A Competence Model for Case-Based Reasoning

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Abstract. Case-based reasoning is an Artificial Intelligence problem solving technique that emphasises the role of memory and past experience during future problem solving. In brief, new problems are solved by retrieving and adapting the solutions to similar problems (called *cases*) that have been previously stored in a memory structure called a *case-base*. The competence of a case-based system depends critically on the cases in the case-base. However, the precise relationship between cases and overall competence is a complex one. For example, certain cases can be critical with respect to competence, while others may be redundant. In this paper we present, and evaluate, an effective model of case competence. Furthermore, we argue that this model has an important role to play in future CBR research in areas such as the evaluation and benchmarking of case-based techniques, as well as in the development of new techniques for intelligent case authoring and maintenance support.

1 Introduction

Case-based reasoning (CBR) is a relatively recent approach to problem solving that has been embraced by the Artificial Intelligence (AI) community. Unlike many traditional AI problem solving approaches, which emphasise first-principles search as the algorithmic heart of intelligent reason and action, the case-based reasoning approach emphasises the role of memory, experience, and reuse. Rather than trying to solve new problems by reasoning from first-principles, CBR systems reuse solutions to similar problems that have been encountered in the past. At the heart of every case-based reasoner is a repository of problem solving experiences (*cases*) stored in a *case-base*. Each case corresponds to a particular problem, and stores a description of the problem and its solution. To solve a new target problem, a CBR system *retrieves* a similar case from the case-base and *adapts* its solution to fit the target [1].

The competence of a case-based system refers to the range of target problems that a system can successfully solve. Clearly, there is a strong relationship between the competence of a CBR system and the cases in its case-base, however, the precise nature of this relationship is not clear. Previous work has shown how different cases can make very different types of competence contribution. Some cases may be critical with respect to competence while others may be redundant [8]. Other research has investigated ways of evaluating and validating case-bases and CBR systems [3,4]. To date however, there has been only limited progress in developing an effective and truly predictive model of actual case competence. In this paper we present and evaluate such a model

2 A Theoretical Model of Case Competence

In any model of case-base competence there are a number of factors that must be taken into account including the number, density, and distribution of cases in the case-base; see also the work of Lieber [3] and O'Leary [4] for a more detailed discussion of the importance of case density and distribution. In this section we present a model of competence based on these factors and on the novel idea of a *competence group*. In short, we will demonstrate that competence can be estimated by locating and measuring the competence contributions of independent groups of related cases within the case-base.

2.1 Retrieval, Adaptation & Coverage

Competence of course is all about the number and type of target problems that a given system can solve. This will obviously depend as much on the proficiency of the retrieval and adaptation components in a CBR system as it will on statistical properties of the case-base such as size and density. Therefore, any model of competence must take account of the retrieval and adaptation characteristics of a given system [3; 8].

For a target problem space $T=\{t_1,...,t_m\}$ and a case-base $C=\{c_1,...,c_n\}$, we can model the retrieval and adaptation characteristics of a CBR system by introducing the concepts of a *retrieval-space* and an *adaptation-space*. The retrieval space denotes the set of cases that are retrieved for a given target problem (Equation 1). The adaptation space is the set of cases that can be adapted to solve a given target problem (Equation 2).

1. $\text{RetrievalSpace}(t \in T) = \{c \in C : c \text{ is retrieved for } t\}$
2. $\text{AdaptationSpace}(t \in T) = \{c \in C : c \text{ can be adapted to solve } t\}$

A given target problem can only be solved if it results in the retrieval of an adaptable case; that is, if there is an intersection between its retrieval-space and adaptation-space. Using this idea we define the *coverage* of a case to be the set of target problems that a given case can solve (see Equation 3)

3. $\text{Coverage}(c \in C) = \{t \in T : c \in \text{RetrievalSpace}(t) \cap \text{AdaptationSpace}(t)$

As it stands, this method for calculating coverage is computationally intractable. Due to the sheer size of the target problem space, computing these sets for every case and target problem is not a viable option. Moreover, even if we could enumerate every possible target problem instance, it would be very difficult to know what subset of these problems the system would actually encounter in practice. Clearly, the best we can do is to find some approximation to these sets. One very useful approximation is to assume that the case-base itself is a representative sample of the target problem space. This leads to a far more tractable definition of coverage as shown in Equation 4.

4. $\text{Coverage}(c \in C) = \{c' \in C - \{c\} : c \in \text{RetrievalSpace}(c') \cap \text{AdaptationSpace}(c')$

Although this assumption may seem like a large step to take, it is in fact a valid one, and one that is implicitly made by all CBR systems. If a case-base were not a representative sample of the target problem space then there would be little hope for competent problem solving. In fact, the assumption is implicit in all forms of inductive reasoning.

2.2 Competence Groups

In general, cases are rarely distributed evenly across a problem space. Instead, there is usually a tendency for clusters of cases to form, reflecting important and commonly occurring patterns of target problems. Other parts of the problem space may be relatively sparsely populated with cases, because certain problems may seldom occur, and hence may have few or no representatives in the initial case-base. As we shall demonstrate, these clusters of related cases (which we call *competence groups*) are critical to understanding and computing global case-base competence.

The basic idea underlying our definition of a competence group is *shared coverage* (see Equation 5). Cases share coverage if their coverage sets overlap, the critical implication being that such cases make a shared competence contribution. A competence group then is a maximal group of cases that exhibit shared coverage (Equation 6).

5. For $c_1, c_2 \in C, \text{SharedCoverage}(c_1, c_2) \text{ iff } \text{Coverage}(c_1) \cap \text{Coverage}(c_2)$

6. For $G = \{c_1,..,c_p\} \subseteq C$, CompetenceGroup$(G)$ iff

$$\forall c_i \in G, \exists c_j \in G - \{c_i\}: \text{ShareCoverage}(c_i, c_j)$$
$$\wedge \forall c_k \in C - G, \neg\exists c_l \in G: \text{ShareCoverage}(c_k, c_l)$$

An example of two competence groups in a case-base of four cases is depicted in Figure 1. The cases, c1, c2, c3 and c4, and their coverage sets are shown. Three of the cases (c1, c2 and c3) form one group because they share overlapping regions of coverage; c2 is covered by c1 and c3 is covered by c2. In contrast, c4 is sufficiently different from the other cases so that it does not share any coverage and thus forms a second independent competence group.

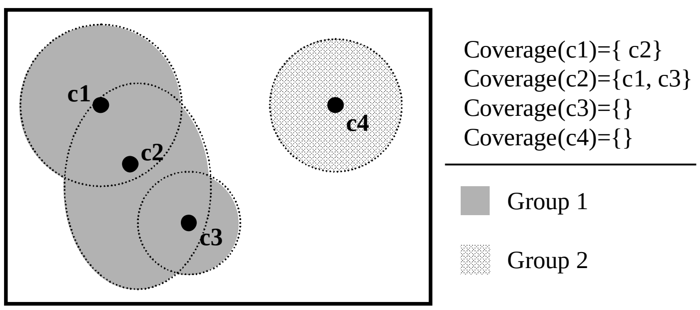

Fig. 1. A case-base with two competence groups.

In general, every case in a case-base will belong to a single group. The number and size of the groups will depend on the number, density and distribution of the cases in the case-base. A sufficiently dense case-base may just have a single group containing all of the cases. A very sparse case-base can have as many groups as there are cases, each group containing just one case; in fact, these lone cases are the pivotal cases described by Smyth & Keane[8].

2.3 Group Coverage

There are two critical points to understand about competence groups. First, by definition, the cases in a group mark out a region of related, overlapping coverage. Second, competence groups are mutually exclusive collections of cases, and therefore their associated regions of coverage do not intersect with any other groups's region of coverage. In short, each competence group defines an independent unit of competence within the case-base.

Group coverage cannot be calculated by simply summing the coverage sets of individual group cases. By definition, these coverage sets overlap with each other, as some regions of the problem space are covered by multiple cases. In computing overall group coverage our model must compensate for this type of redundancy.

In general, larger competence groups will cover larger regions of the target problem space, and therefore contribute greater to overall competence than smaller groups. At the same time, densely packed groups will cover smaller regions than sparsely packed groups; dense groups contain cases with larger coverage overlap and therefore greater coverage redundancy. Therefore, any effective estimate of group coverage must take into account the size and density of the competence groups.

The density of an individual case is defined as the average similarity between this case and other group cases (Equation 7) [1]. In densely packed groups the average similarity between a given case and all other cases in the group will be relatively high, and hence case density will be high. Equation 8 measures the density of the competence group as a whole as the average local density over all cases in the group. Note that the density of a singleton group is 1.

$$7.\quad \mathrm{CaseDensity}(c, G) = \frac{\sum_{c' \in G - \{c\}} \mathrm{Sim}(c, c')}{|G - 1|}$$

$$8.\quad \mathrm{GroupDensity}(G) = \frac{\sum_{c \in G} \mathrm{CaseDensity}(c, G)}{|G|}$$

The coverage of a given competence group is an estimate of the problem space area that the group covers. As indicated above group coverage must be directly proportional to the size of the group but inversely proportional to its density. This leads to the definition of group coverage shown in Equation 9.

$$9.\quad \mathrm{GroupCoverage}(G) = 1 + \left[|G| \bullet (1 - \mathrm{GroupDensity}(G))\right]$$

2.4 Case-Base Coverage

We are now in a position to finally define the coverage of an entire case-base. Competence groups are, by definition, mutually independent sources of competence within a case-base. As such the global competence of a case-base can be defined as the sum of the coverages of all competence groups. Hence, for a given case-base, with competence groups **G** = $\{G_1, \ldots, G_n\}$, the total coverage is defined by Equation 10.

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[1] Sim is taken to be the similarity function used by a given system. It is assumed, without loss of generality, that this function is normalised to return values between 0 and 1, with 1 representing a perfect match.

10. $\text{Coverage}(\mathbf{G}) = \sum_{G_i \in \mathbf{G}} \text{GroupCoverage}(G_i)$

3 Empirical Evaluation

So far we have presented a novel technique for modelling the competence of case-bases in CBR systems. In this section we present empirical evidence in support of this theoretical model. In short, we demonstrate that the competence predictions of the model closely match the actual competence measurements taken from real case-bases and target problem sets. In particular, we look at the relationship between the model's predictions and true competence for a range of different sized case-bases with different degrees of case redundancy and duplication.

3.1 Experimental Setup

The case-base used in this experiment contains cases from the travel domain (available by public ftp from http://www.ai-cbr.org). The case-base contains over 1000 cases describing package holidays from Europe and North Africa. Each holiday case is described by a collection of features (nominal and continuous) such as holiday type, duration, and accommodation. For experimental reasons we decided to hold back 300 randomly chosen cases for use as unseen target problems. A further 700 were used to form the experimental case-bases.

To test our competence model, an experimental holiday recommendation application was built based on the CaBaTa system [2]. When presented with a target problem the system retrieves a collection of best matching cases for presentation to the user. Success occurs when a retrieved case is sufficiently similar to the target problem; that is, when the similarity between a case and target exceeds a predefined similarity threshold, 0.8 in this experiment. In this application then, competence is seen as a measure of the accuracy of the system, namely, the ratio of target problems that have been successfully solved. The retrieval engine uses a standard nearest-neighbour algorithm.

3.2 Experimental Procedure

Materials: The experiment uses the 300 unseen target problems and the 700 travel cases. Three sets of 700 cases are produced from the basic 700 travel cases. The first set, called the *standard set*, corresponds to the original 700 cases. In the second set, called the *redundant set*, each case represents a slight variation on one of the cases in the standard set. Finally, the third set, called the *duplicate set*, is simply an exact copy of the standard set. From these sets we construct 21 case-bases containing from 100 to 2100 cases. The first seven case-bases (containing from 100 to 700 cases) are constructing from the standard set. The next seven (containing from 800 to 1400 cases) are produced by adding cases from the redundant set. The final seven (containing from 1500 to 2100 cases) are produced by adding cases from the duplicate set. Thus, we now have a collection of 21 increasingly large case-bases containing increasing degrees of redundancy and duplication.

Method: For each of the 21 case-bases two measurements are taken. First, the 300 unseen target problems are used to test case-base accuracy, yielding a real competence value for each case-base. Second, a competence model is built for each case-base and case-base coverage is measured, yielding a predicted competence value for each case-base.

3.3 Experimental Analysis

The main objective of this experiment is to demonstrate that the proposed competence model is effective (that is, accurate) for a range of case-bases, with varying degrees of redundancy and duplication. The results, shown in Figure 2, are extremely positive with an obvious correlation between the behaviour of the predicted coverage plot and the actual competence plot. The critical measure of success in this experiment is the correlation coefficient between the two plot lines. In this case the coefficient is over 0.97 which is statistically significant at the 0.001 level; a correlation coefficient of 1 indicates a perfect correlation while a 0 value indicates that there is no relationship.

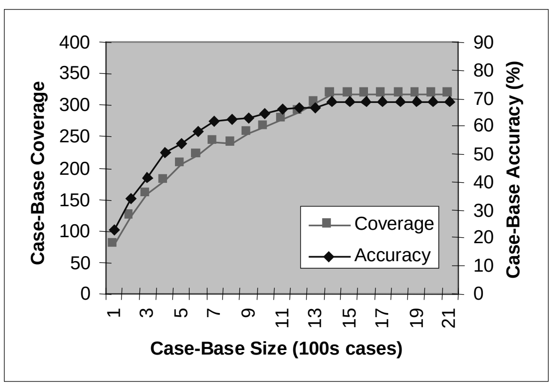

Fig. 2. Predicted Case-Base Coverage vs True Competence (Accuracy).

Looking at the plots in more detail we find that for the first seven case-bases (100 to 700 cases), true competence and predicted coverage increase steadily, since these case-bases contain little or no redundancy and each case makes a significant competence contribution. Once case-bases from the redundancy set are included (increasing case-base sizes from 800 to 1400 cases) true competence begins to increase more slowly, and again is matched by the model's prediction. These case-bases contain increasing degrees of redundancy and so the new cases do not contribute as much to competence. Finally, the duplicate set case-bases (1500 to 2100 cases) contain exact copies of existing cases and so true competence does not increase at all. Again this is matched by the model's predictions.

4 Conclusions

Competence has always been a crucial evaluation concern in any AI system. In case-based reasoning there is a strong relationship between the competence of a system and the cases in the case-base. However, the precise nature of this relationship is complex and not well understood. In this paper we have provided a theoretical model that allows the competence of a case-base to be evaluated and predicted. The model takes account of factors such as the size of the case-base and the density, distribution and local coverage of individual cases.

A critical innovation in the model is the competence group. We have shown how to locate competence groups in a case-base and how to measure their competence contributions. The importance of competence groups stems from the fact that they represent the fundamental units of competence within the case-base. The total competence of the case-base can be calculated directly from the competence contributions (group coverage) of each competence group.

The paper has also included an empirical evaluation of the competence model, carried out using a publicly available benchmark case-base. The evaluation results show a near-perfect correlation between the predictions of the model and true competence for a wide range of case-base sizes and conditions.

The availability of such a model also opens up a range of new application possibilities. For example, the model has important applications in case maintenance, learning and deletion [5; 6]. In particular, as CBR systems scale up to address more complex real-world problems their case-bases rapidly grow in size. Research has shown that this type of growth can have an adverse affect on problem solving efficiency (see [7]) and may lead to the need for some pruning or deletion process to be applied to the case-base. The difficulty is in choosing cases that do not contribute to efficiency or competence. However, most strategies borrowed from the machine learning literature focus only on the former factor. This can lead to competence degradation in CBR systems[8]. One solution is to use a competence model to guide the deletion process and in this role the current model can play a vital role.

The model can also be used to assist case-base designers during the authoring process. As cases are added to the case-base during the authoring stage a competence model can be generated and updated. The designer can use this model to gain insight into the emerging competence of the case-base. The model can be used to help the designer visualise the topology of the evolving case-base, to highlight regions of high and low competence.

Work is already underway developing an authoring assistant that makes use of the competence model. An initial prototype has been built and preliminary results are positive, with users reporting genuine benefits from the visualisation facility. Future research will also continue to investigate new application possibilities, as well as evaluating the effectiveness of the model for a wider range of CBR domains.

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