Learning Action Strategies for Planning Domains using Genetic Programming

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- A collection of ordered rules is called a policy
- A good policy can solve planning problems without searching
- Our aim is to find policies for planning domains using genetic programming
- Our system for doing this is called L2Plan (Learn to Plan)

Previous Results

- L2Act (Khardon, 1999):

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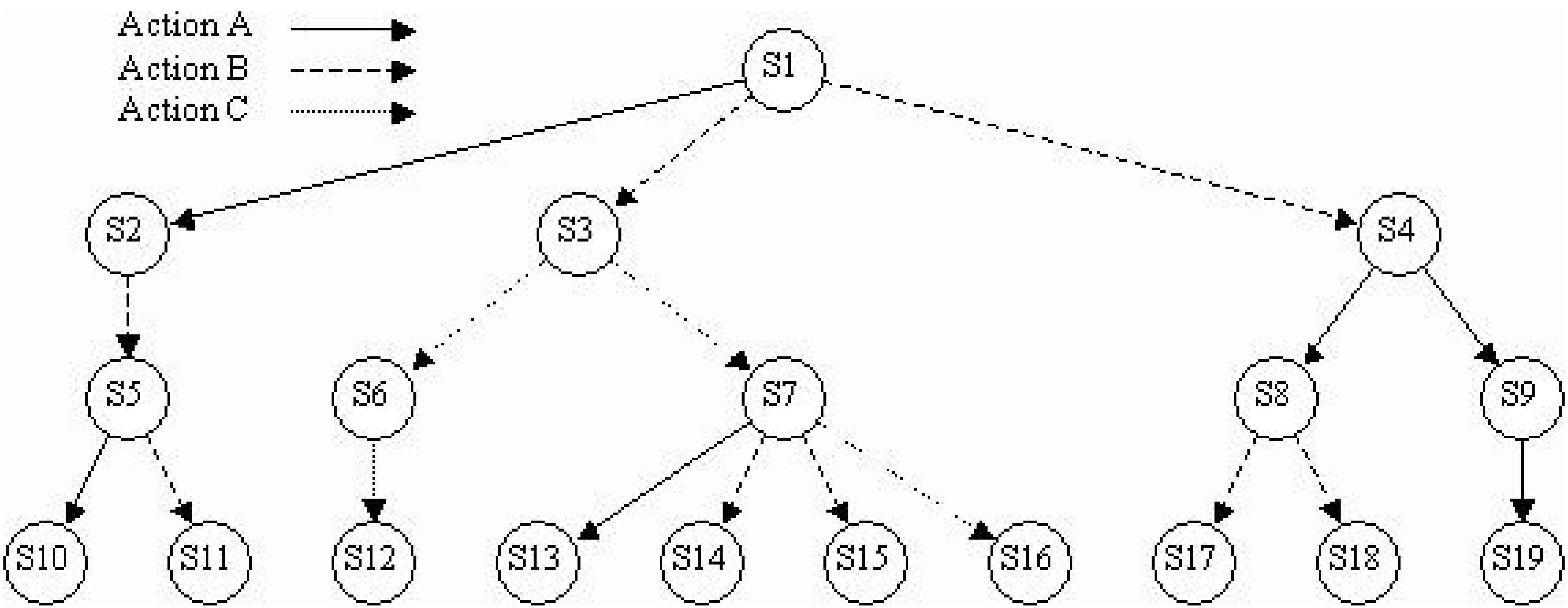
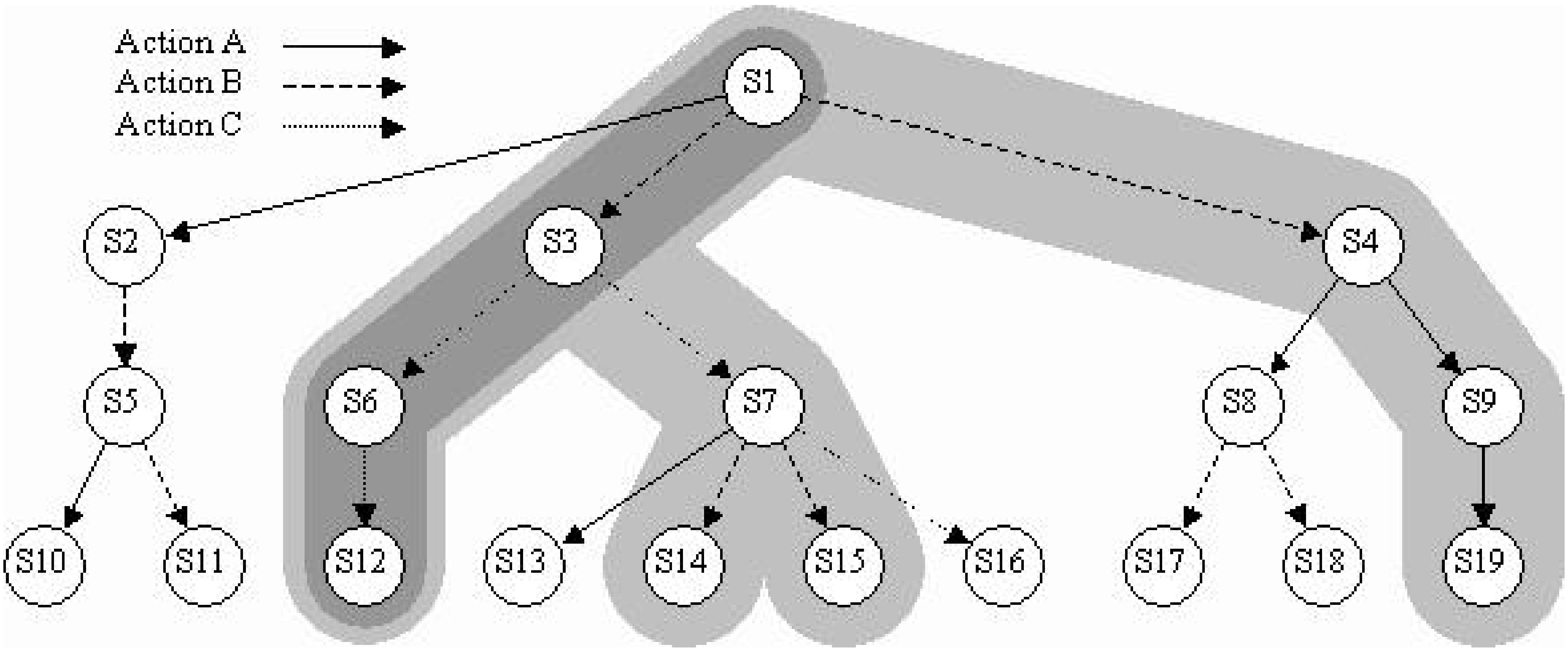
- Incomplete generalisation from examples

Planning as a Tree Search



Policy Restricted Planning



Example Planning Domain

```
(define (domain blocksworld)
(:predicates (clear ?x)
             (on-table ?x)
             (on ?x ?y))
(:action move-block-to-block
  :parameters (?bm ?bf ?bt)
  :precondition (and (clear ?bm) (clear ?bt) (on ?bm ?bf))
  :effect (and (not (clear ?bt)) (not (on ?bm ?bf))
               (on ?bm ?bt) (clear ?bf)))
(:action move-block-to-table
  :parameters (?bm ?bf)
  :precondition (and (clear ?bm) (on ?bm ?bf))
  :effect (and (not (on ?bm ?bf)) (on-table ?bm) (clear ?bf)))
(:action move-table-to-block
  :parameters (?bm ?bt)
  :precondition (and (clear ?bm) (clear ?bt) (on-table ?bm))
  :effect (and (not (clear ?bt)) (not (on-table ?bm))
               (on ?bm ?bt))))
```

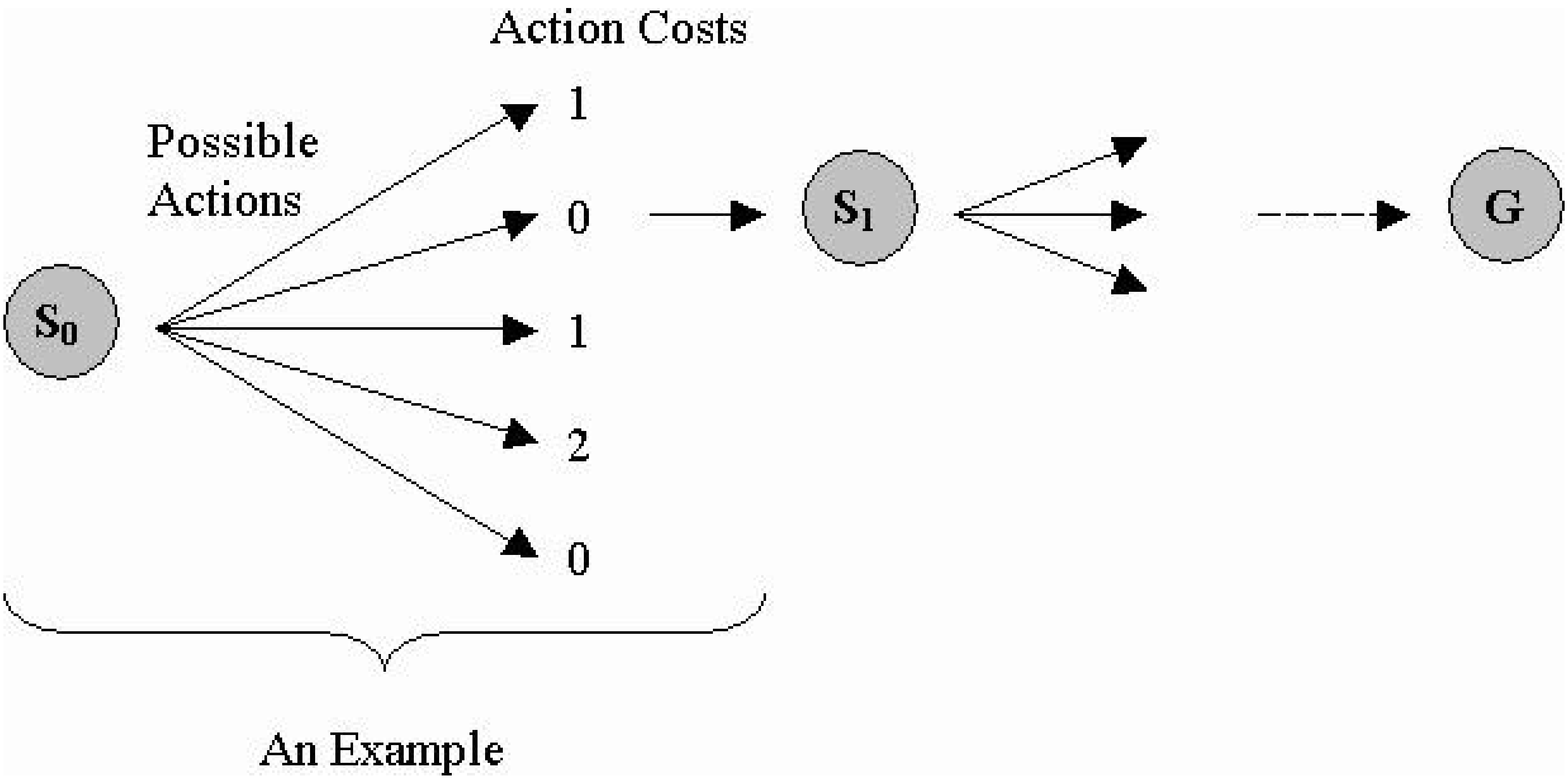
What is a Policy?

```
(define (policy blocks1)
(:rule make_well_placed_block_1
  :condition (and (on ?bm ?bf) (wp ?bt))
  :goalCondition (and (on ?bm ?bt))
  :action move-block-to-block ?bm ?bf ?bt)
(:rule make_well_placed_block_2
  :condition (and (wp ?bt))
  :goalCondition (and (on ?bm ?bt))
  :action move-table-to-block ?bm ?bt)
(:rule make_well_placed_block_3
  :condition (and (on ?bm ?bf))
  :goalCondition (and (on-table ?bm))
  :action move-block-to-table ?bm ?bf)
(:rule move_non_wp_block_to_table
  :condition (and (on ?bm ?bf) (not (wp ?bm)))
  :goalCondition (and )
  :action move-block-to-table ?bm ?bf))
```

Example Problem

```
(define (problem large-a)
  (:domain blocksworld)
  (:length 6)
  (:objects 1 2 3 4 5 6 7 8 9)
  (:init (on 3 2) (on 2 1) (on-table 1)
         (on 5 4) (on-table 4) (on 9 8)
         (on 8 7) (on 7 6) (on-table 6)
         (clear 3) (clear 5) (clear 9))
  (:goal (and (on 1 5) (on-table 5) (on 8 9)
              (on 9 4) (on-table 4) (on 2 3)
              (on 3 7) (on 7 6) (on-table 6)
              (clear 1) (clear 8) (clear 2))))
```

Generating Training Examples



L2Plan: Implementation

- Population of randomly generated policies
- Run each policy on training examples
- Fitness function:

$$F(p_i) = \frac{1}{1 + \left(\sum_{j=1}^{n} C(p_i, e_j)\right) / n}$$

- Tournament selection
- Generational algorithm with elitism
- Various crossover and mutation operators
- Mutation-based local search

Genetic Operators

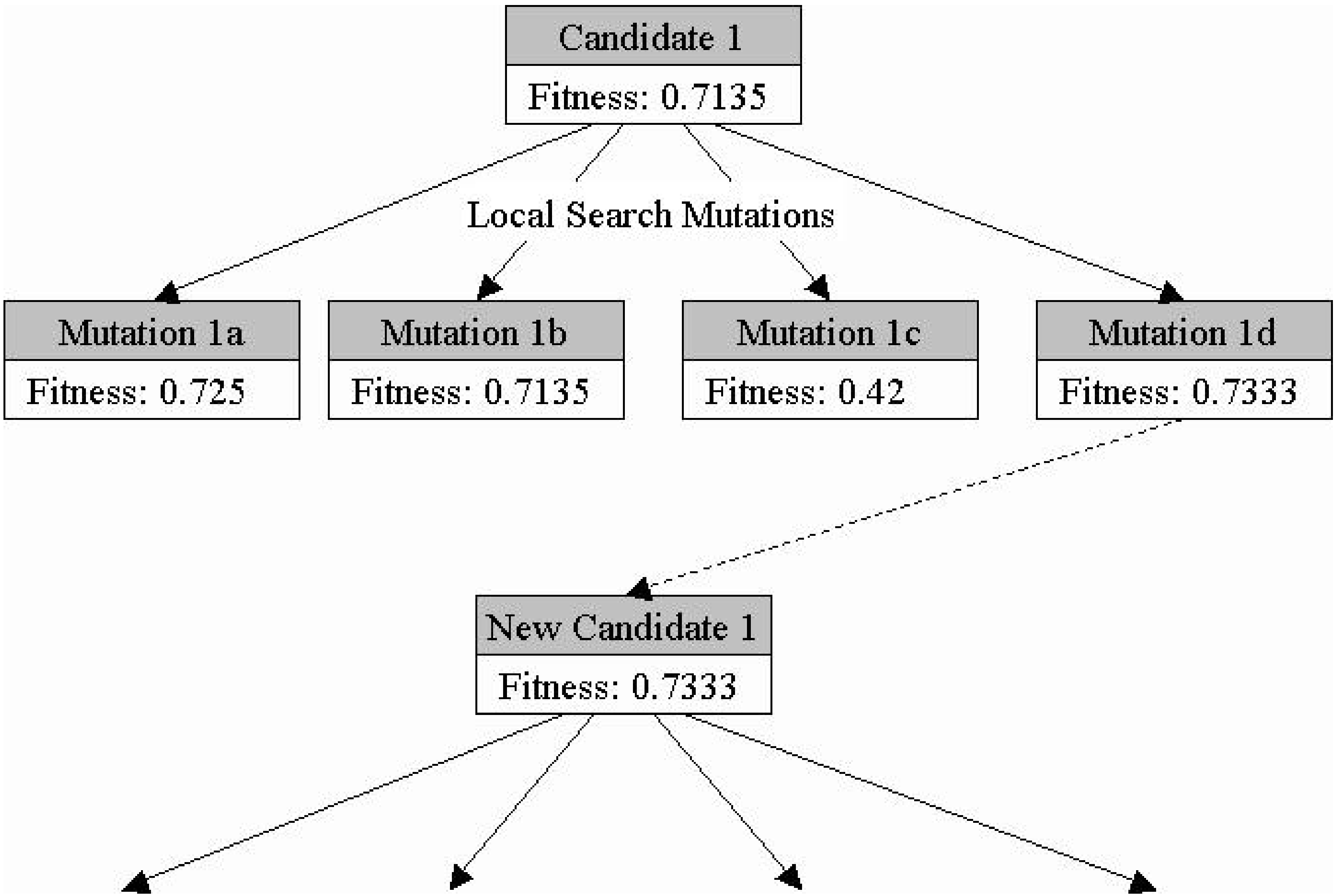
Crossover operators:

- Single point rule level crossover
- Single rule swap crossover
- Similar action rule crossover

Mutation operators:

- Rule addition mutation
- Rule deletion mutation
- Rule swap mutation
- Rule condition mutation

Local Search



Evaluating the Policies

Two forms of policy restricted planning:

- breadth-first planning
- first-action planning

Metrics tracked by the policy tester:

- number of test problems solved
- number of test problems solved optimally (fewest actions)
- number of extra steps taken on average
- number of states examined during the search

Blocks World Results

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	first-action planning				breadth-first planning			
	Sol	Opt	Extra	Nodes	Sol	Opt	Extra	Nodes
5 blocks	100	100	0.00	5.76	100	100	0.00	7.14
10 blocks	100	86	0.15	12.51	100	94	0.07	17.60
15 blocks	100	65	0.57	21.02	100	88	0.15	41.12
20 blocks	100	46	0.91	29.63	100	84	0.21	99.02
hand-coded	100	34	1.26	29.98	100	100	0.00	197.42

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- Better results than L2Act and EvoCK
- Learnt policy out-performs hand-coded policy under first-action planning

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2 objects, 5 cities	100	95	0.05	6.05	100	100	0.00	9.37
2 objects, 10 cities	100	96	0.04	6.87	100	100	0.00	11.97
4 objects, 5 cities	100	80	0.20	10.38	100	100	0.00	27.98
4 objects, 10 cities	100	76	0.25	12.91	100	100	0.00	62.04
hand-coded	100	74	0.28	12.94	100	100	0.00	68.76

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- Very good performance obtained
- Slightly out-performs the hand-coded policy

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Further work:

- Application to more domains required
- Support for typed version of PDDL required
- Investigation of the use of description logic in the rules
- Further planning strategies beyond first-action or breadth-first: e.g. repeated first-action planning with reinforcement of better plans