Data Mining Methods for Case-Based Reasoning in Health Sciences

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Abstract. Case-based reasoning (CBR) systems often refer to diverse data mining functionalities and algorithms. This article locates examples, many from health sciences domains, mapping data mining functionalities to CBR tasks and steps, such as case mining, memory organization, case base reduction, generalized case mining, indexing, and weight mining. Data mining in CBR focuses greatly on incremental mining for memory structures and organization with the goal of improving performance of retrieval, reuse, revise, and retain steps. Researchers are aiming at the ideal memory as described in the theory of the dynamic memory, which follows a cognitive model, while also improving performance and accuracy in retrieve, reuse, revise, and retain steps. Several areas of potential cross-fertilization between CBR and data mining are also proposed.

1 Introduction

Case-based reasoning (CBR) systems have tight connections with machine learning and data mining as exemplified by their description in data mining (Han et al. 2012) and machine learning (Mitchell 1997) textbooks. They have been tagged by machine learning researchers as *lazy* learners because they defer the decision of how to generalize beyond the training set until a target new case is encountered (Mitchell 1997), by opposition to most other learners, tagged as *eager*. Even though a large part of the inductive inferences are definitely performed at *Retrieval* time in CBR (Aha 1997), mostly through sophisticated similarity evaluation, most CBR systems also perform inductive inferences at *Retain* time. There is a long tradition within this research community to study what is a memory, and what its components and organization should be. Indeed CBR methodology focuses more on the memory part of its intelligent systems (Schank 1982) than any other artificial intelligence (AI) methodology, and this often entails learning declarative memory structures and organization. This article proposes to review the main data mining functionalities and how they are used in CBR systems by describing examples of systems using them and analyzing which roles they play in the CBR framework (Aamodt and Plaza 1994). The research question addressed is to determine the extent to which data mining functionalities are being used in CBR systems, to enlighten possible future research collaborations between these two fields, particularly in health sciences applications. This paper is organized as follows. After the introduction, the second section highlights major concepts and techniques in data mining. The third section reviews the main CBR cycle and principles. The fourth section explains relationships between CBR and machine learning. The following sections dive into several major data mining functionalities and how they relate to CBR. The ninth section summarizes the findings and proposes future directions. It is followed by the conclusion.

2 Data Mining Functionalities and Methods

Data mining is the analysis of observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner (Hand et al. 2001). Traditionally described as a misnomer, knowledge discovery or knowledge discovery in databases is a preferred term. Some functionalities are clearly well defined and researched, among which (Han et al. 2012):

- **Classification / prediction:** classification is a supervised data mining method applied to datasets containing an expert labeling in the form of a categorical attribute, called a class; when the attribute is numeric, the method is called prediction. Examples of classifiers include neural networks, support vector machines (SVMs), naïve Bayes, and decision trees.
- **Association Mining**: association mining mines for frequent itemsets in a dataset, which can be represented as rules such as in market basket analysis. It is an unsupervised method. The most famous algorithm in this category is a priori algorithm.
- **Clustering:** clustering finds groups of similar objects in a dataset, which are also dissimilar from the objects in other clusters. In addition to the similarity-based methods like K Means, some methods use density-based algorithms or hierarchical algorithms.

Considerations for evaluating the mining results vary in these different methods, however a set of quality measurements are traditionally associated with each, for example accuracy or error rate for classification, and lift or confidence for association mining.

These core functionalities can be combined and applied to several data types, with extensions to the underlying algorithms or completely new methods.in addition to the classical nominal and numeric data types. Well researched data types are graphs, texts, images, time series, networks, streams, etc. We refer to these extensions as multimedia mining.

Other types of functionalities, generally combined with the core ones are for example feature selection, where the goal is to select a subset of features, sampling, where the goal is to select a subset of input rows, and characterization, where the goal is to provide a summary representation of a set of rows, for example those contained in a cluster.

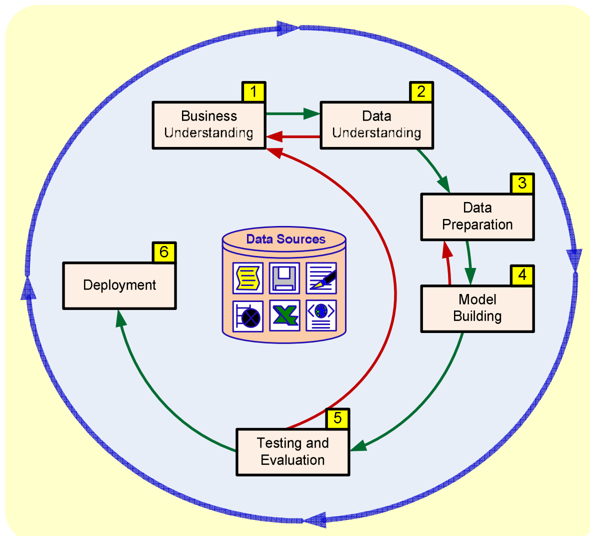

Fig. 1. CRISP-DM data mining process (Han et al. 2012)

Finally, the CRISP-DM methodology has been described to guide the data mining process (see Fig. 1) (Han et al. 2012). This methodology stresses the importance of stages preparing for and following the actual model building stage: data preparation, dealing with issues such as data consolidation, data cleaning, data transformation, and data reduction, which can require up to 85% of all the time dedicated to a project.

3 CBR Cycle and Methods

Case Based Reasoning is a problem solving methodology that aims at reusing previously solved and memorized problem situations, called cases. Traditionally, its reasoning cycle proceeds through steps (see Fig. 2). This article will refer to the major steps as Retrieve, Reuse, Revise, and Retain (Aamodt and Plaza 1994).

4 CBR and Machine Learning

CBR systems are generally classified as data mining systems because they can perform classification or prediction tasks. From a set of data – called cases in CBR – the classification or prediction achieved gives the case base a competency beyond what the data provide. If CBR systems are in par with data mining systems in such tasks as classification and prediction, there is, though an important difference. CBR systems start their reasoning from knowledge units, called cases, while data mining systems most often start from raw data. This is why case mining, which consists in mining raw data for these knowledge units called cases, is a data mining task often used in CBR. CBR systems also belong to instance based learning systems in the field of machine learning, defined as systems capable of automatically improving their performance over time. Although there is much commonality between data mining and machine learning, their definitions and goals are different. CBR systems are problem-solving systems following a reasoning cycle illustrated in Fig. 1. However as long as they learn new cases in their retain step, they are qualified as learning systems, thus belonging to machine learning system.

For this article, we will focus on identifying which data mining functionalities and methods are used in CBR, and what is their result in the CBR memory.

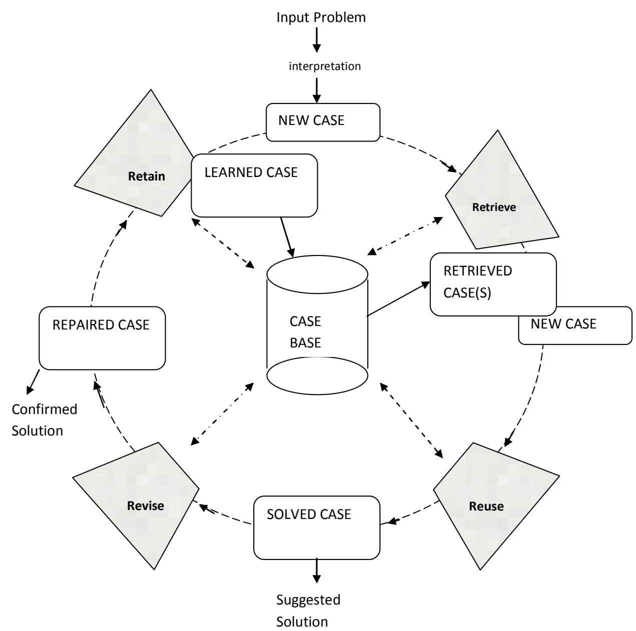

Fig 2. The classical CBR reasoning cycle (Aamodt and Plaza 1994)

First of all, since data mining emerged in the 90’s from scaling up machine learning algorithms to large datasets, let us review what machine learning authors have been saying about CBR. They consider case-based reasoning systems as either analogical reasoning systems (Michalski 1993), or instance based learners (Mitchell 1997). Michalski (1993) presents the analogical inference, at the basis of case-based retrieval, as a dynamic induction performed during the matching process. Mitchell (1997) refers to CBR as a kind of instance based learner. This author labels these systems as *lazy* learners because they defer the decision about how to generalize beyond the training data until each new query instance is encountered. This allows CBR systems to not commit to a global approximation once and for all during the training phase of machine learning, but to generalize specifically for each target case, therefore to fit its approximation bias, or induction bias, to the case at hand. He points here to the drawback of overgeneralization that is well known for eager learners, from which instance based learners are exempt (Mitchell 1997).

These authors focus their analysis on the inferential aspects of learning in case-based reasoning. Historically CBR systems have evolved from the early work of Schank in the theory of the dynamic memory (Schank 1982), where this author proposes to design intelligent systems primarily by modeling their memory. Ever since Schank's precursory work on natural language understanding, one of the main goals of case-based reasoning has been to integrate as much as possible memory and inferences for the performance of intelligent tasks. Therefore focusing on studying how case-based reasoning systems learn, or mine, their memory structures and organization can prove at least as fruitful as studying and classifying them from an inference standpoint.

From a memory standpoint, learning in CBR consists in the creation and maintenance of the structures and organization in memory. It is often referred to as case base maintenance (Wilson and Leake 2001). In the general cycle of CBR, learning takes place within the reasoning cycle - see (Aamodt and Plaza 1994) for this classical cycle. It completely serves the reasoning, and therefore one of its characteristics is that it is an *incremental* type of mining. It is possible to fix it after a certain point, though; in certain types of applications, but it is not a tradition in CBR: *learning is an emergent behavior from normal functioning* (Kolodner 1993). When an external problem-solving source is available, CBR systems start reasoning from an empty memory, and their reasoning capabilities stem from their progressive learning from the cases they process. Aamodt and Plaza (1994) further state that *case-based reasoning favours learning from experience*. The decision to stop learning because the system is judged competent enough is not taken from definitive criteria. It is the consequence of individual decisions made about each case, to keep it or not in memory depending upon its potential contribution to the system. Thus often the decisions about each case, each structure in memory, allow the system to evolve progressively toward states as different as ongoing learning, in novice mode, and its termination, in expert mode. If reasoning and thus learning are directed from the memory, learning answers to a process of prediction of the conditions of cases recall (or retrieval). As the theory of the dynamic memory showed, recall and learning are closely linked (Schank 1982). Learning in case-based reasoning answers a disposition of the system to anticipate future situations: *the memory is directed toward the future* both to avoid situations having caused a problem and to reinforce the performance in success situations.

More precisely, learning in case-based reasoning, takes the following forms:

1. Adding a case to the memory: it is at the heart of CBR systems, traditionally one of the main phases in the reasoning cycle, and the last one: *Retain* (Aamodt

and Plaza 1994). It is the most primitive learning kind, also called learning by consolidation, or rote learning.

2. Explaining: the ability of a system to find explanations for its successes and failures, and by generalization the ability to anticipate.
3. Choosing the indices: it consists in anticipating *Retrieval*, the first reasoning step.
4. Learning memory structures: these may be learnt by generalization from cases or be provided from the start to hold the indices for example. These learnt memory structures can play additional roles, such as facilitating reuse or retrieval.
5. Organizing the memory: the memory comprises a network of cases, given memory structures, and learned memory structures, organized in efficient ways. Flat and hierarchical memories have been traditionally described.
6. Refining cases: cases may be updated, refined based upon the CBR result.
7. Discovering knowledge or metareasoning: the knowledge at the basis of the case-based reasoning can be refined, such as modifying the similarity measure (weight learning), or situation assessment refinement. For example d'Aquin et al. (2007) learn new adaptation rules through knowledge discovery.

5 Classification / Prediction and CBR

Since CBR is often used as a classifier, other classifiers are generally used in ensemble learning to combine the CBR expertise with other classification/prediction algorithms. Another type of combination of classifier is to use several CBR systems as input to another classifier, for example SVM, applied to the task of predicting business failure (Li and Sun 2009).

Another notable class of systems is composed of those performing *decision tree induction* to organize their memory. INRECA (Auriol et al. 1994) project studied how to integrate CBR and decision tree induction. They propose to preprocess the case base by an induction tree algorithm, namely a decision tree. Later refined into an *INRECA tree* (see Fig. 2), which is a hybrid between a decision tree and a k-d tree, this method allows both similarity based retrieval and decision tree retrieval, is incremental, and speeds up the retrieval. This system was used in biological domains among others.

6 Association Mining and CBR

Association mining, although not looking closely related to CBR, can be resorted in several scenarios. Main uses are for case mining and case base maintenance.

Wong et al. (2001) use fuzzy association rule mining to learn cases from a web log, for future reuse through CBR.

Liu et al. (2008) use frequent item sets mining to detect associations between cases, and thus detect cases candidate for removal from the case base and thus its reduction (Retain step).

7 Clustering and CBR

Memory structures in CBR are foremost cases. A case is defined as a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of a reasoner (Kolodner 1993). For many systems, cases are represented as truthfully as possible to the application domain. Additionally, data mining methods have been applied to cases themselves, features, and generalized cases. These techniques can be applied concurrently to the same problem, or selectively. If the trend is now to use them selectively, probably in the near future CBR systems will use these methods more and more concurrently.

7.1 Case mining

Case mining refers to the process of mining potentially large data sets for cases (Yang and Cheng 2003). Researchers have often noticed that cases simply do not exist in electronic format, that databases do not contain well-defined cases, and that the cases need to be created before CBR can be applied. Instead of starting CBR with an empty case base, when large databases are available, preprocessing these to learn cases for future CBR permits to capitalize on the experience dormant in these databases. Yang and Cheng (2003) propose to learn cases by linking several database tables through *clustering* and *Support Vector Machines (SVM)*. The approach can be applied to learning cases from electronic medical records (EMRs).

7.2 Generalized case mining

Generalized case mining refers to the process of mining databases for generalized and/or abstract cases. Generalized cases are named in varied ways, such as prototypical cases, abstract cases, prototypes, stereotypes, templates, classes, ossified cases, categories, concepts, and scripts – to name the main ones (Maximini et al. 2003). Although all these terms refer to slightly different concepts, they represent structures that have been abstracted or generalized from real cases either by the CBR system, or by an expert. When these prototypical cases are provided by a domain expert, this is a knowledge acquisition task. More frequently they are learnt from actual cases. In CBR, prototypical cases are often learnt to structure the memory. Therefore most of the prototypical cases presented here will also be listed in the section on structured memories.

In medical domains, many authors mine for *prototypes*, and simply refer to *induction* for learning these. CHROMA (Armengol and Plaza 1994) uses induction to learn prototypes corresponding to general cases. Bellazzi et al. organize their memory around prototypes (Bellazzi et al. 1998). The prototypes can either have been acquired from an expert, or induced from a large case base. Schmidt and Gierl (1998) point that prototypes are an essential knowledge structure to fill the gap between general knowledge and cases in medical domains. The main purpose of this prototype learning step is to guide the retrieval process and to decrease the amount of storage by erasing redundant cases. A generalization step becomes necessary to learn the knowledge contained in stored cases.

Others specifically refer to *generalization,* so that their prototypes correspond to generalized cases. For example Malek proposes to use a *neural network* to learn the prototypes in memory for a classification task, such as diagnosis (Malek 1995). Portinale and Torasso (1995) in ADAPTER organize their memory through E-MOPs (Kolodner 1993) learnt by generalization from cases for diagnostic problem-solving. Maximini et al. (2003) have studied the different structures induced from cases and point out that several different terms exist, such as generalized case, prototype, schema, script, and abstract case. The same terms do not always correspond to the same type of entity. They define three types of cases. A point case is what we refer to as a real or ground case. The values of all its attributes are known. A generalized case is an arbitrary subset of the attribute space.

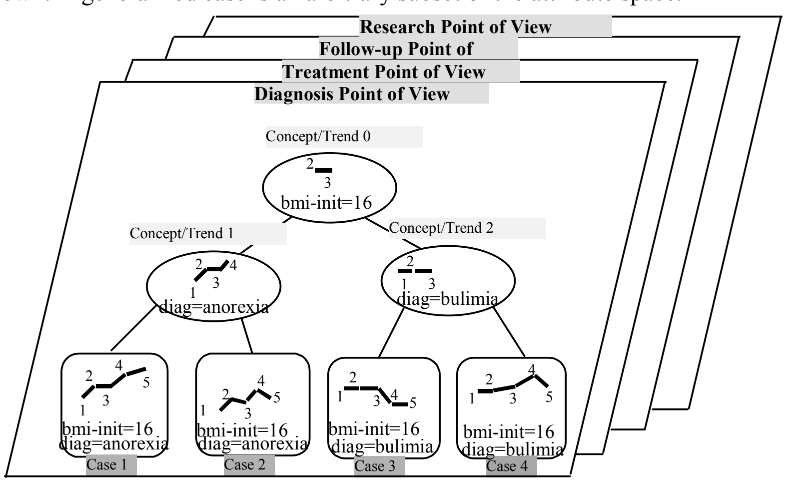

Fig. 3. Hierarchical memory organization in MNAOMIA: concepts are learnt during CBR for diagnosis, treatment, and/or follow-up, and can be reused by research task (Bichindaritz 1995)

There are two forms: the attribute independent generalized case, in which some attributes have been generalized (interval of values) or are unknown, and the attribute dependent generalized case, which cannot be defined from independent subsets of their attributes.

Finally, many authors learn *concepts* through *conceptual clustering*. MNAOMIA (Bichindaritz 1995) learns concepts and trends from cases through *conceptual clustering* (see Fig. 3). Perner learns a hierarchy of classes by *hierarchical conceptual clustering*, where the concepts represent clusters of prototypes (Perner 1998).

Dìaz-Agudo and Gonzàlez-Calero (2003) use *formal concept analysis* (FCA) – a mathematical method from data analysis - as another induction method for extracting knowledge from case bases, in the form of *concepts*. The authors point to one notable advantage of this method, during adaptation. The FCA structure induces dependencies among the attributes that guide the adaptation process (Dìaz-Agudo et al. 2003). Napoli (2010) stresses the important role FCA can play for classification purposes in CBR, through learning a case hierarchy, indexing, and information retrieval.

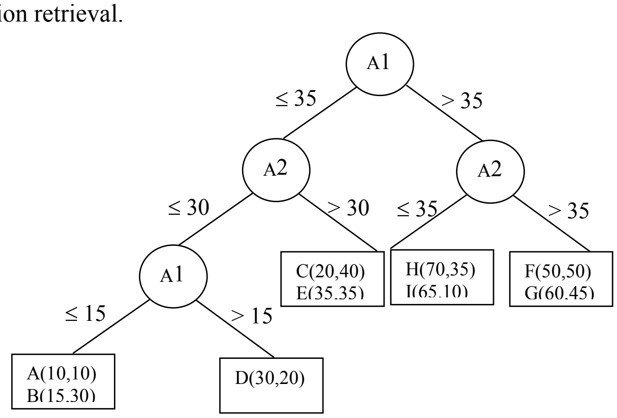

Fig. 4. Tree memory organization in INRECA using k-d trees (Auriol et al. 1994)

7.3 Mining for Memory Organization

Efficiency at case retrieval time is conditioned by a judicious memory organization. Two main classes of memory are presented here: unstructured – or flat – memories, and structured memories.

Flat memories

Flat memories are memories in which all cases are organized at the same level. Retrieval in such memories processes all the cases in memory. Classical nearest neighbor (kNN) retrieval is a method of choice for retrieval in flat memories. Flat memories can also contain prototypes, but in this case the prototypical cases do not serve as indexing structures for the cases. They can simply replace a cluster of similar cases that has been deleted from the case base during case base maintenance activity. They can also have been acquired from experts. Flat memories are the memories of predilection of kNN retrieval methods (Aha 1997) and of so-called memory-based systems.

Structured memories

Among the different structured organizations, the accumulation of generalizations or abstractions facilitates the evaluation of the situation the control of indexation.

Structured memories, dynamic, present the advantage of being declarative. The important learning efforts in declarative learning are materialized in the structures and the dynamic organization of their memories. In medical imaging, Perner learns a hierarchy of classes by *hierarchical conceptual clustering*, where the concepts are clusters of prototypes (Perner 1998). She notes the advantages of this method: a more compact case base, and more robust (error-tolerant).

MNAOMIA (Bichindaritz 1995) proposes to use *incremental concept learning*, which is a form of hierarchical clustering, to organize the memory. This system integrates highly data mining with CBR because it reuses the learnt structures to answer higher level tasks such as generating hypotheses for clinical research (see Fig. 3), as a side effect of CBR for clinical diagnosis and treatment decision support. Therefore this system illustrates that by learning memory structures in the form of concepts, the classical CBR classification task improves, and at the same time the system extracts what it has learnt, thus adding a knowledge discovery dimension to the classification tasks performed.

Another important method, presented in CHROMA (Armengol and Plaza 1994), is to organize the memory like a hierarchy of objects, by *subsomption*. Retrieval is then a classification in a hierarchy of objects, and functions by substitution of values in slots. CHROMA uses its prototypes, induced from cases, to organize its memory. The retrieval step of CBR retrieves relevant prototypes by using subsomption in the object oriented language NOOS to find the matching prototypes.

Many systems use personalized memory organizations structured around several layers or *networks*, for example neural networks (Malek 1995).

Another type of memory organization is the *formal concept lattice*. Dìaz-Agudo and Gonzàlez-Calero (2003) organize through formal concept analysis (FCA) the case base around *Galois lattices*. Retrieval step is a classification in a concept hierarchy, as specified in the FCA methodology, which provides such algorithms (Napoli 2010). The concepts can be seen as an alternate form of indexing structure.

Yet other authors take advantage of the *B-tree structure* implementing databases and retrieve cases using database SQL query language over a large case base stored in a database (West and McDonald 2003).

8 Feature Selection and CBR

Feature mining refers to the process of mining data sets for features. Many CBR systems select the features for their cases, and/or generalize them. Wiratunga et al.

(2004) notice that transforming textual documents into cases requires dimension reduction and/or feature selection, and show that this preprocessing improves the classification in terms of CBR accuracy – and efficiency. These authors induce a kind of decision tree called boosted *decision stumps,* comprised of only one level, in order to select features, and *induce rules* to generalize the features. In biomedical domains, in particular when data vary continuously, the need to abstract features from streams of data is particularly prevalent. Other, and notable, examples include Montani et al., who reduce their cases time series dimensions through *Discrete Fourier Transform* (Montani et al. 2004), approach adopted by other authors for time series (Nilsson and Funk 2004). Niloofar and Jurisica propose an original method for generalizing features. Here the generalization is an abstraction that reduces the number of features stored in a case (Niloofar and Jurisica 2004). Applied to the bioinformatics domain of micro arrays, the system uses both *clustering* techniques to group the cases into clusters containing similar cases, and *feature selection* techniques.

Table 1. Data mining functionalities versus CBR steps map – methods italicized represent future directions

	Classification / prediction	***Association mining***	***Clustering***	***Feature selection***
Data preparation / Metareasoning	**Ensemble learning**	**Case mining**	**Case mining**	
Retrieve	***Opportunistic similarity knowledge mining***			
Reuse	***Opportunistic reuse knowledge mining***			
Revise	***Opportunistic revise knowledge mining***			
Retain	**Memory organization**	**Case base reduction**	**Generalized case mining** **Memory organization**	**Indexing** **Weight learning**

9 Discussion and Future Directions

In addition to the main functionalities listed above, multimedia mining extends the algorithms to the form taken by cases and the type of their features for the same kinds of applications previously listed.

In summary, if we map the different data mining functionalities and the CBR steps / tasks, we notice on Table 1 that the steps benefitting the most from data mining are Retain, Data preparation and Metareasoning. This is not surprising because these steps are the most involved in declarative knowledge learning or updating. However the processing intensive steps such as Retrieve, Reuse and Revise do not seem to resort to data mining beside the dynamic induction mentioned in Section 4.

Interesting areas to explore could be feature selection functionality for case mining, data preparation, or metareasoning. Retrieve, Reuse, and Revise could also explore the use of data mining. For retrieval, in addition to weight learning already mentioned, learning similarity measures (Stahl 2005), or improving on an existing one, would be valuable. For reuse or revise, learning adaptation rules or revision rules or models would be highly pertinent – and some work has started in these areas (Badra et al. 2009). These synergies could take place during the Retain step, but also in an opportunistic fashion during the processing steps (see Table 1).

We can also foresee such synergies with Big Data for the processing of large datasets in distributed main memory that can make efficient use of data mining during processing on a larger scale. It is therefore very important for CBR researchers and professionals to gain expertise in data mining advances and their applicability to CBR.

CBR research focuses mostly on the model building stage of CRISP-DM. Other aspects of the CRISP-DM methodology would also be interesting for CBR synergies, for example aspects of data understanding, data preparation, testing, evaluation, and deployment in relationship with CBR to make this methodology more robust to fielded applications.

10 Conclusion

CBR systems make efficient use of most data mining tasks defined for descriptive modeling. We can list among the main ones encountered in biomedical domains, cluster analysis, rule induction, hierarchical cluster analysis, and decision tree induction. The motivations for performing an incremental type of data mining during CBR are several folds, and their efficiency has been measured to validate the approach. The main motivations are the following:

- Increase efficiency of retrieval mostly, but also of reuse, revise, and retain steps.
- Increase robustness, tolerance to noise.
- Increase reasoning accuracy and effectiveness.
- Improve storage needs.
- Follow a cognitive model.
- Add functionality, such as a synthetic task like generating new research hypotheses as a side effect of normal CBR functioning.
- Perform metareasoning, such as knowledge discovery to learn new adaptation rules.

The memory organization maps directly into the retrieval method used. For example, generalized cases and the like are used both as indexing structures, and organizational structures. We can see here a direct mapping with the theory of the dynamic memory, which constantly influences the CBR approach. The general idea is that the learned memory structures and organizations condition what inferences will be performed, and how. This is a major difference with database approaches, which concentrate only on retrieval, and also with data mining approaches, which concentrate only on the structures learned, and not on how they will be used. Opportunistic use of data mining during the retrieval, reuse, and revise steps would bring a more robust dimension to CBR by learning when a need arises, instead of, or in addition to, systematically at Retain. The ideal CBR memory is one which at the same time speeds up the retrieval step, and improves effectiveness, efficiency, and robustness of the task performed by the reasoner, and particularly the reuse performed, influencing positively both the retrieval, the reuse and the other steps. Researchers do not want to settle for a faster retrieval at the expense of less accuracy due to an overgeneralization. And they succeed at it.

Future work involves revisiting these data mining techniques in the framework of the knowledge containers identified by Richter (2003) and constantly tracking novel methods used as they appear. The variety of approaches as well as the specific and complex purpose lead to thinking that there is space for future models and theories of CBR memories, in particular embracing metareasoning and opportunistic approaches more systematically, and where data mining will play a larger role.

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