LP-based Heuristics for Cost-optimal Planning

Florian Pommerening[1] Gabriele Röger[1] Malte Helmert[1] Blai Bonet[2]

[1]University of Basel, Switzerland

[2]Universidad Simón Bolívar, Venezuela

June 24, 2014

- Recent interest in heuristics based on linear programming
  - Certified "hot topic"
    (AAAI 2013 Spotlight Talk: What's Hot at ICAPS?)
  - Landmarks, state equation, PDBs, optimal cost partitioning
- Contributions
  - Common framework
  - Combination of heuristic values beyond the maximum
  - Theoretical tool to show dominance

A framework for LP-based heuristics

Background

- Classical planning tasks
  - States assign values to variables
  - Operators allow to manipulate states
  - Implicitly defined transition system
- Finding optimal solutions
  - Cheapest sequence of operators from initial state to a goal
  - Common approach: $A^* +$ admissible heuristic

Operator-counting Constraints

Operator occurrences in potential plans

(2,1,0)

(1,1,2) (0,0,0)

(1,2,1) (0,0,1)

(1,3,1) (3,0,2)

(2,2,0) (3,2,2)

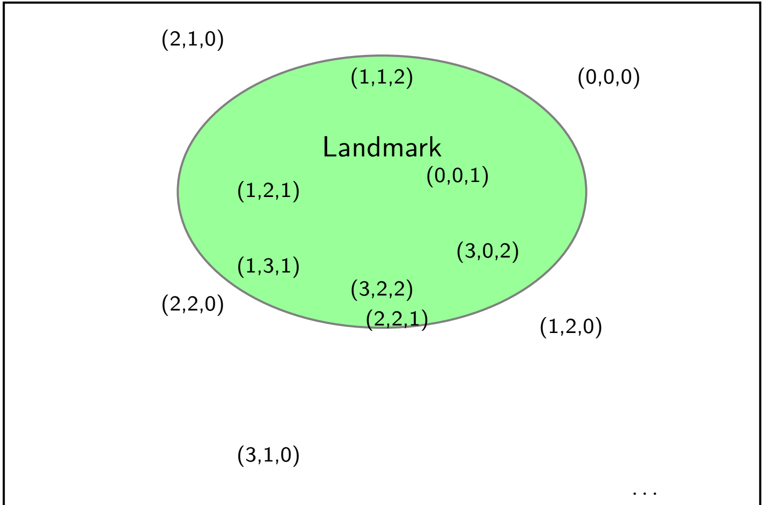
(2,2,1) (1,2,0)

(3,1,0)

...

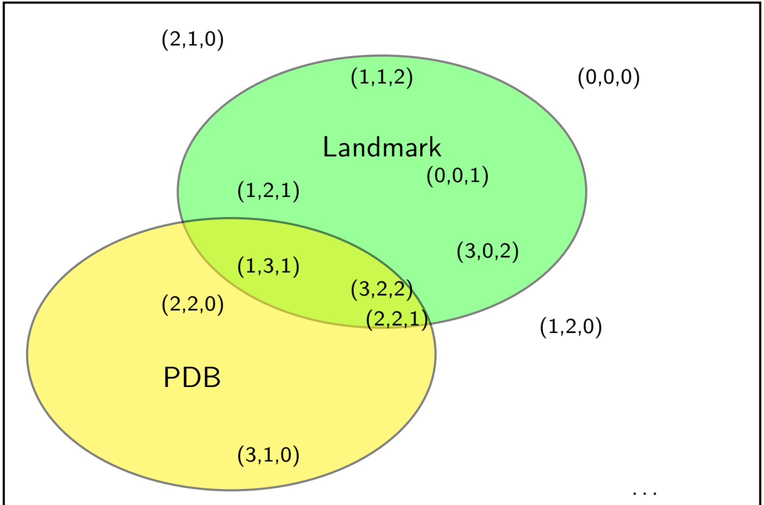
Operator-counting Constraints

Operator occurrences in potential plans



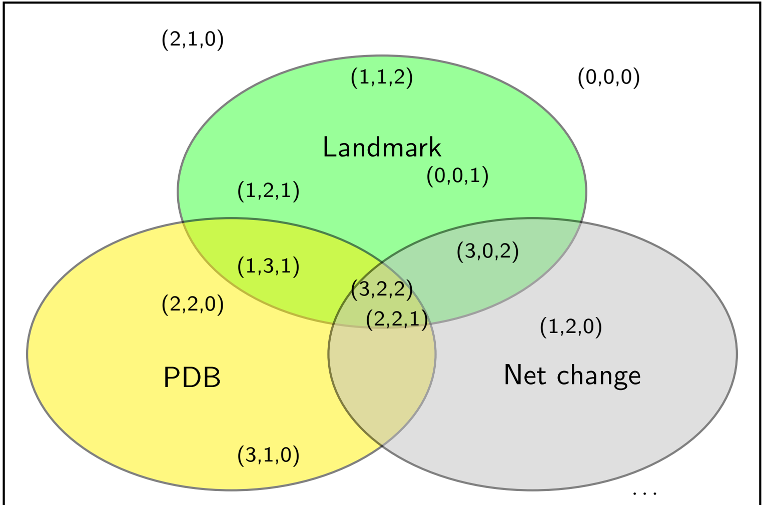
Operator-counting Constraints

Operator occurrences in potential plans



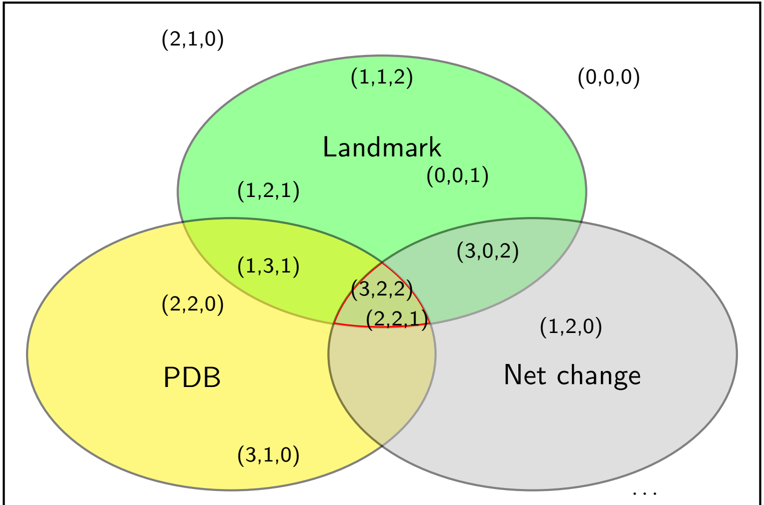
Operator-counting Constraints

Operator occurrences in potential plans



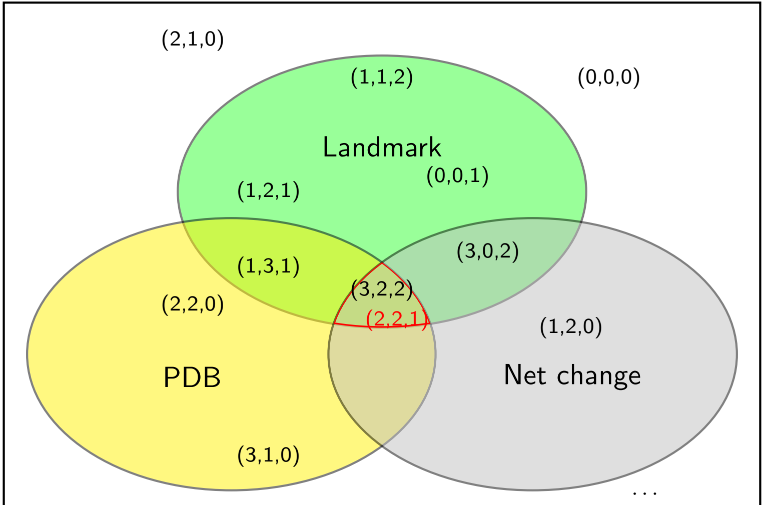
Operator-counting Constraints

Operator occurrences in potential plans



Operator-counting Constraints

Operator occurrences in potential plans



Operator-counting Constraints

- Operator-counting constraint
  - Linear constraints
  - Operator-counting variable Y_o for each operator
  - Satisfied by occurrences in any plan
  - Example: $\mathsf{Y}_{o_1} \geq 2\mathsf{Y}_{o_2}$
- IP/LP heuristics
  - Minimize $\sum_{o \in \mathcal{O}} \mathsf{cost}(o) \cdot \mathsf{Y}_o$ subject to some operator-counting constraints
  - LP relaxation solvable in polynomial time
  - Admissible heuristics

How do existing heuristics fit?

Example 1: Disjunctive Action Landmarks

- Disjunctive action landmarks
  - Set of operators
  - At least one has to be used in any plan

Landmarks constraints

$$\sum_{o \in L} \mathsf{Y}_o \geq 1$$

- Existing heuristic
  - Optimal cost partitioning for landmarks (Karpas and Domshlak 2009)
  - Extended by Keyder, Richter, and Helmert (2010)
  - Formulation by Bonet and Helmert (2010) fits the framework

Example 2: Pattern Databases

- Pattern databases
  - Admissible
  - Only subset of operators is relevant

Post-hoc optimization constraints

$$h^P(s) \leq \sum_{o \text{ relevant for } P} \mathsf{cost}(o) \cdot \mathsf{Y}_o$$

- Existing heuristic
  - Post-hoc optimization (Pommerening, Röger, and Helmert 2013)
  - Minor reformulation fits the framework

Example 3: Net Change

- Net change for a value of a variable
  - Operators produce or consume the value

Net change constraints

- Number of producers and consumers must balance out
- Lower bound estimation for operators that sometimes produce/consume.

- Existing heuristic
  - State-equation heuristic (van den Briel et al. 2007, Bonet 2013, Bonet and van den Briel 2014)
  - Fits the framework

Example 4: Explicit State Abstractions

- Explicit State Abstractions
  - PDBs, Merge&Shrink, CEGAR, . . .
- Existing heuristic
  - Optimal cost partitioning heuristic (Katz and Domshlak 2010)
  - Dual LP: new perspective on same problem
  - Dual constraints are operator-counting constraints

Theoretical Results

Combination of Heuristic Values

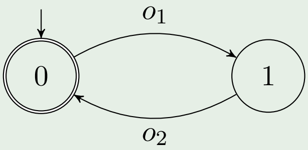
Theorem

The LP heuristic for a set of operator-counting constraints dominates the maximum over LP heuristics for the individual constraints

- Better way to combine different sources of information
- Dominance can be strict

Example: Positive interaction between constraints

State-equation heuristic



Landmark constraint

$$L = \{o_1\}$$

Dominance of heuristics

- LP heuristics as analytic tool
- General scheme to show dominance of h_1 over h_2
  1. h_1 is the LP heuristic with constraints C_1
  2. h_2 is the LP heuristic with constraints C_2
  3. Every solution of C_1 satisfies constraints in C_2
  4. $h_1 \geq h_2$

Dominance of heuristics

Theorem

$$h^{\mathsf{OCP}}_{Sys_1} \leq h^{\mathsf{SEQ}}$$

- $h^{\mathsf{OCP}}_{\mathsf{Sys}_1}$
  - Optimal cost partitioning heuristic
  - Abstractions: one projection to each goal variable
- h^{SEQ}
  - State-equation heuristic
- A counter example shows $h^{\mathsf{SEQ}} \not\leq h^{\mathsf{OCP}}_{\mathsf{Sys}_1}$

Implied constraints

- Safety-based improvement of the state-equation heuristic (Bonet 2013)
  - Net change constraints contain lower bound estimation
  - Corresponding upper bound estimation can be added
  - Some inequalities become equalities

Theorem

The safety-based improvement cannot increase the heuristic value of the state-equation heuristic.

Empirical Results

Results

Individual Constraints

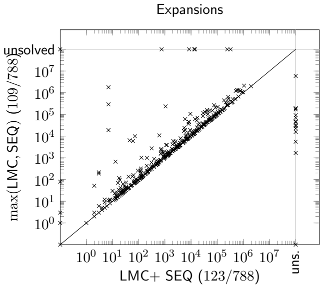
SEQ	PhO-Sys[1]	PhO-Sys[2]	LMC	OPT-Sys[1]
630	587	631	744	443

Combination of Constraints

LMC + PhO-Sys[2]	LMC + SEQ	PhO-Sys[2] + SEQ	LMC + PhO-Sys[2] + SEQ	$h^{\text{LM-cut}}$
758	**788**	672	763	763

Interaction of Constraints

- Comparing combination in LP with maximum
- Coverage is unchanged
- Stronger heuristic estimates (synergy)
    - Fewer expansions
    - More tasks solved with perfect heuristic



Conclusion

Conclusion

- Common framework for LP-based heuristics
  - Operator-counting constraints
  - IP/LP heuristics
  - Fits many existing heuristics
- Can be used to prove properties of heuristics
- Combination of information from different sources
  - Stronger estimates than through maximization
  - Synergy effects

Conclusion

- Common framework for LP-based heuristics
  - Operator-counting constraints
  - IP/LP heuristics
  - Fits many existing heuristics
- Can be used to prove properties of heuristics
- Combination of information from different sources
  - Stronger estimates than through maximization
  - Synergy effects
- Poster presentation today in the second session (17:30)