PROTOS: AN EXEMPLAR-BASED LEARNING APPRENTICE

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(REV.) MARCH 1988 AI87-53

* Support for this work was provided by the Army Research Office under grant #ARO DAAG29-84-K-0060 and the National Science Foundation under grant #IRI-8620052.
Protos: An Exemplar-Based Learning Apprentice

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Abstract

Building Protos, a learning apprentice system for heuristic classification, has forced us to scrutinize the usefulness of inductive learning and deductive problem solving. While these inference methods have been widely studied in machine learning, their seductive elegance in artificial domains (e.g., mathematics) does not carry-over to natural domains (e.g., medicine). This paper briefly describes our rationale in the Protos system for relegating inductive learning and deductive problem solving to minor roles in support of retaining, indexing, and matching exemplars. The problems that arise from "lazy generalization" are described along with their solutions in Protos. Finally, an example of Protos in the domain of clinical audiology is discussed.

1. Introduction

Learning and reasoning from exemplars is a promising alternative to inductive learning and deductive reasoning. Exemplar-based learning involves remembering and indexing specific training cases. Reasoning from learned exemplars involves interpreting a new case by recalling a similar exemplar for guidance. In contrast, inductive learning generalizes specific training cases to form an abstract description. Reasoning involves deducing that a new case is subsumed by the abstract description. While this distinction might appear inconsequential, it has far-reaching implications, ranging from psychological validity to the feasibility of machine learning programs for diagnostic expert systems.

Our development of Protos, a learning apprentice for heuristic classification tasks, provides impetus and context for the study of exemplar-based systems. The primary goal of our Protos research is to develop a general mechanism for acquiring classification knowledge while providing interactive assistance to users. The requirements for such a system forced us to reconsider the popular wisdom in machine learning that training should be compiled and compressed into generalizations. Before turning to our solution, we briefly review the major requirements of the Protos system.

1 Support for this research was provided by the Army Research Office under grant number ARO DAAG29-84-K-0060 and the National Science Foundation under grant number IRI-8620052.
First, the polymorphy of natural concepts must be centrally addressed in both the knowledge representation and the algorithms for learning and problem solving. Artificial domains, which have been the primary focus for machine learning researchers, permit simpler representations and algorithms. Concepts in artificial domains can be "classically defined" [Smit81] using a set of necessary and sufficient conditions. Examples of such concepts are "a forked position in chess" [Mint84], "a prime in number theory" [Lena76], and "a good problem-state for applying substitution in symbolic integration" [Mitc83, Port86a]. However, the significant variability among instances of natural concepts prevents inductive learning of a uniform set of necessary and sufficient conditions. For example, consider inductive learning of the concepts "science," "friend," or "pollutant." If general descriptions for such concepts can be formed, they will be so vague as to be useless for classification of new cases. Abstract definitions also preclude other uses of concepts such as exclusion of near-misses, generation of examples of concepts, explanation, guiding the interpretation of new cases, etc. [Scha86, Port86a]. Protos satisfies the requirement to address concept polymorphy by focusing on learning and indexing exemplars of each concept.

Second, classification of new cases has two interrelated requirements. The first requirement is that Protos must learn and apply concept models. The identity of new cases is frequently unclear due to concept polymorphy and incomplete or noisy case descriptions. Models can be employed effectively to guide the interpretation of individual cases [Weis78, Niu82]. Related to this is the requirement for efficient generation of explanations. An explanation relating a new case to a generalized concept is commonly constructed by deducing that the general concept entails the specific case [Buch84, Mitc86, DeJo86]. This can involve considerable deductive inference. The amount of inference required is a function of the "distance" between the new case, described in the instance language, and the concept description, described in the generalization language. These two requirements are satisfied in Protos by using learned exemplars, instead of general concepts, as the targets for matches with new cases. An exemplar can provide specific guidance in interpreting an unclear case and can be efficiently matched because of proximity.

The primary lesson of Protos is that learning-apprentice systems for heuristic-classification tasks should be "lazy generalizers." Inductive learning is "eager" generalization which assumes that (1) generalizations can be formed, (2) problem solving is primarily deductive inference from generalizations, and (3) classification is the primary application of learned knowledge. There have been numerous efforts to relax these assumptions, ranging from transformational-matching systems [Keda85, McCa81] to probabilistic systems [Buch84, Zade85]. We concluded that inductive learning and deductive classification should play only a minor role in Protos [Port86a]. Exemplar-based learning and problem solving have considerable psychological support [Bare87, Mede83a, Smit81, Broo78] and together provide a unified solution to the problems faced by a learning apprentice system: learning
and representing polymorphic concepts, classifying unclear cases, and efficiently generating explanations.

The next section describes the problems that are inherent in exemplar-based systems and discusses their solutions in Protos. We are in the process of applying Protos to the domain of clinical audiology. Section 3 details how Protos processed a typical case. Section 4 describes our preliminary evaluation of the performance of Protos as a learning apprentice.

2. Issues in Exemplar-based Systems and Their Solutions in Protos

Exemplar-based systems raise a number of questions. This section answers these questions in the context of the Protos algorithm shown in Figure 1. Examples are drawn from the Protos knowledge structure shown in Figure 2.

2.1 What Unites the Exemplars of a Category?

Category cohesiveness requires that the underlying commonality of the category members be explicit in the representation. In Protos, each exemplar of a category is represented by features and explanations of each feature's relevance to the category. For example, Figure 2 shows two exemplars of the category chairs and the explanations of their features. The network of domain knowledge with the embedded exemplars is called a category structure in Protos. Each node in the
category structure is either an exemplar-containing category or a domain primitive. For example, the node labelled armrests might contain exemplary armrests, each described with armrest features and explanations of their relevance.

2.2 How are the Exemplars Indexed for Efficient Retrieval?

The first step in processing a new case is to efficiently identify a matching exemplar. This section describes the three primary indexing mechanisms which Protos uses to retrieve exemplars. The methods for learning indices are described in section 2.5.

The first indexing mechanism relies on cues gleaned from features of the new case (see line 2 of the Protos algorithm). Each cue, called a reminding (cf., [SCHA82, KOLO83]) is a link in the category structure from a feature to an exemplar or category (cf., “cue validity of features” in [ROSC78, MEDI83B]). For example, the
feature backrest in Figure 2 provides a reminding to the category of chairs while the feature pedestal is idiosyncratic to the exemplar chair 1. The features of a new case typically provide numerous reminding which are heuristically combined into a few candidate classifications for the new case. For example, if the features of a new case include backrest and pedestal, Protos is reminded of the category chairs and the exemplar chair 1. These two reminding are heuristically combined, yielding a strong reminding to chair 1.

The second form of indexing relies on the prototypicality of exemplars with respect to their containing categories. Prototypicality provides a partial ordering on the exemplars of a category. The prototypicality of an exemplar is determined by family resemblance, the extent to which its features overlap those of other category members [Rosc75]. Protos may use prototypicality (see line 3 of the algorithm) to select an exemplar from a category in the set of candidate classifications. If there are reminding to a particular exemplar in the category, it is selected. Otherwise, an exemplar is selected from the category based on prototypicality. For example, given a new case which evokes reminding to chairs but no reminding to particular exemplars, Protos prefers chair 1 based on prototypicality.

The third indexing mechanism is based on the differences between pairs of “neighboring” exemplars in the category structure (cf., [Kolo83]). This mechanism is used in line 5 of the algorithm after Protos constructs a match with a retrieved exemplar (the subject of the next section) and notes featural mismatches. Protos attempts to improve the match by considering neighbors of the retrieved exemplar. Those difference links from the exemplar which are labelled with one or more of the noted mismatches are traversed to hill-climb to an improved match. For example, if a new case partially matches chair 2 but has the additional feature of armrests, then the difference link to chair 1 is traversed.

2.3 How are Exemplars Used During Problem Solving?
Each exemplar in the category structure is a model for interpretation of new cases. However, only those exemplars which are similar to the new case are useful. Initially, the reminding are used to retrieve an exemplar based on expectation of similarity. The true similarity is then determined by knowledge-based pattern matching (see line 4 of the algorithm). Knowledge-based pattern matching uses the domain knowledge in the category structure to construct an explanation of the equivalence of the exemplar and the new case. The explanation is the justification for concluding the presence of criterial features of the exemplar based on the observed features of the new case. For example, Protos might match the feature legs(4) in a new case to pedestal in the exemplar chair 1 based on the knowledge:

\begin{align*}
\text{legs(4)} & \overset{\text{specialization}}{\rightarrow} \text{seat support} \overset{\text{specialization}}{\leftarrow} \text{pedestal}
\end{align*}

This suggests that the features are equivalent because each provides evidence for the functional feature, seat support.
Protos gauges the amount of effort to expend on knowledge-based pattern matching between a new case and a retrieved exemplar. Effort is determined by multiple factors, including the combined strength of the remindings from the features of the case to the exemplar, the prototypicality of the exemplar, and the degree of direct match between the case and the exemplar. In summary, knowledge-based pattern matching (deductive inference) is used in Protos to confirm expectations about a new case. The amount of effort expended in the process is restricted, lest Protos “see mirages.”

2.4 How is the Category Structure Learned?
The category structure is learned from training provided by the teacher. The teacher provides cases for Protos to classify. When Protos fails, the teacher explains the correct answer (see line 7 of the algorithm). The cases described to Protos become exemplars and the accompanying explanations become domain knowledge in the category structure. Past research has ignored the role of explanations in training and assumed that a teacher could compensate for a narrow communication channel by either providing numerous training examples (e.g., [QUIN86]) or relying on the learner’s a priori knowledge (e.g., [MITC86]).

Protos expects an explanation of the relevance of each feature of a new case to the category to which the case is assigned. If Protos is unable to generate an explanation for a feature then the teacher assists. The teacher provides domain knowledge in the form of terms and predefined relations, which Protos integrates into the category structure. For example, consider the case of a hanging chair suspended from the ceiling by ropes, with neither legs nor pedestal. Protos cannot form a close match with either chair 1 or chair 2 until the teacher provides the information in the form of an explanation that:

\[
\text{chair ropes} \xrightarrow{\text{specialization}} \text{seat support}.
\]

2.5 How are the Indices for Exemplars Learned?
As described in section 2.2, there are three types of indices for exemplars in the category structure: remindings, prototypicality, and differences. Protos learns and adjusts these indices during the course of training. This section describes the learning process.

Remindings are heuristic estimates of the likelihood of particular exemplars or categories being relevant to the processing of a new case. Initially these remindings are learned analytically. A teacher-supplied explanation which strongly relates a feature to a category or an exemplar is compiled into a reminding link. For example, the explanation:

\[
\text{seat} \xrightarrow{\text{enables}} \text{holds(person)} \xrightarrow{\text{function}} \text{chairs}
\]

suggests that seat should remind Protos of the category chairs.
When a reminding associated with a feature does not contribute to finding a successful classification, Protos reassesses its validity. Since remindingings are compiled by analyzing explanations, Protos attempts to reassess a reminding by checking the consistency of the reminding with both the current state of its domain knowledge and the competing remindingings. If analysis does not indicate that the reminding should be adjusted, Protos weakens the reminding to reflect diminished confidence; a reminding which continues to be weakened over time is eventually removed.

Protos estimates prototypicality by noting an exemplar's successful use in problem solving. When an exemplar closely matches a new case, the exemplar exhibits family resemblance within its category. The more new cases which are successfully matched by the exemplar, the more prototypical it becomes.

If Protos misclassifies a case, it installs difference links in the category structure to avoid similar near misses in the future. As discussed above, difference links allow Protos to improve a tentative match by identifying neighbors of the matched exemplar which may provide better matches.

2.6 When are Exemplars Generalized?
As described in section 2.4, each new case presented by the teacher is integrated into the category structure. This integration may involve merging the new case with an existing exemplar. Protos attempts to merge the descriptions if knowledge-based pattern matching determines they are highly similar and the teacher concurs. Specifically, all of the important features of the exemplar must be accounted for by explanations to features of the new case. This means that Protos considers the exemplar and the new case to be equivalent with respect to its goals and training.

As a result of a merge, the features of the exemplar might be generalized. For example, consider the new case, chair 2’, which is the same as exemplar chair 2 in Figure 2 except it is made of metal instead of wood. Protos would merge the new case with the exemplar after constructing the following explanation for the mismatched features:

\[
\text{metal} \xrightarrow{\text{specialization}} \text{rigid material} \xleftarrow{\text{specialization}} \text{wood}.
\]

This explanation suggests that the exemplar feature wood can be generalized to rigid material in the resulting merged exemplar.

Another important source of exemplar generality is knowledge-based pattern matching. An exemplar implicitly represents all of the cases (seen or unseen) which are reachable by transforming the exemplar’s features using domain knowledge. Therefore, the generality of an exemplar can increase with the amount of domain knowledge in the category structure.

3. An Example of Classifying and Learning
This section demonstrates how Protos learns while providing interactive assistance to the user/teacher. Our example is from the domain of clinical audiology which
involves the evaluation and diagnosis of hearing disorders. We trained Protos with 200 sequential cases from Baylor College of Medicine. Each case presented to Protos consisted of patient-reported symptoms, patient history information, and the results of routine tests. This is the data that a clinician considers when diagnosing a patient. We believe that clinical audiology is representative of a large set of heuristic classification tasks for which Protos is appropriate.

We now describe the twenty-fourth case of hearing disorder processed by Protos. For clarity, this case is called NewCase. Protos is presented with the features of NewCase which represent the results of tests of the patient's hearing and the biomechanical and physiological status of the patient's ear. These features are:

- `air(moderate)`
- `bone(normal)`
- `speech-intell(normal)`
- `tympr-pr(negative)`
- `tympr-peak(flat)`
- `ipsi-AR(absent)`
- `contra-AR(absent)`
- `other-i-AR(normal)`
- `other-c-AR(absent)`

As shown in Figure 3, Protos is reminded of multiple diagnostic categories by the features of NewCase. Line weights indicate the strengths of the reminders. These "raw" reminders are heuristically combined to determine the most likely classifications for this case. As a result of this process, *otitis media* and *malleus fixation* emerge as the most likely categories.

The next step is to select an exemplar to serve as a model for NewCase. The reminding to *otitis media* is strongest, so Protos tries it first. Exemplar selection is based on prototypicality since Protos has no reminders to specific exemplars. Protos retrieves Case-17-1-R which is currently the most prototypical exemplar of *otitis media* in the category structure. The results of matching the two cases are illustrated in Figure 4(a). All of the featural matches are direct except for
Figure 4
Featural Matches from Protos's Attempts to Classify NewCase
(a) The First Attempt  (b) The Second Attempt

the match between air(moderate) and air(abnormal). This match is justified by
the explanation air(moderate) has generalization air(abnormal). Protos presents
this evidence, but the teacher rejects the diagnosis. The teacher approves of the
explanation of the match but insists on considering the alternatives.

As a consequence of the teacher's rejection of the diagnosis, Protos weakens
the remembrings in the category structure which led to the misclassification. Protos
then tries to match an exemplar of the category malleus fixation. Case-13-1
is selected as the most prototypical of this category. The result of using this case as
a model for NewCase is illustrated in Figure 4(b). All featural matches are direct
except for the match between other-contra-AR(absent) and fullness. This match is
explained by:

other-c-AR(absent) co-occurs with conductive-HL which requires fullness.

Presented with all of the evidence, the teacher accepts the diagnosis of malleus fixa-
tion. In an effort to improve the overall match, Protos asks about the unmatched
exemplar feature air(severe). The teacher tells Protos that
air(moderate) has generalization air(abnormal) which has specialization air(severe).

Next Protos complains that the explanation linking other-c-AR(absent) to fullness
is weak. Actually, the explanation is wrong, and the teacher corrects Protos by
telling it that conductive-HL only occasionally requires fullness. The teacher then
provides the correct explanation:

(tymp-peak(flat) AND air(moderate)) is usually sufficient for fullness.

Since the teacher has provided new information, Protos retries the match. Figure
5 shows the result, which is accepted by the teacher without further revision.

Because all of the features of Case-13-1 are matched, Protos suggests that NewCase
and Case-13-1 be merged. The teacher agrees. As a result of this decision, Protos
increases the prototypicality of Case-13-1, and NewCase is not added to the category
structure. During the merging operation, Protos notes the explanation:

air(moderate) has generalization air(abnormal) which has specialization air(severe)
and suggests that the feature \textit{air(severe)} of Case-13-1 be generalized to \textit{air(abnormal)}; the teacher concurs.

Since Protos found a mismatch to Case-17-1-R of \textit{otitis media} before successfully matching Case-13-1 of \textit{malleus fixation}, it suggests installing a difference link between the two exemplars to note how they differ. The teacher agrees and accepts this disposition of the case.

4. Experimental Evaluation of Protos

During the application of Protos in the domain of clinical audiology, data was collected to assess the system's learning and classification performance. This section summarizes our empirical evaluation of Protos.

Professional training for clinical audiology typically requires two years of graduate school culminating in a Masters degree. Before becoming practicing clinicians, students must pass a national examination and serve a clinical-fellowship year following graduation. In the course of their graduate training, students see between 150-200 cases and then an additional 900-1200 cases in their clinical-fellowship year. To be consistent with this amount of training, we decided that Protos should learn to perform demonstrably well given a training set of 200 cases. A database of 200 consecutive cases was obtained from the Audiology Clinic at Baylor College of Medicine in Houston, Texas. This training set was presented to Protos by the domain expert without the participation of a knowledge engineer.

The overall growth of the category structure as a function of the number of cases presented is shown in Figure 6. Protos learned 24 diagnostic categories, which were represented with 120 exemplars. We were surprised that so many exemplars were retained in the category structure. Protos made little use of exemplar merging and generalization for two reasons. First, many of the categories are highly polymorphic and good generalizations (which are complete, consistent, and can be operationalized) do not exist. Second, a shortcoming in the explanation language prevented the domain expert from giving \textit{conditional} explanations of featural equivalence during
presentation of the first hundred cases. Using this form of explanation, an earlier explanation could be more correctly expressed as:

IF the category is malleus fixation THEN
air(moderate) has generalization air(abnormal) which has specialization air(severe)
which equates the two values of air only in the context of this particular diagnosis. The expert estimated that this language facility would have allowed additional explanations enabling Protos to discard 30-40 of the retained exemplars. (Accordingly, a conditional explanation capability was incorporated into Protos after presentation of the first hundred cases.)

The primary measure of the performance of Protos is its accuracy in classifying new cases. Table 1 summarizes this performance.\(^2\) After relatively little training, Protos' performance far exceeded the performance that the expert estimated would be typical of a human student with similar experience. Throughout the learning process, Protos correctly classified more than 80% of the cases. Much to our satisfaction, this performance was unaffected by continued growth of the category

\(^2\) Since Protos is designed to perform heuristic classification (classifying cases into known categories) the first occurrence of each new category is excluded from this data.
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**Table 2**

Classification Effort Expended

structure. After the 200 training cases, Protos was presented with a normal mix of 26 test cases and demonstrated similar performance.

The problem solving efficiency of Protos can be measured by the amount of effort expended during classification. There was a gradual increase in the average number of diagnostic hypotheses pursued and the number of matches attempted during the training process (Table 2). However, this increase was not apparent to the teacher. The average number of matches per case which Protos determined to be strong enough to discuss with the teacher was constant through the training and test sets; most of the effort in the classification process was independent of the teacher.

5. Summary

Protos is a learning apprentice for heuristic classification tasks. During the early design of Protos we concluded that inductive learning and deductive problem solving were unsuitable. The polymorphy of natural concepts coupled with the requirements for efficient classification and explanation precluded such simple solutions. We adopted an exemplar-based approach to learning and problem solving which was supported by considerable psychological evidence. We addressed the problems that arose from exemplar-based, “lazy generalization” and built the Protos system. While expert performance is not our primary concern, it is essential to our research paradigm to evaluate our methods by constructing and testing an expert system. This allows us to explore the “scaled-up” behavior of the methods. We have taught Protos about clinical audiology and have found that it quickly evolved into an expert system with a modest training set.

Acknowledgements

The construction of Protos could not have succeeded without the generous assistance of Claudia Porter, Joe Ross and Todd Stock. Adam Farquhar and Ken Murray also provided useful comments. Professor James Jerger, of the Baylor College of Medicine in Houston, Texas, graciously allowed access to the audiology clinic records which provided the database used to evaluate Protos’ performance.
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