

An Empirical Study of Perfect Potential Heuristics

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Motivation

Context:

- ▶ Optimal classical planning

Goals:

- ▶ Learn more about the topology of different domains
 - ▶ Study the characteristics of h^*
- ▶ Understand the limitations of potential heuristics

Potential Heuristics

- ▶ States are represented as sets of facts
- ▶ A feature f is a set of facts and it has size $|f|$
- ▶ A feature f is true in a state s if $f \subseteq s$

Definition (Potential Heuristic)

A weight function w associates a set of features \mathcal{F} with weights. It induces a potential heuristic

$$h_w^{\text{pot}}(s) = \sum_{f \in \mathcal{F}} w(f)[f \subseteq s].$$

The dimension of h_w^{pot} is the size of its largest feature f .

- ▶ Higher dimension = more complex interactions between facts

Potential Heuristics

What if state s is unsolvable? Then $h_w^{\text{pot}}(s)$ should be ∞ .

$$h_{w_1, w_2}(s) = \begin{cases} \infty & \text{if } h_{w_2}^{\text{pot}}(s) > 0 \\ h_{w_1}^{\text{pot}}(s) & \text{otherwise.} \end{cases}$$

h_{w_1, w_2} is a **perfect potential heuristic** if

- ▶ $h_{w_1}^{\text{pot}}(s)$ is perfect for all solvable states s
- ▶ $h_{w_2}^{\text{pot}}$ captures all unsolvable states correctly

Optimal Correlation Complexity

Definition (Optimal Correlation Complexity of a task)

The **optimal correlation complexity of a planning task** Π is the minimum dimension of a perfect potential heuristic for Π .

This gives us some insight about the complexity of the interactions between facts of the task.

Optimal Correlation Complexity

We study optimal correlation complexity of IPC domains **empirically**

Computing optimal correlation complexity is **hard**

We need...

- ▶ ... h^* for all (reachable) state space
- ▶ ...to find a **good set of features**
- ▶ ...to efficiently find a **weight function**

Computing a Perfect Potential Heuristic

Exact methods for finite and infinite values:

- ▶ Linear programs over the entire state space
- ▶ Initial set of candidate features \mathcal{F} ; augment it as needed
- ▶ Potential heuristics found has **optimal dimension**

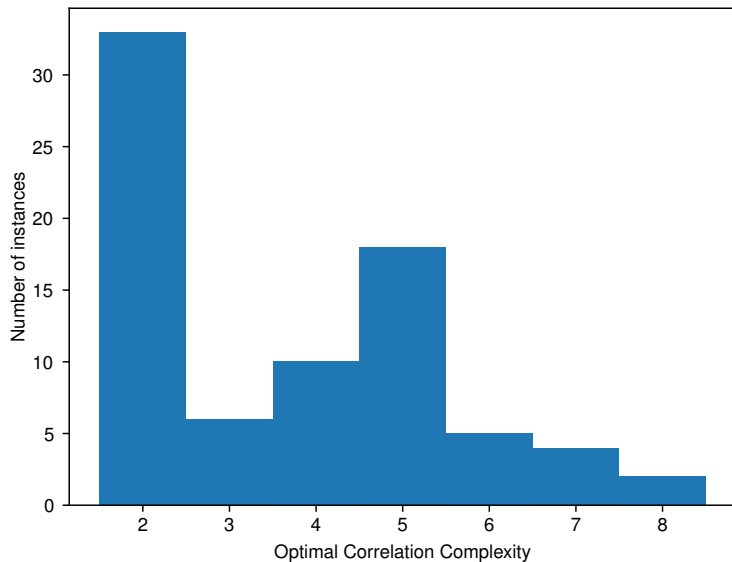
Experiments

Using Fast Downward and IPC domains

- ▶ 30 minutes and 3.5 GB per task
- ▶ 301 tasks over 38 domains where we can compute the perfect heuristic for the entire state space
 - ▶ Sample size is considerably small

Results

Histogram of optimal correlation complexities



Results

Lower bounds for the optimal correlation complexity per domain

| Domain | Lower Bound |
|-------------------------|-------------|
| gripper | 7 |
| hiking-opt14 | 6 |
| miconic | 7 |
| movie | 2 |
| nomystery-opt11 | 5 |
| organic-synthesis-opt18 | 6 |
| psr-small | 8 |
| rovers | 8 |
| scanalyzer-08 | 5 |
| scanalyzer-opt11 | 5 |
| storage | 5 |
| tpp | 5 |
| transport-opt08 | 6 |
| vistall-opt11 | 8 |
| zenotravel | 4 |

Results

Lower bounds for the optimal correlation complexity per domain

| Domain | Lower Bound |
|-------------------------|-------------|
| gripper | 7→5 |
| hiking-opt14 | 6 |
| miconic | 7→6 |
| movie | 2 |
| nomystery-opt11 | 5→4 |
| organic-synthesis-opt18 | 6→1 |
| psr-small | 8→4 |
| rovers | 8→5 |
| scanalyzer-08 | 5 |
| scanalyzer-opt11 | 5 |
| storage | 5→4 |
| tpp | 5→4 |
| transport-opt08 | 6→4 |
| vistall-opt11 | 8→7 |
| zenotravel | 4 |

Significant lower complexity considering **only reachable states**

Results

Lower bounds for the optimal correlation complexity per domain

| Domain | Lower Bound |
|-------------------------|-------------|
| gripper | 7 → 5 |
| hiking-opt14 | 6 |
| miconic | 7 → 6 |
| movie | 2 |
| nomystery-opt11 | 5 → 4 |
| organic-synthesis-opt18 | 6 → 1 |
| psr-small | 8 → 4 |
| rovers | 8 → 5 |
| scanalyzer-08 | 5 |
| scanalyzer-opt11 | 5 |
| storage | 5 → 4 |
| tpp | 5 → 4 |
| transport-opt08 | 6 → 4 |
| vistall-opt11 | 8 → 7 |
| zenotravel | 4 |

Significant lower complexity considering **only reachable states**

Also **to detect unsolvable states**

- ▶ Maximum dimension needed to detect unsolvable states was 3

Computing a (Quasi-)Perfect Potential Heuristic

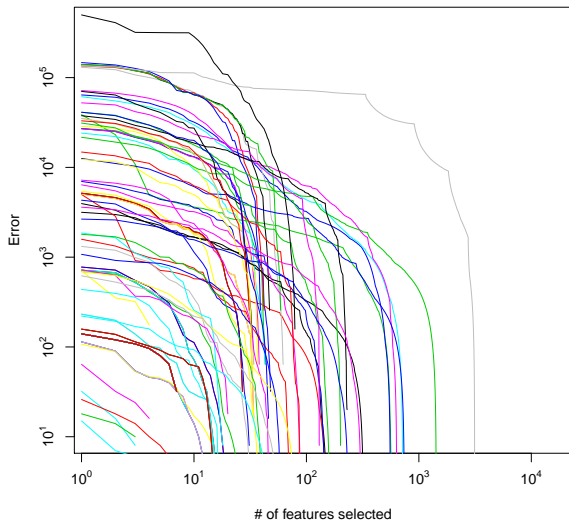
How close can we get with features of limited size?

Minimal Error for Finite Values:

- ▶ Starts with an “empty” potential heuristic
- ▶ Iteratively selects feature minimizing the **error** of the heuristic
- ▶ Once no feature up to size n reduces the error, add features of size $n + 1$ to feature pool

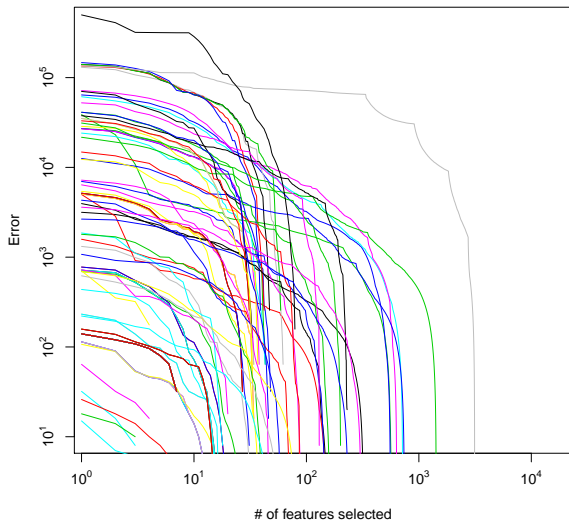
Results

Remaining error per feature added. (One line per instance.)



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Remaining error per feature added. (One line per instance.)



Only a few features of a given size are very important

Conclusion

Recap

- ▶ We investigated the “shape” of h^* in several domains
- ▶ **Bad news:** Even easy domains need perfect potential heuristics with high dimension
- ▶ **Good news:** Only a small number of large features already reduce the heuristic error significantly

Open Question

- ▶ How to automatically identify an informative subset of high-dimensional features?
 - ▶ We could find good weights using an FPT algorithm

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 - ▶ We could find good weights using an FPT algorithm