Generalizing Multiple Examples in Explanation Based Learning

Gunther Sablon

Luc De Raedt

*Maurice Bruynooghe**

Departement of Computer Science, K.U.Leuven
Celestijnenlaan 200A, B-3030 Heverlee, Belgium
Phone : +32/16/200656
Email ...mcvax!prlb2!kulcs!gunther,
gunther@kulcs.uucp
Telex : 23674 kuleuv b Telefax : +32/16/205308

ABSTRACT

Presenting multiple examples to an Explanation Based Learning system may lead to a lot of quite similar rules. This has a negative effect on the overall problem solving performance. The problem can be alleviated by combining several rules into one. We present a method to generalize rules by locating common parts and differences in order to obtain a more useful set of rules.

1. Introduction.

In most Explanation Based Learning systems (cf. [Mitchell 86], [De Jong 86], [Hirsch 87], [Kedar-Cabelli 87]) learning from multiple examples leads to a lot of rules, one for each example. In recent work (cf. [Minton 87], [Keller 87], [Minton 88]) it is recognized that not all learned concept descriptions have the same level of utility. Because most EBL systems operationalize rules instead of concepts (cf. [Keller 87]), some concept descriptions may contain very specific and redundant rules. One way to achieve concept operationalization is to derive more general rules and operationalize the generalized subconcepts where possible. In this way, one tries to find an equilibrium (possibly temporarily) in the generality/operationality trade-off (cf. [Segre 87]) to improve the operationality of the whole concept. In the rest of the paper we assume that operationality of a concept description takes into account (as in [Keller 87]) : *usability* by the performance system (learned rules must be evaluable) and *utility* to the performance system (learned rules must improve the systems performance).

We define a *concept* as a set of objects from a universe, determined by a concept definition. To describe concept definitions we use the Horn Clause subset of first order logic (cf. [Kowalski 79], [Genesereth 87] for more details on Horn Clause Logic and its terminology). A concept definition is a set of Horn clauses that expresses the necessary and sufficient conditions to belong to the concept.

In the second section we briefly review classical EBL and in the third one we discuss its drawbacks when confronted with multiple examples. In the fourth section we present a solution which generalizes the rules. It will be demonstrated on an example. After a discussion we finally discuss related work.

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2. Explanation Based Learning.

The four inputs of a classical Explanation Based Learning system (cf. [Mitchell 86],[De Jong 86]) are :

- a concept definition of the concept to be operationalized
- a training example
- a domain theory : a set of rules, describing why the training example is a positive example
- an operationality criterion.

By means of these four inputs one tries to determine an operational generalization of the training example, which forms a sufficient condition to belong to the concept. General knowledge is transformed into more operational knowledge.

EBL can be considered as lemma generation (cf. [Kowalski 79]) controlled by an example. In the earlier EBL systems only the usability aspect of the operationality criterion was taken into account. When a clause $A \leftarrow B_1, \dots, B_m$ is used to solve the example, B_i is a call to a non-usable concept and, in the example, a clause $P \leftarrow C_1, \dots, C_k$ is used to solve the instance of B_i , then resolution is applied on both clauses and the resolvent $(A \leftarrow B_1, \dots, B_{i-1}, C_1, \dots, C_k, B_{i+1}, \dots, B_m) \theta$ is derived with θ the mgu of B_i and P . This step is repeated until one obtains a clause $A \leftarrow D_1, \dots, D_n$ with all D_i calls to usable predicates. This clause is added to the knowledge base as a lemma (cf. [Kedar-Cabelli 87] for an implementation in PROLOG).

3. A problem when several examples are presented.

When several examples are presented, each of them results in a new usable generalization. One can wonder whether the resulting set of clauses still improves the overall performance of the system (cf. [Keller 87], [Minton 88]).

Example : consider the following clauses with the PROLOG computation rule (i.e. depth-first, left-to-right) :

$$P \leftarrow q_1, \dots, q_n, r_1, s_1, \dots, s_m$$

$$P \leftarrow q_1, \dots, q_n, r_2, s_1, \dots, s_m$$

...

$$P \leftarrow q_1, \dots, q_n, r_k, s_1, \dots, s_m$$

where p, q_i, r_h, s_j may be arbitrary atoms in first order logic.

Suppose all these clauses have just been added to the PROLOG knowledge base. For examples only covered by the last clause, performance will be rather bad, since the subgoals $q_1, \dots, q_n$ have to be executed k times. Therefore the utility of this kind of system is low, and the obtained concept description can hardly be called operational. A better performance for PROLOG would be obtained by :

$$p \leftarrow q_1, \dots, q_n, r, s_1, \dots, s_m$$

$$r \leftarrow r_1$$

$$r \leftarrow r_2$$

...

$$r \leftarrow r_k$$

Although r is possibly not an operational concept, the overall problem solving behaviour of this set of rules is better than for the previous set, because backtracking is avoided. The utility of the concept definition has increased. Furthermore, r can be operationalized using the examples from which the rules were derived. All this must be seen in the context of operationality/generality trade-off (cf. [Segre 87], [Braverman 88]).

This example shows that learning may actually slow down the system (cf. [Markovitch 88], [Tambe 88], [Minton 88]) and that generalization by combining rules is useful.

4. Generalizing learned rules.

4.1. A new resolution strategy.

The idea is then to replace too specific rules by one or more general ones so that the operability of the concept will improve. Observed from the viewpoint of corresponding proof trees, one can see this as the second generalization step of EBL : structural generalization (cf. [De Jong 86], [De Jong 88]). This generalization step will go as deep as possible, not only generalizing the structure, but also the meaning of the proof trees.

We will describe the technique as applied on two examples. We suppose two examples E_1 and E_2 are given such that applying EBL as described in section 2 yields two different clauses.

Without loss of generality, we can assume that the same clause is used at the top level of both examples¹. Let $A \leftarrow B_1, \dots, B_m$ be that clause. With B_i a call to a non-usable concept, we can distinguish two cases :

- In both examples, the same clause $P \leftarrow C_1, \dots, C_k$ is used to solve the instance of B_i : the clause is then replaced by $(A \leftarrow B_1, \dots, B_{i-1}, C_1, \dots, C_k, B_{i+1}, \dots, B_m) \theta$ with θ the mgu of B_i and P .
- Both examples use a different clause to solve the instances of B_i . Let $B_i \theta_1$ and $B_i \theta_2$ be the two instances.
 - One can find a clause $P \leftarrow C_1, \dots, C_k$ such that there is a proof for $B_i \theta_1$ and a proof for $B_i \theta_2$ starting with that clause : replace then both subproofs by the new subproofs, so that the first case becomes applicable (to prevent infinite looping, one might put a bound on the depth of the proof trees of both examples and apply this step only if the depth bound is not exceeded).
 - Otherwise B_i is considered as pseudo-operational ; the instances $B_i \theta_1$ and $B_i \theta_2$ are used to learn two new clauses for B_i and make B_i operational.

This transformation is repeated until one obtains a clause $A \leftarrow D_1, \dots, D_n$ where all calls D_i are usable or pseudo-operational.

The algorithm is implemented in BIM-Prolog on Sun Workstations.

4.2. Example.

In order to give a clear example we will illustrate the technique on a small one, adapted from the hate-kill example of [Mitchell 86]. Larger examples and results can be found in [Sablon 88]. Suppose the knowledge base contains among others the clauses of fig. 1. Suppose also that the trees t_1 (fig. 2) and t_2 (fig. 3) have been derived from the examples $\text{kill}(\text{jack}, \text{john})$ and $\text{kill}(\text{sam}, \text{robert})$. Furthermore, suppose that the two derived clauses are selected to generalize.

First we apply resolution using the same clauses of both the examples. The clause in the top of both t_1 and t_2 is the same : by consequence it is also used in the resulting common proof tree (fig. 4). For the subgoals of the common clause (i.e. $\text{hate}(_x, _y)$, $\text{possess}(_x, _z)$ and $\text{weapon}(_z)$) we do the same. For the instantiation of $\text{hate}(_x, _y)$ both proof trees again use the same clause, so the common proof tree uses it also. For its subgoals we have : the instantiations of $\text{married_to}(_x, _u)$ are leaves in t_1 and t_2 , so it is a leaf of the common proof tree. For $\text{loves}(_y, _u)$ both proof trees use a different clause. We try to find a correspondence in meaning. Neither of the two clauses used

1) Note that if both proof trees do not use the same top level rule for A , we can immediately apply the second step on A .

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{ 1 } kill(_x,_y) ← hate(_x,_y) , possess(_x,_z) , weapon(_z) .
{ 2 } hate(_x,_y) ← married(_x,_u) , loves(_y,_u) .
{ 3 } loves(_y,_u) ← is(_u,_v) , likes(_y,_v) .
{ 4 } loves(_y,_u) ← seduce(_u,_y) .
{ 5 } loves(_y,_u) ← attracted_to(_y,_u) .
{ 6 } loves(_y,_u) ← adores(_y,_u) .

{ 7 } attracted_to(_y,_u) ← seduce(_u,_y) .
{ 8 } attracted_to(_y,_u) ← charms(_y,_u) .
{ 9 } attracted_to(_y,_u) ← is(_u,_v) , likes(_y,_v) .

{ 10 } possess(_x,_z) ← buy(_x,_z) .
{ 11 } possess(_x,_z) ← steal(_x,_z) .
{ 12 } possess(_x,_z) ← giveto(_w,_x,_z) .

{ 13 } weapon(_z) ← sharp(_z) , steel(_z) .
{ 14 } weapon(_z) ← sharp(_z) , solid(_z) .
{ 15 } weapon(_z) ← gun(_z) .

{ 16 } solid(_z) ← steel(_z) .

{ 17 } married_to(john,lisa).
{ 18 } married_to(sam,emma).

{ 20 } is(lisa,blond).
{ 21 } likes(jack,blond).

{ 22 } seduce(emma,robert).
{ 23 } give_to(peter,sam,knife2).
{ 24 } buy(john,knife1).
{ 25 } sharp(knife1).
{ 26 } sharp(knife2).
{ 27 } solid(knife1).
{ 28 } steel(knife2).

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Figure 1. Part of a knowledge base.

for $\text{loves}(_y,_u)$ (cf. 3 and 4) in the proof trees is more general than the subtree in the other proof tree. There are more clauses for $\text{loves}/2$ in the knowledge base (cf. 5 and 6).

The first one can be used to prove both instantiations of $\text{loves}(_y,_u)$: it is part of the common proof tree. For $\text{attracted_to}(_y,_u)$ there is no known clause to prove both instantiations, so it must be pseudo-operational. We cannot extend the common proof tree any further for $\text{attracted_to}(_y,_u)$. What we can do is use the two subtrees to operationalize $\text{attracted_to}/2$. In this case the subtrees are only of depth two, so that this operationalization does not yield any new clause.

Next atom is $\text{possess}(_x,_z)$. Since there is no correspondence in meaning between t_1 and t_2 , it is a leaf in the common proof tree. The corresponding subtree of t_1 is used to operationalize its root.

For the third atom $\text{weapon}(_z)$ a different clause is used in both proof trees. But the clause of t_1 can be used in t_2 too, so it is in the common proof tree. $\text{Sharp}(_z)$ and $\text{solid}(_z)$ are both leaves of t_1 , so the common proof tree comes to an end.

Figure 2. Proof Tree t_1 of the First Selected Example.

Figure 3. Proof Tree t_2 of the Second Selected Example.

Figure 4. Generalized clause and corresponding proof tree.

5. Discussion.

The desired equilibrium between generality and usability depends on the definition of a conceptual distance (cf. [Michalski 83]) between different examples (or, alternatively, between the corresponding proof trees). The distance allows one to select the examples whose rules should be combined. The larger the distance between examples to be generalized is allowed, the more general and less usable, but the more useful the new rule will be. Consequently, the conceptual distance is highly dependent upon the desired utility of the concept definition. Combining usability and utility we can optimize the operability.

Each time a new example is presented, adding its corresponding rule can decrease operability, because certain objectives with respect to utility are no longer reached. As mentioned above, this can happen when a concept description becomes too redundant. Therefore generalization should be considered (using the conceptual distance) each time a new example is presented. In general, one could apply techniques as in [Keller 87] or [Minton 88] to detect the need for generalization.

The purpose of the second step of the algorithm in section 4.1 is to identify possible common parts of proof trees with respect to their meaning. Especially when certain (sub)problems have several possible proof trees, it is important to recognize possible common parts. Structurally generalizing without taking into account their meaning, may lead to overgeneralized rules. The particular situation of having several possible proofs occurs in each EBL system after learning new rules. So it is very useful to perform this step in EBL systems.

6. Related Work.

The roots of our EBL method lie in the work of [Mitchell 86], [De Jong 86] together with others as [Hirsch 87] and [Kedar-Cabelli 87]. Our notions of operability (usability and utility) are based on the work of [Keller 87] and [Minton 88].

In [Braverman 88] boundaries of operability are searched. We extend this notion to the new definition of operability by searching boundaries of generality. The advantage of our method is that the derived rules are more general, therefore more useful and more operational since we also operationalize the subgoals on the boundary. Another difference is that their search for a boundary of operability is based upon (the generalized proof tree of) only one example, while in our search several examples are used. This increases the probability that the new rule will be more useful.

According to [Mitchell 86], our method is also related to the one of [Kedar-Cabelli 84] and [Kedar-Cabelli 85]. Their technique also recognizes common parts of proof trees, but uses analogy on the differing portions. The difference between their approach and ours is that our system also compares the meaning of subtrees which use different rules. Comparing proof trees uses domain knowledge, so that new deduced knowledge is still correct.

Furthermore techniques as generalizing number (cf. [Shavlik 87a], [Shavlik 87b] and [Cohen 88]) are related to generalizing from rules that use recursive predicates. [Cohen 88] also applies his method on generalizing from multiple examples. However, he concentrates on the structure of the proof trees with respect to repeated rule applications, while we concentrate on the meaning. Hence, we believe that the techniques are complementary.

7. Conclusion.

We have developed a technique for EBL in the case of multiple examples. A new derived rule is not just added to the knowledge base when the operability criterion is no longer reached. Instead this rule is generalized, together with existing rules, in order to operationalize the concept description. Furthermore the subconcepts are operationalized. In this way we achieve an equilibrium in the trade-off between generality and operability.

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