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Towards an expert system in ion-exclusion chromatography by means of multiple classification ripple-down rules

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Abstract

We describe the development and maintenance of an expert system to advise on the configuration of systems for ion-exclusion chromatography. The aim of the system is to define appropriate conditions for the separation of desired groups of acids or bases. The system is implemented in a rule-based system, multiple classification ripple-down rules, which offers multiple conclusions from rules based on the attributes of the system. In this case the attributes include physical and chemical properties of the solutes and the availability of instrumentation and accessories. With this information the method conditions can be defined for the detector, mobile-phase, whether suppression is to be used, and other ion-exclusion chromatography method conditions. A unique feature is that some conditions may be filled in by the program or be given by the user. Because of the nature of the ''ripple-down rules'' approach, in which new knowledge is always added as an amendment to an existing conclusion (and therefore cannot interfere with other conclusions), the expert or user can maintain and alter the system easily according to their own needs without the help of a software engineer. The system was developed and tested using cases from published papers on ion exclusion chromatography. For a set of 83 cases, although the expert system only agreed with the published conditions in 53% of cases, when the predictions were assessed by a recognized ion chromatography expert, 88% were pronounced ''workable''. © 1998 Published by Elsevier Science B.V.

Keywords: Ion-exclusion chromatography; Expert systems; Artificial intelligence

1. Introduction

1.1. General introduction

Artificial intelligence (AI) and in particular expert systems (ESs) are playing an increasingly important role in providing ''built-in'' intelligence in current analytical methods such as nuclear magnetic resonance (NMR), high-performance liquid chromatography (HPLC) and ion chromatography (IC). Overviews of the use of expert systems in analytical chemistry been given by Bridge [1] and by Peris [2]. Many of the published systems have been applied to problems in development of HPLC [3]. This paper describes the development and maintenance of an ES to advise on the configuration of ion-exclusion chromatography systems. The system is implemented in a rule-based system, MCRDR (multiple classification ripple-down rules), in which the developer offers multiple conclusions from rules based on the attributes of the system. In this case the attributes include physical and chemical properties of the solutes and

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the availability of instrumentation and accessories. With this information the method conditions can be defined for the detector, mobile-phase, whether suppression is to be used, and other ion-exclusion chromatography method conditions.

Ion exclusion is a well known chromatographic technique for separating strong acids as a class from weak acids using a high-capacity sulfonated ion-exchange resin [4]. The ion-exclusion chromatography mechanism of solute retention is based on the phenomenon that neutral analyte molecules penetrate the resin while ionic analytes having the same charge as the fixed ion on the ion-exchange resin are repelled or, in other words, excluded from it. Therefore by this mechanism acidic compounds can be separated on a cation-exchange resin and basic compounds on an anion-exchange resin. The aim of the expert system is to define appropriate conditions for the separation of desired groups of acids or bases.

1.2. Expert systems

A formal and complete definition of an ES is:

‘‘*Expert systems are a class of computer programs that can advise, analyze, categorize, communicate, consult, design, diagnose, explain, explore, forecast, form concepts, identify, interpret, justify, learn, manage, monitor, plan, present, retrieve, schedule, test and tutor. They address problems normally thought to require human specialists for their solution*’’ [5].

A genuine ES should offer a number of features to the user: it should offer valuable advice in an area requiring expert knowledge; the problem addressed by the expert should be important and sufficiently difficult; it should be able to provide some kind of explanation for its reasoning and it should be able to provide additional assistance to the user both to assist in the consultation of the system and to clarify the advice [6,7].

A key concept underlying the success of an expert system is the importance of the quality of the knowledge base which can determine the usefulness of the ES, regardless of the sophistication of the knowledge representation or inference design it uses [8,9]. To achieve this, knowledge must be extracted from the human expert and transmitted to the computer, a task that is usually done by a knowledge engineer. In general the knowledge engineer, who is usually a computer scientist, needs to have some understanding of the domain in order to successfully translate the response of the expert into rules of the ES. A goal of the RDR approach is to constrain the addition of new rules in such a way that the expert can build and maintain the ES without the intervention of a knowledge engineer.

1.3. MCRDR

MCRDR, like its predecessor RDR [10], bases its acquisition of knowledge on the assumption that the knowledge an expert provides is essentially a justification for a conclusion in a particular context. A major component of the context is the case that has been given a wrong classification by the current ES, and how this differs from other cases for which the classification is correct.

MCRDR is a knowledge acquisition and representation tool which restricts the use of knowledge to the particular context in which it acquires. New knowledge is always added as an amendment to an existing conclusion (and therefore cannot interfere with other conclusions), and the expert or the user can maintain and alter the system easily according to their own needs without the help of a software engineer.

IC is a domain with many experts and users and is one in which the knowledge changes and evolves with time (new methods are published, different uses are found, instrumentation changes). To illustrate the utility of the MCRDR/RDR approach [11–13] an expert system for the configuration of ion-exclusion chromatographic systems was developed and maintained.

2. Theory of MCRDR

2.1. Inference

The MCRDR inference operation is based on searching the knowledge base (KB) represented as a decision list with each decision possibly refined again by another decision list. MCRDR evaluates all the rules in the first level of the KB. It then evaluates the rules at the next level of refinement for each rule that was satisfied at the top level and so on. The process stops when there are no more rules to evaluate or when none of these rules can be satisfied further. The inference process can be viewed as multiple paths from the root of the KB to the conclusions, as shown in Fig. 1. A case that provides a rule in the ES is known as a ''cornerstone'' case.

2.2. Addition of rules

When a case is presented to the system the rules are assessed in order and a conclusion assumed. If the human expert does not agree with this conclusion the following algorithm is processed. First, the system forms a ''cornerstone case list'' which can reach the part of the tree where the new rule will be made (i.e., where the condition which is in dispute is made). The expert is asked to select conditions from a difference list between the present case and one of the cases for the cornerstone case list. The system then tests all cornerstone cases in the list against the conditions selected and deletes cornerstone cases from the list that do not satisfy the condition selected. The expert is then asked to choose conditions from a difference list between the current case and one of the remaining cornerstone cases in the list. The conditions selected are added as a conjunction to the rule. The system repeats this procedure until no cornerstone case remains in the list which satisfies the rule. After the system adds a new rule with the selected conditions, it tests the remaining cornerstone cases associated with the parent rule and any cases which can satisfy the new rule are saved as a cornerstone case of the new rule. Finally the new case is added to the cornerstone case data base. The lists of cornerstone cases for the other rules correctly satisfied by the case (i.e., giving a correct classification for the case) are also updated to include the new case. The system is now ready to run another case and, if the classifications provided are not acceptable to the expert, for more knowledge acquisition.

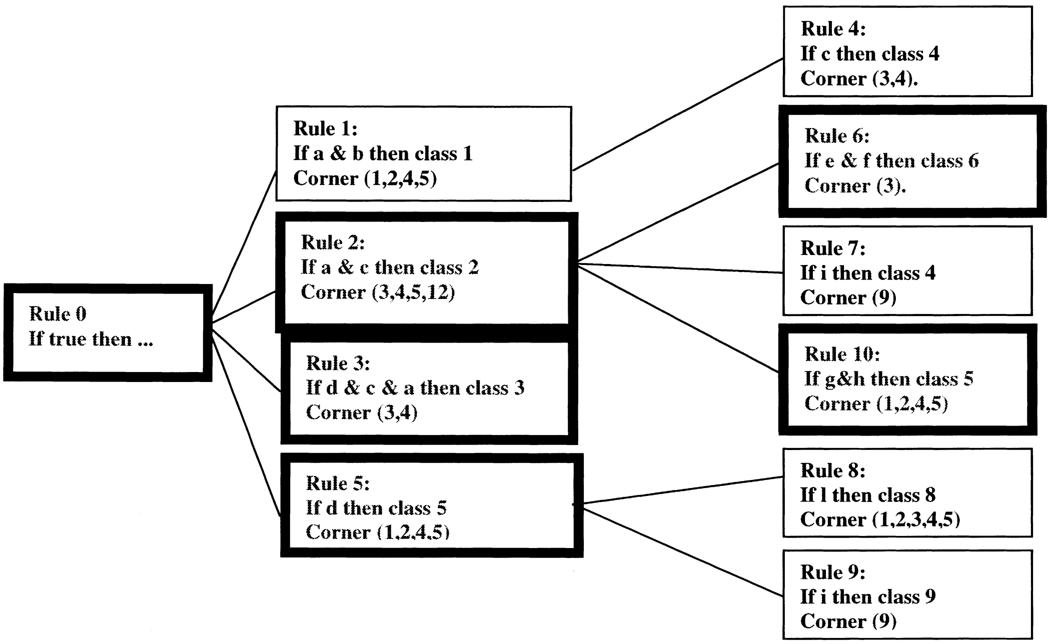

Fig. 1. Schematic of the operation of MCRDR. Highlighted boxes represent rules that are satisfied for the case considered. Rule zero is a default initial rule that allows entry to the MCRDR.

3. Experimental

3.1. Data

Our goal for this work was to develop an expert system for ion-exclusion chromatography; one of us (P.R.H.) developed a database of all the significant published methods employing IC between 1980 and 1996. This amounts to over four thousand examples of IC [14]. The cases that used ion-exclusion chromatography were extracted. Among these cases, only the 83 cases that featured Dionex hardware were used in building the expert system. An example of a case in the database is shown in Table 1. Only the necessary information was extracted from the case and encoded as a series of attribute values (Table 2, column 1).

Separation in ion-exclusion chromatography is influenced by electrostatic forces, adsorption, size and other effects [4,15]. Electrostatic effects are governed by the charge on the solute, the polarizability of the solute and the ion-exchange capacity of the stationary phase. Adsorption effects are governed by the hydrophobicity of the solute, the hydrophobicity of the polymer used in the stationary phase and the amount of organic modifier present in the eluent. Finally, relative sizes of the solute and the pores of the stationary phase lead to size effects. By taking all these factors into consideration other attributes that contribute to these effects were added to the case. These attributes were: (i) charge of the solute, (ii) pK_a values of the solutes, (iii) whether the solute acids are mono-, di- or triprotic, (iv) the hydrophobicity of the solutes and (v) the molecular mass of the solute.

Detection in ion-exclusion chromatography is usually by UV–visible absorbance spectroscopy or conductivity measurement after post-column manipulation, such as the use of suppressors or enhancement columns. Electrochemical detection is used for certain electroactive solutes that cannot be detected by UV or suppressed conductivity. Finally, refractive index is sometimes used as a last resort when other detection methods are inapplicable [4]. Bearing in mind the above, more attributes were automatically added to the case from an internal look-up table that described the nature of the solutes and special characteristics that may lead to the desired detection. These attributes were: (vi) molar absorptivity and wavelength of maximum absorption of the solutes, (vii) whether the solutes were amenable to suppression and hence conductivity detection, (viii) chemical reactivity to form complexes that may increase the conductance or UV absorbance of the solutes and (ix) electrochemical reactivity of solutes and working voltage range. These additional attributes are given for the illustrative example in Table 2 column 3.

The minimum information that a user must supply is the identity of the solutes. The ES first fills in the information as shown in Table 2, then adds any missing attributes by the MCRDR (Table 2, column 4). Thus although information regarding the detector,

Table 1
A typical case for IC from which the ES was built

Attributes	Values
Record	3968
Hardware	Dionex QIC
Column	Dionex AS-1 ion exclusion, 250×2.0 mm I.D.
Packing	Cross-linked polystyrene–divinylbenzene (PS–DVB) cation exchanger
Eluent	2.0 m*M* sulfuric acid; 0.8 ml/min
Solutes	Lactic (6.9), tartaric (8.0), malic (10.0), acetic (13.2)
Detection	Conductivity with various suppresser devices
Detection limit	2 ppm
Sample	White wine
Preparation	Dilution, filtration
Temperature	Ambient

Table 2
A typical case treated by the expert system

Attributes	Haddad Database	Input to ES	Filled out by database in the system	Output by ES	Agree
Sample	Lactic, tartaric, malic, acetic	Lactic, tartaric, malic, acetic	Lactic, tartaric, malic, acetic	Lactic, tartaric, malic, acetic	
Column	Dionex AS-1 ion exclusion			Dionex AS-1 ion exclusion	Yes
Detector	Conductivity			Conductivity	Yes
Mobile phase	H_2SO_4			HCl	No
Column packing	Cross-linked PS–DVB cation exchanger			Cross-linked PS–DVB cation exchanger	Yes
Mobile phase concentration	2.0 m*M*			2.0 m*M*	Yes
Modifier	No			No	Yes
Post column	No			No	Yes
Mobile phase pH	Acidic			Acidic	Yes
Suppressed	Yes			Yes	Yes
Electrode	No			No	Yes
pK_a			3.86, 2.93, 3.40, 4.76		
Charge			$-\partial$, $-\partial$, $-\partial$, $-\partial$		
Molecular mass			90.1, 151, 116.1, 60.05		
Spectroscopic absorbance			No, no, no, no		
Electrochemically active			No, no, no, no		
Conductance			Yes, yes, yes, yes		
Form complex			No, no, no, no		
Hydrogen state			Mono, di, di, mono		
Hydrophobic			Yes, yes, yes, no		
Type			Aliphatic, aliphatic, aliphatic, aliphatic		

mobile phase and column packing may usually be required by the users, if the laboratory only possessed, for example, a conductivity detector, this could be specified and the ES would attempt to build a method around this constraint.

3.2. Software

The expert system shell was written as a client/server application. The user interface was written in Microsoft Visual Basic version 3 for windows. The interface calls a server program for the information it needs using Dynamic Data Exchange (DDE). The server program was written in Visual C++ version 2.0, and it had no interface at all except for its DDE support. The server had a set of commands that allow user to access all the functions of MCRDR.

4. Results and discussion

A 108-rule knowledge base was built from the 83 cases presented to the MCRDR in chronological order of publication. Fig. 2 shows how many rules were added after each case. Initially a large number of rules were added with each new case but as the ES was developed fewer new rules needed to be added. Attributes generated by the ES were then compared with those listed in the cases in the database, with 53% giving a complete match (i.e., every attribute generated was the same as its entry in the database). Table 3 shows the percentage agreement for every individual attribute configured by the ES and the overall agreement for the entire set of attributes. It is seen that the mobile phase was responsible for the greatest level of mismatch. This arose from the interchangeability of sulfuric and

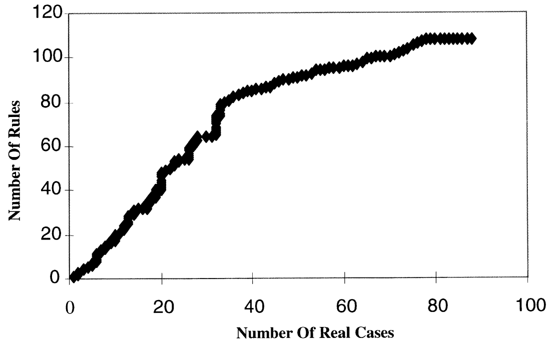

Fig. 2. The number of rules added to the ES as a function of the case considered.

Table 3
The agreement between the original cases and the configuration predicted by the ES

Information	% Agreement
Detector	88
Column packing	93
Mobile phase	56
Modifier	88
Post column	98
Mobile phase pH	78
Suppressed	71
Electrode	93
All	52

hydrochloric acids for many cases. The cases generated by the ES were presented to the expert (P.R.H.) who judged them to be ''not workable'', ''workable'', ''good'', ''very good'' or ''ideal''. The outcome of this evaluation is shown in Table 4, in which the results are expressed as a percentage of the total number of cases studied. Overall only 12% of cases were assessed as ''not workable'', thus 88% could have been employed usefully.

Table 4
Assessment by an expert of the classifications of the ES

Ideal	7%
Very good	33%
Good	25%
Workable	23%
Not workable	12%

5. Conclusion

MCRDR provides a very simple knowledge acquisition strategy which allows experts to build expert systems using only their domain knowledge: no knowledge engineer insight is required. An ES is reported that can advise the configuration of an ion-exclusion chromatography system, providing methods that were considered workable by an expert in 88% of the cases considered. It would be possible for an expert to add rules to account for the differences generated by the 10 ''non-workable'' cases. A more complete MCRDR-ES is being developed from a data base of 361 ion-exclusion chromatography cases and will be released to selected experts for evaluation and development in the near future.

Acknowledgements

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