A Case-Based Reasoning Application for Engineering Sales Support using Introspective Reasoning

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Abstract

This paper describes the implementation of a case-based reasoning application that supports engineering sales staff. The application is distributed and operates on the world wide web using the XML standard as a communications protocol between client and server side Java applets. The paper describes the distributed architecture of the operational prototype, the two case retrieval techniques used, its implementation, trial, and subsequent improvements to its architecture and retrieval techniques using introspective reasoning to improve retrieval efficiency.

Introduction

Western Air is a distributor of HVAC (heating, ventilation and air conditioning systems in Australia with a turnover in 1997 of \$25 million (US dollars). Based in Fremantle the company operates mainly in Western Australia, a geographic area of nearly two million square miles. The systems supported range from simple residential HVAC systems to complex installations in new build and existing factories and office buildings.

Western Air has a distributed sales force numbering about 100. The majority of staff do not operate from head office but are independent, working from home or a mobile base (typically their car). Until recently, sales staff in the field would gather the prospective customer's requirements using standard forms and proprietary software, take measurements of the property and fax the information to Western Air in Fremantle. A qualified engineer would then specify the HVAC system. Typically the engineer would have to phone the sales staff and ask for additional information and the sales staff would have to make several visits to the customer's building and pass additional information back to the head office engineer.

Western Air felt that basing a quote on the price of a previous similar installation gave a more accurate estimation than using prices based on proprietary software, catalogue equipment prices and standard labor rates. To try to help engineers make use of all the past installations a database was created to let engineers search for past installations. The database contained approximately 10,000 records, each with 60 fields describing the key features of each installation and then a list of file names for the full specification. Initially the engineers liked the database and it increased the number of past installations they used as references. However, after the honeymoon ended, they started to complain that it was too hard to query across more than two or three fields at once. And that querying across ten or more fields was virtually impossible. In fact most of them admitted to using the database to laboriously browse through past installations until they found one that looked similar to their requirements.

Prototype Development

Western Air decided that merely improving the efficiency of the engineers in Fremantle would not solve the whole problem. Ideally they would like the sales staff to be able to give fast accurate estimates to prospective customers on the spot. However, they were aware that there was a danger that the less knowledgeable sales staff might give technically incorrect quotes.

The solution they envisaged was to set up a web site that sales staff could access from anywhere in the country. Through a forms interface the prospect's requirements could be input and would be passed to a CBR system that would search the library of past installations and retrieve similar installations. Details of the similar installations along with the FTP addresses of associated files would then be available to the sales staff by FTP. The sales staff could then download the files and use these to prepare an initial quote. All this information would then be automatically passed back to an engineer to authorize or change if necessary. Once an installation was completed its details would be added to the library and its associated files placed on the FTP server.

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The development team comprised:

- a senior engineer from Western Air (one of the firms owners) as project champion,
- an engineer from Western Air to act as project manager and domain expert,
- a consultant Java/HTML programmer,
- a consultant from AI-CBR to advise on CBR issues (resident in the UK), and
- a part-time data entry clerk.

Because the project had the direct involvement of one of the firms owners management commitment was not a problem. It was decided that creating a partially functional prototype was sensible and that a carefully controlled and monitored trial was essential for two reasons:

- 1. It was still not certain that sales staff could create technically sound first estimates and therefore a small carefully monitored trial was essential to avoid losing the firm money.
- 2. There were resource implications since although all sales staff had portable PCs, some were old 486 Windows 3.1 machines and few had modems or Internet accounts.

A fixed (non-negotiable) budget was given to the project of \$32,000 (US) and it was decided that six months would be given for development and trial of the system. The project started in October of 1997 and the trial was planned for March of 1998.

It was decided initially to deal with moderately complex residential HVAC systems because it was felt that this would provide a reasonable test of the system without undue risk. Western Air felt that it was commercially unwise to risk experimentation on high value commercial contracts. Western Air realised they wanted a system that could find similar installations without making the query too complex for the engineers. Web-based CBR applications have been demonstrated for a few years now such as the FAQFinder and FindME systems [Hammond et al., 1996] and those at Broderbund and Lucas Arts [Watson, 1997].

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Since a simple nearest neighbour retrieval algorithm would suffice implementing our own system was a viable

option. Java (Visual Café) was chosen as the implementation language for both the client and server side elements of the CBR system. XML (e<u>X</u>tensible <u>M</u>arkup <u>L</u>anguage) [WWW Consortium, 1997] was used as the communication language between client and server-side applets. The World-Wide Web Consortium (W3C) finalised XML 1.0 in December 1997 as a potential successor to HTML.



Figure 1. System Architecture

System Architecture

On the sales staff (client) side a Java applet is used to gather the customer's requirements and send them as XML to the server. On the server side another Java applet (a *servlet*) uses this information to query the database to retrieve a set of relevant records. The Java servlet then converts these into XML and sends them to the client side applet that uses a nearest neighbour algorithm to rank the set of cases.

Case Representation

Cases are stored within a database. Each record (case) comprises 60 fields used for retrieval and many more used to describe the HVAC installations. In addition, links to other files on the FTP server are included to provide more detailed descriptions. Once retrieved from the database the records are ranked by a nearest neighbour algorithm and dynamically converted into XML for presentation to the client browser. An XML case representation is used by our system [Shimazu, 1998]. XML pages can contain any number of user defined tags defined in a document type definition (DTD) file. Tags are nested hierarchically from a single root tag that can contain any number of child tags. Any child tag in turn can contain any number of child tags. Each tag contains a begin statement (e.g. <Case>) and an end statement (e.g. </Case>).



Figure 2. A Portion of the Symbol Hierarchy for Mechanical Heating & Cooling Systems

Case Retrieval

Case retrieval is a two stage process. In stage one the customer's requirements are relaxed through a process of *query relaxation*. This process takes the original query and relaxes terms in it to ensure that a useful number of records are retrieved from the database. This is similar to the technique used by Kitano & Shimazu [1996] in the SQUAD system at NEC, although as is discussed later, we have improved it efficiency using an introspective learning heuristic.

For example, assume we are trying to retrieve details of installations using Athol B25 equipment. An SQL query that just used "Athol_B25" as a search term might be too restrictive. Using an ordered symbol hierarchy (as in Figure 2) our system knows that "Athol B25" is a type of "Fan Coil" system so the query is relaxed to "Where (((EquipmentReference) = "T31_fan_coil")..)). This query will include equipment from Athol, Sperry and TFR. An ordering of each set of symbols in the hierarchy is obtained through the reference number suffixes to each symbol (e.g. T10, T11, T12, T13, T14 as shown in Figure 2). The symbol hierarchies are stored in tables in the database.

Other specific criteria, elevations or temperatures that are numbers (integers or reals) can be relaxed by using simple ranges (e.g. a temperature of 65° F. could be relaxed to "Between 60 and 70"). Knowledge engineering was required to determine by what amounts numeric features should be relaxed. The relaxation is expressed as a term \pm a percentage (e.g., "Relax_Temp = \pm 10%"). These relaxation terms are stored in tables in the database.

In the second stage the small set of retrieved records are compared by the client-side applet with the original query and similarity is calculated using the simple nearest neighbour algorithm shown in Figure 3. The resulting similarity measure is normalized to give a percentage range of 0% (i.e. completely dissimilar) to 100% (i.e. completely similar). The weighting on the features by default is set to 1 (i.e., all features are by default considered of equal importance) However, the sales engineers can change the feature weightings to reflect client priorities or their own preferences.

Similarity(T, S) =
$$\sum_{i=1}^{n} f(T_i, S_i) \times w_i$$

where:
T is the target case
S is the source case
n is the number of features in each case
i is an individual feature from 1 to *n*
f is a similarity function for feature *i* in cases *T* and *S*
and
w is the importance weighting of feature *I*

Figure 3 The Nearest Neighbour Algorithm

Once an HVAC installation is completed its details are added to the database and its associated files placed on the FTP server. Having a database management system for the case repository has proved essential since it makes it easier to generate management reports and ensure data integrity. It would be almost impossible to maintain a collection of 10,000 cases without a DBMS.

Interface Design

The interface to the system is a standard Java enabled web browser (Netscape or Internet Explorer). The forms within the Java applet were designed to look as similar to the original forms, HVAC specification tools and reports that the sales staff were already familiar with. Microsoft FrontPage 98 and Macromedia's DreamWeaver were the primary tools used to create the web site.

Testing

Two weeks before trial five test scenarios were created that were representative of the range of more complex residential installations the system would be expected to handle in use. These were given to the five sales staff who would initially use the system and they were asked to test the system. Out of the 25 tests (5x5) 22 were correct. Although the remaining three were not specified as expected they were felt to be technically acceptable solutions.

The prototype was rolled out for trial to the five sales staff in March of 1998. Acceptance of the system from the five sales staff was very good once they understood what it was doing. During the month's trial the system dealt with 63 installations all of which were felt to be technically sound. The sales staff had not had to use the expertise of the HVAC engineers at all for this work although the engineers checked the final specifications.

During the trial month the five sales staff were able to handle 63 installation projects without having an HVAC engineer create the specification. This resulted in a considerable saving in engineers time allowing them more time to deal with complex high value commercial HVAC contracts.

Prototype Enhancements

Since its test the original prototype of the system has experienced increasing load performance problems. The Java servlet approach suffered from poor performance because the web server loads, executes and terminates a new servlet program for each user access. Large data sets and complex queries especially burden the system because data querying takes place via the Java servlet program rather than directly via the database. This coupled with the fact that MS Access is not a particularly fast database caused time out problems as the server load increased. To rectify this problem the database was ported to mySQL (http://www.mysql.org) a freeware database with much better performance. In addition Netscape's LiveWire database integration tool was used. This product has excellent database query functions, and importantly, because the LiveWire engine runs within the Netscape Web Server process it can share database connections across all Web accesses.

Introspective Learning

The initial query relaxation method of first performing a precise query and then relaxing the query through successive iterations until a sufficiently large set of cases was retrieved also compounded the performance problems. A suggestion was made to turn this process around – namely, why not relax the initial query far enough to ensure that a large set of cases would be retrieved (e.g. several

hundred cases) and then refine the query to reduce the subset to around twenty cases). The obvious speed advantage in this approach is that only a small sub-set of the whole case-base is used in any subsequent iterations as opposed to the entire case-base in the original query relaxation approach.

However, deciding how much to relax the query was not straightforward so an introspective learning approach was taken. This is an approach in CBR where the reasoning system itself learns over time to modify its internal representation to improve its performance [Markovitch & Scott, 1993]. For example, CBR systems may learn to modify feature weights, adaptation rules [Leake, et al., 1995; Hanney & Keane, 1996], or even learn to forget redundant cases [Smyth & Cunningham, 1996].

A decision was made to log each time a feature was relaxed during the query relaxation process. When the same query term is encountered again the query is automatically relaxed by one of three methods:

- 1) by the precise amount it was relaxed the previous time,
- 2) by the average amount it was relaxed the previous *N* times it had been relaxed (where n is the total number of times it has been relaxed), and
- by the mean amount it was relaxed the previous N times it had been relaxed.

Experiments were then conducted to see which, if any, of these simple heuristics most improved retrieval efficiency. This of course required that we decided what we meant by efficiency, was it:

- Time efficiency, i.e. purely a measure of retrieval speed, or
- Accuracy, i.e., a measure of the quality of the final suggested set of cases.

It was felt by us that both metrics were important so both were considered. Because of problems due to network and server loads and the way command stacks were executed it was difficult to directly measure retrieval speed accurately so the concept of precision was used as an analogue. That is, how many cases were returned in the set of retrieved cases. The fewer the number the more precise. A smaller number of cases would always be processed faster by the system, hence retrieval time would be quicker (unless network traffic beyond our control slowed down the exchange of information).

Therefore, if the query relaxation algorithm returned a single case that was a 100% match to the target case we would have an accuracy rating of a perfect 100% with a precision of 100%. It is worth remembering that this only tests the first stage of retrieval. In the second stage a nearest neighbour algorithm selects the most similar case from the retrieved set.

Testing

Tests were conducted by partitioning the case-base. Approximately one fifth of the cases (2000) were removed at random from the case-base. These were then used in a random sequence as probes to query the case-base. Our hypothesis therefore was that if the introspective learning algorithm worked either the precision or accuracy or both of the system should improve over time.

Results

Three methods were used by the introspective learning algorithm to learn how to relax the query:

- 1) *precise relaxation* i.e., relax query features by the precise amount they were relaxed the previous time.
- 2) average relaxation i.e., relax query features by the average amount they were relaxed the previous N times they had been relaxed (where N is the total number of times it has been relaxed), and
- 3) *mean relaxation* i.e., relax query features by the mean amount they had been relaxed the previous N times they had been relaxed.

The results for percentage accuracy were entirely inconclusive. Percentage accuracy did not improve using either of the three introspective learning algorithms. This is not surprising since the objective of the query relaxation method is not to retrieve the "best" matching case but rather to retrieve a set of good candidate cases upon which the nearest neighbour algorithm can work. However, conversely there was no evidence that introspective learning reduced the accuracy of the set of retrieved cases.



Figure 4 % Precision for Mean Relaxation (Generation is in 100s)

The results for precision were more encouraging, except for when the precise retrieval learning algorithm was used. It's results unsurprisingly showed wild fluctuations as each query relaxation was based purely on the previous query relaxation. Sometimes this worked and sometimes it didn't; in effect the learning algorithm had no long term memory. However, the average and mean relaxation results showed improvement with time. Precision for average relaxation improved from about 64% to 84%, whilst with mean relaxation percentage precision improved from about 64% to 94%. In addition, mean relaxation showed smaller fluctuations because this method is less perturbed by outliers. This shows that the system has been able to improve its precision (i.e., retrieve a smaller set of candidate cases) without harming its accuracy. This would improve the system's overall retrieval time.

Conclusions

This implementation has shown how a distributed CBR system can be created on the web in a relatively short space of time (six months). Implementing the system for web delivery will make the system much more viable. Just a few years ago we would have had to install the entire system (including the database of 10,000 records) on each of the sales staffs PCs. We would then have had to regularly send them updates to the database. This would significantly increase the operational costs of the system. Thus the web is an ideal medium for delivering intelligent support of all types.

The project was most certainly helped by having a ready made case library. Although knowledge engineering work was still required in determining valid ways of relaxing the SQL queries and creating similarity metrics. This was not surprising as the similarity measure is one of the most important *knowledge containers* of any CBR system [Richter, 1998].

XML is a useful communications protocol enabling large packets of formatted information to be exchanged thereby reducing network traffic. As a possible replacement to HTML it should help the web support intelligent applications [Hayes, et al., 1998; Doyle, et al., 1998]. However, we have demonstrated that implementing a simple CBR system is not difficult and is a viable alternative to purchasing a commercial tool. We will see CBR systems playing an increasingly important role in product selection and specification on-line, since similaritybased retrieval is very useful for Internet e-commerce systems [Wilke, et al., 1998].

However, under increasing use the prototype's performance started to become an issue that would reduce its effectiveness. Several measures were taken to improve performance including using a faster database to store the cases, improving the way database access was managed on the server side and improving the way the query relaxation algorithm worked. This later improvement was significant because it involved the use of an introspective learning a accuracy of the algorithm that learns by how much to relax case features during the relaxation process. Our experimental findings show that although the learning algorithm does not improve the accuracy of the system it does improve its precision. For the future we would like to find a way to make the learning algorithm consider the interaction of case features. Currently features are considered in isolation which is obviously a weakness since

there are certainly both strong and weak dependencies between case features.

Acknowledgements

I would like to acknowledge the cooperation of Western Air in the development of this system and in particular their permission to publish. Hideo Shimazu provided valuable information on the use of XML and David McSherry had the idea to improve the efficiency of the query relaxation algorithm.

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