

The More the Merrier?!

Evaluating the Effect of Landmark Extraction Algorithms on Landmark-Based Goal Recognition

Kin Max Piamolini Gusmão
Ramon Fraga Pereira
Felipe Meneguzzi

Pontifical Catholic University of Rio Grande do Sul - Brazil

February 8, 2020

Summary

- **Motivation**
- **Goal Recognition and Landmark-Based Goal Recognition**
- **Experimentation Methodology**
 - Heuristics and Algorithms;
 - Dataset;
 - Evaluation Metrics
- **Results**
 - Missing and Full Observations
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- **Conclusions**

Motivation

- **Explore** different landmark extraction algorithms with landmark-based heuristics for goal recognition;
- **Evaluate** whether more landmarks lead to a more precise recognition;
- **Inform** future fine-tuning of algorithms to enhance recognition precision;

Goal Recognition and Landmark-Based Goal Recognition

- **Goal Recognition:** recognize agent's goal based on it's interactions with the environment;
- **Landmarks:** necessary facts or actions that must be present in any solution plan;
- **Landmark-Based Goal Recognition:** goal recognition techniques that leverage on landmarks.

Experimentation Methodology

- **Heuristics and Algorithms**
- **Dataset**
- **Evaluation Metrics**

Experimentation Methodology: Heuristics and Algorithms

- 2 landmark-based heuristics for goal recognition¹:
 - Goal Completion Heuristic (h_{gc});
 - Landmark Uniqueness Heuristic (h_{uniq}).
- 5 landmark extraction algorithms:
 - *Exhaust*;
 - h^{m2} ;
 - *RHW*³;
 - *Zhu & Givan*⁴;
 - *Hoffmann et al.*⁵
- 2 threshold values: 0% and 10%.

¹ Pereira et al., *Landmark-Based Heuristics for Goal Recognition*. AAAI, 2017.

² Keyder et al., *Sound and complete landmarks for and/or graphs*. ECAI, 2010.

³ Richter et al., *Landmarks revisited*. AAAI 2008.

⁴ Zhu L. e Givan R., *Landmark extraction via planning graph propagation*, 2003.

⁵ Hoffmann et al., *Ordered landmarks in planning*. JAIR, 2004.

Experimentation Methodology: Dataset

- Dataset with goal and plan recognition problems⁶;
- Problems from 15 classical planning domains;
- 6313 problems with missing and full observations with 5 observability levels (10%, 30%, 50%, 70% and 100%);
- 2850 problems with missing, noisy and full observations with 4 observability levels (25%, 50%, 75% and 100%).

⁶ *Pereira F. R. e Meneguzzi F., Goal and plan recognition datasets using classical planning domains. 2017.*

Experimentation Methodology: Evaluation Metrics

- Percentage of extracted landmarks;
- Accuracy (%);
- Spread in \mathcal{G} ;
- Accuracy/Spread in \mathcal{G} ratio;
- Recognition time (s).

Results

- **Missing and Full Observations**
- **Missing, Noisy and Full Observations**

Results: Missing and Full Observations

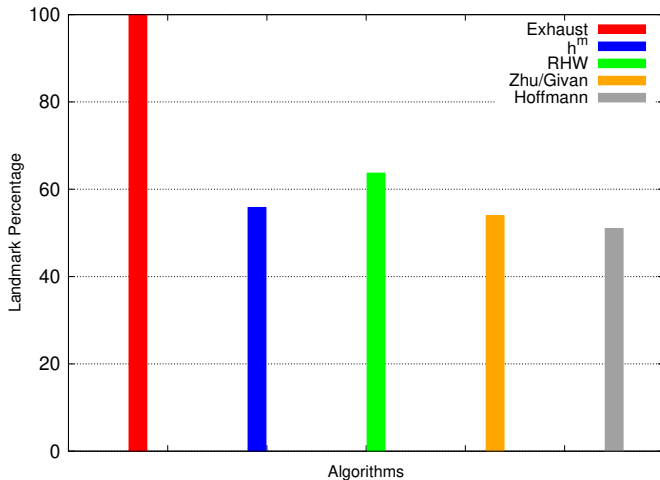


Figure: Percentage of extracted landmarks.

Results: Missing and Full Observations

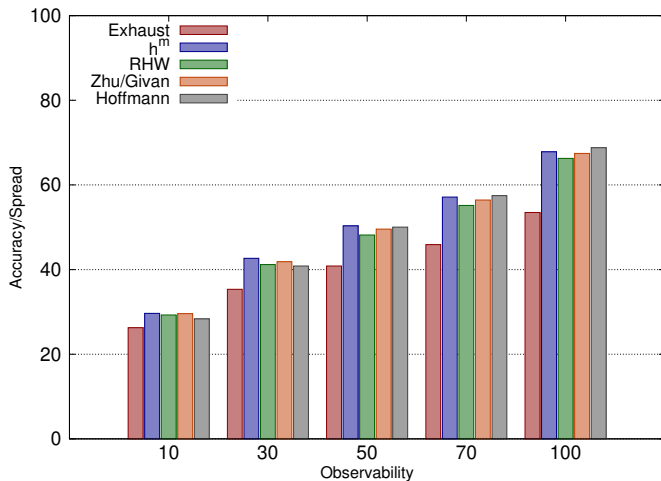


Figure: Accuracy/Spread in \mathcal{G} ratio for h_{gc} .

Results: Missing and Full Observations

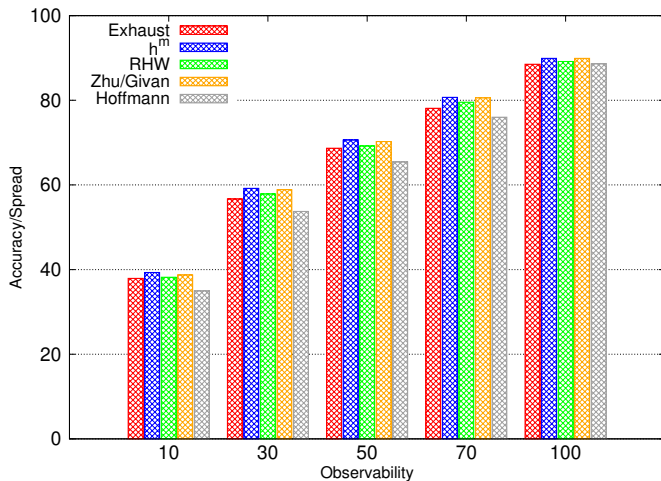


Figure: Accuracy/Spread in \mathcal{G} ratio for h_{uniq} .

Results: Missing and Full Observations

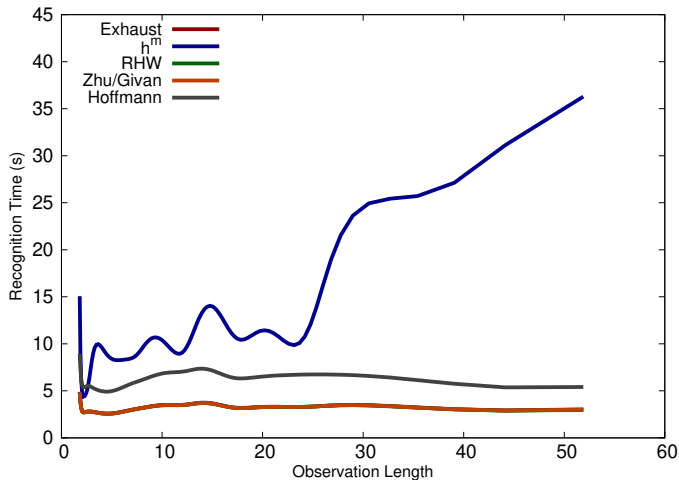


Figure: Recognition time for h_{gc} .

Results: Missing and Full Observations

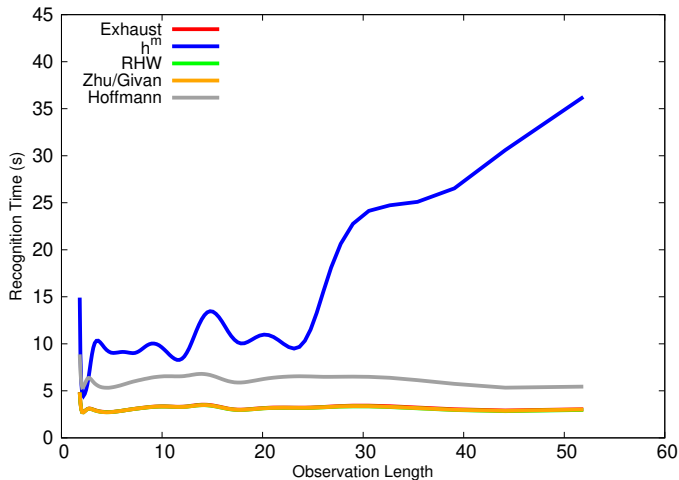


Figure: Recognition time for h_{uniq} .

Results: Missing, Noisy and Full Observations

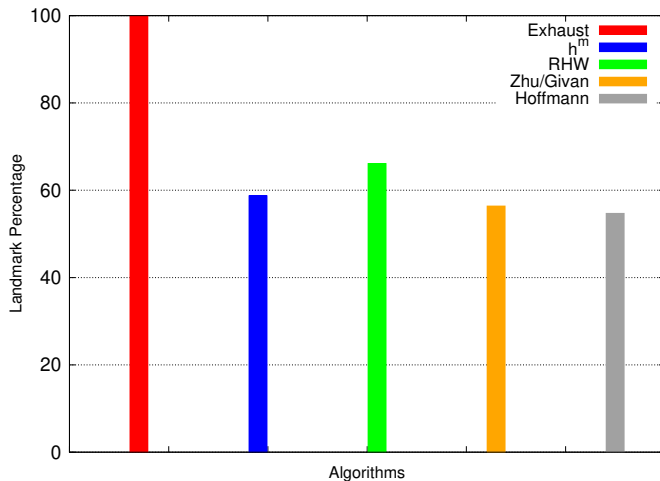


Figure: Percentage of extracted landmarks.

Results: Missing, Noisy and Full Observations

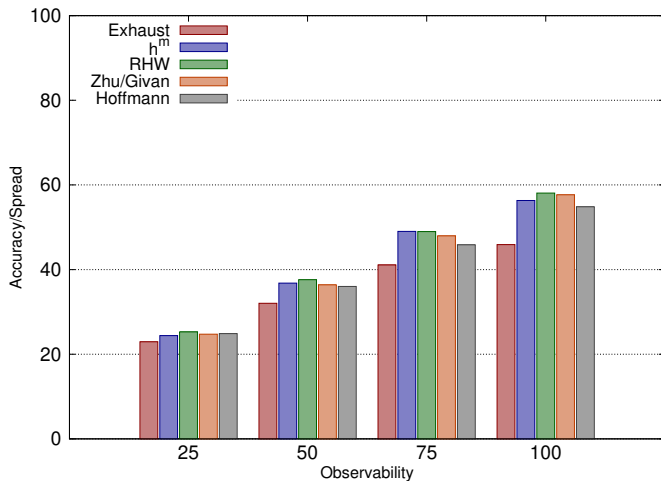


Figure: Accuracy/Spread in \mathcal{G} ratio for h_{gc} .

Results: Missing, Noisy and Full Observations

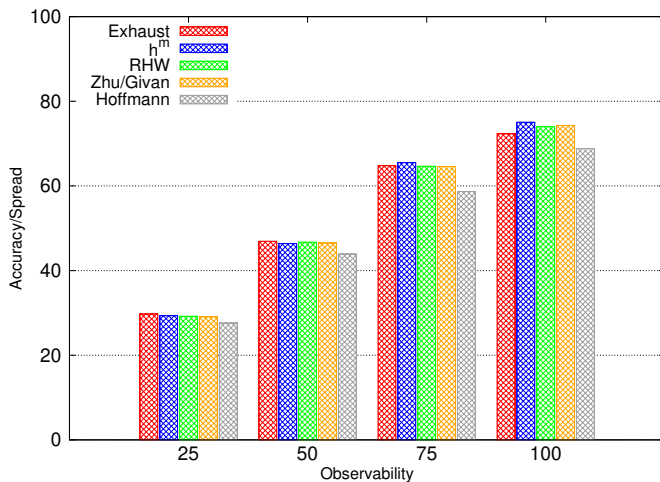


Figure: Accuracy/Spread in \mathcal{G} ratio for h_{uniq} .

Results: Missing, Noisy and Full Observations

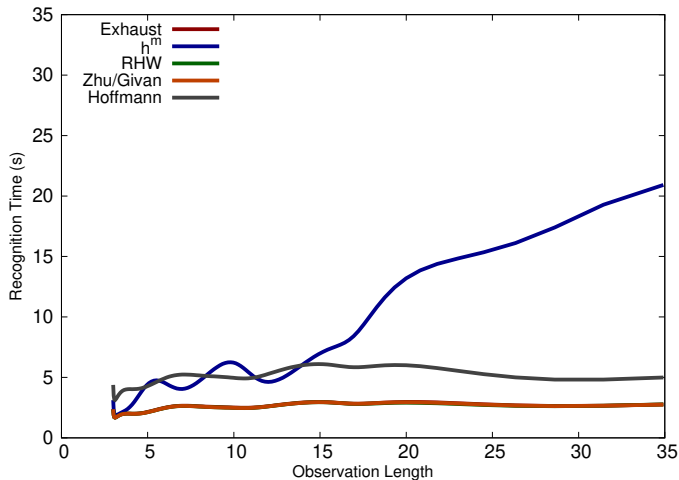


Figure: Recognition time for h_{gc} .

Results: Missing, Noisy and Full Observations

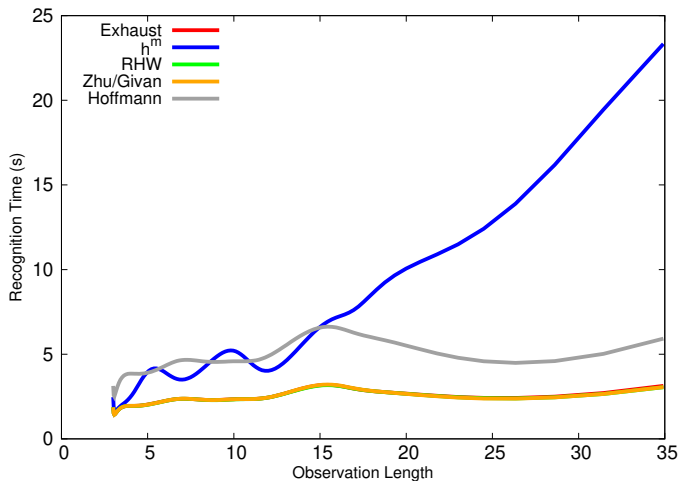


Figure: Recognition time for h_{uniq} .

Conclusions

- Quantity is not more important than quality;
- Algorithms with higher extraction capability obtained better performance with h_{uniq} ;
- Quantity matters more when dealing with noisy observations.

Thank You!

Questions?