

What's Hot in Case-Based Reasoning

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Abstract

Case-based reasoning addresses new problems by remembering and adapting solutions previously used to solve similar problems. Pulled by the increasing number of applications and pushed by a growing interest in memory intensive techniques, research on case-based reasoning appears to be gaining momentum. In this article, we briefly summarize recent developments in research on case-based reasoning based partly on the recent Twenty Fourth International Conference on Case-Based Reasoning.

Introduction

Case-based reasoning (CBR) addresses new problems by remembering and adapting solutions previously used to solve similar problems (Kolodner 1993; Riesbeck & Schank 1989). CBR is an approach to understanding intelligence that is based on two tenets about the nature of the world: problems tend to recur, and similar problems have similar solutions. When the two tenets hold, CBR is an effective reasoning strategy (Leake 1996).

Much of the original inspiration for the CBR approach to understanding intelligence came from the role of memory and reminders in human cognition (Schank 1983). CBR is both a theory for modeling how people use memory to solve problems and a theory of we can design machines that use past experiences to address new situations (Kolodner 1993).

CBR is also a theory of skill and knowledge acquisition (Sussman 1975) that overcomes some of the traditional bottlenecks of expert systems. In CBR, the solution to each new problem becomes the basis for a new case, available to be learned and stored in memory for potential reuse in future despite the utility problem (Smyth & Keane 1995). Thus, CBR favors incremental learning from experience

and acquisition of expertise rather than exhaustive extraction of domain knowledge.

CBR also differs from traditional approaches to machine learning. For example, it differs from the k-nearest neighbors family of methods for classification because it encompasses adaptation and reasoning in addition to reminding and retrieval. It also differs from so-called “transfer learning” in that CBR seeks to learn from a small set of examples and favors lazy learning that takes into account the target problem into the process of learning.

CBR is much closer to analogical reasoning. However, CBR typically assumes that memory is massively populated so that, given a new problem, memory can supply a very similar past case containing an almost correct answer to the new problem. In contrast, analogy encompasses cross-domain transfer of knowledge abstractions between semantically distant domains.

CBR is a general methodology for building AI agents, not a specific technology (Watson 1999). According to this methodology (Aamodt & Plaza 1994; de Mántaras et al. 2015) to address a new situation, the intelligent agent first *retrieves* similar experiences about similar situations from the memory, then *reuses* a past experience in the context of the new situation, next *reviews* the new solution, and finally *retains* the new experience in memory.

Research on CBR over the years has led to a large number of applications (Lenz et al. 1998) in a variety of domains ranging from recommender systems (Bridge et al. 2005), to design (Goel & Craw 2005), education (Kolodner et al. 2005), and law (Rissland & Ashley 2005). According to (Smith 2016), CBR has led to more practical applications than any other AI family of techniques with the exception of expert systems and machine learning. IBM’s Watson system (Ferruci et al. 2010) is a famous example of the power of memory-based reasoning.

New Developments in CBR Research

Research on CBR appears to be gaining momentum because of several reasons: new applications, for example, in knowledge discovery and interactive robotics (Fitzgerald et al. 2015; Floyd et al. 2008; Homem et al. 2016), a closer alliance with research on analogy (Coman & Kapetanakis 2016) and creativity (Kendall-Morwick 2015), and a renewed interest in conversational systems (Aha et al. 2001) (Gu & Aamodt, 2005), and trust and explanation (Floyd & Aha 2016, Leake & McSherry 2005, Goel & Murdock 1996). Thus, CBR research recently has led to several reviews (de Mantaras et al. 2005), books such as (Lopez 2013) and (Richter & Weber 2013), as well as several tools for building CBR systems such as IUCBR (Bogaerts & Leake 2005), jCOLIBRI (Diaz-Agudo et al. 2007) and myCBR (Stahl & Roth-Berghofer 2008).

We highlight the following developments in recent CBR research based in part on the presentations and discussions at the Twenty Fourth International Conference on Case-Based Reasoning (Goel, Diaz-Agudo & Roth-Berghofer 2016) and affiliated workshops (Coman & Kapetanakis 2016) held at Georgia Institute of Technology from October 31 to November 2, 2016:

- Novel approaches to similarity and retrieval (Homem et al. 2016). Similarity and retrieval are among the core constructs in CBR. Recent work uses qualitative measures for similarity and retrieval in the context of robot soccer.
- Advances in adaptation strategies. Case reuse, adaptation and combination have been major lines of research in CBR. Recent proposals include discovering adaptation rules from big data (Jalali & Leake 2015) and retrieving adaptable cases (Bergmann et al. 2016).
- Textual case-based reasoning (Sizov et al. 2015; Weber et al. 2005). In textual case-based reasoning are in the form of unstructured texts. One question here is how extract structured cases from texts.
- Diagrammatic case-based reasoning in which the cases are in the form of images such as drawings or diagrams. One issue here is to how retrieve and reuse diagrammatic representations of cases (Yaner & Goel 2005).
- Use of case-based reasoning in creativity, for example, by combining elements from multiple cases. See (Kendall-Morwick 2015) for proceedings of the ICCBR-2015 workshop on creativity.
- Case generation, knowledge discovery, learning and maintenance of big case bases. See (Coman & Kapetanakis 2016) for proceedings of the ICCBR-2016 workshop on knowledge discovery.

- Relationship between case-based reasoning and analogical reasoning. Again see (Coman & Kapetanakis 2016) for proceedings of the ICCBR-2016 workshop on computational analogy.
- Domain independent techniques and tools such as IUCBR (Bogaerts & Leake 2005), jCOLIBRI (Diaz-Agudo et al. 2007), and myCBR (Stahl & Roth-Berghofer 2008) for constructing case-based systems.
- Hybrid approaches for the different CBR processes, including logic, commonsense reasoning, temporal reasoning, Bayesian networks, machine learning, and deep learning.
- Explanation, transparency and trust of the reasoning results based on the underlying examples (Floyd & Aha 2016; Leake & McSherry 2005).
- Successful applications in a wide variety of domains, including planning, induction, classification, decision support, recommender systems, help desks, legal, health, cooking, games, pattern recognition, natural language processing, vision, robotics, design, education, smart homes and smart cities.

Challenges in CBR Research

The discussions at the Twenty Fourth International Conference on Case-Based Reasoning and affiliated workshops also helped identify several challenges for research on CBR:

- Case acquisition from raw data, including texts and diagrams; ontologies, generalizations, heterogeneous and multimedia data.
- CBR as a cognitive approach to big data; AI with large-scale memories.
- Cognitive aspects of CBR; modeling of human cognition.
- CBR and computational analogy; similarities, bridges.
- CBR and computational creativity; combination of multiple cases.
- Novel applications of CBR, especially in knowledge discovery and robotics.
- Explainability of CBR systems; CBR is an AI technique that can support interactive explanations for users, including both the proposed solution and the reasoning process itself.
- Development, distribution and widespread use of tools for building CBR systems.

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