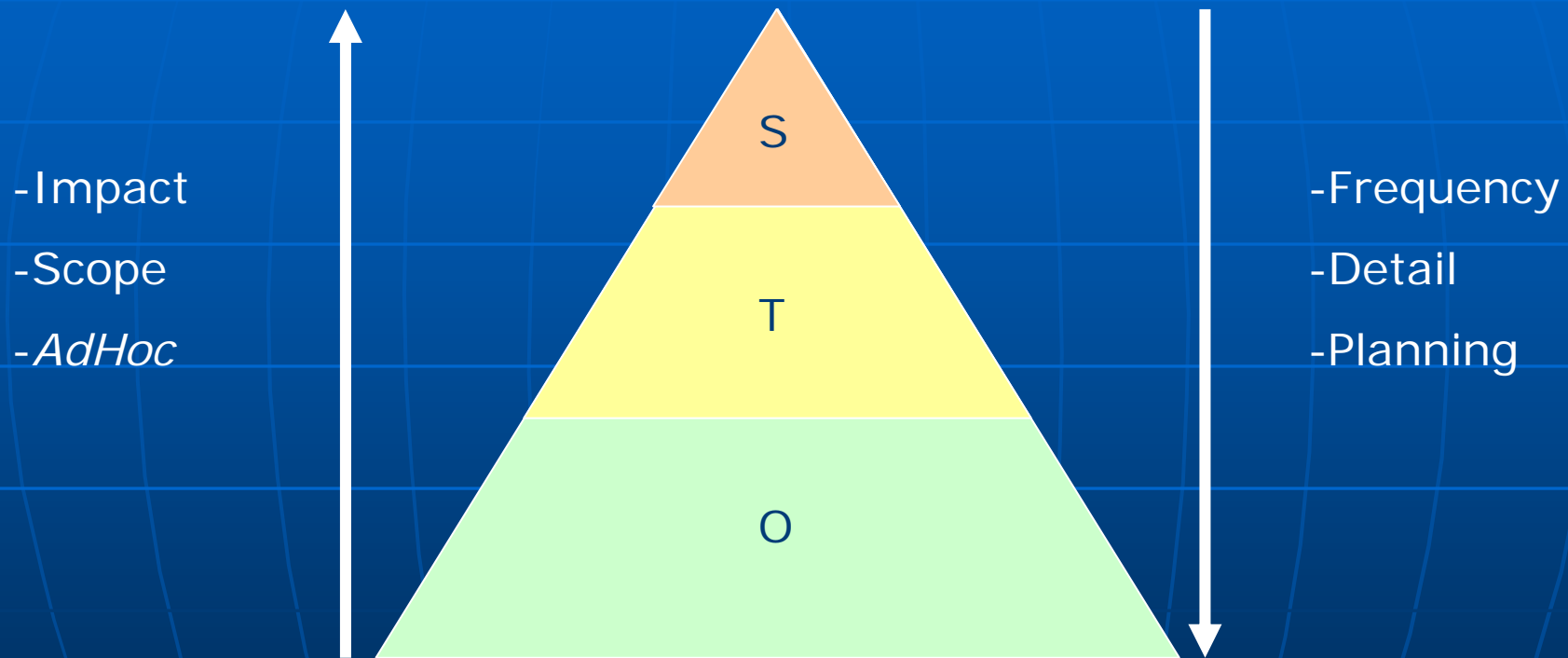


Definition

- A DSS is a particular type of information system, generally computer aided, mainly used to tackle semi-structured decision problems.



Information Systems and DSS



Information Systems Hierarchy

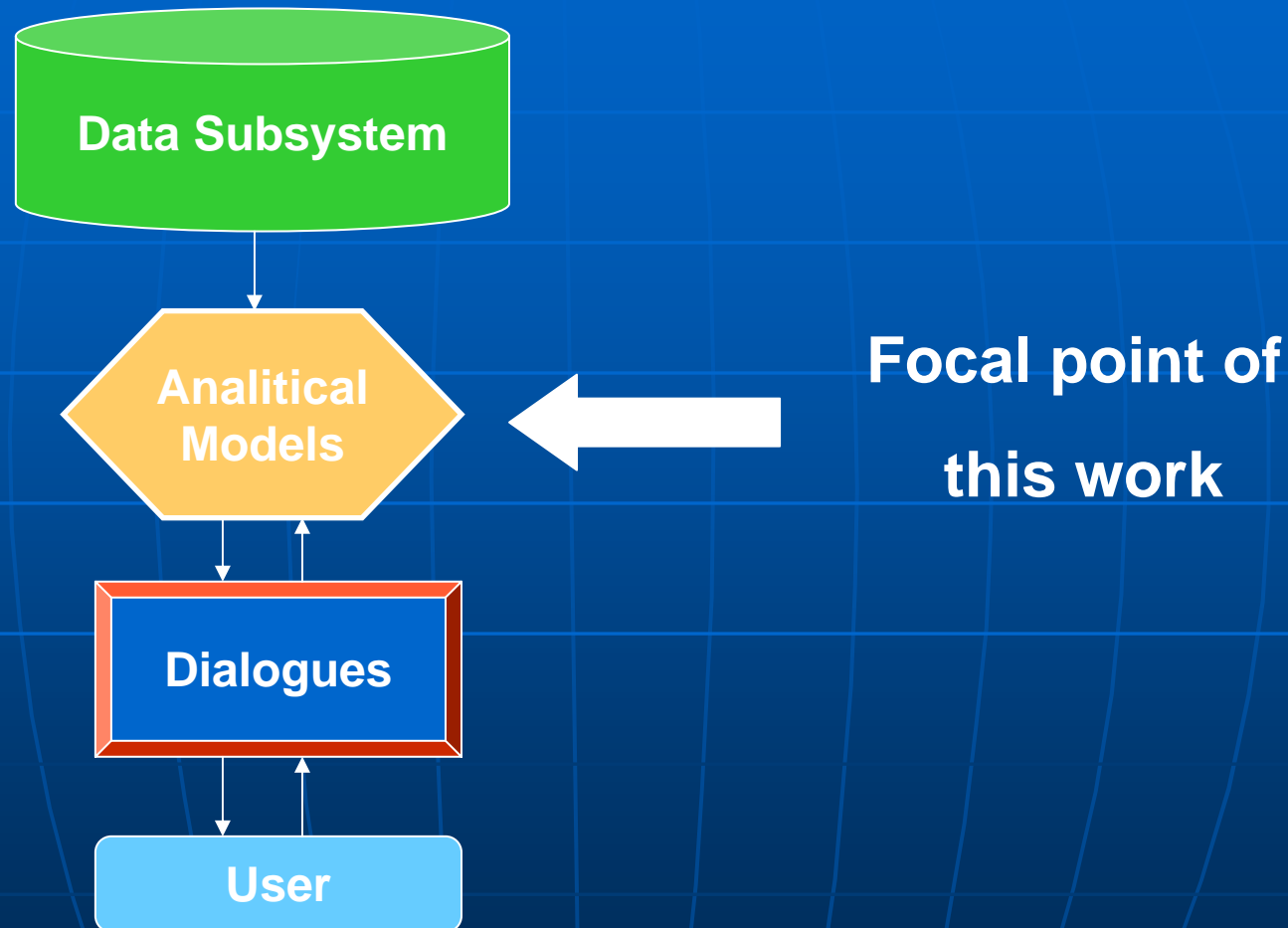


DSS characteristics

- Combine analytical capabilities with intellectual assets of user.
- Generally used on mid-managerial level
- Users can select amongst possible scenarios via decision dialogues
- DSS should be friendly, fast and flexible



Components of a classical DSS



DSS Components



Part III

Intelligent Techniques Utilized



Part III

Intelligent Techniques Utilized

Artificial Neural Networks (ANN)



ISDA'2007 – Rio de Janeiro – Brazil

© Fernando Buarque – fbln@dsc.upe.br

ANN characteristics

- Connexionist model
- Profit from parallelism
- Learn from example
- Can generalize to tackle unknown situations

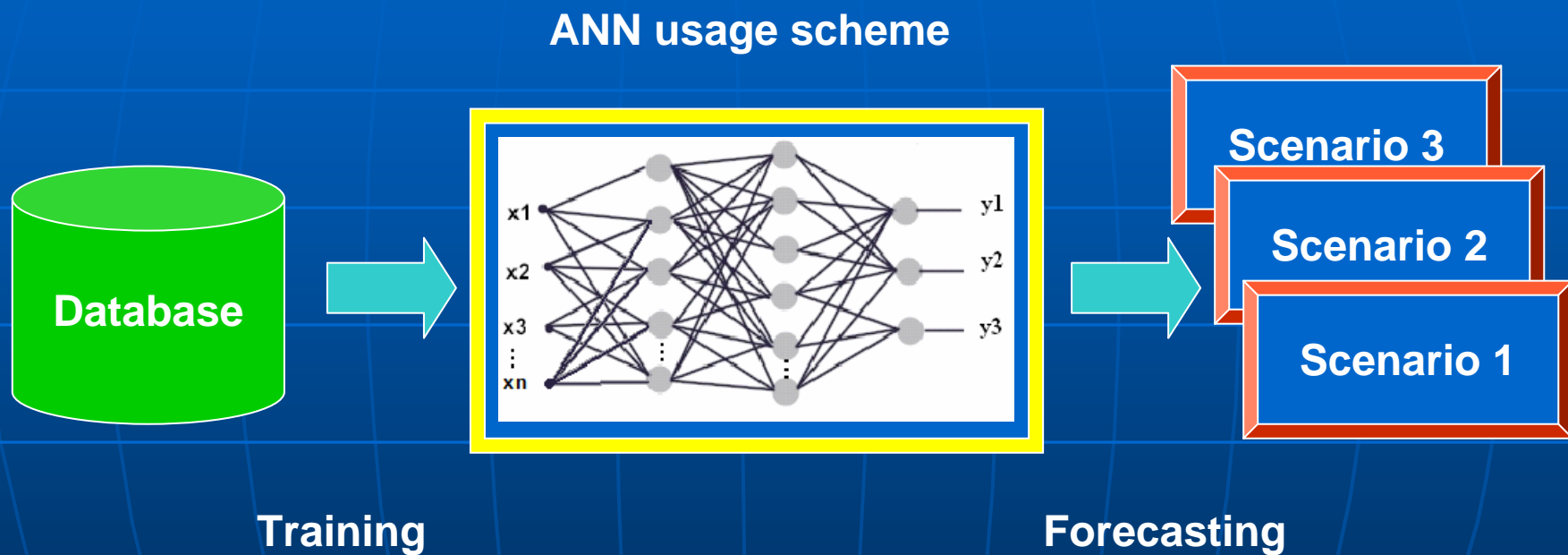


Where ANNs excel

- Used with great efficiency in classification, function approximation and forecasting problems.
- Their predictive ability is highly desirable for forecasting future values for decision scenarios.



Usage of an ANN



Part III

Intelligent Techniques Utilized

Fuzzy Logic (FL)



FL characteristics

- Extension from Aristotelian Logic to deal with uncertainty.
- Uses degrees of membership instead of pertinence operator (e.g. yes – maybe – no vs. yes – no)
- Creates a more realistic description of real world data, offering a better bridging for human-computer interaction.



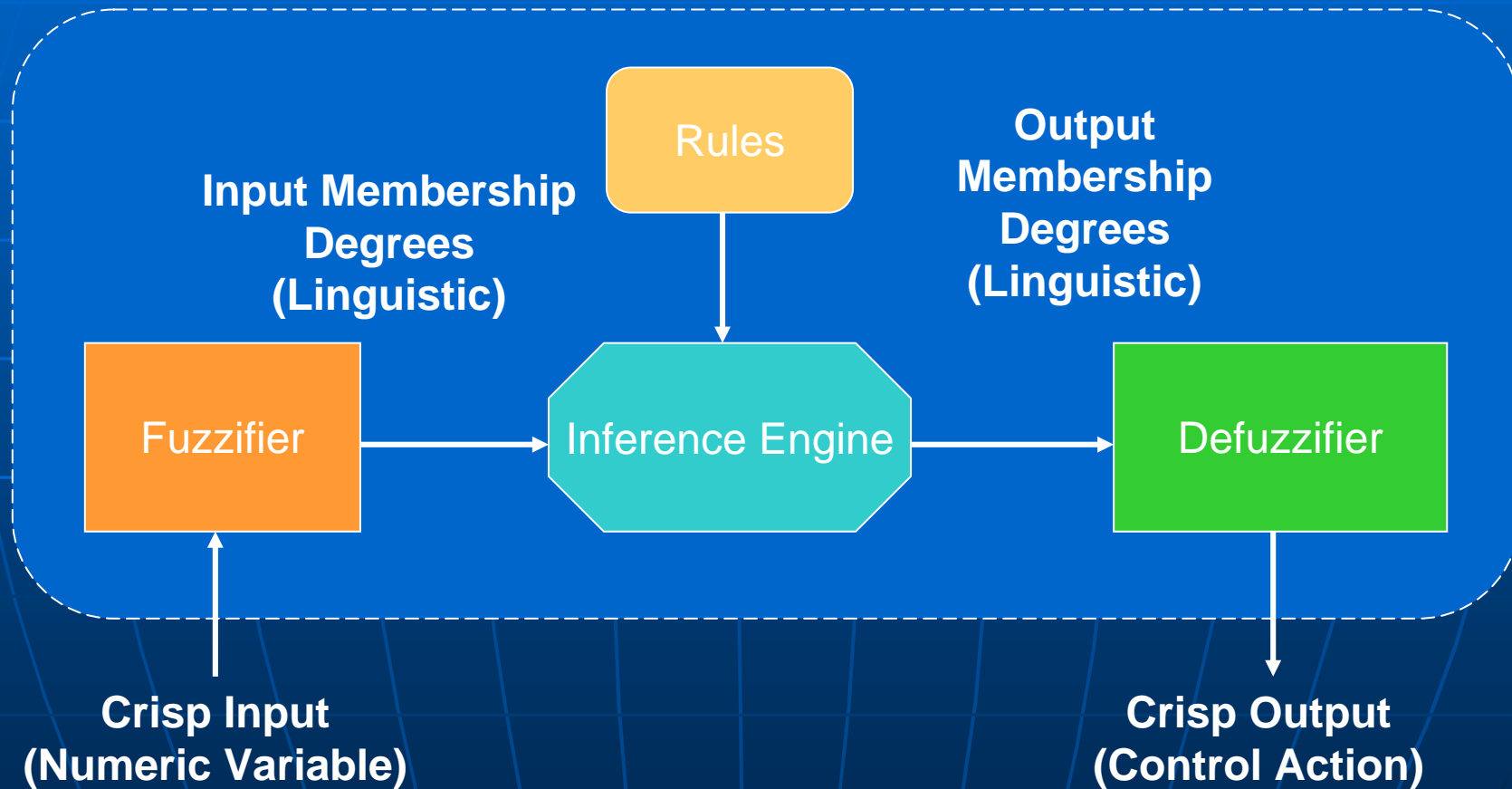
FL Controller operation

- For a given Input Variable (Numeric):
 - 1) Inputs are evaluated according to input membership functions.
 - 2) Membership degrees are evaluated according to rules in 'if-then-else' format
 - 3) Output membership degrees are calculated to define an output crisp value (Control action)



Fuzzy Logic Controller

Scheme of a Fuzzy Logic Controller



Part IV

Hybrid Intelligent Decision Suite (HIDS)



Part IV

Hybrid Intelligent Decision Suite (HIDS)

"An Abstract Model for Decision Making"

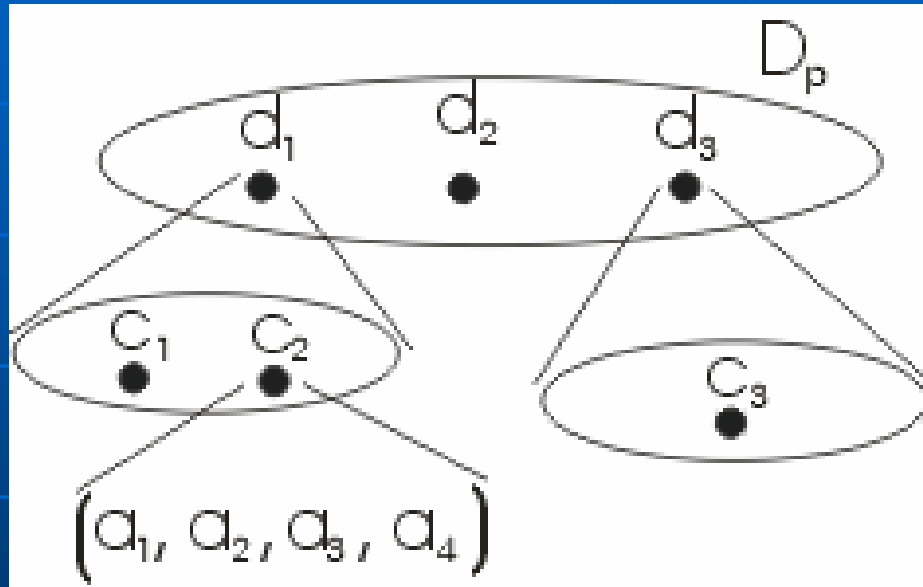


Abstract Model for Decision Making

- Given a decision maker m_k , a decision problem p_k and a sought decision d_k component of decision space D_p .
- Lets assume that each decision is composed of components c_j , so that $d_k = \{c_1, c_2, \dots, c_n\}$,
- Lets assume that each component is composed of attributes a_i , so that $c_j = (a_1, a_2, \dots, a_n)$
- Note that attributes can be either quantitative or qualitative



Decision Space Hierarchy



-Decisions

-Components

-Attributes



Forecasting attributes

- Some attributes can be drawn from a special function used as a predictive element:

$$\Phi(I, A) = (a'_1, a'_2, \dots, a'_n)$$

Predictive Function

- This function maps attributes and inputs into a new set of attributes, after a behavior forecasting.



Contribution from Decision Maker

- Priorities of each decision component
 - $W = \{w_1, w_2, \dots, w_n\}$
- Validity criteria
 - $V = \{v_1, v_2, \dots, v_n\}$
- *ad hoc* metrics for evaluating the attributes of components of a decision
 - $f_i(a_i)$



Relevance of a Component

- Based on vector W and evaluation functions $f_i(a_i)$, it is possible to evaluate the relevance of each component c_j of the decision d_k :

$$R(c_j) = \frac{\sum_{i=0}^n w_i * f_i(a_i)}{\sum_{i=0}^n w_i}$$

Relevance of Component C_j



Evaluating a Decision

- The overall evaluation of each decision is given by function $F(d_k)$, which is the summation of all individually calculated relevance components of a single decision

$$F(d_k) = \sum_{j=0}^n R(C_j)$$

Decision Evaluation Function



Part IV

Hybrid Intelligent Decision Suite (HIDS)

Dealing with The Inverse Problem



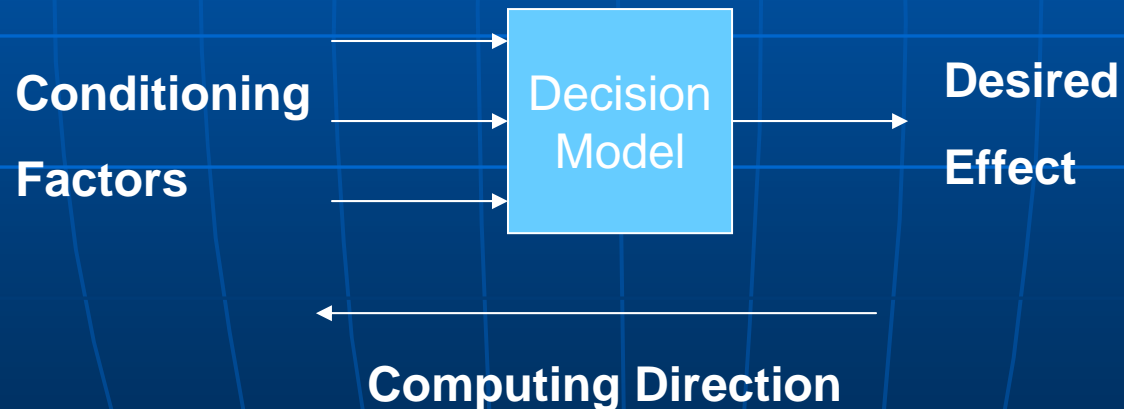
Decisions

- A decision can be seen as a search problem where the decision maker knows the desired outcome and would greatly benefit from knowing its conditioning factors.



The Inverse Problem

- The Inverse Problem can be described as a task where parameters of some model must be obtained from a previously known result or effect.

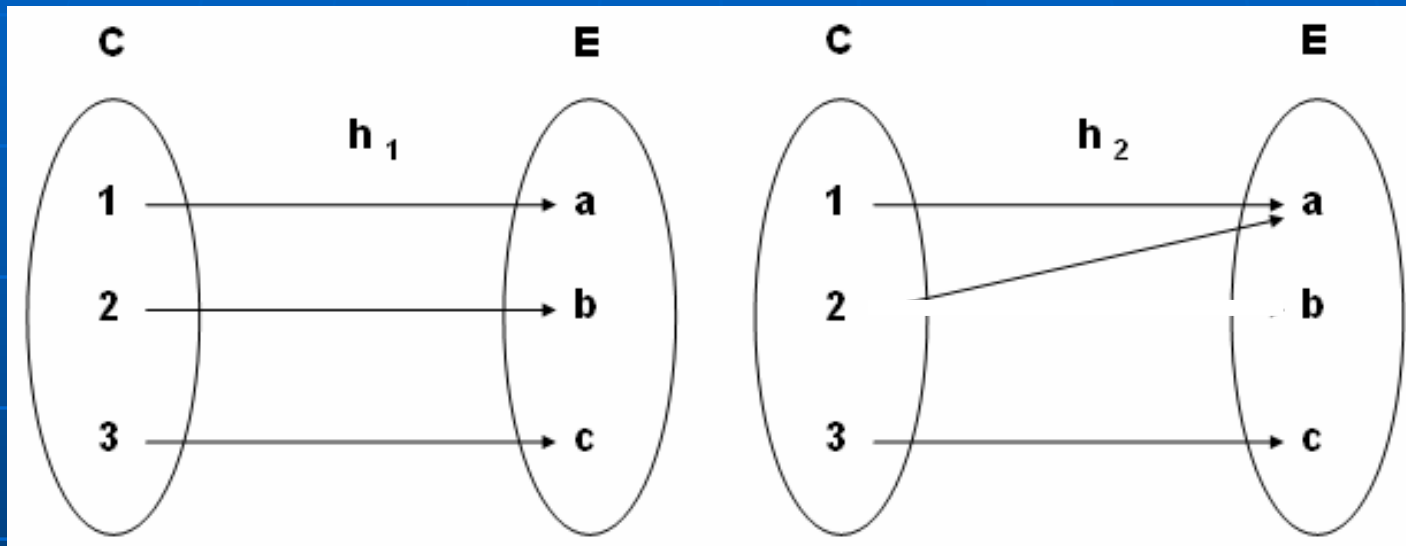


Scheme of inverse computing direction



Considering real problems

Mapping from Conditionings (C) to Effects (E)



- In most decision situations, the functions are non-linear and with many parameters. This makes the Inverse Problem extremely hard to be dealt directly.



HIDS Overview

- In previous works, prediction and search were treated separately.
- In our approach, there are two main elements:
 - Factors: Aspects which may cause relevant impact over a decision.
 - Indicators: ways to check how good or bad the results of a decision were.

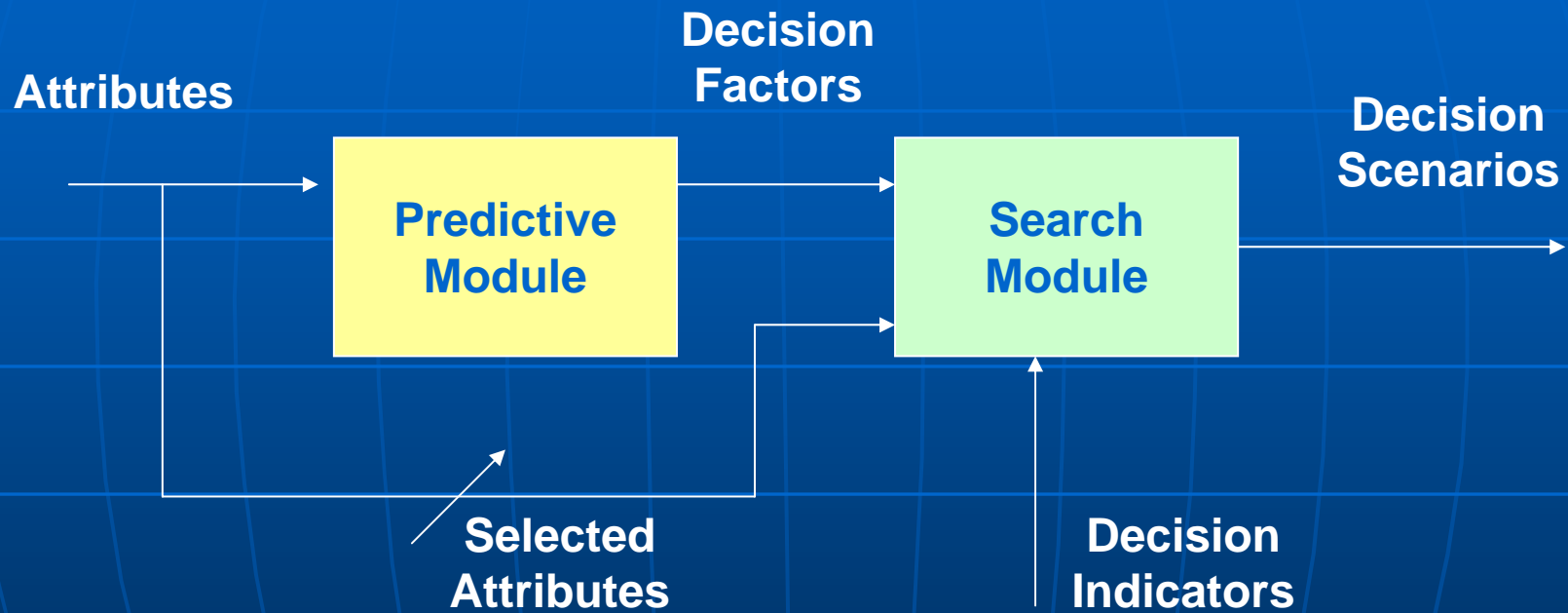


HIDS Rationale

- There are at least two modules in HIDS:
 - Predictive module
 - Search module
- This framework allows for different AI techniques to be used in both constituent modules, combining their abilities to elegantly bypassing the Inverse Problem.



HIDS Schematic view



Hybrid Intelligent Decision Suite scheme – a decision treated as a hole (forecasting and search)



HIDS Processing steps

1. Forecasting of components attributes
2. Define Decision Indicators (Validity criteria and weight vector)
3. Search amongst possible decisions
4. Collection of best scenarios
5. Decision maker evaluation of scenarios
6. Finish or re-start from step 2



Part V

Simulation & Results



Part V

Simulation & Results

Applying HIDS to automobile evaluation



Problem-1 Overview

- The primary objective was to offer valuable information to a project manager about the impact of car setup in relation to their final price
- Based on information available it was possible to offer some input such as (car) model number of doors, engine size, fuel type and a desired maximum prototype value.



Problem-2 Overview

- HIDS is then capable of locating suitable values for remaining parameters trying to match (approximate) the maximum desired price.
- The decision scenarios here are cars with different features which are categorized according to production manager preferences.



UCI Machine Learning Repository

- Training patterns for ANN contained information about:
 - Inputs = { Aspiration, Body Style, Bore, City Mpg, Compression Ratio, Curb Weight, Drive Wheels, Engine Location, Engine Size, Engine Type, Fuel System, Fuel Type, Highway Mpg, Horse Power, Length, Num Cylinders, Num Doors, Peak Rpm, Stroke }
 - Output = { Price }



Automobile Price

- Predictive function Φ maps car features into selling prices:
 - in this database, price is a continuous variable that ranges from 5118 to 45400



Evaluation Functions

- To evaluate decision indicators, three functions were defined: city mpg – mpg , horse power – hp and peak rpm – pr . According to experiment requirements, decision scenarios should maximize mpg and hp , while minimizing pr

$$f_{mpg}(mpg_i) = 1 - (mpg_{max} - mpg_{final})$$

$$f_{hp}(hp_i) = 1 - (hp_{max} - hp_{final})$$

$$f_{pr}(pr_i) = 1 - (pr_{final} - pr_{min})$$



Decision maker informs

- Weight vector:

- $W = \{ W_{\text{mpg}}, W_{\text{hp}}, W_{\text{pr}} \}$

- Validity Criteria:

- $V = \{ \textit{Minimum hp, Maximum hp, Minimum mpg, Maximum mpg, Minimum pr, Maximum pr} \}$



Decision Evaluation

- Relevance of a component

$$R(C_j) = \frac{f_{mpg}(mpg_i) * w_{mpg} + f_{hp}(hp_i) * w_{hp} + f_{pr}(pr_i) * w_{pr}}{w_{mpg} + w_{hp} + w_{pr}}$$

- Evaluation of a decision

$$F(d_k) = \frac{1}{R(C_j)}$$



Experiment setup

- Configuration used for all 2 models:

- $W = \{ W_{\text{mpg}} = 1, W_{\text{hp}} = 1, W_{\text{pr}} = 1 \}$

- $V = \{ \textit{Minimum mpg} = 13, \textit{Minimum hp} = 48, \textit{Minimum pr} = 4150, \textit{Maximum mpg} = 49, \textit{Maximum hp} = 228, \textit{Maximum pr} = 4150 \}$



Experiment attributes

Attributes of evaluated automobiles

Car	Price	mpg	hp	pr
1	13545.32	20.00	140.00	5000.00
2	19225.41	15.00	180.00	4500.00



Experiment setup

- A decision objective was proposed for each experiment:
 - car 1 should have its price reduced to 12500.00
 - car 2 should reach a price of 18000.00



Results

Best decision scenarios obtained for each automobile

Car	Desired Price	Calculated Price	mpg	hp	pr
1	12500.00	12497.09	27.61	140.00	5000.00
1	12500.00	12500.81	20.00	134.00	5000.00
1	12500.00	12502.81	20.00	140.00	4373.91
2	18000.00	18000.08	26.10	180.00	4500.00
2	18000.00	19214.57	15.00	180.00	4152.91
2	18000.00	18422.00	15.00	90.00	4500.00



Problem-1 discussion

- For car 1, changes in *mpg*, *hp* and *pr* were equally effective in reducing price. However, reducing *hp* from 140 to 134, was enough to reach 12500.00 mark.
- For car 2, it was necessary a significant improvement in *mpg*, while other attributes had a poor impact in reducing price. Possibly, car 2 already had a considerably low price for its category.



Part V

Simulation & Results

Applying HIDS to cardiologic diagnosis



Problem-2 Overview

- HIDS was used to create a DSS employed to assist medics on how to reduce patients cardiac risk levels.
- The predictive modules uses an ANN to classify patients within five risk levels
- The search module uses an FL controller to generate scenarios, manipulating ANN inputs.
- The objective is to find the most suitable way to reduce a patient risk level.



Proben-1 Database

- Training patterns for ANN contained information about:
 - Inputs = {age, sex, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, maximum heart rate achieved}
 - Output = {atts. diagnosis of heart disease}



Patient Risk Level

- Predictive Function Φ maps patient information into risk levels:

(0) healthy

(1) To (4) Increasingly sick



Evaluation Functions

- Three functions were defined to evaluate the decision indicators: chest pain type – cpt , serum cholesterol – sc and maximum heart rate – mhr

$$f_{cpt}(cpt_i) = cpt_{final} - cpt_{initial}$$

$$f_{sc}(sc_i) = sc_{final} - sc_{initial}$$

$$f_{mhr}(mhr_i) = mhr_{final} - mhr_{initial}$$



Decision maker inputs

- Validity Criteria

- $V = \{ \textit{Minimum cpt}, \textit{Minimum sc}, \textit{Maximum mhr} \}$

- Weight Vector

- $W = \{ W_{cpt} , W_{sc} , W_{mhr} \}$



Decision Evaluation

- Component Relevance

$$R(C_j) = \frac{f_{cpt}(cpt_i) * w_{cpt} + f_{sc}(sc_i) * w_{sc} + f_{mhr}(mhr_i) * w_{mhr}}{w_{cpt} + w_{sc} + w_{mhr}}$$

- Decision Evaluation

$$F(d_k) = \frac{1}{R(C_j)}$$



Experiment setup

- Configuration used for all 3 patients:

- $W = \{w_{cpt} = 8, w_{sc} = 5, w_{mhr} = 5\}$

- $V = \{ \textit{Minimum cpt} = \textit{No pain}, \textit{Minimum sc} = 0.2, \textit{Maximum mhr} = 0.8 \}$



Experiment attributes

Attributes used for each patient subject to cardiologic diagnosis

Patient	Risk Level	<i>cpt</i>	<i>sc</i>	<i>mhr</i>
1	0.6371	Asymptomatic	0.4166	0.4666
2	0.7122	Asymptomatic	0.2916	0.1466
3	0.8095	Asymptomatic	0.7000	0.2000



Results

Best decision scenarios obtained for each patient

Patient	Risk Level	<i>cpt</i>	<i>sc</i>	<i>mhr</i>
1	0.5535	Asymptomatic	0.4166	0.775
1	0.5983	Asymptomatic	0.2030	0.4666
1	0.2567	No pain	0.4166	0.4666
2	0.5266	Asymptomatic	0.2916	0.7740
2	0.7048	Asymptomatic	0.2090	0.1466
2	0.4600	No pain	0.2916	0.1466
3	0.7637	Asymptomatic	0.700	0.7966
3	0.7777	Asymptomatic	0.2021	0.2000
3	0.6751	No pain	0.7000	0.2000



Problem-2 discussion

- After evaluating the different approaches of treatment, in accordance to patient medical records and respecting previous experiences from the medic staff, it was possible to prioritize procedures and help doctors to make more informed decisions.
- If the best solution for the problem is not found, it is still possible to change some parameters and carry out new simulations very easily.



Part VI

Conclusion



Contributions

- This work presents a new iDSS, the Hybrid Intelligent Decision Suite that:
 - Offers a guided search in the decision space that explores suitable actions in inferred scenarios
 - Inference and search are carried out according to criteria informed by decision maker
- Results suggest that HIDS could be used to assemble useful tools for decision makers



References

1. E. Turban. Decision Support Systems and Expert Systems, 4th. Edition, Prentice-Hall International Editions. New Jersey, USA, 1995.
2. R. Sprague Jr. and H.J. Watson. Decision Support for Management. Prentice-Hall International Editions. New Jersey, USA, 1996.
3. S. Russel and P. Norvig. Artificial Intelligence: A Modern Approach. (2nd ed.) Prentice-Hall Editions. New Jersey, USA, 1995.
4. S. Haykin. Neural Networks – A Comprehensive Foundation. Prentice-Hall International Editions. New Jersey, USA, 1994.
5. F.R.S. Oliveira, D.F. Pacheco, A. Leonel and F.B. Lima Neto, "Intelligent Support Decision in Sugarcane Harvest", Proceedings of IV World Congress on Computers in Agriculture WCCA2006, pp. 456-462, Orlando - USA, 2006.
6. S.S. Madeiro, F.R.S. Oliveira, F.B.A. Alexandre and F.B. Lima Neto, "Intelligent Modeling of Sugar-Cane Maturation", Proceedings of IV World Congress on Computers in Agriculture WCCA2006, pp. 642-648, Orlando - USA, 2006.
7. L. Prechelt. PROBEN1 - A Set of Benchmarks and Benchmarking Rules for Neural Network Training Algorithms. Technical Report 21/94, 38 pages, Fakultät für Informatik, Universität Karlsruhe, Germany, 1994.
8. D.J. Newman, S. Hettich, C.L. Blake and C.J. Merz. UCI Repository of machine learning databases, University of California, Irvine, Dept. of Information and Computer Sciences. USA, 1998.
9. UCI Machine Learning Repository Internet address:
<http://www.ics.uci.edu/~mlern/MLRepository.html>



Future work

- The present version of HIDS may be improved by addition of modules for:
 - automatic evaluation of attribute impact for achieving good decisions
 - learning suitable values for weight vectors (via EMO) and validity criteria
 - intelligent interaction with decision maker
 - further means to consider consequences of past decision in relation to new ones



Thank you !

Fernando Buarque

<http://www.fbIn.pro.br>

fbIn@dsc.upe.br



ISDA'2007 – Rio de Janeiro – Brazil

© Fernando Buarque – fbIn@dsc.upe.br