

Solving Clustered Oversubscription Problems for Planning e-Courses

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Motivation

- Current planning:
 - Planning competition drives planning advancement
 - Very powerful domain-independent techniques, but focus on specific aspects of the planning task (tracks)
- Difficult to address real world applications:
 - requires the use of many features of PDDL, ...
 - requires to compute metrics that use state-dependent fluents
- The application of planning techniques to real problems, sometimes, requires solving interesting associated problems that can be useful in more general contexts

Description

- Application area: the generation of learning designs adapted to students' profiles
- Associated problem: a variation of OSP¹ that we have called clustered oversubscription

¹Oversubscription Problem: Given a set of goals, each one with a utility, obtain a plan that achieves some (or all) the goals, maximizing the utility, as well as minimizing the cost of achieving those goals.

E-learning



LO

<relations> IsBasedOn Disjunction

 Requires Conjunction

<time>

<learningsourcetype> LO1

 LO2

 IMS-MD LON

Course definition

Felder-Soloman Index of Learning Styles

ACTIVE

REFLECTIVE

Doing something active with it. Discussing, applying, or explaining it to others.

Thinking about it quietly first.

SENSING

INTUITIVE

Learning facts.

Discovering possibilities and relationships.

VISUAL

VERBAL

See— pictures, diagrams, flow charts, time lines, films, and demonstrations.

Words— written and spoken explanations.

SEQUENTIAL

GLOBAL

Gain understanding in linear steps.

Learn in large jumps, suddenly "getting it."

PEDAGOGICAL THEORY THAT RELATES:

<learningsourcetype>

+
 Felder's learning styles

=
 Activities Reward

Task1

a11 time reward

a12 time reward

a1n time reward

Task2

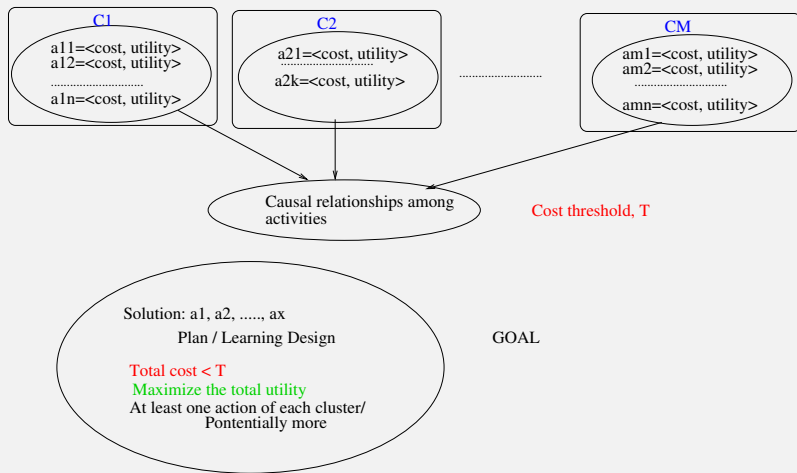
.....

IsBasedOn Taskn

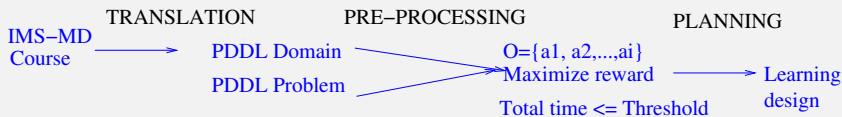
GOAL

GENERATION OF
 LEARNING DESIGNS
 ADAPATED TO
 STUDENTS' PROFILES

Clustered Oversubscription Problem



Approach



PRE-PROCESSING
 (Optimization Component)

1. Linear Programing
2. Heuristic Search

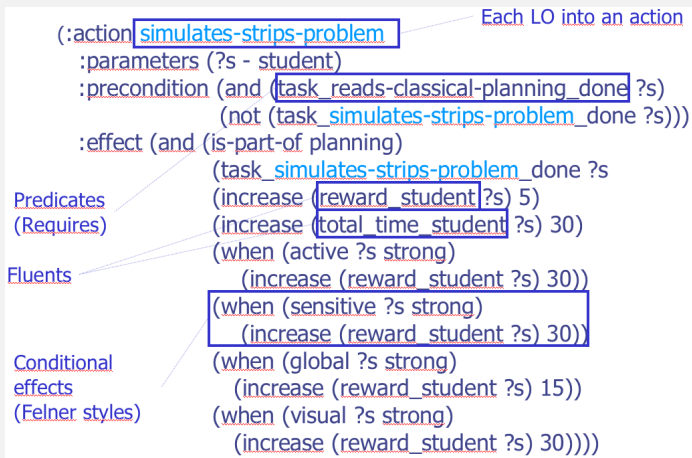
PLANNING
 (Causal Component)

1. PDDL3 Preference goals
2. Plan metric

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Learning Activities Actions



Modelling Actions

```

(:action fictitious-finish-ai-course End of course action
 :parameters (?s - student)
 :precondition
   (and (task_performs-test-introduction_done ?s)
        (task_performs-test-representation-others_done ?s)
        (task_performs-test-production-systems_done ?s)
        (task_performs-test-uninformed-search-unit-2_done ?s)
        (< (total_time_student ?s) (time_threshold_student ?s)))
 :effect (and (is-part-of course) (task_ai-course_done ?s)))

(:action OR-fictitious-strips IsBasedOn relation
 :parameters (?s - student)
 :precondition (and (not (task_strips_done ?s))
                   (or (task_simulates-strips-problem_done ?s)
                       (task_experiments-strips-problem_done ?s)))
 :effect (and (is-part-of planning) (task_strips_done ?s)))

```

Time constraint

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Activities selection

- Formalization:

- $\forall a \in A, a = \langle t, r \rangle$, the goal $O = \{a_1, \dots, a_n\}, a_i \in A$, given $\sum_{a_i = \langle t_i, r_i \rangle \in O} t_i \leq T$, maximizing $\sum r_i$
- Activities are grouped into a set of clusters, $C = \{c_1, \dots, c_m\}, c_i = \{a_1, \dots, a_{c_i}\}$ that can perform the same learning task.
 $\forall c_i \in C$ at least one $a_j \in c_i$ should be in O
- Similar to the well-known knapsack problem in combinatorial optimization, but with the addition of clusters

- Solution:

- Using Linear Programming: optimal
- Using hill-climbing algorithm with backtracking

Linear Programming

```
set A; /* list of activities*/
set T; /*list of tasks*/
param t{a in A}; /* time of each activity in A */
param r{a in A}; /* reward of each activity in A */
param c{a in A, j in T}, binary; /* activity i belongs to task j */
param tt; /* bound time */
var x{a in A}, binary;
maximize treward: sum{a in A} x[a]*r[a];
s.t. time: sum{a in A} x[a]*t[a] <= tt;
s.t. cluster{j in T}: sum{a in A} c[a,j]*x[a] >= 1;
/* there is at least one action per task*/
```

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Modelling

- ① Including the actions in O as PDDL3 preference-goals:

```
(:goal (and (preference p0 (<action-name1> st1))
            (preference p1 (<action-name2> st1))
            ...
            (task_course_done student1 st1)))
```

- ② Using selection as plan metric:

- Domain:
 - add conditional effects to the actions


```
(when (not (action-in-plan ?s <action-name>))
        (increase (penalty ?s) 1))
```
 - Add precondition in end of course action:


```
(>= (reward_student ?s) (reward_threshold_student ?s))
```
- Problem:
 - Initial state: including actions in O as *action-in-plan* predicates
 - Metric:

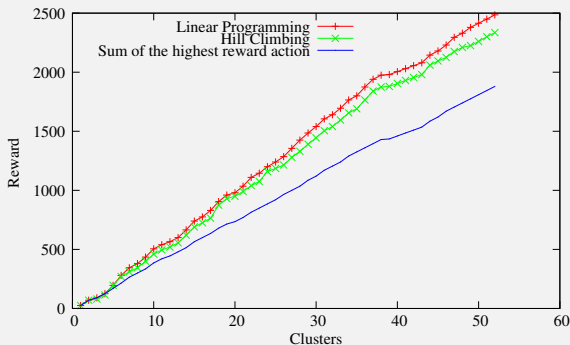
```
(:metric (minimize (penalty student1)))
```

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Computing Set O

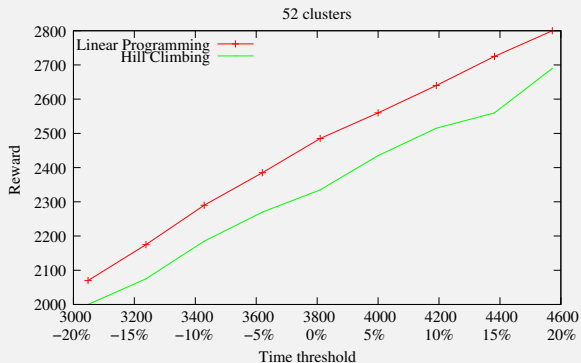
Reward when time limit is the sum of the time of the highest-time activity in each cluster



(LP always found the solution in less than 0.1s while the search-algorithm execution time steadily increased from 0.1 up to 8s)

Computing Set O . All clusters

Reward of 52 clusters when time limit varies from -20 % up to 20 %

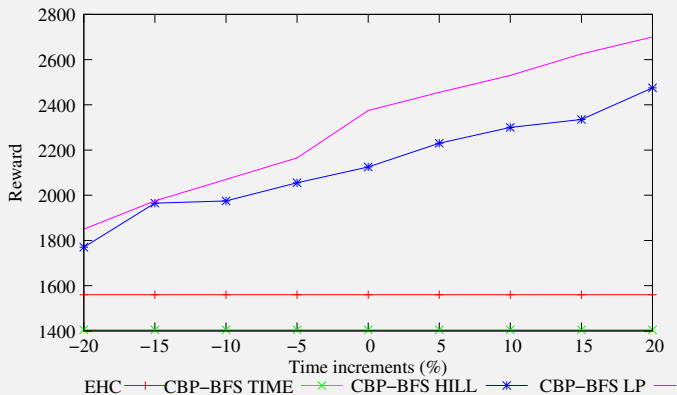


(The execution time was never higher than 18s)

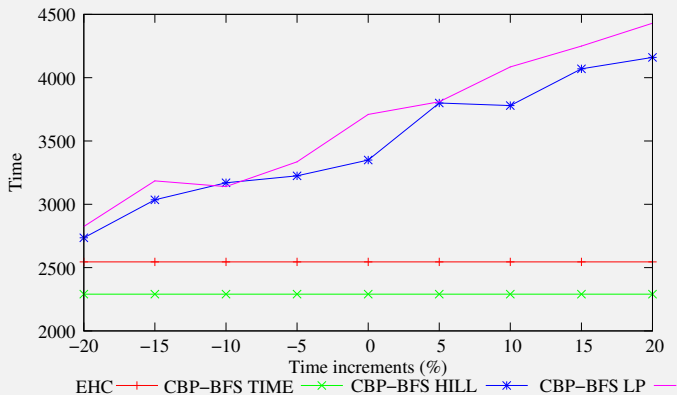
Planning Results. Configurations

- ① EHC: original Enforced Hill-climbing algorithm in Metric-FF
- ② CBP-BFS: CBP planner with BFSearch+Lookahead algorithm
 - Time: minimizing the (*total_time_student*)
 - LP: minimizing (*penalty_student*). LP selection
 - Hill: minimizing (*penalty_student*). Hill-climbing selection
- ③ SGPLAN6: SGPlan6 planner
 - Without preference goals
 - LP: preferences. LP selection (unfeasible plans)
 - Hill: preferences. Hil-climbing selection (unfeasible plans)

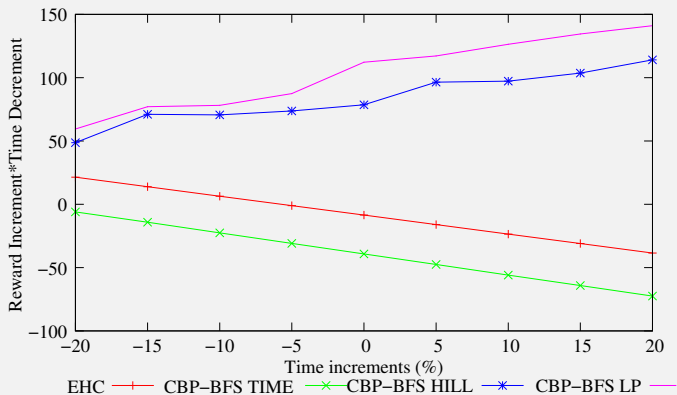
Planning Results. Reward



Planning Results. Time



Planning Results. Both



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Conclusions

- E-learning planning application for generating learning designs adapted to different students' profiles
- Modelled as a *clustered-oversubscription problem*
- Hybrid approach:
 - LP/Heuristic search solves the optimization component
 - Planning solves the causal component:
- Integration:
 - **PDDL3 preference-goals (SGPLAN6 unfeasible plans)**
 - As plan metric: *CBP*
(*penalty, action-in-plan, reward_threshold_student*)

Future Work

- Test the approach in other domains
- Include causal relations in the LP model (without OR relations)