Evaluation of Case Based Reasoning for Clinical Decision Support Systems applied to Acute Meningitis Diagnose

Cecilia Maurente
Facultad de Ingeniería y Tecnologías
Universidad Católica del Uruguay
Montevideo, Uruguay
cmaurente@ucu.edu.uy

Ernesto Ocampo Edye
Facultad de Ingeniería y Tecnologías
Universidad Católica del Uruguay,
Montevideo, Uruguay
eocampo@ucu.edu.uy

Silvia Herrera Delgado, MD
Centro de Referencia Nacional de VIH-SIDA,
Hospital Pereira-Rossell
Montevideo, Uruguay
Silvia@qualisyss.com

Daniel Rodriguez García
Departamento de Ciencias de la Computación
Universidad de Alcalá de Henares
Alcalá de Henares, España
daniel.rodriguez@uah.es

Abstract

This work presents a research about the applicability of Case Based Reasoning to Clinical Decision Support Systems (CDSS), particularly applied to the diagnosis of the disease known as Acute Bacterial Meningitis.

In the last few years, the amount of information available to the medical doctor, who usually finds himself in the situation of making a diagnosis of one or more diseases, has dramatically increased. However, the specialist's ability to understand, synthesize and take advantage of such information in the always-little time during the medical act remains to be developed.

Many contributions have been made by the computer sciences, especially those by Artificial intelligence, in order to solve these problems. This work focuses on the diagnose of the Acute Bacterial Meningitis, and carries out a comparative assessment of the quality of a Clinical Decision Support System made through Case Based Reasoning, in contrast to an already existing CDSS applied to the same task, but developed using a technique called Bayesian expert system.

Keywords: Intelligent Systems, Expert Systems, Case Based Reasoning, Clinical Decision Support Systems, Clinical diagnose, Artificial Intelligence..

I. Introduction

During the clinical usual practice of evaluating a patient and making a clinical diagnosis, the problem of the analysis of signs and symptoms in the patient and the usage of available reference information (related to similar cases, their respective analysis and diagnosis) commonly shows up. In virtue of this and taking into account the reference information (that includes mainly previous experience), the clinical doctor develops and tests a series of hypothesis, eventually reaching a diagnosis or a group of differential diagnoses. Based on these, and generally also on protocols as well as standardized or commonly accepted guidelines, the doctor designs and indicates an appropriate treatment, or else orders ulterior examinations that might pose a threat to the patient's health, and can also be of a considerably higher cost.

The amount of information related to similar cases and the recommended diagnosis and procedure for each of them as well as its complexity has increased drastically. Although this represents a great help to the doctor when it comes to making a clinical assessment and a diagnosis, it requires the doctor's availability of attention and concentration on the information in order to be able to synthesize, analyze and utilize it. Apart from that, it mainly requires a fair deal of time, which is not commonly at the disposal of doctors during the clinical

T. Sobh (ed.), *Innovations and Advances in Computer Sciences and Engineering*,
DOI 10.1007/978-90-481-3658-2_45,

assessment. The available time in a visit to the doctor has not changed significantly in the last few years, if any, it has been reduced. These restrictions can be summed up in two problems: limited rationale and time.

Computer sciences have been applied, during the last 40 years or more, in different ways in order to extend the rationale and help use the available time to take advantage of the information more effectively. For this reason, multiple Artificial Intelligence techniques have been put into practice: pattern analysis, neuronal network, expert systems, Bayesian networks among others.

One of the most recent techniques, which presents several interesting characteristics, is the one known as Case Based Reasoning and it is based on the so common associative paradigm among experts: similar solutions correspond to similar problems.

A recurrent problem of the Clinical Decision Support Systems is that its main approach is computer science-based, applied to a specific working area, in this case the clinical diagnosis, which is performed by the expert, in this particular case, the doctor. This computer science-based approach used in the majority of cases is completely different from the way in which these experts carry out their daily job and, even more from how they develop their reasoning and inference or association processes. As a consequence, many of these systems turn out to be virtually futile due to the difficulty of operation that the expert is required to deal with.

The aim of this research is to demonstrate that the CBR technique is appropriate for the development of CDSSs, used in an independent way or combined with other AI techniques besides proving that its usage allows the development of more accepted and usable CDSSs in this field, in contrast to an already existing reference system, based on Bayesian inference.

II. Clinical Decision Support Systems

A. Main concepts, historical examples of CDSSs

A Clinical Decision Support System is, according to [2], “an algorithm based on computer science that helps the clinical doctor in one or more steps during the process of diagnose”. These are systems that provide information, to help and advise doctors in the process of making a decision of diagnosis. They suggest a range of diagnoses for the expert to adapt that information using his knowledge and experience to the definitive diagnosis.

When using these systems, the interaction between the expert and them is paramount as the system cannot work by itself. It needs to be fed with enough, clear and precise information. The differentiated specific diagnosis is the result of an elaboration made by the doctor who combines his own knowledge and experience with the information provided by the CDSS.

Signs and Symptoms shown by the patient are received as input, and using the knowledge incorporated in the system, the experience and reasoning of the expert, it is elaborated, as output, a list of possible diagnoses, eventually considered according to their certainty.

Two of the first Decision Support Systems that appeared in the marketplace were MYCIN[3] and PROSPECTOR[4]. MYCIN is a system developed at Stanford University, based on rules, designed to diagnose and recommend a treatment for blood infections. The knowledge is represented as a group of IF-THEN rules which have associated to them a certainty factor. PROSPECTOR, (applied to geology instead of medicine) is a system that allows the assessment of places according to diverse criteria: presence of beds and deposits, assessment of geological resources and the selection of a drilling spot. It uses the Bayes theorem as main mechanism to assess the probability of the occurrence of a certain event.

B. Application context – Acute Bacterial Meningitis diagnosis

This investigation is developed using as application case the Acute Bacterial Meningitis (ABM) diagnosis in pediatric patients. Based on de assessment of the signs and symptoms related to this disease, the doctor must develop the corresponding diagnosis, distinguishing between the different possible differential diagnoses.

C. The disease: Acute Bacterial Meningitis

This disease has a high rate of morbidity in pediatric patients and also produces important sequels. It can be seen either in an isolated way or in an epidemic one, and it is of utmost importance to make both an early diagnosis and an immediate treatment.

D. Signs and Symptoms.

As explained in detail in [5], there are, at least 24 signs and symptoms that can be found in a patient with ABM, in an independent or combined form. Such signs and symptoms have different levels of significance in the composition of the clinical presentation that leads to the diagnosis of the disease. In [5] can also be found the combinations of these signs and symptoms according to the way they are assessed by the corresponding doctor, for infants and over two-years-old patients.

E. Differential Diagnoses

The ABM diagnosis is complicated as other diseases present a combination of similar signs and symptoms, what we define as “differential diagnoses”. Among these alternative diseases are found: Acute Viral Meningitis, Tuberculous Meningitis, Encephalitis, Brain Abscess, Meningism, Proximity Meningeal Reaction, Meningeal Hemorrhage, Brain tumor. The doctor has to clearly identify the existence of ABM among all these.

F. The reference system: Acute Bacterial Meningitis diagnosis Expert System based on a Bayesian inference engine ABMDES

The Acute Bacterial Meningitis Diagnose Expert System (ABMDES) used as a reference in comparison to the performance of the proposed Case Based Reasoning system (Acute Bacterial Meningitis Case Based Diagnostic System – AMBCBDS), has been described in [5]. It uses a Bayesian inference engine to suggest the differential diagnoses, each with its corresponding certainty level.

In order to work, the ABMDES uses a database of real cases from pediatric patients that have visited the doctor. Using this data, the probability of the existence of each of the differential diseases (*"PI"*) has been specified. Afterwards, in each disease, for each sign or symptom, two levels of probability have been identified: The probability that the patient suffers from the disease as he has actually shown the symptoms ("PS") and the probability that the patient shows the symptom without having the disease ("PN"). Through a simple user interface, the doctor inputs in the application the group of symptoms that he finds in the patient. From this data, the system, applying the Bayes theorem repeatedly in its inference engine, calculates the accumulated probabilities of the existence of the different possible diseases.

III. Case Based Reasoning

A. *Introduction – general concepts*

Case based reasoning (CBR) is a methodology utilized for the solution of problems and learning within the AI area. Its invention dates back to the late 1970s [6]; certain results could be tracked down from Psychology, where it is demonstrated that on several occasions, human beings solve their problems based on their past experiences, rather than on a profound knowledge of the topic in question. For instance, doctors look for groups of known symptoms, engineers take many of their ideas from previously successful solutions, and programmers reutilize abstract schemes they already know [7;8]. The fundamental concept on which this methodology is based is…*"similar solutions correspond to similar situations or problems"*.

A Case Based Reasoning System (CBRS) consists in, from a base of experiential knowledge (previous cases rightfully identified with their corresponding solutions), analyze the existing correlation with the new suggested problem and, in virtue of the correspondences, adapt and propose the nearest solution. Instead of using an explicit model of the problem for the inference process, it simply utilizes the experience captured in the same way the expert usually inputs and processes it. Another characteristic that differentiate these systems from other approaches of expert systems is the increasing learning, that is given in an automatic and almost transparent way due to the fact that the retained cases are stored as new cases [8;9].

When a new problem appears, the CBRS looks for a previously occurred problem whose description is the most similar taking into consideration the presented characteristics. The solution to that problem is used as a basis to generate the solution to the new problem.

B. *Fundamental principles.*

The CBRS can be defined as a cyclic process named ***"the four Rs"*** [10]: **Recover** the most similar cases, **Reutilize** the cases that might solve the problem, **Revise** the proposed solution if necessary, **Retain** the new solution as part of a new case.

What is a case? "A case is a contextualized piece of knowledge representing an experience". It contains the previous lesson and the context in which that lesson can be applied [10]. It can also be defined as "a complete description of the problem, with its respective solution and also an assessment of the solution's efficiency" [11].

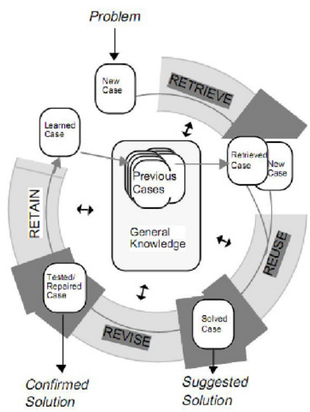

Figure 1 The "four Rs" CBR Cycle, taken from [1]

How can a case be stored? Case storage is a very important aspect that has a direct impact on the design of the CBRS. Some aspects are to be taken into account when creating a case base: the structure and representation of the cases, the memory model used to organize the case base and the selection of indices used to identify each case [7]. The case base is to be organized in manageable structures that support efficient searches and recovery methods. For this purpose, a wide range of possibilities can be used: text files, relational databases, xml files, etc. and, in order to access them rapidly, indices and manifold algorithms. Cases may represent different sorts of knowledge that can be stored in different representation formats, such as objects, semantic webs, tables, etc.

How can a case be recovered? This process could be divided into three tasks: Identifying the characteristics or the indices that describe the new problem; locating the relevant cases and choosing the best candidate, or candidates, among the most relevant cases. Two of the most currently used techniques are: recovery of the closest neighbor, and inductive recovery [2;12].

What does the adaptation consist in? Usually, when a case is recovered, an analysis is carried out to determine the similarity with the presented problem. The adaptation consists in identifying the differences between the recovered case and the current case and afterwards, applying mechanisms (formulas, rules or others) to those differences as to obtain the final solution.

Generally, there are two types of adaptation: structural adaptation, which consists in applying rules and formulas directly to the stored solution, and the derived adaptation, which consists in reutilizing the rules and formulas that generated the recovered solution in order to generate the new solution[10].

What does the revision of a case consist in? After the case has been adapted, it is convenient to verify that the differences with the new one were taken into account. If the obtained solution to the new problem is not the correct one, it is feasible to repair it and in this way, learn from mistakes. Basically two steps are taken: the solution is assessed and its applicability to the real case is determined, and the case to be stored is repaired.

What does the retention consist in? This process consists in incorporating what is useful from the new solution to the knowledge. This involves: Selecting the case information to be retained, in which way to retain it, and how to integrate it to the structure of the memory.

C. *Some existent applications of CBRSs*

The CBRS have been applied in multiple contexts. Some reference examples of CBRS applied to CDSS can be:

- CASEY [13] It is a diagnosis system for heart conditions.
- PROTOS [14] It learns to classify auditory disorders based on the description of the symptoms, analyses result and clinical history.
- PAKAR [15] It is a system that identifies the possible causes of construction pitfalls and suggests corrective measures.

IV. RESEARCH HYPOTHESIS

"A CBRS applied as a help to the clinic diagnosis of the disease known as Acute Bacterial Meningitis is more effective, precise, flexible and intelligent than the ABMDES"

To prove this claim, a CDSS has been developed using CBR, we'll call it Acute Bacterial Meningitis Case Based Diagnose System - ABMCBDS. Both the new one and the reference – ABMDES – systems, have been fed with data taken from a database of the cases of patients (real ones), and the result of the execution of both programs has been classified and processed.

V. CASE BASED REASONING SYSTEM IMPLEMENTATION FOR THE ABM DIAGNOSIS.

A. *Proposed System*

A CBRS was developed applied to the diagnosis of the Acute Bacterial Meningitis of children under the age of twelve months (henceforth ABMCBDS). Previous to its construction, a signs-and-symptoms subgroup was selected. This subgroup is representative of the total of signs and symptoms considered for the ABMDES. This has been done, among other things, to simplify the construction process. The signs and symptoms therefore selected, based on the opinion of an expert in this field, are either highly significant for the choice of a diagnosis among all other available diagnoses, or relatively ambiguous, found in the majority of differential diagnoses, with different importance levels.

The following table indicates these signs and symptoms, and it also displays the specificity level (Very specific –VS, Specific –S, Not specific –NS) of the symptom of the disease (indicated by the clinical doctor) as well as the weight to be taken into account in order to carry out similarity calculations.

Table 1 Case signs and symptoms

Sign or symptom	Specificity	Weight
Convulsions	S	0.65
Consciousness decrease	VS	0.9
Fever	NS	0.3
Bulging fontanelles	VS	0.9
Irritability	VS	0.9
Facial Palsy	NS	0.3
Meningeal signs (Neck and body stiffness)	VS	0.9
Purpuric signs in the skin	S	0.55
Somnolence	VS	0.9
Vomits	NS	0.3

It is important to note that at this stage, the system does not consider the strength of the symptoms, but just their existence or absence.

The group of differential diagnoses to be taken into consideration is then selected. These are:

a. *Acute Bacterial Meningitis.*
b. *Acute Viral Meningitis.*
c. *Tuberculous Meningitis.*
d. *Encephalitis.*
e. *Brain Abscess*
f. *Meningism.*
g. *Proximity Meningeal Reaction.*
h. *Meningeal Hemorrhage.*
i. *Brain Tumor.*

The ABMCBDS is a cyclic process consisting of several phases: recovery of the most similar cases, reutilization of such cases, a revision of the proposed solution and, the retention of the new solution. The system was developed using the JColibri Framework[16;17].

B. *Knowledge representation*

In CBR systems, the case is typically comprised of three components: a problem, a solution to it and sometimes an assessment of the solution's properties. In ABMCBDS, each case represents the situation of a medical visit: the "problem" consists of the description of the signs and symptoms shown by the patient (the "clinical feature"); the "solution" represents the diagnosis given by the doctor in that particular situation; and the "assessment" indicates how accurate a diagnosis is the one given (that is to say, if the system has proposed the diagnosis the expert was expecting, and not a differential diagnosis).

The clinical feature is represented as a "*compound attribute"[17;18]*, which is composed of *"single attributes"* and other components. Each single attribute has a name, a type of data (which permit their comparative assessment; in these case, all data are Boolean type), and the weight (whose incidence affects the similarity calculations). Compound attributes only have a name and a certain weight.

C. *Case recovery – similarity.*

During the ABMCBDS execution, a new visit is registered by the expert (the doctor) as a new case. This new case has only the "problem" part, the clinical feature. The ABMCBDS then proceeds to the recovery of the most similar case/s. In order to do this, the clinical feature of the visit is compared to all other clinical features that compose the Knowledge Base, calculating the similarity to each of them [19]. This similarity calculation is accomplished using a global similarity function for all compound attributes, and local similarity functions for single attributes. The similarity function used for single attributes is that of equality. The global function of a compound attribute is calculated as the weighed summation of the local functions.

Given two cases or situations T and S, the similarity between both is:

$$\text{Similarity}(T, S) = \left(\sum_{i=1}^{n} f(T_i, S_i) * w_i\right) / n$$

In which:

- n is the number of signs and symptoms of each case,
- i is an individual sign or symptom from 1 to n, being n the total amount of symptoms that can exist (a fixed value in the current application) so the symptom referred by this index is always the same in every case (e.g. "fever")
- f is the local or global similarity function for the attribute I (single or compound attribute) in T and S
- W is the weight of the sign or symptom

Comparisons are done between cases on the bases of existence or absence of symptoms.

Additionally, a similarity threshold is defined to delimit the quantity of cases returned by the system, and it was defined as the 85% of the highest similarity value.

D. *Revision*

Once the most similar cases are recovered, the recovered solutions are to be revised. In this stage the expert doctor gives her decision as regards the differential diagnoses, also providing the information about the accuracy assessment of the ABMCBDS. The doctor will then indicate whether the proposed solution is the correct one *("success")* or not (*"failure"*), and, if it is not, also the diagnosis she deems correct. The system's learning is based not only in success but also in failures and mistakes.

E. *Retention and learning*

Once the case is revised, the diagnosis and its corresponding assessment are obtained, and it is ready to be incorporated to the knowledge base. The solution – inferred and proposed diagnosis – to the new presented case could be either from previous success (the solution is correct) or from failure (the solution is not correct).

For the demonstrative implementation of ABMCBDS, simple text files have been used as data structures to store the cases. These are stored sequentially, in separate locations, and the information of each one is registered as a commas-separated text. The main advantage of these kinds of structures is that it is easy to implement and to understand. A further advantage is that adding cases is rather simple and fast, and its insertion order is 1. However, it is clearly not the adequate representation for a large-scale production system as the case recovery turns out to be rather slow when the number of cases is high (the order is N) and it lacks indexation mechanisms.

VI. SIMULATIONS AND OBTAINED RESULTS.

In order to proceed to the comparison of both ABMCBDS and ABMDES, a case base is constructed. This case base is built with the aid of the expert doctor, using the defined signs, symptoms and differential diagnoses. For the development of the case base for the ABMCBDS Montecarlo's method is applied, utilizing it for the simulation of the disease, sings and symptoms probabilities from [5].

Once statistically calculated the appropriate size of the sample, the next step is to compose and extract 51 cases, which were inputted as entry in both systems. For each inputted case, the result (proposed diagnosis) was registered by both systems, and was compared to the expert's own diagnosis, to determine whether the result coincided with the one the expert was expecting or not. With these data, the level of *"precision"* or *"accuracy"* of each system was determined.

As an experiment to compare the ability of both systems to capture experience or knowledge from the expert (another of the studied dimensions), seventeen cases were chosen at random from the case base. The average time that the expert needed (calculated size of the sample) to carry out the visits in ABMCBDS (which implicitly incorporates knowledge and learning) and to build the production rules for the knowledge representation in ABMDES, was taken.

The third test was with reference to the tolerance (Figure 2). The aim of this test was to analyze the impact that the degradation of the entry information would have on each system. With the expert doctor, we were able to analyze and define those symptoms that are usually more difficult to detect, or those whose correct interpretation largely depends on the experience of the doctor.

The "system's effectiveness" is referred to the amount of right answers, that is to say, the answers that verify what the expert had said. The obtained results verify that ABMCBDS is at least 20% more efficient than ABMDES.

The accuracy is inversely proportional to the amount of the system's failures. It was verified that ABMCBDS was more accurate than ABMDES.

The intelligence is defined as the speed at which the system learns. Based on the accomplished experiment, it was verified that the average time that the system required to learn was at least 40% less in ABMCBDS than in ABMDES.

The flexibility of a system is defined as the tolerance it presents towards the lack of specificity of a case. This can occur due to the different abilities of doctor to detect signs and symptoms, or to the doctor's experience. The ABMDES is more sensitive to the absence of a symptom; there is more degradation when there is lack of precision (Figure 2).

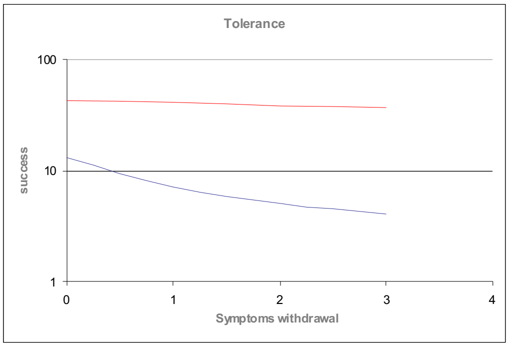

Figure 2 Tolerance to lack of symptoms

VII. Conclusions

The experiments carried out with ABMCBDS and their verification by doctors with great experience in diagnosing the diseases in question, allow us to conclude that this Artificial Intelligence approach applied to the construction of Clinical Decision Support Systems results interesting indeed, given its effectiveness, its learning abilities, and its capacity for capturing the expert's experience.

As stated previously in the Introduction, these kinds of DCSSs are not intended to substitute the expert action, but to help her to analyze and synthesize the huge amounts of experience information that is currently available when dealing with diagnosis situations

In comparison to the already existing reference system ABMDES, built based on a Bayesian inference engine for the diagnosis of the same diseases, the experiments allow us to state:

- ABMCBDS is at least 20% more effective than ABMDES.
- ABMCBDS is at least 20% more accurate than ABMDES.
- ABMCBDS is at least 40% more intelligent than ABMDES.
- ABMCBDS is at least 20% more flexible than ABMDES.

Finally, the ABMCBDS has shown less degradation at the lack of precision of some signs or symptoms that may be difficult to assess, depending on the expert's level of experience.

References

[1] Aamodt, A. and Plaza, E., "Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches," *IOS Press*, vol. Vol. 7: 1 pp. 39-59, 2004.

[2] Berner, E. S. Clinical Decision Support Systems Theory and Practice. 1998. Springer.

[3] John McCarthy. Some Expert System Need Common Sense. 1984. Standford University.

[4] Hart, P. E., R.O.Duda, and M.T.Einaudi, "Prospector-- A Computer-Based Consultation System for Mineral Exploration," *Ματηεματιχαλ Γεολογψ*, vol. 10 pp. 589-610, 1978.

[5] Ocampo, E., Herrera, S., Machado, F., and Ruibal, A. Diseño y construcción de sistema experto de diagnóstico de meningitis aguda supurada, basado en máquina de inferencia bayesiana. 2003. CISIC. 1-10-2003.

[6] Kolodner, J. Case - Based Reasoning. 1993. Morgan Kaufmann.

[7] Pal, S. P. and Shiu, S. C. K., *Foundations of Soft Case-Based Reasoning* New Jersey: Wiley Interscience, 2004.

[8] David B.Leake, "CBR in context: The Present and Future," AAAI Press / MIT Press, 1996, pp. 1-35.

[9] San Miguel Carrillo, J. A. Introducción al Razonamiento Basado en Casos. 2007. Práctica de Inteligencia Artificial II. Universidad de Valladolid.

[10] Watson, I., *Applying Case-Based Reasoning: Techniques for Enterprise Systems* California: Morgan Kaufmann , 1997.

[11] Otavio Alvares, L. Raciocínio Baseado em Casos. 2006. Informática UFRGS.

[12] Díaz Agudo, M. B. Una aproximación ontológica al desarrollo de sistemas de razonamiento basado en casos. 6-40. 2002.

[13] Phyllis Koton. Using experience in learning and problem solving. 1989. Massachusetts Institute of Technology, Laboratory of Computer Science.

[14] Porter, B. W. and Bareiss, E. R. PROTOS: An experiment in knowledge acquisition for heuristic classification tasks. In Proceedings of the First International Meeting on Advnces in Learning (IMAL), Les Arcs. 1986.

[15] Watson, I. D. and Abdullah, S. Developing Case-Based Reasoning Systems: A Case Study in Diagnosing Building Defects. IEE Colloquium on Case-Based Reasoning: Prospects for Applications, Digest. 1994. In, Proc.

[16] Recio García, J. A., Diaz Agudo, B., and González Calero, P. JColibrí 2 Tutorial. 2008. Universidad Complutense de Madrid.

[17] Recio, J. A., Anto, o Sánchez, Díaz, gudo, B., Gonz, ez-Cal, and o, A. jCOLIBRI 1.0 in a nutshell. A software tool for designing CBR systems*. 2005. Spain, Universidad Complutense de Madrid.

[18] Sánchez Ruiz Granados, A. A. jColibrí: estado actual y posibles mejoras. 2004. Universidad Complutense de Madrid, España.

[19] Boagaerts, S. and Leake, D. Facilitating CBR for Incompletely-Described Cases: Distance Metrics for Partial Problem Descriptions. 2004. Indian University.