Recent Themes in Case-Based Reasoning and Knowledge Discovery

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Abstract

Case-based reasoning (CBR) systems have tight connections with machine learning and knowledge discovery and often incorporate diverse knowledge discovery functionalities and algorithms. This article presents themes identified in work presented at recent workshops on synergies between CBR and knowledge discovery. Among the main themes appear Big Data, with cases involving signals, images, texts, and other complex types of data; similarity metric discovery, in the form of weight spaces, feature weights, and feature selection; adaptation knowledge; explainability and transparency; and user centeredness and interactivity. Researchers highlight the advantages of case-based reasoning in terms of its lazy learning, explainability, user centeredness, and interactivity when performing knowledge discovery, as well as how diverse knowledge discovery methods can improve CBR.

Introduction

Case-based reasoning (CBR) systems have tight connections with machine learning and knowledge discovery (KD) (Bichindaritz 2015). In 2014 and 2016, workshops on Synergies between Case-based Reasoning and Knowledge Discovery were held at the International Conference on Case-based Reasoning. This article summarizes the major themes illustrated by the papers presented at these workshops. As instance-based learners, CBR systems possess the advantage of being easy - aka lazy - learners, because they defer the decision of how to generalize beyond the training set until a target new case is encountered. This is in opposition to the way in which most other knowledge discovery systems operate by abstracting models from cases. CBR is also known for its knowledge containers - vocabulary, similarity measure, case base, and adaptation. The case base in and of itself is often a major focus of knowledge discovery in CBR, with its cases, structures, and organization. After a review of major knowledge discovery tasks and how they relate to CBR, recent themes are highlighted.

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start from raw data. This is why case mining, which consists of mining raw data to build cases, is a knowledge discovery task often used in CBR. We have already noted that CBR systems are instance-based learners; Mitchell views the complex, symbolic representations of instances (cases) as distinguishing CBR from other IBL approaches (Mitchell 1997). Furthermore, CBR systems follow a Retrieve, Reuse, Revise, Retain reasoning cycle (Aamodt and Plaza 1994). In the Retain step, new cases learned by the system are added to the case base for future use. This type of machine learning may be viewed as incremental learning or online learning.

The other side of the relationship between CBR and knowledge discovery entails that CBR systems also make efficient use of knowledge discovery techniques for descriptive modeling. In descriptive modeling, as opposed to predictive modeling, the goal is to characterize, explain, and/or better understand the underlying nature of observed data or cases. Among the main techniques encountered are cluster analysis, rule induction, hierarchical cluster analysis, and decision tree induction.

It should be noted that, while knowledge discovery, data mining and machine learning are closely related, there is no clear consensus on the distinctions between them or on when each particular term should be used. In an early seminal paper on knowledge discovery in databases (Fayyad, Piatetsky-Shapiro, and Smyth 1996), it was suggested that knowledge discovery referred to the overall process of discovering useful knowledge from data, while data mining was just one step of the overarching process, in which pattern extraction algorithms were applied. These pattern extraction algorithms, for classification, regression and clustering, were then borrowed from machine learning or from other disciplines partaking in data mining such as pattern recognition, statistics, or mathematics. However, the frontier between machine learning, statistics and pattern recognition has receded over the years. In the current vernacular, the terms knowledge discovery, data mining, and machine learning may be used almost interchangeably. While our 2014 workshop was entitled “Workshop on Synergies Between CBR and Data Mining,” we switched to the term knowledge discovery for our 2016 workshop, as being more inclusive. We take the broad perspective that, whenever a system learns knowledge that is new to it, through the analysis of raw data or cases, for external application or its own internal use, it is engaged in knowledge discovery.

The primary motivations for performing knowledge discovery during CBR are to:

- Increase efficiency, mainly of the Retrieve step, but also of the Reuse, Revise, and Retain steps
- Increase robustness, tolerance to noise
- Increase reasoning accuracy and effectiveness
- Decrease storage needs
- Follow a cognitive model
- Add functionality
- Perform metareasoning, such as knowledge discovery to learn new adaptation rules

We also foresee synergies with Big Data for processing large datasets in distributed memory that can make efficient use of knowledge discovery while processing on a larger scale.

**Recent Themes**

Table 1 shows projects exemplifying recent themes in synergies between CBR and knowledge discovery. Identified themes include:

- **Big Data.** Most systems apply CBR not only to large volumes of data but also to data presenting high levels of complexity, challenge, and opportunity. Dileep and Chakrabarti propose a multi-step similarity assessment functioning at different levels of granularity for textual CBR (Dileep and Chakrabarti 2014). Hromic and Hayes apply a signal processing method based on attack-decay-sustain-release (ADSR) envelopes, which are commonly learned in acoustics signal modeling, to Twitter hashtags in order to construct Twitter datasets suitable for event detection research, particularly research involving CBR (Hromic and Hayes 2014). Zhang, Zhang, and Leake introduce sieve streaming, a recent method for massive data summarization, and adopt it for continuous incremental case base maintenance of cases from a case stream, without access to the full case base (Zhang, Zhang, and Leake 2016). Barua et al. combine independent component analysis (ICA), hierarchical clustering, and CBR to detect ocular artifacts in electroencephalogram (EEG) signals. In empirical experiments, ICA was used in case formulation, hierarchical clustering was used to build the initial case library, and CBR was used to classify signals as EEG or ocular artifact. An overall classification accuracy of 95% was achieved (Barua et al. 2014). Olsson et al. combine signal processing, statistics, machine learning and CBR for diagnosing problems in heavy duty machines. The first three approaches are used for continuous monitoring of machines to detect anomalies, while CBR is used offline, to classify the problems identified and to retrieve cases for manual decision making (Olsson et al. 2014).

- **Similarity Metrics.** Effective feature selection and weight learning are essential to similarity assessment. Sekar and Chakrabarti present a conversational recommender system in which product cases are indexed by their region in preference weight space in order to predict the prospective buyers of any particular product (Sekar and Chakrabarti 2016). Guo, Jerbi, and O’Mahony showcase a job recommender system personalized to users based on a combination of machine learning approaches for feature selection and feature weighting. Jobs in this system are represented in a structured representation with well-defined features, amenable to varied similarity assessment functions using weighted aggregates of features (Guo, Jerbi, and O’Mahony 2014).

- **Adaptation Knowledge.** Improvements in adaptation can have a large impact, especially on classification and prediction performance. Tomasic and Funk explore synergies between CBR and regression analysis in the domain of quality control for automotive assembly. Regression models are used to improve CBR performance by:
Table 1: Projects Illustrating Recent Themes in Case-Based Reasoning and Knowledge Discovery

<table>
<thead>
<tr>
<th>Citation</th>
<th>Themes</th>
<th>CBR Phase</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Adedoyin et al. 2016)</td>
<td>Big Data Explanation</td>
<td>Retrieval</td>
<td>Fraud Detection</td>
</tr>
<tr>
<td></td>
<td>Application</td>
<td></td>
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</tr>
<tr>
<td>(Barua et al. 2014)</td>
<td>Signal Processing</td>
<td>Case Acquisition</td>
<td>Classifying Ocular Artifacts in EEGs</td>
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<tr>
<td></td>
<td>Application</td>
<td>Retrieval</td>
<td></td>
</tr>
<tr>
<td>(Canensi et al. 2014)</td>
<td>Big Data Explanation</td>
<td>Retrieval</td>
<td>Medical Processes</td>
</tr>
<tr>
<td>(Canensi et al. 2016)</td>
<td>Interactivity</td>
<td></td>
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</tr>
<tr>
<td>(Dileep and Chakraborti 2014)</td>
<td>Big Data Knowledge Rich CBR</td>
<td>Retrieval</td>
<td>Textual CBR</td>
</tr>
<tr>
<td>(Eyorokon et al. 2016)</td>
<td>Explanation Interactivity</td>
<td>Retrieval</td>
<td>Conversational CBR</td>
</tr>
<tr>
<td>(Guo, Jerbi, and O’Mahony 2014)</td>
<td>Big Data Application</td>
<td>Retrieval</td>
<td>Job Recommendation</td>
</tr>
<tr>
<td>(Hromic and Hayes 2014)</td>
<td>Big Data Signal Processing</td>
<td>Case Mining</td>
<td>Twitter Datasets for Event Detection</td>
</tr>
<tr>
<td>(Olsson et al. 2014)</td>
<td>Signal Processing</td>
<td>Retrieval</td>
<td>Fault Diagnosis in Heavy Duty Machines</td>
</tr>
<tr>
<td></td>
<td>Application</td>
<td></td>
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</tr>
<tr>
<td>(Sekar and Chakraborti 2016)</td>
<td>Big Data Interactivity</td>
<td>Retrieval</td>
<td>Product Recommendation</td>
</tr>
<tr>
<td>(Tomasic and Funk 2014)</td>
<td>Regression Analysis</td>
<td>Reuse Revise</td>
<td>Quality Control in Manufacturing</td>
</tr>
<tr>
<td>(Zhang, Zhang, and Leake 2016)</td>
<td>Big Data</td>
<td>Retain</td>
<td>Streaming Data</td>
</tr>
</tbody>
</table>

verifying that CBR-recommended adjustments will lead to improved manufacturing outcomes; and adapting retrieved adjustments to ensure that only relevant variables are modified (Tomasic and Funk 2014).

- **Explainability and Transparency.** Canensi et al. mine processes from traces of executed actions in a medical domain while keeping references to the traces through a novel algorithm. The algorithm shows very high precision, i.e., it never includes incorrect paths. Moreover, since the traces from which a model branch was mined are explicitly referenced, the model can be used as an indexing structure, for flexible and efficient trace retrieval (Canensi et al. 2014; 2016). Adedoyin et al. note CBR’s advantage in explainability and transparency, when compared to logistic regression and neural networks, for the task of identifying fraudulent patterns among financial transactions (Adedoyin et al. 2016).

- **User Centeredness and Interactivity.** Eyorokon et al. present a system that supports knowledge discovery using a conversational CBR process. Investigation involves the creation of a knowledge goal trajectory, where an initial knowledge goal is refined, focused, or changed, through a variety of phases in the investigative sequence, in a creative manner in reaction to retrieved information (Eyorokon et al. 2016).

It is worth noting that many papers address more than one theme, as illustrated in Table 1.

**Conclusion**

In this paper, we have reported on the work presented at two recent workshops on Synergies between Case-based Reasoning and Knowledge Discovery, which were held at the International Conference on Case Based Reasoning. The analysis we have carried out has allowed us to identify different roles that knowledge discovery can play to support CBR. As can be expected, knowledge discovery techniques have been adopted for case mining. Moreover, they have been frequently integrated with the Retrieve step, improving similar-
ity calculation, weight learning and indexing. Interestingly enough, examples also exist of the adoption of these techniques in all other steps of the CBR cycle, i.e., Reuse, Revise and Retain.

Moreover, we were able to discover a set of common trends. We found a significant number of applications in Big Data domains (or, at least, in data intensive domains, such as business process management, e-commerce and signal processing). The adoption of knowledge discovery techniques can quite naturally tackle some of the issues presented by this kind of data, and thus facilitate and enhance the implementation of CBR systems in such contexts. We observed an increasing attention to transparency and context-awareness. Knowledge discovery techniques can be used to preserve contextual information in cases, thus facilitating the generation of explanations and justifications of system output. Finally, we noted an increasing interest in the implementation of interactive tools. Here, the integration of CBR and knowledge discovery techniques provides an initial solution to the user, who is then allowed to ask for progressive refinements, being directly involved in the reasoning process.

In summary, knowledge discovery techniques can be deployed in multiple ways, in a wide variety of domains, helping CBR researchers, system implementers and users to manage complex issues. Indeed, as exemplified by the works we have examined, CBR can significantly benefit from integration with knowledge discovery, gaining in reasoning accuracy, effectiveness and transparency. In the future, we plan to extend our analysis, examining how, conversely, the CBR methodology can improve and enhance the performance of systems based on knowledge discovery techniques. This will conclude our investigation of the multiple synergies that can be achieved between these two fields of artificial intelligence research.

References


