A Simple Reachability-Based Complexity Measure for Case-Based Reasoners

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Abstract. Case-Based Reasoning relies on the underlying hypothesis that similar problems have similar solutions. The suitability of a domain to case-based reasoning is assessed by measuring the extent to which this hypothesis holds good in the case base. Several local and global alignment measures have been proposed for measuring the complexity of the case base. However, the existing measures only take similarity knowledge into account while computing complexity. We propose a new complexity measure called Reachability Based Complexity Measure (RBCM) that goes beyond similarity knowledge to include the effects of all knowledge containers in the reasoner. The proposed measure is evaluated on several real-world datasets and results suggest that RBCM corroborates well with the generalization accuracy of the reasoner.

Keywords: Case-Based Reasoning · Complexity · Alignment · Reachability

1 Introduction

Case-Based Reasoning (CBR) is an Artificial Intelligence (AI) paradigm that uses episodic information for reasoning and learning [10, 19]. Past experiences or episodes are stored as problem-solution pairs called cases which are later referred to for solving new problems. The process model in CBR consists of four main steps, namely retrieve, reuse, revise and retain [1]. From a knowledge engineering perspective, a CBR system is said to contain four knowledge containers [16, 17] namely *Case base, Vocabulary, Similarity and Adaptation*. *Case base* is the repository of past experiences, *Similarity* is the retrieval knowledge, *Adaptation* is the re-use knowledge and *Vocabulary* is the language used to describe the domain knowledge present in other containers.

While CBR was originally developed for ill-defined domains, in principle, it can be applied to a wide range of domains ranging from well-defined to ill-defined [10, 7]. But, the applicability of the CBR paradigm relies on two central assumptions. They are *similar problems have similar solutions* and *problems tend to re-occur*. To measure the suitability of CBR to the domain, several alignment measures have been proposed in the literature [11, 13, 3, 15]. The existing measures take only the similarity knowledge into account for estimating the complexity of case base. However, the utility of a case not only depends on the similarity knowledge but also on the vocabulary and adaptation knowledge. This is because the CBR knowledge containers are interdependent on each other [16].

Knowledge can be shifted across containers and the nature of knowledge versus the choice of the container may influence the performance of reasoner [16]. Wilson et al. [22] proposes the idea of Case-Based Reasoner Maintenance urging to go beyond case base maintenance. Recently, Ganesan et al. [7] proposed footprint size reduction to quantify knowledge tradeoffs between containers and also show that the nature of tradeoffs is influenced by the nature of the underlying domain. Leake et al. [12] proposed the idea of ghost cases to move knowledge from the adaptation container to the case base.

As the need for integrated maintenance is well motivated, we propose a complexity measure that quantifies the percentage of case base that cannot be compressed by the current knowledge in reasoner. To formalize the same, we have exploited the idea of reachability from [20]. The proposed *Reachability-Based Complexity Measure (RBCM)* is evaluated on synthetic as well as real-world data sets. The proposed complexity measure corroborates well with the generalization accuracy of the reasoner, thus can be of potential use to a CBR designer or maintenance engineer to quantitatively assess different system configurations.

2 Related Work

Lamontagne [11] proposed a performance indicator called *case cohesion* to guide the selection of similarity schemes for Textual Case-Based Reasoners (TCBR). Case cohesion is defined from the local neighbourhood of textual cases and measures the overlap of neighbours on the problem and solution side. Since adaptation for TCBR systems is complex and very less explored, case cohesion was proposed to be used primarily at the time of case authoring to select an appropriate retrieval scheme. This measure does not take into account the distance of neighbours to a case while measuring its cohesion.

Massie et al. [13, 15] proposed a complexity measure for case base which is obtained by averaging the alignments of its individual cases. Alignment of a case is measured by the average solution similarity of its neighbours weighted by their problem similarities to the case. If c is a case in case base CB, then its local alignment is given by:

$$alignMassie(c) = \frac{\sum_{c' \in NN(c)} simP(c, c') * simS(c, c')}{\sum_{c' \in NN(c)} simP(c, c')} \tag{1}$$

where $NN(c)$ is the local neighbourhood of some size k, $simP(c, c')$ is the problem side similarity of c and c' and $simS(c, c')$ is the solution side similarity of c and c'. Now, the alignment of the whole case base is given by:

$$alignMassie(CB) = \frac{\sum_{c \in CB} alignMassie(c)}{|CB|} \tag{2}$$

The same authors also propose an alignment based case-profiling approach where the case base is represented as a graph of the local alignment scores of its cases plotted in increasing order. This visualization approach can help a maintenance engineer to identify the areas of high noise and/or redundancy in the case base and to decide an appropriate maintenance methodology.

The above two works are examples of local complexity measures because the alignment of a case is calculated only with respect to a small neighbourhood. The big picture i.e. alignment of case base is obtained from these local case complexities. There are also global complexity measures in the literature that attempt to estimate the alignment of case base directly. Some of these are discussed below.

Chakraborti et al. [3] proposed a stacking based visualization approach for textual case bases. Their alignment measure is called *GAME* where the complexity of a case base is related to the compression of the case base image that results from stacking. Raghunadhan et al. [15] propose two complexity measures *alignMST* and *alignCorr*. The first one uses the idea of spanning trees to measure global alignment while the second one uses the correlation of problem and solution side similarities of all cases in case base to measure the same. Zhou et al. [23] propose another global complexity measure for the case base that uses the rank correlation between most similar case rankings in problem space and most similar case rankings in solution space. Dileep and Chakraborti [6] propose a global complexity measure for estimating case base complexity called *weighted Correlation Dimension* which is based on the concept of fractal dimensions.

Cummins and Bridge [4] use several dataset complexity measures to evaluate case base editing algorithms used for case base maintenance. Though this analysis focusses only on classification domains, it presents an interesting application for case base complexity measures.

2.1 Limitation of Existing Complexity Measures

The complexity measures discussed in the previous section use similarity as their primary knowledge source for estimating alignment. Case base alignment is low when similar problems have dissimilar solutions. But, Figure 1 shows how adaptation knowledge can influence the local alignment of cases. Cases $C3$ and $C4$ are similar on the problem side and dissimilar on the solution side. This is an instance of a case ($C3$) having poor local alignment. However, if the reasoner were equipped with some appropriate adaptation knowledge, then a solution of $C3$ can be adapted to give $C3'$, which is more similar to the solution of $C4$ than the solution of $C3$ itself. Thus, the solutions of cases $C3$ and

$C4$ which are initially dissimilar become similar after one of them is adapted to solve the other. This impact of adaptation knowledge is not captured by the existing similarity measures.

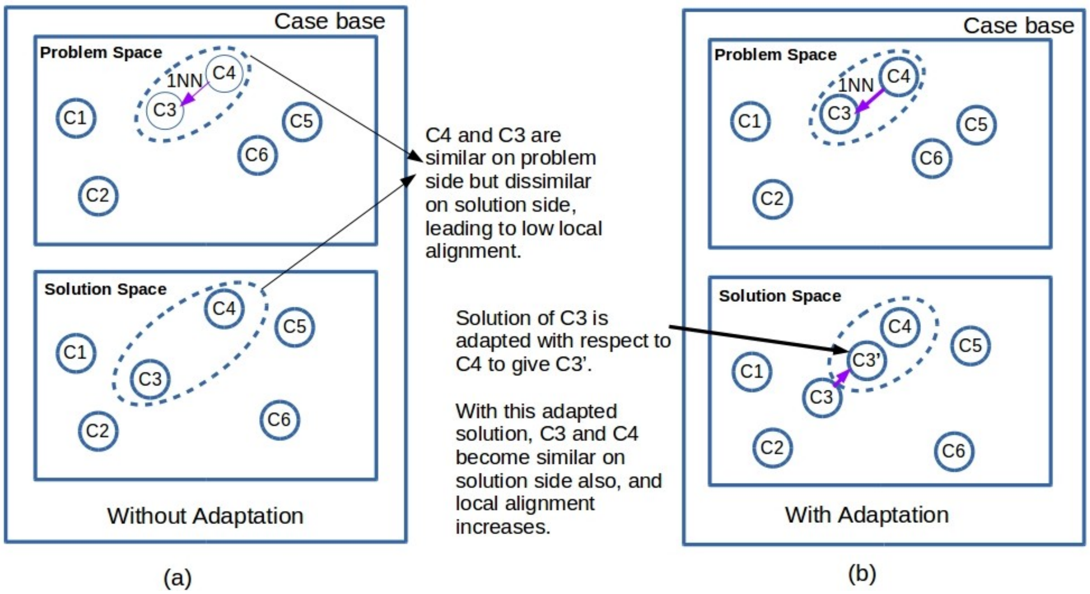

Fig. 1. Example to show that alignment of case base is influenced by adaptation knowledge

Also, the utility of a case in solving a target problem is affected by the knowledge in similarity, adaptation, and vocabulary containers [16, 22, 7]. Hence, the complexity measures of case base need to go beyond just one knowledge container to accommodate the integrated effect of knowledge in all containers.

3 Proposed Approach

In this section, we first discuss the background needed to understand the proposed complexity measure, followed by the details.

3.1 Background

When a case-based reasoner is first deployed, it has a set of cases in its case base. This set of cases are expected to be representative of the problems that will be encountered by the reasoner in the respective domain. As the reasoner solves new problems, it can choose to retain new problem-solution pairs in its case base leading to the learning of further episodic knowledge. Ideally, the reasoner needs expert's intervention to validate a new problem-solution pair before choosing to retain it. But as expert availability is expensive, a reasoner may simply retain all of them. This leads to continuous case base growth resulting in redundancy and noisy cases in the case base. It also hampers the retrieval efficiency and performance of reasoner.

Maintenance of a CBR system aims to optimise the performance of reasoner during its operational lifetime [21]. Some of the performance metrics are retrieval time, adaptation cost and generalization accuracy. As case base is a central source of knowledge in the reasoner, most maintenance policies have targetted the compaction of the case base to improve the retrieval efficiency. The central goal is to select a subset of cases that can have the same problem-solving ability as the entire case base.

The *relative coverage* measure proposed by Smyth et al. [21] is very influential and has been successful in compressing case base efficiently. This success can be attributed to the case competence model assumed by the authors. The authors assume that the global competence of reasoner arises from the local competence of its cases. The local competence of a case c is captured by the notion of *coverage set* and its *unique contribution to global competence* of case base CB is captured by the *relative coverage* measure.

Definition 1. *CoverageSet(c)*= $\{c' \in CB$:*Solves*$(c, c')\}$

Definition 2. *Solves*(c, t) *iff* $c \in$[*RetrievalSpace*$(t) \cap$ *AdaptationSpace*(t)]

where t is a target problem to be solved, $RetrievalSpace(t)$ is the set of cases retrieved for t and $AdaptationSpace(t)$ is the set of cases that can be adapted to solve t. The idea behind relative coverage formulation is that *a case which solves many cases but is itself not solved by many other cases contributes more to the global competence of reasoner*. Retention score [14] extends the idea of relative coverage to account for the single as well as compositional adaptation scenarios.

Definition 3. $RelativeCoverage\ (c) = \sum_{c' \in CoverageSet(c)} \frac{1}{ReachabilitySet(c')}$

Definition 4. *ReachabilitySet(c)*=$\{c' \in C$:*Solves*$(c', c)\}$

Reachability In the above definition of relative coverage, reachability of a case c refers to the set of cases that can be retrieved and adapted to solve c. A case which is highly reachable contributes less to the unique case competence while a case which is less reachable contributes more. In the next section, we explain how this idea of reachability gives rise to a measure of the complexity of the case base that takes into account the knowledge present in all containers.

Footprint Set Based on the relative coverage scores of cases, a variation of Condensed Nearest Neighbour (CNN) [9] algorithm can be used to obtain a minimal set of cases that have the same competence as entire case base. This set is called footprint set [21] and consists of non-redundant cases in the case base. Some of these footprint cases are reachable while others are non-reachable. The reachable footprint cases are the ones that are located in the redundant areas of case base while the non-reachable ones are isolated cases and make a unique contribution to competence.

Solves & Footprint Size Reduction The coverage and reachability measures proposed by Smyth et al. [20] go beyond similarity measure to include the effect of all knowledge containers through its *solves* definition, which is *a case c is said to solve a target problem t if and only if c can be retrieved and adapted to solve t*. In [7], the authors have emphasized that this definition of solves function in the footprint algorithm connects the four CBR containers. Hence, knowledge added to vocabulary/ similarity/ adaptation containers can influence the reduction in footprint size. It is also hypothesized that footprint size [21] quantifies the knowledge contained in the case base. Based on this, the authors propose a measure called *footprint size reduction* to quantify knowledge tradeoffs between containers. Motivated by these observations, footprint size is also used as a complexity measure in our work.

3.2 Reachability based Complexity Measure (RBCM)

As discussed in the above section, revision of knowledge in vocabulary/ similarity/ adaptation containers has its impact on the utility of cases in the case base. Hence, the effective number of cases needed to cover the entire case base decreases as more domain knowledge is added to other containers. This essentially means that addition of domain knowledge to the vocabulary/ similarity/ adaptation containers leads to increased compression of case base.

In addition to the learning that results from accumulating experiences, a case-based reasoner also has the potential to learn from the regularities present in the case base. From the Minimum Description Length (MDL) perspective [18, 8], regularities in data lead to compression and hence to learning. The reachability notion discussed in the previous section allows us to identify the compressible areas in the case base. For example, if a case is highly reachable, then it is amidst similar cases. If a case is less reachable, then it is likely to be present in a less densely populated part of case base.

In this work, we are interested in those cases that are not reachable, i.e. the incompressible case base (CB) knowledge. Motivated by this observation, we propose the following Reachability-Based Complexity Measure (RBCM).

$$\text{RBCM} = \frac{|\{c \in CB : \{Reachability(c) - c\} = \emptyset\}|}{|CB|} \tag{3}$$

Smyth et al. [20] use the term *pivotal cases* to refer to cases which have zero reachability. They say that these pivotal cases make a unique contribution to case competence but also comment that *pivotal cases are generally outliers, being too isolated to be solved by any other case*. We believe that it is more fitting to call pivotal cases as outliers because once the case-based reasoner is deployed, one can expect that it will accumulate more cases similar to those already present in the case base. This is due to the basic CBR assumptions that problem re-occur and similar problems have similar solutions. Hence, if a case is not reachable, it is more likely to be an outlier than to be a source of unique contribution to case base competence. In the next section, we discuss the experiments and results on the use of the proposed complexity measure to evaluate design configurations.

4 Experiments and Results

In this section, we discuss the empirical results on several real-world datasets from the UCI machine learning repository [2, 5]. First, we use the *Iris* dataset to demonstrate how complexity measures can aid in comparing similarity measures. Next, we use a synthetic dataset and *Boston Housing* dataset to show how the proposed complexity measure is different from the existing similarity based alignment measures. Finally, we discuss the results on seven classification datasets. As all the existing alignment measures are solely based on similarity knowledge, we have chosen the measure proposed by Massie et al. [13] to be representative of existing measures. In all the experiments, we have also studied the correlation of footprint size with generalization accuracy. The footprint set is obtained by running a condensed nearest algorithm on the cases ordered based on their relative coverage score assuming that the entire case base belongs to one competence group.

4.1 Iris Dataset

Iris is a widely used benchmark dataset for classification and has three classes. There are 150 cases and each case is described using four attributes namely *sepal length*, *sepal width*, *petal length* and *petal width*. Exploratory data analysis on the dataset revealed that the attributes *petal length* and *petal width* are more important than others.

In this case base, we do not use any adaptation knowledge. Only the similarity knowledge is modified to incorporate domain knowledge. By similarity knowledge, we refer to the attribute weights used to estimate global similarity of cases from their local attribute level similarities. A weight vector of $(0, 0, 3, 2)$ represent the weights of attributes *sepal length*, *sepal width*, *petal length* and *petal width* in the same order. We use different similarity configurations varying from S_1 to S_{12} and measure case base complexity using RBCM and Massie et al.'s [13, 15] method (also discussed in Section 2). 5-fold cross-validated results are summarized in Table 1. Training case base size in each fold was 120.

As shown in Table 1, the proposed measure RBCM exhibits strong negative correlation with generalization accuracy. This can also be seen from Figure 2. AlignMassie exhibits strong positive correlation as expected due to the absence of adaptation knowledge. It is interesting to note that footprint size also has a strong negative correlation with generalization accuracy.

Table 1. 5 fold cross validated results on Iris Dataset

Similarity	Footprint size	Test Accuracy	RBCM	AlignMassie (k=3)
S_1:0032	13	93.33	0.05	0.95
S_2:1100	49.2	72.67	0.29	0.73
S_3:1110	19.4	92	0.08	0.92
S_4:1111	17.4	95.33	0.05	0.94
S_5:1200	51.8	71.33	0.29	0.72
S_6:1234	14.2	95.33	0.05	0.95
S_7:2231	16	95.33	0.06	0.94
S_8:2312	16.2	94	0.06	0.94
S_9:3200	52.6	71.33	0.29	0.72
S_{10}:3211	19.8	92.67	0.06	0.93
S_{11}:4110	25	88	0.12	0.88
S_{12}:4310	27.6	88	0.12	0.85
Pearson Coeff r	-0.9925		**-0.9963**	0.9925

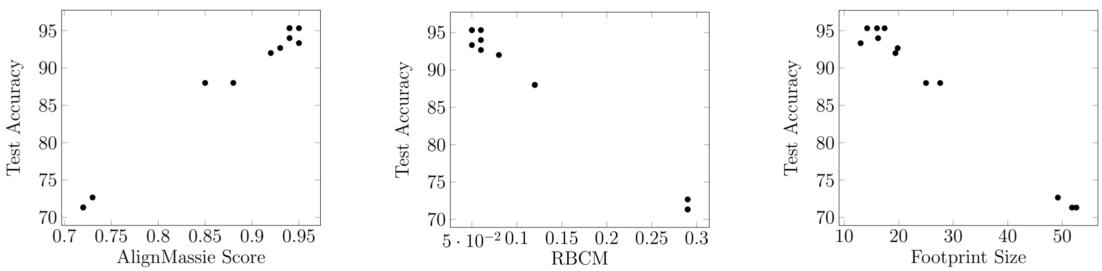

Fig. 2. Correlation of complexity measures with accuracy on Iris dataset.

4.2 Synthetic Case Base

In order to show how a similarity based alignment measure fails to corroborate with generalization accuracy in the presence of adaptation knowledge, we are using a synthetic case base adapted from [7]. This case base consists of 27 cases (Table 2) and is generated using the function $D = 6A + 3B + C$. In each case, (A, B, C) represents the problem component while D is the solution component. A case-based reasoner to predict D given the target problem (A, B, C) is said to solve it when the predicted solution is within 10% of D.

Table 2. Synthetic case base (27 cases) for regression [7].

A,B,C,D	A,B,C,D	A,B,C,D
1,1,1,10	1,1,2,11	1,1,3,12
1,2,1,13	1,2,2,14	1,2,3,15
1,3,1,16	1,3,2,17	1,3,3,18
2,1,1,16	2,1,2,17	2,1,3,18
2,2,1,19	2,2,2,20	2,2,3,21
2,3,1,22	2,3,2,23	2,3,3,24
3,1,1,22	3,1,2,23	3,1,3,24
3,2,1,25	3,2,2,26	3,2,3,27
3,3,1,28	3,3,2,29	3,3,3,30

As discussed in the previous section, we have used different weight vectors to represent different similarity configurations. Adaptation rules used are: R_0 is null adaptation ; R_1 is adding $3 \times (N_A - Q_A)$ to N's solution; R_2 is adding $3 \times (N_A - Q_A) + 2 \times (N_B - Q_B) + (N_C - Q_C)$ to N's solution; R_3 is adding $6 \times (N_A - Q_A) + 3 \times (N_B - Q_B) + (N_C - Q_C)$ to N's solution. From the results summarized in Table 3, it is seen that RBCM shows the strongest correlation with generalization accuracy. It is evident that AlignMassie is unable to detect the impact of adaptation knowledge on generalization.

4.3 Boston

In this case base, the task is to predict the price of a house given 14 other attribute values. There 506 cases and some important attributes are the following:

Table 3. 5 fold cross validated results on Synthetic dataset. Solved% is the percentage of cases whose prediction error is within the Acceptable Prediction Error limit of 10%.

Sim	Adapt	FPsize	Solved%	RBCM	AlignMassie (k=3)
S_0:111	R_0	12.2	15.33	0.78	0.82
S_0:111	R_1	12.2	19.33	0.75	0.82
S_0:111	R_2	8.6	40.67	0.49	0.82
S_0:111	R_3	1	100	0	0.82
S_1:311	R_0	11.8	42	0.55	0.87
S_1:311	R_1	12.4	42	0.55	0.87
S_1:311	R_2	3.6	100	0	0.87
S_1:311	R_3	1	100	0	0.87
S_2:321	R_0	9.4	85.33	0.1	0.88
S_2:321	R_1	9.4	85.33	0.1	0.88
S_2:321	R_2	3.8	100	0.01	0.88
S_2:321	R_3	1	100	0	0.88
Pearson	**Coeff** r	-0.8580		**-0.9974**	0.5806

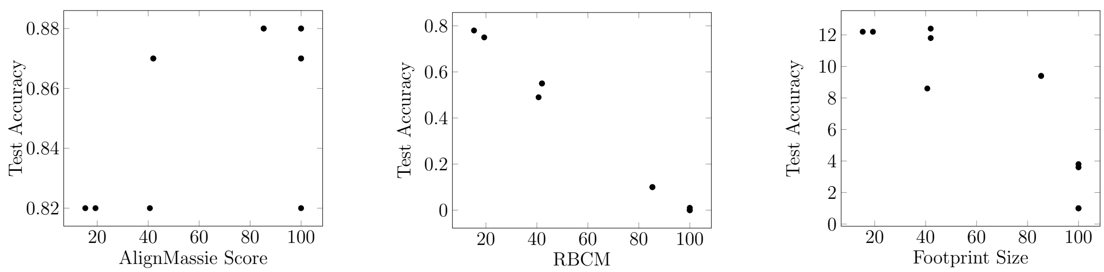

Fig. 3. Correlation of complexity measures with generalization accuracy on synthetic dataset.

INDUS - proportion of non-retail business acres per town.
RM - average rooms per house.
DIS - weighted distances to employment centers.
PTRATIO - pupil to teacher ratio in the neighborhood.
LSTAT - percentage of lower status of the population.

As in the previous case base, similarity knowledge is varied by changing the attribute weights in global similarity estimation. Similarity and adaptation knowledge configurations used for the experiment are listed in Table 4. The results are summarized in Table 5. Footprint size shows the strongest negative correlation with generalization accuracy and RBCM is competitive to footprint size. AlignMassie performs poorly as expected because adaptation knowledge is used.

Table 4. Knowledge Configurations used in Boston Dataset

Similarity Measure	Description
S_0	Uniformly weighs the attributes
S_1	Emphasizes *RM, PTRATIO, LSTAT* uniformly
S_2	Emphasizes *INDUS, DIS* additionally over S_1
Adaptation Measure	**Description**
R_0	Null adaptation
R_1	Three rules based on the following domain knowledge: *If the number of rooms increases, the house price increases*; *If the distance to employment centers increase, the house price decreases*; *If the proportion of lower status population in the housing location is high, the house price decreases*

Table 5. 5 fold cross validated results on Boston Dataset

Sim	Adapt	Footprint size	MAE	Solved%	RBCM	AlignMassie (k=3)
S_0	R_0	295.8	4.08	42.88	0.58	0.87
S_0	R_4	261.2	3.38	51.58	0.49	0.87
S_1	R_0	277.8	3.24	48.42	0.53	0.89
S_1	R_4	250.6	2.76	54.94	0.46	0.89
S_2	R_0	281.4	3.38	47.04	0.55	0.88
S_2	R_4	252.2	2.85	54.55	0.46	0.88
Pearson Coeff r		**-0.9965**			-0.9946	0.4422

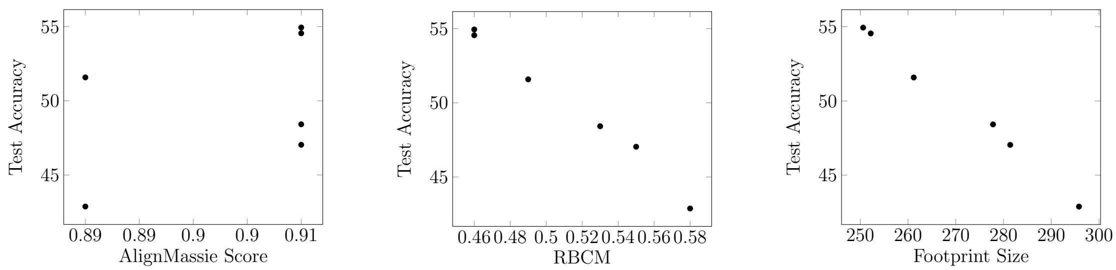

Fig. 4. Correlation of complexity measures with generalization accuracy on Boston housing dataset

4.4 Classification Datasets

In this section, we present the results on seven classification datasets. The case base size and number of attributes per case for these datasets are summarized in Table 6. Wine, Iris, Breast Cancer, Auto-MPG, Abalone are taken from UCI repository while Relpol and Hardware are subsets from 20 Newsgroups dataset. Relpol consists of the documents from religion and politics categories while Hardware consists of the documents from IBM and Mac categories. Feature representation used for textual datasets is Term Frequency-Inverse Document Frequency (TF-IDF)[1]. From the results shown in Table 7, we can see that RBCM is competetive to AlignMassie on classification datasets where it is less likely to use adaptation knowledge. Footprint size also shows strong negative correlation.

Table 6. Datasets

Domain	CB size	Attributes	Classes
Wine	179	13	3
Iris	150	4	3
Breast Cancer	569	31	2
Auto-MPG	392	8	5
Abalone	4177	8	29

Textual	CB size	Vocab	Classes
Hardware	3031	TF-IDF	2
Relpol	1168	TF-IDF	2

Table 7. Results averaged over 5-folds on different classification datasets

Domain	TrainCB Size	TestAcc	FPsize	FP/CBsize	RBCM	AlignMassie
Wine	142.4	96.59	18	0.13	0.04	0.95
Iris	120	94	17.6	0.15	0.05	0.94
Breast	455.2	95.43	53.4	0.12	0.05	0.95
MPG	313.6	93.63	49.8	0.16	0.06	0.93
Abalone	3341.6	20.28	2887.6	0.86	0.8	0.21
Hardware	934.4	48.55	309.6	0.33	0.22	0.75
Relpol	2424.8	95.48	353	0.15	0.05	0.94
Pearson Coeff r				-0.9427	-0.9313	**0.9437**

[1] https://en.wikipedia.org/wiki/Tfidf

5 Discussion

The concept of reachability enables us to get an integrated measure of complexity that takes into account the interaction between knowledge in all CBR containers. RBCM can also be seen as a compression based complexity measure that respects the CBR hypothesis that similar problems have similar solutions. From the experiments, we are able to see that the proposed measure RBCM has a definitive advantage over existing alignment-based measures. Synthetic dataset and Boston housing dataset are examples of scenarios where adaptation knowledge can influence generalization and results show that RBCM outperforms AlignMassie in such scenarios. Results on classification datasets reinforce that RBCM is competitive to the existing similarity based complexity measures.

Though footprint size shows strong corroboration with generalization accuracy, the algorithm used for constructing footprint set can vary and hence a footprint size based complexity measure becomes sensitive to the footprint construction algorithm involved. Also, unlike RBCM, construction of footprint set is computationally expensive and can easily become an overkill when used for evaluating design choices.

6 Conclusion

In this paper, we have proposed a new complexity measure for case base reasoners that takes into account the interaction between knowledge containers. Unlike the existing alignment-based complexity measures that rely only on similarity knowledge, the concept of reachability used in RBCM is able to integrate the impacts of knowledge in all CBR containers on case base. Experiments on regression and classification datasets suggest that RBCM corroborates strongly with generalization accuracy of case-based reasoners. Hence, it can be used by CBR designers and maintenance engineers to quantitatively assess design choices. As part of our future work, we are interested in extending this measure to compositional adaptation framework.

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