in Birnbaum L., and Collins G. (eds), *Machine Learning: Proc. of the Eighth International Conference,* pp.549-553, Chicago, June 1991, Morgan Kaufmann, 1991

A Method for Multistrategy Task-adaptive Learning Based on Plausible Justifications

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Abstract

Multistrategy task-adaptive learning (MTL) comprises a class of methods in which the learner determines by itself which strategy or combination of strategies is most appropriate for a given learning task defined by the learner's goal, the learner's background knowledge (BK) and the input to the learning process. The paper presents a MTL method which is based on building a plausible justification that the learner's input is a consequence of its BK. The method assumes a general learning goal of deriving any useful knowledge from a given input and integrates dynamically a whole range of learning strategies. It also behaves as a single-strategy method when the relationship between the input and the BK satisfies the requirements of the single-strategy method, and the general learning goal of the MTL method is specialized to the goal of the single-strategy method.

1 INTRODUCTION

Most research in machine learning has been so far primarily concerned with the development of single-strategy learning approaches. Such approaches include empirical induction from examples, explanation-based learning, learning by analogy, case-based reasoning, and abductive learning. Single-strategy approaches have specific requirements as to the kind of input information from which they can learn, and the amount of background knowledge needed prior to learning. They also produce different kinds of knowledge. Consequently, they apply to relatively narrow classes of problems. Real-world problems rarely satisfy all the requirements of single-strategy learning methods. However, they usually satisfy *partially* the requirements of several strategies. In this context, there is a need for systems that can apply different strategies in an integrated fashion. Recently, there have been a number of efforts to build such integrated systems (e.g., Lebowitz, 1986; Wilkins, et al., 1986; Minton et al., 1987; Danyluk, 1987; Pazzani, 1988; Tecuci, 1988; Flann and Dietterich, 1989; Shavlik and Towell, 1989; Whitehall, 1990). Most of these systems integrate explanation-based learning and empirical inductive learning.

This paper presents a multistrategy task-adaptive learning (MTL) method that integrates dynamically a whole range of learning strategies, depending on the features of the learning task under consideration. Initial ideas about multistrategy task-adaptive learning have been presented in (Michalski, 1990a, b; Tecuci and Kodratoff, 1990).

2 THE PROPOSED MTL METHOD

2.1 THE LEARNING TASK

The behavior of an intelligent system depends on an internal model of a real world domain. The more adequately this model approximates the real world, the better is the system's behavior. Therefore, a general goal of such a system is to continually improve its world model. Such a general goal may translate to different specific goals, such as to improve efficiency of the model by reorganizing some parts of it, to acquire a new piece of knowledge, or a procedure for performing a new task, to correct the model in view of new experiences, etc. The

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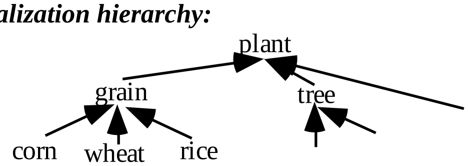
proposed method assumes that the learner's world model, called here "background knowledge", is composed of facts, rules and hierarchies characterizing the world, and representations of the learner's goals, capabilities and actions in the world. It further assumes that the learner starts with an imperfect model, which is incomplete but correct. A learning opportunity arises whenever the system receives new input from a source of information. The method is designed to handle different kinds of input information as, for instance, a fact, examples of a concept or relationship, a specific solution of some problem, etc.

The learner's current goal, its background knowledge, and the input define the *learning task*.

The proposed MTL method is adaptive in that it applies the strategy or the combination of strategies that is most suitable for a given learning task. To illustrate the MTL method, we shall consider a class of learning problems from the area of geography. In this domain, the system tries to acquire geographical facts and rules so it can answer various questions about geography. Let us suppose that the system starts with an initial incomplete knowledge, which includes domain facts, a generalization hierarchy, a determination (Davies and Russell, 1987) and domain rules (Figure 1).

Facts: rainfall(Philippine, heavy)
water-supply(Philippine, high)

Generalization hierarchy:



Determination: rainfall(x, y) >- water-supply(x, z)
(the type of rainfall determines the type of water supply)

Domain rules:

$\forall$ x, climate(x, subtropical) --> temp(x, warm)

$\forall$ x, water-supply(x, high) & temp(x, warm) &
soil(x, fertile-soil) --> grows(x, rice)

Figure 1: The Initial BK of the System

Let us now suppose that the system receives the following input information from Figure 2, representing an example of the relationship "grows(x, y)".

Example 1:
rainfall(Vietnam, heavy) & climate(Vietnam, subtropical) & soil(Vietnam, red-soil) & location(Vietnam, SE-Asia)
: : > grows(Vietnam, rice)

Figure 2: An Example of the Relationship "grows(x, y)"

In general, the system's goal is to derive any useful knowledge about geography from any input it receives. This may be generalizations of Example 1, which link properties of a location with the fact that rice is grown there, abstract characterizations of Example 1, modifications of BK that make it consistent with Example 1, etc. This points to a fundamental difference between MTL learning and single-strategy learning. In MTL, the system may be trying to determine all these kinds of knowledge, if they are desirable according to the system's goal. In single-strategy leaning, only one kind of knowledge would typically be generated.

2.2 UNDERSTANDING THE INPUT

Whenever the system receives an input, it tries to "understand" it by building a *justification tree* which demonstrates that the input is a plausible consequence of the BK, or that it represents new knowledge. The justification tree for the input example from Figure 2 is shown in Figure 3. It demonstrates that the input is indeed an example of the relationship "grows(x, y)". The concept of plausibility is used here in the sense described in (Collins and Michalski, 1989). This is different from the concept of plausibility used by (DeJong, 1989), which is based on qualitative reasoning.

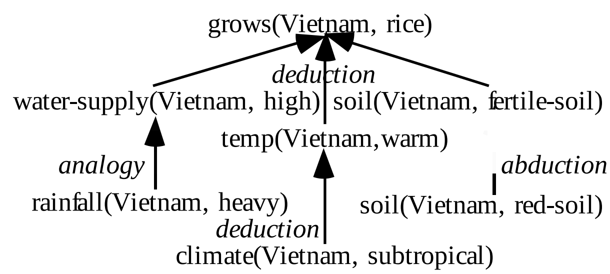


Figure 3: A Plausible Justification of Example 1

The individual inference steps may be a result of different inference types - deduction, analogy or induction. For example, two inference steps in Figure 3 are the results of deduction from BK, as shown in Figures 4 and 5.

Deduction 1:

$\forall$ x, water-supply(x, high) & temp(x, warm) &
soil(x, fertile-soil) --> grows(x, rice)

water-supply(Vietnam, high) & temp(Vietnam, warm) &
soil(Vietnam, fertile-soil)
____
grows(Vietnam, rice)

Figure 4: Proving that Rice Grows in Vietnam

Deduction 2:

$\forall$ x, climate(x, subtropical) --> temp(x, warm)
climate(Vietnam, subtropical)
____
temp(Vietnam, warm)

Figure 5: Proving that Temperature of Vietnam is Warm

Another inference step is a result of the analogical inference illustrated in Figure 6. Because Philippine and Vietnam are similar from the point of view of "rainfall", and the "rainfall" *determines* the "water-supply" (see

Figure 1), the system hypothesized that these two countries may also be similar from the point of view of "water-supply". Thus, the system concluded that "water-supply(Vietnam, high)" from the fact "water-supply(Philippine, high)". This is a very simple form of analogy described in (Davies and Russell, 1987). In general, the MTL method is intended to incorporate different forms of analogy, based on different kinds of similarities, such as similarities among relations, causes, and meta-relations.

Analogy:

similar

rainfall(Philippine,heavy) <-> rainfall(Vietnam,heavy)

determines ↓ ↓ *determines ?*

similar

water-suppl(Philippine,high)<->water-suppl(Vietnam,high)

Figure 6: Analogical Inference

Another type of plausible reasoning is induction, which includes abduction, empirical generalization, and constructive induction (Michalski, 1990a). For instance, in order to demonstrate "grows(Vietnam, rice)", the system needed to prove that "soil(Vietnam, fertile-soil)". However, no deductive or analogical knowledge exists to infer this fact. Therefore, the system made the hypotheses that "soil(Vietnam, fertile-soil)" is a direct consequence of the input fact "soil(Vietnam, red-soil)" and abduced the inference step shown in Figure 7. To illustrate another type of abduction, let us suppose that Example 1 does not contain the fact "soil(Vietnam, red-soil)", but the BK contains the inference rule "∀x, soil(x, red-soil) --> soil(x, fertile-soil)". In this case, the system will abduce the fact "soil(Vietnam, red-soil)" by using the above inference rule.

Abduction:

soil(Vietnam, red-soil) --> soil(Vietnam, fertile-soil)

Figure 7: Abducing an Inference Step

Other inference steps could be done through a combination of empirical generalization and deduction. To illustrate this, suppose that the system failed to prove "soil(Vietnam, fertile-soil)" by methods illustrated above, i.e., by deduction, analogy or abduction. In such a case, it will look for examples in which the predicate "soil" is true. If such examples can be found in BK, then the system tries to inductively generalize them to a rule, as shown in Figure 8. The learned rule is used to produce the plausible inference step in Figure 7. In a more complex case, available examples may not be so easily generalizable to a rule and the system may have to use constructive induction.

Examples:

soil(Cambodia, red-soil) : : > soil(Cambodia, fertile-soil)

terrain-type(Egypt, flat) & soil(Egypt, red-soil)

: : > soil(Egypt, fertile-soil)

Learned rule:

∀x, soil(x, red-soil) --> soil(x, fertile-soil)

Figure 8: Empirically Generalizing Examples into a Rule

The above shows that an inference step in a justification tree may be a result of any type of inference - deductive, analogical or inductive. A natural question is which type of inference is actually used, when more than one applies at a given step, and they produce different conclusions. This is, in fact, a frequent situation in human reasoning, in which different "lines of reasoning" may produce different results. (Collins and Michalski, 1989) argues that people estimate the "strength" of different lines of reasoning, and make their conclusion on the basis of this evaluation. If the lines lead to the same conclusion, they have a strong belief in the result. If the lines lead to different conclusions, and the associated "strengths" are roughly similar, people restrain from making any decisive conclusion. We have not yet conclusively investigated this issue. In the proposed method the system follows the following control strategy: first, it tries to justify a given predicate by deduction. If this attempt fails, the system tries to justify it by analogy and then by abduction. With the lowest preference, it tries to collect facts or examples which can be generalized to a rule that can be used to justify the given predicate deductively, analogically or abductively.

2.3 GENERALIZING THE PLAUSIBLE JUSTIFICATION TREE

Once a justification tree was successfully created, the system analyzes individual inference steps to determine if they could be locally generalized within the constraints of the BK that were used to make these steps. After the inference steps are generalized locally, the system unifies them globally and builds a generalized justification tree.

The deductive steps are replaced by the deductive rules that generated them (see Figure 11). The analogy steps are generalized by considering the knowledge used to derive them. In our example, the step "rainfall(Vietnam, heavy) --> water-supply(Vietnam, high)" was obtained by analogy with "rainfall(Philippine, heavy)" and "water-supply(Philippine, high)", based on the determination "rainfall(x, y) >- water-supply(x, z)". Because the system would infer "water-supply(x, high)" for any x such that "rainfall(x, heavy)", the specific analogical inference is generalized to "rainfall(x,heavy)-->water-supply(x,high)". The generalization of the inductive steps depends on the type of induction performed. In the analyzed case, the system abduced an inference step (see Figure 7). For this abduction, there is no domain knowledge that could be used to generalize it. However, if the system has new examples of the relationship to be learned, it may infer similar abductions that can then be inductively generalized. Let us assume, for instance, that the system receives a new input, described as Example 2.

Example 2:

rainfall(Tunisia, heavy) & climate(Tunisia, subtropical)& soil(Tunisia, red-soil) & near(Tunisia, Mediterranean-Sea) : : > grows(Tunisia, rice)

Figure 9: A New Input

The plausible justification for Example 2 is shown in Figure 10. It provides a new example of abduction

soil(Tunisia, red-soil) --> soil(Tunisia, fertile-soil)

which, together with the abduced step from Figure 7, may be inductively generalized to

$\forall$ x, soil(x, red-soil) --> soil(x, fertile-soil)

Finally, if the inference step "soil(Vietnam, red-soil) --> soil(Vietnam, fertile-soil)" was done by abducing the left hand side of a domain rule or by applying a rule generalized from examples (see Figure 8), then the corresponding branch is replaced by this rule.

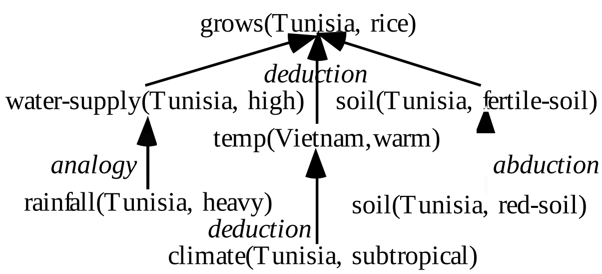


Figure 10: A Plausible Justification for Example 2

The generalization of the inference steps from Figure 3 form the explanation structure shown in Figure 11. This structure is transformed into a generalized plausible justification tree (see Figure 12) by using a technique similar to that of (Mooney and Benett, 1986). The system collects all the constraints from the unifications of the connection patterns, and then applies them globally.

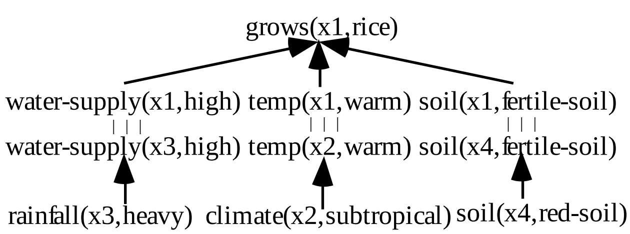


Figure 11: Explanation Structure

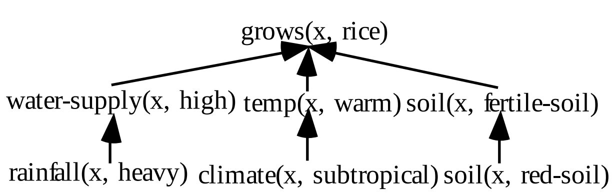


Figure 12: Generalized Plausible Justification Tree

2.4 THE LEARNED KNOWLEDGE

Depending on the learning goal, the system may extract different kinds of knowledge from the generalized plausible justification tree (Figure 12) as, for instance:

- a definition of the relationship "grows(x,rice)", expressed in terms of predicates present in the input example (an "operational" definition):

rainfall(x,heavy)&climate(x,subtropical)&soil(x,red-soil) : : > grows(x,rice)

- the most abstract characterization of the relationship "grows(x, rice)", based on the top part of the justification tree (since this rule was already in the BK, the new knowledge is just that it is an abstract characterization):

water-supply(x,high)&temp(x,warm)&soil(x,fertile-soil) : : > grows(x,rice)

- an *abstraction* of Example 1 (the statement about growing grain is obtained by climbing the generalization hierarchy in Figure 1):

water-supply(Vietnam, high) & temp(Vietnam, warm) & soil(Vietnam, fertile-soil) : : > grows(Vietnam, grain)

- new facts and rules, such as:

water-supply(Vietnam, high)

$\forall$x, soil(x, red-soil) --> soil(x, fertile-soil)

3 AN ANALYSIS OF BASIC CASES

The presented MTL method reduces to a single-strategy method whenever the relationship between the input and the BK satisfies the applicability conditions for such a method and the learning goal is specialized to the goal of the single-strategy method, as illustrated in the following.

3.1 THE INPUT IS ENTAILED BY THE BK

If the input is deductively entailed by BK, then the justification trees in Figure 3 and Figure 12 are logical proofs, and the MTL method reduces to explanation-based learning.

3.2 THE BK NEEDS TO BE AUGMENTED TO UNDERSTAND THE INPUT

Let us now suppose that the relationship between "rainfall" and "water-supply" is not a determination but an implication: $\forall$x,rainfall(x,heavy)-->water-supply(x,high). In this case, in order to build the justification tree of the input, the system only needs to augment the BK with the explanatory hypothesis "soil(Vietnam, red-soil) --> soil(Vietnam, fertile)" (see Figure 13). Therefore, the result of learning is the created explanatory hypothesis and the MTL method reduces to abductive learning.

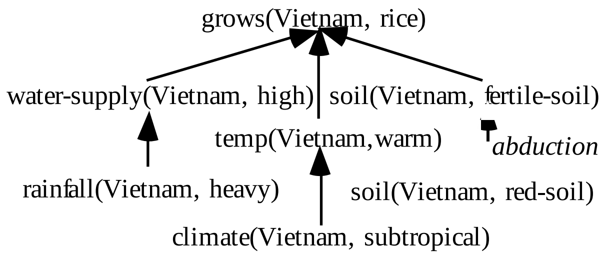


Figure 13: Using Abduction to Build a Plausible Justification Tree of the Input

3.3 THE INPUT IS NEW, NEITHER CONFIRMING NOR CONTRADICTING THE BK

Let us now assume that the BK does not contain the determination and the deductive rules shown in Figure 1. Let us assume, however, that the input consists of Example 1 and Example 2. These examples can be interpreted as being single inference steps and can be inductively generalized to a justification tree, as shown in Figure 14. The result of learning is a definition of the relationship “grows(x, rice)”, which represents the common properties of the input examples. Thus, in this case, the MTL method reduces to empirical induction.

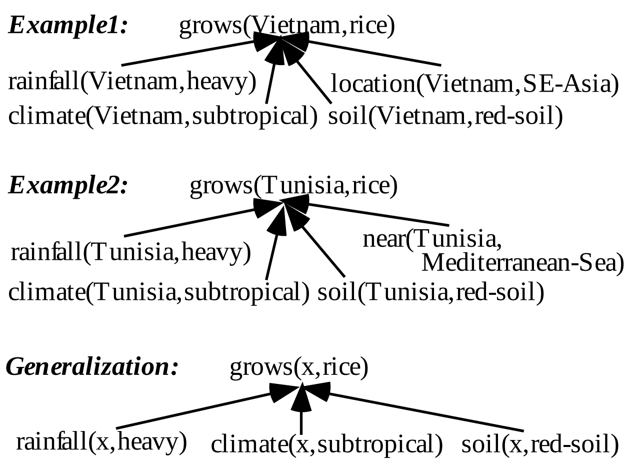


Figure 14: Examples of the Concept "grows(x,rice)" and their Empirical Generalization

3.4 THE INPUT IS SIMILAR TO SOME SEGMENT OF THE BK

Let us finally suppose that the only BK that is related to the input from Figure 2 consists of the facts

rainfall(Philippine, heavy),
water-supply(Philippine, high)

and the determination

rainfall(x, y) >- water-supply(x, z).

In this case, the system can only infer that "water-supply(Vietnam, high)", by analogy with "water-supply(Philippine, high)", as shown in Figure 6. Thus, the MTL method reduces to analogical learning.

4 CONCLUSION

We have presented a method for multistrategy task-adaptive learning (MTL) that integrates dynamically a whole range of learning strategies. The method is based on the idea of "understanding" the input through an exploration of system’s background knowledge, and an employment of different inference types - deduction, analogy and induction. One of the major advantages of the method is that it enables the system to learn in situations in which single-strategy learning methods, or even previous integrated learning methods were insufficient. Therefore, the proposed method has a potential to be applicable to a wide range of problems. Another important aspect of the method is that it reduces to a single-strategy method whenever the applicability conditions for such a method are satisfied. In this respect, the MTL method may be regarded as a generalization of these single-strategy methods. The method has been experimentally implemented in Common Lisp and was tested on problems from the area of geography. Among weaknesses of the current MTL method is that it assumes that the BK is incomplete but correct, and that the input does not contradict it and is error-free. We plan to consider these problems in future research. We also plan to replace some of the existing learning strategies with more advanced ones and to integrate new learning strategies.

Acknowledgements

This research was done in the AI Center of George Mason University. Research activities of the center are supported in part by ONR under grants No.N00014-88-K-0226 and No.N00014-88-K-0397 and in part by DARPA under grant No.N00014-87-K-0874, administrated by ONR.

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