

Incremental LM-cut

Florian Pommerening and Malte Helmert

Universität Basel
Departement Informatik

14.06.2013

Content

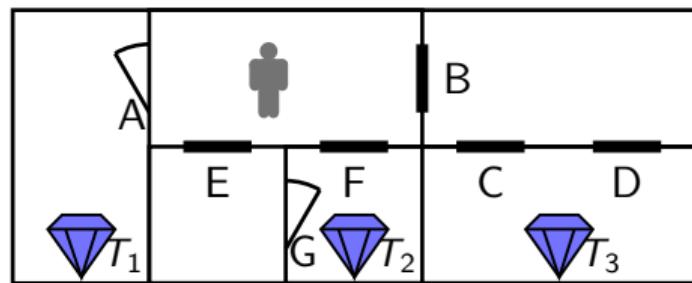
1 Theory

- Planning
- Incremental Computation

2 Practice

3 Conclusion

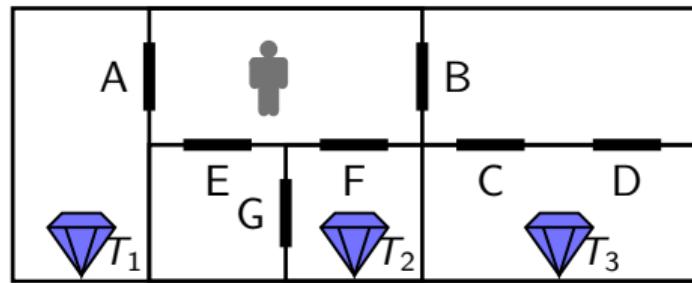
Heuristic Search for STRIPS Planning



- Variables $V = \{A\text{-Is-Open}, B\text{-Is-Open}, \dots\}$
- Initial state $I = \{A\text{-Is-Open}, G\text{-Is-Open}\}$
- Goal state $G = \{\text{Has-}T_1, \text{Has-}T_2, \text{Has-}T_3\}$
- Operators $O = \{o_A, o_B, \dots, p_1, p_2, \dots\}$
- Plan $\pi = \langle p_1, o_F, p_2, o_B, o_C, p_3 \rangle$

- *Heuristic function*
 - Distance estimate
 - Admissibility
- *Search methods*
 - A* Search
 - IDA* Search

Disjunctive Action Landmarks

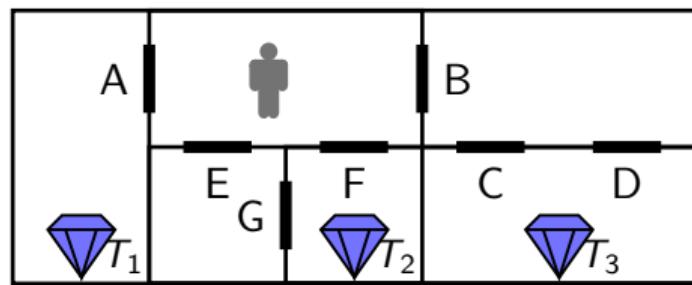


- *Disjunctive action landmarks*
 - Set of operators
 - Every plan contains at least one of them
 - Cost of a landmark: cost of cheapest contained operator
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}, \dots$

$h^{\text{LM-cut}}$

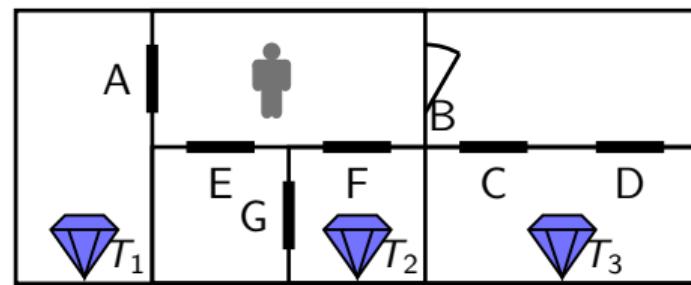
- ① Calculate $h^{\max}(s)$
 - Only achieve most expensive subgoal/precondition
 - $h^{\max}(s) = \infty$ task unsolvable
 - $h^{\max}(s) = 0$ stop searching for landmarks
- ② Use h^{\max} values to discover new landmark L
- ③ Reduce cost of each operator in L by L 's cost
 - Introduces a cost partitioning
 - Sum of landmark costs is admissible heuristic
- ④ Repeat

Incremental Computation (Example)



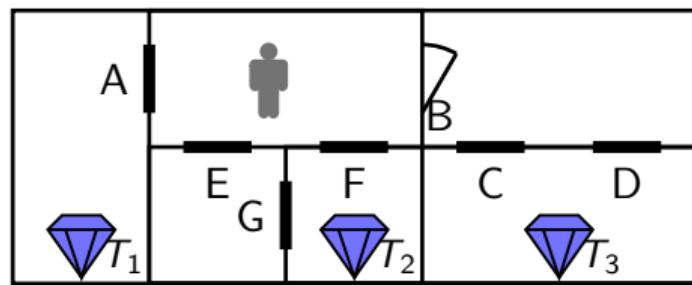
- Discovered landmarks in this state
 - $\{o_A\}$, $\{o_B, o_C, o_D\}$, $\{o_E, o_F\}$
- Landmarks after application of o_B ?

Incremental Computation (Example)



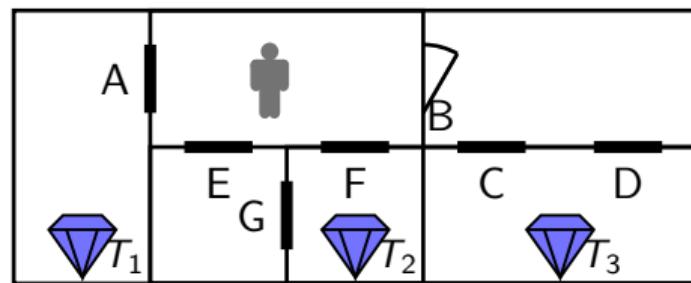
- Discovered landmarks in this state
 - $\{o_A\}$, $\{o_B, o_C, o_D\}$, $\{o_E, o_F\}$
- Landmarks after application of o_B
 - $\{o_A\}$ remains landmark

Incremental Computation (Example)



- Discovered landmarks in this state
 - $\{o_A\}$, $\{o_B, o_C, o_D\}$, $\{o_E, o_F\}$
- Landmarks after application of o_B
 - $\{o_A\}$, $\cancel{\{o_B, o_C, o_D\}}$, $\{o_E, o_F\}$ remain landmarks

Incremental Computation (Example)



- Discovered landmarks in this state
 - $\{o_A\}$, $\{o_B, o_C, o_D\}$, $\{o_E, o_F\}$
- Landmarks after application of o_B
 - $\{o_A\}$, ~~o_B, o_C, o_D~~ , $\{o_E, o_F\}$ remain landmarks
 - Newly discovered landmark: $\{o_C, o_D\}$

Incremental Computation

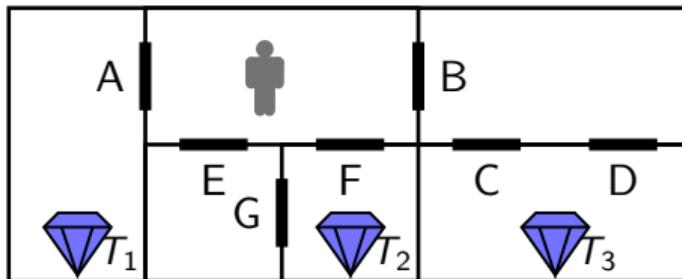
- Successor generated by applying operator o
 - All landmarks not containing o are landmarks in successor
 - Discharge landmarks containing o
 - Return landmark's costs to *remaining cost*
 - Can change h^{\max} value
 - Start LM-cut algorithm with set of known landmarks

Theorem

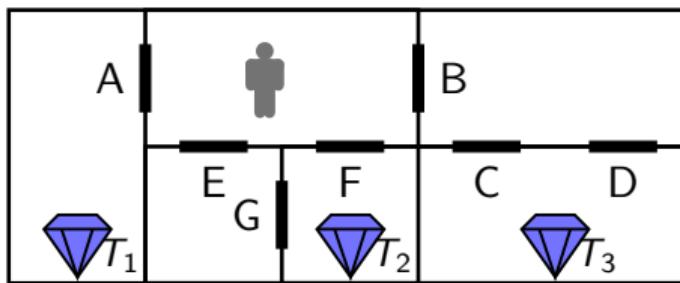
The LM-cut algorithm discovers a new landmark if the h^{\max} cost of the successor increases.

Incremental Computation (Example)

- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$

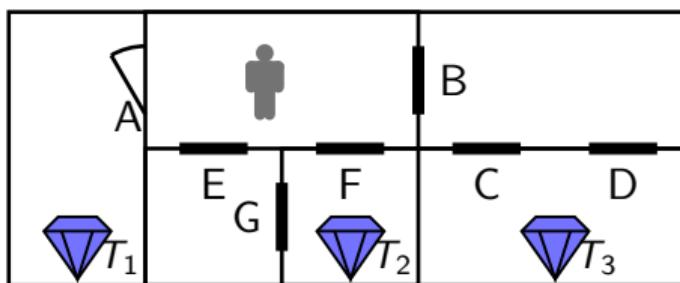


Incremental Computation (Example)



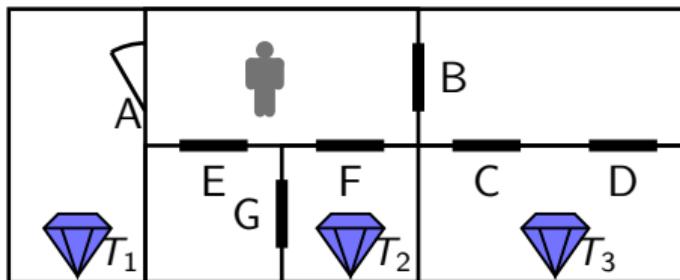
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
- Open door B
- Open door E
- Open door F

Incremental Computation (Example)



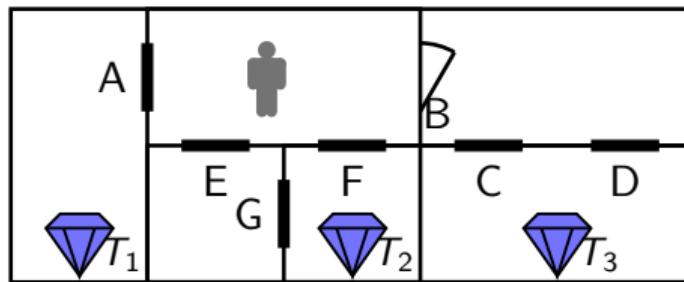
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door F
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$

Incremental Computation (Example)



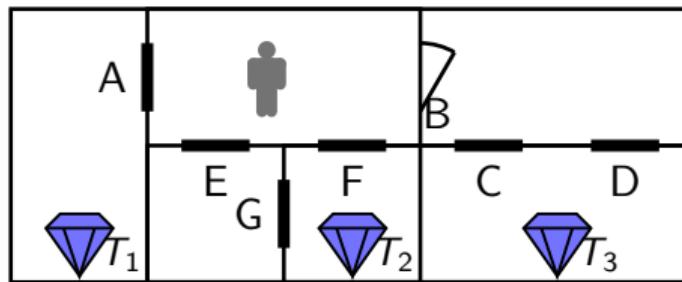
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - ~~$\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$~~
- Open door B
- Open door E
- Open door F

Incremental Computation (Example)



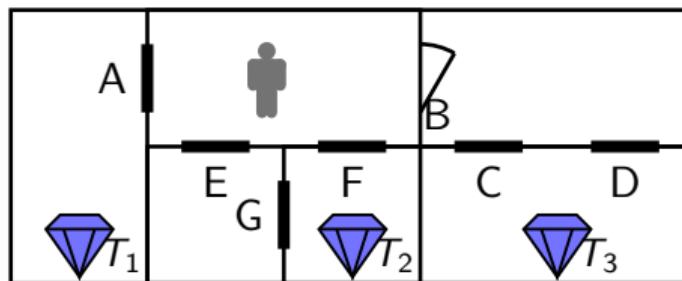
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - ~~$\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$~~
- Open door B
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door F
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$

Incremental Computation (Example)



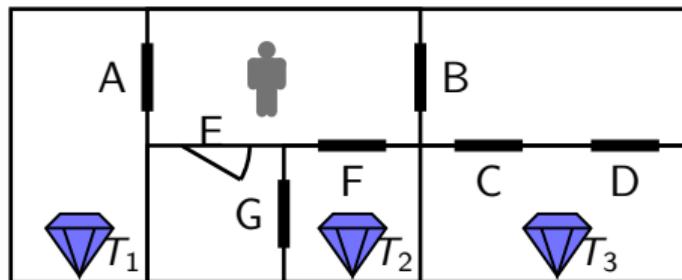
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\cancel{\{o_A\}}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \cancel{\{o_B, o_C, o_D\}}, \{o_E, o_F\}$
- Open door E
- Open door F

Incremental Computation (Example)



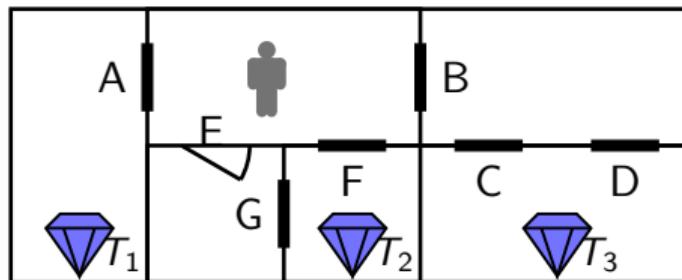
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\cancel{\{o_A\}}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \cancel{\{o_B, o_C, o_D\}}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
- Open door F

Incremental Computation (Example)



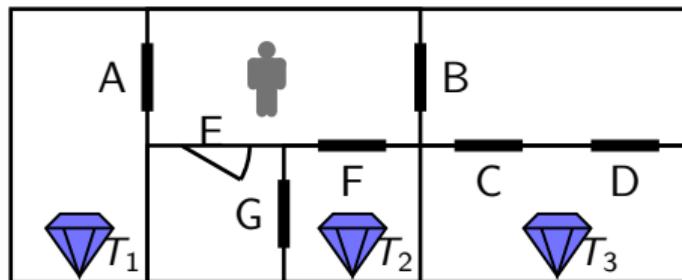
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - ~~$\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$~~
- Open door B
 - $\{o_A\}, \del{\{o_B, o_C, o_D\}}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door F

Incremental Computation (Example)



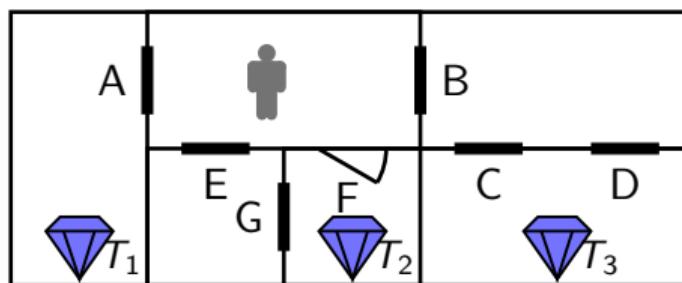
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\cancel{\{o_A\}}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \cancel{\{o_B, o_C, o_D\}}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \cancel{\{o_E, o_F\}}$
- Open door F

Incremental Computation (Example)



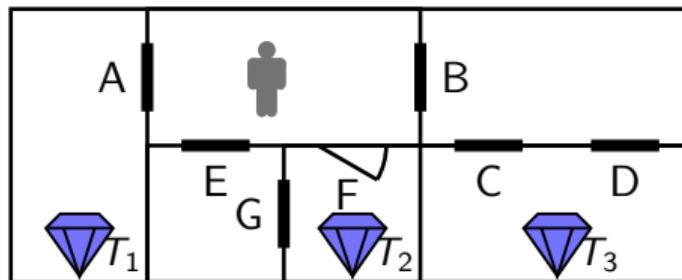
- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - ~~$\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$~~
- Open door B
 - $\{o_A\}, \cancel{\{o_B, o_C, o_D\}}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \cancel{\{o_E, o_F\}}, \{o_F, o_G\}$
- Open door F

Incremental Computation (Example)



- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\cancel{\{o_A\}}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \cancel{\{o_B, o_C, o_D\}}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \cancel{\{o_E, o_F\}}, \{o_F, o_G\}$
- Open door F
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$

Incremental Computation (Example)



- Landmarks in this state
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door A
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$
- Open door B
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}, \{o_C, o_D\}$
- Open door E
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}, \{o_F, o_G\}$
- Open door F
 - $\{o_A\}, \{o_B, o_C, o_D\}, \{o_E, o_F\}$

Content

1 Theory

2 Practice

- Basic Results
- Saving Memory

3 Conclusion

Benchmarks

- Evaluation
 - 1396 tasks in 44 domains
 - Time limit: 30 min
 - Memory limit: 2 GB
- Measured
 - Coverage (number of solved tasks)
 - Search time
 - Failure reason (timeout or out of memory)

Basic Results

- First idea ($h^{\text{LM-cut}}$)
 - Regular A* search
 - Store landmarks for all search nodes
 - (Side note: This makes the heuristic consistent)
- Compare with A*/ $h^{\text{LM-cut}}$
 - Speed-ups by up to an order of magnitude
 - More tasks running out of memory
 - Increased from 31 to 526

Coverage

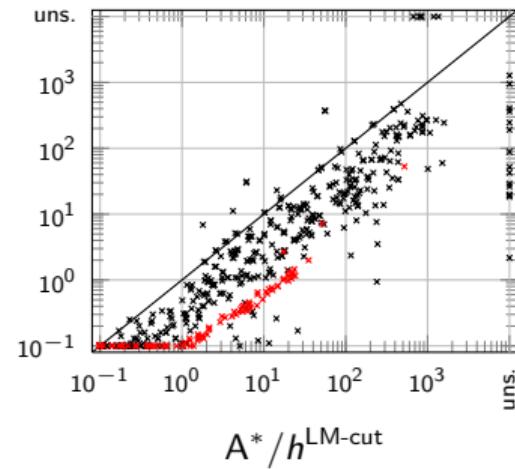
$h^{\text{LM-cut}}$	$h^{\text{iLM-cut}}$
757	762

Removing Landmarks

- Stored landmarks take up too much memory
 - Information can be removed at any time
 - Recompute missing values non-incrementally
- Easy fix ($h_{\text{frontier}}^{\text{iLM-cut}}$)
 - Remove information for closed nodes
 - Only needed again if the node is reopened

Results

- Runtime reduction over baseline
 - 77% (geometric mean)
 - 93% (miconic \times)
- Coverage increased by another 4 tasks



Coverage

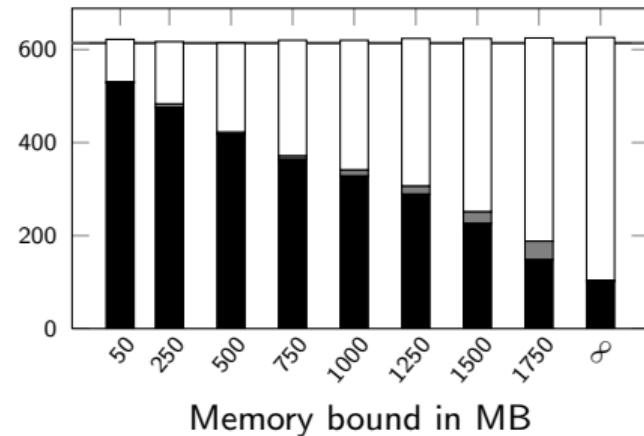
$h^{\text{LM-cut}}$	$h^{\text{iLM-cut}}$	$h^{\text{iLM-cut}}_{\text{frontier}}$
757	762	766

Fixed Memory Bounds

- Why stop because of exhausted memory at all?
 - Can always free up memory
 - Remove stored landmarks
- Fixed memory bound ($h_{\text{bound}}^{\text{iLM-cut}}$)
 - Keep track of used memory
 - Remove half of the stored landmarks when hitting the bound
- Dynamic memory bound
 - Technical problems
 - Measure memory pressure and memory requirements accurately
 - Results estimated from fix bounds

Results

- Improvements even for small bounds (50 MB)
- Increasing limit
 - Less timeouts (■)
 - Memory exhausted more often (□)
- Sweet spot for 500 MB



Coverage

$h^{\text{LM-cut}}$	$h^{\text{iLM-cut}}$	$h_{\text{frontier}}^{\text{iLM-cut}}$	$h_{500 \text{ MB}}^{\text{iLM-cut}}$	$h_{\text{dynamic}}^{\text{iLM-cut}}$
757	762	766	778	786



Local Incremental Computation

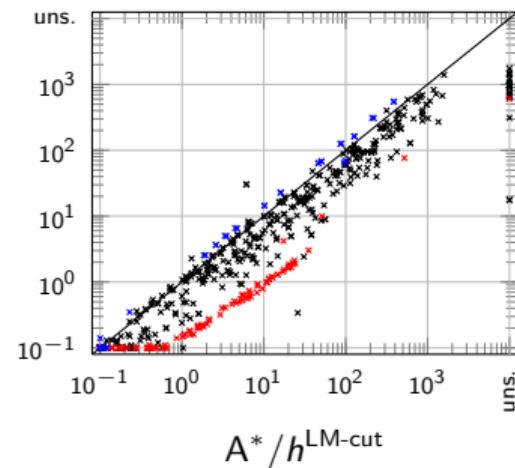
- More generated nodes than expanded nodes
 - Factor 8 in the geometric mean
 - Save work during node generation
 - Additional work during node expansion amortized
- Local incremental computation ($h_{\text{local}}^{\text{iLM-cut}}$)
 - Recompute landmarks for parent node
 - Incremental computation for child nodes
 - Minimal memory overhead

LM-cut Computations

	$h^{\text{LM-cut}}$	$h_{\text{local}}^{\text{iLM-cut}}$
Node generation	Non-incremental	Incremental
Node expansion	0	Non-incremental

Results

- Runtime changes
 - 49% (geometric mean)
 - 89% (miconic \times)
 - +40% (openstacks \times)
- Bad performance of openstacks
 - $h^{\text{LM-cut}}(s) = 1$ for most states s
 - Many 0-cost operators



Coverage

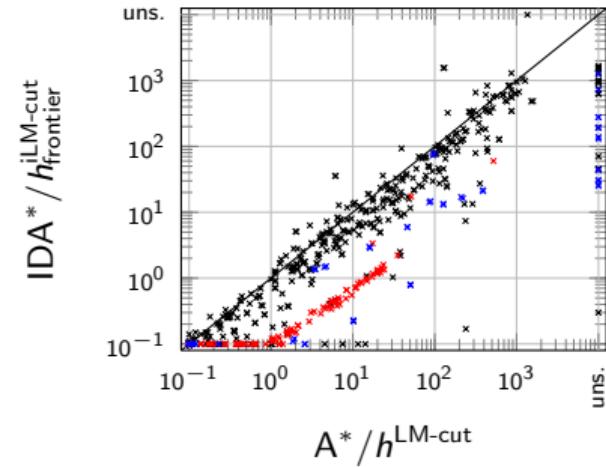
$h^{\text{LM-cut}}$	$h^{\text{iLM-cut}}$	$h_{\text{frontier}}^{\text{iLM-cut}}$	$h_{500 \text{ MB}}^{\text{iLM-cut}}$	$h_{\text{dynamic}}^{\text{iLM-cut}}$	$h_{\text{local}}^{\text{iLM-cut}}$
757	762	766	778	786	783

IDA*

- IDA* Search
 - Classical solution to memory issues with A*
- Here: Sufficient memory for all search nodes
 - Use unlimited transposition table
 - Perfect duplicate detection
 - Store heuristic values for inner nodes
- Remaining advantage over A*
 - Depth-first expansion order
 - Only store landmarks for current branch

Results

- Best Coverage result
- Skewed by openstacks (\times)
 - Better tie-breaking with depth-first order
 - Deeper nodes are preferred
 - Explains 14 tasks



Coverage

A^*						IDA^*
$h^{LM\text{-cut}}$	$h^{iLM\text{-cut}}$	$h_{frontier}^{iLM\text{-cut}}$	$h_{500\text{ MB}}^{iLM\text{-cut}}$	$h_{dynamic}^{iLM\text{-cut}}$	$h_{local}^{iLM\text{-cut}}$	$h_{frontier}^{iLM\text{-cut}}$
757	762	766	778	786	783	790

Content

1 Theory

2 Practice

3 Conclusion

Conclusion

- Incremental computation of LM-cut for STRIPS planning
 - Much faster
 - Higher memory requirements
- Dealing with memory limitations
 - Local computation
 - Fixed bounds
 - IDA*
- Not limited to LM-cut
- Necessary conditions
 - Incremental computation is faster
 - Missing information can be computed non-incrementally



Thank you for your attention!
Any questions?