Modelling the Competence of Case-Bases

Barry Smyth & Elizabeth McKenna

Department of Computer Science
University College Dublin
Belfield, Dublin 4, IRELAND
Barry.Smyth@ucd.ie

Abstract. The competence of a case-based system (the range of problems it can solve) depends critically on the cases in the case-base. However, the precise relationship between cases and overall competence is a complex one. For example, some cases can be critical to competence, while others may be largely redundant. In this paper we present, and evaluate, a new model of case competence. We argue that this model has an important role to play in areas such as the evaluation and benchmarking of case-based techniques, and we demonstrate a novel application of the model as a guide to case-base designers during the case authoring process.

1 Introduction

For the Artificial Intelligence community in general, and the case-based reasoning (CBR) community in particular, system *competence* (or *coverage*), that is the range of target problems that a given system can solve, is a fundamental evaluation criterion ([6], [7], [8]). As such, it is somewhat peculiar that the issue of competence has been frequently passed over during CBR system evaluation and testing. Typically, researchers offer simple measures of competence, such as the percentage of problem solving successes. In our view such simple metrics represent little more that the tip of the iceberg when it comes to understanding the true nature of competence in CBR. They tell us nothing about the underlying source of competence for a given system, and they carry little or no predictive power. This makes it impossible to determine how the competence of a given system will vary under different run-time conditions (e.g., changes in the case-base, adaptation knowledge, or target problem space).

In this paper we focus on the competence of the case-base. We present a novel model of case competence and demonstrate that it is accurate and predictive. The model makes certain assumptions about the nature of cases and case-bases. In particular, we assume that the cases in the case-base are a representative sample of the target problems. We further assume that the problem space is a regular one, namely that the standard "similar problem implies similar solution" CBR hypothesis holds. In the next section we look at how basic factors such as case-base size, case density, and case distribution influence overall case-base competence within the representational bias imposed by these assumptions. In Section 3 the competence model is described in detail. In particular, we explain how the model relies on the novel concept of a competence group, which, we argue, represents the fundamental unit of competence in a case-base. Section 4 presents a range of experimental evidence in support of the new model. Finally, Section 5 demonstrates how the model can be used to assist knowledge engineers during the case authoring process.

2 Basic Factors Affecting Case Competence

The competence of a case-base has to depend on statistical properties such as the size, the distribution, and the density of cases ([2], [4], [5], [9], [11]). It must also rely on problem solving properties such as the coverage of individual cases ([8], [11]), and therefore obviously include the similarity and adaptation knowledge of a given system.. To build an effective model of case competence we must understand how these factors influence real competence, how they interact and evolve within a working system, and how they can be measured.

2.1 Case-Base Size, Density, and Distribution

Previous efforts to understand and measure case competence have concentrated on statistical case-base properties such as size, density and distribution ([4], [5]).

Case-Base Size: Case-base size is an obvious competence factor, and clearly there is some relationship between the number of cases in a case-base and the competence of the resulting system. The number of cases in the case-base is certainly straightforward to measure, but it is not always a good predictor of competence, mainly because different cases can influence competence in different ways [11]. Some cases may be crucial offering viable solutions to a wide range of common target problems, while others may represent unusual problems that rarely occur. Clearly, the former type of case has a larger competence contribution to make than the latter; however care must be taken here since rare (or unusual) cases may make a critical competence contribution that can not be ignored during case-base learning and maintenance (cf. the concept of pivotal cases in [11]). Similarly, case-bases can contain large numbers of redundant or even inconsistent cases, neither of which are acknowledged by a simple count of the number of cases.

Case-Base Density: The density of cases is also a relevant competence factor. The individual competence contribution of a single case within a dense collection will be lower than the contribution of the same case within a sparse group; dense groups contain greater redundancy than sparse groups. Case density is more difficult to measure than case-base size, but can be computed as a function of case similarity. For example, in regular case spaces groups of cases that are densely packed display high degrees of mutual similarity, while sparse groups display low degrees of mutual similarity. For instance, the local density of a case c within a group of cases $G \subseteq C$ is given by Equation 1 below[1].

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

Case-Base Distribution: The distribution of cases also affects competence. If cases are unevenly distributed then we can expect considerable density variation and consequently irregular problem solving competence; a target problem from a densely packed region of the case-base will be solved with a high degree of probability, while a target from a sparse region is likely to be unsolvable. Of course the distribution of solutions is also a factor to be considered. A target problem from a sparsely populated region of the case-base may be readily solved if all problems from the region have very similar solutions, indicating that the region could be covered by a small number of cases or even a single well chosen case.

2.2 Retrieval, Adaptation, and Coverage

Competence is all about the number and type of target problems that a given system can solve. This will depend as much on the proficiency of the retrieval, adaptation and solution evaluation components in a CBR system as it will on the case-base. For example, the case that is finally retrieved to solve a given target problem will depend on the type of similarities that retrieval is designed to detect and prefer. Whether or not an adaptable case is guaranteed by retrieval will depend not only on the available cases but also on the retrieval algorithm. In fact, many retrieval approaches make no such guarantees and run the risk of retrieving non-adaptable cases even when adaptable cases do exist [10]. Any model of case-base competence must take account of the retrieval and adaptation characteristics of a given system.

Smyth & Keane [11] describe a technique for measuring the local coverage of individual cases with respect to a system's retrieval and adaptation characteristics. With this technique we can use the concepts of a *retrieval-space* and an *adaptation-space* (as defined by Equations 2 and 3) to define case *coverage*, the set of problems that a given case can solve.

$$\text{RetrievalSpace}(c \in C) = \{c' \in C : c' \text{ is retrieved for } c\} \quad \textbf{(2)}$$

$$\text{AdaptationSpace}(c \in C) = \{c' \in C : c' \text{ can be adapted to solve } c\} \quad \textbf{(3)}$$

[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.

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

The astute reader will of course notice that the above formulae make no mention of actual target problems. In fact, the proposed technique assumes that the case-base itself is a sufficiently representative sample of the target problem space. Instead of measuring coverage as the set of *target* problems that a case can solve, it is estimated to be the set of other *cases* that a given case can solve. This definition is clearly far more tractable than the true definition of coverage that relies on measurements taken from the actual target problem space; there are simply too may potential target problems to consider. We also claim that the assumption is a reasonable one, and indeed one that underlies the concept of CBR and inductive learning techniques in general.

3 A Model of Case Competence

At this point it may seem that an effective model of competence is actually at hand. For a particular case we can view its local coverage set as a proxy for its local competence contribution, and hence we can compute the overall global competence of the case-base directly, as the summation of local case coverage sets. Unfortunately, it is not this simple. It is certainly true that global competence is related to local case competence, but the relationship is a complex one.

In this section we describe the proposed model in detail. In particular, we explain how the model encodes this crucial relationship between local and global competence by identifying fundamental units of competence within the case-base.

3.1 The Fundamental Unit of Competence

Global competence is an emergent property of the contents and topology of the case-base; it is based on how local case competences interact when they are combined. For instance, case coverage sets can overlap to limit the competence contributions of individual cases, or they may be isolated and exaggerate individual contributions [11]. It is actually possible to have a case with a large local competence that makes little or no contribution to global competence simply because its contribution is subsumed by the local competences of other cases. At the other extreme, there may be cases with relatively small contributions to make, but these contributions may nonetheless be crucial if there are no competing cases. Therefore, for a true picture of the competence of a case-base, we need to look at how the local case coverage sets combine and interact to produce common patterns of competence.

During our research, the importance of this last point gradually changed the way we thought about case competence. The traditional view, which sees ‘the case’ as the fundamental unit of competence, began to lose appeal and we soon realised that such a case-centric perspective was simply too limited and, in practice, quite misleading. We began to look for a different fundamental unit of competence. It is this philosophy that sets this work apart from earlier competence work (e.g., [11]).

As cases are added to a case-base, clusters begin to form to produce well-defined regions of competence. Common problem types are typically represented by large, densely packed clusters, while smaller clusters, or even lone cases, generally represent more unusual problem types. Importantly, these clusters do not overlap (interact) with other clusters, and as such their competence contributions can be treated independently of one another. This is critical because it means that we can calculate global competence directly from the competence contribution of each cluster. We call these clusters *competence groups*, and we believe them to be the fundamental units of competence within the case-base. In the following sections we will describe how they can be identified, how their precise competence contributions can be measured, and as a result, how overall competence can be computed.

3.2 Competence Groups

A competence group is a collection of related cases, which together make a collectively independent contribution to overall case-base competence. The key idea underlying the definition of a competence group is that of *shared coverage* (see Definition 5). Two cases exhibit shared coverage if their coverage sets overlap. This is seen as an indication that the cases in question make a shared competence contribution, and as such belong to a given competence group.

$$\begin{aligned}&\text{For } c_1, c_2 \in C,\\ &\text{SharedCoverage}(c_1, c_2) \text{ iff Coverage}(c_1) \cap \text{Coverage}(c_2)\end{aligned} \qquad \textbf{(5)}$$

This shared coverage relationship provides a way of linking related cases together. Formally, a competence group is a maximal collection of cases exhibiting shared coverage (see Definition 6). Thus, each case in a competence group must share coverage with some other case in the group (this is the first half of the equation). In addition, the group must be maximal in the sense that there are no other cases in the case-base that share coverage with any group member (this is the second half of the equation).

$$\begin{aligned}&\text{For } G = \{c_1, .., c_p\} \subseteq C,\\ &\text{CompetenceGroup}(G) \text{ iff}\\ &\qquad \forall c_i \in G, \exists c_j \in G - \{c_i\} : \text{ShareCoverage}(c_i, c_j) \wedge\\ &\qquad \forall c_k \in C - G, \neg\exists c_l \in G : \text{ShareCoverage}(c_k, c_l)\end{aligned} \qquad \textbf{(6)}$$

According to this definition, in every case-base, every case belongs to one and only one competence group. The number and size of the groups will depend on the density and distribution of cases in the case-base, as well as the retrieval and adaptation characteristics of a system. An extremely dense case-base could have a single group containing all of the cases. In contrast, an extremely sparse case-base might contain as many groups as there are cases, each group containing just a single case; these are the pivotal cases described by Smyth & Keane [11]. Usually, particular case-bases will fall between these extremes, containing many groups of varying sizes, the larger ones representing regions of high competence, the smaller ones, regions of lower competence.

A simple example of two groups in a simple case-base is illustrated in Fig. 1. There are four cases, c1, c2, c3 and c4, and their coverage sets are as shown. The cases c1, c2 and c3 form a group because they share regions of coverage; that is, c2 is covered by c1 and c3 is covered by c2. In contrast, c4 is sufficiently different from the others so that it does not share any coverage. Thus, there are two competence groups, one with three cases (c1, c2 and c3) and a second with just one case (c4).

The essential thing to notice about this example, and about competence groups in general, is that the groups are independent of one another. They are independent in the sense that there is no interaction between their competence contributions because, by definition, there is no shared coverage between different groups. This means that we can calculate global competence directly from the competence contribution of each competence group.

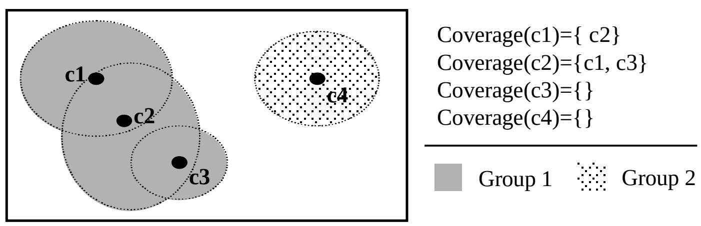

Fig. 1. A simple case-base containing two competence groups. One group contains three cases (c1, c2, c3), the other just a single case (c4). The coverage sets are indicated and also depicted graphically as dotted lines surrounding the cases. The coverage of the groups is depicted as the greyed-out regions.

3.3 Group Coverage

In our model the coverage of a competence group basically corresponds to the area of the target problem space covered by the group. Thus, greater group coverage means more target problems can be solved, and hence a higher competence contribution.

In this sense, group coverage depends on the number and density of cases in a group. In general (for regular problem spaces) larger groups of cases will cover larger regions of the target problem space than smaller groups. Similarly, dense groups will cover smaller regions of the problem space (with greater redundancy) than sparse groups. Measuring group size is straightforward, while group density is defined as the average case density of the group (see Equation 7).

$$\text{GroupDensity}(G) = \frac{\sum_{c \in g} \text{CaseDensity}(c, G)}{|G|} \quad \textbf{(7)}$$

Thus, group coverage must be directly proportional to group size and inversely proportional to group density, which leads to the formula shown in Equation 8.

$$\text{GroupCoverage}(G) = 1 + \left[|G| \bullet (1 - \text{GroupDensity}(G))\right] \quad \textbf{(8)}$$

3.4 Case-Base Coverage

We are now in a position to define a measure of global competence based on group coverage. Because competence groups represent independent, non-interacting units of competence, we can simply sum their coverage estimates to produce and overall case-base coverage value. Hence, for a given case-base, with competence groups **G**= $\{G_1, \ldots, G_n\}$, the total coverage is defined by Equation 9.

$$\text{Coverage}(\mathbf{G}) = \sum_{G_i \in \mathbf{G}} \text{GroupCoverage}(G_i) \quad \textbf{(9)}$$

Thus the proposed model offers a continuous measure of case and case-base competence. Unlike previous work (e.g., [11]) where broad competence categories were identified, the current model allows us to make fine-grained distinctions between the competence of cases.

4 Experimental Analysis

In the proceeding sections, we have presented a novel technique for modelling the competence of case-bases. In this section we present empirical evidence in support of this 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 under a range of conditions (e.g., case-bases composed of cases with varying degrees of redundancy).

4.1 Experimental Setup

In order to test our competence model we need a case-base, a CBR system and a collection of test problems. The case-base chosen is a publicly available benchmark case-base from the travel domain [3][2]. Each case describes a package holiday from

[2] The case-base is available by public ftp from the AI-CBR Web site at http://www.ai-cbr.org

Europe or North Africa, described by a collection of features such as holiday type, duration, and accommodation.

The case-base contains over 1000 different cases. For experimental reasons we decided to hold back 300 randomly chosen cases for use as target problems. A further 700 were used to form the experimental case-bases. None of the 300 target cases appear in the 700 case-base cases.

The CBR system built for reasoning in this domain is essentially a recommendation system based on the CaBaTa system [3]. When presented with a target problem the system retrieves a collection of best matching cases for presentation to the user. The success criterion used is a similarity threshold; if the system does not retrieve any cases within this threshold a failure is announced. Thus true competence (precision or accuracy) is taken to be the percentage of target problems that are successfully solved by using a given case-base. The retrieval engine uses a standard normalised, weighted nearest-neighbour algorithm.

4.2 Coverage vs Competence: Standard Condition

The true test of our model is whether it accurately predicts real system competence. If our model is effective then there should be a high correlation between case-base coverage and system accuracy when it comes to solving unseen target problems.

Materials: This experiment uses the 700 travel cases and the 300 unseen problems. The 700 cases are divided into independent sets containing 100 cases each. Seven case-bases, ranging in size from 100 to 700 cases, are constructed from these sets.

Method: For each of the seven 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.

Results: The results are shown in Figure 2(a) as true competence and case-base coverage plotted against case-base size. The results provide excellent support in favour of the competence model. There appears to be a very close relationship between the two curves and hence a strong correlation between predicted competence (that is, case-base coverage) and true competence (problem solving accuracy). In fact, the correlation coefficient between the two curves is 0.99, which is statistically significant at the 0.001 level.

Discussion: Clearly the results are extremely positive, with a near perfect match between predicted and true competence. However, an important point to realise about this experiment is that the case-bases contain little or no redundancy; all cases contributed to competence in a positive way. In fact, under such conditions case-base size is almost as good a predictor of true competence. Hence, for a more effective and realistic test of the model we must consider the impact of case redundancy on the accuracy of the model's predictions.

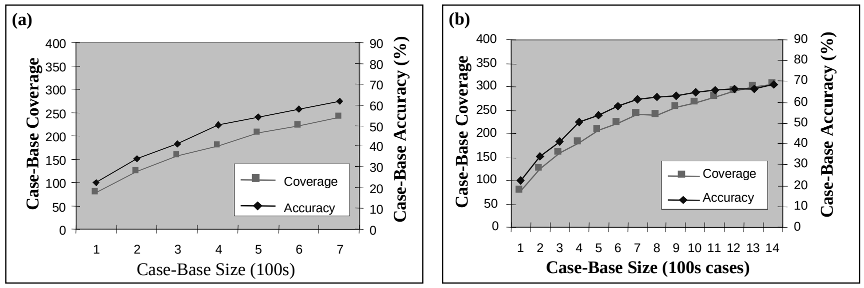

Fig 2. Comparing predicted competence (case-base coverage) to true competence (case-base accuracy) for (a) the Standard Condition and (b) the Redundancy Condition.

4.3 Coverage vs Competence: Redundancy Condition

This experiment is similar to the previous one except in one important respect. This time case-bases that contain varying degrees of redundancy are used in order to assess model accuracy under more realistic and varied case-base conditions. Under these conditions, case-base size is no longer an effective predictor of competence (as we will show). The question is whether case-base coverage remains effective.

Materials: The raw materials of the experiment are the same as those used in the previous one, namely the 300 unseen target problems and the 700 travel cases. However, this time two 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. From these sets we construct 14 case-bases containing from 100 to 1400 cases. The first seven case-bases are the same as those used in the previous experiment. The second seven (containing from 800 to 1400 cases) are produced by adding cases from the redundant set. Thus, we now have a collection of case-bases containing variable degrees of redundancy amongst their constituent cases.

Method: As in the previous experiment, case-base coverage and accuracy values are computed, this time for each of the 14 case-bases.

Results: The results are plotted in Figure 2(b). Again, there is a very close relationship between true and predicted competence. In fact, the correlation coefficient between the two curves is 0.97, which is statistically significant at the 0.001 level.

Discussion: The main objective of this experiment is to demonstrate that the proposed competence model is effective even when case-bases contain redundant cases which contribute little or no competence. As expected, once such low-competence cases begin to be added to the case-base (after the 700 case-base size mark respectively) increases in true competence begin to fall off. The important point about this experiment is that it demonstrates that the model's competence predictions continue to track these true competence changes. The same is not true of case-base size, which does not correlate well with true competence under these conditions.

5 Case Authoring Support

At the present time the level of tool support available to case authors is somewhat lacking [1]; in general, there is little more on offer than a simple statistical analysis of case features. The result is that it is often difficult for authors to decide just what cases to include in a case-base. At best this can lead to wasted effort, with authors spending time acquiring and encoding unnecessary cases. More worrying however is the likelihood of large and inefficient case-bases, containing many redundant cases; such case-bases are difficult to maintain and, because of increased susceptibility to the Utility Problem, may reduce the performance of the resulting CBR system ([2], [9]).

The CASCADE (Case Authoring Support and Development Environment) system has been built to demonstrate one way that the proposed model of competence can be used to assist case authors. At the simplest level CASCADE is an authoring tool, allowing cases to be added, deleted, edited, and displayed. However, the real advance lies in the availability of a competence model that is built up on the fly as cases are added and deleted. Basically, the model is used to help authors visualise the competence of an evolving case-base, highlighting regions of high and low competence. Once authors can recognise these regions they can optimise their effort, concentrating on areas of low competence and avoiding over-populating regions of high competence with redundant cases.

5.1 Visualising Case-Base Competence

At any point during authoring, the CASCADE user can examine the evolving competence model in a number of ways. The most basic way is to examine the constituent cases of a given competence group. It is also possible to examine the size, density, and coverage of the competence groups, and from these measures an overall picture of case-base competence can be drawn as a series of graphs.

Fig. 3 shows one of the CASCADE graphs of group size versus coverage, taken from the competence model for a 200 case case-base from the travel domain. Each point corresponds to a competence group, and the graph can be usefully partitioned into four quadrants as shown. Regions of low competence correspond to groups from quadrants A and B, while regions of high competence correspond to groups from quadrants C and D. Normally, we would expect competence groups to fall into quadrants C and the B. The former represent large competence groups with high coverage, while the later represent small groups with low coverage; both quadrants correspond to groups with low degrees of redundancy. For the author, groups from quadrant B (small size, low coverage) are due further attention as they may correspond to regions of the problem space that are under-represented by the case-base.

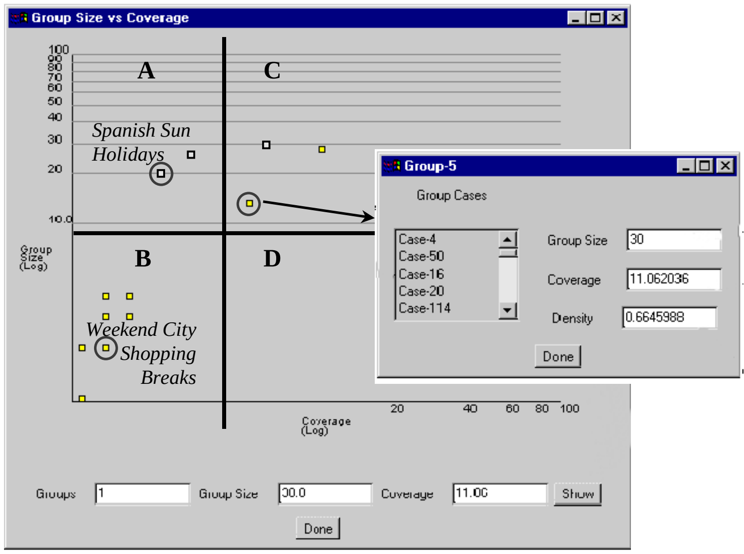

Fig 3. A snapshot from the CASCADE system visualising case-base competence.

Competence groups can also fall into quadrants A and D. Groups from quadrant D (small size, high coverage) are highly desirable since each of their cases must make a significant competence contribution. In contrast, groups from quadrant A (large size, low coverage) are highly undesirable, as these groups must contain many redundant cases making little or no competence contribution.

5.2 Improving Coverage & Reducing Redundancy

Once the case author has identified groups that are in need of further attention he/she can examine the details of individual groups (Fig. 3 shows the details of Group-5 from quadrant C). The author can not only view the cases that make up a group, but also examine a case summary; CASCADE automatically creates case summaries by computing the range of case features across the group cases. Case summaries provide the author with an instant picture of the sort of problems represented by the group.

If a group comes from quadrant B the author can choose to focus on finding new similar cases in order to improve coverage in this region of the problem space (assuming there are new cases to be found). For example, the quadrant B group highlighted in Fig. 3 corresponds to weekend city shopping breaks. The group contains only 2 cases and as such provides poor coverage. If this type of holiday is important, extra time can be spent looking for other short-term shopping breaks to improve the coverage in this region of the problem space.

In contrast, if a group comes from quadrant A (high redundancy) the author can select cases for deletion to reduce redundancy while maintaining group coverage; this can be achieved, by deleting cases with high local density values. For example, the highlighted quadrant A group in Fig. 3 corresponds to summer sun-holidays in the south of Spain. The group contains over 20 cases but offers relatively little coverage (compared to other 20-case groups) since the cases are all remarkably similar. Of course high redundancy may not indicate the need for case deletion and average problem solving performance may actually be improved if the redundant region of the problem space contains the majority of target problems.

Of course, as cases are added to the case-base the number of groups, and their position on this graph will change. Group numbers can increase or decrease (due to group merging), and as redundancy and coverage characteristics change, groups will migrate from one quadrant to another. In general, the author should try to move competence groups into quadrants C and D, and ensure no groups fall into quadrant A. This can be achieved with the help of the above strategies for improving coverage and reducing redundancy, and the author can be confident that the resulting case-base will prove to be both competent and efficient.

6 Conclusions

Competence has always been a crucial evaluation concern in any AI system [6], and 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 presented a theoretical model that allows the competence of a case-base to be evaluated and predicted.

A critical innovation in the model is the concept of a competence group as the fundamental unit of competence in case-bases. We have shown how to locate competence groups in a case-base and how to measure their competence contributions. The total competence of the case-base can be calculated from the sum of 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 (for one particular test case-base) under a variety of conditions.

While the availability of this model also has important implications for case learning and deletion, in this paper we have focused on a novel use of the model in providing valuable case authoring support in the CASCADE system. Future tasks include applying the model in other CBR domains. In particular we will begin to focus on CBR systems that use adaptation as well as the more common retrieval-only systems. Work will also continue on the CASCADE authoring shell.

References

1. Aha, D. & Breslow, L. (1997) Refining Conversational Case Libraries. *Proceedings of the 2nd International Conference on Case-Based Reasoning*. Pp. 267-278, RI, USA.
2. Francis, A.G., & Ram, A. (1993) The Utility Problem in Case-Based Reasoning. *Case-Based Reasoning: Papers from the 1993 Workshop*. AAAI Press (WS-93-01).
3. Lenz, M., Burkhard, H-D, Brückner, S. (1996) Applying Case Retrieval Nets to Diagnostic Tasks in Technical Domains. Proceedings of the 3rd European Workshop on Case-Based Reasoning, pp. 219-233, Springer-Verlag.
4. Lieber, J. (1995) A Criterion of Comparison between two Case-Bases. *Proceedings of the 2nd European Workshop on Case-Based Reasoning*, pp. 87-100, France.
5. O'Leary, D. E. (1993) Verification & Validation of Case-Based Systems. *Expert Systems with Applications*, **6**, pp. 57-66.
6. Preece, A. D. (1992) Towards a Methodology for Evaluating Expert Systems. *Expert Systems*, **7**(5), pp, 14-20.
7. Racine, K. & Yang, Q. (1997) Maintaining Unstructured Case. Proceedings of the 2nd International Conference on Case Based Reasoning, pp. 553-564 RI, USA.
8. Smyth, B (1998) Case-Based Maintenance. *Proceedings of* the 11th International Conference on Industrial & Engineering Applications of AI & Expert Systems. Springer-Verlag.
9. Smyth, B & Cunningham, P. (1996) The Utility Problem Analysed: A Case-Based Reasoning Perspective. Proceedings of the 3rd European Workshop on Case-Based Reasoning, pp. 392-399, Lausanne, Switzerland.
10. Smyth, B. & Keane, M. (1996) Design à la Déjà Vu: Reducing the Adaptation Overhead. (Ed. D. Leake) *Case-Based Reasoning: Experiences, Lessons, & Future Directions*. MIT Press.

11 Smyth, B. & Keane, M. T. (1995) Remembering to Forget: A Competence Preserving Case Deletion Policy for CBR Systems. *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, pp. 377-382. Canada.