Explanation Provision for Decision Aiding in Intelligent Systems

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Abstract

In this paper a relationship between the concepts of "explanation" and "decision", in the context of decision aiding offered by intelligent systems, is discussed. In an example task studied, namely, the use of statistical tests, it is apparent that there is a number of highly critical areas, where the user or learner comes to a decision point or points in the task he is performing or learning how to perform. Some sort of decision support could be used to enable these choices to be made in an informed way. It could offer "intelligent" aid, offering the choices, and recommending solutions, while still leaving the actual decision-making in the hands of the user. The intelligence of the decision aiding architecture presented here, is in providing advice or recommendation that, if asked for by the user, can be backed up by a justification of the reasoning leading to that recommendation. Thus explanation here is taken as the justification of the particular advice given at a decision point.

1. Introduction

Within the context of decision aiding offered by intelligent systems, the theme of this paper is the investigation of operational design aspects, of the relationship between the concepts of "explanation" and "decision". It is assumed that a system whose primary objective is to aid decisions, and not necessarily take them, will actually fulfil its purpose more robustly if it is also able to explain or justify to the person it is helping the reasoning behind its advice.

This paper follows from a previous one on decision support systems [2], where the Fuzzified Task Knowledge Structures formalism was used to represent domain knowledge, and test score semantics [8] to reason for and recommend the most appropriate decisions.

Here, the knowledge components of decision subsystems are considered as parts of an overall intelligent system, such as Expert Systems, Knowledge Based Systems, Intelligent Tutoring Systems. The subsystems have as main aim to intelligently aid decision processes. The problem environment addressed by these intelligent systems within which the need for such a decision aiding process occurs is assumed to be a human activity one, hence an environment where the problem situations are ill-defined, and/or uncertain. Furthermore, since these decision systems are functional, the situations under consideration are task oriented. The actual decision process required to tackle these situations is also viewed as a task.

The formalism of Task Knowledge Structures (TKS) [4,5] has been adopted and extended with the use of Fuzzy Sets [1,9,10], in order to model the knowledge necessary to perform the tasks for which the users of the decision aiding system require assistance. TKSs are assumed to contain all the knowledge necessary to perform tasks, with increasing success below a specific level of detail of problem description. Their fuzzification allows for more degrees of freedom in description, which results in better operational efficiency, i.e. in inferencing and reasoning [1,8].

The overall system, when tackling tasks in human activity environments works in conjunction with the user. It may be designed to fulfil various roles, e.g. tutoring in an ITS. However, it is recognised that in all these systems there are decision points at which the user has to take decisions. Here an approach is presented to a) aiding the user at these decision points and b) to enhance the decision aiding by offering explanations/justifications of the recommendations made by the decision aiding subsystem. The domain knowledge component of the decision aiding subsystem is represented as a fuzzy TKS of decision aiding containing the knowledge to apply fuzzy reasoning and in particular test score semantics. The manner of producing the explanations/justifications is based on a TKS of "explaining" the (fuzzy) reasoning behind the recommended decisions. The TKS of explanation contains the knowledge necessary to explain why specific decisions were recommended.

The next section describes briefly Task Knowledge Structures (TKS), the relevance of Fuzzy Sets to TKSs in general and to the TKS of explanation. Section 3. presents how the approach suggested for aiding decisions and structuring explanations to justify that aid, is applied to an example. In addition, the underlying architecture of a relevant decision aiding knowledge system is suggested with the help of the same example. The conclusions are presented in section 4.

2. Task Knowledge Structures and Fuzzy Sets

Task-related Knowledge Structures [4,5] arose out of a need to model the knowledge people recruit when called upon to perform a task, for use in developing computer based systems. Thus a TKS is a summary representation of the different types of knowledge that are required to carry out a task or tasks.

The structure consists of the following: Goal: the state of affairs that a task can produce. Plan or Goal Substructure: particular formulation and possible ordering of procedures undertaken to achieve a Goal. Procedures: actual procedures for implementing the Goal; it is possible to have alternative sets of procedures and different groupings and/or orderings for the same procedures. Actions and Objects: (lowest level) constituents of Procedures.

These five elements of a TKS are organised as shown in Figure 1.

There were two major reasons why fuzzification was introduced in the representation problem [1]:

a: The inherent fuzzy nature of everything which is described linguistically, i.e. every "label" (name, title) which describes the concepts, could be considered as a fuzzy set. In the case of TKS's most of the goals, tasks, subtasks, objects, etc. are actual fuzzy sets. This realisation also implies that the necessary task analysis for the task knowledge capture is aided greatly by the freedom to avoid early stale quantification.

b: To aid the inference mechanism where most queries/questions are not well defined and consequently fuzzy. Any retrieval mechanism which is based on rules will have to deal primarily with fuzzy rules [10], Fuzzy reasoning [8,10] and syllogistic reasoning [8]. In other words a task, subtask, procedure etc. description stemming out of a TKS structure in response to a query would very rarely be crisp.

The fuzzification of a Task Knowledge Structure is described here starting with the objects. These are considered conceptually as the primitives of the Structure since the last subordinate class of any Structure contains as main entities (here linguistic variables) objects.

For any general basic level category an object X: (Fuzzy predicates etc. are in capital)

is a MEMBER of ... (membership grades);

is USED in procedures ... (frequently, not so frequently,..., rarely);

is RELATED to task objects by ... (strongly, ..., a little);

is ASSOCIATED with actions ... (strongly,..., a little);

has CHARACTERISTIC features ... (very, not so, ...)

is a TYPICAL instance ... (very typical, ..., not so typical, ..., atypical);

it is CENTRAL to procedure ... (very central, enough, not so, not central,...).

where the objects in a classical way can be considered as composite linguistic variables [9].

In order to evaluate the various TKS entities for decision aid, test score semantics were used. The application of test score semantics to a proposition such as a procedure, or to any other TKS component expressed mainly in natural language, results in a form of representation of the meaning of the proposition.

The use of test score semantics follows the steps [8]:

a) Identification of the variables which are constrained by the proposition.

b) Identification of the constraints imposed by the proposition (here the elements of the subordinate object class.

c) Associating with each constraint a test score Ti which represents the degree of satisfaction of the constraint, usually a number between [0,1].

d) Aggregation of the partial test scores usually into a scalar overall test score.

In describing these steps Zadeh [8], emphasises that the meaning of the proposition is represented by the process which leads to the overall test score and not only by the overall test score value itself. However, in the context of the TKS formalism and for "task of decision" domains, the overall test score T is invaluable in the evaluation of options for decision.

3. A knowledge subsystem for decision aiding enhanced with explanation/justification provision.

The knowledge components relevant to the domain "carrying out scientific research" which are part of an overall intelligent system are shown in Figure 2. It depicts a knowledge subsystem containing knowledge about various tasks (analysing a set of data, designing of experiments, undertaking literature review, etc.). The tasks of decision aiding and explanation are also included. The former relates to the domain tasks through the decision points which are an integral part of performing those tasks. The latter contains knowledge about offering explanations/justifications in general as well as to why choices were recommended at the various decision points.

This paper concentrates primarily on the issue of decision aiding and also that of providing explanations/justifications about those decision recommendations.

Here the domain knowledge components and the other two relevant components of the subsystem, the decision aiding component along with that of the explanation/justification are represented as fuzzy TKSs [1].

The decision aiding TKS represents the knowledge necessary to apply fuzzy reasoning through test score semantics. This is to decide which values of constrained variables within the domain TKS are the most appropriate, in relation to a proposition which implies the need for decision making, as was described in the previous section and elsewhere [1]. Figures 3a and 3b show the basic structure of that TKS.

The explanation/justification goal structure of the explanation TKS [6] is given in Figure 4. This is extended by the part of that goal structure relevant to fuzzy reasoning which corresponds to subgoal 2.2 representing the procedural knowledge necessary to provide explanations/justifications of decisions recommended by the system. Subgoal 2.2 contains the specific knowledge needed to utilise the relevant subsets of the domain knowledge as well as the knowledge about fuzzy reasoning in order to generate explanations/justifications to answer to a user querying a recommendation.

At identified decision points the system can offer advice as to what should be decided as was described briefly above and in a previous paper [1]. In the case the user needs explanation/justification of the decision then the relevant part of the TKS is activated in the following way. The stage at which the question is asked within the domain TKS, e.g. goal or procedure or object etc., determines the level at which the justification TKS would be activated, e.g. if the question "why?" is about a variable which corresponds to a "procedure" then (see figure 4.) the path of the subgoal "explain procedure" will be activated.

To illustrate the decision aiding process and the potential explanation provision an example that of analysing a set of data is used. Figure 5. shows the goal substructure of the TKS of analysing a set of data [6]. Subgoal 7 corresponds to the final and most important decision point within that TKS namely: "choosing ... an (appropriate) statistical test". The application of fuzzy reasoning for providing decision aid in the above case is based on test score semantics [8]:

Subgoal 7: Choose and apply statistical test

The corresponding proposition: which expresses the decision point is:

p: "Choose ...the (appropriate) statistical test"

The values of the variable: "statistical test" satisfy through the proposition p the constraints listed below, which originate from the subgoals 1 to 6 in figure 5. The constraints are the actual post conditions of those subgoals and form the necessary information (i.e. the preconditions) for Subgoal 7. They are the fuzzy (elastic) constraints upon the variable "statistical test" in relation to proposition p.

Constraints :

Hypothesis (identified)
Appropriate scale of measurement (identified)
Number of groups (identified)
Number of variables (known)
Non-parametric or parametric statistical tests anticipated as appropriate
Data identified from independent, repeated measures or mixed design

Available tests (values of the variable "statistical test") include:

z test
t test
F test
chi-square test
Binomial test
Kolmogorov-Smirnov (K-S) test
Sign test
Run test
Median test
Mann-Whitney test
Wilcoxon test
etc.

In a likely scenario of the example in use, a user wanting to analyse a set or sets of data will be guided by the system which possesses the required task knowledge the goal structure of which is given in Figure 5. The user will be asked to provide as many as possible preconditions [6] of the subgoals 1 to 6 in Figure 5. As a result of the user being guided by the system to find out and provide the preconditions of the above subgoals, as well as to apply the appropriate procedures relating to these goals according to the system's recommendations, the post conditions of these subgoals/procedures will be obtained. These post conditions provide information necessary for the majority of the preconditions of Subgoal 7, (choose ... the (appropriate) statistical test (for analysing the set(s) of data)). The decision to be taken by the user at any decision point such as the one corresponding to Subgoal 7 will be aided by the TKS of decision aiding (Figures 3a, 3b).

During the decision aiding process the user may also require some explanation or justification as to why the system recommends a specific action or procedure etc. to be followed (in this case the procedure of a specific statistical test). If this is the case then the TKS of explanation (Figure 2) will be activated and according to the goal substructure shown in Figure 4. (Subgoal 2.2) an explanation/justification may be generated. The TKSs of explanation and decision aiding will be activated only if user queries the system.

At the decision point of Subgoal 7 (Figure 5), where "(an appropriate) statistical test" needs to be "determined", the approach for selecting a course of action based on test score semantics and applied by the decision aiding TKS will follow the following steps:

a) The variable of interest is part of the proposition: "Choose ... (an appropriate) statistical test" whose values are actual alternative procedures, corresponding to specific statistical tests such as: t-test; binomial test; Kolmogorov-Smirnov test etc.

b) The constraints imposed upon that variable in relation to each of its values are described primarily through the post conditions of the subgoals 1 to 6, presented above. These post conditions express the necessary requirements for the application of the various tests. Further requirements in addition to the above may be contained in the preconditions of the "procedures" corresponding to the actual tests. It is assumed that the "application" of a statistical test is a procedure while a statistical test is also an object.". In the example and for a specific case of data to be analysed these constraints may be:

preconditions of proposition (Subgoal):"choose (appropriate) test":

Specific hypothesis (identified).
Scale of measurement ordinal.
One (1) group identified.
One (1) variables identified.
Non-parametric statistical test chosen as potentially appropriate.
Data identified as independent.

c) If the user is an expert then he/she can determine scores per constraint on the basis of how much that constraint is satisfied by the proposition (Subgoal) for each value of the variable (each one of the statistical tests). For example, for the binomial test the constraint "scale of measurement ordinal" could be valued with a scalar between [0,1], such as 0.4, while the "one group identified" as 0.7. For the Kolmogorov-Smirnov test the selected values could be 0.8, and 0.6 respectively. In the place of the above membership values in the interval [0,1], fuzzy linguistic quantifiers such "much", "not so much", "little", etc. could be used instead.

However, in general and for the particular example of statistical analysis dealt with here, when novices or partial experts use the system then the determination of scores will have to be previously elicited from experts, and stored.

d) The aggregation of the partial test scores, is achieved through the aggregation operator. One of the most common operators is the minimum, which if applied then the minimum score per value (procedure) will be the aggregated score for that value. In other words the degree to which the proposition with its variable having a specific value (procedure), satisfies each of its corresponding constraints, results in a vector of partial test scores. The minimum value in that vector is the aggregate score. For deciding which is the most appropriate value (procedure) for the proposition in relation to the problem situation (here, find the appropriate statistical test), the best aggregate score may be chosen. In the case of the minimum operator this translates to the maximum of the minimum, which will then give the "value" of the variable to be recommended. The logic behind the choice of the commonly used minimum operator is to get the best of the worst. Nevertheless, the scores for each value constitute a vector which then can be aggregated into a smaller vector according to certain criteria and not necessarily to a scalar [8] Comparing these vectors should lead to a choice of one and consequently to a choice of a value; in the case of the example to a procedure (statistical test). The development and calibration of an appropriate operator for the domain(s) of a decision aiding knowledge system could be a result of extensive studies based on experimentation for corpus data collection for that domain.

Zadeh [8] emphasises that "in test score semantics the meaning of p is represented not by the overall test score but by the procedure which leads to it", where p is the proposition which contains the variable. In the case of the example, the comparisons of the values of the variables, are based on overall test scores which in actual fact correspond to the meaning of the discourse that in turn corresponds to the constraints of that variable. For instance a possible discourse version of these constraints would be:

> "An appropriate statistical test is sought in order to analyse the set of data collected to test, in the first instance, the hypothesis of homogeneity. The scale of data in the identified group is ordinal. There is only one variable. Our limited experience suggests that a non-parametric test would be more appropriate for us.

The above discourse contains the meaning on the basis of which each procedure (statistical test) will be evaluated. However the simple overall test score result is not an effective or useful way of justifying to the user why a particular test is recommended. For while a user accept the system's advice without enquiry, what is important is that the meaning of the discourse which is represented via test score semantics is also represented within the system and is available, if needed, for explanation/justification of the recommended decisions. Here, this representation of the meaning is available to the user through the explanation/justification TKS where in response to the question "why?" the systems provides justification of the meaning of its reasoning for the advice given.

In the case of the example and specifically for the procedure "chi-square test application", the response to the question "why?" by the user, will come from the explanation/justification TKS (Figure 4.), which will follow the instructions contained in its procedure "explain procedure X". That is, via the overall test score, the above discourse and the process, by which its meaning in relation to the current decision is determined, will be made available to the decision maker. The actual return to the user could be:

The recommendation to choose "chi-square test" was made because:

	t-test	binomial test	X^2	K-S test	...
preconditions					...
-specific hypothesis identified	0.6	0.8	0.5	0.1	...
-scale of measurement ordinal	0.3	0.4	0.7	0.8	...
-One groups identified	0.5	0.7	0.7	0.6	...
-One variable identified	0.5	0.7	0.5	0.4	...
-non-parametric tests chosen as potentially more appropriate	0.1	0.7	0.7	0.7	...
-data identified as independent	0.6	0.7	0.8	0.4	...
					...
minimum	0.1	0.4	0.5	0.1	...

Table 1.

The recommendation, for the purposes of the example was based on the minimum operator. Again it should be emphasised that the choice of operator depends on the application and it should be considered carefully.

The values in [0,1] could, as mentioned before, be substituted by fuzzy linguistic quantifiers. These could take the form:

	t-test	binomial test	X^2	K-S test	...
preconditions					...
-specific hypothesis identified	much	very much	much	very little	...
-scale of measurement ordinal	little	not so much	very much	very much	...
-One group identified	much	very much	very much	much	...
-One variable identified	much	very much	much	much	...
-non-parametric tests chosen as potentially more appropriate	not at all	very much	very much	very much	...
-data identified as independent	very much	very much	very much	much	...
					...
minimum	not at all	not so much	much	very little	...

Table 2.

The test score semantics approach is applied in Table 2 as in Table 1. The chi-square test was chosen to be recommended because according to the minimum operator criterion it yielded the max of the min (i.e. much).

A possible justification to the question "why chi-square and not Kolmogorov-Smirnov?" is:

- "Because chi-square satisfies the constraints (specific)'hypothesis' and 'one variable' at least "much", while K-S satisfies the constraint (specific) 'hypothesis' at least "very little""

In addition, there are various computational frameworks based on fuzzy reasoning [3], which can be used to manipulate the linguistic values in the above table in order to incorporate, for example, additional subjective evaluation, brought in by the user. This could take the form of some sort of ordering of the constraints defined again with the help of linguistic quantifiers. An algebra based on fuzzy arithmetic [7] can be used to re-evaluate the scores which were pre-elicited.

5. Summary and conclusions

An intelligent decision aiding subsystem is understood in this paper as a knowledge subsystem which is designed to help the user at critical decision points occurring within a task. It aids the user to take scientifically based actions towards providing solutions to problems.

This paper presents an approach to utilising fuzzified task knowledge models and fuzzy reasoning in order to offer advice to decision makers as well as justification of that advice. The development of the task knowledge models based on the formalism of Task Knowledge Structures (TKS) and the theory of Fuzzy Sets as well as suggestions on the use of fuzzy reasoning to aid decision making, were presented in a previous paper. These Fuzzy Task knowledge Models represent the knowledge necessary to perform a task.

More specifically in the present paper, a framework for the development and utilisation of task knowledge models which are part of intelligent decision aiding systems is proposed. These knowledge models represent task knowledge about i) the domain, ii) the decisions points involved and how to deal with them according to the individual user and his/her task and iii) the justification of the decisions recommended. Their development is based on fuzzy TKSs, and their utilisation on fuzzy reasoning. The approach to reasoning for decision aiding adopted here is based on test score semantics.

The justification of any recommendation exposes the underlying reasoning. This strategy has the attraction of being able to render the meaning of the reasoning proposition(s), expressed in fuzzy logic, into a discourse version readily accessible to the user It thus offers potentially effective explanations of the decision recommendations given by the decision aiding subsystem at critical decision points within the task.

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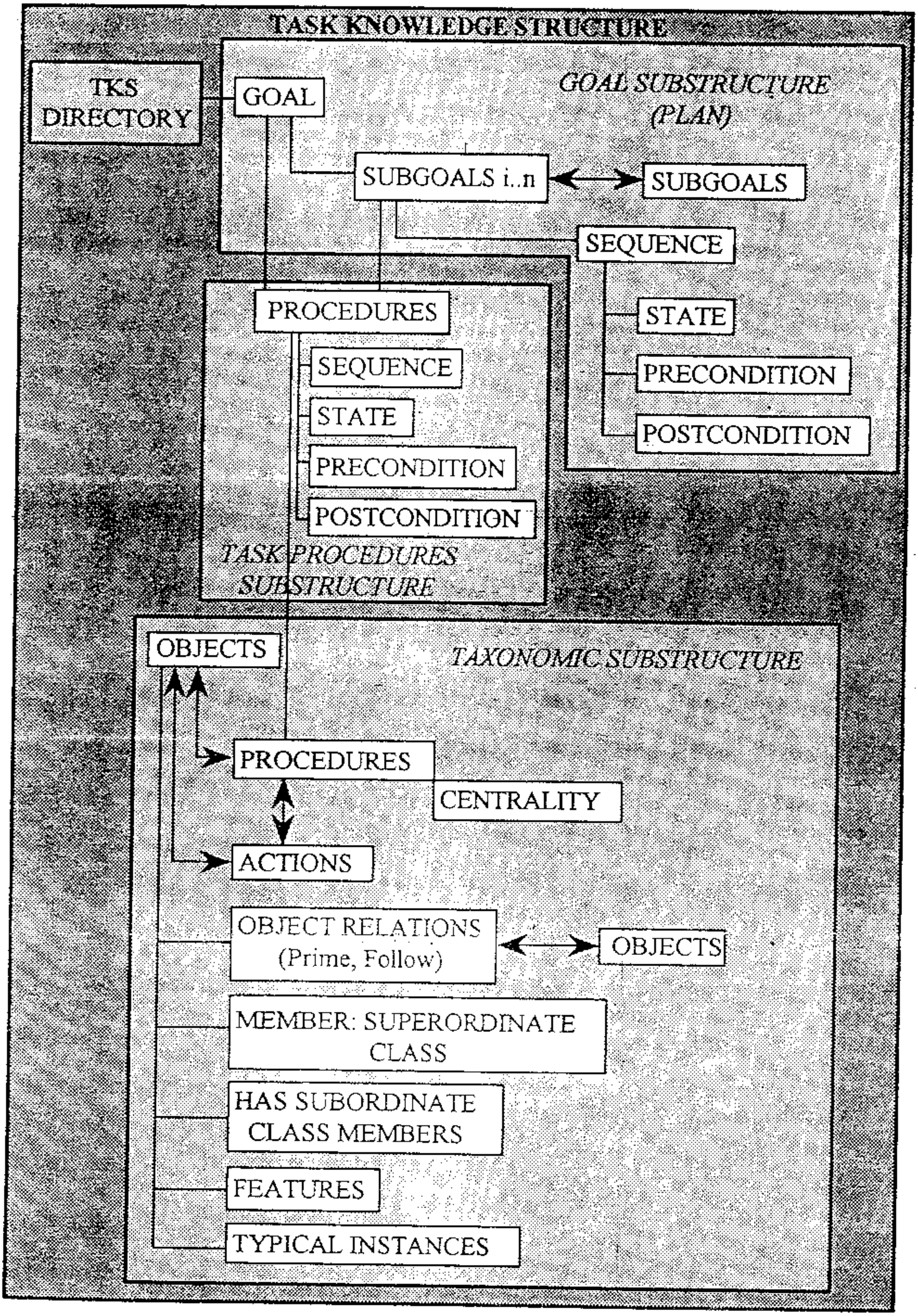

TASK KNOWLEDGE STRUCTURE
TKS DIRECTORY
GOAL
GOAL SUBSTRUCTURE (PLAN)
SUBGOALS i..n
SUBGOALS
SEQUENCE
STATE
PRECONDITION
POSTCONDITION
PROCEDURES
SEQUENCE
STATE
PRECONDITION
POSTCONDITION
TASK PROCEDURES SUBSTRUCTURE
OBJECTS
TAXONOMIC SUBSTRUCTURE
PROCEDURES
CENTRALITY
ACTIONS
OBJECT RELATIONS (Prime, Follow)
OBJECTS
MEMBER: SUPERORDINATE CLASS
HAS SUBORDINATE CLASS MEMBERS
FEATURES
TYPICAL INSTANCES

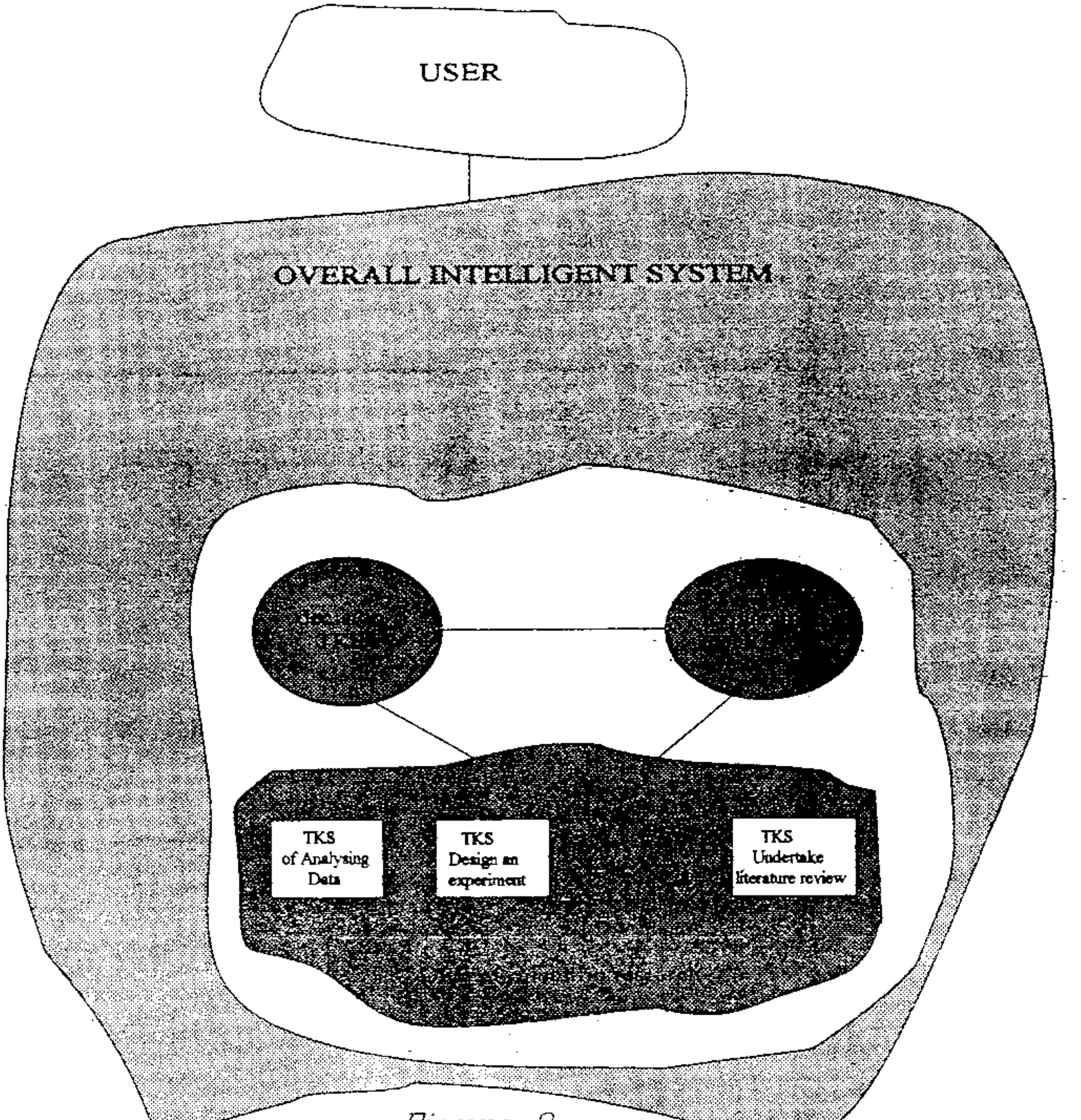

USER
OVERALL INTELLIGENT SYSTEM
TKS
of Analysing
Data
TKS
Design an
experiment
TKS
Undertake
literature review

Figure 2

Decision Aiding TKS

Goal Substructure

Goal
Recommend decision using Test Score Semantics

Subgoal 1	**Subgoal 2**	**Subgoal 3**	**Subgoal 4**
Identify the variable(s) constrained by the proposition	Identify the constraints imposed by the proposition upon the variable(s)	Associate constraints with Ti (test score)	Aggregate the partial Ti s into an overall Ti

Task Taxonomic Substructure

Objects	Actions
Decision	identify
options	associate
variables	aggregate
constraints	look for
proposition	find
test score	evaluate
partial test score	describe
overall test score	choose
aggregation function	

Figure 3a

Subgoal 1:
Identify the variable(s) constrained by the proposition

Procedure 1	
	precondition:
	Question(proposition) implying a decision (options)
	procedure:
	Identify variables in the proposition
	post condition:
	Variables identified

Subgoal 2:
Identify the constraints imposed by the proposition upon the variable(s)

Procedure 1:	
	precondition:
	variables identified
	procedure:
	If variables either Goal/Subgoal- or procedure- or object then the constraints are from the corresponding substructure.
	post condition:
	constraints identified

Subgoal 3:
Associate constraints with Ti (test score)

Procedure 1:	
	precondition:
	variables identified, constraints identified.
	procedure:
	Associate test score (Ti) to the relevant constraints.
	post condition:
	Test scores (Tis) evaluated

Subgoal 4:
Aggregate the partial Ti s into an overall Ti

Procedure 1:	
	precondition:
	Test scores
	procedure:
	Find the aggregation function- aggregate the Tis to obtain an overall test score (or test score vector).
	post condition:
	overall T (vector) for the alternative values of the variable(s) in the proposition

Figure 3b

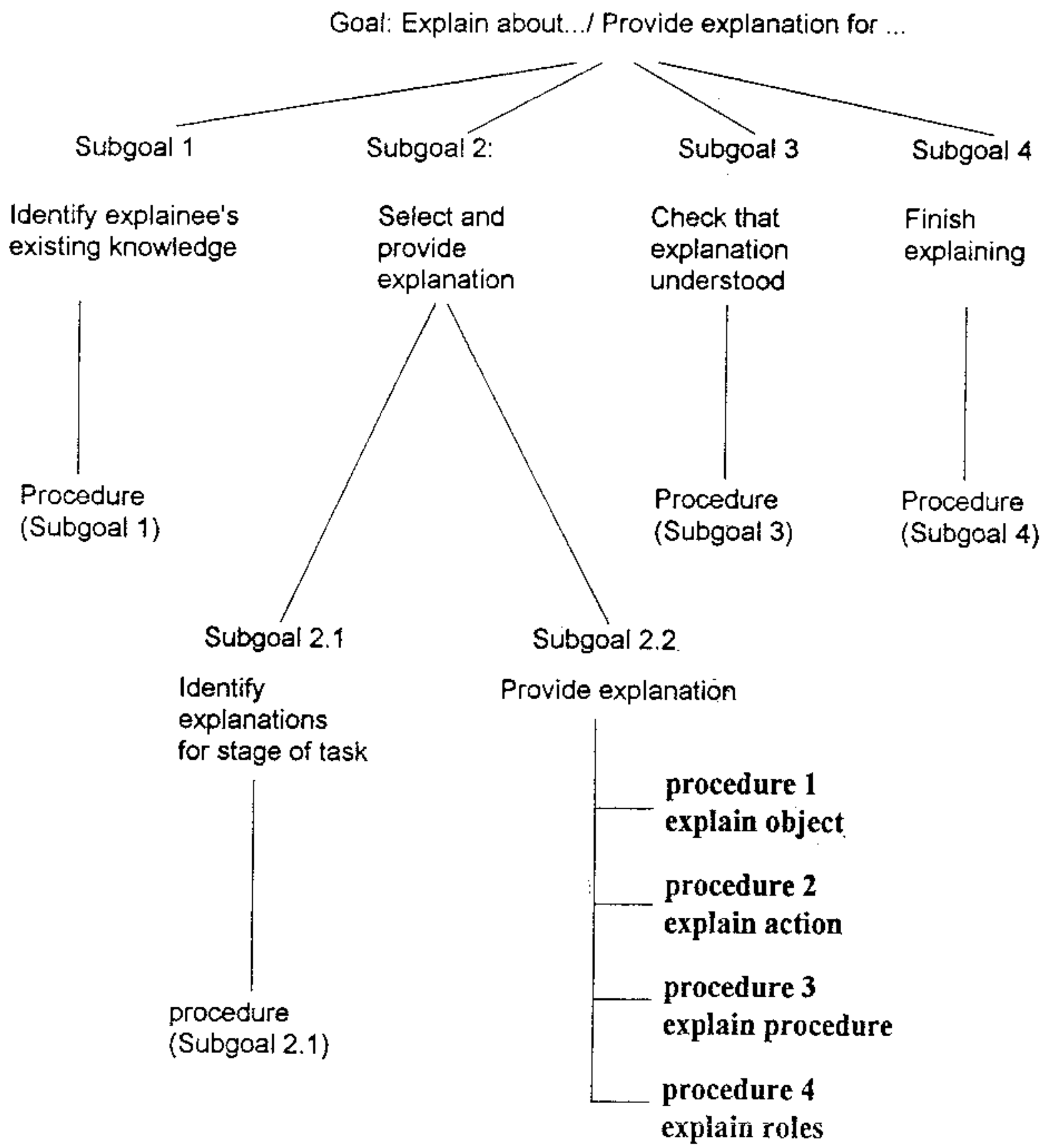
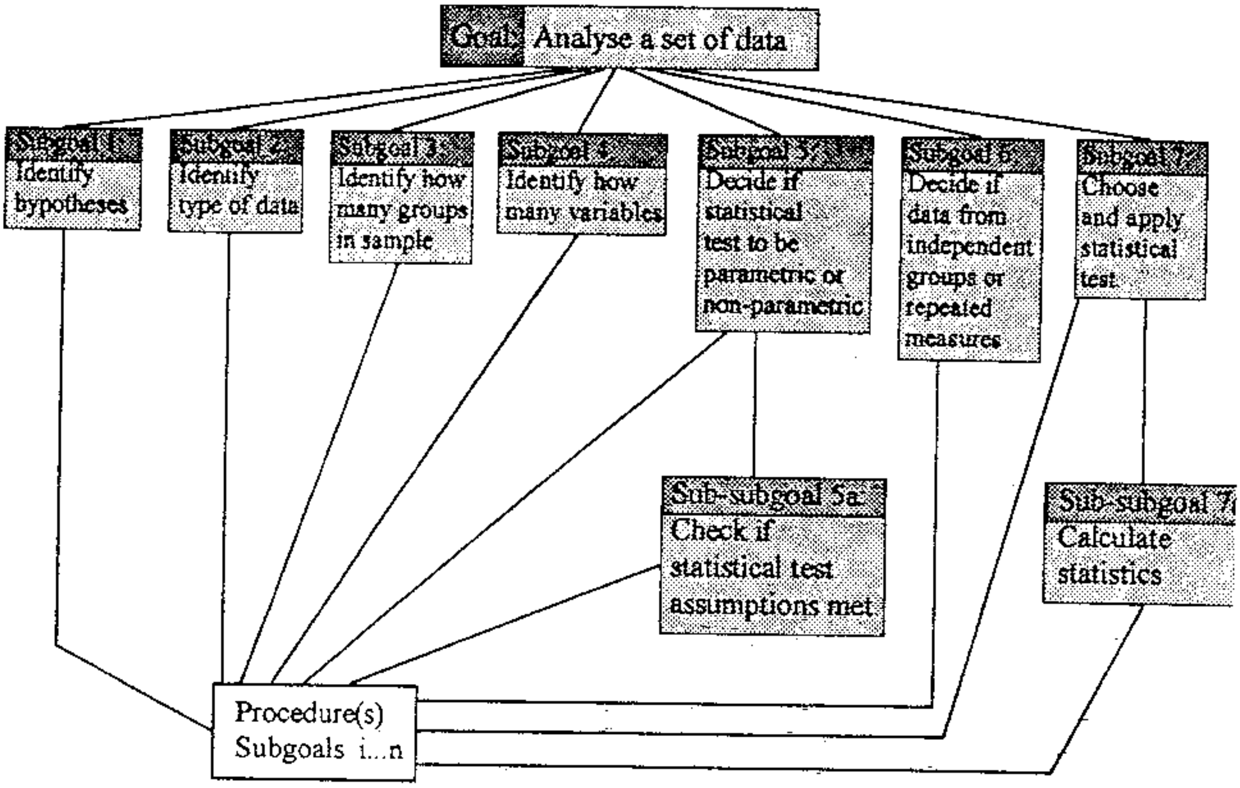

Goal: Explain about.../ Provide explanation for ...
Subgoal 1
Identify explainee's existing knowledge
Procedure (Subgoal 1)
Subgoal 2:
Select and provide explanation
Subgoal 3
Check that explanation understood
Procedure (Subgoal 3)
Subgoal 4
Finish explaining
Procedure (Subgoal 4)
Subgoal 2.1
Identify explanations for stage of task
procedure (Subgoal 2.1)
Subgoal 2.2
Provide explanation
procedure 1 explain object
procedure 2 explain action
procedure 3 explain procedure
procedure 4 explain roles

Figure 4



Goal: Analyse a set of data
Subgoal 1: Identify hypotheses
Subgoal 2: Identify type of data
Subgoal 3: Identify how many groups in sample
Subgoal 4: Identify how many variables
Subgoal 5: Decide if statistical test to be parametric or non-parametric
Subgoal 6: Decide if data from independent groups or repeated measures
Subgoal 7: Choose and apply statistical test
Sub-subgoal 5a: Check if statistical test assumptions met
Calculate statistics
Procedure(s) Subgoals i...n

Figure 5