

Planning and Learning: Explanation-Based Learning

Manuela Veloso
Reid Simmons

Carnegie Mellon University
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Learning in Planning

Opportunities and improvements along several dimensions:

- **Search Efficiency:** Learn control knowledge to guide the planner through its search space.
- **Domain Specification:** Learn the preconditions and effects of the planning actions.
- **Quality:** Learn control knowledge for high quality plans.

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Choices... The Need for Learning!

- Inductive methods
 - Data-intensive
 - Extract a general description of a *concept* from many examples
- Deductive methods
 - Knowledge-intensive
 - Explain and analyze an example
 - Identify the explanation as the sufficient conditions for describing the concept
 - Generalize instantiated explanation to apply to other instances

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Outline

- Explanation-Based Learning
- Planning by Analogy

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Explanation-Based Generalization – EBG, (Mitchell '80s)

Inputs:

- Target concept definition
- Training example
- Domain theory
- Operability criterion

Output:

- Generalization of the training example that is
- sufficient to describe the target concept, and
 - satisfies the operability criterion.

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The SAFE-TO-STACK Example

Input:

- **target concept:** SAFE-TO-STACK(x,y)
- **training example:**

ON(OBJ1,OBJ2)	
ISA(OBJ1, BOX)	ISA(OBJ2, ENDTABLE)
COLOR(OBJ1, RED)	COLOR(OBJ2, BLUE)
VOLUME(OBJ1,1)	DENSITY(OBJ1,0.1) ...

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The SAFE-TO-STACK Example

Input:

• domain theory:

1. NOT(FRAGILE(y)) or LIGHTER(x,y) \rightarrow SAFE-TO-STACK(x,y)
2. VOLUME(x,v) and DENSITY(x,d) \rightarrow WEIGHT(x,v*d)
3. WEIGHT(x1,w1) and WEIGHT(x2,w2) and LESS(w1,w2) \rightarrow LIGHTER(x1,x2)
4. ISA(x,ENDTABLE) \rightarrow WEIGHT(x,5)
5. LESS(0.1,5) ...

• operability criterion:

learned description should be built of *terms* used to describe examples directly, or other "easily" evaluated, such as LESS.

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The SAFE-TO-STACK Example

- Explain why obj1 is SAFE-TO-STACK on obj2.
 - Construct a proof.
 - Do **Goal regression**: regress target concept through proof structure.
 - Proof isolates *relevant features*.



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Generating Operational Knowledge

• Generalize proof:

- Sometimes simply replace constants by variables.
- Prove that all identified relevant features are necessary in general (hard! -- may need a lot of "extra" knowledge, *domain axioms*).

Output:

VOLUME(x,v1) and DENSITY(x,d1) and ISA(y,ENDTABLE)
and
and LESS(v1*d1,5) \rightarrow SAFE-TO-STACK(x,y)

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EBL: A Deductive Learning Method

Why are examples needed?

- Domain theory contains all the information: simply operationalize target concept.
- Examples focus on the relevant operationalizations: characterize only examples that actually occur.

Actual purpose of EBL:

- not to "learn" more about target concept,
- but to "re-express" target concept in a more operational manner (=efficiency).
- control learning.

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EBL in PRODIGY (Minton 87)

Goal: -- improve the efficiency of the planner
-- learn *control rules*.

Control rules:

- Apply at individual decisions.
- Antecedent matches the state of the planner at decision making time.
- Antecedent is operational -- planner can match its state using control rule language.
- Consequent *selects, rejects* or *prefers* particular alternatives.

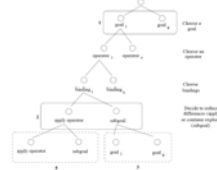
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Target Concepts

Identify the choices of the particular planner:



- Select goal *goal*
- Select operator *op* for achieving *goal*
- Select bindings for operator *op* and goal *goal*
- Decide subgoal if *op* is applicable
- Decide apply *op*

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Examples of Control Rules in PRODIGY

```
(CONTROL-RULE SELECT-OP-UNSTACK-FOR-HOLDING
 (if (and (current-goal (holding <x>))
          (true-in-state (on <x> <y>))))
 (then select operator UNSTACK))

(CONTROL-RULE SELECT-BINDINGS-UNSTACK-HOLDING
 (if (and (current-goal (holding <x>))
          (current-ops (UNSTACK))
          (true-in-state (on <x> <y>))))
 (then select bindings ((<ob> . <x>) (<underob> . <y>))))

(CONTROL-RULE SELECT-OP-PUTDOWN-FOR-ARMEMPTY
 (if (and (current-goal (arm-empty))
          (true-in-state (holding <ob>))))
 (then select operator PUT-DOWN))

(CONTROL-RULE SELECT-BINDINGS-PUTDOWN
 (if (and (current-ops (PUT-DOWN))
          (true-in-state (holding <x>))))
 (then select bindings ((<ob> . <x>))))
```

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Discussion

- Very successful in a variety of domains.
- Learned rules are applied as other rules, i.e. if their antecedent *totally* matches planning situation.
- Utility problem: The more rules learned, the slower the deliberation.
 - Matching cost (cost of utilization)
 - Frequency of application
 - Savings every time it is applied
 - Organization of learned rules!
- If EBL system is eager to learn provably correct, the explanation effort is really large, requiring a *complete* domain theory for generalization.
 - Incremental refinement of learned rules

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Summary – EBL in Planning

- Long-term goal of automating planning efficiency.
- Knowledge in domain theory is not usually effective.
- Explain examples to produce operational control knowledge for decisions.
- Provably correct explanations that generalize to new situations are hard to learn.
- Difficult goal and operator choice interactions can be learned through a combined deductive and inductive approach.
- User's quality metrics can be cast in the learned knowledge.

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