Inductive analysis methods applied on questionnaires

Agneta Robertson, Rudolf Sillén and Jörgen G. Norén

Department of Pedodontics, Faculty of Odontology, Göteborg University, and Public Dental Service, Göteborg; and NovaCast AB, Soft Center, Ronneby; Sweden

Robertson A, Sillén R, Norén JG. Inductive analysis methods applied on questionnaires. Acta Odontol Scand 1998;56:268–275. Oslo. ISSN 0001-6357.

The aim of this study was to evaluate subjective aspects from questionnaires dealing with dental trauma by applying different computerized inductive techniques within the field of artificial intelligence to questionnaires consisting of descriptive variables and of questions reflecting functional, personal, and social effects of patients' oral situation following dental trauma. As the methodology used is new to many readers in odontologic sciences, a detailed description of both the processes and the terminology is given. Utilizing a neural network as a first step in an analysis of data showed if relations existed in the training set, but the network could not make the relations explicit, so other methods, inductive methods, had to be applied. Inductive methods have the potential constructing rules from a set of examples. The rules combined with domain knowledge can reveal relations between the variables. It can be concluded that the usage of methods based on artificial intelligence can greatly improve explanatory value and make knowledge in databases explicit. □ *Aesthetics; artificial intelligence; attitudes; dental trauma; follow-up*

Agneta Robertson, Department of Pedodontics, Faculty of Odontology, Göteborg University, P.O. Box 450, S-405 30 Göteborg, Sweden

Special problems are associated with the analysis of results from questionnaires. Descriptive methods give little information concerning possible patterns within the data. The objective of learning from data is thus to extract knowledge from data files and make it explicit. Learning from data falls into two categories, connectionist and inductive learning. Connectionist learning can generate networks of processing units from data where the topology of the network is decided by the user. Inductive learning, however, can generate rules and patterns from data files, thus generating results understandable to the user.

The use of machine learning methods such as inductive learning, artificial neural nets and evolving rules using genetic algorithms, and other methods within the field of artificial intelligence has developed rapidly in personal computers, and these methods have become powerful (1–11).

Artificial intelligence is concerned with methods for automatic learning where inductive learning is used for knowledge acquisition. A database of examples is used to automatically generate rules based on information theory and the idea of generalizing examples (from processes, experiments, or human experts) to produce general statements or rules. The derived rules are normally given a symbolic description, semantically and structurally similar to those a human expert might produce observing the same examples. The aim of the induction is to find a set of rules that uses information (examples) to reveal the relations between the variables. The inductive system can handle large data sets and complex problems where different types of relations can quickly find rules that are not apparent to people. The output is usually a set of rules graphically displayed as a knowledge tree, making the knowledge transparent. The inductive approach is therefore suitable as a tool in research and development.

Dental trauma in children and adolescents is a common problem, and Andreasen & Andreasen (12) reported that the prevalence of these injuries has increased in the last 10–20 years. There is a need to collect data dealing not only with causes and types of tooth injuries but also with treatment outcome from different aspects. Dental injuries, in contrast to most other injuries, often cause permanent damage and may generate problems for many years after the accident. The maintenance of healthy and aesthetic oral structures over a lifetime is important for physiologic as well as physical reasons. In addition to functional problems, aesthetic problems and poor adaptation may give rise to a number of emotional reactions (13).

The aim of this study was to evaluate subjective aspects from questionnaires dealing with dental trauma by applying different computerized inductive techniques within the field of artificial intelligence.

Materials and methods

Subjects

A total of 155 patients were selected for the investigation. Of these patients 102 participated (35 had left the city and 18 did not appear for unknown reasons). These patients, described in a previous publication (13), were initially treated for an acute dental injury in 1977–78 at the Department of Pedodontics, Faculty of Odontology, Göteborg, Sweden. After the follow-up period the patients were transferred to their regular dentists in the Community Dental Service.

Data from the records

Information was collected relating to cause of injury, diagnosis, number of teeth involved, previous treatment of the injury, and number of dental visits.

Questionnaire

The purpose of the questionnaire was explained to each patient before the oral examination. The questionnaire consisted of 52 questions about the patients' dental injuries and 3 additional questions pertaining to a subjective evaluation of their own teeth. The descriptive variables (9 questions) included in the present study were sex, age, education, occupation, current regular dental care, age at trauma, and etiology. The questionnaire also included functional (6 questions), personal (6 questions), and social questions (5 questions). The complete questionnaire and list of interview questions are available on request from the corresponding author.

Interview

The patients were interviewed for their opinions about the color and anatomic form of the anterior fillings, prosthetic reconstruction, and the color of the injured teeth without reconstruction.

Computerized analysis

A short description of the methodology used for the specific analysis programs will be presented. A more detailed description has been given previously (14).

Preparation of data. Questionnaire responses were numerically coded and processed with a computerized spreadsheet program (Excel 5.0, Microsoft) to generate an ASCII format.

The analysis was performed using an inductive analysis program (XpertRule Analyser, Attar Software Ltd, Lancashire, UK). The results are presented as knowledge trees (14).

A set of questions was selected according to the relevance to a defined outcome, which implies that questions in the questionnaire that could not possibly have any relation to the outcome were regarded as redundant. The different questions were designated as attributes, and the different alternatives for answers were called discrete values. Prior to the analysis the values for some of the attributes were grouped in order to improve

Table 1. Ranking of attributes in the different knowledge trees for the outcome attribute 'dental fear' with the values 'yes' and 'no'

	Rank				
		Pruning			
Attribute	Overall	None	1%	0.1%	LB* = 15
All attributes used					
Memory from follow-ups	1	1	1	1	1
Sex	2	2	2	2	2
Memory from emergency	3	2	2	2	3
Education	4	4			5
Concern	5				
Trauma age	6	3	3	3	
Regular dental care	7	5	4		2
Crown fracture	8				4
Extraction	9	4	3	4	4
Symptoms	10	5			
Luxation injuries	11	7	6		
No. of teeth	12	8			
Age	13				
Endodontic treatment	14	6	5		
Prosthetics	15	4	4		
Ten highest ranked attributes used					
Memory from follow-ups	1	1	1	1	1
Sex	2	2	2	2	2
Memory from emergency	3	3	3	4	3
Education	4	2	4		5
Concern	5	4			
Trauma age	6	4	5	5	4
Regular dental care	7	3	3	3	2
Crown fracture	8	5			6
Extraction	9	6	6		4
Symptoms	10				

* LB = lower branching limit.

Table 2. Ranking of attributes in the different knowledge trees for the outcome attribute 'own thoughts' with the values 'never', 'occasionally', and 'often'

	Rank				
		Pruning			
Attribute	Overall	None	1%	0.1%	LB* = 15
All attributes used					
Memory from follow-ups	1	1	1	1	1
Etiology	2	2	2	2	2
Anxiety for biting	3	3	3	3	
Symptoms	4				
Endodontic treatment	5	4	4	4	4
Memory from emergency	6	4	4	4	4
No. of teeth	7	3	3	3	5
Education	8	3	3	3	2
Sex	9	7			3
Age	10	8			
Extraction	11				
Prosthetics	12	5			
Crown fracture	13	7			
Luxation injuries	14	6	5		3
Eating problems	15	4	4	5	
Bite without problem	16				5
Ten highest ranked attributes used					
Memory from follow-ups	1	3	4	4	2
Etiology	2	3	3	3	3
Anxiety for biting	3	1	1	1	1
Symptoms	4	4			
Endodontic treatment	5	2	2	2	2
Memory from emergency	6	2	2	2	4
No. of teeth	7	4	4	4	
Education	8	5			4
Sex	9	6			
Age	10				

* LB = lower branching limit.

the analysis. The grouping was based on the authors' knowledge of the data from the more traditional analysis of the questionnaire (13). For a discrete attribute each group thus contains a set of values (Tables 1–3).

In XpertRule Analyser the Rank option ranks the attributes using a chi-square test in accordance with their effect on the outcome. This creates the possibility to narrow down the attribute selection. Results using the total attribute selection and a reduced selection will be shown in this article.

Neural network analysis. In the neural network analysis 50% of the examples were randomly selected for training, while the remaining examples were used for testing.

Induction process. The knowledge tree is generated by repeatedly (recursively) splitting the given data set according to different attributes until terminal points (leaves) are reached. The order in which the attributes are used in the knowledge tree depends on a measure of the classification power of each attribute based on entropy and/or chi-square analysis. A forward pruning (cease branching) criterion is used to decide when terminal points are reached. The induction algorithm of XpertRule Analyser is binary in that it creates a two-way branch at every split in the tree.

Pruning. The pruning can be selected as either Error reducing or Statistical pruning. The Error reducing pruning is based on a complexity/accuracy trade-off criteria. The Statistical pruning criterion is based on the widely used chi-square test of independence.

Another method of pruning is to use Lower Limits, whereby the pruning algorithm will decide to prune or to retain a given branch on the basis of a pruning test criterion. This criterion has two overriding criteria relating to the numbers of data records filtering to the various branches of the tree.

Verifying process. The accuracy of the pruned knowledge tree can be validated against the test data set. The test data set is a portion of the development data that is automatically set aside by XpertRule Analyser. The Verify option displays a table showing the accuracy (predictability) of each leaf by comparing the probabilities of the leaf outcome in the training and testing data sets. For each leaf the table also compares the percentages of the training and test data that fall into that leaf.

Generating rules from knowledge trees. This option generates Production rules in the form of 'if - then' rules from any existing knowledge tree(s) that belong to the analysis set.

Definition of outcome attributes and values. Three outcome

Table 3. Ranking of attributes in the different knowledge trees for the outcome attribute 'subjective opinion' with the values 'pleased' and 'not pleased'

	Rank				
		Pruning			
Attribute	Overall	None	1%	0.1%	LB* = 15
All attributes used					
Own thoughts	1	1	1	1	1
Concern	2	4	4		4
Bite without problem	3	3	3		
Anxiety for biting	4	2	2		2
Sex	5				
Symptoms	6	3	3		
Education	7	5	5		3
No. of teeth	8	5	5		
Crown fracture	9				
Eating problems	10				
Regular dental care	11	4	4		4
Age	12	7			
Endodontic treatment	13	6			
Prosthetics	14	6	6		5
Extraction	15				
Luxation injuries	16	3	3		3
Occlusion	17	2	2		2
Trauma age	18	5	5		
Dental fear	19	7			
Ten most important attributes used					
Own thoughts	1	1	1	1	1
Concern	2	6			
Bite without problem	3	3	3		4
Anxiety for biting	4	2	2		2
Sex	5	6			3
Symptoms	6	4	4		
Education	7	3	3		3
No. of teeth	8	5			3
Crown fracture	9	2	2		2
Eating problems	10	7			

* LB = lower branching limit.

attributes and their values were defined on the basis of a previous traditional analysis of the questionnaires (13).

The outcome attribute 'dental fear' denoted if the patients experienced any subjective feeling of fear in seeing a dentist. The values were thus 'yes' and 'no'.

The outcome attribute 'own thoughts' denoted how often the patients thought of their traumatized teeth at the time of data collection. The outcome values were 'never', 'occasionally', and 'often'.

The outcome attribute 'subjective opinion' denoted how pleased the patients were at that time with the form and color of their damaged teeth and reconstructions. The values were 'pleased' and 'not pleased'.

Results and discussion

The results of the ranking procedures are given in Tables 1–3 for all three analyses.

Neural network analysis

'Dental fear'. Concerning the outcome denoted 'dental fear', the network analysis reached a correct classification of 95% in the training set and 89% in the test set after 421 cycles of learning. By excluding 5 attributes with a ranking of 11 or more, the correct classification reached 95% and 93%, respectively, after only 50 cycles.

'Own thoughts'. The data with the outcome attribute 'own thoughts' reached 96% correct classification in the training set and 96% in the test set after 237 cycles. These figures were not improved after exclusion of the least important attributes.

'Subjective opinion'. When 'subjective opinion' was used as an outcome, both the training and the test set reached a correct classification of 96% after 237 cycles of learning.

Conclusion. Utilizing a neural network as a first step in an analysis is obviously a powerful tool for investigating whether possible relations exist within a data file. The option to apply the trained network on a test sample is used to test the reliability of the analysis. However, one must bear in mind that a neural network analysis shows only a possible connection between the chosen outcome and the attributes and gives no explicit view of any rules, which is why further analyses are necessary.

Inductive analysis

For each outcome a specific knowledge tree was chosen on the basis of the classification rate in combination with the size of the tree, which had to be large enough to be feasible and logical to interpret.

'Dental fear'. The ranking of attributes in the different knowledge trees is given in Table 1.

The analysis of questions involving the subjective experience of discomfort showed that using all attributes produced a knowledge tree with 36 leaves consisting of 12 attributes, thus leaving 3 redundant attributes. The classification rates for the 2 outcomes were high, 95% and 99% with 89% and 94%, respectively, in the test set. To remove any statistical noise or errors in the training set, the derived tree was statistically pruned first by a factor of 1% and then by a factor of 0.1%. In the first case the number of attributes was reduced to 9 and in the second case to 5, with 22 and 8 leaves, respectively. The classification rates decreased to 89% and 97%, and 82% and 66%, respectively, for the values 'yes' and 'no'. These figures were lower in the test set.

When the lower branching limit was set to 15, however, the number of leaves was 12, leaving 8 redundant attributes, with only 74% and 89% correctly classified outcomes.

In the second step 5 attributes were excluded according to their high-ranking numbers, indicating the least importance in the ranking analysis for the outcome. Without pruning the number of leaves was 37 based on 9 attributes, thus leaving 1 attribute redundant, with 94% and 97% correctly classified outcomes. Statistical pruning by 1% and 0.1% reduced the number of leaves to 16 and 9, based on 7 and 5 attributes. In the first case the percentage of correctly classified examples was 86% for both outcomes and 69% and 89% after 0.1% statistical pruning.

With the lower branching limit set to 15, the number of leaves was 12 and the number of attributes 7. The values for correctly classified outcomes were 71% and 86%.

The inductive analysis showed that, in the analyses

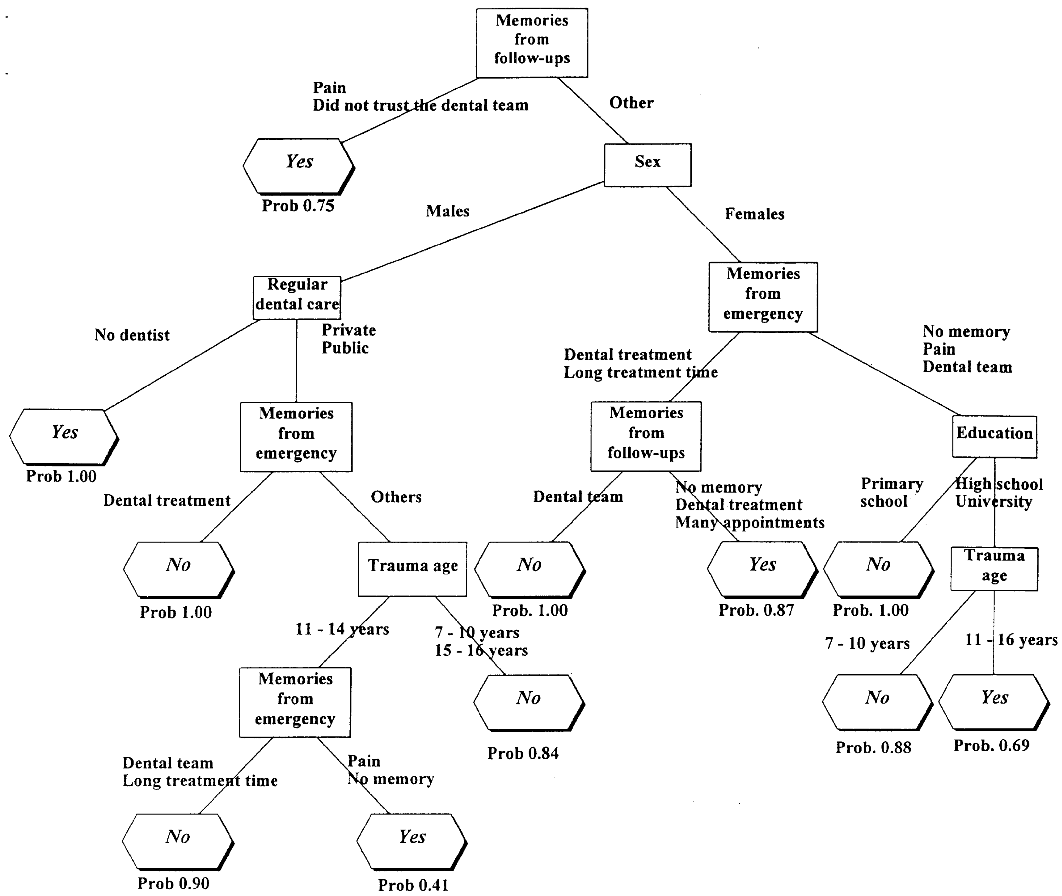

Fig. 1. Knowledge tree for the outcome attribute 'dental fear' with the values 'yes' and 'no'. Five attributes were excluded according to their high-ranking numbers, and the tree was pruned by a factor of 1%.

where no attributes were excluded, the attributes age and concern were always redundant. In the analyses where the 5 highest ranked attributes were excluded, symptoms was redundant. The most important factors for the outcome were memory from the follow-ups and sex. The non-pruned trees are rather limited in their sizes. However, as explanatory models they have to be reduced, and it appears that by using all attributes in the induction process and a pruning factor of 1%, the knowledge tree (Fig. 1) becomes suitably large to be utilized to explain the relations between the attributes and the outcomes (89%, 97%).

In conclusion, it is obvious from the analysis that pain and discomfort play an important role in how the patient experiences the acute situation in a dentist's office. It is thus vital that all dental treatment for children must be carried out as painlessly as possible, and the dental team should minimize discomfort during treatment. The acute and follow-up treatments should not be carried out without considerate use of local anesthetics and other substances for reducing pain and tension. Experiences of pain during treatment increased the risk of developing dental fear.

'Own thoughts'. The ranking of attributes in the different knowledge trees is given in Table 2.

The analysis showed that, using all attributes, a knowledge tree with 30 leaves consisting of 13 attributes was produced, leaving 3 attributes redundant. The classification rates for the 3 outcomes—'never', 'occasionally', and 'often'— were high: 100%, 99%, and 99%, respectively. To remove any statistical noise or errors in the training set, the derived tree was statistically pruned first by a factor of 1% and then by a factor of 0.1%. In the first case the number of leaves was reduced to 15 and in the second case to 11, with 9 and 8 attributes, respectively. The rates of correctly classified outcomes were 100%, 94%, and 72% for pruning level 1%, and for pruning level 0.1% the corresponding figures were 100%, 87%, and 65% for the 3 outcomes.

When the lower branching limit was set to 15, however, the number of leaves was 12, with 9 attributes left, and only 59%, 81%, and 80% correctly classified outcomes.

In all above-described analyses, memory from the follow-ups was the most important attribute.

In the second step 6 attributes were excluded according to their high-ranking numbers, indicating the least importance for the outcome. Without pruning the number of leaves was 40, based on 8 attributes, with 96%, 99%, and 99% correctly classified outcomes. Statistical pruning by 1% and 0.1% reduced the number of leaves to 9 and 8, based on 6 attributes in each case. In both cases the percentages of correctly classified examples for the outcomes 'often' and 'occasionally' were 96% and 81%; for the outcome 'never' the value was 77%.

With the lower branching limit set to 15, the number of leaves was 13 and the number of attributes 7. The values for correctly classified outcomes were 55%, 85%, and 81%.

A pruning factor of 1% using a reduced set of attributes appears to give a satisfactory result with a high classification rate and high explanatory value (Fig. 2).

In conclusion, as was shown in the previous analysis, factors related to pain during dental treatment have a large effect. One can only emphasize the necessity for painless treatment. It is obvious that trauma to the teeth and soft tissue may result in physical and emotional

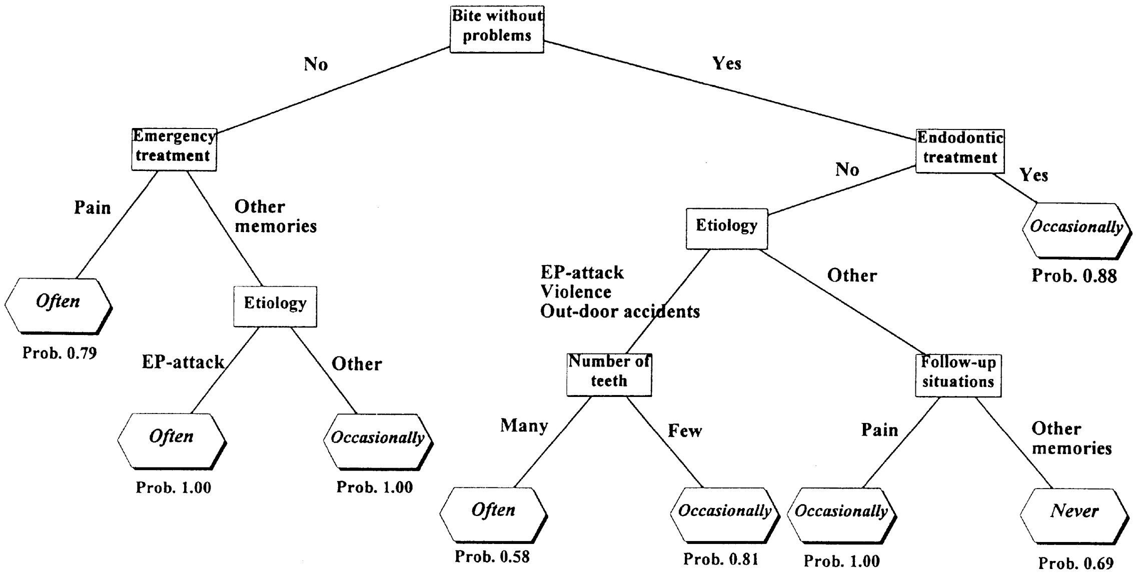

Fig. 2. Knowledge tree for the outcome attribute 'own thoughts' with the values 'often', 'occasionally', and 'never'. Six attributes were excluded according to their high-ranking numbers, and the tree was pruned by a factor of 1%.

complications. In severe cases (many injured teeth), great problems concerning treatment and prognosis arise with requirement for extensive treatment.

'Subjective opinion'. The ranking of attributes in the different knowledge trees is given in Table 3.

The analysis showed that, using all attributes, a knowledge tree with 32 leaves consisting of 16 of the 19 attributes was produced, thus leaving 3 redundant attributes. The classification rates for the 2 outcome values, 'yes' and 'no', were 99% and 97%, respectively. Statistical pruning of 1% and 0.1% was then performed. In the first case the number of leaves was reduced to 18, and in the second case to 2, with 12 attributes and 1 attribute, respectively. The classification rates for pruning level 1% were 100% and 75%, and for pruning level 0.1% the corresponding figures were 77% and 61% for the 2 outcomes.

With a lower branching limit of 15, however, the number of leaves was 12, with 8 attributes left, and only 85% and 73% correctly classified outcomes.

In the second step 9 attributes were excluded according to their high-ranking numbers, indicating the least importance for the outcome. Without pruning the number of leaves was 38, based on the 9 attributes, with 99% and 83% correctly classified outcomes. Statistical pruning by 1% and 0.1% reduced the number of leaves to 9 and 2, based on 6 attributes and 1 attribute, respectively. The percentages of correctly classified examples for outcome values 'yes' and 'no' were 82% and 75% for the 1% pruning level and 76% and 61% for the 0.1% level.

With the lower branching limit set to 15, the number of leaves was 11 and the number of attributes 7. The values for correctly classified outcomes were 95% and 37%.

The most important factor for the outcome is the attribute 'own thoughts'. The tree based on all attributes and pruned at the 1% level appears to be the most useful for interpretation (Fig. 3).

In conclusion, dental injuries, in contrast to most other injuries, often cause permanent damage and may cause problems for many years after the accident, which is reflected in the high position of the attribute 'own thoughts'. Aesthetics plays a major role when the loss of tooth structure involves the anterior teeth. The dental team should therefore take precautions at an early stage to restore the function and perform restorative treatment for the best possible aesthetic result.

Concluding remarks

Utilizing a neural network as a first step in an analysis of data shows if relations may exist in the training set. However, as the network cannot make the relations explicit, other methods have to be applied. Inductive methods, as shown here, have the potential to assist the researcher in making the knowledge explicit and the relations understandable. Further, redundant information is easily found and lack of information is revealed.

With proper understanding of the data, a set of analyses can be made, utilizing the ranking option and inducing different trees that can be pruned. A reasonable level of

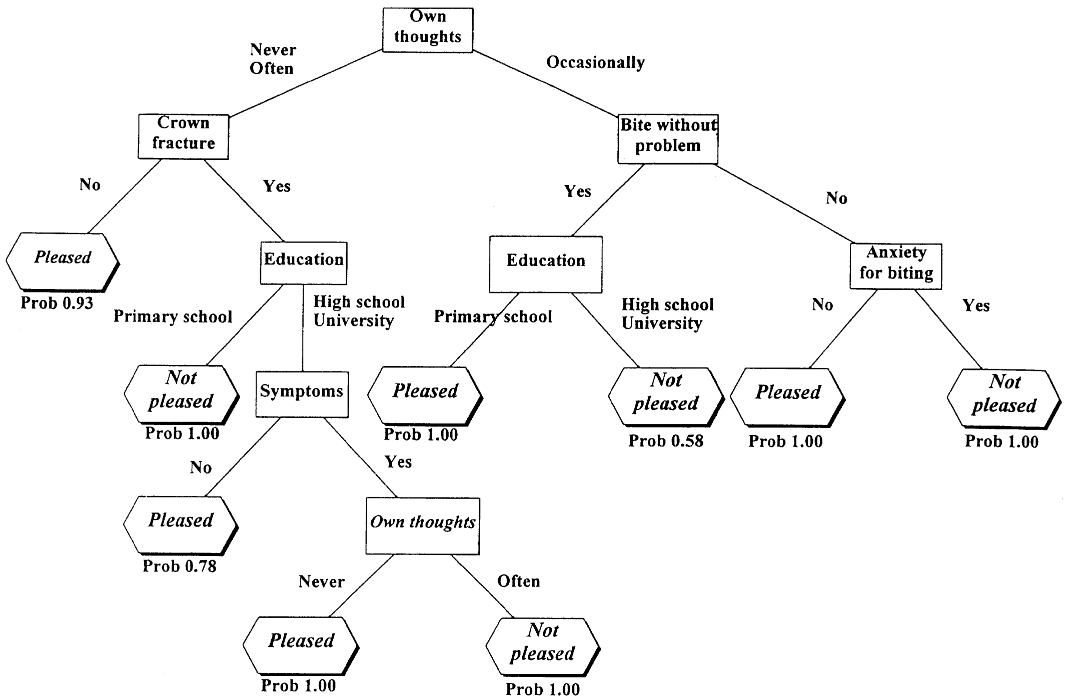

Fig. 3. Knowledge tree for the outcome attribute 'subjective opinion' with the values 'pleased' and 'not pleased'. Nine attributes were excluded according to their high-ranking numbers, and the tree was pruned by a factor of 1%.

correctly classified outcomes will determine which tree has the highest informative and explanatory value. Further, attributes that are redundant, carrying no information in relation to the outcomes, are easily discerned. The tree structure also enables creation of an understandable way of presenting the induced relations.

It is worth noting that there were differences between the analyses depending on whether or not all attributes were used. However, the patterns derived are naturally dependent on the data set and how the attributes interact with each other. It is therefore most important that the exclusion of attributes is performed properly. In sets of data there are always redundant attributes or attributes that cannot possibly affect the outcome. Expert knowledge is thus of great importance in avoiding irrelevant pattern rules. Difficulties will, of course, appear if one is dealing with a totally unknown data file, and non-realistic pattern rules can be produced. Nevertheless, the explicit way of showing the pattern rules as knowledge trees makes it possible to study the rules and gain considerable information about the data file. The interaction between the automatic rule induction and the researcher has also been found to be very creative.

It should be understood that the induction algorithm aims at reducing information uncertainty in the data by selecting the most discriminating attribute at each node in the knowledge tree and the best split or threshold among its values. Thus, the knowledge tree, which is a graphic representation of a set of conjunctive rules, is ideal for discriminating between the outcomes. The rules start at the root node in the tree and follow their respective paths until a terminal node is reached. Each rule represents a homogeneous cluster of the learning data (examples) used. To obtain a full description of such a cluster or population, all cases that belong to the cluster must be considered. Otherwise, some attributes that might not be needed to discriminate the outcomes but are essential to achieve them can be overlooked.

The induction method is normally the best method for a first approach when analyzing data. It is fast and can be used interactively to highlight the information value of each attribute. The algorithm assists the researcher in finding the most important attributes or variables as well as their threshold values. It also traces 'knowledge gaps' and thereby also assists in further investigations. If the problem is a pure classification problem, then induction is the preferred method.

The conclusions derived from the inductive analysis concerning the subjective experiences of patients with dental trauma appear evident, understandable, and logical. Utilizing inductive methods makes the relations explicit and understandable in contrast to conventional qualitative methods applied to questionnaires. The present results also coincide well with the conclusions drawn in the previous article, dealing with the questionnaires used (13). However, in the present article, subjective (qualitative) data and their relations become clear, and a logical analysis of the validity of the results becomes possible.

Analytic systems in the field of artificial intelligence thus have a role to play in medical and odontologic research (15, 16). Within the field of artificial intelligence, decision- and documentation-support systems have been developed and proven to be promising tools also for clinical work in medicine (17).

Acknowledgement.—This study was supported by grants from Stiftelsen Länsförsäkringsbolagens Forskningsfond (project P1/96), Stockholm, Sweden.

References

1. Bratko I, Lavrac N. Progress in machine learning. Wilmslow: Sims Press; 1987.
2. Craven MW, Mural RJ, Hauser LJ, Uberbacher EC. Predicting protein folding classes without overly relying on homology. ISMB 1995;3:98–106.
3. Forsstrom JJ, Irjala K, Selen G, Nystrom M, Eklund P. Using data preprocessing and single layer perceptron to analyze laboratory data. Ann Med 1995;27:509–17.
4. Hennessy D, Gopalakrishnan V, Buchanan BG, Rosenberg JM, Subramanian D. Induction of rules for biological macromolecule crystallization. ISMB 1994;2:179–87.
5. Ioerger TR, Rendell L, Subramaniam S. Constructive induction and protein tertiary structure prediction. ISMB 1993;1:198–206.
6. King RD, Clark DA, Shirazi J, Sternberg MJ. Inductive logic programming used to discover topological constraints in protein structures. ISMB 1994;2:219–26.
7. Michie D. On machine intelligence. 2nd ed. Chichester: Ellis Horwood Ltd.; 1986.
8. Place JF, Truchaud A, Ozawa K, Pardue H, Schnipelsky P. Use of artificial intelligence in analytical systems for the clinical laboratory. Clin Biochem 1995;28:373–89.
9. Quinlan J. Learning from noisy data. In: Michalski R, Carbonell J, Mitchell T, editors. Machine learning. Vol 2. Palo Alto (CA): Tioga; 1986.
10. Salzberg S. Locating protein coding regions in human DNA using a decision tree algorithm. J Comput Biol 1995;2:473–85.
11. Woolery LK, Grzymala-Busse J. Machine learning for development of an expert system to predict premature birth. Biomed Sci Instrum 1995;31:29–34.
12. Andreasen JO, Andreasen FM. Dental traumatology: quo vadis. Endod Dent Traumatol 1990;6:78–80.
13. Robertson A, Norén JG. Subjective aspects of patients with traumatized teeth. A 15-year follow-up study. Acta Odontol Scand 1997;55:142–7.
14. Nilsson T, Lundgren T, Odelius H, Sillén R, Norén JG. A computerized induction analysis of possible co-variations among different elements in human tooth enamel. AIM 1996;8:515–26.
15. af Klercker T. Effects of pruning of a decision-tree for the ear, nose, and throat realm in primary health care based on case-notes. J Med Syst 1996;20:215–26.
16. af Klercker T, Trell E, Lundquist PG. Towards an essential data set for ambulatory otorhinolaryngological care in general practice. Med Inf (Lond) 1994;19:253–67.
17. Klercker T, Klercker M. Decision support system for primary health care in an inter/intranet environment. Comput Methods Programs Biomed 1998;55:31–7.

Received for publication 9 March 1998
Accepted 29 June 1998