

Marvin Abisrror Zarate

**On Selecting Of
Heuristics Functions For Domain Independent
Planning.**

Brasil

2016, v-1.9.5

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Dissertação apresentada á Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Ciência da Computação, para a obtenção do título de *Magister Scientiae*.

Universidade de Viçosa – UFV

Centro de Ciencias Exactas e Tecnologicas (CCE)

Programa de Pós-Graduação

Supervisor: Levi Henrique Santana de Lelis

Co-supervisor: Santiago Franco

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This dissertation is dedicated to my Mother.

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*“Não vos amoldeis às estruturas deste mundo,
mas transformai-vos pela renovação da mente,
a fim de distinguir qual é a vontade de Deus:
o que é bom, o que Lhe é agradável, o que é perfeito.
(Bíblia Sagrada, Romanos 12, 2)*

Abstract

In this dissertation we present greedy methods based on the theory of supermodular optimization for selecting a subset of heuristics functions from a large set of heuristics with the objective of reducing the running time of search algorithms.

Holte et al. ([HOLTE et al., 2006](#)) showed that search can be faster if several smaller pattern databases are used instead of one large pattern database. We introduce greedy methods for selecting a subset of the most promising heuristics from a large set of heuristic functions to guide the A* search algorithm. If the heuristics are consistent, our method selects a subset which is guaranteed to be near optimal with respect to the resulting A* search tree size. In addition to being consistent, if all heuristics have the same evaluation time, our subset is guaranteed to be near optimal with respect to the resulting A* running time. We implemented our method in Fast Downward and showed empirically that it produces heuristics which outperform the state of the art heuristics in the International Planning Competition benchmarks.

Key-words: Heuristics. selection. Submodularity. A*

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Chapter I

Preparation of the research

1 About the Problem

State space search algorithms have been used to solve important real-world problems, such as: Robotics, domain-independent planning, chemical compounds discovery, bin packing, sequence alignment, automating layouts of sewers, and network routing, amount others. In this dissertation we study methods for selecting a subset of heuristic functions while minimizing the search tree size and the running time of search algorithm.

We are interested in selection of heuristics from a large set of heuristics because (HOLTE et al., 2006) showed that search can be faster if several smaller pattern databases are used instead of one large pattern database. In fact, we believe that each heuristic can give us valuable information about the solution of the problem. For example, one heuristic could be helpful in some area of the search tree and other heuristics do not. Then, instead of using one heuristic to find the solution, would be the best to use the most promising heuristics from a large set of heuristics with the objective to find the solution of the problem.

1.1 Problem Formulation

We use search algorithm to solve problems or find the solution knowing the sequence of actions that goes from the start state to the goal state. To solve the problem is required the use of search algorithms. Two well know search algorithms are Depth First Search (DFS) and Breadth First Search (BFS). DFS looks for the solution traversing the search space exploring the nodes in each branch before backtracking up to find the solution. BFS looks for the solution exploring the nodes in the first level, before moving to the next level of nodes. Both search algorithms have the characteristic that generate a larger search space during the search. The search space that these algorithms generate are called Brute force search tree (BFST).

There are other type of algorithms called heuristic search algorithms, which are algorithms that requires the use of heuristics. The heuristic is the estimation of the distance for one node in the search tree to get the goal state. The heuristic search algorithms generate smaller search tree in comparison to the BFST, because the heuristic guides the search to more promising parts of the state space or near to the objective. Also, by reducing the search tree size, the heuristic function guidance might also reduce the overall running time of the algorithm.

There are different approaches to create heuristics, such as: Pattern Databases (PDBs) (HASLUM et al., 2007), and Genetic Algorithm (EDELKAMP, 2007). We call these systems Heuristic Generators. And one of the approaches that have showed most successful results in heuristic generation is the PDBs. The way how PDBs works is the following: The search space of the problem is abstracted, obtaining the remaining problem “pattern”, which is small enough to be solved optimally by blind exhaustive search. The results are stored in a table which are the heuristic function for the original search space.

There exists many ways to take advantage of a large set of heuristic functions. For example: (HOLTE et al., 2006) showed that search can be faster if several smaller PDBs are used instead of one large pattern database. In addition (DOMSHLAK; KARPAS; MARKOVITCH, 2010) and (TOLPIN et al., 2013) showed that evaluating the heuristic lazily, only when they are essential to a decision to be made in the search process is worthy in comparison to take the maximum of the set of heuristics. Then, using all the heuristics do not guarantee to solve the major number of problems in a limit time.

1.2 Aim and Objectives

1.2.1 Aim

The objective of this dissertation is to develop meta-reasoning approaches for selecting heuristics functions from a large set of heuristics with the goal of reducing the running time of the search algorithms employing these functions.

1.2.2 Objectives

- Demonstrate that the problem of finding the optimal subset of heuristics ζ^* of size N for a given problem task is supermodular respect the size of the search tree.
- Develop an approach to find a subset of heuristics from a large pool of heuristics ζ that optimize the number of nodes expanded in the process of search.
- Develop an approach for selecting a subset of heuristics functions based on the size of the search tree and running time.
- Compare SS algorithm for predicting the search tree size of Iterative-Deepening A* (IDA*).
- Use SS as our utility function.

1.3 Scope, Limitations, and Delimitations

We implemented our method in Fast Downward ([HELMERT, 2006](#)) and we test our methods on the 2011 International Planning Competition (IPC) domain instances.

1.4 Justification

Domain-independent planning has obtained interesting results using heuristic search approach in problem solving. Using a proper heuristic to find the solution of the problem will represent in a reduction in the running time.

We use heuristic generators in order to create a large set of heuristics and obtain the most promising heuristics to solve problems.

We believe that our idea of selecting heuristics using the size of the search tree and the running time will help us to solve more problems.

1.5 Hypothesis

We test the following hypothesis:

- **H1:** Test that the greedy algorithms are effective for selecting a subset of heuristics to guide search.
- **H2:** Test that SS is an effective prediction method to our meta-reasoning.

1.6 Contribution of the Dissertation

The main contributions of this Dissertation are:

- Provide a meta-reasoning approach for selecting heuristic functions while minimizing the number of nodes expanded by the selecting heuristics.
- Provide a meta-reasoning approach for selecting heuristic functions while minimizing the running time of the search.

1.7 Organization of the Dissertation

The Dissertation is organized as follows:

1. In Chapter I, the background of the dissertation is provided. Which also includes our motivation and the scope definition.
2. In Chapter II, we review the state of the art in selection of heuristic functions.
3. In Chapter III, we introduce Random Greedy Heuristic Selection (RGHS) and the prediction methods.
4. In Chapter IV, we explain the results obtained by using RGHS and compare it with other planner systems.
5. We conclude in Chapter V.

In the next chapter, the domain 8—tile—puzzle is used to understand the concepts that will be helpful for the other chapters.

Chapter II

Literature Review

2 Background

2.1 Similar Selection Systems

The system most similar to ours is RIDA* (BARLEY; FRANCO; RIDDLE, 2014). RIDA* also selects a subset from a pool of heuristics to guide the A^* search. In RIDA* this is done by starting with an empty subset and trying all combination of size one before trying the combination of size two and so on. RIDA* stops after evaluating a fixed number of subsets. While RIDA* is able to evaluate a set of heuristics with tens of elements, our meta-reasoning is able to evaluate a set of heuristics with thousands of elements.

An optimization procedure which is similar to ours is presented by (RAYNER; STURTEVANT; BOWLING, 2013). The optimization procedure done by Rayner et al. makes near-optimal subset selection only when the objective function is monotone. The problem is that if one sequentially add heuristics to ζ' , the cost of using another heuristic h will not payoff for the extra pruning that h will allow A^* to make. As a result, A^* 's running time is a non-monotone objective function. Rayner et al. limited their experiments to an objective function that only maximize the sum of heuristic values in the state space.

We propose an optimization procedure that guarantees for both monotone and non-monotone objective functions. Furthermore, while Rayner et al.'s optimization procedure is not directly applicable to domain-independent planning. We show how their method can be applied to domain independent planning by having Stratified Sampling to estimate the sum of heuristic values in the state space.

Our meta-reasoning requires a prediction of the number of nodes expanded by A^* using any given subset. The prediction system we choose is Stratified Sampling (SS system (LELIS; ZILLES; HOLTE, 2013)). Even though, SS give us good predictions for Iterative Deepening- A^* , it does not give us good predictions for A^* because it does not count duplicate nodes. However, as part of our proposal, we present SS for predicting the size of the search tree.

2.2 Problem definition

A SAS^+ planning task (BÄCKSTRÖM; NEBEL, 1995) is a 4 tuple $\nabla = \{V, O, I, G\}$. V is a set of *state variables*. Each variable $v \in V$ is associated with a finite domain of

possible D_v . A state is an assignment of a value to every $v \in V$. The set of possible states, denoted V , is therefore $D_{v_1} \times \dots \times D_{v_2}$. O is a set of operators, where each operator $o \in O$ is triple $\{pre_o, post_o, cost_o\}$ specifying the preconditions, postconditions (effects), and non-negative cost of o . pre_o and $post_o$ are assignments of values to subsets of variables, V_{pre_o} and V_{post_o} , respectively. Operator o is applicable to state s if s and pre_o agree on the assignment of values to variables in V_{pre_o} . The effect of o , when applied to s , is to set the variables in V_{post_o} to the values specified in $post_o$ and to set all other variables to the value they have in s . G is the goal condition, an assignment of values to a subset of variables, V_G . A state is a goal state if it and G agree on the assignment of values to the variable in V_G . I is the initial state, and the planning task, ∇ , is to find an optimal (least-cost) sequence of operators leading from I to a goal state. We denote the optimal solution cost of ∇ as C^* .

The state space problem illustrated in the figure 1 is a game that contains square tiles numbered in random order and one tile missing. The particular game showed is the 8-tile-puzzle, which contains 8 tiles numbered from 1 to 8 and one tile empty. The objective of this game is to place the tiles in order by doing moves of the empty tile. For this case, the goal would be reached placing the tiles 1, 2 and 3 in the first row, and 4, 5 and 6 in the following row, and 7, 8 and empty tile in the last row.

(SCHAEFFER; HERIK, 2002) Any tile horizontally or vertically adjacent to the blank can be slid into that position. The problem is to rearrange the tiles from some random initial configuration into a particular desired goal configuration. The 8-puzzle contains 181,440 reachable states, the 15-puzzle contains about 10^{13} reachable states, and the 24-puzzle contains almost 10^{25} states.

Initial			Goal		
4	1	2	1	2	3
8		3	4	5	6
5	7	6	7	8	

Figure 1 – The left tile-puzzle is the initial distribution of tiles and the right tile-puzzle is the goal distribution of tiles. Each one represent a state.

Instead of using an algorithm of Brute force search that will analyze all the possible solutions. We can obtain heuristics from the problem of the slide tile puzzle that will help us to solve the problem.

2.3 Heuristics

Exists many State-space algorithms, and one of the most important and well know is A* ([HART P. E.; NILSSON; RAPHAEL, 1968](#)). It is important, because it helps to resolve many AI applications. A* uses the $f(s) = g(s) + h(s)$ cost function to guide its search. Where, $g(s)$ is the cost of the path from the start state s , and $h(s)$ is the estimated cost to go from s to the goal; $h(.)$ is known as the heuristic function. The heuristic is the mathematical concept that represent to the estimate distance from the node s to the nearest goal state.

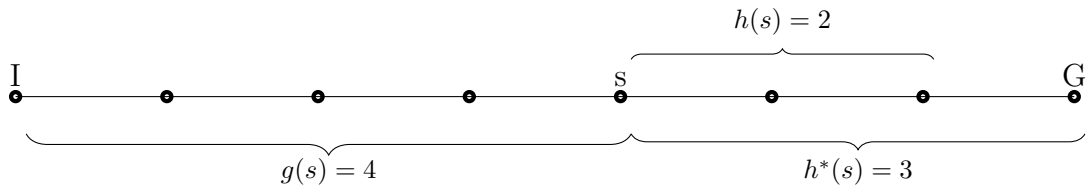


Figure 2 – Heuristic Search: I : Initial State, s : Some Sate, G : Goal State

In the figure 2 the optimal distance from the Initial State I to the state s is 4 and represented by $g(s)$. The $h^*(s) = 3$ represent the optimal distance from s to the Goal State G . And the $h(s) = 2$ is the estimation distance from s to G .

A heuristic function $h(s)$ estimates the cost of a solution path from s to a goal state. A heuristic is admissible if $h(s) \leq h^*(s)$ for all $s \in V$, where $h^*(s)$ is the optimal cost of s . A heuristic is consisten iff $h(s) \leq c(s, t) + h(t)$ for all states s and t , where $c(s, t)$ is the cost of the cheapest path from s to t . For example, the heuristic function provided by a pattern database (PDB) heuristic ([CULBERSON; SCHAEFFER, 1998](#)) is admissible and consistent.

Given a set of admissible and consistent heuristics $\zeta = \{h_1, h_2, \dots, h_M\}$, the heuristic $h_{max}(s, \zeta) = \max_{h \in \zeta} h(s)$ is also admissible and consistent. When describing our method we assume all heuristics to be consistent. We define $f_{max}(s, \zeta) = g(s) + h_{max}(s, \zeta)$, where $g(s)$ is the cost of the path expanded from I to s . $g(s)$ is minimal when A* using a consistent heuristic expands s . We call an A* search tree the tree defined by the states expanded by A* using a consistent heuristic while solving a problem ∇ .

The heuristics can be obtained from each state of the problem. For example, for the problem of the 8-tile-puzzle figure 1 we can get two heuristics.

2.3.1 Out of place (O.P)

Counts the number of objects out of place.

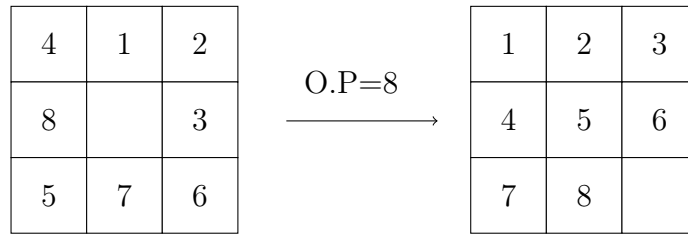


Figure 3 – Out of place heuristic

The tiles numbered with 4, 1, 2, 3, 6, 7, 5, 8, and 4 are out of place then each object count as 1 and the sum would be 8.

2.3.2 Manhatham Distance (M.D)

Counts the minimum number of operations to get to the goal state.

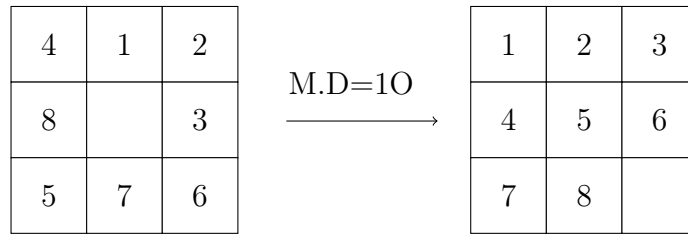


Figure 4 – Manhatham distance heuristic

The tile 4 count 1 to get to the goal position. The tile 1 count 1 to get to the goal position. The tile 2 count 1 to get to the goal position. The tile 3 count 1 to get to the goal position. The tile 6 count 1 to get to the goal position. The tile 7 count 1 to get to the goal position. The tile 5 count 1 to get to the goal position. The tile 8 count 1 to get to the goal position. Then the sum would be 10.

In order to solve the problem, we get the heuristics, which are information from the problem to solve the problem. Exists systems that can create heuristics for each problem. Those systems are called Heuristic Generators.

2.4 Heuristic Generators

Heuristic Generators works by creating abstractions of the original problem space. The approach that has showed more successful results lately is PDB. Which works the following way: The search space of the problem is abstracted, obtaining the remaining problem “pattern”, which is small enough to be solved optimally by blind exhaustive search. The results are stored in a table which are the heuristic function for the original search space.

2.5 Take advantage of Heuristics

The heuristic generators can create hundreds or even thousand of heuristics. In fact, exists different ways to take advantage of those heuristics. For example: If we want to use all the heuristics created by the heuristic generator. It would not be a good idea to use all of them because the main problem involved would be the time to evaluate each heuristic in the search tree, it could take too much time.

One way to take advantage of heuristics would be to take the maximum of the set of heuristics. For example, using three different heuristics $h1$, $h2$ and $\max(h1, h2)$. Heuristic $h1$ and $h2$ are based on domain abstractions and the $\max(h1, h2)$ is the maximum heuristic value of $h1$ and $h2$.

If we have to choose which heuristic to use between $h1$ or $h2$ or $\max(h1, h2)$. The best answer would be $\max(h1, h2)$, because that value would allow to be near from the objective.

Exists different approaches to take advantage from a large set of heuristics. In this dissertation we use the meta-reasoning based on the minimum size of the search tree generated and the minimum evaluation time.

2.6 Number of heuristics created

Let's suppose we have to run our meta-reasoning using M amount of memory available. Then, the question would be: How many heuristics our system should handle in order to avoid out of memory errors?. So, one of the objectives of this dissertation is to find the number of heuristics that our subset ζ' should have.

([HOLTE et al., 2006](#)) observed that maximizing over N pattern databases of size M/N , for a suitable choice N , produces a significant reduction in the number of nodes generated compared to using a single pattern database of size M .

2.7 Heuristic Subset

The heuristic generators systems can create a large number of heuristics. Let's suppose $|\zeta| = 1000$ heuristics were created considering the time and memory available and

we want to select the best $N = 50$ heuristics. This would be:

$$\binom{1000}{50} \approx 10^{85} \text{possibilities}$$

So, try to select heuristics from a large set of heuristics are going to be treated as an optimization problem. Then, in order to obtain a good selection of subset of heuristics, our objective function should guarantee two properties: Monotonicity and Submodularity, that would be explained in the next Chapter.

2.8 Problem Domains

Some of the problems we are trying to solve are the optimal domains for International Planning Competition (IPC).

2.8.1 Blocks world

The domain consists on a set of blocks on the table and a hand robot. The blocks might be distributed over another block or over the table. The goal is to find the plan where the robot places the blocks from one distribution of blocks to another.

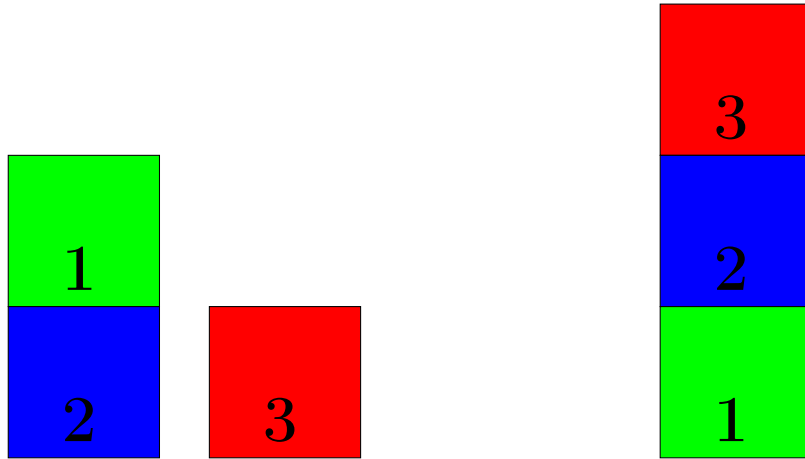


Figure 5 – Blocks world with three blocks.

The solution shown in Figure 5 would be the following plan: unblock number 1 from block number 2; stack block number 2 on block number 1; and finally, stack block number 3 on block number 2.

2.8.2 Barman

This domain consists in a set of drink dispensers, glasses and a shaker that are used by a robot barman to create combination of drinks. The objective is to find the plan of the robot's actions that create the drinks.

2.8.3 Floortile

This domain consists in a robot that can move in four directions (up, down, left and right) and use different colors to paint patterns in floor tiles. They can only use one color at a time and paint in front (up) and behind (down) them, but can change the spray guns to any available. The objective is to find the plan to paint floor tiles only in front for a while because painting behind make the search to reach a dead-end.

2.8.4 Nomystery

This domain consists in a truck that transport and load/unload packages from one node to another considering the resources consumption. For example the fuel is measured based on the weighed graph and each move consumes the edge weight in fuel. The goal is to find the plan that transport the packages based on the resource constrained.

2.8.5 Openstacks

This domain consists in a manufacture that produce only one product at a time. This is because changing one product to another require production stop. The time that last to produce all the elements from one product is called "open" and the time each element of that product to be stored during the production is called "stack". This is an optimization problem where require to order the products to be made in order to maximize the number of stacks that are in simultaneously.

Finding a plan for this problem could be make it using a domain-specific algorithm, however finding an optimal solution is hard.

2.8.6 Parking

This domains consists in locations where cars can be double-parked but not triple-parked. The objective is drive the cars from one configuration parked to another.

2.8.7 Sokoban

This domain consists in a agent and a set of blocks. The agent has to push the blocks in a specified goal location.

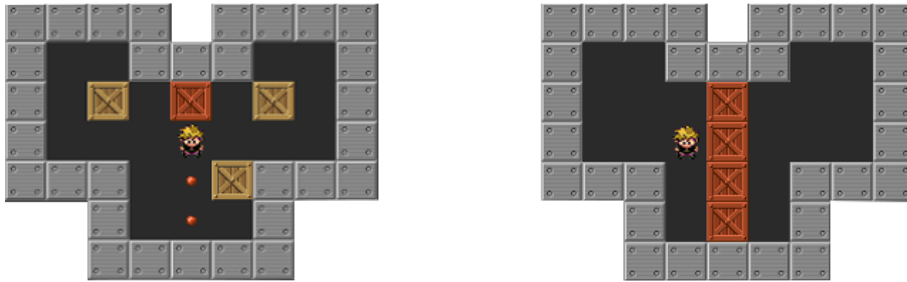


Figure 6 – Sokoban with four blocks solved <<http://sokoban.info/?5>>

The solution shown in Figure 6 is to use the agent to push blocks located in the left figure to the goal distribution of blocks in the right figure.

In the next Chapter, we will introduce the meta-reasoning proposed for selecting heuristics and will expand on the properties of our objective functions.

Chapter III

Approach Proposal

3 Meta-Reasoning for selection

3.1 Random Greedy Heuristic Selection (RGHS)

We present a random greedy algorithm selection for approximately solving the heuristic subset selection problem while optimizing different objective functions. We consider the following general optimization problem.

$$\begin{aligned} & \text{minimize}_{\zeta' \in 2^{|\zeta|}} \Psi(\zeta', \nabla) \\ & \text{subject to } |\zeta'| = N \end{aligned} \tag{3.1}$$

Where $\Psi(\zeta', \nabla)$ is an objective function and N is the desired subset size. N could be determined by a hard constraint such as the maximum number of PDBs one can store in memory. According to (RAYNER; STURTEVANT; BOWLING, 2013) it is unlikely that there is an efficient algorithm for solving Equation 3.1. We use an algorithm based on the work of (BUCHBINDER et al., 2014) we call Random Greedy Heuristic Selection (RGHS) to approximately solve Equation 3.1 for different functions Ψ .

Algorithm 1: Random Greedy Heuristic Selection

Input : problem ∇ , set of heuristics ζ , cardinality N

Output : heuristic subset $\zeta' \subseteq \zeta$ of size N

```

1  $\zeta'_0 \leftarrow \emptyset$ 
2 for  $i = 1$  to  $N$  do
3   Let  $M_i \subseteq \zeta \setminus \zeta'_{i-1}$  be a subset of size  $N$  minimizing  $\sum_{h \in M_i} \Psi(\zeta'_{i-1} \cup \{h\}) - \Psi(\zeta'_i)$ 
4   Let  $h_i$  be a uniformly random element from  $M_i$ 
5    $\zeta'_i \leftarrow \zeta'_{i-1} \cup \{h_i\}$ 
6 return  $\zeta'_N$ 
```

Algorithm 1 shows RGHS. RGHS receives as input a problem ∇ , a set of heuristics ζ , a cardinality size N , and it returns a subset $\zeta' \subseteq \zeta$. In each iteration i RGHS randomly selects a heuristic h_i from a pool M_i of "good" heuristics and adds h_i to ζ' . M_i is defined as follows. $M_i \subseteq \zeta \setminus \zeta'_{i-1}$ is a subset of size N minimizing $\sum_{h \in M_i} \Psi(\zeta'_{i-1} \cup \{h\}) - \Psi(\zeta'_i)$, where ζ'_{i-1} is the subset of heuristics RGHS selects prior to iteration i of the algorithm. M_i contains the N heuristics that when individually combined with ζ'_{i-1} minimizes Ψ the most. RGHS returns ζ' once it reaches the desired size N .

The work of (RAYNER; STURTEVANT; BOWLING, 2013) uses a greedy algorithm introduced by (NEMHAUSER; WOLSEY; FISHER, 1978) for approximately solving the heuristic subset selection problem. In contrast with the RGHS presented above, which is based on the work of (BUCHBINDER et al., 2014), (NEMHAUSER; WOLSEY; FISHER, 1978)’s approach does not offer near-optimality guarantees when the problem’s objective functions is non-monotone. As mentioned before A^* ’s running time is a non-monotone objective function. While RGHS also offers guarantees for non-monotone objective functions, it retains the same guarantees offered by (NEMHAUSER; WOLSEY; FISHER, 1978)’s algorithm when optimizing monotone objective functions (BUCHBINDER et al., 2014). That is why we only consider (BUCHBINDER et al., 2014)’s approach in our theoretical and experimental analyses.

3.2 Approximately Minimizing Search Tree Size

The first objective function Ψ we consider accounts for the number of expansions A^* performs while solving a given planning problem. When solving ∇ using the consistent heuristic function $h_{max}(\zeta')$ for $\zeta' \subseteq \zeta$, A^* expands in the worse case $J(\zeta', \nabla)$ nodes, where

$$J(\zeta', \nabla) = |\{s \in V \mid f_{max}(s, \zeta') \leq C^*\}| \quad (3.2)$$

$$J(\zeta', \nabla) = |\{s \in V \mid h_{max}(s, \zeta') \leq C^* - g(s)\}| \quad (3.3)$$

We write $J(\zeta')$ or simply J instead of $J(\zeta', \nabla)$. RGHS is guaranteed to find near-optimal solutions when we use J as the objective function Ψ , as we now demonstrate. In the following analysis all heuristic functions are assumed to be consistent. We also assume that A^* expands all nodes n with $f(n) \leq C^*$ while solving ∇ , as shown in Equation 3.2.

Lemma 3.2.1. $J(\zeta' \cup \{h\}) \leq J(\zeta')$ for any ζ' and any h .

Proof. Fix ζ' and h . Then

$$\begin{aligned} J(\zeta' \cup \{h\}) &= |\{s \in V \mid h_{max}(s, \zeta' \cup \{h\}) \leq C^* - g(s)\}| \\ &\leq |\{s \in V \mid h_{max}(s, \zeta') \leq C^* - g(s)\}| \\ &= J(\zeta') \end{aligned}$$

Where the inequality follows from the fact that $h_{max}(s, \zeta' \cup \{h\}) \geq h_{max}(s, \zeta')$ for all s .

Let S be a set and ϕ a function over 2^S . ϕ is supermodular if for any A, B, x with $A \subseteq B \subseteq S$ and $x \in S \setminus B$:

$$\phi(A) - \phi(A \cup \{x\}) \geq \phi(B) - \phi(B \cup \{x\}) \quad (3.4)$$

Intuitively, Equation 3.4 captures the idea of diminishing returns. In the context of search tree size, if we add a heuristic function h to a set of heuristics A strictly contained in a set B , then we would expect, then we would expect $J(A) - J(A \cup \{h\})$ to be larger than $J(B) - J(B \cup \{h\})$ as h would "contribute more" to A than to B .

Lemma 3.2.2. J is supermodular.

Proof. Let $A \subset B \subset \zeta$ and $h \in \zeta \setminus B$. By Lemma 3.2.1, $J(A) - J(A \cup \{h\}) \geq 0$ and $J(B) - J(B \cup \{h\}) \geq 0$. We consider two cases.

Case 1. $J(B) - J(B \cup \{h\}) = 0$. Then $J(A) - J(A \cup \{h\}) \geq 0$ yields $J(A) - J(A \cup \{h\}) \geq J(B) - J(B \cup \{h\})$.

Case 2. $J(B) - J(B \cup \{h\}) = k > 0$. Let s_1, \dots, s_k be all the states in V that satisfy $h_{\max}(s_i, B) \leq C^* - g(s_i)$ and $h_{\max}(s_i, B \cup \{h\}) > C^* - g(s_i)$. This implies $h(s_i) > C^* - g(s_i)$, for all $i \in \{1, \dots, k\}$. Further, since $A \subset B$, we have $h_{\max}(s_i, A) \leq h_{\max}(s_i, B) \leq C^* - g(s_i)$, for all $i \in \{1, \dots, k\}$. Consequently, $J(A) - J(A \cup \{h\}) \geq k = J(B) - J(B \cup \{h\})$.

Lemma 3.2.1 and 3.2.2 are sufficient for using a result by (BUCHBINDER et al., 2014) to conclude the following.

Theorem 3.2.3. Let ζ' be a subset selected by GHS. Then $J(\zeta', \nabla)$ is within a factor of $\frac{e+1}{e} \approx 1.36$ of optimal.

3.3 Approximately Minimizing A*'s Running Time

Another objective function Ψ we consider accounts for the A* running time and is defined as follows. Let $T(\zeta', \nabla)$ be an approximation to the running time of A* when using $h_{\max}(\zeta')$ for solving ∇ , defined as follows.

$$T(\zeta', \nabla) = J(\zeta', \nabla) \cdot t_{h_{\max}}(\zeta') \quad (3.5)$$

where, for any heuristic function h , the term t_h refers to the running time used for computing the h -value of any state s .

We assume that t_h to be independent of s , which is a reasonable assumption for several heuristics such as PDBs.

In order to compute the running time of A^* exactly we would also have to account for the time required for node generation and for the operations on A^* 's **OPEN** and **CLOSED** lists. However, these two factors do not depend directly on the heuristic employed. Thus, $T(\zeta', \nabla)$ is reasonable approximation for A^* 's running time for the heuristic subset selection problem.

Theorem 3.3.1. *Suppose $t_{h_i} = t_{h_j}$ for any h_i and $h_j \in \zeta$. Then for any fixed subset size N , **RGHS** yields a subset ζ' that is within a factor $\frac{e+1}{e}$ of optimal with respect to $T(\zeta', \nabla)$*

Proof. Since t_h is constant over $h \in \zeta$, the value $t_{h_{max}}(\zeta')$ is independent of ζ' . Hence the value $T(\zeta', \nabla)$ is a constant factor of $J(\zeta', \nabla)$. The latter is within a factor of $\frac{e+1}{e}$ of optimal by Theorem 3.2.3.

The assumption that $t_{h_i} = t_{h_j}$ for any $h_i, h_j \in \zeta$ often does not hold in domain-independent planning. For example, the **iPDB** heuristic (HASLUM et al., 2007) can be few order of magnitude faster than the Incremental **LM-Cut** (HELMERT; DOMSH-LAK, 2009) heuristic. In order to lift such an assumption we first define A^* 's running time in terms of its computational cost as follows.

$$T(\zeta', \nabla) = J(\zeta', \nabla) + \beta(\zeta') \quad (3.6)$$

Here $\beta(\zeta')$ is the computational cost incurred by using $h_{max}(\zeta')$. $T(\zeta', \nabla)$ accounts for the computational cost of expanding $J(\zeta', \nabla)$ nodes added of the computational cost of employing a set of heuristics ζ' .

We assume that the computational cost $\beta(\zeta' \cup \{h\}) = \beta(\zeta') + \beta(h)$, i.e., the computational cost of employing heuristic h during search is constant and independent of other heuristics in ζ' . Although this assumption is unlikely to hold in practice as $\beta(h)$ depends on the number of times A^* uses h to evaluate nodes during search, which in turn depends on the heuristics in $\zeta' \setminus h$, we expect that the differences of $\beta(h)$ -values to be negligible for different ζ' sets.

T' is clearly non-monotone as the reduction of $J'(\zeta', \nabla)$ caused by the addition of a heuristic to ζ' might not compensate for the increase in $\beta(\zeta')$. We now show that T' is supermodular.

Lemma 3.3.2. *T is supermodular.*

Proof. Let $A \subset B \subseteq \zeta$ and $h \in \zeta \setminus B$. We need to show that $T'(A) - T'(A \cup \{x\}) \geq T'(B) - T'(B \cup \{x\})$. We have that $T'(A) - T'(A \cup \{x\}) = J(A) - J(A \cup \{x\}) - \beta(x)$. and

$T'(B) - T'(B \cup \{x\}) = J(B) - J(B \cup \{x\}) - \beta(x)$. Thus, we have that $J(A) - J(A \cup \{x\}) \geq J(B) - J(B \cup \{x\})$, which according to Lemma 3.2.2 is supermodular.

Since T' is supermodular, another result by (BUCHBINDER et al., 2014) and Lemma 3.3.2 allow us to conclude the following.

Theorem 3.3.3. *Let ζ' be a subset selected by RGHS. Then $T(\zeta', \nabla)$ is within a factor of $\frac{e+1}{e} \approx 1.63$ of optimal.*

3.4 Estimating Tree Size and Running Time

In practice RGHS used approximations of J , T , and T' instead of their exact values. This is because computing J , T , and T' exactly would require solving ∇ . We denote the approximations of J as \hat{J} , and since both T and T' model A^* 's running time, we denote the approximation for both as \hat{T} .

We use the Culprit Sampler (CS) introduced by (BARLEY; FRANCO; RIDDLE, 2014) and the Stratified Sampling (SS) algorithm introduced by (CHEN, 1992) for computing \hat{J} and \hat{T} . Each of the two algorithms has its strengths and weaknesses, which we explore in the experimental Chapter.

Both CS and SS must be able to quickly estimate the values of $\hat{J}(\zeta')$ and $\hat{T}(\zeta')$ for any subset ζ' of ζ so they can be used in RGHS's optimization process.

3.5 Culprit Sampler (CS)

CS runs a time-bounded A^* search while sampling f -culprits and b -culprits to estimate the values of \hat{J} and \hat{T} .

Definition 3.5.1. (*f-culprit*) Let $\zeta = \{h_1, h_2, \dots, h_M\}$ be a set of heuristics. The f -culprit of a node n in an A^* search tree is defined as the tuple $F(n) = \langle f_1(n), f_2(n), \dots, f_M(n) \rangle$, where $f_i(n) = g(n) + h_i(n)$. For any n -tuple F , the counter C_F denotes the number of nodes n in the tree with $F(n) = F$.

Definition 3.5.2. (*b-culprit*) Let $\zeta = \{h_1, h_2, \dots, h_M\}$ be a set of heuristics and b a lower bound on the solution cost ∇ . The b -culprit of a node n in an A^* search tree is defined as the tuple $B(n) = \langle y_1(n), y_2(n), \dots, y_M(n) \rangle$, where $y_i(n) = 1$ if $g(n) + h_i(n) \leq b$ and $y_i(n) = 0$, otherwise. For any binary n -tuple B , the counter C_B denotes the number of nodes n in the tree with $B(n) = B$.

CS works by running an A^* search bounded by a user-specified time limit. Then, **CS** compresses the information obtained in the A^* search (i.e., the f -values of all nodes expanded according to all heuristics h in ζ) in b-culprits, which are later used for computing \hat{J} . The bf-culprits are generated as an intermediate step for computing the b-culprits, as we explain below. The maximum number of f-culprits and b-culprits in an A^* search tree is equal to the number of nodes in the tree expanded by the time-bounded A^* search. However, in practice the number of f-culprits is usually much lower than the number of nodes in the tree. Moreover, in practice, the total number of different b-culprits tends to be even lower than the total number of f-culprits. Given a planning problem ∇ and a set of heuristics ζ , **CS** samples the A^* search tree as follows.

- 1.- **CS** runs A^* using $h_{min}(s, \zeta) = \min_{h \in \zeta} h(s)$ until reaching a user-specified time limit. A^* using h_{min} expands node n if it were to expand n while using any of the heuristics in ζ individually. For each node n expanded in this time-bounded search we store n 's f-culprit and its counter.
- 2.- Let f_{maxmin} be the largest f -value according to h_{min} encountered in the time-bounded A^* search described above. We now compute the set \mathbb{B} of b-culprits and their counters based on the f-culprits and on the value of f_{maxmin} . This is done by iterating over all f-culprits once.

The process described above is performed only once **RGHS**'s execution. The value of $\hat{J}(\zeta', \nabla)$ for any subset ζ' of ζ is then computed by iterating over all b-culprits \mathbf{B} and summing up the relevant values of C_B . The relevant values of C_B represent the number of nodes A^* would expand in a search bounded by b if using $h_{max}(\zeta')$. This computation can be written as follows.

$$\hat{J}(\zeta', \nabla) = \sum_{\mathbb{B} \in B} W(B) \quad (3.7)$$

Where $W(B)$ is 0 if there is a heuristic in ζ' whose y -value in B is zero (i.e., there is a heuristic in ζ' that prunes all nodes compressed into B), and C_B otherwise. If the time-bounded A^* search with h_{min} expands all nodes n with $f(n) \leq C^*$, then $\hat{J} = J$. In practice, however, our estimate \hat{J} will tend to be much lower than J .

The value of \hat{T} is computed by multiplying \hat{J} by the sum of the evaluation time of each heuristic in ζ' . The evaluation time of the heuristics in ζ' is measured in a separate process, before executing **CS**, by sampling a small number of nodes from ∇ 's start state.

3.6 Stratified Sampling (SS)

(CHEN, 1992) presented a method for estimating the search tree size of backtracking search algorithms by using a stratification of the search tree to guide its sampling. We define Chen’s stratification as a type system. In the figure 7 each state of the search space is mapped to the *Type System*.

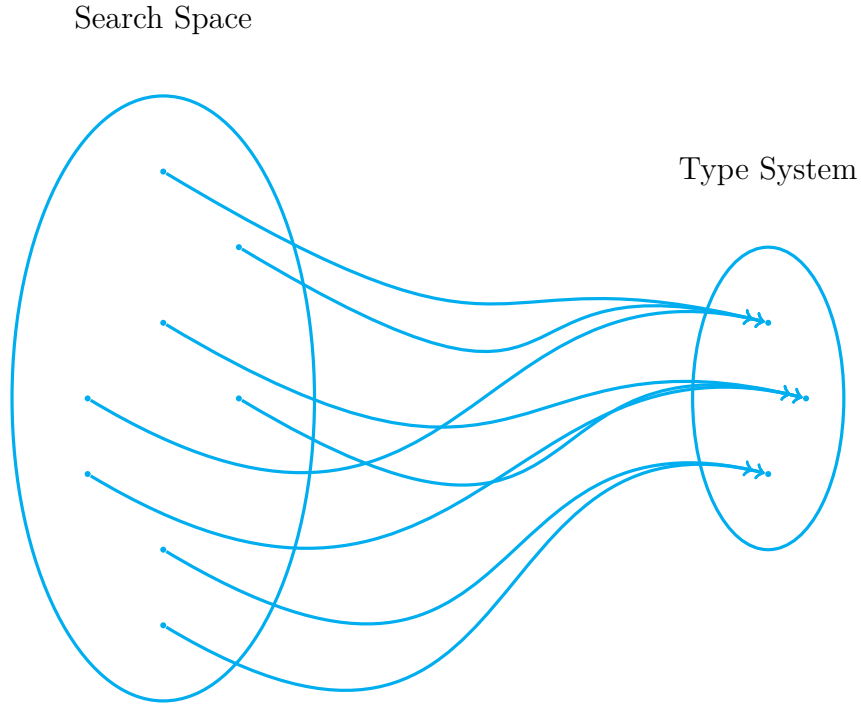


Figure 7 – Type system and the search space representation.

3.6.1 Type System

The *Type System* is a partition of the states in the state space and it is calculated based of any property of each node in the search tree. (LELIS, 2013)

A common mistake about *type system* is to think that it is an abstraction of the state–space. (PRIEDITIS, 1993) defines a state–space abstraction as a simplified version of the problem where:

- The cost of the least–cost path between two abstracted states must less than or equal to the cost of the least–cost path between the corresponding two states in the original state–space.

- Goal states in the original state–space must be goal states in the abstracted state–space.

The difference between state–space abstractions and *type system* is that the last one does not have the two requirements mentioned above. Also, there is not relation between types to argue that the *type system* can be represented as a graph. Furthermore, the relation between *type system* and abstractions is that *type system* can not necessarily be used as abstractions, and abstraction always can be used as a *type system* (PRIEDITIS, 1993).

Definition 3.6.1. *Type System* Let $S = (N, E)$ be a search tree, where N is its set of nodes and for each $n \in N$, $\{n' | (n, n') \in E\}$ is n 's set of child nodes. $TS = \{t_1, \dots, t_k\}$ is a type system for S if it is a disjoint partitioning of N . If $n \in N$ and $t \in TS$ with $n \in t$, we write $TS(n) = t$.

SS is a general method for approximating any function of the form $\varphi = \sum_{n \in S} z(n)$, where z is any function assigning a numerical value to a node. φ represents a numerical property of the search tree rooted at n^* . For instance, if $z(n) = 1$ for all $n \in S$, then φ is the size of the tree.

Instead of traversing the entire tree and summing all z –values, **SS** assumes subtrees rooted at nodes of the same type will have equal values of φ and only one node of each type, chosen randomly, is expanded. This is the key to **SS**'s efficiency since the search trees of practical interest have far too many nodes to be examined exhaustively.

Given a search tree S and a type system TS , **SS** estimates φ as follows. First, it samples the tree and returns a set A of *representative – weight* pairs, with one such pair for every unique type seen during sampling. In the pair $\langle s, w \rangle$ in A for type $t \in TS$, n is the unique node of type t that was expanded during search and w is an estimate of the number of nodes type t in the tree. φ is then approximated by $\hat{\varphi}$, defined as, $\hat{\varphi} = \sum_{\langle s, w \rangle \in A} w \times z(n)$.

By making $z(n) = 1$ for all $n \in S$ **SS** produces an estimate \hat{J} of J . Similarly to our approach with **CS**, we obtain \hat{T} by multiplying \hat{J} by the heuristic evaluation time.

In **SS** the types are required to be partially ordered: a node's type must be strictly greater than the type of its parent. This can be guaranteed by adding the depth of a node to the type system and then sorting the types lexicographically. That is why in our implementation of **SS** types at one level are treated separately from types at another level by the division of A into groups $A[i]$, where $A[i]$ is the set of representative–weight

Algorithm 2: SS, a single probe

Input : root n^* of a tree and a type system T
Output : an array of sets A , where $A[i]$ is the set of pairs $\langle n, w \rangle$ for the nodes n expanded at level i .

```

1  $A[0] \leftarrow \{\langle n^*, 1 \rangle\}$ 
2  $i \leftarrow 0$ 
3 while  $A[i]$  is not empty do
4   for each element  $\langle n, w \rangle$  in  $A[i]$  do
5     for each child  $\hat{n}$  of  $n$  do
6       if  $g(\hat{n}) + h(\hat{n}) \leq d$  then
7         if  $A[i+1]$  contains an element  $\langle n', w' \rangle$  with  $T(n') = T(\hat{n})$  then
8            $w' \leftarrow w' + w$ 
9           with probability  $w/w'$ , replace  $\langle n', w' \rangle$  in
10           $A[i+1]$  by  $\langle \hat{n}, w' \rangle$ 
11         else
12           insert new element  $\langle \hat{n}, w' \rangle$  in  $A[i+1]$ 
13    $i \leftarrow i + 1$ 

```

pairs for the types encountered at level i . If the same type occurs on different levels the occurrences will be treated as if they were different types – the depth of search is implicitly included into all of our type systems.

Algorithm 2 shows SS in detail. Representative nodes from $A[i]$ are expanded to get representative nodes for $A[i+1]$ as follows. $A[0]$ is initialized to contain only the root of the search tree to be probed, with weight 1 (Line 1). In each iteration (Lines 4 through 11), all nodes in $A[i]$ are expanded. The children of each node in $A[i]$ are considered for inclusion in $A[i+1]$ if their f -value do not exceed an upper bound d provided as input to SS. If a child \hat{n} has a type t that is already represented in $A[i+1]$ by another node n' , then a *merge* action on \hat{n} and n' is performed. In a merge action we increase the weight in the corresponding representative–weight pair of type t by the weight $w(n)$ of \hat{n} 's parent n (from level i) since there were $w(n)$ nodes at level i that are assumed to have children of type t at level $i+1$. \hat{n} will replace n' according to the probability shown in Line 9. (CHEN, 1992) proved that this probability reduces the variance of the estimation. Once all the states in $A[i]$ are expanded, we move to the next iteration.

One run of the SS algorithm is called a *probe*. (CHEN, 1992) proved that the expected value of $\hat{\varphi}$ converges to φ in the limit as the number of probes goes to infinity. As (LELIS; STERN; STURTEVANT, 2014), SS is not able to detect duplicated nodes in its sampling process. As a result, since A^* does not expanded duplicates, SS usually

overestimates the actual number of nodes A^* expands. Thus, in the limit, as the number of probes grows large, **SS**'s prediction converges to a number which is likely to overestimate the A^* search tree size. We test empirically whether **SS** is able to allow **RGHS** to make good subset selects despite being unable to detect duplicated nodes during sampling.

Similarly to **CS**, we also define a time-limit to run **SS**. We use **SS** with an iterative-deepening approach in order to ensure an estimate of \hat{J} and \hat{T} before reaching the time limit. We set the upper bound d to the heuristic value of the start state and, after performing p probes, if there is still time, we increase d to twice its previous value. The values of \hat{J} and \hat{T} is given by the prediction produced for the last d -value in which **SS** was able to perform all p probes.

SS must also be able to estimate the values of $\hat{J}(\zeta')$ and $\hat{T}(\zeta')$ for any subset ζ' of ζ . This is achieved by using **SS** to estimate b-culprits (See Definition 3.5.2) instead of the search tree size directly. Similarly to **CS**, **SS** used h_{min} of the heuristics in ζ to decide when to prune a node (See Line 6 of Algorithm 2) while sampling. This ensures that **SS** expands a node n if A^* employing at least one of the heuristics in ζ would expand n according to bound d . The C_B counter of each b-culprit B encountered during **SS**'s probe is given by,

$$C_B = \sum_{\langle n, w \rangle \in A \wedge B(n)=B} w \quad (3.8)$$

We recall that to compute $B(n)$ for node n one needs to define a bound b . Here we use the bound d used by **SS**. The average value of C_B across p probes is used to predict the search tree size for a given subset ζ' . As explained for **CS**, this can be done by traversing over all b-culprits once.

3.7 SS step by step

In the Figure 8, we can see how *Type System* works. In the Level 1, we have the root node, the w initialized with one. Let's suppose that three nodes are generated by the root node in the Level 2. The nodes in the Level 2 have the following types: red, blue and red from left to right respectively, and each node receive the same w of the father. In the Level 2 we apply **SS**'s assumption, two nodes in the same level that have the same type (The same color) root subtrees of the same size and only one node of each type must be chosen randomly to be expanded. There are two nodes with type red in Level 2. In that way, we choose randomly one of them. Let's suppose we choose the right red node. Then, we have

to update the number of nodes with the type red using the w , both red node types have $w = 1$, then we sum the w and the new $w = 2$. As a result, in the Level 2 we will have two nodes of red type and one node with blue type.

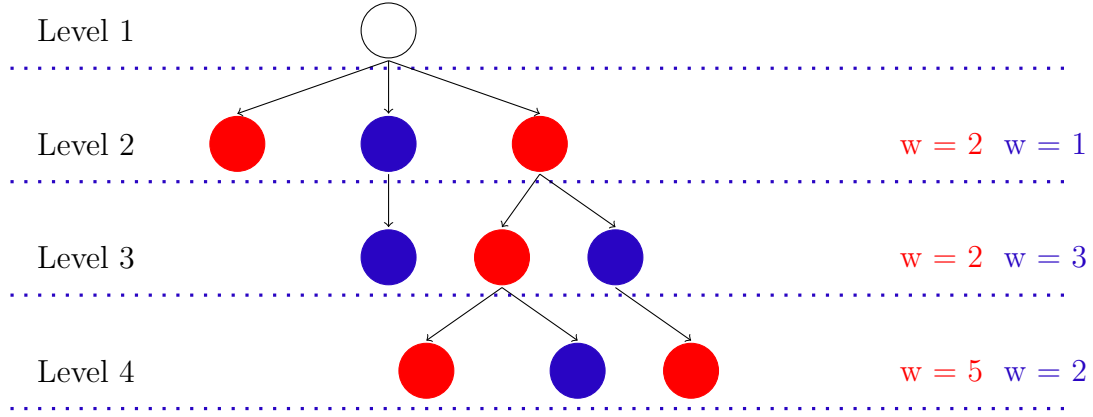


Figure 8 – Search tree using Type System

When nodes in the Level 2 are expanded. The blue node expands one node of type blue and the red node expands two nodes of type red and blue. The question here is how many nodes would be generated in the Level 3? The answer is: $1 \times \text{blue} + 2 \times \text{red} + 2 \times \text{blue}$. So, in the Level 3 we will have 2 nodes of red type and 3 nodes of type blue.

In the Level 3 the w of the node blue would have the same w of the father. The father has $w = 1$, then the child has $w = 1$. The w of the red type and blue type would be 2. Once the w has been updated for each node in the Level 3 we apply the SS's assumption again. There are two nodes with type blue. So, we choose randomly one of them and update their w . Let's choose the right blue type and the updated w would be 3 because 1 from the left blue type plus the 2 from the right blue type.

When nodes in the Level 3 are expanded. They are expanded in the following way: The red node expands two nodes of types red and blue and the blue node expands one of red type. How many nodes would be generated at Level 4, then? The answer is: $2 \times \text{red} + 3 \times \text{red} + 2 \times \text{blue}$. Therefore, in the Level 4, we will have five nodes of type red and two nodes of type blue.

Finally, the number of nodes expanded in the search tree is obtained summing all w plus one (The root node). As a result, the number of nodes expanded in the search tree would be $15 + 1 = 16$.

Chapter IV

Empirical Evaluation

4 Empirical Evaluation

RGHS is guaranteed to find a near-optimal heuristic subset to guide the A^* search granted that it is able to compute the objective function of interest. Thus, the practical effectiveness of RGHS depends on its ability of finding good approximations \hat{J} and \hat{T} . Moreover, RGHS’s effectiveness depends on the value of N and on the quality of the set of heuristics ζ . In order to verify its practical effectiveness, we have implemented RGHS in Fast Downward (HELMERT, 2006) and tested the A^* performance using subsets of heuristics selected by RGHS while minimizing different objective functions.

We run two sets of experiments. In the first set we verify whether the approximations \hat{J} and \hat{T} provided by CS and SS allow RGHS to make near-optimal subset selections. In the second set of experiments we test the effectiveness of RGHS by measuring the total number of problem instances solved by A^* using a heuristic subset selected by RGHS.

In our experiments we implemented an approximation procedure to automatically choose the subset size selected by RGHS, which we now explain. Initially we fix N to a value (in our experiments we use $N = 25$). Then, in every iteration, when computing M_i , RGHS removes from ζ the heuristics that cannot help reducing φ . That is, in iteration i , all heuristics in $\zeta \setminus \zeta'_{i-1}$ that cannot reduce φ when combined with ζ'_{i-1} are removed from ζ . RGHS stops if ζ is empty and returns the current subset ζ' with $|\zeta'| < N$. Likewise, should heuristic h improves the objective function being optimized, then we also allow RGHS to add h to ζ' even if $|\zeta'| > N$. We observed in preliminary experiments that RGHS is robust to the initial value of N , as the total number of problems solved by A^* while guided by a heuristic subset selected by RGHS varied little with N .

In all our experiments we use a type system that assigned the same type for a node with the same f -value. Such a type system has shown to be effective in guiding SS to produce accurate tree size predictions in other application domains (LELIS; ZILLES; HOLTE, 2013; LELIS; OTTEN; DECHTER, 2014).

We ran our experiments on the 2011 International Planning Competition (IPC) instances. We used the 2011 instances instead of the 2014 instances because the former do not have problems with conditional effects, which are currently not handled by PDB heuristics. All experiments are run on 2.67 GHz machines with 4GB, and are limited to 1,800 seconds of running time.

Table 1 – Ratios of the number of nodes expanded using $h_{max}(\zeta')$ to the number of nodes expanded using $h_{max}(\zeta)$

Domain	SS		CS		$ \zeta $	n
	Ratio	$ \zeta' $	Ratio	$ \zeta' $		
Barman	2.15	27.26	2.34	30.68	4790.16	20
Elevators	1.09	18.00	1.04	20.00	155.00	1
Floortile	1.01	45.86	1.01	41.14	136.57	13
Openstacks	1.00	1.00	1.00	1.00	316.62	12
Parking	1.01	7.05	1.01	7.37	17.53	18
Pegsol	1.00	32.00	1.00	48.33	78.00	2
Scanalyzer	1.01	37.29	1.07	21.43	52.14	6
Tidybot	1.03	4.06	1.00	8.19	3259.00	15
Transport	7.33	9.70	1.45	12.90	156.50	9
Visitall	1.00	95.00	1.02	48.00	218.00	2
Woodworking	2.39	83.00	611.72	32.00	346.00	5

4.1 Empirical Evaluation of \hat{J} and \hat{T}

We test whether the approximation \hat{J} provided by CS and SS allows RGHS to make near-optimal subset selections. This test is made by comparing $J(\zeta')$ with $J(\zeta)$, which is minimal. The condition $J(\zeta') \leq \alpha \cdot J(\zeta)$, is sufficient to show that $J(\zeta')$ is within α times optimal with respect to all subsets of any size, for some constant α . We are particularly interested in observing if $J(\zeta')$ is within 1.36 of $J(\zeta)$.

In contrast with objective function J , there is no easy way to find the minimum of T for a subset of fixed size in general. We experiment then with the special case in which all heuristics in ζ have the same evaluation time. This way we are able to test whether the estimates \hat{T} are allowing RGHS to make near-optimal subset selections while minimizing the A* running time. This is because by only selecting heuristics which have the same evaluation time, if RGHS is making near-optimal subset selections with respect to J , then RGHS must also be making near-optimal subset selections with respect to T for a fixed subset size (See Theorem 3.3.1).

We collect values of $J(\zeta)$ and $J(\zeta')$ as follows. For each problem instance ∇ in our test set we generate a set of PDB heuristics using the GA-PDB algorithm (EDELKAMP, 2007) as described by (BARLEY; FRANCO; RIDDLE, 2014) – we call each PDB generated by this method a GA-PDB. We chose to use GA-PDBs in this experiment because they all have nearly the same evaluation time and will allow us to verify whether RGHS is making near-optimal selections not only when minimizing J but also when minimizing T , as

explained above. The number of **GA-PDBs** generated is limited in this experiment by 1,200 seconds and 1GB of memory. Also, all **GA-PDBs** we generate have 2 millions entries each. The **GA-PDBs** generated form out ζ set. **RGHS** then selects a subset ζ' of ζ . Finally, we use $h_{max}(\zeta')$ and $h_{max}(\zeta)$ to independently try to solve ∇ . We call the system which uses A^* with $h_{max}(\zeta)$ the **Max** approach. For **RGHS** we allow 600 seconds for selecting ζ' and for running A^* with $h_{max}(\zeta')$, and for **Max** we allow 600 seconds for running A^* with $h_{max}(\zeta)$. Since we used 1,200 seconds to generate the heuristics, both **Max** and **RGHS** were allowed 1,800 seconds in total for solving each problem. In this experiment we test both **CS** and **SS**.

In this experiment we refer to the approach that runs A^* guided by a heuristic subset selected by **RGHS** using **CS** as **RGHS+CS**. Similarly, we write **RGHS+SS** when **SS** is used as predictor to make the heuristic subset selection.

Table 1 shows the average ratios of $J(\zeta')$ to $J(\zeta)$ for both **SS** and **CS** in different problem domains. The value of J , for a given problem instance, is computed as the number of nodes expanded up to the largest f -layer which is fully expanded by all approaches tested (**Max**, **RGHS** using **SS** and **RGHS** using **CS**). We only present results for instances that are not solved during **RGHS**'s **CS** sampling process. The column " n " shows the number of instances used to compute the averages of each row. We also show the average number of **GA-PDBs** generated ($|\zeta|$) and the average number of **GA-PDBs** selected by **RGHS** ($|\zeta'|$). This experiment shows that for most of the problems **RGHS**, using either **CS** or **SS**, is selecting a near-optimal subset of ζ . For example, in **Tidybot** **RGHS** selects only a few **GA-PDBs** out of thousands when using either **SS** or **CS**. Moreover, the resulting A^* search tree size is on average at most 3% larger than optimal for **RGHS+SS**, and is optimal for **RGHS+CS**.

The exceptions in Table 1 are the ratios for **Barman**, **Transport** and **Woodworking**. In **Transport** **SS** has an average ratio of 7.33 and **CS** of 1.45. By looking at the ratios of **SS** for individual instances of **SS** for individual instances of **Transport** (results now show in Table 1), we noticed that **SS** is able to make optimal selections for all but one of the 9 instances considered in this experiment. Since we do not know a priori what is the instance's optimal solution cost, **SS** samples nodes with f -values much larger than the instance's optimal solution cost. We believe that, in this particular instance of **Transport**, by sampling a portion of the state space that is not expanded during the actual A^* , **SS** is biasing the subset selection to select heuristics that do not contribute to reducing the actual A^* search tree size.

The **SS**'s ability of sampling deep into the search space is not always harmful. For example, **SS** allows **RGHS** to make good selections for instances of the **Woodworking** domain.

By contrast, CS’s systematic approach to sampling only allow a shallow sample of the A* search tree. As a result, RGHS makes a limited selection of heuristics to guide A* search. While RGHS using SS selects an average of 83 heuristics in Woodworking instances, RGHS using CS selects only an average of 32 heuristics. This difference on sampling strategies reflects on the number of problems solved by A*. While RGHS+SS solves 15 instances of the Woodworking domain, RGHS+CS solves only 11. In total, out of the 280 instances of the IPC 2011 benchmark set, RGHS+SS solves 200 problem instances in this experiment, while RGHS+CS only solves 193 problem instances. (The numbers of instances solved are not shown in Table 1).

4.2 Comparison with Other Planning Systems

The objective of this second set of experiments is to test the quality of the subset of heuristics RGHS selects while optimizing different objective functions. Our evaluation metric is coverage, i.e., number of problems solved within a 1,800 second time limit. We note that the 1,800-second limit includes the time to generate ζ , select ζ' , and run A* using $h_{max}(\zeta')$. The ζ set of heuristics is composed of a number of different GA-PDBs, a PDB heuristic produced by the iPDB method (HASLUM et al., 2007) and the LM-Cut heuristic. The generation of GA-PDBs is limited by 600 seconds and 1GB of memory. We use one fourth of 600 seconds to generate GA-PDBs with each of the following number of entries: $\{2 \cdot 10^3, 2 \cdot 10^4, 2 \cdot 10^5, 2 \cdot 10^6\}$. Our approach allows one to generate up to thousands of GA-PDBs. For every problem instance, we use exactly the same ζ set for Max and all RGHS approaches.

4.3 Systems Tested

RGHS is tested while minimizing the A* search tree size (**Size**) and the A* running time (**Time**). We also use RGHS to maximize the sum of heuristic values in the state space (**Sum**), as suggested by (RAYNER; STURTEVANT; BOWLING, 2013). (RAYNER; STURTEVANT; BOWLING, 2013) assumed that one could uniformly sample states in the state space in order to estimate the sum of the heuristic values for a given heuristic subset. Since we are not aware of any method to uniformly sample the state space of domain-independent problems, we adapted the (RAYNER; STURTEVANT; BOWLING, 2013)’s method by using SS to estimate the sum of heuristic values in the search tree rooted at ∇ ’s start state. We write **Size** + **SS** to refer to the approach that used A* guided by a heuristic selected by RGHS while minimizing an estimate of the search tree size provided by SS. We follow the same pattern to name the other possible combinations of objective functions

and prediction algorithms (E.G., **Time+CS**).

In addition to experimenting with all combination of prediction algorithms (**CS** and **SS**) and objective functions (**Time**, **Size**), we also experiment with an approach that minimizes both the search tree size and the running time as follows. First we create a pool of heuristics ζ composed solely of **GA-PDB** heuristics, then we apply **RGHS** while minimizing tree size and using **SS** as predictor. As explained above, in this setting **RGHS** minimizes J and T simultaneously, as all heuristics in ζ have the same evaluation time. We call the selection of a subset of **GA-PDBs** as the *first selection*. Once the first selection is made, we test all possible combinations of the resulting $h_{max}(\zeta')$ added to the **iPDB** and **LM-Cut** heuristics while minimizing the running time as estimated by **CS**—we call this step the *second selection*. We call the overall approach **Hybrid**.

The intuition behind **Hibrid** is that we apply **RGHS** with its strongest settings, I.E., according to Theorem 3.3.1 **RGHS** makes selections that are within the 1.36 factor of optimal with respect to both J and T when selecting from a pool of heuristics with the same evaluation time. After such a selection is made, we reduce the size of the pool of heuristics from possible thousands to only tree (the maximum of a subset of the initial **GA-PDBs**, **iPDB**, and **LM-Cut**). With only three heuristics we are able to choose the exact combination that minimizes the A^* running time the most. The reason we chose to use **SS** instead of **CS** for the first selection in **Hybrid** is that the former is able to make better subset selections in this setting, as suggested by the results discussed in the previous Chapter 3. Finally, as we show below, **CS** is more effective if one is interested in minimizing the A^* running time while selecting from a pool of heuristic with different evaluation times. That is why we use **CS** as predictor for the second selection in **Hybrid**.

We compare the coverage of the **RGHS** approaches with several other state-of-the-art planners. Namely, we experiment with **RIDA*** (BARLEY; FRANCO; RIDDLE, 2014), two variants of **StoneSoup** (**StSp1** and **StSp2**) as described by (NISSIM; HOFFMANN; HELMERT, 2011), two versions of **Symba** (**SY1** and **SY2**), and A^* being independently guided by the maximum of all heuristics in ζ (**Max**), **iPDB**, **LM-cut** and **Merge & Shrink(M&S)** (NISSIM; HOFFMANN; HELMERT, 2011).

The results are presented in Table 2. The results for the **RGHS** approaches are averages computed over 10 independent runs of the planner; the average numbers are truncated to two decimal places in our table. The variance of the results is small, thus we omitted them from the table of results.

4.4 Discussion of the Results

The system that solves the largest number of instances is **Hybrid**— it solves 218.4 problems on average. As explained above, we combine in **Hybrid** the strengths of both **SS** and **CS** in a single system. **SS** is used to greedily select heuristics from a pool of heuristics with similar evaluation time, and only then **CS** is used for selecting heuristics with different evaluation times. This strategy has proven particularly effective on the Barman domain where **Hybrid**’s first selection is able to select good subsets of **GA-PDBs** and its second selection is able to recognize that it must not include the **iPDB** and **LM-Cut** heuristics to the subset selected by its first selection. As a result, **Hybrid** solves more problems on this domain than any other **RGHS** approach.

Time+CS also performed well in our experiments—the approach solves 215 problems on average. Clearly **Hybrid** and **Time+CS** are far superior to all other approaches tested. For example, **Size + SS** and **Sum** solves only 204 and 203 problems, respectively. While minimizing the search tree size or maximizing the sum of heuristic values, **RGHS** will tend to add accurate heuristics to the selected subset, independently of their evaluation time. As a result, if not minimizing the running time, **RGHS** often adds the **LM-Cut** heuristic to ζ' as **LM-Cut** is often the heuristic that is able to reduce the most the search tree size and to increase the most the sum of heuristic values. However, **LM-Cut** is very computationally expensive, and in various cases the search is faster if **LM-Cut** is not in ζ' . Both **Hybrid** and **Time+CS** are able to recognize when **LM-Cut** should not be included in ζ' because they account for the heuristics’ evaluation time.

Table 2 – Coverage of different planning systems on the 2011 IPC benchmarks. For the **RGHS** and **Max** approaches we also present the average number of heuristics **RGHS** selects ($|\zeta'|$).

Domains	Hybrid	CS		SS		Sum	RIDA*	SY1	SY2	StSp1	StSp2	Max	iPDB	LM-Cut	M&S
		Time	Size	Time	Size										
Barman	6.9	4.75	4	4	4	4	4	10	11	4	4	4	4	4	4
Elevators	19	19	19	19	19	19	19	20	20	18	18	19	17	18	12
Floortile	14	14	14	14	14	14	14	14	14	14	14	14	8	14	10
Nomystery	20	20	20	20	20	19	20	16	16	20	20	20	19	14	18
Openstacks	17	17	15	17	15	15	15	20	20	17	17	11	17	15	17
Parcprinter	17.7	18	19	15	16	16	18	17	17	18	18	18	16	17	16
Parking	7	7	1	2	2	2	7	2	1	5	5	2	7	2	7
Pegsol	19	19	19	19	19	19	19	19	20	19	19	19	20	17	19
Scanalyzer	14	13.87	13	12	13	13	14	9	9	14	14	14	10	12	11
Sokoban	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
Tidybot	15.9	16	16	16	16	16	17	15	17	16	16	15	14	16	9
Transport	14	13.37	11	13	13	13	10	10	11	7	8	9	8	6	7
Visitall	18	18	17	17	17	17	18	12	12	16	16	18	16	10	16
Woodworking	15.7	15	15	12	16	16	15	20	20	15	15	16	9	15	9
Total	218.4	215	203	200	204	203	210	204	208	203	204	199	185	180	175

Note that the difference on the number of problems solved by **Time+CS** and **Time+SS**: While the former solves 215 instances, the latter solved only 200. We conjecture that this happens because **SS** is not able to detect duplicated nodes during sampling. As a result, **SS** often overestimates by several orders of magnitude the actual A^* 's running time. Similarly to the **Size** and **Sum** approaches, due to **SS**'s overestimations, **Time+SS** often mistakenly adds the accurate but expensive **LM-Cut** heuristic in cases where the A^* search would be faster without **LM-Cut**'s guidance. For example, although **iPDB** tends to prune fewer nodes than **LM-Cut** in Parking instances, **iPDB** is the heuristic of choice in that domain. This is because its evaluation time is much smaller than **LM-Cut**'s. **Time+CS** solves 7 Parking instances on average as it correctly selects **iPDB** and leaves **LM-Cut** out of ζ' . By contrast, likely due to its prediction overestimation, **Time+SS** wrongly estimates that **LM-Cut** will reduce overall search time and adds the heuristic to its selected subset. Notice, that **Size+CS** and **Size+SS** also does poorly Parking instances as they also always select **LM-Cut**.

RIDA* is the most similar system to **RGHS**, as it also selects a subset of heuristics from a pool of heuristics by using an evaluation method similar to **CS**. **RIDA*** uses a systematic approach for selecting a subset of heuristics. Namely, it starts with an empty subset and evaluates all subsets of size i before evaluating subsets of size $i + 1$. This procedure allows **RIDA*** to consider only tens of heuristics in their pool. By contrast, **RGHS** is able to consider thousands of heuristics while making its selection.

The ability to handle large set of heuristics can be helpful, even if most of the heuristics in the set are redundant with each other.—as is the case with the **GA-PDBs**. The process of generating **GA-PDBs** is stochastic, thus one increases the chances of generating helpful heuristic by generating a large number of them. **RGHS** is an effective method for selecting a small set of informative heuristics from a large set of mostly uninformative ones. This is illustrated in Table 2 on the Transport domain. Compared to systems which use multiple heuristics (**StSp1** and 2, and **RIDA***), **Time+CS** solves the largest number of Transport instances, which is due to the selection of a few key **GA-PDBs**.

The best **RGHS** approach, **Hybrid**, substantially outperforms the number of instances solved by **Max**—**Hybrid** solves on average more than 19 instances than **Max**. Finally, **Hybrid** and **Time+CS** substantially outperforms all other approaches tested, with **RIDA*** being the closest competitor with 210 instances solved.

4.5 Comparison between SS and IDA*

SS is an algorithm that estimates the number of nodes expanded performed by heuristic search algorithm seeking solutions in state space. We apply SS to predict the number of nodes expanded by IDA* in a given f -layer when using a consistent heuristics.

We first ran IDA* for Fast-Downward benchmark for optimal domains. Our evaluation metric is coverage, i.e., number of problems solved within 30 minutes time limit. We note that in 30 minutes non all the instances for a specific domain using a consistent heuristic can be solved. Afterwards, run SS using as a threshold the f -layer for each instance of each domain, this process is executed using different number of probes i.e., 1, 10, 100, 1000 and 5000.

$$\frac{\sum_{s \in PI} \frac{Pred(s,d) - R(s,d)}{R(s,d)}}{|PI|} \quad (4.1)$$

Where PI is the set of problem instances, $Pred(s,d)$ and $R(s,d)$ are the predicted and actual number of nodes expanded by IDA* for start state s and cost bound d . A perfect score according to the measure is 0.00.

The Table 3 shows how the relative-error behaves when SS makes prediction of the number of nodes expanded by IDA* when it is searching with a specific heuristic and cost threshold. The heuristic used in this experiment is *hmax*. Five probes were used: 1, 10, 100, 1000 and 5000. The average value of IDA* and time were used. The relative-error gets a perfect score while increasing the number of probes. For Barman, the relative-error goes from 0.60 for 1 probe to 0.45 for 10 probes, 0.20 for 100 probes, 0.07 for 1000 probes and 0.04 for 5000 probes. In the case of time, while the number of probes increase, SS need to spend more time calculating the size of the search tree. Then, the time increase. For Barman, the time goes from 0.06 *seconds* for 1 probe to 0.32 *seconds* for 10 probes, 3.21 *seconds* for 100 probes, 32.57 *seconds* for 1000 probes and 214.59 *seconds* for 5000 probes. There are domains such as: Parcprinter, Parking, Pegsol and Visitall that have perfect score using 5000 probes. In the case of Tidybot, the relative-error using 1 probe is smaller than using 10 probes. The reason might be the search tree generated for some instances or the stochastic behavior of SS that sometimes it will choose a node that expand a search tree that will be more expensive to expand. The last column n represent the number of instances where IDA* found the number of nodes expanded when it is searching with *hmax* and cost threshold. The 2011 IPC domains contains 20 instances per domain. Floortile only have 2 instances, it means that when running IDA* for all the instances of Floortile only two instances (opt-p01-001.pddl and opt-p03-006.pddl) have found

Table 3 – Comparison between SS and IDA* for 1, 10, 100, 1000 and 5000 probes using *hmax* heuristic.

Domain	<i>hmax</i>												
	IDA*	time	relative-error					time					n
			1	10	100	1000	5000	1	10	100	1000	5000	
Barman	8835990.00	6016.38	0.60	0.45	0.20	0.07	0.04	0.06	0.32	3.21	32.57	214.59	20
Elevators	1012570.00	4987.57	0.84	0.42	0.23	0.13	0.10	1.40	9.85	96.37	994.33	4425.93	20
Floortile	30522300.00	3919.72	2.02	0.62	0.40	0.14	0.11	0.01	0.07	0.69	6.93	36.60	2
Nomystery	6565740.00	3256.86	0.53	0.26	0.07	0.03	0.01	0.07	0.38	3.63	36.35	181.03	20
Openstacks	80108.50	4017.19	0.03	0.03	0.03	0.03	0.03	94.79	774.86	1067.84	10929.00	11174.30	20
Parcprinter	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.35	3.48	17.29	20
Parking	374925.00	5607.50	0.17	0.04	0.01	0.00	0.00	1.79	11.36	114.28	1196.83	5835.03	20
Pegsol	68763.70	5.00	0.17	0.04	0.02	0.01	0.00	0.01	0.04	0.37	3.69	17.88	20
Scanalyzer	8449890.00	4920.58	0.43	0.25	18.63	0.02	0.01	3.13	28.79	273.74	3033.06	10254.00	20
Sokoban	3118530.00	3932.69	0.41	0.26	0.11	0.05	0.04	0.31	2.00	21.42	222.47	1056.61	20
Tidybot	444473.00	5632.08	300.86	1072.40	5.88	0.01	0.01	4.40	26.48	238.76	2747.10	11925.40	20
Transport	2622880.00	2253.51	0.63	0.54	0.24	0.15	0.11	0.09	0.61	5.89	59.37	290.31	20
Visitall	71032400.00	3704.78	0.12	0.04	0.01	0.00	0.00	0.00	0.05	0.56	5.77	28.07	20
Woodworking	5139070.00	4944.76	1.28	0.69	0.27	0.17	0.07	0.15	1.33	13.21	130.82	664.08	20

number of nodes expanded under some threshold. In summary, we proved that for 2011 IPC domains, SS estimations converges to the real search tree size generated by IDA* when the number of probes goes to infinity.

4.6 Comparison between SS and A*

The Table 4 shows that SS is not a good predictor for A* and that is because SS does not count for duplicate nodes and A* does. SS overestimate the A* search tree size. As a result, SS often overestimates by several orders of magnitude the actual A* search tree.

Three heuristics were used: ipdb, LM-Cut and M&S. The last column **n** represent the number of instances solved by A* using the three heuristics. For this experiment we decided to use only the instances that are solved by the three heuristics at the same time. The columns with A* represents the average of number of nodes expanded by A* using a specific heuristic. The column with SS-error represents the relative-error formula 4.1.

For Barman: Using M&S, A* expands in average 6.67e+06 which is less nodes than ipdb-1.72e+07 and LM-Cut-7.45e+06. However, using M&S, SS-error is 1.26e+36, ipdb-8.68e+31 and LM-Cut-2.21e+30. Which indicates that the number of nodes expanded by SS in average is in the order of magnitude of 30 to 40. In Visitall, SS-error shows that SS overestimates A* highly, which represent a very bad prediction of SS. In Openstack: Using the three heuristics, A* expands almost the same number of nodes for the 4 instances solved. And SS-error shows a score near to the perfect and the reason is because SS expands less nodes than A*.

Table 4 – Poor prediction of SS against A* using ipdb, LM-Cut and M&S with 500 probes

Domain	ipdb		LM-Cut		M&S		n
	A*	SS-error	A*	SS-error	A*	SS-error	
Barman	1.72e+07	8.68e+31	7.45e+06	2.21e+30	6.67e+06	1.26e+36	4
Floortile	1.40e+07	1.74e+18	702435	4.68e+14	4.46e+06	1.90e+12	4
Nomystery	40169.7	6.71e+32	267100	6.14e+19	8236	1.20e+20	9
Openstacks	570099	0.61884	570099	0.677425	569984	0.672143	4
Parcprinter	1157	2.56e+22	1363.67	2.33e+21	766.333	6.36e+20	3
Pegsol	841693	2901.39	398221	6859.86	933430	779.017	16
Scanalyzer	337894	3.94e+33	334747	7.58e+31	337833	2.42e+31	3
Sokoban	376755	1.04e+07	45374	2.74e+06	739775	5.60e+08	9
Transport	1.89e+06	2.91e+38	1.49e+06	1.15e+25	1.73e+06	1.50e+29	2
Visitall	253710	1.69e+46	253195	1.69e+46	253521	1.71e+46	8
Woodworking	3.21e+06	2.53e+18	3.20e+06	2.76e+18	3.21e+06	2.48e+18	3

4.7 Approximation Analysis for SS and A*

Here we show that SS is able to make good selection of heuristics ipdb, LM-Cut and GA-PDBs.

So that, in order to understand how SS and A* behaves we have created plots with the fixed range of 2. This way we are going to have 4 different regions as shown in the Figure 9 . The points represent the fraction between the number of nodes expanded by A* using a heuristic i ($J(h_i)$), and the estimate of the number of nodes expanded by SS ($\hat{J}(h_i)$). Points on regions II and III are heuristics that SS correctly chose to be used with A*. Points following on the other regions are those choices, SS made incorrectly.

Points that fall in each of the regions:

- I $J(h_2) > J(h_1)$ for A*, $\hat{J}(h_1) > \hat{J}(h_2)$ according to SS.
- II $J(h_2) > J(h_1)$ for A* and SS agrees.
- III $J(h_1) > J(h_2)$ for A* and SS agrees.
- IV $J(h_1) > J(h_2)$ for A*, $\hat{J}(h_2) > \hat{J}(h_1)$ according to SS.

In the Figure 10 we can see the distribution of the points in each domain. We use three different heuristics ratios: ipdb, LM-Cut(lmcut) and 10 GA-PDBs(gapdb) which are represented by the symbols ■, ● and ▲ respectively. The ipdb ratio is the result of divide two search tree size generated by $h_1 = \text{ipdb}$ and $h_2 = \text{ipdb}$. The LM-Cut ratio is the result of divide two search tree size generated by $h_1 = \text{LM-Cut}$ and $h_2 = \text{LM-Cut}$. When at least one heuristic h_1 or h_2 is GA-PDB then the heuristic ratio is GA-PDB. This experiment was done using 5000 probes for SS and during 30 minutes.

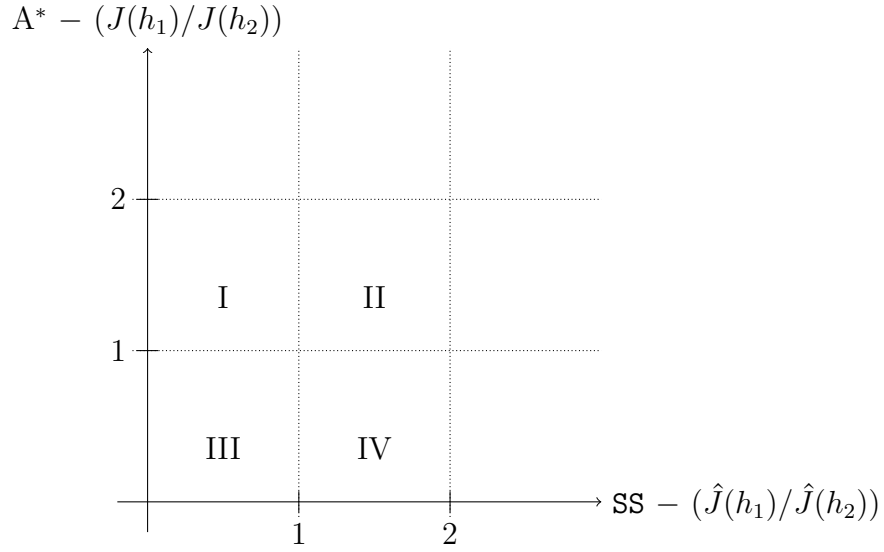


Figure 9 – Cartesian Plane with domain $\langle 0, 2 \rangle$ and range $\langle 0, 2 \rangle$

The eleven plots displayed show the distribution of the heuristic ratios in the four quadrants. We draw the function $y = x$ because **SS** yields a perfect fraction if the point fall in that function. That is why it is important to have such a line as a reference on the plot. We decided to use the same scale on both axis. Otherwise it will be hard to see which points fall on the diagonal line ($y = x$) and which points don't. Furthermore, the scale is 2 for both axis. So, the points that are far away from the quadrants, are set to be in the limit. For example, if any of the ratios r is larger than 1,000 then r will be on the 2 border of the plot.

The points $(0, 0)$, $(1, 1)$, $(2, 2)$ mean that **SS** made a perfect choice and these points represent the function $y = x$. As we are interested in the percentage of points that fall in the quadrants II and III we are going to consider the border only for those quadrants.

The points are dispersed in the positive quadrant of the cartesian plane because we do not have negative number of nodes generated by h_1 or h_2 , and for example just for Tidybot and Woodworking all the points are in the quadrant II or III.



Figure 10 – SS vs A^* ratios for the optimal domains – The number of instances used in each domain are showed next to the name of the Domain.

In Table 5 we present a single number for each domain representing the percentage of choices SS make correctly. From all the domains all are above of the 50% which means that at least the half of the points represent good relation of heuristics. With this experiment

we prove that **SS** is not as bad as we thought it would be when we want to make selection.

Domain	II and III (%)
Elevators	78.57
Floortile	96.08
Nomystery	71.82
Parcprinter	70.50
Pegsol	96.83
Scanalyzer	100.00
Sokoban	89.31
Tidybot	100.00
Transport	51.78
Visitall	98.05
Woodworking	100.00

Table 5 – Percentage of choices **SS** made correctly.

Chapter V

Conclusion

5 Concluding Remarks

This dissertation showed that the problem of finding the optimal subset of size N of a set of heuristics ζ for a given problem task is supermodular with respect to the A^* search tree size and, under mild assumptions, with respect to the A^* running time. Thus, the **RGHS** algorithm which selects heuristics from ζ one at a time is guaranteed to produce a subset ζ' such that the number of nodes expanded by A^* while guided by the heuristic ζ' is no more than approximately 1.36 times optimal. Furthermore, if all heuristics in ζ have the same evaluation time, then we have the same near-optimal guarantee with respect to running time. If the heuristics in ζ have different evaluation times, then the resulting A^* running time is no more than approximately 1.63 times optimal. In addition to minimizing the search tree size and the running time, we also experimented with an objective function that accounts for the sum of heuristic values in the state-space, as suggested by (RAYNER; STURTEVANT; BOWLING, 2013).

Since we cannot compute the values of the objective functions exactly, **RGHS** effectiveness depends on the quality of the approximations we can obtain. We tested two prediction algorithms, **CS** and **SS**, for estimating the values of the objective functions and showed empirically that both **CS** and **SS** allow **RGHS** to make near-optimal subset selections with respect to the search tree size and running time.

Finally, experiments on optimal domain-independent problems showed that **RGHS** minimizing approximations of the A^* running time outperformed all the other approaches tested, which demonstrates the effectiveness of our method for the heuristic subset selection problem.

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