Knowledge Acquisition for Planning with Incomplete Information *

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Abstract

As planning systems begin to solve more realistic problems, one of the most important and time-consuming tasks in developing a planning system is knowledge engineering (desJardins 1994). To autonomously learn planning knowledge, we propose novel approaches to solve some incompleteness problems arising in knowledge acquisition. We use an incremental learning method. We first introduce the native domain assumption that every object of a certain type is functionally homogeneous. Using this assumption, an example is quickly generalized. This method drastically reduces the size of the search space required to acquire an operator definition. We conjecture that this assumption is currently adopted in most planning domains. The assumption, however, causes overly-general operator definitions in a realistic domain. To cope with this incompleteness problem, we make use of the ID3 machine learning system, to specify the incomplete definition by adding a literal that can classify non-homogeneous objects of a type into their own homogeneous subtypes. We show how to learn a unobservable predicate by this technique. A human tends to prefer positive predicates to negative literals. This tendency causes the problem of missing negative preconditions. We induce the negative literals by utilizing the relationship between the two-valued and the three-valued logic systems in planning. The learned negative literal helps prevent an inconsistent planning problem in a noisy state. The expert possesses knowledge not captured in a planning system (desJardins 1994). We developed a method to learn some implicit human knowledge such as opposite concepts by studying structural regularity among operators. This knowledge simplifies the operator definition. A multipurpose intelligent robot should be able to adapt to a unknown task. When an operator is applied in a similar new domain and becomes overly-general, thus not fitting the domain, we introduce an operator splitting method. We first learn missing literals to specialize the operator to the new domain and if the operator is overly-specialized, we split the original operator into two operators.

Introduction

A planner is an inference engine acting like a shell of an expert system. To be commercially successful in the real world, a planning system should have provably rigorous operator definitions for an application domain to be integrated with a planner shell. However, human-generated operator definitions introduce many problems. First, knowledge engineering is expensive. Second, the expert's knowledge is incomplete in reality (desJardins 1994). Most planning systems are designed to operate with complete knowledge of all relevant aspects of the problem domain. Since all the facts in a world cannot be captured completely in a state, a state is an abstraction about a world ignoring some irrelevant details (Knoblock 1994). This abstraction tends to lead AI problems to toy problems when relevant complex details are ignored. Experts may overlook complex negative details in operator descriptions (Carbonell & Gil 1990). Third, the domain expert may not know exactly the actual capabilities of a robot. This requires verification of the robot's physical capabilities. By understanding its own action through experimentation, the robot can revise the initially incorrect or incomplete domain representation incrementally. This method can contribute to automatically learning realistic operator definitions for a complex domain. Fourth, implicit knowledge not encoded in a domain description causes some seemingly simple problems to become unsolvable. Tae and Cook (Tae & Cook 1995) solve some plan failures by automatically learning implicit rules from a human-generated representation.

To automate the acquisition of planning domain knowledge, we are currently building an experimentation-driven operator learning system, called WISER, which is running on top of PRODIGY. Given incorrect and incomplete background knowledge supplied by a domain expert, WISER learns operator preconditions using feedback from the environment. In this paper, we relax Wang's three assumptions that plague most current planning systems: 1) the obser-
An inductive learning system that acquires planning serves an expert’s problem solving method. The purpose of OBSERVER is to avoid the knowledge engineering problem. An initial incomplete operator is refined through the integrated cycles of planning, execution and plan repair. desJardins (1994) developed two knowledge development tools: an operator editor that provides a graphical interface to build and modify incomplete and/or incorrect operators and an inductive learning system that acquires planning knowledge related with missing or incorrect preconditions via feedback from simulators or users.

Either (Ourston & Mooney 1990) and RAPTURE (Mahoney & Mooney 1993) are theory revision systems. Either is given an imperfect expert-supplied rule base and a set of correctly labeled examples. Either sends the positive examples that can not be proven and the negative examples that are proven to ID3, an inductive machine learning method using an information gain heuristic. Either revises its rule base as follows: Provably negative (false negative) examples are specialized by removing rules from the rule base and adding conjuncts to rules. Unprovably positive (false negative) examples are generalized by adding new rules, deleting conjuncts from rules, or adding new disjuncts. RAPTURE (Mahoney & Mooney 1993) combines connectionist and symbolic methods to revise the parameters and structure of a certainty-factor rule base. If the examples cannot be classified correctly, ID3’s information gain heuristic is used to learn new terms and to change the structure of the rule base. Even though there has been a lot of research in the area of rule and concept learning and revision, there has not been much work related to extending the research to the area of planning. This paper is an attempt to integrate these two areas.

**Naive Domain Assumption**

Strips-like operator descriptions (Fikes & Nilsson 1972) model a robot’s predefined actions in terms of a set of preconditions pre(op), an add-list add(op), and a delete-list del(op). An operator includes a list of parameters, op(v1, ..., vm), for m ≥ 0. Each parameter, vi, is type-constrained. The domain theory, DT, specifies the legal actions in terms of a set of operators and inference rules. Inference rules represent deductions to be derived from the existing state. DT also specifies a type hierarchy for objects to reduce the search space. We will learn new inference rules for opposite concepts and new subtypes to represent unobservable literals.

Each type in DT’s type hierarchy consists of a set of objects. Two objects of the same type map to the same variable: var(ob1) ≡ var(ob2). Let two instantiated operators, op1 and op2, be obtained from op(v1, ..., vn) by instantiating each parameter v_k of op to the same object respectively except that the rth parameter is instantiated to different objects of the same type, say a for op1 and b for op2. op1 is obtained by substituting a in op1 to b. These two instantiated operators are called rth substituted-ops, represented as subst(r, op1/op2, a/b).

**Definition:** Given a, b ∈ ty and ∃(op1, op2)[subst(r, op1/op2, a/b)] in a state S, let S_i = apply(op_i, S) and S_j = apply(op_j, S). a is functionally homogeneous to b with respect to op, if var(S_i) ≡ var(S_j) for all S ∈ |S|, the space of states. If a is homogeneous to b with respect to all operators, a is homogeneous to b.
For two instantiated operators, if their instantiated preconditions are both satisfied (or both not satisfied) in a state and their respective actions have the same (variabilized) effects on $S$, such that $\forall j \in \text{add}(op_i) \equiv \text{var}(\text{add}(op_j))$ and $\forall j \in \text{del}(op_i) \equiv \text{var}(\text{del}(op_j))$, we say that the two resources (or objects) $a$ and $b$ are homogeneous.

**Theorem:** A homogeneous relation $\sim$ on the set of objects in a type has the equivalence relation.

The equivalence relation for homogeneity $\sim$ measures the equality of objects in a type $ty$ with respect to their applicability to a set of operators. If $\sim$ is satisfied on a subset of $ty$, defined by $[obj_e] = \{obj \in ty | obj_e \sim obj_j\}$, then $[obj_e]$ forms the subtype of the type. The $n$ equivalence relations, $\{[obj_1], ..., [obj_n]\}$, partition the set of objects of a type into $n$ subtypes. We can choose an object randomly from a subtype $[obj_e]$, and use it as a typical representative for the subtype. If one resource of a subtype is tested for all the operators, no additional resource of the subtype needs to be tested further. Any object is equivalent to a variable.

**Definition:** A naive domain in learning is a domain where every object in a type belongs to one and the only one class.

For $a, b \in ty$, $\text{subst}(r, op_i/op_j, a/b)$ implies $a \sim b$ in the naive domain. This says that there is no advantage to selecting $a$ over $b$ in a naive domain. Therefore, we can experiment with an operator using only one object of a given type and variabilize it without testing any more objects of the type. This assumption facilitates learning an operator definition from one example and reduces the search space drastically.

The generalization or abstraction of objects and concepts is inevitable in a real domain (Knoblock 1994) and the main problem is just to determine the most effective level of generalization for a given domain. Interestingly, the most conservative constant-to-variable generalization method employed both by Gil and by Wang is a specific case of adopting the naive domain assumption. In both of these methods, an object is first initialized to a constant. If more than one object of a type is observed, the constant is generalized into a variable. The observation of at least two objects justifies the generalization of infinitely many objects of the type into one class of homogeneous objects. For example, because there is only one robot in a domain, the Robot-type is represented as a constant, and since there are many boxes, the Box-type is variabilized. However, this method is problematic in a multi-agent environment. Suppose ROBOT1 is out of order and we need to use ROBOT2 for that domain. Unfortunately, we can not use the existing operator definition any more. On the other hand, our method generalizes ROBOT1 to ROBOT-TYPE and ROBOT2 can be unified to the existing definition. Thus, our method is more general.

The advantage of this assumption is that a robot can expedite learning by reducing the size of the search space. However, this advantage comes at a price. The assumption of a naive domain is incomplete for more realistic situations. We use an incremental refinement approach to handle this.

**Learning new terms in incomplete domains**

A robot can expedite learning in simple environments first and then the robot incrementally adjusts its initial action in complex environments, composed of heterogeneous objects, by employing an inductive learning method. Let’s start with an intuitive example of how a new-born baby learns to feed itself. Suppose the Feeding-World is composed of only two resources of two subtypes, $b$ of a bottle-type and $f$ of a finger-type, and the baby is endowed with feeding capabilities. He first starts with a naive world assumption where only one class $[b]$, composed of the objects of bottle-type exists. He learns the preconditions $\{(\text{in-mouth object}) \ (\text{hungry})\}$, and the the effect (not-hungry) after only one action is successfully applied. Soon, the baby may try $f$, its finger. The preconditions are satisfied, but the desired effect does not happen. Given that the baby is supplied with some reasoning ability (say ID3), he may begin to distinguish between the objects of the bottle-type $[b]$ and the objects of the non-bottle-type $[f]$ after a number of examples are given. He learns the new concept for $[\text{bottle-type}]$ and the new preconditions, $\{(\text{in-mouth object})(\text{bottle-type object})(\text{hungry})\}$.

Wang assumes that all the predicates in the state are observable. Wang’s approach results in the following potential problem. A robot has a physical capabilities different from a human. A robot may carry an object up to 500 pounds in weight, while a human up to 100 pounds. Through observations, the robot will learn an overly-specific concept that it can carry the objects only up to 100 pounds. We will relax this assumption and divide the predicates into the observable (such as height) and the unobservable (such as carriable). For example, a robot cannot observe the weight of an object. Given a small number of objects, we can encode carriable(x) in our database. However, if there are infinitely many objects in the domain, it is impossible to
encode each object.

We introduce an autonomous method to learn these types of unobservable predicates incrementally. Each object is described as a vector of observable features, such as \((\text{material shape color width length height})\). Each feature has the associated value. For example, the \text{shape} feature has a value from \((\text{flat round angle})\).

First, the robot learns overly-general operator definitions by assuming that every object is carriable in a naive domain. The robot experiences a plan failure due to the overly-general preconditions. Experimentation relies upon environmental feedback and produces a set of positive and negative (or false-positive) training examples for the preconditions of the faulty operator, such as \(+ (\text{wood flat red narrow short high})\) and \(- (\text{metal flat red wide long high})\). We use ID3, an information-theoretic system, to classify a set of objects into homogeneous subclasses, say positive and negative examples, by selecting the features with the highest discriminating values in terms of the information gain. Information gain is the measurement of how well each feature separates a set of examples into their respective subclasses. (Cherkauer & Shavlik 1994; Quinlan 1986). The information needed to partition training examples is

\[
I(n_1, ..., n_k) = - \sum_{i=1}^{k} \frac{n_i}{N} \log_2 \frac{n_i}{N}
\]

where \(k\) is the number of subclasses, \(n_i\) is the number of examples in the subclass \(i\), and \(N = \sum_{i=1}^{k} n_i\). The expected information required for the tree with \(F\) as root is

\[
E(F) = \sum_{j=1}^{w} \frac{\sum_{i=1}^{k} n_{ij}}{N} I(n_{1j}, ..., n_{kj})
\]

where \(F\) has \(w\) possible values and \(n_{ij}\) represents the number of examples of subclass \(i\) having feature value \(j\). Then the amount of gain by a feature \(F\) is

\[
gain(F) = I(n_1, ..., n_k) - E(F)
\]

The selected features are used for classifying unseen objects into respective subclasses. Our approach learns the functional concept composed of an unobservable predicate, such as \text{carriable}, by learning structural descriptions consisting of observable predicates. This structural concept satisfies the operational criterion of Mitchell et. al (Mitchell, Keller, & Kedar-Cabelli 1986) using only predicates which are easily observable by a robot. The benefit of learning an operational concept for an unobservable literal is that we don’t need to rely on the information given by a human.

![Figure 1: Noisy State and Plan Failure](image)

**Learning missing negative preconditions**

Most current planners cannot handle noisy data. A noisy state causes a plan failure. The robot’s arm is empty in the actual world, but the robot believes that it is holding \text{box1} and tries to execute a plan step, \text{(putdown box1)}. To make a planner robust in the noisy state, we propose a method to add negative constraints to a domain theory.

Knowledge acquisition is the mapping of human knowledge to a machine. Implicit knowledge is the knowledge which the expert believes the machine possesses after the mapping, but the machine actually does not possess. Implicit negative knowledge is difficult to detect and make explicit. For example, given that \text{(arm-empty)} is known to both a human and a machine, \text{¬(holding x)} is known to the human, but not known to the machine. However, negative knowledge is crucial in handling complex real world problems. Carbonell and Gil (Carbonell & Gil 1990) show an incomplete domain theory in which a hidden negative constraint causes a plan failure. The failure is the inevitable result of an expert’s poorly-designed domain theory. We propose a novel method to learn the necessary negative information at the initial design stage of a domain theory by unifying two types of logic systems as follows: A state description uses two-value logic: true or false. Our representation conventionally adopts the Closed-World Assumption. If \(p\) is not in the state, \(¬p\) is inferred. However, the operator description uses three-value logic: true, false, or irrelevant. If \(p\) is not in the preconditions, \(p\) is irrelevant. If \(p\) should not be in the state, \(¬p\) must appear in the preconditions. The knowledge acquisition of a learner is delimited by its language. The WISER description language is a typed first-order logic that allows conjunction and negation. Let \text{PRED}\* represent all the predicates known to WISER. Let \(S\) be a positive state, \(P\) be the set of predicates that are true in \(S\), and \(N\) the set of predicates which are not true in \(S\). Since \{\text{PRED}\* - \text{P}\} are not true by CW\(\Lambda\), they correspond to \(N\). Removing CW\(\Lambda\), \(S\) transits to \(S\* = P + \text{Neg}(\{\text{PRED}\* - \text{P}\})\), where
Neg(X) means the negated value of X. $S^*$ is identical to $S$ and provides a more comprehensive description of the same state. $S^*$ is used for inducing preconditions in this paper. A positive state is represented as the conjunction of predicates. This raw input data constitutes the potentially overly-specific preconditions for the operators in OBSERVER. It does not contain any negative information. Unlike Wang, we adopt three-value logic and transform the positive state to its closure to include the negative information before initializing it to overly-specific preconditions.

Let $PRED^* = \{A, B, C, D, E, F\}$, and the real preconditions $Pre$ of an operator op be $\{A, B, C, \neg D\}$. In a positive state $S_0 = \{A, B, C, E\}$, OBSERVER initializes the preconditions as $\{A, B, C, E\}$ and generalizes it to $\{A, B, C\}$. WISER initializes the preconditions to $\{A, B, C, \neg D, E, \neg F\}$ and generalizes it to $\{A, B, C, \neg D\}$. Given a state $S_1 = \{A, B, C, D\}$, Pre is not met, but op internally fires in Wang’s method.

Let’s give an example of noisy state problems. A human-generated domain theory is incomplete in handling these kinds of problems. The preconditions of pickup are $\{(\neg \text{arm-empty}), (\text{next-to robot box}), (\text{car­riable box})\}$ and the precondition of put-down is $\{(\text{holding box})\}$ in the Extended-Strips domain of the PRODIGY system. Suppose an inconsistent initial state is supplied by a noisy fast-moving camera: $\{(\text{holding box}), (\text{arm-empty}), (\text{next-to robot box}), (\text{carriable box1})\}$. Surprisingly, if the goal state is $\{\neg \text{arm-empty}\}$, PRODIGY generates a plan, PICKUP, and if the goal state is $\{\neg \text{holding box}\}$, PRODIGY generates a plan, PUTDOWN. The result can be catastrophic in the real world. WISER successfully generates more constrained preconditions of PICKUP: $\{\neg \text{holding box}, (\text{arm-empty}), (\text{next-to robot box}), (\text{carriable box})\}$. WISER uses Wang’s algorithm (Wang 1995) to learn new effects. It checks if all the effects of the executed operator are true in the environment. We expand the algorithm by providing a method to refine the preconditions of the executed operator.

Learning opposite concepts from operators

An operator corresponds to an action routine of a robot (Fikes & Nilsson 1972). Since each routine can be processed irrelevant of other routines, each operator is an independent unit in the domain theory. However, even though the operators are unrelated to each other on the surface, they are closely related in a deep structure of human percept. For example, the operators open-dr and close-dr are conceptually seen as opposites. Currently, no approach exists for examining this property between operators. In this section, we examine the structural relationships between operators and induce the opposite relationship between some operators and the opposite concept between some literals. The opposite concept will make an operator definition more succinct.

We represent the structural relationships as directed graphs, $D = (V, E)$, where $V = \{op_1, \ldots, op_n\}$. An arc $e_{ij} \in E$ connects one operator $op_i$ to another operator $op_j$ if $op_j$ can be always applied immediately after $op_i$ is applied. Let $prestate(op)$ be a state in which $op$ can be successfully applied. After $op$ is applied, $poststate(op)$ is calculated as $prestate(op) + add(op) - del(op)$. $e_{ij}$ indicates that $poststate(op_i)$ satisfies the preconditions of $op_j$. For example, given a set of operators, $\{\text{open-dr, close-dr, lock-dr, unlock-dr}\}$, there is an arc from open-dr to close-dr, but no arc from close-dr to lock-dr because a robot may need to subgoal to pickup a key.

We have two types of operators: destructive operators, such as drill, change the states of resources permanently, and non-destructive operators, such as open-dr, change the states temporarily. A change to a resource can be undone by another operator.

Theorem: A non-destructive operator belongs to a cycle.

Proof: Let $op$ be a non-destructive operator. $poststate(op)$ is apply $(op, prestate(op))$. If the preconditions of an operator still hold after the application of $op$, $prestate(op) \subseteq poststate(op)$. Thus, there is an arc from $op$ to itself as a vacuous self-loop. If $prestate(op) \nsubseteq poststate(op)$, let $p = \{p_1, \ldots, p_k\} \subseteq prestate(op)$ and $p \not\subseteq poststate(op)$. Since the resource $R$ is not destroyed by definition, to execute $op$ for $R$ again, $prestate(op)$ must be restored. Hence, there should exist a sequence of operators $op_{j_1}, \ldots, op_{n_{j_1}}$ that establishes $p$, where $op_{j_1}$ immediately follows $op$. Thus, there is a path from $op$ to $op_n$. Since the $poststate(op_n)$ satisfies the $prestate(op)$, there is a directed arc from $op_n$ to $op$. □

For an $n$-cycle, a $poststate(op_i)$ satisfies $prestate(op_{i+1 \mod n})$ for $i = 1, \ldots, n$. As a special case of an $n$-cycle, a 2-cycle is composed of two operators. They form a bipartite complete graph. They are called dual operators. Let $op_i$ and $op_j$ be dual operators, $Dual(op_i) \rightarrow op_j$, and $Dual(op_j) \rightarrow op_i$. One function of $Dual(op)$ is to restore the preconditions of $op$ by undoing the effects of $op$. Recursively, $Dual(Dual(op))$, which is $op$, restores the preconditions of $Dual(op)$ by undoing the effects of $Dual(op)$. Let $op_i$ contain the add-list $A$ and the delete-list $D$. Then, the add-list of $op_j$ is $D$ and the delete-list is
Learning new operators in a unknown domain

A general-purpose intelligent robot should be able to act in many domains including a unknown domain. Currently, a fixed domain theory is built separately for each domain. An operator successfully applied in one domain can ideally be reused in other domains for similar goals. If the operator becomes incomplete and/or incorrect in a new domain, the robot needs to refine it in the new domain and/or induce a new operator.

A training example is obtained by executing an operator in the environment (desJardins 1994; Gil 1992; Wang 1995). If the operator is successfully executed, it constitutes a positive example for the operator. A training example is composed of a sign, a state, and a goal. WISER is guided by positive and negative training examples in learning a new operator like a version space (Mitchell 1978). When an operator definition is overly-generalized and a negative (false positive) training example generates a plan, the example is used to specialize the definition. If the definition is overly-specialized, a positive (false negative) example, which can’t generate a plan, is used to generalize it. WISER specializes an operator by adding a precondition or an effect like EXPO. WISER generalizes an operator by deleting a precondition like OBSERVER. However, if the specialization of an incomplete operator causes an over-specialization, EXPO or OBSERVER can’t handle the complex problems such as an overly-specified effect. WISER splits the problematic operator into the overly-generalized and the overly-specialized operators: the type containing heterogeneous objects is split into homogeneous subtypes, each satisfying its own respective operator. If WISER cannot classify the objects in terms of the known type hierarchy, it induces new subtypes using ID3. This method is not covered in this paper, but it is similar to the one in Section 4. The splitting method and its example are presented.

**Operator Splitting Method**

1. Identify the over-general operator $gop$.

2. Specialize $gop$ to $sop$ by inserting a missing precondition or effect.

3. If a plan is generated for each positive training example, and no plan is generated for each negative training example, return $sop$.

4. $sop$ is over-specialized. Find a subtype $st_2$ of the problematic type $ty$ that correctly distinguishes the positive from the false negative examples for $sop$.

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**Definition:** If two operators, $op_i$ and $op_j$, form a bipartite graph and undo each other, then $op_i$ and $op_j$ constitute opposite concepts.

**PUTDOWN** and **PICKUP** operators have the opposite functionalities of each other. Let $op_i$ and $op_j$ be opposite concepts of each other. $add(op_i)$ and $add(op_j)$ have the opposite functionalities of each other: the opposites. If a literal $p \in A$ is the opposite concept to a literal $q \in A'$, such that $p \leftrightarrow \neg q$, a state $\{p, \neg p\}$ is feasible, but $\{p, q\}$ is not. To find $\{p, q\}$, such as $\{lock, unlock\}$ or $\{arm-empty, holding\}$, we use an experimentation method. We establish $\{p, \neg q\}$ as an initial state and change $\{p\}$ to $\{\neg p\}$. If such a change causes the change from $\{\neg q\}$ to $\{q\}$, $p$ and $q$ constitute the opposite concepts. $\neg q$ can be inferred from $p$. The opposite concept simplifies the operator definition. We can generate more simplified preconditions of PICKUP: $\{(arm-empty), (next-to \ robot \ box), (car\ riable \ box)\}$. This is intuitively more clear to humans.

desJardins (desJardins 1994) proposes as future research to develop automatic tools to verify an operator in relation to the rest of the knowledge base and to simplify operators syntactically by removing redundant preconditions. Our approach could partially contribute to that direction of research.

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**Figure 2:** Graphical representation of two dual operators
5. If no subtype can distinguish between positive and negative examples, send the examples to ID3 to find discriminating features and use them as a subtype, \( st_2 \).

6. Let \( st_1 \) be \( \{ ty \setminus st_2 \} \). \( st_1 \) and \( st_2 \) partition \( ty \). \( st_1 \) defines the resources that belongs to the positive examples for \( gop \) and \( st_2 \) does for \( sop \).

7. Refine \( ty \) further to \( st_1 \) for \( gop \) and to \( st_2 \) for \( sop \).

A robot is given the following operator definitions composed of a name, preconditions, and effects from the Extended-Strip domain.

- **PICKUP**: \( \{ (\text{next-to robot ob}) (\text{carriable ob}) (\text{arm-empty}) \} \{ (\text{del (clear ob)} (\text{arm-empty})) (\text{add (holding ob)}) \} \)

- **PUTDOWN**: \( \{ (\text{holding ob}) \}, \{ (\text{del (holding ob)}) (\text{add (arm-empty)}) \} \)

The new task of the robot is to pick up a box and put it on another box. (It is the task in the Blocksworld domain.) This task is never done in the Extended-Strip domain, but it is similar to the known task of picking up a box and put it on the floor. A new domain usually introduces new (technical) terms not required in other domains. For example, \( (\text{clear ob}) \) and \( (\text{on ob underob}) \) are not necessary in the Blocksworld domain, but are necessary in the Blocksworld domain. New terms are likely to introduce some hidden problems. For simplicity, we assume here that WISER has diagnosed that \( \text{underob} \) cause some problem and that the type of \( \text{underob} \) consists of two subtypes: table-type and box-type.

Let the original Blocksworld domain theory consist of PICKUP, PUTDOWN, STACK, and UNSTACK operators. Note that we want to learn this theory from the Extended-Strip domain theory. A theory, perfect in one domain, becomes incomplete when applied in other domains. Note that in principle our approach is similar to EITHER’s, which restores the original theory from a imperfect theory. PICKUP and UNSTACK are functionally similar: picking up an object \( \text{OBJ1} \) located on another object \( \text{OBJ2} \) if there is no other object on \( \text{OBJ1} \). The only difference between them is the type of \( \text{OBJ2} \). PICKUP is used if \( \text{OBJ2} \) is the table-type. Otherwise, UNSTACK is used. (The same argumentation holds for PUTDOWN and STACK). However, their mechanisms seem to be the same: putting an object on top of another object. Thus, by the naive domain assumption, the robot initially hypothesizes that tables and boxes are homogeneous: \( \text{OBJ1} \) can be put on the top of a box or a table.

When this assumption does not hold, WISER experiments to understand why. Given a training example, \( T_1 \):

- \( (+, (\text{next-to robot boxa}) (\text{carriable boxa}) (\text{arm-empty}) (\text{clear boxa}) (\text{clear boxb}) (\text{on boxa table}) (\text{on boxb table}), (\text{holding boxa})) \)

WISER, running on PRODIGY, can generate and execute the one-step plan PICKUP(boxa). However, for a training example, \( T_2 \):

- \( (-, (\text{next-to robot boxa}) (\text{carriable boxa}) (\text{arm-empty}) (\text{clear boxb}) (\text{on boxa table}) (\text{on boxh boxa}), (\text{holding boxa})) \)

WISER can’t execute the same plan PICKUP(boxa). WISER learns the new definition which includes the missing precondition (clear boxb) as briefly explained in section 5. More discussion on this topic can be found in (Wang 1995).

Note that this newly learned effects are overly-specific since the effect, (clear underob), is not always true in the environment: For example, a planner generates the UNSTACK(boxa table) plan for (T1) as before, but with the different effects (E2):

- \( ((\text{del (on ob underob)}), (\text{arm-empty})), (\text{add (holding ob)}), (\text{clear underob})) \).

However, if underob is instantiated to a box, (clear box) is true and E2 is incomplete. If underob is instantiated to a table, (clear table) is not true. Thus, E1 is incorrect, EXPO can’t handle this situation. To solve this dilemma, we need to reason by splitting the cases. E2 bound to a table is a positive concept for PICKUP, and E1 bound to a box is a positive concept for UNSTACK. By the naive domain assumption again, \( \text{underob} \) is bound only to the table-type in PICKUP, and to the box-type in UNSTACK. WISER splits the operator into two individual operators with the new constraints that \( \text{underob} \) is the table-type for PICKUP and the box-type for UNSTACK:

- **PICK-UP**: \( \{ (\text{next-to robot ob}) (\text{carriable ob}) (\text{arm-empty}) (\text{on ob underob}) (\text{clear ob}) \}, \{ (\text{del (on ob underob}) (\text{arm-empty})) (\text{add (holding ob)}) \} \)

More discussion on this topic can be found in (Wang 1995).
forms is not captured in the system. This introduces incompleteness to the state description occurs. In describing simplifying assumptions an unobservable concept by observable features.

operator, people prefer positive predicates to negative literals and some expert's knowledge in the negative incompleteness to observable to the system. In describing realistic problems. This relaxation introduces some in completeness problems. This relaxation introduces some in­completeness to generating plans before and after learning new knowledge occurs will be generated in the next step. We will further investigate the structural relationships between operators to infer some rules implicit in human mind.

References


125