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Bridging AI Paradigms with Cases and Networks †

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Abstract: For many years, symbolic paradigms have dominated AI, but the impressive accomplishments of neural approaches have made them a new dominant paradigm. However, each of these paradigms has distinct advantages. This talk presents a hybrid paradigm that integrates case-based reasoning (CBR) with network methods to achieve the benefits of both. CBR is a knowledge-based reasoning and learning methodology inspired by human cognition that adapts prior cases—records of prior experiences, to solve new problems. The CBR process supports efficient knowledge-based reasoning and the reuse of structured or unstructured solutions; it is naturally interpretable, can learn from few examples, and provides inertia-free lazy learning. However, the success of CBR depends on similarity and case-adaptation knowledge, which may be hard to acquire. This talk presents opportunities for combining case-based reasoning with neural networks to leverage both paradigms.

Keywords: case-based reasoning; explanation; neural-symbolic systems

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1. Introduction

Artificial intelligence plays a key role in information processing. For many years, the dominant AI paradigm was symbolic, with knowledge-based systems that leveraged deep knowledge. More recently, the dominant AI paradigm has shifted to sub-symbolic methods, as advances in machine learning with deep neural networks, and recently, large language models (LLMs), have promised transformative impact across a broad range of tasks. The symbolic and sub-symbolic paradigms have sometimes been seen as dueling, with the expectation that one will prove the most effective. However, a natural goal is to build systems that combine the strengths of each. This has led to extensive research on neural-symbolic systems and multiple integration strategies [1].

Case-based reasoning (CBR) [2,3] is a methodology for reasoning and learning that is grounded in a cognitive model [4]. CBR can be used for either problem solving or interpretation; it is a lazy learning method that solves new problems by retrieving and adapting solutions of relevant prior cases and that interprets new situations by comparing and contrasting prior examples, and that learns by storing the new cases that result. Presentation of prior cases is a natural form of explanation and CBR can be used effectively in "small data" domains [2]. However, the effectiveness of CBR depends not only on cases but on knowledge for similarity assessment and case adaptation. This knowledge may be hard to acquire, especially for case adaptation, which has traditionally been performed with case adaptation rules. Thus, the ability to generate such knowledge from data could substantially broaden the applicability of CBR.

This talk presents ongoing research on integrating case-based reasoning with network methods by generating case-adaptation knowledge and retrieval knowledge with neural networks. In addition to providing benefits for each process, using networks for both enables optimization to harmonize both, reflecting the fundamental tie between retrieval and intended use. This talk closes by considering additional potential opportunities for integrating CBR with large language models.

2. Case-Based Reasoning

Case-based reasoning is a process of reasoning based on specific prior experiences. It combines the memory of prior episodes, the case base, with processes to retrieve the cases relevant to new situations and adapt them to fit new needs. Thus, the CBR process can be seen as including the following aspects [2]:

$$\text{Case-based reasoning} = \text{retrieval} + \text{analogy} + \text{adaptation} + \text{learning}$$

This process is amenable to processing rich structured solutions, such as processes, designs, and plans. The CBR process supports efficient reasoning through reuse instead of reasoning from scratch; complex solutions need not be re-generated. If domain knowledge is available or easy to capture, it may be incorporated into the process at multiple points, wherever convenient, such as indexing knowledge, similarity knowledge, and adaptation knowledge [5]. Combining cases and knowledge can enable powerful reasoning from small data sets. Case-based reasoning can be applied to capture interactions with information across extended processes, making it appealing for automatic just-in-time information retrieval [6].

CBR systems store specific cases, rather than generalizations, making CBR a lazy learning method. Because a new case can change system behavior immediately without retraining, CBR learning is inertia-free. The CBR process enables the explanation of results in terms of retrieved cases, which has been demonstrated as a mode of explanation found natural by people.

These characteristics contrast with those of network methods. Network methods have achieved impressive performance with minimal knowledge acquisition effort but typically depend on training with large data sets to achieve it. They form conclusions based on generalizations, require retraining new information, and function as "black boxes", as their reasoning processes are opaque.

A classic challenge in CBR is obtaining the knowledge required for case adaptation, which is often captured in a rule-based form. Another challenge is the development of indexing and retrieval knowledge. This problem is especially acute for cases involving hard-to-characterize components, such as medical records including image data. Network systems have proven to be highly successful in tasks such as image processing. Given the complementary properties of the network and CBR approaches, an interesting question is how to integrate CBR with networks into information systems that combine the strengths and mitigate the weaknesses of both [7].

3. Integrations for Feature Extraction and Adaptation

We primarily investigated two types of integrations, as described by Leake et al. [8]. The first, studied by Xiaomeng Ye, focuses on case adaptation, following the case difference heuristic approach [9] of learning adaptations from differences between pairs of cases in the case base. Given the difference between the problem parts of two chosen cases in the case base and the difference between their solutions, the case difference heuristic ascribes the solution difference to the problem difference to generate a new adaptation rule. However, it may be unclear how to generalize these differences. Using neural networks to learn adaptations from pairs of cases in the case base can provide a general method for learning such generalizations.

Adaptation and similarity knowledge are intimately connected. Ideally, the retrieved case will be the most adaptable. When adaptation learning is combined with the network learning of similarity information, it is possible to jointly optimize both similarity and adaptation knowledge, which we have shown can increase system performance.

The second type of integration, as investigated by Zachary Wilkerson, Vibhas Vats, and Karan Acharya of Indiana University, concerns feature extraction from deep neural networks. Network layers can be viewed as successively extracting features from the inputs. Such features can then be used as indices for the retrieval of cases, either to provide explanations for the network process [10] or simply to improve CBR retrieval performance. We are investigating how different network architectures and extraction strategies affect feature quality, as well as combining network-extracted features with knowledge-engineered features. In our studies, this can achieve performance surpassing either approach individually.

4. Conclusions and Future Steps

This talk has presented research drawing from two AI paradigms, symbolic and neural, to exploit strengths and help alleviate the difficulties of both. We are now investigating tighter integrations, especially for coupling network training to the needs of the CBR system.

The explosion of interest in and applications of large language models has prompted both great optimism and great concern. Despite achieving remarkable fluency, as statistical models, LLMs do not capture many important types of information behaviors, such as retention of long-term memories and specific facts, and pose significant problems for the reliability and explainability of the information they provide, which are properties that are fundamentally important to providing useful information. An exciting future opportunity is to drive LLMs with symbolic systems such as case-based reasoners to leverage the strengths of both [11].

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