Informatics in Primary Care 2005;13:23–33

Refereed papers

Application of fuzzy classification in modern primary dental care

Yauheni Veryha
Scientist, ABB Corporate Research, Ladenburg, Germany

Katarzyna Adamczyk
Student, Faculty of Medicine, Jagiellonian University, Cracow, Poland

ABSTRACT

This paper describes a framework for implementing fuzzy classifications in primary dental care services. Dental practices aim to provide the highest quality services for their patients. To achieve this, it is important that dentists are able to obtain patients' opinions about their experiences in the dental practice and are able to accurately evaluate this. We propose the use of fuzzy classification to combine various assessment criteria into one general measure to assess patients' satisfaction with primary dental care services. The proposed framework can be used in conventional dental practice information systems and easily integrated with those already used.

The benefits of using the proposed fuzzy classification approach include more flexible and accurate analysis of patients' feedback, combining verbal and numeric data. To confirm our theory, a prototype was developed based on the Microsoft™ SQL Server database management system for two criteria used in dental practices, namely making an appointment with a dentist and waiting time for dental care services.

Keywords: dental practice, dental service, fuzzy classification, primary dental care

Introduction

Attempts to classify patients' feedback about primary dental care services provided in dental practices are often not easy to address using standard mathematical and statistical approaches, such as moving average, straight-line interpolation, and many others. This is because there are many kinds of assessment criteria (both verbal and numeric) that can be used. Verbal assessment criteria are difficult to incorporate into standard classification schemes designed to produce one general measure based on numeric data to evaluate patients' satisfaction with particular primary dental care services. Fuzzy set theory offers a way to solve such problems.[1] Fuzzy sets provide mathematical meanings to natural language statements and become an effective solution for dealing with uncertainty in verbal data. An important feature of fuzzy sets is that they provide a formalism for incorporating ambiguity in a typical classification scheme that combines both verbal and numeric data.

The aim of our research is to develop a general, effective, computer-aided assessment method based on fuzzy classification to help dental practices in the assessment of patients' feedback about primary dental care services provided. Accurate evaluation of patients' feedback is an important step in providing the highest quality dental care services.

In most practical data classification situations, more than one criterion (attribute) has to be considered simultaneously. Criteria are usually measured with different scales and should be combined into one general measure. Fuzzy set theory with its membership functions is a unique approach that is widely used to form a realistic general measure of the assessment, incorporating ambiguity and lack of numeric data in various criteria.[1–3] In fuzzy set theory, various criteria (both verbal and numeric) can be relatively easily combined into a joint response measure called the aggregated value of the membership, which can be used as the general measure.[4]

A number of different schemes and tools for the implementation of fuzzy sets in database management systems have been proposed in recent years, such as fuzzy querying, fuzzy extension of SQL (Structured Query Language), and fuzzy object-oriented database schemes.[5–9] There are also commercial tools available on the market, like FIDE (Fuzzy Inference Development Environment: for the development of fuzzy logic-based systems) (Aptronix Inc.), FLINT (Fuzzy Logic Interfacing Toolkit: to make fuzzy logic technology and fuzzy rules available within a sophisticated programming environment) (Logic Programming Associates Co.), and FQS (Fuzzy Query System: allowing the user to conduct database queries using the semantic flexibility of Fuzzy SQL) (Sonalysts Inc.). In addition, fuzzy set theory is widely used in medicine; for example, the following application schemes can be mentioned: fuzzy pattern recognition for automatic detection of different teeth substances, database model for medical consultation, expert system using fuzzy logic for rheumatology diagnosis, expert system for the analysis and interpretation of evoked potentials based on fuzzy classification, hybrid intelligence system for diagnosing coronary stenosis, computerised electrocardiogram diagnosis with fuzzy approach, and fuzzy multi-level classifier for medical applications.[10–16]

An alternative approach to fuzzy set theory is the use of expert systems with their predefined expert rules; for example, expert computer system on medical consultation.[17] The approach, based on expert systems, did not find wide application due to the limited options for integration into conventional database management systems, relatively high complexity of implementation, and too high costs for maintenance during the overall system life cycle.

The majority of the above-mentioned fuzzy methods and systems for data mining as well as commercial tools require changing the conventional relational database structure or adding special features to the database management tools, such as modifying the conventional SQL functionality or extracting fuzzy functionality into a separate application as was implemented in FQS.[6,7]

Fuzzy methods are not widely used in relational database systems in practice. The main reason for this is that most database system users do not want to switch to fuzzy database structures or use third-party applications. As a result, they usually do not use fuzzy querying in their information systems. To attract more attention to fuzzy applications from database users we propose to use a framework based on fuzzy classification and conventional SQL queries. The main benefit of our approach is that there is no need to modify the functionality of conventional relational databases and SQL. All manipulations can be done as an extension of the database scheme by applying fuzzy data classification. Furthermore, a number of other benefits of using fuzzy sets and fuzzy classification in data mining become available for users of relational databases as well:[4,18]

- user-friendly data presentation
- precision of data classification
- use of linguistic variables instead of numeric values
- easy-to-use facilities for querying the extended database scheme.

To confirm our theory, we developed a prototype based on the Microsoft™ SQL Server database management system for two common criteria used in dental practices, namely making an appointment with a dentist and waiting time for primary dental care services.

Importance of patients' feedback in dental practices

Dental practices do their best to provide the highest quality services for their patients. To achieve this, it is important to collect patients' opinions about their experiences (making an appointment with a dentist, waiting time for dental care service, etc.) in dental practices. A typical example would entail offering Patient Satisfaction Survey forms at the reception desk and encouraging patients to complete them after their dental appointment. The results of patients' feedback can then be transferred into the database and analysed by the responsible personnel.

The *Modernising Dentistry Programme* begun in the United Kingdom (UK) in 2002 identified the main directions to facilitate the whole system redesign of primary dental care services in the UK and to support modernisation in dental clinics and secondary care.[19] These are shown in Figure 1. The *Modernising Dentistry Programme* recommends using systematic patient feedback to get practice-level feedback.

Involvement of patients in providing feedback helps to generate new ideas, such as revising the whole 'reception' approach by streamlined treatment rooms and a comfortable, relaxing lounge area (based on information from the British Dental Association).[20]

Another interesting example showing the importance of patient feedback is the Montefiore Medical Center (The University Hospital and Academic Medical Center for the Albert Einstein College of Medicine, USA). Montefiore Medical Center, a recognised international centre of patient dental care, became recently the first hospital in New York State to implement an online system, called *Feedback Monitor Pro™ WebForms*, to enhance its customer service efforts relating to effective complaint management. 'We know that every patient's or family's complaint is an opportunity for

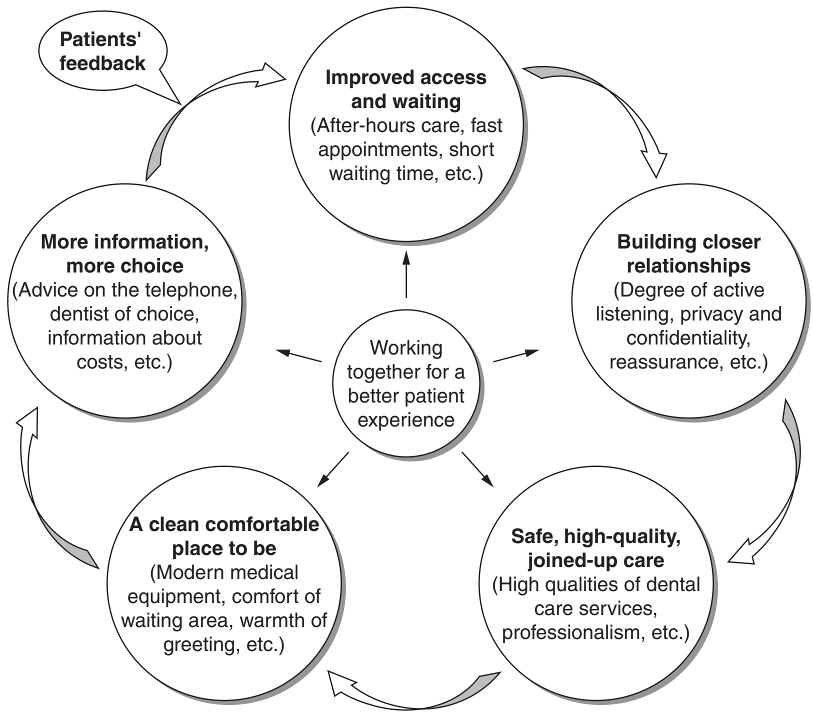


Figure 1 Primary directions from the *Modernising Dentistry Programme* for dental care service improvement

Montefiore Medical Center to show its commitment to quality and patient satisfaction,' said Leslie Bank, Director, Customer Services at Montefiore Medical Center. 'Now we have the tool to assure a quick response and successful recovery, and to provide managers with the information they need to improve service.' 'Being the first in New York to implement this system underscores our commitment to service excellence,' said Bank. 'We know that patient satisfaction is everyone's responsibility, and patients judge us on responsiveness to their needs, not just medical care.'[21]

Conventional data classification in relational databases

To show the difference in data presentation between conventional data classification and fuzzy data classification, the following simple example from dentistry practices can be considered. An example data set (this is a selected data set from continuous tracking of dental care service quality based on patients' feedback) shows a table that contains dentist surname (*Dentist* column), dental care service provided (*Service* column), waiting time of patients until they are invited to start their treatment in the treatment room (*Waiting Time* column), and the number of days that patients had to wait for the first suitable appointment proposed by a dentist (*Appointment* column). An example data relation is presented in Table 1.

According to conventional data classification, we will have to define classes for our example OFFERS table. To define classes, we introduce atomic values for *Appointment* and *Waiting Time* attributes. We define 'acceptable' and 'unacceptable' atomic values for the *Appointment* attribute. The atomic value of 'acceptable' is assigned to the interval of (1–5) and the atomic value of 'unacceptable' is assigned to the interval of (6–10). Similarly, we define 'short' and 'long' atomic values for the *Waiting Time* attribute. The atomic value of 'short' is assigned to 'short' and 'average' *Waiting Time* attribute values. 'Long' atomic value is assigned to 'above average' and 'long' *Waiting Time* attribute values. As soon as the definition of atomic values is finished, it is easy to define all classes for dentists:

C1 – '*Award a bonus*' class with atomic values ('acceptable', 'short')
C2 – '*Complain about appointment*' class with atomic values ('unacceptable', 'short')
C3 – '*Complain about waiting time*' class with atomic values ('acceptable', 'long')
C4 – '*Interfere for improvements*' class with atomic values ('unacceptable', 'long').

A distribution of dentists from the OFFERS table among the introduced classes is graphically presented in Figure 2.

Table 1 OFFERS table

Dentist	Service	Waiting time (subjective patients' feeling)	Appointment (number of days)
Berg	Consultation	Short	7
Berg	Tooth treatment	Above average	6
Berg	Tooth treatment	Short	2
Crow	Consultation	Short	2
Gate	Consultation	Average	4
Gate	Tooth removal	Short	3
Gate	Tooth removal	Above average	8
Gate	Tooth treatment	Short	9
Host	Consultation	Above average	2
Host	Tooth treatment	Above average	4
Merk	Consultation	Average	9
Merk	Consultation	Long	7
Merk	Tooth removal	Above average	8
Roy	Consultation	Long	4
Roy	Tooth removal	Long	2
Thon	Tooth treatment	Long	2
Thon	Tooth treatment	Average	2

	A (appointment)				
Unacceptable	10	**C2**			**C4**
	9	Gate	Merk		
	8			Merk, Gate	
	7	Berg			Merk
	6			Berg	
Acceptable	5	**C1**			**C3**
	4		Gate	Host	Roy
	3	Gate			
	2	Crow, Berg	Thon	Host	Thon, Roy
	1				
		Short	Average	Above average	Long
W (waiting time)		Short		Long	

Figure 2 Conventional non-fuzzy classification of dentists

The most common method of querying relational database tables is through SQL. To find all members of '*Complain about appointment*' class C2 (see Figure 2), one can query the initial OFFERS table with a simple SQL query:

SELECT Dentist FROM Offers WHERE ([Waiting Time] = 'short' or [Waiting Time] = 'average') and (Appointment > 5).

Using the above-presented and other similar SQL queries one can classify all dentists. For example, dentist Gate belongs twice to class C1, once to class C2 and once to class C4 (see Figure 2). Hence, one can say that he most likely belongs to class C1 (two occurrences for class C1 [50 percent] and one occurrence for each of classes C2 and C4 [25 percent for each]). Dentist Thon belongs once to class C1 and once to class C3. This means that he belongs 50 percent to class C1 and 50 percent to class C3. One may continue this comparison in the same way with other dentists. Let us state the following important questions and see that it is not easy to find the answers to them using conventional data classification:

- With the introduction of atomic values the attributes become less accurate since more than one initial value is aggregated into each atomic value (in our example, 'acceptable' and 'unacceptable', 'short' and 'long' terms are used as atomic values). How can we prevent deterioration of data accuracy with the introduction of atomic values?
- Who among the dentists belong to which class more? (The above-presented calculation scheme based on occurrences is not accurate enough since with the introduction of atomic values for classes the attributes become less accurate.)

The main problem of the presented conventional data classification is that it has a discrete boundary definition of atomic values (see Figure 2). Thus, the classification reports based on such conventional data classification are usually not accurate enough. To improve the precision of data classification, we will use the fuzzy data classification methodology of Schindler, as most widely used in practice.[18] However, other fuzzy data classification methodologies could be also potentially used in this work.[1,2]

Fuzzy data classification in relational databases

To get more detailed information about dentist membership of classes, one can introduce fuzzy classification of data and linguistic variables.[4,18] As an example, we can consider the *Appointment* attribute as a linguistic variable. The area of definition of the linguistic variable is domain A (Appointment). Similarly to the assignment of the atomic value, the *Appointment* linguistic variable possesses a set of terms A(Appointment) = {'acceptable', 'unacceptable'} with the verbal terms 'acceptable' and 'unacceptable' that define appropriate equivalence classes (1–5) and (6–10).

The most important feature of linguistic variables is that every term of a linguistic variable represents a fuzzy set. The membership function of the fuzzy set is defined over the domain of the corresponding attribute. For instance, as is shown in Figure 3, we defined (based on the fuzzy sets theory[1]) that the appointment with a dentist within the following five or six days is acceptable and unacceptable at the same time (in both cases the membership function μ has a value of 0.5 [i.e. $\mu_{\text{acceptable}} = 0.5$ and $\mu_{\text{unacceptable}} = 0.5$]) because it is located in the middle of our fuzzy set. Similarly, we defined that an appointment with a dentist within the next seven days is acceptable and unacceptable at the same time (the membership function $\mu_{\text{acceptable}} = 0.33$ and $\mu_{\text{unacceptable}} = 0.67$) and so on.

The membership of an object in a specific class can be calculated by an aggregation over all terms of the linguistic variables that define the class. Terms 'acceptable' and 'short', for instance, describe class C1. Hence, membership in class C1 is a conjunction of the corresponding values of the membership functions $\mu_{\text{acceptable}}$ and μ_{short}.

There exist a number of operators that can be used to calculate conjunctions of membership function values.[4] For example, one can apply the γ-operator which is used as a 'compensatory AND' and was empirically tested by Zimmermann.[4] The membership $\mu_{\tilde{A}_i,\text{comp}}(x)$ of x object with m linguistic variables to the given classes can be calculated based on the following equation:[4]

$$\mu_{\tilde{A}_i,\text{comp}}(x) = \left(\prod_{i=1}^{m} \mu_i(x)\right)^{(1-\gamma)} \left(1 - \prod_{i=1}^{m} (1 - \mu_i(x))\right)^{\gamma},$$

$$x \in X,\ 0 \leq \gamma \leq 1 \qquad (1)$$

where γ is the control parameter with a default value of 0.5 for a symmetric fuzzy set,[4] $\mu_i(x)$ is the membership value of object x (entry in grid in Figure 3 for a given dentist) to a particular linguistic variable (e.g. an appointment with a dentist within the next seven days has a membership $\mu_{\text{acceptable}} = 0.33$ and $\mu_{\text{unacceptable}} = 0.67$), m is the number of linguistic variables. Based on (1), values of dentist membership in classes are calculated and presented in brackets (see Figure 3).

The main benefit of fuzzy data classification becomes clear when one compares the presentation of classes C1, C2, C3 and C4 in Figures 2 and 3. As it is shown in Figure 3 with fuzzy data classification, one cannot only determine members of the given class but also compare the level of the membership in particular

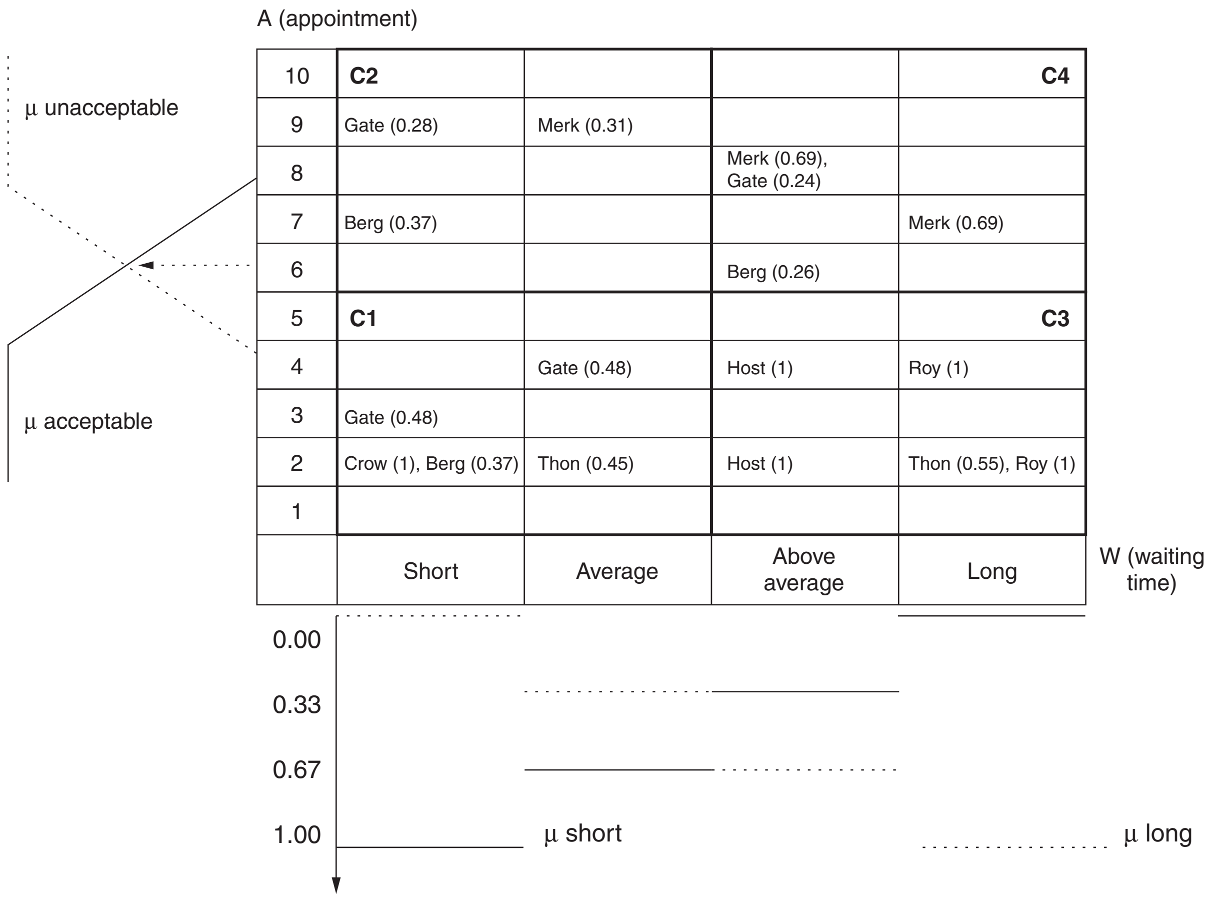


Figure 3 Fuzzy classification of dentists with appropriate membership values to the classes in brackets

classes. For example, based on the fuzzy classification, one can say that dentist Gate belongs more to class C1 than to classes C2 or C4 (see Figure 3). Membership values can be very useful for searching the most representative dentists in the given class. They become important criteria for evaluating dentists; one only needs to compare membership values of dentists in a particular class. For example, if two dentists have the same values of *Appointment* and *Waiting Time* for a particular dental care service, one can compare their membership values in the given class. The dentist with a higher membership value to class C1 provides better services (based on available patient feedback).

Membership value is similar to the deviation in the statistics and shows the distribution of the dentist membership to various classes. For example, to get dentists that belong to class C4 (see Figure 3), one could get data output as a database view (see Table 2) after fuzzy classification. Using the data view shown, one can say that dentist Merk belongs to class C4 more than dentist Berg or dentist Gate because of the higher value of membership function.

The use of fuzzy classification provides higher accuracy of data presentation and gives a more precise description of data in generated reports. The drawback is that membership values of dentists have to be

Table 2 Database view for members of class C4 ('Interfere for improvements')

Dentist	Class	Waiting time	Availability of appointment	Membership value
Merk	C4	Long	Unacceptable	0.69
Berg	C4	Long	Unacceptable	0.25
Gate	C4	Long	Unacceptable	0.23

calculated with relatively complicated mathematical formulae. This can make the SQL querying process somewhat complicated to implement in some cases.

There are different approaches for implementing the presented fuzzy classification in practice. One of the approaches is to use fuzzy querying languages as an extension of the conventional SQL.[2,7] However, an introduction of new clauses into the SQL syntax changes conventional SQL functionality. To attract more users' attention to fuzzy applications, we propose to use only conventional SQL functionality for querying data with fuzzy classification. Database users do not need to add any new clauses to the SQL syntax and can continue using a conventional syntax of SQL, as if there were no fuzzy classification behind the data. This approach provides an added value to the conventional SQL and becomes very attractive for users of existing relational databases in dental practices.

SQL for fuzzy classified data querying

The goal of SQL querying of data with fuzzy classification is to provide database views and/or reports of fuzzy classified data, similar to that presented in Table 2, using easy-to-use and familiar SQL queries. To implement the functionality of SQL for fuzzy classified data querying in relational databases, the best solution is to develop an interpreter as a stored procedure that will translate conventional SQL commands into native SQL queries of a particular database. Users can formulate SQL queries with well-defined and familiar terms and do not need to know definitions of equivalence classes in detail or fuzzy classification details behind the data. In addition, all complex mathematical formulae for calculating membership functions are hidden from users; the interpreter will take care of them. In the prototype developed, the following basic functionality of SQL for fuzzy classified data was implemented:

select <*Object*>
[**into**] <*View*>
from <*Relation*>
[**where**] <*Classification_condition*>

For example, SQL query:

select Dentist **into** [FUZZY CLASSIFIED DENTISTS] **from** OFFERS

performs a classification (see Figure 3) of all dentists from the OFFERS table (see Table 1) into [FUZZY CLASSIFIED DENTISTS] view. [FUZZY CLASSIFIED DENTISTS] view content is presented in Table 3.

Data from [FUZZY CLASSIFIED DENTISTS] view can be again queried using conventional SQL for further data analysis and report generation. An extended SQL query:

select Dentist **from** OFFERS **where** (Appointment = 'unacceptable' and [Waiting Time] = 'long')

will generate the data presented in Table 2. SQL for fuzzy classified data fully complies with the conventional SQL. The only difference is that one needs to use an interpreter that will translate the above-presented SQL queries into the native SQL queries of the given database management system, for example into Transact-SQL of the Microsoft™ SQL Server 2000. To implement the SQL for querying of fuzzy classified data, appropriate database management system extensions will be added.

Fuzzy classification and querying implementation in relational databases

The implementation scheme of SQL for fuzzy classified data querying includes the following steps:

1 Design of database tables or views to query them later using SQL for fuzzy classified data. This step has to be carried out by database owners.
2 Design of database extensions (additional tables that contain linguistic variables, membership values and descriptions of atomic values). This step should be carried out by an expert in the given application area.
3 Design and implementation of the interpreter for SQL transformation into native SQL for the given relational database management system using lexical and syntactical analysis of queries. This step should be carried out by the software developer that will develop an interpreter in the form of the stored procedure for the given database management system.
4 Generation of database reports and views using SQL querying of fuzzy classified data formed in steps 1 and 2.

The scheme of the developed framework implementation in a relational database is shown in Figure 4. Processing of SQL queries by the interpreter includes two main stages:

- syntactical analysis of SQL string clauses for fuzzy classified data querying
- execution of native SQL sub-queries (grouping of objects into classes, calculation of 'compensatory AND' membership of objects to the classes and

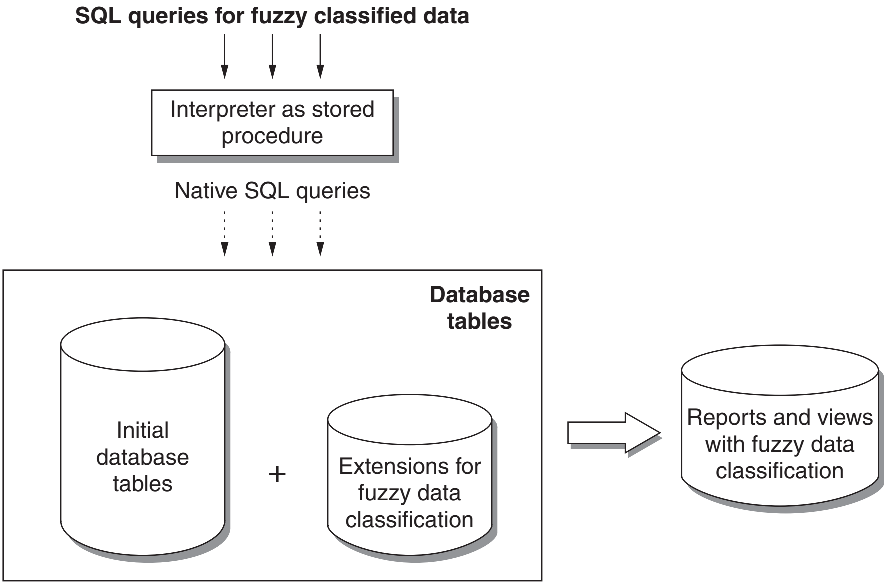


Figure 4 Scheme of fuzzy classification framework implementation in a relational database

calculation of normalised membership of objects to classes) with parameters from SQL clauses for fuzzy classified data querying.

The fuzzy SQL interpreter was developed with the assumption that similar interpreters could be developed for other platforms, like Oracle or SyBase, using their embedded SQL versions. The interpreter was realised as a stored procedure on the Microsoft™ SQL Server 2000 that could translate SQL queries for fuzzy classified data into normal Transact-SQL queries. The syntactical analysis (typical extraction of clauses from query string) of SQL queries for fuzzy classified data was implemented using Transact-SQL functions (SUBSTRING, LTRIM, RTRIM, LEFT and PATINDEX) for strings and embedded Microsoft™ SQL Server 2000 stored procedure (SP_EXECUTESQL).

The initial database scheme of our example in the normalised form is presented in Figure 5.

To extend the current database scheme for working with fuzzy classified data, database scheme extensions (i.e. tables and relationships) were provided for fuzzy classification, as shown in Figure 6.

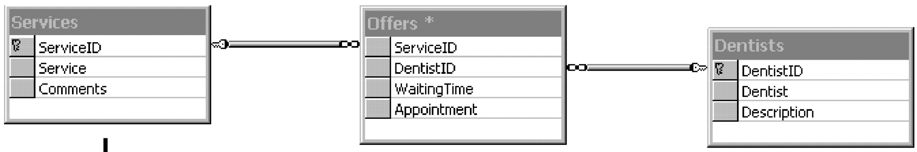
In addition to initial OFFERS, SERVICES and DENTISTS tables (see Figure 5), the following classifications tables were added (see Figure 6): fAPPOINTMENT, fWAITINGTIME, fCLASSES, fCLASSES DEFINITION and fLINGUISTICVARIABLES. These additional tables include the definition of classes, linguistic variables and their dependencies. To query the given database and receive a fuzzy classified data report similar to that shown in Table 3, one might have to execute a very large native Transact-SQL query without an interpreter. Instead of this, one can execute a simple SQL query with the help of the developed fuzzy SQL interpreter and receive the same results, as shown in Figure 7.

Thus, the usage of SQL with the developed fuzzy SQL interpreter is much easier and more user-friendly than the direct use of native Transact-SQL in Microsoft™ SQL Server. The drawback of the presented solution is that it is not flexible enough for possible database structure changes and might require additional programming to implement other operators (currently, it supports only one 'compensatory AND' operator for computing membership function).

Conclusions

We have shown how fuzzy classification can be used in dental care services; in particular, we developed a general and easy-to-use computer-aided assessment method based on fuzzy classification to help dental practices in the assessment of patients' feedback. In comparison to conventional classification approaches, use of fuzzy classification provided a more accurate evaluation of patients' feedback combining verbal and numeric data. Various criteria (both verbal and numeric) can be relatively easily combined into a joint response measure called the aggregated value of the membership, which can be used as the general measure of patients' satisfaction with dental care services provided.

The fuzzy classification and use of conventional SQL queries in our computer-aided assessment method



ServiceID	Service	Comments
1	Consultation	No comments
2	Tooth removal	No comments
3	Tooth treatment	No comments

DentistID	Dentist	Description
1	Crow	Experienced dentist
2	Roy	Experienced dentist
3	Gate	Visiting dentist
4	Merk	Bachelor dentist
5	Host	Dentist
6	Berg	Dentist
7	Thon	Experienced dentist

ServiceID	DentistID	WaitingTime	Appointment
1	7	long	2
2	2	long	2
2	4	above average	8
3	6	above average	6
1	4	average	9
1	1	short	2
1	3	average	4
1	6	short	7
2	3	short	3
1	2	long	4
1	5	above average	2
3	5	above average	4
3	7	average	2
3	3	short	9
3	6	short	2
2	3	above average	8
1	4	long	7

Figure 5 Initial database scheme with content and relationships in our example

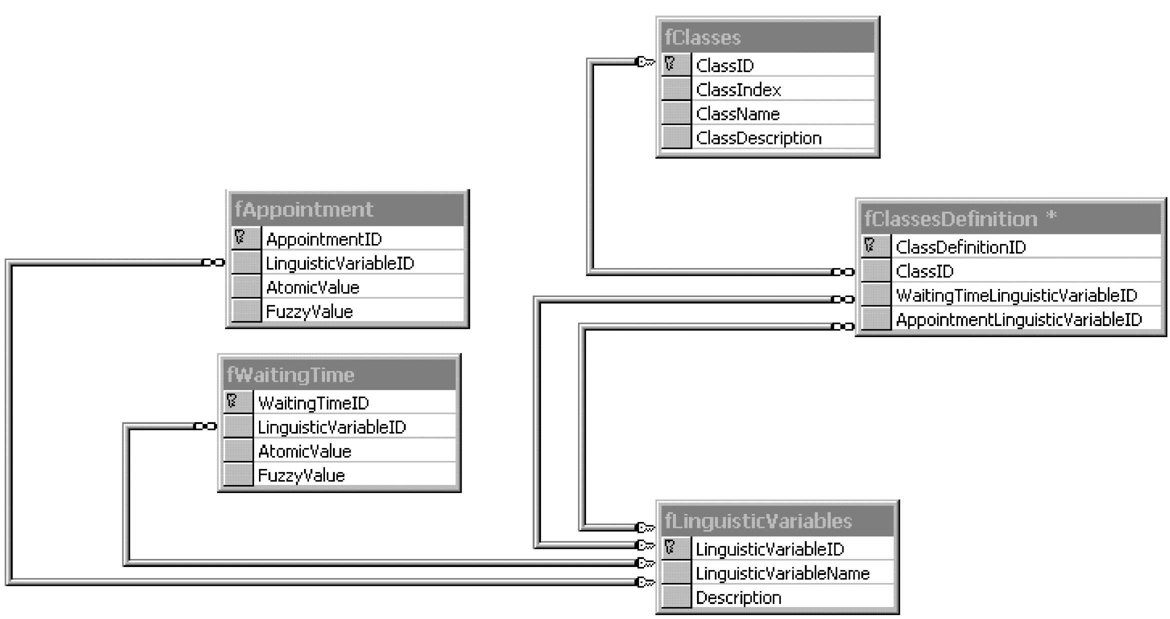
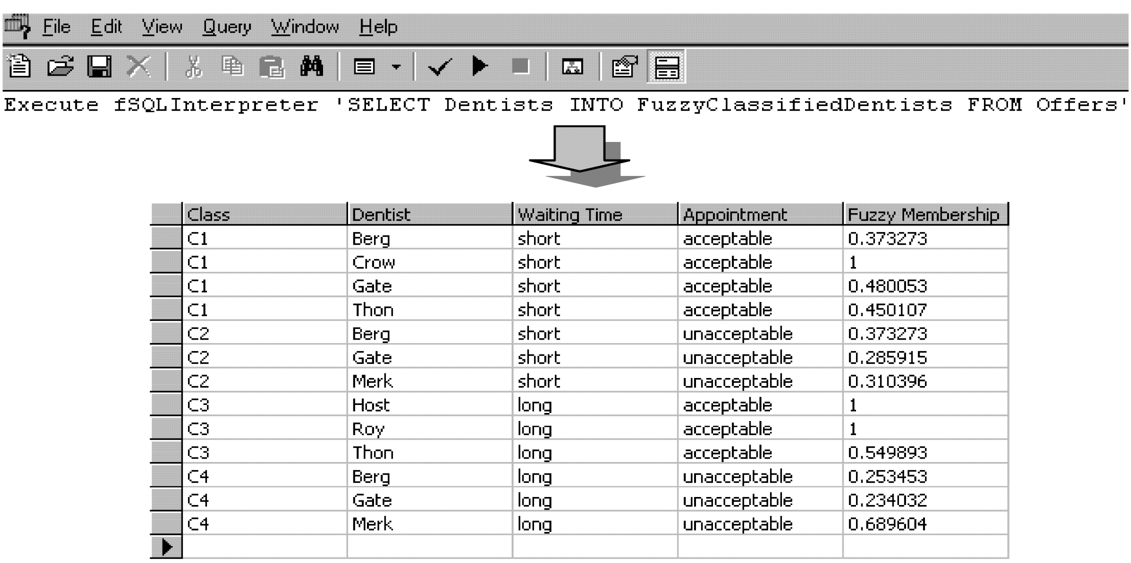


Figure 6 Introduced database extension tables and relationships for fuzzy classification

Table 3 FUZZY CLASSIFIED DENTISTS view

Dentist	Class	Waiting time	Availability of appointment	Membership value
Crow	C1	Short	Acceptable	1
Gate	C1	Short	Acceptable	0.48
Thon	C1	Short	Acceptable	0.45
Berg	C1	Short	Acceptable	0.37
Merk	C2	Short	Unacceptable	0.31
Gate	C2	Short	Unacceptable	0.28
Berg	C2	Short	Unacceptable	0.37
Host	C3	Long	Acceptable	1
Roy	C3	Long	Acceptable	1
Thon	C3	Long	Acceptable	0.55
Merk	C4	Long	Unacceptable	0.69
Berg	C4	Long	Unacceptable	0.26
Gate	C4	Long	Unacceptable	0.24



Class	Dentist	Waiting Time	Appointment	Fuzzy Membership
C1	Berg	short	acceptable	0.373273
C1	Crow	short	acceptable	1
C1	Gate	short	acceptable	0.480053
C1	Thon	short	acceptable	0.450107
C2	Berg	short	unacceptable	0.373273
C2	Gate	short	unacceptable	0.285915
C2	Merk	short	unacceptable	0.310396
C3	Host	long	acceptable	1
C3	Roy	long	acceptable	1
C3	Thon	long	acceptable	0.549893
C4	Berg	long	unacceptable	0.253453
C4	Gate	long	unacceptable	0.234032
C4	Merk	long	unacceptable	0.689604

Figure 7 Fuzzy classified data querying using SQL and fuzzy SQL interpreter as the stored procedure

provided a much needed functionality of more accurate data extraction and analysis compared with conventional non-fuzzy classification and SQL querying. The main practical benefits of using fuzzy classification and SQL querying are the following:

- good integration with conventional databases and high flexibility for data analysis
- data presentation with linguistic variables and fuzzy values in the report generation stage (such data presentation is more descriptive for users since one does not have to 'think in numbers' – one can use descriptive linguistic variables instead)
- possible users of the fuzzy classification approach do not have to make large changes in their existing data structures (which could be quite large) – they

will just have to extend them with a few additional tables that define fuzzy values and linguistic variables.

Future work will include the detailed testing in dental practices of the fuzzy classification framework developed and comparison of implementation of various operators to calculate conjunctions of membership function values in fuzzy classifications.

REFERENCES

1 Zadeh L. *Fuzzy Logic, Neural Networks, and Soft Computing*. New York: ACM Press, 2004.
2 Wertz V, Vandewalle J, Vandewalle J and Espinosa J. *Fuzzy Logic, Identification, and Predictive Control*. Berlin: Springer Verlag, 2004.
3 Han J and Kamber M. *Data Mining: concepts and techniques*. New York: Morgan Kaufmann Publishers, 2001.
4 Zimmermann H. *Fuzzy Set Theory and its Applications*. London: Kluwer, 1992.
5 Bellma M and Vojdani N. Fuzzy prototypes for fuzzy data mining. *Studies in Fuzziness and Soft Computing* 2000;39:175–86.
6 Bosc P and Pivert O. SQLf query functionality on top of a regular relational database management system. *Studies in Fuzziness and Soft Computing* 2000;39:71–91.
7 Kacprzyk J and Zadrozny S. On combining intelligent querying and data mining using fuzzy logic concepts. *Studies in Fuzziness and Soft Computing* 2000;53:67–84.
8 Borgodna G, Leporati A, Lucarella D and Pasi G. The fuzzy object-oriented database management system. *Studies in Fuzziness and Soft Computing* 2000;53:209–36.
9 Dubois D, Nakata M and Prade H. Extended divisions for flexible queries in relational databases. *Studies in Fuzziness and Soft Computing* 2000;39:105–21.
10 Strackeljan J, Behr D and Kocher T. Fuzzy-pattern recognition for automatic detection of different teeth substances. *Fuzzy Sets and Systems* 1997;85:275–86.
11 Anvari M. A database model for medical consultation. *Journal of the American Society for Information Science* 1991;42(8):554–7.
12 Belmonte-Serrano M, Sierra C and Lopez de Mantaras R. RENOIR: an expert system using fuzzy logic for rheumatology diagnosis. *International Journal of Intelligent Systems* 1994;9(11):985–1000.
13 Brai A, Vibert J and Koutlidis R. An expert system for the analysis and interpretation of evoked potentials based on fuzzy classification: application to brainstem auditory evoked potentials. *Computers and Biomedical Research* 1994;27(5):351–66.
14 Cios K, Goodenday L and Sztandera L. Hybrid intelligence system for diagnosing coronary stenosis. Combining fuzzy generalized operators with decision rules generated by machine learning algorithms. *IEEE Engineering in Medicine and Biology Magazine* 1994;13(5): 723–9.
15 Degani R. Computerized electrocardiogram diagnosis: fuzzy approach. *Methods of Information in Medicine* 1992;31(4):225–33.
16 Kuncheva L. Fuzzy multi-level classifier for medical applications. *Computers in Biology and Medicine* 1990; 20(6):421–31.
17 Leung K, Wong F and Lam W. The development of an expert computer system on medical consultation. *International Journal of Biomedical Computing* 1988;23(3): 265–78.
18 Schindler G. *Fuzzy Data Analysis Using Context Based Database Queries.* [In German.] Wiesbaden, Germany: DUV Gabler, 1998.
19 www.modern.nhs.uk
20 www.bda-dentistry.org.uk
21 www.montefiore.org

CONFLICTS OF INTERESTS

None.

ADDRESS FOR CORRESPONDENCE

Yauheni Veryha
Integrated Solutions Group, ABB Corporate Research, Ladenburg, Germany
Collinistr. 5/804
68161 Mannheim
Germany
Tel: +49 (0) 62 03–71 60 24
Fax: +49 (0) 62 03–71 62 53
Email: yauheni.veryha@de.abb.com

Accepted January 2005