Incremental and Non-incremental Learning of Control Knowledge for Planning

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1. **Motivation**
2. Incremental learning. HAMLET
3. Learning by genetic programming. EVOCK
4. Discussion

Motivation for HAMLET

- Control knowledge learning techniques that worked well for linear planning, had problems in nonlinear planning

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- EBL
  - generated over-general or over-specific control knowledge
  - sometimes they required domain axioms
  - utility and expensive chunk problems

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- EBL
  - generated over-general or over-specific control knowledge
  - sometimes they required domain axioms
  - utility and expensive chunk problems
- Pure inductive techniques
  - did not use available domain knowledge: difficulty to focus on what is important
  - required powerful representation mechanisms beyond attribute-value: predicate logic (ILP)
  - huge hypothesis spaces very difficult to search without the use of learning heuristics

Our solution

Incremental approach

- Learning task:
  - Given: a domain theory, a set of training problems (it might be empty), a set of initial control rules (usually empty), and a set of parameters (quality metric, learning time bound, modes, . . .)
  - Output: a set of control rules that "efficiently" solves test problems generating "good quality" solutions

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  - Output: a set of control rules that "efficiently" solves test problems generating "good quality" solutions
- Main idea:
  - Uses EBL for acquiring control rules from problem solving traces
  - Uses relational induction (in the spirit of version spaces) to generalize and specialize control rules

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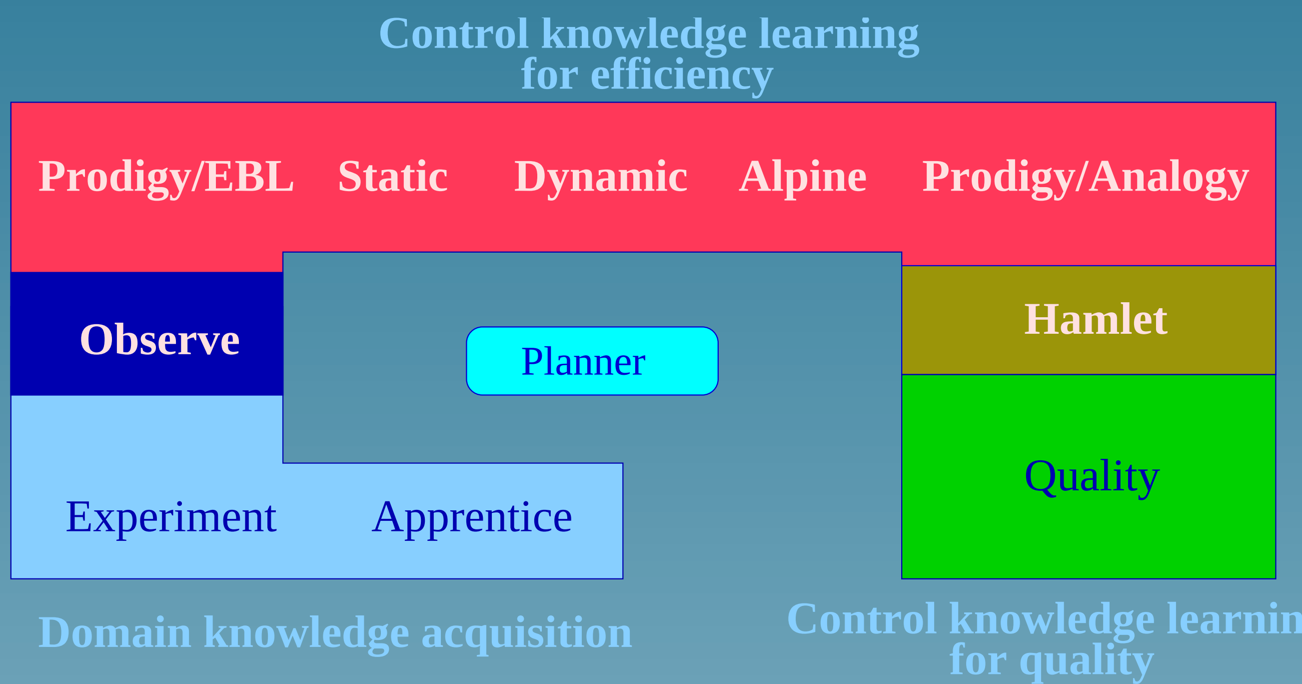
Hybrid Learning. HAMLET

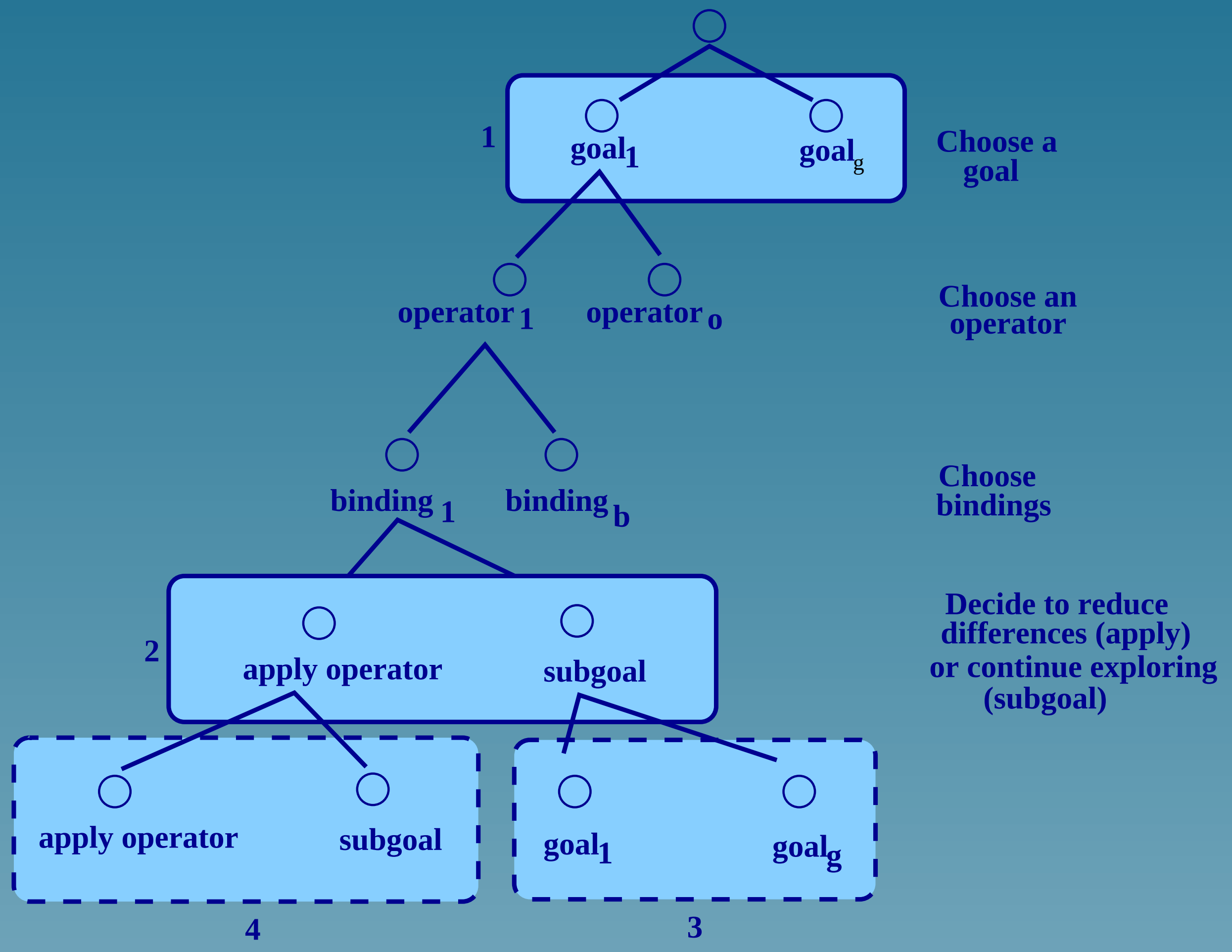
Planning architecture. PRODIGY

- Integrated architecture for non-linear problem solving and learning
- Means-ends analysis with bidirectional search

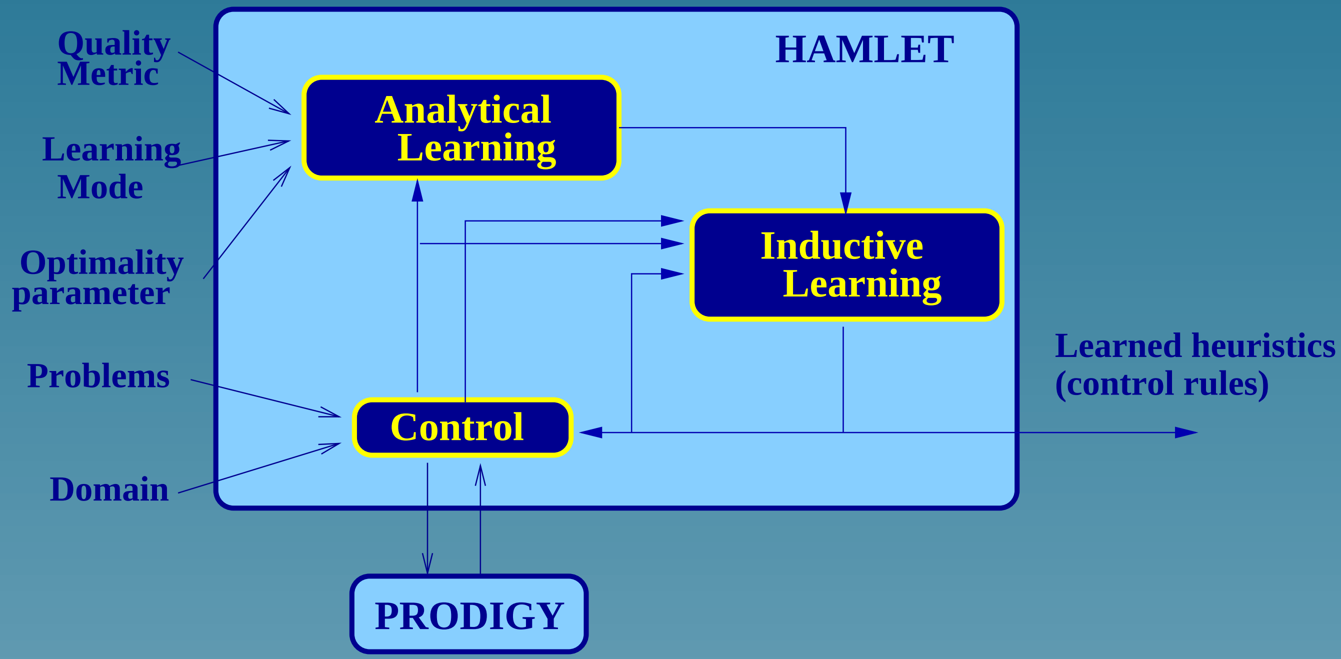


Hybrid Learning. HAMLET

PRODIGY search tree



Incremental learning. HAMLET



Example of control rule

```
(control-rule select-operators-unload-airplane
    (if (current-goal (at <object> <location1>))
        (true-in-state (at <object> <location2>))
        (true-in-state (loc-at <location1> <city1>))
        (true-in-state (loc-at <location2> <city2>))
        (type-of-object <object> object)
        (type-of-object <location1> location))
    (then select operator unload-airplane))
```

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        (type-of-object <object> object)
        (type-of-object <location1> location))
    (then select operator unload-airplane))
```

Difficulties:

- variables have to be bound to different values (cities)
- constants have to be of a specific type (`object` and `location1`)
- there are conditions that might not relate to the goal regression (`loc-at`)

Target concepts representation

(control-rule *name*
  (if (current-goal *goal-name*)
      [(prior-goals (*literal**))]
      (true-in-state *literal*)*
      (other-goals (*literal**))
      (type-of-object *object type*)*)
  (then select **operators** *operator-name*))

(control-rule *name*
  (if (and (applicable-op *operator*)
      [(prior-goals (*literal**))]
      (true-in-state *literal*)*
      (other-goals (*literal**))
      (type-of-object *object type*)*))
  (then decide {**apply**|**sub-goal**}))

(control-rule *name*
  (if (and (current-operator *operator-name*)
      (current-goal *goal-name*)
      [(prior-goals (*literal**))]
      (true-in-state *literal*)*
      (other-goals (*literal**))
      (type-of-object *object type*)*))
  (then select **bindings** *bindings*))

(control-rule *name*
  (if (and (target-goal *literal*)
      [(prior-goals (*literal**))]
      (true-in-state *literal*)*
      (other-goals (*literal**))
      (type-of-object *object type*)*))
  (then select **goals** *literal*))

Analytical learning

- The Bounded Explanation module (EBL)
  - **extracts positive examples** of the decisions made from the search trees
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  - **select** an **operator** to achieve some **goal**
  - **select** bindings for an **operator** when trying to achieve a *goal*
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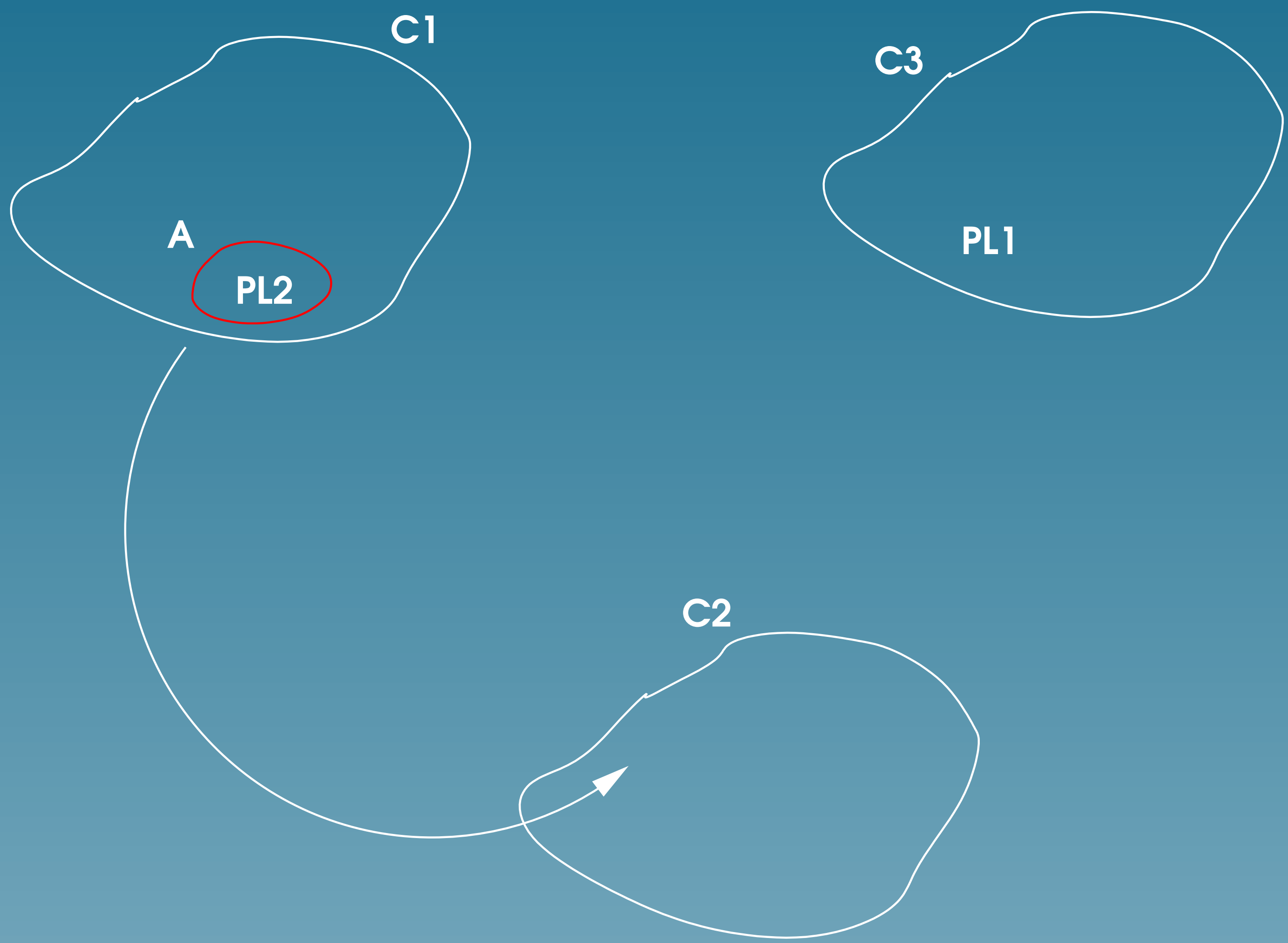
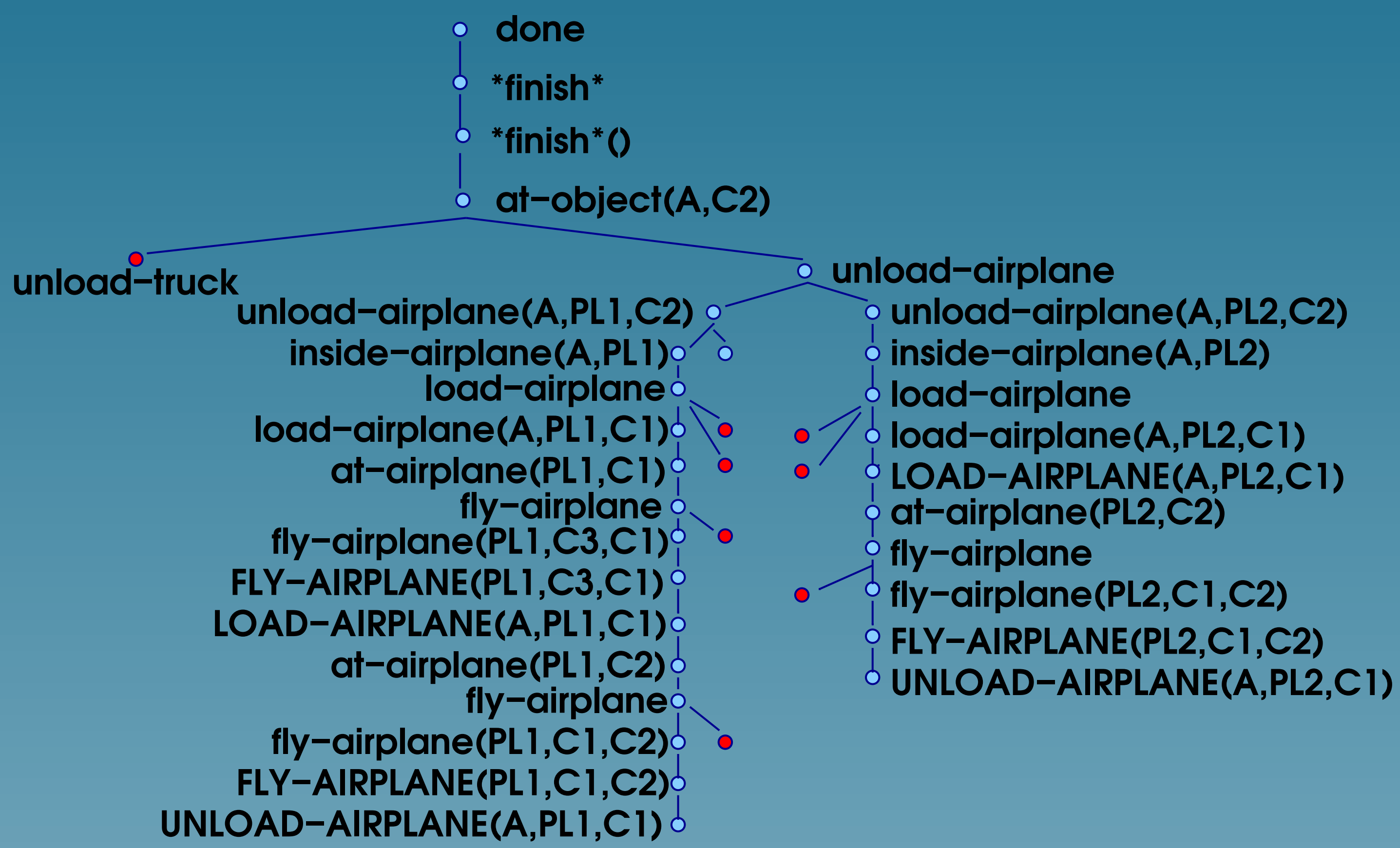
  - **decide** to **apply an operator** for achieving a goal or **subgoal** on an unachieved **goal**
- HAMLET considers multiple target concepts, each one being a disjunction of conjunctions (partially solves the utility problem)

Example of logistics problem



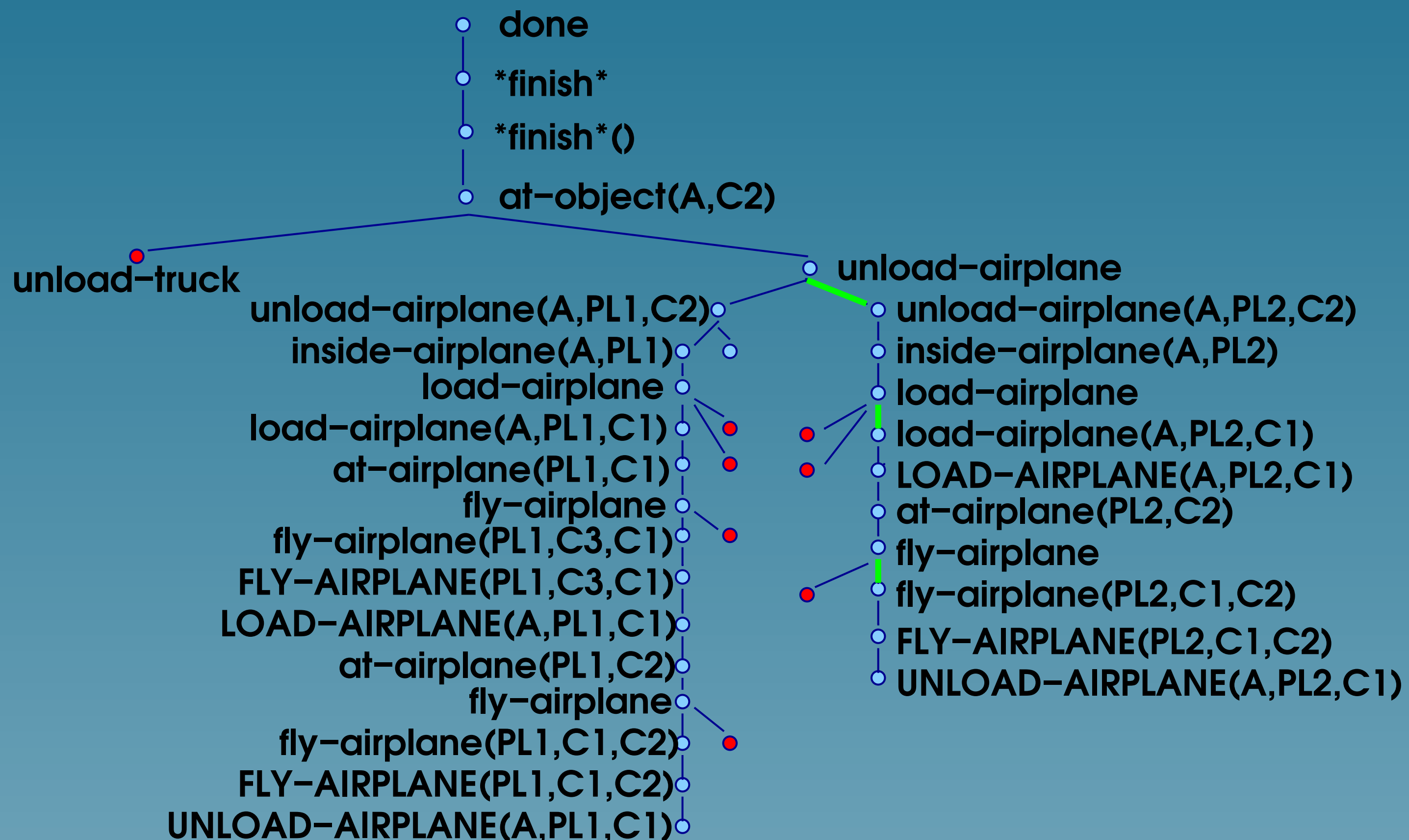
Hybrid Learning. HAMLET

Example of search tree



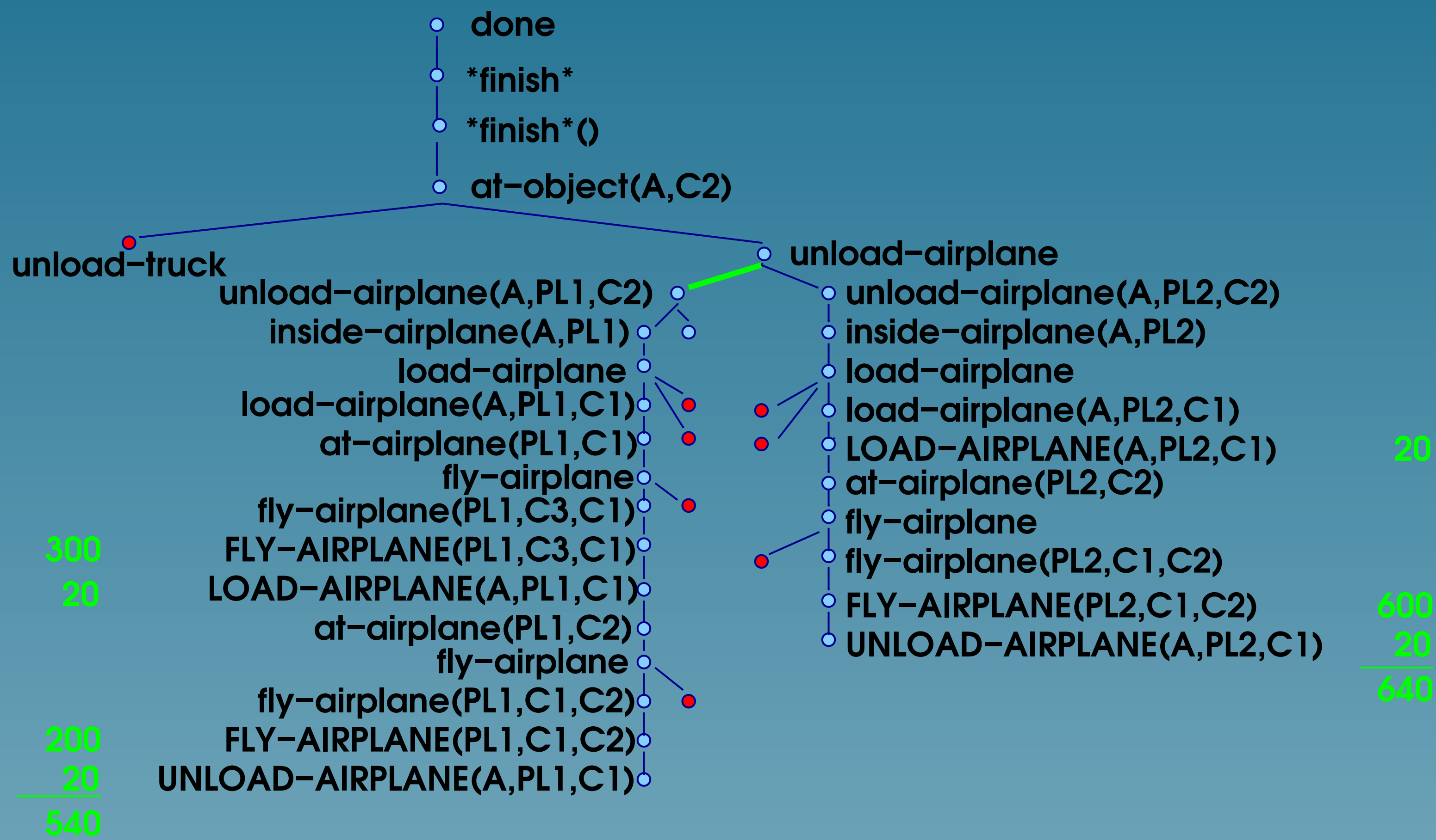
Hybrid Learning. HAMLET

Learning for plan length



Hybrid Learning. HAMLET

Learning for quality



Inductive learning. Generalization

```
(control-rule select-operators-unload-airplane
    (if (current-goal (at-object <object> <airport>))
        (true-in-state (inside-airplane <object> <plane>))
        (true-in-state (at-airplane <plane> <airport>)))
    (then select operator unload-airplane))
(control-rule select-operators-unload-airplane
    (if (current-goal (at-object <object> <airport>))
        (true-in-state (inside-airplane <object> <plane>))
        (true-in-state (at-airplane <plane> <airport1>)))
    (then select operator unload-airplane))
```

Hybrid Learning. HAMLET

Inductive learning. Generalization

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(control-rule select-operators-unload-airplane
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(true-in-state (inside-airplane <object> <plane>)))
(then select operator unload-airplane))

Finding negative examples

- Negative example of a control rule: it was applied at some node that lead to a failure, or a worse solution than the best sibling solution
- Only the **most general** negative examples are stored for each target concept
- They serve two purposes
  - refine an overly general rule
  - establish an upper limit of generalization for future applications of the generalization operators

Inductive learning. Specialization

(control-rule select-operators-unload-airplane
    (if (current-goal (at-object <object> <airport>))
        (true-in-state (inside-airplane <object> <plane>))))
    (then select operator unload-airplane))

(control-rule select-operators-unload-airplane
    (if (current-goal (at-object <object> <airport>))
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Inductive learning. Specialization

(control-rule select-operators-unload-airplane
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(control-rule select-operators-unload-airplane
(if (current-goal (at-object <object> <airport>)))
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Hybrid Learning. HAMLET

Incremental flavor

E1 +

E2 +

Hybrid Learning. HAMLET

Incremental flavor

E1 + ——— R1

E2 + ——— R2

Hybrid Learning. HAMLET

Incremental flavor

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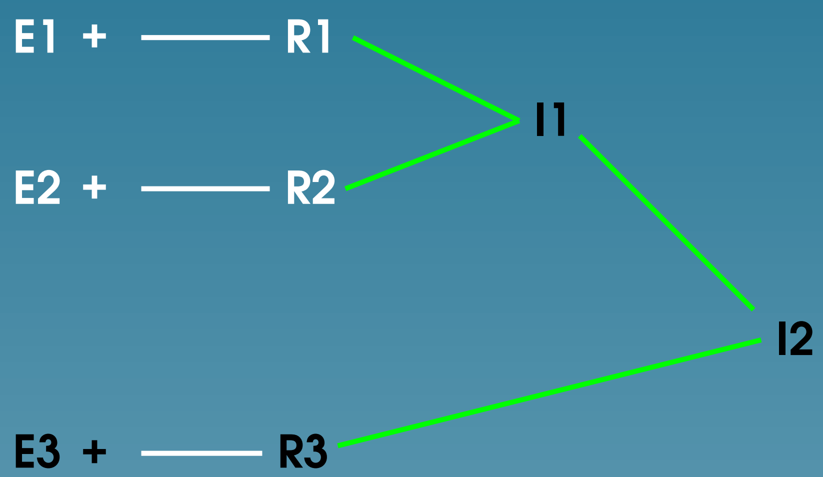
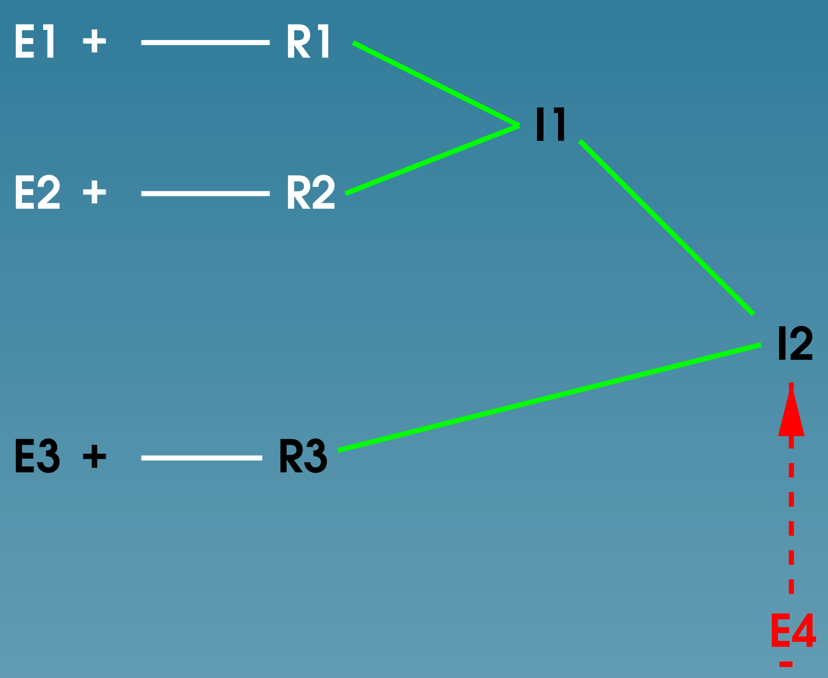


Hybrid Learning. HAMLET

Incremental flavor



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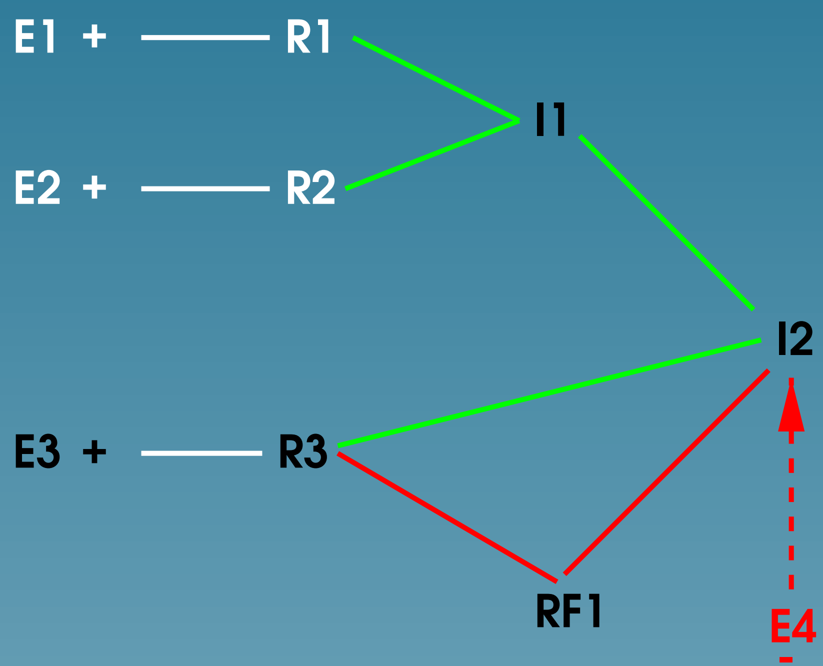

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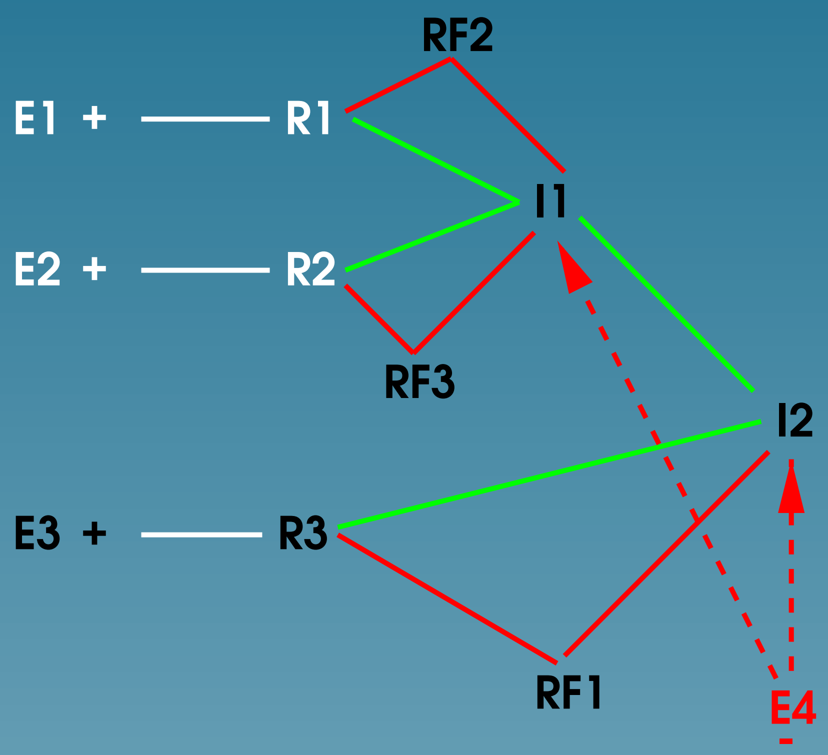

Problems with HAMLET

- It does not always generate better control knowledge by observing more and more examples
  - **incrementality** (partially solved through revisiting problems)
  - generalization and specialization procedures require to **add/delete the right** preconditions
  - it learns from **simple problems** search trees, preferably fully expanded
  - it depends very much on the **training examples** (inductive method): not simple, not difficult (the right examples to learn from might be too difficult)
  - **reduced language** for describing control rules: adding new types of conditions is hard given that generalization/specialization operators are not declaratively represented
- But, it provides a **very good starting point** for another type of learner (machine or human)

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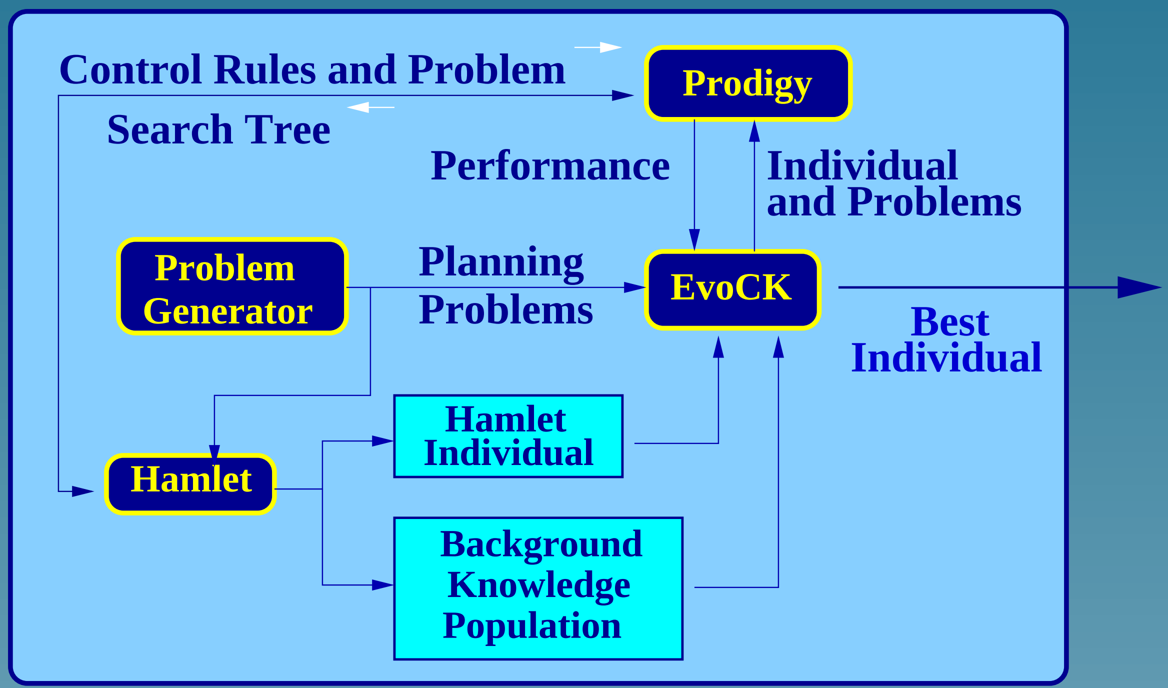
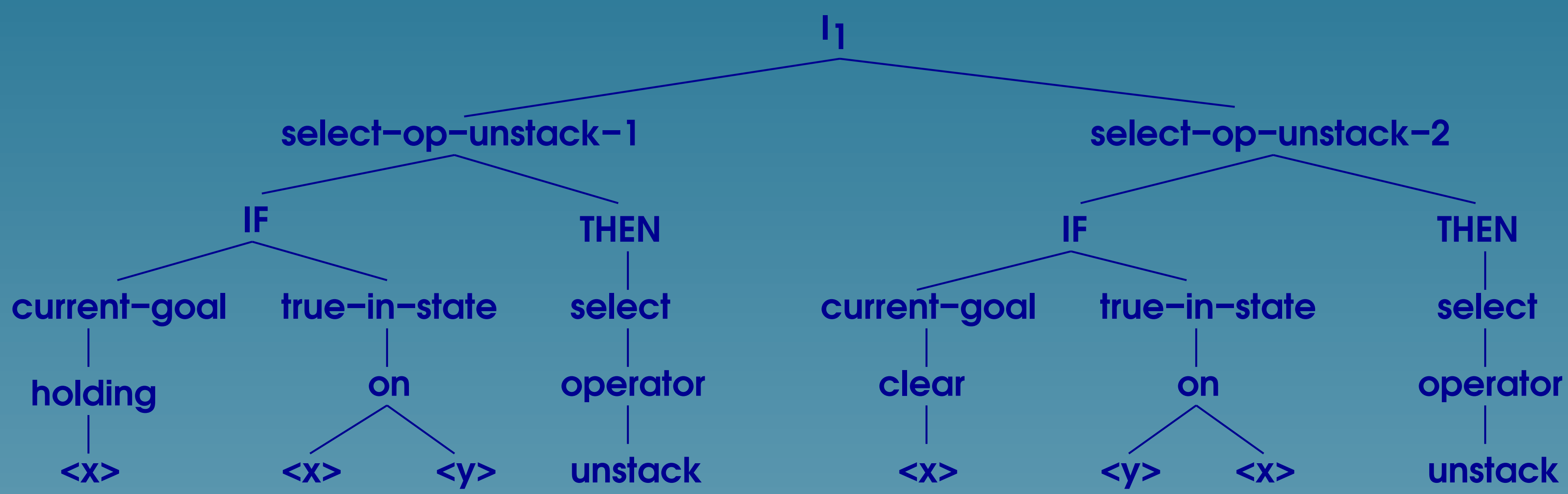
EvoCK architecture



Genetic Programming of control knowledge. EvoCK

- Grammar-based
- Individual: set of control rules
- Genetic operators
  - Crossover (standard, informed, adding)
  - Mutation (standard, removing, adding)
  - Specific (renaming variables, generalization)
- Fitness function
  - Completeness
    - Number of solved problems
    - Number of solved problems better than PRODIGY
  - Generality
  - Compactness

Example of an individual



Learning by genetic programming. EVOCK

Grammar-based GP. Domain-independent

LIST-ROOT-T	$\longrightarrow$	RULE-T | (`list` RULE-T LIST-ROOT-T)
RULE-T	$\longrightarrow$	(`rule` AND-T ACTION-T)
AND-T	$\longrightarrow$	METAPRED-T | (`and` METAPRED-T AND-T)
METAPRED-T	$\longrightarrow$	(`true-in-state` GOAL-T) | (`target-goal` GOAL-T) | (`current-goal` GOAL-T) | (`some-candidate-goals` LIST-OF-GOALS-T)
LIST-OF-GOALS-T	$\longrightarrow$	GOAL-T | (`list-goal` GOAL-T LIST-OF-GOALS-T)
ACTION-T	$\longrightarrow$	(`select-goal` GOAL-T) | (`select-operator` OP-T) | (`select-bindings` BINDINGS-T) | `sub-goal` | `apply`

Learning by genetic programming. EVOCK

Grammar-based GP. Domain-dependent

OP-T	$\longrightarrow$	`load-truck` | `load-airplane` | `unload-truck` | `unload-airplane` | `drive-truck` | `fly-airplane`
BINDINGS-T	$\longrightarrow$	(`load-truck-b` OBJECT-T TRUCK-T LOCATION-T) | (`load-airplane-b` OBJECT-T AIRPLANE-T AIRPORT-T) | (`unload-truck-b` OBJECT-T TRUCK-T LOCATION-T) | (`unload-airplane-b` OBJECT-T AIRPLANE-T AIRPORT-T) | (`drive-truck` TRUCK-T LOCATION-T LOCATION-T) | (`fly-airplane` AIRPLANE-T AIRPORT-T AIRPORT-T)
GOAL-T	$\longrightarrow$	(`at-truck` TRUCK-T LOCATION-T) | (`at-obj` OBJECT-T LOCATION-T) | (`inside-truck` OBJECT-T TRUCK-T) | (`inside-airplane` OBJECT-T AIRPLANE-T)

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Discussion

Related work

- **Linear**: STRIPS [Fikes *et al.*, 1972], Rubik's cube [Korf, 1985], PRODIGY/EBL [Minton, 1988], STATIC [Etzioni, 1993], DYNAMIC [Pérez and Etzioni, 1992], ALPINE [Knoblock, 1991], GRASSHOPER [Leckie and Zukerman, 1998], LEX [Mitchell *et al.*, 1983], ACM [Langley, 1983], LEBL [Tadepalli, 1989], DOLPHIN [Zelle and Mooney, 1993], EXPERIMENTER [Carbonell and Gil, 1990], . . .
- **Nonlinear "classical"**: SOAR [Laird *et al.*, 1986], FAILSAFE [Bhatnagar, 1992], OBSERVE [Wang, 1994], COMPOSER [Gratch and DeJong, 1992], PRIAR [Kambhampati, 1989], SNLP+EBG [Kambhampati and Kedar, 1991], SNLP+EBL [Katukam and Kambhampati, 1994], UCPOP+EBL [Qu and Kambhampati, 1995], QUALITY [Pérez and Carbonell, 1994], SteppingStone [Ruby and Kibler, 1992], UCPOP+FOIL [Estlin and Mooney, 1995], PIPP [Upal and Elio, 1998], PRODIGY/ANALOGY [Veloso, 1994], DerSNLP [Ihrig and Kambhampati, 1996], HAMLET [Borrajo and Veloso, 1997], EVOCK [Aler *et al.*, 2002], ExEL [Reddy and Tadepalli, 1999], . . .

Discussion

More related work

- **Nonlinear "non classical"**: rewrite rules [Ambite *et al.*, 2000, Upal and Elio, 2000], CAMEL [Ilghami *et al.*, 2002], HTN MODELS [Garland *et al.*, 2001], GRAPHPLAN+EBL [Kambhampati, 2000], SATPLAN+FOIL [Huang *et al.*, 2000], generalized policies [Khardon, 1999, Martín and Geffner, 2000], HAP [Vrakas *et al.*, 2003]
- **MDP models:** reinforcement learning [Kaelbling *et al.*, 1996], Q-LEARNING [Watkins and Dayan, 1992], temporal differences [Sutton, 1988, Tesauro, 1992], LOPE [García-Martínez and Borrajo, 2000]

Discussion

HAMLET vs. EVOCK

- HAMLET
  - *knows* about learning in planning
  - learning operators require right examples to modify candidate hypotheses
  - incremental
  - planner and language dependent
- EVOCK
  - does not know it is doing learning in planning
  - learning operators do not require right examples to modify candidate hypotheses
  - non-incremental
  - grammar dependent

Incrementality

- Incrementality allows
  - focusing on one example: juice extraction (EBL)
  - generating the next-best example
  - better approaching changes in target concept (life-long learning)
  - knowing what control rule is responsible for what

Incrementality

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  - knowing what control rule is responsible for what
- Non-incrementality allows
  - having a global view of a distribution of examples
  - reducing the effect of noise or particular examples
  - better deciding what and how to generalize and specialize

Discussion

Incrementality

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  - better approaching changes in target concept (life-long learning)
  - knowing what control rule is responsible for what
- Non-incrementality allows
  - having a global view of a distribution of examples
  - reducing the effect of noise or particular examples
  - better deciding what and how to generalize and specialize

They can be complementary

General discussion

- Learning techniques should reflect somehow the way by which decisions are made by the problem solver **forward vs. backward**
- The knowledge about how to make a decision should be explicit in the meta-state **evaluation functions or cost functions**
- The base problem solver should be able to solve training problems **are easy or incompletely solved problems enough?**
- If quality is important, it should also provide at least two different-quality solutions **all solutions is the optimum**
- If a learning technique acquires individual control knowledge, the decisions should be reproducible to be of use **utility problem**

General discussion

- Learning in problem solving also needs to worry about representativeness of examples **much bigger search spaces**
- It is difficult to add conditions on numbers, negative constrains (and quantification) to the rules **representation**
- Combining machine learning and humans is a very effective approach **mixed initiative, domain axioms, extra predicates, temporal formulae, . . .**

On evaluation of learning in planning

- Difficult task
- What to measure?
  - Efficiency: time, solved problems
  - Quality: solution length (sequential, parallel), makespan, others
  - Combination
- How to compare?
  - with or without prior knowledge
  - domain representation
  - set of problems
- Against what?
  - different learners in different planners
  - knowledge-based planners
  - efficient state of the art planners

Discussion

Still to be solved. Zenotravel

```
(control-rule select-airplane-for-zoom
   (if (current-goal (at-object <object> <airport>))
       (current-operator zoom)
       (true-in-state (at-object <object> <airport1>))
       (true-in-state (at-airplane <plane> <airport2>))
       (cheapest-airplane-for-zoom <object> <plane>
                                   <airport> <airport1>
                                   <airport2>))
   (then select bindings ((<obj> . <object>)
                          (<airplane> . <plane>))))
```

Discussion

More recent and future work

- Mixed initiative
- Effects of knowledge representation
- Effects of prior knowledge
- Learning for multiple criteria
- Learning for HTN+POP planners
- Using numerical predicates on conditions of control rules
- Active learning: on-line generation of appropriate training problems
- Learning for planning and scheduling
- Learning in more recent problem solvers

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