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Case-Based Reasoning at General Electric

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Abstract

General Electric has created case-based reasoning systems for remote diagnostics, call center automation, and internal productivity projects. CBR applications have been used to remotely diagnose x-ray machines, locomotives, and aircraft engines. Call centers have CBR systems that assist call takers in helping customers, provide web based customer self-service, and suggest standard responses to e-mail message. Productivity tools based on CBR have automated the appraisal of residential property for GE Mortgage, helped GE Plastics determine the correct pigments for creating a custom color plastic, and allowed GE Plastics to provide a web based tool for selecting a plastics' color

Introduction

General Electric's (GE) Corporate Research and Development (CRD) Center has been creating and fielding software applications using the Case-Based Reasoning (CBR) methodology (Watson 1997) since 1992. During that time we have developed more than ten applications that are currently working in production. The applications have covered a wide range of domains, but they fall into three basic categories. These are:

- Remote diagnostics
- Call center automation
- Productivity tools

This paper will describe each of these categories while giving example applications. But, before we start a little background information would help you understand GE's need for CBR.

Background

GE is one of the largest and most diversified industrial corporations in the world. It develops, manufactures, and markets a wide variety of products including appliances, plastics, power generators, aircraft engines, medical systems, transportation systems, and financial services. GE CRD goal is to provide technology and leadership for a continuous stream of new products and processes for the company's key initiatives in Services, Six Sigma Quality, e-Business, and Globalization throughout all businesses. The premise of GE's services initiative is that GE with its large installed base of equipment is uniquely positioned to provide information-based services that help our customers. CBR has been found to be very useful for equipment monitoring and remote diagnostics. The Six Sigma Quality initiative involves obtaining measurement data, analyzing the data, making improvements based on the data, and maintaining the improvement by continuing to collect data. This process is similar to the CBR process and the vast amount of data that has been collected by using Six Sigma acts as a series of case-bases for CBR applications. e-Business applications for customer support and internal productivity have relied on CBR to provide the knowledge behind the web site. Finally, globally deployed CBR systems have allowed a consistency in GE's operations throughout the world and the sharing of cases from any location. Because of the fit CBR has with GE CRD's initiatives it has been used on a wide range of applications. The remainder of the paper describes some of those applications.

Remote Diagnostics

One of the recent initiatives at GE has revolved around helping its customers operate its equipment more productively as well as providing long-term service contracts. In either case, it has become important to be able to identify an emerging problem with the equipment before it causes any disruption of service or equipment failure. Remote Diagnostics envisions being able to collect the requisite data from the equipment and apply knowledge based tools to perform this function. This section discusses how CBR systems have been developed and deployed for this task at GE Transportation Systems, GE Medical Systems and GE Aircraft Engines.

ICARUS

Locomotives are extremely complex electromechanical systems with many subsystems and failure modes. The subsystems range from computer system, to control system, propulsion system, lubrication system, power generation system, traction system etc. These subsystems interact closely in order to keep the locomotive running. From a service point of view, however, the configuration of any individual system can be changed or upgraded.

The objective of having remote diagnostics on locomotives is to be able to quickly identify if an equipment failure has already occurred, or is going to occur on-board the locomotive that may result in a locomotive stranded on the tracks. The cost to the railroad of an immobile locomotive on the tracks is quite high, and the associated productivity losses can be even higher. The challenge in designing a diagnostics system for locomotives arises from the fact that it is nearly impossible to articulate the thousands of rules it would take to comprehensively cover the locomotive’s failure modes. In addition, maintaining such a rule-base or equivalent static knowledge base to prevent obsolescence would require a tremendous amount of ongoing effort.

Case-Based Reasoning was identified as a potential approach to creating a maintainable diagnostic system. Various legacy databases were studied to catalog the sources of information that could provide case related information. One significant source of information was historical fault logs generated by the locomotive. These were matched up against the repair history of the locomotive to create cases. A case initially consisted of faults logged up to fourteen days before a repair was performed on the locomotive. There were 600 different types of faults that could be logged, and about 600 different kinds of repairs that could be performed.

A new algorithm was developed to help the system learn weights associated with fault patterns. Fault patterns that were considered included individual faults, combinations of faults, the number of fault occurrences in a day as well as the longest continuous span in days for which a fault occurs. Learning weights allowed the system to isolate the fault indicators that were truly relevant in indicating which fix was to be performed. Cases matched based on weighed features ensured that relevance was assessed on genuine indicators and not noise.

The system (Varma and Roddy, 1999) took about 8 months to develop and was initially deployed on 750 locomotives. Its success and failures at diagnosis were tracked and used to check case quality as well as add more high quality cases to the system. Overall, the system performance continues to improve with time and it is currently able to provide greater than 70% accuracy on more than 75% of the problems.

ELSI

This section examines the use of a case-based diagnostic system built for GE Medical Systems (GEMS). An Error Log Similarity Index (ELSI) (Cuddihy and Cheetham 1999) was first conceived in the early 1990's to solve a diagnostic challenge with Computer Tomography (CT) scanners. GEMS had built an infrastructure to allow service to dial in to imaging equipment and diagnose failures while still on the phone with the customer. Once the service engineer had taken a look at the equipment remotely, the customers' issues could often be resolved over the phone. If parts and repairs were needed, the service engineer could send out a field engineer with the correct parts already in hand. Some of the most promising diagnostic information on the machines was in error logs generated by the computer processes controlling the machines. The error logs, however, had been primarily designed as debugging tools for developers, not as diagnostic tools for service technicians. The logs were not well formatted, and contained a mix of normal status messages and error messages. The messages were documented one-by-one, yet equipment failures were found to generate more complex cascades of errors. Recognizing these combinations of error messages was purely an art form practiced by the more experienced service engineers. An automated system was needed to find these patterns and catalog them, thus creating a common experience base across service engineers. ELSI set out to meet this challenge.

ELSI's primarily case-based approach also provided platform independence (the system could be used on different models and types of equipment), little need for knowledge collection from the equipment designers, and the ability to keep up with design changes as new cases arrived.

ELSI is an 8-step process where the error logs are obtained in step 1 and pre-processed in step 2. In step 3 the logs are compared to other logs with the same fix, and the largest possible blocks of completely matching lines are extracted. When a new case comes in to be diagnosed, its logs are searched for all known blocks, and its similarity to known cases is determined by reporting which past cases share the most symptoms (after weighting) with the new case. In step 4, the blocks of error log are then given weights inversely proportional to the number of different kinds of problems have generated the block. Blocks that appear only for one fix are given the highest weight. Those that appear for many different fixes are thrown out altogether. Steps 5-8 are concerned with updating and reporting tasks.

Using a "confidence" member function (Cheetham 2000) increased the accuracy and lowered the maintenance requirements of the system. The confidence measure played a key role in enabling ELSI to be handed off to users with limited computing skills, where they added hundreds of new cases and ran diagnostics on thousands of problems over several years without requiring major help from the system developers.

Aircraft Engine Monitoring

The CBR application shown here dynamically monitors aircraft engines based on sensor readings taken from the engine to provide an early alarm to aircraft fleet management organization about abnormal engine conditions. To provide early warnings with little false positive alarms the engine's operating region (the "normal" case) is continuously updated. This is in contrast to the approach taken by other aircraft engine CBR systems (e.g., Manago and Auriol, 1995) which focus on static fault diagnosis.

It is desirable to be able to detect abnormal behavior before it causes costly secondary damage or results in equally undesired engine shutdowns. To that end, service providers have long tracked the behavior of engines by measuring and analyzing a multitude of system parameters to become aware of changes that might be indicative of developing failures. However, often faults may not be recognized distinctively because the "normal" operation condition varies unpredictably. This is due in part to large amounts of noise, poor corrections of first principle models or regression models, changes of schedules, maintenance, poorly calibrated and deteriorating sensors, faulty data acquisition, etc. In addition, thermal, chemical, and mechanical wear degrades the performance of the engine. Although these changes are expected, they are hard to predict with necessary accuracy because they are driven to a large degree by a whole host of external factors. For example, the effect of maintenance, such as replacement of parts, is very hard to capture. To retain desirable classification properties these changes must also be echoed in changes of the case-base.

We devised an approach for adaptive CBR (Bonissone et al, 1999), which allows the clusters of cases to adapt to changing environments. In the context of aircraft engine monitoring, cases were defined as one cluster of normal and one or several clusters of abnormal behavior. The center can move and their shape can vary. This was accomplished using slow exponentially-weighted moving average filters that updated the cluster centroid with information from any new data point and fuzzy clustering that allowed the shape of the clusters to be adaptable over time, respectively. After choosing the initial number of clusters, their position and membership, the adaptation of a cluster is performed with the filter. The adaptive CBR scheme was tested with historical gas turbine data.

The tool was developed over a 15 month time span and is currently in use. After training, the system was used for classification of on-line test data. The false negative rate is as low as with traditional trending tools (none observed with the test data available) and the false positive rate improved from 95% to less than 1%.

Call Center Automation

GE has many call centers that were created to help our customers. The people in the call center will answer questions, help diagnose problems, schedule appointments, and provide a wide range of information and services. CBR has been used to provide improved customer service and new ways to meet our customers needs. This section will describe three of these projects.

Call Taker Education

GE Appliances provides a variety of customer services over the phone. One of these is group of about 300 field service order takers who schedule field service personnel to visit customers' homes. It was found that about 20% of the time a field service representative arrived at the home all that was needed was to educate the customer about the appliance. This education could usually have been done over the phone saving time for the customer and field service representative. However, the field service order takers were not trained to diagnose and explain issues over the phone. This training was difficult because of the large number of appliances that can be serviced, complexity of modern appliances, and most importantly the high turnover in the order takers. The solution to this was to create a CBR system to assist the order takers in diagnosing the appliances.

The CBR system created used eGain's k-Commerce tool (Thomas et. al. 1997). Separate case bases were created for each type of appliance. A team of design engineers, phone support technicians, and computer scientists worked on each case base. A pilot test was run for 3 months with 12 order takers providing feedback and suggestions on how to improve the system. Two people were assigned to maintain the knowledge in the case base and the process for introducing a new appliance now includes a step where diagnostic cases are placed in the case base before the product is released to market.

The system was deployed to the 300 order takers in June of 1999. The percentage of calls that could be correctly answered over the phone, without sending a field service representative, increased from 3.9% to 12.3%. Surveys of customer satisfaction also showed the customer preferred having their issues solved without the need for a house visit.

Web Self-Service

After the call taker support tool proved successful, the next step was to make the tool available to our customers by placing it on a public web site. This would allow customers direct access to the information they need. Graphics and other forms of information that could not be used over the phone could also be placed in the CBR system on the public web-site.

Even though the call taker support tool was a web-based application there were still some changes that were needed to deploy it on the web. The user interface needed to be improved. The cases contained jargon, instructions for the order takers, and proprietary information that all had to be removed. New graphics and information needed to be added. Finally, there needed to be a way for customers to get help if they could not find what they wanted in the case-base.

The modifications needed were made in a few months, but the case base is constantly growing and changing. The web self-service tool was made available on the www.geappliances.com web site in early 2000. If issues were not in the cases-base customers could phone or email the call center with the question. The email acted as an indication of which cases were the most important to add.

eMail Response Automation

The down side of asking people to send in email with questions is that you then have to answer all the email messages. We found that it actually took longer for a person at the call center to answer an email message than a phone message. So, a way to help reply to the email was needed.

There are several commercial tools for automating the response to email messages. We selected Cisco's eMail Manager tool. This tool stores replies to frequently asked questions so that they can be reused on future similar questions. In order to select the appropriate reply a decision tree is created where each node in the tree is a rule based on the text in the email message. Each leaf node in the decision tree specifies a set of replies that can be used to answer that specific type of email message. This is really another form of CBR.

The email application was deployed to the GE Appliances call takers in June of 2000. The consistency of answers has improved because now people are sending out approved answers instead of hand crafting every reply. The average time to reply to a message has dropped 40%. And, over 99% of all email messages are answered in less than 5 hours

Productivity Tools

In addition to remote diagnostics and call center applications, CBR has been used to automate processes that were previously done by hand in a manner that was similar to case-based reasoning. This section describes two of these applications then shows how the second application was transformed from an internal productivity tool to an external e-Business tool.

Property Valuation

GE Mortgage used to originate mortgages and buy packages of mortgages for single-family residential properties on a secondary market. In either case, it is important to get an appraisal of the property before granting or purchasing the mortgage. It would be useful to have an automated way of creating the appraisal in order to grant on-line mortgages or purchase packages that can include 1000 mortgages.

The traditional appraisal process uses a CBR approach. The appraiser would select three to five properties similar to the subject. Each property selected would have their sales price adjusted based on differences between it and the subject property. Then the adjusted sales prices would be combined to produce a price estimate for the subject. In 1994, we created a software tool that would automate this process (Bonissone and Cheetham 1998). The tool worked for properties in California. The case-base consisted of every property that had sold in California during the previous five years. The goal of the project was to determine the case selection, sales price adjustment, and sales price combination techniques that would produce the lowest average error in the price estimate.

The tool that was created produced a price estimate and a confidence in that estimate. The confidence value predicted if the error in the estimate would be high, medium, or low. An alternative could be used to appraise a property that had a high predicted error. This could be another semi-automated system or sending a human to appraise the property. The CBR system had a low predicted error on 63% of the properties on which it was tested. The average error on this 63% was 5%.

Color Matching

One of the services that GE Plastics provides is coloring the plastic they sell any color that a customer would request. There are over 40 colorants and usually four or five are used to create a custom color. Selecting the correct formula, which consisted of colorants and the amounts of those colorants, was a time consuming process. Since there was no algorithm to go from a request to a formula the color matchers relied on their experience. They kept a set of filing cabinets that had 2" by 3" chips of every color plastic they created. When a new match was needed they opened the appropriate drawer and selected the most similar colors that had been made in the past. Each chip was numbered and the formula for the chip was stored in another filing cabinet. If one of the chips selected was appropriate they were done. If not they took the formula of the most similar chip and repeatedly adapted it until it was acceptable. This method is CBR (Watson 1998) where the filing cabinet acted as a case-base.

We created a software tool to automate this process (Cheetham and Graf 1997). The plastic chips from the filing cabinet had their colors recorded numerically by using a machine called a spectrophotometer. The colors were combined with the formulas from the other filing cabinet to create a case-base. The tool created allowed for the efficient selection of the best previous color from the case-base. Color theory was used to create algorithms that adapted the amounts of the colorants selected if the best match was not satisfactory. The selection and adaptation used fuzzy logic technology to optimize multiple factors that were all important in determining the best match. Some of these factors included color, cost, opacity, and manufacturability. Whenever the adaptation algorithms were used to create a new color, that color was stored in the case-base for possible future use.

The tool began being used in 1994 at one manufacturing site for one type of plastic. Since then it has expanded to other types of plastic and multiple sites throughout the world. It was very important to our customers that we get the color matches done quickly and this reduced the time needed to create a color match significantly. Furthermore, the tool was good at using low cost colorants, which decreased the cost to produce the plastic.

ColorXpress

Having a tool that creates lower cost color matches faster is good, but it would be better to completely eliminate the need for a color match. Since we had already created the case-base and selection algorithms so that they were easy to use, why not allow our customers to select their own colors from our case-base?

ColorXpress, www.gecolorxpress.com, is a web site that offers customers an opportunity to both color match and order standards on-line. In the past, our customers used a variety of ways to select the color for their products then sent us the color to be matched. Now, ColorXpress can be used to select their colors. Any item selected has already been matched and a sample can be sent to the customer in 48 hours. This both increase the speed of the match and eliminates the need for may custom matches. This also shows how an internal productivity tool can be transformed into an external e-Business tool.

Conclusion

We have shown examples of applications that use CBR for remote diagnostics, call center automation, and productivity tools. Many factors point to an increase in the use of CBR. First, GE and other companies are shifting from producing goods to performing services. If these services are automated the cost of performing service drops and companies realize greater profits. Second, the emphasis on data in quality initiatives combined with the decrease in cost of sensor and data storage have produced vast amounts of data that can be used in CBR systems. Third, the advent of the web as a common user interface has decreased the cost of deploying automated systems. Fourth, large companies who are looking to get economies of scale and globally available services can achieve savings from the automation provided by single CBR systems that can be deployed globally. Finally, by sharing best practices and lessons learned in the creation of these automated systems the cost to create future systems can be reduced. Past mistakes can be avoided and the best features on a previous system can be replicated in a new one.

The authors hope that the best practices and lessons shared in this paper can be used as a case base for successful CBR projects. In order to create a new CBR application, simply find the previous application that is the most similar and apply that technique with some adaptations.

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